CREDIT FRAUD DETECTION

SC1015 PRESENTATION

By: Jerald (U2221612D)
Bryan (U2222849J)
Jonathan (U2223191G)

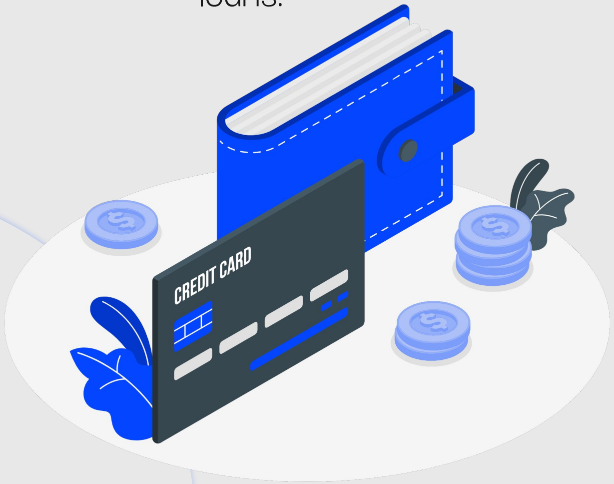
TABLE OF CONTENTS

CSV

DATA SET

MOTIVATION

- Cashless payments are **increasingly common** with the push of such technology
- To **minimise** the **risk** of lending money to customers who may not pay back their loans.
- To understand which **factors** affect people from defaulting credit card loans.



73%

of Singaporeans own at least 1 credit card in 2023

DATA SET

application_data

columns_description

previous_application

FEATURE SELECTION

19/124 Columns in application_data

TARGET | NAME_CONTRACT_TYPE | FLAG_OWN_CAR | FLAG_OWN_REALTY | AMT_CREDIT | AMT_GOODS_PRICE, etc.

PROBLEM DEFINITION

"To find the **highest correlation** of credit card defaulters and to **predict** loan default risk of defaulters."

DATA CLEANING

SPLITTING THE DATA

NUMERICAL

- Finding **NULL** values within dataset
- Fill in missing values with **MEDIAN**

```
[ ]  refined_app.isnull().sum()

SK_ID_CURR                    0
TARGET                        0
NAME_CONTRACT_TYPE            0
FLAG_OWN_CAR                  0
FLAG_OWN_REALTY               0
CNT_CHILDREN                  0
AMT_INCOME_TOTAL              0
AMT_CREDIT                    0
AMT_ANNUITY                  12
AMT_GOODS_PRICE             278
NAME_TYPE_SUITE            1292
NAME_INCOME_TYPE              0
DAYS_BIRTH                    0
DAYS_EMPLOYED                 0
OCCUPATION_TYPE           96391
OBS_30_CNT_SOCIAL_CIRCLE   1021
DEF_30_CNT_SOCIAL_CIRCLE   1021
OBS_60_CNT_SOCIAL_CIRCLE   1021
DEF_60_CNT_SOCIAL_CIRCLE   1021
dtype: int64
```

CATEGORICAL

- Finding **empty values** within dataset
- Fill in missing values with **NULL**

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

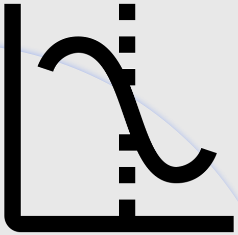
FILLING MISSING VALUES

NUMERICAL

6/13 columns with missing data

```
def median_impute(df,col):
    return df[col].fillna(df[col].median())

refined_num['AMT_ANNUITY'] = median_impute(refined_num,'AMT_ANNUITY')
```



Filling in with **MEDIAN**

CATEGORICAL

2/6 columns with missing data

NAME_TYPE_SUITE: Fill with "***Unaccompanied***"

OCCUPATION_TYPE: Fill with "***NILL***"

```
.fillna
```

REMOVING DUPLICATES

- Ensure each record represents a unique observation
- Affects data analysis:
  - Skewness of results of statistical analysis
  - Increasing size of data set unnecessarily
  - Overfitting in machine learning

```
[ ] df = refined_app.copy()
    df.drop_duplicates(inplace=True)
    print('The amount of frauds in df before dropping duplicates:', len(refined_app[refined_app['TARGET'] == 1]))
    print('The amount of frauds in df after dropping duplicates:', len(df[df['TARGET'] == 1]))

    The amount of frauds in df before dropping duplicates: 24825
    The amount of frauds in df after dropping duplicates: 24825
```

