Machine Learning for Cyber Security Part 1

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1. Introduction

Objectives

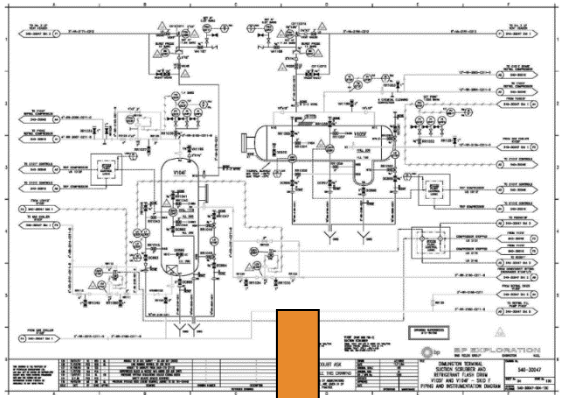
- Understand the main principles of Machine Learning (ML)
- Be exposed to the most relevant tools used in academia and the industry to implement ML-based solutions
- Comprehend a series of real cases where ML is used to solve cybersecurity problems

- 2005-2010: Bachelor of Electronic Engineering (Major in Telecommunications)
    - Tec de Monterrey, Mexico City
- 2010-2012: Teacher/Researcher
    - Research group: Centro de Investigación en Mecánica y Biodiseño (Prof. Rogelio Bustamante)
    - Tec de Monterrey, Mexico City
- 2012-2013: Ms C. Cyber Security and Intelligent Systems
    - Universitat Rovira i Virgili, Tarragona, Spain
- 2013-2016: Ph. D. Computer Science and Mathematics of Security
    - Research group: Sistemas Sensoriales Aplicados a la Industria (Prof. Francesc Serratosa)
    - Universitat Rovira i Virgili, Tarragona, Spain
- 2017-2018: Research Fellow in Computing
    - Research w/ Dr Eyad Elyan and Prof Chrisina Jayne (Industrial collaboration with DNV GL)
    - Robert Gordon University, Aberdeen, UK
- 2018: Lecturer in Computing
    - Placements and Electives Coordinator
    - Robert Gordon University, Aberdeen, UK
- 2020: Senior Lecturer in Computing
    - Research Degrees Coordinator
    - Robert Gordon University, Aberdeen, UK

ROBERT GORDON UNIVERSITY ABERDEEN

Main Achievements

- Published 57 scientific papers in international journals and conferences
- Two patents and several prototypes
- Worked with multiple academic partners:
  - UNAM
  - IPN
  - Tec de Monterrey
  - IMP
  - University of Utah
  - University of Munster
  - Taylors's University (Malaysia)
- Collaboration with the industry:
  - Energy sector: DNV GL, Equinor (Statoil), Total, Baker, AISUS, Mintra Group, etc.
  - Healthcare: NHS, ISSSTE
- EuDIF (RedGlobalMX and Google)



Event	Equip[illegible]ategory	Size	Number
JDY/CELLAR/RJAS/W	Piping	16	
JDY/CELLAR/RJAS/W	Act. Valve	16	0.5
JDY/CELLAR/JASIN/W	Piping	16	
JDY/CELLAR/JASIN/W	Act. Valve	16	0.5
JDY/PROC/JASIN/W	Piping	16	
JDY/PROC/JASIN/W	Act. Valve	16	2
JDY/PROC/JASIN/W	Flange	16	7
JDY/PROC/JASIN/W	Piping	6	
JDY/PROC/JASIN/W	Man Valve	16	3
JDY/PROC/JASIN/W	Piping	2	
JDY/PROC/JASIN/W	Flange	2	2
JDY/PROC/JASIN/W	Inst. Con.	2	2
JDY/PROC/JASIN/W	Man Valve	6	0.5

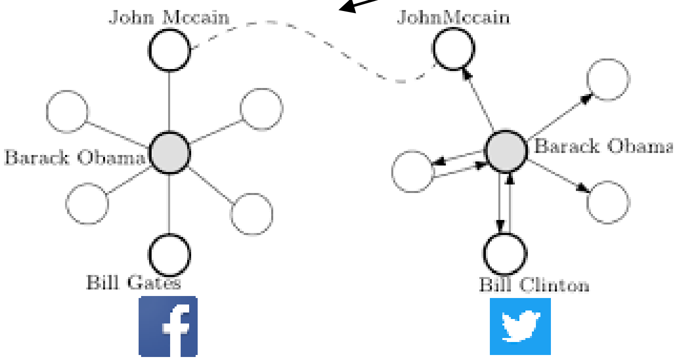
Where am I!?


Iceland
Sweden
Finland
Norway
Estonia
Latvia
Denmark
Lithuania
Russia
Ireland
United Kingdom
Netherlands
Belarus
Poland
Germany
Belgium
Czech Republic
Slovakia
Ukraine
Luxembourg
France
Moldova
Austria
Hungary
Switzerland
Romania
Slovenia
Croatia
Bos & Herz
Serbia
Bulgaria
Portugal
Italy
Montenegro
Macedonia
Spain
Albania
Greece


Aberdeen
United Kingdom

How did I get "here"?

MSc Cyber Security



Networks

Biometrics

2. Fundamentals of ML

Go to www.menti.com and use the code you see on the screen

What is ML?

- “Machine learning is the scientific study of algorithms and statistical models that computer systems use to perform a specific task without using explicit instructions, relying on patterns and inference instead.” — Wikipedia

- “Machine learning at its most basic is the practice of using algorithms to parse data, learn from it, and then make a determination or prediction about something in the world.” — Nvidia

- “Machine learning is the science of getting computers to act without being explicitly programmed.” — Stanford

- **Our working definition**, it’s the statistical discrimination, where the “machine” itself learns the discriminator (mathematical models) using the provided data

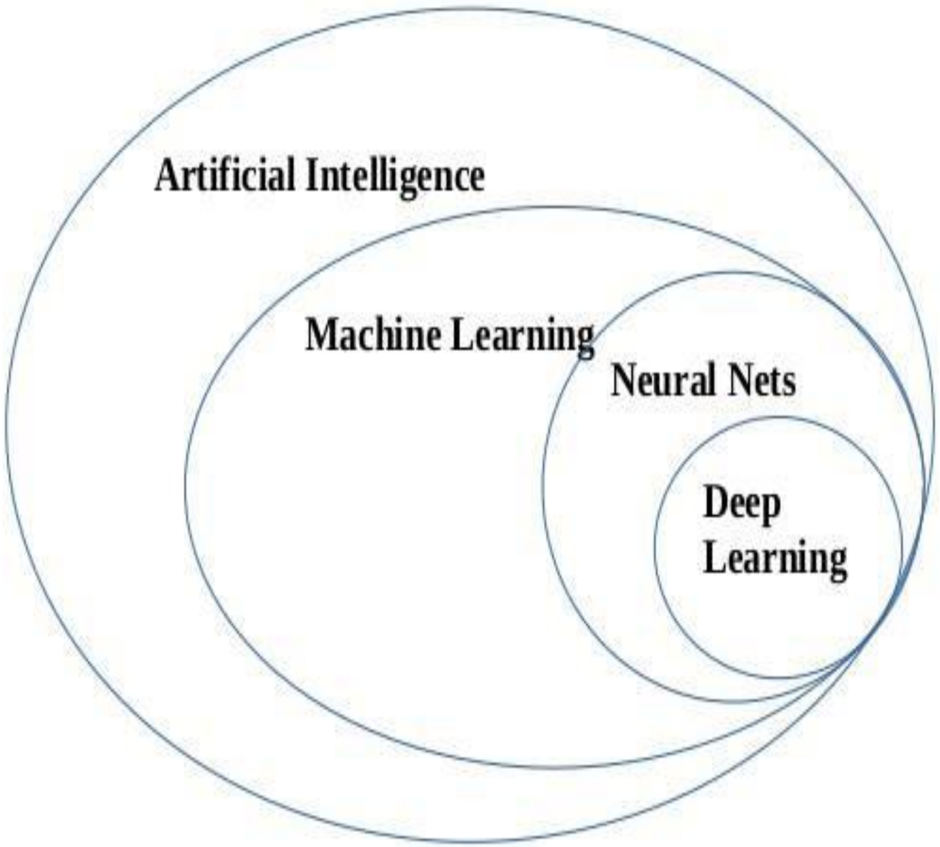
What is ML?

- Artificial Intelligence: Whole knowledge field

- Machine Learning: An important part of AI, but **not** the only one

- Neural Networks: One of popular machine learning types

- Deep Learning: A modern way of building, training and using NN. A new architecture



Why ML?

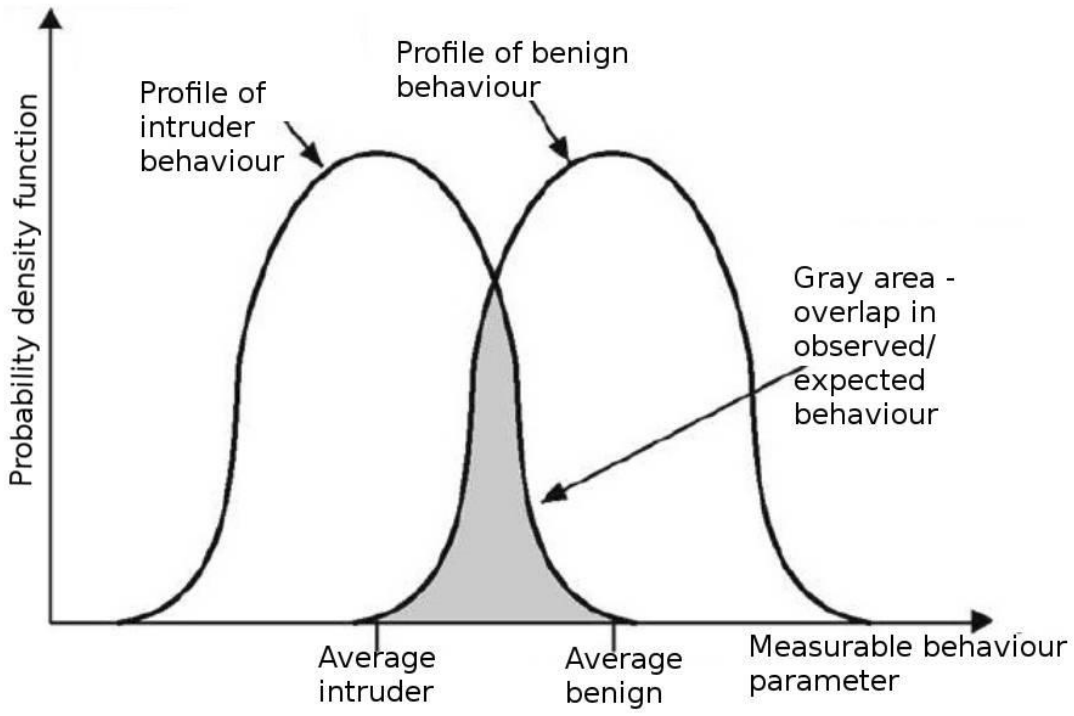
- Imagine you need to buy a house
  - Searched all over, newly built (£400k), year old (£380k), 2-year old (£360), 3- year old (£340), and so on.
  - Price drops by 20k every year, but no less than 100k!
  - Predict the price based on known historical data (regression)
  - But its not that simple, different dates, #bed rooms, present condition, location, seasonal demand spikes, etc
  - How many hidden factors there to determine the house price?
  - An average human can't find these patterns!
- Machine copes with this task much better than a human

TARGET

https://www.forbes.com/sites/kashmirhill/2012/02/16/how-target-figured-out-a-teen-girl-was-pregnant-before-her-father-did/

How ML fits in Cyber Security?

