customer-churn-prediction

April 7, 2024

0.0.1 Project Name : Bank Customer Churn Prediction

0.1 Contribution : Individual

The aim of this project to analyze the bank customer's demographics and financial information which inculdes customer's age, gender. country, credit score, balance and many others to predict whether the customer will leave the bank or not.

0.1.1 Data Dictionary

Column Name	Description
RowNumber	Row number
CustomerId	Unique identification key for different customers
Surname	Customer's last name
CreditScore	Credit score of the customer
Geography	Country of the customer
Age	Age of the customer
Tenure	Number of years for which the customer has been with the bank
Balance	Bank balance of the customer
NumOfProducts	Number of bank products the customer is utilising
HasCrCard	Binary flag for whether the customer holds a credit card with the bank or not
IsActiveMember	Binary flag for whether the customer is an active member with the bank or not
EstimatedSalary	Estimated salary of the customer in Dollars
Exited	Binary flag 1 if the customer closed account with bank and 0 if the customer is retained
Complain	customer has complaint or not
Satisfaction Score	Score provided by the customer for their complaint resolution
Card Type	type of card hold by the customer
Points Earned	the points earned by the customer for using credit card

[1]:
```python
# import library
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
sns.set(palette='colorblind', style='dark')
```

[2]:
```python
# load dataset
dataset = '/content/Customer-Churn-Records.csv'

df = pd.read_csv(dataset)
df.head()
```

[2]:
```
   RowNumber  CustomerId   Surname  CreditScore Geography  Gender  Age  \
0          1    15634602  Hargrave          619    France  Female   42
1          2    15647311      Hill          608     Spain  Female   41
2          3    15619304      Onio          502    France  Female   42
3          4    15701354      Boni          699    France  Female   39
4          5    15737888  Mitchell          850     Spain  Female   43

   Tenure    Balance  NumOfProducts  HasCrCard  IsActiveMember  \
0       2       0.00              1          1               1
1       1   83807.86              1          0               1
2       8  159660.80              3          1               0
3       1       0.00              2          0               0
4       2  125510.82              1          1               1

   EstimatedSalary  Exited  Complain  Satisfaction Score Card Type  \
0        101348.88       1         1                   2   DIAMOND
1        112542.58       0         1                   3   DIAMOND
2        113931.57       1         1                   3   DIAMOND
3         93826.63       0         0                   5      GOLD
4         79084.10       0         0                   5      GOLD

   Point Earned
0           464
1           456
2           377
3           350
4           425
```

0.2 Data Preprocessing Part 1

[3]:
```python
# checking shape of dataset
df.shape
```

[3]: (10000, 18)

Dropping the unecessary columns - RowNumber, CustomerId, Surname

[4]:
```python
# drop columns
drop_col = ['RowNumber', 'CustomerId', 'Surname']

df = df.drop(drop_col, axis=1)
df.head()
```

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

   HasCrCard  IsActiveMember  EstimatedSalary  Exited  Complain  \
0          1               1        101348.88       1         1
1          0               1        112542.58       0         1
2          1               0        113931.57       1         1
3          0               0         93826.63       0         0
4          1               1         79084.10       0         0

   Satisfaction Score Card Type  Point Earned
0                   2   DIAMOND           464
1                   3   DIAMOND           456
2                   3   DIAMOND           377
3                   5      GOLD           350
4                   5      GOLD           425
```

[5]:
```python
# renaming column Exited to Churn
df = df.rename(columns={'Exited':'Churn'})
```

[6]:
```python
# drop null values if any
df.isnull().sum() * 100 / len(df)
```

[6]:
```
CreditScore          0.0
Geography            0.0
Gender               0.0
Age                  0.0
Tenure               0.0
Balance              0.0
NumOfProducts        0.0
HasCrCard            0.0
IsActiveMember       0.0
EstimatedSalary      0.0
Churn                0.0
Complain             0.0
```

```
Satisfaction Score    0.0
Card Type             0.0
Point Earned          0.0
dtype: float64
```

[7]:
```
# checking duplicated values
df.duplicated().sum()
```

[7]:
```
0
```

[8]:
```
# checking more info about the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 15 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  Churn               10000 non-null  int64
 11  Complain            10000 non-null  int64
 12  Satisfaction Score  10000 non-null  int64
 13  Card Type           10000 non-null  object
 14  Point Earned        10000 non-null  int64
dtypes: float64(2), int64(10), object(3)
memory usage: 1.1+ MB
```

[9]:
```
# grouping col by the dtypes
nums = [i for i in df.columns if df[i].dtypes != 'object']
cats = [i for i in df.columns if df[i].dtypes == 'object']
```

[10]:
```
# descriptive statistics nums col
df[nums].describe()
```

[10]:
```
        CreditScore           Age        Tenure        Balance  NumOfProducts  \
count  10000.000000  10000.000000  10000.000000   10000.000000   10000.000000
mean     650.528800     38.921800      5.012800   76485.889288       1.530200
std       96.653299     10.487806      2.892174   62397.405202       0.581654
```

```
min      350.000000     18.000000      0.000000        0.000000       1.000000
25%      584.000000     32.000000      3.000000        0.000000       1.000000
50%      652.000000     37.000000      5.000000    97198.540000       1.000000
75%      718.000000     44.000000      7.000000   127644.240000       2.000000
max      850.000000     92.000000     10.000000   250898.090000       4.000000

         HasCrCard  IsActiveMember  EstimatedSalary         Churn  \
count  10000.00000    10000.000000     10000.000000  10000.000000
mean       0.70550        0.515100    100090.239881      0.203800
std        0.45584        0.499797     57510.492818      0.402842
min        0.00000        0.000000        11.580000      0.000000
25%        0.00000        0.000000     51002.110000      0.000000
50%        1.00000        1.000000    100193.915000      0.000000
75%        1.00000        1.000000    149388.247500      0.000000
max        1.00000        1.000000    199992.480000      1.000000

