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Reciprocal Recommender Systems: Analysis of state-of-art literature, challenges and opportunities towards social recommendation

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ABSTRACT

There exist situations of decision-making under information overload in the Internet, where people have an overwhelming number of available options to choose from, e.g. products to buy in an e-commerce site, or restaurants to visit in a large city. Recommender systems arose as a data-driven personalized decision support tool to assist users in these situations: they are able to process user-related data, filtering and recommending items based on the user's preferences, needs and/or behavior. Unlike most conventional recommender approaches where items are inanimate entities recommended to the users and success is solely determined upon the end user's reaction to the recommendation(s) received, in a Reciprocal Recommender System (RRS) users become the item being recommended to other users. Hence, both the end user and the user being recommended should accept the "matching" recommendation to yield a successful RRS performance. The operation of an RRS entails not only predicting accurate preference estimates upon user interaction data as classical recommenders do, but also calculating mutual compatibility between (pairs of) users, typically by applying fusion processes on unilateral user-to-user preference information. This paper presents a snapshot-style analysis of the extant literature that summarizes the state-of-the-art RRS research to date, focusing on the algorithms, fusion processes and fundamental characteristics of RRS, both inherited from conventional user-to-item recommendation models and those inherent to this emerging family of approaches. Representative RRS models are likewise highlighted. Following this, we discuss the challenges and opportunities for future research on RRSs, with special focus on (i) fusion strategies to account for reciprocity and (ii) emerging application domains related to social recommendation.

1. Introduction

In the last two decades, Recommender Systems (RS) have gained a lot of popularity as an effective information processing and personalized decision support tool to filter relevant information or resources to users in Internet platforms. They are used to assist people in decision-making situations under contexts of "information overload", which are common not only in e-commerce sites, but also in entertainment portals like Spotify and Netflix, social media sites, tourism portals and any other services where optimizing the user's experience in terms of their interaction with the system, becomes imperative [1–4]. In essence, an RS gathers and analyzes users' interaction data with items in the system to build knowledge about their preferences, whereby the system predicts items (e.g. products, services, media, things to see or do, etc.) that the user is likely to be interested in. Most RS learn users' preferences from user–item ratings to undertake this predictive task.

The repertoire of RS approaches has amply expanded since the late 90s, with content-based –*"recommending similar content to what the user liked"* [5]–, collaborative filtering–*"recommending what similar people to the user liked"* [6]–and context-aware–*"recommending items that suit the user's current context"* [7]–being popular approaches [8]. Likewise, there are RS models that provide group recommendations by aggregating members' preferences or individually recommended items [9], as well as RS that integrate user information across multiple domains to build more insight about their taste or needs [10]. Besides, similar to multi-criteria decision-making scenarios [11] where humans naturally tend to judge options according to multiple criteria, in a multi-criteria RS a user may often prefer to rate items (e.g. hotels) using

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several criteria (e.g. food, cleanliness, service), hence these systems were proposed to exploit such ratings [12].

An emerging family of RS approaches arose in the last decade, Reciprocal RS (RRS) [13,14], in which: (i) users become the item being recommended to other users, and (ii) success is determined not only by the end user who requested recommendations, but also by the user(s) being recommended, hence mutual preference or compatibility (*reciprocity*) needs to be measured. In other words, a vital requirement in any RRS is that both users should reciprocate, i.e. both of them should indicate positive feedback on the suggestion to connect with each other in order to deem the matching recommendation as successful. This requisite adds an additional layer of complexity in RRS with respect to the majority of conventional RS, the latter of which typically only seek satisfying the end user preferences. RRS are popular in dating [15,16], recruitment [17], online learning environments [18], and social media platforms [19–22] where reciprocity can yield better matchings between people [13].

Research into classical item-to-user RS has expanded to a sheer range of techniques, algorithms and application areas [1,2,8,12,23,24]. Notwithstanding, although several of the most widespread families of RS algorithms have been translated into a reciprocal setting, the problem of personalized people-to-people recommendation via RRS is still comparatively less represented in the literature, hence it still largely poses a number of challenges and unanswered research questions that deserve further exploration. The most obvious complexity found relates to the *reciprocity requirement*. In this sense, fusion processes are a crucial and distinctive task in most RRS for determining the level of reciprocity or mutual compatibility between two users, predicated on unilateral preferences or recommendation information. Various approaches have been adopted in the RRS literature for fusing unidirectional information between (pairs of) users into reciprocal information [16,25,26], with the most salient ones relying on *aggregation functions*–e.g. harmonic or weighted means between unidirectional user-to-user preferences–for this end [27]. Other well-known examples of ongoing challenges in the research area include: balancing users' different levels of popularity to prevent biased recommendations [25], an accentuated presence of the data sparsity and user cold-start problems [28] and the relative shortage of publicly available datasets to incentivize user studies, owing to privacy concerns. On another note, even though most RRS along the last decade have been developed for a limited range of applications, namely online dating, recruitment, learning and social media, there exist other social matching problems where they could play a very important role and exert significant impact to promote sociability and, ultimately, to contribute to social good. This opportunity goes in parallel with the increasing abundance of new social media platforms and apps built with more specific goals, e.g. house-share, skill-sharing, professional collaboration, and so on [21,29,30].

The aforesaid challenges and identifiable opportunities for future research on RRS, along with the gentle developments witnessed in the RRS literature in the last years and the growing spectrum of consolidated (or potential) real-world applications of RRS, motivate the need for a comprehensive analysis of RRS literature and an elaborated discussion on the current state of affairs in the field. There are recent state-of-the-art surveys in the literature that comprehensively analyze emerging – and comparatively more complex – families of RS along the last years, including: cross-domain RS [31], deep learning based RS [32,33], sequence-aware RS [34], context-aware RS [35], RS leveraging multimedia contents [36] and adversarial RS [37], to name a few. Nonetheless, although Pizzato et al. [15] sat the bases for subsequent RRS developments in the domain of online dating, to our knowledge there are no exhaustive literature analyses focused on state-of-the-art RRS developments and their growing range of applications ever since.

Accordingly, this paper provides a fourfold contribution — for the readership interested in specific parts of this paper, Fig. 1 provides a mind map-like outline of its contents:

1. A formal characterization of RRS with respect to other RS families and the definition of a general RRS conceptual model for RRS guided by preference fusion processes (Section 2).
2. An outline of the algorithmic, fusion and evaluation aspects underlying RRS (Section 3).
3. An exhaustive analysis of existing state-of-the-art studies in the RRS literature, with a triple objective: (i) signaling the key characteristics of existing RRS methodologies and studies conducted in several application domains; (ii) highlighting the recommendation techniques and fusion processes utilized to account for reciprocity; and (iii) analyzing some representative models in further detail (Section 4).
4. A discussion of the challenges, research gaps, opportunities and future research directions in the landscape of RRS (Section 5), emphasizing the underlying fusion processes to capture reciprocity and emerging application areas of RRS.

Following these contributions, Section 6 summarizes the lessons learnt and concludes the paper.

2. Reciprocal Recommender Systems: Characterization and conceptual model

This section formally introduces the reciprocal recommendation problem, describing the main elements of an RRS and its differentiating features with respect to other RS frameworks.

People-to-people recommenders have become an important class of RS in a variety of online services [15,38–40], be it for finding a partner, a job, or simply connecting people with each other. Unlike classical item-to-user recommenders, in an RRS there exist two parties that must be satisfied with the recommendation to deem it as successful, that is to say, reciprocity is fundamental for a potential connection between people to succeed. An RRS is fundamentally different from other two broad classes of RS, where reciprocity is not required:

1. *Item-to-User RS*: Classical RS approaches concentrate on recommending items that represent products or services, such as movies, books, music, hotels, restaurants, etc., for individuals or groups who may potentially consume the recommendable item(s) [1,9]. In most of these approaches only the needs and interests of the target user (or group) need to be met, therefore preference relations are unidirectional and they are defined as user-to-item preferences. In these cases, traditional recommendation strategies are often enough to satisfy the users' needs.
2. *Nonreciprocal User-to-User RS*: These approaches recommend people to *one* target user, considering only one-sided relevance, i.e. no reciprocity is needed because only the interests/needs of the target user influence both the process of recommending people to her/him and the success of the recommendation. Examples include recommending whom to follow on Twitter[1] [5,22,41].

Pizzato et al. defined in [40] a classical item-to-user RS task as follows.

Definition 2.1 (*Recommender System [40]*). Given a user $x \in U$, a recommender $\mathcal{R}(x)$ is a system that recommends a list of items $R \subset I$ such that the (predicted) degree of preference $p_{x,i}$ by x towards every item $i \in R$ is stronger than the preference degree by x towards any item $i' \notin R$:

$$\mathcal{R}_I(x) = \{i : p_{x,i} > p_{x,i'}, \forall i \in R, \forall i' \notin R\} \quad (1)$$

with R being the list of recommended items for x.

[1] http://twitter.com.

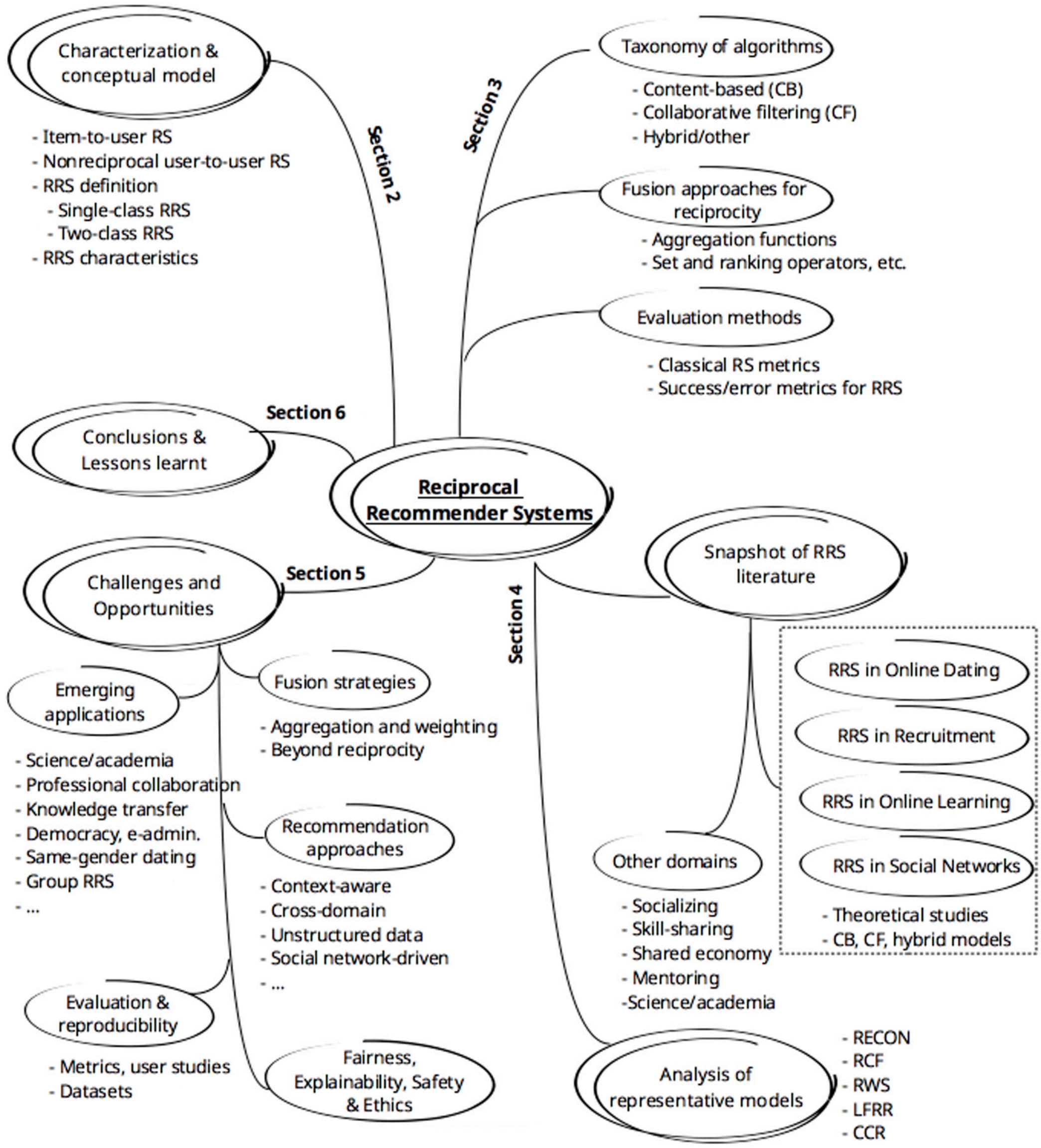

Fig. 1. Outline of the structure and contents of the paper.

Based on Definition 2.1, we formalize two classes of user-to-user recommender. An overview that emphasizes unidirectional user recommendation in social media was conducted in [42].

Definition 2.2 (*Unidirectional user-to-user RS*)**.** Let $x \in U$ be a user. An unidirectional (nonreciprocal) user-to-user recommender $\mathcal{R}_U(x)$ is a system that recommends users y such that:

(i) $y \in R \subset U$ and $y \neq x$, for every $y \in R$.
(ii) The degree of preference or interest by x for every y in R, denoted $p_{x,y}$, is stronger than her/his preference degree towards any other user $y' \neq x$ not belonging to R.

$$\mathcal{R}_U(x) = \{y : p_{x,y} > p_{x,y'}, \forall y \in R, \forall y' \notin R\} \tag{2}$$

In an item-to-user RS (see Eq. (1)) the set of all recommendable items is I. By contrast, in a nonreciprocal user-to-user recommender (see Eq. (2)) we generally have that, for every target user $x \in U$ the set of recommendable entities are also users in U.

Definition 2.3 (*Reciprocal Recommender System*)**.** Given two users $x, y \in U$, $x \neq y$, let x be the subject user who accesses a system to obtain recommendations, and let y be an object user[2] who is susceptible to being recommended to x. A reciprocal recommender, denoted by $\mathcal{RR}_U(x)$ is a system whose output combines two unidirectional user-to-user recommenders $\mathcal{R}_U(x)$ and $\mathcal{R}_U(y)$, intending to simultaneously satisfy the interests of both x and any $y \in \mathcal{RR}(x)$.

$$\begin{aligned}\mathcal{RR}_U(x) = \{y : y \in \mathcal{R}_U(x) \text{ and}\\ x \in \mathcal{R}_U(y)\} = \{y : p_{x\leftrightarrow y} > p_{x\leftrightarrow y'}, \forall y \in R, \forall y' \notin R\}\end{aligned} \tag{3}$$

where $p_{x\leftrightarrow y}$ is a level of mutual preference or compatibility (reciprocity) between x and y, frequently obtained by using an aggregation or combination function ϕ, i.e. $p_{x\leftrightarrow y} = \phi(p_{x,y}, p_{y,x})$ [27].

Users y can only be recommended to a subject user x if a sufficient level of reciprocity is predicted in terms of mutual interest. Such reciprocity is measured by combining $\mathcal{R}_U(x)$ and $\mathcal{R}_U(y)$, often aggregating x's preference score for y and vice versa. This conceptual model is visually represented in Fig. 2. As we can observe, two preference

[2] In RRS literature, recommendable users are sometimes referred to as *items*, to distinguish them from the target user x. Notwithstanding, the inherent requirement in RRS of jointly meeting both users' interests is still kept.

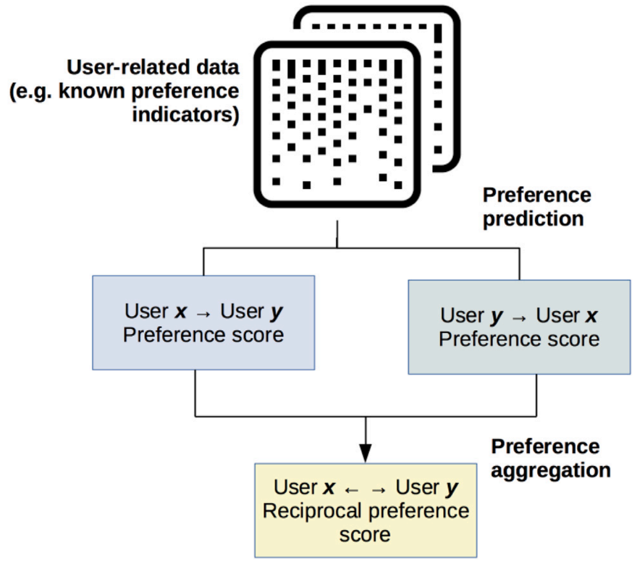

Fig. 2. General RRS conceptual model.

scores are predicted: one denoted $p_{x,y}$ that represents how much x would be interested in y (e.g. for starting a relationship) and one that represents how much y would be interested in x, denoted $p_{y,x}$. The subsequent aggregation step is a fundamental principle of most RRS in the literature. The choice of how to fuse information from both sides is a crucial aspect in RRS research to date [26,43], albeit having still received little attention to date. Intuitively, if y is recommended to x, then x would be also likely to become a recommendation for y. Regardless of who the subject user is, the recommendation is successful if both parties respond to it positively.

With the rise of Internet and mobile app services aimed at connecting people, the range of application domains where RRS research can be implemented has subtly increased in recent years. Some of these applications motivate us to subdivide the previous RRS definition into two variants, depending on whether or not the set of all users U is homogeneous or not. These two variants are introduced below.

Definition 2.4 (*Single-class RRS*)**.** Let x, y and $\mathcal{RR}_U(x)$ be as introduced in Definition 2.3. If any user $x \in U$ can be recommended any other user $y \in U \setminus \{x\}$, then $\mathcal{RR}_U(x)$ is a single-class RRS.

Definition 2.5 (*Two-class RRS*)**.** Let x, y and $\mathcal{RR}_U(x)$ be as introduced in Definition 2.3. If U is partitioned into two disjoint user sets U_X and U_Y, such that if $x \in U_X$ then $y \in U_Y$ and vice versa, then $\mathcal{RR}_U(x)$ is a two-class RRS.

In a two-class RRS, users are divided in two classes, e.g. male and female, job seeker and recruiter, etc., such that the subject user and object user cannot belong to the same class of users in order to be eligible for mutual recommendation. Interestingly, this has been by far the most investigated type of RRS, largely due to the prevalence of heterosexual online dating and recruiting as the most investigated application domains for RRS approaches. Table 1 extends the discussion on differences between traditional and reciprocal recommenders provided in [40], by summarizing the distinctive features of RRSs with respect to the other related frameworks formalized above.

Remark 2.1. It is worth highlighting the difference between RRSs and another type of recommender that has attained importance in the last years: multi-stakeholder RS [44–46]. Unlike RRS where both parties involved are users seeking recommendations, in a multi-stakeholder recommender not only the interests of the target user(s) are sought, but also those from other parties seeking other forms of benefit e.g. sellers of a product, providers of a service, advertisers, etc. A multi-stakeholder RS is a broader generalization of an RRS. Our overview focuses its scope on RRS-related studies solely.

3. Algorithms, fusion approaches and evaluation methods for RRS

This section examines the methodologies, processes and common evaluation practices in the development of reciprocal recommendation models. It starts by providing a broad categorization of the algorithmic approaches underlying existing literature (Section 3.1) followed by a summary of fusion approaches frequently employed to integrate reciprocity (Section 3.2). The section concludes providing a bird's-eye view of evaluation methods used to validate reciprocal recommenders (Section 3.3).

3.1. Taxonomy of algorithms for reciprocal recommendation

In line with traditional RS, most of the RRS literature distinguishes between several families of algorithms to produce reciprocal recommendations, many of which are used to guide the preference prediction process depicted in Fig. 2: *content-based*, *memory-based collaborative filtering*, *model-based collaborative filtering* and *hybrid* methods. Each of these families of algorithms encompasses in turn a number of specific techniques employed under their core principles. Accordingly, a two-level categorization of algorithms underlying RRS is shown in Table 2. An additional class, *Other*, is included to classify some approaches that are comparatively less common within the general RS landscape or they do not closely abide to the principles behind the other classes. It is worth highlighting that the list of works shown in Table 2 ("Representative works" column) is merely a representative example of RRS models featuring the use of the listed algorithms. Consequently, this list is not intended to be exhaustive: an exhaustive overview including these and other RRS works is provided in Section 4, divided into several application domains.

