SEXUAL ASSAULT AND TINDER: BUILDING A RISK ASSESSMENT MODEL

A Thesis
In STS 4600
Presented to
The Faculty of the
School of Engineering and Applied Science
University of Virginia
In Partial Fulfillment of the Requirements for the Degree
Bachelor of Science in Computer Science

By
Stephen Dolan

February 22, 2022

On my honor as a University student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments.

ADVISORS

Rider Foley, Department of Engineering and Society

Introduction

Matchmaking software like Tinder that allows users to meet sexual partners in their geographical vicinity has significantly changed the way young adults approach dating. Dating applications have been gaining increasing popularity with upwards of 40% of people having met a sexual partner online (Daneback, 2007). Some find this software to be greatly beneficial for their dating lives because it expands their pool of potential partners and makes dating more accessible (Ranzini et al., 2016). However, with the wide availability of partners whom users have not met in person first, there also comes clear risks associated with matchmaking software. Tinder use is associated with being a victim of sexual assault (Shapiro et al., 2017), having contracting sexually transmitted infections (Ciocca, 2020), and even misogyny (Thompson, 2018). However, people are also more likely to use Tinder if they rate higher on extravert scales (Timmermans et al., 2017) and have prior sexual experience (Shapiro et al., 2017), things that are also associated with sexual violence (Walker et al., 2011). This shows that matchmaking technology by itself is impossible to separate from the behavior of individual users, making sexual assault prevention a very complicated issue. Should change come at the societal level, technological level, or legal level? Most people would agree that some combination of all of them is needed, but the focus appears to always fall on societal and legal avenues. I argue that if technology plays a role in sexual assault, certainly technology should also play a role in sexual assault prevention.

The question, then, becomes: how should matchmaking software companies use their technological power to mitigate sexual assault? The current response has been to work with social organizations such as the Rape, Abuse & Incest National Network (RAINN) to accommodate survivors. Match Group (the group that owns Tinder), has worked with RAINN to redesign of the sexual assault reporting process to better support survivors with significant trauma and give them "more agency over what step they want to take next" (Thompson, 2022). They also use a large database crossing multiple dating services to block users that have been reported across all platforms through blocking based on IP, phone number, or email (Tinder, 2022). The current corporate approach to sexual assault is certainly a net positive on their userbase, but focuses solely on responding to violence. To truly combat sexual assault, companies like Tinder must go beyond accommodating survivors and use their technology to prevent violence from occurring in the first place. Tinder already has massive amounts of user data such as profile data, messages, and unmatching patterns. They could also likely gain access to even more such as criminal records, alternative social media accounts, or even new feedback systems for all encounters. Using all of this data, I argue that Tinder has a responsibility to develop a preventive model that would flag accounts for sexual assault before they are allowed to use their platform.

The Software Design of Tinder and Actor Network Theory

The relationship between matchmaking software and sexual assault can be greatly misunderstood if all of the focus is placed on the technology. Currently, Tinder does not decide what qualifies as assault on behalf of a person, they only offer a reporting system. Similarly, matchmaking software companies leave it almost entirely up to the individual to decide whether a potential encounter is safe or unsafe. Tinder provides small suggestions. telling users to meet in public or inform friends of where you are going (Thompson, 2022). The choice, however, is ultimately up to the user. It would be easy, then, to simply take all blame off of the technology and focus on implementing social change so that people did not use the technology for harm.

This is a gravely idealistic view: sexual assault is one of the most universally despised crimes, yet there has been little change in its frequency despite social efforts (Rape in the United States, 2023). Matchmaking software has both the platform and the data to influence user decisions to reduce harm much faster than social change by itself. Therefore, to properly review the design and use of matchmaking software we must consider both the technology and the social factors. If we ignore one, change will come much slower.

Combining these two approaches is essentially resolving the conflicting ideologies of technological determinism (the view that technology is a driver for social development) and social constructivism (the view that social development shapes technology). Bruno Latour provides such a solution to the dichotomy in "Where Are the Missing Masses? The Sociology of a Few Mundane Artifacts" (1992), introducing his own type of actor-network theory where pieces of technology are "artifacts" that play a role in the social construction of technology. Latour discusses the *delegation of responsibilities* to humans which, according to Latour, can help control the "erratic behavior" of a larger group of humans but can cause simple tasks to have "incredible cost". Delegation to technology, on the other hand, often creates imperfect solutions at a lesser cost and shapes the behavior of humans (Latour, 1992). He also defines discrimination, the idea that technology can be unintentionally designed to be used by certain groups, and prescription which he defines as "the moral and ethical dimension of mechanisms" (Latour, 1992). Lastly, Latour defines inscription which he says is the placement of ideas of builders and users into technology, much like authors place ideas of themselves and their readers in a story.

