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Credit Card Approval Model

A credit card is a type of payment card in which charges can be made against a line of credit. A credit card issuer can accept or deny an application for a credit card with reason. There are many different factors considered by credit card issuers when considering a credit card applicant. Some factors that are considered, but not limited to, are the applicants age, property ownership, income level and even the education level. Throughout this project, we will analyze a credit card approval dataset. The credit card approval dataset is from Kaggle.com.

To begin, we import our dataset in Python. This data is split into two tables connected by the ID, which is a unique identification number for each applicant. The other factors being considered in this data are shown below.

Code_gender	The gender of the applicant (male or female)
Flag_own_car	if the applicant owns a car or not
Flag_own_Realty	If the applicant owns a property
Cnt_children	The number of children the applicant has
Amt_income_total	The annual income amount of the applicant
Name_income_amount	The income category of the applicant (working, commercial associate or other)
Name_education_type	The education level of the applicant (secondary, higher education or other)

Name_family_status	The applicants marital status (married, single/not married or other)
Name_housing_type	The applicants way of living (house/apartment, with parents or other)
Months_balance	The month of the extracted data is the starting point, backwards, 0 is the current month, -1 is the previous month, and so on
Status	0: 1-29 days past due 1: 30-59 days past due 2: 60-89 days overdue 3: 90-119 days overdue 4: 120-149 days overdue 5: Overdue or bad debts, write-offs for more than 150 days C: paid off that month X: No loan for the month

An important step to analyzing data is cleaning the data. We can use data visualization techniques to consider which factors need cleaning. We can see that there are a significant number of missing values from the factor occupation type (see Appendix line 7). To keep our intended model, the most accurate it could be, we will remove the applicants who did not give their occupation type. The decision to exclude these applicants from our model is in accordance with the actions of most financial institutions. If you don’t include your occupation on an application the requires it, your application won't even be considered. Another important step in data cleaning is to remove duplicate entries (see Appendix line 15). We know that entries in this dataset can be duplicates if their unique identification number is duplicated. One reason for a duplicate entry in this dataset may be because they have applied for the credit card more than once. Another step used to clean the data is to covert categorical factors to numerical outputs that can be used in our model (see Appendix line 18).

We used data visualization tools to analyze the different factors included in this data set (see Appendix line 13). From the output, we can that there are about three hundred thousand applicants that have applied for this credit card that are married. When a person identifies as married, their income is combined with their spouse. A combined income could potentially contribute to their approval or disproval. About fifty thousand applicants are single or not married. And less than fifty thousand people are either in a civil marriage, separated, or a widow. It is imperative to consider all the possibilities with the data given to us because it can potentially affect the model we are trying to create for predictive use.

The next step in analyzing this dataset is to perform feature selection. Feature Selection is a feature engineering component that involves the removal of irrelevant features and picks the best set of features to train a robust machine learning model. Some of the methods

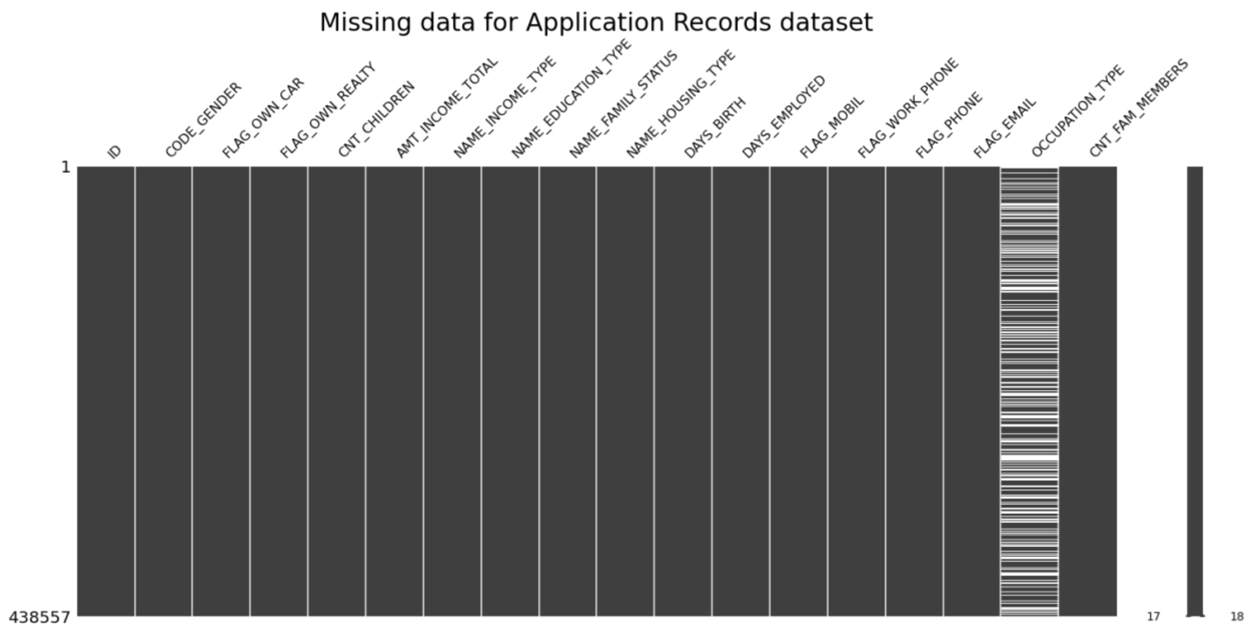
Once we have all the features that are going to be included in our model, we use different methods to create the best model. The methods we are going to test are logistic regression, KNeighbors classifier, SVC, decision tree, random forest classifier, xgb classifier and cat boost classifier. After creating a model with each method, we run a ROC curve to detect which model is statistically better.

