Reputation-Enhanced Recommender Systems

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Abstract. Recommender systems are pivotal components of modern Internet platforms and constitute a well-established research field. By now, research has resulted in highly sophisticated recommender algorithms whose further optimization often yields only marginal improvements. This paper goes beyond the commonly dominating focus on optimizing algorithms and instead follows the idea of enhancing recommender systems with reputation data. Since the concept of reputation-enhanced recommender systems has attracted considerable attention in recent years, the main aim of the paper is to provide a comprehensive survey of the approaches proposed so far. To this end, existing work are identified by means of a systematic literature review and classified according to carefully considered dimensions. In addition, the resulting structured analysis of the state of the art serves as a basis for the deduction of future research directions.

Keywords: recommender systems, decision support systems, reputation, trust, reputation-enhanced recommender systems

1 Introduction

The rise of the World Wide Web has made sharing and accessing various kinds of information easier and faster than ever before. However, this trend has also led to the phenomenon of information overload, which may overwhelm users in the course of their decision making processes [17]. Recommender systems are intended to solve this problem by making users aware of only those items they are probably interested in [18, 31]. Because of the constantly high research interest in the development of techniques predicting how much users will like different items, recommender algorithms are highly sophisticated by now. Further optimization efforts often yield only marginal improvements [26, 33]. Therefore, it has been suggested to broaden the horizon of recommender systems research and integrate relevant concepts from related fields.

Trust and reputation systems show substantial connections to recommender systems, especially to collaborative filtering systems [19]. Thus, there are several proposals on trust-enhanced recommender systems [41]. These systems consider trust in the form of explicitly declared trust or friendship relationships (e.g. web of trust on Epinions[1]) in the recommendation process. However, these trust links are only available in small numbers because modern online platforms are typically characterized by short-term interactions in a "universe of strangers" [14]. In addition to this main limitation, the explicit declaration of trust relationships requires considerable efforts from users [5].

Because of these drawbacks of explicit trust links, this paper specifically focuses on the enhancement of recommender systems with reputation data. Reputation is another kind of construct relevant when taking advice from others [5]. It is closely linked to trust [19] or even used to establish trust ("reputation-based trust" [6]). However, it fits the aforementioned peculiarities of modern online platforms better. Reputation values are calculated on a global scale instead of being limited to the trust links of one single user. On the one hand, this mitigates the problem of sparsely available personal trust links. On the other hand, reputation values are computationally less expensive because they are computed once for the entire community whereas trust values have to be determined from the perspective of every individual user [28]. Since the concept of reputation-enhanced recommender systems has attracted considerable attention in recent years, several combination approaches have been proposed. In this paper, we comprehensively identify the existing methods by means of a systematic literature review based on well-established guidelines and classify them according to carefully considered dimensions. Thus, the state of the art of reputation-enhanced recommender systems is revealed in an exhaustive manner. Moreover, we are able to point out possible directions for future work in this research stream. In general, our results also provide an important basis for the further exchange of ideas between recommender and reputation systems researchers.

The remainder of the paper is organized as follows. Section 2 introduces the main principles of recommender and reputation systems and relates them to each other according to their similarities and differences. Based on this, Section 3 discusses the process and the outcomes of a systematic literature review on reputation-enhanced recommender systems. This, in turn, leads to the formulation of future research directions in Section 4. Section 5 concludes the paper.

2 Background

Modern Internet platforms, such as e-commerce marketplaces and social media websites, are omnipresent in today's society. Recommender and reputation systems are pivotal decision support components of these platforms.

2.1 Recommender Systems Principles

As already mentioned, the main motivation for the use of recommender systems is the information overload problem [31]. To tackle this issue, recommender systems are supposed to provide users with only the most relevant information

[1] `http://www.epinions.com/`

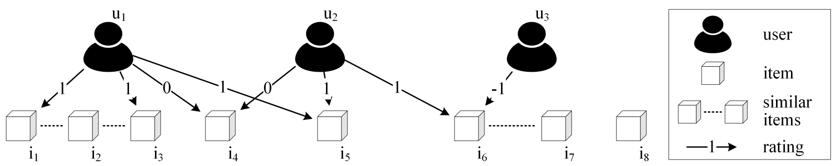

Fig. 1. Exemplary user-item relations using $\{-1, 0, 1\}$ as possible rating values.

and only those items that are worth considering. This is done by predicting the ratings of the items a particular user has not rated yet and recommending those which receive the highest predicted ratings. Figure 1 depicts the entities and relationships considered in the two main types of recommender systems: collaborative filtering and content-based filtering [3].

