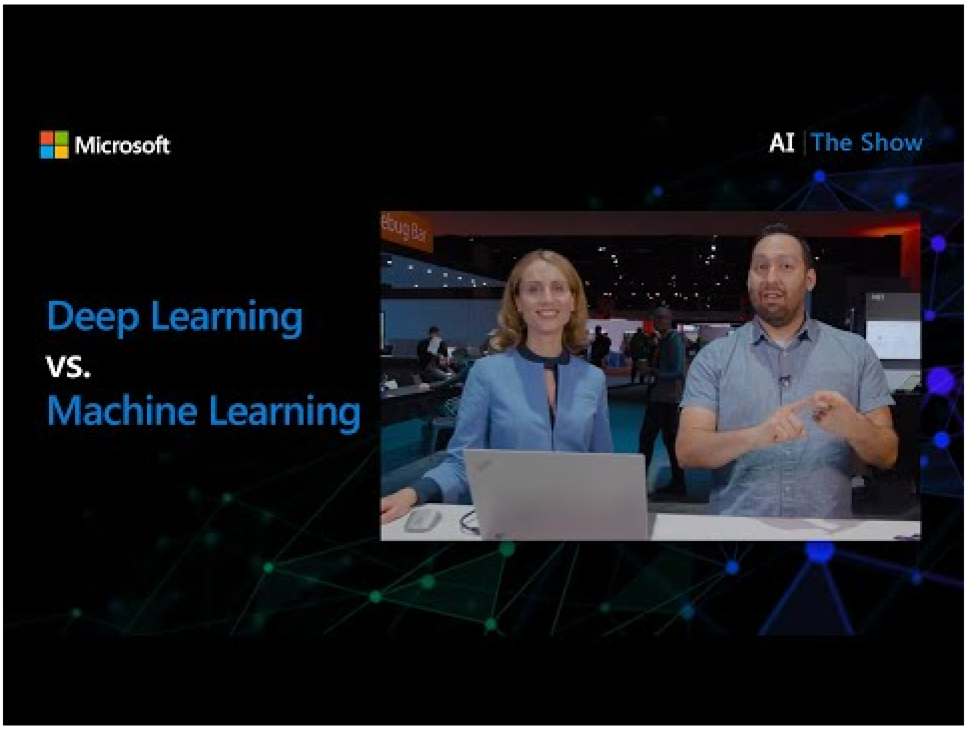
Introduction to Machine Learning



> 🎥 Click the image above for a video discussing the difference between Machine Learning, AI, and Deep Learning.

Pre-lecture quiz

Introduction

Welcome to this course on classical machine learning for beginners! Whether you're completely new to this topic, or an experienced ML practitioner looking to brush up on an area, we're happy to have you join us! We want to create a friendly launching spot for your ML learning and would be happy to evaluate, respond to, and incorporate your feedback.

> 🎥 Click the image above for a video: MIT's John Guttag introduces Machine Learning

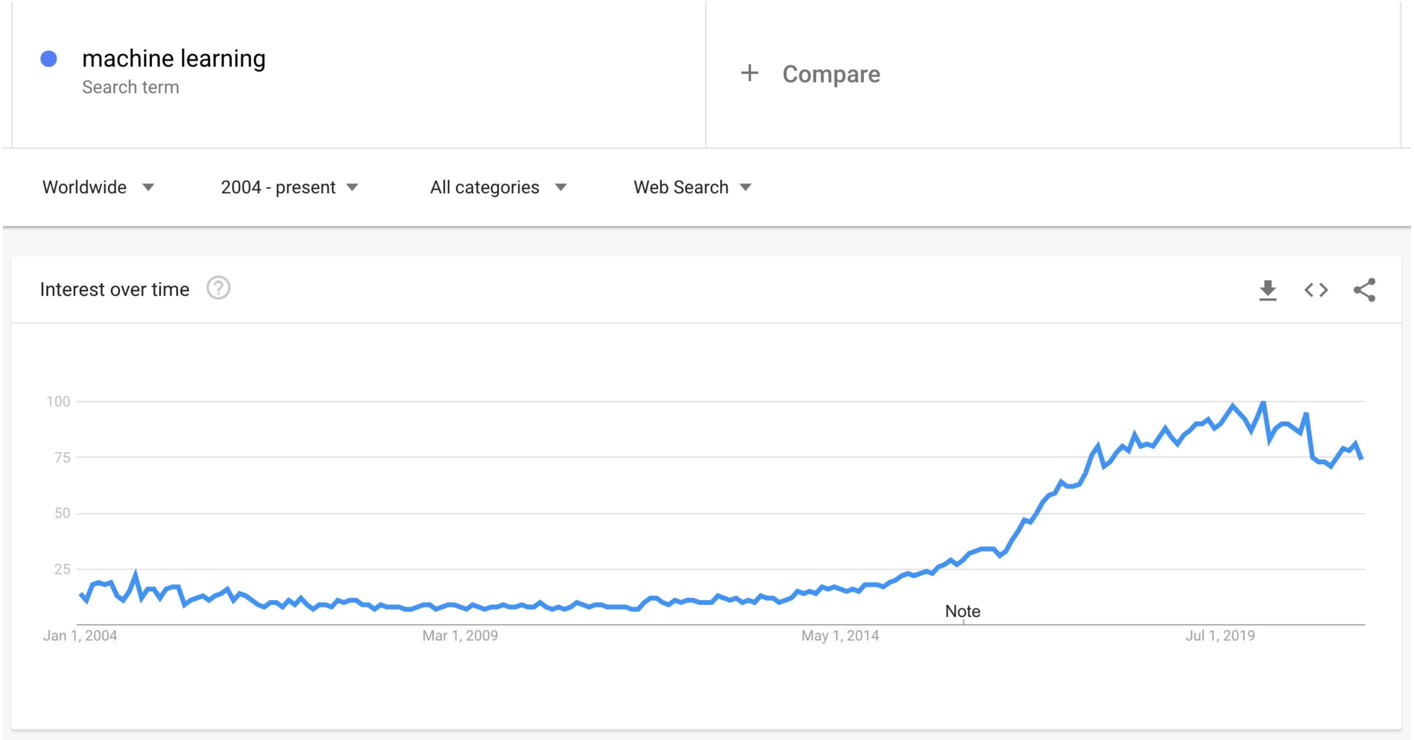
Getting started with Machine Learning

Before starting with this curriculum, you need to have your computer set up and ready to run notebooks locally.