           Complain  Satisfaction Score  Point Earned
count  10000.000000        10000.000000  10000.000000
mean       0.204400            3.013800    606.515100
std        0.403283            1.405919    225.924839
min        0.000000            1.000000    119.000000
25%        0.000000            2.000000    410.000000
50%        0.000000            3.000000    605.000000
75%        0.000000            4.000000    801.000000
max        1.000000            5.000000   1000.000000
```

[11]:
```
# descriptive statistics cats col
df[cats].describe()
```

[11]:
```
       Geography Gender Card Type
count      10000  10000     10000
unique         3      2         4
top       France   Male   DIAMOND
freq        5014   5457      2507
```

[12]:
```
df.head()
```

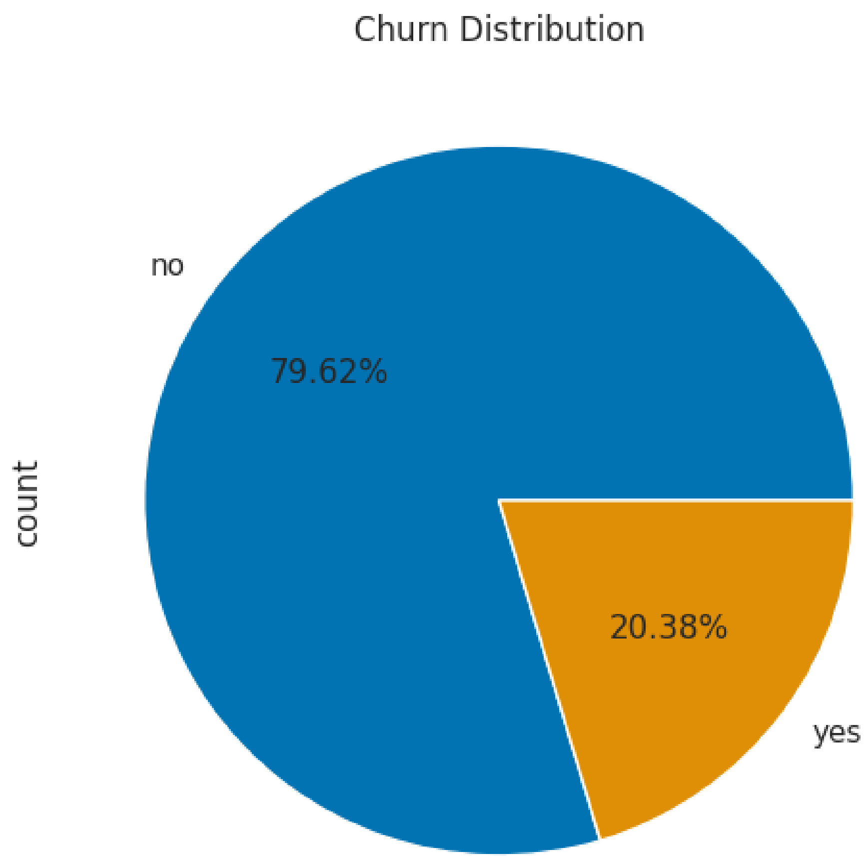
[12]:
```
   CreditScore Geography  Gender  Age  Tenure    Balance  NumOfProducts  \
0          619    France  Female   42       2       0.00              1
1          608     Spain  Female   41       1   83807.86              1
2          502    France  Female   42       8  159660.80              3
3          699    France  Female   39       1       0.00              2
4          850     Spain  Female   43       2  125510.82              1

   HasCrCard  IsActiveMember  EstimatedSalary  Churn  Complain  \
0          1               1        101348.88      1         1
1          0               1        112542.58      0         1
```

```
2         1              0        113931.57      1         1
3         0              0         93826.63      0         0
4         1              1         79084.10      0         0

   Satisfaction Score Card Type  Point Earned
0                   2   DIAMOND           464
1                   3   DIAMOND           456
2                   3   DIAMOND           377
3                   5      GOLD           350
4                   5      GOLD           425
```

0.3 Explorative Data Analysis (EDA)

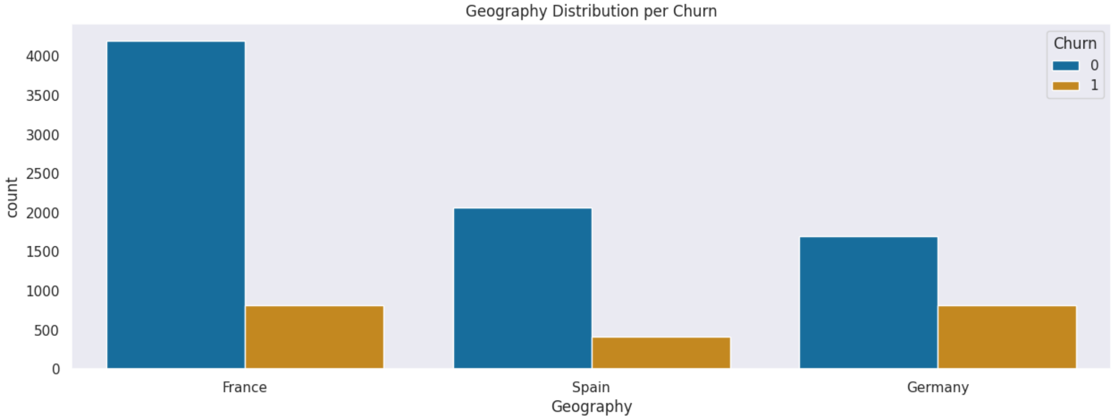
In the exploratory data analysis, I will be looking at the distribution of the data, the coorelation between features and the target variable and the relationship between the features and the target variable.

[13]:
```python
plt.figure(figsize=(6,6))
df['Churn'].value_counts().plot(kind='pie', autopct='%.2f%%', labels=['no',␣
↪'yes'])
plt.title('Churn Distribution')
plt.show()
```



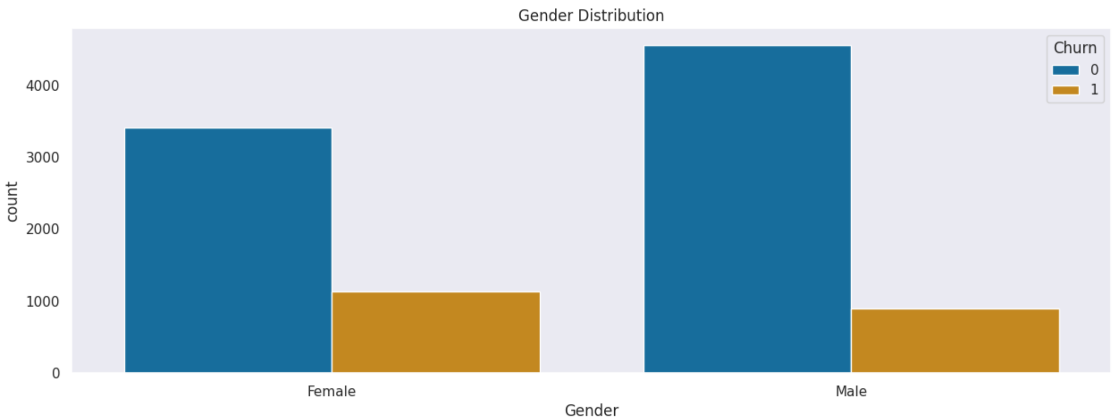
The pie chart clearly visulaizes the customer churn in the dataset. The majority of the customers in the dataset continue to use the serivces of the bank with only 20.38% of the customers churning.

[14]:
```
plt.figure(figsize=(15,5))
sns.countplot(data=df, x='Geography', hue='Churn')
plt.title('Geography Distribution per Churn')
plt.show()
```



This graph shows the number of customers of each gender along with the amount of churn. The majority of customers come from France, followed by Spain and Germany. However in contrast to that Germany has the highest number of customer curn followed by France and Spain. From this we can infer that German customers are more likely to churn than the customers from other countries.

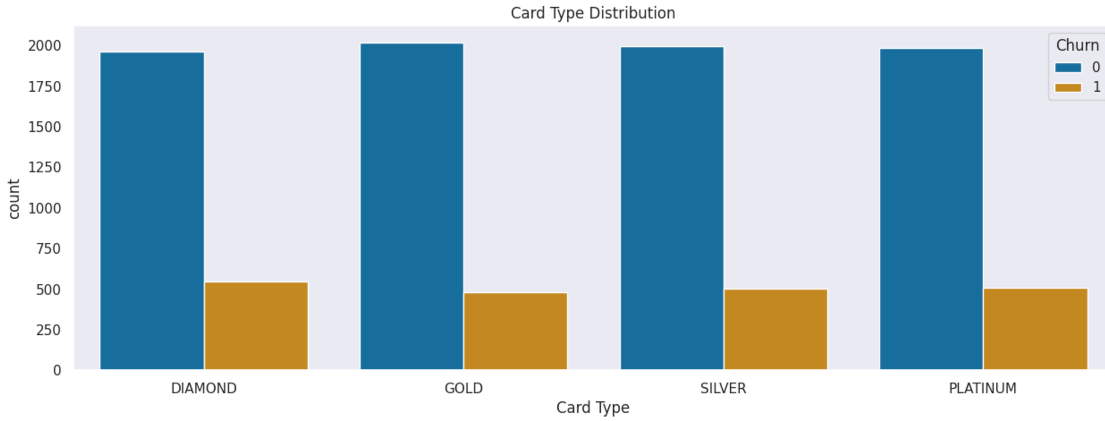
[15]:
```
plt.figure(figsize=(15,5))
sns.countplot(data=df, x='Gender', hue='Churn')
plt.title('Gender Distribution')
plt.show()
```



This graph shows the number of customers of each gender along with the number of churners. The male gender has the largest number of customers, followed by the female gender. From this we can conclude that male customers are more likely to churn than female.

[16]:
```
plt.figure(figsize=(15,5))
sns.countplot(data=df, x='Card Type', hue='Churn')
plt.title('Card Type Distribution')
```

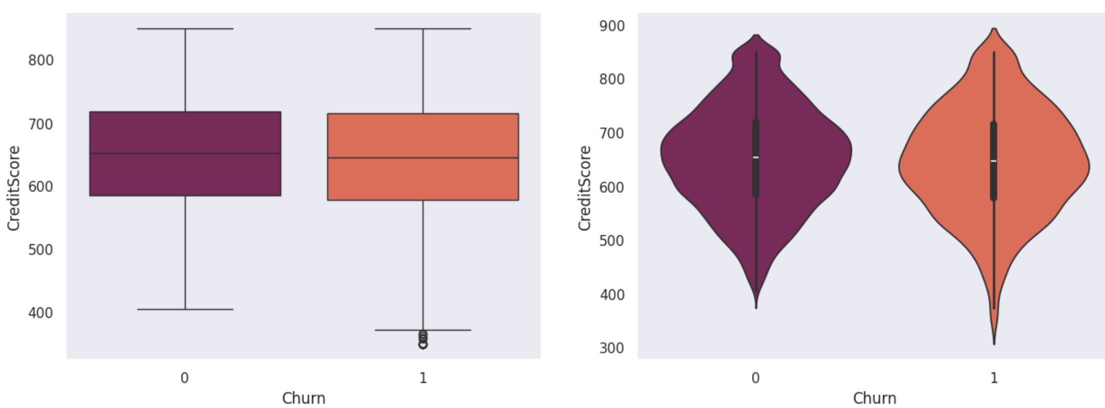
```
plt.show()
```



The graph above shows the number of customers for various types of cards along with the number of churners. It can be concluded that there is not really a significant difference between the four types of customer cards.

