Improving Portfolio Management with Signals from Financial News: A Thesis Proposal

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Abstract

The goal of portfolio management is to maximize investment returns while reducing investment risk. Reinforcement learning-based portfolio management continuously seeks characteristics in past data to maximize returns. Existing financial text information processing methods are not optimized for investment decision events, making it difficult to accurately reflect the actual impact of financial text information on investment. Additionally, differences in the quality of financial text information result in noisy data. In view of these limitations, this research proposal has two main goals. The first goal is to find effective ways to extract signals present in the financial news and the second goal is to eventually use the signals from the news articles to improve portfolio management. More specifically, in our proposal we focus on analysing sentiment signals from the financial news articles and we observe the effect of the sentiment scores on reinforcement learning based portfolio management approaches. We did an initial investigation to observe the effect of sentiment scores in portfolio management. In our experiments, we randomly selected eight stocks from Dow Jones Industrial Average index for experiments and verified that our model can significantly improve cumulative returns 117.3% while reduce max drawdown 15.2%. It greatly improves the performance of reinforcement learning-based investment management methods.

1 Introduction

In recent years, portfolio management based on reinforcement learning (RL) has become a popular research direction. In traditional human-driven portfolio management, news and financial reports are often important reference factors that greatly influence asset price trends and have a significant impact on investment decisions (Almahdi and Yang, 2017; Jiang et al., 2017; Liang et al., 2018). Generally, market sentiment is mostly represented through news text-type information (Du and Tanaka-Ishii, 2020; Sawhney et al., 2021), and there are also some numerical information indicators that predict future stock price trends through price, trading volume, and other numerical information. Or,it can allow both text-type information and price information as inputs, but in only one type as a sentiment indicator (Ye et al., 2020). These methods either only allow numerical information input or only allow text content, and information fusion has not been achieved.

Currently, the methods that combine news text information mainly fall into two categories: 1) using subjective judgments by humans as labeled news datasets to train a sentiment classification model (Yang et al., 2020), and 2) using the price trend after the news as a label to train a sentiment classification model (Ye et al., 2020). These two methods have drawbacks. First, using human subjective judgments as labels may reflect the meaning of news, but it may not correspond to the actual trend, and there may be problems such as lagging or lower-than-expected news sources that cause discrepancies between news sentiment and reality. Second, prices trend are used as labels, it will depart from the core expression of news information and be disturbed by Price fluctuations.

This thesis proposal focus on a market sentiment representation model that integrates text and numerical technical indicators to optimize portfolio. The study includes two steps: one is to use artificially labeled data to train a sentiment classification model to classify news text and obtain a news sentiment index, and the other is to use Informer combined with historical price trends to train a price trend predictor and obtain a price trend index. Using the price trend index to modify the news sentiment index, we obtain a new market sentiment index that

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incorporates human judgment of stock news and uses technical trends to correct human judgment and more accurately grasp market changes. In the experiment, we used a stock dataset for verification. The experimental results show that using our new market sentiment index for portfolio management outperforms traditional portfolio management. In summary, the investment portfolio management scheme based on reinforcement learning and market sentiment indicators proposed in this article can help investors better adapt to market fluctuations and improve returns.

This paper is organized as follows. In Section 2, we described the existing background work related to the thesis proposal. In Section 3, we described the portfolio management framework in detail along with the available dataset and evaluation framework. In Section 4 we focus on the different research questions that we have already addressed and also plan to explore in future. In Section 5, we conclude this proposal.

2 Background

This article presents an integrated model for stock market sentiment analysis, which combines predictive modeling of stock prices, sentiment classification of financial texts, and reinforcement learning techniques. We provide an overview of the relevant technologies for each component, which will be used to create a new market sentiment model that enhances investment portfolio management tasks.

Reinforcement learning. Proximal Policy Optimization (PPO) algorithm (Schulman et al., 2017). PPO updates the policy function by performing proximal optimization, which uses a scaling factor to control the update magnitude and avoid instability issues (Yang et al.). PPO has achieved excellent results in many reinforcement learning tasks, including Atari games and robot control, and has become a popular algorithm due to its simplicity and ease of implementation.

