Churn Prediction using Logisitic Regression

Data Dictionary

There are multiple variables in the dataset which can be cleanly divided in 3 categories:

Demographic information about customers

customer_id - Customer id

vintage - Vintage of the customer with the bank in number of days

age - Age of customer

gender - Gender of customer

dependents - Number of dependents

occupation - Occupation of the customer

city - City of customer (anonymised)

Customer Bank Relationship

customer_nw_category - Net worth of customer (3:Low 2:Medium 1:High)

branch_code - Branch Code for customer account

days_since_last_transaction - No of Days Since Last Credit in Last 1 year

Transactional Information

current_balance - Balance as of today

previous_month_end_balance - End of Month Balance of previous month

average_monthly_balance_prevQ - Average monthly balances (AMB) in Previous Quarter

average_monthly_balance_prevQ2 - Average monthly balances (AMB) in previous to previous quarter

current_month_credit - Total Credit Amount current month

previous_month_credit - Total Credit Amount previous month

current_month_debit - Total Debit Amount current month

previous_month_debit - Total Debit Amount previous month

current_month_balance - Average Balance of current month

previous_month_balance - Average Balance of previous month

churn - Average balance of customer falls below minimum balance in the next quarter (1/0)

Churn Prediction using Logisitic Regression

Now, that we understand the dataset in detail. It is time to build a logistic regression model to predict the churn. I have included the data dictionary again here for reference.

- Load Data & Packages for model building & preprocessing
- Preprocessing & Missing value imputation
- Select features on the basis of EDA Conclusions & build baseline model
- Decide Evaluation Metric on the basis of business problem
- Build model using all features & compare with baseline
- Use Reverse Feature Elimination to find the top features and build model using the top 10 features & compare

Loading Packages

In [34]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import KFold, StratifiedKFold, train_test_split
from sklearn.metrics import roc_auc_score, accuracy_score, confusion_matrix, roc_cu
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
warnings.simplefilter(action='ignore', category=UserWarning)
```

Loading Data

In [35]:

```
df = pd.read_csv('churn_prediction.csv')
```

Missing Values

Before we go on to build the model, we must look for missing values within the dataset as treating the missing values is a necessary step before we fit a logistic regression model on the dataset.

In [36]:

```
pd.isnull(df).sum()
```

Out[36]:

```
customer_id                       0
vintage                           0
age                               0
gender                          525
dependents                     2463
occupation                       80
city                            803
customer_nw_category              0
branch_code                       0
days_since_last_transaction    3223
current_balance                   0
previous_month_end_balance        0
average_monthly_balance_prevQ     0
average_monthly_balance_prevQ2    0
current_month_credit              0
previous_month_credit             0
current_month_debit               0
previous_month_debit              0
current_month_balance             0
previous_month_balance            0
churn                             0
dtype: int64
```

The result of this function shows that there are quite a few missing values in columns gender, dependents, city, days since last transaction and Percentage change in credits. Let us go through each of them 1 by 1 to find the appropriate missing value imputation strategy for each of them.

Gender

For a quick recall let us look at the categories within gender column

In [37]:

```
df['gender'].value_counts()
```

Out[37]:

```
Male      16548
Female    11309
Name: gender, dtype: int64
```

So there is a good mix of males and females and arguably missing values cannot be filled with any one of them. We could create a seperate category by assigning the value -1 for all missing values in this column.

Before that, first we will convert the gender into 0/1 and then replace missing values with -1

In [38]:

```
#Convert Gender
dict_gender = {'Male': 1, 'Female':0}
df.replace({'gender': dict_gender}, inplace = True)

df['gender'] = df['gender'].fillna(-1)
```

Dependents, occupation and city with mode

Next we will have a quick look at the dependents & occupations column and impute with mode as this is sort of an ordinal variable

In [39]:

