1. Project Summary

This is a Machine Learning project which is meant to predict whether an applicant is a good or a bad client. Models will be built using the personal information of customers and their historical tendencies to pay back loans. Predictions will be made using labels that are not found in any of the datasets.

There is flexibility there as we are able to use any formula to generate corresponding binary credit status. Credit scores of either 0 or 1 will be generated and used as target labels.

2. File system

.gitignore
decision_tree.ipynb
logistic_regression.ipynb
neural_network.ipynb
pre_processing.ipynb
random_forest.ipynb
README.md

+---Output
credit_decision_tree_optimized.pdf
credit_decision_tree_optimized.png
credit_decision_tree_preoptimized.pdf
credit_decision_tree_preoptimized.png
full_data.csv
pre_encoded.csv

+---Resources
application_record.csv
credit_record.csv

3. Preprocessing

3.1 Datasource

Two .csv datasets (application_record.csv and credit_record.csv) were used for the project. They retrieved from Kaggle via the url:

https://www.kaggle.com/datasets/rikdifos/credit-card-approval-prediction/download?datasetVersionNumber=3

3.1.1 Application Record

Contains application records of customers and their personal information to be considered as the features to enable prediction. There is an ID column that enables merging with credit_record.csv.

3.1.2 Credit record

It contains previous credit records of customers in “application_record.csv”. It contains previous monthly loan repayment records for customers. There is an ID column that enables merging with application_record.csv.

The two datasets will be subsequently merged enabling us to extract features and target labels for model building.

3.2 Limitations of Datasets

- One major challenge of these two data sets is that there is no distinctive target column for either "Good Credit" or "Bad Credit". To solve this issue, Binary values will be deduced using the credit record dataset.
- Also, the data is heavily unbalanced potentially adding to the need to apply optimization if the desired accuracy is not achieved.

3.3 Data Base Engineering

Data is extracted and loaded in their raw form into the database for scalability purposes which will allow for prospective applications and credit records to be added in the future.

Tools:

- PostgreSQL

Loading Data Frames into DB as Tables

In [6]:
```
protocol = 'postgresql'
username = 'postgres'
password = pw
host = 'localhost'
port = 5432
database_name = 'creditCheck_db'
rds_connection_string = f'{protocol}://{username}:{password}@{host}:{port}/{database_name}'
engine = create_engine(rds_connection_string)

Base = declarative_base()
```

In [10]:
```
# Creating poke table
class credit_record(Base):
    extend_existing=True
    __tablename__ = "credit_record"

    cr_id = Column("CR_ID", Integer, primary_key = True)
    id_ = Column("ID", Integer)
    month_balance = Column("MONTHS_BALANCE", Integer)
    status = Column("STATUS", String)
```

3.4 Credit Record Engineering

The relevant columns in the credit record Table are the "ID", "MONTHS_BALANCE", and "STATUS" columns.

Credit Record Engineering

In [19]:
```
credit_record_df.head()
```

Out[19]:

	CR_ID	ID	MONTHS_BALANCE	STATUS
0	0	5001711	0	X
1	1	5001711	-1	0
2	2	5001711	-2	0
3	3	5001711	-3	0
4	4	5001712	0	C

The dataset has a "STATUS" column which contains values with these explanations.

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

3.4.1 Converting STATUS values To Target Labels

We dropped all STATUS columns with “X” values as we couldn’t conclude whether a customer with no loan for a particular month should be considered as a customer with good credit or bad credit for that month.

```
print(credit_record_df.STATUS.unique())
```

```
['X' '0' 'C' '1' '2' '3' '4' '5']
```

```
# Since the "X" value signifies "No Loan for the month", this can be counted as irrelevant
# to whether or not they defaulted and if used could create bias
# There are a lot of account numbers with a month_balances with corresponding status labeled as "X" so can't be used
credit_record_df.drop(credit_record_df[credit_record_df["STATUS"] == "X"].index, inplace = True)
credit_record_df.head()
```

It became also clear that our target label values could be deduced using the following formula.

