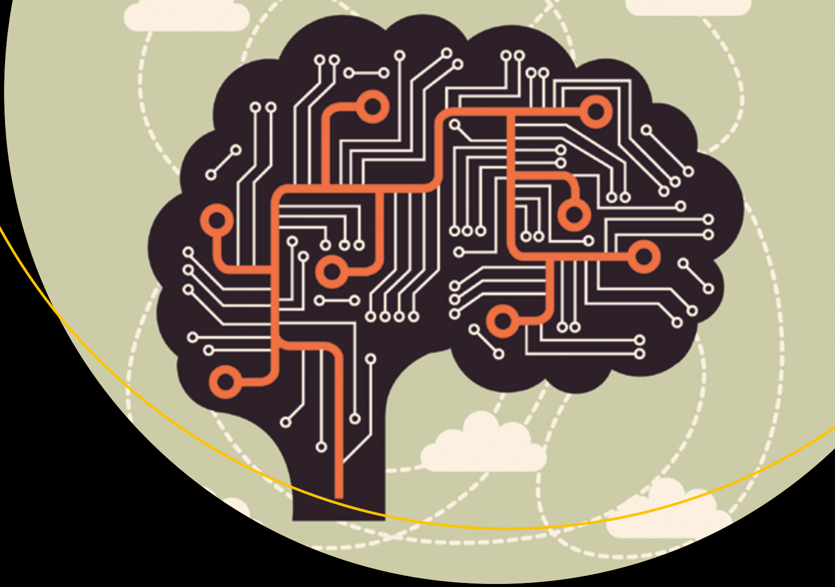

Deep Learning with Azure

Building and Deploying Artificial Intelligence Solutions on the Microsoft AI Platform

Mathew Salvaris
Danielle Dean
Wee Hyong Tok

Apress®

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Dedicated to our families and friends
who supported us as we took away from our personal time
to learn, develop, and write materials for this book.

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Jayden, and Adrian

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Foreword

Artificial intelligence (AI) at its core is about empowering people and organizations to reason and interact with the increasingly digital world all around us. Whether it be in health care or in financial services or in government, AI is helping transform customer experiences, business models, and operational efficiencies in a dramatic way. In this book, Mathew, Danielle, and Wee Hyong present a practical overview of why the impact of AI and deep learning has accelerated recently and illustrate how to build these solutions on the Microsoft Cloud AI platform. They build on their experiences as leading data scientists at Microsoft working both with the product group as well as with external customers. In this book you will see a fresh perspective on how to approach building AI solutions: from the common types of models to training and deployment considerations for end-to-end systems.

This topic is very near to my heart. As a Corporate Vice President and CTO of Artifical Intelligence at Microsoft, I have had the privilege of leading the development of many of our AI products mentioned in this book. Take Unilever, for example: They have built a collection of chat bots with a master bot to help their employees interact with human resources services and all services inside the enterprise. Jabil uses AI for quality control in the circuit board manufacturing process. Cochrane uses AI to classify medical documents and organize information for systematic reviews. Publicis used AI to build an app for makeup recommendations. eSmart Systems has a connected drone with deep learning-based defect detection for inspecting power lines in the energy sector. AI is even being used to identify and conserve snow leopards in the Himalayas. AI is becoming the new normal.

Contrast these examples to enterprise IT systems of the past. We first developed systems of record for enterprises to operate. We had enterprise resource planning (ERP) systems. We had customer resource management (CRM) systems. Most of these were rather siloed and served specific individual functions, with highly structured and curated data. Then the Web came along, and the Internet came along, and we built systems to interact with our customers over the Web. We started building Software as a Service (SaaS) applications hosted in the cloud.

Now what we have at our disposal thanks to the type of technologies and techniques mentioned in this book are **systems of intelligence in the cloud**. A system of intelligence integrates data across all those systems of record, connects you to the systems of engagement, and creates a connected enterprise that understands, reasons, and interacts in a very natural way. Built as a collection of interoperating SaaS applications, these systems collect and organize all relevant data and interactions in the cloud. They constantly learn using AI and deliver new experiences. Live online experiments constantly explore a space of possibilities to teach and derive new AI capabilities. All this is done with the power of the cloud.

When you are building powerful systems like this, you need a very comprehensive platform. It's not just one or two components, or a few components from open source integrated with existing enterprise applications. You can't just take a deep learning tool, learn with a little bit of data, put the model in a virtual machine on the cloud, and build a system of intelligence. You need a comprehensive collection of platform services that only a cloud platform can bring, including systems for identity and security. This is the differentiation of the Microsoft AI platform. It is cloud-powered AI for next-generation systems of intelligence.

I am a big believer in democratizing AI for developers. A lot of AI itself should be almost as simple as calling a sort function. You just call a sort function, and you get an output. The Microsoft AI platform provides a wealth of prebuilt AI like speech recognition, translation, image understanding, optical character recognition (OCR), and handwriting recognition, many of which are built on top of advanced deep learning technology explained in this book. Many of these prebuilt AI capabilities can be fine-tuned with your own data. Developers can use such prebuilt AI to understand the content of every type of media and information —videos, images, natural handwriting—and organize and reason with it. For the use cases where prebuilt AI can solve the problem, these services dramatically increase developer productivity and time to market.

When prebuilt AI isn't flexible enough, there is the ability to build custom AI models on top of a powerful computing layer. This is all a part of the Azure cloud, and of course behind it are the innovations in hardware, the latest CPUs, field-programmable gate arrays (FPGAs), graphics processing units (GPUs), and more to come. Tools such as Azure Machine Learning and Visual Studio Tools for AI allow rapid AI model development using the state-of-the-art deep learning frameworks and open source toolkits. These models can be delivered as docker containers that can be hosted anywhere, in the cloud or on-premises.

Mathew, Danielle, and Wee Hyong have outlined in this book an overview of these different options for developing and deploying AI solutions with a specific focus on deep learning. In the last few years, deep learning has transformed AI, leading to an explosion of use cases. Now, software can learn to interpret the content and meaning of text, images, and video, almost as well as humans can. Applications can understand speech and text, have dialogues with humans in natural ways, and complete actions and tasks on behalf of users. The authors showcase how the best of open source, the best of Microsoft's own AI technology, and the best of the cloud can all come together in one platform to enable you to build novel systems of intelligence.

I invite all of you to take advantage of the power of the cloud and AI coming together as illustrated in this book. AI-infused SaaS applications are the new normal!

Joseph Sirosh
Corporate Vice President and CTO of Artificial Intelligence, Microsoft
July 2018

Introduction

This book spans topics such as general techniques and frameworks for deep learning, starter guides for several approaches in deep learning, and tools, services, and infrastructure for developing and deploying AI solutions using the Microsoft AI platform. This book is primarily targeted to data scientists who are familiar with basic machine learning techniques but have not used deep learning techniques or who are not familiar with the Microsoft AI platform. A secondary audience is developers who aim for an introduction to AI and getting started with the Microsoft AI platform.

It is recommended that you have a basic understanding of Python and machine learning before reading this book. It is also useful to have access to an Azure subscription to follow along with the code examples and get the most benefit from the material, although it is not required to read the book.

How This Book Is Organized

In Part I of the book, we introduce the basic concepts of AI and the role Microsoft has related to AI solutions. Building on decades of research and technological innovations, Microsoft now provides services and infrastructure to enable others who want to build intelligent applications with the Microsoft AI platform built on top of the Azure cloud computing platform.

We introduce machine learning and deep learning in the context of AI and explain why these have become especially popular in the last few years for many different business applications. We outline example use cases utilizing AI, especially employing deep learning techniques, which span from several verticals such as manufacturing, health care, and utilities.

In the first part of the book, we also give an overview of deep learning, including common types of networks and trends in the field. We also discuss limitations of deep learning and go over how to get started.

In Part II, we give a more in-depth overview of the Microsoft AI platform. For data scientists and developers getting started using AI in their applications, there are a range of solutions that are useful in different situations. The specific services and solutions will continue to evolve over time, but two main categories of solutions are available.

The first category is custom solutions built on the Microsoft Azure AI platform. Chapter 4, "Microsoft AI Platform," discusses the services and infrastructure on the Microsoft AI platform that allow one to build custom solutions, especially Azure Machine Learning services for accelerating the life cycle of developing machine learning applications as well as surrounding services such as Batch AI training and infrastructure such as the Deep Learning Virtual Machine.

The second category is Microsoft's Cognitive Services, which are pretrained models that are available as a REST application programming interface (API). In other words, the models are already built on a set of data and users can use the pretrained model. Some of these are ready to use without any customization. For example, there is a text analytics service that allows one to submit text and get a sentiment score for how positive or negative the text is. This type of service could be useful in analyzing product feedback, for example. Other Cognitive Services are customizable, where you can bring your own data to customize the model. These services are covered in more detail in Chapter 5, "Cognitive Services and Custom Vision."

In Part III, we cover three common types of deep learning models—convolutional neural networks, recurrent neural networks, and generative adversarial networks—that are useful to understand in building out custom AI solutions. Each chapter includes links to code samples for understanding the type of network and how one can build such a network using the Microsoft AI platform.

In the final part of the book, Part IV, we consider architecture choices for building AI solutions using the Microsoft AI platform along with sample code. Specifically, Chapter 9, “Training AI Models,” covers options for training neural networks such as Batch AI service and DL workspace. Chapter 10, “Operationalizing AI Models,” covers deployment options for scoring neural networks such as Azure Kubernetes Service for serving real-time models as well as Spark using the open source library MMLSpark from Microsoft.

Note Bibliographic information for each chapter is provided in the Notes section in the Appendix of the book.

PART I

Getting Started with AI

CHAPTER 1

Introduction to Artificial Intelligence

Intelligence can be defined in many ways, from the ability to learn to deal with new situations to the ability to make the right decisions according to some criterion, for example (Bengio, 2010). Standard computers and even basic calculators can be thought to be intelligent in some ways, as they can compute an outcome based on human-programed rules. Computers are extremely useful for mundane operations such as arithmetic calculations, and the speed and scale at which they can tackle these problems has greatly increased over time.

However, many tasks that come naturally to humans —such as perception and control tasks—are extremely difficult to write formal rules or programs for a machine to execute. Often it is hard to codify all the knowledge and thought processes behind information processing and decision making into a formal program on which a machine can then act. Humans, on the other hand, over their lifetime can gather vast amounts of data through observation and experience that enables this human level of intelligence, abstract thinking, and decision making.

Artificial intelligence (AI) is a broad field of study encompassing this complex problem solving and the human-like ability to sense, act, and reason. One goal of AI can be to create smart machines that think and act like humans, with the ability to simulate intelligence and produce decisions through processes in a similar manner to human reasoning. This field encompasses approaches ranging from prescriptive, immutable algorithms for tasks previously performed only by intelligent beings (e.g., arithmetic calculators) to attempts to enable machines to learn, respond to feedback, and engage in abstract thought.

AI is transforming the world around us at an ever-increasing pace, including personalized experiences, smart personal assistants in devices like our phones, speech-to-speech translation, automated support agents, precision medicine, and autonomous driving cars that can recognize objects and respond appropriately, to name just a few. Even through products such as search or Microsoft Office 365, AI is having a useful impact on most people's day-to-day lives. Technology has come a long way from the early days of the Internet in terms of how humans interact with computers. There is an increasing expectation that humans should be getting information in intelligent ways, and be able to interact with devices that hold access to information in natural ways. Creating these types of experiences often requires some type of AI.

> *AI is going to disrupt every single business app—whether an industry vertical like banking, retail and health care, or a horizontal business process like sales, marketing and customer support.*
>
> —Harry Shum, Microsoft Executive VP, AI and Research

Of course, with the rise of AI and intelligent systems comes potential drawbacks and concerns. Despite potential transformative experiences and solutions based on AI, there are ethical issues that are important for both the creators and users of AI to recognize. Technology will continue to shape the workforce and economy as it has in the past as AI automates some tasks and augments human capabilities in others (Brynjolfsson & Mitchell, 2017). Media portrayals often pit the human versus the machine, and this is exacerbated through stories of computers playing games, especially against humans. Computers have been able to beat humans in games such as chess for decades, but with recent AI advances, computers can also surpass human abilities in more sophisticated games where brute force computing power isn't practical, such as the abstract board game Go or the video arcade game Ms. Pac-Man (Silver et al., 2016; van Seijen, 2017).

However, we believe that the discussion should not be framed in a binary of human versus machine. It is important to develop AI that augments human capabilities, as humans hold "creativity, empathy, emotion, physicality, and insight" that can be combined with AI and the power of machines to quickly reason over large data to solve some of society's biggest problems (Nadella, 2016). After all, there is an abundance of information in the world today from which we can learn, but we are constrained by our human capability to absorb this information in the constraints of time. AI can help us achieve more in the time that we have.

Of course, safeguards will need to be put in place as algorithms will not always get the answer right. Then there is debate over what "right" even means. Although computers are thought to be neutral and thus embody the value of being inclusive and respectful to everyone, there can be hidden biases in data and the code programmed into AI systems, potentially leading to unfair and inaccurate inferences. Data and privacy concerns also need to be addressed during the development and improvement of AI systems. The platforms used for AI development thus need to have protections for privacy, transparency, and security built into them. Although we are far from artificial general intelligence and from the many portrayals of a loss of control of AI systems due to computers with superintelligence from popular culture and science fiction works, these types of legal and ethical implications of AI are crucial to consider.

We are still in the early days of the infusion of AI in our lives, but a large transformation is already underway. Especially due to advances in the last few years and the availability of platforms such as the Microsoft AI Platform, upon which one can easily build AI applications, we will see many innovations and much change to come. Ultimately, that change will mean more situations where humans and machines are working together in a more seamless way. Just imagine what's possible when we put our efforts toward using AI to solve some of the world's greatest challenges such as disease, poverty, and climate change (Nadella, 2017).

Microsoft and AI

AI is central to Microsoft's strategy "to build best-in-class platforms and productivity services for an intelligent cloud and an intelligent edge infused with **artificial intelligence** ("AI")" (Microsoft Form 10-K, 2017). Although this statement is new, AI is not new to Microsoft. Founder Bill Gates believed that computers would one day be able to see, hear, and understand humans and their environment. Microsoft Research was formed in 1991 to tackle some of the foundational AI challenges; many of the original solutions are now embedded within Office 365, Skype, Cortana, Bing, and Xbox. These are just some of the Microsoft products that are infused with many different applications of AI. Even in 1997, Hotmail with automated junk mail filtering was built on a type of AI system with classifications that improve with data over time.

Let's look at just a few specific examples today. A plug-in available for PowerPoint called Presentation Translator displays subtitles directly on a PowerPoint presentation as you talk in any of more than 60 supported languages; you can also directly translate the text on the slides to save a version of your presentation in another language, thanks to speech recognition and natural language processing technologies (Microsoft Translator, 2017). SwiftKey is a smart keyboard used by more than 300 million Android and iOS devices that has learned from 10 trillion keystrokes on the next word you want to type and saved 100,000 years of time (Microsoft News, 2017).

Bing—powered by AI with both intelligent search and intelligent answers—powers more than one third of all PC search volume in the United States. Continuing developments, such as Visual Image Search and a new partnership to bring Reddit conversations to Bing answers, continue to infuse intelligence into search (Bing, 2017b). The personal AI assistant Cortana helped answer more than 18 billion questions with more than 148 million active users across 13 countries (Linn, 2017). Seeing AI was launched to assist the blind and low-vision community by automatically describing the nearby visual field of people, objects, and text.

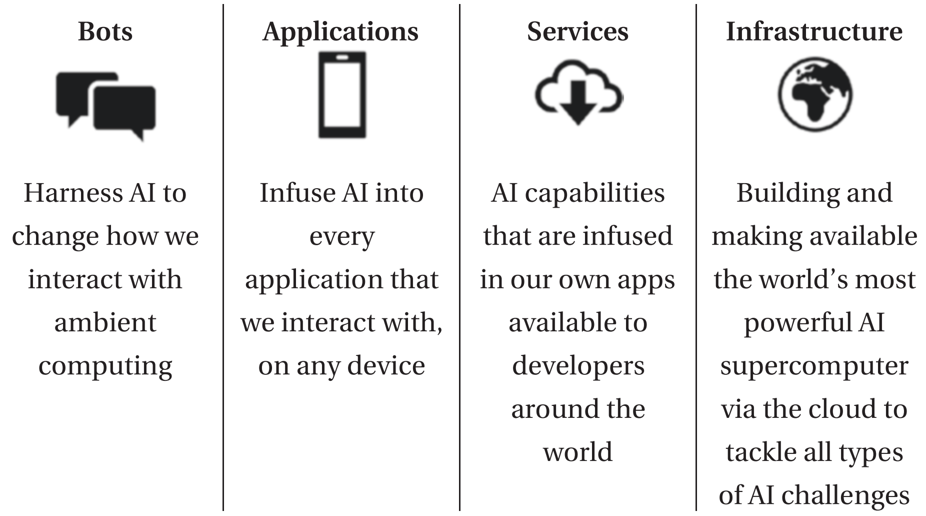
Although these technologies are infused within many products and applications, Microsoft also aims to democratize AI technology so that others can build intelligent solutions on top of their services and platforms. Microsoft's Research and AI group was founded in 2016 to bring together engineers and researchers to advance the state-of-the-art of AI and bring AI applications and services to market. Microsoft is taking a four-pronged approach as visualized in Figure 1-1:

1. Agents that allow us to interact with AI such as Cortana and bots enabled through the Microsoft Bot Framework.

2. Applications infused with AI such as PowerPoint Translator.

3. Services that allow developers to leverage this AI such as the Cognitive Services handwriting recognition application programming interface (API).

4. Infrastructure that allows data scientists and developers to build custom AI solutions including specialized tools and software for speeding up the development process.



Bots	Applications	Services	Infrastructure
Harness AI to change how we interact with ambient computing	Infuse AI into every application that we interact with, on any device	AI capabilities that are infused in our own apps available to developers around the world	Building and making available the world's most powerful AI supercomputer via the cloud to tackle all types of AI challenges

***Figure 1-1.** Microsoft's four-prong approach to democratizing AI*

Thus, the vast infrastructure of the Azure cloud and AI technology used within Microsoft and the larger open-source community are now being made available to organizations wanting to build their own intelligent applications. The Microsoft AI Platform on Azure is an open, flexible, enterprise-grade cloud computing platform that is discussed in more detail in Chapter 4. As a simple example of the power of Microsoft's cloud platform, just one node of Microsoft's FPGA fabric was able to translate all 1,440 pages of the novel *War and Peace* from Russian to English in 2.5 seconds in 2016. Then using the entire capability rather than just a single node, all of Wikipedia can be translated in less than one tenth of a second (Microsoft News, 2017). Microsoft is focused on creating agents and applications infused with AI, and then making this same technology available through services and infrastructure. We are at the tip of the iceberg of what is possible with AI and through the democratization of these AI technologies, many challenges will be solved across the world.

We are pursuing AI so that we can empower every person and every institution that people build with tools of AI so that they can go on to solve the most pressing problems of our society and our economy.

—Satya Nadella, Microsoft CEO

Machine Learning

Although there are many subfields and applications within AI, machine learning (ML) has become extremely popular as a practical tool for many AI-infused applications available today and is the focus of this book. ML is a branch of computer science where computers are taught to process information and make decisions through giving access to data from which computers learn. There are many excellent reference materials on this subject that are outside the scope of this book. Typical ML tasks include classification, regression, recommendations, ranking, and clustering, for example. AI is thus a broader concept than ML, in that ML is one research area within AI around the idea machines can learn for themselves once given access to the right type of data (Marr, 2016).

With classical ML approaches, there are well-established methodologies for utilizing data points that are already useful features or representations themselves, such as data points that capture age, gender, number of clicks online, or a temperature sensor reading as examples. Computers learn how to model the relationship between these sets of input features and the outcome they are trying to predict; the algorithm chosen by the human constrains the type of model the computer is able to learn. Humans also hand-craft the representations of the data, a step often called *feature engineering,* and feed these representations into the ML model to learn. The most common type of ML is supervised machine learning, where the model has labels that are supposed to represent the ground truth against which to learn. The process of the computer learning the parameters within the model is often called *training*.

For example, suppose a telco is aiming to address issues with customer churn. The process with which they could approach this problem using traditional supervised ML techniques is described here. They would like to identify customers who are likely to churn so they can proactively reach out and give them incentives to stay. To build this model, they would first gather relevant raw input data such as the usage patterns of their customers and demographic data such as those pictured in Table 1-1.

Table 1-1. *Example Raw Tables Capturing Information from Customers at a Telco That Needs to Be Processed Before It Can Be Fed into a Machine Learning Model*

Customer Information			**Phone Records**		
Name	**Gender**	**Sign-Up Date**	**Name**	**Call Length**	**Date**
Mary	F	29.01.2011	Mary	12	30.01.2011
Thomas	M	20.06.2013	Mary	1	01.02.2011
Danielle	F	05.05.2014	Mary	3	01.02.2011
Wee Hyong	M	01.09.2012	…	…	…
Mathew	M	15.11.2012	Thomas	22	21.06.2012
Ilia	M	19.02.2013	…	…	…
…	…	…			

Some preprocessing, such as structuring the data by some measure of time, aggregating data points as needed, and joining different tables together that are relevant to whether a customer churns or not, is completed on the raw input data. This is followed by feature engineering to create representations of these customer data to feed into the model, such as creating a feature that represents the length of time with the telco, which is found based on the date the customer signed up for service. Creating a relevant representation of the data is very important for the ML model to be able to discern the patterns within the data, and is usually heavily guided by domain knowledge, as illustrated in Figure 1-2, for example.

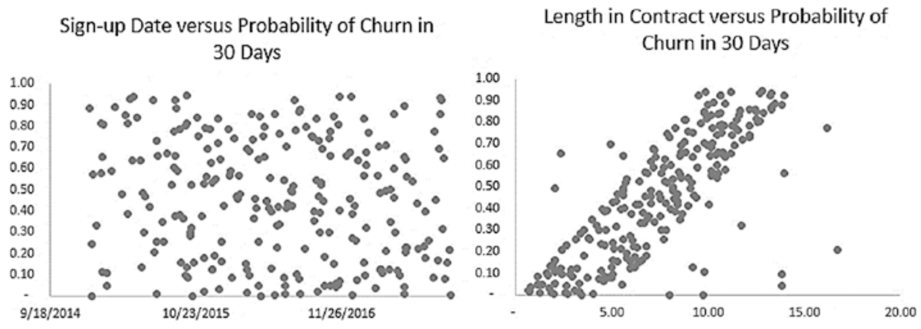


Figure 1-2. *The representation of data is very important; for example, examining the sign-up date at any given point in time might reveal little relationship to the probability of churn within 30 days, but examining the length in the contract at that point in time might reveal a strong relationship in that individuals are more likely to churn within 30 days if they have been in the contract for a longer period of time*

Then historical outcomes, a label of which customers churned or not within a certain amount of time, for example, would be matched to these data and used for the training process of the supervised ML algorithm, as shown in Table 1-2. Applying the trained model to a hold-out set of test data to understand how well it will generalize to new customers, the model would be evaluated based on how well it predicted the historical churn outcomes. After iterating on the preprocessing, feature engineering, and model selection process of trying different models to find the optimal pipeline, this would then be applied to new raw customer telco data to predict which customers are likely to churn in the future.

Table 1-2. *Example Output of Simple Feature Engineering and Matching to the Label of Churn in the Next 30 days*

Name	Month	Total Phone Min	Months with Telco	Churn Next 30 Days
Mary	2.2011	44	0	0
Mary	3.2011	51	1	0
…	…	…	…	…
Thomas	6.2013	152	0	0
Thomas	7.2013	201	1	0
Thomas	8.2013	120	2	1

Note In this case, 0 represents that the individual did not churn, and 1 represents that the individual did churn.

This traditional, supervised ML approach as summarized in Figure 1-3 works for many problems and has been used extensively across many industries. In operations and workforce management, ML has been used for predictive maintenance solutions and smart building management, as well as enhanced supply chain management. For example, Rockwell is able to save up to $300,000 a day through predictive maintenance solutions that monitor the health of pumps in offshore rigs (Microsoft, 2015). In marketing and customer relationship scenarios, ML is used to create personalized experiences, make product recommendations, and better predict customer acquisition and churn. In finance, fraud detection solutions and financial forecasting are often aided by ML-backed solutions.

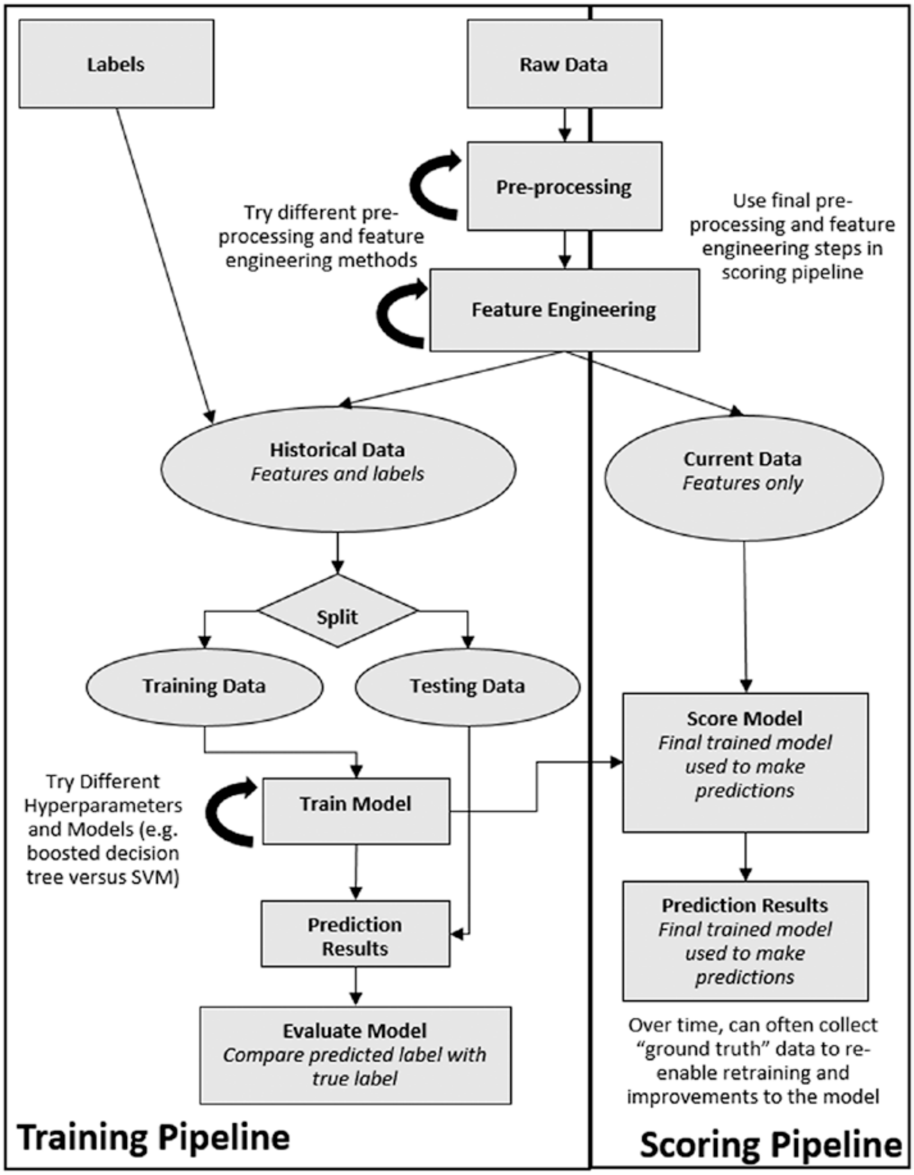

Labels
Raw Data
Pre-processing
Try different pre-processing and feature engineering methods
Use final pre-processing and feature engineering steps in scoring pipeline
Feature Engineering
Historical Data
Features and labels
Current Data
Features only
Split
Training Data
Testing Data
Score Model
Final trained model used to make predictions
Try Different Hyperparameters and Models (e.g. boosted decision tree versus SVM)
Train Model
Prediction Results
Prediction Results
Final trained model used to make predictions
Evaluate Model
Compare predicted label with true label
Over time, can often collect "ground truth" data to re-enable retraining and improvements to the model
Training Pipeline
Scoring Pipeline

Figure 1-3. *Approach for classical, supervised machine learning solutions*

Deep Learning

Although traditional ML approaches work well for many scenarios as discussed earlier, much of the world is quantized in a representation that has no easily extractable semantics, such as audio snippets or pixels in an image.

For example, programming a computer to recognize whether there is a flamingo in each of the images in Figure 1-4 would be exceedingly difficult. These images are represented to a computer as a matrix of pixel values ranging from 0 to 255. Standard colored images have three channels of red, green, and blue and images can be thus represented as three two-dimensional matrices. It's tough to even define which combination of numerical values represents the color pink, let alone process them to identify a flamingo. Even taking a traditional ML approach and hand-crafting features to recognize parts of the image such as a beak and feathers and legs would take very specialized knowledge and a large investment of time to build the different representations from the raw pixel values well enough on top of a large set of images from which the computer could then learn.

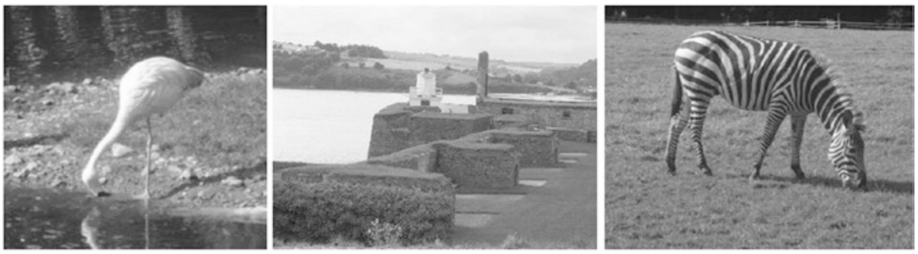


Figure 1-4. *Example images where a machine with AI might be asked questions that require it to process, understand, and reason. An example is whether or not there is a flamingo in each of these images, and hand-crafting features for traditional machine learning approaches is quite difficult and time-consuming.*

Similarly, traditional natural language processing requires complex and time-consuming task-specific feature engineering. For processing speech, different languages, intonations, environments, and noise create subtle differences that make crafting relevant features extremely difficult.

Deep learning, which is the focus of this book, is a further subfield of AI and ML that has especially shown promise on these types of problems without easily extractable semantics such as images, audio, and text data (Goodfellow, Bengio, & Courville, 2016). With deep learning approaches, a multilayer deep neural network (DNN) model is applied to vast amounts of data. Deep learning models often have millions of parameters; therefore they require extremely large training sets to avoid overfitting. The goal of the model is to map from an input to an output (e.g., pixels in an image to classification of image as flamingo; audio clip to transcript). The raw input is processed through a series of functions. The basic idea is that supervised deep learning models learn the optimal weights of the functions mapping this input data to the output classification through examining vast amounts of data and gradually correcting itself as it compares the predicted result with the ground truth labeled data.

The early variants of these models and concepts dating back to the 1950s were based loosely on ideas on how the human brain might process information and were called *artificial neural networks*. The model learns to process data through learning patterns. First are simple patterns such as edges and simple shapes, which are then combined to form more complicated patterns through the many layers of the model. Current models often include many layers—some variants even boast over a hundred layers—and hence the terminology *deep*. The model thus learns high-level abstractions automatically through the hierarchical nature of processing information.

Although data still need to be processed and shaped to fit into a deep learning model, there is no longer a need to hand-craft features, as the raw input (e.g., pixel values in an image) is fed directly into the model. The model learns the features (attributes) of the input data automatically.

There is thus no need for features that represent subparts of the pictures, such as the beak and leg in the flamingo example earlier. Deep learning approaches show promise for learning patterns in the input data to be able to classify directly based on the raw input rather than constructing features manually. Instead, often more time is spent selecting the structure of the network, also called the network architecture, and tuning the hyperparameters, the parameters within the model that are set before the learning process even begins. This has given rise to the idea that network architecture engineering is the new feature engineering (Merity, 2016). Deep learning has also shown promise in several areas of ML where traditional methods also work well, such as forecasting for predicting future values in a time series and recommendation systems that aim to predict the preference a user would have for a given item. More details on specific types of deep learning models as well as recent trends in deep learning are covered in Chapters 2 and 3, respectively.

Rise of Deep Learning

The basic ideas and algorithms behind deep learning have been around for decades, but the massive use of deep learning in consumer and industrial applications has only occurred in the last few years. Two factors have especially driven the recent growth in AI applications, and especially deep learning solutions: increased computation power accelerated by cloud computing and growth in digital data.

Deep learning models require lots of experimentation and often run on large training data, thus requiring a large amount of computing resources, especially hardware such as GPUs and FPGAs that are magnitudes more efficient than traditional CPUs for the computations in a DNN. Cloud computing—running workloads remotely through the Internet in a data center with shared resources—opens access to cheaper hardware and computing power. Resources can be spun up on demand and suspended when no longer in use to save on cost, without investments in new hardware.

With the Internet and connected devices, there is an increasing digitization of our world and massive amounts of data are being collected. Of course, understanding how to organize and harness this information is critical to advancing AI applications. One data collection project that changed AI research was the ImageNet data set, originally published in 2009, which evolved into a yearly competition for AI algorithms, such as which algorithm could classify the images by objects with the lowest error rate (Russakovsky et al., 2015). Deep learning has emerged recently as a powerful technique thanks in large part to the collection of this ImageNet data set. “Indeed, if the artificial intelligence boom we see today could be attributed to a single event, it would be the announcement of the 2012 ImageNet challenge results” (Gershgorn, 2017).

Specifically, in 2012, a deep learning solution drastically improved over the previous year’s results for classifying objects, as shown in Figure 1-5. This solution changed the direction of computer vision research, and accelerated the research of deep learning in other fields such as natural language processing and speech recognition. Continuing more advanced deep learning research, in 2015, Microsoft Research submitted an entry with an architecture called ResNet with 152 layers that was the first time an algorithm surpassed human classification (He, Zhang, Ren, & Sun, 2015).

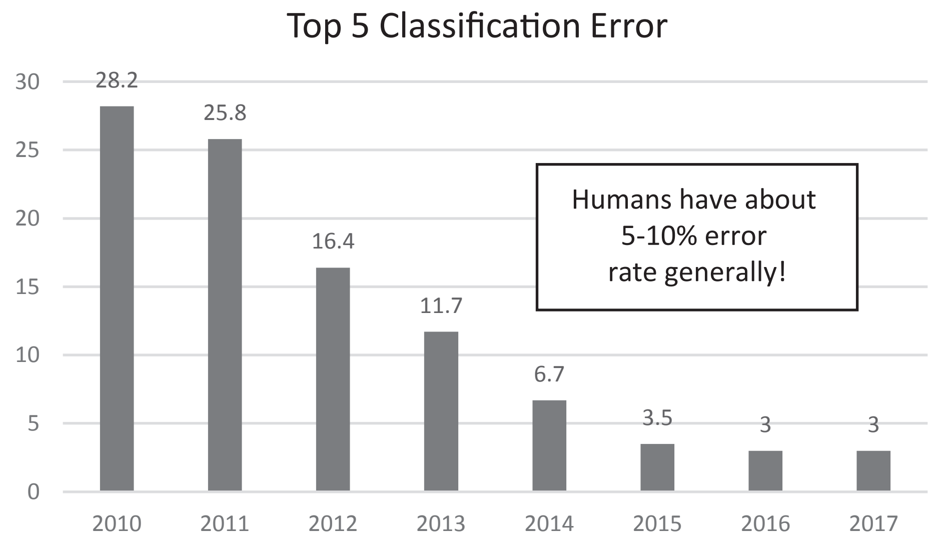


Figure 1-5. *Yearly winning solution's top five classification error rate on ImageNet data for image classification in ILSVRC (Russakovsky et al., 2015)*

This ImageNet data and competition is by no means a pure academic exercise. Many of the architectures used in this competition are often used in industry, many pretrained models on the ImageNet data are made available to the public, and many deep learning computer vision applications are seeded by this work. This is especially true for transfer learning approaches, which are discussed in more detail in Chapter 2.

One thing ImageNet changed in the field of AI is suddenly people realized the thankless work of making a dataset was at the core of AI research. People really recognize the importance the dataset is front and center in the research as much as algorithms. (Gershgorn, 2017)

—Li Fei-Fei

Of course, as one might infer from the drastic improvement in the ImageNet results over the last few years and discussion of the ResNet-152 architecture from Microsoft, there have also been recent advances in algorithms supporting deep learning solutions and tools available to create such solutions. Thus, computational power accelerated by cloud computing, growth in data (especially open labeled data sets), and advanced algorithms and network architectures have together drastically changed what is possible with AI in just the last few years.

Not only can deep learning techniques surpass humans in image recognition, but they are also pushing other areas, such as approaching human level in speech recognition. In fact, some of the first breakthroughs in deep learning happened in speech recognition (Dahl, Yu, Deng, & Acero, 2011). Then in October 2016, Microsoft reached human parity in the word error rate on the Switchboard data set, a corpus of recorded telephone conversations used for more than 25 years to benchmark AI systems (Xiong et al., 2016). These type of innovations are why speech recognition systems on personal devices and computers have improved so drastically in the last few years.

Similarly for natural language processing, on January 3, 2018, Microsoft reached a score of 82.6% on the SQuAD machine reading comprehension data set comprised of Wikipedia articles. Using these data, the computer reads a document and answers a question, and was found to outperform humans on the answers (human performance is at about 82.3%; Linn, 2017; Rajpurkar, Zhang, Lopyrev, & Liang, 2016).

However, it is important to note that these achievements are for a specific problem or application, and do not represent an AI system that can generalize to new tasks. It can also be relatively straightforward to create examples that the computer fails on, so-called adversarial examples (Jia & Liang, 2017). Additionally, the performance of the system could drop dramatically even if the original task is modified only slightly. For example, although computers might now classify general images better than humans, as shown on ImageNet data discussed earlier, giving open-ended answers to questions about images is still far from human performance; there was over 10% difference in accuracy as of June 2017 on the VQA 1.0 data set for visual question answering (AI Index, 2017).

Additionally, deep learning as a general approach still has many limitations such as the inability to reason and lack of understanding. In some cases it can also be more difficult to tune deep learning systems than traditional systems, such as when there is a certain aspect on which it is not doing well, which in some cases could be easier to account for in a traditional ML model with fewer parameters. Other ML and AI fields of research exist and solve other types of problems more accurately than deep-learning-based approaches. There is also much potential around the combination of deep learning with other AI research areas such as reinforcement learning. More details around recent advances, trends, and limitations are discussed in Chapter 3.

In this book, we focus mainly on deep learning approaches within AI and applications where intelligent technology can use deep learning to create solutions that empower people and businesses. These solutions include enabling better engagement with customers, transformation of products, and better optimization of operations, for example. Deep learning applications can often be developed in such a way that they learn and improve over time as more data are collected and often create experiences that connect people and technology in more seamless ways. This book is meant to serve as an introduction to how to develop deep learning solutions with the Microsoft AI Platform. For a more comprehensive overview of deep learning in general including more about the theory and advanced topics, the book by Bengio, Goodfellow, and Courville (2016) is highly recommended.

Applications of Deep Learning

Some classic computer vision problems that can be tackled using deep learning are shown in Figure 1-6, such as being able to classify images and find objects within the images. These common technical problems underlie many different end user applications. For example, photo search applications such as Microsoft's Photo App that allow users to type in descriptions of objects (e.g., "car") or concepts (e.g., "hug") and return relevant results provide a useful capability built through using DNNs.

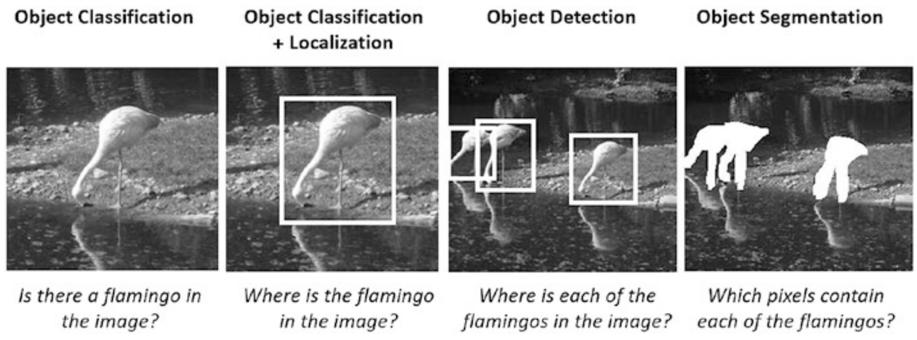

Object Classification
Object Classification + Localization
Object Detection
Object Segmentation
Is there a flamingo in the image?
Where is the flamingo in the image?
Where is each of the flamingos in the image?
Which pixels contain each of the flamingos?

Figure 1-6. *Example computer vision problems*

Many deep learning applications for computer vision surround health care and the medical realm, in subfields where doctors commonly inspect patients or test results visually, such as in dermatology, radiology, and ophthalmology. Imagine the possibilities in that a radiologist can inspect thousands of scans, but a computer can be shown and learn from millions. Humans globally will benefit from the democratization of these services, which will over time become even more accurate and efficient. Project InnerEye is one example, a research project from Microsoft for building innovative tools for automatic, quantitative analysis of three-dimensional radiological images to assist expert medical practitioners.

Examples also abound in manufacturing and utilities. Take eSmarts, a power and utility company based in Norway that provides an automated energy management system, for example. They use drones to collect images of power lines and then analyze them using DNNs to automatically detect faults (Nehme, 2016). Specifically, eSmarts does object detection on the images to detect discs and then predict whether they are faulty. They mix real images with synthetic images they have created to create a large enough data set to be able to predict. Similarly, Jabil, one of the leading design and manufacturing solution providers, is optimizing manufacturing operations by analyzing images of their circuit board assembly line to automatically detect defects (Bunting, 2017). Doing this reduces the number of boards that have to be manually inspected by the operators watching the line and increases their throughput.

Analyzing natural language data is another common use of deep learning. The goal of these applications broadly is for computers to process natural language, classify text, answer questions, summarize documents, and translate between languages, for example. Natural language processing often requires several layers of processing, from the linguistic level of words and semantics to parts of speech and entities, to the type of end user applications shown in Figure 1-7 (Goldberg, 2016).

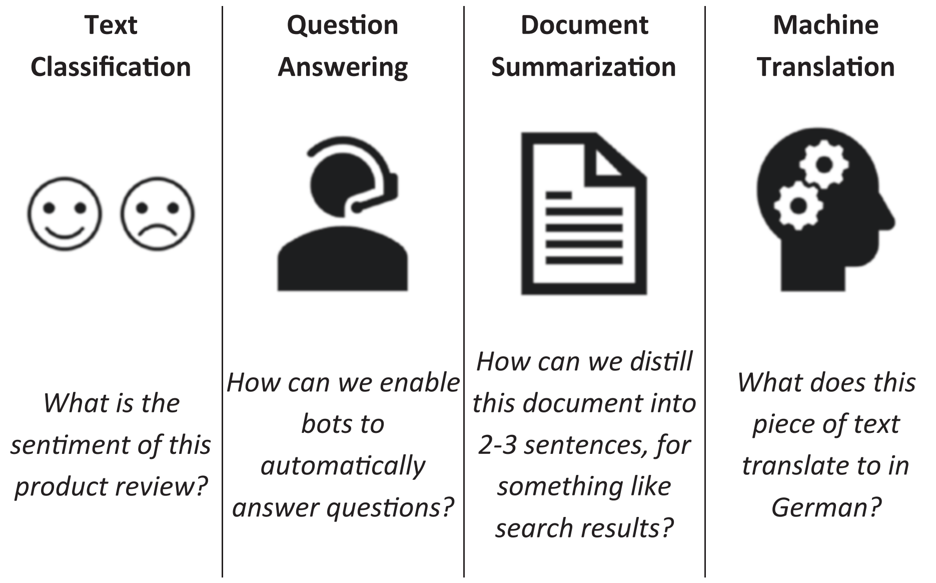

Text Classification
What is the sentiment of this product review?
Question Answering
How can we enable bots to automatically answer questions?
Document Summarization
How can we distill this document into 2-3 sentences, for something like search results?
Machine Translation
What does this piece of text translate to in German?

Figure 1-7. *Example applications of natural language processing from text*

Translating audio data to text is another common application of deep learning. An example application using deep learning for speech recognition, Starship Commander is a new virtual reality (VR) game from Human Interact, where players are active agents in the sci-fi universe (Microsoft Customer Stories, 2017). Human Interact is building the lifelike experiences in the game around human speech, allowing users to influence the storyline and direction of the game through their voice. To enable this, the game needs to recognize speech and understand the meaning of that speech based on the users' underlying intent. Microsoft's Custom Speech Service allows developers to build on top of a speech recognition system that, using deep learning, can overcome obstacles such as speaking style and background noise. Developers can even train with a custom script to recognize the key words and phrases from the game to build a truly custom speech recognition system more quickly and easily than building from scratch.

This is just the first step of recognizing what words were uttered—the game then needs to understand what the user means. Imagine the user is giving a command to start the engine of a ship. There are many ways someone could give that command. Microsoft's Language Understanding Service infers the users' underlying intent, translating between the speech recognized by the game and what the user actually means.

The only reason we can build a product like this is because we are building on the deep learning and speech recognition expertise at Microsoft to deliver an entertainment experience that will be revolutionary.

—Alexander Mejia,
Owner and Creative Director, Human Interact

Of course, these are just some simple examples that showcase how deep learning can bring value to business and consumer applications. Deep learning has shown tremendous potential for applications around speech, text, vision, forecasting, and recommenders, for example (see Figure 1-8), and we expect to see tremendous use of deep learning in many industries and more applications in the future.

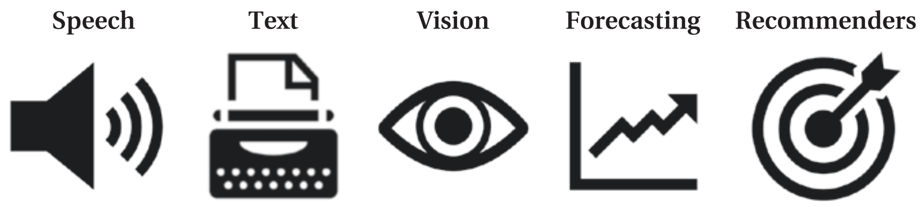


Figure 1-8. *Example areas where deep learning solutions have demonstrated great performance*

Interacting with more applications through speech and text rather than menus, chatting with bots on a company's web site or human resources page to solve routine problems quickly, innovative photo applications that allow natural search and manipulation, and finding relevant information quickly from documents are just some example scenarios where deep learning will drive forward value to businesses and consumers.

Summary

This chapter introduced the concepts of AI, ML, and deep learning as summarized in Figure 1-9. Buildingon decades of research and technological innovations as mentioned briefly in this chapter, Microsoft now provides services and infrastructure to enable others who want to build intelligent applications—including powerful deep learning applications as discussed in this book—through the Microsoft AI Platform built on the cloud computing platform Azure.

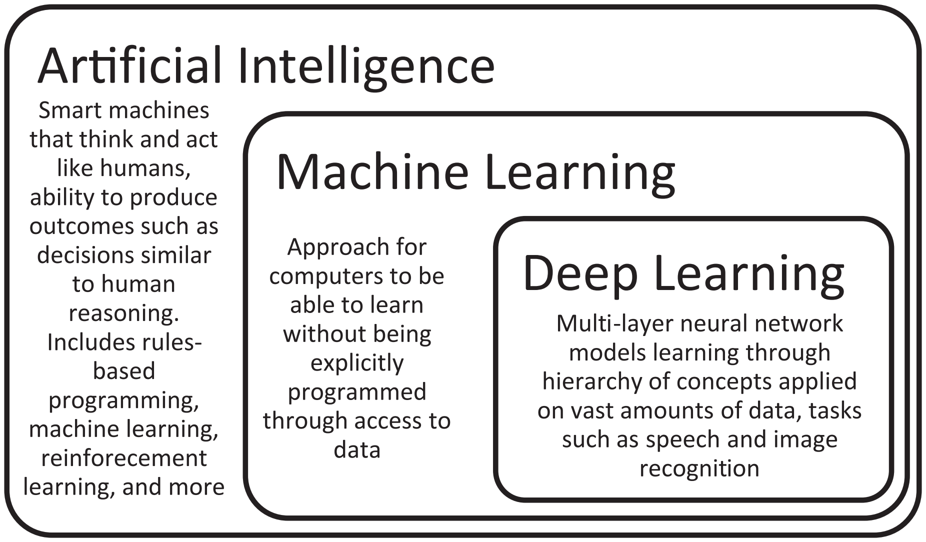

Artificial Intelligence
Smart machines that think and act like humans, ability to produce outcomes such as decisions similar to human reasoning. Includes rules-based programming, machine learning, reinforecement learning, and more
Machine Learning
Approach for computers to be able to learn without being explicitly programmed through access to data
Deep Learning
Multi-layer neural network models learning through hierarchy of concepts applied on vast amounts of data, tasks such as speech and image recognition

Figure 1-9. *Visualization of relationship between artificial intelligence, machine learning, and deep learning*

This chapter also discussed reasons behind the recent rise of deep learning such as increased computational power and increased data set sizes, especially for labeled data such as ImageNet, which has been made available publicly. These have propelled forward research in areas such as computer vision, natural language processing, speech recognition, and time series analysis. We are also seeing many valuable applications built on deep learning in areas such as health care, manufacturing, and utilities. We believe this trend will continue, but that other areas of AI research will also be useful in the future.

In the next chapter, we introduce common deep learning models and aspects needed to get started with deep learning. In Chapter 3, we then discuss some of the emerging trends in deep learning and AI as well as some of the legal and ethical implications mentioned briefly in this chapter in more detail.

CHAPTER 2

Overview of Deep Learning

In Chapter 1, we gave an overview of AI and the basic idea behind deep learning. We discussed how deep learning—applying artificial neural network models with a large number of layers—has yielded state-of-the art results for several research areas, such as image classification, object detection, speech recognition, and natural language processing.

Deep learning has also shown promise in many applications across areas such as health care, manufacturing, and retail. In 2017, for example, an AI system did as well as dermatologists in identifying skin cancer and a model could diagnose irregular heart rhythms from single-lead electrocardiogram (ECG) signals better than a cardiologist (Esteva et al., 2017; Rajpurkar, Hannun, Haghpanahi, Bourn, & Ng, 2017). We believe this trend will continue: Deep learning will bring value to more scenarios across many industries and progress toward improved AI experiences will continue to accelerate.

In this chapter we briefly go over the basics of several types of networks that are now commonly used. We also describe the data science workflow for deep learning projects including a description of some of the popular tools and technologies that data scientists and developers need to get started when working on a deep learning project. This chapter also provides practical techniques for getting started with deep learning projects, without spending significant time in training a convolutional neural network using large data sets like ImageNet from scratch.

This chapter is simply an overview of deep learning and the building blocks for developing deep-learning-based solutions. In the third part of this book, these basic concepts are built on for introducing in more detail several common network models. These later chapters (e.g., Chapter 6) provide sample code that one can follow. Although this chapter also covers the basic ideas of training and scoring deep learning models, we discuss more specifics along with sample code for training and scoring on Azure in the fourth part of this book.

Common Network Structures

There are many variations of artificial neural network models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), generative adversarial networks (GANs), and autoencoders, for example, as shown in Table 2-1. Today, most problems require data scientists to select the appropriate network type and network structure for the problem at hand. Data scientists spend time trying different problem formulations and exploring different hyperparameters (e.g., type of network structure), and see which works for their specific problem. In the sections that follow, we describe briefly each of these types of network structures.

