Naive Bayes classifiers are built on Bayesian classification methods. These rely on Bayes's theorem, which is an equation describing the relationship of conditional probabilities of statistical quantities.

Create a Model using Naive Bayes classifiers to predict whether a passenger on the titanic would have been survived or not.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
%matplotlib inline
```

```
titanic = pd.read_csv("/content/train.csv")
titanic.head()
```

| | PassengerId | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 0 | 3 | Braund, Mr. Owen Harris | male | 22.0 | 1 | 0 | A/5 21171 |
| **1** | 2 | 1 | 1 | Cumings, Mrs. John Bradley (Florence Briggs Th... | female | 38.0 | 1 | 0 | PC 17599 |

```
print("Shape of dataset:", titanic.shape) # shape of dataset
```

```
Shape of dataset: (891, 12)
```

```
print("Columns present in dataset:\n", titanic.columns) # columns present in dataset
```

```
Columns present in dataset:
 Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

```
titanic.isnull().sum() # check total null values inside data
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
```

```
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

```
# fill values of age column

titanic.fillna(titanic.mean(), inplace = True)
titanic.isnull().sum()
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

```
# fill values of Embarked column

titanic["Embarked"].fillna("S", inplace = True)
titanic.isnull().sum()
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         0
dtype: int64
```

```
# drop Cabin column because it has lot of null values. 687/891

drop_cabin = titanic.isnull().sum()[titanic.isnull().sum() > (50/100 * titanic.shape[0])]
drop_cabin
```

```
Cabin    687
dtype: int64
```

```
drop_cabin.index
```

```
Index(['Cabin'], dtype='object')
```

```
titanic.drop(drop_cabin.index, axis = 1, inplace = True)
titanic.isnull().sum()
```

```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Embarked       0
dtype: int64
```

```
titanic.describe()
```

| | PassengerId | Survived | Pclass | Age | SibSp | Parch | Fare |
|---|---|---|---|---|---|---|---|
| **count** | 891.000000 | 891.000000 | 891.000000 | 891.000000 | 891.000000 | 891.000000 | 891.000000 |
| **mean** | 446.000000 | 0.383838 | 2.308642 | 29.699118 | 0.523008 | 0.381594 | 32.204208 |
| **std** | 257.353842 | 0.486592 | 0.836071 | 13.002015 | 1.102743 | 0.806057 | 49.693429 |
| **min** | 1.000000 | 0.000000 | 1.000000 | 0.420000 | 0.000000 | 0.000000 | 0.000000 |
| **25%** | 223.500000 | 0.000000 | 2.000000 | 22.000000 | 0.000000 | 0.000000 | 7.910400 |
| **50%** | 446.000000 | 0.000000 | 3.000000 | 29.699118 | 0.000000 | 0.000000 | 14.454200 |
| **75%** | 668.500000 | 1.000000 | 3.000000 | 35.000000 | 1.000000 | 0.000000 | 31.000000 |
| **max** | 891.000000 | 1.000000 | 3.000000 | 80.000000 | 8.000000 | 6.000000 | 512.329200 |

```
titanic.corr()
```

| | PassengerId | Survived | Pclass | Age | SibSp | Parch | Fare |
|---|---|---|---|---|---|---|---|

```
titanic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          891 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Embarked     891 non-null    object
dtypes: float64(2), int64(5), object(4)
memory usage: 76.7+ KB
```

```
# create a new column Family size by adding SibSp and Parch

titanic["FamilySize"] = titanic["SibSp"] + titanic["Parch"]
titanic.head()
```

| | PassengerId | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Far |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 0 | 3 | Braund, Mr. Owen Harris | male | 22.0 | 1 | 0 | A/5 21171 | 7.250 |
| **1** | 2 | 1 | 1 | Cumings, Mrs. John Bradley (Florence Briggs Th | female | 38.0 | 1 | 0 | PC 17599 | 71.283 |

```
# drop SibSp and Parch because we create new column FamilySize instaed of them

titanic.drop(["SibSp", "Parch"], axis = 1, inplace = True)
titanic.head()
```

| | PassengerId | Survived | Pclass | Name | Sex | Age | Ticket | Fare | Embarked | F |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Braund | | | | | | |

```
titanic.corr()
```

