

Aim: Write a program to demonstrate the working of decision tree based on ID3 algorithm. Use an appropriate data set for building the decision tree and apply knowledge to classify a new sample.

Description: Decision tree is a supervised learning technique that can be used for both classification and regression problems, but mostly it is preferred for solving classification problems. It is a tree structured classifier where internal nodes represent the features of a dataset, branches represent the decision rules and each leaf node represents the outcome.

- In a decision tree there are two nodes, which are the decision node and leaf node. Decision nodes are used to make any decision and have multiple branches, whereas leaf nodes are the output of those decisions and do not contain any further branches.
- In order to build a tree, we use the CART algorithm, which stands for classification and regression tree algorithm.

↳ Decision Tree is a tree structure which is built by dividing the data into smaller and smaller sets.

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Algorithm:

Step-1: Begin the tree with the root node, says S , which contains the complete dataset.

Step-2: Find the best attribute in the dataset using Attribute Selection Measure (ASM).

Step-3: Divide the S into subsets that contains possible values for the best attributes.

Step-4: Generate the decision tree node, which contains the best attribute.

Step-5: Recursively make new decision trees using the subsets of the dataset created in step-3. Continue this process until a stop stage is reached where you cannot further classify the nodes, and called the final node as a leaf node.

Attribute Selection Measures: (ASM)

While implementing a decision tree, the main issue arises that how to select the best attribute for the root node and for sub-nodes. So, to solve such problems there is a technique which is called as Attribute Selection Measure or ASM. By this measure

ment, we can easily select the best attribute for the nodes of the tree. There are two popular techniques for ASM, which are

- Information Gain
- Gini Index

Information Gain: Information gain is the measurement of changes in entropy after the segmentation of a dataset based on an attribute.

→ It calculates how much information a feature provides us about a class.

Entropy is the measure of disorder in a data set.

Entropy = $-\sum p_i \log_2 p_i$ where p_i is the probability of class i .

Information Gain = Entropy(S) - [Weighted Avg] * Entropy(Each feature)]

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Program:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
import matplotlib.pyplot as plt
from sklearn import metrics
```

```
data = pd.read_csv('c:/users/PRAVEEN/downloads/code/
ML/exp-4.3/trees.csv')
```