Latour's actor-network theory can be directly applied to matchmaking software to examine how the technology itself and society surrounding it can best be constructed. How do we mitigate the role matchmaking software clearly plays in sexual violence? Currently, we seem to delegate the parsing of partners for potential sexual violence solely to the userbase. Tinder has more data than the individual user about past chat logs and reports. Tinder could even implement new feedback systems where messaging, unmatching, and in person encounters could all be rated to help warn users of potential risky accounts.

Yet, there are certainly clear downsides to delegating sexual violence risk assessment to companies like Tinder such as discrimination against those with a criminal record: which can have racial implications as well (Henkels, 2020). If Tinder were to use artificial intelligence to analyze risk, they would run the risk of the same AI discrimination (Ferrer et al., 2010) that we see in many other systems. Is there a middle ground where some risk assessment can be delegated to the software without succumbing to the drawbacks of machine learning? This middle ground can only be reached by delegating both part of the input and the interpretation of the output to users. Users would certainly have to be instructed on how the model works and the potential downsides of it as well. Inscription, too, plays a role as using AI would leave Tinder having to make assumptions about how their users view AI. Are users competent enough to know to what extent AI can be trusted and not blindly follow Tinder's model? Latour's provides a framework that helps us consider how the technical and the social can both be considered to solve complex problems. In our case, this framework provides a path to understanding how matchmaking software companies could create a preventive flagging model while considering proper inscription and delegation to key social groups.

Case Context

Sexual assault in the United States has remained around the same rate per capita (Rape in the United States, 2023) despite significant social change such as banning the use of survivors' sexual history to discredit them in court, the funding of crisis centers, and the #MeToo movement (Washington Coalition of Sexual Assault Programs, 2021). Matchmaking software companies' current approach to mitigating sexual assault on its platform is overall reactive as opposed to preventitive. However, there is nobody who has more data on individual dating habits like messaging, unmatch rates, and reports than these same companies. Companies could certainly also get more data such as implementing a rating system for all online and in person interactions. This data would then be used with artificial intelligence to assess risk.

AI models have become increasingly powerful in the last two decades, leading to an explosion in the use of AI (Chugh, 2022). In this case, much of the data that matchmaking software companies would use is text from conversations between users. This data is perfect for a specific type of machine learning: natural language processing (NLP). NLP is a type of artificial intelligence concerned with giving computers the ability to decipher meaning from text and spoken words beyond their literal translation. One simple example of the power of NLP is topic segmentation and recognition: where a model is trained to separate text into smaller topics (Reynar, 1999). In fact, natural language processing has been specifically used to "extract and classify instances of interpersonal violence" (Botelle, 2022) from text records. Another similar NLP model used twitter text to identify potential intimate partner violence (Al-Garadi, 2022). They claim that their model "can be an essential component for a proactive social media-based intervention and support framework, while also aiding population-level surveillance and large-scale cohort studies" (Al-Garadi, 2022). Different AI models such as decision trees have even been used to predict larger crime trends with high accuracy (Patil, 2020). Clearly, preventative measures using AI models is a completely realistic application of the data that matchmaking software companies already have access to.

Although the application of artificial intelligence to crime prevention is certainly promising, there are several significant challenges that come with the positive effects. Artificial intelligence is often associated with discrimination (Ferrer et al., 2010). Since AI algorithms are trained on existing data, if there are racial discrepancies (or anything of that nature) in the data because of past discrimination, the model will “discriminate” as well. A clear example of this is in criminal risk assessment algorithms which have been shown to place greater risk along racial lines (Hao, 2019). Black people have been shown to be disproportionally falsely convicted of sexual assault within the justice system (Mogavero, 2022), so it is likely that past report data would be skewed in the same way. This means that assessing risk in dating applications carries the same discrimination risks because report data likely has inherent bias.

