Assignment Date: 21 September 2022

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Student Roll Number: 611219106045

Maximum Marks: 2 Marks

1.Download the dataset from the source here:

About the dataset:

This dataset is all about churn modelling of a credit company. It has the details about the end user who are using credit card and also it has some variables to depicit the churn of the customer.

RowNumber - Serial number of the rows

CustomerId - Unique identification of customer

Surname - Name of the customer

CreditScore - Cipil score of the customer

Geography - Location of the bank

Gender - Sex of the customer

Age - Age of the customer

Tenure - Repayment period for the credit amount

Balance - Current balance in thier creidt card

NumOfProducts - Products owned by the customer from the company

HasCrCard - Has credit card or not (0 - no , 1 - yes)

IsactiveMember - Is a active member or not

EstimatedSalary - Salary of the customer

Exited - Churn of the customer

```
import warnings
warnings.filterwarnings("ignore")
```

```
import pandas as pd
import numpy as np
```

```
import seaborn as sns
import matplotlib.pyplot as plt
```

2. Load the dataset

```
df = pd.read_csv("Churn_Modelling.csv")
df.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Ba
0	1	15634602	Hargrave	619	France	Female	42	2	
1	2	15647311	Hill	608	Spain	Female	41	1	838
2	3	15619304	Onio	502	France	Female	42	8	1596
3	4	15701354	Boni	699	France	Female	39	1	
4	5	15737888	Mitchell	850	Spain	Female	43	2	1255

```
df.tail()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure
9995	9996	15606229	Obijiaku	771	France	Male	39	5
9996	9997	15569892	Johnstone	516	France	Male	35	10
9997	9998	15584532	Liu	709	France	Female	36	7
9998	9999	15682355	Sabbatini	772	Germany	Male	42	3
9999	10000	15628319	Walker	792	France	Female	28	4

3 a). Univariate analysis

```
#checking for categorical variables
category = df.select_dtypes(include=[np.object])
print("Categorical Variables: ",category.shape[1])

#checking for numerical variables
numerical = df.select_dtypes(include=[np.int64,np.float64])
print("Numerical Variables: ",numerical.shape[1])
```

```
Categorical Variables:  3
Numerical Variables:  11
```

```
df.columns
```

```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
```

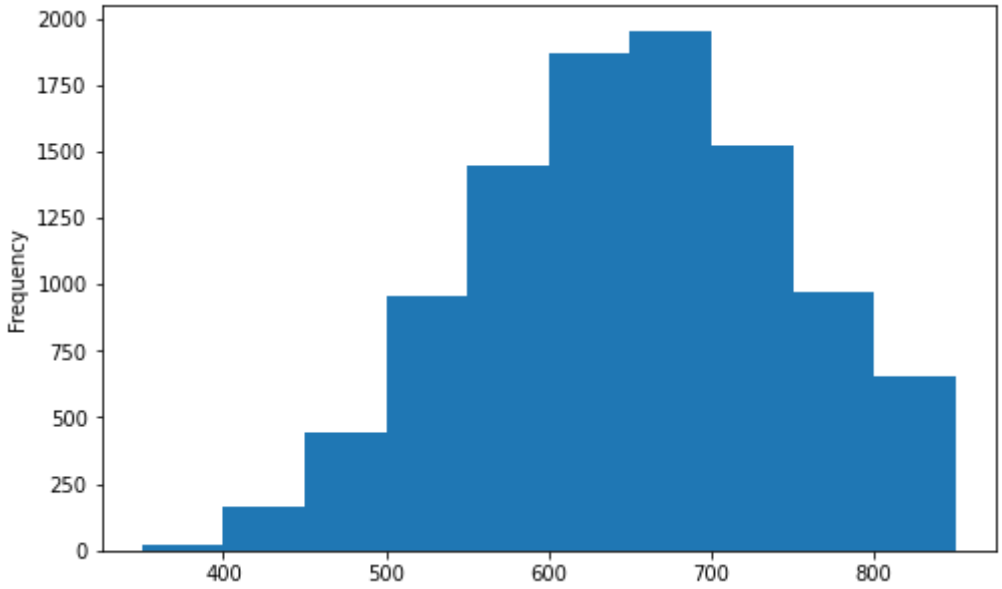
```
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

```
df.shape
```

```
(10000, 14)
```

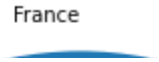
```
credit = df['CreditScore']
credit.plot(kind="hist",figsize=(8,5))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba39dc0a10>
```



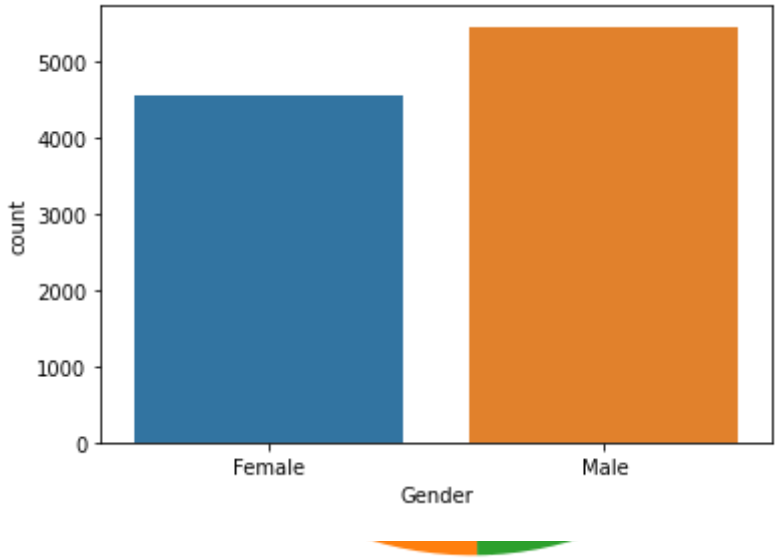

