IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received May 29, 2020, accepted July 21, 2020, date of publication July 24, 2020, date of current version August 19, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3011713

Portfolio-Based Ranking of Traders for Social Trading

ZIMAO LIU AND QIANG MA, (Senior Member, IEEE)
Graduate School of Informatics, Kyoto University, Kyoto 6068501, Japan

Corresponding author: Qiang Ma (qiang@i.kyoto-u.ac.jp)

This work was supported in part by JSPS KAKENHI Number JP19H04116.

ABSTRACT Social trading is a social network service (SNS) trading platform where users can share their investment experience and knowledge. One of the notable features of social trading is that this platform allows users to imitate the transactions conducted by other traders simply by following them. However, finding and following expert traders is the key challenge of social trading. To this end, systems and methods have been developed to rank traders. One of the drawbacks of the conventional methods is that there is no financial theory to support them. In this paper, a novel ranking method to discover expert traders based on the portfolio theory, is proposed. The experimental results obtained with a real dataset demonstrate that this method is superior to conventional methods. In addition, the discovered expert traders can be enlisted to develop better portfolio constructions for any given risk level.

INDEX TERMS Social trading, portfolio, ranking, fintech, entity mining.

I. INTRODUCTION

Social trading is a new investment platform that does not require users to have financial knowledge [1], [2]. A social trading service is located in a community where ensemble expert traders communicate investment strategies while also making their own deals. A notable feature of social trading is that users can simply "imitate" or "copy" the trades of the experts in order to achieve profits. This imitation mechanism guarantees the authenticity of the strategies from the traders. On the other hand, there are many traders with different trading strategies in a social trading service. To achieve reasonable and consistent returns, discovering expert traders to follow and imitate is one of the key challenges in social trading.

Zulutrade[1] has provided its own ranking system that takes many features into consideration: maturity, which denotes how long a trader has been performing; exposure, which indicates the number of open positions a trader might have at one time; and drawdown, which denotes the number of ups and downs a trader has experienced. Instead of developing a ranking system, eToro[2] publishes indices about traders, such as return and risk, each month, to support users' decisions. In addition, eToro launched a new concept called top trader portfolios, which uses traders as assets in order to construct portfolios. However, the top trader portfolio tends to simply allocate every selected trader evenly. Unfortunately, this does not achieve the best investment results.

Lee and Ma [3], [4] proposed a system named who-to-follow (W2F) to support users that are trying to find expert traders. Three measures-performance, risk, and consistency-are used to rank traders in W2F. However, although W2F introduced a relevance feedback function for decision support, their method is heuristic and does not have the support of financial engineering. In our previous work [5], we proposed the notion of trader-based-portfolios. We constructed an efficient frontier of trader-based-portfolios to achieve better profits. In contrast, W2F tends to rank traders in a high-risk-high-return manner. Meanwhile, the trader-based-portfolio based method prefers to select traders to construct a portfolio in a low-risk-low-return fashion. Neither of these methods support users who can specify the acceptable risk levels and flexibility needed to improve. This makes it difficult to apply them to real cases in which users reveal their risk attitudes.

By introducing a novel notion of possible frontier of trader-based-portfolios, this study proposes a method to rank traders based on their returns and losses while comparing the maximum return of the Pareto point at a certain risk level. The main contributions of this work are summarized as follows:

The associate editor coordinating the review of this manuscript and approving it for publication was Zhan Bu.

[1]https://www.zulutrade.com/
[2]https://www.etoro.com/

- We propose a novel notion of possible frontier. Due to the non-negative constraints of the trader-based-portfolio, our previous method only extracted the Pareto points in a short range over a meaningful interval [5] to rank the traders. By estimating the expected maximum return at a certain risk level, a possible frontier that approximates the efficient frontier is constructed in this study.
- We propose a novel ranking method of social traders. By using the possible frontier, the traders can be ranked based on their expected return loss and consistency, and a reasonable trader-based portfolio can be constructed for any risk level using the top-ranked traders.
- The experimental results using a real dataset reveal that this method achieves higher Sharpe ratios [6] and can be used to construct portfolios for any given risk level.

The remainder of this paper is organized as follows. Section II introduces the related work. Section III defines the ranking task and briefly discusses the concepts related to the portfolio theory. Section IV describes the possible frontier and the two ranking measures based on it: the return loss and consistency. Section V provides an overview of the experimental results and Section VI delivers the conclusion of this paper.

II. RELATED WORK

As a new investment platform, social trading is receiving significant attention, especially in the domains of finance and economics; substantial work regarding the characteristics of social trading from the viewpoints of social network services (SNSs) and financial systems is required [7]–[11].

In conventional financial markets, assets such as value stocks, venture capital, and hedge funds are analysis targets. Meanwhile, for social trading services, expert traders are more important. Although social trading is to a certain extent an SNS, it has unique characteristics. It is necessary to consider the task difficulties [12] to evaluate the traders; thus, the methods developed for finding expert users (e.g. opinion leaders, influencers, etc.) in a typical SNS cannot be directly applied. Pan *et al.* [2] showed that the social network structure may influence the decisions people make; however, rankings based on the numbers of followers is not comparable to those based on profits.

Lee and Ma [3], [4] proposed a trader recommendation system with relevance feedback functions known as W2F. Specifically, they proposed three measures to rank traders: performance, risk, and consistency. A notable feature of their method is the notion of consistency, which evaluates the performance of traders in the long term. Their experimental results demonstrated that their approach to achieving stable rankings for traders produced better returns from the high-ranked traders. However, parameter tuning based on the users' feedback makes it difficult for users without investment knowledge. In addition, W2F applies many of the heuristics without the corresponding support of financial theories.

