K-Nearest Neighbor Classification

Agenda

- KNN Classification Algorithm
- Solving Business Problems using KNN Algorithm
- Hands-on

Sample Business Problem

- Let’s assume a money lending company “XYZ” like UpStart, IndiaLends, etc.
- Money lending XYZ company is interested in making the money lending system comfortable & safe for lenders as well as for borrowers. The company holds a database of customer details.
- Using customer’s detailed information from the database, it will calculate a credit score(discrete value) for each customer.
- The calculated credit score helps the company and lenders to understand the credibility of a customer clearly.
- So they can simply take a decision whether they should lend money to a particular customer or not.

Sample Business Problem

- The customer’s details could be:
  - Educational background details
    - Highest graduated degree
    - Cumulative grade points average (CGPA) or marks percentage
    - The reputation of the college
    - Consistency in his lower degrees
    - Cleared education loan dues
  - Employment details
    - Salary
    - Years of experience
    - Got any onsite opportunities
    - Average job change duration

Sample Business Problem

- The company(XYZ) uses these kind of details to calculate credit score of a customer
- The process of calculating the credit score from the customer's details is expensive
- To reduce the cost of predicting credit score, they realized that the customers with similar background details are getting a similar credit score
- So, they decided to use already available data of customers and predict the credit score by comparing it with similar data
- These kinds of problems are handled by the K-nearest neighbor classifier for finding the similar kind of customers

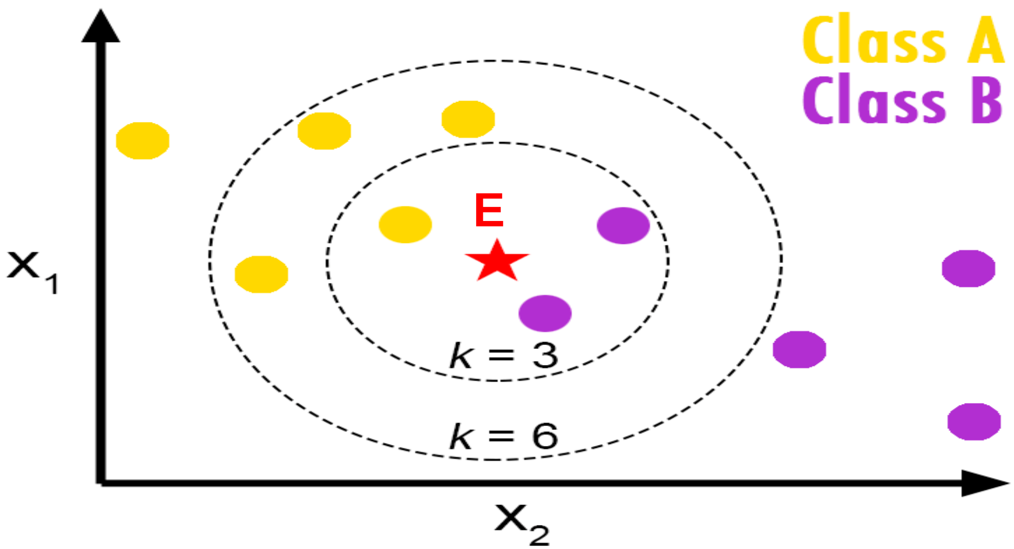
Introduction

- K-nearest neighbor classifier is one of the introductory supervised classifier, which every data science learner should be aware of
- Fix & Hodges proposed K-nearest neighbor classifier algorithm in 1951 for performing pattern classification task
- For simplicity, this classifier is called as KNN Classifier
- KNN addresses the pattern recognition problems and also the best choices for addressing some of the classification related tasks
- The simple version of the K-nearest neighbor classifier algorithms is to predict the target label by finding the nearest neighbor class
- The closest class will be identified using the distance measures like Euclidean distance

K_Nearest Neighbour Algorithm

To determine the class of a new example E:

- Calculate the distance between E and all examples in the training set
- Select K-nearest examples to E in the training set
- Assign E to the most common class among its K-nearest neighbors



Distance Between Neighbors

Each example is represented with a set of numerical attributes

Jay:
Age=35
Income=95K
No. of credit cards=3

Rina:
Age=41
Income=215K
No. of credit cards=2

- "Closeness" is defined in terms of the Euclidean distance between two examples

- The Euclidean distance between $X=(x_1, x_2, x_3, \ldots x_n)$ and $Y=(y_1, y_2, y_3, \ldots y_n)$ is defined as:

$$D(X,Y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

$$\text{Distance (Jay,Rina)} = \sqrt{(35-41)^2 + (95{,}000-215{,}000)^2 + (3-2)^2}$$

K_Nearest Neighbours: Example

Customer	Age	Income	No. credit cards	Response
Jay	35	35K	3	No
Rina	22	50K	2	Yes
Hema	63	200K	1	No
Tommy	59	170K	1	No
Neil	25	40K	4	Yes
Dravid	37	50K	2	?

K_Nearest Neighbours: Example

Customer	Age	Income	No. credit cards	Response	Distance from Dravid
Jay	35	35K	3	No	$\sqrt{(35-37)^2+(35-50)^2+(3-2)^2}$ $= 15.16$
Rina	22	50K	2	Yes	15
Hema	63	200K	1	No	152.23
Tommy	59	170K	1	No	122
Neil	25	40K	4	Yes	15.74
Dravid	37	50K	2	?	0

K_Nearest Neighbours

Jay:
Age=35
Income=95K
No. of credit cards=3

Rina:
Age=41
Income=215K
No. of credit cards=2

Distance (Jay, Rina)=sqrt $[(35-45)^2 + \mathbf{(95{,}000-215{,}000)^2} + (3-2)^2]$

- Distance between neighbors could be <u>dominated</u> by some attributes with relatively large numbers (e.g., income in our example)

- **Important to normalize some features**
  (e.g., map numbers to numbers between 0-1)

  <u>Example</u>: Income
  Highest income = 200K
  Davis's income is normalized to 50/200, Rina income is normalized to 50/200, etc.)

K_Nearest Neighbours

Normalization of Variables				
Customer	**Age**	**Income**	**No. credit cards**	**Response**
Jay	55/63= 0.175	35/200= 0.175	3/4= 0.75	No
Rina	22/63= 0.34	50/200= 0.25	2/4= 0.5	Yes
Hema	63/63= 1	200/200= 1	1/4= 0.25	No
Tommy	59/63= 0.93	170/200= 0.175	1/4= 0.25	No
Neil	25/63= 0.39	40/200= 0.2	4/4= 1	Yes
Dravid	37/63= 0. 58	50/200= 0.25	2/4= 0.5	Yes

K-Nearest Neighbor

- Distance works naturally with numerical attributes
  d(Rina,Johm)= $\sqrt{(35-37)^2+(35-50)^2+(3-2)^2}$ =**15.16**
- What if we have nominal attributes?

<u>Example</u>: Married

Customer	Married	Income	No. credit cards	Response
Jay	Yes	35K	3	No
Rina	No	50K	2	Yes
Hema	No	200K	1	No
Tommy	Yes	170K	1	No
Neil	No	40K	4	Yes
Dravid	Yes	50K	2	Yes

Non-Numeric Data

- Feature values are not always numbers
- Example
  - Boolean values: Yes or no, presence or absence of an attribute
  - Categories: Colors, educational attainment, gender
- How do these values factor into the computation of distance?

