# Corporate default prediction

## Statistics for Data science - AEM University of Brescia

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# Research questions

- What are the consequences of applying different resampling methods? Is the more complex the better?
- What's the most efficient way to make a model of a corporate probability of default?

# Overview of data: Basic information

- Data is sourced from Orbis - Private company database
- Geographical location of companies are developed countries in Europe
- in period 2018-2020
- observations were filtered with following criteria:
  - Active, bancrupt or dissolved at time $t$
  - With known value of some financial ratios at time $t-1$
  - Standardised legal form: Private and public limited company
  - Entity type: corporate
  - known and higher than 5 number of employees at time $t-1$

# Data preprocessing

- Variables with more than 25% not available values were dropped
- Categorical variables were one-hot-encoded
- NAs were imputed with the median of a given variable
- Preprocessed dataset was split into training (80%) and testing dataset

For feature engineering, additional 20 new variables were introduced from initial 30, briefly:

- For some financial data like revenue, net proft, a relative change from previous year was introduced
- Most of the original variables were a standard positions from finacial statement, thus financial ratios were introduced with some basic arithmetic operations.

# Resampling methods

Corporate default data is known to have a huge class imbalance problem.

In order to adress the problem and investigate their modeling consequences, I further apply 3 resampling methods to the training dataset:

- Oversampling
- Undersampling
- Synthetic Minority Over-sampling Technique (SMOTE) [N. Chawla, et. al, 2002]

Further modeling workflow is done for datasets resampled with each of the methods above, in order to compere them.

# Applied models (1/3): Penalized logistic regression

$$\min_{w,c} \frac{1-\rho}{2}\beta^T\beta + \rho||\beta||_1 + C\sum_{i-1}^{n} \ln e^{-y_i(X_i^T\beta+c)} + 1$$

Where:

- $\rho$ parameter regulating preference for l-2 or l-1 regularizaton
- C paraemters regulating preference to regularization

Both of the parameters above were tuned with a grid search over corss validated results.

# Applied models (2/3): XGBoost - Gradient boosted decision trees

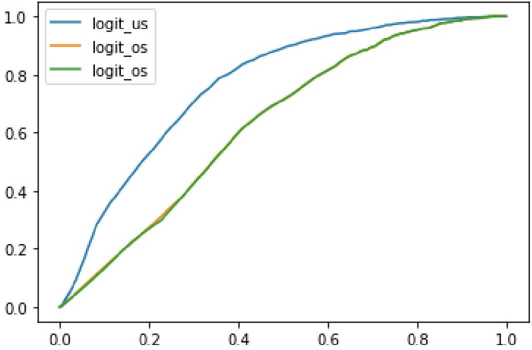
- A workhorse ML model, based on an ensemble of decision trees [T. Chen, C. Guestrin, 2016].
- Trained with a gradient boosting algorithm based on Friedman et al. 2000
- The model is trained in a sequential way, each training round consists of function estimated from previous round and a newly trained one.
- The objective function both tries to minimize log-loss and a regularization term, which penalizes number of leaves and a l-2 norm of leaf score
- all in all, a complex model....
- In herein project, the hyperparameters were tuned with random search.

# Applied models (3/3): Multilayer perceptron

- Basic "vanilla" model of artificial neural networks
- Estimates weights of "neurons" iteratively with backpropagation
- Just like the previous model, can generalize non-linear patterns and has a regularization in a objective function

For this project, the hyperparameters were tuned with a random search.

# model fitness comparison - ROC



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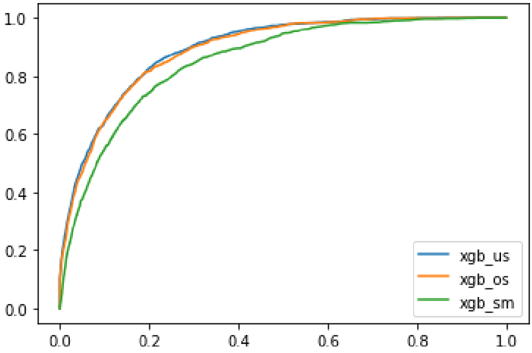

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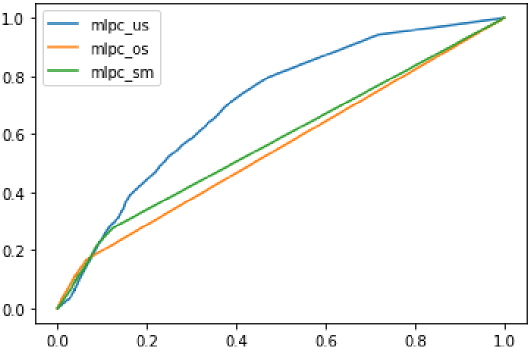

# References


- N. V. Chawla, et. al, SMOTE: Synthetic Minority Over-sampling Technique, Journal of Artificial Intelligence Research 16, 2002
- T. Chen, C. Guestrin, XGBoost: A Scalable Tree Boosting System, 2016
- J. Friedman, T. Hastie, and R. Tibshirani. Additive logistic regression: a statistical view of boosting. Annals of Statistics