Project 1 (Final) - DataLab mentorship program - 18/10/2023

Credit card risk analysis

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Credit card risk analysis

- **Goal:** predict if an applicant is **'good' or 'bad' client**,
- The definition of 'good' or 'bad' is not given → **I choose the criterium for the label**.
- Dataset: two tables that can be merged by the client ID
  - application_record.csv
  - credit_record.csv

Application record: 17 features

- ID: Client number
- CODE_GENDER: Gender (🚫 not used to train for ethical concerns)
- CNT_CHILDREN: Number of children
- AMT_INCOME_TOTAL: Annual income
- CNT_FAM_MEMBERS: Family size
- OCCUPATION_TYPE: Occupation (a lot of missing values: inputed as “not provided”)
- DAYS_BIRTH: Birthday. Count backwards from current day (0), -1 means yesterday
- DAYS_EMPLOYED: Start date of employment. Count backwards from current day(0). If positive, it means the person currently unemployed.

- 💡Engineered features
  - AMT_INCOME_PER_PERSON
  - AMT_INCOME_PER_CHILD
  - “EMPLOYED”

Credit record: 2 features

- **ID: Client number**
- **MONTHS_BALANCE:** Record month. The month of the extracted data is the starting point, backwards, 0 is the current month, -1 is the previous month, and so on
    - **Some clients have a record of 62 months**
- **STATUS:**
    - **C: paid off that month**
    - **0: 1-29 days past due**
    - 1: 30-59 days past due
    - 2: 60-89 days overdue
    - 3: 90-119 days overdue
    - 4: 120-149 days overdue
    - 5: Overdue or bad debts, write-offs for more than 150 days
    - X: No loan for the month

The good, the bad and the Julius

- **Good clients**
  - Looking at the 3 last months they
  - Never paid in retard: C
  - Paid at most with 29 days in retard: 1
- **Class 0**

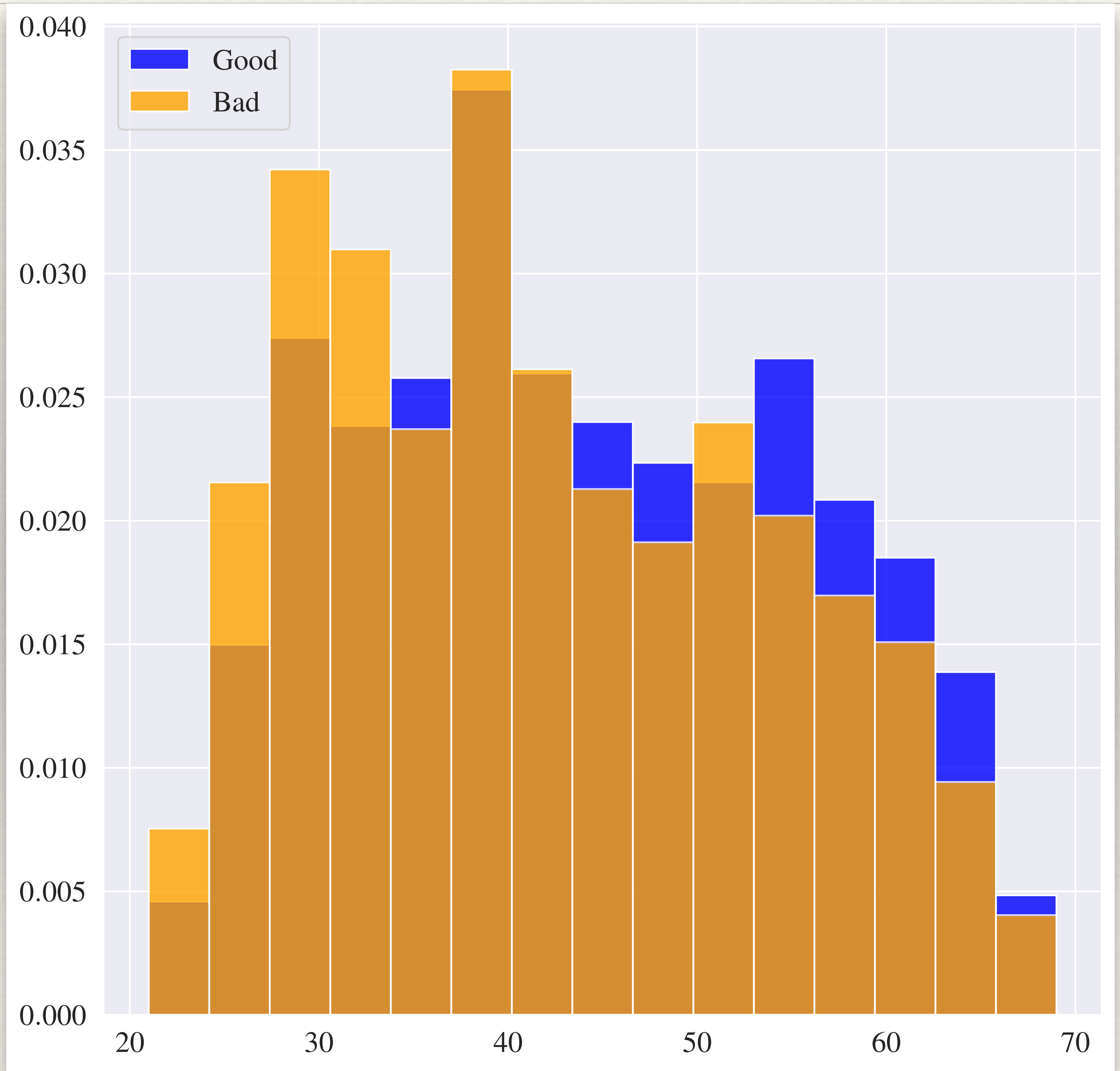
- **Bad clients**
  - Looking at the 3 last months they were in retard of more than 29 days
  - **Class 1**

