Assignment-2 Submission

Indian Institute of Technology Delhi

Dating Platform: Analysis and Trade-offs

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1 Introduction

We are living in a world of digital products. With the advancing algorithms having the power to predict human behaviour, there are various tools that are built to ease the human experience. Every product is disrupting entire industries on its own. OTT platforms for cinema halls, social media for conventional media, online education for schools and coaching institutes etc. Each product has the power to transform human behaviour completely, and thus there is a strong need to understand the complexity of informatizing social phenomena in the world. For this assignment, we will use the example of a dating platform where users can specify their characteristics and desired characteristics of a partner. The goal of the system is to recommend matching profiles.

Link to the form: Dating Platform Form

2 Analysis of responses based on different demographics

In the questionnaire, we asked the respondents about their demography based on various parameters relevant to the dating platform like age, gender, language etc. Next, we analysed the responses and correlations among their preferences. The following are the key points of the detailed analysis:

2.1 Age

Even after our intended efforts to include responses from diverse age groups, maximum interest was shown by people aged 19-25 (followed by 25-30 and 15-19). This shows that this group is the primary audience of the product. This question caters to the concept of **"Know your customers"**, which is essential for building good software products.

2.2 Gender

Among different genders, we got the maximum response from males (around 75%) followed by females. This shows that a majority of users are males. Interestingly, our percentage is similar to the user base of Tinder, a famous dating platform.

Interestingly, we got no responses from the non-binary or transgender group. This shows that there is still a strong need for an inclusive environment to have a dating culture for all groups. Also, it indicates a strong need for a separate platform that caters to the dating needs of excluded groups.

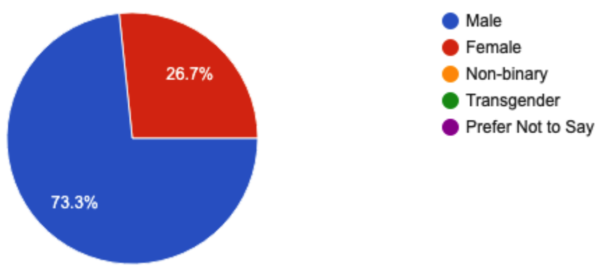

Figure 1: Pie chart showing the response distribution based on gender

Contrary to the superstition that women are more restricted in sharing information, the responses of female respondents were very liberal and open to engagement with the platform. Most women favour "the number of swipes should not be limited".

2.3 Place of birth

Next, we also asked about the place of birth of the individuals. More than 70% of the respondents were from urban metropolitan areas, followed by semi-urban (20%) and rural (7%).

This shows that people from urban areas are more interested in and open to dating than rural people. It reflects the social stigma that exists around dating in rural areas. This is primarily due to the parents and family's patriarchal mindset and conservative nature. The platform and the recommendation algorithm should be made to keep this natural imbalance and taboo around dating in rural areas. This data point caters to the concept of **"factoring societal imbalances in the algorithm"**.

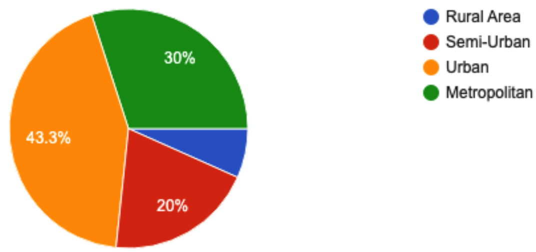

Figure 2: Urban and metropolitan areas dominate the responses

People from rural areas were also more sceptical about the authenticity of the platform and less open to sharing all the information. All the rural respondents filled “Only Age” against the question “Do you wish to make your birthday public”. One male respondent from a rural area demanded that there should be “Proper authentication using video call by any agent.” Responses from urban areas were relatively diverse regarding privacy and ethical questions.