```
geo = df['Geography'].value_counts()
geo.plot(kind="pie",figsize=(10,8))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba39ddad10>
```



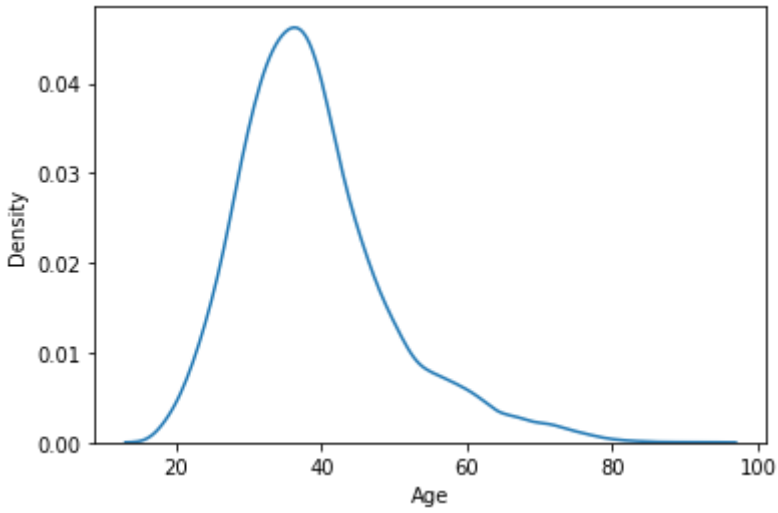

```
sns.countplot(df['Gender'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba397d8610>
```



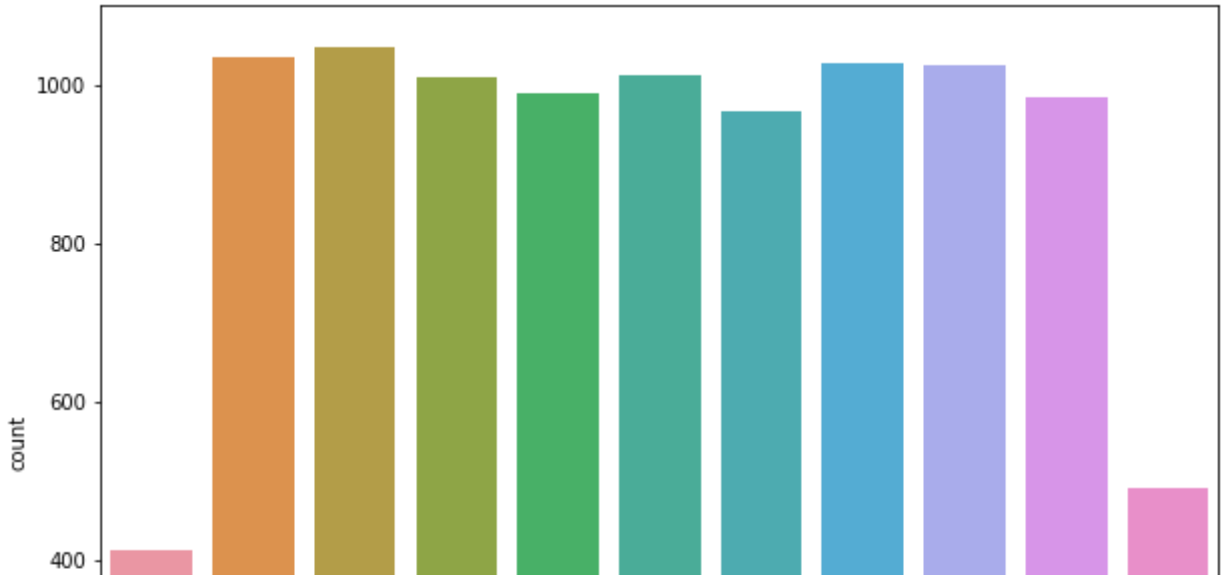

```
sns.distplot(df['Age'],hist=False)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba39776b10>
```



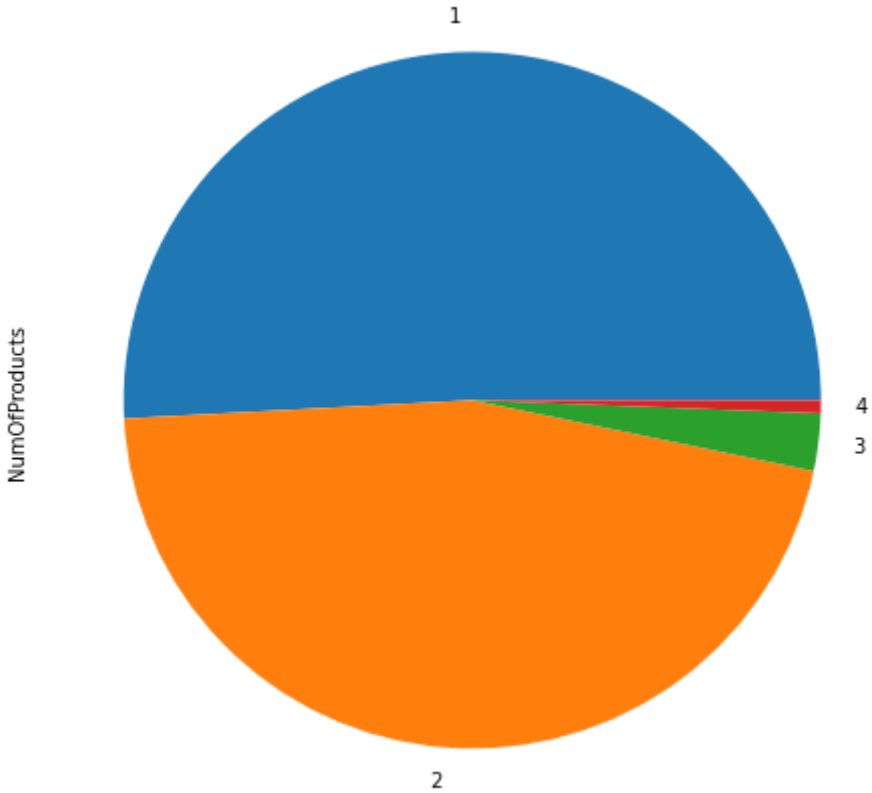

