Recommender Systems meet Finance: A literature review

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Abstract. The present work overviews the application of recommender systems in various financial domains. The relevant literature is investigated based on two directions. First, a domain-based categorization is discussed focusing on those recommendation problems, where the existing literature is significant. Second, the application of various recommendation algorithms and data mining techniques is summarized. The purpose of this paper is providing a basis for further scientific research and product development in this field.

1 INTRODUCTION

Recommender Systems [63] are information filtering and decision supporting systems that present items in which the user is likely to be interested in a specific context. We consider *users* the active entities that perform *interactions* (e.g. viewing, purchasing, rating, etc.) in the system. We call *items* the objects with which the user can interact (e.g. products, movies, songs, etc.). The parameter setting that characterizes the environment (e.g. time, device, location) is defined as *context*; furthermore, we consider the actual preferences (e.g. filters, rules, item types) as *constraints* of the recommendations. Both users and items can be described by *metadata* (e.g. age, gender for users; genre, price for items). Recommender systems apply several data mining algorithms such as popularity-based methods, collaborative- [67] and content-based filtering [58], hybrid techniques [9], knowledge-based methods [79, 24] or case-based reasoning [74] depending on the characteristics of the domain, the quality of available data and the business goals.

Recommendation services offer several level of personalization, starting from manually defined "editorial picks" to complex context-aware hybrid solutions. Businesses often mix various types of carousels in the same page to cover diversified collection of recommendations. Although the majority of the recommender algorithms focuses on capturing user preferences, non-personalized techniques can also be considered as building blocks of a complex service (e.g. first carousel shows personalized recommendations, the second one contains the most popular items in the last week).

Recommender systems appeared in the mid-1990s, however, they are receiving significant attention since the Netflix Prize [3]. Nowadays, recommender systems are applied in a very broad scale of domains [48] such as movies (Netflix), books (Amazon) or music (Spotify). Generally speaking, recommender systems are useful in any domains, where a significant amount of choice exists in the system and users are interested in just a small portion of items.

Compared to the subjects of conventional recommender systems, financial products usually require a long-term significant financial commitment as their utility is not realized immediately depending on several external factors (like market returns, governmental regularizations, currency, etc.); furthermore, expert knowledge is necessary to judge which one is a good choice. In order to reduce the risk of such a choice, users tend to formulate stricter expectations to these products than to conventional e-commerce ones, thus applying a recommender system in financial domains is a challenging task. Users typically protect their personal data, which is especially true for financial services, causing privacy risk issues in recommender systems [61, 17] and requiring more complex alternative personalization methods. As privacy issues are significant in financial services, personal metadata and individual transactional data are often missing, which causes user cold-start problem for recommender systems.

From a business prospective, a common challenge that several financial institutions are facing is the lack of an intelligent decision support system [13]. As sales activities of financial products requires expert knowledge, recommender systems offer great benefits for financial services by either improving the efficiency of sales representatives or automatizing decision making process for the clients. Therefore, a significant demand is observed for these decision support systems.

In this literature review, we investigate the existing application of recommender system techniques focusing on the financial domains. First, we perform domain-based categorization, distinguishing the most developed fields; then we discuss the applications in less developed financial domains. Second, we summarize the most often applied recommender system methods and additional techniques that are indirectly used for recommendations.

2 DOMAIN-BASED REVIEW

In our terminology, a financial domain is a specific area of finance that can be properly identified, modeled and developed based on its specific properties. For example, we consider stocks and portfolios as two different domains in this context, because in the first case an individual stock should be recommended, but in the second one a composition of financial assets should be selected, which is a different recommendation scenario. Based on the work of Burke and Ramezani [10], a domain can be characterized by the following aspects: (1) *heterogeneity* that captures the diversity of items' properties in a domain, (2) *churn* that characterizes the level of novelty and expected lifespan of the items, (3) *interaction style* that describes how the users are able to express their preference, (4) *preference stability* that characterizes the degree of variation of user preferences over time, (5) *risk* that determines the expected tolerance of the users for false recommendations and (6) *scrutability* that refers to the demand for explanation of recommendations.

In the following subsections, we propose a categorization of scientific contribution in financial services considering these properties. First, we introduce the applications in online banking systems and

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we discuss two general-purpose multi-domain solutions. Second, we walk through on well-defined financial products such as loans, insurance policies and riders, real estate and stocks. Third, we introduce the standard portfolio selection problem and we discuss various techniques of personalized asset allocation. Finally, we collect other less studied domains.

