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Electric Love: Analyzing Human Mate Selection Dynamics in a Digital Environment

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Human mate selection behavior in digital environments is, despite the rise of online dating, not well understood. In this paper, swiping apps are simulated by using an agent-based model. Implementing empirically derived data from other studies, the aim of this study is to investigate the fairness of such platforms. Our model predicts that positive evaluations (Likes) and reciprocal positive evaluations (Matches) of agents are highly unevenly distributed. We calculated a Gini coefficient for the likes agents receive and modulate system conditions to increase the fairness on the platform. We found conditions under which the system is fairer towards both female and male agents. Substantial inequalities never fully disappear when changing various factors in the system, hinting at the fundamental principle of swiping apps for the cause of said inequalities.

1. Introduction

Mate finding is a crucial factor for the population dynamics of all sexually reproducing life-forms, thus also for humans. There has been a strong trend towards digital environments as a place to meet potential partners (Baker 2002, 363; Rosenfeld et al. 2019; Silva et al. 2019, 45). Especially dating platforms increase the chances of finding potential partners. These platforms have lost most of their stigma in society (Finkel et al. 2012, 13; Gibbs et al. 2011, 71) and have become widely accepted (Pewresearch 2016). Although the exact intentions of users on such platforms vary (Tyson et al. 2016, 7; Lefebvre 2018, 1215-1216), the main goal is to find a romantic partner – either in the form of a consensual short-term agreement , a dedicated long-term relationship, or anything in between those extremes (Timmermanns and Caluwé 2017, 348). Intimate relationships play an important role in the personal life of most people and contribute significantly to their happiness and life satisfaction (Diener and Seligman 2002, 82). Therefore, there is a huge market for computer programs and internet sites supporting the finding of intimate partners. With the rising popularity of digital platforms, other forms of dating are being replaced at a fast pace (Rosenfeld et al. 2019). A subtype of such platforms are so-called swiping apps. They have a game like structure and tens of millions of users all over the world (BBC 2016). Swiping apps can be perceived as unfair and may have a negative impact on users by harming their feelings of self-worth (Strubel and Petrie 2017, 37). Further, they drive unequal distributions of dating opportunities, which is related to male violence (Seffrin 2017). These mentioned issues and others like unrealistic expectations and social isolation can be tackled by models like the one proposed in this study. There has been empirical research on swiping apps (e.g. Timmermanns et al. 2018; Silva et al. 2019) but to the best of our knowledge, no multi-agent model of populations mating with swiping apps has been made, despite them being a highly relevant research target. Only this kind of architecture captures simultaneously parameters within and between individuals straightforwardly. In this study, we modelled a population of autonomous agents that use a hypothetical swiping app and investigated the impact of various parameters like physical attractiveness, the ratio of men and women, and the time people spend on the app. The aim of this study is to identify key characteristics of swiping apps: How are the markers of success, Likes and Matches, distributed among the users? How could the system be changed to increase fairness on the platform? How do different sex ratios affect this complex system? Especially the last question can only be investigated using a computer model, since one cannot simply change the user sex ratio on an existing swiping app. For the sake of modelling parsimony, there is a focus on heterosexual couples. Homosexual and bisexual individuals are out of scope, although there are clear plans to include them in future iterations of the model.

In order to define the terms that we use in this study precisely, as their definition might change over time and their connotation might be affected by zeitgeist, we will define the meanings we use in the following. We want to understand the word “date” in such a way that it refers to a meeting of two people, who have romantic interest in each other, with the motivation of forming an intimate relationship. The word “dating platforms” refers to websites (“dating sites”) and computer applications (“dating apps”), that help to connect people with the goal of forming intimate relationships via the internet (a process called “online dating”). For further clarification, we want to use capital letters when talking about “Likes” (positive evaluations of other users’ profiles) and “Matches” (reciprocal Likes), so their meaning can be distinguished from the usual meanings of those words.