```
plt.figure(figsize=(10,8))
sns.countplot(df['Tenure'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba39694350>
```



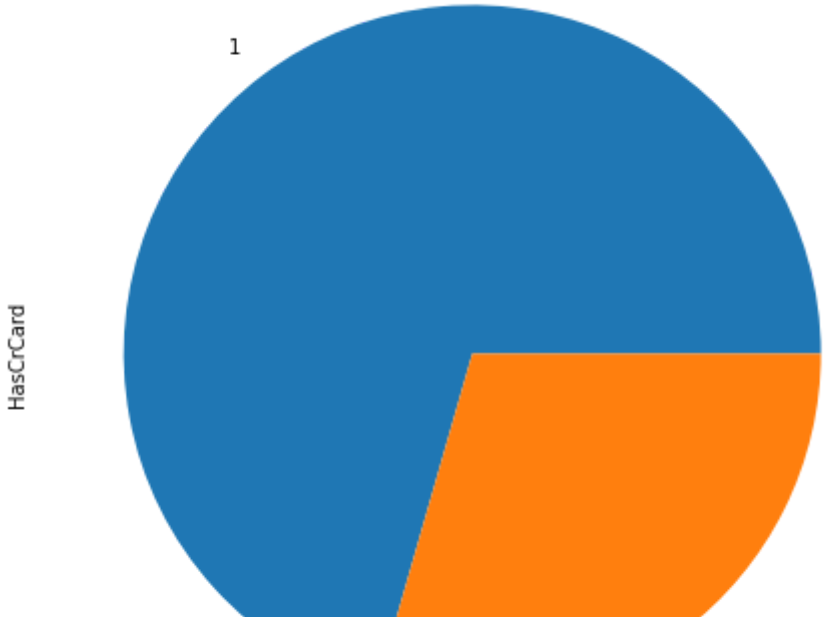

```
product = df['NumOfProducts'].value_counts()
product.plot(kind="pie",figsize=(10,8))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba396f3b90>
```



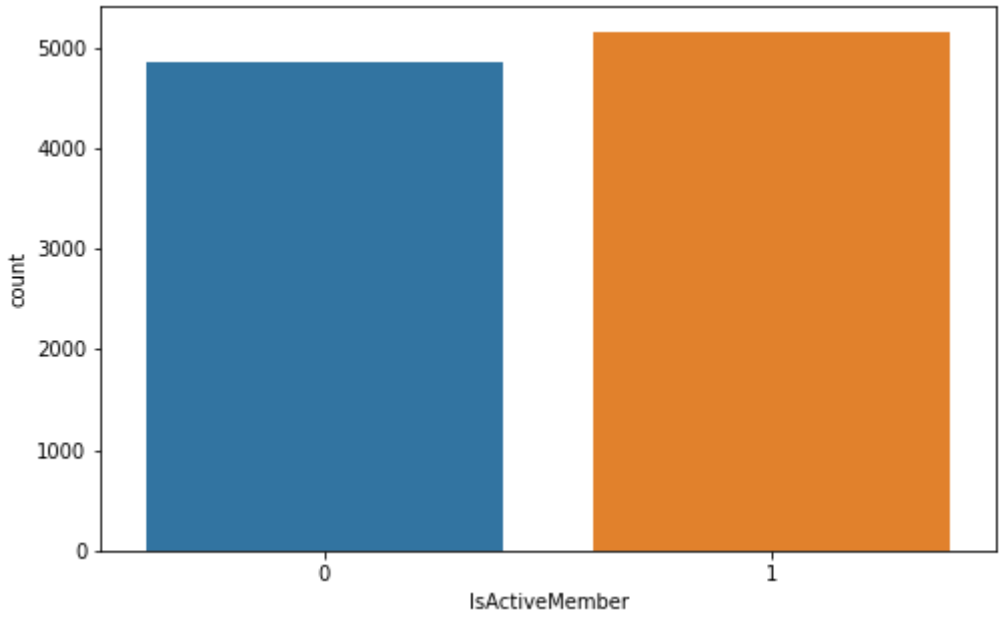

```
cr = df['HasCrCard'].value_counts()
cr.plot(kind="pie",figsize=(10,8))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba3953ded0>
```



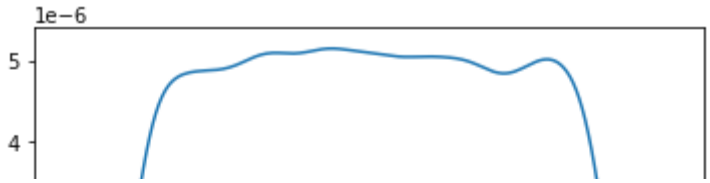

```
plt.figure(figsize=(8,5))
sns.countplot(df['IsActiveMember'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba3961ebd0>
```



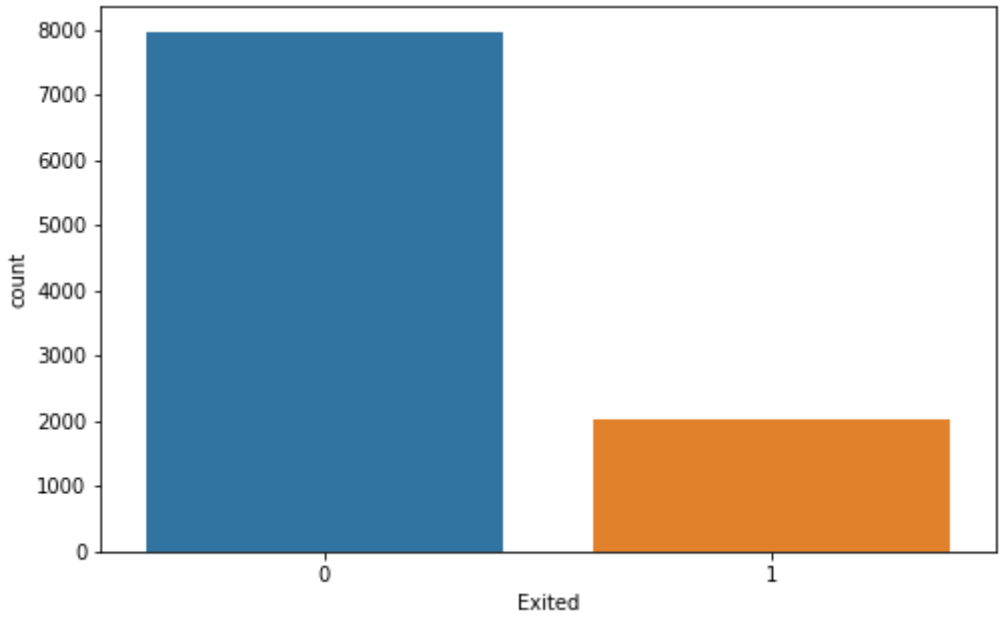

