Bank Customer Churn Analytics

The scenario is to build a model to predict whether bank customers would churn or not. The churn rate, also known as the rate of attrition refers to the rate at which bank customers stop doing business with the bank.

Dataset details

The dataset in churn.csv contains the churn status of 10,000 customers, along with 14 attributes that include:

- **RowNumber**
- **CustomerId**
- **Surname**
- **CreditScore** - Customer's credit score
- **Geography** - Geographical location
- **Gender (male, female)**
- **Age**
- **Tenure** - number of years the person was a customer at that bank
- **Balance** - Account balance
- **EstimatedSalary** - Estimated salary
- **NumOfProducts** - Number of products that a customer purchased through the bank
- **HasCrCard** - Credit card status (whether or not a customer has a credit card)
- **IsActiveMember** - Active member status (whether or not the person is an active bank customer)
- **Exited** - Whether a customer has left the bank or not

Import Relevant Libraries

In [118…
```
# import relevant libraries

import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from collections import Counter
from imblearn.over_sampling import SMOTE
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
import lightgbm as lgb
from sklearn.metrics import accuracy_score, classification_report
from sklearn.model_selection import cross_validate, KFold
from scipy import stats
from scipy.stats import chi2_contingency
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

In [119…
```
# observing the dataset

df_cc_raw = pd.read_csv("churn.csv")
df_cc_raw.head(10)
```

Out[119]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Ba
0	1	15634602	Hargrave	619	France	Female	42	2	
1	2	15647311	Hill	608	Spain	Female	41	1	83
2	3	15619304	Onio	502	France	Female	42	8	1596
3	4	15701354	Boni	699	France	Female	39	1	
4	5	15737888	Mitchell	850	Spain	Female	43	2	125
5	6	15574012	Chu	645	Spain	Male	44	8	113
6	7	15592531	Bartlett	822	France	Male	50	7	
7	8	15656148	Obinna	376	Germany	Female	29	4	115
8	9	15792365	He	501	France	Male	44	4	142
9	10	15592389	H?	684	France	Male	27	2	134

In [120…
```
df_cc_raw.shape
```

Out[120]:
```
(10000, 14)
```

In [121…
```
df_cc_raw[df_cc_raw['Exited'] == 0].shape
```

Out[121]: (7963, 14)

In [122…
```
df_cc_raw[df_cc_raw['Exited'] == 1].shape
```

Out[122]: (2037, 14)

Only around 20% left the bank - there is a class imbalance ratio that needs to be dealt with. This will be dealt with under the Model Building section of this report using SMOTE.

Data Cleaning and Transformation

In [123…
```
# changing column names to more appropriate names
df_cc_raw.rename(columns = {'Geography':'Country'}, inplace=True)
df_cc_raw.head(1)
```

Out[123]:

	RowNumber	CustomerId	Surname	CreditScore	Country	Gender	Age	Tenure	Balanc
0	1	15634602	Hargrave	619	France	Female	42	2	0.

In [124…
```
# dropping duplicate rows
df_cc_raw.drop_duplicates(subset=['RowNumber', 'CustomerId'], inplace=True)
```

In [125…
```
# dropping RowNumber, CustomerId, Surname columns as they are irrelevant in
df_cc_raw.drop(columns=['RowNumber', 'CustomerId', 'Surname'], inplace=True)
df_cc_raw.shape
```

Out[125]: (10000, 11)

In [126…
```
# checking for NA values
df_cc_raw.isna().sum()
```

Out[126]:

	0
CreditScore	0
Country	0
Gender	0
Age	0
Tenure	0
Balance	0
NumOfProducts	0
HasCrCard	0
IsActiveMember	0
EstimatedSalary	0
Exited	0

dtype: int64

The columns do not have any rows with NA values. It would also be a good idea to check the type of data in each column to observe if there is anything peculiar.

In [127…

```
# observing type of data in each column
df_cc_raw.dtypes
```

Out[127]:

	0
CreditScore	int64
Country	object
Gender	object
Age	int64
Tenure	int64
Balance	float64
NumOfProducts	int64
HasCrCard	int64
IsActiveMember	int64
EstimatedSalary	float64
Exited	int64

dtype: object

All columns have the expected data type.

In [128…

```
# checking values/categories in categorical columns - will be useful later c
cat_col_array = ["Country", "Gender"]
for i in cat_col_array:
    print(df_cc_raw[i].unique())
```

```
['France' 'Spain' 'Germany']
['Female' 'Male']
```

Exploratory Data Analysis

In [129…

```
# creating an array for categorical variables
cat_cols = [col for col in df_cc_raw.columns if (df_cc_raw[col].nunique() <=
cat_cols
```

Out[129]: ['Country', 'Gender', 'NumOfProducts', 'HasCrCard', 'IsActiveMember']

In [130…

```
# creating an array for numerical variables
num_cols = [col for col in df_cc_raw.columns if col not in cat_cols and col
num_cols
```

Out[130]: ['CreditScore', 'Age', 'Tenure', 'Balance', 'EstimatedSalary']

In [131…

```
# observing descriptive statistics for the numerical columns
for col in num_cols:
    print(f'Descriptive Statistics for "{col}" : \n {df_cc_raw[col].describe
```

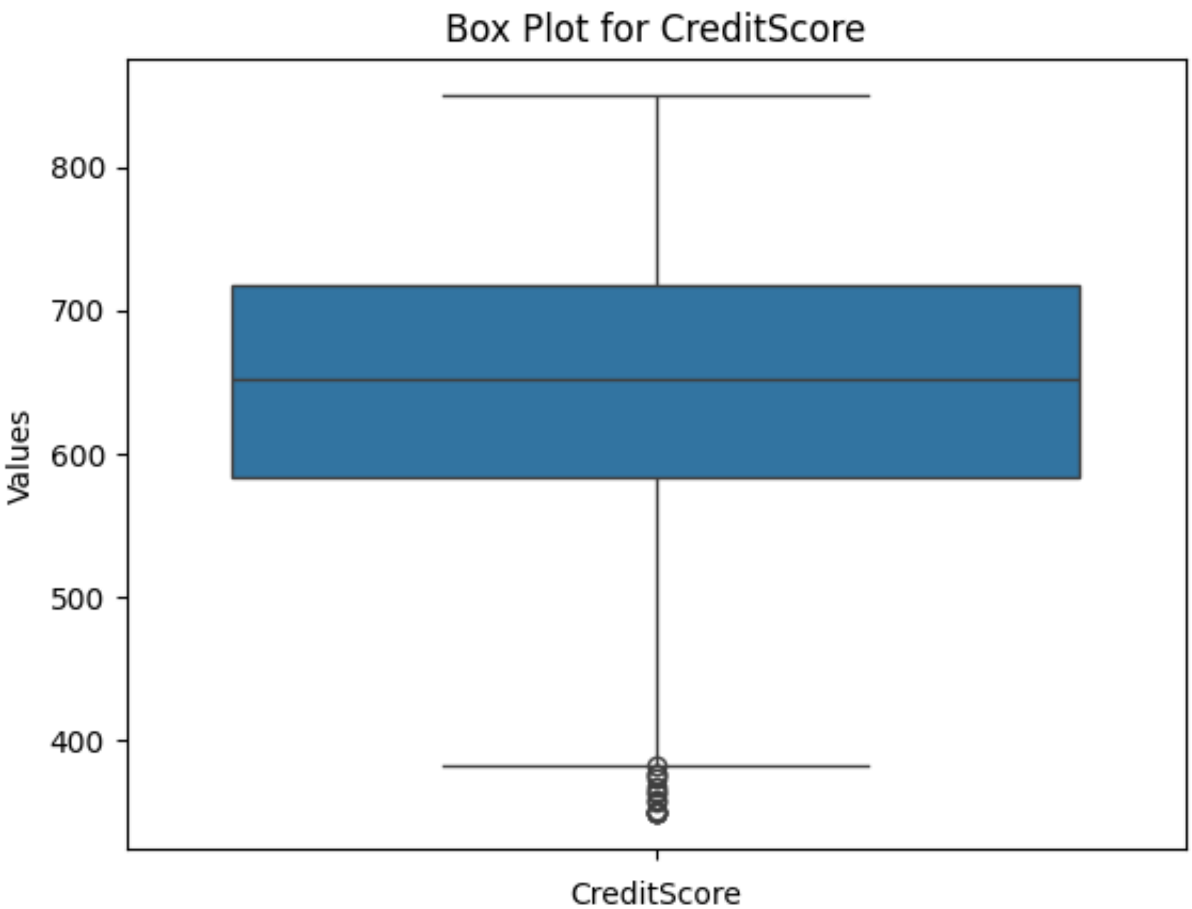
```
Descriptive Statistics for "CreditScore" :
 count    10000.000000
mean       650.528800
std         96.653299
min        350.000000
25%        584.000000
50%        652.000000
75%        718.000000
max        850.000000
Name: CreditScore, dtype: float64

