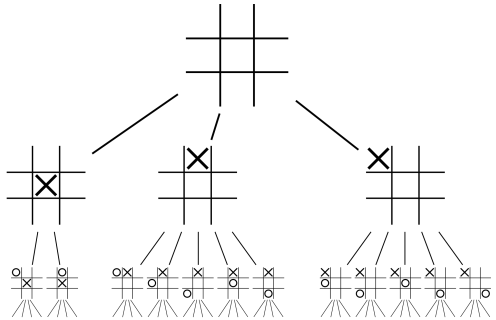
Introduction to Machine Learning

Julie LaChance

Slides adapted from Wells Santo (AI4ALL)
and Agata Foryciarz (Princeton)

Recap

- **Artificial Intelligence**: A field of computer science that attempts to have computers make decisions intelligently



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- If someone tries to describe to us how a cheetah looks, we *might* have an idea of a cheetah
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- Humans learn and gain intelligence by seeing examples

Machine Learning

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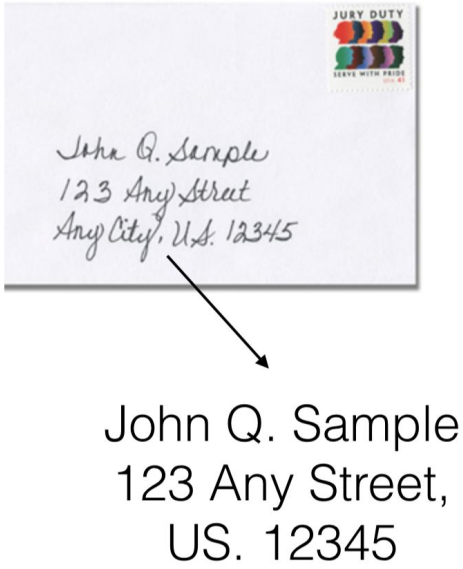
- **Machine Learning** (ML) is an approach to teach computers how to make decisions and predictions, by giving them the ability to learn from data

Why use Machine Learning?

- Computers can be programmed to follow instructions



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- Example: Writing a program to look at handwritten text and figure out what it says
- There are too many different handwriting styles for us to create instructions to capture *all* variations
- Machine learning allows us to solve this task by learning from examples

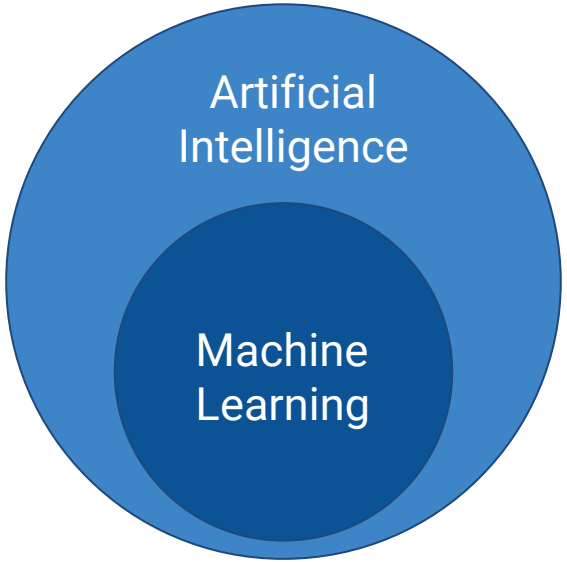
Machine Translation

Benefits of using ML for translation:

1. Can translate a language that you have no idea how to speak
2. Can reduce the time spent programming
3. Can easily reuse the same approaches to learn new languages

How is ML different from AI?

- Machine learning is a type of artificial intelligence



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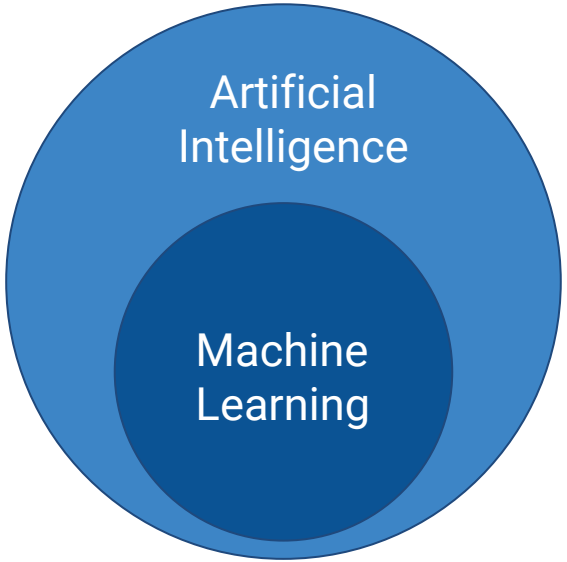

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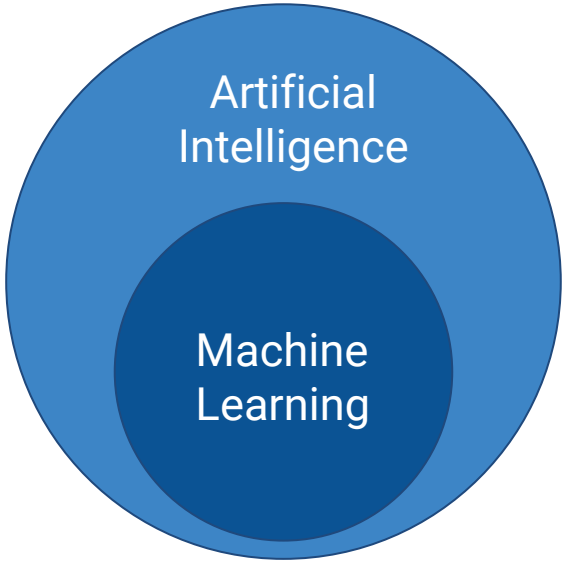