To better understand each of the main families of algorithms within the scope of reciprocal user-to-user recommendation, their basic principles are outlined below:

1. **Content-based (CB) Reciprocal Recommendation**: Algorithms under this category intend to (i) recommend similar users y to those liked by the subject user x, while (ii) ensuring reciprocity in recommendations from the viewpoint of y's interests. The two core pieces of information are user profiles and user preferences.

Table 1
Differences between RRSs and other frameworks for item and user recommendation.

Recommender framework	Features
Traditional item-to-user recommender	– The user receives recommendations consisting in items i (products, services, etc.) from an item set I. – An item can be generally recommended to multiple users separately, subject to its availability. – The target user is the only entity determining the success of the recommendation (except for multi-stakeholder RS [44]). – Users/items might continue being part of the system after a successful recommendation takes place. *Applications*: e-commerce, leisure, tourism, food, retail, etc.
Nonreciprocal user-to-user recommender	– The user receives recommendations consisting in other users. – A user can be recommended to multiple users, all of whom can simultaneously accept the recommendation. – The target user is the only entity determining the success of the recommendation. – Users might continue being part of the system after a successful recommendation takes place. *Applications*: social media (e.g. following Twitter users).
Reciprocal Recommender (RRS)	– The *subject* user x receives recommendations consisting in *object* users y, some of whom might in turn be recommended the subject user. – In some application areas, if the two users agree to connect with each other, then they are no longer available for being recommended to anyone else. Besides, in some contexts users may no longer need using the system after a successful recommendation. – Both x and y must be satisfied with the recommendation in order to deem it as successful.
Single-class RRS	– The user set U is homogeneous: any two others are potentially recommendable to each other. *Applications*: social media (connecting user profiles), homosexual dating, finding friends, online learning, shared economy, skill share platforms.
Two-class RRS	– The user set U is divided into two classes of users: only pairs of users from a different class each can be mutually recommended. *Applications*: heterosexual dating, recruitment, student–supervisor matching.

Table 2
Taxonomy of algorithms used in RRS literature.

RS family	Algorithms/techniques	Representative works
Content-based (CB)	Preference-to-profile similarity	[16,47–49]
	Profile-to-profile similarity	[50,51]
	Multi-criteria matching	[18,52–54]
	Deep Learning	[55]
	Graph embedding	[56]
	Markov Models	[57]
	Binary classification, regression	[29,58,59]
	Preference learning, e.g. Latent Dirichlet Allocation	[60,61]
	Stable matching	[62,63]
Memory-based CF	Clustering of similar users	[64–68]
	Neighborhood-based	[16,38,69–71]
	Probabilistic neighborhood-based	[72]
	Social network/graph analysis	[73–79]
	Friend-of-friend mechanisms	[80,81]
	Instance-based learning	[82]
Model-based CF	Learning classifiers e.g. SVM, AdaBoost, etc.	[25,83,84]
	Factorization/latent factor models	[43,85,86]
Hybrid	Association rules	[87,88]
	Collaborative filtering and Markov Models	[89,90]
	Word embeddings	[21]
	Semantic or knowledge-based matching	[91,92]
	Context-aware matrix factorization	[93]
Other	Multi-objective optimization	[94,95]
	Genetic algorithms	[96]

User preferences can be explicit, e.g. users may indicate the attributes sought in other users [50,97] or, as occurs in most approaches, they are implicitly learnt from user activity in the system, namely user–user interactions such as expressions of interest, viewed user profiles or messaged users [48,55]. By observing user x's interactions with other users, it is possible to build a representation of her/his interests or preferred attributes in other users. Then, an unilateral preference value from x to y

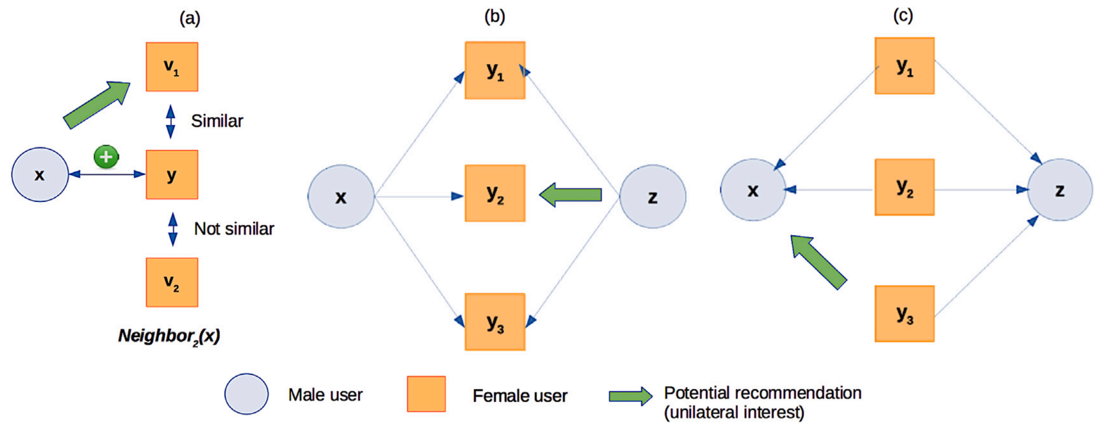

Fig. 3. Predicting unilateral preferences in (a) CB, (b) CF under interest similarity, and (c) CF under attractiveness similarity, in an online dating example.

is usually predicted based on the similarities between this preference representation and the properties (typically the profile) of any recommendable user y unknown to x.

2. **Collaborative Filtering-based (CF) Reciprocal Recommendation**: In classical recommendation, CF boils down to producing recommendations for x guided by the identification of users with similar behavior or interests to those of x. In a user-to-user setting, the goal is to observe the preferences of users who *interact similarly* as x with other users in the system. User profile information is less relevant in CF, where the task typically concentrates on analyzing the dynamics of user–user interactions and identifying users z with similar interactions to x [16], thereby recommending to x "unknown" users y with whom z has interacted in a way that indicates positive interest from z to y. Intuitively, an additional requirement would be to meet reciprocity from y's side. Similar to classical RS, the CF process can be done by operating on the raw data directly (**memory-based CF**) or by training a model upon the data at hand [43] and using it to make predictions of users' interests in unknown users to them (**model-based CF**). Two popular approaches used in various CF-RRS are based on interest similarity and attractiveness similarity [16,38], which are illustrated and compared against CB in Fig. 3:
   - *Interest similarity* is determined by active user interaction. Assuming a two-class RRS scenario, if two users x, z in the same class initiate positive interactions with several users y_j in common, x and z have similar taste.
   - *Attractiveness similarity* is determined by passive user interaction. If x, z receive positive interactions from various users y_j in common, x and z have similar attractiveness.
3. **Hybrid**: This category considers approaches that adopt the principles from two or more families of recommendation approaches. This may include models that combine CB and CF e.g. combining user profile and neighborhood information [87], incorporating knowledge-based mechanisms in CB or CF [91], integrating contextual awareness in CF [93], etc (see Table 2).

3.2. Fusion approaches for capturing reciprocity

As stated earlier, analyzing whether potential reciprocal interest exists or not between users is a fundamental requirement in any RRS: without fulfilling this reciprocity requirement, little guarantees would exist for the "matching recommendation" to be a success. Fusion methods, such as the aggregation of unilateral preferences into bidirectional preferences, constitute a common necessary step towards generating reciprocal recommendations. Table 3 provides a summary of different fusion methods that have been used in RRS to account for the reciprocity requirement inherent to this family of RS.

Some of the existing fusion methods are interpretable enough to give an easily observable indicator of the level of mutual compatibility between the subject user x and an object user y. This is the case of preference aggregation strategies. As discussed in earlier sections, preference aggregation is the most traditional approach to measure the level of mutual preference between two users x and y. It boils down to aggregating the two unilateral preferences degrees by one user for the other:

$$p_{x\leftrightarrow y} = \phi(p_{x,y}, p_{y,x})$$

with $\phi : [0,1] \times [0,1] \rightarrow [0,1]$ an aggregation function [27]. This approach has been adopted by the most popular RRS models [16,48], mainly by using the harmonic mean operator over two aggregation inputs [18,43,49]:

$$p_{x\leftrightarrow y} = \phi_H(p_{x,y}, p_{y,x}) = \frac{2}{p_{x,y}^{-1} + p_{y,x}^{-1}}$$

Rather than arbitrarily, the choice of the harmonic mean operator ϕ_H to combine preference scores into mutual preference indicators [40, 48], is motivated by its tendency to provide aggregated results closer to the minimum of its inputs. In practice, this property largely reflects a core requirement in any RRS: both users should be (predicted as) *sufficiently* interested in one another, in order to produce recommendations that are likely to succeed. In [26], the performance of an RRS under other mean operators, namely the arithmetic mean $\phi_A(p_{x,y}, p_{y,x}) = \frac{p_{x,y} + p_{y,x}}{2}$ and geometric mean $\phi_G(p_{x,y}, p_{y,x}) = \sqrt{p_{x,y} \cdot p_{y,x}}$, was compared and experimentally proved as inferior. This arguably goes in line with the higher optimism exhibited by the arithmetic and geometric means, which in the RRS domain translates into a (sometimes prohibitive) relaxation of the aforesaid requirement between users' preferences for each other. Generally, it holds that $\phi_H(\cdot) \leq \phi_G(\cdot) \leq \phi_A(\cdot)$.

The cross-ratio uninorm [103] is a mixed-behavior aggregation function that was also analyzed in the comparative studies made in [26,43], leading to interesting results. Its behavior can shift between optimistic, pessimistic and neutral depending on the actual aggregation inputs $p_{x,y}, p_{y,x} \in [0,1]$ being higher or lower than an intermediate or neutral value of 0.5, Given two unilateral preference scores $p_{x,y}$ and $p_{y,x}$ their aggregated value obtained by the cross-ratio function is given by:

$$\mathcal{U}(p_{x,y}, p_{y,x}) = \frac{p_{x,y} \cdot p_{y,x}}{p_{x,y} \cdot p_{y,x} + (1 - p_{x,y}) \cdot (1 - p_{y,x})} \quad (4)$$

The performance of the cross-ratio aggregation was analyzed in two collaborative filtering-based RRS models [16,43], being reported as comparable or slightly superior to that of the harmonic mean in [16],

Table 3
Summary of fusion methods utilized for reciprocity integration and some representative RRS using them.

Fusion approach	Representative RRS models/studies
Harmonic mean	Pizzato et al.[47,48], Prabhakar et al. [98], Xia et al. [16], Potts et al. [18]
Harmonic mean combined with sum	Sudo et al. [56]
Sum of similarities/distances	Almalis et al. [17], Yu et al. [99]
Product operator	Ting et al. [86], Li and Li [77]
Weighted mean	Kleinermann et al. [25], Xia et al. [95]
Multiple averaging and uninorm aggregation functions	Neve and Palomares [26,43]
Matrix multiplication	Jacobsen and Spanakis [60]
Set intersection of recommendable users	Yacef and McLaren [49], Kutty et al. [85]
Aggregation (union) of probabilities	Pizzato and Silvertrini [100]
Average similarity between x and previous successful interactions with y	Liu et al. [51]
AND-like verification of both preference-profile similarities	Chen and Nayak [65], Kunegis et al. [75]
Community-level matching	Alsaleh et al. [64,101]
Inverse product between recommendation ranks	Mine et al. [102]

under some concrete settings. Further research would be needed to find more improvements e.g. by using weighted versions of these operators and analyzing the rationale behind the behavior of these operators under the scope of the whole RRS pipeline.

Other works have considered simpler fusion strategies such as a sum or product of unidirectional preferences [17,86]. These fusion approaches fail to yield a reciprocity indicator that is representative of the two inputs. Besides, calculating $p_{x\leftrightarrow y}$ as a sum of unidirectional preference values presents the limitation of not being able to discriminate between different pairs of inputs that may lead to the same aggregation result. For example, $p_{x\leftrightarrow y} = q$ could be the result of either (i) aggregating two balanced or equal unidirectional preference values $q = q/2 + q/2$, or (ii) aggregating two inputs one of which represents total lack of interest from one user for the other, i.e. $q = q + 0$. Thus, the semantics and interpretability of the fusion results are lost.

Beyond aggregation functions or other fusion operators that yield a quantifiable indicator of mutual preference, some studies used less common fusion strategies to reflect reciprocity, for instance: (i) logical connectives [75], (ii) set intersection operations between the two users' recommendation lists [49], (iii) set intersections between similar users to x and those reciprocally liked by potential matches y, or (iv) aggregating the ranking positions of x and y in each other's recommendation lists [102]:

$$p_{x\leftrightarrow y} = \frac{1}{rank(R_x(y)) \cdot rank(R_y(x))} \tag{5}$$

In the latter case of ranking fusion, $p_{x\leftrightarrow y}$ should not be interpreted as a degree of mutual preference, but rather as an aggregated ranking estimate, with its value – and consequently the potential positions of x and y in each other's recommendation lists – being highly dependent on the other users being recommended in both lists and their ranked positions.

Some gaps and areas for improvement, mainly related to the use of aggregation functions in RRS [27] are discussed along with other RRS challenges in Section 5. To summarize, we argue that aggregation functions to combine preference scores and fusion methods for unilateral recommendation lists or rankings, would constitute two promising directions for further study of RRS models from a reciprocity and fusion viewpoint.

3.3. RRS evaluation methods

There are a number of metrics that are used to evaluate recommender systems of diverse nature, with RRS being no exception. For instance, as described in [104], one could use metrics used to evaluate information retrieval systems such as precision, recall, F1, Mean Reciprocal Rank (MRR), Mean Average Precision (MAP), Spearman Rank Correlation Coefficient (SPRCC), Normalized Discounted Cumulative Gain (nDCC), and coverage; as well as metrics used in machine learning systems such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Area Under Curve (AUC). Similarly, it can also be important to measure recommender systems on characteristics related to the user experience such as trust, novelty, serendipity and fairness; as well as metrics such as real-time performance, scalability and robustness are used to measure how system can be applied from an engineering perspective [105].

It is important that during the development of a recommender system developers may optimize their system towards the metrics that are important for their business objective. For instance: a recommender for related legal documents should have high recall, while advertisements strive for high precision. These metrics can mostly be used in offline experiments, but also when measuring performance when experiments are done online with real users.

When implementing RRS, one may need to look beyond the evaluation metrics of traditional recommender systems [106]. Although most of the metrics above are relevant to RRS implementations, RRS have the extra complexity that a truly successful recommendation can only be defined once it is both (1) accepted by the user who received the recommendation and (2) accepted by other user who was the subject of the recommendation.

Under the RRS scenario, recommendations need an action from two parties, hence becoming necessary to define metrics that capture success and/or failure indicators [15] evidenced by historical interaction data, some of which are listed in Table 4. Examples of such metrics are:

- *Precision*: Given a recommendation list of size n, *precision at n* ($P@n$) accounts for the proportion of successful recommendations in that list:

$$P@n = \frac{\#successful}{n} \tag{6}$$

Table 4
Common success and failure indicators in RRS.

	Target user	Recommended user
Success	Actioned On Recommendation	Accepted Contact
Failed	Not Actioned on Recommendation	N/A
Failed	Actioned on Recommendation	Rejected Contact
Unknown	Actioned on Recommendation	Not read contact request
Failed	Actioned on Recommendation	Read contact and ignored after N days

- *Success rate*: The success rate at n ($S@n$) accounts for both successful and failed recommendations. It is given by the ratio of the number of successful recommendations and the *known* (both successful and failed) recommendations in a list of size n:

$$S@n = \frac{\#successful}{\#successful + \#failed} \tag{7}$$

- *Failure rate*: This metric, denoted $F@n$, tells use whether the recommendation strategy helps minimizing negative responses, thus being important for evaluating user satisfaction:

$$F@n = \frac{\#failed}{\#successful + \#failed} \tag{8}$$

- *Recall*: This measure, denoted $R@n$, indicates how close a recommendation list of size n is to including all known successful interactions, hence it is used to assess reliability:

$$R@n = \frac{\#successful}{\#known\_successful\_interactions} \tag{9}$$

Similarly, based on the notion of successful and failed interactions, other information retrieval measures and machine learning metrics can be adapted to a RRS context. For instance:

- *RR*: Reciprocal Rank evaluates a recommendations list by the highest ranked successful match:

$$RR = \frac{1}{\text{Rank of first successful recommendations}} \tag{10}$$

  Because failed and rejected recommendations can be very costly in reciprocal domains [69], one could also replace the rank of the first successful recommendation by the rank of the first failed recommendation and aim at minimizing that metric.
- *AP*: Average Precision evaluates a list of recommendations by calculating the average precision at n ($P@n$) for all successful matches in that list. Because we are looking at lists of size n we will define AP as:

$$AP@n = \frac{1}{\#successful} \sum_{k=1}^{n} (P@k \times rel(k)) \tag{11}$$

  where $rel(k)$ is a flag that is set to 1 if item at k is successful, and to 0 otherwise.
- *AUC*: Area Under the ROC Curve is a measure of performance for classification jobs that relies on the measurement of the True Positive Rate (a.k.a Recall) against True Negative Rate. In order to measure AUC one must know all successful recommendations as well as failed recommendations. It is important to notice that due to the asynchronous responses from users in reciprocal domains, recommendations may sit on a *Unknown* state for a significant time.

Classical RS considerations in online evaluation and user studies, e.g. A/B tests, generally apply to RRS, particularly the high cost of conducting experiments with live users. Notwithstanding, additional intricacies may arise wherever they are feasible, for instance whether or not live users in different testing groups (e.g. model versions, baselines) should be freely recommended to each other or not.

4. Analysis of state-of-the-art RRS literature and representative models

This section takes a tour through the state-of-the-art research done so far on RRSs. The current solutions available to reciprocal recommendation are summarized by highlighting some of data/information types and techniques used to predict user preferences. Different examples of fusion processes utilized to calculate mutual compatibility are likewise highlighted. Firstly, a broad snapshot of extant RRS literature is provided, structured by the main application domains addressed (Section 4.1). Secondly, a small number of representative RRS models are analyzed with the purpose of illustrating in more detail the use of different recommendation strategies, prediction and fusion techniques in RRS (Section 4.2).

4.1. A snapshot of RRS literature

This part overviews models and related studies in **online dating**, which is the most widespread application of RRS research (Section 4.1.1), followed by **recruitment** (Section 4.1.2), **online learning** (Section 4.1.3), **social networks** (Section 4.1.4), and **other domains** (Section 4.1.5).

4.1.1. Reciprocal recommendation in online dating

Online dating platforms, where people attempt to date another person or find a partner via the Internet, have become the most popular area where innovations in RRS research have emerged [16,43,69,87]. One of the earliest studies on RS for online dating was published in 2007 [107], without practical considerations for reciprocity but hinting at the necessity of capturing this requirement in later research. Although the first subsequent approaches in this domain were prominently CB solutions, the trend in recent years shows a gentle shift towards improved models based on CF and hybrid methods. This subsection offers a panoramic view of RRS for online dating highlighting both theoretical and user-centered studies (Table 5) and implemented models (Table 6).

The earliest comprehensive analysis of RRS for online dating can be attributed to Pizzato et al. in [40], who coined the first definition of RRS, identified the key personalization challenges against conventional RS and proposed a number of techniques to address them. Specific requirements were identified in domains other than dating that would also benefit from reciprocity, e.g. expertise matching [114] and job-candidate matching [115,116]. In [15] the authors conducted an online dating case study predicated on diverse success and evaluation metrics, whereas in [108] they investigated the sensitivity of three different RRS to detect scammers, namely dubious users who can be potentially harming to other users and the system itself due to their likelihood of becoming popular. The study shows that CB approaches seem more robust against such dubious users.

