Credit Scoring

Assess potential loan customer's creditworthiness

Background

A fintech company has collected historical data of their loan customers. Machine learning based credit scoring is required to categorize the "good" customers from the "bad".

Columns description

- Feature_X: feature of a customer, represented in numerical format.

```
- E.g: loan size, job_code.
- Data dictionary or definition of the features are available.

    - Target: good customer is 0 | bad customer = 1
```

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt


%matplotlib inline

from sklearn import set_config
set_config(print_changed_only=False)

import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
df = pd.read_csv('InputData.csv')
df.drop(columns=['Unnamed: 0'],inplace=True)
```

Checking Missing Values (NaN)

In [3]:

```
df.isna().sum()
```

Out[3]:

```
feature_1       0
feature_2       0
feature_3       0
feature_4       0
feature_5       0
               ..
feature_1042    0
feature_1043    2
feature_1044    2
feature_1045    2
target          0
Length: 1046, dtype: int64
```

Since there is no further informations about these missing values, so these values would be dropped, otherwise we can fill with certain value or with either, mean, median, or modes.

Similarly, bfill, backfill and pad methods can also be used.

In [4]:

```
df.dropna(inplace=True)

#df.fillna(method ='mean', inplace = True) => For Example

df.isna().sum()
```

Out[4]:

```
feature_1       0
feature_2       0
feature_3       0
feature_4       0
feature_5       0
               ..
feature_1042    0
feature_1043    0
feature_1044    0
feature_1045    0
target          0
Length: 1046, dtype: int64
```

Checking target columns

In [5]:

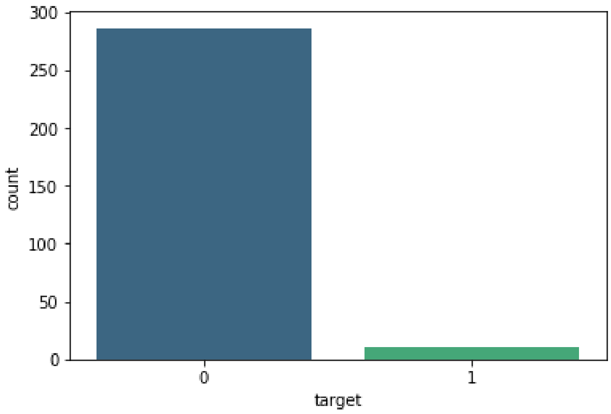
```
df["target"].value_counts()

print(pd.crosstab(index=df['target'],columns='count',normalize=True)*100)

ax = sns.countplot(x=df['target'], data=df, palette='viridis')

plt.show()
```

```
col_0       count
target
0       96.296296
1        3.703704
```



96,3% customers are good (0)

3.7% customers are bad (1)

The target column is imbalanced, so it is needed to be handled properly. In this case, random oversampling will be applied

SPLITING DATA

In [6]:

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix, f1_score,roc_auc_score, recall
_score, precision_score, accuracy_score

X = df.drop(columns=['target'])
y = df['target']

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify = y, train_size = .8,
random_state=42)
```

Checking shape of X_train and X_test

In [7]:

```
X_train.shape
```

Out[7]:

```
(237, 1045)
```

In [8]:

```
X_test.shape
```

Out[8]:

```
(60, 1045)
```

Target Engineering

Handling Imbalanced Data

SMOTE: Synthetic Minority Oversampling Technique

SMOTE is an oversampling technique where the synthetic samples are generated for the minority class. This algorithm helps to overcome the overfitting problem posed by random oversampling. It focuses on the feature space to generate new instances with the help of interpolation between the positive instances that lie together.

In [9]:

```
import imblearn
from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=42)

X_train_sm, y_train_sm = sm.fit_sample(X_train, y_train)
```

In [10]:

```
X_train_sm.shape
```

Out[10]:

```
(456, 1045)
```

In [11]:

```
y_train_sm.shape
```

Out[11]:

```
(456,)
```

FEATURE SELECTION - DROPPING CONSTANT FEATURES

Since there are over 1000 columns, certain method needs to be applied. In this case Variance Threshold is used.

