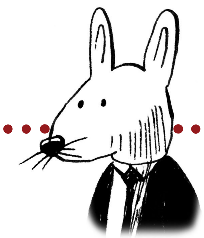
grokking Deep Learning

introducing deep learning: why you should learn it | 1



In this chapter

- Why you should learn deep learning
- Why you should read this book
- What you need to get started

> "Do not worry about your difficulties in Mathematics. I can assure you mine are still greater."
>
> —Albert Einstein

Welcome to *Grokking Deep Learning*

You're about to learn some of the most valuable skills of the century!

I'm very excited that you're here! You should be, too! Deep learning represents an exciting intersection of machine learning and artificial intelligence, and a very significant disruption to society and industry. The methods discussed in this book are changing the world all around you. From optimizing the engine of your car to deciding which content you view on social media, it's everywhere, it's powerful, and, fortunately, it's fun!

Why you should learn deep learning

It's a powerful tool for the incremental automation of intelligence.

From the beginning of time, humans have been building better and better tools to understand and control the environment around us. Deep learning is today's chapter in this story of innovation.

Perhaps what makes this chapter so compelling is that this field is more of a *mental* innovation than a *mechanical one*. Much like its sister fields in machine learning, deep learning seeks to *automate intelligence* bit by bit. In the past few years, it has achieved enormous success and progress in this endeavor, exceeding previous records in computer vision, speech recognition, machine translation, and many other tasks.

This is particularly extraordinary given that deep learning seems to use *largely the same brain-inspired algorithm* (neural networks) for achieving these accomplishments across a vast number of fields. Even though deep learning is still an actively developing field with many challenges, recent developments have lead to tremendous excitement: perhaps we've discovered not just a great tool, but a window into our own minds.

Deep learning has the potential for significant automation of skilled labor.

There's a substantial amount of hype around the potential impacts of deep learning if the current trend of progress is extrapolated at varying speeds. Although many of these predictions are overzealous, I believe one merits your consideration: job displacement. I think this claim stands out from the rest because even if deep learning's innovations stopped *today*, there would already be an incredible impact on skilled labor around the globe. Call-center operators, taxi drivers, and low-level business analysts are compelling examples where deep learning can provide a low-cost alternative.

Fortunately, the economy doesn't turn on a dime; but in many ways we're already past the point of concern, given the current power of the technology. It's my hope that you (and people you know) will be enabled by this book to transition from perhaps one of the industries facing disruption into an industry ripe with growth and prosperity: deep learning.

It's fun and creative. You'll discover much about what it is to be human by trying to simulate intelligence and creativity.

Personally, I got into deep learning because it's fascinating. It's an amazing intersection between human and machine. Unpacking exactly what it means to think, to reason, and to create is enlightening, engaging, and, for me, inspiring. Consider having a dataset filled with every painting ever painted, and then using that to teach a machine how to paint like Monet. Insanely, it's possible, and it's mind-bogglingly cool to see how it works.

Will this be difficult to learn?

How hard will you have to work before there's a "fun" payoff?

This is my favorite question. My definition of a "fun" payoff is the experience of witnessing something that I built *learning*. There's something amazing about seeing a creation of your hands do something like that. If you also feel this way, then the answer is simple. A few pages into chapter 3, you'll create your first neural network. The only work involved until then is reading the pages between here and there.

After chapter 3, you may be interested to know that the *next* fun payoff occurs after you've memorized a small snippet of code and proceeded to read to the midway of chapter 4. Each chapter will work this way: memorize a small code segment from the previous chapter, read the next chapter, and then experience the payoff of a new learning neural network.

Why you should read this book

It has a uniquely low barrier to entry.

The reason you should read this book is the same reason I'm writing it. I don't know of another resource (book, course, large blog series) that teaches deep learning *without assuming advanced knowledge of mathematics* (a college degree in a mathy field).

Don't get me wrong: there are really good reasons for teaching it using math. Math is, after all, a language. It's certainly more *efficient* to teach deep learning using this language, but I don't think it's absolutely necessary to assume advanced knowledge of math in order to become a skilled, knowledgeable practitioner who has a firm understanding of the "how" behind deep learning.

