

Artificial Intelligence: Human Intelligence exhibited by machine.

Narrow AI: Computers can do a specific/one thing very well.

General AI: Computers can do multiple things like humans. We are very far away from this. Machine Learning: Approach to try and achieve AI through systems that can find patterns in data. Stanford Univ - Science of getting computers to act without being explicitly programmed.

**Deep Learning: One of the techniques to implement machine learning.** 

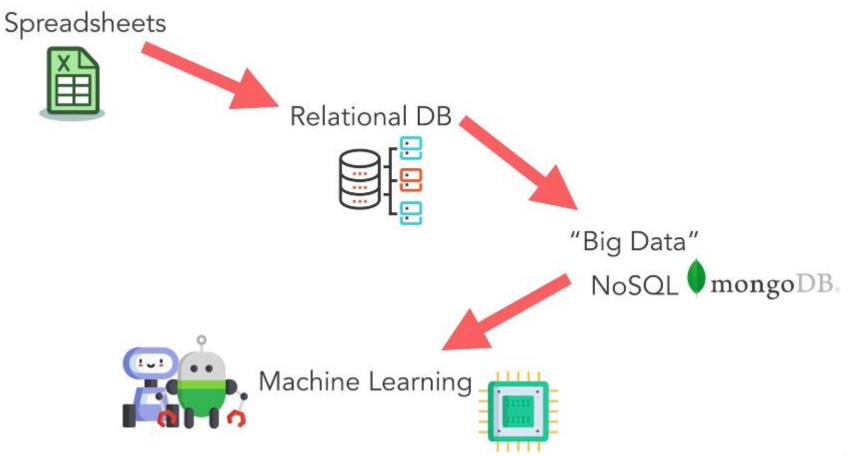
**Data Science: Analysing Data** 

### Play Ground

https://teachablemachine.withgoogle.com/

https://ml-playground.com/#

### How did we get here?



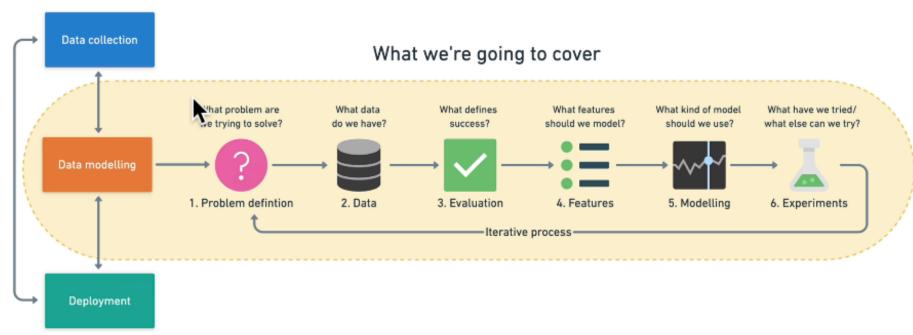
### YouTube Recommendation Engine

https://ml-playground.com/#

- X Axis Duration of Video
- Y Axis Likes to the Video

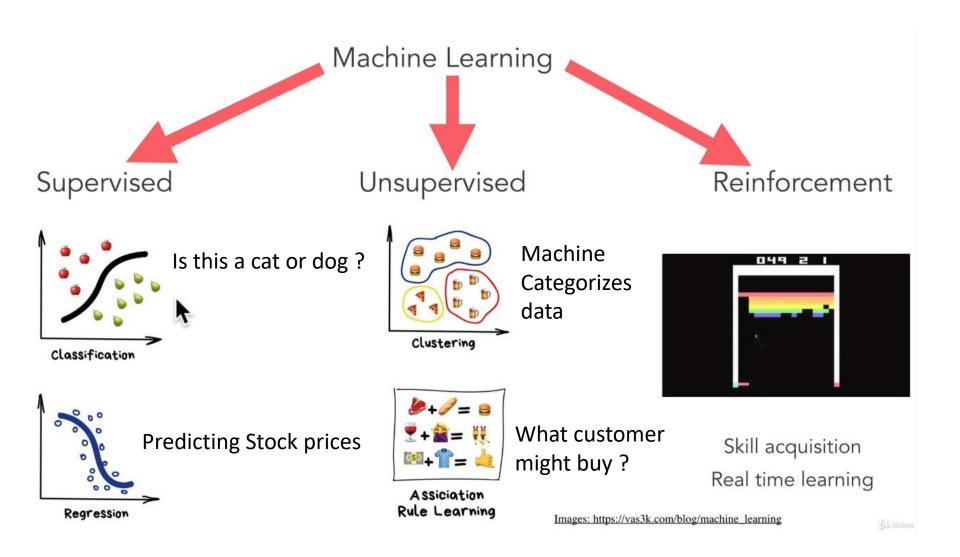
### Framework

Steps in a full machine learning project