| | PassengerId | Survived | Pclass | Age | Fare | FamilySize |
|---|---|---|---|---|---|---|
| **PassengerId** | 1.000000 | -0.005007 | -0.035144 | 0.033207 | 0.012658 | -0.040143 |
| **Survived** | -0.005007 | 1.000000 | -0.338481 | -0.069809 | 0.257307 | 0.016639 |
| **Pclass** | -0.035144 | -0.338481 | 1.000000 | -0.331339 | -0.549500 | 0.065997 |
| **Age** | 0.033207 | -0.069809 | -0.331339 | 1.000000 | 0.091566 | -0.248512 |
| **Fare** | 0.012658 | 0.257307 | -0.549500 | 0.091566 | 1.000000 | 0.217138 |
| **FamilySize** | -0.040143 | 0.016639 | 0.065997 | -0.248512 | 0.217138 | 1.000000 |

```
# filtered alone persons/passengers

titanic["Alone"] = [0 if titanic["FamilySize"][i] > 0 else 1 for i in titanic.index]
titanic.head()
```

| | PassengerId | Survived | Pclass | Name | Sex | Age | Ticket | Fare | Embarked | F |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 0 | 3 | Braund, Mr. Owen Harris | male | 22.0 | A/5 21171 | 7.2500 | S | |
| **1** | 2 | 1 | 1 | Cumings, Mrs. John Bradley (Florence Briggs Th | female | 38.0 | PC 17599 | 71.2833 | C | |

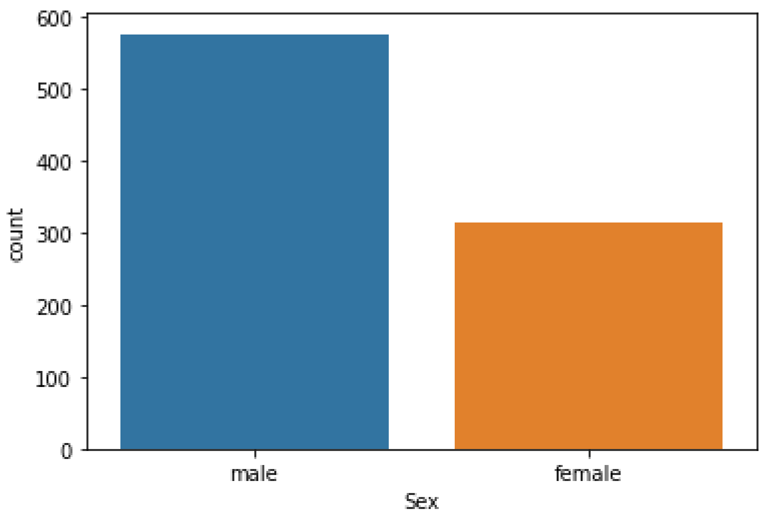
```
titanic.corr()
```

| | PassengerId | Survived | Pclass | Age | Fare | FamilySize | Alone |
|---|---|---|---|---|---|---|---|
| **PassengerId** | 1.000000 | -0.005007 | -0.035144 | 0.033207 | 0.012658 | -0.040143 | 0.057462 |
| **Survived** | -0.005007 | 1.000000 | -0.338481 | -0.069809 | 0.257307 | 0.016639 | -0.203367 |
| **Pclass** | -0.035144 | -0.338481 | 1.000000 | -0.331339 | -0.549500 | 0.065997 | 0.135207 |
| **Age** | 0.033207 | -0.069809 | -0.331339 | 1.000000 | 0.091566 | -0.248512 | 0.179775 |
| **Fare** | 0.012658 | 0.257307 | -0.549500 | 0.091566 | 1.000000 | 0.217138 | -0.271832 |
| **FamilySize** | -0.040143 | 0.016639 | 0.065997 | -0.248512 | 0.217138 | 1.000000 | -0.690922 |
| **Alone** | 0.057462 | -0.203367 | 0.135207 | 0.179775 | -0.271832 | -0.690922 | 1.000000 |

Filtered out survived ratio according to conditions and visualize them

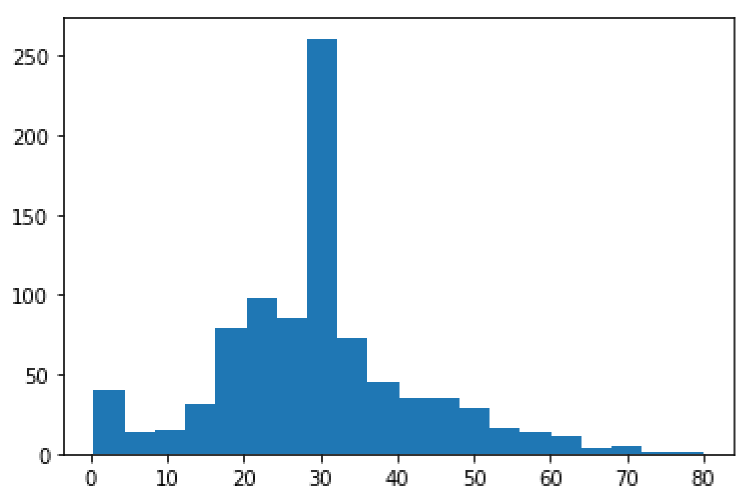
```
# sex ratio of passengers

sb.countplot(x = "Sex", data = titanic);
```



