Fraudulent Transactions Data

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Data pipeline

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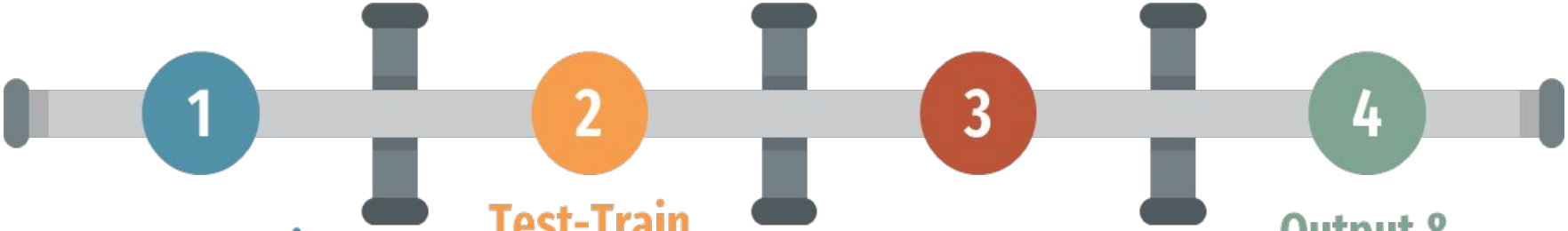

Pre-Processing

- Analysis of data set (https://www.kaggle.com/datasets/chitwanmanchanda/fraudulent-transactions-data)
- Feature Engineering
  - Parsing the feature types in numeric;
  - Dropping non-informative features;
  - Handling multi-collinearity.

Test-Train splitting

- Splitting → 70% - 30 %
- Cross validation for better results

Model selection

Picking the best model and using resamplingtechniques to manage unbalanceness.

Output & Metrics

Reporting our results.

Exploratory Data Analysis (EDA)

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Main aspects

- Data set size ⟶ 186 MB
- Number of features ⟶ 10
- Number of examples ⟶ 6362620
- General info:

```
#   Column          Dtype
---  ------          -----
0   step            int64
1   type            object
2   amount          float64
3   nameOrig        object
4   oldbalanceOrg   float64
5   newbalanceOrig  float64
6   nameDest        object
7   oldbalanceDest  float64
8   newbalanceDest  float64
9   isFraud         int64
10  isFlaggedFraud  int64
```

- Target variable ⟶ ‘isFraud’

Fraudulent distribution over features

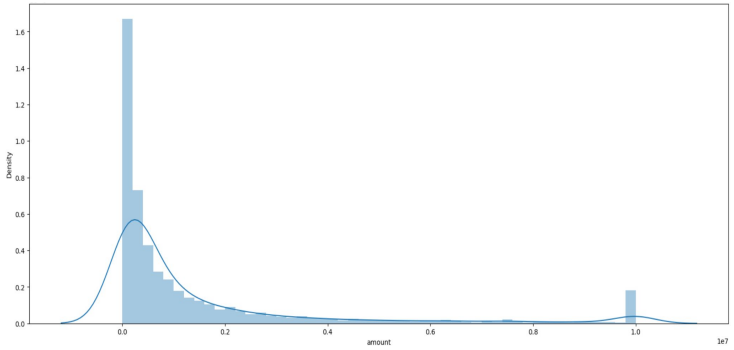
- type of non-fraudulent transactions

```
CASH_OUT    2233384
PAYMENT     2151495
CASH_IN     1399284
TRANSFER     528812
DEBIT         41432
```

