High Frequency Trading Price Prediction using LSTM Recursive Neural Networks

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KAROL DZITKOWSKI

k.dzitkowski@gmail.com

TOMASZ KOZICKI

tom.kozicki@o2.pl

Warsaw University of Technology

Abstract

The Recurrent Neural Network (RNN) is an extremely powerful model for problems in machine learning that require identifying complex dependencies between temporally distant inputs. It is often used in solving NLP problems, therefore it can be suitable also for stock market prediction. In this work I will try to use recurrent neural network with long short term memory to predict prices in high frequency stock exchange. This paper will show results of implementing such a solution on data from NYSE OpenBook history which allows to recreate the limit order book for any given time.

I. INTRODUCTION

Long Short Memory RNN architecture has been proved to be suprisingly successive in sequence prediction resolving a problem with vanishing and exploding gradients. In this work I will use Hochreiter & Schmidhuber (1997) version of LSTM layer. The Long Short-Term Memory (LSTM) is a specific RNN architecture whose design makes it much easier to train. While wildly successful in practice, the LSTM's architecture appears to be ad-hoc so it is not clear if it is optimal, and the significance of its individual components is unclear - which was checked by Google in [1]. The aim of this work is to see if the solution will be suitable for predicting prices in stock markets, which are one of the most difficult time series to predict. Basing on time series data from NYSE OpenBook (which includes every ask and bid prices for one day) I will try to predict next bid or ask value. If there exist any long or short term dependency with historical data, my LSTM model should outperform basic perceptron which will be used for comparison. I will also check if changing LSTM model to GRU (Gated Recurrent Unit - Cho et al. 2014.) will decrease an error rate to establish which solution is best. All technical implementation will be done in Python using Keras [2] library based on Theano. For performance reasons most computations will be done on GPU using NVIDIA CUDA 7.5 technology.

II. USED METHOD

In order to gain some persistent knowledge in the network people invented Recurrent Neural Networks which address this issue. They are networks with loops inside them, allowing information to persist. In that way they are able to learn some long term dependencies between data in several time points. Usually we consider an unrolled RNN with some length
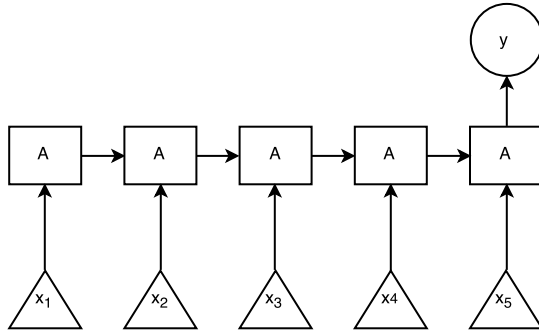
creating chain-like structure.

Figure 1: *Recursive Neural Network*

This way they seem to be related to sequences or lists, therefore it will be natural architecture of a network for all time series. In a normal, basic version the hidden layer A is just single *sigmoid* or *tanh* layer. Due to the fact that for learning such an architecture uses Backpropagation Through Time (BPTT) it is usually very difficult to train such networks. The problem is known as vanishing and exploding gradient which makes it impossible for the network to learn long term dependencies. It is solved by using Long Short Term Memory Networks (LSTM) that handles layer A differently. In that model A is more complex structure containing several *tanh* and *sigmoid* layers and +, * operators.
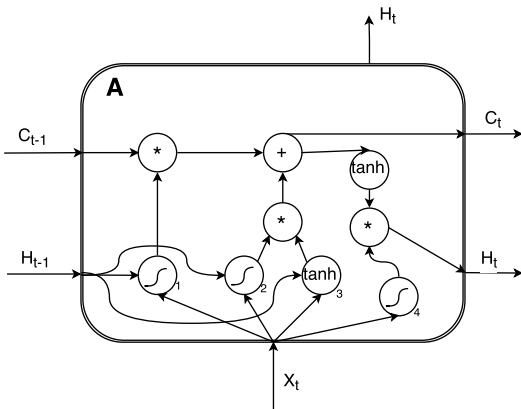

