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Foundations and Trends® in Human–Computer Interaction

Published, sold and distributed by:
now Publishers Inc.
PO Box 1024
Hanover, MA 02339
USA
Tel. +1-781-985-4510
www.nowpublishers.com
sales@nowpublishers.com

Outside North America:
now Publishers Inc.
PO Box 179
2600 AD Delft
The Netherlands
Tel. +31-6-51115274

The preferred citation for this publication is M. D. Ekstrand, J. T. Riedl and J. A. Konstan, Collaborative Filtering Recommender Systems, Foundations and Trends® in Human–Computer Interaction, vol 4, no 2, pp 81–173, 2010

ISBN: 978-1-60198-442-5

Foundations and Trends® in Human–Computer Interaction
Volume 4 Issue 2, 2010

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Foundations and Trends® in Human–Computer Interaction, 2010, Volume 4, 4 issues. ISSN paper version 1551-3955. ISSN online version 1551-3963. Also available as a combined paper and online subscription.

Foundations and Trends® in
Human–Computer Interaction
Vol. 4, No. 2 (2010) 81–173

DOI: 10.1561/1100000009

Collaborative Filtering Recommender Systems

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Abstract

Recommender systems are an important part of the information and e-commerce ecosystem. They represent a powerful method for enabling users to filter through large information and product spaces. Nearly two decades of research on collaborative filtering have led to a varied set of algorithms and a rich collection of tools for evaluating their performance. Research in the field is moving in the direction of a richer understanding of how recommender technology may be embedded in specific domains. The differing personalities exhibited by different recommender algorithms show that recommendation is not a one-size-fits-all problem. Specific tasks, information needs, and item domains represent unique problems for recommenders, and design and evaluation of recommenders needs to be done based on the user tasks to be supported. Effective deployments must begin with careful analysis of prospective users and their goals. Based on this analysis, system designers have a host of options for the choice of algorithm and for its embedding in the surrounding user experience. This paper discusses a wide variety of the choices available and their implications, aiming to provide both practicioners and researchers with an introduction to the important issues underlying recommenders and current best practices for addressing these issues.

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1

Introduction

Every day, we are inundated with choices and options. What to wear? What movie to rent? What stock to buy? What blog post to read? The sizes of these decision domains are frequently massive: Netflix has over 17,000 movies in its selection [15], and Amazon.com has over 410,000 titles in its Kindle store alone [7]. Supporting discovery in information spaces of this magnitude is a significant challenge. Even simple decisions — what movie should I see this weekend? — can be difficult without prior direct knowledge of the candidates.

Historically, people have relied on recommendations and mentions from their peers or the advice of experts to support decisions and discover new material. They discuss the week's blockbuster over the water cooler, they read reviews in the newspaper's entertainment section, or they ask a librarian to suggest a book. They may trust their local theater manager or news stand to narrow down their choices, or turn on the TV and watch whatever happens to be playing.

These methods of recommending new things have their limits, particularly for information discovery. There may be an independent film or book that a person would enjoy, but no one in their circle of acquaintances has heard of it yet. There may be a new indie band in another city whose music will likely never cross the local critic's radar. Computer-based systems provide the opportunity to expand the set of people from whom users can obtain recommendations. They also enable us to mine users' history and stated preferences for patterns that neither they nor their acquaintances identify, potentially providing a more finely-tuned selection experience.

There has been a good deal of research over the last 20 years on how to automatically recommend things to people and a wide variety of methods have been proposed [1, 140]. Recently, the *Recommender Systems Handbook* [122] was published, providing in-depth discussions of a variety of recommender methods and topics. This survey, however, is focused primarily on *collaborative filtering*, a class of methods that recommend items to users based on the preferences other users have expressed for those items.

In addition to academic interest, recommendation systems are seeing significant interest from industry. Amazon.com has been using collaborative filtering for a decade to recommend products to their customers, and Netflix valued improvements to the recommender technology underlying their movie rental service at $1M via the widely-publicized Netflix Prize [15].

There is also a growing interest in problems surrounding recommendation. Algorithms for understanding and predicting user preferences do not exist in a vacuum — they are merely one piece of a broader user experience. A recommender system must interact with the user, both to learn the user's preferences and provide recommendations; these concerns pose challenges for user interface and interaction design. Systems must have accurate data from which to compute their recommendations and preferences, leading to work on how to collect reliable data and reduce the noise in user preference data sets. Users also have many different goals and needs when they approach systems, from basic needs for information to more complex desires for privacy with regards to their preferences.

In his keynote address at the 2009 ACM Conference on Recommender Systems, Martin [90] argued that the algorithms themselves are only a small part of the problem of providing recommendations to users. We have a number of algorithms that work fairly well, and while there is room to refine them, there is much work to be done on user experience, data collection, and other problems which make up the whole of the recommender experience.

1.1 History of Recommender Systems

The capacity of computers to provide recommendations was recognized fairly early in the history of computing. Grundy [123], a computer-based librarian, was an early step towards automatic recommender systems. It was fairly primitive, grouping users into "stereotypes" based on a short interview and using hard-coded information about various sterotypes' book preferences to generate recommendations, but it represents an important early entry in the recommender systems space.

In the early 1990s, collaborative filtering began to arise as a solution for dealing with overload in online information spaces. Tapestry [49] was a manual collaborative filtering system: it allowed the user to query for items in an information domain, such as corporate e-mail, based on other users' opinions or actions ("give me all the messages forwarded by John"). It required effort on the part of its users, but allowed them to harness the reactions of previous readers of a piece of correspondence to determine its relevance to them.