### 1. Problem Definition

## Types of machine learning



### When not to use machine learning?

 Will simple hand coded instructions based system work? If yes, then use it.

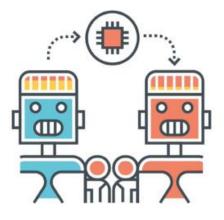
### Main types of machine learning



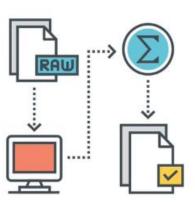
Supervised Learning



Unsupervised Learning



Transfer Learning



Reinforcement Learning

### Supervised learning



Classification

- "Is this example one thing or another?"
- · Binary classification = two options
- Multi-class classification = more than two options



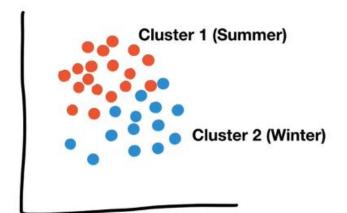
#### Regression

- · "How much will this house sell for?"
- "How many people will buy this app?"

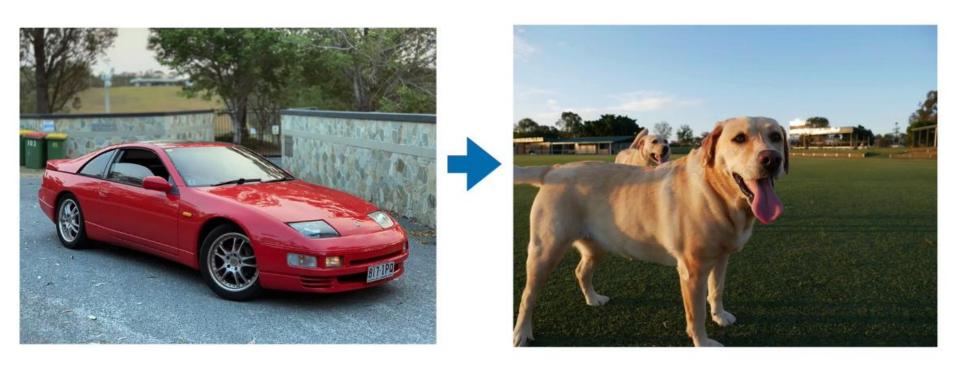
### Unsupervised learning

customer	Purchase 2	Purchage 2	
1	Sunglasses	Singlet	
2	Jacket	Snow boots	
3	Sunscreen	Beach towel	

