Influence of hyperparameters on online aggregation with countable experts

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Abstract. Aggregating forecasts from multiple experts is a valuable method to improve prediction accuracy. Our work examines the influence of hyperparameters on the accuracy of the aggregation algorithm for a countable number of experts. We implement a time series generator with specified properties and an aggregating forecasting model. We conduct a series of experiments with various hyperparameters of the algorithm (including initialization weights, mixing scheme, train window). The experiments confirm that these hyperparameters have a significant influence on the algorithm's performance.

Keywords. *online learning; aggregating algorithm; prediction with experts' advice; Fixed Share, Mixing Past Posteriors (MPP)*

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Our work focuses on the problem of online time series forecasting using expert advice, particularly when dealing with a countable number of experts. This means that the pool of potential experts is not fixed beforehand, but rather new experts can be introduced dynamically over time. Inspired by the algorithm developed in [1], which tackles online prediction with countable experts, we investigate the critical role of hyperparameter optimization in achieving optimal performance. Our approach makes no assumptions about the underlying nature of the data, allowing it to handle deterministic, stochastic, or other types of time series.

The standard online learning framework for prediction with expert advice involves a master algorithm aggregating predictions from a set of expert models. At each time step, the master algorithm combines expert predictions, makes its own prediction, and then receives feedback in the form of a loss function. The goal is to minimize the difference between the master's cumulative loss and the best expert's cumulative loss, a metric known as regret. Traditional algorithms like Fixed Share [2] and Mixing

Past Posteriors (MPP) [3] assume a fixed set of experts. However, in many real-world scenarios, the set of experts can expand dynamically. This necessitates algorithms that can handle countable expert sets, like the GMPP algorithm proposed in [1], where new experts can be introduced at each time step.

This paper explores how key hyperparameters affect the GMPP algorithm's performance. We use a synthetic time series generator with specific properties to conduct an experimental study, which helps us control the underlying data dynamics and evaluate the impact of different hyperparameter configurations.

Our goal is to provide useful insights into the best hyperparameter settings for the GMPP algorithm, making it easier to use in real-world time series forecasting tasks with countable expert sets. We emphasize the importance of hyperparameter optimization for achieving optimal performance and contribute to a better understanding of online aggregation with countable experts. This work helps pave the way for more robust and adaptable forecasting solutions.

References

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