A survey on recommendation systems for financial services

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Abstract

Recently, there is difficulty in extracting useful information from huge online information due to the rapid growth of the internet. Therefore, the Recommendation system (RS) is needed for the improvement of many services such as entertainment, e-commerce, healthcare, and financial services. It is an effective tool in the service industry, as it is used for guiding users to an interesting thing from the large space of random things. A recommendation system can discover patterns in input movements and generating system recommendations based on the patterns, thus it can significantly supplement the decision-making process of a stock trader. So, there are many methods for the recommendation process such as collaborative filtering, content-based and hybrid recommendations. Recommendation algorithm can be selected based on the existing research problem. This paper presents a review of the recommendation system, its types, and its applications. Then, this paper concentrated on the finance recommendation system, its operation, and its different finance sectors.

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1 Introduction

A recommender system is a tool to supervise the user to a useful item based on his preference. It is a subclass from data filtering systems [33]. It is software that enables the user to achieve the best items for use [57]. It plays a key role in information filtering and achieving a useful one. The main goal of the recommendation system is user satisfaction. As it is based on guiding the user to the best choice from multiple choices. Its operation is based on extracting the best item from multiple items based on the user profile. It compares the user profile to extract his rating. It can be defined as direct output based on the user input (preference). Nowadays, a recommendation system is extremely applied in many fields to enhance their performance. Many fields such as books, research articles, products in e-commerce, movies, healthcare information, etc. need the recommender system to supervise the user to a useful item based on the user view. The recommendation system can do many tasks to enhance the performance of these services. Firstly, finding some good items or all good items required by the user. Secondly, it can recommend a sequence or a bundle to provide a user with a searched item and other interesting items related to the same research area that may be useful for the user just browsing to guide the user to browse in the area that can be useful for his work. In addition, RS can improve the user profile by accepting his likes and dislikes then extracts his preferences and reply based on them. The recommendation system passes into these phases: extract preferences and dislikes of the user, compare these preferences with those of another user to discover the similarity between users, and recommend items based on these similarities. The block diagram of the recommendation system is illustrated in Fig. 1.

In recent years, recommendation system development becomes an attractive point for the research area as it can be used for system automation. Figure 2 presents the process of recommendation process. Many researchers turn to develop recommendation systems in their research. There is a need to present a useful survey that helps the researchers and users to learn about a recommendation system, its basics, its types, its importance, and finally the recent work in recommendation system development. With the rapid growth of the Internet and E-commerce, information overloading has become a big problem that makes it hard to extract useful information for users [2018]. There are some recommendation systems are developed to solve this problem and facilitate extracting user information such as [52–54]. firstly, [52] addressed sparse data and extract useful information from user's data. Secondly, [53] proposed
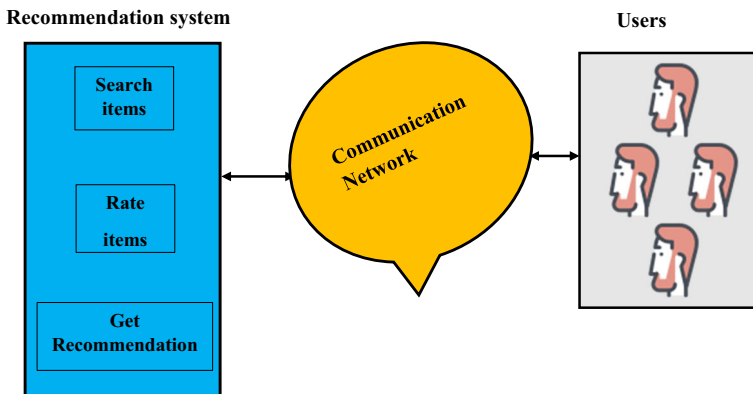

Fig. 1 Communication between users and the recommendation system

a novel correlative denoising autoencoder (CoDAE) method to improve social-aware recommendation performance by taking correlations between users with multiple roles into account. CoDAE can extract robust data from social media content. Finally, [54] developed an improved deep autoencoder model, named Sparse Stacked Denoising Autoencoder (SSDAE) to address the data-sparse and imbalance problems for social networks.

In conclusion, this paper introduces an efficient outline of the recommendation system, its components, its categories, and its application areas. Then we will introduce a simple overview of the finance recommendation system and its different finance sectors:

- Present a systemic review of the recommendation system, its taxonomy, its structure, and its application areas.
- Support an efficient comparison between various categories of recommendation systems.
- Present a systemic review of the finance recommendation system, its finance sectors
- Introduce a systemic review of some recent proposals on the recommendation system based on its taxonomy
- Present a systemic review of some recent proposals on the finance recommendation system based on its finance sectors.