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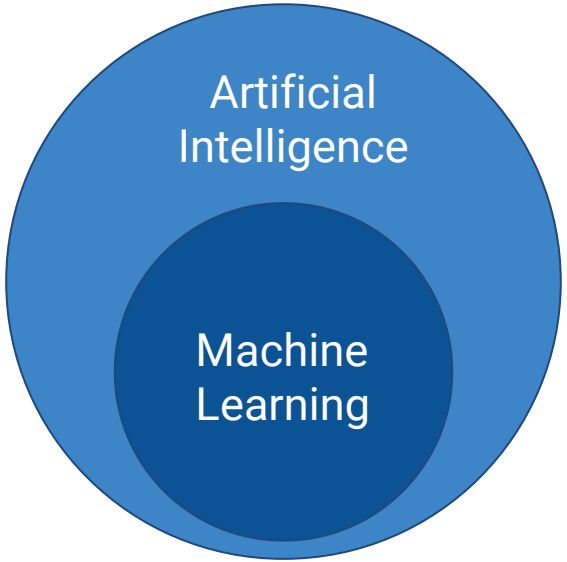

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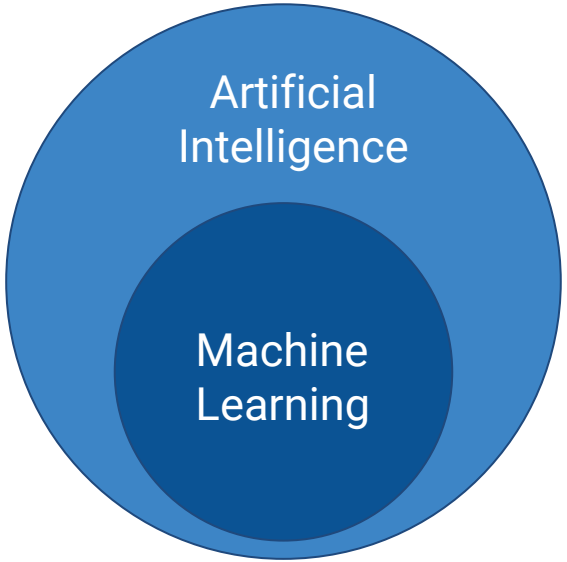
- Many of the latest AI systems all make use of ML
- For this reason, many people use the terms AI and ML interchangeably



Yesterday

Friday Lecture

Machine Learning in the News

Machine learning predicts World Cup winner
MIT Technology Review - Jun 12, 2018
But in recent years, researchers have developed **machine-learning** techniques that have the potential to outperform conventional statistical ...

FIFA World Cup: **Machine learning** predicts two possible winners
Digit - Jun 13, 2018

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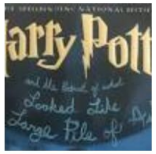

This **Harry Potter** AI-generated fanfiction is remarkably good
The Verge - Dec 12, 2017
Botnik Studios created the three-page chapter, titled "**Harry Potter** and ... which the company refers to as "collaborating with **machines**," mixes ...

'He began to eat Hermione's family': bot tries to write **Harry Potter** book ...
Blog - The Guardian (blog) - Dec 13, 2017

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Adobe is using machine learning to make it easier to spot Photoshopped images

New research uses AI to automate traditional digital forensics

By James Vincent | @jjvincent | Jun 22, 2018, 11:00am EDT

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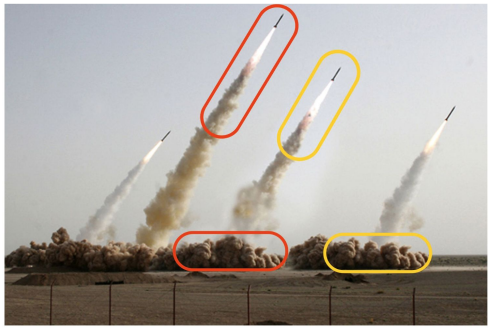

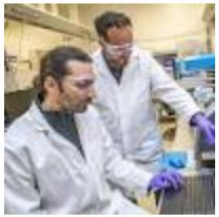

New **machine learning** approach could accelerate bioengineering
Science Daily - Jun 1, 2018
Machine learning, however, uses data to train a computer algorithm to make predictions. The algorithm learns a system's behavior by analyzing ...

Scientists Use **Machine Learning** to Speed Up Biofuel Production
R & D Magazine - Jun 1, 2018

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Activity

Machine learning in the world around you

https://royalsociety.org/topics-policy/projects/machine-learning/machine-learning-in-the-world-around-you-infographic/

Types of Machine Learning

Supervised Learning

- The first type of machine learning we will learn about is called **supervised learning**

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- Or say we have a collection of emails and want to identify which emails are spam and which are not
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- How are they all related?

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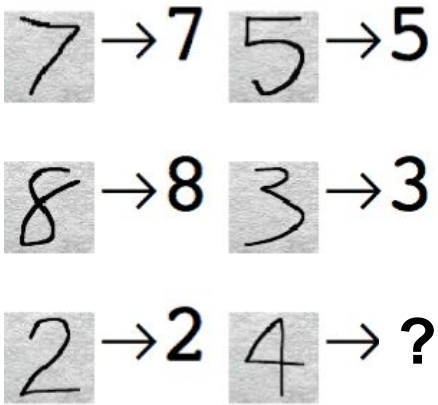
- For example, we can take an email as input and assign it the label *spam* or *not spam*
- Or, we can take an image as input and assign it with the label *cheetah*, *dog*, *wolf*, etc.
- A specific instance of our data (one particular email or image) is called an **example**

Supervised Learning

- With supervised learning, we learn from examples that are already labelled



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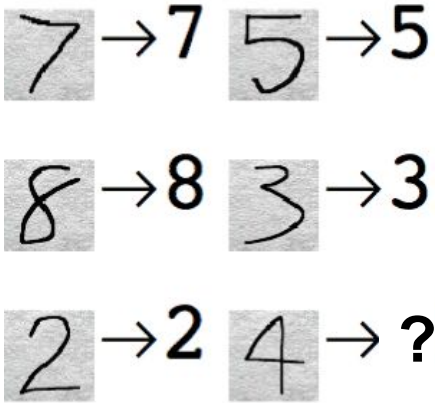