Dealing with Non-Neumeric Data

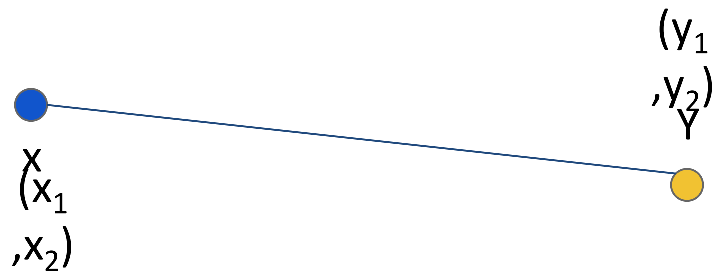
- Boolean values => convert to 0 or 1
  - Applies to yes-no/presence-absence attributes
- Non-binary characterizations
  - Use natural progression when applicable; e.g., educational attainment: GS, HS, College, MS, PHD => 1,2,3,4,5
  - Assign arbitrary numbers but be careful about distances; e.g., color: red, yellow, blue => 1,2,3
- How about unavailable data?
  (0 value not always the answer)

Distance measures

- How to determine similarity between data points
- Let x = (x1,…,xn) and y = (y1,…yn) be n-dimensional vectors of data points of objects g1 and g2
  - g1, g2 can be two different genes in microarray data

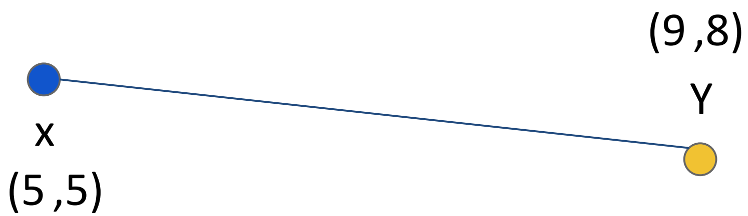
How to calculate distance using Math?

1. Euclidean Distance



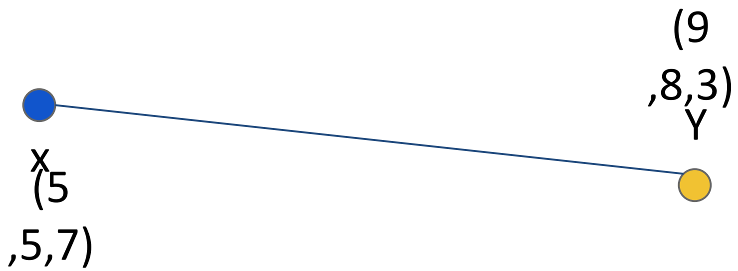
$$d = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2}$$

