University of Amsterdam

Bachelor Thesis

YouTube's Treatment of Conspiracy Content: an Analysis of the YouTube Algorithm

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Abstract

YouTube is the second most popular website on the internet. It brings in over 34.6 billion page views each month, most of which consist of videos being watched. Of those videos, 70% are found through YouTube's recommendation algorithm. Unfortunately, this recommender system, like most, is sensitive to filter bubbles. In recent years, conspiracy content has been gaining popularity on the website, partially because of the way in which the algorithm handles it. To gain a better understanding of how the algorithm deals with conspiracies, an experiment was setup wherein brand-new YouTube accounts were made to watch conspiracy content adhering to different watch strategies. After watching fifteen conspiracy videos, all accounts ended up with significantly more conspiracy recommendations than the baseline. Accounts that watched conspiracy videos that were recommended to them by YouTube ended up in filter bubbles especially quickly. While accounts ended up in a filter bubble after watching between three and six videos, getting out of a filter bubble took considerably longer. This suggests that YouTube's algorithm is indeed susceptible to the creation of filter bubbles consisting of conspiracy content.

Keywords: Recommender systems, Conspiracy theories, Filter bubbles, YouTube, Machine learning

1 Introduction

YouTube attracts an average of 34.6 billion page views per month, making it the world's largest video-sharing website and the second most popular website on the entire internet (Neufeld, 2021). The overwhelming majority of those page views come from users watching videos, 70% of which are recommended to users by YouTube's algorithm (Cooper, 2020). All types of content get produced and consumed on the website. However, conspiracy content has been booming on YouTube (Donzelli et al., 2018). Alt-right (or far-right) and conspiracy channels are starting to grow their audiences, which could have many negative consequences for society at large. For example, the number of people who are distrustful of science is increasing, a development in which conspiracy content on YouTube plays a role (Tufekci, 2018). Whenever this increased distrust relates to important topics, such as believing in the efficacy of vaccines, it can create genuine dangers to the public. As it turns out, more than half of the American population has doubts about - or is definitely against - taking the COVID-19 vaccine (Rosenbaum, 2021).

To better understand how YouTube's algorithm (and recommender algorithms in general) allow(s) conspiracy content to thrive, this research will investigate how quickly the algorithm develops a preference for conspiracy video; in other words: how many videos a user needs to watch before they get sent *down the rabbit hole.*

This research is based on the assumption that YouTube's recommender system is susceptible to the creation of filter bubbles. This concept, coined by Pariser (2011), has been studied in-depth on many social media websites, YouTube included. While results vary slightly, the common finding is that the YouTube algorithm does indeed create filter bubbles and that watching extremist and conspiracy content makes it more likely to do so (Bryant, 2020; O'Callaghan et al., 2013; Ledwich and Zaitsev, 2020). This effect can lead to the radicalization of impressionable users, with deleterious consequences. However, an important factor herein is how quickly a user's recommendations turn into a bubble. If the user has enough time to be exposed to other types of content, they might stray away from the more extreme, preventing them from adopting a potentially harmful view (Bozdag and van den Hoven, 2015). That is why this research looks at how *quickly* a user could end up in a filter bubble on YouTube. To do so, brand-new accounts will be made to watch YouTube videos according to different watch strategies; after each video watched, the recommendations of the user will be labeled as being either conspiracy content or regular content by a machine learning classifier, to determine whether or not the user is in a bubble.

1.1 Research question

For this research the following research question has been formulated: *What is the impact of different watch strategies on the number of conspiracy videos that have to be watched until a user's YouTube recommendations start preferring conspiracy content?* In this scenario, 'preferring' will be defined as the situation in which the amount of conspiracy videos present in the recommendations is significantly higher than that of the baseline.

To assist in answering the research question, the following sub-questions will be answered:

- How do different watch strategies on YouTube influence the type of conspiracy content that is recommended to a user?
- How long does it take for YouTube recommendations to stop preferring conspiracy videos, once they have started doing so?
- What type of classifier is suitable for labeling conspiracy videos on YouTube?

2 Theoretical Framework

2.1 Filter bubbles on social media

Whenever the user of a website finds themselves in their own information universe, in which the content and recommendations play into the user's preexisting opinions and believes, they are in a filter bubble (Pariser, 2011). Users are by themselves in such bubbles and each bubble is unique. Different bubbles can have overlap, but each bubble is precisely tuned to an individual. In traditional media, a user makes a conscious *choice* what types of opinions they want to hear, for example by choosing to watch a broadcaster with a specific political opinion. Online this decision is implicit: based on the user's behavior, their content is filtered automatically by an algorithm, without explicit consent.

2.2 Filter bubbles on YouTube

Previous research has found that YouTube's recommendation algorithm runs the risk of creating filter bubbles. Roth et al. (2020) came to this conclusion after they analyzed YouTube recommendations based on content. YouTube has two distinct types of recommendations: recommendations based on the user's viewing behavior and recommendations based on the content of the current video a user is watching. In their research, Roth et al. focused predominantly on recommendations based on content. They found that such recommendations could quickly lead to a decrease in information diversity (thus, filter bubbles) and that this decrease happened sooner for videos with a lot of views; the more views a video had, the less diverse its related recommendations. They speculate that this can be explained by the fact that YouTube tends to store more information about videos with a high view count, allowing the algorithm to give better recommendations for such videos. They also predict that, whenever the algorithm has more information about a user to its disposal, it can combine said information with the information it has about a certain video, which could lead to an even stronger limitation of recommendations. According to Ledwich and Zaitsev (2020), a user's viewing behavior is responsible for approximately 70% of their recommendations; this behavior could therefore play a big role in the creation of filter bubbles on YouTube.

Once a YouTube user has entered a filter bubble, it can be difficult to escape it. The most common way to help users get out of a filter bubble is by exposing them to content covering viewpoints other than their own (Bozdag and van den Hoven, 2015). However, for YouTube, this could form an issue. YouTube makes its money by displaying advertisements to a user. The longer a user stays on the website, the more profit YouTube can make. As a result, YouTube's algorithm prefers recommending videos that are likely to generate a lot of watch time (Maack, 2019). As it turns out, controversial content (such as conspiracies) tends to have a higher audience retention: people keep watching controversial content for longer (Birch, 2019). Whenever content is surprising (which conspiracy theories often are), it is more likely to capture and keep a user's attention. Thus, by showing the user more diverse content, the algorithm would actively hinder its own goal. Because of this design, filter bubbles are commonplace on YouTube.

2.3 Conspiracy content on YouTube

YouTube has limited rules with regards to the spread of conspiracy videos (YouTube, 2021). As long as the content does not directly incite violence or endangers the public health (e.g. misinformation about the COVID-19 virus), objectively incorrect ideas are allowed to be shared on YouTube. As a result, YouTube is a home to multiple conspiracy communities. Conspiracy theories such as 'the earth is flat and the government is hiding it from us', 'the world will end soon and only followers of this specific religion will be spared', and 'the world is ruled by cannibalistic, satanic pedophiles' (better known as QAnon) gather millions of views on the platform (Paolillo, 2018; Miller, 2021). Though such videos could be considered harmful to society, they are not suppressed by YouTube. Whenever a user shows interest in this type of content, they will be recommended similar videos, even when YouTube is aware of their harmful nature (Ledwich and Zaitsev, 2020; Maack, 2019).

2.4 The YouTube algorithm

The YouTube algorithm tries to recommend videos based on the expected watch time they will generate, rather than the probability of a user clicking on them (Covington et al., 2016). This decision was made in order to decrease the likelihood of misleading videos (also known as *clickbait*) being recommended. However, gathering feedback about videos through their watch time can cause a lot of noise, making it difficult to measure user satisfaction. As it turns out, even when a users enjoy a certain video, they are unlikely to watch it completely. On average, users watch around 50-60% of a video before they switch it off (Park et al., 2016). But, videos that are well-structured, or especially interesting, can improve this percentage up till 70-80%, where nearly half of the viewers actually finish the video in its entirety (Lang, 2018). After a video has been watched, there is a 41.6% chance that the user decides to watch a recommended video. Which recommendation the user will choose, follows a Zipf-distribution ($\alpha = 0.78$) with regards to the position of the video in the list of recommendations (Zhou et al., 2010).