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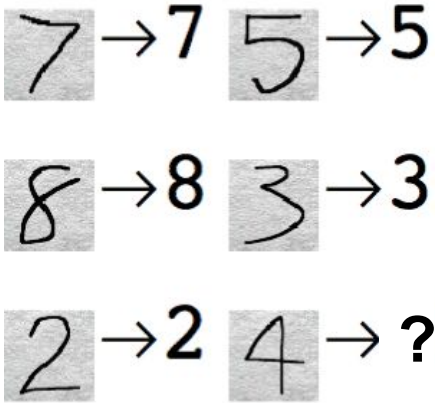
- For instance, say we want to figure out from an image of a handwritten number what digit it is
- We look at many labelled examples and then try to predict the label of a new, unseen example



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  - Determining if mail is spam or not spam
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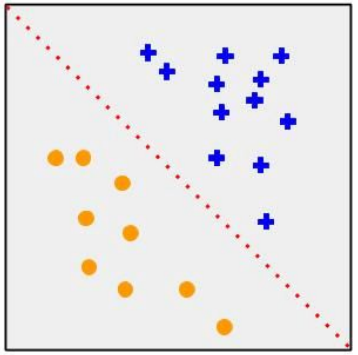

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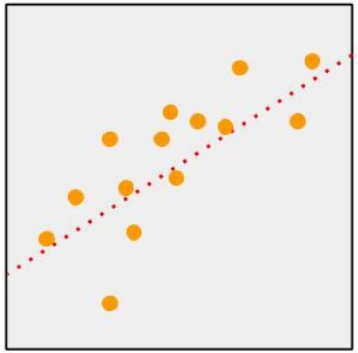

Regression

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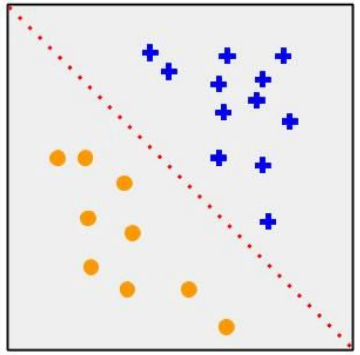
- **Regression:** When the output (label) is a *real number*
  - Determining tomorrow's temperature
  - Determining the cost of coffee in 2020



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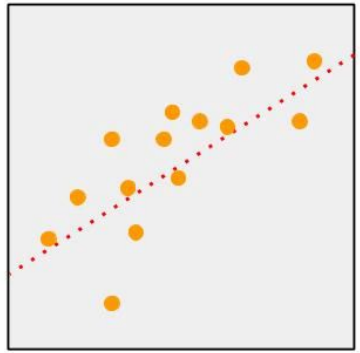

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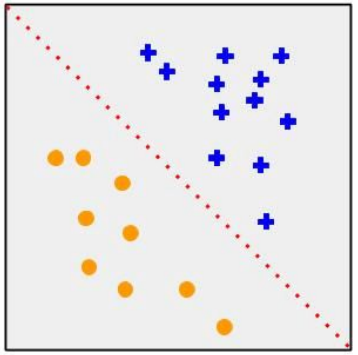

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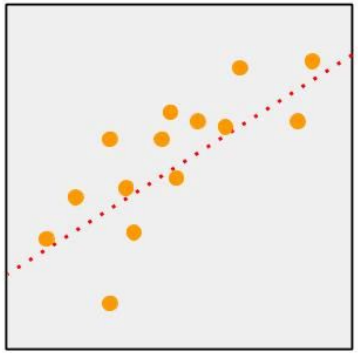

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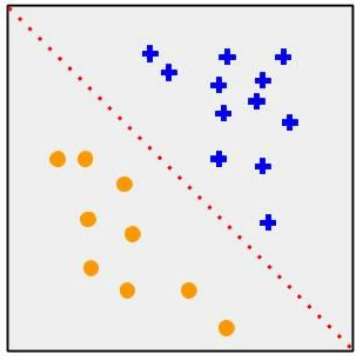

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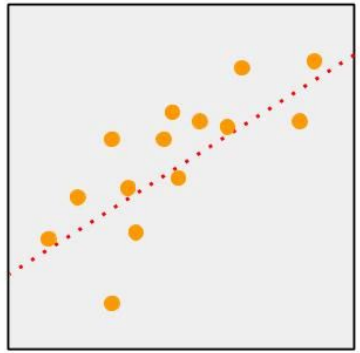

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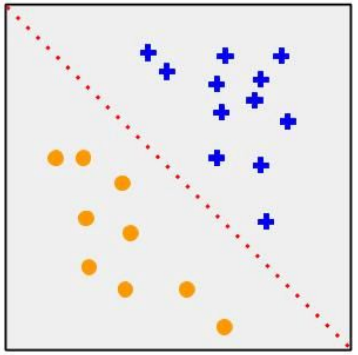

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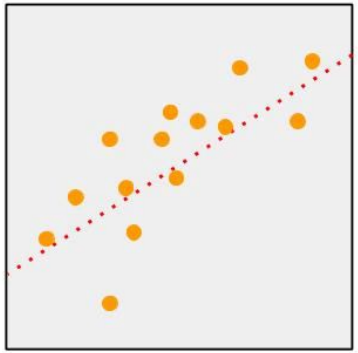

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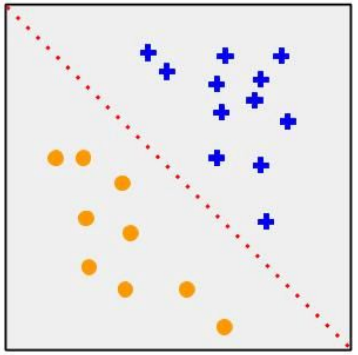
- We say that this output is **continuous**



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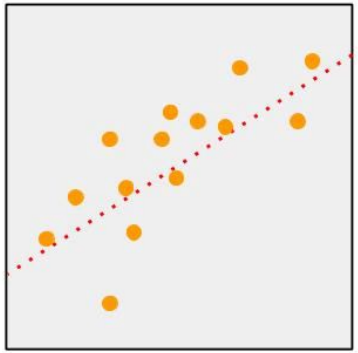