The rest of this paper is organized as follows: Section 2 presents the background and preliminary knowledge regarding the recommendation system. Section 3 introduces the applications of the recommendation system in different domains, especially in the finance domain. Section 4 describes the related work on the recommendation system and finance recommendation system. Whereas section 5 introduces a discussion about the recommendation system and its taxonomy. Finally, Section 6 present the conclusion and future scope of this paper.
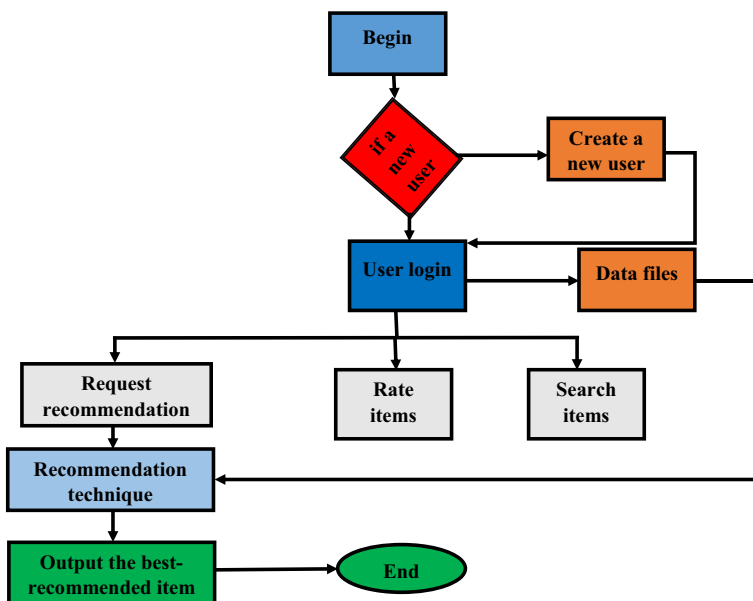

Fig. 2 Recommendation Process

2 Preliminary knowledge

The classification of the recommendation system based on its information filtering process is shown in Fig. 3.

2.1 Collaborative filtering

- *Principles*: Collaborative filtering is based on information filtering using methods based on participation between the agents, data sources, and opinions [2, 32, 36]. It can be used in web-based services, marketing, and automatic prediction as it collects information from the user and outputs its preferences based on these data [78]. Therefore, this filtering type can be used in a collection of similar users in the same groups based on their similar preferences. CF assumes that if two people have the same viewpoint on one subject then they have the same opinion in another subject. Figure 4 describes the operation of CF. There are some proposals based on CF recommender such as [2, 36, 28, 74, 77].
- *Discussion*: CF is a successful filtering type, and it is widely used in many applications [2]. Its main advantage is that it does not depend on machine analyzable content and therefore it is capable of accurately recommending complex items such as movies without requiring an "understanding" of the item itself. But it suffers from three problems such as:
- First, the first-rare problem is known as the Cold start. As Cold start is categorized into User Cold start and Item Cold start.
- **User Cold start:** For a new user there is not enough data to make recommendations accurately.
- **Item Cold start:** For a novel item there is not enough data to make recommendations accurately.
- Second, scalability: In many systems that make recommendations, there are millions of users and products. Thus, it is necessary to calculate recommendations from getting a large amount of calculation power.
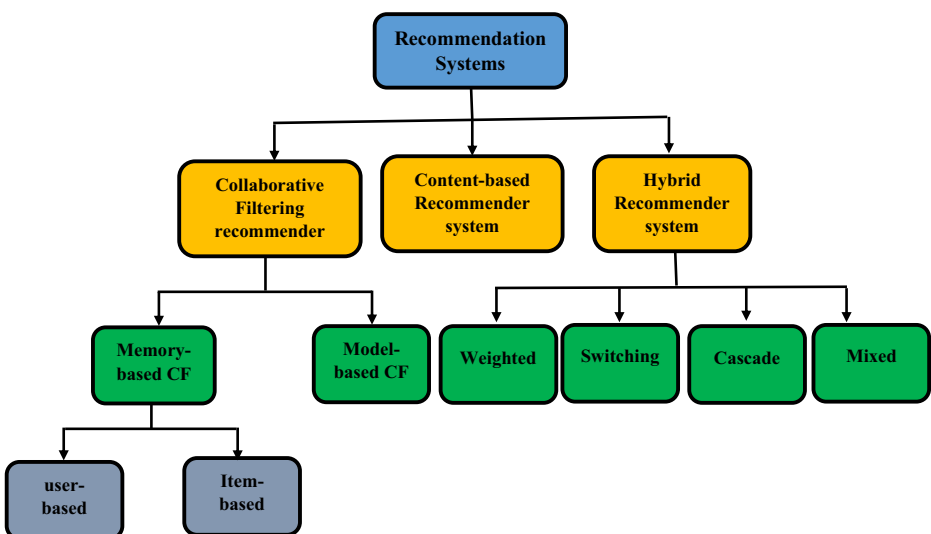

Fig. 3 Taxonomy of Recommendation System

- Third, the sparsity: The number of items sold on major e-commerce sites is extremely large. The most active users will only have rated a small subset of the overall database. Thus, even the most popular items have very few ratings.

