DeepScalper: A Risk-Aware Deep Reinforcement Learning Framework for Intraday Trading with Micro-level Market Embedding

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Abstract

Reinforcement learning (RL) techniques have shown great success in quantitative investment tasks, such as portfolio management and algorithmic trading. Especially, intraday trading is one of the most profitable and risky tasks because of the intraday behaviors of the financial market that reflect billions of rapidly fluctuating values. However, it is hard to apply existing RL methods to intraday trading due to the following three limitations: 1) overlooking micro-level market information (e.g., limit order book); 2) only focusing on local price fluctuation and failing to capture the overall trend of the whole trading day; 3) neglecting the impact of market risk. To tackle these limitations, we propose DeepScalper, a deep reinforcement learning framework for intraday trading. Specifically, we adopt an encoder-decoder architecture to learn robust market embedding incorporating both macro-level and micro-level market information. Moreover, a novel hindsight reward function is designed to provide the agent a long-term horizon for capturing the overall price trend. In addition, we propose a risk-aware auxiliary task by predicting future volatility, which helps the agent take market risk into consideration while maximizing profit. Finally, extensive experiments on two stock index futures and four treasury bond futures demonstrate that DeepScalper achieves significant improvement against many state-of-the-art approaches.

1 Introduction

Recent years have witnessed significant development of algorithmic trading, due to its instant and accurate order execution, and capability of analyzing and processing large amount of data related to the financial market. One of the most profitable and risky tasks is intraday trading, which tries to seize profitable long and short trading opportunities within the same trading day [Lee and Ready, 1991]. Traditional intraday trading strategies [Moskowitz et al., 2012; Bollinger, 2002] discover trading opportunities based on heuristic rules. However, rule-based methods exhibit poor generalization ability and only perform well in certain market conditions [Deng et al., 2016]. Another paradigm is to trade based on financial prediction. Deep learning techniques have been introduced to predict future price [Ding et al., 2015]. Many other data sources such as economic news [Hu et al., 2018], frequency of prices Zhang et al. [2017], social media [Xu and Cohen, 2018] and investment behaviors [Chen et al., 2019] have been added as extra information to improve the prediction performance. Gradient boosting decision tree frameworks such as LGBM [Ke et al., 2017] are widely used for predicting future price as well. Nevertheless, the high volatility and noisy nature of the financial market make it extremely hard to predict future price accurately [Fama, 1970]. In addition, there is a noticeable gap between prediction signals and profitable trading actions [Feng et al., 2019]. Thus, the overall performance of prediction-based methods is not satisfying as well.

Similar to video games, algorithmic trading also interacts with the environment (financial market) and maximizes the accumulative profit. Recently, deep reinforcement learning (DRL) is considered as an appealing approach for algorithmic trading. Jiang et al. [2017] used DDPG to dynamically optimize cryptocurrency trading. Deng et al. [2016] applied fuzzy learning and deep learning to improve financial signal representation. Yu et al. [2019] proposed a model-based RL framework for daily frequency trading. Liu et al. [2020] proposed an adaptive DDPG-based framework with imitation learning. Wang et al. [2021a] introduced a hierarchical DRL approach with realistic consideration of execution fee. Despite their remarkable performance in algorithmic trading, most existing DRL methods mainly focus on relatively low frequency (e.g., day-level), which have three limitations to perform well in intraday trading. First, micro-level market information is often neglected and only macro-level market information (e.g., daily price and volume) is used [Deng et al., 2016]. Second, a professional intraday trader makes trading decisions based on analyzing both local (e.g., minute-level) price fluctuation and long-term overall price trend [Admati and Pfleiderer, 1988]. However, most existing works share a limited horizon and fail to capture the overall trend [Zhang et al., 2020]. Third, the impact of market risk is overlooked [Liu et al., 2020]. The RL agent faces the problem of balancing exploration and exploitation. Random exploration with-
out taking market risk into account may bring great loss.