```
X = data.drop(['playtennis'], axis=1)
y = data['playtennis']
```

```
X = pd.get_dummies(X)
y = y.map({'yes':1, 'no':0})
```

```
x_train, x_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=1)
```

```
clf = DecisionTreeClassifier()
```

```
clf.fit(x_train, y_train)
y_pred = clf.predict(x_test)
```

Accuracy = 90.00%

Humidity_Normal <= 0.5
 Gini = 0.49
 samples = 7
 value = [4, 8]
 class = No

True

False

Gini = 0.0
 samples = 3
 value = [3, 0]
 class = No

Gini = 0.0
 Outlook_Rain <= 0.5
 Gini = 0.375
 samples = 4
 value = [1, 3]
 class = Yes

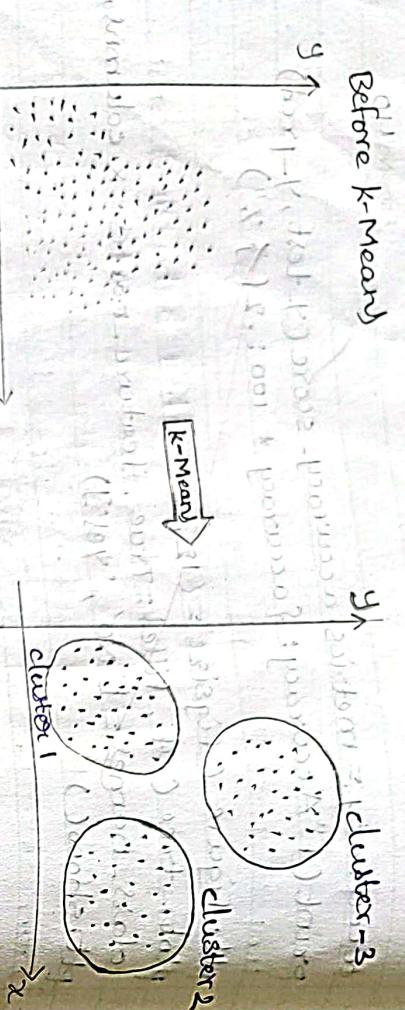
True

False

Gini = 0.0
 samples = 3
 value = [0, 2]
 class = Yes

Gini = 0.0
 samples = 1
 value = [1, 0]
 class = No

Correct: 5, Wrong: 1
 (Not, X) Jhonny OLS = 100% - 10%



K-Means Algorithm for clustering:

start

Number of cluster k

centroid

Distance of objects to centroids

No object more group

End

Grouping based on minimum distance

Aim: Apply EM algorithm to cluster a Heart Disease data set. Use the same data set for clustering using K-means algorithm. compare the results of these two algorithms and comment on the quality of clustering. You can add python ML library classes/ API in the program.

Description:

K-Means Algorithm: The K-Means algorithm is an iterative clustering algorithm used to partition a dataset into K distinct clusters. It is one of the most popular and widely used clustering algorithms due to its simplicity and efficiency. The goal of the K-Means algorithm is to minimize the within-cluster variance by iteratively assigning data points to the nearest cluster centroid and updating the centroid positions.

Algorithm steps:

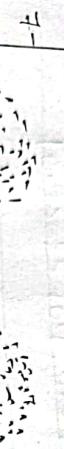
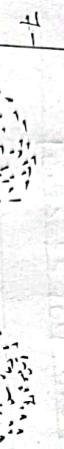
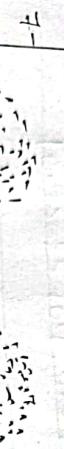
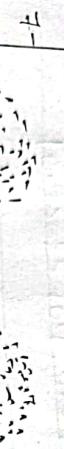
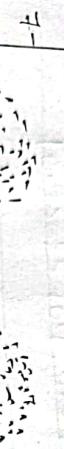
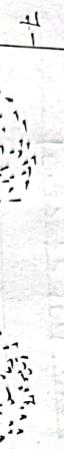
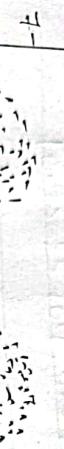
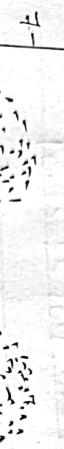
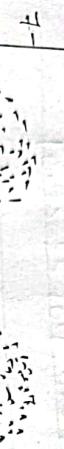
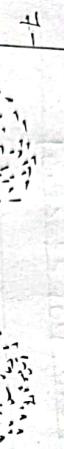
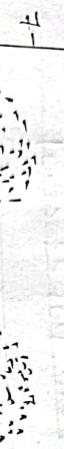
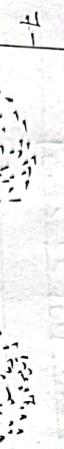
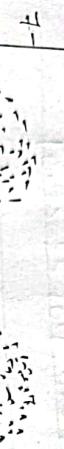
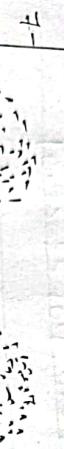
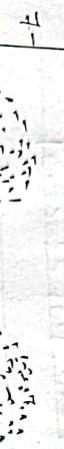
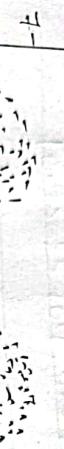
