A Limit Order Book based Deep Learning Model for Cryptocurrency Price Trend Prediction

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***Abstract*—A deep learning framework to capture the high dynamics of the Limit Order Book as studied from a cryptocurrency market is proposed. Specifically for Bitcoin, the most popular cryptocurrency to date. Models are designed and trained, as to allow a short-term price movement prediction, which in turn could be potentially used in a High Frequency Trading environment.**

***Index Terms*—Deep Learning, High Frequency Trading, Limit Order Book, Trend Prediction.**

I. Introduction

PREDICTING the market has become a common task for anyone working on some type of investment that involves trading. For those who trade, timing is a key point for a successful trading strategy, there are of course some other elements for having success, however, being correct at the right time makes things easier.

Different input data is being used by predictive models, however, for very short-term horizons, the most common type of input data is transaction data and the Limit Order Book (LOB). These inputs are the most granular type of data someone can use in order to have a better market perspective about the future's market direction [1].

In this research the focus is made on the first 10 LOB levels (price and volume). A Deep Learning model is fed with this data as to predict one of three possible outcomes for the market price direction: Up, Down or Stationary.

II. Related Work

Investment industry has always been interested in successfully predicting financial time series, such task is considered one of the most challenging tasks in modern time series prediction [2].

The financial time series are particularly complex, dynamic, chaotic, non-linear and highly noisy. Some hypotheses have been presented suggesting the impossibility of predicting the future value or direction of an asset. One of them, is the Efficient-Market-Hypothesis (EMH) supported by Fama in [3]. Despite the implications of this hypothesis, the scientific community has proposed different ways to predict the market.

With the appearance of Electronic Communication Networks (ECNs) in the 90's, electronic trading received a big boost, this allowed automatic trading to be established [4]. In addition to this, the increase in demand for better yields investment has kept researchers and participants in a continuous improvement work to the implementation of better models.

One of the techniques that has grown the most in recent years, is the use of Machine Learning (ML) for the prediction of time series, many studies have shown better results compared to classic time series prediction techniques [5].

Recently, traditional DL models have been significantly outperforming ML-based models. This is due to having the advantage of learning characteristics of unsupervised characteristics, a great capacity for generalization and a robust training power for Big Data [6].

There are relatively very few research papers dealing with the LOB as well as to applying some ML or DL model. One of the initial works that was published, that also inspired others to continue this line of research, is the work by Kercheval and Zhang in [7]. They proposed a framework to capture the dynamics of the high-frequency LOB in order to use this knowledge to make real-time predictions. The focus was to properly predict the mid-price movement direction in a very short-term.

One of the important contributions of this research was to establish a set of features for which the model would be fed. The proposed attributes were divided into three categories: basic, time-insensitive and time-sensitive. The basic set is just composed of the 10 first levels of the LOB for each side (price and volume), the rest of the features are derived from the basic and contain some other metrics involving order types. A total of 82 features are proposed.

Results showed that after training a multi-class Support Vector Machine (SVM) model, the proposed framework is effective in predicting the price movements.

After this finding, the scientific community started to put attention on the same task, and Ntakaris et. al. in [8], created the first publicly available benchmark dataset of high-frequency data for mid-price trend prediction. This same dataset is the one that is evaluated for proposing state-of-the-art models. They also proposed an experimental protocol for evaluation. Even though the dataset is very useful, the data is

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already pre-processed and there is not much room left for any pre-processing step before training a model. Some baseline models were also presented by using two regression models: Ridge Regression (RR) and the SLFN network-based regression model.

More complex models started to appear in hopes of improving state-of-the-art performance. Models like Long Short-Term Memory (LSTM), Multilayer Perceptron (MLP) and SVM [9]. Also, by using Convolutional Neural Networks (CNN) in [10].

Some hybrid models were proposed as well, like the one combining the ability of the CNN to extract features and the LSTM ability to model sequential data [11]. On this research, new stationary features were proposed instead of the raw prices, these new features can be readily extracted from the Limit Order Book. Results showed that by using such features, LSTMs and CNNs models improved their performance. It should be noted that just the price features were made stationary, volume features are not, however in longer horizons, distribution of volume sizes might as well suffer from shifts.

