ConvLOB

Stock prices forecasting through CNNs

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Task

In today's financial markets most trades are performed electronically and the majority is automated. Therefore by analyzing this vast amount of transactions an opportunity has risen.

Develop a deep neural network that leverages the attention mechanism to predict future stock price movements in the F1-2010 high-frequency LOB Dataset.

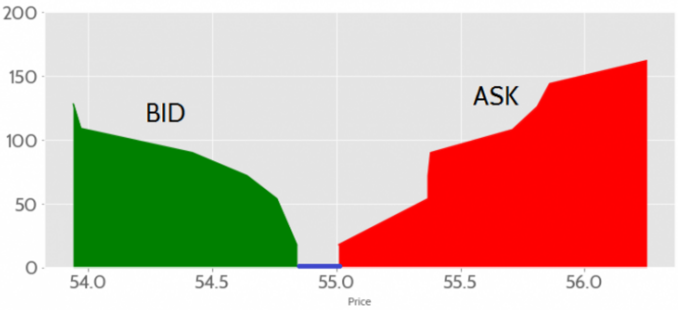
Limit Order Book (LOB)

The Limit Order Book (LOB) has three components: **buy orders**, **sell orders** and **order history**. These are organized in **price levels**. Buy/sell (ask/bid) limit orders will sit in the order book until an order of the opposite type matches their price

Both **bid** and **ask** orders are characterized by a price and volume.

$$(p_a, v_a, p_b, v_b) \tag{1}$$

The distance between the highest bid order and the lowest ask order is called **spread**, the average betweem them is also called **mid price**.


200
150
100
50
0
BID
ASK
54.0
54.5
55.0
55.5
56.0
Price

Dataset

We used the *F1-2010* dataset in order to train and test our model. Its data consist of high-frequency limit order data extracted from the *Nasdaq Nordic* stock market, for a window of 10 consecutive days.

We have a total of 40 features for each timestamp, since each state of the LOB contains 10 levels of both buy and sell orders. Data have been used as follows:

- We used 5 days for training, and 2 days for validation i.e. a 80/20 data split.
- Last 3 days for testing.

Normalization

In order to obtain the best possible performances, data are already normalized using z-score normalization:

$$z = \frac{x - \mu}{\sigma} \tag{2}$$

Labelling

In order to create labels that somehow represent the direction of changes in price, we use the mid price:

$$p_t = \frac{p_a + p_b}{2} \tag{3}$$

We may use **strict** or **smooth** labelling, in F1-2010 the latter is applied by default.
Labels are computed using the mean of k steps' mid-prices, comparing the percentage change against a threshold α:

Smooth labelling

$$m_t = \frac{1}{k} \sum_{i=0}^{k} p_{t+1} \tag{4}$$

$$l_t = \frac{m_t - p_t}{p_t} \tag{5}$$

$$l_t > \alpha \Rightarrow \quad \uparrow \tag{6}$$

$$l_t = \alpha \Rightarrow \quad \rightarrow \tag{7}$$

$$l_t < \alpha \Rightarrow \quad \downarrow \tag{8}$$

Model Architecture

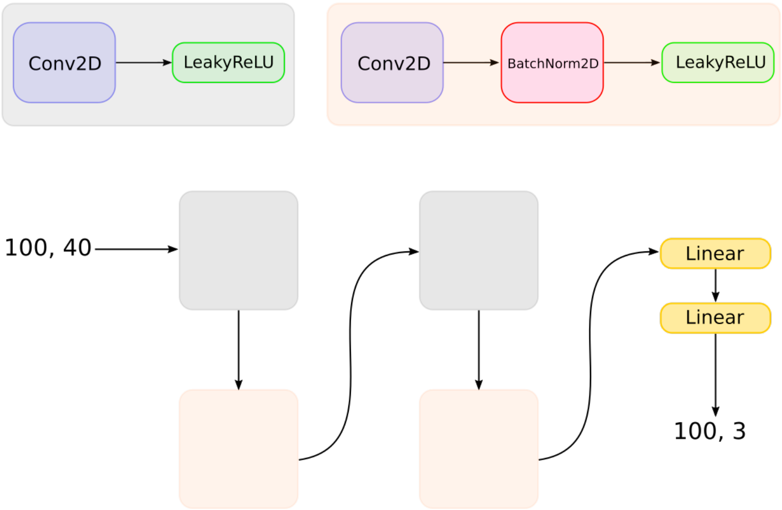
Our models' architectures revolve around 3 main layers:

- Convolutional modules.
- Multi-head attention modules.
- Classification heads.

Convolutional model

This model is inspired by reference paper's model, we exploit 2D temporal convolution, thus we need to reshape input data to a compatible shape.

$$100, 40 \longrightarrow 100, 40, 1$$

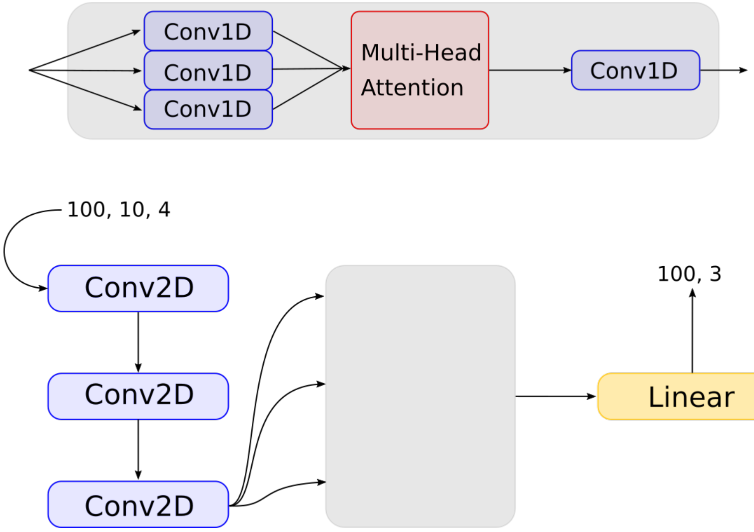

Conv2D
LeakyReLU
Conv2D
BatchNorm2D
LeakyReLU
100, 40
Linear
Linear
100, 3

Attention model

Again we use 2D temporal convolutions, yet data is reshaped in a more channel-centered model.

$$100, 40 \longrightarrow 100, 10, 4$$

Furtherly to learn sequential data we introduce a multi-head attention module.


Conv1D
Conv1D
Conv1D
Multi-Head Attention
Conv1D
100, 10, 4
Conv2D
Conv2D
Conv2D
100, 3
Linear

Convolutional model

Epochs	36
LR	1×10^{-3}
F1	60
Cohen K	0.36

Attention model

Epochs	99
LR	1×10^{-3}
F1	59.2
Cohen K	0.38

Thank you for your attention.