So, why should you learn deep learning using this book? Because I'm going to assume you have a high school–level background in math (and that it's rusty) and *explain everything else you need to know as we go along*. Remember multiplication? Remember x-y graphs (the squares with lines on them)? Awesome! You'll be fine.

It will help you understand what's *inside* a framework (Torch, TensorFlow, and so on).

There are two major groups of deep learning educational material (such as books and courses). One group is focused around how to use popular frameworks and code libraries like Torch, TensorFlow, Keras, and others. The other group is focused around teaching deep learning itself, otherwise known as the *science under the hood* of these major frameworks.

Ultimately, learning about *both* is important. It's like if you want to be a NASCAR driver: you need to learn both about the particular model of car you're driving (the framework) and about driving (the science/skill). But just learning about a framework is like learning about the pros and cons of a Generation 6 Chevrolet SS before you know what a stick shift is. This book is about teaching you what deep learning is so you can then be prepared to learn a framework.

All math-related material will be backed by intuitive analogies.

Whenever I encounter a math formula in the wild, I take a two-step approach. The first is to translate its methods into an intuitive *analogy* to the real world. I almost never take a formula at face value: I break it into *parts*, each with a story of its own. That will be the approach of this book, as well. Anytime we encounter a math concept, I'll offer an alternative analogy for what the formula is actually doing.

> "Everything should be made as simple as possible, but not simpler."
>
> —Attributed to Albert Einstein

Everything after the introduction chapters is "project" based.

If there's one thing I hate when learning something new, it's having to question whether what I'm learning is useful or relevant. If someone is teaching me everything there is to know about a hammer without actually taking my hand and helping me drive in a nail, then they're not really teaching me how to use a hammer. I know there will be dots that aren't connected, and if I'm thrown out into the real world with a hammer, a box of nails, and a bunch of two-by-fours, I'll have to do some guesswork.

This book is about giving you the wood, nails, and hammer *before* telling you what they do. Each lesson is about picking up the tools and building stuff with them, explaining how things work as we go. This way, you won't leave with a list of facts about the various deep learning tools you'll work with; you'll have the ability to use them to solve problems. Furthermore, you'll understand the most important part: when and why each tool is appropriate for each problem you want to solve. It is with this knowledge that you'll be empowered to pursue a career in research and/or industry.

What you need to get started

Install Jupyter Notebook and the NumPy Python library.

My absolute favorite place to work is in Jupyter Notebook. One of the most important parts of learning deep learning (for me) is the ability to stop a network while it's training and tear apart absolutely every piece to see what it looks like. This is something Jupyter Notebook is incredibly useful for.

As for NumPy, perhaps the most compelling case for why this book leaves nothing out is that we'll be using only a single matrix library. In this way, you'll understand *how* everything works, not just how to call a framework. This book teaches deep learning from absolute scratch, soup to nuts.

Installation instructions for these two tools can be found at http://jupyter.org for Jupyter and http://numpy.org for NumPy. I'll build the examples in Python 2.7, but I've tested them for Python 3 as well. For easy installation, I also recommend the Anaconda framework: https://docs.continuum.io/anaconda/install.

Pass high school mathematics.

Some mathematical assumptions are out of depth for this book, but my goal is to teach deep learning assuming that you understand only basic algebra.

Find a personal problem you're interested in.

This might seem like an optional "need" to get started. I guess it could be, but seriously, I highly, highly recommend finding one. Everyone I know who has become successful at this stuff had some sort of problem they were trying to solve. Learning deep learning was just a "dependency" to solving some other interesting task.

For me, it was using Twitter to predict the stock market. It's just something I thought was really fascinating. It's what drove me to sit down and read the next chapter and build the next prototype.

And as it turns out, this field is *so new*, and is changing *so fast*, that if you spend the next couple of years chasing one project with these tools, you'll find yourself becoming one of the leading experts in that *particular problem* faster than you might think. For me, chasing this idea took me from barely knowing anything about programming to a research grant at a hedge fund applying what I learned, in around 18 months! For deep learning, having a problem you're fascinated with that involves using one dataset to predict another is the key catalyst! Go find one!