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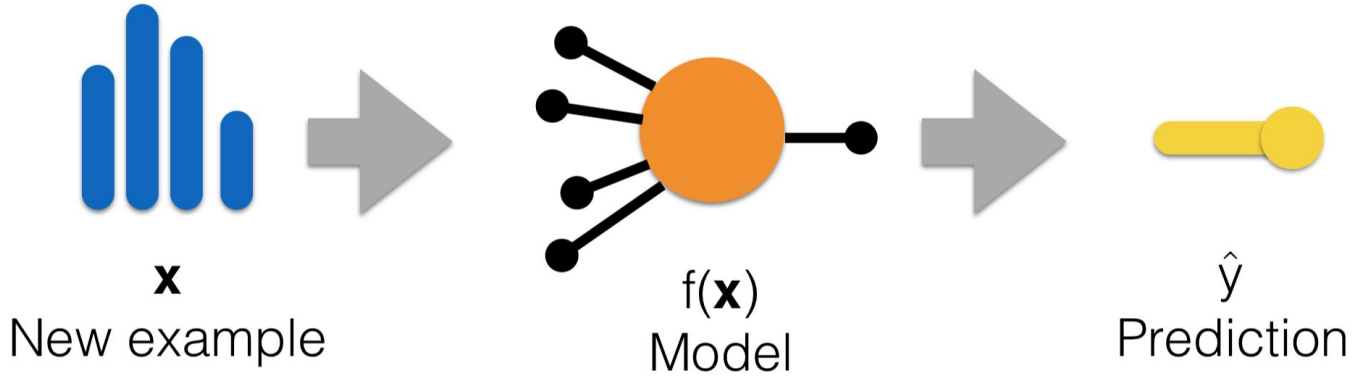

Unsupervised Learning

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Discussion - Classification and Regression

Which method would you use for each of the following tasks:

- Predicting tomorrow's weather based on past weather reports
- Predicting a dog's breed based on their fur color
- Filtering spam emails

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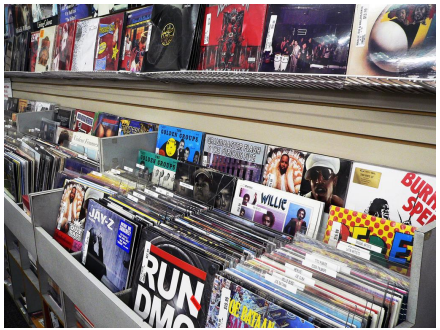

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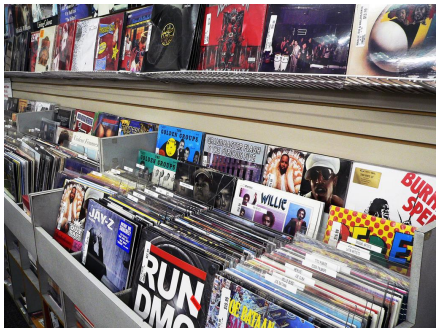

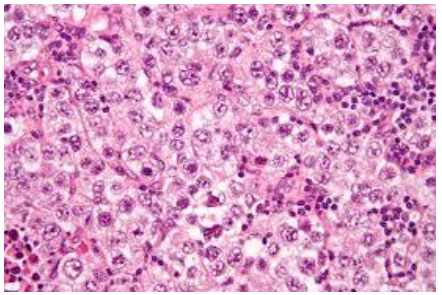

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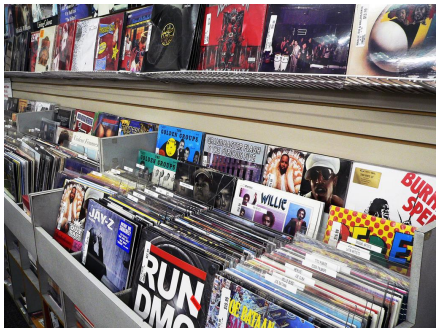
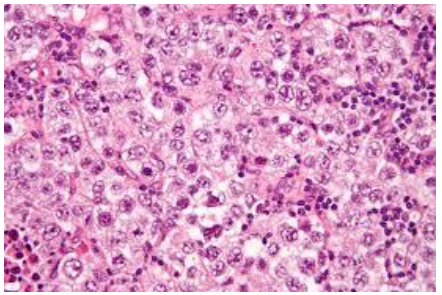
- Unsupervised learning helps us with finding patterns and similarities within our data in order to discover new groupings for them





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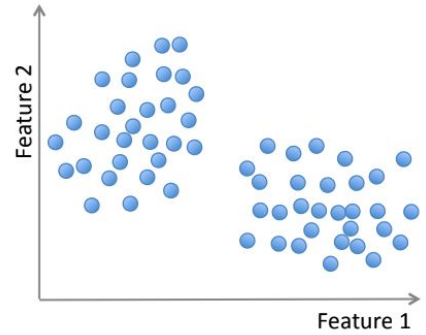

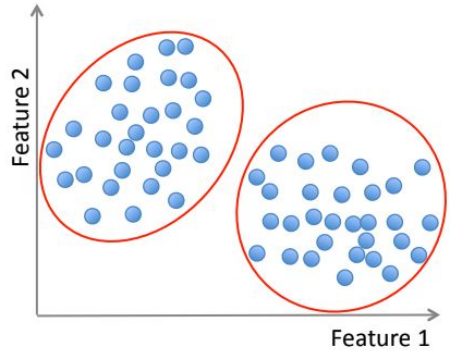

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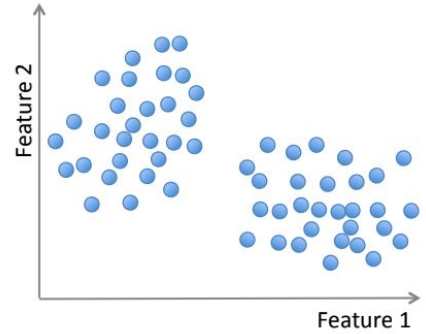
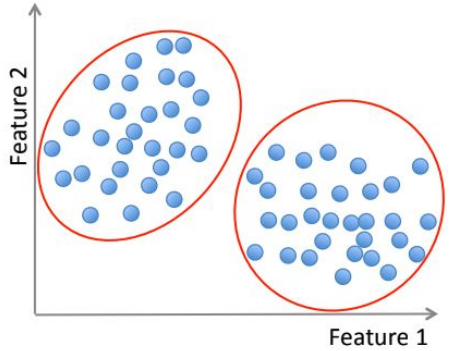
- These inferences could be:
  - Different ways to group that data
  - Anomalies that exist in the data
  - Finding new patterns in the data





