A Survey on Finding Novelty in the Recommender Systems by Adding Lower Similar Items in the Top-N List

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Abstract— The Internet has made it very challenging to find useful information from the vast amount of online data. Recommender systems aim to suggest items that are both useful and unexpected to users. These items are beneficial for the retailers and also surprisingly fit the consumers' preferences. However, existing methods struggle to provide novelty due to the skewed distribution of observed data for popular and tail items. User satisfaction with recommender systems depends on how well the system matches the user's needs and how much it helps the user make decisions. Accuracy alone is not sufficient, because the quality of recommendation also matters. The quality of recommendation is defined by how well it meets or exceeds the customer's expectations, and the user will not be happy with some of the repeated and "not so interesting" suggestions. We reviewed the papers to understand how to introduce novelty in recommendations to improve user satisfaction.

Key words: Novelty, Lower Similar Items, Top-N List

I. INTRODUCTION

Recommender systems are becoming more popular and important. The efficiency of the recommender systems depends on the traditional algorithms used in them. The challenge of today's recommender systems is to find the suitable algorithms to satisfy the users' expectations. Most of the previous research has focused on improving the accuracy of recommender systems. However, accuracy alone is not enough, because the quality of recommendation also matters.

For example, suppose you have a video recommender system. If all the recommendations you get are for videos you already know and watched, you would not like such a system. Even though the system has good accuracy, it gives redundant and boring recommendations.

II. RECOMMENDER SYSTEM EVALUATION

There are multiple dimensions for recommender system evaluation, as recommendation systems have multiple characteristics [1]. It is too simplistic to use just one dimension and metric for evaluating the diverse recommendation systems and application domains. The author [1] explored various dimensions that can be important for evaluating a recommendation system. We ranked these dimensions below according to their relative importance, along with the measures to assess the dimension. Some of these dimensions are qualitative while others are quantitative.

They classified these dimensions into four categories, based on different aspects of the recommendation system. The categories they used are: Recommendation-centric, User-centric, System-centric and Delivery-centric.

1) Recommendation-centric dimensions measure the quality of the recommendations produced by the recommendation system itself: by their coverage, accuracy, diversity and confidence level in the generated recommendations.
2) User-centric dimensions evaluate how well the recommendation system meets the needs of its target end-users. This includes trustworthiness, novelty, serendipity, usefulness of the recommendations from the users' point of view, and risks associated with the recommendations from the users' perspective.
3) System-centric dimensions mainly provide ways to assess the recommendation system itself, rather than the recommendations or user perspective. It includes evaluation of the robustness of the recommendation system, its learning rate with new data, its scalability with data size, its stability with data change, and degree of privacy support in the context of shared recommendation system datasets.
4) Delivery-centric dimensions primarily focus on the usability of the recommendation system in the context of use, including its user-friendliness (broadly assessed) and support for user configuration and preferences.

Recommendation-centric Correctness Coverage Diversity Recommender Confidence	System-centric Robustness Learning Rate Scalability Stability Privacy
User-centric Trustworthiness Novelty Serendipity	Delivery-centric Usability User Preferences

Utility Risk	

Table 1: Dimensions for Recommender Evaluation [1]

- Trustworthiness: How reliable are the recommendations that you give is what trustworthiness means.
- Recommender Confidence: How certain are you that your recommendations are suitable for the users is what recommender confidence means.
- Novelty: How good are you at recommending items that users have not seen or heard of before is what novelty means.
- Serendipity: How much do you surprise users with recommendations that they did not expect but still find useful is what serendipity means.
- Utility: How much benefit do users get from following your recommendations is what utility means.
- Risk: How much risk do users face when they accept your recommendations is what risk means.
- Robustness: How well can the system handle bias or false information that may affect its recommendations.
- Learning Rate: How quickly can the system learn from new information and change its recommendations accordingly.
- Usability: How user-friendly is the system? Will users find it easy to use it in the right way.
- Scalability: How well can the system cope with increasing number of users, data size and algorithm complexity.
- Stability: How stable are the recommendations over time? Will they change drastically or remain similar?
- Privacy: How secure are the user's privacy? Are there any potential threats to their personal information?
- User preference: How do users feel about the system? Do they like it or not?