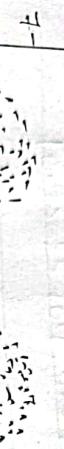
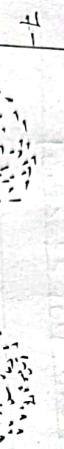
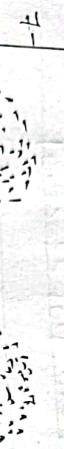
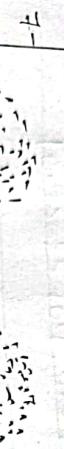
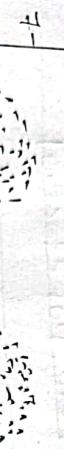
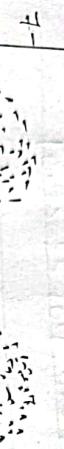
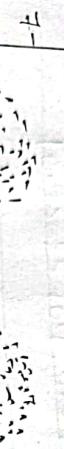
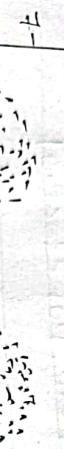
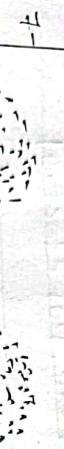
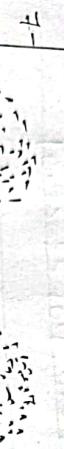
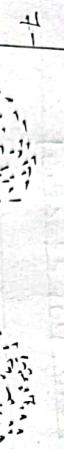
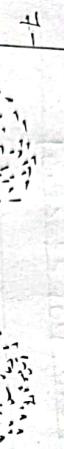
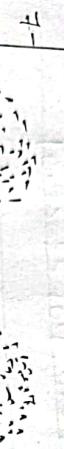
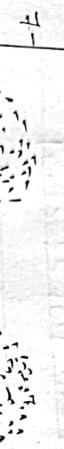
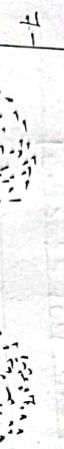
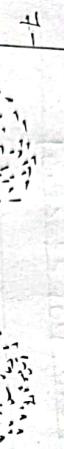
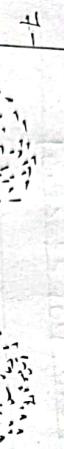
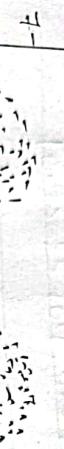
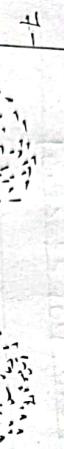
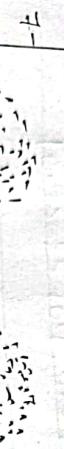
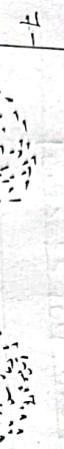
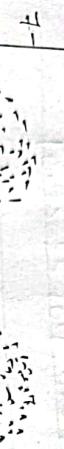
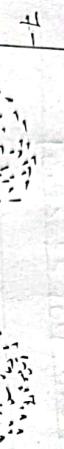
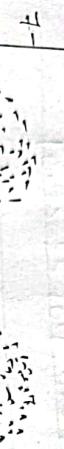
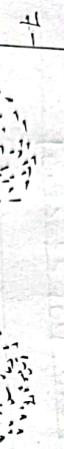
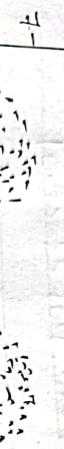
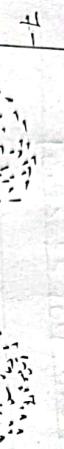
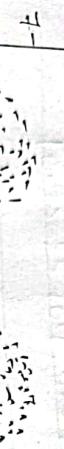
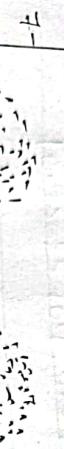
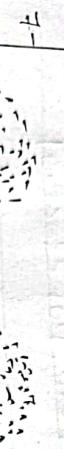
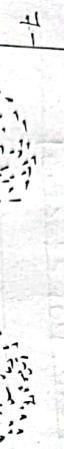
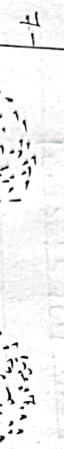
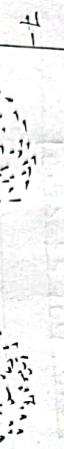
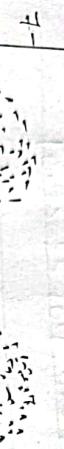
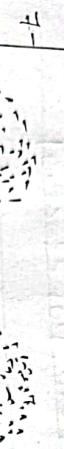
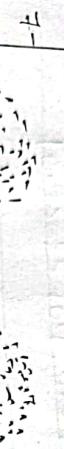
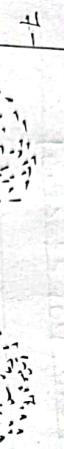
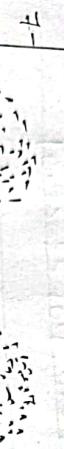
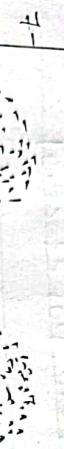
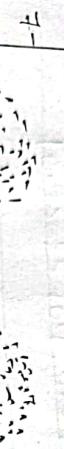
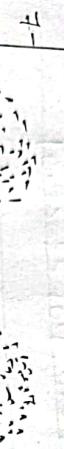
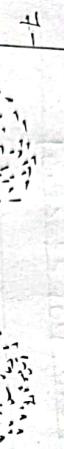
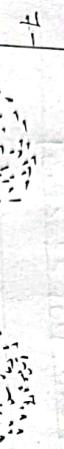
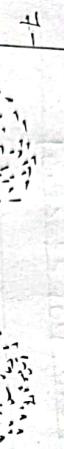
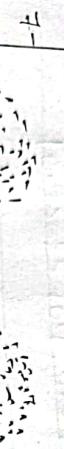
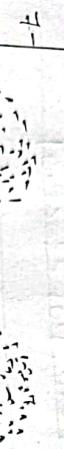
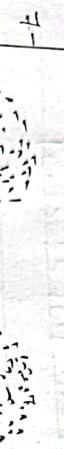
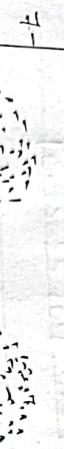
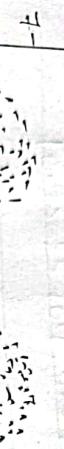
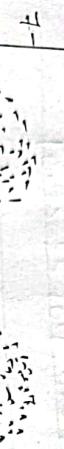
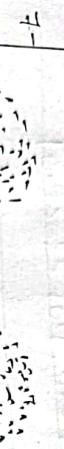
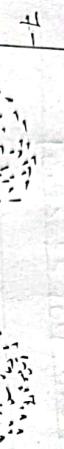
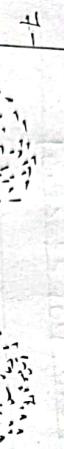
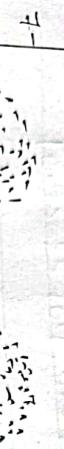
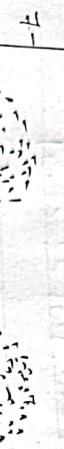
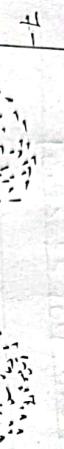
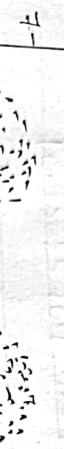
