# MUTUAL FUND RECOMMENDATION SYSTEM WITH PERSONALIZED EXPLANATIONS

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**Abstract** - *Mutual funds provide a higher return on investment in spite of having high risk factors as compared to other investment options. Consequently, investors are in a dilemma while choosing the right funds for investing. As a result, an efficient recommendation system along with an explanation for the same is required to aid the investors make the correct choice. In this paper we intend to review various existing models, theories and discussions stressing on mutual funds' investments and their returns. Further, we propose a model that can give an explanation for the recommendations made by using a knowledge graph machine learning model. Also, we aim to personalize these recommendations based on the user investment propensity.*

***Key Words*: Mutual Fund, Knowledge Graph, recommendation system, Deep Learning**

## 1. INTRODUCTION

A financial entity that gathers the money of several investors and invests them in different financial securities such as bonds, stocks and short term debt is termed as 'Mutual Fund'. The prediction and estimation of mutual funds' performance is a key ingredient for investors and financial institutions today, but parallelly figuring out the best funds to invest becomes challenging. In this paper, we intend to develop a machine learning model that can provide recommendations along with explanations for the same with the help of knowledge graph machine learning model. The proposed model will consider multiple hidden factors along with factors such as ratio of expense, fund manager experience, past performance and assets under management that influence the general performance of mutual funds' markets.

### 1.1 Problem

Common mutual fund recommendation systems base their results on market performance rather than personalizing the investment portfolio of the investors. Additionally, the recommendation systems don't have an ability to provide an explicit explanation of why a fund was recommended to the user.

### 1.2 Motivation

Mutual funds are a popular investment choice for investors today. Individual investors often lack skills to invest in the market directly. They have limited ability to manage the market fluctuations. Hence, mutual funds become a straightforward investment option for investors intending to invest in equities and other complex asset classes. Mutual funds need to be professionally managed, should reduce risks and offer returns that can beat inflation as well as be sufficient enough to provide good returns. Due to these reasons mutual funds are examined extensively for their performance.

A mutual fund scheme should be able to take care of the financial requirements of wealth creation according to an investor. But in the present scenario, choosing a good mutual fund scheme has become very challenging, just like stocks. The rapid growth of multiple schemes of mutual funds has created a dilemma for investors. Although investment in schemes of a mutual fund is a good idea for sustainable wealth creation, choosing a good mutual fund has become the one of the biggest challenges for an ordinary investor.

### 1.3 Challenges

Since recommender systems are based on high quality data, if we are not able to crunch and analyze it properly, we may not be able to make the most of the recommendation system. Public datasets are scarcely available for the use-case. Several small datasets have to be combined to create a larger dataset. This, however, poses a huge challenge of data preprocessing as the format of data is different in all the databases.

The cold start problem: When we rely on user data, it has several down-sides to it. When a new user adds new items to the catalog, it becomes difficult for the algorithm to predict the taste and preferences of the new user leading to less accurate recommendations.

## 2. LITERATURE SURVEY

[1] In this paper authors have used a knowledge graph–based structure to develop an explainable mutual fund recommendation system based on deep learning techniques. The proposed recommendation system based on knowledge

graph and deep personalized recommendation system exhibited a considerably high accuracy and it is easy to interpret. They have also demonstrated the effectiveness of the proposed model for providing customized explanations by using a case study. They have not only generated simple explanations with the original model but also generated the composition of explanations with customized ratings. They have also generated special recommendations for a customer in the data set to demonstrate the ability of the proposed model to produce customized recommendations.

[2] The paper proposes a method of personalized equity recommendation system based on transfer learning. This includes several steps. Firstly, a portfolio is created for both equity funds as well as the investor (using modern portfolio theory). Secondly, a profile of the stock market is created. The concept of transfer learning is then used with this profile in the equity market. Finally, a recommendation system which is utility based is created using the idea of prospect theory. This approach is best for investors that have a very limited past history of investing. The output of this paper shows significant increment in accuracy when compared to the traditional methods such as collaborative filtering(which is a form of similarity based recommendation system). However, overall accuracy is low(0.32), due to various factors.

