Final Project Paper for CS 3950

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1 Introduction

For our research proposal, we decided to analyze the YouTube video recommendation system, specifically when it comes to political videos. Professor Mislove's paper is about Facebook's ad delivery system and how it can be gamed to target ads to specific partitions of the user base. We propose a training set for Google's YouTube social network and hope to show that YouTube skews political content recommendation to users based on this training data.

1.1 Summary

Discrimination through optimization [1] explores the ways that Facebook delivers different kinds of advertisements to different demographics regardless of the targeting options selected by advertisers. Mislove et al. created various advertisements and paid to disseminate them to users. They were primarily concerned with ads based on housing, jobs, and credit as there are anti-discrimination that prevent ads of those nature from being withheld based on protected demographic indicators like race and gender.

The results of their experiments confirmed that Facebook discriminates ad delivery based on the content of the ads without the permission or knowledge of the advertisers. For example, ads for the lumber industry were shown to more men than women and more white users than black users while ads for janitor jobs were shown to more women and more black users. These results show discrimination on the part of Facebook with potential liability for both Facebook and the advertisers who are themselves unaware of the mechanisms that make such discrimination possible.

1.2 Other Papers

Gupta et al. [2] discuss how the presentation of ads on YouTube can have a large impact on their conversion rate. YouTube is the second most popular search engine after Google, this huge user base makes YouTube a compelling subject to research social media marketing.

Mislove et al. touch on the differences in price when advertising to women vs. advertising to men. The paper by Lambrecht and Tucker [3] expand the disparity in advertising prices by exploring the difference between how often an ad for a STEM career is viewed by men vs how often it is viewed by women. Despite the fact that women were more likely to engage with the advertisement than men, more men than women saw the ad. This is because of the cost associated with advertising to women is higher than the cost of advertising to men. This implies there will be a skew of who sees what kinds of ads along gender lines based on how much each advertiser is willing to pay.

The patent by Wang [4] is for a new kind of media advertising that not only targets ads based on demographic information but also based on customized online profiles created with the information from a users previous internet activity. If someone has been responsive to content related to beds for example, that person is more likely to receive advertisements for mattresses. This reflects a new wave of advertising directly to individual consumers as opposed to just broad demographic groups.

"The Making of a YouTube Radical" [5] describes how to YouTube algorithm has lead to many young men to the alt-right by often recommending misleading and politically reactionary content.

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The size of the alt right on YouTube is much bigger than that of the far left. Inflammatory speech tends to generate more interest and viewership among the YouTube audience. Similarly to Facebook discrimination of ad delivery, it is more of an unintended consequence of the algorithms that the platforms use for recommendation.

Finally, the paper by Manoel et al. [6] attempts to answer whether or not there is a pipeline from moderate news sites to the alt right and their findings were somewhat inconclusive. When factoring in channel recommendations and user engagement (commenting, liking etc.) there seems to be a pathway from the more moderate side of YouTube to the extreme right. More often than not however, political videos seemed to link away from politics all together.

1.3 Weaknesses

One weakness is that Misolve et al. use the same bidding price and strategy for all ad campaigns. As Lambrecht and Tucker describe, spending the same amount on ads for men and women can easily skew results to delivering more ads to men than to women. This concern is raised in [1] but it is important to acknowledge that this data may be skewed by these market effects.

One other point raised by Wang is that advertisements now are targeted based on much more than demographic data. Internet activity can greatly skew the kinds of ads that will be sent to an individual. It would have been interesting to see how the delivery algorithm changes if some of these dummy accounts were searching for lumberjack jobs or certain credit opportunities. Would this history mitigate the initial biases Facebook puts in place? In other words, *what effects do a user's internet history have on the content that gets recommended to them?*

2 Proposed Idea

In order to explore how internet history can affect the content that social media platforms recommend to certain users, we have decided to monitor recommended videos from YouTube. There are no publicly available datasets for the kinds of videos watched by different racial or gender demographics so monitoring patterns among videos generally watched by protected demographic groups is difficult. However, given the plethora of outwardly political and highly partisan content on YouTube, exploring the relationships between user's political identities and the political videos that YouTube tends to recommend is a good alternative.