Good Credit = 0

Bad Credit = 1

```
# Replace categorical credit status values with binary values
credit_record_df = credit_record_df.apply(lambda x: x.replace({'C': 0, '0' : 0, '1' : 1, '2' : 1, '3' : 1, '4' : 1, '5' : 1}, reg
display(credit_record_df['STATUS'].head())
display(credit_record_df['STATUS'].value_counts())
```

C: paid off that month = Good Credit = 0

0: 1-29 days past due = Good Credit = 0

All other STATUS values will be replaced with Bad Credit = 1.

The averages of all the monthly statuses of a customer were calculated and any status value of more than 0 was classed as 1 (Bad credit), whiles all 0 values were classed as 0 (Good credit). This way all float values will also be replaced with binary values.

```
# Replace float values with binaries
credit_record_df["Status2"] = credit_record_df["STATUS"].apply(lambda x: 1 if x > 0 else 0)
credit_record_df.rename(columns = {"STATUS" : "MONTH_BAL_AVG", "Status2" : "STATUS"}, inplace = True)
credit_record_df = credit_record_df.drop(columns="MONTH_BAL_AVG", axis=1)

credit_record_df.head()
```

	ID	STATUS
0	5001711	0
1	5001712	0
2	5001717	0
3	5001718	1
4	5001719	0

3.5 Application record data Engineering

The relevant columns in the credit record Table are:
'CODE_GENDER', 'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'DAYS_BIRTH', 'DAYS_EMPLOYED', 'FLAG_MOBIL', 'FLAG_WORK_PHONE', 'FLAG_PHONE', 'FLAG_EMAIL', 'OCCUPATION_TYPE' and 'CNT_FAM_MEMBERS' columns.

```
application_record_df.head()
```

	AR_ID	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE	NAME_EDUCATIO
0	0	5008804	M	Y	Y	0	427500.0	Working	Higher e
1	1	5008805	M	Y	Y	0	427500.0	Working	Higher e
2	2	5008806	M	Y	Y	0	112500.0	Working	Secondary / se
3	3	5008808	F	N	Y	0	270000.0	Commercial associate	Secondary / se
4	4	5008809	F	N	Y	0	270000.0	Commercial associate	Secondary / se

3.5.1 Merging both datasets and dropping irrelevant columns

Both data sets were merged and the irrelevant columns were dropped finally.

Merging both datasets

```
# Merge the two datasets keeping only IDs common to both dataframes
full_df = application_record_df.merge(credit_record_df, on=['ID'], how='inner')
display(full_df.head().T)
full_df.shape
```

	0	1	2	3	4
AR_ID	0	1	2	3	5
ID	5008804	5008805	5008806	5008808	5008810
CODE_GENDER	M	M	M	F	F
FLAG_OWN_CAR	Y	Y	Y	N	N
FLAG_OWN_REALTY	Y	Y	Y	Y	Y
CNT_CHILDREN	0	0	0	0	0
AMT_INCOME_TOTAL	427500.0	427500.0	112500.0	270000.0	270000.0
NAME_INCOME_TYPE	Working	Working	Working	Commercial associate	Commercial associate
NAME_EDUCATION_TYPE	Higher education	Higher education	Secondary / secondary special	Secondary / secondary special	Secondary / secondary special
NAME_FAMILY_STATUS	Civil marriage	Civil marriage	Married	Single / not married	Single / not married
NAME_HOUSING_TYPE	Rented apartment	Rented apartment	House / apartment	House / apartment	House / apartment
DAYS_BIRTH	-12005	-12005	-21474	-19110	-19110