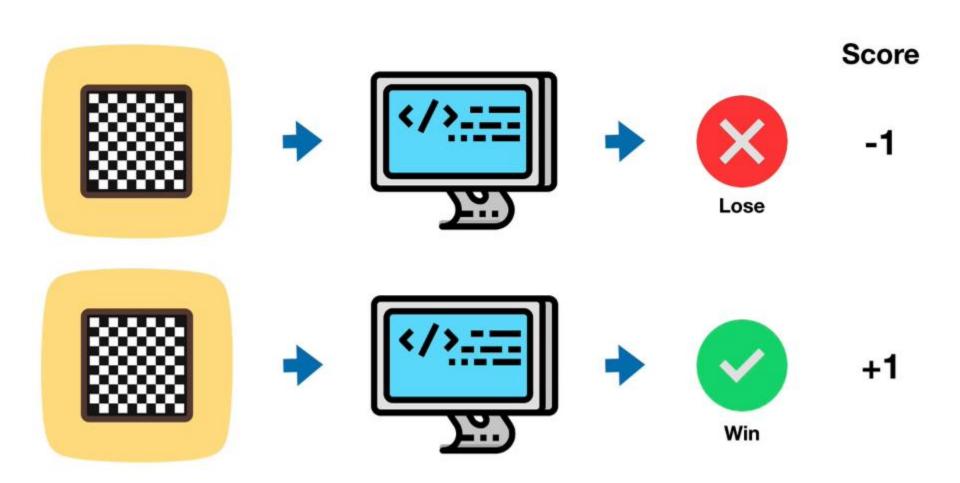




## Transfer Learning



### Reinforcement Learning



### **Problem Definition**

Matching your problem



"I know my inputs and outputs."



Supervised Learning



"I'm not sure of the outputs but I have inputs."



Unsupervised Learning



"I think my problem may be similar to something else."

Transfer Learning

# 2.Data

"What kind of data do we have?"

### Types of Data

#### Rows

	ID	weight	Sex	Blood Presture	Chest	Heart disease?
s	4326	IIOKg	Μ	120/00	4	Yes
lumns	5681	64159	F	130	,	No
ပိ	7911	BIKg	M	130	0	NO

Table 1.0: Patient records



Structured



From: <u>daniel@mrdbourke.com</u> Hey Daniel,

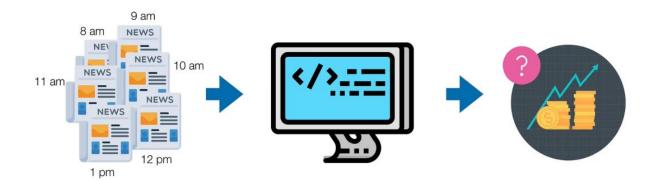
First of all, thank you for being so amazing. This machine learning course is incredible. Thank you for keeping it simple!

#### Unstructured

### Types of Data ....



**Static** 



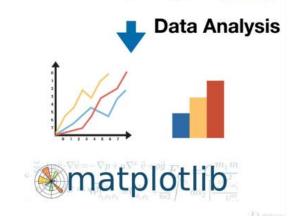
**Streaming** 

### A data science workflow



Machine learning model

Heart disease?

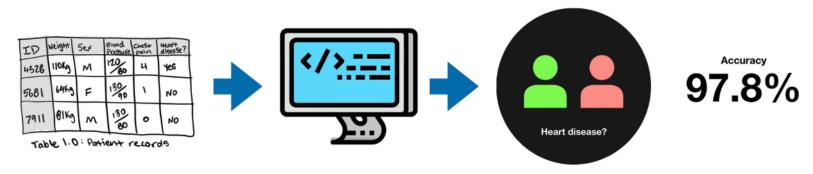


## 3. Evaluation



"What defines success for us?"

### "For this project to be worth pursuing further, we need a machine learning model with over 99% accuracy."

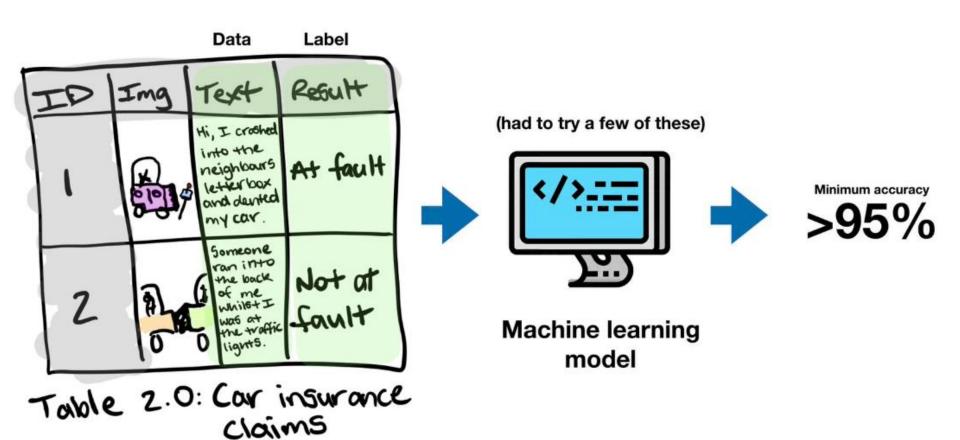


Machine learning model

## Types of metrics

Classification	Regression	Recommendation
Accuracy	Mean absolute error (MAE)	Precision at K
Precision	Mean squared error (MSE)	
Recall	Root mean squared error (RMSE)	

### Classifying Car insurance claims



## 4. Features



"What do we already know about the data?"

