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ソーシャルトレーディングサービスにおけるポートフォリオの最適化

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Abstract Nowadays social trading services are becoming more and more popular among people who are interested in investments. One of the notable features of social trading services is that we can simply "copy" the trades of experts traders to achieve profits. In addition, to reduce the risk, we can establish traders-base-portfolios, such as Top-Trader-Copyfunds in eToro. In this paper, we propose an optimization mechanism for traders-base-portfolios by applying portfolio theory in financial engineering. By introducing the concept of consistency of portfolio, our method achieves reasonable returns and reduces the times of re-balancing portfolio.

Key words Social trading, portfolio, financial engineering, optimization, consistency

1. Introduction

With the trend of converge between financial system and social network, a new transaction model called social trading is developing rapidly. Social trading is the process through which online investors rely on user generated financial content gathered from various Web 2.0 applications as the major information source for making financial decisions. It introduces a new way of analyzing financial data by providing a ground to compare and copy trades, techniques and strategies[1]. On social trading platforms, you can get real transaction information of every traders instead of just hearing what they say. Especially, you can follow them by a simple click if you approve their investment strategy. When you follow a certain trader, social trading services will do the same action as him/her at the same time automatically on your account. In other words, you can get same profit as the trader who you have followed. In contrast, if you think the trader you are following whose strategy no longer satisfies your opinion, you can just stop your following.

The core challenge of social trading is analyzing traders[2]. In other words, we should distinguish expert traders. In existing research, methods used to estimate and rank traders have been proposed[2][3]. These methods only focus on how to estimate and rank traders, and there is no support for selecting traders based on portfolio theory.

In this paper, we propose a new concept, traders-based-portfolio, and propose an optimization mechanism to realize it.To the best of our knowledge, this task haven't been studied yet. Although eToro has proposed a transaction model called Top-Trader-CopyFunds which establish traders-base-portfolios[9], their algorithms have not been published, and portfolio optimization has not been done. Moreover, they don't support customized portfolio[10]. Thus, in this paper, we aim to propose a optimization method which can support customized portfolio.The major contributions of this paper is summarized as follows.

- We propose a concept named traders-base-portfolio, and apply Markowitz Mean-Variance Portfolio Theory to it, more reasonable asset allocation towards traders can be recommended to users so that the highest profit with the lowest risk can be reached.
- We consider the consistency of performance of portfolio to optimize traders-base-portfolios. As a result, users can get quite satisfied profit during a relative long period without re-balancing frequently.

2. Related Work

2.1 Social Trading Services

Pan et al.[4] proved that social network can influence people's decisions, but the ranking based on number of followers is irrelevant to the rankings of the traders based on their profits. Moreover, both the rankings based on profits and the number of followers are irrelevant to their further profits. In other words, the conventional methods used for user profiling in SNS may not work well in social trading services.

2.2 Traders analysis

Takeda et al.[3] propose a analysis method towards traders. They apply NMF method to reveal the characteristic of traders, especially the situations the traders are good at. However, the portfolios is not discussed in their method.

Lee et al.[2] propose a customized recommendation system based on users' feedback and their ranking measures for traders. Lee et al. propose three measures for ranking traders: performance, risk and consistency. One of the notable features of their work is that they propose the notion of

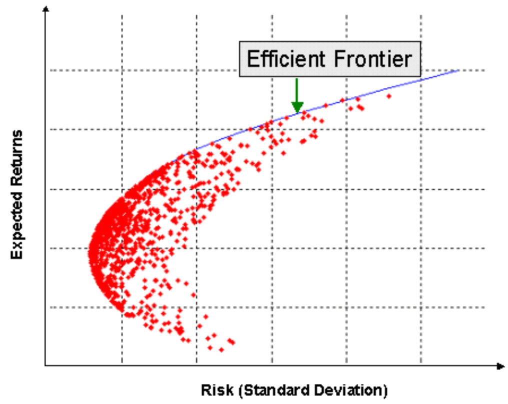

Figure 1 Efficient frontier[5]

consistency to estimate traders. Their results demonstrate their method could achieve stable rankings. Different from their work, we focus on portfolios optimization.

