Supervised Learning and Rare Events

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Econometrics v Machine Learning

Data generating process $y = \alpha + x'\beta + \epsilon$:

Econometrics: Identify causal effects $\Rightarrow \widehat{\beta}$

Machine Learning: Make accurate predictions $\Rightarrow \widehat{y}$

"... Applying machine learning to economics requires finding relevant $\widehat{y}$ cases."

Mullainathan and Spiess, 2017

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Methodological aspects related to empirical modelling of rare events lend themselves to application of Machine Learning methods.

Machine Learning Modul

Goal

– Use supervised learning algorithms to predict reporting errors

Challenge: Rare events data

– Availability of training data

– Modelling uncommon structure of events (reporting errors)

German Securities Holdings Statistics

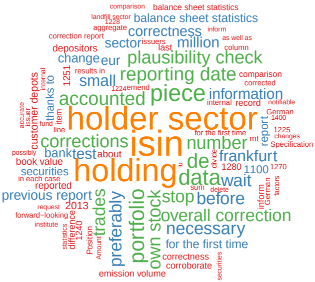
Securities Holdings Statistics

- German banks provide monthly reports of securities holdings (security-by-security)
- DQM with labor intensive manual case-by-case evaluations

Machine Learning: Data Sources

Two Data Sources

1. Text Mining of Written Inquiries



- $\approx$ 10 000 Documents
- Unstructured Data
- Automated isolation of keys in text data
- Takes tables and pictures in documents into account

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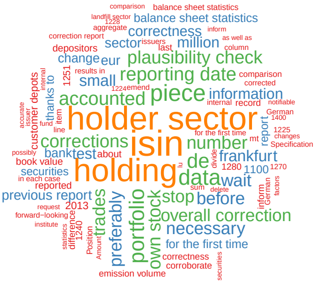

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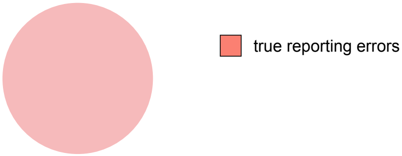
2. Different Versions of the Report

Compare first (pre-DQM) to final (post-DQM) report

Machine Learning: Data Sources

Combination of both data sources

- Both data sources have strengths and weaknesses
- Improve training data by combining both data sources



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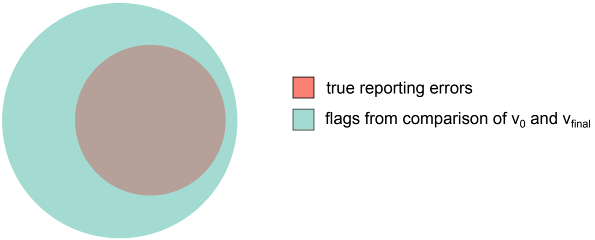

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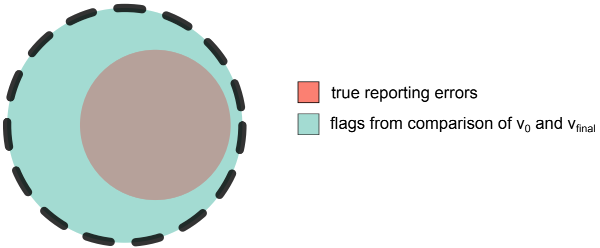

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Machine Learning: Algorithmus

Data Driven Approach

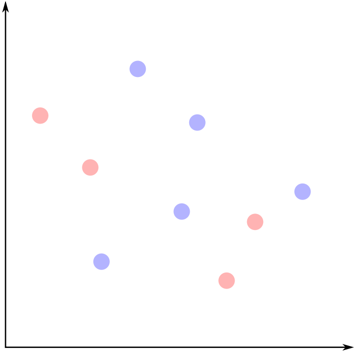
- Randomized-Grid Search for optimal Hyperparameters
- Combination of different algorithms (Stacking)

Method

- Ensemble of algorithms: Nearest-neighbour Clustering, Random Forest, Logit
- Weighting of algortithms' predictions with Stacking (Logit)
- Measurement errors as a Rare Event:
  1. Oversampling of erroneous data points (SMOTE)
  2. Undersampling of correct data points
  3. Weighted Loss Function

Method: SMOTE and Weights

SMOTE



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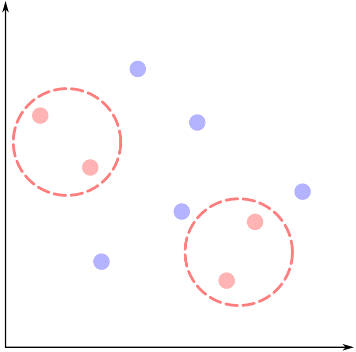

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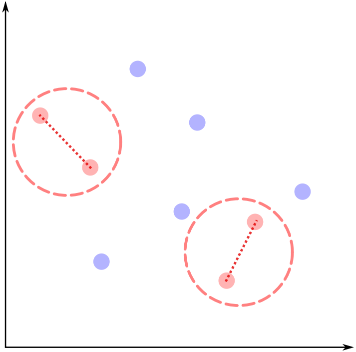

