# Introduction to Machine Learning

Group 2: Final Project Presentation

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# Data Cleaning

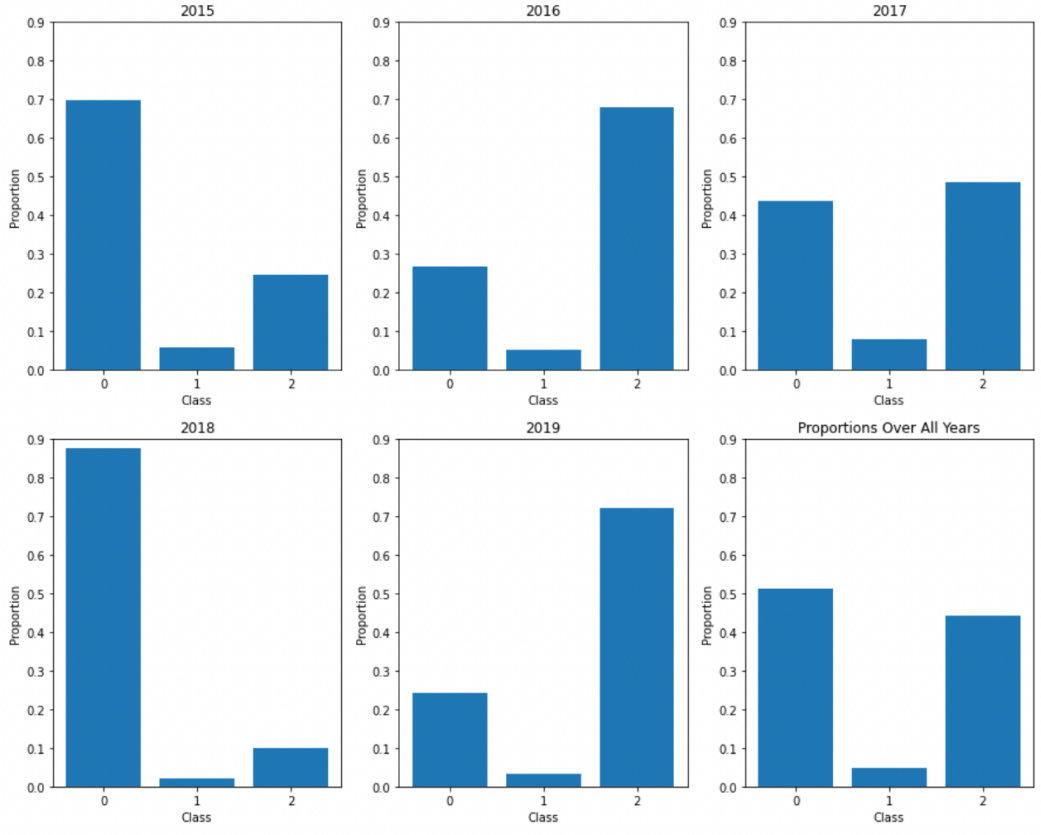


- Concatenating the Datasets: Creating an excess return feature and modifying the existing class feature
- Dealing with NaN's:Threshold of 30%, KNN-imputer
- Dealing with Outliers: Isolation Forest Algorithm, works well with high volume data and can detect data anomalies considering multiple variables

