

Introduction to Data Science

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Outline

- k Nearest Neighbors (kNN)
- Naïve Bayes

Machine Learning Algorithms

Machine Learning

Supervised learning: Train a model with known input and output data to predict future outputs to new data.

Classification

Support vector machine (SVM)

K-nearest-neighbors

Discriminant analysis

Neural Networks

Naive Bayes

Regression

Linear Regression

Assembly Methods

Decision trees

Neural Networks

Unsupervised Learning: Segment a collection of elements with the same attributes (clustering).

Clustering

K-means, k-medoids fuzzy C-means

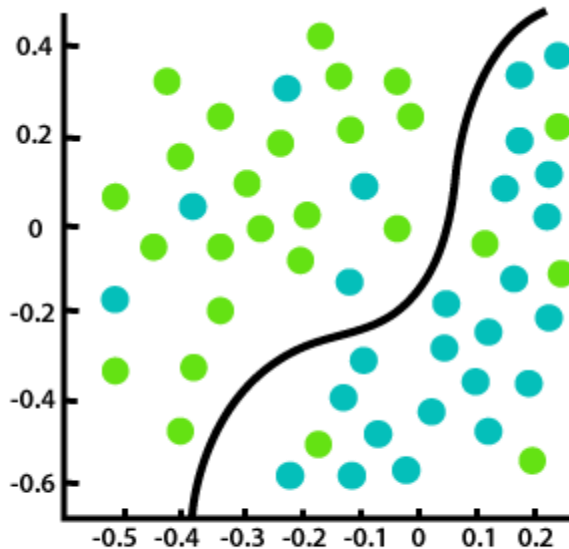
Hidden Markov models

Neural Networks

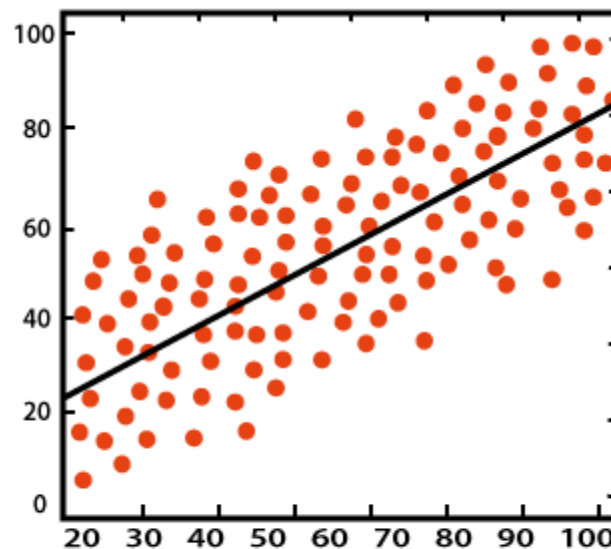
Gaussian mixture

Supervised Machine Learning Algorithms

- **Classification:** A classification problem is when the output variable is a category, such as “red” or “blue” or “disease” and “no disease”.
- **Regression:** A regression problem is when the output variable is numeric, such as “age” or “weight”.



Classification

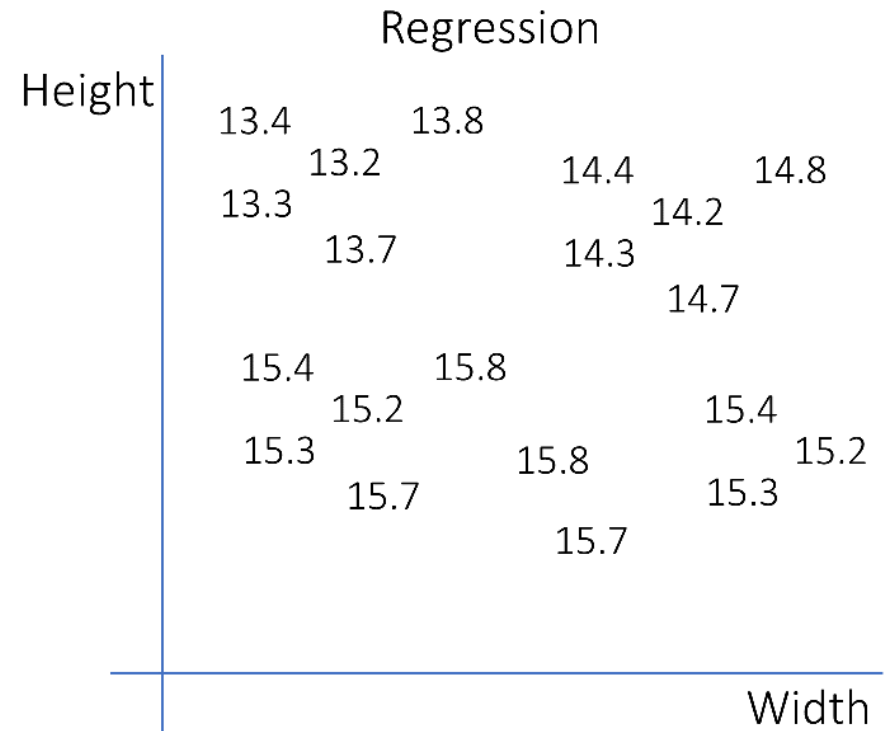


Regression

The scatter plot, titled "Classification", displays three distinct classes of data points on a 2D coordinate system. The vertical axis is labeled "Height" and the horizontal axis is labeled "Width".