[3] This paper focuses on using a time-series model named Prophet model instead of traditional RNN or LSTM for prediction of the fund price. To begin with, an investment propensity diagnostic list is prepared based on the Korea Council for Investor Education. The fund information also contains the risk level that can be matched with the investment propensity of the user. For determining the fund risk level, K-means algorithm is suggested along with an elbow method with 4 classes(High risk, high return, high risk low return and so on). The prophet model further accurately predicts the future price of the fund. The training time for this model is significantly less than traditional ML models. (1.4s for Prophet model) and 2.1 seconds for LSTM with similar accuracy.

[4] This paper focuses on building a portfolio recommender system especially for novice and 1st-time investors. Network analysis is the proposed method in this paper which generates 2 types of networks namely 1-mode network and 2-mode network. Depending on user preferences, a mutual fund portfolio is selected and analyzed. The credibility of external funds is given by an external agency. Based on the 2 types of graphs created after completing previous steps, individual stocks of the funds are analyzed using centralized measures and these stocks are recommended to the user.

[5] In this paper, the systematized machine-learning based approaches for Stock Market Prediction (SMP) were surveyed and explained. Different methodologies, developments and future directions were studied. A study for NASDAQ price prediction compared three ANN models namely MLP, dynamic artificial neural network and autoregressive control heteroscedasticity which concluded that multi-linear perceptron surpassed DAN2 and GARCH. The two methods used for SMP were Classification and Regression. It was also observed that SVM was the most accepted SPM technique. ANN and DNN provided high accuracy along with faster predictions.

[6] The paper it was observed that deep learning and ensemble methods provided favorable and viable solutions for the problem of forecasting performances of multiple mutual funds which are measured by Sharpe ratios. The monthly-based time series data was for more than 600 open-end mutual funds was used to calculate the year-to-year Sharpe ratios. Higher accuracy in forecasting fund's sharpe ratios was observed with long-short term memory (LSTMs) and gated recurrent units (GRUs) deep learning methods both trained with modern Bayesian optimization. The purpose of this paper was to address various challenges faced while forecasting predictions of various mutual funds with the help of deep learning approaches with a comparison against popular traditional statistical approaches. Based on model quality the ranking order was Ensemble, LSTM, GRUs, ARIMA, ETS and Theta respectively.

[7] Krist Papadopoulos (2019), in his paper investigates various collaborative filtering approaches with latent variable models for predicting sparse and large mutual fund redemptions by advisors. It tests different advisor characteristics for applicability in the collaborative filtering framework. The paper provides a technique for financial institutions to predict large mutual fund redemptions to prepare more effective client sales interactions with advisors. It uses models like WLR-MF (Weighted Logistic Regression Matrix Factorization), WLS-MF (Weighted Least Squares Matrix Factorization) and WMF (Weighted Matrix Factorization) for prediction and concludes that WMF produced highest test performance in all metrics.

[8] Pendaraki, Beligiannis and Lappa (2016) in their paper discuss approaches for prediction of mutual funds' performance and net asset value using artificial neural networks and genetic programming. They compare the forecasting results of the ANN approach with that of GP approach to predict the mutual fund performance and concludes that ANN's results outperforms that of GP's results for prediction of mutual funds' net asset value where as GP's results outperforms that of ANN's results in prediction of mutual funds' returns. This prediction can further be used for our mutual fund recommendation system. The paper presents sampling and grouping of input data, ANN approach concerning the application of multilayer perceptrons methodology and GP approach for prediction.

[9] This paper proposes an innovative methodology to construct a mutual fund portfolio in order to increase the profit over time and avoid risks. The proposed methodology analyzes the historical data based on regression analysis. It

helps in grouping of stocks to minimize risk and maximize returns using a curve fitting technique.

[10] AI has made banking services more personalised. Marketing strives to provide precise financial services. Precision marketing faces scalability challenges, delayed starts, and a lack of transaction data for many clients and commodities. Deep learning was used to improve collaborative filtering by some academics. The typical matrix factorization approach is more efficient, but it has limited the recommendation model's capacity to account for nuanced item interactions. In this article, they have suggested using a Graph DCF algorithm to make tailored suggestions for mutual funds. Using the sequential perspective, we can build the graph-structured network by joining the nodes representing our customers with those representing their purchases and the corresponding redeemed trade orders. By doing so, we may construct a wide variety of hidden connections between shoppers who share similar tastes and preferences. Next, an aggregate function that takes into account similarities in buying patterns produces an embedding vector for each customer node. Finally, the suggested deep embedded collaborative filtering system forecasts a customer's willingness to purchase a mutual fund based on a variety of qualities and attributes of both the mutual fund and the consumer. DECF approaches outperformed deep learning methods like DCF and NCF, as evidenced by experimental results on a real-world data set from Taiwan Commercial bank. Compared to commonly used methods, the suggested GraphDCF algorithm performed better (by up to 2.3%).

