

Bank Customer Churn Prediction

Initialization

Dependencies


```
In [1]: import pandas as pd
```

```
In [2]: data = pd.read_csv("Bank Customer Churn Prediction.csv")
```

```
In [3]: data.head()
```

Out[3]:

	customer_id	credit_score	country	gender	age	tenure	balance	products_number	credit_card
0	15634602	619	France	Female	42	2	0.00	1	1
1	15647311	608	Spain	Female	41	1	83807.86	1	0
2	15619304	502	France	Female	42	8	159660.80	3	1
3	15701354	699	France	Female	39	1	0.00	2	0
4	15737888	850	Spain	Female	43	2	125510.82	1	1



Data Info

```
In [4]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 12 columns):
#   Column                Non-Null Count  Dtype
---  -
0   customer_id           10000 non-null  int64
1   credit_score           10000 non-null  int64
2   country                10000 non-null  object
3   gender                 10000 non-null  object
4   age                    10000 non-null  int64
5   tenure                 10000 non-null  int64
6   balance                10000 non-null  float64
7   products_number        10000 non-null  int64
8   credit_card            10000 non-null  int64
9   active_member          10000 non-null  int64
10  estimated_salary        10000 non-null  float64
11  churn                   10000 non-null  int64
dtypes: float64(2), int64(8), object(2)
memory usage: 937.6+ KB
```

```
In [5]: data.describe()
```

Out[5]:

	customer_id	credit_score	age	tenure	balance	products_number	cre
count	1.000000e+04	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	1000
mean	1.569094e+07	650.528800	38.921800	5.012800	76485.889288	1.530200	
std	7.193619e+04	96.653299	10.487806	2.892174	62397.405202	0.581654	
min	1.556570e+07	350.000000	18.000000	0.000000	0.000000	1.000000	
25%	1.562853e+07	584.000000	32.000000	3.000000	0.000000	1.000000	
50%	1.569074e+07	652.000000	37.000000	5.000000	97198.540000	1.000000	
75%	1.575323e+07	718.000000	44.000000	7.000000	127644.240000	2.000000	
max	1.581569e+07	850.000000	92.000000	10.000000	250898.090000	4.000000	

Columns

In [6]: `data.columns`

Out[6]: Index(['customer_id', 'credit_score', 'country', 'gender', 'age', 'tenure', 'balance', 'products_number', 'credit_card', 'active_member', 'estimated_salary', 'churn'], dtype='object')

EDA

1. How many total countries are there

In [7]: `data['country'].unique()`

Out[7]: array(['France', 'Spain', 'Germany'], dtype=object)

2. Plot all the countries on a geographic graph

In [8]: `country = {'Country': data['country'].value_counts().index, 'Value': data['country'].value_counts().values}`

In [9]: `import plotly.express as px`

```
fig = px.choropleth(country,
                    locations="Country",
                    locationmode="country names",
                    color="Value",
                    hover_name="Country",
                    title="Country Values on a World Map",)
fig.show()
```