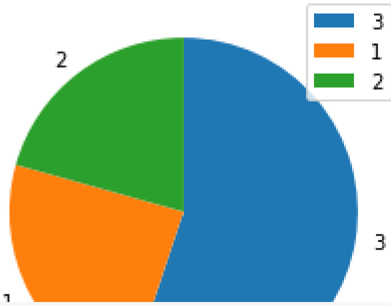

```
# age distribution

plt.hist(x = titanic["Age"], bins = 20);
```



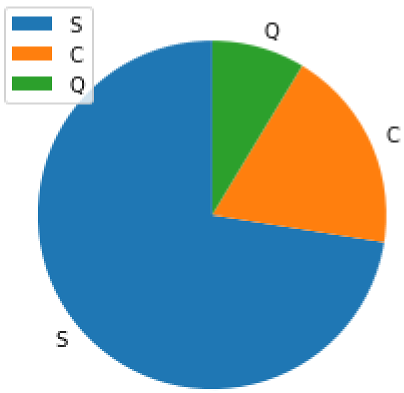

```
# passenger class
x = titanic["Pclass"].value_counts()
plt.pie(x, labels = x.index, startangle = 90, counterclock = False);
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7fc5c7899210>
```



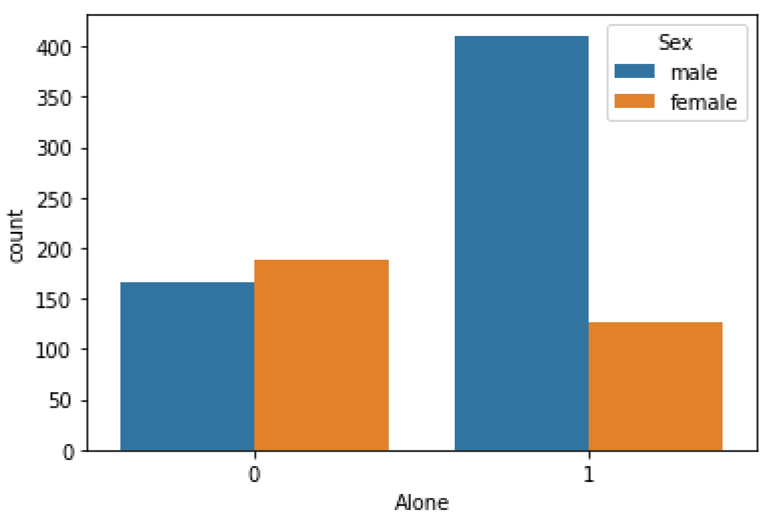

```
#Embarked
y = titanic["Embarked"].value_counts()
plt.pie(y, labels = y.index, startangle = 90, counterclock = True);
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7fc5c77fec90>
```



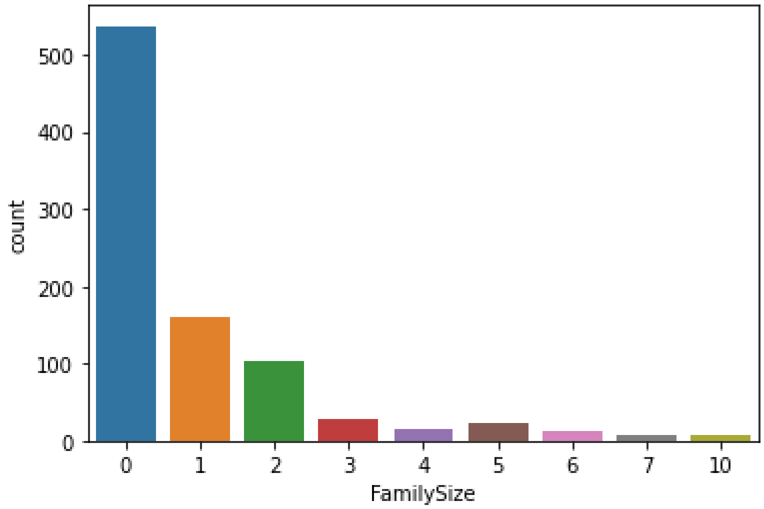

```
# survive rate of alone person according to their sex

sb.countplot(x = "Alone", hue = "Sex", data = titanic);
```



