Topic 3 Lecture - Introduction to Computer Vision and Machine Learning

Aims of the Session

- Learn the basics on how images are imported to our computers and converted into data

Resources for the Lecture

- Introduction to Computing and Programming in Python: A Multimedia Approach. Mark Guzdial, Barbara Ericson. Pearson, 2016.
- Various others mentioned throughout the lecture!

How does an image look *digitally*?

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- These are the main **compression algorithms** used to store images:

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Compression Algorithms

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- Best algorithms are the ones that achieve best visual quality with reduced size.

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- Best algorithms are the ones that achieve best visual quality with reduced size.

8.9M

68.34K

- The importance of compression

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In [1]:

```
import warnings
warnings.filterwarnings('ignore')
from IPython.display import HTML
HTML('<iframe width="560" height="315" src="https://www.youtube.com/embed/NMk
```

Out[1]:

- Fortunately, this is **NOT** our problem in this module!

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- We are going to work with images in *simpler* ways

Images as arrays/matrices

- Using the `numpy` module

Images as arrays/matrices

- Using the `numpy` module
- Complementing by using the `OpenCV` module, which will let us import and manipulate images

- When we import an image, the first thing we will get is a **bitmap**

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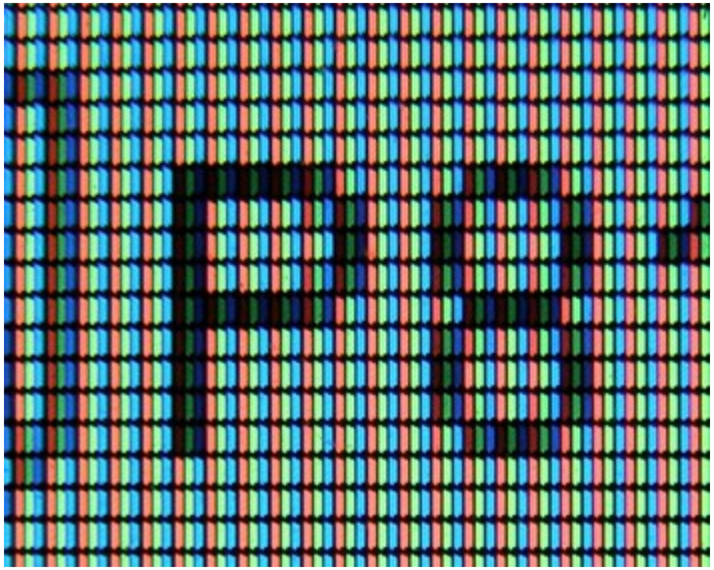

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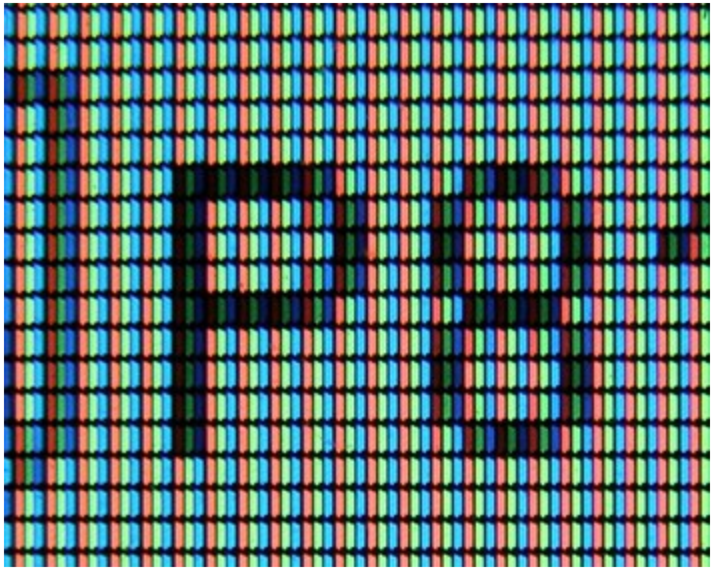

- Each pixel will be represented as a value within an $n \times m$ matrix

Grayscale Images

Grayscale Images

- A 2D grid of pixels

Grayscale Images

- A 2D grid of pixels
- Two ways to represent them:

1. Standard: from 0 (black) to 255 (white) with 254 gray values in between.

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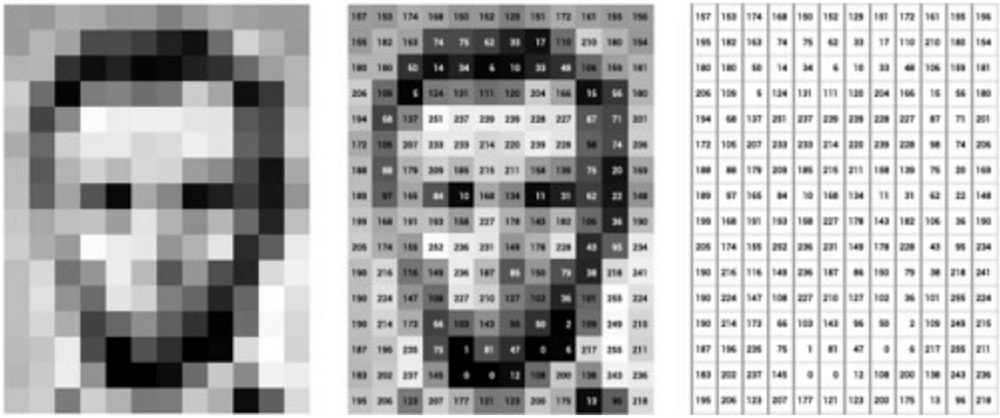

1. Normalised: from 0 (black) to 1 (white) with "infinite" gray values in between.

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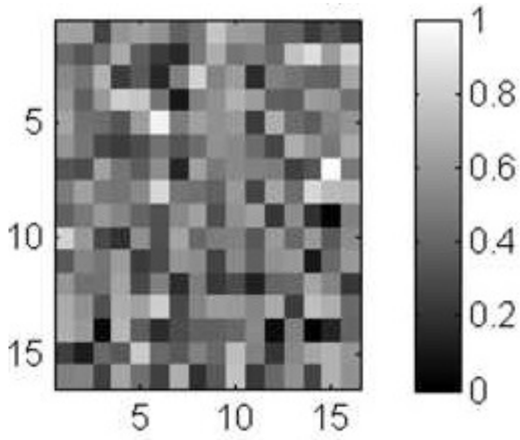
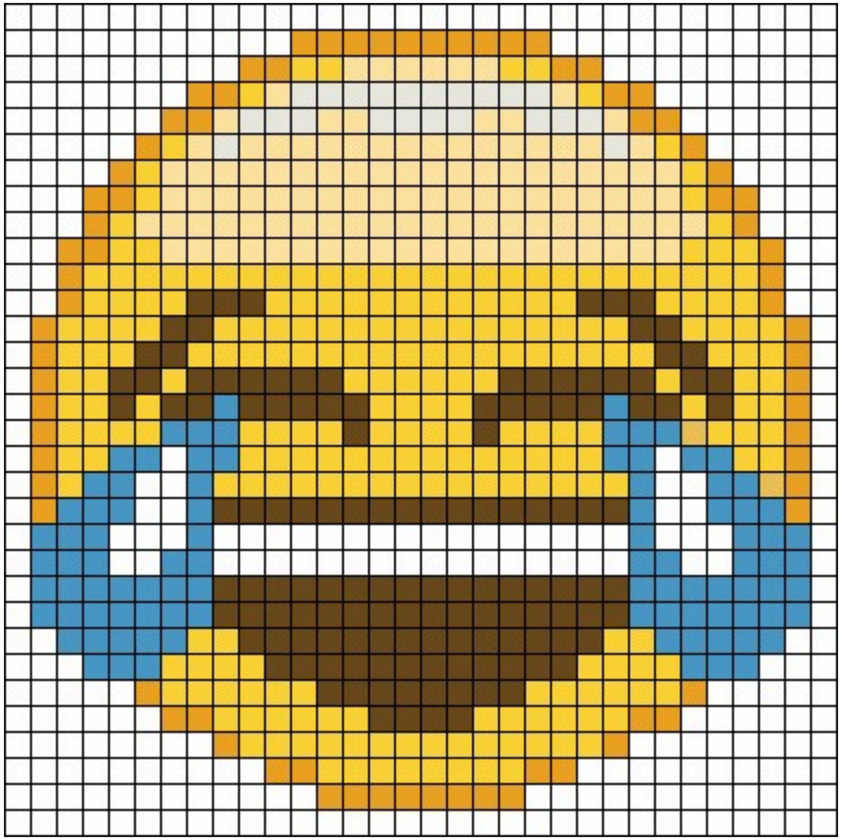


IS IT POSSIBLE TO CONVERT BETWEEN STANDARD $\leftrightarrow$ NORMALISED?

