The Tinder Desirability Score and Significance of Variations of Conditions

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I. Abstract

Algorithms play a large part in social life, affecting many aspects of individual choice and interaction. When matching mechanisms are incorporated into online platforms, with the goal of enhancing user experience by determining the other users to which they are exposed, they are able to build devices that attract and retain a large user base to fuel further development. Tinder is one such two sided matching market platform that has become a widespread cultural phenomenon amongst young adults and an ever growing user base. When it was revealed that the dating app uses data to give every user a desirability rating, users and the public criticized this score for its social implications. I explore the desirability score in this paper and incorporate it into the deferred acceptance matching algorithm and explore extension studies of increasing efficiency by grouping users by the desirability score, symmetric results with either side proposing, and differences in population size which ultimately affects the score distribution of the other side in the final matching. We find that the desirability score enforces a uniform preference system for all users of a side such that which side takes what action becomes symmetric, which could have significant social implications when applied; that grouping users by the desirability score in matching niches tends to be efficient and fast; and that the various conditions of the population may lead to one side ending up better off than the other regardless of actions. All of these suggest that controversial as it is, is the desirability score the key to successful application of two-sided matching algorithms?

II. Introduction

Algorithms play a large part in social life, affecting many aspects of individual choice and interaction. After the work of Gale and Shapley on matching markets in the 60s, the application of algorithms to matching markets has become a large focus of the academic community [1].

When these mechanisms are incorporated into online platforms, with the goal of enhancing user experience by determining the other users to which they are exposed, they are able to build devices that attract and retain a large user base to fuel further development. Still, algorithms which play such large part in the lives of individuals remain practically invisible to the users themselves. They are seldom informed on how data is processed, and due to the algorithms' proprietary and opaque nature, users on average are unaware of the exact nature of the mechanisms which greatly impact their lives both online and the effects thereof offline [2].

Tinder is one such platform that has become a widespread cultural phenomenon amongst young adults and an ever growing user base. Tinder packages and gamifies the social maneuver of dating into a bite sized online platform with a shiny bow and instant gratification, giving users the ability to sift through tens upon hundreds of potential dating aspects in a single sitting by swiping left or right [3].

However, there are many critics who point out its superficial and impersonal nature, as well as its detrimental effect on the commodification of complex social aspects like attractiveness and dating. The height of this blatant commodification came in 2016, when it was revealed that the dating app uses data to give every user a desirability rating. This score was commonly known as the Elo score, a system which ranks users' attractiveness dependent on how many people "swiped right" ie. liked and possibly matched with the user. Users and the public criticized this score for its social implications as well as the possible societal factors that may play into it, such as certain races tending to score lower than others [4].

The score was accused of both over simplifying and over complicating the dating process by assigning a claimed objective number to a complex trait, and inciting a new wave of complex blog articles where users try to figure out how to manipulate and discover their Elo score by theorizing the various ways that this Elo score might be used in the algorithm, as well as the effects of those variations. In this paper, I will explore some of the various ways the Elo desirability score might be used by Tinder and how it effects the outcome. Namely, I will be exploring ways that Tinder may implement the algorithm (based on public speculation and the user experience) given the data on the desirability of each user, and discussing how that effects the social utility in various market population conditions.

We will explore the base case effect and implication of the desirability score, how Tinder might use it based on public speculation, and discuss how real life conditions in which populations vary and change might affect the matching algorithms and the final utility.

III. Literature Review

A. Tinder

Tinder is a catalyst towards a new world of online dating in which the serious and complex search for love and connection becomes a swiping game. Namely, it is extremely simple for users to create an account, upload some photos, and begin swiping through a queue of other users filtered by age and proximity. Users swipe right to signal that they "like"someone, and left to signal that they dislike someone based on photos, a short bio, and various other information like social media, university, job, etc. When both users swipe right on each others profiles, they "match" and a chat feature becomes available between the matched users, with the intention that the two users talk to each other and meet in person or exchange other means of communication [5].

This type of two sided matching algorithms have been well studied in the computer science and mathematics academic communities, and especially regarding the application to asymmetric markets such as in online dating in which not ideal conditions like different desirability distributions and behavioral fallacies affect and confound the market. The creation and use of a desirability score for each user as explained in the introduction has been socially controversial but possibly effective in addressing some of these algorithmic matching efficiency issues found in application.

B. Related Work

We now explore the different related studies related to Tinder and to two sided matching algorithms and confounding conditions in such markets. We will aim to extend the speculation around how the Tinder algorithm uses this desirability score in their matching algorithm.