- **Configure your machine with these videos**. Learn more about how to set up your machine in this set of videos.
- **Learn Python**. It's also recommended to have a basic understanding of Python, a programming language useful for data scientists that we use in this course.
- **Learn Node.js and JavaScript**. We also use JavaScript a few times in this course when building web apps, so you will need to have node and npm installed, as well as Visual Studio Code available for both Python and JavaScript development.
- **Create a GH account**. Since you found us here on GitHub, you might already have an account, but if not, create one and then fork this curriculum to use on your own. (Feel free to give us a star, too :))
- **Explore Scikit-Learn**. Familiarize yourself with Scikit-Learn, a set of ML libraries that we reference in these lessons.

What is Machine Learning?

The term 'Machine Learning' is one of the most popular and frequently used terms of today. There is a nontrivial possibility that you have heard this term at least once if you have some sort of familiarity with technology, no matter what domain you work in. The mechanics of Machine Learning, however, are a mystery to most people. For a Machine Learning beginner, the subject can sometimes feel overwhelming. Therefore, it is important to understand what Machine Learning actually is, and to learn about it step by step, through practical examples.



> Google Trends shows the recent 'hype curve' of the term 'machine learning'

We live in a universe full of unusual and interesting mysteries. Great scientists such as Stephen Hawking, Albert Einstein, and many more have devoted their lives in search of meaningful information that uncovers the mysteries of the world around us. This is the human condition of learning: a human child learns new things and uncovers the structure of their world year by year as they grow to adulthood.

A child's brain and senses perceive the facts of their surroundings and gradually learn the hidden patterns of life which help the child to craft logical rules to identify learned patterns. The learning process of the human brain makes humans the most sophisticated living creature of this world. Learning continuously by discovering hidden patterns and then innovating on those patterns enables us to make ourselves better and better throughout our lifetime. This learning capacity and evolving capability is related to a concept called brain plasticity. Superficially, we can draw some motivational similarities between the learning process of the human brain and the concepts of machine learning.

The human brain perceives things from the real world, processes the perceived information, makes rational decisions, and performs certain actions based on circumstances. This is what we called behaving intelligently. When we program a facsimile of the intelligent behavioral process to a machine, it is called Artificial Intelligence (AI). Although the terms can be confused, Machine Learning

(ML) is an important subset of Artificial Intelligence. **ML is concerned with using specialized algorithms fetching meaningful information and finding hidden patterns from perceived data to corroborate the rational decision-making process**.

What you will learn in this course

In this curriculum, we are going to cover only the core concepts of Machine Learning that a beginner must know. We cover what we call 'Classical Machine Learning'. To understand broader concepts of Artificial Intelligence or Deep Learning, a strong fundamental knowledge of Machine Learning is indispensable, and so we would like to offer it here. You will additionally learn the basics of Regression, Classification, Clustering, Natural Language Processing, Time Series, and Reinforcement Learning, as well as real-world applications, the history of ML, ML and Fairness, and how to use your model in a web app.

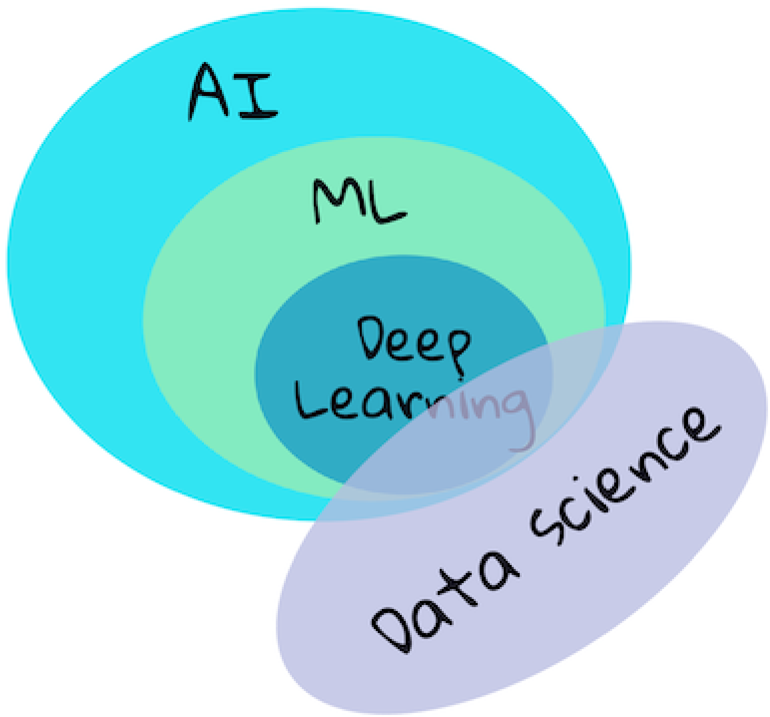
In this course you will learn:

- Core concepts of Machine Learning
- The definition of "Classical Machine Learning"
- Regression
- Classification
- Clustering
- Natural Language Processing
- Time series
- Reinforcement learning
- Real world applications
- History of ML and ML and fairness

We will not cover

To make for a better learning experience, we will avoid the complexities of neural networks, 'Deep Learning' - many-layered model-building - and AI, which we will discuss in a different curriculum.

- Deep Learning
- AI



> A diagram showing the relationships between AI, ML, Deep Learning, and Data Science. Infographic by [Jen Looper] inspired by [this graphic]

Why learn Machine Learning

Machine Learning is defined as the creation of automated systems that can learn hidden patterns from data to infer intelligent decisions.

The major motivation behind leveraging Machine Learning is to create automated systems that can learn hidden patterns from data to infer intelligent decisions. This motivation seem to be loosely inspired by how the human brain learns certain things based on the data it perceives from the outside world.

✅ Think for a minute why a business would want to try to use Machine Learning strategies vs. creating a hard-coded rules-based engine.

Applications of Machine Learning

Applications of Machine Learning are now almost everywhere, and are as ubiquitous as the data that is flowing around our societies, generated by our smart phones, connected devices, and other systems. Considering the immense potential of state-of-the-art Machine Learning algorithms, researchers have been exploring their capability to solve multi-dimensional and multi-disciplinary real-life problems with great positive outcomes.

You can use Machine Learning in many ways:

- Predict the likelihood of disease from a patient's medical history or reports.
- Leverage weather data to predict weather events.
- Understand the sentiment of a text.
- Detect fake news to stop the spread of propaganda.

Finance, economics, earth science, space exploration, biomedical engineering, cognitive science, and even fields in the humanities have adapted Machine Learning to solve the arduous, data-processing heavy problems of their domain.

Machine Learning automates the process of pattern-discovery by finding meaningful insights from real-world or generated data. It has proven itself to be highly valuable in business, health, and financial applications, among others.

