Scania dataset

Unbalanced dataset and custom objectives.

Overall metrics: 170 Features, 60 000 lines

Train: 60 000 lines, 98.3 % are “neg” or Class 0

Test : 16 000 lines, 97.7% are “neg” or Class 0

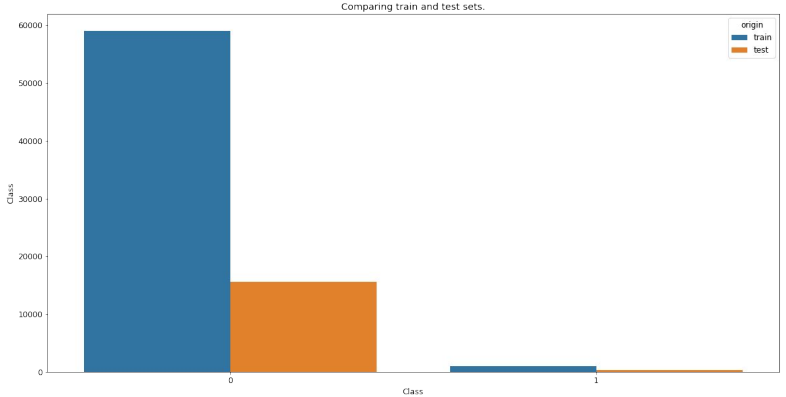
7 Histograms : AG, AY, AZ, BA, CN, CS and EE.

100 “Counters” : positive numbers.

Business objective:

=>Misclassified Class 1: $500

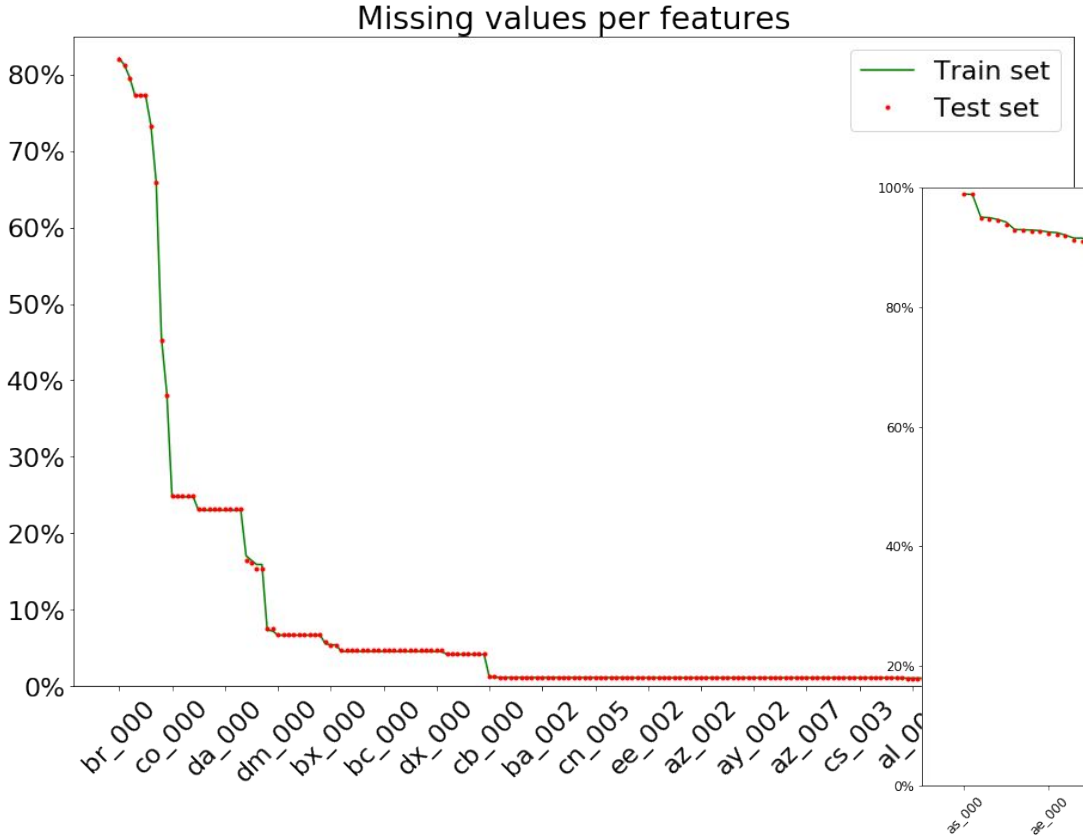
=>Misclassified Class 0: $10

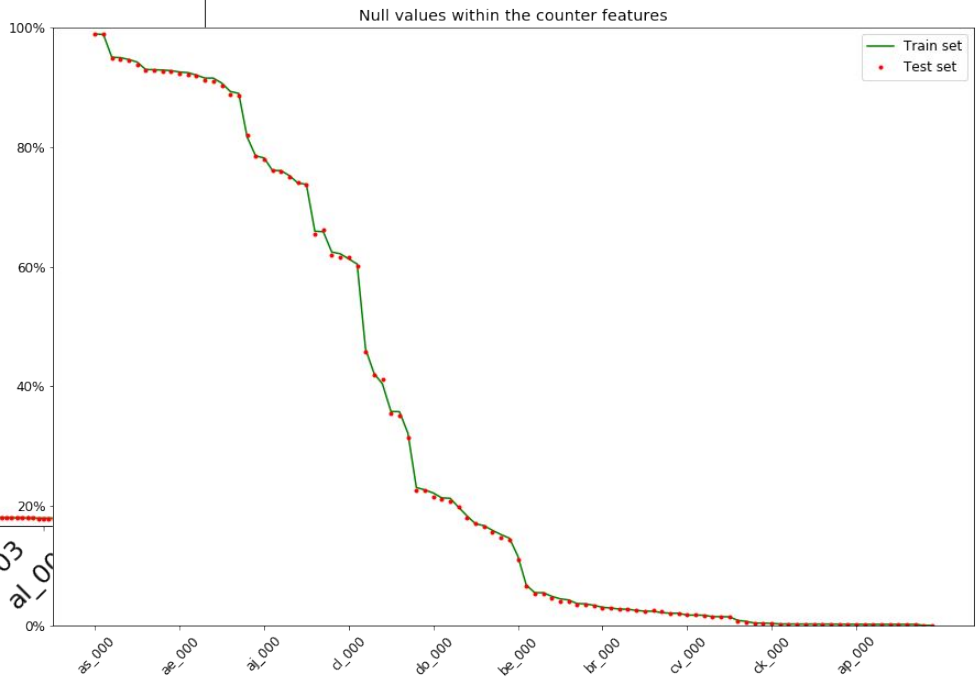


Best published solution $9 920 cost (lower is better):