Tinder: Timmermans and Caluwe explore the various motivations that users have for using Tinder as framed by the lens of psychological study. Namely, they analyze the behavioral effects which affect the matching market on Tinder and which ultimately skews the population characteristic distributions away from that of the general population, thereby further complicating the application of the matching algorithm. They find that extraversion, conscientiousness, and openness to experience influence Tinder use and that mobile dating apps such as Tinder are most commonly used by young single adults during emerging adulthood [6].

Two-Sided Matching Application: Fong explores the search and matching in online marketplaces, emphasizing how user behavior responds to the presence of other users on the platform, ie. "market thickness." Fong observes that unlike standard settings in which firms benefit from increasing customer based, two-sided markets such as online dating react more complicatedly to changes in market thickness due to endogenous adjustment of search and selectivity. It is concluded that individuals become more selective when they believe they have more potential matches, and less selective when they are told they have more competition. In addition, increasing market size does not necessarily increase match quality, but selectivity can be adjusted [7].

This suggests that the signals of this market thickness such as the quality and number of users that are shown to a given user as well as various other aspects of the Tinder app affect the selectivity of the user, which affects both the efficiency of the match and the final utility of the individual user.

Population : Tyson et al. found that male users were less selective in their swiping and liking habits, and they sent more positive signals than females. Females tended to be less selective and sent less positive signals. This intuitively mirrors real world courtship behavior, and serves to exacerbate the complication of asymmetrical markets in applying the two sided matching algorithm [8].

C. Contribution

I will contribute to the public study of the social phenomenon and matching algorithm application that is Tinder by studying some variations of how they might be implementing their matching algorithms using their desirability score, as well as the effects of these variations varied with the variations in the market population itself.

IV. Methodology

Here we describe the methodology we employed for simulating data and for implementing the baseline and extension algorithms, as well as how we plan to interpret and analyze results.

Data

We simulated the data for this paper for several reasons. Firstly, we needed to see the effects of the desirability score on various market and population conditions, and the best way to control the population data is to simulate our own. This does mean both that there is room for further research based on various samplings of real data as well as that we can explore the various and occasionally conflicting social phenomenon that has been observed among the population of dating apps. In addition, this allows us to control for these effects so we can establish a baseline.

We simulated the data by initially choosing some population size p and a Gaussian distribution with mean and standard deviation for each of female and male populations in the market, and we assign each user desirability scores sampled randomly from the Gaussian.

A. Baseline

We simulated the data for the baseline by choosing a population size $p = 1000$ (500 female and 500 male), and we sample each user's score in both the male and female population from a Gaussian distribution centered at 5, with standard deviation of 1.5. This sampling seemed to produce distributions most similar to the expected attractiveness of a given randomly sampled sample of the entire world if scored from 1-10. Namely, it is a normal distribution centered around 5 and with fewer and fewer individuals out to the extremes.

We then conduct a male proposing deferred acceptance algorithm on the population until the algorithm terminates when all possible moves have been made. We chose a deferred acceptance for the sake of simplicity and removing as many confounding variables as possible. We chose male proposing as the base case to reflect the real life scenario in which males are more often sending signals as in the literature review, but we also plan to explore female proposing scenarios later.

Note that we do not claim stability, because it is entirely possible that the final population would have blocking pairs. We take this into account but assume in this case that agents do not have full information so they are unable to leave the market to improve their payoff.

We then measure the total utility of male and female agents at the end of the matching based on the final matching, where the desirability score of the matched agent represents the utility that the agent gets from the matching. We return both a total male utility and a total female utility and we will analyze this.

B. Extensions

We will now explain the methodology of each of the extensions, pertaining to both how they are implemented, and some of the motivations between the parameter or implementation choices.

1) Grouped Exposure: We group the users by score such that they exist within pockets of other users with similar scores, and we implement the same deferred acceptance from the baseline amongst the individual groups. We choose the limit between female score s_f and male score s_m such that $|s_m - s_f| < \epsilon = 0.5$ both to keep the pocket small enough to make a difference, and also to simulate a possible suspected use of the desirability score where users are mainly shown people with similar scores [4]. We will discuss this further in the analysis below.

2) Female Proposing: We implement the baseline method on the entire population, but this time females propose in the algorithm. This is to determine if female proposing changes the final utilities significantly. It should be noted it will also be constructive to do this on other extensions in which female and male populations are different, but we suspect that the utilities will be same in both female proposing and male proposing because the desirability score by its nature assumes everyone views attractiveness (and therefore gains utility from matches) similarly.

