Recurrent Neural Networks (RNN) for stock market prediction

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*Abstract*— The stock market prices generate sequential data in batches that is an ideal candidate for applying Machine Learning and Big Data management. There are several factors that affect the stock market prices which make it challenging for machine learning algorithms to train a model and these include irrational and rational trends, market talks, physiological versus physical factors and in the modern time even tweets from strong personalities can swing the prices with no pattern that a model can analyze and learn.

In this project we attempt to develop a RNN (Recurrent Neural Network) with memory popularly known as LSTM (Long Short-Term Memory). We aim to train this model with historical data for 1 ticker symbol from the last 5 years. With this trained model we will try to predict the live price and trend of the ticker on a stock market trading day.

Keywords—Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN), Machine Learning, Alpaca API.

# Introduction and background work

RNN model is a type of neural network that is used in predicting outcome in continuous data and can comprehend provided data better than any other machine learning algorithm [1]. LSTM model is a type of RNN model which can store details related to data for longer time frames and later utilizes that information to process, predict and classify it [2].

Investment corporations have been researching and investing to explore how AI or machine learning models can be utilized to improve the understanding of the stock market movement and accurately predict stock prices. The historical market data that is readily available and distributed by various APIs can be fed to Machine Learning models that can be tuned to give out its predictions based on the trends it analyzed in the historical data.

Historically the analysis and studying of market trends are done by humans in investment companies which provide users with research and possible stock trends, and it is a thriving market. Even though the consensus by every stock expert is that the prices cannot be predicted correctly because of the underlying market sentiment and various other factors that can affect the prices, it cannot be denied that the historical data available has a wealth of information to determine trends at least on an average day where external influences are low. There are investment and banking companies hiring machine learning analysts to build predictive model to prepare software that allows algo trading or predicting prices for users who subscribe to their services.

In this project, we first started working on getting real time streaming data for stock prices using Alpaca API [6]. We used the historical data provided from Alpaca to get data from stock market for development during off market hours and weekends.

Once we got the necessary ticker data from the API following is the plan, we formulated to get the whole system working. Data received as JSON from the stock market on a web socket is sent to a Kafka topic. This JSON is consumed by a Spark streaming application that reads data written to the above Kafka topic. The received data is sent as batches to a reading function that would process it and update the test data set that would be used by our custom LSTM model. Then we use the data to train the model and give out a predicted stock price for the next time step (5 minutes). Once this is done, we would replace the trained model with the new model and wait for the next data coming to the streaming application.

To achieve this, we had to build our custom LSTM model. To ensure we had a baseline to refer to, we did some analysis using the tensorflow LSTM library and ran some numbers to ensure we have data to compare to. Next step was to build the model. We used the numpy library for basic matrix calculations and array management. After numerous attempts we were able to build a basic LSTM model with 1 hidden layer that was giving out results with a fair accuracy.

While running the model on the test data we realized that the speeds observed were unrealistic for real world computation. With further analysis we realized that using GPU would give us better results. We used the numba library to make changes to the model code to make it suitable to be run on GPU. With the new LSTM module, we observed that the performance improved drastically. We decided to keep both versions of the code as the initial LSTM class is more readable and organized in comparison. Also, the GPU version needs more work to make it compatible with numba to observe more performance improvement.

# Theoretical and conceptual study

We as human beings do not forget everything we have learned and start analyzing and understanding things from scratch. Generally, normal neural networks are not able to learn from past events which is their vital shortcoming. They are not able to process details from one step to another. This issue is addressed by Recurrent Neural Networks (RNN) because they have loops inside them which allows information to stay within them [5].

Diagram

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Figure 1: Loops inside Recurrent Neural Network [5].

In figure 1, *A* (piece of neural network) gets *Xt* as the input and outputs *Ht* as the outcome. The loop that is shown in this figure enables the details to move from one step to another. We can think of recurrent neural network as something that has several duplications of an identical network and each duplicated network is transferring a message to a successor [5].

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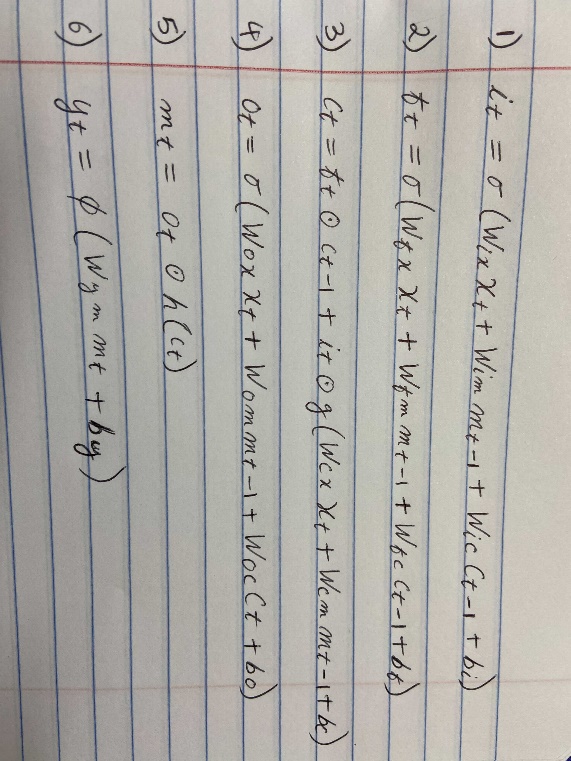
Figure 2: Unrolled Recurrent Neural Network [5].

Based on figure 2, we can come to a conclusion that RNN are related to lists and sequences. This chain-like nature of RNN is the natural architecture of neural networks. RNNs have been successfully applied in several subfields of computer science such as speech recognition, image captioning, language modelling etc. A very special type of RNN known as LSTM has also been successfully used for many tasks which is a much better version of RNN [5].

RNN are capable of making predictions based on past events that are recent. They can learn by using past details. However, if the gap between the past event and the current step is large then RNNs are not able to connect the information. So, in this scenario, LSTM helps in resolving this shortcoming. LSTMs are a special type of RNN because they help in preventing long-term dependency problem [5].

Memory blocks are the special units of LSTM inside the recurrent hidden layer. Memory cells are a part of memory blocks which have the ability to self-connect and store network’s temporal state. They also contain gates which are a special multiplicative units to control the flow of information. Output gate and input gate were included in each memory block inside the original architecture. The flow from input activations to the memory cell is controlled by the input gate. The flow from cell activations to the rest of the network is controlled by the output gate. Memory block was later on expanded further by adding the forget gate to it which resolved the weakness that LSTM models had with operating continuous input stream data that is not divided into arrays. Memory cell’s internal state is scaled by the forget gate before including it as input to the cell through the connection of the cell that is self-recurrent, thus adaptively forgetting or rebooting the cell’s memory. Furthermore, to learn accurate timings of the outputs, peephole connections was included inside the modern LSTM architecture from its internal cells to the gates in the same cell [3].

Input sequence and output sequence are utilized by the LSTM network to compute a mapping between them by utilizing the following equations iteratively from t=1 to T, to calculate the network unit activations:



The term W in these equations depict the weight matrices, for example, from the input gate to the input, *Wix* is the matrix of weights. For peephole connections, *Wic*, *Wfc*, *Woc* are the diagonal weight matrices. Term *b* denotes bias vector, sigma depicts the logistic sigmoid function, and *c*, *f*, *i*, and *o* are cell activation vectors, forget gate, input gate, and output gate. All of these have the same size as the cell output activation vector *m*. Symbol dot is the element-wise product of the vectors, *h* and *g* are the cell output activation functions and cell input. Normally, *theta* and *tanh* are utilized as softmax and network output activation function [3].

Equation 1 is the input gate. Weight matrices used in this equation embody the memory of the cell. The input *Xt* used in this equation is in the current input timestep, whereas *c* and *m* are indexed with the preceding timestep. Every matrix *W* in this equation can be considered as a matrix multiplication or a linear layer. With this equation we can take several linear combinations of *x*, *m*, *c* and match *m* and *c* with the dimensionality of input *x*. In PyTorch deep learning framework, the hidden state parameters are conceptualized as the dimensionalities of *c* and *m*. Hidden states used to be previously referred as neurons but that term is now deprecated. Furthermore, the term *b* also called bias vector, is a fragment of the linear layer and is a trainable vector. The value that we get as the outcome is in the dimensionality of the hidden and cell vector. Thus, we get a non-linear activation function to initiate non-linearities which permits the learning of more complex representations after three linear layers from different inputs. Sigmoid function is mostly used in this scenario [4].

Equation 2 is the forget gate and it is very similar to equation 1. One thing to note here is that the weight matrices in this equation are different. This implies that we would receive a different set of linear combinations which will give different results. We may want to apply different steps while modelling even though the equations might be similar [4].

Equation 3 is the new cell vector. This equation is another linear combination of the hidden and input vectors which makes it different from the previous equations. Purpose of this equation is to keep track of previous states. In this equation we filter the information of the new cell by implementing an element-wise product with the input gate vector *i*. After this the forget gate vector becomes operational. Element-wise vector multiplication is first performed with the previous cell vector rather than just appending the filtered input details [4].

Equation 4 can be called as the almost new output. New computed cell state will be utilized in this equation as compared to equations 1 and 2. This equations helps in computing the output vector of a single cell in a specific timestep [4].