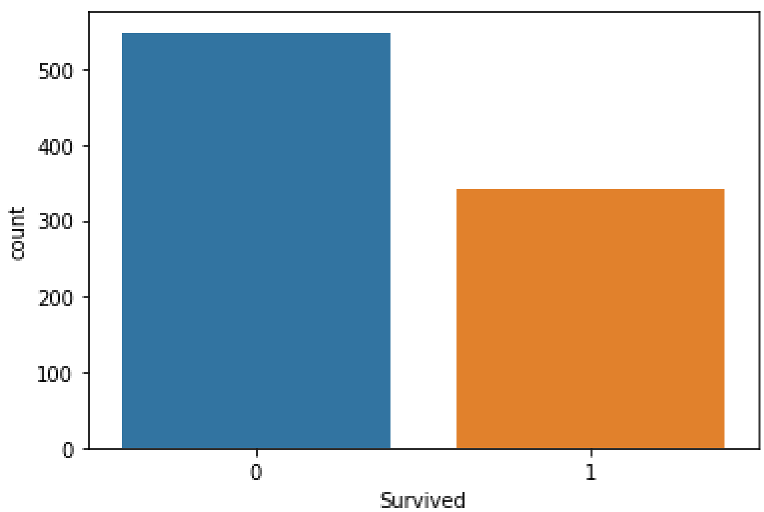

```
# survive rate of family
```

```
sb.countplot(x = "FamilySize", data = titanic);
```



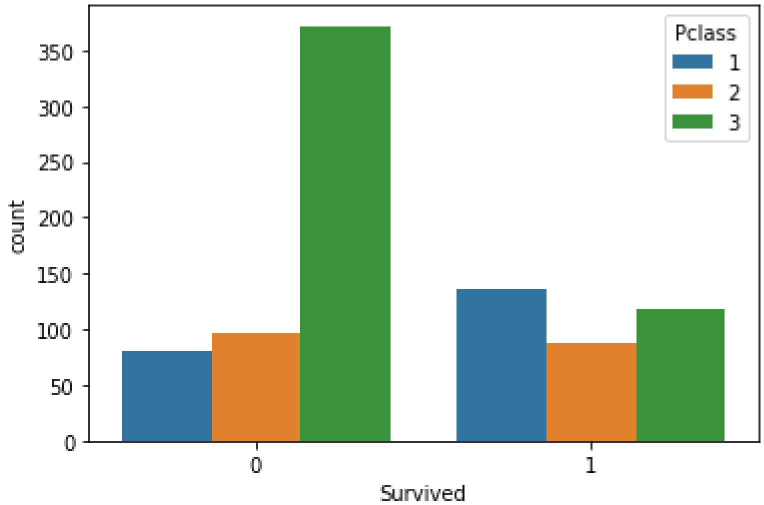

```
# total survived passengers

sb.countplot(x = "Survived", data = titanic);
```

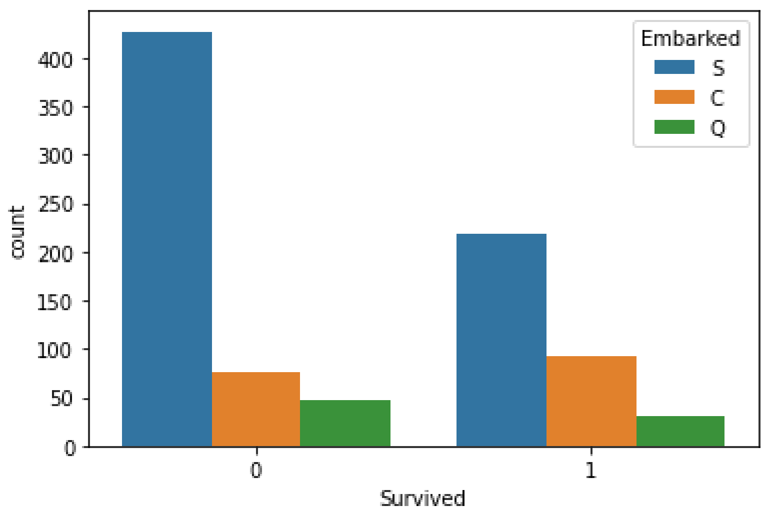



```
# survived ratio according to sex
sb.countplot(x = "Survived", hue = "Sex", data = titanic);
```


```
# accoring to pclass
sb.countplot(x = "Survived", hue = "Pclass", data = titanic);
```

