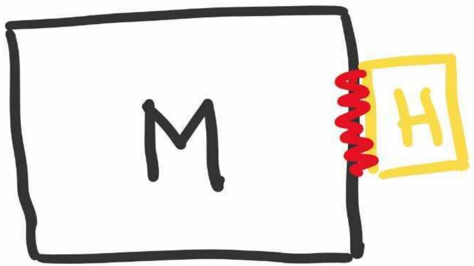
Introduction

Boston University CS 506 - Lance Galletti

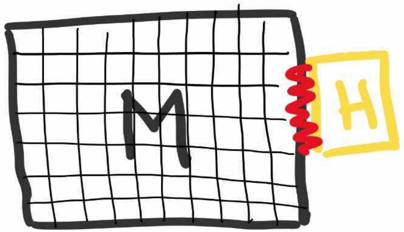
Data Science

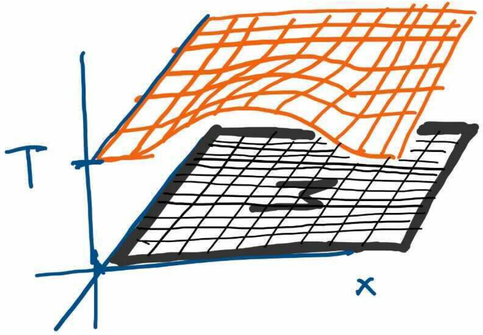
- Collection of methods and tools that allow for extracting knowledge from data
- Cross-disciplinary:
    - Math
    - Statistics
    - Computer Science
    - Domain Expertise
- Know what you don’t know!

Knowledge = Testable Predictions



Knowledge = Testable Predictions





at time t_0

Knowledge = Testable Predictions

Model:

f(x, y, t) => temperature

“Heat Diffusion”

VS

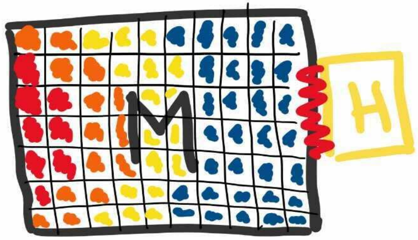
Magic

Which theory should we use?

How to distinguish or unify them?

Knowledge = Testable Predictions

Scientific perspective: look at what each theory anticipates!



Knowledge = Testable Predictions

If you can equally well explain every outcome, how can you have a definitive / deterministic anticipation of events?

If you’re equally good at explaining every outcome, you have zero knowledge.

Confirmation Bias

In a class just like this one, imagine playing the following game…

Confirmation Bias

I announce “(2, 4, 6) follows the rule”.

Here are the examples submitted by one of the participants:

- (2, 4, 3) -> NO
- (6, 8, 10) -> YES
- (1, 3, 5) -> YES

After which, they proceed to write down their hypothesized rule. Would you have wanted to try more examples? If so, which and for what reason?

Confirmation Bias

Let's take a poll:

A. (100, 102, 104)
B. (5, 7, 9)
C. (1, 2, 3)

Confirmation Bias

Challenges of Data Science:

- Not all examples contribute similar amounts of information
- A set of examples may not always be representative of the underlying rule
- There may be infinitely many rules that match the examples provided

So Data Science is VERY DIFFICULT!!! All models are wrong but some are useful

Confirmation Bias

Positive Examples VS Negative Examples

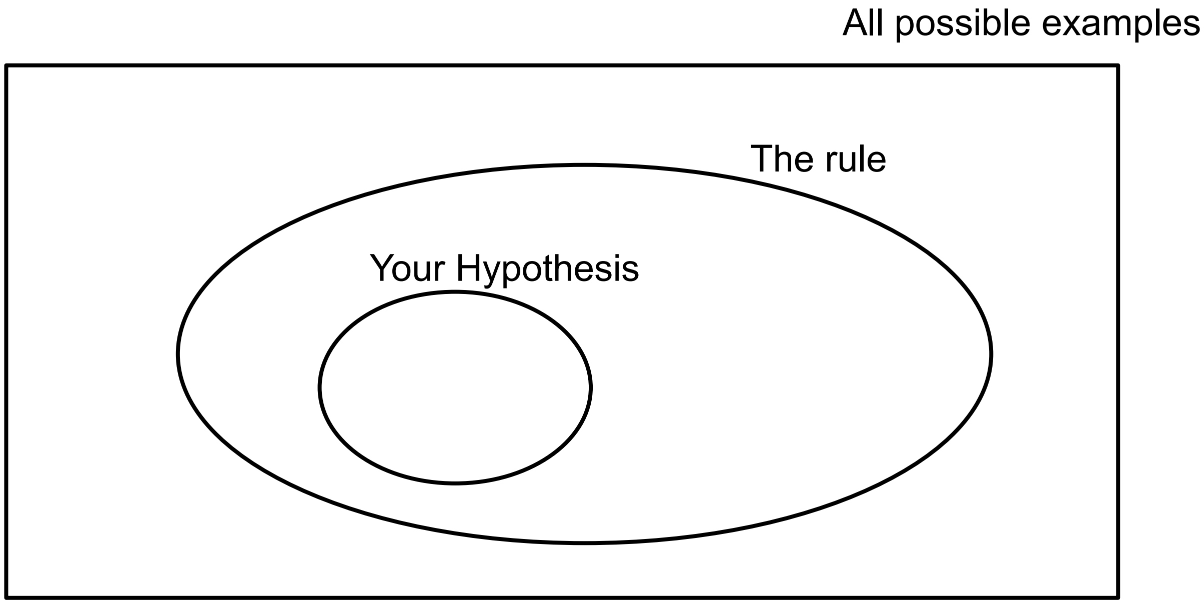
assuming the hypothesis h is (x, x+2, x+4) which type of examples are the following:

- (2, 4, 3)
- (6, 8, 10)
- (1, 3, 5)

