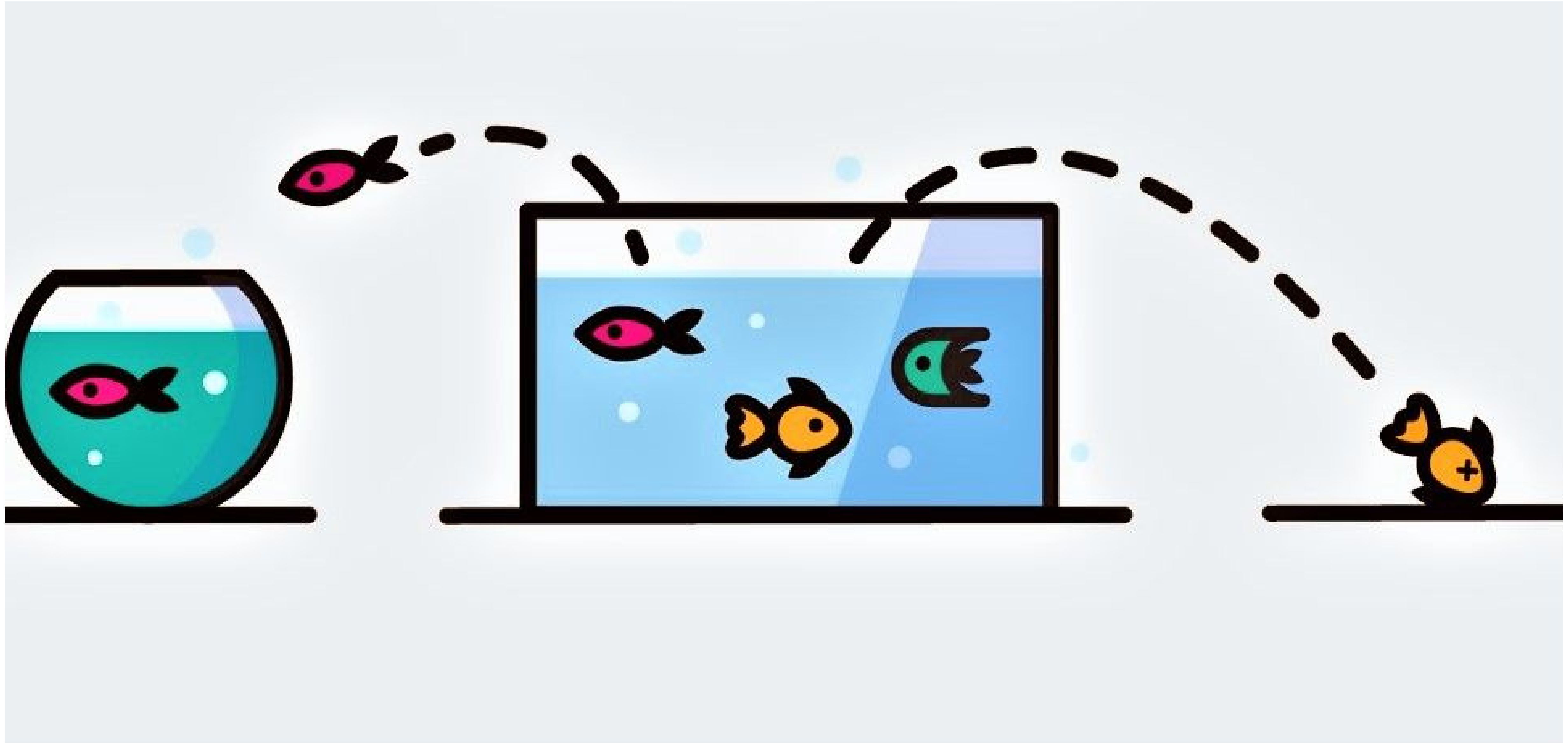
Customer Churn Prediction

Business Problem

A manager at the bank is disturbed with more and more customers leaving their credit card services. They would really appreciate if one could predict for them who is gonna get churned so they can proactively go to the customer to provide them better services and turn customers' decisions in the opposite direction.

Customer Churn

Customer churn or ***customer attrition*** is the phenomenon where customers of a business no longer purchase or interact with it.



Dataset

- Dataset shape (10127,21)
- Each observation represents a customer
- Some features: *age*, *salary*, *marital status*, *credit card limit*, *credit card category*, etc.
- Target variable: ***Attrition_Flag***
- Basically the dataset is a snapshot of the clients in a 12 months period
- No missing values

	CLIENTNUM	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	Income_Category	Card_Category	Months_on_book
0	768805383	Existing Customer	45	M	3	High School	Married	$60K - $80K	Blue	39
1	818770008	Existing Customer	49	F	5	Graduate	Single	Less than $40K	Blue	44
2	713982108	Existing Customer	51	M	3	Graduate	Married	$80K - $120K	Blue	36
3	769911858	Existing Customer	40	F	4	High School	Unknown	Less than $40K	Blue	34
4	709106358	Existing Customer	40	M	3	Uneducated	Married	$60K - $80K	Blue	21

Procedure

1. Exploratory Data Analysis

This will help us to get some insights and have a preliminary idea on the features that are causing clients to leave the organization

2. Data Preprocessing and Model Building

In order to build a model that can predict whether a customer is going to leave or not, so as to take action before it happens

3. Clustering and Model Comparison

To test whether clusters can split the target variable and improve the performance of the model

Exploratory Data Analysis

Some Numbers

Categorical

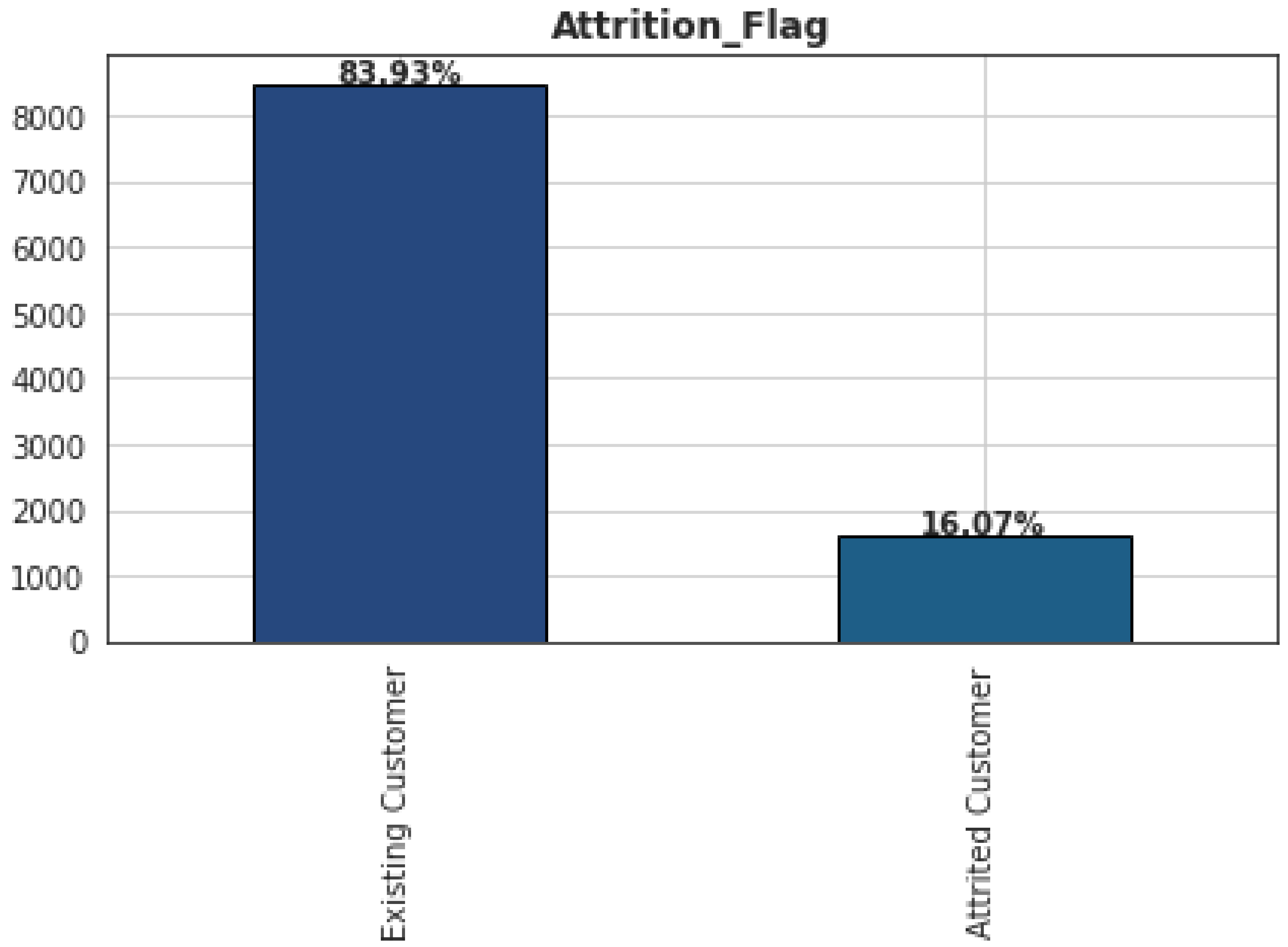
- 31% of the customers are graduated
- 35% has an income less than $40K
- 93% has the Blue Card
- 53% has 2 or 3 dependents

Numerical

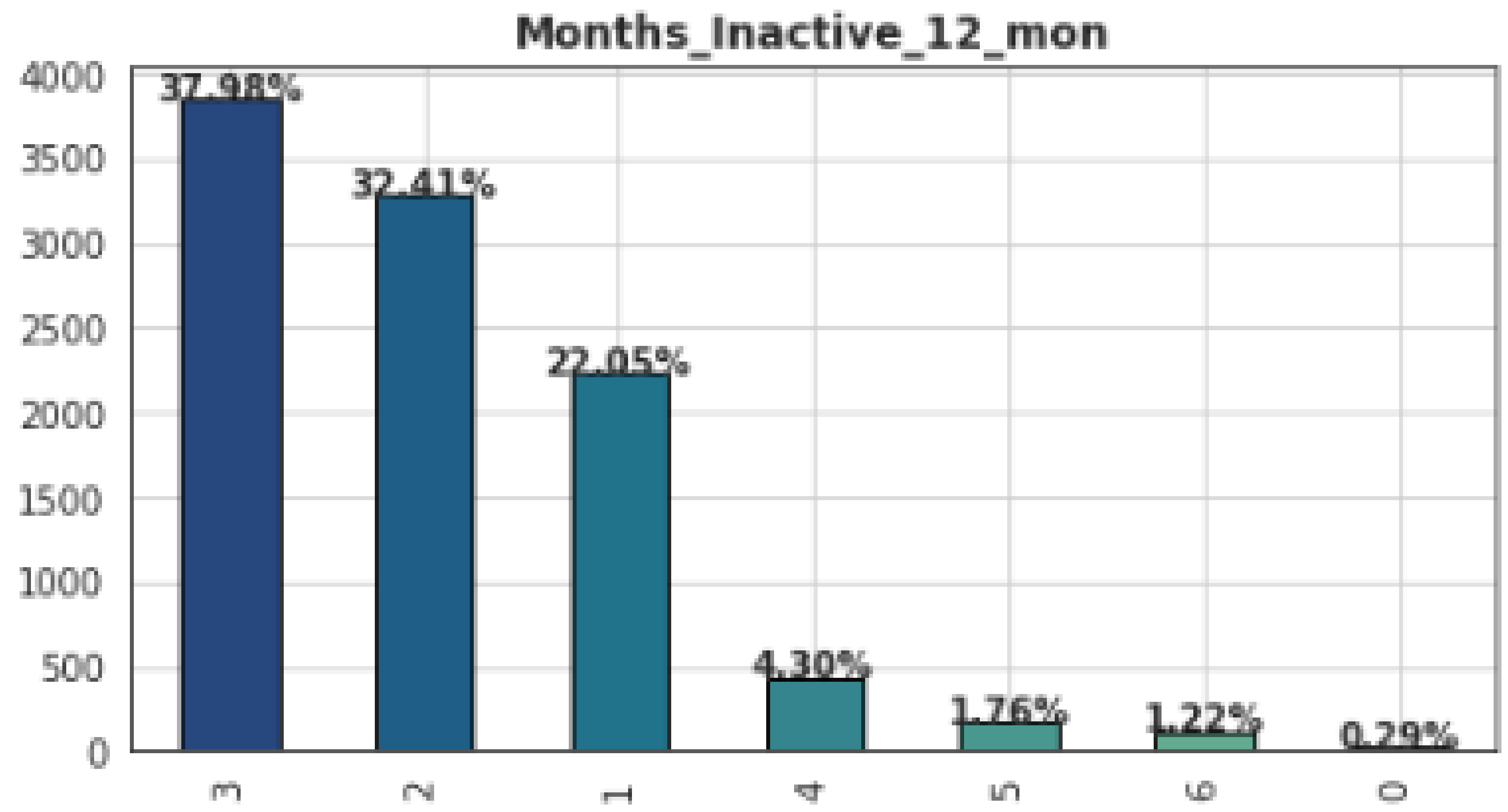
- Mean age is 46
- Median credit limit is $4549
- 75% has a total transactions amount of $4741 or less
- Median total transactions count is 67