2. 3 Markowitz Mean-Variance Portfolio Theory

Markowitz Mean-Variance Portfolio Theory[5] is a mathematical framework which shows the relationship between expected return and risk of different portfolios. This theory is also well known as the modern portfolio theory. The expected return and risk constitute a two-dimensional coordinate system. In this system, every point represents a portfolio. Through this model, as Figure 1 shows, a boundary showing how can we set portfolio to take the minimum risk getting a certain return can be gotten. According to assumption of risk averse, we also calculate out a point which has the lowest risk value among all of the point in this system called the minimum variance point.

3. Traders Base Portfolio

In this paper, we propose a new concept, traders-base-portfolio. In this section, at first, we brief the conventional asset-base-portfolio and then introduce our traders-base-portfolio and discuss the way to realize it.

3. 1 Asset-base-portfolio

For traditional asset portfolio, suppose there are n products and the assign weights are $\omega_i, (i = 1, 2, \ldots, n)$, the expected return and risk are defined as follows:

- Assuming return of each product is denoted as $r_i, (i = 1, 2, \ldots, n)$, corresponding expectation is $E(r_i), (i = 1, 2, \ldots, n)$. The expected return is calculated as follows:

$$E(r) = \sum_{i=1}^{n} \omega_i E(r_i) \tag{1}$$

- The risk of a portfolio is expressed as the standard deviation of its return, σ. The variance of return is expressed as follows.

$$\sigma^2 = \sum_{i,j=1}^{n} \omega_i \omega_j \sigma_{ij} \tag{2}$$

where σ_{ij} is the covariance of returns between two assets, when $i = j, \sigma_{ij} = \sigma_i^2$.

3. 2 trader-base-portfolio

We propose a new concept called trader-based-portfolio. In our concept, comparing with assets-base-portfolio, assets are replaced by traders. However, the properties of a trader is not as simple as those of an asset. How to estimate the expected return and risk of a trader is the challenge. Of course, we know that performance or ROI(return of investment) is one of important element in evaluation system of person[6][7]. But in addition, other measures of person such as number of transaction, which are not only depended on ROI, must be observed.

When evaluate a trader, we should not neglect their transaction strategy. For example, if a company wanted to list, it should satisfy some conditions at first. Then they must declare some details about listing such as time and so on. In contrast to assets, such as list companies, traders in social trading services possess more freedom on transactions. They can start or close investments at any time without any preparation or declaration. Besides that, some of them prefer long term strategy, so that their operation occur suddenly and their profits remain 0 in a relatively long period. This is another point of traders different from assets.

3. 2. 1 Risk and Return: Traders Analysis

In this work, we use the notions, performance and risk, which are proposed by Lee et al. [2], to model the traders-base-portfolio. The main reason why we choose Lee et al.'s measures is that they consider well the consistency of traders.

- *Performance* denotes the ability of a trader compared with other traders. The assumption is adopted that high-performance traders have the ability to make profits in the future. Lee et al. use profits, winning/losing ratios, and relationships between the news and trades of traders to estimate their performance levels.
- *Risk* denotes the loss probability of trades. Lee et al. use indicators such as drawdown and position opening time in trades to estimate the risk level of a trader.

3. 2. 2 Efficient Frontier

In modern portfolio theory[8], a model for calculating the relationship between expected return and risk can be established as follows:

$$\begin{aligned} \text{minimize} \quad & \frac{1}{2} \sum_{i,j=1}^{n} \omega_i \omega_j \sigma_{ij} \\ \text{subject to} \quad & E(r) = \sum_{i=1}^{n} \omega_i E(r_i) \\ & \sum_{i=1}^{n} \omega_i = 1 \end{aligned} \tag{3}$$

In a portfolio, obviously, the sum of weights is no more then one. When a user put all of his assets into the market, the sum equals one. If user still have balance after the investment, the sum will less then one. However balance also can be seen as a product, so the second constrain was set as equal to one.