Table 2-1. *Common Network Structures and Common Applications*

CNNs	**RNNs**	**GANs**	**Autoencoders**
Image classification, object detection	Natural language processing, time series analysis	Text to image creation, image to image translation	Dimensionality reduction, anomaly detection, recommender systems

Convolutional Neural Networks

CNNs are simply neural networks that make use of the convolution operator in at least one of their layers. CNNs are feedforward neural network models that are a foundational network especially for computer vision problems. Feedforward implies that information is always fed in one direction in the network and there are not any loops in the network structure. CNNs have also been used in other areas such as speech recognition and natural language processing for certain tasks.

CNNs work on the premise of translation invariance; for images, this builds on the idea that an object within the image is the same object even if it is moved, as illustrated in Figure 2-1. This is important, as the network does not have to relearn what each object is in every position of the image. This requires significantly less data to train and can generalize better to learning how to process images than if we had to separately learn how to recognize objects at each location as would be required in a multilayer perceptron (MLP).

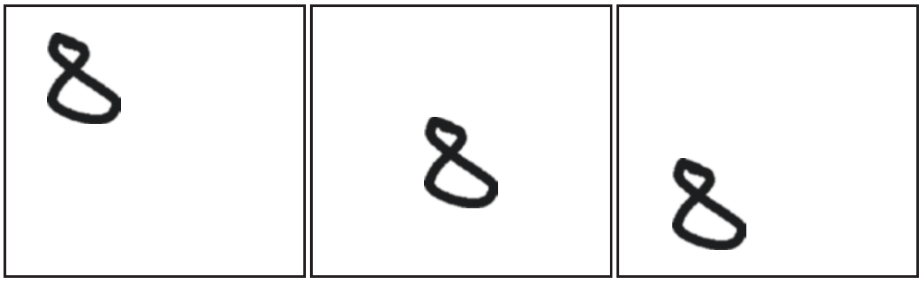


Figure 2-1. *CNNs allow for translation variance; for example, the handwritten digit "8" is still an 8 even if it is moved within the image. This concept helps the network learn how to process images more effectively than simply applying a vanilla neural network model with hidden layers.*

For example, if we want the model to be able to learn to identify what is a cat, no matter where the cat is located in the image it shares the same characteristics from which the model should learn: how to identify fur, cat ears, tail, and so on.

In CNNs, the input image is fed through what is often called a filter or kernel, which acts as a feature detector in the network. You can think of these feature detectors as trying to learn aspects such as edges, shapes, or patterns within the image. This is done by applying the feature detector on one patch of the image at a time through sliding windows, with the results of this convolution operation saved into what is called a convolved image or feature map. CNNs hold the property of translation invariance as mentioned earlier, as the filters share the same weights as applied to each image patch that after applying form the convolved image. The depth of a convolutional layer in a neural network corresponds to the number of filters used in that layer.

A form of down-sampling through the use of pooling layers is used to reduce the size of the data going through and remove the potentially redundant aspects that the network at that stage has learned to react to. A "max pooling" layer for example simply takes the maximum value from the output of the convolved image for each window of the image as shown in Figure 2-2, where the stride represents the number of pixels by which the window jumps. Convolution and pooling layers are used in many combinations, transforming an input image into an array that is then input into at least one fully connected layer that feeds out to the predicted output classes as visualized in Figure 2-3. The fully connected layers simply act as a classifier to predict the output class.

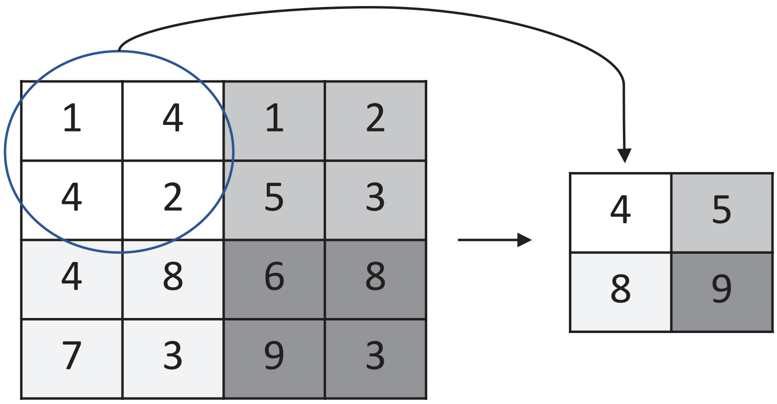


Figure 2-2. *Max pooling operation with 2 by 2 filters with stride of two*

In other words, CNNs can be conceptually split into two main pieces, both of which are optimized together:

1. **The automatic feature extractor** creates the hidden feature state—features that represent aspects of image that are relevant for classification—and is made up of layers such as convolutional and pooling layers.

2. **The classifier** is a fully connected neural network made up of at least one layer that classifies the hidden feature state.

The automatic feature extractor part of CNN enables the network to learn aspects such as edges and shapes of the image without having to explicitly program the network to compute these features as was done with the use of algorithms such as scale-invariant feature transform (SIFT).

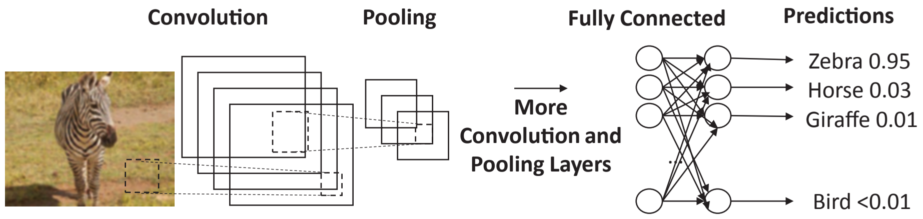


***Figure 2-3.** Basic building blocks of convolutional neural networks (CNNs)*

Importantly, CNNs automatically learn the values of the filters ("feature detectors") through training the network on large amounts of labeled data using a concept called backpropagation, continuing to improve the weights within the network until the classification error is minimized. In the early layers of the networks, the network typically creates filters that look to be recognizing aspects of the images such as edges, basic shapes, and colors. Later layers learn increasingly complex patterns until all of these patterns put together can help the network learn the classification of the input.

There are many ways to combine the fundamental building blocks of convolutional layers, pooling layers, and fully connected layers among other aspects of CNNs such as stride (number of pixels by which filters are slid over the image), dropout (used to reduce overfitting), and types of activation functions that introduce nonlinearity to the network and process the output of each layer. There are also many ways to train and formulate the network, and much research centers around how to design the layers, connections, and aspects such as depth versus width. More details and sample code can be found in Chapter 6, so we only describe briefly the basics required for an overview of deep learning as well as to understand some of the trends related to CNNs that will be discussed in Chapter 3.

Recurrent Neural Networks

RNNs directly make use of sequential information. Sequences passed to the network could be in the input, output, or even both. The RNN processes sequences of data through what is sometimes called a "state" or "memory." Unlike CNNs, which are feedforward networks, RNNs contain loops in the network structure, as illustrated in Figure 2-4 and Figure 2-5. However, note that CNNs have increasingly been shown to be useful for analyzing sequential information as well, as is mentioned in more detail in Chapter 7.

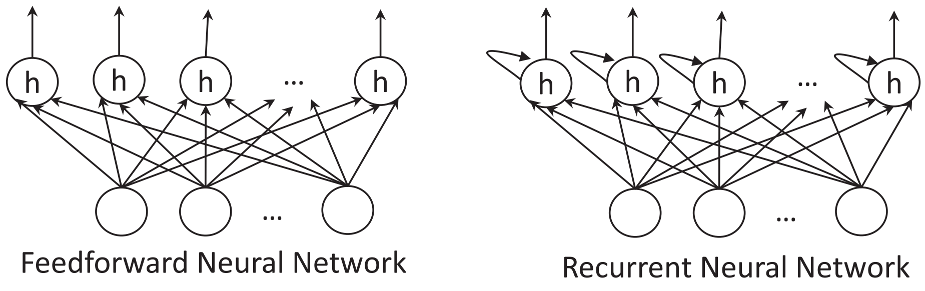


Figure 2-4. *Recurrent neural networks have a loop in the network structure and process data over sequences*

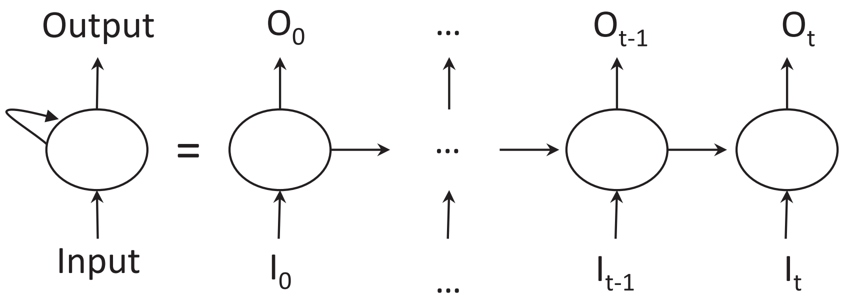


Figure 2-5. *RNNs process information over sequences. Often this sequence represents information over time, such that a loop in the RNN can be "unrolled" to see that the output at a given point in time is a function of the inputs at previous points in time.*

RNNs have been successful in many natural language processing tasks, as the meaning of a word in a sentence is dependent on the other words surrounding it. RNNs have also been useful in other applications such as time series prediction, speech recognition, and handwriting recognition.

A "vanilla" RNN processes a sequence of vectors with a single "hidden" vector by applying a recurrence formula at each step. This formula takes both the current vector as well as the previous state. Variants of RNNs have been proposed that are able to better process longer sequences such as long short term memory networks (LSTMS). More details on RNNs along with sample code can be found in Chapter 7.

In Figure 2-6, an example application of both CNNs and RNNs is shown in the automatic generation of image descriptions in the alt text of images pasted within a PowerPoint file. CNNs are used to classify the objects within the image and RNNs are used to generate the sentence description based on those objects.

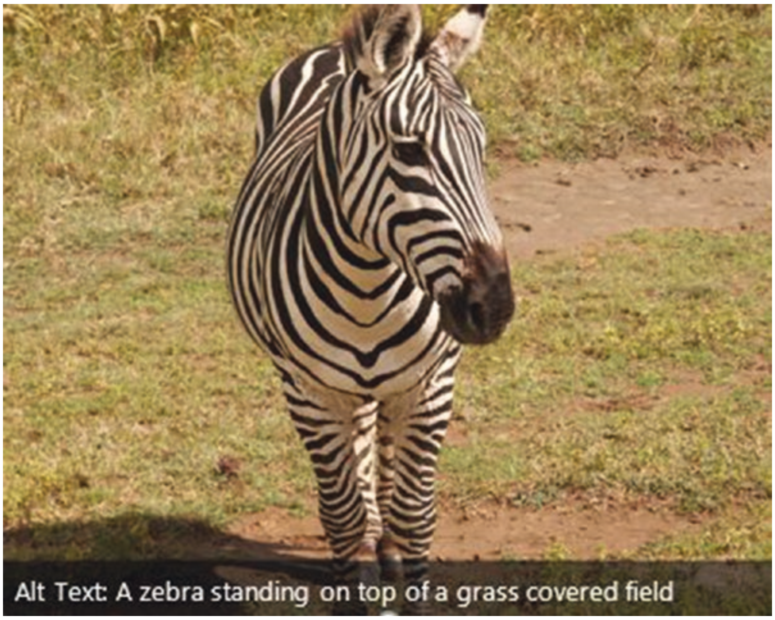

Alt Text: A zebra standing on top of a grass covered field

Figure 2-6. *Image descriptions are created automatically for images in PowerPoint through use of both CNNs and RNNs*

Generative Adversarial Networks

GANs are a more recent development in deep learning that actually solves a given problem through training two separate network models in competition with each other (Goodfellow et al., 2014). In recent years, GANs have shown tremendous potential and have been applied in various scenarios, ranging from image synthesis, enhancing the quality of images (superresolution), image-to-image translations, to text-to-image generation, and more. In addition, GANs are the building blocks for advancements in the use of AI for art, music, and creativity (e.g., music generation, music accompaniment, poetry generation, etc.).

GANs are emerging as powerful techniques for both unsupervised and semisupervised learning. A basic GAN consists of the following:

- **A generative model** (i.e., generator) generates an object. The generator does not know anything about the real objects and learns by interacting with the discriminator. For example, a generator can generate an image.
- **A discriminative model** (i.e., discriminator) determines whether an object is real (usually represented by a value close to 1) or fake (represented by a value close to 0).
- **An adversarial loss** (or error signal) is provided by the discriminator to the generator such that it enables the generator to generate objects that are as close as possible to the real objects.

More details about GANs are included along with sample code Chapter 8.

We expect that GANs will become more popular in the coming years, even outside of the use of creative applications, as they have potential to address how to create unsupervised learning methods that would greatly expand the reach of ML applications. Today, these types of models take a long time to train and are notoriously difficult to tune, and we expect that research will continue to advance the practicality of these networks for real applications. As this type of technology sees more real-world applications, improves on quality, and expands to more mediums such as videos, we believe more debate will surface over their use. For example, the implications of not being able to discern true content from fake are quite far-reaching, with examples already highlighted in the media such as near-realistic fake words inserted into videos of politicians speaking (Metz & Collins, 2018).

Autoencoders

Autoencoders are another type of a feedforward network and have been used for applications such as dimensionality reduction, anomaly detection, and learning generative models. These neural network models have an input layer, an output layer, and at least one hidden layer in between. Importantly, autoencoders have the same number of units in the input layer as the output layer, and their purpose is thus to reconstruct the original values in the input layer. Of course, these are designed in such a way that they do not copy the input data exactly but are restricted so that they can only learn approximately, such as having a smaller dimension than the input data, as one example. Autoencoders thus learn most relevant properties to reconstruct the input data. As such, they can be useful for unsupervised learning applications where there is no target value for prediction or for learning features for input into another algorithm. They have shown promise for many applications such as recommender systems (Kuchaiev & Ginsburg, 2017).

Deep Learning Workflow

For many AI projects, deep learning techniques are often used as the building block for building innovative solutions ranging from image classification and object detection to image segmentation, image similarity, and text analytics (e.g., sentiment analysis, key phrase extraction). Often, people will ask, “How do I get started with using deep learning in my team?” To get started with deep learning, it is important to understand the tools and technologies that are used in deep learning projects and the workflow for building a solution.

Given the business requirements for an innovative solution, a data scientist will need to map it to one or more deep learning tasks. For example, let’s say a retail business wants to create an end-to-end customer shopping experience for mobile devices, where customers can take a photo of a shirt or a dress, and an application running on the mobile device can then match it to the shirts and dresses in the shopping catalog. To achieve this, the data scientist maps this to an image similarity problem: Take a new input image, and match it against all the shirts and dresses in the catalog. The top *N* images will be returned to the mobile application. While working with the application developers, other requirements need to be addressed as well, like identifying and cropping the image to just the person wearing the shirt or dress, for example. This will require the use of both object detection and image classification.

Once the deep learning task is identified, a typical deep learning workflow will include the following:

1. Identify relevant data set(s).
2. Preprocess the data set.
3. Train the model.
4. Check the performance of the model.

5. Tune the model.
6. Deploy the model.
7. Iterate and collect more data to enable retraining.

Finding Relevant Data Set(s)

Most companies wanting to get started with deep learning projects often face difficultly when trying to find relevant data set(s) that they can use for training their deep learning models for a specific business scenario. In addition, the data set needs to be labeled. For example, to train a CNN to identify the type of clothing (e.g., polo shirt, t-shirt, dress, jeans), a data set consisting of images of clothing, with labels denoting whether the image is a shirt, dress, t-shirt, or jeans is required. These images can come from the existing product catalogs, public image data sets (e.g., diverse set of images from ImageNet, CIFAR-10, Deep Fashion), and scraped from various web sites.

To seed the initial training and validation data set if data are not already available, data scientists often use a search engine (Figure 2-7) for performing an image search on a specific class (e.g., jeans), where the image owner has labeled the image as free to use for commercial use.

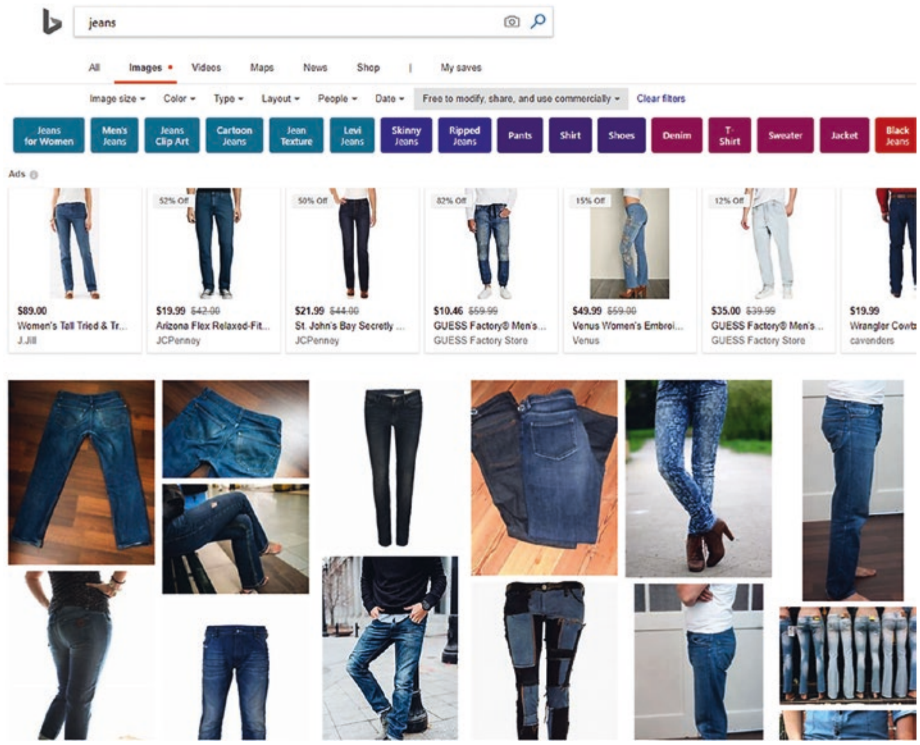

jeans
All
Images
Videos
Maps
News
Shop
My saves
Image size
Color
Type
Layout
People
Date
Free to modify, share, and use commercially
Clear filters
Jeans for Women
Men's Jeans
Jeans Clip Art
Cartoon Jeans
Jean Texture
Levi Jeans
Skinny Jeans
Ripped Jeans
Pants
Shirt
Shoes
Denim
T-Shirt
Sweater
Jacket
Black Jeans
Ads
$89.00 Women's Tall Tried & Tr... J.Jill
52% Off $19.99 $42.00 Arizona Flex Relaxed-Fit... JCPenney
50% Off $21.99 $44.00 St. John's Bay Secretly ... JCPenney
82% Off $10.46 $59.99 GUESS Factory® Men's... GUESS Factory Store
15% Off $49.99 $59.00 Venus Women's Embroi... Venus
12% Off $35.00 $39.99 GUESS Factory® Men's... GUESS Factory Store
$19.99 Wrangler Cowb cavenders

Figure 2-7. *Results returned from an image search using Bing*

Data Set Preprocessing

After the data scientist has acquired the relevant image data sets, he or she will need to prepare them for training. Often, many real-world image data sets are imbalanced (commonly known as the *minority class problem*). This means there might be more images for a specific class (e.g., polo shirts), and fewer images for another class (e.g., t-shirts). To solve the imbalanced data set problem, a data scientist applies various tricks to increase the number of images in the minority class or down-sample from the more frequent classes until parity is achieved.

Another commonly used preprocessing technique is data augmentation to help the model generalize over multiple conditions, to improve its invariance to aspects such as rotation, translation, and scaling. This includes applying various transformation to the image, such as scaling, rotating, random cropping of the image, flipping the image, adjusting the brightness and contrast, and more. Various data augmentation capabilities are supported in the different deep learning frameworks.

Training the Model

After the data set has been preprocessed and prepared, the data scientist is ready to start designing the deep learning model architecture and training the model. The key ingredients that enable effective modeling and training of deep learning models are (1) choosing a deep learning toolkit, and (2) training using hardware such as GPUs. This is discussed in more detail in the next section in this chapter.

Depending on the size of the data set, the model can be trained on a local machine (e.g., laptop, PC, Mac) or using infrastructure available in the public cloud, such as Microsoft Azure. Azure provides both NC-series virtual machines (VM) with Nvidia GPUs, as well as a managed service, called Azure Batch AI, which enable you to easily scale up and down GPUs that you need for your deep learning jobs. This will be covered in more detail in Chapters 4 and 9.

Validating and Tuning the Model

During training of the deep neural network, there are several key metrics that will provide insights on the learning efficiency and the quality of the models at each epoch. An *epoch* refers to a full pass of the training data set. Two metrics are commonly tracked: (1) loss function, and (2) training and validation accuracy.

By evaluating the *loss function* at each epoch, the quality of the model at the end of each epoch can be evaluated. A lower loss is a good indication of a better model. There are many hyperparameters that are set before the learning process even begins—the learning rate is one important hyperparameter that can have a significant impact on the results of the model. By plotting loss (y axis) and epochs (x axis), whether the learning rate has been set appropriately can be understood: A good learning rate leads to a lower loss in a shorter amount of time. Often, the learning rate is tracked for both the training and validation data set. However, it is also important to make sure that the model has not overfit the training data. Figure 2-8 shows an example of different learning rates. In practice, the learning rate curves are not smooth and it is possible to modify the learning rate over the training process as needed. This is just one example of the type of validating and tuning that is required during the process of training a deep learning model.

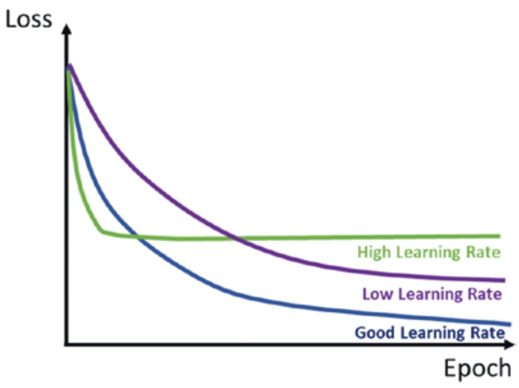


Figure 2-8. *Different learning rates. Illustration inspired by Stanford cs231n course available at `http://bit.ly/StanfordCS231n`.*

The second metric commonly tracked is *the training and validation accuracy*. By charting the accuracy (y axis) and epoch (x axis), it can be understood whether the model has overfit the training data set. If the training and validation accuracy curves are close to each other, then very little overfitting has occurred. If the training and validation curves are far apart, overfitting has occurred, and it is important to revisit the model, as it does not generalize to new data as expected. Figure 2-9 shows how to identify overfitting by looking at the accuracy curves for the training and validation data set.

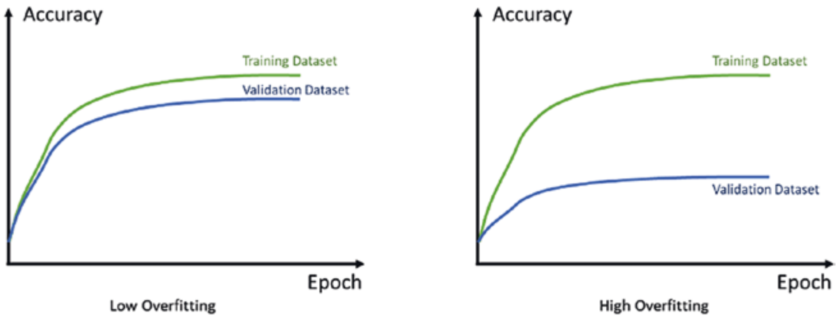


Figure 2-9. *Identifying overfitting using training and validation accuracy*

Deploy the Model

Once the quality of the model is high enough for the requirements of the solution, the next step is to deploy it. Today, deep learning models can be deployed to the cloud as REST APIs, run in a batch on a schedule, deployed onto mobile devices (e.g., iPhones, Android phones, iPads, and more), or edge devices (e.g., Internet of Things [IOT] gateways). This depends on how you are thinking about using the trained deep learning model. For example, if you are developing a web application, and you are enriching it with AI, it makes sense to operationalize your deep learning models as REST APIs, which can be easily consumed by the web application. If you are developing a mobile application, you should consider both connected and disconnected scenarios, as well as latency requirements. You will either have the models running offline on the mobile device, or a hybrid model where you have both combinations of models that run on device and REST APIs that provide more powerful functionality in the cloud.

To deploy the deep learning models as REST APIs, several options exist. You can leverage Azure Machine Learning Operationalization services (more details will be covered in subsequent chapters in the book) to host the model in a docker container, and expose one or more REST endpoints, or you can build your own hosting stack (e.g., use of Flask, CherryPy backed by high-performing web server like NGINX). You can easily deploy this hosting stack on Microsoft Azure, as well. Depending on the scenario, you might want to run the model in batch mode on a large set of data on a schedule. The type of hardware such as GPUs is also a relevant factor to consider. More details are discussed in Chapter 10.

For more consideration around approaching data science workflows in general, including deep learning projects, we suggest the Microsoft Team Data Science Process available at `http://bit.ly/MSFT_TDSP`. This includes an overview of the data science life cycle, a suggested standardized project structure and infrastructure, and resources for data science projects.

Deep Learning Frameworks & Compute

As mentioned earlier, two key ingredients you need for performing deep learning training are (1) use of a deep learning framework, and (2) performing training using a GPU. General-purpose computing on GPUs especially through efficient use of matrix multiplication has been accelerated through frameworks such as CUDA and OpenCL. These have enabled higher level libraries such as cuDNN on top of CUDA for building deep neural nets; cuDNN underpins popular deep learning libraries.

There are now many popular deep learning frameworks such as Tensorflow, PyTorch, CNTK, MXNet, and Caffe2, as well as popular higher level APIs such as Keras and Gluon. The choice of a deep learning toolkit depends on many factors, including the availability of good tutorials and existing implementations of model architectures and pretrained models, skill sets of the AI talents in the company, flexibility of the toolkit in expressing complex deep neural networks, availability of built-in helper functionalities (e.g., rich set of APIs for data augmentation and transformation), ability to effectively leverage both CPUs and GPUs, and ability to perform distributed training.

We recommend the deep learning comparison repo available at `http://bit.ly/DLComparisons` for understanding differences between different deep learning frameworks on a few common scenarios, with example frameworks considered as illustrated in Figure 2-10. This repo has several stated goals:

1. A "Rosetta Stone" of deep learning frameworks to allow data scientists to easily leverage their expertise from one framework to another.
2. Optimized GPU code using the most up-to-date highest level APIs.
3. A common setup for comparisons across GPUs (potentially CUDA versions and precision).
4. A common setup for comparisons across languages (Python, Julia, R).
5. The possibility to verify expected performance of own installation.
6. Collaboration between different open source communities.

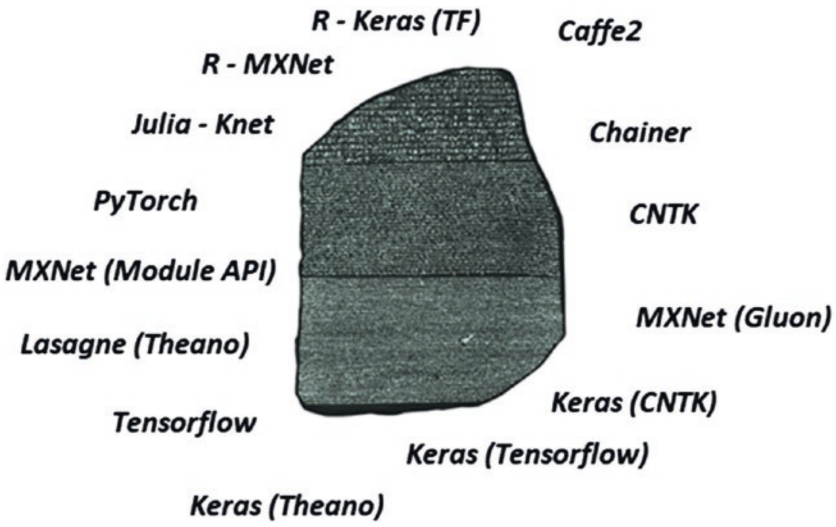


Figure 2-10. *We recommend the "Rosetta Stone" for deep learning frameworks available on GitHub at* `http://bit.ly/DLComparisons` *with timings for different variants of Azure GPU VMs available for running deep learning code*

The comparisons in the repo are not meant to suggest anything about the overall performance of the different frameworks because they omit important comparisons such as availability of pretrained models as just one example. Yet they serve as a nice way to get started and compare many popular frameworks for common scenarios.

Note Keras is emerging as a popular deep learning library, due to its ability to provide high-level abstractions for modeling deep neural networks, and the flexibility to choose different back ends (e.g., TensorFlow, CNTK, Theano).

In 2017, Facebook and Microsoft announced the ONNX open source format for deep learning models to enable data scientists to train a model in one framework but deploy it in another, for example.

Since the announcement, other companies and developers of popular frameworks have joined this open source interoperability standard effort for transferring deep learning models between frameworks. There are also packages that allow converting directly from one framework to another, such as MMdnn, which helps users directly convert between different frameworks as well as visualize the model architecture.

Many of the deep learning libraries also include various ML algorithms. Most of these deep learning libraries support distributed training, and this helps a lot for doing deep learning at scale. Most of the deep learning libraries have Python wrappers. If you are an R user, you can also use R interfaces for some of the deep learning libraries (e.g., R interfaces to TensorFlow, Microsoft Cognitive Toolkit [CNTK], Keras, and more). In this book, we focus on the use of the libraries for modeling deep neural networks. Figure 2-11 shows several deep learning libraries, and the code activity on GitHub.

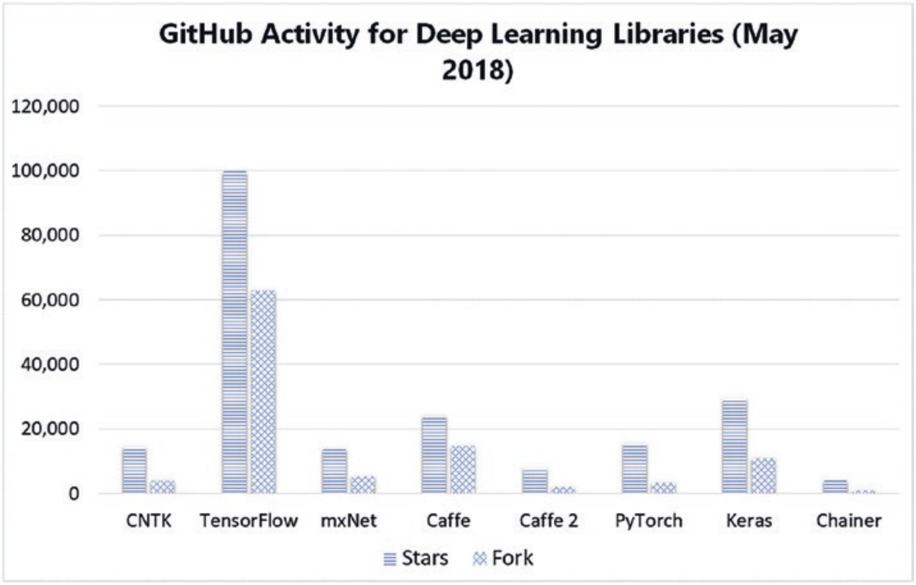


Figure 2-11. *GitHub Stars/Fork for deep learning libraries*

Although most of the examples in this book use Tensorflow, the Microsoft AI Platform supports any open source framework. In addition, we include a few examples of using other frameworks, such as a pedagogical example showing how one can train a CNN model using many different deep learning frameworks using the Microsoft Batch AI service in Chapter 9.

GPUs make the training of deep learning models possible within a reasonable time frame. In recent years, innovations in both algorithms and availability of faster GPUs have enabled the training of deep learning models to be completed quickly. For example, the training of CNNs like ResNet-50 using the publicly available ImageNet data set used to take 14 days or more before 2017. Within months in 2017, the time taken to train ResNet-50 decreased significantly, from an hour to approximately 15 minutes. Preferred Network was able to train ResNet-50 CNN model with ChainerMN with 1,024 P100 GPUs in 15 minutes in November 2017, for example.

Jump Start Deep Learning: Transfer Learning and Domain Adaptation

A major trend to jump starting deep learning solutions has been to build prior knowledge into the development of the model so it does not learn solely from the data of the problem at hand. Two common ways this is done is through a concept called transfer learning in computer vision and domain adaptation mainly through the use of word embeddings in natural language processing.

Transfer learning is especially useful in computer vision tasks such as image classification and object detection. The basic idea is that we want to be able to transfer our learning from one application to another. Transfer learning enables data scientists to quickly adapt existing pretrained models (e.g., AlexNet, ResNet-50, InceptionV3, etc.) to new domains. For example, a CNN can be trained on the large ImageNet data with millions of examples. This CNN then internally holds the representation of how to process images well, such as how to detect edges, shapes, and patterns to distinguish between objects. We thus want to be able to use this knowledge, captured within the weights of the network to use in a classification scenario with significantly less data, such as distinguishing between types of shirts on a retail web site or distinguishing between defects and nondefects through images taken on a manufacturing assembly line, for example.

Thus to jump start deep learning projects in computer vision, for example, we recommend data scientists leverage pretrained models that are trained using publicly available data sets such as ImageNet, CIFAR-10, and COCO. These data sets contain millions of images (from diverse domains) and have been carefully curated by the respective research labs (often through crowd-sourcing efforts) and annotated with class labels.

The pretrained models are used to jump start image classification, object detection, and image segmentation problems. These pretrained models, trained on large image data sets, are used either as featurizers for new images, or to further fine-tune to adapt to domain-specific images (e.g., medical x-ray images, PCB circuit board images, etc.) to improve on the quality of the predictions. Table 2-2 shows the different types of transfer learning. Table 2-3 shows the input and output initialization required for each type of transfer learning.

***Table 2-2.** Different Types of Transfer Learning*

Type	How Is Transfer Learning Used?	How to Train?
Standard DNN	None	Train featurization and output jointly
Headless DNN	Use the features learned on a related task	Use the features to train a separate classifier
Fine-tune DNN	Use and fine-tune features learned on a related task	Retrain featurization and output jointly with a small learning rate
Multitask DNN	Learned features need to solve many related tasks	Share a featurization network across both tasks

***Table 2-3.** Initialization of Inputs and Outputs of a Deep Learning Model Using Transfer Learning*

Type	How to Initialize Featurization Layers	Output Layer Initialization
Standard DNN	Random	Random
Headless DNN	Learn using another task	Separate ML algorithm
Fine-tune DNN	Learn using another task	Random
Multitask DNN	Random	Random

Natural language processing has also been accelerated by pretrained models, but in this case, it is often in the training of the representation of words that goes into the deep learning model known as word embeddings. Taking a step back, in natural language processing, words were typically represented through one-hot encoding, where each word is represented by a vector of length equal to the size of the vocabulary; all values are zeros except at the position that corresponds to that word in the vocabulary, which has the value of 1. Models would need to learn from scratch with just the data of the problem at hand every time to understand how to process the words and what their meaning was in the context of the specific natural language processing task. In contrast, word embeddings are low-dimensional vectors that encode semantic meaning of words, encoding semantically related words close to each other in the embedding vector space.

Importantly, word embeddings can be trained on large, unlabeled data and many pretrained word embeddings are made available for use in other natural language processing tasks. By using a pretrained word embedding such as one trained on Google News, knowledge about how words are related to each other is embedded into the model built with them.

Word embedding vectors are learned using so-called word2vec algorithms such as Skip-Gram and CBOW. These are simple neural network models that aim to predict words in a window around each word. The concept is that semantically related words will appear in similar context and thus obtain similar vector representations. Of course, domain-specific word embeddings might be beneficial to better represent words within the model, and recent research has also focused on how to allow better domain adaptation between natural language processing applications.

Models Library

Many pretrained deep neural networks are available for each of the deep learning libraries. For example, Microsoft CNTK and TensorFlow provide pretrained models for several state-of-the-art CNNs (AlexNet, GoogLeNet, ResNet, and VGG). Caffe's Model Zoo provides a rich set of 40 and more pretrained models for state-of-the-art CNN (ResNet, Inception, VGG, etc.), and supporting various scenarios (e.g., car model identification, recognizing different landmarks and places, scene recognition, etc.). Google Word2Vec is a popular pretrained word-embedding model with many available tutorials.

You can use these pretrained models to jump start your deep learning projects, or further fine-tune the network for your business scenarios. This will often save significant amounts of time training the base models on a diverse data set.

More Info Find out more about example pretrained models:

CNTK Pretrained Image Model: `http://bit.ly/CNTKModels`
TensorFlow Official Model: `http://bit.ly/TensorflowModels`
Caffe Model Zoo: `http://bit.ly/CaffeModels`
Tensorflow Word2Vec: `http://bit.ly/TensorflowWord2Vec`

Summary

This chapter briefly introduced several common types of neural networks including CNNs, RNNs, and GANs, which are discussed in more detail along with sample code in later chapters. We also discussed the deep learning workflow, the nuts and bolts of starting a deep learning project and some of the libraries that can be used to develop and train deep neural networks. To help jump start deep learning projects, data scientists and developers can leverage pretrained models as the foundations for featurizing images or use them to further customize and fine-tune to adapt for your business domains. In the next chapter, we discuss some of the trends in the deep learning field as well as some of the limitations of this type of modeling approach.

CHAPTER 3

Trends in Deep Learning

This chapter discusses some of the trends in deep learning and related fields. We cover specifically which trends might be useful for what tasks as well as discuss some of the methods and ideas that could have far-reaching implications but have yet to be applied to many real-world problems. We finish by covering briefly some of the current limitations of deep learning as well as some other areas of AI that seem to hold promise for future AI applications, and discuss briefly some of the ethical and legal implications of deep learning applications.

Variations on Network Architectures

One of the first trends in the field of deep learning was to build deeper networks with more layers to solve problems with increasing complexity. However, training such deep networks is difficult, as they are harder to optimize, and accuracy can degrade rather than improve. As mentioned in Chapter 1, Microsoft released a network structure in 2015 that builds on the concept of residual learning with their architecture called ResNet (He, Zhang, Ren, & Sun, 2015). Instead of trying to learn a direct mapping of the underlying relationship between an input and output within the network, the difference or residual between the two is learned. With this concept, training of networks substantially deeper than previously used before became possible, with a network of 152 layers winning the 2015 ILSVRC competition on the ImageNet data. A class of networks called Inception networks alternatively focus on wide architectures where not all layers are simply stacked sequentially, aiming to increase both performance as well as computational efficiency of neural network models (Szegedy, Liu, et al., 2014).

Note To accelerate development, practitioners should leverage network architectures from the research community such as Resnet-152 rather than trying to build and train CNNs from scratch.

Residual Networks and Variants

There have been many suggested network architectures in recent years, and this trend continues to result in more network architecture choices. Many architectures rely on modifications to ResNets, such as ResNeXt, MultiResNet, and PolyNet (Abdi & Nahavandi, 2017; Xie, Girshick, Dollár, Zhuowen, & He, 2017; Zhang, Li, Loy, & Lin, 2017). Combining different types of approaches has also been considered such as Inception-ResNet (Szegedy, Ioffe, & Vanhoucke, 2016). In contrast, FractalNet is an extremely deep architecture that does not rely on residuals (Larsson, Maire, & Shakhnarovi, 2017).

DenseNet

DenseNet is another popular network structure where each layer is connected to all other layers; its popularity lies in that it allows a substantial reduction in the number of parameters through feature reuse while alleviating a problem related to training of the networks called vanishing gradients (G. Huang, Liu, van der Maaten, & Weinberger, 2018).

Small Models, Fewer Parameters

Related to the reduction of the number of parameters with DenseNet, another trend in CNNs is for the creation of more efficient networks that are built on fewer parameters and have a smaller model size. In general, larger networks enable more accurate predictions, but there are clever ways of creating architectures and conducting model compression to achieve performance close to or at par with larger networks. These networks can thus be run faster and with less processing power, which can be especially useful, for example, on embedded and mobile devices where the computational power and storage are limited.

SqueezeNet, introduced by Iandola et al. (2016), is described as having accuracy similar to AlexNet with 50 times fewer parameters and model size less than 0.5 MB, using depth-wise separable convolutions to reduce the number of parameters. MobileNet is another example that was designed specifically for mobile and embedded vision applications (Howard et al., 2017), which has recently been extended with MobileNetV2. Besides designing efficient smaller networks, alternatives include pruning weights from existing deep networks, pruning filters, and quantizing weights within the network (Mittal, Bhardwaj, Khapra, & Ravindran, 2018). As one example, by pruning certain connections in the VGG16 architecture, the size can be reduced by a factor of 49 without modifying the predictions from the model (Han, Mao, & Dally, 2016).

In practice, we recommend data scientists try many network structures based on the current research that are often made available through model zoos and different deep learning frameworks as was described Chapter 2. Data scientists must try the different options and consider the trade-offs between aspects such as ease of training and speed of scoring the models as required for the specific data set and problem at hand.

Capsule Networks

CNNs are a fantastic architecture and have been one of the key reasons for the resurgence of neural networks. As mentioned earlier, CNNs work on the premise of translation invariance. This translation invariance is limited, however, and they have significant drawbacks that stem from the fact that they do not deal with other translations such as size, illumination, and rotation of the input well as shown in Figure 3-1. This is usually overcome by providing many examples, augmenting the data with translated and generally modified examples, and as discussed earlier, pooling layers.

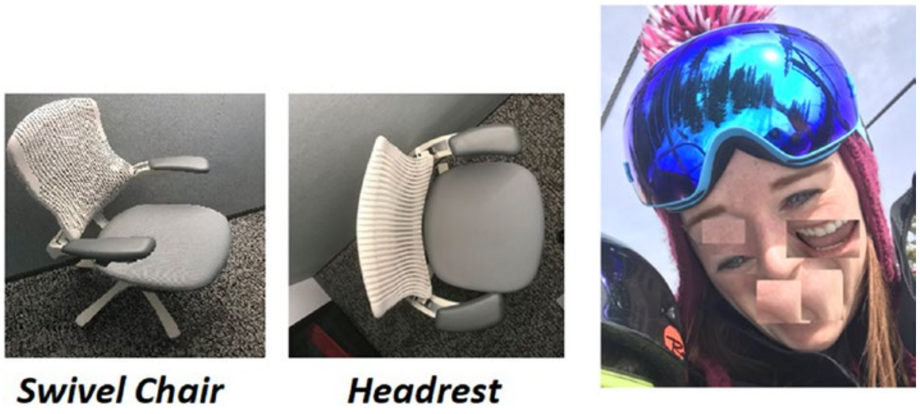


Figure 3-1. *CNNs do not build an internal representation of objects and thus struggle to understand objects when viewed from a different angle, and they can be fooled when parts of the object are out of order. In this case, a model thinks the same chair is a different object when viewed from above and thinks the face is a person even though parts of the face are moved around. Capsule networks are designed to tackle this problem in a more natural way using the idea of inverse graphics.*

In general, CNNs do not intrinsically care about the spatial and orientational relationship between the items in the image; they only care whether these features exist. Higher level features are simply a combination of lower level features. Furthermore, CNNs use methods that reduce the spatial dimensions of the data and in effect increase the receptive field, the field of view of the higher level nodes. This allows the nodes to detect higher level features in larger regions of the input image. One of the methods of doing this is max pooling, which we explained in Chapter 2. By using max pooling, though, the CNNs lose spatially acuity. For this reason, max pooling is viewed as a bit of an anathema by Hinton and therefore he sought to devise a new architecture, capsule networks (Sabour, Frosst, & Hinton, 2017).

Capsule networks are inspired by the idea of inverse graphics. In traditional graphics we describe an object and its pose parameters and through the process of rendering, the object is displayed on a screen. In inverse graphics we want to observe a scene and from it infer the objects and their poses.

A capsule in a capsule network tries to predict the presence and properties of a particular object at a given location in the scene. Capsules output vectors rather than scalars and the length of the vector encodes the estimated probability of the object being present at that particular location and the orientation encodes the pose parameters of the object.

Capsule networks also use a novel way of passing information between layers called dynamic routing. This means that the routing is not fixed beforehand, but determined dynamically during its execution. The method to achieve this proposed by Sabour, Frosst, and Hinton (2017) is called routing by agreement. The architecture of capsule networks is very similar to that of CNNs: Layers of capsules succeed each other with lower level features detected by the lower capsule and the higher level capsules composing these features to create higher level features. In routing by agreement, the lower level capsule outputs n-dimensional vectors whose length encodes the probability and its orientation in the n-dimensional space for the pose of the object detected. The subsequent capsule layer takes the input of all these capsules and then through an iterative process determines the weights of the inputs. In essence each layer's estimation of the pose parameters is matched against the pose parameters of the subsequent layer. The closer the match, the higher the weights between the subsequent capsules. The scalar product of the vectors is used as the measure of similarity. This means that the weights between capsules are not static but change depending on the capsule vectors present.

Capsule networks have demonstrated state-of-the-art results and require fewer training examples than CNNs due to their pose invariance. Training them is still slow, though, due to the iterative nature of dynamic routing, and they still remain to prove themselves across all the computer vision domains currently dominated by CNNs.

Object Detection

Another trend in deep learning is the use of meta-architectures, building out on top of previous solutions to solve other types of problems. In analyzing images, for example, the ideas and pieces of CNNs are used as a backbone beyond image classification problems to solve problems such as object detection and image segmentation. One foundational model in object detection, for example, was the R-CNN model, which simply proposed cropping each image externally to the model using a region proposal method such as selective search, extracting features from each cropped image based on a CNN model, and then classifying each cropped image with support vector machine models (SVMs; Girshick, Donahue, Darrell, & Malik, 2013). In object detection, the trend has been to use the latest network architecture as feature extractors, but also emerging, improved meta-architectures as well as improved approaches for performance. For example, faster R-CNN and R-FCN are alternative meta-architectures that also build on standard CNNs but also predict bounding boxes using "anchors" during training, which are boxes overlaid on the image at different locations, scales, and aspect ratios (Ren, He, Girshick, & Sun, 2015; Dai, He, & Sun, 2016).

The YOLO approach (You only look once: unified real-time object detection; see Figure 3-2) uses a simple CNN applied to the entire image (Redmon, Divvala, Girshick, & Farhadi, 2015). YOLO was the first approach to make real-time object detection practically possible through framing object detection not as a classification problem with bounding boxes, but as a regression problem to bounding boxes and associated class probabilities. Other related approaches such as SSD, MultiBox, and YoloV2 have been released recently along the trend of providing models that run faster while aiming to maintain good accuracy levels (Liu et al., 2015; Redmon & Farhadi, 2016; Szegedy, Reed, Erhan, Anguelov, & Ioffe, 2014).

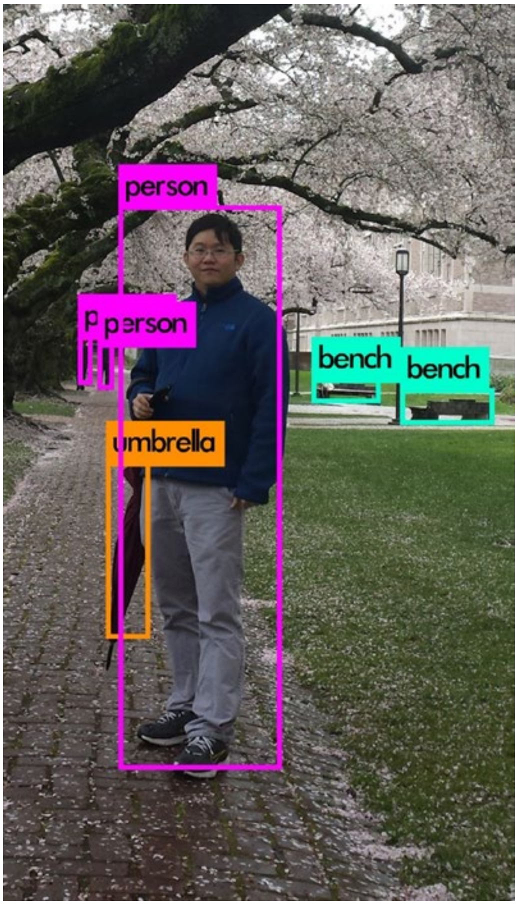


Figure 3-2. *Applying a pretrained object detection model to find objects using YOLO*

In practice, trade-offs might need to be made between setting up the solution for accuracy of results versus speed of inference depending on whether the application has requirements such as real-time performance. Different meta-architectures, choices made during training such as the CNN architecture used as the feature extractor, image resolution, hardware, and software make broad generalizations about the ideal approach hard to make (J. Huang et al., 2017).

Object Segmentation

Many recent proposals explored how to reduce the need for the bounding box for object detection and explored segmentation neural network models such as LinkNet, as well as to use more specialized networks for other vision tasks, such as CortexNet for identifying actions on images rather than categorizing single frames (Culurciello, 2017). Mask R-CNN and focal loss for dense object detection are other recent trends in object detection that have been open sourced by Facebook AI Research within a software system called Detectron and are thus available to run on the Microsoft AI Platform (He, Gkioxari, Dollar, & Girshick, 2017; Lin, Goyal, Girshick, He, & Dollar, 2017). This marks truly exciting progress in object segmentation!

More Sophisticated Networks

The types of networks discussed in this chapter are just some examples within the broad space of deep learning. There are many ways to formulate deep neural networks as well as combine with other methodologies within a broader solution. As an example within the field of speech translation, Microsoft Research recently found state-of-the-art results on a large benchmark data set, the English–French translation campaign from 2014 at `http://bit.ly/2EzMeRY` using what was coined a deliberation network (Tian, 2017). This network builds on top of a simple LSTM architecture, combined with dual learning that is inspired by how humans deliberate. The premise is simple: A first-pass decoder goes over the sentence similar to creating a rough draft, whereas the second-pass decoder takes both the original input as well as the rough draft as input to get to the final solution. This is just one example, and there are numerous others of combining deep learning technologies together or with other methodologies as part of a larger solution as well.

Similar to CNNs and RNNs, there has been large growth in the variety of proposed types and uses of GANs. There have also already been many commercial applications of GANs. For example, Microsoft worked with Getty Images, which provides stock photos, to explore image-to-image translation, such as turning a sunny beach photo into an overcast beach photo to provide more options to their customers (Liakhovich, Barraza, & Lanzetta, 2017). Microsoft Research also developed a "drawing bot" based on GANs that is able to create images based on only a text description, images that are based only on the computer's "imagination" (Roach, 2018). The AttnGAN model proposed for this purpose was able to outperform previous state-of-the-art models in early 2018, producing a nearly threefold boost in image quality for text-to-image generation on an industry standard test (Xu et al., 2017).

Automated Machine Learning

Another area of ML that has been garnering interest the last few years is that of automatic ML and smart hyperparameter tuning (Bergstra, Yamins, & Cox, 2013; Domhan, Springenberg, & Hutter, 2015; Fusi & Elibol, 2017; Golovin et al., 2017; Li, Jamieson, DeSalvo, Rostamizadeh, & Talwalkar, 2016). Both these areas of research try to make use of historical information, optimization, and metalearning to be able to automatically or semiautomatically arrive at optimal ML pipelines, neural network topologies, and so on.

Another such piece of work centered around using reinforcement learning and LSTMs to create new neural network architectures (Zoph & Le, 2016). Reinforcement learning (RL) is a subfield of AI that is designed to have software agents automatically determine the optimal behavior to maximize performance, through a reward feedback process. It is a type of automated learning mechanism. The resulting CNN architecture called NASNet achieved state-of-the-art results on the CIFAR10 data set at the end of 2017 and is 1.05 times faster than the previous state-of-the-art model. Others have recently focused on more efficient search mechanisms such as leveraging current networks and reusing trained network weights (Cai, Chen, Zhang, Yu, & Wang, 2017). In the future we will probably see further endeavors in this area as computation becomes even quicker and the scale up and out of cloud infrastructure is fully realized.

Related to architecture search, the field of neuroevolution has recently received more visibility in the research and industrial community. This is a subfield of AI that aims to understand and invoke an evolutionary process similar to the one that produced the form of intelligence in human brains within a computer. Whereas NASNet and related areas of research focus on trying to automate the creation of networks, most applications of deep learning today require a human to specify the architecture of the neural network. Rather than having a fixed network architecture that we aim to optimize, researchers in the field of neuroevolution study the process of learning itself.

