# On Discovering non-Obvious Recommendations: Using Unexpectedness and Neighborhood Selection Methods in Collaborative Filtering Systems

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## ABSTRACT

This paper proposes a number of studies in order to move the field of recommender systems beyond the traditional paradigm and the classical perspective of rating prediction accuracy. We contribute to existing helpful but less explored recommendation strategies and propose new approaches targeting to more useful recommendations for both users and businesses. Working toward this direction, we discuss the studies we have conducted so far and present our future research plans. The overall goal of this research program is to expand our focus from even more accurate rating predictions toward a more holistic experience for the users, by providing them with non-obvious but high quality recommendations and avoiding the *over-specialization* and *concentration bias* problems. In particular, we propose a new *probabilistic neighborhood-based method* as an improvement of the standard $k$-nearest neighbors approach, alleviating some of the most common problems of collaborative filtering recommender systems, based on classical metrics of dispersion and diversity as well as some newly proposed metrics. Furthermore, we propose a concept of *unexpectedness* in recommender systems and operationalize it by suggesting various mechanisms for specifying the *expectations of the users* and proposing a recommendation method for providing the users with unexpected but high quality personalized recommendations that fairly match their interests. Besides, in order to generate utility-based recommendations for Massive Open Online Courses (MOOCs) that better serve the educational needs of students, we study the satisfaction of users with online courses vis-à-vis student retention. Finally, we summarize the conclusions of the conducted studies, discuss the limitations of our work and also outline the managerial implications of the proposed stream of research.

## Categories and Subject Descriptors

H.1.2 [**Models and Principles**]: User/Machine Systems - Human Factors; H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval - Information filtering, Selection process, Retrieval models; I.2.6 [**Learning**]: Parameter learning

## Keywords

Algorithm Design; Unexpectedness; Recommender Systems


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## 1. INTRODUCTION

Over the last two decades, a wide variety of different types of recommender systems (RSes) has been developed and successfully used across several domains [9]. During this time, many researchers have focused mainly on the development and improvement of efficient algorithms for more accurate rating predictions. Although the recommendations of the latest class of systems are significantly more accurate than they used to be a decade ago [13] and the broad social and business acceptance of RSes has already been achieved, there is still a long way to go in terms of satisfaction of the actual needs of the users [23, 7]. This is primarily due to the fact that many existing RSes focus on providing even more accurate rather than more useful recommendations. Besides, common recommenders, such as collaborative filtering (CF) algorithms, recommend products based on prior sales and ratings. Hence, they tend not to recommend products with limited historical data, even if these items would be rated favorably. These recommenders can create a rich-get-richer effect for popular items while this *concentration bias* can prevent what may otherwise be better consumer-product matches [17]. At the same time, common RSes usually recommend items very similar to what the users have already purchased or liked in the past [1]. This *over-specialization* of recommendations, however, is often inconsistent with sales goals and consumers' preferences. Some of the main problems pertaining to this narrow rating prediction focus of many existing recommender systems [16, 2] and the ways to broaden the current approaches have been discussed in [26].

Even though the aforementioned rating prediction perspective is the prevailing paradigm in recommender systems, there are other approaches that try to alleviate the problems pertaining to this narrow focus and have been gaining significant attention in the field of RSes [20]. In particular, some of the most recent perspectives maintain that recommender systems should make the users familiar with the various product categories and the whole product catalog. In addition, RSes should provide personalized recommendations from a wide range of items and enable the users to find relevant items that are hard to discover. Also, they should increase user satisfaction and engagement while offering a superior user experience. Recommender systems should also be able to reduce user search costs, improve the quality of decisions that consumers make, and increase their welfare. Besides, from a business perspective, RSes should increase the overall sales volume and conversion rates as well as promote items from the long tail that usually exhibit significantly lower marginal cost and, at the same time, higher marginal profit.