2.1 Online banking and multi-domain solutions

By the rapid growth of information technology, the banking industry changed significantly in the last decade. With the spreading of online payment solutions in various devices, a massive online data flow appeared in bank systems centralizing data from multiple domains. Banks are forced to change technologies that is capable to handle big data and exploit business value from the massive information flow. Yahyapour [84] and Asosheh et al. [2] investigate the introduction of recommender systems into Iranian banking system using Technology Acceptance Model. Based on the results of their questionnaire, there is a significant willingness to introduce such a solution in banking systems, which primarily depends on perceived ease of use, usefulness and the bank's attitude.

In order to exploit the value of contextual information of transactional data, Gallego and Huecas [30] and Vico and Huecas [81] developed context-aware recommender prototypes. Based on credit card using history and geolocation data, they implemented a clustering-based method that provides personalized recommendation about money spending opportunities close to the user. They find high user satisfaction of using such a solution; however, they also consider the importance of privacy issues. Fano and Kurth [22] introduce a concept of interactive management tool that assists in personal resource (money) allocation. For the optimization of this objective, they propose an algorithm, which considers expenses, financial goals and time of attainment. Yu [86] introduces a prototype of online personal finance management tool, which is capable to provide insurance planning, asset allocation and investment recommendation. Overall, a number of works are published for banking sector; however, all of them seem to be non-production concept only.

Felfernig et al. [27, 26] present two general-purpose knowledge-based recommender systems with intelligent user interface, which can be flexibly applied on various financial products. The authors prefer knowledge-based algorithms over the conventional collaborative- and content-based filtering, because they can be applied more efficiently in multi-criteria-based financial decisions. For those cases, when no results can be shown for a multi-constraint setting, Felfernig and Stettinger [28] propose a constraint diagnosis and repairing technique.

Related to online banking and multi-domain solutions, the products are basically heterogeneous. The churn rate depends on the type of items accessed by these systems; however, we consider it low in banking environment. As these solutions offer interactive user interfaces, the interactions are explicit. We argue that the user preference is unstable, because it strongly depends on the actual goal of the user. These systems focus on money management and spending opportunities, thus we identify high risk and significant demand for explanation.

2.2 Loan

A *loan* is lending money from one entity (individual or organization) to another one with specified conditions. Under a loan product, we mean a debt with a promissory note specifying the amount of money borrowed, the interest rate and the dates of payment. In this domain, the recommendation problem is finding the right product of the loan company for the borrower, which both satisfies his financial needs and will be likely to be paid back by the borrower. Felfernig et al. [25] propose a real-time constraint-based recommender application that supports sales between the representatives and consumers focusing on loan recommendation problem.

Microfinance is a type of banking service that supports low-income individuals and groups, who would otherwise have no opportunity to borrow money. In the last couple of years, the peer-to-peer (P2P) lending became popular, in which individuals or groups have opportunity to invest money by lending to another parties using a P2P lending marketplace. In this context, the recommendation task is to find an appropriate pairing between the lenders and individuals who need loans. Choo et al. [15] propose a maximum-entropy-based recommendation method to solve this problem using the dataset of Kiva P2P lending marketplace. Lee et al. [43] also developed a solution for Kiva, using collaborative filtering techniques for finding a fair pairing of microfinance. Significant work is published by Guo et al. [37], who formulate an instance-based credit risk assessment model for evaluating risk and return of each individual loan. San Miguel et al. [66] introduce a P2P loan recommendation method via social network. They design a data framework architecture, which is capable to integrate both public and private data dealing with privacy issues. Bhaskar and Subramanian [7] introduce an adaptive recommender system that assists microfinance institutions. They discuss the impact and limitations of such a system in an Indian case study.

Based on the properties of this domain, we argue that loans are less heterogeneous; however, we distinguish between basic loan products and microfinance solutions. We think that the churn rate for conventional products is low, but for microfinance is typically higher. The interaction type is explicit for both opportunities and the individual transactions are rare. We argue that the preference of a user is unstable, because the demand for loans can change by personal financial status. Loans are definitely risky products; therefore, the explanation of recommendations is required.