All in all, previous research has found that YouTube's algorithm is sensitive to filter bubbles and that it has a tendency to recommend conspiracy content. It is also speculated that the algorithm makes decisions based on the user's viewing behavior, which it combines with the content of videos. In order to keep the user on the website as long as possible, which is profitable for YouTube, the algorithm prefers recommending videos that it suspects the user will watch for a longer period of time, even when they may contain harmful content. Based on this information, further research can be done on the origination of filter bubbles and the spread of conspiracy content on YouTube. For example, little is known about how quickly a user's recommendations adapt to a user's behavior, even though this is a critical aspect when it comes to the creation of so-called *rabbit holes*. Furthermore, no research has been done into the way different types of videos (recommendations in different locations, random videos, etc.) influence YouTube's algorithm. For example, whenever a user primarily watches recommended videos, the algorithm could see this as implicit positive feedback, which could cause a snowball-effect.

3 Methodology

3.1 Watching conspiracy videos

In order to determine how different watch strategies affect the YouTube algorithm, a python script was created to automatically log into a Google account and proceed to watch YouTube videos. The script was made using Selenium WebDriver: a suite of tools used for browser automation.

In the following sections, each aspect of the initial experiment will be explained. Firstly, an explanation will be given about how to log into Google accounts using a python bot. Then, the watch strategies as mentioned in the research question will be defined, followed by a description of their video watching behavior. Afterwards, some restrictions about the videos being watched will be mentioned. Additionally the actual script allowing the bots to be run will be described. Lastly, the precise form of the output of the script will be explained.

3.1.1 Google login

Due to Google's strict policy regarding automation within their ecosystem, many obstacles are put into place to prevent users from logging into a Google account using automated software such as a selenium script. To circumvent this restriction, two steps had to be taken. Firstly, the selenium WebDriver had to be accompanied by the selenium-stealth package, which removes metadata about the current browser, so that it is less obvious that a WebDriver is being used. Additionally, because this metadata was removed, the Google login service was unable to check what browser the client was using. This results in a warning to the user that their current browser may be insecure, which prohibits them from logging in. To avoid this warning, the Google account needs to have been created within a WebDriver, such as Google's ChromeDriver or Mozilla's GeckoDriver. Therefore, all twenty accounts were manually created in ChromeDriver. Since Google accounts require a phone number verification upon creation, six free (prepaid) SIM cards were ordered from various providers in order to create the accounts. Each SIM card could create two to three accounts before it was blocked due to being used too many times.

3.1.2 The watch strategies

After all accounts had been created, they were subdivided into four distinct watch strategies, making for a total of five accounts per strategy.

1. **Random videos (baseline)** The first watch strategy is the simplest one. The bots following it will watch random *non-conspiracy* videos from a dataset (for a description of the dataset see 3.3). This watch strategy is used as the baseline to compare the other three strategies to.

2. **Random conspiracies** The second strategy is similar to the first: the adhering bots watch random *conspiracy* videos from the dataset.

3. **Watch-next recommendations** The penultimate strategy starts off in the same way as strategy 2: it chooses a random conspiracy video from a dataset to watch. However, it then watches the four most similar videos in the dataset (based on cosine similarity) in order to allow the algorithm to get a feel for the user's interests. After watching those five initial videos, it starts looking at the recommended videos displayed next to the current video and chooses the recommendation that is most likely to be a conspiracy video (out of the first twenty recommendations). These recommendations consist of a combination of recommendations based on the content of the current video and the personalized recommendations of the user. It is expected that, by using this strategy, bots are likely to go *down the rabbit hole* and eventually end up in a filter bubble.

4. **Homepage recommendations** Finally, the last strategy is similar to the previous one, though with one alteration: rather than choosing a recommended conspiracy video from the list of recommendations next to the current video, it will choose a recommended video from the YouTube homepage of the account (again out of the first twenty recommendations). Compared to the third strategy, this will lead to the user watching more personalized recommendations rather than content-based recommendations, possibly speeding up the creation and/or increasing the strength of the filter bubble.

For strategy 3 and 4, the likelihood of a recommendation being a conspiracy video was estimated by a neural network using the title, description, transcript, channel description, and channel keywords of the specific video. Though this is more information than a regular user would have to their disposal, it has to be kept in mind that humans are able to interpret the thumbnail of the recommendations and can have foreknowledge about the channel that is uploading the video or the subject being mentioned in the title. Thus, the choice was made to allow the neural network to consider the transcript and look at general information about the uploader to balance the scales.

Each strategy was executed by five different accounts in order to decrease the probability of a random streak of videos altering the result. The individual accounts watched a total of fifteen videos as described by their watch strategy for a total of three hundred videos watched by the script.

Additionally, to simulate real-world user behavior, the average watch time for the videos was normally distributed with a mean of 55% and a standard deviation of 25% (Park et al., 2016; Lang, 2018). The watch time was not be able to exceed a value of 100 or subceed a value of 0, as a video cannot be watched for more than 100% or less than 0%. In the same vein, the clicking behavior of users was simulated as accurately as possible. Whenever none of the recommendations were predicted to be conspiracy videos, the probability of a user clicking on a video at position k within a given list of recommendations (its click-through rate: CTR), was determined using the following formula:

$$CTR(k; N, \alpha) = \frac{1/k^{\alpha}}{\sum_{n=1}^{N}(1/n^{\alpha})} \tag{1}$$

Wherein N is the total number of recommendations and α is the distribution's exponent value ($\alpha = 0.78$) (Zhou et al., 2010). Using this formula, when considering the first twenty recommendations, the first recommendation will have a click-through rate of approximately 20.6%, after which the CTR quickly decreases, until a probability of 1.9% at the twentieth recommendation.

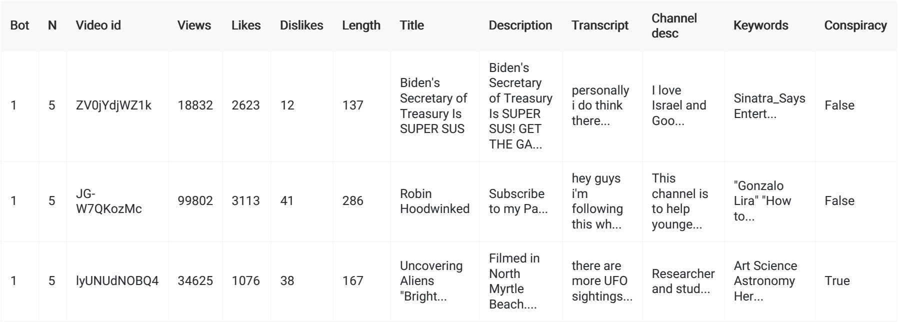
3.1.3 Running the bots

After the accounts were logged in, they started watching YouTube videos according to their watch strategy. However, some restrictions were put into place to make sure running the bots did not take too long, as three hundred videos had to be watched in total. For example, the bots were not allowed to watch videos over an hour long, nor were they allowed to watch live streams, as those could theoretically go on infinitely. Additionally, the random videos at the start of the third and fourth strategy were first manually inspected to make sure the bots would not start the experiment by watching a falsely flagged conspiracy video. Considering the way in which the dataset was created (see 3.3), it is possible that some videos that are flagged as conspiracy videos are, in reality, normal videos. This could happen whenever a conspiracy channel uploads a regular video (e.g. a holiday video, promotion of some product, etc.). These *false positives* are far and few between, however, having one of them be selected as the first video for strategy 3 or 4 had to be prevented, as that could have greatly altered the final results. With these restrictions in mind, the following script was created and run for all twenty bots, keeping track of the videos they watched and the homepage recommendations they had after each video:

```
Algorithm 1: Watch YouTube videos according to a watch strategy
Data: User information and a video dataset
Result: The watched videos and homepage recommendations of the
        user
for twenty bots do
    initialize WebDriver;
    log into Google account;
    for fifteen videos do
        if there is a recommendation to be watched then
            go to the link;
        else
            pick a random video to watch based on usertype;
            determine how long it will get watched;
            go to the link;
        get video metadata and store for overview of watched videos;
        watch video for given amount of time;
        if usertype == 3 then
            pick recommendation next to current video to watch next;
            determine watch time for found recommendation;
        go to YouTube homepage;
        store current recommendations for overview;
        if usertype == 4 then
            pick homepage recommendation to watch next;
            determine watch time for found recommendation;
return watched videos and homepage recommendations;
```

Running the script for all twenty bots resulted in two different datasets: the first containing the videos watched by the bots and the second containing the homepage recommendations for all bots, after each number of videos watched. To determine the influence of the watch strategies on the algorithm, the recommendations were labeled as being either conspiracy or non-conspiracy videos by the classifier. By then grouping all recommendations by their watch strategy and the number of videos watched before them (e.g. the recommendations after the third video watched by all bots with strategy one), it was possible to calculate aggregates about general statistics of the recommendations, such as view count and video duration, and the percentage of conspiracy videos present among them. This lead to four groups with fifteen entries of different statistics (one for each video watched). In order to find out whether any of the differences between the groups were significant at any point, a number of independent samples t-tests were performed.