Sentiment classification of financial texts. Early approaches relied on rule-based and manual coding, but recent advances in machine learning and AI have greatly improved performance. Deep learning models such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs) are now widely used for sentiment classification (Kim, 2014; Elman, 2010). BERT, which uses a Transformer architecture and pre-training on large amounts of unannotated data, has achieved state-of-the-art results in multiple NLP tasks (Devlin et al., 2018). However, due to the high level of domain-specific vocabulary in finance, a domain-specific pre-trained model such as FinBERT may be more effective in financial sentiment classification (Yang et al., 2020).

Predictive modeling of stock prices. LSTM has been widely used for time series prediction due to its ability to handle long sequences using gating mechanisms (Hochreiter and Schmidhuber, 1997). However, it faces challenges with increasingly long sequences and poor performance in extreme cases. Informer uses a Transformer architecture that can process both long and short sequences while effectively learning and extracting features at different time scales (Zhou et al., 2020). It also incorporates attention mechanisms and adaptive lengths to further improve prediction performance.

3 Problem Description

We use reinforcement learning to solve the stock trading problem. $S = \{s_1, s_2, \ldots, s_N\}$ denote a set of N stocks. Our goal is to design a stock trading model that utilizes information from financial news about stocks and interacts with the market environment to execute stock trades. The model generates trade decisions by observing market conditions and receives rewards and state updates in the subsequent time steps. Stock markets are influenced by economic factors, social media, news, and many other factors that are uncertain and difficult to observe. The typical Markov Decision Process (MDP) used in reinforcement learning requires the environment to be fully observable (Ilmanen, 2012), making it challenging to integrate stock impact information for decision-making. To address this issue, we use the Partially Observable MDP (POMDP) model (Jaakkola et al., 1995), which extends from the Markov Decision Process model to simulate the stock trading environment. Then, the key components of the stock trading environment are as follows:

State observations: For each time-step τ, the status s_τ consists of two parts: o_τ represent stock trading account status and o_m denote the market information status. At the current time-step, the account balance and the holdings of each stock together constitute o_τ. The market information status o_m including financial news which related with the stock released during a T-day lookback period.

Trading actions: At each time-step τ, the agent has three options: buy, sell, and hold. On the basis of these three decisions, we design a trading volume vector a_τ for the stock sets S, which is decided by the agent to increase, decrease or keep the same on the basis of the current stock holdings. we use n to represent the volume of stock we already hold. h represents the maximum buying amount of a single stock. One of three possible trading actions is taken on each stock s :

1) Buying action $a[s] \in [1, h]$ results in $n_{\tau+1}[s] = n_\tau[s] + a[s]$, where a[s] $\in \mathbb{Z}^+$; or

2) Holding action $a[s]$ use 0 represent results in $n_{\tau+1}[s] = n_\tau[s]$; or

3) Selling action $a[s] \in [1, n_\tau[s]]$ results to $n_{\tau+1}[s] = n_\tau[s] - a[s]$.

Rewards: The change in the total value of the account when the state changes from s_τ to $s_{\tau+1}$ after the trading action is defined as the reward. For each value account change, we define a return r, as:

$$r\left(s_\tau, a_\tau, s_{\tau+1}\right) =$$

$$\left(b_{\tau+1} + p_{\tau+1}^T n_{\tau+1}\right)\left(b_\tau + p_\tau^T n_\tau\right) - c_\tau$$

The account balance is denoted by b_τ, n_τ represents the number of stocks held at the current time-step . p_τ is used to denote the price at this time-step τ. At the same time, we also consider the issue of transaction fee rate for each trading action, we use c_τ to representand.

3.1 Dataset

Datasets consists of two parts: daily closing asset prices, trading volume, technical indicators such as MACD, RSI and financial news from 2018-07-01 to 2021-03-01. Among them, daily closing asset prices and technical indicators are collected from Yahoo Finance[1] and financial news from Investing[2]. As far as the financial news information is concerned, there is a huge difference in the amount of news data between different companies (Ye et al., 2020), as can be found by Table 1 the number of news for the eight stocks we randomly selected from dow30 varies greatly, in line with the highly uneven distribution of overall financial information. We split the dataset based on date range from 2018-07-01 to 2020-07-01 for training, 2020-07-01 to 2020-09-01 for validation, and 2020-09-01 to 2021-03-01 for testing, and the divided dataset was used with all models and experiments.

