How Classification Works :-

Amazon Dataset

$r_i \longrightarrow$ Text $\longrightarrow$ Vector

$\longrightarrow$ +ve / -ve

$\rightarrow r_i \longrightarrow (v_i\ ,\ +ve/-ve)$

{Given a review Text, determine/predict if review is +ve/-ve

$\rightarrow y = f(x)$

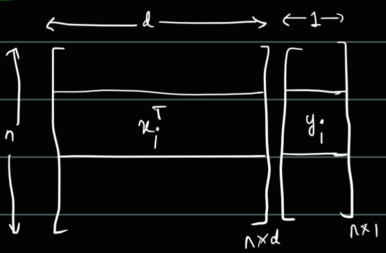
In most ML problems, we are trying to find this $f()$ function.

Amazon Dataset :-

training dataset $\longrightarrow$ Algorithm $\boxed{f}$ (training stage)

(testing dataset) $x_q \longrightarrow \boxed{f} \longrightarrow y_q$ (testing / evaluation stage)

Data Matrix Notation :-



$r_i \longrightarrow$ Text $\longrightarrow$ vector

class (+ve / -ve)

$y = f(x)$

For Amazon Dataset, $D = \left\{ (x_i, y_i)_{i=1}^{n} \;\middle|\; x_i \in \mathbb{R}^d, y_i \in \{0,1\} \right\}$

$r_i \longrightarrow$ vector x_i

$y = f(x)$

$\rightarrow$ If target class = 2, (like Amazon Dataset), classification is called Binary Classification

= n, " " " Multi Class Classification (IRIS dataset, MNIST dataset)

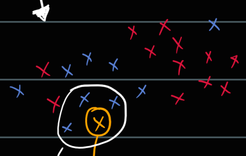
If y_i is not finite, it becomes regression. $y_i \in \mathbb{R}$ not a set of finite values.

$\rightarrow$ classification $\rightarrow$ Discrete values , Regression $\rightarrow$ continuous variables

$\rightarrow$ Algorithms like Decision trees, random forests can perform classification as well as regression

K-Nearest Neighbours :-

Assume $D = \{(x_i, y_i) \mid x_i \in \mathbb{R}^2\ y_i \in \{0,1\}\}$



$\times \rightarrow$ positive (1)

$\times \rightarrow$ Negative (0)

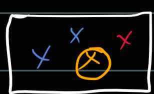
Query point (x_q)

Neighbourhood of x_q. Geometrically all points close to x_q are positive.

We can conclude x_q is positive

Steps in KNN :-

① Find 'K' nearest points. Let K=3 in this example. $= \{x_1, x_2, x_3\}$



$\{y_1, y_2, y_3\}$ $\longrightarrow$ In this case, majority = positive

② Majority vote b/w $\{y_1, y_2, y_3 \ldots, y_K\}$

(Avoid taking even 'K', as there could be a chance of tie)

→ In SCIKIT learn, there are 3 methods to calculate nearest neighbours

(i) Bruteforce :- Effective in small datasets.

(ii) KD tree :- distance information for the sample. The basic idea is that if point A is very distant from point B, and point B is very close to point C, then we know that points A and C are very distant, *without having to explicitly calculate their distance.* In this way, the

(iii) Ball tree :- A ball tree recursively divides the data into nodes defined by a centroid C and radius r, such that each point in the node lies within the hyper-sphere defined by r and C. The number of candidate points for a neighbor search is reduced through use of the *triangle inequality*:

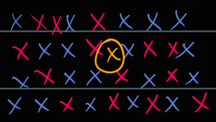
$$|x+y| \leq |x| + |y|$$

→ KNN is not used in realtime applications as it is a lazy algorithm.

Failure cases of KNN :-

→ when point is very far away from rest of the points. Taking the nearest neighbours doesn't make much sense.

→ Very jumbled randomly spread data.



No useful information in this type of spread.

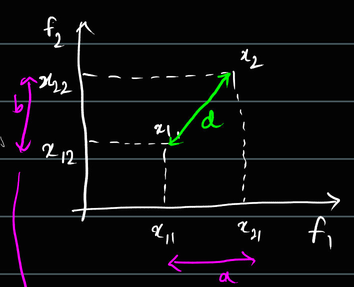
Most ML algos fail when data is like this.

→ Determining threshold.

Note:-Determining Threshold is Data-Specific

1. Take Train Data
2. Take each point in data-set and compute its distance from its first neighbor and store all these distance
3. Sort them, some are small and some are large
4. Take 99.99% percentile as your threshold, let's name it D-99
5. Now for our Query point, if its distance from its first neighbor is greater than D-99 then take it as an outlier and don't classify it

Distance Measures :-



$$\begin{array}{c} \quad f_1 \quad f_2 \\ x_1 = (x_{11}, x_{12}) \end{array}$$

$$x_2 = (x_{21}, x_{22})$$

d = len of shortest line from x_1 to x_2

$$d = \sqrt{(x_{21}-x_{11})^2 + (x_{22}-x_{12})^2} = ||x_1 - x_2|| \longrightarrow \text{Eucledian distance.}$$

if $x_1 \in \mathbb{R}^d$ & $x_2 \in \mathbb{R}^d$, $||x_1 - x_2||_2 = \left(\sum_{i=1}^{d} (x_{1i} - x_{2i})^2\right)^{1/2}$

L2 Norm of a vector

→ if only one vector ie, $||x_1||_2 \longrightarrow$ distance of x_1 from origin $= \left(\sum_{i=1}^{d} x_{1i}^2\right)^{1/2}$

(a+b)

Manhattan Distance :- $\sum_{i=1}^{d} |x_{1i} - x_{2i}|$.

Also written as $||x_1 - x_2||_1$. L1 Norm. $||x_1||_1 = \sum_{i=1}^{d} |x_{1i}|$

L_p Norms :- corresponding value is called Minkowski Distance

$$||x_1 - x_2||_p = \left(\sum_{i=1}^{d} |x_{1i} - x_{2i}|^p\right)^{1/p}$$

If $p=2$, Minkowski distance = Eucledian Distance

If $p=1$, Minkowski distance = Manhattan Distance.

$$||x_1||_p = \left(\sum_{i=1}^{d} |x_{1i}|^p\right)^{1/p}$$

→ Distances are b/w two points. Norms are b/w two vectors.

ex:- Eucledian distance (x_1, x_2) = L2 Norm of $(x_1 - x_2) = ||x_1 - x_2||_2$

Hamming Distance :-

Used for Boolean Values (ex:- Binary Bag of Words)

$x_1 = [0,1,1,0,1,0,1,1,1]$

$x_2 = [1,0,1,1,0,1,0,0,1]$

Hamming Dist (x_1, x_2) = # of locations where Binary Vectors differ.

For above example :- HD = 7

→ Can also be used for strings - Number of locations where strings differ

→ Can also be used for Gene Sequencing. They are basically sequence of letters