Finally, we solve this model as follows:

$$\sigma_i = \sqrt{L_i \begin{bmatrix} r_i & 1 \end{bmatrix} \begin{bmatrix} e^T S_i^{-1} e & -R_i^T S_i^{-1} e \\ -e^T S_i^{-1} R_i & R_i^T S_i^{-1} R_i \end{bmatrix} \begin{bmatrix} r_i \\ 1 \end{bmatrix}} \tag{4}$$

$$= \sqrt{L_i e^T S_i^{-1} e r_i^2 + 2L_i(-e^T S_i^{-1} R_i) r_i + L_i R_i^T S_i^{-1} R_i} \tag{5}$$

where $L_i = \frac{1}{e^T S_i^{-1} e R_i^T S_i^{-1} R_i - (R_i^T S_i^{-1} e)^2}$, $R = \begin{bmatrix} E(r_1) \\ E(r_2) \\ \vdots \\ E(r_n) \end{bmatrix}$, and $e = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}$, $S = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \dots & \sigma_{1n} \\ \sigma_{21} & \sigma_2^2 & \dots & \sigma_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \dots & \sigma_n^2 \end{bmatrix}$.

Now, we draw efficient frontier of every month whatever data of products we get. Especially, in traders-base-portfolio, we assume that every trader operates independently. Thus, we have

$$\sigma_{ij} = \begin{cases} \sigma_i^2 & i = j \\ 0 & i \neq j \end{cases}$$

, Matrix

$$S = \begin{bmatrix} \sigma_1^2 & 0 & \dots & 0 \\ 0 & \sigma_2^2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_n^2 \end{bmatrix}$$

. As the result, we also can rewrite Equation 5 as follows:

$$\sigma_i = \sqrt{\sum_{i=1}^{n} \frac{1}{\sigma_i^2} r_i^2 - 2\sum_{i=1}^{n} E(r_i) \frac{1}{\sigma_i^2} r_i + \sum_{i=1}^{n} E(r_i)^2 \frac{1}{\sigma_i^2}}$$

From Equation 5, we get the minimum variance point as follows:

$$\left(\frac{e^T S_i^{-1} R_i}{e^T S_i^{-1} e}, \sqrt{\frac{1}{e^T S_i^{-1} e}}\right)$$

Furthermore, we rewrite it as

$$\left(\frac{\sum_{i=1}^{n} \frac{E(r_i)}{\sigma_i^2}}{\sum_{i=1}^{n} \frac{1}{\sigma_i^2}}, \sqrt{\frac{1}{\sum_{i=1}^{n} \frac{1}{\sigma_i^2}}}\right)$$

under independent assumption. In this coordinate point, the first value is stand for expected performance of traders-base-portfolio and the second one represents risk counterpart.

From this expression, it is proved that the risk must be a positive value. Moreover if we get a point on the efficient frontier, we also get the corresponding weight through this relationship as follows:

$$W_i = L_i \; S_i^{-1} \begin{bmatrix} R_i & e \end{bmatrix} \begin{bmatrix} e^T S_i^{-1} e & -e^T S_i^{-1} R_i \\ -R_i^T S_i^{-1} e & R_i^T S_i^{-1} R_i \end{bmatrix} \begin{bmatrix} r_i \\ 1 \end{bmatrix}$$

$$= L_i \; (S_i^{-1} R_i e^T S_i^{-1} e - S_i^{-1} e R_i^T S_i^{-1} e) r_i + L_i \; (S_i^{-1} e R_i^T S_i^{-1} R_i - S_i^{-1} R_i e^T S_i^{-1} R_i)$$

According to the equation of W_i mentioned above, we can calculate the weight of a point on the efficient frontier through performance.

3.2.3 Consistency of Portfolio

Although all of the points on efficient frontier are ideal portfolio points, don't forget these points are efficient only in one given term (one month, etc.). However, a certain portfolio is efficient point according to historical data can't represent its effect in future. If the portfolio we chose performed well in recent months but turns worse suddenly in next month, we may undertake huge loss unless we do rebalance before the trend turning worse further. For a user, especially who doesn't have a lot of financial knowledge, rebalance frequently may need huge management cost. So the portfolio point we want to adopt is the one which is efficient during a quite long period. In other words, the point should always keep short distance with the efficient frontier.