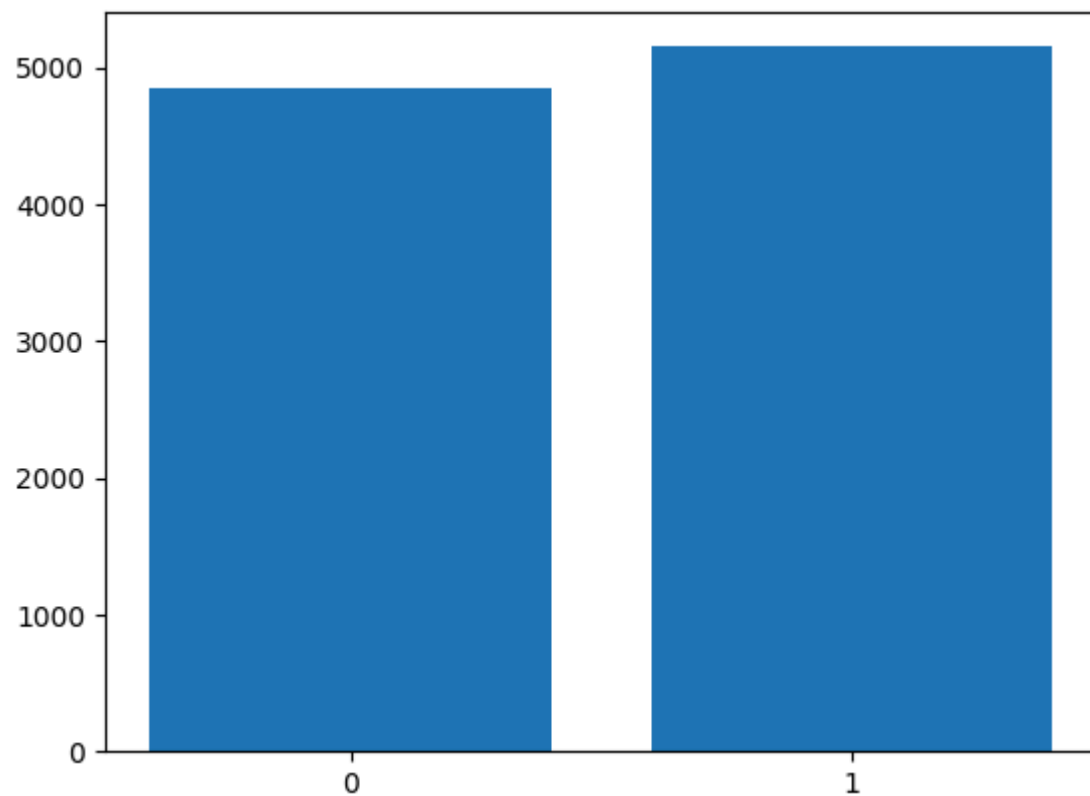
3. How many accounts are active and how many are inactive

In [10]: `import matplotlib.pyplot as plt`

```
activeMembers = data['active_member'].value_counts()

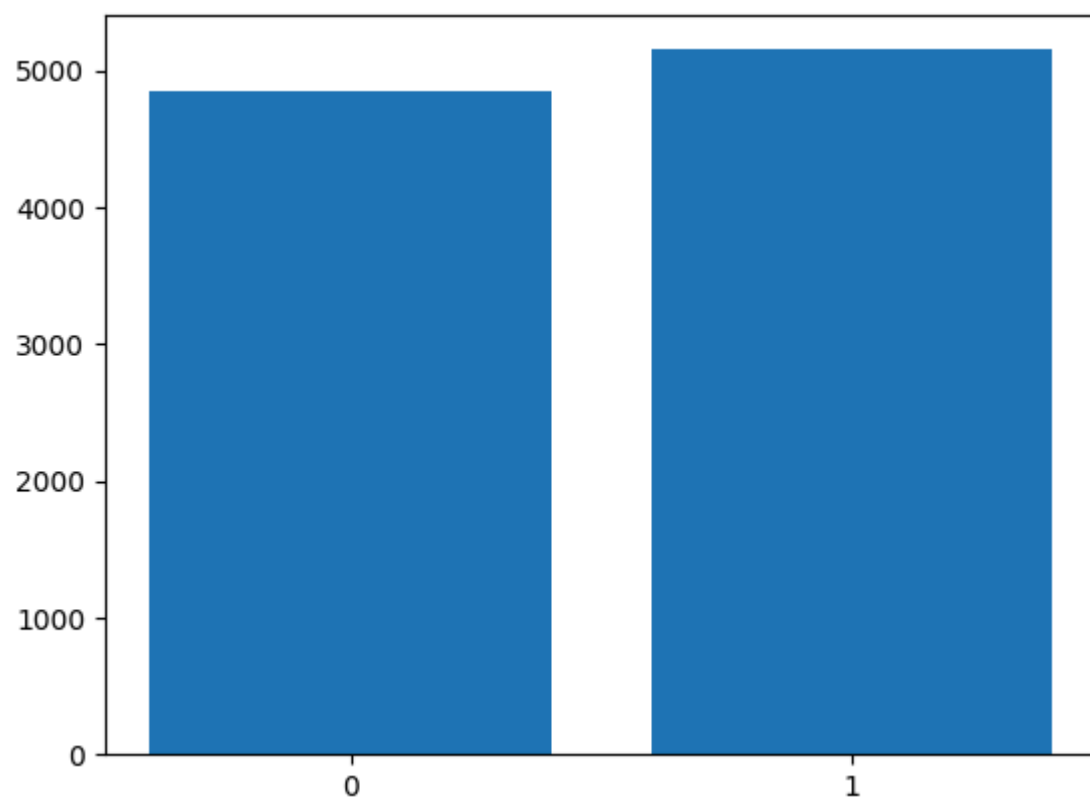
plt.xticks([0,1])
plt.bar(activeMembers.index, activeMembers.values)
```

```
plt.show()
```