In the near future, understanding the basics of Machine Learning is going to be a must for people from any domain due to its widespread adoption.

🚀 Challenge

Sketch, on paper or using an online app like Excalidraw, your understanding of the differences between AI, ML, Deep Learning, and Data Science. Add some ideas of problems that each of these techniques are good at solving.

Post-lecture quiz

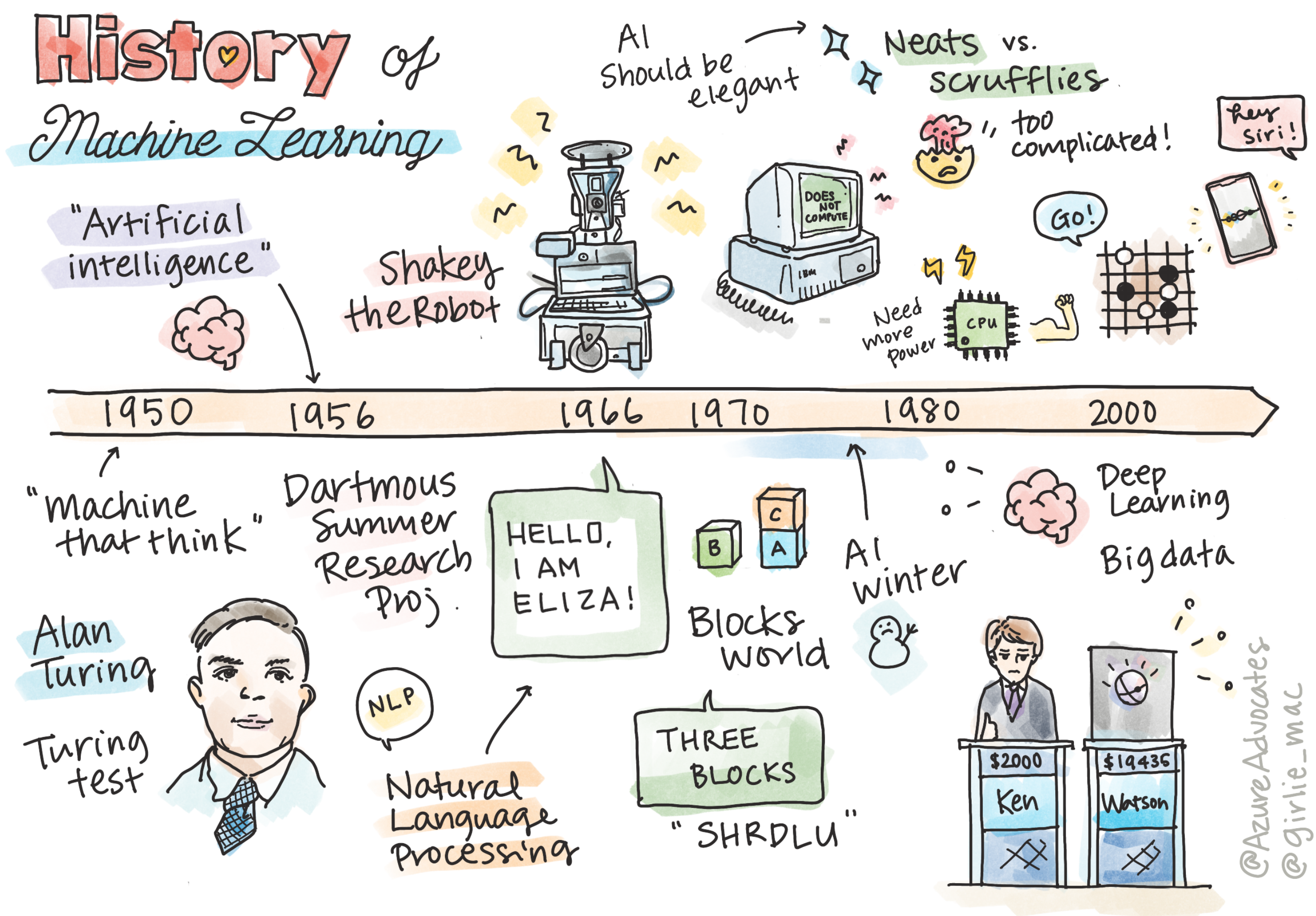
Review & Self Study

To learn more about how you can work with ML algorithms in the cloud, follow this Learning Path.

Assignment

Get up and running

History of Machine Learning



> Sketchnote by [Tomomi Imura](https://www.twitter.com/girlie_mac)

[Pre-lecture quiz]

In this lesson, we will walk through the major milestones in the history of Machine Learning and Artificial Intelligence.

The history of Artificial Intelligence, AI, as a field is intertwined with the history of Machine Learning, as the algorithms and computational advances that underpin ML fed into the development of AI. It is useful to remember that, while these fields as distinct areas of inquiry began to crystallize in the 1950s, important algorithmical, statistical, mathematical, computational and technical discoveries predated and overlapped this era. In fact, people have been thinking about these questions for hundreds of years: this article discusses the historical intellectual underpinnings of the idea of a 'thinking machine.'

Notable Discoveries

- 1763, 1812 Bayes Theorem and its predecessors. This theorem and its applications underlie inference, describing the probability of an event occurring based on prior knowledge.
- 1805 Least Square Theory by French mathematician Adrien-Marie Legendre. This theory, which you will learn about in our Regression unit, helps in data fitting.
- 1913 Markov Chains named after Russian mathematician Andrey Markov is used to describe a sequence of possible events based on a previous state.
- 1957 Perceptron is a type of linear classifier invented by American psychologist Frank Rosenblatt that underlies advances in deep learning.
- 1967 Nearest Neighbor is an algorithm originally designed to map routes. In an ML context it is used to detect patterns.
- 1970 Backpropagation is used to train feedforward neural networks.
- 1982 Recurrent Neural Networks are artificial neural networks derived from feedforward neural networks that create temporal graphs.

✅ Do a little research. What other dates stand out as pivotal in the history of ML and AI?

1950: Machines that Think

Alan Turing, a truly remarkable person who was voted by the public in 2019 as the greatest scientist of the 20th century, is credited as helping to lay the foundation for the concept of a 'machine that can think.' He grappled with naysayers and his own need for empirical evidence of this concept in part by creating the Turing Test, which you will explore in our NLP lessons.

1956: Dartmouth Summer Research Project

"The Dartmouth Summer Research Project on Artificial Intelligence was a seminal event for artificial intelligence as a field," and it was here that the term 'Artificial Intelligence' was coined (source).

> Every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it.

The lead researcher, mathematics professor John McCarthy, hoped "to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it." The participants included another luminary in the field, Marvin Minsky.