If we translate this idea into financial meaning, compensating for pursuing the stability of portfolio, we prefer to suffer the least loss on expected return when we choose to undertake a certain risk, or to take the least additional risk when we choose to get a certain expected return. It is to say, we should consider both the shortest distance of total additional risk and expected return loss.

However, as shown in Equation 5, $r_i \propto \sigma_i$. So only if one side can be guaranteed, the other side also can be guaranteed naturally. For convenience, we choose to inspect risk by using σ_i^2. According to the idea mentioned above, we define the total distance as follows:

$$D = \sum_{i=1}^{n} (\sigma_{0i}^2 - \sigma_i^2) \tag{6}$$

where

$$\sigma_{0i} = \sqrt{W_0^T S_i W_0} \tag{7}$$

is the risk of a certain point representing the corresponding portfolio in the i-th month. The portfolio point which have the minimum distance, D, is the most consistent portfolio point.

The information of investments of traders has its own valid-time. It is to say, The older the information is, the smaller the impact will it have on future. So we apply forgetting curve to risks in months, and refine Equation 6 as follows:

$$D = \sum_{i=1}^{n} p_i(\sigma_{0i}^2 - \sigma_i^2) \tag{8}$$

where $p_i = \frac{e^{\frac{-(n-i)}{S}}}{\sum_{i=1}^{n} e^{\frac{-(n-i)}{S}}}$. S is a positive value called forgetting rate, and we let $S = 1$. Then we take Equation 5 and 7 into 8, we get equation 9 as follows:

$$D = \sum_{i=1}^{n} p_i(W_0^T S_i W_0 - (L_i a_i (W_0^T R_i)^2 - 2L_i b_i W_0^T R_i + L_i c_i)) \tag{9}$$

where $a_i = e^T S_i^{-1} e, b_i = R_i^T S_i^{-1} e, c_i = R_i^T S_i^{-1} R_i$. Then we get a portfolio which has the shortest total distance as follows:

$$W_0 = (\begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_n \end{bmatrix}^T P \begin{bmatrix} L_1 a_1 & 0 & \dots & 0 \\ 0 & L_2 a_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & L_n a_n \end{bmatrix} \begin{bmatrix} R_1^T \\ R_2^T \\ \vdots \\ R_n^T \end{bmatrix}$$

$$- \sum_{i=1}^{n} p_i S_i)^{-1} \begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_n \end{bmatrix}^T P \begin{bmatrix} L_1 b_1 \\ L_2 b_2 \\ \vdots \\ L_n b_n \end{bmatrix}$$

, where $P = \begin{bmatrix} p_1 & 0 & \dots & 0 \\ 0 & p_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & p_n \end{bmatrix}$.

If and only if we set portfolio with the weight W_0, the portfolio point will locate where is not far from efficient frontier unless some situation out of consideration happens, such as some traders' performance in portfolio turn down greatly.

4. Experiments

We conducted experiments to evaluate our propose methods. Because that, no matter what kind of investment strategy we adopt, the final target is to get more profit, we take total profit as our evaluation measure.

4.1 Dataset

We use the dataset provided by Lee et al.[2], which contains transaction information of 1212 traders from June 2015 to November 2015 on Zulutrade. We found that not all of the traders conduct transaction in every month. We assume that the performance and risk of such a trader in a month respectively equal to 0 and 100000 so that assign him/her a weight zero.