2.1 Explanation of Idea

We were inspired by the papers by Roose [5] and Ribeiro et al. [6] to explore the potential pipelines within the YouTube recommendation system that lead from more moderate political videos to those on the extreme of the political spectrum. In order to do this, we have created a browser extension that will monitor recommended videos and will follow the chain of the top recommended videos to observe patterns in the algorithm. Our goal is to see what the most common paths along the political spectrum are for different users depending on their political background.

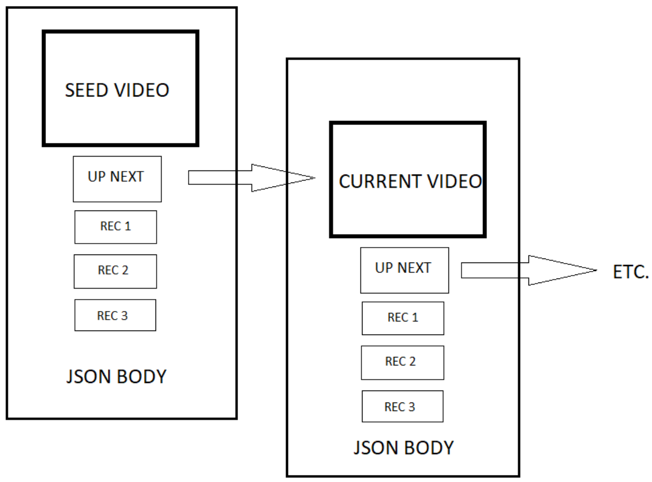
2.2 Explanation of Extension

Activating the extension on any YouTube video will log the name of the video and the recommended videos to a JSON element then click the link to the "up next" video, which is the top recommendation as determined by YouTube. This process will repeat for video after video and then will produce a JSON file of all of the videos that were visited (see figure 1). After we have received results from different users, we will aggregate the data into flowcharts that will display the different paths that stemmed from the same video.

2.3 What Sets Us Apart

Whereas the other experiments related to video recommendation have focused on pathways that lead to political extremes in a controlled context, ours factors in the effect that user profiles have on the kinds of political videos that people are recommended. As described by Google employees Davidson et al. [7] the recommendation system is designed to tailor recommendations to specific users in order

Figure 1: Visual representation of the JSON body



to keep them as invested as possible. In order to fully example the recommendation system it is important to use accounts with rich histories. Another difference is that out experiment is looking at patterns across the entire political spectrum as opposed to just looking at the alt-right.

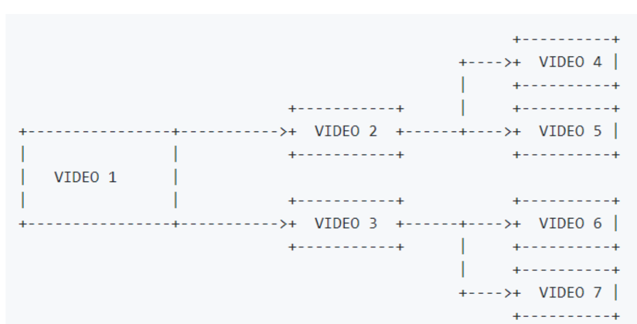
3 Experiment

github: Our Repo

3.1 Datasets and Preprocessing

For each user we will receive a profile of the individual (with varying amounts of detail depending on their level of privacy) as well as 4 lists of JSON elements, one for each of the seed videos. Each element will have the username of the participant, the link to the current video, and the links to the recommended videos (see below for example). We will then aggregate the data we have received to create a map of every one of the recommendations that stemmed from each seed video, see figure 2 for representation.