The workshop is credited with having initiated and encouraged several discussions including "the rise of symbolic methods, systems focussed on limited domains (early expert systems), and deductive systems versus inductive systems." (source).

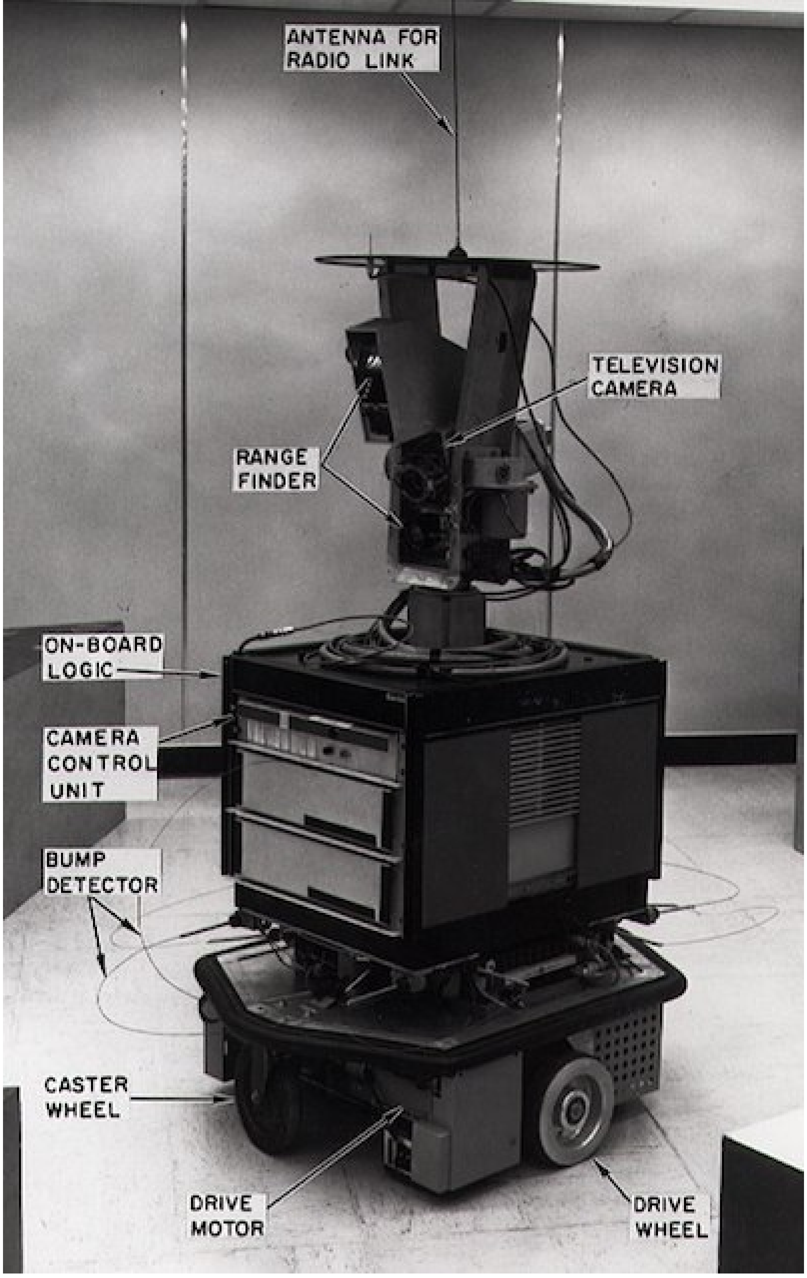
1956 - 1974: "The Golden Years"

From the 1950s through the mid '70s, optimism ran high in the hope that AI could solve many problems. In 1967, Marvin Minsky stated confidently that "Within a generation ... the problem of creating 'artificial intelligence' will substantially be solved." (Minsky, Marvin (1967), Computation: Finite and Infinite Machines, Englewood Cliffs, N.J.: Prentice-Hall)

Natural Language Processing research flourished, search was refined and made more powerful, and the concept of 'micro-worlds' was created, where simple tasks were completed using plain language instructions.

Research was well funded by government agencies, advances were made in computation and algorithms, and prototypes of intelligent machines were built. Some of these machines include:

- Shakey the robot, who could maneuver and decide how to perform tasks 'intelligently'.



> Shakey in 1972

- Eliza, an early 'chatterbot', could converse with people and act as a primitive 'therapist'. You'll learn more about Eliza in the NLP lessons.

```
  Welcome to
                    EEEEEE  LL      IIII   ZZZZZZ   AAAAA
                    EE      LL       II       ZZ   AA   AA
                    EEEEE   LL       II     ZZZ    AAAAAAA
                    EE      LL       II    ZZ      AA   AA
                    EEEEEE  LLLLLL  IIII ZZZZZZ    AA   AA

  Eliza is a mock Rogerian psychotherapist.
  The original program was described by Joseph Weizenbaum in 1966.
  This implementation by Norbert Landsteiner 2005.


ELIZA: Is something troubling you ?
YOU:   Men are all alike.
ELIZA: What is the connection, do you suppose ?
YOU:   They're always bugging us about something or other.
ELIZA: Can you think of a specific example ?
YOU:   Well, my boyfriend made me come here.
ELIZA: Is it important to you that your boyfriend made you come here ?
YOU:   He says I'm depressed much of the time.
ELIZA: I am sorry to hear that you are depressed.
YOU:   It's true. I am unhappy.
ELIZA: Can you explain what made you unhappy ?
YOU:
```

> A version of Eliza, a chatbot

- "Blocks world" was an example of a micro-world where blocks could be stacked and sorted, and experiments in teaching machines to make decisions could be tested. Advances built with libraries such as SHRDLU helped propel language processing forward.

markup

```
[![blocks world with SHRDLU](https://img.youtube.com/vi/QAJz4YKUwqw/0.jp
```

> 🎥 Click the image above for a video: Blocks world with SHRDLU

1974 - 1980: "AI Winter"

By the mid 1970s, it had become apparent that the complexity of making 'intelligent machines' had been understated and that its promise, given the available compute power, had been overblown. Funding dried up and confidence in the field slowed. Some issues that impacted confidence included:

- **Limitations**. Compute power was too limited.

- **Combinatorial explosion**. The amount of parameters needed to be trained grew exponentially as more was asked of computers, without a parallel evolution of compute power and capability.
- **Paucity of data**. There was a paucity of data that hindered the process of testing, developing, and refining algorithms.
- **Are we asking the right questions?**. The very questions that were being asked began to be questioned. Researchers began to field criticism about their approaches:
  - Turing tests came into question by means, among other ideas, of the 'chinese room theory' which posited that, "programming a digital computer may make it appear to understand language but could not produce real understanding." (source)
  - The ethics of introducing artificial intelligences such as the "therapist" ELIZA into society was challenged.

