Case-based Recommender Systems for Personalized Finance Advisory

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1 Abstract

Wealth Management is a business model operated by banks and brokers, that offers a broad range of investment services to individual clients to help them reach their investment objectives. Wealth management services include investment advisory, subscription of mandates, sales of financial products, collection of investment orders by clients. Due to the complexity of the tasks, which largely require a deep knowledge of the financial domain, a trend in the area is the exploitation of recommendation technologies to support financial advisors and to improve the effectiveness of the process.

The talk presents a framework to support financial advisors in the task of providing clients with personalized investment strategies. The methodology is based on the exploitation of case-based reasoning and the introduction of a diversification technique. A prototype of the framework has been used to generate personalized portfolios, and its performance, evaluated against 1,172 real users, shows that the yield obtained by recommended portfolios overcomes that of portfolios proposed by human advisors in most experimental settings.

2 Introduction

Wealth management services have become a priority for most financial services companies. As investors are pressing wealth managers to justify their value proposition, turbulences in financial markets reinforce the need to improve the advisory offering with more customized and sophisticated services. As a consequence, a recent trend in wealth management is to improve the advisory process by exploiting recommendation technologies. However, some peculiarities of the financial domain make hard to put into practice the most common recommendation approaches, as the Content-Based (CB) or the Collaborative Filtering (CF). As regards CB recommenders, the available content, which is necessary to feed a CB recommendation algorithm, is very inadequate and not meaningful, since each user can be just modeled through her *risk profile*[2] along with some demographical features. Similarly, financial products are described through a *rating*[3] provided by credit rating agencies, an average *yield* on different time intervals and the *category* it belongs to. In this recommendation setting a pure CB strategy is likely to fail, since the overlap between features is very poor. Moreover, the over-specialization problem [1], typical of CB recommenders, may collide with the fact that turbulence and fluctuations in financial markets suggest to change and diversify the investments over time. Similarly, CF algorithms can hardly be adopted because of the well-known *sparsity* problem, which makes very difficult to identify the neighbors of the target user.

These dynamics suggest to focus on different recommendation paradigms. Given that financial advisors have to analyze and sift through several *investment portfolios*[4] before providing the user with a solution able to meet her investment goals, the insight behind our recommendation framework is to exploit Case-Based Reasoning (CBR) to tailor investment proposals on the ground of a case base of previously proposed investments.

3 Methodology

Our recommendation process is based on the typical CBR workflow described in [2] and sketcted in Figure 3. Our pipeline is structured in three different steps:

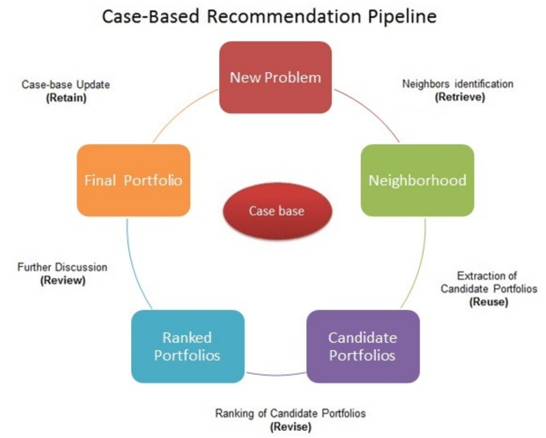

Figure 1. Case-Based Reasoning for Personalized Wealth Management

(1) Retrieve and Reuse: retrieval of similar portfolios is performed by representing each user through a feature vector: risk profile, inferred through the standard *MiFiD* questionnaire[5], investment goals, temporal goals, financial experience, and financial situation have been chosen as features. Each feature is represented on a five-point ordinal scale, from very low to very high. Next, *cosine similarity* is adopted to retrieve the most similar users (along with the portfolios they agreed) from the case base.

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[2] 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.

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

[4] http://en.m.wikipedia.org/wiki/Portfolio_(finance)

[5] http://en.wikipedia.org/wiki/Markets_in_Financial_Instruments_Directive

(2) Revise: *candidate solutions* retrieved at step 1 are typically too many to be consulted by a human advisor. Thus, the Revise step further filters this set to obtain the final solutions. To revise the candidate solutions, four techniques are compared:

(a) Basic Ranking: portfolios are ranked in descending *cosine similarity* order, according to the scores returned by the RETRIEVE step. The first k portfolios are returned to the advisor as *final solutions*.

