Lecture 4
Big Data Predictive Analytics

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Agenda

- Introduction
- K-Nearest Neighbor
- Applying KNN on Big Data
- Naïve Bayes classifier
- Applying Naïve Bayes classifier on Big Data
- Performance Evaluation of classifiers

Introduction

Introduction

- **Predictive Analytics** use **Predictive Data Mining** techniques which use **Supervised Machine Learning** techniques.

Introduction

- *Classification* is an instance of Supervised Machine Learning and is widely used for prediction purposes.

- In classification, a classifier is given a set of examples that are already classified (i.e. given a class label), and from these examples, the classifier learns to assign a label to unseen examples.

- Examples of classification problems include:
  - Given an email, classify if it is spam or not.
  - Given a handwritten character, classify it as one of the known characters.

Introduction

- **Examples of Classification Techniques:**
  - **K-Nearest Neighbor (KNN)**
  - **Naïve Bayes**
  - **Decision Trees (DT)**
  - **Support Vector Machines (SVM)**
  - **Neural Networks**

K-Nearest Neighbor

K-Nearest Neighbor

- K-nearest neighbors is an algorithm that stores all available cases and classifies new cases based on a **similarity measure** (e.g., distance functions).

- KNN algorithm at the training phase just stores the dataset and when it gets new data, then it classifies that data into a category that is much similar to the new data.

K-Nearest Neighbor

- The K-NN working can be explained on the basis of the below algorithm:

Step 1 – For implementing any algorithm, we need dataset. So during the first step of KNN, we must load the training as well as test data.

Step 2 – Next, we need to choose the value of K i.e. the nearest data points. K can be any integer.

Step 3 – For each point in the test data do the following –

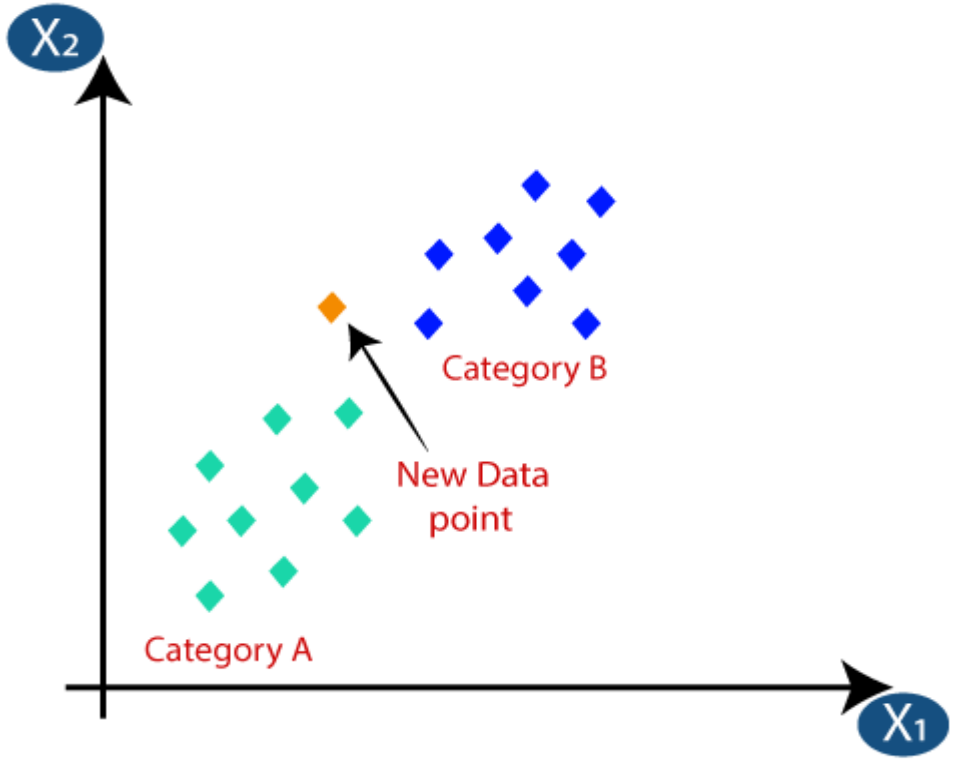
3.1 – Calculate the distance between test data and each row of training data with the help of any of the method namely: Euclidean, Manhattan or Hamming distance.