- **Julius Discarded**
  - Didn't touch their credit cards
  - **Class -1**

Outline

- Preliminaries
  - Data exploration
  - Data preprocessing
- Main results
  - Model trained: XGBoost
  - Rejected inference
- Conclusions and perspectives

Younger clients are mostly bad clients



- Youngest client: 21 years old
- The more experienced in life: 69 years old

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General encoding and scaling

- **Numerical features→Robust scaler**
  - Good against outliers
- **Categorical features→Target encoder**
  - Features are replaced with a blend of posterior probability of the target given particular categorical value and the prior probability of the target over all the training data. **(drawback: is prompt to overfitting)**

Training method

- **Training set** with 23 562 lines
- **Calibration set** with 2 049 lines
  - To calibrate the model and the threshold for f_1, precision and recall scores
- **Test set** with 6 403 lines
- **Naïve model**: is it possible to correctly classify only using **only** the age?
  - $f(age) = -\, age$
  - AUC=0.55→Baseline

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Training method

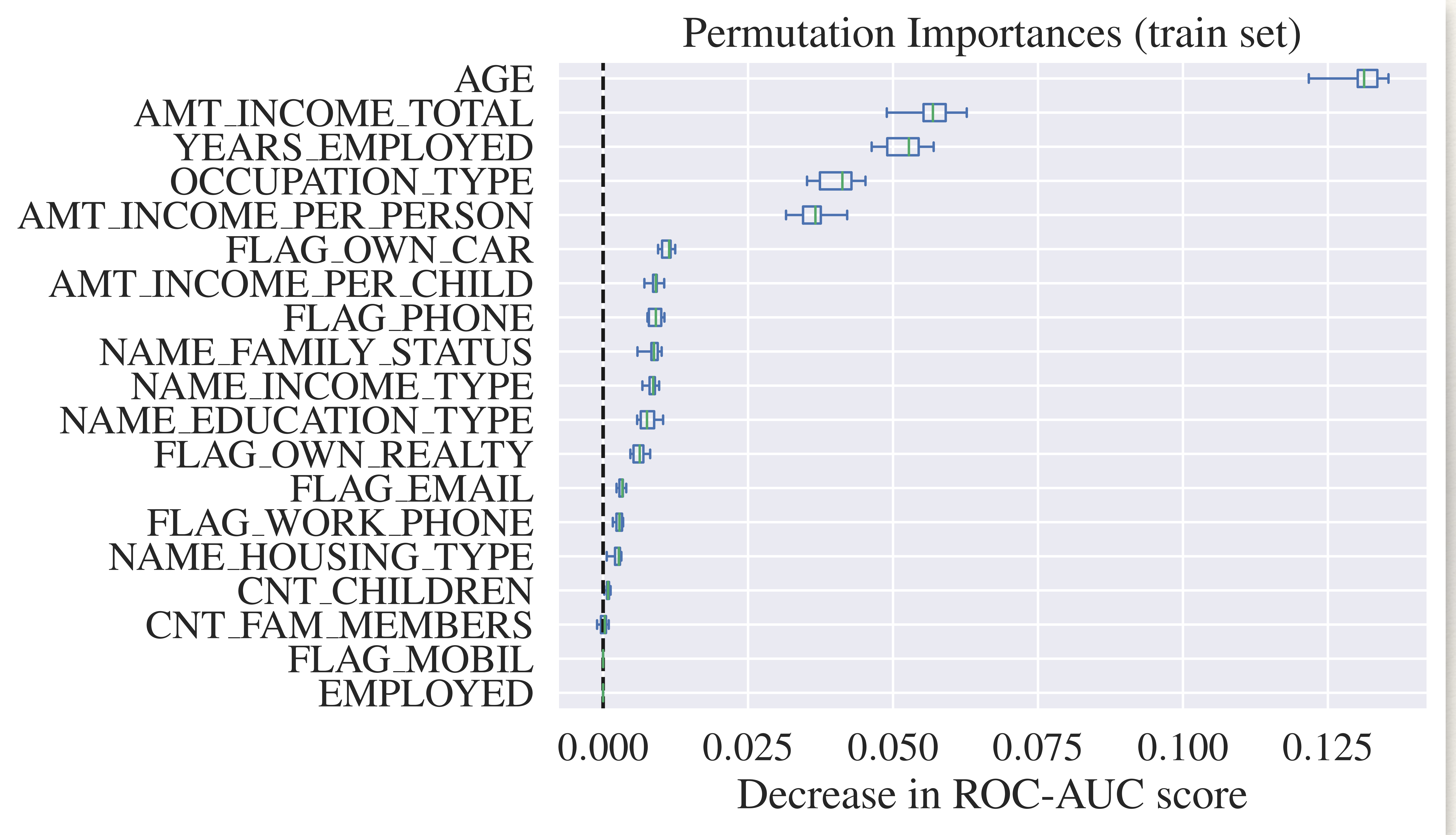
- **Machine learning models**
  - Logistic regression
  - Random Forest
  - **XGBoost**
  - KNeighrestNeighbors
- **Hyperparameter tuning** with **Random search** looking for the highest AUC in the parameter space.
  - Up to 100 iterations
- **10-fold Cross-validation** in the training set for each of the models

XGBoost model: AUC = 0.68, f_1=0.23

- Optimal hyperparameters:
  - n_estimators=266
  - max_depth=27
  - max_leaves=5
- AUC = 0.68 (10-fold cross validated)
- f_1 = 0.24 (10-fold cross validated)
  - Threshold: 0.3
  - Precision: 0.24
  - Recall: 0.24

	Good	Bad
Predicted Good	5994	177
Predicted Bad	176	56

Feature permutation importance



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What can we say about people that did not get the credit card?