To tackle the above limitations, we propose DeepScalper, a DRL-based framework for intraday trading. Specifically, to efficiently incorporate both micro-level and macro-level market information, we propose an encoder-decoder architecture to learn robust market embedding. To capture the overall price trend, we design a novel hindsight reward function with a long-term profit regularizer to provide the agent with the long-term horizon. To take market risk into consideration, we firstly compute volatility as a coherent measure of risk. Then, we apply volatility prediction as an auxiliary task to help the agent aware of the market risk while maximizing profit. To evaluate DeepScalper’s performance, we conduct extensive experiments on two stock index futures and four treasury bond futures. The results demonstrate that DeepScalper successfully captures the overall price trend and strikes a great balance between risk and profit. DeepScalper significantly outperforms many baselines in terms of total return and three risk-adjusted criteria. Ablation studies demonstrate the effectiveness of proposed components.

2 Problem Formulation

In this section, we firstly introduce necessary preliminaries and the objective of intraday trading. In addition, we formulate intraday trading as a Partially Observable Markov Decision Process (POMDP).

2.1 Intraday Trading

Intraday trading is a fundamental quantitative finance task, where traders long and short one particular financial asset within the same trading day to maximize future profit. At the beginning of a trading day, traders are allocated some cash into the account. During the trading time, traders make trading decisions through analyzing market information (e.g., price, volume and LOB). Later on, they submit limit orders, which represent their trading decisions, to the matching system. The matching system will execute orders at best available price, volume and LOB. Later on, they submit limit orders, and then return execution results to traders. At the end of the trading day, all remaining positions are closed at market price to avoid overnight risk. Traders hold 100% cash again.

Definition 1. (OHLCV) We denote OHLCV vector at time \( t \) as \( \mathbf{x}_t = (p_t^h, p_t^l, p_t^b, p_t^c, v_t) \), where \( p_t^h \) is the high price, \( p_t^l \) is the low price, \( p_t^b \) is the close price and \( v_t \) is the volume.

Definition 2. (Technical Indicator) A technical indicator indicates a feature calculated by a formulaic combination of the original OHLCV to uncover the underlying pattern of the financial market. We denote the technical indicator vector at time \( t \): \( \mathbf{y}_t = \bigcup_{k} y_t^k \), where \( y_t^k = f_k(\mathbf{x}_{t-h}, ..., \mathbf{x}_t, \theta^k) \), \( \theta^k \) is the parameter of technical indicator \( k \).

Definition 3. (Limit Order) A limit order is an order placed to long/short a certain number of shares at a specific price. It is defined as a tuple \( l = (p_{\text{target}}, \pm q_{\text{target}}) \), where \( p_{\text{target}} \) represents the submitted target price, \( q_{\text{target}} \) represents the submitted target quantity, and \( \pm \) represents the trading direction (long/short).

Definition 4. (Limit Order Book) As shown in Figure 1(a), a limit order book (LOB) is a public available table containing aggregate information of limit orders by all market participants. It is widely used as market microstructure [Madhavan, 2000] in finance to represent the relative strength between buy and sell side. We denote an \( m \) level LOB at time \( t \) as \( \mathbf{b}_t = (p_t^{b_1}, q_t^{b_1}, q_t^{b_1}, p_t^{b_2}, q_t^{b_2}, ..., p_t^{b_m}, q_t^{b_m}) \), where \( p_t^{b_i} \) is the level \( i \) bid price, \( q_t^{b_i} \) is the level \( i \) ask price, \( q_t^{b_i} \) and \( q_t^{b_i} \) are the corresponding quantities.

Definition 5. (Matching System) The matching system is an electronic system that matches the buy and sell orders for the financial market. It is usually used to execute orders for different traders in the exchange.

Definition 6. (Position) Position \( s_t \) at time \( t \) is the amount and direction of a financial asset owned by traders. It represents a long (short) position when \( s_t \) is positive (negative).

Definition 7. (Net Value) Net value is the normalised sum of cash and value of financial assets held by a trader. The net value at time \( t \) is denoted as \( n_t = (c_t + p_t^b \times |s_t|)/c_t \), where \( c_t \) is the cash at time \( t \) and \( c_t \) is the initial amount of cash.

The objective of intraday trading is to maximize accumulative profit within a period of multiple continuous trading days (e.g., half a year).