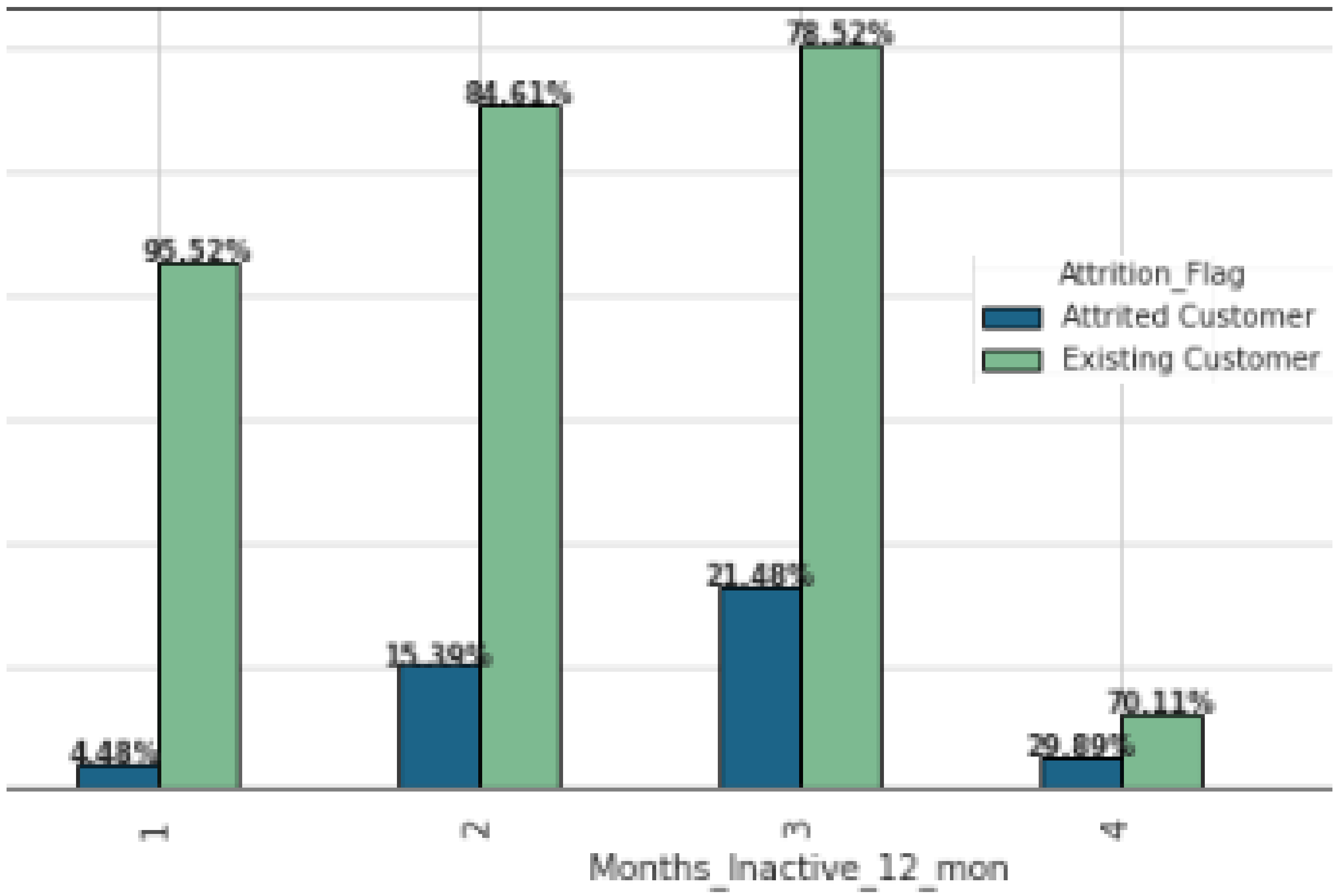
Unbalanced Dataset

Only 16% of customers left the bank. This is a clear example of an ***unbalanced dataset***.



No. of months of inactivity in the last 12 months





It can be seen that as months of inactivity grow, the percentage of clients leaving increases. We have only taken into account the first 4 months of inactivity since they represent almost 97% of the data.

T-Test on The Target Variable

A t-test is a statistical test that is used to compare the ***means of two groups***. It is often used in hypothesis testing to determine whether two groups are different from one another.

```
significance_level = 0.01
significant_features = []

# The 2 groups
existing = df.loc[df.Attrition_Flag=="Existing Customer"]
attrited = df.loc[df.Attrition_Flag=="Attrited Customer"]

for n, feature in enumerate(numerical):

    ax = plt.subplot(5, 2, n + 1)


    df.groupby("Attrition_Flag",as_index=False).mean()[feature].plot.bar(edgecolor="black",ax=ax, color=[colors[1],colors[5]])
    ax.set_xticklabels(["Attrited Customer","Existing Customer"],rotation=0)
    # p-value
    pval = stats.ttest_ind(a= existing[feature],
                    b= attrited[feature],
                    equal_var=False)[1]

    ax.set_title("{} (p-value: {:.3}) ".format(feature,pval),fontweight="bold", fontsize=18)
    # significant features
    if pval < significance_level:
        significant_features.append(feature)
```

Results

Significant Features (p-value < 0.01):