Descriptive Statistics for "Age" :
 count    10000.000000
mean        38.921800
std         10.487806
min         18.000000
25%         32.000000
50%         37.000000
75%         44.000000
max         92.000000
Name: Age, dtype: float64

Descriptive Statistics for "Tenure" :
 count    10000.000000
mean         5.012800
std          2.892174
min          0.000000
25%          3.000000
50%          5.000000
75%          7.000000
max         10.000000
Name: Tenure, dtype: float64

Descriptive Statistics for "Balance" :
 count     10000.000000
mean      76485.889288
std       62397.405202
min           0.000000
25%           0.000000
50%       97198.540000
75%      127644.240000
max      250898.090000
Name: Balance, dtype: float64

Descriptive Statistics for "EstimatedSalary" :
 count     10000.000000
mean     100090.239881
std       57510.492818
min          11.580000
```

```
25%        51002.110000
50%       100193.915000
75%       149388.247500
max       199992.480000
Name: EstimatedSalary, dtype: float64
```

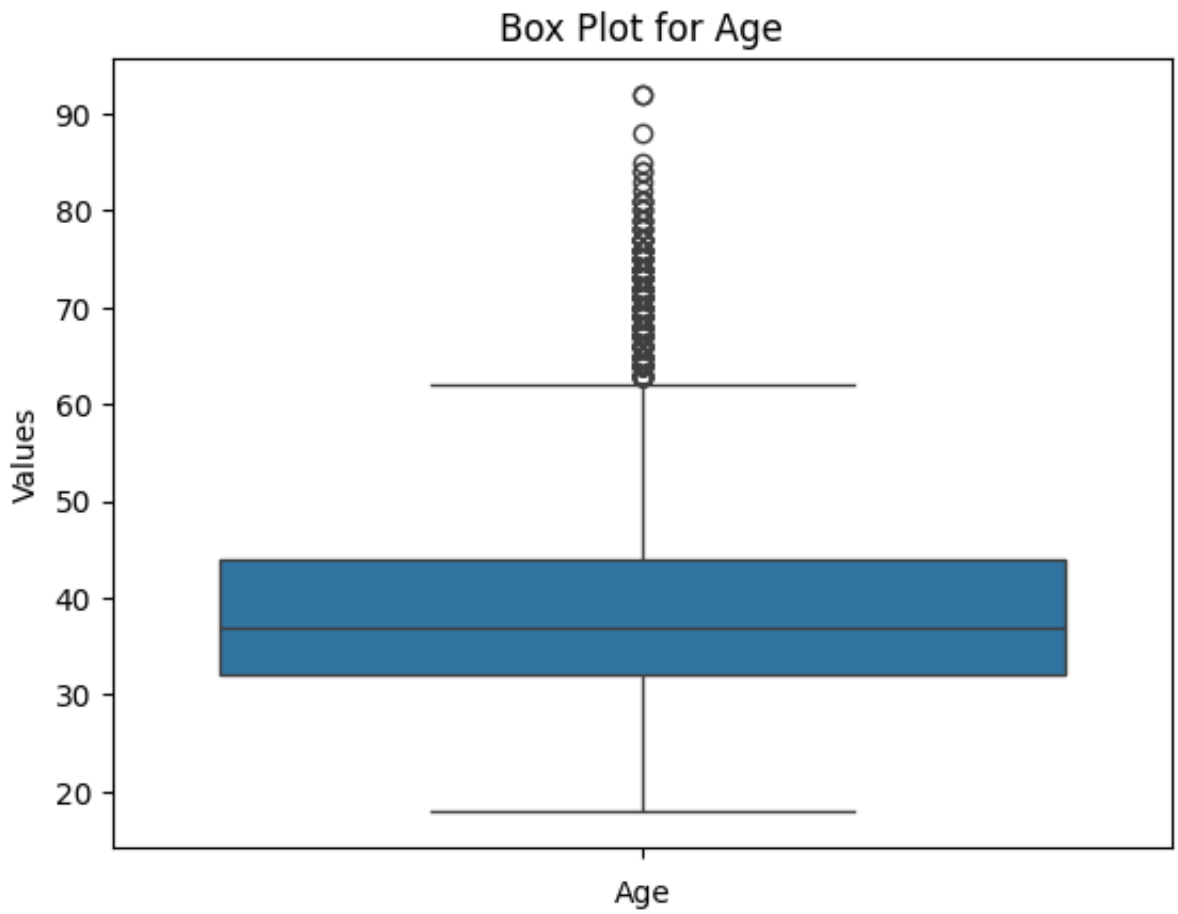
In [132…

