K-Nearest Neighbor Classification

Agenda

- ➢ KNN Classification Algorithm
- ➢ Solving Business Problems using KNN Algorithm
- ➢ Hands-on
- ➢ Compare Multiple Classification Algorithms

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's 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

   ➢ Whether to take the education loan or not

   ➢ Cleared education loan dues

  ➢ Employment details

   ➢ Salary

   ➢ Year of experience

   ➢ Got any onsite opportunities

   ➢ Average job change duration

Sample Business Problem

➢ The company(XYZ) use's these kinds 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 using it 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
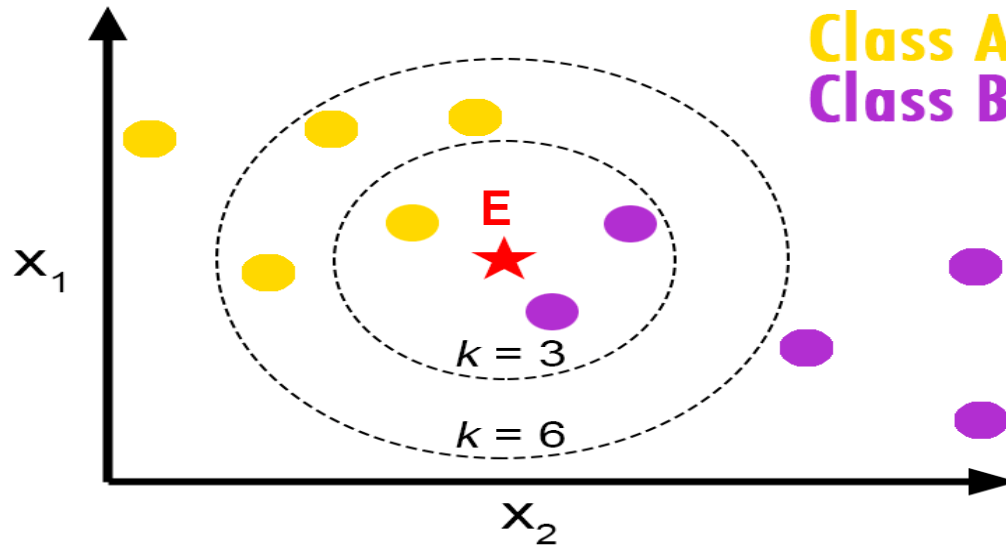
Introduction

➢ K-nearest neighbor classifier is one of the introductory <u>supervised classifier</u>, 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

➢ K-nearest neighbor classifier mostly represented as KNN, even in many research papers too

➢ KNN addresses the pattern recognition problems and also the best choices for addressing some of the <u>classification related</u> 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,…x_n) and Y =(y_1,y_2, y_3,…y_n) is defined as:

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

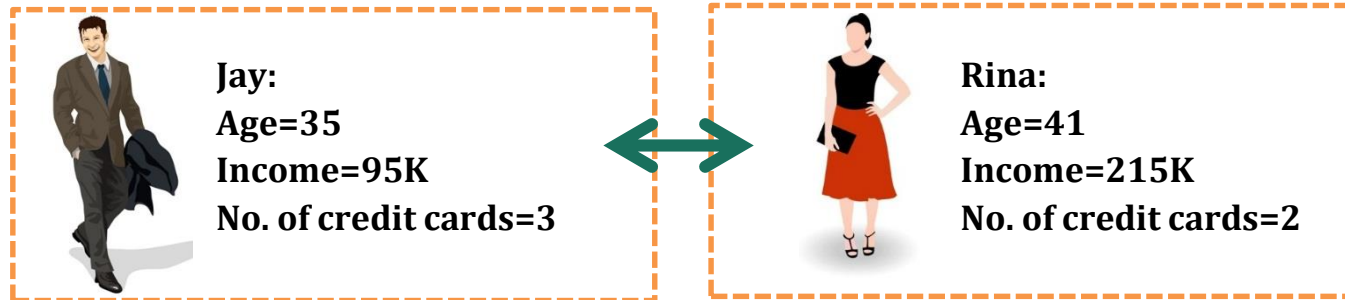$$\text{Distance (Jay,Rina)} = \sqrt{(35-41)^2 + (95{,}000-215{,}000)^2 + (3-2)^2}$$

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 $[(35-45)^2+(95,000-215,000)^2+(3-2)^2]$

- 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 = 500K
Davis's income is normalized to 95/500, Rina income is normalized to 215/500, 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
  $d(Rina, Johm) = \sqrt{(35-37)^2 + (35-50)^2 + (3-2)^2} = \textbf{15.16}$
- What if we have nominal attributes?

