Politics of Designing a Digitally Personalized Experience

A Research Paper submitted to the Department of Engineering and Society

Presented to the Faculty of the School of Engineering and Applied Science

University of Virginia, Charlottesville, Virginia

In Partial Fulfillment of the Requirements for the Degree
Bachelor of Science in Computer Science

By

Kaleb Getachew

Spring 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.

Advisor

Sean Ferguson, Department of Engineering and Society

What is Digital Personalization?

Within a daily occurrence, people are faced with many decision-making situations countless times, many of which are unconscious. Naturally, experts or friends are the first point of contact to aid in decision making, but with the widespread use of the internet of things (IoT) within the 21st century, the transfer of information has become very rapid, leading to the tracking and storing of user data for data driven personalization. This has placed a lot more influence and power on the part of large technology companies.

Throughout the summer of 2021, my responsibilities as a Software Engineering Intern within the World Ready Team at PayPal included all things related to preparing the product for the world and vice versa. I worked in conjunction with two other interns and various other professionals from different departments to ensure users from all sectors were tended to and had a meaningful experience while interacting with the company's product suite. Furthermore, the team worked specifically on converting, preparing, and personalizing Polish data for live use this upcoming year. The overarching task was to improve user satisfaction whenever users would visit the page, through the use of relevant Natural Language Processing (NLP) models. This meant ensuring everything displayed is easily understood, accessible, and most of all relatable for each user. All of which was achieved based on data collected on each individual user.

At the core of creating a personalized digital experience, recommender systems play a huge role in engaging users. With the recent advances in Artificial Intelligence (AI), data analytics and big data over the past years, opportunities have arisen for recommender systems to embrace the impressive achievements of AI. Recommender systems create advanced insights into the relationships between users and items, presenting more complex data representations, and discovering comprehensive knowledge in demographical, textural, virtual and contextual data. Streaming services are one such medium that have a major influence on the reasoning and way of thinking of the users. Big Technology Companies (BTCs) like Netflix create a personalized web/digital-experience based on consumer collected data to intentionally improve overall customer satisfaction amongst many other unintended consequences. Before delving into the world of 'personalization', this term must be defined. Throughout the remainder of the paper, the Oxford Academic definition of personalization will be used; it is the "strategic creation, modification, and adaptation of content and distribution to optimize the fit with personal characteristics, interests, preferences, communication styles and behaviors (Bol, 2018)." This paper will aim to investigate the consequences and potential use cases of creating a personalized digital experience, specifically through Recommender Systems.

Case Study: Netflix

In order to explore the effect and potential use cases of digital personalization, we can look at a specific case study in a much larger context of BTCs that utilize user data for the sake of customer satisfaction and retention. One such company is Netflix and their cunning use of recommender systems and algorithms. This STS topic will evaluate the consequences as well as the potential use cases of creating a personalized digital experience through the use of recommender systems.

Netflix was founded in 1997 in the United States. The company was originally intended to be a mail video club, wherein users would order movies on their website and receive them via mail. With time, the company launched video-streaming services as a complimentary service to their DVD mailing enterprise. The popularity of the on-demand service grew exponentially (from 2007 to the present) and the streaming was offered as a stand-alone service in November of 2010. Netflix as a BTC has a goal of “entertaining the world, whatever your taste, and no matter where you live, we give you access to best-in-class TV shows, movies, and documentaries. We’re streaming in more than 30 languages and 190 countries, because great stories can come from anywhere and be loved everywhere (Netflix, 2021).” Netflix imagines a future where people from across the world and languages rely on their platform to be entertained.

Much of Netflix’s rise to popularity can be attributed to their pioneering efforts in the streaming industry. They were one of the first BTCs that had played a major role in creating the streaming world, by utilizing all of the current advancements made in technology. One of their clear and powerful tools of achieving this futuristic goal has been their recommender systems and algorithms. Through this they have been able to retain their popularity and influence within the world. However, much is entailed to achieve a goal of that magnitude.

