Bank Customer Churn

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import os
```

Objective:

Churn prevention allows companies to develop loyalty programs and retention campaigns to keep as many customers as possible.

Dataset Description:

RowNumber—corresponds to the record (row) number and has no effect on the output.

CustomerId—contains random values and has no effect on customer leaving the bank.

Surname—the surname of a customer has no impact on their decision to leave the bank.

CreditScore—can have an effect on customer churn, since a customer with a higher credit score is less likely to leave the bank.

Geography—a customer's location can affect their decision to leave the bank.

Gender—it's interesting to explore whether gender plays a role in a customer leaving the bank.

Age—this is certainly relevant, since older customers are less likely to leave their bank than younger ones.

Tenure—refers to the number of years that the customer has been a client of the bank. Normally, older clients are more loyal and less likely to leave a bank.

Balance—also a very good indicator of customer churn, as people with a higher balance in their accounts are less likely to leave the bank compared to those with lower balances.

NumOfProducts—refers to the number of products that a customer has purchased through the bank.

HasCrCard—denotes whether or not a customer has a credit card. This column is also relevant, since people with a credit card are less likely to leave the bank.

IsActiveMember—active customers are less likely to leave the bank.

EstimatedSalary—as with balance, people with lower salaries are more likely to leave the bank compared to those with higher salaries.

Exited—whether or not the customer left the bank.

]:
```
```

]:
```
df = pd.read_csv('churn.csv')
df.head()
```

```python
df = pd.read_csv('churn.csv')
df.head()
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedS
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	1013
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	1125
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	1139
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	938
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	790

```python
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
```

```
 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
```

```python
df.shape
```

```
(10000, 14)
```

```python
df.dtypes
```

```
RowNumber            int64
CustomerId           int64
Surname             object
CreditScore          int64
Geography           object
Gender              object
Age                  int64
Tenure               int64
Balance            float64
NumOfProducts        int64
HasCrCard            int64
IsActiveMember       int64
```

```
IsActiveMember       int64
EstimatedSalary    float64
Exited               int64
dtype: object
```

```
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
```

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

```
df.shape
```

```
(10000, 11)
```

```
df.Geography.unique()
```

```
array(['France', 'Spain', 'Germany'], dtype=object)
```

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
object_col = df.dtypes[df.dtypes==np.object]
object_col = object_col.index.to_list()
```

```
object_col
```

```
['Geography', 'Gender']
```

```
for col in object_col:
    df[col] = le.fit_transform(df[col])
```

```
df.info()
```

```
<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  int32
 2   Gender           10000 non-null  int32
 3   Age              10000 non-null  int64
 4   Tenure           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), int32(2), int64(7)
memory usage: 781.4 KB
```

```python
df = df.astype('float')
```

```python
df.info()
```

```
<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  float64
 1   Geography        10000 non-null  float64
 2   Gender           10000 non-null  float64
 3   Age              10000 non-null  float64
 4   Tenure           10000 non-null  float64
 5   Balance          10000 non-null  float64
 6   NumOfProducts    10000 non-null  float64
 7   HasCrCard        10000 non-null  float64
 8   IsActiveMember   10000 non-null  float64
 9   EstimatedSalary  10000 non-null  float64
```

```
 9   EstimatedSalary  10000 non-null  float64
 10  Exited           10000 non-null  float64
dtypes: float64(11)
memory usage: 859.5 KB
```

```python
feature_col = [x for x in df.columns if x!='Exited']
```

```python
df.describe()
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSala
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.0000
mean	650.528800	0.746300	0.545700	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.2398
std	96.653299	0.827529	0.497932	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.4928
min	350.000000	0.000000	0.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.5800
25%	584.000000	0.000000	0.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.1100
50%	652.000000	0.000000	1.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.9150
75%	718.000000	1.000000	1.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.2475
max	850.000000	2.000000	1.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.4800

```python
df_org =df.copy()
corr = df.corr()
corr
```

```
df_org =df.copy()
corr = df.corr()
corr
```