Colour Images

Colour Images



- Each pixel has three `channels` : $\color{red}{red}$, $\color{green}{green}$ and $\color{blue}{blue}$

- Each pixel has three `channels` : red, $green$ and $blue$
- Images with colour are often called RGB images

Option 1

Option 1

- If a colour image is imported, a matrix will be produced, this time with three values per pixel instead of one

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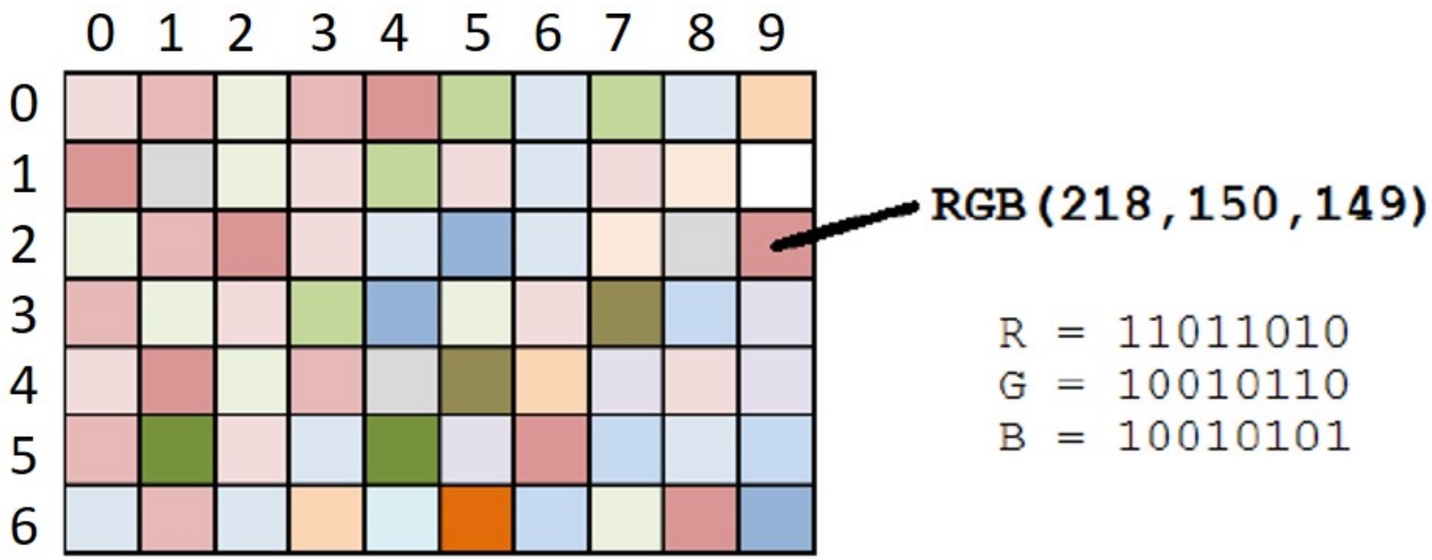
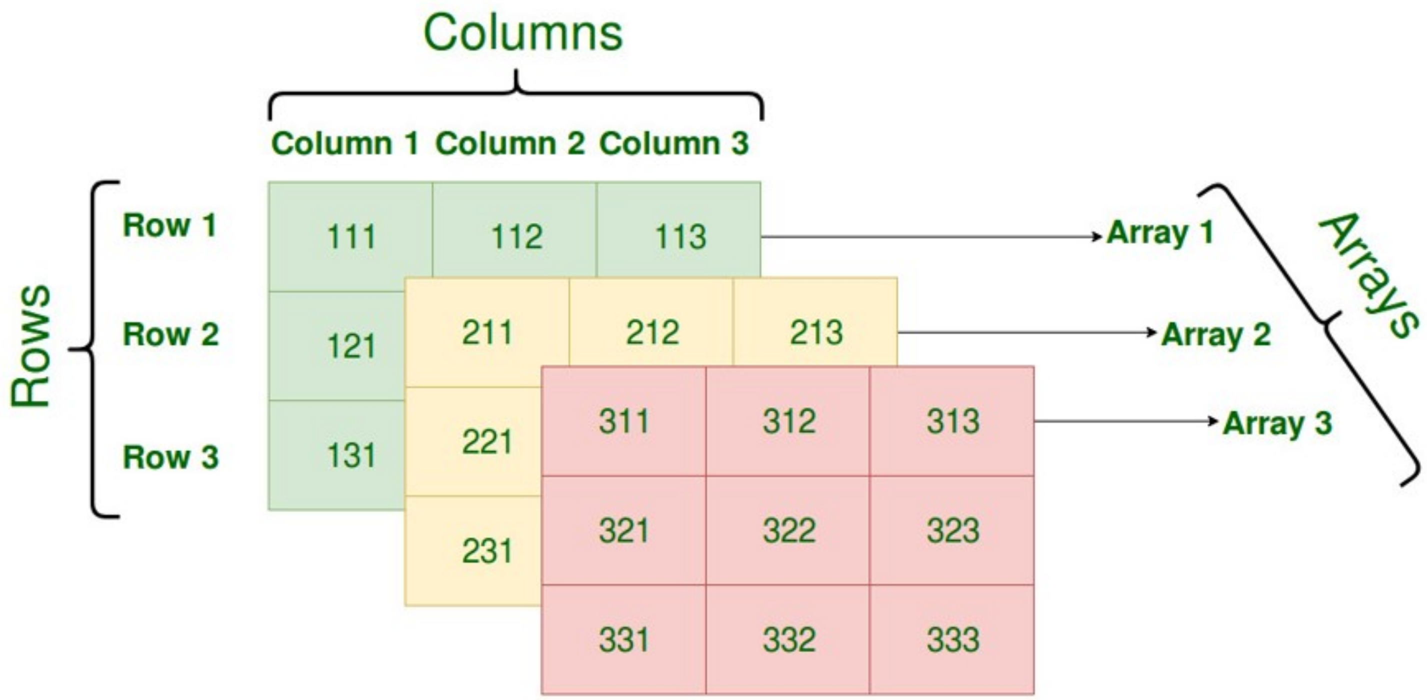
- If a colour image is imported, a matrix will be produced, this time with three values per pixel instead of one
- The three values will be stored in a tuple