- type of fraudulent

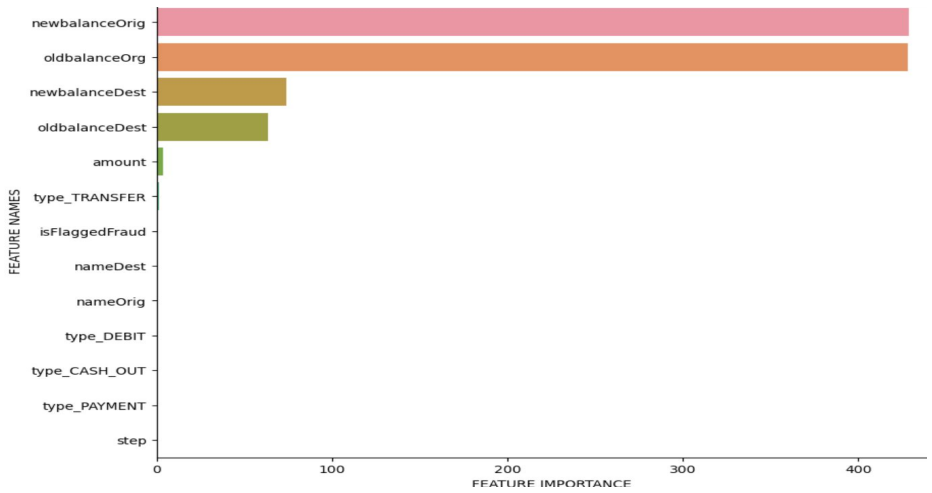
```
CASH_OUT    4116
TRANSFER    4097
```

- number of flagged transactions ⟶ 16
- amount of money for fraudulent transactions



Main issues

- High VIF (Variable Importance Feature) for features about accounts balance and feature hierarchy



	feature	VIF
5	newbalanceOrig	428.693436
4	oldbalanceOrg	428.309108
7	newbalanceDest	73.946539
6	oldbalanceDest	63.765295

critical features in terms of multi-collinearity

- Unbalanced data → fraudulent transaction 0.13%
- Non-informative features

```
0    6362604
1         16
Name: isFlaggedFraud, dtype: int64
```

Feature engineering

- Handling categorical variables:
  - one-hot encoding of transaction types
  - dropping ‘isFlaggedFraud’

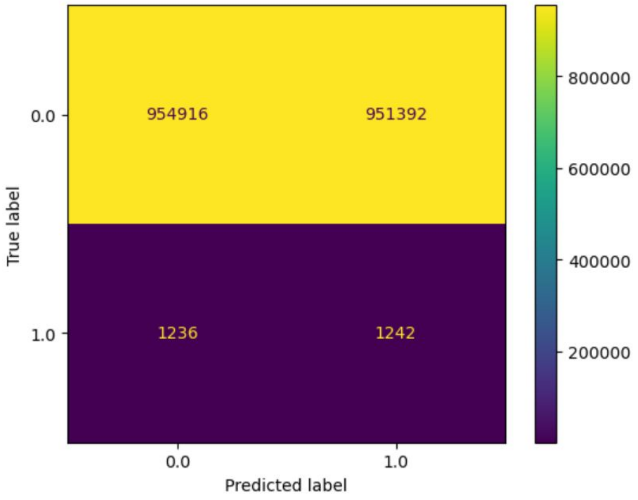
type_CASH_OUT	type_DEBIT	type_PAYMENT	type_TRANSFER
0	0	1	0
0	0	1	0
0	0	0	1

- Hashing strings (Customer ID) in numbers
- Handling the problematic variables in **terms of multi-collinearity**

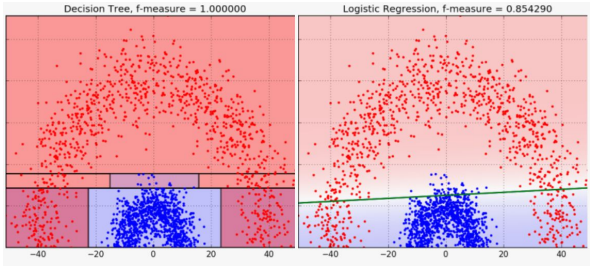
source_bal_change	destinationBal
0	0.0
0	0.0
0	0.0
0	21182.0
0	0.0