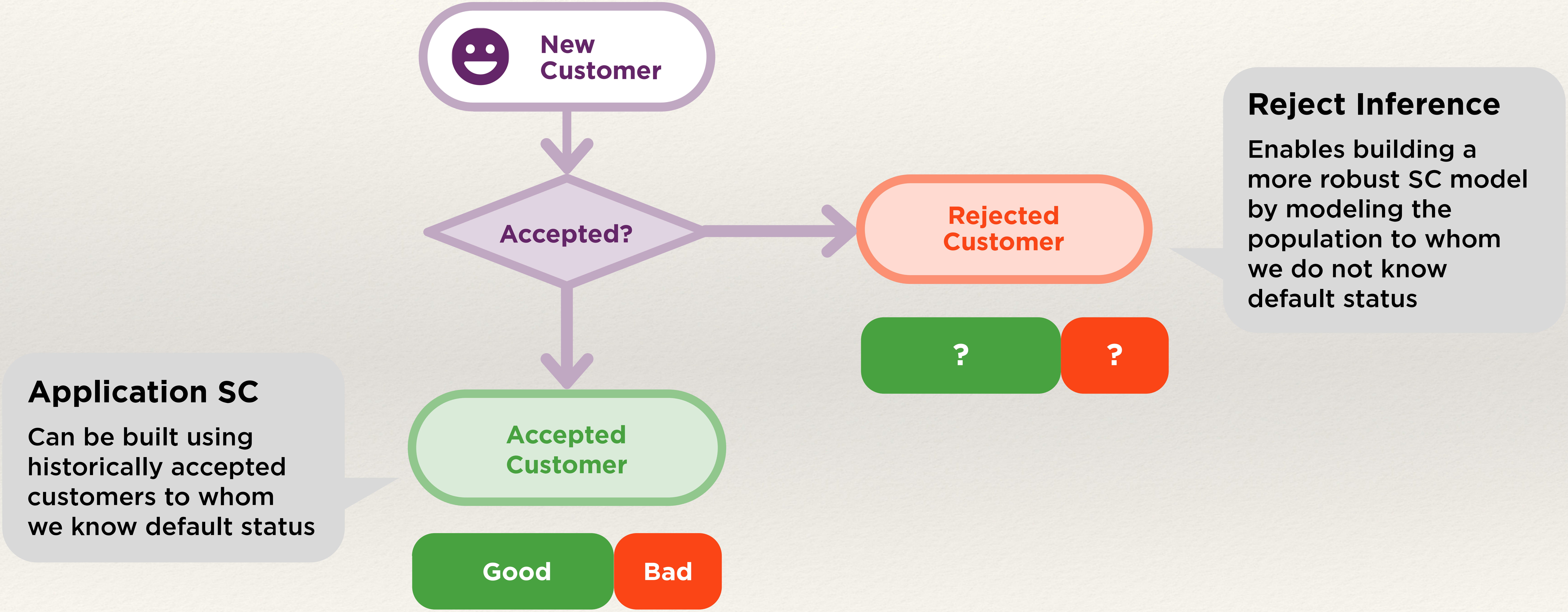


Image taken from https://altair.com/newsroom/articles/credit-scoring-series-part-six-segmentation-and-reject-inference

Rejected inference

Observed values

$\mathcal{M}$ rule		Good	Bad
	Got the credit line	48516	156
	Rejected	????	????

Can't be evaluated because they were … rejected!