DATA VISUALISATION

NUMERICAL DATA

Target (whether individuals defaulted)

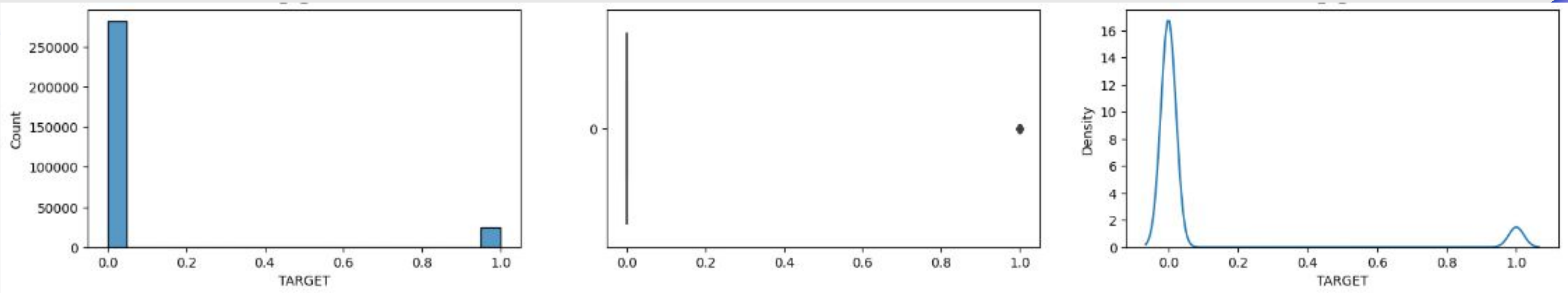
Heavily skewed - more 0s than 1s

Repercussions:

1. Biased model
2. Poor performance of minority class
3. Misleading evaluation metrics

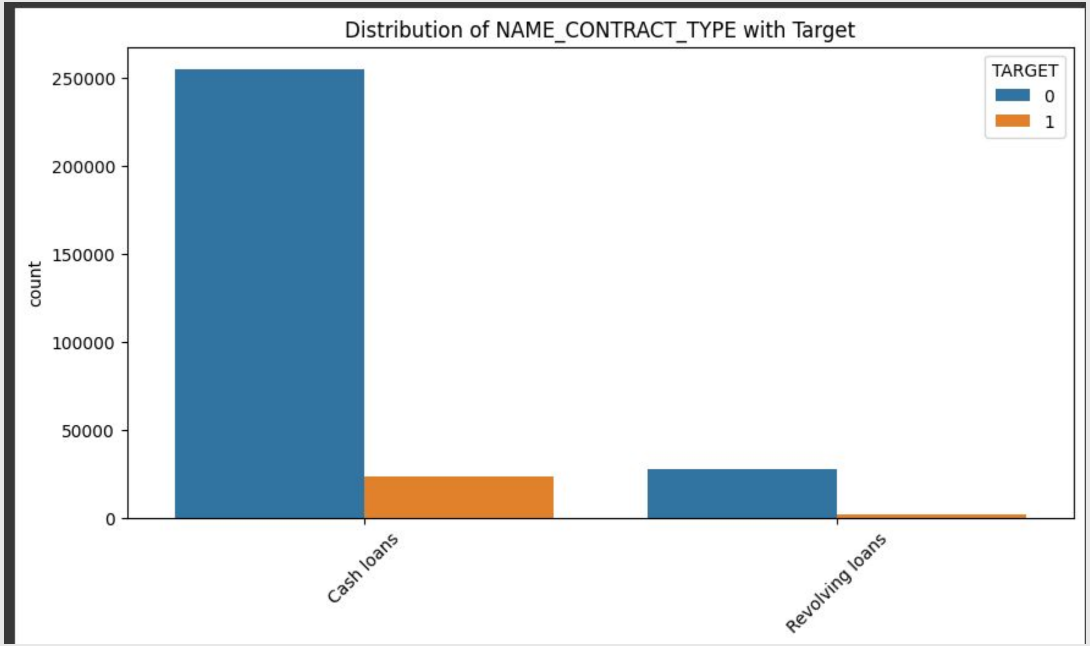
Possible solutions:

1. Undersampling of majority class
2. Oversampling of minority class (SMOTE)
3. Cost-sensitive learning
4. Ensemble method