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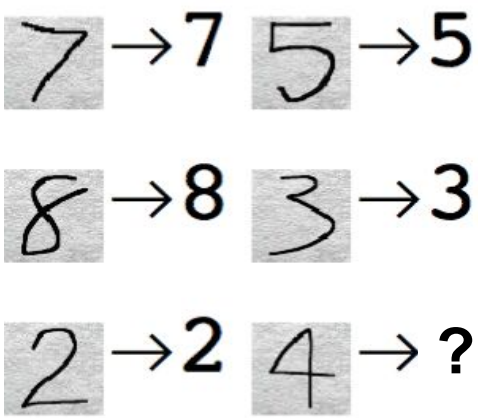
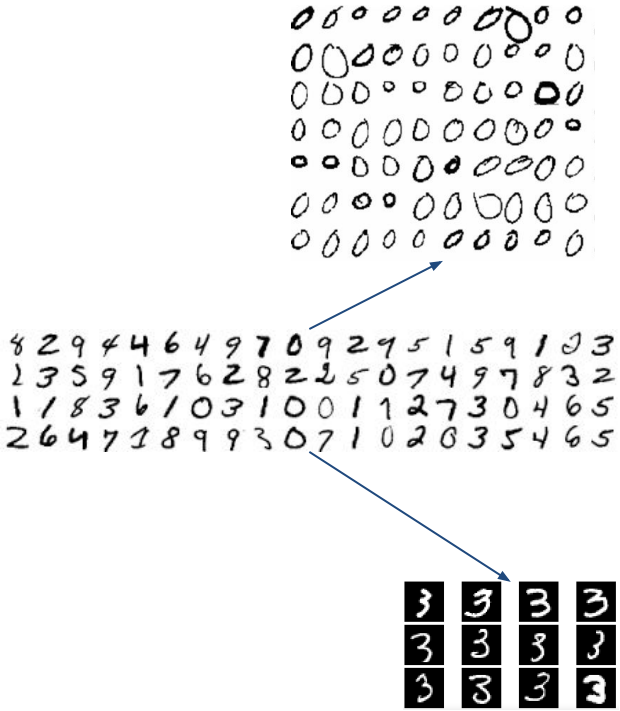
- When we have labelled data (supervised learning), there is an expectation of what the “right” answer is

- When we do not have labelled data (unsupervised learning), we want to discover potentially new patterns in the data

Supervised vs Unsupervised

Which method is supervised, and which is unsupervised? Why?





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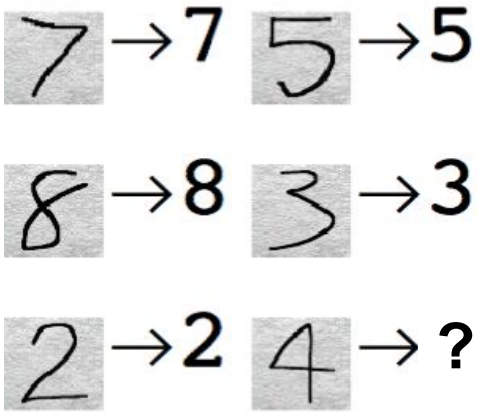
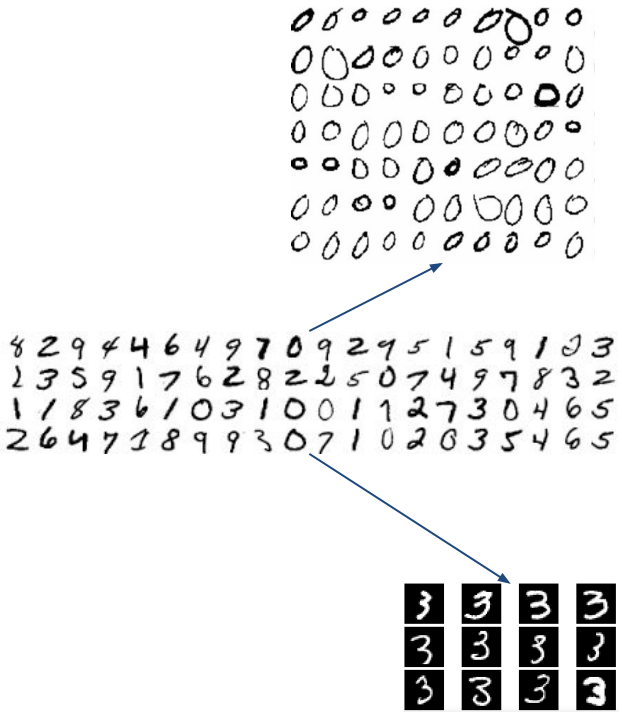


Supervised Learning



Unsupervised Learning

Reinforcement Learning

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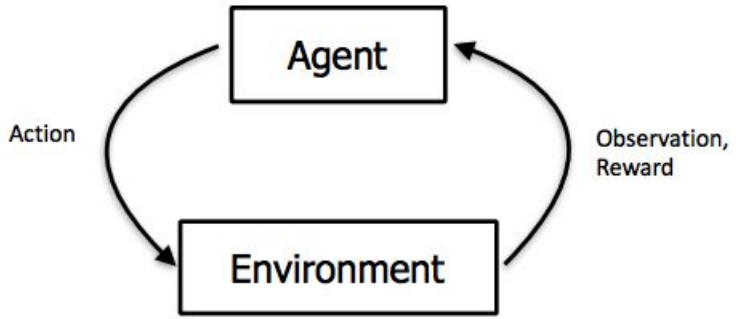
- Based on how we learn about good decisions from *rewards* and bad decisions from *penalties*
- For example, if I touch a hot stove and it burns my hand, I might learn never to touch a hot stove again
- Or if I press a button and get a piece of candy, I might learn to want to press that button again

