# CSE445 Presentation

on

**"Banking Loan Prediction Problem"**

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Presented by

**CSE445 Section-02 Group-02 Fall-2020**

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We worked on an application based problem ‘bank loan prediction problem’.

Where a bank created a digital team to analyze the collected data to predict the future customers (marketing lead) based on the previous loan request.

Source Link: https://www.kaggle.com/arashnic/banking-loan-prediction

Human Supervision –> Supervised Learning

Dataset increment –> Batch Learning

Predictive Model Building –> Model-based Learning

Predict loan approval -> Binary Classification (discrete value, only 2 result)
[label was only -> yes (1) or no (0)]

## Get the data



Our main challenge -> data collection

Used Kaggle dataset

train.csv -> containing about 70 k instances

test.csv -> containing about 30 k instances

As there was noise in our dataset, we used train.csv file for both training and testing purpose.

We will see the observation later during feature selection part.

```
[51] # import necessary libraries
     import pandas as pd
     import seaborn as sns
     import numpy as np
     import matplotlib.pyplot as plt
     %matplotlib inline
     from sklearn.impute import SimpleImputer
```

```
[52] # load train_data
     train_dataset_link = 'https://github.com/SabiqulHassan13/cse445.2-fall20-project-dataset/blob/main/train.csv?raw=true'
     train_df = pd.read_csv(train_dataset_link)
```

```
[53] train_df.shape
```

```
(69713, 22)
```

```
train_df.head()
```

| | ID | Gender | DOB | Lead_Creation_Date | City_Code | City_Category | Employer_Code | Employer_Category1 | Employer_Category2 | Monthly_Income |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | APPC90493171225 | Female | 23/07/79 | 15/07/16 | C10001 | A | COM0044082 | A | 4.0 | 2000.0 |
| 1 | APPD40611263344 | Male | 07/12/86 | 04/07/16 | C10003 | A | COM0000002 | C | 1.0 | 3500.0 |

```
55] train_df.describe()
```

| | Employer_Category2 | Monthly_Income | Existing_EMI | Loan_Amount | Loan_Period | Interest_Rate | EMI | Var1 | Approved |
|---|---|---|---|---|---|---|---|---|---|
| count | 65415.000000 | 6.971300e+04 | 69662.000000 | 42004.000000 | 42004.000000 | 22276.000000 | 22276.000000 | 69713.000000 | 69713.000000 |
| mean | 3.720187 | 5.622283e+03 | 360.928751 | 39429.982859 | 3.890629 | 19.213570 | 1101.466242 | 3.948446 | 0.014631 |
| std | 0.807374 | 1.747671e+05 | 2288.517927 | 30727.595990 | 1.167491 | 5.847136 | 752.661394 | 3.819214 | 0.120073 |
| min | 1.000000 | 0.000000e+00 | 0.000000 | 5000.000000 | 1.000000 | 11.990000 | 118.000000 | 0.000000 | 0.000000 |
| 25% | 4.000000 | 1.650000e+03 | 0.000000 | 20000.000000 | 3.000000 | 15.250000 | 649.000000 | 0.000000 | 0.000000 |
| 50% | 4.000000 | 2.500000e+03 | 0.000000 | 30000.000000 | 4.000000 | 18.000000 | 941.000000 | 2.000000 | 0.000000 |
| 75% | 4.000000 | 4.000000e+03 | 350.000000 | 50000.000000 | 5.000000 | 20.000000 | 1295.000000 | 7.000000 | 0.000000 |
| max | 4.000000 | 3.838384e+07 | 545436.500000 | 300000.000000 | 6.000000 | 37.000000 | 13556.000000 | 10.000000 | 1.000000 |

