Overview of Machine Learning Systems

MLOps is a set of tools and best practices for bringing ML into production.

“ML algorithms” is usually what people think of when they say machine learning, but it’s only a small part of the entire system.

A diagram of a computer

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Machine learning is an approach to   
(1) learn   
(2) complex patterns from   
(3) existing data and use these patterns to make   
(4) predictions on   
(5) unseen data

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1. Learn: the system has the capacity to learn

if you want to build an ML system to learn to predict the rental price for Airbnb listings, you need to provide a dataset where each input is a listing with relevant characteristics (square footage, number of rooms, neighborhood, amenities, rating of that listing, etc.) and the associated output is the rental price of that listing. Once learned, this ML system should be able to predict the price of a new listing given its characteristics

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1. Complex patterns: there are patterns to learn, and they are complex ML solutions are only useful when there are patterns to learn. Sane people don’t invest money into building an ML system to predict the next outcome of a fair die because there’s no pattern in how these outcomes are generated.4 However, there are patterns in how stocks are priced, and therefore companies have invested billions of dollars in building ML systems to learn those patterns

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there might be a pattern in how Elon Musk’s tweets affect cryptocurrency prices. How‐ ever, you wouldn’t know until you’ve rigorously trained and evaluated your ML models on his tweets. Even if all your models fail to make reasonable predictions of cryptocurrency prices, it doesn’t mean there’s no pattern.

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A diagram of software

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1. Existing data: data is available, or it’s possible to collect data Because ML learns from data, there must be data for it to learn from. It’s amusing to think about building a model to predict how much tax a person should pay a year, but it’s not possible unless you have access to tax and income data of a large population. In the zero-shot learning (sometimes known as zero-data learning) context, it’s possible for an ML system to make good predictions for a task without having been trained on data for that task. However, this ML system was previously trained on data for other tasks, often related to the task in consideration

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1. Predictions: it’s a predictive problem ML models make predictions, so they can only solve problems that require predictive answers. ML can be especially appealing when you can benefit from a large quantity of cheap but approximate predictions. In English, “predict” means “estimate a value in the future.” For example, what will the weather be like tomorrow? Who will win the Super Bowl this year? What movie will a user want to watch next?

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1. Unseen data: unseen data shares patterns with the training data The patterns your model learns from existing data are only useful if unseen data also share these patterns. A model to predict whether an app will get downloaded on Christmas 2020 won’t perform very well if it’s trained on data from 2008, when the most popular app on the App Store was Koi Pond. What’s Koi Pond? Exactly

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6. It’s repetitive

Humans are great at few-shot learning: you can show kids a few pictures of cats and most of them will recognize a cat the next time they see one. Despite exciting progress in few-shot learning research, most ML algorithms still require many examples to learn a pattern. When a task is repetitive, each pattern is repeated multiple times, which makes it easier for machines to learn it.

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1. The cost of wrong predictions is cheap Unless your ML model’s performance is 100% all the time, which is highly unlikely for any meaningful tasks, your model is going to make mistakes. ML is especially suitable when the cost of a wrong prediction is low. For example, one of the biggest use cases of ML today is in recommender systems because with recommender systems, a bad recommendation is usually forgiving—the user just won’t click on the recommendation.

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1. It’s at scale:

Having a problem at scale also means that there’s a lot of data for you to collect, which is useful for training ML models

1. The patterns are constantly changing:

Today an indication of a spam email is a Nigerian prince, but tomorrow it might be a distraught Vietnamese writer.

Machine Learning Use Cases

Recommendation system, assisting people in many of their daily activity.

Enterprise applications might have stricter accuracy requirements but be more forgiving with latency requirements.

improving a speech recognition system’s accuracy from 95% to 95.5% might not be noticeable to most consumers, but improving a resource allocation system’s efficiency by just 0.1% can help a corporation like Google or General Motors save millions of dollars.

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