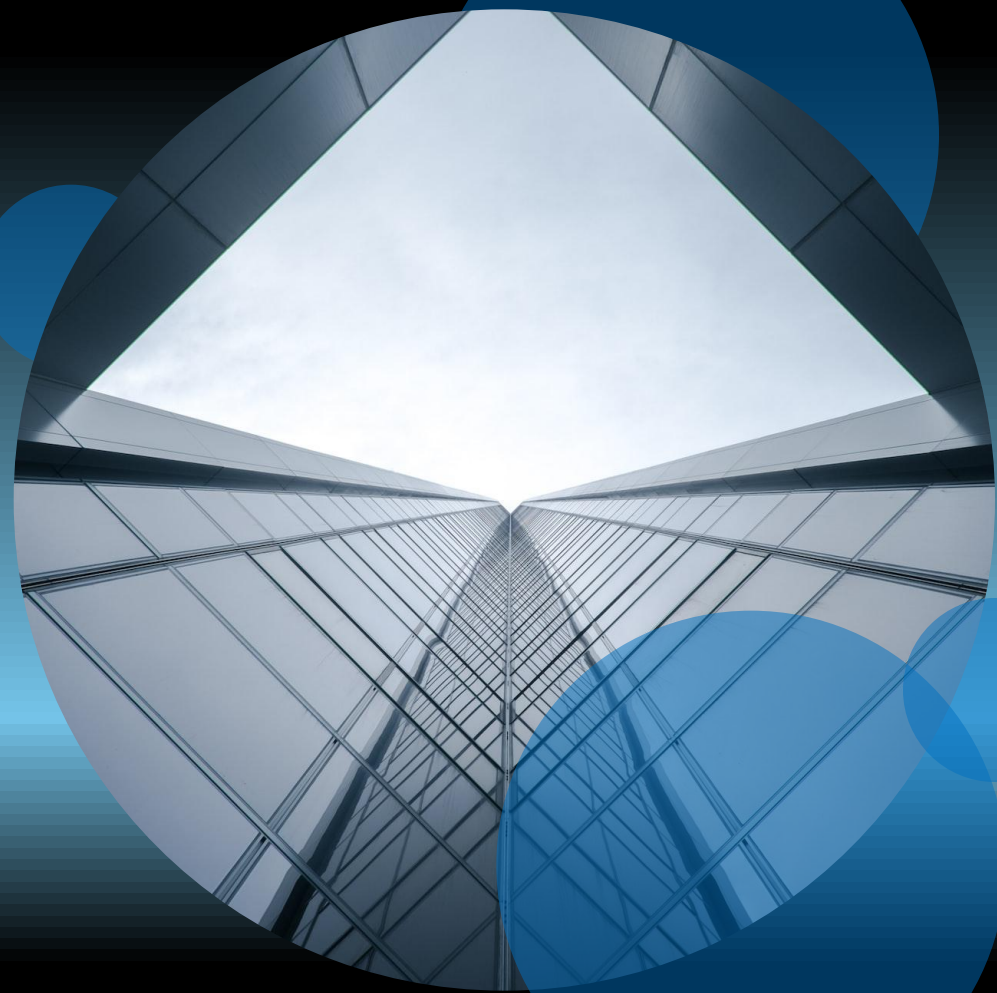


Loan – Default Prediction

A Profiling Approach

Georgios Panos – Royal Institute of Technology (KTH)



Loan Default and its Hallmarks

Problem Space



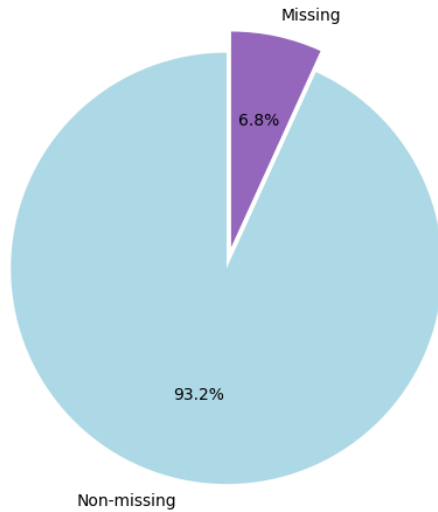
Problem Statement

Loan interests is a source of income for the banks and their defaults compound damages to their revenues.

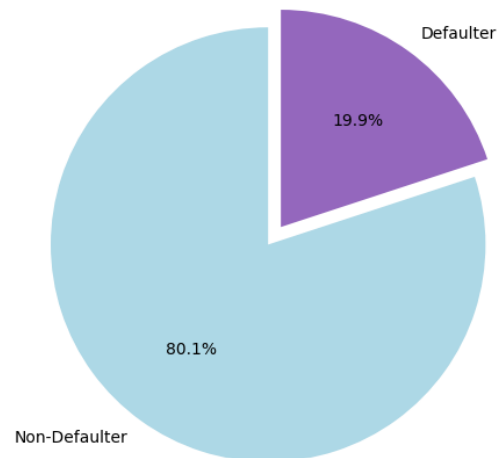
- Which **loan applicant** is most certainly going to **default** in the future, given a loan approval?
- Can we identify the **driving forces** and use **prediction models** to guide us through the loan approval decision?
- Can we **profile** the **loan applicants** in relation to the data management system of the bank institution?

The “Quirks” of the Dataset

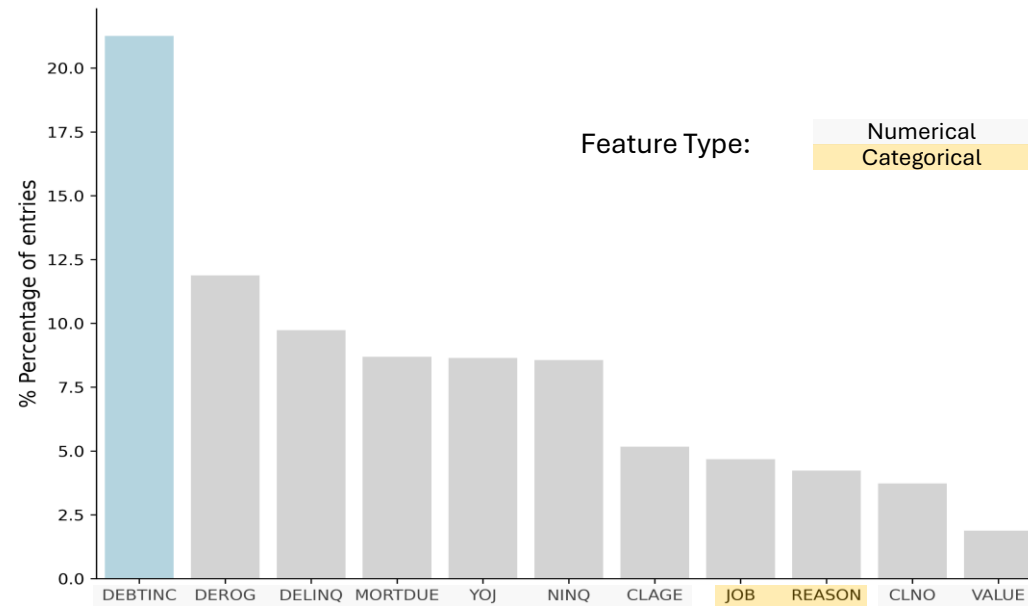
The dataset contains 5960 observations in total with.....



How many loan defaulters?



Data Incompleteness per Feature

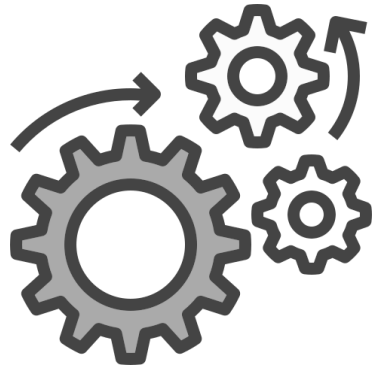


Key – Points from EDA

- **BAD** variable is the class of defaulters/non-defaulters.
- The features **DEBTINC**, **DEROG**, **DELINQ** seem to be correlated with loan defaults.
- **VALUE** and **MORTDUE** are correlated and might be **redundant**.
- Dataset contains **high variation** among its numerical features.
- Many **outliers** to the features, especially those above in the **defaulter class**.
- The **JOB** variable is **not stratified enough**.

Learning From Data

Moderate Imputation



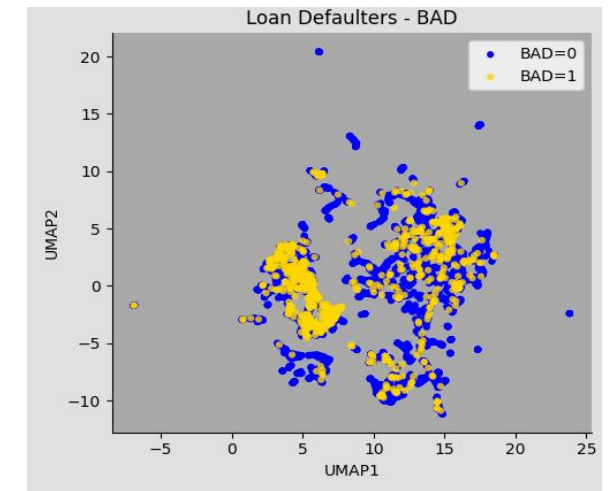
- Kept entries with maximum one **NA**
- **Median** imputation for numeric
- **Mode** imputation for the categories
- Big threshold in outlier filtering.

The boy who cried wolf




- Test and optimize three different ML algorithms based on recall, and ROC auc. Weight – imbalance aware.
- Predict as **many True Positives** as possible.

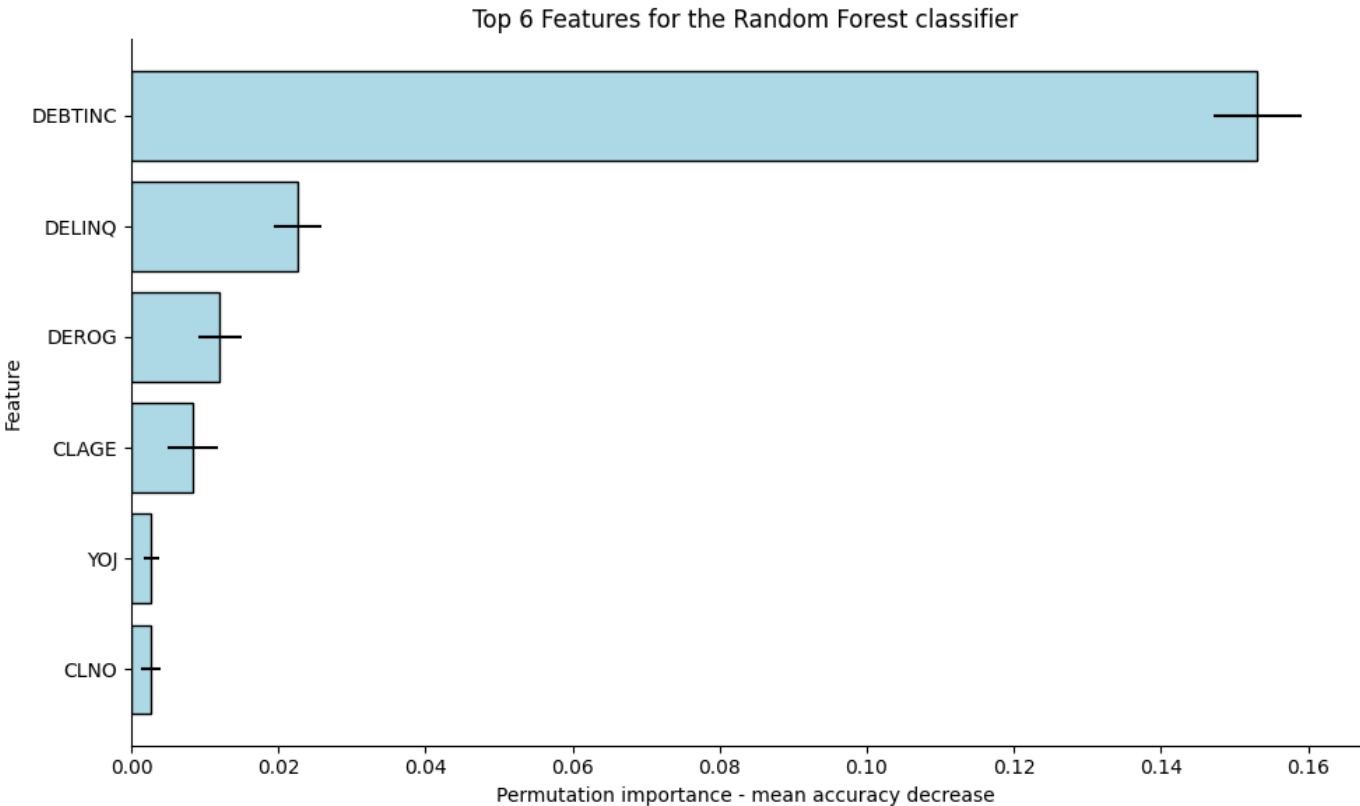
Global Profiling Analysis



- Identification of **highly informative** features.
- **Profiling** of the loan defaulters and the bank handling system.

Classifiers and Feature Importance Results

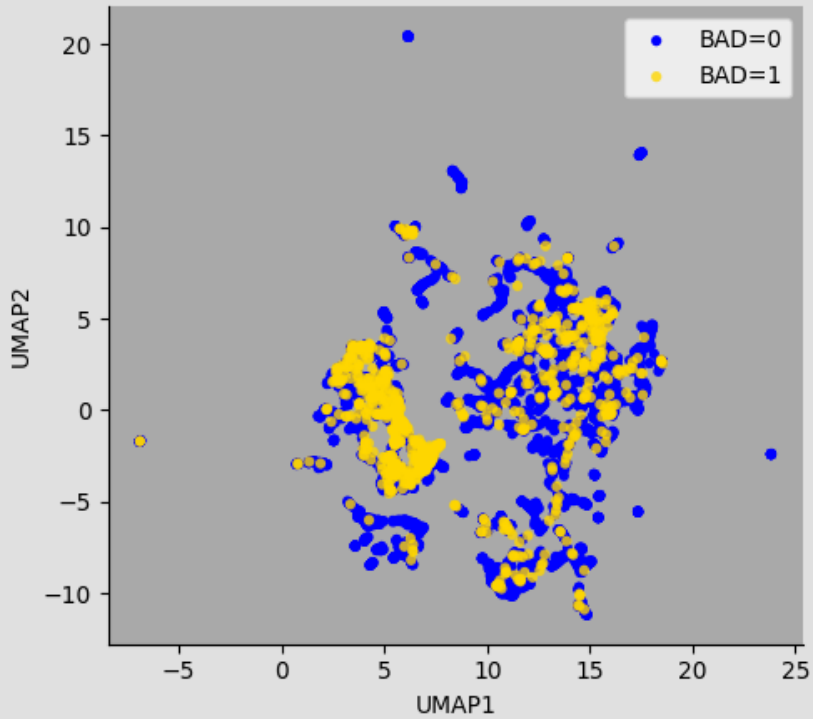
Model	True Positive Rate/ Recall (avg)	True Positive Rate/ Recall (positive class)	Precision	ROC-auc
L2-Logistic	0.72	0.56	0.7	0.81
Decision Tree	0.8	0.78	0.73	0.87
 Random Forest	0.84	0.8	0.77	0.92



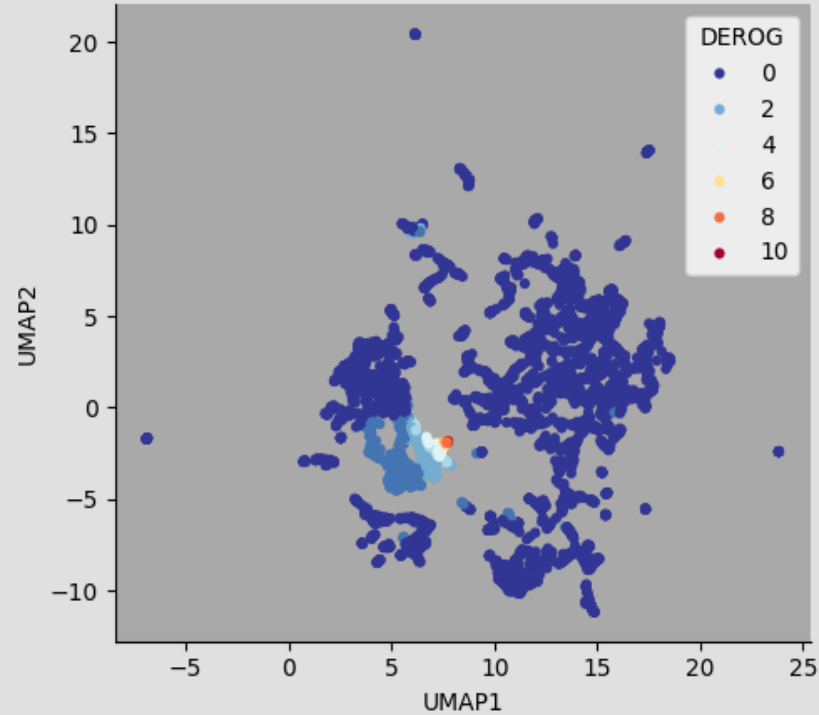
Profile analysis using top 6 features

Bank clients 2D Profiles based on the most informative features of the classifier

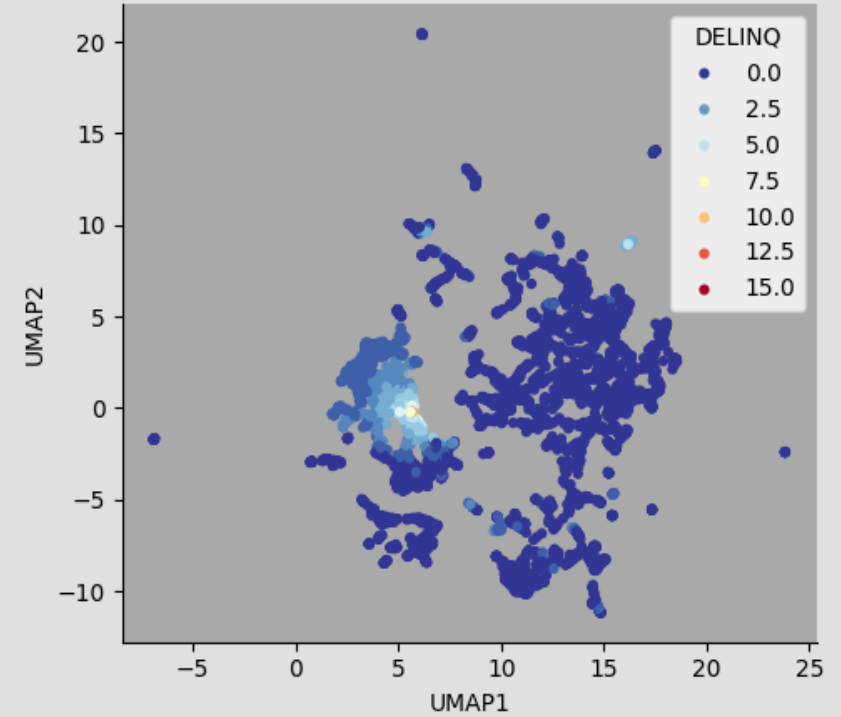
Loan Defaulters - BAD



Derogatory Marks - DEROG



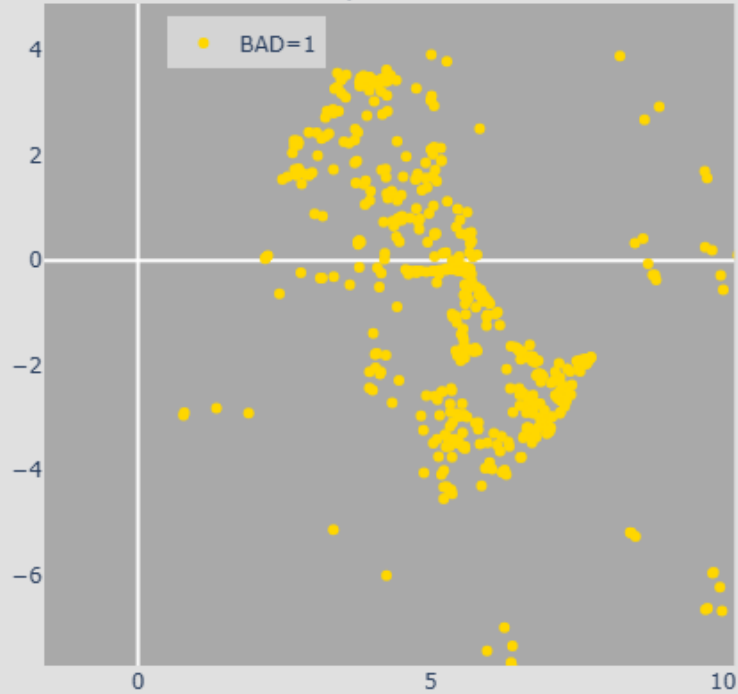
Delinquency Marks - DELINQ



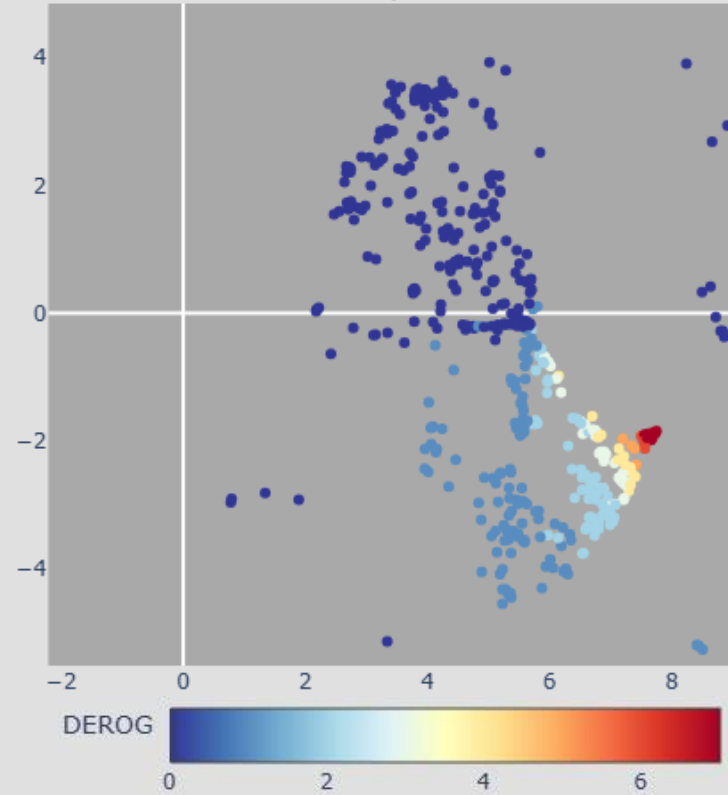
In-depth exploration of the small island

Bank clients 2D Profiles based on the most informative features of the classifier

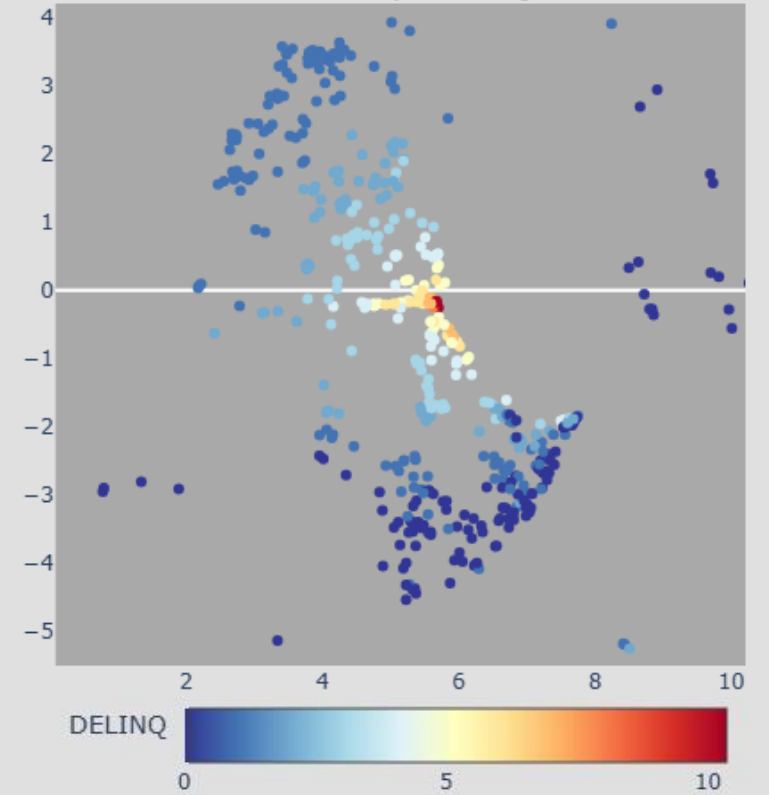
Profile by Loan Default



Profile by DEROG



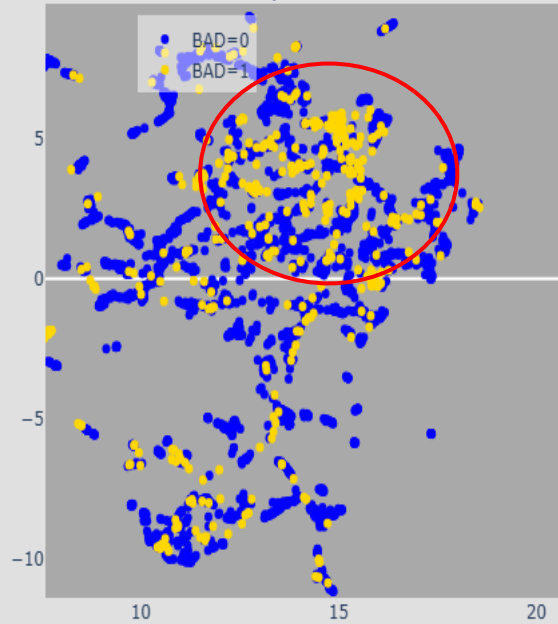
Profile by DELINQ



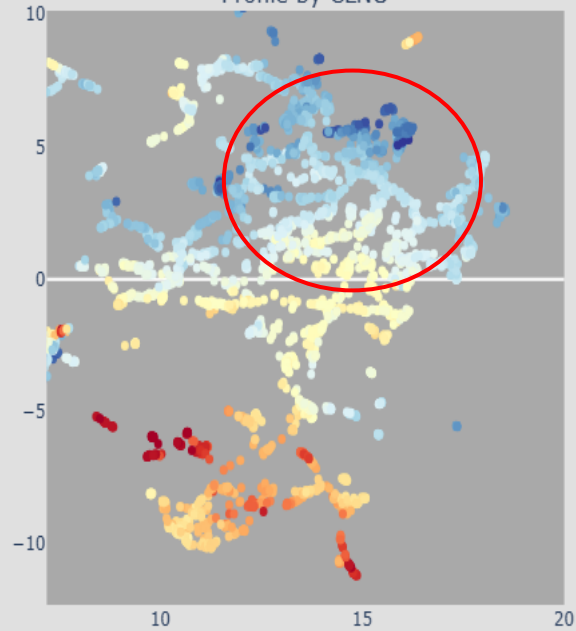
What about the Big island?

Bank clients 2D Profiles based on the most informative features of the classifier

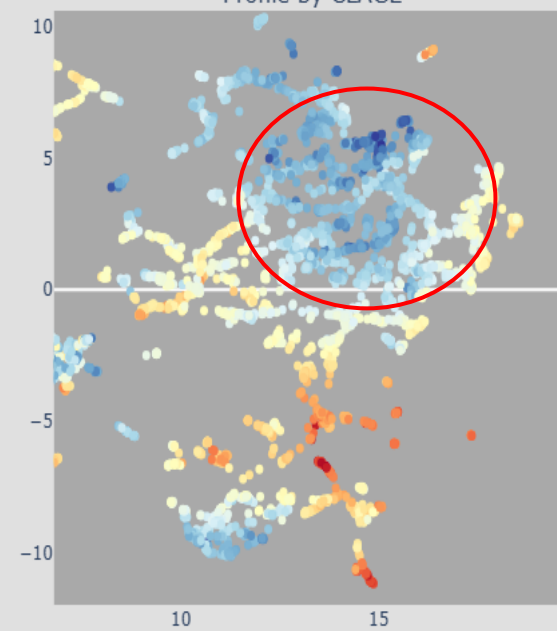
Profile by Loan Default



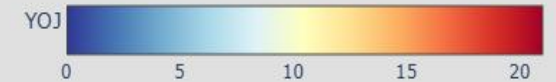
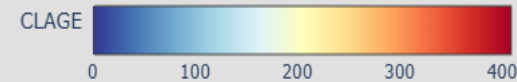
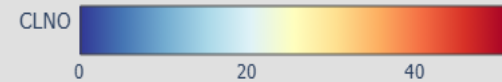
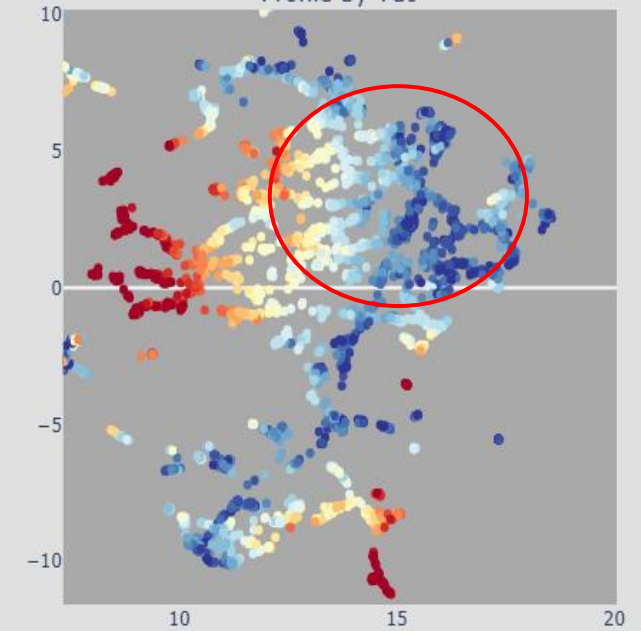
Profile by CLNO



Profile by CLAGE



Profile by YOJ





Recommendations



Then bank should investigate the **missing records** regarding the client/borrower handling. Investment in better **data management practices** to cover the **incompleteness** is an important step.



Since some defaulters have delinquency marks, the bank should consider **internal handling practices**, if they are applicable. The model is not aware of them.



Need to expand the information retrieval regarding **age, income, profession** and **political & marital status**. These parameters might have an influence loan default in **absence of credit marks**.



Given **appropriate data curation**, the model will aid the loan approval decision, and the profiles could unearth hidden relationships.