- Class 1 (x marks):** There are 8 'x' marks located primarily in the upper-left region of the plot.
- Class 2 (Stars):** There are 8 stars located primarily in the upper-right region of the plot.
- Class 3 (Triangles):** There are 8 triangles located in the lower-left and lower-right regions of the plot.

The plot illustrates a linearly separable dataset where the classes are distributed across different regions of the 2D space.



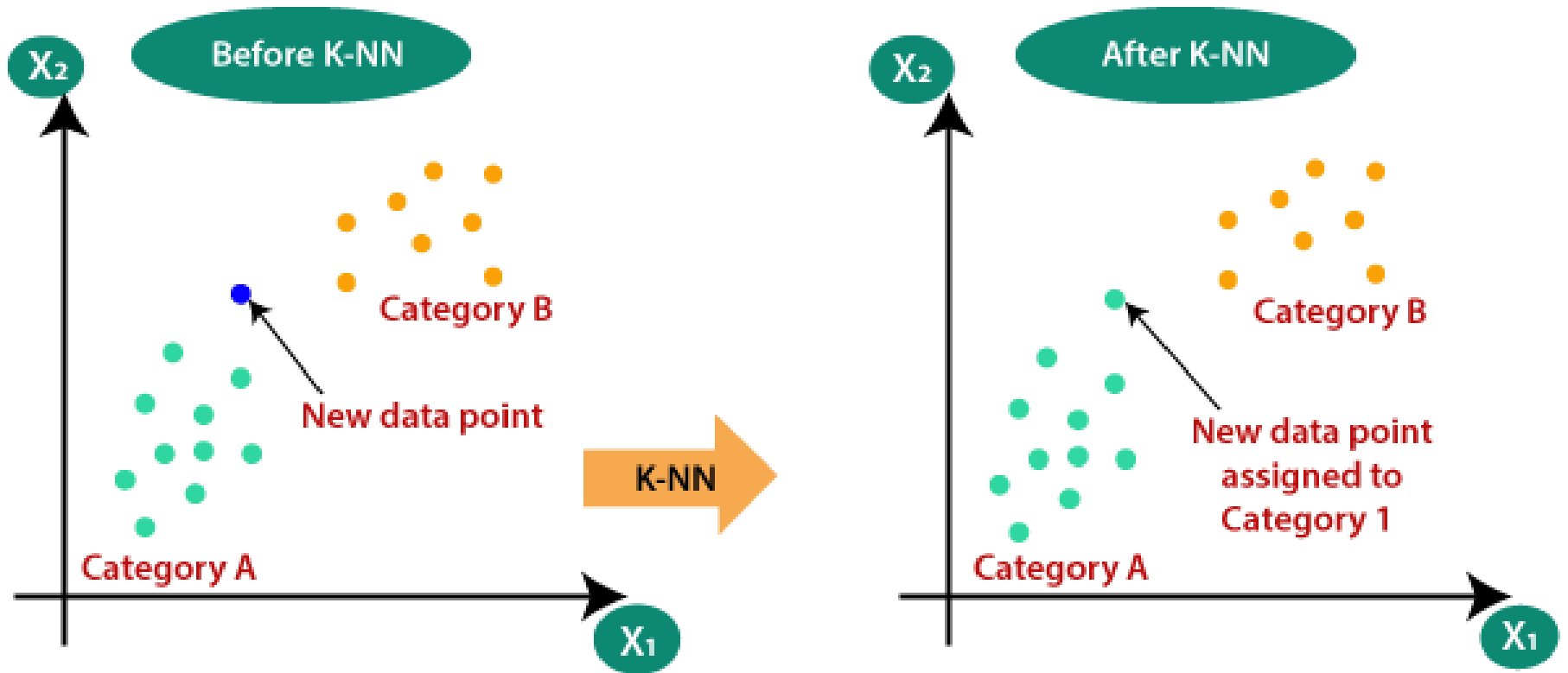
k Nearest Neighbors

- K-Nearest Neighbors (kNN) is one of the simplest Machine Learning algorithms based on Supervised Machine Learning technique.
- A case is classified by a majority vote of its neighbors, with the case being assigned to the class most common amongst its K nearest neighbors measured by a distance function.
- The algorithm assumes the similarity between the new case/data and available cases and put the new case into the most suitable category.
- The algorithm stores all the available data and classifies a new data point based on the similarity.