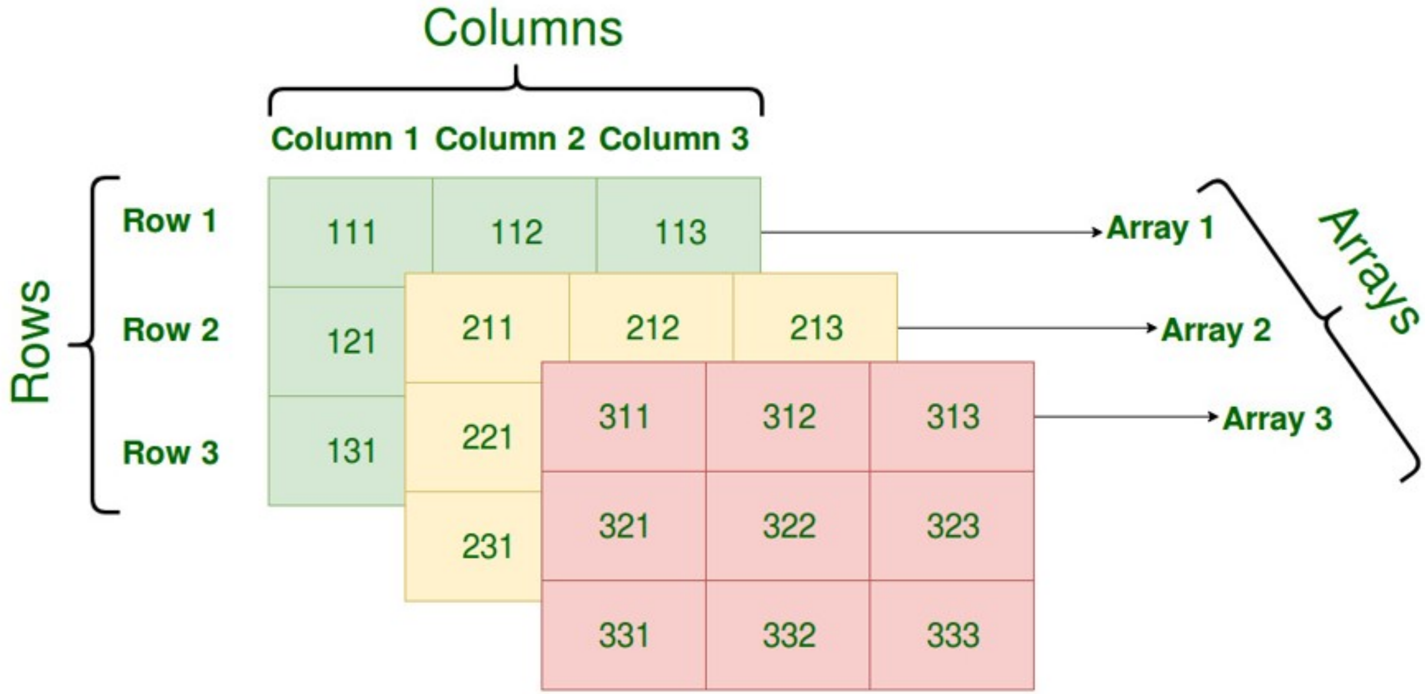

0 1 2 3 4 5 6 7 8 9
0
1
2
3
4
5
6
RGB(218,150,149)
R = 11011010
G = 10010110
B = 10010101

Option 2

Option 2

- When importing a colour image in `OpenCV`, a 3D array will be produced, with the third dimension representing the three channels


Columns
Column 1
Column 2
Column 3
Rows
Row 1
Row 2
Row 3
111
112
113
121
131
211
212
213
221
231
311
312
313
321
322
323
331
332
333
Array 1
Array 2
Array 3
Arrays



- Advantage of option 2: Faster to do calculations and transformations

HOW MANY COLOURS CAN BE REPRESENTED USING THIS STANDARD?

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CAN RGB BE NORMALISED?

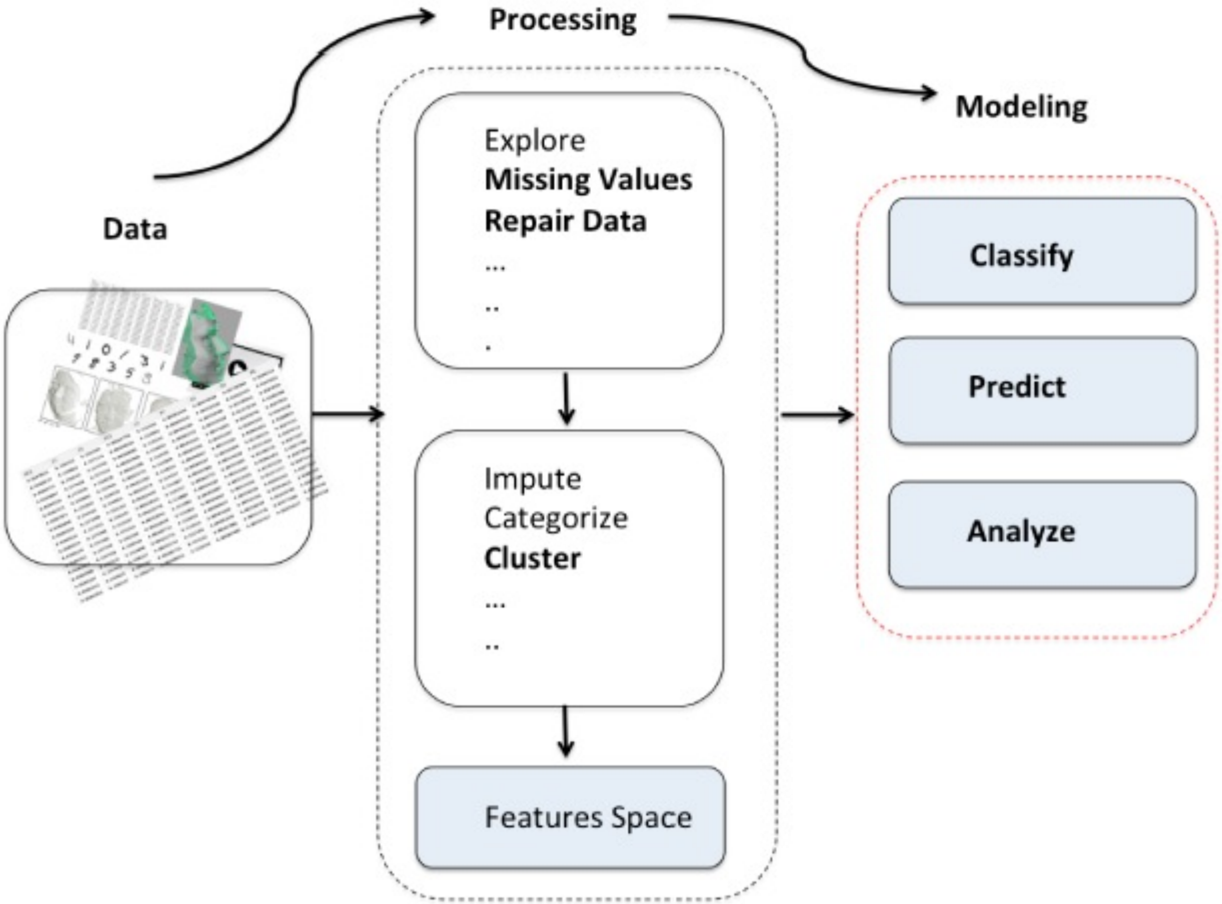
HOW MANY COLOURS CAN BE REPRESENTED USING THIS STANDARD?

CAN RGB BE NORMALISED?

ARE THERE ANY OTHER STANDARDS THAT CAN REPRESENT MORE COLOURS?

Machine Learning

- Machine learning: An automatic function that maps $x \rightarrow y$ based on the input data


Processing
Modeling
Data
Explore
Missing Values
Repair Data
...
..
.
Impute
Categorize
Cluster
...
..
Features Space
Classify
Predict
Analyze

Types of Machine Learning

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Supervised Learning

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Supervised Learning

- Aims to learn a function that, given a sample of data and desired outputs, approximates a function that maps inputs to output

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- Done in the context of **classification** (when mapping input to output label) or **regression** (when mapping input to continuous output)

Types of Machine Learning

Supervised Learning

- Aims to learn a function that, given a sample of data and desired outputs, approximates a function that maps inputs to output
- Done in the context of **classification** (when mapping input to output label) or **regression** (when mapping input to continuous output)
- The "correct" output will be deduced from the `training` data, therefore the model requires a reliable base

Examples of Supervised Learning Algorithms

Regression

Regression

- The simplest ML out there! A line (or curve) that adapts to the data points and tries to do a prediction based on the existing data and how it adapts to a mathematical function

