```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
import io
```

Read the Dataset

```
from google.colab import files
uploaded=files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.
Saving bank.csv to bank.csv

```
df=pd.read_csv(io.StringIO(uploaded['bank.csv'].decode('utf-8')))
df.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1

2. Drop the Columns which are unique for all users

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

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

```
df.isna().any()
df.isna().sum()
```

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

BiVariate Analysis

```
print(df.shape)
df.info()
```

```
(10000, 11)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CreditScore      10000 non-null  int64
```

```
 1   Geography        10000 non-null  object 
 2   Gender           10000 non-null  object 
 3   Age              10000 non-null  int64  
 4   Tenure           10000 non-null  int64  
 5   Balance          10000 non-null  float64
 6   NumOfProducts    10000 non-null  int64  
 7   HasCrCard        10000 non-null  int64  
 8   IsActiveMember   10000 non-null  int64  
 9   EstimatedSalary  10000 non-null  float64
 10  Exited           10000 non-null  int64  
dtypes: float64(2), int64(7), object(2)
memory usage: 859.5+ KB
```

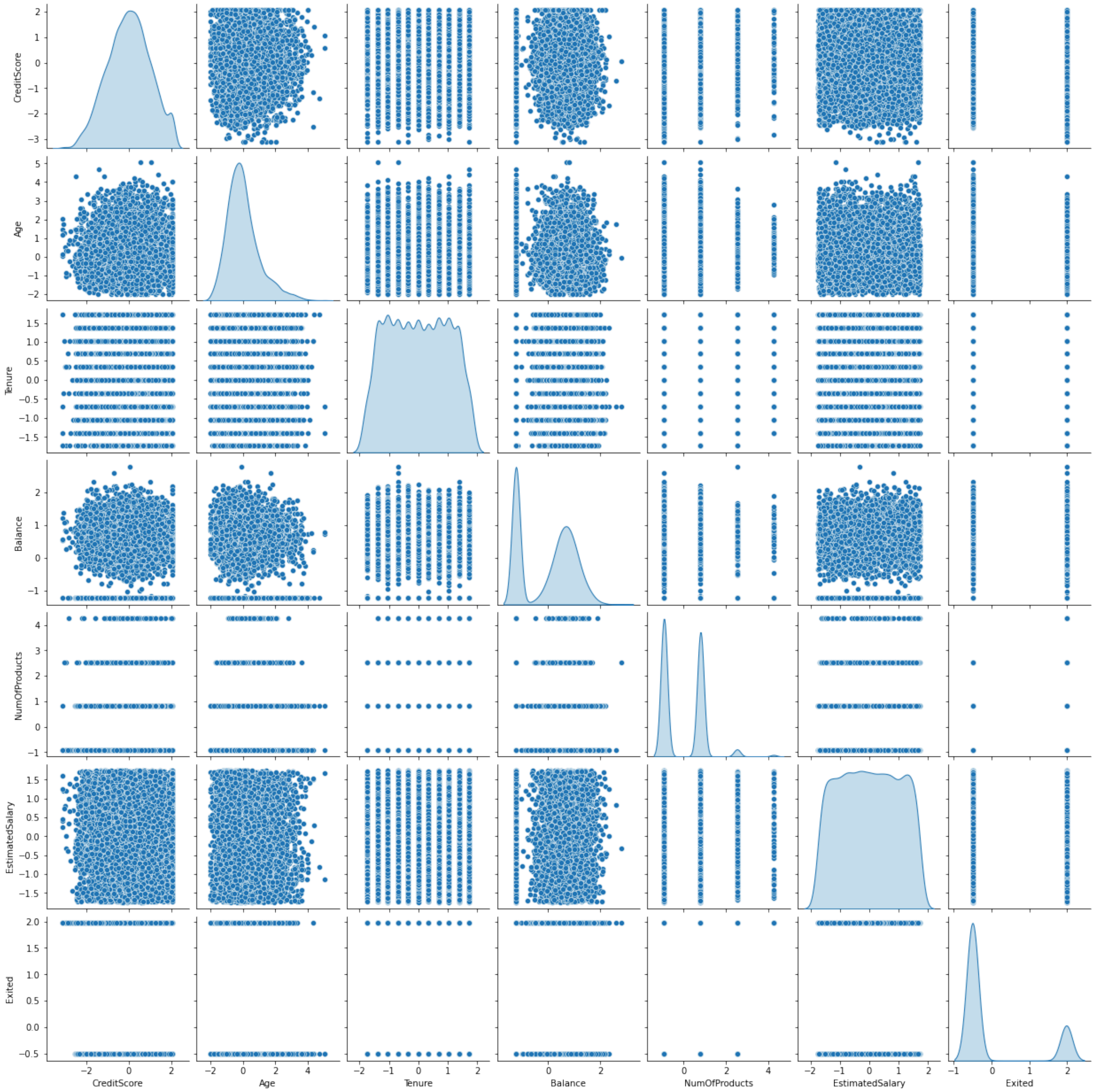
```
df.describe()
```

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exi
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000	10000.000