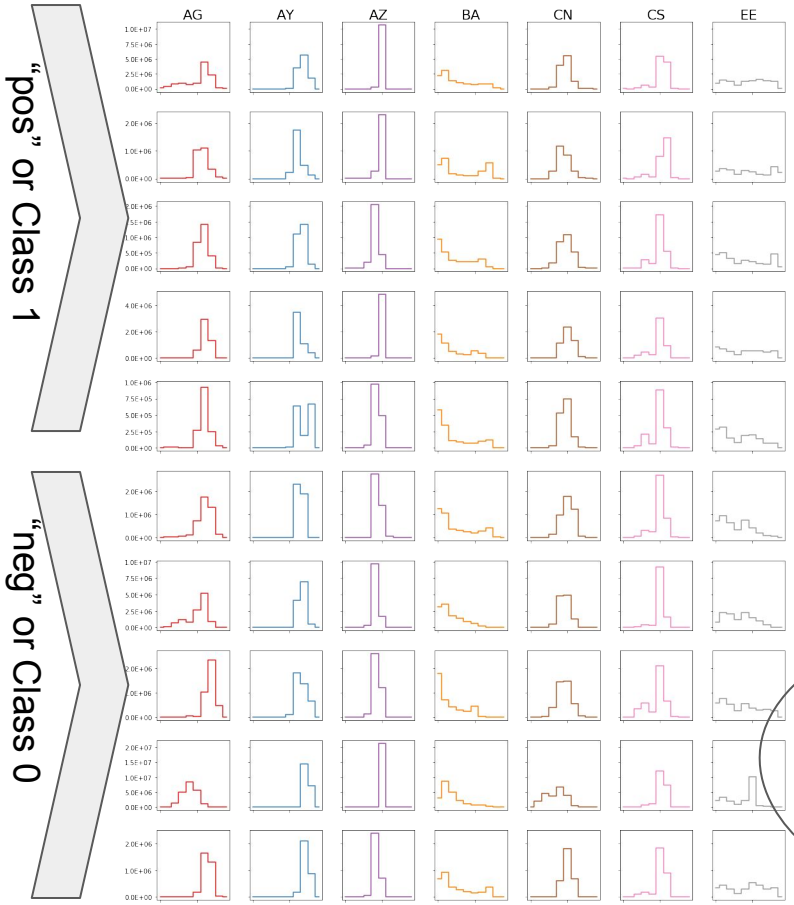
- Recall of 97%
- Precision of 40%

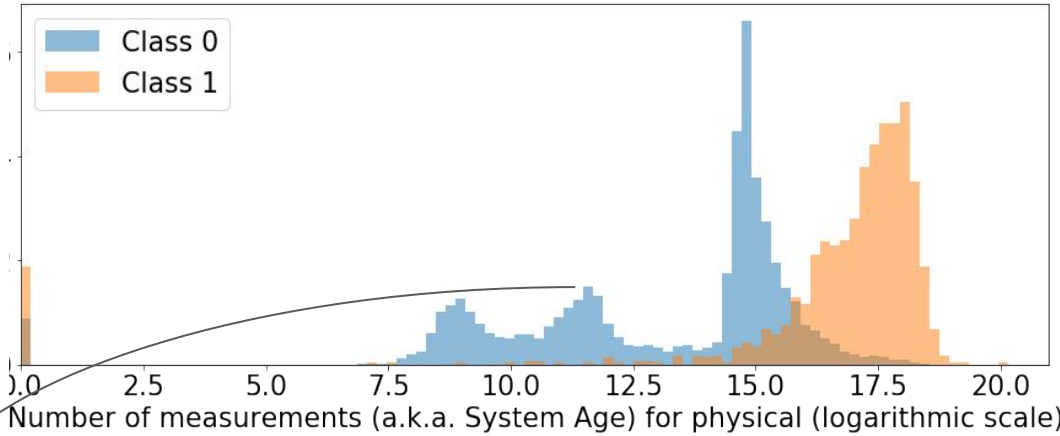
Curated dataset : equivalent missing and null values