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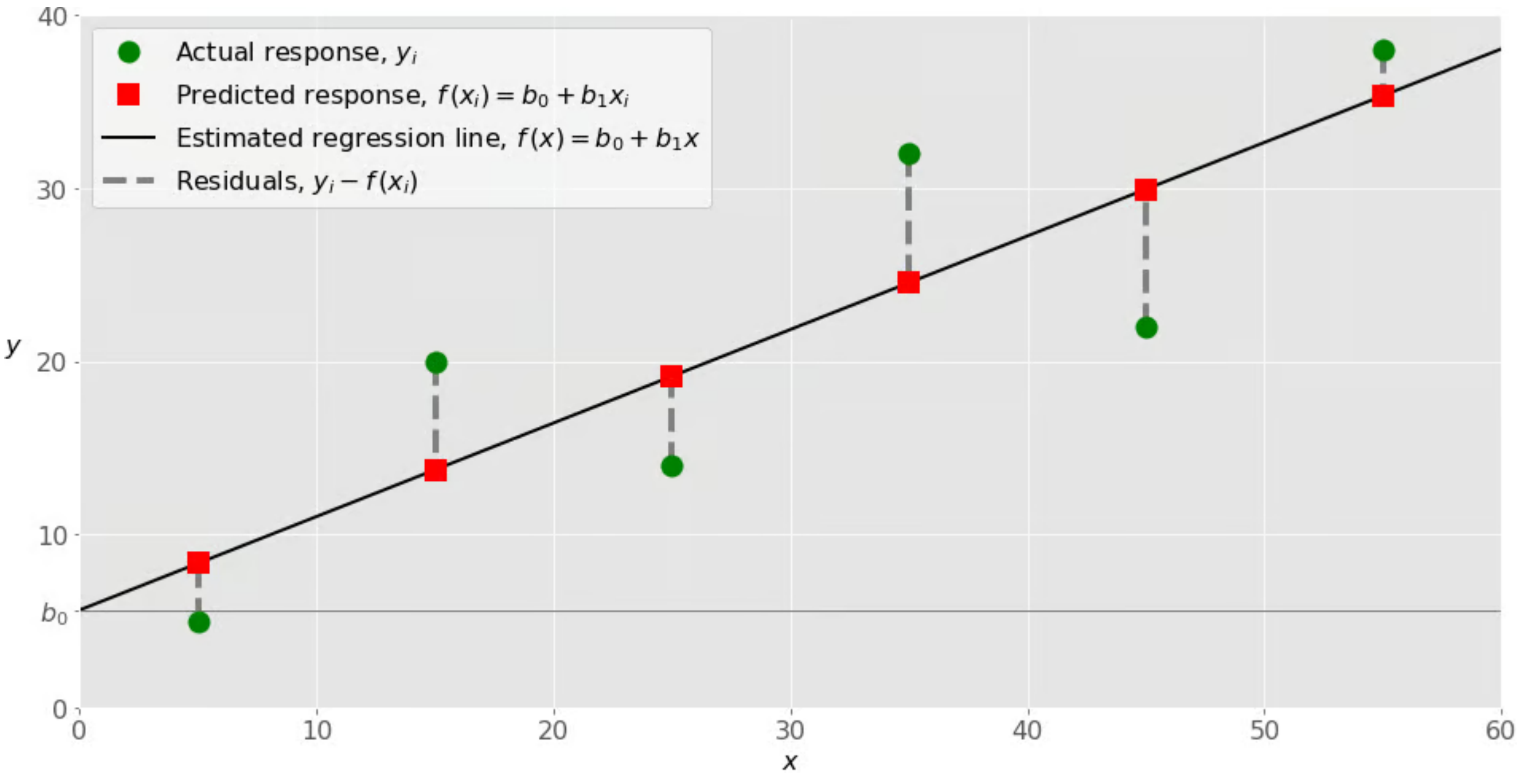

Source

- There's a version called logistic regression which uses a probability curve, which in turn can be adapted for binary classification!

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Source

- Also very simple code to implement

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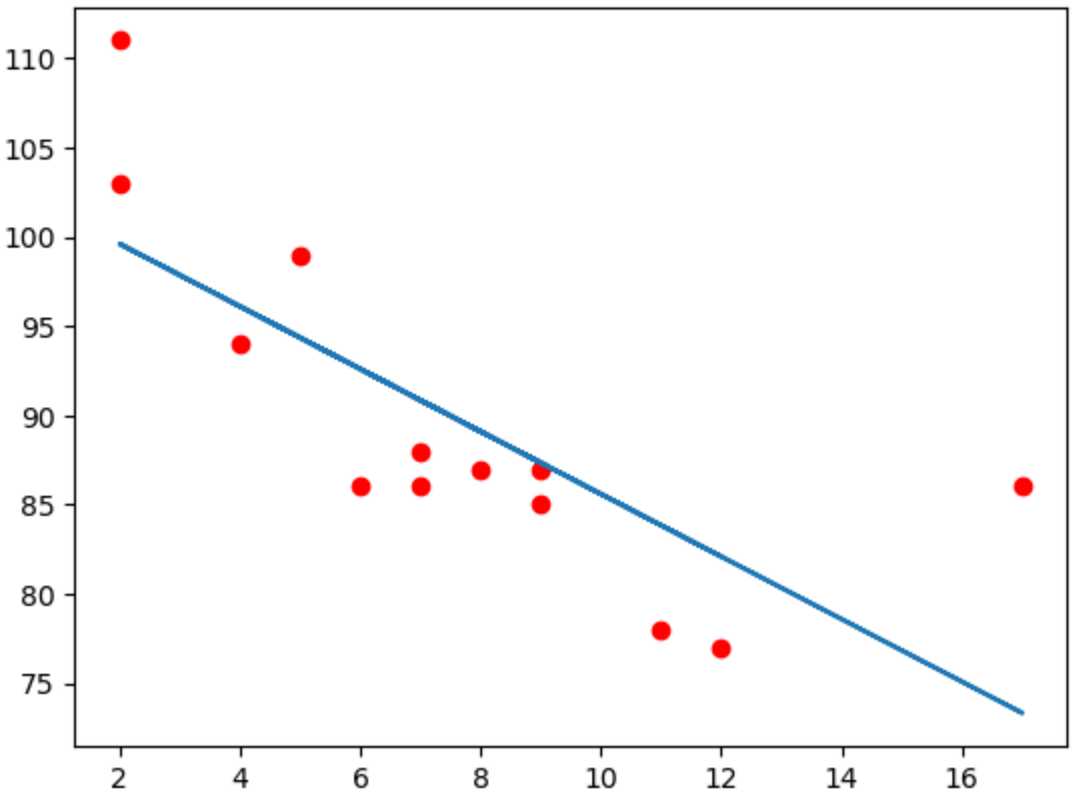
In [2]:

```
# Source: https://www.w3schools.com/python/python_ml_linear_regression.asp

import matplotlib.pyplot as plt
from scipy import stats

x = [5,7,8,7,2,17,2,9,4,11,12,9,6]
y = [99,86,87,88,111,86,103,87,94,78,77,85,86]

# This is the lin reg, one line of code!
slope, intercept, r, p, std_err = stats.linregress(x, y)

def myfunc(x):
  return slope * x + intercept

mymodel = list(map(myfunc, x))

plt.scatter(x, y, color='red')
plt.plot(x, mymodel)
plt.show()
```



110
105
100
95
90
85
80
75
2
4
6
8
10
12
14
16

K Nearest Neighbours

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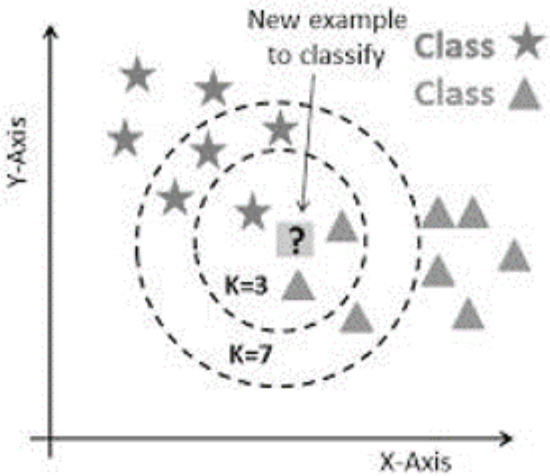
- Advantages: Simple to implement, robust to noisy training data, and effective if training data is large