At the same time, various AI schools of thought began to form. A dichotomy was established between "scruffy" vs. "neat AI" practices. *Scruffy* labs tweaked programs for hours until they had the desired results. *Neat* labs "focused on logic and formal problem solving". ELIZA and SHRDLU were well-known *scruffy* systems. In the 1980s, as demand emerged to make ML systems reproducible, the *neat* approach gradually took the forefront as its results are more explainable.

1980s Expert systems

As the field grew, its benefit to business became clearer, and in the 1980s so did the proliferation of 'expert systems'. "Expert systems were among the first truly successful forms of artificial intelligence (AI) software." (source).

This type of system is actually *hybrid*, consisting partially of a rules engine defining business requirements, and an inference engine that leveraged the rules system to deduce new facts.

This era also saw increasing attention paid to neural networks.

1987 - 1993: AI 'Chill'

The proliferation of specialized expert systems hardware had the unfortunate effect of becoming too specialized. The rise of personal computers also competed with these large, specialized, centralized systems. The democratization of computing had begun, and it eventually paved the way for the modern explosion of big data.

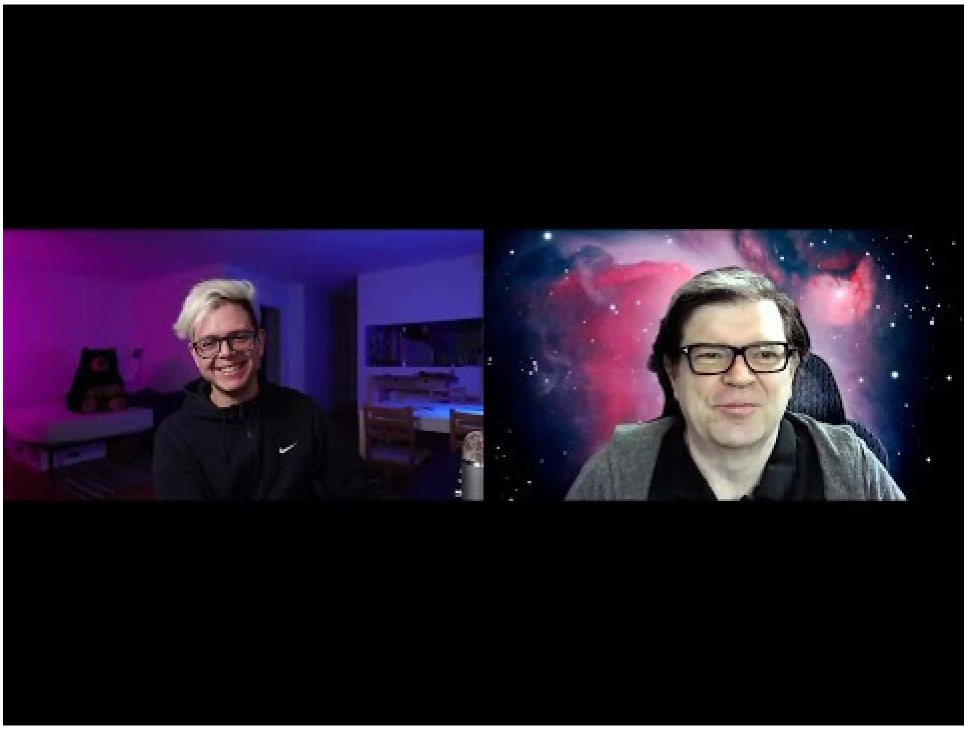
1993 - 2011

This epoch saw a new era for ML and AI to be able to solve some of the problems that had been caused earlier by the lack of data and compute power. The amount of data began to rapidly increase and become more widely available, for better and for worse, especially with the advent of the smartphone around 2007. Compute power expanded exponentially, and algorithms evolved alongside. The field began to gain maturity as the freewheeling days of the past began to crystallize into a true discipline.

Now

Today, Machine Learning and AI touch almost every part of our lives. This era calls for careful understanding of the risks and potentials effects of these algorithms on human lives. As Microsoft's Brad Smith has stated, "Information technology raises issues that go to the heart of fundamental human-rights protections like privacy and freedom of expression. These issues heighten responsibility for tech companies that create these products. In our view, they also call for thoughtful government regulation and for the development of norms around acceptable uses" (source).

It remains to be seen what the future holds, but it is important to understand these computer systems and the software and algorithms that they run. We hope that this curriculum will help you to gain a better understanding so that you can decide for yourself.



> 🎥 Click the image above for a video: Yann LeCun discusses the history of Deep Learning in this lecture

🚀Challenge

Dig into one of these historical moments and learn more about the people behind them. There are fascinating characters, and no scientific discovery was ever created in a cultural vacuum. What do you discover?

[Post-lecture quiz]