#### Feature variables can be

- Numerical
- Categorical

#### **Feature engineering**

- Deriving new features from existing one.

#### **Feature Coverage**

- Checking if values are correctly populated for a feature or not? Do not use it if it is not well covered.

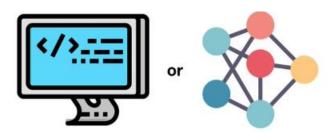
Feature variables Target variable				Target variable	Derived feature			
T	ID	weight	Sex	Heav4 Rotte	Chest	Heart disease?	visit in a	most eaten food
1	4326	110kg	M	81	4	Yes	Yes	Friks
	5681	6449	F	61	١	No	Yes	7
	7911	81Kg	M	57	0	NO	NO	?
Table 1.0: Patient records								

# 5. Modelling Part 1 — 3 sets

"Based on our problem and data, what model should we use?"

### 3 parts to modelling

1. Choosing and training a model



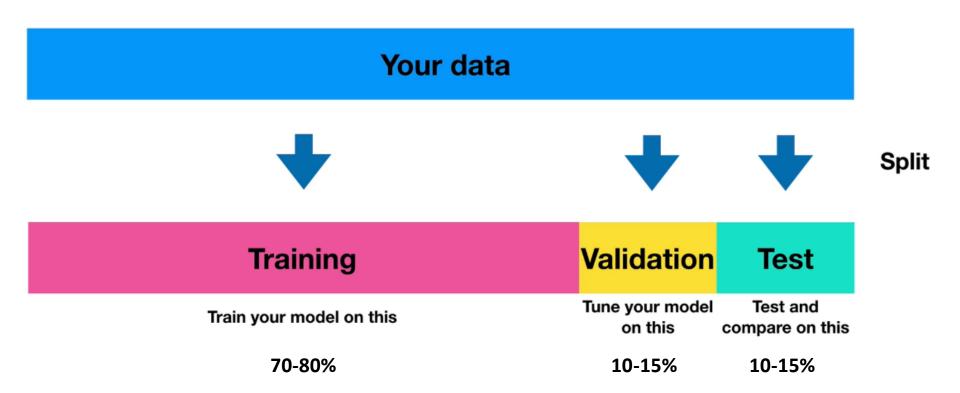
2. Tuning a model



3. Model comparison



### Training, validation and test sets

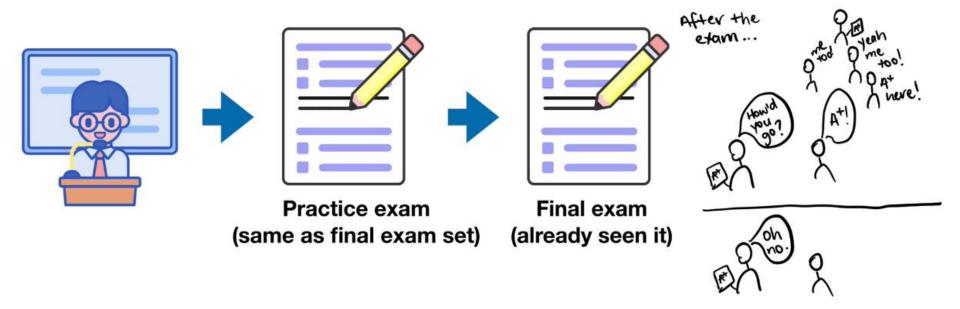