Appendix

In [7]

```
missing1 = msno.matrix(AR)

missing1.set_title("Missing data for Application Records dataset", fontsiz
e = 30)
```

Out [7]



In [15]

```
AR = AR.drop_duplicates('ID', keep='last') #remove duplicate values and ke
ep the last entry of the ID if its repeated.
AR.drop('OCCUPATION_TYPE', axis=1, inplace=True) #dropped the missing valu
es in occupation type.
```

In [18]

```
open1=pd.DataFrame(CC.groupby(["ID"])["MONTHS_BALANCE"].agg(min))
open1=open1.rename(columns={'MONTHS_BALANCE':'begin_month'})
indiv=pd.merge(AR,open1,how="left",on="ID") #merge to record data

#convert categoric features into numeric

indiv["Gender"] =  indiv['Gender'].replace(['F','M'],[0,1])
```

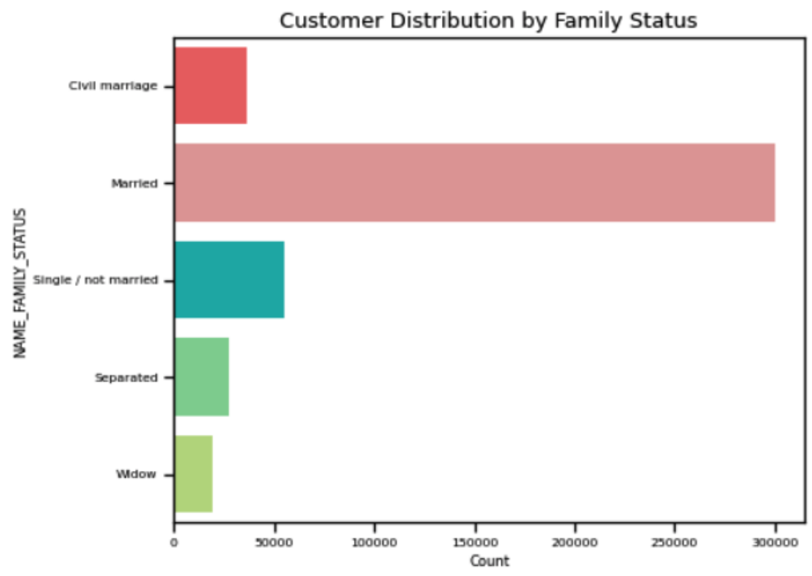
```
indiv["Own_Car"] = indiv["Own_Car"].replace(["Y","N"],[1,0])
indiv["Own_Realty"] = indiv["Own_Realty"].replace(["Y","N"],[1,0])
indiv["Is_Working"] = indiv["Income_Type"].replace(["Working","Commercial
associate","State servant","Pensioner","Student"],[1,1,1,0,0])

indiv["In_Relationship"] = indiv["Family_Status"].replace(["Civil marriage
","Married","Single / not married",

"Separated","Widow"],[1,1,0,0,0])

housing = {'House / apartment' : 'House / apartment',
                   'With parents': 'With parents',
                    'Municipal apartment' : 'House / apartment',
                    'Rented apartment': 'House / apartment',
                    'Office apartment': 'House / apartment',
                    'Co-op apartment': 'House / apartment'}

indiv["Housing_Type"] = indiv['Housing_Type'].map(housing)

household = {'Single / not married':'Single',
                     'Separated':'Single',
                     'Widow':'Single',
                     'Civil marriage':'Married',
                    'Married':'Married'}

indiv["Family_Status"] = indiv["Family_Status"].map(household)

education = {'Secondary / secondary special':'secondary',
                     'Lower secondary':'secondary',
                     'Higher education':'Higher education',
                     'Incomplete higher':'Higher education',
                     'Academic degree':'Academic degree'}


indiv["Education"] = indiv["Education"].map(education)

income = {'Commercial associate':'Working',
                  'State servant':'Working',
                  'Working':'Working',
                  'Pensioner':'Pensioner',
                  'Student':'Student'}
indiv["Income_Type"] = indiv["Income_Type"].map(income)

indiv["Household_Size"] = indiv["Children_Count"] + indiv["In_Relationship
"].apply(lambda x: 2 if x==1 else 1)

indiv["Age"] = round((indiv.Birthday/365)*-1)

indiv["Experience"] = indiv.Employment_Date/365
indiv['Experience']=indiv['Experience'].apply(lambda v : int(v*-1) if v <0
else 0)

indiv=indiv.drop(columns=['Employment_Date','Birthday','Children_Count'])
```

```
indiv= pd.get_dummies(indiv, columns=['Income_Type', 'Education','Family_S
tatus',"Housing_Type"])
```