There are two taxonomies of CF such as Memory-Based CF and Model-Based CF as the following:

- *Memory-Based* CF
- ***Principles***: It is the earlier algorithm, and it is widely used in commercial applications [2, 36]. This type of CF is based on processing user data to output similarities between the users or the items. Some applications apply memory-based CF such as Neighbor-based CF. also, some proposals are based on the improvement of memory-based CF such as [2, 36, 78].
- ***Discussion***: There are some advantages of memory-based CF such as easily adding new data, it is easy in its implementation, it does not consider the content of the item. But it has some disadvantages such as its performance decrease with scattered data, it depends on user input, recommend only for existing users/items, and it is not scalable with a large dataset.

There are two subclasses from the memory-based class that are user-based and item-based.

a) ***User-Based***: In this technique, the recommendation is based on the similarity between the users [52]. Some proposals are based on user-based CF such as [7, 53, 74].

b) ***Item-based***: This technique generates recommendations according to the similarity between the items to find the relationship with the items that have been rated by the user previously [52]. Some proposals are based on item-based CF such as [28, 53, 70].

- *Model-Based* CF

- ***Principles: Model***-based CF is based on data mining and training. It uses machine learning mechanisms to train user data to find patterns [33]. It is a pre-built filtering mechanism used to predict the user likes [2]. There are many model-based fields including Bayesian networks, clustering models, latent semantic models that are proposed in [2, 17, 47]
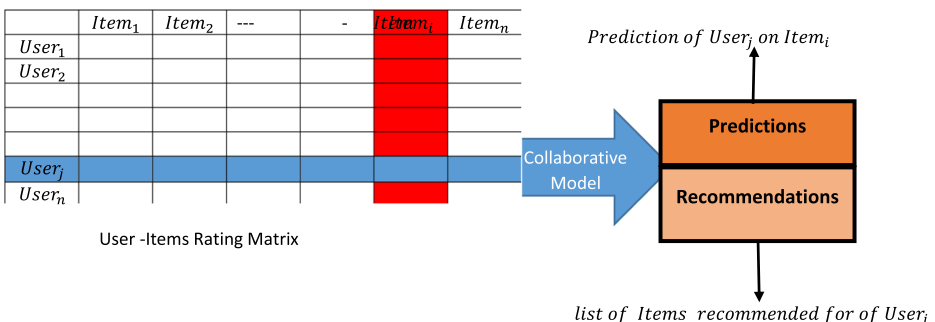

Fig. 4 Operation of Collaborative Filtering Recommendation System

- **Discussion:** There are some advantages of model-based CF such as its ability in working with sparse data than memory-based CF, it provides more scalability with a large database. But there are some disadvantages such it is costly, has a gap between prediction and scalability [33], and loss of some useful information in the dimensionality reduction process [33].

2.2 Content-based recommender system

- **Principles:** This taxonomy is based on a profile of the user's preference and item description. As it selects items for the user that likes the items that the user preferred in the past [64]. It makes training between the current item and the items that the user previously preferred to recommend the best one for the user , [33, 41, 46, 64]. It calculates the similarity between items based on the features related to the compared ones [57]. This technique built its user profile based on the weighted vector of item characteristics [33]. The weights provide the importance of each characteristic to the user [33]. The operation of Content-based is shown in Fig. 5. Some proposals are built on this taxonomy such as [46, 64].
- **Discussion**: it has some advantages such as it is user-independent, transparency, and the ability to work with a novel item. But it has some disadvantages such as it suffers from a serendipity problem, as it has limited novelty recommendations. But it has a serendipity problem when the user faces the recommended items. In the normal case, the recommended items should be familiar for the user as he/she likes the old, preferred items. But, in some cases, the recommended items are spectacular for the user.

2.3 Hybrid recommender system

- **Principles:** This catalog combines two or more filtering algorithms to solve their limitation such as the combination of collaborative filtering with content-based filtering [15, 46, 47]. The idea of hybrid recommendation is the combination of two algorithms can solve the weakness and problems of these individual algorithms [47]. The block diagram of hybrid recommendation is shown in Fig. 6. Some proposals are based on hybrid recommender such as in [29, 30, 58].
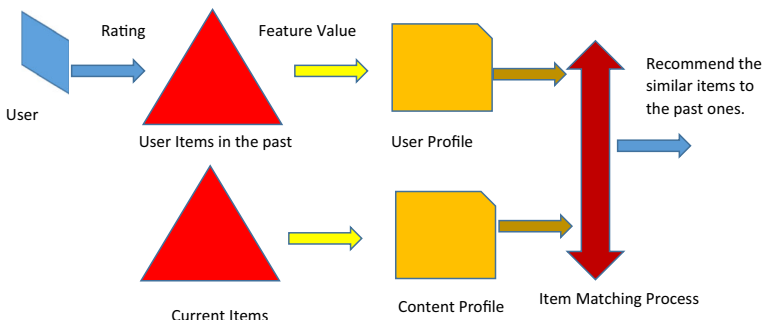

Fig. 5 Operation of Content-based Recommendation System

- **Discussion**: Building hybrid systems supplies a more correct and effective recommendation than a single algorithm besides overcoming the disadvantages of these individual algorithms [47]. A hybrid system is an improvement of pure recommendation systems. There are four subclasses from the hybrid recommendation system described in this paper such as weighted, switching, mixed, and cascade hybrid recommendation.

2.3.1 Weighted hybridization

- **Principles**: It combines the scores of the recommended item based on the results available on the recommendation techniques involved in the system [59]. It uses the results of the individual recommendation techniques to provide a recommendation list by working with the scores them [76]. An example of this hybridization way is the P-Tango system, which combines collaborative and content-based recommender with equal weights in the first stage. But it adjusts their score based on the user rating [59, 76]. Proposals in [18, 22, 37] are based on weighted hybridization.
- **Discussion:** The advantage of this hybridization way is that all strengths of all recommender systems are applied in the recommendation process.

2.3.2 Switching hybridization

- **Principles:** In this algorithm, the recommendation system switches between the recommendation algorithms until reaching the best confidence [13]. First, it trains the first algorithm, if this training cannot produce high confidence, then it repeats the training by applying the second one [13]. The switching between recommendation algorithms is based on some constraints [61]. There is some proposal based on this taxonomy such as [5, 23].
- **Discussion:** The main advantage of this taxonomy is that it provides the measurement of the weakness and strength of the individual recommenders. But it is a disadvantage that is represented in its complexity for the recommendation process.
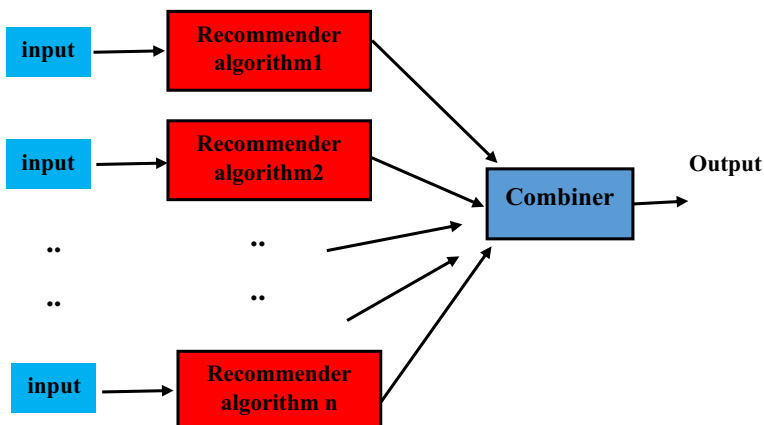

Fig. 6 Hybrid Recommendation System Process

2.3.3 Cascade hybridization

- ***Principles:*** It presents as a staged recommendation process. In the first stage, a recommendation technique is used to extract the user and item ranking [18]. This taxonomy arranges the recommendation techniques into buckets with equal preferences. Some proposals are based on this taxonomy such as [34, 71].
- ***Discussion:*** The main advantage of cascade hybrid recommender is that it avoids working the lower priority(second) technique on the item that well-recommended by the first one. Also, it is efficient taxonomy as the second recommendation technique is worked only on the items that need added description.

2.3.4 Mixed hybridization

- ***Principles:*** Mixed hybridization presents many different recommenders [18]. In this taxonomy, two techniques are employed on different data. As, where one technique is applied to measure the data, another one can work on other data separately. Finally, the results of these two techniques are mixed to offer their outcome [18]. Some proposals are based on this taxonomy such as [27, 48, 80, 84].
- ***Discussion:*** There are some advantages of this taxonomy such as elimination of start-up problem that appears with a new user or novel item. Also, the second advantage is the appearance of the niche-finding property with a novel item.

