Loaning 101

To loan or not to loan? That is the question

A Data Mining Project for Computational Learning

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3 Predictive Data Mining Problem

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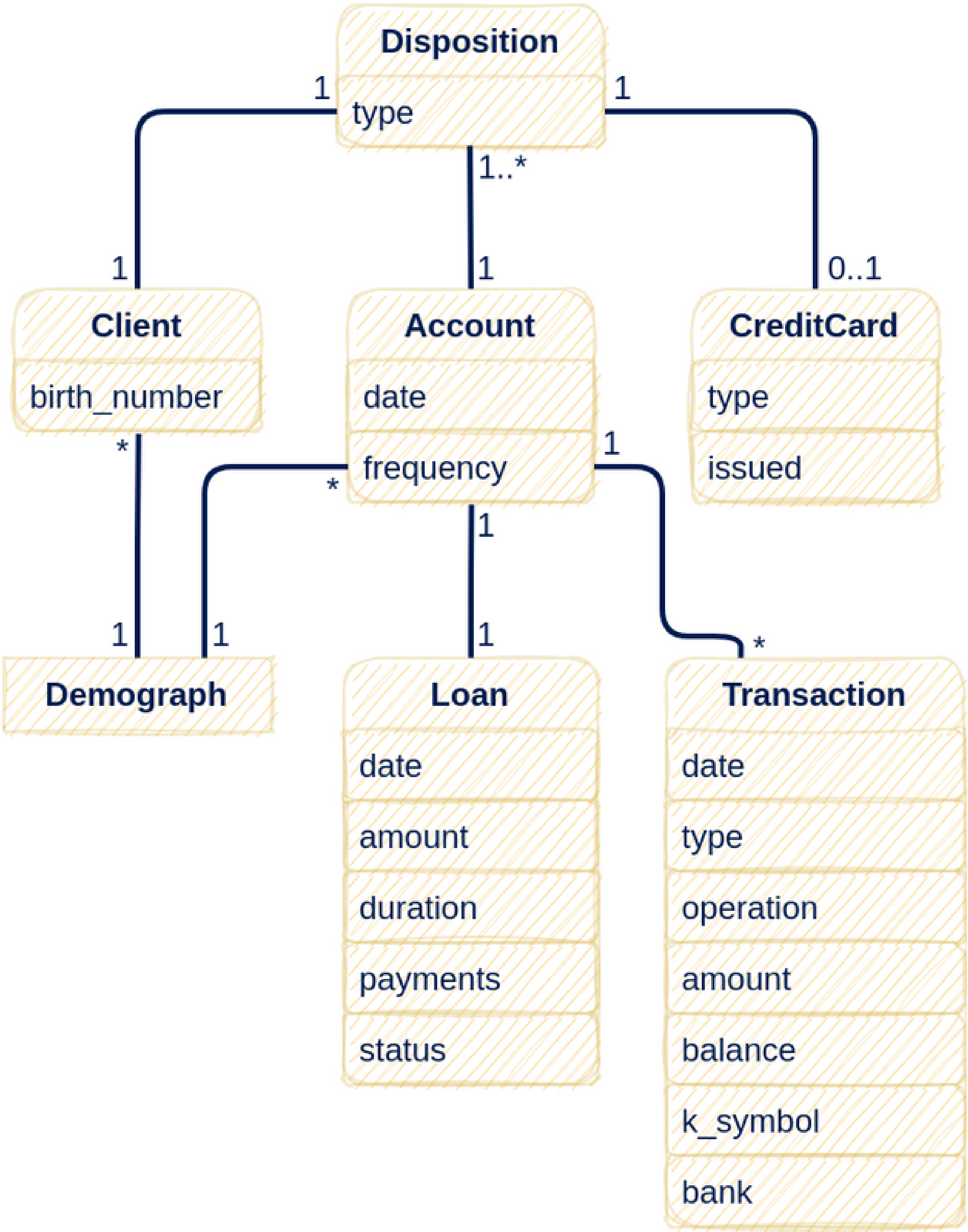
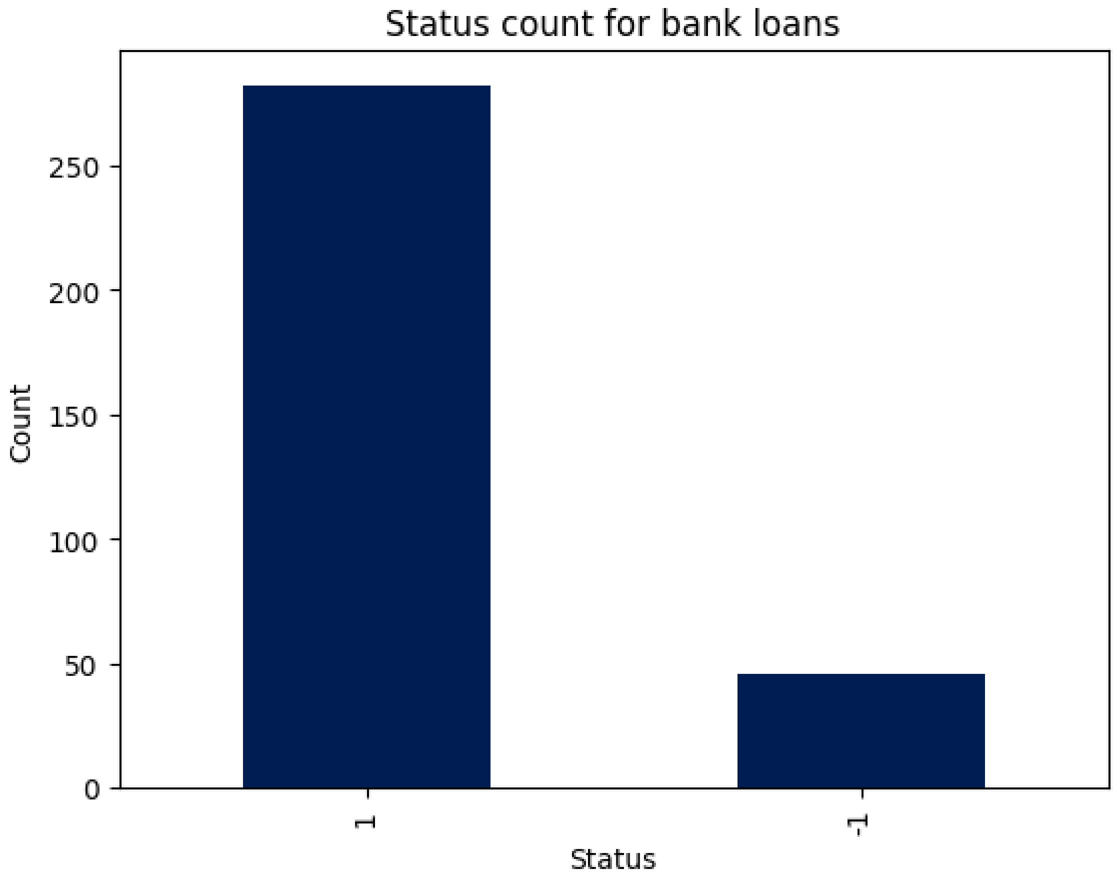
Domain Description

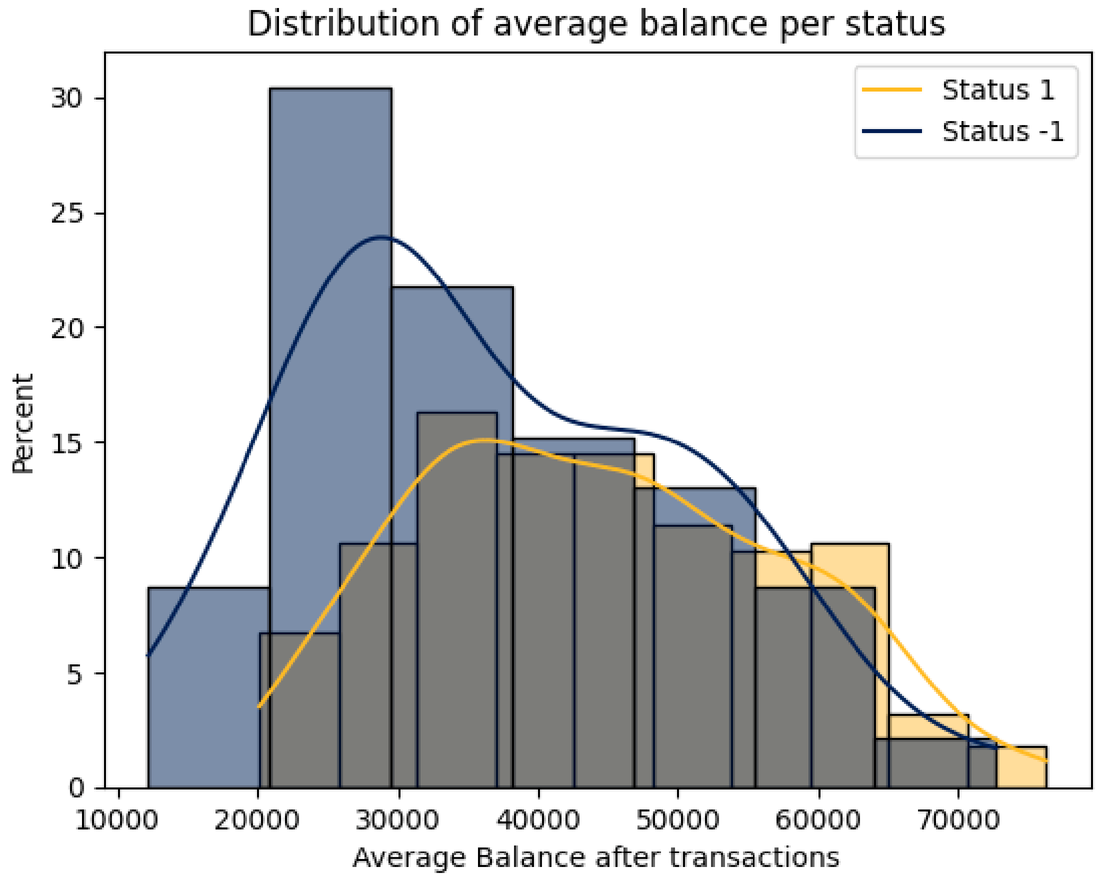
The various datasets comprise information on a bank's clients, their accounts (including transactions made within several months), the granted loans, the credit cards issued, as well as some demographic information.