### 3 sets



**Generalization** – The ability for a machine learning model to perform well on data it hasn't seen before.

### When things go wrong?



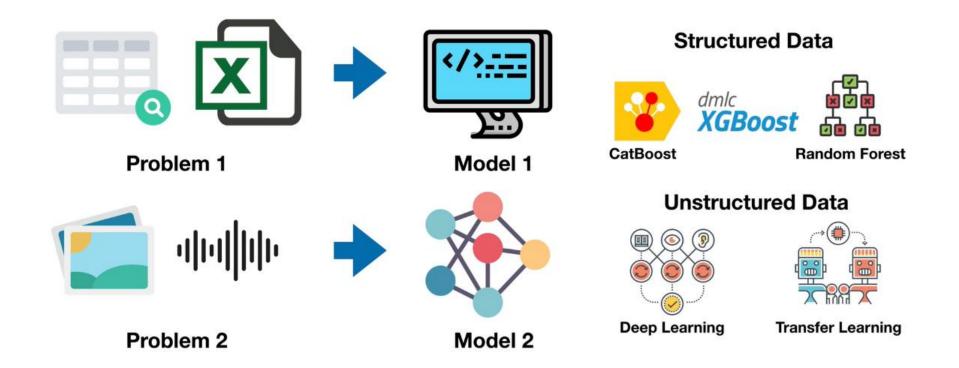
Machine really did not learn anything, it just memorized what it solved in training part.

## 5. Modelling Part 2 — Choosing

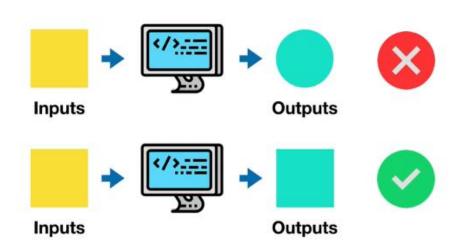


"Based on our problem and data, what model should we use?"

### Choosing a model



## Training a model

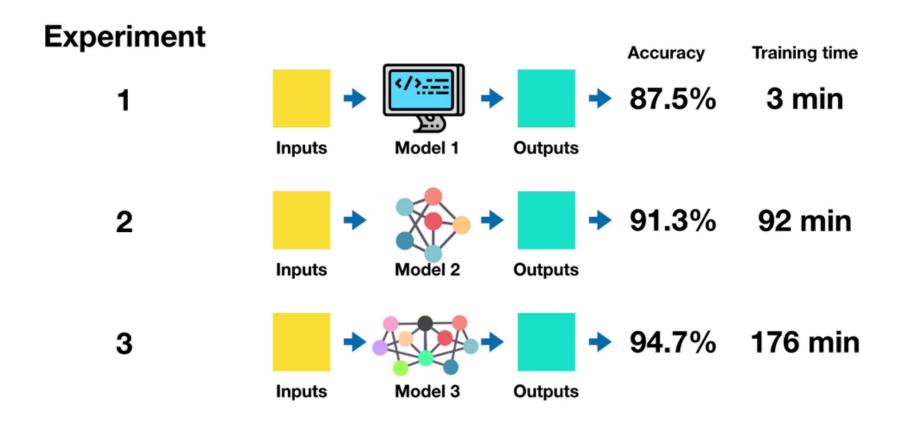


X (data) y (lab						
ID	weight	Sex	Heave   Rote	Chest	Heav't disease?	
4326	llokg	M	81	4	Yes	
5681	64Kg	F	61	١	No	
7911	BIKg	M	57	0	NO	

Table 1.0: Patient records

**Training Data** 

#### **Goal - Minimize time between experiments**



Sometimes for smaller %age extra of Accuracy, we end up spending lot of time. We should avoid that.