Collaborative filtering [15, 38] is based on the idea that people tend to agree with people they agreed with in the past and thus captures the typical human behavior of relying on the opinions of acquaintances with similar tastes. When employing the user-based nearest neighbor algorithm, as one particular form of collaborative filtering, the predicted ratings for each item are calculated by aggregating the ratings of the other users weighted by their similarities (in rating behaviors) to the user in focus. Ratings can take different forms such as $\{0, 1\}$ (has experiences, has no experiences), $\{-1, 0, 1\}$ (negative, neutral, positive), and $\{1, 2, 3, 4, 5\}$ (opinions from very negative to very positive). In the example depicted in Figure 1, user u_1 is similar to u_2 as both assigned the same rating to item i_4 and i_5, respectively. u_1 is less similar to u_3 as they do not have any ratings in common. Since u_2 has positively rated i_6, which has not been rated by u_1 yet, a user-based collaborative filtering system would recommend i_6 to u_1.

By contrast, content-based filtering [27] assumes that people will like items similar to the ones they liked in the past. It is solely based on the user's own ratings and the similarities of items determined according to their features. In the example depicted in Figure 1, u_1 has positively rated i_1 and i_3. Since i_2 is similar to i_1 and i_3, a content-based filtering system would recommend i_2 to u_1.

2.2 Reputation Systems Principles

Reputation systems [19] are needed because users usually have no or only few direct experiences with other users on digital platforms. Thus, a user does not know whether to trust another user or not. Reputation systems can alleviate this issue by assisting the user in determining the trustworthiness of other users. Figure 2 depicts the entities and relationships involved in the calculation of users' reputation values indicating their trustworthiness.

After each encounter, users are able to rate the behavior of their counterpart. In e-commerce, for example, a customer can judge a seller's behavior according to factors like on-time delivery and adequate product quality. Similar to recommender systems, common rating scales are $\{-1, 0, 1\}$ and $\{1, 2, 3, 4, 5\}$. The

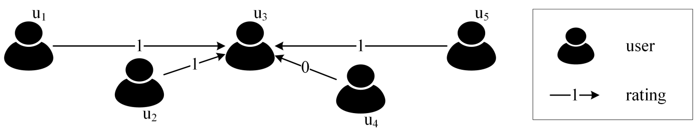

Fig. 2. Exemplary user-user relations using $\{-1, 0, 1\}$ as possible rating values.

reputation system collects the feedback data and employs them to calculate a reputation value for each user according to the following process [35]. At first, the reputation system may filter or weight the ratings depending on different parameters such as the timestamp of the encounter. Then, it aggregates the ratings by employing one of several possible aggregation techniques (e.g. arithmetic mean). Finally, the reputation system communicates the aggregated reputation values to the users of the platform. In the example depicted in Figure 2, u_3 has received one neutral and three positive ratings. As a result, a reputation system using no filtering or weighting criteria and using the arithmetic mean as its aggregation technique would assign a reputation value of 0.75 to u_3.

2.3 Relating Reputation Systems to Recommender Systems

As can be inferred from the remarks in the preceding subsections, the main similarity of recommender and reputation systems is that both kinds of decision support systems are based on user experiences and feedback [19]. Moreover, the two kinds of systems are frequently applied in similar contexts. Besides e-commerce as the most important of the common application areas, other examples include online communities, service selection, and peer-to-peer networks. These fundamental similarities make combined considerations feasible and allow creating a common feedback model as depicted in Figure 3. The model includes two sets of entities: users $U = \{u_1, u_2, ..., u_n\}$ and items $I = \{i_1, i_2, ..., i_m\}$. Users can have experiences with items, which are referred to as the set of item ratings $IR \subseteq U \times I$ (with rating values $r_{IR} : IR \mapsto R$). IR is usually focused on by recommender systems. Furthermore, users can have experiences with other users, which are referred to as the set of user ratings $UR \subseteq U \times U$ (with rating values $r_{UR} : UR \mapsto R$). UR is usually focused on by reputation systems.