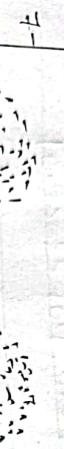
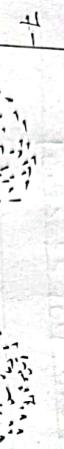
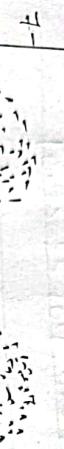
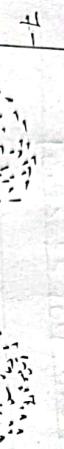
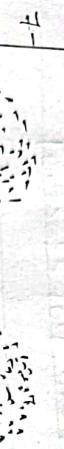
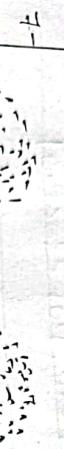
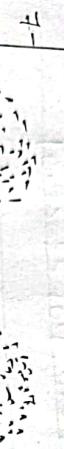
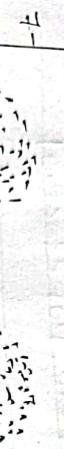
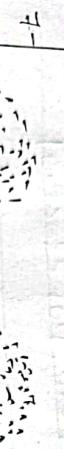
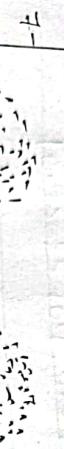
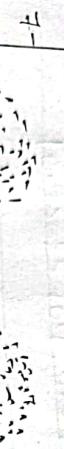
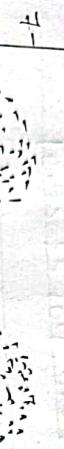
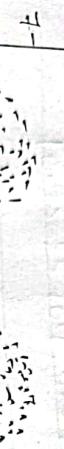
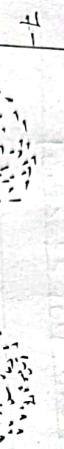
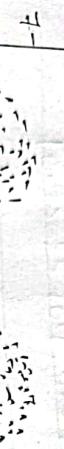
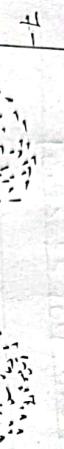
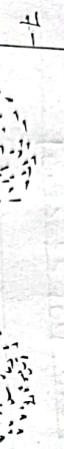
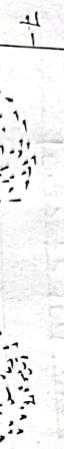
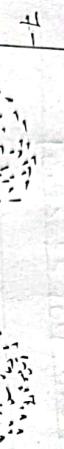
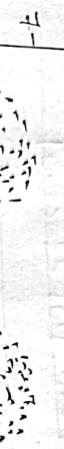
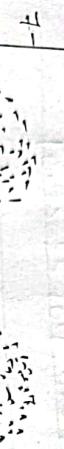
- Step-1: Select the number k, to decide the no. of clusters.
- Step-2: select Random k points (or) centroids.
- Step-3: Assign each data point to their closest centroid which will form the predefined k-clusters.
- Step-4: calculate the variance and place a new centroid of each cluster.
- Step-5: Repeat the 3rd step which mean reassign each data point to the new closest centroid of each cluster.

↳ Step 5: If any blob of a cluster is not in the cluster, then go to step-4
↳ Else go to FINISH.

Step-6: The model is ready

Generated Data

↳ Data is generated by using k-means



Q1 Answer

1. $\text{X} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$ and $\text{Y} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$

2. $\text{X} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$ and $\text{Y} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$

3. $\text{X} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$ and $\text{Y} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$

4. $\text{X} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$ and $\text{Y} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$

5. $\text{X} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$ and $\text{Y} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$

K-Means clustering

(a) $\text{data} = \text{np.random.rand}(100, 2)$

6.

7. $\text{X} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$

8.

9. $\text{X} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$