mean	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881	0.203
std	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492818	0.402
min	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000	0.000
25%	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000	0.000
50%	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000	0.000
75%	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500	0.000
max	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480000	1.000

Before performing Bivariate analysis, Lets bring all the features to the same range

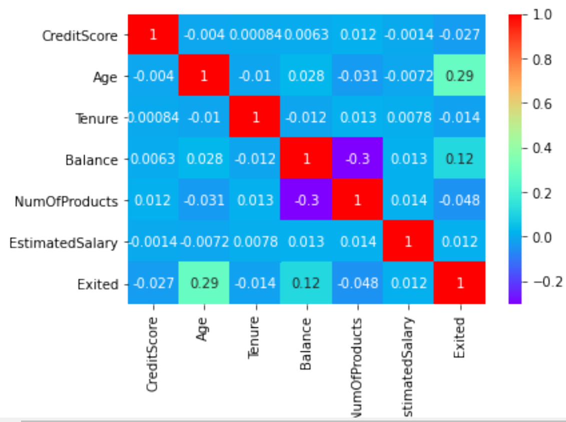
```
## Scale the data
scaler=StandardScaler()
## Extract only the Numerical Columns to perform Bivariate Analysis
subset=df.drop(['Geography','Gender','HasCrCard','IsActiveMember'],axis=1)
scaled=scaler.fit_transform(subset)
scaled_df=pd.DataFrame(scaled,columns=subset.columns)
sns.pairplot(scaled_df,diag_kind='kde')
```

```
<seaborn.axisgrid.PairGrid at 0x7fe8126f0940>
```




```
sns.heatmap(scaled_df.corr(),annot=True,cmap='rainbow')
```

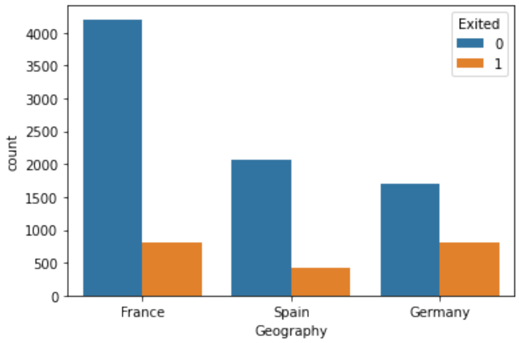
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe7cb4ef9b0>
```

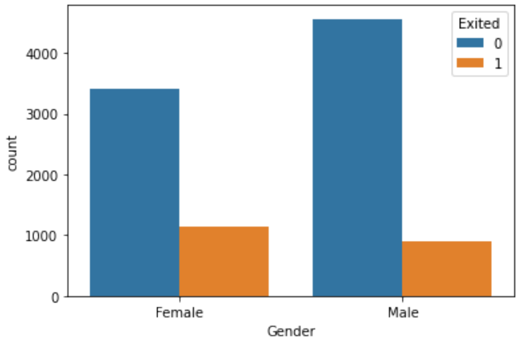


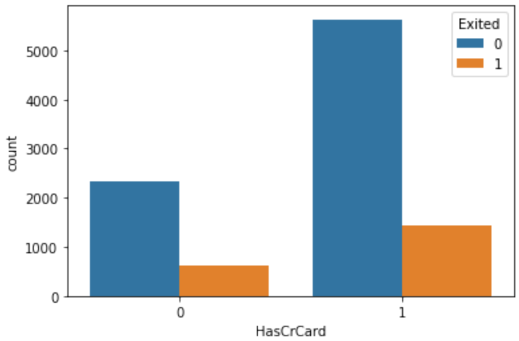
From the above plots, We can see that there is no significant Linear relationship between the features

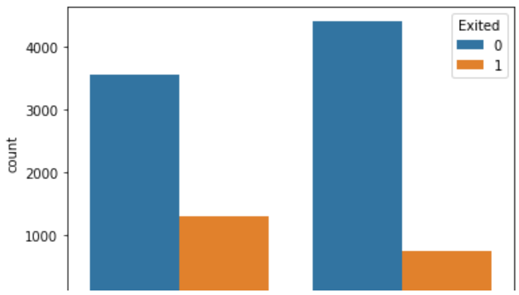
```
## Categorical Features vs Target Variable
sns.countplot(x='Geography',data=df,hue='Exited')
plt.show()
```