Total_Revolving_Bal

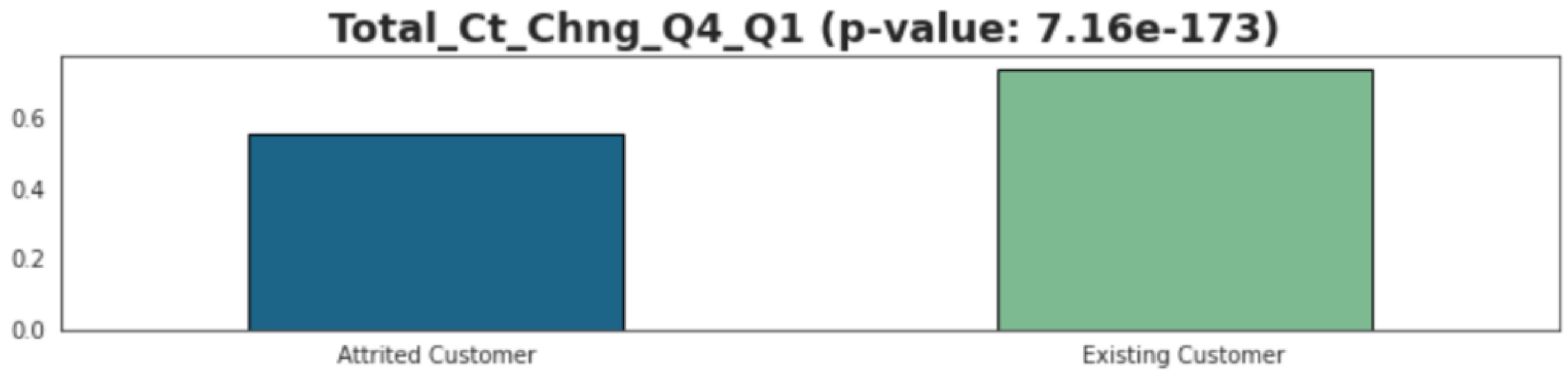
Total_Amt_Chng_Q4_Q1

Total_Trans_Amt

Total_Trans_Ct

Total_Ct_Chng_Q4_Q1

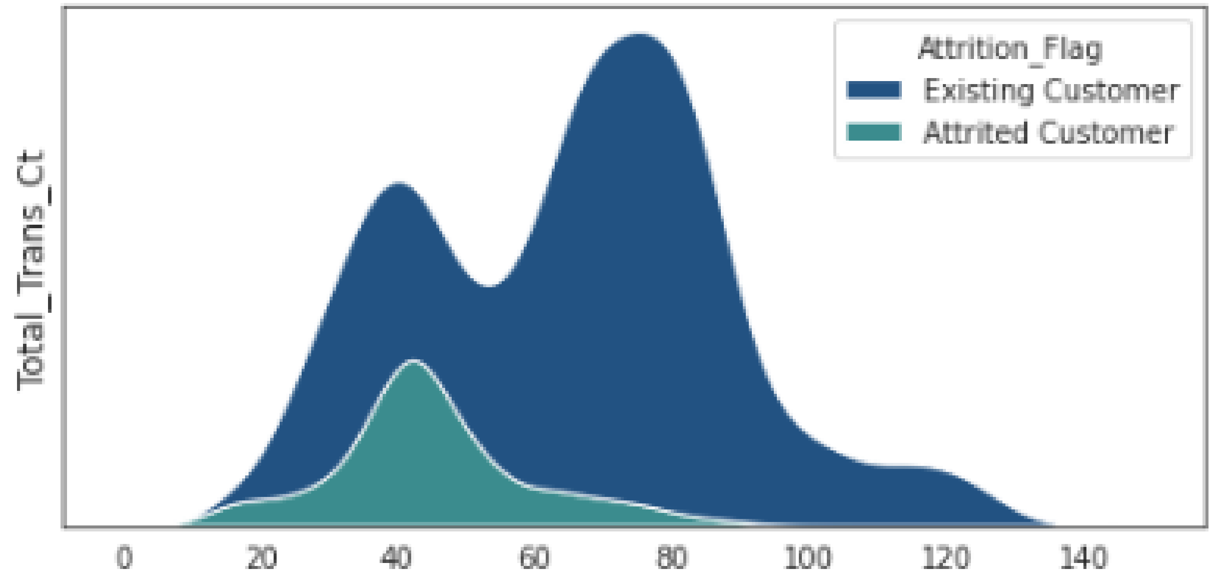
Avg_Utilization_Ratio

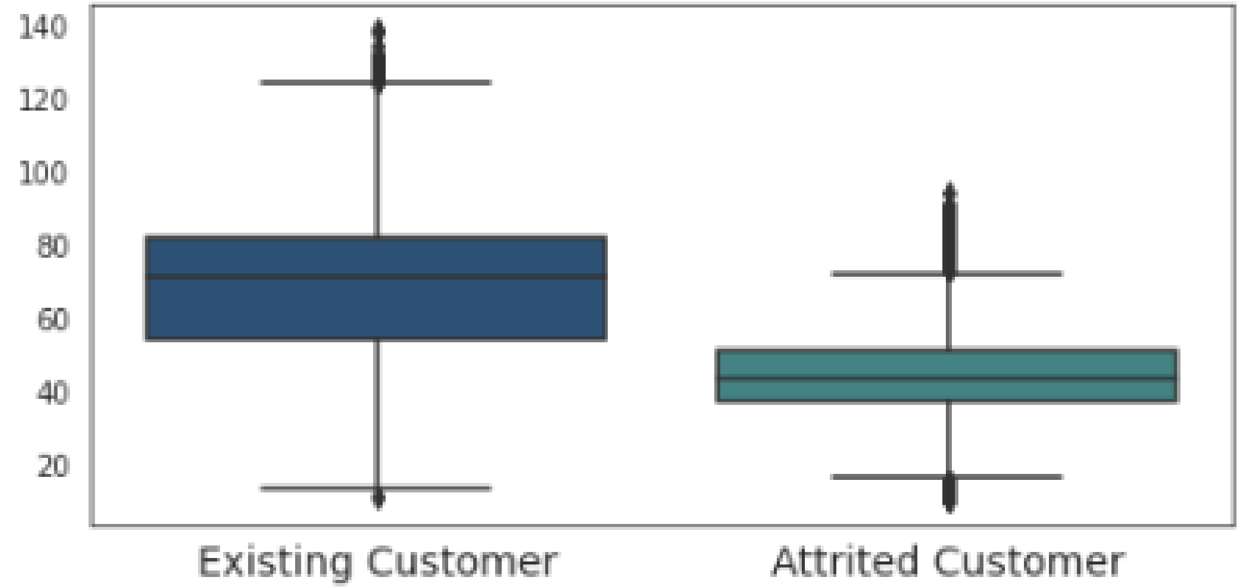


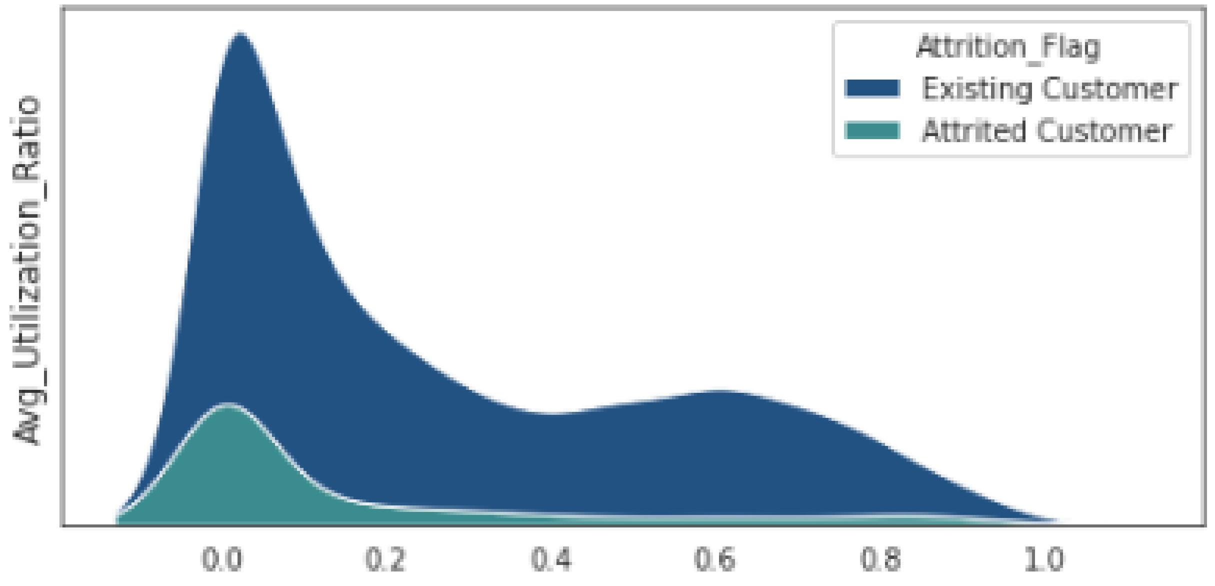
Variable with the lowest p-value

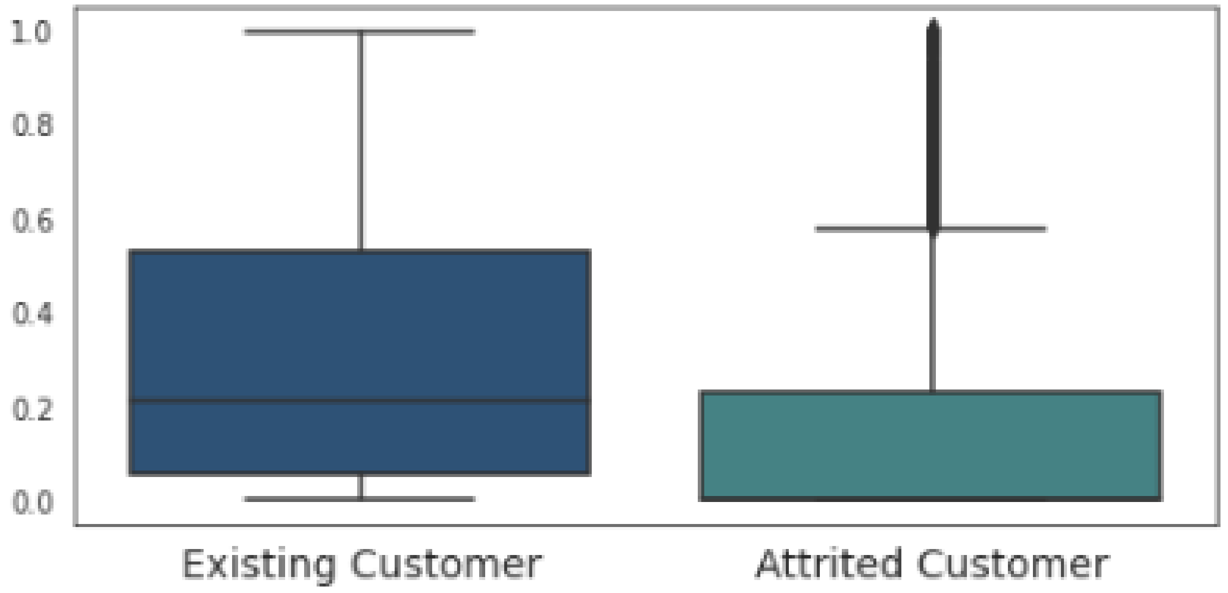
We can see that all the significant features are **related to the client activity levels**, except for *Total_Revolving_Bal* which is the total revolving balance on the credit card.

Let's try with the Median



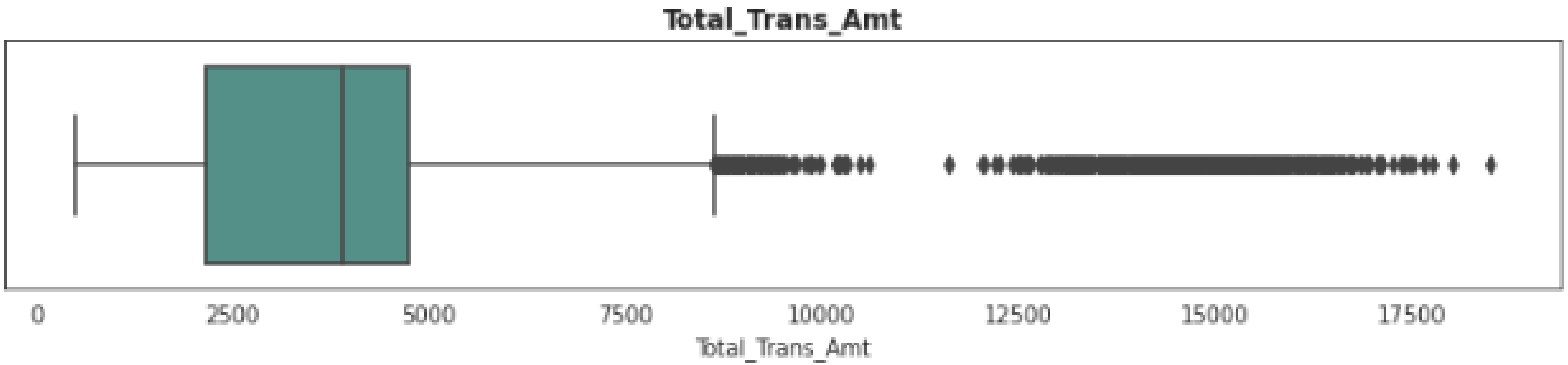






The previous results are confirmed even if we use the median instead of the mean, as can be seen in the two graphs used as examples.

Outliers



Some of the numerical variables present outliers. Removing them could lead to better performance of a predictive model, but in this case they are ***natural outliers*** (and ***not recording errors***) so they should not be removed. In the image it can be seen that some clients may exceed $17500 in total transactions amount.

What EDA Suggests

- The customers of the bank are ***relatively young with lower income levels***
- The most important features that help to predict whether a customer is going to leave are those related to the ***activity levels***
- Outliers ***shouldn't always be removed***, especially if they aren't due to recording errors

Data Preprocessing and Model Building

Label Encoding

```
#percentage of attrited customers that we are going to lose if we just drop the missing values
attrited = df.Attrition_Flag.value_counts()[1]
missing_attrited = 0
for feature in features_missing:
    value = df[df[feature] == "Unknown"]["Attrition_Flag"].value_counts()[1]
    missing_attrited += value
print("{:.2%}".format(missing_attrited / attrited))
```

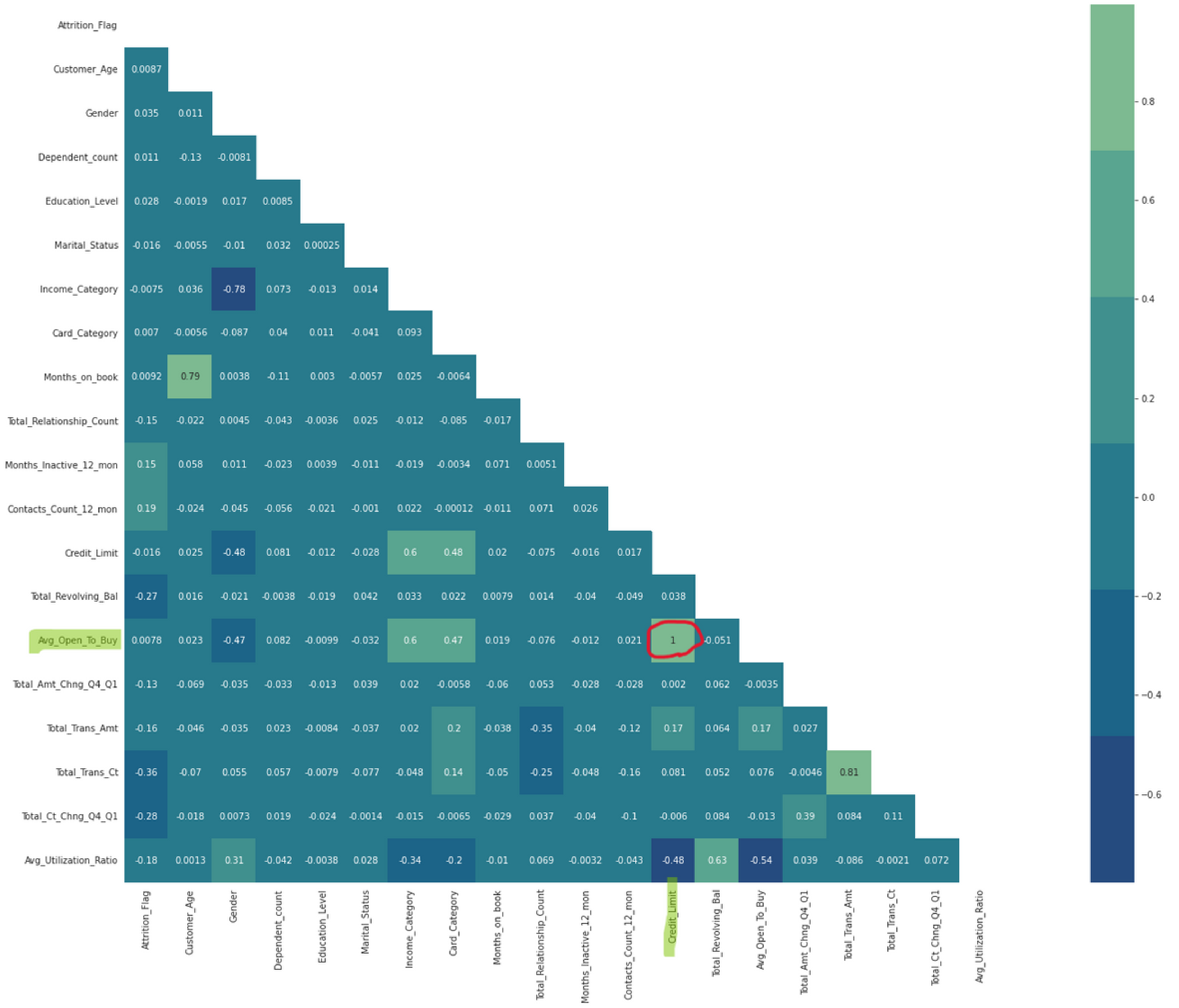
```
35.16%
```

```
data["Attrition_Flag"] = data["Attrition_Flag"].replace({'Existing Customer':0, 'Attrited Customer':1})
data["Gender"] = data["Gender"].replace({'M':0, 'F':1})
data['Education_Level']= data['Education_Level'].replace({'Uneducated':0, 'High School':1, 'College':2, 'Graduate':3,'Post-Graduate':4, 'Doctorate':5})
data['Income_Category']= data['Income_Category'].replace({'Less than $40K':0, '$40K - $60K':1, '$60K - $80K':2, '$80K - $120K':3, '$120K +':4})
data['Card_Category']= data['Card_Category'].replace({'Blue':0, 'Silver':1, 'Gold':2, 'Platinum':3})
```

```
data["Marital_Status"] = data["Marital_Status"].map({"Single":0, "Married":1, "Divorced":2})
```

After seeing the low number of rows with the value *'Unknown'*, we decided to delete them. Then we have changed the value inside the categorical columns from strings to **numerical** in order to develop our model.

Correlation Matrix



From the correlation matrix you can see that the variable *Avg_Open_To_Buy* is **highly correlated** with the variable *Credit_Limit* so we decided to drop it (no additional information from it).

Model Building

```
def sampling_and_model(df,model,method,scaled,plot):
    X = df.drop("Attrition_Flag", axis=1)
    y = df.Attrition_Flag
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, stratify=y, random_state=42)

    if method=="undersampling":
        under = RandomUnderSampler(random_state=42)
        X_train,y_train = under.fit_resample(X_train,y_train)

    if method=="smote":
        over = SMOTE(random_state=42)
        X_train, y_train = over.fit_resample(X_train, y_train)

    if method=="both":
        over = SMOTE(random_state=42,sampling_strategy=0.5)
        under = RandomUnderSampler(random_state=42,sampling_strategy=0.7)
        X_train, y_train = over.fit_resample(X_train, y_train)
        X_train, y_train = under.fit_resample(X_train, y_train)

    if scaled==True:
        scaler = MinMaxScaler()
        model.fit(scaler.fit_transform(X_train),y_train)
        y_pred = model.predict(scaler.transform(X_test))
        prob = model.predict_proba(scaler.transform(X_test))[:,1]
        fpr, tpr, _ = roc_curve(y_test,prob)
    else:
        model.fit(X_train,y_train)
        y_pred = model.predict(X_test)
        prob = model.predict_proba(X_test)[:,1]
        fpr, tpr, treshold = roc_curve(y_test,prob)
```

Our dataset was unbalanced and to solve this problem we defined a function where we tried 2 techniques:

- **Undersampling** that duplicate the members of the minority class
- **SMOTE** constructs new samples by observing the attributes of all samples and then alter the values just so that they stay within the range observed in the minority-class.

We have also tried to use the <u>two methods together</u> (*'both'*).

