Ryerson University
Data Science & Analytics Graduate Studies

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Deep Learning to enhance momentum Trading Strategies using LSTM on the Canadian Stock Market

Rafik Matta

Supervisor: Dr. Alexey Rubstov

Objective

Applying machine learning techniques to historical stock market data has recently gained traction, mostly focusing on the American stock market. This paper aims to add to the literature by applying similar methods to the Canadian stock market, focusing on time series analysis for basic momentum as a starting point. Using long-short term memory (LSTM), a type of recurrent neural network, we do a comparative analysis of the results of the LSTM to a simpler logistic regression (LOGIT) approach as well as a basic momentum strategy for portfolio formation.

Background

With the recent proliferation of machine learning in financial research due to increased awareness and access to powerful hardware, we aim implement the use of modern machine learning techniques on Canadian stock data, similar to recent research that has been doing so for US stock data. Our main aim is to add to the existing literature for the Canadian Stock market which is scarce. We aim to replicate and enhance a well studied stock market phenomena called momentum, using recurrent neural networks in the form of long-short term memory networks (LSTMs). LSTMs are particularly suitable for this task as they do well with time series data and have shown promise in literature for the US Stock Market as well as other assets and financial instruments such as derivates.

Methodology

Our methodology is a multi-step approach to experimentation that borrows from standard data science, machine learning, financial analysis and statistical analysis practices as follows:

1. We first perform an exploratory data analysis to determine appropriateness of the models being applied
2. The raw data is then split into overlapping study periods (by time), composed of training sets (for in-sample training) and trading sets (for out-of-sample predictions)
3. The classification results of a basic classification with logistic regression are used to serve as a benchmark for comparison as a simple and well understood machine learning stochastic method
4. The LSTM is used to predict similar classification results (Fig 1)
5. A basic momentum strategy following Jegedeesh and Titman (1993) is applied for portfolio construction. This uses basic returns and selects for the winners and losers at the end of each month creating a long-short portfolio
6. A similar portfolio construction method is applied to the output of both the LOG and LSTM
7. Finally, the financial performance of the basic momentum strategy, LOG, and LSTM are assessed and compared.