```
for col in num_cols:
  print(f'Box Plot for "{col}": \n')
  sns.boxplot(data = df_cc_raw[col])
  plt.title(f"Box Plot for {col}")
  plt.xlabel(col)
  plt.ylabel("Values")
  plt.show()
```

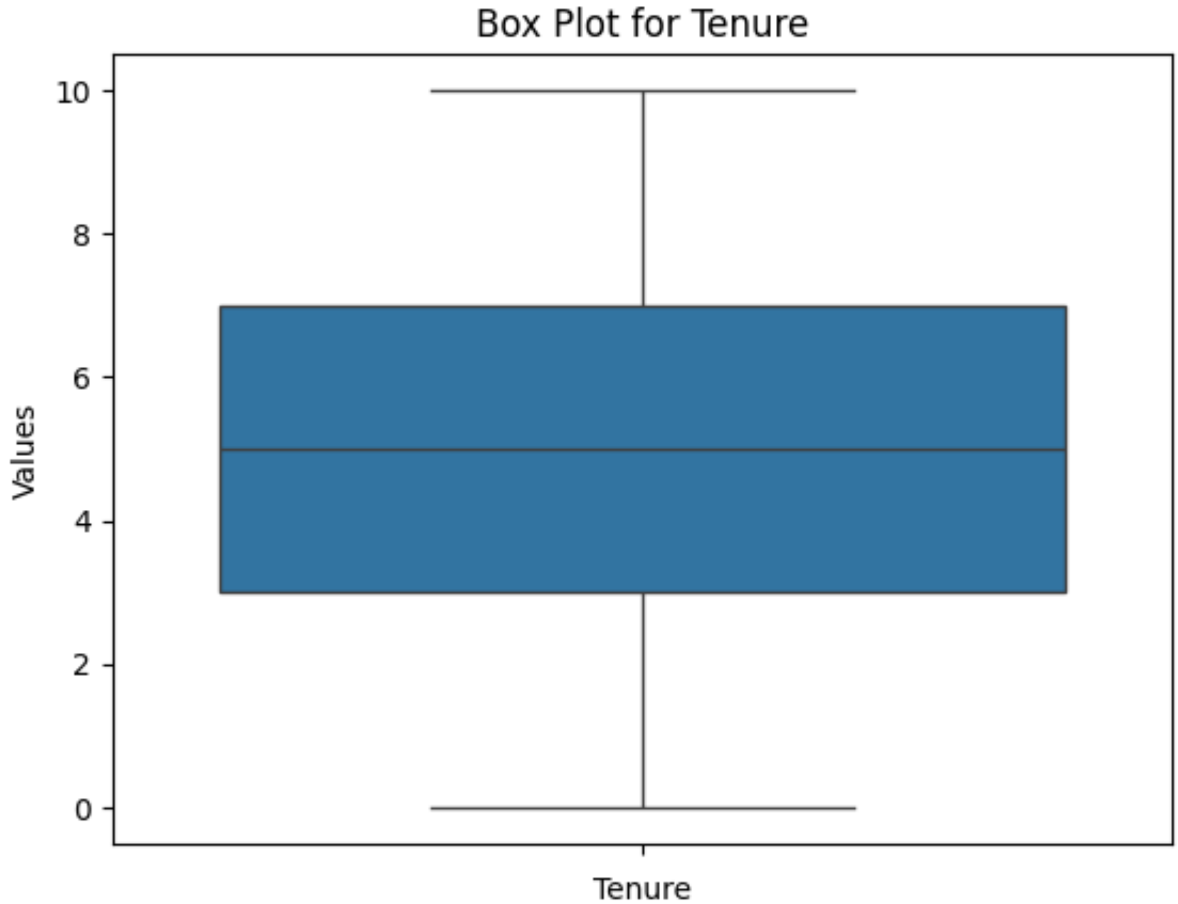
```
Box Plot for "CreditScore":
```



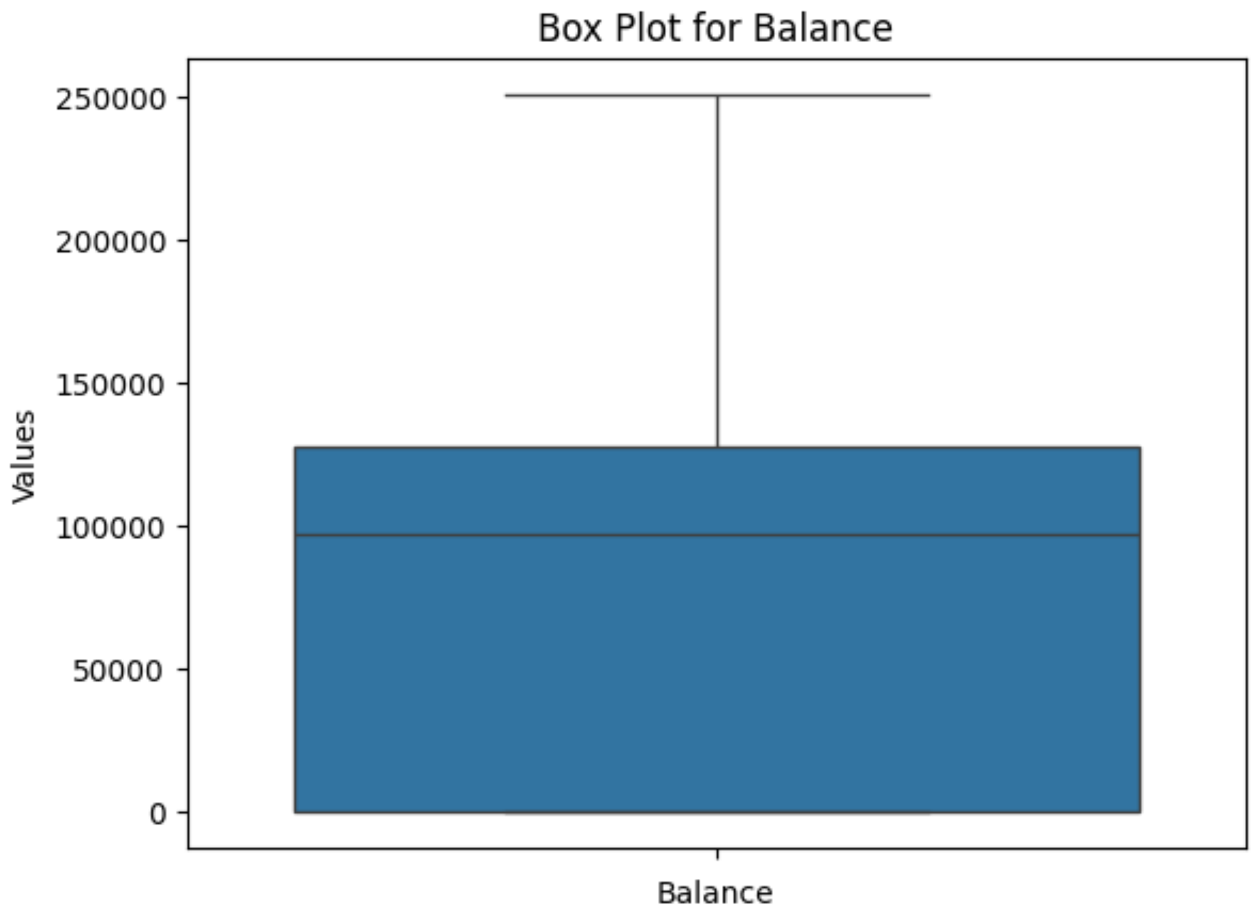