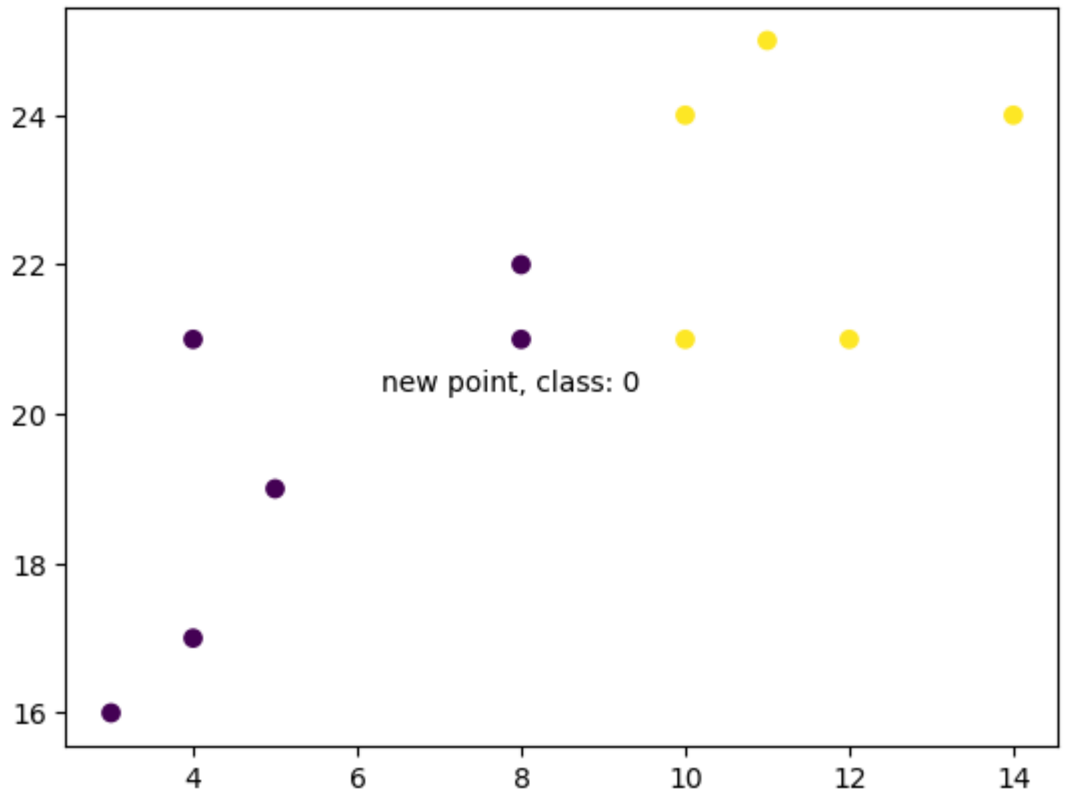
K Nearest Neighbours

- Classify by a majority vote of neighbours
- 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


New example
to classify
Class
Class
Y-Axis
K=3
K=7
X-Axis

In [3]:

```python
# Source: https://www.w3schools.com/python/python_ml_knn.asp

import matplotlib.pyplot as plt
from sklearn.neighbors import KNeighborsClassifier

x = [4, 5, 10, 4, 3, 11, 14 , 8, 10, 12]
y = [21, 19, 24, 17, 16, 25, 24, 22, 21, 21]
classes = [0, 0, 1, 0, 0, 1, 1, 0, 1, 1]
data = list(zip(x, y))

# Two lines of code to declare and "fit" the model!
knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(data, classes)

# Test it
new_x = 8
new_y = 21

new_point = [(new_x, new_y)]
prediction = knn.predict(new_point)
plt.scatter(x + [new_x], y + [new_y], c=classes + [prediction[0]])
plt.text(x=new_x-1.7, y=new_y-0.7, s=f"new point, class: {prediction[0]}")
plt.show()
```


new point, class: 0
24
22
20
18
16
4
6
8
10
12
14

Decision Tree/Random Forest

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- Segment the predictor space into multiple regions

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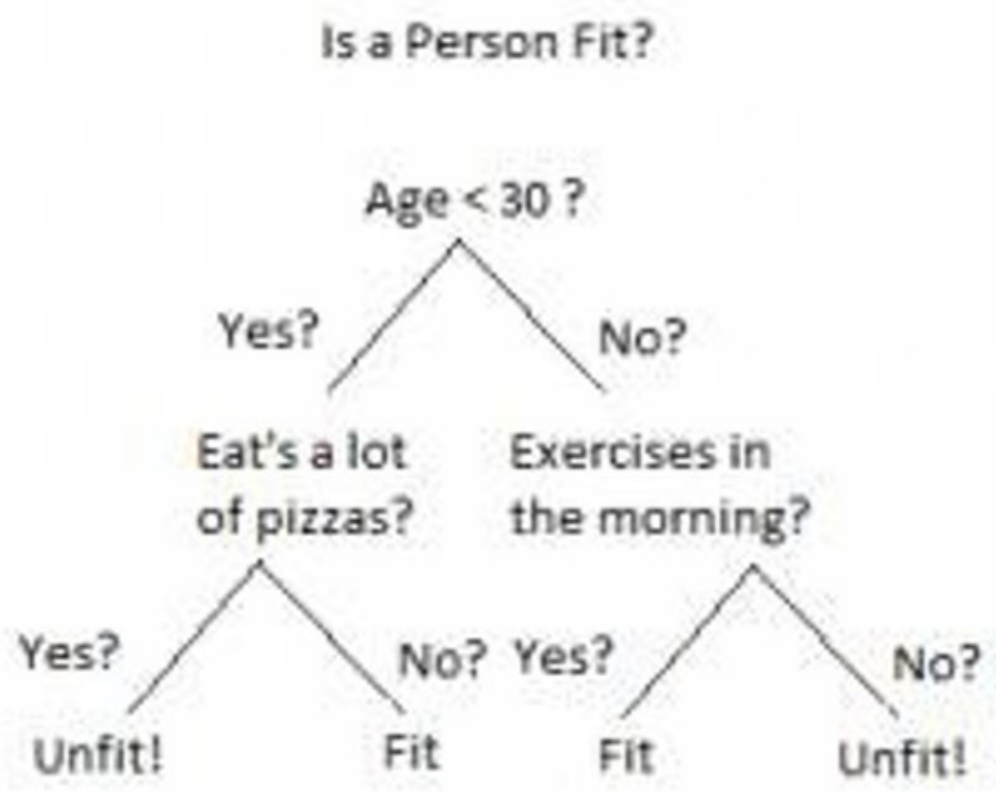
- Each region has only a subset of the training dataset

Decision Tree/Random Forest

- Segment the predictor space into multiple regions
- Each region has only a subset of the training dataset
- High variance $\rightarrow$ Small changes in the training data can give an entirely different decision tree model


Is a Person Fit?
Age < 30 ?
Yes?
No?
Eat's a lot of pizzas?
Exercises in the morning?
Yes?
No?
Yes?
No?
Unfit!
Fit
Fit
Unfit!