The study in [110] investigates the difference between explicit and implicit user preferences in online dating. Explicit preferences are given by desired features in a dating partner, whereas implicit preferences are learnt upon user activity in the system. Besides implicit preferences being reported as a much better predictor, it is also hinted that users could benefit from a suitable presentation of their implicit preferences, using them to compare against explicit preferences and adjusting them accordingly. The temporal behavior and preferences of users in dating

Table 5
Summary of theoretical studies and analyses related to RRS in online dating.

Authors	Aspects investigated
Pizzato et al. [15,40]	Earliest definition of RRS and identification of domain-specific challenges. Comprehensive case studies in online dating.
Pizzato et al. [108]	Investigates sensitivity of RRS models to scammers, assessing their impact on various CB and CF-based approaches.
Xia et al. [109]	Analyzes temporal behavior, messaging and replying patterns, and user correlations under different attributes. Investigates how implicitly inferred preferences from behavior deviate from explicitly stated preferences.
Akehurst et al. [110]	Differences between implicit and explicit user preferences in online dating.
Felmlee & Kreager [111]	Finding "invisible communities" from messaging graph data. Attributes like relationship homophily and attractiveness can clearly characterize clusters.
Li et al. [112]	Facial attractiveness information from user pictures as a means to overcome the sparsity problem when mining graphical data.
Su & Hu [113]	Gender attribute differences in the processes of selecting a potential partner.
Vitale et al. [68]	Computational complexity analyses with synthetic and real-world data.

sites were analyzed in [109] based on messaging and replying patterns, discovering among other facts that males tend to seek younger females and females prioritize socio-economic status or education level of male users. Another study [113] focuses on gender attribute differences in the processes of selecting a potential partner, showing that female users tend to be the only ones who consider how a male user suits their preferences, and what his requirements would in turn be like. From a sociological perspective, in [111] graph data about message exchanges are mined to identify clusters of users who tend to interact with each other in dating sites. Evidence suggests that "invisible communities" are created, with attributes like relationship homophily and attractiveness being useful to characterize them. In [112], facial attractiveness is inferred from user photos to overcome the sparsity problem by mining graphical data. Despite the effectiveness of using image data in producing accurate and diverse recommendations, the approach is subject to privacy concerns. Lastly, the performance of online dating RRS has been explored in [68], analyzing the computational complexity via experiments with synthetic and real data.

Content-based RRS (CB-RRS) have been amply investigated in the online dating domain, where it is more frequent to find available user profile metadata explicitly describing users' features and interests than in conventional RS domains such as e-commerce. RECON [47,48], analyzed in detail in Section 4.2, is one of the best known CB-RRS for online dating, with numerous models being based on it. Tu et al. [61] developed an RRS framework founded on a *Latent Dirichlet Allocation* model, where user preferences are learnt by observing correlated user profile features with reply actions. Experiments with real data from the *Baihe.com* dating site show that these learnt preferences are better predictors of success than explicitly stated interests, however the model assumes that $p_{x,y}$ and $p_{y,x}$ are symmetric and equivalent, hence reciprocity is not analyzed. Meanwhile, the RRS in [97] provides a unique example in the literature, being based on questionnaires in which users express their preferences about a potential partner and they also indicate how important each question is to them. This is one of the few systems that rely exclusively on explicit information supplied by users to estimate reciprocal preferences, without taking user–user interactions into consideration.

Alanazi and Bain investigated RRS models for dating that incorporate *temporal* features and dynamic preference modeling. Their first solution in [57] relies on Hidden Markov Models (HMM) to dynamically generate recommendations, by observing the temporal evolution of user behavioral patterns. The recommendation problem is represented as a bipartite graph of nodes representing female and male users, such that new edges (potential matches) are predicted given a known sequence of past interactions. With a nearly 50% success rate, these models achieved a comparably higher success rate than other CB-RRS that existed so far. Further approaches from the same authors were later proposed in [89,90], including a hybrid RRS based on HMMs, called CFHMM-HR (*CF Hidden Markov Models Hybrid Recommender*) that extends the one in [57] by introducing an initial CF stage to devise a candidate list of recommendations by using known algorithms such as ProCF [72]. The top N recommendations are then fed into the content-based HMM model. CFHMM-HR outperforms its content-based counterpart by drastically improving the success rate from under 50% to 60%–70%.

Among recent CB-RRS models for online dating, a framework based on multi-criteria utility theory has been proposed in [54] to account for the notion of algorithmic fairness and promote efficient and equitable recommendation decisions. Multi-criteria ratings on attractiveness, sincerity, fun, etc., are inferred to estimate users' preferences by fusing them using a weighted averaging strategy in which the weights are learnt by optimization. An exploratory analysis on the Speed-Dating Experiment dataset,[3] shows that a reasonable trade-off between optimizing utilities and recommender performance is achieved. In [56], graph embedding is utilized for mapping feature vectors from multiple data sources into a common representation space. Lastly, the *COUPLENET* deep learning model [55] bets on recommending potential couples based on text data in widespread social media platforms e.g. Twitter, instead of relying on dedicated dating sites. *COUPLENET* is also able to provide explainable recommendations.

Given the ample variety of classical RS models based on **Collaborative Filtering** [6,123–125], it is not surprising that some popular CF techniques like neighborhood-based methods, matrix factorization, graph and neural network-based approaches have been used as the foundation to build RRS solutions. Some of these CF approaches for online dating are briefly outlined below, whereas three representative CF-RRS models are featured in detail in Section 4.2: RCF [16] and the two recent approaches RWS [25] and LFRR [43].

An early study that sat some bases for further CF-RRS research is attributed to Cai et al. [38]. They propose *SocialCollab*, a neighborhood-based algorithm that predicts potential users a given user may like to contact by considering the dual notion of attractiveness and interest-based similarity later considered in other works [16]. This work defines some key principles for CF-RRS in dating: (i) if people with similar preferences to x like y, then x will like y, (ii) if x likes people with similar attractiveness to y, x will like y. *SocialCollab* was tested against two traditional CF approaches in which object users are merely modeled as items, showing clear improvements despite the notion of reciprocity is still not fully considered in this work: y is recommended to x based on similarity indicators found between x and neighbor users of y, but not vice versa. A closely related study from the same authors [117] investigates the problem of reciprocal link prediction between users from

[3] Speed Dating Experiment dataset: https://www.kaggle.com/annavictoria/speed-dating-experiment.

Table 6
Summary of RRS models in online dating (citations in "quotation marks" are analyzed in detail in Section 4.2)

RS family	Authors	Key features
Content-based	Pizzato et al. "[47]", [48]	Preferences are modeled as frequency distributions on attributes' values. First models introducing the harmonic mean to aggregate unidirectional preference scores into reciprocal preference scores.
	Alanazi & Bain [57]	HMMs to predict user–user interactions based on past interactions.
	Sudo et al. [56]	Graph embedding for mapping feature vectors in different domains into a common representation space.
	Tu et al. [61]	Latent Dirichlet Allocation to learn preferences from messaging behavior and profile features.
	Otakore and Ugwu [97]	Preferences explicitly inferred from questionnaires.
	Tay et al. [55]	Deep learning approach upon text data in widespread social media platforms e.g. Twitter. Explainability in RRS.
	Zheng et al. [54]	Multi-criteria utility framework to account for algorithmic fairness.
Collaborative filtering	Pizzato et al. [100]	Probabilistic neighborhood-based. Popularity-aware
	Al-Zeyadi et al. [73]	Graph analysis on past movement patterns.
	Cai et al. [38,72,117]	Attractiveness and interest similarity in neighborhood-based CF.
	Chen et al. [65–67,118]	Clustering of similar users. Community-level matching.
	Kleinermann et al. [119], "[25]"	AdaBoost classifier to predict recommended user's response. Popularity-aware. Explainability in RRS.
	Kunegis et al. [75]	Dual preferences modeled by complex numbers.
	Kutty et al. [76,85]	Tensor model of user attributes-interactions. Popularity-aware.
	Li & Li [77]	Bipartite network. Compatibility as product of predicted ratings.
	Nayak et al. [82,83]	Instance-based learning, assigning weights to profile criteria.
	Neve & Palomares "[26,43]"	Two Latent Factor Models, one for each user class. Effects of different aggregation operators in calculating reciprocal preferences.
	Qu et al. [94]	Optimization considering clicks and reciprocated interactions.
	Ting et al. [86]	Transfer learning. Compatibility as product of predicted ratings.
	Xia et al. "[16]"	Multiple neighborhood and similarity functions. Harmonic mean.
	Yu, Zhao et al. [70,71]	Reciprocal bipartite network. Attractiveness and interest similarity.
Hybrid	Alanazi & Bain [89,90]	HMMs to predict interactions, preceded by CF.
	Alsaleh et al. [64,101]	Hybrid community-level matching.
	Akehurst et al. "[87]", Koprinska & Yacef [88]	Determining interaction groups for x based on CB and CF.
	Ramanathan al. [120]	Matrix factorization. Incorporating dislike information.
	Rodríguez et al. [91]	Integration of knowledge-based approach in CB filtering.
	Yu et al. [99,121]	Community detection to address user cold-start problem.
	Zhang et al. [122]	Incorporates influence of facial features.

disjoint classes, namely predicting the sign of a link in heterogeneous user networks considering not only positive preference indicators but also negative ones. Based on [117], the computational efficiency issue is later addressed by the authors in [72] by defining an asymmetric similarity based on probabilities of acceptance or rejection of recommendations. This sits the bases for a probabilistic RRS model called *ProCF* that reported an improved performance, tractable computational complexity, and the ability to prevent biased results by highly popular users.

Classical approaches for people recommendation in social networks [126] do not apply to bilateral and bipartite social network structures, which are often used in two-class RRS. CF models for reciprocal recommendation in bipartite social networks [70,71] typically consider both users' taste and attractiveness, with strong mutual matches being typically predicted when both aspects co-occur. In [77] *local* and *global* reciprocal utilities, which capture users' mutual preferences and the overall reciprocal network quality, are modeled by bipartite networks. A mutual relevance score is calculated as the product of two unidirectional relevance metrics to filter recommendations for x. Similarly, RecoMPA [73] is an RRS based on movement patterns and graph analysis to predict future user–user interactions based on past ones. Frequently occurring movement patterns are detected to produce recommendations: users y who appear in frequent movement patterns where similar users to x have taken part, are likely to be recommended to x. The graph-theoretical approach in [75] introduces a representation based on complex numbers that jointly captures likeness and similarity between users, both in a dual positive–negative scale. Performance results are independent of the users' class (gender), which makes this model directly applicable to homosexual online dating.

Forming communities in large and sparse social networks helps reducing the number of users that an RRS would need to analyze and overcoming the new-user cold-start problem [101]. Based on this principle, a repertoire of studies on RRS for dating, predominantly CF-driven, have been undertaken [64–67,76,82,83,85,101,118]. These include: (i) clustering-based methodologies [66,67,118], where users are clustered based on potential dates whom neighbor users in x cluster have contacted; (ii) follow-up approaches [65] that fully incorporate the notion of reciprocity by checking that x preferences align with y profile and vice versa in a nearest-neighbor model that applies feature weighting; (iii) an instance-based learning algorithm [82] that assigns weights to profile criteria (height, body type, etc.) depending on their frequency of appearance, extended in [83] by using *Support Vector Machines* in the prediction task; (iv) a hybrid system [64,101] that applies a different clustering strategy depending on the class of the subject user, e.g. for a male subject user x, male users are clustered based on their attributes, whereas female users are grouped predicated on preferences for male users; (v) a tensor Space-based approach [85] that jointly models user attributes and interactions in user networks, with promising results in terms of efficiency; and (vi) a *Social Network Analysis* approach [76] on bipartite graphs to identify communities of recommendable users around popular ones so as to reduce popularity bias. Besides [76], another popularity-aware solution from different authors [100] combines CF and stochastic matching – a class of stable matching algorithms – ensuring that every user receives as many recommendations as those in which they have been recommended to others, thereby preventing that popular users are overly recommended and unpopular ones are neglected.

Regarding CF-RRS that train a learning model upon data (model-based approaches) [43], the *Reciprocal Ranking* (RRK) model was proposed in [94] with the aim of jointly considering unilateral feedback e.g. clicks made by a user, and bilateral feedback e.g. reciprocated interaction. RRK optimizes an objective function via matrix factorization that incorporates both aspects of feedback to predict mutual preference. The probability of a match is determined upon the products of latent feature vectors of both users, after which a gradient descent method is employed to optimize them. The model was tested on real user data from a Czech dating site combined with synthetically generated data, demonstrating improvements of up to 14%–17% with respect to existing methods IBCF [127] and CSVD [86], as well as an adapted baseline of the nonreciprocal *Learning to Rank* algorithm in [128]. A transfer-learning based CF model was also proposed by [86] by extending Collective Matrix Factorization [129]. The recommender only relies on ratings and like/dislike clicks to predict preferences, with data from the *Libimseti* dating site.

Finally, there exist a few more examples of **hybrid RRS in online dating** besides the previously outlined ones [64,90,101]. Following their previous work [70], Yu et al. in [121] concentrate on the problem of learning from experienced users to produce successful recommendations for new users. For this, they detect communities of likeminded users employing an analogous preference modeling procedure to the one in RECON [48]. Subsequently, in [99] the authors describe a more comprehensive case study using real-world data from an US dating site and hint at various directions for future work, e.g. investigating the effect of using different community detection algorithms. Meanwhile, the RRS in [122] extracts user preferences from bipartite reciprocal networks combined with various classifiers, studying the influence of facial features in recommendation results. A more recent approach [91] combines CB and knowledge-based recommendation in the *BlindDate* model, where a similarity matrix is built from a multi-graph conceptual model. Knowledge integration through a semantic weighted similarity measure contributes to a higher precision than non-hybrid baselines, yet the nature of the model makes it less generalizable. Lastly, Ramanathan et al. [120] suggest encoding (previously neglected) 'dislikes' and 'matches' alongside 'likes' information to learn better latent representations for users. Based on this, they combine a suite of matrix factorization, learning-to-rank and neural network algorithms with a profile metadata-driven strategy to cope with cold users.

4.1.2. Reciprocal recommendation in recruitment

Recommending people to people in the recruitment domain largely pertains scenarios where a job seeker looks for potential job recommendations, and both job seekers and recruiters' interests need to align. Despite the smaller number of works in this application compared to online dating, current literature covers RRS approaches based on diverse recommendation strategies. Further, besides general-purpose job recommenders, some approaches have been made specifically for graduate students' recruitment.

Among the experimental findings with implications on RRS for recruitment, the study in [130] introduces a methodology for characterizing online recruitment services and monitoring the demand-offer of employment via preference elicitation, showing great variations in demand/offer ratios across professional areas. Correlations between explicit and implicit job feedback are analyzed in [131] to identify cases in which a candidate shows interest in a recommendation. Although clicks are a more frequent indicator of preference, it is concluded that replies can predict better whether a recommendation is relevant. Meanwhile, in [132] it is revealed that implicit feedback is a more powerful indicator of users' broad interests. The same authors suggest in [133] that classical RS tend to predict better from the job seeker viewpoint, but more attention should be paid to reciprocity from the recruiter side.

There are several studies that investigate RRS for recruitment using CB approaches. The solution in [116] matches recruiters and candidates based on inferring implicit preferences on companies/recruiters, with similarities being determined by considering a vector representation of such preferences and resume information. By contrast, the method in [17] accounts for recruiter needs in the process of job recommendation, and in [59] the preferences of the job seeker are matched to the characteristics of the job ad, casting the recommendation task as a binary classification problem to predict whether the job seeker may click on an advertised job. A mobile system called iHR+ [137] was developed upon a hybrid approach [136] where the job seeker and recruiter provide self-description and explicit preferences. Meanwhile, the approach proposed in [62] is formulated as a stable matching problem between multiple candidates and multiple jobs in a centralized manner, such that the output is a set of matching pairs $M = \{(x_i, y_j), x_i \in X, y_j \in Y\}$. Its use in recommendation tasks is, therefore, severely limited to single-recommendation scenarios where $|X| = |Y|$. An RRS for graduates recruitment was presented in [134], where graduate job seekers' profiles are collated with profiles from past graduated who were previously hired. A more recent RRS for graduates recruitment [60], operates by extracting topic distributions and using a probabilistic topic model (*Latent Dirichlet Allocation*) to build a common latent representation space. This results in two matrices, describing student courses and jobs, respectively. This model was validated both offline and through user study involving 28 graduates. An employer-oriented RRS [51] was built to help recruiting graduates in situations such as job fairs, modeling an employer as a set of recently hired graduates. The authors later shift their focus towards graduate-oriented recommendation in the rating prediction method proposed in [50].

There are still few CF approaches for RRS in the recruitment domain. The work in [84] implements different classification methods fed by job applications of similar candidates to the target user and their preferences for jobs, showing that Support Vector Machine classifiers provide the most promising results.

Regarding hybrid approaches, prior to the above discussed system iHR+ [137], the same authors presented iHR [136], which combines traditional CB and CF with reciprocal filtering, applying a product operator to calculate reciprocity. A real case study in Xiamen Talent Service Center where iHR is deployed shows that most users prefer the results yielded by considering reciprocity. Another hybrid RRS for recruitment was introduced in Hong et al. [138]. It groups users based on their activity level in the system by using a clustering algorithm. Depending on the cluster the user belongs to, a different filtering approach is

Table 7
Summary of existing RRS models and studies in recruitment.

RS family	Authors	Key features
Theoretical studies	Cardoso et al. [130]	Characterization of employment offer and demand.
	Kille et al. [131]	Analyzes correlation between explicit and implicit feedback on jobs.
	Reusens et al. [132,133]	Identifies best indicators of job seekers' preferences. Analyzes the impact of reciprocity versus non-reciprocity.
Content-based	Almalis et al. [17]	Minkowski-based distances. Centered on organizations' needs.
	Ding et al. [134]	Graduate student recruitment. Analyzes past successful graduates.
	Jacobsen & Spanakis [60]	Latent Dirichlet Allocation model on students' curricula.
	Lian et al. [59]	Binary classification to predict clicks on jobs.
	Liu et al. [50,51]	Graduate student recruitment. Employers modeled by recently hired graduates. Employer-oriented and graduate-oriented models.
	Saini et al. [62]	Privacy-oriented stable matching.
	Yu et al. [116]	Matching employer preferences with candidates' attributes.
Collaborative filtering	Ozçan et al. [84]	Multiple classifiers driven by job applications made by similar candidates.
Hybrid/other	Cakir et al. [135]	Deep matrix factorization.
	Hong et al. [136–138]	Mobile app implementation. Combining profiles and similar users' access history to job/candidate profiles
	Mine et al. [102]	Bidirectional feedback patterns. Reciprocity by inverse product of ranks.
	Xia et al. [95]	Walrasian Equilibrium multi-objective optimization. Fairness in RRS.

applied: whilst some users might have registered enough activity in the system to rely on a CF process, most passive users would benefit more from CB recommendations. The job matching recommender in [102] relies on bidirectional feedback patterns, that is, actions performed by a job seeker (resp. recruiter) coupled with the response given by the other party to the action. Reciprocity is only analyzed after the generation of unidirectional recommendation lists for both parties, by calculating the inverse of the product between x rank in y's recommendation list, and vice versa (see Eq. (5) in Section 3.2).

A recent model called *WE-Rec* (Walrasian Equilibrium-based recommendation) [95] attempts to address the scarcely investigated problem of social fairness in reciprocal recommendation, namely to protect vulnerable groups from discrimination, mistreatment and inequality issues. WE-Rec defines the reciprocal recommendation task as a multi-objective optimization problem according to three fairness criteria, using the economic notion of Walrasian equilibrium.