- Monitoring (user/systems) activities to search for known attacks and/or suspicious activities
- Signature/misuse based detection
  - Contain a database of recognised attacks
  - Activity is compared with signature database
  - Zero Day go undetected!



How ML fits in Cyber Security?

- Anomaly/behaviour based
  - Use tools borrowed from Machine Learning (ML)
  - Assumption → behaviour differ
  - Have a notion of normal activity
  - Learnt from previously seen benign activities
  - **High false positive rate!**

ML Components

- Goal: Predict results based on incoming data:

1. Training data
   - Want forecast stocks? Find the price history
   - Want to detect spam? Find samples of spam/non-spams

- How to gather?
  - Manual (accurate, expensive) and automatic (cheaper)
  - Google use their customers to label data
- Collecting a good quality dataset is extremely difficult
  - Garbage in, garbage out
  - Companies may be happy to reveal algorithms, but not the data!

ML Components

2. Features

- Individual measurable characteristic, factors for a machine to look at
  - Organised in a table, features are column names
- Choosing right features is a crucial
  - Informative, discriminating and independent
- Domain knowledge is essential here

3. Algorithms

- Multiple algorithms for one problem (spot-check different algorithms)
- The method you choose affects the precision, performance, and size of the final model
- If the data is bad, even the best algorithm won't help!

Types of Data

- Structured
  - Easily mapped to identifiable column headers
- Unstructured
  - Cannot be mapped
- Semi-structured
  - A mix
- Labelled
  - Contains tags
- Unlabelled
  - Doesn't

ID	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize	BareNuc	BlandChrom	NormNucl	Mit	Class
1000025	5	1	1	1	2	1	3	1	1	benign
1002945	5	4	4	5	7	10	3	2	1	benign
1015425	3	1	1	1	2	2	3	1	1	malignant
1016277	6	8	8	1	3	4	3	7	1	benign
1017023	4	1	1	3	2	1	3	1	1	benign
1017122	8	10	10	8	7	10		7	1	malignant
1018099	1	1	1	1	2	10	3	1	1	benign
1018561	2	1	2	H	2	1	3	1	1	benign
1033078	2	1	1	1	2	1	1	1	5	benign
1033078	4	2	1	1	2	1	2	1	1	benign

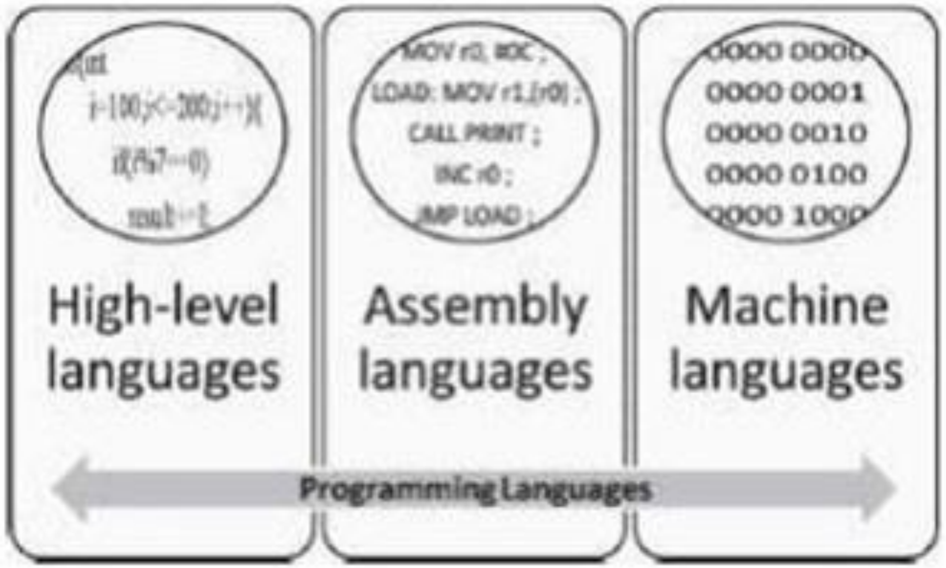
labels

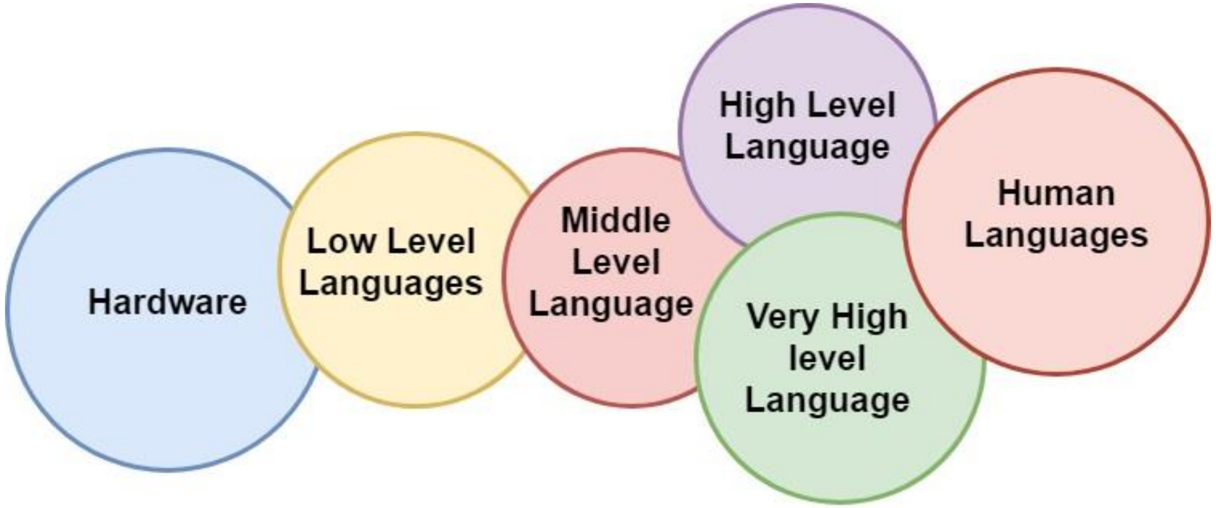
ID	Clump	UnifSize	UnifShape	MargAdh	SingEpiSize	BareNuc	BlandChrom	NormNucl	Mit
1000025	5	1	1	1	2	1	3	1	1
1002945	5	4	4	5	7	10	3	2	1
1015425	3	1	1	1	2	2	3	1	1
1016277	6	8	8	1	3	4	3	7	1
1017023	4	1	1	3	2	1	3	1	1
1017122	8	10	10	8	7	10		7	1
1018099	1	1	1	1	2	10	3	1	1
1018561	2	1	2	H	2	1	3	1	1
1033078	2	1	1	1	2	1	1	1	5
1033078	4	2	1	1	2	1	2	1	1

3.1. Tools for ML

Go to www.menti.com and use code the code you see on the screen

Types of Programming Languages





Why to Use High-Level?

- Widely used
- Huge growing ecosystems
- Industry is on board!
- Data-driven
- Leads to dashboards

- CONS: Speed
  - May be crucial in CyberSec, but there are ways to solve it

Why ML Top Programming Languages

vs

TIOBE Index

Jul 2023	Jul 2022	Change	Programming Language	Ratings	Change
1	1		Python	13.42%	-0.01%
2	2		C	11.56%	-1.57%
3	4	^	C++	10.80%	+0.79%
4	3	v	Java	10.50%	-1.09%
5	5		C#	6.87%	+1.21%
6	7	^	JavaScript	3.11%	+1.34%
7	6	v	Visual Basic	2.90%	-2.07%
8	9	^	SQL	1.48%	-0.16%
9	11	^	PHP	1.41%	+0.21%
10	20	^^	MATLAB	1.26%	+0.53%

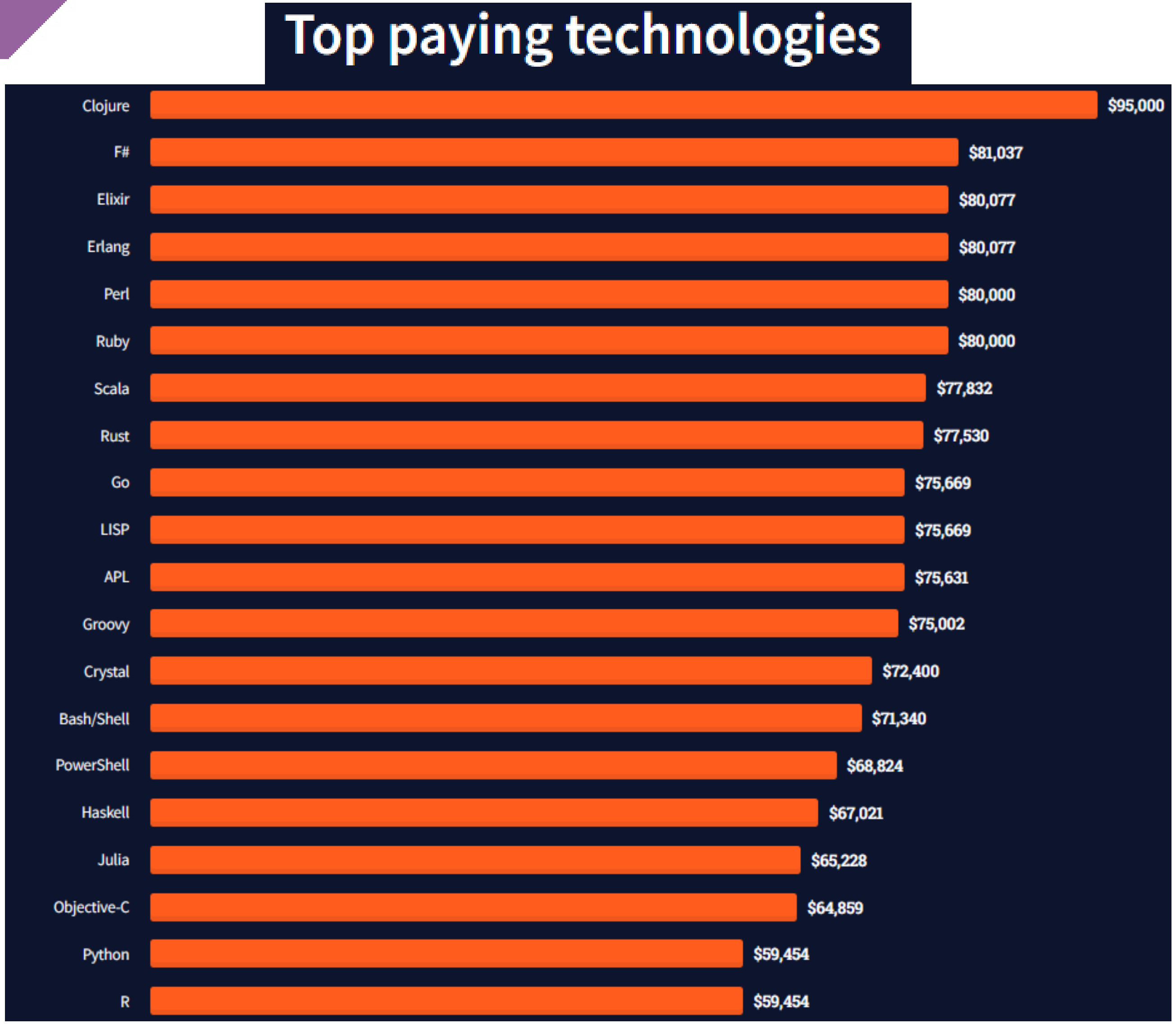
TIOBE Index

11	18	⇑		Fortran	1.25%	+0.49%
12	21	⇑		Scratch	1.07%	+0.35%
13	12	⌄		Go	1.07%	-0.07%
14	8	⇓	ASM	Assembly language	1.01%	-0.64%
15	14	⌄		Delphi/Object Pascal	0.98%	-0.08%
16	15	⌄		Ruby	0.91%	-0.08%
17	29	⇑		Rust	0.89%	+0.47%
18	10	⇓		Swift	0.88%	-0.39%
19	19			R	0.87%	+0.11%
20	26	⇑		COBOL	0.86%	+0.33%