2. Fundamental Mechanics of Swiping Apps

Swiping apps generally make use of a double opt-in principle: users must display a reciprocal initial interest in each other before a conversation is possible. This is managed by the app in the following way. Each user sees other users’ profiles based on geographical proximity. A profile consists of at least one photograph and often, but not always, a very short self-written description. Photos are dominant and the main determinant of the user’s decision to like or dislike a profile (Chan 2017, 248). However, written descriptions can increase the perceived attractiveness (Tyson et al. 2016, 6). The profiles are organized in a way that each user sees only one profile at a time (Timmermanns and Caluwé 2017, 341). Before being able to see another profile, users must decide to either “like” or “dislike” the profile shown. The liking or disliking is done by swiping the photo to the right (for liking another user’s profile) or the left (for disliking it) respectively – hence the common name “swiping apps” for such apps. After the decision is made, the profile gets discarded. When two users “like” each other, they have a “Match”, and the users get notified about this. This enables the two people to chat. Naturally, the conversation goes on for a while before users meet for a date. Meeting rates vary across studies (Timmermans and Courtois 2018, 66; Lefebvre 2018, 1220). The people who do meet their Matches most often do so within a week (Iqbal 2019). 35% of relationships emerging from swiping apps last for over 6 months (Simpletexting 2020) which undermines the hypothesis that dating apps are only used for “quick hookups”.

3. Methods

We designed a multi-agent model. Agents in the model represent users on a hypothetical swiping app. Although size and distance play no role in the model, the spatial design is useful for evaluating the number of connections of individual agents to other agents in the network. One time step represents 30 seconds. This section explains the whole process of agent creation, the liking process, and the emergence of Matches. Agents represent users of the app, and their attractiveness value represents the attractiveness of their profile. In section 3.1 exact numbers can be found. Two types of agents are created: females and males. Agents get uniformly randomly distributed and oriented across a 2D map and get assigned one numeric value that represents attractiveness (called FATT for females and MATT for males). Another value assigned is the interaction time available for the day (called ITT). Both values mentioned are normally distributed. Interaction time that is available for the day refreshes every 2880 time steps (one day in the simulation). In this section, a female agent serves as an example - males work analogously. The description below describes in pseudo-code how a number of female agents is created and initialized.

```
create_females(number):
    self.ITT ← random_normal(mean=30.0, std_dev=5.0);
    self.FATT ← random_normal(mean=5.0, std_dev=2.0);
```

If a user still has interaction time left for the day, they visit another users profile.

```
For each of time_steps:
    For each of females:
        if self.ITT > 0 then:
            jump_to_position(choose_random_one_of(males));
```

A unidirectional check is performed. Agents compare the attractiveness of the profiles with their own and primarily "like" agents that are about as attractive as they are, which is modulated by FSF and MSF (female/male selection factor). There is some leeway, and random element to this: within a certain range (LW), a random number, which can also be negative, is added to the attractiveness of the other agent. This represents different preferences users may have. If the profile is still attractive enough after this, it gets a like and the agents have a directional link. If not, there is a dislike, and the agent will not see this profile again.

```
if (other_user.MATT ± self_LW) > (self.FATT * FF)then:
    create_like_to(other.user);
```

There is also a match-check. If the agent already has a like from the profile she is looking at, and she reciprocally likes it, a Match happens.

```
if in_like_from this other.user exists then:
    create_match_with(other.user);
```

This liking process takes time, which is subtracted from the daily time this agent *can* spend on the app and gets simultaneously added to the time the agent *has* already spent (TS).

```
self.ITT ← self.ITT - 0.5;
self.TS ← self.TS + 0.5;
```

Every 120 time steps (one hour in the simulation) there is a small chance for an agent to leave the app. This is regulated by the variable TOR (turnover rate). Simultaneously new agents join the app at the same rate, which keeps the size of the population roughly stable. The variable PF regulates the probability of female and male agents joining the app.

```
for each of agents:
     z ← random_float(1.0);
     x ← random_float(1.0);
     if (z < TOR) then:
         die;
            if (x < (PF) then:
                   create_females(1);
            else:
                   create_males(1);
```

3.1. Experimental Data Analysis

We exported the data generated from the model and plotted the results. To show the distributions of Likes and Matches, we stopped the run after varying amounts of time, with varying sex ratios in the system, and used scatterplots with logarithmic scales (figure 1 and figure 2). To show unequal distributions of likes we used the Lorenz curve for illustration (figure 3) and report the Gini coefficient for likes received as a measurement of fairness (table 2). To get three levels of fairness in the system, we did a parameter sweep and report three different settings. We conducted 100 runs for each experiment and report the average results.