Stock Code	Quantity	Average Length
AAPL	2586	370.13
CAT	1142	115.34
DIS	1363	131.08
GS	2431	289.99
INTC	1630	144.60
JPM	2360	247.14
MMM	482	105.07
MSFT	2298	210.68

Table 1: The codes of 8 stocks in the data set and the average length and quantity of corresponding news.

3.2 Evaluation Metrics

We chose **Sharpe ratio (SR)**, the **Cumulative Return (CR)**, and the **Max Drawdown (MDD)** which commonly used in the financial field as our evaluation metrics for evaluating model performance.The Sharpe ratio is a measure of the risk and return of an investment portfolio(Sharpe, 1964). We use R_p denote the return of the investment portfolio,the rise-free rate use R_f to represent. σ_p is standard deviation of the portfolio's annualized return. Then we could calculate $SR = \frac{R_p - R_f}{\sigma_p}$. The CR is the change in the investment over time and is computed using the initial (b_0) and the final(b_f) account balance as: $CR = \frac{b_f - b_0}{b_0} * 100\%$. MDD represents the unit rate of change from the highest net asset value r_p to the lowest net asset value r_t after the highest net asset value. The calculation method of MDD can be expressed as: $MDD = \frac{r_t - r_p}{r_p} * 100\%$. Larger values (in magnitude) of MDD indicate higher volatility.

4 Research Questions

We employ reinforcement learning as our decision-making model for portfolio management. As given in Figure 1, this model not only incorporates technical indicators such as historical stock prices and trading volumes but also incorporates text information such as news and research reports. We designe a novel stock sentiment index model that combines heterogeneous information such as news and prices to ensure access to information that may cause asset

[1]https://finance.yahoo.com
[2]www.investing.com

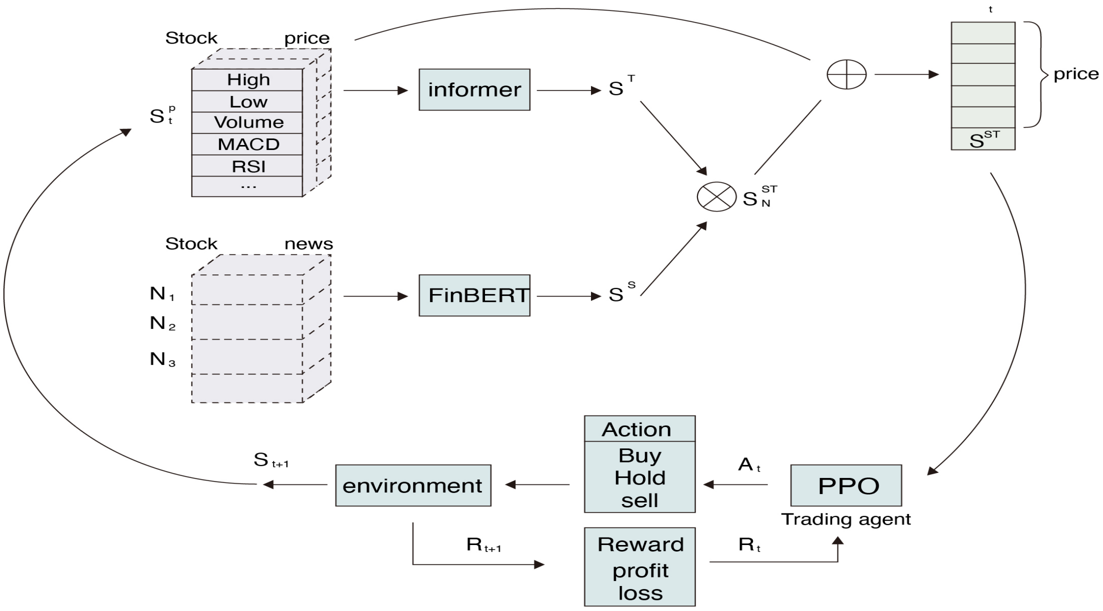

Figure 1: The framework of our proposed method.Sentiment index network (top), reinforcement learning for trading decision (bottom)

value fluctuations. After obtaining the company's sentiment index, we combine it with technical indicators such as prices and trading volumes and input them into the reinforcement learning network for training. Our FinSRL model can integrate information content and sources of any form in the market to ensure that the model does not miss any important information that may cause market fluctuations.