4.2 Experiments and Results

We use all of the traders to optimize the portfolio for future profit by analyzing transaction data in past two months. We conduct such task from June to November. As a result, we

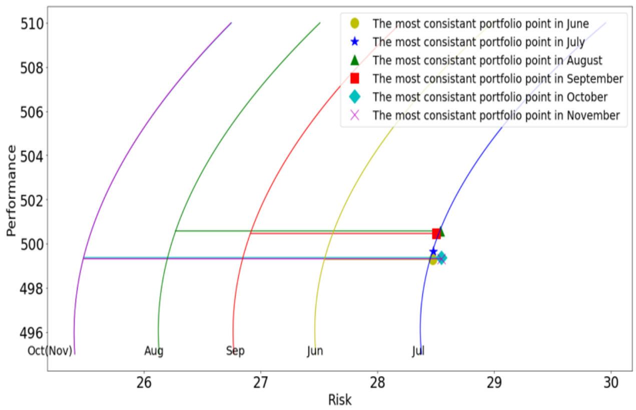

Figure 2 Efficient frontier and the shortest total distance point in every month containing all traders. The shorter the sum of length of lines parallel to horizontal axis is, the more stable portfolio we adopt.

Table 1 Distance of performance and risk(all the traders, training by using two months' data)

Distance	Performance($r_i - r_{0i}$)	Risk($\sigma_{0i} - \sigma_i$)
June	8.1100996152105722	0.93067198720439848
July	0.057046765970653723	0.0034331052945475449
August	14.08559282613453	2.2698472452429854
September	10.972013671466925	1.5945072634308985
October	18.404209225303248	3.0675911016049788
November	18.498963610342116	3.0702551545669081

got portfolio points and efficient frontiers of every month as shown in Figure 2. Every point is the shortest total distance point in corresponding months, i.e. the consistent portfolio point. We also calculate the distance between the portfolio point we got and a point which has the same performance on efficient frontier. In contrast, the distance between the portfolio point and a point which has the same risk on efficient frontier are shown in Table 1. The shorter distance is, the better effect of portfolio has in a quite long period.

From Table 2, we know the performance and risk scores adopting the shortest total distance point in each month. From Figure 2 and Table 1, we find that the distance between the shortest total distance points and their corresponding efficient frontier is a little bit far. We found that in the first two months, there are 128 traders who did transactions in June but interrupted in July. Due to our assumption, the person

Table 2 Performance and risk(all the traders, training by using two months' data)

Value	Performance	Risk
June	499.2745037250786	28.476086123005032
July	499.66068630375054	28.476338917596873
August	500.5624175524962	28.540078048731395
September	500.46593659849987	28.50645110104131
October	499.3608822333491	28.548845840967306
November	499.30810961077475	28.54938229650563

Table 3 Top 10 traders and their weights(training by using two months' data)

Trader	Weighted average of performance	Weight
150013	1463.763548	0.07502219
123508	1063.657934	0.06252558
121116	945.123046	0.27546606
208747	902.725915	0.06809619
138999	862.112287	0.03964989
124533	780.951511	0.141217
171380	773.175580	0.0510555
18384	755.846408	0.0469327
279971	721.064529	0.05440525
289636	702.636835	0.18560342

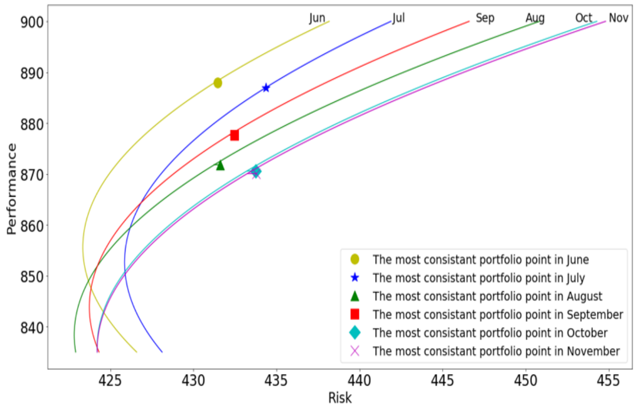

Figure 3 Efficient frontier and the shortest total distance point in every month(top 10 traders, training by using two months' data)

who stops trading or interrupt in some months or come in later shows quite large fluctuation on monthly performance and risk. Because of this kind of people, the efficient frontier of July turns worse. There are also some new traders enter market in next 4 months. So the efficient frontier of next 4 months turns better. This can also explain why the point we get far from efficient frontier especially in next 4 months. Because of this, we have to avoid choosing some traders who are unstable rather than choose all of them.