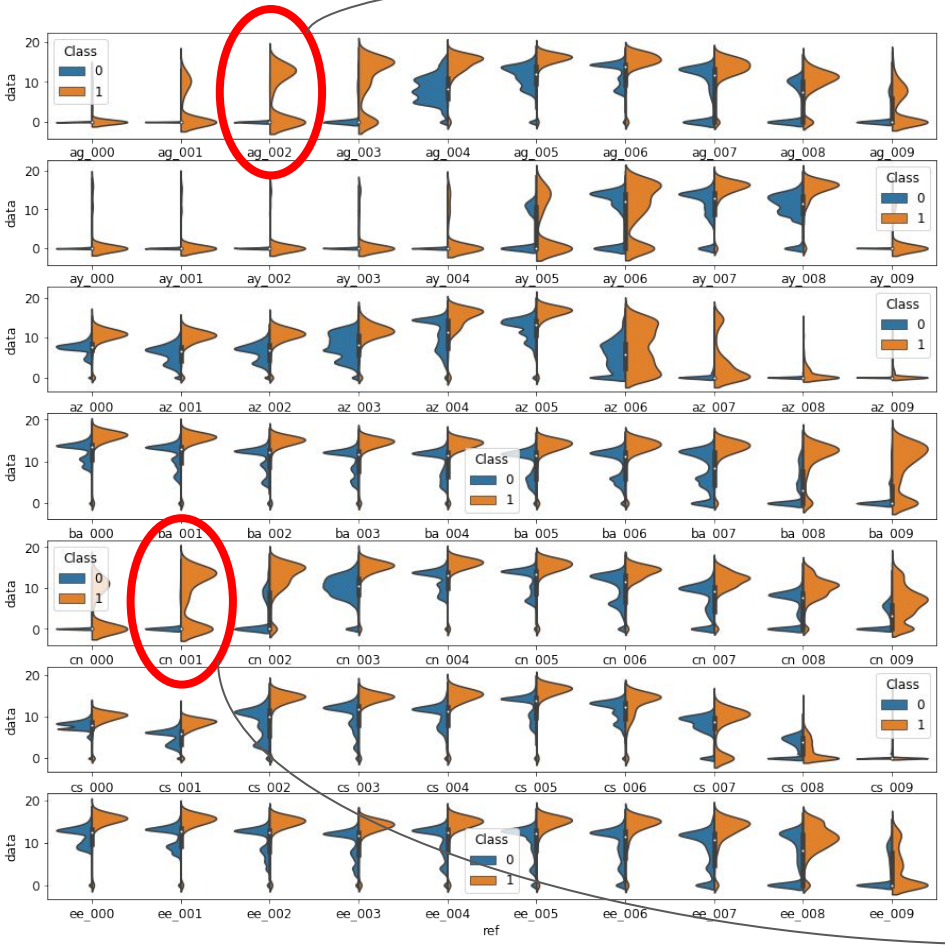
Histograms : system age

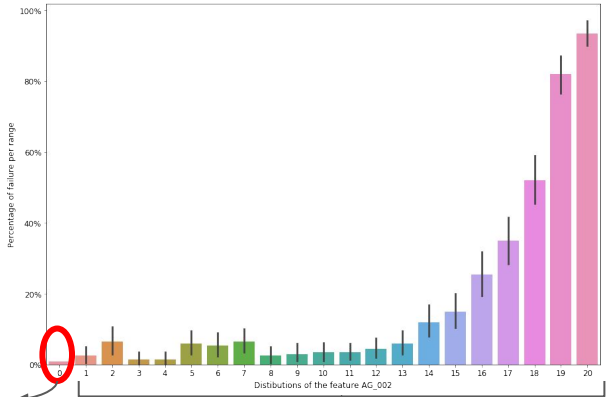




! Surface have been scaled : Class 0 is more than 50 times Class 1

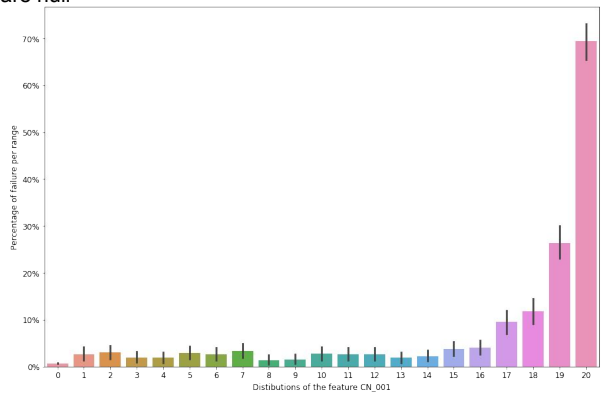
Overview