There have been many institutions that have studied the implications of algorithms on the creative process. While crafting Netflix’s original title ‘House of Cards’, and the possible outcomes and consequences of those decisions for user’s behavior and further content creation. Ed Finn, a tenured Arizona State University Professor and author of “What Algorithms Want: Imagination in the Age of Computing”, argues that “this app has assembled a sophisticated algorithm model for describing the cultural relationships among individual film and television works, a model that fully embraces the gap between computation and culture (Finn, 2017).” Coupled with their yearly rise in subscribers, from only having 22 million in 2011, to skyrocketing to 214 million in 2021, their influence seems to only be exponentially increasing. Through their algorithm they have been able to quantify many different tags and emotions of films to better equip their recommender systems. This begs the question of Netflix’s moral and ethical responsibility, if any, to moderate what they publish towards a huge global audience.

Furthermore, we have to consider the question of how truly reliable these algorithms and recommender systems truly are, and to what extent they are an “objective force”. An “objective force” in the sense of providing an unbias result for a given problem. Even if they are deemed as an “objective force”, the abstraction of the models does not result in an objective result. Information becomes lost in translation when data is being wrangled and interpreted. By the beginning process, the raw data is considered to be the full knowledge, in context, and at the end of the process a result is reached, but for reasons unknown. In addition, that same result has to be contextualized to fit the problem at hand, which means more human involvement, which could lead to more bias and uncertainty on the part of the “objective force”.

Impact and Responsibility of BTCs

The digital streaming industry is very unique from any other industry in the fact that it is able to create an immersive experience, both visually and audibly, for the individual user to learn and experience various stories, accounts, and tales from across the real and fictional worlds. Throughout history the concept of diversity has evolved and its evolution has been fundamental in shaping relationships between people. Dating back to the 18th century, many intellectual circles took to foreign countries to broaden their minds and learn more about the world and its intricacies, thinking a better person would know more about the world they live in. Through the wake of the ‘discovery’ and conquest of the New World, reflections and inspiration on foreign practices, attitudes and ways of living had become commonplace (Grenier, 1989). Meaning that through diversity people are able to fully understand one another through their thoughts and ideas.

With the evolution of technology, the way we interact with others across the globe has also changed dramatically. The ideas and history of people throughout the world and time is accessible with a touch of a button. According to Natalie Helberger, a professor of Information law at the University of Amsterdam, states that there are three main frameworks to highlight the way people think, in terms of diversity. They are: *individual autonomy, deliberative autonomy* and *adversarial autonomy* (Helberger et al., 2018).

Under an *individual autonomy* perspective, the idea is to give individuals a tool to exploit their different interests. This is what most recommender systems are built for and are also known as 'content-based recommender', they extend the individuals a choice providing them with more opportunities to realize their interests. In this case, we can imagine recommender systems and algorithms providing users a set of films they would be most interested in. The issue with the individual perspective is the lack of change, users will be recommended very similar titles and will more than likely stick to "what sells".

Pursuing a *deliberative* perspective, the aim is to promote the public debate, showing divergent opinions and helping people in constructing a critical view. Here, recommender systems can be designed to make users explore films far from their preferences that they otherwise would not think to entertain, this makes them aware of the unknown parts of the film panorama.

With an *adversarial* perspective, the focus is to broaden the debate highlighting non-dominant visions. Similar to the previous case, recommender systems can serve as a way to promote underrepresented groups, whether subcultures or non-mainstream film styles, through a non-regulated manner. This allows other independent filmmakers an opportunity to contribute to the conversation through their films.

Along with the three frameworks described above, recommender systems themselves are not completely reliable, the technical brilliance that is poured into them is not without its faults. Milano et. al (2020) considers the many facets of ethical challenges that are incorporated to building recommender systems. There are a total of four main areas of ethical concerns that I have chosen to highlight. They are, Inappropriate Content, Privacy, Autonomy and Personal Identity, and Social Effects.