3) Different Populations : We implement the baseline male proposing deferred acceptance on the entire population, but we vary the populations of women and men to reflect certain real life conditions.

We set the male population size to be less than the male one with the same score distribution. We choose the male one because we expect that the female case will be symmetric to the male case in terms of results. We will explore this further in the female proposing section as well.

V. Baseline Simulation Results

The baseline algorithm we implemented is as defined in the methodology, with data generated as specified as shown in Fig 1. It employs male proposing deferred acceptance on the entire population to create a final matching output. Then, I find the utility of the output by summing for the desirability score of each match for each agent. That is, I assume that the desirability score of the match serves to represent the utility a user gets out of the match as in the methodology.

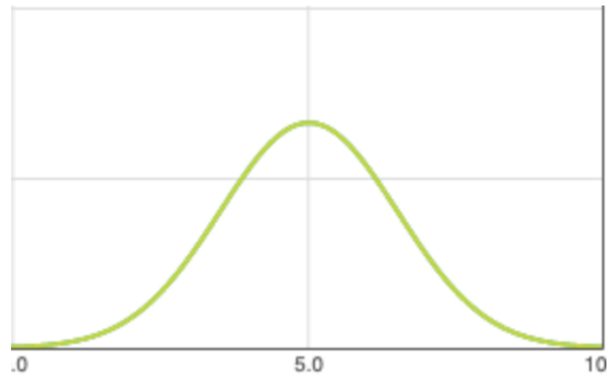

Fig. 1. Score distributions for male and female populations

We find that over 50 iterations of male proposing deferred acceptance in which the population scores are sampled from the same distribution, we have the following distribution of utilities as in Fig 2.

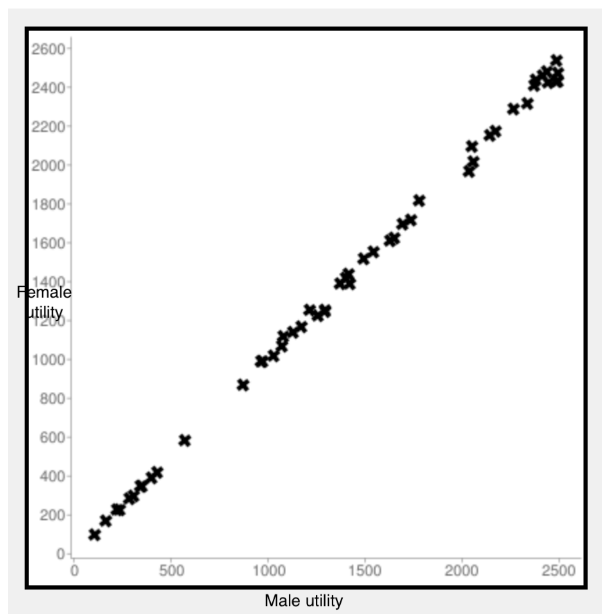

Fig. 2. Utility distributions for male and female populations

It is clear by the distribution shown in Fig 2. that the male and female utilities are relatively similar to each other but it varies significantly in value. We hypothesize that this is because depending on the distribution, sometimes the matching concludes with an inefficient matching.

The desirability score essentially serves to map each person to an average "attractiveness" which represents the utility they offer as a potential match to the average person. By the desirability score, male and females have essentially uniform preferences and thereby gain similar utilities from the final matching.

Namely, for man m and woman w and utility of match $\mu_w(m)$, in the final match the woman w will have had no other m' such that $\mu_w(m') > \mu_w(m)$ (and the symmetric case as well for men proposing to other women). By this, it is consistent that the men and women have similar utilities/desirability scores overall.

What is missing from this algorithm is that it only considers the optimal and rational conditions under which the deferred acceptance is done. Even with the uniform preferences of the desirability score, there are still variations in the conditions of the population which affects things, as well as variations in the ways in which Tinder may use the score. We will explore this in the extension.

The flaws of the baseline algorithm are also that it assumes that agents have optimal and rational selection, and that the algorithm is not dynamic to account for users entering and leaving the market. However for the purposes of being a baseline of this simulation it is sufficient to provide a baseline for us to compare results.

VI. Extensions

The extensions I will explore will still pertain to the variations of the deferred acceptance algorithm and the use of the desirability score, however I will vary the conditions to represent real market conditions and possible speculated uses of the desirability score. These account for some of the conditions not addressed in the simple model of the baseline.

