Decision Support Systems 53 (2012) 418–424

Contents lists available at SciVerse ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

Input online review data and related bias in recommender systems

Selwyn Piramuthu [a,c,*], Gaurav Kapoor [a], Wei Zhou [b,c], Sjouke Mauw [d]

[a] Information Systems and Operations Management, University of Florida Gainesville, Florida 32611-7169, USA
[b] ESCP Europe, Paris, France
[c] RFID European Lab, Paris, France
[d] Université du Luxembourg, Faculté des Sciences, de la Technologie et de la Communication (FSTC), 6, rue Richard Coudenhove-Kalergi, L-1359, Luxembourg

ARTICLE INFO

Article history:
Received 19 January 2011
Received in revised form 1 November 2011
Accepted 12 February 2012
Available online 17 February 2012

Keywords:
Sequential bias
Online reviews
Recommender system

ABSTRACT

A majority of extant literature on recommender systems assume the input data as a given to generate recommendations. Both implicit and/or explicit data are used as input in these systems. The existence of various challenges in using such input data including those associated with strategic source manipulations, sparse matrix, state data, among others, are sometimes acknowledged. While such input data are also known to be rife with various forms of bias, to our knowledge no explicit attempt is made to correct or compensate for them in recommender systems. We consider a specific type of bias that is introduced in online product reviews due to the sequence in which these reviews are written. We model several scenarios in this context and study their properties.

1. Introduction

Potential customers sometimes have the option of using recommender systems (e.g., amazon.com, buzzillions.com, consumersearch.-com, digg.com, Google AdSense, Netflix challenge, prorevs.com, slashdot.com) as convenient (although not completely reliable) automated sources of information in situations where there is a lack of other alternatives. These systems are for the most part used to supplement rather than to supplant the real thing which is recommendation from a known and completely reliable expert source.

Source of input for recommender systems include (implicit) past behavior (e.g., consumer transaction data, bookmark, page view time, from and to link for a Web page, social network) and (explicit) customer reviews. Both implicit and explicit data complement each other in terms of information content since the former records the behavior (i.e., customer A bought widget X) while the latter records details of this customer's (dis-)satisfaction with this purchase. Recommendations are generated based on (dis-)similarity between the characteristics of the user being recommended to and others in the database as well as (dis-)similarity between item of interest and related items. Several methods are used in the process including collaborative filtering (e.g., amazon.com) and content filtering (e.g., Music Genome Project used in pandora.com). Collaborative filtering uses the (dis-)similarity information across users and items (e.g., [15]). Content filtering, on the other hand, is based on the characteristics of users and items. Adomavicius and Tuzhilin ([1]) provide an excellent overview of this general area.

Given the popularity of recommender systems, several facets of such systems have been extensively studied including mining user-generated review data for implicit as well as explicit patterns, attacks, interface design, among others (e.g., [5,6,8,16]). Other than attacks, which explicitly manipulate input data to achieve an intended recommendation (e.g., manipulate reviews so an item of interest enters or leaves the set of highly recommended items), other aspects of input data (e.g., bias) have not received their fair share of attention from researchers in this area.

Bias in user-generated reviews can take several forms including personal (based on past experience, interest, attitude), extreme reviews (overly positive or negative), context (e.g., review of a camera's resolution characteristics can be positively or negatively biased based on its use – pictures for high-resolution printing vs. posting low-resolution pictures online), temporal (early vs. late adopters of a product may have different perspectives on the same product), awareness effect ([7]), herd behavior ([3]), and confirmation bias ([2]).

Sequential bias is a variant of first-impression bias (e.g., primacy–recency effect) and is also influenced by pre-existing (positive, negative) bias. Thus, the role played by first impression bias cannot be overestimated ([4,14]). Therefore, the review that is first seen by a prospective customer of the product of interest plays a significant role in purchase decisions that follow. These reviews are quite influential since prospective purchasers of reviewed products rely heavily on these reviews in making their purchase decisions (e.g., [20]). The sequence in which reviews are written play an appreciable role in how the reviews that follow later in the sequence are written. For example, if a reviewer is favorable to the product reviewed, she might

* Corresponding author at: Information Systems and Operations Management, University of Florida Gainesville, Florida 32611-7169, USA. Tel.: +1 352 392 8882.
E-mail address: selwyn@ufl.edu (S. Piramuthu).

0167-9236/$ – see front matter © 2012 Elsevier B.V. All rights reserved.
doi:10.1016/j.dss.2012.02.006

be biased to write stronger reviews to somehow compensate for the effects of existing negative reviews and vice versa. The reviews thus written are biased, in part, due to their position in the sequence of reviews. In turn, the recommender systems that use these biased reviews to generate their recommendations will clearly generate biased recommendations due, in part, to this sequential bias.

We purport to fill this gap in extant literature by specifically considering sequential bias present in consumer reviews and the consequence of this bias on resulting recommendations generated. In other words, while recommender systems use user-generated data as-is, we believe there is a need to rid this data of sequential bias to provide better or less-biased recommendations. By explicitly acknowledging the existence of sequential bias and actively employing means to remove it from input data to recommender systems, one can alleviate its effect in the recommendations. We are, therefore, interested in the scenario where a customer purchases/experiences a product and then proceeds to provide a written review of this product online. During this process, the customer also has a chance to read existing reviews on this product before writing a review. It is precisely these existing reviews that causes sequential bias in the next review that is written.