Figure 2: Represents a rough outline of the graph that will be created to represent which videos get recommended



One challenge we may run into with processing the data we have received is one expressed by Ribeiro et al. [7]. Youtube's recommendations are often not directly related to the topics presented in the video so it is very likely that most of the recommended videos we receive will not be political at all. With the relatively small sample space that we have at our disposal, we have to be sure to use enough users to counteract the amount of inconclusive data we may receive. It is also possible that based on a specific user's history, certain videos will be recommended repeatedly to just one user. We have to flag these outliers in order to prevent our averages from being skewed in one direction based on one users activity.

```
{
  "channel": channelName,
  "link": video url,
  "recommended": [{ "channel": channelName
                    "link": video url
                    "title": video title
                  },...]
}
```

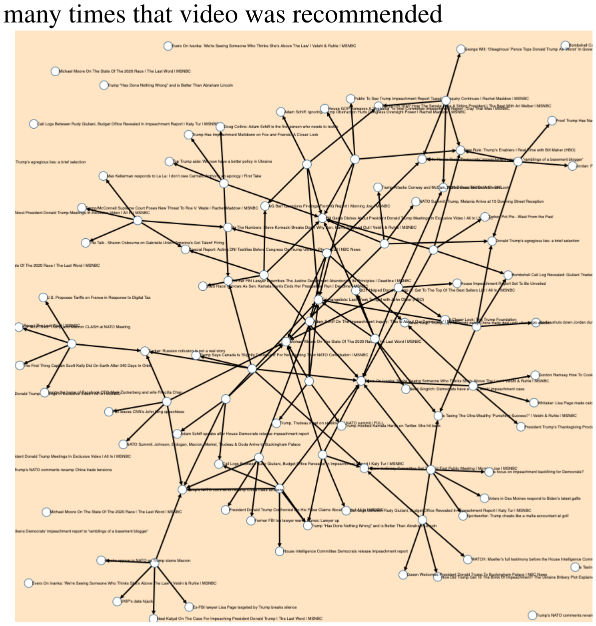
3.2 Experiment Setup

We have selected 4 videos to act as our seeds. One from an alt-right channel (Daily Wire), one from a mainstream conservative news organization (Fox News), one from a mainstream liberal news org (MSNBC), and one from a leftist channel (Contrapoints). Each subject will use the extension described above on each of these 4 videos. As our control, we will new Google accounts with no activity on browser windows with cleared caches and browser history. We will also use two brand new Google accounts, one of which is "trained" by having it exclusively watch conservative videos while the other exclusively watches progressive videos. See repository above for more details about how data is collected.

3.3 Baseline Results

Our original baseline results were relatively inconclusive as we did not actually clear our browser history. The recommended videos immediately veered off towards Dave Chappelle and Top Gear and did not show much besides the fact that the extension and visualization work. Our real baseline results showed that the untrained channels that started on MSNBC and Fox News received mostly recommendations from political videos on similar cooperate channels. MSNBC was majority NBC affiliates and CNN while Fox News was almost entirely Fox affiliates. The blank channels that started on Contrapoints and the Daily Wire veered away from political content almost immediately.

Figure 3: The graph of all recommended videos. The number of directed edges pointing towards a vertex represent how many times that video was recommended



3.4 Final Results

In order to create accounts that simulated users of differing political leanings we "trained" new YouTube accounts by having them watch playlists of videos from channels on the political left and right. One of the channels nicknamed "righty" was exposed to a playlist of Ben Shapiro's media appearances while "lefty" watched a playlist called "Bryan's Leftist YouTube List".

Anecdotal evidence, the in class hand-raise experiment, our results seems to suggest that training Youtube channels impacts the pattern of video recommendations at least as much as data from the current video does. Figures 4 and 5, shown below, both represent channels that had the same Fox News video as their seed. Figure 4 displays the recommendation graph for lefty while figure 5 displays the graph for righty. Righty has significantly more cycles, meaning that many of the same videos were repeatedly recommended and those videos had a similar political bent. Lefty on the other hand has a graph that is much closer to a tree. The video recommendations were coming from a larger pool and were not repeating as often.

Another outcome is that when righty began on the Daily Wire seed video, the recommendations very quickly all became Fox News as opposed to content with Ben Shapiro specifically. This is not too surprising as it is fair to assume that people who watch Daily Wire and more likely to watch Fox news as they have similar political leanings. Interestingly, the same phenomenon did not happen for lefty. When lefty began at the Contrapoints video, the recommendations quickly veered away from political content yet again. It is hard to say exactly why this happened but it leads us to believe that there is a much higher association between right wing users and right wing content on YouTube than there is left wing users and mainstream liberal news.