In this paper, we introduce the discussion of recommendation system applications in various fields, especially in finance. Several efficient papers are cited in our work from different publishers such as springer, Elsevier, Public Library of Science (PLOS), etc. Figure 7 describes the statistics of the cited papers in our work.
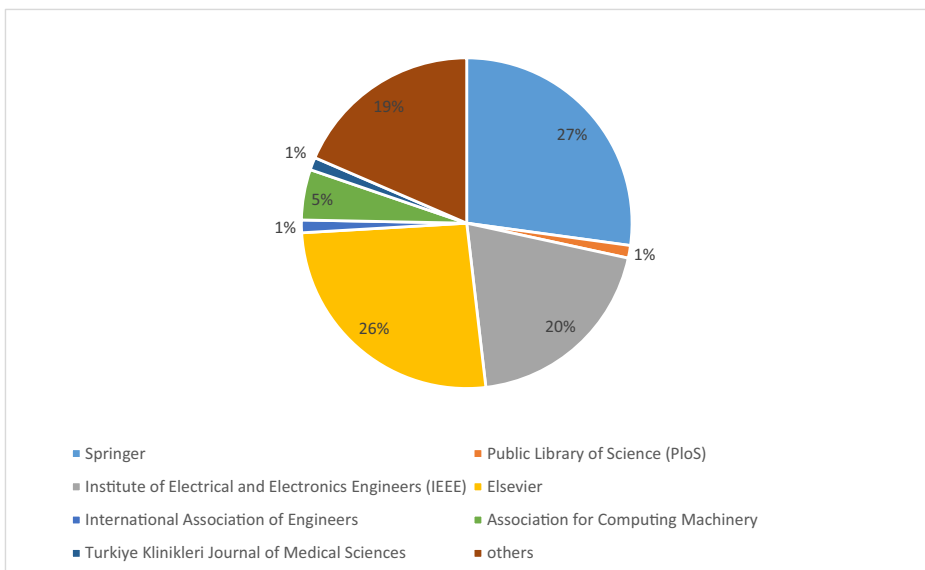

Fig. 7 Statistics of the cited publishers

3 Applications of recommendation system

Recently, the recommendation process represented high importance in most applications such as E-commerce, research, healthcare, bookstore, and finance. The taxonomy of recommendation system applications is shown in Fig. 8.

A. *Recommendation system in the E-Commerce field:* This field needs the recommendation system to select the best item for the user [33]. With the rapid growth of the internet, many products can be offered online for the shopping process. Consequently, there is a need for a recommender system to guide the user to the best one based on user preferences. This system saves time for the user instead of searching the whole product until obtaining the required one [33, 57]. So, recommendation system in e-commerce provides more useful ways for shopping, auction, and product comparison process easily [14, 26, 43, 57, 72].

B. *Recommendation system in the Research field:* The recommender system works useful in the research area than classical information techniques [57]. It plays a significant role in many effective internet sites such as Amazon, YouTube, Yahoo, etc. [57]. This property enables the recommender system in the research area from opening many points for the researcher. Also, it enables the researcher from moving beyond a catalog of important research related to his research point [20, 50, 62].

C. *Recommendation system in the Healthcare field:* The Healthcare recommendation system plays a significant role in improving the health care area. It enables the doctor and patient from working together to supply more care for the patient [60]. It supplies a more convenient service for the patient in the healthcare domain [81]. Many healthcare recommender systems work in supplying more participation between doctors and patients based on patient preferences and similarities between the doctor and patient [81]. It results in a more-centric patient diagnosis and the best way for his treatment [42]. As healthcare data suffers from sparsity and noise, there is a need for a healthcare recommender system to solve this problem [4]. The Healthcare recommender system converts healthcare unstructured data into a structured one [4]. In healthcare, the recommendation system plays a role in decision – making process and it helps in improving the infrastructure effectiveness [31].

D. *Recommendation system in the Book-Store field:* In this area, the recommendation system helps the user to find the best book by offering a list of important books to the user and
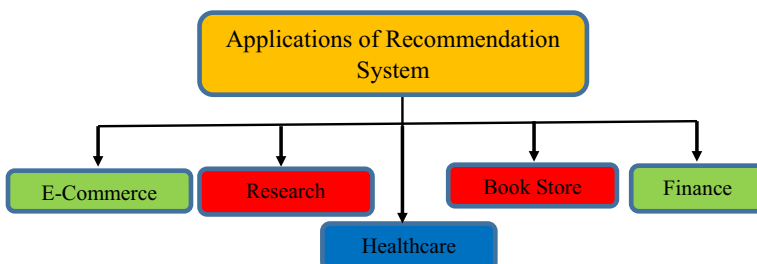

Fig. 8 Taxonomy of recommendation system applications

enables the user from selecting the best one [57]. Also, recommendation enables the user from achieving the more centric point in the book [21, 57].

E. *Recommendation system in the Finance Sector:* Recommender Systems are information filtering and decision supporting systems that introduce items in which the user is likely to be interested in a particular context. In the finance domain, we consider users the active entities that perform interactions (e.g., viewing, Selling, buying, rating, etc.) in the system. In recommender, items are the objects with which the user can interact (e.g., products, stock markets, songs, etc.) [25, 73]. Metadata can be used to describe both users and items (e.g., age, gender for users; genre, the price for items). Recommender systems can apply several data mining algorithms such as popularity-based methods, collaborative and content-based filtering, hybrid techniques, knowledge-based methods, or case-based reasoning depending on the characteristics of the domain, the quality of available data, and the business goals. Recommendation services offer services that help the investor from taking the best decision about dealing with the market, product, loan, etc. [25, 83]. There are many finance sectors in which recommendation principles can be applied such as banking, stock, and insurance. The classification of the recommendation system in different finance sectors is shown in Fig. 9.