The remainder of the paper is organized as follows. We discuss related background information and literature in the next section. We study the dynamic associated with sequential bias and its effect on recommender systems in Section 3. Section 4 concludes this paper with a brief discussion.

2. Background and related literature

A generic framework of a recommender system is given in Fig. 1. Both implicit and explicit data are used as input to the system, which uses these to generate (i.e., learn and store explicit knowledge in) the knowledge-base. The knowledge-base essentially comprises both explicit and implicit patterns extracted from (implicit & explicit) input data. The recommender system then waits for a user to enter the system. Upon arrival of a user, who could be a potential customer, the system takes a snap-shot of this user's characteristics and matches this with learned knowledge to generate appropriate recommendations in a timely manner. In what follows, the recommendations would be used to update system configuration either automatically or via human interference. Consequently, these new updates would eventually alter online users' behavior towards pricing and recommendation. The closed loop assures that normal system performance can be maintained at a stabilized level according to the theory of automation.

Although it is generally assumed that what consumers do (i.e., implicit or past behavior data) provides better information for recommender systems than what they say (explicit or consumer review data), both these data provide complementary information that are beneficially utilized in recommender systems. While both explicitly and implicitly generated data are used in recommender systems, we are interested in only explicit (i.e., user-generated reviews) input data in recommender systems. The use of user-generated explicit recommendation data has its associated challenges. We provide a brief overview of several such challenges and then some related literature in this area.

2.1. Some challenges

Recommender systems face several challenges when dealing with explicit input data. A list of a selected few of these challenges include: (a) strategic source manipulations (e.g., profile injection attacks such as sybil, shill, random, sampling, average, bandwagon), (b) those associated with equally weighted input (e.g., user-generated reviews for a computer and a pack of chewing gum are not treated differently), (c) the endemic sparse matrix and the difficulty in generating useful patterns from such a matrix, cold start problem that arises when a user or product is new to the system and the absence of historical data on these entities and their characteristics, (d) differences in user risk tolerance levels, (e) staleness of data used in generating recommendations, (f) seasonality and trends in consumer preferences and their effect on user-generated reviews, and (g) general input data bias. We are interested in the bias which occurs due to the characteristics of the reviewed item (e.g., price, familiarity, stake to the customer, whether this item was purchased as a gift to someone else, the relationship of the purchaser to the giftee), the presence of extraneous stimulus whereby the item would not have been explicitly purchased had it not been for promotions and bundling, the highly self-selective nature of providing reviews and the sequential manner in which reviews are written. We are specifically interested in the latter – i.e., the sequence in which reviews are written and the (mostly unintended) bias that is introduced in these reviews resulting from its position in the sequence.

When perusing existing reviews on the product of interest, the intensity/magnitude of the reviewer's sentiment as well as the positivity (or negativity) of reviews on various product features/characteristics (as well as the overall review of this product) certainly affect the reader. Several studies in the social sciences suggest that people often assign more weight to negative information than positive information of equal intensity (e.g., [9,17]). Mizerski ([12]) found that product attributes rated unfavorably exert greater influence than those rated favorably on consumers' attributions, beliefs and attitudes. This phenomenon has been termed the negativity effect (bias). Ahluwalia ([17]) found that highly committed consumers showed positivity effect (bias) where they weigh positive information more than negative information. I.e., there is evidence for both positivity and negativity effect depending on consumer as well as product characteristics.

In addition to the introduction of unintentional bias in user-generated product reviews, there also exists bias that are intentionally introduced due to professional relationships and friendships ([21]) and others with ulterior motives (e.g., [19,22,23]). Buzz marketing (e.g., [18]) is a variation on the same theme with the explicit intention of promoting a product, service, or idea.

2.2. Related literature

The literature on recommender systems is extensive and covers a wide spectrum of related issues. We list a few from among these here. Since online product reviews are not strictly regulated, there are opportunities for the introduction of 'fake' or intentionally biased reviews. A

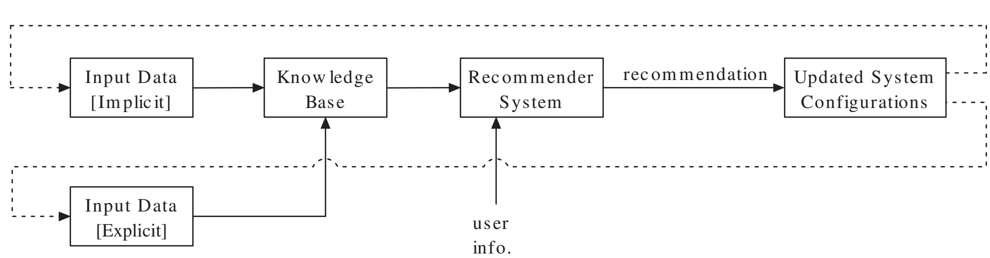

Fig. 1. A generic recommender system framework.