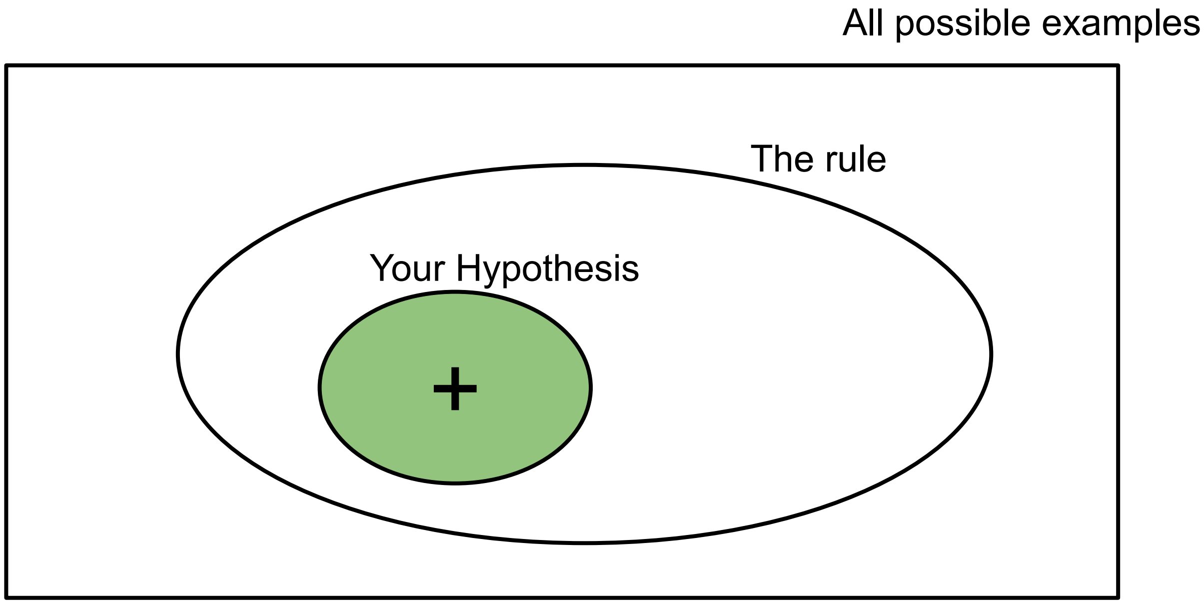
Confirmation Bias

- Both positive and negative examples can falsify a hypothesis
- Tendency to choose positive ones over negative ones

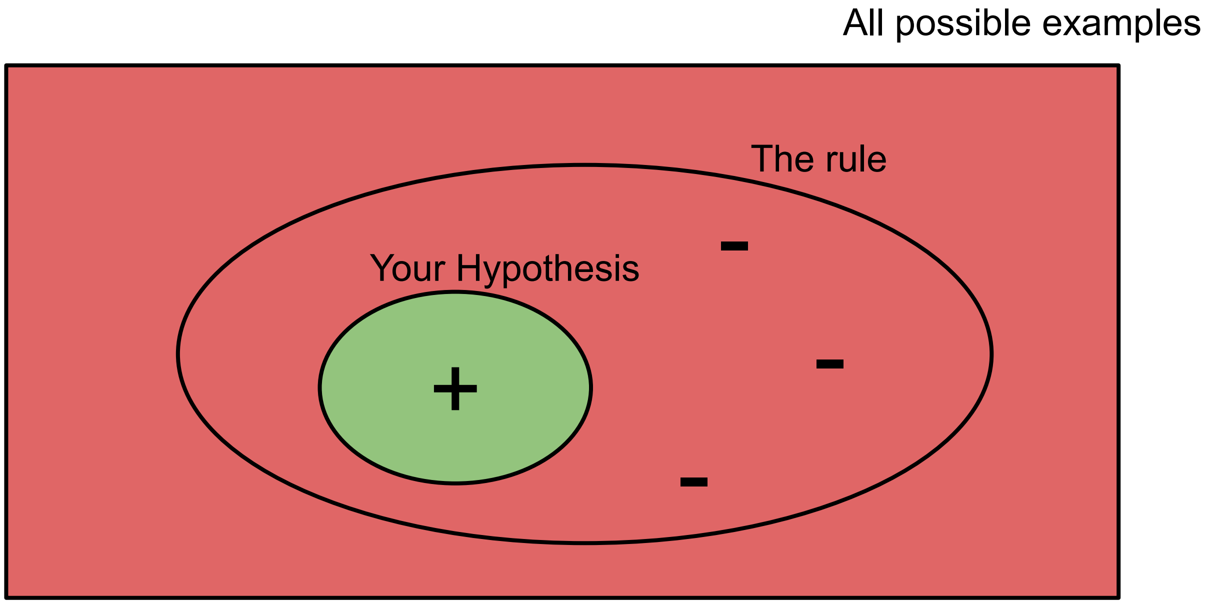
Confirmation Bias



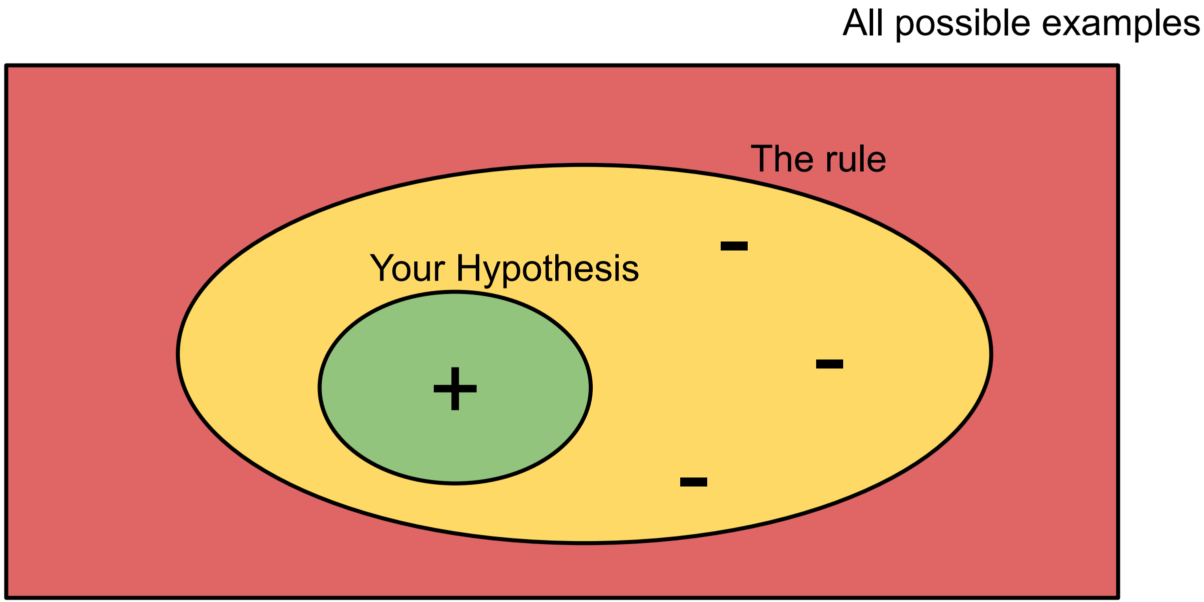
Confirmation Bias



Confirmation Bias



Confirmation Bias



Confirmation Bias

Let’s take a poll:

A. (100, 102, 104)
B. (5, 7, 9)
C. (1, 2, 3)

Confirmation Bias

The rule was (a < b < c).
If you only tried positive examples of either (x, x + 2, x+4) or (x, 2x 3x) you would only get confirmation.

For reference, this exercise was first introduced by Wason P.C in 1960 as part of a journal in experimental psychology.