2.2 Partially Observable MDP Formulation

There are countless events and activities that impact the financial market. In general, these events and activities are classified into macroeconomics and microeconomics. However, one can never observe the real market states due to the existence of unpredictable events and activities. For instance, nobody knows the result of a presidential election in advance or whether orders can be executed at desired prices. The essence of intraday trading is exactly a partially observable sequential decision-making problem about when and how much to trade one particular financial asset.

The POMDP formulation is constructed by a 7-tuple \((S, A, T, R, O, Z, \gamma)\). Specifically, \( S \) is a finite set of states. \( A \) is a finite set of actions. \( T : S \times A \times S \rightarrow [0, 1] \) is a state transition function, which consists of a set of conditional transition probabilities between states. \( R : S \times A \rightarrow R \) is the reward function, where \( R \) is a continuous set of possible rewards and \( R \) indicates the immediate reward from taking an action in a state. \( O \) is a set of observations. \( Z : S \times A \times O \rightarrow [0, 1] \) is the observation transition function and \( \gamma \in [0, 1) \) is the discount factor. For the deterministic policy, the goal of an agent is to learn a policy \( \pi : S \rightarrow A \), which maximizes the expected discounted reward \( J = \mathbb{E}[\sum_{t=1}^{\infty} \gamma^{t-1} R_t] \). \( R_t \) refers to the immediate reward at time \( t \). The action-value function \( Q^\pi = \mathbb{E}[\sum_{t=1}^{\infty} \gamma^{t-1} R_t | \pi] \) is introduced to estimate the performance of policy \( \pi \).

Observation. Due to the particularity of the financial market, the observation \( o_t \in O \) at time \( t \) can be divided into three parts: micro-level market observation \( o_t^m \in O^m \), macro-level market observation \( o_t^{\mu} \in O^{\mu} \) and trader’s private observation set \( o_t^{p} \in O^{p} \). Specifically, we use a vector \( \mathbf{y}_t \) of ten technical indicators and OHLCV vector \( \mathbf{x}_t \) as macro-level observation, the historical LOB sequence \( \{b_{t-h}, ..., b_t\} \) with length
Figure 1: (a) An example of 3-level limit order book (b) Motivation of hindsight reward function

$h + 1$ as micro-level observation and trader’s private observation $z_t = (s_t, c_t, t_t)$, where $s_t$, $c_t$ and $t_t$ are the current position, cash and remaining time. The whole observation set can be denoted as $O = (O^p, O^z, O^h)$. Compared to previous formulations, we introduce LOB and trader’s private observation as extra information to improve the performance of decision making.

**Action.** Previous works [Deng et al., 2016; Liu et al., 2020] normally stipulate the agent trades a fixed quantity at market price and define the action space with three actions (long, hold and short). However, traders have the freedom to decide both target price and quantity in the real market. We use a more realistic action space, which represents a limit to decide both target price and quantity in the real market. 2020 normally stipulate the agent trades a fixed quantity at market price and define the action space with three actions.

**Reward.** In the literature, account profit is the most common and intuitive reward function. Previous works also propose Differential Sharpe ratio [Moody and Saffell, 1999] and maximum drawdown [Wang et al., 2021b] as alternative options. However, we find all these reward functions fail to capture the long-term trend for intraday trading. We design a novel hindsight reward function to conquer this issue in the next section.

3 DeepScalper

In this section, we introduce our framework, DeepScalper (DS), to address the POMDP for intraday trading. We introduce intraday market embedding, hindsight reward, risk-aware auxiliary task and RL optimization orderly. Figure 2 presents an overview of DeepScalper.