Lastly, in a recent study [135], deep neural network-based matrix factorization is applied in a model that, although not inherently reciprocal, motivates the need for RRS research based on deep learning.

4.1.3. Reciprocal recommendation in online learning

Online learning platforms allow teachers and learners to educate – and be educated – without the necessity of meeting in a physical classroom. These platforms have similar connectivity features as social networks, often presenting a large and diverse body of learners [49,98,139]. The continuous growth of Internet capabilities, the demand for professional learners to access flexible and ubiquitous learning resources, or even the appearance of unprecedented circumstances in which social distancing becomes inevitable, constitute various reasons that led different education systems to adopt partial or fully online learning as their norm [140]. Interestingly, RRS applications in online learning are predominantly based on CB approaches where learners and teachers' profile information are exploited. Existing works show a variety of specific learning scenarios to tackle via reciprocal recommendation: peer matching in MOOCs and university courses, group formation, learner-question matching in forums and student–supervisor matching. Unlike online dating where preferences can be implicitly inferred from interaction data, in learning platforms, specially massive ones, learners generally provide information by themselves and, depending on the application, they might state explicit preferences on the attributes of users they would like to learn with [98]: interests, age group, location, etc.

Various MOOC (*Massively Open Online Course*) incentivize group activities, in which learners form groups to study or do homework together. In this sense, one of the existing studies addressing the problem of matching pairs of learners in MOOCs [98] is inspired by the ideas implemented in RECON [48]. As opposed to other classical RS engines in MOOCs where actual courses are recommended, in [98] reciprocity is deemed as an inherent requisite for recommending peers to study with. The authors use student data released by MITx and HarvardX courses.[4] In essence, the algorithm builds a similarity matrix of compatibility scores between users, by observing user x interests in attribute values exhibited by other users y. A reciprocal score is calculated upon the number of user x preferences that match y attributes and vice-versa. The model is validated using both accuracy measures (precision and recall) and ranking quality measures (an adapted version of NDCG), showing drastic improvements in accuracy but only slight improvements in rankings, with respect to a non-reciprocal baseline.

Several RRS approaches and analyses for peer learner recommendation in MOOCs have been introduced in [139,141,142]. In [139,141] a controlled user study was conducted during a MOOC, showing that for a subgroup of users who utilized a peer RRS, completion and engagement rates improved. Recommendations were generated using data from a questionnaire. In [142], the authors conduct a comparative study about the impact of using different peer recommendation strategies. Approaches to compare include one using socio-demographic information of learners and one based on progress made in the MOOC, with the former hinting at better results. RiPPLE, a course-level platform for reciprocal peer recommendation [18], defines compatibility as a function of learners' requests, competencies, availability and preferences,

[4] HarvardX Person-Course Academic Year 2013 De-Identified dataset, version 3.0: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/26147.

Table 8
Summary of existing RRS models in online learning.

RS family	Authors	Key features
Theoretical studies	Labarthe et al. [139,141], Bouchet et al. [142]	Effects of peer recommendations in MOOCs in learner engagement. Study of different recommendation strategies in MOOCs.
Content-based	Prabhakar et al. [98] Rajagopal et al. [143] Potts et al. [18] Mitchell & Dragon [52] Yacef & McLaren [49]	Peer matching in learning platforms. Inspired by RECON [48] Dissimilarity to recommend complementary learning peers. Peer matching, based on compatibility criteria. Student group formation, based on performance criteria. Inspired by RECON and CCR [87]. Group formation, via optimization from individual recommendation lists.
Hybrid	Yang et al. [93] Zhang et al. [92]	Context-aware matrix factorization. Learner marching in forums. CB–CF for recommending student–supervisor allocations.

all of which are specified by the learner. A mixture of Gaussian and logistic functions parameterized by the aforesaid criteria (particularly competency), are used together with the harmonic mean aggregation to measure learner compatibility. Other works [143] focus on the notion of dissimilarity to recommend learning peers' that could complement each other well, based on their understanding of a topic. They define a symmetric matching mechanism that measures similarity between users' interests and how dissimilarly they interpret those interests.

Learning in groups has numerous pedagogical benefits, but MOOC platforms generally do not provide RRS-based tools for small group collaboration by forming tailored groups predicated on learners' interests and goals. The first effort to investigate this issue under a reciprocal recommendation viewpoint can be found in [49], inspired by prior studies [48,87]. The proposed model identifies relevant learner features (cognitive, problem-solving strategies, social and demographic information, past interactions, etc.). An optimization approach then takes individual recommendation lists as an input, and creates groups in which necessary skill-sets are combined. The study addresses the very scarcely investigated problem of reciprocal group formation, yet it lacks an actual implementation and evaluation. A similar idea is formulated in [52] for recommending groups based on students' conceptual understanding, where instructors request student group suggestions based on performance and assessment criteria.

Among the comparatively fewer RRS for learning based on hybrid strategies, the question recommender in [93] utilizes context-aware matrix factorization to predict learners' interest in questions posted in MOOC discussion forums, modeling their expertise and capacity as constraints and using constrained optimization for matching learners with questions they would be interested in answering. Their optimization approach is flexibly designed to be adapted to other state-of-the-art techniques. In [92], a CB–CF framework is proposed to recommend supervisors to higher education students, which is fundamental for students' success. The framework takes into account indirect relevance with previously supervised students by the supervisor and the mutual matching between student and supervisor thinking styles.

4.1.4. Reciprocal recommendation in social networks

Social network sites (SNSs, also commonly referred to as OSNs: online social networks) have emerged at the second half of the 2000s as a means for Web users to connect and share information with one another. Generally speaking, there are two types of SNSs [42]: the first is a symmetric (confirmed) SNS, which is based on bi-directional relationships that have to be confirmed by both sides. Typically, one user sends an invitation and the other has to accept the invitation for the connection to form. This type of SNSs includes Facebook and LinkedIn. The second type is an asymmetric SNS, in which one use can connect or follow another user, without a requirement for their confirmation. This type of SNSs includes Twitter and Instagram. The network structure created over time in each of the two SNS types is rather different [42]: the asymmetric type naturally renders a much more skewed degree distributions, with some celebrities having over a hundred million followers.

RRS are relevant for the first type of SNSs, which is based on symmetric, or reciprocated connections (whereas the asymmetric type is based on uni-directional ties [144]). Early studies of RRS in such SNSs were among the first of people recommendation on the Web and showed great success in growing the number and density of connections within SNSs [4,80]. The fried-of-the-friend (FOAF) approach, which recommends individuals with most common friends, showed good performance and was the baseline approach adopted by leading symmetric SNSs. Yet, approaches that aggregated information across a variety of sources showed to outperform the FOAF method [80]. Aggregation is conducted by collecting collaboration and social interaction signals from multiple social media sources, e.g. indicators of co-authoring wiki pages with someone, commenting or being commented in a blog, co-edited shared docs, and so forth [145]. These signals reflect familiarity relationships, rather than shared similarities. The aggregation approach also has benefits in coping with the cold start problem for new SNS users [146]. Interviews with users who used RRS for inviting people to connect, indicated that the entry barrier to accept such recommendations is high, since they not only have to consider the recommended person, but also their reaction to the invite and whether or not they will accept [4] Explanations played a key role in such RRS, showing the "evidence" for the recommendation and making people more comfortable sending invitations when such evidence was provided [4].

Later studies examined the long-term effects and dynamics of RRSs in symmetric SNSs. One aspect was that over time, users exhausted the list of recommended individuals and connected to most of their potential ties. Since the network is symmetric, most connections are performed with familiar people [42,157]. The recommendations suggested by RRSs therefore became less effective and were frequently ignored. To complement this, recommendation of unfamiliar people, often complete strangers, has been suggested [147,148]. Aside from the effect on the individual users, the global network effects were also studied [152]. It was found that different algorithms for RRS render over time very different network structures, in terms of characteristics such as degree distribution and betweenness centrality. For instance, the FOAF algorithm has a strong rich-get-richer tendency, rendering a diverse degree distribution with high centrality. RRSs were also found to play key role in expertise location, social stream consumption, reputation inference, and 'liking' activity [19,149–151,158].

More recent work expanded the usage scenarios for RRS in confirmed/symmetric social networks. Recommendations at events, such as academic conferences, for people to meet at the venue, commonly provided using mobile devices, have become popular [78,155,159,160]. Recommendation in networks with multiple types of connections, sometimes positive and negative, have also emerged, often applying different graph-based approaches [74,79,96]. Recommendations within online groups and university campuses also employed RRS to connect people within smaller communities [81,153,156]. An interesting more complex RRS scenario proposed contacts to address as a group, e.g., 'university colleagues', 'coworkers', 'family', or 'friends' [154]. This kind of RRS facilitates communication in groups (as in WhatsApp) and can save a considerable amount of time in the group initialization process on a mobile device.

Table 9
Summary of existing RRS studies and models in symmetric social networks.

RS family	Authors	Key features
Theoretical studies	Chen et al. [80]	Effect of aggregating of relationship information for recommendation in social networks.
	Guy et al. [4,147,148]	Role of explanations in the success of people recommendation. Recommendation of unfamiliar people (strangers).
	Guy et al. [19,149–151], Jacovi et al. [144]	People recommendation in enterprise settings: expertise location, social stream consumption, Reputation inference, 'liking' activity.
	Daly et al. [152]	Effects of global network structural characteristics (distribution, centrality, etc.).
Models	Du et al. [81]	Friend recommendation in university campuses.
	Eirinaki et al. [74], Nepal et al. [153]	Trust and reputation-based.
	Grob et al. [154]	Community-aware method for group formation.
	Quercia & Capra [78]	Friend recommendation using mobile phones. Proximity-driven link prediction.
	Samanthula & Jiang [155]	Privacy-aware friend recommendation.
	Symeonidis et al. [79]	Link prediction in SNS with positive/negative links.
	Silva et al. [96]	Genetic algorithm and graph-based.
	Zhang et al. [156]	Trust and ranking-based model. Studies factors than influence trust and probability of friendship.

4.1.5. Reciprocal recommendation in other domains

Existing works for recommending people in domains beyond dating, recruitment, learning and social networks, generally produce recommendations from a single end user perspective [20,22,41,161]. However, some approaches have emerged in very recent years to incorporate reciprocity in innovative application areas, including: socializing, skill sharing, shared economy, mentoring and academic/scientific collaboration.

There are early studies that do not consider reciprocity but sit some bases for RRS in social applications, such as: an approach that combines data mining and referral processes for expertise recommendation inspired by yellow-pages services [114], a Web system called *Twittomender* for profiling users and recommending whom to follow in Twitter in order to form relationships between users [20], and a community-based approach to user recommendation in social media sites like Twitter and Weibo [161] where matrix factorization allows to extract latent characteristics at community level. Moreover, in [53] database query results are used as input for an RRS that intrinsically considers reciprocity in the process of building such vectors upon queries. This study shows a real life scenario on OutdoorActive,[5] a platform for undertaking outdoor social activities.

An insightful analysis with potential implications in socializing contexts requiring reciprocal recommendations, is provided in [162] by investigating interpersonal and socio-spatial aspects alongside ideas from environmental psychology to explain the dynamics of serendipitous interactions, recommending new people to interact with nearby based on predicting interaction willingness. A recent study [63] applies a variant of Gale–Shapley stable matching algorithm for social event organization in order to meet the interest of potential attendees and event organizers themselves. This is done by capturing user profiling for event selection and event rules for attendee selection. The recommender can effectively predict the event invitation and acceptance to a high extent.

There are also various contributions for addressing the contextual data challenges for improving social matching [163–166], laying strong foundations for context-aware RRS devised as social matching systems. One of these contributions presents a mobile system, *Encount'r* [163], based on passive context-awareness.

In the context of skill-sharing platforms, one of the latest hybrid approaches to reciprocal recommendation is HRRS (*Hybrid RRS*), presented in [21]. HRSS is a single-class RRS for facilitating user matching in skill sharing platforms where connections between users, public content shared by users and user-to-content preference indicators coexist. The model was implemented and evaluated in the recipe sharing social network *Cookpad*,[6] where users interact with each other to post, follow and share recipes. The hybridization in this model lies in combining reciprocal preferences between users (reciprocal matching in Fig. 4), and similarities on the grounds of content items commonly liked by them (nonreciprocal matching in Fig. 4).

In the area of shared economy, [167] investigates the characteristics of reciprocal relationships in two-sided markets and present an heuristic approach for recommender design, primarily aimed at calculating optimal compatibility scores between pairs of agents. The impact of context-awareness on *Peer-to-Peer Variable Service Transaction systems* (P2P-VST) to foster user engagement has been explored in [30]. Even less active users are more likely to accept a recommended transaction if it is convenient in terms of location and time, thereby showing the importance of designing context-aware RRS in this domain. The concept of *timebanking* has also received some attention from an RRS viewpoint [58], with a model for P2P marketplaces where peers provide services to each other in exchange for tokens. Their algorithm uses text mining and regression to predict interests in offers, requests and user profiles. The complimentarity between users' skills and needs is observed to produce matchings. A subsequent study [168] proposes removing the distinction that exists in [58] between service providers and recipients, thus advocating single-class RRS. They introduce *WithShare*, a mobile app for recommending people to engage with to create synergies in coproduction activities.

A recent contribution [169] analyzes the mentor–mentee matching problem in the live platform *Codementor*, with a learning-to-rank approach that aims at predicting, for a mentee x, the mentor willingness to assist x and the mentee's likelihood of acceptance of the recommended mentor y. This is the first effort to explore personalized mentor-to-mentee recommendation with views on reciprocity. In a similar but more scientific context, there are studies with clear implications for reciprocal recommendation in academia, for instance [29] where a supervised learning framework is proposed to find researchers who

[5] OutdoorActive: https://www.outdooractive.com/en/.

[6] Cookpad Inc.: https://www.cookpadteam.com.

Table 10
Summary of existing RRS models in other application domains.

RRS domain	Authors	Key features
Socializing	Wenzel & Kiebling [53]	Similarity vectors built upon queries.
	Kim et al. [162]	Interpersonal, socio-spatial and environmental psychology aspects.
	Mayer et al. [163–166]	Context-aware RRS for social matching.
	Yin et al. [63]	Social event organization. Stable matching.
Skill-sharing	Neve & Palomares [21]	Integrates user-to-user preferences and user-to-item preferences on content shared by other users. Single-class RRS.
Shared economy	Goswami et al. [167]	Heuristic optimization approach for maximizing compatibility in two-sided markets.
	Chen et al. [168]	Single-class RRS for co-production activities.
	Doryab et al. [30]	Context-aware expertise matching in P2P systems.
	Jung et al. [58]	Text mining and regression to predict interests in timebanking.
Mentoring	Li [169]	Learning-to-rank for mentor–mentee matching.
Science/academia	Daud et al. [29]	Citation-driven scientific collaboration prediction.

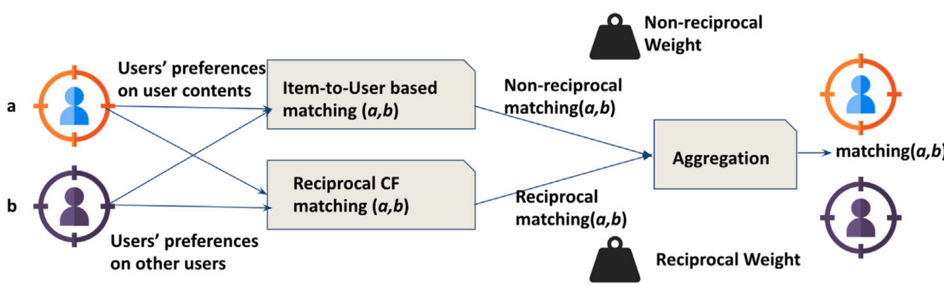

Fig. 4. Illustration of the HRRS model [21], envisaged for skill-sharing or content-sharing platforms where users can share contents and like other users' content.

have cited each other and predict potential reciprocal links, thereby fostering collaborations. They perform experiments on *CiteSeer* data, showing a 96% prediction accuracy with author-related features being a better predictor than paper-related features.

4.2. Analysis of representative RRS models

This subsection describes several RRS systems in more detail, which are either well-known foundation models or selected examples of state-of-the-art solutions in the area. These models were initially conceived for online dating, although some of them have been later extended into other domains: RECON [48], RCF [16], RWS [25], LFRR [43] and CCR [87].

4.2.1. RECON: REciprocal CONtent-based recommender for online dating

RECON [48] is one of the best-known CB-RRS in the literature. It was designed in accordance with the general properties of reciprocal recommenders (Fig. 2). The system builds upon two studies: a method focused on learning implicit preferences from users' past contacts history [47], and the standalone RECON model that incorporates the implicit preference learning method [48]. The proposed method in [47] learns implicit user preferences by modeling messages sent/exchanged between users as indicators of preference. Concretely, it predicts users' preference values towards attributes shown by other users (e.g. being tall, non-smoker, having brown eyes, etc.) by observing their interaction history with other users, for example messages exchanged with people who exhibited certain attributes. Formally, let $\mathcal{A}_x = \{v_{x,a}, \forall a \in A\}$ be the profile of user x, with A a finite set of user attributes a, e.g. *eye color*, and $v_{x,a}$ the value exhibited by user x for attribute $a \in A$, e.g. *brown*, in her profile. Thus, $\mathcal{A}_x$ is utilized as the "content" features of the user. Preferences are then inferred using statistical methods. Let m be the number of times x indicated preference towards a user y with attribute value $v_{y,a}$ on the attribute a. The preferences $p_{x,a}$ of x towards the different values of an attribute a, $\mathcal{V}(a)$, are given by the following distribution:

$$p_{x,a} = \{(v, m) : \forall \text{ unique values } v \in \mathcal{V}(a)\} \quad (12)$$

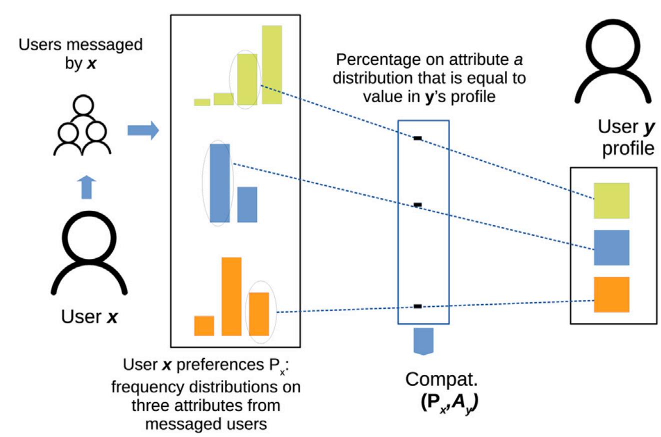

Fig. 5. RECON calculates preferences $p_{x,y}$ as compatibility degrees between preferences of x and profile of y.

Based on this modeling of user preferences, the full RECON model [48] predicts unidirectional preference scores (how much a user x likes a user y) by collating one user's preference distribution $p_{x,a}$ with the attribute values in other users' profile. Unidirectional preference values are then aggregated into a bidirectional indicator of mutual preference, $p_{x\leftrightarrow y}$, using the harmonic mean. Algorithm 1 summarizes the procedure followed by RECON to recommend the top-N users to a subject user x, with $Compat.(P_x, \mathcal{A}_y)$ calculated as shown in Fig. 5.

