The Recommendation Systems Behind Today’s Echo Chambers
Aayushi, Peter, Chris

Introduction

The world is a complicated and scary place. With thousands of companies and millions of products, the overload of choices in one’s daily life can be overwhelming. Algorithms are becoming autonomous and more powerful. How can an individual be expected to sort through all possible options available to them when looking for new music on Spotify, or pick their next read from the near endless selection of books on Amazon? It would take over 5 years of non-stop rocking to sample each of the 35 million songs on Spotify for just 5 seconds, and, assuming you’re a fast reader, over 11 years of reading to go through the synopsis of the over 12 million books available on the Amazon Kindle. No ordinary individual could possibly spend that much time finding things they might enjoy. Enter recommendation algorithms. However, these algorithms along with narrowing down the choices user have are also impacting the decisions users take. A doctor won’t question if an algorithm suggests signs of cancer, or a military man won’t question to shoot in the location recommended by the algorithm.

Recommendation algorithms come in all shapes and sizes from collaborative filtering and matrix decomposition to clustering and deep learning. Each system is complex in its own way and differs in how they take in and process data, but they all share one key similarity— purpose. Recommendation algorithms are made to recommend! They are employed by companies to take in user data to generate a list of suggested future content or products for the purpose of increasing user retention. Netflix’s algorithms show users shows they might like to win screen time and Amazon shows users products they might like to squeeze a little more cash from their wallets. These algorithms are incredibly useful tools for companies to give users what they want while also helping users to not be overwhelmed by too many choices. Sounds like a win-win, but is that really the case?
How much can recommendation systems really be trusted? All of the examples brought up so far have been limited to the entertainment and retail industries, but the reach of recommendation systems is much further than that. Algorithms that make recommendations are present almost everywhere. They don’t just help people decide what to watch next, they also aid doctors making diagnoses and commanders in reaching decisions. In the heat of the moment, it may be difficult to question the validity of the conclusion the algorithm has reached despite the impact that conclusion may have on the lives of countless people. With lives potentially on the line, the data that recommendation systems use to operate must be spot on for the given circumstances, and even if the data is perfect, end users should be wary of what the algorithms are giving them.

Properly feeding in the right data to recommendation systems is fundamental to ensuring they behave as expected especially when the stakes are high, but overtraining can lead to another fundamental problem, and that is the echo chamber effect. Users who follow recommendations that are given to them might find themselves falling down a rabbit hole of similar content constantly being thrown at them by the system. The problem exacerbates because the data for such system is fed in real time. Thus, being fed the same data for a user, makes the data bias. In such a case the user experience may begin to degrade and that’s not a good thing, but is it harmful? In most cases, probably not; flawed systems will just cause users to become disengaged and cause the company to lose money. Being exclusively recommended songs by Taylor Swift on Spotify might make for a bad experience but it doesn’t harm the user. On the other hand, being recommended fake news or articles that promote bigotry and hate on Facebook might make the user happy as it may reinforce their beliefs, but it could have negative repercussions to other users in the system and perhaps even some outside it.

Recommendation systems are a fundamental tool in helping companies keep customers engaged and interested in their products and services while also removing a great deal of the mental stress from over choice faced by users. The benefits of recommendation systems can improve the lives of consumers and the profits of
companies if properly utilized, but the risks and flaws of such systems must be taken into consideration when they are being built. A company can only truly realize the benefits of a recommendation system and ensure an improved user experience if they develop their algorithms in a way that ensures consistent, reliable results without overtraining to the point where the echo chamber effect can negatively impact the system and its results.

**Supporting Detail**

The autonomous learning algorithms used in the field of recommendation commonly fall into two categories — content-based and collaborative filtering methods, with the latter being the one that is more commonly implemented.

Content-based recommendation algorithms suggest items to the users from lists of hundreds if not millions of potential options. It does this by matching candidates with one another based on their similarities. Data from these matched candidates is processed and used to generate new recommendations for the pair or group while ignoring data from users outside of the cluster. For example, Spotify can detect what songs users like and dislike from the number of playbacks they have for a song and recommend other songs of the same genre of the pieces that the user shows a preference for.