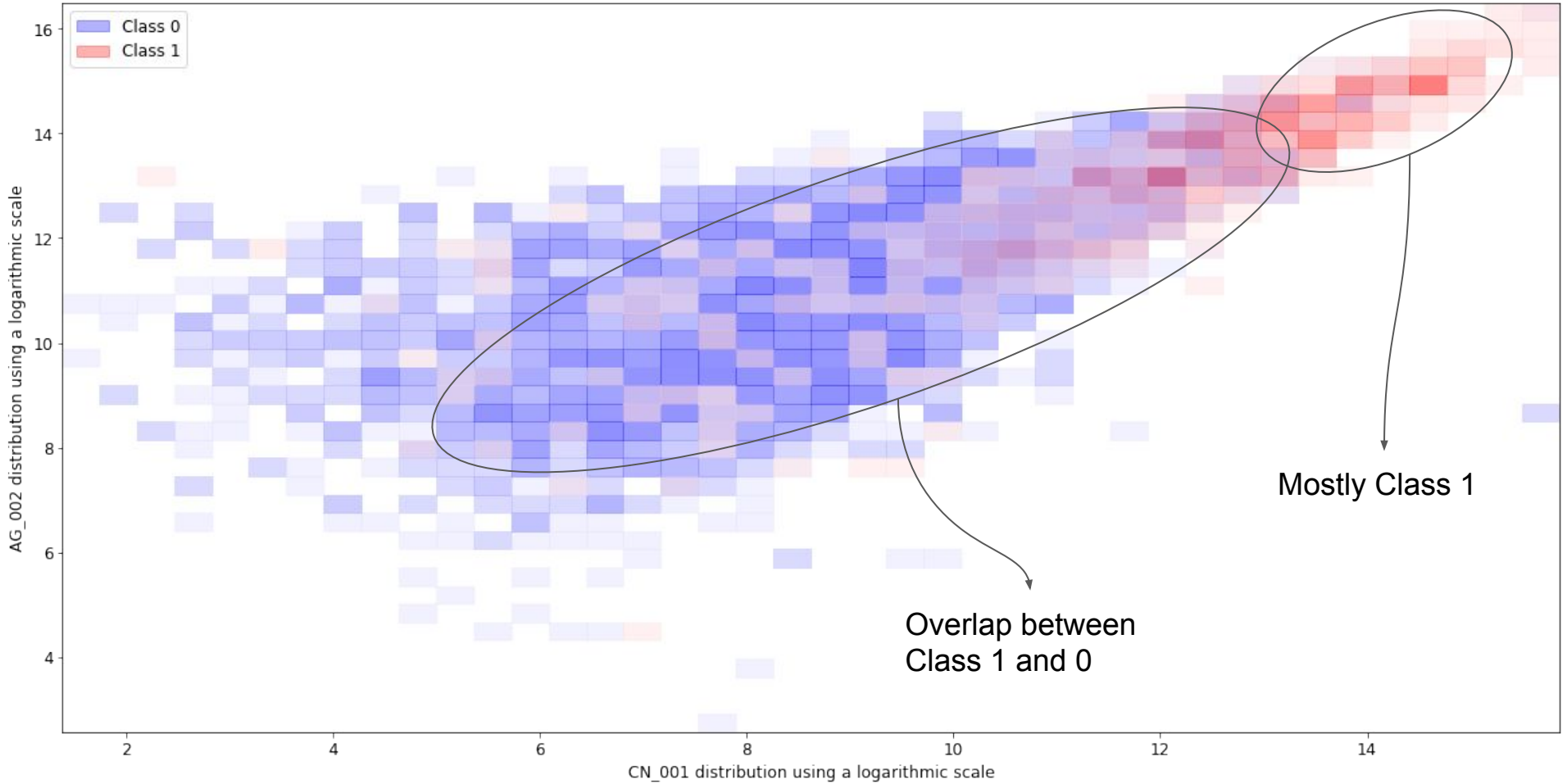


Majority of the measurements are null

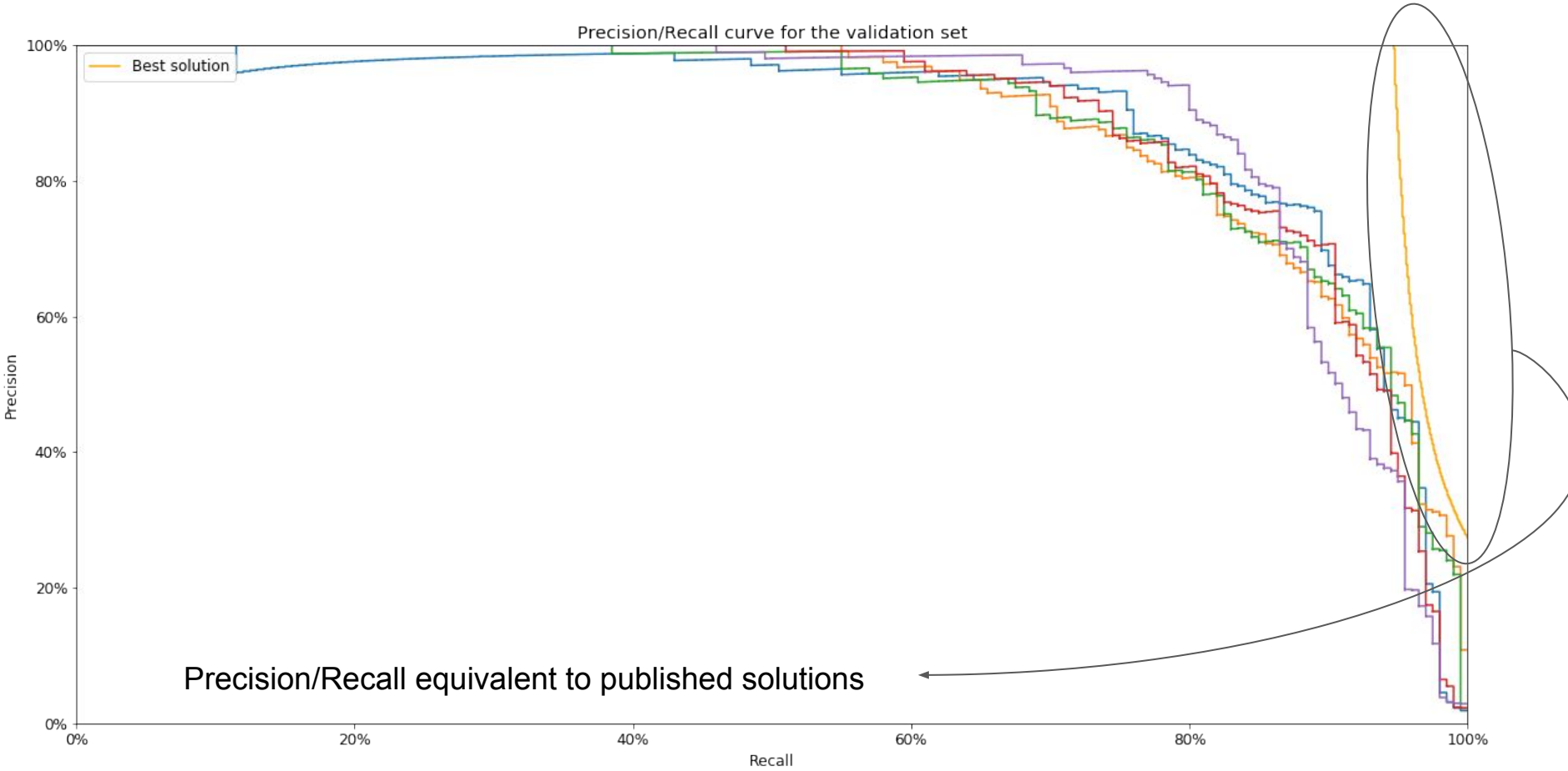
20 buckets of 200 measurements



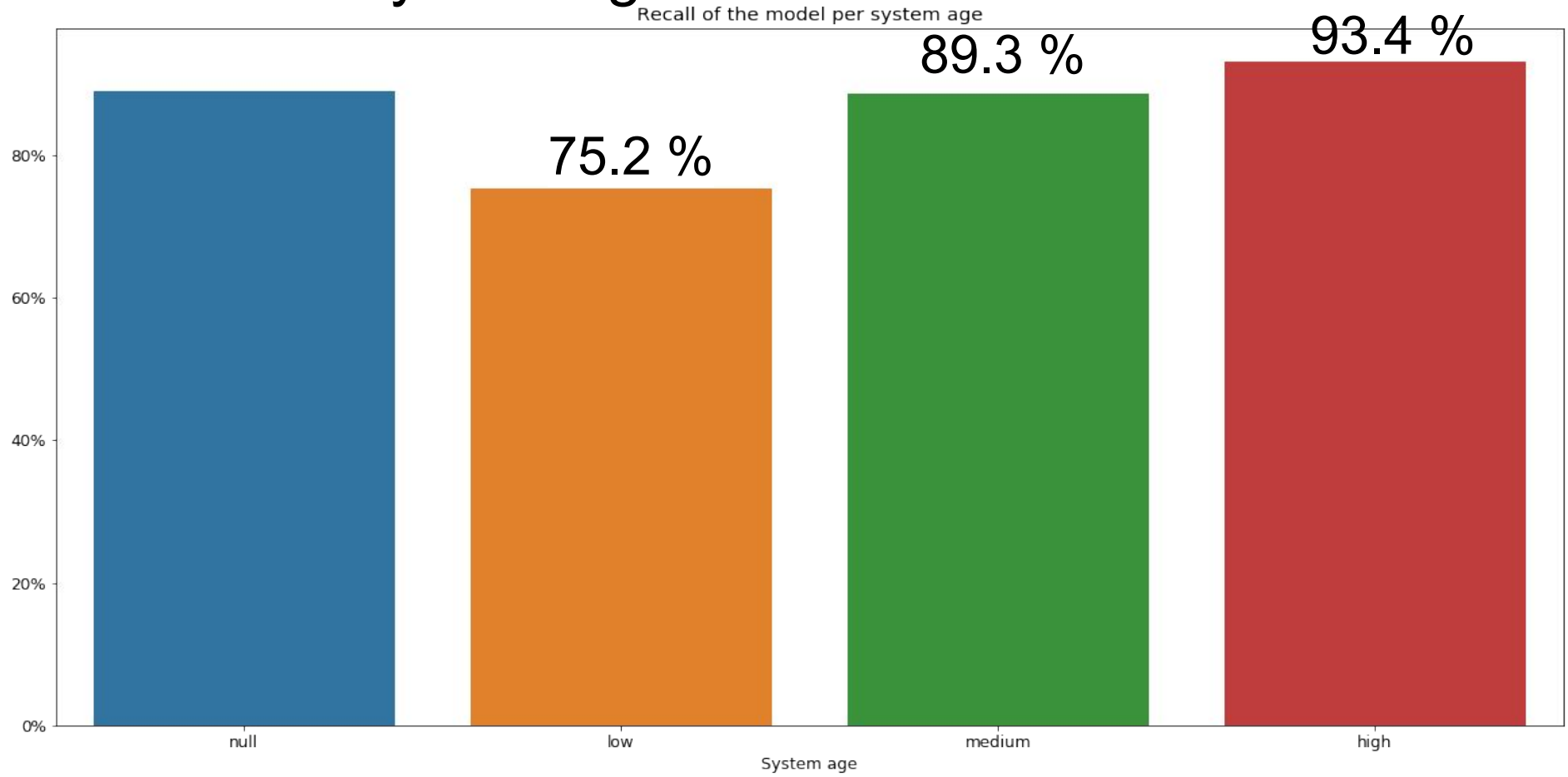
Closer look at AG_002 and CN_001 (log scale)



