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Long short-term memory networks for CSI300 volatility prediction with Baidu search volume

Yu-Long Zhou, Ren-Jie Han, Qian Xu, Qi-Jie Jiang, Wei-Ke Zhang

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Present Address

Yu-Long Zhou, School of Mathematics, Sun Yat-Sen University, Guangzhou, P. R. China

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Summary

Intense volatility in financial markets affects humans worldwide. Therefore, relatively accurate prediction of volatility is critical. We suggest that massive data sources resulting from human interaction with the Internet may offer a new perspective on the behavior of market participants in periods of large market movements. First, we select 28 key words, which are related to finance as indicators of the public mood and macroeconomic factors. Then, those 28 words of the daily search volume based on Baidu index are collected manually, from June 1, 2006 to October 29, 2017. We apply a Long Short-Term Memory neural network to forecast CSI300 volatility using those search volume data. Compared to the benchmark GARCH model, our forecast is more accurate, which demonstrates the effectiveness of the LSTM neural network in volatility forecasting.

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