Importing the required libraries

```
#Importing tensorflow libraries
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, BatchNormalization
from tensorflow.keras import optimizers
```

```
#Importing required libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score, recall_
import matplotlib.pyplot as plt
import seaborn as sns
```

1. Read the dataset

```
from google.colab import drive
```

```
drive.mount('/content/drive/')
```

```
    Drive already mounted at /content/drive/; to attempt to forcibly remount, call d
```

```
dataset_file = '/content/drive/MyDrive/Colab Notebooks/PG AIML Deep Learning Project/
```

```
df = pd.read_csv(dataset_file)
```

```
df.head()
```

Basic Profiling of dataset

```
print ("Shape of Data")
print (df.shape)
print ("")
print ("Columns")
print (df.columns)
print ("")
```

```
Shape of Data
(10000, 14)

Columns
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   RowNumber        10000 non-null  int64  
 1   CustomerId       10000 non-null  int64  
 2   Surname          10000 non-null  object 
 3   CreditScore      10000 non-null  int64  
 4   Geography        10000 non-null  object 
 5   Gender           10000 non-null  object 
 6   Age              10000 non-null  int64  
 7   Tenure           10000 non-null  int64  
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64  
 10  HasCrCard        10000 non-null  int64  
 11  IsActiveMember   10000 non-null  int64  
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64  
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB
```

```
df.describe()
```

	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance
count	10000.00000	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000
mean	5000.50000	1.569094e+07	650.528800	38.921800	5.012800	76485.889288
std	2886.89568	7.193619e+04	96.653299	10.487806	2.892174	62397.405202
min	1.00000	1.556570e+07	350.000000	18.000000	0.000000	0.000000
25%	2500.75000	1.562853e+07	584.000000	32.000000	3.000000	0.000000

```
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
```

2. Drop the columns which are unique for all users like IDs

```
# to check if we have any duplicate records for the same customer
for i,j in enumerate (df.columns):
    print ( 'column Name : %s' %str(j)+     ' -----> Unique : %s' %str(df[j].is_unique
```

```
column Name : RowNumber -----> Unique : True
column Name : CustomerId -----> Unique : True
column Name : Surname -----> Unique : False
column Name : CreditScore -----> Unique : False
column Name : Geography -----> Unique : False
column Name : Gender -----> Unique : False
column Name : Age -----> Unique : False
column Name : Tenure -----> Unique : False
column Name : Balance -----> Unique : False
column Name : NumOfProducts -----> Unique : False
column Name : HasCrCard -----> Unique : False
column Name : IsActiveMember -----> Unique : False
column Name : EstimatedSalary -----> Unique : False
column Name : Exited -----> Unique : False
```

Insight: **RowNumber and CustomerId are unique and they can be dropped**

```
# Preserving original dataset
df_raw = df
```

```
# Dropping RowNumber and CustomerId
df=df.drop(['RowNumber','CustomerId'],axis=1)
```

```
df.shape
```

```
(10000, 12)
```

```
# Surname may not add any value and so dropping that column as well

# Dropping Surname
df=df.drop(['Surname'],axis=1)
```

```
df.columns
```

```
Index(['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance',
       'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary',
       'Exited'],
      dtype='object')
```

Object columns: [Geography, Gender]

```
df['Geography'].unique().shape
```

```
(3,)
```

```
df['Gender'].unique().shape
```

```
(2,)
```

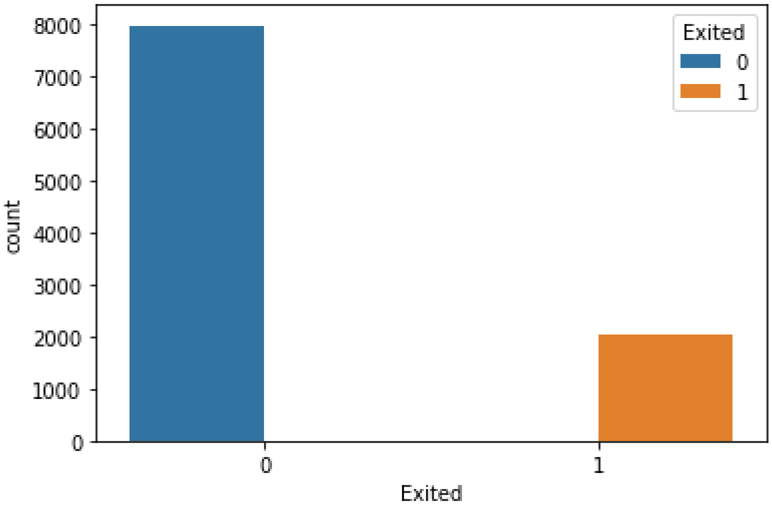
```
df.columns
```

```
Index(['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance',
       'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary',
       'Exited'],
      dtype='object')
```