First lightGBM on the dataset



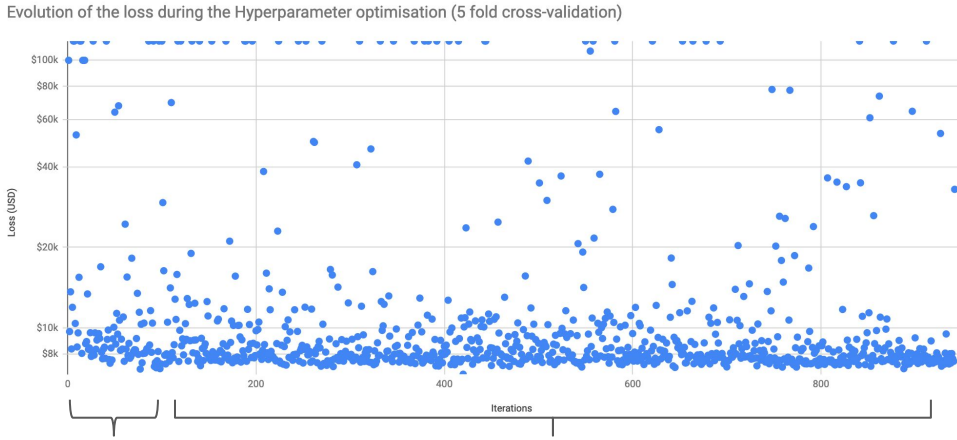
Recall and system age



Hyperparameter tuning using hyperopt

Estimator : Tree of Parzen Estimators (TPE)

- High risk of over-fitting
- High dimensional space:
  - Different imbalance dataset settings
    - Unbalance: True
    - Scale_pos_Weight
  - Avoid overfitting :
    - Feature fraction
    - Reg alpha
    - Reg lambda
- Custom function:
  - Custom score : Output actual cost to business on the validation set using variable “threshold” in decision.
  - Custom loss function with parameter “Beta” to increase weight of type II errors.



Rapid improvement during first 100 iterations

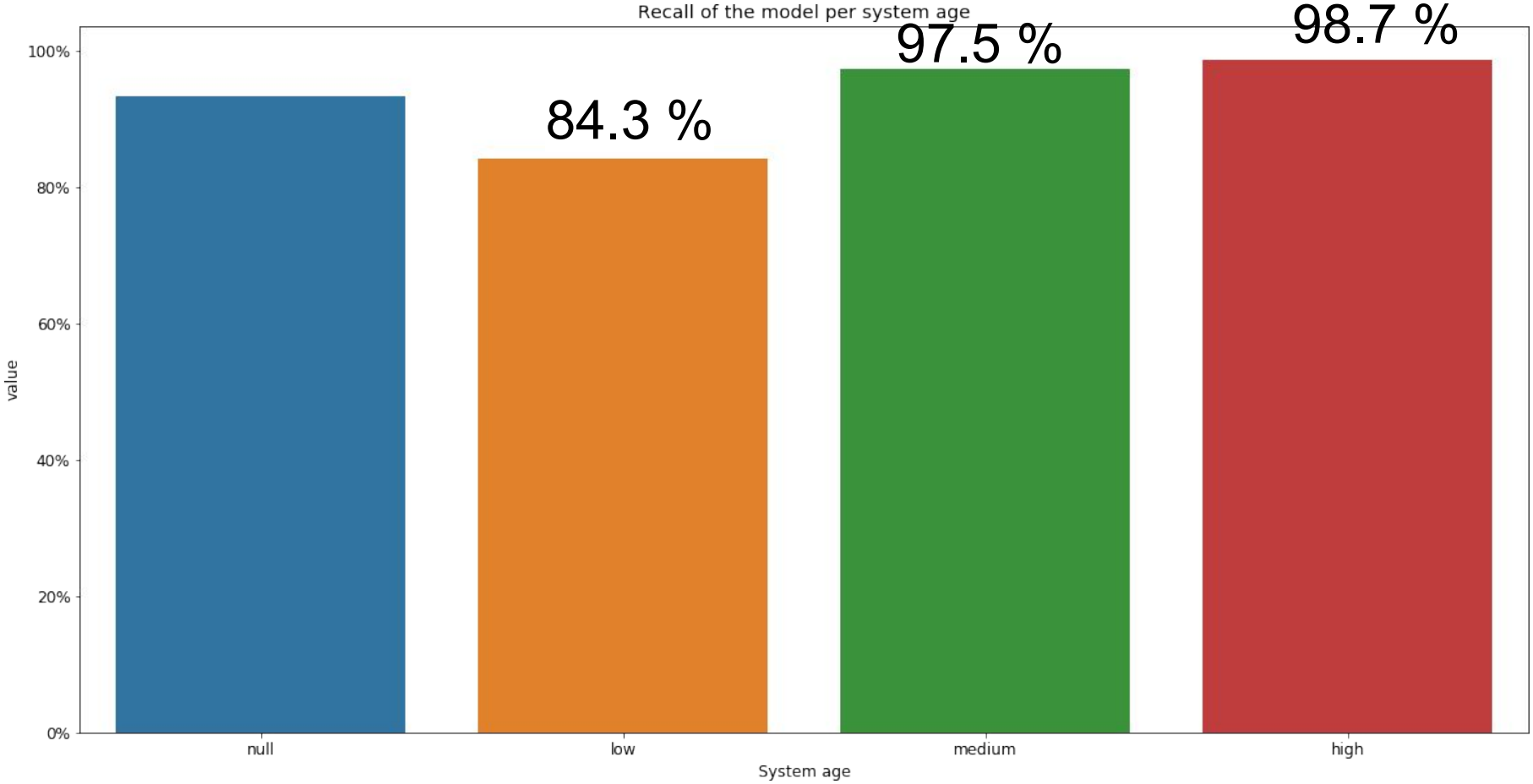
Variability remained high but still gradual improvements

Very important for end-result, 2nd optimisation on reduce space for “threshold” and “beta” only was required