```
[17]: fig, ax = plt.subplots(1,2,figsize=(15, 5))
sns.boxplot(x='Churn', y='CreditScore', palette='rocket',data=df, ax=ax[0])
sns.violinplot(x='Churn', y='CreditScore', palette='rocket',data=df, ax=ax[1])
```

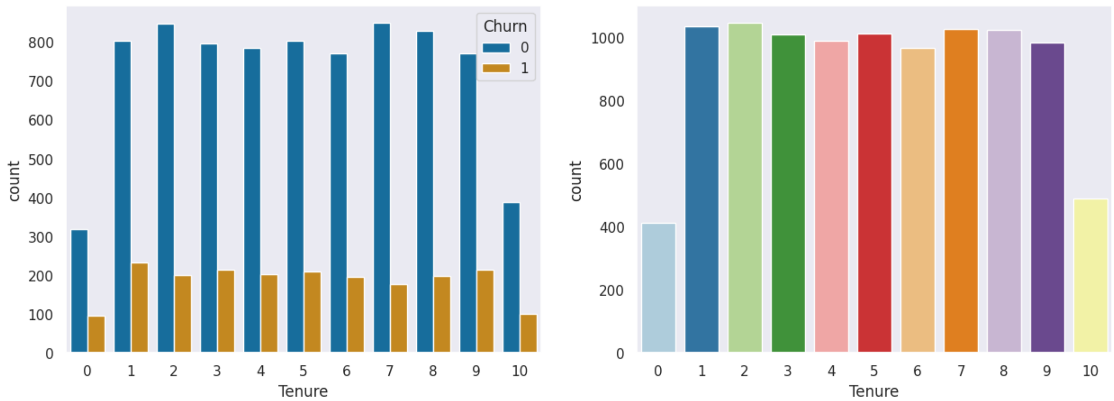
```
[17]: <Axes: xlabel='Churn', ylabel='CreditScore'>
```



The boxplot and violinplot shows the distribution of curstomer's credit score along with their churn. In the boxplot, the median of both the churn and non churn customers are almost same. In addition to that, the shape of violinplot is also similar for both the churn and non churn customers. However some churn customers have low credit score, but on the whole, the credit score is not a good indicator of churn.

[18]:
```
fig, ax = plt.subplots(1, 2, figsize=(15,5))
sns.countplot(data=df, x='Tenure', hue='Churn', ax=ax[0])
sns.countplot(data=df, x='Tenure', ax=ax[1], palette='Paired')
```

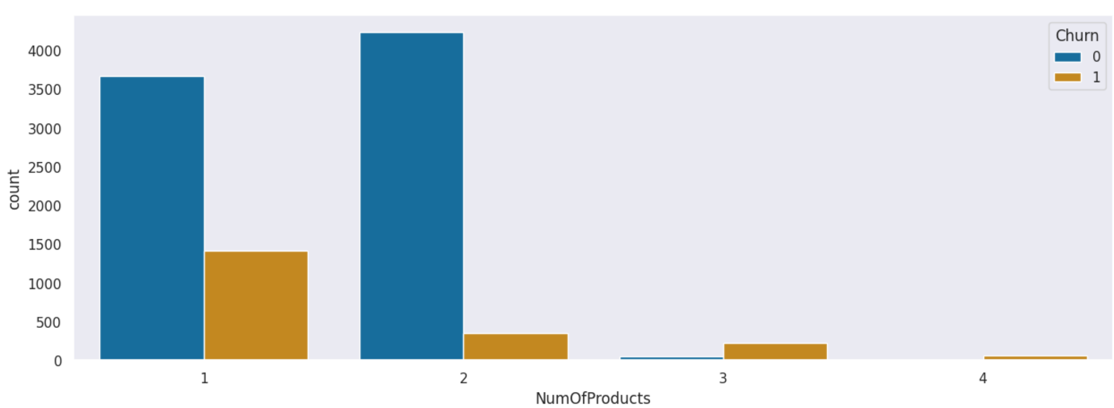
[18]: <Axes: xlabel='Tenure', ylabel='count'>



Tensure refers to the time (in years) that a customer has been a client of the bank. Majority of the customers in the dataset have a tenure between 1-9 years, having equal distribution among them. There are very few customers with a tenure of less than 1 years or more than 9 years. Looking at the churn of these customers based on their tenure, it can be observed that customers with tenure 1-9 years have higher churn count with maximum in customers with 1 year tenure followed those with 9 year tenure. However customers more than 9 years on tenure counts for the least churn. This is because the customers with higher tenure are more loyal to the bank and less likely to churn.

[19]:
```
plt.figure(figsize=(15,5))
