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Original Article

Forecasting Financial Time Series with Grammar-Guided Feature Generation

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Abstract

The application of machine learning techniques to forecast financial time series is not a recent development, yet it continues to attract considerable attention because of the difficulty of the problem that is compounded by the nonlinear and nonstationary nature of the time series. The choice of an appropriate set of features is crucial to improve forecasting accuracy of machine learning techniques. In this article, we propose a systematic way for generating rich features using context-free grammars. Our proposed methodology identifies potential candidates for new technical indicators that consistently improve forecasts compared with some well-known indicators. The notion of grammar families as a compact representation to generate a rich class of features is exploited, and implementation issues are discussed in detail. The proposed methodology is tested on closing price data of major stock market indices, and the forecasting performance is compared with some standard techniques. A comparison with the conventional approach using standard technical indicators and naive approaches is shown.

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