- 4500 accounts
- 5369 clients
- 328 loans
- 396685 transactions
- 177 credit cards
- 77 districts



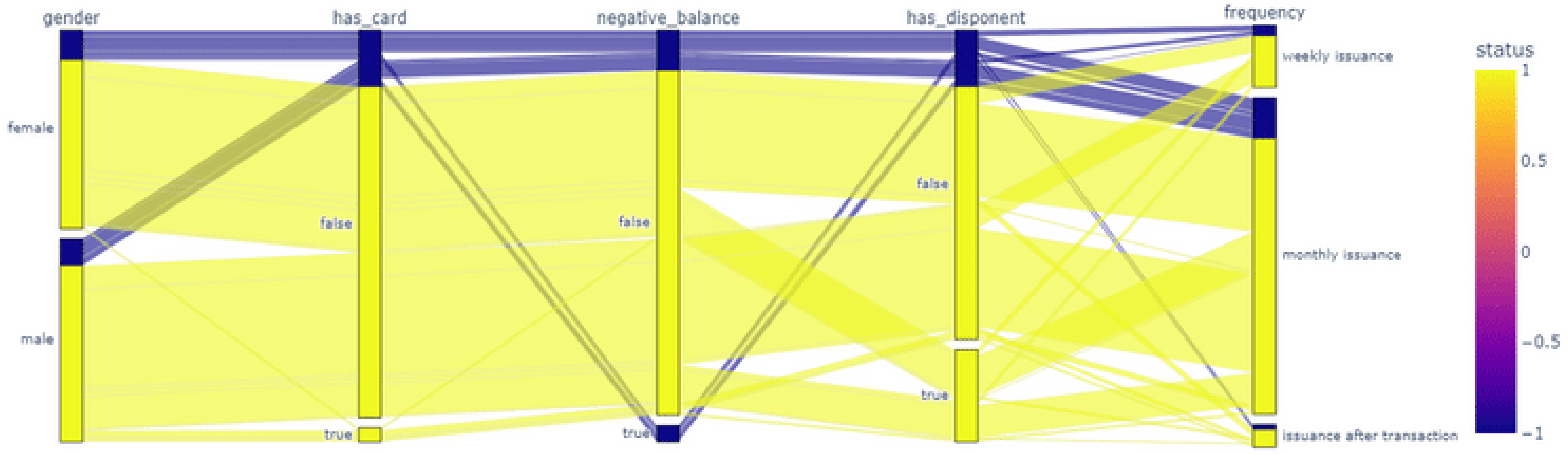


- status class is imbalanced



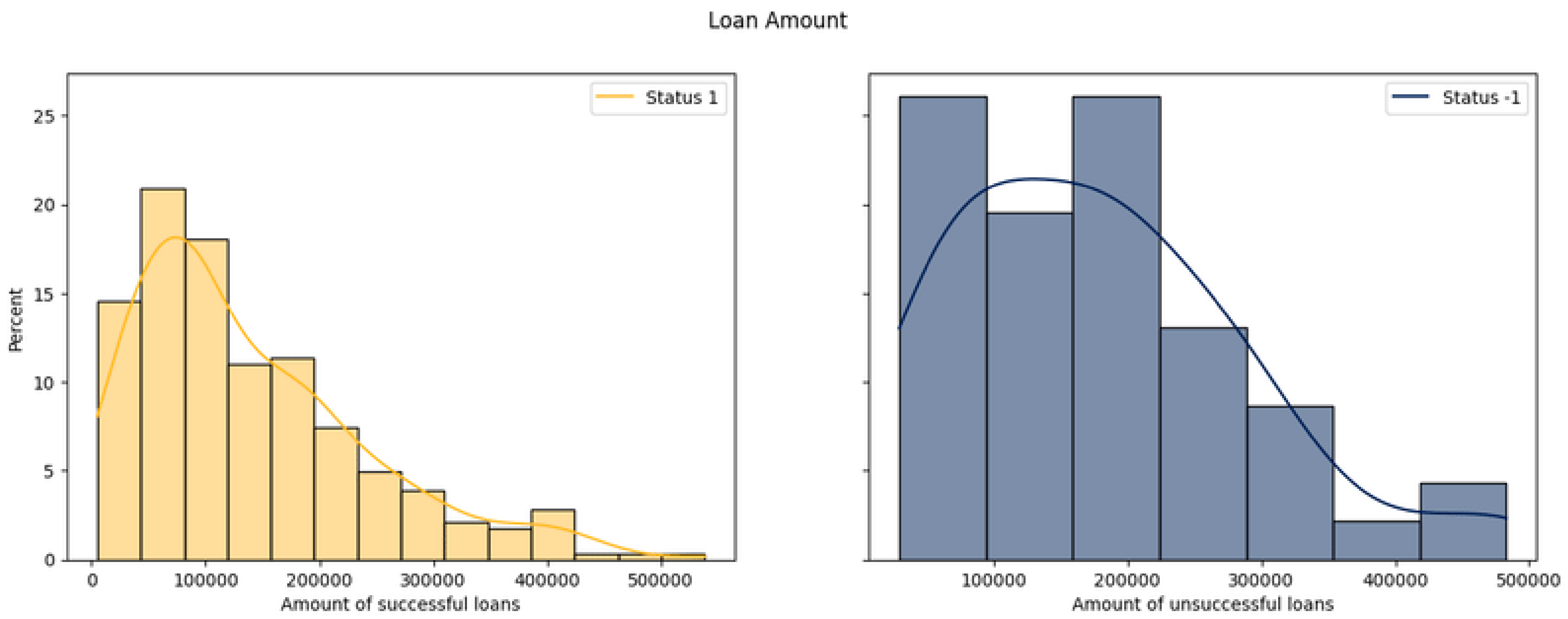
- loans associated with accounts with a lower average balance after transactions are more likely to be unsuccessful

Exploratory Data Analysis



- accounts with cards are mainly owned by males
- loans associated with accounts that have had a negative balance tend to be fraudulent
- accounts that have had a negative balance do not have a disponent nor cards associated
- loans associated with accounts with disponents tend to be successful

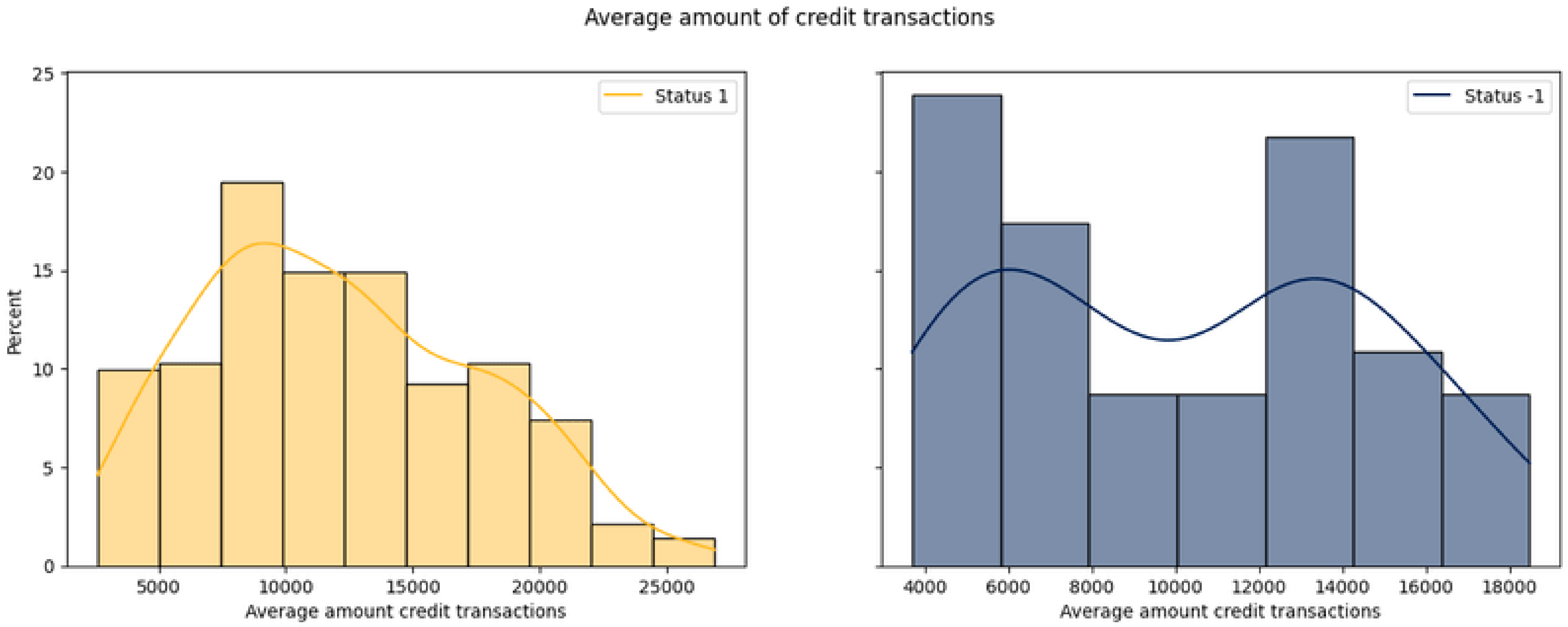
Exploratory Data Analysis



- amount follows a F-distribution as expected in the loan market
- loans with an amount higher than 500000 tend to be successful