Moving beyond the classical perspective of the rating prediction accuracy, the main objective of this stream of research is to extend existing but less explored paradigms of RSes as well as propose new approaches that will result in more useful recommendations for both users and businesses. Working toward this direction, we discuss the studies we have conducted so far and present our future research plans. In particular, we shift our focus from even more accurate rating predictions and aim at offering a better experience to the users by avoiding the over-specialization and concentration bias of recommendations and providing the users with non-obvious (unexpected) but high quality recommendations that fairly match their interests.

## 2. RELATED WORK

Two of the most important problems of many recommender systems that have been identified in the literature and hinder user satisfaction are the *over-specialization* and *concentration* bias of recommendations. The problem of over-specialization is often practically addressed by introducing randomness in the recommendation procedure [11], filtering out items which are too similar to items the user has rated in the past [14], or increasing the diversity of recommendations [32]. Regarding the concentration bias of recommendations, [19] compared different RS algorithms with respect to aggregate diversity and their tendency to focus on certain parts of the product spectrum and showed that popular algorithms may lead to an undesired popularity boost of already popular items. Finally, [17] showed that this concentration bias can create a rich-get-richer effect for popular products leading to a subsequent reduction in profits and sales diversity.

Other streams of research that improve recommender systems going beyond rating prediction accuracy include work on *human-computer interaction* (HCI) [30], which involves the study and design of the interaction between users and RSes, as well as *explanations* for recommendations [28] that provide transparency into the recommendation process exposing the reasoning and data behind each recommendation. Besides, other approaches pertain to *diversification* [8, 31], which maximizes the variety of items in a recommendation list, *group recommenders* [27], which recommend items for groups of people, rather than individuals, and recommendation *sequences* [25], where sequences of ordered items are recommended instead of single items.

## 3. RESEARCH STUDIES

In this stream of research, working toward providing even more useful recommendations for both users and businesses and effectively moving beyond the narrow focus of the rating prediction accuracy, we designed a number of research studies to explore issues related to several new approaches.

In particular, Section 3.1.1, focusing on neighborhood selection, proposes a new *probabilistic neighborhood-based approach* ($k$-PN) as an improvement of the standard $k$-nearest neighbors ($k$-NN) algorithm, alleviating some of the most common problems of collaborative filtering recommender systems, based on classical metrics of dispersion and diversity as well as some newly proposed metrics. Then, Section 3.1.2 proposes a concept of *unexpectedness* in recommender systems and fully operationalizes it by suggesting various mechanisms for specifying the expectations of the users and proposing a recommendation method for providing the users with non-obvious but high quality personalized recommendations that fairly match their interests based on specific metrics of unexpectedness. Finally, Section 3.2 studies the satisfaction of students with massive open online courses (MOOCs) vis-à-vis student retention, in order to generate utility-based recommendations using the aforementioned methods and then experimentally evaluate the corresponding approaches in a real-world application. All these research studies go beyond the classical perspective of RSes and aim at providing the users with non-obvious but high quality recommendation sets that fairly match their interests and they will remarkably like. Thorough discussions of these concepts, implementation details, and experimental results are provided in [3, 4, 5, 6].

### 3.1 Beyond over-specialization

Sections 3.1.1 and 3.1.2 address the over-specialization and concentration bias problems in recommender systems focusing on *unexpectedness* and the related concepts of coverage, novelty, serendipity, and diversity of recommendation lists [4, 5].