4. How many people does have credit and how many does not

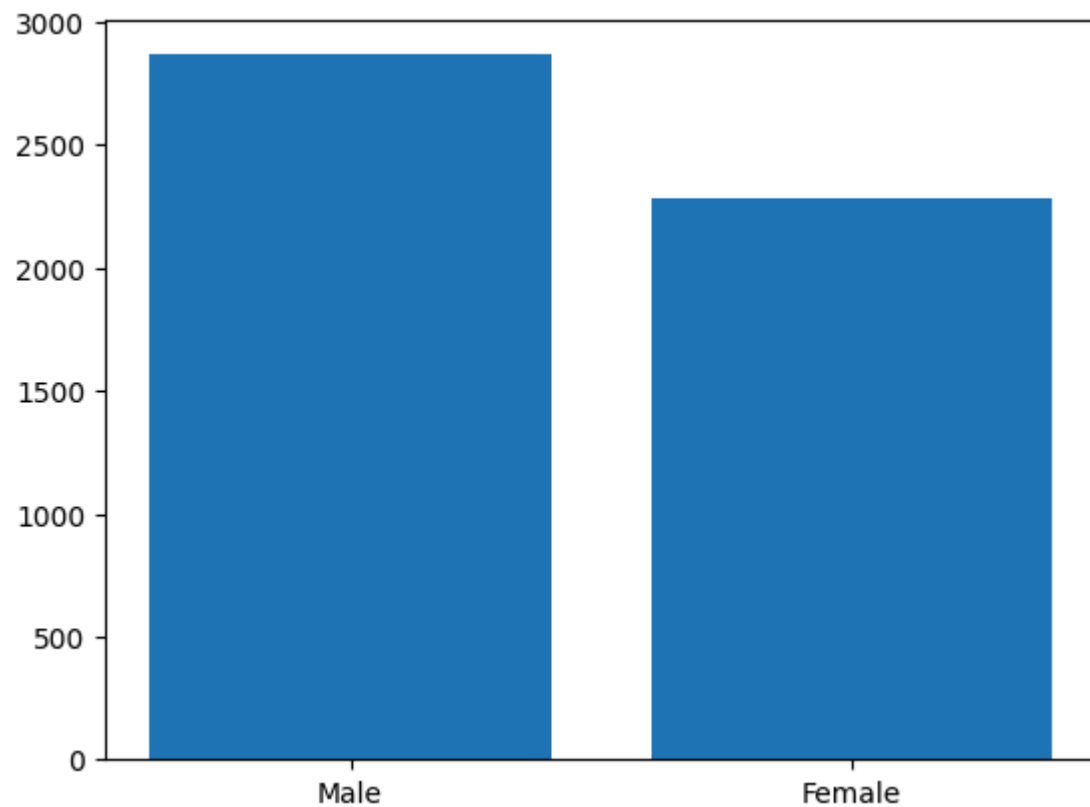
```
In [11]: activeCreditCards = data['active_member'].value_counts()  
  
plt.xticks([0,1])  
plt.bar(activeCreditCards.index,activeCreditCards.values)  
  
plt.show()
```