3. Perform bivariate analysis and give your insights from the same (5 points)

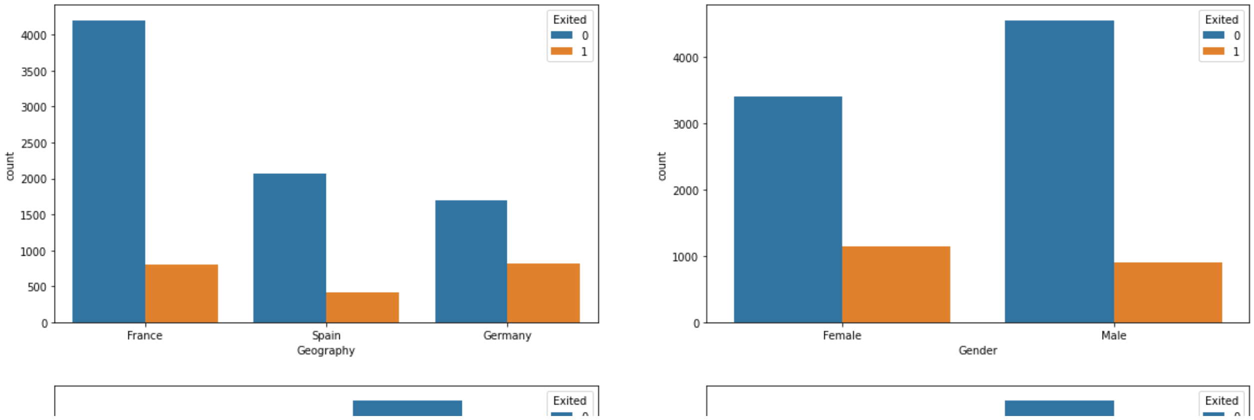
```
sns.countplot(x='Exited', hue = 'Exited',data = df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3f920e3c50>
```



```
 # We first review the 'Status' relation with categorical variables
fig, axarr = plt.subplots(2, 2, figsize=(20, 12))
sns.countplot(x='Geography', hue = 'Exited',data = df, ax=axarr[0][0])
sns.countplot(x='Gender', hue = 'Exited',data = df, ax=axarr[0][1])
sns.countplot(x='HasCrCard', hue = 'Exited',data = df, ax=axarr[1][0])
sns.countplot(x='IsActiveMember', hue = 'Exited',data = df, ax=axarr[1][1])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3f908ceb70>
```