4.1 RQ1: What is the Effect of Noise in Sentiment Prediction for Portfolio Management?

The quality of financial news varies greatly depending on its type and source, and its impact on stocks also differs significantly. Only a small portion of the massive amount of financial news can truly affect stock prices. Therefore, processing a large amount of financial information inevitably leads to a significant amount of useless noise. This study explores the impact of noise on portfolio management and efficiently filters it out.

4.1.1 Sentiment Model

In the design of sentiment models, we combine two existing methods to improve the accuracy of sentiment indicators. Specifically, we use FinBERT to classify the sentiment of news text content. FinBERT is based on BERT and was fine-tuned on a large amount of financial text data, achieving better results in sentiment classification for financial news. Since FinBERT is trained on data annotated by 16 economics professors, the resulting sentiment classification can reflect the impact of various types of news text information on company or industry development relatively accurately. However, there may be differences in subjective annotations among the professors, so we compensate for this issue by using historical stock prices to predict future price trends. Specifically, we trained an Informer model to predict stock price fluctuations and correct the sentiment indicators. Through experimentation, we found that sentiment indicators based on news sentiment classification are more accurate than those based on price trend prediction by compare the cumulative returns. Therefore, we use the sentiment index of news as the basic indicator and add price prediction as the correction factor to obtain a new sentiment indicator S^{st} that contains comprehensive information from both data types.

$$S^{st} = \begin{cases} S^s + \alpha * S^t, & \text{if } S^s \cdot S^t > 0 \\ S^s, & \text{if } S^s \cdot S^t \leq 0. \end{cases}$$

To obtain S^{st}, we first obtain the sentiment classification index S^s of stock on a given day, and then use the trained Informer model to predict the stock's price trend for the next day, obtaining the price trend prediction state S^t. If S^t and S^s have the same trend prediction direction, we couple the two states; if S^s and S^t have different trend prediction directions, we only retain S^s.

4.1.2 Trading

We achieve significant improvements in the performance of specific tasks using the FinBERT basic language model and the Informer price trend model, compared to other models such as LSTM used in SARL and Chen (Ye et al., 2020; Yang et al., 2020; Yfc and Shh, 2021). However, due to the specificity of financial market trading, any risks and opportunities should be treated with caution. Moreover, since the impact of news information on stock prices varies over time according to Chen (Yfc and Shh, 2021), we have set up an emotion intensity filtering layer K. Only when the absolute value of market sentiment in the environment state is greater than K, will the market sentiment will then be applied to the trading process. After filtering the sentiment intensity layer, the state with sentiment S^{st} is combined with environmental information such as stock prices and trading volume S^p to form an environment state $S(S^p, S^{st})$ with market sentiment. S then processed by a reinforcement learning neural network to output an action.For a single stock, the action space is defined as $\{-k, \ldots, -1, 0, 1, \ldots, k\}$, where k and $-k$ presents the number of shares we can buy and sell, and $k \leq h_{\max}$ while $h_{\max}$ is a predefined parameter that sets as the maximum amount of shares for each buying action.

