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**.
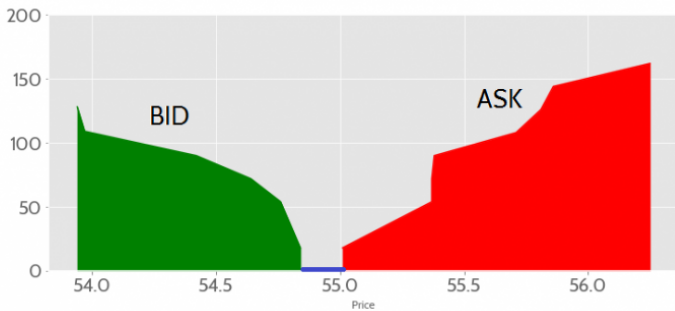
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Dataset

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.
- 2 days were used for validation i.e. we have a 80/20 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:

$$p_t = \frac{p_a + p_b}{2} \qquad (3)$$

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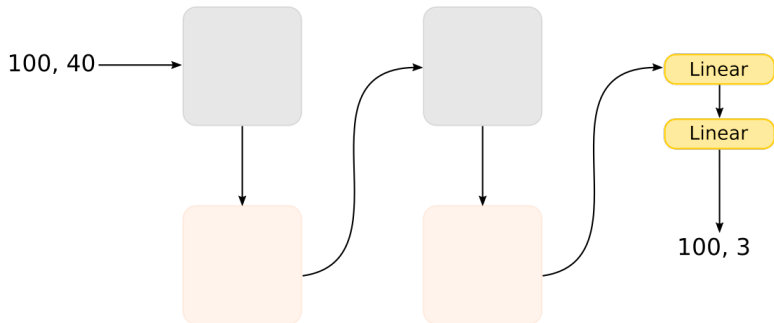
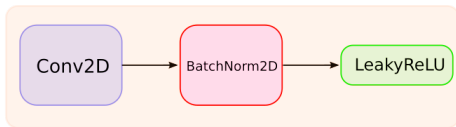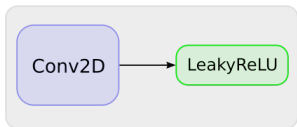$$100, 40 \longrightarrow 100, 40, 1$$

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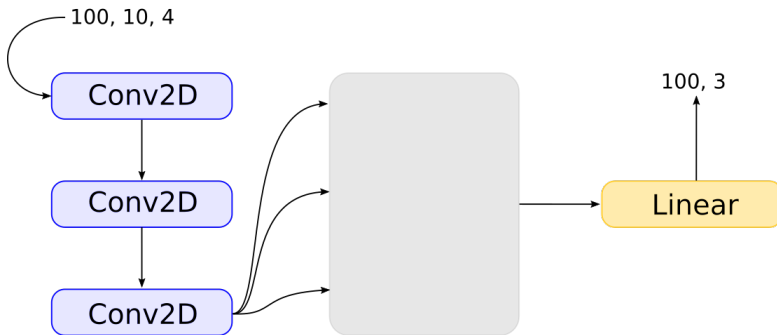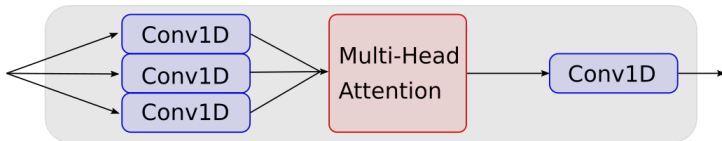○○

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.

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Convolutional model

	Epoch	LR	F1	Cohen K
Tsantedekis et. al	-	-	55.21	0.35
CNN	36	0.001	**60**	0.36
Att	99	0.001	59.2	**0.38**

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Thank You.