3 Choosing variables

The following are the key points that were considered while choosing variables for the questionnaire:

1. If we have not contacted the person or the demographic person, we may have no idea about the individual’s previous experiences. In this case, our system will miss out on essential variables. Nevertheless, since people might not be comfortable sharing personal past experiences, we did not include the question in the form. **We also refrained from using the deceptive design practice of confirm shaming.** An unethical way was to ask the question and give the option as “fill past information” and “No. I do not wish to get better matching profiles on my feed”.

2. If given more time, we would have collected more responses from rural areas, people from the LGBT community and people from older age groups. A micro-social category is widow males and females looking to use such a platform. Currently, the representation of the social groups mentioned above is significantly less.

3. There were many variables that were demanded in the form. For example, information about the future preferred country/city of stay was asked by nearly 70% of the respondents. More than 80% of the responses asked for smoking and drinking habits to be displayed on the profile. We also omitted certain variables like **financial background** on the profile based on form responses.

4 Tradeoffs while choosing variables

4.1 Information v/s privacy

Dating platforms are unique because people are open to sharing information, but they also want ample information about potential partners. More information would lead to better matching, but it will also hamper the privacy of the individual and might lead to a bad image and fewer users.

4.2 UI space and relevant variables

Since dating apps have a "swipe-based" UI, the first glance at the profile should show the most relevant information. It should show variables that may lead to a feeling of interest and attraction. **The variables that ignite immediate interest in the profile are profile picture, occupation, age and place of stay.**

We also need to show variables that can lead to immediate rejection of the profile. We can classify such variables as "reject variables". **Variables that might lead to rejection (rejection variables) are smoking and drinking habits, religion (sadly) and age.**

4.3 Information overhead and paradox of choice

We also need to understand that there are variables that might be relevant to some and irrelevant to others. Religion, for example, might be irrelevant for some and a major deciding factor for others.

Showing too much information would lead to the idea of finding "the perfect one", eventually leading to a paradox of choice. This means that you might get recommendations that match 80-85% to your preference, but you still optimise for "the perfect match".

5 Controversial variables

Some variables and characteristics have the power to create social clusters among dating partners. Some variables were "controversial" and required deeper understanding and debate before coming to a decision.

5.1 Political inclination

If the political inclination is shown in the profile, it can lead to users rejecting profiles from the opposite party. Not showing these variables might lead to these topics coming up later, which may lead to a bad dating experience.

This is the tradeoff between enhancing user satisfaction or sticking with one's own ethical principles as the system designer. In our system, we would prefer to disclose the political inclination at the end of the profile. Doing this shows all other information beforehand, leading to less clustering as the user creates a rough decision by the time it reaches the end.

5.2 Financial background

Financial background is another relevant variable the user considers before making a decision. This has the tradeoff of better dating experience and building of clusters and the algorithm becoming classist. The dilemma was resolved by the form where the respondents denied showing their financial background on the profile.

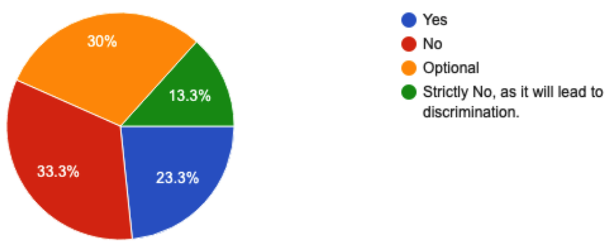

Figure 3: User preference of showing financial background

5.3 Religion

Religion can be one of the most important variables for some people when choosing a date. On the one hand, including it may enhance an individual's decision-making. On the other hand, it may lead to strong clustering, and social biases may affect our algorithm. For this, we can randomly expose different religious profiles to users. Responses, on the other hand, suggested the inclusion of religion. **Note that the question was framed in terms of "comfort" rather than its relevance as a key decision-making variable.**

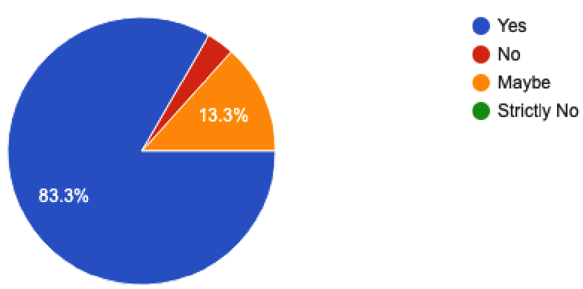

Figure 4: Showing religion on the profile as preference

5.4 Height, Weight and Body measurements

Another critical aspect in the domain of dating is looks. Acknowledging the privacy of individual, two questions were framed. One was regarding height and weight, while the other was about body measurements. This is one of the questions in which the response was consistent across all genders.