#### *3.1.1 Probabilistic Neighborhoods*

In [6], we propose a new probabilistic method for neighborhood selection in collaborative filtering models. In particular, we illustrate the practical implementation of the proposed approach presenting a specific variation of the classical $k$-nearest neighbors ($k$-NN) CF method in which the neighborhood selection is based on an underlying probability distribution instead of just the $k$ neighbors with the highest similarity level to the target user. For the probabilistic neighborhood selection ($k$-PN), we use an efficient method for weighted sampling [29] of $k$ neighbors without replacement that also takes into consideration the similarity levels between the target user and the $n$ candidate neighbors. The key intuition for this *probabilistic nearest neighbors* collaborative filtering method is two-fold. First, using the neighborhood with the most similar users in order to estimate unknown ratings and recommend candidate items, the generated recommendation lists usually consist of known items with which the users are already familiar. Second, because of the multi-dimensionality of users' tastes, there are many items that the target user may like and are unknown to the $k$ most similar users to her/him. The theoretical motivation for this approach is based on ensemble learning theory according to which the generalization error of an ensemble, in addition to the bias and variance of the individual estimators (and the noise variance), also depends on the covariance between the individuals. Thus, we propose the use of probabilistic neighborhood selection in order to alleviate the aforementioned problems and move beyond the limited focus of rating prediction accuracy.

To investigate this claim, we conducted an empirical study and tested the proposed method in a very large number of experimental settings. In detail, we used a number of probability distributions from different families with various location and shape parameters in order to compare the proposed probabilistic method for neighborhood selection against the standard collaborative filtering approach in terms of popular evaluation metrics for item prediction accuracy, utility-based ranking, diversity, and dispersion as well as a newly proposed metric of mobility of recommendations.

The experimental results illustrate that the proposed method generates recommendation lists that are very different from those generated based on the classical collaborative filtering approach and alleviates the over-specialization and concentration bias problems. We also demonstrate that using probability distributions which sample mainly from the nearest neighbors and also some further neighbors, the proposed method outperforms, by a wide margin in most cases, the standard user-based $k$-NN method in terms of both item prediction accuracy and utility-based ranking measures, such as the F-measure and the normalized discounted cumulative gain (nDCG), across various experimental settings. This performance improvement is due to the reduction of covariance among the selected neighbors and is in accordance with the ensemble learning theory. Additionally, we showed that the performance improvement is not achieved at the expense of other popular performance measures that go beyond the rating prediction accuracy, such as catalog coverage, aggregate diversity, recommendation dispersion, and mobility. Finally, we identified a particular implementation of the $k$-PN method that consistently performs well across various experimental settings.

#### 3.1.2 Expecting the Unexpected

In [4, 5], we propose a concept of unexpected recommendations as recommending those items that significantly depart from the expectations of the users. We also suggest a method for generating such recommendations, based on the utility theory of economics, as well as specific metrics to measure the unexpectedness of recommendation lists.

In particular, we formally define the concept of *unexpectedness* in recommender systems taking into account the actual *expectations* of the users and discuss how the concept of unexpectedness is differentiated from various related notions, such as novelty, serendipity, and diversity. Following the Greek philosopher Heraclitus, we approach this problem of finding and recommending unexpected items by first capturing the items expected by the users. Toward this direction, we suggest several mechanisms for specifying users' expectations that can be applied across various domains. Such mechanisms include the past transactions performed by the users, knowledge discovery and data mining techniques, and experts' domain knowledge. Besides, we formulate and fully operationalize the notion of unexpectedness and present an algorithm for providing unexpected recommendations of high quality that are hard to discover but fairly match the users' interests, based on the *utility theory* of economics. Moreover, we propose specific performance metrics to measure the unexpectedness of the generated recommendation lists taking into account also the usefulness of individual items.

Using "real-world" data sets, various examples of sets of expected recommendations, and different utility functions and distance metrics, we were able to test the proposed method in a large number of experimental settings including various levels of sparsity, different mechanisms for specifying users' expectations, and different cardinalities of these sets of expectations. The empirical study showed that all the examined variations of the proposed method significantly outperformed in terms of unexpectedness the standard baseline algorithms, including item-based and user-based $k$-Nearest Neighbors [22], Slope One, and Matrix Factorization [24]. This demonstrates that the proposed method indeed effectively captures the concept of unexpectedness since, in principle, it should do better than unexpectedness-agnostic methods. Furthermore, the proposed method for unexpected recommendations performed at least as well as, and in some cases even better than, the baseline algorithms in terms of the classical accuracy-based measures, such as root-mean-square error (RMSE) and the F-measure, as well as other popular performance measures, such as catalog coverage, aggregate diversity, serendipity, and the Gini coefficient. In addition, we presented a number of actual recommendation examples, generated by the proposed method and the employed baseline approaches, and provided insightful qualitative comments and recommendation explanations.