```
df['dependents'].value_counts()
```

Out[39]:
```
0.0     21435
2.0      2150
1.0      1395
3.0       701
4.0       179
5.0        41
6.0         8
7.0         3
9.0         1
52.0        1
36.0        1
50.0        1
8.0         1
25.0        1
32.0        1
Name: dependents, dtype: int64
```

In [40]:
```
df['occupation'].value_counts()
```

Out[40]:
```
self_employed    17476
salaried          6704
student           2058
retired           2024
company             40
Name: occupation, dtype: int64
```

In [41]:
```
df['dependents'] = df['dependents'].fillna(0)
df['occupation'] = df['occupation'].fillna('self_employed')
```

Similarly City can also be imputed with most common category 1020

In [42]:
```
df['city'] = df['city'].fillna(1020)
```

Days since Last Transaction

A fair assumption can be made on this column as this is number of days since last transaction in 1 year, we can substitute missing values with a value greater than 1 year say 999

In [43]:
```
df['days_since_last_transaction'] = df['days_since_last_transaction'].fillna(999)
```

Preprocessing

Now, before applying linear model such as logistic regression, we need to scale the data and keep all features as numeric strictly.

Dummies with Multiple Categories

In [44]:
```
# Convert occupation to one hot encoded features
df = pd.concat([df,pd.get_dummies(df['occupation'],prefix = str('occupation'),pref
```

Scaling Numerical Features for Logistic Regression

Now, we remember that there are a lot of outliers in the dataset especially when it comes to previous and current balance features. Also, the distributions are skewed for these features if you recall from the EDA. We will take 2 steps to deal with that here:

- Log Transformation
- Standard Scaler

Standard scaling is anyways a necessity when it comes to linear models and we have done that here after doing log transformation on all balance features.

In [45]:

```
num_cols = ['customer_nw_category', 'current_balance',
            'previous_month_end_balance', 'average_monthly_balance_prevQ2', 'avera
            'current_month_credit','previous_month_credit', 'current_month_debit',
            'previous_month_debit','current_month_balance', 'previous_month_balanc
for i in num_cols:
    df[i] = np.log(df[i] + 17000)

std = StandardScaler()
scaled = std.fit_transform(df[num_cols])
scaled = pd.DataFrame(scaled,columns=num_cols)
```

In [46]:

```
df_df_og = df.copy()
df = df.drop(columns = num_cols,axis = 1)
df = df.merge(scaled,left_index=True,right_index=True,how = "left")
```

In [47]:

```
y_all = df.churn
df = df.drop(['churn','customer_id','occupation'],axis = 1)
```

Model Building and Evaluation Metrics

Since this is a binary classification problem, we could use the following 2 popular metrics:

1. Recall
2. Area under the Receiver operating characteristic curve

Now, we are looking at the recall value here because a customer falsely marked as churn would not be as bad as a customer who was not detected as a churning customer and appropriate measures were not taken by the bank to stop him/her from churning

The ROC AUC is the area under the curve when plotting the (normalized) true positive rate (x-axis) and the false positive rate (y-axis).

Our main metric here would be Recall values, while AUC ROC Score would take care of how well predicted probabilites are able to differentiate between the 2 classes.

Conclusions from EDA

- For debit values, we see that there is a significant difference in the distribution for churn and non churn and it might be turn out to be an important feature
- For all the balance features the lower values have much higher proportion of churning customers
- For most frequent vintage values, the churning customers are slightly higher, while for higher values of vintage, we have mostly non churning customers which is in sync with the age variable
- We see significant difference for different occupations and certainly would be interesting to use as a feature for prediction of churn.

Now, we will first split our dataset into test and train and using the above conclusions select columns and build a baseline logistic regression model to check the ROC-AUC Score & the confusion matrix

Baseline Columns

In [48]:

```
baseline_cols = ['current_month_debit', 'previous_month_debit','current_balance','
                 ,'occupation_retired', 'occupation_salaried','occupation_self_emp
```

In [49]:

```
df_baseline = df[baseline_cols]
```

Train Test Split to create a validation set

In [50]:

```
# Splitting the data into Train and Validation set
xtrain, xtest, ytrain, ytest = train_test_split(df_baseline,y_all,test_size=1/3, r
```

In [51]:

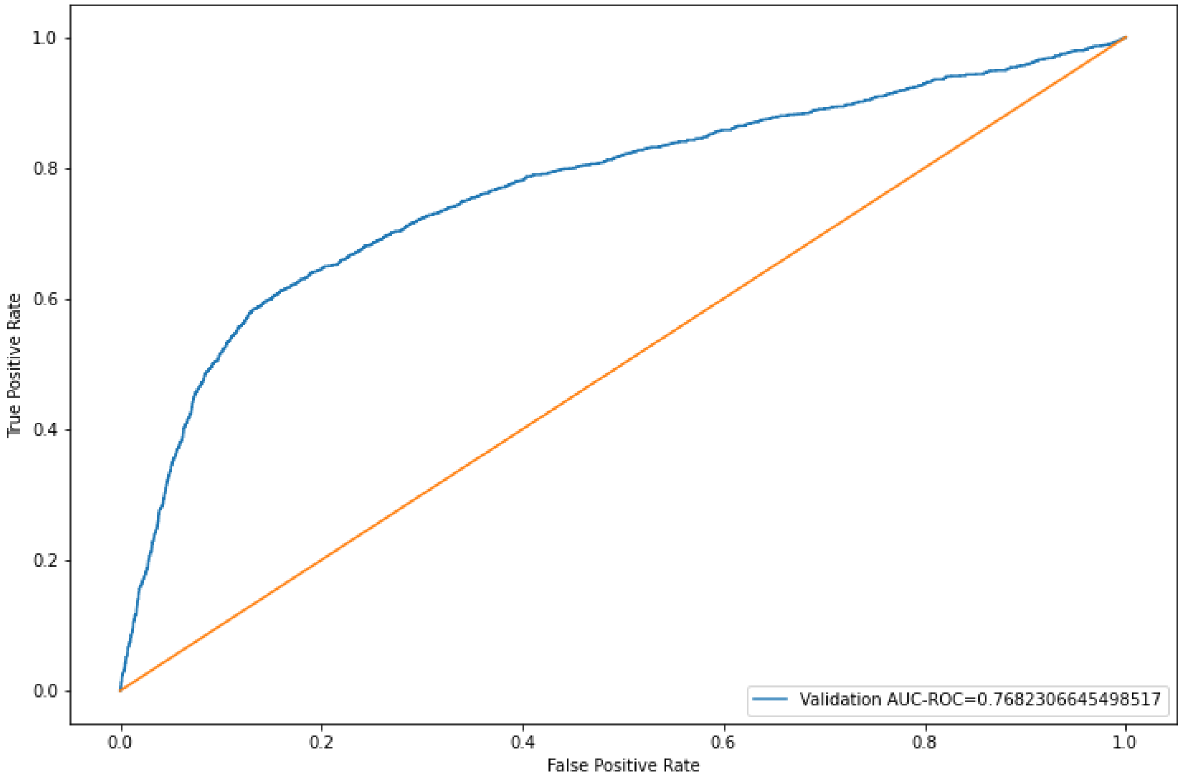
```
model = LogisticRegression()
model.fit(xtrain,ytrain)
pred = model.predict_proba(xtest)[:,1]
```

AUC ROC Curve & Confusion Matrix

Now, let us quickly look at the AUC-ROC curve for our logistic regression model and also the confusion matrix to see where the logistic regression model is failing here.

In [19]:

```
from sklearn.metrics import roc_curve
fpr, tpr, _ = roc_curve(ytest,pred)
auc = roc_auc_score(ytest, pred)
plt.figure(figsize=(12,8))
plt.plot(fpr,tpr,label="Validation AUC-ROC="+str(auc))
x = np.linspace(0, 1, 1000)
plt.plot(x, x, linestyle='-')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc=4)
plt.show()
```



In [52]:

```
# Confusion Matrix
pred_val = model.predict(xtest)
```

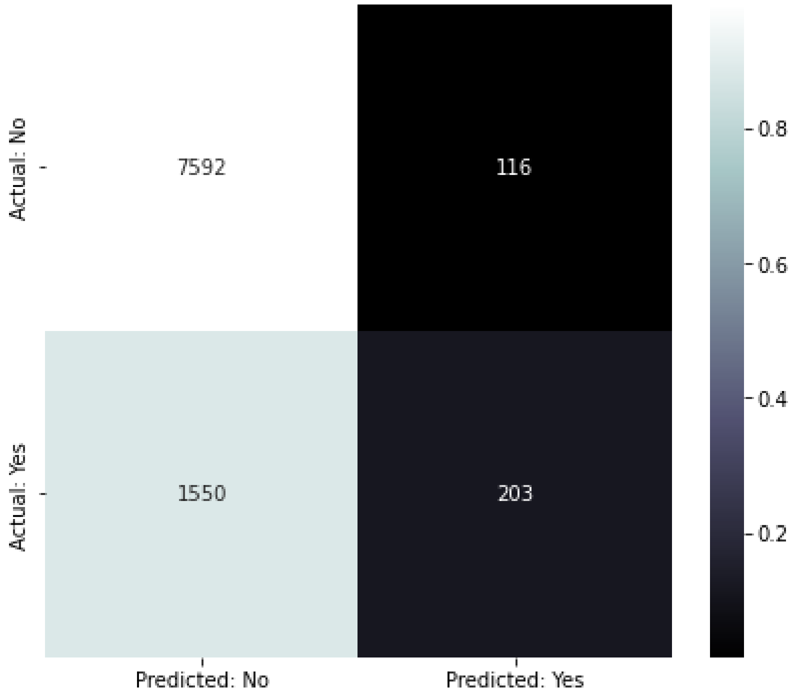
In [53]:

```
label_preds = pred_val

cm = confusion_matrix(ytest,label_preds)


def plot_confusion_matrix(cm, normalized=True, cmap='bone'):
    plt.figure(figsize=[7, 6])
    norm_cm = cm
    if normalized:
        norm_cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        sns.heatmap(norm_cm, annot=cm, fmt='g', xticklabels=['Predicted: No','Predi

plot_confusion_matrix(cm, ['No', 'Yes'])
```



In [54]:

```
# Recall Score
recall_score(ytest,pred_val)
```

Out[54]:

```
0.11580148317170565
```

Cross validation

Cross Validation is one of the most important concepts in any type of data modelling. It simply says, try to leave a sample on which you do not train the model and test the model on this sample before finalizing the model.

We divide the entire population into k equal samples. Now we train models on k-1 samples and validate on 1 sample. Then, at the second iteration we train the model with a different sample held as validation.

In k iterations, we have basically built model on each sample and held each of them as validation. This is a way to reduce the selection bias and reduce the variance in prediction power.

Since it builds several models on different subsets of the dataset, we can be more sure of our model performance if we use CV for testing our models.

In [55]:

```
def cv_score(ml_model, rstate = 12, thres = 0.5, cols = df.columns):
    i = 1
    cv_scores = []
    df1 = df.copy()
    df1 = df[cols]

    # 5 Fold cross validation stratified on the basis of target
    kf = StratifiedKFold(n_splits=5,random_state=rstate,shuffle=True)
    for df_index,test_index in kf.split(df1,y_all):
        print('\n{} of kfold {}'.format(i,kf.n_splits))
        xtr,xvl = df1.loc[df_index],df1.loc[test_index]
        ytr,yvl = y_all.loc[df_index],y_all.loc[test_index]
        # Define model for fitting on the training set for each fold
        model = ml_model
        model.fit(xtr, ytr)
        pred_probs = model.predict_proba(xvl)
        pp = []

        # Use threshold to define the classes based on probability values
        for j in pred_probs[:,1]:
            if j>thres:
                pp.append(1)
            else:
                pp.append(0)