III. NOVELTY IN RECOMMENDER SYSTEMS

Recommendations that are novel are those that the user was not aware of before. For applications that need such recommendations, a simple and common method is to remove the items that the user has already used. However, this may reduce the user's trust in the system and make them leave. For example, in Figure, we can see a problem that may occur when using a recommender system like those of online stores (Amazon.com, Netflix, etc.). The user profile consists of some albums by the Beatles, so a recommendation engine that only cares about accuracy may suggest a list of other albums by the Beatles and some other artists (Pink Floyd, Bob Dylan). Even though the user may like these albums, the recommendation is not very helpful.

You Searched for Items Recommended

Figure 1: Not So Useful Recommendations [15]

One possible drawback of the playlist is that it does not offer much variety, as it only features albums from the Beatles, a well-known band that does not need much introduction. Perhaps a smaller number of albums from the Beatles, along with some other musical works from different artists, would have been more suitable to explore the band's style and also discover new sounds and genres.

Another issue to consider is the order of the items in the playlist, which can affect how the user perceives them. When a recommender system selects the top-n items that are most relevant for a given user, the order in which they are presented can influence the user's attention, satisfaction, and choice.

A related concept is novelty, which refers to how surprising or unexpected an item is for a user. Novelty is important to show the Long Tail effect, which describes the situation where some items are very popular and others are less popular (Figure 2). Recommender systems can provide value by suggesting less known items to more users, instead of focusing on highly-popular items [7].

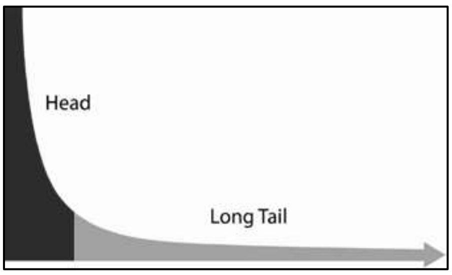

Fig. 2: The long tail effect [7]

IV. DEFINITION OF NOVELTY

Item novelty can be understood as the degree of difference between an item and "what has been seen" in a certain context. According to the WordNet dictionary [5], novel (adj.) has two meanings:
"New–Not existing before or not experienced before"; "Refreshing–Providing a pleasant change or contrast".

For example, familiar (adj.) is defined as "Easily recognized or understood" [5].

Based on this definition, "Novel item" Should have these three features: (1) Unknown: The user has not encountered the item before; (2) Satisfactory: The user finds the item appealing or useful; (3) Dissimilarity: The item is different from the items in the user's profile.

Recommender systems that explicitly ask the user about the unknown and satisfactory aspects of items may ruin the user experience, so it is better to estimate these aspects from the user's profile. Assuming that dis (i, profu) is the measure of difference between item i and the set of items in the user's profile, the formula for novelty is as follows [5]:

$$novelty\ (i,u)\ =\ p\ (i\mid like,u)\ \times\ p\ (i\mid unknown,u)\ \times\ dis\ (\,i,profu) \tag{1}$$

Traditional recommender systems mainly predict the probability of the user liking the item based on the user's preferences from their profile history. This covers the first aspect of novelty. The novelty in recommender systems refers to how much the recommended items diverge from what the users have already seen before [10].

V. MODELS OF NOVELTY

A. Distance Based:

We can also model the relative novelty of an item with respect to a set of items in a Euclidean space. This can be calculated as the average or minimum distance between the item and the other items in the set [12]:

$$novelty\ (i/s)\ =\ min\ d(I,j) \tag{2}$$

Where d is a distance measure. For example, we can define the distance as

$$d\ (i,j)\ =\ 1-\ sim(i,j) \tag{3}$$

For some similarity measure (cosine-based, Pearson correlation, etc., normalized to [0,1]) based on the item features (content-based view) or their user interaction patterns (collaborative view).