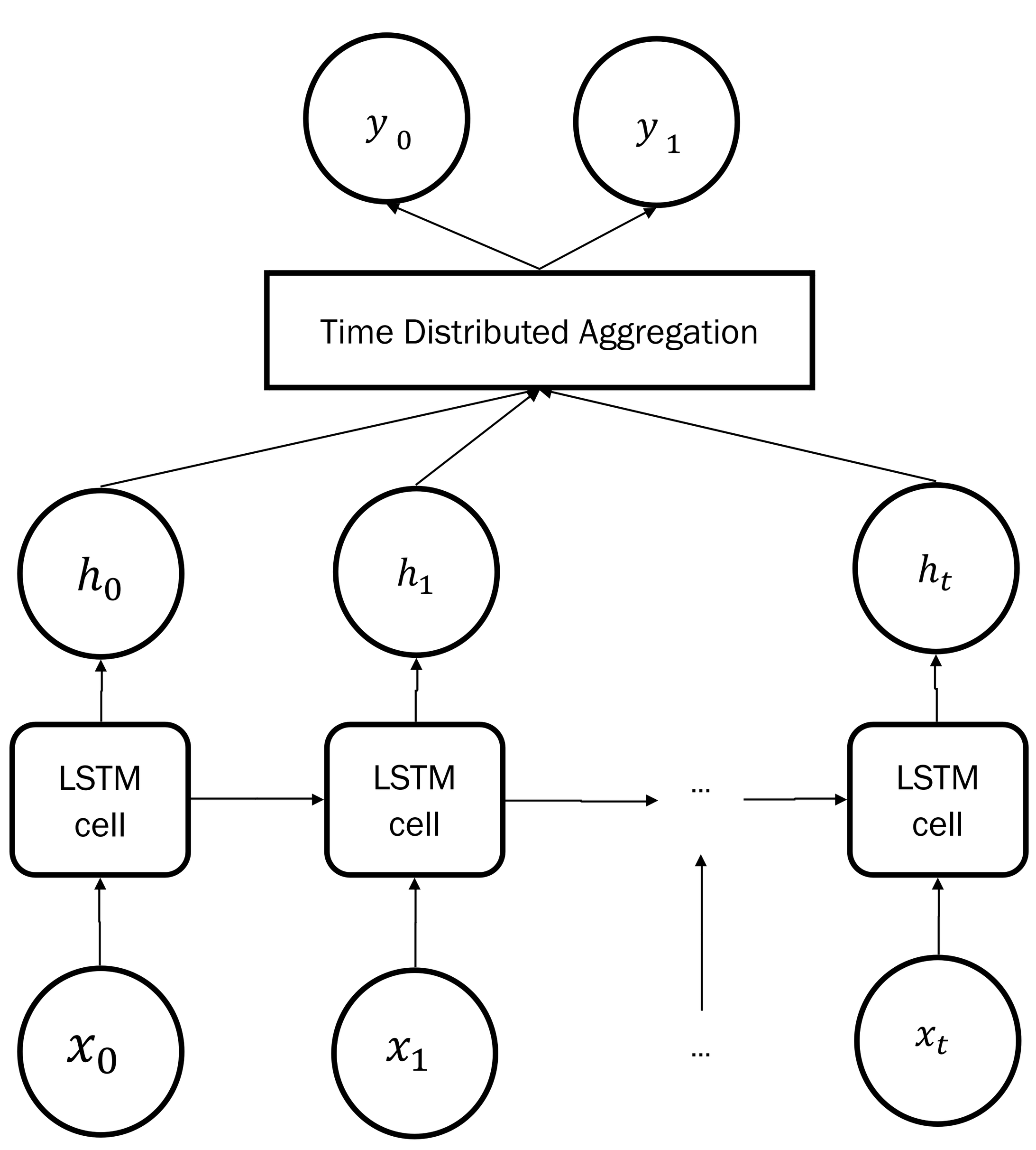

Fig 1. LSTM Architecture

Results

Overall, the LSTM formed portfolio performed substantially better than both the LOG as well as the basic momentum portfolios. This can be seen in Fig 2.

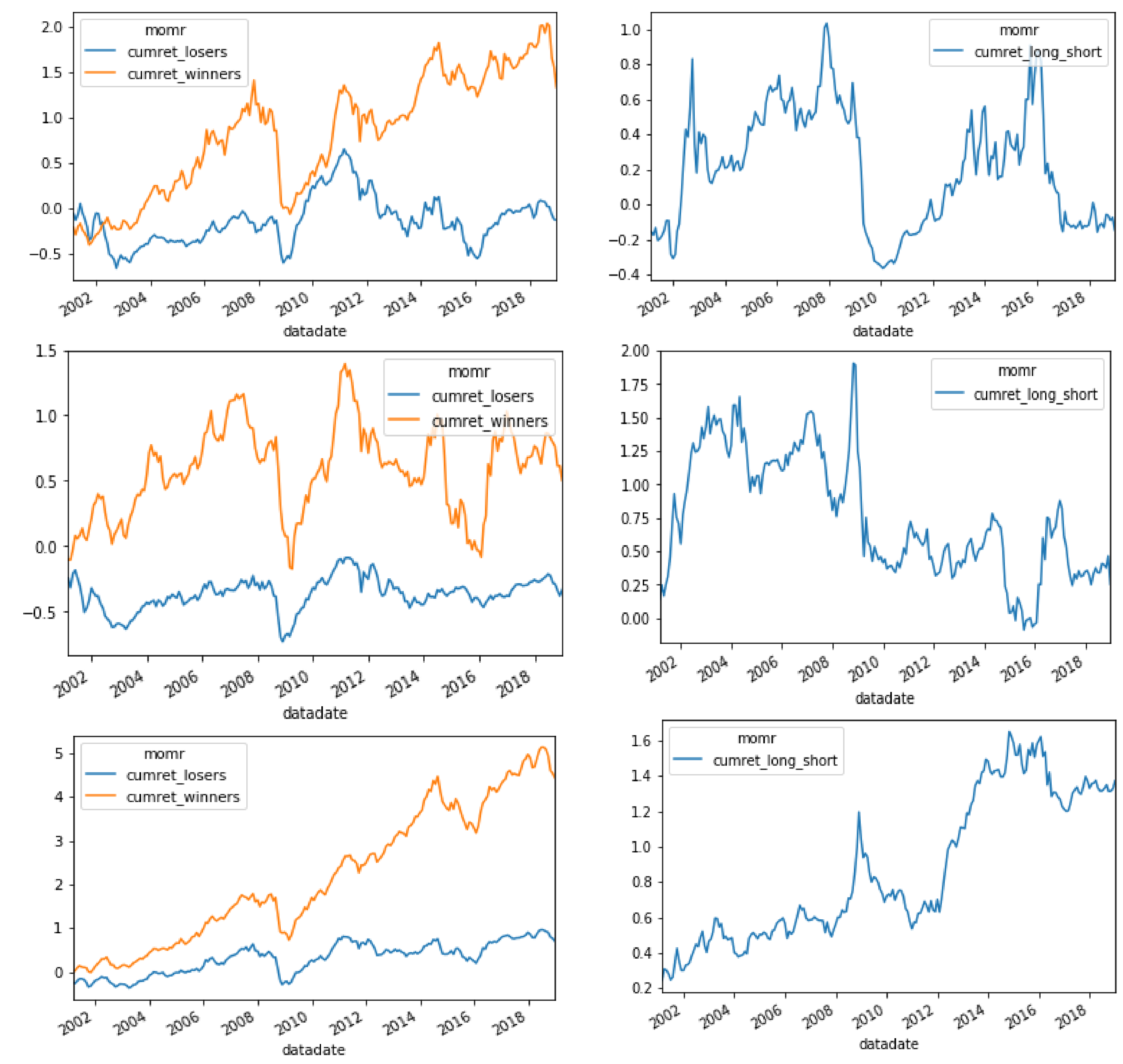

Fig 2. Portfolio Performance for Winner vs Loser Portfolio (Left), and Long-Short Portfolio (right) going from Basic Momentum (top), LOG (middle), and LSTM (bottom).