]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exit
CreditScore	1.000000	0.007888	-0.002857	-0.003965	0.000842	0.006268	0.012238	-0.005458	0.025651	-0.001384	-0.0270
Geography	0.007888	1.000000	0.004719	0.022812	0.003739	0.069408	0.003972	-0.008523	0.006724	-0.001369	0.0359
Gender	-0.002857	0.004719	1.000000	-0.027544	0.014733	0.012087	-0.021859	0.005766	0.022544	-0.008112	-0.1065
Age	-0.003965	0.022812	-0.027544	1.000000	-0.009997	0.028308	-0.030680	-0.011721	0.085472	-0.007201	0.2853
Tenure	0.000842	0.003739	0.014733	-0.009997	1.000000	-0.012254	0.013444	0.022583	-0.028362	0.007784	-0.0140
Balance	0.006268	0.069408	0.012087	0.028308	-0.012254	1.000000	-0.304180	-0.014858	-0.010084	0.012797	0.1185
NumOfProducts	0.012238	0.003972	-0.021859	-0.030680	0.013444	-0.304180	1.000000	0.003183	0.009612	0.014204	-0.0478
HasCrCard	-0.005458	-0.008523	0.005766	-0.011721	0.022583	-0.014858	0.003183	1.000000	-0.011866	-0.009933	-0.0071
IsActiveMember	0.025651	0.006724	0.022544	0.085472	-0.028362	-0.010084	0.009612	-0.011866	1.000000	-0.011421	-0.1561
EstimatedSalary	-0.001384	-0.001369	-0.008112	-0.007201	0.007784	0.012797	0.014204	-0.009933	-0.011421	1.000000	0.0120
Exited	-0.027094	0.035943	-0.106512	0.285323	-0.014001	0.118533	-0.047820	-0.007138	-0.156128	0.012097	1.0000

```
for x in range(corr.shape[0]):
    corr.iloc[x,x] = 0.0
corr
```


```
for x in range(corr.shape[0]):
    corr.iloc[x,x] = 0.0
corr
```


]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exit
CreditScore	0.000000	0.007888	-0.002857	-0.003965	0.000842	0.006268	0.012238	-0.005458	0.025651	-0.001384	-0.0270
Geography	0.007888	0.000000	0.004719	0.022812	0.003739	0.069408	0.003972	-0.008523	0.006724	-0.001369	0.0359
Gender	-0.002857	0.004719	0.000000	-0.027544	0.014733	0.012087	-0.021859	0.005766	0.022544	-0.008112	-0.1065
Age	-0.003965	0.022812	-0.027544	0.000000	-0.009997	0.028308	-0.030680	-0.011721	0.085472	-0.007201	0.2853
Tenure	0.000842	0.003739	0.014733	-0.009997	0.000000	-0.012254	0.013444	0.022583	-0.028362	0.007784	-0.0140
Balance	0.006268	0.069408	0.012087	0.028308	-0.012254	0.000000	-0.304180	-0.014858	-0.010084	0.012797	0.1185
NumOfProducts	0.012238	0.003972	-0.021859	-0.030680	0.013444	-0.304180	0.000000	0.003183	0.009612	0.014204	-0.0478
HasCrCard	-0.005458	-0.008523	0.005766	-0.011721	0.022583	-0.014858	0.003183	0.000000	-0.011866	-0.009933	-0.0071
IsActiveMember	0.025651	0.006724	0.022544	0.085472	-0.028362	-0.010084	0.009612	-0.011866	0.000000	-0.011421	-0.1561
EstimatedSalary	-0.001384	-0.001369	-0.008112	-0.007201	0.007784	0.012797	0.014204	-0.009933	-0.011421	0.000000	0.0120
Exited	-0.027094	0.035943	-0.106512	0.285323	-0.014001	0.118533	-0.047820	-0.007138	-0.156128	0.012097	0.0000

```
corr.abs().idxmax()
```

]:

```
CreditScore            Exited
Geography             Balance
```

```
Gender                      Exited
Age                         Exited
Tenure              IsActiveMember
Balance              NumOfProducts
NumOfProducts              Balance
HasCrCard                   Tenure
IsActiveMember              Exited
EstimatedSalary      NumOfProducts
Exited                         Age
dtype: object
```

```python
skew_col = df.skew().sort_values(ascending=False)
if 'Exited' in skew_col:
    skew_col.drop('Exited',inplace=True)
```

```python
skew_col = skew_col.loc[skew_col>0.75]
skew_col
```

```
Age    1.01132
dtype: float64
```