As mentioned before, Netflix works in a global market, reaching audiences across the entire globe. Certain regions and countries have their own moral standards they abide with, which may be contrary to another region/country's beliefs. Souali et. al (2011) considers the issue of recommender systems that are not culturally appropriate, and proposes a form of 'ethical database'. This database would essentially contain relevant and appropriate content for each country/region of the world. Through this method, viewers from each country/region would choose from a pre-selected database of content to consume. The only work on the side of Netflix would be to create the 'ethical databases' beforehand for each specific region/country.

Privacy issues are one of the primary challenges that recommender systems face, this seems inevitable due the majority of the commercially successful recommender systems are based on a hybrid or collaborative filtering techniques that heavily rely on user data in addition to user choice. Privacy risks occur in at least four stages of any professional setting. First, they can arise at the point of data collection or even without the user's explicit consent, through illicit tracking or purchasing from other companies. Second, once the data is stored, there is the further risk it may be leaked to external agents, or become subject to de-anonymization attempts (Narayanan 2008). At both stages, privacy breaches expose users to risks, which may result in loss of utility or in rights violations. Third, and independently of how securely data is collected and stored, privacy concerns also arise at the stage of inferences that the system can (enable one to) draw from the data. Users may not be aware of the nature of these inferences, and they may object to this use of their personal data if they were better informed. Privacy risks do not only concern data collection because, for example, an external agent observing the recommendation that the system generates for a given user may be able to infer some sensitive information about the user (Friedman et al. 2015). Extending the notion of informed consent to the indirect inferences from user recommendations appears difficult. Finally, there is also another subtle, but important, systemic issue regarding privacy, which arises at the stage of collaborative filtering: the system can construct a model of the user based on the data it has gathered on other similar users' interactions. In other words, as long as enough users interact and share their data with the system, the system may be able to construct a fairly accurate profile even for those users about whom it has less data. This indicates that it may not be feasible for individual users to be shielded completely from the kinds of inferences that the system may be able to draw about them. It could be a positive feature in some domains, like medical research, but it may also turn out to be problematic in other domains, like recruitment or finance.

The user-centered recommendation framework proposed by Paraschakis (2017), also introduces explicit privacy controls, shifting the power from the hands of the BTCs to the people. Users will be able to decide whether their data can be shared, and with whom. However, user-centered approaches have their limits, as they may constitute a mere shift in responsibility, placing an undue burden on the users. Would this responsibility be fairly placed on the users? Or rather does it belong with the companies themselves? One potential problem within this solution is the addition of more metadata. The recommenders systems can make sensitive predictions about the user based on their privacy settings, for example, a user who has a very private approach to data sharing could be labeled as "paranoid", drawing out more data than intended. It seems that regardless of where the power of privacy lies, there will always be some amount of information being taken from the users. For this reason, ethical steps need to be taken at the macro level, ensuring that all the major problems with privacy are addressed.

Recommender systems can encroach on individual users' autonomy, by providing recommendations that nudge users in a particular direction, by attempting to "addict" them to some types of contents, or by limiting the range of options to which they are exposed (Burr et al. 2018). These interventions can range from being benign (enabling individual agency and supporting better decision-making by filtering out irrelevant options), to being questionable (persuasion, nudging), and possibly malign [being manipulative and coercive (Burr et al. 2018)]. Recommender systems attempt to draw commonalities between similar users no matter how absurd the commonalities may be. For example, the household size. Although it may not seem worthy of holding information, recommender systems could find a commonality between certain groups of people and claim that feature is statistically significant. By classifying users into a particular demographic, recommonder systems could 'trap' their users into viewing the same set of content for a period of time. It is imperative that the three frameworks mentioned earlier need to be utilized within all recommender systems. By providing a diverse set of content, users will have the option to pick and choose which titles intrigue them, without necessarily 'trapping' them into 'what sells'.

