A Framework for Model-Less Causal and Non-Causal Time-Series Forecasting

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This project proposes a fully model-free, parameter-free framework for time-series forecasting based on discretization and relative transition frequency matrices (RTFMs). Existing time-series forecasting frameworks rely on models and parameter tuning, which introduces complexity and limitations when data is scarce. The framework takes as input three time-series: a autocorrelation time-series (Xt), a correlation time-series (Yt), and a causality time-series (Z). A final forecast is produced by summing the output RTFMs for each input. The method was validated using data on U.S. aggravated assault cases (Xt), U.S. average temperature (Yt), and gallons of ethanol consumed per capita in the U.S. (Z). Forecast accuracy was evaluated using mean absolute deviation (MAD), mean squared deviation (MSD), and mean absolute percentage error (MAPE). The proposed method achieved a MAPE of 0.33%, outperforming the double exponential method (6%) and Winter's method (7%) on the same dataset. These results suggest that this model-free, frequency-based approach is a competitive alternative to classical model-based forecasting methods, especially in a low-sample setting. Limitations include in-sample evaluation and single-domain testing; future work will apply walk-forward validation across multiple datasets and benchmark against additional methods including ARIMA and machine learning based approaches.

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