Equation 5 can be called as the new context. This equation is used to compute the new hidden state. The aim of this equation is to combine the cell vector *ct* with the computed output vector *ot*. Equation 4 is just creating an output but in this equation, we are also injecting the vector called cell [4].

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Figure 3: Long Short-Term Memory Unit diagram [4].

In figure 3, it is shown that a cell receives another cell and hidden state as inputs from the preceding timestep. And the current timestep sends the input vector to a cell. A hidden state and the new cell state are outputted by each cell inside LSTM. These outputs are utilized in processing the subsequent timestep. The output of the cell is its hidden state.

Following are the three architectural diagrams of our LSTM project:

Diagram

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Figure 4: Backend Architecture diagram.

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Figure 5: Code Architecture diagram.

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Figure 6: System Application Architecture diagram.

# Results and analysis

We tried running LSTM library model on different datasets with several parameter combinations. There are three levels of data being tracked in the graph. The blue line represents the close price of Apple stock based on the historical data. The red segment predicts the future price of the stock centered on the historical close price, while the green line indicates the actual state of the stock price on the ground.

From the graph, we can safely conclude that the real stock price went up while our model also predicted that the price of the stock would go up. This clearly shows how powerful LSTMs are for analyzing time series and sequential data.

For layer activation functions, we use *relu* and *sigmoid* algorithm while *adam*, *adamax,* and *sgd* for Keras API optimizers.

After we saw the results, we analyzed and concluded that graph numbers 3, 7, and 9 configurations are more realistic.

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Graphical user interface, chart

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Figure 7: Graph 1 (dataset: apple\_data.csv).

Parameters we used in graph 1:

• **Loop\_back = 1**

• **Batch size = 20**

• **Activation = ‘relu’**

• **Epochs = 5**

• **Optimizer = adam**

• **Loss = ‘mse’**

Chart

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Figure 8: Graph 2 (dataset: apple\_5min\_data.csv).

Parameters we used in graph 2:

**• Loop\_back = 1**

**• Batch size = 20**

**• Activation = ‘relu’**

**• Epochs = 5**

**• Optimizer = adam**

**• Loss = ‘mse’**

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Figure 9: Graph 3 (dataset: apple\_5min\_data.csv).

Parameters we used in graph 3:

**• Loop\_back = 10**

**• Batch size = 32**

**• Activation = ‘relu’**

**• Epochs = 20**

**• Optimizer = adam**

**• Loss = ‘mse’**

Chart

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Figure 10: Graph 4 (dataset: apple\_5min\_data.csv).

Parameters we used in graph 4:

**• Loop\_back = 50**

**• Batch size = 24**

**• Activation = ‘relu’**

**• Epochs = 50**

**• Optimizer = adam**

**• Loss = ‘mse’**

Graphical user interface, application, Word

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Figure 11: Graph 5 (dataset: apple\_5min\_data.csv)

Parameters we used in graph 5:

**• Loop\_back = 100**

**• Batch size = 24**

**• Activation = ‘relu’**

**• Epochs = 100**

**• Optimizer = adam**

**• Loss = ‘mse’**

Graphical user interface

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Figure 12: Graph 6 (dataset: apple\_5min\_data.csv)

Parameters we used in graph 6:

**• Loop\_back = 10**

**• Batch size = 32**

**• Activation = ‘sigmoid**

**• Epochs = 20**

**• Optimizer = adam**

**• Loss = ‘mse’**

Chart, line chart

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Figure 13: Graph 7 (dataset: apple\_5min\_data.csv)

Parameters we used in graph 7:

**• Loop\_back = 10**

**• Batch size = 32**

**• Activation = ‘relu’**

**• Epochs = 20**

**• Optimizer = adamax’**

**• Loss = ‘mse’**

Chart

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Figure 14: Graph 8 (dataset: apple\_5min\_data.csv)

Parameters we used in graph 8:

**• Loop\_back = 10**

**• Batch size = 32**

**• Activation = ‘relu’**

**• Epochs = 20**

**• Optimizer = sgd**

**• Loss = ‘mse’**

Chart, line chart

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Figure 15: Graph 9 (dataset: apple\_5min\_data.csv)

Parameters we used in graph 9:

**• Loop\_back = 15**

**• Batch size = 32**

**• Activation = ‘relu’**

**• Epochs = 25**

**• Optimizer = adam**

**• Loss = ‘mse’**

# Conclusion and future work

In this paper, we discussed what RNN and LSTM are and how LSTM works from a conceptual standpoint. We shared architectural images of our LSM project. We also displayed our results that we got by running LSTM library model. While working on this project we realized how powerful LSTMs actually are and if used properly, they can help tremendously in accurately predicting real world data.

**Future Work**: We are currently using only 1 hidden layer which is giving us fair accuracy. In the future we can work on increasing the hidden layers which can help in improving the accuracy.

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