We explore the application of Machine Learning for predicting the return of the VW stock by using the information of stock returns in its supply chain. Starting a house race between Elastic Net, Decision Trees, XGBoost, and LightGBM, we find that Elastic Net generates the highest prediction accuracy across forecast horizons. A trading strategy based on this analysis leads to increased trading profits if, in three times compared with a simple buy and hold strategy.

## Dataset and features

We identified 70 companies in the supply chain of Volkswagen AG from the Volkswagen page [4] and several other sources for the supply chain of VW (e.g., Pakistan [5]).

### Splitting the dataset

To mitigate the risk of overfitting, we deviate the dataset into three subsamples. Regeneration is controlled by the tuning of the aforementioned hyperparameters. First, using a given combination of hyperparameters, the vector parameter $\theta_0$ is estimated on the training sample. Second, the model prediction gets evaluated, in terms of forecast RMSE, on the validation sample. A search across provided hyperparameter combinations points to the specification that delivers the lowest error on the validation sample. After that, we use a test sample that the model has never seen before to ultimately determine the performance in terms of the RMSE and several additional metrics.

### Turning knowledge into profit

We set up our strategy as follows. We start with a bankroll of 1,000 EUR. If we do not own stock, we buy one position if our forecast predicts that the stock price will increase by more than the predetermined threshold $\theta$ over the period $A$. Conversely, if we predict a decrease in the stock price below the threshold over the period $A$, we sell the stock and go short one position. If we predict an increase, we close the short position and go long again. Here, we abstract from transaction costs. Thus, bid and ask prices are the same, which in our case is the closing price of the VW stock.

**Figure 1**: Trajectory of the VW Stock

The evolution of the VW stock during our observation period from 01-01-2005 to 01-05-2020. The period start was triggered by a labeled takeover attempt of VW by Porsche [3].

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### References

1. AP (2020) Squeezing the accelerator. The Economist https://www.economist.com/ business/2020/05/05/squeezing-the-accelerator
2. Kuest, R. (2015) Group award for the best suppliers (e.g., Eisert [2]). Of those, we only analyze the return of a trading strategy. Due to personal risk-tolerance and regulations in the banking industry, it will be necessary to measure the ML-based trading strategies’ risk in terms of standard deviations, maximum drawdowns, and several other risk measures.

### Future work

Seeing the results, it will be fruitful to combine different ML methods. For example, Guo et al. [5] combine both LightGBM and LSTM models to predict the direction of the Apple stock. They only achieve an accuracy of 54.1%, but it would be interesting to enhance their approach to our regression problem with the information of the whole supply chain. Additionally, here we only analyzed the return of a trading strategy. Due to personal risk-tolerance and regulations in the banking industry, it will be necessary to measure the ML-based trading strategies’ risk in terms of standard deviations, maximum drawdowns, and several other risk measures.

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### Conclusion

This study provides evidence that trading strategies based on machine learning models and supply chains outperform simple buy and hold strategies. The Elastic Net generates a trading profit 1.5 times those of the buy and hold strategy in our base-case scenario. Further, using regression models instead of classification models, we can enhance the trading thresholds and only execute trades with an expected profit above a predetermined threshold.