85gflgcl1

November 18, 2024

1 Data Collection and Preparation

[ ]:
```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, roc_auc_score, classification_report, confusion_matrix
```

[ ]:
```
data = pd.read_excel('account_churn_project.xlsx')
```

[ ]:
```
print(data.shape)
```

```
(10127, 21)
```

[ ]:
```
print(data.head())
```

```
   identification         churn_flag  age gender  number_dependants  \
0       768805383  Existing Customer   45      M                  3
1       818770008  Existing Customer   49      F                  5
2       713982108  Existing Customer   51      M                  3
3       769911858  Existing Customer   40      F                  4
4       709106358  Existing Customer   40      M                  3

     education civil_status           income account_category  account_age  \
0  High School      Married      $60K - $80K             Blue           39
1     Graduate       Single   Less than $40K             Blue           44
2     Graduate      Married     $80K - $120K             Blue           36
3  High School      Unknown   Less than $40K             Blue           34
```

```
4   Uneducated      Married     $60K - $80K            Blue           21

   …  inactivity  past_contacts  card_Limit  balance  open_to_use  \
0  …           1              3       12691      777        11914
1  …           1              2        8256      864         7392
2  …           1              0        3418        0         3418
3  …           4              1        3313     2517          796
4  …           1              0        4716        0         4716

   change_per_quarter_amount  total_transaction_amount  \
0                       1335                      1144
1                       1541                      1291
2                       2594                      1887
3                       1405                      1171
4                       2175                       816

   total_transaction_count  change_per_quarter_quantity  average_use
0                       42                         1625           61
1                       33                         3714          105
2                       20                         2333            0
3                       20                         2333           76
4                       28                           25            0

[5 rows x 21 columns]
```

[ ]:
```python
# 1. Check data types
print("Data types:")
print(data.dtypes)
```

```
Data types:
identification                 int64
churn_flag                    object
age                            int64
gender                        object
number_dependants              int64
education                     object
civil_status                  object
income                        object
account_category              object
account_age                    int64
total_num_services             int64
inactivity                     int64
past_contacts                  int64
card_Limit                     int64
balance                        int64
open_to_use                    int64
change_per_quarter_amount      int64
total_transaction_amount       int64
```

```
total_transaction_count         int64
change_per_quarter_quantity     int64
average_use                     int64
dtype: object
```

[ ]:
```
# 2. Check for missing values
print("\nMissing values by column:")
print(data.isnull().sum())
```

```
Missing values by column:
identification                 0
churn_flag                     0
age                            0
gender                         0
number_dependants              0
education                      0
civil_status                   0
income                         0
account_category               0
account_age                    0
total_num_services             0
inactivity                     0
past_contacts                  0
card_Limit                     0
balance                        0
open_to_use                    0
change_per_quarter_amount      0
total_transaction_amount       0
total_transaction_count        0
change_per_quarter_quantity    0
average_use                    0
dtype: int64
```

[ ]:
```
# 3. Descriptive statistics
print("\nDescriptive statistics:")
print(data.describe())
```

```
Descriptive statistics:
       identification           age  number_dependants   account_age  \
count    1.012700e+04  10127.000000       10127.000000  10127.000000
mean     7.391776e+08     46.325960           2.346203     35.928409
std      3.690378e+07      8.016814           1.298908      7.986416
min      7.080821e+08     26.000000           0.000000     13.000000
25%      7.130368e+08     41.000000           1.000000     31.000000
50%      7.179264e+08     46.000000           2.000000     36.000000
75%      7.731435e+08     52.000000           3.000000     40.000000
```

```
max      8.283431e+08     73.000000          5.000000     56.000000

       total_num_services    inactivity  past_contacts    card_Limit  \
count        10127.000000  10127.000000   10127.000000  10127.000000
mean             3.812580      2.341167       2.455317   9280.019552
std              1.554408      1.010622       1.106225   9013.924409
min              1.000000      0.000000       0.000000   1439.000000
25%              3.000000      2.000000       2.000000   2787.000000
50%              4.000000      2.000000       2.000000   5363.000000
75%              5.000000      3.000000       3.000000  13576.000000
max              6.000000      6.000000       6.000000  34516.000000

            balance   open_to_use  change_per_quarter_amount  \
count  10127.000000  10127.000000               10127.000000
mean    1162.814061   7988.004345                 689.673645
std      814.987335   9054.851654                 297.521767
min        0.000000      3.000000                   0.000000
25%      359.000000   1463.500000                 579.000000
50%     1276.000000   4199.000000                 715.000000
75%     1784.000000  11456.000000                 844.000000
max     2517.000000  34516.000000                3397.000000

       total_transaction_amount  total_transaction_count  \
count              10127.000000             10127.000000
mean                4404.086304                64.858695
std                 3397.129254                23.472570
min                  510.000000                10.000000
25%                 2155.500000                45.000000
50%                 3899.000000                67.000000
75%                 4741.000000                81.000000
max                18484.000000               139.000000

       change_per_quarter_quantity   average_use
count                 10127.000000  10127.000000
mean                    591.557322    249.842500
std                     323.649708    272.424923
min                       0.000000      0.000000
25%                     438.500000      3.500000
50%                     655.000000    132.000000
75%                     786.000000    463.000000
max                    3714.000000    999.000000
```

[ ]:

```python
# 4. Check for duplicates
print("\nNumber of duplicates:")
print(data.duplicated().sum())
```

```
Number of duplicates:
```

0

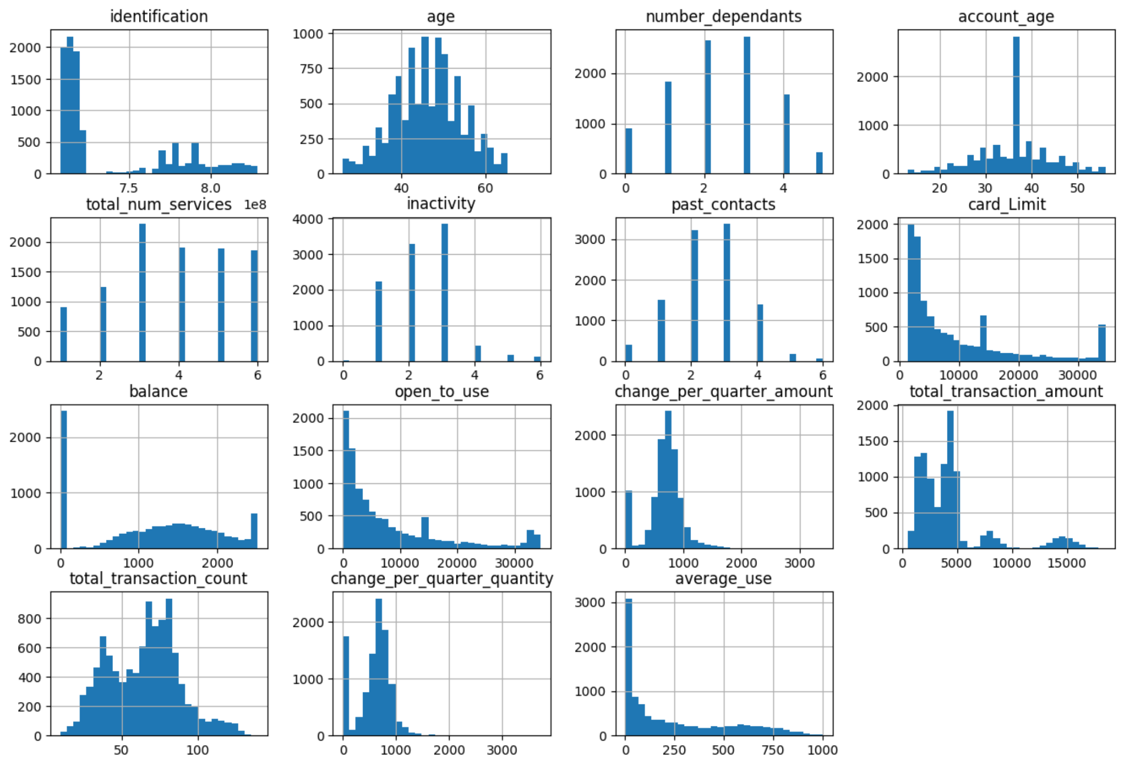
[ ]:
```
# 5. Check value ranges
# Checking age
print("\nChecking inconsistent ages (less than 0 or greater than 120):")
print(data[(data['age'] < 0) | (data['age'] > 120)])

# Ensure all of this columns are positive or zero)
# List of columns you want to verify for int64 type and positive/zero values
columns = ['number_dependants', 'account_age', 'card_Limit', 'balance',␣
↪'open_to_use',
                    'total_transaction_amount', 'total_transaction_count',␣
↪'change_per_quarter_amount',
                    'change_per_quarter_quantity', 'average_use']

for column in columns:
    print(f"\nChecking {column} for negative values:")
    print(data[data[column] < 0])
```

```
Checking inconsistent ages (less than 0 or greater than 120):
Empty DataFrame
Columns: [identification, churn_flag, age, gender, number_dependants, education,
civil_status, income, account_category, account_age, total_num_services,
inactivity, past_contacts, card_Limit, balance, open_to_use,
change_per_quarter_amount, total_transaction_amount, total_transaction_count,
change_per_quarter_quantity, average_use]
Index: []

[0 rows x 21 columns]

Checking number_dependants for negative values:
Empty DataFrame
Columns: [identification, churn_flag, age, gender, number_dependants, education,
civil_status, income, account_category, account_age, total_num_services,
inactivity, past_contacts, card_Limit, balance, open_to_use,
change_per_quarter_amount, total_transaction_amount, total_transaction_count,
change_per_quarter_quantity, average_use]
Index: []

[0 rows x 21 columns]

Checking account_age for negative values:
Empty DataFrame
Columns: [identification, churn_flag, age, gender, number_dependants, education,
civil_status, income, account_category, account_age, total_num_services,
inactivity, past_contacts, card_Limit, balance, open_to_use,
change_per_quarter_amount, total_transaction_amount, total_transaction_count,
```

```
change_per_quarter_quantity, average_use]
Index: []

[0 rows x 21 columns]

Checking card_Limit for negative values:
Empty DataFrame
Columns: [identification, churn_flag, age, gender, number_dependants, education,
civil_status, income, account_category, account_age, total_num_services,
inactivity, past_contacts, card_Limit, balance, open_to_use,
change_per_quarter_amount, total_transaction_amount, total_transaction_count,
change_per_quarter_quantity, average_use]
Index: []

[0 rows x 21 columns]

Checking balance for negative values:
Empty DataFrame
Columns: [identification, churn_flag, age, gender, number_dependants, education,
civil_status, income, account_category, account_age, total_num_services,
inactivity, past_contacts, card_Limit, balance, open_to_use,
change_per_quarter_amount, total_transaction_amount, total_transaction_count,
change_per_quarter_quantity, average_use]
Index: []

[0 rows x 21 columns]

Checking open_to_use for negative values:
Empty DataFrame
Columns: [identification, churn_flag, age, gender, number_dependants, education,
civil_status, income, account_category, account_age, total_num_services,
inactivity, past_contacts, card_Limit, balance, open_to_use,
change_per_quarter_amount, total_transaction_amount, total_transaction_count,
change_per_quarter_quantity, average_use]
Index: []

[0 rows x 21 columns]

Checking total_transaction_amount for negative values:
Empty DataFrame
Columns: [identification, churn_flag, age, gender, number_dependants, education,
civil_status, income, account_category, account_age, total_num_services,
inactivity, past_contacts, card_Limit, balance, open_to_use,
change_per_quarter_amount, total_transaction_amount, total_transaction_count,
change_per_quarter_quantity, average_use]
Index: []

[0 rows x 21 columns]
```

```
Checking total_transaction_count for negative values:
Empty DataFrame
Columns: [identification, churn_flag, age, gender, number_dependants, education,
civil_status, income, account_category, account_age, total_num_services,
inactivity, past_contacts, card_Limit, balance, open_to_use,
change_per_quarter_amount, total_transaction_amount, total_transaction_count,
change_per_quarter_quantity, average_use]
Index: []

[0 rows x 21 columns]

Checking change_per_quarter_amount for negative values:
Empty DataFrame
Columns: [identification, churn_flag, age, gender, number_dependants, education,
civil_status, income, account_category, account_age, total_num_services,
inactivity, past_contacts, card_Limit, balance, open_to_use,
change_per_quarter_amount, total_transaction_amount, total_transaction_count,
change_per_quarter_quantity, average_use]
Index: []

[0 rows x 21 columns]

Checking change_per_quarter_quantity for negative values:
Empty DataFrame
Columns: [identification, churn_flag, age, gender, number_dependants, education,
civil_status, income, account_category, account_age, total_num_services,
inactivity, past_contacts, card_Limit, balance, open_to_use,
change_per_quarter_amount, total_transaction_amount, total_transaction_count,
change_per_quarter_quantity, average_use]
Index: []

[0 rows x 21 columns]

Checking average_use for negative values:
Empty DataFrame
Columns: [identification, churn_flag, age, gender, number_dependants, education,
civil_status, income, account_category, account_age, total_num_services,
inactivity, past_contacts, card_Limit, balance, open_to_use,
change_per_quarter_amount, total_transaction_amount, total_transaction_count,
change_per_quarter_quantity, average_use]
Index: []

[0 rows x 21 columns]
```