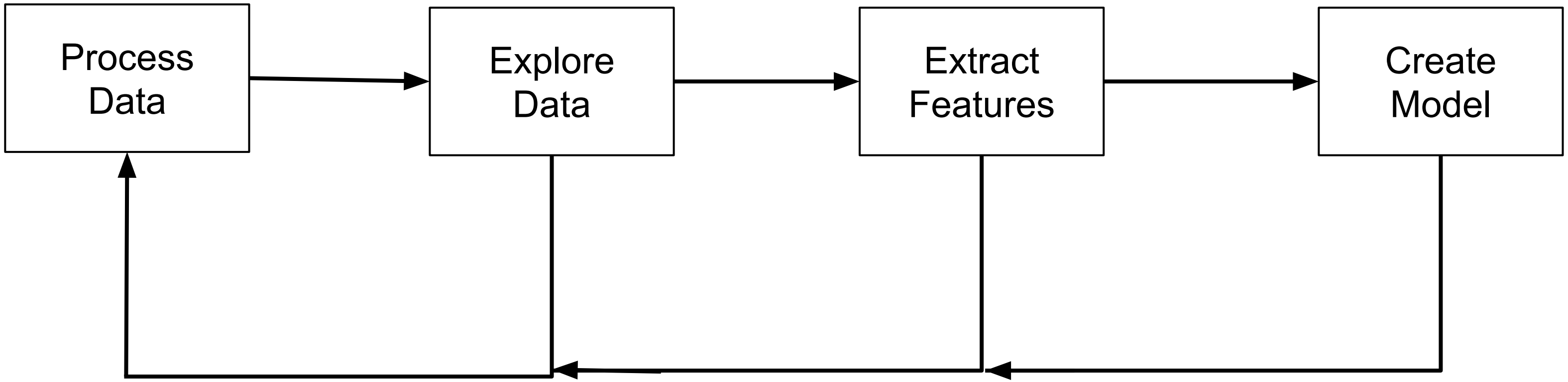
Confirmation Bias

Data Science Workflow (simplified)

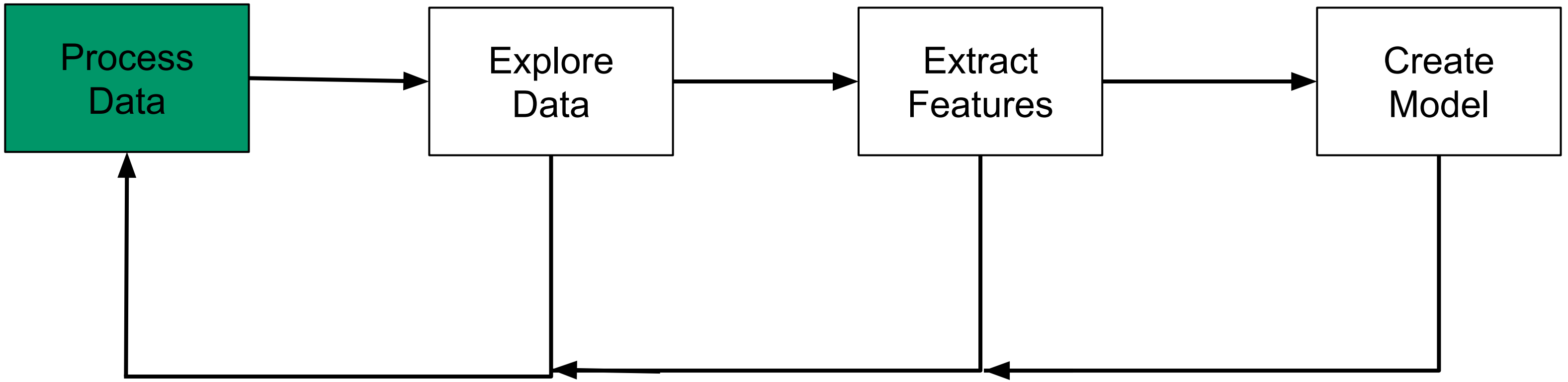
First ask what and **who** the model is used / intended for

- Is it just the general trend that is important of the exact predictions that are important?
- Is this a problem that **needs** predictive tools to solve?

Data Science Workflow (simplified)



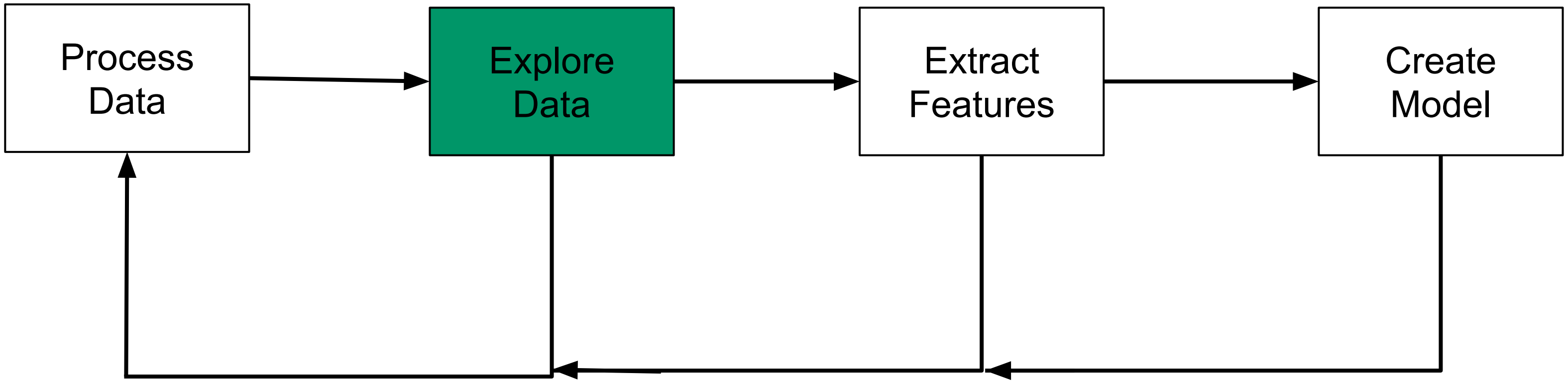
Data Science Workflow (simplified)



Data Processing

- What data should and shouldn’t be used for the task?
- What to do with missing data?
- What to do with inconsistent data?
- What assumptions are you making with the transformations of the data?