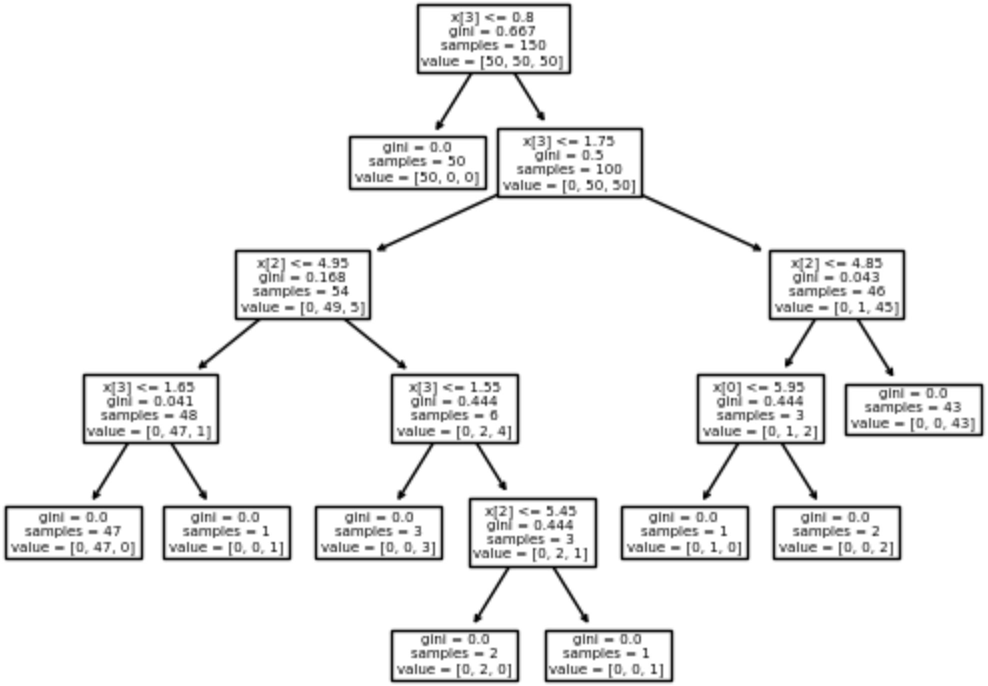
In [4]:

```python
# Source: https://scikit-learn.org/stable/modules/tree.html

from sklearn.datasets import load_iris
from sklearn import tree

iris = load_iris()
X, y = iris.data, iris.target

## Again, classifier is just two lines of code
clf = tree.DecisionTreeClassifier()
clf = clf.fit(X, y)

# You can even visualise the tree
tree.plot_tree(clf)
```

Out[4]:

```
[Text(0.5, 0.9166666666666666, 'x[3] <= 0.8\ngini = 0.667\nsamples =
150\nvalue = [50, 50, 50]'),
 Text(0.4230769230769231, 0.75, 'gini = 0.0\nsamples = 50\nvalue = [5
0, 0, 0]'),
 Text(0.5769230769230769, 0.75, 'x[3] <= 1.75\ngini = 0.5\nsamples =
100\nvalue = [0, 50, 50]'),
 Text(0.3076923076923077, 0.5833333333333334, 'x[2] <= 4.95\ngini =
0.168\nsamples = 54\nvalue = [0, 49, 5]'),
 Text(0.15384615384615385, 0.4166666666666667, 'x[3] <= 1.65\ngini =
0.041\nsamples = 48\nvalue = [0, 47, 1]'),
 Text(0.07692307692307693, 0.25, 'gini = 0.0\nsamples = 47\nvalue =
[0, 47, 0]'),
 Text(0.23076923076923078, 0.25, 'gini = 0.0\nsamples = 1\nvalue =
[0, 0, 1]'),
 Text(0.46153846153846156, 0.4166666666666667, 'x[3] <= 1.55\ngini =
```

```
0.444\nsamples = 6\nvalue = [0, 2, 4]'),
 Text(0.38461538461538464, 0.25, 'gini = 0.0\nsamples = 3\nvalue =
[0, 0, 3]'),
 Text(0.5384615384615384, 0.25, 'x[2] <= 5.45\ngini = 0.444\nsamples
= 3\nvalue = [0, 2, 1]'),
 Text(0.46153846153846156, 0.08333333333333333, 'gini = 0.0\nsamples
= 2\nvalue = [0, 2, 0]'),
 Text(0.6153846153846154, 0.08333333333333333, 'gini = 0.0\nsamples =
1\nvalue = [0, 0, 1]'),
 Text(0.8461538461538461, 0.5833333333333334, 'x[2] <= 4.85\ngini =
0.043\nsamples = 46\nvalue = [0, 1, 45]'),
 Text(0.7692307692307693, 0.4166666666666667, 'x[0] <= 5.95\ngini =
0.444\nsamples = 3\nvalue = [0, 1, 2]'),
 Text(0.6923076923076923, 0.25, 'gini = 0.0\nsamples = 1\nvalue = [0,
1, 0]'),
 Text(0.8461538461538461, 0.25, 'gini = 0.0\nsamples = 2\nvalue = [0,
0, 2]'),
 Text(0.9230769230769231, 0.4166666666666667, 'gini = 0.0\nsamples =
43\nvalue = [0, 0, 43]')]
```


x[3] <= 0.8
gini = 0.667
samples = 150
value = [50, 50, 50]
gini = 0.0
samples = 50
value = [50, 0, 0]
x[3] <= 1.75
gini = 0.5
samples = 100
value = [0, 50, 50]
x[2] <= 4.95
gini = 0.168
samples = 54
value = [0, 49, 5]
x[2] <= 4.85
gini = 0.043
samples = 46
value = [0, 1, 45]
x[3] <= 1.65
gini = 0.041
samples = 48
value = [0, 47, 1]
x[3] <= 1.55
gini = 0.444
samples = 6
value = [0, 2, 4]
x[0] <= 5.95
gini = 0.444
samples = 3
value = [0, 1, 2]
gini = 0.0
samples = 43
value = [0, 0, 43]
gini = 0.0
samples = 47
value = [0, 47, 0]
gini = 0.0
samples = 1
value = [0, 0, 1]
gini = 0.0
samples = 3
value = [0, 0, 3]
x[2] <= 5.45
gini = 0.444
samples = 3
value = [0, 2, 1]
gini = 0.0
samples = 1
value = [0, 1, 0]
gini = 0.0
samples = 2
value = [0, 0, 2]
gini = 0.0
samples = 2
value = [0, 2, 0]
gini = 0.0
samples = 1
value = [0, 0, 1]

Naive Bayes

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- Probabilistic classifier inspired by the Bayes theorem, assumes attributes are conditionally independent

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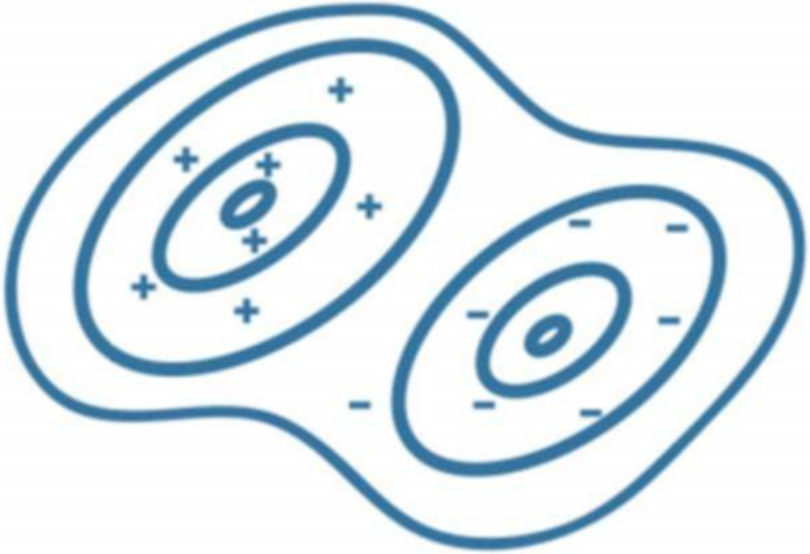
- Advantages: small amount of training data required, extremely fast
- Disadvantages: zero probability problem, if the conditional probability is zero for a particular attribute...