Review & Self Study

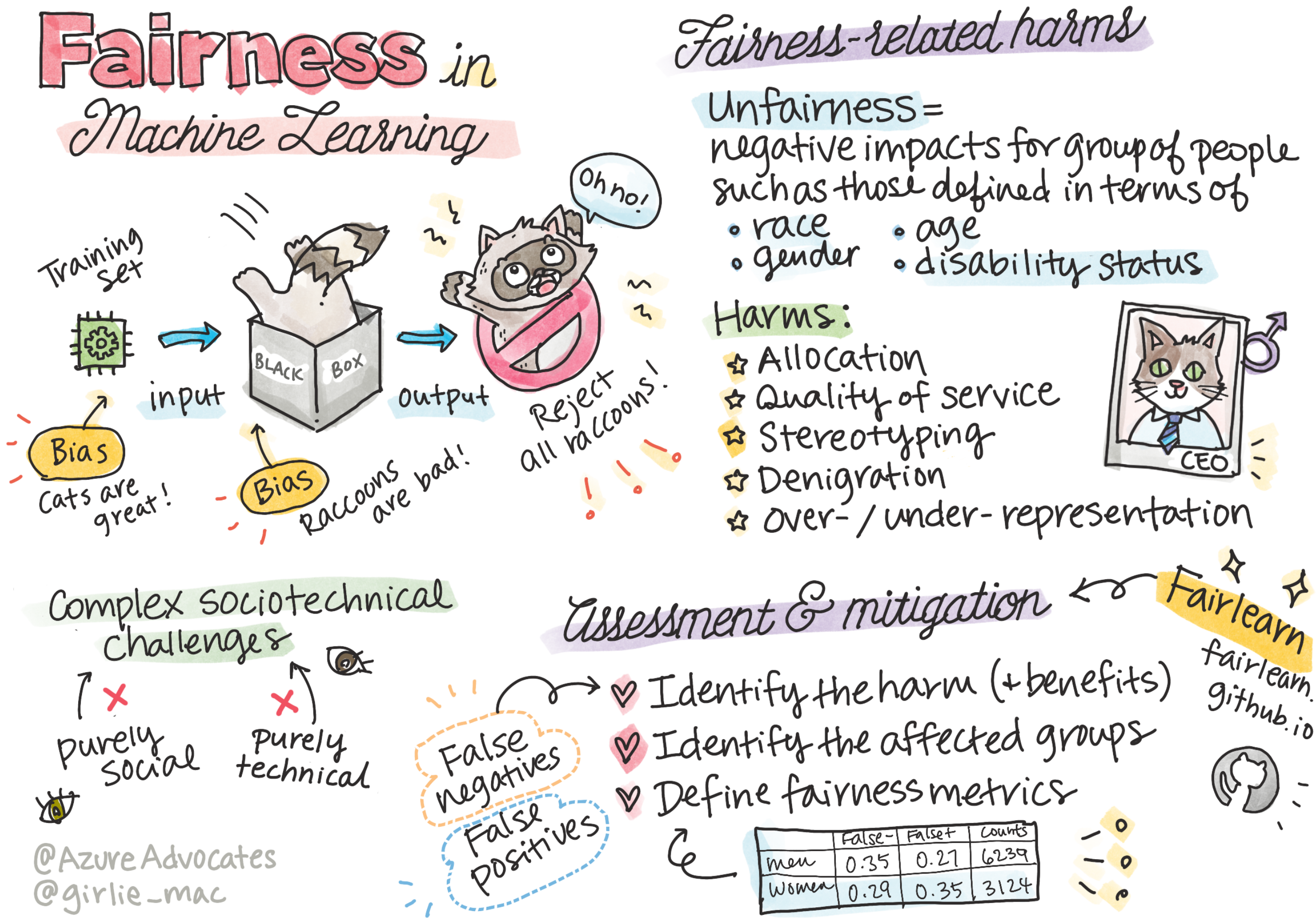
Here are items to watch and listen to:

[This podcast where Amy Boyd discusses the evolution of AI]

Assignment

[Create a timeline]

Fairness in Machine Learning



> Sketchnote by Tomomi Imura

Pre-lecture quiz

Introduction

In this curriculum, you will start to discover how machine learning can and is impacting our everyday lives. Even now, systems and models are involved in daily decision-making tasks, such as health care diagnoses or detecting fraud. So it is important that these models work well in order to provide fair outcomes for everyone.

Imagine what can happen when the data you are using to build these models lacks certain demographics, such as race, gender, political view, religion, or disproportionately represents such demographics. What about when the model's output is interpreted to favor some demographic? What is the consequence for the application?

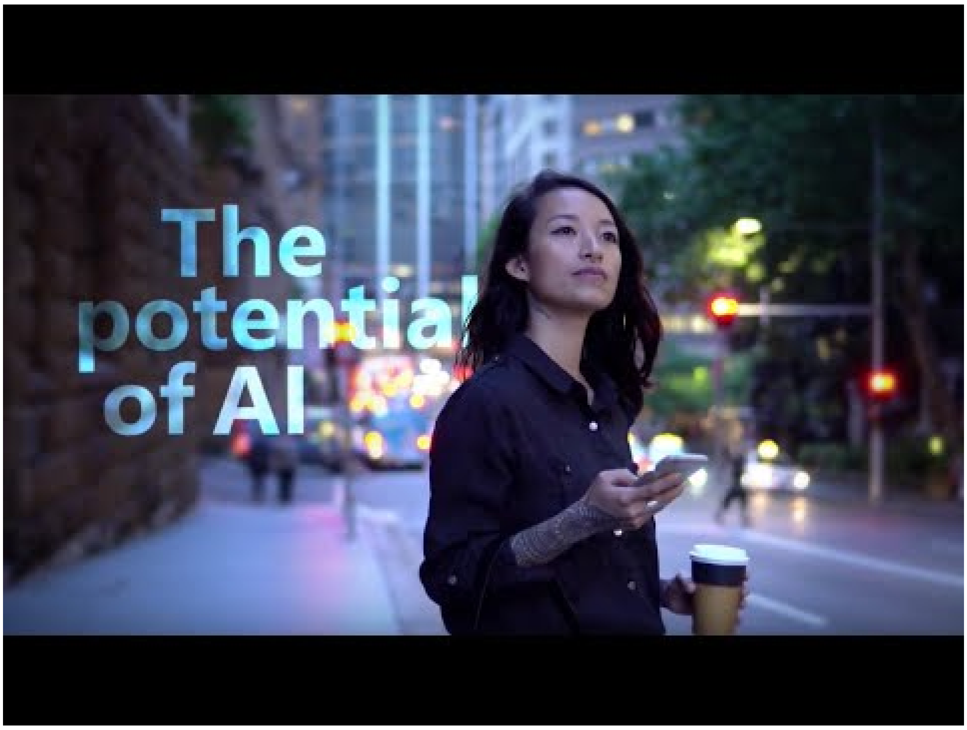
In this lesson, you will:

- Raise your awareness of the importance of fairness in machine learning.
- Learn about fairness-related harms.
- Learn about unfairness assessment and mitigation.

Prerequisite

As a prerequisite, please take the "Responsible AI Principles" Learn Path and watch the video below on the topic:

Learn more about Responsible AI by following this Learning Path



> 🎥 Click the image above for a video: Microsoft's Approach to Responsible AI

Unfairness in data and algorithms

> "If you torture the data long enough, it will confess to anything - Ronald Coase

This statement sounds extreme, but it is true that data can be manipulated to support any conclusion. Such manipulation can sometimes happen unintentionally. As humans, we all have bias, and it's often difficult to consciously know when you are introducing bias in data.

Guaranteeing fairness in AI and machine learning remains a complex sociotechnical challenge. Meaning that it cannot be addressed from either purely social or technical perspectives.

Fairness-related harms

What do you mean by unfairness? "Unfairness" encompasses negative impacts, or "harms", for a group of people, such as those defined in terms of race, gender, age, or disability status.

The main fairness-related harms can be classified as:

- **Allocation**, if a gender or ethnicity for example is favored over another.
- **Quality of service**. If you train the data for one specific scenario but reality is much more complex, it leads to a poor performing service.
- **Stereotyping**. Associating a given group with pre-assigned attributes.
- **Denigration**. To unfairly criticize and label something or someone.
- **Over- or under- representation**. The idea is that a certain group is not seen in a certain profession, and any service or function that keeps promoting that is contributing to harm.