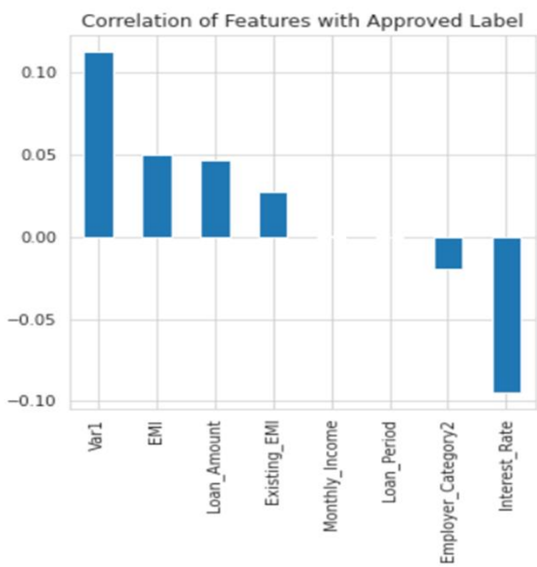
```
6] train_df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 69713 entries, 0 to 69712
Data columns (total 22 columns):
 #   Column                               Non-Null Count  Dtype
---  ------                               --------------  -----
 0   ID                                   69713 non-null  object
 1   Gender                               69713 non-null  object
 2   DOB                                  69698 non-null  object
 3   Lead_Creation_Date                   69713 non-null  object
 4   City_Code                            68899 non-null  object
 5   City_Category                        68899 non-null  object
 6   Employer_Code                        65695 non-null  object
 7   Employer_Category1                   65695 non-null  object
 8   Employer_Category2                   65415 non-null  float64
 9   Monthly_Income                       69713 non-null  float64
 10  Customer_Existing_Primary_Bank_Code  60322 non-null  object
 11  Primary_Bank_Type                    60322 non-null  object
 12  Contacted                            69713 non-null  object
 13  Source                               69713 non-null  object
 14  Source_Category                      69713 non-null  object
 15  Existing_EMI                         69662 non-null  float64
 16  Loan_Amount                          42004 non-null  float64
 17  Loan_Period                          42004 non-null  float64
 18  Interest_Rate                        22276 non-null  float64
 19  EMI                                  22276 non-null  float64
 20  Var1                                 69713 non-null  int64
 21  Approved                             69713 non-null  int64
dtypes: float64(7), int64(2), object(13)
memory usage: 11.7+ MB
```

```
# check null values
train_df.isnull().sum()
```

```
ID                                      0
Gender                                  0
DOB                                    15
Lead_Creation_Date                      0
City_Code                             814
City_Category                         814
Employer_Code                        4018
Employer_Category1                   4018
Employer_Category2                   4298
Monthly_Income                          0
Customer_Existing_Primary_Bank_Code  9391
Primary_Bank_Type                    9391
Contacted                               0
Source                                  0
Source_Category                         0
Existing_EMI                           51
Loan_Amount                         27709
Loan_Period                         27709
Interest_Rate                       47437
EMI                                 47437
Var1                                    0
Approved                                0
dtype: int64
```

Due to noise (missing value mainly) in dataset, there was not that much correlation

```
# Correlation of Approved label with all features

plt.figure(figsize=(5, 5))
plt.title("Correlation of Features with Approved Label")
train_df.corr()['Approved'].drop(index='Approved').sort_values(ascending=False).plot(kind='bar')
plt.show()
```



## Features selection part

```
# data preprocessing
```

```
# manual feature selection
# drop some features seems not related

features_to_drop = ['ID', 'DOB', 'Lead_Creation_Date', 'City_Code', 'Employer_Code', 'Customer_Existing_Primary_Bank_Code', 'Source']
train_df.drop(features_to_drop, axis=1, inplace=True)
```

```
train_df.head()
```