10.

11. $\text{X} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$

12.

13. $\text{X} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$

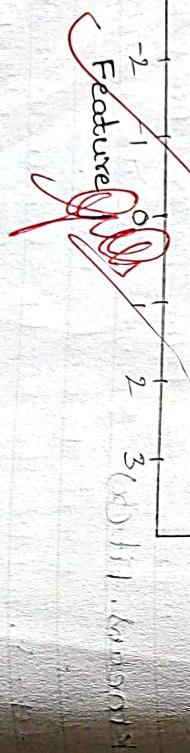
14.

15. $\text{X} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$

16. $\text{X} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$

17. $\text{X} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$

18. $\text{X} = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 & 20 \end{bmatrix}$



~~plt.scatter(x[:,0], x[:,1], c=labels, s=50, cmap='viridis')~~

~~plt.scatter(x[:,0], x[:,1], c='red', s=200, alpha=0.75, marker='x')~~

~~plt.title('K-means clustering')~~

~~plt.xlabel('Feature 1')~~

~~plt.ylabel('Feature 2')~~

~~plt.show()~~

Aim: Assuming a set of documents that need to be classified, use the naive Bayesian classification model to perform this task. Built-in Java classes/APL can be used to write the program, calculate the accuracy, precision and recall for your data set.

Description:

Naive Bayes: Naive Bayes algorithm is a supervised learning algorithm, which is based on Bayes theorem and used for solving classification problems.
→ It is mainly used in text classification that includes a high dimensional training dataset.
→ It is a probabilistic classifier, which means it predicts on the basis of the probability of an object.

Example:

~~spam filtration~~
~~sentimental analysis~~
classifying articles

Naive: It is called Naive because it assumed that the occurrence of a certain feature is independent of the occurrence of other features.

Bayes: It is called Bayes because it depends on the principle of Bayes Theorem.

Bayes Theorem: Bayes Theorem is also known as Bayes Rule or Bayes law which is used to determine the probability of a hypothesis with prior knowledge. It depends on the conditional probability.

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

where, $p(A)$ is prior probability
 $p(B)$ is Marginal probability

$P(A)$ is prior probability
 $P(B)$ is Marginal probability

$P(A|B)$ is posterior probability
 $P(B|A)$ is likelihood probability

Working of Naive Bayes classifier!

- convert the given dataset into frequency tables.
- generate likelihood table by finding the probabilities of given features.
- Now, use Bayes theorem to calculate the posterior probability.

