Value at Risk estimation using **N**atural **G**radient **Boosting** for Probabilistic Prediction **model**

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Short introduction to the analyzed problem

- **Motivations:** The area of market risk forecasting using machine learning is not very popular among scientists. Only a few scientific publications deal with this problem. Most often them use very complex neural networks model (Bayesian Long Short-Term Memory, Variational Autoencoders etc.), which in the end are not able to rationally outperform the benchmark (classical econometric models) in case of VaR and capital requirements exceedances. The relatively new NGBoost model seems to be an interesting alternative to well established approaches.
- **Novel approach introduction:** NGBoost allows for probabilistic predictions which is the approach where the model outputs a full probability distribution over the entire outcome space. This functionality fits perfectly, among others to the problem of quantile distribution estimation in highly nonlinear environments.
- **Purpose of the work and main hypothesis:** The aim of this project is to estimate the 1-day 1% and 2.5% Value at Risk measure (based on daily logarithmized rates of return) for S&P 500 index using the NGBoost model with multiple explanatory variables. The model will be tested under special conditions of sudden increased volatility, i.e. during the first wave of the COVID-19 pandemic. I put forward a hypothesis: Will the NGBoost model perform better in the formal backtesting procedure than the GARCH econometric models in the case of 1% and 2.5% VaR estimation during COVID-19 period?

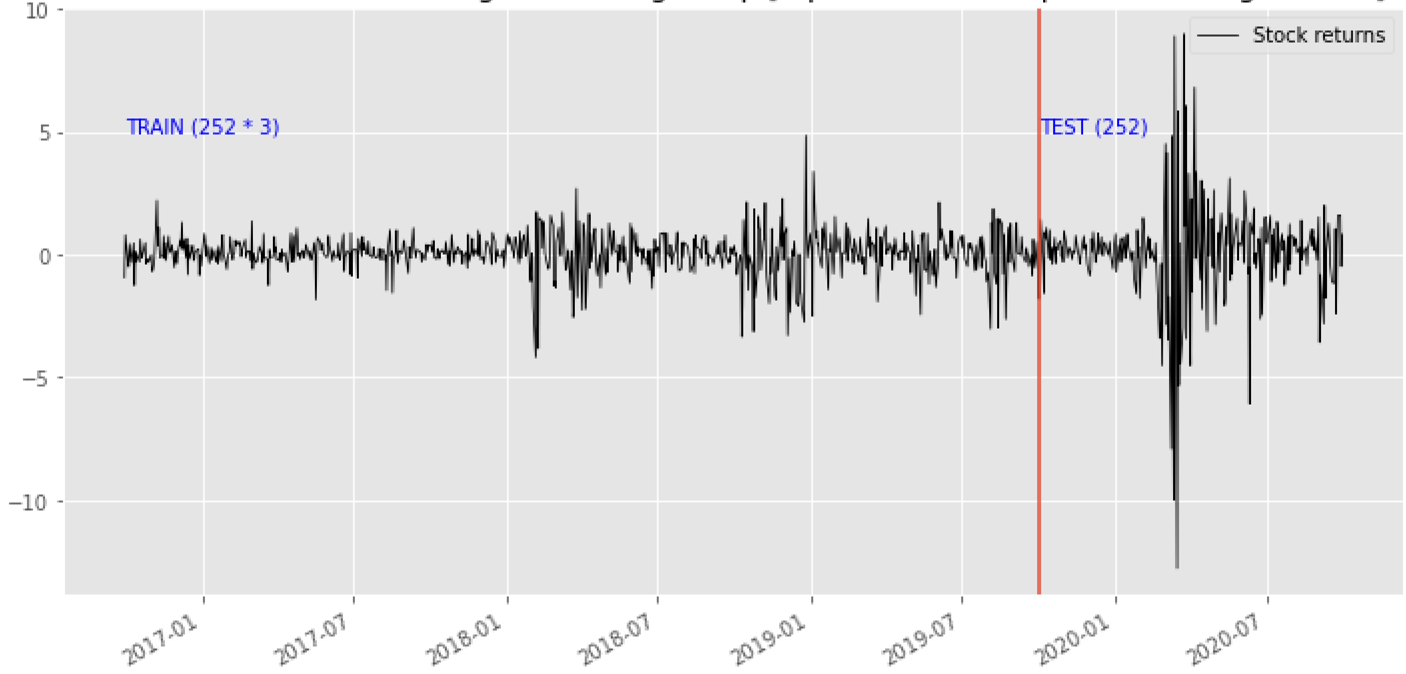
Dataset description

- Dataset provides daily Open price, Close price, Highest price, Lowest price, Volume information for the S&P 500 index.

