AN INVESTMENT PORTFOLIO RECOMMENDATION SYSTEM FOR INDIVIDUAL E-COMMERCE USERS

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Abstract
Choosing appropriate portfolio which can maximize the revenue in a bearable risk level is the most crucial decision for investors. Traditionally, this kind of decision requires a great deal of efforts and time, and usually made by financial professionals. It’s difficult for people without professional knowledge to choose appropriate investment portfolio by themselves. The objective of this paper is to develop a recommendation system which can recommend specific investment plan for different risk preference Internet investors. In the proposed recommendation system, the VaR method is used to measure the risk level of securities and risk preference of investors. In addition, a collaborative filtering algorithm is adopted to recommend portfolio that satisfy risk preference and requirements of investors, by considering the investor’s history behavior and the history behavior of nearest neighbor investors with similar risk preference. Finally, experiments are conducted to demonstrate the feasibility of the proposed recommendation system.

Keywords: Recommendation system, Investment portfolio, Collaborative filtering, VaR method

1 INTRODUCTION
Investment portfolio consists of stock, bonds, derivative and so on, it is possessed by investors and financial institutions in order to spread risk and obtain profit. In another word, investors and financial institutions build a portfolio in order to control risk and gain as much profit as possible. Generally speaking, investors can be divided into three types: national, enterprises and individual investors. Because of the difference of political status and economic strength between different investors and investment organizations, their investment objective, investment method and investment effect are different. As shown in Table 1, Nation invest to gain the maximize profit and focus on the overall efficiency of state economy, enterprises invest to make the enterprise survive and develop, and the purpose of individual investors is from personal interests, maximize the personal utility and interests, thus improve the quality of life.

As shown in table 1, there are three main investment subjects: commercial bank, institutional investor and individual investor. They have different invest products, different consideration when choosing portfolio, and different selection principle.

Commercial banks [1] mainly invest bill, national debt, inter-bank bond and so on. When choosing investment portfolio, they aims at minimize the risk and meet the expected earnings.

Institutional investors [2] mainly invest stocks, and they focus on minimize unsystematic risk, determine the weight of each security according to investors’ utility and time management of investment behavior.

Individual investors invest bank deposits [3], stocks, bonds, securities investment funds and so on. The objective of individual investors is simple: obtain maximum profit in a bearable risk level. Online investors is a type of individual investors, so this paper choose the products which are usually invested by individual investors like stocks, bonds and funds.

Investment is not a topic which just discussed by wealthy people and professional investors. Now, with the development of e-commerce, individual investors are become more and more widespread and the investment volume become petty. It is practical for people to choose investment portfolio in e-commerce platform according to their risk preferences. However, it is difficult for individual user to choose optimal investment portfolio by itself. If ordinary investors invest by themselves, it will consume a lot of time and usually cannot find the best investment solution to face their risk preferences and current situations. Therefore, a recommendation system which can build portfolio to meet the risk preferences and actual needs of ordinary investors is necessary.

Recommender systems (RS) is a type of information filtering system which aims to predict the ‘rating’ or ‘preference’ a user would give an item [4]. The information used to do the recommend can be obtained directly.

Table 1. Investmeant subjects.

<table>
<thead>
<tr>
<th>Users</th>
<th>Products Mainly Included in Portfolio</th>
<th>Considerations When Choosing a Portfolio</th>
<th>Selection Principle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commercial Bank</td>
<td>Bill, national debt, inter-bank bond, etc</td>
<td>Risk under the VaR measurement</td>
<td>Risk minimization</td>
</tr>
<tr>
<td>Institutional Investor (financial intermediaries)</td>
<td>Stocks</td>
<td>Expected yields</td>
<td>Earnings to meet expected earnings</td>
</tr>
<tr>
<td>Individual Investor</td>
<td>Bank deposits, stocks, bonds, securities investment funds, etc</td>
<td>Return on equity risk</td>
<td>Minimize unsystematic risk</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Investors utility</td>
<td>Determine the weights for each stock according to investors utility</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Portfolio rebalancing</td>
<td>Optimum balance cycle again</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Expected yields</td>
<td>Maximize returns</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Risk</td>
<td>Risk minimization</td>
</tr>
</tbody>
</table>
Collaborative filtering algorithms are used in recommender systems to recommend specific investment portfolio for different risk preference online individual investors. This RS can give recommendations based on the behavior of the investors which have similar risk preference with target investor, such as geographical location and so on. This paper uses the collaborative filtering algorithm of RS, to give more accurate and acceptable recommend to investors based on the behavior of the investors which have similar behavior with the target investor. Based on these properties, RS can be used to give portfolio recommendation to target users, and these recommendations are conform to the trend of e-business.