Beyond discrimination, the amount and type of data that matchmaking software companies require to construct a model are questionable as well. Over the past 5 years, there has been more and more pushback as people find out about the data that companies collect and use. Possibly the most clear example of a company's response to this pushback was the release of iOS 14 by Apple, which changed privacy settings so that apps had to ask for explicit permission to track (O'Flaherty, 2021). This had an immense impact on both big tech and the average user. Many companies such as Facebook saw significant damage to their income, losing $10 billion in revenue (Leswing, 2022). Although companies like Tinder clearly have the right to use message data that people send on their application, we could certainly see similar pushback matchmaking companies start doing extensive monitoring of user data.

Lastly, another challenge faced by exploring a risk assessment model for matchmaking software surrounds balancing false positives with false negatives. This problem begins as early as data labeling. Do you label all reports as sexual assault even though statistically a small percentage will not be truthful? When tweaking the model, do you prioritize all risks of sexual violence being correctly labeled, or do you prioritize minimizing the amount of non-violent encounters that are incorrectly labeled as potentially violent. The labeling and interpretation of sexual violence data is a complicated issue that tech companies must approach thoughtfully to best suit their userbase. Overall, sexual assault risk assessment is clearly a very complicated issue with a lot of moving parts. That being said, the groundwork for such a model has been laid— the technological potential is already here.

Research question

How should matchmaking software companies go about creating a risk assessment model for sexual assault prevention?

Methods

Due to the sensitive nature of the topic, I relied on literature review and case studies instead of primary sources. I used case studies to examine real life situations of violence to build basic ideas of prevention. These case studies came from online newspaper articles covering cases of sexual assault related to dating apps. I examine the before, during, and after of each case to map out both the actual response and a potential alternative response from matchmaking software companies. I also looked into victims' perspectives to see how they interacted with report systems. These cases provide a good picture of the aftereffects of violence on dating apps, as well as the victims perception of the role of dating apps in sexual assault prevention. I also used literature review to combine the leading expertise in artificial intelligence to form the technological basis for a potential risk assessment algorithm. I searched for natural language processing models that assigned risk to text and, among these models, found the ones that use informal text between individuals such as messaging or social media in the past 5 years. This literature shows whether there is similar technology to my proposed model and, if there is, the limitations. Lastly, to address legal and social factors leading to report rates, I searched for interaction between matchmaking software companies and law enforcement in the past 5 years and searched for research on increasing sexual assault report rates by social groups. Together, these methods paint a picture of how risk assessment can best be done by matchmaking software companies.

Results

Matchmaking software companies have a responsibility to use the technology to help prevent sexual assault. This solution must come both from the combination of several different technologies and social engineering to ensure that they are used in the right way. Through examining past cases of sexual assault and past uses of artificial intelligence, I found that there is a strong potential to employ a risk assessment model that uses current matchmaking software data. One component of this model should include natural language processing of text messages between individuals on dating apps to determine potential violence. More generally, artificial intelligence models could use a combination of text, past reports, social media presence, and criminal records to identify high risk individuals. Beyond the model itself, software companies would need to ensure that users are aware of their role in providing the data which fuels this model. Software companies would also need to properly educate users on the power and limitations of their risk assessment model so that it is not misused. Overall, I found that risk assessment is indeed a viable avenue for sexual assault prevention in dating apps if software companies properly collect data and educate their users on data collection and interpretation.

Case Studies

Through examining case studies of sexual violence related to dating apps, it becomes clear that there is enough data to prevent at least some cases of sexual assault, but only if there is proper user adoption. First, one crucial case is of convicted sex offender Tom Rodwell who assaulted 5 different women that he met on dating apps. Rodwell sent violent texts to multiple women on dating apps and showed many warning signs of disregard for consent. For example, one woman that he met twice said that during their first encounter, he said he would “get her pregnant” and threw her contraceptive pills in the bin (Jackson, 2022). This is not an offense that is explicitly reportable because dating apps focus on violence as opposed to general disrespect of boundaries. However, if a more expansive report system was in place, Rodwell could have been flagged based on that interaction alone. He also sent a text asking when he could "rape her again” (Jackson, 2022). If violent texts were used to assess risk, it seems certain that Rodwell would have been flagged for potential violence. Yet, with Tinder’s current model, no preventative action was taken until after 5 assaults had already occurred. Even then, legal action was the only reason that Rodwell was able to be stopped.