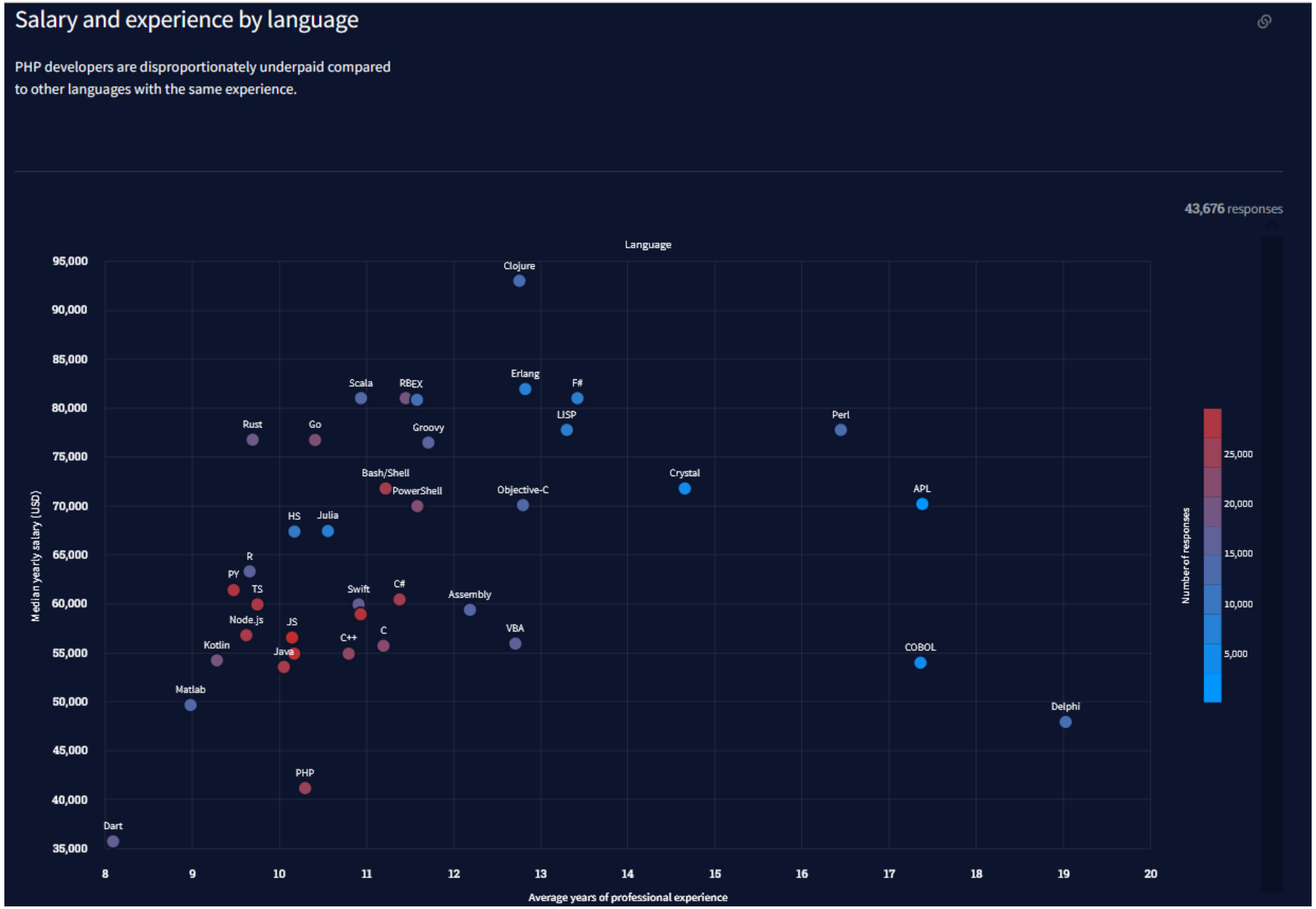
IEEE

Rank	Language	Type	Score
1	Python		100.0
2	Java		95.4
3	C		94.7
4	C++		92.4
5	JavaScript		88.1
6	C#		82.4
7	R		81.7
8	Go		77.7
9	HTML		75.4
10	Swift		70.4

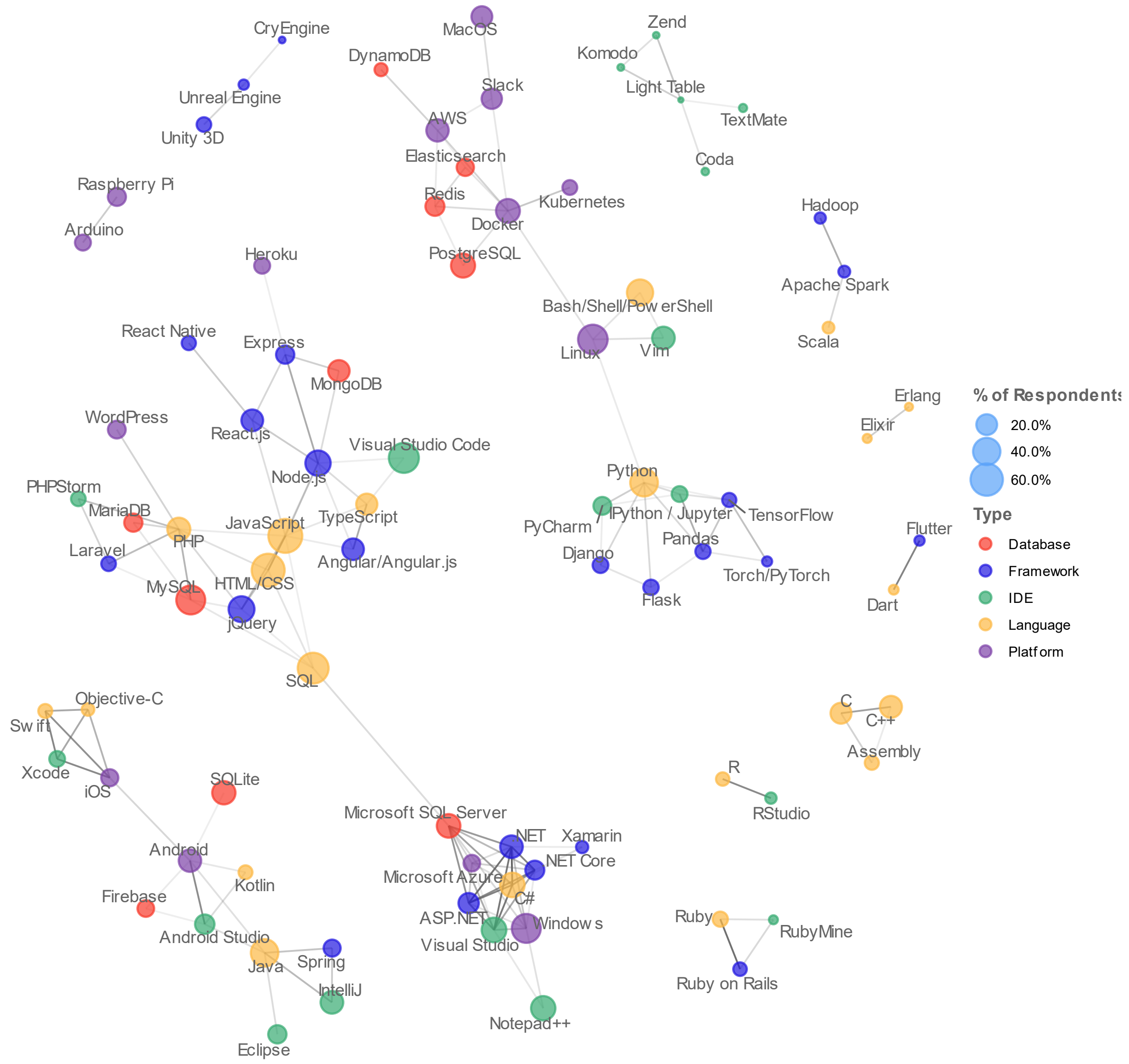
https://spectrum.ieee.org/top-programming-languages/



https://insights.stackoverflow.com/survey/2021


Salary and experience by language
PHP developers are disproportionately underpaid compared to other languages with the same experience.
43,676 responses
Language
Median yearly salary (USD)
Average years of professional experience
Number of responses
Clojure
Scala
RBEX
Erlang
F#
LISP
Perl
Rust
Go
Groovy
Bash/Shell
PowerShell
Objective-C
Crystal
APL
HS
Julia
R
PY
TS
Swift
C#
Assembly
Node.js
JS
C++
C
VBA
COBOL
Kotlin
Java
Matlab
Delphi
PHP
Dart

How they connect?



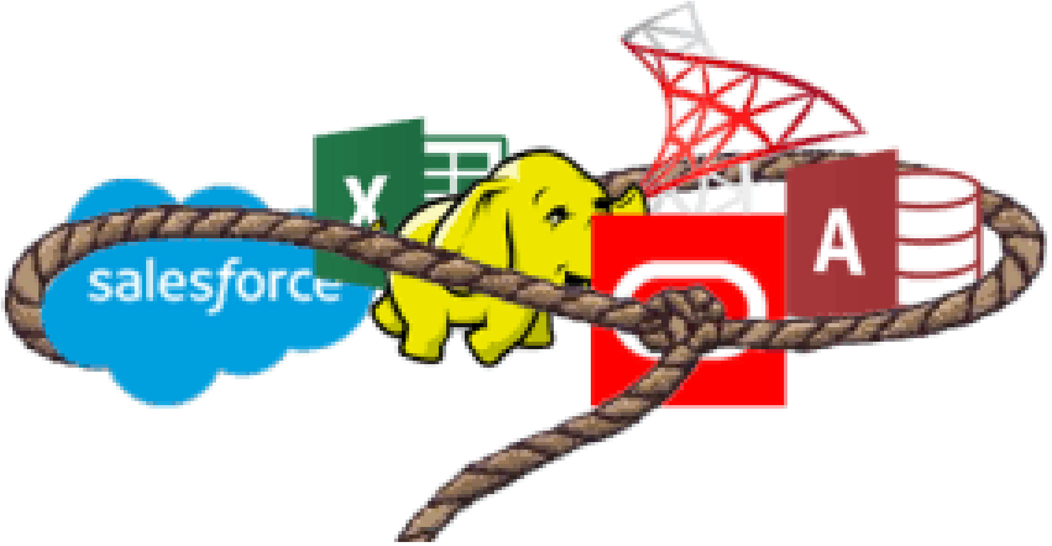
https://insights.stackoverflow.com/survey/2019

What are R and Python?

- Open-source programming language for statistical analysis, graphics, data science and machine learning.
- Command-line based, however, complementary tools provide a friendly user interface(s).
- Will require you to learn both syntax and semantics.

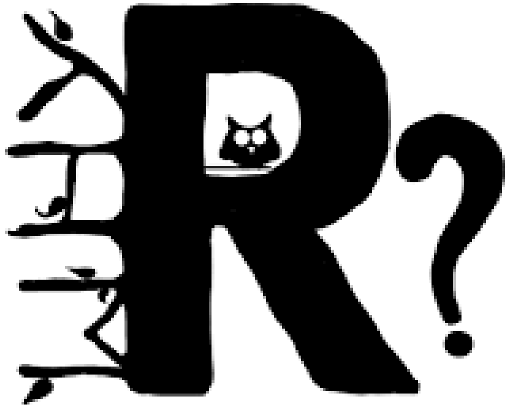
What do we use them for?