A. Grouped Exposure

In the basic deferred acceptance algorithm with the entire population, it is assumed that the entire male population can propose to any female. This assumes both that users have complete information on the matching mechanism and the market. However, when speculating about how Tinder uses the desirability score, we hypothesize that a possible way in which it is utilized is by dividing the population into groups such that all the people they are shown are people with similar desirability scores to them, with whom if they matched would be part of an efficient matching.

Namely, for man m, all the women W_m that he can propose to are such that $|\mu_m(w) - \mu_w(m)| < \epsilon$ for all $w \in W$ and some limited range of desirability score ϵ.

This extension also is more accommodating to the dynamic user entry and exit in and out of the market in that it does not require a complete repeat of the matching mechanism if a user entered or left the market. Namely, the profiles which a given user is shown remains more or less the same making it more robust against user entry or exit because it only affects a small group.

We can see below the implementation of this extension with the same distribution of scores.

It is clear that with Fig. 3 males and females also have approximately similar utilities as in the base case results (note the scale of the data). However, note that differently from the

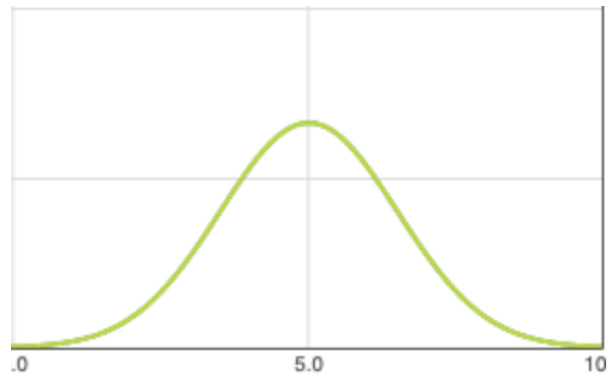

Fig. 3. Score distributions for male and female populations

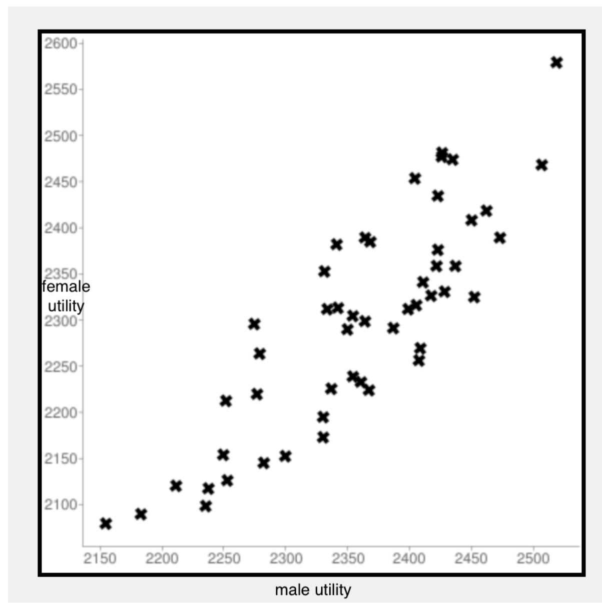

Fig. 4. Male and female utility under grouped exposure with $\epsilon = 0.5$ and baseline score distributions.

base case, all utilities are consistently around the the 2000s range. This is consistent with our expectation that the grouped exposure within some ϵ very small leads to more users getting more efficiently matched.

Interestingly, although we do not empirically report on this, it is also intuitively and by observation evident that the algorithm takes much less time to run. This could be because the socially optimal matching is already being suggested with the blocking groups. Namely, users are shown profiles that they have the best chance of getting matched with and that they should be matched with for socially optimal outcome.

B. Female Proposing

In the basic deferred acceptance algorithm with the entire population, we implemented it with male proposing due to the reasons in the methodology. But here, we explore the effect of female proposing on the market. Generally during deferred acceptance, male proposing means we would get the male-optimal matching from lecture, but the introduction of the desirability score creates a uniform average preference/utility for each user across the population such that we expect the female case to be symmetric to the male case. This is also why we do not do the female proposing case for the other extensions because we expect the symmetric case to apply. Additionally, doing it with female proposing also explores other facets not considered by our base case such as in female proposing markets.

Regarding implementation, we will implement the deferred acceptance with the same score distribution from the baseline except with female proposing.

We use the same score distribution as shown.