### Remember

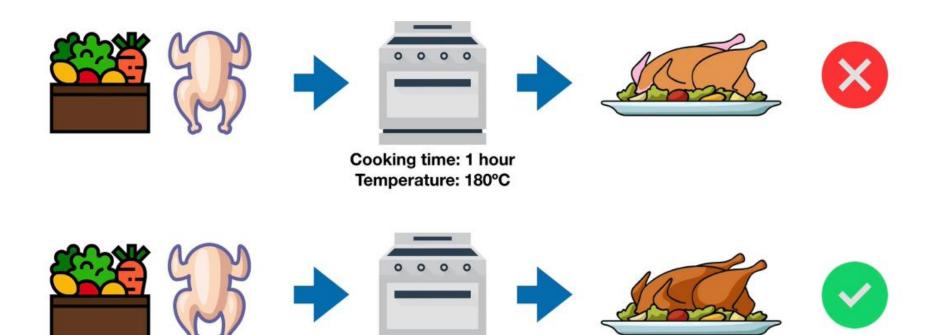
- Some models work better than others on different problems
- Don't be afraid to try things
- Start small and build up (add complexity) as you need

## 5. Modelling Part 3 — Tuning



"Based on our problem and data, what model should we use?"

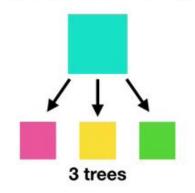
### **Tuning**

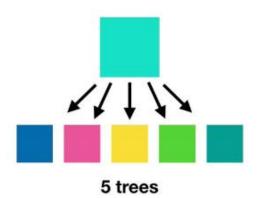


Cooking time: 1 hour Temperature: 200°C

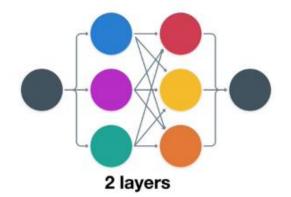
## Tuning...

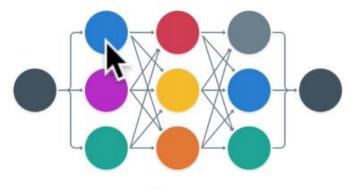
#### **Random Forest**





#### **Neural Networks**





3 layers

#### Remember

- Machine learning models have hyperparameters you can adjust
- A models first results aren't its last
- Tuning can take place on training or validation data sets



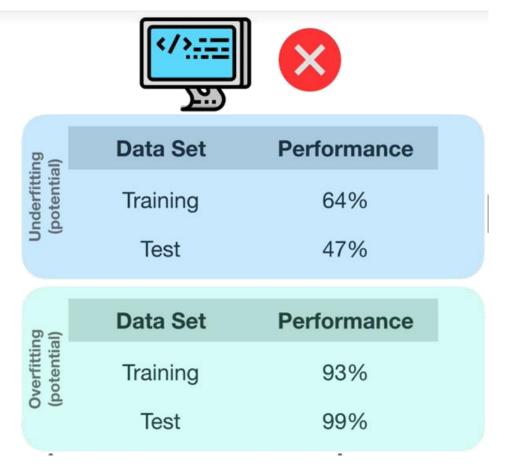
## 5. Modelling Part 4 — Comparison

"How will our model perform in the real world?"