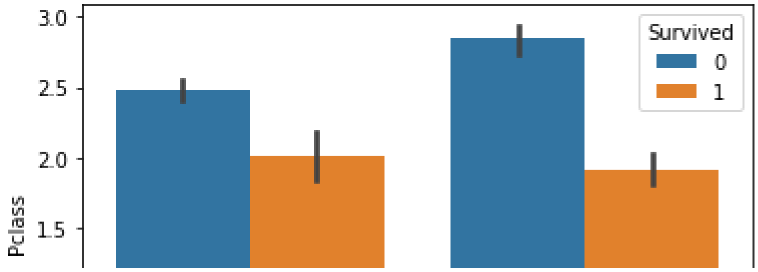



```
# according to embarked
sb.countplot(x = "Survived", hue = "Embarked", data = titanic);
```




```
# accroding to sex and passenger class
sb.barplot("Sex", "Pclass", hue = "Survived", data = titanic);
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass th
  FutureWarning
```




## Label Encoding for Sex and Embarked


```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
titanic["Sex"] = le.fit_transform(titanic["Sex"])
titanic["Embarked"] = le.fit_transform(titanic["Embarked"])
print("Encoded values for Sex:", titanic["Sex"].unique())
print("Encoded values for Embarked:", titanic["Embarked"].unique())
```

```
Encoded values for Sex: [1 0]
Encoded values for Embarked: [2 0 1]
```

```
titanic.head()
```

| | PassengerId | Survived | Pclass | Name | Sex | Age | Ticket | Fare | Embarked | Fam: |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 0 | 3 | Braund, Mr. Owen Harris | 1 | 22.0 | A/5 21171 | 7.2500 | 2 | |
| **1** | 2 | 1 | 1 | Cumings, Mrs. John Bradley (Florence Briggs Th | 0 | 38.0 | PC 17599 | 71.2833 | 0 | |

## Features and Target

```
features = titanic[["Pclass", "Sex", "Age", "Fare", "Embarked", "FamilySize", "Alone"]]
target = titanic["Survived"]
```

## Divide data for training and testing

```
from sklearn.model_selection import train_test_split

xtrain, xtest, ytrain, ytest = train_test_split(features, target, test_size = 0.3, random_sta
print("Shape of xtrain:", xtrain.shape)
```

```
print("Shape of ytrain:", ytrain.shape)
print("Shape of xtest:", xtest.shape)
print("Shape of ytest:", ytest.shape)
```

```
Shape of xtrain: (623, 7)
Shape of ytrain: (623,)
Shape of xtest: (268, 7)
Shape of ytest: (268,)
```

## Create a model and train the data

```
from sklearn.naive_bayes import GaussianNB

gnb = GaussianNB()
gnb.fit(xtrain, ytrain)
```

```
GaussianNB(priors=None, var_smoothing=1e-09)
```

## Test the testing data and make prediction

```
ypred = gnb.predict(xtest)
print("Prediction made by model:\n", ypred)
```

```
Prediction made by model:
 [0 0 1 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1
 1 0 1 0 0 0 0 0 0 1 0 1 1 1 0 1 1 0 0 1 1 1 0 0 1 0 0 0 1 0 0 0 0 0 1 0 0
 0 0 0 0 1 0 0 0 0 0 0 1 1 0 1 1 0 0 0 0 1 0 1 1 0 0 0 1 0 1 0 0 0 1 1 0 0
 0 1 1 0 1 0 0 0 0 1 0 1 0 1 1 1 1 0 0 1 1 1 1 0 0 1 0 1 1 0 1 0 1 0 1 1 1
 0 0 1 1 1 0 0 1 0 1 0 0 0 1 1 0 0 0 1 0 0 0 0 0 0 1 0 0 0 1 0 1 0 0 1 0 1
 0 1 0 1 0 0 1 0 1 1 1 0 1 1 0 0 0 0 1 1 0 0 0 0 1 0 1 0 0 0 0 0 0 1 1 1 0
 0 0 1 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 1 0 1 0 0 0 0 1 1 1 1 0 0 0 1 1
 0 0 0 1 0 0 0 1 0]
```

## Confusion Matrix and Accuracy

```
from sklearn.metrics import confusion_matrix, accuracy_score

matrix = confusion_matrix(ytest, ypred)
print("Confusion Matrix of a model:\n", matrix)
```

```
Confusion Matrix of a model:
 [[154  24]
 [ 20  70]]
```

```
accuracy = accuracy_score(ytest, ypred)
print("Accuracy of mdoel: {}%".format(accuracy*100))
```

```
Accuracy of mdoel: 83.5820895522388%
```