2.3 Insurance

In the insurance domain, an *insurance policy* is a contract between the insurer and the insured (policyholder). For an initial payment (premium), the insurer takes obligation to pay compensation for insured if loss caused by perils under the terms of policy. As standard policies have little room for customization, *insurance riders* are introduced to extend benefits that is purchased separately from the basic policy. Both insurance policy and insurance rider can be the object of personalized recommendation problem.

Mitra et al. [52] discuss a high-level concept of recommending both insurance policies and riders. In their short paper, they summarize the potential business benefits of introducing recommender systems in this domain. For insurance policy recommendation, Rahman et al. [60] implemented a real-time web-based application. They apply a case-based reasoning algorithm to support insurance sale agents to offer the most suitable policies for their clients. Another real-time cloud- and web-based application was developed by Abbas et al. [1], which recommends health insurance policies. The system applies multi-attribute utility-based theory that finds the most similar products to the preference of the user based various criteria (e.g. premium, co-pay, co-insurance, benefits). Life insurance recommendation problem is also investigated by Gupta and Jain [38]. Their short paper discusses the application of association rule mining for such problem focusing on cold-start problem; however, it does not publish empirical results or architectural description. Rokach et al. [65] investigate the main domains of recommender systems comparing them to the insurance sector highlighting the main differences. In their work, they apply a basic item-to-item collaborative-filtering-based method as a possible solution for the recommending insurance riders.

Based on the study published by Rokach et al. [65], the insurance domain is quite small, the interactions are indirect and the attention span of the users is low; therefore, the size and quality of available dataset is low. The items are typically complex, the constraints of users are high; however, they have little expertise. We consider this domain homogeneous with low item churn rate. We think that the user preference is more stable for insurance than loans; however, we also note that a user is likely not to be interested in a same product after contracting one. Insurance products are less risky than loans, but the demand for explanation is still high.

2.4 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 for personal residence. Therefore, buyers pay special attention to find the proper choice considering several various preferences, which leads to a multi-criteria decision problem. In this review, we primarily consider real estate as a type of investment.

The application of recommender systems in real estate domain has relatively weak literature, relevant papers were presented in the last five years only. One of the most significant contribution is published by Yuan et al. [87]. They propose a combination of ontological structure and case-based reasoning for real estate recommendation problem; furthermore, they implement a web-based application with map visualization interface. Daly et al. [18] introduce a transportation time calculator to extend conventional metadata of real estate. In their work, they also propose a method to find the trade-off between multi-criteria. Wang et al. [82] apply a simple similarity-based collaborative-filtering method for personalized ranking of real estate; however, their data were collected by questionnaires. Quantitative and qualitative criteria for decision making is investigated by Ginevičius et al. [33], who present a study about the application of recommender systems for real estate management. Another study is published by Kafi et al. [42], which discusses a "fuzzification" method on the metadata of real estate and the implementation of their solution, called Fuzzy Expert System.

As real estate can be described by the same well-defined features (e.g. price, size, rooms), this domain is homogeneous. We argue that the churn rate of items is significant, because items usually become unavailable after a purchase. The interactions can be both implicit (e.g. browsing) and explicit (e.g. purchasing), we argue that browsing data is frequent but purchase events are quite rare. We consider the preference of a user stable; however, it can change over the time in long term. Purchasing real estate is expensive and risky transaction, thus proper explanation is required.

2.5 Stocks

A *stock* is a type of security, which represents ownership in a company and claims on its assets, earnings and dividends. Stocks are traded in stock market, where the prices are controlled by traders' bids (buy price) and offers (sell price). They are held to gain profit on both dividends and the difference of selling-buying price. As stock market can be volatile depending on economic events and market news, the estimation of future profit (utility) is very challenging task. Interpreting the recommendation problem in this context, those profitable stocks should be recommended to the investor that meet his risk-aversion preference and trading behavior.

2.5.1 Non-personalized stock recommendation

The application of decision support systems in stock market has significant literature. Most of the contributions focus on improving the accuracy of predicting future returns (or trends) [89, 47, 14], providing buy/sell signals [16, 83, 12] or introducing automatic trading solutions [19, 40]; however, majority of these papers ignore the personalization factor. Nonetheless, global ranking of available stocks can be considered as non-personalized recommendations. A number of papers pointed out on the observation that groups have greater knowledge than individuals and they can provide better market predictions, calling it the "wisdom of crowds" [39, 80, 36]. Eickhoff and Muntermann [20] present significant correlation between the prediction power of stock analysts and a set of social media users. Stephan and Von Nitzsch [75] report that individuals cannot beat the market substantially; however, inexperienced investors can take benefits from online communities. Several works consider the application of natural language processing methods on financial news [70, 69, 32, 49] and social networks texts [64, 4]. A comprehensive review about techniques of opinion mining and sentiment analysis is published by Ravi and Ravi [62].