You'll probably need some Python knowledge

Python is my teaching library of choice, but I'll provide a few others online.

Python is an amazingly intuitive language. I think it just might be the most widely adopted and intuitively readable language yet constructed. Furthermore, the Python community has a passion for simplicity that can't be beat. For these reasons, I want to stick with Python for all the examples (Python 2.7 is what I'm working in). In the book's downloadable source code, available at www.manning.com/books/grokking-deep-learning and also at https://github.com/iamtrask/Grokking-Deep-Learning, I provide all the examples in a variety of other languages online.

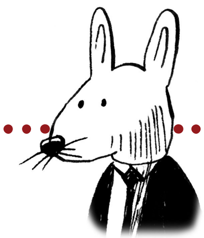
How much coding experience should you have?

Scan through the Python Codecademy course (www.codecademy.com/learn/python). If you can read the table of contents and feel comfortable with the terms mentioned, you're all set! If not, then take the course and come back when you're done. It's designed to be a beginner course, and it's very well crafted.

Summary

If you've got a Jupyter notebook in hand and feel comfortable with the basics of Python, you're ready for the next chapter! As a heads-up, chapter 2 is the last chapter that will be mostly dialogue based (without building something). It's designed to give you an awareness of the high-level vocabulary, concepts, and fields in artificial intelligence, machine learning, and, most important, deep learning.

fundamental concepts: how do machines learn? | 2



In this chapter

- What are deep learning, machine learning, and artificial intelligence?
- What are parametric models and nonparametric models?
- What are supervised learning and unsupervised learning?
- How can machines learn?

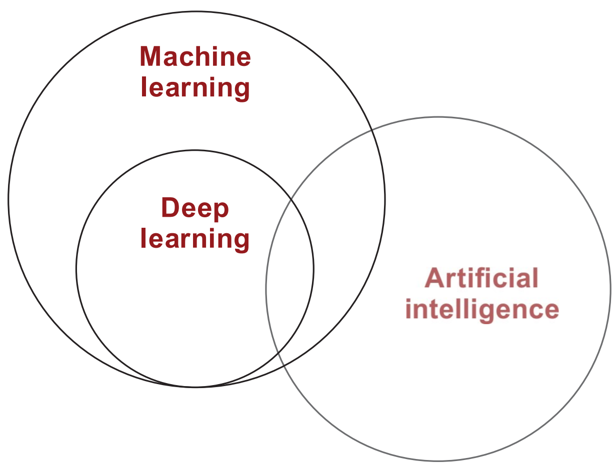
> Machine learning will cause every successful IPO win in five years.
>
> —Eric Schmidt, Google executive chairman, keynote speech, Cloud Computing Platform conference, 2016

What is deep learning?

Deep learning is a subset of methods for machine learning.

Deep learning is a subset of machine learning, which is a field dedicated to the study and development of machines that can learn (sometimes with the goal of eventually attaining general artificial intelligence).

In industry, deep learning is used to solve practical tasks in a variety of fields such as computer vision (image), natural language processing (text), and automatic speech recognition (audio). In short, deep learning is a subset of *methods* in the machine learning toolbox, primarily using *artificial neural networks*, which are a class of algorithm loosely inspired by the human brain.



Notice in this figure that not all of deep learning is focused around pursuing generalized artificial intelligence (sentient machines as in the movies). Many applications of this technology are used to solve a wide variety of problems in industry. This book seeks to focus on teaching the fundamentals of deep learning behind both cutting-edge research and industry, helping to prepare you for either.

What is machine learning?

> *A field of study that gives computers the ability to learn without being explicitly programmed.*
>
> —Attributed to Arthur Samuel

Given that deep learning is a subset of machine learning, what is machine learning? Most generally, it is what its name implies. Machine learning is a subfield of computer science wherein *machines learn* to perform tasks for which they were *not explicitly programmed.* In short, machines observe a pattern and attempt to imitate it in some way that can be either direct or indirect.