        # Calculate scores for each fold and print
        pred_val = pp
        roc_score = roc_auc_score(yvl,pred_probs[:,1])
        recall = recall_score(yvl,pred_val)
        precision = precision_score(yvl,pred_val)
        sufix = ""
        msg = ""
        msg += "ROC AUC Score: {}, Recall Score: {:.4f}, Precision Score: {:.4f} "
        print("{}".format(msg))

         # Save scores
        cv_scores.append(roc_score)
        i+=1
    return cv_scores
```

In [56]:
```
baseline_scores = cv_score(LogisticRegression(), cols = baseline_cols)
```

```
1 of kfold 5
ROC AUC Score: 0.7644836090843695, Recall Score: 0.0751, Precision Score: 0.5766

2 of kfold 5
ROC AUC Score: 0.7782221765491728, Recall Score: 0.0751, Precision Score: 0.6639

3 of kfold 5
ROC AUC Score: 0.7552863140894919, Recall Score: 0.1350, Precision Score: 0.6425

4 of kfold 5
ROC AUC Score: 0.7582120314576289, Recall Score: 0.1169, Precision Score: 0.6508

5 of kfold 5
ROC AUC Score: 0.7621987119607405, Recall Score: 0.1103, Precision Score: 0.5800
```

Now let us try using all columns available to check if we get significant improvement.

In [57]:
```
all_feat_scores = cv_score(LogisticRegression())
```

```
1 of kfold 5
ROC AUC Score: 0.7343580310348371, Recall Score: 0.1122, Precision Score: 0.5086

2 of kfold 5
ROC AUC Score: 0.7681882643099374, Recall Score: 0.1968, Precision Score: 0.6809

3 of kfold 5
ROC AUC Score: 0.7392296104306182, Recall Score: 0.1673, Precision Score: 0.5714

4 of kfold 5
ROC AUC Score: 0.7613998546186537, Recall Score: 0.2281, Precision Score: 0.6469

5 of kfold 5
ROC AUC Score: 0.7588260785190838, Recall Score: 0.1730, Precision Score: 0.5987
```

There is some improvement in both ROC AUC Scores and Precision/Recall Scores. Now we can try backward selection to select the best subset of features which give the best score.

Reverse Feature Elimination or Backward Selection

We have already built a model using all the features and a separate model using some baseline features. We can try using backward feature elimination to check if we can do better. Let's do that next.

In [58]:

```
from sklearn.feature_selection import RFE
import matplotlib.pyplot as plt

# Create the RFE object and rank each feature
model = LogisticRegression()
rfe = RFE(estimator=model, n_features_to_select=1, step=1)
rfe.fit(df, y_all)
```

Out[58]:

```
RFE(estimator=LogisticRegression(), n_features_to_select=1)
```

In [59]:

```
ranking_df = pd.DataFrame()
ranking_df['Feature_name'] = df.columns
ranking_df['Rank'] = rfe.ranking_
```

In [60]:

```
ranked = ranking_df.sort_values(by=['Rank'])
```

In [61]:

```
ranked
```

Out[61]:

	Feature_name	Rank
13	current_balance	1
16	average_monthly_balance_prevQ	2
7	occupation_company	3
15	average_monthly_balance_prevQ2	4
21	current_month_balance	5
22	previous_month_balance	6
19	current_month_debit	7
10	occupation_self_employed	8
9	occupation_salaried	9
11	occupation_student	10
20	previous_month_debit	11
17	current_month_credit	12
12	customer_nw_category	13
8	occupation_retired	14
3	dependents	15
14	previous_month_end_balance	16
1	age	17
2	gender	18
18	previous_month_credit	19
6	days_since_last_transaction	20
4	city	21
0	vintage	22
5	branch_code	23

The balance features are proving to be very important as can be seen from the table. The RFE function can also be used to select features. Lets select the top 10 features from this table and check score.

In [62]:

```
rfe_top_10_scores = cv_score(LogisticRegression(), cols = ranked['Feature_name'][:
```

```
1 of kfold 5
ROC AUC Score: 0.7986881101633954, Recall Score: 0.2281, Precision Score: 0.7362