```
Box Plot for "Age":
```



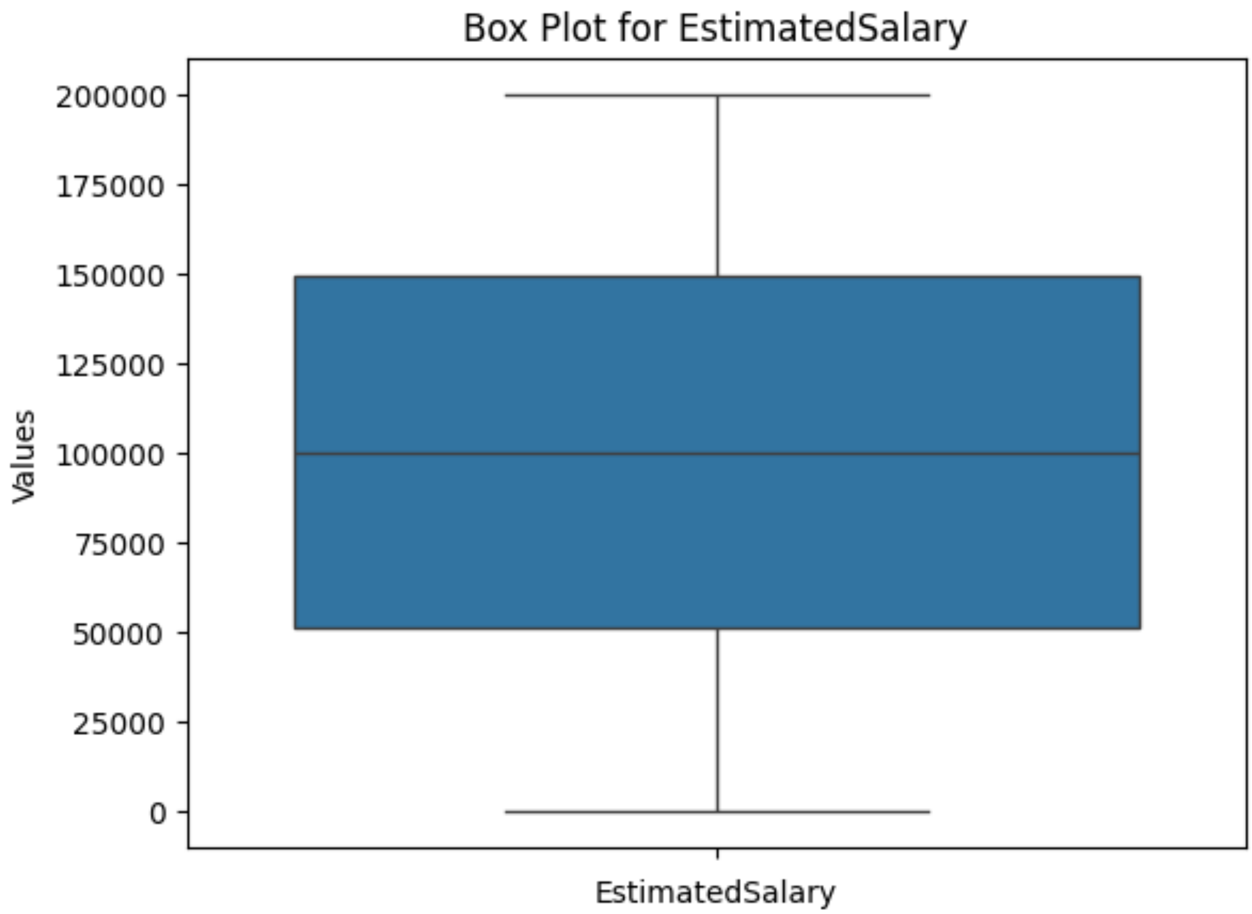

```
Box Plot for "Tenure":
```




```
Box Plot for "Balance":
```




```
Box Plot for "EstimatedSalary":
```

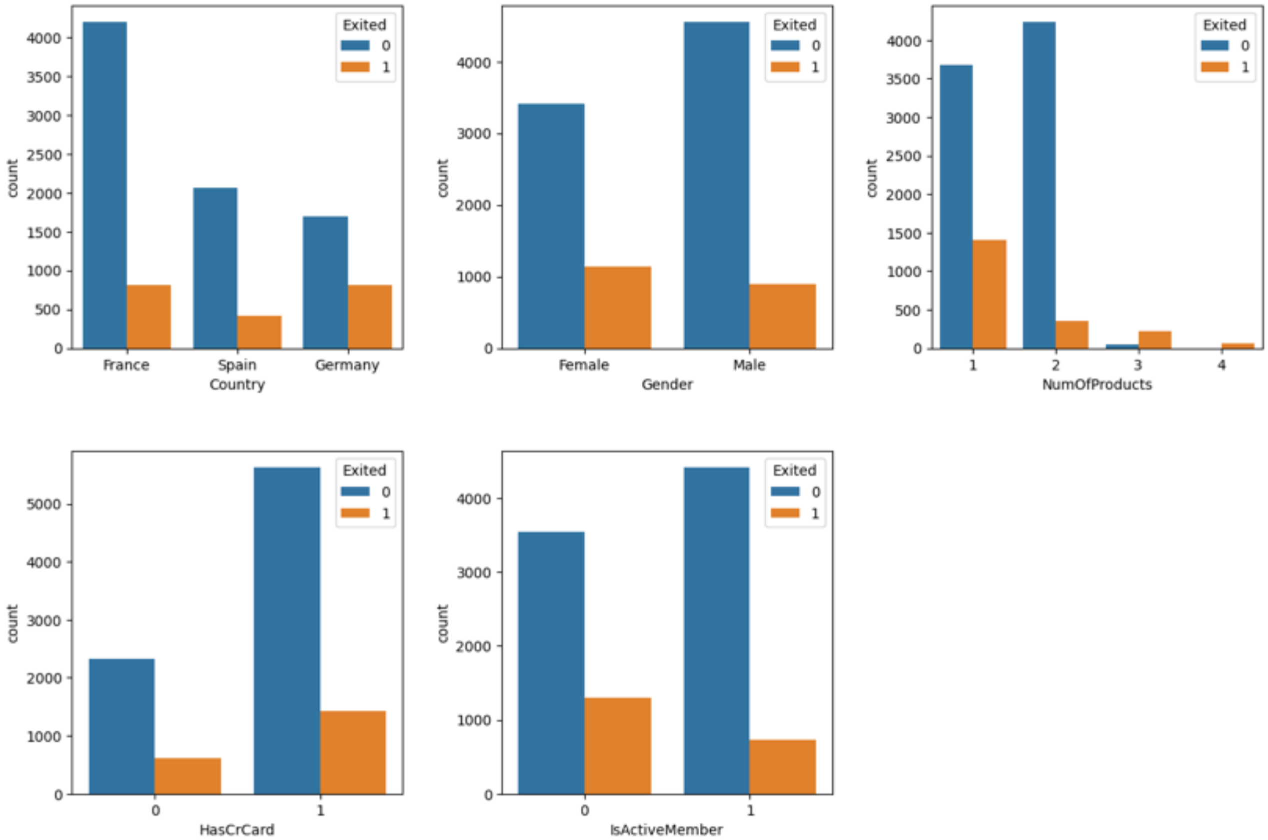


In [133…

```
# creating a function to plot categorical and numerical variables by attriti

def plotbytarget(df, array, function_name, hue):
    fig, axarr = plt.subplots(2, 3, figsize=(15, 10))  # Adjust the grid siz

    sns_function = getattr(sns, function_name)
    for index, col in enumerate(array):
        sns_function(x=col, hue=hue, data=df, ax=axarr[index // 3][index % 3

    fig.subplots_adjust(hspace=0.3, wspace=0.3)