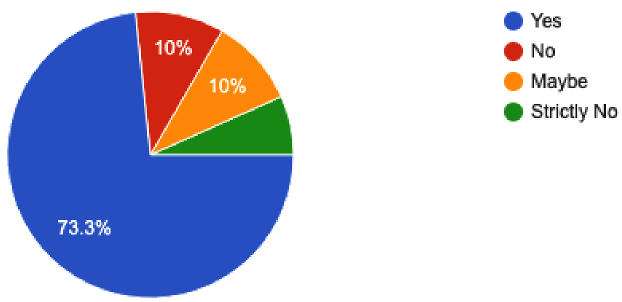

Figure 5: Preference of people in sharing height and weight

While people are relatively open about height and weight, they are not very comfortable sharing their body measurements. In the case of body measurements, responses were diverse. Most of the “Yes” came from male respondents. Interestingly, most of “Strictly No” also came from male respondents. This is also true percent-wise, so there is no bias of high base value of the number of male respondents.

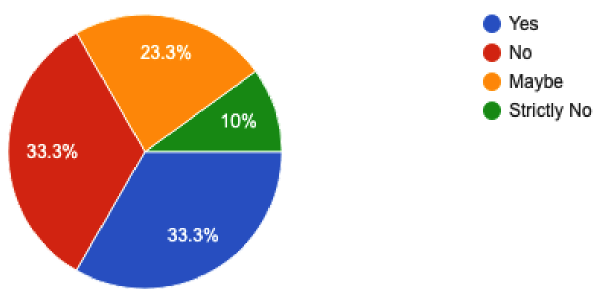

Figure 6: Preference of people in sharing body measurements

6 Choosing categories and range of variables

While choosing categories and a range of variables, the proper analysis needed to be done to refine the following analysis. Following are some of the considerations that were made:

6.1 Age

There is no singular range for age. Contrary to the common break-point of 18, our form did not have 18 as a dividing range. Since it is a dating platform, we divided the range based on the change in dating preference and frequency with age.

There was a division between 19-25 and 25-30 as these are the range of college period and stability/marriage period. Both periods have very different relationships with dating platforms. All ages 40 and above were considered as one category because there is no drastic change in preference after age 40.

6.2 Form open to different option

Every multi-option answer also had a column of other. The main idea is that users may have a different opinion that does not fit in either of the options listed in the form. Although the other option is rarely used, whenever it is used, it shows strong opinions on the subject matter.

It was due to this option that we got the response of having "Proper authentication using video call by any agent" given by an individual that led to key insights in the behaviour of people from rural areas.

6.3 Multiple options on the same opinion.

We showed multiple options on the same opinion. We explored all the possibilities for a response and created them as options to get a deeper understanding of individuals' reasoning behind choosing a particular option. For example, in the case of getting users' preferences on the message system, we not only asked about privacy preferences but also about the detailed features they wish. This also leads to more willingness of respondents to write custom features they wish to be in the system.

