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Examiner report on PhD thesis "Essays in Time-Series Forecasting" by Filip Stanek.

This is a very good PhD thesis with two chapters already published as journal articles. The thesis makes three important contribution contributions to the area of forecasting. First, it proposes a new forecast evaluation method for stationary time series. The new method uses in-sample fit in addition to the standard out-of-sample evaluation and achieves good empirical results on the M4 dataset. The second chapter focuses on the multivariate volatility models and compares several versions of BEKK models by adding regularisation towards diagonal and scalar structures. Again, this contribution has practical recommendations for performing multivariate volatility forecasting via diagonal variants of volatility models estimated on a short rolling window to achieve the best forecasting performance. The final chapter describes the winning method of the M6 forecasting competition that balances the benefits of the global models with series-specific latent parameters to account for heterogeneity.

The thesis satisfies the formal and content requirements for a PhD thesis in economics, and I recommend awarding the PhD degree without a formal defence. My comments are below; comments for Sections 1 and 2 are optional, as they have already been published. The main comments for Section 3 are binding.

Sincerely,

Andrey Vasnev

Main comments

1. Stationarity is the critical assumption in Chapter 1. As it is formulated now, the stationarity of X_t is required. However, it should be possible to relax this assumption with the stationarity of the forecasting errors. The indirect support of this can be seen in the performance on the M4 dataset, where many series were non-stationary. The ETS and autoARIMA will be able to handle deterministic and stochastic trends, for example, as long as the innovations are stationary. This relaxation will make the method more general, and you might be able to get another publication using your idea.
2. With the COVID behind us, there are very few stationary series available. You might want to think about how to extend your method to the interrupted series; see Rob Hyndman's ITS paper https://robjhyndman.com/papers/fits.pdf
3. The background is not complete without forecast combinations that proved to be very successful in M4 competition. Here are some suggestions of the latest papers in this area to look at
    a. Xiaoqian Wang, Rob J Hyndman, Feng Li, Yanfei Kang (2023) Forecast combinations: an over 50-year review. International Journal of Forecasting, 39(4), 1518-1547.
    b. Frazer et al. (2023) https://doi.org/10.48550/arXiv.2308.05263
    c. Radchenko, P., Vasnev, A., Wang, W. (2023). Too similar to combine? On negative weights in forecast combination. International Journal of Forecasting, 39(1), 18-38.
4. In some areas contrast function is called the loss function, and loss is called risk; see Chen and Liu (2023) https://doi.org/10.1016/j.jeconom.2022.06.003
5. The optimal weight problem (1.17) reminds me of the optimal weight in the forecast combination area. You might want to check this area; see Rob Hyndman's overview paper in 3.a above, including shrinkage for the covariance matrix, negative weights, and equal weights.
6. The idea in section 1 is applied to forecast selection, but you can equally design a forecast combination instead.
7. For Section 2, I would recommend checking your method for the latest data period.

8. Your method in Section 3 is based on the same idea as Montero-Manso et al. (2020) https://doi.org/10.1016/j.ijforecast.2019.02.011 Only they used statistical models that were parametrised for a particular time series, while you use ML models instead. Please investigate this paper and include it in your references.
9. Your method also uses an implicit combination (across the meta parameters). Combinations are very successful in forecasting. If you connect your paper closer to this area, it will have a broader reach. Check Xiaoqian Wang, Rob J Hyndman, Feng Li, Yanfei Kang (2023) Forecast combinations: an over 50-year review. International Journal of Forecasting, 39(4), 1518-1547.
10. One-step formulation of your problem is in line with the recommendations of Frazer et al. (2023) https://doi.org/10.48550/arXiv.2308.05263 and can explain the excellent performance of your method.
11. Page 86, second paragraph: your stationarity assumption does not hold for stock prices. Please investigate and adjust it for the financial time series. You probably want to focus on returns and say something about mean stationarity, volatility clustering, etc.
12. Section 3.5.2 needs more details on missing values: what percentage of the data did you impute? Are your results sensitive to the imputation method?
13. Section 3.5.4 seems to be out of place. Perhaps you can leverage Makridakis et al. (2023) https://doi.org/10.48550/arXiv.2310.13357 to support your argument.

Smaller comments:

14. Last line on page 77: change ‘doesn’t’ to ‘does not’
15. Page 78, 7th line from the bottom: use Greek letters consistently