

A Review Paper on Recommender System Type's and Evaluation Metrics

Anshu Singla¹, Geeta Gupta², Mohit Rathore³

¹Anshu Singla<Anshu008in@gmail.com>

²Geeta Gupta<geeta.gupta@gmail.com>

³Mohit Rathore mohitrathore15@gmail.com
Haryana, India, 121005

Abstract—A very simple definition of Recommender System is “Any system that produces personalized recommendations as output or helps the user in guiding in a personalized way to get interesting or useful objects from a large collection of useful options.” This Review paper presents the study in the field of recommender systems and describes the current generation of recommendation methods which is usually divided into the three main categories: content-based recommender system, collaborative recommender system, Utility Based, Knowledge Based and hybrid recommendation techniques. This paper prescribes different terms applicable to an even broader range of applications for improvement in accuracy of recommendation algorithms. The research carried out has focused on improving the accuracy of recommender systems. In this paper, we propose that the recommender system should move beyond the conventional accuracy criteria and take some other criteria into account, such as coverage, diversity, serendipity, scalability, adaptability, risk, novelty and so on. These extensions include, among others, improvement of understanding of users and items, incorporation of the contextual information into the recommendation process, support for multi-criteria ratings, and provision of more flexible and less intrusive types of recommendations.

Introduction—E-Commerce has proliferated in terms of variety and quantity, the end-users spend considerable time to select the products and services. Recommender systems became very interesting field of research area in present time from the time of coming of the first paper on collaborative filtering in 1990s. There has been so much work done on the better algorithms of recommender field in industry as well as in academia. Even then interesting work is open in this area due to very much use of recommendation techniques in practical use of online shopping and in other web area too. Examples of such applications include recommending books, CDs and other products at Amazon.com, movies by MovieLens, videos on youtube, various things on ebay.com. Many vendors are using recommendation capabilities into their e-commerce technologies.

Types of Recommender System

Content Based Recommender System:

- objects defined by their associated features
- learn profile of the user's interests based on the features present in objects the user has rated.
- long-term models, updated as more evidence about user preferences is observed.

Collaborative Systems :

- aggregate ratings or recommendations of objects.
- recognize commonalities between users on the basis of their ratings.
- generate new recommendations based on inter-user comparisons.
- possibly, use time-based discounting of ratings.

Utility-based :

- make suggestions based on a computation of the utility of each object for the user
- employ constraint satisfaction techniques to locate the best match
- no long-term generalizations about users

Knowledge-based :

- functional knowledge: how a particular item meets a particular need .
- can reason about the relationship between a need and a possible recommendation
- no long-term models.

Hybrid Recommender System:

- Combine multiple methods in order to take advantage of strengths and alleviate drawbacks .
- Weighted ◻ scores/votes of several recommendation techniques combined together to produce a single recommendation.
- Switching ◻ system switches between recommendation techniques depending on the current situation.
- Mixed ◻ recommendations from several different recommenders presented at the same time.

However, inspite of all these advances, the current generation of recommender systems still requires more and more improvements and correction to make recommendation methods more effective and applicable to an even broader range of real-life applications including recommending vacations certain types of financial services to investors. and products to purchase in a store made by a “smart” shopping cart .for example Imagine you are using a video recommender system. Suppose all of the recommendations you got are for videos you have already watched. Even if the system were very good at ranking all of the videos you have watched in order of preference, this still would be a poor recommender system. Would you like to use such a system? Absolutely not, on the accuracy of the example has good performance, but it is not difficult to see the shortcomings: repeated redundant r e c o m m e n d a t i o n s . These improvements include better methods for representing user behavior and the information about the items to be recommended, more advanced recommendation modeling methods, incorporation of various contextual information into the recommendation process, utilization of multi-criteria ratings, development of less intrusive and more flexible recommendation methods that also rely on the measures that more effectively determine performance of recommender systems.

we divided this metrics into two parts. evaluation criteria based on the recommender algorithm and evaluation criteria independent on the recommender.