3.2. The Simulation

The standard conditions aim to reflect real data (see section 4). Agent population consists of 400 agents (133 females and 267 males).

Table 1. Parameters used in the model.

Parameter	Full Name	Standard Value (units)	Reasoning/Source
PF	Proportion of females	0,33 (dmnl)	There are significantly more men on swiping apps (Iqbal 2019; Netimperative 2019; Clement 2020)
TOR	Turnover Rate	0,01225 (dmnl)	About 21% of users of the most popular swiping app do not return to the app the next week (Iqbal 2019)
self.FATT / self.MATT	Female / Male Attractiveness	Normally Distributed, μ 5.0, σ 2.0 (dmnl)	Attractiveness ratings are observed to be normally distributed (Gynther et al. 1991, 747; Fink et al. 2006, 437). Mean and standard deviation are assumed.
FSF/MSF	Female / Male Selection Factor	1.6 for Females 0.95 for Males (dmnl)	People "aim up" when looking for partners (Lee et al. 2008, 670). Women are more selective than men (Clark and Hatfield 1989; Buss and Schmitt 1993) and many men casually like most of the profiles (Iqbal 2019).
self.ITT	Interaction Time for the Day	Normally Distributed, μ 30, σ 3 (min)	People spend about 30 min/day on the app. There is little difference between women and men (Iqbal 2019). We assume normal distribution.

4. Results

The distribution of the number of Likes among males is predicted to be highly unequal by our model. It is predicted to follow an uneven distribution, in which a few successful females and males receive many Likes and Matches, while most of the remaining agents are predicted to receive a low number of Likes. The fewer female agents are available on the app, the more unequal the distribution of Likes among the male agents gets. For female agents, the distribution of Likes is more equal, and they generally receive significantly more likes than men do.

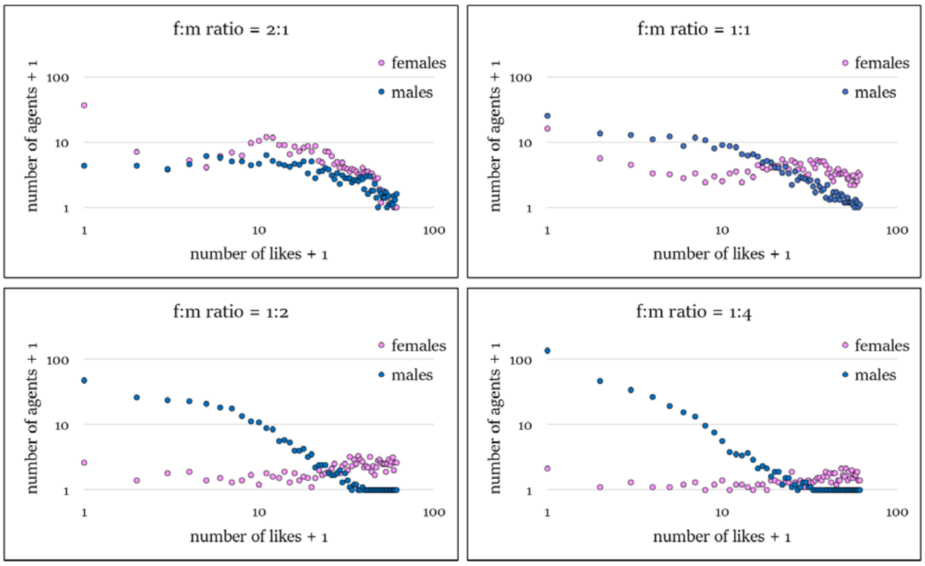

Fig. 1. Distributions of Likes received by males and females at various sex ratios.

The distribution of the number of Matches among males and females is predicted to be highly unequal by our model. Most agents have a low number of matches, while some have a high number of matches. Females generally have higher number of matches, except when they make up most of the users.