2.5.2 Personalized stock recommendation

In order to provide personalized recommendations, individual information is required about the investor; however, explicit user preferences are not available in most of the cases. One way to overcome this difficulty is providing a user interface, where investor can specify his preferences. An early solution was implemented by Liu and Lee [45], which offers a set of features for analyzing and picking stocks based on preferences specified by the investor. Yoo et al. [85] propose a graphical user interface, which calculates personalized recommendations based on Moving Average Convergence Divergence (MACD) indicator and user interactions. Seo et al. [72] introduce a management tool that applies multiple agents to collect information about the stocks and provides stock recommendations based on what the investor is holding. Chalidabhongse and Kaensar [11] design a framework, which uses stochastic technical indicator on stock returns. The solution considers both explicit preferences and user interactions for personalized recommendations.

Some of the works assume that user attributes and individual user transactions are available in the data set. Yujun et al. [88] propose a stock recommender algorithm based on big order net inflow. They argue that using just big orders underscores low-valued stocks and reduce computational requirement for advanced algorithms. They introduce a fuzzy-based method, which recommends stocks that were selected by similar users. Taghavi et al [78] propose a concept of classical recommender system for ranking stocks. In their work, they combine hybrid techniques with various information collector agents. Although their concept is quite close to conventional recommender systems in e-commerce, they do not publish empirical results. The application of standard collaborative-filtering methods is also investigated by Sayyed et al. [68]; however, they present a preliminary concept only.

2.5.3 Characteristics of stock market

Due to its variability over time, stock market is more difficult to characterize than previous domains. We argue that stocks are heterogeneous, because they represent companies from various sectors. The churn rate is low, because companies leaves stocks exchange very rarely. Considering bidding and trading transactions, the interaction style is rather implicit with very high volume. We argue that the user preference is unstable, because it is strongly driven by news and the ever changing global economy. Recommending stocks is very risky; therefore, a particular good explanation is required; however, it is a quite challenging task.

2.6 Asset allocation and portfolio management

A *portfolio* is a composition of finite number financial assets with various weights. It is well observed phenomena, that diversification reduces the risk of an investment, because the specific risk of each component become insignificant; therefore, portfolios offers better risk-return tradeoff than individual stocks. The technique of portfolio composition is often called *asset allocation*. In this context, the recommendation tasks are selecting assets and estimating their optimal weights in portfolio meet individual preferences and risk-aversion.

2.6.1 Modern Portfolio Theory

One of the most well-known portfolio selection model (Modern Portfolio Theory, MPT) was published by Markowitz [50]. His model can be interpreted as a two-step recommendation problem. First, well-diversified portfolios offer the best risk-return tradeoff for every risk level, these set of portfolios are the object of recommendation. Second, an investor is modeled by his risk-aversion utility function, which scores every investment opportunity based on risk and expected return. Investors select those portfolios that maximize his utility function. The practical drawback of this theoretical model is finding efficient portfolios requires complex calculation and estimating the individual utility function itself is challenging task.

Based on MPT, several works are published for asset allocation [73, 8]; however, the first concepts of automated solutions appears in the early 2000s. Elton and Gruber [21] argues that investors often make irrational decisions; therefore, automatized recommendations are advantageous for preventing irrational portfolio selections. Sycara et al. [77] present an overview of the application of intelligent agents in portfolio management. They highlight the specificity of this domain such as heterogeneity of information, dynamic change of environment, time-dependency and cost-constraints. Several researchers extend MPT by fuzzy techniques for modeling risk-aversion [90], estimating risk of portfolios [6] and composing optimal portfolios [23, 57]. For generating efficient portfolios, Nanda et al. [55] integrate a stock clustering method, Raei and Jahromi [59] apply two types of multi-criteria decision methods. Although the aforementioned works propose various type of sophisticated portfolio weighting methods, they are just non-personalized models.