2 of kfold 5
ROC AUC Score: 0.8050442914397288, Recall Score: 0.2234, Precision Score: 0.7556

3 of kfold 5
ROC AUC Score: 0.7985130070256687, Recall Score: 0.2205, Precision Score: 0.7250

4 of kfold 5
ROC AUC Score: 0.7935095616193245, Recall Score: 0.2120, Precision Score: 0.7360

5 of kfold 5
ROC AUC Score: 0.7942222838028076, Recall Score: 0.1911, Precision Score: 0.6745
```

Wow, the top 10 features obtained using the reverse feature selection are giving a much better score than any of our earlier attempts. This is the power of feature selection and it especially works well in case of linear models as tree based models are in itself to some extent capable of doing feature selection.

The recall score here is quite low. We should play around with the threshold to get a better recall score. AUC ROC depends on the predicted probabilities and is not impacted by the threshold. Let us try 0.2 as threshold which is close to the overall churn rate

In [63]:
```
cv_score(LogisticRegression(), cols = ranked['Feature_name'][:10].values, thres=0.
```

```
1 of kfold 5
ROC AUC Score: 0.7986881101633954, Recall Score: 0.8308, Precision Score: 0.2836

2 of kfold 5
ROC AUC Score: 0.8050442914397288, Recall Score: 0.8375, Precision Score: 0.2902

3 of kfold 5
ROC AUC Score: 0.7985130070256687, Recall Score: 0.8279, Precision Score: 0.2897

4 of kfold 5
ROC AUC Score: 0.7935095616193245, Recall Score: 0.8213, Precision Score: 0.2840

5 of kfold 5
ROC AUC Score: 0.7942222838028076, Recall Score: 0.8108, Precision Score: 0.2927
```

Out[63]:
```
[0.7986881101633954,
 0.8050442914397288,
 0.7985130070256687,
 0.7935095616193245,
 0.7942222838028076]
```

We observe that there is continuous improvement in the Recall Score. However, clearly precision score is going down. On the basis of business requirement the bank can take a call on deciding the threshold. Without knowing the metrics relevant to the business, our best course of action is to optimize for AUC ROC Score so as to find the best probabilites here.

Comparison of Different model fold wise

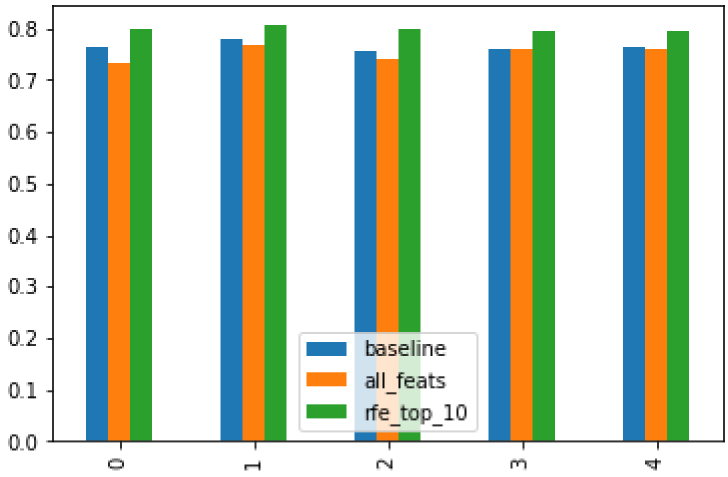
Let us visualise the cross validation scores for each fold for the following 3 models and observe differences:

- Baseline Model
- Model based on all features
- Model based on top 10 features obtained from RFE

In [64]:
```
results_df = pd.DataFrame({'baseline':baseline_scores, 'all_feats': all_feat_score
```

In [65]:
```
results_df.plot(y=["baseline", "all_feats", "rfe_top_10"], kind="bar")
```

Out[65]:
```
<AxesSubplot:>
```



Here, we can see that the model based on RFE is giving the best result for each fold and students are encouraged to try more feature selection techniques and fine tune to get the best results.

In [ ]: