IBOVESPA index volatility forecasting using neural networks

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Introduction

In the financial market context, **volatility**, a measure of financial instrument's price variation tendency over time, has important uses such as in risk management and option contracts pricing. Specially for risk management, the ability to accurately forecast an asset's volatility over arbitrary time horizons is highly desirable, and many methods and models have been developed towards that end.

This works proposes using a long short-term memory **recurrent neural network (RNN)** to forecast the IBOVESPA index volatility, illustrated in Figure 2. IBOVESPA is Brazil's main stock market index, composed by stocks that represent 85% of total trading in the country's sole stock exchange, B3 [1]. By using a multitude of prices series correlated to the index to train the recurrent network it is expected that complex related patterns will be learned and the produced forecast would be more accurate than more traditional models such as GARCH.

Recurrent Neural Network

A **RNN** is a neural network specialized for processing sequences of variable length allowing for dependencies through time to be learned, where each position in the input sequences is seen as a time step. In particular, a long short-term memory (LSTM) network is a recurrent network further specialized for handling long term dependencies by using gates and dynamically created paths to control the influence of past values over state updates, as can be seen in Figure 1.

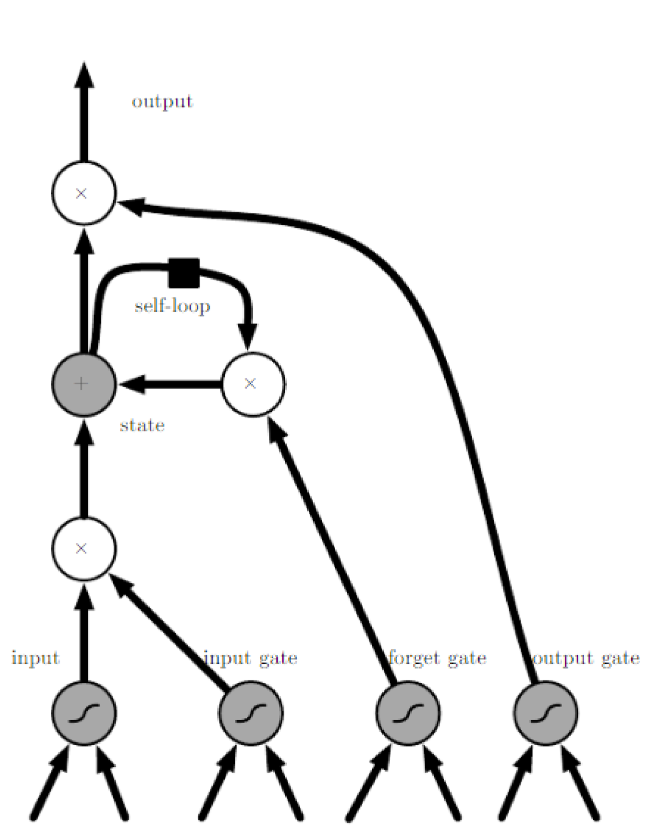

Figure 1: LSTM cell block diagram. [2]