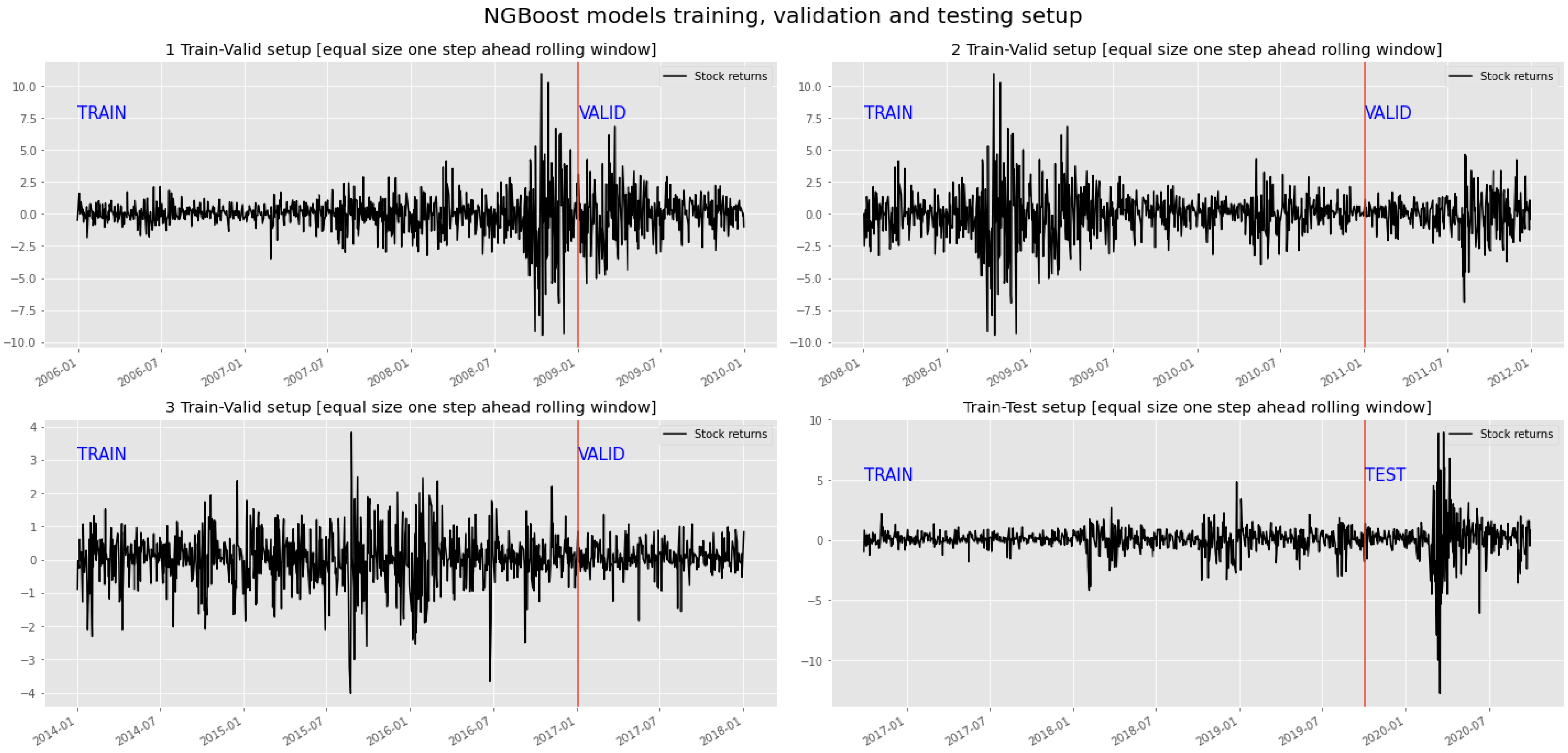
  For the purposes of the study, the target variable is the logarithmized rate of return $r_t = \ln(\frac{p_t}{p_{t-1}})$. The data covers the period from January 1, 2006 to September 30, 2020. The data comes from the website stooq.pl.
- The models will be trained, validated and tested in a one-step-ahead approach in a moving/sliding time window (always the same length of the training set - 3 * 252 days, and the validation/test set – 252 days).
- The dataset is divided into time windows: in-sample dataset (train), out-of-sample dataset (validation) and out-of-sample out-of-time dataset (test, which will undergo final backtesting). These windows vary depending on the modeling approach:
  - In case of econometric models I defined only two periods: training and testing, because here we do not deal with hyperparameters tuning [visualization on the following pages]
  - In case of machine learning models I definded 4 periods: 1 training and validation , 2 training and validation, 3 training and validation, final training and testing (analogy to econometric models periods!) [visualization on the following pages]. First three periods will be used in a cross validation with „number of VaR exceeds" metric!