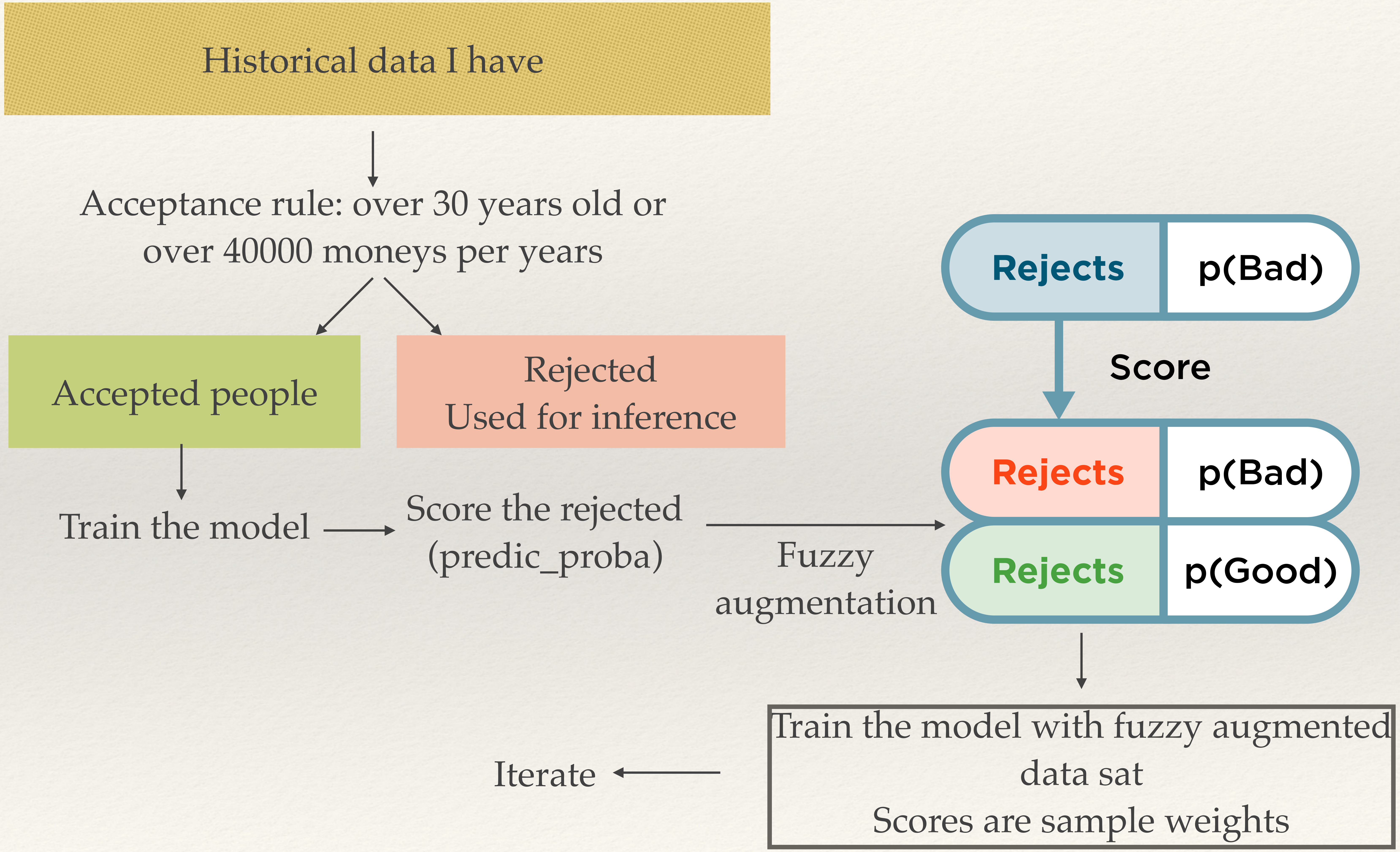