Reinforcement Learning

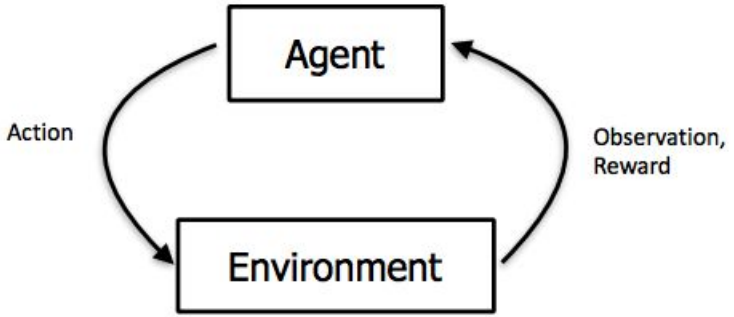
- Frames the question of intelligence as getting the most reward in a particular environment

- Learn from trial-and-error by taking different actions and seeing which actions give you the most reward



Reinforcement Learning

- Particularly useful for tasks where we need to learn how to make sequential decisions
- Like playing a video game or manueving a robot



Discussion: Supervised, Unsupervised and Reinforcement Learning

Which method would you use for each of the following:

- Predicting the best next move of a self-driving car based on visual information about the environment
- Finding the most attractive advertisement to show to a user on Google based on a search query
- Predicting a student's GPA based on their past grades
- Finding the best move in a game of chess based on the current board arrangement

Data

Describing data to computers

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- For example, we can't just show a computer an image on its own
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- The simplified properties that we use to describe our data to computers are called **features**

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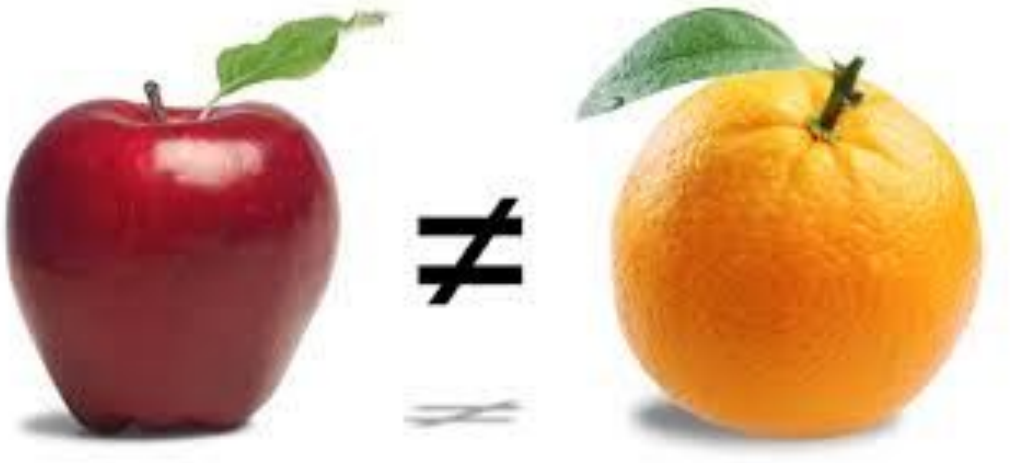
- Used to quantify attributes of an example in a way that a computer can understand
- Picking *what* features to use is a really important task in machine learning (**feature selection**)
- Features can be:
  - Binary (yes / no)
  - Real-valued (any real number)
  - Discrete (small number of specific values)

Example: Apple vs Orange

- Say we wanted to teach a computer how to tell the difference between apples and oranges

- What features might be useful for it to know?

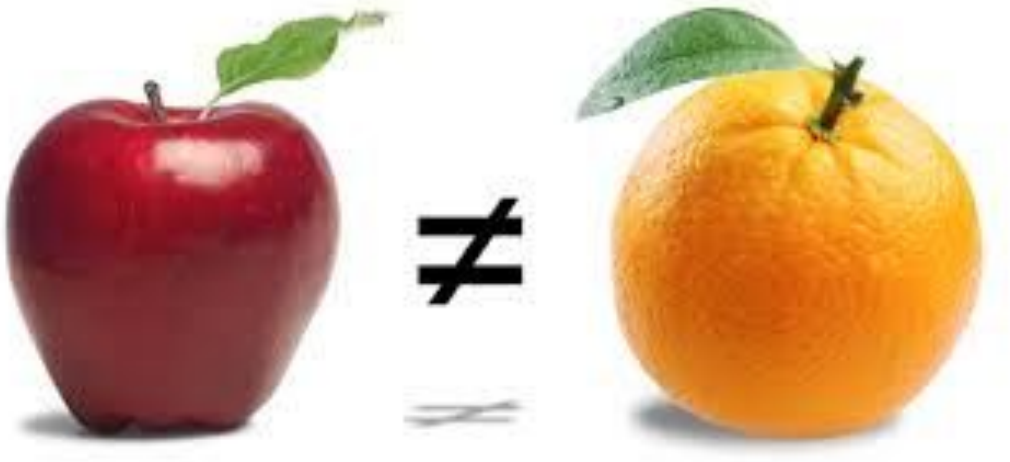


Example: Apple vs Orange

- Say we wanted to teach a computer how to tell the difference between apples and oranges

- What features might be useful for it to know?

- Size?
- Shape?
- Color?
- Has seeds?



Examples and Datasets

- An **example**, **x**, is a particular instance of data (could be a picture, an email, a sentence, a song) which is represented by a set of features

$\mathbf{x} = (x_1, x_2, x_3, \ldots)$ like $\mathbf{x} = (1.5, \text{green}, \text{yes})$

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- A **dataset** is a collection of labelled or unlabelled examples

  $D = \{(\mathbf{x_1}, y_1), (\mathbf{x_2}, y_2), \ldots\}$
  like D = {((1.5, green, yes), apple), ((1.5, orange, yes), orange)}

Fitting to your data

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- In machine learning terms, if we understand our data well, we say it has a **good fit**
- But we also want to do well on future data that we have not yet seen!