Models & Results

	SMOTE	UnderSampling	Both	Best_Method
Logistic Regression	0.8830	0.9002	0.8894	UnderSampling
K-Nearest Neighbor	0.8360	0.8408	0.8361	UnderSampling
Support Vector Machines	0.9291	0.9227	0.9338	Both
Decision Tree	0.8903	0.8800	0.9057	Both
Random Forest	0.9857	0.9776	0.9859	Both
XGBoost	0.9852	0.9824	0.9873	Both

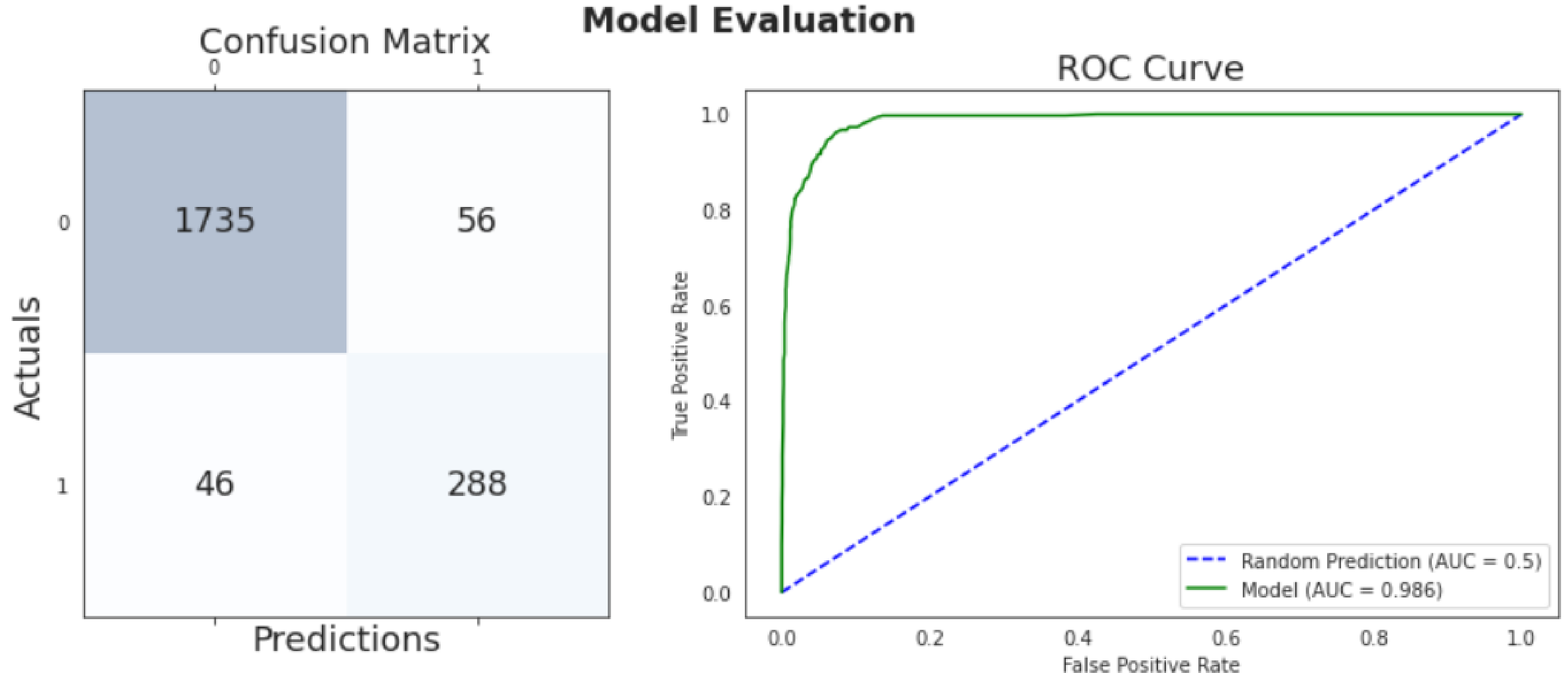
These are the models we tested with their respective results. We used the **AUC score** as metric to assess the goodness of the models, the two highest are for the **Random Forest** and **XGBoost**.

Model comparison

Random Forest

	precision	recall	f1-score	support
0	0.97	0.97	0.97	1791
1	0.84	0.86	0.85	334
accuracy			0.95	2125
macro avg	0.91	0.92	0.91	2125
weighted avg	0.95	0.95	0.95	2125

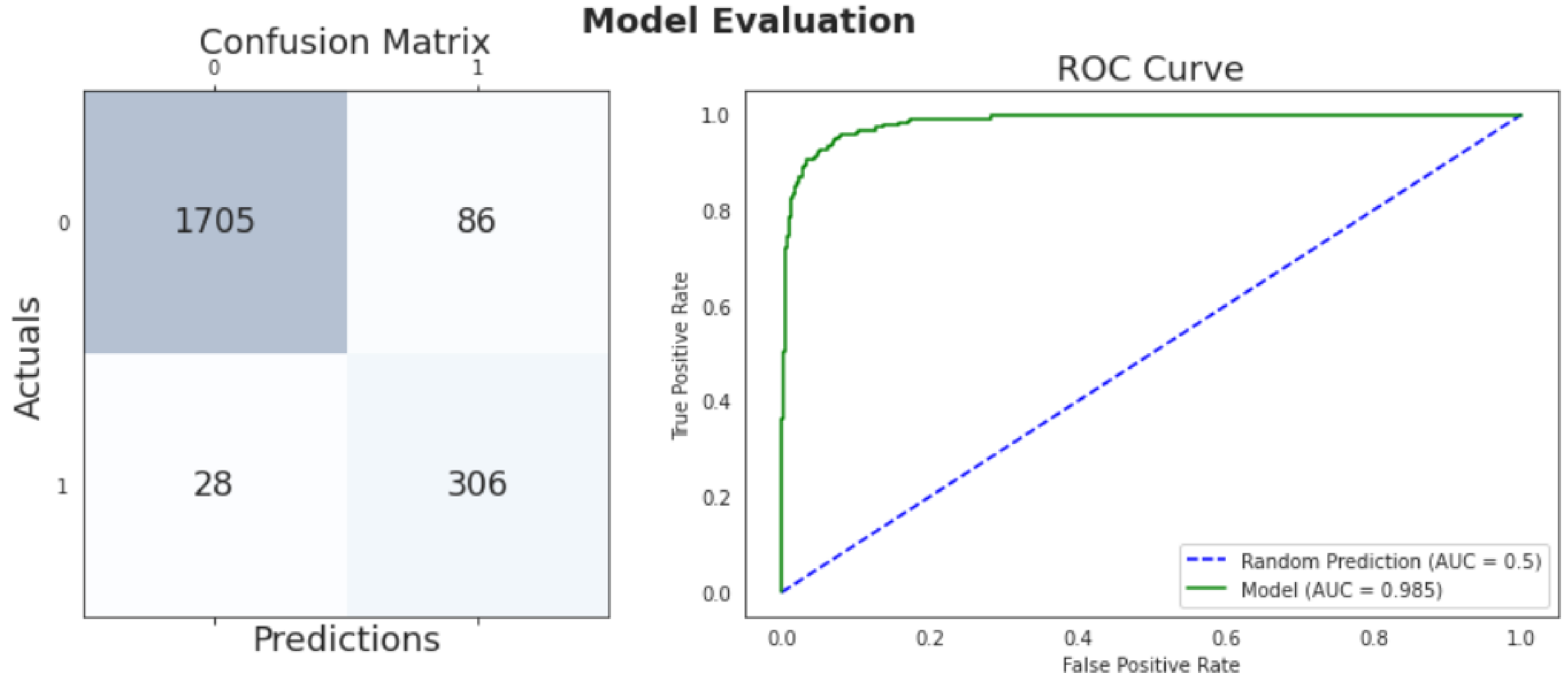
AUC Score: 0.9857



XGBoost

	precision	recall	f1-score	support
0	0.98	0.95	0.97	1791
1	0.78	0.92	0.84	334
accuracy			0.95	2125
macro avg	0.88	0.93	0.91	2125
weighted avg	0.95	0.95	0.95	2125

AUC Score: 0.9852



To confirm the results we made a confusion matrix and a classification report. From these we can see how well the two models predict the churn for a client.

Neural Network

```
import tensorflow as tf
import keras

tf.random.set_seed(42)

model = keras.Sequential([
    keras.layers.Dense(12, activation = keras.activations.relu),
    keras.layers.Dense(6, activation = keras.activations.relu),
    keras.layers.Dense(1, activation=tf.keras.activations.sigmoid)
])
```

After splitting and scaling the dataset we defined a neural network by using the library Keras. We created a model with **three-layers**: the first layers of the model contains ***12 neurons*** that take the input from the data and applies the **ReLU** activation.

The second layer contains ***6 neurons*** that takes the input from the preceding layer and applies again a **ReLU**. The third layer has only ***one neuron*** that takes the input from the preceding layer, applies a **Sigmoid** activation and gives the classification output as 0 or 1.

Later we compiled the model by using ***binary_crossentropy*** as loss and ***Adam*** as optimizer with a learning rate of 0.01

```
model.compile(loss=keras.losses.binary_crossentropy,
              optimizer=tf.keras.optimizers.Adam(learning_rate=0.01),
              metrics=['accuracy','AUC'])
```

Then we used X_train and y_train for training the model and run it for *400 epochs* with a *batch size* of *128.*

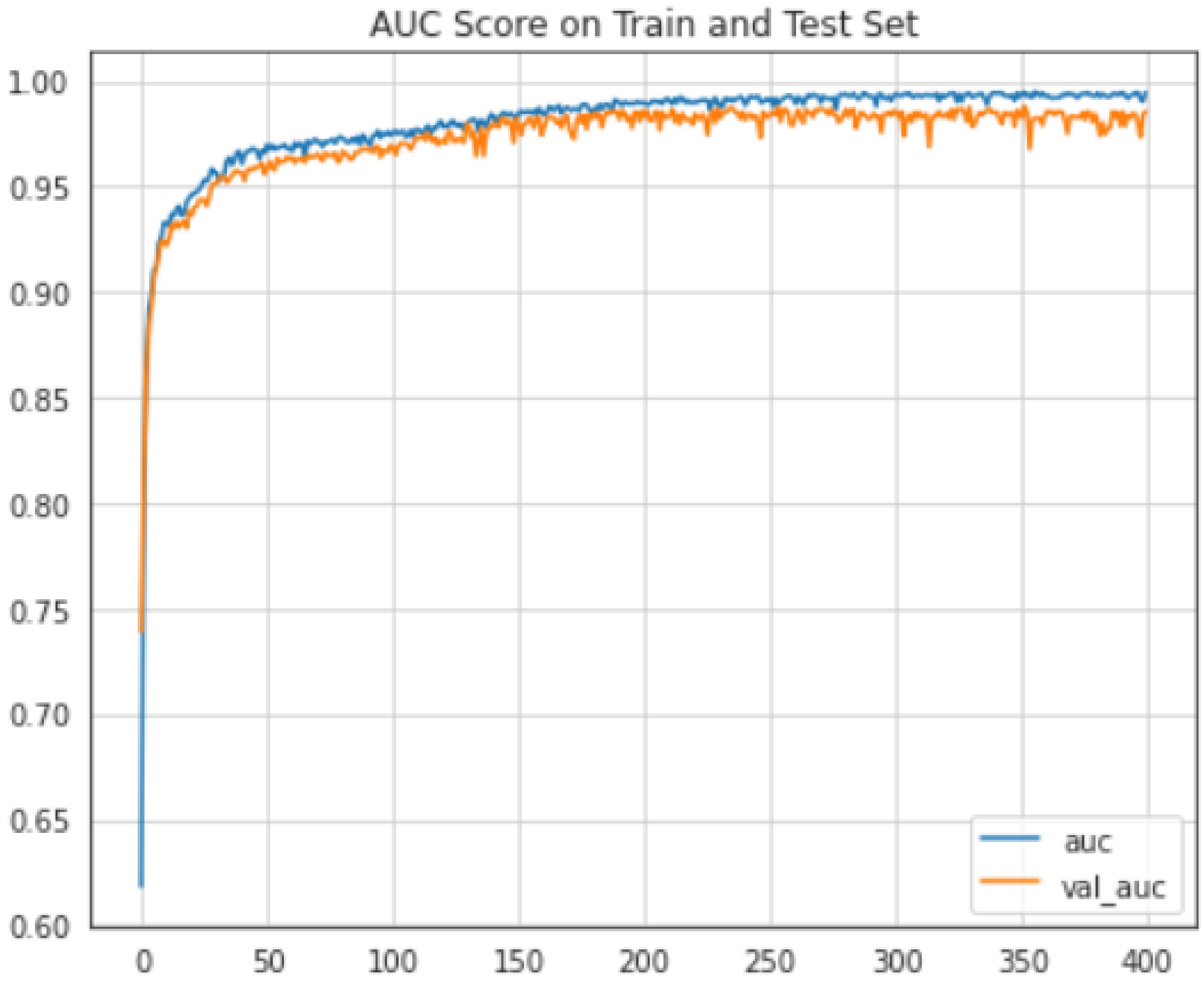
```
history = model.fit(X_train, y_train, epochs=400, batch_size=128, validation_data=(X_test, y_test), verbose=0)
```