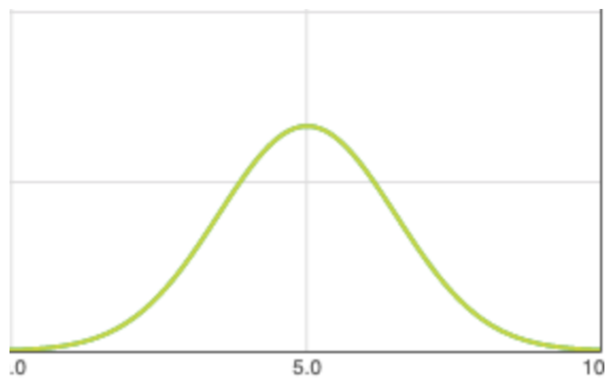

Fig. 5. Score distributions for male and female populations

We see the findings below. We can see that there is a

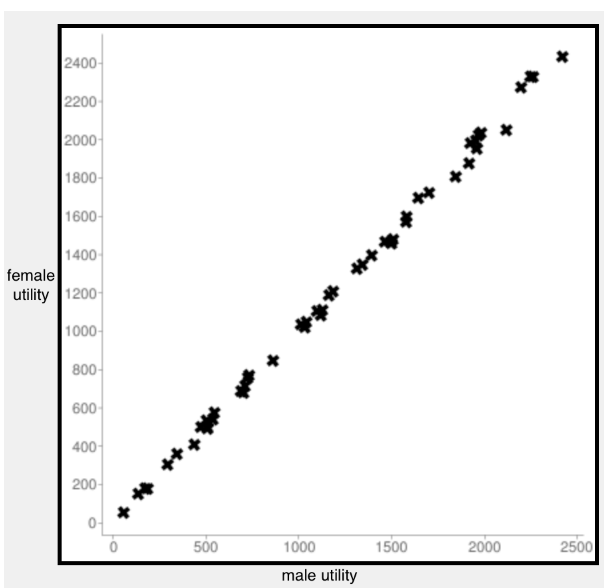

Fig. 6. Male and female utility under female proposing deferred acceptance with baseline population score distributions.

very similar distribution to the baseline results such that the female and male utilities are very similar in the female proposing deferred acceptance algorithm. This is consistent with our hypothesis because the utilities determined by the desirability score, and this essentially makes all preferences uniform within the population in each side, which means that male proposing versus women proposing are symmetric cases.

This suggests that the desirability score could possibly serve to even out the utility differences caused by behavior differences between the two sides in the matching market.

C. Different Populations

Size: In the basic deferred acceptance algorithm with the entire population, it is assumed that the two sides have the same population size. This leads to all users being matched in every iteration by the construction of the deferred acceptance algorithm.

Now we will look at the case in which there are unequal population sizes, and look at the final utilities of the two sides. This is applicable in that there are many two sided markets in which there are more users on one side than the other, especially in online dating markets [7]. Note that we will assume the symmetric case applies for women and men as shown above.

Regarding implementation, we will change the male population size to be 1/4, 1/3, and 1/2 the population of the female one and compare it to the baseline.

We use the same score distribution.

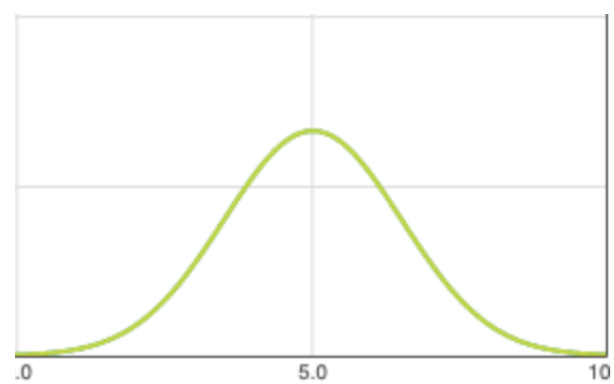

Fig. 7. Score distributions for male and female populations

We find the results as shown.

Examining the data, the first thing that is evident is that the total utility of the population decreases proportionally to the decrease in male population size compared to the utilities from the baseline population size. This intuitively is what we expect, since having some fraction of the population of one side means only some fraction of matches happen. Asserting that no match means 0 utility, we can observe that the total utility of the match decreases proportionally with the population decrease of either one side. Note, we refrain from applying changes to both sides' population sizes though because we apply this without loss of generality. Namely, if the male population were to decrease by 1/4 and the female by 1/2, there would still only be 1/4 of the original population matched.