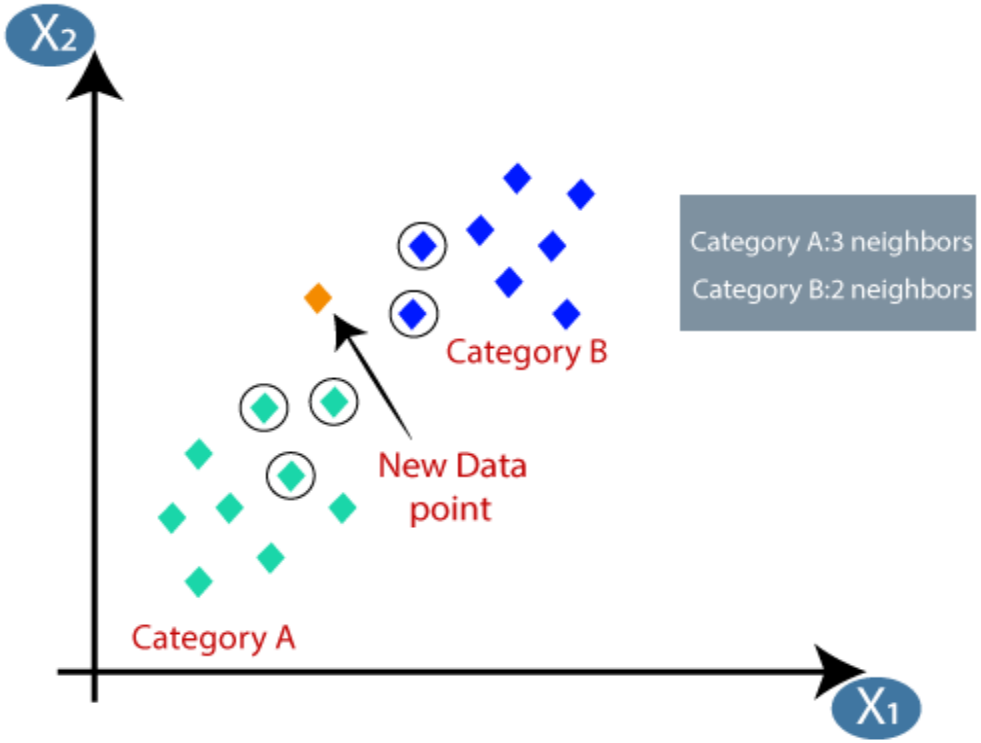
3.2 – Now, based on the distance value, sort them in ascending order.

3.3 – Next, it will choose the top K rows from the sorted array.

3.4 – Now, it will assign a class to the test point based on most frequent class of these rows.

K-Nearest Neighbor





K-Nearest Neighbor

- **Distance functions:**

1. Euclidean Distance:

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

n is the number of features

2. Manhattan Distance:

$$D = \sum_{i=1}^{n} |x_i - y_i|$$

n is the number of features

K-Nearest Neighbor

➢ **Distance functions:**

3. Hamming Distance:

- It is a measure of the number of instances in which corresponding symbols are different in two strings of equal length. It is suitable for categorial features.

$$D_H = \sum_{i=1}^{n} |x_i - y_i|$$

n is the number of features

$$x = y \Rightarrow D = 0$$

$$x \neq y \Rightarrow D = 1$$

K-Nearest Neighbor

- **Example:**

Height (in cms)	Weight (in kgs)	T Shirt Size
158	58	M
158	59	M
158	63	M
160	59	M
160	60	M
163	60	M
163	61	M
160	64	L
163	64	L
165	61	L
165	62	L
165	65	L

New customer has height 161cm and weight 61kg.

What is his T Shirt Size?

