Using LSTM Network to predict Stock Prices

Franklin Jia - frankyj3@Stanford.edu

Introduction

- **Stock Price Prediction** is a difficult task to tackle given only publicly available data
- Predicting stock prices is best achieved by using a LSTM (Long Short Term Memory) because of its ability to remember information in the past
- **My goal is to build an LSTM network that can predict the prices of the following day, as well as the general tendency for a specified window of time.**

Data Preparation

- **Yahoo! Finance** publicly available data for S&P500 from January 3rd, 1050 until February 23, 2018
- **Closing Prices** were extracted from the the csv file using pandas
- Split the dataset into **windows** of a specified size, with the last value representing the price of the next day to be predicted
- **Normalize** the dataset by dividing prices within a window by the first price in that window and subtracting 1

Hyperparameter Tuning

Hyperparameter Tuning

- Tuned batch size, number of hidden units in layer, timesteps, number of layers, and number of epochs

Results (See Tables in Hyperparameter Results)

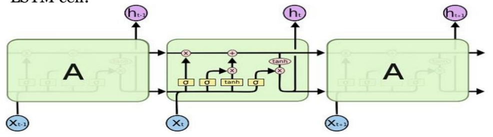
- Increasing batch size had little to no effect on the RMSE so chose **larger batch size** to decrease training time
- Increasing number of hidden units decreased RMSE dramatically in the beginning, so chose 30 to **balance training time and complexity** when RMSE stabilized
- Increasing timestep led to inncreasing RMSE, but increase was marginal, therefore intuitively **larger timestep** should enable algorithm to learn more about how past affects future
- Number of layers didn't affect the RMSE much so chose a more complex network with an RMSE that was still reasonable (**3 LSTM layers**)
- Number of epochs (50) chosen to **balance RMSE and runtime**

Model

Setup:
Coded in Python and used Keras with Tensorflow backend to build the model

Model:

- Linear stack of layers: **3 LSTM layers** of **30 units** each, fed into a Dense layer with **linear activation**
- Minimize **Root Mean Square Error** and used **RMSProp** as optimizer
- LSTM cell:



- LSTM cell has **forget, input,** and **output** gates which allow it to better capture long-term dependencies than standard RNN's

Prediction:

- **Day-by-Day** takes the test examples and predicts the next price and strings these predictions together
- **Whole Sequence** starts with the first window in test set, predicts next price, then cuts out the oldest price in window and appends the predicted price and predicts the next price on this new window (effectively shift by 1 using predicted data)
- **Tendency** performs the same process as Whole Sequence but only for a set number of days n. After n steps, it shifts forward by n and takes that window from test set and repeats.

Hyperparameter Results

Constant Hyperparameters: batch_size=512, num_epochs=10, cell_state_size=30, num_layers=1										
Time Step	1	5	10	20	30	50	75	100	150	200
RMSE	15.6342	16.1263	17.8642	17.2667	19.3238	18.7191	20.1120	23.5684	22.0322	23.1279

Constant Hyperparameters: batch_size=512, num_epochs=10, timestep=100, cell_state_size=30, num_layers=1					
Number of Layers	[1, 30, 1]	[1, 30, 30, 1]	[1, 30, 30, 30, 1]	[1, 30, 30, 30, 30, 1]	[1, 30, 30, 30, 30, 30, 1]
RMSE	23.0648	24.5531	28.0774	40.5112	35.5278

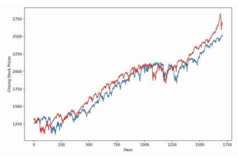
Constant Hyperparameters: batch_size=512, timestep=100, cell_state_size=30, layers=3									
Number of Epochs	1	5	10	20	50	70	100	150	200
RMSE	38.9027	33.8085	29.1995	30.3862	16.9379	18.1954	22.4314	15.9138	17.6349

Constant Hyperparameters: batch_size=512, num_epochs=10, timestep=50, num_layers=1							
Cell State Size	1	5	10	20	30	50	100
RMSE	82.7455	22.5114	23.6805	21.2036	19.2802	19.0261	17.0686

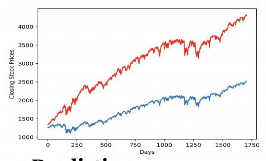
Constant Hyperparameters: num_epochs=70, timestep=50, cell_state_size=20, num_layers=1				
Batch Size	64	128	256	512
RMSE	15.7528	18.3372	17.4127	19.8010

Model Evaluation

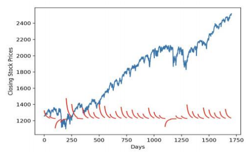
Day-by-Day Prediction



Whole Sequence Prediction



Next-50-Days Prediction



- The Day-by-Day Prediction scheme seems to be able to do a good job predicting the price at next day
- Predict Whole Sequence scheme looks like it has the general idea correct, but predicts at a scale that is much larger than actual movement
- Next-N-Days scheme seems to be predicting trends incorrectly, predicting downswings where there should be upswings

Conclusion and Future Work

- Both the Day-by-Day and Whole Sequence predictions proved to be rather successful at predicting the movement of the stock price
- The Next-N-Days prediction clearly still needs work as it is unable to predict the trends of the stock price correctly over the time period. This may be a result of compounding errors from using predictions from previous timesteps in the window for next timestep.

For future work, I'd like to focus on:

- Fixing Next-N-Days Prediction
- Building another network to predict stock price movement based on news articles and integrating that network with this one to see the results of predictions
- Making a framework to utilize my model real-time