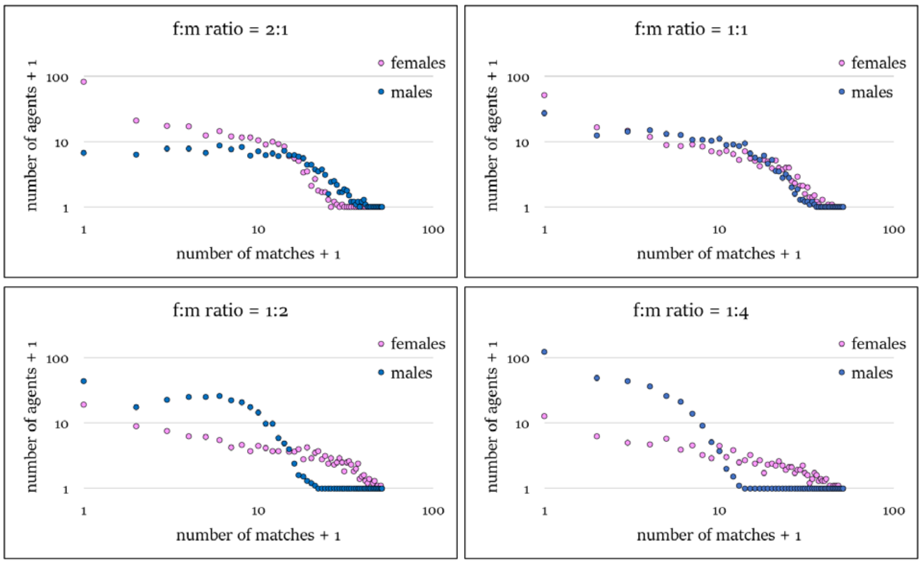

Fig. 2. Distributions of Likes received by males and females at various sex ratios.

A Lorenz curves for the likes of male and female agents is shown below. The resulting Gini coefficient is significantly higher for males than it is for females. For both genders, it increases when they become the majority of users.

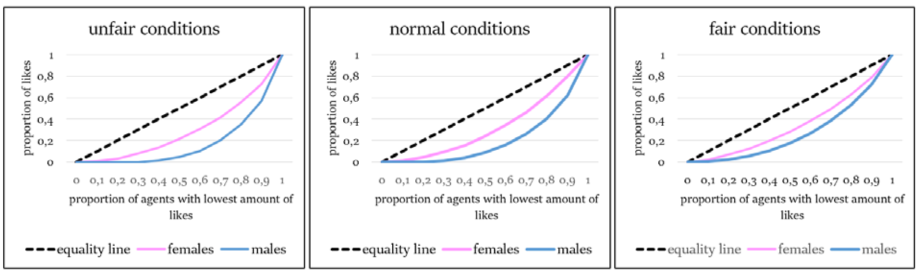

Fig. 3. Lorenz curves as fairness measurement for female and male agents.

Different parameter settings influence the Gini coefficient for female and male likes. Table 2 presents three different combinations of settings with different Gini coefficients.

Table 2. different settings and fairness outcomes.

Label	Female Selectivity	Female: Male Ratio	Time People Spend on App	Gini Coefficient (female likes)	Gini Coefficient (male likes)
Fair Conditions	Low	1:2	High	0,302	0,444
Cormal Conditions	Moderate	1:3	Moderate	0,387	0,582
Unfair Conditions	High	1:9	Low	0,401	0,660