Feature selector that removes all low-variance features.

- This feature selection algorithm looks only at the features (X), not the desired outputs (y), and can thus be used for unsupervised learning.
- Drop all columns that are either constant, or close to constant for numerics, and columns that have only one value for factors or ordered columns.
- The threshold number is 0

In [12]:

```
from sklearn.feature_selection import VarianceThreshold

constant_filter = VarianceThreshold(threshold=0.0)
constant_filter.fit(X_train_sm)
```

Out[12]:

```
VarianceThreshold(threshold=0.0)
```

Features that has 0 variances will be eliminated

In [13]:

```
SUM_constant_filter=len(X_train_sm.columns[constant_filter.get_support()])

print(f'SUM of constant filter: {SUM_constant_filter}')
```

```
SUM of constant filter: 837
```

Showing which are those constant features

In [14]:

```
constant_columns = [column for column in X_train.columns
                    if column not in X_train.columns[constant_filter.get_support()]]

print(f'Constant Features SUM: {len(constant_columns)}\n\n')

for column in constant_columns:
    print(column)
```

```
Constant Features SUM: 208


feature_7
feature_101
feature_119
feature_120
feature_126
feature_128
feature_146
feature_171
feature_217
feature_222
feature_223
feature_224
feature_225
feature_235
feature_236
feature_237
feature_247
```

```
feature_250
feature_251
feature_253
feature_261
feature_262
feature_263
feature_264
feature_266
feature_270
feature_271
feature_272
feature_278
feature_279
feature_280
feature_281
feature_282
feature_283
feature_288
feature_311
feature_312
feature_313
feature_314
feature_315
feature_316
feature_317
feature_318
feature_321
feature_322
feature_323
feature_324
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feature_382
feature_383
feature_392
feature_393
feature_394
feature_395
feature_398
feature_399
feature_412
feature_413
feature_416
feature_417
feature_418
feature_419
feature_420
feature_421
feature_422
feature_423
feature_424
feature_425
feature_426
feature_439
feature_440
feature_441
```

```
feature_442
feature_443
feature_444
feature_445
feature_446
feature_447
feature_448
feature_449
feature_450
feature_457
feature_458
feature_459
feature_460
feature_461
feature_462
feature_469
feature_470
feature_471
feature_472
feature_473
feature_474
feature_480
feature_485
feature_504
feature_505
feature_508
feature_509
feature_514
feature_515
feature_516
feature_517
feature_531
feature_532
feature_555
feature_556
feature_559
feature_560
feature_561
feature_562
feature_579
feature_580
feature_583
feature_584
feature_589
feature_598
feature_599
feature_618
feature_619
feature_622
feature_623
feature_624
feature_625
feature_626
feature_627
feature_648
feature_649
feature_652
feature_653
feature_654
feature_655
feature_666
feature_667
feature_668
feature_669
feature_670
feature_671
feature_681
feature_682
feature_683
feature_684
feature_685
feature_686
feature_708
feature_709
feature_715
feature_717
feature_752
```

```
feature_754
feature_798
feature_800
feature_803
feature_804
feature_805
feature_806
feature_817
feature_818
feature_819
feature_824
feature_837
feature_840
feature_841
feature_843
feature_851
feature_852
feature_853
feature_854
feature_856
feature_860
feature_861
feature_862
feature_866
feature_867
feature_868
feature_869
feature_870
feature_871
feature_907
feature_922
feature_924
feature_938
feature_939
feature_940
feature_941
feature_942
```

In [15]:

```
train_features = constant_filter.transform(X_train)
test_features = constant_filter.transform(X_test)

print(train_features.shape, test_features.shape)
```

```
(237, 837) (60, 837)
```