Through offline evaluation experiments conducted in an Australian dating site, the authors demonstrated that RECON outperformed a baseline guided by manual user search, as well as nonreciprocal user-to-user recommenders [170]. Moreover, RECON contributed to alleviating the user cold-start problem [28], as per a cross-validation in which it delivered successful recommendations for numerous users whom actually received an expression of interest by the end user, according to ground-truth data. By contrast, RECON showed a few areas needing improvement:

Algorithm 1 Function $ReciprocalRecommender(x, N)$ in RECON (adapted from [48])

Input: User x, number of recommendations N
Output: List of scored recommendations $R = \{(y_1, s_1), \dots, (y_N, s_N))\}$

Find user x preferences: $P_x = \{p_{x,a}, \forall a \in A\}$
$R = \{(y, s_y), \forall$ users y not messaged by $x\}$
for all users $y \in R$ **do**
    $s_y \leftarrow$Compat.$(P_x, \mathcal{A}_y)$
    if $s_y > 0$ **then**
        Find user y preferences P_y
        Calculate reciprocal preference score using the **harmonic mean**:
        $s_y \leftarrow p_{x\leftrightarrow y} = \dfrac{2}{\left((s_y)^{-1} + (\text{Compat.}(P_y, \mathcal{A}_x)^{-1})\right)}$
    end if
end for
Sort users in R by reciprocal score: $R \leftarrow \{(y_1, s_1), (y_2, s_2) \dots (y_K, s_K) : s_{y_i} \geq s_{y_{i+1}}\}$
Return $\{(y_1, s_1), \dots, (y_N, s_N)\}$

1. Preferences are modeled as discrete distributions on attribute values, hence continuous numerical attributes like age need to be discretized, which might result in loss of valuable information.
2. It is sensitive to bias caused to highly popular users, some of whom can end up being recommended to an unduly high number of users in the opposite gender. On the contrary, new and less popular users may be unlikely to appear in recommendations. A few subsequent RRS have focused on addressing this popularity issue [25,95].

4.2.2. RCF: Reciprocal Collaborative Filtering

Xia et al. [16] presented a configurable RRS model that can be instantiated into several CB and CF algorithms, of which the main contribution is the earliest memory-based CF solution for online dating fully relying on reciprocity, later termed as RCF for *Reciprocal CF* in [25]. RCF introduces a nearest-neighbor based strategy combined with a similarity measure, to eventually estimate the compatibility or mutual preference between users in a dating site. The preference of user x for user y, $p_{x,y}$, is determined as the similarity between the behavioral patterns (either in terms of interest or attractiveness) of x and those of users $z \neq x$ who have had positive historical interactions with y. The authors introduce two views of similarity between users in the same class (e.g. same gender):

(i) *Interest similarity* between user x and user z. It describes preference similarity, whereby if two users sent an expression of interest (EoI) to the same user, then they share common interests. Xia et al. define the interest similarity between x and z as:

$$sim(x, z) = \frac{EoI_{from}(x) \cap EoI_{from}(z)}{EoI_{from}(x) \cup EoI_{from}(z)} \tag{13}$$

where the set $EoI_{from}(x)$ is determined as,

$$EoI_{from}(x) = \{y : y \text{ has received an EoI from } x\} \tag{14}$$

This Jaccard Index-based similarity measure determines the likelihood that x will like y, thereby being used as the estimator for $p_{x,y}$.

(ii) *Attractiveness similarity* between x and z, calculated on the grounds that if two users receive an EoI from the same user in the opposite class, then they have common attractiveness:

$$sim(x, z) = \frac{EoI_{to}(x) \cap EoI_{to}(z)}{EoI_{to}(x) \cup EoI_{to}(z)} \tag{15}$$

In addition to similarity between users in the same class, assuming the representation of users in a two-class RRS and interactions between them as a bipartite graph, RCF incorporates two functions to determine the neighborhood of user y. Unlike the previous similarity measures, the neighborhood of y in this context is a set of users who had some form of interaction with x, in other words, $Neighbor(y)$ returns a set of users z in the opposite class (gender) to that of y. Two possible ways to define this function are introduced: $Neighbor(y) = EoI_{from}(y)$ and $Neighbor(y) = EoI_{to}(y)$. RCF can employ different combinations of similarity measures and neighboring functions to deliver recommendations, which results in a flexible and versatile framework, with algorithms that may behave differently.

Algorithm 2 Reciprocal score calculation in the RCF algorithms (adapted from [16])

Input: subject user x, object user y
Output: reciprocal preference score

1: $p_{x,y} \leftarrow 0.0$
2: $p_{y,x} \leftarrow 0.0$
3: **for all** users $z \in Neighbor_1(y)$ **do**
4:     $p_{x,y} \leftarrow p_{x,y} + sim(x, z)$
5: **end for**
6: **if** $|Neighbor_1(y)| > 0$ **then**
7:     $p_{x,y} \leftarrow \dfrac{p_{x,y}}{|Neighbor_1(y)|}$
8: **end if**
9: **for all** users $v \in Neighbor_2(x)$ **do**
10:     $p_{y,x} \leftarrow p_{y,x} + sim(y, v)$
11: **end for**
12: **if** $|Neighbor_2(x)| > 0$ **then**
13:     $p_{y,x} \leftarrow \dfrac{p_{y,x}}{|Neighbor_2(x)|}$
14: **end if**
15: **if** $p_{x,y} > 0$ and $p_{y,x} > 0$ **then**
16:     **Return** $p_{x\leftrightarrow y} = \dfrac{2}{(p_{x,y})^{-1} + (p_{x,y})^{-1}}$
17: **else**
18:     **Return** 0.0
19: **end if**

The general RCF procedure to calculate reciprocity between two users is described in Algorithm 2, and illustrated in Fig. 6. After initializing the two unidirectional preference scores (lines 1–2), in lines 3–8 a function $Neighbor_1(y)$ is used to identify the set of most similar users or neighbor users of y, and their similarities with x are calculated and then normalized to estimate $p_{x,y}$. The function $sim(x, z)$ in line 4 can be instantiated as either the interest similarity or attractiveness similarity defined above. A similar procedure is followed to calculate $p_{y,x}$ (lines 9–14), after which the harmonic mean is finally used to return the reciprocal preference.

Similarly as RECON in CB-RRS literature [48], RCF has been often used as benchmark for comparison against recent solutions. RCF has the advantages of not requiring a pre-trained data model, having a relatively easy-to-understand set of principles, and outperforming prior CB approaches in terms of accuracy metrics. Given its memory-based nature, its main shortcoming is its difficulty to scale well into larger datasets containing millions of users, as experimentally demonstrated in later CF approaches such as [43].

4.2.3. RWS: Reciprocal Weighted Score

In [25] Kleinermann et al. developed RWS. This model adopts some ideas from RCF [16] and extends them into a model-based approach. The main innovation of RWS is its approach to adequately balance pairwise recommendations based on the differences between user popularity levels. The authors discuss the importance of user popularity in RRS research. Specially in the online dating domain, a popular user who receives a high number of EoIs (some of them, intuitively, as a result of reciprocal recommendations) might lead her/him to ending up overwhelmed, whereas less popular users might struggle to find suitable matches or end up leaving the system if they only try to

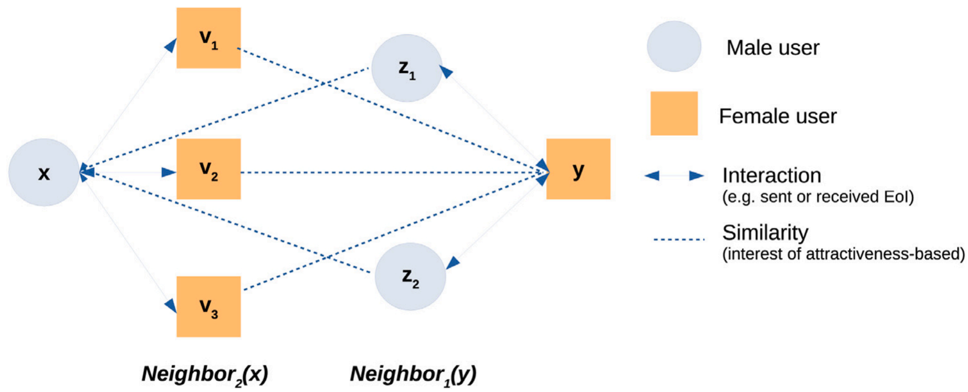

Fig. 6. RCF procedure for determining reciprocal preference between x and y upon interaction with other users (neighborhood) and similarity to users in the same class. *Source:* Adapted from [16].

interact with highly popular ones who normally will not reciprocate. Accordingly, RWS relies on an optimization process to compute an importance weight α_x associated to x. This weight indicates her/his degree of influence in successful interactions with other users. The value for α_x is determined by observing the user's interaction history, namely the relative influence of $p_{x,y}$ with respect to $p_{y,x}$ in past successful interactions with other users y. Importantly, RWS computes the two unidirectional preference estimates differently: it applies RCF to calculate x's potential interest in y, $p_{x,y}$, after which it trains an *AdaBoost* classification model to predict the likelihood of response by y towards x, hence the prediction task for $p_{y,x}$ is formulated as a likelihood estimate. The reciprocal score is calculated as:

$$p_{x\leftrightarrow y} = \alpha_x \cdot p_{x,y} + (1-\alpha) \cdot p_{y,x} \tag{16}$$

Experiments show that RWS succeeds in better balancing recommendation load between popular users and less popular ones. Albeit it does not outperform RCF in providing appealing recommendations, RWS shows improvements in terms of accuracy, achieving a better balanced recommendations that were more likely to satisfy both parties regardless of their popularity. A parallel study was conducted by the same authors in [119], focused on investigating user reactions to explanations provided for their recommendations. The study found that providing users with reciprocity-driven explanations for their recommendations was influential in their decision to accept the recommendation or not, which suggests that explainability in RRS is a research direction deserving further study.

4.2.4. LFRR: Latent Factor Reciprocal Recommender

Neve and Palomares recently presented LFRR [43], a model that extrapolates latent attributes from a preference matrix using matrix factorization. Focused on heterosexual online dating, LFRR considers two preference matrices: one representing female user preference towards male users, and one describing male user preference for female users. Matrix factorization is used to train two latent factor models, one for each of the two matrices. To do this, the likelihood that user x may be interested in user y is defined as the dot product between x's preference vector (a row $\mathbf{p}_x$ in one of the preference matrices) and y's attribute vector $\mathbf{q}_y$, which describes y's traits based on other users' known preferences towards her (a column in the same preference matrix). These two latent vectors with smaller dimension than rows/columns in the original matrices, are calculated by LFRR using the matrix of known ratings $R = (r_{x,y})$ as a training set, a regularization parameter λ and the following function error to be minimized by *Stochastic Gradient Descent* (SGD):

$$\min_{q,p} \sum_{r_{x,y}\in R} (r_{x,y} - \mathbf{q}_y^T \mathbf{p}_x)^2 + \lambda(\|\mathbf{q}_y\|^2 + \|\mathbf{p}_x\|^2) \tag{17}$$

Thus, LFRR uses SGD to calculate latent factor matrices that could be used to predict preference values more efficiently when the original number of users – i.e. the matrix dimensionality – is very large. The LFRR recommendation process is illustrated in Fig. 7.

LFRR was tested against a large-scale real dataset from *Pairs*, a popular dating site in Japan owned by *Eureka Ltd*,[7] to which millions of users are subscribed. The model was validated for various settings of time intervals for which user interaction data were gathered to build the initial preference matrices. LFRR showed similarly promising performance metrics to the baseline model RCF [16], in both precision, recall and F1 scores. However, for larger datasets, LFRR managed to generate recommendations in real time, in scenarios where RCF showed to be intractable, significantly outperforming it in terms of computational efficiency under similar accuracy results. In short, LFRR maintained a similar effectiveness to state-of-the-art solutions, combined with the added advantage of a much higher efficiency. The study is accompanied by an evaluation of the effect of using different aggregation operators for the fusion of unidirectional preferences between users, suggesting that both the widely adopted harmonic mean and uninorm operators (a class of mixed-behavior aggregation function [103]) contribute to better predictions. A more comprehensive study of the effect of different aggregation strategies in RRS is provided by the same authors in [26].

4.2.5. CCR: Content Collaborative Reciprocal Recommender

The first hybrid RRS combining the strengths of multiple RS families was presented by Akehurst et al. [87], and further illustrated by Koprinska and Yacef in [88]. Their model integrates distance metrics for CB and CF in the recommendation process. For its CB part, CCR calculates the distance between two users' content attributes, e.g. age and location information in the user profile. For its CF part, the underlying principles are that "similar people like and dislike similar people", and "similar people are liked or disliked by similar people". The most distinctive aspect of CCR consists in determining interaction groups for every subject user, predicated on the two aforesaid principles and by using the interaction history data of similar users, i.e. looking at the users whom x liked and liked by x. Some characteristics of the interaction-based process to predict preferences between users are briefly discussed below:

- Given a user x and data describing EoI-like interactions from/to x, several interaction groups can be defined: users whom x likes, users whom x is liked by, users whom x dislikes, users whom x is disliked by, and users whom x is *reciprocally* liked by. Noticeably, the latter of these groups is the intersection of the first two.
- The two RS approaches in the hybrid method are applied sequentially. The content-based process is conducted first to find a set of users S_x who have similar profile to x. Secondly, the

[7] Eureka Ltd website: https://eure.jp/en/about/.

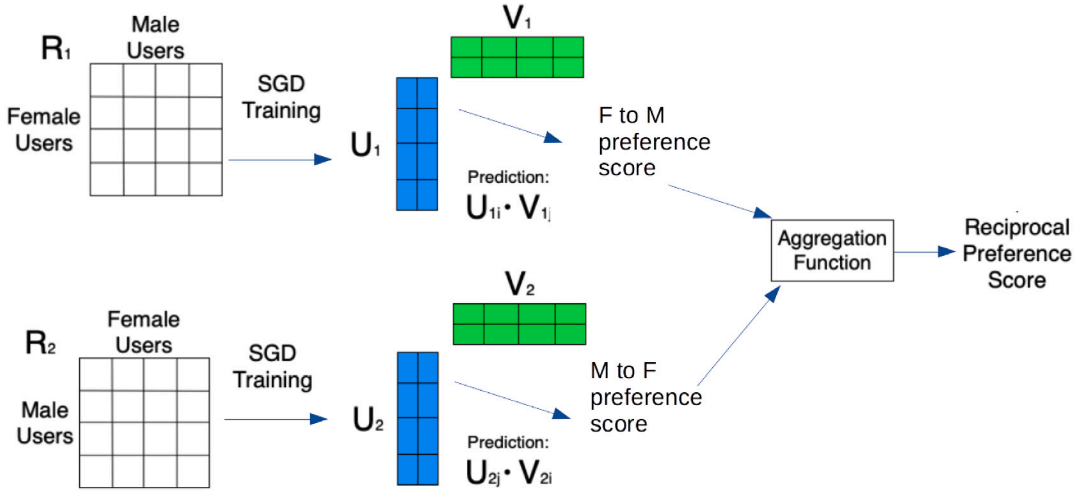

Fig. 7. Visual overview of the LFRR model.
Source: [43].

interactions of users in S_x are analyzed. Concretely, for every user in S_x, the list of all users that she/he has had reciprocal interest with is extracted, thereby producing several lists of candidate recommendations for x, one from each similar user in S_x. The support of each candidate user in these lists is calculated to finally rank all candidates into the final list for x.

The evaluation of CCR was conducted on a dataset of an online dating site, against a baseline approach in which random neighbor users were utilized without looking at profile similarity. The results reported a success rate of nearly 70%, which was twice as high as that of the baseline. Success was measured as the proportion of recommended users who received or sent an EoI from/to the test user x and resulted in a positive response, compared to those which did not. The effectiveness against other coetaneous RRS approaches had not been investigated in [87]. One advantage of the model is its ability to alleviate the cold start problem by providing new users with recommendations purely based on their profiles. Given the memory-based nature of its CF similarity computations, this model may also suffer from limitations when scaling it up to larger datasets, specially under the presence of numerous interaction groups, due to the computational complexity underlying the calculation of distances across groups.

5. Challenges and research opportunities in reciprocal recommendation

Following the analysis of RRS literature and representative models, this section is devoted to unaddressed – or insufficiently explored – challenges in the topic. In line with these challenges, we propose opportunities and directions for future research to address them. Different fusion strategies for determining reciprocity and application domains of RRS research are firstly highlighted. The research area is still at an earlier stage of development than classical RS, hence we consider it particularly important at this stage to (i) identify new application domains where RRS could bring promising advances and to (ii) summarize the state of affairs and limitations in current methodologies. The discussion is organized under five perspectives, as illustrated in Fig. 8.

A common challenge to the perspectives discussed below should be highlighted at this point: analyzing the well-known **cold-start** and **sparsity** problems within the scope of RRS. These are amply studied problems in standard RS, but given the special characteristics in RRS they reach a new dimension here, still at a very early stage of research. In general terms, problems stemming from information and data sparsity are aggravated in RRS, since user–user interactions are less frequent than user–item interactions in conventional RS sites, hence data density tends to be even lower. Therefore, it would be promising to investigate these problems. Several of the challenges below could help alleviating the sparsity and cold-start problems to some extent. In particular, examples of strategies that a priori could help improving results are:

- Community formation in large social networks, increasing density by reducing the number of users to consider. This has been used in previous proposals [64] (see Section 4.1.1) and relates to challenges **B7, C7** below.
- Deploying hybrid models like CCR (Section 4.2.5) that combine CB, CF and other schemes in reciprocal recommendation and allow generating recommendations solely based on user profiles when necessary [120] (see challenges **C1,C2**).
- Incorporating social information through opinion analysis, sentiment analysis or any techniques for extracting information from social media [42,111], as hinted in challenges **C4, C7**.
- Integrating information extracted from multiple domains [10] to improve data density, as outlined in challenge **C5**.

5.1. Perspective A: Fusion strategies and reciprocity

A1. Exploring aggregation and weighting strategies. As explained in Section 3.2, a remarkably important aspect in the design of a reciprocal recommendation scheme is the method adopted for aggregating unidirectional preferences or recommendation information between two users into a bidirectional result reflecting the extent of mutual interest that may exist between them. Accordingly, in spite of the various fusion strategies adopted in RRS literature, a worthwhile line of research would be to exhaustively analyze the wide spectrum of existing of aggregation operators with diverse behavior and properties [27]. Furthermore, weighted aggregation may need to take into proper account the importance of each user being matched according to multiple criteria: popularity, influence, level of commitment, etc. Supervised learning methods can be utilized to learn from data about the importance of users in a holistic manner. Furthermore, results from recent studies [26] suggest that performing elaborated sensitivity analyses in existing models by exploring new aggregation functions and parameters could lead to new performance insights.