[ ]:
```
data.hist(bins=30, figsize=(15, 10))
plt.show()
```



[ ]:
```python
# Map churn_flag values to binary (1 for Existing Customer, 0 for Attrited␣
↪Customer)
data['churn_flag'] = data['churn_flag'].map({'Existing Customer': 0, 'Attrited␣
↪Customer': 1})

# Map gender values ('M' becomes 0, 'F' becomes 1)
data['gender'] = data['gender'].map({'M': 0, 'F': 1})

# Transform categorical data into dummy/indicator variables
df_encoded = pd.get_dummies(data)

# Display the first 5 rows of the encoded DataFrame
print(df_encoded.head())
```

```
   identification  churn_flag  age  gender  number_dependants  account_age  \
0       768805383           0   45       0                  3           39
1       818770008           0   49       1                  5           44
2       713982108           0   51       0                  3           36
3       769911858           0   40       1                  4           34
4       709106358           0   40       0                  3           21

   total_num_services  inactivity  past_contacts  card_Limit  …  \
0                   5           1              3       12691  …
```

```
1                      6           1              2         8256  …
2                      4           1              0         3418  …
3                      3           4              1         3313  …
4                      5           1              0         4716  …

   income_$120K +  income_$40K - $60K  income_$60K - $80K  \
0           False               False                True
1           False               False               False
2           False               False               False
3           False               False               False
4           False               False                True

   income_$80K - $120K  income_Less than $40K  income_Unknown  \
0                False                  False           False
1                False                   True           False
2                 True                  False           False
3                False                   True           False
4                False                  False           False

   account_category_Blue  account_category_Gold  account_category_Platinum  \
0                   True                  False                      False
1                   True                  False                      False
2                   True                  False                      False
3                   True                  False                      False
4                   True                  False                      False

   account_category_Silver
0                    False
1                    False
2                    False
3                    False
4                    False

[5 rows x 38 columns]
```

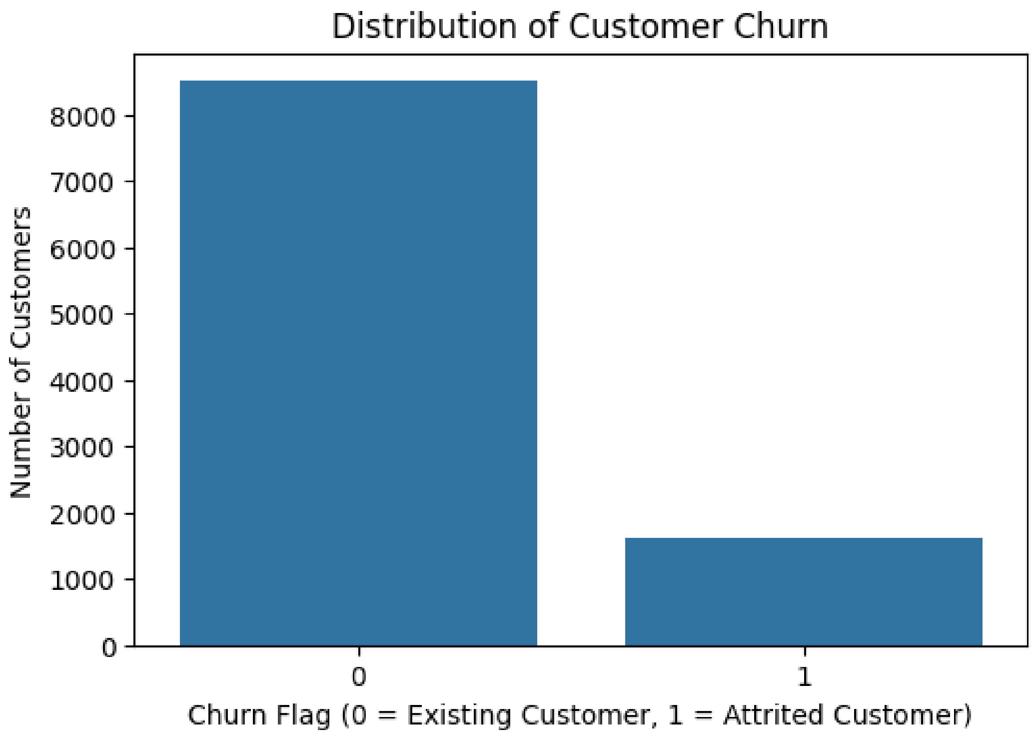
[ ]:
```
# Create new features
df_encoded['card_utilization'] = df_encoded['balance'] /␣
 ↪df_encoded['card_Limit']
```

[ ]:
```
df_encoded.to_excel('modified_file .xlsx', index=False)
```

2 Exploratory Data Analysis

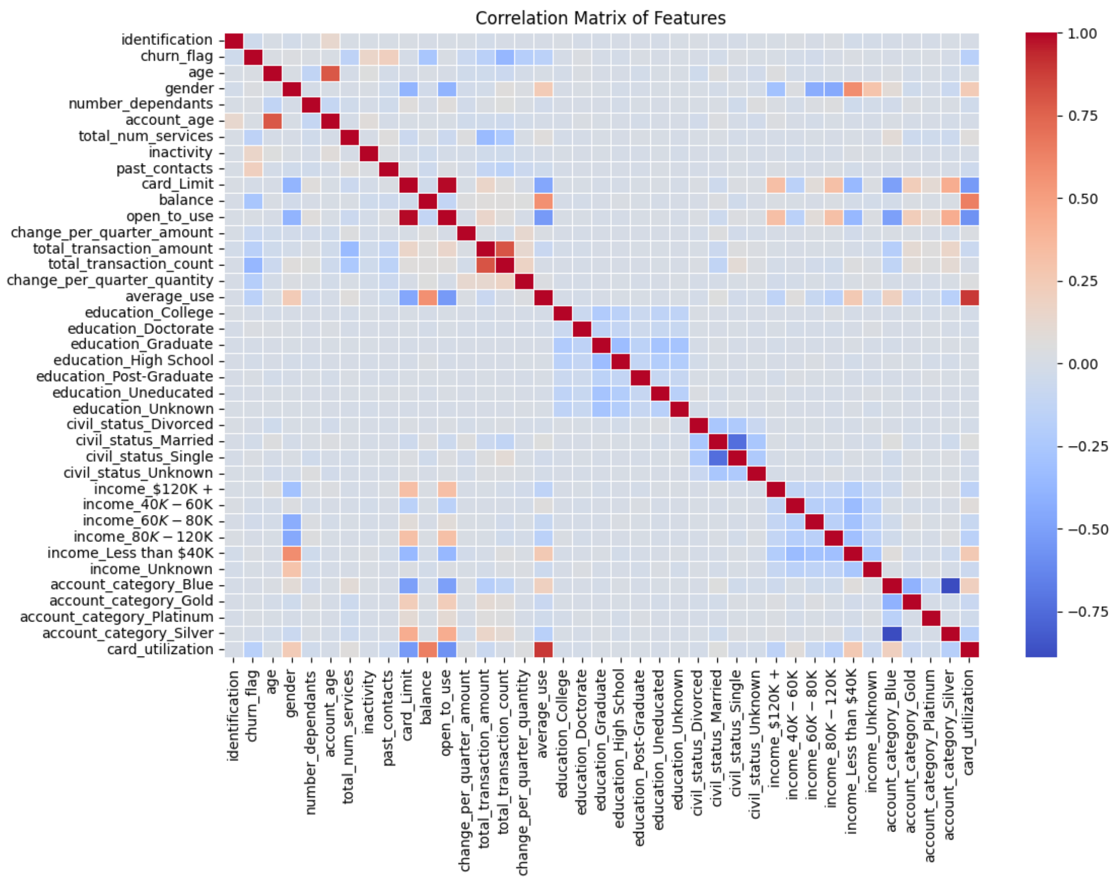
3 Visualizing Customer Churn with a Count Plot

[ ]:
```
plt.figure(figsize=(6,4))
# Create a count plot to display the distribution of churn flag Customer
ax = sns.countplot(x='churn_flag',data=df_encoded)
plt.title('Distribution of Customer Churn')
plt.xlabel('Churn Flag (0 = Existing Customer, 1 = Attrited Customer)')
plt.ylabel('Number of Customers')
plt.show()
```



