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Personalized finance advisory through case-based recommender systems and diversification strategies

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ABSTRACT

Recommendation of financial investment strategies is a complex and knowledge-intensive task. Typically, *financial advisors* have to discuss at length with their wealthy clients and have to sift through several *investment proposals* before finding one able to completely meet investors' needs and constraints. As a consequence, a recent trend in wealth management is to improve the advisory process by exploiting recommendation technologies. This paper proposes a framework for recommendation of asset allocation strategies which combines *case-based reasoning* with a novel diversification strategy to support financial advisors in the task of proposing diverse and personalized investment portfolios. The performance of the framework has been evaluated by means of an experimental session conducted against 1172 real users, and results show that the yield obtained by recommended portfolios overcomes that of portfolios proposed by human advisors in most experimental settings while meeting the preferred risk profile. Furthermore, our diversification strategy shows promising results in terms of both diversity and average yield.

1. Introduction

Financial service firms such as banks, brokerages, family offices, life insurance companies and trusts offer investment services to their clients and help them reach their objectives. Such investment services typically include advisory on investment strategies, discretionary portfolio management in which clients delegate portfolio management to experts, sales of financial products offered by the firm or third parties, and collection and transmission of trading orders to financial markets. Clients are classified into segments based on their available assets as Retail, Affluent, High Net Worth Individuals (HNWI), or Ultra High Net Worth (UHNW) individuals and are treated differently, with different products and services proposed to meet their needs.

After the 2008 financial crisis, all financial service firms increased their focus on investment services, as they are profitable but do not involve credit risk nor stress banks' capital requirements. At about the same time specific regulations such as MiFID[1] in Europe or Retail Distributions Review (RDR)[2] in the UK, were established to protect investors and their assets. Firms wanting to expand their market share and meet regulatory requirements had to invest heavily in new processes and IT platforms to improve their offerings, quality of service and compliance. Indeed, to know the clients and to deliver them personalized investment proposals is today considered an essential facet of a fruitful and effective advisory strategy [2]. IT investments were oriented towards increasing transparency, delivering better and more timely client reporting, but did not influence the investment decision-making process.

In the last few years the rapidly moving scenario has been further revolutionized by the technology trends subsumed under the term digitization, which despite hesitations, will deeply and unavoidably transform the wealth management industry [4]. The effects of digitization include reduction of the number of physical branches and the transition of business transactions to online channels. A part of the digitization trend is online advice sites, sometimes called "robo-advisors", which let clients get advice online, anytime at a lower cost [1]. Online advice platforms support the do-it-yourself (DIY) attitude of clients and put pressure on professional advisors who follow the traditional wealth management model of personal interactions and paper-based processes [3].

To cope with online competition and with pressure on costs coming from the increased regulatory requirements, advisors should now make the most of their time and maximize the quality of their advice while operating with efficiency. Efficiency is particularly important when working with clients of the Affluent segment, who are much more numerous than the HNWI and UHNW segments. An example of platform-supported efficiency are advisors receiving intelligent help to quickly sift through past data and exploiting the past experience of

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[1] http://en.wikipedia.org/wiki/Markets_in_Financial_Instruments_Directive.
[2] http://www.fsa.gov.uk/rdr.

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the firm to give the best possible solutions to their clients. This brings in the idea that recommendation technologies could be adapted in the investment service context and be the advisors' assistant in the new operating environment.

2. Goal and contributions

As proved by many success stories, Recommender Systems (RS) [5] can provide users with high-quality personalized suggestions and can effectively support people in real-time decision making tasks. However, the application of such technology in the *financial domain* is neither trivial nor straightforward, since some peculiarities of this domain make it hard to put into practice the most common recommendation paradigms such as the content-based (CB) [6] and the collaborative filtering (CF) [7] ones.

Indeed, in this particular setting each user can be just modeled through his *risk profile*[3] along with some demographical features, while each financial product is described through a *rating*[4] provided by credit rating agencies, an average *yield* at different time intervals and the *category* it belongs to. This makes a pure CB strategy very likely to fail, since content-based information is too poor and not meaningful to feed a CB recommendation algorithm. Moreover, the over-specialization problem [8], typical of CB recommenders, may collide with the fact that turbulence and fluctuations in financial markets suggest changing and diversifying the investments over time. Similarly, CF algorithms can hardly be adopted because of the well-known *sparsity* problem, which arises when it is very difficult to identify the neighbors of the target user.