In our previous work, we proposed a concept called trader-based portfolios. This concept takes traders as assets to construct portfolios for reducing investment risk [5]. To the best of our knowledge, this is the first work to apply portfolio theory [13] to rank social traders. We constructed an efficient frontier of traders so that they could be ranked. Because there is no short-selling in social trading, we also introduced non-negative constraints to obtain meaningful Pareto points. This is an interval of the original efficient frontier that satisfies the non-negative constraint, which helps us find more meaningful results in recommender systems [14]. The experimental results demonstrate that this method can find expert traders and can construct low-risk-low-return portfolios in comparison to W2F.

III. PRELIMINARY

A. PROBLEM DEFINITION

The input of the proposed method is a set of traders and their historical transaction records; the output is the ranking list of these traders. The top-k traders can be selected for the users to follow.

(Traders) Trader i with their historical trading records is represented as follows:

$$i = \{T_1, T_2, \ldots, T_m\} \tag{1}$$

$$T_x = \{pf_{x1}, pf_{x2}, \ldots, pf_{xn_{xi}}\} \tag{2}$$

where, T_x denotes the transactions of trader i in the x-th month, and pf_{xy} is the profit of the y-th transaction in T_x.

(Portfolio) A portfolio p is represented with a weight vector as follows:

$$p = [\omega_1, \omega_2, \ldots, \omega_n], \tag{3}$$

where ω_i is the weight allocated to the trader i. Thus, a trader can also be represented as one portfolio. For instance, the portfolio $p_j = [0, 0, \ldots, \omega_j = 1, \ldots, 0]$ denotes the trader j.

Portfolios are useful for distributing and reducing investment risks. Modern portfolio theory [15] shows that a portfolio should be constructed to pursue the expected return with the lowest risk. A positive weight ($\omega > 0$) denotes the ratio of capital we should invest on the corresponding asset. In contrast, a negative weight denotes short selling, which plays a dramatically important role in the stock market [16]–[19].

B. EFFICIENT FRONTIER

Markowitz mean-variance portfolio theory [15], also known as modern portfolio theory, is a mathematical framework for representing the relationship between the expected return and risk of different portfolios. The expected return and risk consist of a two-dimensional coordinate system in which every point represents a portfolio. Using this model, a boundary can be identified to show how the user can specify a portfolio with minimum risk to obtain a certain return. Under a risk-averse

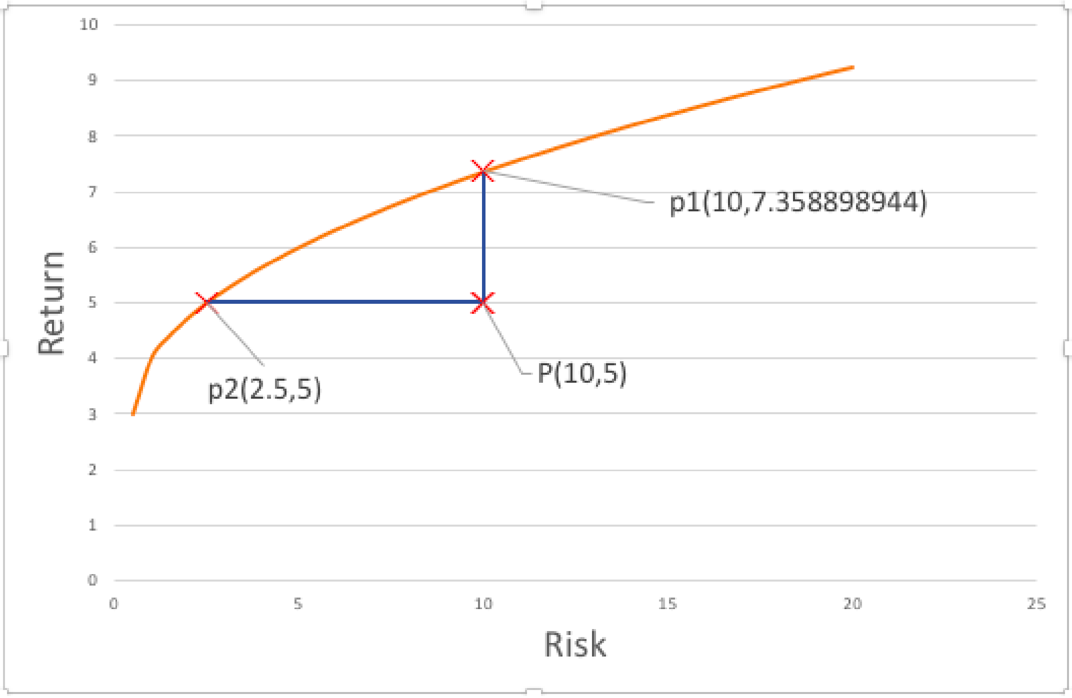

FIGURE 1. Efficient Frontier. In this example, portfolio $P2$ obtains the same return as P with a lower risk than that of $P2$; portfolio $P1$ obtains a higher return than P. $P1$ and $P2$ are two Pareto points for the efficient frontier.

assumption, a point at the upper-left area denotes a low risk and a high return. In other words, the upper-left boundary indicates portfolios that perform better.