Neuroevolution researchers have found interesting results that we believe will influence more strongly applications of AI in the future. One example from neuroevolution is the concept of novelty search, the idea that optimizing for novelty might provide better results than optimizing for the direct outcome. Stanley (2017) illustrated the concept through the problem of trying to find a model for a robot to learn how to walk. One might guess that the best way to get an amazing walking robot would be to artificially combine together the models of the best walkers from the previous generation. However, the robots who are good at walking in the first generations might just be lurching forward unreliably. In contrast, robots that try oscillating their legs in a regular pattern fall down right away but could lead to more robust walking in the future, so simply breeding based on the best in the past might not be beneficial for the future. This field has also benefited tremendously by the increased computation power available today and we expect to see more advances and direct impact on the deep learning field.

Recently algorithms and processes for deriving AI from the field of neuroevolution have been applied to the deep learning architecture search problem and compared against reinforcement learning type approaches that resulted in NASNet. Real, Aggarwal, Huang, and Le (2018) found that regularized evolution approaches performed better than reinforcement learning at early search stages and generally found that they produced similar or higher accuracy results without having to retune parameters. The new architecture from this evolutionary search process called AmoebaNets resulted in state-of-the-art results for several image classification tasks at the beginning of 2018.

Hardware

Deep neural networks involve a vast amount of computation, often using very large data sets to calculate the composition of an extremely parameter-heavy model. GPUs, which were originally designed for computations around rendering graphics on the computer, have accelerated the use of deep learning because they enable a high degree of parallelism within the GPU card. GPUs can provide higher throughput and efficiency for certain categories of applications compared with CPUs, including the types of computations required for deep learning training and inference. GPUs have a well-defined instruction set and fixed data width (specific precision integer and floating-point values).

GPUs have become increasingly more powerful over time, as mentioned in Chapter 2. For example, the release of the NVIDIA Tesla V100 in May 2017 touted 2.4 times faster training of ResNet-50 DNN than the P100 released a year earlier (Durant, Giroux, Harris, & Stam, 2017). In addition, there has been recent research on mixed precision training, allowing for a reduction in the memory consumption and thus shortening the training or inference time (Micikevicius, 2017).

More Specialized Hardware

Hardware has continued to specialize with the specialization of field programmable gate arrays (FPGAs) and application-specific integrated circuits (ASICs) for neural network modeling, moving toward more specialized hardware that is more efficient, as pictured in Figure 3-3. FPGAs are integrated circuits that do not have a predefined instruction set or fixed data width like GPUs. FPGA acceleration works by having the FPGA handle the extremely computing-intensive tasks that have been designed to be accelerated by the hardware, while the CPU handles other operations. They provide potential for ultralow latency calculations through optimizing numerical precision for inference, as well as potential to evolve to new ML application areas. They can run low-precision workloads for optimal efficiency using much less power and thus run much cheaper than GPUs.

Increasing use of FPGA technology is an especially promising trend in the AI space because of FPGA's reconfigurability and its access to both the hardware and software level. This is especially promising for its potential for compromise between flexibility and specialization. ASICs are more performant for the application for which they are designed, but they are not useful for general-purpose computing, as they cannot be reconfigured after manufacturing.

In other words, FPGAs are more flexible than ASICs as they can be used and then repurposed for workloads beyond just deep learning and AI applications, including graph analytics, database acceleration, and data encryption, for example. Programming FPGAs requires support from specialized compilers, and it is relatively much harder than compilers used for traditionasl processors.

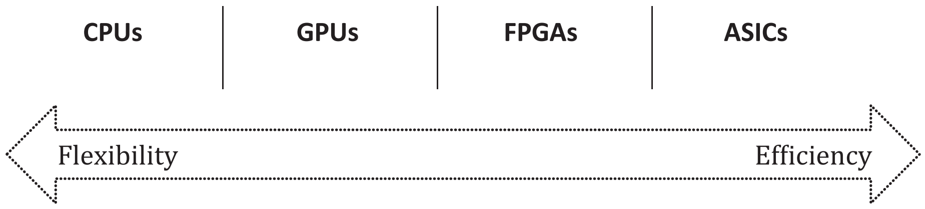


Figure 3-3. *Alternatives for processing computations such as those in deep learning models*

Hardware on Azure

Microsoft has been investing in specialized hardware for use both in their own products as well as for others to use through their Azure cloud computing platform. To accelerate Bing's search ranking algorithm, for example, FPGAs were programmed for that sole purpose and resulted in double the throughput at just 10 percent more power (Feldman, 2016). In 2016, Altera FPGAs were installed across every Azure cloud server datacenter at the time as Microsoft prepared to release capabilities as third-party offering. The ability to use FPGAs for deep learning inference that was announced in early 2018 is mentioned in more detail in Chapter 10.

Quantum Computing

As hardware such as more advanced GPUs and FPGAs continues to advance and specialize to enable deep learning, the future of how computing is conducted might also change dramatically in the longer term thanks to ongoing research in areas such as quantum computing. Quantum computing is a fundamentally different way of computing compared to today's computers. Rather than the foundational building block of a bit in today's computers, quantum computing builds on quantum bits called *qubits* that exist as a mixture of states at a given point in time and that can be manipulated all at once. It's not clear yet what types of problems are most applicable to quantum computing, although there are some clear applications such as cryptography. Unfortunately, building quantum computers is extremely difficult and they are extremely hard to use as well as scale. So far, they can only be used for a limited set of computing tasks. Qubits are extremely sensitive to the surrounding environment and interference results in calculation errors. Microsoft is working on developing more general-purpose quantum computers to help solve today's intractable problems through research on "topological qubits" that has the potential to completely revolutionize AI by opening up completely new computing potential.

> *The problems we're looking at solving with a quantum computer are the problems that, today, require age-of-the-universe time scales. … Some of these problems literally require billions and billions and billions of years to solve. And on a quantum computer, what we've shown in some recent research, is that you can solve some of these problems in a matter of say, weeks, days, hours, seconds.*
>
> —Krysta Svore, Microsoft Research

Although this is an area of active research, Microsoft has released quantum computing development tools and programming language for quantum algorithm development. Other areas of research include approximate computing, using less precision as well as allowing random small mistakes that can cancel out over time, to save energy and increase efficiency of computations. Many believe quantum computing has much potential to accelerate the development and application of AI, but the full power and potential is yet to be seen.

Limitations of Deep Learning

Deep learning has led to many incredible advances in the application of AI. Deep neural networks work by transforming an input vector to a target output vector, a complicated transformation created simply through a series of simple transformations. With massive data and computing power, the relatively simple concept of neural network models can be used to effectively map between many inputs and outputs such as recognizing speech from audio snippets. We believe deep learning will continue to play a large role in the advancement of AI applications, but that we need to understand the limits and capabilities to apply the technology in the right scenarios and in appropriate ways.

Be Wary of Hype

In fact, we should be careful not to overestimate the abilities of deep learning models. They do not learn abstract concepts or "understand" in a way that is relatable to humans. From an early age, humans are able to reason and maintain abstract models of the world, consider hypothetical situations, and make decisions through critical thinking. These neural networks importantly cannot reason or do long-term planning in this way and by themselves do not represent any type of general intelligence. After all, even if an algorithm can predict what an object is, that does not imply the algorithm actually understands the properties of the object, how it would interact with its environment, what it is used for, or where it came from. So, although computers can learn from massive data to distinguish between different types of birds better than humans, for example, humans are still far superior at extrapolation, interpretation, and inference, such as understanding a complex scene.

Similarly, in natural language processing, humans are able to understand nuances in aspects such as word ordering and context, whereas neural network models struggle to understand broader abstract concepts and contextual information that can be useful to understanding language. For example, when someone says, “The couch will not fit through the door, as it’s too big,” it is obvious to a human that “it” refers to the couch as we understand the concepts of couch and door and that the statement would not make sense if “it” referred to the door. Although there have been many advancements in using sequences of words and broader associations between words in language models, they still do not learn in the same way as humans.

Note Deep learning is an incredibly powerful technique, but we believe it will not lead to artificial general intelligence by itself. Deep learning also has limitations—such as inability to understand higher level concepts—of which developers of AI applications should be cognizant.

Limits on Ability to Generalize

As stated by Chollet (2017), “Models can only perform local generalization, adapting to new situations that must stay very close from past data, while human cognition is capable of extreme generalization, quickly adapting to radically novel situations, or planning for long-term future situations.” In fact, there might often be less to the accuracy of the models than we actually attribute to them; for instance, Ribeiro, Singh, and Guestrin (2016) found that the model was able to distinguish between wolves and dogs because of the white snow patches in the background of wolf images, not because it actually understood the difference between them. Jo and Bengio (2017) also provided quantitative evidence that deep CNNs do not learn higher level abstract concepts, but rather surface statistical regularities. They showed that CNNs trained with one class of Fourier image statistics but validated on different types of Fourier image statistics showed up to a 28 percent gap in accuracy, even though perceptually to a human they are not far off the original unfiltered data set.

This limitation of deep learning models to understand abstract or fully realized representations of concepts is well-illustrated in a recent trend in deep learning around both the creation as well as aim to defend against *adversarial examples,* synthetic examples that are created by modifying an input image in a particular fashion such that it makes the model believe the image belongs to another class with high confidence, as illustrated in Figure 3-4. It is very straightforward to create adversarial examples that are undetectable to the human eye—the equivalent of optical illusions that fool humans, only for a computer. There has been significant recent research on defending from adversarial examples, trying to make a model or algorithm robust such that these types of perturbations do not fool the model. As of early 2018, there are still no robust defenses to adversarial attacks, and research has only shown how robust adversarial attacks can be, even in the physical world. For instance, some adversarial examples can even be printed out on standard paper, photographed with a smartphone, and continue to fool the model (Kurakin, Goodfellow, & Bengio, 2016).

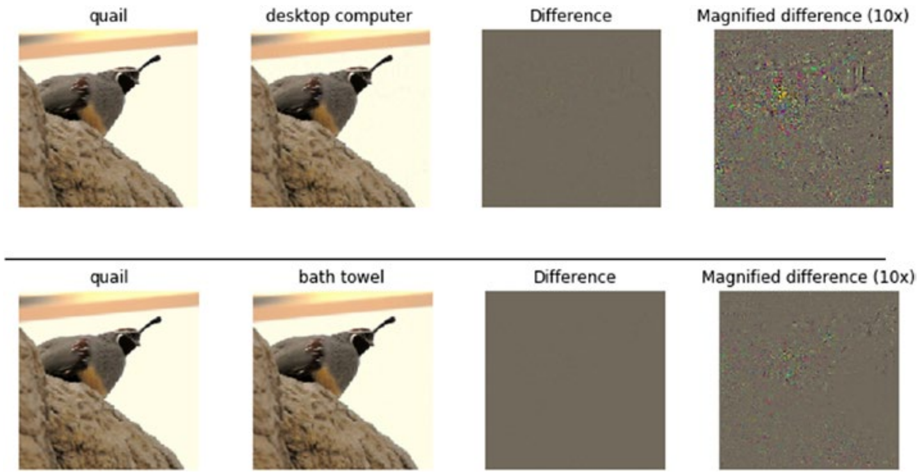


Figure 3-4. *Example adversarial examples. With slight changes to the pixel values (often unnoticeable to the human eye), the model can be tricked to incorrectly classify the quail as other objects, such as a desktop computer or a bath towel.*

Data Hungry Models, Especially Labels

Deep learning models also are limited by the vast amount of data that is required to train the network. This is especially made difficult by the requirement for high-quality, curated labels from which the model can learn. Although techniques such as transfer learning and word embeddings as mentioned earlier are able to somewhat alleviate this problem in some contexts, deep learning is not able to learn from explicit definitions or complete many types of tasks that are not simple input to output pairings. Although incredibly powerful, it is clear that deep learning alone is not a solution for artificial general intelligence. As another example, deep learning even struggles to represent a basic sorting algorithm.

Many of these limitations of deep learning are actually limitations of ML algorithms in general, such as the inability to inherently distinguish correlation from causation. After all, deep learning is simply a statistical technique that excels at optimizing a mapping from an input to an output. However, unlike some simpler methodologies, explaining the solutions of deep neural networks can be extremely difficult. Engineering the network as needed can also be quite hard, such as trying to debug when something goes wrong or when one wants to tune a specific aspect of the modeling results. Although deep learning has many limits and is just one tool that can be used among many, we believe that deep learning will serve as a stepping stone to many future advances in AI, as we discuss later.

Reproducible Research and Underlying Theory

With the rise in popularity of deep learning, the number of research papers has increased dramatically every year. Recently, researchers have begun raising more concerns about the reproducibility of these papers, for example, when code is not released or specific details that are important to reproduce the result are not included. This is exacerbated by the lack of theoretical understanding about how to best develop these type of networks as well as optimize them, in addition to how many of the papers in the field require vast computing resources to reproduce. In practice, overfitting is common and very different results can be obtained depending on the type of evaluation method and split of the data.

Rahimi recently brought this issue of lack of theoretical underpinning to light in his December 2017 NIPS talk "Machine Learning Has Become Alchemy." His point was that we lack clear theoretical explanations of why deep learning works and how to understand when it does not, often called the black box problem. An example exception is the idea of information bottleneck, which posits a network gets rid of the noisy extraneous details like squeezing the information through a bottleneck, and only the features that are relevant to general concepts are retained (Tishby & Zaslavsky, 2015). Others have also cautioned that theory in general often lags behind empirical results and that being too cautious has the risk of leading to another "AI Winter,"[1] when instead continued research into how models can be used to solve real problems can propel us forward.

Nonetheless, it is clear that deep learning works for many applications in practice and is a useful tool for practitioners, and we need to understand both its usefulness and its weaknesses so that AI can continue bringing more value to society in the future. We believe the more open the community can be, in terms of publishing code associated with research as well as data when possible, the more it will help the field progress forward.

[1]Lighthill released a report in 1973 that suggested AI was a failure and too superficial to be used in practice, leading to a massive reduced interest in the field.

Looking Ahead: What Can We Expect from Deep Learning?

Although acknowledging deep neural networks are a statistical methodology with many limits, we are optimistic that deep neural networks will be used as a foundational building block within an increasing number of more sophisticated methodologies that will emerge over time. The use of dynamic networks, for example, which uses deep neural networks but allows the networks to change dynamically as a function of the data fed into the model over time, has risen recently.[2] The combination of deep neural networks embedded within reinforcement learning systems has also solved increasingly complex problems. LeCun (2018) suggested that "differentiable programming" should be the rebranding of deep learning to mark the transformation toward a new type of software that is differentiable and optimizable. Karpathy (2017) suggested that "[n]eural networks are not just another classifier, they represent the beginning of a fundamental shift in how we write software … they are Software 2.0.".

We expect research will continue to propel the practicality of deep learning forward, such as potential breakthroughs in optimizing neural network architectures as discussed earlier. Some areas of research are also still largely unsolved, such as the ability to learn from unlabeled data, also known as unsupervised learning, where there is much room for innovation. Additionally, we expect more work to focus on program synthesis and graph networks, as well as more applications of adversarial networks.

[2]Frameworks such as MXNet/Gluon, PyTorch, and Chainer support these types of networks, and we expect this trend to continue.

Ethics and Regulations

Finally, it is clear that there are ethical concerns, around aspects such as bias, security, privacy, and appropriate use of deep learning and AI technologies. These ethical considerations will start to increasingly affect the development of AI systems as laws and regulations are enacted to constrain the impact of these systems. As mentioned earlier, for example, deep learning systems today are vulnerable to adversarial examples, even in the physical world, which poses a security risk. Then besides the security implications, there are ethical considerations around bias as well.

Bias in AI and ML algorithms is typically described and studied in terms of statistical bias, a mathematical construct to describe the difference between an expected value and the true value of the parameter being estimated. Depending on the type of model, bias can be introduced in different ways. But even when a system is not mathematically biased, it can be biased in the popular culture's interpretation of the word.

The popular culture definition of bias is normally associated with some form of prejudice or preferential treatment toward a particular group. This is usually felt to be unfair. It should be noted that fairness is culturally defined and varies throughout history. Therefore, unfairness is really in the application of bias. The tricky part about this is that people normally assume that computers will be unbiased, and that the outcomes made from mathematical models will be fairer than those made by humans. By their very nature, though, deep learning models will display some bias in this sense of the word, because the driving force in them is the real-world data on which these models are built. Unfortunately, these true historical data are rooted with bias.

For some applications of deep learning where there are high-stakes outcomes such as hiring or loan applications, it is clear that this can have very detrimental effects. Take, for example, the use of word embeddings that represent words in a lower dimensional space. It is clear that word embeddings are biased, an example being word embeddings trained on Google News articles. These word embeddings have biased embedded relationships between words that can be extracted very easily such as "man is to computer programmer as women is to homemaker" (Bolukbasi, Chang, Zou, Saligrama, & Kalai, 2016). This can have detrimental effects on applications of deep learning with word embeddings when applied without consideration of these type of issues. For example, recruiters are increasingly using algorithms to automatically match resumes to job openings. If word embeddings are applied blindly within this process, however, and historical data favors that "successful" people in the role were mostly men, the outcomes of this process can be argued to be detrimental. O'Neil (2016), in her book *Weapons of Math Destruction,* outlined many ways in which algorithms can be used to a detrimental effect in the era of big data, and it is important to be cognizant of the potential for harm.

Unfortunately, bias can be difficult to detect and remove. In 2015 as another example, a photo application improperly labeled a dark-skinned person as a "gorilla," which prompted a quick and immediate apology. Had the company been aware of this, they surely would not have deployed this technology. AI and ML predictive modeling is inherently more difficult to test than traditional software applications, however. After all, in a classical software system, an input will generate a known output, but this is not true for AI-based systems. AI-based systems are evaluated based on their statistical results and these results can often change from one run of the data to the next. Unless adequate testing methodologies for AI-based systems are developed, deploying AI-based systems could encounter major roadblocks to deployment.

Not only are there ethical and cultural issues, but there are a host of legal implications as well. Fortunately, bias in ML applications has become increasingly discussed in both the research and industry communities. However, it is important to recognize that technological advances alone will not solve the problem; there is no one-size-fits-all solution to this. Testing of AI models and development of fair systems will undoubtedly require an interdisciplinary approach to achieve the goal of building safe, widely distributed AI.

Summary

This chapter discussed some of the trends in the deep learning space, such as the search for optimal network architectures both for accuracy as well as speed. We also went through two recent exciting developments in neural networks for computer vision, the first tackling the limitations of CNNs through capsule networks and the other using neural networks to try and define optimal architectures with minimal human intervention with automated ML techniques.

We discussed several other trends in deep learning, including more specialized hardware as well as the use of pretrained models to seed solutions with fewer data than required to build a deep learning solution from scratch. We finally discussed some limitations of deep learning of which developers should be cognizant, such as the inability of these models to understand abstract concepts, as well as some of the legal and ethical concerns, including adversarial examples and bias in models from the underlying data on which they are built.

Next Chapter 4 describes how you can use the tools, infrastructure, and services on the Microsoft AI Platform to manage the development life cycle of your deep learning projects and models, to train at scale, and to operationalize it quickly as web APIs.

PART II

Azure AI Platform and Experimentation Tools

CHAPTER 4

Microsoft AI Platform

This chapter introduces the Microsoft AI Platform, which is a set of services, infrastructure, and tools for building intelligent applications powered by AI. The Microsoft AI Platform runs on the Microsoft Azure cloud computing environment, which provides computing as a utility where you pay for what you use rather than what you own. For more details on the broader Azure Platform, please see the e-book *Developer's Guide to Microsoft Azure* (Crump & Luijbregts, 2017). The Microsoft AI Platform enables data scientists and developers to create AI solutions in an efficient and cost-effective manner.

Although Microsoft has other offerings for developing AI solutions such as Machine Learning Server, which can be deployed on-premises in addition to the cloud as well as hybrid offerings, this chapter focuses primarily on the cloud computing platform that for reasons described later is most applicable to developing deep learning solutions. In practice, the models developed with the Microsoft AI Platform can then be deployed in many locations such as on the cloud for real-time highly scalable applications, on the edge through Azure IOT, or within a database such as a stored procedure hosted within SQL Server, for example. The Microsoft AI Platform is a flexible, open, enterprise-grade set of services, tools, and infrastructure that allow developers and data scientists to maximize their productivity in developing AI solutions.

https://doi.org/10.1007/978-1-4842-3679-6_4

Developing a deep learning solution requires lots of experimentation, lots of computing power—often using advanced hardware such as GPUs and FPGAs as discussed in Chapter 3, and often lots of training data. There is a need to be able to run training at scale. Cloud computing, with the ability to scale up and down easily with various levels of management—from raw infrastructure to managed services—makes doing data science including training and scoring deep learning models a more practical reality.

In fact, developing a deep learning solution requires carefully setting up many aspects, such as data storage, development environment, scheduling for training and scoring, cluster management, and managing costs, among other aspects. Deep learning solutions are notorious for their difficult configurations, such as ensuring drivers and software compatibility. It is important to store data in a location that can scale with increasing volume and enable collecting more data to improve solutions over time. These data must also be stored in a location that is secure and compliant with local regulations. Development environments must fit the needs of the developer or data scientist creating the code and allow workflows such as moving from a laptop to the cloud. Deep learning training workflows must be scheduled and monitored. The Azure cloud computing environment enables scaling up and down for cost control, has various levels of product offerings to address these aspects, from raw infrastructure with VMs already configured for deep learning to fully managed services with pretrained models ready to consume.

Of course, not all these services are necessary for a single given solution, but rather taken together provide a platform on which any type of intelligent application can be built leveraging the best of open-source technology as well as decades of research within Microsoft on both AI algorithms as well as tooling for development. By building on top of the Azure platform, developers and data scientists can leverage infrastructure that scales virtually infinitely, with enterprise-grade security, availability, compliance, and manageability. In the sections that follow, the main services, infrastructure, and tools available on the Microsoft AI Platform are outlined as visualized in Figure 4-1. To use the platform, an Azure subscription is required. For a free trial, please visit http://bit.ly/TrialAzureFree.

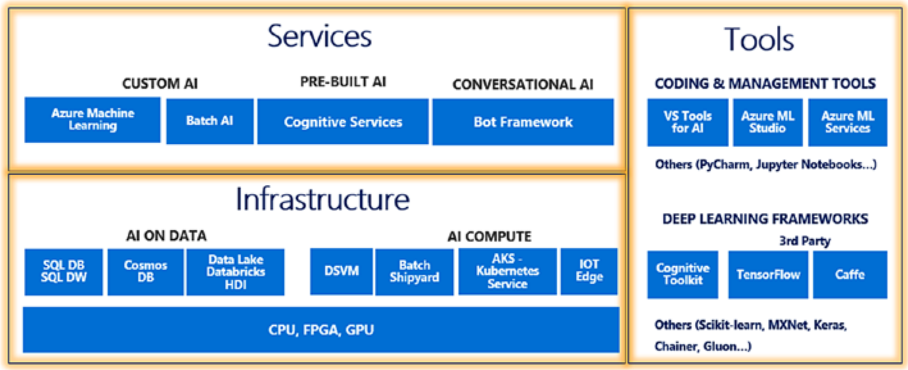


Figure 4-1. *Microsoft AI Platform*

After outlining the Microsoft AI Platform, steps for setting up a deep learning VM (DLVM) are described, which is required for running the code samples provided in later chapters as well as Part IV.

Services

The Microsoft AI Platform is composed of a series of services from fully managed software services to services for building custom AI applications. Depending on the scenario and flexibility required, different solutions might be applicable. The services are broken into three main areas:

1. **Prebuilt AI**. These leverage prebuilt models within an application through algorithms that are already built to see, hear, speak, and understand with Cognitive Services.

2. **Conversational AI**. These build natural interaction into an application through the Bot Framework, which has connectors to common channels such as Facebook Messenger, Slack, Skype, and Bing.

3. **Custom AI Services**. These adapt to a scenario with the flexibility of Azure Machine Learning services, Batch AI service or both.

Prebuilt AI: Cognitive Services

Cognitive Services are a set of services available to developers and data scientists to build AI solutions, with capabilities around vision, speech, language, knowledge, and search (see Table 4-1). The Cognitive Services are of two main types:

1. Pretrained models available as REST APIs, ready to consume in end user applications without any customization required.

2. Bring-your-own-data services, such as Custom Vision Service, which allows a developer to create a custom image classification model without any background in computer vision or deep learning by simply uploading images of different classes and clicking a button to train the model.

Table 4-1. *Example Cognitive Services Available on the Microsoft AI Platform*

Vision	Language	Speech	Search	Knowledge
Computer vision	Text analytics	Speaker recognition	Web search	Academic knowledge
Face	Spell check	Speech	Image search	Entity linking service
Emotion	Web language model	Speech Service[a]	Video search	Knowledge exploration
Content Moderator	Linguistic analysis		News search	Recommendations
Video Indexer	Translator		Autosuggest	QnA maker
Vision Service[a]	Language Understanding[a]		Search[a]	Decision Service[a]

[a]*Custom Cognitive Service with bring-your-own-data capabilities.*

As just one example, the ability to search is a feature in almost every application but is often difficult to implement as it requires natural language processing and language-specific linguistics among other aspects. Azure Search provides the underlying search engine—developers need to create an index to help search and fill it with data, and Azure Search takes care of everything underneath, with rich features such as intelligent filtering, search suggestions, word decompounding, and geo-search.

These services are popular, as they are simple to add into applications. Just a few lines of code are required to integrate a model such as an emotion detection model into a customer service experience application. Given the breadth of Cognitive Services and Custom Cognitive Services available for use today, these services are described in more depth in the Chapter 5.

Conversational AI: Bot Framework

The Bot Framework includes tools and services to enable developers to build bots that converse with users. For example, a developer can easily develop a bot that interacts with users on a web site to guide them through purchasing a product or service rather than having to navigate through the web page. Through this framework, one can develop once and then expose the bot through many channels that are included within the Bot Framework, such as Skype, Facebook, and the Web. Bots can be built with the Bot Builder Software Development Kit (SDK) using C# or Node.js or with the Azure Bot Service.

Bots can be built to converse naturally, especially using advanced capabilities with integration of Cognitive Services such as the Language Understanding Intelligence Service (LUIS) and integrations with other cognitive services. As a managed service in Azure, it is scalable, and costs are only occurred for the resources that are used.

Custom AI: Azure Machine Learning Services

Azure Machine Learning services were released in public preview in late 2017. These services are useful for building custom AI solutions and helping to accelerate the end-to-end development of intelligent applications.

- Develop, deploy, and manage models at scale.
- Develop with the tools and frameworks popular in the open source community.

Azure Machine Learning services provide a framework to manage a data science project. With these services, one can bring the computing environment most applicable for training their AI models, for example:

1. Data Science Virtual Machine.
2. Spark on Databricks or HDInsight.
3. Azure Batch AI.

These computing environments are described later in this chapter.

The experimentation service helps to manage project dependencies, scale out training jobs, and enable sharing of data science projects. Model management service uses docker container-based deployment to help data scientists and developers deploy solutions on a single node (on the cloud or on-premises) as well as scale out cluster deployments such as Azure Container Services, as well as edge deployment via Azure IOT Edge.

As of this writing, Azure Machine Learning services works with Python and is available in several Azure regions. In addition, there are AI extensions for Visual Studio and Visual Studio Code discussed in the "Tools" section later in this chapter that allow interacting with the Azure Machine Learning platform (`http://bit.ly/aivisstdio`). As the service is updating frequently, we focused on the core computing environments in this book and suggest reading the current documentation on Azure Machine Learning services available at `http://bit.ly/AMLservices`.

Custom AI: Batch AI

Batch AI is a managed service that enables data scientists and developers to easily train deep learning and other AI models at scale with clusters of GPUs. With Batch AI, one can create a clusters of nodes including GPUs when required, and then turn the cluster off when the job is complete and thus stop the bill. It allows one to construct a framework-specific configuration using either containers or VMs. This is ideal for experimentation, such as doing parameter sweeps or experiments, testing different network architectures, or doing hyperparameter tuning in general. It also enables multi-GPU training for frameworks that allow training across nodes when training data are very large. An example with associated code for training deep learning models with Batch AI is included in Chapter 9. Batch AI can also be used for embarrassingly parallel batch scoring scenarios.

Batch AI is built on top of Azure Batch, which is a cloud-scale resource management and task execution tool. With Batch AI, you only pay for the computing that you use, with both standard and low-priority VMs available. There is no added charge for job scheduling or cluster management in general. Low-priority VMs provide a cost-efficient solution for jobs that are lower priority, such as learning and experimentation.

Related to Batch AI, Batch Shipyard is an open source tool that is a precursor to the managed Batch AI service that also runs on top of the Azure Batch infrastructure. Batch Shipyard supports both Docker and Singularity containers and scenarios important to developing deep learning solutions such as hyperparameter tuning. Batch Shipyard can also be utilized for batch scoring of deep learning models. More details about Batch AI and Batch Shipyard can be found in Part IV of the book.

Infrastructure

In this section, we outline infrastructure available for AI computing, such as the Data Science Virtual Machine (DSVM), Spark clusters, and infrastructure for managing deployment of containers as well as infrastructure for storing data on which AI can be built such as SQL DB, SQL Datawarehouse, Cosmos DB, and Data Lake.

Data Science Virtual Machine

The DSVM is a preconfigured environment in the cloud for data science and AI modeling, development, and deployment. It comes in a Windows Server version as well as Linux, and a specialized version for deep learning known as DLVM, which runs on a GPU. As can be seen in Figure 4-2, popular languages for data science development such as Python, R, and Julia are ready to use immediately, and data connected from many data stores such as SQL Data Warehouse, Azure Data Lake, Azure Storage, and Azure Cosmos DB are available. Many ML and AI tools come preinstalled, such as many of the popular deep learning frameworks. Data scientists and developers can then customize the VM as needed for their use. There is also a variant specialized for geospatial analysis, the Geo AI DSVM: `http://aka.ms/dsvm/geoai/docs`.

DSVMs are extremely popular with data scientists for the following reasons:

- They provide an analytics desktop in the cloud with easy setup, and the ability to transfer projects more easily between colleagues.
- They have on-demand elastic capacity, ability to turn off and on (e.g., stopping the VM at night if no jobs are running).
- There are examples and templates built in to get started with data science and deep learning.
- There is an ability to connect into other services such as using DSVM as the computing target within a project managed through Azure Machine Learning services or as compute for Batch AI service.
- They are easy to use for data science training and education due to ease of setup and cost savings versus purchasing hardware and managing the software oneself.

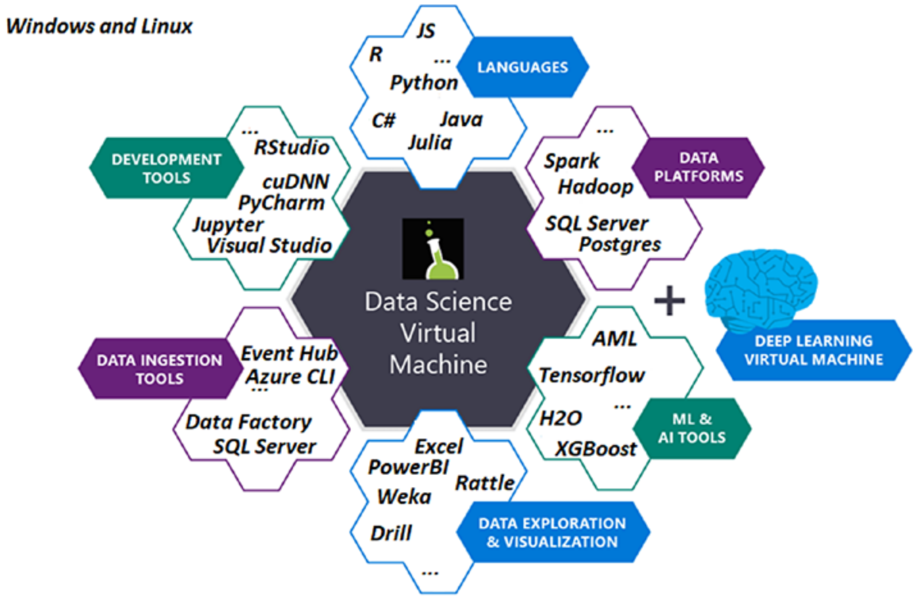


***Figure 4-2.** Features of the Data Science Virtual Machine as described at* `http://bit.ly/DataScienceVM`

Especially relevant for deep learning, setting up a GPU-based system can be extremely difficult with all of the necessary drivers and configurations. The DLVM makes the setup significantly easier, and can be provisioned with up to four GPU cards on a single VM. There are no software costs to the VM, and the pricing starts at $0.90/hour for NC6 series.

DSVM can be used both for experimentation and for simple deployment scenarios, such as running simple web services using Flask combined with capabilities such as Azure Automation, Azure Functions, and Azure Data Factory to trigger jobs running using a DSVM.

Spark

There are several options for running Spark on Azure, including Azure Databricks, Azure HDInsight, and leveraging the Azure Distributed Data Engineering Toolkit (AZTK) as core examples. Databricks is a managed platform for Spark with a rich experience for both data scientists and developers, such as a team collaboration experience and version control capabilities. The service handles much of the tuning of the cluster for developers, so is thus ideal for users who might not know or want to configure Spark, but it is not as flexible in terms of how the cluster can be configured. HDInsight is a fully managed cloud service for open source analytics such as HBase, Hive, Storm, and others in addition to Spark.

The AZTK is an open source Python Command-Line Interface (CLI) application for provisioning on-demand Spark clusters in Azure. The Spark clusters run in Docker containers with bring-your-own Docker image flexibility and are provisioned within 5 minutes on average, with low-priority VMs available for an 80 percent discount. This toolkit is useful for running a distributed Spark workload on demand such as batch workloads and can be scheduled to spin up and down such as through the use of Azure Functions. It has a rich Python SDK for programmatic control of clusters and jobs. AZTK is the most flexible option in terms of supporting all VM types including GPUs, which is especially helpful for deep learning scenarios.

For all of these Spark infrastructure options, Microsoft Machine Learning for Apache Spark (MMLSpark) provides a number of deep learning and data science tools for Apache Spark including integration with the deep learning framework CVTK. Spark has also seen recent improvements in support for deep learning applications through collaborations aimed toward improving support for aspects such as image data support as discussed at `http://bit.ly/SparkImage`.

Container Hosting

Azure Kubernetes Service (AKS) is a fully managed Kubernetes container orchestration service. Users might also choose other orchestrators through the original version, known as ACS. With the fully managed version of AKS, the only cost is for the VMs that are used for the tasks at hand; in other words, the management infrastructure is completely free. AKS is a generic computing platform and extremely flexible. For AI workloads, this type of service is often used to host scalable AI models for real-time scoring, although AKS can also be used for scalable AI training as well. Azure Machine Learning services include a model management service that eases the deployment of AI models as a REST API to Azure Container Services as illustrated in Figure 4-3.

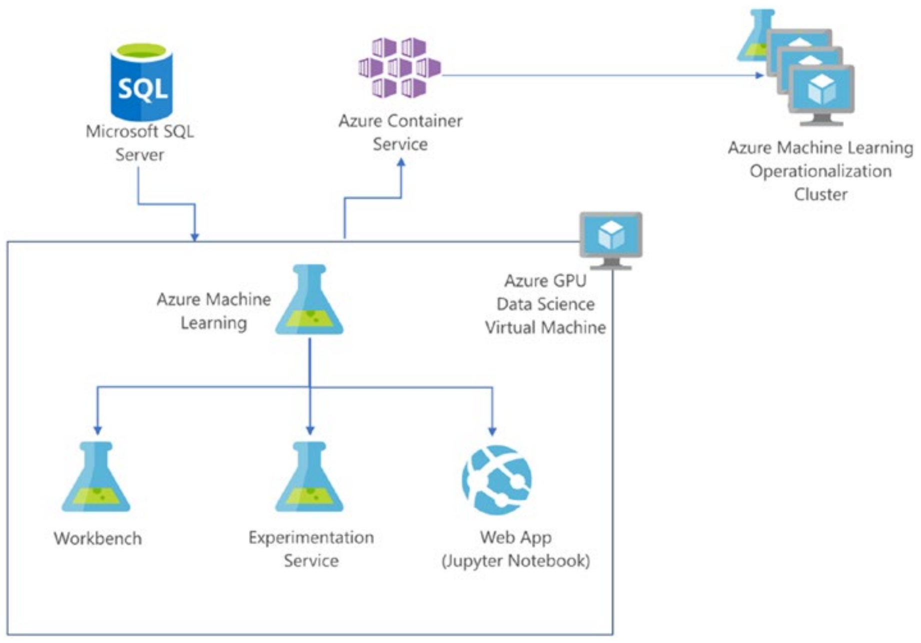

Microsoft SQL Server
Azure Container Service
Azure Machine Learning Operationalization Cluster
Azure Machine Learning
Azure GPU Data Science Virtual Machine
Workbench
Experimentation Service
Web App (Jupyter Notebook)

Figure 4-3. *Example deep learning solution architecture where data are stored in SQL Server, code is developed with a Deep Learning Virtual Machine managed by Azure Machine Learning services, and it is deployed as a Rest API to Azure Container Services as described at* *`http://bit.ly/DLArch`*.

Azure Container Services gives customers the benefit of open source Kubernetes along with built-in management to ease the complexity and operational overhead. AKS comes with automated upgrade, scaling ability, and self-healing accessible through a control plane hosted on Azure. For those who want even more flexibility, ACS Engine is an open source project that allows developers to build and use custom Docker-enabled container clusters.

Developers can also host containers using Azure Container Instances, where a container can be hosted without a container orchestrator, which is especially useful for testing or hosting a simple application that does not require scaling. Azure App Service is a collection of hosting and orchestration services comprised of Web App, Web App for Containers, and Mobile App. Web App, for example, enables developers to host web applications or APIs whereas Web App for Containers enables one to deploy and run containerized web apps with images from Docker Hub or a private Azure Container Registry.

Data Storage

Azure SQL Database is a relational cloud database as a service, with built-in intelligence, specially built for applications with individual updates, inserts, and deletes (OLTP). Azure SQL Data Warehouse is a warehouse not strictly for OLTP workloads in that it is desired to be more straightforward to use for larger databases, with additional feature ability to pause to save on costs. SQL Database supports more active connections and concurrent queries than SQL Data Warehouse, whereas SQL Data Warehouse supports Polybase, which is a technology that accesses data outside of the database via the T-SQL language. Often these services are used in conjunction with a larger data architecture.

Azure Cosmos DB is a globally distributed, multimodel database service that enables extremely low latency and massively scalable applications. It has native support for NoSQL and can support key-value, graph, column, and document data all in one service. Several different APIs including SQL, Apache Cassandra, and MongoDB can be used to access data, and multiple consistency choices are offered for low-latency and high-availability options such as strong, bounded staleness, and eventual. This offering is extremely useful for disparate types of data.

Azure Data Lake Store is a no-limits data lake that stores unstructured, semistructured, and structured data, which are optimized for big data analytics workloads. It is massively scalable and built to the open Hadoop Distributed File System (HDFS) standard, thus integrating into many tools easily and allowing a straightforward migration of existing Hadoop and Spark data to the cloud. Data Lake Store can store trillions of files and a single file can be larger than one petabyte in size. Azure Blob Storage is a separate storage option that is a more general-purpose object store, including for big data analytics workloads, and comparison between them can be found at `http://bit.ly/LakeVBlob`.

Tools

Several tools and toolkits for developing and deploying AI solutions were mentioned within the previous sections as they related to services and infrastructure for AI, such as AZTK for deploying a Spark infrastructure and Batch Shipyard for executing batch and High Performance Computing (HPC) container workloads. In this section, we include a nonexhaustive summary of several other tools that are available on the Microsoft AI Platform.

Azure Machine Learning Studio

Azure Machine Learning Studio is a serverless environment for training and deploying ML models. Studio provides a graphical user interface (GUI) with the ability to drag and drop easily configured modules for data preparation, training, scoring, and evaluation. Many prebuilt algorithms are included for common scenarios such as regression and classification, and extensibility is enabled through R and Python scripting modules where custom code can be inserted and connected to other modules. Although it is extremely useful for quickly developing custom ML solutions on smaller data set sizes, we do not recommend Azure Machine Learning

Studio for developing deep learning solutions, as the size of input data is limited, as well as the hardware it is run on. Today, there is no ability to bring your own computing environment or manage scale-out computing across nodes with Azure Machine Learning Studio. Because of these factors, we recommend Azure Machine Learning services for developing deep learning solutions instead.

Integrated Development Environments

With Microsoft Azure, any integrated development environment (IDE) or editor can be used to create AI applications. In several of the popular IDEs, there are plug-ins or extensions available that make it even simpler, such as publishing directly to Azure. For example, Visual Studio Code Tools for AI is an extension for Visual Studio Code that is a cross-platform open source IDE. Visual Studio Tools for AI is an extension for Visual Studio for developing AI applications with an ability to set remote computing contexts. At the time of this writing, we recommend using Visual Studio Tools for AI and include an example using this later in this chapter.

These IDEs have nice features to accelerate development, but, of course, other popular IDEs such as PyCharm and RStudio can be used to develop the code that will run on the Microsoft AI Platform and more extensions will become available over time. In addition, Jupyter notebooks can be leveraged and is already set up for development on the DSVM. Azure Notebooks are another option for running code with hosted Jupyter notebooks; Azure Notebooks is completely free, but these do not run on GPUs so are not as practical for deep learning solutions.

Deep Learning Frameworks

The Microsoft AI Platform is an open platform that builds on the best of open source technology. Deep learning frameworks such as the Microsoft Cognitive Toolkit (CNTK), Tensorflow, Caffe, and PyTorch, which are all open source projects, are supported throughout many of the tools, services, and infrastructure already mentioned. The DLVM comes preconfigured with many of the popular frameworks, and these frameworks can be used to develop AI solutions and be deployed on Azure, on Azure IOT Edge, or Windows Machine Learning, for example. These frameworks were discussed in more detail in Chapter 2.

Broader Azure Platform

In practice, there are many other components of Azure that are often used to build AI solutions, to complement the AI-specific services with other requirements such as dealing with ingestion and processing of streaming data flows, authentication, and dashboarding. For example, Azure IOT Hub allows developers to securely connect IOT assets to the cloud, Azure Stream Analytics enables SQL-like processing of real-time data, and Power BI builds on top of many different data sources to enable rich, interactive visualizations surfaced in dashboards.

A couple of other commonly used services are Azure Functions and Azure Logic Apps, illustrated in an architecture in Figure 4-4. Azure Functions is a serverless service that enables developers to simply write the code they would like to execute without worrying about the underlying infrastructure on which to run the code, paying only when the code is run. The function that is written—in languages such as C#, Node.js, and Java—can be run on a schedule or triggered by an event such as an HTTP request or event in another Azure service. For example, a function can be triggered every time a new image is uploaded into Azure Blob Storage, which resizes the image and calls out to an AI model hosted through one of the example. Azure Logic Apps are also serverless and paid only when run, and can automate a business process. As a simple example, Azure Logic Apps can be activated when an e-mail arrives in Office 365, which then triggers a process to check on data in SQL Server and send a text message to an end user after verification. In addition to the services from Microsoft, there is also a marketplace of services and tools built on top of the Azure ecosystem.

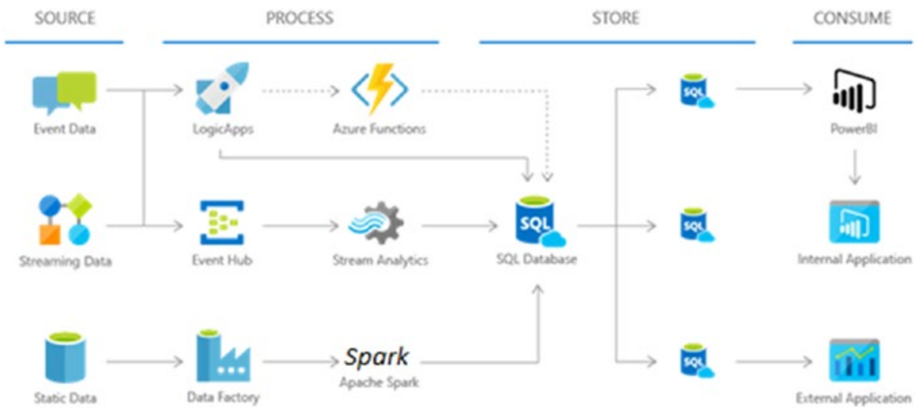


Figure 4-4. *Example architecture with the integrated components on the Azure Platform to manage data flows into end applications from* *http://bit.ly/AzureSQLArch*.

Getting Started with the Deep Learning Virtual Machine

In the code examples that follow in the third part of this book, a GPU-enabled machine will be needed. If you are planning on using your own GPU-enabled machine to follow along with the code examples, you can skip this section; if not, read on. As we mentioned earlier, Azure offers a VM already preconfigured with many deep learning and ML libraries called DSVM/DLVM. We can create a DLVM using the portal or the Azure CLI. For instruction on provisioning a VM, see http://bit.ly/CreateDLVM. You can install the Azure CLI locally by following the instructions at http://bit.ly/AzureCLI. If you don't want to install anything, you can simply go to https://shell.azure.com/ and use the CLI from there. Instructions on how to provision a DLVM/DSVM using the CLI can be found at http://bit.ly/DLVM-CLI.

To save you time and effort, Listing 4-1 is a snippet of a set of commands that will create a Linux DSVM for you on an NC6 VM. It will also increase the drive size to 150 GB, open the appropriate port for the Jupyter notebook server, and create a Domain Name Service (DNS) name based on the name you gave the VM. The Azure CLI and by extension the Azure cloud shell are very powerful and accessible tools that can save you a lot of time.

Listing 4-1. Create VM

```
BASH

location=eastus
resource_group=myvmrg
name=myvm
username=username
password=password

az group create --location $location --name $resource_group

az vm create \
    --resource-group $resource_group \
    --name $name \
    --location $location \
    --authentication-type password \
    --admin-username $username \
    --admin-password $password \
    --public-ip-address-dns-name $name \
    --image microsoft-ads:linux-data-science-vm-
    ubuntu:linuxdsvmubuntu:latest \
    --size Standard_NC6 \
    --os-disk-size-gb 150

az vm open-port -g $resource_group -n $name --port 9999
--priority 1010
```

Please make sure that you change the username and password to something appropriate in Listing 4-1. Also, the code in Listing 4-1 will create the VM in the EastUS region; if you would rather have it in a different region, feel free to change it. Once the VM is up and running you should be able to Secure shell (ssh) into it using the DNS name given to your VM as well as the username and password you specified.

Running the Notebook Server

We are assuming that you have a Linux DLVM/DSVM set up and you are able to ssh into it. Once you have ssh'd into the machine, start the Jupyter notebook server. You can download the notebooks to the VM from `http://bit.ly/Ch06Notebooks`. Then navigate to the folder to which you downloaded the notebooks and run the code shown in Listing 4-2 in the terminal.

Listing 4-2. Start Notebook Server

```
BASH

source activate py35
jupyter notebook -ip=* --port=9999 -no-browser
```

Navigate to your browser and enter the IP or DNS of your VM such as `mydlvm.southcentralus.cloudapp.azure.com:9999`. Don't forget the port number at the end.[1] You will be asked to enter an authorization token, which can be seen in the terminal. If you want to configure your Jupyter notebook to use a username and password or set it up so that you don't have to enter the port number or the other arguments, follow the guide at `http://bit.ly/jupyternbook`.

[1]The appropriate port must be open on the VM. For instructions on how to do this, please refer to the section on DSVM earlier in chapter.

Summary

This chapter outlined the Microsoft AI Platform set of services, tools, and infrastructure for building AI solutions. Building AI solutions requires lots of experimentation and specialized hardware for deep learning, and leveraging cloud computing combined with service and tools accelerates the development process of intelligence applications.

Additionally, AI is being infused in other ways across Microsoft's products as well, such as on-premises solutions for AI such as SQL Server 2017 and Microsoft Machine Learning Server. SQL Server 2017 runs on Windows Server, Linux, and Docker and enables advanced in-database ML with scalable Python and R-based analytics. With SQL Server, models can be trained within the database without having to move data and predictions can be made naturally through stored procedures and native ML functions within the database engine. This capability is included within Azure SQL DB as well.

In the next chapter, a more detailed overview is available on the prebuilt AI that is available to infuse directly into applications.

CHAPTER 5

Cognitive Services and Custom Vision

Chapter 4 introduced the tools, infrastructure, and services that are available to build the next generation of intelligent applications. These together form a platform that empowers data scientists and developers to build, train, and deploy ML and deep learning models on the intelligent cloud and intelligent edge.

As one option within the Microsoft AI Platform, organizations getting started on AI have the flexibility to use prebuilt AI capabilities using Cognitive Services. This enables organizations to jump start their AI efforts quickly and use Cognitive Services as the basis for developing intelligent, innovative applications. In this chapter, we describe how to use Cognitive Services. We also illustrate how to customize deep neural network models for computer vision tasks using the Custom Vision service as one example of a customizable cognitive service.

Prebuilt AI: Why and How?

For years, researchers in the deep learning communities have been making tremendous progress on algorithms and leveraging state-of-art hardware to train deep learning models using publicly available large data sets (e.g., ImageNet, CIFAR-10, CIFAR-100, Places2, COCO, MegaFace, Switchboard, and many more). These public data sets are often used in competitions,

https://doi.org/10.1007/978-1-4842-3679-6_5

and as a method for benchmarking for deep learning algorithms. In addition, many commercial and research organizations leverage private data sets to further improve the quality of their models.

To train a high-performing deep learning model often requires a significant amount of computing resources. Chapter 2 described the amount of computing resources required to train a classifier on ImageNet (ranging from 256 to 1,024 Nvidia P100 GPUs). Even though training time has been decreasing significantly over time (from days to minutes), not every organization has at their disposal a large amount of GPU resources, nor the means to keep these GPU resources updated with both the latest hardware and software over time.

Researchers spend a significant amount of time fine-tuning their models. For example, the accuracy of classifying objects in the ImageNet data set has improved significantly from 71.8 percent to 97.3 percent (Russakovsky et al., 2015). Another example is the significant improvement made by researchers working on speech recognition using the Switchboard data set. Using a combination of neural-network-driven acoustic and language models, CNNs, and bidirectional long- and short-term memory models, Microsoft researchers reduce the error rate for speech recognition to 5.1 percent (Xiong et al., 2016). The deep-learning-based speech recognition models surpass the performance of professional human transcribers.

Pretrained deep learning models enable organizations to leverage the significant innovations made by researchers over the years and use the models immediately to solve common AI problems. For example, we can leverage speech-to-text APIs that are backed by high-quality speech models, or computer vision APIs that are trained on large data sets of faces, scenes, celebrities, and more. These enable organizations to quickly develop intelligent applications without spending a significant amount of time training the models.

In Chapter 2, we introduce how transfer learning can be applied for computer vision tasks, where you can leverage pretrained models as base models and adapt them to new domains by providing new labeled images. To make it easier for organizations to use custom deep learning models, Custom Vision (one of the Cognitive Services) enables you to upload your images and train a custom image classifier quickly with the press of a few buttons. Similarly, you can customize acoustic models using Custom Speech (another cognitive service) through uploading domain-specific data (`.wav` files, text files, or both) to improve accuracy in various environments.

More Info Find out more about creating custom acoustic and language model using Custom Speech Service at `http://bit.ly/CustomSpeech/`.

In this chapter, we focus on computer vision services. We walk through different types of prebuilt computer vision services that you can use out of the box. We then describe how to use the Custom Vision Service to train custom image classifiers.

Cognitive Services

Cognitive Services enables developers to get started quickly by leveraging prebuilt AI models. To develop an AI application that uses one or more of the Cognitive Services, developers leverage the APIs provided by each of the Cognitive Services. This enables developers to develop intelligent applications using various programming languages (e.g., C#, Java, JavaScript, PHP, Python, Ruby, etc.).

