PROVIDING A SERVICE FOR INTERACTIVE ONLINE DECISION AIDS THROUGH ESTIMATING CONSUMERS' INCREMENTAL SEARCH BENEFITS

Completed Research Paper

Hao Wang
Tsinghua University
School of Economics and Management
Beijing, China
wangh6.06@sem.tsinghua.edu.cn

Xunhua Guo
Tsinghua University
School of Economics and Management
Beijing, China
guoxh@sem.tsinghua.edu.cn

Qiang Wei
Tsinghua University
School of Economics and Management
Beijing, China
weiq@sem.tsinghua.edu.cn

Guoqing Chen
Tsinghua University
School of Economics and Management
Beijing, China
chengq@sem.tsinghua.edu.cn

Abstract

Consumer information search has been a focus of research nowadays, especially in the context of online business environments. One of the research questions is to determine how much information to search (i.e., when to stop searching), since extensive literature on behavior science has revealed that consumers often search either "too little" or "too much", even with the help of existing interactive online decision aids (IODAs). In order to address this issue, this paper introduces a new approach to IODAs with effective estimation of the incremental search benefits. In doing so, the approach incorporates two important aspects into consideration, namely point estimation and distribution estimation, so as to make use of the relevant information by combining both current and historical facts in reflecting the behavioral patterns of the consumers in search. Moreover, experiments based on data provided by Netflix illustrate that the proposed approach is effective and advantageous over existing ones.

Keywords: Business intelligence, consumer information search, consumer decision support, incremental benefits of search, benefit estimation, interactive online decision aids

Introduction

Consumer information search (CIS) , the process through which a consumer surveys his or her environment for appropriate information to select a product or service from available options (De Bruyn et al. 2008; Solomon 1999), has attracted numerous research efforts in economics, management science, information science, marketing science, etc., for decades (Adam 2001; Bakos 1997; Diehl 2005; Diehl and Zauberman 2005; Huang et al. 2009; Janssen and Non 2009; Kim et al. 2010; Lynch Jr and Ariely 2000; McCall 1970; Punj and Staelin 1983; Stigler 1961; Wang and Benbasat 2009). CIS incurs both benefits and costs to consumer decision making, and the net benefits (the benefits minus the corresponding costs incurred by CIS) are what consumers want to increase during the process of search (Fox and Hoch 2005; Kim et al. 2010; Nelson 1970; Ratchford 1982; Ratchford and Srinivasan 1993; Stigler 1961).

In order to help consumers increase the net benefits of CIS in the context of pervasive e-business applications nowadays, interactive online decision aids (IODAs), a special type of information systems for business decision support involving services of comparison shopping agents, search engines and recommender systems, are widely developed and adopted by e-retailers and information intermediaries, such as Amazon, Netflix and PriceGrabber (Haubl and Trifts 2000; Iyer and Pazgal 2003; Montgomery et al. 2004; Wang and Benbasat 2009; Xiao and Benbasat 2007). With the help of IODAs, consumers could search for and choose from options that are sequentially sorted from best to worst based on specific ranking principles (Diehl and Zauberman 2005). For example, comparison shopping agents rank relevant products based on their prices (Montgomery et al. 2004); search engines and recommender systems sort the products a consumer may prefer according to the products' relevance scores or estimated ratings (Adomavicius and Tuzhilin 2005; Salton 1991). Theoretically, the ordered set provided by IODAs would increase the expected net benefits of CIS (Weitzman 1979). Empirical studies have also revealed that IODAs could reduce search effort, lower transaction price and improve choice quality (Gordon and Lenk 1991; Haubl and Trifts 2000).

Although information systems such as IODAs are generally considered helpful and are increasingly becoming a key element for online services, which would play an important role in gaining customer satisfaction and competitive advantage, related studies have shown that consumers are still searching either "too much" or "too little" (Diehl 2005; Diehl and Zauberman 2005; Zwick et al. 2003). On the one hand, considering the fact that products and services are becoming more and more "personalized" and "customized", searching more would increase the net benefits of CIS for the consumers who search "too little". On the other hand, considering the fact that the costs of CIS are still high, especially the cognitive costs for processing information and the opportunity costs of time spent on information search, searching less would increase the net benefits of CIS for the consumers who search "too much" (Diehl 2005; Klein and Ford 2003; Montgomery et al. 2004; Punj and Moore 2009).

In search, an effective strategy is twofold: 1) selection sub-strategy, i.e., the order of products to inspect; 2) stopping sub-strategy, i.e., when to stop inspecting products (Weitzman 1979). Notably, existing IODAs mainly focus on the former, whereas the latter witnesses little or insufficient progress (Browne et al. 2007; Haubl and Trifts 2000). Theoretically, a consumer should stop searching when the expected incremental benefits of search are less than the corresponding costs (Huang et al. 2009; Moorthy et al. 1997; Ratchford et al. 2003; Stigler 1961). Unfortunately, consumers themselves are usually unable to accurately estimate the incremental benefits of search and therefore tend to perform far from the optimal search strategy (Zwick et al. 2003).

For example, suppose that a consumer wants to select a movie to watch in the weekend and gets a list of ordered recommendations with descending ratings estimated by a recommender system from *Netflix* or *MovieLens*. After having inspected several top items in the list, e.g., reading the descriptions, reviews, ratings and other information about these movies, the consumer may wonder whether she or he should continue inspecting more items in the list or not. Without external supports, the consumer, with limited information she or he possesses at hand about the whole list of movies and their potential values, might make the stopping decision based on her or his intuitively estimated incremental benefits of search, which could lead to a result far from the optimal search.

In this paper, we propose a new prediction approach as a service of IODAs, which is capable of effectively estimating the incremental benefits of continued search. Such a service would create value for both consumers and merchants (Huang et al. 2007; Punj and Moore 2009), since search quality, and consequently consumer satisfaction and royalty, would be improved by narrowing down the gap due to the "too much" - "too little" problem (Lal and Sarvary 1999; Montazemi et al. 2008; Punj and Moore 2009; Zhang and Wedel 2009). For illustrative purposes, Figure 1 depicts the framework of the consumer decision process, where the elements related to our current work are highlighted as boxes in bold.