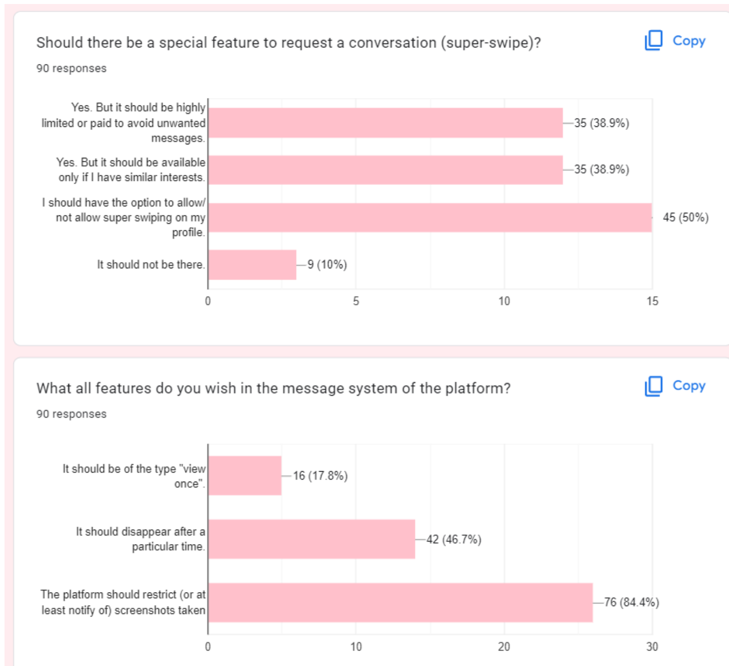

Figure 7: Multiple options against similar response about the messaging system

6.4 Inclusiveness in the form

The form tried to be as inclusive to all the categories as possible. The following decisions were made in this direction:

1. All the gender categories were listed, not just male and female.
2. Every Yes/No question also had the option of maybe/optional to respect an individual's uncertainty and abstaining decision to fall in one of the boolean responses of yes/no.
3. The options were made multiple choice wherever possible.

7 Comparison with existing platforms

With all the analysis and understanding, we also analysed the tradeoffs done by existing platforms. Since commercial platforms have maximising variable as profit, number of users etc., we have looked at their approaches that are different from that of public view. For our discussion, we are considering Tinder and Bumble as they are the top 2 used dating applications.

7.1 Limiting the number of swipes

Both Tinder and Bumble have limited number of swipes per day. They charge a premium to get more swipes per day. The ethical side given by the apps is that it is done to avoid spamming of right swipes on profiles. Another reason is obviously profit making. But our survey shows that more people are in favour of having no swipe limit on the platform. The response is same across all genders and demographics.

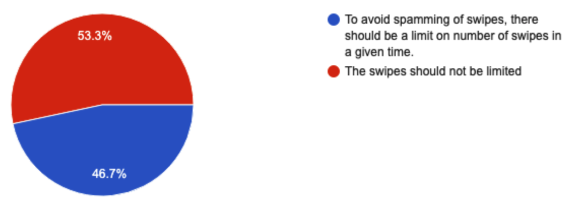

Figure 8: Public opinion on number of swipes.

There can be an argument that the percentages are both close to 50%. But when asked about ethical point of view of charging money for extra swipes, there was a greater majority against this concept.

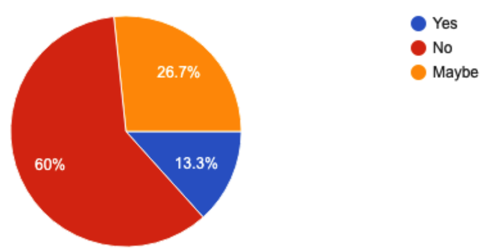

Figure 9: Do you feel it is ethical to charge for extra swipes?

7.2 Dictating conversation rules

In Bumble, there is a concept that women will make the first move in conversation. Otherwise, the conversation does not get started. This "rule" based conversation gives a sense of authoritarian decision. Furthermore, it also strengthens the gender stereotypes that exist in the society. Rightly, the survey responses were against such decisions.

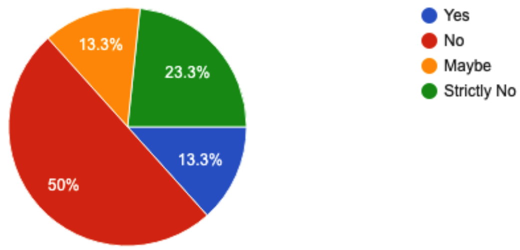

Figure 10: Views on having a rule based setting in the platform

7.3 Editing on profiles

Survey reveals that there are diversified opinion on the frequency of editing but most of the responses were in favour of allowing editing in the profiles. There is a certain limit on editing profiles on these platforms. Tinder, for example does not allow users to edit the name once it is filled. Bumble also have some restriction on updating preferences.