Dropping these constant features from X_train

In [16]:

```
X_train_sm.drop(constant_columns,axis=1)
```

Out[16]:

	feature_1	feature_2	feature_3	feature_4	feature_5	feature_6	feature_8	feature_9	feature_10	feature_11	...	f
0	1.000000e+06	-999.000000	2.100000e+07	3000000.0	28	0	263.000000	89.022731	94.000000	263.000000	...	
1	1.500000e+06	-999.000000	4.000000e+06	500000.0	22	0	263.000000	0.719261	1.000000	263.000000	...	
2	1.500000e+06	-999.000000	5.500000e+06	-999.0	27	0	269.000000	761.542396	87.000000	269.000000	...	
3	9.000000e+05	800000.000000	3.850000e+06	-999.0	36	0	252.000000	0.564729	1.000000	252.000000	...	
4	1.500000e+06	-999.000000	8.000000e+06	1500000.0	32	0	333.000000	0.266685	1.000000	333.000000	...	
...	...	...	...	...	...	...	...	...	...	...	...	
451	1.893217e+06	-999.000000	4.069979e+06	-999.0	27	0	366.366020	30.953829	9.044317	366.366020	...	
452	8.405122e+05	340193.528198	4.962049e+06	-999.0	27	0	265.940636	133.770830	37.044246	265.940636	...	
453	3.844875e+06	-999.000000	6.844875e+06	-999.0	34	1	243.551247	0.673893	1.000000	243.551247	...	
454	1.976728e+06	10660.216532	4.525599e+06	-999.0	26	0	271.138938	0.238406	1.000000	271.138938	...	

	feature_1	feature_2	feature_3	feature_4	feature_5	feature_6	feature_8	feature_9	feature_10	feature_11	...	f
455	9.072342e+05	407048.895309	5.228937e+06	999.0	28	0	252.996557	77.908199	21.065061	252.996557	...	

456 rows × 837 columns

MODELING

In [17]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
```

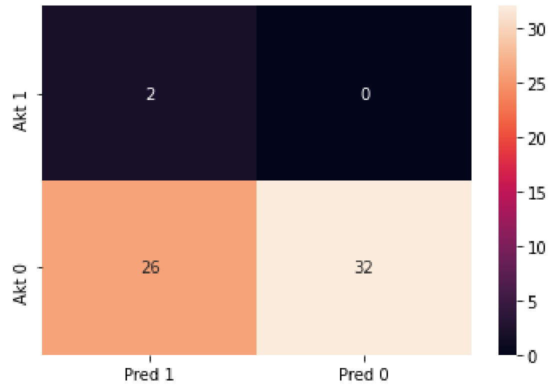
KNN Classifier

In [18]:

```
KNN = KNeighborsClassifier()

KNN.fit(X_train_sm, y_train_sm)

KNN_predict = KNN.predict(X_test)

print(classification_report(y_test, KNN_predict))

acc_base_KNN = accuracy_score(y_test, KNN_predict)
recall_base_KNN = recall_score(y_test, KNN_predict)
precision_base_KNN = precision_score(y_test, KNN_predict)
f1_base_KNN = f1_score(y_test, KNN_predict)


print('\n\nacc score: ', acc_base_KNN)
print('recall score: ', recall_base_KNN)
print('precision score: ', precision_base_KNN)
print('f1 score: ', f1_base_KNN)

print('\n\ntrain accuracy KNN base: ', KNN.score(X_train_sm, y_train_sm))
print('test accuracy KNN base: ', KNN.score(X_test, KNN_predict))
print()
print()

KNN_CM = confusion_matrix(y_test, KNN_predict, labels=[1 , 0])
print(pd.DataFrame(data=KNN_CM, index=["Akt 1" ,"Akt 0"], columns=["Pred 1", "Pred 0"]))

KNN_DF = pd.DataFrame(data=KNN_CM, index=["Akt 1" ,"Akt 0"], columns=["Pred 1", "Pred 0"])
sns.heatmap(KNN_DF, annot=True)
plt.show()
```

```
              precision    recall  f1-score   support

           0       1.00      0.55      0.71        58
           1       0.07      1.00      0.13         2

    accuracy                           0.57        60
   macro avg       0.54      0.78      0.42        60
weighted avg       0.97      0.57      0.69        60



acc score:  0.5666666666666667
recall score:  1.0
precision score:  0.07142857142857142
f1 score:  0.13333333333333333


train accuracy KNN base:  0.8618421052631579
test accuracy KNN base:  1.0


       Pred 1  Pred 0
```

```
       Pred 1  Pred 0
Akt 1       2       0
Akt 0      26      32
```



Logistic Regression

In [19]:

```python
LogReg = LogisticRegression()

LogReg.fit(X_train_sm, y_train_sm)

LogReg_predict = LogReg.predict(X_test)

print(classification_report(y_test, LogReg_predict))

acc_base_LogReg = accuracy_score(y_test, LogReg_predict)
recall_base_LogReg = recall_score(y_test, LogReg_predict)
precision_base_LogReg= precision_score(y_test, LogReg_predict)
f1_base_LogReg = f1_score(y_test, LogReg_predict)


print('\n\nacc score: ', acc_base_LogReg)
print('recall score: ', recall_base_LogReg)
print('precision score: ', precision_base_LogReg)
print('f1 score: ', f1_base_LogReg)

print('\n\ntrain accuracy LogReg base: ', LogReg.score(X_train_sm, y_train_sm))
print('test accuracy LogReg base: ', LogReg.score(X_test, LogReg_predict))
print()
print()

LogReg_CM = confusion_matrix(y_test, LogReg_predict, labels=[1 , 0])
print(pd.DataFrame(data=LogReg_CM, index=["Akt 1" ,"Akt 0"], columns=["Pred 1", "Pred 0"]))

LogReg_DF = pd.DataFrame(data=LogReg_CM, index=["Akt 1" ,"Akt 0"], columns=["Pred 1", "Pred 0"])
sns.heatmap(LogReg_DF, annot=True)
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.96      0.86      0.91        58
           1       0.00      0.00      0.00         2

    accuracy                           0.83        60
   macro avg       0.48      0.43      0.45        60
weighted avg       0.93      0.83      0.88        60



acc score:  0.8333333333333334
recall score:  0.0
precision score:  0.0
f1 score:  0.0


train accuracy LogReg base:  0.8179824561403509
test accuracy LogReg base:  1.0
```

```
      Pred 1  Pred 0
Akt 1       0       2
Akt 0       8      50
```

Decision Tree Classifier

In [20]:

```
DT = DecisionTreeClassifier()

DT.fit(X_train_sm, y_train_sm)

DT_predict = DT.predict(X_test)

print(classification_report(y_test, DT_predict))

acc_base_DT = accuracy_score(y_test, DT_predict)
recall_base_DT = recall_score(y_test, DT_predict)
precision_base_DT= precision_score(y_test, DT_predict)
f1_base_DT = f1_score(y_test, DT_predict)


print('\n\nacc score: ', acc_base_DT)
print('recall score: ', recall_base_DT)
print('precision score: ', precision_base_DT)
print('f1 score: ', f1_base_DT)

print('\n\ntrain accuracy DT base: ', DT.score(X_train_sm, y_train_sm))
print('test accuracy DT base: ', DT.score(X_test, DT_predict))
print()
print()

DT_CM = confusion_matrix(y_test, DT_predict, labels=[1 , 0])
print(pd.DataFrame(data=DT_CM, index=["Akt 1" ,"Akt 0"], columns=["Pred 1", "Pred 0"]))

DT_DF = pd.DataFrame(data=DT_CM, index=["Akt 1" ,"Akt 0"], columns=["Pred 1", "Pred 0"])
sns.heatmap(DT_DF, annot=True)
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.98      0.86      0.92        58
           1       0.11      0.50      0.18         2

    accuracy                           0.85        60
   macro avg       0.55      0.68      0.55        60
weighted avg       0.95      0.85      0.89        60



acc score:  0.85
recall score:  0.5
precision score:  0.1111111111111111
f1 score:  0.18181818181818182
```

```
train accuracy DT base:  1.0
test accuracy DT base:  1.0


       Pred 1  Pred 0
Akt 1       1       1
Akt 0       8      50
```

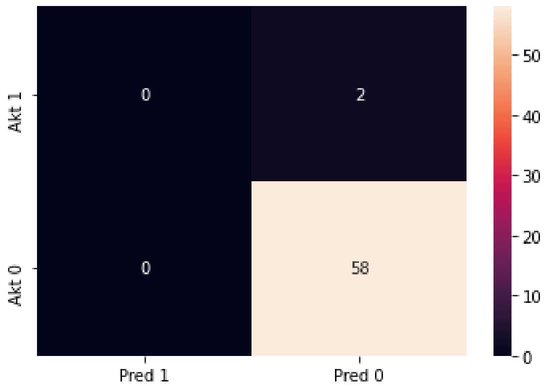
Random Forest Classifier

In [21]:

```
RF = RandomForestClassifier()

RF.fit(X_train_sm, y_train_sm)

RF_predict = RF.predict(X_test)

print(classification_report(y_test, RF_predict))

acc_base_RF = accuracy_score(y_test, RF_predict)
recall_base_RF = recall_score(y_test, RF_predict)
precision_base_RF = precision_score(y_test, RF_predict)
f1_base_RF = f1_score(y_test, RF_predict)


print('\n\nacc score: ', acc_base_RF)
print('recall score: ', recall_base_RF)
print('precision score: ', precision_base_RF)
print('f1 score: ', f1_base_RF)

print('\n\ntrain accuracy RF base: ', RF.score(X_train_sm, y_train_sm))
print('test accuracy RF base: ', RF.score(X_test, RF_predict))
print()
print()

RF_CM = confusion_matrix(y_test, RF_predict, labels=[1 , 0])
print(pd.DataFrame(data=RF_CM, index=["Akt 1" ,"Akt 0"], columns=["Pred 1", "Pred 0"]))

RF_DF = pd.DataFrame(data=RF_CM, index=["Akt 1" ,"Akt 0"], columns=["Pred 1", "Pred 0"])
sns.heatmap(RF_DF, annot=True)
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.97      1.00      0.98        58
           1       0.00      0.00      0.00         2

    accuracy                           0.97        60
   macro avg       0.48      0.50      0.49        60
weighted avg       0.93      0.97      0.95        60



acc score:  0.9666666666666667
recall score:  0.0
precision score:  0.0
```

```
f1 score:  0.0


train accuracy RF base:  1.0
test accuracy RF base:  1.0


       Pred 1  Pred 0
Akt 1       0       2
Akt 0       0      58
```



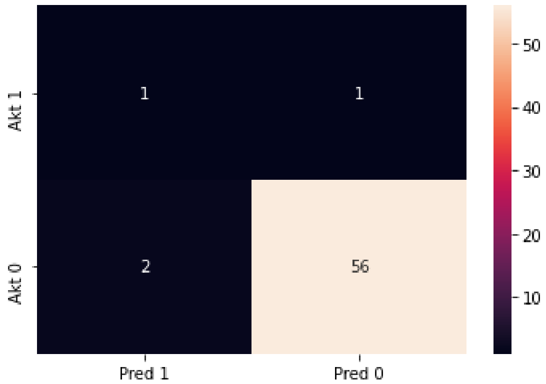
XG Boost Classifier

In [22]:

```python
XGB = XGBClassifier()

XGB.fit(X_train_sm, y_train_sm)

XGB_predict = XGB.predict(X_test)

print(classification_report(y_test, XGB_predict))

acc_base_XGB = accuracy_score(y_test, XGB_predict)
recall_base_XGB = recall_score(y_test, XGB_predict)
precision_base_XGB= precision_score(y_test, XGB_predict)
f1_base_XGB = f1_score(y_test, XGB_predict)


print('\n\nacc score: ', acc_base_XGB)
print('recall score: ', recall_base_XGB)
print('precision score: ', precision_base_XGB)
print('f1 score: ', f1_base_XGB)

print('\n\ntrain accuracy XGB base: ', XGB.score(X_train_sm, y_train_sm))
print('test accuracy XGB base: ', XGB.score(X_test, XGB_predict))
print()
print()

XGB_CM = confusion_matrix(y_test, XGB_predict, labels=[1 , 0])
print(pd.DataFrame(data=XGB_CM, index=["Akt 1" ,"Akt 0"], columns=["Pred 1", "Pred 0"]))