Fitting to your data

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Fitting to your data

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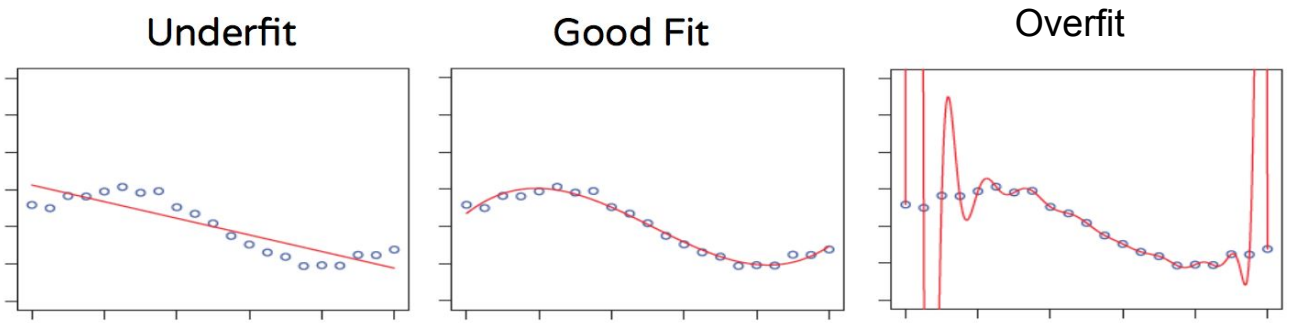
- We look at existing data to try to learn patterns that help us generalize -- we do not want to just memorize
- It's like preparing for a math test:
  - Memorizing would be memorizing the answers to the specific questions asked on a practice test
  - Generalizing would be understanding the rules used in the practice test and applying them to the actual test

Fitting to your data

- When we don't even fit well to the data we've seen, this is called **underfitting**

- When we fit too well to the data we've seen, but do not generalize well, this is called **overfitting**



Discussion

Think about a few scenarios where overfitting could be dangerous.

What types of applications should be most concerned about overfitting?

Using data to improve our system

- How do we learn to generalize well?

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  - **Training Set**: data used to train a model
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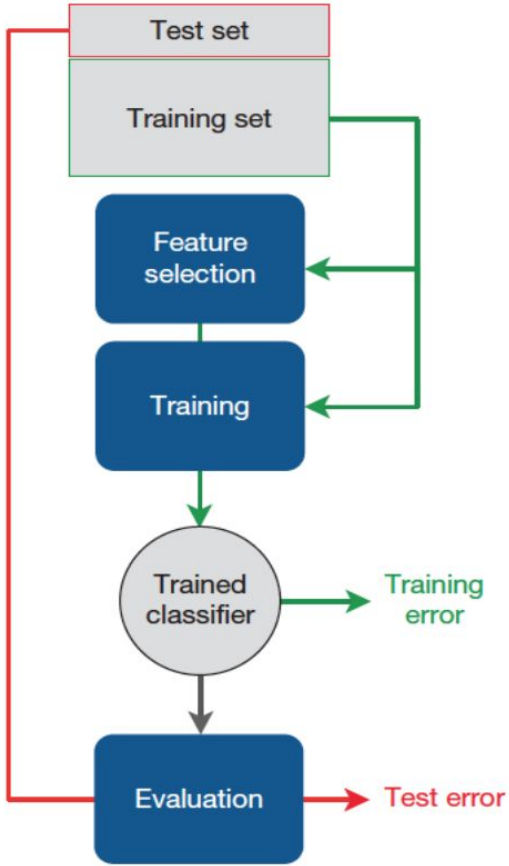
- We then measure performance in two ways:
  - **Training Error**: how well the model performs on data we have seen
  - **Test Error**: how well the model performs on unseen data



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- Free sources of data that we can use are often called **open-source datasets**

The Importance of Datasets

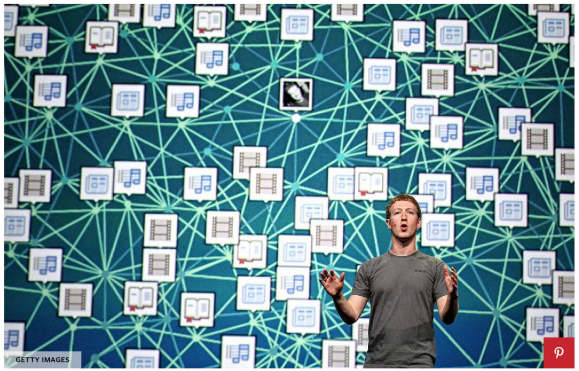
The world's most valuable resource is no longer oil, but data

The data economy demands a new approach to antitrust rules

How Much Money Facebook Gets From Selling Your Data

Mark Zuckerberg is making bank on your information.

Jun 19, 2018



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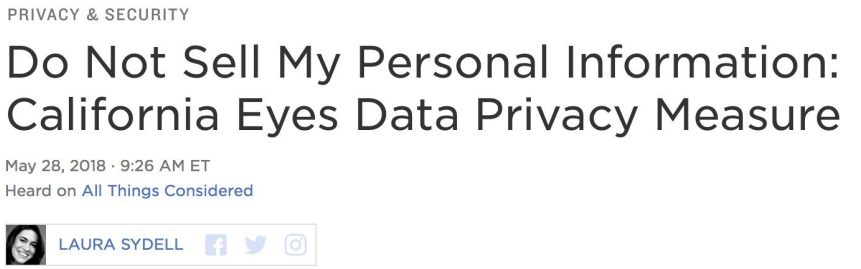
- A good dataset can help your machine learning algorithm, but **a bad dataset can hurt**
- Not all open-source datasets are good: some may not be labelled accurately or contain missing or biased information

Discussion

Often, datasets generated by users are

Data Protection and Privacy

- The collection and selling of data has brought up legal questions of privacy and anonymity