In [13]

```
fig, axes = plt.subplots(1,2)
plot3=sns.countplot(y=AR.NAME_FAMILY_STATUS,linewidth=1.2, ax=axes[1])
plot3.set_title("Customer Distribution by Family Status")
plot3.set_xlabel("Count")

fig.set_size_inches(14,5)

plt.tight_layout()


plt.show()
```

Out [13]



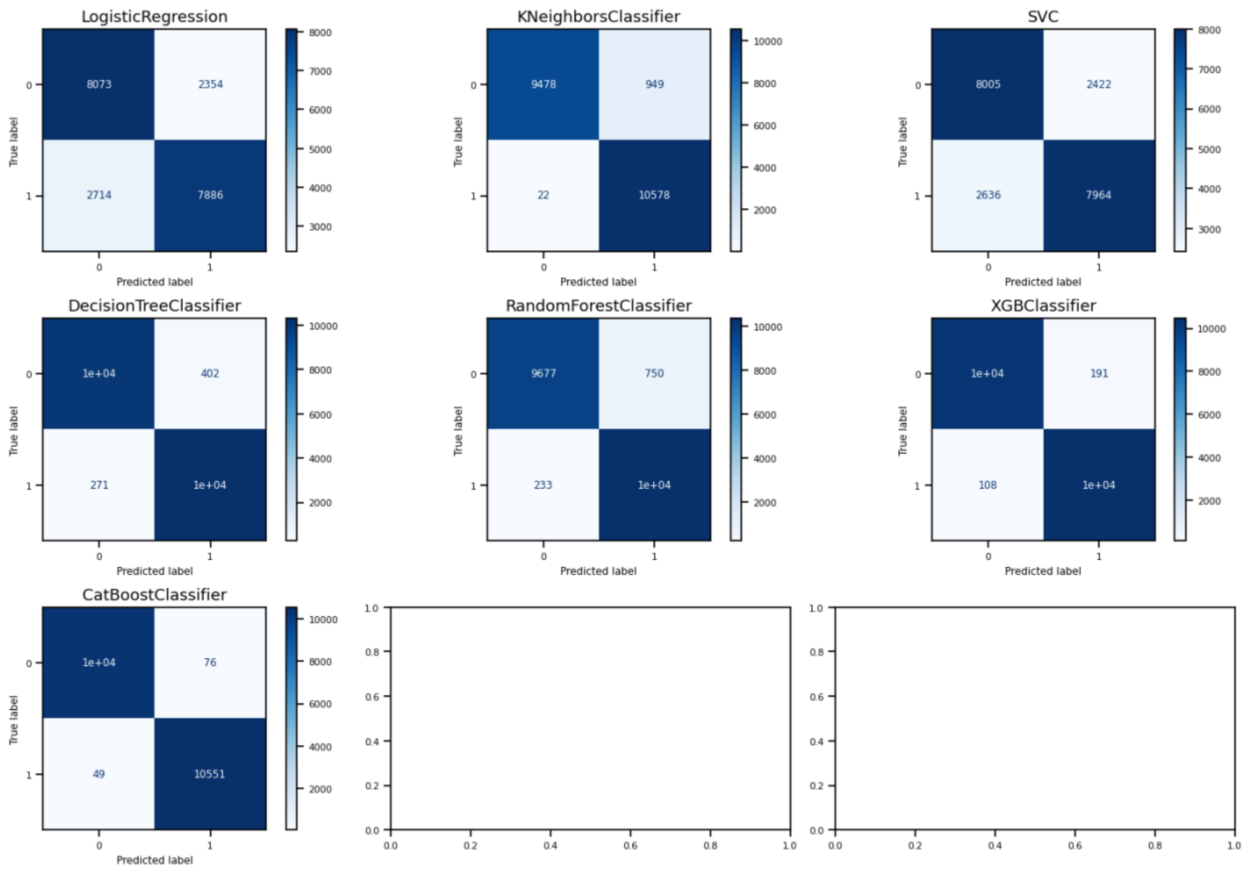
In [59]

```
classifiers = {
    "LogisticRegression" : LogisticRegression(),
    "KNeighbors" : KNeighborsClassifier(),
    "SVC" : SVC(C = 0.8,kernel='linear',probability=True),
    "DecisionTree" : DecisionTreeClassifier(),
    "RandomForest" : RandomForestClassifier(n_estimators=250,max_depth=12,
min_samples_leaf=16),
    "XGBoost" : XGBClassifier(max_depth=12,
                              n_estimators=250,
                              min_child_weight=8,
                              subsample=0.8,
                              learning_rate =0.02,
                              seed=42),
    "CatBoost" : CatBoostClassifier(iterations=250,
                          learning_rate=0.2,
                          od_type='Iter',
                          verbose=25,
                          depth=16,
                          random_seed=42)
}
result_table = pd.DataFrame(columns=['classifiers','accuracy','presicion',
'recall','f1_score','fpr','tpr','auc'])

for key, classifier in classifiers.items():
    classifier.fit(X_train, y_train)
    y_predict = classifier.predict(X_test)

    yproba = classifier.predict_proba(X_test)[::,1]

    fpr, tpr, _ = roc_curve(y_test,  yproba)
    auc = roc_auc_score(y_test, yproba)

    conf_matrix = confusion_matrix(y_test,y_predict)

    result_table = result_table.append({'classifiers':key,
                                        'accuracy':accuracy_score(y_test,
y_predict),
                                        'presicion':precision_score(y_test
, y_predict, average='weighted'),
                                        'recall':recall_score(y_test, y_pr
edict, average='weighted'),
                                        'f1_score':f1_score(y_test, y_pred
ict, average='weighted'),
                                        'fpr':fpr,
                                        'tpr':tpr,
                                        'auc':auc
                                         }, ignore_index=True)

result_table.set_index('classifiers', inplace=True)
```