- Exploratory and statistical data analysis.
- Visualisation and graphics.
- Data preparation (data wrangling).
- Machine learning and modelling.



Why these tools?

- Free.
- Easy to use.
- Have packages for everything.
- Have great online support community.
- Statistics tools AND programming languages.
- Available across platforms.
- Similar to MATLAB.
- Robust for visualisations.
- You can produce reports of your work easily.

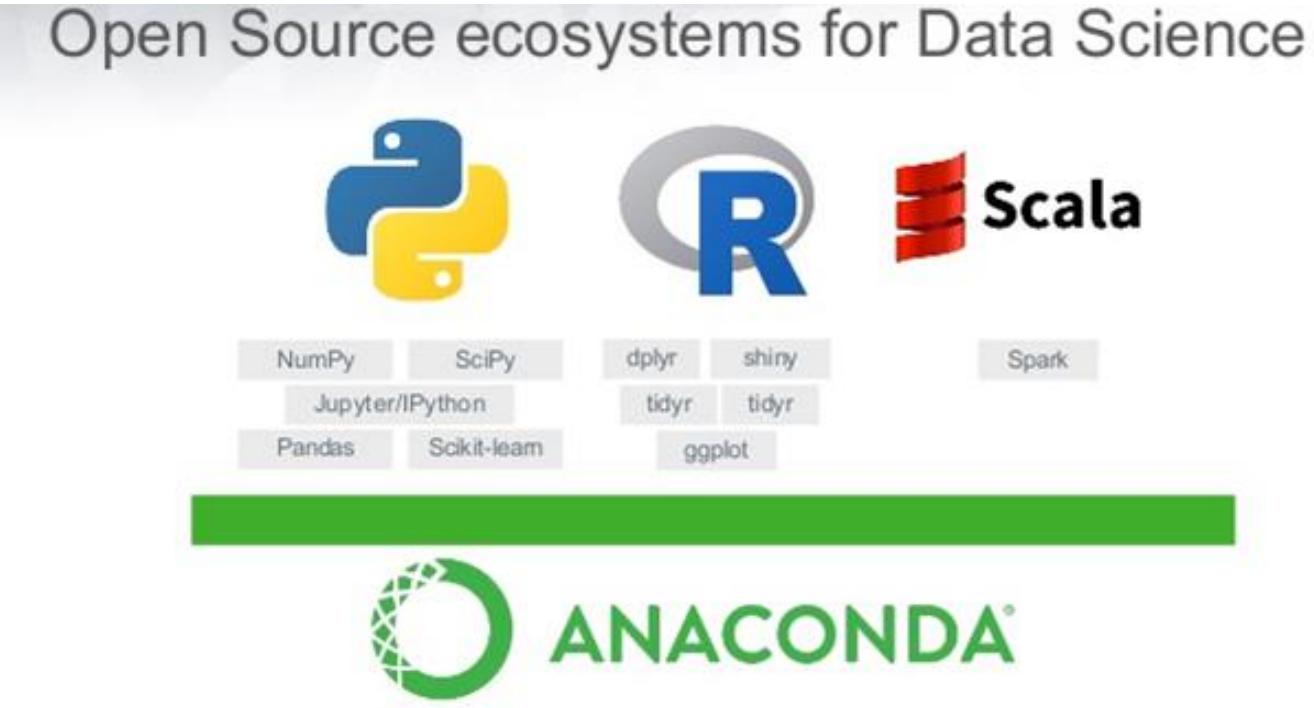


How to Install?

1. Download R
- http://cran.r-project.org/
2. Download RStudio (IDE)
- http://www.rstudio.com
3. Download Python
- https://www.python.org/downloads/
4. Download an IDE
- https://www.spyder-ide.org/
- https://www.jetbrains.com/pycharm/
- https://jupyter.org/

OR Download Anaconda!

https://www.anaconda.com/



Where to Learn?

- Coursera
  - https://www.coursera.org/
- Datacamp
  - https://www.datacamp.com/
- RGU offers online short courses!
  - https://www.rgu.ac.uk/study/courses/3274-introduction-to-data-science-with-python-15-credits-at-scqf-level-9

3.2. Demo of Python and R

- R in RStudio
- Python in
  - Console
  - Spyder
  - PyCharm
  - Jupyter Notebook
  - Rise Slides

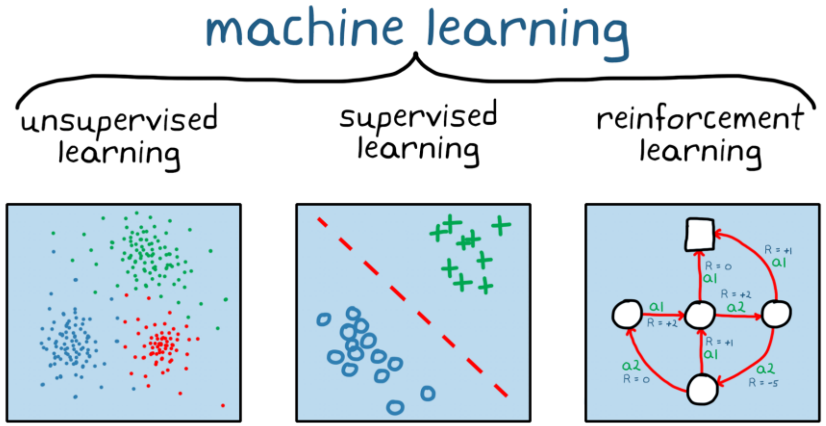
3.3. Demo of Online Notebook Platforms

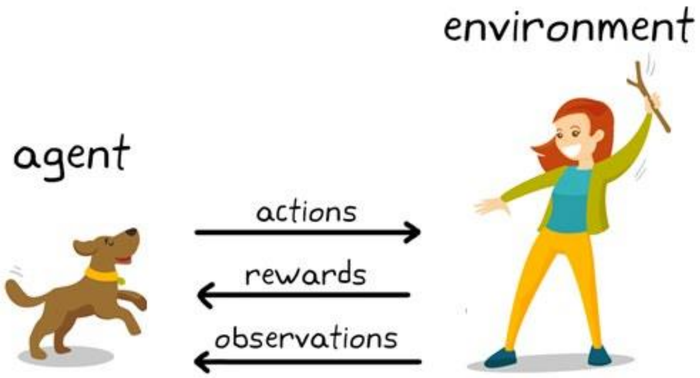
- Google Colab (mostly for Python)
- Kaggle (both, plus a great data source)
- HuggingFace

4.1 Types of ML

(Main) Types

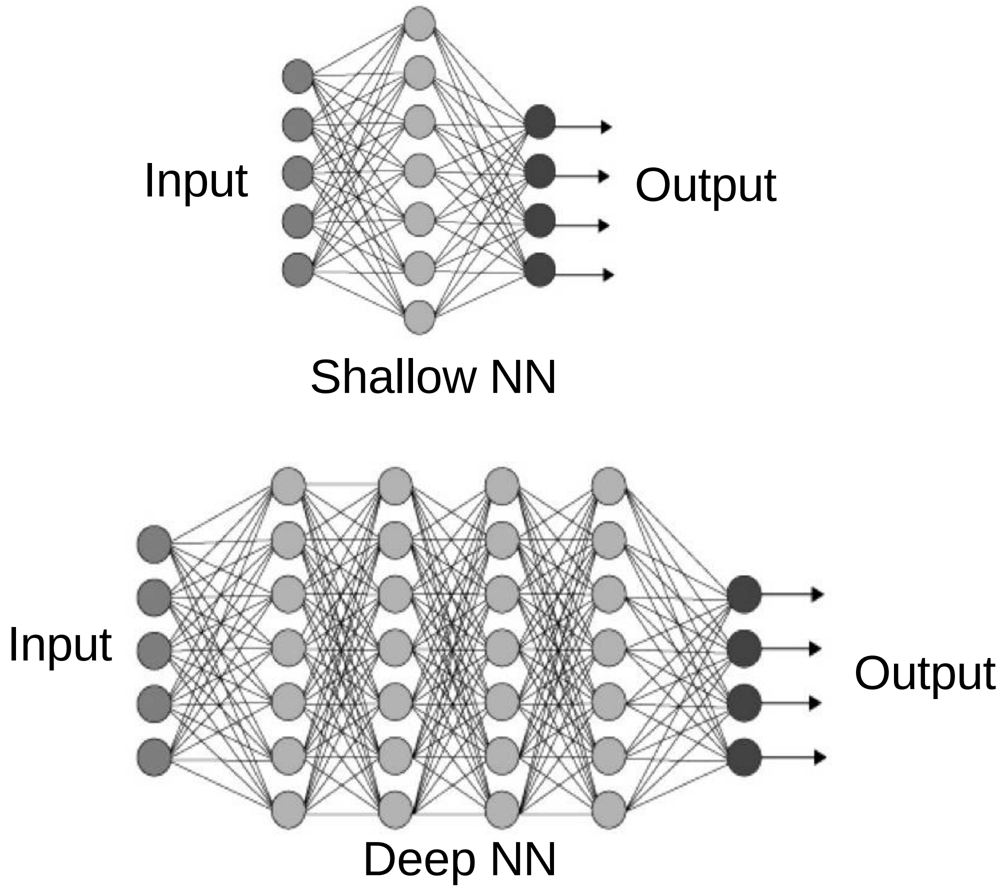
- Supervised
  - Learn from labelled data, used to classify or predict
  - e.g. object recognition systems, spam detectors
- Unsupervised
  - Initial data is not labelled, insights are drawn by processing data (structure is unknown in advance), clustering, association, anomaly detection.
  - e.g. user behaviour analysis, market basket analysis
- Reinforcement
  - No supervisor, only a reward signal is used for an agent to determine if they are doing well or not
  - Type of dynamic programming, system learns from its environment, maximises the gain
  - Reward, no training data involved, learns on the go via trial and errors (rewards and punishments)
  - e.g. self driving cars to navigate through the traffic https://www.youtube.com/watch?v=W2CAghUiofY&feature=emb_logo