| | Gender | City_Category | Employer_Category1 | Employer_Category2 | Monthly_Income | Primary_Bank_Type | Contacted | Source_Category | Existin |
|---|---|---|---|---|---|---|---|---|---|
| 0 | Female | A | A | 4.0 | 2000.0 | P | N | G | |
| 1 | Male | A | C | 1.0 | 3500.0 | P | Y | G | |
| 2 | Male | C | C | 4.0 | 2250.0 | G | Y | B | |
| 3 | Male | C | A | 4.0 | 3500.0 | G | Y | B | |
| 4 | Male | A | A | 4.0 | 10000.0 | P | Y | B | 2 |

```
print(train_df.columns)
```

```
Index(['Gender', 'City_Category', 'Employer_Category1', 'Employer_Category2',
       'Monthly_Income', 'Primary_Bank_Type', 'Contacted', 'Source_Category',
       'Existing_EMI', 'Loan_Amount', 'Loan_Period', 'Interest_Rate', 'EMI',
       'Var1', 'Approved'],
      dtype='object')
```

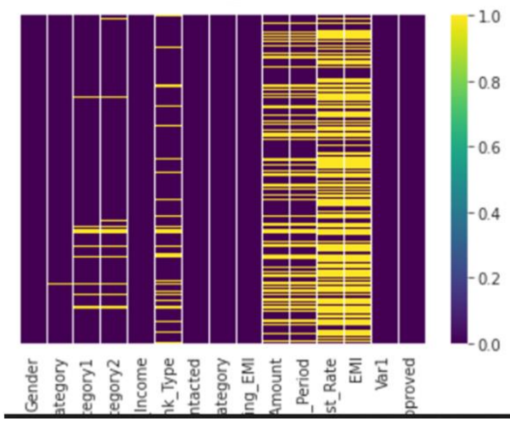
Checked unique value of categorical features for processing

```
# check unique value of categorical features

categorical_features = ['Gender', 'City_Category', 'Employer_Category1', 'Primary_Bank_Type', 'Contacted', 'Source_Category']

for item in categorical_features:
    print(train_df[item].unique())
```

```
['Female' 'Male']
['A' 'C' 'B' nan]
['A' 'C' 'B' nan]
['P' 'G' nan]
['N' 'Y']
['G' 'B' 'C' 'E' 'F' 'D' 'A']
```

```
# visualize the missing data in train_dataset
sns.heatmap(train_df.isnull(), yticklabels=False, cbar=True, cmap='viridis')
```

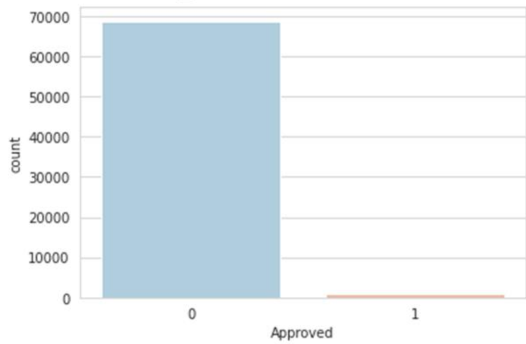
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f56d404f438>
```



see the comparison of loan approved on dataset against 2 condition

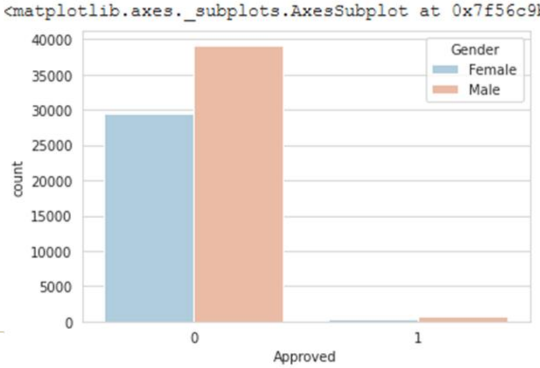
```
# see the comparison of loan approved on train_dataset
sns.set_style('whitegrid')
sns.countplot(x='Approved', data=train_df, palette='RdBu_r')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f56c9b0e3c8>
```




```
# observe loan approved by gender on train_dataset
sns.set_style('whitegrid')
sns.countplot(x='Approved', hue='Gender', data=train_df, palette='RdBu_r')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f56c9b50208>
```



Process categorical features with one hot encoding