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

In [5]:

```
# Credit: https://www.kaggle.com/code/nizamudma/iris-data-classification-usin

from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB

#split data for train and test
x_train,x_test,y_train,y_test=train_test_split(X,y,test_size=0.15)

# No surpise, two lines
bc=GaussianNB()
bc.fit(x_train,y_train)

# Predict samples from the text set
print(bc.predict(x_test))
```

```
[0 1 2 1 1 0 0 2 0 2 0 0 0 2 1 1 1 0 0 2 2 0 0]
```

Support Vector Machine (SVM)

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- Discriminative classifier defined by a separating hyperplane

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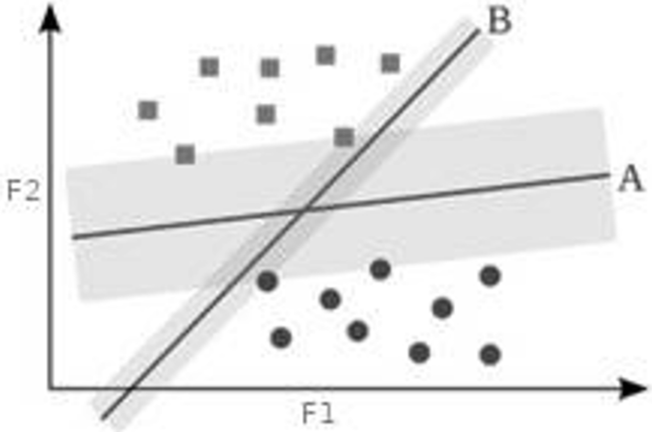
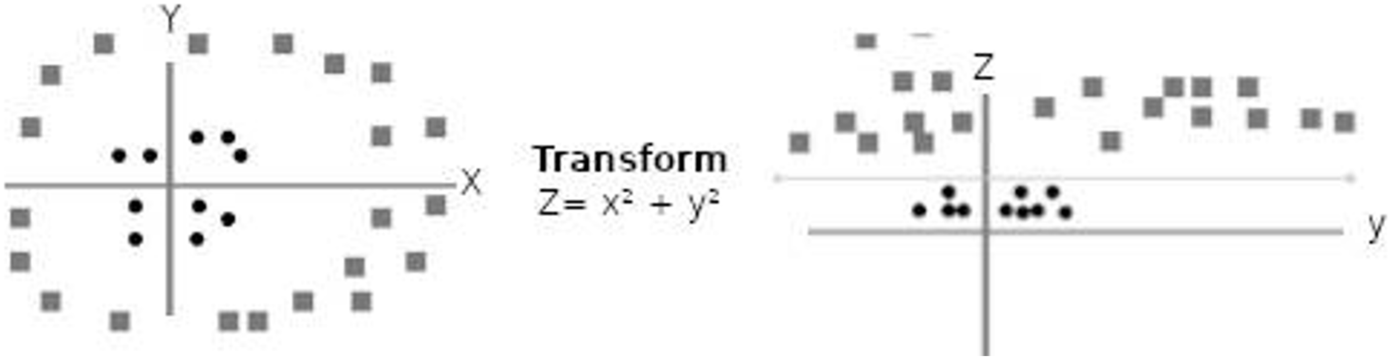
- Tuning parameters in SVM classifier
    - Kernel - transformation method, e.g. Polynomial and exponential kernels
    - Regularisation - how much to avoid misclassifying each training example
    - Gamma - how far the influence of a single training example reaches, high gamma → only nearby examples

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
  - Regularisation - 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
  - A good margin is one where this separation is larger for both the classes


B
A
F2
F1

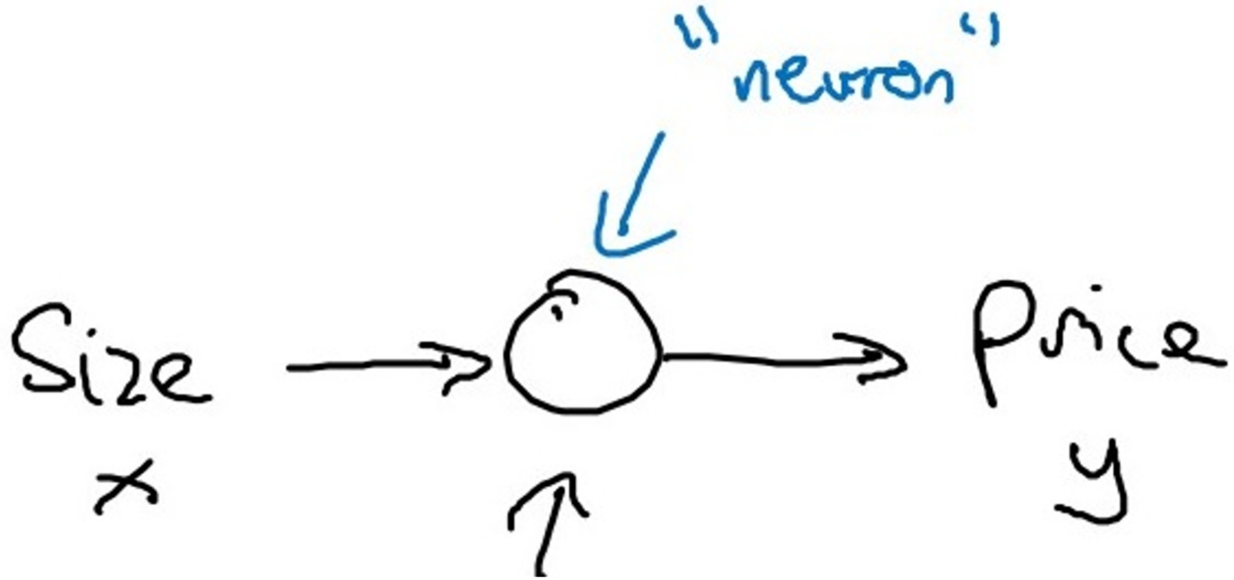

Y
X
Transform
$Z = x^2 + y^2$
Z
y

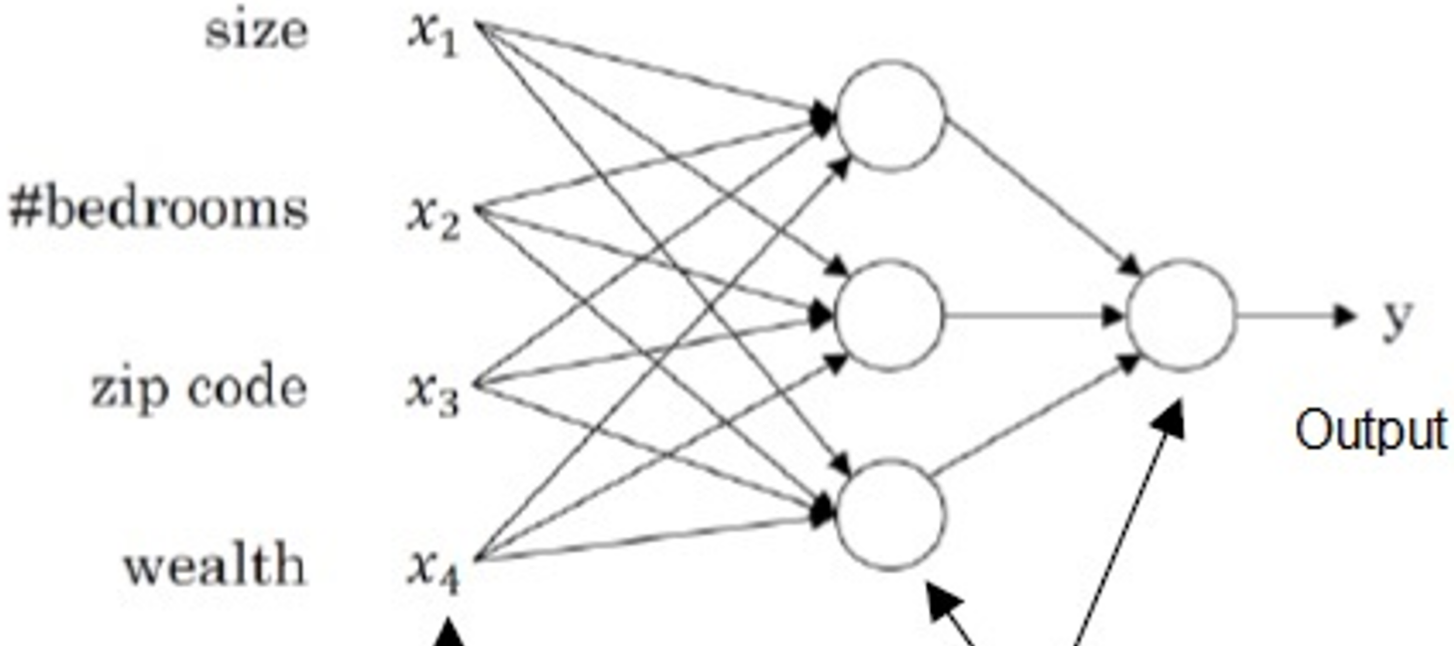
- We will do this one in Lab Topic 5! But trust me, again it is two lines of code...