F. *Banking-finance sector:* banks are now implementing comprehensive digital transformations to meet evolving needs and supply faster and better customer experiences for digital services. In banking, the recommendation helps the Bank manager from taking the correct or near correct decision about the loan process [49, 68]. At this point, the recommender helps in Determining whether the user deserves the loan or not based on the analysis of user data. For example, if the customer class is young (ex. Age < 15 years), the loan application may be rejected. Else if this customer is of average age, the loan application can be rejected.

• *Stock Market Finance Sector:* In the Stock market area, the recommendation helps the investor from taking the correct or near correct decision about the stock trading process. At this point, the recommender helps in Determining the extent to which the investor benefits from the stock [25]. From the stock price prediction process, the future close price of the stock can be predicted as well as its future trend. From the analysis of investor data and stock predictions, the recommendation system can help the investor in making the right decision in dealing with the stock. For example, if the stock that an investor owns has a positive future trend, the investor is recommended for holding this stock as its price will be upgraded. For this stock, the system recommends the investor to buy it. For the stock with a constant close price, the system recommends the investor to hold it. So, the finance
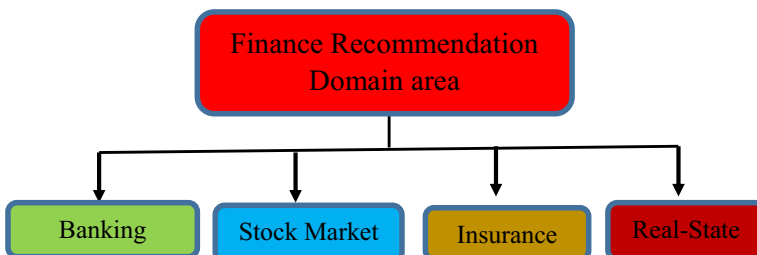

Fig. 9 Taxonomy of Finance Recommendation Systems

recommendation system plays an effective role in the stock market trading process. The recommendation system helps the investor from improving his profit and saving his money from the loss [67, 82].

- *Insurance:* In the insurance area, an insurance policy is a contract between the insurer and the insured (policyholder) [83]. For a first payment, the insurer takes the obligation to pay a payment for the insured if the loss is caused by perils under the terms of the policy. As standard policies have little room for customization, insurance riders are introduced to increase benefits that are bought separately from the basic policy. Both insurance policy and insurance rider can be the object of a personalized recommendation problem [83]. Some proposals are based on insurance recommender systems such as [6, 16].

- *Real estate:* Real estate is a property consisting of the land, its natural resources, and the buildings on it. The purchase of real estate is a rare and expensive transaction, which may be undertaken for investment or personal residence [79, 83]. Therefore, buyers pay special attention to finding the proper choice considering several various preferences, which leads to some decision-making problems. From this point, a recommendation system can help the buyers from taking the right decision about the real estate buying process. There is some proposal that is based on real estate RS such as [56].

4 State of the art

A recommender system is defined as a decision-making strategy for users under complex information environments. RS is an intelligent system that supports users with information useful to them. It plays an effective role in the past two decades in supplying better recommendations to the users. This section surveys the (1) recent research on CF-based recommender systems and (2) recent research on Content-based recommender systems and (3) recent research on Hybrid recommender systems and (4) recent research on finance recommender systems.

- **CF RS:** In 2020, [3] the authors proposed a genetic-based collaborative filtering recommender system (BLIGA) based on semantic information and historical rating data. Through standard evaluation metrics. Also, in [8] the authors proposed an incorporation-based recommendation method, to solve the sparsity problem of SVD-based strategies. In the initial step, similar users and items are collected. Then, data is generated according to co-rated values. Besides, [54] the authors proposed a deep autoencoder model to learn social representations for a recommendation. Where deep representations and matrix factorization models are incorporated into a uniform framework for the recommender system. In addition to, the authors proposed an efficient privacy-preserving collaborative filtering recommendation model [75]. Finally, [53] the authors proposed a novel correlative denoising autoencoder method to extract robust representations from sparse inputs of ratings and social networks for the recommendation.

In 2019, in [52] the authors proposed Enhanced Collaborative Autoencoder to extract robust information from generated soft data. In 2018, the authors of [40] presented a new bio-inspired clustering ensemble model through aggregating swarm intelligence and fuzzy clustering models for user-based collaborative filtering. The proposed recommendation models have

been evaluated on the real-world large-scale datasets of Yelp and TripAdvisor for recommendation accuracy and stability.

- **Content-Based RS:** In 2020, [55] the authors proposed a health recommender system to help patients in decision-making to recommend better health advice depending on the analysis of profile health records and patient database. In addition to [44], the authors proposed a recommendation system that will help future students in choosing the most suitable private universities for getting admission. In 2019, [11] the authors proposed a recommendation technique that considers the variable and complex semantics of multi-valued properties and the level of uncertainty or fuzziness inherent in the representations of users and items for the e-commerce domain.