3.1 Intraday Market Embedding

To learn a robust intraday market embedding, we propose two encoders to represent the market from micro-level and macro-level respectively. For **micro-level encoder.** We choose LOB data and trader’s private observation to learn the micro-level market embedding. LOB is widely used to analyze the micro-level strength of buy and sell side and trader’s private observation is considered insightful to capture micro-level trading opportunities [Nevmyvaka et al., 2006]. At time $t$, we have a sequence of historical LOB embedding $(b^h_{t+k}, ..., b^h_t)$ and trader’s private observation embedding $(z_{t+k}, ..., z_t)$, where $k + 1$ is the sequence length. As shown in Figure 2(a), we feed them into two different LSTM layers, and concatenate the last hidden states $h^m_t$ and $h^z_t$ of the two LSTM layers as the micro-level embedding $e^m_t$ at time $t$. For **macro-level encoder.** We pick the raw OHLCV data and technical indicators for learning the macro-level embedding. The intuition here is that OHLCV reflects original market status and technical indicators offer extra insight. At time $t$, we firstly concatenate OHLCV vector $x_t$ and technical indicator vector $y_t$ as input $v_t$. As shown in Figure 2(b), the concatenated embedding is then fed into a multilayer perceptron (MLP). The output of MLP is applied as the macro-level embedding $e^z_t$ at time $t$.

Finally, we concatenate the micro-level embedding and macro-level embedding together as the market embedding $e_t$. Our market embedding is better than that of previous works since it incorporates micro-level market information.

3.2 Hindsight Reward

Through observing trading behaviors, we find trading based on only short-term horizon market information is one major reason why agents trained with previous reward functions perform poorly in intraday trading. Even though the agent performs well at capturing local trading opportunities, ignoring the overall price trend could lead to significant loss. Figure 1(b) demonstrates the motivation of hindsight reward function. Considering a trader buys the stock before 10 am, the trader feels happy at 10:10 since the stock price increases. However, if the trader misses the selling chance at 10:10 and holds the stock longer, he/she will get a negative profit since the stock price decreases continuously after 10:10. Due to randomness of financial market, it is extremely hard to fully understand it and sell at the highest price. The proper reward function is supposed to evaluate the trading action from both short-term and long-term perspectives. We design a hindsight reward function with a term of instant profit, long-term profit and transaction fee:

$$r_t = w \times (p^c_t - p^c_{t+1}) - \delta \times p^c_t \times q_t$$

where $p^c_t$ is the close price at time $t$, $w$ is the weight of long-term profit, $h$ is the long-term profit horizon length, $\delta$ is the transaction fee rate and $q_t$ is the executed order quantity at time $t$.

The instant profit term represents the profit of selling the financial asset right after buying it. The long-term profit term represents the profit of holding the financial asset for a period of $h$. The transaction fee term is applied to take trading cost into consideration. We combine these three terms as the hindsight reward function to make the evaluation of trading actions more reasonable. The hindsight reward function somehow ignores details of price fluctuation between $t + 2$ to $t + h - 1$ and focuses on the trend of this period. This design is very computationally efficient and shows robust performance in practice.

3.3 Risk-aware Auxiliary Task

Volatility is widely used as a coherent measure of risk in finance [Bakshi and Kapadia, 2003]. As shown in Figure 2(c), we propose volatility prediction as an auxiliary task to help the agent aware of the market risk while maximizing profit. The definition of volatility is the variance of return sequence: $y_{vol} = \sigma^2(r)$. $r$ is the vector of return at each time step. Volatility prediction is a regression task with market embedding $e_t$ as input and $y_{vol}$ as target. We feed the market embedding into a single layer MLP with parameters $\theta_v$. The

| Qty  | Price  | Price  | Qty  |
|------|--------|--------|------|
| 100  | 9.9    | 10.0   | 450  |
| 30   | 9.8    | 10.1   | 200  |
| 150  | 9.7    | 10.2   | 100  |

![Figure](image-url)
output \(y_{\text{vol}}\) is the predicted volatility. We train the network by minimizing the mean squared error loss function:

\[
y_{\text{vol}} = MLP(e_t, \theta_e) \quad L_{\text{vol}}(\theta_d) = (y_{\text{vol}} - \hat{y}_{\text{vol}})^2
\]

We analyze reasons why volatility prediction is an effective auxiliary task to improve the trading policy learning as follows: 1) It is consistent to the general trading goal, which is to maximize long-term profit under certain risk tolerance. 2) Future volatility is easier to predict comparing to future price. For instance, considering the day that the president election result will be announced, nobody can know the result in advance, which will lead the stock market to increase or decrease. However, everybody knows this result will have a huge impact on the stock market, which makes the future volatility higher. 3) Intuitively, future price and volatility prediction are two closely related tasks. Learning value function approximation and volatility prediction simultaneously can help the agent learn a more robust market embedding.