    if len(cat_cols) < 6:
        for i in range(len(cat_cols), 6):
            fig.delaxes(axarr[i // 3][i % 3])
    plt.show()
```

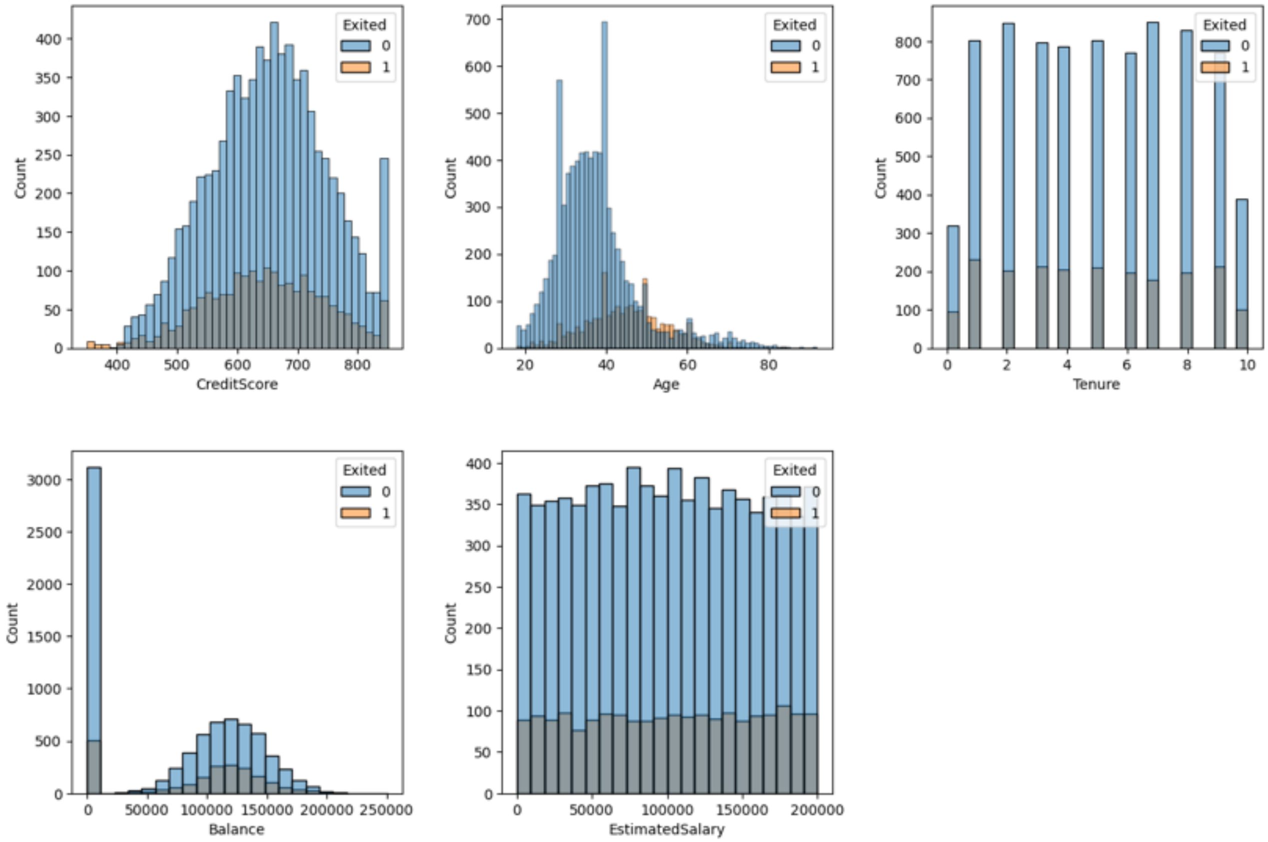
In [134…

```
# plotting categorical variables

plotbytarget(df_cc_raw, cat_cols, 'countplot', 'Exited')
```



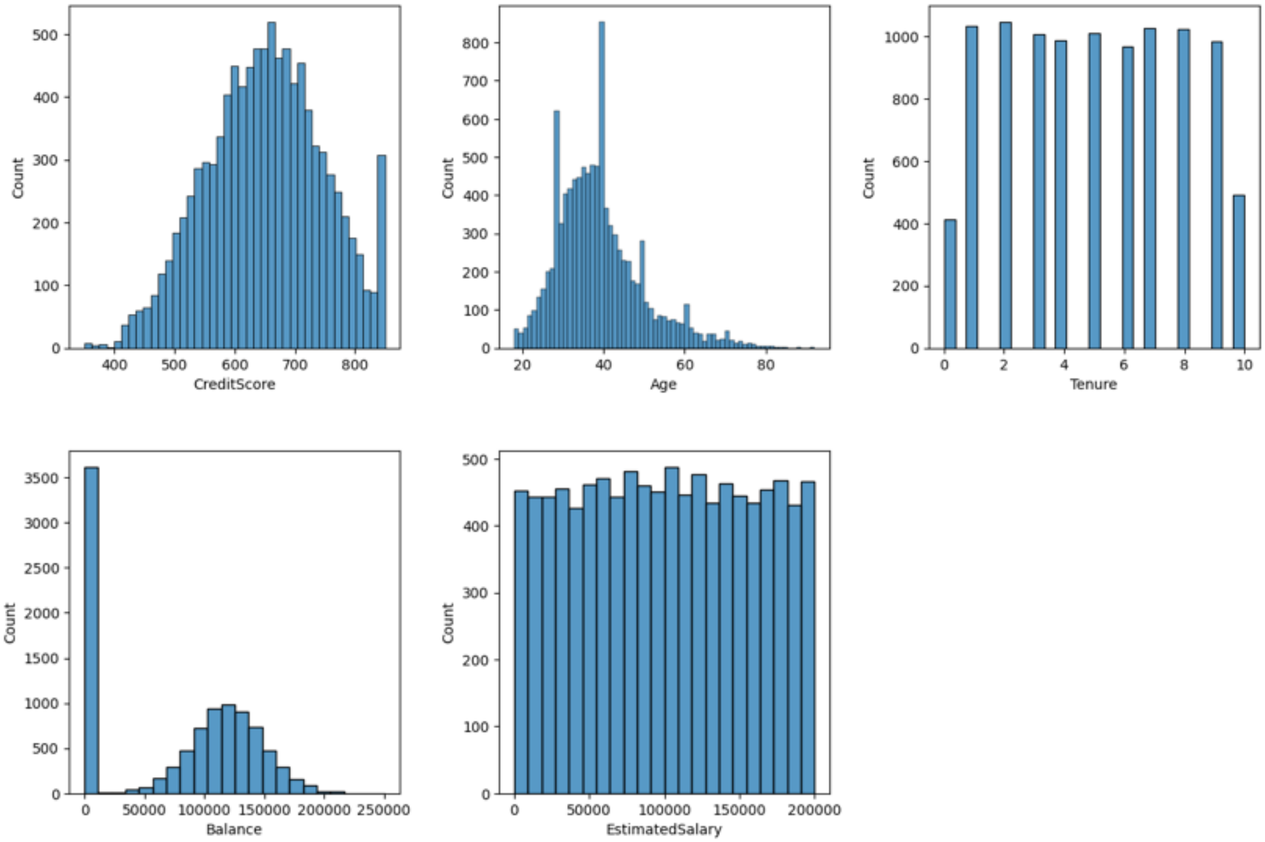
In [135…

```
# plotting numerical variables

plotbytarget(df_cc_raw, num_cols, 'histplot', 'Exited')
```



The above plots offer a view of the class imbalance in the dataset. As seen above, the observations for churned customers are far less than the observations for customers who have not churned.

In [136…
```
plotbytarget(df_cc_raw, num_cols, 'histplot', hue=None)
```



From the above data, it can be seen that there is a wide range of values. This increases complexity and may make it hard for the model to capture patterns effectively. In addition the following outlines problems in each variable:

- **CreditScore and Age**: The distributions are skewed and may have outliers
- **Balance and EstimatedSalary**: High variance
- **Tenure**: Raw tenure values can vary significantly based on age - makes age a confounding variable between tenure and target variable.

To deal with skewness, outliers, and variance, the data could be put into bins. This will also reduce the wide range of values observed into smaller distinct bins (extreme values are treated equally), which would allow the model to make clearer distinctions on how each bin affects the target variable.

To deal with the confounder in tenure, tenure values could be normalized based on age. A normalized value would provide a consistent scale that accounts for different age groups, making it easier for the model to interpret the individual effect of tenure.

The above changes except standardizing tenue will be made in feature engineering section of the "Model Building" part of this report.

In [137…

```
df_cc_raw.isna().sum()
```

Out[137]:

	0
CreditScore	0
Country	0
Gender	0
Age	0
Tenure	0
Balance	0
NumOfProducts	0
HasCrCard	0
IsActiveMember	0
EstimatedSalary	0
Exited	0

dtype: int64

In [138…