Figure 1 shows the classification table

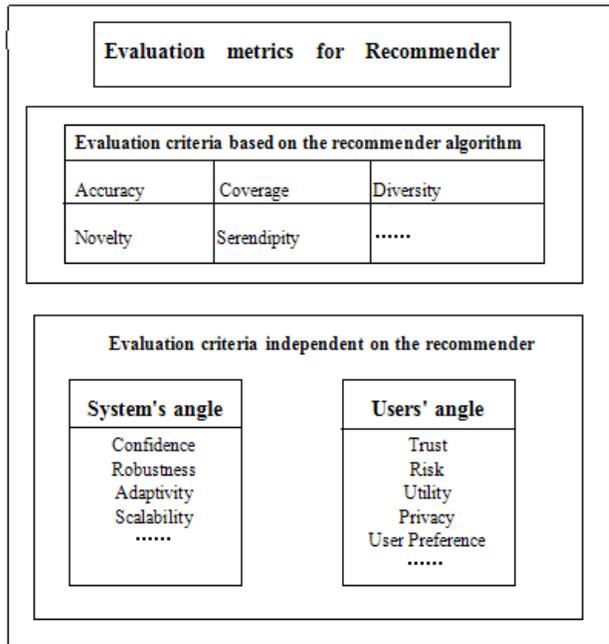


Figure 1

Evaluation criteria based on recommender algorithms

• **Accuracy**

It has been very important that accuracy should be used by using different algorithms. Accuracy can be divided among three categories.

1. The accuracy of rating's predictions
2. The accuracy of usage predictions and
3. The accuracy of rankings of items.

For the different categories, we need to use different metrics or formula to express, for example, if we use scoring prediction, we often use Root Mean Squared Error (RMSE), while ordering items according to the user's preferences, we can try to determine the correct order on a set of items for each user and measure how close a system comes to this correct order.

• **Coverage**

Accuracy and coverage always inter related or dependet on each other .

The coverage also has two definitions:

- (1) the percentage of the items for which the system can able to generate a recommendation,
- (2) the percentage of the available items which effectively are ever recommended to a user. Though different authors differ with respect to terminology.

Journal of Applied Science

- **Novelty**

Novelty recommendations are recommendations for items that the user is unknown for them and did not know about them. In applications that require novel recommendation, a very easy and effective approach is to filter out those items that the user already has been rated or used.

- **Serendipity**

Serendipity is a measure of how surprising the successful and interesting recommendations are. For example, in a video recommendation system, user A is Modi's fans. Then recommendation system makes a list based on user preferences of Modi's other video's, although the user hasn't watched before, but this can be only treated as a new recommendation not a surprise one. Serendipity has two characteristics: surprising and attractive. That means a highly serendipitous recommendation should help a user to find a surprising and interesting item.

- **Diversity**

Diversity is described as the opposite of similarity. In some cases suggesting a set of similar items can not be as useful to the user. Consider, for example, for a coupon, presenting a list with 5 recommendations, all for the same company, varying only on the choice of items, may not be considered useful as suggesting five different items from different companies.

- **Confidence**

Confidence in the recommendation can be defined as the system's trust in its recommendations or predictions. If the recommended content has a good explain it means the system's trust will go high, and system having a good degree of trust systems will tend to have more quality.

- **Scalability**

Scalability is very important for large data set. As recommender systems are designed to work on large collections of items, so one of the goals of the designers of such systems is to scale up to real data sets. That's Why Algorithms used should be designed as per if there will be need to scale on large data ,no need to optimize algorithm again.

- **Adaptivity**

Real recommendation systems may operate in a setting where the item collection changes rapidly, or where trends in interest over items may shift. Perhaps the most obvious example of such systems is the recommendation of news items or related stories in online newspapers.

- **User Preference**

When we are trying to improve a recommender system, it is very important to know that why people favors one system over the other. Typically, it is easier to understand that when comparing specific properties. So, while user satisfaction is essential to measure, breaking satisfaction into smaller components is helpful to understand the system and improve it.

- **Trust**

Generally we considers that confidence is the system trust in its ratings, But here we refer trust as the user's trust in the system recommendation. In the recommender system, sometimes the user will find something he/she viewed or purchased in the recommendation list, though the user might think that novelty is used to increase trust in system from user's perspective, because to some extent the user would believe that the system can able to predict the tastes accurately.

