In [1]:

```
import pandas as pd
import numpy as np                          # For mathematical calculations
import seaborn as sns                       # For data visualization
import matplotlib.pyplot as plt
import seaborn as sn                        # For plotting graphs
import io
%matplotlib inline
import warnings                             # To ignore any warnings
warnings.filterwarnings("ignore")
```

In [4]:

```
filepath2 = r"C:\Users\91623\OneDrive\Desktop\projects\bank_curn\bank.csv"
df= pd.read_csv(filepath2)
print(df)
```

```
      CustomerId    Surname  CreditScore Geography  Gender  Age  Tenure  \
0       15634602   Hargrave          619    France  Female   42       2
1       15647311       Hill          608     Spain  Female   41       1
2       15619304       Onio          502    France  Female   42       8
3       15701354       Boni          699    France  Female   39       1
4       15737888   Mitchell          850     Spain  Female   43       2
...          ...        ...          ...       ...     ...  ...     ...
9995    15606229   Obijiaku          771    France    Male   39       5
9996    15569892  Johnstone          516    France    Male   35      10
9997    15584532        Liu          709    France  Female   36       7
9998    15682355  Sabbatini          772   Germany    Male   42       3
9999    15628319     Walker          792    France  Female   28       4

        Balance  Num Of Products  Has Credit Card  Is Active Member  \
0          0.00                1                1                 1
1      83807.86                1                0                 1
2     159660.80                3                1                 0
3          0.00                2                0                 0
4     125510.82                1                1                 1
...         ...              ...              ...               ...
9995       0.00                2                1                 0
9996   57369.61                1                1                 1
9997       0.00                1                0                 1
9998   75075.31                2                1                 0
9999  130142.79                1                1                 0

      Estimated Salary  Churn
0            101348.88      1
1            112542.58      0
2            113931.57      1
3             93826.63      0
4             79084.10      0
...                ...    ...
9995          96270.64      0
9996         101699.77      0
9997          42085.58      1
9998          92888.52      1
9999          38190.78      0

[10000 rows x 13 columns]
```

In [5]:

```
df.head()
```

Out[5]:

	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	Num Of Products	Has Credit Card	Is Active Member	Estimated Salary	Churn
0	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

In [7]:

```
df=df.drop('CustomerId',axis=1)
```

In [8]:

```
df.columns = df.columns.str.lower()
```

In [10]:

```
unique = [feature for feature in df.columns if len(df[feature].unique())>0 and len(df[feature].unique())<100]
for feature in unique:
    print("{} has {} unique values : {} {}".format(feature,len(df[feature].unique()),df[feature].unique(),"\n")
```

```
geography has 3 unique values : ['France' 'Spain' 'Germany']

gender has 2 unique values : ['Female' 'Male']

age has 70 unique values : [42 41 39 43 44 50 29 27 31 24 34 25 35 45 58 32 38 46 36 33 40 51 61 49
 37 19 66 56 26 21 55 75 22 30 28 65 48 52 57 73 47 54 72 20 67 79 62 53
 80 59 68 23 60 70 63 64 18 82 69 74 71 76 77 88 85 84 78 81 92 83]

tenure has 11 unique values : [ 2  1  8  7  4  6  3 10  5  9  0]

num of products has 4 unique values : [1 3 2 4]

has credit card has 2 unique values : [1 0]

is active member has 2 unique values : [1 0]

churn has 2 unique values : [1 0]
```

In [14]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10000 entries, 0 to 9999
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   surname           10000 non-null  object
 1   creditscore       10000 non-null  int64
 2   geography         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   num of products   10000 non-null  int64
 8   has credit card   10000 non-null  int64
 9   is active member  10000 non-null  int64
 10  estimated salary  10000 non-null  float64
 11  churn             10000 non-null  int64
dtypes: float64(2), int64(7), object(3)
memory usage: 1015.6+ KB
```

In [15]:

```
df= df.dropna()
```

In [16]:

```
df.describe()
```

Out[16]:

	creditscore	age	tenure	balance	num of products	has credit card	is active member	estimated salary	churn
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.00000	10000.000000	10000.000000	10000.000000
mean	650.528800	38.921800	5.012800	76485.889288	1.530200	0.70550	0.515100	100090.239881	0.203700
std	96.653299	10.487806	2.892174	62397.405202	0.581654	0.45584	0.499797	57510.492818	0.402769
min	350.000000	18.000000	0.000000	0.000000	1.000000	0.00000	0.000000	11.580000	0.000000
25%	584.000000	32.000000	3.000000	0.000000	1.000000	0.00000	0.000000	51002.110000	0.000000
50%	652.000000	37.000000	5.000000	97198.540000	1.000000	1.00000	1.000000	100193.915000	0.000000
75%	718.000000	44.000000	7.000000	127644.240000	2.000000	1.00000	1.000000	149388.247500	0.000000
max	850.000000	92.000000	10.000000	250898.090000	4.000000	1.00000	1.000000	199992.480000	1.000000

In [17]:

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

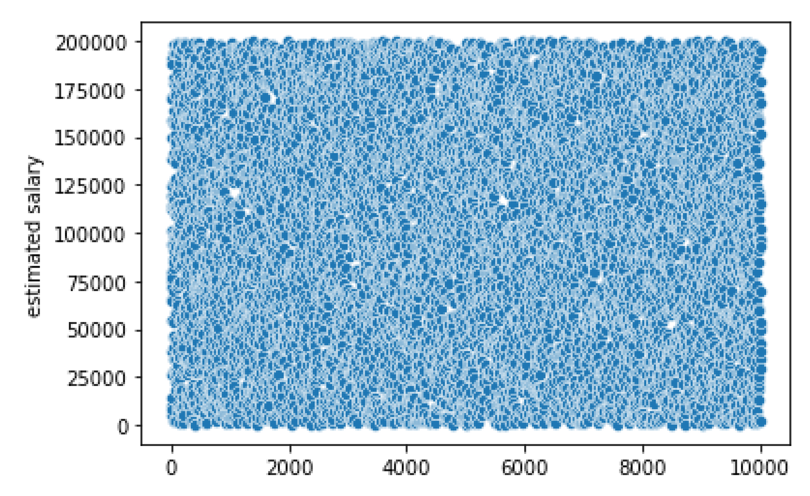
In [18]:

```
df1=df
```

In [31]:

Out[31]:

```
<AxesSubplot:ylabel='estimated salary'>
```



In [ ]:

In [ ]:

In [19]:

```
list1=['gender','geography']
for i in list1:
    df1[i]=le.fit_transform(df1[i])

df1.head()
```

Out[19]:

	surname	creditscore	geography	gender	age	tenure	balance	num of products	has credit card	is active member	estimated salary	churn
0	Hargrave	619	0	0	42	2	0.00	1	1	1	101348.88	1
1	Hill	608	2	0	41	1	83807.86	1	0	1	112542.58	0
2	Onio	502	0	0	42	8	159660.80	3	1	0	113931.57	1
3	Boni	699	0	0	39	1	0.00	2	0	0	93826.63	0
4	Mitchell	850	2	0	43	2	125510.82	1	1	1	79084.10	0

In [21]:

```
df1=df1.drop('surname',axis=1)
```

In [22]:

```
df1
```

Out[22]:

	creditscore	geography	gender	age	tenure	balance	num of products	has credit card	is active member	estimated salary	churn
0	619	0	0	42	2	0.00	1	1	1	101348.88	1
1	608	2	0	41	1	83807.86	1	0	1	112542.58	0
2	502	0	0	42	8	159660.80	3	1	0	113931.57	1
3	699	0	0	39	1	0.00	2	0	0	93826.63	0
4	850	2	0	43	2	125510.82	1	1	1	79084.10	0
...	...	...	...	...	...	...	...	...	...	...	...
9995	771	0	1	39	5	0.00	2	1	0	96270.64	0
9996	516	0	1	35	10	57369.61	1	1	1	101699.77	0
9997	709	0	0	36	7	0.00	1	0	1	42085.58	1
9998	772	1	1	42	3	75075.31	2	1	0	92888.52	1
9999	792	0	0	28	4	130142.79	1	1	0	38190.78	0

10000 rows × 11 columns

In [ ]:

In [ ]:

In [23]:

```
x=df1.drop(['churn'],axis=1)
```

In [24]:

```
y=df1['churn']
```

In [32]:

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test =train_test_split(x,y, test_size=0.25,random_state=2529)
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

Out[32]:

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

In [33]:

```
from sklearn.linear_model import LogisticRegression
lr=LogisticRegression()
lr.fit(x_train,y_train)
y_pred = lr.predict(x_test)
```

In [34]:

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

```
[[2012    0]
 [ 488    0]]
              precision    recall  f1-score   support

           0       0.80      1.00      0.89      2012
           1       0.00      0.00      0.00       488

    accuracy                           0.80      2500
   macro avg       0.40      0.50      0.45      2500
weighted avg       0.65      0.80      0.72      2500
```

In [35]:

```
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
rfc_pred=rfc.predict(x_test)
```

In [36]:

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

```
[[1957   55]
 [ 276  212]]
              precision    recall  f1-score   support

           0       0.88      0.97      0.92      2012
           1       0.79      0.43      0.56       488

    accuracy                           0.87      2500
   macro avg       0.84      0.70      0.74      2500
weighted avg       0.86      0.87      0.85      2500
```

In [37]:

```
from sklearn import tree
clf = tree.DecisionTreeClassifier()
clf.fit(x_train,y_train)
clf_pred=clf.predict(x_test)
```

In [38]:

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

```
[[1742  270]
 [ 263  225]]
              precision    recall  f1-score   support

           0       0.87      0.87      0.87      2012
           1       0.45      0.46      0.46       488

    accuracy                           0.79      2500
   macro avg       0.66      0.66      0.66      2500
weighted avg       0.79      0.79      0.79      2500
```

In [39]:

```
from sklearn.svm import SVC
svC=SVC()
svC.fit(x_train,y_train)
svC_pred=svC.predict(x_test)
```

In [40]:

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

```
[[2012    0]
 [ 488    0]]
              precision    recall  f1-score   support

           0       0.80      1.00      0.89      2012
           1       0.00      0.00      0.00       488

    accuracy                           0.80      2500
   macro avg       0.40      0.50      0.45      2500
weighted avg       0.65      0.80      0.72      2500
```

In [41]:

```
from sklearn.naive_bayes import GaussianNB
gnb = GaussianNB()
gnb.fit(x_train,y_train)
gnb_pred=gnb.predict(x_test)
```

In [45]:

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

```
[[1943   69]
 [ 450   38]]
              precision    recall  f1-score   support

           0       0.81      0.97      0.88      2012
           1       0.36      0.08      0.13       488

    accuracy                           0.79      2500
   macro avg       0.58      0.52      0.50      2500
weighted avg       0.72      0.79      0.73      2500
```

In [ ]: