Are User-Generated Item Reviews Actually Beneficial for Recommendation?

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Abstract

User-generated item reviews are widely believed to represent a valuable source of information for recommendation. However, a recent empirical analysis of review-based algorithms by Sachdeva and McAuley puts this this belief into question. In this paper, we analyze the recommender systems literature that seeks to improve recommendation by using item reviews as auxiliary information. We identify the ways in which the information condensed in item reviews is represented. We then point out particular goals, such as performance improvement, and problems, such as cold-start and sparsity, that have been adressed by using item reviews. We arrive at the same conclusion as Sachdeva and McAuley that item reviews can be beneficial, yet are not beneficial per se. The field is saturated with methods that leverage item reviews yet lacks studies on when and why certain methods are beneficial. The current state-of-the-art therefore does not yield a definitive answer to the question whether using item reviews is actually beneficial for recommendation.

Keywords

recommender systems, item reviews, natural language processing, deep learning

1. Introduction

Traditionally, recommender systems utilize user ratings and item attributes to suggest items to users that are tailored to their preferences. To date, a large body of literature identifies user-generated item reviews (hereafter: item reviews) as a rich source of information that allows to improve recommendation. The earliest systems that integrate item reviews emerged between 2005 and 2010 [1, 2, 3]. The rapid growth of machine learning, and deep learning in particular, put strong natural language processing techniques into the hands of recommender systems researchers to make use of item reviews.

Although the utilization of item reviews for recommendation generally leads to more accurate recommendations, and it therefore appears obvious that item reviews are beneficial for recommendation, the findings by Sachdeva and McAuley [4] put this view into question. They find that state-of-the-art systems that make use of item reviews often cannot outperform simple baseline systems. Notably, the difference between using and not using item reviews is often insignificant. They come to the conclusion that it is not at all clear whether and how item reviews benefit recommendation.

Intrigued by this conclusion, we set out to address the following research questions:

1. *Are item reviews beneficial for recommendation?*
2. *In what situations are item reviews beneficial?*
3. *How are item reviews beneficial?*

On the basis of a literature review, we arrive at the following position: It is important to understand what kind of information condensed in item reviews, if any, is beneficial for recommendation, and how that information can be leveraged. We now present the findings of our literature review

2. Analysis

We present the underlying methodology of our literature review. We then touch on how the information condensed in item reviews can be represented. We close by pointing out goals and problems that have been addressed by leveraging item reviews.

2.1. Methodology

We first searched papers based on three recent papers that leverage item reviews for recommendation: [4, 5, 6]. Based on title and abstract, we then collected a sample of 50 papers for further reviewing. After two rounds of filtering the papers for relevance, we found only 36 papers relevant. We first sorted the papers by publication year. We then labeled each paper by the way that item reviews were used. Finally, we applied labels for the goals

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and problems that the authors addressed by leveraging the information condensed in item reviews.

An overview of our literature review can be found in the appendix. We confer the gentle reader to these three survey papers [7, 8, 9] for further details on the utilization of item reviews for recommendation. Our literature review is different from these prior surveys, since we challenge the popular view that item reviews are beneficial for recommendation per se.

2.2. Review Representations

Item reviews are widely believed to be a rich source of information for recommendation. However, many distinct ways to utilize the information condensed in item reviews have been proposed in the literature. We adapt the list of widely used methods to extract and represent the information condensed in item reivews by Chen et al. [7] from 2015 to describe the current state-of-the-art:

- *Frequent Terms*: Words extracted by statistical models according to their frequency.
- *Keywords*: Keywords are important descriptions that represent semantic information on items.
- *Auxiliary Properties*: Meta information such as the length and timestamp of an item review.
- *Item Aspects*: Fine-grained topics such as the location and food quality of a restaurant, which are discussed in the item review.
- *Aspect Sentiment*: Combination of item aspect and user sentiment that represent not explicitly pronounced user preferences.
- *Contextual Opinion*: Opinions that vary with the context of item usage, e.g. visiting a restaurant during work or on a date.
- *Term-based User/Item Profile*: Profiles based on the terms used in item reviews that represent individual users or items.
- *Review Embedding*: The above hand-crafted approaches are depend on human intervention. State-of-the-art deep learning methods such as deep encoders and transformer-based encoders allow to embed and represent item reviews as vectors without human intervention.

This list is not exhaustive, yet highlights the most popular approaches to represent item reviews. We now tend to the goals pursued by extracting and representing the information condensed in item reviews.

2.3. Goals

A majority of relevant papers (25 out of 36 papers) aim to utilize item reviews for the improvement of recommendation performance. Apart from the primary goal of performance improvement, some authors have address minor goals. We compile the following list of goals pursued by leveraging item reviews for recommendation:

- *Performance Improvement*: Improving recommendation performance with respect to the usual performance metrics.
- *Recommendation Explanation*: Explaining to the user why and how a recommendation is generated. Also referred to as 'transparency'.
- *Review Ranking*: Ranking item reviews to for instance filter item reviews by their usefulness.
- *Novel Systems*: Creating novel recommender systems that do not fit into the main categories of collaborative filtering, content-based filtering, and knowledge-based systems or mixtures thereof.
- *Context Inference*: Infering the context of a user on the basis of his or her item review.
- *De-Biasing*: Reducing, or ideally removing, bias such as gender or popularity bias.

This list is not exhaustive, yet highlights the most popular goals pursued by utilizing item reviews for recommendation. We now tend to the problems pursued by utilizing the information condensed in item reviews.

2.4. Problems

A number of recommender systems implementations utilize item reviews to alleviate the traditional cold-start and sparsity problem. Beyond these widely addressed problems, various other niche problems have been addressed in the literature. We compile the following list of problems addressed in the context of utilizing item reviews for recommendation:

- *Cold-Start*: The problem that recommender systems may struggle to recommend new items and or recommending items of interest to new users.
- *Sparsity*: The problem that a large portion of user-item interactions such as ratings or clicks are unknown to a recommender system.
- *Spurious Correlations*: The problem that some correlations between items are only apparent in item reviews and not for instance in ratings.
- *Review Ambiguity*: The problem that item reviews can have different meanings depending on for instance the reviewer's personality.

This list is not exhaustive, yet highlights the most popular problems that have been addressed by utilizing item reviews for recommendation. We now discuss the research questions put forth in the introduction.

3. Discussion

We first discuss the general benefit of using item reviews for recommendation. We then focus on the popular use of item reviews for performance improvement. We close with what we conclude to be the main limitations of the current state-of-the-art and point out a future direction.

3.1. General Benefit of Using Item Reviews

We hold that whether or not item reviews are beneficial for recommenation can only be decided by proving the following three claims. First, item reviews actually contain information useful for recommendation. Second, the usefulness of an item review can be identified. And third, that useful information can be extracted. Interestingly, it is widely assumed that item reviews contain useful information. However, not always do item review-based features present useful information [6].

The second and third claims are usually shown by evaluating the effectiveness with which a goal (see Section 2.3) or a problem (see Section 2.4) is addressed by using item reviews. Since the first claim is never established, we cannot conclude that item reviews are actually beneficial for recommendation. We can only conclude that item reviews can be beneficial for recommendation, as underpinned empirically by Sachdeva and McAuley [4]. Therefore, we cannot clearly answer Research Questions 2 and 3. We thus have a closer look on the popular goal of performance improvement using item reviews.

3.2. Performance Improvement Using Item Reviews

Improved recommendation performance through higher accuracy would be reached if the recommender systems results are better suited to the task at hand due to the use of item reviews, meaning lower error rates and better overall evaluation results. Item reviews can be profitably exploited towards this goal. Another measure of performance is the robustness of systems. This relates to the question whether there are improvements in the way that typical problems of recommender systems are faced (see Section 2.4). As discussed above, this is another area where item reviews are commonly utilized.

Recommender systems achieve higher accuracy and robustness from the utilization of item reviews. Generally, researchers exploit item reviews in order to improve the results of existing recommendation models. Recommender systems based only on item reviews are rare, and those which we found are often meant to be embedded into a larger recommender system.

3.3. Limitation and Future Direction

We find that representing item reviews as a combination of item aspects and aspect sentiment (see Section 2.2) receive particular attention as of late. The field moves towards ever more sophisticated methods that leverage item reviews. These more sophistaced methods are often simply believed to be superior to traditional methods. Research on the advantages or disadvantages of approaches towards item review utilization are rare.

It is unclear whether less popular methods are employed and compared against less popular methods because they are less effective or whether they are simply believed to be less effective. It would not be the first time that technically sophisticated methods in recommendation are simply believed to be superior to traditional methods without properly showing that this is the case [10]. We argue that it is helpful to study item review representations independently from goals and problems.

4. Conclusion

We address the question if, and under which circumstances, recommendation benefits from the use of user-generated item reviews. Towards this goal, we identify and analyze 36 papers that leverage item reviews for recommendation published between 2010 and 2022. We do not find clear indications in the literature in which circumstances item reviews can be considered to be consistently beneficial for recommendation.

The literature clearly shows that utilizing item reviews can be beneficial for recommendation. However, the literature fails to show when utilizing item reviews benefits recommendation and why. The widespread belief that using item reviews for recommendation is beneficial per se hampers a deeper understanding of whether or not this belief holds true. The benefit of using item reviews remains ambiguous. We therefore argue that the field needs to first establish a basic understanding of why and how item reviews can benefit recommendation rather than showing that it potentially can.

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A. Appendix

We present a tabular overview of our categorization of the 36 papers we find relevant for the convenience of the gentle reader.

Table 1
List of relevant papers analyzed in the literature review sorted by year of publication. Full dots mark that a an item in either of the three categories Review Representations (see Section 2.2), Goals (see Section 2.3), and Problems (see Section 2.4) have been addressed in a paper. Numbers in parentheses indicate the overall number of occurrences of an item.