5. Empirical Support for the Model

Empirical data was used whenever available, see table 1. Men are over-represented on dating apps. Reasons for this are debatable: maybe this is because they, on average, show more interest in sex (Baumeister et al. 2001), have a harder time finding mates in the offline world, or other. Depending on source and specific platform, the proportion of males on swiping apps varies between 65% and 93% (Iqbal 2019; Netimperative 2019). Compared to other means of dating, swiping apps promote especially quick evaluations of others (David & Cambre 2016). This may result in exaggerated importance of physical attractiveness, which already plays a big role in mate selection (Walster et al. 1966, 508; Feingold 1990; Sprecher et al. 1994). Physical attractiveness also affects which people the users are aiming for (Hitsch et al. 2005, 3). They tend to aim for people that are on average a bit more attractive than they are themselves (Lee et al. 2008, 675). Lastly, evaluation of attractiveness also depends on varying factors like mood or blood alcohol level (Jones et al. 2003, 1073; Lass-Hennemann et al. 2010). Overall, women are significantly more selective when finding intimate partners (Clark and Hatfield 1989; Buss and Schmitt 1993). These findings are integrated into our model: Users primarily like other users that are about as attractive as they are themselves, with females showing a higher selectivity, both males and females having some random leeway in their evaluations, and attractiveness values being normally distributed among the user population. At any point users can and sometimes do leave the app. There are two main reasons for this, users feel dissatisfied because of a lack of success, or they have success and do not feel the need for the app anymore (Lefebvre 2018, 1217). This leads to a high turnover rate: about 20% of users do not return in the next week (Iqbal 2019).

6. Limitations

This pioneering study has some limitations. For one, it needs a lot of computing power. This makes runs with large numbers of users impossible, or at least very time consuming. Second, the model does not include anything that is going on in the user's head, except from a simple rule on how to evaluate whether a user should like a profile or not. But this fact can be viewed as a strength of the system since the model is therefore inherently parsimonious in its assumptions. Modern swiping apps have special functions e.g. "Super-Likes" or "Icebreakers". These serve as additional ways to get attention on the app and only a very limited supply is given to users. Another advanced feature are "dating app algorithms". The profiles users see are not completely random. Profiles that are suggested are based on calculations made by algorithms behind the scenes (Rosenfeld et al. 2019). How these algorithms work is a business secret, and different apps use different algorithms. Such extras are not implemented in the model.

7. Discussion

Our model predicts that Likes and Matches are very unevenly distributed among the agent population. Furthermore, there is a high inequality, especially for males, among the distribution of Likes. This is indicated by the high Gini coefficient for the likes received by males and females. The Gini coefficient for males is in fact higher than that of over 90% of the world's economies (Elvidge et al 2012). Such an inequality was suspected (Medium 2015) but never quantitatively analyzed or shown. It helps to explain seemingly contradicting reports of user experiences with promiscuity and endless options on one side (Vanity Fair 2015) and frustration and loneliness on the other (The Guardian 2016). Considering the relationship between inequality and crime rates (Fajnzylber et al. 2005) this can be not only seen as unfair, but as problematic. This unfairness may be what is driving the high rate of users artificially improving their profiles: many users try to increase their perceived attractiveness by using make up (Osborn 1996), specific camera angles (Sedgewick et al. 2017), displaying wealth (Tskhay et al. 2017), using picture editing software for their profile pictures, or simply lying about any of these attributes or even personality characteristics. The model helps to explain why so many people are pressured into these kinds of behavior, since inequalities are related to unwanted behavior. Two main factors can drive or reduce this inequality: the sex ratio in the agent population and the selectivity of agents. Especially the skewed sex ratio, in combination with the fact that dating apps replace all other forms of dating (Rosenfeld et al 2019) and the link between uneven dating opportunities and violent crime among males (Seffrin 2017) are cause for concern. These factors may be artificially influenced by providers of swiping apps if they want to make their swiping app fairer. One way to lower the selectivity may be to follow up suggestions of very attractive profiles with less attractive ones, to make the latter seem more desirable (Taubert et al 2016). However, high female selectivity is the norm as can be seen when looking at the low percentage of profiles they like (Bilton 2014; Tyson et al 2016, 7). Because of psychological literature pointing to the fact that attractive people are popular romantic targets (e.g. Walster et al. 1966, 508), one can assume that the few likes given out by females go to the same few attractive males. The high selectivity of females is in line with evolutionary psychology (Clark and Hatfield 1989; Buss and Schmitt 1993) and the gravitation towards the same few male individuals is further evidence for mate copying by females (Dunn and Doria 2010). This model assumes that attractiveness is very much objective and produces results that align with reality. This can be interpreted as evidence that beauty is not entirely subjective, as suggested by psychologists (Langlois et al 2003), and that the only practical way to reduce unfairness on swiping apps is to change the underlying mechanics.

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