One of the main premises of the proposed method is that the users' expectations should be explicitly considered in order to provide them with unexpected recommendations of high quality that are hard to discover but fairly match their interests. Hence, the greatest improvements in terms of both unexpectedness and accuracy were observed in the experiments using the more accurate sets of user expectations. Moreover, the use of utility functions of standard form illustrates that the proposed method can be easily implemented in existing recommender systems as a new component that enhances unexpectedness of recommendations, without the need to further modify the current rating prediction procedures.

### 3.2 Massive Open Online Learning

In [3], we study the satisfaction of students with *Massive Open Online Courses* (MOOCs) vis-à-vis student retention in order to use the aforementioned approaches and generate utility-based recommendations for online courses that better serve the educational needs of students.

In particular, MOOCs are a recent development in the area of e-learning and distant education that has remarkably expanded during the last years. MOOCs are larger in scale than traditional courses, have no restrictions on individual participation, are globally distributed across a variety of networks, and aim at revolutionizing the way education happens. Such massive online courses are offered in a wide range of topics by dozens of top universities with the vision to provide free high-level education all over the world. Even though MOOCs have been broadly accepted, the very high drop-out rates indicate that much more should be done in order to satisfy the actual educational needs of the students. Tackling this important problem, we employ interdisciplinary research methods that complement each other. More specifically, we employ the *Grounded Theory Method* (GTM) on quantitative data, a less frequently applied paradigm which prioritizes exploration of the given phenomenon in a inductive *theory development* paradigm. In addition, we integrate state-of-the-art *econometric, text mining, opinion mining, and machine learning techniques* with the iterative approach of GTM, building both explanatory and predictive models, toward a more complete and in-depth analysis of the information captured by user-generated content. Overall, we present a novel mixed-methods analysis using a real-world data set with user-generated online reviews, where we both identify the emergent concepts related to different *student*, *course*, *platform*, and *university* characteristics that affect student retention and study their relative effect in a hedonic-like framework. Applying the methodological ideas of GTM to explanatory quantitative analysis and predictive models and going beyond descriptive statistics of coded verbal data, we contribute to the related literature by discovering new rich findings and provide actionable insights with significant implications for both MOOCs and traditional education.

The proposed approach and the corresponding findings have several implications for the universities and platforms offering online courses. They can be utilized for real-time detection of dissatisfied students as well as the design of better and more engaging courses that will increase retention rates. In detail, the results suggest that the course characteristics (e.g. estimated difficulty, workload, duration, whether there is automated grading, etc.) are important determinants of students' satisfaction and suggest useful guidelines for course design. For instance, MOOCs in general should have a specific instructor-based timetable, but for the most difficult courses students should be allowed to follow their own pace. Also, the findings suggest that there is room for improvement in the current form of certifications, which should be redesigned in order to become more useful for the students and further motivate them to successfully complete the corresponding course by ensuring knowledge verification and student identification. Additionally, while better technical solutions are needed for automatically providing feedback and evaluating the assignments of the students, peer assessment remains an important component of the learning process in MOOCs. Besides, professors and course instructors are the most important factor in online course retention and have the largest positive effect on the probability of a student to successfully complete a course. Our results also illustrate that, in addition to discussion forums, improved mechanisms or complementary technologies, such as wikis, are still needed in order to successfully advise, assist, connect, and motivate the students. Furthermore, our results show that open textbooks, in contrast to paid textbooks, have a positive effect. Finally, apart from the implications in education and the methodological ideas of GTM, we also discuss the managerial implications of the proposed analytical approach in other domains, such as social media and online commerce.