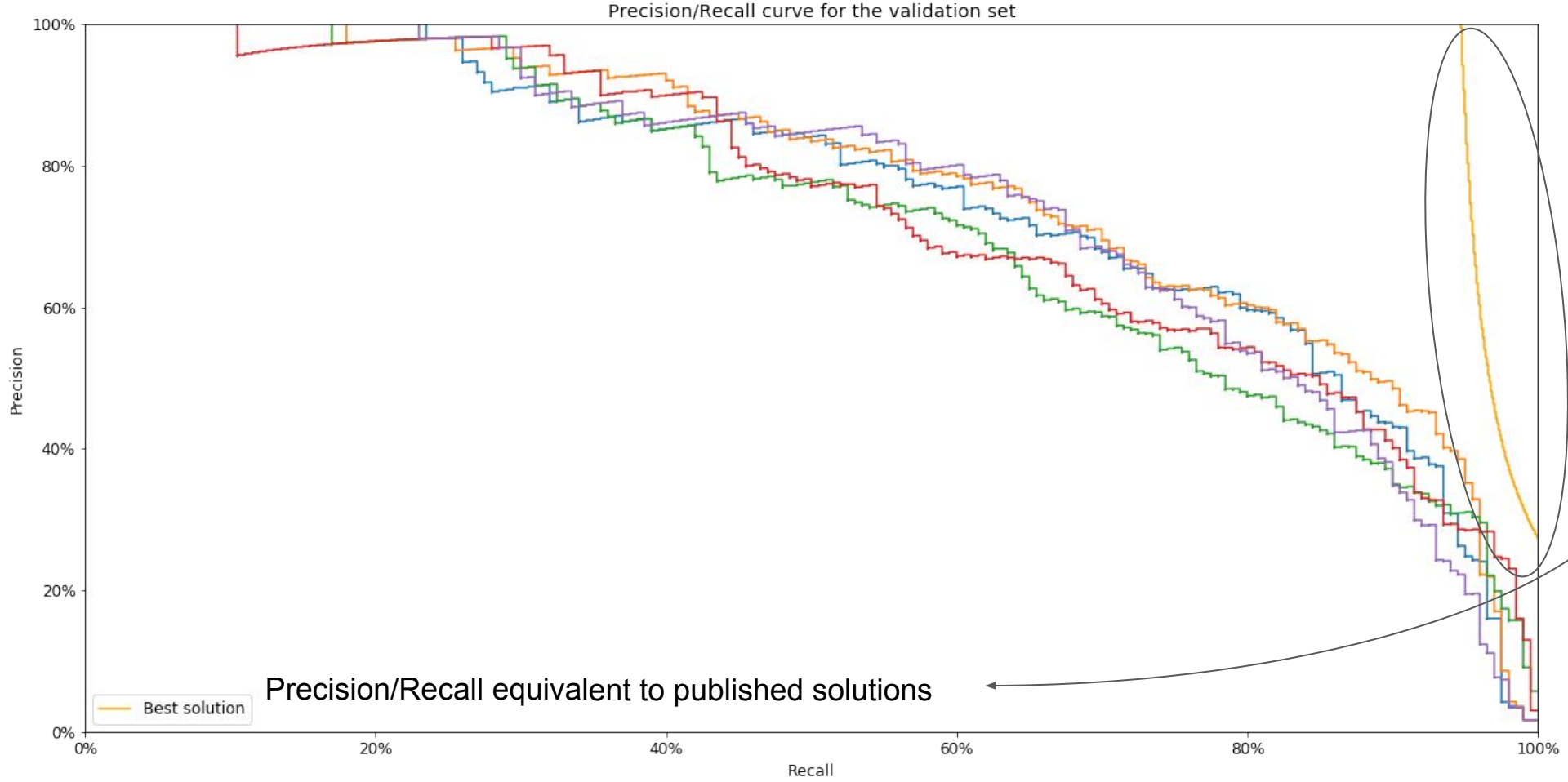
Ref :

- https://lightgbm.readthedocs.io/en/latest/Parameters-Tuning.html#deal-with-over-fitting
- https://github.com/hyperopt/hyperopt

Optimized lightGBM: recall on validation set.



RandomForest: Precision/Recall during cross-validation



LightGBM and RandomForest

LightGBM:

- No feature engineering and missing value handling.
- Likely to overfit
- High correlation between hyper-parameters
- Required custom functions to address business objective
- Very fast (#20 sec per training)

	Prediction 0	Prediction 1
Class 0	15233	392
Class 1	9	366

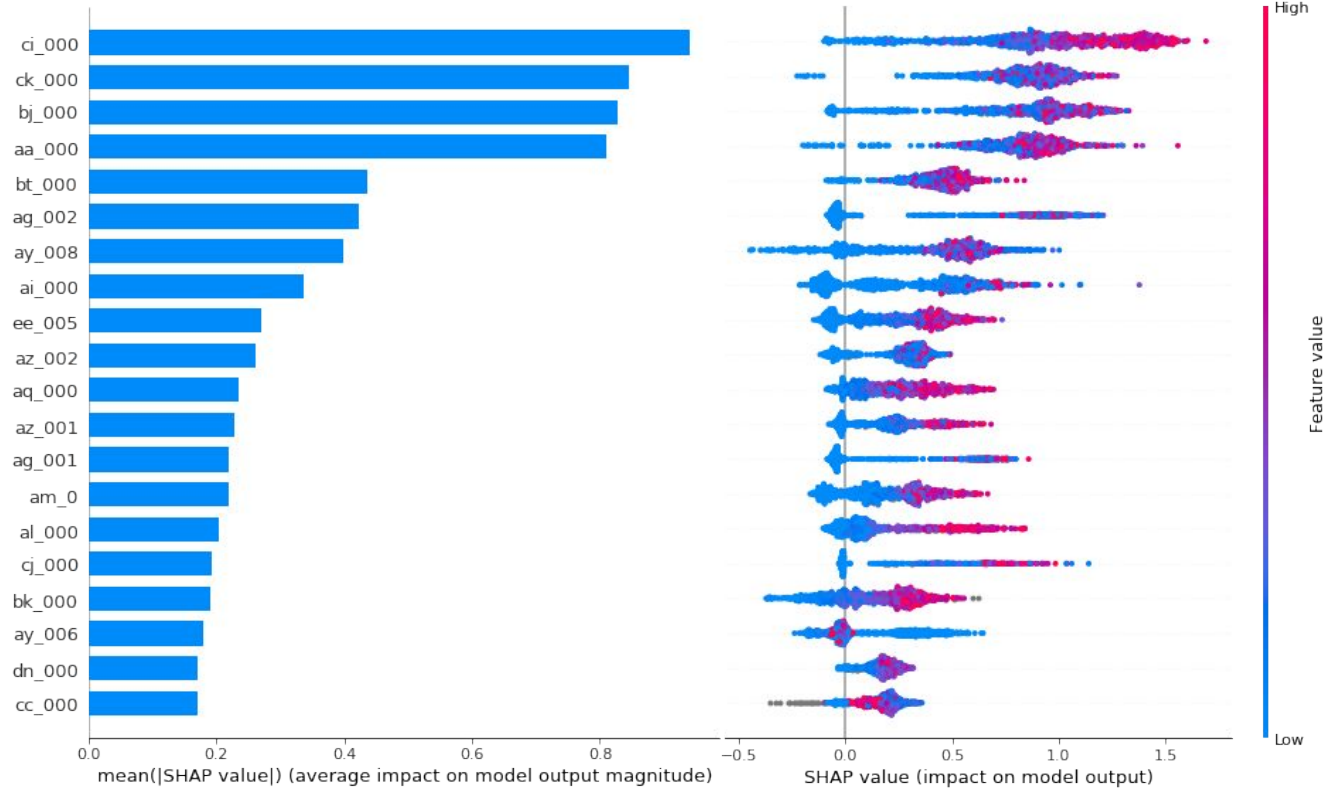
RandomForest:

- Missing values handling via “SoftImpute”
- Little to no over-fitting
- Hyper-parameter tuning was simple (but long)
- Customer scorer to select right model, but not need for further customization
- Slow (#25 minutes per training)