```
sns.countplot(x='Gender',data=df,hue='Exited')
plt.show()
sns.countplot(x='HasCrCard',data=df,hue='Exited')
plt.show()
sns.countplot(x='IsActiveMember',data=df,hue='Exited')
plt.show()
```





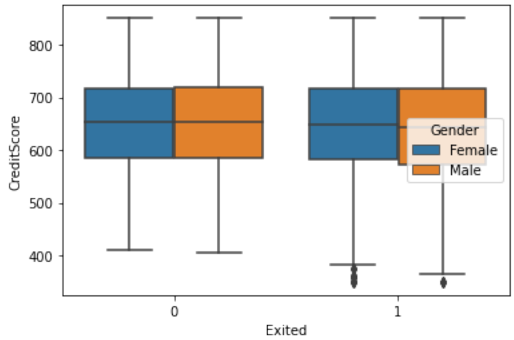




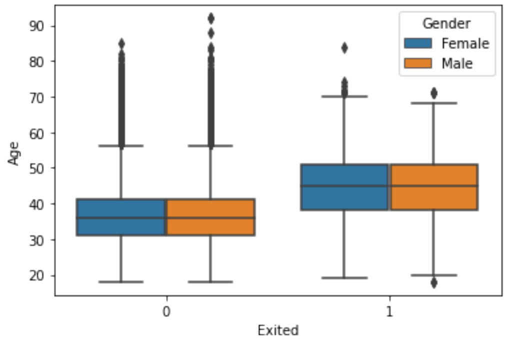
Analysing the Numerical Features relationship with the Target variable. Here 'Exited' is the Target Feature.

```
subset=subset.drop('Exited',axis=1)
for i in subset.columns:
  sns.boxplot(df['Exited'],df[i],hue=df['Gender'])
  plt.show()
```

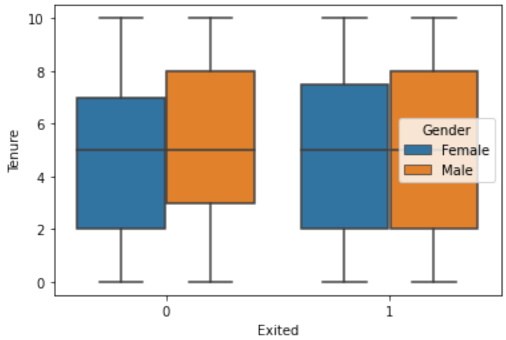
```
/usr/local/lib/python3.6/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x,
  FutureWarning
```




```
/usr/local/lib/python3.6/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x,
  FutureWarning
```




```
/usr/local/lib/python3.6/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x,
  FutureWarning
```