```
sns.distplot(df['EstimatedSalary'],hist=False)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba394d8950>
```




```
plt.figure(figsize=(8,5))
sns.countplot(df['Exited'])
```

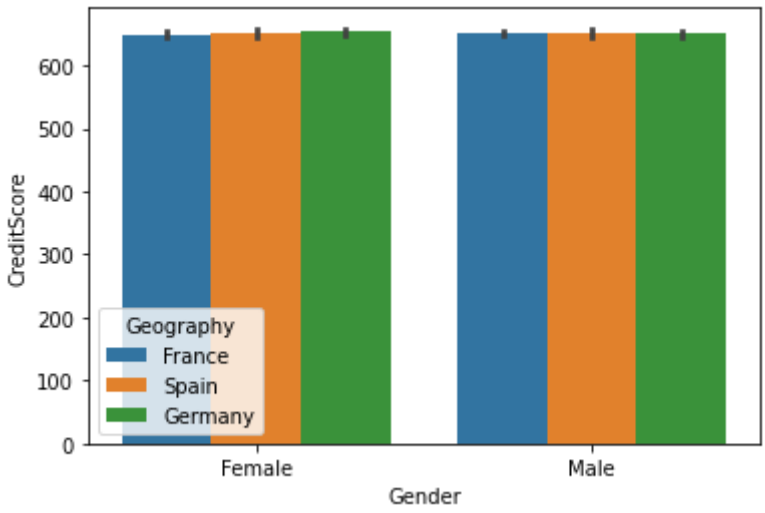
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba394e1750>
```



3 b). Bivariate analysis

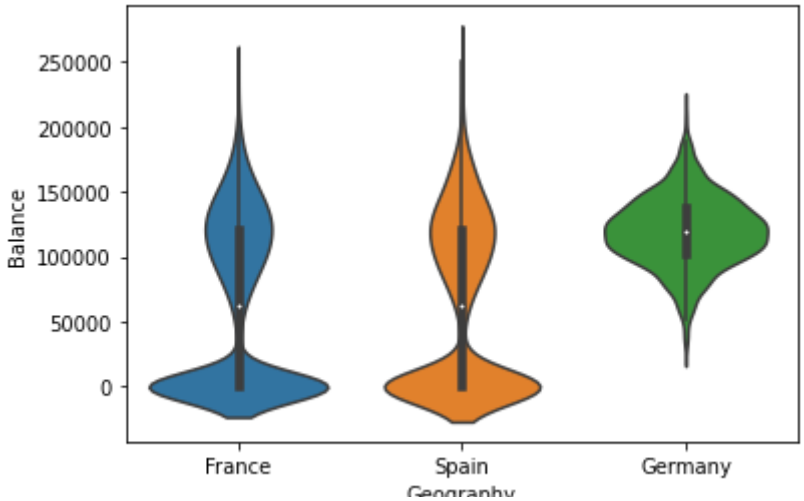
```
sns.barplot(x='Gender',y='CreditScore',hue='Geography',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba39425f90>
```



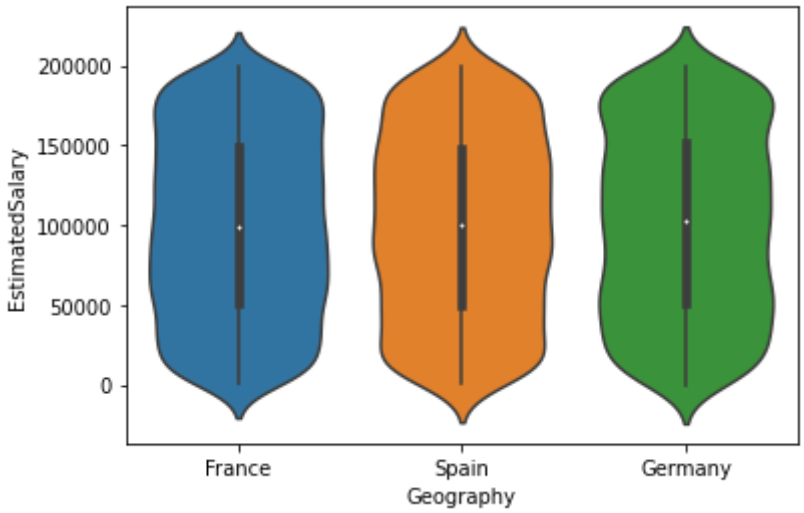

```
sns.violinplot(x='Geography',y='Balance',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba39349b50>
```