- **Privacy**

Due to increasing hacking, users need to take security into account. In a collaborative filtering system, inspite a user discloses his/her preferences on their wish over items to the system in hoping of find useful recommendations. However, it is important for many users to whom their preferences should be private.

Journal of Applied Science

Recommendation Approach	Recommendation Technique	
	Heuristic-based	Model-based
Content-based	<p>Commonly used techniques:</p> <ul style="list-style-type: none"> • TF-IDF (information retrieval) • Clustering <p>Representative research examples:</p> <ul style="list-style-type: none"> • Lang 1995 • Balabanovic & Shoham 1997 • Pazzani & Billsus 1997 	<p>Commonly used techniques:</p> <ul style="list-style-type: none"> • Bayesian classifiers • Clustering • Decision trees • Artificial neural networks <p>Representative research examples:</p> <ul style="list-style-type: none"> • Pazzani & Billsus 1997 • Mooney et al. 1998 • Mooney & Roy 1999 • Billsus & Pazzani 1999, 2000
Collaborative	<p>Commonly used techniques:</p> <ul style="list-style-type: none"> • Nearest neighbor (cosine, correlation) • Clustering • Graph theory <p>Representative research examples:</p> <ul style="list-style-type: none"> • Resnick et al. 1994 • Hill et al. 1995 • Shardanand & Maes 1995 • Breese et al. 1998 • Nakamura & Abe 1998 • Aggarwal et al. 1999 • Delgado & Ishii 1999 • Pennock & Horwitz 1999 • Sarwar et al. 2001 	<p>Commonly used techniques:</p> <ul style="list-style-type: none"> • Bayesian networks • Clustering • Artificial neural networks • Linear regression • Probabilistic models <p>Representative research examples:</p> <ul style="list-style-type: none"> • Billsus & Pazzani 1998 • Breese et al. 1998 • Ungar & Foster 1998 • Chien & George 1999 • Getoor & Sahami 1999 • Pennock & Horwitz 1999 • Goldberg et al. 2001 • Kumar et al. 2001 • Pavlov & Pennock 2002 • Shani et al. 2002 • Yu et al. 2002, 2004 • Hofmann 2003, 2004
Hybrid	<p>Combining content-based and collaborative components using:</p> <ul style="list-style-type: none"> • Linear combination of predicted ratings • Various voting schemes • Incorporating one component as a part of the heuristic for the other <p>Representative research examples:</p> <ul style="list-style-type: none"> • Balabanovic & Shoham 1997 • Claypool et al. 1999 • Good et al. 1999 • Pazzani 1999 • Billsus & Pazzani 2000 	<p>Combining content-based and collaborative components by:</p> <ul style="list-style-type: none"> • Incorporating one component as a part of the model for the other • Building one unifying model <p>Representative research examples:</p> <ul style="list-style-type: none"> • Basu et al. 1998 • Condliff et al. 1999 • Soboroff & Nicholas 1999 • Ansari et al. 2000 • Popescul et al. 2001

Table : Classification of recommender systems research.

References

- “Evaluating Recommender Systems”, Wen Wu¹, Liang He^{2*}, Jing Yang²
Department of Computer Science and Technology East China Normal University
Shanghai, China¹51111201013@ecnu.cn ²{lhe, [jyang](mailto:jyang@cs.ecnu.edu.cn)}@cs.ecnu.edu.cn
- “Towards the Next Generation of Recommender Systems”: A Survey of the
State-of-the-Art and Possible Extensions Gediminas Adomavicius¹ and
Alexander Tuzhilin²
- Burke, R., 2002: “Interactive Critiquing for Catalog Navigation in e-Commerce”
- Burke, R., 2002: “Hybrid Recommender Systems: Survey and Experiments”
- Herlocker, J. L., J. A. Konstan, A. Borchers, and J. Riedl. An algorithmic framework
for performing collaborative filtering. In *Proc. of the 22nd Annual International ACM
SIGIR Conference on Research and Development in Information Retrieval (SIGIR '99)*.
1999.
- Linden, G., B. Smith, and J. York. Amazon.com Recommendations: Item-to-Item
Collaborative Filtering. *IEEE Internet Computing*, Jan.-Feb. 2003.
- McSherry, D. 2002: “Diversity-Conscious Retrieval”.