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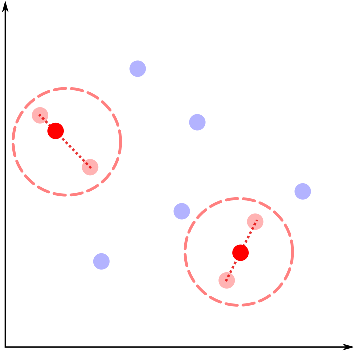

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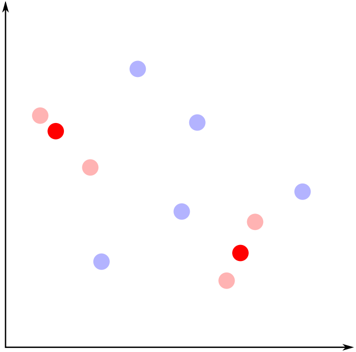

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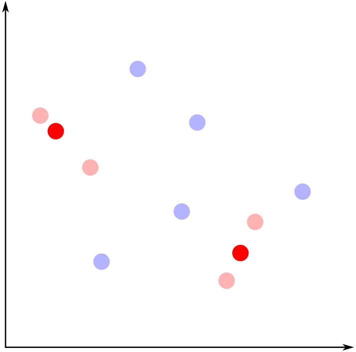

Weighted Loss Function

$$L(X, y, \beta) = \sum_{i=1}^{n} \color{red}{w_i} * f\left(\underbrace{y_i - g(x_i, \beta)}_{\text{prediction error}}\right)$$

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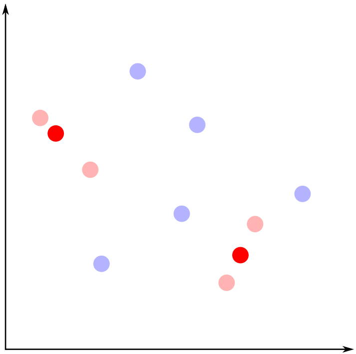

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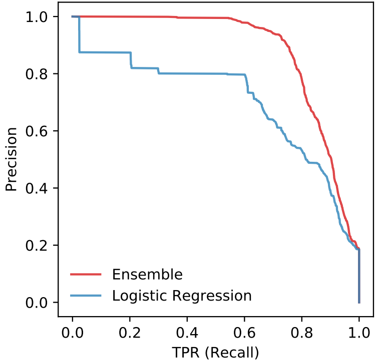
with

$$w_i = \begin{cases} n_{y_i=1}^{-1} & if \quad y_i = 1 \\ n_{y_i=0}^{-1}, & if \quad y_i = 0. \end{cases}$$

Results

Results for 2017: Out-of-sample Performance



- Recall and Precision of 80%
- Performance is superior to Logit
- Performance is even better if we consider the size of the reporting errors

Alternative: (Automated) Rule Based Approach

Advantages and Disadvantages in Comparison to a Rule Based approach

+ Algorithm learns rules
+ Complexity of rules (very) weakly related to cost
+ Automated update of rules
+ Optimization for out-of-sample performance
+ Prediction of (continuous) probability allows for prioritization

– Potential for overfitting
– Transparency
– **Requires data on measurement errors**
– **Learning on historic data**

Discovering New Types of Measurement Errors

Goal

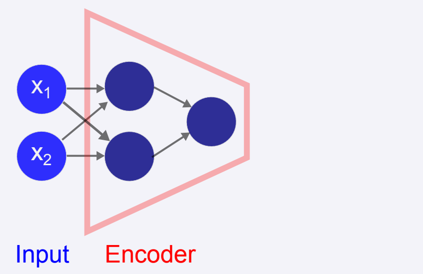
- Isolation of anomalous data points that were not recognized as measurement errors in the past

Challenges

- Interpretation of results (Unsupervised Approach)

Discovering New Types of Measurement Errors

Idea: Autoencoder



- Deep Learning approach
- Simplified 'synthetic' version of the dataset contains information on structure of the data
- Use reconstruction error to discover anomalies

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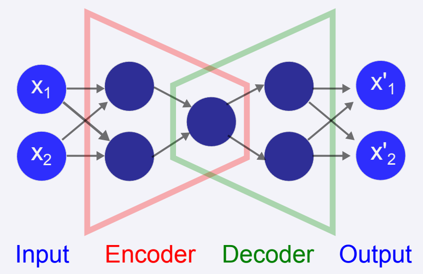

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Discovering New Types of Measurement Errors

First Results

- Successful isolation of anomalous data points in German securities holdings data
- Some of the anomalous data points were classified as measurement errors in the past
- Potential for discovery of novel types of measurement errors
- Largest potential if there is little domain knowledge regarding the data

Conclusion

- Deriving training data from written inquiries and reports is feasible
- Data-driven approach to model selection
- Implementation (ongoing)
  - Microservice architecture with Docker Container
  - Deployment of trained model
- External validity: Similar results with simulated data
- Extension with autoencoder can address issues related to data availability and novel errors

Feature Engineering