5. How many people are male and female with active accounts

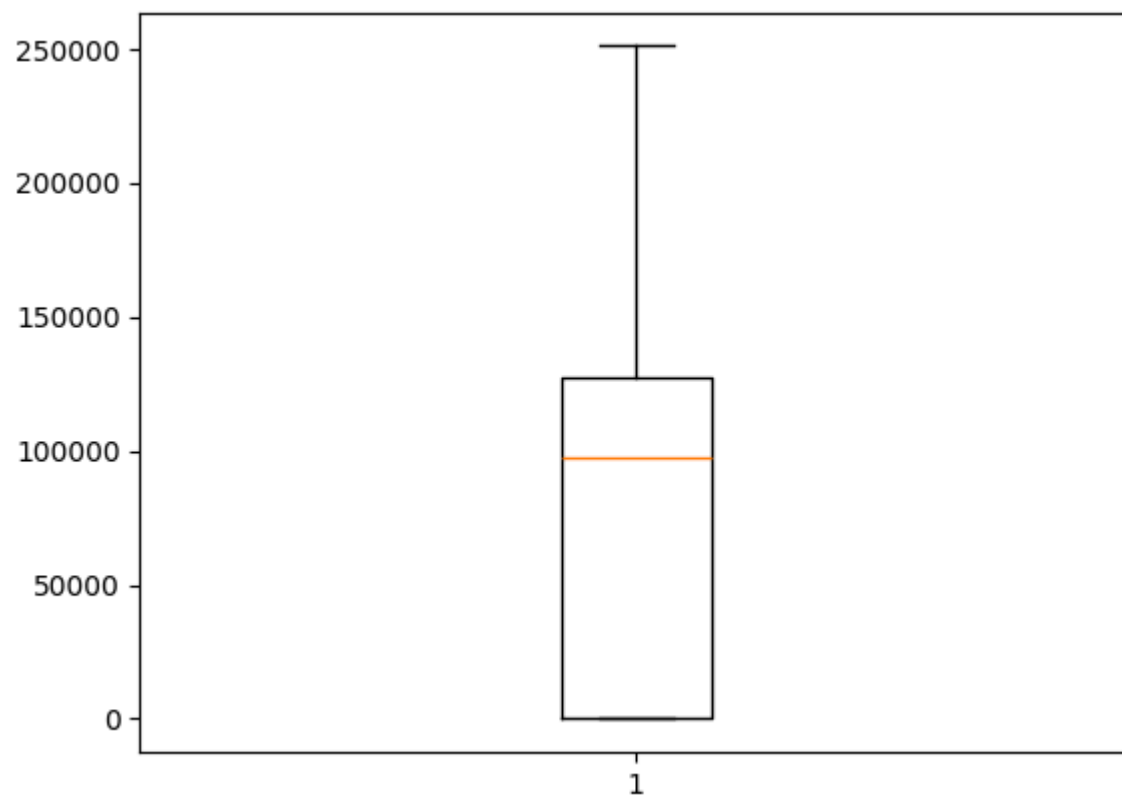
```
In [12]: genderBasedData = data[data['active_member'] == 1]['gender'].value_counts()

plt.bar(genderBasedData.index, genderBasedData.values)
plt.show()
```