1. Euclidean Distance



$$d = \sqrt{(5-9)^2 + (5-8)^2} = 5$$

1. Euclidean Distance



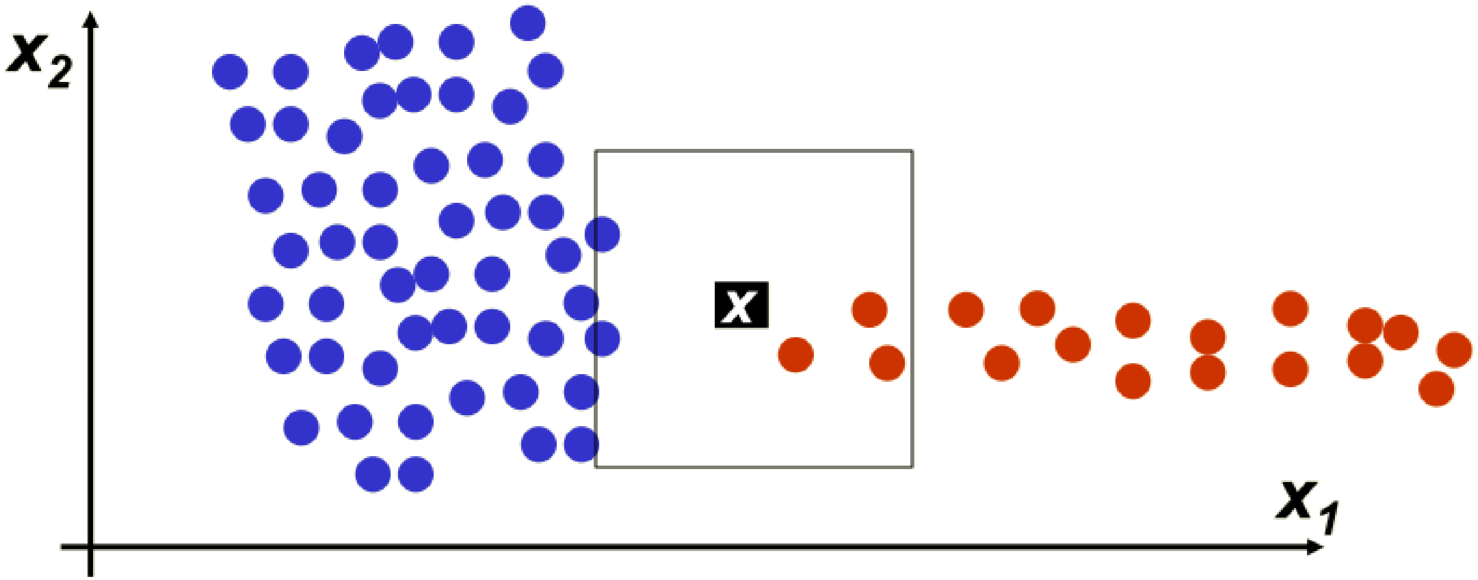
$$d = \sqrt{(5-9)^2 + (5-8)^2 + (7-3)^2} = 6.4$$

L2 Norm

k-NN Variations

- Value of k
  - Larger k increases confidence in prediction
  - Note that if k is too large, decision may be skewed
- Weighted evaluation of nearest neighbors
  - Plain majority may unfairly skew decision
  - Revise algorithm so that closer neighbors have greater “vote weight”

How to Choose "K"?



- For k = 1, …,5 point x gets classified correctly
  - red class
- For larger k classification of x is wrong
  - blue class

How to Choose ”K”?

- Selecting the value of K in K-nearest neighbor is the most critical problem.
- A small value of K means that noise will have a higher influence on the result i.e., the probability of overfitting is very high.
- A large value of K makes it computationally expensive and defeats the basic idea behind KNN (that points that are near might have similar classes).
- A simple approach to select K is $K = \sqrt{n}$
- It depends on individual cases, at times best process is to run through each possible value of K and test our result