Example: 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)

Preprocessing Your Dataset

- ➢ Dataset may need to be preprocessed to ensure more reliable data mining results
- ➢ Conversion of non-numeric data to numeric data
- ➢ Calibration of numeric data to reduce effects of disparate ranges
    - ➢ Particularly when using the Euclidean distance metric

Distance measures

- How to determine similarity between data points
  - using various distance metrics
- 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
  - n can be the number of samples

Distance measure

- Euclidean distance

$$d(g_1, g_2) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

- Manhattan distance

$$d(g_1, g_2) = \sum_{i=1}^{n}\left|(x_i - y_i)\right|$$

- Minkowski distance

$$d(g_1, g_2) = \sqrt[m]{\sum_{i=1}^{n}(x_i - y_i)^m}$$

Correlation distance

- Correlation distance

$$r_{xy} = \frac{Cov(X,Y)}{\sqrt{(Var(X) \cdot Var(Y)}}$$

- Cov(X,Y) stands for covariance of X and Y
  - degree to which two different variables are related
- Var(X) stands for variance of X
  - measurement of a sample differ from their mean

Correlation distance

- Variance

$$Var(X) = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{X})^2}{n-1}}$$

- Covariance

$$CoVar(X,Y) = \frac{\sum_{i=1}^{n}(x_i - \overline{X})(y_i - \overline{Y})}{n-1}$$

  - Positive covariance
    - two variables vary in the same way
  - Negative covariance
    - one variable might increase when the other decreases
  - Covariance is only suitable for heterogeneous pairs

Correlation distance

- Correlation

$$r_{xy} = \frac{Cov(X,Y)}{\sqrt{(Var(X) \cdot Var(Y))}}$$

- – maximum value of 1 if X and Y are perfectly correlated
- – minimum value of 0 if X and Y are exactly opposite
- – d(X,Y) = (1 + r$_{xy)/2}$

Cosine distance

- Cosine distance
  - Used in document comparison

  - $$\cos(\theta) = \frac{X^T Y}{\|X\|\|Y\|}$$

Summary of similarity measures

- Using different measures for clustering can yield different clusters
- Euclidean distance and correlation distance are the most common choices of similarity measures for microarray data
- Euclidean vs Correlation Example
  - g1 = (1,2,3,4,5)
  - g2 = (100,200,300,400,500)
  - g3 = (5,4,3,2,1)
  - Which genes are similar according to the two different measures?

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"
- Other distance measures

Other Distance Measures

- City-block distance (Manhattan dist)
  - Add absolute value of differences
- Cosine similarity
  - Measure angle formed by the two samples (with the origin)
- Jaccard distance
  - Determine percentage of exact matches between the samples (not including unavailable data)
- Others

Distance-Weighted Nearest Neighbor Algorithm

- Assign weights to the neighbors based on their 'distance' from the query point
  - Weight 'may' be inverse square of the distances
- All training points may influence a particular instance