Secondly, we can observe that while there are a few low outliers, most of the utilities end up being fairly high and

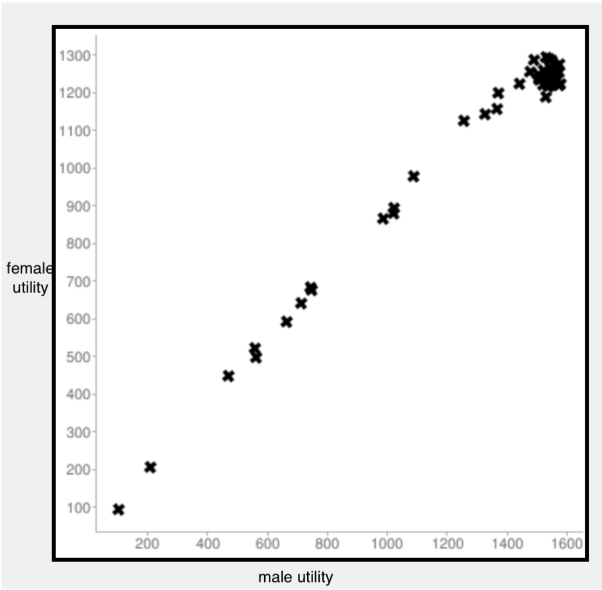

Fig. 8. Female and male utilities when the male population size is 1/2 the female one, same score distribution.

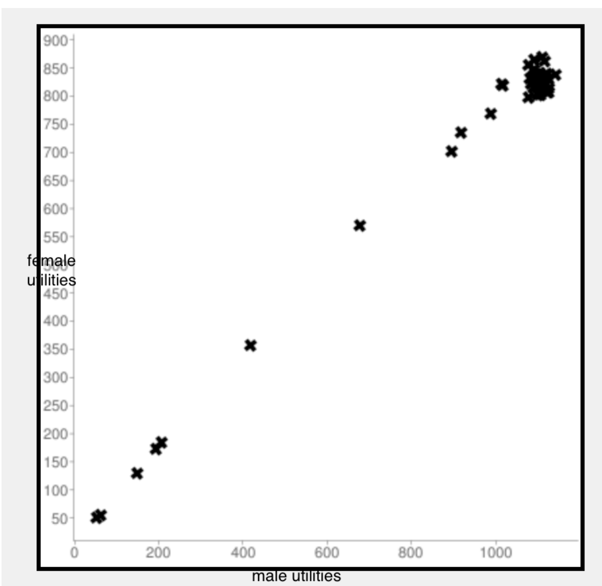

Fig. 9. Female and male utilities when the male population size is 1/3 the female one, same score distribution.

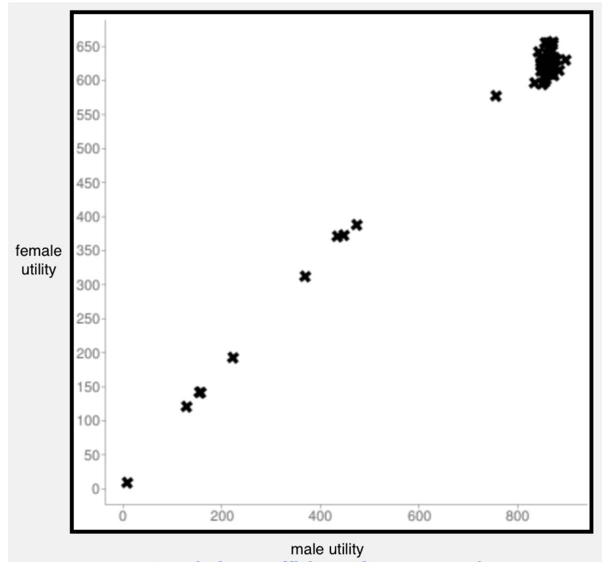

Fig. 10. Female and male utilities when the male population size is 1/4 the female one, same score distribution.

clustered in the top right corner of the data. This suggests that with a few exceptions, most of the final matches tend to be relatively efficient and is interesting. This suggests that compared to the baseline, having fewer users on one side actually leads to a more efficient outcome (relative to population sizes).

Finally, the results show that the utility of the male population in the final matching is higher than that of the female population in the data. This is what we expected in that we expected that the highest desirability women would match with the highest desirability men, producing a similar final utility, if not a lower one for the females because of the similar distribution of the male desirability scores. This is consistent with the intuition and the construction of the deferred acceptance algorithm. Namely, since there are fewer men, they all get the top proportion of highest desirability score women, whereas the male scores are still randomly sampled from the same distribution as the women, so the males get utility whereas the females get about the same (albeit with less matches total).