2.6.2 Personalized portfolio selection

Musto et al. [54, 71, 53] propose a case-based reasoning methodologies for asset allocation, which consider user metadata for personalization. In their work, recommended portfolios are calculated based on what similar users selected applying various combining strategies. The authors provide empirical results of neighbor selection- and asset allocation methods in terms of average yield and intra-list-diversity of portfolios. Garcia-Crespo et al. [31] and Gonzalez-Carrasco et al. [34] introduce a fuzzy model that transforms the ontology of investor (education, age, income, risk-aversion, etc.) and the ontology of portfolio (market risk, interest rate, liquidity, returns, etc.) to a unified bi-dimensional matrix, where dimensions are psychological and social behavior features. Portfolios are recommended based on the distance of investor and portfolio models. The authors also discuss the architecture the solution and compare the value of applied accuracy measures with other domains. Beraldi et al. [5] present a decision support system for assisting strategic asset allocation using stochastic optimization method. In their solution, an investor can define his strategy by setting its parameters (initial cash, period, type of assets and currency). Based on these criteria, portfolios are generated maximizing the tradeoff between expected final wealth, Conditional Value at Risk and risk aversion parameter. The authors provide a detailed high-level architecture and performance measurement of their solution.

2.6.3 Characteristics of portfolio management

As portfolios can contain various assets, the portfolio management is heterogeneous. Although the churn rate may vary by the type of domains, we consider it low, because the assets are purchased for long-term investment. On the other hand, portfolios are basically unique and they always change if reallocation is performed. Assuming an interactive user interface, the interaction type is explicit, because investors can specify both their preferences or the desired weight of assets in portfolios. The stability of user preference may vary over time, but it is less unstable than stock exchange, because portfolios are typically composed for long-term investment. The risk of such investment is still high and explanation is desired in this domain.

2.7 Other financial domains

In this subsection, we discuss the financial domains that have weak literature in recommender systems. We mention only the most significant differences in characteristics from the aforementioned domains.

An emerging domain of investment opportunities is venture finance. *Venture capital* is a type of private equity that is offered for startup companies as seed funding. This kind of investment is typically risky, but expects high returns on promising companies. As companies typically need only a few rounds of funding, the item churn is high in this case. The goal in this domain is to find an advantageous matching between the venture capital firms and their investment partners. Related to this problem, Stone et al. [76] published a relevant work focusing on the application of collaborative filtering. They report that the domain is characterized by extremely sparse long-tailed data, thus the efficient use of conventional recommender system methods is challenging. Continuing their work, Zhao et al. [91] investigate diversification techniques in this field. The authors propose 5 algorithms for ranking startups and a quadratic portfolio weight optimization method considering risk-aversion levels.

Stock fund is a fund that principally invests in stocks. The composition of stock fund is defined by fund manager focusing on a certain sector or a level of risk. Due to its diversification level, stock funds are less risky than stocks; however, they often cannot be traded in stock market thus the amount of transactions is low. Matsatsinis and Manarolis [51] introduce a hybrid application for stock fund recommendation problem. To reduce the sparsity issues, they propose the combination of collaborative filtering and multi-criteria decision analysis. Lacking individual real data on transactions, they evaluate the proposed model on simulated investment behavior.

Jannach and Bundgaard-Joergensen [41] apply knowledge-based techniques to design a web-based advisory tool to improve the completeness of a *business plans*. In this context, the personalization of related questions is considered as a type of recommendation problem. The application also provides a summary of financials, level of completeness and aggregated advices. The risk of recommendation is low and the explanation is not critical in this case.

3 METHOD-BASED REVIEW

In this section, we categorize relevant scientific contributions based on the applied methodologies. First, we walk through the standard recommendation methods such as collaborative-filtering, content-based filtering, knowledge- and case-based recommender systems. Second, we discuss various hybrid techniques and additional data mining and machine learning methods that indirectly applied for recommendation problems in financial services. Further domain-related studies, architectures and user interface designs are not discussed in this section.

3.1 Collaborative filtering

One of the most often used technique in recommender systems is *collaborative filtering (CF)* [67]. As this method require interactions only, it can be applied in various domains. Collaborative filtering is able to extract latent behavioral pattern in transactional data that cannot be modeled by metadata; therefore, collaborative filtering methods usually have higher accuracy than metadata-based methods. On the other hand, their efficiency strongly depends on the sparsity of data and the novelty of items (cold-start problem); furthermore, it is quite challenging to explain the output of CF algorithms, which is a strong disadvantage for risky financial domains.