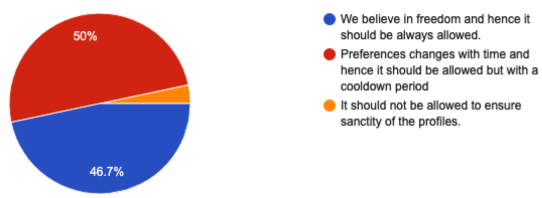

Figure 11: Views on having the option to edit user profile

8 Biases and Mitigation Measures

Machine Learning algorithms are often black-box methods with little to no explainability(specially deep learning methods). Thus it becomes extremely necessary we explicitly tackle the bias issues in such algorithms. For example, over 83% of the surveyees wanted religion to be present on their profile. This would mean people are more likely to date people from same religion. Similarly revealing full name in profile will lead to people judging other based on caste, and this phenomenon will creep into dataset on which machine learning model will be trained. This would create social clusters, which in turn the machine learning algorithm will pick up. Similarly consider the case of financial status/occupation. Again the result would be similar to the previous case. Also here we should note that interestingly only 11 out of 90 users were of the opinion that including financial background in profile would lead to discrimination. Thus, on real data, it is expected that machine learning algorithms will pick up the bias, and most likely amplify the case. Similar is the case with other variables such as rural/urban population, horoscope, language where a stark divide between the two would be created. In order to fix these biases there are multiple methods that can be used. For example, we can explicitly decrease the weightage of variables that can cause bias(eg: religion, caste, financial background etc.) in simple algorithms(eg: Logistic Regression) or such as one discussed in first part of Section **??**. This can be done by adding a bias parameter to the parameter(eg: adding a small number in say parameters of all religions will ensure, that there is always certain probability of considering each of them), or downscaling parameters by a factor. However for models with latent variables(deep learning models), even by downweighting some parameters, bias cannot be fully mitigated because, it is often possible for them to infer these variables using certain other variables(eg: religion can be inferred from name, or some complex interaction of preferences). To fix this issue, we can pre-process the dataset in such a manner, such that effect of bias decreases. Specifically, say there are x examples of people of same religion A dating, and x examples of people of same religion B dating, we will augment dataset such that number of cases of people A and B dating will come nearer to x. This way by balancing dataset we can remove bias from the dataset. Moreover, we can apply a more explainable model(say decision tree) on top of our deep learning model to increase explainability. We can then apply rule based or simple heuristic methods to strip the predictions of bias more easily.

9 Bonus

The recommendation system can be implemented using various methods. Traditional methods, such as Collaborative based or Content-based, are used for user-item recommendation systems. However, in contrast to them, here, the task is to recommend a user to the user, i.e. here, input space and output space are the same. For such a scenario, the algorithms are generally termed Reciprocal recommendation systems, where recommendations are not symmetric. We propose a very simplistic approach based on [4] for this assignment. Consider there are n users $U = \{u_1, u_2, ...u_n\}$. Each user has v preferences/variables based on their response to the form. Mathematically, $P_i = \{p_1, p_2...p_v\}$. For now, we consider that these variables will be based on what was filled in the form. However, we can later easily extend them to latent variables as well. Define L_i as the learned preferences of user x, which is updated with time. Initially, each user gets a recommendation based on their preferences, i.e. users with similar preferences are recommended higher. Now, whenever a user x likes user y, L_i is updated as

$$L_{x,j} = L_{x,j} + w_j * P_{y,j} \tag{1}$$

Here w_j is some model parameter that can be fixed or learned as well (For now, consider it to be constant). Next, we will normalize L, such that its norm is 1.