XGB_DF = pd.DataFrame(data=XGB_CM, index=["Akt 1" ,"Akt 0"], columns=["Pred 1", "Pred 0"])
sns.heatmap(XGB_DF, annot=True)
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.98      0.97      0.97        58
           1       0.33      0.50      0.40         2

    accuracy                           0.95        60
   macro avg       0.66      0.73      0.69        60
weighted avg       0.96      0.95      0.95        60



acc score:  0.95
```

```
acc score:  0.95
recall score:  0.5
precision score:  0.3333333333333333
f1 score:  0.4


train accuracy XGB base:  1.0
test accuracy XGB base:  1.0


       Pred 1  Pred 0
Akt 1       1       1
Akt 0       2      56
```



In [26]:

```python
data = {
    "K Nearest Neighbors" : [acc_base_KNN, precision_base_KNN, recall_base_KNN, f1_base_KNN,(KNN.score(X_train, y_train))],
    "Logistic Regression" : [acc_base_LogReg, precision_base_LogReg, recall_base_LogReg, f1_base_LogReg,LogReg.score(X_train, y_train)],
    "Decission Tree" : [acc_base_DT, precision_base_DT, recall_base_DT, f1_base_DT,DT.score(X_train, y_train)],
    "Random Forest"  : [acc_base_RF, precision_base_RF, recall_base_RF, f1_base_RF,RF.score(X_train, y_train)],
    "XG Boost" : [acc_base_XGB, precision_base_XGB, recall_base_XGB, f1_base_XGB,XGB.score(X_train, y_train)]
}

print('Model Score Comparison:\n\n',pd.DataFrame(data=data, index=['Accuracy', 'Precision', 'Recall', 'F1 Score','Train Model Accuracy']).T)
```

```
Model Score Comparison:

                      Accuracy  Precision  Recall  F1 Score  \
K Nearest Neighbors  0.566667   0.071429     1.0  0.133333
Logistic Regression  0.833333   0.000000     0.0  0.000000
Decission Tree       0.850000   0.111111     0.5  0.181818
Random Forest        0.966667   0.000000     0.0  0.000000
XG Boost             0.950000   0.333333     0.5  0.400000

                     Train Model Accuracy
K Nearest Neighbors              0.801688
Logistic Regression              0.810127
Decission Tree                   1.000000
Random Forest                    1.000000
XG Boost                         1.000000
```

Confusion Matrix for Classification Model

- Accuracy is literally how good our model is at predicting the correct category (classes or labels). If our dataset is pretty balanced and every category has equal importance, this should be our go-to metric to measure our model's performance.
- Precision is the ratio of what our model predicted correctly to what our model predicted. For each category/class, there is one precision value. We focus on precision when we need our predictions to be correct, i.e. ideally we want to make sure our model is right when it predicts a label. For example, if we have a Loan underwriting model that predicts whether to approve or reject a

loan request, our priority is being right for all those cases where our model predicted to approve the loan as we will lose money when it approved a loan ideally it should reject. We don’t lose money when it tells us to reject the loan as we still have that money with us.

- Recall is the ratio of what our model predicted correctly to what the actual labels are. Similar to precision, for each category/class, there is one recall value. We focus on recall when we have a FOMO(Fear Of Missing Out) situation. Ideally, you want the model to capture all examples of a particular class. For example, airport security scanning machines have to make sure the detectors don’t miss any actual bombs/dangerous items, and hence we are okay with sometimes stopping the wrong bag/traveler.

- F1 score is used, if we want our model to have a balanced precision and recall score, we average them to get a single metric. Here comes, F1 score, the harmonic mean of recall & precision.

Summary

- There is little value of either True Positive or False Positive on each models.

- Precision Score from classification report is being used, in order to minimize False Positive, which we don't predict bad customer as good customer, because the risk of losing money is higher.

- Since XGB Model has the highest precision score, in this case XG Boost model will be selected

- To increase the score of the mode, dataset that has high variance, so it will be good if the selected features in the dataset which has variance more than a fix threshold.

Export Model

In [24]:

```
import joblib
```

In [25]:

```
joblib.dump(XGB,'Credit Scoring XGB Model')
```

Out[25]:

```
['Credit Scoring XGB Model']
```