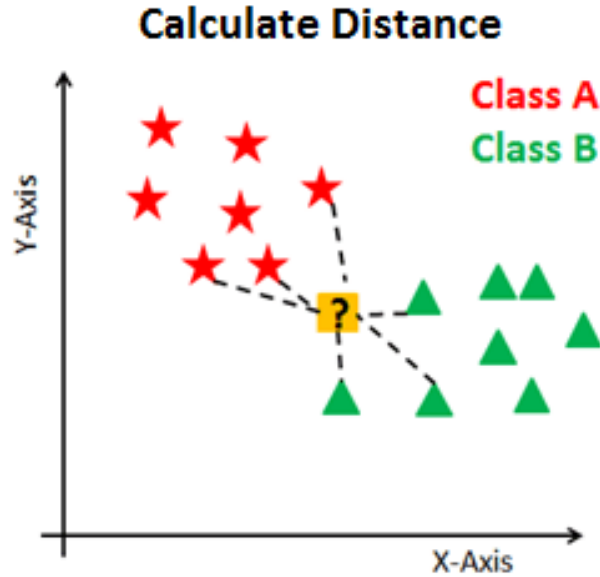
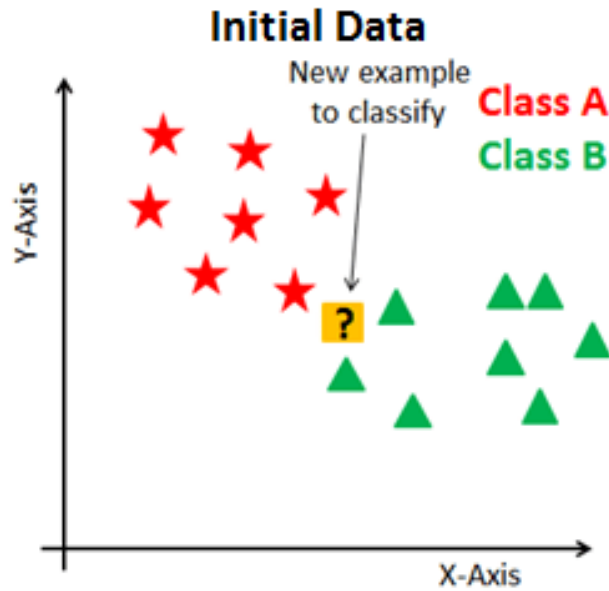
k Nearest Neighbors

- It can be used for Regression as well as for Classification but mostly it is used for the Classification problems.
- KNN is a non-parametric algorithm, which means it does not make any assumption on underlying data.
- It is also called a lazy learner algorithm because it does not learn from the training set immediately instead it stores the dataset and at the time of classification, it performs an action on the dataset.
- 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.

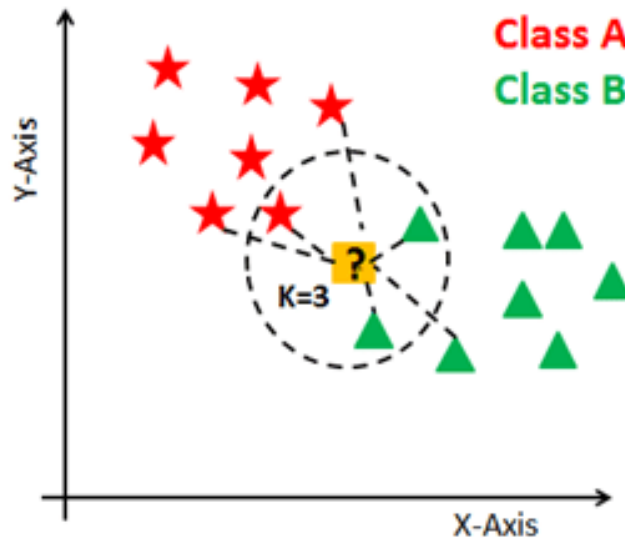
Why kNN?