How to Choose "K"?
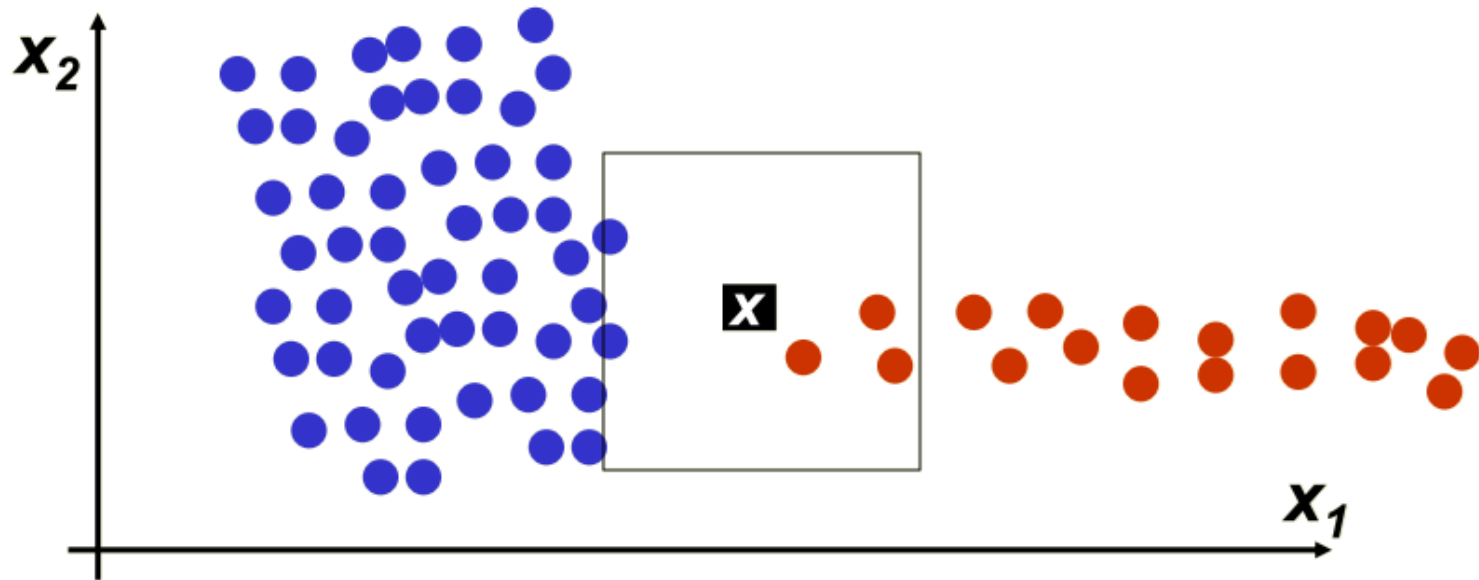
- For k = 1, ...,5 point x gets classified correctly
  - red class
- For larger k classification of x is wrong
  - blue class

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 ith 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.

K = 3
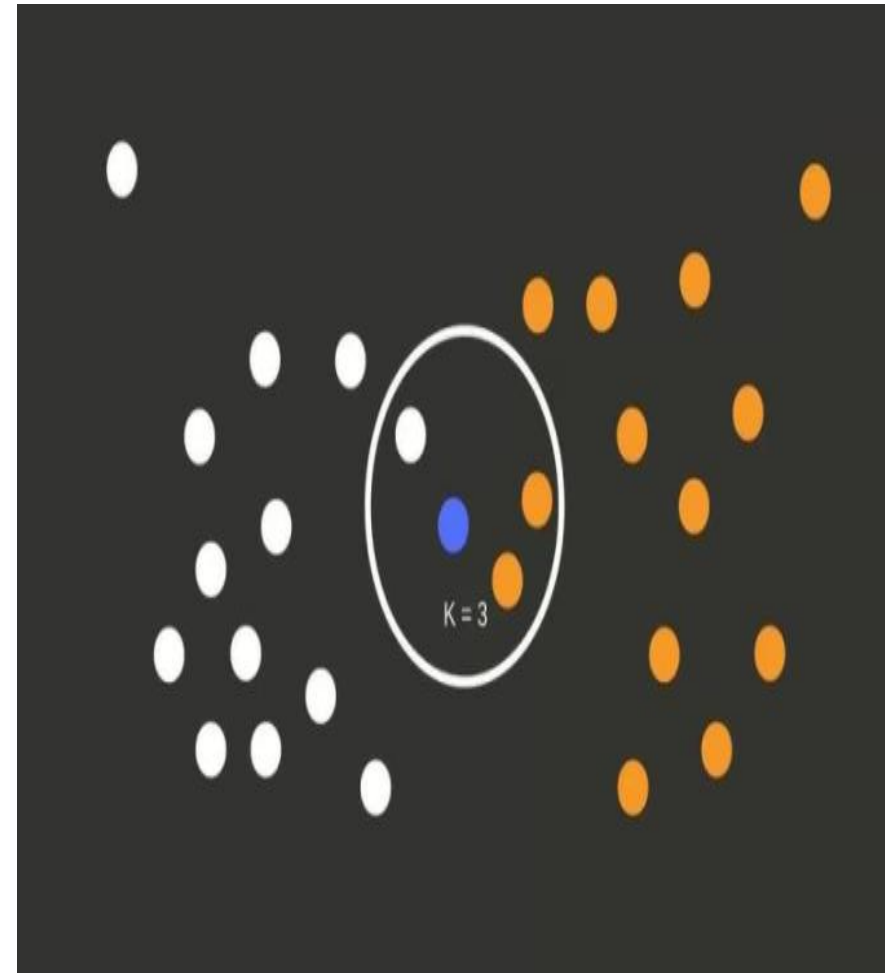
Condensed Nearest Neighbor Data Reduction Rule