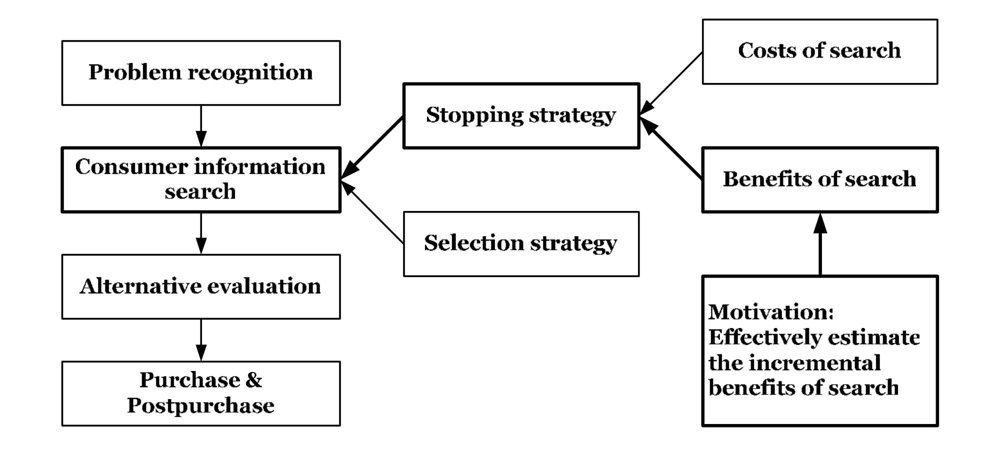

Figure 1. The Position of the Study in Consumer Decision Process

This paper is organized as follows. Related literature and the notations of incremental benefits of search are introduced in next section. Subsequently, our new approach to estimating incremental benefits is presented, followed by the experiments based on real data obtained from *Netflix*. The last section provides some discussion on future work and concludes the paper.

Related Literature and Notations

Benefits of CIS

Generally speaking, in marketing research and other business domains, the benefits of CIS are considered difficult to measure (Ratchford and Srinivasan 1993). The benefits of CIS may include, for instance, a lower price for a given product, a preferred style of merchandise, a higher-quality product, and greater confidence in the choice (Ratchford and Srinivasan 1993). Assuming that a consumer only selects one product after each search process, traditional studies in economics, management science and marketing science use the expected value of the maximum of all the inspected products' utilities as the expected benefits of CIS (Hauser and Wernerfelt 1990; Nelson 1970; Ratchford 1982).

Formally, suppose that the set of consumers is C and the set of products is S, where $|C| = M$ and $|S| = N$. The utilities of product $s \in S$ to consumer $c \in C$ after browsing, after inspecting and after purchasing, are denoted as $\tilde{\tilde{u}}_{cs}$, $\tilde{u}_{cs}$, u_{cs}, respectively, which are usually assumed to be random variables in previous studies. For convenience, $\tilde{\tilde{u}}_{cs}$, $\tilde{u}_{cs}$, u_{cs}, are also named browsed utility, inspected utility and experienced utility of product s to consumer c (Hauser and Wernerfelt 1990; Salisbury and Feinberg 2010). $\tilde{\tilde{u}}_{cs}$ is an important factor which largely affects whether product s would be inspected by consumer c, and $\tilde{u}_{cs}$ is a factor which largely affects whether product s would be purchased by consumer c. Usually, consumer c inspects s if $\tilde{\tilde{u}}_{cs}$ exceeds some threshold and selects s if $\tilde{u}_{cs}$ is the highest utility of all inspected ones when stopping searching. u_{cs} is the utility of product s to consumer c after purchasing and experiencing it.

Suppose that after inspecting a set of products, say $S_1 \subseteq S$, consumer c selects the product s_1* where $s_1* \in \arg\max_{s \in S_1}(\tilde{u}_{cs})$ ($\arg\max_{x \in X} f(x) = \{x \mid \forall z \in X : f(z) \le f(x)\}$). The benefits of inspecting S_1 to consumer c are $B(c, S_1) = u_{cs_1*}e^{-d|S_1|} - B(c, \varnothing)$, where d is the discount rate of inspecting a product (discount rate of inspecting a product is used to convert benefits to present values after searching), $B(c, \varnothing)$ is the default benefits if consumer c inspects no products. d can be estimated by the interest rate and the time of inspecting a product on average (Hauser and Wernerfelt 1990; Moe 2006; Weitzman 1979), i.e., $d \approx \frac{i}{1+i}\frac{t}{T}$, where i is the annual interest rate, T is the time of one year, t is the time of inspecting a product to consumer c on average. Usually, $i << 1$ and $t << T$ during search, so $d \approx 0$. Therefore, the benefits of inspecting S_1 to consumer c can be expressed as $B(c, S_1) = u_{cs_1*} - B(c, \varnothing)$.

Suppose that after inspecting S_1, consumer c does not select product s_1* but continues to inspect another set of products, $S_2 \subseteq S$, and selects the products s_2* where $s_2* \in \arg\max_{s \in S_1 \cup S_2}(\tilde{u}_{cs})$. Then, the benefits of inspecting $S_1 \cup S_2$ to consumer c are $B(c, S_1 \cup S_2) = u_{cs_2*} - B(c, \varnothing)$. Therefore, the incremental benefits of inspecting S_2 after inspecting S_1 to consumer c are $B(c, S_2 \mid S_1) = B(c, S_1 \cup S_2) - B(c, S_1) = u_{cs_2*} - u_{cs_1*}$.

Considering consumers' limited information processing and decision making capability, usually the purchased product may not be the one with the highest experienced utility of all inspected products, i.e. $u_{cs_1*} \le \max_{s \in S_1}(u_{cs})$ (Bettman et al. 1998; Guadagni and Little 2008; Moe 2006). Since the influence of consumers' capabilities on their choices is very hard to measure, most existing studies simply assume that the consumer can select the product with highest experienced utility of all inspected ones, i.e. $u_{cs_1*} = \max_{s \in S_1}(u_{cs})$ (Hauser and Wernerfelt 1990; Kim et al. 2010; Nelson 1970; Ratchford 1982). Therefore, the benefits of inspecting S_1 to consumer c are $B(c, S_1) = \max_{s \in S_1}(u_{cs}) - B(c, \varnothing)$; the incremental benefits of inspecting S_2 after inspecting S_1 to consumer c are $B(c, S_2 \mid S_1) = B(c, S_1 \cup S_2) - B(c, S_1) = \max_{s \in S_1 \cup S_2}(u_{cs}) - \max_{s \in S_1}(u_{cs})$.