## 3. PROPOSED SYSTEM

### 3.1 Problem Statement

This project aims to propose an explainable mutual fund recommendation system that provides precise recommendations with personalized explanations where the knowledge of deep neural embedding techniques along with the traits of knowledge graph is leveraged to design a model to obtain high accuracy recommendation and appropriate explanations.

### 3.2 Problem elaboration

Currently, the existing mutual fund recommendation systems present are majorly based on the best performing mutual fund in the market. The personalization of the mutual fund along with predicting the performance of the mutual fund is not considered in depth. Not considering all the factors together reduces the accuracy and doesn't take into account the amount of risk an investor can take. We would like to develop a model that takes into account all the associated factors to give better accuracy and also personalize the recommendations.

We aim to research about the hidden factors affecting the performance of the mutual fund market and therefore explain why a specific fund is recommended.

After gathering all the factors affecting the funds, the factors will be ranked in descending order of their impact and accordingly give a weight to each factor.

The proposed model can be developed by combining and preprocessing several databases of mutual funds. A machine learning model related to knowledge graphs can be used for explaining why a recommendation is made. For personalization of recommendation, different portfolios can be created for different investors and for the funds as well. Then, by comparing these portfolios, different funds can be recommended to the user.

The requirement of data is of primary importance and can be fulfilled by using various open source databases as well as scraping data from credible sources. We need to develop a strategy to store this copious amount of data and effectively perform analytics on it at the same time. Once a model has been developed using this data, a user-friendly web interface needs to be developed so that the end user can use the functionalities provided with ease. The web interface will contain the profile of each user and personalized recommendations for them along with the explanation of why the fund was recommended to increase the user's trust in the system. For evaluating the profile of the user and their investment propensity, a questionnaire will be provided to all the users during the registration process of the website.

### 3.3 Proposed system

Knowledge Graph–Based Recommendation Method

Sellers of a fund must give a fund recommendation for the next month at the end of each and every month. The seller relies on the features of the previous status and predicts the funds the customer will buy during the following month. Generally, the manager of customer relationship should respond to why a fund is recommended to a customer. Moreover, customers cannot be told that a fund is recommended for them because it has a high score in the recommendation system. Such a response may reduce customers' confidence in the seller's perception. Hence, the manager of customer relationship should target to give precise recommendations along with personalized explanations. Everyone should be able to receive customized recommendations based on their distinct traits and behavioral history as well as customized explanations for the recommendations.

We will use Deep neural embedding techniques and the traits of the knowledge graph leveraged in the model to obtain a high recommendation accuracy and appropriate explanations. To obtain multi condition explanations, the training process of the model will be modified and a calculation method will be added for the uniqueness of the explanations, which means that the explanation model should tend to provide those explanations that are less frequently generated. This mechanism will show our belief that the less frequently the explanation generates, the more confidence that the explanation is persuasive. In general, the developed model will comprise of two processes: utilizing the deep neural embedding of the knowledge graph and producing the reasons and other uses of related recommendations. In the deep neural embedding process, features of customers and funds will be extracted. Moreover, the knowledge graph enables the model to learn structural details. These vectors will be trained to match the implicit feedback from the user, the knowledge graph can be used to determine the missing relations between entities. Consequently, the system can determine the appropriate funds to be recommended.

UI:

We aim to create an interface where users will be able to get personalized investment (mutual funds) recommendations on the basis of their constraints. We will require financial capital, risk capacity etc. as input from the user. We aim to provide a generated explanation to the user to back our recommendation. Thus the user will be confident that the recommendation is not just a result of any biased model.