Figure 2: *Recursive Neural Network*

LSTM handles and passes something called the cell state. It can add or remove information to/from the cell and in that way he stores historical data. Mathematical definition of that architecture is shown below, where x_t is our input, H_{t-1} is the previous output and W_m are the weights in layer m:

$$\alpha_t = \sigma(W_1 * x_t + W_1 * H_{t-1} + b_1)$$
$$\beta_t = \sigma(W_2 * x_t + W_2 * H_{t-1} + b_2)$$
$$\gamma_t = tanh(W_3 * x_t + W_3 * H_{t-1} + b_3)$$
$$\theta_t = \sigma(W_4 * x_t + W_4 * H_{t-1} + b_4)$$

then the new cell state and output are:

$$C_t = \alpha_t * C_{t-1} + \beta_t * \gamma_t$$
$$H_t = \theta_t * tanh(C_t)$$

Data from NYSE contains information about the symbol of stock, event type, price and volume as well as very precise time to microseconds. Each record is either bid or ask wchich is indicated by (Side) field of the data.

Table 1: *Selected TAQ NYSE OpenBook Fields*

Symbol	Char(11)
TradingStatus	Char(1)
SourceTime	Int(4)
SourceTimeMicroSecs	Int(2)
PriceScaleCode	Int(1)
PriceNumerator	Int(4)
Volume	Int(4)
Side	Char(1)

For me the most important are price, volume na side data, because I will use them among others as an input to the network. Network will be always trained only for one symbol and for events of submission. I am going to experiment with different inputs, probably using some feature extraction, or choosing custom subset of features by myself. Inputs I am going to consider are:

- Time - Time since last ask or bid

- Price - Ask or bid price

- MidPrice - Difference between highest bid and lowest ask price divided by 2

- Volume - Volume of last ask or bid

- Side - Boolean indicating if it was bid or ask

- PriceDiff - Difference of price between last bid or ask

The same inputs will be used to learn ordinary perceptron with one hidden layer. Number of nodes in the hidden layer in that (testing) perceptron will be optimized to maximize its performance. The problem we want to solve is classification - we want to estimate if a price (of ask or bid) will be lower, higher or the same in the next transaction.

For the estimation of performance of my neural networks I will use a mean error loss function:

$$err(t) = \frac{\sum\limits_{i=1}^{t}(y_i \neq Y_i)}{t-1}$$

III. Implementation details

All development will be done using Python language in version 2.7 using Unix system. Keras library will be used for development of the solution, since it provides all necessary layer types including LSTM in the version described above as well as GRU. Since it uses Theano under the hood it is possible to swich on GPU usage, involving that time consuming computations will be executed on my NVIDIA graphic card using CUDA technology.

I. Test data providing

As a basic data that our program operates on we have chosen a NYSE OpenBook Ultra data set from 03/04/2013. The data for given stock symbol is parsed from large binary file and can be conveniently saved to the database and/or file. Then this message book is transformed into an order book message by message to capture the transaction price changes in each moment of time, as well as the history of other stock parameters for further building of the features.

II. Algorithms

Classes NeuralNetwork and ClassificationPerformance implements:

- *Feature selection*
  A method of performing feature selection with greedy forward selection using cross validation. We will try to use only selected features in neural network learning procedure. It gets testing data and neural network in parameters and returns a list of numbers of features to use.

- *Crossvalidation*
  A method of using neural network training, cross validating it N times with different test and train data sets randomly choosen from whole dataset. It returns a vector of error rates (training and testing). Data is split in proportion defined by a parameter.

- *T-Student significance test*
  A method *compare* in ClassificationPerformance class uses t-student distance between error rates of two different neural networks, and basing on pvalue is states if there exists significant difference between two solutions. We will use that to determine if really one neural network performs better than the other.

IV. Early Results

Attached is text file „CIBA_earlyResults.txt" which contains execution of the program for 19k events of the *AIG* stock order book. Both RNN and MLP report high accuracy from the beginning of iterations. This is very suspicious behaviour that can be explained by the data set characteristics in the next paragraph. As we

can see the cross validation correctly divides the samples for training and testing and the feature selection chooses the best features. Due to no negligible differences in performance the program reports that RNN and MLP are not significantly different.