However, the main reason that makes CB and CF strategies very likely to fail lies in the absence of a real user history (in terms of positive and negative ratings) for the financial domain. Indeed, each user typically keeps its asset allocation strategy constant for a long period of time, so it is not possible to accumulate enough ratings to trigger a classic recommendation process relying on the analysis of previous preferences of the users or on the analysis of rating patterns within the community of users. Due to these dynamics, it is necessary to focus on different recommendation paradigms. Knowledge-based Recommender Systems (KBRS) [9], for example, provide users with recommendations by typically matching preferences and domain constraints with a set of possible solutions. This insight fits well with the financial domain since there is a clear relationship between the risk profile of the target user and the asset classes he is more inclined to invest in [10].

However, due to the complexity of the *knowledge acquisition* step, which is mandatory for KBRS, the research in the area shifted the focus to a subclass of KBRS called case-based recommender systems (CBRS) [12]. CBRS avoid the bottleneck of explicit knowledge acquisition by adopting *case-based reasoning* (CBR) [11], a problem solving methodology that tries to solve new problems by re-using specific past experiences stored in some example cases. Specifically, CBRS recommendations rely on the retrieval and adaptation of the suggestions proposed in similar settings, which are drawn from a set – called *case base* – of (effective) previously proposed solutions.

This paper proposes a framework for *recommendation of asset allocation strategies* relying on case-based reasoning. The framework is the outcome of a joint research with Objectway Financial Software aimed at improving the advisory process implemented in OFS Advice,[5] a platform for investor-centric wealth management. OFS Advice defines and tailors an investment proposal in terms of *asset allocation* and *product recommendations* that meet all the investor's objectives.

The proposed framework merges the advantages of KBRS with the simplicity of a recommendation process which avoids explicit knowledge acquisition. Furthermore, a strategy to provide users with diverse investment solutions is integrated, in order to effectively deal with market fluctuations and flocking. In the experimental session our framework has been compared to a k-NN baseline as well as to recommendations provided by human advisors in both in-vitro and in-vivo ex-post evaluation.

To sum up, the contributions of the paper can be summarized as follows:

1. It introduces a novel framework for recommendation of asset allocation strategies;
2. It evaluates the effectiveness of CBRS recommendation strategies in a special (and, to best of our knowledge, not yet evaluated) domain;
3. It proposes a greedy diversification algorithm able to diversify the investment strategies over time;
4. It evaluates the effectiveness of the framework through an extensive *ex-post evaluation*.

The paper is organized as follows: Section 3 provides an overview of the literature. The framework for recommendation of asset allocation strategies is described in Section 4, while Section 5 provides a thorough description of the experimental design as well as the outcomes of the evaluation. Finally, the conclusion and the research to be carried on are sketched in Section 6.

3. Related work

Recommendation of financial investment strategies is a very controversial and complex topic. Generally speaking, this research line has a strong relationship with the area of *human decision-making* [13]. It is not by chance that many researchers tried to investigate human behavioral patterns in the areas of both financial decision-making [17,18,20] and asset allocation [19]. The complexity of the task is also confirmed by several works that aim to learn whether some relationship exists between psychological traits of wealthy clients and the investment proposals they choose [15]. Given that some research already underlined the (positive) role of case-based reasoning strategies in human-decision making tasks [14], CBR was chosen as the backbone of our framework for financial recommendations. However, the adoption of this strategy in the financial domain has been poorly investigated, with the exception of the model proposed by Chuang [21], which exploits CBR for bankruptcy detection.

The first attempts towards the usage of CBR in recommendation-related tasks date back to the early 2000s in the e-commerce [38], restaurant [36], and tourism [37] domains. In the first case CBR was adopted to support users' choices through a conversational interface, while in the others CBR is triggered according to users' preferences, typically expressed as a logical query on the case base. The only difference between our approach and the state of the art ones lies in the way user preferences are represented. In our setting, a user is represented according to her financial-based as well as demographical characteristics, while in the above mentioned attempts a user is modeled through her preferences in the food domain or through her travel wishes (town, hotel features, weekdays, activities and so on). Furthermore, differently from our framework, none of the state of the art approaches takes into account diversity issues.

As regards recommender systems in the financial domain, in [16] Yu proposes an architecture of a decision-support system for the financial domain. This is a very preliminary attempt, since no technical and methodological details are provided for the implementation of each recommendation step. The main contribution in the area is due to Felfernig et al. [33], who proposed a framework for the development of KBRS which is the main building block of FSAdvisor [32], a platform

[3] The Risk Profile is defined as "an evaluation of an individual or organization's willingness to take risks". Typically, this value is obtained by conducting the above mentioned standard MiFiD questionnaire.

[4] http://en.wikipedia.org/wiki/Credit_rating.

[5] http://www.objectway.com/EN/financial-software/FS-Advisors-Network-MIFID-advice.asp.