4 Visualizing the Correlation Matrix of Features

[ ]:
```
plt.figure(figsize=(12,8))
corr_matrix = df_encoded.corr()
sns.heatmap(corr_matrix, annot=False, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Matrix of Features')
plt.show()
```

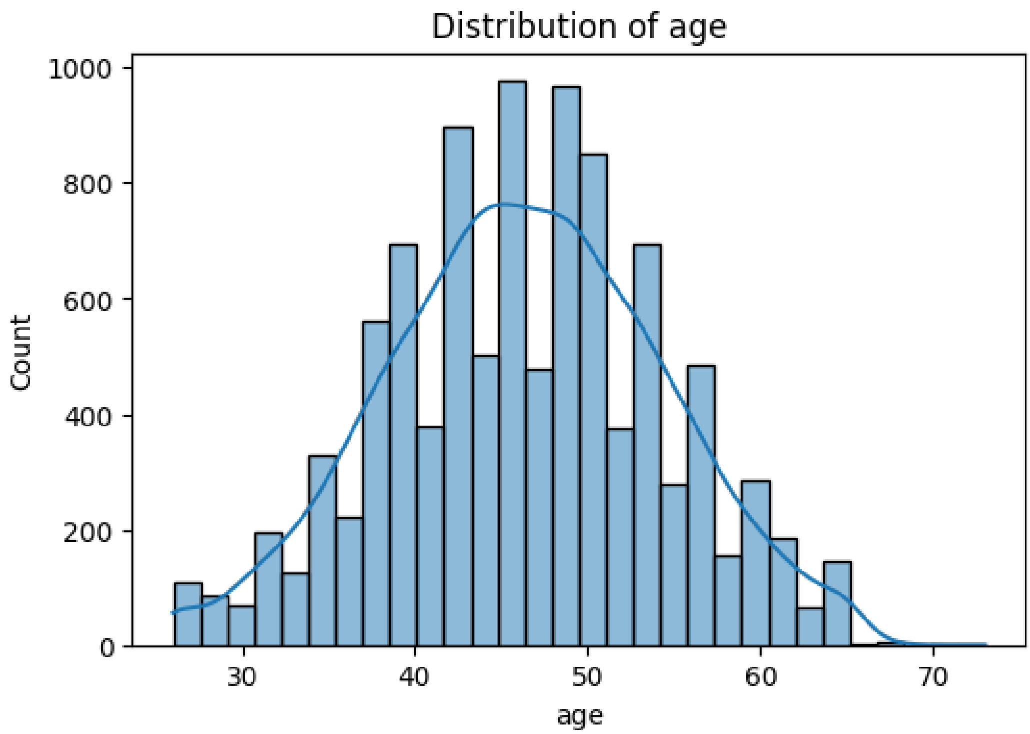


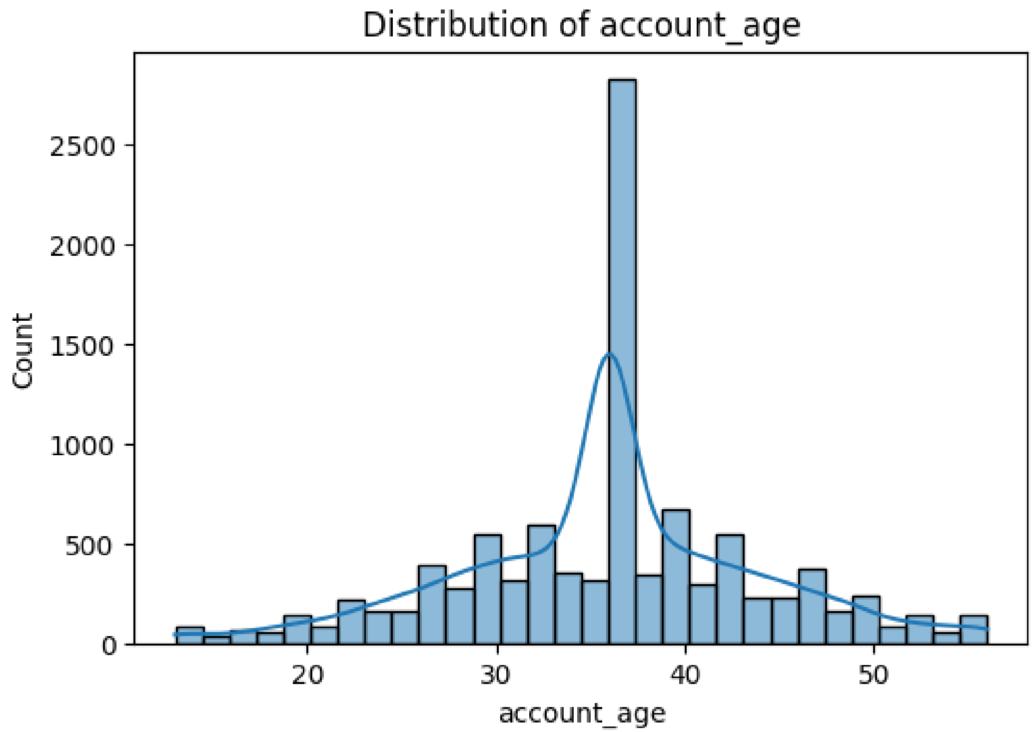

```
[ ]: corr = df_encoded.corr()
     target_corr = corr['churn_flag'].abs().sort_values(ascending=False)
     print(target_corr.head(10))
```

```
churn_flag                      1.000000
total_transaction_count         0.371403
balance                         0.263053
past_contacts                   0.204491
change_per_quarter_quantity     0.195368
card_utilization                0.177722
total_transaction_amount        0.168598
average_use                     0.163300
inactivity                      0.152449
total_num_services              0.150005
Name: churn_flag, dtype: float64
```

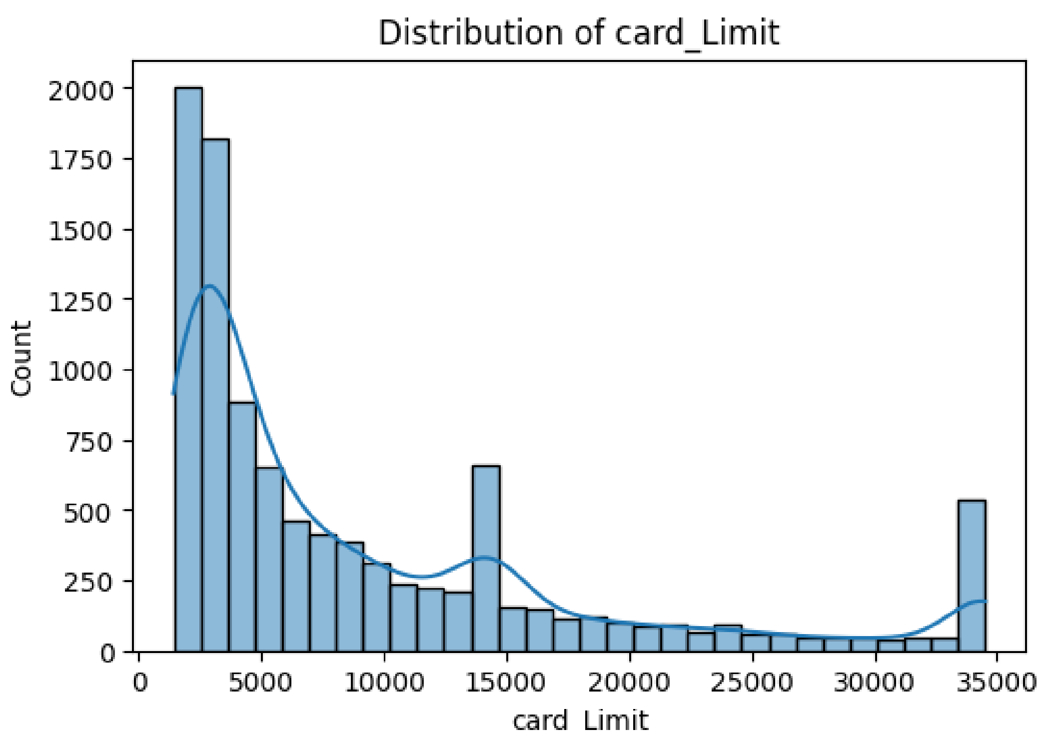
```
[ ]: # Visualize numerical distributions
     num_vars = ['age', 'account_age', 'card_Limit', 'balance',␣
      ↪'total_transaction_amount']
     for col in num_vars:
```

```python
plt.figure(figsize=(6, 4))
sns.histplot(df_encoded[col], kde=True, bins=30)
plt.title(f'Distribution of {col}')
plt.show()
```