B. Popularity Based:

The novelty of an item can be related to a set of observed events on all the items. A common way to define the generic novelty of an item is by the amount of information that its observation gives, in terms of some distribution that involves the item. This is expressed in Information Theory as:

$$novelty\ (i)\ =\ I\ (i)\ =\ -log2\ p\ (i) \tag{4}$$

Where p(i) is the probability that i is observed, and I(i) is also called self-information or surprise.
We can also define a user-relative novelty variant as

$$novelty\ (i/u)\ =\ -log2\ p(i/u) \tag{5}$$

This means that we only consider the observations of the target user,

Another popularity model based on discovery is to consider the probability p(k/i) that an item is known or familiar to (rather than chosen by) a random user. In this case, we define generic and user-relative novelty as:

$$novelty\ (i)\ =\ 1-p(k/i) \tag{6}$$

$$novelty\ (i/u)\ =\ -log2\ p(k/I,u) \tag{7}$$

C. Novelty Base Models:

The models that we use to define novelty in the previous section can use different estimation methods, depending on the type and availability of observation data, the choice of random variables and any extra restriction on the observed events that we use to estimate the distributions [12]. We broadly distinguish three main categories of user-item relationships:

- Choice: an item is used, picked, selected, accessed, browsed, bought, etc. There may be a frequency associated with this event, or it may be binary (e.g. one-time purchase).
- Discovery: an item has/has not been seen before. This is a binary fact, regardless of the frequency of interaction, or how much the user likes or dislikes the item.
- Relevance: in the context of RS, relevance can be related to notions of preference, i.e. how much a user enjoys or likes an item, or how useful the item is.

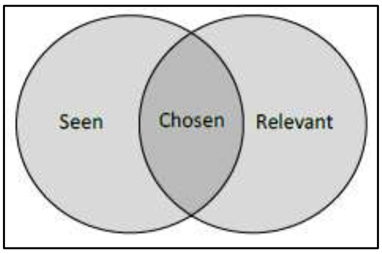

Fig. 3: Ground Models [12]

A chosen item must have been seen, and relevant items are more likely to be chosen than irrelevant ones. As a simplification, they [12] assume that relevant items are always chosen if they are seen (as shown in Figure 1…4), irrelevant items are never chosen, and items are discovered regardless of their relevance. In terms of probability distribution, these assumptions can be written as:

$$p(chosen) \sim p\ (seen) p\ (relevant) \quad (8)$$

In general terms, (1) reflects a factor of item popularity, where high novelty values correspond to long-tail items that few users have interacted with, and low novelty values correspond to popular head items. If we want to emphasize highly novel items, we may also consider the log of the inverse popularity:

$$nov\ (i \mid ?)\ =\ -log2\ p(seen\ |i, ?\ ) \quad (9)$$

VI. RELATED WORKS

The work done by the eminent personalities in the past will always pave the way for the future discoveries. As the saying goes, preparation is the key to success, and without preparation, failure is inevitable. This section gives a brief overview of the previous work done by the researchers that are related to the topic and that helped to create a platform for my work.

The limitations of building recommender systems with only accuracy as the goal have been pointed out in recent research. For example, McNee and Konstan [2006] argue that recommendation evaluation needs to go beyond traditional accuracy metrics.

Wen Wu et.al. Analyzed various evaluation criteria beyond traditional accuracy for different recommender algorithms to judge their meaningful performance. They compared five algorithms from different aspects and showed that the preference of different algorithms varies from person to person. [5]

Neil Hurley et.al. Explored solution strategies to the optimization problem and demonstrated the importance of the control parameter in achieving desired system performance. To better capture the user's range of preferences, they divided the user profile into clusters of similar items and composed the recommendation list of items that match well with each cluster, rather than with the whole user profile. This is used to increase the chance of finding novel or unusual items that are relevant to the user and introduce a methodology to evaluate their performance in terms of novel item retrieval. They formulated the trade-off between diversity and matching quality as a binary optimization problem, with an input control parameter allowing explicit tuning of this trade-off. [23]

Liang Zhang et.al. Studied research results about definition and algorithm of novel recommendation, and defined novelty of item in recommendation system. User satisfaction and support to the user's decision making using Novelty. The novelty to recommend can effectively identify the item that the user is familiar with and ensure certain accuracy. [16]

Liang Zhang et.al. Embedded Dissimilarity and the time-popularity in the traditional collaborative filtering algorithm. By using time popularity outdated popular items can better identified. The ability of predicting user's future needs and coverage of recommended list improved, and ability of recommending long tail items were enhanced. [11]

Pablo Castells et.al. To derive metric schemes that take item position and relevance into account, addressed in the novelty and diversity metrics. Two novel features in novelty and diversity measurement, ranking sensitivity and relevance-awareness are introduced in a generalized way. [12]