The second key case study surrounds Emily C., a woman who was assaulted by a man she met on Bumble (Picciani, 2020). This case provides a good picture of the after effects of violence on dating apps, as well as the perspective of victims on dating app's role in sexual assault prevention. After her assault, Emily reported the man using Bumble's report feature. Shockingly, she saw him appear again and again on Bumble, Tinder, and other dating apps. According to Emily, "It's like being assaulted twice … They failed their users" (Picciani, 2020). Through speaking with her and other women who are victims, Picciani found that many victims never think to report sexual assault to dating apps or, if they do, don't think that these companies could have any role in actually preventing further violence. Emily's futile reports and other users' lack of faith in prevention go hand in hand. Until users are educated on real-life prevention being done by software companies, they will not actually use the systems put in place. The fact that even basic report systems now are not being used, means that for more complex systems such as artificial intelligence models, user adoption and education are extremely important.

Results: Artificial Intelligence Literature Review

In terms of actually creating a viable risk assessment algorithm, the literature shows that natural language processing is a realistic option for interpreting violence from text. NLP has been specifically used to "extract and classify instances of interpersonal violence" (Botelle, 2022) from text records. This model was able to identify perpetrators from victims and, crucially, was able to distinguish occurrences of sexual assault at a very high rate (almost 100% recall). Although this model used more clear-cut text obtained from mental healthcare transcripts as opposed to text messages between people, it is a sign that NLP can be used to identify sexual assault from written text. In terms of more informal text, another NLP model that used Twitter text to identify potential intimate partner violence (Al-Garadi, 2022). Unlike the study that used more formal records, this model uses plain tweets found by searching on keywords. The data was collected by manually searching tweets and labeling them as violent or non-violent. They claim that their model "can be an essential component for a proactive social media-based intervention and support framework, while also aiding population-level surveillance and large-scale cohort studies" (Al-Garadi, 2022). Beyond that, this model also showed no gender or racial bias. This makes it very clear that matchmaking companies could use messaging data to label conversations as "violent" or "non-violent". Even a model as simple as this to help flag dangerous accounts would be miles ahead in preventing sexual assault compared to the current system where users are only banned after being officially reported many times.

Legal Review

This proposed system, like any attempt to mitigate sexual assault, is certainly influenced by legal actors such as the police and the court system. Current communication between software companies and law enforcement is very limited. In terms of communication from matchmaking companies to police, the ability to share data is not the problem, as matchmaking companies already have the proper Terms and Conditions to share data with law enforcement. Tinder's official policy is that they "[work] to promptly investigate reported crimes, assess and take appropriate action, and fully cooperates with law enforcement in any investigation" (Tinder). However, this relies on users actually reporting crimes to law enforcement in the first place. Given that sexual assault is the most under-reported crime with around 63% of sexual assaults being unreported (National Sexual Violence Resource Center, 2015), relying on reports to law enforcement is not a very viable option. In an attempt to seek out some of these unreported cases, law enforcement such as the New South Wales police department has asked companies for a "portal" for police to access reports of sexual assaults made to dating apps, but not yet to the police (McCormack, 2021). This same police department even proposed an AI flagging system much similar to the one I am proposing. Match Group (the company that owns Tinder and Hinge) declined both proposals.

In essence, the problem is that Tinder is unwilling to provide user data to police unless that user has already reported to the police, but most sexual assaults go unreported to law enforcement. The reason that many sexual assaults reported to dating applications are not reported to police is primarily because victims do not believe that a report to the police will result in any significant effect (Kimble, 2018). It becomes clear, then, that social efforts to increase the report, prosecution, and conviction rates of sexual assaults are a crucial component of mitigating sexual assaults connected with dating apps. Simple changes in law enforcement methods such as using Sexual Assault Nurse Examiner or SANE programs to speak with victims results in much higher prosecution and conviction rates (Bulman, 2009). Changes like this can help increase report rates by combatting the belief that reporting to law enforcement has no effect. Increasing legal reporting has exponential effects on decreasing sexual assault, it would directly increase the number of prosecutions and convictions, which is turns increases the amount of data shared, which increases convictions again, and so on. Beyond direct effects, if report rates are increased and communication between software companies and law enforcement increases too, there would be positive effects for the proposed risk assessment model as well. There will be more data and, more importantly, more accurate data as more training data can be properly labeled as an instance of assault if there are more reports. Thus, social change such as implementing SANE programs is a crucial piece in mitigating sexual assault by increasing communication between law enforcement and matchmaking companies.