Figure 5-1 shows how an application interacts with Cognitive Services. The application issues a request to a Cognitive Services URL. For example, a Request URL for using Cognitive Services to tag an image (identify what are the tags for objects found in an image) is `https://[location].api.cognitive.microsoft.com/vision/v1.0/tag`, where location refers to one of the support geographical regions where the APIs are created (e.g., West US, West US 2, East US, East US 2, West Europe, Southeast Asia, etc.). For a list of supported regions for Cognitive Services, refer to `http://bit.ly/CogServices`.

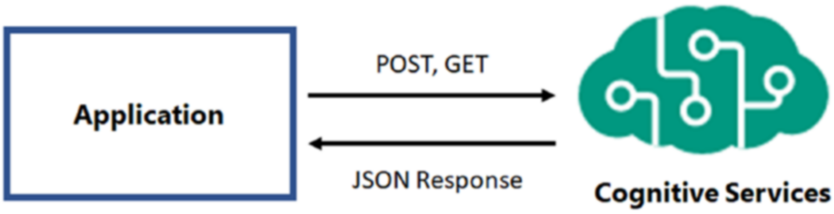
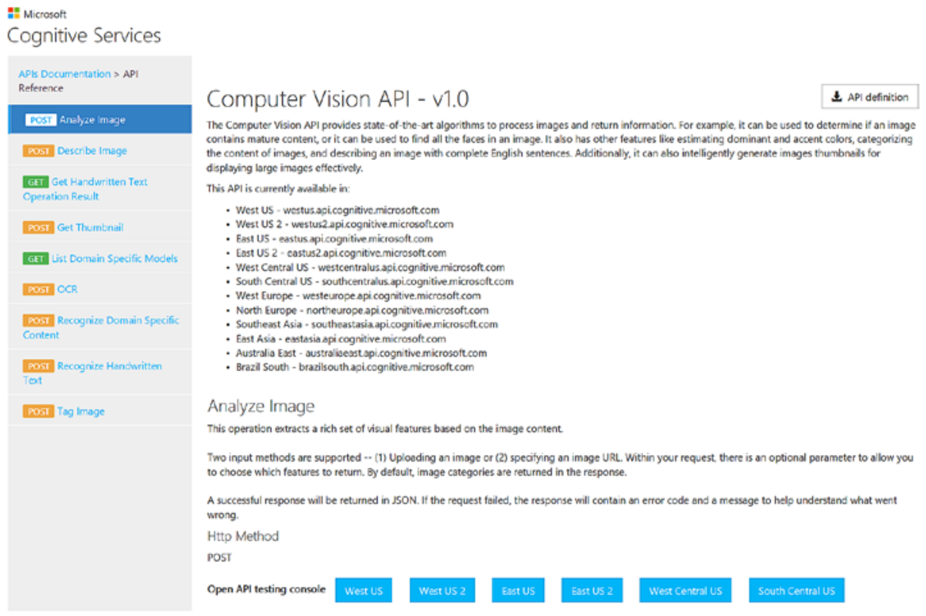


Figure 5-1. *Application using Cognitive Services*

Figure 5-2 shows the REST API documentation for Computer Vision APIs. When issuing a request to Cognitive Services, you will need to provide the *content type* and *subscription key* (referred to as *Ocp-Apim-Subscription-Key*) in the Request header. After the request has been processed, the results are returned as a JSON object. In Figure 5-3, you can see the tags (e.g., grass, outdoor, sky, etc.) that are returned after the application submits an image for tagging.


Microsoft
Cognitive Services
APIs Documentation > API Reference
POST Analyze Image
POST Describe Image
GET Get Handwritten Text Operation Result
POST Get Thumbnail
GET List Domain Specific Models
POST OCR
POST Recognize Domain Specific Content
POST Recognize Handwritten Text
POST Tag Image
API definition

Computer Vision API - v1.0

The Computer Vision API provides state-of-the-art algorithms to process images and return information. For example, it can be used to determine if an image contains mature content, or it can be used to find all the faces in an image. It also has other features like estimating dominant and accent colors, categorizing the content of images, and describing an image with complete English sentences. Additionally, it can also intelligently generate images thumbnails for displaying large images effectively.

This API is currently available in:

- West US - westus.api.cognitive.microsoft.com
- West US 2 - westus2.api.cognitive.microsoft.com
- East US - eastus.api.cognitive.microsoft.com
- East US 2 - eastus2.api.cognitive.microsoft.com
- West Central US - westcentralus.api.cognitive.microsoft.com
- South Central US - southcentralus.api.cognitive.microsoft.com
- West Europe - westeurope.api.cognitive.microsoft.com
- North Europe - northeurope.api.cognitive.microsoft.com
- Southeast Asia - southeastasia.api.cognitive.microsoft.com
- East Asia - eastasia.api.cognitive.microsoft.com
- Australia East - australiaeast.api.cognitive.microsoft.com
- Brazil South - brazilsouth.api.cognitive.microsoft.com

Analyze Image

This operation extracts a rich set of visual features based on the image content.

Two input methods are supported -- (1) Uploading an image or (2) specifying an image URL. Within your request, there is an optional parameter to allow you to choose which features to return. By default, image categories are returned in the response.

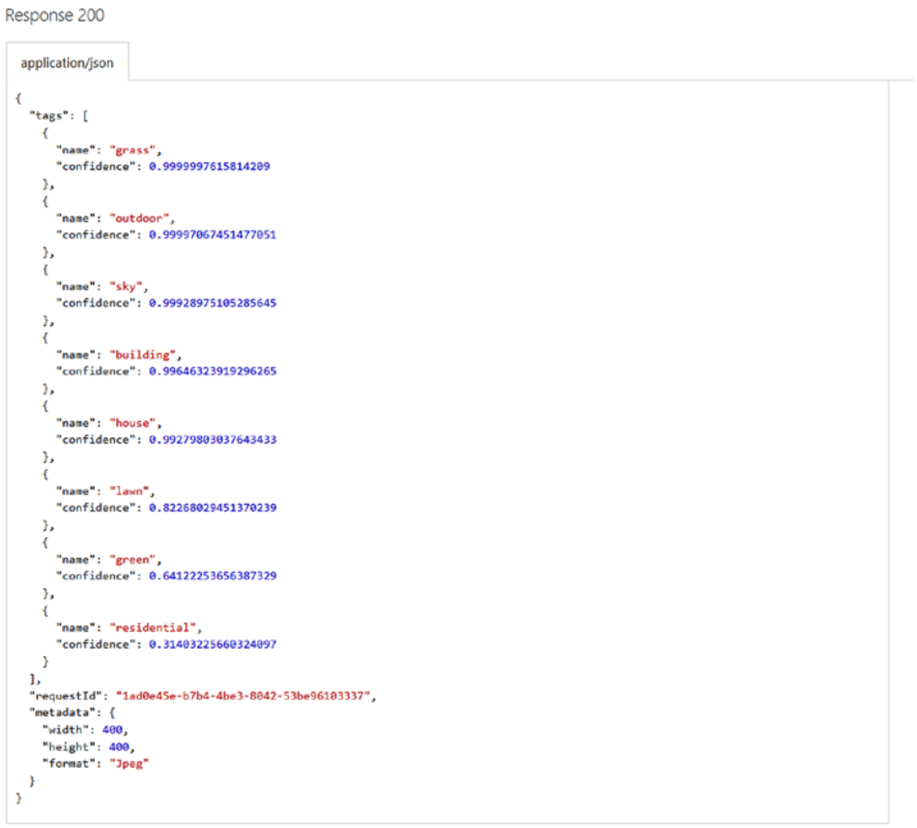
A successful response will be returned in JSON. If the request failed, the response will contain an error code and a message to help understand what went wrong.

Http Method

POST

Open API testing console

Figure 5-2. *REST API documentation for Computer Vision API. Source:* [*http://bit.ly/ComVisionAPIv1*](http://bit.ly/ComVisionAPIv1).


Response 200

application/json

```
{
  "tags": [
    {
      "name": "grass",
      "confidence": 0.9999997615814209
    },
    {
      "name": "outdoor",
      "confidence": 0.99997067451477051
    },
    {
      "name": "sky",
      "confidence": 0.99928975105285645
    },
    {
      "name": "building",
      "confidence": 0.99646323919296265
    },
    {
      "name": "house",
      "confidence": 0.99279803037643433
    },
    {
      "name": "lawn",
      "confidence": 0.82268029451370239
    },
    {
      "name": "green",
      "confidence": 0.64122253656387329
    },
    {
      "name": "residential",
      "confidence": 0.31403225660324097
    }
  ],
  "requestId": "1ad0e45e-b7b4-4be3-8042-53be96103337",
  "metadata": {
    "width": 400,
    "height": 400,
    "format": "Jpeg"
  }
}
```

Figure 5-3. *JSON response for tag image request*

What Types of Cognitive Services Are Available?

Cognitive Services provides a powerful set of prebuilt AI services, as follows.

- *Vision*: Provides state-of-the-art image processing algorithms that provide image classification, captioning, optical character recognition (OCR), and content moderation.

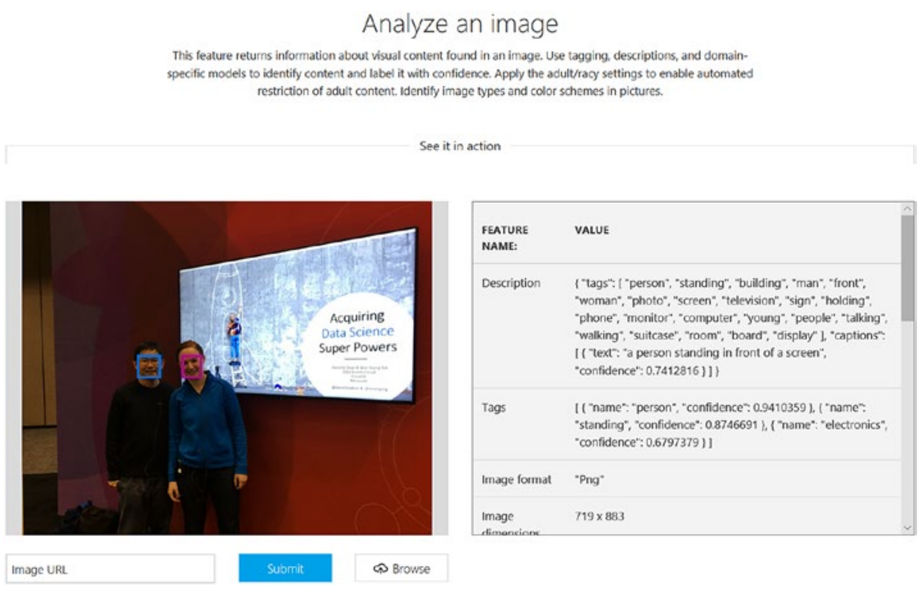
- *Knowledge*: Provides APIs to enable you to quickly extract question–answer pairs from user-provided frequently answered questions (FAQs), documents, and content. Other Knowledge APIs include custom decision service, knowledge exploration, and named entity recognition and disambiguation.
- *Language*: Language Understanding (LUIS) enables developers to integrate powerful natural language understanding capabilities into various applications. Other Language services include Bing Spell Check, Text Analytics, Translations, and more.
- *Speech*: Provides APIs for real-time speech translation, converting speech to text, speaker recognition, and customizing speech models.
- *Search*: Provides APIs that provide developers with instant access to various Bing capabilities. These include the ability to perform autosuggestion, news search, web search, image search, video search, and custom search.

In this chapter, we describe how to use the Computer Vision APIs that are available as part of Cognitive Services. We refer the interested reader to continue exploring other Cognitive Services by visiting `http://bit.ly/MSFTCogServices`. All Cognitive Services follow a similar request–response pattern, and you will be able to apply and adapt what you have learned from using the Computer Vision APIs to the other Cognitive Services.

Computer Vision APIs

Computer Vision APIs provide you with information about the objects that are found in an image. These APIs are based on years of research in applying deep learning algorithms to understand the content of an image. In this book, we describe some of these techniques for performing image classification and more. Using the Computer Vision APIs, these powerful image processing techniques are now available as prebuilt AI that you can use as the basis for creating innovative applications.

After the image is analyzed, the Computer Vision APIs return the tags that are most relevant to the image, and a caption describing the image. Figure 5-4 shows how to use the Computer Vision APIs to analyze an image and the returned results. The caption “a person standing in front of a screen” is also returned with a confidence score of 0.74.



Analyze an image

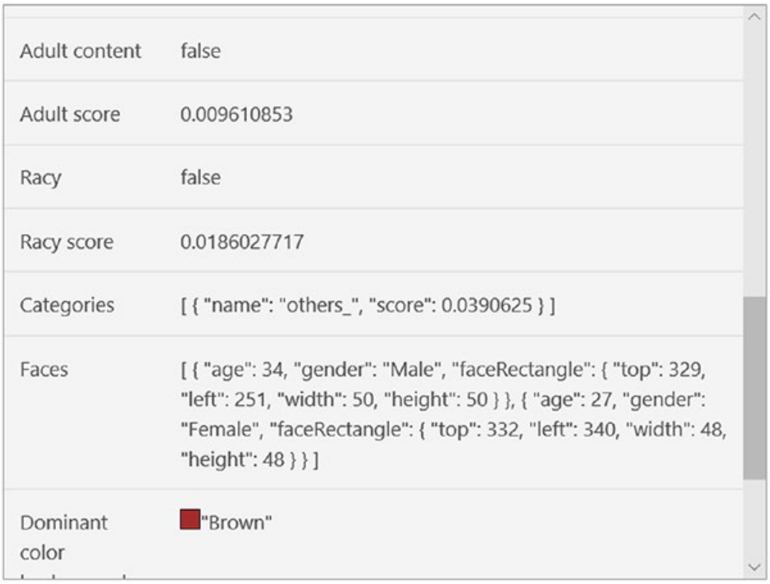
This feature returns information about visual content found in an image. Use tagging, descriptions, and domain-specific models to identify content and label it with confidence. Apply the adult/racy settings to enable automated restriction of adult content. Identify image types and color schemes in pictures.

See it in action

FEATURE NAME:	VALUE
Description	{ "tags": ["person", "standing", "building", "man", "front", "woman", "photo", "screen", "television", "sign", "holding", "phone", "monitor", "computer", "young", "people", "talking", "walking", "suitcase", "room", "board", "display"], "captions": [{ "text": "a person standing in front of a screen", "confidence": 0.7412816 }] }
Tags	[{ "name": "person", "confidence": 0.9410359 }, { "name": "standing", "confidence": 0.8746691 }, { "name": "electronics", "confidence": 0.6797379 }]
Image format	"Png"
Image dimensions	719 x 883

Figure 5-4. *Using the Computer Vision APIs*

In addition, the Computer Vision APIs identified the faces in the image and returned information about the predicted gender and age for each of the faces. Figure 5-5 shows that there are two faces found in the image. One of the faces is a male, age 34, and the other face is a female, age 27. The bounding boxes for each of the faces are returned. The predicted age is dependent on many factors within the image.



Adult content	false
Adult score	0.009610853
Racy	false
Racy score	0.0186027717
Categories	[{ "name": "others_", "score": 0.0390625 }]
Faces	[{ "age": 34, "gender": "Male", "faceRectangle": { "top": 329, "left": 251, "width": 50, "height": 50 } }, { "age": 27, "gender": "Female", "faceRectangle": { "top": 332, "left": 340, "width": 48, "height": 48 } }]
Dominant color	🟥"Brown"

Figure 5-5. *Using Computer Vision APIs to analyze the image*

Other information about the image is returned as well. For example, the image is analyzed for whether it contains adult or inappropriate content. This is extremely useful for developers who are building web sites that enable user-contributed content. This enables developers to moderate the content that has been uploaded by analyzing the uploaded images for objectionable content.

More Info To learn more about the Computer Vision APIs, visit `http://bit.ly/MSFTCompVision`.

Using the Computer Vision APIs, developers can build innovative applications. For example, the How-Old.net site (shown in Figure 5-6) was built using Computer Vision APIs. You see the results returned in Figure 5-7.

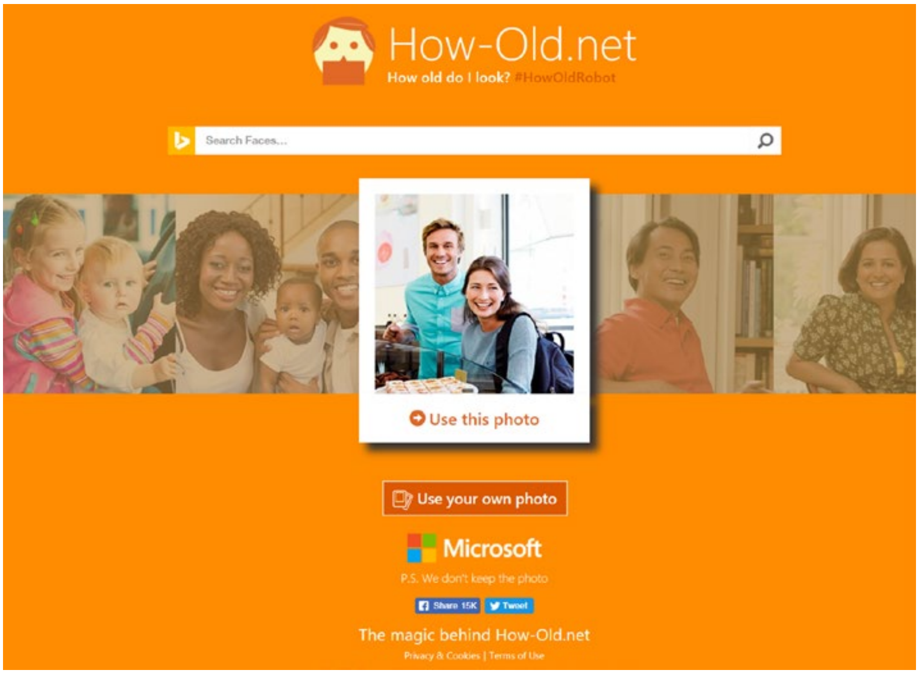

How-Old.net
How old do I look? #HowOldRobot
Search Faces...
Use this photo
Use your own photo
Microsoft
P.S. We don't keep the photo
Share 15K
Tweet
The magic behind How-Old.net
Privacy & Cookies | Terms of Use

***Figure 5-6.** How-Old.net*

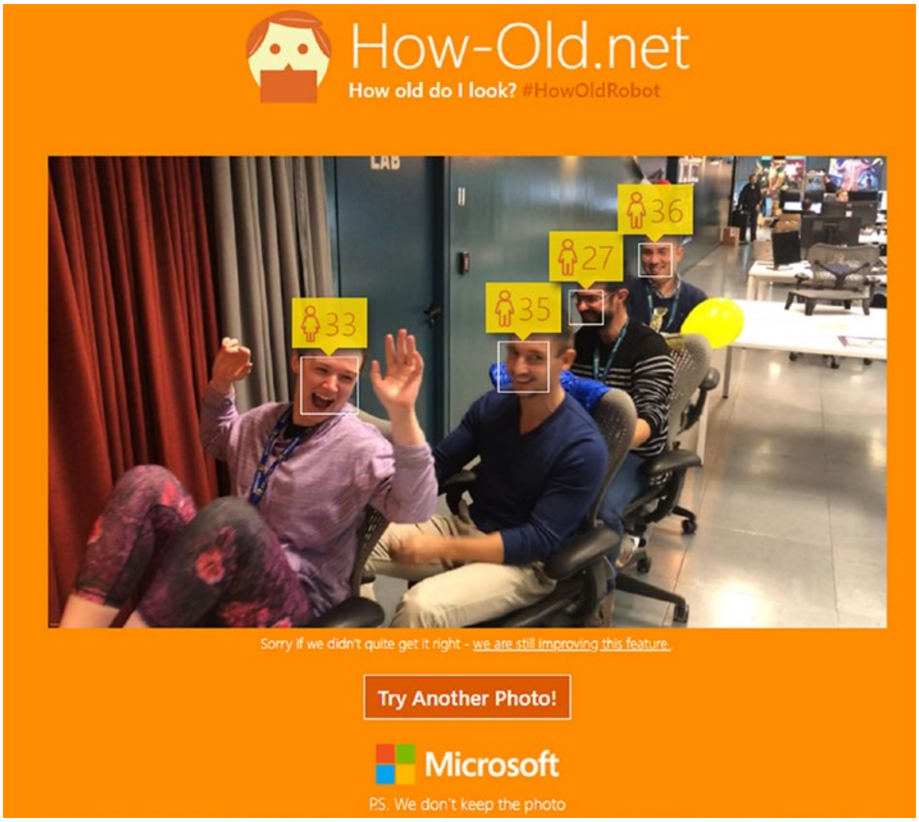

How-Old.net
How old do I look? #HowOldRobot
36
27
35
33
Sorry if we didn't quite get it right - we are still improving this feature.
Try Another Photo!
Microsoft
P.S. We don't keep the photo

Figure 5-7. *Results from How-Old.Net*

Another example of an innovative application built using Computer Vision APIs is the Intelligent Kiosk. The Intelligent Kiosk consists of a set of intelligent experiences that showcase how to use Cognitive Services. It enables any ordinary web camera to be connected to a PC and turned into an intelligent camera.

One of the intelligent experiences, available as part of the kiosk, is the Realtime Crowd Insights samples (shown in Figure 5-8). Realtime Crowd Insights uses the Computer Vision APIs as the foundation for capturing real-time information about the people interacting with the kiosk. These include understanding the number of unique people that are standing in front of the kiosk, counting of unique faces, and looking at the overall emotions. This sample provides the basis for developing interactive and intelligent experiences for kiosks that are deployed in retail malls and more.

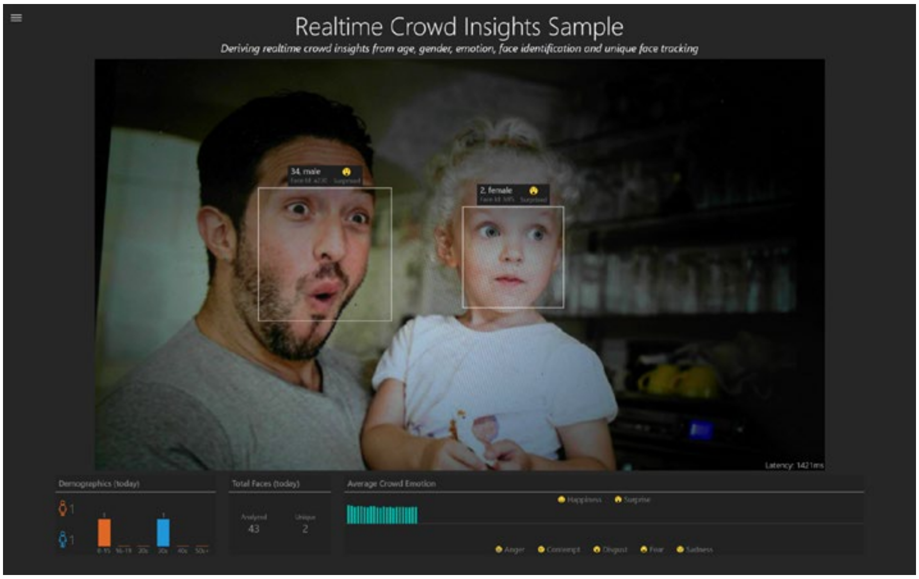
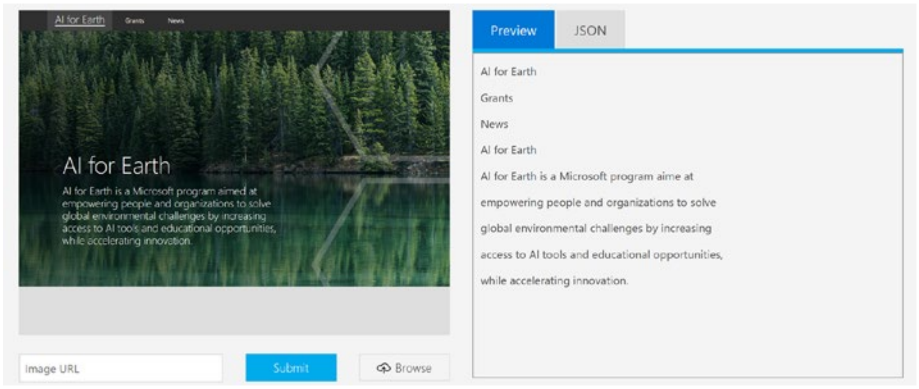


Figure 5-8. *Intelligent Kiosk Realtime Crowd Insights*

More Info The code for Intelligent Kiosk is open source and is available at `http://bit.ly/IntelligentKiosk`.

How to Use Optical Character Recognition–

The Computer Vision APIs enable you to perform OCR for printed and handwritten text. To do this, you can upload an image or provide the URL where the image is stored. The APIs will detect the text in the image and return in a JSON payload the characters that are recognized. Various languages are supported, including UNK (Autodetecting the language), English, Danish, Dutch, French, German, and many more. In Figure 5-9, we uploaded an image (shown on the left). You will see that the OCR APIs analyzed the image and returned the text found in the image (shown on the right).


AI for Earth
Grants
News
AI for Earth
AI for Earth is a Microsoft program aimed at empowering people and organizations to solve global environmental challenges by increasing access to AI tools and educational opportunities, while accelerating innovation.
Image URL
Submit
Browse
Preview
JSON

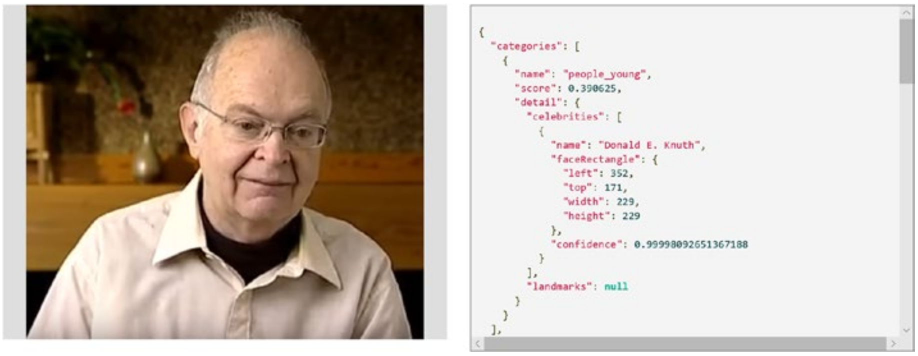
AI for Earth
Grants
News
AI for Earth
AI for Earth is a Microsoft program aime at
empowering people and organizations to solve
global environmental challenges by increasing
access to AI tools and educational opportunities,
while accelerating innovation.

Figure 5-9. *Using the OCR APIs*

More Info To learn more on using the OCR capabilities for Cognitive Services, visit `http://bit.ly/MSFTocr`.

How to Recognize Celebrities and Landmarks

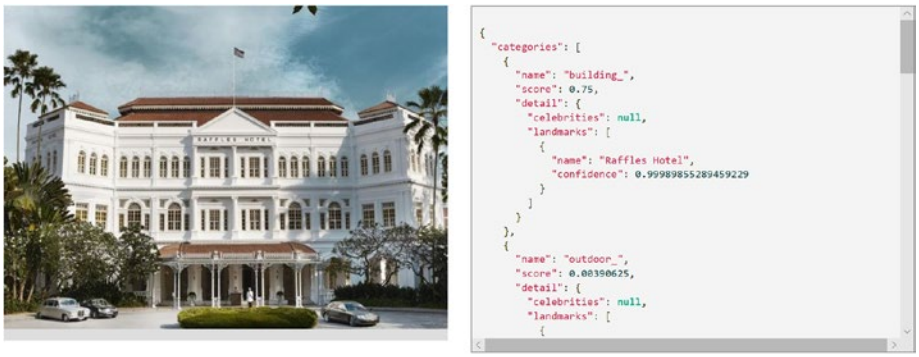
The Computer Vision APIs enable you to recognize celebrities and landmarks. Cognitive Services refer to these as domain-specific models. To find out about the different domains (e.g., celebrities, landmarks) supported, you can use the `/models GET` request. Figure 5-10 shows how this is used to recognize "Donald E. Knuth" from the image provided on the right. Cognitive Services recognizes up to 200,000 celebrities.



```
{
  "categories": [
    {
      "name": "people_young",
      "score": 0.390625,
      "detail": {
        "celebrities": [
          {
            "name": "Donald E. Knuth",
            "faceRectangle": {
              "left": 352,
              "top": 171,
              "width": 229,
              "height": 229
            },
            "confidence": 0.99998092651367188
          }
        ],
        "landmarks": null
      }
    }
  ],
```

Figure 5-10. *Using domain-specific models for celebrities*

In addition, the Computer Vision APIs can also recognize landmarks. Figure 5-11 shows how the API recognized Raffles Hotel, a tourist attraction in Singapore. Cognitive Services recognizes up to 9,000 natural and man-made landmarks.



```
{
  "categories": [
    {
      "name": "building_",
      "score": 0.75,
      "detail": {
        "celebrities": null,
        "landmarks": [
          {
            "name": "Raffles Hotel",
            "confidence": 0.99989855289459229
          }
        ]
      }
    },
    {
      "name": "outdoor_",
      "score": 0.00390625,
      "detail": {
        "celebrities": null,
        "landmarks": [
          {
```

Figure 5-11. *Using domain-specific models for landmarks*

More Info To learn more on using Cognitive Services to recognize celebrities and landmarks, visit `http://bit.ly/CelebLand`.

How Do I Get Started with Cognitive Services?

To get started with using Cognitive Services, log in to the Azure Portal (`portal.azure.com`). After you have logged in to the Azure Portal, you can choose to create a New Azure Resource. Select AI + Cognitive Services**.** In Figure 5-12 you will see all the Cognitive Services listed in the window.

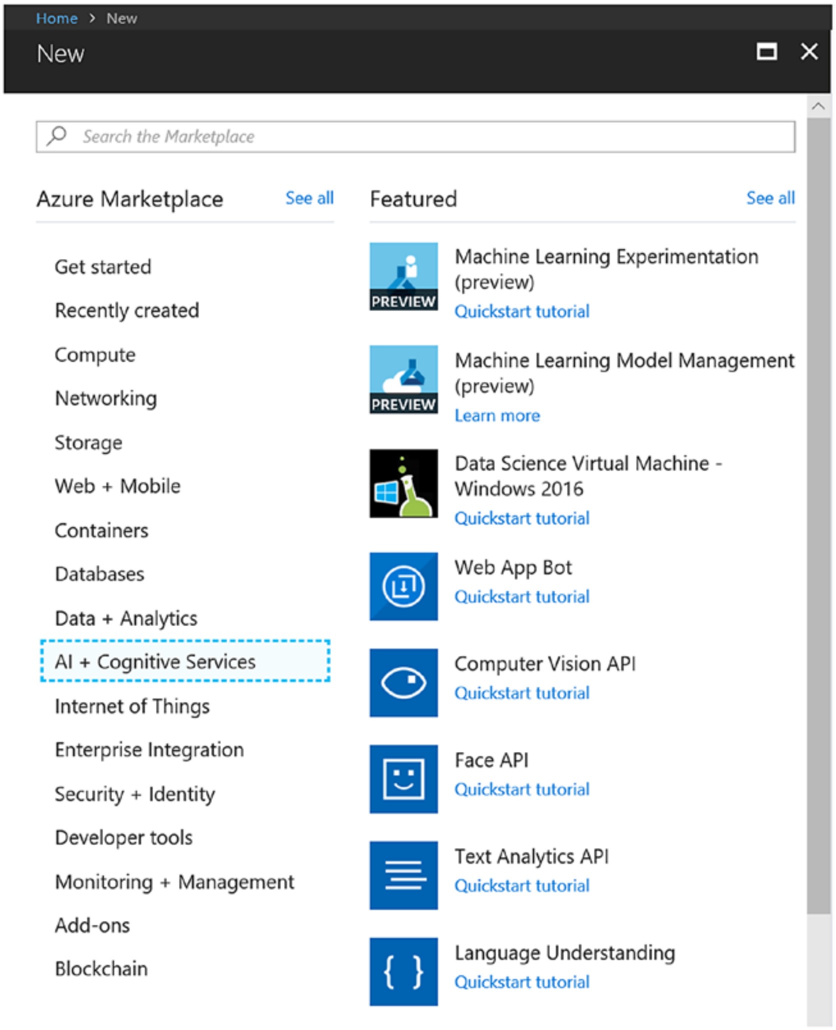
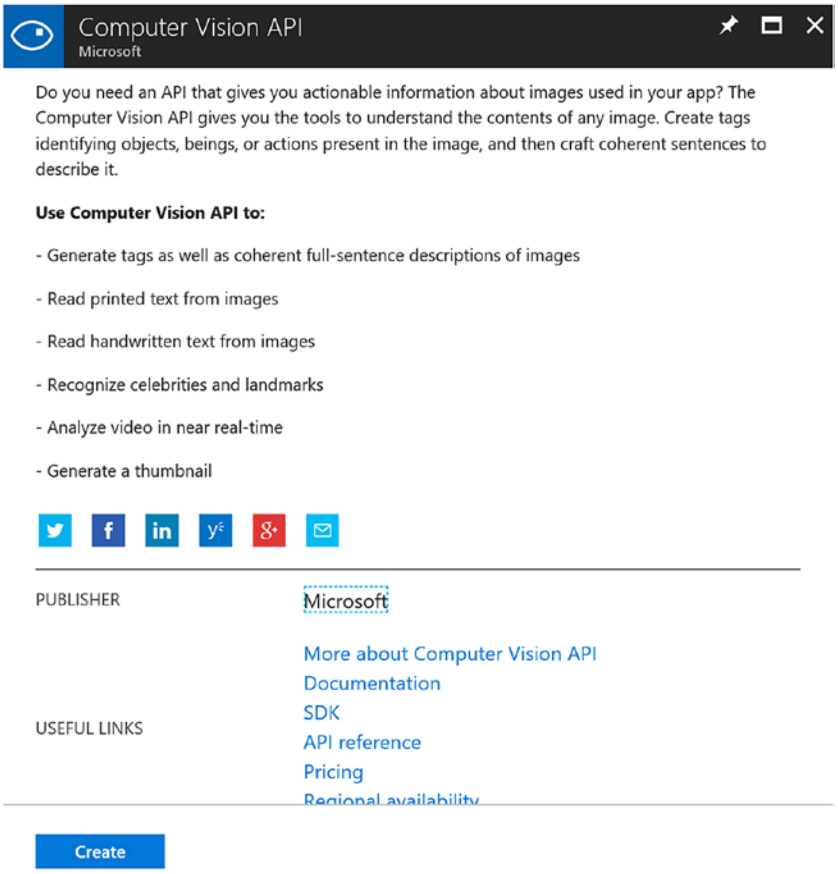


Figure 5-12. *Creating a new Cognitive Services instance*

For illustration, let us select the Computer Vision API. Figure 5-13 shows the screenshot for creating a new Computer Vision API. After you click Create, you will be asked to name the API (shown in Figure 5-14) and select the pricing tier for the API. For Computer Vision APIs, two tiers are available: FO Free and S1 Standard. The FO Free tier supports up to 20 calls per minute and 5,000 calls per month. The S1 Standard tier supports 600 calls per minute. Both tiers enable you to use the Computer Vision APIs to analyze the content of an image, identify the most relevant tags, perform auto-captioning, perform OCR, and generate the thumbnail.



Computer Vision API
Microsoft

Do you need an API that gives you actionable information about images used in your app? The Computer Vision API gives you the tools to understand the contents of any image. Create tags identifying objects, beings, or actions present in the image, and then craft coherent sentences to describe it.

Use Computer Vision API to:

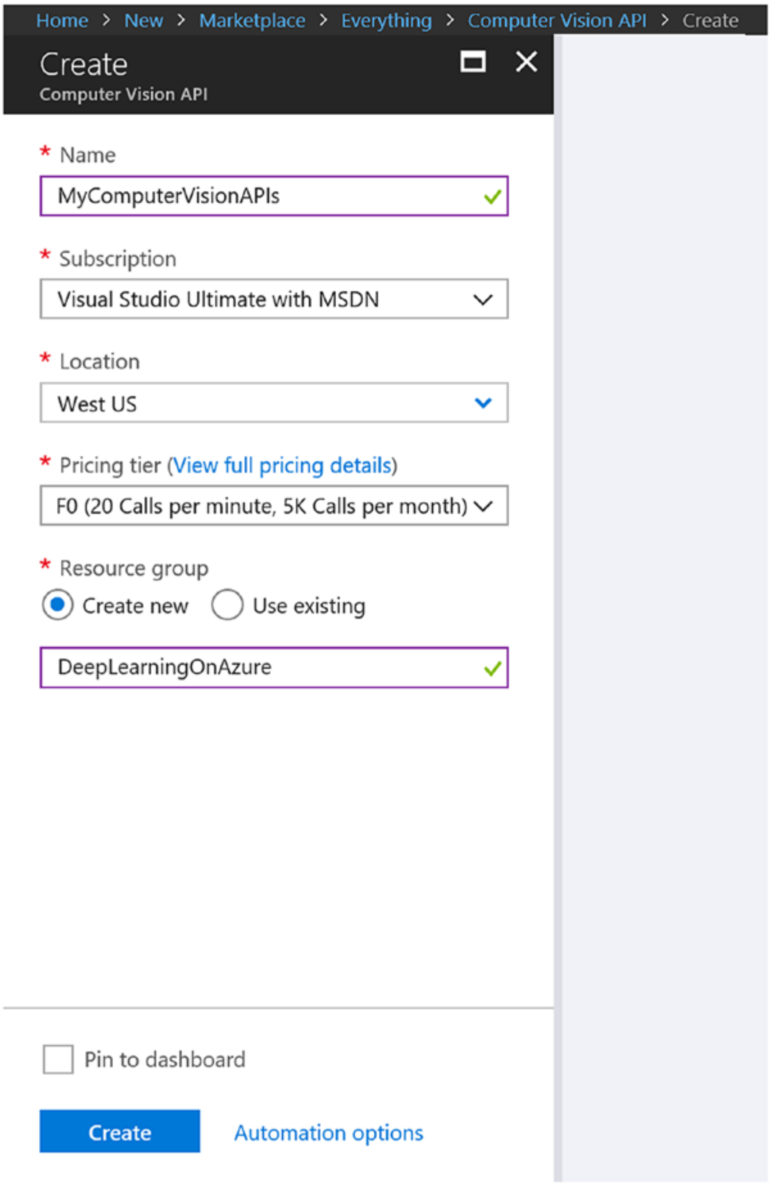
- Generate tags as well as coherent full-sentence descriptions of images
- Read printed text from images
- Read handwritten text from images
- Recognize celebrities and landmarks
- Analyze video in near real-time
- Generate a thumbnail

PUBLISHER Microsoft

USEFUL LINKS
More about Computer Vision API
Documentation
SDK
API reference
Pricing
Regional availability

Create

Figure 5-13. Create a new Cognitive Services Computer Vision API


Home > New > Marketplace > Everything > Computer Vision API > Create

Create
Computer Vision API

* Name
MyComputerVisionAPIs ✓

* Subscription
Visual Studio Ultimate with MSDN

* Location
West US

* Pricing tier (View full pricing details)
F0 (20 Calls per minute, 5K Calls per month)

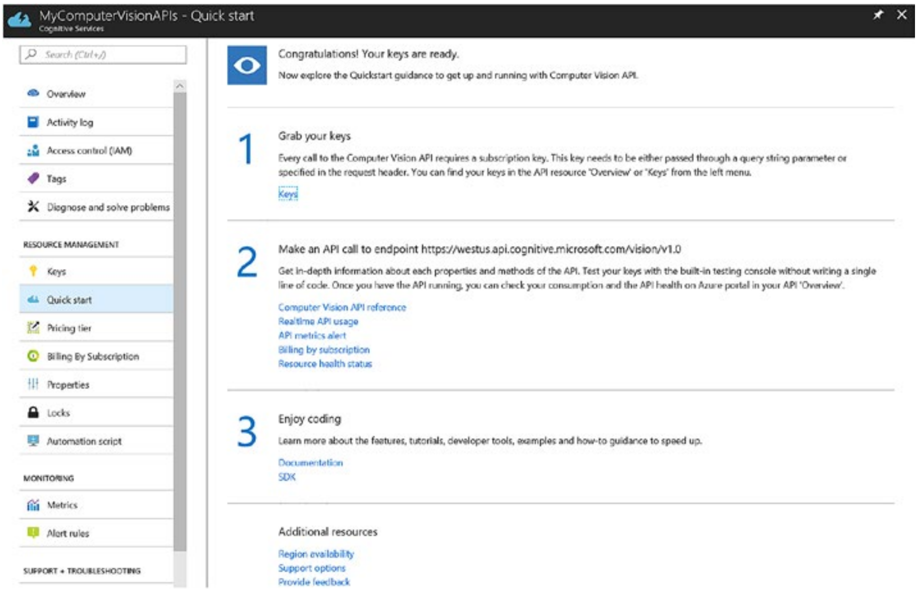
* Resource group
● Create new ○ Use existing
DeepLearningOnAzure ✓

☐ Pin to dashboard

Create
Automation options

***Figure 5-14.** Configuring the Computer Vision APIs*

After the Computer Vision API has been created, you can manage it using the Azure Portal. Figure 5-15 shows how you can manage the newly created Computer Vision API. To use the API in your application, you will need to specify the API key. You can click Keys in the management window, which will show you the keys that are available. Figure 5-16 shows the two keys that are available. You can make use of the Primary and Secondary key during key rotation. You can use either of the keys in your application. This is specified as part of the Request header. If you are developing a .NET application to use Cognitive Services, the key is specified as part of the API call. Listing 5-1 shows the sample code for accessing the Computer Vision APIs. For example, you should replace the `"{subscription key}"` placeholder in the code with the subscription key that you obtained from the Azure Portal.



Congratulations! Your keys are ready.

Now explore the Quickstart guidance to get up and running with Computer Vision API.

1 Grab your keys

Every call to the Computer Vision API requires a subscription key. This key needs to be either passed through a query string parameter or specified in the request header. You can find your keys in the API resource 'Overview' or 'Keys' from the left menu.

Keys

2 Make an API call to endpoint https://westus.api.cognitive.microsoft.com/vision/v1.0

Get in-depth information about each properties and methods of the API. Test your keys with the built-in testing console without writing a single line of code. Once you have the API running, you can check your consumption and the API health on Azure portal in your API 'Overview'.

Computer Vision API reference
Realtime API usage
API metrics alert
Billing by subscription
Resource health status

3 Enjoy coding

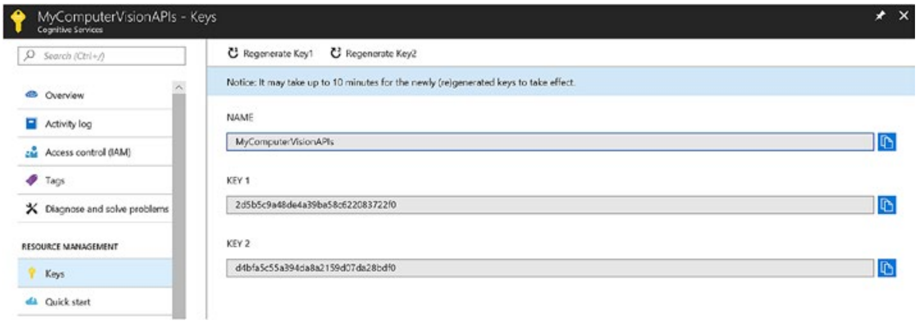
Learn more about the features, tutorials, developer tools, examples and how-to guidance to speed up.

Documentation
SDK

Additional resources

Region availability
Support options
Provide feedback

Figure 5-15. *Managing Cognitive Services*



Notice: It may take up to 10 minutes for the newly (re)generated keys to take effect.

NAME
MyComputerVisionAPIs

KEY 1
2d5b5c9a48de4a39ba58c622083722f0

KEY 2
d4bfa5c55a394da8a2159d07da28bdf0

Figure 5-16. *Obtain the keys for Cognitive Services*

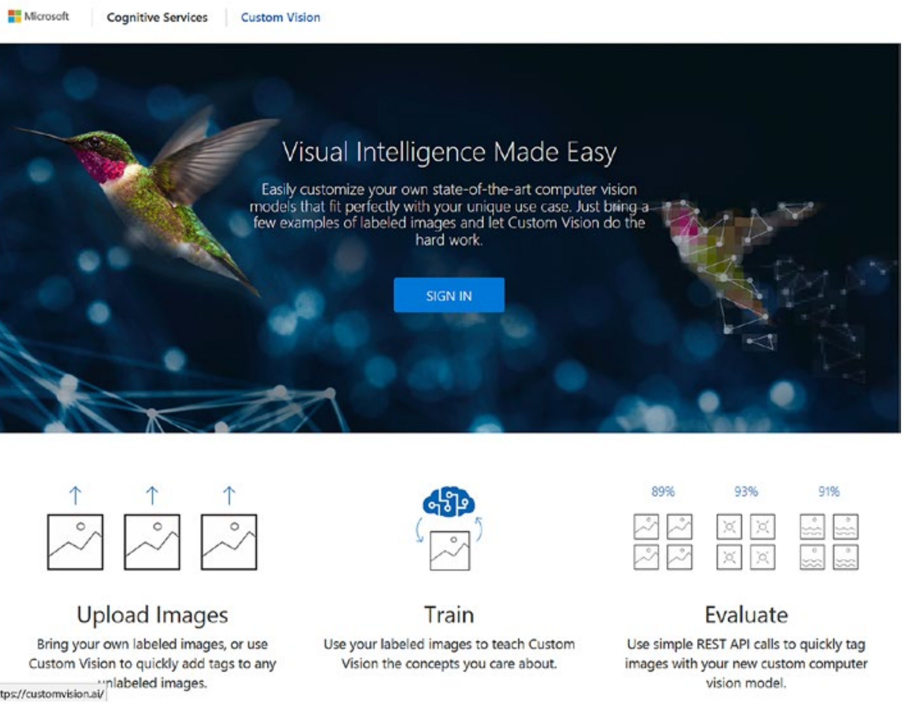
Listing 5-1. Sample Code to use Cognitive Services (Computer Vision APIs)

```
C#
using System;
using System.Net.Http.Headers;
using System.Text;
using System.Net.Http;
using System.Web;

namespace CSHttpClientSample {
  static classProgram {
    static voidMain() {
       MakeRequest();
       Console.WriteLine("Hit ENTER to exit...");
       Console.ReadLine();
    }

    static async voidMakeRequest() {
      var client = new HttpClient();
      var queryString =
        HttpUtility.ParseQueryString(string.Empty);
      // Request headers
      client.DefaultRequestHeaders.Add(
        "Ocp-Apim-Subscription-Key",
        "{subscription key}");

      // Request parameters
      queryString["visualFeatures"] = "Categories";
      queryString["details"] = "{string}";
      queryString["language"] = "en";

      var uri =
"https://westcentralus.api.cognitive.microsoft.com/vision/v1.0/
analyze?" + queryString;

      HttpResponseMessage response;

      // Request body
      byte[] byteData =
        Encoding.UTF8.GetBytes("{body}");

      using (
         var content =
           new ByteArrayContent(byteData))
         {
            content.Headers.ContentType =
              new MediaTypeHeaderValue("<content>");

            response =
              await client.PostAsync(uri, content);
         }
     } // method MakeRequest
   } // Program
} // namespace
```

Custom Vision

In Chapter 2, we described how data scientists can make use of transfer learning to adapt CNNs to new domains. For example, a Resnet-50 CNN trained on ImageNet data can be adapted for image classification in other domains (e.g., health care, retail, manufacturing, etc.).

Custom Vision is part of the family of Cognitive Services. Custom Vision enables you to quickly customize state-of-the-art computer vision models for your scenario, with a small set of labeled images. Underneath the hood, Custom Vision uses transfer learning and data augmentation techniques to train a custom model for your scenario. Figure 5-17 shows the main page for the Custom Vision service.



Visual Intelligence Made Easy

Easily customize your own state-of-the-art computer vision models that fit perfectly with your unique use case. Just bring a few examples of labeled images and let Custom Vision do the hard work.

Upload Images

Bring your own labeled images, or use Custom Vision to quickly add tags to any unlabeled images.

Train

Use your labeled images to teach Custom Vision the concepts you care about.

Evaluate

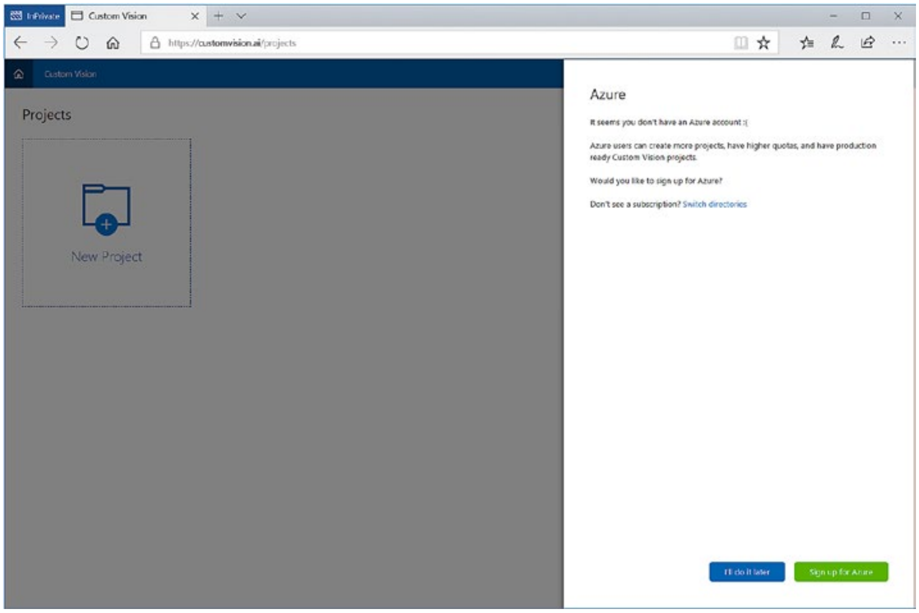
Use simple REST API calls to quickly tag images with your new custom computer vision model.

Figure 5-17. *Custom Vision (customvision.ai)*

More Info Did you know that you can use Custom Vision programmatically? Using C# or Python, you can programmatically create a Custom Vision project, add tags, upload images, and train the project. After the custom vision models are trained, you can retrieve the prediction URL and test the custom image classifier. To find out more, visit `http://bit.ly/CustomVisionProg`.

Hello World! for Custom Vision

In this section, we will learn how to get started with Custom Vision. On the `customvision.ai` page, click Sign In. During the first sign in to Custom Vision, you will need to accept the terms of use. You will be prompted to indicate whether you want to use an Azure account, which will enable you to work with more Custom Vision projects. If you do not sign in to Azure, you will have access to fewer quotas. Figure 5-18 shows the initial page after you sign in. If you do not have an Azure subscription, you can click I'll Do It Later.