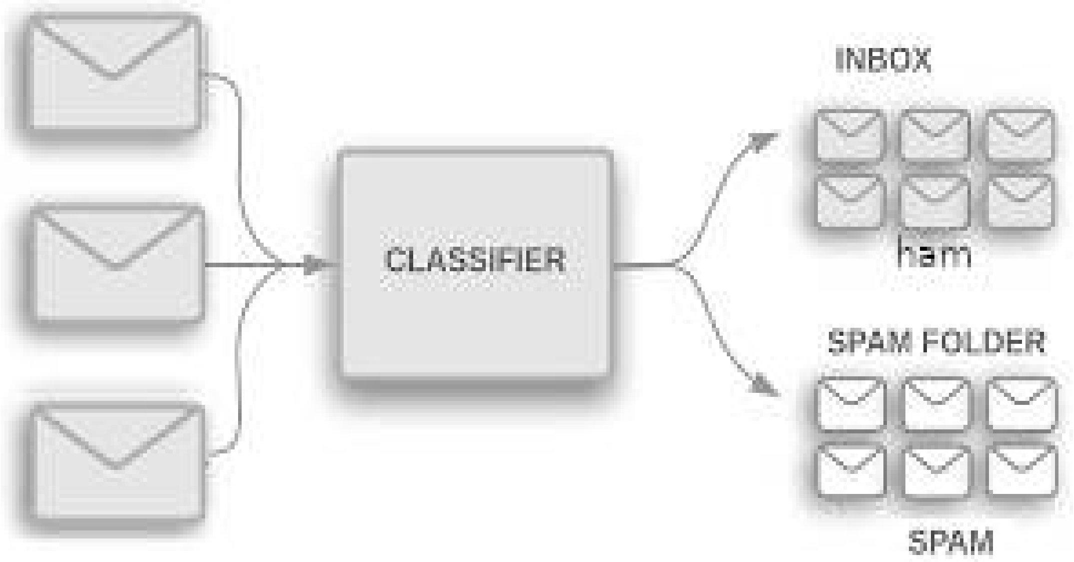


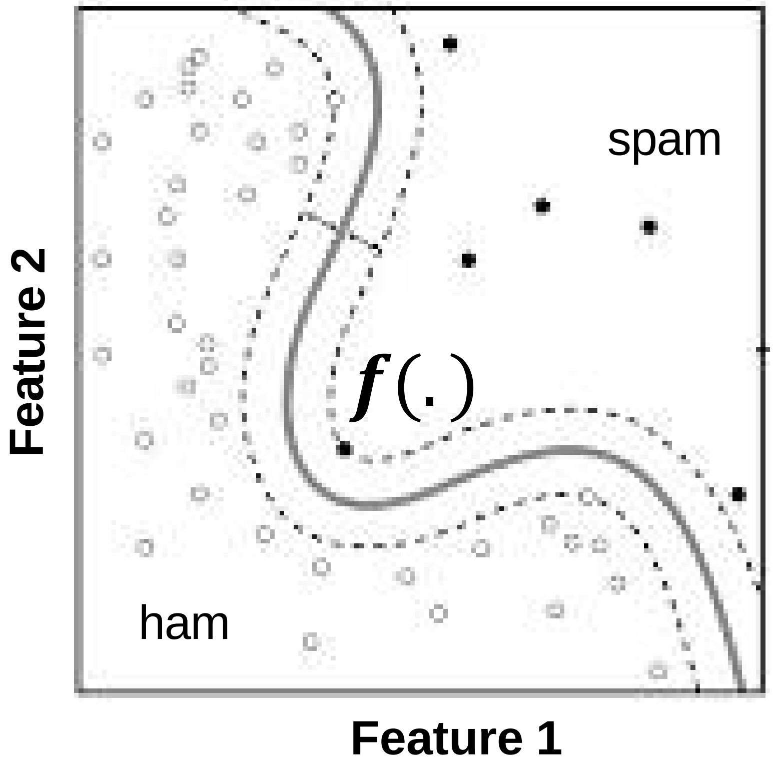
(More) Types

- Semi-Supervised
  - Initial training data is incomplete, both labelled and unlabelled data are used in the training
- Deep
  - Neural networks (NN) with number of hidden layers Back-propagation to train deep neural nets
- Active
  - User constantly feeds algorithm with labels
  - Used for NLP tasks (systematic reviewing)
- Imitation
  - Used mostly in robotics



Solving a problem using ML logic



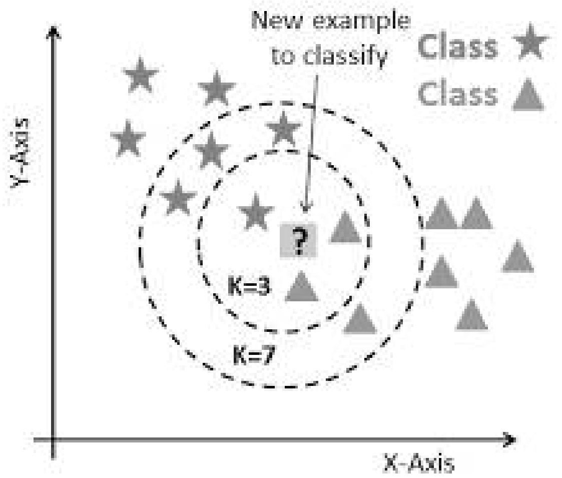


K Nearest Neighbours (KNN)

% R CODE

```
library(caret)
fit.knn <- train(Species~.,
        data=dataset, method="knn")
predicted= predict(fit.knn,x_test)
```

- Classified by a majority vote of neighbours
  - K is an integer specified by human
  - Non-parametric algorithm - not making any assumption on data distribution
  - Lazy algorithm - does not really learn any model and make generalisation of the data
- Advantages: Simple to implement, robust to noisy training data, and effective if training data is large
- Disadvantages: Need to determine the value of K computation cost is high



Decision Tree

```
library(caret)
fit.dt <- train(Species~.,
        data=dataset, method="rpart")
predicted= predict(fit.dt,x_test)
```

- Simplest and easiest classification model
- Supervised Machine Learning
- Segment the predictor space into multiple regions
- Each region has only a subset of the training dataset
- High variance → Small change in the training data can give an entirely different decision trees model
- Led to better classifiers → Random Forests

Naïve Bayes (NB)

- Probabilistic classifier inspired by the Bayes theorem
- Assumes attributes are conditionally independent
- Advantages: small amount of training data required, extremely fast
- Disadvantages: zero probability problem, if the conditional probability is zero for a particular attribute ...
- “Hard” to understand, simple to implement

```
x <- cbind(x_train,y_train)
fit <-naiveBayes(y_train ~ ., data = x)
predicted= predict(fit,x_test)
```

Posterior

Attributes likelihoods

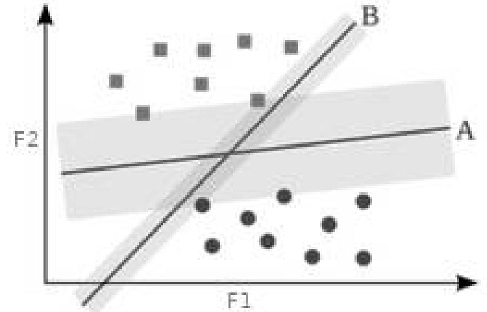
$$P(y|x_1, ..., x_n) = \frac{P(x_1|y)P(x_2|y)...P(x_n|y)P(y)}{P(x_1)P(x_2)...P(x_n)}$$

Predictor prior

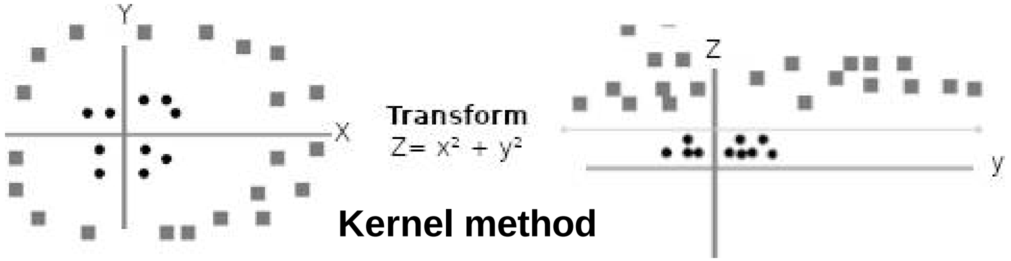
Class prior

```
x <- cbind(x_train,y_train)
fit <-svm(y_train ~ ., data = x)
predicted= predict(fit,x_test)
```

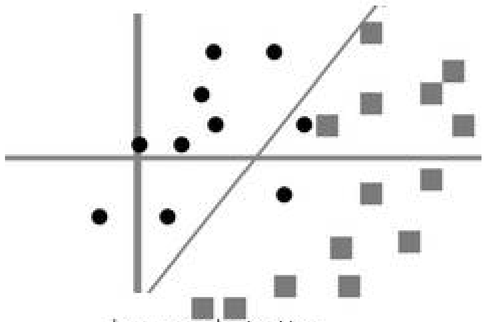
Support Vector Machine (SVM)



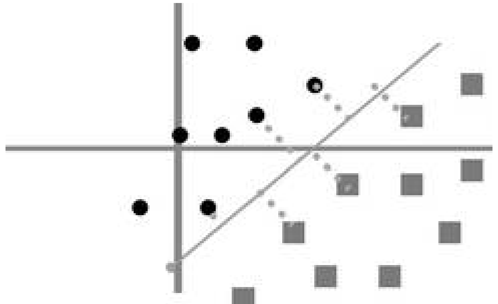
- Discriminative classifier defined by a separating hyperplane
- Tuning parameters in SVM classifier
  - Kernel - transformation method, e.g. Polynomial and exponential kernels
  - Regularization - how much to avoid misclassifying each training example
  - Gamma - how far the influence of a single training example reaches, high gamma → only nearby examples
- A margin in SVM is a separation of line to the closest class points
  - Good margin is one where this separation is larger for both the classes



Kernel method



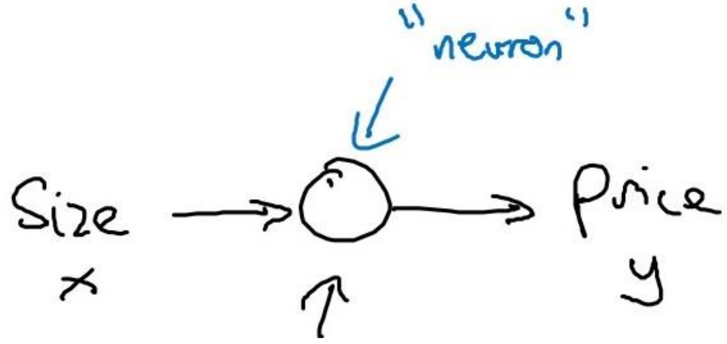
low regularization

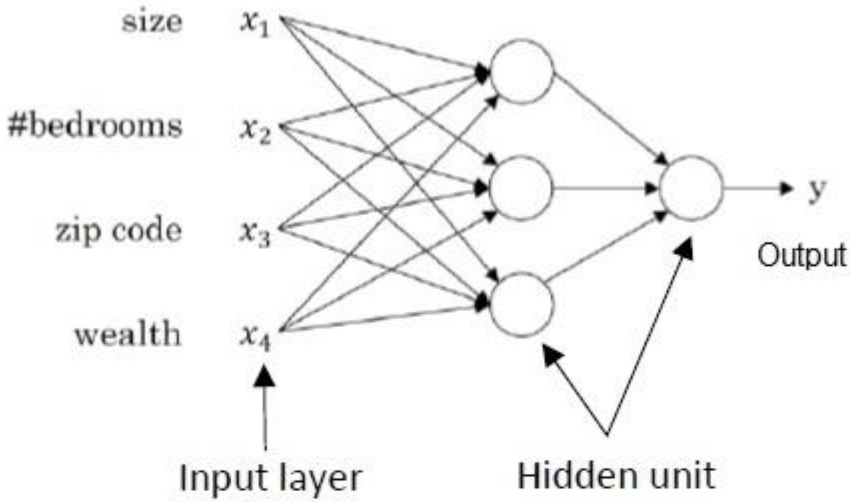


High Gamma

Neural Network (NN)

