Recurrent Neural Networks in Forecasting S&P 500 index

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Objectives

The objective of this research is to predict the movements of the S&P 500 index using variations of the recurrent neural network. The variations considered are the simple recurrent neural network, the long short term memory and the gated recurrent unit. In addition to these networks, we discuss the error correction neural network which takes into account shocks typical of the financial market. In predicting the S&P 500 index, we considered 14 economic variables, 4 levels of hidden neurons of the networks and 5 levels of epoch. From these features, relevant features were selected using experimental design. The selection of an experiment with the right features is chosen based on its accuracy score and its Graphical Processing Unit (GPU) time. The chosen experiments (for each neural network) are used to predict the upward and downward movements of the S&P 500 index. Using the prediction of the S&P 500 index and a proposed strategy, we trade the S&P 500 index for selected periods. The profit generated is compared with the buy and hold strategy.

Introduction

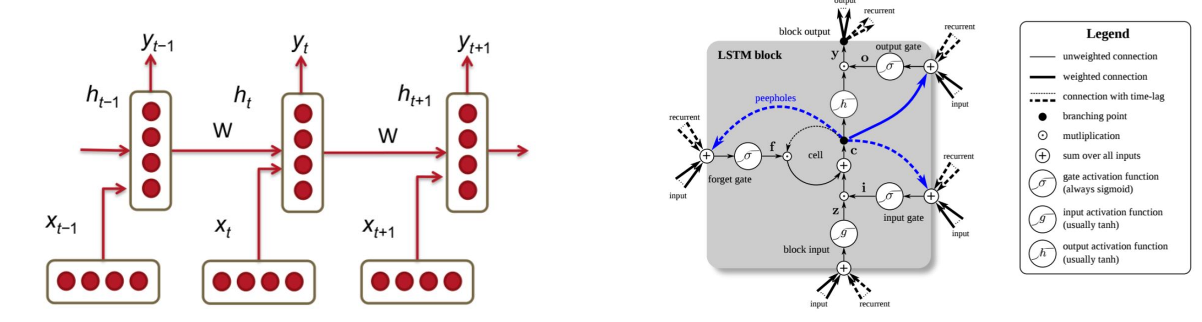

Figure 1: Simple RNN and LSTM

The simple RNN architecture in Figure 1 can be mathematically express as: $h_t = \sigma(W^{hh}h_{t-1} + W^{hx}x_t)$, and $\hat{y}_t =$ softmax $(W^{yh}h_t)$.. Using the back propagation algorithm: $\triangle W = -\eta\frac{\partial E}{\partial W}$ to update the weight. The LSTM archictecture is different in the sense that it usesa complex activation function that includes: *forget gate, new memory and final memory functions*.

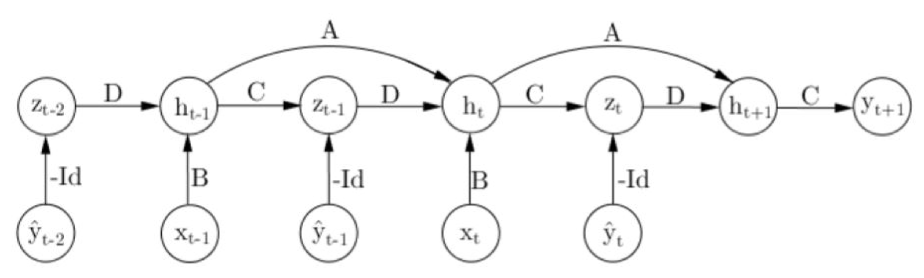

Figure 2: ECNN

Results 1

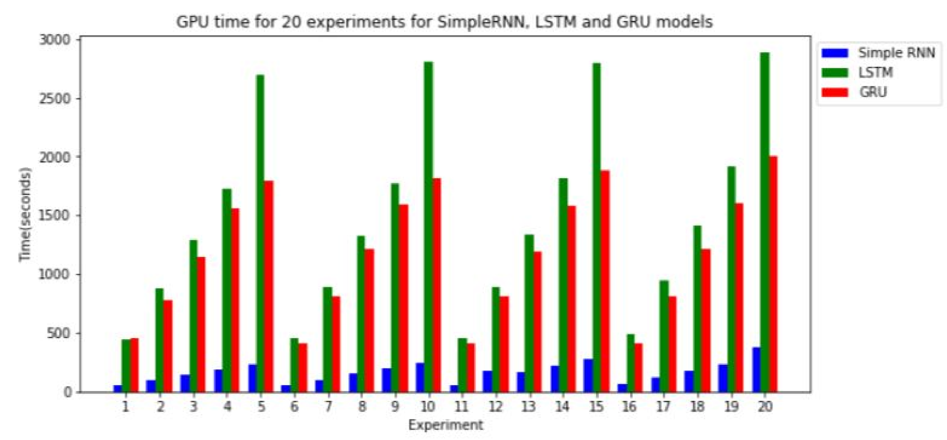

Figure 3: GPU time for 20 experiments

From Figure 4 and Figure 3, we select the experiment with best accuracy and least gpu time. Based on this, we will use the features of experiment 11 for the simple recurrent neural network i.e. the features of the Simple RNN model are: SPYt-1, JNJ, IXIC, and the parametres are: 75 hidden neurons and 40 epochs. Similaryly, the long short term memory we will use experiment 2, for the gated recurrent unit model we will use experiment 6. We observe that on average, experiment 6 performs best in the three different neural network models with a mean accuracy score of 74%.

In predicting the movement of the S&P 500 index for the next 99 days, the selected model for the simple recurrent neural network model predicted 74 trends correctly. Out of the 55 downward trends, only 15 were misclassified as upward trends. Also, out of the 44 upward trends, 10 were misclassified as downward trends. The long-short term memory model and the gated recurrent unit model both forecast 73 trends correctly, they misclassified 16 downward trends as upward trends and 10 upward trends as downward trends.

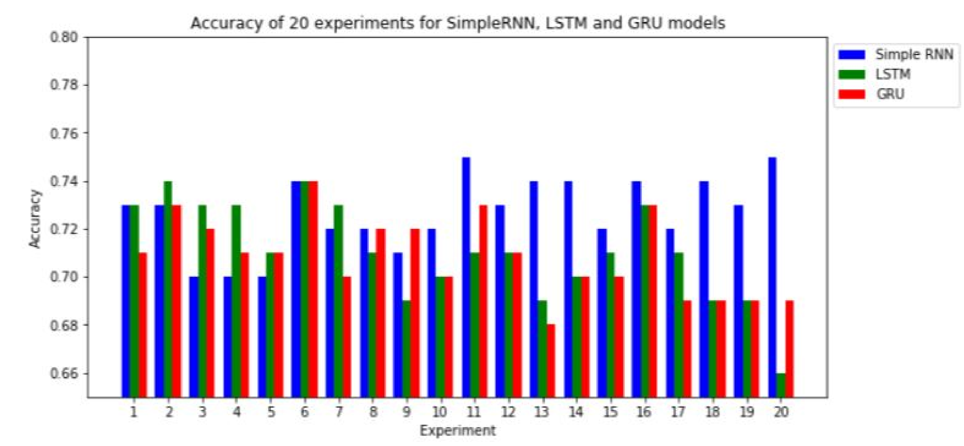

Figure 4: Accuracy plot of 20 experiments

Materials & Methods

Features	Description
SPYt-1,SPYt-2,SPYt-3	Previous daily price of S&P 500 index
HIS, FCHI, FTSE, GDAXI, IXIC, DJI	Stock indices
XOM, PG, GE, MSFT, JNJ	SPY asset with strong weight average
25, 50, 75, 100	Number of neurons in the hidden layer
40, 80, 120, 160, 200	Number of epoch

Figure 5: Features for forecasting S&P 500 index

- The market indexes covers 1st January, 2009 to 1st April, 2017.
- Apply the neural models to each of the selected experiments from the experimental design.
- Compare trading profit of best experiment to the *buy and hold strategy*.

Results 2

Figure 6 shows the simulation of the profit generated for the trading periods (1 week, 1 month, 3 months, 6 months, 9 months and 1 year), using the buy and hold strategy and the proposed strategy based on the Simple RNN forecast.

Figure 6: Profit simulation of trading strategies

Conclusion

- We discussed and applied the Simple RNN, LSTM and GRU to forecasting S&P 500 closing price.
- Using experimental design, for each of Simple RNN, LSTM and GRU we performed 20 experiments to determine which of the experiments give the best accuracy score and the least gpu time.
- We find these features: SPYt-1, JNJ, IXIC closing price relevant and uncorrelated. Furthermore, it was sufficient to use 75 hidden neurons and 40 epochs for the Simple RNN model, 25 neurons and 80 epochs for the LSTM model and 50 neurons and 40 epochs for the GRU model.
- The three selected experiments for these models were able to predict the movement of S&P 500 index closing price with an accuracy of 75%, 74% and 74% respectively.
- We compared the profit generated (for different trading periods) from *buy and hold strategy* with that based on Simple RNN predictions. We find that the Simple RNN performs better.

References

[1] R. Neuer H. Zimmermann and R. Grothmann. *Modelling and Forecasting Financial Data*. Springer US, 2002.

[2] S. Hochcreiter and J. Schmidhuber. Long-short term memory. *Journal of Neural Computation*, 9(45):1735–1780, 1997.

Future Research

In this research, we only discussed the Error correction neural network from a theoretical perspective. Further work could involve implementing and applying ECNN to time series prediction problems.

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