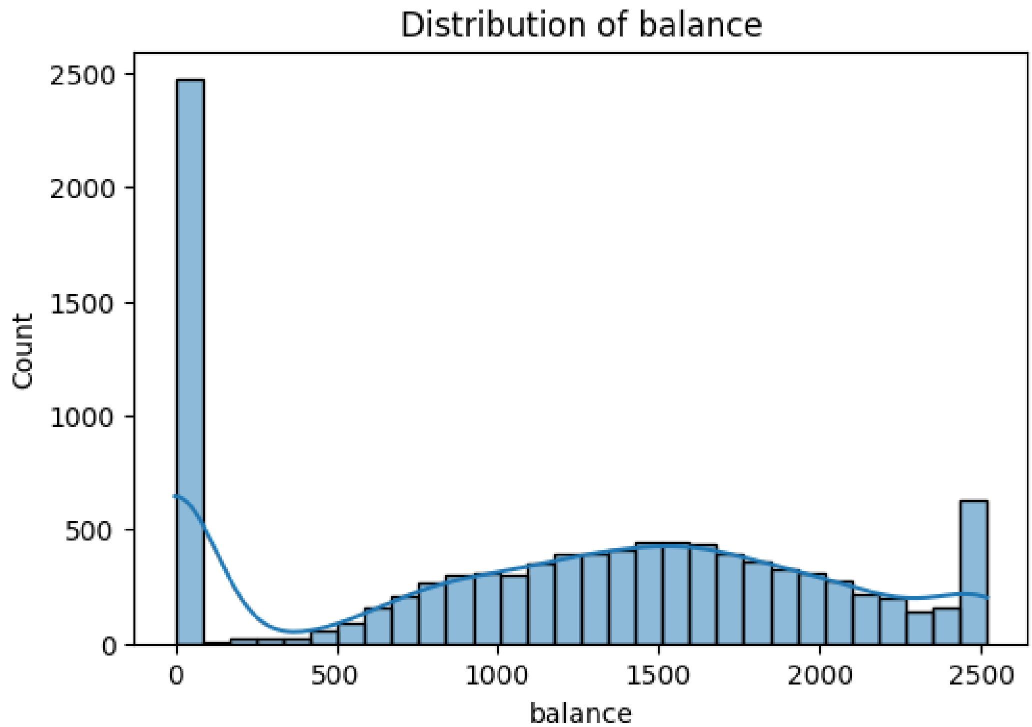


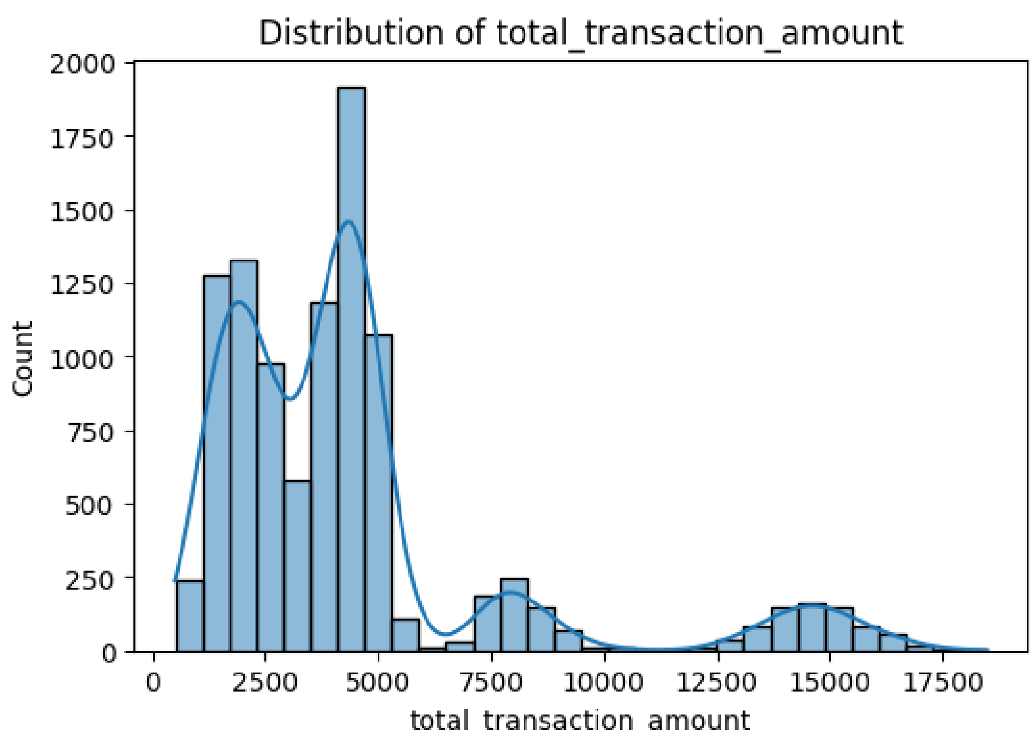


Distribution of account_age
2500
2000
1500
1000
500
0
Count
20
30
40
50
account_age



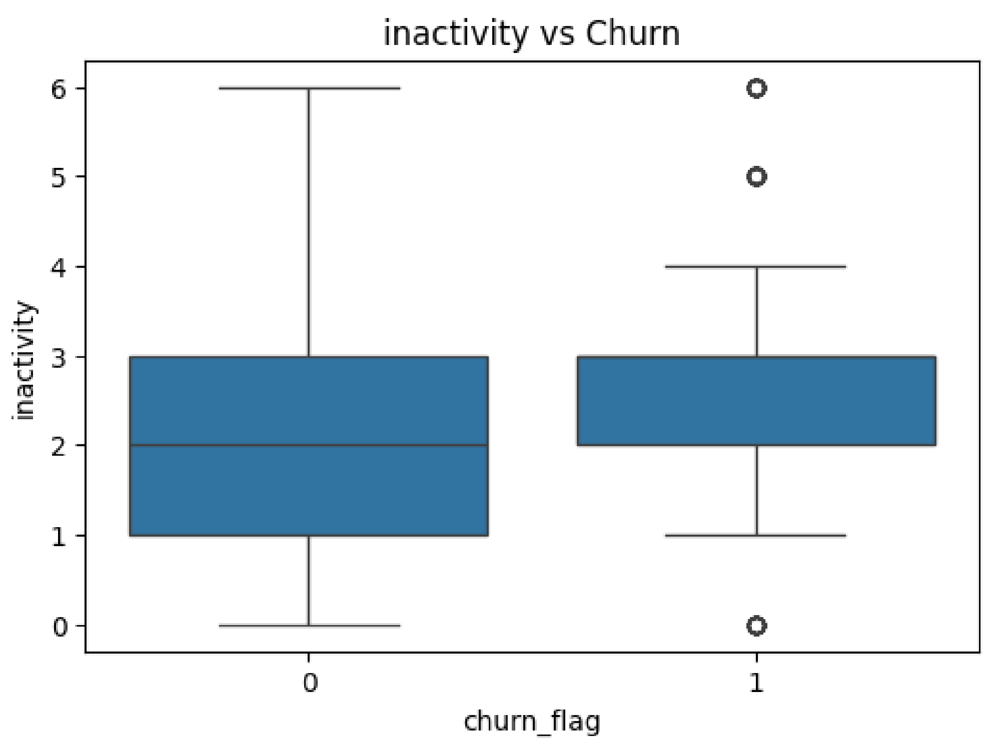
Distribution of card_Limit
2000
1750
1500
1250
1000
750
500
250
0
Count
0
5000
10000
15000
20000
25000
30000
35000
card_Limit

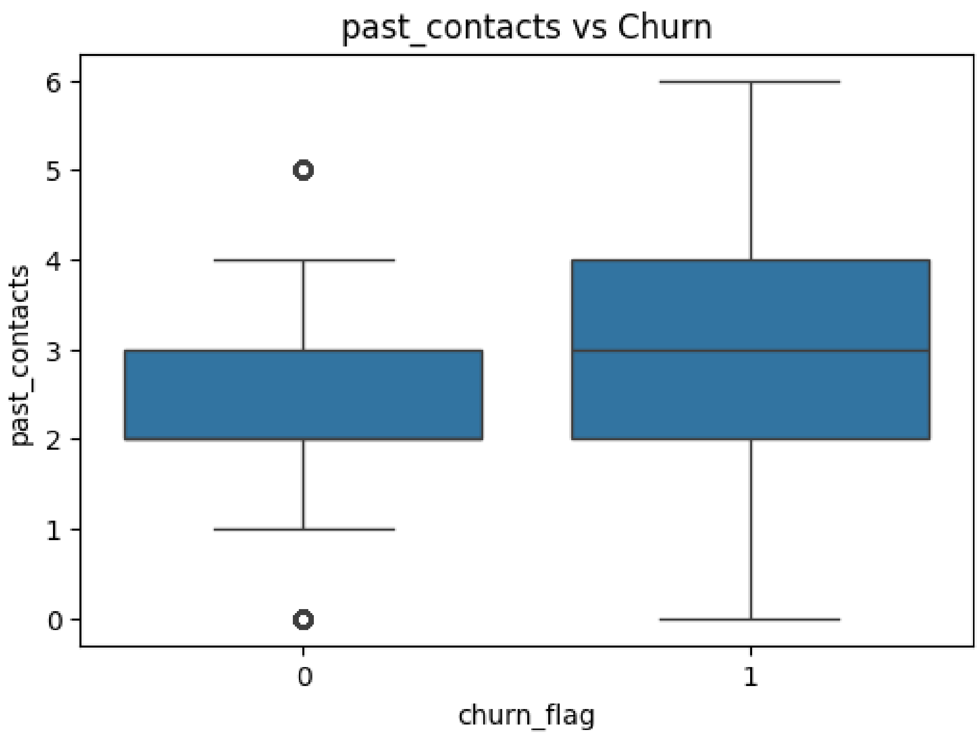

Distribution of balance
Count
balance
0
500
1000
1500
2000
2500

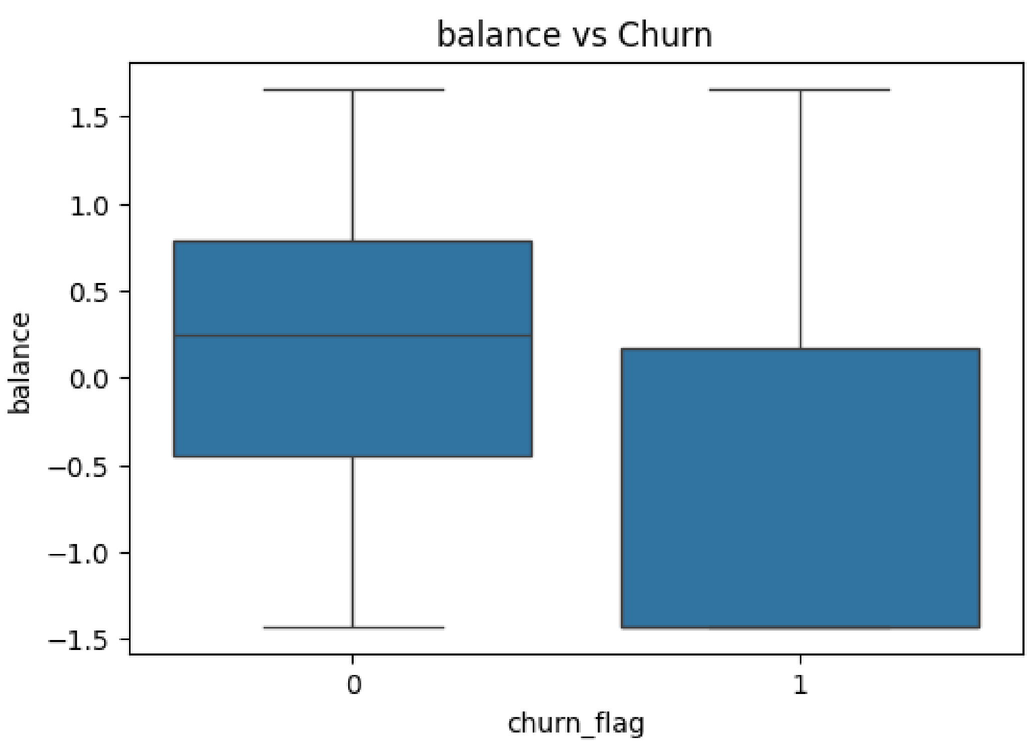

Distribution of total_transaction_amount
Count
total_transaction_amount
0
250
500
750
1000
1250
1500
1750
2000
2500
5000
7500
10000
12500
15000
17500