### 3.4 Algorithm

Building Knowledge Graph:

Let us denote the knowledge base as G = {E, R}, where E = {e1, ..., e|E|} is the set of all entities and R = {r1, ...,r|R|} is the set of relations between these. The, we can construct $S \subseteq E \times R \times t$ as a set of triplets. S = {h,r, t}, which shows that the head entity h has a relation r with the tail entity t. Consider, S = {Joe, bought, Book 1} indicates that the entity Book 1 was bought by head entity Joe. We can complete the graph by knowledge graph embedding. Knowledge graph completion has two main goals: (1) to predict the relationship between a given head entity and tail entity {h, unknown, t} and (2) to predict the tail entities most likely to have a relation with a given head entity {h,r, unknown} .We will use a series of translation-based methods. All the entities and relations will be projected to a low-dimensional latent space. Let $V \in Rd$, $Vt \in Rd$, and $Vr \in Rd$denote the latent vectors of the head entity, tail entity, and relation, respectively. Translation-based methods view the relation as a translation function to translate the head entity to the corresponding tail entity, as trans( Vh ,Vr ) = Vt .

All entities and relations should be projected to a unified latent space because our aim is to utilize heterogeneous information for different types of relations to explain our recommendations. Therefore, we will adopt a modified version, which gives us the following probability estimation:

$$\mathbf{P}( V_t \,|\, \mathbf{trans}\,(V_h , V_r)) \quad \frac{e^{(Vh + Vr).\,Vt}}{\Sigma_{\,Vt \in Vt}\; e^{(Vh\,,\,Vr).Vt}} \tag{1}$$

where trans( $V_h$ ,$V_r$ ).$V_t$ denotes the dot product of ( $V_h$ + $V_r$ ) and $V_t$. Because computing $\Sigma_{Vt \in Vt}\ e^{(Vh,Vr).Vt}$ is infeasible, we can change our target into a ranking problem such that we would like the probability of V with relation exists with trans( $V_h$ ,$V_r$ ) greater than other $V_t'$ . So that we can ignore the denominator shared and focus on improving the value of:

$$\mathbf{P}( V_h ,V_r ,V_t ) = \mathbf{trans}( V_h ,r).V_t \tag{2}$$

We can then define the loss function as negative log-likelihood as follows:

$$\mathbf{L(S)= -\ \Sigma_{(Vh,Vr,Vt) \in S} \log \sigma\,(trans( V_h ,V_r).V_t ) + (V_h ,V_r ,V_t )\ S\ \ log(trans( V_h ,V_r).V_t' )} \tag{3}$$

where σ denotes the *sigmoid* function, which can convert the value to probabilities that fall in the range (0,1). We will be considering 8 types of entities and 10 types of relations. The 8 entities are:

1. User: A user is one who purchases or interacts with funds through the recommender system.
2. Fund: A fund refers to a mutual fund that a user purchases and is the item to be recommended in the recommender system.
3. Income Range: The income range is the range that the user's income falls into. Four income ranges exist.
4. Occupation: Occupation refers to the user's occupation.
5. Product: A product refers to the product that the user trades with.
6. Market type: The market type refers to the type of market that the mutual fund is invested in.
7. Risk type: It refers to the level of risk in a mutual fund.
8. Top5 funds: It refers to the funds with the top 5 selling volumes during the previous month.

The 10 types of relations can be divided into three categories:

Relations between the user and the fund, relations related to the user, and relations related to the fund.

These relations are:

1. Purchase: The user purchases the fund during the current month.
2. Redeem: The user may redeem the mutual fund units or shares during the month.

3. Purchase last month: The user purchases the fund during the last month.

4. Purchase the month before last: The user purchases the fund during the month before the last month.

5. Income range as: This relation between the user and income range describes the user's income range.

6. Work as: This relation between the user and occupation denotes the occupation of the user.

7. Trade with last time: This relation between the user and product denotes the product that the user traded with the previous time.

8. Belongs to which market: This relation between the fund and market type describes the market type of the fund.

9. Belongs to which risk type: This relation describes the risk type that the fund belongs to.

10. Belongs to Top5 funds or not: This relation indicates whether a fund belongs to the Top5 best-selling funds.

Thus we can have triplets such as (Joe, purchased last month, Fund A) that can help learn knowledge graph embeddings of each entity and relation.

**Building recommendations with deep neural knowledge graph embeddings:**

After constructing the knowledge base S according to the entities and relations described in the previous section, we move on to training and building our model.