For example, an online recommender system offers a very long list of movies to consumer c who wants to select one. The list and the corresponding browsed utilities, inspected utilities and experienced utilities are illustrated in Table 1. Considering the costs of search and the large number of recommendations, the consumer cannot inspect all recommended movies but may browse the list and select some to inspect (inspecting the movies may involve reading descriptions, ratings and reviews, or watching trailers and samples). After browsing the top 3 recommendations, the consumer decides to inspect movie 1 and movie 3, which are more attractive in terms of browsed utilities. After inspecting these two movies, the consumer finds that movie 3 is the best of all inspected ones. Therefore, the benefits of inspecting the two movies for the consumer are $B(c, S_1) = u_{c\text{Mv3}} - B(c, \varnothing)$, where $S_1 = \{\text{Mv1, Mv3}\}$. Suppose that the consumer decides to search more, and therefore browses another two movies, movies 4 and 5, and decides to inspect movie 5. After inspecting movie 5, the consumer finds that movie 5 is worse than movie 3. For the consumer, the incremental benefits of inspecting movie 5, given having inspected movies 1 and 3, are $B(c, S_2 \mid S_1) = B(c, S_2 \cup S_1) - B(c, S_1) = u_{c\text{Mv3}} - u_{c\text{Mv3}} = 0$, where $S_1 = \{\text{Mv1, Mv3}\}$, $S_2 = \{\text{Mv5}\}$. Then, the consumer stops searching and purchases movie 3. After watching movie 3, the consumer feels that the experienced utility of this movie is 4, i.e., $u_{c\text{Mv3}} = 4$.

It is worth noting that $\tilde{\tilde{u}}_{cs}$, $\tilde{u}_{cs}$ and $u_{c,s}$ are all used as utility variables by research models to explain or predict consumer behavior. Consumers themselves may not, or not explicitly, use these variables during search. However, the models built on them were found to explain and predict consumer behavior very well, which indicates that these assumptions are reasonable (Bettman et al. 1998; Guadagni and Little 2008; Kim et al. 2010; Moe 2006).

Table 1. Browsed Utilities, Inspected Utilities and Experienced Utilities of Movies to Consumer c

Products	$\tilde{\tilde{u}}_{cs}$	$\tilde{u}_{cs}$	u_{cs}
Mv1	1	4	∅
Mv2	0	∅	∅
Mv3	1	5	4
Mv4	0	∅	∅
Mv5	1	3	∅
…	…	…	…

As discussed above, incremental benefits of CIS depend on the experienced utilities of products to consumers, which are difficult to measure (Samuelson and Nordhaus 2001; Stiglitz 1997). Traditional studies in marketing science usually treat the experience utilities as latent variables to predict consumer behavior without directly measuring them (Hauser et al. 2010; Kim et al. 2010; Moe 2006; Salisbury and Feinberg 2010). Some studies used survey data from consumers to measure the experienced utilities of products (Foxall and James 2003; Lynch Jr and Ariely 2000; Ratchford and Srinivasan 1993), which might be inconvenient and relatively biased (Moe 2006). With the development of IODAs, consumers' ratings on purchased products could be used to explicitly represent and measure products' experienced utilities (Adomavicius and Tuzhilin 2005; Bhattacharjee et al. 2006). For example, after watching a movie, the consumer selects a number in a rating scale to reflect his experienced utility of the movie. The rating scale, denoted as $K = \{1, 2, \ldots, k\}$, is 1-10 on *IMDb* and 1-5 on *Netflix* and *MovieLens* (Adomavicius and Tuzhilin 2005). Given the ratings as an explicit measure of products' utilities, the incremental benefits of search can be expressed as

$$B\left(c, S_2 \mid S_1\right) = B\left(c, S_2 \cup S_1\right) - B\left(c, S_1\right) = \max_{s \in S_2 \cup S_1}\left(r_{cs}\right) - \max_{s \in S_1}\left(r_{cs}\right) \tag{1}$$

where r_{cs} is the rating for product s from consumer c .

IODAs

Interactive online decision aids (IODAs) are a special type of decision support system (DSS), aimed at facilitating consumers' decision making (Wang and Benbasat 2009; Xiao and Benbasat 2007). These aids elicit the preferences of consumers for products, either explicitly or implicitly, carry out a set of search and evaluation operations on behalf of consumers, and provide consumers with product recommendations ordered by some ranking principles (Wang and Benbasat 2009; Xiao and Benbasat 2007). Compared with traditional information search process described by Stigler (1961), selecting favorite products from the ordered list of recommendations provided by IODAs leads to less search efforts, more available alternatives, and better final decision (Fleder and Hosanagar 2009; Haubl and Trifts 2000; Montgomery et al. 2004), thereby increases the net benefits of CIS to consumers.

IODAs can be classified into three groups by their main functions: comparison shopping agents, search engines and recommender systems (Haubl and Trifts 2000; Montgomery et al. 2004; Wang and Benbasat 2009). Comparison shopping agents (such as Shopzilla and PriceGrabber), also known as shopbots, assist consumers in comparing prices and other attributes of products offered by a large number of online sellers (Montgomery et al. 2004). Search engines (such as Google and Bing) select and rank products for consumers according to the relevance between their input key words (named search queries) and the descriptions of the products (Deshpande and Karypis 2004; Wang et al. 2008). Recommender systems (such as those provided by *Amazon*, *Netflix* and *MovieLens*), also known as recommender agents, recommendation systems, or recommendation agents, provide consumers with a list of products that they may prefer (Adomavicius and Tuzhilin 2005). These recommendations are selected and ranked based on consumers' historical behavior, e.g., browsing, purchasing and rating (Adomavicius and Tuzhilin 2005; Fleder and Hosanagar 2009; Huang et al. 2007). It is worth noting that many existing e-retailers and information intermediaries, such as *Amazon*, *Netflix* and *PriceGrabber*, have combined the three types of IODAs into an integrated one which offers all the services of comparison, search and recommendation.

In the perspective of computer science, the main task of IODAs is to rank products for consumers according to their interests and preferences, from most preferred to least. The task is relatively easy for comparison shopping agents, for the order of provided products are determined by consumers' requests. For instance, consumers can use comparison shopping agents to rank products by their prices or sales volume.

Different from comparison shopping agents, search engines receive no direct ranking rules but only search queries from consumers (Robertson and Zaragoza 2007; Wang et al. 2008). Search engines rank products by the relevance between search queries and descriptions of products, based on the assumption that the queries reflect consumers' needs and preference, and the more relevant a product's descriptions are, the more likely it may satisfy the consumers' needs and be purchased (Robertson and Zaragoza 2007; Wang et al. 2008). In order to measure relevance, all search queries and products' descriptions are usually converted into weight vectors with the tf-idf model (Salton 1991), a model used in information retrieval to reflect the main features of text documents, and the relevance between a search query and a product's description is estimated by the cosine similarity between their corresponding vectors (Salton 1991).