3.5.2 Encoding Categorical columns

```
# Encoding NAME_INCOME_TYPE column
name_income_type_mapper = {'Working': 2, 'Commercial associate': 2, 'Pensioner': 1, 'State servant': 3, 'Student': 0}
pre_encoded_df["NAME_INCOME_TYPE"] = pre_encoded_df["NAME_INCOME_TYPE"].replace(name_income_type_mapper)

#  Encoding NAME_EDUCATION_TYPE column
name_education_type_mapper = {'Higher education': 3, 'Secondary / secondary special': 1, 'Incomplete higher': 2,
 'Lower secondary': 0, 'Academic degree': 3}
pre_encoded_df["NAME_EDUCATION_TYPE"] = pre_encoded_df["NAME_EDUCATION_TYPE"].replace(name_education_type_mapper)

#  Encoding NAME_FAMILY_STATUS column
name_family_status_mapper = {'Civil marriage': 3, 'Married': 4, 'Single / not married': 0, 'Separated': 1, 'Widow': 2}
pre_encoded_df["NAME_FAMILY_STATUS"] = pre_encoded_df["NAME_FAMILY_STATUS"].replace(name_family_status_mapper)

#  Encoding NAME_HOUSING_TYPE column
name_housing_type_mapper = {'Rented apartment': 1, 'House / apartment': 2, 'Municipal apartment': 1, 'With parents': 0,
```

```python
# Encoding binary categorical (CODE_GENDER, FLAG_OWN_CAR, FLAG_OWN_REALTY) variables using get_dummies
final_df = pd.get_dummies(pre_encoded_df)

# Move the status index to the end
final_df = final_df.reindex(columns = [col for col in final_df.columns if col != 'STATUS'] + ['STATUS'])
final_df.head().T
```

	0	1	2	3	4
CNT_CHILDREN	0.0	0.0	0.0	0.0	0.0
AMT_INCOME_TOTAL	427500.0	427500.0	112500.0	270000.0	270000.0
NAME_INCOME_TYPE	2.0	2.0	2.0	2.0	2.0
NAME_EDUCATION_TYPE	3.0	3.0	1.0	1.0	1.0
NAME_FAMILY_STATUS	3.0	3.0	4.0	0.0	0.0
NAME_HOUSING_TYPE	1.0	1.0	2.0	2.0	2.0
DAYS_BIRTH	-12005.0	-12005.0	-21474.0	-19110.0	-19110.0
DAYS_EMPLOYED	-4542.0	-4542.0	-1134.0	-3051.0	-3051.0

3.5.3 Exporting final dataframe to a .csv file for use in model engineering

```python
print(f"Good Credit: {len(final_df[final_df['STATUS'] == 0])}")
print(f"Bad Credit: {len(final_df[final_df['STATUS'] == 1])}")
```

```
Good Credit: 28819
Bad Credit: 4291
```

```python
final_df.to_csv("Output/full_data.csv", index=False)
```

4. Model Engineering

4.1 Supervised Learning

Since we now have target labels, we will be building supervised learning labels.

4.1.1 Classification Method

4.1.2 Binary classification

There are two class labels (Good Credit “0” and Bad Credit “1”) for our classification.

4.1.3 Model selection

We are considering 4 Models for our project utilizing a mix of different optimization methods to enhance our efficiency.

1. Random Forest
2. Decision Tree
3. Logistic Regression
4. Neural Network

4.1.3.1 Random Forest

4.1.3.1.1 Training with the preoptimized or non-resampled dataset

```
# Displaying results
print("Confusion Matrix")
display(cm_df)
print(f"Accuracy Score : {acc_score}")
print("Classification Report")
print(classification_report(y_test, predictions))
```

```
Confusion Matrix
```

	Predicted 0	Predicted 1
Actual 0	6958	286
Actual 1	692	342

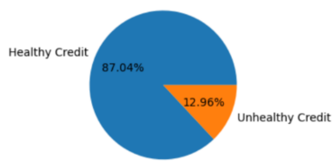
```
Accuracy Score : 0.8818555206571635
Classification Report
              precision    recall  f1-score   support

           0       0.91      0.96      0.93      7244
           1       0.54      0.33      0.41      1034

    accuracy                           0.88      8278
   macro avg       0.73      0.65      0.67      8278
weighted avg       0.86      0.88      0.87      8278
```

4.1.3.1.2 Training with the optimized or non-resampled dataset

Checking for imbalance

```
# Checking for Balance
counter = Counter(y)
print(counter)
print(f"Heavily imbalanced: {round((np.sum(y) / len(y)) * 100, 2)}%")
```

```
Counter({0: 28819, 1: 4291})
Heavily imbalanced: 12.96%
```

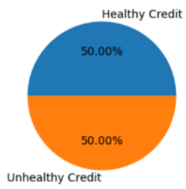


Fixing data imbalance

```
# transform the dataset
oversample = SMOTE()
X, y = oversample.fit_resample(X, y)
```

```
# summarize the new class distribution
counter_resampled = Counter(y)
print(counter_resampled)
```

```
Counter({1: 28819, 0: 28819})
```



