Paul Resnick and Hal R. Varian, Guest Editors

Recommender Systems

IT IS OFTEN NECESSARY TO MAKE CHOICES WITHOUT SUFFICIENT personal experience of the alternatives. In everyday life, we rely on recommendations from other people either by word of mouth, recommendation letters, movie and book reviews printed in newspapers, or general surveys such as *Zagat's* restaurant guides.

Recommender systems assist and augment this natural social process. In a typical recommender system people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients. In some cases the primary transformation is in the aggregation; in others the system's value lies in its ability to make good matches between the recommenders and those seeking recommendations.

The developers of the first recommender system, Tapestry [1], coined the phrase "collaborative filtering" and several others have adopted it. We prefer the more general term "recommender system" for two reasons. First, recommenders may not explictly collaborate with recipients, who may be unknown to each other. Second, recommendations may suggest particularly interesting items, in addition to indicating those that should be filtered out.

This special section includes descriptions of five recommender systems. A sixth article analyzes incentives for provision of recommendations.

Figure 1 places the systems in a technical design space defined by five dimensions. First, the contents of an evaluation can be anything from a single bit (recommended or not) to unstructured textual annotations. Second, recommendations may be entered explicitly, but several systems gather implicit evaluations: GroupLens monitors users' reading times; PHOAKS mines Usenet articles for mentions of URLs; and Siteseer mines personal bookmark lists. Third, recommendations may be anonymous, tagged with the source's identity, or tagged with a pseudonym. The fourth dimension, and one of the richest areas for exploration, is how to aggregate evaluations. GroupLens, PHOAKS, and Siteseer employ variants on weighted voting. Fab takes that one step further to combine evaluations with content analysis. ReferralWeb combines suggested links between people to form longer referral chains. Finally, the (perhaps aggregated) evaluations may be used in several ways: negative recommendations may be filtered out, the items may be sorted according to numeric evaluations, or evaluations may accompany items in a display.

Figures 2 and 3 identify dimensions of the domain space: The kinds of items being recommended and the people among whom evaluations are shared. Consider, first, the domain of items. The sheer volume is an important variable: Detailed textual reviews of restaurants or movies may be practical, but applying the same approach to thousands of daily Netnews messages would not. Ephemeral media such as netnews (most news servers throw away articles after one or two weeks) place a premium on gathering and distributing evaluations quickly, while evaluations for 19th century books can be gathered at a more leisurely pace. The last dimension describes the cost structure of choices people make about the items. Is it very costly to miss a good item or sample a bad one? How do those costs compare to the benefits of hitting a good one? This cost structure is likely to interact with technical design choices. For example, when the costs of incorrect decisions are high, as they would be, say, with evaluations of medical treatments, evaluations that convey more nuances are likely to be more useful.

Next, consider the set of recommendations and the people providing and consuming them. Who provides recommendations? Do they tend to evaluate many items in common, leading to a dense set of recommendations? How many consumers are there, and do their tastes vary? These factors also will interact with technical choices. For example, matching people by tastes automatically is far more valuable in a larger set of people who may not know each other. Personalized aggregation of recommendations will be more valuable when people's tastes differ than when there are a few experts.

Social Implications

Recommender systems introduce two interesting incentive problems. First, once one has established a profile of interests, it is easy to free ride by consuming evaluations provided by others. Moreover, as Avery and Zeckhauser argue, this problem is not entirely solved even if evaluations are gathered implicitly from existing resources or from monitoring user behavior. Future systems will likely need to offer some incentive for the provision of recommendations by making it a prerequisite for receiving recommendations or by offering monetary compensation. Second, if anyone can provide recommendations, content owners may generate mountains of positive recommendations for their own materials and negative recommendations for their competitors. Future systems are likely to introduce precautions that discourage the "vote early and often" phenomenon.

Recommender systems also raise concerns about personal privacy. In general, the more information individuals have about the recommendations, the better they will be able to evaluate those recommendations. However, people may not *want* their habits or views widely known. Some recommender systems permit anonymous participation or participation under a pseudonym, but this is not a complete solution since some people may desire an intermediate blend of privacy and attributed credit for their efforts.