The knowledge graph is not fixed in our system. We regard the user and fund entities for every month as different nodes. Several entities exist in our knowledge graph because we can add numerous statuses of users and funds to the graph. Each entity and relation is represented as an embedded vector to construct the knowledge graph. This relation is the linear translation from the head to the tail entity. Our goal is to make the embedded entities and relations approximate Eq. 2 as much as possible for the triplets that exist in S = {h,r, t} , and to minimize them otherwise. Considering the deep neural network embedding layers, the computation procedure should consider the features of the user and fund entities as initialization vectors. To integrate the knowledge graph into a recommendation system, we will first, train the knowledge graph to embed each entity in the latent vector. Next, the latent vector will be used as the input of the recommender system. This strategy is called *one-by-one learning*. We will regard the recommender system as a part of the knowledge graph, which indicates the purchase relation. Also, we will use the deep learning-based knowledge graph construction learning rather than simply adding latent vectors to fit the optimization function, which can adopt the situation of the dataset that the numbers of triples connected by each relation varies greatly.

Our recommender model's goal is to find the missing connections between the target user and fund candidates. In our proposed system, we use a neural network defined as F(·) with parameters Θ to do the task.

For recommendations, the aim is to obtain explicit and implicit feedback from the target user. Explicit feedback includes rating predictions, which correctly reflect the preferences of the items that users interact with. With regard to implicit feedback, we only know whether interactions exist between users and items. Existing interactions are regarded as positive feedback, whereas others are regarded as negative feedback. Such feedback is implicit because positive feedback does not indicate that users like the items. Moreover, the absence of interaction between users and items does not indicate that the users do not like the items; rather, these could be disliked or potentially preferred items. The feedback R can be expressed as follows:

$$R_{u,i}\begin{cases}1, & \text{Interactions exist between user } u \text{ and item } i\\ 0, & \text{Otherwise}\end{cases} \tag{4}$$

In the proposed method, implicit feedback is considered because we only know whether the user purchases the funds. After the feedback is converted into knowledge base form, it can be represented as a probability of $\{V_h,V_r,V_t\}$ as follows:

$$P(\{Vuser, Vpurchase, Vfund\}\ S) \tag{5}$$

$$=\begin{cases}1, & \text{If } \quad \text{user} \quad u \text{ purchase fund } i\\ 0, & \text{Otherwise}\end{cases}$$

The negative sampling method will be used to minimize the loss defined in Eq. 3 for training our knowledge graph. Our graph is extended whenever a new entity enters it. Listing every possible link between entities is unfeasible. This process is not only exhausting but also defeats the purpose of knowledge graph completion. Therefore, negative sampling will be performed on the dynamic triplets. Consider the example of purchase-related triplets. For each transaction, the tail entity of the observed triplet {user u, purchase, fund i}, which represents the type of funds, is replaced with other funds that are not purchased by the user. The new triplet is denoted as {user u, purchase, fund i'}. By repeating the aforementioned procedure k times, k negative samples will be obtained for each positive sample. The selection of k in the experiment is discussed in the following section. Although increased sampling may improve the accuracy of the model, the corresponding training cost would also increase sharply. The entire training procedure of the developed model is presented in Algorithm 1. After the model is well trained, we can determine the funds recommended by the model. The procedure of obtaining the recommended funds is presented in Algorithm 2. First, the target user's features are fed into the model and the embedding of the purchase relation is obtained. Next, to acquire the embeddings of all the candidate funds, the funds' features are fed into the trained deep neural network. The Eq. 2 values are obtained for different funds, which are then ranked according to the obtained values.