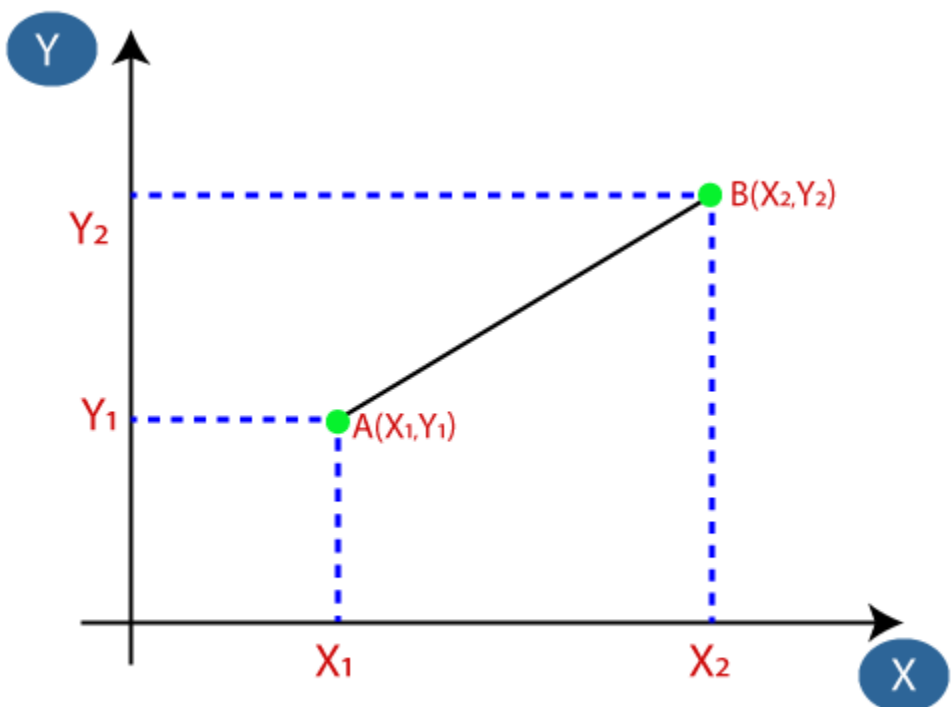
How kNN Works?



Finding Neighbors & Voting for Labels



How kNN Works?