After Resampling, the accuracy score is **0.92** which is an improvement over the **0.88** for preoptimization

```python
# Displaying results
print("Confusion Matrix")
display(cm_df)
print(f"Accuracy Score : {acc_score}")
print("Classification Report")
print(classification_report(y_test, predictions))
```

```
Confusion Matrix
```

	Predicted 0	Predicted 1
Actual 0	6648	573
Actual 1	637	6552

```
Accuracy Score : 0.916030534351145
Classification Report
              precision    recall  f1-score   support

           0       0.91      0.92      0.92      7221
           1       0.92      0.91      0.92      7189

    accuracy                           0.92     14410
   macro avg       0.92      0.92      0.92     14410
weighted avg       0.92      0.92      0.92     14410
```

4.1.3.2 Decision Tree

4.1.3.2.1 Training with the preoptimized or non-resampled dataset

```python
# Displaying results
print("Confusion Matrix")
display(cm_df)
print(f"Accuracy Score : {acc_score}")
print("Classification Report")
print(classification_report(y_test, predictions))
```

```
Confusion Matrix
```

	Predicted 0	Predicted 1
Actual 0	6865	379
Actual 1	673	361

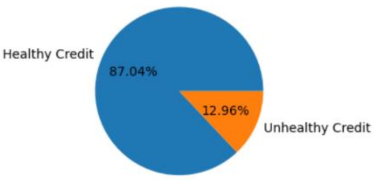
```
Accuracy Score : 0.8729161633244745
Classification Report
              precision    recall  f1-score   support

           0       0.91      0.95      0.93      7244
           1       0.49      0.35      0.41      1034

    accuracy                           0.87      8278
   macro avg       0.70      0.65      0.67      8278
weighted avg       0.86      0.87      0.86      8278
```

4.1.3.2.2 Training with the optimized or non-resampled dataset

Checking for imbalance

```python
# Checking for Balance
counter = Counter(y)
print(counter)
print(f"Heavily imbalanced: {round((np.sum(y) / len(y)) * 100, 2)}%")
```

```
Counter({0: 28819, 1: 4291})
Heavily imbalanced: 12.96%
```

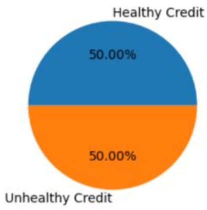


Fixing data imbalance

```python
# transform the dataset
oversample = SMOTE()
X, y = oversample.fit_resample(X, y)
```

```python
# summarize the new class distribution
counter_resampled = Counter(y)
print(counter_resampled)
```

```
Counter({1: 28819, 0: 28819})
```



After Resampling, the accuracy score is **0.90** which is an improvement over the **0.87** for preoptimization

```
# Displaying results
print("Confusion Matrix")
display(cm_df)
print(f"Accuracy Score : {acc_score}")
print("Classification Report")
print(classification_report(y_test, predictions))
```

Confusion Matrix

	Predicted 0	Predicted 1
Actual 0	6531	690
Actual 1	769	6420

```
Accuracy Score : 0.8987508674531576
Classification Report
              precision    recall  f1-score   support

           0       0.89      0.90      0.90      7221
           1       0.90      0.89      0.90      7189

    accuracy                           0.90     14410
   macro avg       0.90      0.90      0.90     14410
```

4.1.3.3 Logistic Regression

4.1.3.3.1 Training with no Optimization

Preoptimization parameters

```
# Print the classification report for the model
print("Classification Report")
print(classification_report(y_test, testing_predictions))
```

```
Classification Report
              precision    recall  f1-score   support

           0       0.87      1.00      0.93      7219
           1       0.00      0.00      0.00      1059

    accuracy                           0.87      8278
   macro avg       0.44      0.50      0.47      8278
weighted avg       0.76      0.87      0.81      8278
```

The data is highly unbalanced as all were predicted as good loans.

```
# Generate a confusion matrix for the model
testing_matrix = confusion_matrix(y_test, testing_predictions)
testing_matrix_df = pd.DataFrame(
    testing_matrix, index=["Actual 0", "Actual 1"], columns=["Predicted 0", "Predicted 1"]
)
print("Confusion Matrix")
display(testing_matrix_df)
# Calculating the accuracy score
accuracy_score1 = accuracy_score(y_test, testing_predictions)
print(f"Accuracy Score : {accuracy_score1}")
```