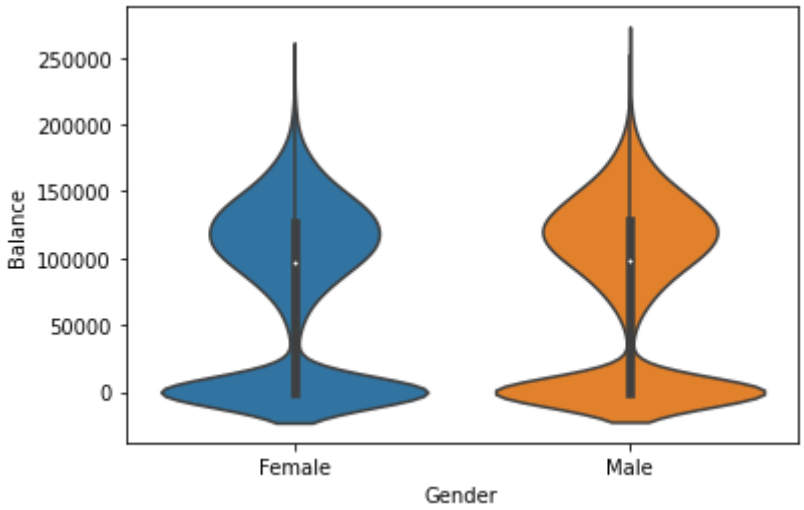

```
sns.violinplot(x='Geography',y='EstimatedSalary',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba392b4250>
```



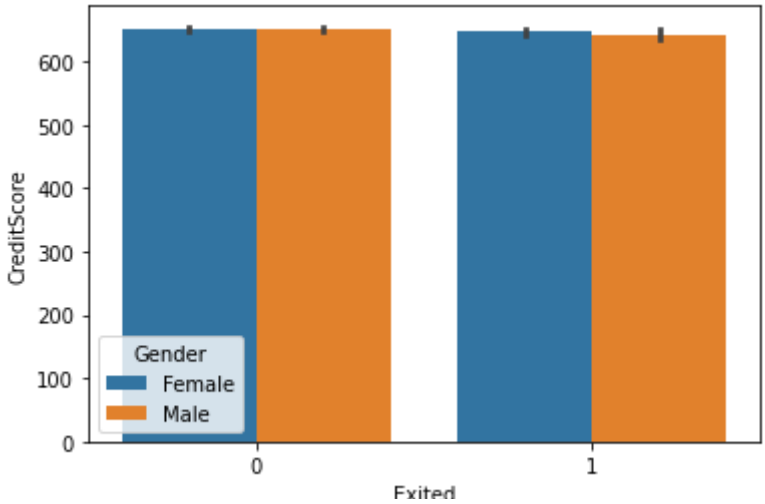

```
sns.violinplot(x='Gender',y='Balance',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba39229350>
```



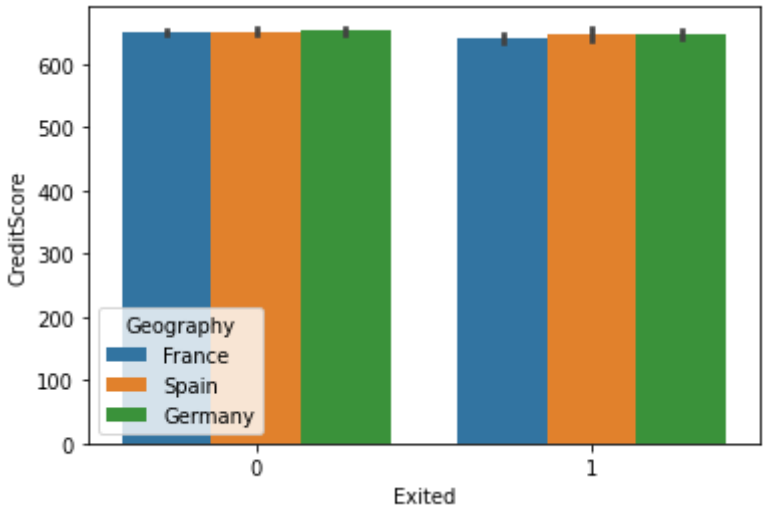

```
sns.barplot(x='Exited',y='CreditScore',hue='Gender',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba39199f90>
```



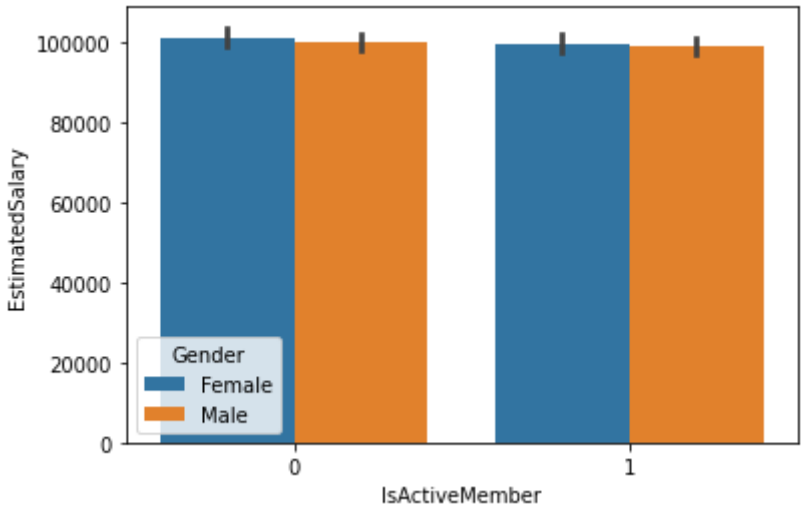

```
sns.barplot(x='Exited',y='CreditScore',hue='Geography',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba397b1f50>
```



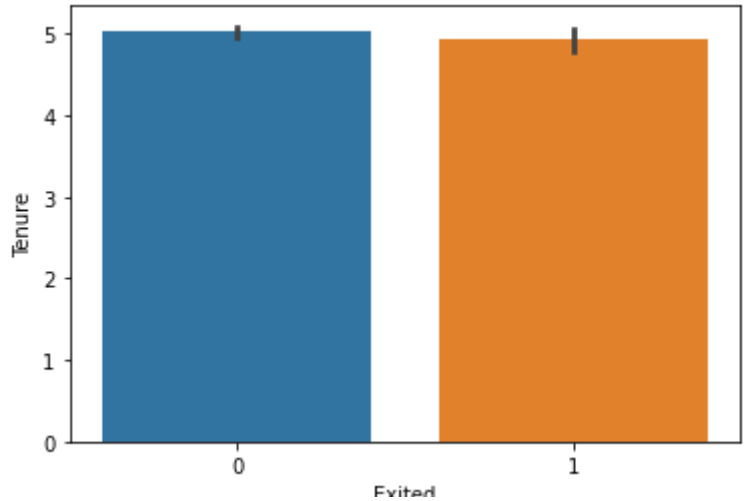

```
sns.barplot(x='IsActiveMember',y='EstimatedSalary',hue='Gender',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba391ad610>
```




```
sns.barplot(x='Exited',y='Tenure',data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba39425b90>
```