Example DataFrame



Bot	N	Video id	Views	Likes	Dislikes	Length	Title	Description	Transcript	Channel desc	Keywords	Conspiracy
1	5	ZV0jYdjWZ1k	18832	2623	12	137	Biden's Secretary of Treasury Is SUPER SUS	Biden's Secretary of Treasury Is SUPER SUS! GET THE GA...	personally i do think there...	I love Israel and Goo...	Sinatra_Says Entert...	False
1	5	JG-W7QKozMc	99802	3113	41	286	Robin Hoodwinked	Subscribe to my Pa...	hey guys i'm following this wh...	This channel is to help younge...	"Gonzalo Lira" "How to...	False
1	5	lyUNUdNOBQ4	34625	1076	38	167	Uncovering Aliens "Bright...	Filmed in North Myrtle Beach....	there are more UFO sightings...	Researcher and stud...	Art Science Astronomy Her...	True

Figure 1: An example of the experiment's output

3.1.4 Outputs of the experiment

To create the initial recommendation dataset, the bots stored the following information about their top twenty recommendations after each video watched:

- the id of the bot that had gotten the recommendations;
- the amount of videos watched before the recommendation was given;
- the URL of the video being recommended;
- the URL of the channel that uploaded the recommendation.

To then allow the classifier to label the videos, and to calculate the aggregates per strategy, additional data was gathered using YouTube's API. For each recommendation, the title, description, transcript, (dis)likes, views, video duration, channel description, and channel keywords were collected. The title, description, transcript, channel description, and channel keywords were collected in order for the classifier to label the videos, as will be further explained in section 3.3. The other features were collected in order to calculate the aforementioned aggregates. An example of the output can be seen in figure 1.

3.2 Leaving the filter bubble

To find out how quickly different users can get out of a filter bubble after they have gotten into one, an additional experiment similar to the one described before was set up. This experiment however, was significantly simpler. Rather than having different bots behave differently, all bots behaved the exact same way. After the bots adhering to strategy 2, 3, or 4 had gotten into a filter bubble, this experiment was performed on them in order to see how long it takes for users adhering to different watch strategies to leave a filter bubble once they find themselves in one.

3.2.1 The setup

Considering the experiment studies the way in which users leave a filter bubble, only the bots that had actually gotten into a filter bubble were used. This means that the first five bots, which were used as a baseline, were ignored. The remaining bots went through the same starting procedure as they did in the earlier experiment: the WebDriver was initialized and the bots logged into their corresponding accounts. The same restrictions for videos (e.g. maximum watch time) from the other experiment applied. However, rather than the bots watching videos adhering to their original strategy, all bots watched random non-conspiracy videos from the dataset. Once again, after each video, the bots stored their homepage recommendations. Through doing so, it became possible to see how many videos would have to be watched, for each bot, before their recommendations started looking similar to that of the baseline again. Thus, the following script was created:

Algorithm 2: Getting out of a filter bubble

```
Data: User information and a video dataset
Result: The watched videos and homepage recommendations of the
        user
for fifteen bots do
    initialize WebDriver;
    log into Google account;
    for fifteen videos do
        pick a random non-conspiracy video to watch;
        determine how long it will get watched;
        go to the link;
        get video metadata and store for overview of watched videos;
        watch video for given amount of time;
        go to YouTube homepage;
        store current recommendations for overview;
return watched videos and homepage recommendations;
```

After the script had been run, the same steps were taken as in the previous experiment: the title, description, transcript, channel description, and channel keywords of each recommendation were downloaded, after which the classifier predicted whether or not each recommendations was a conspiracy video. Then, the recommendations were grouped by watch strategy and number of videos watched. In doing so, the results could be used to determine how quickly the recommendations for each watch strategy returned back to normal. By then analyzing the results again using independent samples t-tests, the *strength* (or *inescapability*) of the filter bubbles created by different watch strategies could be measured.

3.3 Machine learning

3.3.1 Data gathering

To answer the research question, it is necessary to determine which YouTube videos can be considered conspiracy videos. Considering the large amount of videos getting recommended, determining each video manually is simply not possible. There are two possible ways to solve this problem. Firstly, there is a dataset which contains nearly 7000 YouTube channels that have been manually labeled based on their political view - almost 3000 of which were labeled as conspiracy channels (Ledwich and Zaitsev, 2020); whenever a video is made by one such channel, it can be considered a conspiracy video. However, due to the enormous amount of existing YouTube channels, the odds of a video being uploaded by a channel that is not present in this dataset are very large. For those videos, a supervised machine learning classifier was used. To optimize performance, five different classifiers have been trained and compared: k-nearest neighbors, support-vector machine, neural network, logistic regression, and ridge regression.

In order to train these machine learning algorithms, a training dataset was created. To get a labeled dataset of conspiracy and non-conspiracy videos, use was made of the aforementioned channel dataset made by Ledwich and Zaitsev (2020). For each channel in that dataset, the title, description, and transcript of the ten most recently uploaded videos were downloaded using YouTube's API. Videos uploaded by a conspiracy channel were then labeled as conspiracy videos, and videos uploaded by a channel from a different category were labeled as normal videos. Additionally, the channel description and channel keywords (which are used for targeted advertising on YouTube) were added to each video. The final dataset contained 65.683 unique YouTube videos, 22.156 of which were considered conspiracy videos.

3.3.2 Data cleaning

However, this dataset was not yet suitable for machine learning, as the data was still messy. Therefore, multiple steps were taken in order to clean the data. Firstly, the two classes (conspiracy and non-conspiracy) were balanced, so that the classifier would not develop a bias for non-conspiracy videos. Rather than opting for balancing the two classes through the use of class-weights (a technique where weights are attributed to classes, thereby telling the classifier that getting a prediction correct for a certain, underrepresented class is more important), the choice was made to undersample the data in order to equalize both classes (both containing 22.156 videos, for a total of 44.312 videos) (Lemaître et al., 2017; Sun et al., 2006). As there was plenty of data in the dataset, undersampling was more convenient than implementing class-weights. After both classes had been balanced, the text for each video had to be translated into English. Since the original dataset by Ledwich and Zaitsev (2020) also contained channels by non-English speakers, these videos had to be automatically translated. Then, a few common cleaning methods were applied: all text was converted to lowercase, after which special characters, such as emojis were removed, whereafter stop words were removed and all words were stemmed using the porter stemmer (Karaa, 2013). Finally, each video was TF-IDF vectorized to allow the classifiers to function.

