2 RECIPROCAL RECOMMENDATION

In this section, we present a brief introduction of RRSs. In particular, we focus on fusion approaches and aggregate functions to compute reciprocal preference scores that represent the degree of mutual preference.

In a RRS for online dating, unilateral preference scores $p_{x,y} \in [0, 1]$, representing the preference of man $x \in X$ for woman $y \in Y$, and the opposite $p_{y,x} \in [0, 1]$ are predicted as in standard recommender systems, where $X$ and $Y$ are the set of men and women, respectively. Each of these scores is predicted by content-based [26] or collaborative filtering-based [25, 31] algorithms. To take into account the "reciprocity", bilateral preference scores $p_{x,y}$ are calculated using some fusion approaches. The most common fusion approach is to aggregate unilateral preference scores: $p_{x,y} = \phi(p_{x,y}, p_{y,x})$ with some aggregate function $\phi : [0,1] \times [0,1] \rightarrow [0,1]$.

Various implementations of the aggregation function have been explored, e.g., harmonic mean [26, 31], arithmetic mean [24, 25], geometric mean [24, 25], cross-ratio uniform [3], matrix multiplication [16], weighted mean with optimized weighting parameters [20] and multiplicative inverse of rank multiplication [22].

Although several fusion approaches are used in studies and practice, fusion approaches have been relatively less analyzed. Most of them try to capture the reciprocity of preferences but rarely take into account the capacities of the users. The introduction of matching theory in RRS would be a promising treatment of this point.

3 MATCHING WITH TRANSFERABLE UTILITY

We briefly introduce the Choo and Siow [8] model, which extends matching with transferable utility (TU matching) [4, 29]. TU matching model assumes that two types of agent choose their partner in the decentralized market, and monetary transfer occurs between agents who are matched. Transfers can be interpreted as, for example, wages in job matching markets, share of household economy in marriage markets, or gifts in dating markets. We consider equilibrium matching, in which the demands of both sides coincide by adjusting the transfer amount, just as prices in a market economy. TU matching model has been used for the theoretical and empirical analyses of marriage markets.

Let $\tau_{x,y}$ be the transfer between $x$ and $y$ that occurs if they are matched. The values that $x$ and $y$ obtain from the match are $u_{x,y}$ and $u_{y,x}$, respectively. Namely, $u_{x,y} = p_{x,y} + \tau_{x,y}$, $u_{y,x} = p_{y,x} + \tau_{x,y}$. We assume $\tau_{x,y} \geq 0$ and $\tau_{x,y} \leq \min(u_{x,y}, u_{y,x})$.
\( \epsilon_{x, y} + \tau_{x, y} \), where \( \epsilon_{x, y}, \epsilon_{y, x} \) are the prediction errors of unilateral preferences \( p_{x, y}, p_{y, x} \). They also have the option of remaining “unmatched” and staying single. The utilities for the remaining unmatched are \( u_{x, 0} = \epsilon_{x, 0}, u_{y, 0} = \epsilon_{y, 0} \). Since we assume \( p_{x, 0} = p_{0, x} = \tau_{x, 0} = \tau_{0, y} = 0 \). Given transfers \( \tau_{x, y} \), each user chooses the other user who maximizes his/her value. Let \( \mu_{x, y} \) and \( \mu_{y, x} \) be the probabilistic demand of \( x \in X \) towards \( y \in Y \cup \{0\} \) and that of \( y \in Y \) toward \( x \in X \cup \{0\} \), respectively:

\[
\mu_{x, y} = \min_{y’ \in Y \cup \{0\}} \left( \arg \max_{y’} u_{x, y’} \right), \quad \mu_{y, x} = \min_{x’ \in X \cup \{0\}} \left( \arg \max_{x’} u_{x’, y} \right).
\]

As known in TU matching literature [8, 12], there exists a transfer \((\tau_{x, y})_{x \in X, y \in Y}\) such that the demands of both sides coincide \( \mu_{x, y} = \mu_{y, x} \) for each \((x, y) \in X \times Y\) pair, and we call this \( \mu \) the equilibrium matching.

To compute \( \mu \), we assume that the distribution \( P \) of errors \( \epsilon_{x, y}, \epsilon_{y, x} \) is the standard type-I extreme value distribution (the standard Gumbel distribution), as in [8]. Then, for each \( x \in X, y \in Y \), we have

\[
\mu_{x, y} = \mu_{y, x} = \exp \left( \frac{p_{x, y} + p_{y, x}}{2} \right) \sqrt{\mu_{x, 0} \mu_{y, 0}},
\]

where \( \mu_{x, 0}, \mu_{y, 0} \) are the probabilities with which they choose to remain unmatched. One can interpret the term \( \frac{p_{x, y} + p_{y, x}}{2} \) as a reciprocal preference in the context of RRSs and the term \( \sqrt{\mu_{x, 0} \mu_{y, 0}} \) as a factor that reflects the capacity of the users. Combining this with the following constraint:

\[
\sum_{y \in Y} \mu_{x, y} + \mu_{x, 0} = 1 \quad \forall x \in X, \quad \sum_{x \in X} \mu_{y, x} + \mu_{y, 0} = 1 \quad \forall y \in Y,
\]

we can derive the equilibrium matching by solving a convex optimization.