Then, another hybrid approach combining convolutional filters and LSTM modules called DeepLOB was proposed in [12]. It remarkably beat all state-of-the-art results on the public dataset mentioned before, and something, that is worth mentioning, is that they also tested on a much larger dataset from the London Stock Exchange, and the out-of-sample prediction accuracy remains the same. This generalization results, reveal something inherent to the market, the existence of universal features on the dynamics of the LOB.

If we talk about cryptocurrencies and LOBs, the number of research papers decrease even more. Jha et al., in [13], investigated the ability of predicting the mid-price direction on cryptocurrency markets (Bitcoin). The data is comprised of a depth of 50 levels of the LOB with snapshots every 100ms. Even though snapshots are taken every 100ms data is not continuous. However, good results were obtained by predicting over a 2 second time horizon.

LOB and transaction data-based models have been proved to have predictive power for the mid-price trend prediction task. Best results have been obtained by using DL techniques.

This demonstrates that there are some non-linear relationships in the data that some more simple models cannot learnt. Different approaches have been conducted, still, more research must be done, especially on cryptocurrency markets.

The present research focuses on this gap by implementing a DL predictive model for the pair BTC/USD. Apart for filling this research gap, the present work's contributions are as follows: 1) Test the LOB informational content for predictive models, 2) It solves the problem of dealing with high dimensionality from the LOB by applying a DL model, and 3) A new preprocessing method for generating stationary features is proposed.

To the best of our knowledge, this is the first work that uses cryptocurrency LOB data without any type of sampling for the mid-price movement prediction task.

III. Methodology

The work started by collecting the raw transactional data. Data was provided by a third vendor called Kaiko, which is a digital asset data provider. A total of two months of transaction data is used for the period from August 25th, 2020, to October 25th, 2020 (62 days in total). The data comes from the Coinbase exchange, and it is provided in two separate files for each day during the period. One file contains the time series of events or transactions, and the other, is an hourly snapshot of the full LOB. Both files are needed in order to reconstruct the LOB.

This data could be extracted via the Coinbase API, however, many details must be considered in order to have a reliable dataset, i.e., with no missing information, otherwise reconstruction would not be possible.

Once the data is collected, the second step was to reconstruct the LOB and just take the first 10 levels of information for every change in the LOB. A change could be a new order, a change in an existing order, cancelling an order, filling an order, etc. Even though the data came from a data provider, some information was missing, and some duplicated. Then, a cleaning step was performed before reconstruction. Details for reconstruction can be found at Coinbase Official Documentation API: https://docs.pro.coinbase.com/.

After having reconstructed the LOB for two months, a dataset split is made as to separate the data into the following splits: Training, Validation and Test set. Validation and Test set are made of LOB data from October 24th and October 25th respectively. While the rest was used for training. Validation set was used for model selection and early stopping, and results were reported directly from the test set.

Before feeding the model with the raw reconstructed LOB, a preprocessing step was performed. Some previous works had been using the raw features from the LOB, and just the z-score normalization is used for every individual feature.

In this work new stationary features out of the raw features are created to avoid price and volume shifts on the data. This would in theory, allow the model to be used not just for the market/cryptocurrency it was trained on, but on different markets, with different instruments.

A. Price Stationary Features

For the price features, the relative prices of all price levels to the best bid $b(t)$, and the best ask $a(t)$ were considered, as it is presented in [14]. Equations for computing the stationary features are shown below:

$$\delta^b(p) \coloneqq \frac{b(t) - p}{b(t)} \tag{1}$$

$$\delta^a(p) \coloneqq \frac{p - a(t)}{a(t)} \tag{2}$$

The above equations contain the relative prices on their numerators, these represents how spread the price levels are with respect to the top levels at each side, i.e., best bid and

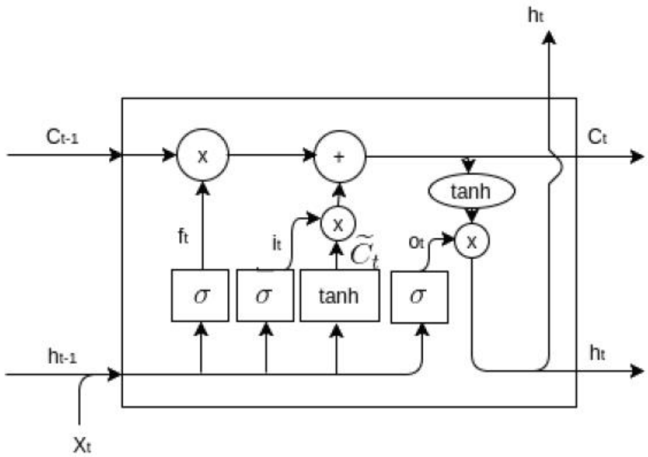

Fig. 1. Long Short-Term Memory Cell.

best ask. These differences are then divided by $b(t)$ and $a(t)$ respectively generating scaled features not dependent on current prices. This would allow a model to be trained over LOB time series data with price shifts.