3 c). Multivariate analysis

```
gp1 = df.groupby('Gender')['Geography'].value_counts()
gp1.plot(kind='pie',figsize=(10,8))
print(gp1)
```

```
gp2 = df.groupby('Gender')['Age'].mean()
print(gp2)
```

```
Gender
Female    39.238389
Male      38.658237
Name: Age, dtype: float64
```

```
gp3 = df.groupby(['Gender','Geography'])['Tenure'].mean()
print(gp3)
```

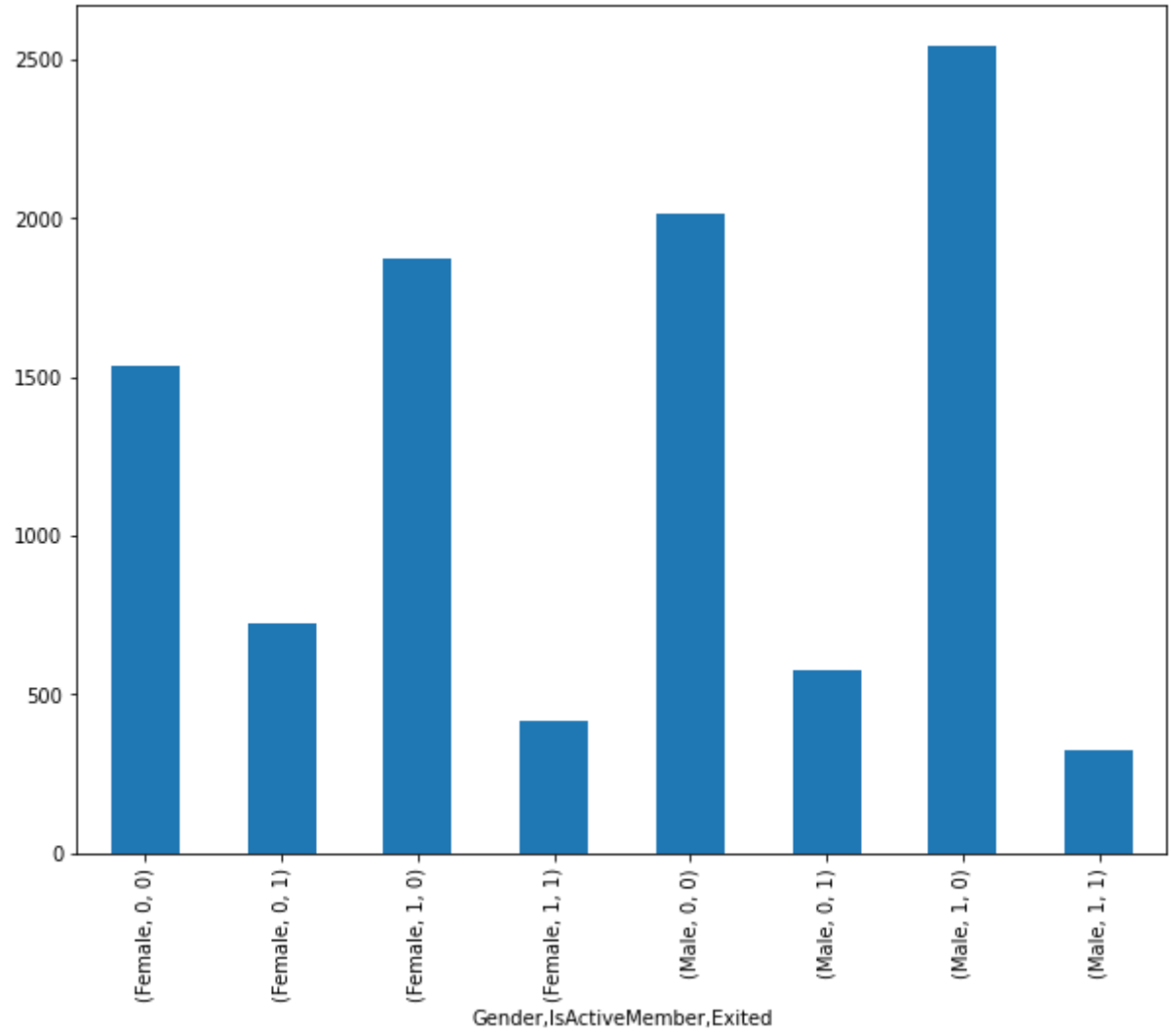
```
Gender  Geography
Female  France       4.950022
        Germany      4.965633
        Spain        5.000000
Male    France       5.049401
        Germany      5.050152
        Spain        5.057637
Name: Tenure, dtype: float64
```

```
gp4 = df.groupby(['Gender','HasCrCard','IsActiveMember'])['EstimatedSalary'].mean()
gp4.plot(kind="line",figsize=(10,8))
print(gp4)
```

```
Gender  HasCrCard  IsActiveMember
Female  0          0                102006.080352
                   1                102648.996944
        1          0                101208.014567
                   1                 98510.152300
Male    0          0                 99756.431151
```

```
gp5 = df.groupby(['Gender','IsActiveMember'])['Exited'].value_counts()
gp5.plot(kind='bar',figsize=(10,8))
print(gp5)
```

```
Gender  IsActiveMember  Exited
Female  0               0         1534
                        1          725
        1               0         1870
                        1          414
Male    0               0         2013
                        1          577
        1               0         2546
                        1          321
Name: Exited, dtype: int64
```




```
gp6 = df.groupby('Exited')['Balance','EstimatedSalary'].mean()
print(gp6)
```

```
                Balance  EstimatedSalary
Exited
```

```
0       72745.296779     99738.391772
1       91108.539337    101465.677531
```