```
# performing one-hot encoding on the categorical variables
df_cc_raw_encoded = pd.get_dummies(df_cc_raw, columns=['Gender', 'Country'])
```

In [139…

```
df_cc_raw.isna().sum()
```

Out[139]:

	0
CreditScore	0
Country	0
Gender	0
Age	0
Tenure	0
Balance	0
NumOfProducts	0
HasCrCard	0
IsActiveMember	0
EstimatedSalary	0
Exited	0

dtype: int64

In [140…

```
df_cc = df_cc_raw_encoded
df_cc.head()
```

Out[140]:

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Esti
0	619	42	2	0.00	1	1	1	
1	608	41	1	83807.86	1	0	1	
2	502	42	8	159660.80	3	1	0	
3	699	39	1	0.00	2	0	0	
4	850	43	2	125510.82	1	1	1	

Testing feature importance using Hypothesis Testing

Among the 13 features in this dataset, there are a few features that intuitively stand out as significant factors to predicting attrition rate. The following section will use hypothesis testing to test the generalized implication of these factors on the attrition rate.

The first relationship to be tested is estimated salary. Does the estimated salary differ across customers that left and customers that stayed? A difference in means t-test will be used to answer this question.

The reason a t-test is used is because the population mean is unknown.

Hypothesis:

$$H_0 : \mu_a = \mu_n$$

$$H_1 : \mu_a \neq \mu_n$$

Where μ_a is the average salary for attrition customers and μ_n is the average salary for non-attrition customers.

In [141…

```
# comparing the sample means from dataset

df_exited = df_cc[df_cc['Exited']==0]
df_n_exited = df_cc[df_cc['Exited']==1]
mu_a = df_exited['EstimatedSalary'].mean()
mu_n = df_n_exited['EstimatedSalary'].mean()
print(f'The attrition mean is: {mu_a} \nThe non-attrition mean is: {mu_n}')
```

```
The attrition mean is: 99738.39177194524
The non-attrition mean is: 101465.67753068237
```

The mean estimated salary does not appear to be significantly different. Let us test if this conclusion can be generalized:

In [142…

```
t_stat, p_val = stats.ttest_ind(df_exited['EstimatedSalary'], df_n_exited['E
print(f't_stat: {t_stat} \np-value: {p_val}')

alpha=0.05
if p_val < alpha:
    print("Reject the null hypothesis: There is a significant difference bet
else:
    print("Fail to reject the null hypothesis: There is no significant diffe
```

```
t_stat: -1.209653638019264
p-value: 0.22644042802223352
Fail to reject the null hypothesis: There is no significant difference betwe
en estimated salaries of exited customers and non-exited customers.
```

Testing at a 0.05 level of significance (α):

The p-value > α, so I fail to reject null and conclude that there is not enough evidence to suggest that there is a significant difference between those estimated salaries of customers who left versus those that did not.

Another interesting question that can be explored is: does the country of origin determine difference in attrition?

Since this question is testing the relationship between two categorical variables, the chi-square test of independence will be used to make a generalized claim.

H_0 : The country of origin is independent of whether the customer leaves (i.e., there is no association between the two variables).

H_1 : The country of origin is not independent of whether the customer leaves (i.e., there is an association between the two variables).

In [143…

```
# creating a contingency table
contingency_table = pd.crosstab(df_cc_raw['Country'], df_cc_raw['Exited'])
```

In [144…

```
# performing the chi-square test
chi2, p, dof, expected = chi2_contingency(contingency_table)

print(f'Chi-Square statistic: {chi2}')
print(f'P-value: {p}')
print(f'Degrees of freedom: {dof}')
print('Expected frequencies:')
print(expected)


alpha = 0.05
if p < alpha:
    print("Reject the null hypothesis: There is a significant association be
else:
    print("Fail to reject the null hypothesis: There is no significant assoc
```

```
Chi-Square statistic: 301.25533682434536
P-value: 3.8303176053541544e-66
Degrees of freedom: 2
Expected frequencies:
[[3992.6482 1021.3518]
 [1997.9167  511.0833]
 [1972.4351  504.5649]]
Reject the null hypothesis: There is a significant association between count
ry of origin and customer exit.
```

Findings from EDA:

- Most of the customers are from France. Spain has the lowest churn rate, compared to France and Germany. Additionally, country of origin has a significant impact on customer exit.
- Most customers have credit cards
- Most numerical continuous columns do not have any outliers, with the exception of age and creditscore. Albeit unlikley, these values are still possible and should be considered in the data - therefore, they will not be defined as outliers
- Some customers are both over the age of 60 and have credit scores below 400. However, they can't be considered as outliers as albeit unlikely, these occurences are still possible
- Very few customers have more than two bank products
- Inactive customers have a higher churn rate
- Gender and tenure years have little impact on a customer's decision to close a bank account
- Estimated salary has little to no impact on a customer's decision to close a bank account

Model building to predict customer exit

In [145…

```
# setting seed to ensure consistency
SEED = 123
```

In [146…

```
# creating training and testing data
X = df_cc.drop(columns='Exited', axis=1)
y = df_cc['Exited']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, ra
```

In [147…

```
# applying SMOTE to generate synthetic observations and remedy class imbalan
sm = SMOTE(random_state=SEED)
X_train_res, y_train_res = sm.fit_resample(X_train, y_train)
```

In [148…

```
# standardizing tenure
X_train_res['normalized_tenure'] = X_train_res['Tenure']/X_train_res['Age']