Euclidean Distance between A₁ and B₂ = $\sqrt{(X_2 - X_1)^2 + (Y_2 - Y_1)^2}$

Distance functions

Euclidean

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

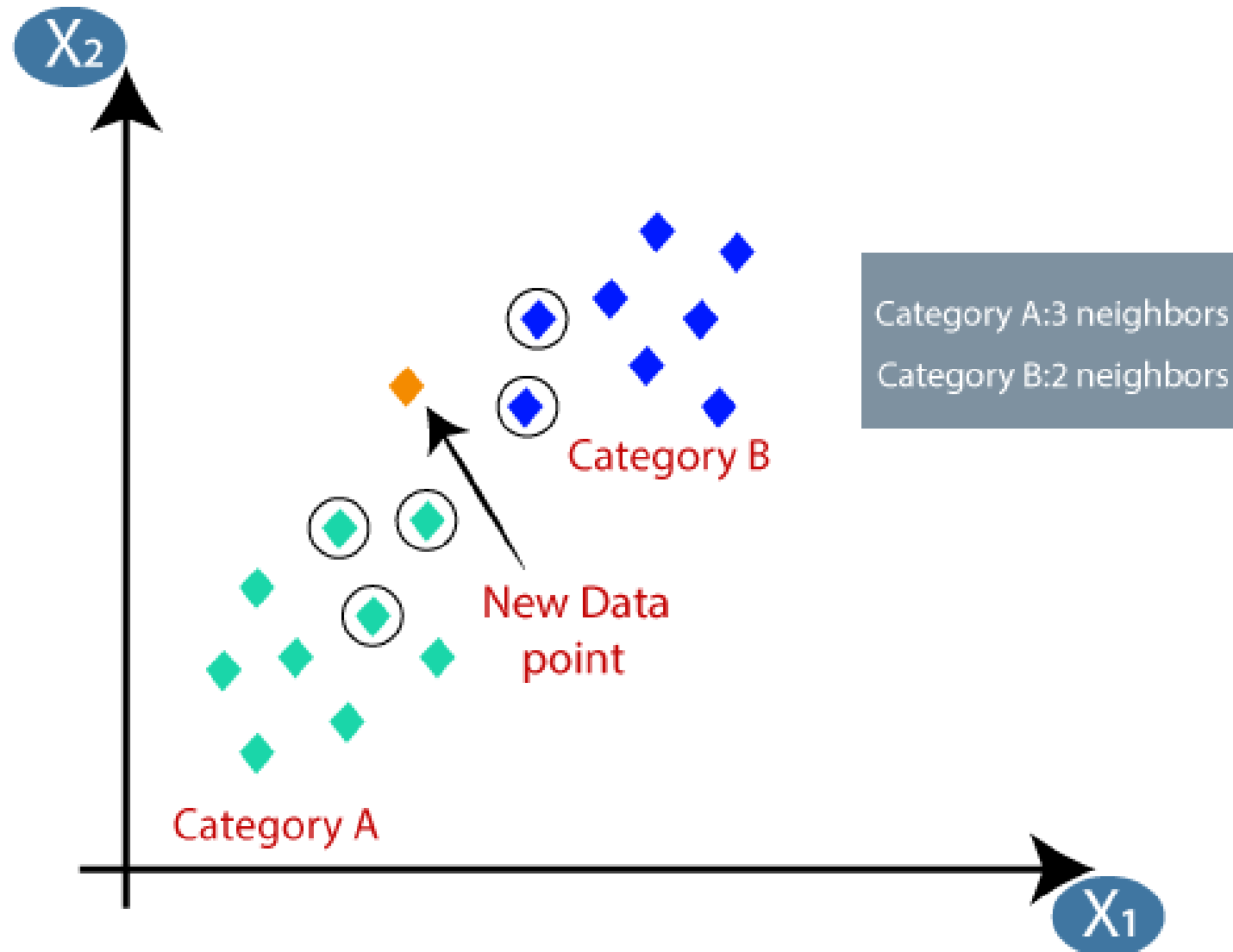
Manhattan

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

Minkowski

$$\left(\sum_{i=1}^k (|x_i - y_i|)^q \right)^{1/q}$$

How kNN Works?



How kNN Works?

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

Step-1: Select the number K.

Step-2: Calculate the Euclidean distance of all the data points from the point in question.

Step-3: Take the K nearest neighbors as per the calculated Euclidean distance.

Step-4: Among these k neighbors, count the number of the data points in each category.

Step-5: Assign the new data points to that category for which the number of the neighbor is maximum.

Step-6: Our model is ready.

How kNN Works?

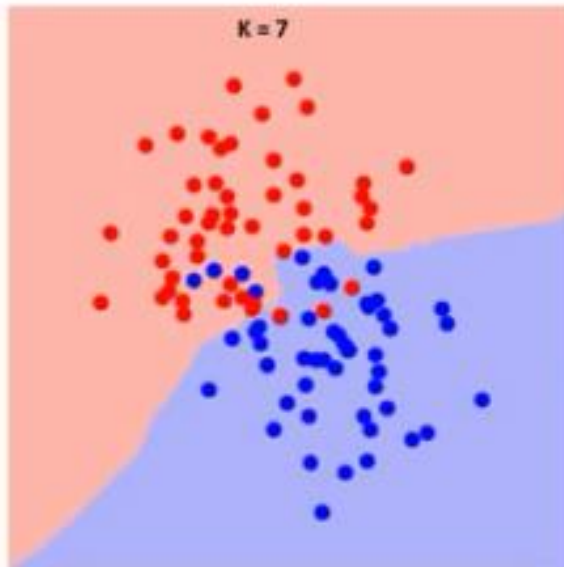
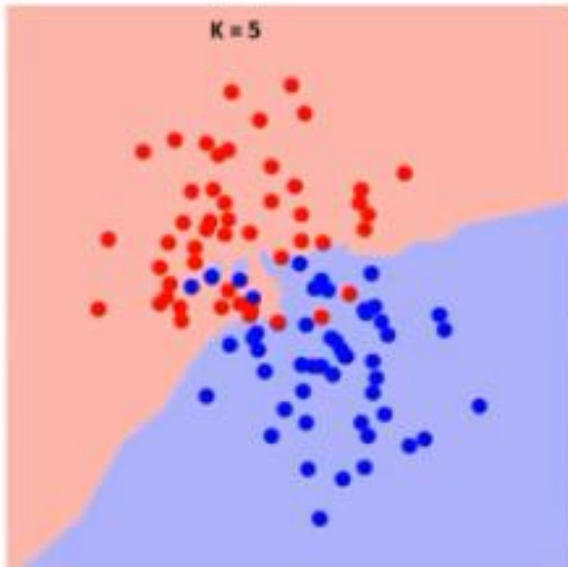
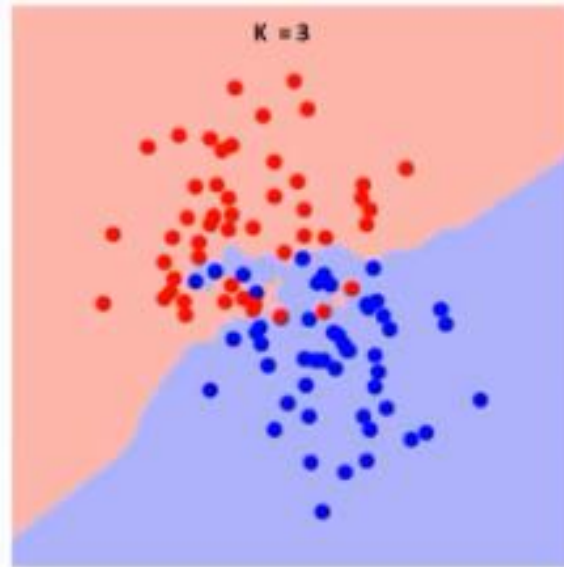
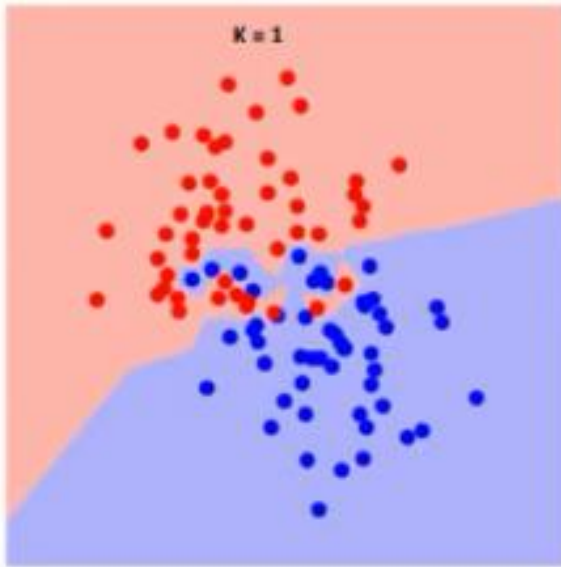
1. Load the data
2. Initialise the value of k
3. For getting the predicted class, iterate from 1 to total number of training data points
 1. Calculate the distance between test data and each row of training data. Here we will use Euclidean distance as our distance metric since it's the most popular method. The other metrics that can be used are Chebyshev, cosine, etc.
 2. Sort the calculated distances in ascending order based on distance values
 3. Get top k rows from the sorted array
 4. Get the most frequent class of these rows
 5. Return the predicted class