  - we identified four problematic variables extremely interrelated
  - we reduced them to two columns (one-hot encoding and reporting the difference between pairs values)
  - considered sources:
    - https://quantifyinghealth.com/vif-threshold/
    - https://www.tandfonline.com/doi/abs/10.1080/09720502.2010.10700699?journalCode=tjim20#:~:text=Multicollinearity%20is%20a%20statistical%20phenomenon%20in%20which%20two%20or%20more,relationships%20among%20the%20explanatory%20variables

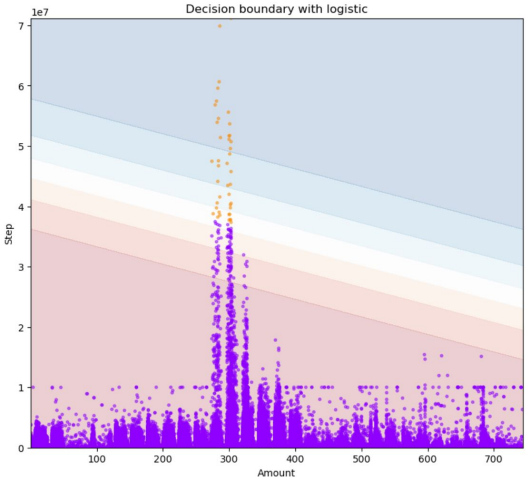
Logistic Regression

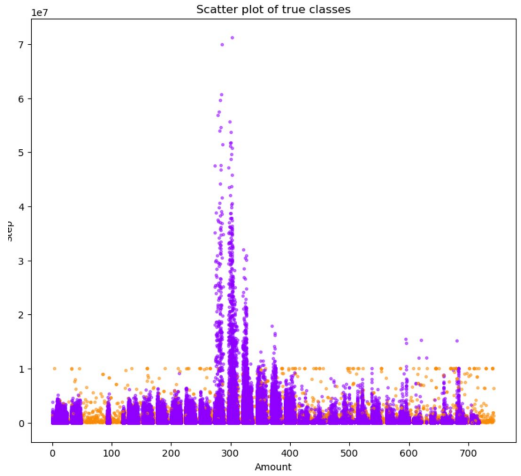


The logistic regression model has a really bad performance due to his ‘linear’ decision boundary



The example on the left is not related to our data set but well represents how decision boundaries are defined for **decision tree** models.
Source:
https://blog.bigml.com/2016/09/28/logistic-regression-versus-decision-trees/#:~:text=Decision%20Trees%20bisect%20the%20space,generalize%20to%20planes%20and%20hyperplanes.