Neural Network (NN)

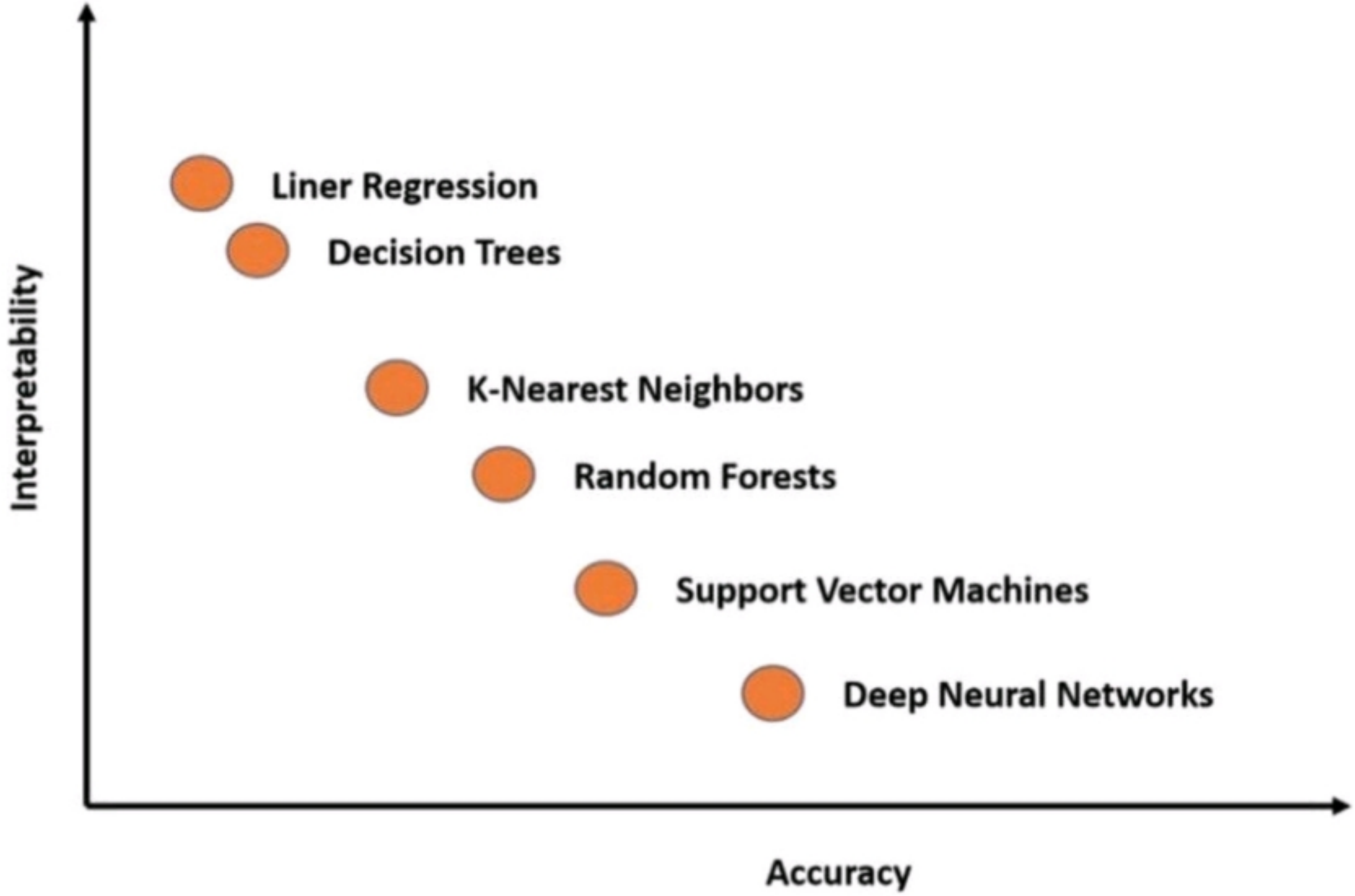
Neural Network (NN)

We will talk **EXTENSIVELY** about them later on


"neuron"
Size
x
Price
y


size
#bedrooms
zip code
wealth
y
Output

Accuracy and Interpretability



Semi-supervised Learning

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- Aims to label unlabelled data points using knowledge learned from a small number of labelled data points

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- Aims to label unlabelled data points using knowledge learned from a small number of labelled data points
- Learning with both unlabelled and labeled data points
- Used when large amounts of data are costly to label

Assumptions of Semi-supervised Learning

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- `Continuity` : Data points that are "close" have a common label

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- `Cluster` : Data naturally forms discrete clusters, most common to share label

Assumptions of Semi-supervised Learning

- `Continuity` : Data points that are "close" have a common label
- `Cluster` : Data naturally forms discrete clusters, most common to share label
- `Manifold` : Data lies in a lower dimensional space than the input space

Examples of Semi-supervised Learning Algorithms

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Transductive SVM

Examples of Semi-supervised Learning Algorithms

Transductive SVM

Label Propagation

Unsupervised Learning

Unsupervised Learning

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- Finds inherent patterns of data

Unsupervised Learning

- Does not have (or need) any labelled outputs, so its goal is to infer the natural structure present within a set of data points
- Finds inherent patterns of data
- Most common tasks: **clustering** and **exploratory data analysis**

Examples of Unsupervised Learning Algorithms

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K-means Clustering

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K-means Clustering

Principal Component Analysis (PCA)

Examples of Unsupervised Learning Algorithms

K-means Clustering

Principal Component Analysis (PCA)

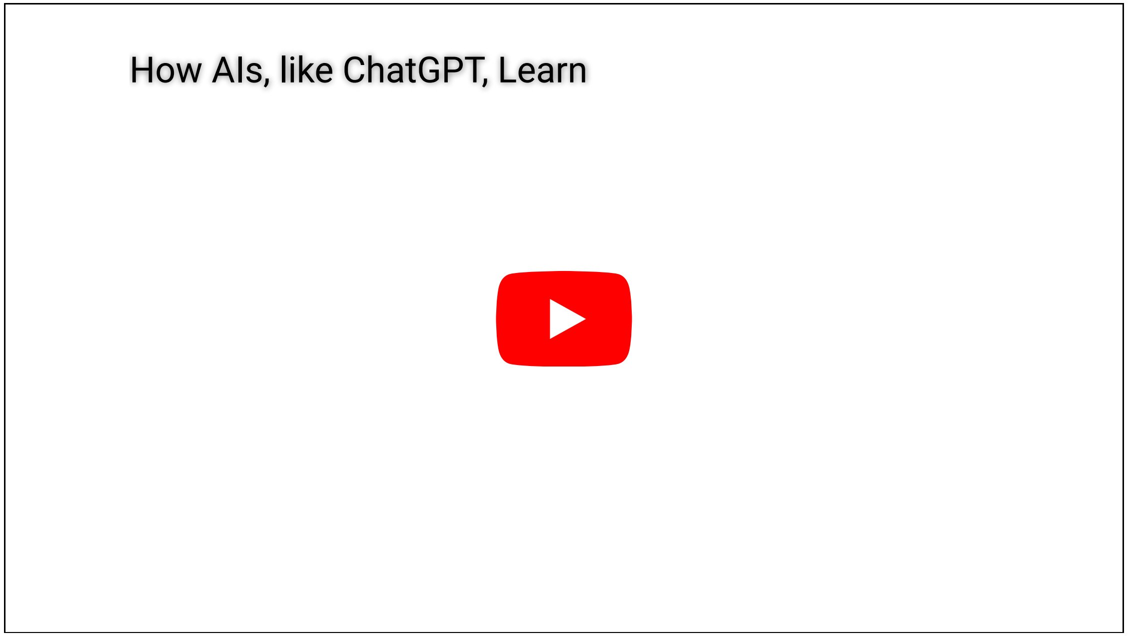
Autoencoders

A simpler explanation of what I just said

In [6]:

```python
import warnings
warnings.filterwarnings('ignore')
from IPython.display import HTML
HTML('<iframe width="560" height="315" src="https://www.youtube.com/embed/R9OH
```

Out[6]:



As you can see, we can do more things beyond classification, such as **detecting** where the object lies in the image, **recognise** it from a pool of similar objects, **segment** where it is or even **track** it in a video feed!