(b) Greedy Diversification: this strategy implements the diversification algorithm described in [3]. The algorithm tries to diversify the *final solutions* by iteratively picking from the original set of *candidate solutions* the ones with the best compromise between *cosine similarity* and *intra-list diversity* with respect to the previously picked solutions. At each step of the strategy, the solution with the best compromise is removed from the set of candidate solutions and is stored in the set of final solutions.

(c) FCV: *Financial Confidence Value (FCV)* calculates how close to the optimal one is the distribution of the asset classes in a portofolio, according to the average historical yield obtained by each class. Given a set of asset classes A, for each portfolio p the set P, of the asset classes in it, and its complement $\overline{P}$ are computed. Next, FCV is formally defined as:

$$FCV(p) = Y(p)^{log(\lambda)+1} \tag{1}$$

$$Y(p) = \sum_{i=1}^{|P|} p_{a_i} * y_{a_i} \qquad \lambda = \frac{\sum_{i=1}^{|P|} y_{a_i}}{\sum_{k=1}^{|\overline{P}|} y_{a_k}} \tag{2}$$

where p_{a_i} and y_{a_i} are the percentage and the average yield of the *i-th* asset class in the portfolio, respectively. $Y(p)$ is the total yield obtained by the portfolio, and λ is a drift factor which calculates the ratio in terms of average yield between the asset classes in the portfolio and those which are not in. For values of $\lambda \geq 1$, it acts as a boosting factor (for $\lambda \ll 1$, it acts as a dumping factor). Through this strategy, all the *candidate solutions* are ranked according to the FCV score and the*top-k* solutions are returned to the advisor.

(d) FCV + Greedy: this combined strategy first uses the greedy algorithm to diversify the solutions, then exploits the FCV to rank the portfolios and obtain the *final solutions*.

(3) Review and Retain: in the Review step the user and the human advisor can further discuss and modify the portfolio, before generating the final solution for the user. If the monthly yield obtained by the newly recommended portfolio is acceptable, the solution is stored in the case base and can be used in the future as input to resolve similar cases.

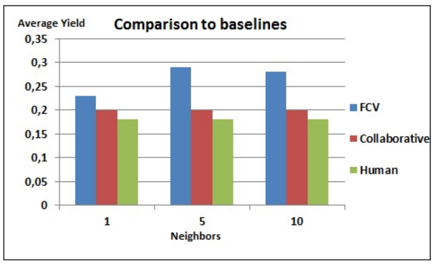

Figure 2. In vitro evaluation

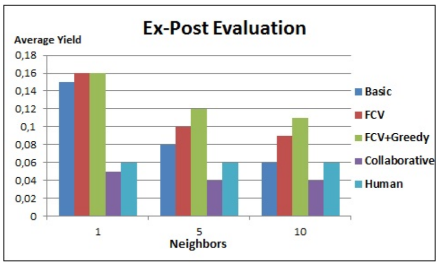

Figure 3. Ex-post evaluation

The performance of the framework has been evaluated in an experimental session against 1,172 real users. Results show that the yield obtained by recommended portfolios overcomes that of portfolios proposed by human advisors in many experimental settings. As shown in Figure 2, FCV significantly outperforms human recommendations (the average monthly yield increases from 0.18 to almost 0.30) for all the neighboorhood (put on the *X axis*) taken into account. The experimental results were further confirmed by an ex-post evaluation performed on real financial data from January to April 2014. As shown in Figure 3, this experiment provided very interesting results: beyond confirming the goodness of FCV-based ranking and the statistically significance of the gap with respect to both collaborative and human baselines, the most interesting outcome was that the combination of the diversification technique and FCV can further improve the performance of the proposed portfolios. This result suggests that the integration of the approaches can make the framework even more effective. This is due to the fact that a combined strategy can merge the advantages of a ranking based on past performance, as FCV, with an algorithm that may lead to more diverse recommendations. This makes the investment strategy better, since the human advisor does not base her investment proposal on a set of very similar portfolios, but rather on a set of *diversified solutions* which is more stable and effective, especially when market fluctuations have to be tackled.

4 Deployment of the framework

A demo version of the platform is available online[6].

Given that the platform is supposed to be of aid for financial advisors, it lets the advisor to select the current user as well as the recommendation technique to be adopted. Next, the ”Recommendation” button shows the most promising portfolios for the target users along with the distribution of the asset classes. The distribution can be further discussed by user and advisor before coming to the final proposal which is stored in the case base.

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