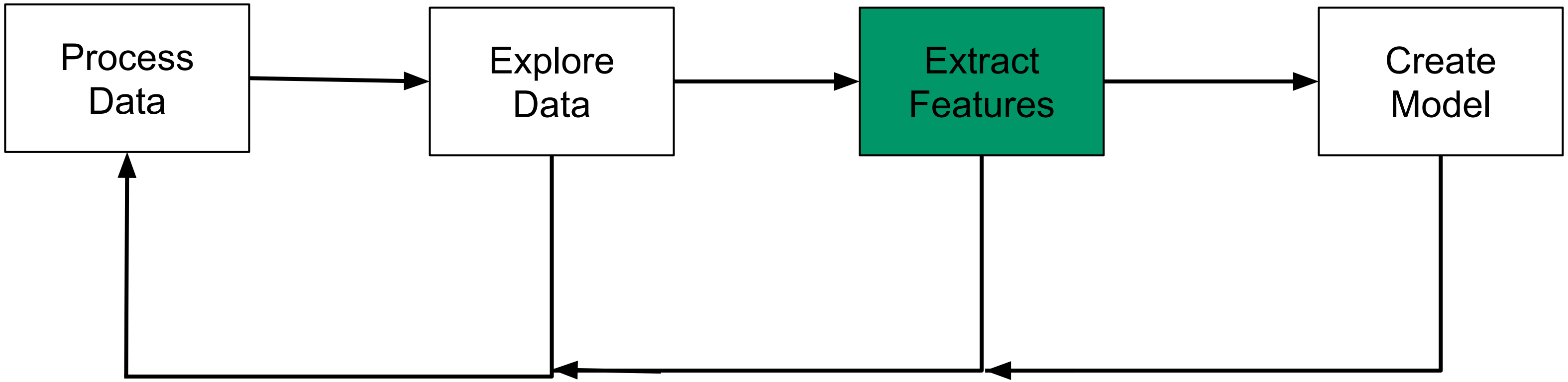
Data Science Workflow (simplified)



Exploratory Data Analysis

- Describe, contextualize, and visualize the data
- What might be related to what you're trying to predict?
- Are there imbalances in the data?

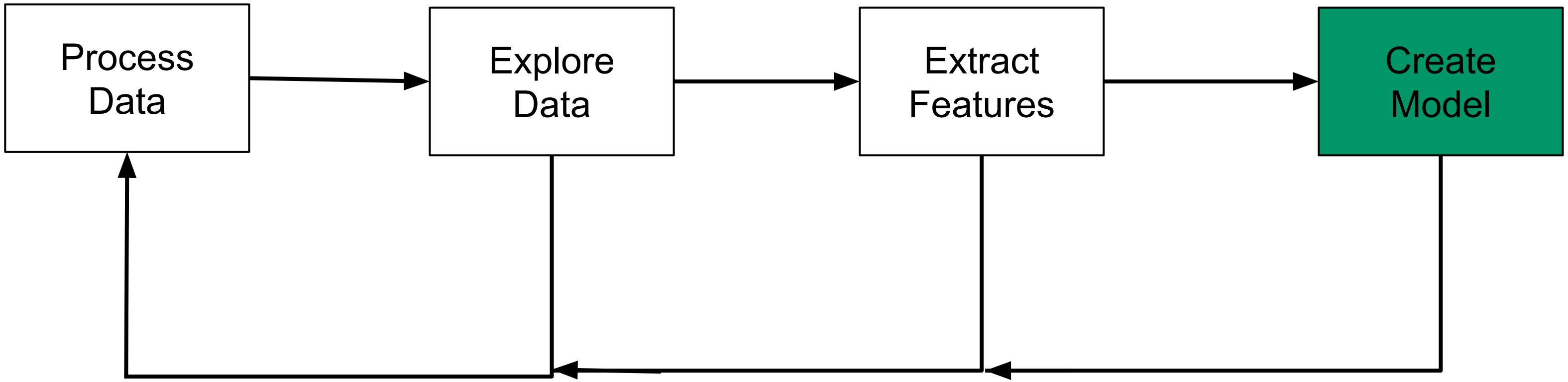
Data Science Workflow (simplified)



Feature Extraction

- Are the features provided by the dataset the best features to use for the task?
- What other features can be extracted?
- Should existing features be transformed?

Data Science Workflow (simplified)



Finding the right model

- The success of this step depends entirely on the work done in previous steps - remember: **garbage in, garbage out!** (it’s all about the data)
- Is your model easy to explain?
- When your model fails, can you explain why?

Types of Data

Types of Data - Records

m-dimensional points / vectors

Example: (name, age, balance) -> (“John”, 20, 100)

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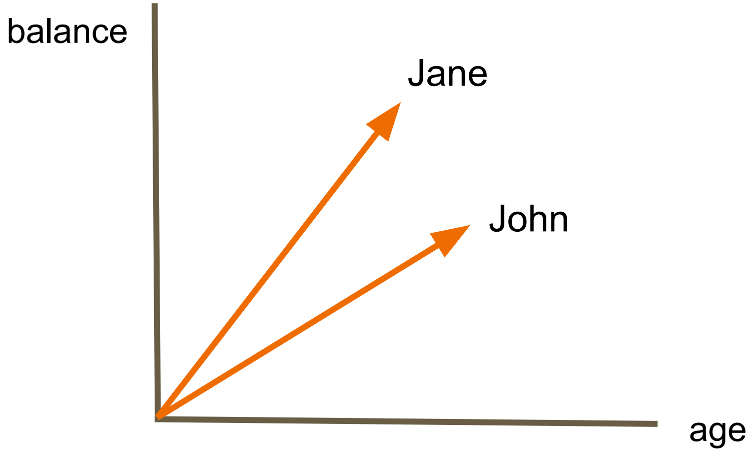
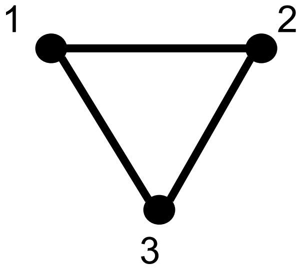


Types of Data - Graphs

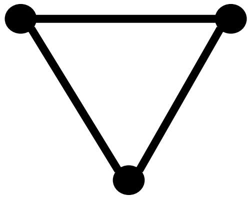
Nodes connected by edges

Example:



Adjacency Matrix

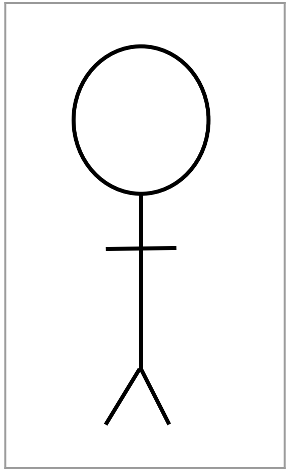
$$
\begin{array}{cc}
 & \begin{array}{ccc} 1 & 2 & 3 \end{array} \\
\begin{array}{c} 1 \\ 2 \\ 3 \end{array} & \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{pmatrix}
\end{array}
$$