```
# categorical feature conversion
# applied one hot encoding

train_df = pd.get_dummies(train_df, drop_first=True)
```

```
train_df.head()
```

| | Employer_Category2 | Monthly_Income | Existing_EMI | Loan_Amount | Loan_Period |
|---|---|---|---|---|---|
| 0 | 4.0 | 2000.0 | 0.0 | NaN | NaN |
| 1 | 1.0 | 3500.0 | 0.0 | 20000.0 | 2.0 |
| 2 | 4.0 | 2250.0 | 0.0 | 45000.0 | 4.0 |
| 3 | 4.0 | 3500.0 | 0.0 | 92000.0 | 5.0 |
| 4 | 4.0 | 10000.0 | 2500.0 | 50000.0 | 2.0 |

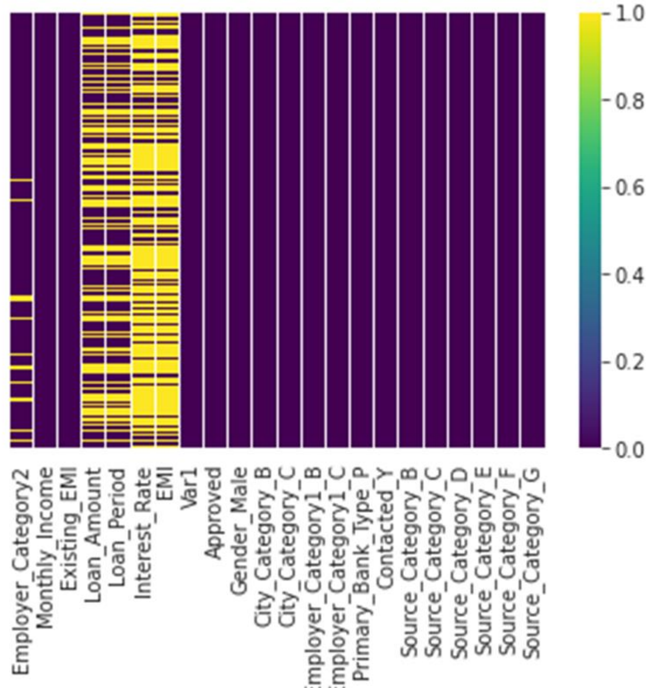
```
# check null values
train_df.isnull().sum()
```

```
Employer_Category2       4298
Monthly_Income              0
Existing_EMI               51
Loan_Amount             27709
Loan_Period             27709
Interest_Rate           47437
EMI                     47437
Var1                        0
Approved                    0
Gender_Male                 0
City_Category_B             0
City_Category_C             0
Employer_Category1_B        0
Employer_Category1_C        0
Primary_Bank_Type_P         0
Contacted_Y                 0
Source_Category_B           0
```

Process categorical features with one hot encoding