### 3.4 RL Optimization with Action Branching

Our intraday trading problem is formulated as a discrete partially observable sequential decision making problem with two action dimensions: price and quantity. We address it with the Branching Dueling Q-Network [Tavakoli et al., 2018] as shown in Figure 2(d). Formally, we have two action dimensions with \(|p| = n_p\) discrete relative price levels and \(|q| = n_q\) discrete quantity proportions. The action value \(Q_d\) at state \(s \in S\) and the action \(a_d \in A_d\) are expressed in terms of the common state value \(V(s)\) and the corresponding (state-dependent) action advantage [Wang et al., 2016] \(\text{Adv}_d(s, a_d)\) for \(d \in \{p, q\}\):

\[
Q_d(s, a_d) = V(s) + (\text{Adv}_d(s, a_d) - \frac{1}{n_d} \sum_{a_d \in A_d} \text{Adv}_d(s, a_d))
\]

We train our Q-value function approximator as Q-Network with parameter \(\theta_q\) based on the one-step temporal-difference learning:

\[
y_a = \gamma \max_{a'_d \in A_d} Q_d(s', a'_d, \theta'_q), \quad d \in \{p, q\}
\]

\[
L_q(\theta_q) = E_{(s,a,r,s') \sim D}\left[\frac{1}{N} \sum_{d \in \{p,q\}} (y_d - Q_d(s, a_d, \theta_q))^2\right]
\]

where \(D\) denotes a prioritized experience replay buffer. \((p,q)\) denotes the joint-action tuple \((p, q)\). The overall loss function is defined as:

\[
L = L_q + \eta \ast L_{\text{vol}}
\]

where \(\eta\) is the relative importance of the auxiliary task. We use stochastic gradient descent to minimize the loss function.

### 4 Experiment

In this section, we evaluate DeepScalper on six different financial futures from two datasets: treasury bond and stock index. We summarize the datasets, describe the evaluation metrics, introduce baseline methods for comparison and perform extensive experiments to demonstrate the effectiveness of DeepScalper. We further validate the effectiveness of proposed components by ablation study.

#### 4.1 Datasets

We collect data of six different financial futures from wind\(^1\), which belongs to the following two datasets:

**Stock index** contains the minute-bar OHLCV and LOB data of two representative stock index futures (IC, IF) in Chinese market. IC is a stock index future calculated based on 500 small and medium market capitalization stocks. IF is another stock index future, which focuses on the top 300 large capitalization stocks. For each stock index future, we split the dataset with May-Dec, 2019 for training and Jan-April, 2020 for testing.

**Treasury bond** contains the minute-bar OHLCV and LOB data of four treasury bond futures (T01, T02, TF01, TF02). These treasury bond futures are mainstream treasury bond futures with the highest liquidity in Chinese market. For each treasury bond, we use 2017/11/29 - 2020/4/29 for training and 2020/04/30 - 2020/07/17 for testing.

#### 4.2 Experiment Setup and Preprocessing

Since the price and order volume are at different scale for each financial asset, we normalize them through dividing them by the first price and volume respectively. For missing data, we fill the empty price with the previous one and

\(^1\)https://www.wind.com.cn/
missing volume as zero to keep the consistency of time series data. We consider many practical constraints to make our experiments more realistic. The transaction fee rate $\delta$ is set as $2.3 \times 10^{-5}$ and $3 \times 10^{-6}$ for stock index futures and treasury bond futures respectively. Since leverage such as margin loan is widely used in the future market for intraday trading, we apply a fixed five times leverage to amplify the return and volatility.