After the recommended funds are determined, the knowledge graph is used to generate explanations for pairs of arbitrary users and funds. We regard the process of generating an explanation as finding the latent explanation path in the latent space. Our recommendation approach involves finding the fund entities that may have purchase relations with the user entity. To obtain explanations, we attempt to find other latent relations between the user entity and the fund entities, which may be linked to other entities. It may be a sequence that passes through several intermediate entities and relations. The concept of an explanation path is displayed in We search for all the entities that the head and tail entities can reach, irrespective of whether explicit relations exist between them. The procedure is repeated until all possible paths have been identified, after which we compute the strength of each path by using Eq. 1. We start with both sides of the user and fund, regard them as head entities, sum up all the relations from the head entities to the intermediate entity along the path, regarding the intermediate entity as the tail entity, and multiply the two products computed using Eq. 1. In a general form, the score can be computed as follows:

$$P(V_m|V_{user}, V_{R_{from\ user}}, V_{R_{from\ fund}}, V_{fund})$$

$$= \ P(V_m|trans(V_{user}, V_{R_{from\ user}}))$$

$$X\ P(V_m|trans(\ V_{fund}, V_{R_{from\ fund}}))$$

$$= P(V_m|trans\left(V_{user}, \sum_{r\in user\to m} V_r\right)$$

$$P(V_m|trans(V_{fund}, \sum_{r\in fund\to m} V_r) \qquad (6)$$

where *m* indicates the middle entity, Vm denotes the vector of the intermediate entity, and Rfrom entity x represents the sum of the relations along *entity x* to the intermediate entity. After all the possible explanation paths are computed, the one with the highest value is adopted to obtain explanations. The entire computation procedure of constructing explanations is presented in Algorithm 3.

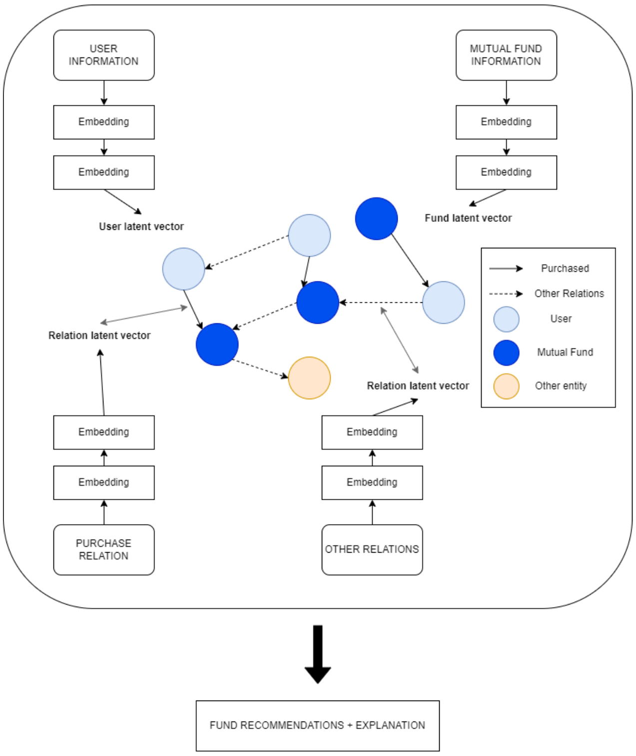


**Fig -1:** Flow of proposed algorithm

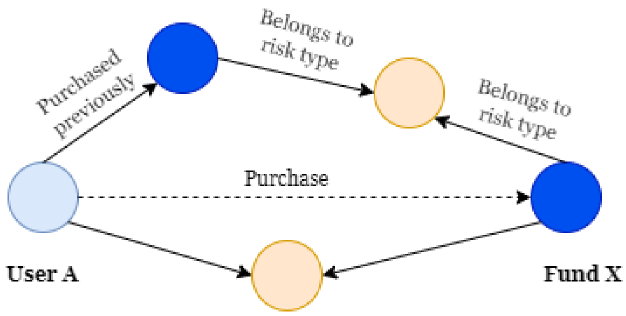


**Fig -2:** Explanation of composition

## 4. CONCLUSION

After carefully considering and reviewing several relevant papers, we have provided relative analysis of various machine learning model approaches for mutual fund recommendation systems. We have thus identified issues faced in the current Mutual Fund recommendation domain. To provide an efficient solution, we have proposed a Knowledge Graph based recommendation model combined with Deep Learning embeddings to provide personalized recommendations. The developed model will comprise of two processes: utilizing the deep neural embedding of the knowledge graph and generating the explanations and other applications of related recommendations. In the deep neural embedding process, features of customers and funds will be extracted. Moreover, the knowledge graph enables the model to learn structural details. Consequently, the system will be able to recommend most appropriate funds as per the needs of the user along with a valid explanation to back the recommendation claim. Further, personalized recommendation will be influenced by investment propensity of the customer.

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