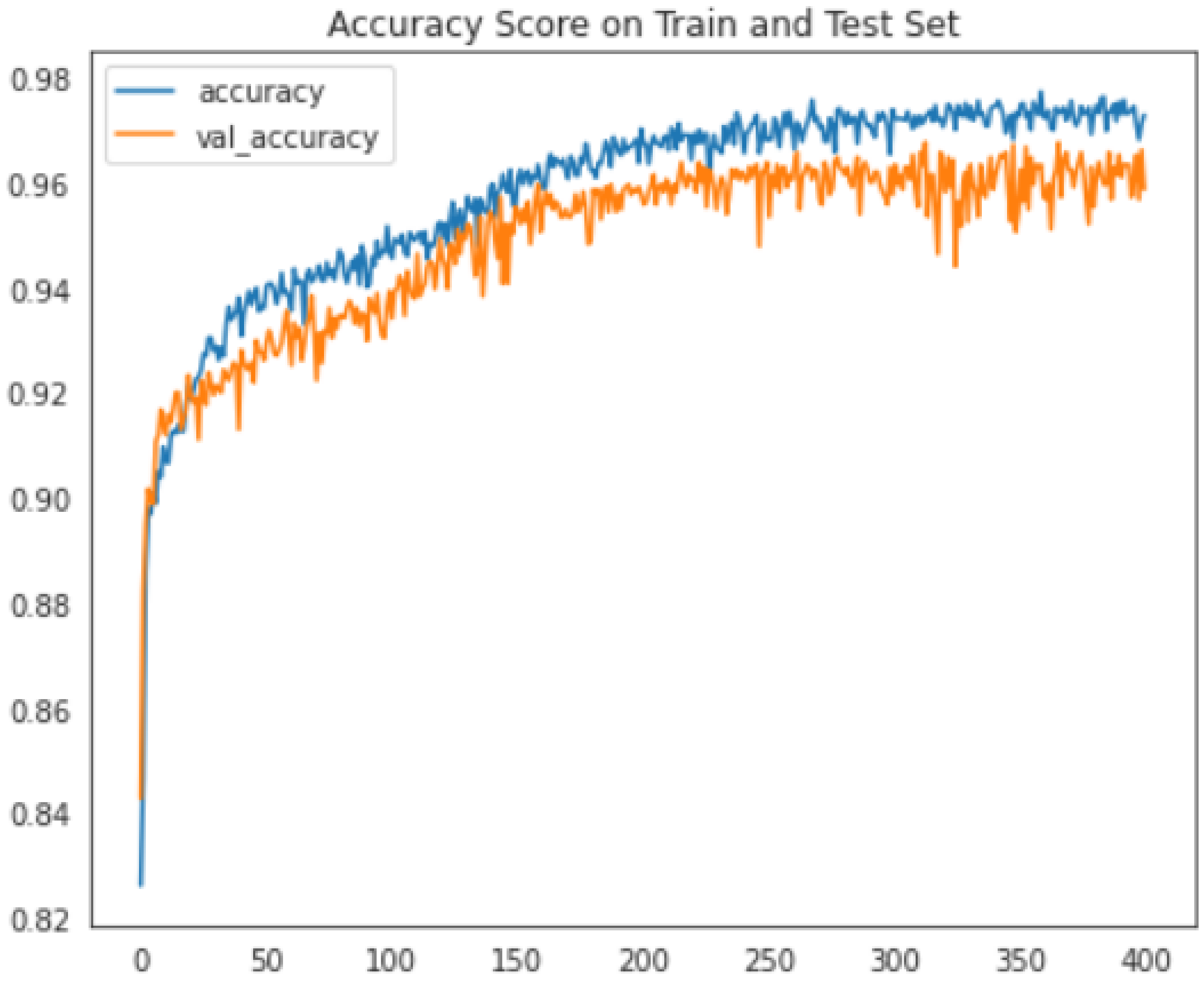
After the training, the model is evaluated on X_test and y_test.

```
loss, accuracy, auc = model.evaluate(X_test, y_test)
print(f"Model loss on the test set: {loss}")
print(f"Model accuracy on the test set: {100*accuracy:.3f}%")
print(f"Model AUC on the test set: {auc:.3f}")
```

```
67/67 [==============================] - 0s 932us/step - loss: 0.1080 - accuracy: 0.9586 - auc: 0.9856
Model loss on the test set: 0.10798574239015579
Model accuracy on the test set: 95.859%
Model AUC on the test set: 0.986
```

The AUC is **0.9856** and this is a very good result, to better evaluate we also checked whether the neural network is overfitting or not thanks to the graph below but it seems to work well.





In the end we also plotted the classification report and confusion matrix to get a complete view of the neural network performance.

	precision	recall	f1-score	support
0	0.98	0.97	0.98	1791
1	0.85	0.90	0.87	334
accuracy			0.96	2125
macro avg	0.91	0.93	0.92	2125
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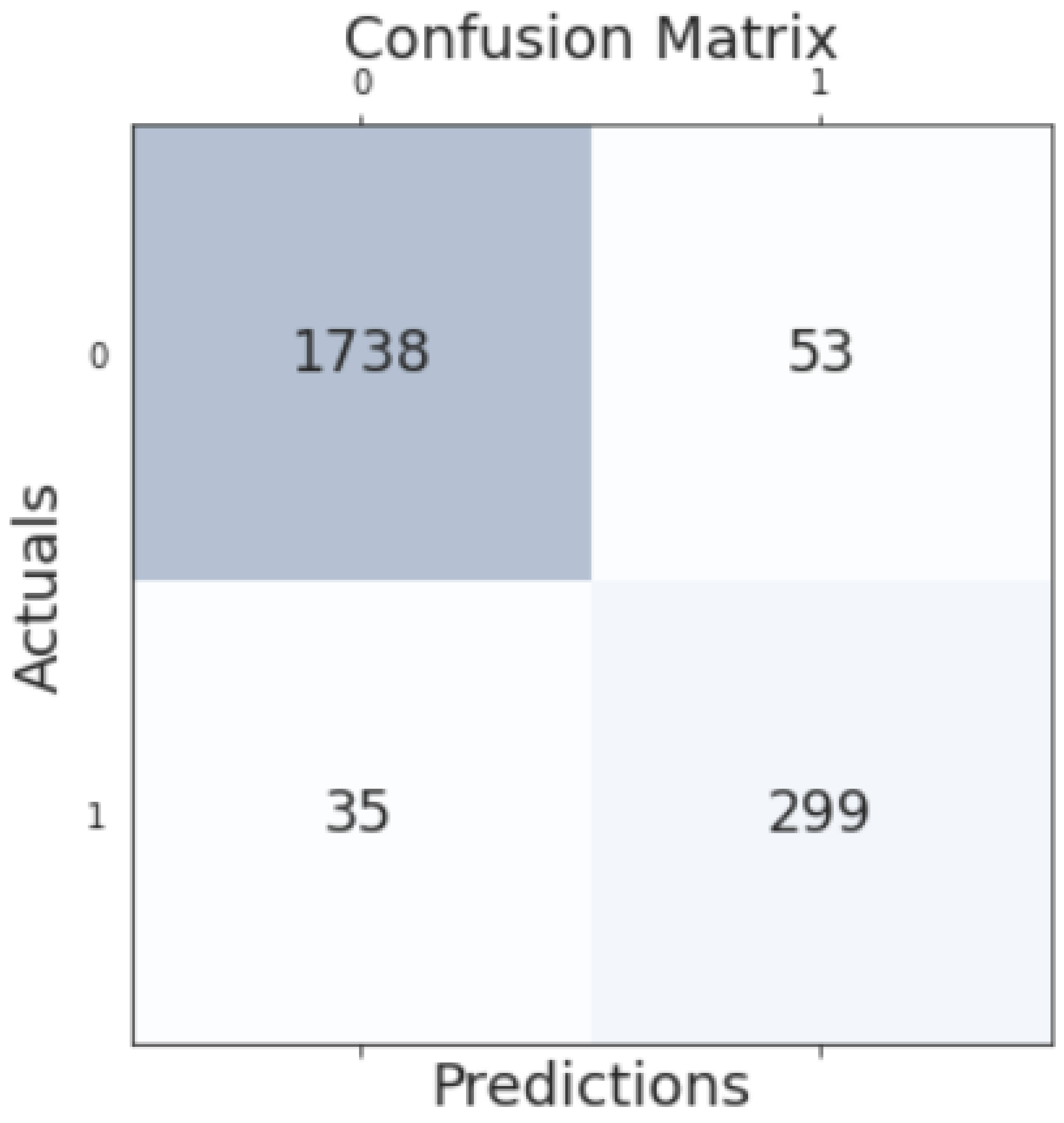


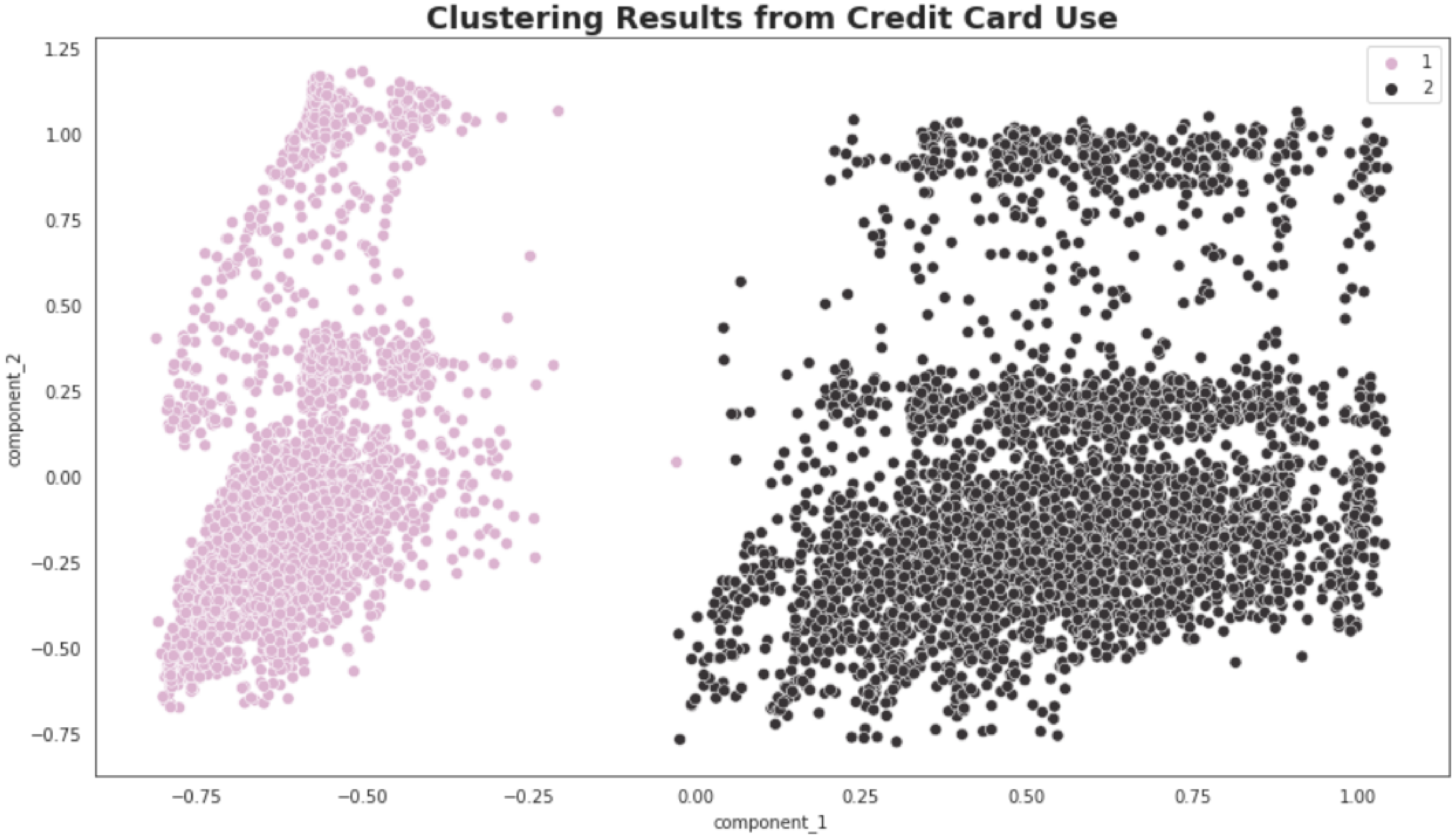
Clustering

Underlying idea

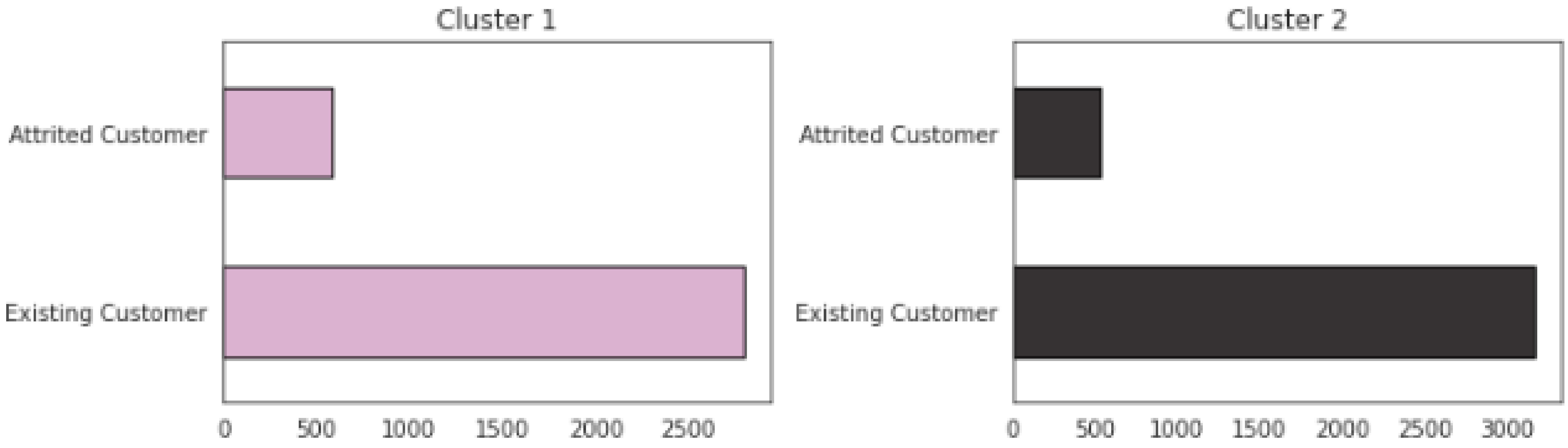
We wanted to see out of curiosity if by giving information about the clusters of customers we could improve the results of the models.
To do this we will use the **clusters' information as a new feature**.
Firstly, we see how the entire dataset behaves with clustering and how the clusters are different (K-Means algorithm to perform the clustering).
In order **to avoid leakage** of information and getting distorted results we fit the algorithm on the training set and then predict the results of the test set.

