Naive Bayes Classifier

- is a supervised learning model
- uses Bayes' Theorem
- works on conditional probability / posterior probability
- conditional probability, P(A|B) = P(A ∪ B)/P(A)
- used to find probability of event A if probability of event B is already known
- e.g. supermarket case, if user buys bread and eggs, what is probability of user buying milk
- e.g. if a person is wearing a saree is a feature, and we know the probability of person wearing saree, what will be probability of person being female ?

```
import numpy as np
import pandas as pd
import statsmodels
import statsmodels.api as sm
from statsmodels.formula.api import ols
import statsmodels.stats.multicomp
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
```

```
import numpy as np
import pandas as pd
import sklearn
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
```

```
from google.colab import files
uploaded=files.upload()
# CDAC_DataBook.xlsx
# to be used with google colab

# import os
# os.chdir(r'C:\Users\surya\Downloads\PG-DBDA-Mar23\Datasets')
# os.getcwd()
# to change current working directory to specified path
# to be used while running on local system
```

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```
df = pd.read_excel('CDAC_DataBook.xlsx', sheet_name='iris')
df.head()
```

	Sepal_length	Sepal_width	Petal_length	Petal_width	Species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

```
x_train, x_test, y_train, y_test = train_test_split(df.drop('Species', axis=1), df.Species, test_size=0.25)
```

▼ GaussianNB().fit(x_train, y_train)

```
mod1 = GaussianNB().fit(x_train, y_train)
```

▼ mod1.predict(x_test)

```
y_pred = mod1.predict(x_test)
```

▼ confusion_matrix(y_test, y_pred)

```
print(confusion_matrix(y_test, y_pred))
```

```
[[12  0  0]
 [ 0 11  3]
 [ 0  0 12]]
```

```
1
```

▼ KNN classifier

- K-Nearest Neighbour classifier

- selects `k` number of neighbours, and then selects the response with highest frequency as the final response
-

import KNeighborsClassifier

```
import numpy as np
import pandas as pd
import sklearn
from sklearn.neighbors import KNeighborsClassifier as knc
from sklearn.model_selection import train_test_split
```

```
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```

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3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

```
x_train, x_test, y_train, y_test = train_test_split(df.drop('Species', axis=1), df.Species, test_size=0.25)
```

KNeighborsClassifier(n_neighbors=4).fit(x_train, y_train)

```
mod2 = knc(n_neighbors=4).fit(x_train, y_train)
```

model.predict(x_test)

```
y_pred2 = mod2.predict(x_test)
```

confusion_matrix(y_test, y_pred)

```
print(confusion_matrix(y_test, y_pred))
# confusion matrix for naive Bayes classifier
```

```
[[6 4 3]
 [2 4 4]
 [4 3 8]]
```

```
print(confusion_matrix(y_test, y_pred2))
# confusion matrix for KNN classifier
```

```
[[13  0  0]
 [ 0 10  0]
 [ 0  1 14]]
```

- ROC curve: receiver operating characteristic curve
- indicates preicision, recall value
- higher the area under the curve, higher the precision

Unsupervised learning Models

- there is no response in training data
- used to discover hidden patterns
- uses machine learning algorithms to analyze and cluster unlabeled datasets

Clustering Model

- we make atleast three clusters
- each cluster has one center point called centeroid
- one point in a specific cluster is closer to the centeroid of that cluster as compared to the centroid of other clusters in dataset
- majorly used in marketing industry to analyse

Partitional Clustering

K-Means

- is a clustering model, unsupervised learning model
-

import KMeans

```
import numpy as np
import pandas as pd
import sklearn
from sklearn.cluster import KMeans
```

```
from google.colab import files
uploaded=files.upload()
# clusters.xlsx
# to be used with google colab

# import os
# os.chdir(r'C:\Users\surya\Downloads\PG-DBDA-Mar23\Datasets')
# os.getcwd()
# to change current working directory to specified path
# to be used while running on local system
```

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Saving clusters.xlsx to clusters.xlsx

```
df = pd.read_excel('clusters.xlsx')
df.head()
```

KMeans(n_clusters=3).fit(dataSet)

```
mod3 = KMeans(n_clusters=3).fit(df)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the v
  warnings.warn(
```

model.cluster_centers_

```
mod3.cluster_centers_
# prints centroids from each of the clusters
```

```
array([[43.2, 16.7],
       [29.6, 66.8],
       [55.1, 46.1]])
```

mod.labels_

```
mod3.labels_
# prints the cluster to which each of the record is associated
```

```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0], dtype=int32)
```

model.predict(2-D List)

```
mod3.predict([[47, 14]])
# returns the array index of the cluster to whose centroid,
# this point is closest to
```