Machine learning ~= Monkey see, monkey do

I mention direct and indirect imitation as a parallel to the two main types of machine learning: *supervised* and *unsupervised.* Supervised machine learning is the direct imitation of a pattern between two datasets. It's always attempting to take an input dataset and transform it into an output dataset. This can be an incredibly powerful and useful capability. Consider the following examples (*input* datasets in bold and *output* datasets in italic):

- Using the **pixels** of an image to detect the *presence* or *absence of a cat*
- Using the **movies you've liked** to predict more *movies you may like*
- Using someone's **words** to predict whether they're *happy* or *sad*
- Using weather sensor **data** to predict the *probability of rain*
- Using car engine **sensors** to predict the optimal tuning *settings*
- Using news **data** to predict tomorrow's stock *price*
- Using an input **number** to predict a *number* double its size
- Using a raw **audio file** to predict a *transcript* of the audio

These are all supervised machine learning tasks. In all cases, the machine learning algorithm is attempting to imitate the pattern between the two datasets in such a way that it can *use one dataset to predict the other*. For any of these examples, imagine if you had the power to predict the *output* dataset given only the **input** dataset. Such an ability would be profound.

Supervised machine learning

Supervised learning transforms datasets.

Supervised learning is a method for transforming one dataset into another. For example, if you had a dataset called Monday Stock Prices that recorded the price of every stock on every Monday for the past 10 years, and a second dataset called Tuesday Stock Prices recorded over the same time period, a supervised learning algorithm might try to use one to predict the other.

If you successfully trained the supervised machine learning algorithm on 10 years of Mondays and Tuesdays, then you could predict the stock price on any Tuesday in the future given the stock price on the immediately preceding Monday. I encourage you to stop and consider this for a moment.

Supervised machine learning is the bread and butter of applied artificial intelligence (also known as narrow AI). It's useful for taking *what you know* as input and quickly transforming it into *what you want to know*. This allows supervised machine learning algorithms to extend human intelligence and capabilities in a seemingly endless number of ways.

The majority of work using machine learning results in the training of a supervised classifier of some kind. Even unsupervised machine learning (which you'll learn more about in a moment) is typically done to aid in the development of an accurate supervised machine learning algorithm.

For the rest of this book, you'll be creating algorithms that can take input data that is observable, recordable, and, by extension, *knowable* and transform it into valuable output data that requires logical analysis. This is the power of supervised machine learning.

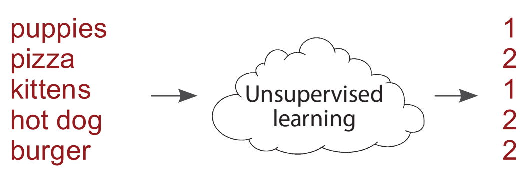
Unsupervised machine learning

Unsupervised learning groups your data.

Unsupervised learning shares a property in common with supervised learning: it transforms one dataset into another. But the dataset that it transforms into is *not previously known or understood*. Unlike supervised learning, there is no "right answer" that you're trying to get the model to duplicate. You just tell an unsupervised algorithm to "find patterns in this data and tell me about them."

For example, *clustering a dataset into groups* is a type of unsupervised learning. Clustering transforms a sequence of *datapoints* into a sequence of *cluster labels*. If it learns 10 clusters, it's common for these labels to be the numbers 1–10. Each datapoint will be assigned to a number based on which cluster it's in. Thus, the dataset turns from a bunch of datapoints into a bunch of labels. Why are the labels numbers? The algorithm doesn't tell you what the clusters are. How could it know? It just says, "Hey scientist! I found some structure. It looks like there are groups in your data. Here they are!"

I have good news! This idea of clustering is something you can reliably hold onto in your mind as the definition of unsupervised learning. Even though there are many forms of unsupervised learning, *all forms of unsupervised learning can be viewed as a form of clustering*. You'll discover more on this later in the book.