Compared with the first two, recommender systems receive no explicit requests from consumers, let alone direct ranking rules. Instead, recommender systems implicitly use consumers' behavior records (such as purchasing or rating records) to estimate consumers' preferences (ratings) to products and rank recommendations according to the estimated ratings (Adomavicius and Tuzhilin 2005; Fleder and Hosanagar 2009; Huang et al. 2007). For instance, Netflix and MovieLens recommend a list of movies to a consumer based on the movies' predicted ratings from the consumer generated by some business intelligence (BI) methods. One of the BI methods widely used to predict consumers' ratings for movies is collaborative filtering based on the assumption that consumers with similar tastes in the past tend to have similar tastes in the future (Adomavicius and Tuzhilin 2005; Jahrer et al. 2010). Therefore, a consumer's rating for a movie can be predicted by the other "similar" consumers' ratings for the same movie and for other "similar" movies.

A New Approach to Estimating Benefits of CIS

As shown above, Equation (1) indicates that the main task of estimating the incremental benefits of search is reduced to estimate the maximum utilities of inspected products, $\max_{s\in S_1}(r_{cs})$. Since r_{cs} is unknown until consumer c watches and rates the product s, an approach aimed at effectively estimating $B(c,S_2 \mid S_1)$ needs to estimate $\max_{s\in S_1}(r_{cs})$ first. Given an approach (APP) which is developed to estimate $B(c,S_2 \mid S_1)$, the corresponding estimation can be expressed as

$$\hat{B}^{APP}(c,S_2 \mid S_1) = E\left(B(c,S_2 \mid S_1) \mid APP\right) = E\left(\max_{s\in S_2\cup S_1}(r_{cs}) \mid APP\right) - E\left(\max_{s\in S_1}(r_{cs}) \mid APP\right) \quad (2)$$

where $E\left(\max_{s\in S_1}(r_{cs}) \mid APP\right)$ is the expected value of $\max_{s\in S_1}(r_{cs})$ estimated by APP.

Equation (2) indicates that estimations of the same incremental benefits may be different when different approaches are used, which is reasonable. This is comparable to the case that different weather forecasters may present different predictions of the probability of rain at the same location on the same day (DeGroot and Fienberg 1983). In other words, some forecasters may predict better than others.

As mentioned before, prediction approaches for CIS in the computer science area, such as search engines and recommender systems, are built on some basic assumptions, e.g., consumers with similar tastes in the past tend to have similar tastes in the future. Similarly, prediction approaches in economics, management science and marketing science also rely on some basic assumptions. For example, many approaches assume that utilities (ratings) of the same product for consumers are independent and obey the same distribution determined by the product's characteristics; utilities of different products are independent (Adam 2001; Weitzman 1979). In this paper, our approach is developed on a reasonable assumption which follows the idea of latent sematic analysis (Hofmann 2004) and is formulated as follows:

Assumption 1

> Unknown ratings (r_{cs}'s) belong to some disjoint groups, named latent classes. Given these latent classes, ratings in the same class can be viewed as independent and identically distributed (i.i.d.) random variables and ratings in different classes are independent.

Assumption 1 is a generalization of some widely used assumptions in the research area of CIS from the perspectives of information systems, economics, management science and marketing science (Adam 2001; Adomavicius et al. 2011; Fleder and Hosanagar 2009; Hofmann 2004; Kramer et al. 2007; Stigler 1961; Wang et al. 2008; Weitzman 1979). For example, some related studies assume that consumers belongs to different disjoint groups and ratings for a product from consumers in the same consumer group obey the same distribution while ratings from consumers in different consumer groups are independent; other studies assume that products belong to different disjoint groups, and ratings from a consumer for products in the same product group obey the same distribution while ratings for products in different product groups are independent (Adomavicius et al. 2011; Fleder and Hosanagar 2009; Hofmann 2004; Kramer et al. 2007; Wang et al. 2008). By and large, these assumptions are special cases of Assumption 1, as they all satisfy that ratings belong to disjoint groups which are determined by the ratings' corresponding consumers (or the ratings' corresponding products) and the consumer groups (or the product groups). Meanwhile, ratings in the same group obey the same distribution while ratings in different groups are independent to each other. Moreover, in Assumption 1, the latent classes of ratings can also be found based on their context information (Adomavicius and Tuzhilin 2005), such as when or where to purchase the product, besides their corresponding consumers or movies.

Given this assumption, researchers may use clustering/classification methods to find out the disjoint groups (latent classes). Examples of effective (general-purpose) methods include k-means, DBSCAN, and their variations for clustering, as well as Decision Tree, SVM, CBA, GARC, etc., for classification (Chen et al. 2006; Hastie et al. 2003; Vapnik 1995). It is worth mentioning that different clustering/classification methods may result in different latent classes and their corresponding performances for predicting ratings are different. A clustering/classification method is said to satisfy Assumption 1 if it can find the latent classes which satisfy the requirements as stated in Assumption 1.

Suppose that a clustering/classification method *CL* satisfies Assumption 1 and the corresponding set of rating groups generated by *CL* is G. Let $P_g(x)$ denote the probability distribution function that ratings obey in group $g \in G$. For a rating r_{cs}, the group $g \in G$ that contains r_{cs} is $g = CL(r_{cs})$. Given these notations, the algorithm of *NTP* to estimate the benefits of search is presented in Figure 2.

Given Assumption 1,

$$E\left(\max_{s\in S_1}(r_{cs}) \mid NTP\right) = E\left(\max_{s\in S_1}(r_{cs}) \mid CL\right) = E\left(\max_{s\in S_1}(r_{cs}) \mid G\right) = \sum_{x=1}^{\infty}\left(1-\prod_{s\in S_1} P_{CL(r_{cs})}(r_{cs} < x)\right) \tag{3}$$

To illustrate the algorithm, suppose that the rating scale is $K = \{1, 2, \ldots, k\}$ and a specific *CL* clusters ratings into k groups, i.e., $G = \{g_1, \ldots, g_k\}$, where $r_{cs} \in g_i$ if and only if $r_{cs} = i$, $i \in K$. In this case, the probability distribution in each group is a degenerated distribution, i.e., $P_{g_i}(x) = 1$ if $x = i$ and $P_{g_i}(x) = 0$ if $x \neq i$. Given a consumer c and a set of products S_1 to inspect, $CL(r_{cs}) = g_{r_{cs}}$, $\forall s \in S_1$.

1. Selecting (or developing) a clustering/classification method *CL* which is used to group ratings;
2. Training *CL* on historical data so that given an unknown rating r_{cs} its corresponding group $CL(r_{cs})$ is determined;
3. Estimating the probability distribution of ratings in each group based on historical data, i.e., estimate $P_g(x)\ \forall g \in G$;
4. Calculating $E\left(\max_{s\in S_1}(r_{cs}) \mid NTP\right)$ and $E\left(\max_{s\in S_2\cup S_1}(r_{cs}) \mid NTP\right)$ with equation (3)
5. $\hat{B}^{NTP}(c,S_2 \mid S_1) = E\left(\max_{s\in S_2\cup S_1}(r_{cs}) \mid NTP\right) - E\left(\max_{s\in S_1}(r_{cs}) \mid NTP\right)$.