sns.countplot(x='NumOfProducts', hue='Churn', data=df)
```

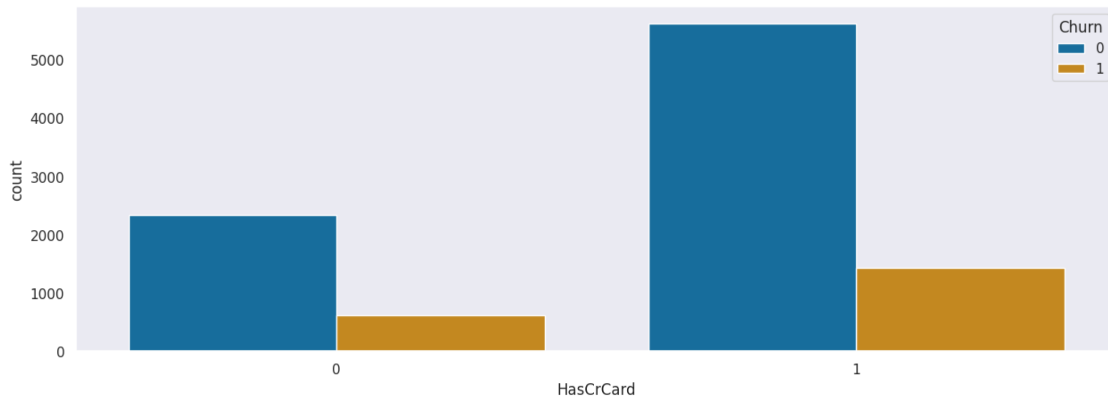
[19]: <Axes: xlabel='NumOfProducts', ylabel='count'>



In the dataset, we have customers in four categories according to the number of products purchased. The customers with purchase or 1 or 2 products are highest in number and have low churn count in comparison to the non churn customers in the category. However, in the category where customers have purchased 3 or 4 products the number of leaving customers is much higher than the non leaving customers.

[20]:
```
plt.figure(figsize=(15,5))
sns.countplot(x='HasCrCard',hue='Churn', data=df)
```

[20]: <Axes: xlabel='HasCrCard', ylabel='count'>



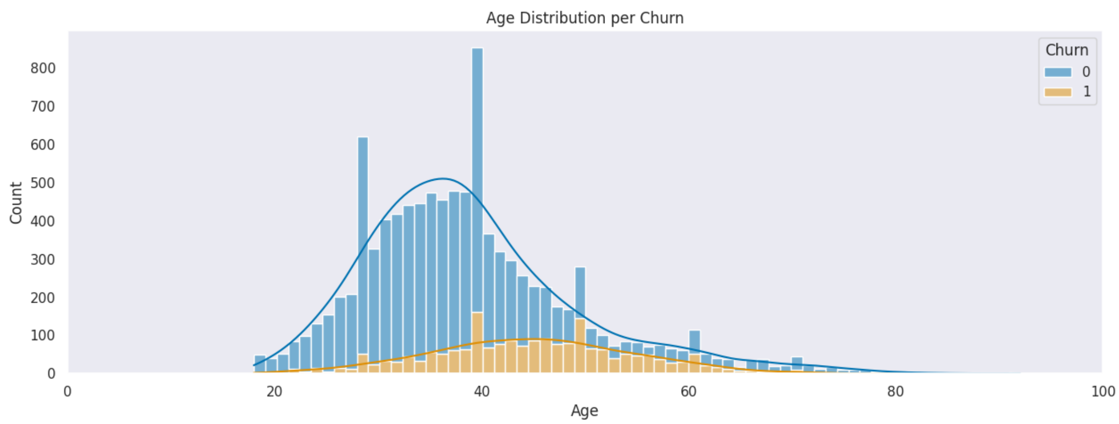
Majoity of the customers have credit cars i.e. nealy 70% of the customers have credit cards leaving 30% of the customers who do not have credit cards. Moreover, the number of customers leaving the bank are more whom have a credit card.

[21]:
```
plt.figure(figsize=(15,5))
sns.countplot(x='Complain',hue='Churn', data=df)
```

[21]: <Axes: xlabel='Complain', ylabel='count'>

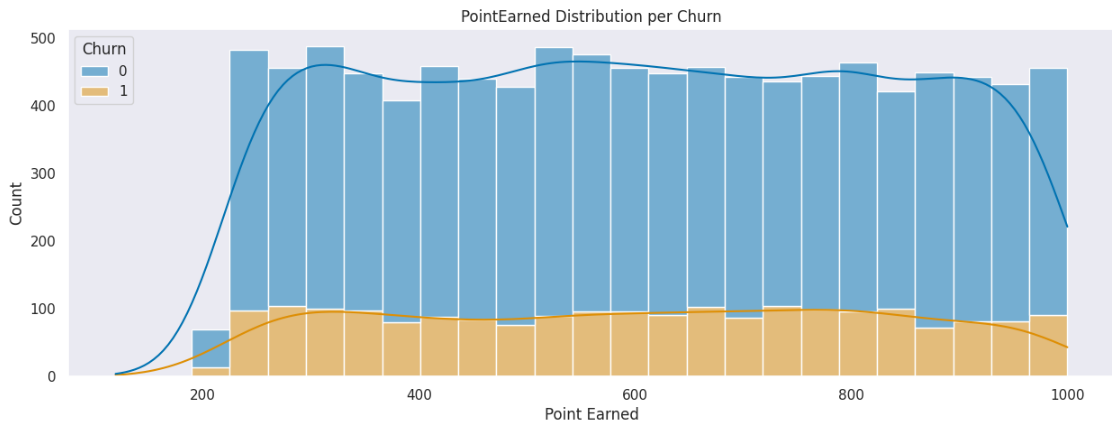
The graph above shows that the number of customers who complain is dominated by customers who have credit cards.

[22]:
```
plt.figure(figsize=(15, 5))
sns.histplot(data=df, x='Age', hue='Churn', multiple='stack',kde=True)
plt.title('Age Distribution per Churn')
plt.xlim(0,100)
plt.show()
```



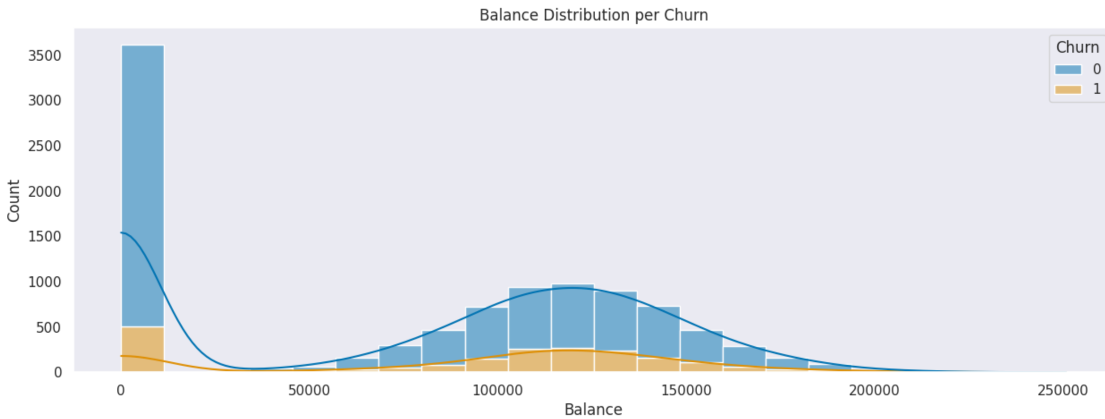