# creating bins for relevant columns
X_train_res['cred_score_binned'] = pd.qcut(X_train_res['CreditScore'], 6, la
X_train_res['age_binned'] = pd.qcut(X_train_res['Age'], 8, labels=[1,2,3,4,5
X_train_res['est_salary_binned'] = pd.qcut(X_train_res['EstimatedSalary'], 1
```

The 'Balance' variable needs to be treated differently. As observed in the above graph, there are a large number of customers with 0 balance. This creates heavy skew in the data. Hence, if balance were binned like the other variables, the edges of the first two bins would be 0, which is incorrect. This problem can be solved by using the "rank" function and then creating bins. This is shown below:

In [149…
```
X_train_res['balance_binned'] = pd.qcut(X_train_res['Balance'].rank(method="
```

In [150…
```
# checking for NaN values as logistic regression does not fit NaN values
X_train_res.isna().sum()
```

Out[150]:

	0
CreditScore	0
Age	0
Tenure	0
Balance	0
NumOfProducts	0
HasCrCard	0
IsActiveMember	0
EstimatedSalary	0
Gender_Female	0
Gender_Male	0
Country_France	0
Country_Germany	0
Country_Spain	0
normalized_tenure	0
cred_score_binned	0
age_binned	0
est_salary_binned	0
balance_binned	0

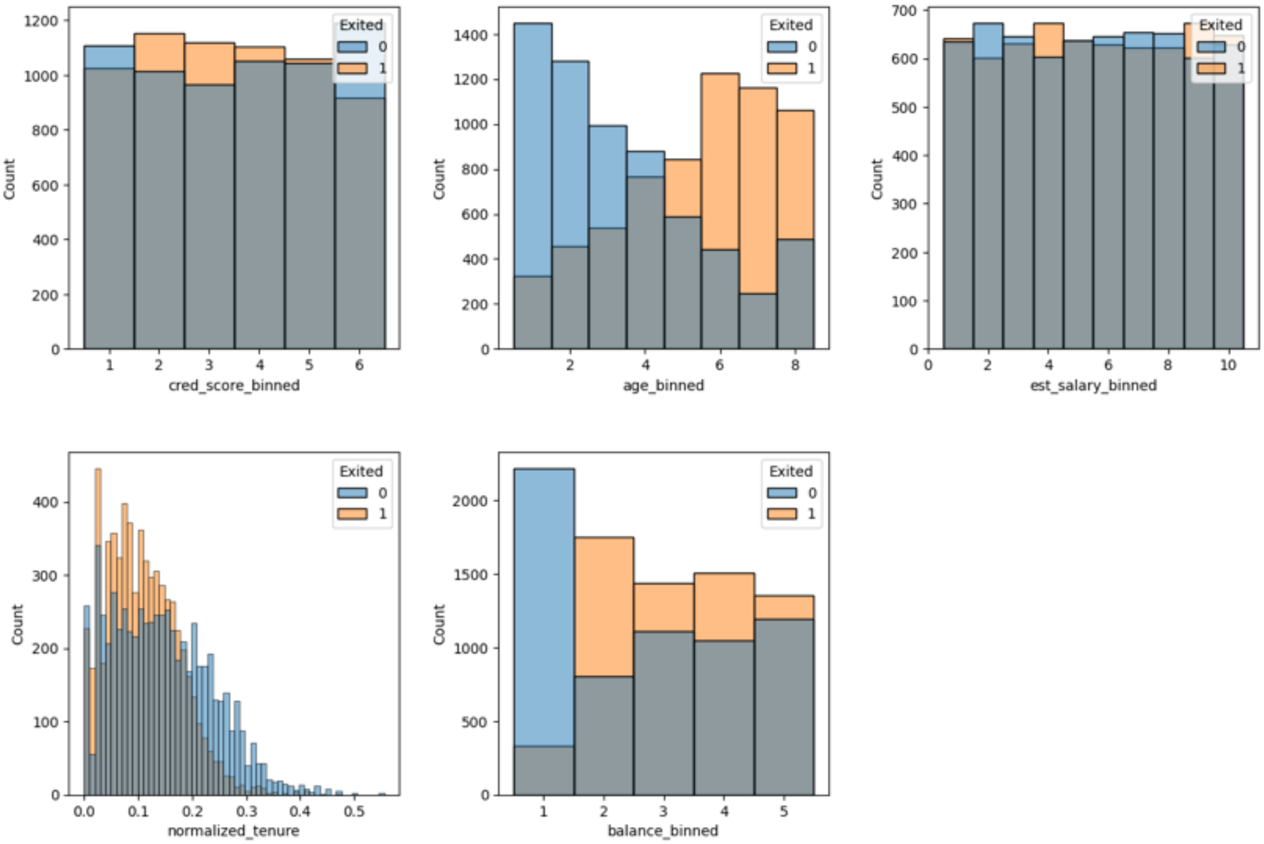
dtype: int64

In [151…
```
# checking shape to ensure training data is correctly formatted
print(f'{X_train_res.shape}, {y_train_res.shape}')
```

```
(12754, 18), (12754,)
```

In [152…

```
train = pd.concat([X_train_res, y_train_res], axis=1)

# plotting the numerical columns to observe bins and synthetic observations
new_num_cols = ['cred_score_binned', 'age_binned', 'est_salary_binned', 'nor
plotbytarget(train, new_num_cols, 'histplot', 'Exited')
```



In order to make predictions using the model, the feature engineered columns need to be present in the **X_test** set as well. This is done below:

In [153…

```
# standardizing tenure
X_test['normalized_tenure'] = X_test['Tenure']/X_test['Age']

# creating bins for relevant columns
X_test['cred_score_binned'] = pd.qcut(X_test['CreditScore'], 6, labels=[1,2,
X_test['age_binned'] = pd.qcut(X_test['Age'], 8, labels=[1,2,3,4,5,6,7,8])
X_test['est_salary_binned'] = pd.qcut(X_test['EstimatedSalary'], 10, labels=
X_test['balance_binned'] = pd.qcut(X_test['Balance'].rank(method="first"), 5
```

In [154…
```
# fitting the logistic regression and random forest models

log_model = LogisticRegression(max_iter=1000)
rf1_model = RandomForestClassifier(max_depth=4, max_features=4, min_samples_
rf2_model = RandomForestClassifier(max_depth=8, max_features=6, min_samples_
lgbm_model = lgb.LGBMClassifier(
    learning_rate=0.7,
    max_delta_step=2,
    n_estimators=100,
    max_depth=10,
    objective='binary',
    random_state=SEED,
    verbose=-1)
```

In [155…
```
# performing cross validation to calculate mean scores and select best model

kf = KFold(n_splits=5, shuffle=True, random_state=42) # defining number of s

# listing valuation metrics
scoring = ['accuracy', 'precision', 'recall', 'roc_auc']

log_cv = cross_validate(log_model, X_train_res, y_train_res, cv=kf, scoring=
rf1_cv = cross_validate(rf1_model, X_train_res, y_train_res, cv=kf, scoring=
rf2_cv = cross_validate(rf2_model, X_train_res, y_train_res, cv=kf, scoring=
lgbm_cv = cross_validate(lgbm_model, X_train_res, y_train_res, cv=kf, scorin

log_mean_scores = {i: np.mean(log_cv[f'test_{i}']) for i in scoring}
rf1_mean_scores = {i: np.mean(rf1_cv[f'test_{i}']) for i in scoring}
rf2_mean_scores = {i: np.mean(rf2_cv[f'test_{i}']) for i in scoring}
lgbm_mean_scores = {i: np.mean(lgbm_cv[f'test_{i}']) for i in scoring}

'''
rf_cv is a dictionary and rf_cv[i] accesses the value for every ith
key in rf_cv
'''

print(f"Logistic Regression Mean Scores:")
for i in log_mean_scores:
    print(f'{i}:{log_mean_scores[i]}')

print(f"\nRandom Forest Model 1 Scores:")
for i in rf1_mean_scores:
    print(f'{i}:{rf1_mean_scores[i]}')

print(f"\nRandom Forest Model 2 Scores:")
for i in rf2_mean_scores:
    print(f'{i}:{rf2_mean_scores[i]}')

print(f"\nLightGBM Model Mean Scores:")
for i in lgbm_mean_scores:
    print(f'{i}:{lgbm_mean_scores[i]}')
```

```
Logistic Regression Mean Scores:
accuracy:0.6980601225201959
precision:0.6947006855589353
recall:0.70777885950577
roc_auc:0.755554366173925

Random Forest Model 1 Scores:
accuracy:0.8239769102466544
precision:0.8365023863600067
recall:0.8054712169975549
roc_auc:0.9037947076386151

Random Forest Model 2 Scores:
accuracy:0.8689036978962499
precision:0.8856852710379588
recall:0.8470963806072598
roc_auc:0.9417889045724417

LightGBM Model Mean Scores:
accuracy:0.8848205317407245
precision:0.8976099252821923
recall:0.8687275567480477
roc_auc:0.9503031860538812
```

In [156…