Cluster Analysis: 2 clusters

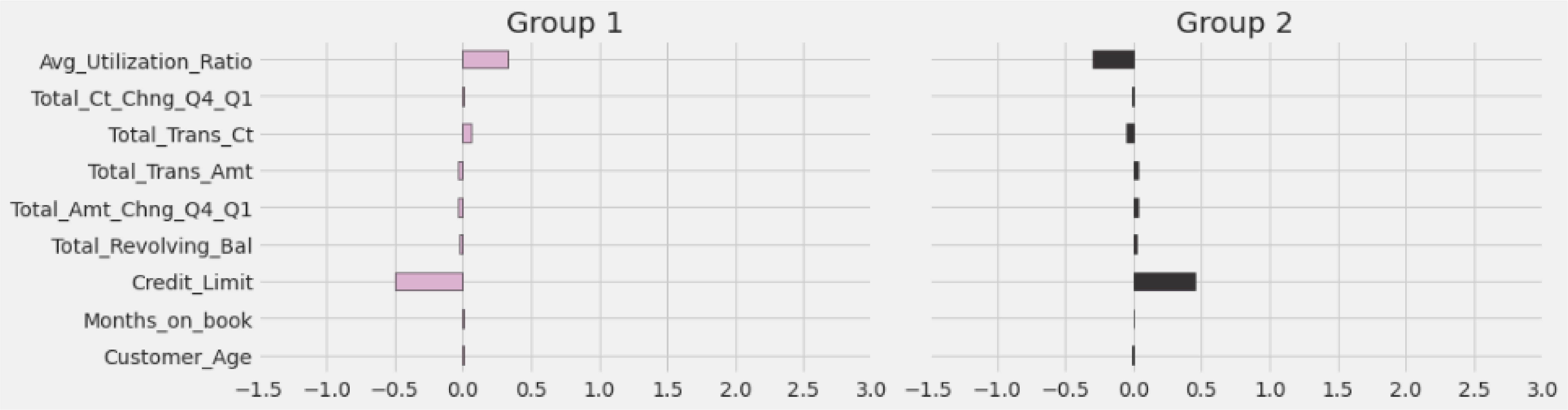
By dividing into 2 clusters we wanted to see if it could distinguish the groups of attrited and existing customers. To verify the goodness of the clustering we used the Silhouette score and obtained a value of 0.56 which is quite good.

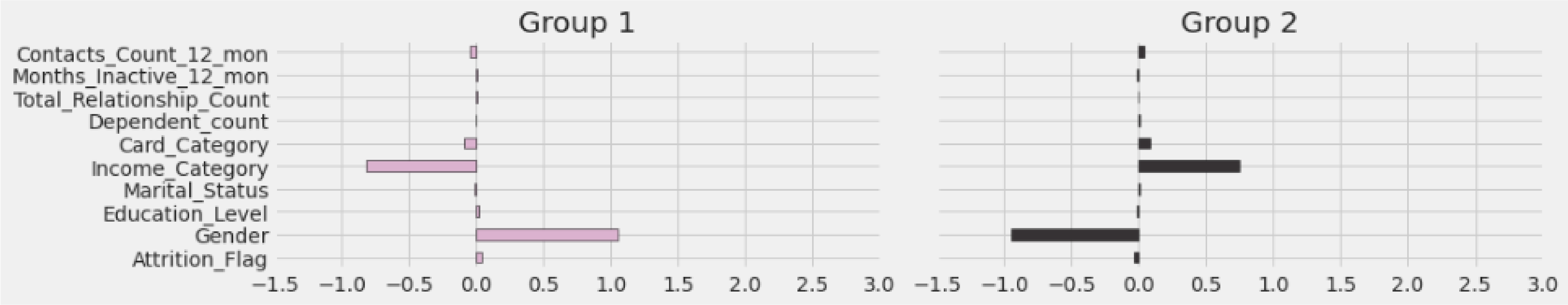


Cluster Analyisis 1



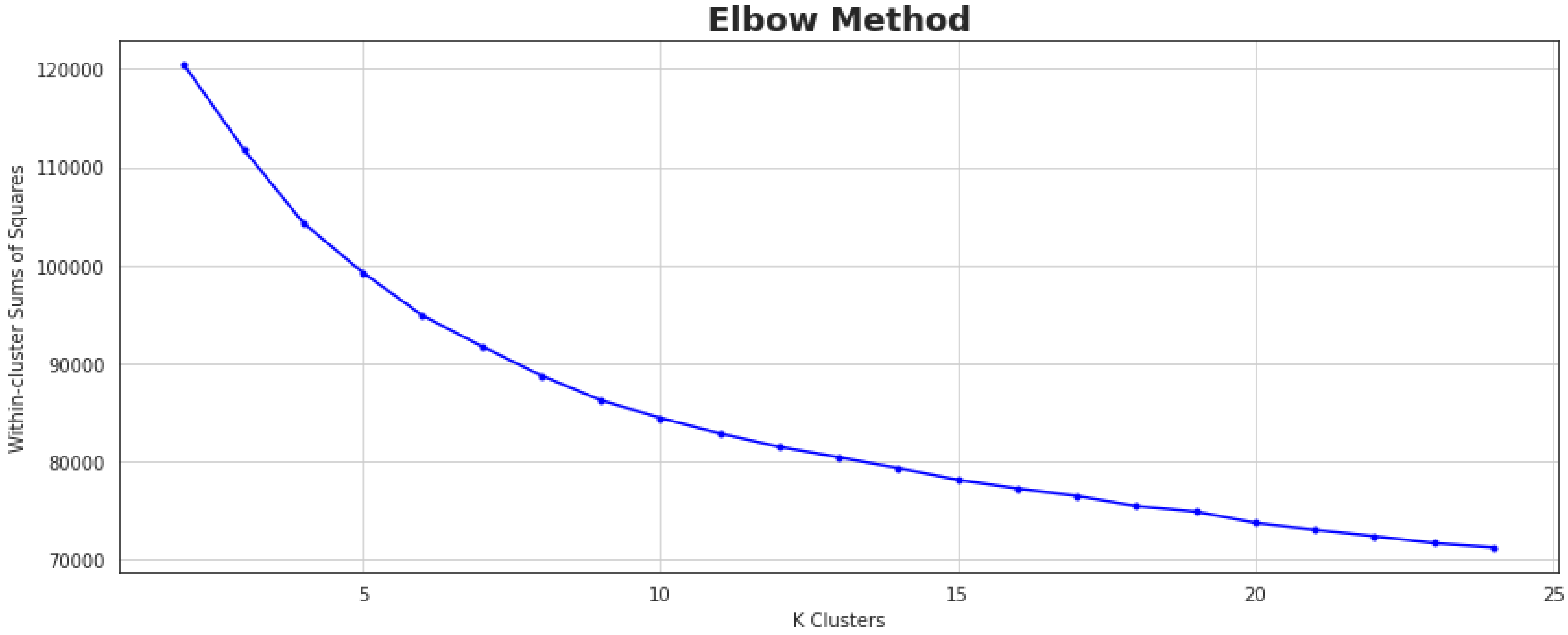
We can see immediately that the clusters aren't based on the Attrited/Existing Customer status. Let's dive deeper into the distinction between the two clusters.





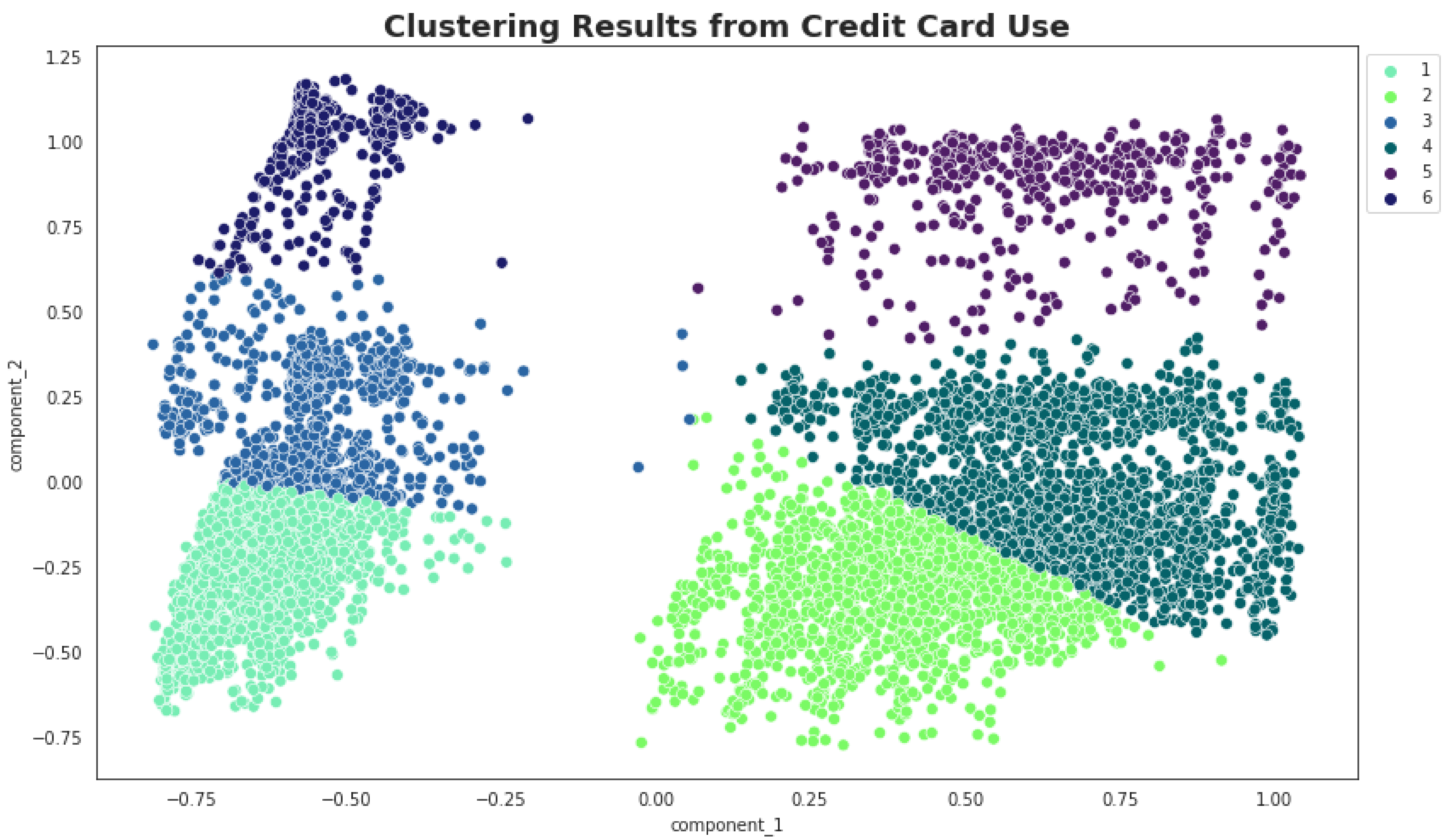
If we divide in 2 clusters the distinctions between them a mainly in the *Avg_Utilization_Ratio*, *Avg_Open_To_Buy*, *Credit_Limit*, *Income_Category* and *Gender*.