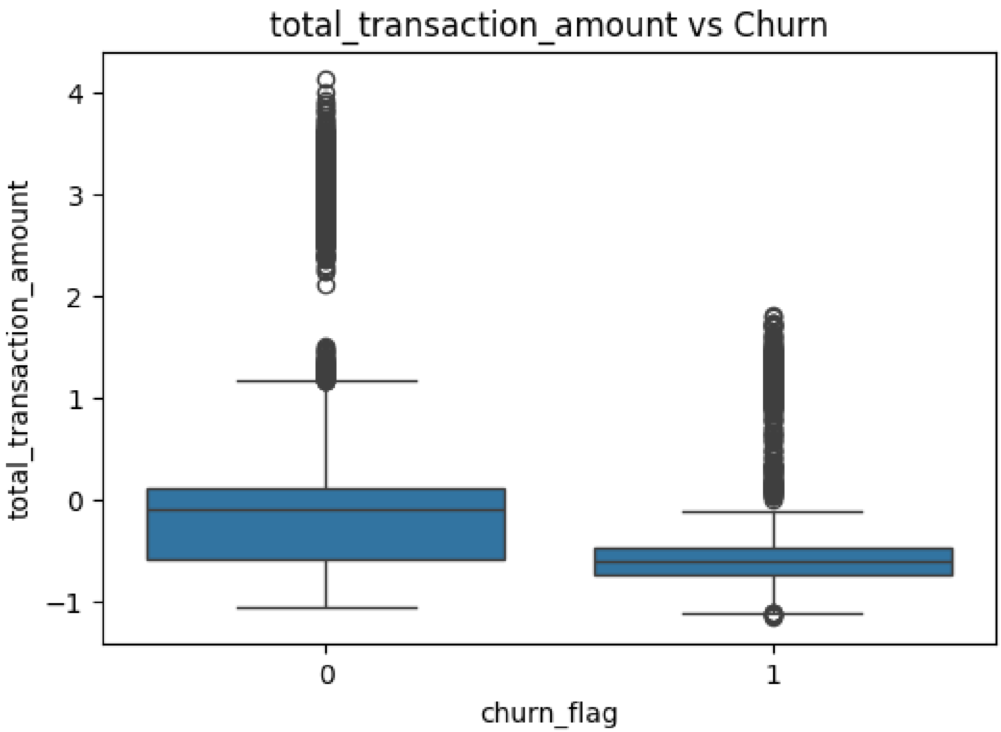
[ ]:
```
# Boxplots for relationships

key_features =␣
 ↪['inactivity','past_contacts','balance','total_transaction_amount','total_transaction_count
#'age', 'balance', 'card_Limit',␣
 ↪'total_transaction_amount','total_transaction_count','past_contacts','change_per_quarter_qu
#all_columns = df_encoded.columns
#columns_to_plot = [col for col in all_columns if col not in ['churn_flag',␣
 ↪'identification']]

#for feature in columns_to_plot:
   # plt.figure(figsize=(6, 4))
   # sns.boxplot(x='churn_flag', y=feature, data=df_encoded)
   # plt.title(f'{feature} vs Churn')
   # plt.show()

print('0 = existing custumers; 1 = attrited custumers')
for feature in key_features:
    plt.figure(figsize=(6, 4))
    sns.boxplot(x='churn_flag', y=feature, data=df_encoded)
    plt.title(f'{feature} vs Churn')
    plt.show()
```

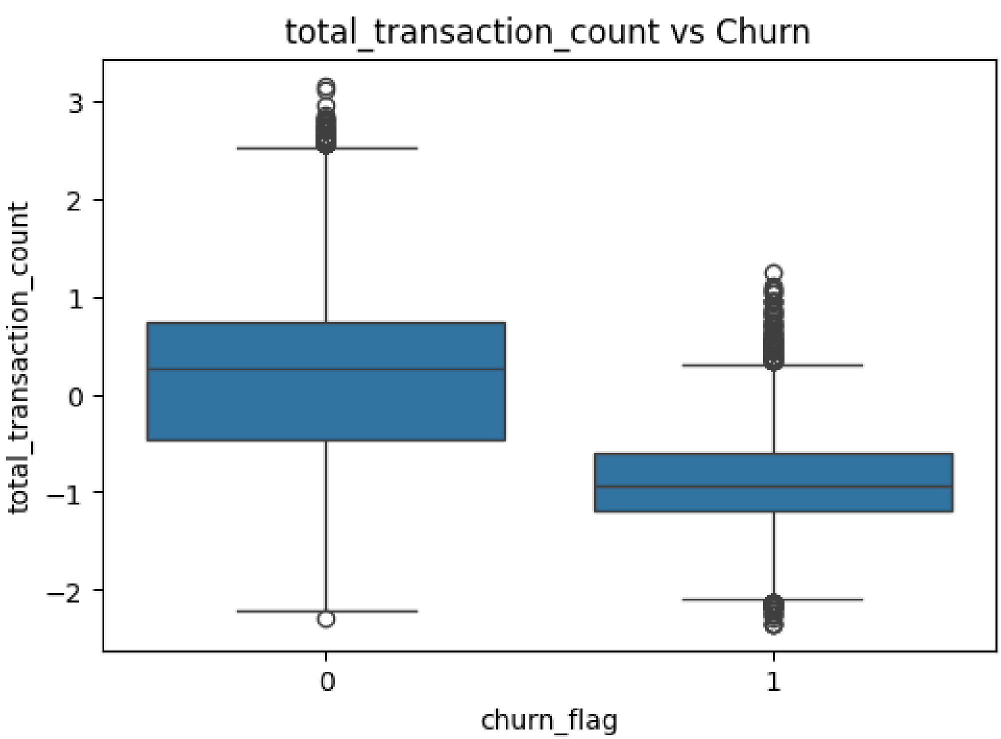
```
0 = existing custumers; 1 = attrited custumers
```

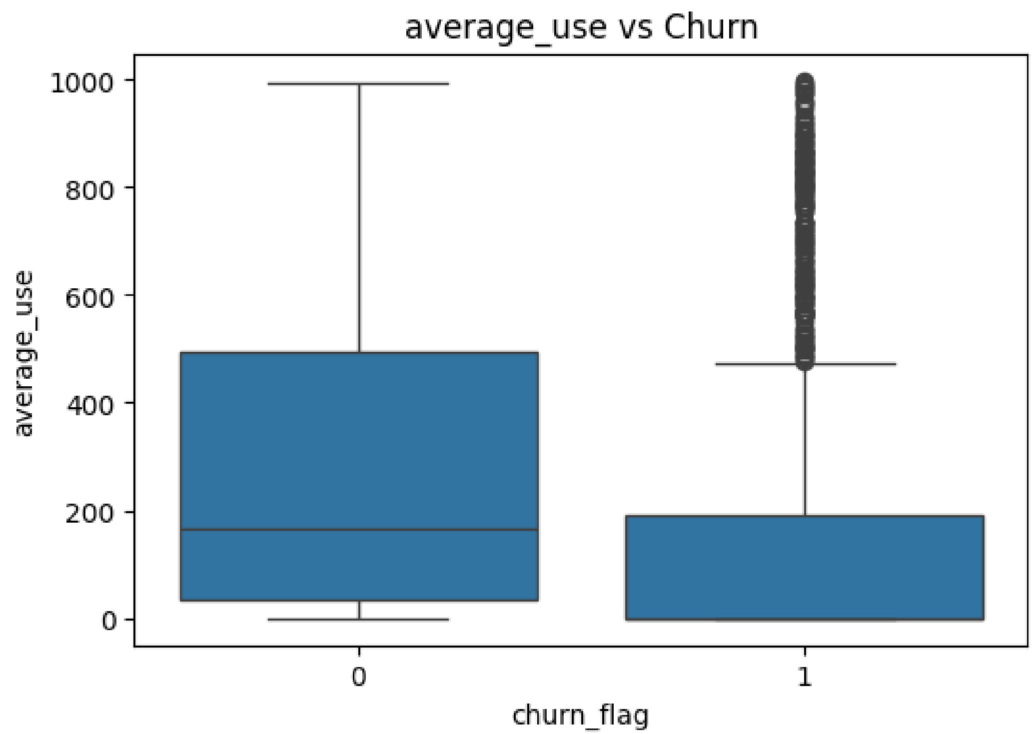



past_contacts vs Churn
past_contacts
6
5
4
3
2
1
0
0
1
churn_flag


balance vs Churn
balance
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
0
1
churn_flag


total_transaction_amount vs Churn
total_transaction_amount
4
3
2
1
0
−1
0
1
churn_flag

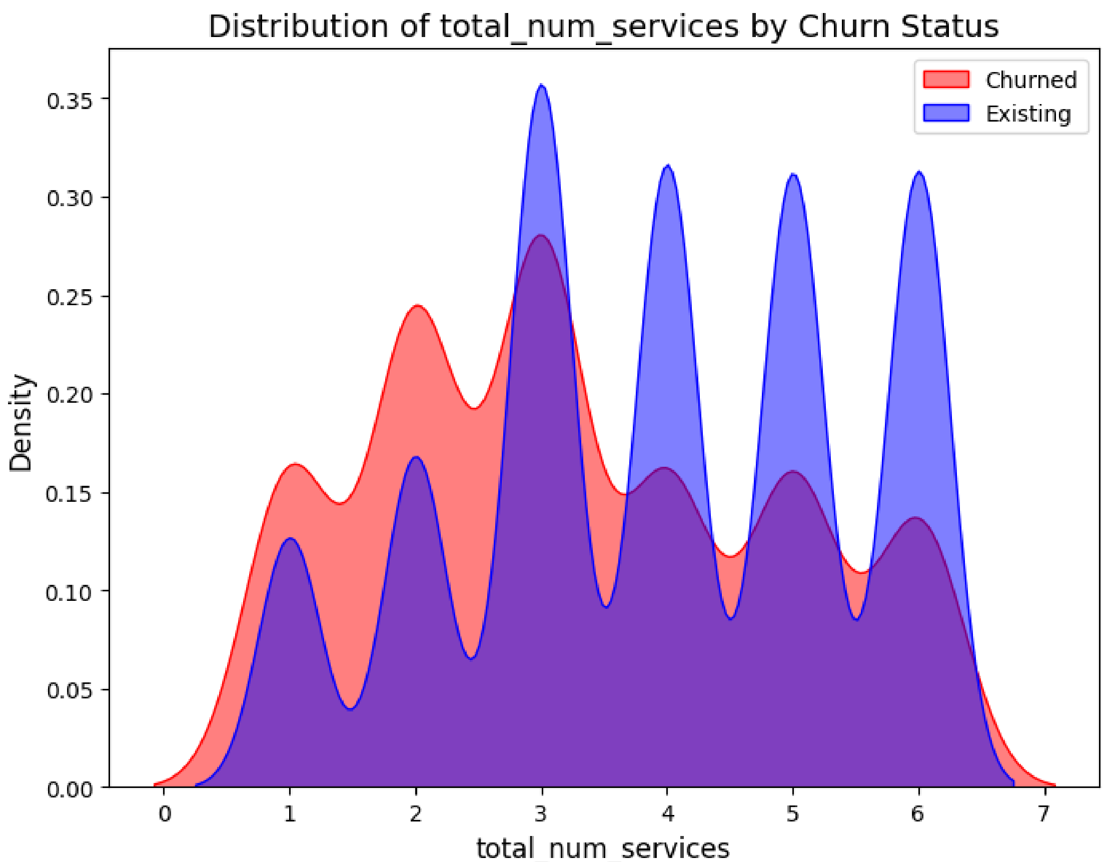

total_transaction_count vs Churn
total_transaction_count
3
2
1
0
−1
−2
0
1
churn_flag