Moreover, recommender and reputation systems differ in certain facets and assumptions, which makes combined considerations potentially meaningful [19]. Recommender systems emphasize the similarity of users regarding their subjective tastes whereas reputation systems are especially applied to taste-independent aspects [20]. Therefore, the calculations of (collaborative filtering) recommender systems are typically based on the opinions of local communities consisting of the most similar users [3]. As opposed to this, the calculations of reputation systems are mostly done on a global basis because reputation is considered as a collective measure of trustworthiness [19]. Thus, recommendation values are subjective and determined from the perspective of one particular entity whereas reputation values are objective and the same from the perspectives of all entities.

Fig. 3. Common feedback model of recommender and reputation systems.

3 State of the Art

Based on the background information introduced in the previous section, we survey the state of the art of reputation-enhanced recommender systems. To this end, we conduct a systematic literature review following the well-recognized guidelines by Webster and Watson [45] and Levy and Ellis [22]. In particular, we act on the eight-step process by Okoli and Schabram [30], which specifies these guidelines in detail.

3.1 Literature Review Protocol

In order to fulfill the demand of vom Brocke et al. [42] that not only the findings of a literature review but also the process of searching and filtering the literature should be comprehensively described, the implementation of each of Okoli and Schabram's eight steps [30] is discussed in the following.

1) Purpose of the literature review. By systematically examining the existing ways to enhance recommender systems with reputation data and relating them to one another, the state of the art of this research stream is revealed.

2) Protocol and training. When conducting a systematic literature review, it is crucial to act according to a detailed protocol. The most important aspects are pointed out for each step within this subsection. Training is not applicable to this paper because the literature review has essentially been conducted by the first author only. Nevertheless, conceptual feedback by the co-authors has been taken into consideration.

3) Searching for the literature. The main issue to consider regarding the literature search is systematics. In this literature review, the following five digital libraries are used: ACM Digital Library, AIS Electronic Library, IEEE Xplore Digital Library, ScienceDirect, and Scopus. As demanded by vom Brocke et al. [42], they are chosen because they provide access to the journals and conference proceedings that are most relevant to the topic of this paper. In order to discover as many potentially relevant publications as possible, we use the very general search phrase "recommend* AND reputation". We also use the search phrase "collaborative AND reputation" because there are several publications in the recommender systems field mentioning only collaborative filtering instead of recommender systems in general. Since recommender systems are relevant in multiple research disciplines (e.g. computer science, engineering, mathematics), we do not exclude any of them from the initial search. We also do not exclude any work based on the year of publication. Moreover, we search for both journal articles and conference papers. The initial search carried out in November 2016 resulted in 420 hits at ACM, 19 hits at AIS, 341 hits at IEEE Xplore, 241 hits at ScienceDirect, and 1,367 hits at Scopus.

4) Practical screen. Since we use very general search phrases and do not exclude any disciplines from our search, we receive a high number of initial search results (especially considering the narrow focus of this paper). All these publications enter the screening process by title, in which many of the clearly irrelevant ones can be removed. The relevance of the remaining papers is then judged based on their abstracts. Again, they are removed only if they are clearly not applicable to the scope of the literature review. If there are any doubts about their relevance, they are kept for the time-consuming full text review. In order to be relevant, a proposal first of all has to contain both an actual recommender and an actual reputation component. On the one hand, this excludes papers using the term "recommendation" to describe a rating or second-hand information in the reputation systems domain. On the other hand, this also excludes work creating recommendations by simply ranking items according to their reputation values. In addition, publications are considered as relevant only if the calculations of recommendation and reputation values as well as the combinations of recommender and reputation components are sufficiently described.

5) Quality appraisal. Publications may be judged based on the ranking of their outlets. Since we examine an emerging research stream for which the number of publications in top journals and at top conferences is still low, however, we do not limit our focus to highly recognized and popular work only.

6) Data extraction. In this step, the information from those publications the full text review brings forth as relevant are collected. In order to be able to compare the publications in a structured manner, we develop a dedicated taxonomy as a basis for the data extraction step (cf. Section 3.2). Particular attention is paid to the hybridization approach, the type of recommender system, and the evaluation described in the paper.

7) Synthesis of studies. Based on the notes of the data extraction step, the relevant publications are analyzed in detail. With the help of our taxonomy, we provide a structured overview of existing work (cf. Section 3.3) and are able to identify directions for future research efforts (cf. Section 4).

8) Writing the review. Presenting the insights gained in the synthesis step concludes the eight-step process of conducting a systematic literature review.

3.2 Taxonomy Development

As previously described, the data extraction step requires the excerption of the publications judged as relevant in the full text review. In the following, a taxonomy providing a clear structure for this activity is developed.

First and foremost important, reputation-enhanced recommender systems can be analyzed according to their **hybridization approaches**. Following Burke's [10] overview of methods for the hybridization of two or more recommendation techniques, we define the first dimension for distinguishing different approaches

Table 1. Combining recommender and reputation systems based on their data bases.

	recommender system	reputation system	data base dimension
1	IR	UR	different data bases
2	UR	IR	
3	IR	IR	same data base
4	UR	UR	

to enhance recommender systems with reputation data: the *hybridization method* dimension. We adapt the methods listed by Burke [10] to the hybridization scenario of this paper, resulting in the following six categories:

- *Weighted:* The respective outputs of a recommender and a reputation system are combined based on a weighting factor.
- *Switching:* If a recommender system is not able to generate enough suggestions, a reputation system is used instead or in addition.
- *Mixed:* The outputs of both systems may be presented at the same time. In particular, the final recommendation value is high only if both individual values are high.
- *Rec-rep-cascade:* A reputation system refines the output of a recommender system.
- *Rep-rec-cascade:* A reputation system pre-filters the input for a recommender system.
- *Augmentation:* Reputation data is considered directly within the calculations of the recommender system.

Furthermore, Figure 3 (cf. Section 2.3) shows that there are two kinds of data bases in connection with recommender and reputation systems: IR used for item-related feedback and UR used for user-related feedback. Although it is most common for recommender systems to operate on IR and for reputation systems to operate on UR, both systems can also use the respective other data base. For example, there are recommender systems for contact recommendation on online social network sites (i.e. employing UR) as well as reputation systems for the taste-independent judgment of products (i.e. employing IR). Therefore, when enhancing recommender systems with reputation data, there are four combination possibilities regarding the chosen data base of the systems (cf. Table 1). Based on these four possibilities, we deduce the second dimension of the taxonomy employed for the data extraction: the *data base* dimension. It features two categories. First, recommender and reputation systems can use *different data bases*. Second, they can use the *same data base*.

In addition, reputation-enhanced recommender systems can be compared according the underlying **types of recommender system**. Therefore, the third dimension focuses on the *recommendation approach*. Regarding its categories, we distinguish between the three commonly accepted approaches [3]: content-based filtering (*CbF*), collaborative filtering (*CF*), and hybrid (*CbF/CF*). Although the ideas behind recommendation algorithms are generally applicable to different contexts, the respective publications typically focus on a specific domain.

This constitutes the fourth dimension of the taxonomy: the *application area* dimension. Possible values include *movies*, *products*, and *hotels*. However, we do not define a fixed list of categories for this dimension at this point because there is no comprehensive list in the literature we could rely on.

Apart from the characteristics of the developed systems, it is crucial to judge publications according to their **evaluations** because not all kinds of evaluation may proof the value of a proposal equally well. For example, real-world case studies are more meaningful than fictional scenarios by far. Here, we rely on the "how" of evaluation as described by Prat et al. [32] and adapt the dimensions and categories that are most relevant to our analysis. First, there is the *evaluation technique* dimension with its categories: *case study*, *field study*, *action research*, *static analysis*, *dynamic analysis*, *controlled experiment*, *simulation*, *testing*, *informed argument*, *scenario*, *survey*, and *focus group*. And second, there is the *relativeness* dimension with its categories: *absolute* and *relative*.

3.3 Overview of Existing Work

In total, our full text review consists of 82 papers published between 2004 and 2017. In the following, the ideas of the work finally judged as relevant to the scope of this paper are comprehensively described. The remarks are structured according to the hybridization method dimension. In addition, Table 2 compares the publications according to the complete taxonomy developed in Section 3.2. Please note that Abdel-Hafez et. al [1] describe two distinct hybridization approaches in their paper.