Adjacency List

1 : {2, 3}
2 : {1, 3}
3 : {1, 2}

Types of Data - Images



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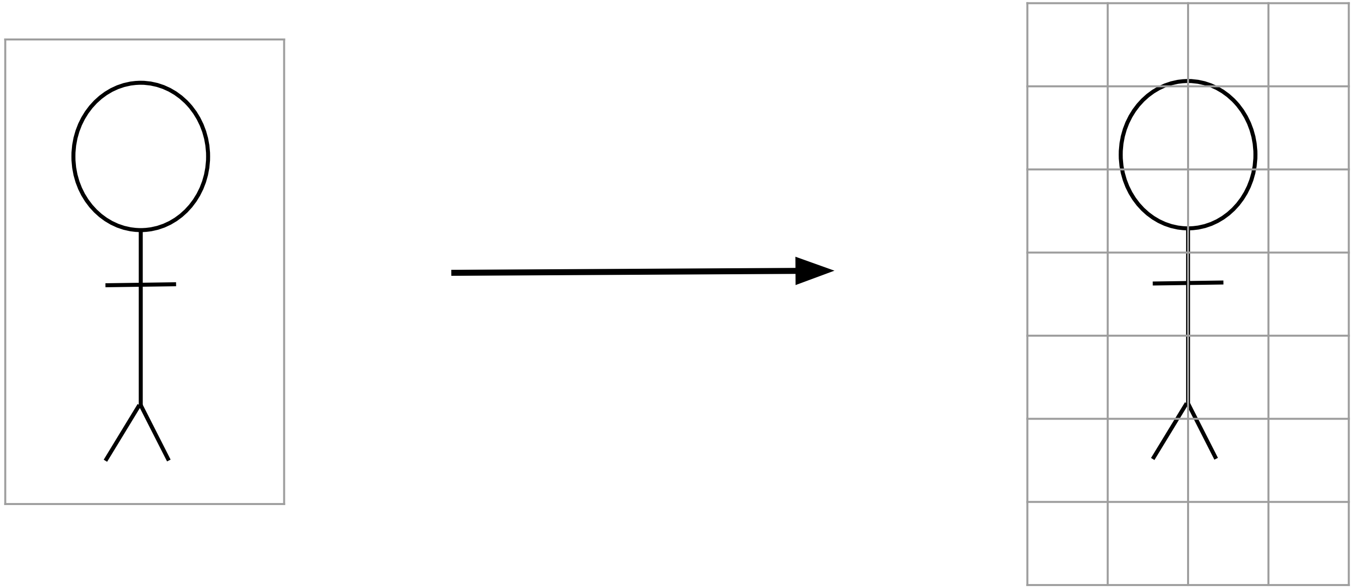

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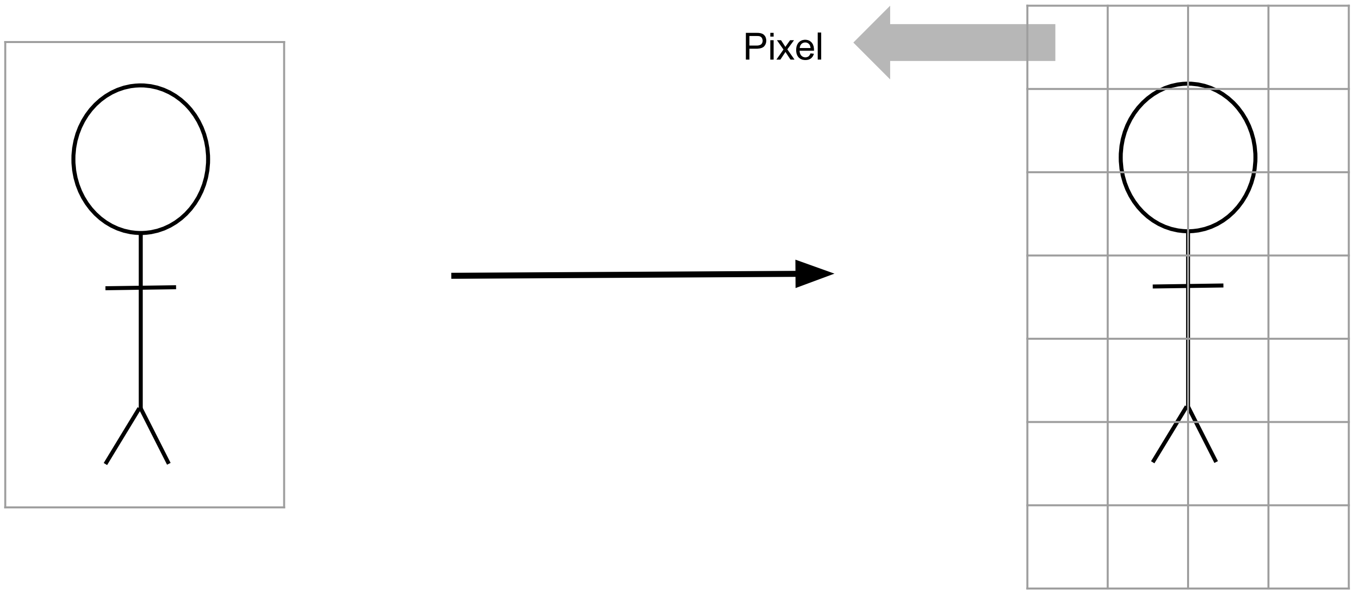
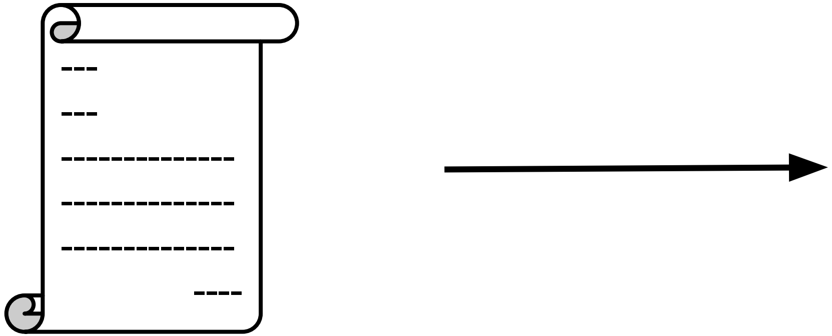
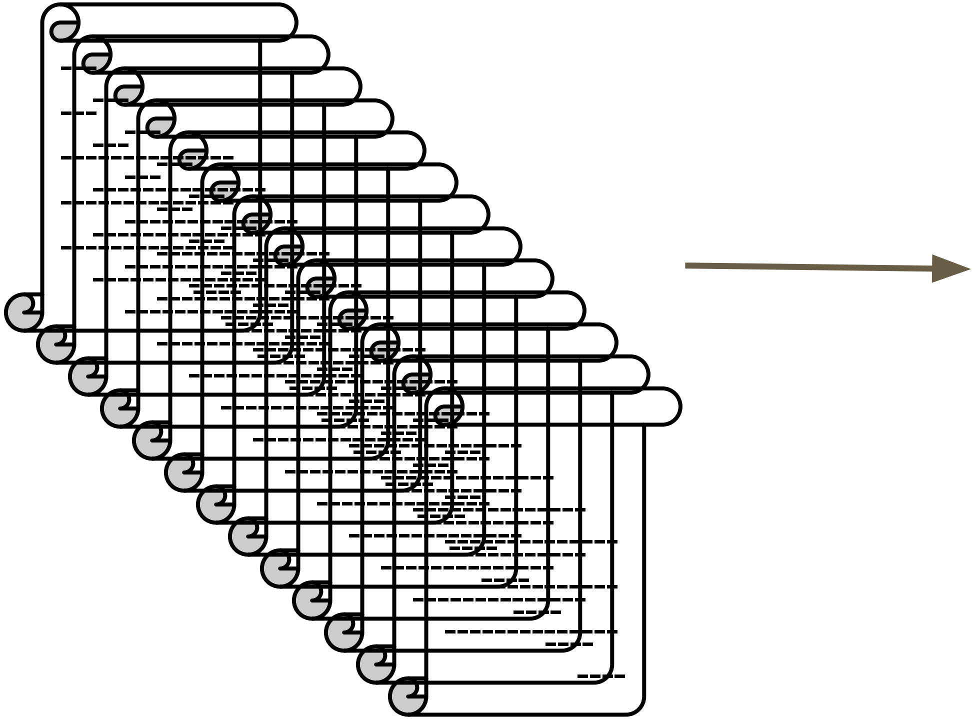