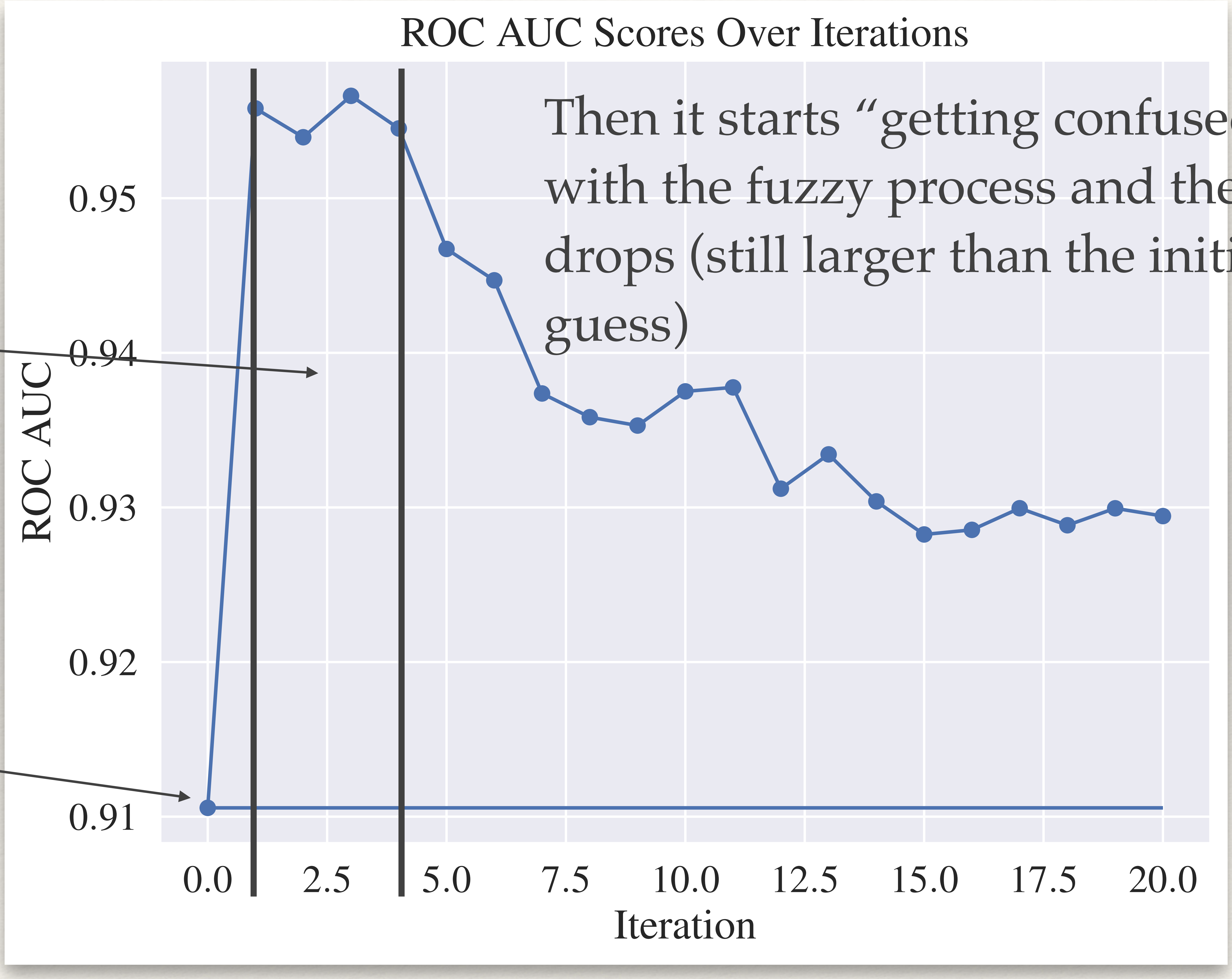