- **Hybrid Recommendation System:** In 2020, [9] the authors proposed a hybrid recommender model for Chemical Compounds recommendation process. In addition to [51] where the authors proposed a hybrid recommender system that combines the item-based collaborative filtering technique with the demographic-based approach to implicitly infer customer preferences from transaction data in the banking area. Finally, [59] the authors proposed a hybrid recommender model called Deep Semantic-based Topic Driven Hybrid RS that employs item description semantics affected by its topics information. The proposed model captures the semantics of textual information and incorporates topic details into it to extract the embedding. Then, it integrates these embeddings into Probabilistic Matrix Factorization (PMF).

- **Finance RS:** In the finance domain, there are many finance sectors where recommendation systems are involved such as:

- *Banking RS:* In 2020, [12] the authors presented a study that measures the systemic risk contributions of Turkish banks and finds the systemically important banks of Turkey during the period from 2005 to 2016. Also, [45] the authors proposed a reverse stress test method based on a stochastic simulation optimization system that enables users to derive the critical combination of risk factors. In addition to [49] where a hybrid financial product recommendation method is proposed for private banking when recommending banking products. Finally, in [38], the authors proposed the RS model that merges the advantages of a transformer in the processing time series, an R-Transformer (Recommendation system based on transformer) network. In 2019, [63] a hybrid method based on dimension reduction technique is introduced. This method can predict the missing values in data to offer +recommendation to customers.

- *Real-estate RS:* In 2020, [19] the authors presented an overview of real estate recommender then they implemented a fully functional recommendation system for property listings in Turkey. In 2019, [10] the authors introduced a hybrid filtering technique that is used for recommending real-estate consisting of collaborative and content-based filtering to recommend the smallest price and best facilities real estate to users. Also, [66] a real estate recommender system is developed for Zingat.com. which is a hybrid of collaborative and content filtering approaches.

- *Insurance RS:* In 2020, [35] a recommendation system is proposed for car insurance, to allow agents to perfect upselling performances, by selecting customers who are most likely to subscribe to an added cover. In 2019, [24], the authors implemented a random forest to recommend insurance products and compared them with ID3, C4.5, Nave-Bayes, and Nearest-neighbor.

- *Stock Market RS:* In 2020, [82] the authors proposed collaborative filtering RS and constructed a stock prediction algorithm. In 2019, [39] the authors proposed a prediction model based on a bidirectional cyclic neural network to recommend users with the right decision. Also, in [1] the authors proposed a Recommender System that computes the data, shadowing the manual work, and gives efficient recommendations to overcome stock accumulation. Their proposed RS creates space for new stock for sale to improve the business profit using the item collaborative filtering technique. In 2018, [65] a stock recommendation system is proposed based on concerning the correlation between the Guba-based sentiment of the retail investors and the stock market trends in China. The proposed method measures the investors' sentiment by exploiting the large volumes of emotional texts posted in Guba, which is an online social platform for individual investors to share news and opinions for their favorite stocks. In 2017, [69] a stock trading prediction and recommendation system are proposed in user-friendly form. The recommendation system can support the user with the decision about buying or selling the stocks in the next step. Information granulation is applied to transform raw time series into meaningful and interpretable granules, and the more effective non-uniform partitioning method for prediction is introduced.

It is perceived that several authors introduced much research on recommendation systems and finance recommendation systems. Most of the techniques develop recommendation models using either ML or DL techniques and some researchers develop prediction models based on sentiment analysis of social news. This paper introduced an overview of the recommendation system, its architecture, its classification, and its applications. Then, the finance recommendation system is discussed in this paper with its Some research on recommendation systems and finance recommendation systems are described in this paper.

5 Discussion and open points

In this paper, we discussed different recommendation techniques, their benefits, and their problems.

- First, the collaborative recommendation technique is based on user preferences and opinions on some points. It is widely used in many applications, but it suffers from the first-rare problem. Two taxonomies of collaborative recommendation are memory-based and model-based collaborative recommender. Memory-based is based on user data processing to find similarities between the users. It has some advantages, especially in easily adding a novel item, but it suffers from data sparsity. It is divided into two taxonomies (user-based and item-based). The model-based collaborative is based on the prediction of user preferences. It is a useful technique with sparsity data, but it is a costly technique.
- Secondly, a content-based recommendation system is based on a user profile that has his preferences and item description. It recommends the item based on its similarity with other items that are already recommended by the user. It is a useful technique when working with a novel item. But it has a serendipity problem when the user faces the recommended items. In the normal case, the recommended items should be familiar for the user as it likes the old, preferred items. But, in some cases, the recommended items are spectacular for the user, serendipity knows this problem.