Time is discreted into 1 min interval and we assume the agent can only long/short a financial future at the end of each minute. The account is initialized with cash enough to buy 50 shares of the asset at the beginning. The maximum holding position is 50. We set the look-ahead horizon $h = 180$ for the hindsight reward function. As for neural network architectures, the number of hidden units in the two LSTMs of our framework is 64. We set the hidden units of all MLP layers to 128 with ReLU as the activation function. We set learning rate as $10^{-3}$ and training epoch as 10. Following the iterative training scheme in [Nevmyvaka et al., 2006], we augment traders’ private observation repeatedly during the training to improve data efficiency. We run experiments with 5 different random seeds and report the average performance.

### 4.3 Evaluation Metrics

Four metrics are used in our experiments, which can be divided into two categories: 1) profit criterion, including Total Return (TR); 2) risk-adjusted profit criterion, including Sharpe Ratio (SR), Calmar Ratio (CR), and Sortino Ratio (SoR). The detailed definitions of these metrics are provided in Appendix A.

### 4.4 Baselines

We compare DeepScalper with several advanced methods, including 1) three traditional finance methods: Buy & Hold (BAH), Mean Reversion (MV) [Poterba and Summers, 1988] and Time Series Momentum (TSM) [Moskowitz et al., 2012]; 2) two deep learning methods: MLP and GRU [Chung et al., 2014]; 3) one tree-based method: LGBM [Ke et al., 2017]; 4) one reinforcement learning method: DRLT [Zhang et al., 2020]. More descriptions of baseline methods are presented in Appendix B.

we also present two variants of DeepScalper (DS) for comparison: **DS-NH**, which removes the long-term reward term from the hindsight reward function and **DS-NA**, which removes the risk-aware auxiliary task.

| Models | Stock Index | Treasury Bond |
|--------|-------------|---------------|
|        | T(R%)       | T(R%)         |
| BAH    | 5.65        | -14.26        |
| MV     | 8.39        | -0.59         |
| TSM    | 27.6        | -3.02         |
| MLP    | 0.74        | 0.39          |
| GRU    | 5.66        | 1.02          |
| LGBM   | 7.62        | 1.45          |
| TSM    | 8.17        | 3.38          |
| DS-NH  | 9.74        | 4.17          |

Table 1: Performance on stock index and treasury bond dataset

### 4.5 Results

In Table 1, we report the average performance of baselines and DeepScalper on stock index and treasury bond datasets respectively. In the stock index dataset, DeepScalper performs the best in all 4 metrics. Specifically, it outperforms the second best by 31%, 33%, 21% and 8% in terms of TR, SR, CR and SoR. In the treasury bond dataset, DeepScalper outperforms the second best by 14%, 11%, 30% in terms of TR, SR and CR. As for SoR, DeepScalper achieves the second best. DS-NA achieves the best performance, which is slightly better (2%) than DeepScalper. One possible reason is that volatility prediction is not directly relevant to control downside return variance.

We show the net value vs. trading days of the test period for each financial future from the two datasets in Figure 3. We intentionally exclude BAH, DS-NH and DS-NA to make the figure easy to follow. More detailed results are available in Appendix C. For traditional methods, we find MV achieves a decent performance for most financial futures. In comparison, TSM’s performance is much worse. One possible reason for TSM’s failure is that there is no evident momentum effect within the market for intraday trading. For deep learning models, the overall performance of GRU is better than MLP due to its ability to learn the temporal dependency of indicators. As for gradient boosting tree model, it achieves slightly better performance than deep learning models. The average performance of RL methods is the best. Furthermore, we conduct comprehensive ablation studies on TF01 to show...
the effectiveness of each components in Table 2.

| Macro | Micro | Hindsight | Volatility | TR(%) | SR |
|-------|-------|-----------|------------|-------|----|
| √     |       | √         |            | 3.45  | 4.42|
| √     |       | √         | √          | 3.47  | 4.43|
| √     | √     | √         |            | 3.62 (+0.15) | 4.81 (+0.38) |
| √     | √     | √         | √          | 4.05 (+0.58) | 5.03 (+0.60) |
| √     | √     | √         | √          | 5.36 (+1.89) | 5.72 (+1.29) |
| √     | √     | √         | √          | 6.97 (+3.50) | 6.10 (+1.67) |

