Practical Deep Learning Approach for Intraday Futures Trading

Yuyuan Cui [1] **Ziyan Wang** [1]

Abstract

This project proposal provides an outline for using deep learning and reinforcement learning approach for developing systematic futures trading strategies in intraday timeframe.

1. Introduction

Deep learning has been a popular topic in quantitative financial trading. Xiong, Liu, Zhong, Yang and Walid (2018) used deep reinforcement learning to obtain optimal strategy in the complex and dynamic stock market (Xiong et al., 2018). Sezer, Ozbayoglua, and Dogdub (2017) used DNNs for optimizing daily technical indicators for stock trading (Sezer et al., 2017). However, few studies have focused on applying deep learning approach to intraday and tick-level data for trading. As tick data provides a much larger dataset for training than daily data, and that various order placement types provide more options for action, there is plenty of opportunities to use complicated deep learning architecture for both prediction and strategy formulation.

2. Problem Statement

The objective is to design deep learning models that maximize trading profit for IH futures[1] based on tick-level high frequency data. We will build two individual models in this project. The first one focuses on short-term price movement prediction only and we will manually formulate a simple trading strategy based on its predictions. The second model uses deep reinforcement learning and will output trading actions on its own. In addition, we will set up a passive market-making strategy as benchmark[2]. By comparing their performance, we can evaluate the applicability of reinforcement learning and deep learning in intraday futures trading with various degrees of human experience intervention.

3. Dataset and Algorithms

The dataset we use is tick data of IH futures and potentially other products' tick data in China's CFFEX exchange in 2018[3]. The data include all book updates and trade events. We will construct features from 1) moving averages of trade price and quote price, 2) moving averages of book size and imbalance, 3) cross assets price changes and 4) weighted-mid price change in look-back period. Look-back window lengths of 1 min, 5 min and 10 min will be used.

For the first model, we will use LSTM model for intraday price change prediction. A set of prediction horizon (1 min, 5 min and 10 min) will be experimented. A static take profit / stop loss strategy is applied on the prediction to generate trade actions. The size of look-back window and the strategy parameters are optimized based on validation dataset.

For the second one, we model the stock trading process as a Markov Decision Process (MDP) with Deep Deterministic Policy Gradient (DDPG) algorithm (Xiong et al., 2018). The expected reward of taking action a_t is calculated with

$$Q_\pi(s_t, a_t) = E_{s_{t+1}}[r(s_t, a_t, s_{t+1}) + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1})]$$

where s_t and a_t are the state and action at time t, $r(s, a, s')$ is the change of the portfolio value when action a is taken at state s and arriving at the new state s', γ is a discount factor, and $Q_\pi(s, a)$ is the action-value function.

4. Performance Evaluation

For price change prediction, evaluate the LSTM model using mean-squared error (MSE) of predicted compared with actual price change in the testing dataset. We will also compare MSE against benchmark model using OLS regression.

The final performance of the two models are evaluated by running on testing period and comparing trading profit against benchmark passive market making strategy. Measures includes total return, Shape Ratio and maximum drawdown[4]. No transaction fee is assumed. We will use the first 9 months of the data for training, October data for validation, and the last two months for testing.

[1] IH future is based on SSE 50 Index, one of the most popular index futures traded in CFFEX

[2] enter and exit a position on best bid and offer

[3] CFFEX exchange website

[4] A maximum drawdown (MDD) is the maximum observed loss from a peak to a trough of a portfolio, before a new peak is attained

References

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