A content-based recommendation approach may seem straightforward and intuitive, but does not allow for new items to be introduced to the user. If the algorithm only produces suggestions based on the user’s historic viewing and ‘like’ ratings, any content that is deemed uninteresting per the user’s personal preference will not be shown. In this sense, content-based recommendation algorithms will fail to expand the horizons of their users, leading to a possible echo chamber.

Modern-day recommendation systems most commonly implement collaborative filtering methods, as it is the more mature option. For you as the end user, Spotify has a good idea of what songs or artists you prefer and keeps a list of them. Your music preference list is compared to that of every other user Spotify has and the algorithm identifies which user lists have the greatest overlap with your own. Items from these
selected lists that you have not yet listened to are then recommended to you in your ‘Discover Weekly’ playlist. This should contain the songs or artists that people with a similar music taste to your own listen to on a regular basis.

Now, let’s look under the hood. These content and collaborative filtering algorithms are commonly powered using machine learning algorithms. The aforementioned ‘lists’ that Spotify creates for each user in its user base when implementing collaborative filtering algorithms is essentially a matrix of 0s and 1s. These entries do not necessarily have to be tied down to a specific song, or artist— they could be indicative of other features, such as preferred tempo range or preferred vocalist genre. These matrices are then compared to one another using similarity features to determine how closely aligned the data each matrix represents is, and product and item recommendations are pulled from the highest similarity ranked matrices.

Just like that of a content-based recommendation system, a collaborative filtering method also sounds simple and intuitive. Logically, you’d want to find people with similar music tastes, and recommend to one based on what others like them are listening to. However, over specialization of content is still prevalent within collaborative filtering. These filtering algorithms recommend items based on previous users’ ratings and viewings. As a result, the suggested products are typically already have an extensive list of user interaction, in lieu of other results that the user actually would would be looked upon more favorably by the user that might be newer and lacking in historical data.

**Potential Solutions**

One such potential method to resolve these issues with the recommendation systems is using a person in the middle. This solution combines human expertise with computer efficiency, primarily helping to keep a check on the suggestions that end up being shown to the end user. Recommendation systems built primarily based on machine learning algorithms are dependent on data. With the data being updated in real time for recommendation systems, the data used on the model might become biased
itself. This is due to how recommendations are generated — if users subscribe to the suggestions the algorithms offer, their tastes are guided towards what the data indicates they should like. And when their data is used to propose items for other users, these suggestions can compound. If companies trust autonomous algorithms with no checks in place on the data or resulting suggestions, the recommendations can circle in on itself, and be biased. By adding human involvement in the pipeline, monitoring for data overfitting can be accounted for.

Giving people more control over their feed is a potential solution providing user multiple views of the content and favoring exploration. However, this requires selecting the content with which the user should start thus making the overall implementation of the algorithm difficult. This would lead to a cold start (determining content for a new user) and would require to treat every user whenever the user wants to determine the content of the feed.

Another possible solution is opposite extremism. This method involves switching the content displayed to the other extreme, in an attempt to radicalize the substance shown. Google Jigsaw current utilizes such a method in its projects tackling the subject of violent content online. The algorithm is trained to display content from the opposite spectrum should it detect that the user viewing violent content. Advancing this and providing opposite or different content to the user, in general, would fix this problem of over-specialization.

Categorizing some topics as to not amplify topics can prevent the echo chamber effect, especially for negative content. This implementation requires segregating that content for each user that has been viewed multiple times. This implementation requires that once some content has been viewed multiple times over a period of time, the content should not be specialized anymore, the results should be radicalized.

**Necessary Infrastructure**

In order for a solution to the concerns surrounding the over specialized suggestions current day recommendation algorithms produce to exist and be supported, software companies providing services utilizing such systems within their products must
recognize the dangers of overtraining without regularization on the data amassed. Recognizing and internalizing these concerns only serves to move forward with legislation that will in turn, better introduce regulations on the kinds of curated content users are shown in their news sources and data feeds.