Let’s take a look at the examples.

Allocation

Consider a hypothetical system for screening loan applications. The system tends to pick white men as better candidates over other groups. As a result, loans are withheld from certain applicants.

Another example would be an experimental hiring tool developed by a large corporation to screen candidates. The tool systemically discriminated against one gender by using the models were trained to prefer words associated with another. It resulted in penalizing candidates whose resumes contain words such as "women’s rugby team".

✅ Do a little research to find a real-world example of something like this

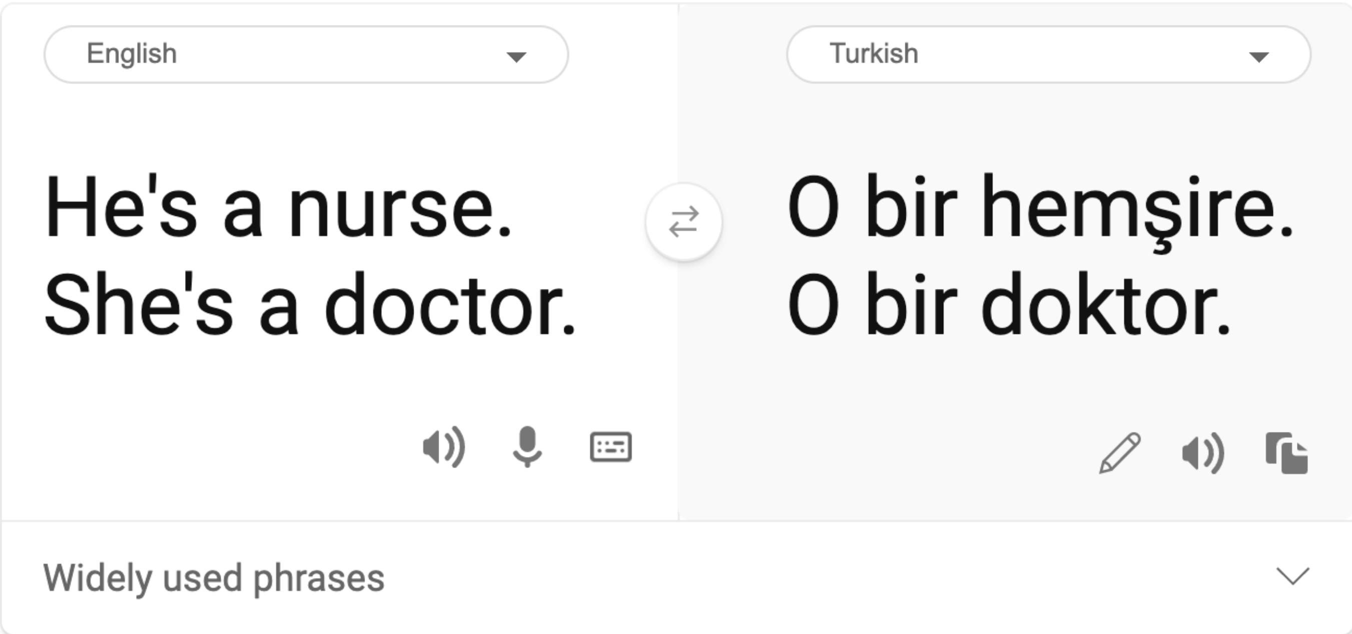
Quality of Service

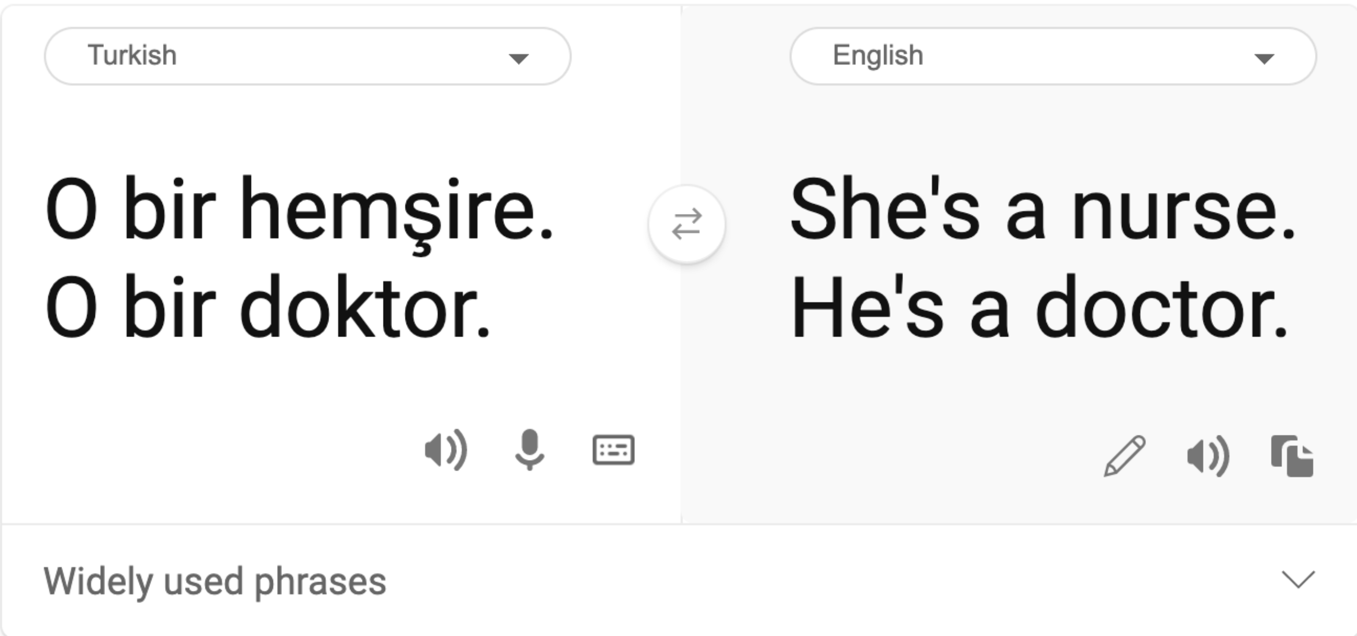
Researchers found that several commercial gender classifiers had higher error rates around images of women with darker skin tones as opposed to images of men with lighter skin tones. Reference

Another infamous example is a hand soap dispenser that could not seem to be able to sense people with dark skin. Reference

Stereotyping

Stereotypical gender view was found in machine translation. When translating "he is a nurse and she is a doctor" into Turkish, problems were encountered. Turkish is a genderless language which has one pronoun, "o" to convey a singular third person, but translating the sentence back from Turkish to English yields the stereotypical and incorrect as "she is a nurse and he is a doctor".