- The third taxonomy of the recommendation system is a hybrid recommender that is based on the combination of two or more recommendation techniques together. Its main advantage is collecting advantages of the individual recommendation techniques and limiting their disadvantages. The classification of the hybrid recommendation system is weighted-hybrid, switching-hybrid, mixed-hybrid, and cascade-hybrid.
- First, a weighted hybrid is based on mixing the scores of the recommended item based on the result of individual recommendation techniques. Its main advantage is using all strengths of individual recommendation techniques in the resulting hybrid system.
- Second, switching-hybrid is based on switching between individual recommendation techniques until achieving the technique that produces the best confidence.
- Third, mixed hybrid is based on working two or more recommendation techniques together, each on separate data. It can end the start-up problem related to the addition of a novel item.
- Finally, cascade-hybrid is based on ordering recommendation techniques into a sequence with equal preferences. Its main advantage is applying the next technique only if it is necessary for the item that is not successfully recommended by the earlier one. Table 1 presents an efficient comparison between the recommendation categories and Table 2 presents an efficient comparison between the recommendation applications where Table 3 presents an efficient comparison between the finance recommendation categories.

Then, we introduced a simple overview of the finance recommendation system, as the recommendation process plays an effective role in different finance sectors.

- Firstly, banking uses the recommendation on its different processes that are based on decision making such as loan application.

Table 1 Comparison between the recommendation taxonomy

Recommendation _ algorithm	Basics	Taxonomy	Advantages	Drawbacks	2020 Research work
Collaborative Filtering	It is based on information filtering, agent participation, opinion, and data sources.	• Memory--based • Model-based	• does not depend on machine analyzable content.	• User Cold Start • Item Cold Start • Scalability • Sparsity	[53] [54] [56] [3] [8]
Content-based	It is based on a profile of the user's preference and item description, and items similarity.	None.	• user--independent • transparency • solve item cold start problem.	• serendipity problem • limited novelty recommendation	[40] [55]
Hybrid	Combination of two or more filtering algorithms	• Weighted • Switching • Mixed • Cascade	• More accurate • More effective • Used to enhance poor recommender.	• Complexity	[15] [11] [9]

Table 2 Applications of recommendation system

Application	Basics	Research work
E-Commerce	• select the best item for the user. • provides more useful ways for shopping, auction, and product comparison process.	[14, 26, 43, 72]
Research	• RS enables the recommender system in the research area from opening many points for the researcher. • it enables the researcher from moving beyond a catalog of important research related to his research point.	[20, 50, 62]
Healthcare	• RS plays a significant role in improving the health care area. • It enables the doctor and patient from working together to supply more care for the patient.	[4, 31, 42]
Bookstore	• RS helps the user to find the best book by offering a list of important books to the user and enables the user to select the best one. • it enables the user from achieving the more centric point in the book.	[21]
Finance	• Recommendation services offer services that help the investor from taking the best decision about dealing with the market, product, loan, etc	[25, 83]

- Secondly, the real estate selling decision-making process is based on the recommendation process in deciding on selling the right real estate with balancing factors such as price and location.
- Thirdly, in the insurance finance sector where the recommendation plays a key role for the insurer to increase his benefits from an insurance policy.
- Fourthly, the stock finance sector where the recommendation system can be used to recommend the investor with the right stock for buying, the right time to sell his stock. Finally, in this paper, we illustrate the importance of recommendation and finance recommendation systems, their importance in different applications in our life.

Every recommendation system is built per the requirements and needs of the application, and it has not one strict model for building. Consequently, the technology of model building varies from one application to another but, the whole model is included in the subject of the recommendation. So, future work can be an implementation of an efficient finance

Table 3 Classification of Finance recommendation systems

Finance field	Basics	Research work
Banking-finance	• The recommendation helps the Bank manager from taking the correct or near correct decision about the loan process.	[49, 68]
Stock Market	• RS helps the investor from taking the correct or near correct decision about the stock trading process. • It helps in Determining the extent to which the investor benefits from the stock.	[67, 82]
Insurance	• An insurance policy is a contract between the insurer and the insured. • RS is used for customization; insurance riders are introduced to increase benefits that are bought separately from the basic policy.	[6, 16]
Real estate	• The purchase of real estate is a rare and expensive transaction, which may be undertaken for investment or personal residence. • RS can help the buyers from taking the right decision about the real estate buying process.	[79] [56]

recommendation system for the stock process based on an analysis of stock historical data and news sentiment analysis.

6 Conclusion and future scope

This paper described the definition of the recommendation system and its importance in our life. Likewise, all types of recommendation systems have been described in this paper, and their advantages and problems. Additionally, this paper indicated some proposals that were based on building a new recommendation system or that improves an existing one. Then it described some applications of the recommendation system in our life and indicates practical examples of these applications. The finance recommendation system and its application in different finance sectors have been described in this paper. Finally, this work offers some suggestions for building a recommendation system. In the plan, there are several points regarding the recommendation system as follows:

- Provides the literature on the application of deep learning approaches in finance sectors.
- Develop a deep learning model for recommendation systems in financial services.
- Perform a systematic evaluation of model preprocessing, input data, and performance evaluation of using recommender system in finance and banking.

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