A2. Fusion methods beyond reciprocity. Given the strongly social character of any RRS, a possible research line to be pursued in relation to preference fusion methods is the analysis of the social environment surrounding the user. This implies exploiting existing information about user connections in a social network, their trust and influence with

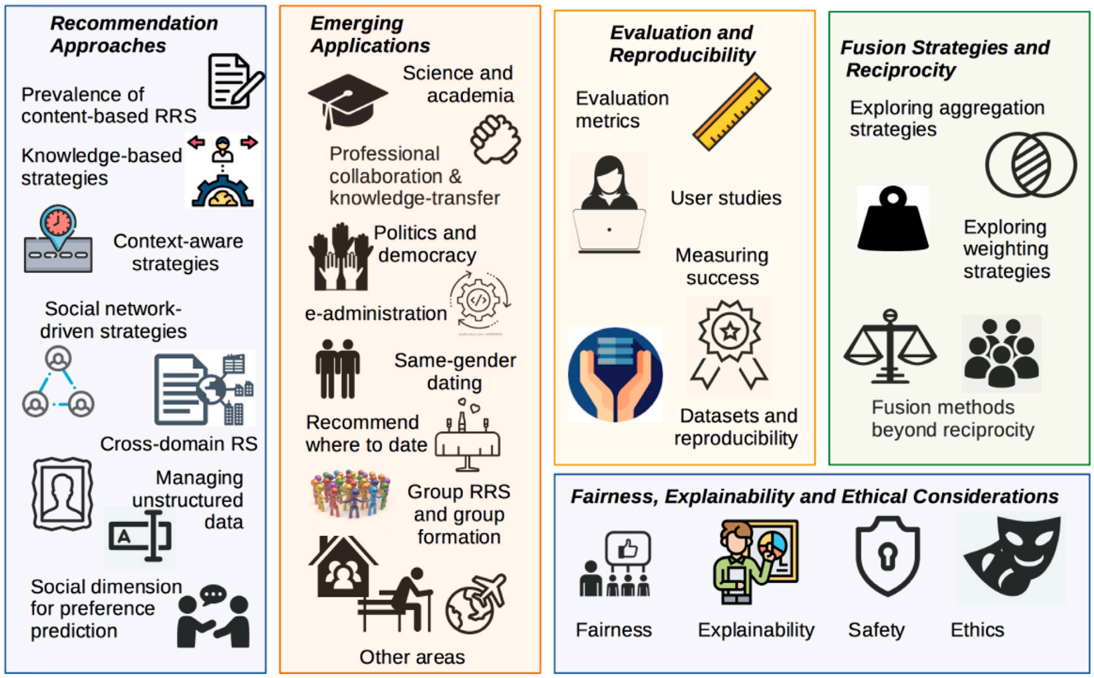

Fig. 8. Challenges and opportunities for RRS research.

other users, popularity with a specific type of users, etc. Considerations on investigating different fusion methods to aggregate user preferences should not be limited to calculating reciprocal preference scores only. Instead, in domains pervaded by multiple views of user data, it may be interesting to explore multi-criteria aggregation processes [27,103] that meaningfully combine information from several dimensions [171], be it for instance to consider various criteria of similarity between users, to aggregate positive and negative preference information as recent studies hint [120], to combine multiple preference values $p_{x,y}$ regarding attractiveness, common interests, contextual convenience, etc., into one, or to weigh aggregation inputs based on multiple aspects like popularity, user profile reliability, etc.

5.2. Perspective B: Emerging applications

B1. Science and academia: As pointed out in the analysis of RRS literature, academic and scientific collaboration has still been very scarcely investigated from the viewpoint of reciprocal recommendation [29]. The same occurs with the student–supervisor matching problem, as briefly outlined in the analysis of RRS for learning [92], hence more research is needed in these domains by defining new models and hybrid strategies, incorporating unstructured and social relationship data as suggested in [172], and modeling the academic priorities of students, researchers and professors more holistically.

B2. Professional collaboration & knowledge-transfer: In the landscape of RRS for professional purposes, there is an increasing demand for tools that not only recommend someone to hire, but also foster collaborative participation in joint projects, for instance based on the crowdfunding paradigm. In this way, creative and entrepreneur users may contact each other by virtue of these tools, thereby initiating common projects to work on. There exists a recent initiative in this line that still does not consider the incorporation of a dedicated recommender engine: the *precipita*[8] initiative by the FECYT Spanish federation, aimed at connecting researchers and citizens to promote the dissemination of science through crowdfunding.

B3. Politics and democracy: Another practical application in high demand for solutions that could involve integrating RRS-based services, is in public contexts such as politics, e.g. by developing models that estimate the reciprocity between citizens' and politicians' interests. Reciprocity in this context needs to consider, for instance, the level of interest or concern by a politician in a group of people with the characteristics exhibited by the user in question. This would make it possible to recommend what/*whom* to vote for a particular participatory democracy problem, helping citizens in these – often important and complex – decision making events with an increasingly larger number of alternatives to choose from. Research opportunities are therefore open at the intersection between RRS and collective decision-making at large-scale [173].

B4. Electronic administration: An specially interesting possibility in the public domain is that of electronic administration. In current times we are witnessing a dramatic sociological shift in which the use of technology is more paramount than ever. This shift demands that most administrative platforms need to evolve in the sense of being merely a tool to undertake bureaucratic processes electronically. Instead, these platforms should adopt a much more active role in which collaborative citizen participation plays a fundamental role. Given the reciprocity characteristics of RRS, it may be useful to recommend like-minded citizens to each other in the process of leveraging electronic administration tools oriented towards citizen collaboration, for making decisions that affect the wider population. This kind of tool could create relevant social matching recommendations that lead to improved decision-making results at a collaborative level, hence potentially leading to positive steps forwards from a societal viewpoint and increased citizen satisfaction.

B5. Same-gender dating: Inclusiveness, equality and diversity considerations in favor of minority communities, such as LGBTQ groups, are a topic of increasing significance everywhere [174], with the landscape of AI and information systems being no exception. This prompts the importance of investigating these considerations within the scope of RRS, where numerous online dating approaches for opposite-gender

[8] https://www.precipita.es.

relationships have been proposed, but none of these studies has been extended to homosexual dating nor other contexts where people exhibit different sexual orientation or identity. Additionally, more and more online dating firms provide services for non-heterosexual dating across different countries. We therefore argue that single-class RRS can be investigated to adapt existing RRS solutions for online dating [16,43,48,119] into same-gender dating scenarios where both users belong to the same class. Multi-class RRS can be also taken into consideration as a new concept for dating services that accommodate multiple sexual orientations.

B6. Recommend *whom* to date and *where*: Another interesting direction in the scope of online dating would be not only to recommend a user to date with, but also to incorporate mutual preference and contextual factors to recommend a suitable venue (cafe, pub, eateries, etc.) to meet. Put another way, devising recommendations on "meeting person y in place l" would bring together the strengths of RRS and classic RS for suggesting places to visit.

B7. Group reciprocal recommendation and group formation: RRS research so far focused on one-to-one matching, but the increasing use of online interest group platforms like *Meetup* and *OutdoorActive*, as well as group online learning, raises the need for reciprocal models at group level. Example situations that motivate this challenge include recommending a *Meetup* group to a user, recommending a group to all members of another group, or forming new groups of like-minded users [49,52], based on compatibility between their existing and potential members. Extending current RRS models into many-to-one or many-to-many frameworks clearly requires incorporating aggregation strategies (see challenge A2), particularly inspired by group decision making frameworks [173].

B8. Other unexplored areas: house-share, loneliness prevention and travel: There exist other areas that could benefit from incorporating RRS research which, to the best of our knowledge, have not done so as of yet. One of them is house-share, i.e. finding a housemate/roommate or a group of them in the house rental market. Depending on the specifics of the problem, both existing one-to-one RRS and group-level ideas (see B7 above) can be developed for matching compatible people to share accommodation. Loneliness is another critical problem in nowadays society that puts people welfare at risk, specially among elderly and vulnerable groups, hence we stress the potential impact that much of the advances made on RRS research could have if they are oriented towards this societal challenge through loneliness prevention. Lastly, although many RS have been developed in the tourism domain [2,3], solo travel has become a popular trend in the last years. Despite solo travel poses attractive factors such as freedom and flexibility, travelers also tend to benefit from meeting other similar people, both fellow travelers or locals alike, e.g. to go out together or to learn from the local culture. Therefore, there is room for interesting applications of single-class and two-class RRS to suggest matches between travelers, or between travelers and locals, respectively.

5.3. Perspective C: Recommendation approaches

C1. Prevalance of CB-RRS. In classical RS literature, CF and hybrid models tend to outperform CB models, specially with regards to prediction accuracy [1,175]. This trend is also observed in evaluations made between with CB-RRS and CF-RRS, as shown throughout the analysis in Section 4. In spite of this, RRS research as of its current state still shows a predominance of CB models, specially in recruitment and online learning [17,98,116,137], suggesting that more attention should be paid to other approaches.

C2. Knowledge-based strategies. As outlined earlier, despite the sheer abundance of advanced and specialized techniques that have been developed in classical RS contexts, there are still less significant progress in RRS beyond CB, CF and hybrid strategies. Therefore, we argue that at this stage there is still a long way ahead in studying and applying latest innovative RS techniques by adapting them to the particular requirements inherent to RRS. A possible starting point would be put a higher focus on knowledge-based systems such as [91], which might be specially useful in cases where rating information is particularly limited and other families of techniques perform poorly by themselves. An RRS that incorporates knowledge-based principles would generate recommendations based on explicit statements of what the user is looking for, along with rules representing knowledge about the domain in question. With these characteristics at hand, hybrid models integrating knowledge management could be a suitable approach from the perspective of reciprocal recommendation, as systems usually do not have much rating history of prior user evaluations of other users.

C3. Context-aware strategies. In some domains, aspects like temporal or location data can play a key role in the success of the recommendations produced. In fact, context-aware RS [7] incorporate contextual factors like time or location in the recommendation process. These aspects clearly have a direct impact when extrapolated to the scope of RRS, as users' preferences towards other people undoubtedly evolve over the time [90], or they greatly depend on the time and location. In dating and socializing, for instance, we might be interested in meeting one kind of person or another depending on our current circumstances. This applies to both romantic relationships, friendships, professional partnerships, collaborations, etc. Since such circumstances change over the time, so do people interests regarding other people to connect with. The same occurs with location, depending on which people might be interested in meeting different kinds of people (in town, on a trip, etc.).

C4. Social network-driven strategies. Given the distinctive characteristics exhibited by RRS, another problem deserving further attention relates to techniques which have demonstrated success in social RS [41,42]. These systems have succeeded in generating unidirectional recommendations upon data extracted via social network analysis, such as information inherent to the network structure or data describing influence, popularity or trust between users. Consequently, the key proposed idea is to take these social network features into account for defining new RRS strategies whose mutual matching recommendations are perceived as more useful. In the same line, another interesting challenge lies in investigating new RRS techniques based on sentiment analysis or similarly extracted information from social media, e.g. microblogs, comments posted by users, etc.

C5. Cross-domain reciprocal recommendation. Some e-commerce sites like eBay and Amazon utilize user preferences and feedback information from multiple domains, which can result in better recommendations richly informed by data from various environments [10,176]. RS following this approach are known as *cross-domain reciprocal recommenders*. The challenge of sparsity, cold start and lack of sufficient user information has been evident in RRS domains. For this reason, an encouraged research direction to explore refers to cross-domain solutions for reciprocal recommendation, whereby users' information can be aggregated and integrated from their (often multiple) profiles in diverse online platforms and social media.

C6. Managing unstructured data. Most CB-RRS assume the existence of structure user profile metadata, yet they are limited to deal with unstructured data such as unrestricted text written by users to describe themselves and the type of users they are interested in. In the context of online dating, experiments conducted in industrial settings - e.g. by OkCupid[9] - reported physical attractiveness as an attribute shown not only in users' text profiles, but most importantly in their pictures. These are clearly two examples of relevant unstructured data in this

[9] https://www.gwern.net/docs/psychology/okcupid/weexperimentonhumanbeings.html.

domain for predicting interest in other users: text and images [36]. The latter are used infrequently owing to their difficulty of being incorporated into recommendation processes. In various nonreciprocal user recommendation domains, these data are usually removed from public datasets for privacy reasons. Additionally, photos and text submitted by users are generally unlabeled and therefore harder to train prediction models on them. Despite the expounded limitations, new solutions to make use of unstructured data without compromising users' privacy might need to be investigated in order to foster significant advances in CB-RRS.

C7. Social dimension for preference prediction: Another fundamental aspect to consider in the design of reciprocal recommendation models pertains the adoption of an appropriate prediction strategy to estimate preference values. For this reason, it is crucial is to deepen into the social dimension of preference modeling and working on techniques that infer implicit communities [101,111], measure user popularity [25,177], their social influence level in social media contexts to investigate the propagation level of such influence, and estimating the extent of its propagation when users are not connected [172] through link prediction strategies.

5.4. Perspective D: Evaluation and reproducibility

D1. Evaluation metrics: As a result of the literature analysis conducted, we have identified that most proposed RRS so far have been validated using offline techniques, with very few studies including real user evaluation. Albeit offline evaluation helps measuring various aspects of model performance, it solely considers the system effectiveness at the time of generating recommendations. In nowadays society where technology is put at the forefront of services to aid users in virtually any situation, it is paramount to use and propose new evaluation metrics that are more user-centered and reciprocity-aware. Aspects including satisfaction, utility, usability, serendipity, etc., need to be reformulated for their implantation and validation in RRS, based on real user interaction.

D2. User studies: On another note, users are sometimes reluctant to interact with systems during their trial, specially when these systems require personal information about themselves. Rather than as an obstacle to the realistic validation of RRS, this should be viewed as an opportunity to investigate alternative approaches that facilitate and incentivize these interaction-based studies.

D3. Measuring success: Success in an RRS is typically measured in terms of whether the two users being recommended to one another signal a positive reaction to such recommendation to the system. This can occur explicitly, e.g. both users give positive feedback in a job matching app, or implicitly, e.g. they start a relationship and therefore they stop using a dating app. Nevertheless, current research has paid little attention to the relationship between success from the users perspective, and other success factors concerning the provider of the service. For instance, in platforms where some of its users pay for "premium" services and some others do not, it might sometimes happen that optimal recommendations for pairs of users might result in otherwise avoidable revenue losses if both users stop paying such premium fees. Albeit this topic may open up dilemmas, it is worth considering aspects like balancing user satisfaction, business revenue for the RRS service provider, and an ethical balance between both. The exploration of multi-stakeholder approaches is likewise needed [45,46], specially to consider scenarios where other actors beyond the two users being recommended are influenced by the recommender performance from the system side.

D4. Datasets and reproducibility: Evaluating RRS models evidently requires adequate datasets with sufficient high-quality data describing both user–system and user–user interactions, user-related information, etc. An ample majority of experimental evaluations of RRS, specially in the online dating domain, rely on corporate data, which is in most cases private and not shareable across the scientific community. Even in other domains like social networks where relationship data are gathered, these are normally compiled for specific research and not fully made available in general. In recruitment, collections of CVs or *LinkedIn* profiles might also be collected for a clear purpose only and not shared, where person–recruiter connections represent a reciprocal acceptance for a position. Still, these collected data tend to include successful job connections only, not reflecting unsuccessful ones.

There are some exceptions to this rule at the time of writing, e.g. Kaggle's previously mentioned *Speed Dating Experiment* data, the datasets used in [98] for online learning, the *Twitter Friends* dataset[10] which includes data about followed profiles by users and hashtags employed by the user, or meetups data from *meetup.com*.[11] Meanwhile, there are illustrative github repositories for beginners into RRS for dating[12]: they do not provide raw datasets but showcase the experimental use of RRS models. The annual *RecSys Challenge* launched by the *ACM RecSys* conference series had focused on job recommendations in its 2016 and 2017 editions,[13,14] co-sponsored by *XING*,[15] with potentially useful datasets to validate RRS for recruitment.

Despite this small number of available datasets, we suggest it is clearly necessary to promote (where possible) more validation of models through public data and, most importantly, to increase efforts in making new forms of non-sensitive and high-quality available data for encouraging reproducible research — specially in cases when readily available datasets and their underlying data properties may not fit the experimental purposes/nature of a given research work.

5.5. Perspective E: Fairness, explainability and ethical considerations

Popularity bias has been identified as a major challenge to consider in RRS, and several studies have already proposed different strategies to deal with this issue [72,85,100,177], hence their significance in upcoming RRS models has been justified. *Fairness* [95] is a related concept and sometimes a consequence of poorly managing popularity biases, which should receive much more attention in domains like recruitment and learning to ensure equal opportunities for everyone [54]. *Explainable recommendations* in a reciprocal setting [119] also need further research, as this aspect has still been barely investigated in RRS, deserving more importance: explanations would have an impact on two users instead of one end user in these contexts [4], therefore it should be intimately linked to the notion of reciprocity, being always generated at the intersection of both parties' interests and characteristics.

Ethical considerations clearly play an important role in RRS where (i) people personal data are more exploited than in most other RS, and (ii) considerations for emotional behavior and changes of users when they interact with recommendations should be accounted for [178] (an aspect not broadly investigated within RRS so far). Besides, scenarios where users are not always honest when publishing profile information constitute another challenge in CB approaches. In online services aimed at socially connecting users, some users tend to be deceptive in order to attract attention, specially new users in the system. Profiles may be a successful predictor for initial expression of preference towards the user. However, they might fail to predict the consequences of an actual match between users, e.g. a friendship or relationship, unless veracity of user profile information could be effectively analyzed and determined. More research seems necessary in identifying dubious users in online dating [179] and other RRS applications.

[10] Twitter Friends data: https://www.kaggle.com/hwassner/TwitterFriends.

[11] Kaggle meetup data: https://www.kaggle.com/sirpunch/meetups-data-from-meetupcom.

[12] Need-a-date repository: https://github.com/Jennytang1224/Need_a_Date.

[13] Recsys 2016 challenge: http://2016.recsyschallenge.com.

[14] Recsys 2017 challenge: http://www.recsyschallenge.com/2017/.

[15] XING: https://xing.com.