Both incentive and privacy problems arise in an evaluation-sharing system familiar to our readers: the peer review system used in academia. With respect to incentives, every editor knows the best source for a prompt and careful review is an author who currently has an article under consideration. With respect to privacy, blind and double-blind refereeing are common practices. These practices evolved to solve problems inherent to the refereeing process, and it may be worthwhile to consider ways to incorporate such practices into automated systems.

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Figure 1. The technical design space

	Contents of recommendation	Explicit entry?	Anonymous?	Aggregation	Use of recommendations
GroupLens	a) numeric: 1–5 b) seconds	a) explicit b) monitor reading time	pseudonymous	personalized weighting based on past agreement among recommenders	display alongside articles in existing summary views
Fab	numeric: 1–7	explicit	pseudonymous	personalized weighting; combined with content analysis	selection/ filtering
ReferralWeb	mention of a person or a document	mined from public data sources	attributed	assemble referral chain to desired person	display
PHOAKS	mention of a URL	mined from usenet postings	attributed	one person one vote (per URL)	sorted display
Siteseer	mention of a URL	mined from existing bookmark folders	anonymous	frequency of mention in overlapping folders	display

	Type of items	How many	Lifetime	Cost structure
GroupLens	netnews articles	thousands per day	1–2 weeks	misses unimportant false positive very small cost hits small value
PHOAKS, SiteSeer, Fab	URLs	hundreds per day	2 days–2 yesars	misses unimportant false positives small cost hits medium value
ReferralWeb	people	a few million reachable on-line	many years	depends on how referral chain will be used

Figure 2. The domain space—characteristics of items evaluated

	Recommenders	Density of recommendations	Consumers	Comsumer Taste variability
GroupLens	All subscribers	somewhat dense within newsgroup	Subscribers	high for some newsgroups
Fab	All subscribers	somewhat dense among people served by same collector agent	Subscribers	unknown
ReferralWeb	All authors of on-line documents	reflects density of underlying social network	Any Web user	unknown
PHOAKS	All usenet authors	extremely sparse	Any Web user	unknown
Siteseer	All subscribers	sparse	Subscribers	high

Figure 3. The domain space—characteristics of the participants and the set of evaluations

between unbiased recommendations and advertisements in order to maintain credibility with their readers.

There are economies of scale in recommender systems: The bigger the set of users, the more likely I am to find someone like me. Hence, other things being equal, I would prefer to use the biggest system. When several recommender systems start to compete in a given market, we should expect to see very intense competition since there is likely to be only one eventual survivor. This argument suggests that a possible market structure will be one or two big players in each medium or subject area who then subcontract with sellers of products to provide recommendations as a value-added service. For example, a book rating/review service might operate autonomously and sell its recommendation services to a number of independent online bookstores. It should be noted the independence of the rating/review service may also help to solve the problem of credibility.

A flurry of commercial ventures have recently introduced recommender systems for products ranging from Web URLs to music, videos, and books. In the coming years, we can look forward to continued technical innovation, and a better understanding of which technical features are best suited to various characteristics of the items evaluated and the people who participate in the process. ■

Business Models

Maintenance of a recommender system is costly, and it is worth thinking about what business models might be used to generate revenues sufficient to cover those costs. One model is to charge recipients of recommendations either through subscriptions or pay-per-use. A second model for cost recovery is advertiser support, as Firefly (http://www.firefly.com) seems to provide. Presumably advertisers would find such systems very useful since they generate detailed marketing information about consumers. If a user revealed a taste for, say, cyberpunk books, publishers could make sure the users saw ads targeted to that market. A third model is to charge a fee to the owners of the items being evaluated. For example, filmmakers pay a fee for official ratings of their movies.

The latter two business models both carry a danger of corruption. Mass market computer magazines that carry ads and reviews are often accused of biasing reviews toward companies that are heavy advertisers. In this case, the perception of bias is almost as bad as the reality. Recommender systems that collect fees from advertisers or others who may have a vested interest in the contents of the recommendations must be very careful to make sure that users recognize the difference

Reference

1. Goldberg, D. Nichols, D., Oki, B. M., and Terry, D. Using collaborative filtering to weave an information tapestry. *Commun. ACM 35*, 12 (Dec.1992), 61—70.

Paul Resnick (presnick@research.att.com) works for AT&T Labs-Research in Murray Hill, N.J.

Hal R. Varian (hal@sims.berkeley.edu) is Dean of the School of Information Management and Systems at the University of California, Berkeley.