If we want to get greater profits, we must know how to choose superior traders. From a simple thinking, a trader who can always get considerable profit can called a good trader. Moreover, because we pay more attention to new information, we calculate weighted average of performance using the data in first two months applying forgetting curve as weight for ranking. We try to extract top 10 traders to establish portfolio as Table 3 shows. Comparing with all traders situation(Figure 2), Figure 3 illustrates portfolio containing top 10 traders. Because we pay attention to the most consistent portfolio point in every month, we should know the performance and risk of every portfolio point and the distance of performance and risk in every month. The Table 4 and 5 show these two things respectively.

Table 4 Performance and risk(top 10 traders, training by using two months' data)

Value	Performance	Risk
June	887.9791770360478	431.4577104563235
July	886.9115339847481	434.3519749255239
August	871.7741130062736	431.59538004341204
September	877.6540122563949	432.4648268321026
October	870.62588742563	433.7572145553955
November	870.1311580944555	433.78984817829416

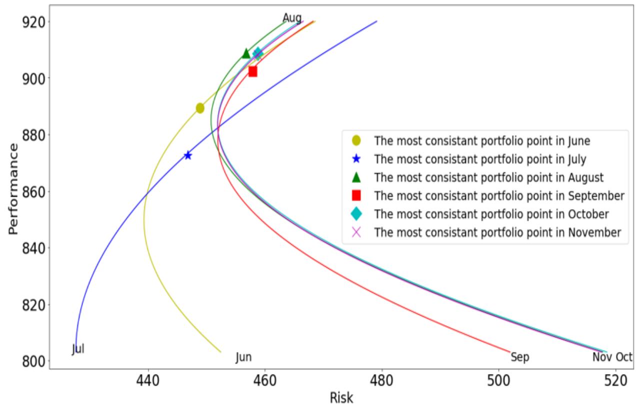

Figure 4 Efficient frontier and the shortest total distance point in every month(top 10 traders, training by using three months' data)

From Figure 3, Table 4 and 5, we can find that the points of every month we get almost on the efficient frontier counterpart. If time goes one month further, we can take the first three months as our training set to observe what happens in next month to get Figure 4. For the same reason with the situation which is trained by using two months' data, we also can get top 10 traders list, performance and risk and distance of performance and risk as Table 6, 7 and 8 shows. From Table 6, 7 and 8 and Figure 4, we find the portfolio changes. Users can choose to re-balance for getting higher performance with undertaking more risk. Of course, they also can keep the original portfolio for pursuing lower risk.

For comparison, we use weighted average of score which is proposed by Lee et al. as our baseline to extract top 10 traders. We get portfolios as shown in Table 9 and Figure 5.

According to the performance and risk of the most consis-

Table 5 Distance of performance and risk(top 10 traders, training by using two months' data)

Distance	Performance($r_i - r_{0i}$)	Risk($\sigma_{0i} - \sigma_i$)
June	0.33205084242467819	0.16238448620612189
July	0.049070117925225532	0.024039165768556359
August	0.69867661249259072	0.35205050212528022
September	0.60837860298011037	0.30293545482930995
October	0.98415225003964224	0.51428007449686675
November	0.98763690769749246	0.5172977811319015

Table 6 Top 10 traders and their weights(training by using three months' data)

Trader	Weighted average of performance	Weight
150013	1443.875636	0.07870424
123508	1068.667837	0.06816397
121116	926.900749	0.30008888
208747	883.600962	0.07235353
138999	849.448740	0.0440811
171380	785.991220	0.05710249
124533	781.473114	0.15443267
279971	759.757360	0.05338903
18384	759.223012	0.0516218
31525	727.413512	0.11932654

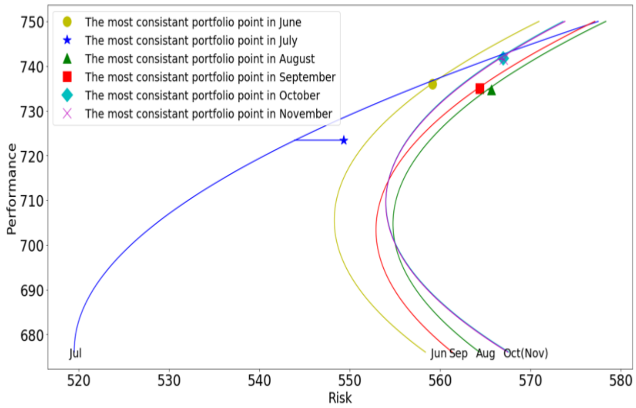

Figure 5 Efficient frontier and the shortest total distance point in every month(top-10 traders ranking by score, training by using three months' data)

tent portfolio points and the distance of their performance and risk as Table 10 and 11 shows, we recognize that choosing traders based on scores calculated by the methods proposed by Lee et al. get lower performance with higher risk.

Table 7 Performance and risk(top 10 traders, training by using three months' data)

Value	Performance	Risk
June	889.4060267729466	448.85644549160884
July	872.5412793348214	446.7652302162294
August	908.7311608871717	456.7445094967478
September	902.3506636090767	457.8524485472984
October	908.6660983592232	458.7193642754851
November	908.086710145872	458.75134867046825

Table 8 Distance of performance and risk(top 10 traders, training by using three months' data)

Distance	Performance($r_i - r_{0i}$)	Risk($\sigma_{0i} - \sigma_i$)
June	0.021056360527495599	0.010035516777293196
July	0.71407663414140643	0.38175501367595643
August	0.074206570926889981	0.0371268407855041
September	0.80288010924948594	0.36927321804773783
October	0.17251125147890889	0.093125444889210485
November	0.17479801501167458	0.094571425125991482

Table 9 Top 10 traders and their weights ranking by Lee et al.'s method.(training by using three months' data)

Trader	Weighted average of score	Weight
244074	9166.160352	0.05501889
279971	8518.375442	0.09976396
18384	8442.962811	0.09694424
281619	8343.728434	0.08462322
123508	8316.837677	0.12798115
231859	8262.157129	0.06884028
281614	8150.845381	0.11670179
208747	8108.640322	0.13625267
176142	7993.258273	0.09345038
123787	7859.187251	0.11967278

Table 10 Performance and risk(top 10 traders ranking by Lee et al.'s method, training by using three months' data)

Value	Performance	Risk
June	736.0663609714056	559.1472078137663
July	723.3601253633401	549.3299180171672
August	734.7803190346106	565.6867737422998
September	735.0468725901458	564.3631126155421
October	741.7307941123765	566.9819422342525
November	741.523661812833	567.0038169793258

Furthermore, the distance between portfolio points and the efficient frontier are farther than those of our method.

5. Conclusion

In this paper, we propose a new concept, traders-base-portfolio, and propose methods to realize it in term of supporting users in social trading services.

We propose the concept of consistency of portfolio. From the comparative experiments, traders who are extracted by weighting performance with forgetting curve perform better than traders who are extracted by Lee et al.'s method.

Although we get better performance and shorter distance by following top 10 traders ranking by weighted average of performance,

- We still want to explore that which kind of trader to choose can let portfolio points lay on efficient frontier with shorter distance.

Table 11 Distance of performance and risk(top 10 traders ranking by Lee et al.'s method, training by using three months' data)

Distance	Performance($r_i - r_{0i}$)	Risk($\sigma_{0i} - \sigma_i$)
June	0.061141980141769636	0.042869414986512311
July	5.1021324532031258	5.4264693141647058
August	0.53698823135550811	0.37495190517358878
September	0.18216960944437233	0.12910730041960505
October	0.62334785995324182	0.4831745839433097
November	0.64871824286171886	0.50412013860443494

- To explore what kind of trader can pull up performance and draw down risk at the same time.
- If users have their own expectation on performance and risk, find a way to satisfy their demand.

6. Acknowledgment

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