**Metrics of Success**

The metrics of success for any software or algorithm are different as per various perspectives, they are: For a technical system designer, it is *how efficient is this algorithm?*, For an end-user, it is *does this system give me cool results and better results?* For a marketer, it is *does this system help me push product?*

Looking at the system designer and end user aspect- after using the potential solutions- the success could be measured as:

1) Using a person in the middle: The algorithm’s efficiency in itself is not impacted because of this approach. However, human interaction makes the overall process slow. This would definitely improve the content provided to the end user but if the overall processing is slow the user experience may be impacted.

2) Giving people more control over feed: This would enhance the user experience, but it requires additional algorithms for maintenance. This requires algorithms to provide content which is not biased by any factor related to the user, however still provides results accordingly.

3) The opposite extremism: Implementing such algorithm where opposite content is displayed for particular users is not that difficult. This affects users by providing content that is at a totally different extreme. This would satisfy some users. The others who want to watch such content would be affected negatively. Also, this algorithm only solves the problem of repetitive display of negative content and no potential effect on other problems.

4) Segregating “do not amplify topics: Although this has a similar impact on users as the opposite extremism, implementing this idea is easier. Also, this solution too only solves the echo chamber of negative content.
Next Steps

First and foremost, there must be a conversation about the potential issues that come along with recommendation algorithms, and, luckily, it seems that this conversation has already started. Users of major media platforms have begun to speak out and companies are taking action. Facebook has said that it will take on the spread of fake news on its site and Youtube has taken steps to prevent videos promoting conspiracy theories from showing up in users’ suggested feed. These actions are major steps toward improving recommendation systems that are already in place, but will they be enough?

We cannot rely on companies to act within the best interest of society on their own. Government regulation is not the right solution for this situation. There is no way to regulate trust in an algorithm and it would be tricky to implement any form of legislation to resolve the more serious side echo chamber problem. As annoying and deceptive as fake news and conspiracy theory videos and stories may be, it is not the government’s place to decide what news and ideas should or should not be available online. It falls to the individual platforms to take responsibility to prevent echo chambers of conspiracies and hate from forming by excluding these forms of content from their recommendation systems, and the only way to get companies to do that is through conversation. Facebook and Youtube did not act on a whim, they took the actions they did in response to public outcry. Users spoke out and held these big companies accountable for what was happening on their platforms and it was the combined voice of the concerned majority that brought about change.

The use of data in the modern day can be scary. Big businesses have a lot of information that they can and do use, sometimes in ways that are not ethical. It is up those who are knowledgeable on what data is being collected and how it is being used to inform the masses so that the conversations that need to be had can begin. Public opinion is the best way to pressure organizations into change while also bringing attention to potential legislation that needs to be made. Speech has allowed for the communication of ideas and has helped us build the impossible. Having conversations
about technology will not only bring about new innovations but also make sure that we remain skeptical of the things we create. Technology can only be worthwhile to everyone if the concerns of all are heard and addressed.
References

Click Here to Kill Everybody, Bruce Schneier

https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=7148534
https://www.wired.com/story/creating-ethical-recommendation-engines/
https://redirectmethod.org/pilot/#results
https://blog.statsbot.co/recommendation-system-algorithms-ba67f39ac9a3
https://www.researchgate.net/post/What_are_the_open_problems_in_collaborative_filtering_recommenders
https://www.quora.com/How-many-songs-are-there-in-Spotify-in-total
https://www.kdpcommunity.com/s/question/0D5f400000FHsBVCA1/how-many-books-are-there-for-sale-on-amazon?language=en
https://blog.statsbot.co/recommendation-system-algorithms-ba67f39ac9a3
https://www.complex.com/music/2019/01/youtube-removing-conspiracy-theories-from-recommended-videos
http://people.stern.nyu.edu/padamopo/On%20Over-Specialization%20and%20Concentration%20Bias%20of%20Recommendations.pdf