This histtogram visualizes the age distribution and the churn count of the customers. The majority of the customers are from age group 30-40 years old. However the customer churn count is highest for the customersof age 40 and 50. In addition to that customers from age group 20-25 years old count for the lowest churn count. Therefore, age plays a significant role in customer churn, where late adults are more likely to churn as compared to young adults with minimal churn count.

[23]:
```
plt.figure(figsize=(15, 5))
sns.histplot(data=df, x='Point Earned', hue='Churn', multiple='stack',kde=True)
plt.title('PointEarned Distribution per Churn')
plt.show()
```



The histogram above visualizes the distribution of points earned and the number of customer churn. The majority of customers who leave are higher around 450. However, yes churn tends to be lower than no.

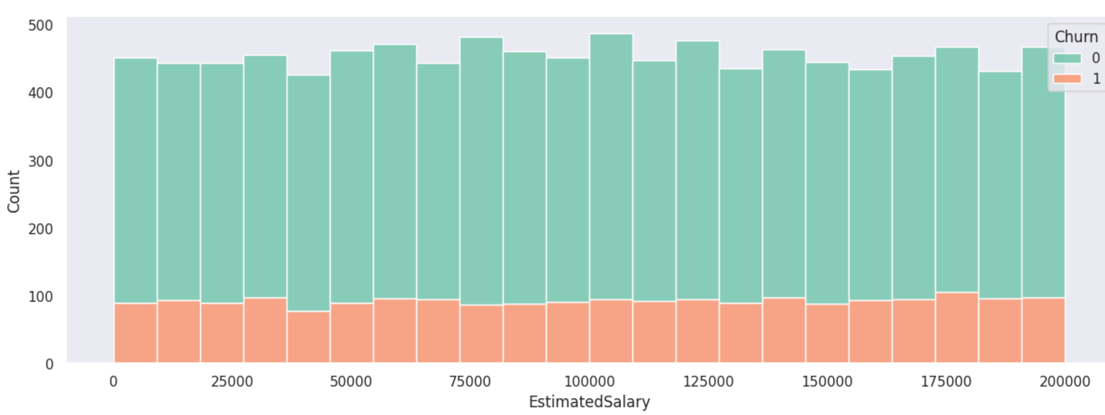
[24]:
```
plt.figure(figsize=(15, 5))
sns.histplot(data=df, x='Balance', hue='Churn', multiple='stack',kde=True)
plt.title('Balance Distribution per Churn')
plt.show()
```



A huge number of customers have zero bank balance which also resulted in them leaving the bank. However, customer having bank balance between 100000 to 150000 are more likely to leave the bank after the customers with zero bank balance.

[25]:
```
plt.figure(figsize=(15,5))
sns.
 ↪histplot(data=df,x='EstimatedSalary',hue='Churn',multiple='stack',palette='Set2')
```

[25]: <Axes: xlabel='EstimatedSalary', ylabel='Count'>



This graph shows the distribution of the estimated salary of the customers along with the churn count. On the whole the there is no definite pattern in the salary distribution of the customers who churned and who didn't. Therefore estimated salary is not a good predictor of churn.

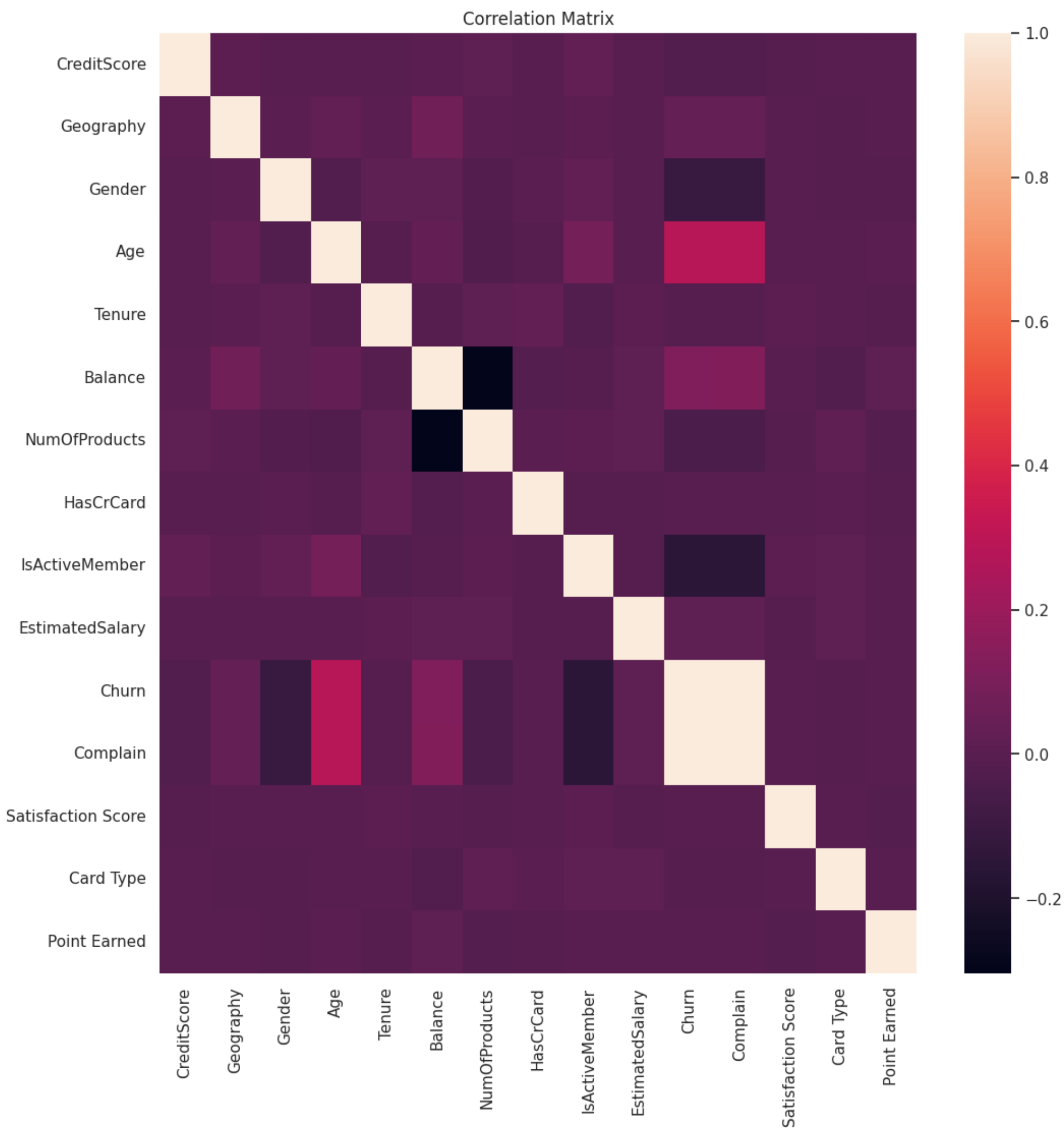
0.4 Data Preprocessing Part 2

[26]:
```
# label encoding
from sklearn.preprocessing import LabelEncoder