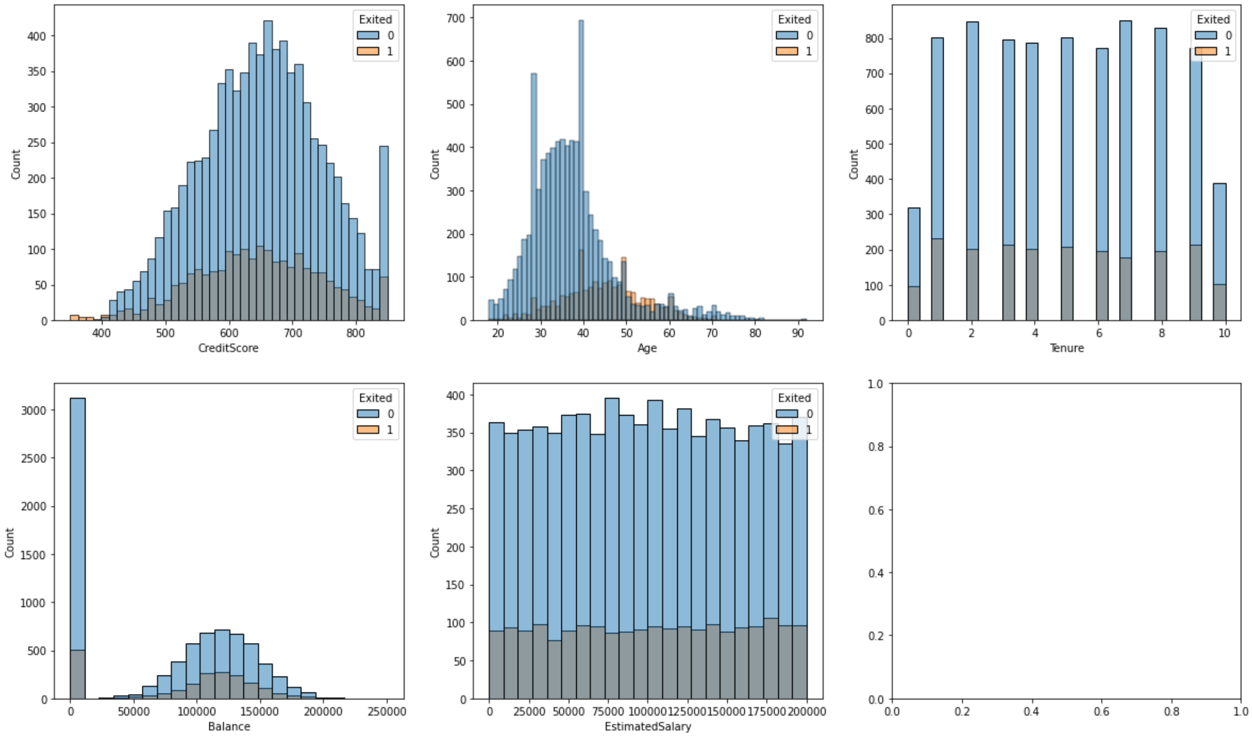


Insights

- (2000 out of 10000) 20% of total customers have exited status
- France has more customers than other two countries (Spain & Germamny)
- Looking at the bar graph, % of exited status is more in Female than that of male
- It looks like, customers with credit card churning out more than that of customers with no credit card
- . As expected, Non-Active member churning out more than that of Active members

```
# We first review the 'Status' relation with categorical variables
fig, axarr = plt.subplots(2, 3, figsize=(20, 12))

sns.histplot(data=df, x="CreditScore", hue="Exited",ax=axarr[0][0])
sns.histplot(data=df, x="Age", hue="Exited",ax=axarr[0][1])
sns.histplot(data=df, x="Tenure", hue="Exited",ax=axarr[0][2])
sns.histplot(data=df, x="Balance", hue="Exited",ax=axarr[1][0])
sns.histplot(data=df, x="EstimatedSalary", hue="Exited",ax=axarr[1][1])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3f9069b198>
```



Insights

- Credit Score is uniformly distributed for both retained and churned customers
- Per Age distribution chart, younger customers looks to be more retained than that of old customers
- Balance also looks to be uniformly distributed for othe retained and churned customers

4. Distinguish the feature and target set and divide the data set into training and test sets (5 points)

```
df.head()
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard
0	619	France	Female	42	2	0.00	1	1
1	608	Spain	Female	41	1	83807.86	1	0
2	502	France	Female	42	8	159660.80	3	1
3	699	France	Female	39	1	0.00	2	0
4	850	Spain	Female	43	2	125510.82	1	1

```
df['Exited'].value_counts()
```

```
df['Exited'].value_counts()

     0    7963
     1    2037
     Name: Exited, dtype: int64
```

```
df.columns

     Index(['CreditScore', 'Geography', 'Gender', 'Age', 'Tenure', 'Balance',
            'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary',
            'Exited'],
           dtype='object')
```

```
df.shape

     (10000, 11)
```

```
#one hot encoding for categorical columns:

df = pd.get_dummies(df, columns=['Geography', 'Gender'])
```

```
df.columns

     Index(['CreditScore', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
            'IsActiveMember', 'EstimatedSalary', 'Exited', 'Geography_France',
            'Geography_Germany', 'Geography_Spain', 'Gender_Female', 'Gender_Male'],
           dtype='object')
```

```
df.shape

     (10000, 14)
```

```
X_data=df[['CreditScore', 'Geography_France',
       'Geography_Germany', 'Geography_Spain', 'Gender_Female', 'Gender_Male', 'Age',
       'NumOfProducts', 'HasCrCard', 'IsActiveMember', 'EstimatedSalary']]

y_data=df[['Exited']]
```

```
X_train, X_test, y_train, y_test = train_test_split(X_data, y_data, test_size = 0.3,
```

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

     (7000, 13)
     (3000, 13)
```

```
(7000, 1)
(3000, 1)
```