In modern portfolio theory, the model for calculating the relationship between the expected return and the risk is established as follows:

$$\begin{aligned} \text{minimize} \quad & \frac{1}{2}\sum_{i,j=1}^{n} \omega_i \omega_j \sigma_{i,j} \\ \text{subject to} \quad & E(r) = \sum_{i=1}^{n} \omega_i E(r_i) \\ & \sum_{i=1}^{n} \omega_i = 1 \end{aligned} \tag{4}$$

An efficient frontier to determine the relationship between the risk and return can be constructed from this model. Figure 1 shows the shape of the efficient frontier and some important points for this two-dimensional space. All the portfolio points are located under the efficient frontier, and a portfolio point on the efficient frontier (i.e., Pareto point) has the best investment outcome for a certain risk level. In other words, according to the risk-averse assumption, a Pareto point is the optimal portfolio to achieve the best return among the portfolios of the same risk. As shown in Figure 1, point $p1$ has the same risk as P but a higher return, whereas point $p2$ has the same return as P but at a lower risk.

In regard to the extensions of modern portfolio theory, various constraints have been discussed [20]–[22]. Green [23] derives the conditions for the existence of positively weighted frontier portfolios. Best and Grauer [24] derive the algebraic conditions using the expected return vector and the covariance matrix for a Pareto portfolio to have all the positive weights. These works reveal that the range of the frontier portfolios with positive weights is short and will decrease as the number of assets increases. Furthermore, Boyle [25] proved that no matter how many assets are taken into consideration, the Pareto portfolio with only positive weights will always exist.

In social trading, users can allocate some of their funds to replicate another traders' activity and copy every move they make in real time.[3] When users copy an operation, the choices are either to follow or not to follow. If the users choose to follow a certain trader, the weight allocated to this person in the portfolio is positive; otherwise, the weight is zero. It is recognized that short selling is meaningless in social trading services and negative weights are not permitted in the portfolios constructed from the social traders [5]. Figure 2 illustrates the difference of the efficient frontiers with and without non-negative constraints.

C. TRADER-BASED PORTFOLIO

The notion of the trader-based portfolio was introduced in our previous work [5]. The idea is simple: replace assets or products with traders using modern portfolio theory. However, the properties of a trader are not as simple as those of an asset and there are no standard definitions of the risk and

[3]https://www.etoro.com/trading/social/

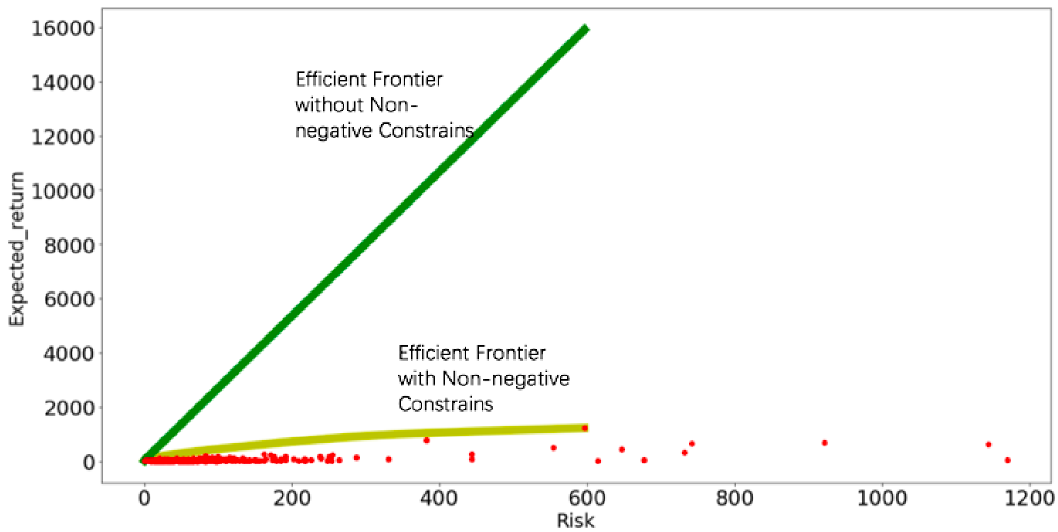

FIGURE 2. **Efficient frontiers with and without a non-negative constraint.**

return of a trader[4].[5] In this study, the definitions of the return and risk of a trader introduced by our previous work [5] are followed, which are as follows:

- Return of a trader i, $E(r_i)$ is the average profit made or lost by i in a certain period (one month in this work), which is defined as follows:

$$E(r_i) = return_i = \frac{\sum_{y=1}^{n} pf_y}{n}, \tag{5}$$

where pf_y is the profit of the y-th transaction by trader i in that period.

- Risk is the potential deviation from the expected return of a trader, which is defined as the standard deviation of profits in a certain period as follows:

$$\sigma_i = risk_i = \sqrt{\frac{1}{n}\sum_{y=1}^{n}(pf_y - return_i)^2} \tag{6}$$

To compare two traders from the value of risk (VOR) aspect, each trader also can be represented as a two-dimensional vector comprising their return and risk, i.e., $i = [E(r_i), \sigma_i]$.

Hence, based on portfolio theory, the expected return and risk of a trader-based portfolio can be defined as follows:

- Expected return:

$$E(r) = \sum_{i=1}^{n} \omega_i E(r_i), \tag{7}$$

where $E(r_i)$ denotes the expected return of the trader $i, (i = 1, 2, \ldots, n)$.