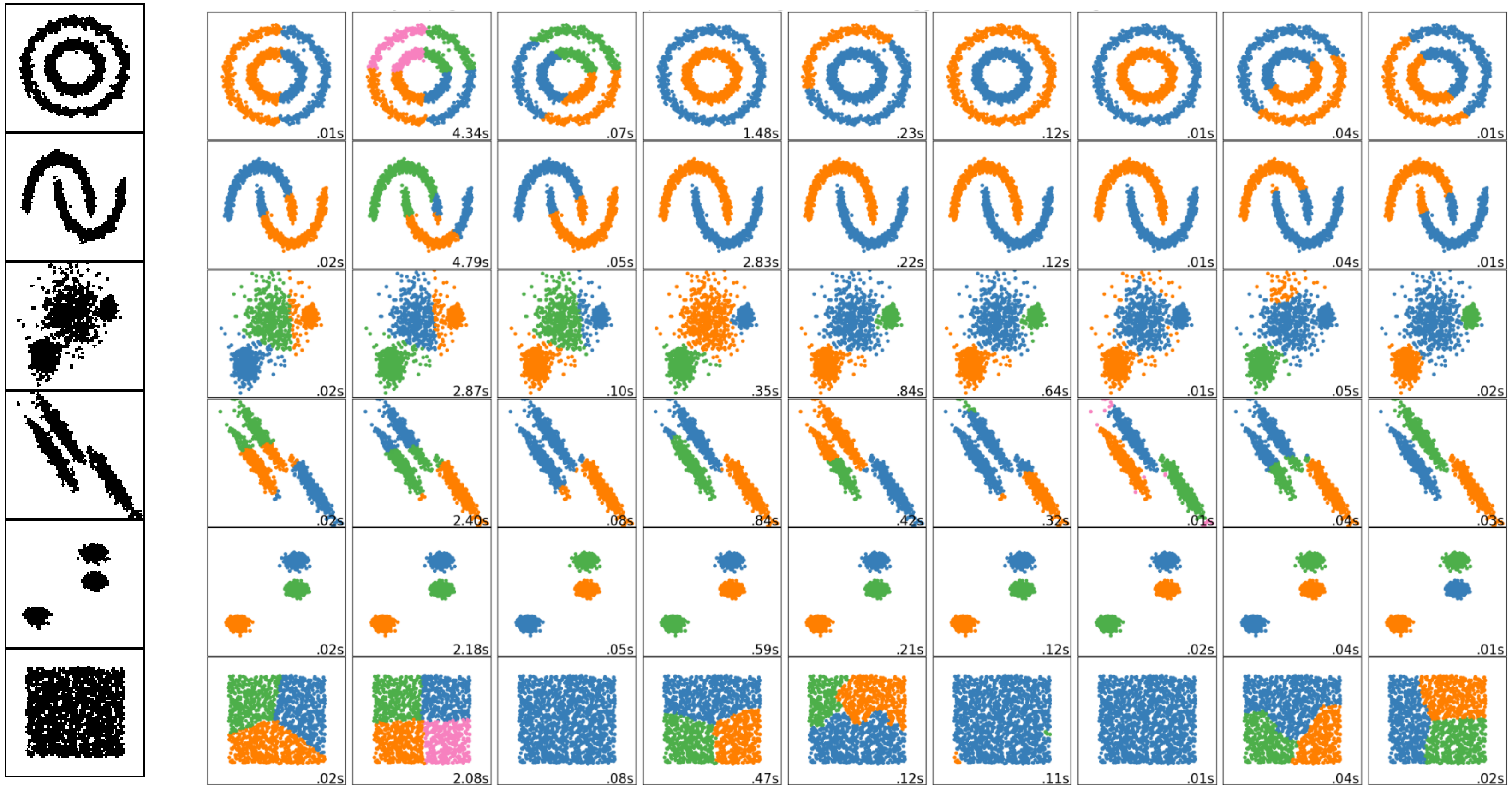
- Each “neuron” is trained to be activated/deactivated given certain weights and biases
- Multiple neurons work together to solve a multi-variable problem
- If more layers are added to the NN model, second-order relations can be discovered
- There are “easy models” that can be implemented in three lines of code, but if you want to do it properly, you need to be more skilled!



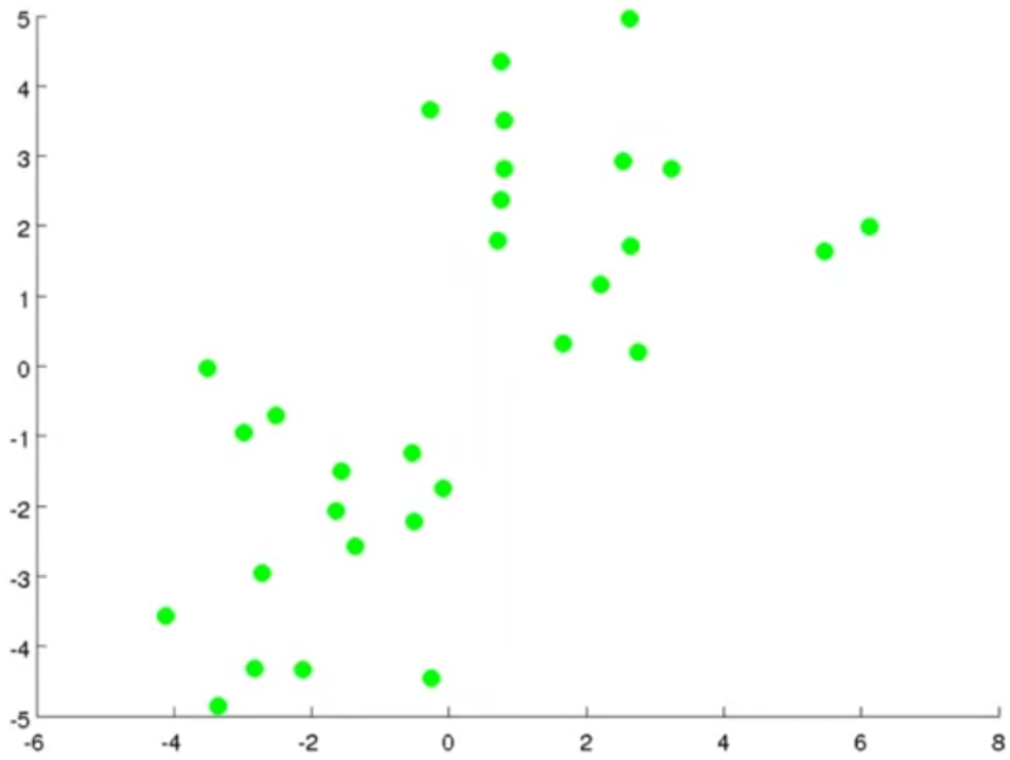


Clustering (unsupervised) with K Means

- Not to be confused with KNN!
- Two main steps:
  1. Cluster assignment
  2. Centroid recalculation

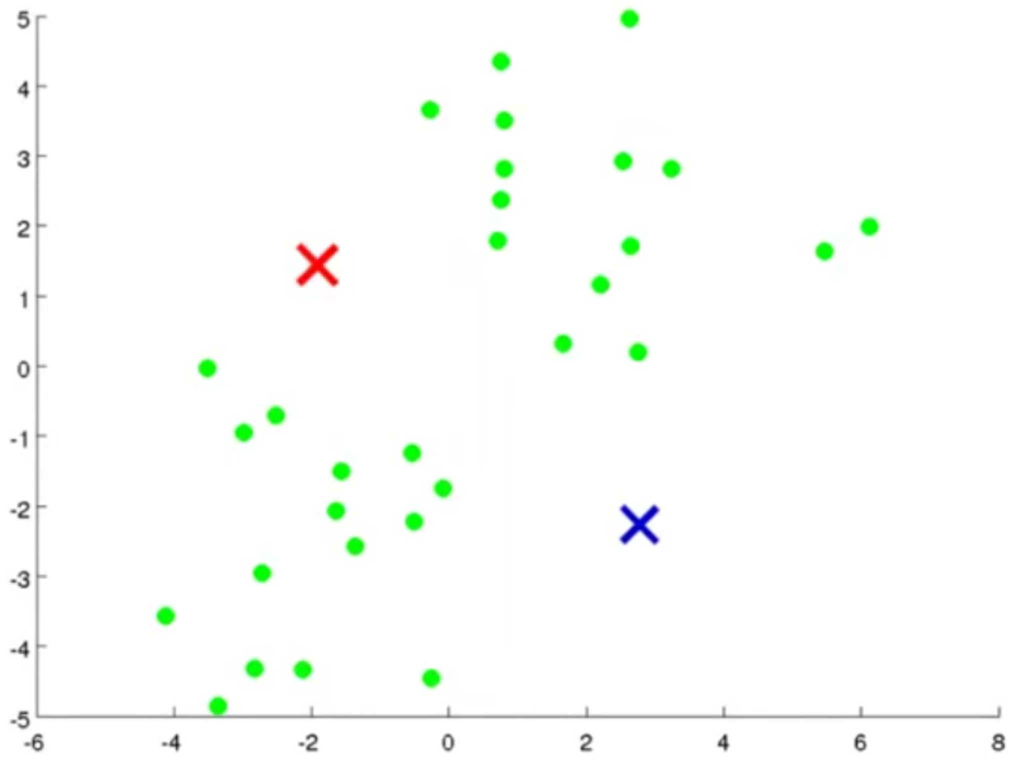


Example



https://www.youtube.com/watch?v=Ao2vnhelKhI

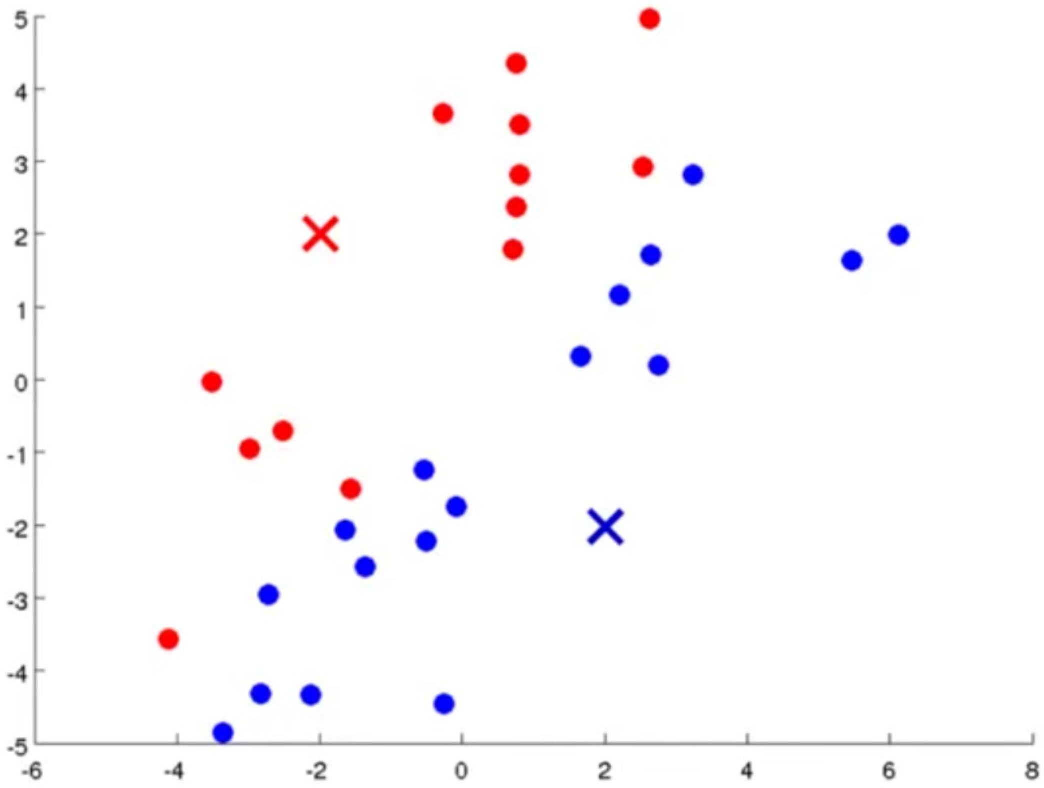
1. Select the number of clusters & randomly initialise k centroids.