In [60]

```
fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(15,10))

for cls, ax in zip(list(classifiers.values()), axes.flatten()):
    plot_confusion_matrix(cls,
                          X_test,
                          y_test,
                          ax=ax,
                          cmap='Blues')
    ax.title.set_text(type(cls).__name__)
plt.tight_layout()
plt.show()
```

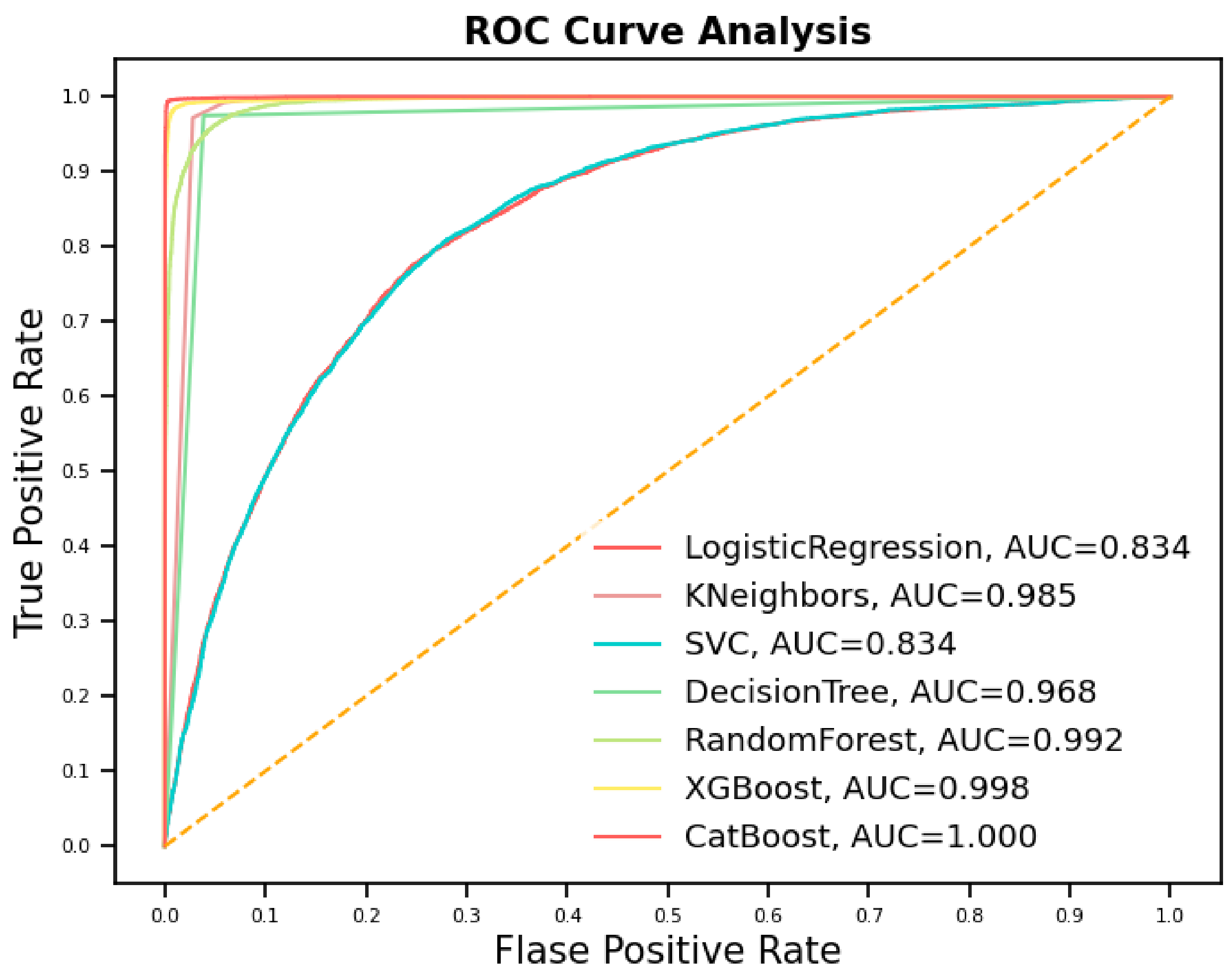
Out [60]



In [61]

```
fig = plt.figure(figsize=(8,6))

for i in result_table.index:
    plt.plot(result_table.loc[i]['fpr'],
             result_table.loc[i]['tpr'],
             label="{}, AUC={:.3f}".format(i, result_table.loc[i]['auc']))

plt.plot([0,1], [0,1], color='orange', linestyle='--')

plt.xticks(np.arange(0.0, 1.1, step=0.1))