```
# visualize the missing data in train_dataset
sns.heatmap(train_df.isnull(), yticklabels=False, cbar=True, cmap='viridis')
```

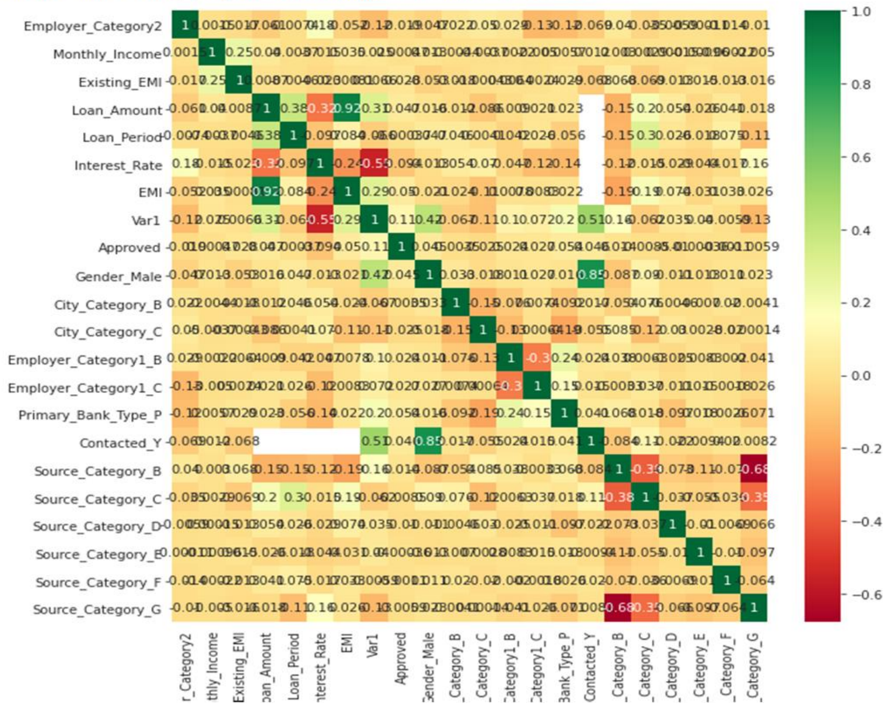
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f56c9a46be0>
```



|Correlation coefficients| are < 0.35 -> low or weak correlations

```
# sns.heatmap(train_df[top_corr_features].corr(), annot = True, cmap="RdYlGn")

corr_mat = train_df.corr()
plt.figure(figsize=(10, 10))
sns.heatmap(train_df.corr(), annot = True, cmap="RdYlGn")
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f56c99d7550>



Replace the missing continuous values with median value of each column

Because some features like loan amount, existing emi etc. would effect the prediction

```
# fill up the missing value of features

features_to_fill = ['Employer_Category2', 'Existing_EMI', 'Loan_Amount', 'Loan_Period', 'Interest_Rate', 'EMI']

for item in features_to_fill:
#     print(item)
    median = train_df[item].median()
    train_df[item].fillna(median, inplace=True)
#     mean = train_df[item].mean()
#     train_df[item].fillna(mean, inplace=True)
```

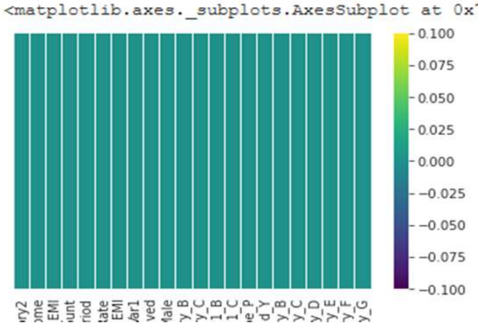
Now there is no missing value in our dataset

```
train_df.isnull().sum()
```

```
Employer_Category2        0
Monthly_Income            0
Existing_EMI              0
Loan_Amount               0
Loan_Period               0
Interest_Rate             0
EMI                       0
Var1                      0
Approved                  0
Gender_Male               0
City_Category_B           0
City_Category_C           0
Employer_Category1_B      0
Employer_Category1_C      0
Primary_Bank_Type_P       0
Contacted_Y               0
Source_Category_B         0
Source_Category_C         0
Source_Category_D         0
Source_Category_E         0
Source_Category_F         0
Source_Category_G         0
dtype: int64
```

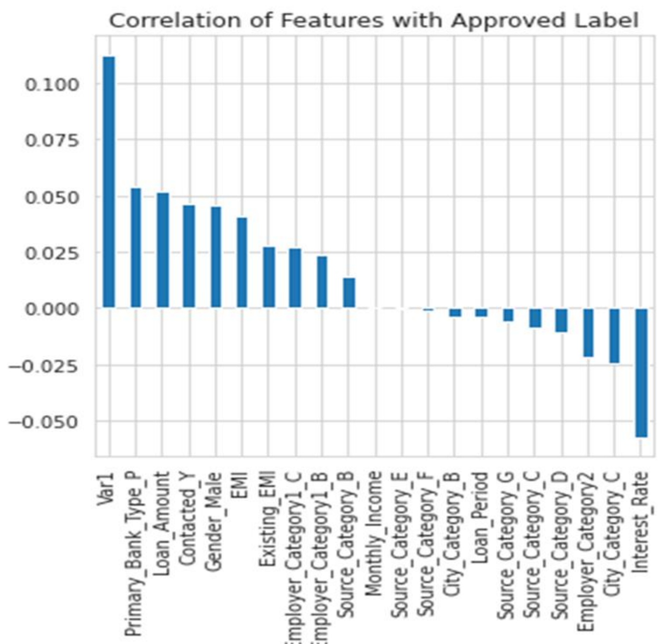
```
# visualize the missing data in train_dataset
sns.heatmap(train_df.isnull(), yticklabels=False, cbar=True, cmap='viridis')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f56c945f2e8>
```



There is not drastic change in our correlation matrix, It means our feature extraction would not effect our prediction result