CATEGORICAL DATA

UNDERSAMPLING



CORRELATION (RAW DATA)

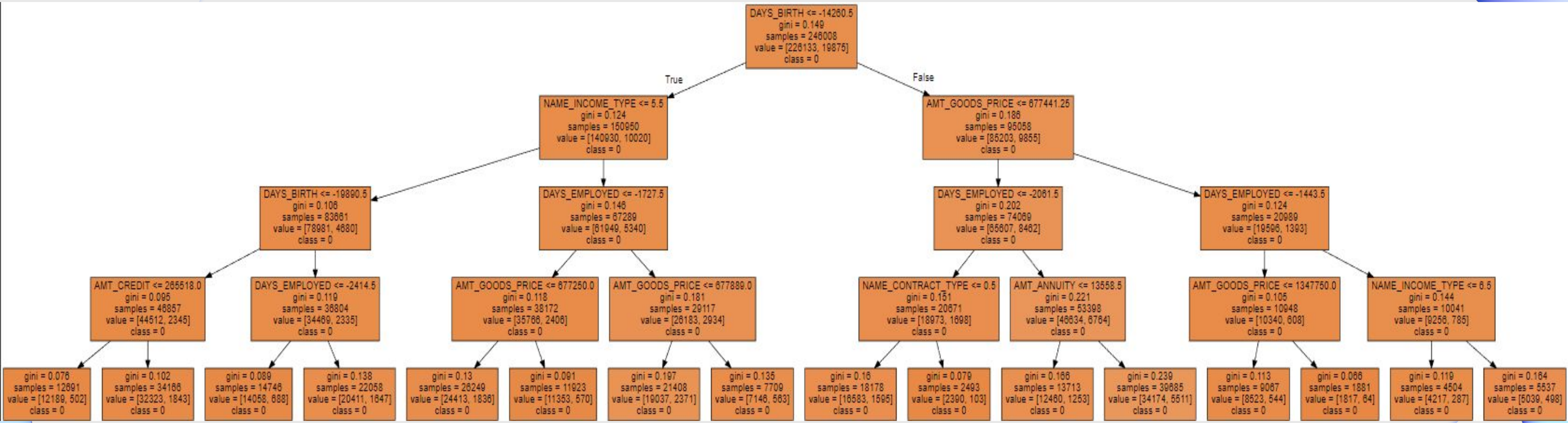
TARGET

DAYS EMPLOYED
DAYS BIRTH

```
DAYS_EMPLOYED                 0.071695
DAYS_BIRTH                    0.063464
AMT_GOODS_PRICE              -0.029617
AMT_INCOME_TOTAL             -0.024722
AMT_CREDIT                   -0.020198
AMT_ANNUITY                   0.015305
CNT_CHILDREN                  0.010850
OBS_60_CNT_SOCIAL_CIRCLE     -0.009135
SK_ID_CURR                    0.007665
OBS_30_CNT_SOCIAL_CIRCLE     -0.007648
DEF_30_CNT_SOCIAL_CIRCLE           NaN
DEF_60_CNT_SOCIAL_CIRCLE           NaN
Name: TARGET, dtype: float64
The most correlated factor with TARGET is 'DAYS_EMPLOYED', with a correlation value of 0.0717.
Number of frauds (TARGET = 1) after dropping outliers: 1597
```