plt.xlabel("Flase Positive Rate", fontsize=15)

plt.yticks(np.arange(0.0, 1.1, step=0.1))
plt.ylabel("True Positive Rate", fontsize=15)

plt.title('ROC Curve Analysis', fontweight='bold', fontsize=15)
plt.legend(prop={'size':13}, loc='lower right')

plt.show()
```

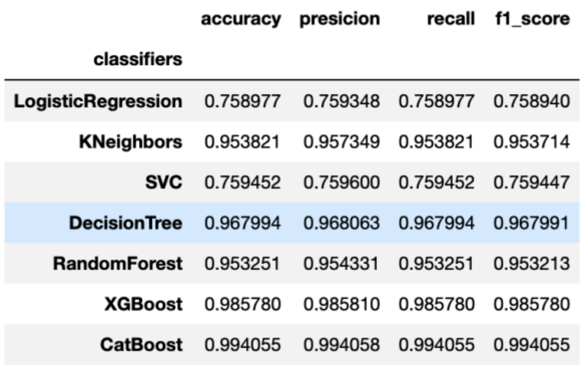
Out [61]



In [62]

```
result_table.iloc[:,:4]
```

Out [62]



	accuracy	presicion	recall	f1_score
classifiers				
LogisticRegression	0.758977	0.759348	0.758977	0.758940
KNeighbors	0.953821	0.957349	0.953821	0.953714
SVC	0.759452	0.759600	0.759452	0.759447
DecisionTree	0.967994	0.968063	0.967994	0.967991
RandomForest	0.953251	0.954331	0.953251	0.953213
XGBoost	0.985780	0.985810	0.985780	0.985780
CatBoost	0.994055	0.994058	0.994055	0.994055