Denigration

An image labeling technology infamously mislabeled images of dark-skinned people as gorillas. Mislabeling is harmful not just because the system made a mistake because it specifically applied a label that has a long history of being purposefully used to denigrate Black people.

> 🎥 Click the image above for a video: AI, Ain't I a Woman - a performance showing the harm caused by racist denigration by AI

Over- or under- representation

Skewed image search results can be a good example of this harm. When searching images of professions with an equal or higher percentage of men than women, such as engineering, or CEO, watch for results that are more heavily skewed towards a given gender.

> This search on Bing for 'CEO' produces pretty inclusive results

These five main types of harms are not mutually exclusive, and a single system can exhibit more than one type of harm. In addition, each case varies in its severity. For instance, unfairly labeling someone as a criminal is a much more severe harm than mislabeling an image. It's important, however, to remember that even relatively non-severe harms can make people feel alienated or singled out and the cumulative impact can be extremely oppressive.

✅ **Discussion**: Revisit some of the examples and see if they show different harms.

	Allocation	Quality of service	Stereotyping	Denigration	Over- or under-representation
Automated hiring system	x	x	x		x
Machine translation					
Photo labeling					

Detecting unfairness

There are many reasons why a given system behaves unfairly. Social biases, for example, might be reflected in the datasets used to train them. For example, hiring unfairness might have been exacerbated by over reliance on historical data. By using the patterns in resumes submitted to the company over a 10-year period, the model determined that men were more qualified because the majority of resumes came from men, a reflection of past male dominance across the tech industry.

Inadequate data about a certain group of people can be the reason for unfairness. For example, image classifiers a have higher rate of error for images of dark-skinned people because darker skin tones were underrepresented in the data.

Wrong assumptions made during development cause unfairness too. For example, a facial analysis system intended to predict who is going to commit a crime based on images of people’s faces can lead to damaging assumptions. This could lead to substantial harms for people who are misclassified.

Understand your models and build in fairness

Although many aspects of fairness are not captured in quantitative fairness metrics, and it is not possible to fully remove bias from a system to guarantee fairness, you are still responsible to detect and to mitigate fairness issues as much as possible.

When you are working with machine learning models, it is important to understand your models by means of assuring their interpretability and by assessing and mitigating unfairness.

Let’s use the loan selection example to isolate the case to figure out each factor's level of impact on the prediction.

Assessment methods

1. **Identify harms (and benefits)**. The first step is to identify harms and benefits. Think about how actions and decisions can affect both potential customers and a business itself.

2. **Identify the affected groups**. Once you understand what kind of harms or benefits that can occur, identify the groups that may be affected. Are these groups defined by gender, ethnicity, or social group?

3. **Define fairness metrics**. Finally, define a metric so you have something to measure against in your work to improve the situation.

Identify harms (and benefits)

What are the harms and benefits associated with lending? Think about false negatives and false positive scenarios:

False negatives (reject, but Y=1) - in this case, an applicant who will be capable of repaying a loan is rejected. This is an adverse event because the resources of the loans are withheld from qualified applicants.

False positives (accept, but Y=0) - in this case, the applicant does get a loan but eventually defaults. As a result, the applicant's case will be sent to a debt collection agency which can affect their future loan applications.

Identify affected groups

The next step is to determine which groups are likely to be affected. For example, in case of a credit card application, a model might determine that women should receive much lower credit limits compared with their spouses who share household assets. An entire demographic, defined by gender, is thereby affected.

Define fairness metrics

You have identified harms and an affected group, in this case, delineated by gender. Now, use the quantified factors to disaggregate their metrics. For example, using the data below, you can see that women have the largest false positive rate and men have the smallest, and that the opposite is true for false negatives.

✅ In a future lesson on Clustering, you will see how to build this 'confusion matrix' in code

	False positive rate	False negative rate	count
Women	0.37	0.27	54032
Men	0.31	0.35	28620
Non-binary	0.33	0.31	1266

This table tells us several things. First, we note that there are comparatively few non-binary people in the data. The data is skewed, so you need to be careful how you interpret these numbers.

In this case, we have 3 groups and 2 metrics. When we are thinking about how our system affects the group of customers with their loan applicants, this may be sufficient, but when you want to define larger number of groups, you may want to distill this to smaller sets of summaries. To do that, you can add more metrics, such as the largest difference or smallest ratio of each false negative and false positive.

✅ Stop and Think: What other groups are likely to be affected for loan application?

Mitigating unfairness

To mitigate unfairness, explore the model to generate various mitigated models and compare the tradeoffs it makes between accuracy and fairness to select the most fair model.

This introductory lesson does not dive deeply into the details of algorithmic unfairness mitigation, such as post-processing and reductions approach, but here is a tool that you may want to try.

Fairlearn

Fairlearn is an open-source Python package that allows you to assess your systems' fairness and mitigate unfairness.

The tool helps you to assesses how a model's predictions affect different groups, enabling you to compare multiple models by using fairness and performance metrics, and supplying a set of algorithms to mitigate unfairness in binary classification and regression.

- Learn how to use the different components by checking out the Fairlearn's GitHub
- Explore the user guide, examples
- Try some sample notebooks.
- Learn how to enable fairness assessments of machine learning models in Azure Machine Learning.
- Check out these sample notebooks for more fairness assessment scenarios in Azure Machine Learning.

🚀 Challenge

To prevent biases from being introduced in the first place, we should:

- have a diversity of backgrounds and perspectives among the people working on systems
- invest in datasets that reflect the diversity of our society
- develop better methods for detecting and correcting bias when it occurs

Think about real-life scenarios where unfairness is evident in model-building and usage. What else should we consider?

Post-lecture quiz

Review & Self Study

In this lesson, you have learned some basics of the concepts of fairness and unfairness in machine learning.

Watch this workshop to dive deeper into the topics:

- YouTube: Fairness-related harms in AI systems: Examples, assessment, and mitigation by Hanna Wallach and Miro Dudik Fairness-related harms in AI systems: Examples, assessment, and mitigation - YouTube

Also, read:

- Microsoft's RAI resource center: Responsible AI Resources – Microsoft AI
- Microsoft's FATE research group: FATE: Fairness, Accountability, Transparency, and Ethics in AI - Microsoft Research

Explore the Fairlearn toolkit

Fairlearn

Read about Azure Machine Learning's tools to ensure fairness

- Azure Machine Learning

Assignment

Explore Fairlearn