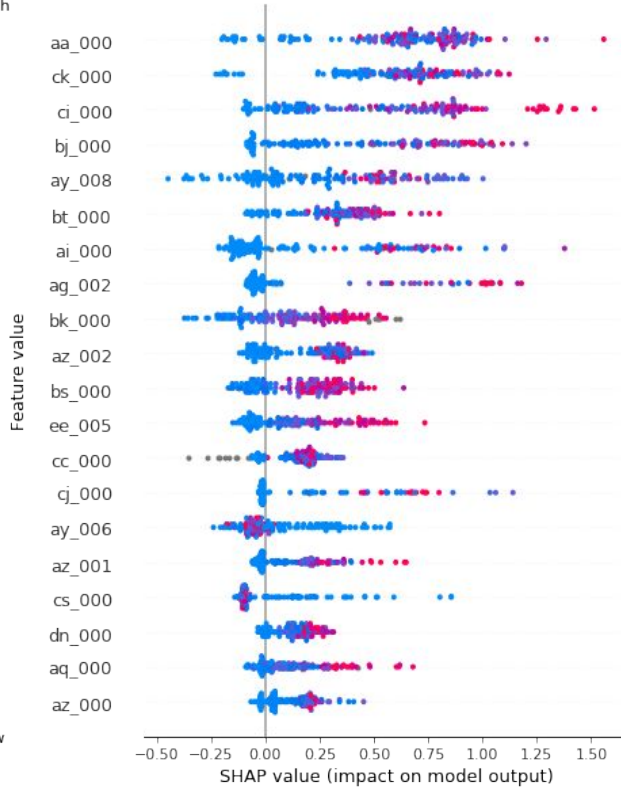
	Prediction 0	Prediction 1
Class 0	15066	559
Class 1	9	366

Understanding the model drivers

SHAP for Class 1



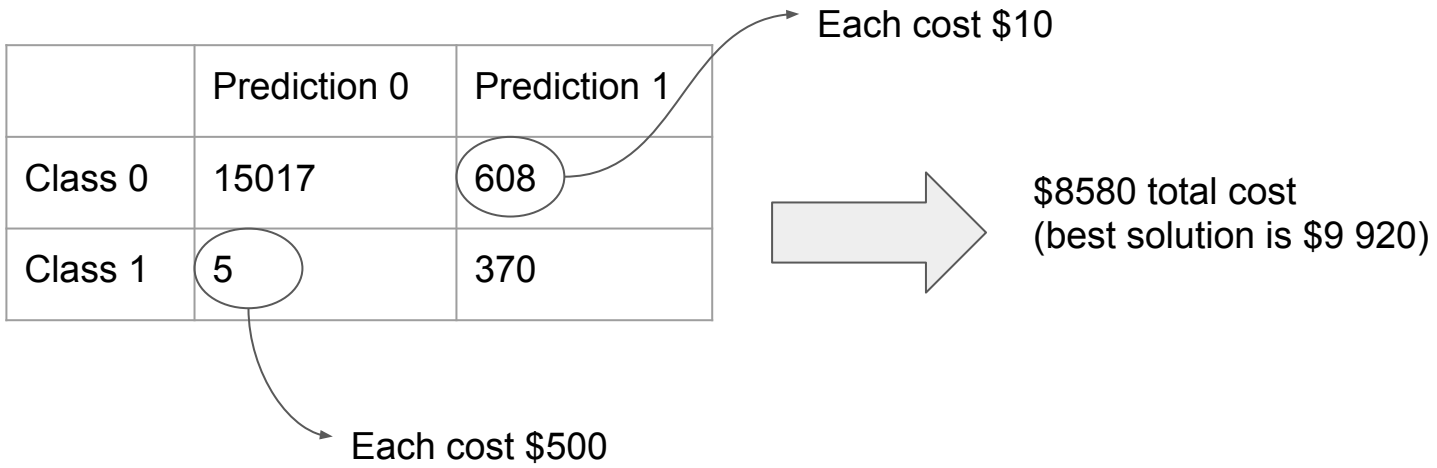
SHAP summary for misclassified



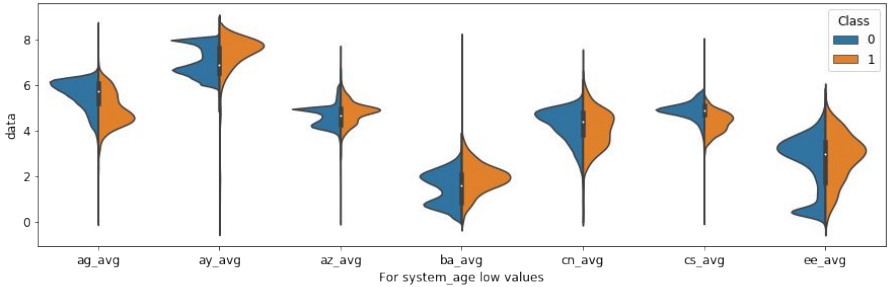
Model Stacking ?

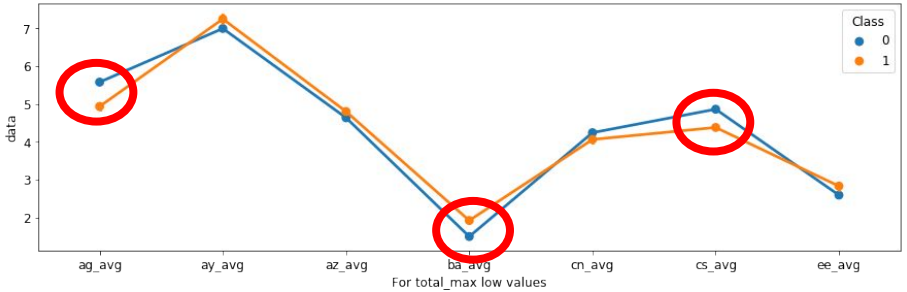
Stacking the Model using an “OR” logic as it is critical not to “miss” a Class 1:

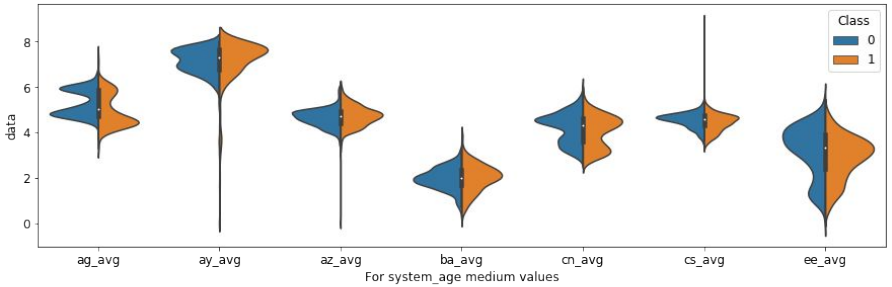
- Number of positive from lightGBM: 758
- Number of positive from Random Forest: 925
- Number of positive from using both model: 978