6. Conclusions and lessons learnt

Reciprocal recommenders aiming at "matching people with the right people" have attained recent attention by researchers and practitioners to develop personalized user match recommendations. This paper introduced and formally characterized the concept of Reciprocal Recommender Systems (RRS), highlighting its differentiating characteristics from other recommender approaches. The primary contributions include a thorough literature analysis of the state-of-the-art research on RRS to date and its main application domains, discussing the underlying recommendation approaches utilized to integrate reciprocity in the recommendation process, and describing in detail a number of representative models. Following our literature analysis, we identified and discussed a number of relevant challenges and opportunities for future research on RRS. Amongst the various lessons learnt throughout this study, we emphasize: (1) the attention paid to a small number of application areas to date, with numerous emerging applications in online social matching not having been sufficiently investigated yet; (2) the opportunities to study novel fusion and recommendation strategies for combining user–user preferences still not applied in this context; (3) the potential implications of considering multiple sources of data; and (4) the possibilities of extending RRS principles for people-to-people recommendation at a collective level.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] C.C. Aggarwal, Recommender Systems: The Textbook, first ed., Springer International Publishing, 2016.
[2] J. Borrás, A. Moreno, A. Valls, Intelligent tourism recommender systems: a survey, Expert Syst. Appl. 41 (16) (2014) 7370–7389.
[3] H. Chiang, T. Huang, User-adapted travel planning system for personalized schedule recommendation, Inf. Fusion 21 (2015) 3–17.
[4] I. Guy, I. Ronen, E. Wilcox, Do you know?: Recommending people to invite into your social network, in: Proceedings of the 14th International Conference on Intelligent User Interfaces, IUI '09, 2009, pp. 77–86.
[5] R. García, X. Amatriain, Weighted content based methods for recommending connections in online social networks, in: W. Geyer, J. Freyne, B. Mobasher, S.S. Anand (Eds.), Proceedings of the 2nd ACM RecSys'10 Workshop on Recommender Systems and the Social Web, 2010, pp. 68–71.
[6] D. Bokde, S. Girase, D. Mukhopadhyay, Matrix factorization model in collaborative filtering algorithms: A survey, Procedia Comput. Sci. 49 (2015) 136–146.
[7] G. Adomavicius, A. Tuzhilin, Context-aware recommender systems, in: F. Ricci, et al. (Eds.), Recommender Systems Handbook, second ed., Springer, 2015.
[8] F. Ricci, L. Rokach, B. Shapira, Recommender Systems Handbook, second ed., Springer, 2015.
[9] A. Felfernig, L. Boratto, M. Stettinger, M. Tkalčič, Group Recommender Systems: An Introduction, Springer, 2018.
[10] I. Cantador, I. Fernández-Tobías, S. Berkovsky, P. Cremonesi, Cross-domain recommender systems, in: F. Ricci, L. Rokach, B. Shapira (Eds.), Recommender Systems Handbook, Springer, 2015, pp. 919–959.
[11] E. Triantaphyllou, Multi-criteria Decision Making Methods: A Comparative Study, Springer, 2000.
[12] D. Monti, G. Rizzo, M. Morisio, A systematic literature review of multicriteria recommender systems, Artif. Intell. Rev. (2020) 1–42, in press, http://dx.doi.org/10.1007/s10462-020-09851-4.
[13] I. Palomares, Reciprocal Recommendation: matching users with the right users, in: Proceedings of the 43rd ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR '20, 2020, in press.
[14] L.A. Pizzato, A. Bhasin, Beyond friendship: The art, science and applications of recommending people to people in social networks, in: Proceedings of the 7th ACM Conference on Recommender Systems, RecSys '13, 2013, pp. 495–496.
[15] L. Pizzato, T. Rej, J. Akehurst, I. Koprinska, K. Yacef, J. Kay, Recommending people to people: the nature of reciprocal recommenders with a case study in online dating, User Model. User Adapt. Interact. 23 (2014) 447–488.
[16] P. Xia, B. Liu, Y. Sun, C. Chen, Reciprocal recommendation system for online dating, in: Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2015, ASONAM '15, 2015, pp. 234–241.
[17] N.D. Almalis, G.A. Tsihrintzis, N. Karagiannis, A content based approach for recommending personnel for job positions, in: IISA 2014, the 5th International Conference on Information, Intelligence, Systems and Applications, 2014, pp. 45–49.
[18] B.A. Potts, H. Khosravi, C. Reidsema, A. Bakharia, M. Belonogoff, M. Fleming, Reciprocal peer recommendation for learning purposes, in: Proceedings of the 8th International Conference on Learning Analytics and Knowledge, LAK '18, 2018, pp. 226–235.
[19] I. Guy, I. Ronen, N. Zwerdling, I. Zuyev-Grabovitch, M. Jacovi, What is your organization 'like'? A study of liking activity in the enterprise, in: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI '16, ACM, New York, NY, USA, 2016.
[20] J. Hannon, M. Bennett, B. Smyth, Recommending Twitter users to follow using content and collaborative filtering approaches, in: Proceedings of the Fourth ACM Conference on Recommender Systems, RecSys '10, 2010, pp. 199–206.
[21] J. Neve, I. Palomares, Hybrid reciprocal recommender systems: Integrating item-to-user principles in reciprocal recommendation, in: Companion Proceedings of the Web Conference 2020, WWW '20, 2020, pp. 848–854.
[22] E. Tsourougianni, N. Ampazis, Recommending who to follow on twitter based on tweet contents and social connections., Soc. Netw. 2 (2013) 165–173.
[23] A. Defazio, T. Caetano, A graphical model formulation of collaborative filtering neighbourhood methods with fast maximum entropy training, in: Proceedings of the 29th International Conference on Machine Learning, ICML'12, 2012, pp. 555–562.
[24] C. Trattner, D. Elsweiler, Food Recommender Systems: Important Contributions, Challenges and Future Research Directions, Cornell University (2017).
[25] A. Kleinerman, A. Rosenfeld, F. Ricci, S. Kraus, Optimally balancing receiver and recommended users' importance in reciprocal recommender systems, in: Proceedings of the 12th ACM Conference on Recommender Systems, Recsys'18, ACM, 2018, pp. 131–139.
[26] J. Neve, I. Palomares, Aggregation strategies in user-to-user reciprocal recommender systems, in: 2019 IEEE International Conference on Systems, Man and Cybernetics, SMC'19, 2019, pp. 4031–4036.
[27] G. Beliakov, A. Pradera, T. Calvo, Aggregation Functions: A Guide for Practitioners, first ed., Springer International Publishing, 2007.
[28] J. Gope, S.K. Jain, A survey on solving cold start problem in recommender systems, in: 2017 International Conference on Computing, Communication and Automation, ICCCA, 2017, pp. 133–138.
[29] A. Daud, W. Ahmed, T. Amjad, J.A. Nasir, N.R. Aljohani, R.A. Abbasi, I. Ahmad, Who will cite you back? Reciprocal link prediction in citation networks, Libr. Hi Tech. 35 (2017) 509–520.
[30] A. Doryab, V. Bellotti, A. Yousfi, S. Wu, J.M. Carroll, A.K. Dey, If it's convenient: Leveraging context in peer-to-peer variable service transaction recommendations, in: Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, vol. 1, 2017, pp. 1–28.
[31] M.M. Khan, R. Ibrahim, I. Ghani, Cross domain recommender systems: A systematic literature review, ACM Comput. Surv. 50 (3) (2017) 36.
[32] S. Zhang, L. Yao, A. Sun, Y. Tay, A. Sun, Deep learning based recommender system: A survey and new perspectives, 52, (1) 2018, 5,
[33] Z. Ali, P. Kefalas, K. Muhammad, B. Ali, M. Imran, Deep learning in citation recommendation models survey, Expert Syst. Appl. 162 (2020) 113790.
[34] M. Quadrana, P. Cremonesi, D. Jannach, Sequence-aware recommender systems, ACM Comput. Surv. 51 (4) (2018) 66.
[35] N.M. Villegas, C. Sánchez, J. Díaz-cely, G. Tamura, Characterizing context-aware recommender systems: A systematic literature review, Knowl. Based Syst. 140 (2018) 173–200.
[36] Y. Deldjoo, M. Schedl, P. Cremonesi, G. Pasi, Recommender systems leveraging multimedia content, ACM Comput. Surv. 53 (5) (2020) 106:1–106:38.
[37] Y. Deldjoo, T. Di Noia, F.A. Merra, A survey on adversarial recommender systems: from attack/defense strategies to generative adversarial networks, ACM Comput. Surv. (2020) in press, http://dx.doi.org/10.1145/3439729.
[38] X. Cai, M. Bain, A. Krzywicki, W. Wobcke, Y.S. Kim, P. Compton, A. Mahidadia, Collaborative filtering for people to people recommendation in social networks, in: J. Li (Ed.), AI 2010: Advances in Artificial Intelligence - 23rd Australasian Joint Conference. Proceedings, in: Lecture Notes in Computer Science, vol. 6464, Springer, 2010, pp. 476–485.
[39] Y.S. Kim, A. Mahidadia, P. Compton, X. Cai, M. Bain, A. Krzywicki, W. Wobcke, People recommendation based on aggregated bidirectional intentions in social network site, in: B.-H. Kang, D. Richards (Eds.), Knowledge Management and Acquisition for Smart Systems and Services, 2010, pp. 247–260.

[40] L. Pizzato, T. Rej, T. Chung, K. Yacef, I. Koprinska, J. Kay, Reciprocal Recommenders, in: 8th Workshop on Intelligent Techniques for Web Personalization and Recommender Systems, 2010.

[41] J. Sanz-Cruzado, P. Castells, Information retrieval models for contact recommendation in social networks, in: L. Azzopardi, B. Stein, N. Fuhr, P. Mayr, C. Hauff, D. Hiemstra (Eds.), Advances in Information Retrieval - 41st European Conference on IR Research, ECIR, Proceedings, Part I, in: Lecture Notes in Computer Science, vol. 11437, Springer, 2019, pp. 148–163.

[42] I. Guy, People recommendation on social media, in: Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2018, pp. 570–623.

[43] J. Neve, I. Palomares, Latent factor models and aggregation operators for collaborative filtering in reciprocal recommender systems, in: Proceedings of the 13rd ACM Conference on Recommender Systems, Recsys'19, ACM, 2019, pp. 219–227.

[44] Y. Zheng, Multi-stakeholder recommendations: Case studies, methods and challenges, in: Proceedings of the 13th ACM Conference on Recommender Systems, RecSys '19, 2019, pp. 578–579.

[45] H. Abdollahpouri, G. Adomavicius, R.D. Burke, I. Guy, D. Jannach, T. Kamishima, J. Krasnodebski, L. Pizzato, Multistakeholder recommendation: Survey and research directions, User Model. User-Adapt. Interact. 30 (2020) 127–158.

[46] H. Abdollahpouri, R. Burke, Multi-stakeholder recommendation and its connection to multi-sided fairness, in: RMSE Workshop At ACM RecSys'19, 2019.

[47] L. Pizzato, T. Chung, T. Rej, I. Koprinska, K. Yacef, J. Kay, Learning user preferences in online dating, in: Proceedings of the Preference Learning (PL-10) Tutorial and Workshop, European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases, ECML PKDD, 2010.

[48] L. Pizzato, T. Rej, T. Chung, I. Koprinska, J. Kay, RECON: A reciprocal recommender for online dating, in: Proceedings of the Fourth ACM Conference on Recommender Systems, RecSys '10, 2010, pp. 207–214.

[49] K. Yacef, B.M. McLaren, Supporting learners ' group formation with reciprocal recommender technology, in: 3rd Workshop on Intelligent Support for Learning in Groups, Held in Conjunction with ITS, 2015.

[50] R. Liu, Y. Ouyang, W. Rong, X. Song, C. Tang, Z. Xiong, Rating prediction based job recommendation service for college students, in: ICCSA'16, Proceedings, 2016.

[51] R. Liu, Y. Ouyang, W. Rong, X. Song, W. Xie, Z. Xiong, Employer oriented recruitment recommender service for university students, in: ICIC'16, Proceedings, 2016.

[52] E. Kimmich Mitchell, T. Dragon, Intelligent group suggestions based on students' conceptual understanding: (abstract only), in: Proceedings of the 49th ACM Technical Symposium on Computer Science Education, SIGCSE '18, Association for Computing Machinery, 2018, p. 274.

[53] F. Wenzel, W. Kießling, A preference-driven database approach to reciprocal user recommendations in online social networks, in: S. Hartmann, H. Ma (Eds.), Database and Expert Systems Applications - 27th International Conference, DEXA 2016, Proceedings, Part II, in: Lecture Notes in Computer Science, vol. 9828, Springer, 2016, pp. 3–10.

[54] Y. Zheng, T. Dave, N. Mishra, H. Kumar, Fairness in reciprocal recommendations: A speed-dating study, in: Adjunct Publication of the 26th Conference on User Modeling, Adaptation and Personalization, UMAP '18, Association for Computing Machinery, 2018, pp. 29–34.

[55] Y. Tay, A.T. Luu, S.C. Hui, CoupleNet: Paying attention to couples with coupled attention for relationship recommendation, in: Proceedings of 12th International AAAI Conference on Web and Social Media, ICWSM, 2018.

[56] K. Sudo, N. Osugi, T. Kanamori, Numerical study of reciprocal recommendation with domain matching, Japan. J. Stat. Data Sci. 2 (2019) 221–240.

[57] A. Alanazi, M. Bain, A people-to-people content-based reciprocal recommender using hidden markov models, in: Proceedings of the 7th ACM Conference on Recommender Systems, Recsys'13, ACM, 2013, pp. 303–306.

[58] H. Jung, V. Bellotti, A. Doryab, D. Leitersdorf, J. Chen, B.V. Hanrahan, S. Lee, D. Turner, A.K. Dey, J.M. Carroll, "MASTerful" matchmaking in service transactions: Inferred abilities, needs and interests versus activity histories, in: Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, CHI '16, 2016, pp. 1644–1655.

[59] J. Lian, F. Zhang, M. Hou, H. Wang, X. Xie, G. Sun, Practical lessons for job recommendations in the cold-start scenario, in: Proceedings of the Recommender Systems Challenge 2017, in: RecSys Challenge '17, Association for Computing Machinery, 2017.

[60] A. Jacobsen, G. Spanakis, It's a Match! Reciprocal recommender system for graduating students and jobs, in: M.C. Desmarais, C.F. Lynch, A. Merceron, R. Nkambou (Eds.), Proceedings of the 12th International Conference on Educational Data Mining, 2019.

[61] K. Tu, B.F. Ribeiro, D.D. Jensen, D. Towsley, B. Liu, H. Jiang, X. Wang, Online dating recommendations: matching markets and learning preferences, in: C. Chung, A.Z. Broder, K. Shim, T. Suel (Eds.), 23rd International World Wide Web Conference, WWW '14, ACM, 2014, pp. 787–792.

[62] A. Saini, F. Rusu, A. Johnston, PrivateJobMatch: A privacy-oriented deferred multi-match recommender system for stable employment, in: Proceedings of the 13th ACM Conference on Recommender Systems, RecSys '19, 2019, pp. 87–95.

[63] Z. Yin, T. Xu, H. Zhu, C. Zhu, E. Chen, H. Xiong, Matching of social events and users: a two-way selection perspective, World Wide Web 23 (2019) 853–871.

[64] S. Alsaleh, R. Nayak, Y. Xu, L. Chen, Improving matching process in social network using implicit and explicit user information, in: X. Du, W. Fan, J. Wang, Z. Peng, M.A. Sharaf (Eds.), Web Technologies and Applications - 13th Asia-Pacific Web Conference, APWeb 2011. Proceedings, in: Lecture Notes in Computer Science, vol. 6612, Springer, 2011, pp. 313–320.

[65] L. Chen, R. Nayak, A reciprocal collaborative method using relevance feedback and feature importance, in: 2013 IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies, IAT, vol. 1, 2013, pp. 133–138.

[66] L. Chen, R. Nayak, Y. Xu, Improving matching process in social network, in: 2010 IEEE International Conference on Data Mining Workshops, 2010, pp. 305–311.

[67] L. Chen, R. Nayak, Y. Xu, A recommendation method for online dating networks based on social relations and demographic information, in: 2011 International Conference on Advances in Social Networks Analysis and Mining, 2011, pp. 407–411.

[68] F. Vitale, N. Parotsidis, C. Gentile, Online reciprocal recommendation with theoretical performance guarantees, in: Proceedings of the 32nd International Conference on Neural Information Processing Systems, NIPS'18, Curran Associates Inc., Red Hook, NY, USA, 2018, pp. 8267–8277.

[69] L.A. Pizzato, T. Rej, K. Yacef, I. Koprinska, J. Kay, Finding someone you will like and who won't reject you, in: Proceedings of the 19th International Conference on User Modeling, Adaption, and Personalization, UMAP'11, 2011, pp. 269–280.

[70] M. Yu, K. Zhao, J. Yen, D. Kreager, Recommendation in reciprocal and bipartite social networks: A case study of online dating, in: Proceedings of the 6th International Conference on Social Computing, Behavioral-Cultural Modeling and Prediction, SBP'13, Springer-Verlag, 2013, pp. 231–239.

[71] K. Zhao, X. Wang, M. Yu, B. Gao, User recommendations in reciprocal and bipartite social networks–An online dating case study, IEEE Intell. Syst. 29 (2) (2014) 27–35.

[72] X. Cai, M. Bain, A. Krzywicki, W. Wobcke, Y.S. Kim, P. Compton, A. Mahidadia, ProCF: Probabilistic collaborative filtering for reciprocal recommendation, in: J. Pei, V.S. Tseng, L. Cao, H. Motoda, G. Xu (Eds.), Advances in Knowledge Discovery and Data Mining, Springer Berlin Heidelberg, 2013, pp. 1–12.

[73] M. Al-Zeyadi, F. Coenen, A. Lisitsa, User-to-user recommendation using the concept of movement patterns: A study using a dating social network, in: Proceedings of 9th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management. KDIR, 2017.

[74] M. Eirinaki, M. Louta, I. Varlamis, A trust-aware system for personalized user recommendations in social networks, IEEE Trans. Syst. Man Cybern: Syst. 44 (4) (2014) 409–421.

[75] J. Kunegis, G. Gröner, T. Gottron, Online dating recommender systems: the split-complex number approach, in: RSWeb '12, Proceedings, 2012.

[76] S. Kutty, R. Nayak, L. Chen, A people-to-people matching system using graph mining techniques, World Wide Web 17 (3) (2014) 311–349.

[77] L. Li, T. Li, MEET: a generalized framework for reciprocal recommender systems, in: Proceedings of the 21st ACM International Conference on Information and Knowledge Management, CIKM '12, 2012.

[78] D. Quercia, L. Capra, FriendSensing: Recommending friends using mobile phones, in: Proceedings of the Third ACM Conference on Recommender Systems, RecSys '09, 2009, pp. 273–276.

[79] P. Symeonidis, E. Tiakas, Y. Manolopoulos, Transitive node similarity for link prediction in social networks with positive and negative links, in: Proceedings of the Fourth ACM Conference on Recommender Systems, RecSys '10, 2010, pp. 183–190.

[80] J. Chen, W. Geyer, C. Dugan, M. Muller, I. Guy, Make new friends, but keep the old: Recommending people on social networking sites, in: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI '09, 2009, pp. 201–210.

[81] Z. Du, L. Hu, X. Fu, Y. Liu, Scalable and explainable friend recommendation in campus social network system, in: S. Li, Q. Jin, X. Jiang, J.J.J.H. Park (Eds.), Frontier and Future Development of Information Technology in Medicine and Education, in: Lecture Notes in Electrical Engineering, vol. 269, Springer Netherlands, 2014, pp. 457–466.

[82] R. Nayak, M. Zhang, L. Chen, A social matching system for an online dating network: A preliminary study, in: 2010 IEEE International Conference on Data Mining Workshops, 2010, pp. 352–357.

[83] R. Nayak, Utilizing past relations and user similarities in a social matching system, in: Proceedings of the 15th Pacific-Asia Conference on Advances in Knowledge Discovery and Data Mining - Volume Part II, PAKDD'11, 2011, pp. 99–110.

[84] G. Özcan, S.G. Ögüdücü, Applying different classification techniques in reciprocal job recommender system for considering job candidate preferences, in: 2016 11th International Conference for Internet Technology and Secured Transactions, ICITST, 2016, pp. 235–240.