K-Nearest Neighbor

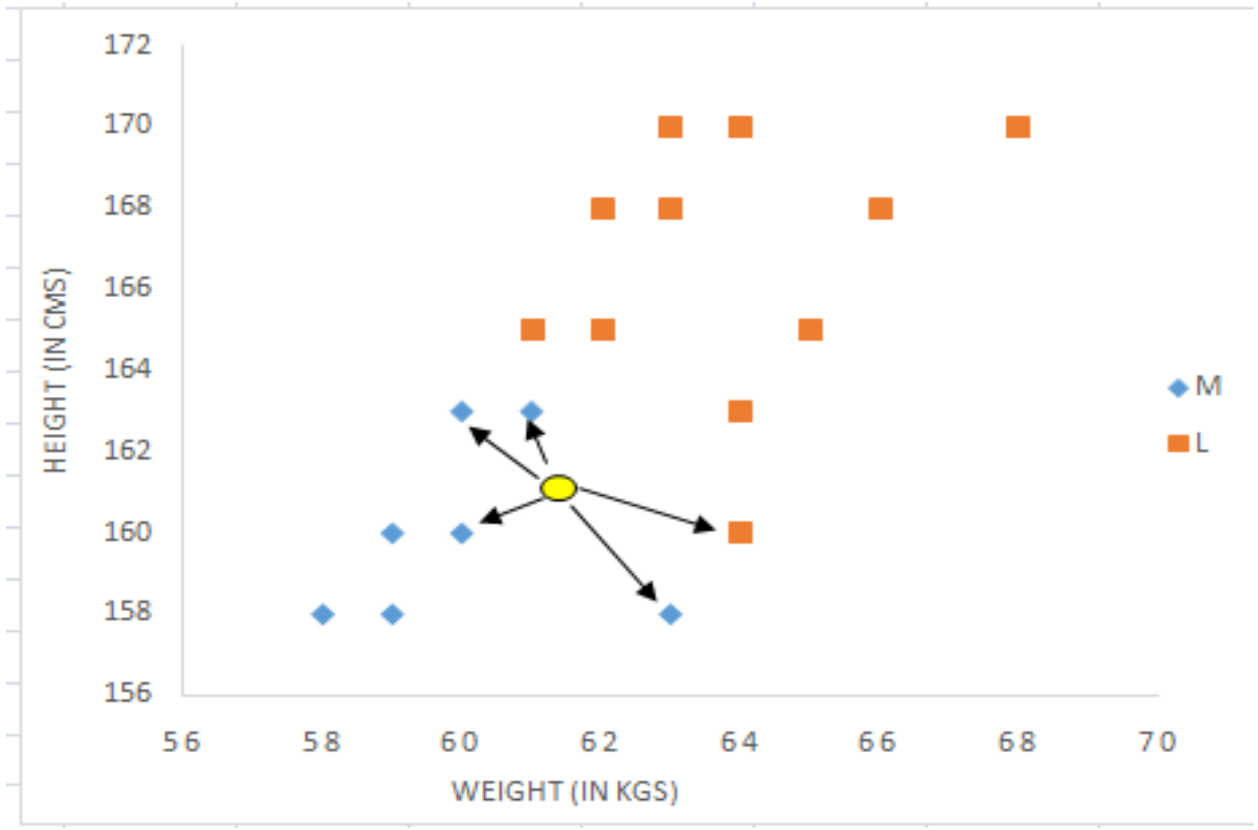
- **Example:**

Height (in cms)	Weight (in kgs)	T Shirt Size	Distance	
158	58	M	4.2	
158	59	M	3.6	
158	63	M	3.6	
160	59	**M**	2.2	**3**
160	60	**M**	1.4	**1**
163	60	**M**	2.2	**3**
163	61	**M**	2.0	**2**
160	64	**L**	3.2	**5**
163	64	L	3.6	
165	61	L	4.0	
165	62	L	4.1	
165	65	L	5.7	

Euclidean Distance is used.
For K=5,
T shirt Size=M

K-Nearest Neighbor

- **Example:**



K-Nearest Neighbor

What are the limitations of KNN?

K-Nearest Neighbor

- **Normalization and Standardization:**
  - When independent variables in training data are measured in different units, it is important to **scale the variables** before calculating distance.
  - For example, if one variable is based on height in cms, and the other is based on weight in kgs then **height will influence more** on the distance calculation.
  - Scaling the variables can be done by any of the following methods:

$$Xs = \frac{X - min}{\max - min}$$

Normalization

$$Xs = \frac{X - mean}{s.d.}$$

Standardization

K-Nearest Neighbor

- **Handling categorial features:**
  - Hamming Distance can be used
  - Can assign a number to each category

K-Nearest Neighbor

- **How to find best K value?**
  - **Cross-validation** is a way to find out the **optimal K value**. It estimates the validation error rate by holding out a subset of the training set from the model building process.
  - Cross-validation (let's say 10 fold validation) involves randomly dividing the **training set** into 10 groups, or folds, of approximately equal size. 90% data is used to train the model and remaining 10% to validate it. The error rate is then computed on the 10% validation data. This procedure repeats 10 times each time with a different fold. It results to 10 estimates of the validation error which are then averaged out.
  - The process is repeated for different values of K. The value of K that yields the smallest average error is selected.