This overall data suggests that the side with a smaller population will gain relatively more utility from the final matching under the uniform preferences asserted by the desirability score. This could be because reducing the population size of one side effectively changes the score distribution of the other. Namely, only the top percentile will get matched or even considered, and therefore the score distribution of the other side (and therefore the match utility of the lesser population side) increases.

VII. Conclusion

From the extension study, I am able to see that the desirability score is significant in the two sided matching market in that the score essentially serves to ”score” each individual on how attractive they are, and thereby uniformly assigns preferences. Namely, this desirability score assigns each user a utility for being matched with them based on their previous and current history [4], and this essentially establishes an average ”match utility” for this user and allows all users to have uniform preferences for the other side of potential match profiles. This assumes of course that users are rational and prefers a profile and potential match with a higher desirability score over a lower one. Of course it can be argued that individual tastes amongst different demographics can deviate from the calculations of the mysterious and controversial desirability score, but for the purposes of this simulated exploration of the score, we are able to observe a few interesting things from the uniformity of the preferences caused by this desirability score.

Firstly, consider that from the baseline, we are able to determine that because of the uniform preferences, the cases in which male proposing and female proposing leads to male optimal and female optimal outcomes respectively is no longer the case. It is generally the case that male and female final total utilities tend towards being very similar. This is interesting both socially and mathematically in that it eliminates gender differences, such as women being at a disadvantage due to the social expectation that men should send the romantic interest signal, and that it creates a symmetric case for deferred acceptance in which either side proposing is symmetric. This is very different from the things we saw in lecture.

Then, since the base case is almost entirely assuming ideal and equal conditions of population, desirability score distributions, and rationality, we use it as a base case to compare against our extension results which isolates and explores further conditions and the effects of the desirability score.

From the first extension, we are able to observe that when the users are only shown profiles which have desirability scores similar to theirs, they are able to achieve a more efficient outcome. This is consistent with our expectations since showing each user only profiles that they should match with in the final matching–that is, profiles with desirability scores close to that of the user's–for the socially optimal outcome should lead to a faster resolution to a socially optional outcome. We find that this is a possible and very likely use of the desirability score by Tinder in that it leads to a more efficient and higher utility matching, and most likely also leads to faster matching, which is overall better for user satisfaction than full market full information matching as implemented in the baseline. The desirability score allows Tinder to create this kind of system and mechanism such that this efficiency is possible, if not slightly controversial in the public eye.

This has applications to fields such as online dating, but also to other fields such as college admissions or job searching. Namely, any two sided matching market in which users have different levels of quality and have preference can incorporate this technique. For example, they could mainly show students the colleges which would most likely be a good match for them based on their statistics, or vice versa only show colleges students who would be most likely to accept them and who they would most likely want to accept based on some scoring or ranking system of the college.

More studies can be done without the assumptions of the baseline. For example, we assumed in the baseline and in this model that the users are all completely rational and go for the highest desirability scores, which is why the groups shown to each individual were constructed in this way. But there may be other motivations and behavioral effects which may confound this and there may be a better way to group the users and the profiles they are shown other than by score, such as by history and tracking individual user preferences and adjusting for the scores based off that data.

I am also able to conclude from the female proposing deferred acceptance algorithm in the second extension that the female proposing cases is symmetric to the male one. Namely, this is the opposite of what was expected from deferred acceptance algorithms (at least from lecture) in which male proposing tends to lead to the male optimal solution and the female proposing leads to the female optimal solution. We attribute this symmetry to the uniformity of preference within the agents in each population enforced by the desirability score as stated above.

More research could be done into the algorithmic effects of female proposing in other online dating apps such as Bumble, or in female dominated markets in which the male proposing social paradigm does not exist.

This has applications to two sided markets as well because this essentially makes it such that the mechanism by which the proposing/signalling happens is no longer as crucial to the final payoff and thereby well being of the user. It has possibly very significant implications for two sided matching markets. However, the limitation of this extension is that it only concerns two sides in which populations which are fairly identical in condition, so this extension was more useful in making observations within the paper itself about the symmetry of female versus male side decisions.

From the final extension in which we change the population size of the male side, also noting the symmetry of the female case and without loss of generality for changing both, we find that the total utility decreases proportionally with changing either one side. This was consistent with our expectations since the lowest population size side essentially gets to choose from the top percentile of the other side's population.