3.3.3 Performance optimization

After splitting the dataset into a training, test, and validation set, the hyperparameters of each algorithm were tuned to get the optimal performance (Feurer and Hutter, 2019). Performance was measured using four distinct metrics: the accuracy, which shows the share of correct predictions; the recall, which shows what fraction of truly positive samples were correctly labeled as such; the precision, which shows what part of the positive predictions were correct; and the F1-score, which is the harmonic mean of the recall and precision (Sokolova and Lapalme, 2009). For each classifier, different configurations of hyperparameters (such as the kernel and the penalty-parameter) were systemically tested - each possible combination was tried. The classifiers were trained on the training set and the optimal hyperparameters were determined based on the performance of the classifiers on the validation set. By saving these performance measures for every configuration, for every classifier, the optimal configuration of each classifier could be determined. Lastly, the classifiers were equipped with their optimal hyperparameters and then tested for the final time on the test set. By comparing the performance of every optimally configured classifier on the test set, the best-performing classifier could be chosen (Reitermanova, 2010).

Additionally, the added value of using a machine learning ensemble was measured. By having each classifier make a prediction for all videos in the dataset, a new dataset was created. In this new dataset, each sample was a video, and the features consisted the predictions made by the different classifiers. By using all possible combinations of the five aforementioned classifiers, and then having a neural network use those features as input, a machine learning ensemble was created. This ensemble was then optimized in a similar way to the classifiers individually.

4 Results

In the following two sections, the results of the experiments will be given. First, the changes in content will be shown for whenever a user is actively watching conspiracy content. Afterwards, the results for the second experiment are set forth, wherein users are trying to escape a filter bubble after they have ended up in one. The results of both experiments are in part based on the predictions made by the classifier. An overview of the performance of the different classifiers, together with an explanation of why the support-vector machine was chosen to do the predictions, can be read in section 4.3.

4.1 The recommended content

4.1.1 The types of recommendations

Conspiracy recommendations

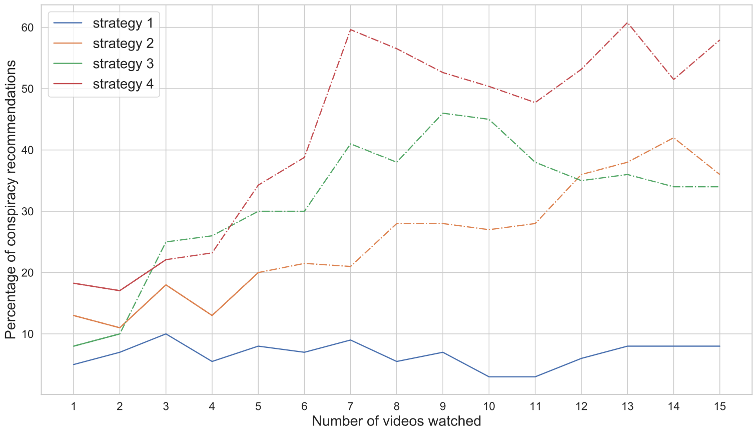


Figure 2: The average ($N = 5$) percentage of conspiracy recommendations after each number of videos watched per strategy. Each measure is based on the top twenty recommendations of the five accounts for the strategy. A dashed line indicates a significant difference compared to the baseline (strategy 1) at $\alpha = 0.05$.[1]

All strategies, excluding the baseline, led to an increased number of conspiracy recommendations on the user's homepage. For all strategies, this increase was significant, meaning filter bubbles were indeed being created. However, the strategies all behaved differently, as can be seen in figure 2.

Strategy 2 (random conspiracy videos) took the longest out of all the strategies to get into a filter bubble. Only after having watched six videos did the difference between it and the baseline become significant. After having increased significantly, the percentage of conspiracy videos being recommended to the users of strategy 2 kept steadily growing, eventually plateauing at 42%.

Strategy 3 (top conspiracy recommendation next to the watched video) got into a bubble the quickest. After watching only three videos did the dif-

[1] Significance for each measure was tested using multiple independent samples t-tests. The tests compared the five percentage values after each number of videos watched per strategy to the five percentage values of the baseline (strategy 1) at that same number of videos watched. The tests were done for each strategy individually.

	Betweenness centrality	Clustering coefficient
Strategy 1	1.597418e-07	0.001592
Strategy 2	0.000000e+00	0.000000
Strategy 3	2.198488e-06	0.009512
Strategy 4	1.136934e-04	0.039018

Table 1: The average betweenness centrality and clustering coefficient of each strategy's network. A node having a higher betweenness centrality indicates that it is present on more shortest paths between other nodes, meaning it is located more centrally within the network. A higher clustering coefficient indicates the network as a whole is more clustered, meaning more ties between triplets are present.

ference compared to baseline become significant. However, following this head start, the increase came to a halt rather quickly. After reaching its peak of 46% at nine videos watched, the percentage of conspiracy recommendations started to decline again, eventually settling around 35%. Though most values are slightly higher, strategy 3's course mimics that of strategy 2 until the decline.

Strategy 4 (top conspiracy recommendation on the YouTube homepage) took slightly longer to get into a filter bubble than strategy 3. However, considering that these strategies are identical up until video five and the difference between the two strategies was insignificant ($p > 0.05$), this dissimilarity is negligible. As soon as homepage recommendations started getting watched, the percentage of conspiracy recommendations increased drastically, reaching a peak of 60.8%. Similarly to strategy 3, once the number of conspiracy recommendations reached a peak, it was followed by a decrease.

To better understand how the different strategies affected the recommendations provided by the algorithm, a directed network of each strategy was created and analyzed. For each strategy, the networks is constructed as follows: the set of nodes consists of all videos watched by the five accounts of the strategy, plus, for every watched video V the top twenty homepage recommendations that were present after watching V. An edge between two nodes $V1$ and $V2$ indicates that for at least one bot, $V2$ was recommended directly after watching $V1$. The different networks are displayed in figure 3. It can be seen that strategies 1 and 2 have barely any cross-class edges (strategy 1 has two in total, strategy 2 has zero), while strategies 3 and 4 have a lot of connections between the two separate classes. This stronger connection also becomes apparent when looking the networks' betweenness centrality and clustering coefficient (table 1).

When looking at the conditional probabilities of cross- and within-class edges per network (table 2), it can be seen that regardless of the strategy, regular videos are highly likely to recommend more regular videos. However,

[2] In other words, the values represent the conditional, class-dependent out-degrees of the nodes. The probabilities therefore can be interpreted as the likelihood of a node belonging to a certain class having an outgoing edge to a node of the same or opposite class.

	$P(C \mid R)$	$P(R \mid C)$	$P(C \mid C)$	$P(R \mid R)$
Strategy 1	0.065493	NaN	NaN	0.934507
Strategy 2	NaN	0.750000	0.250000	NaN
Strategy 3	0.185714	0.663043	0.336957	0.814286
Strategy 4	0.105263	0.560673	0.439327	0.894737

Table 2: Conditional probabilities of cross- and within-class edges for each network. Values indicate the probability of an edge going to a class, given it starts in another (in the form: $P(end \mid start)$).[2]

	Betweenness centrality	Clustering coefficient
Strategy 1	0.000000	0.000000
Strategy 2	0.000000	0.000000
Strategy 3	0.000012	0.016064
Strategy 4	0.000747	0.058816

Table 3: The average betweenness centrality and clustering coefficient of each strategy's sub-network consisting of only conspiracy recommendations.

the more personalized the strategy, the higher the probability of conspiracy videos recommending more conspiracy videos. This supports the creation of filter bubbles, as users are more likely to be recommended content similar to that which they already watched. A similar relation is shown in the probability of cross-class edges for the strategies: the more personalized the strategy, the lower the probability of cross-class edges being present. This, too, can cause filter bubbles, as users are less likely to be recommended content that is different from that which they have already watched.

When solely looking at the conspiracy recommendations of each strategy, it once more becomes clear that the recommendations of strategies 3 and 4 are connected more strongly than those of strategies 1 and 2 (appendix A.1). However, these networks are somewhat deceiving, as an edge not being present does not necessarily indicate there is no link between the two nodes; it could also simply be that the recommendations coming from that node were not checked (i.e., the recommendation was not chosen to be watched, hence its outgoing recommendations could not be stored). Yet, even with these missing edges, the clustering coefficient and betweenness centrality of strategies 3 and 4 end up being higher than those of strategies 1 and 2, as can be seen in table 3.