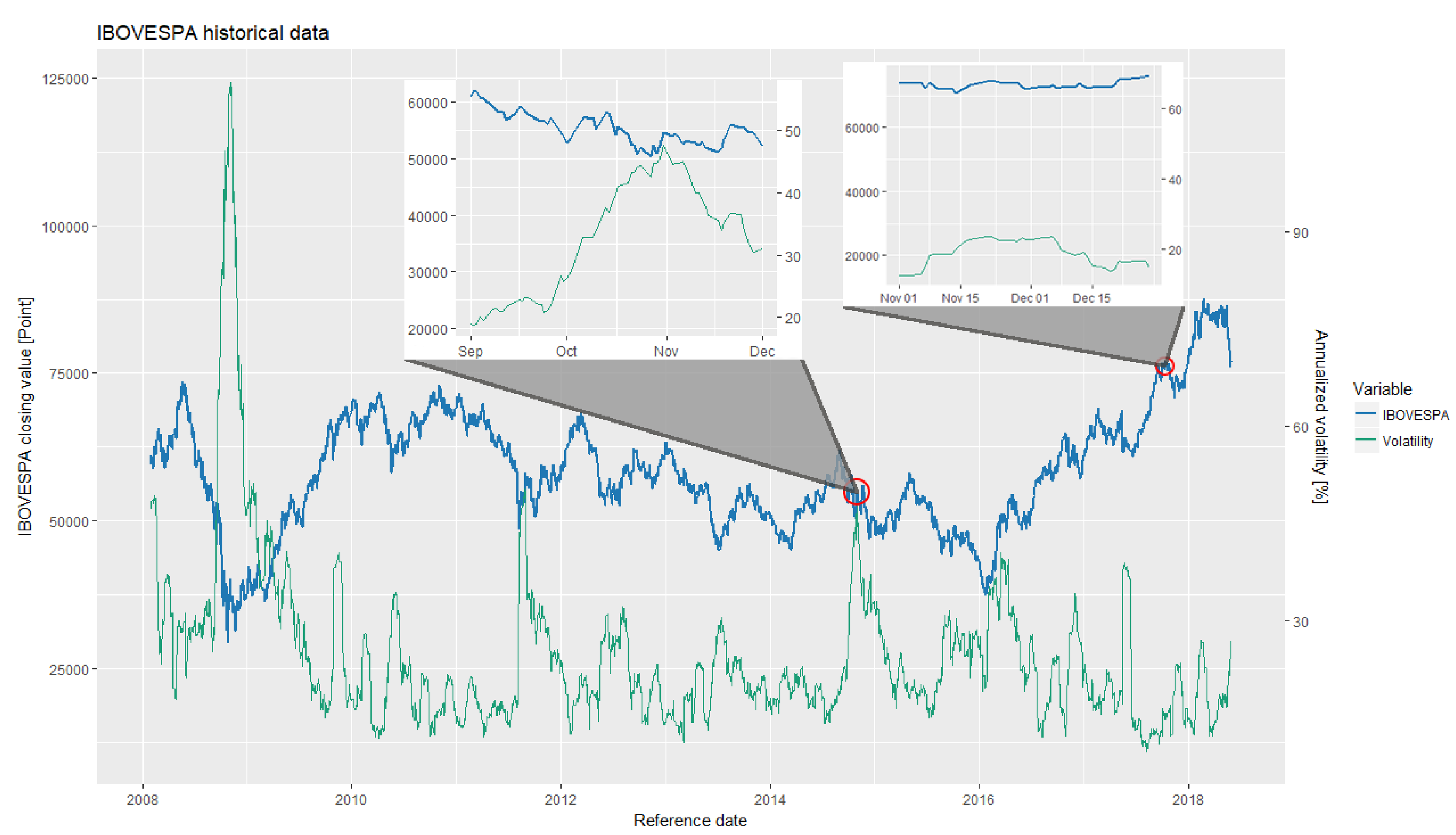

Figure 2: IBOVESPA historical data and its volatility series. A period of high volatility and another of low volatility are shown in the zoomed cut ins.

Dataset

A dataset with 10 years of daily trading data and economic indicators was built and analyzed, mainly by the conditional correlation over time to the index, resulting in the choice of the log-returns for the following time series inputs for training the neural network:

- IBOVESPA close points (IBOV)
- Dollar exchange rate
- Crude oil barrel spot price (WTI)
- 5 years interest rates
- Petrobras preferred stock spot price (PETR4)
- Vale common stock spot price (VALE3)
- Bradesco Bank preferred stock spot price (BBDC4)

All series were used both as is (vanilla series) and after passing through basic outlier removal (cleaned series) in order to also study the effect of outliers on forecasting. The volatility measurement used was the standard deviation of log-returns over 20 days periods.

Implementation

Ultimately, two RNNs with different architectures and a dual-stage attention-based RNN (DA-RNN) were implemented on PyTorch. The RNNs were composed of a dual-layer LSTM unit and a linear activation layer to produce the output, trained using the Adam optimizer over a segregated dataset in which the last 60 days of sample were removed for testing and the 502 days of sample prior to that were used as a validation set, the network with lowest loss over the validation set was picked. The DA-RNN added an attention mechanism in between the LSTM layers and was trained by batching the training dataset and minimizing the mean batch error.

For the sake of comparison, simple ARIMA and GARCH models were also fit to the data by using the *forecast* and *fGarch* packages in R. The ARIMA model was fit using *auto.arima* and a GARCH(1, 1) model was optimized with *garchFit*.