Discussion

Preventing sexual assault is an extremely complicated problem with many actors at play. It is only through the combination of social efforts such as implementing SANE programs and technological advancements such as NLP risk assessment models that real substantial change will happen. This is made even more clear through the lens of actor network theory. Delegating all of the responsibility to a risk assessment model would certainly be unsuccessful: people are needed both to actually use the risk assessment model to influence their decisions and to actually build the training dataset through reports. However, social aspects such as current legal systems can't even get most victims to report assault, let alone prevent or punish it. Clearly, the technical and social aspects must be combined, but it is not so simple as to just implement social and technological change at the same time and hope that it fixes things. The changes must be executed for and with each other. For example, engineers must consider Latour's idea of inscription when building the risk assessment model. Engineers must make assumptions about how users view AI. Will they trust it at all? Will they blindly follow it? The answers to these questions must be inscribed in the technology when designing the risk assessment model or even the strongest model will not be used properly. It's clear from the SANE program that sexual assault response benefits greatly from being culturally sensitive, developmentally appropriate, and trauma-informed. Thus, these moral values must also be prioritized in any reporting system as well or, through Latour's language, prescribed into any reporting technology that is developed. Although there are many complex actors at play, one thing remains clear: we do have the tools to mitigate sexual assault. Legal and software systems must implement more accommodating report systems and software companies must investigate risk assessment models using NLP.

Matchmaking software companies are not alone in facing the decision of whether to use AI risk assessment models or not. Risk assessment in other fields, however, does not face many of the same challenges. In medicine, using AI to diagnose a patient using an X-ray does not factor in social factors such as race nearly as much as trying to classify potential violence (Hogan, 2021). Still, the conclusion that companies must emphasize trust and education surrounding AI models holds. Through looking at extremely serious cases such as sexual assault, we can see that users not having trust that companies have their best interests in mind leads to less people using the protection features.

Given that my proposed solution is essentially an extension of a few academic papers that did not involve real world application, there are many limitations to this research. Possibly the biggest limitation on creating a risk assessment model would be creating the data for the training set itself. In Al-Garadi's paper that used Twitter text to assess risk, they manually went through tweets with keywords and labeled them as violent or non-violent. If matchmaking companies did a similar approach, they would be guessing which interactions were violent and which were not. This would mean that the algorithm is way more broad and likely assigning risk in way more places than it actually occurs (which could be a viable choice, but is definitely not ideal). If companies were to use text surrounding instances of reported violence, the model would be much more accurate in labeling interactions as violent. However, given that current report rates are low, the model would be relying on a small number of cases. Building an accurate risk assessment model is still possible, but would require significant effort to obtain a good training dataset.

In the future, further study should introduce expert opinions such as people in positions of power at matchmaking software companies and leading experts in NLP. Leaders at software companies could provide a key perspective into whether a risk assessment model would be legally sound and trusted by the user base. To turn this hypothetical into reality, employees of dating app companies would have to be consulted. Secondly, further study would need to consult leading experts in NLP to answer questions of how a dataset could be built and whether there would be implicit bias in the algorithm. Even though it appears that we could simply extend existing models to make a sexual violence risk assessment model in dating apps, experts in the field would certainly have to be involved to actually build it.

Beyond the direct applications of this research, I believe that there are several key takeaways that I can generally use as a software engineer. First of all, this research shows that when developing any outward facing tool, the user base must be considered. Specifically, in the case of many dating apps' report systems, the feature is severely underused because reports are viewed as not having any effect. This shows that if you don't take action from user input, that user input will stop coming. More broadly, it shows that no tool is beyond the importance of user trust. Secondly, if I ever find myself in a more managerial role deciding which way to approach a new problem, I will be far more likely to use academic literature. In this case, there were many similar risk assessment models that gave me key insight into whether my idea was actually possible or not. Especially regarding AI, the most recent solutions for problems may come from academia and not the corporate world.

Conclusion

Currently, matchmaking software companies are clearly not doing enough to prevent sexual assault. Inconsistent report systems with low usage rates have little effect on stopping even the most obvious repeat offenders. Dating applications have more than enough information to improve risk assessment within their systems by using natural language processing among other technologies to predict when encounters may include violence. Combining this risk assessment model with social change such as implementing SANE programs would increase report rates, data for the model, and thus mitigate sexual assault. The two areas of this topic needing the most further research are the development of an actual model, specifically building a significantly sized dataset to train on, and the expansion of user trust in the system itself. The proposed approach is by no means a perfect solution— it may not even be accurate enough to use in the real world. However, it remains clear that dating applications play too large of a role and have too much data on their hands to not try to develop some type of preventative measure against sexual assault.

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