Table 2: Ablation studies on the effectiveness of each component

4.6 Effect of Hindsight Reward Function

We firstly show that the hindsight reward function is not sensitive to hyperparameter selection. Figure 4(a) is the trading day vs. net value curve of DeepScalper trained with different weight importance $w$. With the increase of $w$, the agent tends to trade with a long-term horizon and achieves higher profit. The general shape of each line is similar with smooth improvement. DeepScalper with $w = 0.1$ achieves the highest profit. Figure 4(b) shows the impact of hindsight horizon $h$ on DeepScalper’s performance. We observe that DeepScalper’s total return gradually increases by moving $h$ from 30 to 180 and decreases when $h > 180$.

Moreover, we compare the trading behaviours of agents trained with and without hindsight reward function in a trading day with decreasing trend in Figure 5. The general good intraday trading strategy in that day is to short at the start of the day and long at the end of the day. We observe an agent’s trading behaviours in details and find the agent trained without hindsight reward function (Figure 5a) performs well in capturing local trading opportunities and overlooks the long-term trend of the whole trading day. In comparison, an agent trained with hindsight reward function (Figure 5b) trades large volume of short actions at the start of the trading day, which indicates that it is aware of the decreasing trend in advance. This kind of trading actions is smart since it catches the big price gap of the overall trend and somehow ignores the local gain or loss. More trading behaviours comparison examples are available in Appendix D.

4.7 Effect of Risk-aware Auxiliary Task

Since financial market is noisy and RL training process is unstable, the performance variance among different random seeds is a major concern of RL-based trading algorithms. Intuitively, taking market risk into consideration can help the RL agent behave more stable with lower performance variance. We run experiments 5 times with different random seeds and report the relative variance relationship between RL agents trained with/without auxiliary task ($>0$ means RL agents trained with auxiliary task get lower variance) in Figure 6(a). We find that RL agents trained with the risk-aware auxiliary task achieve lower TR variance in all 6 financial assets and lower SR variance in 67% of financial assets. We further test the impact of auxiliary task importance $\eta$ on DeepScalper’s performance. Naturally, the scale of volatility is smaller than return, which makes $\eta = 1$ a decent option to start. In practice, we test $\eta \in [0, 0.5, 1]$ and find the improvement of the auxiliary task is robust to different importance weights as shown in Figure 6(b).

5 Conclusion

In this paper, we focus on the problem of intraday trading with practical constraints via deep reinforcement learning. We propose DeepScalper, a DRL framework, which can learn robust market embedding incorporating both micro-level and macro-level market information. In addition, we design a novel hindsight reward function to encourage a long-term horizon for capturing the overall price trend. Moreover, we propose volatility prediction as an auxiliary task to help the agent aware of market risk while maximizing profit. Extensive experiments on two stock index futures and four treasury bond futures demonstrate that DeepScalper significantly outperforms many advanced methods.
References

Anat R Admati and Paul Pfleiderer. A theory of intraday patterns: Volume and price variability. *The Review of Financial Studies*, 1(1):3–40, 1988.

Gurdip Bakshi and Nikun Kapadia. Delta-hedged gains and the negative market volatility risk premium. *The Review of Financial Studies*, 16(2):527–566, 2003.

John Bollinger. *Bollinger on Bollinger Bands*. McGraw-Hill New York, 2002.

Chi Chen, Li Zhao, Jiang Bian, Chuxiao Xing, and Tie-Yan Liu. Investment behaviors can tell what inside: Exploring stock intrinsic properties for stock trend prediction. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 2376–2384, 2019.

Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555*, 2014.

Yue Deng, Feng Bao, Youyong Kong, Zhiquan Ren, and Qionghai Dai. Deep direct reinforcement learning for financial signal representation and trading. *IEEE Transactions on Neural Networks and Learning Systems*, 28(3):653–664, 2016.

Xiao Ding, Yue Zhang, Ting Liu, and Junwen Duan. Deep learning for event-driven stock prediction. In *Proceedings of the 24th International Conference on Artificial Intelligence*, page 2327–2333, 2015.

Eugene F Fama. Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2):383–417, 1970.