Applying KNN on Big Data

Applying KNN on Big Data

- Despite the promising results shown by the k-NN in a wide variety of problems, it lacks scalability to address Big datasets.
- The main problems found to deal with large-scale data are:
  - **Runtime:** The complexity of the traditional k-NN algorithm is $O((n \cdot D))$, where n is the number of instances and D the number of features.
  - **Memory consumption:** For a rapid computation of the distances, the k-NN model may normally require to store the training data in memory. When TR is too big, it could easily exceed the available RAM memory.

Applying KNN on Big Data

- These drawbacks motivate the use of Big Data techniques to distribute the processing of KNN over a cluster a nodes.
- A MapReduce-based approach for k-Nearest neighbor classification can be applied.
- This allows us to simultaneously classify large amounts of unseen cases (test examples) against a big (training) dataset.

Applying KNN on Big Data

- First, the training data will be divided into multiple splits.
- The **map phase** will determine the k-nearest neighbors in the different splits of the data.
- As a result of each map, the k nearest neighbors together with their computed distance values will be emitted to the reduce phase.

Applying KNN on Big Data

- Afterwards, the **reduce phase** will compute the definitive neighbors from the list obtained in the map phase.
- The reduce phase will determine which are the final k nearest neighbors from the list provided by the maps.
- This parallel implementation provides the exact classification rate as the original k-NN model.

Naïve Bayes classifier

Naïve Bayes

- Naïve Bayes is a probabilistic classification method based on Bayes' theorem (or Bayes' law).
- Bayes' theorem gives the **relationship between the probabilities of two events and their conditional probabilities**.
- A naïve Bayes classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of other features.

Naïve Bayes

- The input variables are generally **categorical**, but variations of the algorithm can accept continuous variables.
- There are also ways to convert continuous variables into categorical ones. This process is often referred to as the ***discretization of continuous variables***.
- The output typically includes a class label and its corresponding probability score.

Naïve Bayes: Bayes' Theorem

- The ***conditional probability*** of event C occurring, given that event A has already occurred, is denoted as $P(C|A)$, which can be found using the following equation:

$$P(C|A) = \frac{P(A \cap C)}{P(A)}$$

$$P(C|A) = \frac{P(A|C) \cdot P(C)}{P(A)}$$

where C is the class label $C \in \{c1, c2, \ldots cn\}$ and A is the observed attributes $A = \{a1, a2, \ldots am\}$

Naïve Bayes: Bayes' Theorem

- A more general form of Bayes' theorem assigns a classified label to an object with multiple attributes $A = \{a1, a2, \ldots am\}$ such that the label corresponds to the largest value of $P(ci|A)$.

$$P(c_i|A) = \frac{P(a_1, a_2, \ldots, a_m|c_i) \cdot P(c_i)}{P(a_1, a_2, \ldots, a_m)}, i = 1, 2, \ldots n$$

Naïve Bayes classifier

- With two simplifications, Bayes' theorem can be extended to become a naïve Bayes classifier.
- **The first simplification** is to use the conditional independence assumption. That is, each attribute is conditionally independent of every other attribute given a class label c*i*.
- **The second simplification** is to ignore the denominator *P* (a1, a2,..am) because it appears in the denominator for all values of *i*, removing the denominator will have no impact on the relative probability scores and will simplify calculations.

Naïve Bayes classifier

- Naïve Bayes classification applies the two simplifications mentioned earlier and, as a result, P (ci | a1, a2,..am) is proportional to the product of P (aj | ci) times P (ci).

$$P(c_i|A) \propto P(c_i) \cdot \prod_{J=1}^{m} P(a_j|c_i) \qquad i = 1,2,\ldots n$$

Naïve Bayes classifier

- Building a naïve Bayes classifier requires knowing certain statistics, all calculated from the training set.
- The first requirement is to collect the probabilities of all class labels, $P(c_i)$.
- The second thing the naïve Bayes classifier needs to know is the conditional probabilities of each attribute a_j given each class label c_i, namely $P(a_j \mid c_i)$. For each attribute and its possible values, computing the conditional probabilities given each class label is required.

Naïve Bayes classifier

- For a given attribute assume it can have the following values {x,y,z} and assume that we have two class labels {c1 and c2}.
- Then the following probabilities need to be computed:
  - P(x | c1)
  - P(x | c2)
  - P(y | c1)
  - P(y | c2)
  - P(z | c1)
  - P(z | c2)

Naïve Bayes classifier

- After that, the naïve Bayes classifier can be tested over the testing set.
- For each record in the testing set, the naïve Bayes classifier assigns the classifier label c*i* that maximizes:

$$P(c_i) \cdot \prod_{j=1}^{m} P(a_j | c_i)$$

where:

- m is the number of features (dimensions)
- i is the index of class labels
- j is the index of features (dimensions)
- a1 is the value of the first feature in the test record
- a2 is the value of the second feature in the test record…….