		Review Representations								Goals						Problems			
Paper	Year	Frequent Terms (4)	Keywords (2)	Auxiliary Properties(3)	Item Aspects (20)	Aspect Sentiment (14)	Contextual Opinion (1)	Term-based User/Item Profile (8)	Review Embedding (7)	Performance Improvement (25)	Recommendation Explanation (9)	Review Ranking (4)	Novel Systems (3)	Context Inference (4)	De-Biasing (3)	Cold-Start (4)	Sparsity (5)	Spurious Correlations (1)	Review Ambiguity (1)
Terzi et al. [11]	2010	•	◦	◦	◦	◦	◦	◦	◦	•	◦	◦	◦	◦	◦	◦	◦	◦	◦
Zhang and Tran [12]	2011	◦	◦	•	◦	◦	◦	◦	◦	◦	•	•	◦	◦	◦	◦	◦	◦	◦
Ling et al. [13]	2014	◦	◦	◦	•	◦	◦	◦	◦	•	•	◦	◦	◦	◦	•	◦	◦	◦
Chen et al. [7]	2015	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦
Chen and Chen [14]		◦	◦	◦	•	•	◦	◦	◦	•	◦	◦	◦	◦	◦	◦	◦	◦	◦
Zhang [15]		◦	◦	◦	•	•	◦	•	◦	•	•	◦	◦	◦	◦	•	◦	◦	◦
Zheng et al. [16]	2017	◦	◦	◦	•	◦	◦	◦	◦	•	◦	◦	◦	◦	◦	•	•	◦	◦
Seo et al. [17]		◦	◦	◦	•	•	◦	•	◦	•	◦	◦	◦	◦	◦	◦	◦	◦	◦
Paul et al. [18]		◦	◦	◦	•	•	◦	◦	◦	◦	◦	•	◦	◦	◦	◦	◦	◦	◦
Musto et al. [19]		◦	◦	◦	•	•	◦	•	◦	•	◦	◦	◦	•	◦	◦	◦	◦	◦
Lahlou et al. [20]	2018	◦	◦	◦	◦	•	◦	◦	◦	•	◦	◦	◦	•	◦	◦	◦	◦	◦
Lu et al. [21]		◦	◦	◦	•	•	◦	•	◦	◦	•	◦	◦	•	◦	◦	◦	◦	◦
Hyun et al. [22]		◦	◦	◦	◦	•	◦	◦	◦	•	◦	◦	◦	◦	◦	◦	◦	◦	•
Bhagat and Pawar [23]		◦	◦	◦	•	◦	◦	◦	◦	•	◦	◦	◦	◦	◦	◦	◦	◦	◦
Hernández-Rubio et al. [9]	2019	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦
Xia et al. [24]		◦	◦	◦	•	•	◦	•	◦	•	◦	◦	◦	•	◦	◦	◦	◦	◦
Alexandridis et al. [25]		◦	◦	◦	•	•	◦	•	◦	•	◦	◦	◦	◦	◦	◦	◦	◦	◦
Al-Ghuribi and Noah [8]		◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦
Ni, Jianmo, et al. [26]		◦	◦	◦	•	•	◦	•	◦	◦	•	◦	◦	◦	◦	◦	◦	◦	◦
Wu, Ga, et al. [27]		•	◦	◦	◦	◦	◦	◦	◦	•	•	◦	•	◦	◦	◦	•	◦	◦
Rafailidis and Crestani [28]		◦	◦	◦	◦	◦	◦	◦	•	•	◦	◦	◦	◦	◦	◦	◦	◦	◦
Salah et al. [29]	2020	•	◦	•	•	◦	◦	◦	◦	◦	◦	◦	•	◦	◦	◦	•	◦	◦
Sachdeva and McAuley [4]		◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦	◦
Penha and Hauf [5]		•	◦	◦	•	◦	◦	◦	◦	•	◦	◦	◦	◦	◦	◦	◦	◦	◦
Peña et al.[30]		◦	◦	◦	•	•	◦	•	◦	•	◦	◦	◦	◦	◦	◦	◦	◦	◦
Zhou et al. [31]		◦	◦	◦	◦	•	◦	◦	◦	•	◦	◦	◦	◦	•	◦	◦	◦	◦
Luo et al. [32]		◦	◦	◦	•	◦	◦	◦	•	•	•	◦	◦	◦	◦	◦	◦	◦	◦
Liu et al. [33]		◦	•	◦	◦	◦	◦	◦	•	•	◦	•	◦	◦	◦	◦	◦	◦	◦
Antognini et al. [34]	2021	◦	◦	◦	•	◦	◦	◦	•	•	•	◦	◦	◦	◦	◦	◦	◦	◦
Eichinger [6]		◦	•	◦	◦	◦	◦	◦	◦	•	◦	◦	◦	◦	◦	◦	•	◦	◦
Aslanyan and Frasincar [35]		◦	◦	◦	•	◦	◦	◦	◦	•	◦	◦	◦	◦	◦	◦	◦	◦	◦
Kostric et al. [36]		◦	◦	◦	•	•	•	◦	◦	◦	◦	◦	•	◦	◦	◦	◦	◦	◦
Lin et al. [37]		◦	◦	◦	◦	◦	◦	◦	•	•	◦	◦	◦	◦	•	◦	◦	◦	◦
Wang et al. [38]		◦	◦	•	•	◦	◦	◦	◦	◦	◦	•	◦	◦	◦	◦	◦	◦	◦
Pan et al. [39]	2022	◦	◦	◦	◦	◦	◦	◦	•	•	•	◦	◦	◦	•	•	◦	•	◦
Zhang et al. [40]		◦	◦	◦	◦	◦	◦	◦	•	•	◦	◦	◦	◦	◦	◦	•	◦	◦