The recommendation network of each strategy

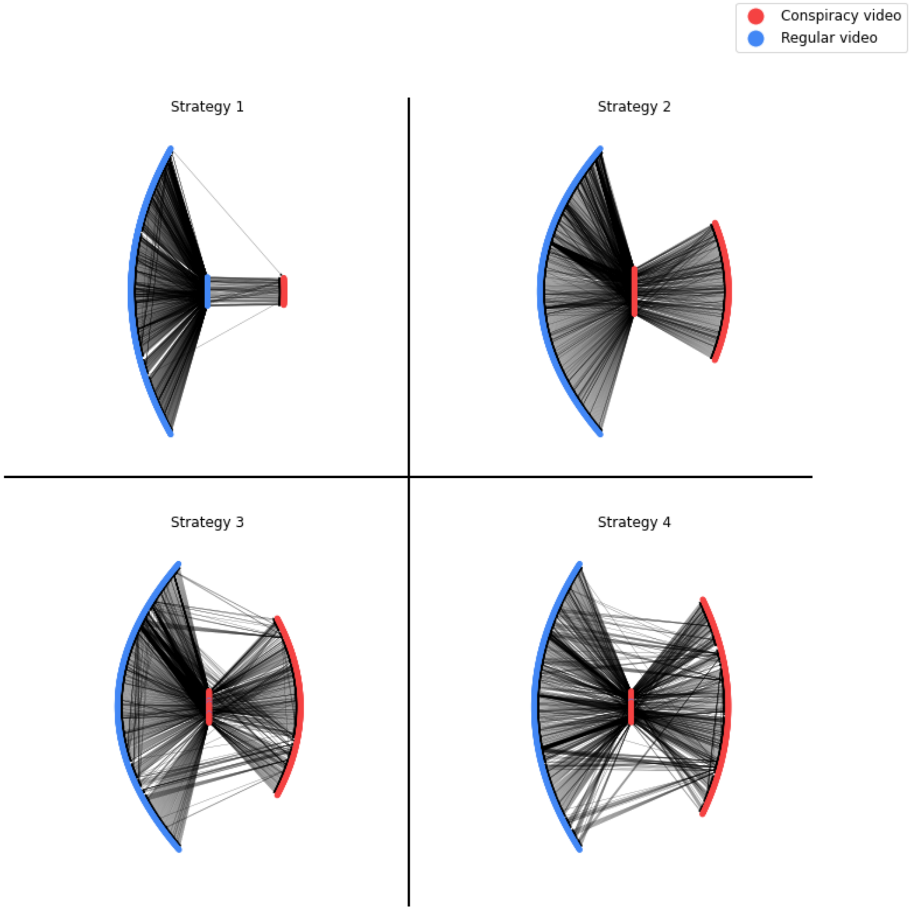


Figure 3: The networks of homepage recommendations of each strategy. Nodes are videos. An edge from node $V1$ to node $V2$ indicates $V2$ was recommended to a user directly after watching $V1$. Blue and red nodes indicate regular and conspiracy videos, respectively. Nodes on the left are regular videos that were recommended, nodes on the right are conspiracy videos that were recommended, and videos in the middle are videos that were watched, but not recommended (i.e. from the dataset). Nodes with outgoing edges on the left/right side are videos that were recommended and then chosen to be watched, thus also having outgoing recommendations. Note that most recommendations were not watched (and thus not all possible recommendation links could be checked).

Cosine similarity of conspiracy recommendations

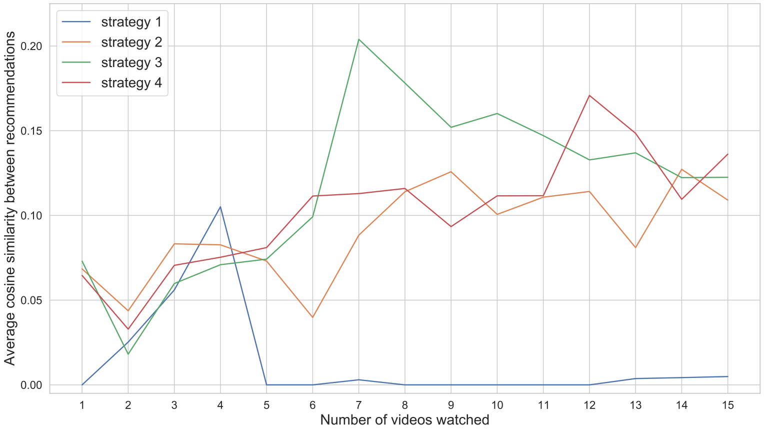


Figure 4: The average ($N = 5$) cosine similarity of the homepage conspiracy recommendations per strategy after each number of videos watched (based on the TF-IDF representations of the recommendations, as described in 3.3.2). Each measure consists of the first twenty recommendations of the five users for each strategy.

4.1.2 Characteristics of the recommended content

Recommendation similarity A filter bubble is often paired with a decrease in information diversity (Nguyen et al., 2014). As a result, one would expect an inverse relationship between the similarity of the recommendations of each strategy and the extent to which they are in a filter bubble (i.e., the stronger the bubble, the less diverse the recommendations). As is shown in figure 4, this is indeed the case. While the similarity of the recommended *conspiracy* content increased (figure 4), the similarity of *non-conspiracy* recommendations stably hovered between 0.05 and 0.1, showing similar behavior to that of the baseline (appendix A.2).

Every strategy, excluding the baseline, eventually led to a decreased diversity of the recommended conspiracy content. The similarity increased relatively slowly, however, when compared to the speed with which the different strategies ended up in filter bubbles. Only after six to eight videos did all the different strategies start showing a clear increase in similarity, while it took the strategies only a handful of videos to end up in a bubble.

While strategy 1 showed comparable behavior to the other strategies initially, its similarity values soon flat-lined. This was predominantly caused by the fact that, in figure 4, only the conspiracy videos are compared. Since strategy 1 oftentimes did not have any conspiracy videos within its recommendations, there were no videos present to be compared, thus leading to a non-existing similarity.

The other strategies all showed approximately the same trend. For the first few videos, the similarity values stayed close to normal; however, after about six videos the similarity between conspiracy recommendations started increasing steadily, eventually evening out around 0.125. Considering the non-conspiracy recommendations of all strategies had similarity values that stayed more-or-less the same throughout all fifteen videos, the trend of *all* recommendations was similar to that of the conspiracy recommendations, albeit with slightly lower values (appendix A.3).

View count As a user watches more videos, the algorithm will get a better understanding of their preferences. This would, in theory, allow it to recommend more fine-tuned (and thus less generic) content. Because of this, it was expected that the average number of views (i.e. the popularity) of recommendations would decrease, the more videos a user watched. This hypothesis was confirmed by the experiment; the average popularity of recommended videos dropped quickly for all strategies, including the baseline (appendix A.4). For all strategies, the average view count of recommendations started at more than ten million. This number then rapidly decreased, already dropping into the single millions or hundreds of thousands after five videos watched. Thus, it was confirmed that YouTube starts by recommending very popular content, as that is most likely to cater to the largest audience. However, after the user has watched a few videos, thereby giving the algorithm a better idea of their interests, the recommendations become more personalized and therefore less generic.

Video duration Lastly, it was hypothesized that the average duration of recommendations would increase as the filter bubbles became stronger. Considering that the YouTube algorithm optimizes for expected watch time, rather than expected user satisfaction, it would make sense that recommendations would end up consisting of increasingly longer videos, as those would garner more watch time. However, there seemed to be no trend in the average duration of the recommended videos for any of the strategies (appendix A.5). For each strategy, the average length of the recommended videos stayed about the same, spiking up or down sporadically.

4.2 Leaving the filter bubble

While it took only a handful of videos before users' recommendations started preferring conspiracy content, undoing this preference required far more videos to be watched. While the algorithm quickly adjusted to the new type of content being watched, it did not stop recommending conspiracy content, even after the users had watched fifteen non-conspiracy videos (figure 5).

