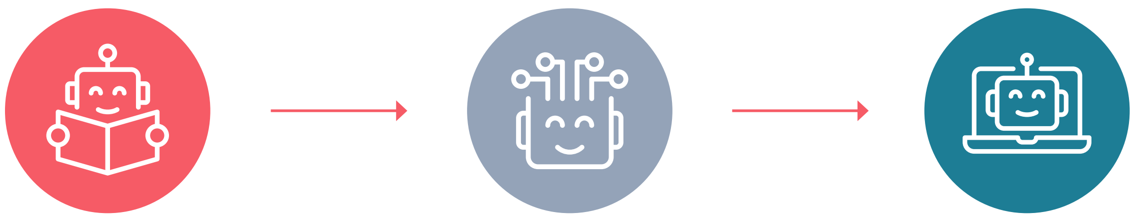
CHAPTER 1

Three Steps to Career Growth

The rapid rise of AI has led to a rapid rise in AI jobs, and many people are building exciting careers in this field. A career is a decades-long journey, and the path is not straightforward. Over many years, I've been privileged to see thousands of students, as well as engineers in companies large and small, navigate careers in AI.

Here's a framework for charting your own course.

Three key steps of career growth are **learning foundational skills, working on projects** (to deepen your skills, build a portfolio, and create impact), and **finding a job.** These steps stack on top of each other:



LEARNING

Initially, you focus on **learning foundational skills.** Chapters with the cover topics about learning foundational technical skills.

PROJECTS

After having gained foundational technical skills, you will begin **working on projects.** During this period, you'll also keep learning. Chapters with the focus on projects.

JOB

Later, you will work on **finding a job.** Throughout this process, you'll continue to learn and work on meaningful projects. Chapters with the focus on a job search.

These phases apply in a wide range of professions, but AI involves unique elements. For example:

LEARNING

Learning foundational skills is a career-long process:

AI is nascent, and many technologies are still evolving. While the foundations of machine learning and deep learning are maturing — and coursework is an efficient way to master them — beyond these foundations, keeping up-to-date with changing technology is more important in AI than fields that are more mature.

PROJECTS

Working on projects often means collaborating with stakeholders who lack expertise in AI:

This can make it challenging to find a suitable project, estimate the project's timeline and return on investment, and set expectations. In addition, the highly iterative nature of AI projects leads to special challenges in project management: How can you come up with a plan for building a system when you don't know in advance how long it will take to achieve the target accuracy? Even after the system has hit the target, further iteration may be necessary to address post-deployment drift.

JOB

Inconsistent opinions on AI skills and jobs roles:

While searching for a job in AI can be similar to searching for a job in other sectors, there are also important differences. Many companies are still trying to figure out which AI skills they need, and how to hire people who have them. Things you've worked on may be significantly different than anything your interviewer has seen, and you're more likely to have to educate potential employers about some elements of your work.

As you go through each step, you should also build a supportive community. Having friends and allies who can help you — and who you strive to help — makes the path easier. This is true whether you're taking your first steps or you've been on the journey for years.

CHAPTER 2

Learning Technical Skills for a Promising AI Career

LEARNING

In the previous chapter, I introduced three key steps for building a career in AI: learning foundational technical skills, working on projects, and finding a job, all of which is supported by being part of a community. In this chapter, I'd like to dive more deeply into the first step: learning foundational skills.

More research papers have been published on AI than anyone can read in a lifetime. So, when learning, it's critical to prioritize topic selection. I believe the most important topics for a technical career in machine learning are:

Foundational machine learning skills: For example, it's important to understand models such as linear regression, logistic regression, neural networks, decision trees, clustering, and anomaly detection. Beyond specific models, it's even more important to understand the core concepts behind how and why machine learning works, such as bias/variance, cost functions, regularization, optimization algorithms, and error analysis.

Deep learning: This has become such a large fraction of machine learning that it's hard to excel in the field without some understanding of it! It's valuable to know the basics of neural networks, practical skills for making them work (such as hyperparameter tuning), convolutional networks, sequence models, and transformers.

Math relevant to machine learning: Key areas include linear algebra (vectors, matrices, and various manipulations of them) as well as probability and statistics (including discrete and continuous probability, standard probability distributions, basic rules such as independence and Bayes' rule, and hypothesis testing). In addition, exploratory data analysis (EDA) — using visualizations and other methods to systematically explore a dataset — is an underrated skill. I've found EDA particularly useful in data-centric AI development, where analyzing errors and gaining insights can really help drive progress! Finally, a basic intuitive understanding of calculus will also help. The math needed to do machine learning well has been changing. For instance, although some tasks require calculus, improved automatic differentiation software makes it possible to invent and implement new neural network architectures without doing any calculus. This was almost impossible a decade ago.

Software development: While you can get a job and make huge contributions with only machine learning modeling skills, your job opportunities will increase if you can also write good software to implement complex AI systems. These skills include programming fundamentals, data structures (especially those that relate to machine learning, such as data frames), algorithms (including those related to databases and data manipulation), software design, familiarity with Python, and familiarity with key libraries such as TensorFlow or PyTorch, and scikit-learn.

This is a lot to learn!
Even after you master everything on this list, I hope you'll keep learning and continue to deepen your technical knowledge. I've known many machine learning engineers who benefitted from deeper skills in an application area such as natural language processing or computer vision, or in a technology area such as probabilistic graphical models or building scalable software systems.

How do you gain these skills? There's a lot of good content on the internet, and in theory, reading dozens of web pages could work. But when the goal is deep understanding, reading disjointed web pages is inefficient because they tend to repeat each other, use inconsistent terminology (which slows you down), vary in quality, and leave gaps. That's why a good course — in which a body of material has been organized into a coherent and logical form — is often the most time-efficient way to master a meaningful body of knowledge. When you've absorbed the knowledge available in courses, you can switch over to research papers and other resources.

Finally, no one can cram everything they need to know over a weekend or even a month. Everyone I know who's great at machine learning is a lifelong learner. Given how quickly our field is changing, there's little choice but to keep learning if you want to keep up.

How can you maintain a steady pace of learning for years? If you can cultivate the habit of learning a little bit every week, you can make significant progress with what feels like less effort.

The Best Way to Build a New Habit

One of my favorite books is BJ Fogg's, Tiny Habits: The Small Changes That Change Everything. Fogg explains that the best way to build a new habit is to start small and succeed, rather than start too big and fail. For example, rather than trying to exercise for 30 minutes a day, he recommends aspiring to do just one push-up, and doing it consistently.

This approach may be helpful to those of you who want to spend more time studying. If you start by holding yourself accountable for watching, say, 10 seconds of an educational video every day — and you do so consistently — the habit of studying daily will grow naturally. Even if you learn nothing in that 10 seconds, you're establishing the habit of studying a little every day. On some days, maybe you'll end up studying for an hour or longer.