I. Imbalanced data set

The problem that occurred during test phase turned out to be originating with data approach. As the response value for our vector of features we have choosen indicator wheter the transaction price for a given stock has dropped, stayed the same or risen. This results in response variable being mainly dominated by the second case, because transactions on NYSE OpenBook occur much less often than we initialy expected, making below around 10 percent of overall entries. Above leads to the poor learning performance of the neural networks. It is just easier for them to assume no transaction price change since it is the correct choice most of the time.

V. Revieved solution

Because we did not get satisfactory results, we had to change our solution in case of features and balance of classes in our data. Ultimately we got balanced data and many more features, and better results. Below we exmplain detailed final solution:

I. Data set

TUTAJ OPISZ JAK BALANSUJESZ DANE - ZE ROBISZ UNDERSAMPLING - OPISZ TEN ALGORYTM TROCHE MOZE?

II. Features and output

TUTAJ OPISZ JAK TWORZYSZ ORDER BOOKA I JAKIE FEATURES Z NIEGO BIERZESZ ROWNIEZ OPISZ JAKIE TERAZ MAMY KLASY CZYLI CO ZNACZA - CZYLI JAK ZMIENIL SIE OUTPUT, CZYM JEST TEN PRICE NASTEPNIE NAPISZ JAK ZALEZY

ILOSC FEATURES OD LEVEL I ZE MOZNA GO USTAWIAC

NAPISZ ZE UZYWALISMY FEATURE SELECTION ALE WYSZLO NAM ZE WSZYSTKIE SA TAK SAMO WAZNE PRAWIE I TUTAJ JAKO GLUPI DOWOD DAMY TEN WYKRESIK:
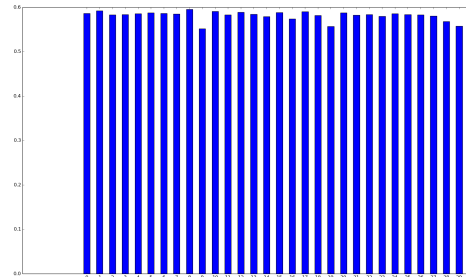

Figure 3: *Features importance*

III. Networks

At the end we resigned from using GRU network and instead focus on LSTM comparing it to ordinary MLP. In learning we used Stochastic gradient descent optimizer with categorical crossentropy loss function. Below we present actual models of networks used:

```
PERCEPTRON:
model = Sequential()
model.add(TimeDistributedDense(output_dim=self.hidden_cnt,
                               input_dim=self.input_dim,
                               input_length=self.input_length,
                               activation='sigmoid'))
model.add(TimeDistributedMerge(mode='ave'))
model.add(Dropout(0.5))
model.add(Dense(self.hidden_cnt, activation='tanh'))
model.add(Dense(self.output_dim, activation='softmax'))

LSTM:
model = Sequential()
model.add(LSTM(output_dim=self.hidden_cnt,
               input_dim=self.input_dim,
               input_length=self.input_length,
               return_sequences=False))
model.add(Dropout(0.5))
model.add(Dense(self.hidden_cnt, activation='tanh'))
model.add(Dense(self.output_dim, activation='softmax'))
```

IV. GPU usage

Because of the fact that our NN are learning slowly, and teaching them is time consuming we found useful to switch on BLAS and CUDA enabled devices usage by Theano library. To do that it was sufficient to create a file /.theanorc

with content:

```
[global]
floatX = float32
device = gpu1

[blas]
ldflags = -L/usr/local/lib -lopenblas

[nvcc]
fastmath = True
```

Using that new architecture and solution we received our final results.

VI. Final Results

TUTAJ TRZEBA POZBIERAC NASZE OS-TATECZNE WYNIKI, CO NAM WYSZLO, NASZE WYKRESY

VII. Conclusion

KROTKIE PODSUMOWANIE TEGO CZEGO SIE NAUCZYLISMY I CO NAM WYSZLO Z NASZEGO REASERCHU

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