Conspiracy recommendations when leaving the filter bubble

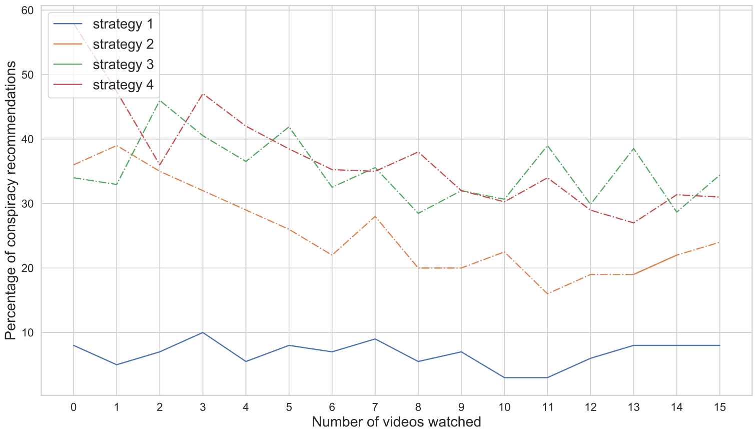


Figure 5: The percentage of conspiracy recommendations after each number of videos watched per strategy while trying to escape a filter bubble. Each measure is based on the top twenty recommendations of the five accounts for the strategy. A dashed line indicates a significant difference compared to the baseline (strategy 1) at $\alpha = 0.05$.

For all strategies, the percentage of conspiracy recommendations rapidly decreased from its initial value. However, the number of conspiracy recommendations soon leveled-out for all three strategies at a value still significantly higher than that of the baseline. In other words, while the algorithm is quick to reflect a change in users' watching behavior, it does not 'forget' what has been watched in the past for quite some time.

Strategy 2 and 3 decreased by approximately the same amount, although strategy 3 constantly stayed at a higher percentage, as that strategy's initial percentage was higher than that of strategy 2. Strategy 4 dropped quite a bit more than the other two strategies; it ended up with practically the same values as strategy 3, even though its initial value was over 20% higher (57.9% as opposed to 34%).

Yet, for all three strategies did the number of conspiracy recommendations not return to baseline, even after having watched all fifteen videos. Considering only three to six videos had to be watched before the users ended up in a filter bubble, it is quite concerning that getting out of that bubble takes several times more videos. Someone can end up in a filter bubble before they even realize it, but once they are in one, it will be difficult for them to get out.

Classifier performance

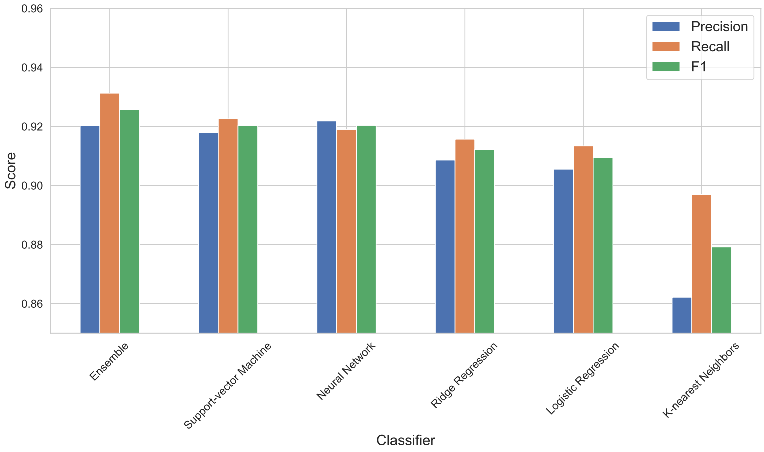


Figure 6: Metrics for each classifier with optimized hyperparameters

4.3 Machine learning

The hyperparameter tuning led to impressive scores for all classifiers. When making predictions for the test set, the best-performing classifier was the support-vector machine making use of the Radial Basis Function (RBF) kernel and a penalty parameter (C-value) of 10. The SVM was tied for F1-score with the neural network using the identity activation function, with 10 hidden layers of 10 neurons. Ridge regression with a sparse-cg solver and penalty (alpha) value of 0.1 took third place, very closely followed by logistic regression with an L2 penalty, a penalty (C) value of 20 and a newton-cg solver. The worst-performing classifier was also the simplest of the bunch: the k-nearest neighbors classifier (K=1). Although its performance was still formidable, it did substantially worse than the others. An overview of all metrics for each classifier can be seen in figure 6. The ten best-performing configurations for each classifier can be found in appendix B.1.

Noteworthy is the fact that the optimal ensemble actually outperformed the support-vector machine by a slight margin. This ensemble, consisting of the SVM, the neural network, and the k-nearest neighbor classifiers, got slightly higher scores than the runner-up across the board. The ensemble had a sixteen-way tie for best-performing parameters, all of which contained at least the SVM, neural network, and k-NN classifiers.

Though the ensemble outperformed the other classifiers, it has a significant drawback: its training time is significantly larger than that of the individual classifiers. Support-vector machines are infamous for their slowness when there is a lot of training data, and neural networks can require a lot of training time whenever the number of neurons gets large (Burges and Schölkopf, 1997; Kamarthi and Pittner, 1999). Requiring both algorithms to run would therefore require a lot of additional training time. Considering the marginal performance increase, the cost outweighs the benefit. As a result, when taking everything into account, the support-vector machine is the best classifier for labeling conspiracy videos on YouTube.

Additionally, for predicting the likelihood of recommendations being conspiracy videos in real-time, the best-performing classifier was the neural network. The predicted likelihood was used to find the most likely conspiracy recommendation after each video watched, which was done for strategy 3 and 4. Here, the neural network is preferred over the support-vector machine, as neural networks are better optimized for providing probabilities of samples belonging to a certain class (Specht, 1990).

5 Discussion

The results indicate that the YouTube algorithm is indeed susceptible to the creation of filter bubbles, even when it comes to harmful content such as conspiracy videos. Through using actual YouTube accounts and making use of different watch strategies, it was shown that a user's individual watching behavior influences the strength of the created filter bubble and impacts how quickly such a bubble can emerge. In line with expectations, watching more personalized content on YouTube creates stronger filter bubbles and does so more quickly, while watching less personal content leads to weaker bubbles, which take longer to materialize. Furthermore, the findings indicate that, regardless of the strength of the filter bubble a user is in, leaving a filter bubble requires significantly more videos to be watched than needed to enter a filter bubble. Even after a user has watched fifteen unrelated videos, the algorithm is still inclined to recommend content based on the original filter bubble. This could indicate that the first few videos that a user watches on YouTube are incredibly important to the content ecosystem they will eventually end up in. If this is true, it will be important to disincentivize new YouTube users from consuming potentially harmful content (such as conspiracy videos), as that could shape the future of their recommendations. However, more research will have to be done in order to confirm or deny this claim.

Previous research on the topic of filter bubbles consisting of radical and conspiracy content on YouTube has shown conflicting results. For example Hosseinmardi et al. (2020) found no evidence of extremist filter bubbles being created by the YouTube algorithm. On the other hand, Roth et al. (2020) and Faddoul et al. (2020) did find evidence supporting the claim that the YouTube algorithm is vulnerable to such filter bubbles. This discrepancy could be explained by the difference in approach between the research; Hosseinmardi et al. look at user behaviour indirectly (through a national web panel), while Roth et al. and Faddoul et al. opt for a more direct approach (actually using the YouTube website, although while not logged in). This research complements their research, as it shows how the algorithm behaves in a real-world scenario: having a user actually use the website, while logged in on their own account. As a result, this research more accurately conforms the original definition of a filter bubble by Pariser (2011); the bubbles created in the experiments are completely personal, solely based on users' watch and click behavior.

Additionally, it was found that YouTube's algorithm initially recommends extremely popular content. This is a typical example of a cold-start problem, wherein a recommender system does not yet have sufficient data about a user to give a relevant recommendation (Lam et al., 2008). However, only a handful of videos need to be watched before the algorithm starts giving more fine-tuned recommendations, even when it could potentially be harmful content. This is quite concerning, as it enables brand-new users to go *down the rabbit hole* in a matter of just a few videos.