Figure 2. The Algorithm of *NTP*

Therefore, we have $E\left(\max_{s\in S_1}(r_{cs}) \mid NTP\right) = \sum_{x=1}^{\infty}\left(1-\prod_{s\in S_1} P_{CL(r_{cs})}(r_{cs} < x)\right) = \max_{s\in S_1}(r_{cs})$ and $\hat{B}^{NTP}(c,S_2 \mid S_1) = E\left(\max_{s\in S_2\cup S_1}(r_{cs}) \mid NTP\right) - E\left(\max_{s\in S_1}(r_{cs}) \mid NTP\right) = \max_{s\in S_2\cup S_1}(r_{cs}) - \max_{s\in S_1}(r_{cs})$. Compared with Equation (1), it indicates that the *NTP* can achieve the performance that its estimations of incremental benefits of search predicted are the same as the actual incremental benefits of search, i.e., $\hat{B}^{NTP}(c,S_2 \mid S_1) = B(c,S_2 \mid S_1)$.

It is worth noting that some methods in computer science and economics could be adapted to fit the work of estimating the benefits and incremental benefits of CIS, although they were originally developed for other purposes. For example, point-estimation methods, e.g., collaborative filtering, were originally developed to predict the ratings of consumer/movie pairs. In order to predict the benefits of inspecting a set of movies, we may aggregate the estimated ratings of these movies generated by the point-estimation method and take the largest estimated rating as the estimated benefits of inspecting these movies for the consumer. Besides, estimating the distribution of the maximum of a set of variables, instead of directly estimating each variable, is widely used in economics. The distribution-estimation method could also be used to estimate the benefits and incremental benefits of CIS.

More concretely, in order to estimate $\max_{s\in S_1}(r_{cs})$, the first type of prediction approach (hereafter referred to as *FTP*) relies on estimating consumers' ratings on non-rated products (i.e., unknown r_{cs}). Suppose $\hat{r}_{cs}^{RP}$ is the estimation of r_{cs} predicted by a rating prediction method (hereby referred to as *RP*), such as a collaborative filtering algorithm used in the *Netflix Prize* contest. Then the estimation of $\max_{s\in S_1}(r_{cs})$ generated by a *FTP* based on a *RP* is

$$E\left(\max_{s\in S_1}(r_{cs}) \mid FTP\right) = E\left(\max_{s\in S_1}(r_{cs}) \mid RP\right) = \max_{s\in S_1}\left(\hat{r}_{cs}^{RP}\right) \tag{4}$$

One problem for *FTP* is that existing *RP*s still have a long way to go to be perfect (Jahrer et al. 2010). Even the *RP* of the Grand Prize winner of *Netflix Prize* contest only achieves a root-mean-square error (RMSE) of 0.8567 in a rating scale of 1-5 (RMSE is the square root of the averaged squared difference between each prediction and the actual value. $RMSE = \sqrt{E\left(\left(\hat{\theta}-\theta\right)^2\right)}$, where $\hat{\theta}$ is the estimation of the actual θ. For details please refer to http://www.netflixprize.com). It has also been noted that with only *RP*s (let along they are usually far from the optimal), the incremental benefits of search could hardly be estimated in a satisfactory manner (Vovk 2004; Vovk 2009).

On the other hand, a second type prediction approach (hereafter referred to as *STP*) relies on estimating the distribution of $\max_{s\in S_1}(r_{cs})$, instead of directly estimating each r_{cs}. Specifically, such an *STP* assumes that each r_{cs} obeys a distribution function of $P_s(x)$, where $x \in K = \{1, 2, \ldots, k\}$ and K is the rating scale. Moreover, unknown ratings for different products are assumed to be independent and $P_s(x)$ can be effectively estimated from historical data. Given the distribution estimation (*DE*), the distribution of $E\left(\max_{s\in S_1}(r_{cs}) \mid STP\right)$ is $\Pr\left(E\left(\max_{s\in S_1}(r_{cs}) \mid STP\right) < x \mid DE\right) = \prod_{s\in S_1} P_s(r_{cs} < x)$. Therefore, the estimation of $\max_{s\in S_1}(r_{cs})$ is expressed as (Adam 2001; Kim et al. 2010; Nelson 1970; Weitzman 1979)

$$E\left(\max_{s\in S_1}(r_{cs}) \mid STP\right) = E\left(\max_{s\in S_1}(r_{cs}) \mid DE\right) = \sum_{x=1}^{\infty}\left(1 - \prod_{s\in S_1} P_s(r_{cs} < x)\right) \quad (5)$$

One problem for *STP* is that the benefits of search are only determined by the set of inspected products in these prediction methods, and consumer personalization is neglected.

As a matter of fact, both *FTP* and *STP* can be viewed as special cases of *NTP*. Specifically, *NTP* degenerates to *FTP* when $CL(r_{cs}) = g_{\hat{r}_{cs}^{RP}}$ and $P_{g_i}(x) = 1$ if $x = i$ ($P_{g_i}(x) = 0$ if $x \neq i$); and to *STP* when $CL(r_{cs}) = g_s$, $\forall s \in S$. For the sake of simplicity, in the following discussions, we will use CL^{NTP}, CL^{FTP} and CL^{STP} to denote the corresponding clustering/classification methods of *NTP*, *FTP* and *STP*, respectively.

Experiments

In this section, we compare the performance of the three approaches, *NTP*, *FTP* and *STP,* on the well-known consumer rating data of *Netflix Prize* (http://www.netflixprize.com). The *Netflix Prize* is an open competition for the best prediction methods to estimate user ratings for films (i.e., best *RP*s). This competition was held by *Netflix*, an American corporation that offers both on-demand video streaming for the internet and flat rate online video rental of DVDs. On 21 September 2009, the grand prize of US$1,000,000 was given to the BellKor's Pragmatic Chaos team who beat *Netflix*'s own algorithm for predicting ratings by 10% (http://www.netflixprize.com). The data of *Netflix Prize* are now widely used by many studies in the areas of information systems, computer science, management science, and marketing science (Adomavicius et al. 2011; Jahrer et al. 2010).