```
Program:  
import seaborn as sns  
from sklearn.model_selection import train_test_split  
from sklearn.naive_bayes import GaussianNB  
from sklearn.metrics import accuracy_score, classification_report
```

```
iris = sns.load_dataset('iris')
```

sepal length sepal width petal length petal width

```

0 5.1 3.5 1.4 0.2
1 4.9 3.0 1.4 0.2
2 4.7 3.2 1.3 0.2
3 4.6 3.1 1.5 0.2
4 5.0 3.6 1.4 0.2
5 5.4 3.9 1.7 0.4
6 4.6 3.4 1.4 0.3
7 5.0 3.4 1.5 0.2
8 4.5 2.3 1.3 0.3
9 4.5 2.3 1.3 0.3
10 4.4 1.7 1.4 0.2
11 4.9 3.1 1.5 0.1
12 4.7 1.8 1.7 0.4
13 4.4 1.4 1.3 0.2
14 4.1 1.5 1.3 0.1
15 5.8 4.0 1.2 0.2
16 5.7 3.8 1.5 0.3
17 5.4 3.4 1.4 0.3
18 5.1 3.3 1.5 0.2
19 5.9 3.0 1.6 0.2
20 5.4 3.9 1.3 0.4
21 5.1 3.5 1.4 0.3
22 4.8 3.4 1.9 0.4
23 5.7 3.8 1.5 0.3
24 5.1 3.3 1.3 0.2
25 5.7 3.0 1.5 0.2
26 5.1 3.0 1.9 0.2
27 5.4 3.9 1.7 0.4
28 5.1 3.3 1.8 0.2
29 4.5 2.3 1.3 0.3
30 4.4 1.4 1.3 0.2
31 4.8 3.0 1.4 0.3
32 4.3 1.3 1.3 0.1
33 5.8 4.0 1.2 0.2
34 5.7 3.8 1.5 0.3
35 5.4 3.4 1.4 0.3
36 5.1 3.3 1.3 0.2
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49 5.7 3.8 1.5 0.3
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52 5.9 3.0 1.6 0.2
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55 4.8 3.4 1.7 0.4
56 5.7 3.8 1.5 0.3
57 5.1 3.3 1.3 0.2
58 5.4 3.9 1.7 0.4
59 5.1 3.3 1.5 0.2
60 4.5 2.3 1.3 0.3
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63 5.8 3.0 1.2 0.2
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107 4.1 1.5 1.3 0.1
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121 4.4 1.4 1.3 0.2
122 4.1 1.5 1.3 0.1
123 5.8 3.0 1.2 0.2
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125 5.4 3.4 1.4 0.3
126 5.1 3.3 1.3 0.2
127 5.9 3.0 1.6 0.2
128 5.4 3.9 1.3 0.4
129 5.1 3.5 1.4 0.2
130 4.8 3.4 1.7 0.4
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133 5.4 3.9 1.7 0.4
134 5.1 3.3 1.5 0.2
135 4.5 2.3 1.3 0.3
136 4.4 1.4 1.3 0.2
137 4.1 1.5 1.3 0.1
138 5.8 3.0 1.2 0.2
139 5.7 3.8 1.5 0.3
140 5.4 3.4 1.4 0.3
141 5.1 3.3 1.3 0.2
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143 5.4 3.9 1.3 0.4
144 5.1 3.5 1.4 0.2
145 4.8 3.4 1.7 0.4
146 5.7 3.8 1.5 0.3
147 5.1 3.3 1.3 0.2
148 5.4 3.9 1.7 0.4
149 5.1 3.3 1.5 0.2
150 4.5 2.3 1.3 0.3
  
```

(A) 9 (A) 10 (A) 11 (A) 12 (A) 13 (A) 14 (A) 15

$y = \text{iris}['species']$

y

$x_train, x_test, y_train, y_test = \text{train_test_split}(x, y, test_size = 0.2, random_state = 42)$

model = GaussianNB()

model.fit(x_train, y_train)

$y_pred = \text{model.predict}(x_test)$

accuracy = accuracy_score(y_test, y_pred)

print('Accuracy: ', accuracy * 100, '%')

print('Classification Report: ')

print(classification_report(y_test, y_pred))

	setosa	versicolor	virginica
accuracy	1.00	1.00	1.00
macro avg	1.00	1.00	1.00
weighted avg	1.00	1.00	1.00

→ hidden layer accelerated and improved the efficiency of the network by recognizing just the most important information from the inputs and discarding the redundant information.

W. R. (W. R. S.) L. ROSENBERG
BOSTON, MASSACHUSETTS, U.S.A.

Missouri Association for the Advancement of Negroes (MANA) 1960