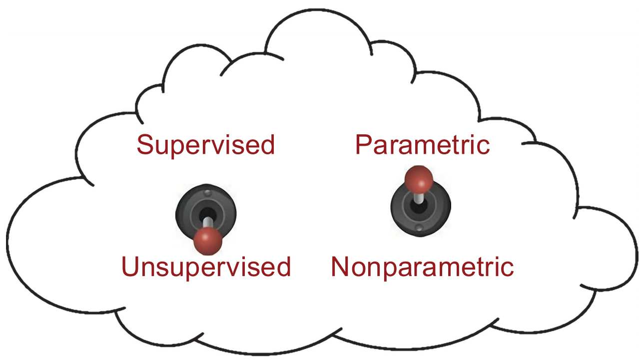


Check out this example. Even though the algorithm didn't tell what the clusters are named, can you figure out how it clustered the words? (Answer: 1 == cute and 2 == delicious.) Later, we'll unpack how other forms of unsupervised learning are also just a form of clustering and why these clusters are useful for supervised learning.

Parametric vs. nonparametric learning

Oversimplified: Trial-and-error learning vs. counting and probability

The last two pages divided all machine learning algorithms into two groups: supervised and unsupervised. Now, we're going to discuss another way to divide the same machine learning algorithms into two groups: parametric and nonparametric. So, if we think about our little machine learning cloud, it has two settings:



As you can see, there are really four different types of algorithms to choose from. An algorithm is either unsupervised or supervised, and either parametric or nonparametric. Whereas the previous section on supervision is about the *type of pattern* being learned, parametricism is about the way the learning is *stored* and often, by extension, the *method for learning*. First, let's look at the formal definitions of parametricism versus nonparametricism. For the record, there's still some debate around the exact difference.

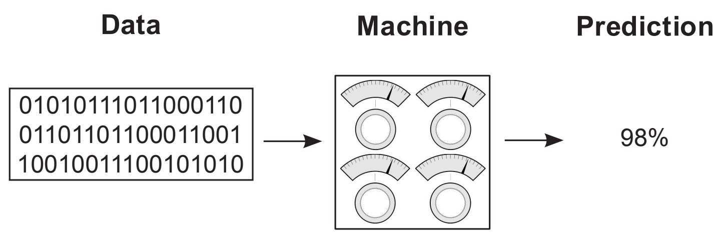
> A parametric model is characterized by having a fixed number of parameters, whereas a nonparametric model's number of parameters is *infinite* (determined by data).

As an example, let's say the problem is to fit a square peg into the correct (square) hole. Some humans (such as babies) just jam it into all the holes until it fits somewhere (parametric). A teenager, however, may count the number of sides (four) and then search for the hole with an equal number (nonparametric). Parametric models tend to use trial and error, whereas nonparametric models tend to count. Let's look closer.

Supervised parametric learning

Oversimplified: Trial-and-error learning using knobs

Supervised parametric learning machines are machines with a fixed number of knobs (that's the parametric part), wherein learning occurs by turning the knobs. Input data comes in, is processed based on the angle of the knobs, and is transformed into a *prediction*.



Learning is accomplished by turning the knobs to different angles. If you're trying to predict the probability that the Red Sox will win the World Series, then this model would first take data (such as sports stats like win/loss record or average number of toes per player) and make a prediction (such as 98% chance). Next, the model would observe whether or not the Red Sox actually won. After it knew whether they won, the learning algorithm would *update the knobs* to make a more accurate prediction the next time it sees the *same or similar input data*.

Perhaps it would "turn up" the "win/loss record" knob if the team's win/loss record was a good predictor. Inversely, it might "turn down" the "average number of toes" knob if that datapoint wasn't a good predictor. This is how parametric models learn!

Note that the entirety of what the model has learned can be captured in the positions of the knobs at any given time. You can also think of this type of learning model as a search algorithm. You're "searching" for the appropriate knob configuration by trying configurations, adjusting them, and retrying.

Note further that the notion of trial and error isn't the formal definition, but it's a common (with exceptions) property to parametric models. When there is an arbitrary (but fixed) number of knobs to turn, some level of searching is required to find the optimal configuration. This is in contrast to nonparametric learning, which is often count based and (more or less) adds new knobs when it finds something new to count. Let's break down supervised parametric learning into its three steps.