var = ['Geography', 'Gender', 'Card Type']
le = LabelEncoder()

for i in var:
    le.fit(df[i].unique())
    df[i]=le.transform(df[i])
    print(i,df[i].unique())
```

```
Geography [0 2 1]
Gender [0 1]
Card Type [0 1 3 2]
```

[27]:
```
#normalize the continuous variables
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
df[['CreditScore','Balance','EstimatedSalary']] = scaler.
 ↪fit_transform(df[['CreditScore','Balance','EstimatedSalary']])
```

[28]:
```
plt.figure(figsize=(12,12))
sns.heatmap(df.corr(),annot=False,cmap='rocket')
plt.title('Correlation Matrix')
plt.show()
```



There is no significant coorelation among the variables.So, I will proceed to model building.

[29]:
```
df.sample(5)
```

[29]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	\
1500	-0.212407	0	1	50	1	0.087538	1	
9506	0.325625	0	1	69	6	-1.225848	2	
5927	-0.760786	1	0	43	3	0.824668	1	
482	1.525851	0	1	37	8	-1.225848	3	
1739	0.667069	0	1	23	7	1.005525	2	

```
      HasCrCard  IsActiveMember  EstimatedSalary  Churn  Complain  \
1500          0               1        -0.634421      1         1
9506          0               1         0.860998      0         0
5927          0               0         0.435603      1         1
482           0               0         0.185941      0         0
1739          1               0        -0.609181      0         0

      Satisfaction Score  Card Type  Point Earned
1500                   1          1           912
9506                   2          2           547
5927                   3          3           839
482                    4          3           860
1739                   1          0           385
```

[30]:
```python
X = df.drop('Churn', axis=1)
y = df['Churn']
```

[31]:
```python
# train test split
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
```

For predicting the churn of customers, depending on the data of the customers, we will use the following models:

- Decision Tree Classifier
- Random Forest Classifier

0.4.1 Decision Tree Classifier

[32]:
```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV

#creating Decision Tree Classifer object
dtr = DecisionTreeClassifier()

#defining parameter range
params = {
    'max_depth': [4,8,12,16],
    'min_samples_leaf': [2,4,6,8],
    'min_samples_split': [2,4,6,8],
    'criterion': ['gini', 'entropy'],
    'random_state': [0,42]
}

#Creating grid search object
```

```
grid_dtr = GridSearchCV(dtr, param_grid=params, cv = 5, scoring = 'roc_auc',␣
↪n_jobs = -1, verbose = 2)

#Fitting the grid search object to the training data
grid_dtr.fit(X_train, y_train)

#Printing the best parameters
print('Best parameters found: ', grid_dtr.best_params_)
```

```
Fitting 5 folds for each of 256 candidates, totalling 1280 fits
Best parameters found:  {'criterion': 'gini', 'max_depth': 4,
'min_samples_leaf': 2, 'min_samples_split': 6, 'random_state': 0}
```

[33]:
```
dtr = DecisionTreeClassifier(criterion= 'gini', max_depth= 4, min_samples_leaf=␣
↪6, min_samples_split= 2, random_state= 0)

# fitting the model
dtr.fit(X_train, y_train)
```

[33]:
```
DecisionTreeClassifier(max_depth=4, min_samples_leaf=6, random_state=0)
```

0.4.2 Random Forest Classifier

[34]:
```
from sklearn.ensemble import RandomForestClassifier

#creating Random Forest Classifer object
rfc = RandomForestClassifier()

#defining parameter range
params = {
    'max_depth': [4,8,12,16],
    'min_samples_leaf': [2,4,6,8],
    'min_samples_split': [2,4,6,8],
    'criterion': ['gini', 'entropy'],
    'random_state': [0,42]
}

#Creating grid search object
grid_rfc = GridSearchCV(rfc, param_grid=params, cv = 5, scoring = 'roc_auc',␣
↪n_jobs = -1, verbose = 2)

#Fitting the grid search object to the training data
grid_rfc.fit(X_train, y_train)

#Printing the best parameters
print('Best parameters found: ', grid_rfc.best_params_)
```

```
Fitting 5 folds for each of 256 candidates, totalling 1280 fits
Best parameters found:  {'criterion': 'entropy', 'max_depth': 12,
'min_samples_leaf': 2, 'min_samples_split': 6, 'random_state': 42}
```

[35]:
```
rfc = RandomForestClassifier(criterion= 'gini', max_depth= 4, min_samples_leaf=␣
↪2, min_samples_split= 2, random_state= 0)

# fitting the model
rfc.fit(X_train, y_train)
```

[35]:
```
RandomForestClassifier(max_depth=4, min_samples_leaf=2, random_state=0)
```

predicting the customer churn usng dtr and rfc

[36]:
```
# training accuracy
print('training accuracy: ',dtr.score(X_train,y_train))

print()

# testing accuracy
print('testing accuracy: ', dtr.score(X_test,y_test))
```

```
training accuracy:  0.9985

testing accuracy:  0.999
```

[37]:
```
# decision tree classifier
dtr_pred = dtr.predict(X_test)
```

[38]:
```
#Training accuracy
print('Training accuracy: ', rfc.score(X_train, y_train))

print()