The objective of this paper is to propose a RS which can recommend specific investment portfolio for different risk preference online individual investors. This RS can give recommend portfolios not only consider the risk preference of target investor, but also the social hierarchy of target investor, such as level of education, gender, occupation, geographical location and so on. This paper uses the collaborative filtering algorithm of RS, to give more accurate and acceptable recommend to investors based on the behavior of the investors which have similar behavior with the target investor. The rest of this paper is organized as follows. Section 2 reviews literature on the method to filtering items and the method to measure the risk of securities. Section 3 introduces the portfolio recommendation model based on the related work. Experiments are conducted in Section 4 to demonstrate the feasibility of the investment portfolio recommendation model. Finally, Section 5 is on conclusions and future work.

2 RELATED WORK

2.1 Collaborative filtering algorithm (CF)

Filtering algorithms are used in recommender systems to filter the items which satisfied the demand of target users. In RS, the most widely used filtering algorithms is collaborative filtering algorithm (CF), mainly include User-based collaborative filtering algorithm and Item-based collaborative filtering algorithm.

- **User-based collaborative filtering algorithm** [6]: generate recommend list according to the view of other users. It is based on the assumption that if the user's grade for an item is similar with other users, then their grades for other items are similar. Collaborative filtering recommendation system use statistical techniques to search a number of nearest neighbors of target user [7], and then give a prediction score to the item which the target user did not grade based on the score of nearest users, then choose several top scores items as recommend result and feedback it to the user. The user-based CF is the mainstream technology used in recommendation system, system's advantages are obvious. Firstly, it is easy to understand; secondly, when the number of users and items can be controlled in a certain range, the result will be good timeliness; and finally, it can provide cross category recommendations, and realize the intelligence of e-commerce. But this technology need to use other users' evaluation information, and largely depends on the overlapping level of users' evaluation information, so when users' evaluation data is sparse, this approach is not ideal. So user-based CF only adapted to the condition which have fewer items and dense users' evaluation data.

- **Item-based collaborative filtering algorithm**: predict the score of the target item according to the score of similar items given by users, it is based on the assumption that if the majority of users give similar score to some items, then the target user will score these items similarly [8]. Essentially, item-based CF is a kind of content-based recommendation technology. By use the properties between projects, it find the similar projects of the items which purchased by current user, and produce recommendations. Therefore, it solved the problem of data sparsity in user-based CF, but it can't get away from the nature weakness of content-based recommendation, which is it can only provide recommendations about the products which the user is familiar with. Although it use the grade of items provided by users as the project properties instead of some attribute value used to describe the items themselves, and provide more novelty recommend than pure content-based recommend, it still lack of cross-genre recommend and the ability of serendipity.

- **Hybrid filtering** uses a combination of CF with demographic filtering or CF with content-based filtering [9]. Hybrid filtering is usually based on bioinspired or probabilistic methods such as genetic algorithms and fuzzy genetic, neural networks, Bayesian networks, clustering, and latent features (such as SVD) [10]. Clustering-based recommender systems suffer from relatively low accuracy and coverage [11], and presents a new multi-view clustering method to address these issues. The method iteratively clusters users from the perspectives of both rating patterns and social trust relationships. This approach demonstrates that clustering-based recommender systems are suitable for practical use.