Cluster Analysis with Elbow Method

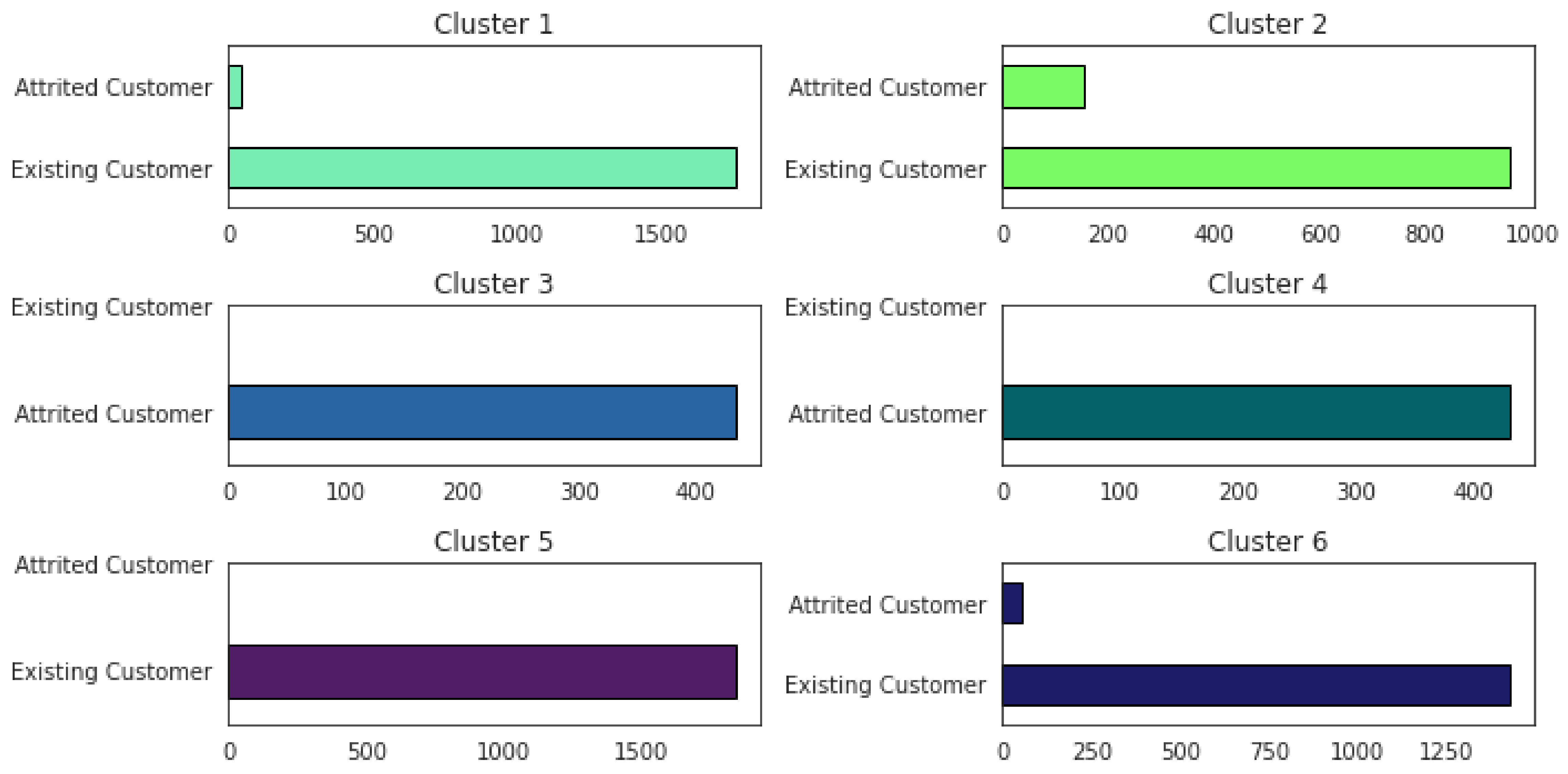


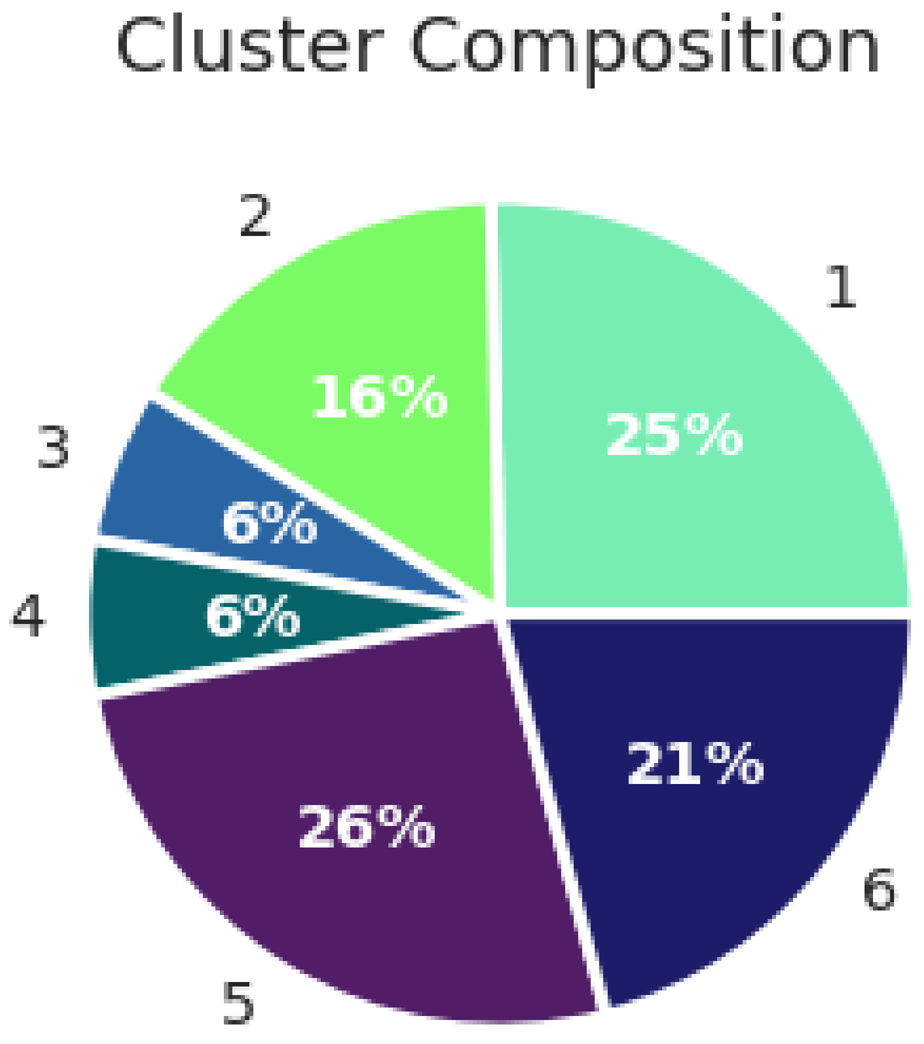
Since 2 clusters weren't able to separate attrited customers from the existing ones, we've used the elbow method to choose another k.

6 seems like a *reasonable number of clusters* looking ad the plot.



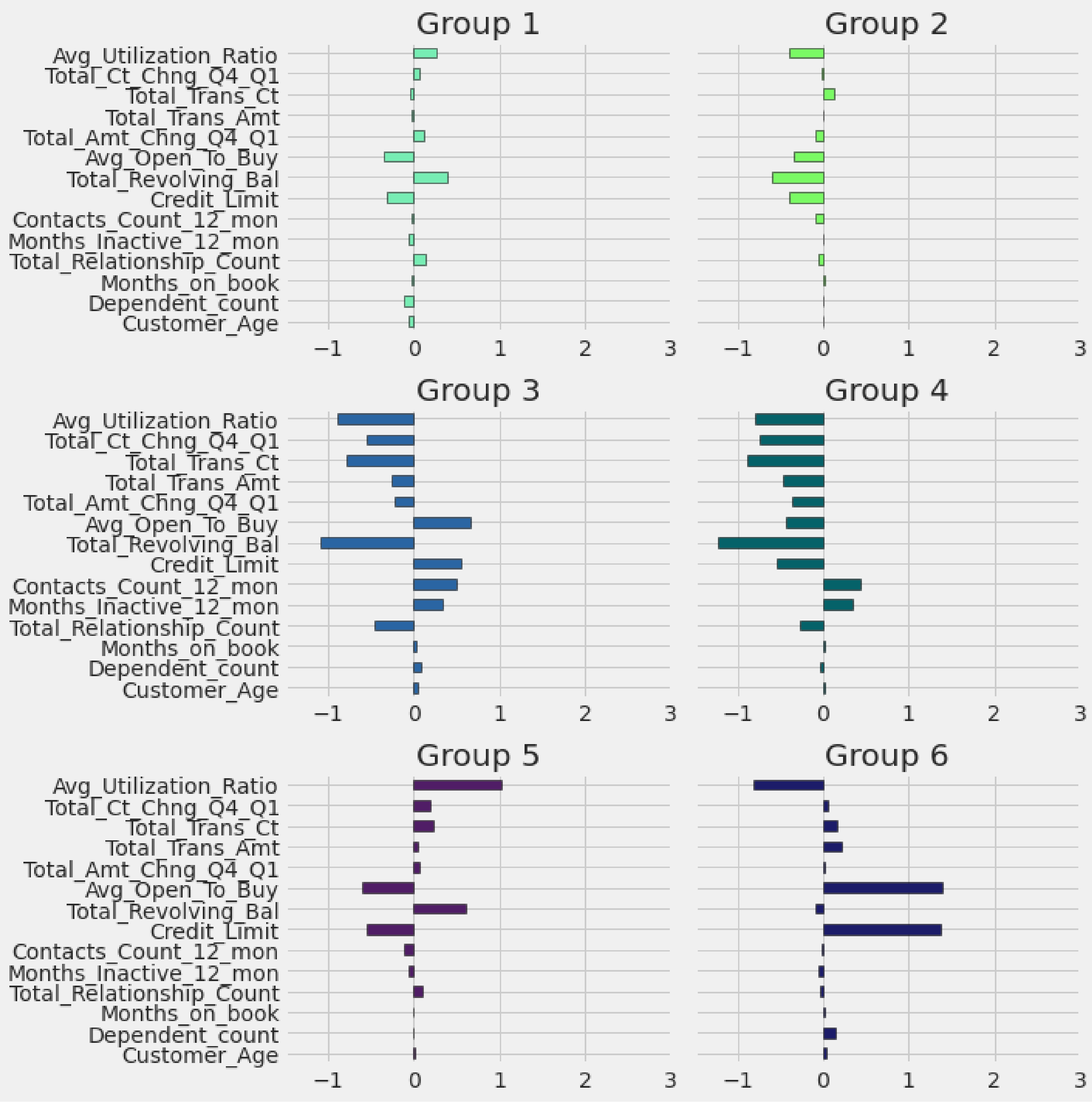
The **Silhouette Score** obtained by using six clusters is **0.48**, which is still an acceptable result.



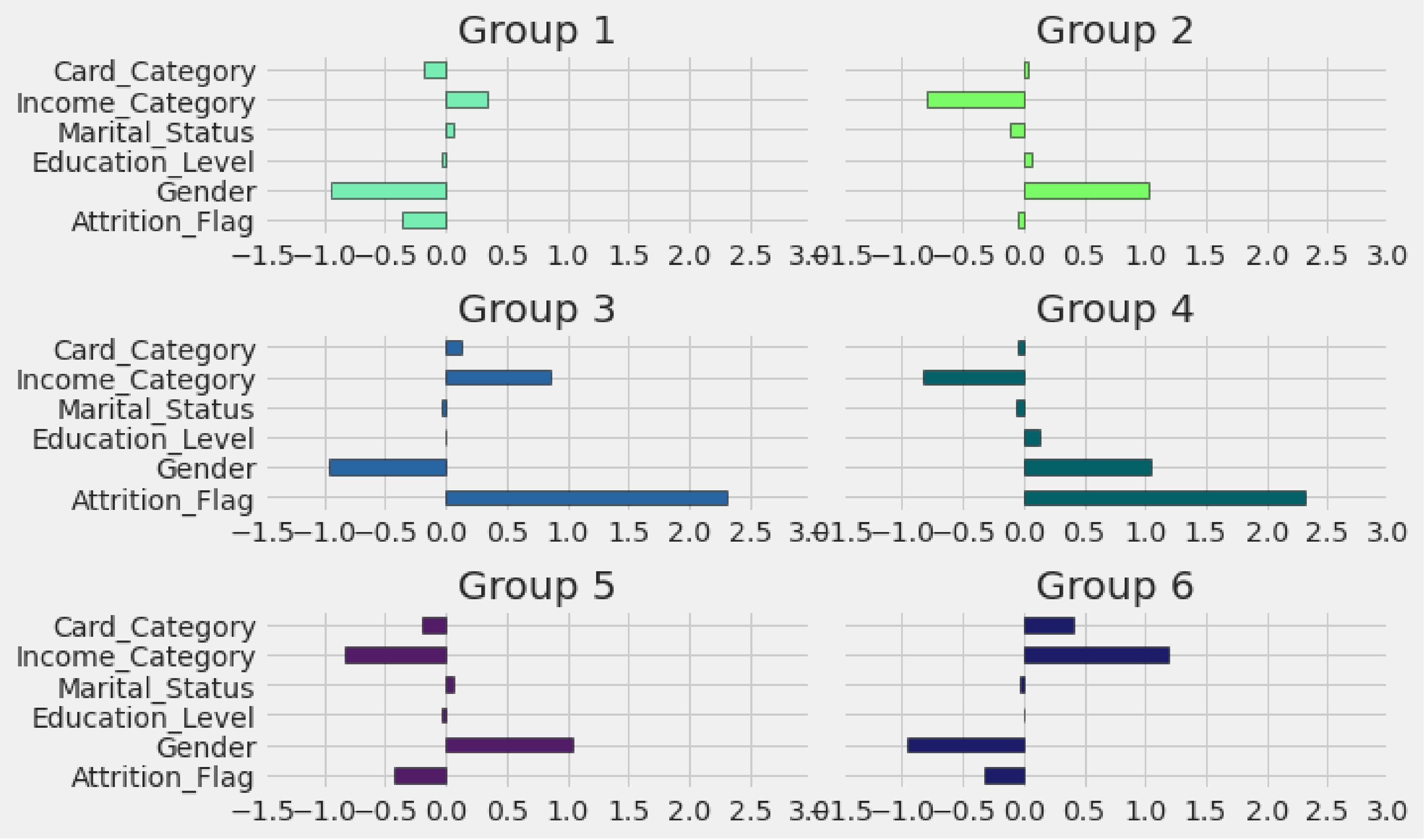


With 6 clusters we can see that we were able to identify two groups mostly composed of Attrited Customers (group 3 and 4). Let's see their characteristics.