To see all of the results in both JSON and graph form, see the backend section of the linked repository.

4 Summary

Stepping back from the actual implementation details leaves us somewhere interesting. From our results, we can see in these few examples, YouTube changing what its recommending to us based on our political affiliation. This is not a groundbreaking discovery, they do this openly. What they do not do openly is classify videos by political bent. From [8], YouTube CEO says that the YouTube algorithms have no concept of politics. However, we think that our results go against this view. Also, even if YouTube's algorithms don't have a concept of politics, is that relevant if the algorithms act as if they do have a concept of politics, i.e. recommending different users different videos from the same seed video.

Our investigation into the YouTube's recommendation system didn't leave us satisfied. Our results were only for a handful of trials and trained accounts, also, we had no way of quantifying the results we did get and relied on subjective human experience of our visualization to guide our thinking about the data. However, we think that further research in this area could prove fruitful, especially with respect to Machine Learning techniques for classifying and quantifying a 'political score' for the recommended videos. In addition, we think that the raw data we've collected over the past few months could be used in interesting ways for anyone that was interested enough to use it.

5 Things We Learned

Before starting this project, we had never built a Chrome Extension, never built a backend in Python, and had only minimal experience with D3.js, the library that generated the visualizations. After the project, we have an easily extendable extension, a solid backend, and clean visualizations. Of course, all of these things could be improved, but overall, we are happy with the technical results of our project.

Our biggest takeaway, from a non-technical perspective, would be that you must talk to others about your research if you want to be successful. Whether you talk to your Professors, partners in the research, or other peers, you will be confronted ideas that, by yourself, you would not have confronted. The big picture summary of our experience is that research is fundamentally difficult. We tried our best and are proud to have achieved the results that we have.

Figure 4: The graph of all recommended videos from a ’Left-leaning’ user account, seeded from a Fox News video.

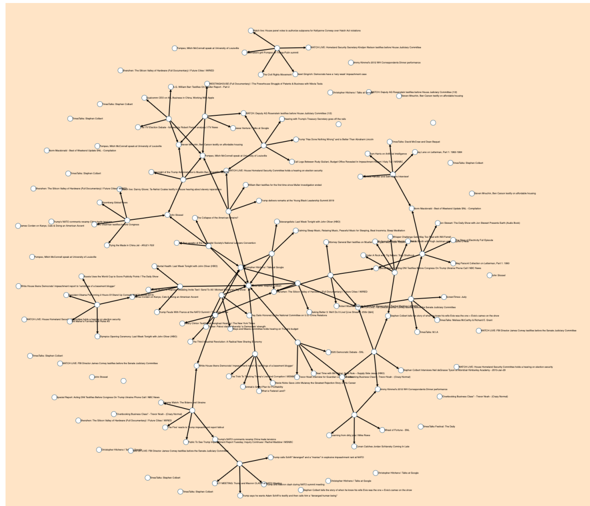
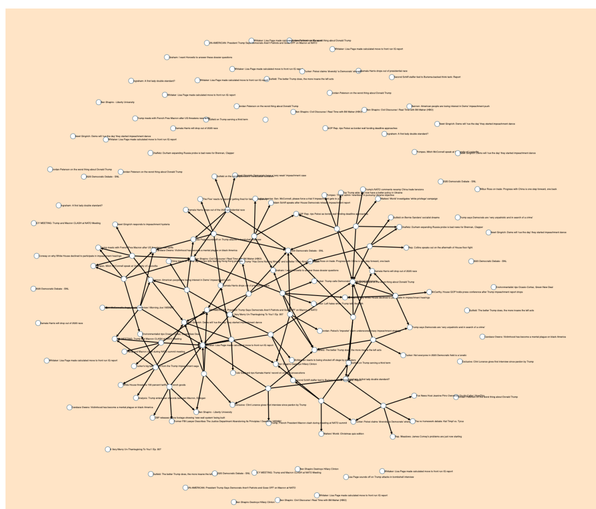


Figure 5: The graph of all recommended videos from a ’Right-leaning’ user account, seeded from a Fox News video.



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