Dataset description – cont’d

Econometric models training and testing setup [equal size one step ahead rolling window]



Dataset description – cont’d



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Dataset description – cont'd

Descriptive statistics for final training and testing period (same for econometric and machine learning models)

	count	mean	std	min	25%	50%	75%	max	skewness	kurtosiss
Final training period (2016-09-29 - 2019-10-01)	756	0.040097	0.805931	-4.18426	-0.2421	0.058973	0.443732	4.840324	-0.64889	5.512918
Final testing period (2019-10-02 - 2020-09-30)	252	0.053309	2.146715	-12.7652	-0.46783	0.232585	0.823434	8.968316	-0.90692	9.552796

Description of the selected models

- **Benchmark models:**
  - Simple statistical approaches: Historical simulation, Gaussian parametric mean-VaR, Laplace parametric mean-VaR
  - Econometric approaches (SOTA): GARCH (1,1), GARCH-t (1,1), GARCH-st (1,1), QML-GARCH (1,1)
- **My challengers:**
  - NGBoost – VaR estimation as the quantile of the full probability distribution of stock returns returned by the model
  - NGBoost – VaR estimation in the GARCH style i.e. model mean + model variance * quantile(model standardized residuals)
  - Ensembling with best NGBoost (in case of hyperparameters) and GARCH-st(1,1) by simple arithmetic mean
  - Switching model between best NGBoost (in case of hyperparameters) and GARCH-st(1,1)

Description of the selected metrics / backtesting

- **Loss function for NGBoost models**: negative log-likelihood
- **Main evaluation metric:** number of exceeds VaR
- **Additional formal VaR tests:** Kupiec test (unconditional coverage), Christoffersen test (conditional coverage) and Engle test (dynamic quantile).
- What is more I will also finally take into account the amount of financial provisions related to the VaR forecast.

List of the model hyperparameters

1. The output distribution (Normal, Laplace, T-student)
2. The base learner (any Sci-kit Learn estimator, default: 3-depth Decision Tree) and it’s hyperparameters (I will try: Elastic Net, SVR, DT and RF)
3. The number of boosting iterations (default: 500)
4. Learning rate (default: 0.01)
5. ~~The percent subsample of columns and rows to use in each boosting iteration (default: 1.0)~~

I will test most of these parameters (1,3,4) in a specially designed cross-validated random search procedurę (mentioned in the dataset description chapter).I will look for the best base learner out of the cross-validated random search procedure due to computational limitations.

I will also consider which variables (and their lags) are the most relevant for the output, because here NGBoost does not support time series problem from the default, I have to lag/shift variables to establish time series matrix-form.

List of ML packages

- Data wrangling: pandas, numpy
- Data visualization: matplotlib, seaborn
- Econometric modeling: arch, pyflux, scipy, statsmodels
- Machine learning modeling: ngboost, sklearn
- Others: tqdm, pickle, time

References

- Abad, P., Benito, S. and López, C., 2014. A comprehensive review of Value at Risk methodologies. The Spanish Review of Financial Economics, 12(1), pp.15-32.
- Buczyński, M. and Chlebus, M., 2018. Comparison of Semi-Parametric and Benchmark Value-At-Risk Models in Several Time Periods with Different Volatility Levels. e-Finanse, 14(2), pp.67-82.
- Buczyński, M. and Chlebus, M., 2020. Old-fashioned parametric models are still the best: a comparison of value-at-risk approaches in several volatility states. The Journal of Risk Model Validation.
- Chlebus, M., Dyczko, M. and Woźniak, M. 2019. Nvidia’s stock returns prediction using machine learning techniques for time series forecasting problem. https://www.wne.uw.edu.pl/files/6415/9481/5844/WNE_WP328.pdf
- Duan, T., Avati, A., Ding, D., Thai, K., Basu, S., Ng, A. and Schuler, A. 2019. NGBoost: Natural Gradient Boosting for Probabilistic Prediction. https://arxiv.org/abs/1910.03225v4
- Szubzda, F. and Chlebus, M., 2020. Comparison of Block Maxima and Peaks Over Threshold Value-at-Risk models for market risk in various economic conditions. Central European Economic Journal, 6(53), pp.70-85.