4 APPLICATION AND CHALLENGES IN ONLINE DATING

Tapple is a Japanese online dating platform that serves more than 7 million registered users. Once onboarded, users are shown the photos and profile information of recommended candidates (Fig 1: Left). They can send either “like” or “nope” to the recommended candidates. A candidate user who receives “like” can either “thank” for matching or “sorry” for rejecting. They are “matched” if the like recipient responds with “thank” and then allowed to chat (Fig 1: Right).

The application procedure is shown in Fig. 2. Unilateral preference scores between men and women \( p_{x, y} \) and the opposite \( p_{y, x} \) are predicted by matrix factorization (MF) using unilateral historical feedback such as “likes” and “thanks”. When using a conventional RRS approach, the following preference fusion step integrates unilateral scores into a reciprocal score \( p_{x, y} \). In the prediction step for each man \( x \) and each woman \( y \), the system sorts the candidate users according to \( p_{x, y} \) and recommends the users at the top of the ranked list.

Our project at tapple is to replace off-the-shelf fusion procedure with a cutting-edge MTRS. To this end, we implemented a new TU-matching algorithm based on Choo and Siow [8]. Unlike standard RRSs, which only rely on preferences, our MTRS considers both preferences and capacities by constructing a reciprocal score with transfer \( \tau_{x, y} \). Our MTRS thus mitigates the extreme concentration of “likes” and “matches” for enhancing overall user experience.

Scalability is a critical challenge for MTRSs, whereas this point has not been explored in depth. To allow efficient estimation of equilibrium matching, we adopt the recently proposed iterative proportional fitting procedure (IPFP) [9, 12]. We can obtain the optimal \( \mu_{x, 0} \) and \( \mu_{y, 0} \) by iteratively applying the following closed-form update formulas:

\[
\sqrt{\mu_{x, 0}} = \frac{1 - \left( \frac{1}{2} \sum_{y \in Y} \tilde{p}_{x, y} \sqrt{\mu_{y, 0}} \right)^2}{\frac{1}{2} \sum_{y \in Y} \tilde{p}_{x, y} \sqrt{\mu_{y, 0}}}, \\
\sqrt{\mu_{y, 0}} = \frac{1 - \left( \frac{1}{2} \sum_{x \in X} \tilde{p}_{x, y} \sqrt{\mu_{x, 0}} \right)^2}{\frac{1}{2} \sum_{x \in X} \tilde{p}_{x, y} \sqrt{\mu_{x, 0}}},
\]

where \( \tilde{p}_{x, y} = \exp \left( p_{x, y} + p_{y, x} \right) \).

Still, the above implementation does not meet the requirements in computational feasibility in tapple due to the million-scale users.

Although Chen et al. [7] also conduct offline experimentation with MF, they randomly sample 1, 000 men and 305 women for each experiment. 3 On the contrary, our

3https://www.cyberagent.co.jp/news/detail/id=26472
approach enables individual matching due to the unilateral preferences based on MF while maintaining scalability by approximating the estimation of equilibrium matching.

5 FUTURE DIRECTIONS

There are many other considerable future research directions. The Application of other Matching Algorithms: In addition to TU matching, various matching algorithms are presented in non-transferable (NTU) matching, in which two types of agent are matched by a centralized authority and no monetary transfers occur between matched agents, such as the pioneering work of Gale and Shapley [11]. Most NTU matching algorithms rely on the preference orderings of people and are therefore suitable to combine with learning-to-rank methods [6]. MTRSs meets algorithmic fairness: There is a large literature on matching with various constraints, for example, matching algorithms with affirmative actions [14] and regional constraints [19]. Its application in MTRSs could be helpful for fairness issues in RSSs [5]. Bandit algorithms and MTRSs: As in standard RSSs, it is also important in RSSs to balance exploration and exploitation. In matching theory, matching with bandit algorithms in which agents learn their own preferences in the process is a growing literature [17, 21], and its application in RSS would be interesting future work. Online Experiment: The experiment design should be carefully tailored for RSSs in the sense that users interact with each other through the platforms, which obviously violates SUTVA. Structural estimation should also aid in robust evaluation [10, 18, 23].

SPEAKER BIO

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