5. Normalize the train and test data (10points)

```
from sklearn.preprocessing import StandardScaler
```

```
# create scaler
scaler = StandardScaler()
# fit and transform in one step
X_train = scaler.fit_transform(X_train)
X_test = scaler.fit_transform(X_test)
# inverse transform
#inverse = scaler.inverse_transform(standardized)
```

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

```
(7000, 13)
(3000, 13)
(7000, 1)
(3000, 1)
```

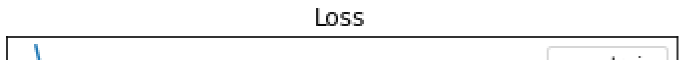
6. Initialize & build the model. Identify the points of improvement and implement the same. (20)

```
#creating an empty model
model = Sequential()

#Adding layers:
#Output layer with sigmoid for binary classification
model.add(Dense(64, input_shape = (13,), activation = 'relu'))
model.add(Dense(32, activation = 'relu'))
model.add(Dense(1, activation = 'sigmoid'))
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
```

```
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 64)                896
_________________________________________________________________
dense_1 (Dense)              (None, 32)                2080
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 33
=================================================================
Total params: 3,009
Trainable params: 3,009
Non-trainable params: 0
_________________________________________________________________
```

```
sgd = optimizers.Adam(lr = 0.01)
model.compile(optimizer = 'sgd', loss = 'binary_crossentropy', metrics = ['accuracy']



# After many iterations on batch_size, epoch, settled on batch_size = 10 and epochs =

history = model.fit(X_train, y_train ,validation_split=0.10, batch_size = 10, epochs =



# plot loss during training
from matplotlib import pyplot
pyplot.subplot(211)
pyplot.title('Loss')
pyplot.plot(history.history['loss'], label='train')
pyplot.plot(history.history['val_loss'], label='test')
pyplot.legend()

# plot accuracy during training
pyplot.subplot(212)
pyplot.title('Accuracy')
pyplot.plot(history.history['accuracy'], label='train')
pyplot.plot(history.history['val_accuracy'], label='test')
pyplot.legend()
pyplot.show()
```



```
results = model.evaluate(X_test, y_test.values)
```

```
94/94 [==============================] - 0s 2ms/step - loss: 0.3526 - accuracy:
```

7. Predict the results using 0.5 as a threshold

```
#prediction variable
y_pred = model.predict(X_test)
y_pred = (y_pred > 0.5).astype(int)
```

8. Print the Accuracy score and confusion matrix

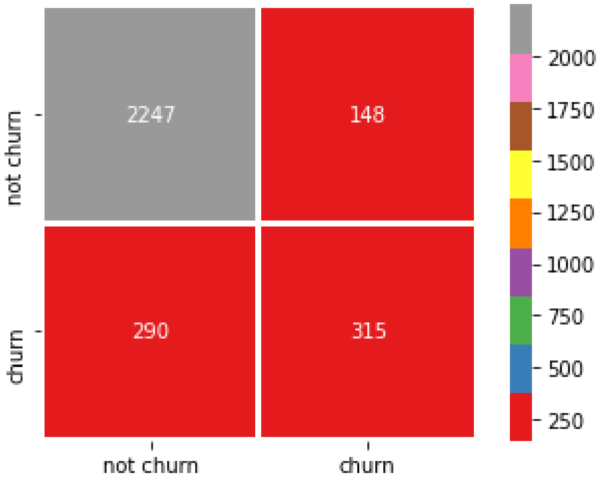
```
#Model score calculation
from sklearn.metrics import accuracy_score
score=accuracy_score(y_pred,y_test)
print ("Accuracy :" +str(score))
```

```
Accuracy :0.854
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.89      0.94      0.91      2395
           1       0.68      0.52      0.59       605

    accuracy                           0.85      3000
   macro avg       0.78      0.73      0.75      3000
weighted avg       0.84      0.85      0.85      3000
```

```
conf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix,annot=True,fmt = "d",square = True,
 xticklabels=["not churn","churn"],
 yticklabels=["not churn","churn"],
 linewidths = 2,linecolor = "w",cmap = "Set1")
plt.subplots_adjust(wspace = .3,hspace = .3)
```



not churn
churn
2247
148
290
315
not churn
churn
2000
1750
1500
1250
1000
750
500
250