# 4. DISCUSSION AND FUTURE WORK

Successfully completing the aforementioned work will help the recommender systems field move further beyond the perspective of rating prediction accuracy. Following the proposed stream of research and adhering to our main objective of improving the usefulness of recommendations for both users and businesses, we both contribute to existing helpful but less explored recommender systems approaches and propose new valuable perspectives. Working toward this direction, we discussed the studies we have conducted so far and presented in detail some of our future research plans. In particular, the studies discussed in Section 3 move our focus from further improving the rating prediction accuracy and aim at offering a holistic experience to the users by avoiding the over-specialization and concentration bias of classical recommender systems and providing the users with non-obvious but high quality personalized recommendations that fairly match their interests.

In detail, Section 3.1.1, focusing on neighborhood selection, proposes a novel probabilistic neighborhood-based method ($k$-PN) as an improvement of the standard $k$-nearest neighbors recommendation algorithm, alleviating some of the most common problems of collaborative filtering recommender systems, based on classical metrics of dispersion and diversity as well as some newly proposed metrics. Then, Section 3.1.2 proposes a concept of *unexpectedness* in recommender systems and fully operationalizes it by suggesting various mechanisms for specifying the expectations of the users and proposing a recommendation method for providing the users with non-obvious but high quality personalized recommendations that fairly match their interests based on specific metrics of unexpectedness. Finally, Section 3.2 examines the satisfaction of students with massive open online courses (MOOCs) vis-à-vis student retention in order to generate utility-based recommendations using the aforementioned methods and then experimentally evaluate the corresponding approaches in a real-world application.

The aforementioned research studies have important managerial implications. Adhering to our main research objective, we work toward the direction of providing more useful recommendations for both users and businesses. Avoiding obvious and expected recommendations while maintaining high predictive accuracy levels, we can alleviate the common problems of over-specialization and concentration bias and, therefore, we have the potential to further increase user satisfaction and engagement and offer a superior experience to the users [12, 21]. In addition, unexpectedness and its related notions can improve the welfare of consumers by allowing them to locate and buy products that otherwise they would not have purchased. Introducing unexpectedness in RSes can vastly reduce customers' search costs by recommending items that the users would rate highly but it would be quite unlikely to discover on their own. As a result, the inefficiencies caused by buyer search costs are reduced, while the ability of markets to optimally allocate productive resources is increased [10]. Furthermore, the generated recommendations should be useful not only for the users but for the businesses, too. The proposed approach exhibits a potential positive economic impact based on the direct effect of increased sales and willingness-to-pay as well as the enhanced customer loyalty leading to lasting and valuable relationships [18] through offering more useful recommendations from a wider range of items and making the users familiar with the whole product catalog. Apart from the significant gains in producer welfare from the additional sales [15], businesses might also leverage revenues from market niches [17]. Thus, there is a potential positive economic impact based on the effect of recommending items from the long tail and not focusing mostly on bestsellers that usually exhibit higher marginal costs and lower profit margins because of acquisition costs, licenses, and increased competition.

As part of our future work, we would like to further optimize and streamline the proposed methods as well as to integrate them with related existing approaches in the fields of web search and data mining. Moreover, we would like to implement and evaluate the proposed approaches in both MOOCs and a traditional on-line retail setting. Besides, we would like to conduct a series of live controlled experiments with human subjects in order to study the on-line user behavior, examine and actively adjust the trade-off between exploration (e.g. unexpectedness, serendipity, diversity, etc.) and exploitation (e.g. accuracy) of recommender systems, and better evaluate the proposed perspectives in a user-centric framework for top-$N$ recommendations. In addition, we plan to investigate how the proposed recommendation approaches and perspectives can be effectively combined with traditional approaches in hybrid recommender systems aiming at accurate and non-obvious recommendation lists that the users will remarkably like.

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