k=2

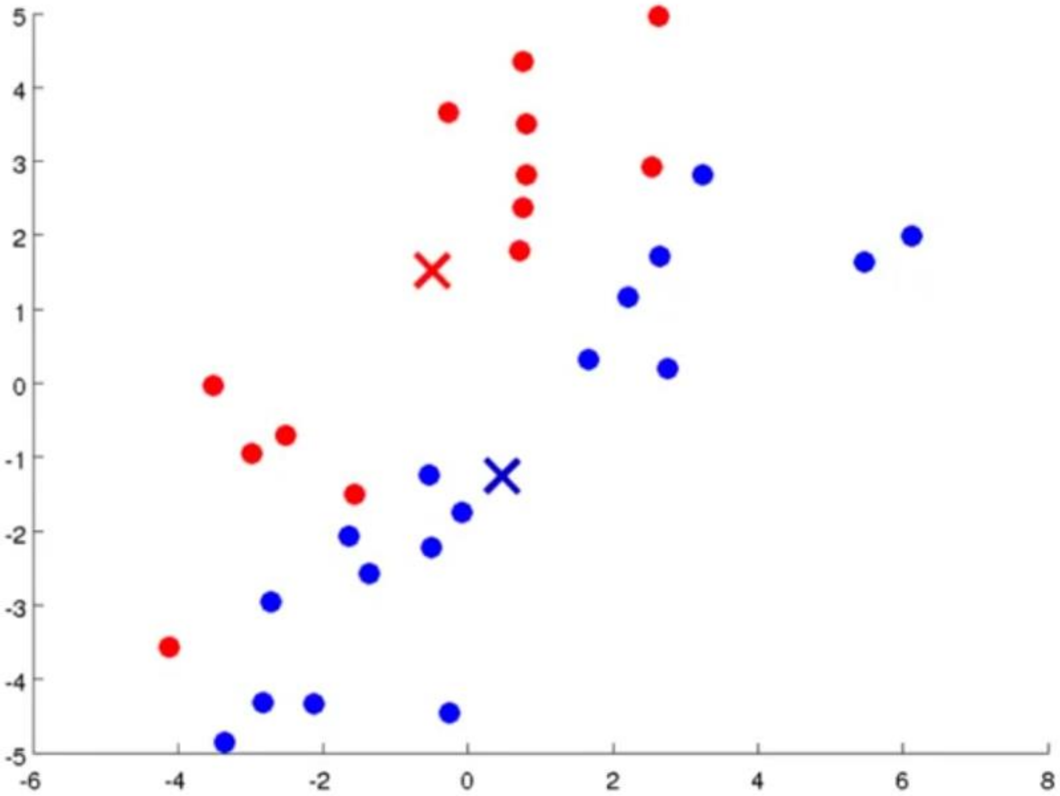
https://www.youtube.com/watch?v=Ao2vnhelKhI

2. Assign each data point to a cluster (red or blue) according to the minimum distance to a centroid.



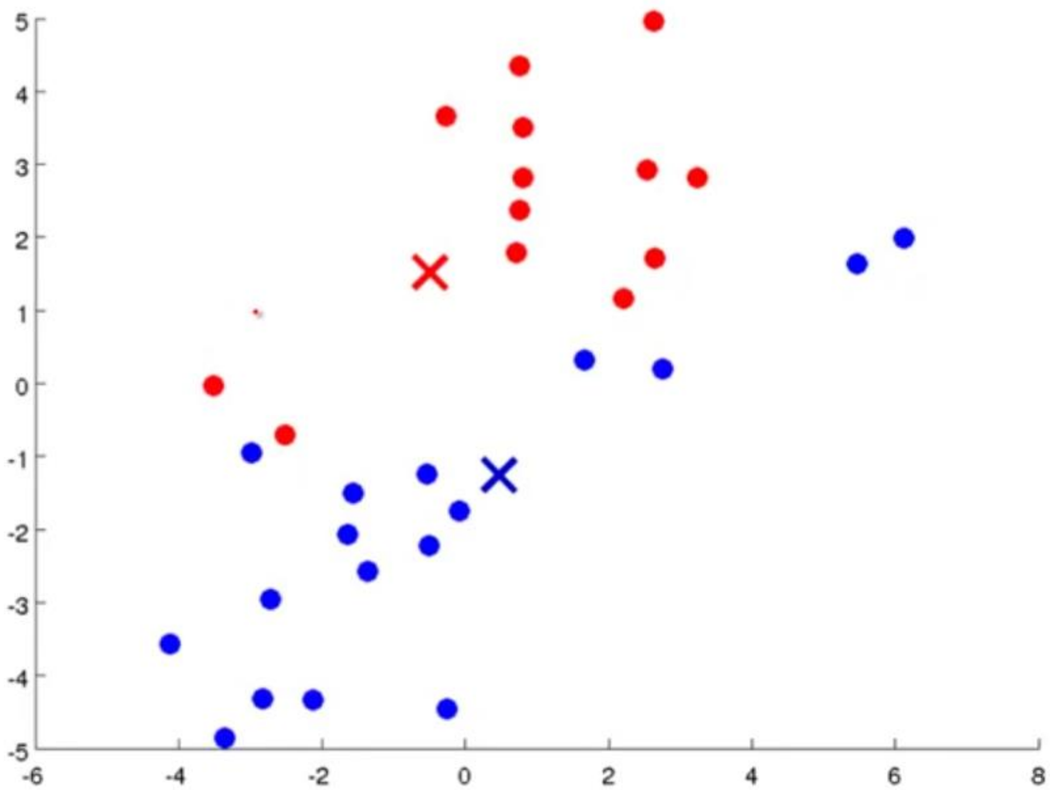
https://www.youtube.com/watch?v=Ao2vnhelKhI

3. Compute the mean of each cluster and *move the centroid* to that position.



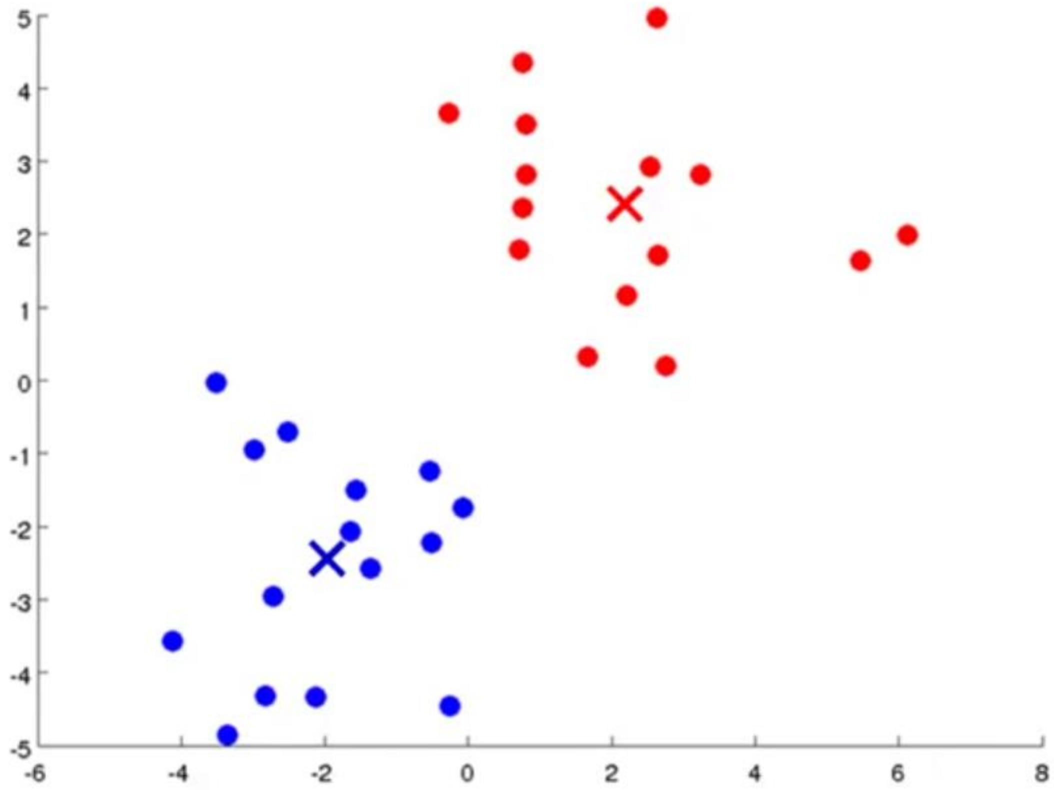
https://www.youtube.com/watch?v=Ao2vnhelKhI

4. Compute a new set of clusters based on the new centroids.



https://www.youtube.com/watch?v=Ao2vnhelKhI

5. Iterate until clusters don’t change (convergence).



https://www.youtube.com/watch?v=Ao2vnhelKhI

4.2 Practical Example (Iris)

Link to online Jupyter Notebook:
https://colab.research.google.com/drive/1gDVOrqs3d3Ycb7X2wY7XC9oCMsKzb0j7?usp=sharing

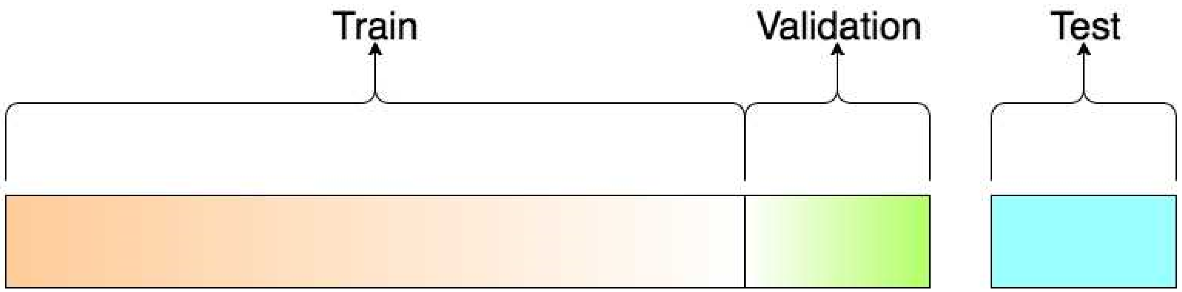
5. Evaluating ML

Evaluating ML

- Now that we know how to implement (basic) ML algorithms, we need to assess their effectiveness

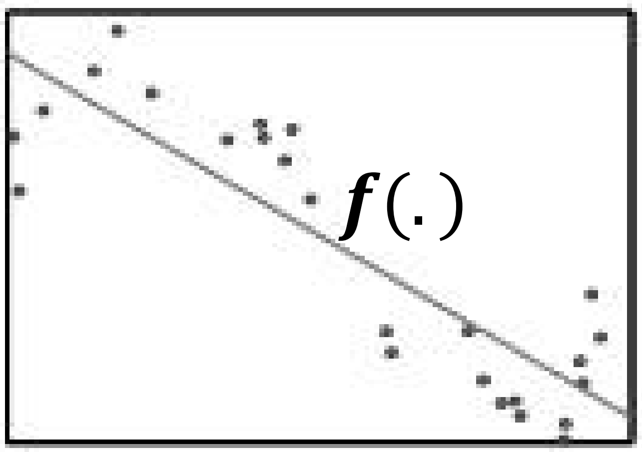
- Accuracy is **not** the only way!

