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An equity fund recommendation system by combing transfer learning and the utility function of the prospect theory

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Abstract

Investors in financial markets are often at a loss when facing a huge range of products. For financial institutions also, how to recommend products to the right investors, especially those without previous investment records is problematic. In this paper, we develop and apply a personalized recommendation system for the equity funds market, based on the idea of transfer learning. First, using modern portfolio theory, a profile of equity funds and investors is created. Then, the profile of investors in the stock market is applied to the fund market by the idea of transfer learning. Finally, a utility-based recommendation algorithm based on prospect theory is proposed and the performance of the method is verified by testing it on actual transaction data. This study provides a reference for financial institutions to recommend products and services to the long tail customers.

Keywords: Personalized recommendation; Prospect theory; Equity fund; Transfer learning

1. Introduction

The Chinese stock market took a great beating in 2015 and in response the Chinese financial regulatory agencies strongly urged a rebalancing of market participants to encourage small or medium investors to participate indirectly in the capital market through financial products based on the principles of investor appropriateness. However, there is a vast array of products in the financial market and the difficulties of providing a personalized service in an information overloaded environment become more and more acute. In addition, with increasing competition, financial institutions have to consider the cost and efficiency of marketing. To this end, many scholars are exploring ways to improve financial information services, and personalized recommendation technologies have been applied to the financial area,[1] such as insurance, venture capital and P2P microfinance,[2–4] with promising results. However,

Abbreviations: MPT, modern portfolio theory; SRI, socially responsible investment; VAR, value at risk.

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for financial investors, the concern is more on high return, low risk products, which is different from the e-commerce or advertising arena.

Compared with the stock market, the range of equity funds available to invest in is relatively small, and banks or securities companies pay more attention to high value investors, which makes the domain characterized by extremely sparse long-tailed data. Thus, the efficient use of conventional recommender system methods is not appropriate.[5]

This paper proposes a combination of modern portfolio theory, transfer learning and prospect theory for equity funds recommendation. It makes two contributions, one is to deal with the problems of data sparsity and long tails in the equity fund market by applying the idea of transfer learning; the second is to propose a utility-based recommendation method using prospect theory to provide support for funds marketing.

2. Research review

An equity fund is a financial product that is principally invested in stocks. The composition of the equity fund is decided by the fund manager, focusing on a certain sector or level of risk. Due to their diversification, equity funds are less risky than individual stocks. In this section, two lines of related research are reviewed including personalized and non-personalized recommendations.

2.1. Non-personalized recommendation

Most of the contributions in this area focus on improving the accuracy of predicting future returns (or trends) and risks for stock funds using different methods. *Jorion* (2001) introduced the concept of Value at Risk (*VAR*) and various calculation methods, which laid the foundation for fund risk measurement.[6] *Leite* and *Cortez* (2014) analyzed the performance and investment style of internationally-oriented *Socially Responsible Investment* (*SRI*) funds, domiciled in eight European markets.[7] *Markowitz* (1952) published *Modern Portfolio Theory* (*MPT*),[8] which is one of the most well-known portfolio selection models used for equity funds. In MPT, well-diversified portfolios offer the best risk-return tradeoff for every risk level and investors select those portfolios that maximize their utility function. Several researchers have extended *MPT* by using fuzzy techniques to estimate the risk of portfolios and build optimal portfolios.[9,10] However, all these studies[6−10] ignore the personalization factor. A comprehensive ranking of available funds can be considered to be a type of non-personalized recommendation, such as in the website http://fund.jrj.com.cn.

2.2. Personalized recommendation

The essence of personalized recommendation is to help users find what they are interested in from a mass of products based on their behavioral characteristics. So user behavior feature description is the key step of personalized recommendation system. An effective personalized information service technology to solve the problem of information overload in making recommendations has been successfully applied in the fields of e-commerce, advertising, films, books, music and so on. With the rapid development of financial markets, recommendation technology has also been introduced in the marketing of financial products.[11] Combined with *MPT* and risk management theory to profile user's investment and risk preference, scholars have proposed many personalized recommendation methods suitable for financial investment (e.g., stocks, P2P lending, and venture capital) that are based on conventional recommendation methods, such as collaborative-filtering, content-based filtering, knowledge-based recommender systems and various hybrid techniques,[3,4,12] especially for personalized stock recommendation.[13] However, to our knowledge, research on personalized recommendation of equity funds is relatively rare. One example is *Matsatsinis* and *Manarolis* (2009) who introduced a hybrid application for equity fund recommendation.[14] They combined collaborative filtering with multi-criteria decision analysis to address sparsity issues for equity fund recommendation. Due to the unavailability of real transaction data the proposed model was evaluated on simulated investment behavior.