Weighted. McNally et al. [29] introduce a weighted hybridization approach for the HeyStaks social search platform [36] in which recommender and reputation values are based on different data bases. The recommender component determines the relevance scores of the search results with respect to a given search query whereas the reputation component aggregates the reputation scores of those HeyStaks members that are responsible for the existence of the search results. Alotaibi and Vassileva [4] pursue a similar approach for their recommender system for scientific papers. The recommender component is based on the content similarity between a candidate paper and the user's current interests as well as on the ratings other users have assigned to the paper. The reputation component relies on the reputation of the author of the candidate paper (e.g h-index). In the crowdsourcing recommender of Wang et al. [43], the recommender component identifies appropriate tasks based on user similarities whereas the reputation component relies on the reputations of the task requesters. The system proposed by Cui et al. [13] combines the reputation value of an item (determined according to its favorable rating ratio) with the recommendation value of the user providing the respective item. Abdel-Hafez et al. [1] describe a weighted hybridization method in which the recommender and the reputation system use the same data base. The first step is to perform the Borda count method separately for the ranked output lists of the recommender system and the reputation system. By assigning weights to the two Borda count lists, the weighted sum of the Borda count scores is determined for each item. The item

Table 2. Publications compared according to the developed taxonomy.

ref.	hybridiz. method	data base	recommend. approach	application area	evaluation technique	relative-ness
[4]	weighted	different	CbF/CF	documents	n/a	n/a
[13]	weighted	different	CF	products	contr. exp.	relative
[29]	weighted	different	CF	search	contr. exp.	relative
[43]	weighted	different	CF	crowdsourcing	contr. exp.	relative
[1]	weighted	same	CF	movies	case study	relative
[2]	weighted	same	CF	movies	case study	relative
[44]	weighted	same	CbF/CF	products	case study	relative
[7]	switching	same	CF	restaurants	scenario	relative
[8]	switching	same	CF	tourism	scenario	relative
[9]	switching	same	CF	restaurants	scenario	relative
[18]	mixed	same	CF	hotels	scenario	absolute
[47]	mixed	same	CF	applications	simulation	absolute
[48]	mixed	same	CbF	tourism	simulation	absolute
[12]	rec-rep-c.	different	CbF/CF	products	n/a	n/a
[1]	rec-rep-c.	same	CF	movies	case study	relative
[21]	rec-rep-c.	same	not def.	products	contr. exp.	absolute
[16]	rep-rec-c.	different	CbF/CF	documents	simulation	absolute
[40]	rep-rec-c.	different	CF	services	contr. exp.	absolute
[49]	rep-rec-c.	different	CF	products	case study	absolute
[11]	augment.	different	CF	news	simulation	absolute
[23]	augment.	different	CbF	documents	case study	relative
[24]	augment.	different	CbF	documents	case study	relative
[25]	augment.	different	CbF/CF	blog articles	case study	relative
[34]	augment.	different	CF	products	contr. exp.	relative
[37]	augment.	different	CF	web services	contr. exp.	relative
[39]	augment.	different	CF	products	case study	relative

with the highest total score is recommended to the user. Abdel-Hafez et al. [2] introduce a recursive variant of this approach. In another proposal belonging to this category, Wang et al. [44] suggest the weighted enhancement of a product's recommendation value with its reputation and its purchase frequency.

Switching. The switching method is used by Bedi et al. [7] in their restaurant recommender termed SRPRS. The system produces a list of recommendations based on the degrees of importance of the items retrieved from similar users. Only if the recommendation list does not contain as many items as requested, it is extended based on the degrees of importance of all items whose reputation values are greater than some threshold. The ideas of SRPRS can also be found in two other proposals identified in the literature review: MARST [8] and SAPRS [9]. Although the exact items considered for these systems may slightly differ (MARST considers not only restaurants but also hotels and points of interest), they all focus on scenarios in which the recommender and the reputation component rely on the same data base.

Mixed. The service recommender developed by Yazidi et al. [48] is divided into several subsystems. Among others, there is a recommender component identifying relevant services based on the user's context and profile as well as a reputation component managing the reputation value of the services. A service is recommended only if it is positively evaluated by all subsystems. Yan et al. [47] describe a system to recommend the usage of mobile applications based on the applications' local recommendation values as well as their public reputation values. The applications are recommended only if they possess both a high personalized recommendation value and a high public reputation value. Jøsang et al. [18] introduce an operator which returns a high total value only if both the recommendation and the reputation score are high. This is supposed to "amplify the discriminating power" [18]. Similarly to the approaches employing the switching method, the systems based on the mixed method all combine recommender and reputation systems relying on the same data base.

