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Source

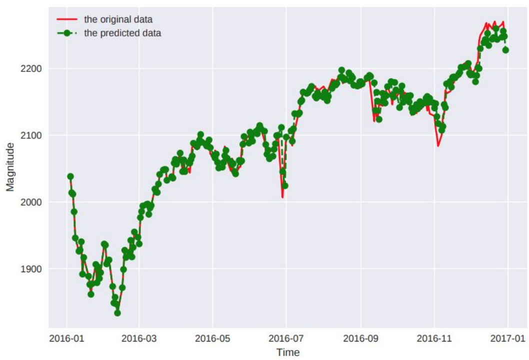
This paper employed a hybrid Wavelet + HFCM (High-Order Fuzzy Cognitive Map) method to create a one-step ahead predictive model for stock prices. FCMs have long been used to predict stationary time series, and the authors believed that using higher orders and introducing a Haar wavelet transform would allow it to predict non-stationary time series such as stock market data, as well as a variety of other types of time series data.

An HFCM is a type of fuzzy-modeling approach to predict time series. A FCM (Fuzzy Cognitive Map) can be represented as a directed graph where nodes represent concepts relevant to a given domain and edges represent causal relations between nodes; each edge has a weight value between -1 to 1 that reflects the nature of this causal relationship. A tanh of a weighted sum of the connections leading into a node is used to update the nodes at each step. However, in FCMs, the state value of each node at iteration T+1 only depends on all connected nodes at iteration T; as a result, they cannot effectively model long-term dependencies. To deal with this, HFCMs (higher-order FCMs) introduce a "memory parameter" that allows preceding values to have a greater impact on node values. The node networks can be created manually before being updated with ridge regression.

The approach used by the authors has two steps. First, the time series is normalized into the range [-1, 1]. The time series is then converted into a multivariate time series using a Haar wavelet transform (the level of the transform is determined experimentally by choosing the one that yields the lowest RMSE). Ridge regression is used to optimize the weight matrix for the HFCM by decomposing the HFCM into connections between individual nodes, which can be optimized separately and therefore more quickly. The optimized HFCM then predicts future values by summing up the values of all nodes in the HFCM while still in the "wavelet space" before reconstructing the original time series by reversing the wavelet transform and normalization.

I was able to find the code source for the paper on GitHub and attempt to replicate their results. Running the predictive model on the S&P 500 data used by the authors, I obtained a RMSE of 22.82 and MAPE of 0.223%; the former is comparable to the RMSE mark of 16.11

found in the paper. Below is a comparison of the graph given in the paper (left) and the graph I created with matplotlib (right) while replicating the paper's methods, which do appear similar. Due to the relatively promising results and reproducibility of the results, which were replicated on a variety of different time series from non-financial sources, this seems like a promising approach.



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