MACHINE LEARNING

DECISION TREE



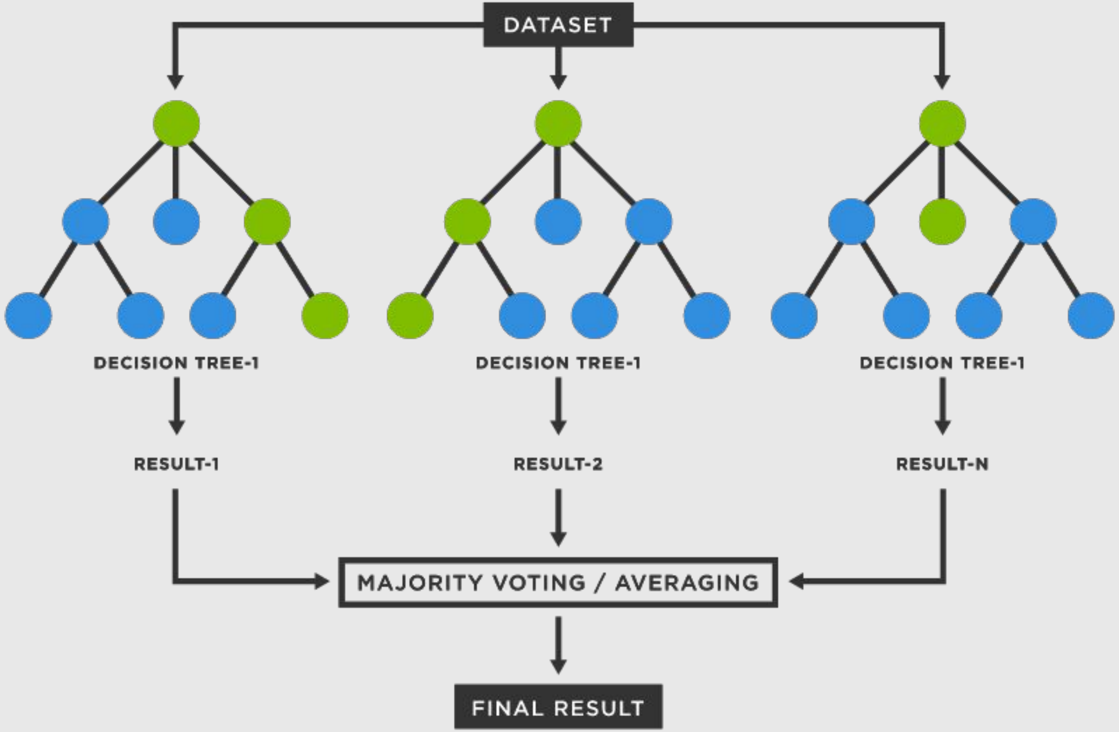
DECISION TREE

Train Accuracy	Test Accuracy	Precision	Recall	F1 Score
91.92%	91.95%	0	0	0

	Predict Safe (0)	Predict Fraud (1)
Actual Safe (0)	56553	**0**
Actual Fraud (1)	**4950**	0

True Positive Rate	0%
False Positive Rate	0%

RANDOM FOREST



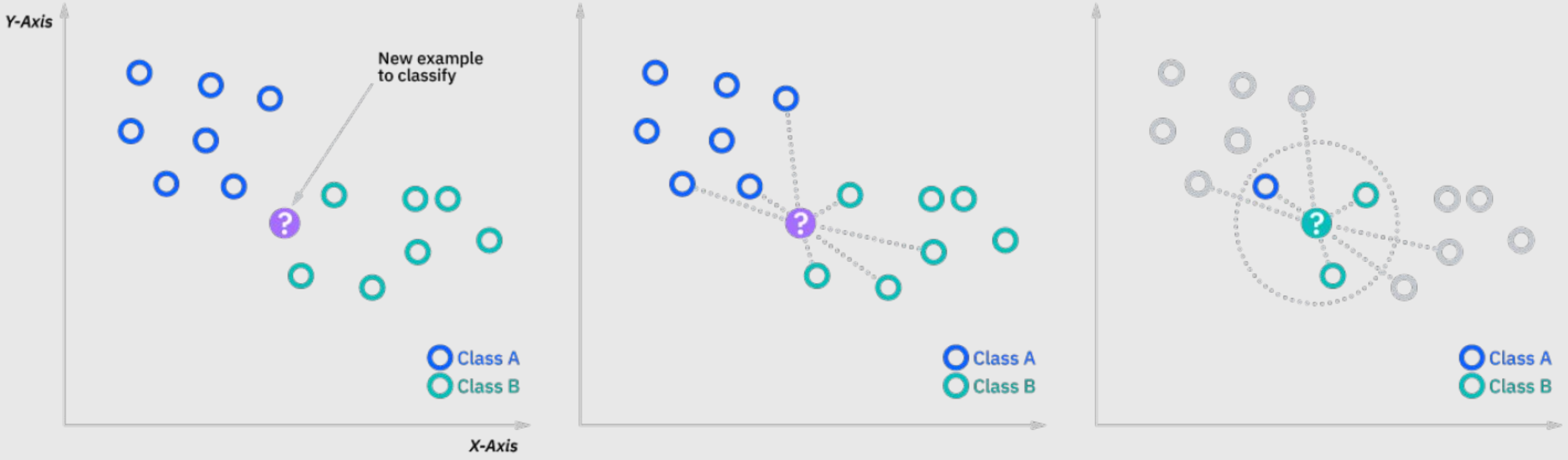
RANDOM FOREST

Train Accuracy	Test Accuracy	Precision	Recall	F1 Score
98.40%	91.87%	0.2298	0.0040	0.0079

