Supervised Deep Learning for Optimized Trade Execution

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In this project, we assume that the optimal execution strategy can be expressed as a pure function of the following 6 variables: t the remaining time before the end of the time horizon, i the remaining inventory to sell, the price level, price trend, limit order book volume mismatch as well as the bid-ask spread at the decision point. Following the convention in [1], we group the 6 input variables into two categories, i.e., the **private variables** consisting of t and t that is specific to the Optimized Trade Execution problem, and the **market variables** consisting of the rest of the four. Output of the model is represented by **action**, the price at which to place a limit order. The model can be expressed mathematically as

action = f(t, i, price level, price trend, vol mismatch, bid-ask spread),

where f is an unknown function to be learned.

To estimate the function f, we develop a supervised deep learning model as described below. The model is implemented with Tensorflow and Tensorflow Keras provided by Google Brain, using Python. Implementation of the model can be found in the file Model.py.

- **Input Layer** The input layer consists of simply the 6 parameters of the function f. Detailed definitions, rationales and extractions of these variables are provided in Section 4.2 and 4.3.
- Hidden Layers The model is composed of 5 fully-connected hidden layers with 256 neurons each. Activation functions for each layer is, correspondingly, leakyReLu, sigmoid, dropout with a rate of 0.5, leakyReLu, sigmoid. These activations are chosen after taking into consideration the nature of the problems. For example, noting the sparse activation characteristic of the leakyReLu activation and that the outputs are discrete, we chose leakyReLu to denoise the training process. Another advantage of the leakyReLu is its computational efficiency and ability to avoid dead neurons. The sigmoid activation is chosen for its ability to capture non-linear relationships. A Dropout layer is chosen in the middle to denoise and speed up the descent.
- Output Layer The output layer represents the predicted action given the input. The output variable, *action*, is discrete for computational efficiency. Moreover, having a discrete output is important to avoid overfitting.

- 4 Model Training
- 4.1 Data Description
- 4.2 Market Variables
- 4.3 Private Variables
- 5 Results
- 6 Remarks
- 7 Conclusion

References

[1] Yuriy Nevmyvaka, Yi Feng, Michael Kearns. Reinforcement Learning for Optimized Trade Execution. Proceedings of the 23rd International Conference on Machine Learning, Pittsburgh, PA, 2006.