```
/usr/local/lib/python3.6/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x,
  FutureWarning
```

Insights from Bivariate Plots

1. The Avg Credit Score seem to be almost the same for Active and Churned customers
2. Young People seem to stick to the bank compared to older people
3. The Average Bank Balance is high for Churned Customers
4. The churning rate is high with German Customers
5. The Churning rate is high among the Non-Active Members

```
  FutureWarning
```

4. Distinguish the Target and Feature Set and divide the dataset into Training and Test sets

```
X=df.drop('Exited',axis=1)
y=df.pop('Exited')
```

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.10,random_state=5)
X_train,X_val,y_train,y_val=train_test_split(X_train,y_train,test_size=0.10,random_state=5)
print("X_train size is {}".format(X_train.shape[0]))
print("X_val size is {}".format(X_val.shape[0]))
print("X_test size is {}".format(X_test.shape[0]))
```

```
X_train size is 8100
X_val size is 900
X_test size is 1000
```

```
## Standardising the train, Val and Test data
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
num_cols=['CreditScore','Age','Tenure','Balance','NumOfProducts','EstimatedSalary']
num_subset=scaler.fit_transform(X_train[num_cols])
X_train_num_df=pd.DataFrame(num_subset,columns=num_cols)
X_train_num_df['Geography']=list(X_train['Geography'])
X_train_num_df['Gender']=list(X_train['Gender'])
X_train_num_df['HasCrCard']=list(X_train['HasCrCard'])
X_train_num_df['IsActiveMember']=list(X_train['IsActiveMember'])
X_train_num_df.head()
## Standardise the Validation data
num_subset=scaler.fit_transform(X_val[num_cols])
X_val_num_df=pd.DataFrame(num_subset,columns=num_cols)
X_val_num_df['Geography']=list(X_val['Geography'])
X_val_num_df['Gender']=list(X_val['Gender'])
X_val_num_df['HasCrCard']=list(X_val['HasCrCard'])
X_val_num_df['IsActiveMember']=list(X_val['IsActiveMember'])
## Standardise the Test data
num_subset=scaler.fit_transform(X_test[num_cols])
X_test_num_df=pd.DataFrame(num_subset,columns=num_cols)
X_test_num_df['Geography']=list(X_test['Geography'])
X_test_num_df['Gender']=list(X_test['Gender'])
X_test_num_df['HasCrCard']=list(X_test['HasCrCard'])
X_test_num_df['IsActiveMember']=list(X_test['IsActiveMember'])
```

```
## Convert the categorical features to numerical
X_train_num_df=pd.get_dummies(X_train_num_df,columns=['Geography','Gender'])
X_test_num_df=pd.get_dummies(X_test_num_df,columns=['Geography','Gender'])
X_val_num_df=pd.get_dummies(X_val_num_df,columns=['Geography','Gender'])
X_train_num_df.head()
```

	CreditScore	Age	Tenure	Balance	NumOfProducts	EstimatedSalary	HasCrCard	IsActiveMember	Geography_France	Geography
0	-1.178587	-1.041960	-1.732257	0.198686	0.820905	1.560315	1	1	1	
1	-0.380169	-1.326982	1.730718	-0.022020	-0.907991	-0.713592	1	0	0	
2	-0.349062	1.808258	-0.693364	0.681178	0.820905	-1.126515	1	0	0	
3	0.625629	2.378302	-0.347067	-1.229191	0.820905	-1.682740	1	1	1	
4	-0.203895	-1.136967	1.730718	0.924256	-0.907991	1.332535	1	1	0	