How to select the value of K in kNN?

Below are some points to remember while selecting the value of K in the K-NN algorithm:

- There is **no way to determine** the best value for "K", so we need to try some values to find the best out of them. The most preferred value for K is 5.
- A very low value for K such as $K=1$ or $K=2$, can be noisy and lead to the effects of outliers in the model.
- Large values for K are good, but it may find some difficulties.

How to select the value of K in kNN?



kNN Example

X	Y	Label
7	7	A
7	4	A
3	4	B
1	4	B

New Point = (3, 7)

kNN Example

New Point = (3, 7)

X	Y	Label	
7	7	A	$(3-7)^2 + (7-7)^2$
7	4	A	$(3-7)^2 + (4-7)^2$
3	4	B	$(3-3)^2 + (4-7)^2$
1	4	B	$(3-1)^2 + (4-7)^2$

X	Y	Label	
3	4	B	9
1	4	B	13
7	7	A	16
7	4	A	25

Advantages and Disadvantages of kNN?

Advantages:

- It is simple to implement.
- It is robust to the noisy training data
- It can be more effective if the training data is large.

Disadvantages:

- Always needs to determine the value of K which may be complex some time.
- The computation cost is high because of calculating the distance between the data points for all the training samples.

kNN Implementation

Implement kNN Algorithm

Machine Learning Algorithms

Machine Learning

Supervised learning: Train a model with known input and output data to predict future outputs to new data.

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Bayes Theorem

- Bayes' Theorem is a simple mathematical formula used for calculating conditional probabilities.
- Conditional probability is a measure of the probability of an event occurring given that another event has (by assumption or evidence) occurred.

The diagram shows the formula for Bayes' Theorem with arrows pointing from descriptive labels to the mathematical terms. The labels are: 'Probability of B occurring given evidence A has already occurred' pointing to $P(B|A)$; 'Probability of A occurring' pointing to $P(A)$; 'Probability of A occurring given evidence B has already occurred' pointing to $P(A|B)$; and 'Probability of B occurring' pointing to $P(B)$.

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

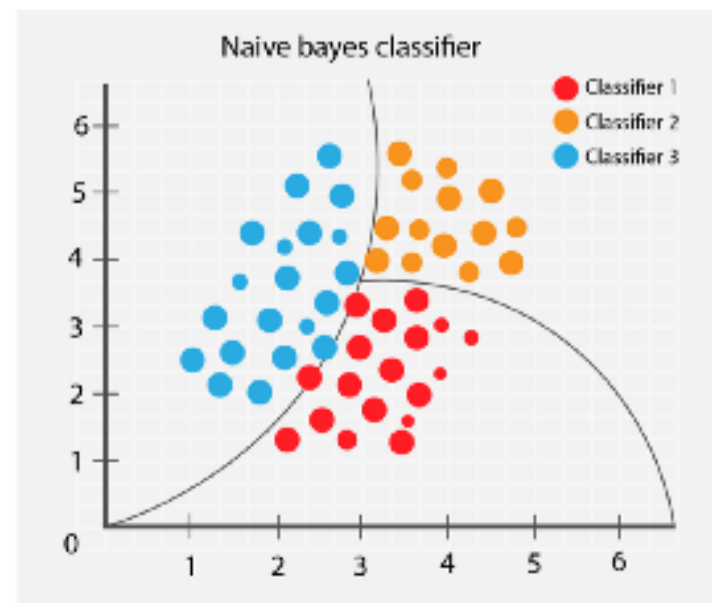
Naïve Bayes

In machine learning, naive Bayes classifiers are a family of simple "probabilistic classifiers" based on applying Bayes' theorem with strong (naive) independence assumptions between the features.