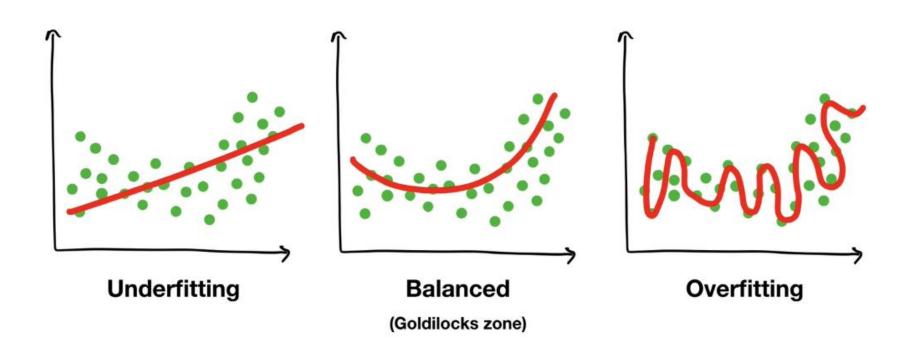
### **Model performance**



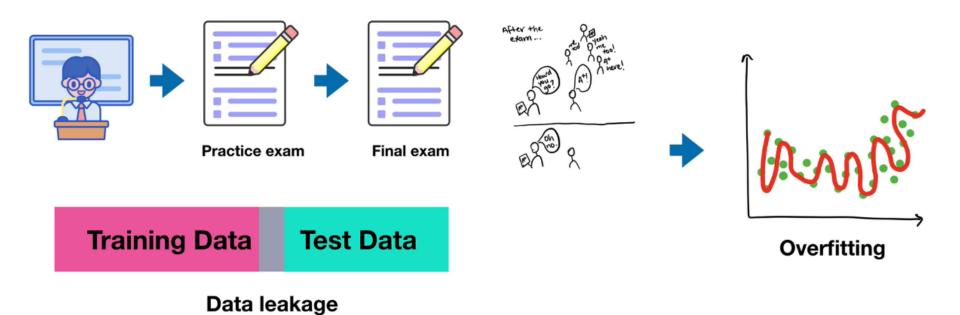
Data Set	Performance
Training	98%
Test	96%



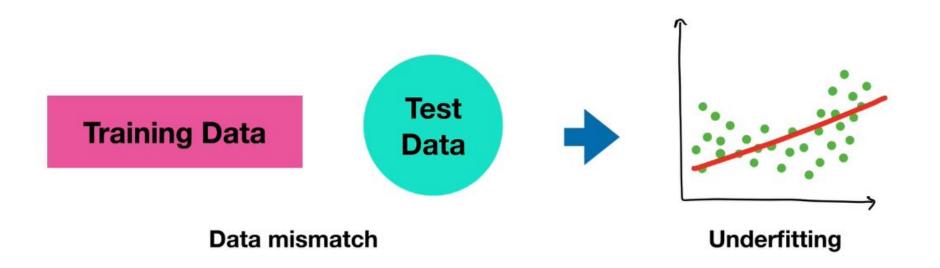
## **Overfitting and Underfitting**



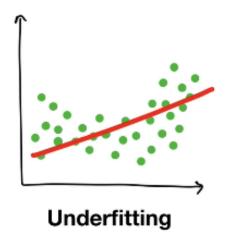
## **Overfitting and Underfitting**



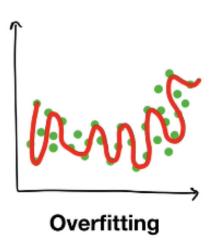
### **Overfitting and Underfitting**



#### Fixes for Overfitting and Underfitting

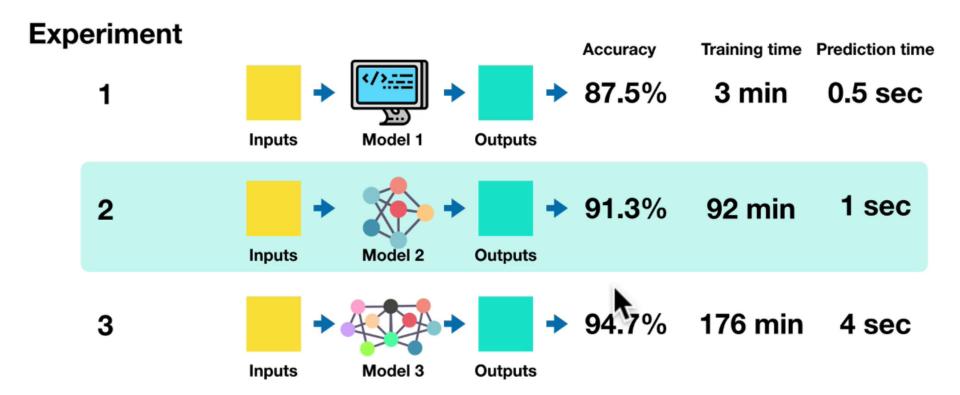


- Try a more advanced model
- Increase model hyperparameters
- Reduce amount of features
- Train longer



- Collect more data
- Try a less advanced model

#### Comparison



#### Remember

- Want to avoid overfitting and underfitting (head towards generality)
- Keep the test set separate at all costs
- Compare apples to apples
- One best performance metric does not equal best model

# 6. Experimentation



"How could we improve/what can we try next?"

#### **Experimentation**

Try out a different approach for improving the machine learning model

#### **Tools**



#### **Tools mapping**

