Meta-learning in movement prediction problem of aperiodic time-series data

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Analysis and forecasting on time-series data have received great attention from both the research community and businesses due to its popularity and the great benefits it brings in terms of economics and academia. However, while research on periodic time-series data has been expanded and achieved many positive results, aperiodic time-series data such as foreign exchange, stock price has not been studied in depth. Compared to periodic time-series data, this type of data has more complex properties, creating its own difficulties and needs to be solved by specially designed methods.

This paper proposes `Temporal-ML`, a new approach that combines Model-Agnostic Meta-Learning (`MAML`) and Bidirectional Long Shot-Term Memory (`BiLSTM`) to solve the problem of movement prediction (upward, downward) of aperiodic time-series data. The goal of the algorithm is to combine the ability to selectively extract temporal dependencies of `BiLSTM` and the ability to synthesize models with high generalization of `MAML`. Accordingly, `Temporal-ML` not only efficiently extracts temporal dependencies but also extract correlations between different datasets in the context of multi-source data.

In our experiments, we compare `Temporal-ML` and `NHITS` (state-of-the-art (SOTA) model in 2023) on two aperiodic time-series datasets `USD/JPY` (foreign exchange rate between US dollar and Japanese yen, sampled hourly from 2000 to 2024) and `multi-fx` (foreign exchange rate of 60 currency pairs between 18 countries, sampled daily from 2014 to 2024). The results on the two aperiodic datasets show the superiority of the proposed algorithm over `NHITS` on all classification metrics. On the periodic data, `Temporal-ML` achieves results equivalent to the baseline model. These results demonstrate the superiority of the proposed algorithm on aperiodic data as well as the equivalence of the SOTA model on periodic data.

Additionally, this work conducts an ablation study to deeply analyze the influence of each component in `Temporal-ML`. Based on the obtained results, the thesis proves the role of each component as well as the rationality in choosing algorithms in the combination process.

In summary, this work emphasizes the importance of designing a specific method for aperiodic time-series data. The discoveries in this thesis not only help to solve the difficulties in the process of analyzing and predicting aperiodic time-series data, but also directly promote the research community in finding effective solutions on this type of data. Consequently, the research can move from movement prediction to value-specified prediction.