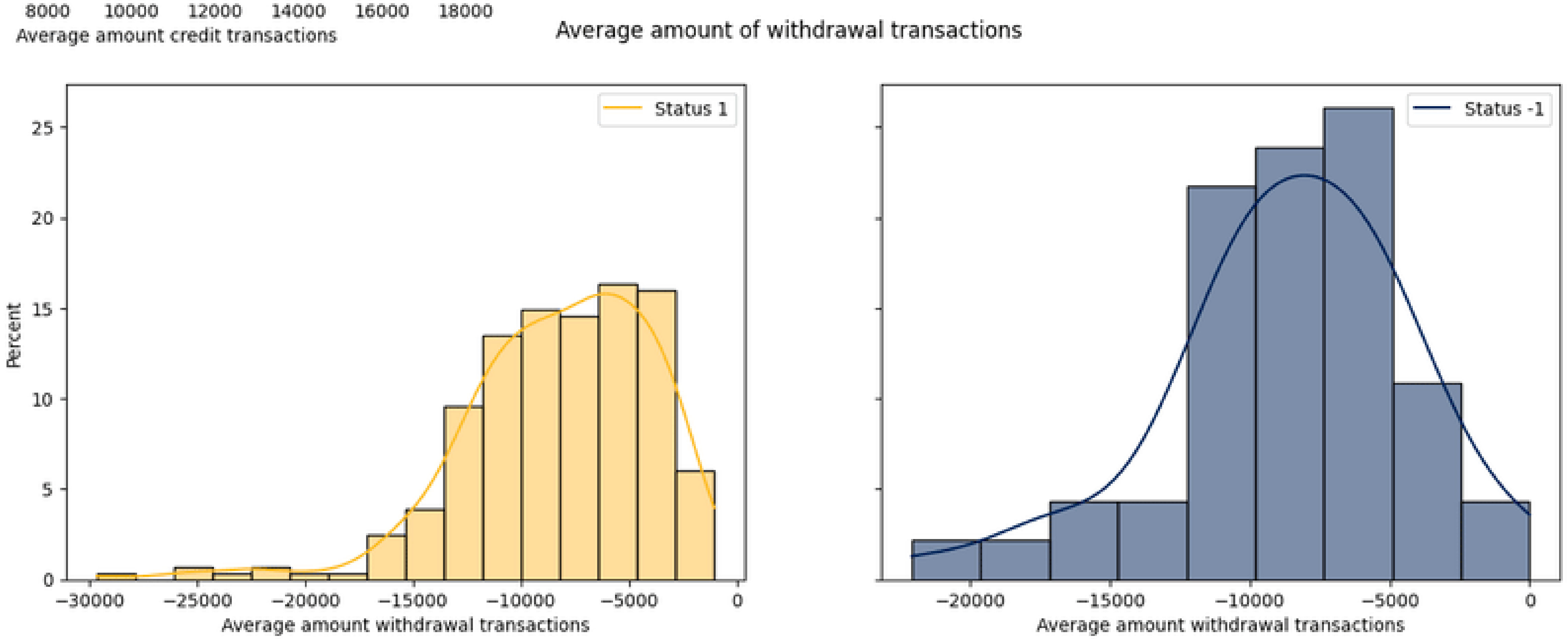
Exploratory Data Analysis

Exploratory Data Analysis


Average amount of credit transactions

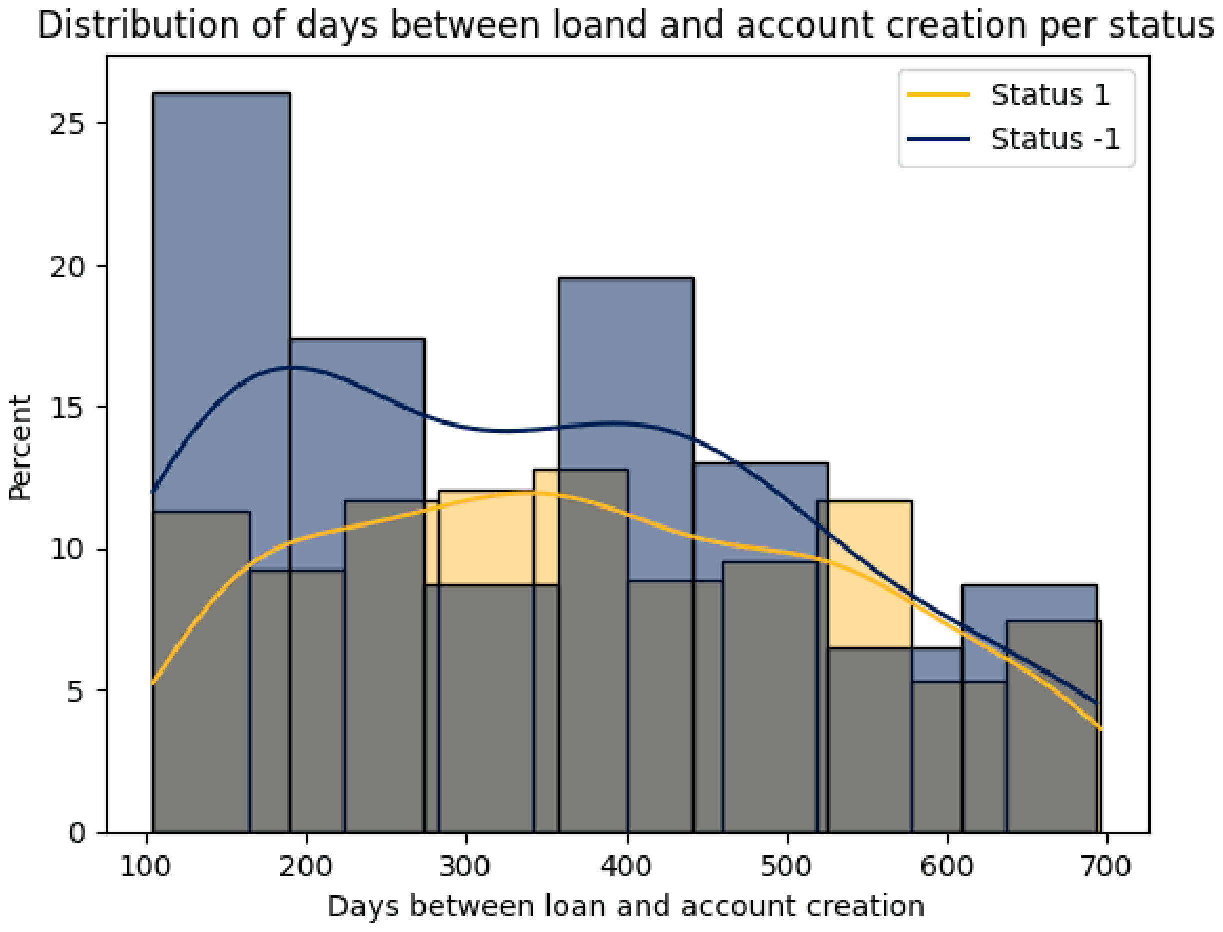
loans associated with accounts where the credits' average amount is

- higher tend to succeed, as there is no record of unsuccessful loans where this value is higher than 18000
- around 10000 tend to be successful

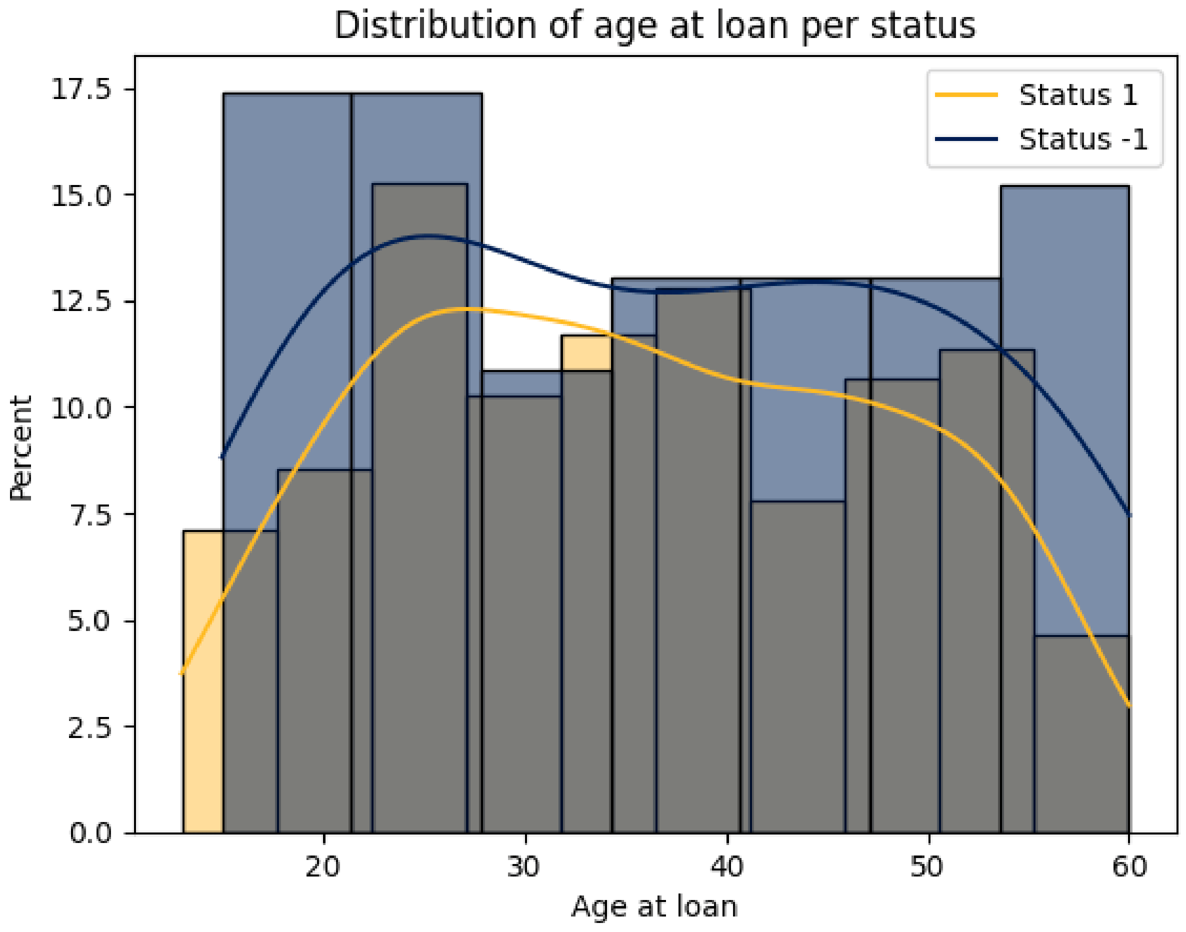

Average amount of withdrawal transactions

loans associated with accounts where the withdrawal' s average amount is

- higher tend to succeed, as there is no record of unsuccessful loans where this value is higher than ~25000 (in absolute value)
- near 0 tend be fraudulent



Distribution of days between loand and account creation per status



Distribution of age at loan per status

- unsuccessful loans have a higher percentage for lower values however when taking into account the absolute number, nothing can be concluded

- age at loan distribution follows the expected pattern, not having a significant impact on the loan status
- peculiar loan issuance to underages

Exploratory Data Analysis

Exploratory Data Analysis

Cardless accounts have no records of successful loans

Loans whose payments are fewer than 2000 and over 8000 payment units are prone to succeed

Accounts that have already had a negative balance have no records of successful loans

Districts with a higher rate of committed crimes have a higher average salary

Accounts that have an average balance below 20000 have no records of successful loans

The Moravia region contains almost 50% of fraudulent cases

Predictive Data Mining Problem

Problem Definition

Binary Classification Problem

Predict the probability of being a positive class

Positive Class

Default Loan = -1

Performance Metric

AUC - measures the ability of a classifier to distinguish between two classes

Aiming to provide help in the loan granting decision process, resulting in a revenue increase by avoiding conceding loans to savage clients. We ought to **predict whether or not a granted loan will end successfully**

Feature Engineering

Financial features

- Number of transactions
- Transaction average amount & average amount per type
- Minimum & maximum transaction amount
- Credit ratio & withdrawal ratio
- Average, minimum, maximum & standard deviation transactions balance
- Has had a negative balance
- If the last transaction had a negative balance
- Average amount and count for each operation & k_symbol
- Days between account creation & loan granting