$$L_{x,j} = \frac{L_{x,j}}{||L_x||} \tag{2}$$

Now for each user x, we will define compatibility with other user y, by using dot product between the two's $\vec{P}$ vectors. Specifically,

$$Compat(x, y) = \frac{\sum_{j=1}^{v} L_{x,j} * P_{y,j}}{\sum(L_{x,j}! = 0)} \tag{3}$$

Note that the above equation is not symmetric. The above equation is adapted from the famous paper [4] for a similar task. Although, their communication between users happens using messages, whereas modern apps are based on simple likes and dislikes, thus we adjusted the algorithm accordingly. Once we have defined the *Compat* function, we define the ranking of recommendation y to user x as:

$$rank_{y \in U - \{x\}} Compat(x, y) \tag{4}$$

This way, we get the ranking function over each user y for a user x. However, note that while this algorithm gives the best match for a user, reciprocity is necessary for a match to be successful. To incorporate such a behaviour, we can take the harmonic mean between the two compatibilities and define a new score for ranking as:

$$\frac{2 * Compat(x, y)^p * Compat(y, x)}{Compat(x, y)^p + Compat(y, x)} \tag{5}$$

Harmonic mean ensures that if x likes y, but y would have a very low liking for x, then the overall score would be very low! Also, note that ^{p} exponent is only to remove symmetricity as per requirements (p=1 implies symmetric nature)

9.1 Incorporating complex variables

Our survey showed that users are not only interested in simple variables, such as what kind of movies a person likes, but also complex variables, such as based on facial features. For example, over 60% of the users were comfortable with our algorithm recommending them matches based on their profile pictures. In order to incorporate such behaviours, we can use a neural network-based model(say CNNs) and append the output to $\vec{P}$ as discussed in the previous section. Further, we can use graph convolutional networks [1] to further incorporate complex interactions between multiple users.

10 Technological Fixes

Even with a good and accurate algorithm and good user interface for our platform, many challenges must be addressed separately. While some of these can be fixed to some extent by improving our platform technically, some of the challenges requires collaborating with relevant stakeholders.

1. Consider the case that our platform provides a match between two users. However, how can we make sure the Date went well or not? For example, if the Date did not go well, how do we consider such a complex variable in the algorithm? We can fix this issue to some extent by taking feedback from users sometime after the match.

2. However, while the previous scenario still had a solution to some extent, now consider a scenario where a lousy actor created a lot of fake accounts to trap other users. What if a user indulges in cyberbullying [3]? Alternatively, in the Date, what if one of the users indulges in criminal activity [2] [5]? Then on whom would the onus lie? In order to make our platform safe, while we can apply robust machine learning algorithms to remove fake accounts and users suspected of criminal activities, we cannot certainly weed them out completely. Moreover, aggressive banning of users would mean certain deserving and genuine users will be deprived of using our platform. Thus even complex technological methods cannot fix the issue. Thus we will have to work with local government and law enforcement agencies to ensure that our platform provides a safe environment for the users.

3. While the previous discussion focused on law and order; we should also consider the fairness issues in our platform. For example, as discussed in 8, we may need to eliminate biases to ensure our platform is fair. While there did exist a partial technological fix for it, what about those users who cannot create their profiles efficiently? For example, if a user cannot click good photos, he/she might get rejected more often than other users. Similar is the case for other things on the profile. This is a fairness issue, as a person should not be penalised for something that is not a core function of the platform. To fix this, we can either educate users on how to

make better profiles directly through the platform or perhaps we can use automated tools to improve profiles(for example, applying machine learning algorithms to improve profile picture.) However, more ethical concerns arise because of this. There can also be design changes. We can have a section called "Candid photos". This would have the idea that one will have to click photos on the spot and upload them on the platform. This would ensure that edited filtered images are not uploaded and that the uploaded photos match best with the actual appearance of the individual.

4. Now consider another angle, what if a person constantly gets rejections(no matches) on the platform? This could lead to a state of clinical depression for the user. Technological fixes cannot always directly improve the situation. As platform creators, we should include various psychologists and mental health teams to ensure such situations do not occur, and even if they do, appropriate steps are taken at the right time.

References

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