Azure

It seems you don't have an Azure account :(

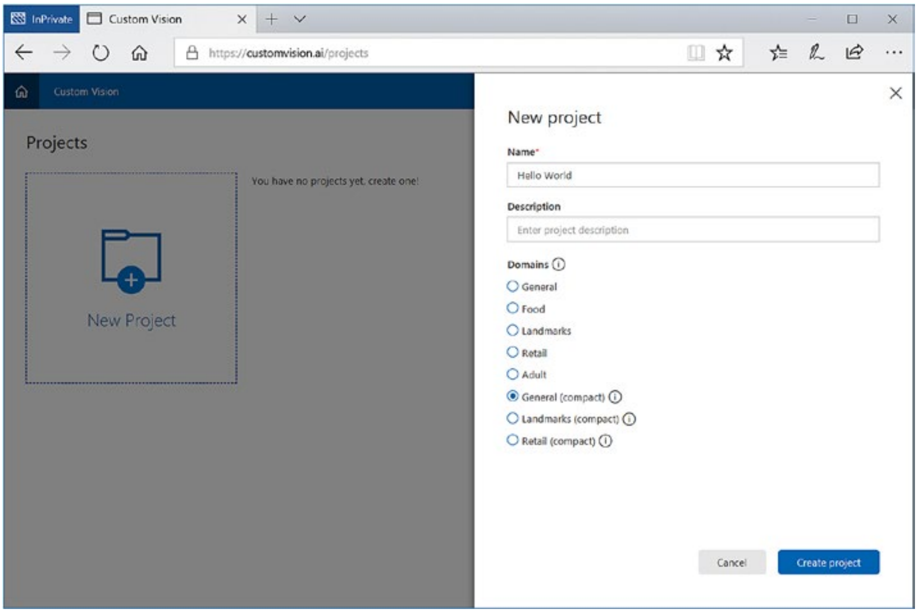
Azure users can create more projects, have higher quotas, and have production ready Custom Vision projects.

Would you like to sign up for Azure?

Don't see a subscription? Switch directories

Figure 5-18. *Custom Vision first sign in*

After you sign in, you can create your first Custom Vision project by clicking New Project. As shown in Figure 5-19, we create our first Hello World Custom Vision project. Several domains are provided that will enable you to customize the base model that is most relevant to your scenario. In this example, we selected General (Compact). Compact domains enable you to export the trained models, which we cover in a later section.


InPrivate
Custom Vision
https://customvision.ai/projects
Custom Vision
Projects
New Project
You have no projects yet, create one!

New project

Name*: Hello World

Description: Enter project description

Domains:
- General
- Food
- Landmarks
- Retail
- Adult
- [✓ General (compact)]
- Landmarks (compact)
- Retail (compact)

Cancel | Create project

Figure 5-19. *Creating your first Custom Vision project*

Figure 5-20 shows an example of the intelligent zoo app that we want to develop. After you click Create Project, we are ready to get started (shown in Figure 5-21). In this scenario, we want to develop an application that will enable children who are visiting the zoo to be able to take a picture of an animal and find out more information about each animal.

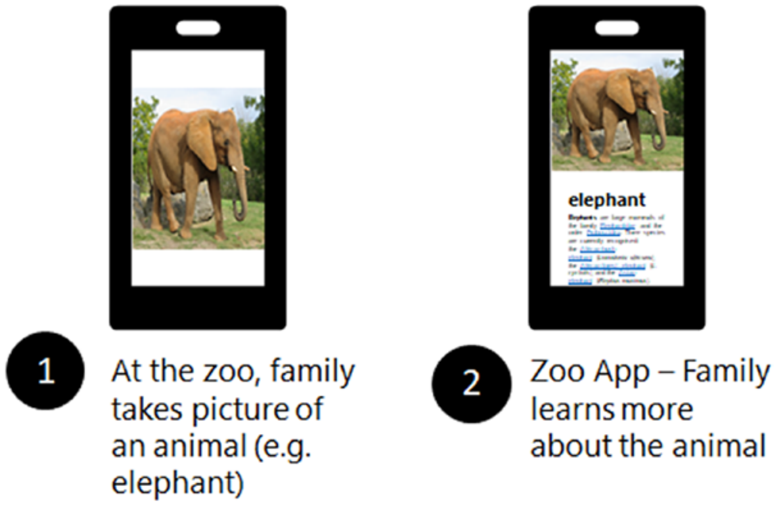
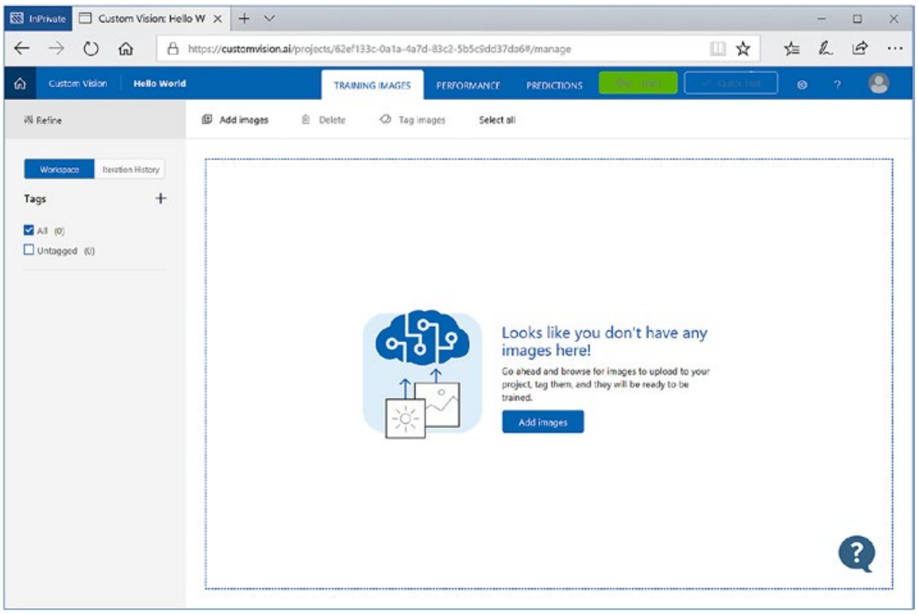

elephant
1
At the zoo, family takes picture of an animal (e.g. elephant)
2
Zoo App – Family learns more about the animal

Figure 5-20. *Scenario: Intelligent Zoo app*



Looks like you don't have any images here!

Go ahead and browse for images to upload to your project, tag them, and they will be ready to be trained.

Figure 5-21. *Hello World Custom Vision project*

We will need to build a custom image classifier for animals. To do this, we will leverage Custom Vision to train a custom classifier to distinguish between different types of animals, giraffes and elephants. To train the classifier, we upload training images of a giraffe (shown in Figure 5-22) and elephants to Custom Vision. You can find images of giraffes and elephants using an image search in a search engine (e.g., Bing). After all the images are uploaded (shown in Figure 5-23), we are ready to train the classifier. Click Train.

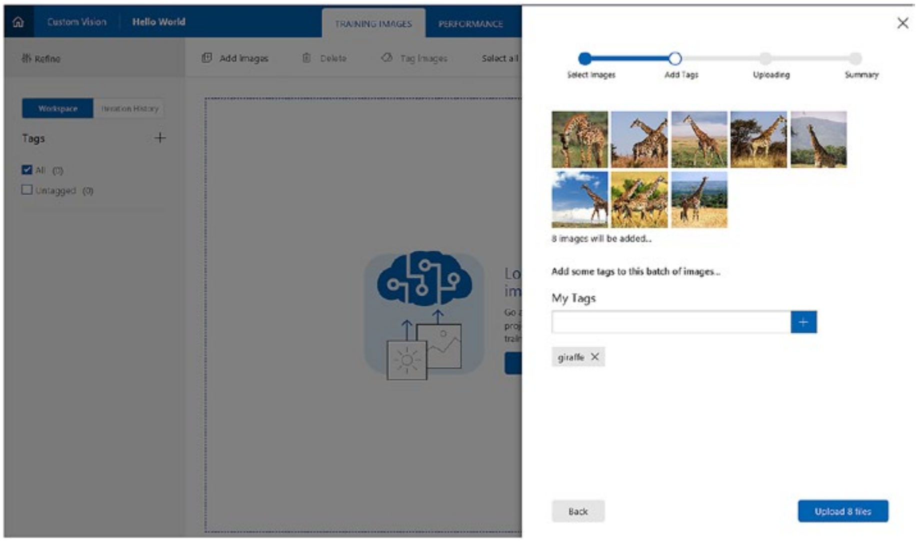


Figure 5-22. *Uploading pictures of giraffes to Custom Vision*

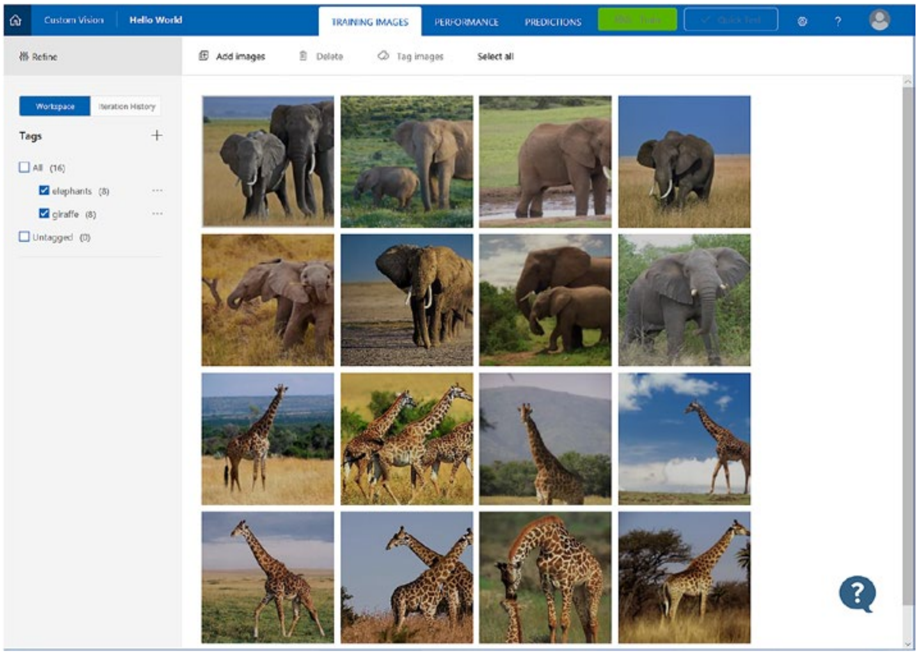
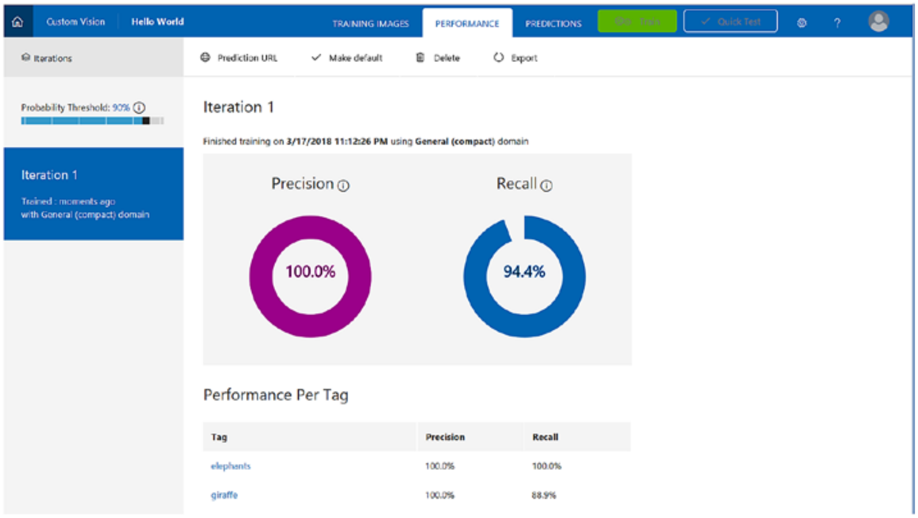


Figure 5-23. *Training images for giraffes and elephants*

After training is completed, you will see the evaluation results shown in Figure 5-24. The overall precision and recall metrics are returned. In addition, the performance for each tag (i.e., label or class) is also shown below. To use the Custom Vision mode, click Prediction URL. This corresponds to a REST endpoint that can be used in any application.



Iteration 1

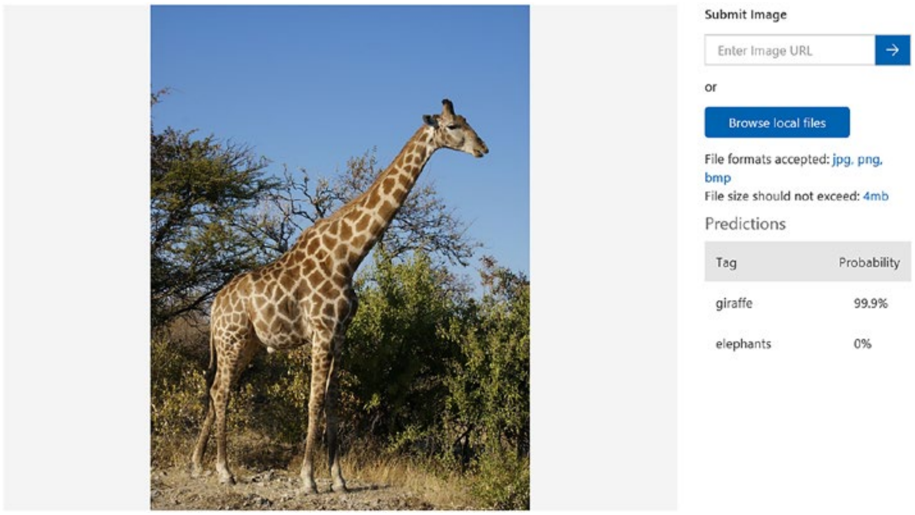
Finished training on 3/17/2018 11:12:26 PM using General (compact) domain

Performance Per Tag

Tag	Precision	Recall
elephants	100.0%	100.0%
giraffe	100.0%	88.9%

Figure 5-24. *Evaluation results from Training Iteration 1*

In addition, we can test the model by clicking Quick Test. We can either provide a URL to an image or upload an image to test the custom Computer Vision model. Figure 5-25 shows the result of uploading a test image and the results returned by the classifier.



File formats accepted: jpg, png, bmp
File size should not exceed: 4mb

Predictions

Tag	Probability
giraffe	99.9%
elephants	0%

Figure 5-25. *Quick Test using a test image of a giraffe*

Congratulations! We have just completed the training of a custom deep learning model using training images, corresponding to giraffes and elephants. To fully realize the scenario shown in Figure 5-20, we need to continue improving the custom image classifier by uploading images of other animals found in the zoo to Custom Vision. Using a limited set of training images per animal, we can quickly build a custom image classifier for animals.

Exporting Custom Vision Models

After we have trained the model, we can develop an application that uses the prediction URL provided. We might also want the model to run on devices (e.g., iPhone, iPads, Android tablets). The choice of whether you use a prediction URL or running devices on models depends on your use case. In situations where you want to be able to perform inferences when Internet connectivity is not available, or where you require low latency, having the models running on the device will be a good design choice.

To do this, and to develop applications that can consume the model offline, Custom Vision enables you to export the model. Click Export. This button is available only if we are using Compact models. You can export the models as CoreML, TensorFlow, or ONNX models. In addition, you can also export the Dockerfile to enable you to build a container that is able to serve the model.

Figure 5-26 shows the platforms that are available when exporting the models. Once we choose the relevant platform to export, the relevant files can be downloaded (e.g., `.mlmodel` for CoreML, `.zip` for TensorFlow, and `.onnx` for ONNX models). These models can then be easily integrated into iOS, Android, or Windows applications.

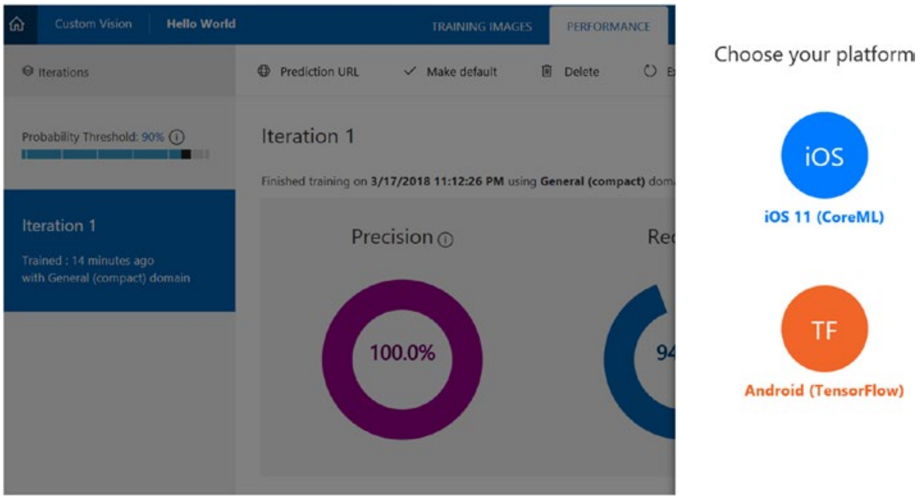


Figure 5-26. *Exporting Custom Vision models to CoreML or TensorFlow*

Summary

This chapter discussed the different types of Cognitive Services that are available as part of the Microsoft AI Platform. These prebuilt AI capabilities enable developers in your organization to get started immediately with realizing the value of AI to develop innovative applications. In addition, we also illustrated how to adapt pretrained deep learning models for computer vision to new data using Custom Vision. This enables you to quickly train an image classification model by bringing your own data. To enable you to do AI on the intelligent edge (IoT edge device, iOS and Android devices), Custom Vision enables you to explore CoreML and TensorFlow models. This chapter only touched the surface of the different Cognitive Services available on the Microsoft AI Platform. We encourage you to explore others in more depth as well, such the Language Understanding service, Azure Search, and Custom Speech service, depending on your use case and needs.

In the next set of chapters, rather than focus on using prebuilt AI capabilities as discussed here, we instead focus on an overview of how to build custom deep learning models, starting with an overview of common models such as CNNs in the next chapter.

PART III

AI Networks in Practice

CHAPTER 6

Convolutional Neural Networks

CNNs are a prime example of neuroscience influencing deep learning (LeCun, Bottou, Bengio, & Haffner, 1998). These neural networks are based on the seminal work done by Hubel and Wiesel (1962). They discovered that individual neuronal cells in the visual cortex responded only to the presence of visual features such as edges of certain orientations. From their experiments they deduced that the visual cortex contains a hierarchical arrangement of neuronal cells. These neurons are sensitive to specific subregions in the visual field, with these subregions being tiled to cover the entire visual field. They in fact act as localized filters over the input space, making them well suited to exploiting the strong spatial correlation found in natural images. CNNs have been immensely successful in many computer vision tasks not just because of the inspiration drawn from neuroscience, but also due to the clever engineering principles employed. Although they have traditionally been used for applications in the field of computer vision such as face recognition and image classification, CNNs have also been used in other areas such as speech recognition and natural language processing for certain tasks.

This chapter briefly describes what convolution is and how it relates to neural networks. It then explains the various elements that make up the CNN architecture and what effects they have, and why CNNs do so well. Finally, it covers the usual steps to training CNNs before diving into a

M. Salvaris et al., *Deep Learning with Azure*,

number of practical examples, using the CIFAR10 data set to train a CNN using Jupyter notebooks.

One of the first successful applications of CNNs was in the 1990s, reading zip codes using the LeNet architecture from Yann LeCun and colleagues (LeCun, Boser, et al., 1989). However, CNNs were widely popularized in 2012 with the AlexNet (Krizhevsky, Sutskever, & Hinton, 2012) architecture, which won the ImageNet Large Scale Visual Recognition Competition (ILSVRC) as mentioned in Chapter 1 and led to a breakthrough in the computer vision field. Since then, there have been many useful developments and recommended architectures from researchers such as VGGNet (Simonyan & Zisserman, 2014) and ResNet (He, Zhang, Ren, & Sun, 2016). We do not recommend a specific neural network architecture because this is still a fast-moving field with new breakthroughs happening frequently. Instead, we recommend that practitioners pick out an architecture already available that has been developed and tested by researchers, and if necessary tweak it.

The Convolution in Convolution Neural Networks

To keep things simple when talking about convolution we will be talking about discrete convolution. Mathematically, convolution is the simple summation of the pointwise multiplication of two functions. The summations can take place in one or more dimensions, so for grayscale images the summation would take place over two dimensions and over three dimensions in color images.

Convolution is similar to cross-correlation and in many deep learning libraries the implementation is actually cross-correlation even though it is referred to as convolution. For all practical purposes in the CNNs this is just an implementation detail and does not really affect the resulting behavior of the model. To get an intuitive feeling of how convolution behaves, there is a simple example illustrated in Figure 6-1.

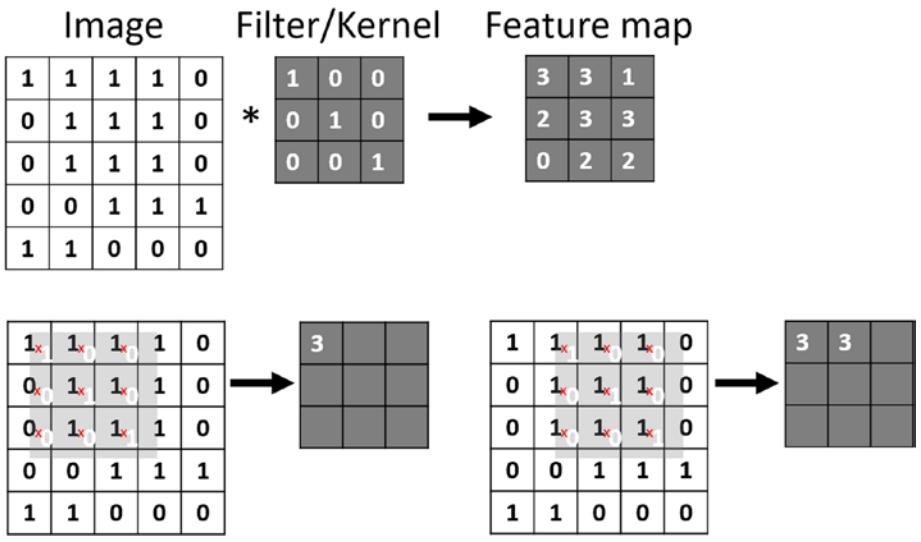


Figure 6-1. *Convolution in CNNs*

In this example the image is represented by a 5 × 5 matrix and each pixel can only take on two values, 1 or 0. We have a convolution kernel that detects diagonal lines. Convolution kernels are sometimes referred to as filters or feature detectors. By convolving our kernel with the image we get our feature and activation map. The top left value of our feature map is created by multiplying all the values in the overlapping matrices and then summing the result. In the bottom row of the image we can see that applying the kernel to our image we get a value of three. The kernel is applied to the nine pixels in the top left area of our image. If we were to flatten out the values row wise we would have the vector [1,1,1,0,1,1,0,1,1]. The kernel would correspond to the vector [1,0,0,0,1,0,0,0,1]. If we multiply the two vectors element wise as so [1*1, 1*0, 1*0, 0*0 ...] we will end up with the vector [1,0,0,0,1,0,0,0,1], which we sum to get the value 3. In essence we are computing the dot product of the two vectors to end up with a scalar value.

We then shift the kernel right by one—this is often referred to as the *stride*—and do the same thing again. Notice that the feature map is smaller than the original image. To mitigate this, CNNs often employ padding of the input image so that the resulting feature map does not reduce in size, as this constant reduction would limit the number of successive convolutions that could be applied. This is just a simple example, as real color images have three color channels—red, green, and blue—and the pixel value of each channel is represented by an integer between 0 and 255. For a single image, our input would be a three-dimensional matrix with the width, height, and number of channels. Depending on the deep learning framework you use, some expect the channels to be first CHW or channels to be last HWC.

Convolution Layer

CNNs employ convolution in what are referred to as *convolution layers,* which are simply a number of convolution kernels represented by the weights of each convolution layer. The dimensions and stride of the convolution are usually predefined, but the weights are learned as the network is trained. A CNN will typically have many convolution layers and each convolution layer will have its own set of learned kernels or filters.

Figure 6-2 is a selection of convolution filters taken from a pretrained CNN. The top row is of six filters from the first convolution layer. The bottom row is from the last convolution layer in the CNN. Going from the top to the bottom, it looks like the convolution layers are looking at ever more complex patterns. The first layer is encoding direction and color. The second layer seems to be more interested in spot and grid textures. The final layer looks like a complex combination of various textures. From this we can see that as we go through the network the patterns become more intricate, so the deeper the network the more complex patterns the convolution layers will learn to extract.

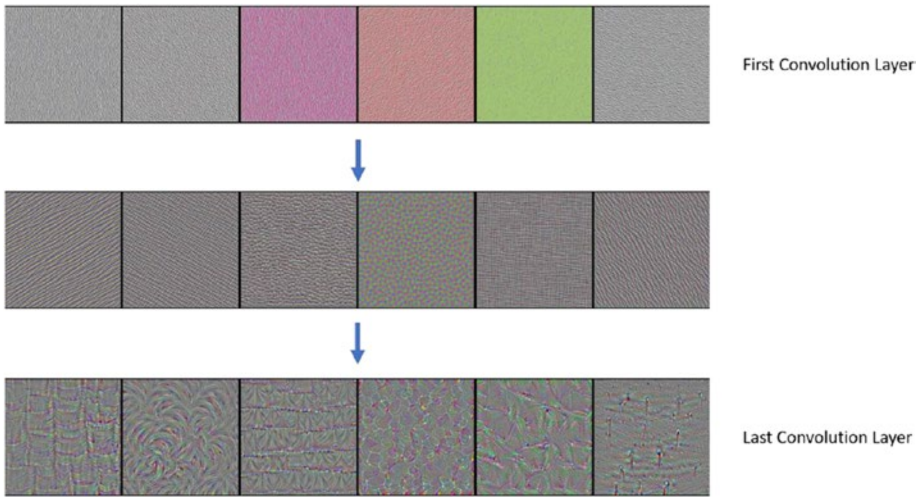


Figure 6-2. *Visualization of convolution layers. For more detailed visualizations take a look at Zeiler and Fergus (2013).*

Another interesting thing to note is that if we look at the first and last filter on the middle row it seems like they could be slightly rotated variations of the same filter. This highlights one of the deficiencies of CNNs: They are not rotation invariant. This is something Hinton has tried to overcome with capsule networks, as discussed in Chapter 3.

Pooling Layer

Convolution is not equivariant, meaning that on their own they do not deal well with scaling and rotation of the input (Sabour, Frosst, & Hinton, 2017). A common type of layer in modern CNNs to help deal with this is a pooling layer, with the most popular pooling layer being the max pooling layer. Max pooling replaces the output of spatially adjacent outputs with the max of those values. Generally pooling layers replace the outputs with some form of summary statistic based on those outputs.

Generally, the pooling layer's purpose is to make neural networks locally invariant to small translations of the input, and its essence to care more about whether a feature is detected rather than where exactly it is in the input. This does, in turn, reduce the spatial acuity of the model and is considered a limitation of CNNs; however, pooling layers have proven to be extremely useful.

Activation Functions

Activation functions are very important in CNNs and artificial neural networks in general. Without them CNNs would simply be a series of linear operations and would not be able to do the amazing things they do today. Activation functions are simply nonlinear transformations of the output of a neuron in a layer. They are referred to as activation functions because they draw their inspiration from the threshold and fire activation of biological neurons. There are a number of different activation functions with different properties and specialization, but we go over only the most common types here.

Sigmoid

Sigmoid or logistic is a nonlinear function, which squashes the input between the values of 0 and 1 (Figure 6-3).

$$f(x) = \frac{1}{1+e^{-x}}$$

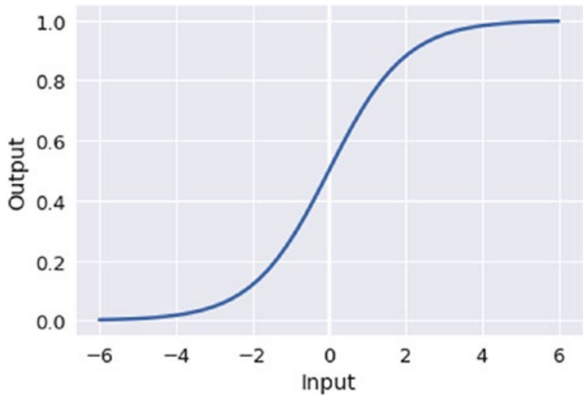


Figure 6-3. *Sigmoid function*

In recent years it has fallen out of favor due to a number of drawbacks:

- It suffers from the vanishing gradient problem. Near the extreme values of 1 and 0 the gradient is flat, meaning as values approach those extremes the neurons saturate, and the weights do not update during backpropagation. Furthermore, neurons connected to this neuron get very tiny weight updates, in essence starving them of the much-needed information.
- The output is not zero centered.

Tanh

Tanh or hyperbolic tangent functions are very similar to sigmoid functions; in fact, they are a simply scaled version of sigmoid functions so that they are centered around 0. Tanh squashes the output between the values of -1 and 1 (Figure 6-4). In practice Tanh is often preferred to sigmoid, but it still suffers from the vanishing gradient problem.

$$f(x)=\frac{1-e^{-2x}}{1+e^{-2x}}$$

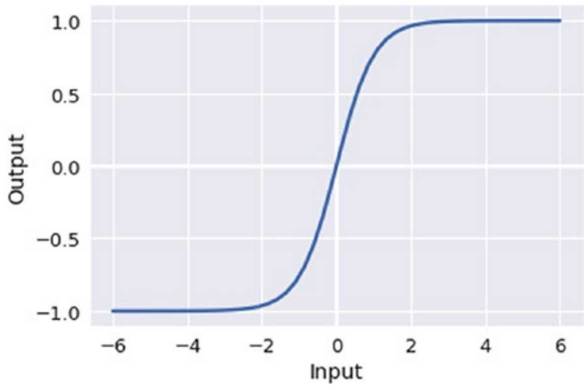


Figure 6-4. *Tanh*

Rectified Linear Unit

The rectified linear unit (ReLU; see Figure 6-5) is probably the most used activation function nowadays (LeCun, Bengio, & Hinton, 2015).

$$f(x) = \max(0, x)$$

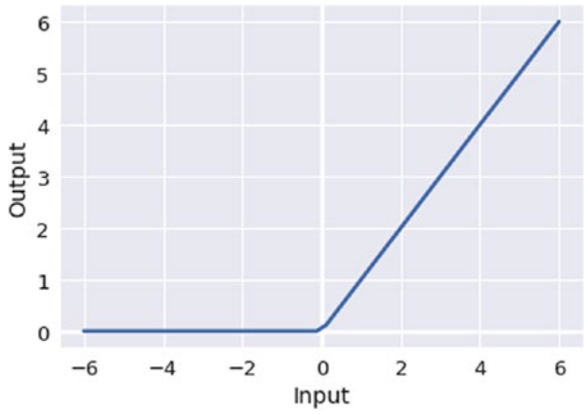


Figure 6-5. *Rectified linear unit (ReLU)*

With the ReLU activation function, when the input is greater than zero, then output is the same as the input; when it is less than zero, the output is zero. Its popularity is mainly due to a couple of facts. First, it does not saturate or suffer from the vanishing gradient problem in the positive region. Second, it is a computationally efficient function and it also leads to sparse activations that also confer computational benefits. It does still suffer from a couple of drawbacks though:

- If the output of the function is less than zero during the forward pass, no gradient is propagated backward during the backward pass. This means that weights do not get updated. If neurons in the CNN exhibit this behavior consistently, the neurons are said to be dead, which means they no longer contribute to the network and are in essence useless. If this happens to a significant portion of your CNN, it will stall and fail to learn.
- For classification tasks, it cannot be used in the output layer because its output isn't constrained between well-defined boundaries.

CNN Architecture

CNNs are typically constructed by stacking multiple layers on top of each other (Figure 6-6). A common configuration is the following: First, there is a convolution layer where multiple kernels convolve the input and produce a number of feature maps. These then pass through a nonlinear activation function such as ReLU, which is then followed by a pooling layer. These three stages are often combined in various ways to create the first few layers of a CNN. The output of the final layer is flattened and then fed through one or more fully connected layers. The activation function of the final layer is usually a softmax or sigmoid that squashes the output between 0 and 1.

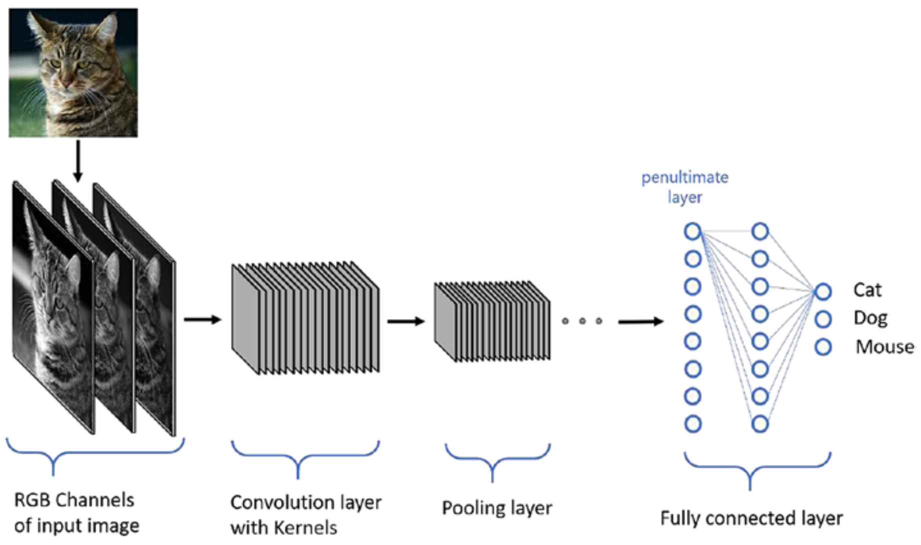


Figure 6-6. *CNN architecture*

Training Classification CNN

So far we have defined what a CNN looks like and how the information is propagated forward, but we have not described how it learns. The process of training a CNN is as follows:

1. We have a predefined architecture with a number of convolution and polling layers, plus our final fully connected layers. The weights of the CNN are initialized randomly based on some distribution.

2. We present the training images as a minibatch to our CNN, a four-dimensional matrix (batch size, width, height, and channels).

3. We complete a forward pass through the networks with the images being passed through the convolution, pooling layers, and activation functions, and finally we get the output probabilities for each class for each image in the minibatch.
4. We compare the probabilities to the true labels and calculate the error.
5. We use backpropagation to calculate the gradients of the error with respect to the weights of the CNN and we use gradient descent to update the weights.
6. This process is repeated either for a set of epochs[1] or until other conditions are met.

This is a simplified view of what happens, but it captures the core of what it takes to train a CNN, an objective function, a method to calculate the gradients, and an optimization method.

The objective or loss function determines how we will calculate the difference between what we expected the network to do and what it did. In essence it will calculate the error for our model. Common loss functions are mean squared error (MSE) and cross-entropy. Now once we have the error, we need to update the weights of the network in the right direction so that our predictions become a little better next time. This is done by a method called backpropagation.

The optimization method most commonly used by CNNs is minibatch gradient descent, often referred to as stochastic gradient descent (SGD), even though SGD is slightly different from minibatch gradient descent. Minibatch gradient descent seeks to optimize the objective function by iteratively updating the weights of the CNN based on the gradients in each minibatch. Due to the nonlinearities in CNNs, the solution space is

[1]Epoch refers to the CNN having seen the whole training set.

often nonconvex and therefore there are no guarantees of convergence. For practitioners this can be quite frustrating, but CNNs work surprisingly well even without this guarantee. The main parameter in all variants of gradient descent is the learning rate, which determines the magnitude of the updates applied to the weight of the network. A variant of SGD also includes a momentum term that tries to accelerate learning by preserving the direction of travel through the parameter space. It does this by adding a fraction of the weight update of the previous time step to the current update. Other optimization algorithms include Adam, RMSProp, and so on.

Why CNNs

As mentioned earlier, CNNs were inspired by neuroscience but they also make use of sound engineering principles that also confer advantages. These are sparse connectivity and parameter sharing. Current research indicates neurons also share these features. A typical human neuron has 7,000 connections (cf. 10^{11} neurons in the brain). Similarly, each neuronal cell type shares specific functional parameters. A great example of the latter are retinal ganglion cells, which all implement effectively the same type of convolutional kernel (opposing center-surround). The weights of these kernels were “learned” through evolution of gene expression patterns.

In traditional neural networks such as multilayer perceptrons (MLPs), every layer is fully connected to every single node of the next layer. As you increase the number of layers and the number of nodes, the number of parameters explodes. In CNNs the connections are usually much smaller than the input because the kernel is convolved over the input, which is represented by the previous layer. Therefore in an image that is made of thousands of pixels, the convolution kernel can be just a few tens of pixels. This reduction in parameters improves the efficiency of the model both in terms of memory and also in terms of computation due to the reduction in the amount of computation required.

The second benefit is parameter sharing. In standard neural networks, the input weights for each node in the next layer are only used for that node, whereas in CNNs the same kernel is used many times. Therefore, instead of learning different parameters for each node, we learn a set of kernels for all the nodes.

Training CNN on CIFAR10

In this next section, we go step by step in training a CNN on the CIFAR10 data set (Krizhevsky 2009; Krizhevsky, Nair, & Hinton, n.d.). We use TensorFlow as the deep learning library to build our CNN with. The CIFAR10[2] data set is an often used data set that in total contains 60,000 32 × 32 color images across 10 classes (see Figure 6-7). These are split into 50,000 training and 10,000 test. The code for this section can also be found in the notebook `Chapter_06_01.ipynb` (`http://bit.ly/Nbook_ch06_01`).

More Info We recommend provisioning an Azure DLVM to run the code examples in this chapter. Please see the Chapter 4 for more information.

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[2]CIFAR stands for the Canadian Institute for Advanced Research. They are partly responsible for funding Hinton and LeCun during the neural network winter, leading to the eventual resurgence of neural networks as deep learning.

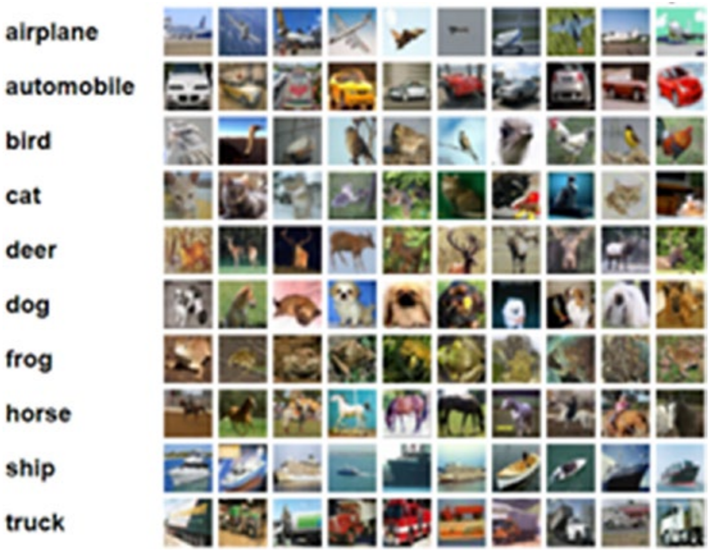


Figure 6-7. *CIFAR10 data set*

The first thing we will do is define our CNN (see Listing 6-1). It isn't very deep and only has two convolutional layers. The first convolution layer has 50 filters and the second 25, each with a dimension of 3 × 3. The first convolution layer uses ReLU activation and the second convolution layer carries out ReLU activation before using max pooling. After that we need to reshape our Tensor into a 2D matrix with the first dimension being the size of our batch. After that we pass it into a fully connected layer of 512 nodes with ReLU activation. Finally, we introduce our final dense layer, which has 10 outputs, one for each of our classes.

Listing 6-1. CNN with Two Convolution Layers

PYTHON

```
def create_model(model_input,
                 n_classes=N_CLASSES,
                 data_format='channels_last'):
```

```
    conv1 = tf.layers.conv2d(model_input,
                             filters=50,
                             kernel_size=(3, 3),
                             padding='same',
                             data_format=data_format,
                             activation=tf.nn.relu)
    conv2 = tf.layers.conv2d(conv1,
                             filters=50,
                             kernel_size=(3, 3),
                             padding='same',
                             data_format=data_format,
                             activation=tf.nn.relu)
    pool1 = tf.layers.max_pooling2d(conv2,
                                    pool_size=(2, 2),
                                    strides=(2, 2),
                                    padding='valid',
                                    data_format=data_format)
    flatten = tf.reshape(pool1, shape=[-1, 50*16*16])
    fc1 = tf.layers.dense(flatten, 512, activation=tf.nn.relu)
    logits = tf.layers.dense(fc1, n_classes, name='output')
    return logits
```

An important element in training neural networks is defining the loss function and optimization to use (see Listing 6-2). Here we are using cross-entropy as our loss function and SGD with momentum as our optimization function. SGD is the standard optimization method for deep learning. The two parameters we have to define are the learning rate and momentum.

Listing 6-2. Initialize Model with Optimization and Loss Method

PYTHON

```
def init_model_training(m, labels, learning_rate=LR,
momentum=MOMENTUM):
    cross_entropy = tf.nn.sparse_softmax_cross_entropy_with_logits(
                                                        logits=m,
                                                        labels=labels)
    loss = tf.reduce_mean(cross_entropy)
    optimizer = tf.train.MomentumOptimizer(learning_rate=
    learning_rate,
                                                  momentum=momentum)
    return optimizer.minimize(loss)
```

Now we have the functions to create and train our CNN, so we need the methods to prepare the data and feed it to our CNN in batches, shown in Listing 6-3.

Listing 6-3. Prepare the CIFAR 10 Data

PYTHON

```
def prepare_cifar(x_train, y_train, x_test, y_test):

    # Scale pixel intensity
    x_train = x_train / 255.0
    x_test = x_test / 255.0

    # Reshape
    x_train = x_train.reshape(-1, 3, 32, 32)
    x_test = x_test.reshape(-1, 3, 32, 32)

    x_train = np.swapaxes(x_train, 1, 3)
    x_test = np.swapaxes(x_test, 1, 3)
    return (x_train.astype(np.float32),
            y_train.astype(np.int32),
            x_test.astype(np.float32),
            y_test.astype(np.int32))
```

The `prepare_cifar` function accepts the training images and test images as arrays and the labels as vectors. Before we can use the images with our CNN we need to do some preprocessing. First we scale the pixel values between 0 and 1, then we reshape it so that the matrix is in the channels last configuration. This means that the image data will be shaped (examples, height, width, channels). Channels refers to the RGB channels in the image.

Next we define the minibatch function that will return a matrix of shape (`BATCHSIZE`, 32, 32, 3) if we have defined our data to be channel last (see Listing 6-4). We also need to shuffle the data, as we do not want to feed the CNN the training samples in any meaningful order as this might bias the optimization algorithm.

Listing 6-4. Minibatch Generator

```
PYTHON

def minibatch_from(X, y, batchsize=BATCHSIZE, shuffle=False):
    if len(X) != len(y):
        raise Exception("The length of X {} and y {} don't \
                        match".format(len(X), len(y)))

    if shuffle:
        X, y = shuffle_data(X, y)

    for i in range(0, len(X), batchsize):
        yield X[i:i + batchsize], y[i:i + batchsize]
```

Next, we load the data, as shown in Listing 6-5.

Listing 6-5. Load Data

```
PYTHON

x_train, y_train, x_test, y_test = prepare_cifar(*load_cifar())
```

Then we create placeholders for our data and labels, as shown in Listing 6-6, and create the model.

Listing 6-6. Placeholders for the Data and Labels

```
PYTHON

X = tf.placeholder(tf.float32, shape=[None, 32, 32, 3])
y = tf.placeholder(tf.int32, shape=[None])
# Initialise model
model = create_model(X, training)
```

We then initialize the model and start the TensorFlow session.

Listing 6-7. Initialize Model and Start the Session

```
PYTHON

train_model = init_model_training(model, y)
init = tf.global_variables_initializer()
sess = tf.Session()
sess.run(init)
```

Next we train the model for the desired number of epochs. During this process we execute the forward pass, calculate the loss, and then propagate the error backward and update the weights. This can take a considerable amount of time depending on the computational resources you have at your disposal. Azure notebooks run the deep learning training on CPU and have limited computational resources. One of the preferred environments to train these neural networks on is the DSVM or DLVM, which come in multiple configurations, including with GPUs. See Listing 6-8.

Listing 6-8. Loop over the Training Data for N Epochs and Train Model

```
PYTHON

for j in range(EPOCHS):
    for data, label in minibatch_from(x_train, y_train,
    shuffle=True):
        sess.run(train_model, feed_dict={X: data,
                                         y: label})
    # Log
    acc_train = sess.run(accuracy, feed_dict={X: data,
                                              y: label})
    print("Epoch {} training accuracy: {:0.4f}".format(j,acc_train))
```

Now that we have the trained model, we want to evaluate it on our test data, as shown in Listing 6-9.

Listing 6-9. Evaluate Model on Test Data

```
PYTHON

y_guess = list()
for data, label in minibatch_from(x_test, y_test):
    pred=tf.argmax(model,1)
    output=sess.run(pred,feed_dict={X:data})
    y_guess.append(output)
```

This piece of code feeds minibatches to the CNN and appends them to a list.

Finally, we evaluate the performance of the model against the true labels, as shown in Listing 6-10.

Listing 6-10. Print out the Accuracy of Our Model

PYTHON

```
print("Accuracy: ", sum(np.concatenate(y_guess) ==
                        y_test)/float(len(y_test)))
```

Depending on how long you trained the network, you will get differing error rates. After three epochs the network achieved an accuracy of 64 percent on the test set.

This was just a simple exercise to illustrate how you can create and train your own neural network. Feel free to play around with the layers and see how it affects performance.

Creating your own architecture is fun but optimizing these structures can be laborious and frustrating. For an ML practitioner, a more fruitful strategy is to use state-of-the-art architectures that researchers have published and cut out the laborious process of trying to generate your own network.

Training a Deep CNN on GPU

In this section we are going to build on what we learned in the previous section and construct a deeper CNN. For this you almost definitely need a GPU-enabled machine whether this is your own or in the cloud. We are going to be using the CIFAR10 data set, but this time we will be basing our CNN architecture on the VGG architecture (Simonyan & Zisserman, 2014). We slowly build up the network using the standard building blocks used in CNNs and see how adding these to our network affects performance. All the steps can been found in the notebook `Chapter_06_03.ipynb` (`http://bit.ly/Nbook_ch06_03`).

If you feel that this is a bit of a leap, there is another notebook that we do not cover here that goes into how the outputs of each layer are affected by the properties set for that layer (see `http://bit.ly/Nbook_ch06_02`).

Model 1

As mentioned earlier, we will be using the CIFAR10 data set, so our inputs will be 32 × 32 color images and the task is to classify them into one of ten classes. We will be basing our model on the VGG architecture (Simonyan & Zisserman, 2014). With this in mind, our first network is shown in Listing 6-11.

Listing 6-11. CNN with Two Convolution Layers

PYTHON

```
conv1_1 = tf.layers.conv2d(X,
                           filters=64,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
conv1_2 = tf.layers.conv2d(conv1_1,
                           filters=64,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
pool1_1 = tf.layers.max_pooling2d(conv1_2,
                                  pool_size=(2,2),
                                  strides=(2,2),
                                  padding='valid',
                                  data_format=data_format)
relu2 = tf.nn.relu(pool1_1)
flatten = tf.reshape(relu2, shape=[-1, 64*16*16])
fc1 = tf.layers.dense(flatten, 4096, activation=tf.nn.relu)
fc2 = tf.layers.dense(fc1, 4096, activation=tf.nn.relu)
model = tf.layers.dense(fc2, N_CLASSES, name='output')
```

We have two convolution layers followed by a max pooling layer, which makes up the featurizing portion of our CNN. The classification part of our CNN is made up of two fully connected dense layers and our final output is the same size as the number of classes we expect.

Our model gets an accuracy of 72.1 percent on the test set after training for 20 epochs. We can also see that it achieves 100 percent on the training set a few epochs before we stop training. It would usually be prudent to stop the model earlier, and there are usually callbacks that can be used in any of the frameworks to do this. We are simply not using these here to try and keep things simple. By running the notebook you should get similar results.

Model 2

With the second model we add a second convolution block. In keeping with the VGG architecture, we add two convolution layers each with 128 filters as well as a max pooling layer (see Listing 6-12). This time we will train it for 10 epochs.

Listing 6-12. CNN with Four Convolution Layers

```
PYTHON
# Block 1
conv1_1 = tf.layers.conv2d(X,
                           filters=64,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
conv1_2 = tf.layers.conv2d(conv1_1,
                           filters=64,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
pool1_1 = tf.layers.max_pooling2d(conv1_2,
                                  pool_size=(2,2),
                                  strides=(2,2),
                                  padding='valid',
                                  data_format=data_format)
# Block 2
conv2_1 = tf.layers.conv2d(pool1_1,
                           filters=128,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
conv2_2 = tf.layers.conv2d(conv2_1,
                           filters=128,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
pool2_1 = tf.layers.max_pooling2d(conv2_2,
                                  pool_size=(2,2),
                                  strides=(2,2),
                                  padding='valid',
                                  data_format=data_format)

relu2 = tf.nn.relu(pool2_1)
flatten = tf.reshape(relu2, shape=[-1, 128*8*8])
fc1 = tf.layers.dense(flatten, 4096, activation=tf.nn.relu)
fc2 = tf.layers.dense(fc1, 4096, activation=tf.nn.relu)
model = tf.layers.dense(fc2, N_CLASSES, name='output')
```

After training it for 10 epochs you should find the performance of your model has improved slightly.

Model 3

Let's add another convolution block. This time, though, we increase the number of filters to 256, again in keeping with the VGG architecture. See Listing 6-13.

Listing 6-13. CNN with Seven Convolution Layers

```
PYTHON
# Block 1
conv1_1 = tf.layers.conv2d(X,
                           filters=64,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
conv1_2 = tf.layers.conv2d(conv1_1,
                           filters=64,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
pool1_1 = tf.layers.max_pooling2d(conv1_2,
                                  pool_size=(2,2),
                                  strides=(2,2),
                                  padding='valid',
                                  data_format=data_format)
```

```
# Block 2
conv2_1 = tf.layers.conv2d(pool1_1,
                           filters=128,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
conv2_2 = tf.layers.conv2d(conv2_1,
                           filters=128,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
pool2_1 = tf.layers.max_pooling2d(conv2_2,
                                  pool_size=(2,2),
                                  strides=(2,2),
                                  padding='valid',
                                  data_format=data_format)
# Block 3
conv3_1 = tf.layers.conv2d(pool2_1,
                           filters=256,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
conv3_2 = tf.layers.conv2d(conv3_1,
                           filters=256,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
```

```
conv3_3 = tf.layers.conv2d(conv3_2,
                           filters=256,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
pool3_1 = tf.layers.max_pooling2d(conv3_3,
                                  pool_size=(2,2),
                                  strides=(2,2),
                                  padding='valid',
                                  data_format=data_format)

relu2 = tf.nn.relu(pool3_1)
flatten = tf.reshape(relu2, shape=[-1, 256*4*4])
fc1 = tf.layers.dense(flatten, 4096, activation=tf.nn.relu)
fc2 = tf.layers.dense(fc1, 4096, activation=tf.nn.relu)
model = tf.layers.dense(fc2, N_CLASSES, name='output')
```

Once you have trained the model for 10 epochs you should find that the performance has increased again, albeit by a smaller margin. You should notice that with each additional layer we get better results, but the returns diminish with each successive block.

Model 4

Due to the large number of free parameters CNNs can benefit from regularization. One way to regularize is to use dropout (see Listing 6-14), which we talked about in Chapter 2. The dropout layer will randomly during the forward pass zero a certain proportion of its outputs. This means it will not participate in the forward calculations but also not receive any weight updates (Srivastava, Hinton, Krizhevsky, Sutskever, & Salakhutdinov, 2014). Dropout can reduce the dependence of the CNN or any deep learning on one or a small number of *neurons*. This in turn can make the model robust to absence of information.