Applying Naïve Bayes classifier on Big Data

Applying Naïve Bayes classifier on Big Data

- Applying MapReduce with Naïve Bayes classifier significantly decreases computation times allowing its application on Big Data problems.
- First, the training data will be divided into multiple splits.
- During the **map phase**, each map processes a single split, and computes statistics of the input data.
- For each attribute, the map outputs a <Key, Value> pair, where
  - Key is the class label,
  - Value is {AttributeValue, the frequency of attribute value within that class label}

Applying Naïve Bayes classifier on Big Data

- In the **reduce phase**, the reduce function aggregates the number of each attribute value within each class label.
- For each attribute, the reduce function outputs a <Key, Value> pair, where:
  - Key is the class label,
  - Value is {AttributeValue, Σi the frequency of attribute value within that class label}

    where i is the number of mappers.

Performance Evaluation of classifiers

Performance Evaluation of classifiers

- A ***confusion matrix*** is a specific table layout that allows visualization of the performance of a classifier.
- The following figure shows the confusion matrix for a two-class classifier:

		Predicted Class	
		Positive	Negative
Actual Class	Positive	True Positives (TP)	False Negatives (FN)
	Negative	False Positives (FP)	True Negatives (TN)

Performance Evaluation of classifiers

- ***True positives*** (TP) are the number of positive instances the classifier correctly identified as positive.
- ***False positives*** (FP) are the number of instances in which the classifier identified as positive but in reality are negative.
- ***True negatives*** (TN) are the number of negative instances the classifier correctly identified as negative.
- ***False negatives*** (FN) are the number of instances classified as negative but in reality are positive.

Performance Evaluation of classifiers

- The ***accuracy*** (or the ***overall success rate***) is a metric defining the rate at which a model has classified the records correctly.
- It is defined as the sum of TP and TN divided by the total number of instances, as shown in the following equation:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%$$

Performance Evaluation of classifiers

- The ***false positive rate*** (FPR) shows what percent of negatives the classifier marked as positive.
- The FPR is also called the ***false alarm rate*** or the ***type I error rate .***
- FPR is computed as follows:

$$FPR = \frac{FP}{FP + TN}$$

Performance Evaluation of classifiers

- ***Precision*** is the percentage of instances marked positive that really are positive. It is computed as follows:

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

- ***Recall*** is the percentage of positive instances that were correctly identified. It is also called ***true positive rate*** (TPR). It is computed as follows:

$$TPR\ (or\ Recall) = \frac{TP}{TP + FN}$$

Performance Evaluation of classifiers

- ***F1-score*** is the harmonic mean of the precision and recall:

$$F_1 = 2 \cdot \frac{\mathrm{precision} \cdot \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}}$$

Performance Evaluation of classifiers – Multi classes

- **Micro-average and Macro-average:**
  - The **micro-average** precision and recall scores are calculated from the sum of classes' true positives (TPs), false positives (FPs), and false negatives (FNs) of the model.
  - The **macro-average** precision and recall scores are calculated as arithmetic mean (or weighted mean) of individual classes' precision and recall scores.
  - The **macro-average** F1-score is calculated as arithmetic mean (or weighted mean) of individual classes' F1-score.

Performance Evaluation of classifiers – Multi classes

- **Exercise:**

No	Actual	Predicted	Match
1	Airplane	Airplane	✓
2	Car	Boat	X
3	Car	Car	✓
4	Car	Car	✓
5	Car	Boat	X
6	Airplane	Boat	X
7	Boat	Boat	✓
8	Car	Airplane	X
9	Airplane	Airplane	✓
10	Car	Car	✓

Performance Evaluation of classifiers – Multi classes

- **Exercise:**

	Airplane	Boat	Car
Airplane	2	1	0
Boat	0	1	0
Car	1	2	3

Confusion matrix

Label	True Positive (TP)	False Positive (FP)	False Negative (FN)
Airplane	2	1	1
Boat	1	3	0
Car	3	0	3

TP, FP, FN calculated from the confusion matrix

Performance Evaluation of classifiers – Multi classes

- **Exercise:**
  - **Calculate micro-average, macro-average, and weighted macro-average of precision, recall and F1-score.**

Thank You