Rec-Rep-Cascade. Constantinov et al. [12] propose a rec-rep-cascade hybridization using different data bases. First, a recommender system determines a product the customer is supposed to be particularly interested in. Then, a reputation system depicts information relevant for the assessment of the trustworthiness of the sellers offering the product. Because of the limited size of the platform, the reputation information is limited to only one seller. On a larger platform, however, there would be many providers offering the same item. Then, the reputation system helps determine the most trustworthy one. In contrast, Abdel-Hafez et al. [1] consider a cascade hybridization of a recommender and a reputation system relying on the same data base. They enhance a recommender system's output by re-sorting the top-M recommendations based on their reputation values. Thus, only the top-M items according to the recommender system enter the second step of the cascade. Finally, the top-N ($N < M$) items of the re-sorted list are recommended to the user. Similarly, the idea of Ku and Tai [21] is to provide one or more item recommendations to the user at first. Then, the user is supposed to take a look at the reputation of the items and probably also at their rating distributions. As opposed to the other publications discussed in this section, the authors do not propose a new system but conduct a study on the effects of recommendation information and reputation information on buying intentions.

Rep-Rec-Cascade. Tserpes et al. suggest that "providers that systematically fail to comply with their obligations against the consumers will be isolated" [40] and thus to use reputation data as a pre-filtering mechanism prior to the recommendation process. Guo et al. [16] realize this by extending their document recommendation system with a reputation component keeping track of the reputation values of the users according to their activities and the acceptance rates of the documents shared by them. If the reputation value of a user drops below a particular group's threshold, he can no longer access this group and his sharing activities are no longer considered in any recommendations. The recommender system introduced by Yu et al. [49] also excludes users with negative reputation values from the item recommendation process.

Augmentation. In contrast to the proposals discussed so far, the following approaches integrate the reputation data directly into the computation process of the recommender system. In all of them, the recommender component is concerned with items whereas the reputation values belong to users (e.g. sellers, providers). Qian et al. [34] as well as Tang et al. [39] employ the users' reputation values to control the importance of the ratings in the matrix factorization process of their product recommenders. Cimini et al. [11] use the reputations of news item creators to replace or at least supplement the consideration of similarity values in the collaborative filtering calculations of their news recommender system. The news item creators' reputation values are based on the number of users that have liked the respective news items. Similarly, Su et al. [37] use the reputations of web service users to enhance the similarity calculations within the collaborative filtering process of their quality of service prediction approach. The reputation values are calculated according to the beta-family of probability density functions [46]. Liu et al. [25] suggest to overcome the limitation of content-based filtering systems of recommending only items similar to the ones a user has previously liked by augmenting the user's rating matrix with his group's preference scores. The group's preference score for an item is derived according to the reputation of the users who have pushed the particular item. A user's reputation value, in turn, is based on the amount of articles pushed by him as well as the number of users following these articles. Liu et al. [23, 24] also use this idea for a document recommender based on the similarity between the topic interests of a community and the target documents. The topic interests are determined according to the topics collected by the community and the reputation of the users who have collected them. The users' reputation values, in turn, are based on the number of push interactions indicating that other users found a document helpful.

3.4 Limitations of the Literature Review

Overall, our review serves as a comprehensive summary of the state of the art of reputation-enhanced recommender systems and can, as such, be used for understanding or new research. Even though we ensured a high quality of the review by relying on well-recognized guidelines, there are some limitations to discuss.

Analyzing the literature according to a newly developed taxonomy carries the risk that the insights gained might be of little value if the dimensions are poorly defined. To mitigate this potential shortcoming, we derived the data base dimension from commonly accepted principles regarding recommender and reputation systems and kept its values generalized. The hybridization method dimension is based on published research as it adapts the values of Burke's [10] work on hybrid recommender system. The same applies to the recommendation approach and evaluation dimensions, which rely on the remarks of Adomavicius and Tuzhilin [3] and Prat et al. [32], respectively.