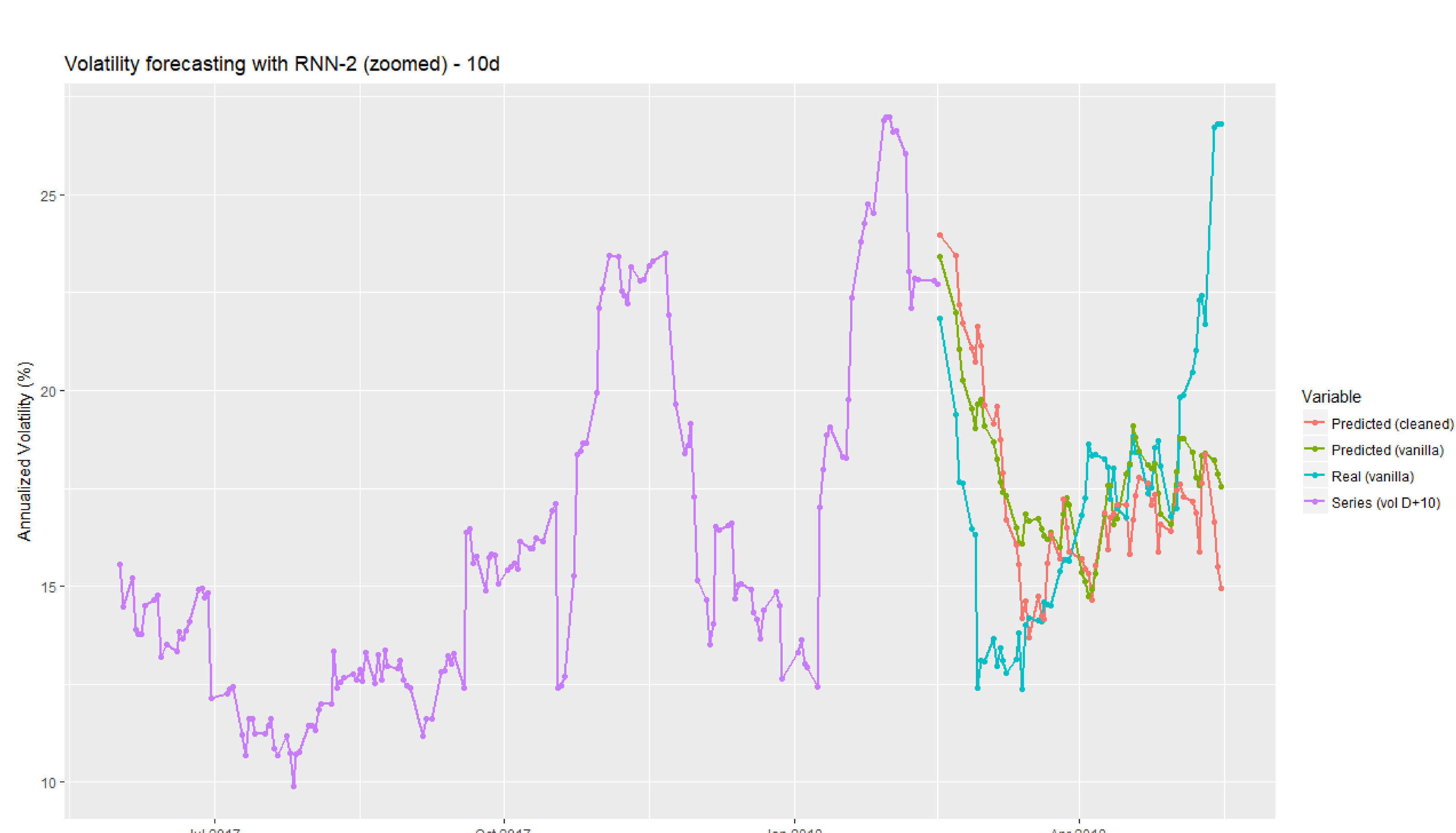

Figure 3: Forecasting results for the best performing recurrent neural network.

Experiments and results

Every implemented model was fit over the vanilla (Van.) and cleaned (Clean) datasets in order to generate forecasts for time horizons of 10 and 21 days for the last 60 days of sample. The predictions were then compared to the real values by mean squares (MSE) and mean percent (MPE) errors. A comparison of the best performing model results to real values in the 10 days forecast case can be seen in Figure 3 and a comparison of the errors between models for the same horizon forecast is presented in Table 1.

Model	MSE	MPE
ARIMA Van.	24.13	23.11%
ARIMA Clean	293.75	80.30%
GARCH Van.	27.07	29.00%
GARCH Clean	22.53	24.85%
RNN-1 Van.	19.92	22.89%
RNN-1 Clean.	19.65	20.25%
RNN-2 Van.	11.96	16.06%
RNN-2 Clean	16.80	17.42%
DA-RNN Van.	21.52	21.97%
DA-RNN Clean	22.67	21.20%

Table 1: Forecast accuracy by model - 10 days prediction

Conclusion

Results suggest recurrent neural networks are capable of producing significantly more accurate forecasts when compared to other methods. The difference in results between networks suggests further architecture and training method tweaking would likely improve results even further. It is also possible that adding other relevant series to the network's input could lead forecasts even closer to real values.

References

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[2] Ian Goodfellow, Yoshua Bengio, and Aaron Courville.
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[3] Source code, dataset and thesis.
https://github.com/ogaw4/MAC0499-Ibovespa-Volatility.