PRIVACY & SECURITY

Do Not Sell My Personal Information: California Eyes Data Privacy Measure

May 28, 2018 · 9:26 AM ET

Heard on All Things Considered

LAURA SYDELL

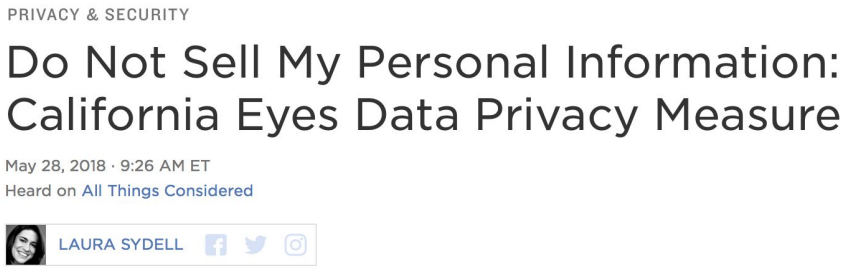
Facebook Gave Data Access to Chinese Firm Flagged by U.S. Intelligence

GDPR And The Trusted Framework For Data Privacy

Data Protection and Privacy

- The collection and selling of data has brought up legal questions of privacy and anonymity

- Because data can sometimes contain personal or sensitive information, we should follow good practices to protect privacy: this is called **data stewardship**



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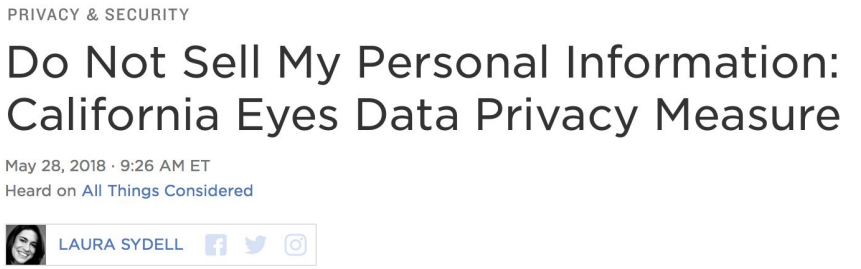
- Because data can sometimes contain personal or sensitive information, we should follow good practices to protect privacy: this is called **data stewardship**
- Laws like the EU's **GDPR** have been passed to help protect consumer data



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Discussion

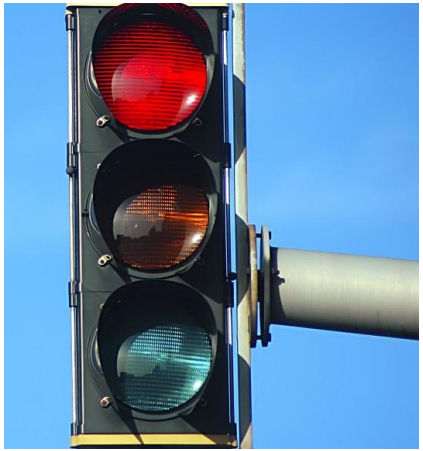
What are possible ways you can imagine gathering data while protecting users' privacy?

What sources of data might be more sensitive require more care in using?

Evaluation

How can we tell how good our system is?

- We mentioned earlier that we want to fit our data well -- how do we measure this?



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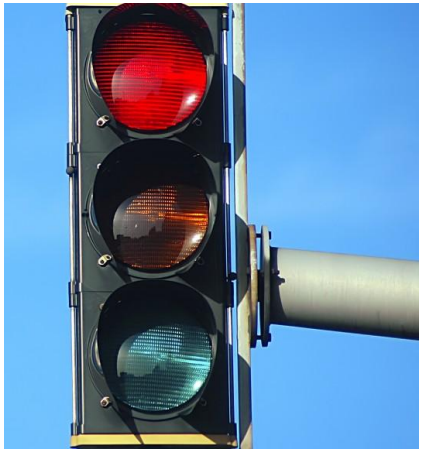
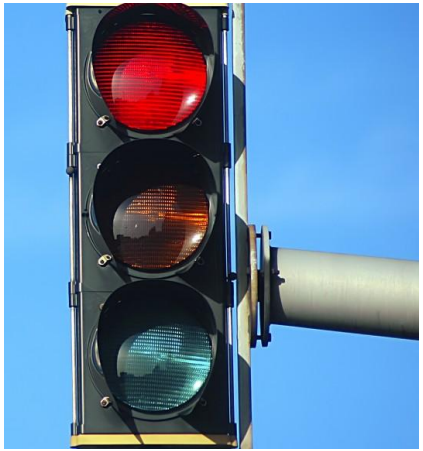


How can we tell how good our system is?

- We mentioned earlier that we want to fit our data well -- how do we measure this?
- One way is to look at the **accuracy** of a model
- Say we have 100 images of street lights that we want to classify as being green, yellow, or red
- If our model correctly classifies 95 of these 100 images, then we say our model has a 95% accuracy



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- There are different types of mistakes that we can make
- Take the example of detecting whether there is a fire in your home or not
- **False Positive (FP)**: When you think there is a fire, but there isn't
- **False Negative (FN)**: When you think there is not a fire, but there is
- Are these errors equally bad?

Other Metrics for Evaluation

	Actual: Yes	Actual: No
Predicted: Yes	True Positive (TP)	False Positive (FP)
Predicted: No	False Negative (FN)	True Negative (TN)

This table, when filled in with actual numbers,
is called a **confusion matrix**

Other Metrics for Evaluation

- **Precision**: Probability that a positive prediction is actually correct, TP / (TP + FP)

- **Recall** (or Sensitivity): Probability that an actually positive outcome is predicted correctly, TP / (TP + FN)

- **Specificity**: Probability that an actually negative outcome is predicted correctly, TN / (TN + FP)

- **F1 Score**: Combines precision and recall (how well do we predict a positive outcome -and- how good are our positive predictions)

  (2 * precision * recall) / (precision + recall)

Concepts Learned

- Machine Learning
- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning
- Models
- Features
- Examples and datasets
- Overfitting vs underfitting
- Accuracy
- True Positive / False Positive
- Precision / Recall