Image taken from https://altair.com/newsroom/articles/credit-scoring-series-part-six-segmentation-and-reject-inference

ROC-AUC comparing the “hidden” target to the prediction after some iterations.

The model is able to classify well within 4 iterations

Not so good initially



Then it starts “getting confused” with the fuzzy process and the ROC drops (still larger than the initial guess)

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Conclusions and perspectives

- We performed a credit card risk analysis where we treated data and trained several models with a given rule for classification, created important features and used techniques such as hyper parameter tuning and cross-validation to corroborate the results
    - Obtained good results with XGBoost model
    - Consider other rule of good/bad clients?
- Rejected inference demonstrated high ROC-AUC for the rejected clients.

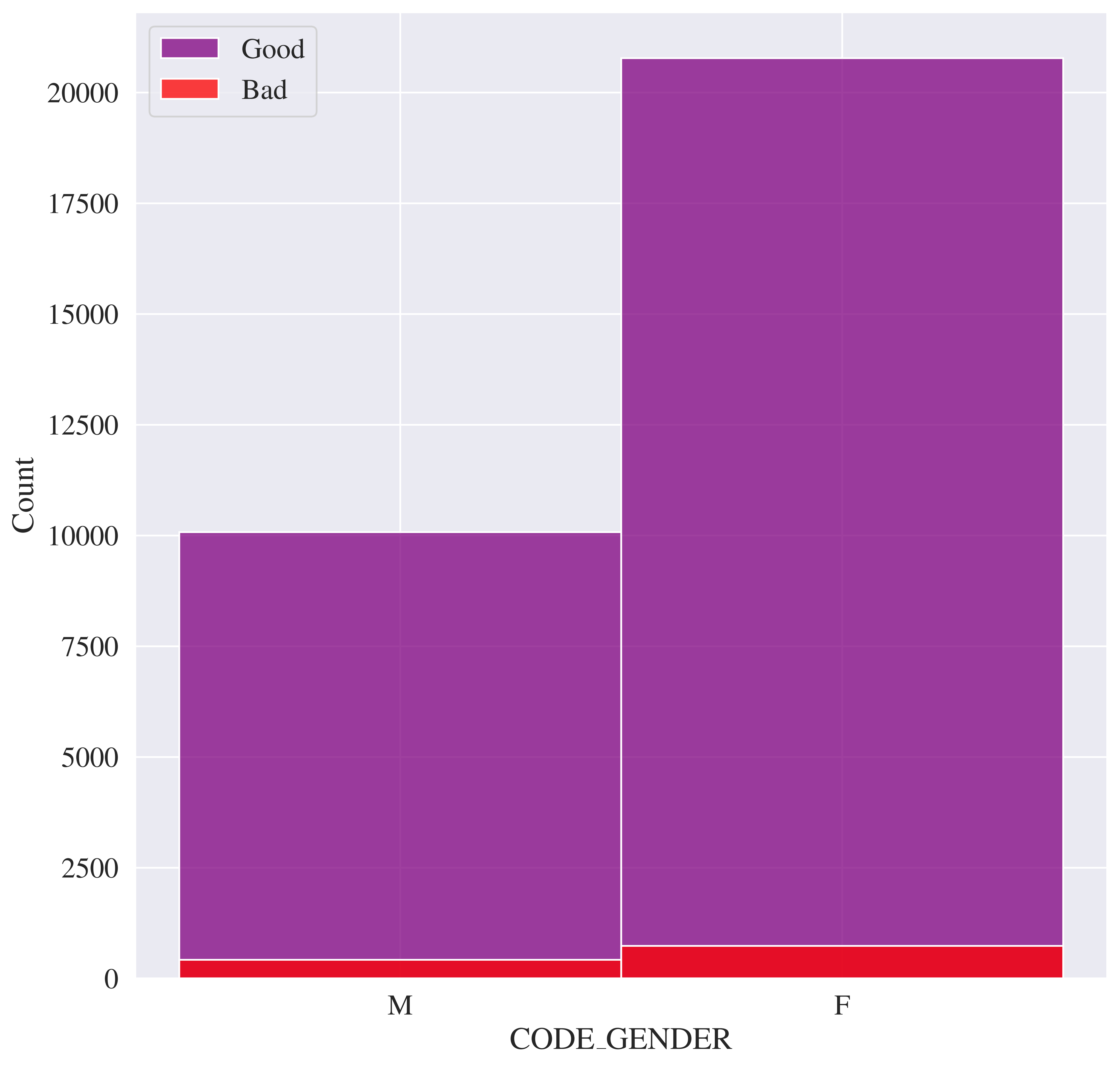
Thanks for the attention!