Qiang Guo et.al. Presented an improved algorithm, called biased heat conduction (BHC), which could simultaneously improve the accuracy and diversity. This algorithm is used to simultaneously identify users' mainstream and special preferences, resulting in better performance than the standard heat conduction algorithm. Recommendation lists generated by the BHC algorithm are of competitively higher diversity and remarkably higher accuracy than those generated by the standard HC algorithm. [22]

Punam Bedi et.al. (1) Developed a new Novelty Score (NS) metric based on item frequency and inverse user frequency for unseen items. (2) Developed Modified Collaborative Filtering Approach for Novel Recommendations (MCFNR) which applies this metric to generate novel recommendations. This is applicable in MCFNR removes the problem of popularity bias while maintaining the relevance by introducing the concept of novelty in the recommendations. The results show that the value of evaluation metrics for MCFNR is better than the CF technique which implies that, recommendation quality for novel recommendation surpasses the traditional collaborative filtering technique for persistent users. [24]

Jinoh Oh et.al. Proposed an efficient novel-recommendation method called Personal Popularity Tendency Matching (PPTM) which recommends novel items by considering an individual's Personal Popularity Tendency. PPT helps to diversify recommendations by reasonably penalizing popular items while improving the recommendation accuracy. By experiments they show that this method, PPTM, is better than other methods in terms of both novelty and accuracy. [13]

De Master et.al. Proposed an Information Retrieval approach to the evaluation and enhancement of novelty and diversity in Recommender Systems and a new formalization and unification of the way novelty and diversity are evaluated on Recommender Systems, considering rank and relevance as additional and meaningful aspects for the evaluation of recommendation lists. Which provide new ways of stating, formalizing and addressing the problems of novelty and diversity in RS and Metric framework for novelty and diversity provides a platform for analysis of common components of metrics based on simple properties of recommendation lists. The Experiments conducted on datasets from Movie Lens and Last.fm provided empiric evidence of the effectiveness of their IR diversification approach and allowed for observation and analysis of the characteristics of the different metrics derived from the framework. [14]

Praveen Chandar et.al. Modeled the expected utility of a ranked list by estimating the utility of a document at a given rank using preference judgments and define evaluation measures based on the same. Which can easily handle relevance assessments against multiple user profiles, and that they are robust to noisy & incomplete judgments and also most well-suited for assessments done by crowd-sourcing. They incorporate novelty and diversity, but can also incorporate any property that influences user preferences for one document over another also has several advantage over the existing measures based on explicit subtopic judgments. [17]

Qihua Liu et.al. They integrated a user preference matching algorithm based on communities of interests and a diverse information recommendation algorithm based on trustable neighbors to develop a hybrid information recommendation model that allows for both accuracy and diversity. In a personalized recommender system which provides users with customized information by mining the binary relations between users and items. This model can increase the diversity of recommendations with only a minimal loss of accuracy. [18]

Moreira et al. observed that by focusing on recommendations of long-tail items, which are usually more interesting for users, it was possible to reduce the bias caused by extremely popular items and to observe a better alignment of accuracy results in offline and online evaluations. [25]

Elbadrawy et.al. Proposed method for top-n recommendation of new items given binary user preferences. Learning multiple global item similarity functions and learning user-specific weights that determine the contribution of each global similarity function in generating recommendations for each user. [26]

VII. Conclusion

In conclusion, this survey paper examined the concept of finding novelty in recommender systems by incorporating lower similar items into the Top-N list. Through an extensive review of existing research and methodologies, we have gained valuable insights into the challenges and potential solutions in improving the novelty aspect of recommendation algorithms.

The analysis of various approaches highlighted the importance of considering both user preferences and item similarities when aiming to enhance novelty in recommender systems. By including lower similar items in the Top-N list, we observed potential improvements in diversification and user satisfaction.

While this survey paper sheds light on the significance of incorporating lower similar items, it also emphasizes the need for further research and experimentation. The exploration of different algorithms, techniques, and evaluation metrics can contribute to a more comprehensive understanding of how novelty can be effectively integrated into recommender systems.

Overall, this survey paper provides a comprehensive overview of the topic and serves as a foundation for future studies in enhancing the novelty aspect of recommender systems. By continuously striving to improve recommendations through innovative approaches such as incorporating lower similar items, we can create more personalized and satisfying experiences for users across various domains.

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