	Predict Safe (0)	Predict Fraud (1)
Actual Safe (0)	56486	**67**
Actual Fraud (1)	**4930**	20

True Positive Rate	0.40%
False Positive Rate	0.11%

K-NEAREST NEIGHBORS



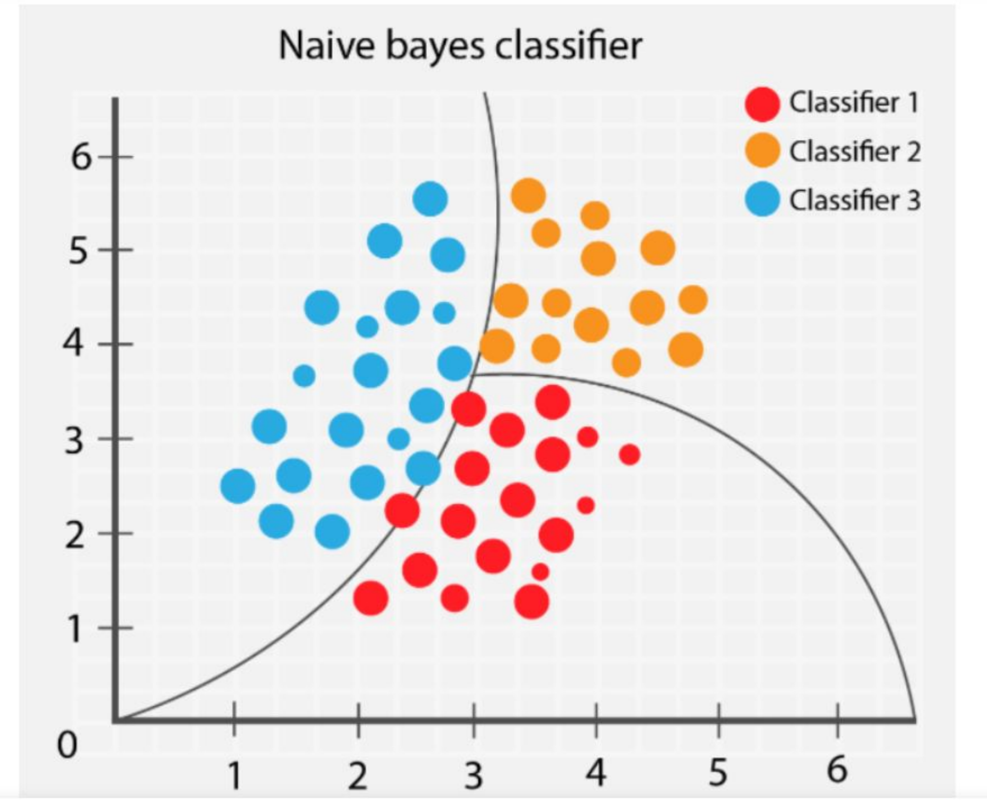
K-NEAREST NEIGHBORS

Train Accuracy	Test Accuracy	Precision	Recall	F1 Score
92.70%	90.29%	0.1308	0.0365	0.0571

	Predict Safe (0)	Predict Fraud (1)
Actual Safe (0)	55351	**1202**
Actual Fraud (1)	**4769**	181

True Positive Rate	3.65%
False Positive Rate	2.12%

NAIVE BAYES


Naive bayes classifier
Classifier 1
Classifier 2
Classifier 3
6
5
4
3
2
1
0
1
2
3
4
5
6

NAIVE BAYES

Train Accuracy	Test Accuracy	Precision	Recall	F1 Score
91.30%	91.40%	0.0687	0.0054	0.0101

	Predict Safe (0)	Predict Fraud (1)
Actual Safe (0)	56187	**366**
Actual Fraud (1)	**4923**	27

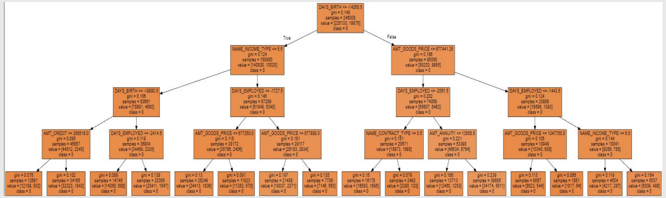
True Positive Rate	0.54%
False Positive Rate	0.64%