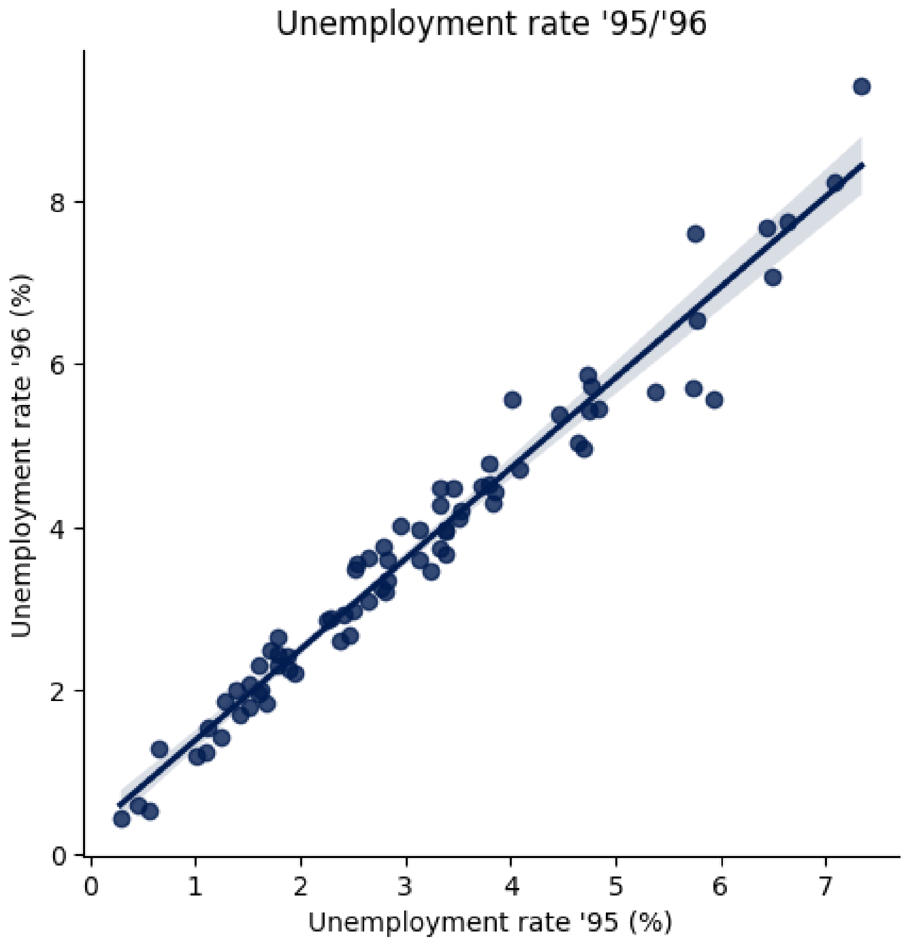
Client Account features

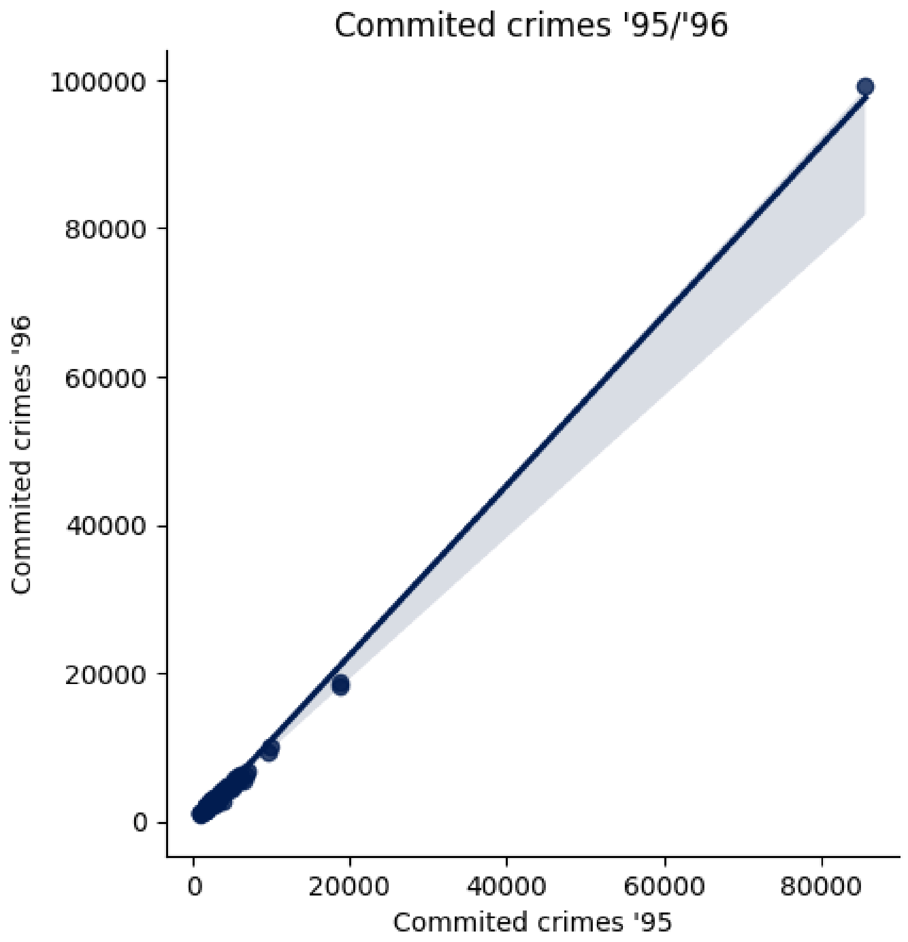
- Gender
- Age loan
- Number of disponents / has disponents
- Number of cards / has cards
- Same client and account's district

Demographic features

- Criminality growth
- Unemployment growth
- Average committed crimes
- Average unemployment rate

Data Preparation





Missing Data

Unemployment rate '95 and *No. of committed crimes '95* missing values were **replaced** by correspondent '96 values.

**Columns with more than 75% null values were removed.*

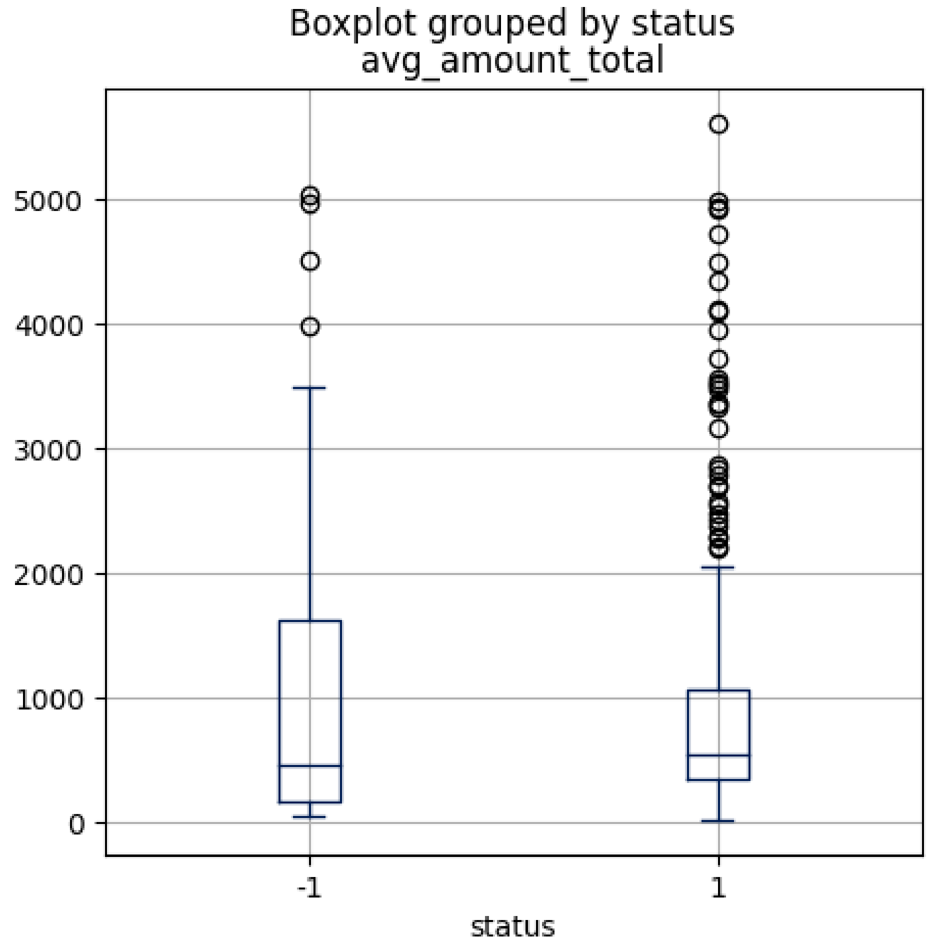
Data Preparation

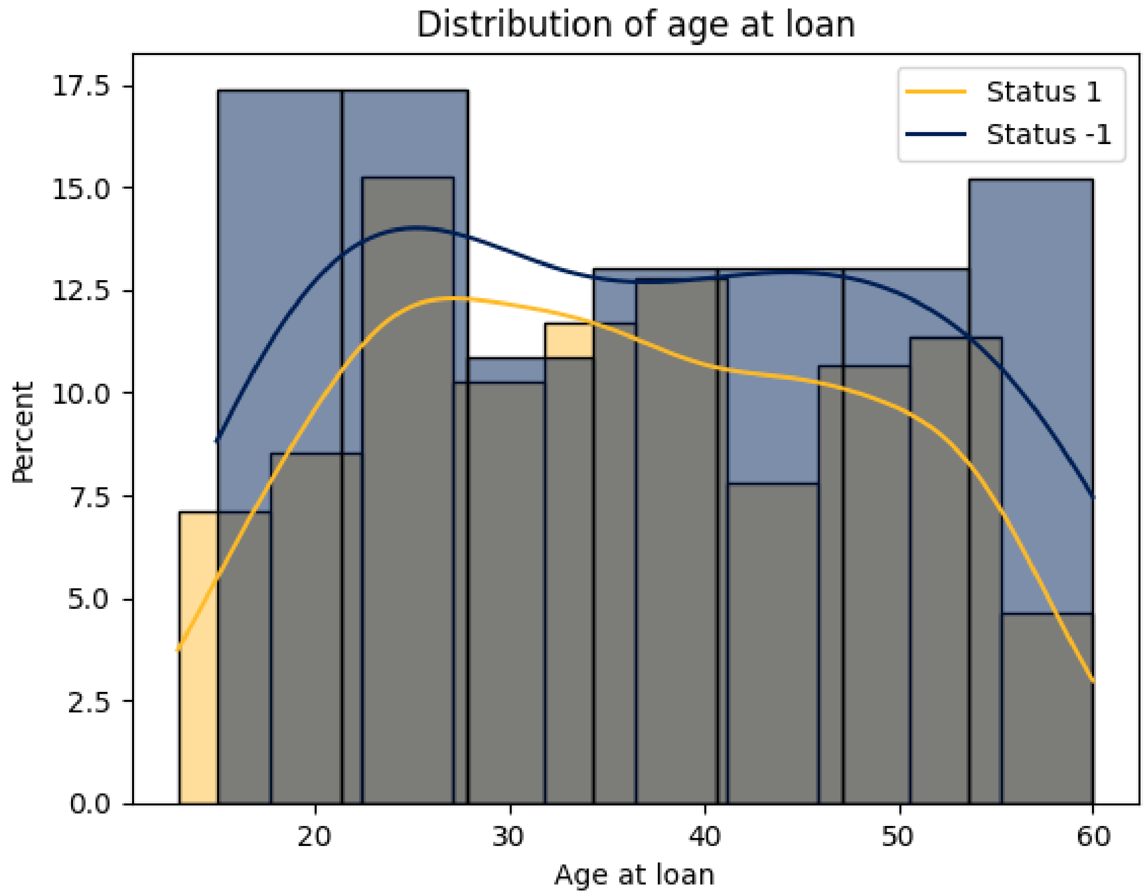
Outliers

- a dataset without the amount outliers
- a dataset without ages at loan under 18

These two datasets were created to evaluate the impact of these outliers' presence.