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)}$$

using Bayesian probability terminology, the above equation can be written as

$$\text{Posterior} = \frac{\text{prior} \times \text{likelihood}}{\text{evidence}}$$



Naïve Bayes Classifiers

- Naive Bayes classifiers are a collection of classification algorithms based on Bayes' Theorem.
- It is not a single algorithm but a family of algorithms where all of them share a common principle, i.e., every pair of features being classified is independent of each other.
- The reason why it is called 'Naïve' because it requires rigid independence assumption between input variables.

Assumptions of Naïve Bayes Classifiers

- The fundamental Naïve Bayes assumption is that each feature makes an:
 - independent
 - equal
- contribution to the outcome.

Example No.	Color	Type	Origin	Stolen?
1	Red	Sports	Domestic	Yes
2	Red	Sports	Domestic	No
3	Red	Sports	Domestic	Yes
4	Yellow	Sports	Domestic	No
5	Yellow	Sports	Imported	Yes
6	Yellow	SUV	Imported	No
7	Yellow	SUV	Imported	Yes
8	Yellow	SUV	Domestic	No
9	Red	SUV	Imported	No
10	Red	Sports	Imported	Yes

- We assume that **no pair of features are dependent**. For example, the color being 'Red' has nothing to do with the Type or the Origin of the car. Hence, the features are assumed to be Independent.

- Secondly, each feature is given the same importance. For example, knowing the only Color and Type alone can't predict the outcome perfectly. So, none of the attributes are irrelevant and assumed to be **contributing Equally** to the outcome.

How Naïve Bayes work?

Example No.	Color	Type	Origin	Stolen?
1	Red	Sports	Domestic	Yes
2	Red	Sports	Domestic	No
3	Red	Sports	Domestic	Yes
4	Yellow	Sports	Domestic	No
5	Yellow	Sports	Imported	Yes
6	Yellow	SUV	Imported	No
7	Yellow	SUV	Imported	Yes
8	Yellow	SUV	Domestic	No
9	Red	SUV	Imported	No
10	Red	Sports	Imported	Yes

$$P(y|X) = \frac{P(X|y)P(y)}{P(X)}$$

$$X = (x_1, x_2, x_3, \dots, x_n)$$

$$P(y|x_1, \dots, x_n) = \frac{P(x_1|y)P(x_2|y)\dots P(x_n|y)P(y)}{P(x_1)P(x_2)\dots P(x_n)}$$

$$P(y|x_1, \dots, x_n) \propto P(y) \prod_{i=1}^n P(x_i|y)$$

How Naïve Bayes work?

Outlook	Temp	Humidity	Windy	Play Golf
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No

How Naïve Bayes work?

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Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No

today = (Sunny, Hot, Normal, False)

How Naïve Baves work?

Outlook	Temp	Humidity	Windy	Play Golf
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No

Outlook

	Yes	No	P(yes)	P(no)
Sunny	2	3	2/9	3/5
Overcast	4	0	4/9	0/5
Rainy	3	2	3/9	2/5
Total	9	5	100%	100%

How Naïve Baves work?

Outlook	Temp	Humidity	Windy	Play Golf
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No

Temperature

	Yes	No	P(yes)	P(no)
Hot	2	2	2/9	2/5
Mild	4	2	4/9	2/5
Cool	3	1	3/9	1/5
Total	9	5	100%	100%

How Naïve Baves work?

Outlook	Temp	Humidity	Windy	Play Golf
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No

Humidity

	Yes	No	P(yes)	P(no)
High	3	4	3/9	4/5
Normal	6	1	6/9	1/5
Total	9	5	100%	100%

How Naïve Baves work?

Outlook	Temp	Humidity	Windy	Play Golf
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No

Wind

	Yes	No	P(yes)	P(no)
False	6	2	6/9	2/5
True	3	3	3/9	3/5
Total	9	5	100%	100%

How Naïve Baves work?

Outlook	Temp	Humidity	Windy	Play Golf
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No

Play		P(Yes)/P(No)
Yes	9	9/14
No	5	5/14
Total	14	100%

How Naïve Baves work?