A naive hypothesis about an algorithm that supposedly optimizes for watch time, is that the content it recommends would become increasingly longer. While no support was found for the claim that recommendations become gradually longer, this does not indicate that the algorithm does not optimize for watch time. After all, recommending a ten minute video that the algorithm expects the user to watch in its entirety leads to more watch time than recommending a 45 minute video that the algorithm expects the user to abandon after a few minutes.

5.1 Future Research

This research attempted to carry out the experiment in the most realistic way possible. Thus, additional insights were gained into the way in which the YouTube algorithm behaves in a real-world setting. While this method requires additional labor to set up (as the process of creating new accounts can be time-consuming), the ability to research the YouTube-algorithm in such a realistic scenario arguably outweighs the drawbacks. However, due to the required time for setting up additional accounts and having them watch videos (which can take up a lot of time), this method is costly to apply on a large scale. As a result, the main limitation of this research is the fact that a fairly limited number of accounts was used. While the results are significant, having a sample size of just five accounts per strategy can put a limit on making definitive claims; after all, some results might have been affected by coincidence. Therefore, future research using this method should be done on a larger scale. A possibility to carry out similar research on such a scale, would be to make use of either a larger number of computers, or cloud computing, and running the experiment for each account in parallel. Moreover, in order to limit the time required to create and set-up each account, this workload could be spread over a number of individuals.

Firstly, it would be interesting to create a network similar to that of figure 3, but instead of only clicking on one recommendation after each video, a breadth-first search method could be used to find *all* edges present between videos. The current network shows promising differences between the strategies, even though the number of observations is limited. Based on the current results, it seems that the full recommendation networks of the more personalized strategies will resemble a Watts-Strogatz network, combining a high average clustering with low average path lengths (Watts and Strogatz, 1998). These characteristics would make a breadth-first crawl more feasible, as many recommendations will have already been watched in another branch of the search tree. Future research will have to be done to find out if the recommendations do indeed resemble Watts-Strogatz networks.

Furthermore, the results of the second sub-question, wherein the number of videos required to leave a filter bubble was examined, were somewhat inconclusive. Even after fifteen videos, the users' recommendation had not yet gone back to baseline. However, this could be influenced by the fact that the algorithm knows almost nothing about the user, other than that they enjoy conspiracy content. A user with a more extensive watching history could therefore possibly escape a similar filter bubble more quickly, as the algorithm then has other types of content to fall back on. Future research could look into just how long it takes before a user's recommendations start looking like the baseline again after watching conspiracy content, both for brand-new and older users. Additionally, this experiment could be done for different types of content. Considering conspiracy content tends to lead to more watch time on average, YouTube's algorithm could potentially be more averse to stop recommending conspiracy content as opposed to different, less captivating genres.

6 Conclusion

The goal of this research was to find out how different watch strategies affect the speed with which a user's YouTube homepage recommendations start preferring conspiracy content. Through the use of twenty brand-new YouTube accounts, an experiment was conducted in which different watch strategies were used to watch conspiracy content. The watch strategies were set-up to have an increasing level of personalization, in order to find a connection between the level of personalization and the speed with which a filter bubbles emerges. It was established that users who watch more personalized content tend to not only have their recommendations prefer conspiracy content more quickly, but also have this preference be stronger. This is in line with the original hypothesis. Additionally, it was found that, on YouTube, it is significantly more difficult to escape a filter bubble than to end up in one, regardless of the level of personalization (although increased personalization does lead to the filter bubbles remaining *stronger* for longer).

While previous research on the topic has already been done, this research made use of indirect or less-personalized methods to gather information about YouTube's algorithm. Furthermore, the results found by previous research have been contradictory to a certain degree. By therefore setting up the experiments in such a way that they accurately reflect real user behavior, new insights were gained into the way in which the YouTube algorithm is susceptible to filter bubbles. While this research has been relatively small-scale, the results are decisive: the YouTube algorithm is vulnerable to filter bubbles, even when it comes to harmful content.

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Appendices

All of the data and code used for this research is publicly available on GitHub.

A

Conspiracy recommendation network of each strategy

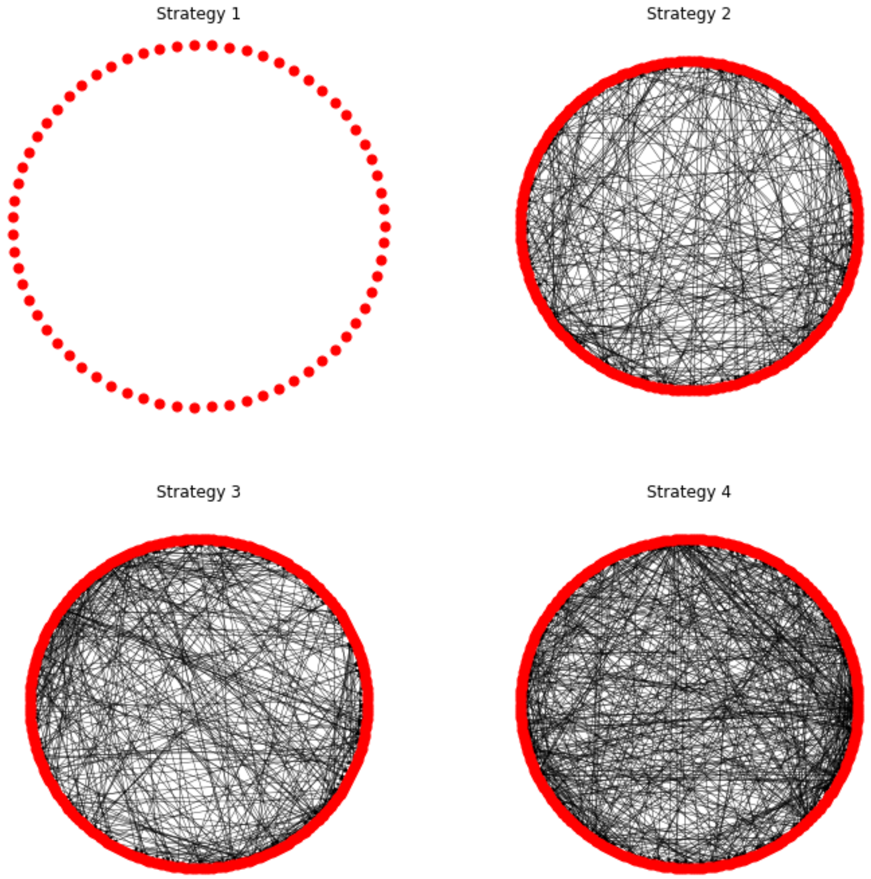

Figure A.1: The recommendation networks of each strategy if only conspiracy videos are kept.

B

Cosine similarity (regular videos)

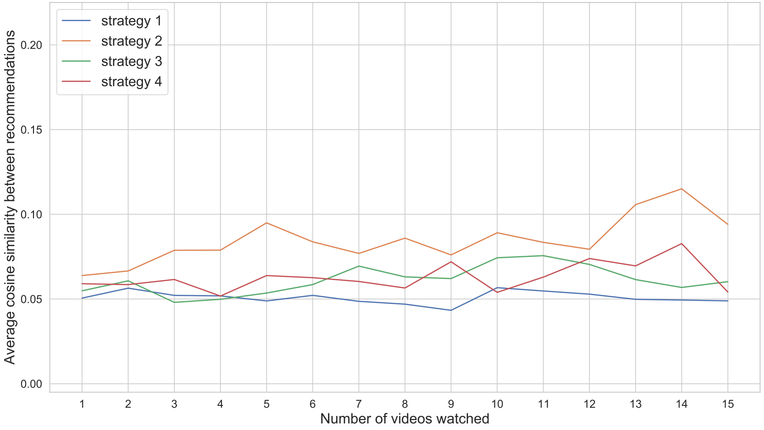

Figure A.2: Cosine similarity of regular recommendations

Cosine similarity (all videos)