```python
# printing the cross_validate dictionary and the mean_score dictionaries to
# that I can define the compare_models function in the next cell

print(f'rf1_cv : {rf1_cv} \nlog_mean_scores : {log_mean_scores}')
```

```
rf1_cv : {'fit_time': array([0.84578705, 0.75356531, 0.73636627, 0.77394843,
0.8079555 ]), 'score_time': array([0.07396078, 0.06918955, 0.07065654, 0.071
316  , 0.0692153 ]), 'test_accuracy': array([0.82124657, 0.82124657, 0.82516
66 , 0.82673461, 0.8254902 ]), 'train_accuracy': array([0.82897187, 0.827599
73, 0.82867784, 0.83063805, 0.82751862]), 'test_precision': array([0.8403565
6, 0.8369028 , 0.8229082 , 0.84659557, 0.83574879]), 'train_precision': arra
y([0.84068627, 0.83887313, 0.8419459 , 0.84545828, 0.84256979]), 'test_recal
l': array([0.80015432, 0.79748823, 0.8162772 , 0.8018648 , 0.81157154]), 'tr
ain_recall': array([0.81007676, 0.81109151, 0.81211059, 0.80825147, 0.805217
73]), 'test_roc_auc': array([0.90218478, 0.90435479, 0.90622036, 0.9050052 ,
0.90120841]), 'train_roc_auc': array([0.90991792, 0.90692968, 0.90661943, 0.
90648807, 0.90763901])}
log_mean_scores : {'accuracy': 0.6980601225201959, 'precision': 0.6947006855
589353, 'recall': 0.70777885950577, 'roc_auc': 0.755554366173925}
```

In [157…

```
# creating function to determine best model for each valuation metric
def compare_models(scores1, scores2, scores3, scores4, model_names):
    metrics = list(scores1.keys())
    for i in metrics:
        print(f"\nComparison of {i}:")
        print(f"{model_names[0]}: {scores1[i]}")
        print(f"{model_names[1]}: {scores2[i]}")
        print(f"{model_names[2]}: {scores3[i]}")
        print(f"{model_names[3]}: {scores4[i]}")
        best_model = max((scores1[i], model_names[0]), (scores2[i], model_na
                         (scores4[i], model_names[3]))
        print(f"Best model for {i}: {best_model[1]} with score {best_model[0

compare_models(log_mean_scores, rf1_mean_scores, rf2_mean_scores, lgbm_mean_
```

```
Comparison of accuracy:
Logistic Regression: 0.6980601225201959
Random Forest 1: 0.8239769102466544
Random Forest 2: 0.8689036978962499
LightGBM: 0.8848205317407245
Best model for accuracy: LightGBM with score 0.8848205317407245

Comparison of precision:
Logistic Regression: 0.6947006855589353
Random Forest 1: 0.8365023863600067
Random Forest 2: 0.8856852710379588
LightGBM: 0.8976099252821923
Best model for precision: LightGBM with score 0.8976099252821923

Comparison of recall:
Logistic Regression: 0.70777885950577
Random Forest 1: 0.8054712169975549
Random Forest 2: 0.8470963806072598
LightGBM: 0.8687275567480477
Best model for recall: LightGBM with score 0.8687275567480477

Comparison of roc_auc:
Logistic Regression: 0.755554366173925
Random Forest 1: 0.9037947076386151
Random Forest 2: 0.9417889045724417
LightGBM: 0.9503031860538812
Best model for roc_auc: LightGBM with score 0.9503031860538812
```

As observed from the above, the best model for every valuation metric is the LightGBM model, with an accuracy of 88.7%. This means that the model identifies 88.7% of churned customers accurately.

A more detailed account of the trade-off between accuracy and precision and why it may be important for a firm is given below after visualizing the confusion matrix.

In [160…

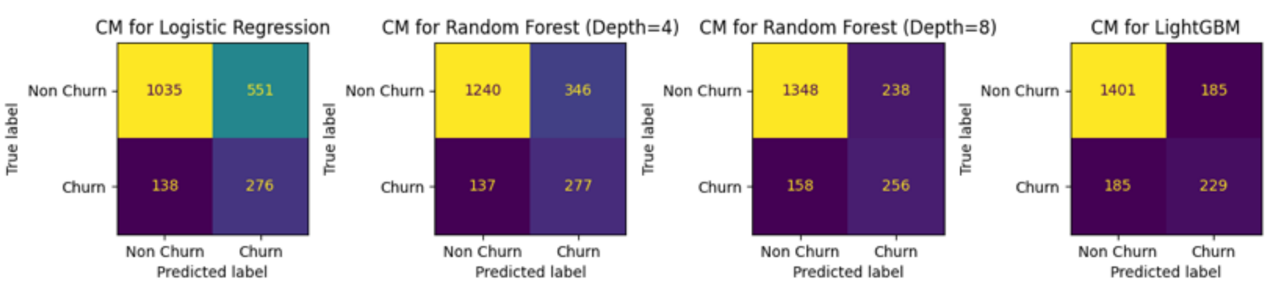
```
models_dict = {"Logistic Regression":log_model,
               "Random Forest (Depth=4)":rf1_model,
               "Random Forest (Depth=8)":rf2_model,
               "LightGBM":lgbm_model}
```

In [162…

```
'''
Comparing values predicted by the models to the values provided by the datas
the original models were trained using the cross-validate function which doe
cannot be used for predictions.
'''
def plot_confusion_matrix(models_dict, X_test=X_test, y_test=y_test):
  num_models = len(models_dict)

  # creating subplots for clean visualization of confusion matrix
  fig, axs = plt.subplots(1, num_models, figsize=(3*num_models, 3))

  # re-traning each model to predict values & plotting confusion matrix
  for idx, (model_name, model) in enumerate(models_dict.items()):
    model.fit(X_train_res, y_train_res)
    y_pred = model.predict(X_test)

    # plotting confusion matrix
    conf_matrix = confusion_matrix(y_test, y_pred)

    # displaying confusion matrix
    ConfusionMatrixDisplay(confusion_matrix=conf_matrix, display_labels=['Nc

    axs[idx].set_title(f'CM for {model_name}')

  plt.tight_layout()
  plt.show()
```

In [163…

```
plot_confusion_matrix(models_dict)
```



Logistic Regression

- **True negatives:** 1035
- **True positives:** 276
- **False negatives:** 138
- **False positives:** 551
  - Accuracy: 0.66
  - Precision: 0.33

Random Forest (depth = 4)

- **True negatives:** 1240
- **True positives:** 277
- **False negatives:** 137
- **False positives:** 346
  - Accuracy: 0.76
  - Precision: 0.44

Random Forest (depth = 8)

- **True negatives:** 1348
- **True positives:** 256
- **False negatives:** 158
- **False positives:** 238
  - Accuracy: 0.81
  - Precision: 0.0.52

LightGBM

- **True negatives:** 1401
- **True positives:** 229
- **False negatives:** 185

- **False positives:** 185
    - Accuracy: 0.82
    - Precision: 0.56

Key Takeaways

- Logistic Regression model has lowest precision - hence it misclassifies numerous non-churners as churned customers
- LightGBM has the best precision at 55.3%, which means that more than half the positive predictions are correct
- LightGBM provides the best balance of accuracy and precision. This holds true for the accuracy and precision values calculated after cross-validation as well (done earlier)
- Random Forest models improve with a higher depth (depth=8 performs better than depth=4)

The decision to choose one of the above models depends on the firm's values. For example, if **false positives** carry high costs the firm should pick a model with higer precision i.e. the LightGBM or Random Forest (depth=8). Some examples of this include:

- **Retention programs:** The company might spend unnecesary resources offering retention programs to incorrectly identifies churners (false positives)
- **Opportunity cost:** If too many false positives are predicted by the model, the firm would focus on customers who were never at risk, missing opportunities to improve the experience of loyal customers who could be upsold
- **Customer segmentation:** Firm might incorrectly segment loyal customers under a category like "at-risk"

```
In [ ]:
```