- There are numerous metrics that help us understand how well our algorithms are performing

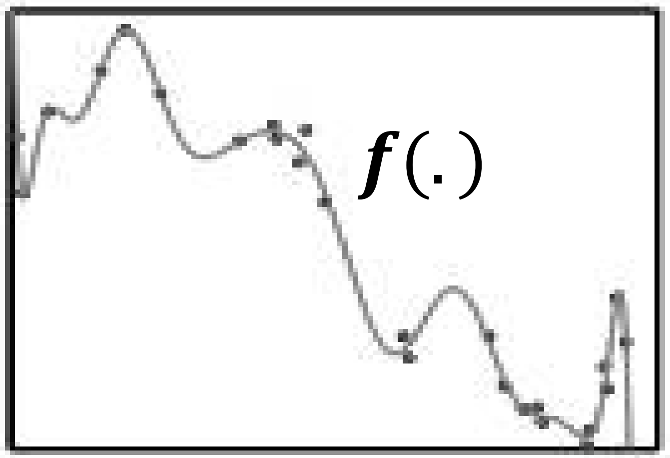


Over/Under Fitting

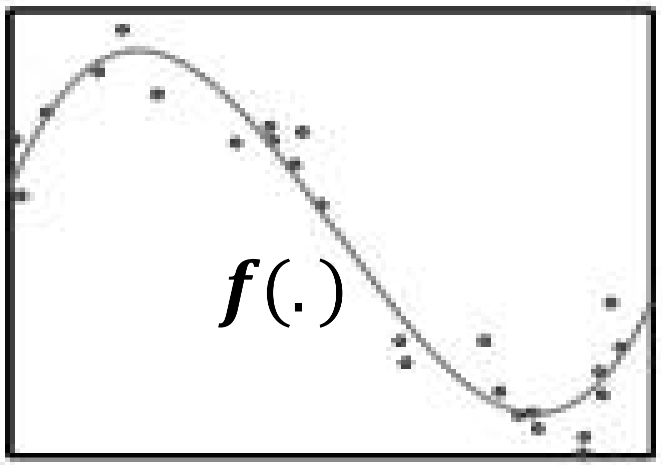
- Assume we want to fit a regression to a series of observations:



Underfitting



Overfitting



Good fit

Assuming a binary scenario

- True Positives (TP)
  - This is what many people think accuracy is (but it's not!)
  - Samples from the positive class that are classified correctly
- True Negatives (TN)
  - How many samples from the negative class are **NOT** classified as being from the positive one
- False Positives (FP)
  - How many samples from the negative class are classified as being from the positive class
  - Also known in statistics as **False Alarms** or **Type I Error**
- False Negatives (FN)
  - How many samples from the positive class are classified as being from the negative class
  - Also known in statistics as **Type II Error**

So what is the accuracy?

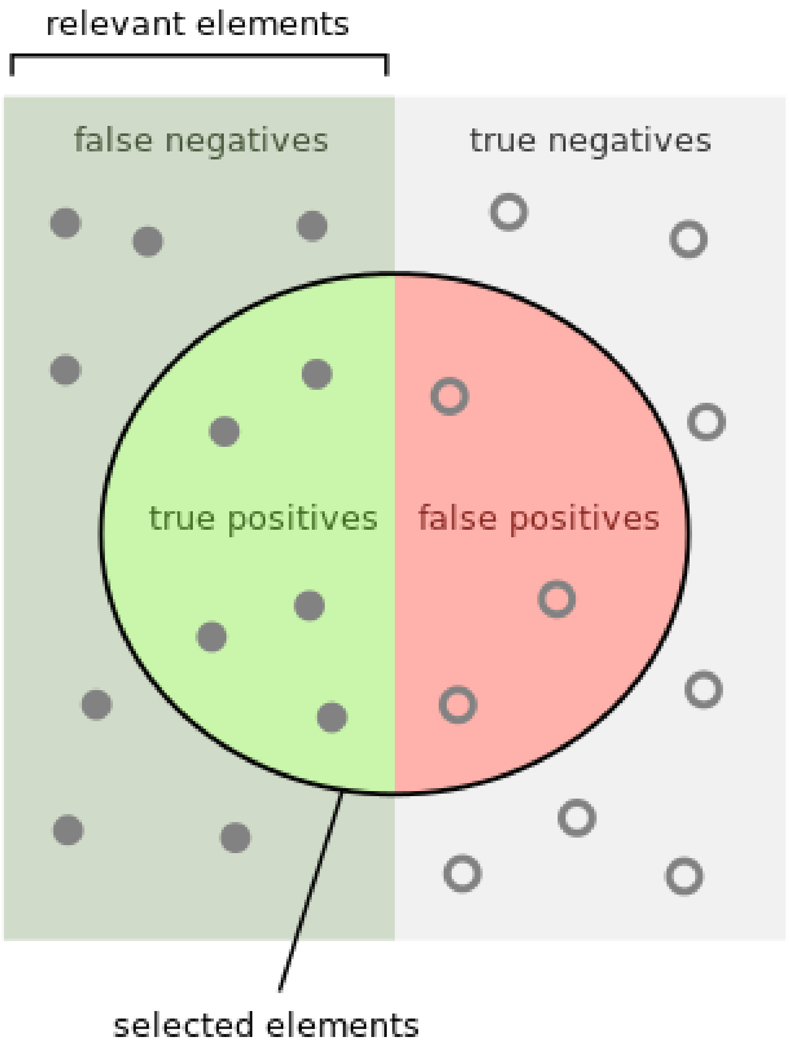
$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- Value between 0 and 1
- Not a suitable metric for **imbalanced** scenarios
- Why?

Precision and Recall

- These metrics focus on the balance between the relevant and irrelevant elements

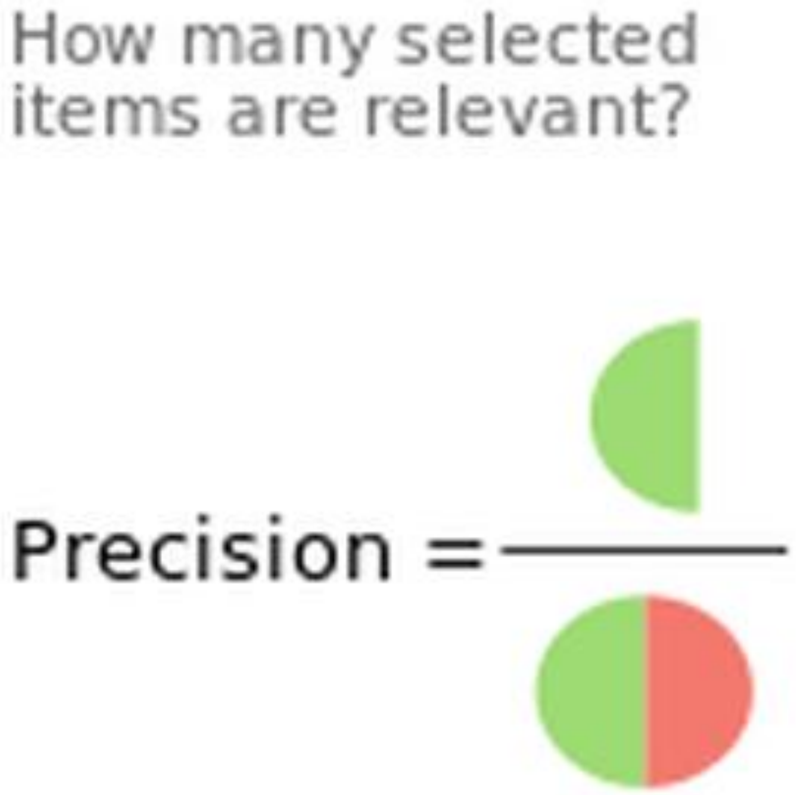
- Consider if the positive case is easy to find



Precision

$$Precision = \frac{TP}{TP + FP}$$

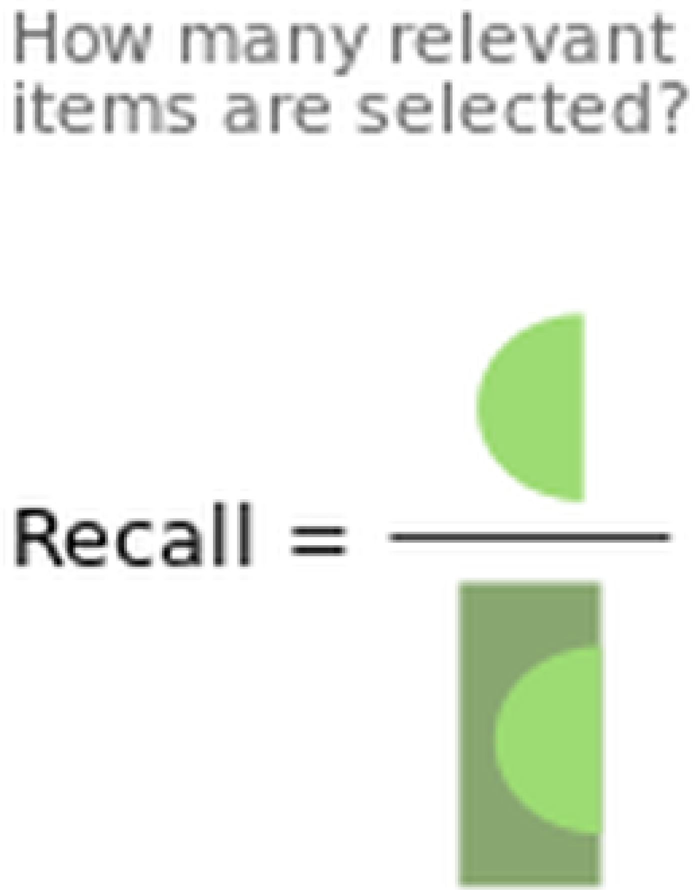
- How much of what I **have** I **need**?



Recall

$$Recall = \frac{TP}{TP + FN}$$

- How much of what I **need** I **have**?



F1-score

- Harmonic mean between precision and recall

- Helps gauge both

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} = \frac{2 \times TP}{(2 \times TP) + FP + FN}$$

- There are different interpretations and variations

Confusion Matrix

		Actual class	
		Cat	Dog
Predicted class	Cat	5	2
	Dog	3	3

Confusion Matrix

		Actual class	
		Cat	**Non-cat**
Predicted class	**Cat**	5 True Positives	2 False Positives
	Non-cat	3 False Negatives	3 True Negatives

Multiclass

- There are many ways to adapt the aforementioned metrics to these scenarios, the most common one being the **One vs All** approach
  - Comparing a metric of one class against the rest as if these were a single class
- Considering that you can still calculate precision, recall and F1-score for each class (against the rest), another commonly used approach is macro/weighted/micro metrics:
  - Macro: Arithmetic mean
  - Weighted: multiply each by number of sample
  - Micro: Harmonic mean → accuracy

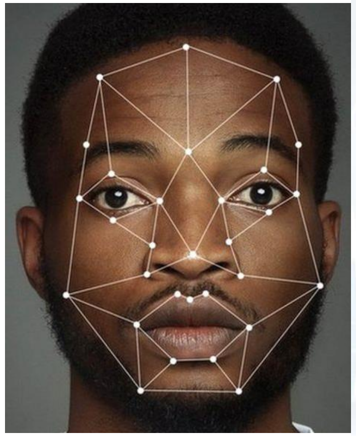
6. Final Considerations

Final Considerations

```python
import time

t = time.perf_counter()
# do stuff
x=0
for i in range(1000):
    x=x+i
# stuff has finished
print('Elapsed time: ',time.perf_counter() - t)
```

- Runtime
  - Not very academic, but **HUGELY** important in practice!
- How “green” is my algorithm?
  - https://medium.com/codex/what-are-the-greenest-programming-languages-e738774b1957
- How “ethical” is my algorithm
  - Data privacy
  - Jobs that it will take/create?
- Check that our algorithms are NOT racist!
  - https://sitn.hms.harvard.edu/flash/2020/racial-discrimination-in-face-recognition-technology/
- End of days!
  - ChatGPT
  - Dall-E



"Homework"

- Review the classical concepts of programming
  - Data structures (string, int, Boolean, etc)
  - Conditional (if/else, while, for)
  - Creating functions

- Get familiar with Python and/or R
  - Do a course according to your level
  - Practice!
    - https://www.w3schools.com/python/python_exercises.asp
    - https://projecteuler.net/