```
# Correlation of Approved label with all features

plt.figure(figsize=(5, 5))
plt.title("Correlation of Features with Approved Label")
train_df.corr()['Approved'].drop(index='Approved').sort_values(ascending=False).plot(kind='bar')
plt.show()
```



Split our dataset into 2 parts

-> train dataset (80%) -> test dataset (20%)

We kept a way to store model prediction result for comparison later.

```
80] # split train and test data
    from sklearn.model_selection import train_test_split

    X = train_df.drop(['Approved'], axis=1)
    y = train_df['Approved']

    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
81] # observe splitted dataset
    print("train_split: ", X_train.shape, y_train.shape)
    print("test_split: ", X_test.shape, y_test.shape)

    train_split:  (55770, 21) (55770,)
    test_split:  (13943, 21) (13943,)
```

```
82] # all scores to compare later
    all_scores = pd.DataFrame()
```

## Data Preprocessing



We applied 5 machine learning algorithms on our dataset

-> logistic regression

-> decision tree

-> random forest

-> XGBoosts

-> Support Vector Machine – SVM (didn’t get compiled)

A helper function to reduce result processing after train the dataset with a particular ML model

```
[83] from sklearn.metrics import plot_confusion_matrix, accuracy_score, precision_recall_fscore_support
     from sklearn.metrics import plot_roc_curve, plot_precision_recall_curve

     # helper function
     def model_predictions(name, model, X, y, title):
         y_pred = model.predict(X)
         accuracy = accuracy_score(y, y_pred)
         precision, recall, f1, support = precision_recall_fscore_support(y, y_pred, average='binary')
         scores = pd.DataFrame(columns=['Accuracy','Precision','Recall','F1'])
         scores.loc[name] = [accuracy, precision, recall, f1]
         print('==================================================')
         print(title)
         print(scores)
         return scores
```

Train with logistic regression

```
# train logistic regression model
from sklearn.linear_model import LogisticRegression

log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)
```

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

Result with logistic regression

No over fitting and under fitting, as accuracy are almost same on both cases

```
# again confusion matrix
model_predictions('LOG-REG', log_reg, X_train, y_train, 'Logistic Regression Train-Set Scores')
log_reg_result = model_predictions('LOG-REG', log_reg, X_test, y_test, 'Logistic Regression Test-Set Scores')

all_scores = all_scores.append(log_reg_result)
```

```
==================================================
Logistic Regression Train-Set Scores
        Accuracy  Precision  Recall   F1
LOG-REG  0.985297        0.0     0.0  0.0
==================================================
Logistic Regression Test-Set Scores
        Accuracy  Precision    Recall        F1
LOG-REG  0.985226        0.5  0.004854  0.009615
```

Train with decision tree

```
# train Decision Tree model
from sklearn.tree import DecisionTreeClassifier

dec_tree = DecisionTreeClassifier()
dec_tree.fit(X_train, y_train)
```

```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=None, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

