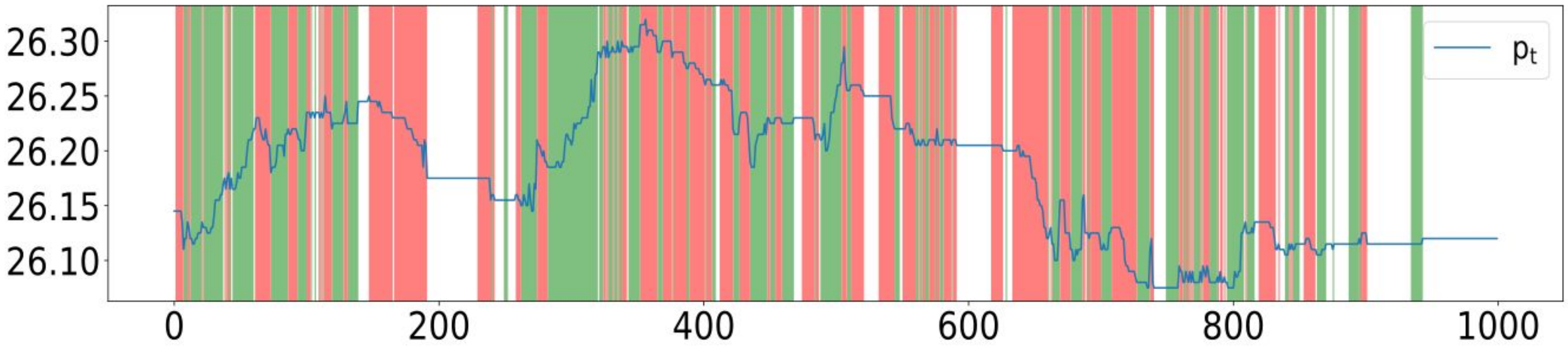
Price movement prediction with DL

Task

Develop a **deep neural network** to **predict future stock price movements** in a large-scale high-frequency **LOB data**.



Limit Order Book (LOB)

The Limit Order Book (LOB) represents a snapshot of the supply and demand for an exchange traded instrument at a given time.

Two types of orders:

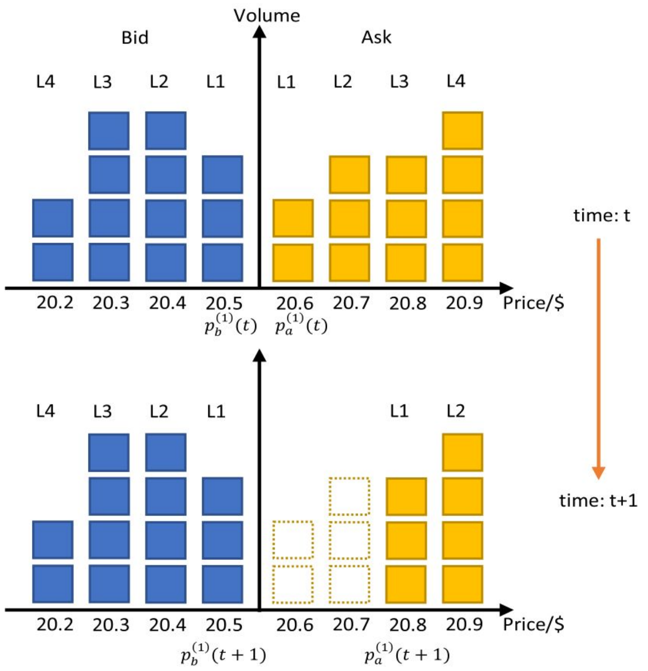
- **Bid** orders: orders to **buy** an asset **at or below** a specified price.
- **Ask** orders: orders to **sell** an asset **at or above** a specified price.

Orders are sorted into different levels based on their submitted prices.

Limit Order Book (LOB)

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

The example shows the LOB in two following time steps. The bottom plot shows the action of an incoming market order to buy 5 shares.



Dataset

To train and test our model, we use the **FI-2010 dataset**, limit order data extracted from the Nasdaq Nordic stock market for a time of **10 consecutive days**.

Each state of the LOB contains 10 levels on each side. Therefore, we have a total of 40 features at each timestamp.

- **Training + Validation**: first 7 days (80/20).
- **Testing**: last 3 days.

Input data

We use the 100 most recent states of the LOB as an input to our model:

$$X = [x_1, x_2, \ldots, x_t, \ldots, x_{100}]^T \in \mathbb{R}^{100 \times 40}$$

where

$$x_t = [p_a^{(i)}(t), v_a^{(i)}(t), p_b^{(i)}(t), v_b^{(i)}(t)]_{i=1}^{n=10}$$

and *p* and *v* respectively represent the price and volume.

Normalization

The performance of machine learning algorithms often depends on how the data is normalized.