4. Descriptive statistics

```
df.describe().T
```

	count	mean	std	min	25%	50%	
CreditScore	10000.0	650.561300	96.558702	383.00	584.00	652.000	
Geography	10000.0	0.746300	0.827529	0.00	0.00	0.000	
Gender	10000.0	0.545700	0.497932	0.00	0.00	1.000	
Age	10000.0	38.660800	9.746704	18.00	32.00	37.000	
Tenure	10000.0	5.012800	2.892174	0.00	3.00	5.000	
Balance	10000.0	76485.889288	62397.405202	0.00	0.00	97198.540	127
NumOfProducts	10000.0	1.530200	0.581654	1.00	1.00	1.000	
HasCrCard	10000.0	0.705500	0.455840	0.00	0.00	1.000	
IsActiveMember	10000.0	0.515100	0.499797	0.00	0.00	1.000	
EstimatedSalary	10000.0	100090.239881	57510.492818	11.58	51002.11	100193.915	149
Exited	10000.0	0.203700	0.402769	0.00	0.00	0.000	

5. Handling the missing values

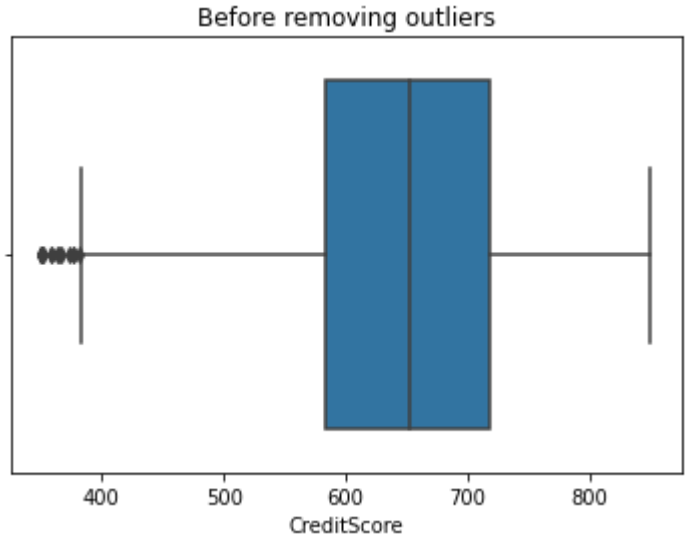
```
df.isnull().sum()
```

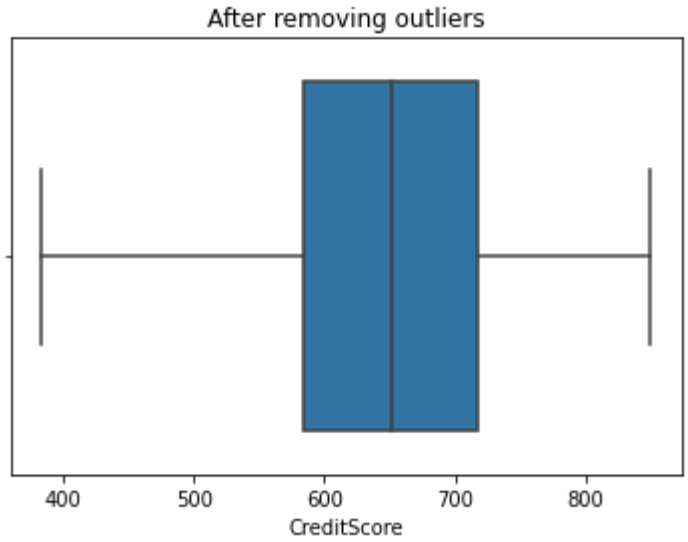
```
RowNumber          0
CustomerId         0
Surname            0
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

There is no missing value in the dataset

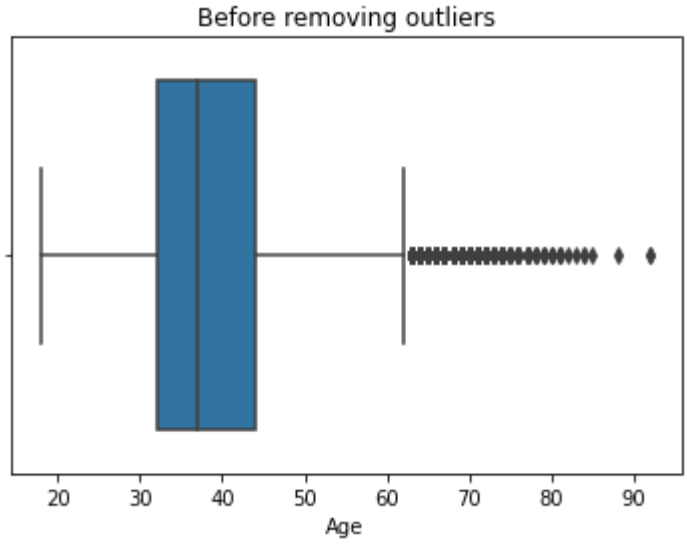
6. Finding outliers

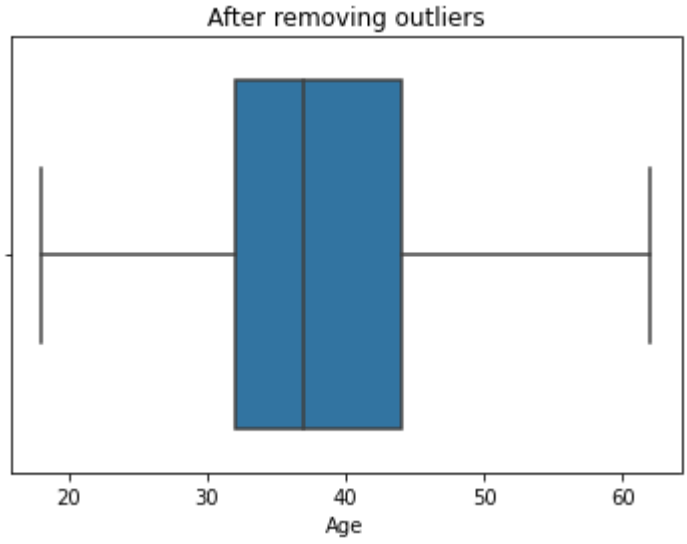
```
def replace_outliers(df, field_name):
    Q1 = np.percentile(df[field_name],25,interpolation='midpoint')
    Q3 = np.percentile(df[field_name],75,interpolation='midpoint')
    IQR = Q3-Q1
    maxi = Q3+1.5*IQR
    mini = Q1-1.5*IQR
    df[field_name]=df[field_name].mask(df[field_name]>maxi,maxi)
    df[field_name]=df[field_name].mask(df[field_name]<mini,mini)