Partly intentional, recommender systems being used within the news and social media industry, by nature tend to run the risk of insulating users from exposure to different viewpoints, creating self reinforcing biases and ‘filter bubbles’ that are damaging to the normal functioning of public debate, group deliberation and democratic means. As mentioned previously, the way humans interact has evolved along with technology. This feature of recommender systems can have a negative effect on social utility and interaction. In fact, a recent study on the spread of propaganda against vaccines has been linked to a decrease in herd immunity (Burki 2019). In turn, the dissemination of misinformation has led to the decreasingly lower chances of immunity for the entire population. Issues such as this not only affect the people spreading propaganda but also the whole of the population. This begs the question of the responsibility that these BTCs have in mediating the content that is being shared on their platform.

Discussion

Now that we have a thorough understanding of the world of recommender systems, and their role within BTCs, we have now evaluated the role these companies play and what responsibilities they should or should not have. Firstly, it should be noted that the creation of a personalized digital experience is not only just centered around the recommender systems or algorithms. The entirety of the experience begins from user data collection, to storage and management, to analysis and preprocessing, and then it is finally fed through into the recommender systems to arrive at a potential list of content to recommend. Human created tactics to use the systems and algorithms are also just as important, the engineers who run these infrastructures play a very large part in determining the effect of the whole process.

Examining the data collection process for creating a personalized digital experience by BTCs, we notice that most of the data collection is derived from use of the BTCs’ platform. For example with Netflix, although they retrieve basic information such as names, gender, and age, a vast majority of the data is based on what titles users have seen and what similar people have seen.

Data storage and management is solely attributed to the companies that hold the user's information. In the past Netflix has had previous data breaches regarding watch history, information, and even unreleased titles within certain regions/countries. Some ways to ensure that companies' storage and management methods are up-to-date are to require specifications regarding the software and frequent testing of company resources. Although breaches are inevitable, efforts must still be made to protect their user audience.

Analysis, preprocessing and the engineers that work with the technology play a very managerial role in terms of being responsible for the day-to-day maintenance and operation of the recommender systems. It is imperative to have educated engineers in charge of these operations to handle any nuanced challenges with the right ethics and people in mind. In addition, it is also important to have others around the technology community to observe and keep the power and responsibilities of the BTCs in check. Without any sort of checks and balances between the people and large institutions, they will dominate all facets of human life.

Conclusion

Through this exploration we can see that the creation of a personalized digital experience through the use of recommender systems is the evolution of the digital world. The nearly infinite potential of these systems is something to marvel at within the world of technology, however, strong actions and regulations need to be enacted to ensure that BTCs are handling their power in an ethical and effective manner.

References

Adomavičius, G., Bockstedt, J. C., Curley, S. P., & Zhang, J. (2013). Do Recommender Systems Manipulate Consumer Preferences? A Study of Anchoring Effects. Information Systems Research, 24(4), 956–975. http://www.jstor.org/stable/24700286

Biddle, Gibson. "A Brief History of Netflix Personalization (Part One, from 1998 to 2006)." Gibson Biddle's "Ask Gib" Product Newsletter, Gibson Biddle's "Ask Gib" Product Newsletter, 17 May 2021, https://askgib.substack.com/p/a-brief-history-of-netflix-personalization.

Bol, Nadine, et al. "Understanding the Effects of Personalization as a Privacy Calculus: Analyzing Self-Disclosure across Health, News, and Commerce Contexts†." *Journal of Computer-Mediated Communication*, vol. 23, no. 6, 2018, pp. 370–388., https://doi.org/10.1093/jcmc/zmy020.

Burr C, Cristianini N, Ladyman J (2018) An analysis of the interaction between intelligent software agents and human users. Mind Mach 28(4):735–774. https://doi.org/10.1007/s11023-018-9479-0

Dean, Brian: "Netflix Subscriber and Growth Statistics: How Many People Watch Netflix in 2021?" *Backlinko*, 7 Oct. 2021, https://backlinko.com/netflix-users.