# testing accuracy
print('testing accuracy: ', rfc.score(X_test, y_test))
```

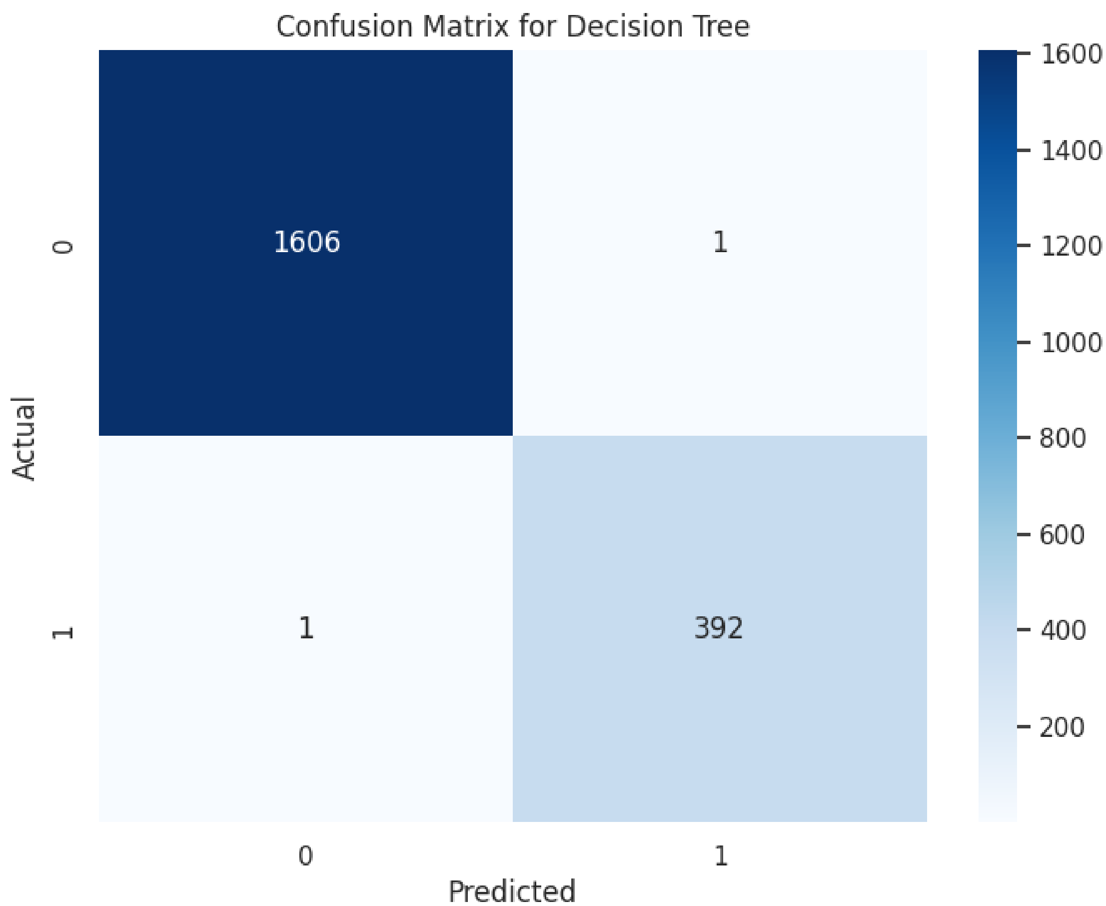
```
Training accuracy:  0.9985

testing accuracy:  0.999
```

[39]:
```
# random forest classifier
rfc_pred = rfc.predict(X_test)
```

0.5 Model Evaluation

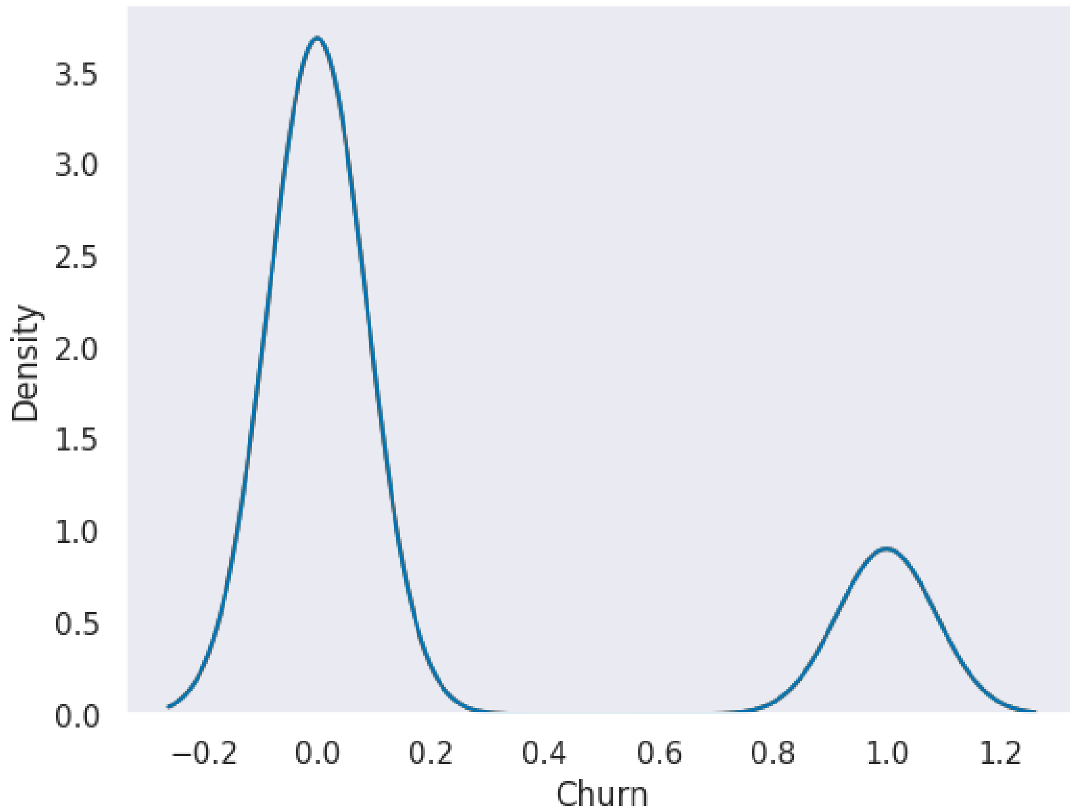
0.5.1 Decision Tree Classifier

[40]:
```
# confusion matrix heatmap
from sklearn.metrics import confusion_matrix

plt.figure(figsize=(8,6))
sns.heatmap(confusion_matrix(y_test,dtr_pred),annot=True,fmt='d',cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix for Decision Tree')
plt.show()
```



[41]:
```
# distribution plot
ax = sns.distplot(y_test, hist=False, color='r', label='Actual Value')
sns.distplot(dtr_pred, hist=False, color='b', label='Fitted Values' , ax=ax)
```

[41]: <Axes: xlabel='Churn', ylabel='Density'>



the resulting plots apparently overlap, that shows that the model is very accurate lol.

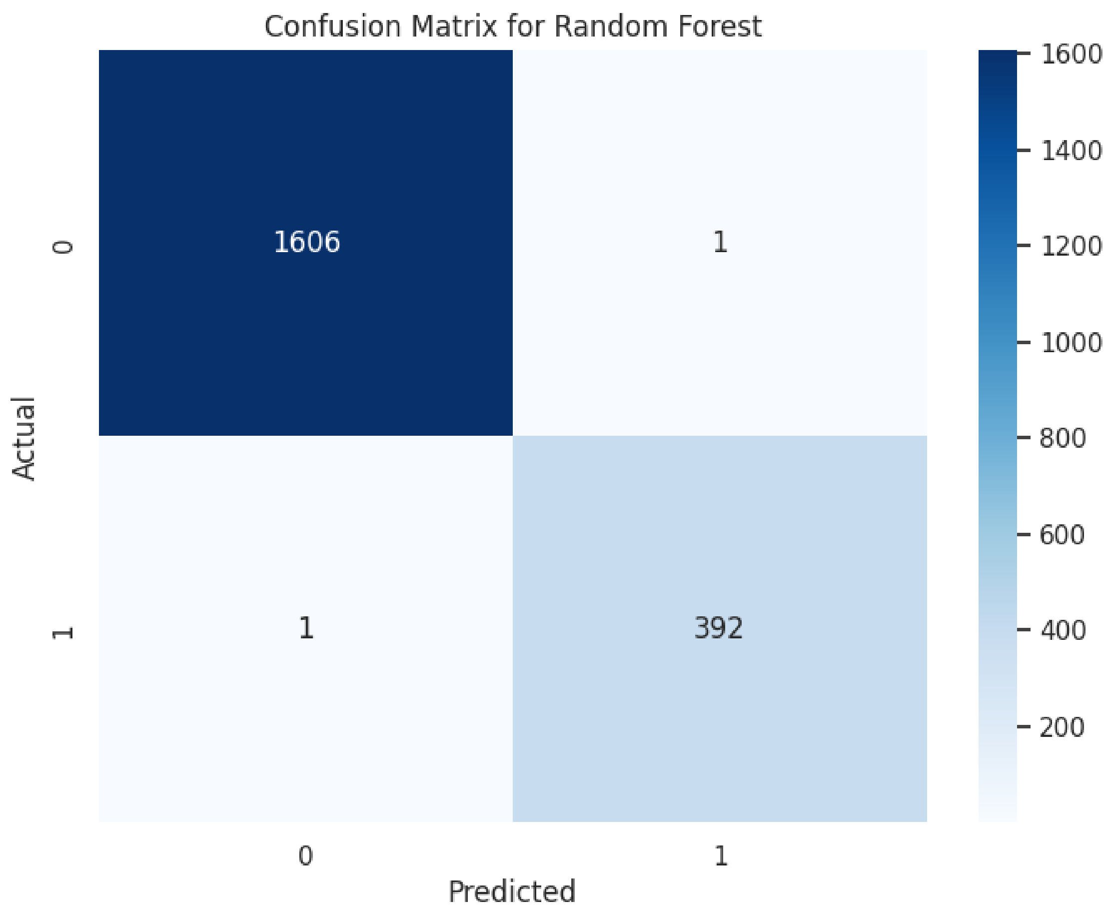
[42]:
```
# classification report
from sklearn.metrics import classification_report, accuracy_score,␣
↪mean_absolute_error, r2_score