B. Volume Stationary Features

For the volume features, the relative volumes and symmetry between both sides of the book, i.e., sells and buys where used. Then for each LOB state, at every price level, the volume is defined as follows [15]:

$$s_k^b = \frac{v_k^b}{\bar{\bar{v}}} \tag{3}$$

$$s_k^a = \frac{v_k^a}{\bar{\bar{v}}} \tag{4}$$

For $k = 1, 2, \ldots, 10$, where k is the number of price levels on the reconstructed LOB, v_k^b and v_k^a are the volumes at the *kth* level on the bids and asks sides respectively, and $\bar{\bar{v}}$ is given by:

$$\bar{\bar{v}} = \sum_{i=1}^{H} \left(v_k^a + v_k^b \right) \tag{5}$$

By doing this scaling on the volume features, relative volume at each price level as well as the imbalance (degree of symmetry) between both sides of the book is represented.

C. Long Short-Term Memory

Since the LOB data is a multivariate time series data, a Long Short-Term Memory (LSTM) model was used. The LSTM is one of the best DL models dealing with sequential data. The LSTM model was proposed in [16] as a solution to the vanishing gradient problem and can handle long-term dependencies in the sequence. The architecture of a LSTM Cell is shown in Fig. 1. The governing equations of the LSTM are given as follows:

$$i_t = \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi}) \tag{6}$$

$$f_t = \sigma\left(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf}\right) \tag{7}$$

$$g_t = tanh\left(W_{ig}x_t + b_{ig} + W_{hg}h_{t-1} + b_{hg}\right) \tag{8}$$

$$o_t = \sigma(W_{io}x_t + b_{io} + W_{ho}h_{t-1} + b_{ho}) \tag{9}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \tag{10}$$

$$h_t = o_t \odot tanh(c_t) \tag{11}$$

Where h_t is the hidden state at time t, c_t is the cell state at time t, h_{t-1} is the hidden state of the previous layer at time $t-1$, or the initial hidden state at time 0. i_t, f_t, g_t, o_t are the input, forget, cell, and output gates respectively. The sigmoid function is represented by σ, and the $\odot$ represents the Hadamard product, or element-wise product.

Every LSTM cell receives three inputs, the previous cell state c_{t-1}, the previous hidden state h_{t-1}, and the input x_t at time t. At every time step a hidden state h_t is fed back to the next time step, while the cell state c_t is being modified through all time steps by the forget gate f_t and the input gate i_t, that removes and adds new information respectively.

For the task at hand, x_t is a vector of 40 features, i.e., $x_t \in R^{40}$, corresponding to the prices and volumes of the first 10 price levels in the LOB, for both sides of the book. And the number of time steps to look back on the series is 100. Then the input for the LSTM is of shape 100x40.

The architecture of the LSTM-based model is shown in Fig. 2, where a dropout layer is added after the LSTM layers for regularization, and a linear mapping is done for final classification before being fed to a Log Softmax function to output the final probabilities of the different classes.

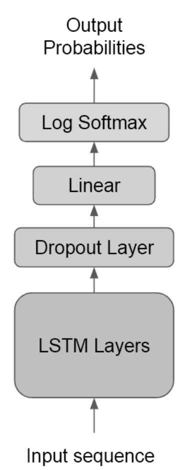

Fig. 2. LSTM-based architecture.

D. Task Description and Data Labeling

The metric to be predicted is the direction of the mid-price $p(t)$, which is a virtual price calculated from the best bid $b(t)$, and the best ask $a(t)$ at time t, and it is given by [14]:

$$p(t) = \frac{a(t) + b(t)}{2} \quad (12)$$

The direction of the mid-price $p(t)$, was determined by using the labeling method proposed by Marcos Lopez de Prado in [17]. In [17] some drawbacks about using some other labeling methods like in [9, 12, 13] are presented. Then in order to deal with these drawbacks, an alternative labeling method is proposed by Lopez de Prado, which is called: the Triple-Barrier Method (TBM). Such method is presumably better suited for real training scenarios.