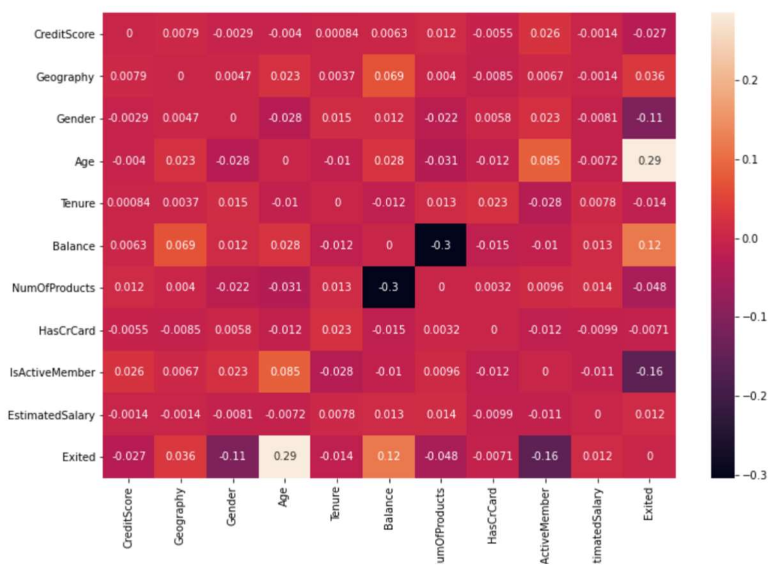
```python
for col in skew_col.index.to_list():
    df[col] = np.log1p(df[col])
```

```python
skew_col = df.skew().sort_values(ascending=False)
skew_col
```

```
Exited             1.471611
NumOfProducts      0.745568
Geography          0.500916
Age                0.203360
Tenure             0.010991
EstimatedSalary    0.002085
IsActiveMember    -0.060437
```

```python
ax = plt.figure(figsize=(12,8))
sns.heatmap(corr,annot=True)
```

<AxesSubplot:>



```
from sklearn.preprocessing import StandardScaler
ss = StandardScaler()
df[feature_col] = ss.fit_transform(df[feature_col])
```

Summary of EDA:

After loading dataset i checked for null values but their was no missing in any column.

Then i checked skewness and applied log1p transform to make it like normal disturbution.

Checked Correlation but didn't tooked any action beacuse dataset donot have alot of features to drop them for elimation of correlation.

Droped Unnecessary columns from dataset.

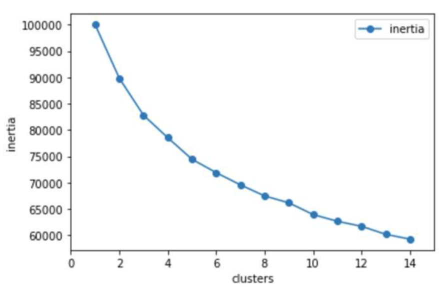
As we know its not good idea to cluster dataset without scaling data, So before applying clustering technique i scaleed data.