MODEL COMPARISON

	model	train_acc	test_acc	precision	recall	f1_score
1	Decision Tree	0.919210	0.919516	0.000000	0.000000	0.000000
2	Random Forest	0.984074	0.918752	0.229885	0.004040	0.007941
3	K-Nearest Neighbours	0.927096	0.902915	0.130875	0.036566	0.057161
4	Gaussian Naive Bayes	0.913023	0.914004	0.068702	0.005455	0.010107

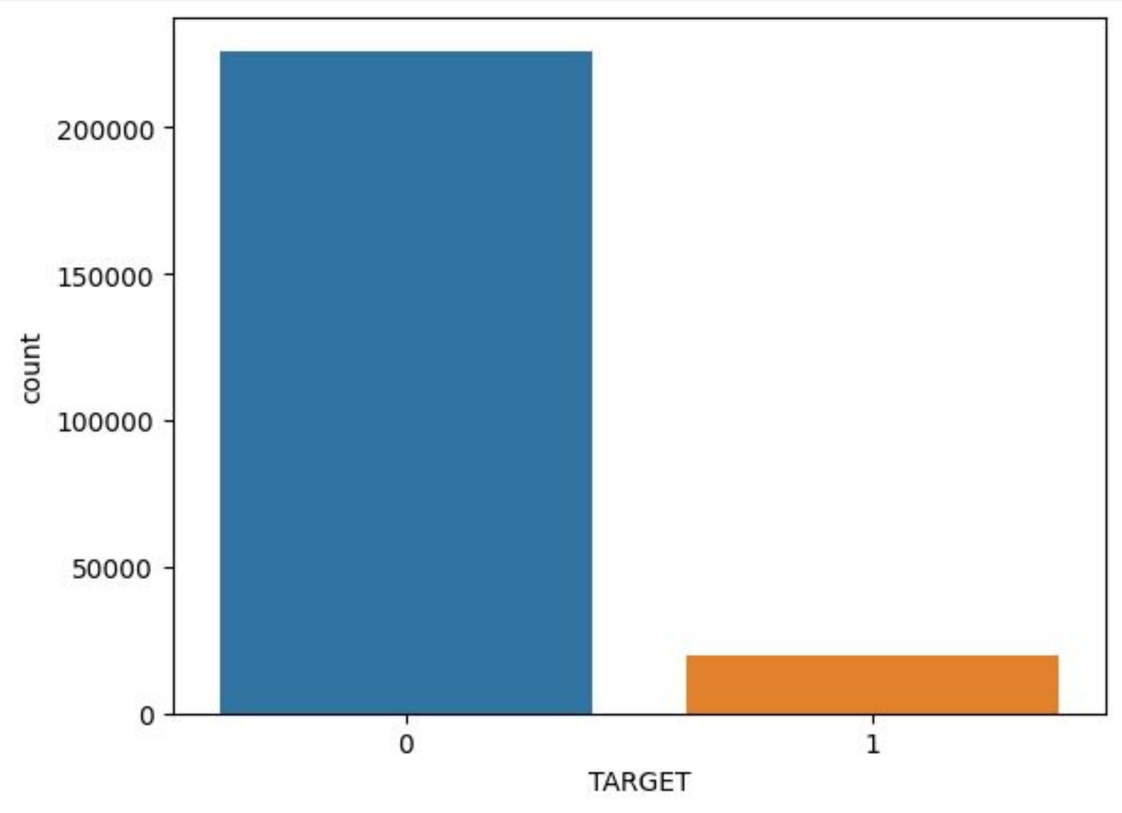
MODEL COMPARISON

- Highest test accuracy: **Decision Tree Classifier**
  - **91.95%**
  - Predicts all customers as safe (target=0)
  - Useless at detecting if customer will default