Confusion Matrix

	Predicted 0	Predicted 1
Actual 0	7219	0
Actual 1	1059	0

Accuracy Score : 0.8720705484416525

4.1.3.3.2 Using Class weights to reduce imbalance

```python
# Print the balanced_accuracy score of the model
train_balanced_accuracy=balanced_accuracy_score(y_train, training_predictions)
print(f"Train Accuracy Score : {train_balanced_accuracy}")
test_balanced_accuracy=balanced_accuracy_score(y_test, testing_predictions)
print(f"Test Accuracy Score : {test_balanced_accuracy}")
```

```
Train Accuracy Score : 0.540184039237257
Test Accuracy Score : 0.5310482606687499
```

```python
# Calculating the accuracy score
accuracy_score1 = accuracy_score(y_test, testing_predictions)
print(f"Accuracy Score : {accuracy_score1}")
```

```
Accuracy Score : 0.5552065716356608
```

```python
# Print the classification report for the model
print("Classification Report")
print(classification_report(y_test, testing_predictions))
```

```
Classification Report
              precision    recall  f1-score   support

           0       0.88      0.56      0.69      7219
           1       0.14      0.50      0.22      1059

    accuracy                           0.56      8278
   macro avg       0.51      0.53      0.46      8278
weighted avg       0.79      0.56      0.63      8278
```

The accuracy score greatly reduced to 56%

Confusion Matrix

	Predicted 0	Predicted 1
Actual 0	4068	3151
Actual 1	531	528

```
Accuracy Score : 0.5552065716356608
```

4.1.3.3.3 Auto Optimization using Hyperparameter tuning¶

```python
param_grid = {
    'C': [0.001, 0.01, 0.1, 1, 10, 100],
    'class_weight': ["balanced"],
    'tol': [0.000001, 0.000005, 0.00001, 0.0001, 0.001],
    'penalty':["l2", "none"],
    'solver':["lbfgs", "newton-cg", "saga"],
    'max_iter': [50, 100, 150, 200, 550]
}
param_grid
```

```
{'C': [0.001, 0.01, 0.1, 1, 10, 100],
 'class_weight': ['balanced'],
 'tol': [1e-06, 5e-06, 1e-05, 0.0001, 0.001],
 'penalty': ['l2', 'none'],
 'solver': ['lbfgs', 'newton-cg', 'saga'],
 'max_iter': [50, 100, 150, 200, 550]}
```

```
# List the best parameters for this dataset
print(grid_clf.best_params_)
```

```
{'C': 0.01, 'class_weight': 'balanced', 'max_iter': 50, 'penalty': 'l2', 'solver': 'saga', 'tol': 0.001}
```

```
# List the best score
print(grid_clf.best_score_)
```

```
0.5467947170617254
```

```
# Make predictions with the hypertuned model
predictions = grid_clf.predict(X_test_scaled)
predictions
```

```
array([0, 0, 1, ..., 0, 0, 0], dtype=int64)
```

```
# Score the hypertuned model on the test dataset
grid_clf.score(X_test_scaled, y_test)
```

```
0.5565353950229524
```

```
# Calculate the classification report
print(classification_report(y_test, predictions,
                            target_names=["0", "1"]))
```

```
              precision    recall  f1-score   support

           0       0.89      0.56      0.69      7219
           1       0.14      0.50      0.23      1059

    accuracy                           0.56      8278
   macro avg       0.52      0.53      0.46      8278
weighted avg       0.79      0.56      0.63      8278
```