plt.title("Before removing outliers")
sns.boxplot(df['CreditScore'])
plt.show()
plt.title("After removing outliers")
replace_outliers(df, 'CreditScore')
sns.boxplot(df['CreditScore'])
plt.show()
```





```
plt.title("Before removing outliers")
sns.boxplot(df['Age'])
plt.show()
plt.title("After removing outliers")
replace_outliers(df, 'Age')
sns.boxplot(df['Age'])
plt.show()
```



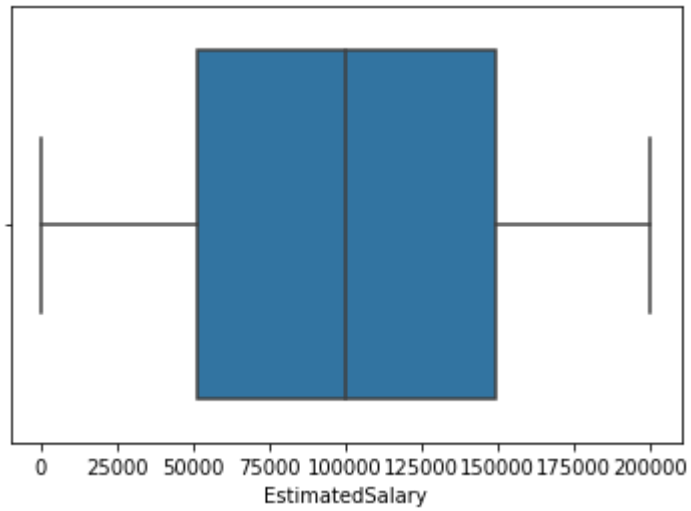



```
sns.boxplot(df['Balance'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba38bfb5d0>
```

```
sns.boxplot(df['EstimatedSalary'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba38b74a50>
```



Outliers from Age and Credit Score columns are removed

7. Check for categorical column and perform encoding.

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

```
df['Gender'] = le.fit_transform(df['Gender'])
df['Geography'] = le.fit_transform(df['Geography'])
```

```
df.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Ba
0	1	15634602	Hargrave	619.0	0	0	42.0	2	
1	2	15647311	Hill	608.0	2	0	41.0	1	838
2	3	15619304	Onio	502.0	0	0	42.0	8	159
3	4	15701354	Boni	699.0	0	0	39.0	1	
4	5	15737888	Mitchell	850.0	2	0	43.0	2	125

Only two columns(Gender and Geography) is label encoded

Removing unwanted columns and checking for feature importance

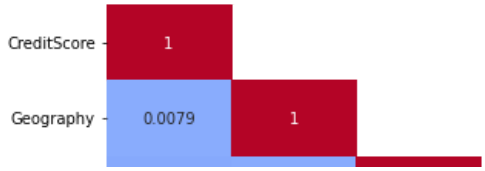
```
df = df.drop(['RowNumber','CustomerId','Surname'],axis=1)
```

```
df.head()
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard
0	619.0	0	0	42.0	2	0.00	1	1
1	608.0	2	0	41.0	1	83807.86	1	0
2	502.0	0	0	42.0	8	159660.80	3	1
3	699.0	0	0	39.0	1	0.00	2	0
4	850.0	2	0	43.0	2	125510.82	1	1

```
plt.figure(figsize=(20,10))
df_lt = df.corr(method = "pearson")
df_lt1 = df_lt.where(np.tril(np.ones(df_lt.shape)).astype(np.bool))
sns.heatmap(df_lt1,annot=True,cmap="coolwarm")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fba38ae3c90>
```



1. The Removed columns are nothing to do with model building.

2. Feature importance also checked using pearson correlation.

8. Data Splitting


```
target = df['Exited']
data = df.drop(['Exited'],axis=1)
```


```
print(data.shape)
print(target.shape)
```

```
(10000, 10)
(10000,)
```

9. Scaling the independent values

```
from sklearn.preprocessing import StandardScaler
se = StandardScaler()
```

```
data['CreditScore'] = se.fit_transform(pd.DataFrame(data['CreditScore']))
data['Age'] = se.fit_transform(pd.DataFrame(data['Age']))
data['Balance'] = se.fit_transform(pd.DataFrame(data['Balance']))
data['EstimatedSalary'] = se.fit_transform(pd.DataFrame(data['EstimatedSalary']))
```

```
data.head()
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrC
0	-0.326878	0	0	0.342615	2	-1.225848	1	
1	-0.440804	2	0	0.240011	1	0.117350	1	
2	-1.538636	0	0	0.342615	8	1.333053	3	
3	0.501675	0	0	0.034803	1	-1.225848	2	
4	2.065569	2	0	0.445219	2	0.785728	1	

10. Train test split

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(data,target,test_size=0.25,random_state=1
```

```
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(7500, 10)
(2500, 10)
(7500,)
(2500,)
```