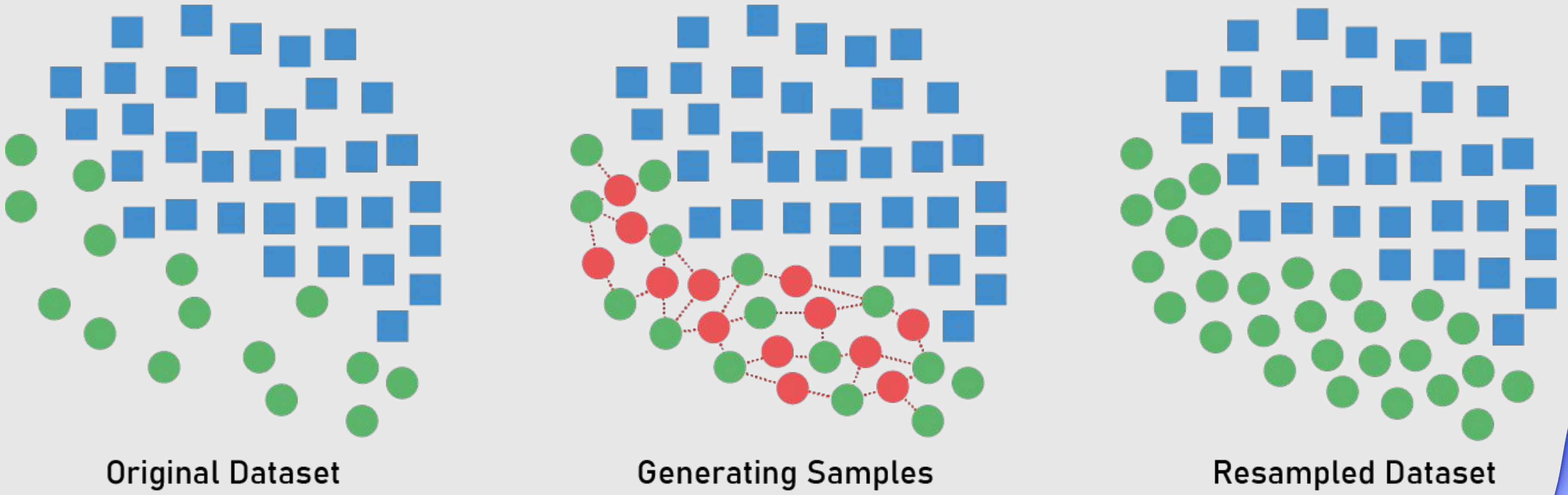


- Highest Recall (TPR): **K-Nearest Neighbors**
  - **3.65%**
  - Extremely low detection rate
  - Takes extremely long time to predict