Types of Data - Text



List of words

Types of Data - Corpus of Documents



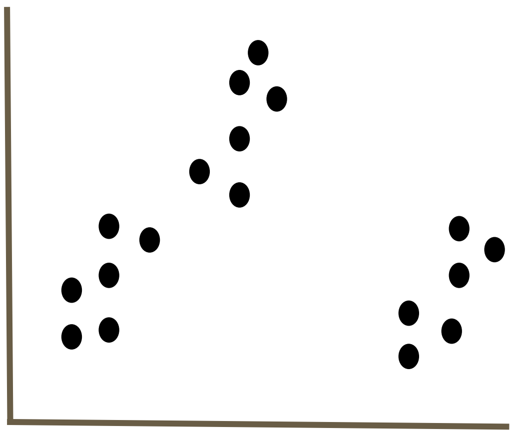
	w_1	w_2	…	w_m
D_1	1	0	…	1
D_2	0	0	…	0
…	…	…	…	…
D_n	1	1		1

Types of Learning

- Unsupervised Learning
- Supervised Learning

Unsupervised Learning

Goal: Find interesting structure in the data



Unsupervised Learning

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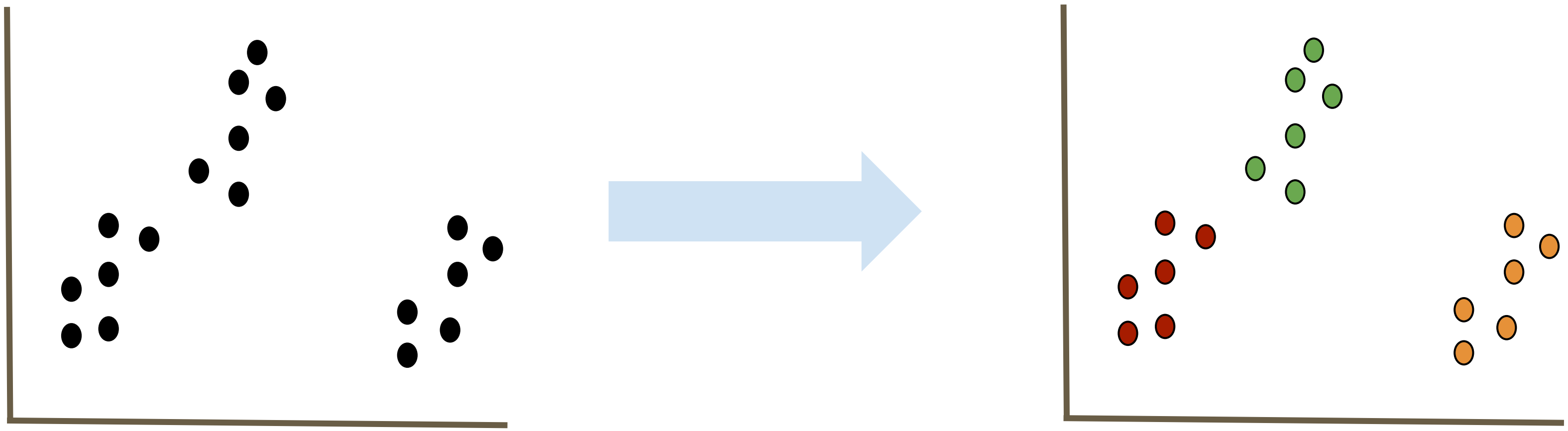

This type of unsupervised learning is referred to as clustering

Unsupervised Learning

What are some linear algebraic properties of the matrix of data? What does that tell me about the data?

$$\textbf{n}\text{ data points}\left\{\underbrace{\begin{pmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots & & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & & \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nj} & \cdots & x_{nm} \end{pmatrix}}_{\textbf{m}\text{ features}}\right.$$

Unsupervised Learning

Dataset: Collection of Articles

Question: Are these articles covering the same topics?

Unsupervised Learning

Goals:

1. Better understand / describe the data
    a. Data exploration / visualization step
    b. Find anomalies
    c. Recommender Systems (similar users might be recommended the same things, emails similar to those marked as spam could be spam etc.)
2. Extract Features
3. Fill in gaps in data
    a. Data preprocessing step
4. Make learning algorithms faster
    a. Get rid of noise

Supervised Learning

cricket chirps / min	temperature
10	40
5	37
17	53
55	103
40	78

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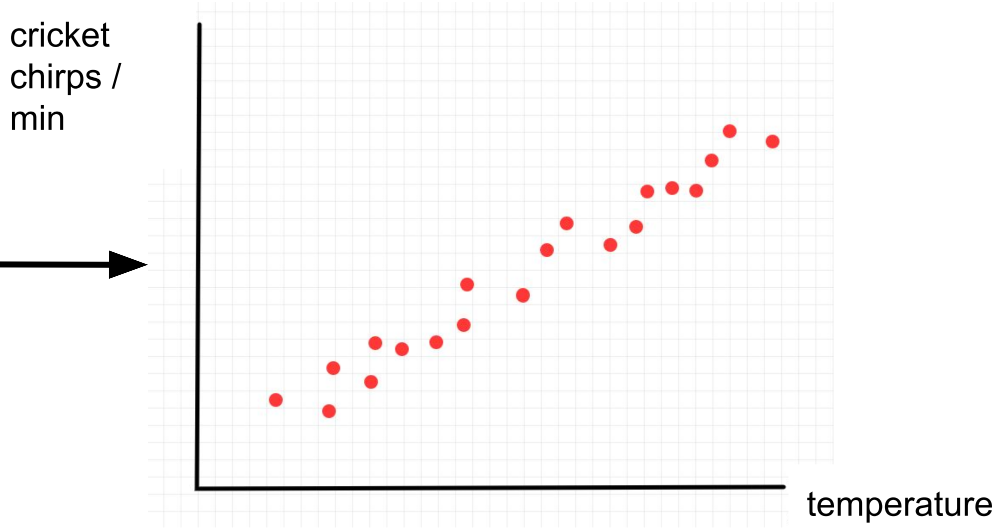