Based on the fact that individual investors always follow their friends and other people who have similar risk preference and current situation, this paper mainly uses User-based collaborative algorithm, because User-based CF can provide recommendation based on other people who have similar risk preference with target user, and investors always choose products which can maximize profit, so other similar investors' investment behavior can be reference and effective. In User-based collaborative algorithm, the rating data of users can be expressed by a m×n order matrix A(m,n), m lines represents m users, n columns represent n items, the ith row jth column element represents the score of item j evaluated by user i, then the User ratings data matrix is as Table 2.

The core of the User-based CF is the nearest neighbor query, nearest neighbor is a group of users whose purchase behavior and grade behavior are similar with the current user, the measurement of the similarity of user i and user j has three methods as follows, the similarity

<table>
<thead>
<tr>
<th>Table 2. User rating data matrix.</th>
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<td><strong>User</strong></td>
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between user i and user j can be denote as sim\(i,j\):

- Cosine: users’ grade as vector of the n space dimensions, if a user set the grade of the item as 0, then the similarity between users can be measured by cosine angle between vectors, give the grade of user i and user j in n space dimensions as \(\mathbf{u}, \mathbf{j}\), then the similarity between user i and user j sim\(i,j\) is as follows:

\[
\text{sim}(i,j) = \cos(\mathbf{u}, \mathbf{j}) = \frac{\mathbf{u} \cdot \mathbf{j}}{||\mathbf{u}|| \cdot ||\mathbf{j}||}
\]

(1)

Molecules as two score vector inner product, the denominator is the product of two items score vector module.

- correlation-based similarity: let the items which graded by both user i and user j to be \(I_i, I_j\), then the similarity between user i and user j sim\(i,j\) can be measured by Pearson correlation coefficient formula:

\[
\text{sim}(i,j) = \frac{\sum_{c \in I_i} (\mathbf{R}_{ci} - \overline{R}_c)(\mathbf{R}_{cj} - \overline{R}_c)}{\sqrt{\sum_{c \in I_i} (\mathbf{R}_{ci} - \overline{R}_c)^2 \sum_{c \in I_j} (\mathbf{R}_{cj} - \overline{R}_c)^2}}
\]

(2)

\(R_{ci}\) represents the grade for item i from user c, \(R_{cj}\) represents the grade for item j from user c, \(\overline{R}_c\) represents the average grade of item i and item j respectively.

- Adjusted Cosine similarity\[13]\: cosine similarity method does not take into account the problem of different user scale, adjusted cosine similarity modified this problem by subtracting the average score of items. Let the items which graded by both user i and user j to be \(I_i, I_j\) and \(\overline{R}_i, \overline{R}_j\) the represent the item graded by user i and user j respectively, then the similarity between item i and item j is as follows:

\[
\text{sim}(i,j) = \frac{\sum_{c \in I_i} (\mathbf{R}_{ci} - \overline{R}_i)(\mathbf{R}_{cj} - \overline{R}_j)}{\sqrt{\sum_{c \in I_i} (\mathbf{R}_{ci} - \overline{R}_i)^2 \sum_{c \in I_j} (\mathbf{R}_{cj} - \overline{R}_j)^2}}
\]

(3)

The objective of nearest neighbor query is for each user u, search the user set \(C=u, C_2, ..., C_k\) let u not belong to this user set C, and the similarity between \(C_i\) and u sim\(u, C_i\) must be the highest one, sim\(u, C_i\) take the second place, the rest can be done in the same manner.

This paper chooses adjusted cosine similarity to calculate the similarity between investors, and select several most similar investors as nearest neighbors.

After obtain the nearest neighbor by using the similarity measurement method above, next step should form relevant recommend. Let \(N_{Ni}\) represents the nearest neighbor set of user u, \(P_{ui}\) represents the predicted score of item i from user u, then \(P_{ui}\) can be calculate by the following formula\[13]\:

\[
P_{ui} = R_{ui} + \frac{\sum_{n \in N_{Ni}} \text{sim}(u, n) \times (R_{ni} - \overline{R}_n)}{\sum_{n \in N_{Ni}} \left| \text{sim}(u, n) \right|}
\]

(4)

\(\text{sim}(u,n)\) represents the similarity between user \(u\) and user \(n, \overline{R}_n\) represents item \(n\)’s score from user \(n, R_{ui}\) and \(R_{ni}\) represents the average score given by user \(u\) and user \(n\) respectively. After give the predict score to the unscored items through the formula above, feedback to the current user with several top prediction score items.

2.2 VaR method

VaR method is the most widely used method to manage the financial risk, several approaches can be used to calculate VaR, mainly include Variance - covariance method, historical simulation method, Monte Carlo Simulation and so on \[14\], the most practical method in China is Variance - covariance method.

Let \(W\) represents the initial value of portfolio, the terminal expected return of is \(R\), mathematical expectation is \(\mu\) and standard deviation is \(\sigma\), in a certain confidence interval \(\varepsilon\), the lowest value of portfolio until terminal is:

\[
W^* = W(1 + \sigma^*)
\]

(5)

\(\sigma^*\) is the relevant minimum rate of return (generally negative), then:

\[
\text{Value at Risk} = E(W) - W^* = -W(\sigma^* - \mu)
\]

(6)

VaR also can be derived by probability distribution of the value of portfolio:

From the definition of VaR:

\[
c = \int_{-\infty}^{\gamma} f(W) dW
\]

(7)

This equation is equivalent to:

\[
1 - c = \int_{\gamma}^{\infty} f(W) dW = \int_{\gamma}^{\infty} f(\gamma) d\gamma = \int_{-\infty}^{\gamma} \Phi(\varepsilon) \sigma d\varepsilon
\]

(8)

\(\Phi(\varepsilon)\) represents standard normal distribution.

\[
P(\sigma < \sigma^*) = -F \left( \frac{\sigma - \mu}{\sigma} \right) = 1 - \varepsilon
\]

(9)

\[
\frac{\sigma^* - \mu}{\sigma} = \frac{c}{\varepsilon}
\]

So

\[
\sigma^* = \mu + \alpha \sigma
\]

(10)

Substitute this formula into the definition of VaR:

\[
\text{VaR} = E(W) - W^* = -W(\mu + \alpha \sigma - \mu) = -\alpha \sigma W
\]

(11)

This is the general expression of VaR under the assumption of normal distribution. Standard deviation of portfolio is calculated from variance-covariance matrix of portfolio, hence this method is called Variance - covariance method.

VaR method is not only a method to measure the risk level of securities, but also can measure the risk preference of investors.

3 PORTFOLIO RECOMMENDATION MODEL

In order to provide valuable recommendation for target user who have specific risk preference, this paper...
combines VaR method with User-based CF, provides accurate portfolio recommendation to users based on their subjective information and risk preferences. As shown in Figure 1 the portfolio recommendation system can be divided into three parts. First, User-based CF is used to select the top IN securities which satisfied the information of nearest neighbors and the information of the target user as a portfolio. Nearest neighbors are similar with target user in the level of education, location, gender, occupation, age and so on. This step based on the assumption that: investors who have similar basic situation will have similar risk preference. Then determine the risk level of portfolio; this can be realized by give a weight for each security included in the top IN securities, and calculate the weighted average of the VaR of these securities. Finally, the weighted average of VaR should be matched with the risk preference of the target user, the weight of each security can be calculated by linear programming, the objective function of linear programming is to maximize the return of the portfolio, and the constraints is the risk level of portfolio should be matched with the risk preference of target user, and the sum of weight equals 1. After calculating the weight of each security, this model is able to give a recommendation to target user, the recommend portfolio is the securities which are the top IN securities with the calculated weight.

![Figure 2. Process of the model.](image)

The properties of this recommend portfolio can be summarized as follows:
- Match the risk preference of target user
- Maximize the profit under certain risk preference
- Take the information of nearest neighbors into consideration
- Take the subject information of target user into consideration

<table>
<thead>
<tr>
<th>Input data</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Users - project matrix ( R_{mxn} ), include m users, n items, each element of this matrix ( T_{ij} ) represent the grade information of item ( j ) provided by user ( i )</td>
<td>The set of recommend items and the weight of each item</td>
</tr>
<tr>
<td>Similarity between user m and user n ( \text{sim}(m,n) )</td>
<td></td>
</tr>
<tr>
<td>Define a certain similarity as the minimum nearest neighbor similarity ( I_{min} ), only if the similarity between user m and user n larger than ( I_{min} ), can this two users be seen as nearest neighbor</td>
<td></td>
</tr>
<tr>
<td>Amount of recommendation N</td>
<td></td>
</tr>
<tr>
<td>Return and VaR of each security</td>
<td></td>
</tr>
<tr>
<td>Expectation , standard derivation and initial value of securities</td>
<td></td>
</tr>
<tr>
<td>Risk preference of investors ( W_i )</td>
<td></td>
</tr>
</tbody>
</table>

Table 2 shows the input and output of the model. The input of this model includes the grade information of users, similarity between users, the boundary of similarity, amount of recommendation, return and VaR of each security, expectation , standard derivation and initial value of securities and risk preference of target user. The output of this model are recommended portfolio and weights of each security. The process of this model take into consideration the subjective information of target user and the information of nearest neighbors, and the result give accurate weights of each security of this portfolio, aims at obtain maximum profit in a bearable risk level.

As shown in Figure 2, the process of the portfolio recommendation model is as follows:

Step1. Calculate the similarity between target user \( u \) and other users using formula (3), choose the top UN users whose similarity are larger than \( I_{sim} \) as the nearest neighbors;

\[
\text{sim}(i) = \frac{\sum_{c \in C}(R_{ci} - \bar{R}_i)(R_{cj} - \bar{R}_j)}{\sqrt{\sum_{c \in C}(R_{ci} - \bar{R}_i)^2} \cdot \sqrt{\sum_{c \in C}(R_{cj} - \bar{R}_j)^2}}
\]

Step2. According to the historical grade information of user \( u \) and the information obtained from the nearest neighbors, give prediction to unscored items using formula (4);

\[
P_{ui} = \bar{R}_u + \frac{\sum_{n \in UN_{u}} \text{sim}(u,n) * (R_{ui} - \bar{R}_i)}{\sum_{n \in UN_{u}} (\text{sim}(u,n))}
\]

Step3. Ordering the predicted scores of the unscored items, choose the top IN items as a set.

Step4. Calculate the VaR value of the IN securities based on the expectation, standard deviation and initial value of these securities;

Step5. Give each item weight \( w_i \), \( i = 1,2,\ldots,IN \), and \( w_1 + w_2 + \cdots + w_{IN} = 1 \) (14)

Step6. Calculate the weighted average of VaR of securities using formula (13), work out the weight \( w_i \) to make sure the weight average of VaR matching with the risk preference of investors;

\[
\text{VaR} = E(W) - W^* = -W (\mu + \alpha \sigma - \mu) = -\alpha \sigma W
\]

Step7. Obtain the target portfolio.

The process of this model take into consideration the subjective information of target user and the information of nearest neighbors, and the result give accurate weight of
each security of this portfolio, aims to obtain maximum profit in a bearable risk level.

4 EMPIRICAL ANALYSIS

In this section, an empirical analysis is operated to demonstrate the feasibility of the model. Assume that the target investor is an ordinary investor who invest through Internet, consider the current situation of target user and nearest neighbors, User-based CF can select several securities, use the VaR of these securities, this model can form a portfolio according to the risk preference of target user. The process of User-based CF can be realized by coding in computer, assume the result of the User-based CF as the follow table, the VaR of top 5 securities has already been calculated, and the expected return of each security is given.

Table 4. Results of user-based CF.

<table>
<thead>
<tr>
<th>Security</th>
<th>VaR(%)</th>
<th>Profit (RMB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.51</td>
<td>6.54</td>
</tr>
<tr>
<td>2</td>
<td>0.15</td>
<td>3.21</td>
</tr>
<tr>
<td>3</td>
<td>1.21</td>
<td>4.58</td>
</tr>
<tr>
<td>4</td>
<td>0.36</td>
<td>3.68</td>
</tr>
<tr>
<td>5</td>
<td>-0.64</td>
<td>2.56</td>
</tr>
</tbody>
</table>

The target user can choose top IN items to form a portfolio, then give each portfolio a weight, and calculate the weighted average VaR of this portfolio, use the risk of the portfolio to match the risk preference of target user. The objective function and constraints are in same pattern, using formula (14):

Max = weighted profit of portfolio

s.t. \( \sum w_i \times VaR_i = \text{VaR}_{\text{target}} \) ; \( \sum w_i = 1 \) ;

There are two constraints and one objective function, so if the target user choose top two securities of the User-based CF result, the optimal solution of weight and maximum profit will be exclusive, but if the target user choose more than two securities, the optimal solution will not be exclusive, but each solution will be usable. So there will be two scenarios.

4.1 Scenario 1: Choose top two securities

Assume that the target user only consider the top two securities, then give a weight \( w_1 \) to security 1 and give a weight \( w_2 \) to security 2, assume the risk preference of target user is \( \text{VaR}_{\text{target}} = 1.28 \), then the weight of each security can be determined by the following process:

Max = 6.54\( w_1 \) + 3.21\( w_2 \) ;

s.t. 1.51\( w_1 \) + 0.15\( w_2 \) = 1.28 ;

\( w_1 + w_2 = 1 \);

Figure 3. Code of Lingo.

Figure 4. Solution of Lingo.

The problem can be solved by Lingo, from the result of Lingo, the solution of \( w_1 \) is 0.83, the solution of \( w_2 \) is 0.17, and the maximum profit is 5.97.

This result means that the target user can spend 83% of the fund to invest security 1 and spend 17% of the fund to invest security 2, in this way the target user can obtain the maximum profit 5.97 under the certain risk preference.

4.2 Scenario 2: Choose more than two securities

Assume that the target user chose more than two securities as a portfolio. For example, if the target user chose three securities as a portfolio, the code of Lingo will be modified into the following form:

Max = 6.54\( w_1 \) + 3.21\( w_2 \) + 4.58\( w_3 \) ;

s.t. 1.51\( w_1 \) + 0.15\( w_2 \) + 1.21\( w_3 \) = 1.28 ;

\( w_1 + w_2 + w_3 = 1 \);

Figure 5: Code of Lingo when choose 3 securities

Figure 6. Solution of Lingo when choose 3 securities.

The solution of choose top three securities shows a similar result of choose top two securities, but the solution is not unique, the result only shows one of the solutions, but all of the solutions is usable for the target user, so each solutions can be recommended to the target user, and the choice is in the hands of the target user.

Figure 7. Sensitivity analysis.
The sensitivity analysis of choose top three securities is shown in Figure 7, the result shows that in the following case, the optimal solution will not change:

- The risk preference increase 0.23 or decrease 1.13;
- The expected return of security 1 decrease 1.57 or increase infinitely;
- The expected return of security 2 decrease 5.55 (but the current value is 3.21 and the return must be positive, so the allowable decrease is 3.21) or increase infinitely;
- The expected return of security 3 increase 1.23 or decrease to 0.

The result of the empirical analysis proves that this portfolio recommendation model is useful in the above scenarios, these two scenarios contains almost all of the possible conditions, so basically this model can be used in most investment cases.

5 CONCLUSION
With the development of society and e-commerce, people have more opportunity to invest by themselves, but most of the investors are not professional, they invest only by their intuition and advice from their friends, but this is not efficient. This paper proposed an approach for ordinary investors to invest their funds efficiently, helped them to obtain maximum profit based on their risk tolerance. Using risk preference and the subject information of target users and their nearest neighbors, this paper realized the objective of providing intelligent recommendation for target user. This method basically based on the User-based collaborative filtering algorithm, choose the top IN items of the result of user-based CF as a portfolio, and use linear programming to calculate the weight of each security in the purpose of maximize the profit in a certain risk preference level. The portfolio recommendation system basically solve the problem of provide efficiently portfolio recommendation to ordinary investors.

In future study, more constraints will be concerned into this model, such as financial index of securities, time period of the investment and so on. More constraints can help the Portfolio Recommendation Model provide more accurate recommendations.

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