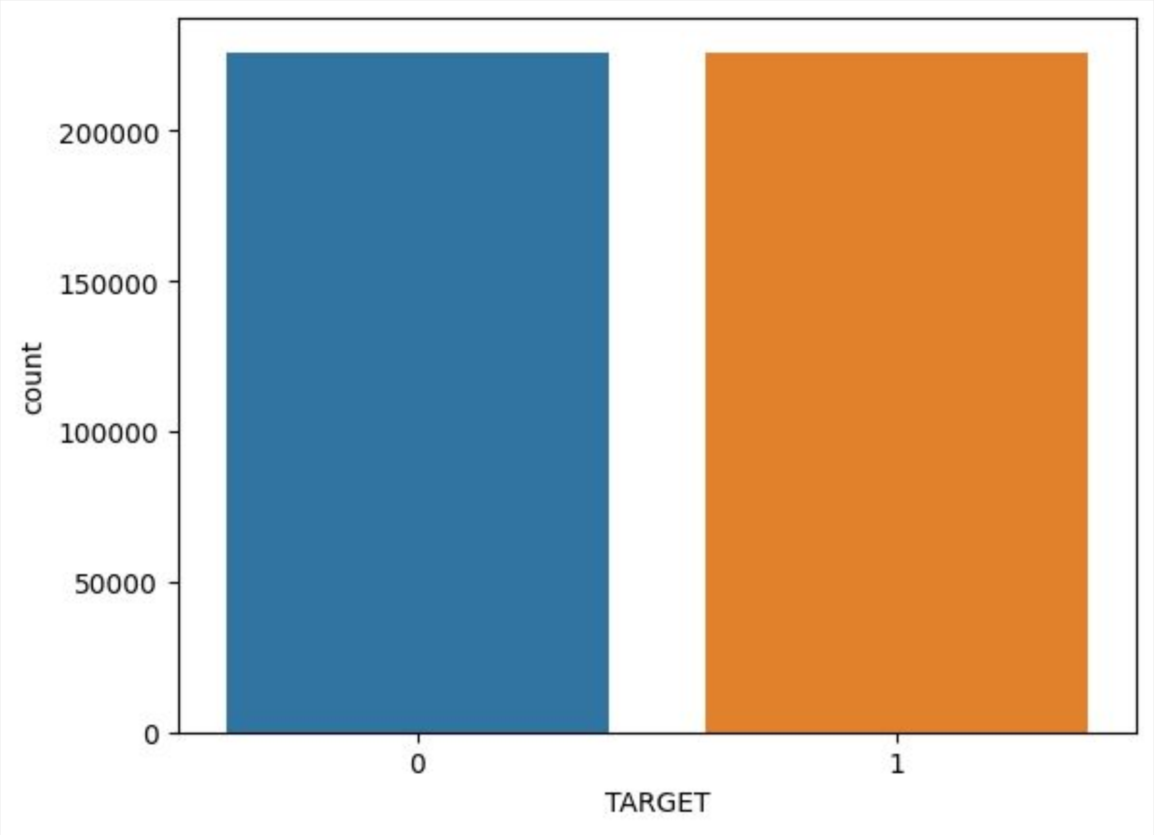
IMBALANCED TRAINING DATASET



SYNTHETIC MINORITY OVER-SAMPLING TECHNIQUE (SMOTE)



RESAMPLED TRAINING DATASET



CORRELATION (SMOTE)

TARGET

OWNING A FLAT
OWNING A CAR

```
FLAG_OWN_CAR                -0.278647
FLAG_OWN_REALTY             -0.210410
DAYS_EMPLOYED                0.142916
NAME_CONTRACT_TYPE          -0.127142
DAYS_BIRTH                   0.124180
AMT_GOODS_PRICE             -0.065508
AMT_INCOME_TOTAL            -0.051444
AMT_CREDIT                  -0.044920
NAME_INCOME_TYPE             0.027394
OCCUPATION_TYPE             -0.023302
OBS_60_CNT_SOCIAL_CIRCLE    -0.019977
OBS_30_CNT_SOCIAL_CIRCLE    -0.018194
NAME_TYPE_SUITE             -0.016024
CNT_CHILDREN                 0.008865
AMT_ANNUITY                  0.003912
SK_ID_CURR                   0.001456
DEF_30_CNT_SOCIAL_CIRCLE          NaN
DEF_60_CNT_SOCIAL_CIRCLE          NaN
Name: TARGET, dtype: float64
The most correlated factor with TARGET is 'FLAG_OWN_CAR', with a correlation value of -0.2786.
```

Model Comparison - SMOTE

Rank	model	train_acc	test_acc	precision	recall	f1_score
4	Decision Tree	0.725909	0.692487	0.089975	0.309495	0.139418
1	Random Forest	0.993763	0.897013	0.128755	0.048485	0.070443
3	K-Nearest Neighbours	0.926815	0.724013	0.097429	0.293939	0.146349
2	Gaussian Naive Bayes	0.497342	0.893339	0.063922	0.023838	0.034726

Model Comparison - SMOTE

- Sacrifice accuracy to improve model robustness
  - Decreased Accuracy
  - Increased Recall / F1 Score

- Highest test accuracy: **Random Forest Classifier**
  - **89.70% Accuracy**
  - Low recall: **4.84%**

- Highest Recall (TPR): **Decision Tree Classifier**
  - **30.94% Recall**
  - Low accuracy: **69.24%**

Model Comparison - SMOTE

	model	train_acc	test_acc	precision	recall	f1_score
3	**K-Nearest Neighbours**	**0.926815**	**0.724013**	**0.097429**	**0.293939**	**0.146349**

BEST OVERALL MODEL: **K-Nearest Neighbours**

GOOD

COMPROMISE

BETWEEN

ACCURACY

&

RECALL

CONCLUSION

INSIGHTS & TAKEAWAYS

1 EDA

Understand overview of data

2 FEATURE SELECTION

Reduce training time

AND

Model performance not affected

3 SMOTE

REDUCES ACCURACY

BUT

INCREASES PERFORMANCE

RECOMMENDATIONS

INSIGHTS & RECOMMENDATIONS

Contributing Factors

DAYS_EMPLOYED & DAYS_BIRTH

OUTCOME

SMOTE

✓ Address class **imbalance** in dataset
– under represented –

✗ **INTRODUCE**
NOISE
OVERFITTING

THANK YOU