A significant finding from this extension study was that decreasing the population size of one side essentially serves to skew the desirability scores of the other side and thereby the utilities of this side upwards. Namely, we found that by decreasing the male population size, the final male utilities tended to be significantly higher than the final female utilities from the matching. This intuitively was expected since effectively skewing the female desirability scores upwards results in higher matching utility for the males, whereas the males are still sampled from the same distribution and so the female utilities from the match do not necessarily increase relatively. Essentially, only the top percentile of desirability scoring females are matched whereas the males are still the distributed the same in desirability score.

Further research could be done into whether manually changing the skew of the desirability scores of one side but not changing the population size would accomplish the same effect. Another area of exploration could be changing the male population size with male proposing, but since we have found the female and male proposing cases to be symmetric as stated earlier, we do not explore this and assume that results are similar with males ending up with higher total utility from the matching. We will leave these other extension subjects for further research in the future.

In general pertaining to the desirability score, more research into this field could be done into the how this affects the various demographics, both socially outside of the controversial desirability score within the score. For example, it would be interesting to measure the utilities and matching scores of those users who are scored higher in desirability verses those scored lower.

Additionally, another related area of study could be the way that the desirability score is dynamically updated. For example, if the desirability score was calculated by the rate at which other users liked, or ”swiped right” on a user, then if the user’s profile was initially shown to lower desirability users who were more likely to swipe right, they would have a higher score, and if they were shown to higher desirability individuals, they would have a lower desirability score. Therefore, this desirability score almost seems paradoxical in that it both affects and is calculated from the user’s interaction with other users in the market. Of course, this is all speculation around an algorithm shrouded in mystery.

Another area of research would be in incorporating considerations about the cost of spending time in the market, or ”swiping” for example. In this case, we could consider that there is a significant cost to remaining in the market in that it is time wasted, so we have to also balance the cost of the length of time the matching algorithm takes in addition to the final utility. Although, it should be noted that with dynamic user entry and exit, it is entirely possible that there is another aspect in which a user might want to ”wait for something better” which is not something addressed in deferred acceptance by the nature of deferred acceptance.

Therefore, the baseline algorithm did not fail to analyze the base case with optimal conditions in that it was able analyze the effect of having a desirability score on the deferred acceptance matching algorithm.

However, the purpose of this problem is to provide insight and analysis into real life applications of the desirability score in matching markets, so while the base line algorithm is sufficient in analyzing matching utility in a hypothetical situation, real life applications would need to consider other conditions such as how Tinder is actually applying this algorithm, which we explored in the first extension, the symmetry of the market, which we explored in the second extension, and the various conditions of the population, which we explored in the third extension.

By exploring these extensions and isolating the conditions, we are able to gain more insight into the effects of the conditions on the matching algorithm and of the real life applications of the desirability score in cases such as the Tinder algorithm. Despite the controversial nature of this desirability score, it does in fact have some very interesting effects and implications for the matching mechanisms and algorithms.

References

[1] D. Gale and L. S. Shapley. College admissions and the stability of marriage.The American MathematicalMonthly, 69(1):9–15, 1962.

[2] Cédric Courtois, Elisabeth Timmermans, Cracking the Tinder Code: An Experience Sampling Approach to the Dynamics and Impact of Platform Governing Algorithms, Journal of Computer-Mediated Communication, Volume 23, Issue 1, January 2018, Pages 1–16

[3] Kao, Anthony, ”Tinder: True Love or a Nightmare?” (2016). Pop Culture Intersections. 16.

[4] Carr, Austin. “I Found Out My Secret Internal Tinder Rating And Now I Wish I Hadn’t.” Fast Company, Fast Company, 10 May 2017

[5] Ranzini G, Lutz C. Love at first swipe? Explaining Tinder self-presentation and motives. Mobile Media Communication. 2017;5(1):80-101.

[6] Elisabeth Timmermans, Elien De Caluwé, To Tinder or not to Tinder, that’s the question: An individual differences perspective to Tinder use and motives, Personality and Individual Differences, Volume 110, 2017, Pages 74-79.

[7] Fong, Jessica, Search, Selectivity, and Market Thickness in Two-Sided Markets: Evidence from Online Dating (June 12, 2020).

[8] Gareth Tyson, Vasile Claudiu Perta, Hamed Haddadi, and Michael C. Seto. A first look at user activityon tinder.CoRR, abs/1607.01952, 2016.

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