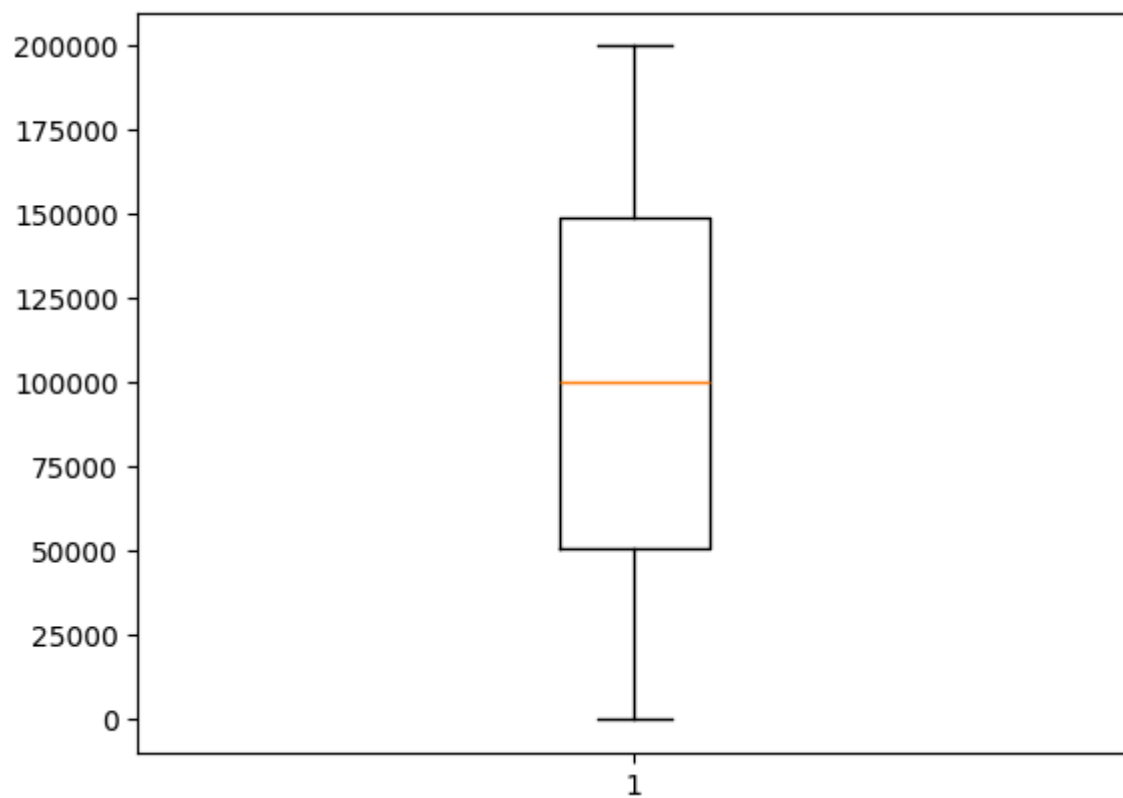


6. Make box plot for balance and estimated salary

```
In [13]: plt.boxplot(data['balance'])
plt.show()
```



```
In [14]: plt.boxplot(data['estimated_salary'])
plt.show()
```



It confirms that there are no outliers

Feature Engineering

1. Convert gender value into 0 and 1

```
In [15]: data['gender'] = data['gender'].apply(lambda x: 1 if x == 'Male' else 0)
data.head()
```

```
Out[15]:
```


	customer_id	credit_score	country	gender	age	tenure	balance	products_number	credit_card
0	15634602	619	France	0	42	2	0.00	1	1
1	15647311	608	Spain	0	41	1	83807.86	1	0
2	15619304	502	France	0	42	8	159660.80	3	1
3	15701354	699	France	0	39	1	0.00	2	0
4	15737888	850	Spain	0	43	2	125510.82	1	1

2. Do feature engineering in country section

```
In [16]: dummies = pd.get_dummies(data['country'], dtype=int)
combinedDf = data.join(dummies)
combinedDf.head()
```

Out[16]:

	customer_id	credit_score	country	gender	age	tenure	balance	products_number	credit_card
0	15634602	619	France	0	42	2	0.00	1	1
1	15647311	608	Spain	0	41	1	83807.86	1	0
2	15619304	502	France	0	42	8	159660.80	3	1
3	15701354	699	France	0	39	1	0.00	2	0
4	15737888	850	Spain	0	43	2	125510.82	1	1



Data Preprocessing

Train and test split

```
In [17]: from sklearn.model_selection import train_test_split
columnsForPrediction = ['credit_score', 'gender', 'age', 'tenure', 'balance', 'products_number']
X = combinedDf[columnsForPrediction]
y = combinedDf['churn']

X_train,X_test,y_train,y_test = train_test_split(X,y,random_state=35,shuffle=True)
```

Scaling

```
In [18]: from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

scaled_data = scaler.fit_transform(X_train)
scaled_test_data = scaler.transform(X_test)

scaled_data = pd.DataFrame(scaled_data)
scaled_test_data = pd.DataFrame(scaled_test_data)
```

Model Training

```
In [32]: from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.ensemble import RandomForestClassifier
```

```
In [33]: classifier = RandomForestClassifier(random_state=42)
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
```

```
In [34]: accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy * 100:.2f}%')

conf_matrix = confusion_matrix(y_test, y_pred)
conf_matrix
```

Accuracy: 85.44%

```
Out[34]: array([[1915,  79],
               [ 285, 221]])
```