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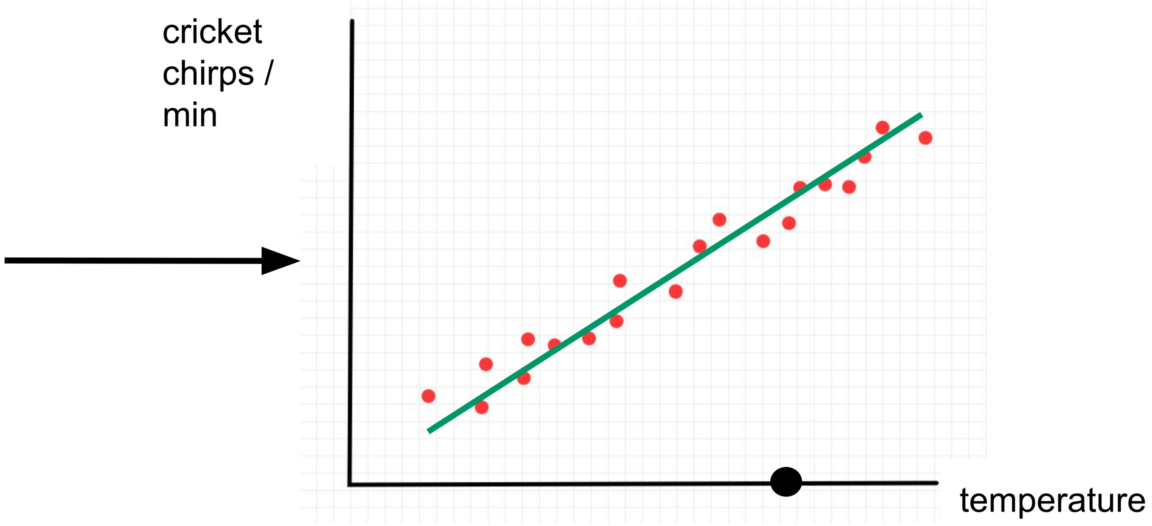

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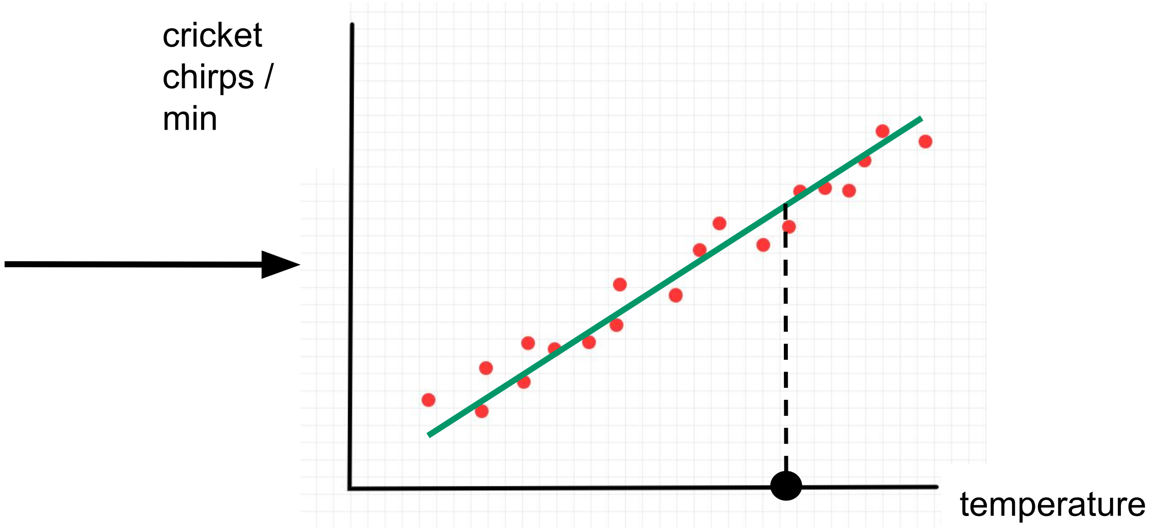

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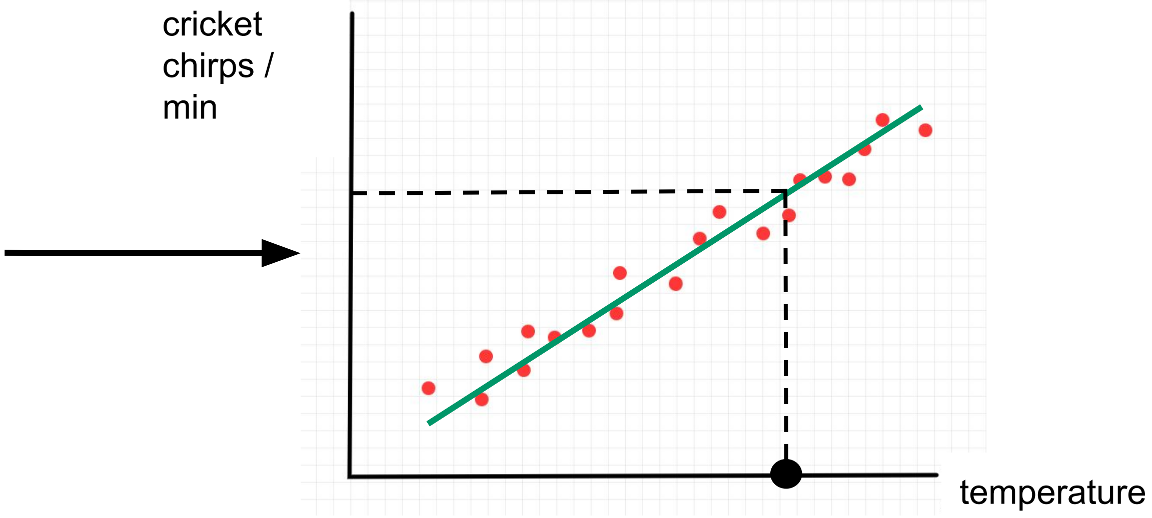