Listing 6-14. CNN with Seven Convolution Layers and Dropout

```
PYTHON
# Block 1
conv1_1 = tf.layers.conv2d(X,
                           filters=64,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
conv1_2 = tf.layers.conv2d(conv1_1,
                           filters=64,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
pool1_1 = tf.layers.max_pooling2d(conv1_2,
                                  pool_size=(2,2),
                                  strides=(2,2),
                                  padding='valid',
                                  data_format=data_format)
# Block 2
conv2_1 = tf.layers.conv2d(pool1_1,
                           filters=128,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
conv2_2 = tf.layers.conv2d(conv2_1,
                           filters=128,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
pool2_1 = tf.layers.max_pooling2d(conv2_2,
                                  pool_size=(2,2),
                                  strides=(2,2),
                                  padding='valid',
                                  data_format=data_format)
# Block 3
conv3_1 = tf.layers.conv2d(pool2_1,
                           filters=256,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
conv3_2 = tf.layers.conv2d(conv3_1,
                           filters=256,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
conv3_3 = tf.layers.conv2d(conv3_2,
                           filters=256,
                           kernel_size=(3,3),
                           padding='same',
                           data_format=data_format,
                           activation=tf.nn.relu)
pool3_1 = tf.layers.max_pooling2d(conv3_3,
                                  pool_size=(2,2),
                                  strides=(2,2),
                                  padding='valid',
                                  data_format=data_format)
```

```
relu2 = tf.nn.relu(pool3_1)
flatten = tf.reshape(relu2, shape=[-1, 256*4*4])
fc1 = tf.layers.dense(flatten, 4096, activation=tf.nn.relu)
drop1 = tf.layers.dropout(fc1, 0.5, training=training)
fc2 = tf.layers.dense(drop1, 4096, activation=tf.nn.relu)
drop2 = tf.layers.dropout(fc2, 0.5, training=training)
model = tf.layers.dense(drop2, N_CLASSES, name='output')
```

When we ran this model we saw our accuracy increase further to 80 percent. Dropout is a very effective regularization technique and almost all CNN architectures make use of it, including VGG.

The VGG architecture actually has even more layers than our final model, but it was designed to tackle the ImageNet data set, which contains a lot more data than the CIFAR10 data set. Adding further layers with the limited data available would quickly prove untenable. We would have to spend a lot of effort to try and ensure that our model does not overfit the data.[3]

Transfer Learning

Training a CNN from scratch often requires a large amount of data. One strategy to overcome this limitation is to use transfer learning, as mentioned in Chapter 2. This means that we use a predefined network that has been trained on a much larger but similar data set. We then use that network for our problem; in other words, transferring the learning that the network has from other data onto our problem. The simplest approach is to simply remove the topmost layers and use the output from these penultimate layers as features in our own ML model. This can be another neural network such as MLP or a classical ML model such as Support Vector Machines or Random Forest.

[3]We also implemented the same notebooks using Keras, which can be found at http://bit.ly/Ch06Keras.

Another approach is to replace the topmost fully connected layers and then freeze certain layers and retrain it. Freezing layers means that the weights of these layers are not updated during training. Which layers to freeze depends on a number of factors, including the similarity between the data sets used and so on. Retraining more layers can often improve the accuracy of the model, but also increases the possibility of overfitting.

Almost all network topologies published have pretrained weights for the ImageNet data set, one of the largest image classification data sets and more or less the standard for image classification problems. This data set consists of millions of images spanning multiple classes (ImageNet, n.d.). Using pretrained CNNs trained on ImageNet is an easy way to get very good results for image classification tasks.

Summary

This chapter briefly described what constitutes a CNN. We have explained why convolution is useful in computer vision tasks, as well as what the shortcomings of CNNs are. We went through a simple example of creating a CNN in TensorFlow and then expanded on it through a series of steps and observed the effect it had on the performance of the model. This chapter has only scratched the surface of the vast information on CNNs, with many great books covering the theory behind them. The next chapter goes over a different deep learning architecture, RNNs, which are well suited to the tasks of sequence modeling such as language translation.

CHAPTER 7

Recurrent Neural Networks

The previous chapter showed how a deep learning model—specifically CNNs—could be applied to images. The process could be decoupled into a feature extractor that figures out the optimal hidden-state representation of the input (in this case a vector of feature maps) and a classifier (typically a fully connected layer). This chapter focuses on the hidden-state representation of other forms of data and explores RNNs. RNNs are especially useful for analyzing sequences, which is particularly helpful for natural language processing and time series analysis.

Even images can be thought of as a subset of sequence data; if we shuffle the rows and columns (or channels) then the image becomes unrecognizable. This is not the case for spreadsheet data, for example. However, CNNs have a very weak notion of order and typically the kernel size for a convolution is in the single digits. As these convolutions are stacked on top of each other, the receptive field increases, but the signal also gets dampened. This means that CNNs typically only care about temporary spatial relationships, such as a nose or eye. In Figure 7-1, we can imagine that we have shuffled a sequence, preserving order only within local groups, but most CNNs will still classify it the same, even though it makes no sense overall.

https://doi.org/10.1007/978-1-4842-3679-6_7

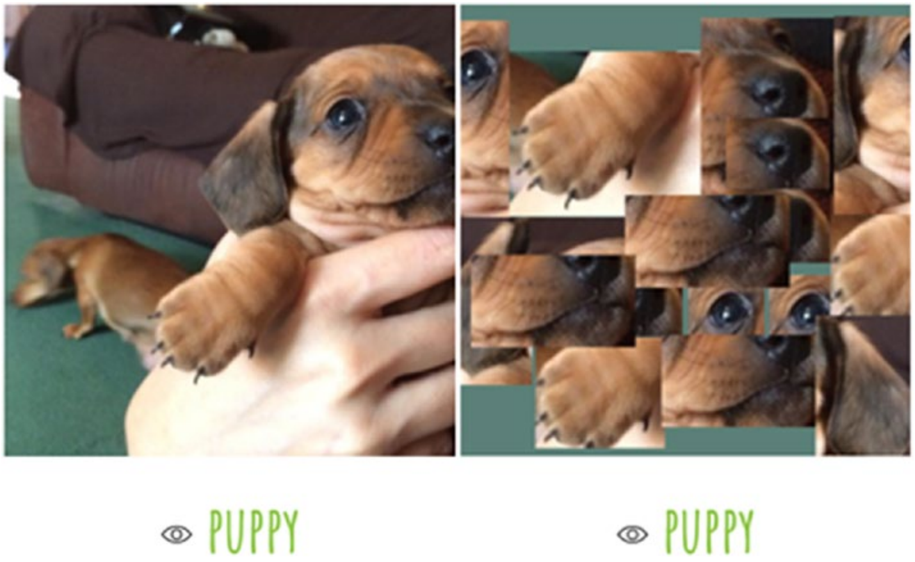


***Figure 7-1.** CNNs have a weak concept of order, as can be seen by applying ResNet-121 trained on ImageNet to a shuffled image*

For some other forms of data, the relationship between members of the sequence becomes even more important. Music, text, time series data, and more all depend heavily on a clear representation of history. For example the sentence, "I did not watch this movie yesterday but I did really like it," differs from "I did watch this movie yesterday but I did not really like it," or even "This is a lie—I really did not like the movie I watched yesterday." Not surprisingly, word order is key. For a CNN to capture a relationship across so many words, the kernel size has to be much larger than the number of hidden units required for an RNN to capture the same relationship (and at some point, it will no longer be possible).

To see why we need a new deep learning structure for these kinds of sequences, let's first examine what happens if we try to hack together a basic neural network to predict the last digit of a sequence. If we imagine that we have a sequence of numbers (from 0–9) such as [0, 1, 2, 3, 4] and [9, 8, 7, 6, 5], we can represent each number as a 10-dimensional vector that is one-hot encoded. For example, the number 2 could be encoded as [0, 0, 1, 0, 0, 0, 0, 0, 0, 0] and 6 as [0, 0, 0, 0, 0, 0, 1, 0, 0, 0]. To train a network to predict the last digit of the sequence we can attempt two different approaches.

First, we can concatenate the four one-hot encoded vectors and thus create a hidden state that exists in 40-dimensional space. The neural network then adjusts a weights matrix (size 40 × 10) and a bias matrix (size 10 × 1) to map this to the label (the last number), which exists in a 10-dimensional space. Second, we can sum the input vectors together and create a hidden state that exists in 10-dimensional space and train the network to map this to the label instead.

The issue with the second approach is that by summing the one-hot encoded vector for 2 and 3, for example, we get [0, 0, 1, 1, 0, 0, 0, 0, 0, 0] and with this hidden state it is not possible to know whether the input sequence was [2, 3] or [3, 2] and thus whether the next number should be 4 or 1. The first approach does not have this issue because we can clearly see that [0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0] corresponds to [2, 3]. However, another issue arises when we see that we have learned a weights matrix that is of size (40 × 10). Our neural network can only work with an input of four numbers.

Hence, by summing inputs we can work with variable-length sequences, but we cannot preserve order. In contrast, by concatenating inputs we can preserve order, but we have to work with a sequence of a fixed size. RNNs solve this by representing history as a fixed-dimension vector that handles inputs that are variable-length sequences (and as we will see in the sequences-to-sequence section, also variable-length outputs).

The operation of an RNN can be represented as the second neural network in the preceding example: summing input vectors, but with the modification that after every summation we multiply the hidden state by some number. This number remains the same for all time steps and thus RNNs make use of weight sharing, in a similar manner to CNNs.

If we imagine this number to be 0.5 then we can represent [2] as [0, 0, 1*0.5, 0, 0, 0, 0, 0, 0, 0] and [2, 3] as [0, 0, 1*0.5*0.5, 1*0.5, 0, 0, 0, 0, 0, 0], which is now a fixed-size hidden state and different from [3, 2], which is represented as [0, 0, 1*0.5, 1*0.5*0.5, 0, 0, 0, 0, 0, 0]. In practice, we also apply a nonlinearity (add a bias term, and use a different weights matrix for input X and hidden); however, as seen earlier, those are not necessary to understand the fundamental concept behind RNNs.

We can see that the hidden state in any given time period is a function of all previous hidden states. This means if we have a very long sequence (perhaps 100 entries) then we will end up with an entry that gets multiplied by the weights matrix 100 times. If we imagine this matrix to be scalar (like earlier), if it is less than 1 then the entry will tend to 0, and if it is above 1 then it will explode toward infinity. We cover this later as the vanishing/exploding gradient problem.

RNN Architectures

One of the most exciting features of RNNs is their ability to work in different design patterns. In contrast with CNNs, which are constrained to operate with fixed input and output structures like images, RNNs offer more flexibility due their ability to manage variable sequences of inputs and outputs.

Figure 7-2 shows different design patterns for RNNs. Figure 7-2(a) shows the typical structure of a vanilla neural network (no RNN) with a fixed-size input and output sequence; one example of this is image classification. Figure 7-2(b) shows the one-to-many pattern, which is the typical structure used in image captioning, where the input is an image, and the output is a sequence of words describing the image. Figure 7-2(c) shows the many-to-one pattern. One application of this pattern is sentiment analysis, where the input is a text and the output is a boolean (positive or negative). Figure 7-2(d) shows the synchronous many-to-many pattern.

An example of this could be video captioning, where we want to set a tag to each video frame. Finally, Figure 7-2(e) shows the asynchronous many-to-many representation, which is the typical case of machine translation, where the input could be text in English and the output text in Spanish.

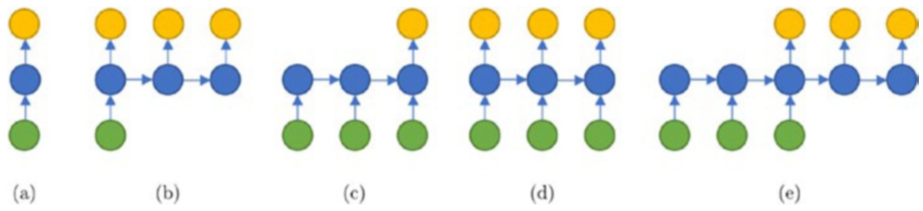


Figure 7-2. *Bottom layer is the inputs, in the middle are the hidden states, and the top layer is the outputs. (a) Vanilla network (no RNN) with single input, hidden state, and single output. (b) One-to-many pattern. (c) Many-to-one pattern. (d) Synchronous many-to-many pattern. (e) Asynchronous many-to-many pattern, also referred as encoder–decoder.*

Apart from the previous design patterns, RNNs vary depending on how the interconnection between the different layers is performed. The standard case is where the RNN has recurrent connections between hidden units, as depicted in Figure 7-3. In this case, the RNN is Turing-complete (Siegelmann, 1995), and therefore can simulate any arbitrary program. In essence, an RNN repeatedly applies a nonlinear function, with trainable parameters to a hidden state, which make them suitable for sequence modeling tasks.

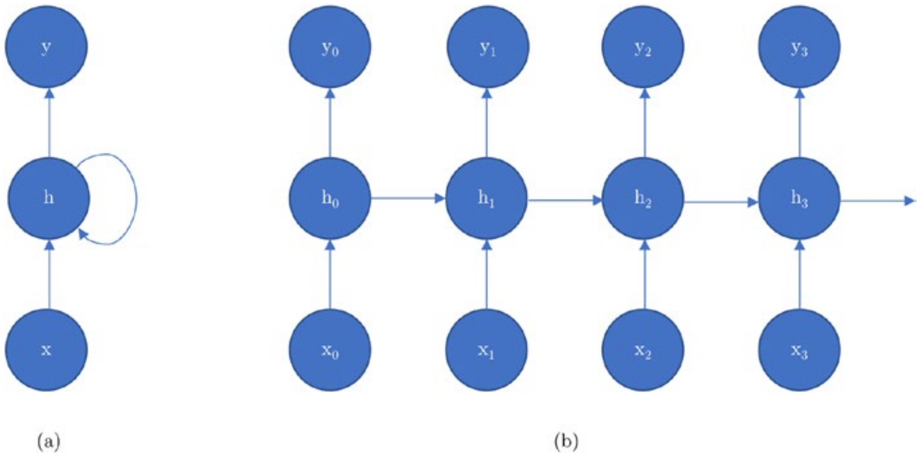


Figure 7-3. *(a) RNN with recurrent connection between hidden states. (b) Unrolled RNN, showing the connection between hidden states.*

However, their recurrent structure constrains each step computation to depend on completing the previous step, making the network difficult to parallelize and scale. Similar to CNNs, training an RNN involves computing the gradient of the loss function with respect to the weights. This operation involves computing a forward propagation, moving from left to right through in Figure 7-3(b), followed by a backward propagation, moving from right to left, to update the weights. This training process is expensive because the forward propagation is inherently sequential, and thus cannot be parallelized. The backpropagation algorithm applied in RNNs is called backpropagation through time (BPTT), and is discussed in detail later in this chapter.

A solution to the slow training limitation can be found in the output recurrent structure shown in Figure 7-4. The RNNs from this family connect each output with the future hidden state, eliminating the hidden-to-hidden connections. In this scenario, any loss function comparing the prediction and target at a specific time step can be decoupled; therefore, the gradient for each step is computed independently and parallelized.

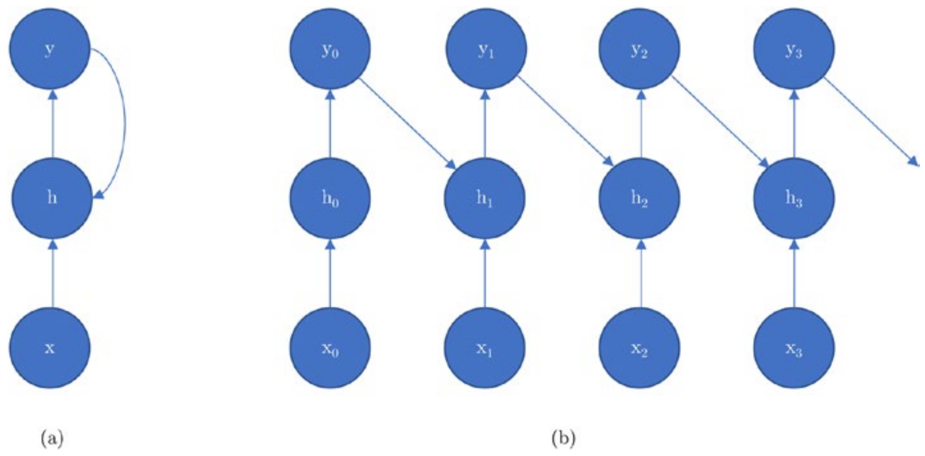


Figure 7-4. *(a) RNN with output recurrent connection. (b) Unrolled structure of an RNN with output recurrence.*

Unfortunately, RNNs with output recurrent connections are less powerful than their counterparts containing hidden-to-hidden connections (Goodfellow et al., 2016). For example, they cannot simulate a universal Turing machine. Due to the lack of hidden-to-hidden connections, the only signal that is transferred to the next step is the output, which unless it is very high dimensional and rich, could miss important information from the past.

The structures seen until now share the idea that all sequences are forward sequences, meaning that the network captures information of the present state based on past states. However, there are some cases where the relationships in the opposite direction are also valuable. Such is the case of speech recognition or text understanding. In some languages, the linguistic relationships between the different words can be dependent on the future or the past. In English, for example, the verb is usually located in the middle of the sentence, whereas in German, the verb tends to be at the end of the sentence. To address this phenomenon, bidirectional recurrent neural networks were proposed (Schuster & Paliwal, 1997).

Bidirectional recurrent neural networks (BiRNNs) have a layer of hidden connections that moves forward through time and a layer that moves backward (see Figure 7-5). This structure allows the output to learn representations of its near future and past states, at the price of making the training process computationally more expensive.

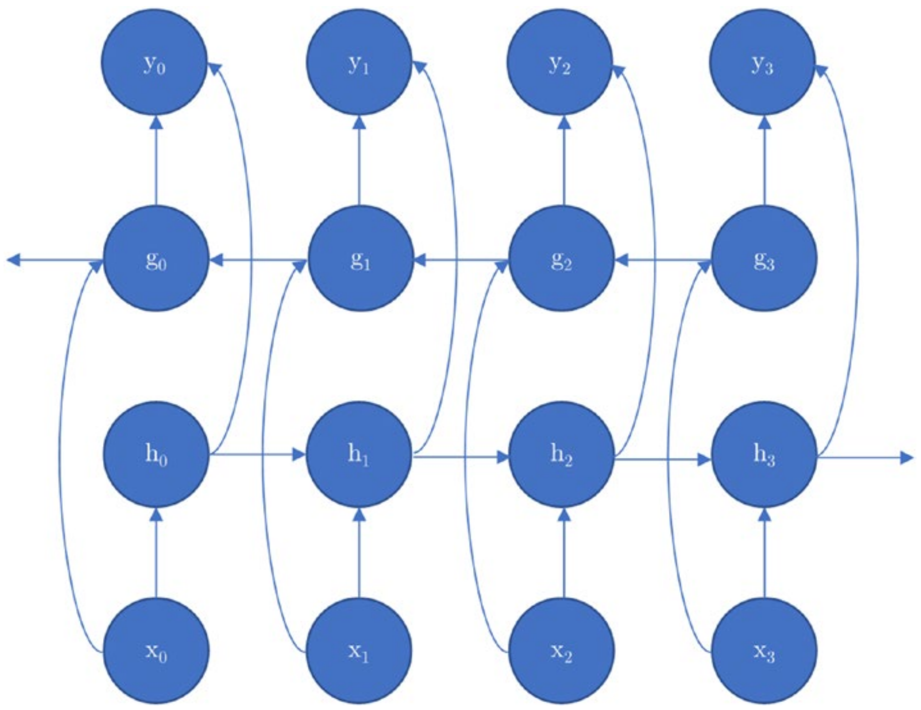


Figure 7-5. *Bidirectional RNN. BiRNNs contain a layer of forward connections to encode future dependencies, h, and a layer of backward connections to encode past dependencies, g. In the presented structure, each hidden unit is connected to another hidden unit and to the output.*

Training RNNs

RNN training shares some similarities with the CNN training method that we saw in the previous chapter, but in the RNN case, the algorithm used is called BPTT (Werbos, 1990). The underlying idea behind BPTT is simply to apply the same generalized backpropagation algorithm to the unrolled computational graph. The steps of training an RNN are as follows:

1. We have an RNN architecture like the ones shown in Figure 7-3, Figure 7-4, and Figure 7-5. The weights are initialized based on some distribution.

2. We input the sequences as minibatches to the RNN as (batch size, sequence size). The sequence size can have a variable length depending on the framework you are using.

3. We compute the forward propagation by unrolling the graph and obtaining the predicted output at each time step.

4. We compare the predicted output with the true labels and accumulate the error (or loss) across each time step.

5. We apply backpropagation by computing the gradient of the loss with respect to the weights and use gradient descent to update the weights.

6. This process is repeated for a number of epochs or until some exit criteria are met.

For long sequences, there is a high cost of updating the weights. For instance, the gradient of an RNN with sequences of length 1,000 is equivalent to a forward and a backward pass in a neural network with 1,000 layers (Sutskever, 2013).

Therefore, a practical approach for training RNNs is to compute BPTT in a sliding window of the unrolled graph, which is referred as truncated BPTT (Williams & Peng, 1990). The idea is simple: Each complete sequence is sliced into a number of smaller subsequences and BPTT is applied to each of these parts. This approach works well in practice, especially in word modeling problems (Mikolov, Karafiát, Burget, Černocký, & Khudanpur, 2010), but the algorithm is blind to dependencies between different windows.

Gated RNNs

Due to the iterative nature of the propagation error in RNNs, in some cases, the loss gradients can vanish as they get backpropagated in time. This is referred to as vanishing gradients (Bengio, Simard, & Frasconi, 1994). A vanishing gradient means in practice that the loss gradient is a small quantity, therefore the process of updating the weights can take too long. More rarely, the gradient can explode, producing gradients exponentially large, referred to as exploding gradients. This also makes RNNs difficult to train on sequences with long temporal dependencies.

A solution to the vanishing and exploding gradient problem is the LSTM RNN (Gers, Schmidhuber, & Cummins, 2000; Hochreiter & Schmidhuber, 1997), which is a network type specially designed to learn long-term relationships. For it, they substitute the hidden units of standard RNNs with a new block called the LSTM cell. The intuition behind these cells is that they allow control of the amount of information that is going to be passed to the next state and use a forgetting mechanism to stop the information that is not useful anymore.

The LSTM block (see Figure 7-6) is composed of a state unit and three gating units: forget gate, input gate, and output gate. At a high level, the state unit handles the information transfer between the input and the output, and contains a self-loop. The gating units, which simply set their weights to a value between 0 and 1 via a sigmoid function, control the amount of information that is going to come from the input, go to the output, and be forgotten from the state unit.

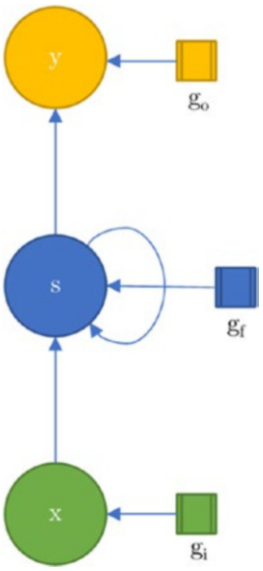


Figure 7-6. *Schema of an LSTM. It has three units: input x, state s, and output y, which are controlled by three gates: input gate g_i, forget gate g_f, and output gate g_o. The state unit contains a self-loop.*

Empirical work has shown that the key components of the LSTM are the forget gate and the output activation functions, and that there is no significant difference in terms of accuracy when comparing an LSTM with its other variants (Greff, Srivastava, Koutník, Steunebrink, & Schmidhuber, 2017).

A variant of the LSTM is the gated recurrent unit (GRU; Cho et al., 2014), which simplifies the structure of the LSTM using a slightly different combination of gating units. Specifically, they lack the output gate, which exposes the full hidden content to the output. In contrast, the LSTM unit uses the output gate to control the amount of memory that is seen.

This lack of the output gate in GRUs makes them computationally less expensive, but it could lead to a suboptimal memory representation, which might be the reason an LSTM tends to remember longer sequences. For a more detailed comparison between LSTMs and GRUs, please refer to Chung, Gulcehre, Cho, & Bengio, 2014).

Sequence-to-Sequence Models and Attention Mechanism

Sequence-to-sequence models (Cho et al., 2014; Sutskever, Vinyals, & Le, 2014) are a relatively recent architecture that have created many exciting possibilities for machine translation, speech recognition, and text summarization. The basic principle is to map an input sequence to an output sequence, which can be of a different length, a variant of Figure 7-2(e) This is accomplished by combining an input RNN (or an encoder) that maps a variable-length sequence to a fixed-length vector with an output RNN (or a decoder) that maps a fixed-length vector to a variable-length sequence. As an example, see the blog post with associated tutorial for generating music using an LSTM sequence-to-sequence model with Azure Machine Learning from Erika Menezes available at `http://bit.ly/MusicGenAzure`.

Sequence-to-sequence models in the realm of machine translation (called neural machine translation [NMT]) have largely replaced phrase-based machine translation because they do not require lots of manual tuning for each subcomponent (and for each language). NMT (shown in Figure 7-7) models might have different RNN structures for the encoder and the decoder component; the structure of the RNNs can vary in several ways: cell type such as GRU or LSTM, number of layers, and directionality (unidirectional or bidirectional).

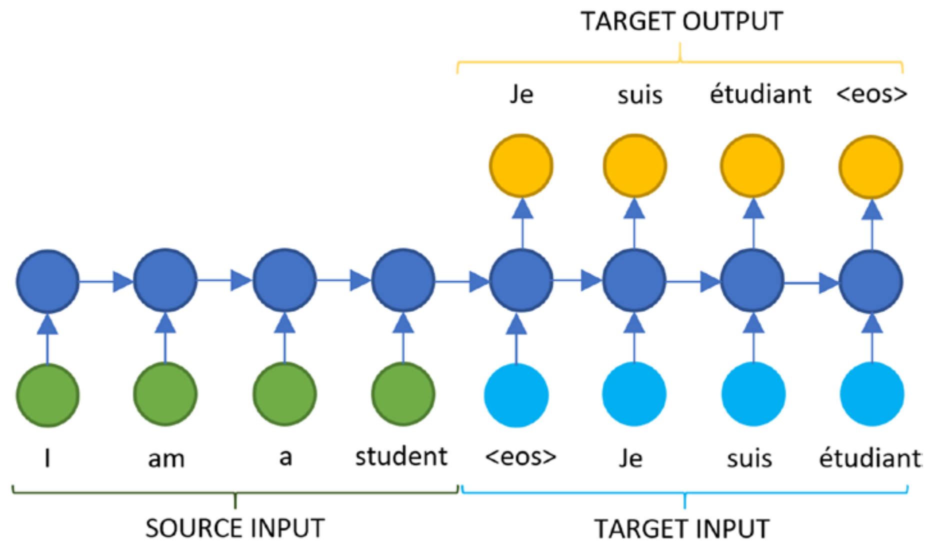


Figure 7-7. *Example of a simple NMT architecture during training for English–French*

It has been empirically observed (Cho et al., 2014) that NMT models struggle to translate long sentences. This is because the network must compress all the information from the input sentence into a single fixed-length vector, irrespective of the length of the sentence.

Consider this sentence: "I went to the park yesterday to play badminton and my dog jumped into the pond." We can see there are (at least) two components: "I went to the park yesterday to play badminton" and "my dog jumped into the pond." We might not care about the first component when attempting to translate the second component (and vice versa). However, an NMT model has no choice but to use the hidden vector that would contain both components to produce an input. Ideally, we would have a model that assigns importance to the input words for each output word. In that case the relative importance of the words in the first component would be very low when parts of the second component are being translated. Not everything is required in a sentence to translate some words.

The attention mechanism (Bahdanau, Cho, & Bengio, 2014; Yang et al., 2016) attempts to do just that: It tries to create a weighted average that aligns the important components from the input sentence for each word in the output sentence. The main difference from a standard NMT model is that instead of encoding the whole input sentence into a single fixed-length vector, the input sequence is encoded into a sequence of fixed-length vectors, a "random access memory," and different vectors are weighted differently for each word in the translation. This means that the model is now free to create longer sequences of hidden vectors for longer sentences and learn which of those to focus on during the decoder stage.

Putting these components together, the mechanism might look like Figure 7-8. The network first encodes each unit of the input sentence (usually a word) into a distributed feature vector. The hidden state becomes the collection of these feature vectors. Then during the decoder stage, the model predicts each word iteratively using all previously generated predictions along with the sequence of feature vectors, where it has learned how much attention to place on each feature vector (input word) for each of target words it predicts.

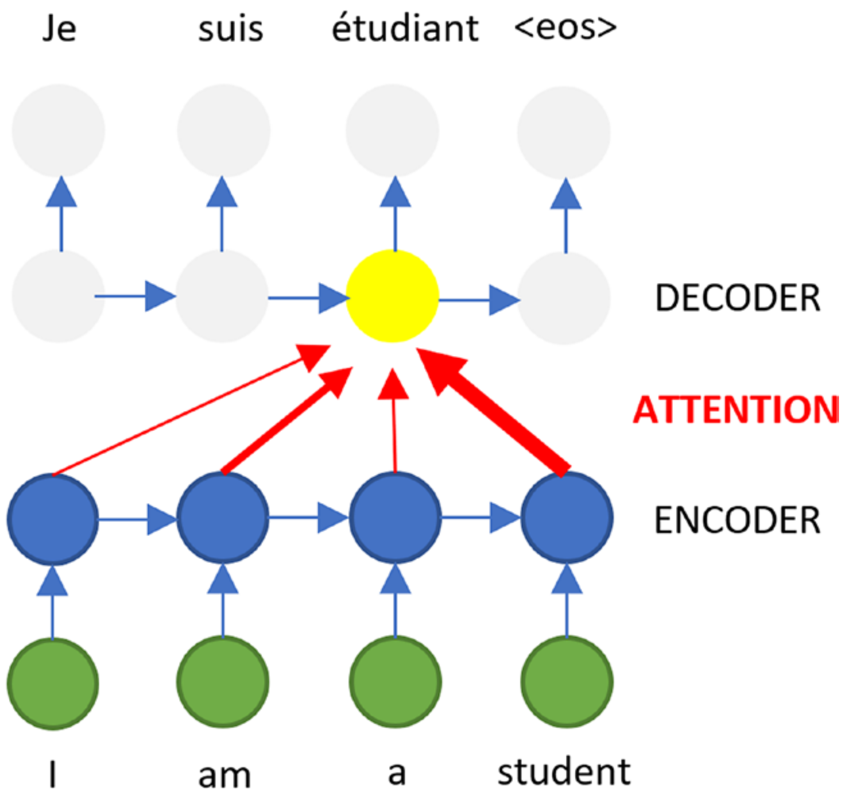


Figure 7-8. *Example of attention being applied. Note that "student" has the highest weighting (represented by line thickness) during prediction of "étudiant."*

This approach of jointly aligning words (which words from input are needed to predict output) and translating has empirically achieved state-of-the-art results over hand-crafted methods and basic sequence-to-sequence models and is the core component behind most of the online translation services (Klein, Kim, Deng, Senellart, & Rush, 2017).

RNN Examples

In this section, we are going to study two examples of RNNs implemented in TensorFlow. The code is available at http://bit.ly/AzureRNNCode. The first example runs sentiment analysis in TensorFlow as well as several other frameworks. The second example builds off the example in Chapter 6 to illustrate the differences between CNNs and RNNs on image classification. The third example uses RNNs for time series analysis.

More Info We recommend provisioning an Azure DLVM to run the code examples in this chapter. Please see Chapter 4 for more information.

Example 1: Sentiment Analysis

We first highly recommend the examples available at http://bit.ly/DLComparisons, which at the time of this writing include six different Python deep learning framework implementations for an RNN (GRU) to predict sentiment on the IMDB movie review data set, as well as an implementation in R (Keras with TensorFlow back end) as well as Julia (Knet). These examples include training times for an NC series DLVM (NVIDIA Tesla K80 GPU) as well as an NC_v2 series DLVM (NDIVIA Tesla P100 GPU) so one can follow along and also compare timings to make sure the setup is correct.

Example 2: Image Classification

In Chapter 6, we saw how a CNN is typically used to classify an image. Here, we examine how to do the same but with an RNN. Although this is not a traditional application of RNNs, it illustrates that it is often possible to decouple the neural network architecture to the problem type and to illustrate some differences between CNNs and RNNs.

The data for a CNN is loaded as [number of examples, height, width, channels]. For an RNN we simply reshape this to [number of examples, height, width*channels] (see Listing 7-1).[1] This means that for the CIFAR data we will have 32 time steps (rows of pixels) where each row contains 32*3 (number of columns * number of channels) variables. For example, the first time step will contain [row1_column1_red_pixel, row1_column1_green_pixel, row1_column1_blue_pixel, row1_column2_red_pixel, … , row1_column32_bue_pixel].

Listing 7-1. Loading Data

```
PYTHON

# Original data for CNN
x_train, x_test, y_train, y_test = cifar_for_library(channel_
first=False)
# RNN: Sequences of 32 time-steps, each containing 32*3 units
N_STEPS = 32 # Each step is a row
N_INPUTS = 32*3 # Each step contains 32 columns * 3 channels
x_train = x_train.reshape(x_train.shape[0], N_STEPS, N_INPUTS)
x_test = x_test.reshape(x_test.shape[0], N_STEPS, N_INPUTS)
```

We can then create a network architecture consisting of 64 basic RNN cells and apply that to each time step of our input tensor, as shown in Listing 7-2. We will collect the output from the last time step and apply a fully connected layer with 10 neurons.

[1]This might be different between CPU and GPU.

Listing 7-2. Create Network Architecture

PYTHON

```
def create_symbol(X, n_steps=32, nhid=64, n_classes=10):
    # Convert x to a list[steps] where element has shape=2
      [batch_size, inputs]
    # This is the format that rnn.static_rnn expects
    x=tf.unstack(X,n_steps,axis=1)
    cell=tf.nn.rnn_cell.BasicRNNCell(nhid)
    outputs,states=tf.contrib.rnn.static_rnn(cell,x,dtype=tf.
    float32)
    logits=tf.layers.dense(outputs[-1],n_
    classes,activation=None)
    return logits
```

To train a model, we need to create a training operator that is an optimizer (in this example, Adam) that works on a loss (and the loss is a function of the prediction and ground-truth labels), as shown in Listing 7-3.

Listing 7-3. Define How Model Will Be Trained

PYTHON

```
def init_model(m, y, lr=LR, b1=BETA_1, b2=BETA_2, eps=EPS):
    xentropy=tf.nn.sparse_softmax_cross_entropy_with_
    logits(logits=m,labels=y)
    training_op= (tf.train.AdamOptimizer(lr,b1,b2,eps)
                           .minimize(tf.reduce_mean(xentropy)))
    return training_op
```

To start training we need to create our placeholders and initialize the variables in the graph, as displayed in Listing 7-4.

Listing 7-4. Placeholders and Initialization

```
PYTHON

# Placeholders
X = tf.placeholder(tf.float32, shape=[None, N_STEPS, N_INPUTS])
y=tf.placeholder(tf.int32,shape=[None])  # Sparse
# Initialize model
sym = create_symbol(X)
model = init_model(sym, y)
sess = tf.Session()
sess.run(tf.global_variables_initializer())
```

We can then train our model as shown in Listing 7-5.

Listing 7-5. Training Model

```
PYTHON

for j in range(EPOCHS):
    for data,label in yield_mb(x_train,y_train,BATCHSIZE,
    shuffle=True):
        sess.run(model,feed_dict={X:data,y:label})
```

The generator to supply our data is created as shown in Listing 7-6.

Listing 7-6. Generator to Supply Data to Model

```
PYTHON

def shuffle_data(X, y):
    s=np.arange(len(X))
    np.random.shuffle(s)
    X=X[s]
    y=y[s]
    return X,y
```

```
def yield_mb(X, y, batchsize=64, shuffle=False):
    if shuffle:
        X,y=shuffle_data(X,y)
    # Only complete batches are submitted
    for i in range(len(X) //batchsize):
        yield X[i*batchsize:(i+1) *batchsize],
        y[i*batchsize:(i+1) *batchsize]
```

To get a prediction on our test data we apply an `argmax()` operation on the model's predictions to pick the most likely class (see Listing 7-7). If we wanted class probabilities, we would first apply a softmax transformation; however, this is only needed for training and comes bundled with the loss function for computational efficiency.

Listing 7-7. Get Prediction

PYTHON

```
for data, label in yield_mb(x_test, y_test, BATCHSIZE):
    pred=tf.argmax(sym,1)
    output=sess.run(pred,feed_dict={X:data})
```

Note that creating generators, creating placeholders, initializing variables, and training with `feed_dict` is a rather low-level API and useful only to help show how everything works. In practice, all of these can be abstracted away by using TensorFlow's Estimator API.

Example 3: Time Series

In the next example we are going to predict Microsoft stock using an LSTM. We will start by getting the data into a data frame, as shown in Listing 7-8. The data are the stock value of Microsoft from 2012 to 2017, obtained from `http://bit.ly/MSFThist`. The `.csv` file contains a first column with the date, four columns with the price of the share (open, high, low, and close) and some other information that we are not going to use. From the four price values, we are going to take the mean for simplicity. We are going to predict just one step into the future because the longer we predict, the less accurate the prediction will be. You can also play with different hyperparameters.

Listing 7-8. Define Hyperparameters and Read in Historical Data

```
PYTHON

EPOCHS = 5
TEST_SIZE = 0.3
TIME_AHEAD = 1 #prediction step
BATCH_SIZE = 1
UNITS = 25
df = pd.read_csv('https://ikpublictutorial.blob.core.windows.
net/book/MSFT_2012_2017.csv')
df = df.drop(['Adj Close', 'Volume'], axis=1)
mean_price = df.mean(axis = 1)
```

The next step is to normalize the data and generate the train and test sets, as shown in Listing 7-9.

Listing 7-9. Normalize Data and Create Training and Test Sets

```
PYTHON

scaler = MinMaxScaler(feature_range=(0, 1))
mean_price = scaler.fit_transform(np.reshape(mean_price.values,
(len(mean_price),1)))
train, test = train_test_split(mean_price, test_size=TEST_SIZE,
shuffle=False)
print(train.shape) #(1056, 1)
print(test.shape) #(453, 1)
```

Then we need to perform a reshaping, so the data can be added to the model, as shown in Listing 7-10. We also define the time ahead that we are going to predict; normally, the smaller this value is, the more accurate the prediction will be.

Listing 7-10. Reshape Data for Model

PYTHON

```
def to_1dimension(df, step_size):
    X,y= [], []
    for i in range(len(df)-step_size-1):
        data=df[i:(i+step_size),0]
        X.append(data)
        y.append(df[i+step_size,0])
    X,y=np.array(X),np.array(y)
    X=np.reshape(X, (X.shape[0],1,X.shape[1]))
        return X,y
X_train, y_train = to_1dimension(train, TIME_AHEAD)
X_test, y_test = to_1dimension(test, TIME_AHEAD)
```

The next step is to define and train the model, as displayed in Listing 7-11. In this case we use a basic LSTM cell, but you can try to use a GRU or a BiLSTM.

Listing 7-11. Define and Train Model

PYTHON

```
def create_symbol(X, units=10, activation='linear',
time_ahead=1):
    cell=tf.contrib.rnn.LSTMCell(units)
    outputs,states=tf.nn.dynamic_rnn(cell,X,dtype=tf.float32)
    sym=tf.layers.dense(outputs[-1],1,activation=None,name='out
    put')
    return sym

X = tf.placeholder(tf.float32, shape=[None, 1, TIME_AHEAD])
y = tf.placeholder(tf.float32, shape=[None])

sym = create_symbol(X, units=UNITS, time_ahead=TIME_AHEAD)

loss = tf.reduce_mean(tf.squared_difference(sym, y)) #mse
optimizer = tf.train.AdamOptimizer()
model = optimizer.minimize(loss)

init = tf.global_variables_initializer()
sess = tf.Session()
sess.run(init)

for i in range(EPOCHS):
    ii=0
    while(ii+BATCH_SIZE) <=len(X_train):
        X_batch=X_train[ii:ii+BATCH_SIZE,:,:]
        y_batch=y_train[ii:ii+BATCH_SIZE]
        sess.run(model,feed_dict={X:X_batch,y:y_batch})
        ii+=BATCH_SIZE
    loss_train=sess.run(loss,feed_dict={X:X_batch,y:y_batch})
    print('Epoch {}/{}'.format(i+1,EPOCHS),' Current loss: {}'.
    format(loss_train))
```

Finally, we are going to calculate the root mean squared error (RMSE) of the test set prediction, as shown in Listing 7-12.

Listing 7-12. Calculate Test Set RMSE

PYTHON

```
y_guess = np.zeros(y_test.shape[0], dtype=np.float32)
ii = 0
while(ii + BATCH_SIZE) <= len(X_test):
    X_batch=X_test[ii:ii+BATCH_SIZE,:,:]
    output=sess.run(sym,feed_dict={X:X_batch})
    y_guess[ii:ii+BATCH_SIZE] =output
    ii+=BATCH_SIZE

y_test_inv = scaler.inverse_transform([y_test])
pred_test = scaler.inverse_transform([y_guess])
score = math.sqrt(mean_squared_error(y_test_inv, pred_test))
print('Test RMSE: %.2f' % (score)) #3.52
```

Looking at Figure 7-9, it seems that the LSTM is predicting the stocks well. Now you can play with different time horizons or LSTM parameters. This was a simple example of using LSTMs for time series analysis to illustrate the concept of using LSTMs in forecasting.

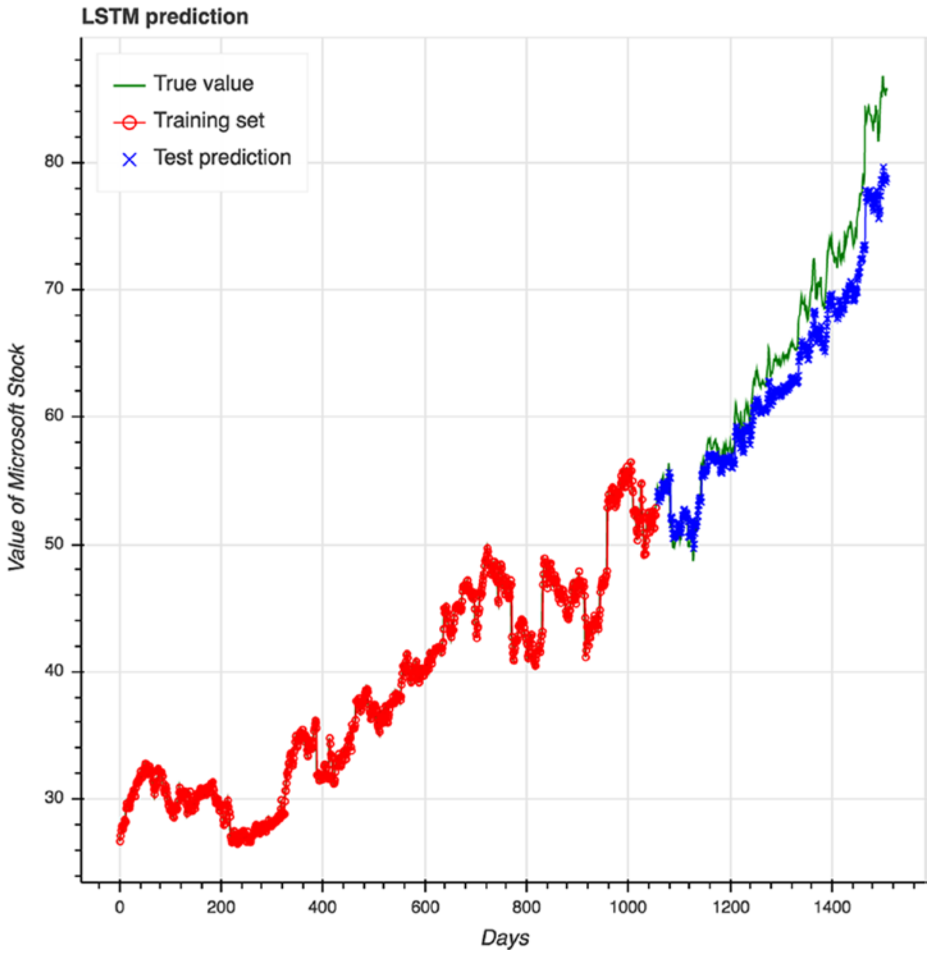


Figure 7-9. *Stock forecasting using an LSTM*

For another example of using LSTMs for time series analysis, we recommend the tutorial for predictive maintenance using Azure Machine Learning services available at `http://bit.ly/DLforPM`. We also recommend the blog post by Andrej Karpathy on the Unreasonable Effectiveness of Recurrent Neural Networks available at `http://bit.ly/RNNEffective`.

Summary

This chapter introduced RNNs and different variants that are useful for building applications on top of sequence data. These models are especially useful for natural language processing and time series analysis, although the application of RNNs can be quite broad. The chapter finished with two practical "how-to" examples, and a reference to a recommended resource for trying different deep learning frameworks for an RNN (GRU) example for sentiment analysis on the Azure DLVM. In the chapter that follows, we next dive into a completely different type of deep learning network that is a more recent development and shows promise for many applications as well.

RNNs have become increasingly popular in the last few years, but recently we have seen a trend back to CNN architectures for sequence data, perhaps partly owing to CNN being easier to train (both from a bare-metal and parameter-tuning perspective).

Stacking attention-encoded vectors in a hierarchical tree can also preserve order within a sequence and capture long-term dependencies. These types of networks are called hierarchical neural attention and are similar to WaveNet, which has been used to synthesize speech.

Temporal convolutional networks that (1) have no information leakage from future to past (i.e., casual), and (2) can take variable-length sequences just like RNNs, have become increasingly popular for pure-sequence tasks that have been previously commonly regarded as RNN territory.

CHAPTER 8

Generative Adversarial Networks

For many AI projects, deep learning techniques are increasingly being used as the building blocks for innovative solutions ranging from image classification to object detection, image segmentation, image similarity, and text analytics (e.g., sentiment analysis, key phrase extraction). GANs, first introduced by Goodfellow et al. (2014), are emerging as a powerful new approach toward teaching computers how to do complex tasks through a generative process. As noted by Yann LeCun (at `http://bit.ly/LeCunGANs`), GANs are truly the "coolest idea in machine learning in the last 20 years."

In recent years, GANs have shown tremendous potential and have been applied in various scenarios, ranging from image synthesis to enhancing the quality of images (superresolution), image-to-image translations, text-to-image generation, and more. In addition, GANs are the building blocks for advancements in the use of AI for art, music, and creativity (e.g., music generation, music accompaniment, poetry generation, etc.).

This chapter describes the secrets behind GANs. We first walk through how GANs are used in various AI applications and scenarios. We then step through code samples for one of the novel GANs, called CycleGAN, to understand how GANs work. For this, we use an Azure DLVM as the computing environment. For details on setting up the DLVM to run the code sample, please see Chapter 4.

https://doi.org/10.1007/978-1-4842-3679-6_8

What Are Generative Adversarial Networks?

GANs are emerging as powerful techniques for both unsupervised and semisupervised learning. A basic GAN consists of the following:

- A *generative model* (i.e., generator) generates an object. The generator does not know anything about the real objects and learns by interacting with the discriminator. For example, a generator can generate an image.
- A *discriminative model* (i.e., discriminator) determines whether an object is real (usually represented by a value close to 1) or fake (represented by a value close to 0).
- An *adversarial loss* (or error signal) is provided by the discriminator to the generator such that it enables the generator to generate objects that are as close as possible to the real objects.

Figure 8-1 shows the interaction between the generator and the discriminator. The discriminator is a classifier that determines whether the image given to it is a real or fake image. The generator uses the noise vector and feedback from the discriminator to try its best to generate images that are as close to real images as possible. This continues until the GAN algorithm converges. In many GANs, the generator and discriminator usually consist of common network architectures modeled after DenseNet, U-Net, and ResNet. Some example network architectures were discussed in Chapter 3.

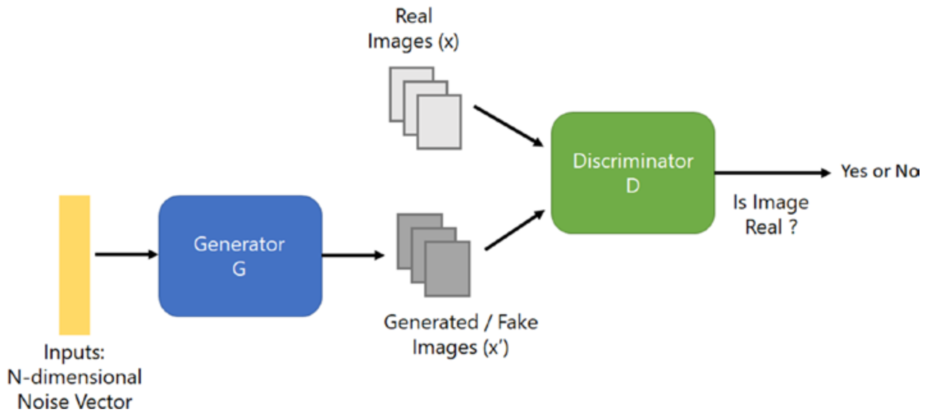


Figure 8-1. *Basic GAN to show the interaction between the generator and discriminator*

Figure 8-2 (inspired by work by Goodfellow et al., 2014) describes the theoretical basis for how a GAN works. The generator (G) and discriminator (D) are represented by the solid line and the dashed lines, respectively. The data generating distribution is denoted by the dotted lines. The two horizontal lines in Figure 8-2 denote the domain from which z is sampled uniformly (lower line), and the domain of x (upper line). The arrows from the lower to the upper line denote the mapping $x = G(z)$. From Figure 8-2, you will notice that over time, as the GAN converges, the solid line and the dotted lines are close to each other (or almost similar). At that point the discriminator D can no longer distinguish between the real and the fake objects generated.

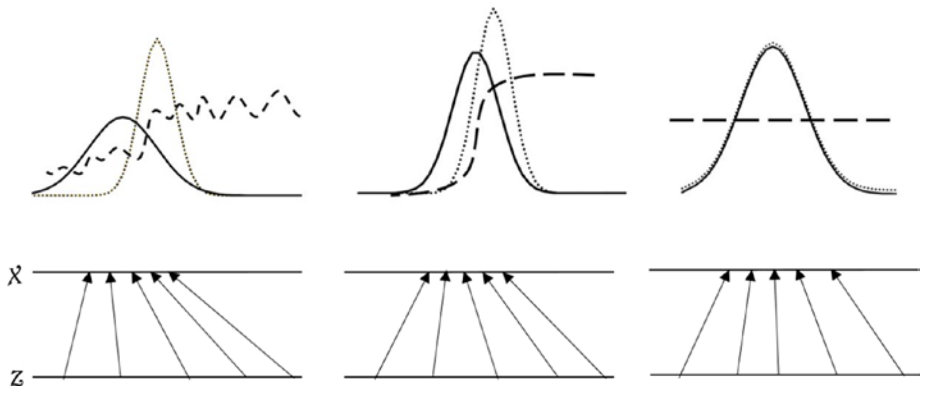


***Figure 8-2.** How GANs work: The generator is generating objects that are so real that the discriminator can no longer tell the difference between real and fake. Source: Goodfellow et al. (2014).*

In the early version of GANs, the generator and the discriminator are implemented as fully connected neural networks (Goodfellow et al., 2014). These GANs are used for generating images from various data sets commonly used in deep learning: CIFAR10, MNIST (handwritten digits), and the Toronto Face Dataset, for example. As the architecture of GANs has evolved, CNNs are increasingly being used. An example of a GAN that uses deep CNNs is DCGANs (Radford, Metz, & Chintala, 2016). A comprehensive overview of different types of GANs can be found in Creswell et al. (2017).

Since 2014, very innovative approaches to using GANs have emerged. GANs have shown promise in the use of AI for creativity, such as art and music generation and computer-aided design (CAD). One of these approaches is to automate the generation of images using text descriptions. InfoGAN (Chen et al., 2016) is an unsupervised approach that can distill the semantic and hidden representations from several well-known data sets (e.g., Digits [MNIST], CelebA Faces, and House Numbers [SVHN]). The secret behind InfoGAN is maximizing the mutual information between latent variables and the observations. The stacked Generative Adversarial Networks (StackGAN; Zhang et al., 2016) was proposed to generate photorealistic images using text descriptions. For example, given the text

"This bird has a yellow belly and tarsus, grey back, wings, and brown throat, nape with a black face," StackGAN will generate the picture of a bird using two stages. In Stage 1, a low-resolution image is computed, which consists of basic shapes and colors. In Stage 2, the results from Stage 1 and the text descriptions are used to create photorealistic high-resolution images.