4.1.3 Deep Reinforcement Learning

We base FinSRL on the Proximal Policy Optimization algorithm (Schulman et al., 2017).which bridges the gap between policy gradient(Sutton et al., 2000) and value approximation methods(Watkins and Dayan, 1992) for RL.The clipped surrogate objective function of PPO is:

$$J^{\mathrm{CLIP}}(\theta) = \hat{\mathbb{E}}_t \Big[\min \Big(r_t(\theta) \hat{A}(s_t, a_t) \\ \operatorname{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon) \hat{A}(s_t, a_t) \Big) \Big]$$

where $r_t(\theta)\hat{A}(s_t, a_t)$ is the normal policy gradient objective, and $\hat{A}(s_t, a_t)$ is the estimated advantage function. The function $\operatorname{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)$ clips the ratio $r_t(\theta)$ to be within $[1-\epsilon, 1+\epsilon]$. The objective function of PPO takes the minimum of the clipped and normal objective. PPO discourages large policy beyond of the clipped interval. Therefore, PPO improves the stability of the policy networks training by restricting the policy update at each training step. We select PPO for stock trading because it is stable, fast, and simpler to implement and tune.

Stock	Without Sentiment		With Sentiment	
	Max	Mean	Max	Mean
JPM	53.38%	32.12%	33.29%	27.77%
CAT	0%	0%	16.1%	6.25%
MMM	0%	0%	21.78%	17.80%
AAPL	8.18%	7.31%	8.94%	8.10%
DIS	0%	0%	48.34%	9.67%
GS	25.24%	12.60%	43.42%	32.49%
INTC	23.42%	17.05%	25.35%	24.58%
MSFT	10.74%	9.80%	13.77%	10.53%

Table 2: Single Trading For Certain Stock. 0% result represent at all test peroid the decision agent did not find any chance to buy this stock

4.1.4 Experiment Setup

In this section, we randomly selected eight stocks from Dow30 for portfolio management experiments using FinSRL. News data was collected from our dataset, evaluation metrics were defined, and differences between different methods were compared to verify the important role of our proposed fusion sentiment indicator algorithm in improving portfolio management return rates.

Single Stock Trading In this section, in order to better observe the impact of news information on stock trading, we first traded a single stock. That is, there is no linkage between stocks, and only buy, hold, and sell operations are made for a certain stock. We selected eight target stocks such as AAPL and JPM for the experiment, and compared the impact of using financial news signals and not using them on stock buying and selling decisions. For each stock, we conducted five experiments with and without news data, and Table 2 shows the cumulative return results for these eight stocks in the test set. By observing the results in Table 2, it can be seen that in most cases, the cumulative return will increase after the introduction of news information. Among them, CAT and MMM default to no buy action when not using news indicators. After adding news information, their return rates are greatly improved. At the same time, compared with other stocks, the results of MSFT and AAPL did not improve much. By comparing the sentiment index distribution chart of individual stocks, it can be found that AAPL and MSFT have significant differences in sentiment index distribution compared

Feature	Trend model	K	CR↑ (Mean)	CR↑(Max)	SR↑(Mean)	MDD ↓(Mean)
P	-	-	15.48	22.69	1.03	15.30
P+PT	Informer	-	1.71	24.54	0.25	52.26
P+PT	LSTM	-	-18.15	-23.72	0.06	52.6
P+N	-	0	23.67	50.03	1.55	14.14
P+N	-	0.7	17.09	25.96	1.05	13.31
P+N	-	0.75	20.06	23.90	1.36	14.52
P+N	-	0.8	29.30	38.95	1.93	14.08
P+N	-	0.85	22.95	26.00	1.37	13.91
P+N	-	0.9	35.00	65.11	2.14	14.32
P+N	-	0.95	16.32	23.59	1.24	15.48
P+PT+N	Informer	0.8	31.83	42.42	2.35	12.95
P+PT+N	Informer	0.9	33.64	58.86	2.43	12.98

Table 3: Profitability Comparison Against Baseline Approaches (mean of 5 runs). Within Components, N = News, P = Prices, PT = Price Trend Pridict. k represent noise filter layer threshold.

Figure 2: K-line chart of CAT from October 20, 2020 to March 1, 2021. Its stock price dropped to the lowest point of this range on October 28, and the model made a decision to buy at this time.

with other stocks. The reason is that AAPL and MSFT are popular stocks with more news and attention, so combining news also brings more noise, which weakens the influence weight of sentiment index in the trading process.

While comparing the returns, we also analyzed the system's decisions. After introducing news information, the model's buy and sell decisions were effectively improved during critical moments. Taking CAT as an example, Figure 2 shows the K-line chart of CAT from October 2020 to March 2021. The low price of the stock in this range was on October 7-8, 2020. The system made a decision to buy during these two days with the use of news information, while a system without news information did not make any instructions during these two days.