KNN algorithm Pseudo Code

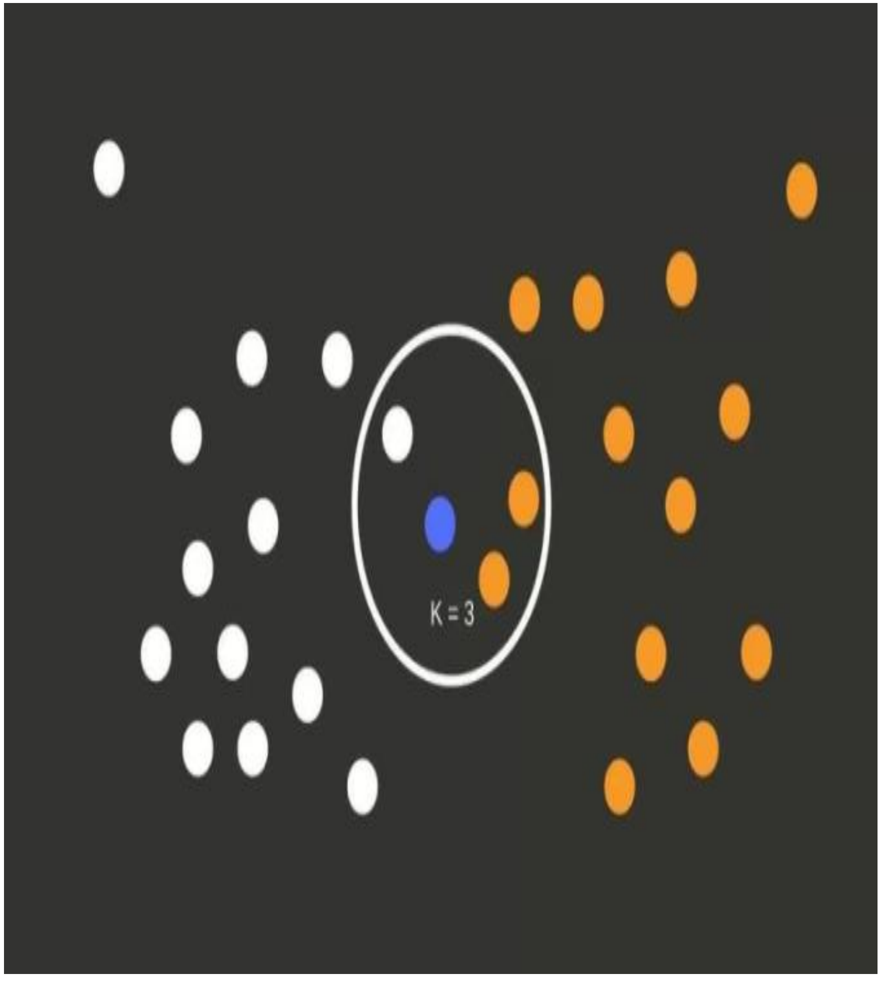
- Let (X_i, C_i) where $i = 1,2,\cdots,n$ be data points. X_i denotes feature values & C_i denotes labels for X_i for each i
- Assuming the number of classes as c, $C_i \in \{1,2,3,\cdots,c\}$ for all values of i
- Let x be a point for which label is not known
- We would like to find the label class using k-nearest neighbor algorithms.

KNN algorithm Pseudo Code

- Calculate $d(x, x_i), i = 1,2, \cdots, n$; where d denotes the Euclidean distance between the points.
- Let's consider a setup with n training samples, where x_i is the training data point.
- The training data points are categorized into c classes.
- Using KNN, we want to predict class for the new data point.
  - So, the first step is to calculate the distance(Euclidean) between the new data point and all the training data points.
  - Next step is to arrange all the distances in non-decreasing order.
  - Assuming a positive value of k and filtering k least values from the sorted list.
  - Now, we have k top distances.
    - Let k_i denotes no. of points belonging to the i^{th} class among k points.
    - If $k_i > k_j$ for all $i \neq j$ then put x in class i

KNN algorithm: Example

- Let's consider the image shown here where we have two different target classes white and orange circles.
- We have total 26 training samples.
- Now we would like to predict the target class for the blue circle
- Considering k value as three, we need to calculate the similarity distance using similarity measures like Euclidean distance.
- If the similarity score is less which means the classes are close.
- In the image, we have calculated distance and placed the less distance circles to blue circle inside the Big circle.



Advantages and Disadvantages

- Advantages
  - Makes no assumptions about distributions of classes in feature space
  - Don’t need any prior knowledge about the structure of data in the training set
  - No retraining is required if the new training pattern is added to the existing training set
  - Can work for multi-classes simultaneously
  - Easy to implement and understand
- Disadvantages
  - Fixing the optimal value of K is a challenge
  - Does not output any models. Calculates distances for every new point (lazy learner)
  - For every test data, the distance should be computed between test data and all the training data. Thus a lot of time may be needed for the testing

Demo Using Python

Sample Code in Python

```
X = [[0], [1], [2], [3]]
y = [0, 0, 1, 1]
from sklearn.neighbors import KNeighborsClassifier
neigh = KNeighborsClassifier(n_neighbors=3)
neigh.fit(X, y) KNeighborsClassifier(...)
neigh.predict([[1.1]])
```

Summary

- KNN classification algorithm
  - Different distance measures
  - KNN algorithm
  - Advantages and disadvantages
- Case study 1 (using KNN)

Thanks!