Numerical Variables



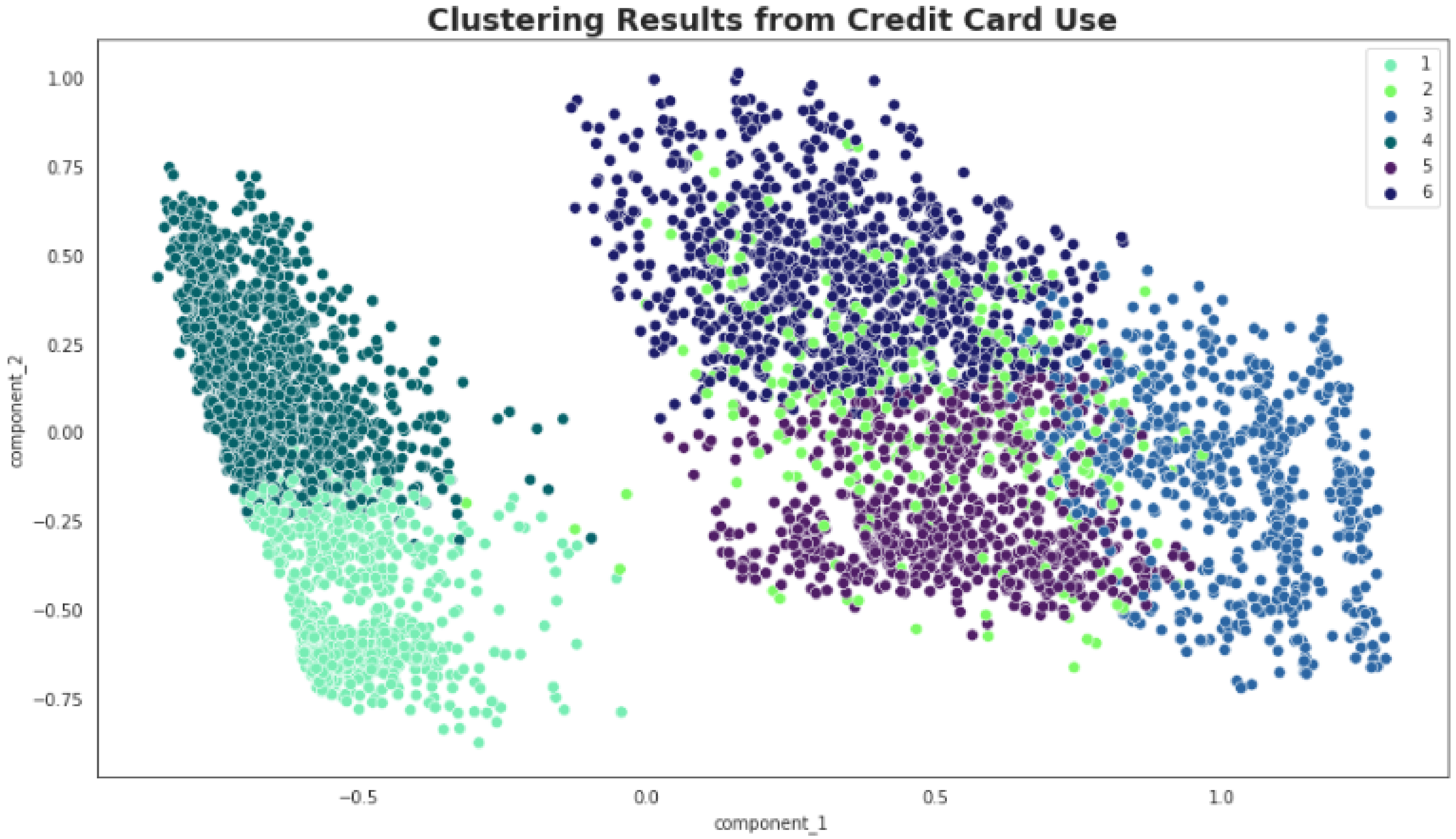
Categorical Variables



We can observe that Group 3 and 4 have in common negative values (on average) of: *Avg_Utilization_Ratio, Total_Ct_Chng_Q4_Q1, Total_Trans_Ct, Total_Trans_Amt, Total_Amt_Chng_Q4_1, Total_Revolving_Bal* and *Total_Relationship_Count.*

Cluster groups as feature

In order not to commit data leakage we'll fit the kmeans clustering only on the training set and then we predict the cluster groups of the training set and test set.



Models & Results

	SMOTE	UnderSampling	Both	Best_Method
Logistic Regression	0.9015	0.9189	0.9074	UnderSampling
K-Nearest Neighbor	0.8498	0.8603	0.8474	UnderSampling
Support Vector Machines	0.9379	0.9391	0.9381	UnderSampling
Decision Tree	0.8759	0.8909	0.8738	UnderSampling
Random Forest	0.9852	0.9815	0.9870	Both
XGBoost	0.9851	0.9865	0.9872	Both

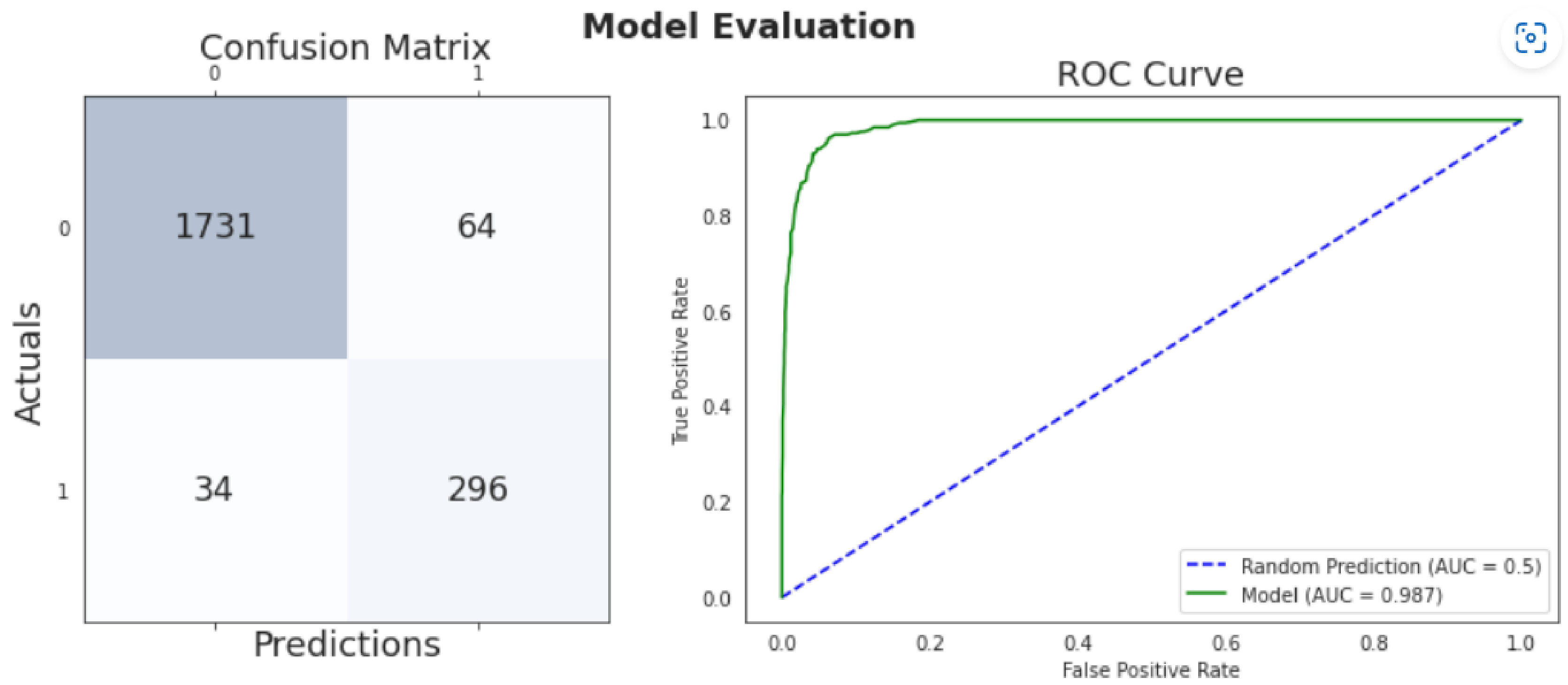
We can see slight improvements in nearly all the models by looking at the **AUC scores**, the two best performing models remain **Random Forest** and **XGBoost.**

Model comparison

Random Forest (Both method)

	precision	recall	f1-score	support
0	0.98	0.96	0.97	1795
1	0.82	0.90	0.86	330
accuracy			0.95	2125
macro avg	0.90	0.93	0.92	2125
weighted avg	0.96	0.95	0.95	2125

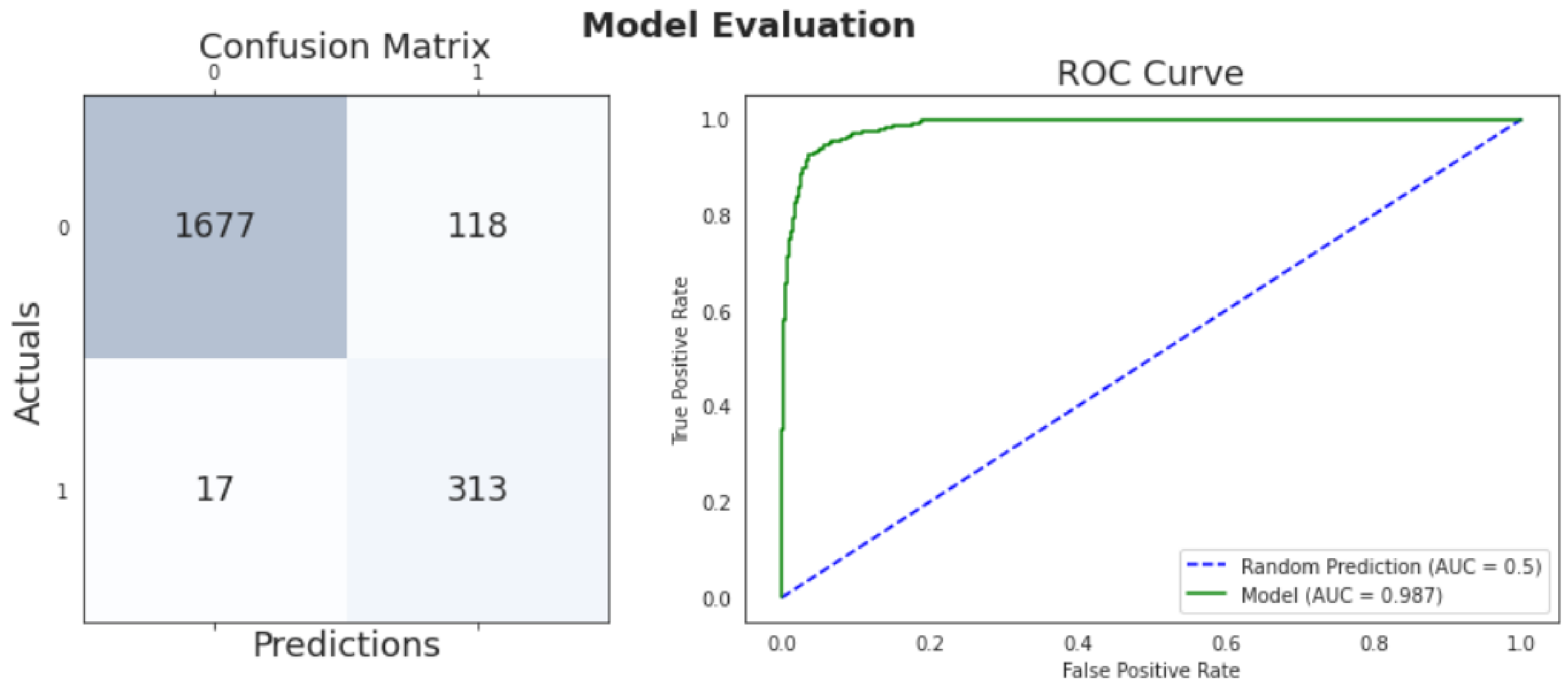
AUC Score: 0.987



XGBoost Undersampling

	precision	recall	f1-score	support
0	0.99	0.93	0.96	1795
1	0.73	0.95	0.82	330
accuracy			0.94	2125
macro avg	0.86	0.94	0.89	2125
weighted avg	0.95	0.94	0.94	2125

AUC Score: 0.9865



Here we can see how well the two models predict the churn for a client as before.

Conclusions

In the end we can state that the cluster analysis **does not produce** the expected results and that the best models to predict the customer attrition remain the **Random Forest, XGBoost** and the **Neural Network**.

The bank manager can now draw enough cues from the EDA to understand which types of customers are most likely to leave.
He can also try to predict whether a client will exit or not through one of the above models.