Among collaborative filtering-based solutions, the majority of works apply item-based nearest-neighbor methods for recommending insurance riders [65], real estate, [82] and venture capital [76]. We also find preliminary concept of the application of similarity-based recommendations for stock market [68]. Lee et al. [43] apply matrix factorization for Bayesian personalized ranking in microfinance services. They propose a fairness-aware optimization with stochastic gradient descent (SGD). A significant contribution is published by Zhao et al. [91], who propose five different collaborative-filtering methods for venture capital domain. CF is also applied in several other hybrid methods; however, we discuss those in a later section.

3.2 Content-based filtering

Content-based filtering (CBF) [58] recommends items based on the metadata of items in user history and other available items; therefore, this method requires metadata and individual interactions only. CBF algorithms can cope with the cold start problem and their recommendations are easy to explain by meta words; however, the models strongly rely on the quality of metadata and they are usually less accurate than collaborative filtering methods.

We find that the metadata-based recommendation problem is usually associated with *multiple-criteria decision analysis (MCDA)* [29]. Due to the complexity of real estate selection problem, MDCA models are often applied in that field. Ginevičius et al. [33] propose a model that handles quantitative and qualitative criteria for real estate management. Daly et al. [18] presents housing recommender system, which considers not just the metadata of a home, but the transportation opportunities to the user specified locations. A metadata-based solution for peer-to-peer lending is proposed by San Miguel et al. [66]; however, it is different from the conventional content-based filtering. The authors introduce a framework that capable to represent user data in vector-based- and semantic user models. We conclude that pure metadata-based methods are not typical in financial domains.

3.3 Knowledge-based recommendation

Knowledge-based recommender systems (KBRS) [79] focus on formalizing the knowledge about a domain based on its specificity, various constraints and ontology of items. The information about a user is usually collected by a knowledge acquisition interface, personalized recommendation is calculated based on the representation of knowledge about the user and available items. The advantage of knowledge-based methods is that the recommendations rely only on the domain-knowledge and constraints of the user preferences; furthermore, they are easy to be explained. On the other hand, the knowledge base itself should be built up and maintained, which can be a significant overhead in operating such an interactive decision support systems and the conflict should be resolved by heuristics when there is no matching item based on the actual constraints [28]. As knowledge-based methods are able to handle complex user preferences that is typical for financial domains, they can be potentially effective solutions assuming that the knowledge acquisition interface is implemented and knowledge about the domain is acquired. Felfernig et al. propose several solutions for recommending various financial products using constraint-based reasoning, which is a type of knowledge-based methods [27, 25, 26]. KBRS is also applied for personalizing questions of business plan analysis [41].

3.4 Case-based recommendation

Case-based recommender systems (CBRS) [46, 74] apply case-based reasoning (CBR) that solves the recommendation problem based on old similar cases. A case is defined in various ways (like product description, user preference, search criteria and outcome of case). CBRS relies on the first two step of case-based reasoning, which is (1) *retrieve* that finds relevant old cases to the current case and (2) *reuse* that applies the knowledge from relevant old cases. An actual case of the user is defined by user profile data or via interactive user interface. In order to find similar cases, similarity of attributes, collaborative patterns or knowledge of the domain are usually applied. On one hand, CBRS can be used for complex problems and it provides explainable recommendations. Based on Musto et al. [53], CBR has better properties than collaborative filtering for financial domains. On the other hand, these methods require a significant amount of data about the cases.

In financial domains, we find a number of case-based recommender systems. Rahman et al. [60] propose a CBR-based application for recommending insurance policies. Musto et al. [54, 71, 53] introduce case-based reasoning for portfolio recommendation. In their works, the authors also propose a diversification technique for weighting candidate solutions in revise step. Yuan et al. [87] introduce a real estate recommender that combines case-based reasoning and ontology of items. Guo et al. [37] applies instance-based method for peer-to-peer recommendation problem and employ kernel regression to find similarity weights of instances in the past.

3.5 Hybrid methods

We consider the combination of the different decision support methods as *hybrid method* [9]. Generally, hybrid recommenders benefit from the advantages of applied techniques, while their weaknesses are reduced. Hybrid methods can be more precise than conventional models; however, the efficient implementation of such solutions can be very difficult for complex problems.