Equity fund investment is risky, but can generate high returns. Since an investor only needs to select a small number of funds, this domain is characterized by extremely sparse long-tailed data.[15] The investors' behavioral characteristics of equity funds market may not be descripted well. And this renders the efficient use of conventional recommender system methods inappropriate. As an important technique in machine learning, transfer learning can recognize and apply knowledge and skills learned in previous tasks to novel tasks. Especially transfer knowledge between two

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similarity tasks.[16] There are enough transaction data of stock market and can profile investors' behavioral characteristics well. So based on the idea of transfer learning, in this paper, we learn the profile of investors in the stock market and transfer it into the equity fund market. And propose a personalized recommendation method applied to equity funds marketing. First, using modern portfolio theory, a profile of equity funds and investors is created. Then, the profile of investors in the stock market is applied to the fund market by the idea of transfer learning. Finally, a utility-based recommendation algorithm based on prospect theory is proposed and the performance of the method is verified by testing it on actual transaction data.

3. Analysis of investor behavior

User behavioral analysis is the basis of personalized recommendation. So, in this section, we try to understand the behavioral characteristics of investors from the perspective of group analysis to lay the foundation for further study of the characteristics of individual investors for personalized recommendation. In this paper, we follow the efficient market and rational investment hypothesis of financial theory.

3.1. Equity fund

The main object of research in this study is equity funds, including common stock funds and partial stock funds. According to the standard fund classification in China, an equity fund is one in which more than 60% of its assets are invested in stock and the stock fund is one of the main forms of China's fund, which we select as the research object in the paper. Table 1 shows the average monthly rate of return and volatility of funds in China from January 2014 to December 2015 based on 612 equity funds, 485 bond funds and 501 monetary funds. Table 1 shows that equity funds are the highest on both indicators, reflecting high profitability and high risk characteristics, which require investors to have relatively high investment capacity and risk tolerance. The return of the equity fund is closely related to stock market performance so, in addition to the return and risk, investors also need to consider the fund's investment strategy, theme and style, and even fund manager's experience and ability etc. Therefore, on the basis of the preference and risk tolerance of investors, this study aims to develop a method of recommending appropriate equity funds to investors.

3.2. Distribution of investment products

In 2015, after experienced a cliff fall in June and a series of rescue measures from the government between July and August, Chinese stock market has entered a relatively stable period. So we collected stock and fund transaction data from a business department of a securities company in Beijing from 1 September 2015 to 30 December 2015; a total of 13 weeks trading data. As the value of a stock or fund is subject to the business environment and economic conditions, we only consider complete transactions in the investigation period in order to make the trading gains or losses comparable. After deleting some transactions that are incomplete (only to sell or buy), there were about 780,000 transactions. These involve nearly 40 thousand investors, in more than 2000 different products (stocks and funds). However, there are only 574 trading records for equity funds, involving 203 investors and 149 funds. In addition to this, data on fund allocation and performance were collected from the *Wind Financial Terminal* (http://www.wind.com).

The distribution in the number of different products purchased by investors is shown in Fig. 1. The x-axis shows the number of different products (including stocks and funds) invested in by an investor, and the y-axis indicates the number of investors, for which descriptive statistics are shown in Table 2. Fig. 1 shows a distribution with heavy tail characteristics in the behavior of investors. That is, the majority of investors have a small number of transactions and only a few popular products are invested in widely.

Table 1
Average monthly rate of return and volatility of funds in China (2014.01.01−2015.12.31) (Data source: Wind database).

	Average monthly return rate (%)	Average monthly volatility (%)
Equity funds	2.7360	0.3592
Bond funds	0.9570	0.0502
Monetary funds	0.3092	0.0027

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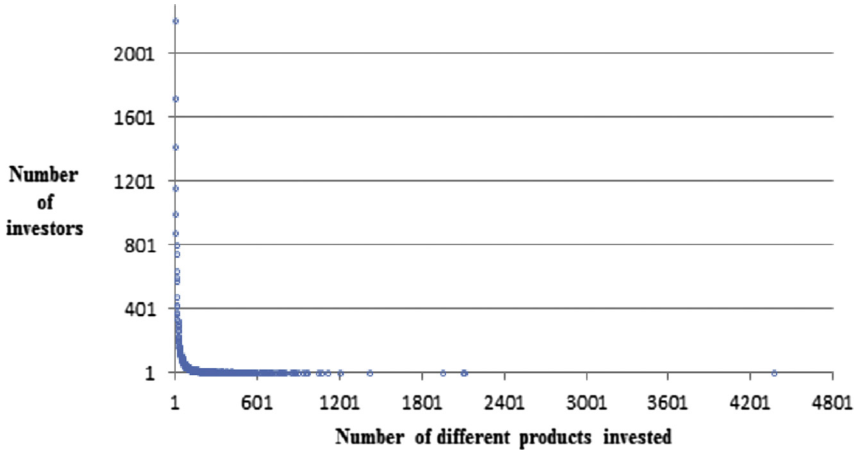

Fig. 1. Distribution of investment products.

Table 2
Data descriptive statistics.

	Mean	Std. deviation	Kurtosis	Skewness	Minimum	Maximum
Number of investors	48.87	183.94	64.92	7.31	1	2206
Number of different products invested	306.12	321.98	57.21	5.58	1	4365

3.3. *Analysis of investor behavior in the equity fund market*

Fig. 2 shows the distribution in the number of investments for each equity fund in the study. As can be seen from the figure, the behavior of investors in equity funds manifests a strong heavy tail and high sparsity. Therefore, the traditional recommendation algorithm such as collaborative filtering can't be used to recommend funds. Hence, we need to find a more appropriate way to recommend equity funds to the right investors.

4. Profile modeling for equity funds and investors

An equity fund investment is a method of portfolio management where the benefits and risks are shared among many investors. Professional fund managers make decisions and keep custody of the assets while the investors share

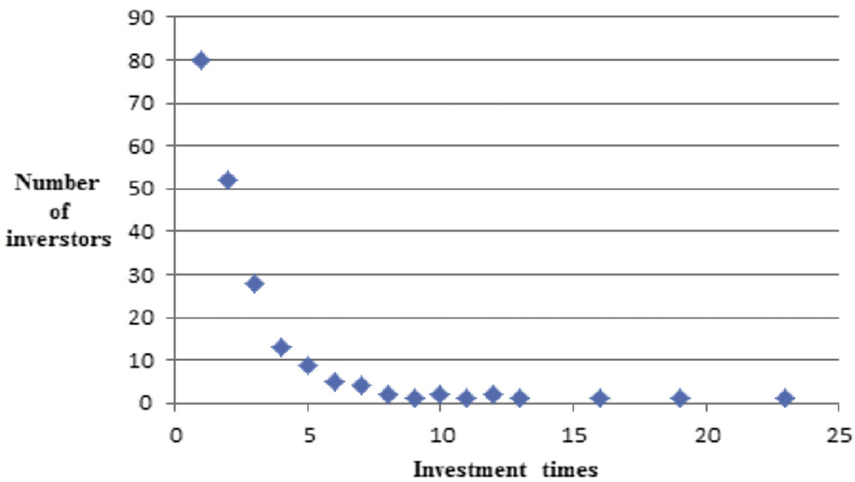

Fig. 2. Distribution of investment occurrences.

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the profits of the fund in proportion to their capital contribution. Based on *MPT*, *Ibbotson* and *Kaplan* (2000) noted that the allocation of fund assets is very important to the total income of the investment, which is in a large part dependent upon the investment strategy of the fund manager.[17] The asset allocation process enables the fund manager to derive the optimal risk and benefit based on the investor's risk tolerance. This section introduces ways to model the profiles of equity funds and investors in terms of return, risk and asset allocation.

4.1. Profiling equity funds

4.1.1. Asset allocation

Asset allocation is one of the most important part of investment and tactical asset allocation is one of the effective strategies of asset allocation. In the investment practice, tactical asset allocation strategies generally include national regional allocation, industry allocation, scale allocation and style allocation. From the perspective of excess returns, the contribution of industry factors is 71%,[18] that means industry allocation is the most important program in the process of asset allocation. Therefore, this paper mainly analyzes the asset allocation of China's equity funds in terms of two aspects: industry allocation and market capitalization.

1. Industry Allocation

Using the result of Grinold (1989) as the industry allocation metrics,[18] the industry allocation in this study is measured by the ratio of the value of the fund's investment in the industry to the fund's total assets, calculated by Eq. (1).

$$IAF_{iq} = IVF_{iq} / TAF_i \tag{1}$$

where IAF_{iq} and IVF_{iq} are the industry allocation and the total investment value of fund F_i in industry q respectively, and TAF_i denote the total assets of fund F_i. In this paper, according to the company profession classification direction in China,[19] let $q = 1, 2, \ldots, 19$.

2. Scale of Market Capitalization

Based on the market value of stocks held by the fund, the scale of market capitalization can be divided into large, medium and small capitalization, quantified as 5, 3, and 1 respectively. The data for market capitalization is taken from the *Wind* database. Let $SIAF_i$ indicate the scale of market capitalization for fund F_i.

4.1.2. Return and risk analysis of equity funds

1. Return evaluation indexes

The return is an important attribute of fund performance evaluation and also the most important attribute for investors. The usual indicators for evaluating fund returns are average rate and annualized rate. This paper uses the average return rate in the period of holding to measure the performance of fund F_i, which is denoted as $AVRF_i$ and calculated by Eq. (2).

$$AVRF_i = \frac{1}{n} \sum\nolimits_{p=1}^{n} RF_{ip} \tag{2}$$

Where RF_{ip} is one of the time series of return rates of the fund and n is the number of data points in the sequence. In this paper, the average return rate in the period of holding is used to evaluate the return. In order to reduce the complexity of computation, we calculate the average return rate in units of a week. There are 13 weeks from Sept 1 to Dec. 30, 2015, so let $n = 13$.

2. Risk assessment indexes

In this study, the standard deviation of returns, the maximum drawdown, and the largest gains are used to measure the risk of fund F_i.[20] These are denoted by $SDRF_\mathrm{i}$, MDF_i and BGF_i respectively. $SDRF_i$ is calculated by Eq. (3).

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$$SDRF_i = \sqrt{\frac{1}{n-1}\sum_{p=1}^{n}\left(RF_i - AVRF_i\right)^2} \tag{3}$$

MDF_i and BGF_i are the largest fall and rise in the review period for fund F_i, respectively.

We use industry allocation, scale of market capitalization, return and risk, to profile the equity fund, denoting F_i as $F_i = ((IAF_{iq}(q = 1, 2, 3\ldots, 19)), SIAF_i, \mathrm{AVR}F_i, SDRF_i, MDF_i,\ BGF_i)$ in this paper.

4.2. Profiling investors in the stock market

From section 3, we can see that compared with investors in the stock market, there are relatively few investors in the equity fund market, so the transaction data is very sparse. Hence it is difficult to accurately describe the behavioral characteristics of investors statistically due to the large sampling variation associated with the small sample size. However, equity fund investment is fundamentally a type of stock portfolio investment. It therefore has some key similarities with stock investment. Drawing on existing research on investors in the stock market[21] and the profile of equity funds above, fund investors are analyzed in terms of investment preference, profit and loss.

4.2.1. Investment preference

The investment preference of equity fund market investors is analyzed using industry and scale preference.

1. Industry preference

The industry preference of investor U_j is expressed as IPU_{jq}, as shown in Eq. (4).

$$IPU_{jq} = IPVU_{jq}/IVU_j \tag{4}$$

where $IPVU_{jq}$ describes the total value invested in the stocks of industry q by U_j, and IVU_j is the total investment in stocks during the investigation period. The greater the value of $IPVU_{jq}$, the more U_j prefers industry q.

2. Scale preference

The scale preference measures the investor preference for companies with different stock market capitalization scales, calculated by Eq. (5).

$$SPU_j = argmax\left(\frac{SPVU_{jp}}{IVU_j}\right),\ p = 1,\ 3,\ 5 \tag{5}$$

Let $SPVU_{jp}$ denote the total invested by U_j in companies with market capitalization scale p. According to SPU_j , the preferences of investors can be divided into three categories, that is: large, medium or small market investors.

4.2.2. Investment profit and loss analysis

As with describing the return and risk of the fund, the following indicators are chosen to measure the profit and loss of investor U_j.

1. Average rate of profit

This expresses the average rate of return in the review period for investor U_j, as shown in Eq. (6).

$$AVRU_j = \frac{\sum SAU_{jp}}{\sum TAU_{jp}} - 1 \tag{6}$$

where SAU_{jp} is the settlement amount from stock p (p = *1,2*, …, m (m is the investment time)) for investor U_j and TAU_{jp} is transaction amount invested by U_j in stock p.

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2. Standard deviation of profits

The standard deviation of returns is denoted as $SDRU_j$ for investor U_j, calculated by Eq. (7).

$$SDRU_j = \sqrt{\frac{1}{m-1}\sum_{p=1}^{m}\left(\frac{SAU_{jp}}{TAU_{jp}} - 1 - AVRU_j\right)^2} \tag{7}$$

3. Maximum profit rate

This describes the maximum profit rate for all profitable stocks, denoted as $MPRU_j$ shown in Eq. (8).

$$MPRU_j = arg\max\left(\frac{SAU_{jp}}{TAU_{jp}} - 1\right), p = 1, 2, \ldots m \tag{8}$$

4. Maximum loss rate

This describes the maximum loss rate for all losses, denoted as $MLRU_j$ as shown in Eq. (9).

$$MLRU_j = \min\left(\frac{SAU_{jp}}{TAU_{jp}} - 1\right), p = 1, 2, \ldots m \tag{9}$$

Finally, we can profile the investor with $U_j = ((IPU_{jq}(q = 1, 2, \ldots, 19)), SPU_j, AVRU_j, SDRU_j, MPRU_j, MLRU_j)$.

5. Personalized recommendation algorithm for stock funds

In this section, we address the "what to buy" problem by generating a personalized candidate investment recommendation list for each investor.

In this study, according to the characteristics of the equity funds and the investor's previous investment in the stock market, based on the idea of transfer learning, the profile of investors in the stock market is applied to the fund market. Then a personalized recommendation for the fund is created by using the profile of investors and funds to construct a utility function based on prospect theory.

As a kind of machine learning, transfer learning uses existing knowledge to solve different but related problems in situations that only have a small amount of data or no data at all. It uses knowledge transferred between domains in which there are some similarities but also differences between fields, tasks or data distributions.[22] Transfer learning has been widely used in many fields and scholars have done much work to develop and improve the model of transfer learning. In this paper, we do not add to current methods but only use the concepts of transfer learning. The characteristics of investors in the stock market are transferred to the equity fund market in order to address the issues of transaction data sparsity and long tail problems in the fund market.

Utility-based recommendation is widely used for personalized recommendation as there is no cold-start and data sparsity problem.[23,24] It operates by finding a utility function for each user.

5.1. Utility function

In general, when the expected return of a new investment is greater than that of the existing one, investors may consider the new investment. Therefore, it can be assumed that only when the return of equity funds is greater than that of stocks, investors will invest in funds. Otherwise they will continue to invest in stocks. Thus, the expectation of investment in the fund market can be assumed to be greater than or equal to the actual profit of stock investment. The expected value may also be used as a reference point for decision making in prospect theory.[25]

Let e_{jk} be the expected value of investor U_j on the attribute C_k, and his/her expectation vector of the equity fund can be denoted as $E_j = (e_{j1}, e_{j2}, \ldots\ldots, e_{jm})$, where m is the number of attributes. Let q_{ik} express the actual value of fund F_i on the attribute C_k, and the actual value of fund F_i can be denoted as $Q_i = (q_{i1}, q_{i2}, \ldots\ldots, q_{im})$.

Construct the decision vector $D_i = (d_{i1}, d_{i2}, \ldots\ldots, d_{im})$ of investor U_j for the fund F_i, where d_{ik} $(k = 1, 2, \ldots, m)$ is as Eq. (10).

$$d_{ik} = q_{ik} - e_{ik} \tag{10}$$

The above decision vector D_i represents the gap between the expected value and the actual value of fund F_i for investor U_j, which is used to construct the value function in this study,[25] shown as Eqs. (11) and (12).

$$V(d_{ik}) = \begin{cases} (d_{ik})^{\alpha}, & d_{ik} \geq 0 \\ -\theta(d_{ik})^{\beta}, & d_{ik} < 0 \end{cases} \tag{11}$$

$$V_i = \sum\nolimits_{k=1}^{m} w_k V(d_{ik}) \tag{12}$$

where w_k is the weight of attribute C_k and V_i describes the prospect value of fund F_i for investor U_j, which is used as the utility function for utility-based recommendation in this paper. The larger the value of V_i, the more fund F_i is suitable for investor U_j. Here, α and β are risk attitude coefficients, and θ is a loss aversion coefficient.

5.2. Recommendation algorithm

The final purpose of this study is to recommend equity funds to the right investors, especially where there is a lack of data on previous investments. Based on the idea of transfer learning and prospect theory, a utility-based recommendation method is proposed, described as follows:

Input: Transaction data of stocks and funds, fund allocation and performance data from the *Wind* database: parameters. M, N, w_k

Output: recommended equity funds.

Step 1: Standardize all data and separate investor trading records for training and testing the model.

Step 2: Profile the equity fund, $F_i = ((SAF_{ij}), SIAF_i, AVRF_i, SDRF_i, MDF_i, BGF_i)$

Step 3: Profile the investor, $U_j = ((IPU_{jq}), SPU_j, AVRU_j, SDRU_j, MPRU_j, MLRU_j)$

Step 4: For investor U_j,

Step 4.1: Calculate the similarity between investor U_j and all funds using Eq. (13).

$$sim(F_i, U_j) = \frac{1}{distance(F_i, U_j)} = 1 \Big/ \sqrt{\sum\nolimits_{k=1}^{n1} (F_{ik} - U_{jk})^2} \tag{13}$$

Here, $sim(F_i, U_j)$ is the similarity between investor $U_j$and the fund F_i.

Step 4.2: Rank funds by the similarity values in descending order and select the Top M funds as the recommended candidate list. $F^C = \{F_i\}, i = 1, 2, \ldots., M$.

Step 4.3: For each fund F_i ($F_i \in F^C$), calculate the prospect value V_i by Eq. (12) based on the attribute set $(AVRU_j, MPRU_j, MLRU_j)$ for the investor corresponding to the properties $(AVRF_i, MDF_i, BGF_i)$ for the fund one by one.

Step 4.4: Reorder funds in F^C by the prospect values in descending order and select the Top N funds as the recommended set $F^R = \{F_i\}, i = 1, 2, \ldots., N$.

Step 4.5: Repeat Steps 4.1 through 4.4 until all investors in the training and test data set have been processed.

5.3. Experiments and results

According to the classifier modeling or parameter estimating process in machine learning, we divide fund the investors into two groups with a 4:1 ratio. One group is used as training data set, to fit the parameters; the other is used as testing data set to assess the performance of the method proposed in this paper. As described in Section 3, the transaction data consists of 203 investors with equity fund transactions, so we select 40 fund investors as the recommended object to test the method, and the other 163 fund investors are used to train parameters $(\alpha, \beta, \theta, w_k(k = 1, 2, 3))$ using the evaluated accuracy of recommendations.

5.3.1. The performance assessing method

In order to test the performance of the proposed method which is referred to as Utility-based RS in this section, we compare the accuracy of its recommendations as calculated by Eq. (14) with the Similarity-based RS, which takes the top N funds to recommend directly from the recommended candidate set F^C in step 4.2.

$$R_N = \frac{1}{t}\sum_{j=1}^{t}\frac{N_{jr}}{N} \tag{14}$$

Here, N_{jr} is the number of funds at the intersection of the two sets of funds, one is invested by the object investor U_j in the test data set, the other is the recommended set F^R, and t is the number of investors used to assess the performance of the method.

5.3.2. The parameter learning method

The value function of the prospect theory proposed by *Tversky* and *Kahneman* (1992) is shown as Eq. (15).[25]

$$V(x) = \begin{cases} x^{\alpha}, x \geq 0 \\ -\theta(x)^{\beta}, x < 0 \end{cases} \tag{15}$$

Here, α and β are risk attitude coefficients, and θ is a loss aversion coefficient. According to their research, investors are more risk averse when their wealth increases and are more sensitive to loss in the investment decision process. On this basis, we consider α and β should be smaller than 1. Also, *Tversky* and *Kahneman* give reference values for these parameters as $\alpha = \beta = 0.88$, $\theta = 2.25$. Based on this, during the experiments, the parameters are initialized as $\alpha = \beta = 0.88$, $\theta = 2.25$ and let $w_k = (0.3, 0.4, 0.4)$ based on our own experience.

We analyze a number of different funds invested by 203 investors and find their mean is 7.64 and the maximum is 16. So, we input $M = 20, N = 4, 5, 6, 7, 8, 9, 10$ respectively.

In the parameter learning process, we aim to find the value for parameters α and β. The other parameters are set as described above. The process is as follows:

(1) Let $\alpha = \beta = 0.88$, $\theta = 2.25$, $w_k = (0.3, 0.4, 0.4)$.
(2) Let $i, \tau, \overline{R_i}$ indicate the experiment time, the change in the parameter and the average recommendation accuracy of *ith* experiment respectively. At the beginning $i = 1$, $\tau = 0.01$, $\overline{R_1} = 0$.
(3) Calculate $\overline{R_i}$ by Eq. (16).

$$\overline{R_i} = \frac{1}{7}\sum_{N} R_N = \frac{1}{7t}\sum_{N}\sum_{j=1}^{t}\frac{N_{jr}}{N} \tag{16}$$

Here, $N = 4, 5, 6, 7, 8, 9, 10$ and $t = 163$.

(4) Adjust the value of α and β individually, and increase the step $\tau = 0.01$ each time. Let $i \leftarrow i + 1$, go to step (3).
(5) Repeat steps (3) and (4) until $\left|\overline{R_i} - \overline{R_{i-1}}\right| < 0.001$.

After learning, the values of the parameters are $\alpha = 1.21, \beta = 1.02, \theta = 2.25$, $w_k = (0.3, 0.4, 0.4)$.

5.3.3. Experimental results

As can be seen from Fig. 3, the proposed Utility-based recommendation method in this study generates more accurate results than the Similarity-based recommendation method.

For example: the funds bought by investor U_i can be denoted as vector (001105, 233009, 000793, 233011, 160512, 100056, 000594, 020001, 001628, 001277). When recommend top-5 funds to investor U_i by Utility-based recommendation method, the fund vector (001105, 100056, 001616, 001477, 257070) is obtained. So $R_5 = \frac{2}{5} = 0.4$. A similar process can calculate the values of other R_N(N = 4, 6, 7, 8, 9, 10), and the value of the R_N for the Similarity-based recommendation method.

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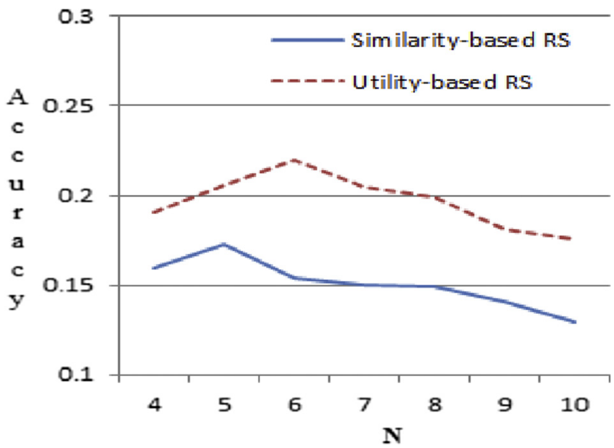

Fig. 3. Recommendation accuracy.

However, compared with the performance of recommendation systems in other areas, such as movies where the recommendation accuracy can exceed 0.32,[26] the recommendation accuracy is still relatively low. This may be due to the following factors:

The first is the particular characteristics of the transaction data that were used for the training and test data, in which the number of fund investors is relatively small and the data is only from one securities business department.

The second is the profile of investors and funds. In this paper, only the statistical information from the open market and the observed trading behavior of investors were used, with some private information not considered. Hence, the results may deviate from those predicted under the strong efficient market hypothesis.[27]

The third is only to consider the rational behavior of investors in building the profile of investors. In fact, research into the Chinese finance market, indicates that the behavior of security investment funds is not completely rational. Their behavior has an irrational component and "herd behavior" is one example of this irrational side.[28]

6. Conclusions

Based on profiling investors and equity funds, a utility-based personalized recommendation method is proposed based on prospect theory and transfer learning. The performance of the algorithm is tested using actual transaction data. This study consists of the research and application of prospect theory and transfer learning, which provides a method for solving problems in the cross-market situation. At the same time, it is an application of personalized recommendation technology in the financial field. However, there are limitations to the proposed algorithm. Firstly, it only solves the "what to buy" question and does not consider "when to buy" or "how much to buy". Secondly, the accuracy of the recommendations supplied by the proposed algorithm should to be improved. Thirdly, a wider range of circumstances and investors should be studied in further experiments to test the wider applicability of the proposed algorithm. Hence, future work will be to improve the profiles of funds and investors to further enhance the recommendations, to test the performance of the algorithm with data from a range of circumstances and investors, and to address the questions of "when to buy" and "how much to buy".

Declaration of interest

There is no actual or potential conflict to declare.

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