- Risk:

$$\sigma = \sqrt{\sum_{i,j=1}^{n} \omega_i \omega_j \sigma_{i,j}}, \tag{8}$$

where $\sigma_{i,j}$ is the covariance of the returns between two traders i and j; if $i = j$, $\sigma_{i,j} = \sigma_i^2$.

By constructing a trader-based portfolio, the different candidate traders that are selected yield various efficient frontiers. By having two efficient frontiers, the one located in the upper-left can provide a higher return and a lower risk. In other words, an efficient frontier located in the upper-left is superior.

As derived from (4), the expression of the efficient frontier can be formulated as follows:

$$\sigma_i = \sqrt{L_i e^T S_i^{-1} e r_i^2 + 2L_i(-e^T S_i^{-1} R_i) r_i + L_i R_i^T S_i^{-1} R_i}, \tag{9}$$

where

$$L_i = \frac{1}{e^T S_i^{-1} e R_i^T S_i^{-1} R_i - (R_i^T S_i^{-1} e)^2} \tag{10}$$

$$R = \begin{bmatrix} E(r_1) \\ E(r_2) \\ \vdots \\ E(r_n) \end{bmatrix}, e = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \tag{11}$$

$$S = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \ldots & \sigma_{1n} \\ \sigma_{21} & \sigma_2^2 & \ldots & \sigma_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \ldots & \sigma_n^2 \end{bmatrix} \tag{12}$$

Although the traders may communicate with others, it is reasonable to assume that they make decisions and operate separately to ensure simplicity; in the trader-based portfolio,

[4] https://www.etoro.com/blog/product-updates/08022015/
[5] https://www.etoro.com/blog/product-updates/02062014/

we assumed that every trader operates independently. Thus, the following equations were obtained:

$$\sigma_{ij} = \begin{cases} \sigma_i^2 & i = j \\ 0 & i \neq j \end{cases} \tag{13}$$

$$S = \begin{bmatrix} \sigma_1^2 & 0 & \dots & 0 \\ 0 & \sigma_2^2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_n^2 \end{bmatrix} \tag{14}$$

As a result, (9) was rewritten as follows:

$$\begin{aligned} \sigma_i &= \sqrt{\sum_{i=1}^{n} \frac{1}{\sigma_i^2} r_i^2 - 2\sum_{i=1}^{n} E(r_i)\frac{1}{\sigma_i^2} r_i + \sum_{i=1}^{n} E(r_i)^2 \frac{1}{\sigma_i^2}} \\ r_i &= \frac{1}{e^T S_i^{-1} e}\left(\sqrt{\frac{e^T S_i^{-1} e \sigma_i^2 - 1}{L_i}} + e^T S_i^{-1} R_i\right) \end{aligned} \tag{15}$$

Moreover, the weight vectors for the Pareto points can be calculated as follows:

$$\begin{aligned} W_i &= L_i(S_i^{-1} R_i e^T S_i^{-1} e - S_i^{-1} e R_i^T S_i^{-1} e) r_i \\ &\quad + L_i(S_i^{-1} e R_i^T S_i^{-1} R_i - S_i^{-1} R_i e^T S_i^{-1} R_i), \end{aligned} \tag{16}$$

IV. PORTFOLIO-BASED RANKING

Portfolio-based ranking is different from asset-based-portfolios, in which each asset is reasonably stable and the traders are free to join and quit social trading at any time. This makes the assessment of expert traders sensitive to the time duration and period for which they are active. In order to rank the traders, they are first assessed over a set time period (one month in this work), and the variance of their performance is estimated for multiple periods.

A. POSSIBLE FRONTIER

Only the Pareto points satisfying the non-negative weight constraint are meaningful in social trading. These meaningful Pareto points tend to be located in the low-risk-low-return area [5]. On the other hand, as reported in [4], users would sometimes take on a risk larger than the boundary Pareto point. This has the largest risk among all of the meaningful points, which would result in a larger return. In order to construct reasonable portfolios for any given risk level, in this paper, a novel approach for a possible frontier is proposed. Intuitively, a possible frontier consists of two kinds of portfolio points. The first is a meaningful point introduced in [5]; the other is a possible optimum point. Here, a possible optimum point denotes the trader-based portfolio that achieves the maximum return at for certain risk, which is greater than the risk of the boundary Pareto point.

To construct a possible frontier, the model (4) is rewritten as follows:

$$\begin{aligned} \text{minimize} \quad & \frac{1}{2}\sum_{i,j=1}^{n} \omega_i \omega_j \sigma_{i,j} \\ \text{subject to} \quad & E(r) = \sum_{i=1}^{n} \omega_i E(r_i) \\ & \sum_{i=1}^{n} \omega_i = 1 \\ & \omega_i \geq 0 \end{aligned} \tag{17}$$

Next, the Karush-Kuhn-Tucker conditions are applied to derive this model. As a result, the following equation is obtained:

$$\begin{bmatrix} \omega_{x,1}^* & 0 & \dots & 0 \\ 0 & \omega_{x,2}^* & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \omega_{x,n}^* \end{bmatrix} (S_x W_x^* - \lambda R_x - \mu e) = \begin{bmatrix} 0 \ 0 \ \dots \ 0 \end{bmatrix}^T \tag{18}$$

where $\omega_{x,j}^*, j = 1, 2, \dots, n$ denotes the weight allocated to the j-th trader for a possible optimum point in the x-th month, and $W_x^* = \left[\omega_{x,1}^* \ \omega_{x,2}^* \ \dots \ \omega_{x,n}^*\right]^T$. λ and μ are the Lagrange multipliers.

It is evident that for every $\omega_{x,j}^*$, either $[S_x W_i^* - \lambda R_x - \mu e]_j = 0$ and $\omega_{x,j}^* \geq 0$ are satisfied or $\omega_{x,j}^* = 0$. As a result, a curve will be developed that consists of all the meaningful points and the possible optimum points. Thus, this is no longer the efficient frontier, which indicates the possible frontier. Figure 4 illustrates the extension of the possible frontier for a meaningful interval.

The construction of a possible frontier can be divided into two tasks. The first task is to construct a meaningful interval using the method introduced in [5]. The second task is to find possible optimum points at the risk level that is greater than the boundary point of the meaningful interval. It should be noted that there is no difference in the possible frontiers constructed by maximizing the returns and minimizing risks. In addition, from the viewpoint of investment support applications, it is common to specify and estimate the acceptable risk levels of users, and then recommend products which maximize the returns at acceptable risk levels.

For a given set Z of traders and risk level *risk*, which is greater than the boundary point of the meaningful interval, the maximum expected return *return* is expected to find the possible optimum point; details are shown in Algorithm 1. The aim is to eliminate the traders that do not satisfy the non-negative constraint from the list of traders that are used to construct the portfolios and to find the maximum return from the portfolios. The time complexity and space complexity of Algorithm 1 are $O(N^3)$ and $O(N)$, respectively. Here, N is the number of traders.

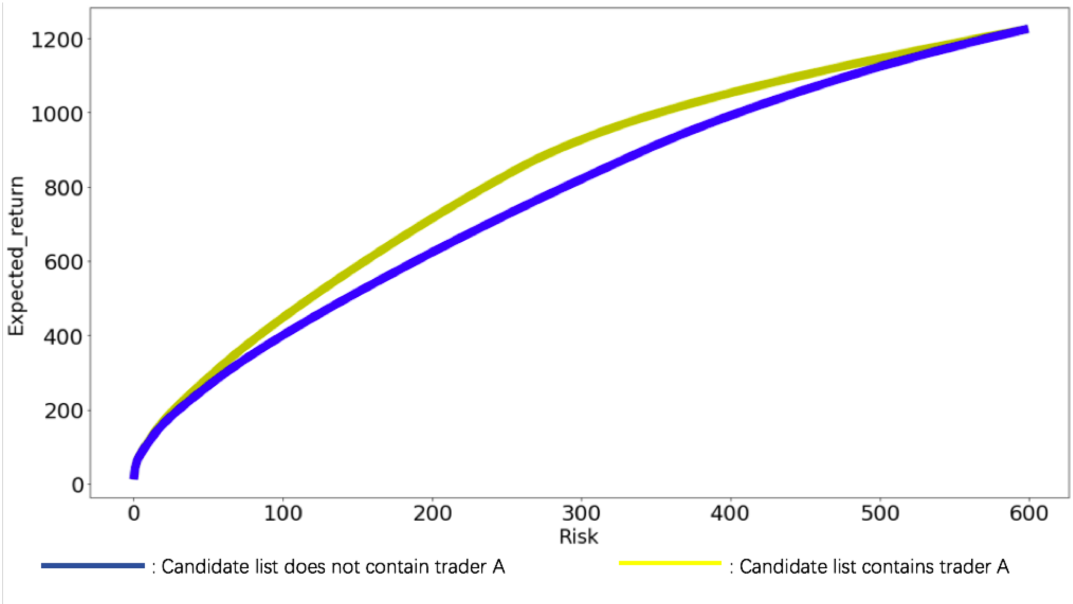

FIGURE 3. Possible frontiers constructed from the trader set with and without Trader A.

Algorithm 1 Estimate the maximum return ($opt_Z(risk)$) to find the optimum point ($risk$, $return$) at the given $risk$ level

Require: Z: a set of traders, $risk$: risk level
 Calculate return R and covariance S of traders in Z
 Calculate $return$ and W by using (15) and (16)
 while $\exists$ trader $i \in Z$, $W_i < 0$ **do**
  $Z = Z - \{i\}$
  Calculate the R and S of Z
  Calculate $return$ and W using (15) and (16)
 end while
 $opt_Z(risk) = return$
 return $opt_Z(risk)$

B. RETURN LOSS

The frontier is constructed from a given trader set by eliminating the traders who may be assigned a negative weight. Using this approach, for a given trader $i \in Z$, two possible frontiers can be constructed from Z and $Z - \{i\}$, respectively. The difference between these two possible optimum points indicates the importance of i. Figure 3 illustrates the difference of the possible frontiers with and without trader A. Therefore, by comparing the possible frontier with and without a trader, the return loss can be calculated to estimate the performance of the trader for a certain risk level.

$$rl_{x,i}(risk) = opt_Z(x, risk) - opt_{Z-\{i\}}(x, risk) \tag{19}$$

where $rl_{x,i}$ denotes the return loss of the trader i in the x-th month and Z denotes the candidate's trader set. In addition, $opt_Z(x, risk)$ denotes the return of the possible optimum point constructed from Z at the $risk$ level in the x-th month, which is calculated by applying Algorithm 1 with transactions in the x-th month. In cases where the $risk$ is not given implicitly, it is possible to assign the $risk$ to trader i in the x-th month.

When comparing other traders in one month, the return loss values for every trader are normalized. The normalized values of the return loss are then adopted as the final return loss value. To rank traders in a certain period, the average return loss can be calculated as the ranking score.

C. CONSISTENCY OF A TRADER

The return loss estimates the performance of a trader for one month (the unit time period). However, this value may vary for a different time duration and cause frequent rebalancing of the portfolio. Detecting perceptually important points to reveal fluctuations is a common approach for time-series data analysis [26]. However, conventional methods often focus on significant changes and will discard small fluctuations, which are sensitive in our trader ranking task. This study considers the consistency of the trader to reveal the variations in the performance of the traders. Here, the idea is that a trader is more consistent when the variation in their performance is low during a longer time period. As a result, the rebalancing frequency can be reduced, which will improve the consistency of the portfolio.

The consistency $con(i, m)$ of trader i during the m months is defined as follows:

$$con(i, m) = 1/\sqrt{(\sum_{x=1}^{m}(rl_{i,x}(risk_x) - \sum_{x=1}^{m} rl_{i,x}(risk_x)/m)^2/m} \tag{20}$$

where $risk_x$ is the $risk$ of trader i in x-th month.

V. EXPERIMENTS

We conducted experiments to evaluate the proposed method using a real dataset. For comparison purposes, the W2F method [4] was used as a baseline.

The results were compared using the following two criteria.

- Efficient frontier: The investment effect was better when the efficient frontier was located near the upper-left area.
- Sharpe ratio: The Sharpe ratio was defined as follows [6]:

$$sharpe = \frac{return}{risk}, \tag{21}$$

where *return* is the return of the assets for a trader or a portfolio, and *risk* is the corresponding risk.

This investigation compared the Sharpe ratios of the top-k traders that were respectively returned by the W2F [4], the return loss (RL), and the combination of the return loss and consistency (RL+C).

- W2F method: The top k traders were selected and ranked by W2F. Due to W2F, only the returns were used to determine the ranks of the traders. This study used the average values of the return $return_L$ and risk $risk_L$ to calculate the Sharpe ratio.

$$return_L = \frac{1}{k} e^T R \tag{22}$$
$$risk_L = \frac{1}{k^2} e^T Se \tag{23}$$

where the expected return R and the covariance (risk) S are calculated with the top-k traders that are selected by W2F.

- RL method: Select the top-k traders ranked using the return loss for the risk $risk_L$.
- RL+C method: A hybrid method that ranks the top-k traders based on the return loss and the consistency of the traders. To handle the uncertainty of traders' behavior and performances [27], it is helpful to estimate traders from multiple aspects in a hybrid manner [28]. In the RL+C method, the ranking score of a trader i during m months is calculated as follows:

$$score(i, m) = \frac{1}{m} \cdot \sum_{x=1}^{m} rl_{i,x}(risk_x) \cdot con(i, m) \tag{24}$$

A. DATA SET

This study used the dataset provided by [4], which contains transaction information for 1,212 traders in 2015 (from January to December) on Zulutrade. If the total number of deals by a trader in a certain month was less than 10, this trader was considered to be inactive. Thus, this study assigned them a weight of zero and the average risk of the traders in that month was their expected return and risk.

B. EXPERIMENTAL RESULTS:SHARP RATIO

The traders were initially assessed using data from January 2015 to June 2015. Following this, traders were recommended every month from July 2015 to December 2015.

TABLE 1. Comparison among three sharpe ratios when selecting the top 5 traders.

k=5	Jul	Aug	Sept	Oct	Nov	Dec
W2F	-0.024	0.068	**1.560**	**1.360**	**3.152**	0.185
RL	0.156	-0.409	0.637	0.818	1.940	1.746
RL+C	**0.367**	**6.563**	1.249	0.735	2.684	**1.907**

TABLE 2. Comparison among three sharpe ratios when selecting the top 10 traders.

k=10	Jul	Aug	Sept	Oct	Nov	Dec
W2F	0.293	0.086	**0.807**	0.611	1.645	0.491
RL	0.730	-0.368	0.438	0.817	1.460	0.122
RL+C	**0.843**	**0.342**	0.468	**0.854**	**3.674**	**1.625**

TABLE 3. Comparison among three Sharpe ratios when selecting the top 15 traders.

k=15	Jul	Aug	Sept	Oct	Nov	Dec
W2F	0.312	0.120	0.757	0.608	1.647	0.490
RL	0.972	-0.118	0.624	3.618	1.526	0.259
RL+C	**1.079**	**1.179**	**1.334**	**4.315**	**3.763**	**2.030**

TABLE 4. Comparison among three sharpe ratios when selecting the top 20 traders.

k=20	Jul	Aug	Sept	Oct	Nov	Dec
W2F	0.311	0.139	0.764	0.624	1.680	0.497
RL	1.090	-0.043	0.599	2.772	1.481	0.347
RL+C	**1.272**	**1.563**	**1.347**	**4.575**	**4.055**	**2.374**

The traders that were recommended for the current month were top-ranked by analyzing the transaction data from January to the final month. As shown in Tables 1, 2, 3 and 4, $sharpe_L$, $sharpe_{RL}$, and $sharpe_{RL+C}$ were compared by selecting the top k ($k = 5, 10, 15, 20$) traders with the respective comparative methods.

As the results indicate, the RL+C achieved the best performance in both cases for the top 10, top 15 and top 20 traders. However, in the case of top 5 traders, the RL+C could not outperform W2F. This is because there are only a few traders and we could not distribute the risk. In addition, the returns from the few existing traders increase in importance. In other words, when there are only a few traders, the benefits from the portfolio may be limited. In comparison with W2F, which was tuned by an expert trader, the RL performance was not stable although it achieved better results in some months. One reason for this is that the RL method is based on portfolio theory, which prefers more assets (traders) to reduce the risk and improve the return. On the other hand, because the RL considers the performance (return loss) for only one month, it is outperformed by the RL+C. This reveals that a stable performance is one of the most important factors for discovering experts in social trading.

In addition, we conducted paired t-tests for the Sharpe ratios for each method. The p-values of (W2F, RL), (W2F, RC+C) and (RL, RL+C) were 0.554,0.00051, and 0.00048,

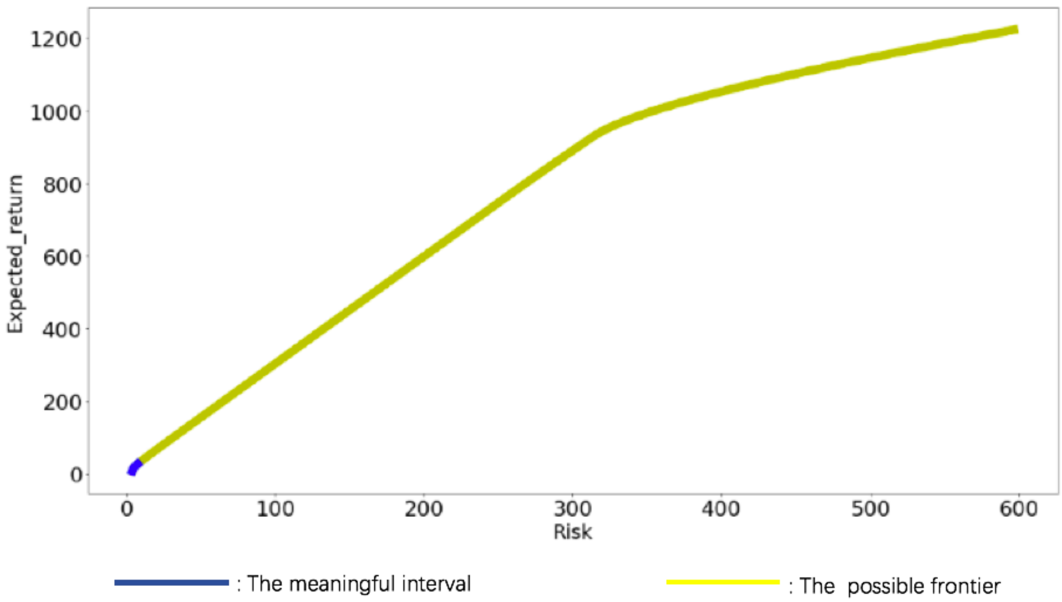

FIGURE 4. **Meaningful interval and possible frontier.**

respectively. These results indicate that the differences of (W2F,RL+C) and (RL, RL+C) are statistically significant.

C. COMPARISON BETWEEN MEANINGFUL INTERVAL AND POSSIBLE FRONTIER

As previously mentioned, the possible frontier is an extension of the meaningful interval proposed in [5] in modern portfolio theory. The possible frontier can handle a flexible range of risk levels in comparison to the meaningful interval.

As presented in Figure 4, this study achieves a meaningful interval and the possible frontier when ten traders are randomly selected. Figure 4 illustrates that the meaningful interval can only handle the risks ranging from the minimum variance point($risk = 4.026$) to the boundary Pareto point($risk = 7.587$). However, the possible frontier can extend this range to $risk = 596.717$. This reveals that the possible frontier can construct more flexible and reasonable portfolios than the meaningful interval. However, we note that it difficult to specify the VOR for a user. Thus, a reasonable support tool will be an area of focus for future work.

VI. CONCLUSION

In this paper, we propose a novelnotion called possible frontier that is based on modern portfolio theory to identify better portfolios and traders in social trading. Based on this notion return loss and consistency are proposed as measurement criteria to discover expert traders. These expert traders are then used to construct a trader-based portfolio to reduce investment risk and to improve returns.

Furthermore, we conducted an experimental evaluation using a real dataset consisting of more than one thousand traders and their transactions in one year. The experimental results demonstrate that the possible frontier builds upon the meaningful interval and provides full backward compatibility. The comparative results show that this method of ranking the traders with the two measures of return loss and consistency is superior to the current state-of-the-art method.

A system to support realization and construction of trader-based portfolios with low rebalancing frequency will be studied for future work. In addition, a user study based on such a system will be conducted to further examine the performance of our proposed method.

REFERENCES

[1] Y. Altshuler, W. Pan, and A. S. Pentland, "Trends prediction using social diffusion models," in *Proc. Int. Conf. Social Comput., Behav.-Cultural Modeling, Predict.* Berlin, Germany: Springer, 2012, pp. 97–104.

[2] W. Pan, Y. Altshuler, and A. Pentland, "Decoding social influence and the wisdom of the crowd in financial trading network," in *Proc. Int. Conf. Privacy, Secur., Risk Trust Int. Conf. Social Comput.*, Sep. 2012, pp. 203–209.

[3] W. Lee and Q. Ma, "Whom to follow on social trading services? A system to support discovering expert traders," in *Proc. 10th Int. Conf. Digit. Inf. Manage. (ICDIM)*, Oct. 2015, pp. 188–193.

[4] W. Lee and Q. Ma, "Discovering expert traders on social trading services," *J. Adv. Comput. Intell. Intell. Informat.*, vol. 22, no. 2, pp. 224–235, Mar. 2018.

[5] Z. Liu and Q. Ma, "Unsupervised method for discovering expert traders on social trading services," in *Proc. IEEE Int. Conf. Big Data Smart Comput. (BigComp)*, Feb. 2019, pp. 1–8.

[6] W. F. Sharpe, "The Sharpe ratio," *J. Portfolio Manage.*, vol. 21, no. 1, pp. 49–58, 1994.

[7] Y.-Y. Liu, J. Nacher, T. Ochiai, M. Martino, and Y. Altshuler, "Prospect theory for online financial trading," *PLoS ONE*, vol. 9, no. 10, 2014, Art. no. e109458.

[8] R. J. McWaters. (2015). *The Future of Financial Services-How Disruptive Innovations are Reshaping the Way Financial Services are Structured, Provisioned and Consumed.* [Online]. Available: http://www3.weforum.org/docs/WEF_The_future__of_financial_services.pdf

[9] L. Celi and B. Rutize. (2016). *The Rapidly Evolving Investor*. [Online]. Available: http://www.econsultsolutions.com/wp-content/uploads/White-Paper-section2.pdf

[10] M. Pelster and A. Hofmann, ''About the fear of reputational loss: Social trading and the disposition effect,'' *J. Banking Finace*, vol. 94, pp. 75–88, Sep. 2018.

[11] F. Röder and A. Walter, ''What drives investment flows into social trading portfolios?'' *J. Financial Res.*, vol. 42, no. 2, pp. 383–411, Jul. 2019.

[12] C. Zhang, Y. Liu, L. Li, N.-N. Zheng, and F.-Y. Wang, ''Joint task difficulties estimation and testees ranking for intelligence evaluation,'' *IEEE Trans. Comput. Social Syst.*, vol. 6, no. 2, pp. 221–226, Apr. 2019.

[13] D. G. Luenberger, *Investment Science*. New York, NY, USA: Oxford Univ. Press, 1997.

[14] X. Luo, M. Zhou, S. Li, D. Wu, Z. Liu, and M. Shang, ''Algorithms of unconstrained non-negative latent factor analysis for recommender systems,'' *IEEE Trans. Big Data*, early access, May 15, 2019, doi: 10.1109/TBDATA.2019.2916868.

[15] H. M. Markowitz, ''Foundations of portfolio theory,'' *J. Finance*, vol. 46, no. 2, pp. 469–477, Jun. 1991.

[16] A. Charoenrook and H. Daouk, ''A study of market-wide short-selling restrictions,'' Dept. Appl. Econ. Manage., Cornell Univ., Ithaca, NY, USA, Working Papers 51180, 2009.

[17] K. W. Ho, ''Short-sales restrictions and volatility the case of the stock exchange of singapore,'' *Pacific-Basin Finance J.*, vol. 4, no. 4, pp. 377–391, Dec. 1996.

[18] G. Grullon, S. Michenaud, and J. P. Weston, ''The real effects of short-selling constraints,'' *Rev. Financial Stud.*, vol. 28, no. 6, pp. 1737–1767, Jun. 2015.

[19] E. Boehmer and J. Wu, ''Short selling and the price discovery process,'' *Rev. Financial Stud.*, vol. 26, no. 2, pp. 287–322, Feb. 2013.

[20] A. Chekhlov, S. Uryasev, and M. Zabarankin, ''Portfolio optimization with drawdown constraints,'' in *Supply Chain and Finance*. Singapore: World Scientific, 2004, pp. 209–228.

[21] H. Kellerer, R. Mansini, and M. G. Speranza, ''Selecting portfolios with fixed costs and minimum transaction lots,'' *Ann. Oper. Res.*, vol. 99, nos. 1–4, pp. 287–304, 2000.

[22] T. Roncalli. (Jan. 31, 2011). *Understanding the Impact of Weights Constraints in Portfolio Theory*. [Online]. Available: https://ssrn.com/abstract=1761625

[23] R. C. Green, ''Positively weighted portfolios on the minimum-variance frontier,'' *J. Finance*, vol. 41, no. 5, pp. 1051–1068, Dec. 1986.

[24] M. J. Best and R. R. Grauer, ''Positively weighted minimum-variance portfolios and the structure of asset expected returns,'' *J. Financial Quant. Anal.*, vol. 27, no. 4, pp. 513–537, 1992.

[25] P. Boyle, ''Positive weights on the efficient frontier,'' *North Amer. Actuarial J.*, vol. 18, no. 4, pp. 462–477, Oct. 2014.

[26] T. Lintonen and T. Räty, ''Self-learning of multivariate time series using perceptually important points,'' *IEEE/CAA J. Autom. Sinica*, vol. 6, no. 6, pp. 1318–1331, Nov. 2019.

[27] J. M. Garibaldi, ''The need for fuzzy AI,'' *IEEE/CAA J. Autom. Sinica*, vol. 6, no. 3, pp. 610–622, May 2019.

[28] Q. Zhao, C. Wang, P. Wang, M. Zhou, and C. Jiang, ''A novel method on information recommendation via hybrid similarity,'' *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 48, no. 3, pp. 448–459, Mar. 2018.