Neither the datasets presented significant improvents in the results.





Dataset Algorithm	Original	Amount Outliers	Age Outliers
Logistic Regression	0.87	0.82	0.87
K-Nearest Neighbours	0.81	0.79	0.75
Random Forest	0.77	0.77	0.76

[Table 1] Best AUC of each dataset using three different algorithms

Data Preparation

Data Transformation

- Format dates
- Encode categories
- Standardize column names
- Fix mislabelled data
- Drop irrelevant features
- Drop highly correlated features
- Drop features with many missing values

Feature Selection

- **Wrapper Based** SequentialFeatureSelector with forward elimination
- **Filter Based** SelectKBest with f_classif

Imbalanced Data

Oversample using **SMOTE**.

Data Preparation

Experimental Setup

Clean and
prepare dataset

Clean

Evaluate

Evaluate models'
performance using
different algorithms
and techniques

- Parameter Tunning
- Normalization & Scaling
- Oversample
- Feature Selection
- Cross Validation

Apply the model with the best
AUC score to the test data and
predict the probability of a
loan being unsuccessful

Test

Submit

Submit a .csv file with the
predictions result to
Kaggle

Results

Oversample

Algorithm	Average AUC
Decision Tree	0.8
Logistic Regression	0.87
Naive Bayes	0.79
K Nearest Neighbours	0.81
Random Forest	0.77
Gradient Boosting	0.79
SVC	0.81
XGBoost	0.75
MLP	0.83

[Table 2] Best AUC results for every algorithm used

What about Feature Selection?

[Table 3] Detailed specification of the model with the best result

Best Result

	Algorithm	Logistic Regression
Parameters	**C**	0.01
	class_weight	balanced
	max_iter	1000
	penalty	l2
	solver	newton-cg

Descriptive Data Mining Problem

Requirements with the end user

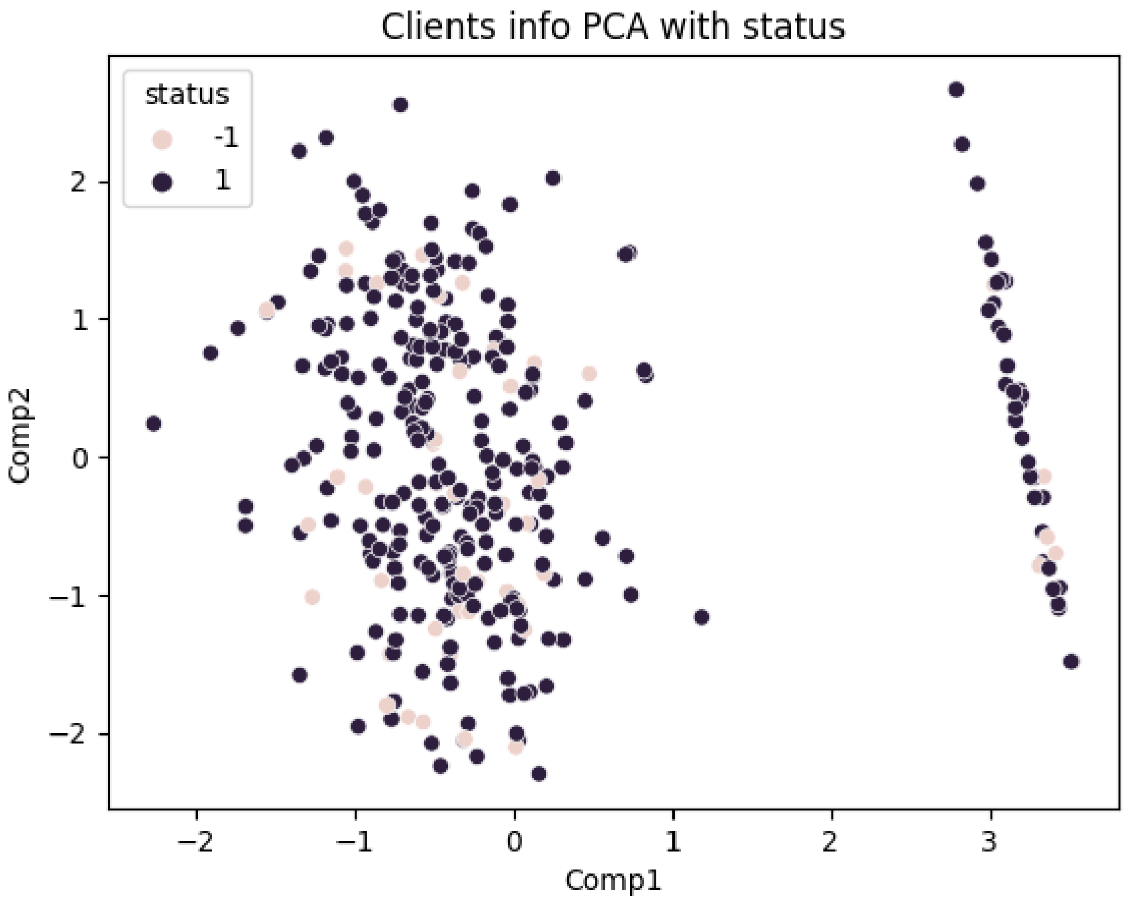
The descriptive problem can be presented as the search for different profiles for the customers of a bank.
This information brings great value to bank managers as after tracing different groups of customers it is possible to create more mutually beneficial solutions, allowing for higher revenues and more satisfied customers.

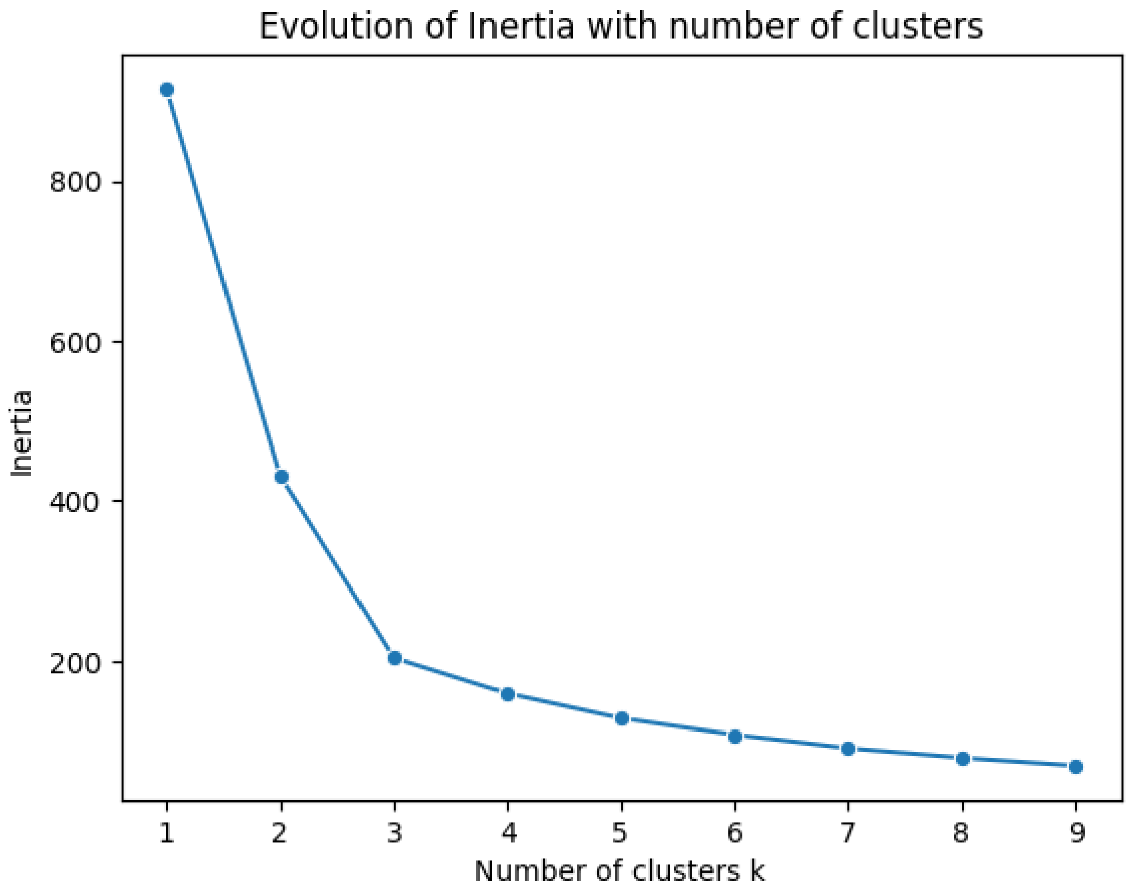
Data Mining goals

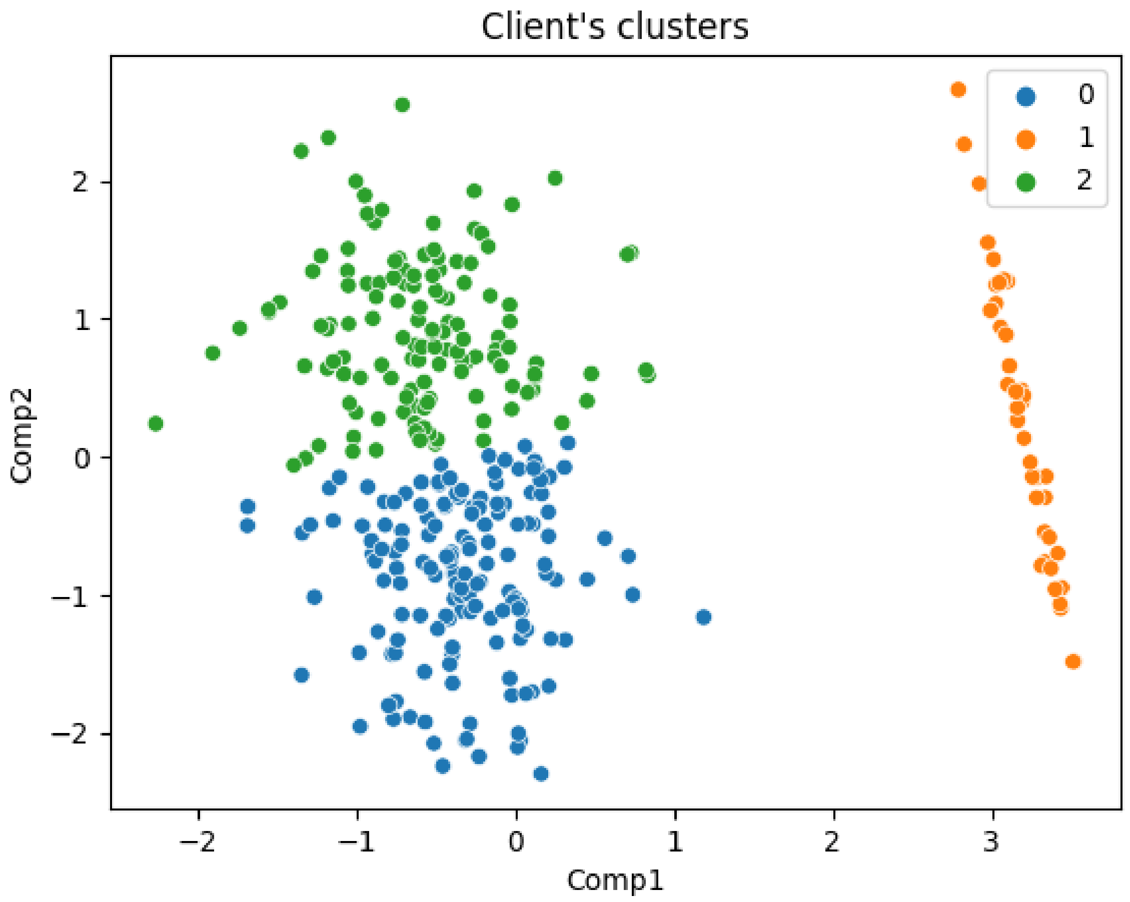
Generate a number of clusters capable of distinguishing different relevant client profiles

Descriptive Problem

Clustering







- PCA was used for reducing the dimensionality of our datasets. Used features: gender, age, avg salary, avg balance & criminality growth

- The Elbow method allowed to find the optimal number of clusters, k

- K-Means was employed for the clusters generation

ANNEX

Business Understanding

Requirements with the end user

Given that the bank stores accurate data about their clients and previous records (transactions, granted loans, etc.), our product aims to help bank managers decide which loan requests should be accepted or not. This will provide help in the loan granting decision process, via a data-based input that will lead to better results, i.e. the bank loans will mostly succeed, resulting in a revenue increase by means of loan interest rates.

By automating the predicting process of loan success payment, our product will avoid money loss while improving decisions, and also decrease labor, thus reducing work expenses.

Business goals

- Reduce the bank's bad credit by 4%
  - Minimize the number of unsuccessful loans to avoid money loss
  - Correctly predict, at least, 8 out of 10 loans
- Automate the process of deciding whether or not a loan should be granted
  - Decrease labour
  - Accelerate the decision process
  - Unbias decisions
- The goal is achieved on time, i.e. the final model must be completed at the end of the due date

Data Mining goals

- Building a model to predict the probability of a loan being successful
- 1 if unsuccessful, 0 otherwise
- Obtain an AUC of, at least, 0.8
- Induce a higher weight for false-negative outcomes, due to the more significant impact they have compared to false positives; although, aiming to decrease both results

Account

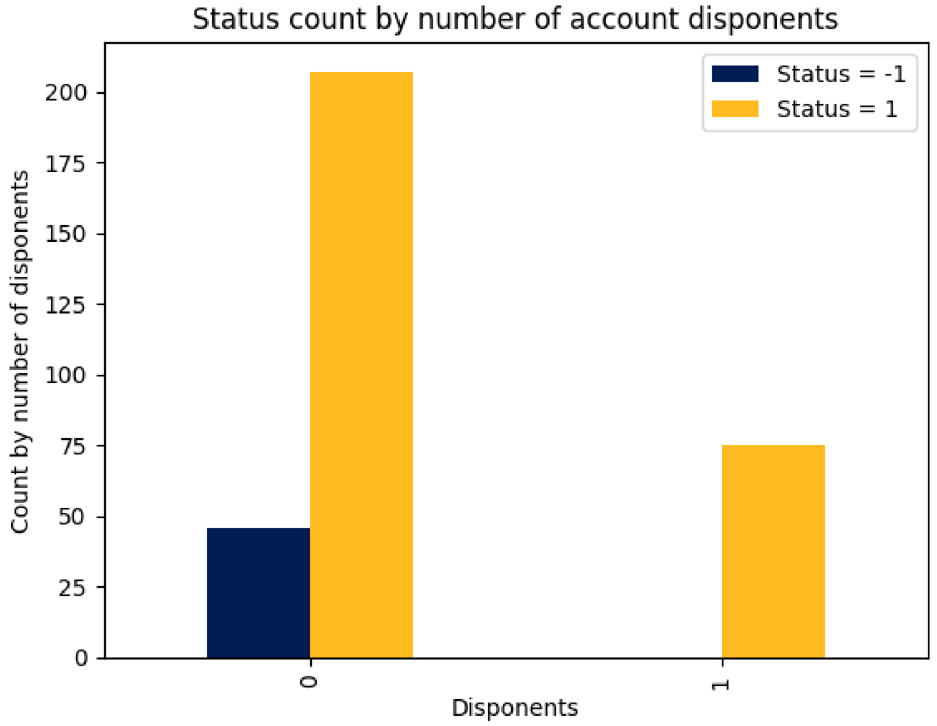
- Format the account **creation date**
- Encode **frequency** into numerical values
- Rename **district_id** to **account_district_id**

Client

- From birth_number extract **gender** and **birth_date**
- Rename **district_id** to **client_district_id**
- Drop **birth_number** as it was no longer needed

Disponent

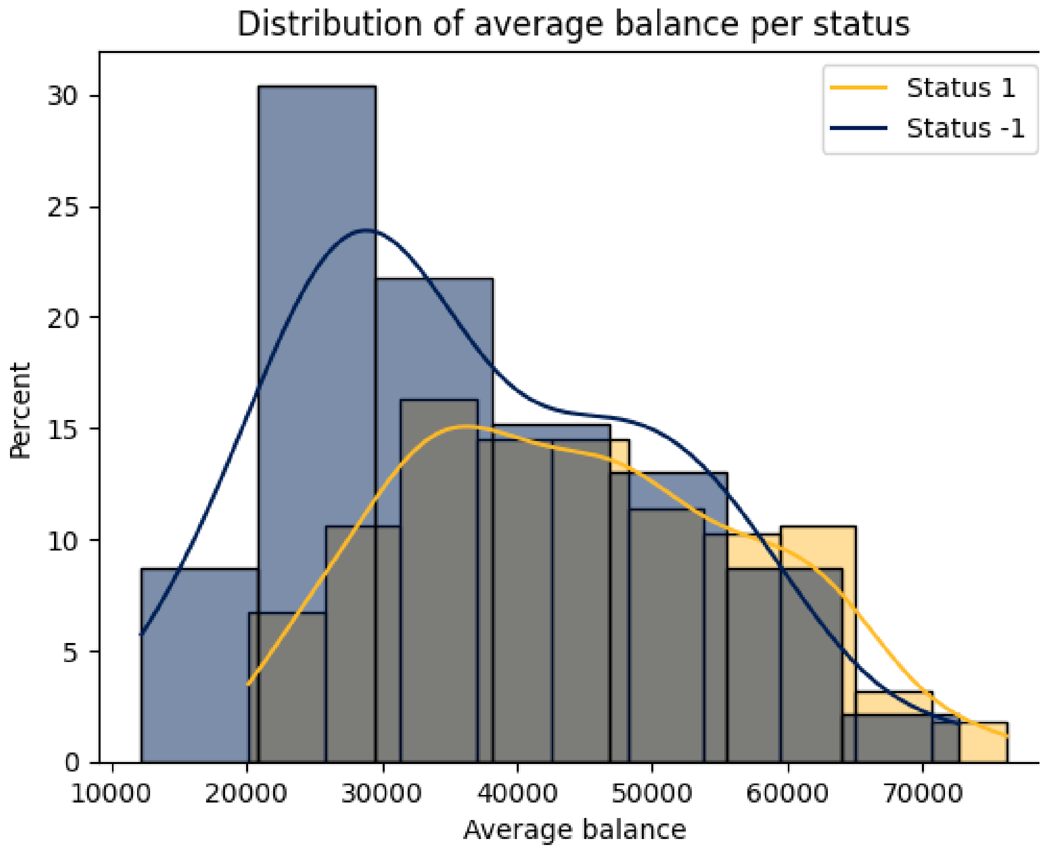
- Drop non-owners, since only an account owner can request a loan
- Calculate the number of disponents per account to evaluate the impact of an account not being managed by only one client
- Create **has_disponent** feature, after concluding that loans associated with accounts with a disponent other than the owner tend to be fraudulent

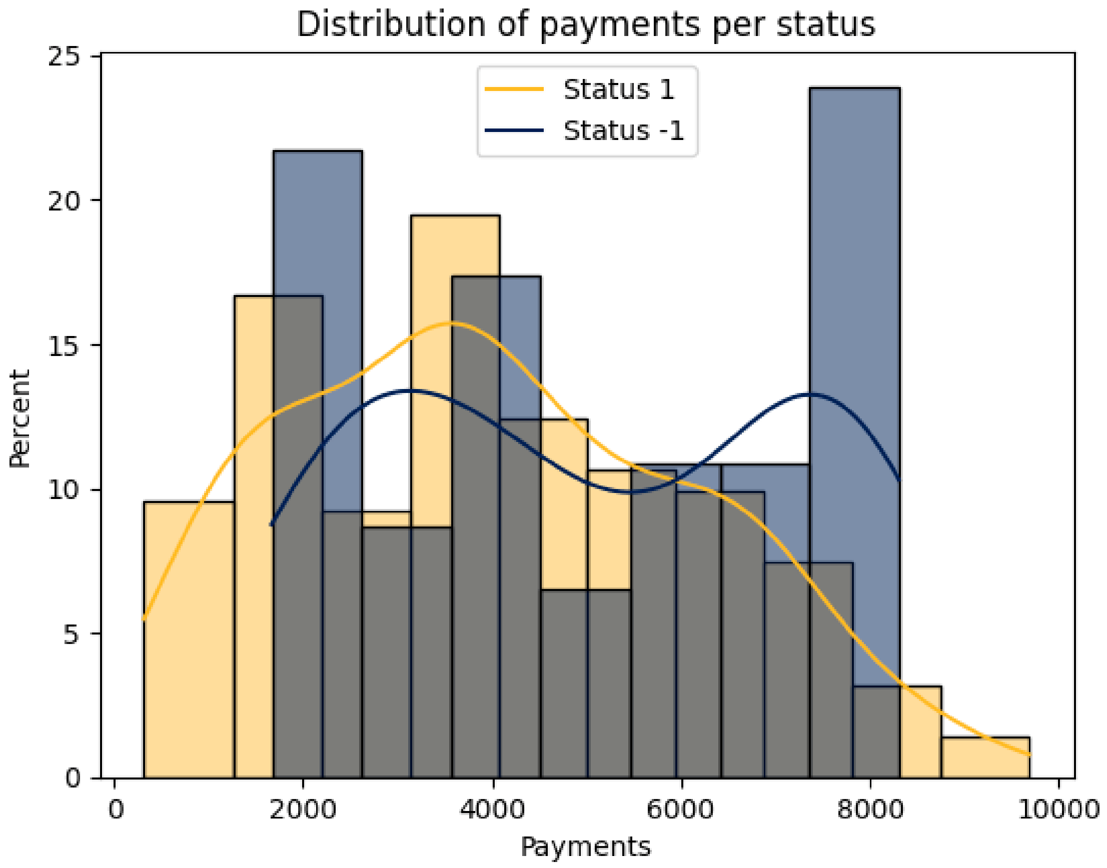


Feature Importance

Card

- Calculate number of cards per account
- Create **has_card** feature, upon verifying that accounts with card had no record of being fraudulent


Distribution of average balance per status


Distribution of payments per status

Transactions

- Replace empty strings with NaN's
- Drop **bank** column for its null values
- Replace null values of **operation** with *interested credit*
- Replace *withdrawal in cash* with *withdrawal* in **type** column
- Calculate **average_amount** by **type**
- Calculate **amount** by type
- Calculate **max**, **min**, **max balance** & **number of transactions**

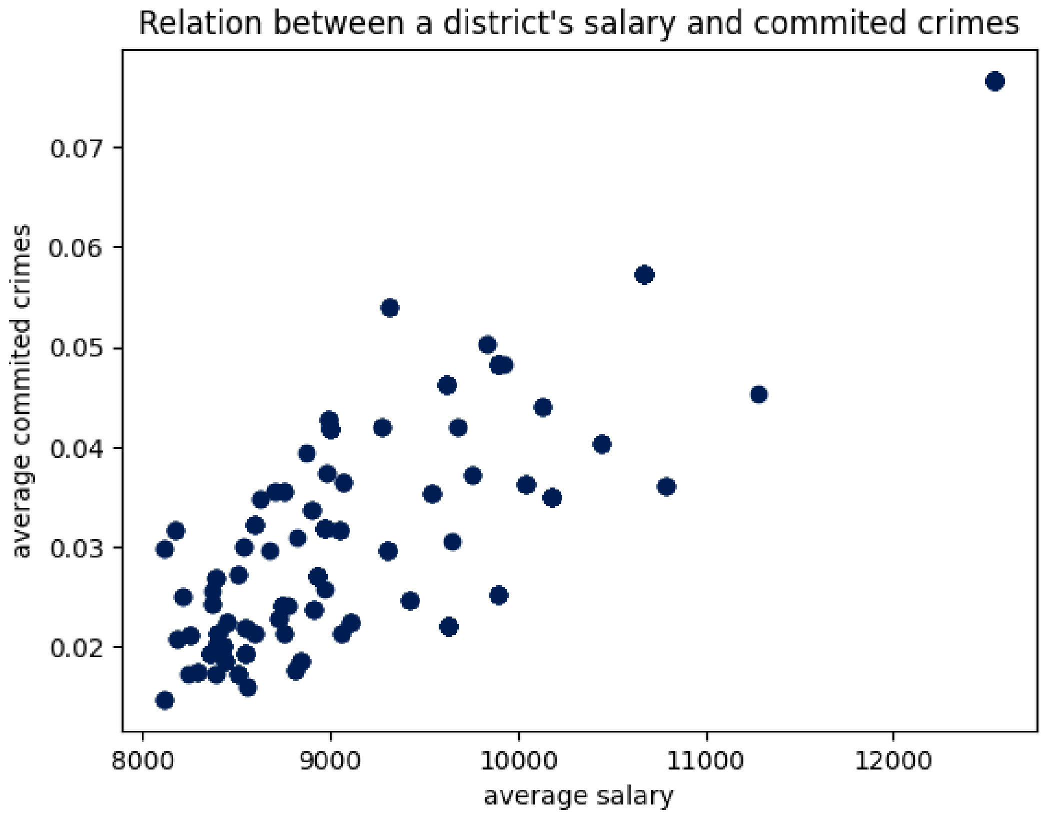
Loan

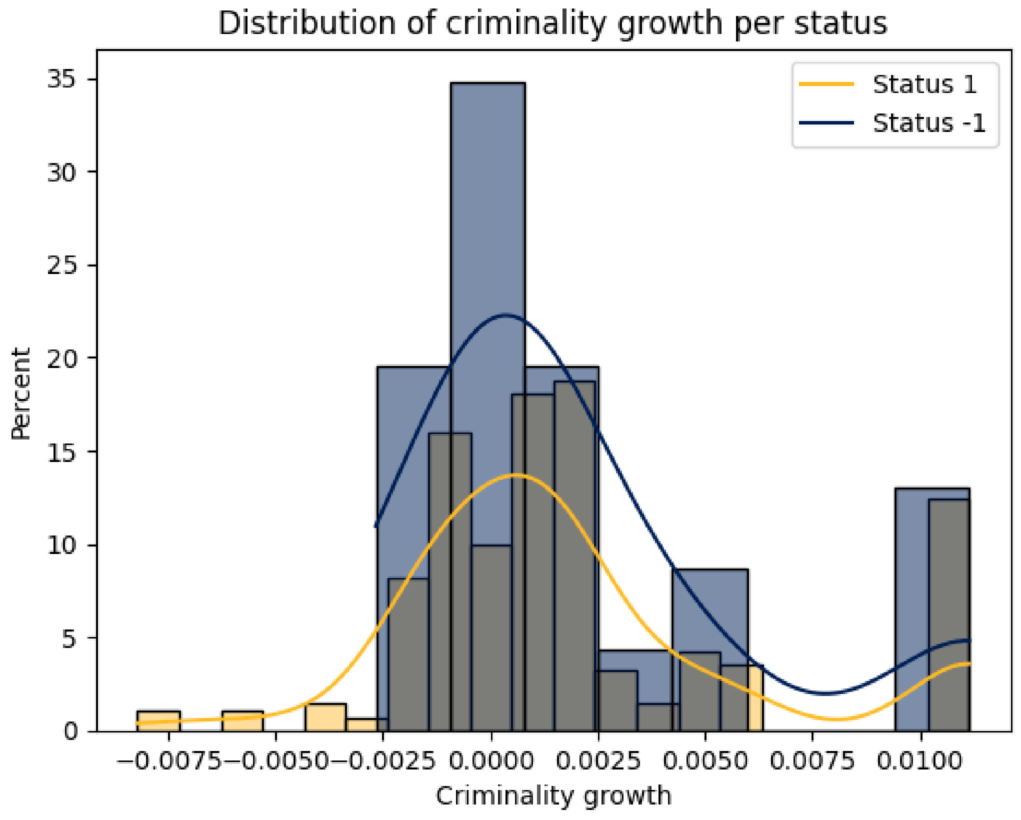
- Format date
- Change **date** to **loan_date**

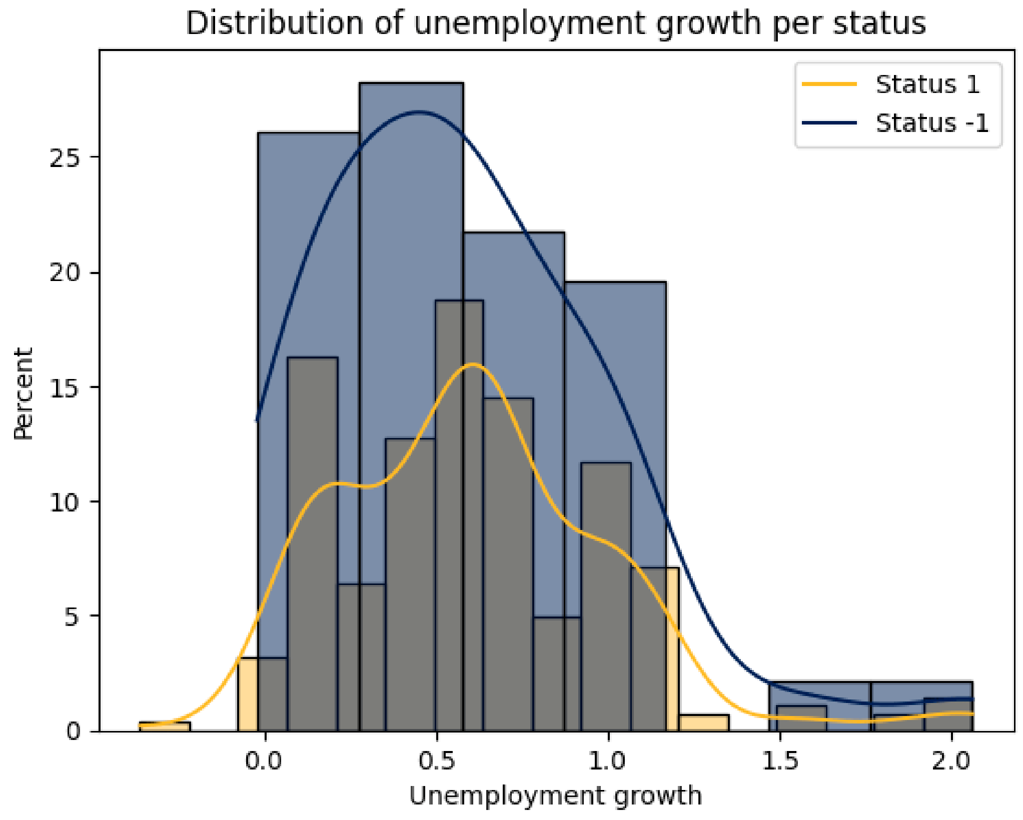
Feature Importance

District

- Replace missing values of **unemployment_rate_95** and **nr_committed_crimes_95** with the correspondent 96 values
- Encode **region** into numerical values


Relation between a district's salary and commited crimes


Distribution of criminality growth per status


Distribution of unemployment growth per status

Feature Importance

Descriptive Ideas

PCA

- Principal Component Analysis was used for reducing the dimensionality of our datasets, increasing interpretability but at the same time minimizing information loss.

Elbow Method

- For several possible number of clusters k:
  - Calculate the within-cluster SSE, also called distortion;
  - Choose the k so that adding another cluster doesn’t yield a much smaller SSE.

Silhouette Coefficient

- The silhouette coefficient was also calculated for evaluating the algorithm's performance.

K-Means

- K-Means is a partition-based method that obtains k groups of a dataset.
  - A fast algorithm that scales well;
  - Uses a stochastic approach that frequently works well.

Cluster	Gender	Age	Average salary	Criminality Growth	Average balance
0	0.732026	68	9127	0.0004	36190
1	0.609756	65	12541	0.0111	42203
2	0.216418	57	9051	0.0008	51735

[Table 3] Average feature values by cluster

Decision Tree

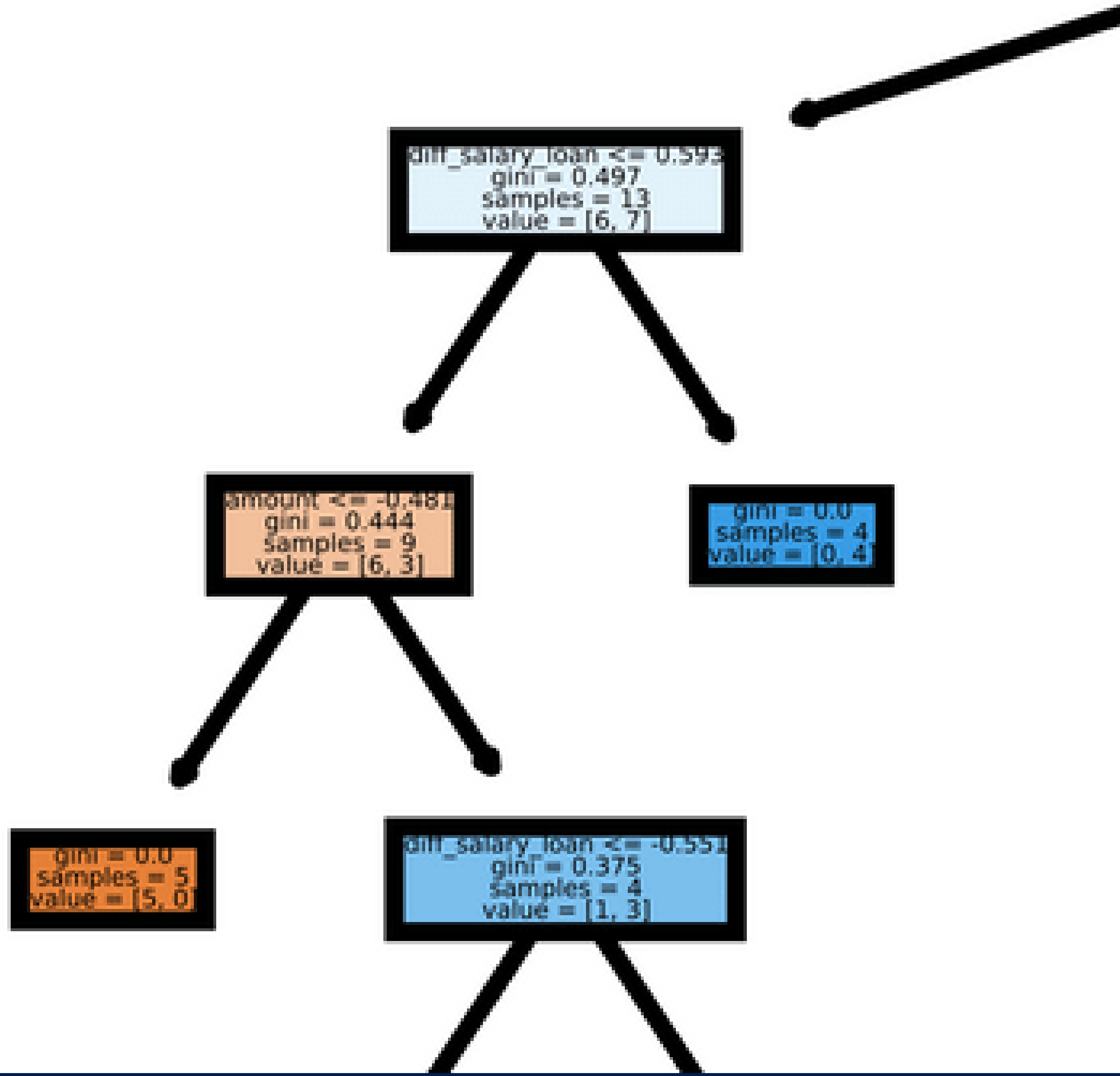
- Decision Trees are easy to understand and interpret - **white-box**;
- Implicitly perform variable screening or feature selection;
- Are prone to creating over-complex trees that do not generalize the data well, i.e., **overfitting**;
- Unstable because small variations in the data might result in a completely different tree being generated. This variance needs to be lowered by methods like bagging and boosting.

Grid search parameters

criterion: ['gini', 'entropy', 'log_loss']
splitter: ['best', 'random']
max_depth: range(1, 7)

Metrics		Oversample	Feature Selection	Feature Selection & Oversample
Fit time	0.001	0.005	0.001	0.001
Score time	0.001	0.001	0.001	0.001
Accuracy	0.895	0.733	0.908	0.786
ROC AUC	0.686	0.649	0.792	0.772
Precision	0.8	0.24	0.75	0.35

[Table 4] Example output of the Decision Tree Algorithm



Predictive Algorithms

Logistic Regression

- Logistic Regression, despite its name, is a linear model for classification rather than regression;
- Analyzes the relationship between one or more independent variables and classifies data into discrete classes;
- Suitable for linearly separable datasets.

Grid search parameters

penalty: ['l2', 'none']
C: [0.01, 0.05, 0.1, 0.2, 0.5, 1.0]
solver: ['newton-cg', 'lbfgs', 'sag', 'saga']
class_weight: ['balanced', None]
max_iter: [500, 1000, 5000, 10000]

Metrics		Oversample	Feature Selection	Feature Selection & Oversample
Fit time	0.002	0.230	0.002	0.012
Score time	0.001	0.003	0.001	0.001
Accuracy	0.886	0.834	0.860	0.807
ROC AUC	0.86	0.907	0.793	0.794
Precision	0.613	0.437	0.0	0.408

[Table 5] Example output of the Logistic Regression Algorithm

Predictive Algorithms

Random Forest

- Random Forest is an ensemble learning method that averages multiple decision trees, trained on different parts of the same data;
- It uses bagging and feature randomness when building each individual tree to try to create and uncorrelated forest of trees whose prediction by committee is more accurate than of any individual tree.

Grid search parameters

criterion: ['gini', 'entropy']
n_estimators: [10, 50, 100, 200]
max_depth: [5, 10, None]
n_jobs: [-1]

Metrics		Oversample	Feature Selection	Feature Selection & Oversample
Fit time	0.071	0.025	0.031	0.008
Score time	0.023	0.010	0.014	0.006
Accuracy	0.899	0.860	0.882	0.877
ROC AUC	0.791	0.785	0.809	0.787
Precision	1.0	0.422	0.816	0.565

[Table 6] Example output of the Random Forest Algorithm

Predictive Algorithms

Naive Bayes

Gaussian

- Gaussian Naive Bayes is the extension of naive Bayes. It is simpler as it only calculates the mean and standard deviation for the training data;
- Assumes that the value of **one feature is independent of the value of any other feature**;
- Simple design and application, and, therefore, suitable in many real-life scenarios.

Metrics		Oversample	Feature Selection	Feature Selection & Oversample
Fit time	0.0007	0.003	0.001	0.012
Score time	0.001	0.001	0.001	0.001
Accuracy	0.458	0.475	0.886	0.851
ROC AUC	0.791	0.808	0.766	0.810
Precision	0.189	0.22	0.85	0.4

[Table 7] Example output of the Naïve Bayes Algorithm

Predictive Algorithms

K-Nearest Neighbours

- K-Nearest Neighbours is a non-parametric, supervised learning classifier, which **uses proximity** to make classifications or predictions;
- The goal is to identify the nearest neighbors of a given query point so that it can assign a class label to that point;
- Is a lazy learner algorithm as it does not learn from the training set immediately instead, stores the dataset and only performs actions on it when its actually classifying the new data.

Grid search parameters

n_neighbors: [4, 5, 6, 7, 10, 15]
leaf_size: [5, 10, 15, 20, 50, 100]

Metrics		Oversample	Feature Selection	Feature Selection & Oversample
Fit time	0.0006	0.001	0.001	0.001
Score time	0.003	0.005	0.007	0.008
Accuracy	0.882	0.62	0.895	0.790
ROC AUC	0.741	0.681	0.816	0.858
Precision	0.9	0.223	0.8	0.388

[Table 8] Example output of the K-Nearest Neighbours Algorithm

Predictive Algorithms

XGBClassifier

- XGBClassifier is a boosting algorithm based on gradient-boosted decision trees algorithm;
- It works by building weak prediction models sequentially, minimizing the error in each next attempt;
- Needs proper **parameter tuning** to avoid overfitting;
- Difficul to interpret, **black-box** model.

Grid search parameters

min_child_weight: [4, 5, 6, 7, 10, 15]
gamma: [0,0.2,0.5,1,1.5,3]
max_depth: [5,8,10,15]
reg_alpha: [1e-5, 1e-2, 0.1, 1]

Metrics		**Oversample**	**Feature Selection**	**Feature Selection & Oversample**
Fit time	0.237	0.449	0.207	0.28
Score time	0.003	0.003	0.003	0.003
Accuracy	0.877	0.838	0.869	0.86
ROC AUC	0.805	0.770	0.772	0.78
Precision	0.686	0.332	0.4	0.59

[Table 9] Example output of the XGBClassifier Algorithm

Predictive Algorithms

SVC

- Support Vector Classification's goal is to find a hyperplane in an N-dimensional space that distinctly classifies the data points;
- Suitable for linearly separable data.

Grid search parameters

C: [1, 10, 50]
gamma: [0.001, 0.0001, 0.01, 1, 'scale', 'auto']
kernel: ['linear', 'poly', 'rbf', 'sigmoid']
degree: [1, 2, 3, 4, 5, 6, 7]
coef0: [0.0, 0.1, 0.3, 0.5, 0.7]
max_iter: [1, 2, 3, 5, 7, 10]
decision_function_shape: ['ovo', 'ovr']
class_weight: [None, 'balanced', dict]

Metrics		Oversample	Feature Selection	Feature Selection & Oversample
Fit time	0.0006	0.004	0.001	0.003
Score time	0.001	0.001	0.001	0.001
Accuracy	0.41	0.58	0.71	0.79
ROC AUC	0.55	0.64	0.64	0.81
Precision	0.15	0.18	0.22	0.77

[Table 10] Example output of the SVC Algorithm

Predictive Algorithms

Assumptions

- Decision Tree's results were due to its sensitivity to small perturbations and easy overfitting.
- Having Logistic Regression with the best results leads us to assume our data is linearly separated.
- KNN has significantly better results with feature selection which means that some of the features used weaken the distribution of the dataset in classes.

Conclusions

- Using oversample retrieves the best results. Without it, classifiers tend to predict a probability towards the negative class (status=1), due to the lack of comparison data.
- RandomForest and XGBClassifier take the longest as they are ensemble learning methods.

Algorithms Analysis

Tools

Project Management and Collaboration

Organization and methodology are crucial in a collaborative project. We used GitHub as the hosting platform for version control and as the project management tool (main issues definition).

Discord was used for communication, remote collaboration sessions, and week planning TODOs.

Finally, we followed a **CRISP-DM** methodology as the base of our data science process. The six commonly described phases were revised cyclically allowing for a sequential improvement over the end-results.

Data visualization, cleaning and training

python™

Matplotlib & Seaborn
Numpy
Pandas
Scikit-learn
Plotly

Future Work

- Invest even more in feature engineer - features are never enough
- Cost-sensitive learning
- A deeper exploration of feature selection
- Help the bank managers to create different client profiles with the results obtained from the descriptive analysis

Conclusions

- By adding new features, we were able to iteratively evaluate and test different algorithms with different datasets, greatly improving our understanding of the problem and the results
- Feature engineering over unused tables brought us the biggest improvements
- Oversampling techniques were crucial since the two classes were imbalanced