Confusion Matrix

	Predicted 0	Predicted 1
Actual 0	4074	3145
Actual 1	526	533

Accuracy Score : 0.5565353950229524

4.1.3.4 Neural Network

4.1.3.4.1 Training with no Optimization

Preoptimization parameters

Preoptimization

```
# Define the model - deep neural net, i.e., the number of input features and hidden nodes for each layer.
number_input_features = len(X_train_scaled[0])
hidden_nodes_layer1 =  20
hidden_nodes_layer2 =  10
outer_layer = 1

# Define the deep learning model
nn_model = tf.keras.models.Sequential()

# First hidden layer
nn_model.add(tf.keras.layers.Dense(units=hidden_nodes_layer1, activation="relu", input_dim=number_input_features))

# Second hidden layer
nn_model.add(tf.keras.layers.Dense(units=hidden_nodes_layer2, activation="relu"))

# Output layer
nn_model.add(tf.keras.layers.Dense(units=outer_layer, activation="sigmoid"))

# Check the structure of the model
print(nn_model.summary())
```

```
# Compile the Sequential model together and customize metrics
nn_model.compile(loss="binary_crossentropy", optimizer="adam", metrics=["accuracy"])
```

```
# Train the model
fit_model = nn_model.fit(X_train_scaled, y_train, epochs=50)
```

```
Epoch 1/50
776/776 [==============================] - 1s 971us/step - loss: 0.4226 - accuracy: 0.8513
```

```
# Evaluate the model using the test data
nn_model_loss, nn_model_accuracy = nn_model.evaluate(X_test_scaled, y_test, verbose=2)
print(f"Loss: {nn_model_loss}, Accuracy: {nn_model_accuracy}")
```

```
259/259 - 0s - loss: 0.3750 - accuracy: 0.8744 - 351ms/epoch - 1ms/step
Loss: 0.3749982416629791, Accuracy: 0.8743658065795898
```

4.1.3.4.2 Auto Optimization using Hyperparameter tuning¶

Auto Optimization using Hyperparameter tuning

```
# Create a method that creates a new Sequential model with hyperparameter options
def create_model(hp):
    nn_model = tf.keras.models.Sequential()

    # Allow kerastuner to decide which activation function to use in hidden layers
    activation = hp.Choice('activation',['relu','tanh','sigmoid'])

    # Allow kerastuner to decide number of neurons in first layer
    nn_model.add(tf.keras.layers.Dense(units=hp.Int('first_units',
        min_value=1,
        max_value=10,
        step=2), activation=activation, input_dim=len(X_train_scaled[0])))

    # Allow kerastuner to decide number of hidden layers and neurons in hidden layers
    for i in range(hp.Int('num_layers', 1, 6)):
```

```
# Run the kerastuner search for best hyperparameters
tuner.search(X_train_scaled,y_train,epochs=20,validation_data=(X_test_scaled,y_test))
```

```
Trial 60 Complete [00h 01m 10s]
val_accuracy: 0.8741241693496704

Best val_accuracy So Far: 0.8750905990600586
Total elapsed time: 00h 17m 16s
INFO:tensorflow:Oracle triggered exit
```

```python
# Get best model hyperparameters
best_hyper = tuner.get_best_hyperparameters(1)[0]
best_hyper.values
```

```
{'activation': 'tanh',
 'first_units': 9,
 'num_layers': 6,
 'units_0': 3,
 'units_1': 9,
 'units_2': 5,
 'units_3': 3,
 'units_4': 9,
 'units_5': 7,
 'tuner/epochs': 20,
 'tuner/initial_epoch': 0,
 'tuner/bracket': 0,
 'tuner/round': 0}
```

```python
best_model = tuner.get_best_models(1)[0]
model_loss, model_accuracy = best_model.evaluate(X_test_scaled,y_test,verbose=2)
print(f"Loss: {model_loss}, Accuracy: {model_accuracy}")
```

```
259/259 - 2s - loss: 0.3752 - accuracy: 0.8751 - 2s/epoch - 6ms/step
Loss: 0.37516242265701294, Accuracy: 0.8750905990600586
```

5. Summary

These models were considered:

1. Random Forest
2. Decision Tree
3. Logistic Regression
4. Neural Network

Model	Accuracy	
	Preoptimized	Optimized
Random Forest	88%	92%
Decision Tree	87%	90%
Logistic Regression	56%	56%
Neural Network	87%	88%

Looking at the results of the models, Random Forest with the highest accuracy of 92% after optimization is clearly the model of choice for further application. It also has a 91% precision which is ideal because since we are looking at financial data, a higher precision avoids a lot of false positives saving the institution a lot. There will be less risk of approving a credit card for an applicant with bad credit.