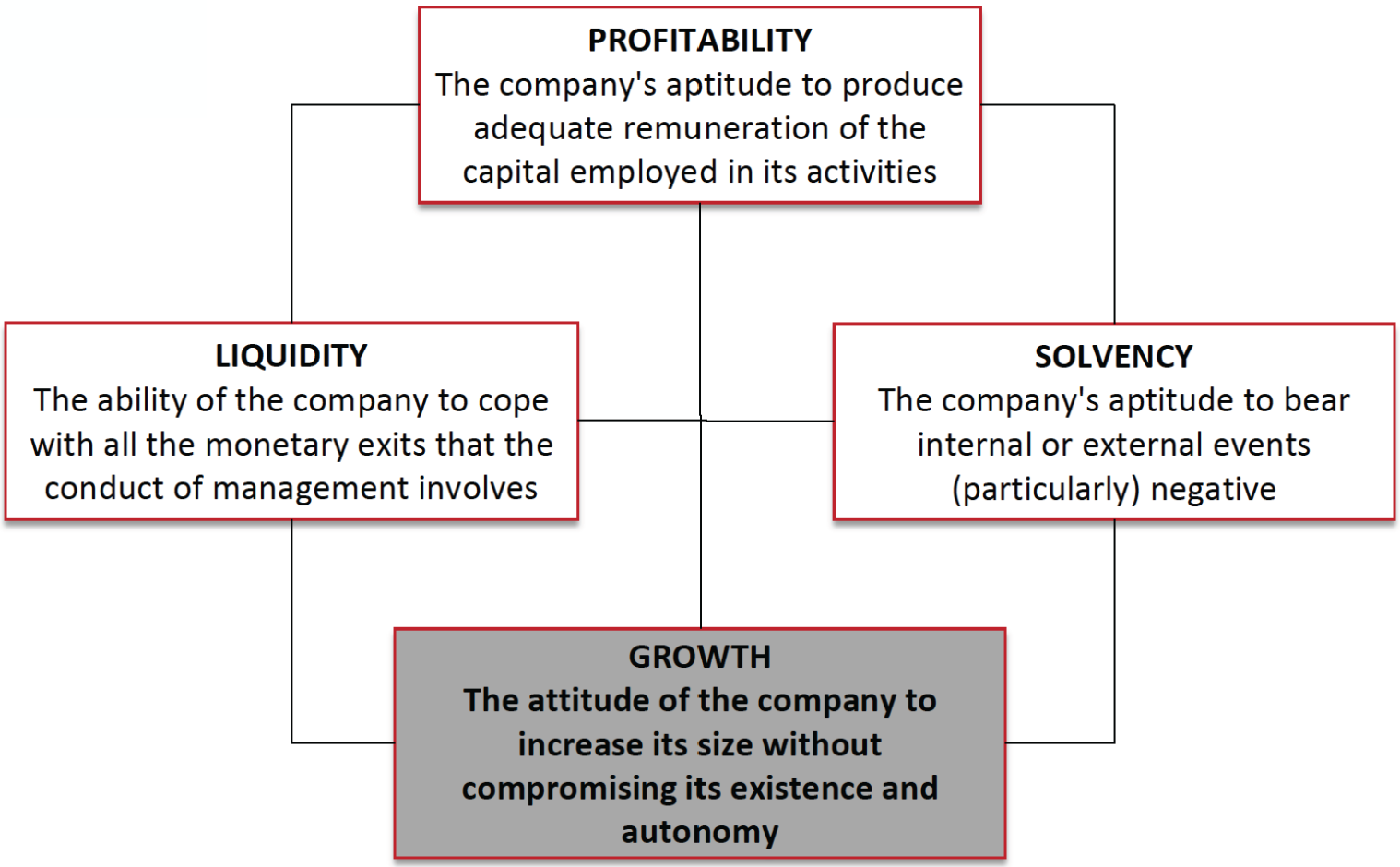
# Class Imbalance



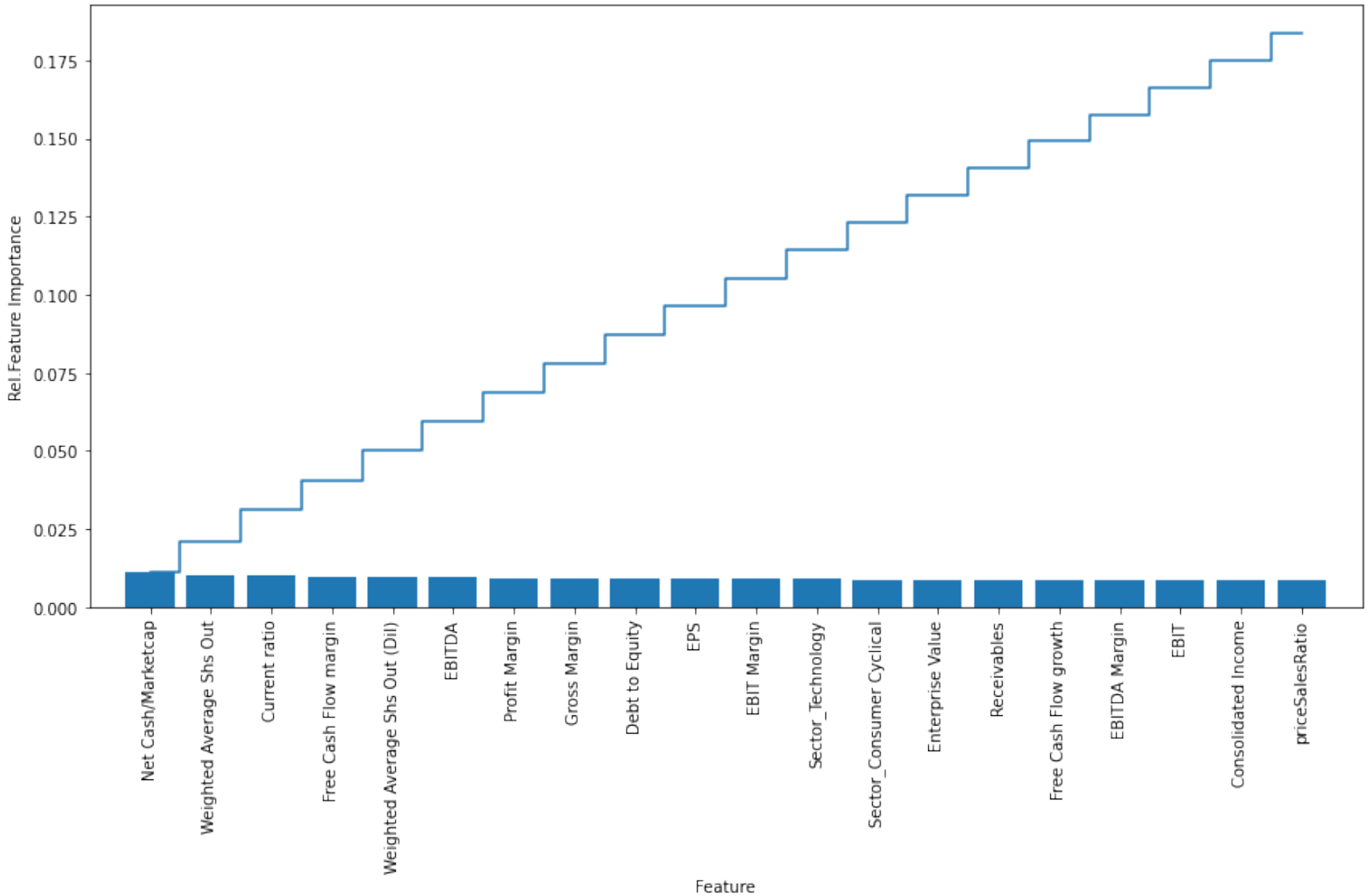
- ▷ SMOTE algorithm and SMOTENC algorithm ⇒ many problems
- ▷ RandomOverSampler as an alternative