Figure 8-3 shows the two stages of the StackGAN.

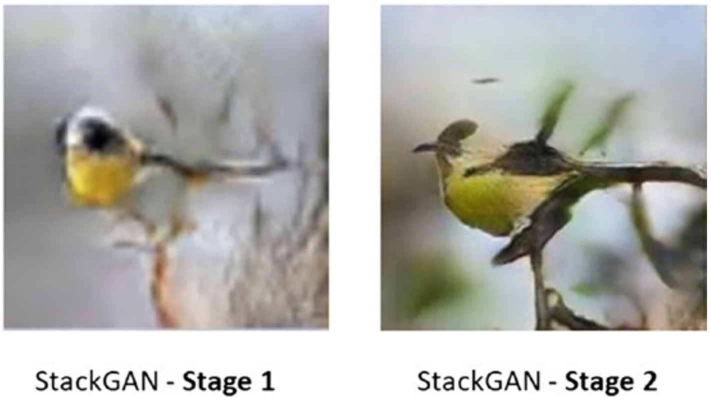


Figure 8-3. *StackGAN: Generation of image from text. Source: Zhang et al. (2016).*

Like StackGAN, Attentional Generative Adversarial Network (AttnGAN) uses a multistage approach. In addition, AttnGan introduced a novel attention-driven approach that focuses (or pays attention) to the different words in the text description and uses this to synthesize fine-grained details for each of the subregions of an image. Figure 8-4 shows how AttnGAN works, and the different parts of the image that it is focusing on for the different words. The first row shows the image generated by different generators, each producing images of different dimension (from 64 × 64, to 128 × 128, to 256 × 256). The second and third row show the top five most attended words (i.e., words with the highest values as defined by each attention model).

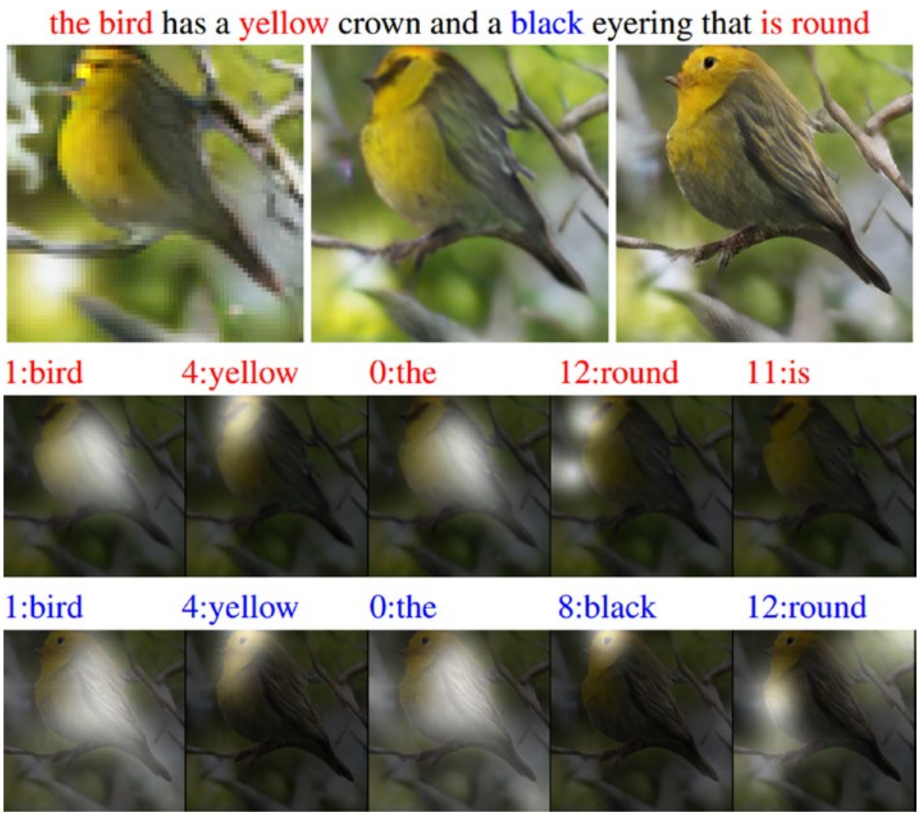


Figure 8-4. *How an AttnGAN uses different parts of the text description to generate details for each region of the image*

Before we dive into the implementation of some of these GANs, it is important to note that many of today's GAN implementations are designed for generating data (e.g., images) from a real-valued continuous data distribution. When trying to apply GANs to generate discrete sequences of data (e.g., text, poetry, music), many existing GAN implementations will not be able to handle it well. In addition, GANs are designed to determine the loss (or adversarial loss) only when the entire sequence of data (e.g., the image) has been generated.

Another interesting type of GAN is **SeqGAN** (Yu, Zhang, Wang, & Yu, n.d.). SeqGAN is a novel approach toward integrating reinforcement learning concepts into GANs to overcome the various challenges faced by existing GANs when used to generate discrete sequences of data. In a SeqGAN, the generator is designed to be an agent of reinforcement learning, where its current state is the generated discrete tokens so far, and the action is the next token to be generated. The discriminator evaluates the generated tokens and provides feedback to help the generator to learn. SeqGAN is shown to be effective in poetry generation, music generation, and application to language and speech tasks.

Today, GANs work well for several types of problems, but they are notoriously difficult to train, as they are not guaranteed to converge on a solution that is optimal, or even stable. Another common issue with GANs is known as mode collapse, where the generator creates samples that have extremely low variety. They require very careful selection of the hyperparameters and parameter initialization among other factors to work well. At the 2016 NIPS workshop on adversarial training, for example, how to explain and fix the issues in training GANs was a main topic (video recordings can be watched at http://bit.ly/NIPS2016). Fortunately, though, many tricks have been used to stabilize the training of GANs. One such trick is to include additional information either in the input space (e.g., adding continuous noise to the input of the discriminator) or adding the information to the output space (e.g., different classes of true examples). Other tricks look at introducing a regularization scheme during training.

Note Learn about the evolution of GANs at http://bit.ly/GANsEvolve.

This chapter walks through one of the GANs, known as Cycle-Consistent Adversarial Networks (CycleGANs). We learn how CycleGANs can be used for image-to-image translation. By walking through the code, we will jump start our understanding of GANs and the innovative applications of GANs in your AI projects. You can leverage the Microsoft AI Platform to train and deploy these GANs to the cloud, mobile, and edge devices.

Cycle-Consistent Adversarial Networks

CycleGANs are a novel approach for translating an image from a source domain X to a target domain Y. One of the strengths of CycleGANs is that the training of the GAN does not require the training data to have matching image pairs. As noted in Zhu, Park, Isola, and Efros (2017), CycleGANs have been successfully applied in the following use cases:

- Translating Monet paintings to photos.
- Style transfer for photos using styles from various famous artists (Monet, Van Gogh, Cezanne, and Ukiyo-e).
- Object transfiguration, where it is used for changing the type of objects found in photos. Figure 8-5 shows how CycleGANs are used in object transfiguration (horse to zebra, zebra to horse, apple to orange, orange to apple, etc.).
- Translating a photo from one season (e.g., summer) to another (e.g., winter).
- Photo enhancement by narrowing the depth of field, and more.

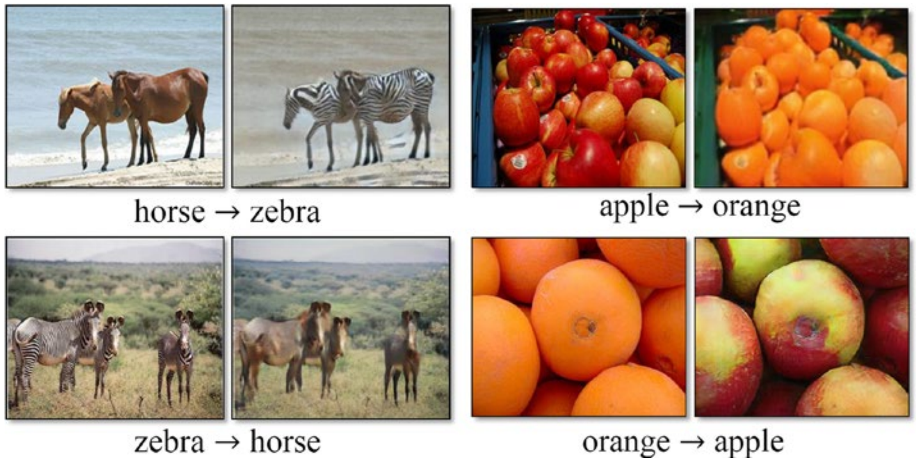


Figure 8-5. *Object transfiguration (horse to zebra, apple to orange). Source: Zhu, Park, Isola, and Efros (2017).*

The goal of CycleGANs is to learn how to map images from one domain X to another domain Y. Figure 8-6 shows the use of two mapping functions G and F, and two discriminators D_X and D_Y. The discriminator D_X is used to verify the images from X and the translated images F(y). Similarly, the discriminator D_Y is used to verify the images from Y and the translated images G(x). The secret behind the effectiveness of using CycleGANs for image translation is the use of a cycle consistency loss. Intuitively, the cycle consistency loss is used to determine whether images from the domain X can be recovered from the translated image.

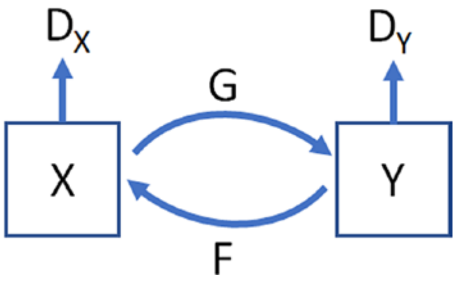


Figure 8-6. *CycleGANs model with two mapping functions G and F, and two adversarial discriminators D_X and D_Y*

Note CycleGANs were first introduced in Zhu et al. (2017). The original implementation of CycleGANs (in PyTorch) is available at http://bit.ly/CycleGAN.

The CycleGAN Code

Let us first walk through the overall CycleGAN code that will be used for training the CycleGANs and then testing it by translating images from a source domain A to a target domain B. For example, the trained CycleGAN will perform object transfiguration and translate a photo consisting of a horse to a zebra (and vice versa). The results are then visualized as an HTML file.

Let us first import the Python libraries that we will use in this code. From Listing 8-1, you will see that we are using TensorFlow, and importing the definition of the CycleGAN from a `model.py` file. We will dive into the details of the `model.py` fie in the later parts of this section.

Note We recommend provisioning an Azure DLVM to run the code examples in this chapter. Please see Chapter 4 for more information.

Listing 8-1. Importing the Required Python Libraries

PYTHON

```python
import os
import tensorflow as tf
from model import cyclegan
```

Next, we define the argument that will be used for training and testing the CycleGAN. From Listing 8-2, you will see that we specified a learning rate of 0.0002 for 200 epochs (denoted by `lr` and `epoch_step`). In addition, we also specified the locations of the directories that we will be using to load the training data, output the test images, and storing the checkpoint files. To enable the value of phase (i.e., train or test) to be modified, we also specified it as a property called `phase`, and defined the relevant getter or setter for it.

Listing 8-2. Specifying the Training and Testing Arguments

```
PYTHON

# Define the argument class
class args:
  dataset_dir='horse2zebra'
  epoch=1
  lr=0.0002
  epoch_step=200
  batch_size=1
  train_size=1e8
  load_size=286
  fine_size=256
  ngf=64
  ndf=64
  input_nc=3
  output_nc=3
  beta1=0.5
  which_direction='AtoB'
  save_freq=1000
  print_freq=100
  continue_train=False,
  checkpoint_dir='./checkpoint'
  sample_dir='./sample'
  test_dir='./test'
  L1_lambda=10.0
  use_resnet=True
  use_lsgan=True
  max_size=50
  _phase='train'

  @property
  def phase(self):
    return type(self)._phase

  @phase.setter
  def phase(self,val):
    type(self)._phase=val
```

Next, we create the relevant directories on the local file system that will be used to load the training data, store the output images, and the checkpoint files (shown in Listing 8-3).

Listing 8-3. Create the Directories for Output, Sample, and Checkpoint

PYTHON

```
os.makedirs(args.checkpoint_dir, exist_ok=True)
os.makedirs(args.sample_dir, exist_ok=True)
os.makedirs(args.test_dir, exist_ok=True)
```

We are now ready to train the CycleGAN (shown in Listing 8-4). As a machine might have multiple devices (CPU or GPU) that can be used for training, we specify `allow_soft_placement` to be `True`. The setting `allow_soft_placement` specifies that if an operation does not have a GPU implementation, it will be run on the CPU.

Next, we specify `gpu_options.allow_growth` to be `True`. TensorFlow defaults to mapping all the GPU memory that is available to the process. This helps in reducing GPU memory fragmentation. By setting `gpu_options.allow_growth` to `True`, the process will start with only the required memory needed, and grow the memory allocated as needed during training.

We are now ready to start training the CycleGAN. After creating the TensorFlow session, we invoke the `train method` of the CycleGAN object, and pass it the arguments that we defined earlier, as shown in Listing 8-4.

Listing 8-4. Training the CycleGAN

```
PYTHON

tfconfig = tf.ConfigProto(allow_soft_placement=True)
tfconfig.gpu_options.allow_growth = True

with tf.Session(config=tfconfig) as sess:
  model=cyclegan(sess,args)
  model.train(args)
```

Note Using a single Tesla K80 GPU, the training of the CycleGAN with 200 epochs will take a while. If you want to test the code, you should reduce the number of epochs.

Later in this chapter, we describe the architecture of the CycleGAN. Before that, let us first look at the training code. Once the training of CycleGAN completes, you are ready to test the CycleGAN. Listing 8-5 shows how we invoke the `test` method of the CycleGAN object. From the arguments shown in Listing 8-2, we are performing a translation of images from Domain A to Domain B. The resulting images are stored in the `test` folder. In addition, an HTML file, `AtoB_index.html`, is written to the `test` folder to enable you to see the image before and after the CycleGAN has performed the translation.

Listing 8-5. Testing the CycleGAN

PYTHON

```
tfconfig = tf.ConfigProto(allow_soft_placement=True)
tfconfig.gpu_options.allow_growth = True

tf.reset_default_graph()
args.phase='test'

with tf.Session(config=tfconfig) as sess:
  model=cyclegan(sess,args)
  model.test(args)
```

Network Architecture for the Generator and Discriminator

To build any type of GAN, it is important to first define the discriminator and generator. Let us explore the network architecture for the generator and discriminator. The role of the generator in any GAN is to generate images that will fool the discriminator. The network architecture for the CycleGAN generator is adapted from the Fast-Neural Style transfer work (Justin, Alexandre, & Li, 2016).

The generator code is shown in Listing 8-6. The generator consists of nine residual blocks that will be used for training with 256 × 256 images (from g_r1 to g_r9). Each residual block has two 3 × 3 layers with convolution, instance normalization, and ReLU applied.

Note Zhu et al. (2017) noted the use of instance normalization in the residual block improves image quality.

Listing 8-6. *CycleGAN generator*

PYTHON

```
def generator_resnet(image, options, reuse=False,
         name="generator"):

    with tf.variable_scope(name):
        # image is 256 x 256 x input_c_dim
        if reuse:
            tf.get_variable_scope().reuse_variables()
        else:
            assert tf.get_variable_scope().reuse is False

        def residual_block(x,dim,ks=3,s=1,name='res'):
            p=int((ks-1)/2)
            y=tf.pad(x, [[0,0], [p,p], [p,p], [0,0]],
              "REFLECT")

            y=instance_norm(conv2d(y,dim,ks,s,
              padding='VALID',name=name+'_c1'),name+'_bn1')

            y=tf.pad(tf.nn.relu(y), [[0,0], [p,p], [p,p],
               [0,0]],"REFLECT")

            y=instance_norm(conv2d(y,dim,ks,s,
               padding='VALID',name=name+'_c2'),name+'_bn2')

            return y+x

        # Justin Johnson's model from
        # https://github.com/jcjohnson/fast-neural-style/
        c0=tf.pad(image, [[0,0], [3,3], [3,3], [0,0]],
             "REFLECT")
```

```
c1=tf.nn.relu(instance_norm(conv2d(c0,options.gf_dim,
   7,1,padding='VALID',name='g_e1_c'),'g_e1_bn'))

c2=tf.nn.relu(instance_norm(conv2d(c1,options.gf_dim*2,
   3,2,name='g_e2_c'),'g_e2_bn'))

c3=tf.nn.relu(instance_norm(conv2d(c2,options.gf_dim*4,
   3,2,name='g_e3_c'),'g_e3_bn'))

# define G network with 9 resnet blocks
r1=residule_block(c3,options.gf_dim*4,name='g_r1')
r2=residule_block(r1,options.gf_dim*4,name='g_r2')
r3=residule_block(r2,options.gf_dim*4,name='g_r3')
r4=residule_block(r3,options.gf_dim*4,name='g_r4')
r5=residule_block(r4,options.gf_dim*4,name='g_r5')
r6=residule_block(r5,options.gf_dim*4,name='g_r6')
r7=residule_block(r6,options.gf_dim*4,name='g_r7')
r8=residule_block(r7,options.gf_dim*4,name='g_r8')
r9=residule_block(r8,options.gf_dim*4,name='g_r9')

d1=deconv2d(r9,options.gf_dim*2,3,2,name='g_d1_dc')
d1=tf.nn.relu(instance_norm(d1,'g_d1_bn'))
d2=deconv2d(d1,options.gf_dim,3,2,name='g_d2_dc')
d2=tf.nn.relu(instance_norm(d2,'g_d2_bn'))
d2=tf.pad(d2, [[0,0], [3,3], [3,3], [0,0]],
       "REFLECT")

pred=tf.nn.tanh(conv2d(d2,options.output_c_dim,7,1,
          padding='VALID',name='g_pred_c'))

return pred
```

The discriminator for the CycleGAN (shown in Listing 8-7) takes an input image and predicts whether it is an original image or an image that is generated by the generator.

Listing 8-7. CycleGAN Discriminator

PYTHON

```python
def discriminator(image, options, reuse=False,
name="discriminator"):

    with tf.variable_scope(name):
        # image is 256 x 256 x input_c_dim
        if reuse:
            tf.get_variable_scope().reuse_variables()
        else:
            assert tf.get_variable_scope().reuse is False

        h0=lrelu(conv2d(image,options.df_dim,
           name='d_h0_conv'))

        # h0 is (128 x 128 x self.df_dim)
        h1=lrelu(instance_norm(conv2d(h0,options.df_dim*2,
           name='d_h1_conv'),'d_bn1'))

        # h1 is (64 x 64 x self.df_dim*2)
        h2=lrelu(instance_norm(conv2d(h1,options.df_dim*4,
           name='d_h2_conv'),'d_bn2'))

        # h2 is (32x 32 x self.df_dim*4)
        h3=lrelu(instance_norm(conv2d(h2,options.df_dim*8,s=1,
            name='d_h3_conv'),'d_bn3'))

        # h3 is (32 x 32 x self.df_dim*8)
        h4=conv2d(h3,1,s=1,name='d_h3_pred')
        # h4 is (32 x 32 x 1)
        return h4
```

The discriminator consists of a first layer that applies a LeakyRelu and convolution to the image. For the subsequent three layers, convolution, instance normalization, and ReLU are applied. A final convolution is applied in the final layer (denoted by *h4*), which produces a one-dimensional output.

More Info The code for this chapter is based on the work by Xiaowei Hu, and available on Github at `http://bit.ly/GANsCode1`. A Jupyter notebook is created to enable you to get started with running the CycleGAN code quickly. The notebook is available on Github at `http://bit.ly/GANsCode2`. We tested the code on an Azure DLVM, with a single Tesla K80 GPU.

Defining the CycleGAN Class

Next, let us look into the CycleGAN class. In the `Train` method found in the `model.py` file, we use the Adam optimizer with a batch size of 1. Listing 8-8 shows how we specify the optimizer that will be used by the discriminator and generator.

Listing 8-8. CycleGAN (`model.py`): Defining the Optimizer Used for the Generator and Discriminator

PYTHON

```
self.d_optim = tf.train.AdamOptimizer(self.lr, beta1=args.
beta1) \
            .minimize(self.d_loss,var_list=self.d_vars)

self.g_optim = tf.train.AdamOptimizer(self.lr, beta1=args.
beta1) \
           .minimize(self.g_loss,var_list=self.g_vars)
```

A CycleGAN consists of two generators (XtoY and YtoX) and two discriminators (D_X and D_Y), as shown earlier in Figure 8-6. You will see this defined in the _build_model method in model.py. From the code in Listing 8-9, you will see how we set the value of the reuse argument to be False during the initial definition of generatorA2B and generatorB2A, and uses the variables real_A and fake_B, respectively. This determines whether variables are reused. In the subsequent definition of generatorB2A and generatorA2B, the value of reuse is set to True, and uses the variables real_B and fake_A. The two discriminators are defined in model.py, as shown in Listing 8-10. The interested reader should deep dive into the code provided to understand the details of the generator.

Listing 8-9. Defining the two generators, generatorA2B and generatorB2A

PYTHON

```
self.real_data = tf.placeholder(tf.float32,
                [None,self.image_size,self.image_size,
                self.input_c_dim+self.output_c_dim],
                name='real_A_and_B_images')

self.real_A = self.real_data[:, :, :, :self.input_c_dim]
self.real_B = self.real_data[:, :, :, self.input_c_dim:self.
input_c_dim + self.output_c_dim]

self.fake_B = self.generator(self.real_A, self.options,
                            False,name="generatorA2B")

self.fake_A_ = self.generator(self.fake_B, self.options,
                            False,name="generatorB2A")
```

```
self.fake_A = self.generator(self.real_B, self.options,
                             True,name="generatorB2A")

self.fake_B_ = self.generator(self.fake_A, self.options,
                              True,name="generatorA2B")
```

Listing 8-10. Defining the Two Discriminators: `discriminatorB` and `discriminatorA`

PYTHON

```
self.DB_fake = self.discriminator(self.fake_B, self.options,
                   reuse=False,name="discriminatorB")

self.DA_fake = self.discriminator(self.fake_A, self.options,
                   reuse=False,name="discriminatorA")
```

Adversarial and Cyclic Loss

During the training of the GAN, the generator G generates images G(x) that are like the images found in Domain Y. At the same time, the discriminator D_Y needs to differentiate between generated images G(x) and the real samples from y. Hence, G is always trying to minimize its adversarial loss, whereas the discriminator D is trying to maximize its loss.

As noted in Zhu et al. (2017), if the capacity of the network is large, the mappings G and F can potentially map input images from the source domain X to any random permutation of images in Domain Y. Hence, it is important to reduce the space of possible mapping functions. One of the secrets of a CycleGAN is the use of a *cycle consistency loss.* The intuition behind the use of a cycle consistency loss is that the learned mapping function should be able to bring a translated image back to its original image.

Results

After we ran the CycleGAN training for 150 epochs, we ran the testing code shown in Listing 8-5. This applies the CycleGAN model to the images found in the `dataset` directory and output the translated image to the `test` directory. An HTML file is also generated. This allows you to visualize the original and the translated image side by side. In the Jupyter notebook provided, the code (shown in Listing 8-11) enables the HTML file to be viewed in a notebook cell.

Listing 8-11. Python Code to Visualize HTML File in the Cell

```
PYTHON

from IPython.display import HTML
HTML(filename='test/AtoB_index.html')
```

In Figure 8-7, we show a subset of the images generated.

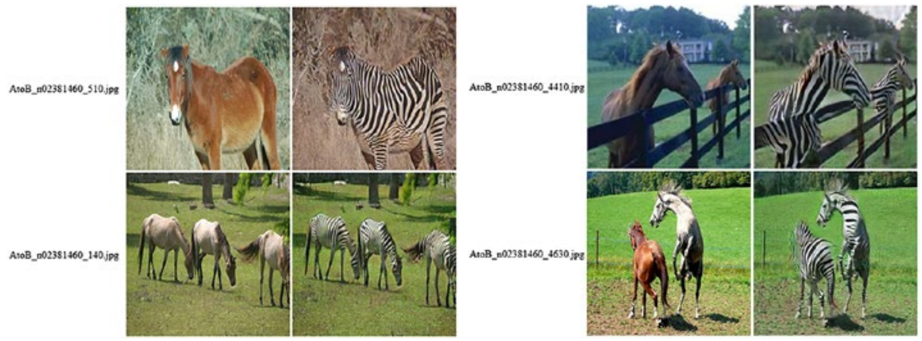


Figure 8-7. *Output from CycleGAN test (after 150 epochs)*

Summary

GANs have tremendous potential to be used in AI for creativity, music, and the arts. Since it was first proposed in 2014, GANs innovations are happening at a breathtaking pace. This chapter described how GANs can be applied to various use cases. We showed the use of the generator and the discriminator in the GAN architecture, and how they are used.

Next, we discussed how CycleGAN works, and showed how it can be used for translation of objects from one domain to another. In the code example given in this chapter, we focus on how to train and test a novel type of GAN, called CycleGAN.

All the code in this chapter is run on a Linux DLVM, available on Azure. More details on choices for training AI models (e.g., GANs), such as the computing environments and how to do training at scale, are discussed in the next chapter.

PART IV

AI Architectures and Best Practices

CHAPTER 9

Training AI Models

Training AI models is usually more demanding than training standard ML models because they are processing intensive and often the data sets involved are larger. That is why if you are serious about deep learning you have to have access to GPUs. In Azure there are a number of ways you can make use of GPUs, on single VMs or in orchestrated clusters of them. In this chapter, we summarize several of the most common methods available as well as the pros and cons of each. Then we expand on the code we wrote in Chapter 6, which used a VGG-like CNN to tackle the CIFAR10 data set using the DLVM as the computing environment. In this chapter, we extend to other training options such as Batch AI and Batch Shipyard, which can both be useful for scaling up or scaling out training. We finish by highlighting briefly some of the other methods of training AI models on Azure that are not as common but might be useful depending on the problem at hand.

Training Options

Azure has a vast number of options for training AI models. We will limit ourselves here to the select few that we feel fulfill the requirements of most workload types. The four ways that we discuss to train AI models are DLVM, Batch AI, Batch Shipyard, and DL Workspace. There is no best way to train an AI model; each method has its benefits and drawbacks and some will be more suited to certain solutions than others. The training of a deep learning

https://doi.org/10.1007/978-1-4842-3679-6_9

model can take place on a single GPU machine or distributed across a number of GPU machines. The most common scenario is to use a single GPU machine per model, as training the model in a distributed fashion needs additional considerations that can be quite tricky to get right but might be necessitated by factors such as the model being too big to fit onto a single GPU machine or wanting to reduce training time.

In this chapter, we do not mention the data processing that is often needed before training an AI model. For example, the raw data will often have to be processed to be readable by a deep learning model, the labels on which the ML algorithm should learn might be stored in a database, or the raw data might come from many sources. There are many tools and options available within the Microsoft AI Platform for this type of work, such as Azure SQL Data Warehouse and CosmosDB for storing different types of data, and Azure Data Factory for data movement, which are outside the scope of this chapter. We assume for purposes here that the data are available in a format that is ready to be trained by an AI model.

Distributed Training

Distributed training is used when the whole data set cannot be stored on a single machine or the model cannot fit on a single GPU, but most often it is used to achieve faster training. The two main types of distributed training are data parallelism or model parallelism.

With data parallelism, the same model will be replicated across many GPUs and will receive different batches of training data. The gradients are then aggregated and then the updates distributed back to the models. In this scenario the communication overhead can be quite substantial so an active area of exploration is how to make this process more efficient by exploring asynchronous updates (Calauzènes & Roux, 2017; Dean et al., 2012; Recht, Re, Wright, & Niu, 2011) or reducing the overhead by compressing or quantizing the weight updates (Lin, Han, Mao, Wang, & Dally, 2017; Recht et al., 2011).

With model parallelism the model is split over multiple GPUs. An example of this might be different layers placed on different GPUs and the forward and backward passes over the model involve network communication across the nodes. This is a far less common scenario and is only necessary if the model cannot fit on a single GPU.

In these scenarios it is assumed that there is only one GPU per VM, often referred to as multinode multi-GPU, but in fact Azure has configurations where there can be up to four GPUs on a single VM. All of the scenarios just explained can be executed on a single-node multi-GPU scenario except the scenario where the data are too large to fit on a single VM. Communication overhead is usually less of a concern in this scenario because it takes place on a single node and can perform even better if the deep learning framework uses Nvidia's NCCL multi-GPU library (`http://bit.ly/nvidianccl`).

Deep Learning Virtual Machine

The DLVM is a single VM that comes in a number of different configurations, some of which have GPUs, and is a specially configured variant of the DSVM. The VM types that have GPUs at the moment are NC, NV, ND, NCv2, and NCv3, with the cheapest being the NC series. These have the corresponding GPUs installed with NVIDIA Tesla K80, M60, P40, P100, and finally V100. They are loosely ordered from the least powerful to the most powerful, with a single K80 providing around 4.4 teraflops and a single V100 offering around 14 teraflops.[1]

Note Even the least powerful GPU (K80) provides significant reductions in training time compared to training AI models on CPUs.

[1]Order and numbers are based on single precision FLOPS; cards with two chips are treated as individual GPUs.

Each VM series can come in three configurations: one GPU, two GPUs, or four GPUs. See the current documentation on all VMs available on Azure at http://bit.ly/AzureVMs and the DSVM at http://bit.ly/AzureDSVM.

By using the DLVM, we can jump straight into tackling our data science problems because all the libraries come preinstalled in a premade Anaconda environment, as illustrated in Figure 9-1. The DLVM is a great option for experimentation but if you want to do large-scale model/data parallel training or simply explore various hyperparameters in parallel, one of the latter options will be better.

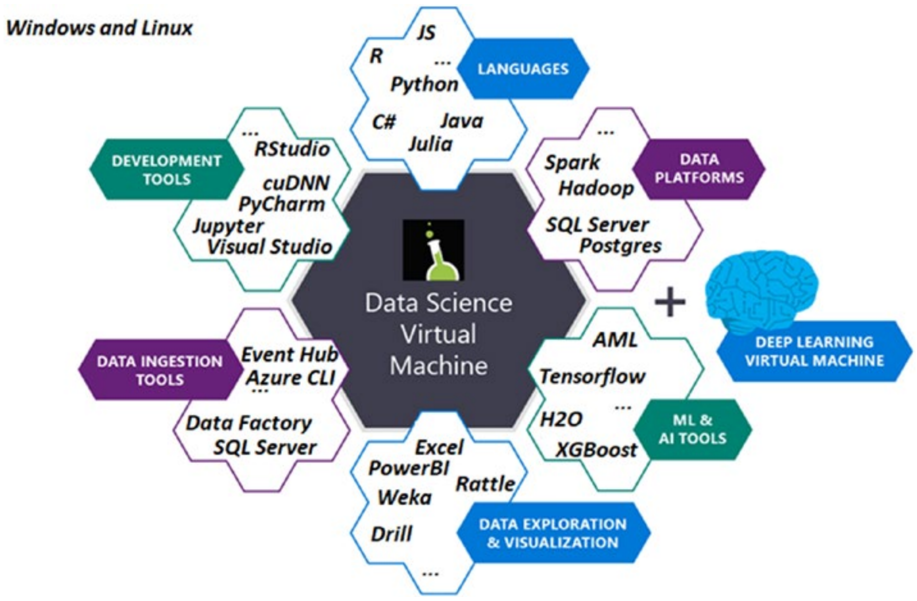


Figure 9-1. *The Data Science Virtual Machine is a preconfigured environment in the cloud for data science and AI modeling, development, and deployment. The Deep Learning Virtual Machine is a special configuration for deep learning workloads*

Batch Shipyard

Batch Shipyard is a general-purpose tool for running container-based batch processing and High Performance Computing (HPC) workloads. By building on top of Azure Batch, Batch Shipyard is able to benefit from its features, such as handling the complexities surrounding large-scale parallel and HPC applications in the cloud, managing aspects such as the VM deployment and management, job scheduling, and autoscaling requirements. There is no extra cost to use Azure Batch when running jobs on Azure; it is a free, value-added service where costs are only incurred for the computing resources consumed and related datacenter movement and storage costs.

Batch Shipyard uses Docker containers, which makes it easy to manage the complex dependencies that come with AI workloads. Batch Shipyard is available as a CLI that can be run locally or in the cloud using the Azure Cloud Shell. The orchestration is managed through easy-to-understand configuration files, which makes it easy to reuse scripts. It already contains a large number of examples for some of the most popular deep learning frameworks (see `http://bit.ly/shipyard24c3`).

The following are some of the pros of using Batch Shipyard:

- It is tied to Azure Batch infrastructure so it is well supported.
- It is easy to use from the CLI and also available in the cloud shell.
- It supports many different types of VMs, including GPUs.
- It supports low-priority nodes, which makes it very efficient.
- It has factory methods to support easy hyperparameter tuning.

Among the disadvantages of using Batch Shipyard are the following:

- It is tied to Batch infrastructure, so there is no support for its own clusters.
- There is no REST API or web front end, only the CLI.

Batch AI

Batch AI is very similar to Batch Shipyard, as it runs on Azure Batch and allows you to run various AI workloads. The core differences between Batch Shipyard and Batch AI are the following:

1. It is a managed service. This means that with Batch Shipyard the CLI is calling out to Azure Batch and setting everything up. With Batch AI there is a service in the cloud that we call to use the CLI, REST API, or SDK, and it orchestrates everything. In practice, this means is there is a far richer way to interact with Batch AI and it is easier to orchestrate as part of a pipeline.
2. Batch AI can execute on a DSVM or DLVM, giving it the ability to run things without containers. This makes it very easy to get started if you do not want to deal with the complexities of containers.
3. Batch AI provides specialized support for running distributed training on a number of deep learning frameworks such as PyTorch, TensorFlow, and so on. In practice, this means that some of the complexities such as setting up Message Passing Interface (MPI) are automatically configured by Batch AI.

These are some of the pros of Batch AI:

- It is a managed service.
- It has multiple ways to interact with the CLI, SDK, and REST APIs.
- It is tied to Azure Batch infrastructure so it is well supported.
- It supports many different types of VM including GPUs.
- It supports low-priority nodes that are very cost-efficient.
- It can support DSVM and DLVM as computing targets.

The following are some of the disadvantages of using Batch AI:

- It does not have feature parity with Batch Shipyard. Batch Shipyard offers some nice methods for hyperparameter search that have not yet made their way to Batch AI.
- It is still in previews and not available in all regions.

Deep Learning Workspace

Deep Learning Workspace (DLWorkspace) is an open source project from Microsoft that allows AI scientists to spin up clusters, either locally or in the cloud, in a turn-key fashion. DLWorkspace uses Kubernetes to manage the jobs across the various nodes. Kubernetes is a popular open source container orchestrator and we will talk more about it in Chapter 10. DLWorkspace provides a web user interface (UI) and a REST API from which one can submit, monitor, and manage jobs. This is quite different from Batch AI and Batch Shipyard, as it does not rely on the Batch infrastructure to manage things, nor is it tied to the Azure infrastructure. This does mean it requires more management by the end user than the other two options, but it offers the greatest amount of flexibility. It is also less mature than the other two options.

The following are some of the advantages of DLWorkspace:

- It is not tied to a particular infrastructure, so it can run on local clusters and in the cloud.
- It uses Kubernetes, a well-known container orchestrator.

Some of the disadvantages of DLWorkspace are as follows:

- It requires more setup than Batch Shipyard or Batch AI.
- It is harder to integrate into a pipeline.
- It is still under heavy development.

Examples to Follow Along

In many of the previous chapters we have demonstrated how to train a deep learning model on a GPU-enabled DLVM, so we do not go over that here. In the sections that immediately follow, we will be making use of the code we wrote in Chapter 6, which used a VGG-like CNN to tackle the CIFAR10 data set, to expand to use Batch Shipyard and Batch AI. If you do not remember what we did there, it would be prudent to go back and refresh your memory.

Training DNN on Batch Shipyard

In this section we go over general steps of how to train a CNN on Batch Shipyard. The steps that we follow to execute our AI script are detailed in the notebook `Chapter_09_01.ipynb`[2] and shown in Figure 9-2.

[2]All the steps are detailed in the notebook *Chapter_09_01.ipynb* which can be found in the Chapter_09 folder `http://bit.ly/CH09Notebooks`.

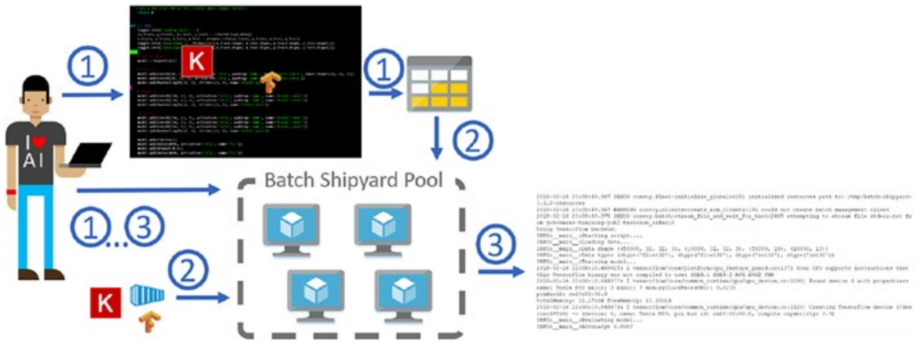


Figure 9-2. *The steps involved in running things on Batch Shipyard. (1) Create the necessary Azure resources, configuration files, and scripts. (2) Call pool create, which will start the process of creating our cluster. At the same time this will pull the script we created into the fileshare. It will also pull the Docker image and make it available to the nodes in the pool. (3) Tell Batch Shipyard to execute the job and detail the output. Once it is all done we will delete the job, cluster, and Azure resources.*

1. As you can see from the steps in Figure 9-2, there are a number of prerequisites required for training your model on Batch Shipyard. The script that will train your model.

2. The Docker container that contains all the dependencies for the script such as the deep learning framework, and so on.

3. An Azure storage account and Azure Batch account.

4. Batch Shipyard configuration files. These can be either YAML or JSON files that will hold all the necessary information to define what we want Batch Shipyard to do for us.

Our model script will be very similar to what we wrote in the `Chapter_06_03.ipynb` notebook, except it will be a Python file rather than a Jupyter notebook and we will add the ability to pass arguments to it. The reason for doing this is to simplify the execution and so that we can see how the model performs with different hyperparameter configurations. This is usually referred to as hyperparameter search and it is an important step in creating AI models. The script will download the CIFAR10 data, create and train our model, and finally evaluate it on the test data set.

With the script prepared, we need to either create our own Docker image or reference a prebuilt one. Many of the most popular deep learning frameworks either provide you with a Docker image or at the very least a Dockerfile you can use to create your image. For people who have not used Docker before, this can be quite daunting. Thankfully there are a number of guides online and the Docker documentation is very good (see `http://bit.ly/dockerstarted`). Here we simply use the Docker image we created for this book.

We will assume that you have created the Azure storage and Batch account. The steps for doing this are outlined in the "Create Azure Resources" section of the accompanying notebook. For Batch Shipyard there are four configuration files:

- `credentials.yaml`: Here we put the credentials for all the resources we use. In our case it is simply the storage account and Batch account.
- `config.yaml`: Specifies the configuration for Batch Shipyard. Here we will simply specify which storage account to use as well as the location of the image we want to use.
- `pool.yaml`: This configuration file defines the properties of our pool, in essence the number of VMs we want to allocate and the types of VMs we wish to allocate.

- `jobs.yaml`: In this configuration file we specify the jobs we wish to execute. We can specify one or more jobs and each job can have one or more tasks. How you split things up will be dependent on the tasks you want to run and how much they share in common. In this file we generally specify what Docker image to use, where to ingress the data from, and what commands to execute. For more details see `http://bit.ly/shipyardjobs`.

From here on in we will be assuming you are running things from a Linux terminal or a Jupyter notebook running on Linux. Now that we have defined our configuration files and our script, we need to create our cluster, which we do in Listing 9-1.

Listing 9-1. Command to Create a Batch Cluster

```
BASH

shipyard pool add --configdir config
```

This command tells Batch Shipyard to create the pool as specified in our `pool.yaml` file located in the `config` directory. This will start the VMs and ingress any files we specified in the configuration files, which in our case is just our model script. Provisioning the pool can take from 5 to 15 minutes depending on the number of VMs specified. The number of VMs you can create is dependent on the quota on your Batch account. If you require more VMs for your Batch account, you can simply request a quota increase through the Azure portal (`http://bit.ly/azbatchquota`).

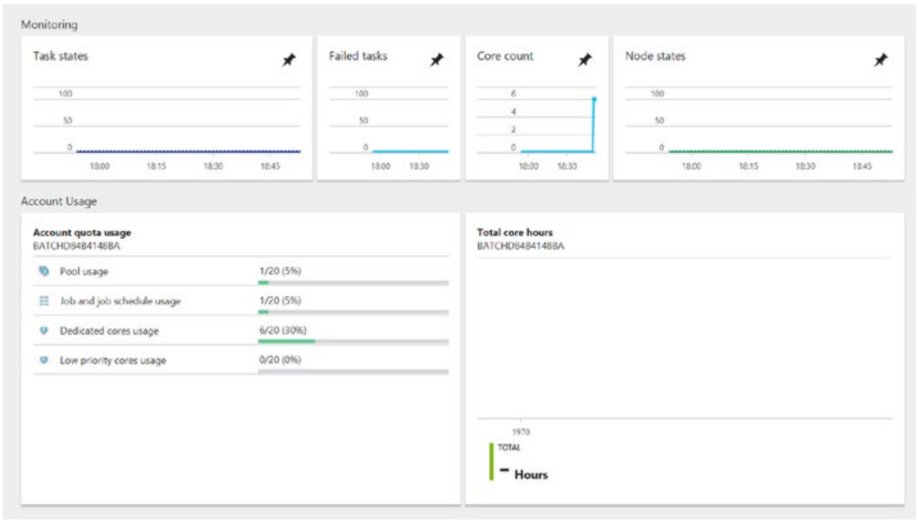
After the pool has been created, we simply add the jobs. Here in Listing 9-2 we submit the job but also interactively tail the output of the task.

Listing 9-2. Submit Job to Batch Shipyard and Tail Output

BASH

```
shipyard jobs add --configdir config --tail stdout.txt
```

If everything goes well you should start seeing the output being streamed to your notebook or terminal. The script will first download the CIFAR data, train the model, and evaluate it. You can also view the state of your cluster and job by visiting the Azure portal, where you should see something similar to Figure 9-3.



Account quota usage
BATCHD84B4148BA

Pool usage	1/20 (5%)
Job and job schedule usage	1/20 (5%)
Dedicated cores usage	6/20 (30%)
Low priority cores usage	0/20 (0%)

Figure 9-3. *Batch dashboard in Azure portal*

By running Listing 9-3, we stream the output of `stderr.txt`. This can be useful to review errors and debug our scripts.

Listing 9-3. Stream Output to Help Review Errors and Debug Scripts

BASH

```
shipyard data files stream -v --filespec my_job_id,my_task_
id,stderr.txt
```

Once you are done with your job, it is best to delete it so it does not count against your active job quota, as we do in Listing 9-4.

Listing 9-4. Delete Batch Shipyard Jobs

```
BASH

shipyard jobs del --configdir config -y -wait
```

Finally, delete your pool with the code shown in Listing 9-5 so you do not incur charges for the VM while not in use.

Listing 9-5. Delete Batch Shipyard Pool

```
BASH

shipyard pool del --configdir config -y
```

This seems like a lot of overhead for executing a single task, but when you need to execute a large number of tasks the initial overhead is tiny compared to the time saved.

Hyperparameter Tuning

Training an AI model or even any type of ML model requires tuning of various hyperparameters that constrain the behavior of our model. Doing so sequentially is laborious and time consuming. By running these experiments in parallel we can save a lot of time and find optimal configurations quicker. One of the key benefits of the cloud and the types of service such as Batch Shipyard and Batch AI is the ability to scale out our computing as needed. This means that we can explore large numbers of configurations and only pay for the computing we need, greatly accelerating the data science process.

As mentioned earlier, Batch Shipyard offers a convenient way for generating hyperparameter tasks called Task Factories. With Task Factories we can generate task parameters in a number of ways such as from random distributions, uniform, gamma, beta, exponential, Gaussian, and so on.

We would define our task factory in the `jobs.yaml` file. Let us imagine we wanted to parameterize our VGG architecture and explore the effects of learning rate on our model. We can achieve this with the task factory specification in Listing 9-6.

Listing 9-6. Task Factory Specification to Generate Hyperparameter Tasks

YAML

```
task_factory:
  random:
    distribution:
      uniform:
        a:0.001
        b:0.1
    generate:10
command: /bin/bash -c "python -m model.py -lr {}"
```

This block of YAML will instruct Batch Shipyard to sample 10 values randomly from a uniform distribution of 0.001 to 0.1 and run the `model.py` script.

Task factories are not limited to generating values from distributions; they can also generate tasks based on custom generators for more complex hyperparameter regimes. For more details on task factories, please check out `http://bit.ly/shipyardtfactory`.

Distributed Training

In the multinode, multi-GPU training scenario, Batch Shipyard handles the setting up of the cluster and distribution of the jobs but does not handle the communication between the nodes. This has to be handled by the deep learning frameworks themselves. Different frameworks use different protocols to pass information between them such as MPI (CNTK, Horovod) or gRPC (TensorFlow). It is important that the appropriate ports are opened and the appropriate processes are started, and this can differ between deep learning frameworks. In Batch Shipyard, such tasks are called multi-instance tasks and need to be specified as such in the jobs configuration file. An example configuration file can be seen in Listing 9-7.

Listing 9-7. Multi-Instance Tasks to Specify Multinode, Multi-GPU Tasks

```
YAML

job_specifications:
- id: tensorflow
  auto_complete:true
  tasks:
  -docker_image:alfpark/tensorflow:1.2.1-gpu
    multi_instance:
      num_instances:pool_current_dedicated
command: /bin/bash -c "/shipyard/launcher.sh /shipyard/mnist_
replica.py"
```

For a detailed walkthrough on how to perform data parallel training in Batch Shipyard, take a look at `http://bit.ly/shipyarddist`.

Training CNNs on Batch AI

Batch AI is in many ways very similar to Batch Shipyard (see Figure 9-4). It offers a Python SDK as well as a CLI. In our example, we outline how to use the CLI because it is slightly easier than the SDK. All of the steps mentioned here are in the accompanying notebook, which you can use to run the example for yourself (`Chapter_09_02.ipynb`).

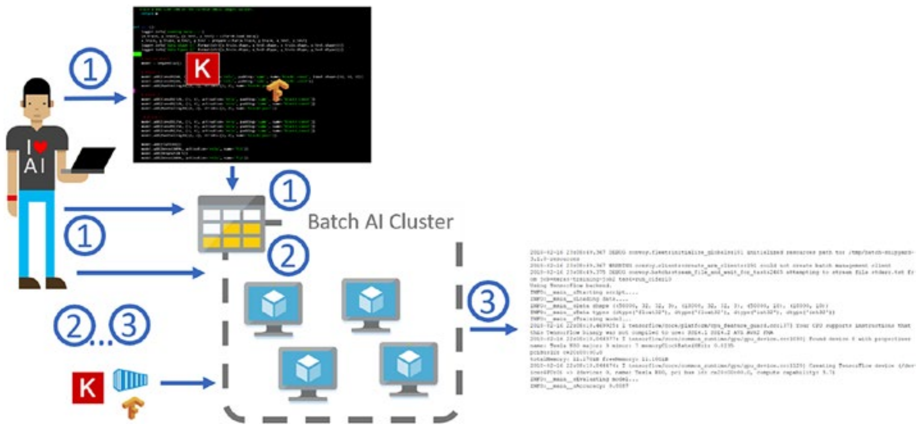


Figure 9-4. *Batch AI training steps: (1) Create the necessary Zzure resources, job configuration files, and scripts, and upload scripts to fileshare. (2) Call cluster create, which will start the process of creating our cluster. It will also pull the Docker image and make it available to the nodes in the pool and mount the fileshare. (3) Run the command specified in the job configuration. Call job stream-file to tail the output from the job. Once training is done delete the job, cluster, and Azure resources.*

Batch AI uses the Azure CLI, which we installed earlier. To register for Batch AI run the code shown in Listing 9-8.

Listing 9-8. Register for Batch AI Service

```
BASH

az provider register -n Microsoft.BatchAI
az provider register -n Microsoft.Batch
```

At the time of writing, Batch AI was only available in the East US region, so that is where we will be creating all our resources. We are going to assume that you have already created a storage account and a fileshare, and have uploaded the script to the fileshare. These steps are in the accompanying notebook (`Chapter_09_02.ipynb`) under the sections "Create Azure Resources" and "Define Our Model." To create our cluster, we run the code in Listing 9-9.

Listing 9-9. Create Batch AI Cluster

```
BASH

az batchai cluster create -l eastus -w workspace --name
my_cluster --vm- size STANDARD_NC6 --image UbuntuLTS --min 1
--max 1 --storage- account- name my_storage_account --storage-
account-key my_ storage_account_key --afs-name my_fileshare
--afs-mount-path azurefileshare --user-name my_username
--password my_password
```

All the values prefixed by `my` should be defined by you and wherever they are intended to should match the Azure resources you already created. In the preceding command, we used the `az batchai cluster create` command to create a Batch AI cluster called `my_cluster` consisting of a single GPU VM node. In this example, the VM runs the default Ubuntu LTS image. If you wish to use the DSVM as the execution target, simply specify `image UbuntuDSVM` instead. The VM specified is an NC6, which has one NVIDIA K80 GPU. We also tell it to mount the fileshare at a folder named `azurefileshare`. The full path of this folder on the GPU compute node is

$AZ_BATCHAI_MOUNT_ROOT/azurefileshare. AZ_BATCHAI_MOUNT_ROOT is an environment variable that is set by Batch AI. Make sure that the storage account and fileshare information match what you created; otherwise the share will fail to mount and your nodes will become unusable.

Creating the pool will take a similar amount of time as Batch Shipyard, around 5 to 15 minutes. To check the status of the cluster, simply run the code shown in Listing 9-10.

Listing 9-10. Check on the Status of the Batch AI Cluster

```
BASH

az batchai cluster list -w workspace -o table
```

To submit a job we have to create a configuration file in a similar way we did for Batch Shipyard. For our purposes the configuration file looks like the code in Listing 9-11.

Listing 9-11. Example Configuration File for Batch AI

```
JSON
{
  "$schema": "https://raw.githubusercontent.com/Azure/BatchAI/
   master/schemas/2017-09-01-preview/job.json",
  "properties": {
    "containerSettings": {
      "imageSourceRegistry": {
        "image": "masalvar/keras_bait"
      }
    },
    "customToolkitSettings": {
      "commandLine": "python $AZ_BATCHAI_INPUT_SCRIPT/cifar10_
       cnn.py"
    },
    "inputDirectories": [
      {
        "id": "SCRIPT",
        "path": "$AZ_BATCHAI_MOUNT_ROOT/azurefileshare/cnn_example"
      }
    ],
    "nodeCount": 1,
    "stdOutErrPathPrefix": "$AZ_BATCHAI_MOUNT_ROOT/azurefileshare"
  }
}
```

For more examples, take a look at `http://bit.ly/baistart`. In the jobs configuration we define our `inputDirectories`, what container we want to use and the commands to execute. In the jobs definition you will notice that under `inputDirectories` we defined an input directory with the id script. This location gets mapped by Batch AI to the environment variable `AZ_BATCHAI_INPUT_SCRIPT`, which we refer to in the `commandLine` variable. Once we have created the job JSON file we execute the job by running the code in Listing 9-12.