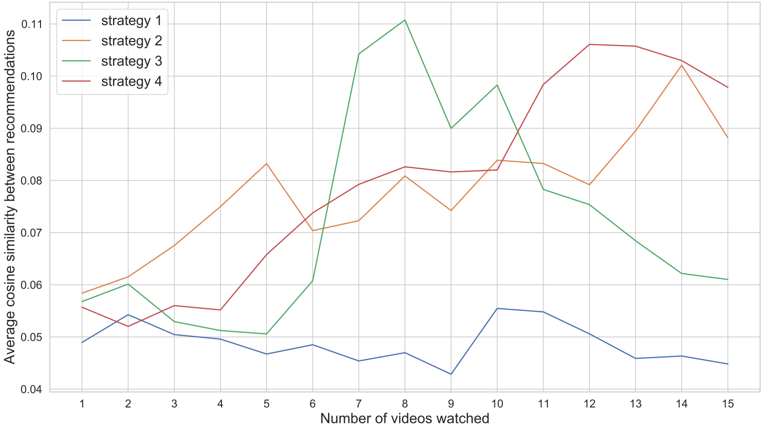

Figure A.3: Cosine similarity of all recommendations

Average view counts

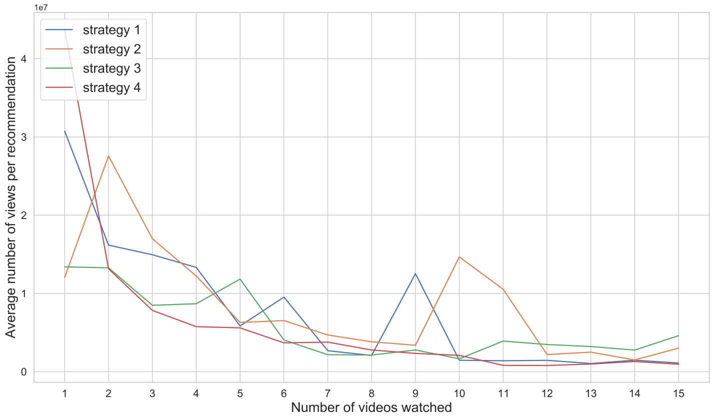

Figure A.4: The average number of views per recommendation of each watch strategy. Each measure consists of the first twenty recommendations of the five users for each strategy.

Average video lengths

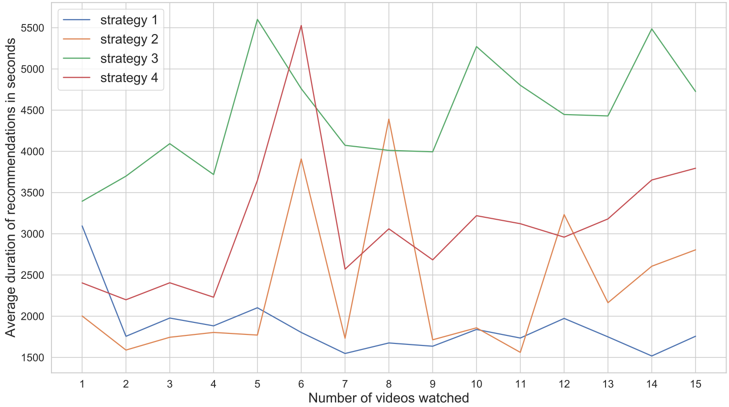

Figure A.5: The average duration of the recommendations of each watch strategy in seconds. Each measure consists of the first twenty recommendations of the five users for each strategy.

Ensemble	Activation	Layers	Neurons	Accuracy	Precision	Recall	F1
svm, nn, knn	logistic	1	20	**0.939318**	**0.948923**	**0.931204**	**0.93998**
svm, nn, knn	relu	1	20	0.939318	0.948923	0.931204	0.93998
svm, nn, knn	identity	1	1	0.939318	0.948923	0.931204	0.93998
svm, nn, knn	identity	10	1	0.939318	0.948923	0.931204	0.93998
svm, nn, knn	logistic	1	10	0.939318	0.948923	0.931204	0.93998
ridge, svm, nn, knn	tanh	10	1	0.939318	0.948923	0.931204	0.93998
svm, nn, knn	tanh	1	10	0.939318	0.948923	0.931204	0.93998
svm, nn, knn	tanh	1	20	0.939318	0.948923	0.931204	0.93998
svm, nn, logr, knn	identity	1	1	0.939318	0.948923	0.931204	0.93998
svm, nn, logr, knn	identity	1	10	0.939318	0.948923	0.931204	0.93998

Ensemble.

Kernel	C	Accuracy	Precision	Recall	F1
rbf	10.0	**0.936309**	0.945473	0.928747	**0.937035**
rbf	100.0	0.935557	0.942289	**0.930713**	0.936465
rbf	1.0	0.925276	0.930163	0.922850	0.926492
poly	10.0	0.916499	**0.946017**	0.886978	0.915547
poly	100.0	0.915246	0.944940	0.885504	0.914257
linear	1.0	0.913741	0.917944	0.912531	0.915229
poly	1.0	0.909729	0.935065	0.884521	0.909091
linear	10.0	0.904965	0.907882	0.905651	0.906765
linear	100.0	0.898195	0.905830	0.893366	0.899555
rbf	0.1	0.878887	0.878906	0.884521	0.881705

Support-vector machine.

Activation	Layers	Neurons	Accuracy	Precision	Recall	F1
identity	10	10	**0.923019**	**0.935484**	0.912039	**0.923613**
identity	25	10	0.921013	0.933031	0.910565	0.921661
relu	10	10	0.919007	0.917561	0.924324	0.920930
identity	10	20	0.916750	0.906056	**0.933661**	0.919652
relu	10	20	0.915998	0.912221	0.924324	0.918233
tanh	10	10	0.915747	0.914592	0.920885	0.917728
relu	1	1	0.915747	0.931876	0.900737	0.916042
tanh	25	20	0.915496	0.919052	0.914988	0.917016
tanh	10	20	0.914744	0.920178	0.912039	0.916091
logistic	1	1	0.913741	0.925516	0.903686	0.914470

Neural network.

Solver	Alpha	Accuracy	Precision	Recall	F1
auto	0.1	**0.918506**	0.919118	**0.921376**	**0.920245**
sparse_cg	0.1	0.918506	0.919118	0.921376	0.920245
sag	0.1	0.918255	**0.919902**	0.919902	0.919902
auto	1.0	0.917252	0.923497	0.913514	0.918478
sparse_cg	1.0	0.917252	0.923497	0.913514	0.918478
sag	1.0	0.917252	0.923497	0.913514	0.918478
sag	10.0	0.878385	0.893002	0.865356	0.878962
auto	10.0	0.878134	0.892549	0.865356	0.878743
sparse_cg	10.0	0.878134	0.892549	0.865356	0.878743
auto	100.0	0.812437	0.854545	0.762162	0.805714

Ridge regression.

Penalty	C	Solver	Accuracy	Precision	Recall	F1
l2	20	newton-cg	**0.918506**	**0.924107**	**0.915479**	**0.919773**
l2	20	saga	0.918506	0.924107	0.915479	0.919773
l2	20	sag	0.918506	0.924107	0.915479	0.919773
l2	10	sag	0.916249	0.920831	0.914496	0.917653
l2	10	newton-cg	0.916249	0.920831	0.914496	0.917653
l2	10	saga	0.916249	0.920831	0.914496	0.917653
l2	10	lbfgs	0.915747	0.919506	0.914988	0.917241
l2	20	lbfgs	0.914744	0.921432	0.910565	0.915966
none	1	sag	0.913992	0.923848	0.906143	0.914909
none	10	saga	0.913240	0.922461	0.906143	0.914229

Logistic regression.

K	Accuracy	Precision	Recall	F1
1	**0.889669**	0.888456	0.896314	**0.892368**
3	0.888415	0.882212	0.901720	0.891859
4	0.879137	0.908899	0.848157	0.877478
5	0.873370	0.858482	0.900246	0.878868
6	0.873119	0.882441	0.866830	0.874566
2	0.872618	**0.935043**	0.806388	0.865963
7	0.868355	0.848891	0.902703	0.874970
8	0.867603	0.867382	0.874201	0.870778
9	0.861585	0.835672	**0.907125**	0.869934
10	0.859579	0.854397	0.873710	0.863946

K-nearest neighbors.

Table B.1: Results of the classifiers on the validation set with different hyperparameters. The best score per metric is written in bold.