We see the underperformance of the LSTM within its AUC of the ROC Curves for all 17 test years in Fig 3.

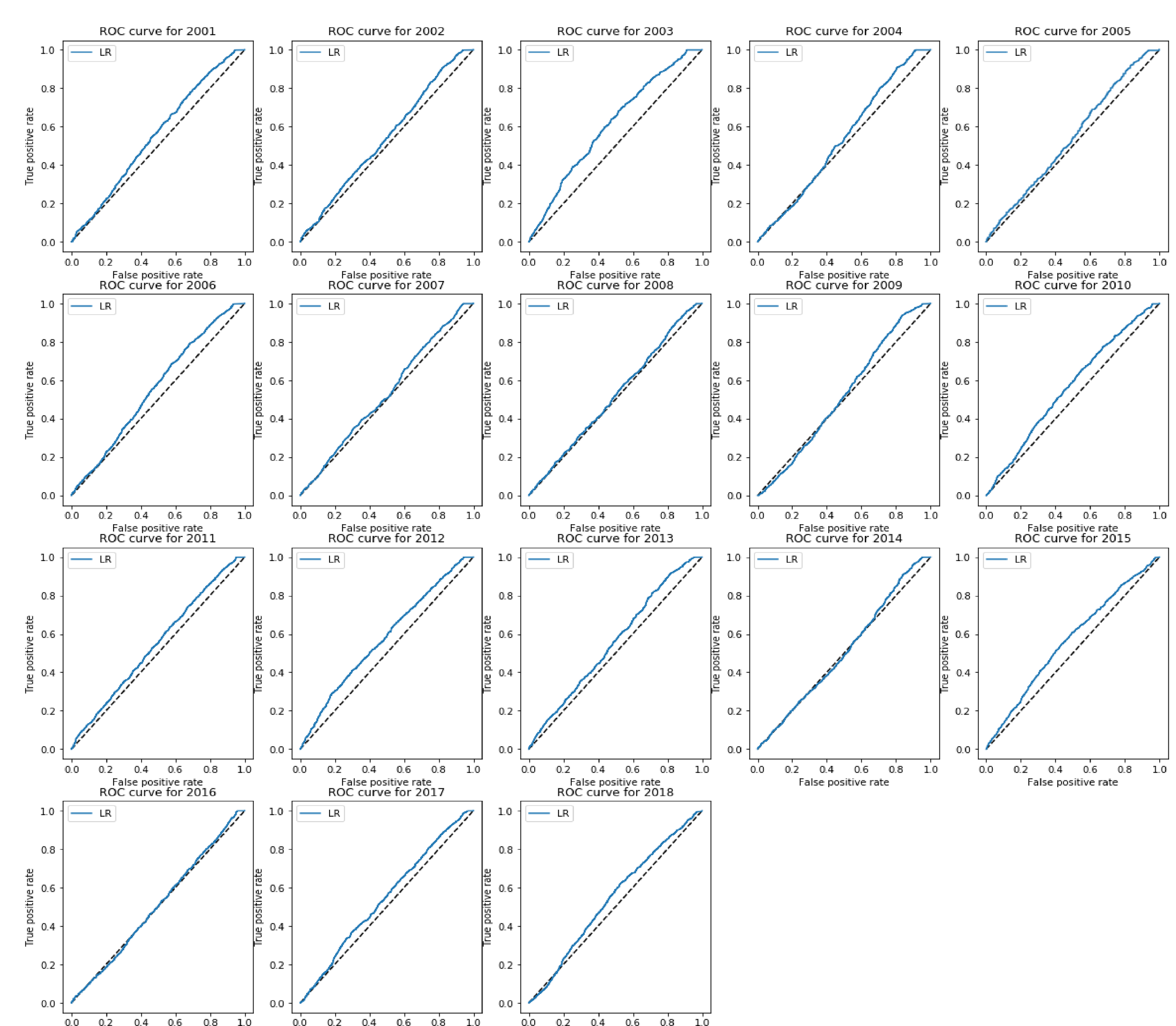

Fig 3. ROC Curve for 17 out of sample years

Conclusions

Although the financial performance of the LSTM shows substantially better returns over the out-of-sample test periods as well as a higher Sharpe Ratio (risk adjusted returns), the results need further investigation given the AUC of the ROC Curve. Our LSTM model does not perform much better than a Random Walk. Similarly, it's average accuracy is lower than the LOG method. We can take multiple approaches to remedy this in future studies, but there is potential that monthly data is not sufficient for an LSTM. Given the financial performance of the LSTM vs. the other approaches, the sentiment is this warrants further study.