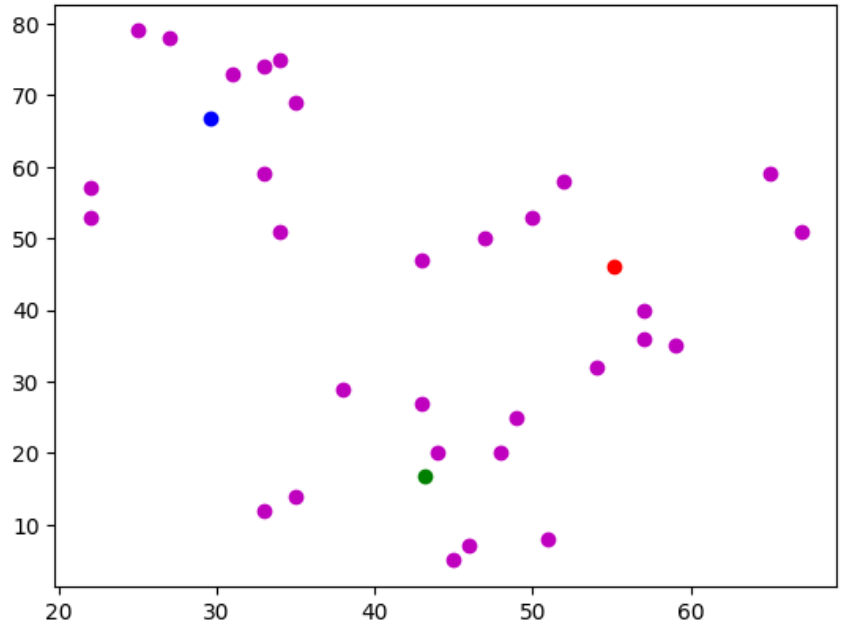
```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does not have valid feature names, but KMeans was fitted with feature names
  warnings.warn(
array([0], dtype=int32)
```

```
from matplotlib import pyplot as plt
```

```
plt.scatter(df.Var1, df.Var2, c='m') # all the points from dataset
plt.scatter(43.2, 16.7, c='g') # centroid1
```

```
plt.scatter(29.6, 66.8, c='b') # centroid2
plt.scatter(55.1, 46.1, c='r') # centroid2
```

```
<matplotlib.collections.PathCollection at 0x7f6b44965960>
```



Deciding on number of clusters

- maximum possible number of cluster is total number of records in dataset, so that each record/point is a unique cluster
- if number of clusters increase, the variation within the cluster will decrease

```
mod4 = KMeans(n_clusters=4).fit(df)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the v
  warnings.warn(
```

```
mod6 = KMeans(n_clusters=6).fit(df)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the v
  warnings.warn(
```

```
mod8 = KMeans(n_clusters=8).fit(df)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the v
  warnings.warn(
```

```
mod8.cluster_centers_
```

```
array([[27.75      , 55.        ],
       [47.33333333,  6.66666667],
       [56.75      , 35.75      ],
       [30.83333333, 74.66666667],
       [34.        , 13.        ],
       [48.        , 52.        ],
       [66.        , 55.        ],
       [44.4       , 24.2       ]])
```

model.inertia_

- prints distance / gain / delta of points from their respective centroid, means how well a dataset was clustered by K-Means
- inertia / gain / delta should be lower value
- number of clusters should be low
- gain / delta comes down as you increase the number of cluster

```
mod3.inertia_
```

```
3649.5
```

```
mod6.inertia_
```

```
1389.2166666666667
```

```
mod8.inertia_
```

```
683.75
```

```
mod10 = KMeans(n_clusters=10).fit(df)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the v
  warnings.warn(
```

```
mod10.inertia_
```

```
437.3333333333333
```

Hierarchical clustering

- output resembles or
- output might be dendrogram (tree-structure),
- finds out which items have similar attributes and creates clusters
- clusters at lowest level will have least differences, and as you go higher in level/altitude of levels, differences will increase
- top/highest level cluster will have all the items / items with maximum possible diffferences

import scipy.cluster.hierarchy

```
import scipy
import scipy.cluster.hierarchy as sch
```

```
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uploaded=files.upload()
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# os.getcwd()
# to change current working directory to specified path
# to be used while running on local system
```

```
df = pd.read_excel('CDAC_DataBook.xlsx', sheet_name='mtcars')
df.head()
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
0	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
1	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
2	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
3	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
4	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2

sch.dendrogram(sch.linkage(df))

```
sch.dendrogram(sch.linkage(df))
```

```
{'icoord': [[25.0, 25.0, 35.0, 35.0],
  [15.0, 15.0, 30.0, 30.0],
  [55.0, 55.0, 65.0, 65.0],
  [45.0, 45.0, 60.0, 60.0],
  [75.0, 75.0, 85.0, 85.0],
  [105.0, 105.0, 115.0, 115.0],
  [95.0, 95.0, 110.0, 110.0],
  [125.0, 125.0, 135.0, 135.0]
```

```
df.iloc[9]
```

```
mpg      19.20
cyl       6.00
disp    167.60
hp      123.00
drat      3.92
wt        3.44
qsec     18.30
vs        1.00
am        0.00
gear      4.00
carb      4.00
Name: 9, dtype: float64
```

```
[215.0, 215.0, 257.34375, 257.34375]
```

Time-Series Modelling

- special form of regression
- only one predictor
- response only depends on time
- variations over time can be analysed
- sequencing of data is extremely important in Time Series
  - order of records is not important in supervised or unsupervised modelling, but in time series modelling, ordering of records matter
  - sequencing of the records is extremely important, so data should be strictly as per time, otherwise results will change
- → Trend: slow variation over a longer period of time
  - e.g. sales of innova increased from its launch in 2005, and sales of qualis decreased from 2005
- → Seasonal variation: varaiation over smaller period of time
  - e.g. variation in car sales over different seasons
- → cyclical variation: when events occur after a fixed time period of years/centuries
  - e.g. 1919 spanish flu, 2019 COVID-19
- → irregular variations: random variations

15.29568648345016

preparing data for Time Series Modelling

- earlier we could remove null/duplicate records for supervised/unsupervised models, but if we remove such records, it'll impact the results, so we cannot remove such records

1. missing values need to be filled with some data
    - better to take data from previous year than copying data from last month
2. outliers need to be checked carefully, as outliers might contain some useful data -

- Error of the forecast = actual Value - Forecast Value

Types of errors

- MAD - Mean Absolute Deviation
- MSQ - Mean Square Error
- MAPE - Mean Absolute Percentage Error
- RMSE - Root Mean Square Error

```
1
```