## Sustainable Growth Model as Fundamental Analysis Framework



# Feature Selection



# Dimension Reduction

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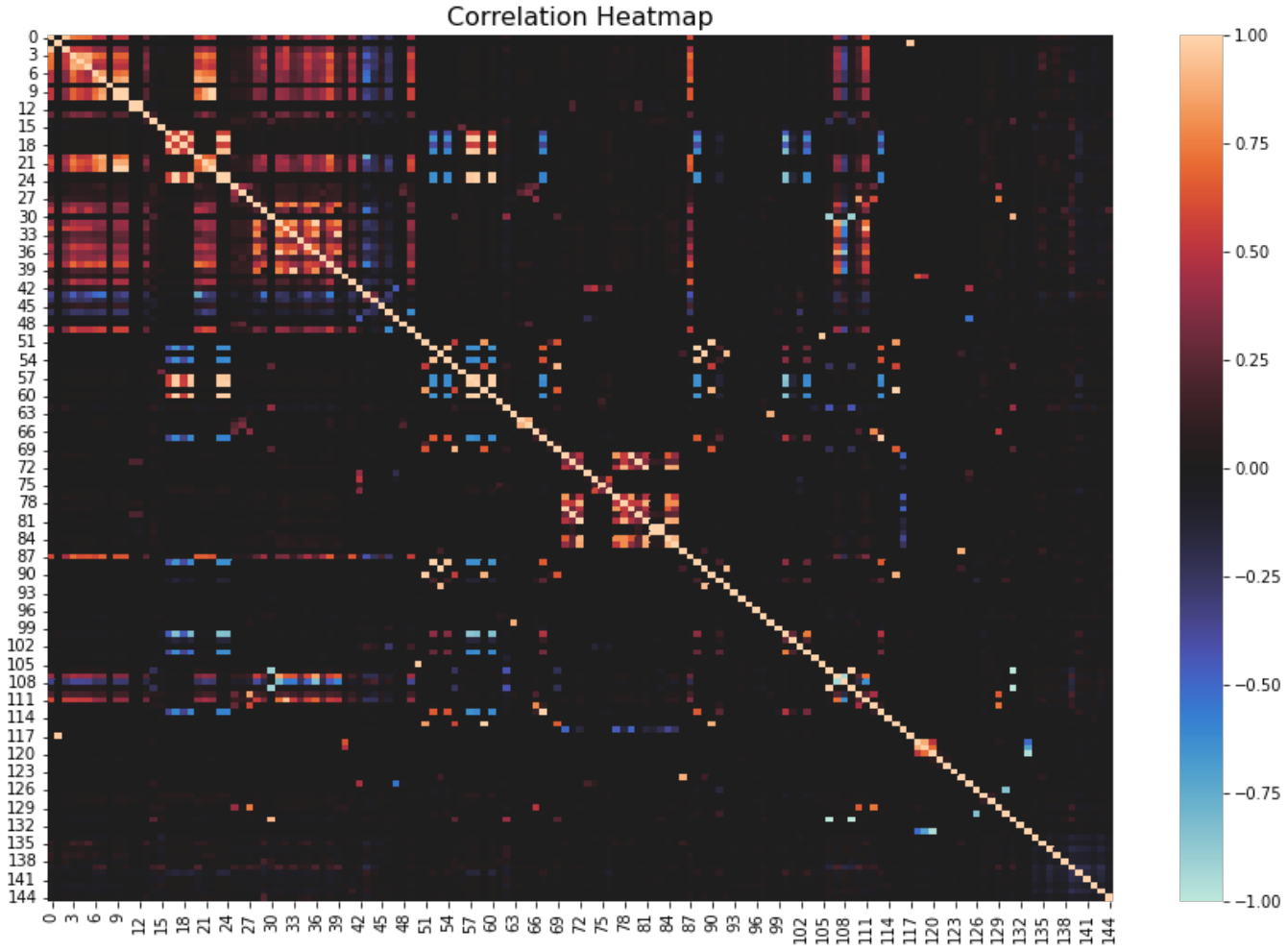
- ▷ Many features are only barely correlated ⇒ PCA problematic
- ▷ Kernel PCA as an alternative



# Results

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**Weighted-Averaged $F_1$-Score:**

$$F_1\text{-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

The weighted average is calculated by taking the mean of all per-class $F_1$-Scores (calculated in a One-vs-Rest approach) whilst considering the number of occurences of each class.

- ▷ Baseline: Choose class randomly according to class proportions in train set
- ▷ Baseline weighted $F_1$-Score: 0.466

| Approach | Log Reg | Naive Bayes | Random Forest | XGBoost | SVM | Neural Network |
|---|---|---|---|---|---|---|
| All Features | 0.508 | 0.358 | 0.544 | 0.578 | 0.470 | 0.540 |
| Feature Sel RF | 0.440 | 0.390 | 0.492 | 0.470 | 0.416 | 0.535 |
| Feature Sel XGB | 0.466 | 0.505 | 0.494 | 0.446 | 0.273 | 0.536 |
| (Kernel) PCA | 0.456 | 0.508 | 0.507 | 0.526 | 0.459 | - |
| Feature Engineering | 0.513 | 0.463 | 0.535 | 0.581 | 0.493 | 0.531 |

- Do our results imply that the "Efficient Market Hypothesis" does not hold?
- Not necessarily, since we do not know whether the heightened prediction reliability of our algorithms translates into a superior market performance
- Risk of an Omitted Variable Bias: Are our algorithms transferable to other situations e.g. markets in other regions?

# References



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