Different Models Trained Using Different Custering Algorithms

```
from sklearn.cluster import KMeans

km_list = list()

for i in range(1,15):
    km = KMeans(n_clusters=i,random_state=42)
    km = km.fit(df[feature_col])

    km_list.append(pd.Series({'clusters':i,'inertia':km.inertia_,'model':km}))
```

```
plot_df = pd.concat(km_list,axis=1).T[['clusters','inertia']].set_index('clusters')

ax = plot_df.plot(marker='o',ls='-')
ax.set_xticks(range(0,15,2))
ax.set_xlim(0,15)
ax.set(xlabel='clusters',ylabel='inertia')
```

```
[Text(0.5, 0, 'clusters'), Text(0, 0.5, 'inertia')]
```




```
from sklearn.cluster import KMeans
km = KMeans(n_clusters=2,random_state=42)
km = km.fit(df[feature_col])

df['kmeans'] = km.predict(df[feature_col])
```

```
df.head(4)
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited	kmeans
0	-0.326221	-0.901886	-1.095988	0.423222	-1.041760	-1.225848	-0.911583	0.646092	0.970243	0.021886	1.0	0
1	-0.440036	1.515067	-1.095988	0.329713	-1.387538	0.117350	-0.911583	-1.547768	0.970243	0.216534	0.0	1

1	-0.440036	1.515067	-1.095988	0.329713	-1.387538	0.117350	-0.911583	-1.547768	0.970243	0.216534	0.0	1
2	-1.536794	-0.901886	-1.095988	0.423222	1.032908	1.333053	2.527057	0.646092	-1.030670	0.240687	1.0	0
3	0.501521	-0.901886	-1.095988	0.135823	-1.387538	-1.225848	0.807737	-1.547768	-1.030670	-0.108918	0.0	0

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

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score,classification_report
from sklearn.model_selection import StratifiedShuffleSplit
```

```
sss = StratifiedShuffleSplit(n_splits=5,random_state=42)

def get_avg_roc(estimator,X,y):
    roc_auc_list = []
    for train_idx,test_idx in sss.split(X,y):
        X_train,X_test = X.iloc[train_idx],X.iloc[test_idx]
        y_train,y_test = y.iloc[train_idx],y.iloc[test_idx]
        estimator.fit(X_train,y_train)
        y_pred = estimator.predict(X_test)
        y_scored = estimator.predict_proba(X_test)[:,1]
        roc_auc_list.append(roc_auc_score(y_test,y_scored))
    return np.mean(roc_auc_list)

estimator = RandomForestClassifier()
roc_auc = get_avg_roc(estimator,X,y)
print("Using kmeans cluster as input to random forest, roc-auc is \"{0}\"".format(roc_auc))
```

```
Using kmeans cluster as input to random forest, roc-auc is "0.8476814218149572"
```

```
from sklearn.cluster import AgglomerativeClustering
```


```
from sklearn.cluster import AgglomerativeClustering
```


```
X2 = df[feature_col]
y = df['Exited']
```

```
ag = AgglomerativeClustering(n_clusters=2,linkage='ward',compute_full_tree=True)
ag = ag.fit(X2)
X2['agglo'] = ag.fit_predict(X2)
```

```
<ipython-input-243-4329a8be967b>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X2['agglo'] = ag.fit_predict(X2)
```

```
sss = StratifiedShuffleSplit(n_splits=5,random_state=42)

def get_avg_roc(estimator,X,y):
    roc_auc_list = []
    for train_idx,test_idx in sss.split(X,y):
        X_train,X_test = X.iloc[train_idx],X.iloc[test_idx]
        y_train,y_test = y.iloc[train_idx],y.iloc[test_idx]
        estimator.fit(X_train,y_train)
        y_pred = estimator.predict(X_test)
        y_scored = estimator.predict_proba(X_test)[:,1]
        roc_auc_list.append(roc_auc_score(y_test,y_scored))
    return np.mean(roc_auc_list)

estimator = RandomForestClassifier()
roc_auc = get_avg_roc(estimator,X2,y)
print("Using Agglomerative cluster as input to random forest, roc-auc is \"{0}\"".format(roc_auc))
```

```
Using Agglomerative cluster as input to random forest, roc-auc is "0.8460685781850428"
```

```python
from sklearn.cluster import DBSCAN

X3 = df[feature_col]
y = df['Exited']
```

```python
db = DBSCAN(eps=0.5,min_samples=3)
db = db.fit(X3)
X3['dbscan'] = db.fit_predict(X3)
```

```
<ipython-input-263-caba3fd15feb>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X3['dbscan'] = db.fit_predict(X3)
```

```python
sss = StratifiedShuffleSplit(n_splits=5,random_state=42)

def get_avg_roc(estimator,X,y):
    roc_auc_list = []
    for train_idx,test_idx in sss.split(X,y):
        X_train,X_test = X.iloc[train_idx],X.iloc[test_idx]
        y_train,y_test = y.iloc[train_idx],y.iloc[test_idx]
        estimator.fit(X_train,y_train)
        y_pred = estimator.predict(X_test)
        y_scored = estimator.predict_proba(X_test)[:,1]
        roc_auc_list.append(roc_auc_score(y_test,y_scored))
    return np.mean(roc_auc_list)

estimator = RandomForestClassifier()
roc_auc = get_avg_roc(estimator,X3,y)
print("Using DBSCAN cluster as input to random forest, roc-auc is \"{0}\"".format(roc_auc))
```

```
Using DBSCAN cluster as input to random forest, roc-auc is "0.8497339639373337"
```


```
Using DBSCAN cluster as input to random forest, roc-auc is "0.8497339639373337"
```


Summary and Explination of Unsupervised Learning Models

I have applied different clustering techniques on this dataset and found that DBSCAN performs little bit better than other clustering technique. And during hyperparameter tunning I found that DBSCAN have high accuraccy for value of number of sample equal to 3 instead of default value of 5.

Summery

Actually in this dataset we have feature of exited or not but that was only for our testing purpose, we want to see how much our clustering technique combine with supervied learning is showing us accurate result. So as key note we can cluster our clients into churn and will not-churn, So that you make policies accordingly.

Suggestion

Although we donot have complex data but still you can apply PCA technique to come up with new feature and see is their any change in accuracy of model etc.