print('Decision Tree Classifier: \n', classification_report(y_test, dtr_pred))
print('Accuracy Model Decision Tree Classifier : {:.2f}%'.
↪format(accuracy_score(y_test, dtr_pred) * 100))
print("Mean Absolute Error: ", mean_absolute_error(y_test, dtr_pred))
print("R2 Score: ", r2_score(y_test, dtr_pred))
```

```
Decision Tree Classifier:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00      1607
           1       1.00      1.00      1.00       393

    accuracy                           1.00      2000
   macro avg       1.00      1.00      1.00      2000
weighted avg       1.00      1.00      1.00      2000
```

```
Accuracy Model Decision Tree Classifier : 99.90%
Mean Absolute Error:  0.001
R2 Score:  0.9936663864042651
```

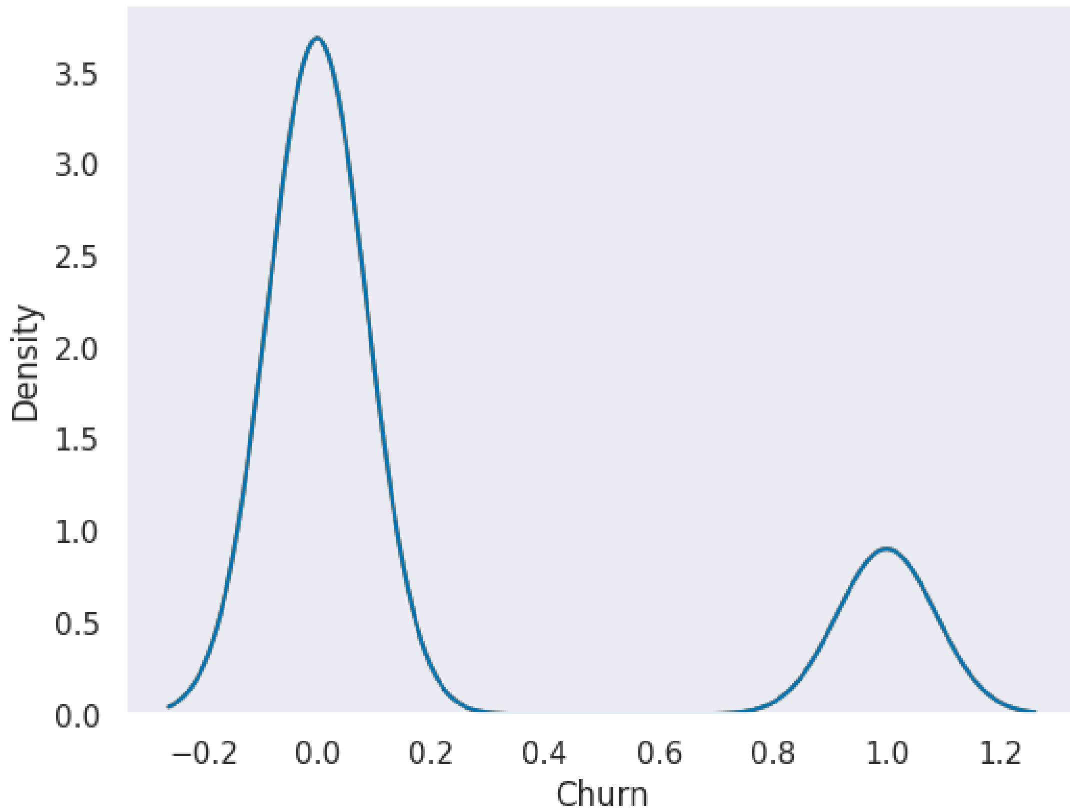
0.5.2 Random Forest Classifier

[43]:
```python
plt.figure(figsize=(8,6))
sns.heatmap(confusion_matrix(y_test,rfc_pred),annot=True,fmt='d',cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix for Random Forest')
plt.show()
```



[44]:
```python
# distribution plot
ax = sns.distplot(y_test, hist=False, color='r', label='Actual Value')
sns.distplot(rfc_pred, hist=False, color='b', label='Fitted Values' , ax=ax)
```

[44]:
```
<Axes: xlabel='Churn', ylabel='Density'>
```



The accuracy model almost same like decision tree classifier lmao

[45]:
```python
# classification report
print('Random Forest Classifier: \n', classification_report(y_test, rfc_pred))
print('Accuracy Model Random Forest Classifier : {:.2f}%'.
 ↪format(accuracy_score(y_test, rfc_pred) * 100))
print("Mean Absolute Error: ", mean_absolute_error(y_test, rfc_pred))
print("R2 Score: ", r2_score(y_test, rfc_pred))
```

```
Random Forest Classifier:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00      1607
           1       1.00      1.00      1.00       393

    accuracy                           1.00      2000
   macro avg       1.00      1.00      1.00      2000
weighted avg       1.00      1.00      1.00      2000

Accuracy Model Random Forest Classifier : 99.90%
Mean Absolute Error:  0.001
```

```
R2 Score:  0.9936663864042651
```

0.6 Conclusion

Both the models were hyperparameter tuned using GridSearchCV. Both the models have equal accuracy score its weird. You can use a method other than the one I used for GridSearchCV, maybe there will be a slight difference, but the hyperparameter tuning process is faster using the Decision Tree Classifier.