SCAN ME

Code available on my GitHub, click here or scan the QR code above.

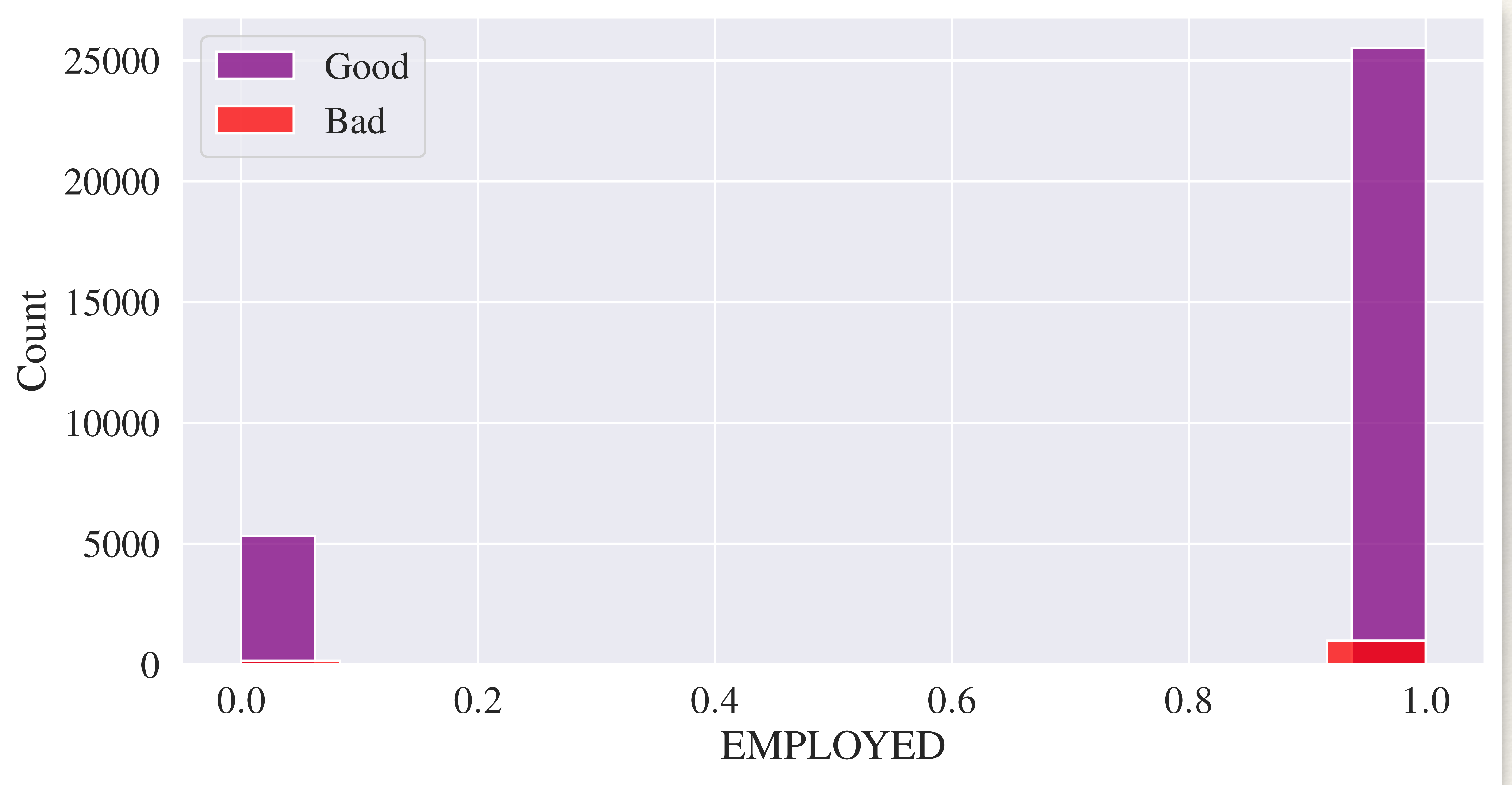
Backup slides

More women than man in the data set.