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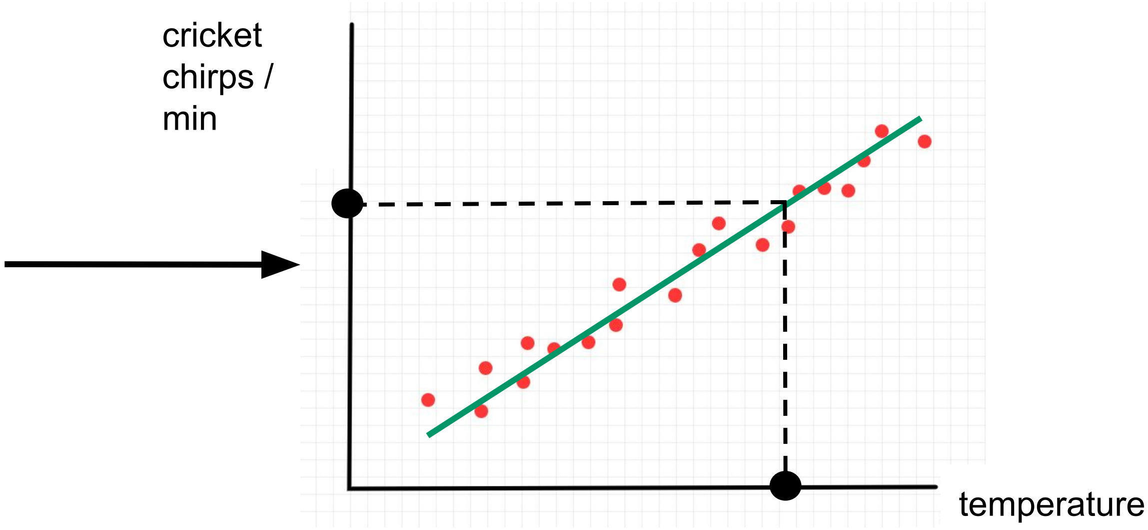

This type of supervised learning is referred to as regression

Supervised Learning

age	tumor size	malignant
20	12	0
22	15	1
47	20	1
59	2	1

Supervised Learning

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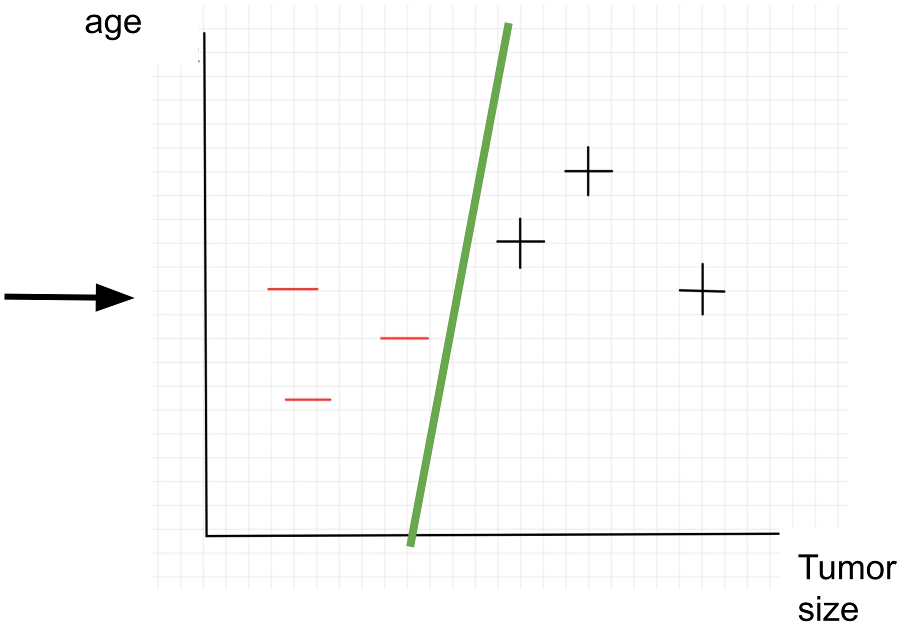

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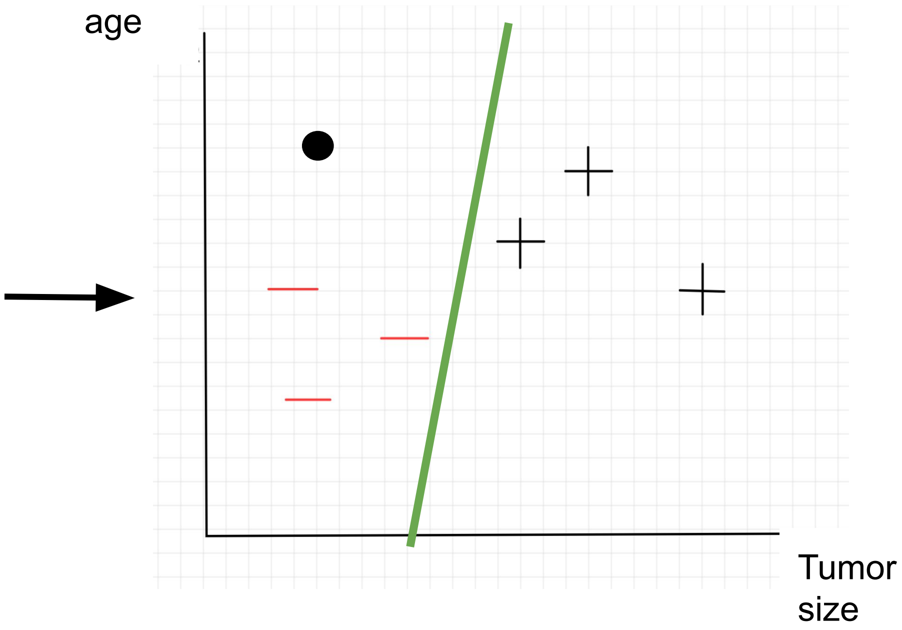

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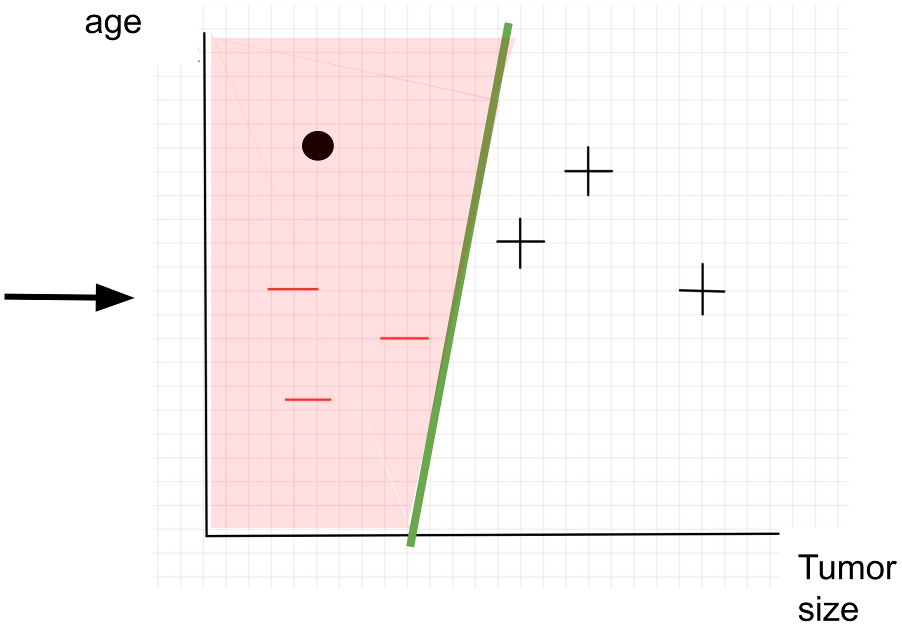

This type of supervised learning is referred to as classification