Portfolio Management we subsequently an experiment on portfolio management. Specifically, we invested these eight stocks in the same portfolio. We set the initial capital to 100,000 and did not hold any stocks in the initial state. Starting from the first day of trading, we dynamically executed buy, hold, and sell operations for each stock based on market conditions. In the trading settings, we set the maximum daily purchase amount for a single stock to 10 to avoid overinvesting in a single stock at once. During this process, we recorded the portfolio's CR, SR and MMD.

4.1.5 Results and Discussion

Here we report the results on datasets and discuss the performance of our's and other baselines. Table 3 shows the experimental results under the PPO trading framework when using different environmental information. P represents using only price and trading volume information, PT represents using future price trend indicators generated by trend prediction models. N represents the sentiment indicator of news after being classified by a sentiment classification model. PT+N represents the sentiment indicator corrected by predicting future price trends. From the results in Table 3, we can see that compared to the experiment using only price information as a reference, the introduction of future price prediction did not significantly improve the cumulative profit of both the Informer and LSTM methods. On the contrary, using only future price trend indicators resulted in a significant reduction in yield. For example, the average cumulative yield of the future price trend indicators obtained using Informer during the experiment was only 1.71%, which is much lower than the yield of the experiment using only price information at 15.48%. It is worth noting that the average cumulative yield of the LSTM experiment was even -18.18%. The accuracy of Informer's price trend prediction is 12.93% higher than that of LSTM, so the accuracy of price trend prediction has a significant impact on the model. When the accuracy is relatively low, it brings a lot of noise to the experiment and affects its accuracy. In the experiment of P+N (price information combined with news sentiment information), it can be found that after adding financial news data, the cumulative profit has increased significantly. Without any processing of the sentiment index, the average cumulative profit has increased by 52.91% compared to using only price. After filtering financial news with a filter layer of k=0.9 and correcting it with future price trend indicators, the yield increased by 117.3% compared to the P experiment, which greatly improves the yield capacity of the investment portfolio management.

The SR measures the risk and return of an investment portfolio, larger the SR, the greater the return that can be obtained per unit of risk. The MMD represents the maximum risk of the portfolio. Therefore, the smaller the MMD, the stronger the model's ability to resist risks. By comparing the experimental results in Table 3, it can be found that after introducing financial news, the yield was improved while the MMD also decreased, enhancing the robustness of the model. When k=0.9, compared with using the sentiment index adjusted by price trends, it can be found that although CR has slightly decreased, the model's SR has greatly improved, and MDD has also decreased to 12.98.

4.2 RQ2: How can the disparity in available news articles for different stocks be addressed?

The difference in attention received by stocks can lead to a huge disparity in the number of news articles. When a stock receives high levels of attention, there will be a large number of relevant news reports, but most of them may not actually affect the stock price. Conversely, when a stock receives low levels of attention, news articles only occur when major events occur. The uneven distribution of historical data between stocks can also affect the training performance of models (Ye et al., 2020).

4.3 RQ3: Which Part of the News Articles are the Most Important for Portfolio Management?

Currently, the majority of news processing methods use headlines for analysis, with a minority analyzing the entire news article. In general, news headlines can summarize the main content of the news, but selecting only the headline in different news types will miss a lot of key information, resulting in an inability to accurately reflect the emotions of the news. Using the entire news article will also bring a lot of useless text information that can interfere with the sentiment model. Therefore, studying the importance of each part of the news on stock impact becomes particularly important.

5 Conclusion

In this thesis proposal, we propose FinSRL, a new general sentiment-enhanced portfolio management framework. It can fully interpret heterogeneous information on the market to help models make decisions. We randomly selected eight stocks from the Dow Jones 30 for experiments. The results show that the use of FinSRL can significantly improve the CR, SP and reduce MMD of portfolio management. Our research results provide new ideas and methods for the financial investment and are expected to be widely used in practice. Later we also discuss about different research questions that I want to investigate in future.

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