This method is path dependent, i.e., a label is determined based on the different mid-price values taken within the prediction horizon. It labels an example or sequence, according to the first bar touched by the price (in this case the mid-price). A diagram showing the method and the bars is shown in Fig. 3.

In an investment scenario, the upper horizontal bar can be seen as profit-taking, and the lower bar, as a stop-loss limit. If the upper barrier is touched first, then the example is assigned a class label Up (+1). If the lower bar is touched first instead, the example is assigned a class label Down (-1), and if no horizontal bar is touched during prediction horizon k (measured in number of events), then the vertical bar is hit, and the example is assigned to class label Stationary (0).

Horizontal bars are positioned according to a threshold α, where in [17], this α is a function of estimated volatility. However, on this research, a fixed α threshold was selected as to not be smaller than the minimum percentage change resulting from a movement of magnitude equal to the tick size, which for the pair BTC/USD in Coinbase is of \$0.01. Then $\alpha = 1x10^-6$.

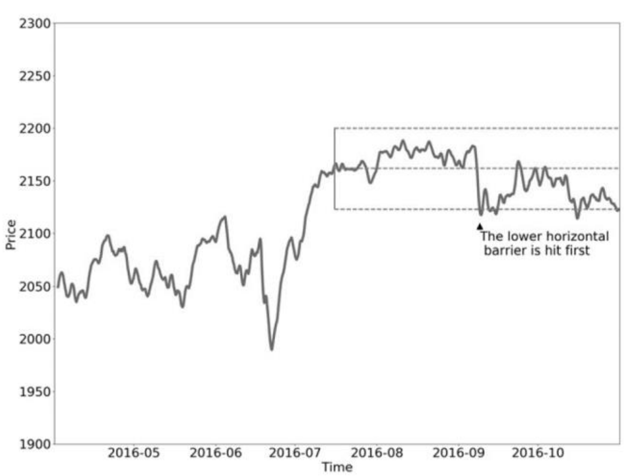

Fig. 3. The Triple Barrier Method [17].

TABLE I
TEST RESULTS

Class	Precision	Recall	F1-score
Down	0.59	0.58	0.59
Stationary	0.90	0.93	0.91
Up	0.59	0.58	0.59
Accuracy			0.73
Macro avg	0.69	0.69	0.69

E. Model selection and evaluation

Model design and selection was made via an iterative process on which best hyperparameters were selected using cross-validation on the validation set.

Finally, the model was tested on the hold-out dataset, i.e., the Test set. The reported metrics are Accuracy, Precision, Recall and the F1-Score. Results were compared against a baseline ZeroR classifier as a baseline, for which the majority class is always predicted.

IV. EXPERIMENTAL SETUP AND RESULTS

After performing a grid search for hyperparameters over the LSTM-based architecture, a single LSTM layer with hidden state size of 64 was determined to be appropriate for the task at hand. Over 6 million examples (sequences of length 100) where used for training. Batch size was set to be 512. Cross Entropy Loss and Adam optimizer with default parameters were used for optimization [18].

During training best model was selected via Early Stopping criteria [19]. Results are reported below in Table I as evaluated on the test dataset.

V. DISCUSSION

The results on Table I are indicative of DL models capacity of dealing with high dimensionality problems like the one at hand. An accuracy of 73% is achieved on a hold-out dataset, although it might seem very high, it should be noted that the test dataset majority class is “stationary” (around 46% of the examples) which is the class that the model best predicts.

The LSTM-based model clearly outperforms a ZeroR classifier on the accuracy metric, i.e., 46% against 73% for this problem.

Surprisingly, it is far easier for the model to identify Stationary movements as compared with Up or Down movements. It is also interesting to see how the performance of the model for the Up or Down movements are almost the same. This might be because of the difficulty for the model to clearly distinguish one class from the other, suggesting both conditions contain an overlap of similar events. However, some other orthogonal source of information is needed to better separate these classes.

VI. CONCLUSION

In this work a Limit Order Book based Deep Learning Model for Cryptocurrency Price Trend Prediction was tested. It was found that LOBs on cryptocurrency markets are very informative for DL predictive models, and that short-time predictions can be made with high accuracy.

In future work, some other sources of information like the order flow imbalance could be implemented as to allow the model to better separate classes.

In general DL models applied to high frequency data for the mid-price prediction movement task are to be explored in the years to come.

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