➢ Working on a big dataset can be an expensive task.

➢ Using the condensed nearest neighbor rule, we can clean our data and can sort the important observations out of it.

➢ This process can reduce the execution time of the machine learning algorithm. But there is a chance of accuracy reduction.

➢ The steps to condense are to divide data points into the following:

  ➢ Outliers: Observations that lie at an abnormal distance from all the data points. Most of these are extreme values. Removing these observations will increase the accuracy of the model.

  ➢ Prototypes: Minimum points in training set required to recognize non-outlier points.

  ➢ Absorbed points: These are points that are correctly identified to be non-outlier points.

Nearest Neighbor Algorithm

➢ Nearest neighbor is a special case of k-nearest neighbor class.

➢ In this case k value is 1 ($k = 1$).

➢ In this case, new data point target class will be assigned to the 1st closest neighbor

Radius Neighbor Algorithm

➢ KNN classifier is also considered to be an instance based learning / non-generalizing algorithm.

➢ It stores records of training data in a multidimensional space.

➢ For each new sample & particular value of K, it recalculates Euclidean distances and predicts the target class

➢ So, it does not create a generalized internal model

➢ Similar to KNN classifier, we can use Radius Neighbor Classifier for classification tasks.

➢ As in KNN classifier, we specify the value of K, similarly, in Radius neighbour classifier the value of R should be defined.

➢ The RNC classifier determines the target class based on the number of neighbors within a fixed radius, r, for each training data point.

Radius Neighbor Algorithm

➢ Measuring similarity with distance between the points using Euclidian method

➢ Other distance measurement methods include Manhattan distance, Minkowski distance, Mahalanobis distance, Bhattacharya distance etc.

➢ Scikit-learn implements two different nearest neighbors classifiers:

    ➢ K Nearest Neighbor Classifier

    ➢ Radius Neighbor Classifier

➢ Radius Neighbor Classifier implements learning based on number of neighbors within a fixed radius 'r' of each training point, where 'r' is a floating point value specified by the user

➢ Determining the optimal K is the challenge in K Nearest Neighbor classifiers. In general, larger value of K supresses impact of noise but prone to majority class dominating

➢ Radius Neighbor Classifier may be a better choice when the sampling is not uniform. However, when there are many attributes and data is sparse, this method becomes ineffective due to curse of dimensionality

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
    - Not impacted by outliers
    - KNN executes quickly for small training data sets
    - Performance asymptotically approaches the performance of the Bayes Classifier
- Disadvantages
    - Fixing the optimal value of K is a challenge
    - Will not be effective when the class distributions overlap
    - 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
    - Computationally intensive ($O(N^2)$)

Demo Using Python

Sample Code in Python

```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]])) [0]


(neigh.predict_proba([[0.9]])) [[ 0.66666667 0.33333333]]
```

Summary

➢ KNN classification algorithm
  ➢ Different distance measures
  ➢ KNN algorithm
  ➢ Advantages and disadvantages
➢ Case study 1 (using KNN)
➢ Hands-on 1
➢ Case study 2 (comparing KNN with other classification methods)
➢ Hands-on 2

Thanks!