Listing 9-12. Execute the Batch AI Job

```
BASH

az batchai job create -w workspace -e experiment --name my_job
--cluster-name my_cluster --config job.json
```

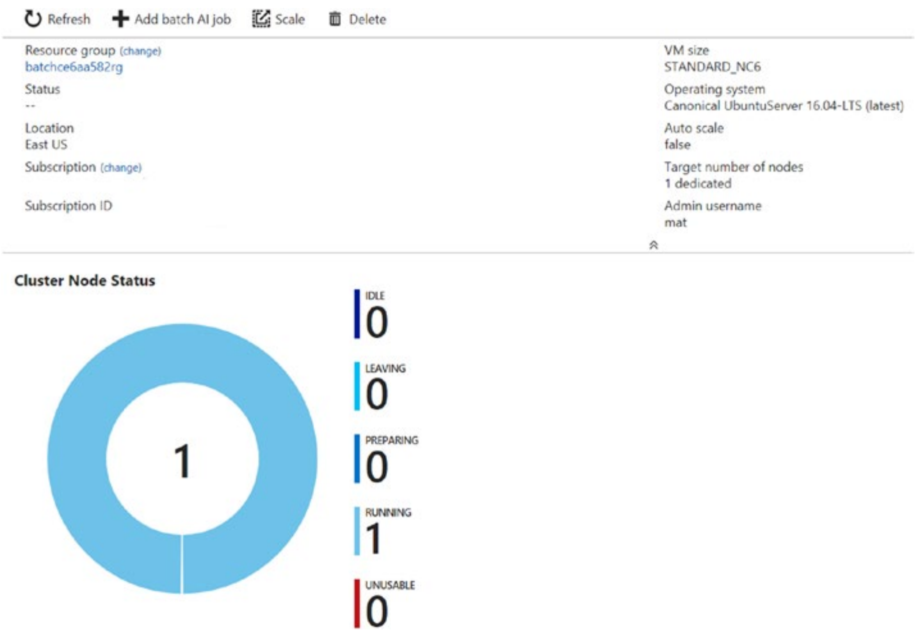
We can monitor the job by running the code in Listing 9-13.

Listing 9-13. Monitor the Batch AI Job

```
BASH

az batchai job list -w workspace -e experiment -o table
```

If you go to the Azure portal and click on the cluster you should see something similar to the image in Figure 9-5. The portal also provides other diagnostics such as the state of each job and the number of jobs in the resource group (see Figure 9-6 and Figure 9-7). This is very convenient for long running jobs when you simply want to check on the state of things from any browser. The information you get from the portal with Batch AI is richer than what you get with Batch Shipyard.

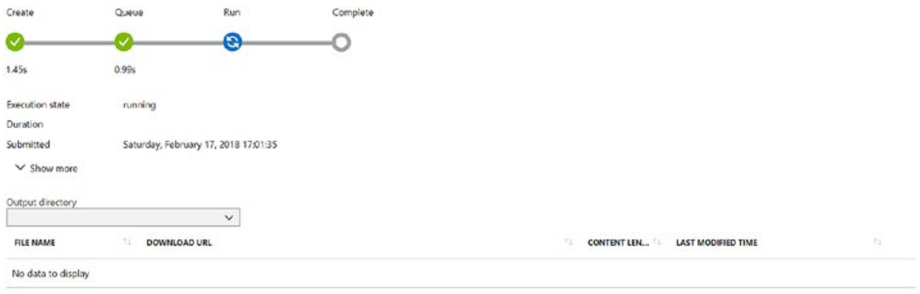


Resource group (change)
batchce6aa582rg
Status
--
Location
East US
Subscription (change)
Subscription ID

VM size
STANDARD_NC6
Operating system
Canonical UbuntuServer 16.04-LTS (latest)
Auto scale
false
Target number of nodes
1 dedicated
Admin username
mat

Cluster Node Status

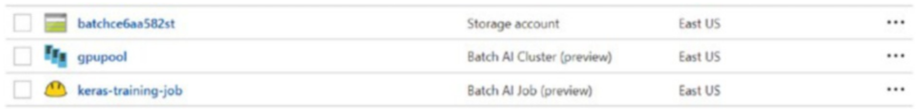
Figure 9-5. *Batch AI cluster dashboard in the Azure portal*



Execution state running
Duration
Submitted Saturday, February 17, 2018 17:01:35

FILE NAME	DOWNLOAD URL	CONTENT LEN...	LAST MODIFIED TIME
No data to display			

Figure 9-6. *Job dashboard for Batch AI*



batchce6aa582st	Storage account	East US	...
gpupool	Batch AI Cluster (preview)	East US	...
keras-training-job	Batch AI Job (preview)	East US	...

Figure 9-7. *Information displayed in the portal for our resource group. Note that our cluster is called `gpupool` and the job `keras-training-job`; these are the names used in the example in the accompanying notebook.*

To tail the output of `stdout` in the same way we did for Batch Shipyard, we simply run the code in Listing 9-14.

Listing 9-14. Stream Output to Help Review Errors and Debug Scripts with Batch AI

```
BASH

az batchai job file stream -w workspace -e experiment --j
my_job --output-directory-id stdouterr --f stdout.txt
```

Once the job is completed, to delete the job we run the code in Listing 9-15.

Listing 9-15. Delete Batch AI Job

```
BASH

az batchai job delete -w workspace -e experiment --name myjob
```

Now we delete the cluster with the code in Listing 9-16 so that we stop incurring any charges for computing.

Listing 9-16. Delete Batch AI Cluster

```
BASH

az batchai cluster delete -w workspace -e experiment --name
mycluster
```

Then finally if we don't want to keep the storage account and the other resources we created we can clear it all up by executing the code in Listing 9-17.

Listing 9-17. If No Longer Needed, Delete Storage Account and Other Resources

```
BASH

az group delete --name myResourceGroup
```

Hyperparameter Tuning and Distributed Training

Hyperparameter tuning in Batch AI is not yet as simple as it is in Batch Shipyard. There is no notion of task factories, so it requires that we create a number of jobs where we pass different parameters to our model. In our jobs example, therefore, the JSON file would be very similar between our jobs, the only difference being the command, and specifically the arguments we pass to the script. The process of hyperparameter tuning can be made easier by using the Batch AI Python SDK rather than the CLI. Have a look at `http://bit.ly/baitsdk` for further details on the Python SDK.

Distributed training is slightly easier in Batch AI than Batch Shipyard for frameworks supported by Batch AI because Batch AI takes care of configuring the necessary internode communication layer such as MPI. At the time of writing, the frameworks supported are Chainer, CNTK, TensorFlow, PyTorch, and Caffe2. For frameworks that are not supported, it is up to the user to supply the appropriate configuration and will be the same as Batch Shipyard. For examples on how to do this, see `http://bit.ly/bairecipes`.

Variation of Batch AI with Python SDK

In the earlier example, we illustrated using Batch AI with the Azure CLI, which is the easiest way to get started. Batch AI can also be used through a Python SDK. The demo example described in this section can be reproduced following the instructions given at `http://bit.ly/deepbait`. In this example, rather than showcasing an example of hyperparameter tuning or distributed training for which there are already examples, nine different deep learning frameworks are used to train a simple CNN on the CIFAR10 data set. In practice, being able to quickly utilize different frameworks can be very useful because state-of-the-art implementations of certain models might only be available in one or a small number of frameworks. Often, though, one would select a single framework and use that framework to do hyperparameter tuning or distributed training as described in this chapter. However, this example also serves the pedagogical purpose of showcasing the flexibility of the Batch AI service as well as different ways one might interact with the service.

In this example, the project was developed and tested on an Azure Ubuntu DLVM. Anaconda Project is used in this case to create the environment and install dependencies, download the data, and allow the user to interact with the project in a straightforward manner to reproduce the demo, such as asking through a command-line prompt for the Azure subscription identifier and name of the resource group in which the Batch AI cluster should be created. The project also comes with makefiles to help with local testing and debugging to allow one to more easily modify the project.

This example also differs from the earlier Batch AI example in the use of Jupyter Notebooks, which are sent directly to the Batch AI cluster rather than Python scripts, as illustrated in Figure 9-8. Using Jupyter Notebooks directly, the code can be processed and output stored directly within the notebooks. This is useful for data scientists already developing within Jupyter Notebooks who would like to showcase results through them (e.g., visualizations created during or after processing). In this case, nine different Jupyter notebooks are created (one for each of the deep learning frameworks), along with associated Docker containers within which the notebooks are run using Batch AI.

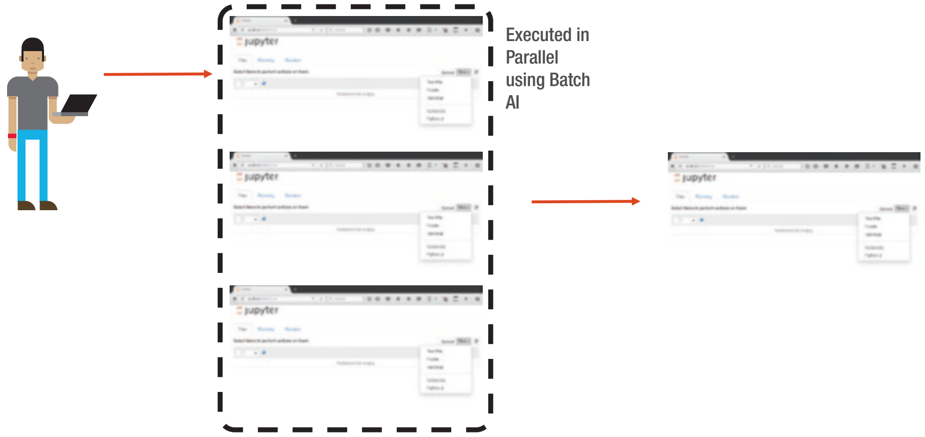


Figure 9-8. *Rather than having to run Jupyter Notebooks in sequence to test different options, they can be executed in parallel using Batch AI*

Each of the notebooks was written to have parameters that can be modified when they are run on the Batch AI cluster. In the example project for illustrative purposes, the number of epochs that are run are modified from the original file when they are run on Batch AI. Specifically, the original notebooks that are sent to the cluster have the following parameters in Listing 9-18 at the top of the notebook as examples.

Listing 9-18. Example Parameters at Top of Script That Are Modified When Run by Batch AI

```
PYTHON
# Parameters
EPOCHS = 10
N_CLASSES=10
BATCHSIZE = 64
LR = 0.01
MOMENTUM = 0.9
GPU = True
```

In the job submission, the Batch AI cluster is told in this case to modify the number of epochs to run (as just one example of a parameter change), and the notebook is modified and run with a different number of epochs. At the end of the run, the notebook contains a cell with all of the parameters it was run with, as well as the output from each cell running stored within the notebook itself. This makes it easy to look through the results: All of the important information is stored right within the notebook.

The steps followed to use nine different deep learning frameworks to run a simple CNN are as follows, illustrated in Figure 9-9.

1. Create Jupyter notebooks to run on Batch AI and transfer them to file storage.
2. Write the data to file storage.

3. Create the Docker containers for each deep learning framework and transfer them to a container registry.
4. Create a Batch AI Pool.
5. Each job will pull in the appropriate container and notebook, and load data from the fileshare.
6. Once the job is completed the executed notebook will be written to the fileshare.

These steps are very similar to those described before in using Batch AI with the CLI, only with Jupyter Notebooks. Besides the parallel processing ability that allows for a reduction in the experimentation time enabled through Batch AI, this scenario also illustrates the power of cloud computing in that many machines can be spun up on demand, used for the processing they are needed for, and then the cluster can be shut down. This provides the data scientist more flexibility at a large reduction in cost, with no special hardware to procure or systems to manage.

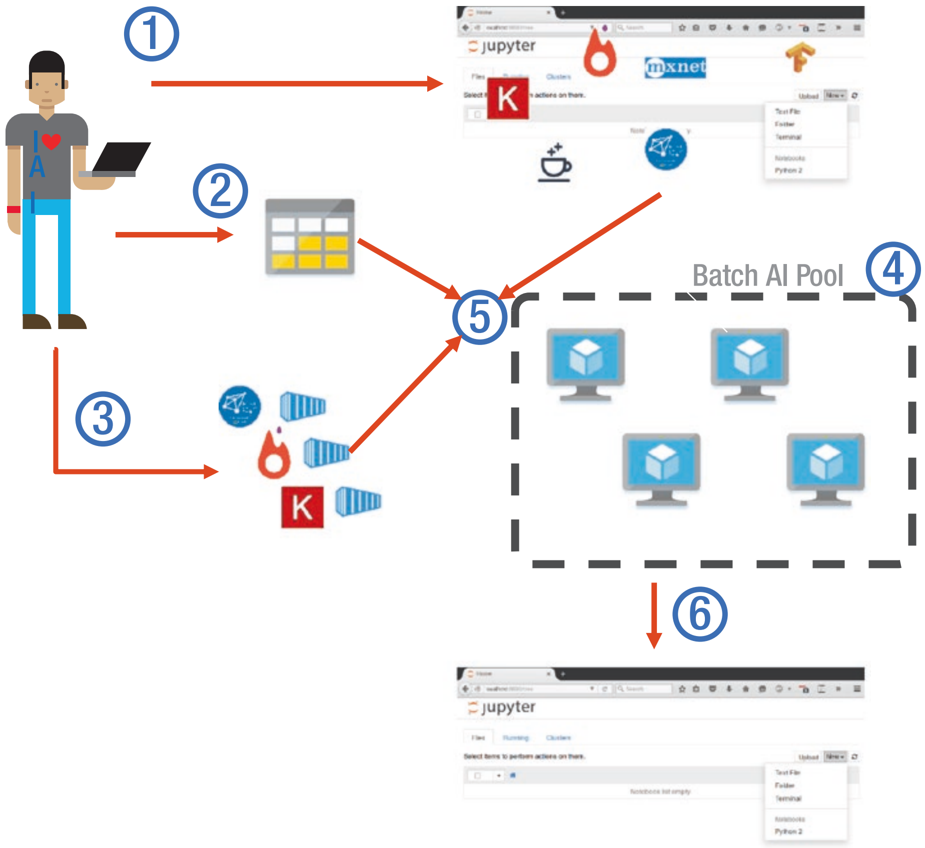
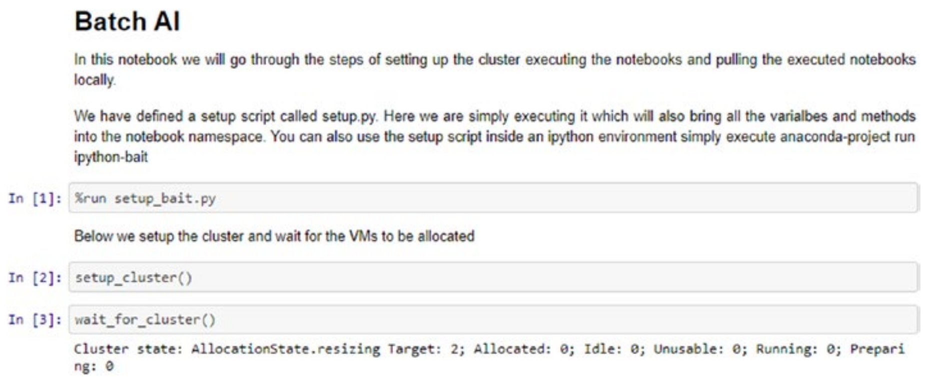


Figure 9-9. *Steps required to run a simple CNN using nine different deep learning frameworks for illustration purposes of the flexibility of Batch AI, with code processed and output stored within Jupyter Notebooks.*

A number of helper functions are included to make interaction with the Batch AI cluster easy, such as the `setup_cluster( )` function shown in Figure 9-10 and `print_jobs_summary( )` as shown in Figure 9-11.



Batch AI

In this notebook we will go through the steps of setting up the cluster executing the notebooks and pulling the executed notebooks locally.

We have defined a setup script called setup.py. Here we are simply executing it which will also bring all the varialbes and methods into the notebook namespace. You can also use the setup script inside an ipython environment simply execute anaconda-project run ipython-bait

```
In [1]: %run setup_bait.py
```

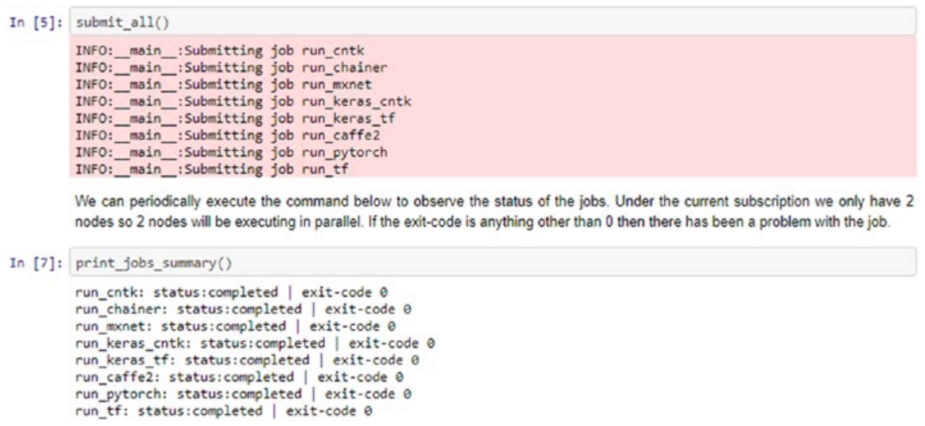
Below we setup the cluster and wait for the VMs to be allocated

```
In [2]: setup_cluster()

In [3]: wait_for_cluster()

        Cluster state: AllocationState.resizing Target: 2; Allocated: 0; Idle: 0; Unusable: 0; Running: 0; Prepari
        ng: 0
```

Figure 9-10. *After the Anaconda Project is set up on a DLVM, the example is run through a Jupyter notebook that contains helper functions to interact with the cluster*



```
In [5]: submit_all()

        INFO:__main__:Submitting job run_cntk
        INFO:__main__:Submitting job run_chainer
        INFO:__main__:Submitting job run_mxnet
        INFO:__main__:Submitting job run_keras_cntk
        INFO:__main__:Submitting job run_keras_tf
        INFO:__main__:Submitting job run_caffe2
        INFO:__main__:Submitting job run_pytorch
        INFO:__main__:Submitting job run_tf
```

We can periodically execute the command below to observe the status of the jobs. Under the current subscription we only have 2 nodes so 2 nodes will be executing in parallel. If the exit-code is anything other than 0 then there has been a problem with the job.

```
In [7]: print_jobs_summary()

        run_cntk: status:completed | exit-code 0
        run_chainer: status:completed | exit-code 0
        run_mxnet: status:completed | exit-code 0
        run_keras_cntk: status:completed | exit-code 0
        run_keras_tf: status:completed | exit-code 0
        run_caffe2: status:completed | exit-code 0
        run_pytorch: status:completed | exit-code 0
        run_tf: status:completed | exit-code 0
```

Figure 9-11. *The `ExploringBatchAI.ipynb` file is used to submit the jobs to Batch AI*

Azure Machine Learning Services

This chapter focused mainly on the computing environments and setup of running AI jobs, which can be done with DLVM, Batch Shipyard, Batch AI, and DLWorkspace as four main examples. Azure Machine Learning services, which were introduced in more depth in Chapter 4, are a set of services that enable building, deploying, and managing AI models in an end-to-end fashion. Azure Machine Learning manages the data science life cycle, such as providing capabilities for model versioning and run history (see `http://bit.ly/amllogging`), tracking models in production, and helping AI developers develop faster. Azure Machine Learning services also aim to ease the deployment process, for example running Docker containers with AI models within a Kubernetes cluster with Azure Kubernetes Services to enable scalable real-time predictions or to run on an edge device using Azure IoT (see Figure 9-12).

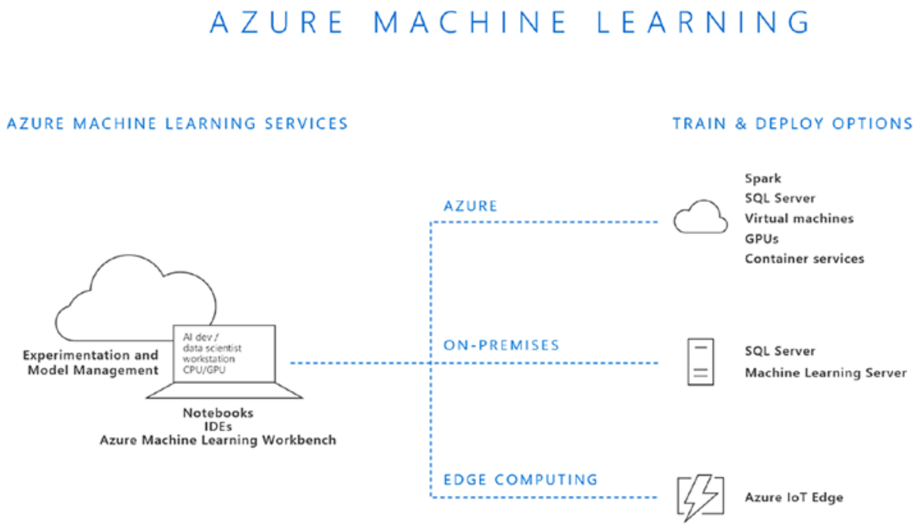


Figure 9-12. *Azure Machine Learning is an open source compatible, end-to-end data science platform. Source:* `http://bit.ly/AMLservices`.

Some of the services mentioned in this chapter, such as the DLVM and Batch AI, can be set up as the computing context within an Azure Machine Learning project. As of this writing, Azure Machine Learning services works with Python and is available in several Azure regions. In addition, there are AI extensions for Visual Studio and Visual Studio Code that allow interacting with the Azure Machine Learning platform (see `http://bit.ly/aivisstdio`). As the service is updating frequently, we focused on the core computing environments in this chapter and suggest reading the current documentation on Azure Machine Learning services available at `http://bit.ly/AMLservices`.

Other Options for AI Training on Azure

There are numerous other options for AI training on Azure that we do not describe in depth, but some of which we mention briefly here. The first example builds on Apache Spark, which is a popular general-purpose engine for big data processing. There are several offerings of Apache Spark on Azure such as Azure Databricks and Azure HDInsight. One popular option for training AI models with Spark is through the use of the MMLSpark library by Microsoft, which provides a number of deep learning and data science tools, available as open source on Github at `http://bit.ly/mmlSpark`. MMLSpark integrates Spark ML pipelines with the deep learning framework CNTK as well as OpenCV. This is especially useful if the data for an AI solution already reside in SPARK. MMLSpark can be used to train deep learning models on GPU nodes and can thus be used on a DLVM attached to the HDInsight Spark cluster as described at `http://bit.ly/MMLSparkGPU`.

Another alternative to attaching a GPU VM to a Spark cluster is utilizing transfer learning to apply a pretrained model using MMLSpark in a parallel fashion on a Spark cluster and then train a classifier using one of the many ML packages in Spark. This was used for snow leopard conservation to predict images containing snow leopards and assist conservation efforts as described in a blog post by Hamilton, Sengupta, and Astala (2017).

AI training can also be scaled out through the use of a cluster of Docker containers such as through the use of Kubernetes. Although we have seen the use of Kubernetes clusters mainly for the deployment and hosting of AI models to date, it is also possible to use them for large-scale training. Zhang and Buchwalter (2017) described how they used Azure Container Services Engine (ACS-engine) that generates Azure Resource Manager templates that are needed to deploy the cluster with everything configured. In their case working alongside the startup Litbit, a Kubernetes cluster was used to scale different types of VM pools (CPU, GPUs) up and down based on the demand of the given workload. Tok (2017) gave an overview of using CNTK with Kubernetes through ACS-engine along with a detailed walkthrough of how to set up the cluster, for both training and deploying deep learning models at scale.

Summary

This chapter presented various options you can use to train your AI model. If you simply want to experiment, then the DLVM is probably the best choice because it is the quickest and easiest to set up. If you are looking to run hyperparameter tuning, distributed training, or model training as part of an automated pipeline, then Batch AI or Batch Shipyard will be the best tools for the job. DLWorkspace is also a good choice for large-scale experimentation, but today we would mostly recommend it only if the other two options are not suitable. The cluster-based method of training might seem daunting at first, but it quickly confers benefits. Batch AI is the easiest to use and set up and Batch Shipyard is the most feature rich. We have only scratched the surface of what is possible with these powerful tools. For detailed documentation, check out `http://bit.ly/azbai`, `http://bit.ly/azshipyard`, and `http://bit.ly/azdlwork`. In the next chapter, we give an overview of different options for deploying trained deep learning models so they can be used within AI applications.

CHAPTER 10

Operationalizing AI Models

The previous chapter covered what constitutes an AI model, the different types of models we can create, and how to train and build these models. An AI model does not become useful until it is deployed somewhere and consumed by the end user. This chapter describes the various options available on Azure to deploy your models. We provide general guidelines on what to use and when, but this is by no means an exhaustive guide to the Azure platform. In the following sections we discuss the metrics over which we compare the various deployment platforms. Then we discuss the platforms we have found to be suitable for deploying ML models and highlight their pros and cons. We also present simple use cases and architectures for each of them so that you get an idea of how they would fit into a larger solution. We also provide a step-by-step tutorial for deployment of a CNN to Azure Kubernetes Services (AKS) with GPU nodes as a hands-on guide for one recommended option for building a real-time request–response AI system.

Operationalization Platforms

A common dichotomy when looking at operationalization of a model is whether the scoring requests will be batch or real time. An example of a batch workload is when we have large number of records given to us infrequently such as every 24 hours, that need to be scored. These records could be images or other types of data. A real-time workload is when the service must always be up and receives a small number of records to score relatively frequently. An example might be a phone app that sends a picture to determine what type of animal is in the picture. The examples provided fit quite nicely into their respective classifications, but in reality things are often a lot less discrete. For example, we might have a real-time workload that requires massive amounts of computing or other constraints on our solution that break key architecture assumptions. That is why it is often better to think about these solutions belonging to a continuum where each solution can be partially stretched beyond what it is ideally suited for.

A key consideration when deploying models is dependency and environment management. This is not a problem unique to AI models: It is common for all types of deployed applications, but it becomes especially acute for AI applications due to their often complicated dependencies and hardware requirements. For this reason, services that use Docker containers are often preferred because this makes it easy to keep the same environment for development and test as well as ensure that all dependencies are satisfied. If you are new to Docker, we recommend the basic overview at `http://bit.ly/DockerDS`.

As we mentioned earlier, AI models also have hardware requirements; these are often less demanding than the training environments but depending on the scenario might still require a reasonable amount of computing resources. That is why another consideration for the deployment options is the hardware available on the platform and specifically the availability of GPUs. Without the GPUs the throughput could be quite limited, meaning that the service will either have to deal with slow responses or have to scale out the compute.

DLVM

The simplest way to operationalize something is to use the same platform that we recommend for experimentation: a VM, and specifically a data science or DLVM. You will already have the dependencies installed and you know that your code will run on the platform. On top of that by using a VM you have the greatest amount of flexibility as far as the hardware configuration is concerned even access to GPUs. This kind of operationalization is only recommended for proof of concepts and pilot workloads because there is no management infrastructure and no way to scale out or distribute the load. With VMs it is also possible to use Docker containers, which would be the recommended way to deploy things as this will make it easier to move to different VMs, but also move to other more suitable platforms that use Docker containers.

Azure Container Instances

Another simple platform to use for operationalization is Azure Container Instances (ACI). ACI is the simplest and fastest way to run a container on Azure; you do not have to know anything about orchestrators such as Kubernetes or provision and manage VMs. It is well suited for hosting simple apps and task automation. It just takes one command to deploy your prebuilt container (see Listing 10-1). For further details on deploying using ACI, go to `http://bit.ly/ACIstart`.

Listing 10-1. Deploy Container on ACI

```
BASH

az container create --resource-group myResourceGroup --name
mycontainer --image microsoft/aci-helloworld --dns-name-label
aci-demo --ports 80
```

Although you can specify the CPU and memory requirements of your application, at the time of writing GPUs were not available for ACI; thus, for workloads requiring GPU, ACI is not an option. The suggested use for ACI would be for short-lived applications that are either triggered or stood up for short periods of time. A typical model deployment scenario using ACI would be to deploy a simple Flask application as a short-lived demo, such as a simple image classification model where there are not any latency or bandwidth requirements. In Figure 10-1 we can see an example scenario. In this scenario the user develops a model and Flask application on a DSVM, and then packages it up into a container that the user can also test on the DSVM before upload to an Azure Container Registry. They then call for the model to be pulled out of our container registry and finally have it deployed on an ACI. With the deployed model they can simply call the endpoint with an image and the classification will be returned back to them.

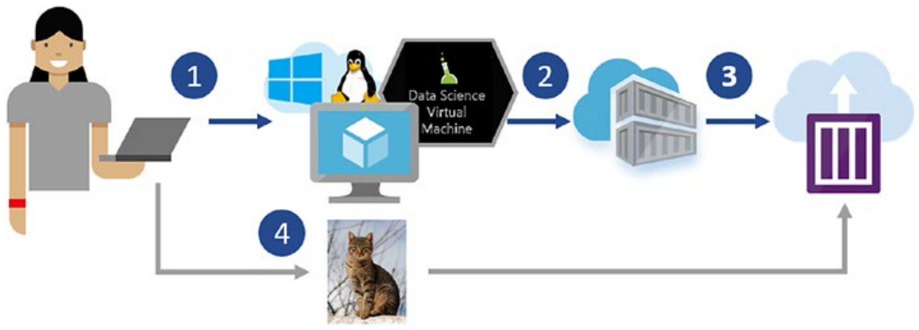


Figure 10-1. *ACI scenario. (1) Develop on DSVM; (2) Push container to container registry; (3) Deploy to ACI; and (4) Send images to deployed model to be scored.*

Azure Web Apps

Azure Web Apps is another quick and easy way of deploying models. They can either be standard Web Apps that are Windows based or Linux Web Apps. Both support a number of programming languages and Linux Web Apps support Docker containers. The use case for Azure Web Apps is the same as ACI. They can be a little harder to set up and configure, but they are also cheaper for longer running deployments. The web apps also offer nice features such as deploying from a git repository as well as a CLI to install packages. For further information on web apps, see `http://bit.ly/AzureWebApps`.

Azure Kubernetes Services

AKS is a managed Kubernetes cluster configuration. It is like a standard Kubernetes cluster except that the management of the master nodes is handled by Azure. This translates to reduced overhead and cost because you only have to pay for the compute of the agent nodes. It uses Kubernetes, which is a popular open source Docker orchestrator, so it is easy to navigate for those familiar with Kubernetes and because it is an open source project there is lots of information from which to draw.

AKS recently enabled deployment to GPU VMs, opening the possibility to run GPU AI models on it. In fact, AKS is our recommended way to deploy real-time workloads. A typical scenario for AKS would be where we need to set up a real-time service that needs to scale with demand and also be fault tolerant. Because we can use any size (SKU) of VM including GPUs this is the ideal solution for demanding applications. The setup and management is considerably more involved than what was shown for the ACI. An example of how to deploy things on an orchestrated container cluster can be found at `http://bit.ly/ACSTutorial`. This uses the older Azure Container Services service, so some of the commands will differ.

The scenario is very similar to the one explained for ACI deployment except that we also have a load balancer so that when a request is made the load can be distributed appropriately between the deployed pods (see Figure 10-2). The creation of the container is omitted from the diagram but would be identical to what is shown in Figure 10-1. Using AKS we can also set up autoscaling rules so that the number of pods and nodes in our cluster can change based on demand.

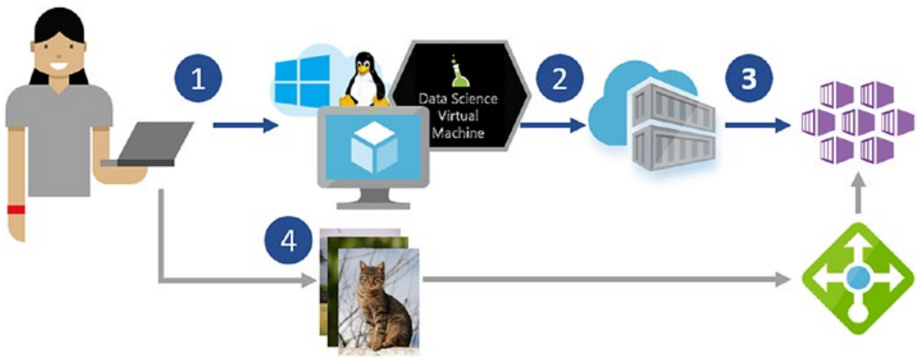


Figure 10-2. *AKS scenario: (1) Develop on DSVM, (2) Push container to container registry, (3) Deploy to AKS, and (4) Send images to service, which get balanced across the pods using load balancer.*

To deploy an AI model on AKS you need the following:

1. Your model and an API to call it.
2. The Flask web application that will handle the requests.
3. A Docker container that contains the model, Flask application, and necessary dependencies.

Once you have these you can create the cluster with the command shown in Listing 10-2. The command will create a cluster called `myGPUCluster` with one node that is an NC6 VM. An NC6 VM has a single K80 GPU that will speed up the inference of our deep learning model considerably compared to CPU. As an example, a single NC6 can handle a throughput of 20 images per second using a ResNet-152 model implemented in TensorFlow. In contrast, a single DS15 with 20 CPU cores can handle a throughput of around 7 images per second. The GPU-based configuration therefore provides nearly three times the throughput at around half the price.

Listing 10-2. Command to Create AKS Cluster

```
BASH

az aks create --resource-group myResourceGroup --name
myGPUCluster --node-count 1 --generate-ssh-keys -s Standard_NC6
```

Once we have the cluster up and running we need to create a manifest file that specifies what we want to deploy and how. The manifest file we are using for this example can be found at `http://bit.ly/AIManifest`. In the manifest file we specify that we want to create a service based on our container, that it requires a GPU, and that we want a load balancer on port 80. We deploy our pod with the command shown in Listing 10-3.

Listing 10-3. Command to Deploy Service Based on Manifest

```
BASH

kubectl create -f ai_manifest.json
```

After around five minutes, our pod should be ready and we can get the IP of our service with the command shown in Listing 10-4 with the output shown in Listing 10-5.

Listing 10-4. Command to Get Service IP

```
BASH

kubectl get service azure-dl
```

Listing 10-5. Results of Command Shown in Listing 10-4

```
BASH-OUTPUT

AME       TYPE          CLUSTER-IP   EXTERNAL-IP  PORT(S)      AGE
azure-dl  LoadBalancer  10.0.155.14  13.82.238.75 80:30532/TCP 11m
```

The IP of our service is under `EXTERNAL-IP`. We can then send our requests to that service and get the response back. We have created a step-by-step tutorial on how to deploy a CNN based on ResNet-152 written in TensorFlow or Keras with a TensorFlow back end and you can find it at `http://bit.ly/AKSAITutorial`.

Azure Service Fabric

Azure Service Fabric (ASF) is a cluster management and orchestration service similar to Kubernetes. ASF has been used internally by Microsoft for many services, including Azure SQL Database, Azure Cosmos DB, and many core Azure services. The draw of ASF is that it is simpler to use than Kubernetes because one can deploy an application simply knowing Docker and does not need to understand a completely new orchestration service. Theoretically it should be possible to run ASF on GPUs, but there are currently no concrete examples of doing so. The use case for service fabric would be identical to the one for AKS with the only caveat that GPU-dependent workloads have been proven on AKS but not ASF (see Figure 10-3).

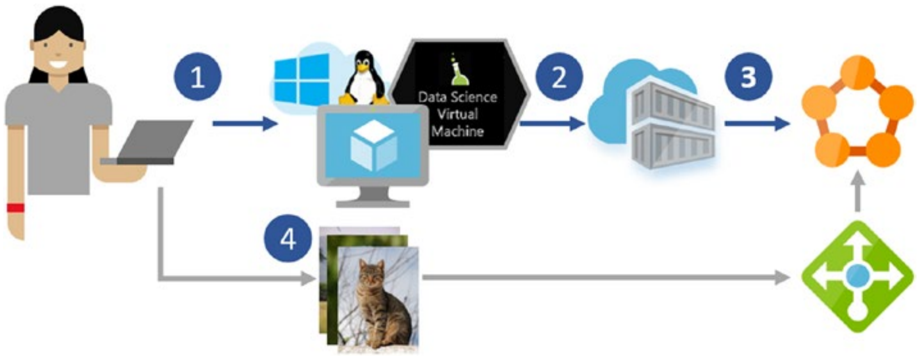


Figure 10-3. *Service Fabric scenario: (1) Develop on DSVM, (2) Push container to container registry, (3) Deploy container to Service Fabric, and (4) Send images to the service to be scored.*

Batch AI

In Chapter 9, we discussed Batch AI, and all the benefits we mentioned previously in terms of flexibility of compute and scalability transfer to operationalization as well. Batch AI is most suited to massively parallel batch scenarios where the cluster can be quickly spun up, the job executed in parallel, and then spun down. Because Batch AI itself does not cost anything, you only need to pay for the compute you use, making it an extremely efficient solution. A scenario for using Batch AI is shown in Figure 10-4. We assume you have already trained the model and have wrapped it in an appropriate API and Docker container and pushed it all to an ACR. The user uploads one or more videos to be processed by our deep learning model. An Azure function receives the notification that data have been uploaded to a blob and spins up the Batch AI cluster. Meanwhile, another Azure function reads the videos and queues them up in an Azure Service Bus. As the cluster comes online it pulls in the appropriate container and spins it up. The application in the container subscribes to the appropriate topic and sees what jobs are available. Each VM now will independently pull a message from the service bus and based on the message will pull the appropriate video from blob storage, process it, and push it back. Once all the jobs are done, the Azure function will destroy the cluster.

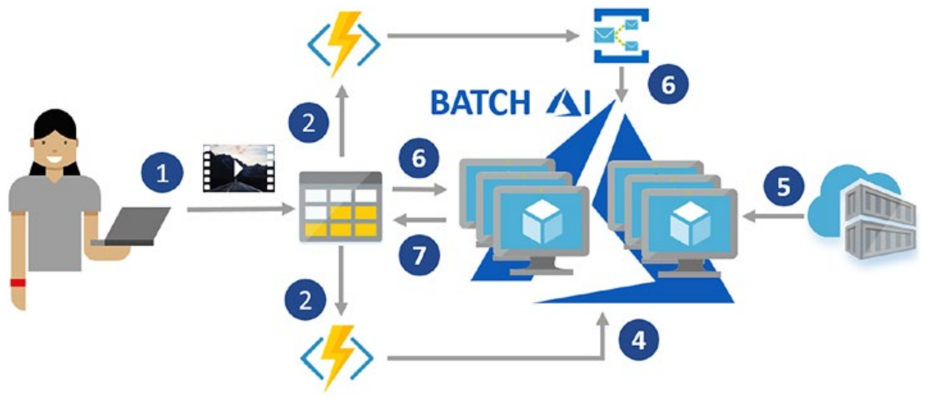


Figure 10-4. *Batch AI scenario: (1) Push videos to storage. (2) The storage triggers Azure function to create a cluster. (3) Azure function starts queuing up the videos found in storage to a service bus. (4) Batch AI cluster spins up. (5) Cluster pulls appropriate image from container registry. (6) The job running on each VM pulls a single message from the service bus and based on the image pulls the appropriate video from storage. (7) Once the video is processed, the results are written back to storage.*

Batch Shipyard is very similar to Batch AI and might offer features that have not made it into Batch AI yet. Batch Shipyard can more or less be brought in as a drop-in replacement for Batch AI in the preceding scenario.

AZTK

Spark is the most popular framework for massively data parallel and High Performance Computing (HPC) workloads. The Azure Distributed Data Engineering Toolkit (AZTK) is a Python CLI application for provisioning on-demand Spark clusters in Azure. It is a convenient and cheap way to get up and running with a Spark cluster. AZTK is able to provision a cluster in 5 to 10 minutes and it is able to make use of dedicated and low-priority VMs, making it very cost-efficient.

AZTK is suited to scenarios where lots of the components are dependent on Spark and the requirement is for ephemeral clusters. AZTK uses Docker containers, meaning it can be quite easy to manage dependencies and ensure that your production environment matches your deployment environment. AZTK can also use GPUs, making it great for solutions that require the data parallelization that Spark offers in combination of the computation power of GPUs. The AZTK version of the scenario shown in Figure 10-4 can be seen in Figure 10-5. In the AZTK scenario we have no need for the Azure Subscription service because we can distribute things using Spark's built-in parallelization. For AZTK we are also using an ACI rather than calling it from the Azure Function because AZTK is written in Python and Python support on Azure Functions was experimental at the time of writing.

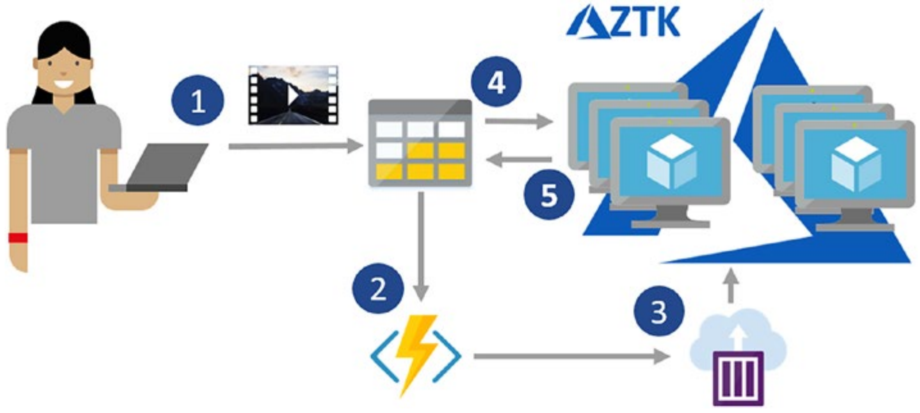


Figure 10-5. *AZTK scenario: (1) Push videos to storage. (2) The storage triggers Azure Function. (3) Azure Function calls ACI that have AZTK installed and spins up an AZTK cluster. (4) The PySpark job starts and begins pulling data from storage and processing it. (5) As the processing of each video is completed the results are written back to storage.*

HDInsight and Databricks

HDInsight (HDI) is a Spark offering from Microsoft. It tends to be a little more expensive than AZTK for on-demand processing and cannot use GPUs. Azure Databricks is another Spark-based platform on Azure, a generally available "first party" Microsoft service. It has a simple single-click start and integrates with Azure services such as Azure Active Directory. Databricks provides an interactive and collaborative notebook experience, as well as monitoring and security tools in the optimized Spark platform.

On-demand Spark clusters can be created using Azure Functions as in the AZTK and Batch AI scenarios, but because of its tighter integration with Azure, on-demand clusters for either Databricks or HDI can be created using Azure Data Factory (see `http://bit.ly/ADFCreateHDI` and `http://bit.ly/DBwithADF`). HDI and Databricks unfortunately do not use Docker containers so dependency management is a little trickier. Because of the tighter integration, the pipeline using HDI and Databricks will be a little simpler but less flexible due to the constraints of Azure Data Factory (see Figure 10-6).

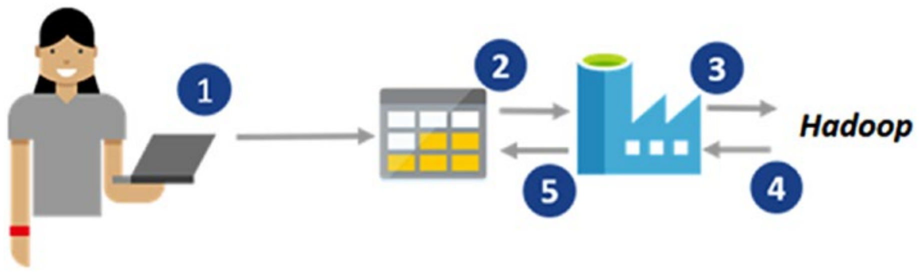


Figure 10-6. *Example Databricks or HDInsight scenario: (1) Push videos to storage. (2) ADF reads the data from storage. (3) It calls HDInsight or Databricks to process the data. (4-5) The data are then streamed back and stored.*

See example deep learning notebooks for Azure Databricks available at `http://bit.ly/DB_DL`.

SQL Server

To perform computig close to where the data are, SQL Server is a great option for deployment when data are already stored in SQL. The ideal scenario for such a deployment would be that SQL Server is already being used or the scenario would benefit from having the model execute as close to the data as possible. The data proximity requirement is usually the result of two things, data gravity and data sensitivity. *Data gravity* refers to the fact that large volumes of data cause a "gravitational pull" on the computation due to the costs of moving the data around. *Data sensitivity* refers to privacy and security concerns when having data cross different systems and the possibility of data being left behind or the security weakened due to the multiple data transfers. SQL Server is very flexible, as it can be installed on Windows and Linux and can be deployed on VMs with GPU to accelerate deep learning scenarios (see `http://bit.ly/SQLServerDeepL`). Both Python and R integration are available for SQL Server so data scientists can use whatever language they are most comfortable with. More examples on deploying models on SQL Server can be found at `http://bit.ly/SQLML`.

Operationalization Overview

We have presented a number of operationalization platforms and it can be hard to choose among them. As we mentioned earlier it is good to think about these services belonging on a continuum that ranges from strictly batch to real time, with services like Batch AI and AZTK belonging to the batch end of the spectrum and services like AKS and ASF belonging to the real-time end of the spectrum. In Figure 10-7 you can see a visual representation of this continuum: On the left are the more batch-like platforms and on the right the more real-time platforms. Figure 10-7 does not imply that the leftmost or rightmost options are the recommended approaches for batch and real-time processing, respectively, only that these platforms are most appropriate for that type of processing.

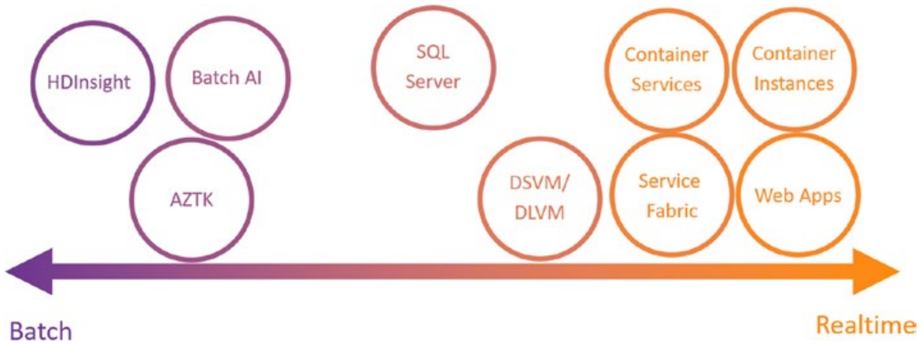


Figure 10-7. *Batch to real-time continuum*

Figure 10-7 is just a general guideline, as it is possible to use these options in many ways. For example, even though Spark on HDI or Azure Databricks are typically associated with batch workloads, there are options for creating real-time workloads, enabled, for example, through MMLSpark Serving as described at `http://bit.ly/MMLSparkStreaming`.

You will have also gleaned from the sections on each of the services that each have strengths and weaknesses. In Figure 10-8 you can see a visual representation of the attributes of each of the services. The services are listed on the left side of the heatmap and the metrics along the top. Each service receives a rating indicated by the color of the box that is based on the color bar on right side of the heatmap. We compare the service across five metrics: speed, scalability, data proximity, debug environment, and ease of deployment.

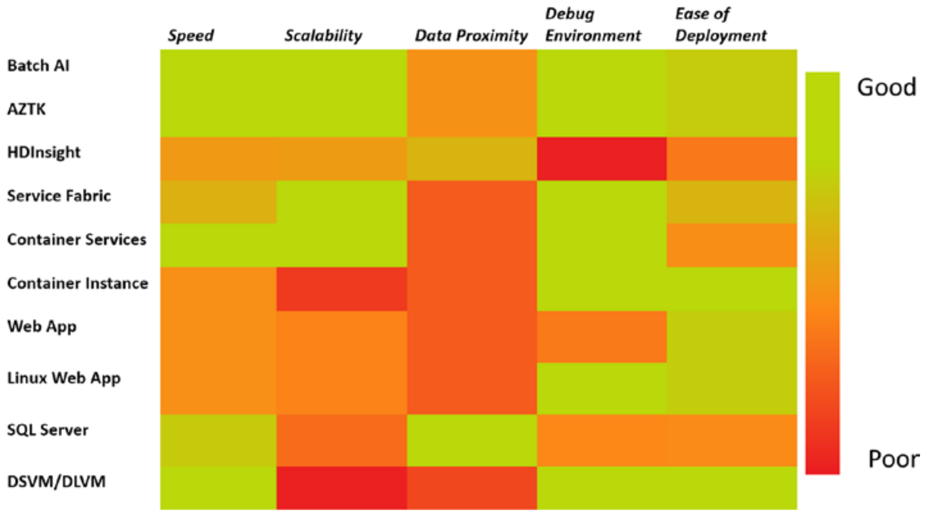


Figure 10-8. *Heatmap of deployment services*

Speed refers to the hardware available to each of the services; for AI models this mainly revolves around whether GPUs are available for it or not. Scalability refers to whether the service can be easily scaled up and out. Data proximity refers to how close the compute is to the data; this is mainly a consideration when we don't want to move the data due to either volume or security reasons. Debug environment refers to how easy it is to develop for the platform; the main consideration across this axis is whether the service uses Docker containers or not. Finally, ease of deployment refers to how easy it is to deploy the model and whether there is a steep learning curve to get things working.

Although there are many nuances and reasons to deviate from this recommendation, for real-time processing of deep learning models, we recommend AKS using GPU nodes. As mentioned earlier, we have created a step-by-step tutorial on how to deploy a CNN based on ResNet-152 written in TensorFlow or Keras with a TensorFlow back end, and you can find it at `http://bit.ly/AKSAITutorial`. For batch processing of deep learning models, at the time of this writing we recommend using Batch AI. An example using TensorFlow can be found at `http://bit.ly/BatchAIEx`.

We focused primarily here on operationalizing deep learning models on Azure. Deep learning models can also be trained on the cloud and then operationalized in different environments, such as IoT edge as discussed in the next section, as well as natively on Windows devices through ONNX as described at http://bit.ly/WindowsONNX.

Azure Machine Learning Services

The preceding example to deploy an AI model to AKS can be a little daunting, especially to those not familiar with Docker. To this end, AML offers options that make operationalization of AI models easier: You simply supply the model file, your dependencies in a YAML file, and finally the model driver file, and it will create the appropriate Docker container and deploy it to AKS (see http://bit.ly/amldeploy). It offers easy and convenient ways to test your deployment locally as well as scale the service as needed. See the blog post by Zhu, Iordanescu, and Karmanov (2018) as an example of using Azure Machine Learning to deploy a deep learning model for detecting diseases from chest x-ray images. Azure Machine Learning also assists in the deployment of deep learning models to IoT edge devices as described at http://bit.ly/DLtoIOT.

In previous chapters we mentioned the usefulness of transfer learning and in this chapter we also highlighted the benefits of using GPUs for inference. AML services now offers the ability to use a pretrained ResNet 50 model on FPGAs for inference. FPGAs offer a considerable speed increase over CPUs and GPUs at a very low cost. Benchmarking showed that a single FPGA could score around 500 images per second and cost less than 0.2 cents to score 10,000 images. To use this service simply follow the instructions given at http://bit.ly/msfpga. It has a number of Jupyter Notebooks that go through how to train your model based on the features, but also how to deploy and test the model.

Summary

This chapter covered a number of operationalization options offered on Azure. It went through the options of deploying models using simple managed services such as ACI and Azure Web Apps to more complicated setups with GPU support such as AKS and Batch AI. We also covered both request–response scenarios as well as batch scenarios. We gave a comparative overview of what we believe the strengths and weaknesses of each of the services offered are. With this guidance you should be able to choose the most appropriate option for your scenario and deploy your model to make your model available within a production AI solution.

APPENDIX

Notes

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