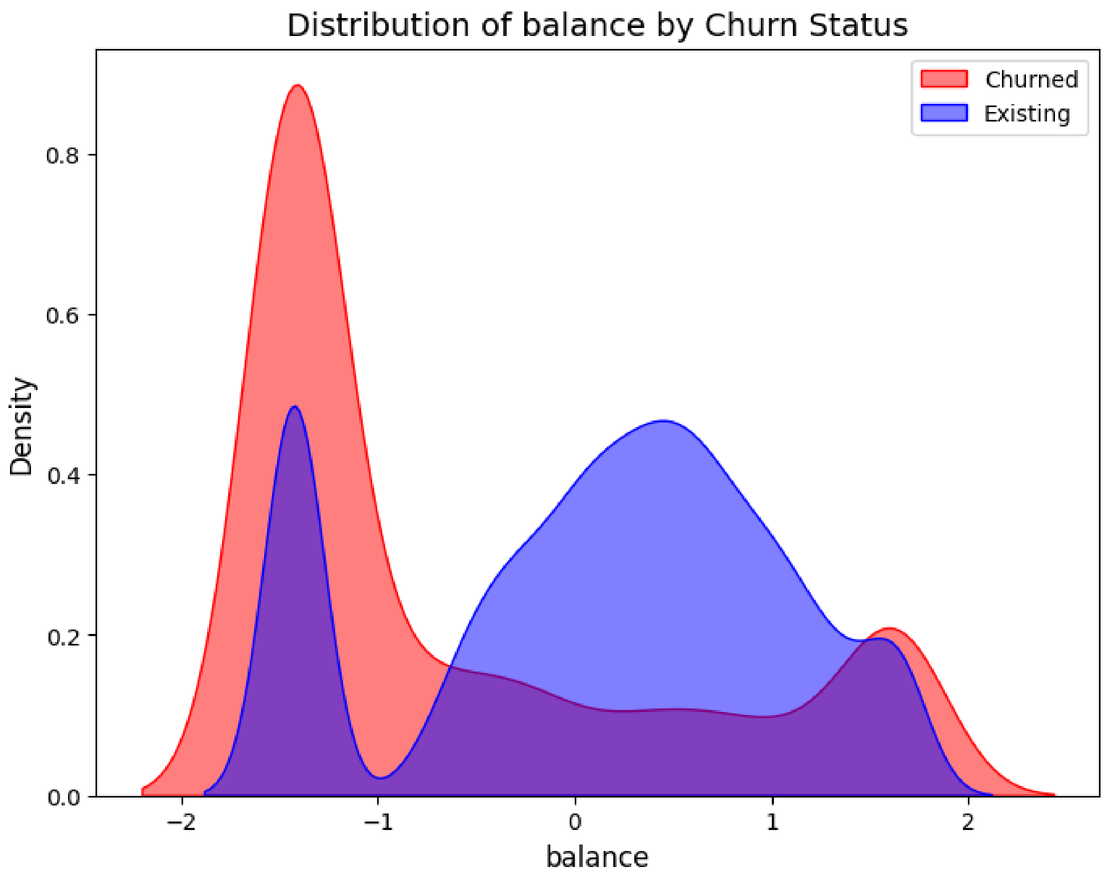


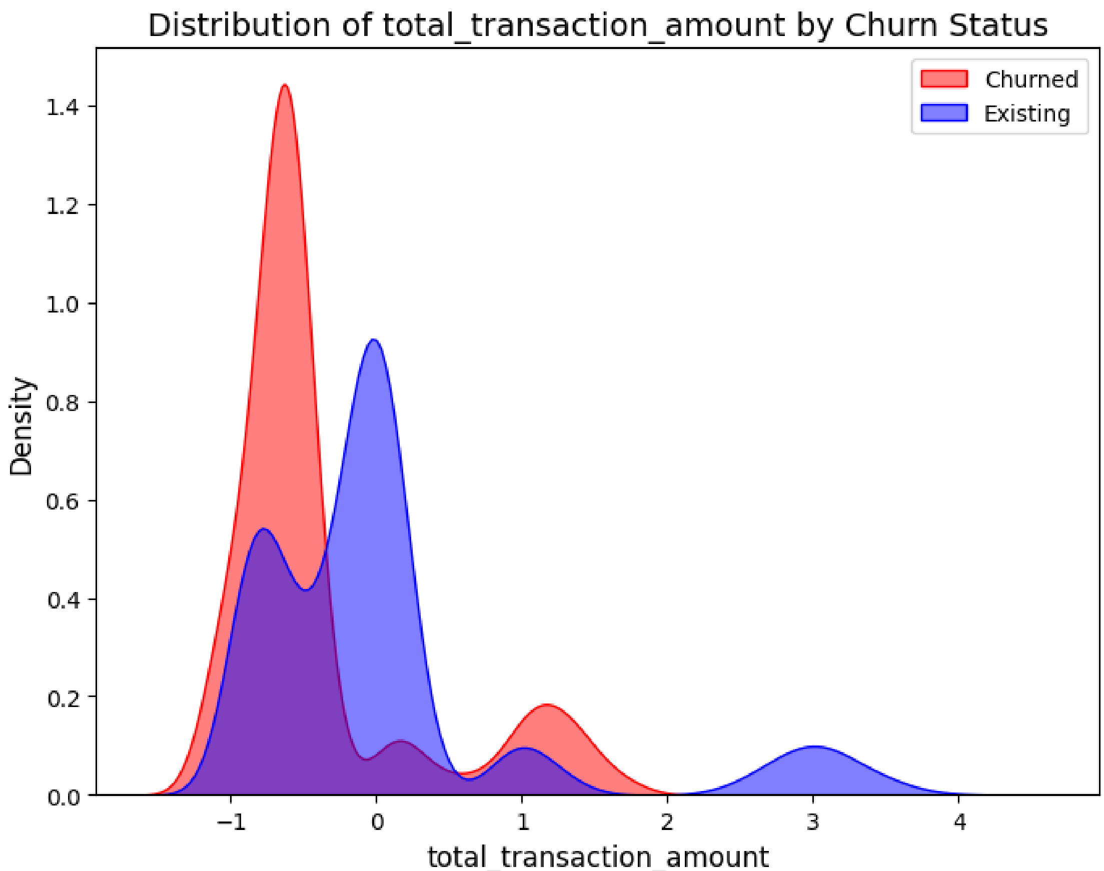

```
[ ]: # Overlay histograms or KDE plots for churned vs. existing customers
#key_features = ['balance',␣
↪'card_Limit','total_transaction_count','past_contacts','change_per_quarter_quantity','avera
key_features = ['total_num_services',␣
↪'balance','total_transaction_amount','total_transaction_count','average_use']

print('0 = existing custumers; 1 = attrited custumers')
for feature in key_features:
#for feature in columns_to_plot:
    plt.figure(figsize=(8, 6))

    # KDE plot for churned customers
    sns.kdeplot(data=df_encoded[df_encoded['churn_flag'] == 1][feature],
                label='Churned', color='red', fill=True, alpha=0.5)

    # KDE plot for existing customers
    sns.kdeplot(data=df_encoded[df_encoded['churn_flag'] == 0][feature],
                label='Existing', color='blue', fill=True, alpha=0.5)

    plt.title(f'Distribution of {feature} by Churn Status', fontsize=14)
    plt.xlabel(feature, fontsize=12)
```

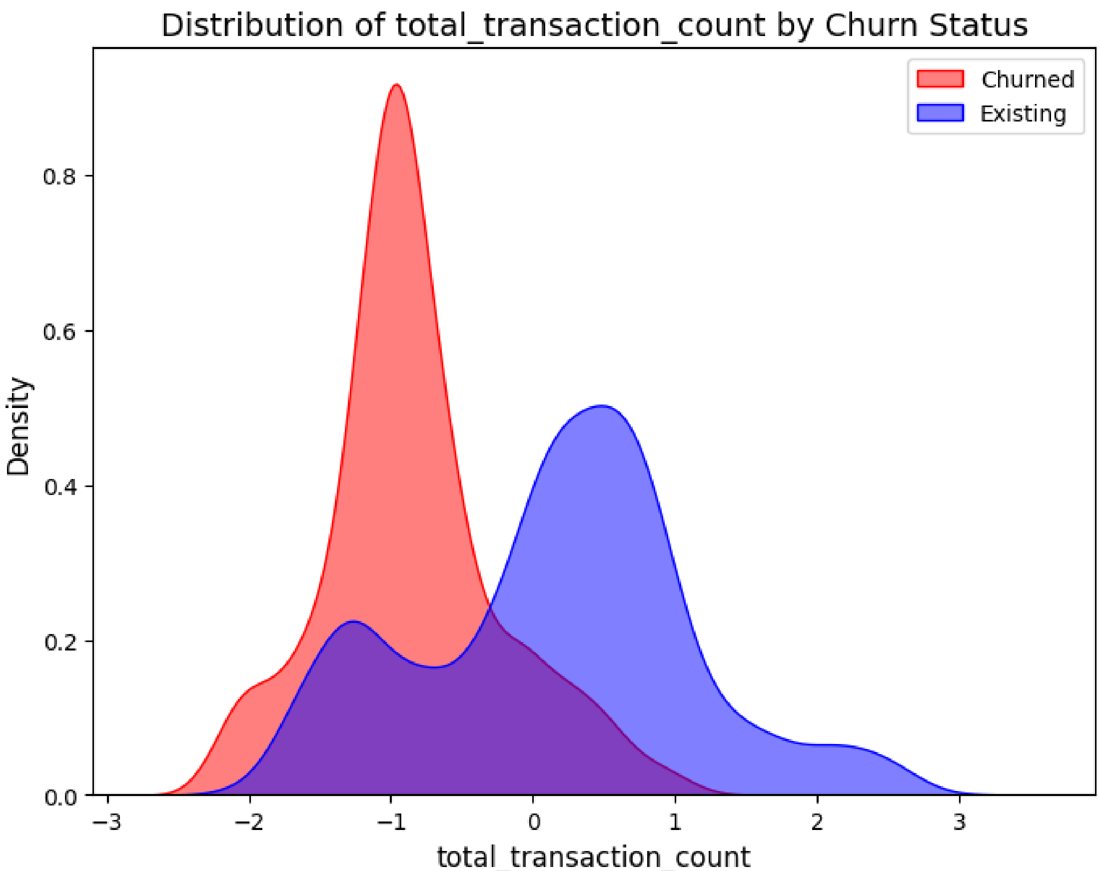
```
    plt.ylabel('Density', fontsize=12)
    plt.legend()
    plt.show()
```

```
0 = existing custumers; 1 = attrited custumers
```