We find hybrid solutions that incorporate credit card transactions in various domains to provide context-aware recommendations based on the location of the user [30, 81]. We argue that hybrid filtering is an efficient solution for cross-domain recommendation. Another hybrid application focuses on finding the most profitable stocks at a right time based on the investor preference [78]. They apply collaborative- and content-based filtering in algorithm level and social, economic and semantical agents in system level. CF and CBF is also combined by Mitra et al. [52] for recommending insurance product and by Choo et al. [15] for microfinancing. In order to reduce sparsity issues for stock fund recommendation, Matsatsinis and Manarolis [51] propose a combination if collaborative filtering and multi-criteria decision analysis.

There are a few applications of *association rule mining (ARM)* [44] in financial domains. A web-based hybrid association rule mining method is proposed for personalized recommendation of insurance products, which also deals with cold-start problem [38]. ARM is used in stock market for predicting trading-based relationships between stocks [56].

3.6 Complementary methods

In this section, we also discuss additional complementary techniques that are integrated to conventional recommender methods. We find that *fuzzy methods* are primarily introduced for stock market and asset allocation. Yujun et al. [88] introduce a fuzzy-based clustering for stock recommendations. A fuzzy-based transformation is introduced by Garcia-Crespo et al. [31] and Gonzalez-Carrasco et al. [34] for portfolio recommendation problem. Fuzzy-based expert systems are proposed for real-estate- [42] and portfolio recommendations [23, 35]. Several variations of fuzzy-based extensions of modern portfolio theory are introduced [90, 6, 57].

We find applications of *artificial neural networks (ANN)* for designing trading decision support systems [16] and extracting information from news [32]. In stock price forecasting, semantic methods are also considered for processing web texts [70] and emotions expressed in Twitter messages [64]. Based on our research, classification methods are usually applied for stock markets. *Support vector machines (SVM)* are used for incorporating information from financial news [69, 49], forecasting stock returns [89, 47] and providing stock buy/sell signals [83].

4 CONCLUSION

In this review, we have discussed the scientific contributions that were addressed to the recommendation problems in financial services in the last 15 years. We have performed a two-way investigation based on financial domains and applied recommendation techniques.

Considering the domains, our finding is the following. Banking institutes have a significant willingness to introduce decision support systems; however, we find just concepts for that problem. There is a great support for personalizing peer-to-peer lending than conventional loan services. Although insurance domain is small, we find a decent number of applications recommending both insurance policies and riders. There are a few papers dealing with real estate recommendation; a decent part of them is empirical study only. There is a huge literature dealing with stock market. A significant part of publications focuses on predicting stock prices and providing buy/sell signals; however, these methods are non-personalized. Several works introduce interactive user interface for managing stocks, but only a few number of papers propose machine learning methods for personalized stock recommendation. We also find a significant literature for asset allocation. On the basis of modern portfolio theory, several methods are introduced to find efficient portfolios for various risk-aversion levels; however, the personalization is realized in selecting risk level only. Some of the works apply machine learning methods to compose personalized portfolios based on individual attributes. Furthermore, we present promising applications of recommender systems for venture finance, stock funds and business plan-related questionnaire.

Several domains can be characterized by homogeneous products; however, we argue that stock exchange, portfolio management and multi-domain solutions are rather heterogeneous. The item churn rate is basically low among the financial domains, except for real estate, where the offers are available until only one transaction by nature. Assuming that user interface is provided, the interaction style is explicit, otherwise implicit data or user profile metadata can be used only. We find that the preference stability is various in these domains depending on individual financial status and the changes of global market. As the object of recommendations are usually related to money spending transactions, we consider all financial domains; therefore, the demand for proper explanation about the recommendations is significant.

Based on our method-based analysis, we conclude that collaborative filtering is applied in various domains where the product itself is well-defined; however, it is limited to handle complex recommendation problems. We find a small number of applications using pure content-based filtering. Due to the specificity of financial domains, multiple-criteria decision analysis and case-based reasoning has significant advantage over collaborative- and content-based filtering. Assuming that a well designed user interface is available, knowledge-based methods has great benefits for assisting personalization problems. We find several hybrid methods combining collaborative- and content-based filtering, we argue that application of association rules is less significant. Investigating other methods, we find that fuzzy techniques are basically applied for portfolio selection problem; furthermore, artificial neural networks and support vector machines are typically used in stock market decision systems.

Summarizing our work, we state that an extensive work is being in progress for investigating applications of recommendation systems in financial services; however, there remain several unexploited opportunities in this field for both scientific research and product development.

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