Decision tree & resampling techniques

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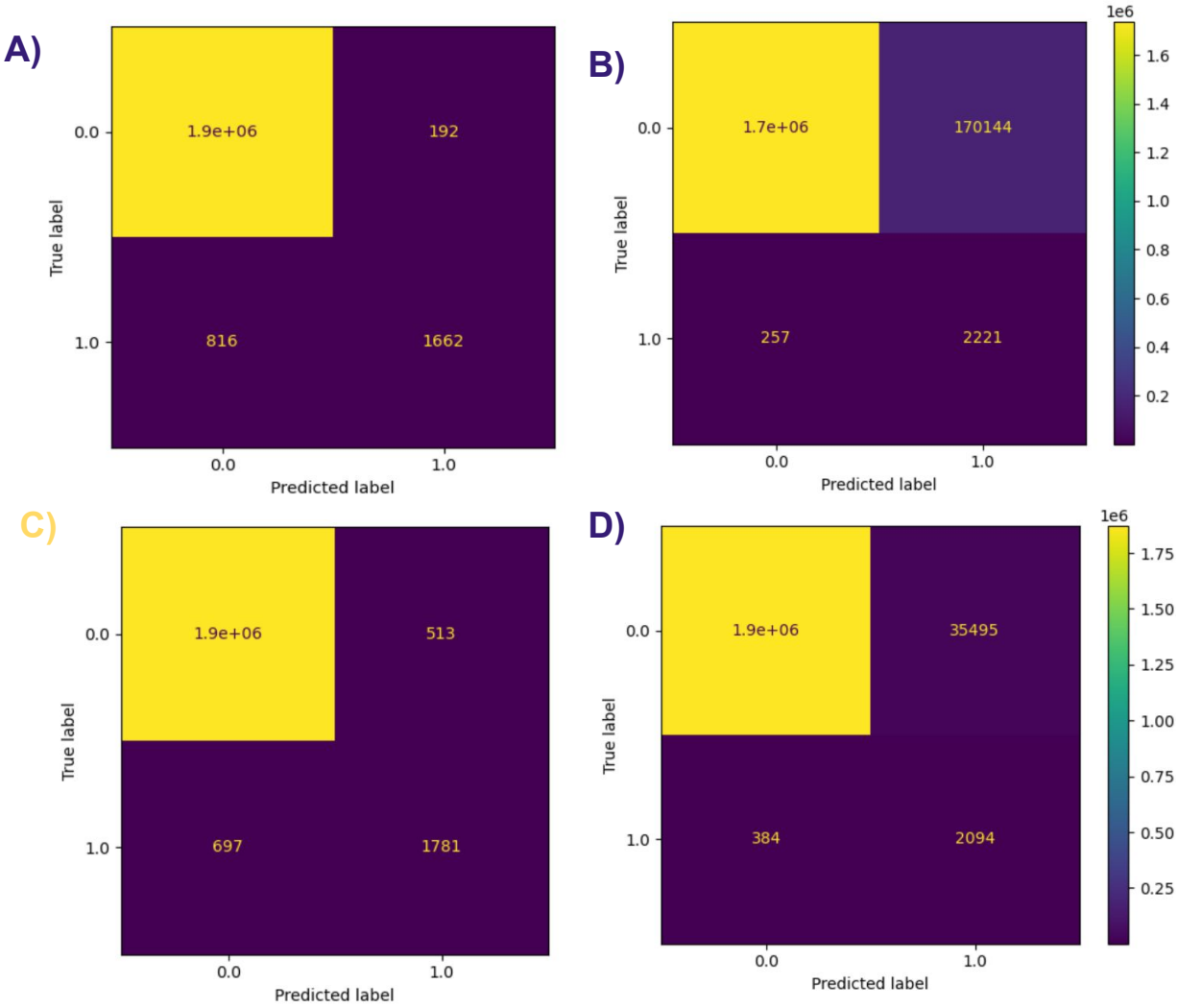

A) DT without resampling
B) DT with **undersampling**
C) DT with **oversampling**
D) DT with **SMOTE**

Goal : our intention is to to minimize the quantity of **false negatives** and we would increase the **recall** but without losing too much efficiency in terms trade-off (precision-recall).

R = TP/(TP+FN)

Further improvements

- Random forest
  - Pros.
    - Powerful and highly accurate
    - Can handle several features at once
    - Run trees in parallel ways
    - Can perform both regression and classification tasks.
    - Produces good prediction that is easily understandable
  - Cons.
    - They are biased to certain features sometimes
    - The algorithm can become quite slow and ineffective for real-time predictions.
    - Worse for high dimensional data

→ In our case we DO NOT gain any improvement in metrics with random forest

- Cross validation

Conclusions

Suggestions for the Bank/Company:

- gather more information about time of a transaction → ‘step’ feature is important according to our analysis but is not really informative given the fact that we don’t know the ‘zero time’ and we can’t extract further information;
- more attention on the ‘transfer’ type cards → they include the most of fraudulent transactions;
- a fundamental point for the company is to concentrate part of their investments on predictive models that minimize **FALSE NEGATIVES**

  → False alarmism preferred over risk of non-detection.

Bibliography

- https://www.kaggle.com/code/kartik2khandelwal/predicting-fraudulent-transactions
- https://github.com/sosamandara/FDS_Final_Project
- Pattern recognition and machine learning, C. Bishop