Three possibilities in the FI-2010 dataset:

1. **Z-score normalization**: $x' = \frac{x-\mu}{\sigma}$
2. Min-Max normalization: $x' = \frac{x-\min(x)}{\max(x)-\min(x)}$
3. Decimal precision normalization: $x' = \frac{x}{10^k}, \quad k = \min_k\{l \mid \max(\frac{|x|}{10^k}) < 1\}$

Labelling

To create **labels that represent the direction of price changes**, we use the **mid-price**:

$$p_t = \frac{p_a^{(1)}(t) + p_b^{(1)}(t)}{2}$$

There are two strategies to compute labels:

- **Strict**
- **Smooth**

Labelling - Strict ❌

We compare the mid-prices at two following time steps:

$$p_{t+1} > p_t \Rightarrow \nearrow$$
$$p_{t+1} = p_t \Rightarrow \rightarrow$$
$$p_{t+1} < p_t \Rightarrow \searrow$$

Problem: financial data is highly stochastic, thus the label set would be noisy.

Labelling - Smooth[1] ✔

We use the mean of the next *k* mid-prices, and we compare the percentage change against a threshold *α* to compute the labels:

$$m_+(t) = \tfrac{1}{k} \sum_{i=0}^{k} p_{t+i}$$

$$l_t = \frac{m_+(t) - p_t}{p_t}$$

$$l_t > \alpha \Rightarrow \nearrow$$

$$-\alpha < l_t < \alpha \Rightarrow \rightarrow$$

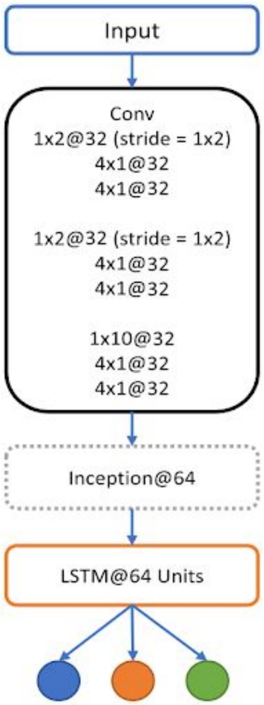
$$l_t < -\alpha \Rightarrow \searrow$$

1: In the FI-2010 dataset, the data is already labelled according to the smooth labeling technique.

Model Architecture

The network architecture comprises three building blocks:

1. **Convolutional Modules**.
2. **Inception Module**.
3. **LSTM Module** + **Classifier**.



Convolutional Modules

Input size = *(1, 100, 40)*.

1. *K = (1, 2)*, *S = (1, 2)*: the **first block** summarises **information between price and volume** at each order book level.
2. *K = (1, 2)*, *S = (1, 2)*: the **second block** integrates **information across bid and ask orders**.
3. *K = (1, 10)*: the **third block** integrates **all information across multiple order book levels** by using a large filter.

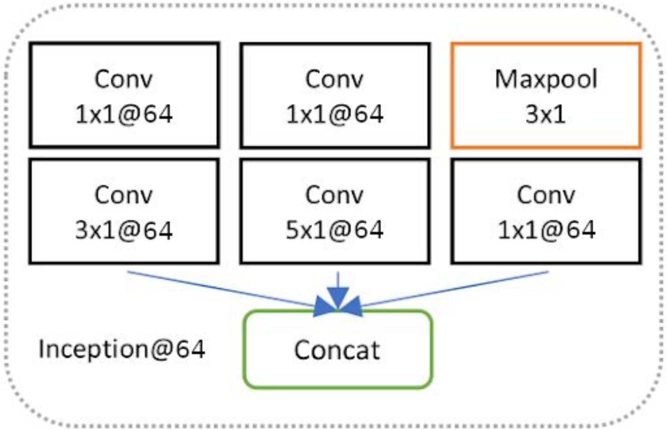
Output size = *(32, 100, 1)*.

Inception Module

Convolutional filters of size *(k, 1)* can be used to capture local interactions amongst data over *k* time steps.

The **Inception Module** is used to capture **dynamic behaviour over multiple timescales**, wrapping several convolutions together.

Output size = *(194, 100, 1)*.



LSTM Module + Classifier

The **LSTM Module** is used to **capture temporal relationships** that exists in the extracted features.

The **final classifier block** uses a **fully connected layer** with a **softmax activation**, and hence the final output elements represent the **probability of each price movement class** at each time step.

Output size = *(1, 3)*.

Hyperparameters

Input window length	100
Projection horizon	10
LOB levels	10
Learning rate	0.0001
Batch size	128
Early stopping	ON
Patience	20

References

[1]: A. Ntakaris, M. Magris, J. Kanniainen, M. Gabbouj, and A. Iosifidis, "Benchmark dataset for mid-price prediction of limit order book data with machine learning methods", J. Forecasting, vol. 37, no. 8, pp. 852–866, 2018.

[2]: M. D. Gould, M. A. Porter, S. Williams, M. McDonald, D. J. Fenn, and S. D. Howison, "Limit order books", Quantitative Finance, vol. 13, no. 11, pp. 1709–1742, 2013.

[3]: Z. Zhang, S. Zohren, and S. Roberts, "DeepLOB: Deep Convolutional Neural Networks for Limit Order Books", IEEE Transactions on Signal Processing, vol. 67, no. 11, pp. 3001–3012, 2019.

The codebase for this project is contained in this GitHub repository.