Another possible limitation is that relevant literature might not be included in our search results. Since we chose five of the most relevant databases, used them with very general search phrases, and conducted forward as well as backward searches, however, it is unlikely that we missed many relevant publications.

4 Future Research Directions

The analysis of the literature yields several observations. First of all, the publication years of the papers suggest a growing interest in reputation-enhanced recommender systems especially since 2011. Turning to the contents of the existing work, important insights on the state of the art of the research stream can be gained by assigning the publications to the different hybridization approaches, whose dimensions and categories are introduced as the most important ones of our taxonomy in Section 3.2.

Table 3. Publications classified according to the hybridization approach dimensions.

	different data bases	same data base
weighted	[4], [13], [29], [43]	[1], [2], [44]
switching		[7], [8], [9]
mixed		[18], [47], [48]
rec-rep-cascade	[12]	[1], [21]
rep-rec-cascade	[16], [40], [49]	
augmentation	[11], [23], [24], [25], [34], [37], [39]	

As Table 3 shows, each hybridization method is covered by at least three proposals. Each category of the data base dimension is covered by multiple publications as well. However, not all combinations of data base and hybridization method categories have been addressed so far. Our search results do not contain any proposals regarding the switching and the mixed hybridization with different data bases as well as the rep-rec-cascade and the augmentation hybridization with the same data base. Therefore, the first future research direction is to investigate whether the missing combinations are applicable to meaningful use cases and whether corresponding systems lead to performance improvements. Abdel-Hafez et al. [1], for example, justify their decision to focus on the rec-rep-cascade hybridization instead of the rep-rec-cascade hybridization with the assumption that personalized recommender-generated lists would be more accurate than non-personalized reputation-generated lists and therefore should be used as the primary candidate recommendation list. Although this assumption is intuitively understandable, its validity is still worth investigating.

Focusing on the evaluation dimensions, Table 2 (cf. Section 3.3) reveals that some of the publications are not thoroughly evaluated by comparing them to related work or not evaluated at all. Those publications that have actually been evaluated all show improvements in terms of the employed metrics, which supports the implicit claim of this paper that enhancing recommender systems with reputation data leads to better recommendation performance. Nevertheless, some of the evaluations are based on fictional and overly simplistic scenarios. Although demonstrations, as these light-weight forms of evaluation should rather be denoted, can show the feasibility and meaningfulness of the proposals, the second future research direction is to investigate how the systems that have been evaluated insufficiently or not at all actually compare to related baseline recommendation techniques using real-world data.

The ultimate goal regarding the evaluation dimensions, and thus the third future research direction, is to not only compare the developed systems to baseline recommendation techniques but also among one another. To determine the best proposal for a specific use case, it is necessary to make the respective evaluations comparable by always using the same metrics and data sets. This is far from being an easy task because not all of the existing approaches are described in sufficient detail to be able to re-implement them and compare them to one another.

5 Conclusion

The marginal improvements that may be achieved from further optimizing highly sophisticated recommender algorithms have motivated scholars to broaden the horizon of recommender systems research and integrate relevant concepts from related fields. Since trust and reputation systems show substantial connections to recommender systems, there have been attempts to consider trust relationships in the recommendation process. However, personal trust links are only available in small numbers on modern online platforms because these are typically characterized by short-term interactions. As the concept of reputation is closely linked to trust but fits the peculiarities of modern online platforms better, this paper focused on the integration of reputation data instead of trust relationships. In fact, the corresponding research stream of reputation-enhanced recommender systems has attracted considerable attention in recent years. Therefore, our main goal was to provide a comprehensive survey of the approaches proposed so far. At first, we identified existing work in a systematic and exhaustive search process. Then, in order to relate the publications to one another, we developed a dedicated taxonomy based on commonly accepted principles and published research. Comparing the proposals according to the taxonomy resulted in a structured overview of the state of the art of the research stream.

On the one hand, our results help stimulate further innovation in reputation-enhanced recommender systems. Future research is not only needed to close or explain the identified gaps but also to improve the existing proposals. After all, there still is constant innovation in the respective research fields of recommender and reputation systems, which is why new hybridization approaches are needed and expected as well. On the other hand, this paper also serves as an important basis for the further exchange of ideas between both communities. For example, future research efforts could investigate the opposite of our approach: how recommender systems may be used to enhance reputation systems.

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