Initialise and build the Model

```
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense

model=Sequential()
model.add(Dense(7,activation='relu'))
model.add(Dense(10,activation='relu'))
model.add(Dense(1,activation='sigmoid'))
```

```
import tensorflow as tf
optimizer=tf.keras.optimizers.Adam(0.01)
model.compile(loss='binary_crossentropy',optimizer=optimizer,metrics=['accuracy'])
```

```
model.fit(X_train_num_df,y_train,epochs=100,batch_size=10,verbose=1)
```

```
Epoch 1/100
810/810 [==============================] - 1s 1ms/step - loss: 0.4511 - accuracy: 0.8054
Epoch 2/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3623 - accuracy: 0.8493
Epoch 3/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3543 - accuracy: 0.8541
Epoch 4/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3433 - accuracy: 0.8561
Epoch 5/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3291 - accuracy: 0.8692
Epoch 6/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3488 - accuracy: 0.8560
Epoch 7/100
```

```
810/810 [==============================] - 1s 1ms/step - loss: 0.3439 - accuracy: 0.8644
Epoch 8/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3399 - accuracy: 0.8615
Epoch 9/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3480 - accuracy: 0.8602
Epoch 10/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3321 - accuracy: 0.8683
Epoch 11/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3329 - accuracy: 0.8614
Epoch 12/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3466 - accuracy: 0.8575
Epoch 13/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3386 - accuracy: 0.8640
Epoch 14/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3342 - accuracy: 0.8667
Epoch 15/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3375 - accuracy: 0.8652
Epoch 16/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3412 - accuracy: 0.8574
Epoch 17/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3256 - accuracy: 0.8652
Epoch 18/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3229 - accuracy: 0.8687
Epoch 19/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3276 - accuracy: 0.8670
Epoch 20/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3399 - accuracy: 0.8581
Epoch 21/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3384 - accuracy: 0.8661
Epoch 22/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3309 - accuracy: 0.8638
Epoch 23/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3441 - accuracy: 0.8592
Epoch 24/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3232 - accuracy: 0.8697
Epoch 25/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3409 - accuracy: 0.8651
Epoch 26/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3361 - accuracy: 0.8622
Epoch 27/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3380 - accuracy: 0.8596
Epoch 28/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3363 - accuracy: 0.8611
Epoch 29/100
810/810 [==============================] - 1s 1ms/step - loss: 0.3347 - accuracy: 0.8636
```

Predict the Results using 0.5 threshold

```
y_pred_val=model.predict(X_val_num_df)
y_pred_val[y_pred_val>0.5]=1
y_pred_val[y_pred_val <0.5]=0
```

```
y_pred_val=y_pred_val.tolist()
X_compare_val=X_val.copy()
X_compare_val['y_actual']=y_val
X_compare_val['y_pred']=y_pred_val
X_compare_val.head(10)
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	y_actual	y_
340	642	Germany	Female	40	6	129502.49	2	0	1	86099.23	1	
8622	706	Germany	Male	36	9	58571.18	2	1	0	40774.01	0	
8401	535	Spain	Male	58	1	0.00	2	1	1	11779.98	1	
4338	714	Spain	Male	25	2	0.00	1	1	1	132979.43	0	
8915	606	France	Male	36	1	155655.46	1	1	1	192387.51	1	
2624	605	Spain	Female	29	3	116805.82	1	0	0	4092.75	0	
2234	720	France	Female	38	10	0.00	2	1	1	56229.72	1	
349	582	France	Male	39	5	0.00	2	1	1	129892.93	0	
3719	850	France	Female	62	1	124678.35	1	1	0	70916.00	1	
2171	526	Germany	Male	58	9	190298.89	2	1	1	191263.76	0	

Confusion Matrix of the Validation set

```
from sklearn.metrics import confusion_matrix
cm_val=confusion_matrix(y_val,y_pred_val)
cm_val
```

From the above confusion matrix, Out of 900 Validation dataset observations, our model accurately predicted 694+88=782 and made 96+22=118 incorrect predictions.

```
Accuracy=782/900
print("Accuracy of the Model on the Validation Data set is 86.89%")
```

```
Accuracy of the Model on the Validation Data set is 86.89%
```

```
loss1,accuracy1=model.evaluate(X_train_num_df,y_train,verbose=False)
loss2,accuracy2=model.evaluate(X_val_num_df,y_val,verbose=False)
print("Train Loss {}".format(loss1))
print("Train Accuracy {}".format(accuracy1))
print("Val Loss {}".format(loss2))
print("Val Accuracy {}".format(accuracy2))
```

```
Train Loss 0.33421364426612854
Train Accuracy 0.8649382591247559
Val Loss 0.348032146692276
Val Accuracy 0.8688889145851135
```