Automated collaborative filtering systems soon followed, automatically locating relevant opinions and aggregating them to provide recommendations. GroupLens [119] used this technique to identify Usenet articles which are likely to be interesting to a particular user. Users only needed to provide ratings or perform other observable actions; the system combined these with the ratings or actions of other users to provide personalized results. With these systems, users do not obtain any direct knowledge of other users' opinions, nor do they need to know what other users or items are in the system in order to receive recommendations.

During this time, recommender systems and collaborative filtering became an topic of increasing interest among human–computer interaction, machine learning, and information retrieval researchers. This interest produced a number of recommender systems for various domains, such as Ringo [137] for music, the BellCore Video Recommender [62] for movies, and Jester [50] for jokes. Outside of computer science, the marketing literature has analyzed recommendation for its ability to increase sales and improve customer experience [10, 151].

In the late 1990s, commercial deployments of recommender technology began to emerge. Perhaps the most widely-known application of recommender system technologies is Amazon.com. Based on purchase history, browsing history, and the item a user is currently viewing, they recommend items for the user to consider purchasing.

Since Amazon's adoption, recommender technology, often based on collaborative filtering, has been integrated into many e-commerce and online systems. A significant motivation for doing this is to increase sales volume — customers may purchase an item if it is suggested to them but might not seek it out otherwise. Several companies, such as NetPerceptions and Strands, have been built around providing recommendation technology and services to online retailers.

The toolbox of recommender techniques has also grown beyond collaborative filtering to include content-based approaches based on information retrieval, bayesian inference, and case-based reasoning methods [132, 139]. These methods consider the actual content or attributes of the items to be recommended instead of or in addition to user rating patterns. Hybrid recommender systems [24] have also emerged as various recommender strategies have matured, combining multiple algorithms into composite systems that ideally build on the strengths of their component algorithms. Collaborative filtering, however, has remained an effective approach, both alone and hybridized with content-based approaches.

Research on recommender algorithms garnered significant attention in 2006 when Netflix launched the Netflix Prize to improve the state of movie recommendation. The objective of this competition was to build a recommender algorithm that could beat their internal CineMatch algorithm in offline tests by 10%. It sparked a flurry of activity, both in academia and amongst hobbyists. The \$1 M prize demonstrates the value that vendors place on accurate recommendations.

1.2 Core Concepts, Vocabulary, and Notation

Collaborative filtering techniques depend on several concepts to describe the problem domain and the particular requirements placed on the system. Many of these concepts are also shared by other recommendation methods.

The information domain for a collaborative filtering system consists of *users* which have expressed preferences for various *items*. A preference expressed by a user for an item is called a *rating* and is frequently represented as a (*User*, *Item*, *Rating*) triple. These ratings can take many forms, depending on the system in question. Some systems use real- or integer-valued rating scales such as 0–5 stars, while others use binary or ternary (like/dislike) scales.[1] Unary ratings, such as "has purchased", are particularly common in e-commerce deployments as they express well the user's purchasing history absent ratings data. When discussing unary ratings, we will use "purchased" to mean that an item is in the user's history, even for non-commerce settings such as web page views.

The set of all rating triples forms a sparse matrix referred to as the *ratings matrix*. (*User*, *Item*) pairs where the user has not expressed a preference for (rated) the item are unknown values in this matrix. Figure 1.1 shows an example ratings matrix for three users and four movies in a movie recommender system; cells marked '?' indicate unknown values (the user has not rated that movie).

In describing use and evaluation of recommender systems, including collaborative filtering systems, we typically focus on two tasks. The first is the *predict* task: given a user and an item, what is the user's likely preference for the item? If the ratings matrix is viewed as a sampling of values from a complete user–item preference matrix, than the predict task for a recommender is equivalent to the matrix missing-values problem.

	Batman Begins	*Alice in Wonderland*	*Dumb and Dumber*	*Equilibrium*
User A	4	?	3	5
User B	?	5	4	?
User C	5	4	2	?

Fig. 1.1 Sample ratings matrix (on a 5-star scale).

[1] The scale is ternary if "seen but no expressed preference" is considered distinct from "unseen".

The second task is the *recommend* task: given a user, produce the best ranked list of n items for the user's need. An n-item recommendation list is not guaranteed to contain the n items with the highest predicted preferences, as predicted preference may not be the only criteria used to produce the recommendation list.

In this survey, we use a consistent mathematical notation for referencing various elements of the recommender system model. The universe consists of a set U of users and a set I of items. I_u is the set of items rated or purchased by user u, and U_i is the set of users who have rated or purchased i. The rating matrix is denoted by $\mathbf{R}$, with $r_{u,i}$ being the rating user u provided for item i, $\mathbf{r}_u$ being the vector of all ratings provided by user u, and $\mathbf{r}_i$ being the vector of all ratings provided for item i (the distinction will be apparent from context). $\bar{r}_u$ and $\bar{r}_i$ are the average of a user u or an item i's ratings, respectively. A user u's preference for an item i, of which the rating is assumed to be a reflection, is $\pi_{u,i}$ (elements of the user-item preference matrix $\mathbf{\Pi}$). It is assumed that $r_{u,i} \approx \pi_{u,i}$; specifically, $\mathbf{R}$ is expected to be a sparse sample of $\mathbf{\Pi}$ with the possible addition of noise. The recommender's prediction of $\pi_{u,i}$ is denoted by $p_{u,i}$.

1.3 Overview

This survey aims to provide a broad overview of the current state of collaborative filtering research. In the next two sections, we discuss the core algorithms for collaborative filtering and traditional means of measuring their performance against user rating data sets. We will then move on to discuss building reliable, accurate data sets; understanding recommender systems in the broader context of user information needs and task support; and the interaction between users and recommender systems.

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