Fuli Feng, Xiangnan He, Xiang Wang, Cheng Luo, Yiqun Liu, and Tat-Seng Chua. Temporal relational ranking for stock prediction. *ACM Transactions on Information Systems (TOIS)*, 37(2):1–30, 2019.

Ziniu Hu, Weiqing Liu, Jiang Bian, Xuanzhe Liu, and Tie-Yan Liu. Listening to chaotic whispers: A deep learning framework for news-oriented stock trend prediction. In *Proceedings of the 11th ACM International Conference on Web Search and Data Mining*, pages 261–269, 2018.

Zhengyao Jiang, Dixin Xu, and Jinjun Liang. A deep reinforcement learning framework for the financial portfolio management problem. *arXiv preprint arXiv:1706.10059*, 2017.

Guolin Ke, Qi Meng, Thomas Finley, Taifeng Wang, Wei Chen, Weidong Ma, Qiwei Ye, and Tie-Yan Liu. Lightgbm: A highly efficient gradient boosting decision tree. pages 3146–3154, 2017.

Charles MC Lee and Mark J Ready. Inferring trade direction from intraday data. *The Journal of Finance*, 46(2):733–746, 1991.

Yang Liu, Qi Liu, Hongke Zhao, Zhen Pan, and Chuanren Liu. Adaptive quantitative trading: An imitative deep reinforcement learning approach. In *Proceedings of 35th the AAAI Conference on Artificial Intelligence*, pages 2128–2135, 2020.

Ananth Madhavan. Market microstructure: A survey. *Journal of Financial Markets*, 3(3):205–258, 2000.

John E Moody and Matthew Saffell. Reinforcement learning for trading. pages 917–923, 1999.

Tobias J Moskowitz, Yao Hua Ooi, and Lasse Heje Pedersen. Time series momentum. *Journal of Financial Economics*, 104(2):228–250, 2012.

Yuriy Nevmyvaka, Yi Feng, and Michael Kearns. Reinforcement learning for optimized trade execution. In *Proceedings of the 23rd International Conference on Machine Learning*, pages 673–680, 2006.

James M Poterba and Lawrence H Summers. Mean reversion in stock prices: Evidence and implications. *Journal of Financial Economics*, 22(1):27–59, 1988.

Arash Tavakoli, Fabio Pardo, and Petar Kormushev. Action branching architectures for deep reinforcement learning. In *Proceedings of the 32nd AAAI Conference on Artificial Intelligence*, pages 4131–4138, 2018.

Ziyu Wang, Tom Schaul, Matteo Hessel, Hado Hasselt, Marc Lanctot, and Nando Freitas. Dueling network architectures for deep reinforcement learning. In *Proceedings of 35th International Conference on Machine Learning*, pages 1995–2003, 2016.

Rundong Wang, Hongxin Wei, Bo An, Zhouyan Feng, and Jun Yao. Commission fee is not enough: A hierarchical reinforced framework for portfolio management. In *Proceedings of the 35nd AAAI Conference on Artificial Intelligence*, 2021.

Zhicong Wang, Biwei Huang, Shikui Tu, Kun Zhang, and Lei Xu. Deeptrader: A deep reinforcement learning approach to risk-return balanced portfolio management with market conditions embedding. In *Proceedings of the 35th AAAI Conference on Artificial Intelligence*, 2021.

Yumo Xu and Shy B Cohen. Stock movement prediction from tweets and historical prices. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics*, pages 1970–1979, 2018.

Pengqian Yu, Joon Sern Lee, Ilya Kulyatin, Zekun Shi, and Sakyasingha Dasgupta. Model-based deep reinforcement learning for dynamic portfolio optimization. *arXiv preprint arXiv:1901.08740*, 2019.

Liheng Zhang, Charu Aggarwal, and Guo-Jun Qi. Stock price prediction via discovering multi-frequency trading patterns. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 2141–2149, 2017.

Zihao Zhang, Stefan Zohren, and Stephen Roberts. Deep reinforcement learning for trading. *The Journal of Financial Data Science*, 2(2):25–40, 2020.