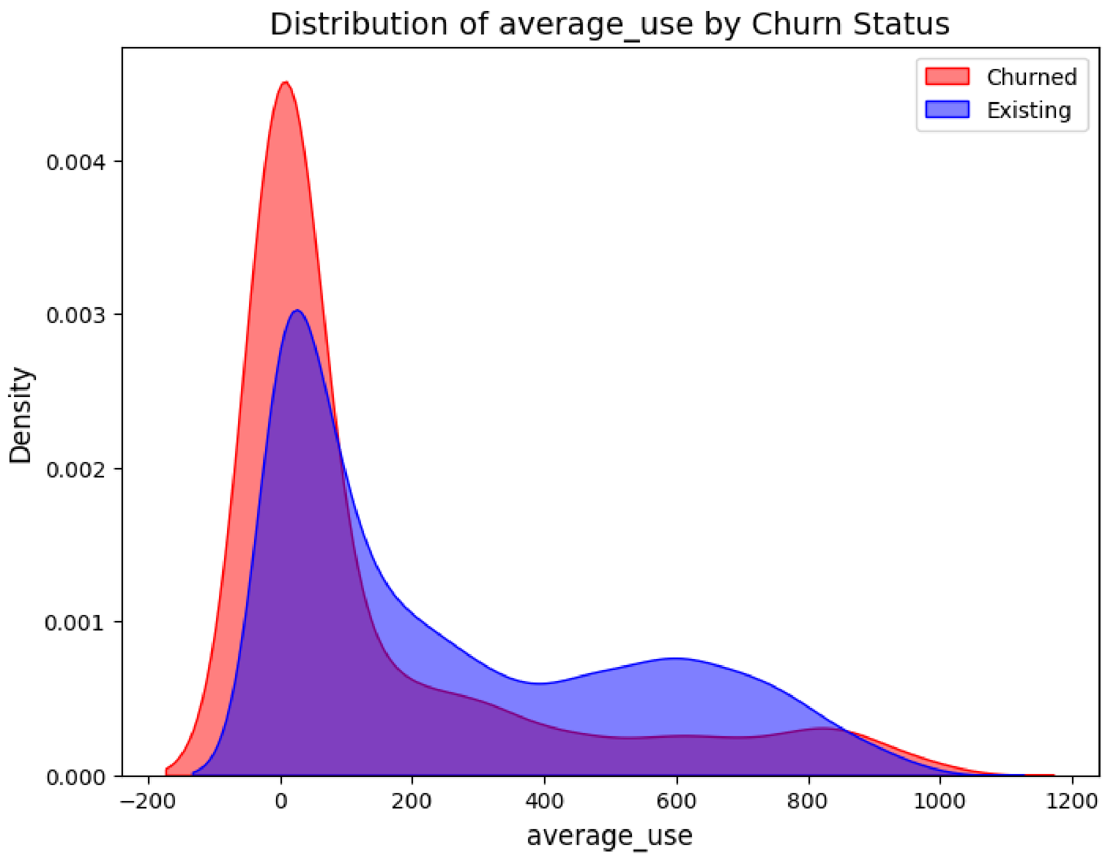



Distribution of balance by Churn Status
Churned
Existing
Density
0.0
0.2
0.4
0.6
0.8
−2
−1
0
1
2
balance


Distribution of total_transaction_amount by Churn Status
Churned
Existing
Density
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
−1
0
1
2
3
4
total_transaction_amount



Distribution of total_transaction_count by Churn Status
Churned
Existing
Density
0.0
0.2
0.4
0.6
0.8
−3
−2
−1
0
1
2
3
total_transaction_count



[ ]:
```
# Scale numerical features
scaler = StandardScaler()
num_cols = ['age', 'number_dependants', 'account_age', 'card_Limit', 'balance',
            'total_transaction_amount', 'total_transaction_count']
df_encoded[num_cols] = scaler.fit_transform(df_encoded[num_cols])

print(df_encoded.head())
```

```
   identification  churn_flag       age  gender  number_dependants  \
0       768805383           0 -0.165406       0           0.503368
1       818770008           0  0.333570       1           2.043199
2       713982108           0  0.583058       0           0.503368
3       769911858           0 -0.789126       1           1.273283
4       709106358           0 -0.789126       0           0.503368

   account_age  total_num_services  inactivity  past_contacts  card_Limit  \
0     0.384621                   5           1              3    0.378431
1     1.010715                   6           1              2   -0.113610
2     0.008965                   4           1              0   -0.650361
3    -0.241473                   3           4              1   -0.662011
```

```
4    -1.869317                     5          1             0   -0.506355

   …  income_$40K - $60K  income_$60K - $80K  income_$80K - $120K  \
0  …               False                True                False
1  …               False               False                False
2  …               False               False                 True
3  …               False               False                False
4  …               False                True                False

   income_Less than $40K  income_Unknown  account_category_Blue  \
0                  False           False                   True
1                   True           False                   True
2                  False           False                   True
3                   True           False                   True
4                  False           False                   True

   account_category_Gold  account_category_Platinum  account_category_Silver  \
0                  False                      False                    False
1                  False                      False                    False
2                  False                      False                    False
3                  False                      False                    False
4                  False                      False                    False

   card_utilization
0          0.061224
1          0.104651
2          0.000000
3          0.759734
4          0.000000

[5 rows x 39 columns]
```

5 Feature Selection

[ ]:

```
corr = df_encoded.corr()
target_corr = corr['churn_flag'].abs().sort_values(ascending=False)
print(target_corr.head(10))
```

```
churn_flag                     1.000000
total_transaction_count        0.371403
balance                        0.263053
past_contacts                  0.204491
change_per_quarter_quantity    0.195368
card_utilization               0.177722
total_transaction_amount       0.168598
average_use                    0.163300
inactivity                     0.152449
```

```
total_num_services             0.150005
Name: churn_flag, dtype: float64
```

6 Model Building

[ ]:
```python
# Split the dataset into training and testing subsets for model development and validation.
# Features and target
X = df_encoded.drop(columns=['churn_flag', 'identification'])
y = df_encoded['churn_flag']

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42, stratify=y)
from sklearn.preprocessing import StandardScaler

# Assuming 'num_cols' contains the numerical features
scaler = StandardScaler()
X_train[num_cols] = scaler.fit_transform(X_train[num_cols])
X_test[num_cols] = scaler.transform(X_test[num_cols])
```

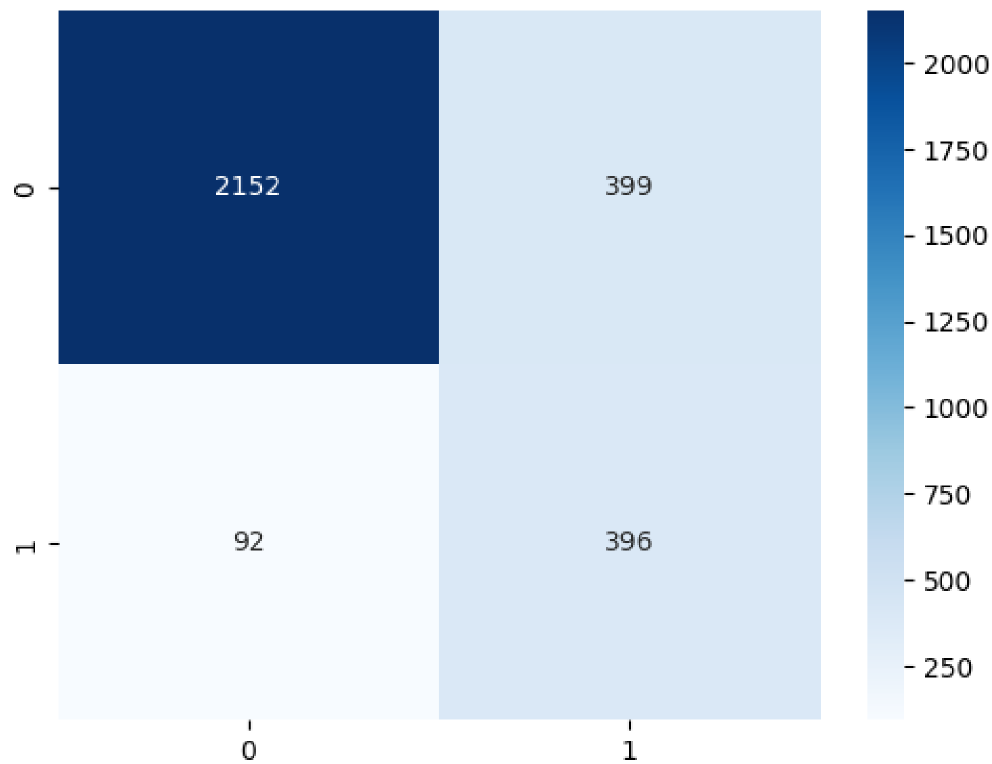
7 Logistic Regression

[ ]:
```python
# Logistic Regression
log_reg = LogisticRegression(class_weight='balanced', random_state=42,max_iter=1000)
log_reg.fit(X_train, y_train)

# Predictions and evaluation
y_pred_log = log_reg.predict(X_test)
print('Logistic Regression Metrics:')
print(classification_report(y_test, y_pred_log))

cm = confusion_matrix(y_test, y_pred_log)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
```

```
Logistic Regression Metrics:
              precision    recall  f1-score   support

           0       0.96      0.84      0.90      2551
           1       0.50      0.81      0.62       488

    accuracy                           0.84      3039
   macro avg       0.73      0.83      0.76      3039
weighted avg       0.88      0.84      0.85      3039
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:469:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[ ]: <Axes: >



8 K-Nearest Neighbors

[ ]:
```
# KNN
from imblearn.over_sampling import SMOTE

# Instantiate SMOTE
smote = SMOTE(random_state=42)
```

```
# Resample the training data
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)

knn = KNeighborsClassifier()
knn_params = {'n_neighbors': [3, 5, 7], 'weights': ['uniform', 'distance']}
knn_grid = GridSearchCV(knn, knn_params, cv=3, scoring='f1')
knn_grid.fit(X_train_resampled, y_train_resampled)

# Best KNN
best_knn = knn_grid.best_estimator_
y_pred_knn = best_knn.predict(X_test)
print('KNN Metrics:')
print(classification_report(y_test, y_pred_knn))
```