```
<module 'keras.datasets.mnist' from 'C:\users\proven\anaconda2\lib\site-packages\keras\utils\datasets\mnist\__init__.py'>
```

卷之三

(10000, 28, 28) (60000, 28, 28)

```
(x_train, y_train), (x_test, y_test) = dataframe.load_data()  
x_train.shape
```

Epoch 1/5 — 135 6ms/step - accuracy: 0.8601 - loss: 0.4861
Epoch 2/5 — 205 5ms/step - accuracy: 0.9548 - loss: 0.1599
Epoch 3/5 — 187 5ms/step - accuracy: 0.9601 - loss: 0.1499
Epoch 4/5 — 187 5ms/step - accuracy: 0.9601 - loss: 0.1499
Epoch 5/5 — 187 5ms/step - accuracy: 0.9601 - loss: 0.1499
Final accuracy: 0.9601

```
x_train, x_test = x_train / 255, x_test / 255
x_train.shape
y_train.shape
x_test.shape
y_test.shape
model = tf.keras.Sequential([
    tf.keras.layers.Flatten(input_shape=(28, 28)),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(10, activation='softmax')
])
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
model.fit(x_train, y_train, epochs=5)
```

```

Epoch 3/5 1875/1875 — 115 6ms/step - accuracy: 0.9667 - loss: 0.1091
Epoch 4/5 1875/1875 — 105 5ms/step - accuracy: 0.9745 - loss: 0.0834
Epoch 5/5 1875/1875 — 105 5ms/step - accuracy: 0.9740 - loss: 0.0741
  
```

```

313/313 — 0s 8814s/step - accuracy: 0.9744 - loss: 0.0864
[0.072090791528511, 0.972900282287]
  
```

```
model.evaluate(x_test, y_test)
```

↳ Writing 2. Update. Go to file.abor

↳ (8488) -> print. angularVelocity. wxyz. yaw. pitch. roll

↳ (0.0) yaw. roll. pitch. yaw

↳ (0.0) roll. pitch. yaw. yaw

↳ (0.0) roll. pitch. yaw. yaw

↳ 1.0

↳ 1.0

↳ (0.0) roll. pitch. yaw. yaw

↳ (0.0) roll. pitch. yaw. yaw

↳ (0.0) roll. pitch. yaw. yaw

↳ 1.0