

Conclusion

This project investigated the effects of post-processing Covid-19 forecasts.

We focused on two families of post-processing algorithms, Conformalized Quantile Regression and Quantile Spread Averaging, and explained key characteristics of each method. Starting from the original CQR and the simplest uniform QSA method, we revealed their theoretical limitations and linked them to empirical findings in real-world data sets. Further, we proposed two modifications within each family which lead to greater flexibility and could potentially solve the detected shortcomings.

Finally, we compared the out-of-sample performance of each method. For the UK Covid-19 Forecasting Challenge data QSA improved the original forecasts by a greater amount than CQR. The best overall performance, however, is achieved by combining information of the individual methods into one ensemble model. Throughout the comparison we gained a deeper understanding by analyzing similarities and differences within and between the two post-processing frameworks CQR and QSA and showed that there is not a single method that dominates its competition across the entire feature space. Rather, the performance ranking highly depends on the original forecasting model, the forecast horizon, the quantile level and, in the context of Covid-19 predictions, the target type, i.e. Covid-19 Cases or Covid-19 Deaths.

From a technical perspective, we developed a fully functional R package which implements all individual post-processing methods and the ensemble model. The package is designed to be easily extendable in the future with few changes to the user interface. Due to computational hurdles that we faced during the implementation of Quantile Spread Averaging we leveraged parallel computing to make computations feasible.

There exist multiple directions to extend our work. The most straightforward approach is to research and implement further post-processing algorithms and compare their effectiveness with the existing methods. Further, one could apply our methods to more general forecasting domains unrelated to Covid-19 predictions and analyze which methods generalize best to new contexts. From a more global perspective, it might be valuable to collaborate with research groups of similar interests and integrate our package into a generic time series forecasting framework that unites the entire process of data pre-processing, constructing prediction models and ultimately fine tuning prediction results via post-processing.

Beyond our own project, we believe that research with respect to developing and understanding post-processing of time series forecasts is far from saturated and there remain many opportunities to consolidate and broaden the current state of knowledge.