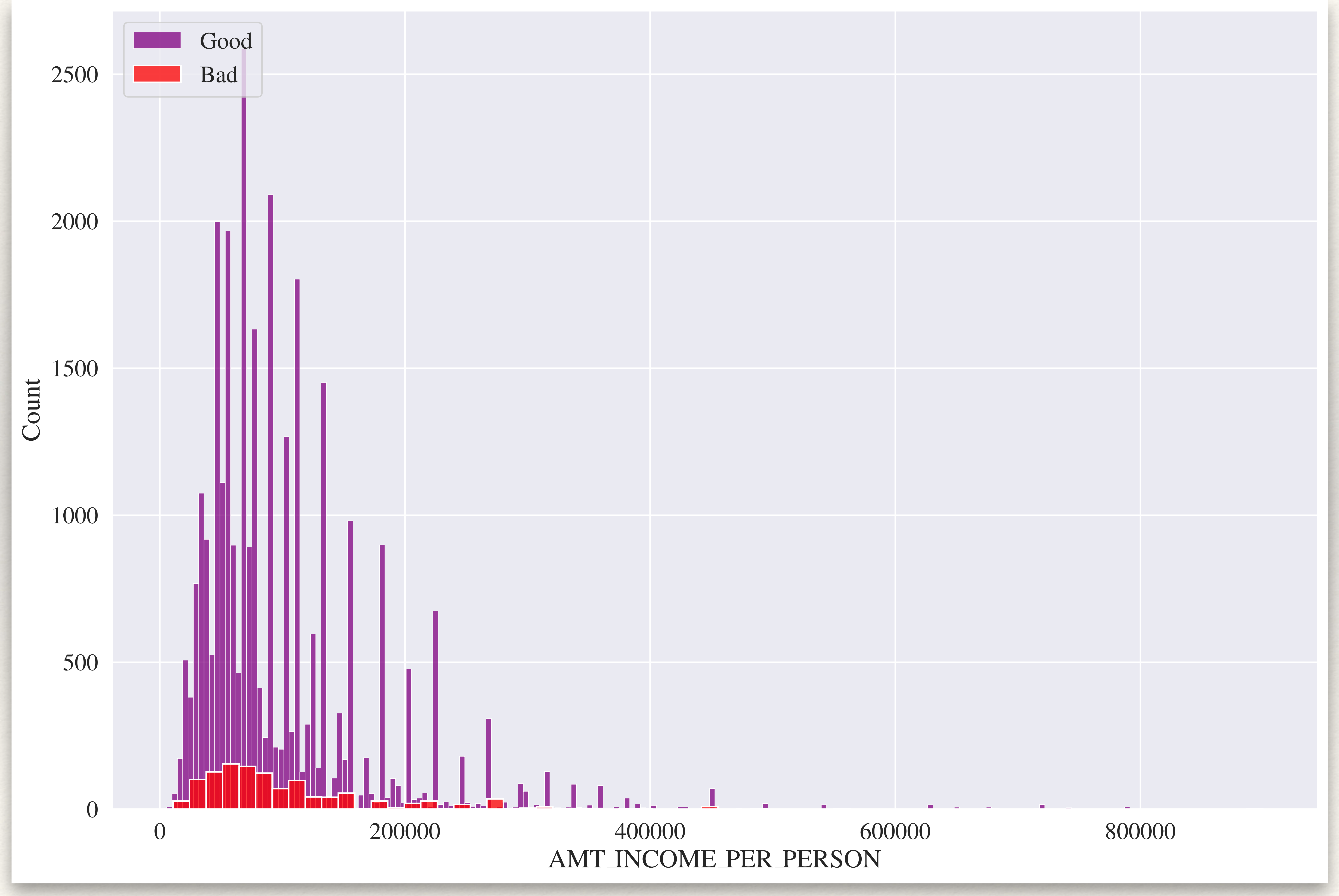


- Feature excluded of the working dataset for a ethical reason: no sexist machine learning model.

More employed (1) than unemployed people (0)



Obvious feature to create: How much of the total income is distributed among the expenses with all the family members?



- **Max: 900000.0 money/person**
- **Min: 5625.0 money/person**