Outlook	Temp	Humidity	Windy	Play Golf
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No

today = (Sunny, Hot,
Normal, False)

$$P(Yes|today) = \frac{P(SunnyOutlook|Yes)P(HotTemperature|Yes)P(NormalHumidity|Yes)P(NoWind|Yes)P(Yes)}{P(today)}$$

$$P(Yes|today) \propto \frac{2}{9} \cdot \frac{2}{9} \cdot \frac{6}{9} \cdot \frac{6}{9} \cdot \frac{9}{14} \approx 0.0141$$

How Naïve Baves work?

Outlook	Temp	Humidity	Windy	Play Golf
Rainy	Hot	High	False	No
Rainy	Hot	High	True	No
Overcast	Hot	High	False	Yes
Sunny	Mild	High	False	Yes
Sunny	Cool	Normal	False	Yes
Sunny	Cool	Normal	True	No
Overcast	Cool	Normal	True	Yes
Rainy	Mild	High	False	No
Rainy	Cool	Normal	False	Yes
Sunny	Mild	Normal	False	Yes
Rainy	Mild	Normal	True	Yes
Overcast	Mild	High	True	Yes
Overcast	Hot	Normal	False	Yes
Sunny	Mild	High	True	No

today = (Sunny, Hot,
Normal, False)

$$P(\text{No}|\text{today}) = \frac{P(\text{SunnyOutlook}|\text{No})P(\text{HotTemperature}|\text{No})P(\text{NormalHumidity}|\text{No})P(\text{NoWind}|\text{No})P(\text{No})}{P(\text{today})}$$

$$P(\text{No}|\text{today}) \propto \frac{3}{5} \cdot \frac{2}{5} \cdot \frac{1}{5} \cdot \frac{2}{5} \cdot \frac{5}{14} \approx 0.0068$$

How Naïve Bayes work?

today = (Sunny, Hot, Normal, False)

$$P(Yes|today) = \frac{P(SunnyOutlook|Yes)P(HotTemperature|Yes)P(NormalHumidity|Yes)P(NoWind|Yes)P(Yes)}{P(today)}$$

$$P(Yes|today) \propto \frac{2}{9} \cdot \frac{2}{9} \cdot \frac{6}{9} \cdot \frac{6}{9} \cdot \frac{9}{14} \approx 0.0141$$

$$P(No|today) = \frac{P(SunnyOutlook|No)P(HotTemperature|No)P(NormalHumidity|No)P(NoWind|No)P(No)}{P(today)}$$

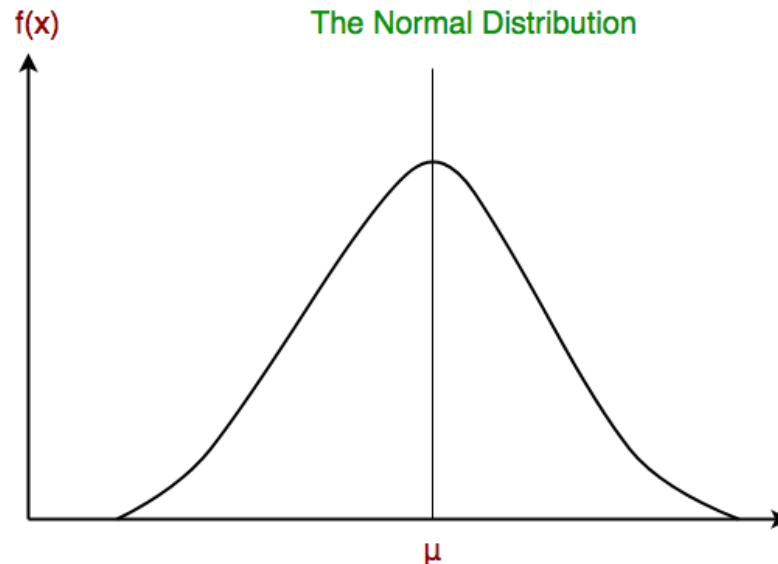
$$P(No|today) \propto \frac{3}{5} \cdot \frac{2}{5} \cdot \frac{1}{5} \cdot \frac{2}{5} \cdot \frac{5}{14} \approx 0.0068$$

Types of Naïve Bayes Classifiers

- **Multinomial Naive Bayes:** This is mostly used for document classification problem, i.e., whether a document belongs to the category of sports, politics, technology etc. The features/predictors used by the classifier are the frequency of the words present in the document.
- **Bernoulli Naive Bayes:** This is similar to the multinomial naive bayes but the predictors are Boolean variables. The parameters that we use to predict the class variable take up only values yes or no, for example if a word occurs in the text or not.

Types of Naïve Bayes Classifiers

- **Gaussian Naïve Bayes:** Continuous values associated with each feature are assumed to be distributed according to a Gaussian distribution. A Gaussian distribution is also called Normal distribution. When plotted, it gives a bell shaped curve which is symmetric about the mean of the feature values.



Naïve Bayes Implemntation

Implement Naïve Bayes Classifier

Summary

- K Nearest Neighbors
- Naïve Bayes