Finn, E. (2017). What algorithms want: Imagination in the age of computing. Cambridge, MA: MIT Press

Fischer, Sara. "'Squid Game' Becomes a Massive Hit." Axios, 5 Oct. 2021, https://www.axios.com/squid-game-netflix-massive-hit-d68c4890-bfc4-4255-bb98-db8b36347617.html.

Friedman, Arik, et al. "Privacy aspects of recommender systems." Recommender systems handbook. Springer, Boston, MA, 2015. 649-688.

Grenier, L. (1989). From diversity to difference: The case of socio-cultural studies of music. New Formations, 1989(9).

"History of Recommender Systems: Overview of Information Filtering Solutions." Onespire Ltd. - SAP and Management Consulting, 20 Sept. 2021, https://www.onespire.net/news/history-of-recommender-systems/.

Horev, Rani. "Bert Explained: State of the Art Language Model for NLP." *Medium*, Towards Data Science, 17 Nov. 2018, https://towardsdatascience.com/bert-explained-state-of-the-art-language-model-for-nlp-f8b21a9b6270.

Jackson, Dan. "The Netflix Prize: How a $1 Million Contest Changed Binge-Watching Forever." Thrillist, https://www.thrillist.com/entertainment/nation/the-netflix-prize.

Koren, Yehuda. "The BellKor Solution to the Netflix Grand Prize" Netflix Prize, Aug. 2009, https://www.netflixprize.com/assets/GrandPrize2009_BPC_BellKor.pdf.

Matrix, Sidneyeve. (2014). The Netflix Effect: Teens, Binge Watching, and On-Demand Digital Media Trends. Jeunesse: Young People, Texts, Cultures. 6. 119-138. 10.1353/jeu.2014.0002.

Milano, S., Taddeo, M. & Floridi, L. Recommender systems and their ethical challenges. AI & Soc 35, 957–967 (2020). https://doi.org/10.1007/s00146-020-00950-y

A. Narayanan and V. Shmatikov, "Robust De-anonymization of Large Sparse Datasets," 2008 IEEE Symposium on Security and Privacy (sp 2008), 2008, pp. 111-125, https://ieeexplore.ieee.org/document/4531148

Netflix Technology Blog. "Selecting the Best Artwork for Videos through A/B Testing." The Netflix Tech Blog, Medium, 3 May 2016, https://netflixtechblog.com/selecting-the-best-artwork-for-videos-through-a-b-testing-f6155c4595f6.

Paraschakis D (2018) Algorithmic and ethical aspects of recommender systems in e-commerce. Malmö. http://muep.mau.se/bitstream/handle/2043/24268/2043_24268%20Paraschakis.pdf?sequence=3&isAllowed=y

"Privacy Statement." Netflix Help Center, https://help.netflix.com/legal/privacy#cookies.

Porcaro, L., Castillo, C., & Gómez, E. (2021). Diversity by Design in Music Recommender Systems. Transactions of the International Society for Music Information Retrieval, 4(1), 114–126. DOI: http://doi.org/10.5334/tismir.106

Roettgers, Janko. “How Netflix Reinvented Its Marketing on Social Media.” Protocol, Protocol - The People, Power and Politics of Tech, 13 Oct. 2020, https://www.protocol.com/netflix-marketing-to-targeted-audiences.

“Stories Move Us.they Make Us Feel More Emotion, See New Perspectives, and Bring Us Closer to Each Other.” *About Netflix*, https://about.netflix.com/en.

K. Souali, A. El Afia and R. Faizi, "An automatic ethical-based recommender system for e-commerce," 2011 International Conference on Multimedia Computing and Systems, 2011, pp. 1-4, https://ieeexplore.ieee.org/document/5945631

Zhang, Q., Lu, J. & Jin, Y. Artificial intelligence in recommender systems. Complex Intell. Syst. 7, 439–457 (2021). https://doi.org/10.1007/s40747-020-00212-w.