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A Novel Weighted Hybrid Recommendation System using Sharpe Ratio for a Profitable Diversified Investment Portfolio

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ABSTRACT

Identifying where to invest and how much to invest can be very challenging for common people who have limited knowledge in the domain. Portfolio managers are financial professionals who spend a lot of time and effort to help investors in investing funds and implementing investment strategies, but not all can afford to consult them. The study aims to develop a weighted hybrid recommendation system that recommends an optimized investment portfolio based on the investor's preferences regarding risk and return. Generally, investors usually ask investment for advice from friends or relatives with similar risk preferences or if they are interested in a particular item, the investors ask for the experience of someone who already has invested in the same item. Therefore, the methodology considers the investor's past behavior and the past behavior of the nearest neighbor investors with similar risk preferences. Using user-based collaborative filtering the number of stocks is recommended using Pearson correlation based on the investor's income, then using another user-based collaborative filtering the number of stocks is recommended based on the investor's age. Weights are assigned to the recommended number of stocks generated based on income and age and their weighted average is finally considered. Finally, the feasibility of the proposed system was assessed through various experiments. Based on the received results, the authors conclude that the proposed weighted hybrid approach is robust enough for implementation in the real world. The novelty of the paper lies in the fact that none of the existing approaches make use of more than one type of weighted recommendation algorithm. Additionally, the final results obtained this way have been never further fortified with the highest Sharpe ratio and minimum risk for the investor. This combination of hybrid and Sharpe ratios has never been explored before.

Keywords: Sharpe ratio; hybrid filtering; investment portfolio; recommendation system; collaborative filtering; investor-based filtering

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INTRODUCTION

A recommendation system can be seen as an algorithm that helps to identify items that are most preferred by a certain investor. These algorithms help companies to cater to their customers in a highly personalized manner. They are broadly classified into three types mainly being, content-based filtering [1], collaborative filtering [2, 3] and hybrid filtering [4]. However, regardless of the algorithm the general idea behind the system is that it takes implicit information like timestamps, geographical location and clicks along with explicit information like recent activity history, gender, birthdate, and profile of the investor and tries to find certain similarities between either item-to-item or user-to-user to identify an item that would be preferred by that user.

An investment portfolio is usually made up of various securities, such as stocks, mutual funds, bonds, exchange traded funds, money market funds and other financial assets. Investment portfolios are usually made with the aim to grow in value and gain high returns. Types of investors can be identified based on their objectives, their investment strategies and investment type. Three main types which can be identified are commercial banks, financial intermediaries and individual investors. Commercial Banks mainly invest in bills, inter-bank bonds and national debt [1]. When choosing an investment portfolio, they aim to minimize risk and meet the expected earnings. Financial intermediaries mainly invest in stocks, mutual funds, etc. and they focus on minimizing unsystematic risk, determining the weight of each security according to investors utility and time management of investment behavior. Individual investors usually invest in bank deposits, stocks, bonds, securities investment funds, etc. Individual investors have a simple objective and that is to maximize profits at a risk tolerable level [1].

Lack of relevant knowledge and inexperience would cost the individual investors a lot of time, effort and cost to invest by themselves and if investment advisors/managers are hired it would result in high cost and low efficiency [1]. Therefore, a recommendation system that can help create an optimal portfolio to meet the investors risk preference and objectives of individual investors is necessary. We now present various filtering methods and Sharpe Ratio.

A. Collaborative Filtering (CF)

Collaborative Filtering (CF) algorithms use the historical interactions between the users and the items to create new recommendations based on the estimated proximity of similar users or similar items. These interactions are stored in a "user-item interaction matrix".

There are mainly two types of CF methods:

- Memory Based CF: They make use of the values of user-item interactions directly, with no model and are usually based on nearest neighbors (NN) search. NN search predicts ratings by referring to users who have similar ratings to that of the target user, or to items rated similar to that of the target item. This assumes that when two users have similar ratings on a few items they have similar ratings on the other items as well also known as user-based CF, or if two items are rated similar by a portion of users, the two items have similar ratings by the remaining users as well also known as item-based CF [2, 3].
- Model Based CF: Here a model is fitted to the training data which is later to predict unseen ratings and produce recommendations. Cluster-based CF, Bayesian classifiers, and regression-based methods are famously used in model-based Collaborative Filtering algorithms [2, 3].

B. Content Based Filtering

Content based filtering takes into consideration not only the "user-item interaction matrix" but also the underlying features of the users like age, gender and profession. It also takes into consideration the item features like price and category.

C. Hybrid methods

A hybrid filtering method uses both collaborative filtering and content-based methods. Since collaborative filtering is able to get more accurate recommendations as more users interact with more items, this approach only uses past user-item interactions making it difficult to recommend to new users who do not have any past interactions also known as the cold start problem, therefore here content-based filtering is used to overcome that problem [4].

It is notable that a recommendation system named "PB-ADVISOR" which is based on fuzzy and semantic technologies and recommends investment portfolios to private bankers has also been explored [5].

D. Sharpe Ratio

The Sharpe Ratio is a well-known ratio that can be used to measure an investment portfolio or even a single stock or investment [6, 7]. Here, we use the Sharpe Ratio to measure the performance of the investment portfolio by adjusting for its risk. Usually, a high Sharpe Ratio means, the investment return is high relative to the amount of risk taken, making it the better investment portfolio [6, 7]. The ratio is compared to a grading threshold of:

1. "Less than 1" — Bad
2. "Between 1 to 1.99" — Adequate/good
3. "Between 2 to 2.99" — Very good
4. "Greater than 3" — Excellent

The purpose of this paper is to propose a recommendation system that can recommend an optimal investment portfolio for individual investors with varying risk preferences.

The rest of this paper is structured as follows. Section two reviews related literature on the various methods used for recommending securities in investment portfolios. Section three introduces the investment portfolio hybrid recommendation model based on the related work. Section four demonstrates the feasibility of the investment portfolio hybrid recommendation model through various demonstrations and finally, section five talks about conclusions and future work.

LITERATURE REVIEW

Research has been done on various methods for recommendations and portfolio optimization in investment portfolios. Recommendation systems for recommending an investment plan for various investors on the internet using the Value at Risk (VaR) method to measure the risk level of the stocks and applying a collaborative filtering algorithm to recommend a portfolio based on the historical behavior of the similar investor have been explored [1]. The investment patterns of a person have been found based on their characteristics using fuzzy data mining techniques. The result is in the form of clusters of investment patterns of similar people [8]. Using Big Order Net Inflow of stock, a selection of stocks with a higher value to the net inflow was added to the pre-recommended stock set and presented to the target investor. Fuzzy clustering methods were used to categorize similar investors and stocks were chosen by the stock set that was once operated by a similar investor. This technique proved to show that the recommended stocks have higher gains after the recommendation [9].

A recommendation system based on a case-based recommendation pipeline of three steps i.e. first the retrieval and reuse of similar investment portfolios, second the revision of portfolios wherein the final set is filtered out and third the review and retain where the human advisor can review and modify the final investment portfolio was explored. The prototype generated personalized portfolios, and the performance was evaluated against real users, which showed the yield obtained by recommendations overcame that of human advisors [10]. For portfolio optimization, many approaches like Value at Risk (VaR) [1], a combination of both VaR and Sharpe ratio [6] and network topology [11] have been proposed.

In one research study, the optimum number of clusters for k-means clustering for stock market data was found using the Davies-Bouldin Index [12]. In another study, portfolio selection from companies that fall in the same cluster based on K-means clustering was done wherein, the financial data of fifty Nifty companies from the year 2012 were taken and the K-means algorithm was applied to it to find the clusters based on the financial data of Price Earning Per Share of the companies. It was found that portfolios could be generated from the clusters which have the minimum average distance [13].

An agent-based framework for diversified portfolio management was also proposed based on the investors high-level goals regarding risk and return. The highest ranked goals were taken into consideration for clustering using a suitable algorithm. The validation agent then selects the most compact cluster from which the portfolio is made and analyzed using the Markowitz model [14, 15].

G. Connor et al. [16] and J. Chen et al. [17] presented semi-parametric models for the selection of portfolio which is optimal. S.E. Satchell and O.J. Williams [18] have lamented the lack of skills and difficulties in predicting the future of financial markets. On the same lines, M. Baddeley et al. [19] lamented the herding behavior in the financial markets. K.D. Shilov and A.V. Zubarev [20] presented the discussion on Bitcoin as a possible investment venue. E.V. Sapir and I.A. Karachev [21] presented a discussion on the investment portfolios in wake of the Russian government's new investment policies. I.A. Ezangina and A.E. Malovichko [22] highlighted the risks in the investments and financial markets in the pandemic era. O.V. Efimova et al. [23] presented the experimental results, on returns on investments, by taking into consideration the three factors of environmental, social and governance performance. A.O. Ovcharov and V.A. Matveev [24] elaborated on the factor of fear while investing in the digital financial asset markets. L.G. Pashtova [25] went a step ahead of investment portfolios and discussed the impact of such investments on the growth of the Russian economy. W.B. Freitas and J.J.R. Bertini [26] advocated the significance of tactical asset allocation for investments resulting in profitable portfolios. Various quantitative techniques have been proposed by P. Brugiere [27].

A detailed structural analysis of various options for the distribution of investment portfolios has been presented by O.S. Sukharev [28]. Various strategies for investment portfolios have been presented by M. Zhang et al. [29]. They have taken into consideration the effect of multiple policies on the optimization of portfolio distribution in the sector of renewable energy. B.B.T. Carmo et al. [30] presented a PROMETHEE V method with linear programming for helping investors with various options and scope of customization for investment portfolios. N. Eriotis et al. [31] investigated and presented a report on the investment portfolios spread over a period of one and a half decades in Greece. An important finding presented by them suggested that the diversification of the portfolio was not successful almost 50% of the time. With a focus on risk management, M.B. Bulturbayevich and N. G'ovsiddin [32] presented a discussion on the possibilities of investment portfolios for commercial banks. Y. Deng et al. [33] presented a specific case of investment portfolio through blockchain by deployment of the Artificial Intelligence techniques. K.T. Park et al. [34] proved that peer-to-peer lending could be a lucrative investment portfolio. M. Li and Y. Wu [35] used the notion of network communication and artificial intelligence to propose a framework for investment portfolios in the field of real estate.

It is noteworthy that all of the above approaches make use of only one type of recommendation

Table 1

Investor attributes considered

Sr. No.	Attribute
1	Age
2	Income
3	Number of Stocks

Source: extracted by authors based on the Federal Reserve Board – 2013 Survey of Consumer Finances by Board of Governors of the Federal Reserve System. URL: https://www.federalreserve.gov/econres/scf_2013.htm (accessed on 23.08.2021).

Table 2

Stock data from four companies

Date	Barclays	Goldmans Sachs	JP Morgan	Morgan Stanley
2017-01-03	20.867758	226.374527	77.569687	39.263435
2017-01-04	21.256769	227.836365	77.712753	39.783302
2017-01-05	21.006685	226.140228	76.997421	39.418495
2017-01-06	21.006685	229.495026	77.006355	39.993069
2017-01-09	20.886276	227.611450	77.059998	38.953350

Source: stock data reported by Yahoo Finance. URL: https://in.finance.yahoo.com/ (accessed on 23.08.2021).

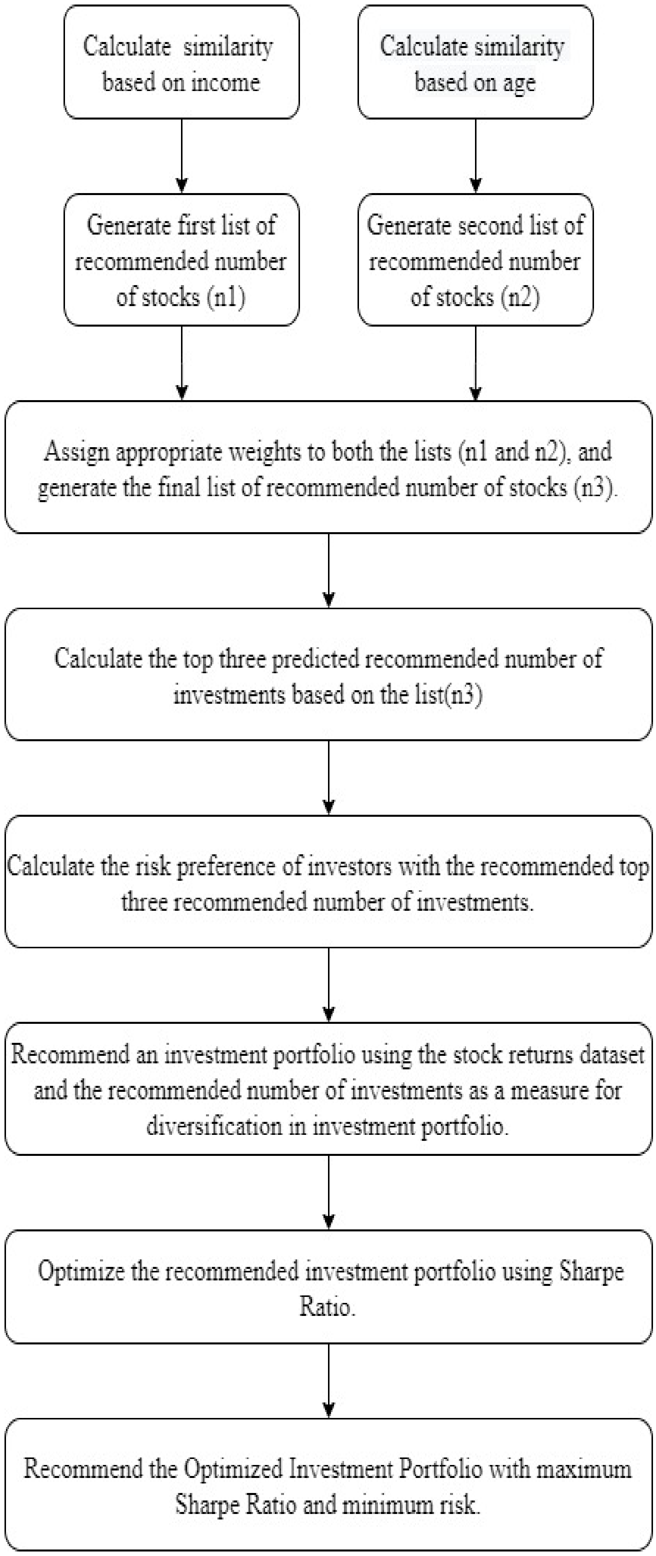

Fig. **Proposed hybrid recommendation model process**

algorithm. In the current paper, the proposed methodology uses a weighted hybrid approach which uses two recommendation algorithms along with the Sharpe ratio for portfolio optimization. This combination of hybrid and Sharpe ratios has not yet been explored before. Generally, investors usually ask for investment advice from friends or relatives with similar risk preferences or if they are interested in a particular item, the investors ask for the experience of someone who already has invested in the same item.

Along with this, tacit knowledge like age, gender, and income level is also considered. Therefore, we used a weighted hybrid recommendation algorithm where the recommendation system has two components:

- one component from the collaborative filtering where users with age are grouped together
- another component from users with similar income

The output of the two components is combined using a weighted average to generate the neighbors list consisting of recommendations of a number of stocks. Additionally, the portfolio is further optimized using the Sharpe ratio.

METHODOLOGY FOR THE PROPOSED PORTFOLIO RECOMMENDATION MODEL

A. Dataset

The investment dataset is taken through publicly available data from The Survey of Consumer Finances (SCF) 2013, which is a survey of families from the USA.[1] The survey includes data about the income of families as well as other financial characteristics as shown in *Table 1*. Live Stock returns data from yahoo finance and is extracted for the investment data.[2] *Table 2* shows the stock data of four companies considered for the present research work.

B. Process of the Proposed Recommendation Model

To provide recommendations for the target investor having specific risk preferences, the proposed model in this paper selects the top three stocks with their respective risk preference. Using user-based collaborative filtering the number of stocks is recommended using Pearson correlation based on investors income, then using another user-based collaborative filtering the number of stocks is recommended based on the investors age. The final recommendation follows a weighted hybrid recommendation system by giving appropriate weights to the recommended number of stocks generated based on income and age and their weighted average is considered. The risk preference of investors is calculated using their number of stocks held in equity shares by their nearest neighbor. The top three recommended number of stocks along with their risk preference is then given to the target investor.

Table 3

Recommended number of stocks based on age

Age-Bin	Correlation	Number of Stocks
46–50	1.0000	2.5194
41–45	0.9940	2.2007
86–90	0.9920	7.2410
51–55	0.9918	5.2424
76–80	0.9912	7.4709
81–85	0.9912	5.2323
66–70	0.9902	6.7517
36–40	0.9899	11.6138
61–65	0.9885	8.9040
71–75	0.9873	9.1750
26–30	0.9837	0.2995
Greater than 90	0.9693	2.2000
56–60	0.9678	4.6550
31–35	0.8549	1.2838
Less than 20	0.1046	0.1538
21–25	–0.4978	0.2771

Source: authors' calculations.

[1] Board of Governors of the Federal Reserve System. Federal Reserve Board — 2013 Survey of Consumer Finances. 2013. URL: https://www.federalreserve.gov/econres/scf_2013.htm (accessed on 23.08.2021).

[2] Yahoo Finance. Yahoo is now a part of Verizon Media. 2020. URL: https://in.finance.yahoo.com/ (accessed on 23.08.2021).

Table 4

Recommended number of stocks based on income

Income-Bin	Correlation	Number of Stocks
Very High	1.0000	13.7324
High	0.5807	1.4659
Medium	0.5331	0.5791
Low	0.4768	0.4192

Source: authors' calculations.

Table 5

Top three recommended stocks of age and income along with respective weights

Age Correlation	Number of Stocks (NS)	Weight (W)	Weighted NS (WNS)	Income Correlation	NS	W	WNS
1.0000	2.5194	0.5	1.2597	1.0000	13.7324	0.5	6.8662
0.9940	2.2007	0.5	1.1003	0.5807	1.4659	0.5	0.7329
0.9920	7.2410	0.5	3.6205	0.5331	0.5791	0.5	0.2895

Source: authors' calculations.

Table 6

Final weighted recommended number of stocks

WNS from Age Correlation	WNS from Income Correlation	Final WNS	Final Recommendations	
			Rounded Value of WNS	Equity Risk Preference
1.2597	6.8662	4.0629	5	Low
1.1003	0.7329	0.9166	1	Low
3.6205	0.2895	1.9550	2	Low

Source: authors' calculations.

Using the recommended number of stocks, a portfolio is created and optimized using the Sharpe risk ratio. The final portfolio with a maximum Sharpe ratio and minimum risk is recommended to the target investor.

A detailed step-by-step procedure of the proposed process is given below while the same is diagrammatically represented in *Fig.*

- Step 1: Calculate the similarity between the target investor (i) and the other investors based on income using Pearson correlation measure. This gives us the first list of recommended numbers of stocks.
- Step 2: Generate the second list of neighbor investors (n2) based on the target investors age.

Table 3 presents the recommended number of stocks based on age. Similarly, with the investor entering their annual income, the model gives the recommended number of stocks to invest in based on the income. Results can be seen in *Table 4*. Using a weighted hybrid recommendation system, the weighted average of the number of stocks is calculated. Here an equal weightage of 0.5 is given to both the factors. The results are shown in *Table 5* and *Table 6*. Assuming the recommended number of stocks is four for the following case, we

Table 7

Recommended optimized portfolio

Portfolio for Maximum Sharpe Ratio		Portfolio for Minimum Sharpe Ratio	
Returns	0.000272	Returns	0.000064
Standard Deviation	0.020553	Standard Deviation	0.019698
Sharpe Ratio	0.013229	Sharpe Ratio	0.003243
Barclays	0.005380	Barclays	0.009600
Goldmans Sachs	0.859740	Goldmans Sachs	0.335106
JP Morgan	0.123275	JP Morgan	0.644385
Morgan Stanley	0.011605	Morgan Stanley	0.010908

Source: authors' calculations.

create an investment portfolio with four different company stocks. The choice of company depends on the target investor. Using the Sharpe Ratio, we can optimize the investment portfolio. The results shown in *Table 7* have the optimized investment portfolio with the maximum Sharpe ratio and the minimum risk. Therefore, the target investor has the option to choose between the two portfolios, i.e. the portfolio with the maximum Sharpe ratio (i.e. the highest risk adjusted returns) and the portfolio with the minimum volatility or variance.

CONCLUSION

This paper proposed a hybrid recommendation model for investors who wish to invest their money efficiently but are unable to get proper financial advice from investment portfolio managers. The proposed model helps investors to maximise their returns and minimise their risk. The proposed model follows a hybrid recommendation system where a weighted average is taken from two user-based recommendation systems, and an optimised investment portfolio is recommended using optimization measures like the Sharpe ratio, a combination that has not been explored before. The proposed model was tested on data from the 2013 US study. Though being tested on the historical dataset is one of the limitations of the present work, neither it subdues the uniqueness of the proposed approach nor does it change the working of the model. We opted for this dataset as it is publicly available, standardized and unbiased. Further, as this dataset contains sufficiently aggregated values and is voluminous enough for benchmarking, we believe that the results obtained on experimentation with this dataset are promising and relevant for analyzing the investor's behavior and making the recommendations. As more features may help the model to provide more accurate recommendations, the future study will be done using more features as well as a dataset comprising historical as well as the latest information of the investors.

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