```
KNN Metrics:
              precision    recall  f1-score   support

           0       0.89      0.80      0.84      2551
           1       0.32      0.50      0.39       488

    accuracy                           0.75      3039
   macro avg       0.61      0.65      0.62      3039
weighted avg       0.80      0.75      0.77      3039
```

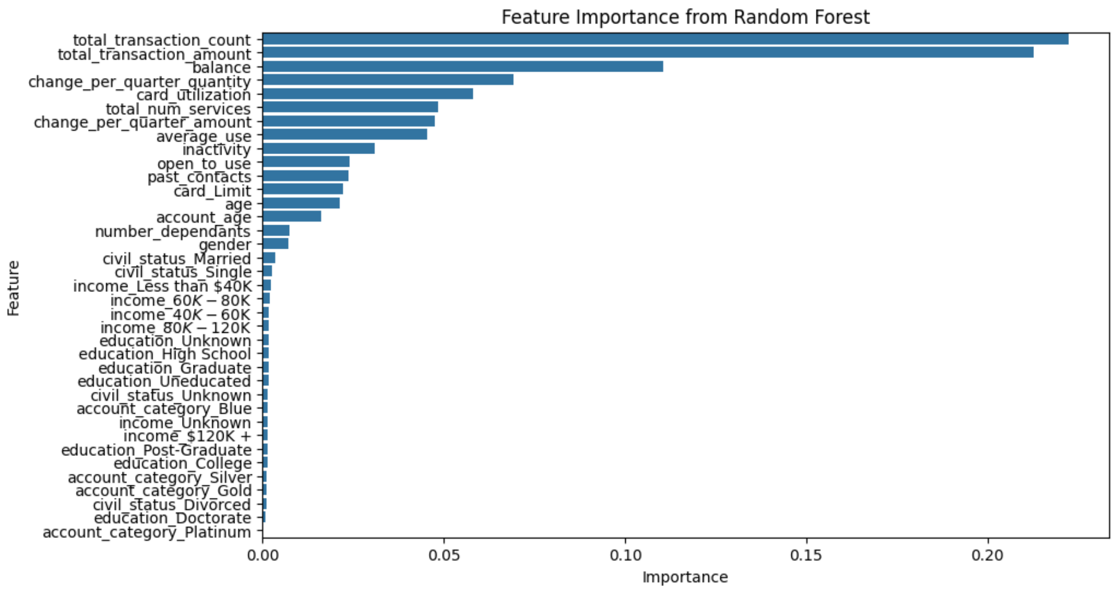
9 Random Forest

[ ]:
```
# Random Forest
rf = RandomForestClassifier(class_weight='balanced', random_state=42)
rf_params = {'n_estimators': [100, 200], 'max_depth': [10, 20, None]}
rf_grid = GridSearchCV(rf, rf_params, cv=3, scoring='f1')
rf_grid.fit(X_train, y_train)

# Best Random Forest
best_rf = rf_grid.best_estimator_
y_pred_rf = best_rf.predict(X_test)
print('Random Forest Metrics:')
print(classification_report(y_test, y_pred_rf))
```

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

           0       0.97      0.96      0.97      2551
           1       0.81      0.83      0.82       488

    accuracy                           0.94      3039
   macro avg       0.89      0.90      0.89      3039
```

```
weighted avg       0.94      0.94      0.94      3039
```

[ ]:
```python
# Feature importance from Random Forest
importances = best_rf.feature_importances_
feature_names = X.columns
feature_importance_df = pd.DataFrame({'Feature': feature_names, 'Importance':
 ↪importances})
feature_importance_df = feature_importance_df.sort_values(by='Importance',
 ↪ascending=False)

# Plot
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=feature_importance_df)
plt.title('Feature Importance from Random Forest')
plt.show()
```



[ ]:
```python
rf = RandomForestClassifier(random_state=42)
rf.fit(X_train, y_train)
feature_importances = pd.DataFrame({'Feature': X.columns,
                                    'Importance': rf.feature_importances_}).
 ↪sort_values(by='Importance', ascending=False)
print(feature_importances)
```

```
                     Feature  Importance
11  total_transaction_amount    0.190330
12   total_transaction_count    0.163504
8                    balance    0.093679
```

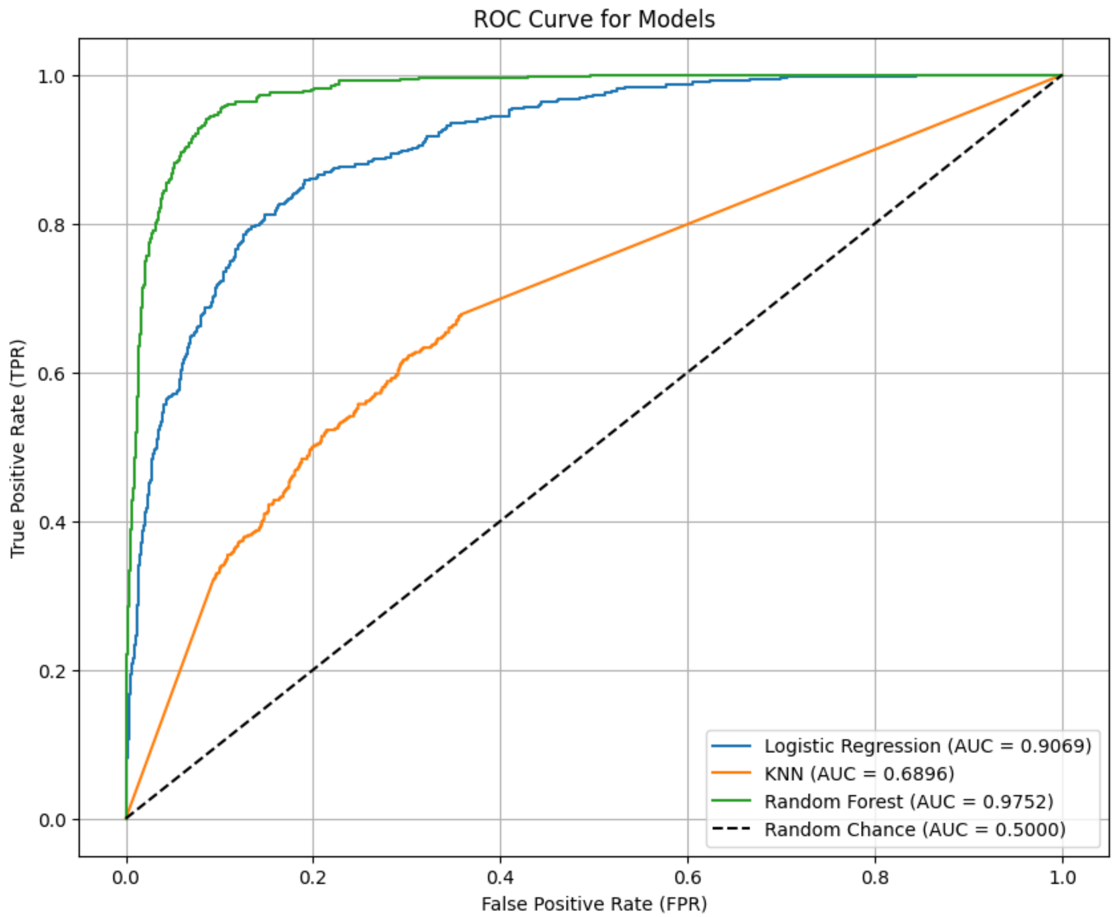
```
4            total_num_services    0.068026
13  change_per_quarter_quantity    0.061804
36             card_utilization    0.058197
10    change_per_quarter_amount    0.054437
14                  average_use    0.045589
7                    card_Limit    0.035678
9                   open_to_use    0.034838
0                           age    0.031312
6                 past_contacts    0.029549
3                   account_age    0.025280
5                    inactivity    0.025108
2             number_dependants    0.014094
1                        gender    0.009217
23         civil_status_Married    0.005549
24          civil_status_Single    0.004867
17           education_Graduate    0.004137
30         income_Less than $40K    0.003749
21            education_Unknown    0.003446
28           income_$60K - $80K    0.003399
18        education_High School    0.003354
27           income_$40K - $60K    0.003321
20         education_Uneducated    0.003131
25         civil_status_Unknown    0.003085
29          income_$80K - $120K    0.003007
15            education_College    0.002658
31               income_Unknown    0.002453
22        civil_status_Divorced    0.002124
26                income_$120K +    0.001976
19      education_Post-Graduate    0.001905
35      account_category_Silver    0.001879
32        account_category_Blue    0.001876
16          education_Doctorate    0.001836
33        account_category_Gold    0.001376
34    account_category_Platinum    0.000231
```

10 Model Evaluation

[ ]:
```python
from sklearn.metrics import roc_auc_score, roc_curve, auc

# Logistic Regression
y_pred_log_proba = log_reg.predict_proba(X_test)[:, 1]  # Probabilities for the␣
↪positive class
log_reg_auc = roc_auc_score(y_test, y_pred_log_proba)
print(f"Logistic Regression AUC: {log_reg_auc:.4f}")

# K-Nearest Neighbors
```

```python
y_pred_knn_proba = best_knn.predict_proba(X_test)[:, 1]  # Probabilities for␣
↪the positive class
knn_auc = roc_auc_score(y_test, y_pred_knn_proba)
print(f"KNN AUC: {knn_auc:.4f}")

# Random Forest
y_pred_rf_proba = best_rf.predict_proba(X_test)[:, 1]  # Probabilities for the␣
↪positive class
rf_auc = roc_auc_score(y_test, y_pred_rf_proba)
print(f"Random Forest AUC: {rf_auc:.4f}")

# Plot ROC Curve for all models
plt.figure(figsize=(10, 8))

# Logistic Regression ROC
fpr_log, tpr_log, _ = roc_curve(y_test, y_pred_log_proba)
plt.plot(fpr_log, tpr_log, label=f"Logistic Regression (AUC = {log_reg_auc:.
↪4f})")

# KNN ROC
fpr_knn, tpr_knn, _ = roc_curve(y_test, y_pred_knn_proba)
plt.plot(fpr_knn, tpr_knn, label=f"KNN (AUC = {knn_auc:.4f})")

# Random Forest ROC
fpr_rf, tpr_rf, _ = roc_curve(y_test, y_pred_rf_proba)
plt.plot(fpr_rf, tpr_rf, label=f"Random Forest (AUC = {rf_auc:.4f})")

# Plot settings
plt.plot([0, 1], [0, 1], 'k--', label="Random Chance (AUC = 0.5000)")
plt.title("ROC Curve for Models")
plt.xlabel("False Positive Rate (FPR)")
plt.ylabel("True Positive Rate (TPR)")
plt.legend(loc="lower right")
plt.grid()
plt.show()
```

```
Logistic Regression AUC: 0.9069
KNN AUC: 0.6896
Random Forest AUC: 0.9752
```


ROC Curve for Models
True Positive Rate (TPR)
False Positive Rate (FPR)
0.0
0.2
0.4
0.6
0.8
1.0
Logistic Regression (AUC = 0.9069)
KNN (AUC = 0.6896)
Random Forest (AUC = 0.9752)
Random Chance (AUC = 0.5000)