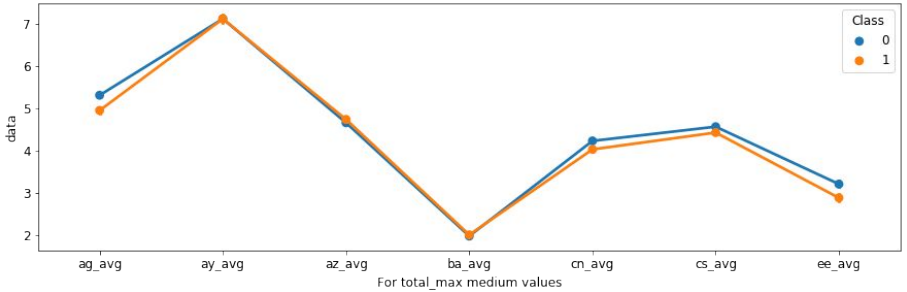


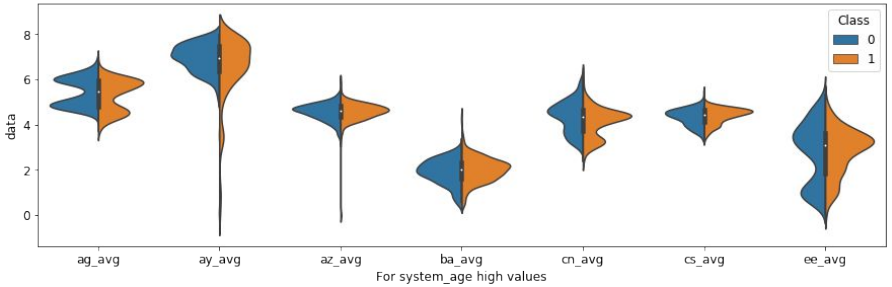
Further feature engineering for linear model

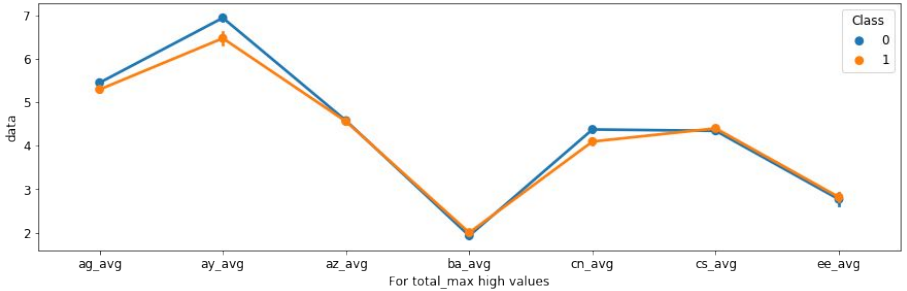




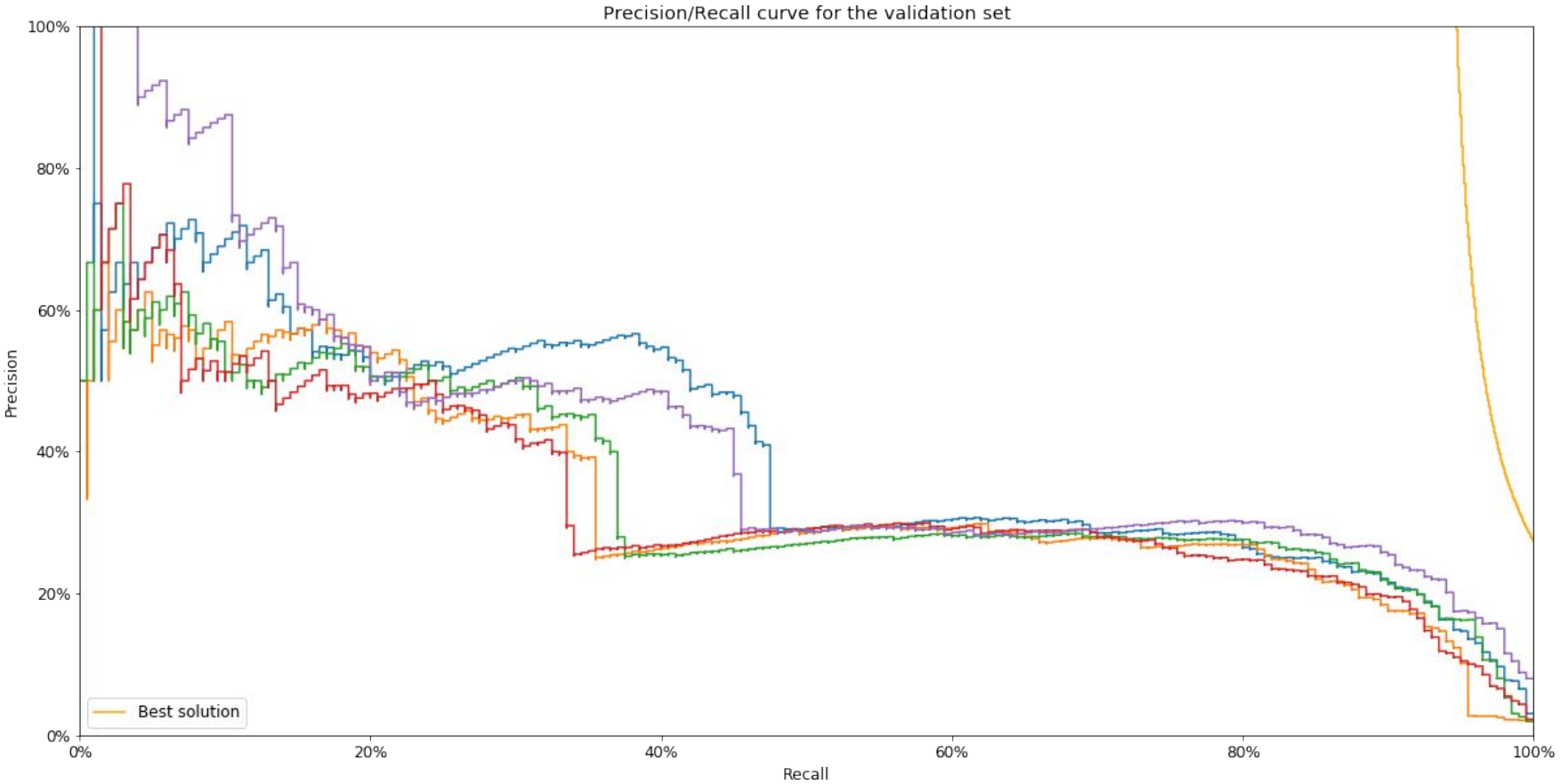








Logistic regression after scaling, PCA, missing values handling.



Conclusion

- State of the art classification can be done with little feature engineering, but would need to be confirmed on more data.
- SHAP graphs allows us to understand the features that are driving the classification and therefore potential explanation of their origin (with domain expertise).
- Classification seems to required some non-linear step (KNN to complete missing values for examples).

Improving classification:

- Get more data on failure of “younger” system to increase detection.
- Dig deeper in “Counter” features to do feature engineering.