Data Description

The data of *Netflix* contain over 100 million ratings from 480 thousand Netflix customers for 17 thousand movies. These data include all ratings received between October, 1998 and December, 2005. The ratings are on a scale from 1 to 5 (integers), i.e., $K = \{1, 2, 3, 4, 5\}$. The rating data of *Netflix Prize* are divided into two datasets: the training dataset, with approximately 100 million ratings, and the probe dataset, with approximately 1.4 million ratings. During the competition, the training dataset is provided for researchers to develop and train prediction methods, e.g., building models and tuning parameters, and the probe dataset is provided for researchers to test the prediction methods.

In using historical data to select or develop *CL* and to estimate the corresponding distributions in each group given the *CL*, probe dataset was randomly divided into two disjoint subsets (in order to avoid a result that the number of ratings per user is too small, the dividing process first randomly splits users of probe dataset into two subsets, and then the ratings from the same users are grouped in the same subset), namely dTraining dataset and test dataset. Training dataset was renamed cTraining. cTraining dataset and dTraining dataset were used to select or develop *CL* and to estimate $P_g(x)$. Test dataset was used to compare the three approaches. The descriptions and usage of these datasets are presented in Table 2.

Table 2. Datasets Used in the Experiment			
Names	cTraining	dTraining	Test
No. of users	480 thousand	240 thousand	240 thousand
No. of movies	17 thousand	17 thousand	17 thousand
No. of ratings	100 million	0.7 million	0.7million
Usage	Training dataset for *CL* or $P_g(x)$	Training dataset for *CL* or $P_g(x)$	Test dataset for comparison

CIS Process Simulation

In the search scenario described above, a consumer inspects products displayed in a list ranked by some ranking method. After inspecting several products, she or he may wonder what the expected incremental benefits would be if she or he continues to inspect several more. In order to simulate this process, for each consumer c, we provided a list of movies which are the corresponding movies of consumer c's ratings in the test dataset, i.e. $LM_c = \{s \mid r_{cs} \in TS\}$ where LM_c is the list of movies for consumer c, TS is the test dataset. Like *Netflix* or *MovieLens*, the movies were ordered according to their predicted ratings estimated by a *RP*, from the highest to the lowest, e.g., $\forall s, s' \in LM_c$, s was ordered before s' in LM_c if $\hat{r}_{cs}^{RP} \geq \hat{r}_{cs'}^{RP}$, where $\hat{r}_{cs}^{RP}$ and $\hat{r}_{cs'}^{RP}$ are the predictions of r_{cs} and $r_{cs'}$ generated by the *RP*. After ranking, the first several movies in the list are supposed to be those have been inspected by the consumer, i.e., S_1, while the rest are those that have not been inspected, i.e., S_2. Given S_1 and S_2, we used *NTP*, *FTP* and *STP* to generate their best estimations for $\max_{s \in S_1}(r_{cs})$, $\max_{s \in S_1 \cup S_2}(r_{cs})$ and $B(c, S_2 \mid S_1)$. These estimations are compared with the actual values of $\max_{s \in S_1}(r_{cs})$, $\max_{s \in S_1 \cup S_2}(r_{cs})$ and $B(c, S_2 \mid S_1)$. The measure used for comparison is RMSE.

Instantiation of Prediction Approaches

In order to carry out a close-to-reality simulation of CIS and achieve the best performances of the three prediction approaches, 18 famous *RP*s from *Netflix Prize* contest were adopted in the experiments. The names of these methods and their performances on probe dataset (measured by RMSE) are presented in Table 3 (Jahrer et al. 2010). For details of these methods, please refer to the related literature (Jahrer et al. 2010).

Table 3. 18 Selected Rating Prediction Methods			
Names of RPs	Performance (RMSE)	Names of RPs	Performance (RMSE)
AFM-1	0.9362	KNN-2	0.8904
AFM-2	0.9231	KNN-3	0.897
AFM-3	0.934	KNN-4	0.9463
AFM-4	0.9391	RBM-1	0.9493
GE-1	0.9079	RBM-2	0.9123
GE-2	0.971	SVD-1	0.9074
GE-3	0.9443	SVD-2	0.9172
GE-4	0.9209	SVD-3	0.9033
KNN-1	0.911	SVD-4	0.8871

These *RP*s were developed based on the cTraining dataset. In the experiments, they were used as 1) ranking methods to order movies for consumers in simulation of CIS; and 2) as *CL*s for *NTP* and *FTP*. Given a *RP*, $CL^{NTP}(r_{cs}) = g_{\hat{r}_{cs}^{RP}}$ and $CL^{FTP}(r_{cs}) = g_{\hat{r}_{cs}^{RP}}$ where $\hat{r}_{cs}^{RP}$ is the best prediction of r_{cs} estimated by the *RP*. The corresponding clustering groups are $G^{NTP} = \{g_i^{NTP} \mid i \in K\}$, $G^{FTP} = \{g_i^{FTP} \mid i \in K\}$ where $K = \{1,2,3,4,5\}$. For example, suppose that the *RP* is AFM-1, which predicts that the rating from consumer 238874 for movie 12785 is 4, then $c = 238874$, $s = 12785$, $\hat{r}_{cs}^{AFM-1} = 4$ and $CL^{NTP}(r_{cs}) = g^{NTP}_{\hat{r}_{cs}^{AFM-1}} = g_4^{NTP}$, $CL^{FTP}(r_{cs}) = g^{FTP}_{\hat{r}_{cs}^{AFM-1}} = g_4^{FTP}$. CL^{STP} did not need any training dataset since it simply clustered ratings by their corresponding movies as discussed in above, i.e., $G^{STP} = \{g_s^{STP} \mid s \in S\}$. $P_{g_i^{NTP}}(x)$ was estimated with the dTraining dataset. $P_{g_i^{FTP}}(x) = 1$ if $x = i$, and $P_{g_i^{FTP}}(x) = 0$ if $x \neq i$. $P_{g_s^{STP}}(x)$ was estimated with the cTraining dataset, since CL^{STP} did not use it and the cTraining dataset was much bigger than the dTraining dataset. For example, given AFM-1, $P_{g_i^{NTP}}(x)$, where $i \in K = \{1,2,3,4,5\}$, the probability distributions of ratings are illustrated in Figure 3; there were approximately 100 thousand ratings for Movie #30 and $P_{g_{30}^{STP}}(x)$ is illustrated in Figure 4.