Result with decision tree

No over fitting and under fitting, as accuracy are almost same on both cases

Accuracy difference 2 %

```
# again confusion matrix
model_predictions('DEC-TREE', dec_tree, X_train, y_train, 'Decision Tree Train-Set Scores')
dec_tree_result = model_predictions('DEC-TREE', dec_tree, X_test, y_test, 'Decision Tree Test-Set Scores')

all_scores = all_scores.append(dec_tree_result)
```

```
==================================================
Decision Tree Train-Set Scores
          Accuracy  Precision    Recall       F1
DEC-TREE  0.998781        1.0  0.916462  0.95641
==================================================
Decision Tree Test-Set Scores
          Accuracy  Precision    Recall       F1
DEC-TREE  0.971025   0.045872  0.048544  0.04717
```

Train with random forest

```
# train random forest model
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(n_estimators=500)
rfc.fit(X_train,y_train)
```

```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=500,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

Result with random forest

No over fitting and under fitting, as accuracy are almost same on both cases

Accuracy difference 1 %

```
# again confusion matrix
model_predictions('RFC', rfc, X_train, y_train, 'Random Forest Train-Set Scores')
rfc_result = model_predictions('RFC', rfc, X_test, y_test, 'Random Forest Test-Set Scores')

all_scores = all_scores.append(rfc_result)
```

```
==================================================
Random Forest Train-Set Scores
     Accuracy  Precision    Recall        F1
RFC  0.998781   0.997333  0.918919  0.956522
==================================================
Random Forest Test-Set Scores
     Accuracy  Precision    Recall        F1
RFC  0.984006   0.052632  0.004854  0.008889
```

Train with XGBoosts

```
# train with XGBoost model
from xgboost import XGBClassifier

xgb = XGBClassifier(n_estimators=1000)
xgb.fit(X_train,y_train)
```

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=3,
              min_child_weight=1, missing=None, n_estimators=1000, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

Result with XGBoosts

No over fitting and under fitting, as accuracy are almost same on both cases

```
# again confusion matrix
model_predictions('XGBoosts', xgb, X_train, y_train, 'XGBoosts Train-Set Scores')
xgb_result = model_predictions('XGBoosts', xgb, X_test, y_test, 'XGBoosts Test-Set Scores')

all_scores = all_scores.append(xgb_result)
```

```
==================================================
XGBoosts Train-Set Scores
          Accuracy  Precision    Recall        F1
XGBoosts  0.986014        1.0  0.041769  0.080189
==================================================
XGBoosts Test-Set Scores
          Accuracy  Precision    Recall        F1
XGBoosts   0.98501   0.285714  0.009709  0.018779
```

Train and Result with SVM (didn't get compiled)

```
# SVM
```

```
# train svm model
# from sklearn.svm import SVC

# svc = SVC(random_state=10, kernel="linear", C=0.3)

# from sklearn.svm import LinearSVC

# svc = LinearSVC()
# svc = LinearSVC(C=1, loss="hinge", penalty='l2', max_iter=100)
# svc.fit(X_train, y_train)
```

```
# again confusion matrix
# svc_result = model_predictions('SVM', svc, X_test, y_test, 'SVM Test-Set Scores')

# all_scores = all_scores.append(svc_result)
```

Could not implement some things

-> cross-validation
-> stratified sampling
-> feature scaling (normalize, standardize)
-> hyper parameters tuning

Result comparison and final decision

```
# final result
all_scores.sort_values(by='F1', ascending=False)
```

| | Accuracy | Precision | Recall | F1 |
|---|---|---|---|---|
| **DEC-TREE** | 0.971025 | 0.045872 | 0.048544 | 0.047170 |
| **XGBoosts** | 0.985010 | 0.285714 | 0.009709 | 0.018779 |
| **LOG-REG** | 0.985226 | 0.500000 | 0.004854 | 0.009615 |
| **RFC** | 0.984006 | 0.052632 | 0.004854 | 0.008889 |

All these models have almost same accuracy.

The dataset can perform well each ML models we applied here.


Thank
you