[85] S. Kutty, L. Chen, R. Nayak, A people-to-people recommendation system using tensor space models, in: Proceedings of the 27th Annual ACM Symposium on Applied Computing, SAC '12, 2012, pp. 187–192.
[86] C.-H. Ting, H.-Y. Lo, S.-D. Lin, Transfer-learning based model for reciprocal recommendation, in: Proceedings, Part II, of the 20th Pacific-Asia Conference on Advances in Knowledge Discovery and Data Mining - Volume 9652, PAKDD 2016, 2016, pp. 491–502.
[87] J. Akehurst, I. Koprinska, K. Yacef, L. Pizzato, J. Kay, T. Rej, CCR - A content-collaborative reciprocal recommender for online dating, in: Proceedings of the 22nd International Joint Conference on Artificial Intelligence, IJCAI, 2011.
[88] I. Koprinska, K. Yacef, People-to-people reciprocal recommenders, in: Recommender Systems Handbook, 2015.
[89] A. Alanazi, A Probabilistic Reciprocal Recommender with Temporal Dynamics (Ph.D. thesis), University of New South Wales, Sydney, Australia, 2016.
[90] A. Alanazi, M. Bain, A scalable people-to-people hybrid reciprocal recommender using hidden Markov models, in: Proceedings of 2nd International Workshop on Machine Learning Methods for Recommender Systems, in Conjunction with 16th SIAM International Conference on Data Mining, 2016.
[91] M.Á. Rodríguez-García, R. Valencia-García, R.C. Palacios, J.M. Gómez-Berbís, BlindDate recommender: A context-aware ontology-based dating recommendation platform, J. Inf. Sci. 45 (5) (2019).
[92] M. Zhang, J. Ma, Z. Liu, J. Sun, T. Silva, A research analytics framework-supported recommendation approach for supervisor selection, Br. J. Educ. Technol. 47 (2) (2016) 403–420.
[93] D. Yang, D. Adamson, C.P. Rosé, Question recommendation with constraints for massive open online courses, in: Proceedings of the 8th ACM Conference on Recommender Systems, RecSys '14, 2014, pp. 49–56.
[94] Y. Qu, H. Liu, Y. Du, Z. Wu, Reciprocal ranking: A hybrid ranking algorithm for reciprocal recommendation, in: PRICAI 2018: Trends in Artificial Intelligence - 15th Pacific Rim International Conference on Artificial Intelligence, Proceedings, Part II, in: Lecture Notes in Computer Science, vol. 11013, Springer, 2018, pp. 455–463.
[95] B. Xia, J. Yin, J. Xu, Y. Li, WE-Rec: A fairness-aware reciprocal recommendation based on Walrasian equilibrium, Knowl. Based Syst. 182 (2019).
[96] N. Silva, I.-R. Tsang, G. Cavalcanti, I.-J. Tsang, A graph-based friend recommendation system using Genetic Algorithm, in: Evolutionary Computation (CEC), 2010 IEEE Congress on, 2010, pp. 1–7.
[97] O. Otakore, C. Ugwu, Online matchmaking using collaborative filtering and reciprocal recommender systems, Int. J. Eng. Sci. 07 (02) (2018) 07–21.
[98] S. Prabhakar, G. Spanakis, O. Zaiane, Reciprocal recommender system for learners in massive open online courses (MOOCs), in: H. Xie, E. Popescu, G. Hancke, B. Fernández Manjón (Eds.), Advances in Web-Based Learning – ICWL 2017, 2017, pp. 157–167.
[99] M. Yu, X.L. Zhang, D. Lee, D. Kreager, Community-based recommendation for cold-start problem: A case study of reciprocal online dating recommendation, in: M. Kaya, J. Kawash, S. Khoury, M. Day (Eds.), Social Network Based Big Data Analysis and Applications, in: Lecture Notes in Social Networks, Springer, 2018, pp. 201–222.
[100] L.A. Pizzato, C. Silvestrini, Stochastic matching and collaborative filtering to recommend people to people, in: Proceedings of the Fifth ACM Conference on Recommender Systems, RecSys '11, 2011, pp. 341–344.
[101] S. Alsaleh, R. Nayak, Y. Xu, Finding and matching communities in social networks using data mining, in: 2011 International Conference on Advances in Social Networks Analysis and Mining, 2011, pp. 389–393.
[102] T. Mine, T. Kakuta, A. Ono, Reciprocal recommendation for job matching with bidirectional feedback, in: Proceedings of the 2013 Second IIAI International Conference on Advanced Applied Informatics, IIAI-AAI '13, 2013, pp. 39–44.
[103] R.R. Yager, A. Rybalov, Uninorm aggregation operators, Fuzzy Sets and Systems 80 (1) (1996) 111–120.
[104] M. Chen, P. Liu, Performance evaluation of recommender systems, Int. J. Perform. Eng. 13 (2017) 1246–1256.
[105] A. Bellogín, A. Said, Offline and online evaluation of recommendations, in: S. Berkovsky, I. Cantador, D. Tikk (Eds.), Collaborative Recommendations - Algorithms, Practical Challenges and Applications, WorldScientific, 2018, pp. 295–328.
[106] D. Parra, S. Sahebi, Recommender systems: Sources of knowledge and evaluation metrics, in: Advanced Techniques in Web Intelligence-2, 2013, pp. 149–175.
[107] L. Brozovsky, V. Petricek, Recommender system for online dating service, 2007, arXiv preprint, arXiv:cs/0703042v1.
[108] L.A. Pizzato, J. Akehurst, C. Silvestrini, K. Yacef, I. Koprinska, J. Kay, The effect of suspicious profiles on people recommenders, in: Proceedings of the 20th International Conference on User Modeling, Adaptation, and Personalization, UMAP'12, 2012, pp. 225–236.
[109] P. Xia, K. Tu, B. Ribeiro, H. Jiang, X. Wang, C.X. Chen, B. Liu, D.F. Towsley, Characterization of user online dating behavior and preference on a large online dating site, in: Social Network Analysis, 2014.
[110] J. Akehurst, I. Koprinska, K. Yacef, L. Pizzato, J. Kay, T. Rej, Explicit and implicit user preferences in online dating, in: Proceedings of the 15th International Conference on New Frontiers in Applied Data Mining, PAKDD'11, 2011, pp. 15–27.
[111] D. Felmlee, D. Kreager, The invisible contours of online dating communities: A social network perspective, J. Soc. Struct. 18 (1) (2017).
[112] Z. Li, Y. Song, X. Xu, Incorporating facial attractiveness in photos for online dating recommendation, Electron. Commer. Res. 19 (2) (2019) 285–310.
[113] X. Su, H. Hu, Gender-specific preference in online dating, EPJ Data Sci. 8 (2019) 1–22.
[114] D. Richards, M. Taylor, P. Busch, Expertise recommendation: A two-way knowledge communication channel, in: Fourth International Conference on Autonomic and Autonomous Systems, ICAS'08, 2008, pp. 35–40.
[115] J. Malinowski, T. Keim, O. Wendt, T. Weitzel, Matching people and jobs: A bilateral recommendation approach, in: Proceedings of the 39th Annual Hawaii International Conference on System Sciences, HICSS'06, vol. 6, 2006, p. 137c.
[116] H. Yu, C. Liu, F. Zhang, Reciprocal recommendation algorithm for the field of recruitment, J. Inf. Comput. Sci. 8 (2011) 4061–4068.
[117] X. Cai, M. Bain, A. Krzywicki, W. Wobcke, Y.S. Kim, P. Compton, A. Mahidadia, Reciprocal and heterogeneous link prediction in social networks, in: P.-N. Tan, S. Chawla, C.K. Ho, J. Bailey (Eds.), Advances in Knowledge Discovery and Data Mining, Springer Berlin Heidelberg, 2012, pp. 193–204.
[118] L. Chen, R. Nayak, Y. Xu, A common neighbour based two-way collaborative recommendation method, in: Proceedings of the 27th Annual ACM Symposium on Applied Computing, SAC '12, 2012, pp. 214–215.
[119] A. Kleinerman, S. Kraus, A. Rosenfeld, F. Ricci, Providing explanations for recommendations in reciprocal environments, in: Proceedings of the 12th ACM Conference on Recommender Systems, Recsys'18, ACM, 2018, pp. 22–30.
[120] R. Ramanathan, N.K. Shinada, S.K. Palaniappan, Building a Reciprocal recommendation system at scale from scratch: Learnings from one of Japan's prominent dating applications, in: Fourteenth ACM Conference on Recommender Systems, RecSys '20, 2020, pp. 566–567.
[121] M. Yu, X. Zhang, D. Kreager, New to online dating? Learning from experienced users for a successful match, in: R. Kumar, J. Caverlee, H. Tong (Eds.), 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, ASONAM 2016, IEEE Computer Society, 2016, pp. 467–470.
[122] X. Zang, T. Yamasaki, K. Aizawa, T. Nakamoto, E. Kuwabara, S. Egami, Y. Fuchida, You will succeed or not? Matching prediction in a marriage consulting service, in: IEEE Third International Conference on Multimedia Big Data, BigMM, 2017, pp. 109–116.
[123] X. Dong, L. Yu, Z. Wu, Y. Sun, L. Yuan, F. Zhang, A hybrid collaborative filtering model with deep structure for recommender systems, in: AAAI, 2017.
[124] Y. Dou, H. Yang, X. Deng, A survey of collaborative filtering algorithms for social recommender systems, in: 2016 12th International Conference on Semantics, Knowledge and Grids, SKG, 2016, pp. 40–46.
[125] Y. Park, S. Park, W. Jung, S. goo Lee, Reversed CF: A fast collaborative filtering algorithm using a k-nearest neighbor graph, Expert Syst. Appl. 42 (2015) 4022–4028.
[126] J. Leskovec, D. Huttenlocher, J. Kleinberg, Predicting positive and negative links in online social networks, in: Proceedings of the 19th International Conference on World Wide Web, WWW '10, 2010, pp. 641–650.
[127] A. Krzywicki, W. Wobcke, X. Cai, A. Mahidadia, M. Bain, P. Compton, Y.S. Kim, Interaction-based collaborative filtering methods for recommendation in online dating, in: L. Chen, P. Triantafillou, T. Suel (Eds.), Web Information Systems Engineering - WISE 2010 - 11th International Conference. Proceedings, in: Lecture Notes in Computer Science, vol. 6488, Springer, 2010, pp. 342–356.
[128] S. Rendle, C. Freudenthaler, Z. Gantner, L. Schmidt-Thieme, BPR: Bayesian personalized ranking from implicit feedback, in: Proceedings of the Twenty-Fifth Conference on Uncertainty in Artificial Intelligence, UAI '09, AUAI Press, Arlington, Virginia, USA, 2009, pp. 452–461.
[129] A.P. Singh, G.J. Gordon, Relational learning via collective matrix factorization, in: Proceedings of the 14th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '08, Association for Computing Machinery, 2008, pp. 650–658.
[130] A. Cardoso, F. Mourão, L. Rocha, A characterization methodology for candidates and recruiters interaction in online recruitment services, in: Proceedings of the 25th Brazillian Symposium on Multimedia and the Web, 2019, pp. 333–340.
[131] B. Kille, F. Abel, B. Hidasi, S. Albayrak, Using interaction signals for job recommendations, in: MobiCASE, 2015.
[132] M. Reusens, W. Lemahieu, B. Baesens, L. Sels, A note on explicit versus implicit information for job recommendation, Decis. Support Syst. 98 (C) (2017) 26–35.
[133] M. Reusens, W. Lemahieu, B. Baesens, L. Sels, Evaluating recommendation and search in the labor market, Knowl. Based Syst. 152 (2018) 62–69.
[134] Y. Ding, Y. Zhang, L. Li, W. Xu, H. Wang, A reciprocal recommender system for graduates' recruitment, in: 2016 8th International Conference on Information Technology in Medicine and Education, ITME, 2016, pp. 394–398.
[135] M. Çakir, S.G. Ögüdücü, R. Tugay, A deep hybrid model for recommendation systems, in: M. Alviano, G. Greco, F. Scarcello (Eds.), AI*IA 2019 - Advances in Artificial Intelligence - XVIIIth International Conference of the Italian Association for Artificial Intelligence, Proceedings, in: Lecture Notes in Computer Science, vol. 11946, Springer, 2019, pp. 321–335.

[136] W. Hong, L. Li, T. Li, W. Pan, IHR: An online recruiting system for xiamen talent service center, in: Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD ’13, 2012, pp. 1177–1185.
[137] W. Hong, C. Yiwei, Q. Jianwei, H. Yin, iHR+: A mobile reciprocal job recommender system, in: 2015 10th International Conference on Computer Science Education, ICCSE, 2015, pp. 492–495.
[138] W. Hong, S. Zheng, H. Wang, J. Shi, A job recommender system based on user clustering, J. Comput. 8 (2013).
[139] H. Labarthe, F. Bouchet, R. Bachelet, K. Yacef, Does a peer recommender foster students’ engagement in moocs? in: 9th International Conference on Educational Data Mining, International Educational Data Mining Society (IEDMS), 2016, pp. 418–423.
[140] World Economic Forum, The COVID-19 pandemic has changed education forever. This is how, 2020, https://www.weforum.org/agenda/2020/04/coronavirus-education-global-covid19-online-digital-learning/. (Accessed July 2020).
[141] H. Labarthe, R. Bachelet, F.R. Bouchet, K. Yacef, Increasing MOOC completion rates through social interactions: a recommendation system, in: European Multistakeholder MOOCs Summit, 2016.
[142] F. Bouchet, H. Labarthe, K. Yacef, R. Bachelet, Comparing peer recommendation strategies in a MOOC, in: Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization, UMAP ’17, Association for Computing Machinery, 2017, pp. 129–134.
[143] K. Rajagopal, J.M. van Bruggen, P.B. Sloep, Recommending peers for learning: Matching on dissimilarity in interpretations to provoke breakdown, Br. J. Educ. Technol. 48 (2) (2017) 385–406.
[144] M. Jacovi, I. Guy, I. Ronen, A. Perer, E. Uziel, M. Maslenko, Digital traces of interest: Deriving interest relationships from social media interactions, in: Proceedings of the 12th European Conference on Computer Supported Cooperative Work, 24-28 September 2011, Aarhus Denmark, ECSCW ’11, Springer London, 2011, pp. 21–40.
[145] D.R. Raban, A. Danan, I. Ronen, I. Guy, Impression formation in corporate people tagging, in: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI ’12, Association for Computing Machinery, New York, NY, USA, 2012, pp. 569–578.
[146] J. Freyne, M. Jacovi, I. Guy, W. Geyer, Increasing engagement through early recommender intervention, in: Proceedings of the Third ACM Conference on Recommender Systems, RecSys ’09, 2009, pp. 85–92.
[147] I. Guy, M. Jacovi, A. Perer, I. Ronen, E. Uziel, Same places, same things, same people?: Mining user similarity on social media, in: Proceedings of the 2010 ACM Conference on Computer Supported Cooperative Work, CSCW ’10, 2010, pp. 41–50.
[148] I. Guy, S. Ur, I. Ronen, A. Perer, M. Jacovi, Do you want to know?: Recommending strangers in the enterprise, in: Proceedings of the ACM 2011 Conference on Computer Supported Cooperative Work, CSCW ’11, 2011, pp. 285–294.
[149] I. Guy, U. Avraham, D. Carmel, S. Ur, M. Jacovi, I. Ronen, Mining expertise and interests from social media, in: Proceedings of the 22Nd International Conference on World Wide Web, WWW ’13, 2013, pp. 515–526.
[150] I. Guy, R. Levin, T. Daniel, E. Bolshinsky, Islands in the stream: A study of item recommendation within an enterprise social stream, in: Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR ’15, 2015, pp. 665–674.
[151] I. Guy, T. Steier, M. Barnea, I. Ronen, T. Daniel, Swimming against the streamz: Search and analytics over the enterprise activity stream, in: Proceedings of the 21st ACM International Conference on Information and Knowledge Management, CIKM ’12, 2012, pp. 1587–1591.
[152] E.M. Daly, W. Geyer, D.R. Millen, The network effects of recommending social connections, in: Proceedings of the Fourth ACM Conference on Recommender Systems, RecSys ’10, 2010, pp. 301–304.
[153] S. Nepal, C. Paris, P. Pour, S. Bista, J. Freyne, A social trust based friend recommender for online communities, in: Collaborative Computing: Networking, Applications and Worksharing (Collaboratecom), 2013 9th International Conference Conference on, 2013, pp. 419–428.
[154] R. Grob, M. Kuhn, R. Wattenhofer, M. Wirz, Cluestr: Mobile social networking for enhanced group communication, in: Proceedings of the ACM 2009 International Conference on Supporting Group Work, GROUP ’09, 2009, pp. 81–90.
[155] B.K. Samanthula, W. Jiang, A randomized approach for structural and message based private friend recommendation in online social networks, in: State of the Art Applications of Social Network Analysis, Springer, 2014, pp. 1–34.
[156] L. Zhang, H. Fang, W.K. Ng, J. Zhang, IntRank: Interaction ranking-based trustworthy friend recommendation, in: Trust, Security and Privacy in Computing and Communications (TrustCom), 2011 IEEE 10th International Conference on, pp. 266–273.
[157] I. Guy, N. Zwerdling, D. Carmel, I. Ronen, E. Uziel, S. Yogev, S. Ofek-Koifman, personalized recommendation of social software items based on social relations, in: Proceedings of the Third ACM Conference on Recommender Systems, RecSys ’09, 2009, pp. 53–60.
[158] M. Jacovi, I. Guy, S. Kremer-Davidson, S. Porat, N. Aizenbud-Reshef, The perception of others: Inferring reputation from social media in the enterprise, in: Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work and Social Computing, CSCW ’14, 2014, pp. 756–766.
[159] J. Bao, Y. Zheng, D. Wilkie, M.F. Mokbel, A survey on recommendations in location-based social networks, ACM Trans. Intell. Syst. Technol. (2013).
[160] S. Scellato, A. Noulas, R. Lambiotte, C. Mascolo, Socio-spatial properties of online location-based social networks, ICWSM 11 (2011) 329–336.
[161] G. Zhao, M.L. Lee, W. Hsu, W. Chen, H. Hu, Community-based user recommendation in uni-directional social networks, in: Proceedings of the 22nd ACM International Conference on Information & Knowledge Management, CIKM ’13, 2013, pp. 189–198.
[162] T. Kim, D. Lee, S.J. Hyun, Y.Y. Doh, UrbanSocialRadar: A place-aware social matching model for estimating serendipitous interaction willingness in Korean cultural context, Int. J. Hum. Comput. Stud. 125 (2019) 81–103.
[163] J. Mayer, Q. Jones, Encount’r: Exploring passive context-awareness for opportunistic social matching, in: Proceedings of the 19th ACM Conference on Computer Supported Cooperative Work and Social Computing Companion, 2016, pp. 349–352.
[164] J.M. Mayer, S.R. Hiltz, L. Barkhuus, K. Väänänen, Q. Jones, Supporting opportunities for context-aware social matching: An experience sampling study, in: Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, 2016.
[165] J.M. Mayer, S.R. Hiltz, Q. Jones, Making social matching context-aware: Design concepts and open challenges, in: Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, 2015, pp. 545–554.
[166] J.M. Mayer, Q. Jones, S.R. Hiltz, Identifying opportunities for valuable encounters: Toward context-aware social matching systems, ACM Trans. Inf. Syst. 34 (1) (2015).
[167] A. Goswami, F. Hedayati, P. Mohapatra, Recommendation systems for markets with two sided preferences, in: 2014 13th International Conference on Machine Learning and Applications, 2014, pp. 282–287.
[168] J. Chen, B.V. Hanrahan, J.M. Carroll, Withshare: A mobile application to support community coproduction activities, IJMHCI 11 (2019) 40–61.
[169] C.-T. Li, Mentor-spotting: recommending expert mentors to mentees for live trouble-shooting in codementor, Knowl. Inf. Syst. (2019) 1–22.
[170] G.G. Gebremeskel, A.P. de Vries, Recommender systems evaluations : Offline, online, time and A/A test, in: 2016 Conference Labs and Evaluation Forum, CLEF, 2016.
[171] Y. Qian, Y. Zhang, X. Ma, H. Yu, L. Peng, EARS: emotion-aware recommender system based on hybrid information fusion, Inf. Fusion 46 (2019) 141–146.
[172] C. Porcel, A. Ching-López, G.L. Oliveira, V. Loia, E. Herrera-Viedma, Sharing notes: An academic social network based on a personalized fuzzy linguistic recommender system, Eng. Appl. Artif. Intell. 75 (2018) 1–10.
[173] R. Ding, I. Palomares, X. Wang, G. Yang, B. Liu, Y. Dong, E. Herrera-Viedma, F. Herrera, Large-scale decision-making: Characterization, taxonomy, challenges and future directions from an artificial intelligence and applications perspective, Inf. Fusion 59 (2020) 84–102.
[174] J. Syed, M. Ozbilgin, Managing Diversity and Inclusion: An International Perspective, SAGE publishing, 2015.
[175] R. Burke, Hybrid recommender systems: Survey and experiments, User Model. User-Adapt. Interact. 12 (2002) 331–370.
[176] I. Fernández-Tobías, I. Cantador, On the use of cross-domain user preferences and personality traits in collaborative filtering, in: F. Ricci, K. Bontcheva, O. Conlan, S. Lawless (Eds.), User Modeling, Adaptation and Personalization - 23rd International Conference, UMAP 2015. Proceedings, in: Lecture Notes in Computer Science, vol. 9146, Springer, 2015, pp. 343–349.
[177] A. Krzywicki, W. Wobcke, X. Cai, M. Bain, A. Mahidadia, P. Compton, Y.S. Kim, Using a critic to promote less popular candidates in a people-to-people recommender system, in: M.P.J. Fromherz, H. Muñoz-Avila (Eds.), Proceedings of the Twenty-Fourth Conference on Innovative Applications of Artificial Intelligence, AAAI, 2012.
[178] Y. Qian, Y. Zhang, X. Ma, H. Yu, L. Peng, EARS: Emotion-aware recommender system based on hybrid information fusion, Inf. Fusion 46 (2019) 141–146.
[179] J. Neve, I. Palomares, Arikui - A dubious user detection system for online dating in Japan, in: 2018 IEEE Int. Conf. on Systems, Man, and Cybernetics, SMC, 2018.

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The authors regret to inform that:

The corrigendum is associated to include the author 2.

James Neve, Intelligent Systems Laboratory, University of Bristol

James Neve did participate in the discussion and preparation of the initial work, by error we did not included him previously.

The authors would like to apologize for any inconvenience caused.

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