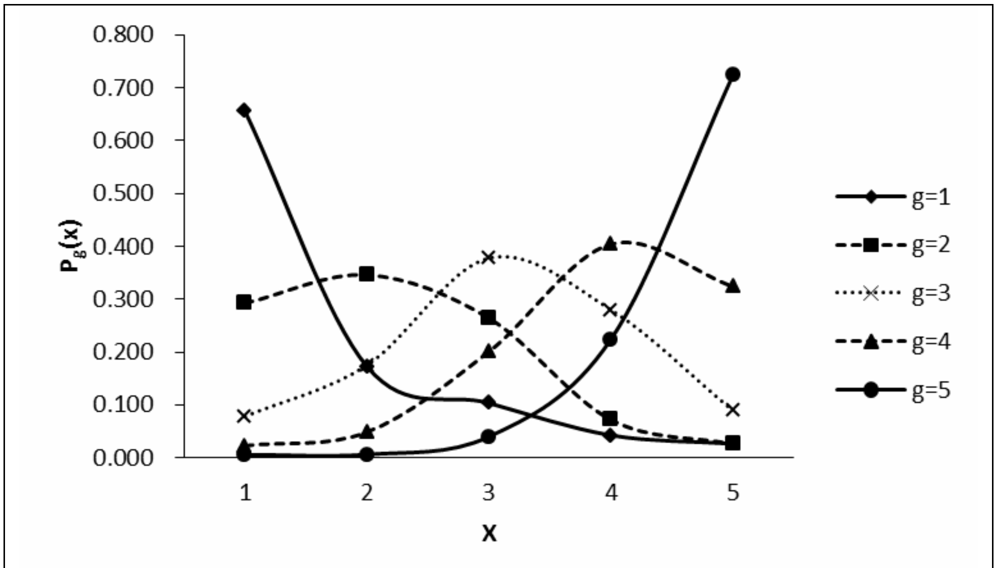

Figure 3. Probability Distribution of Ratings Given *CL*=AFM-1

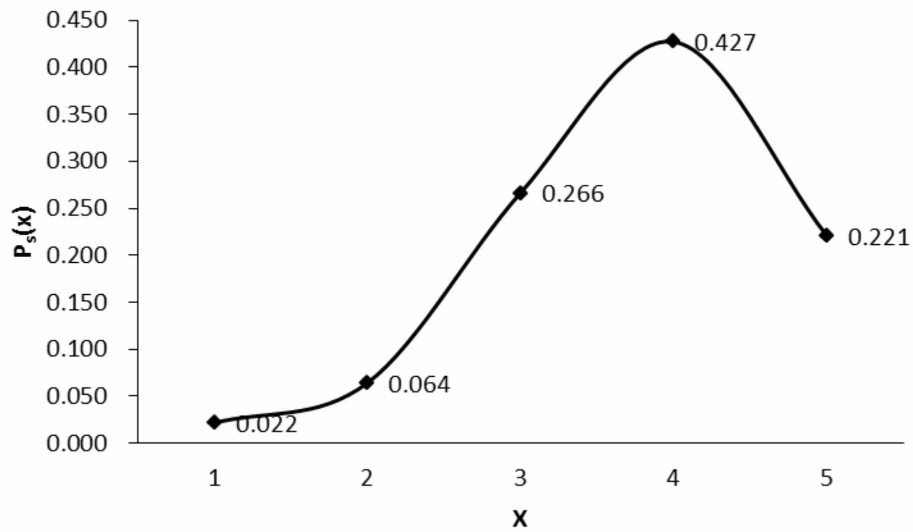

Figure 4. Probability Distribution of Ratings for Movie #30

Example

Here we provide an example to illustrate how the *NTP*, *FTP* and *STP* estimate the incremental benefits of search in the simulated CIS.

Suppose that the selected *RP* is AFM-1 and *NTP*, *FTP* and *STP* have been developed based on cTraining dataset and dTraining dataset. Table 4 is a simple test dataset including the ratings for 4 movies from 3 consumers. The ∅ means there is no rating there. Table 5 are the corresponding estimations of ratings in table 4 predicted by AFM-1. For instance, the ratings from Cm1 for Mv1, Mv3 and Mv4 are 4, 4, 5 respectively, and the corresponding estimations of these ratings by AFM-1 are 4, 5, 4 respectively. There is no rating from Cm1 for Mv2.

Table 4. Simple Test Dataset

	Mv1	Mv2	Mv3	Mv4
Cm1	5	∅	4	5
Cm2	∅	3	3	4
Cm3	3	4	∅	5

Table 5. Estimations of the Simple Test Dataset Predicted by AFM-1

	Mv1	Mv2	Mv3	Mv4
Cm1	4	∅	5	4
Cm2	∅	3	3	3
Cm3	4	4	∅	4

The simulation process is as follows. Given a consumer from test dataset, say Cm 1, suppose that she or he have not watched the rated movies, i.e. Mv1, Mv3 and Mv4. During his/her searching for movies, these 3 movies are ordered in a list according to the ratings predicted by AFM-1 (as shown in Table 5). Since the predicted ratings for these three movies are 4, 5 and 4, the order is (Mv3, Mv1, Mv4). After inspecting the top N_1 (a random integral number between zero and the number of movies in the list) movies in the list, say $N_1 = 1$, Cm1 wonders what the expected incremental benefits of search would be if he/she decides to continue inspecting the rest of the movies. In this case, $S_1 = \{\text{Mv3}\}$, $S_2 = \{\text{Mv1}, \text{Mv4}\}$ .This process repeats for each consumer in the simple test dataset. The S_1's and S_2's for each consumer are presented in Table 6.

Table 6. S_1's and S_2's for Each Consumer

	S_1	S_2
Cm1	Mv3	Mv1, Mv4
Cm2	Mv2,Mv3	Mv4
Cm3	Mv1	Mv2, Mv4

Furthermore, $P_{g_i^{NTP}}(x)$ and $P_{g_i^{STP}}(x)$ estimated based on cTraining and dTraining datasets are presented in Tables 7 and 8.

Table 7. $P_{g_i^{NTP}}(x)$

g \ X	1	2	3	4	5
g_1^{NTP}	0.655	0.172	0.103	0.043	0.026
g_2^{NTP}	0.292	0.346	0.264	0.072	0.026
g_3^{NTP}	0.078	0.175	0.378	0.280	0.089
g_4^{NTP}	0.023	0.049	0.201	0.404	0.324
g_5^{NTP}	0.006	0.006	0.140	0.224	0.624

Table 8. $P_{g_i^{STP}}(x)$

g \ X	1	2	3	4	5
g_1^{STP}	0.053	0.024	0.082	0.205	0.637
g_2^{STP}	0.018	0.066	0.276	0.396	0.245
g_3^{STP}	0.018	0.026	0.105	0.210	0.640
g_4^{STP}	0.055	0.069	0.376	0.358	0.142

The actual values of $\max_{s \in S_1}(r_{cs})$, $\max_{s \in S_1 \cup S_2}(r_{cs})$, $B(c, S_2 | S_1)$ and the estimated values by *NTP*, *FTP* and *STP* are illustrated in Table 9.

Table 9. Incremental benefits estimated by *NTP, FTP, STP*				
		$\max_{s \in S_1}(r_{cs})$	$\max_{s \in S_1 \cup S_2}(r_{cs})$	$B(c, S_2 \mid S_1)$
Cm1	Actual value	4.000	5.000	1.000
	NTP	4.454	4.817	0.363
	FTP	5.000	5.000	0.000
	STP	4.429	4.876	0.447
Cm2	Actual value	3.000	4.000	1.000
	NTP	3.701	3.976	0.274
	FTP	3.000	3.000	0.000
	STP	4.671	4.740	0.069
Cm3	Actual value	3.000	5.000	2.000
	NTP	3.957	4.670	0.713
	FTP	4.000	4.000	0.000
	STP	4.349	4.735	0.386

We use the RMSE to compare the difference between the actual values and the estimated values. $RMSE = \sqrt{E\left(\left(\hat{\theta} - \theta\right)^2\right)}$ where $\hat{\theta}$ is the estimation of the actual θ. Smaller RMSE means better estimation. The RMSE of the estimations for $\max_{s \in S_1}(r_{cs})$, $\max_{s \in S_1 \cup S_2}(r_{cs})$, $B(c, S_2 | S_1)$ by the three approaches are shown in Table 10.

Table 10. The RMSE of estimations			
	RMSE($\max_{s \in S_1}(r_{cs})$)	RMSE($\max_{s \in S_1 \cup S_2}(r_{cs})$)	RMSE($B(c, S_2 \mid S_1)$)
NTP	0.733	0.218	0.929
FTP	0.816	0.816	1.414
STP	1.264	0.459	1.122

Note that the results show that *NTP* is better than *FTP* and *STP* in the estimations of $\max_{s \in S_1}(r_{cs})$, $\max_{s \in S_1 \cup S_2}(r_{cs})$ and $B(c, S_2 | S_1)$.

More Experiments on Different RPs

In order to eliminate the bias generated by the *RP*s, we compare the performances of the three approaches for each of the 18 *RP*s in Table 3. The RMSE results are illustrated in Table 11.

Table11. The comparison of three methods on the dataset of Netflix

		RMSE $\max_{s\in S_1}(r_{cs})$	RMSE $\max_{s\in S_1\cup S_2}(r_{cs})$	RMSE $B(c,S_2 \mid S_1)$			RMSE $\max_{s\in S_1}(r_{cs})$	RMSE $\max_{s\in S_1\cup S_2}(r_{cs})$	RMSE $B(c,S_2 \mid S_1)$
AFM-1	*NTP*	0.550	0.355	0.442	KNN-1	*NTP*	0.519	0.351	0.411
	FTP	0.705	0.668	0.547		*FTP*	0.650	0.609	0.505
	STP	0.733	0.383	0.612		*STP*	0.733	0.383	0.612
AFM-2	*NTP*	0.529	0.350	0.413	KNN-2	*NTP*	0.526	0.348	0.412
	FTP	0.662	0.602	0.493		*FTP*	0.656	0.601	0.493
	STP	0.737	0.383	0.608		*STP*	0.744	0.383	0.617
AFM-3	*NTP*	0.561	0.354	0.456	KNN-3	*NTP*	0.533	0.350	0.422
	FTP	0.726	0.681	0.559		*FTP*	0.661	0.603	0.509
	STP	0.737	0.383	0.616		*STP*	0.738	0.383	0.613
AFM-4	*NTP*	0.562	0.354	0.460	KNN-4	*NTP*	0.556	0.354	0.451
	FTP	0.734	0.703	0.565		*FTP*	0.695	0.616	0.539
	STP	0.737	0.383	0.618		*STP*	0.738	0.383	0.616
GE-1	*NTP*	0.511	0.352	0.401	SVD-1	*NTP*	0.526	0.350	0.413
	FTP	0.648	0.611	0.481		*FTP*	0.657	0.605	0.501
	STP	0.737	0.383	0.612		*STP*	0.735	0.383	0.608
GE-2	*NTP*	0.588	0.359	0.484	SVD-2	*NTP*	0.542	0.352	0.423
	FTP	0.772	0.722	0.582		*FTP*	0.669	0.595	0.516
	STP	0.746	0.383	0.626		*STP*	0.740	0.383	0.608
GE-3	*NTP*	0.561	0.352	0.457	SVD-3	*NTP*	0.518	0.345	0.413
	FTP	0.696	0.622	0.541		*FTP*	0.655	0.601	0.496
	STP	0.744	0.383	0.622		*STP*	0.729	0.383	0.604
GE-4	*NTP*	0.532	0.349	0.422	SVD-4	*NTP*	0.513	0.347	0.401
	FTP	0.668	0.610	0.496		*FTP*	0.664	0.635	0.493
	STP	0.741	0.383	0.616		*STP*	0.733	0.383	0.610
RBM-1	*NTP*	0.587	0.356	0.480	RBM-2	*NTP*	0.537	0.353	0.435
	FTP	0.762	0.713	0.587		*FTP*	0.685	0.643	0.525
	STP	0.746	0.383	0.625		*STP*	0.737	0.383	0.619

Results in Table 11 show that *NTP* performs better than *FTP* and *STP* given any *RP* at all the comparison criteria: RMSE($\max_{s\in S_1}(r_{cs})$), RMSE($\max_{s\in S_1\cup S_2}(r_{cs})$),RMSE($B(c,S_2 \mid S_1)$). It is noteworthy that these results were further supported by paired t-tests revealing the significant advantage of *NTP* for others.

Conclusion

Helping consumers estimate incremental benefits of search is meaningful and beneficial to both consumers and merchants such as e-retailers and information intermediaries. This paper has introduced a new type of prediction approach (namely *NTP*), aimed at taking a combined perspective of both point and distribution estimations of online search benefits. The approach was implemented and tested in a film ratings environment with the experiments on the *Netflix Prize* data consisting of 100 million ratings, revealing that *NTP* performs significantly better than others with the well-known 18 effective rating prediction methods. One of the future studies is to conduct more investigations on large-scale real-world application datasets so as to obtain a variety of clustering/classification methods (*CL*s) that fit well with specific industries and domains.

Finally, it is worth mentioning that the search-stopping strategy for consumers also depends on the estimation of costs, which is not discussed in this paper but deserves more in-depth investigations as well. Similarly, effectively estimating the costs of CIS, such as the opportunity cost of time, is a challenging task (Ratchford and Srinivasan 1993). To a certain extent, the current effort in estimating the search benefits may shed some light in estimating the search costs, which could be a future research direction.

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