Through The YouTube Rabbit Hole

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Abstract

The unrestricted usage of online video-streaming platforms like YouTube is having a negative impact on users' productivity. The feature of YouTube's personalization has made its real recommendations extremely challenging to track accurately. Its engineers revealed that 70 percent of all views are based on the recommendations shown to the users. It is certainly possible to fall into some insane YouTube rabbit holes, but how often YouTube's recommendation algorithm leads one to them is still a matter of discussion.
While studies have revealed the involvement of YouTube's algorithm in the YouTube rabbit hole phenomenon and users' decreased efficiency, the engineers at YouTube deny any such claims.
After conducting a detailed analysis of the recommendations received from 68 videos from diverse channel types, we have calculated the recommended video's relevance with the initial video. These data show how the YouTube algorithm cleverly takes advantage of the short attention spans that people have developed in recent years and lead them to completely unrelated topics after a certain depth. Thus, our study analyses the broad aspects of the recommendation algorithm and the occurrence of YouTube's rabbit hole phenomenon.

1 Introduction

"YouTube's recommendation algorithm has a dark side. It leads users down rabbit holes", says the researchers from Scientific American. [Tuf] The platform that is considered a gateway to information has been accused of recommending extreme content to engage users and make them stay on the site longer.
However, YouTube has defended its video recommendation algorithms amid the allegations that the platform serves up increasingly extreme videos and denied radicalization claims. The company's new managing director for the UK, Ben McOwen Wilson, said "It's what's great about YouTube. It is what brings you from one small area and actually expands your horizon and does the opposite of taking you down the rabbit hole". [19b]
As the overuse of YouTube can have adverse effects on our mental health, we must become wary of the negative effects of the YouTube recommendation system and puzzle out how to prevent them from outweighing the benefits. Hence, it is crucial to analyze the rabbit hole phenomenon to then suggest solutions for the same.

1.1 Problem

While YouTube's usage has grown exponentially, resulting in connecting people, making information readily available to everyone. We have overlooked how it has contributed to the loss of productivity. [19a]

The YouTube rabbit hole phenomenon describes watching endless YouTube recommended videos based on the user's activity after the previous video completes. [Mul19]
Overusing it makes an individual feel lonely, depressed, and anxious. It is a matter of concern because the users don't realize that they have shifted off topic very quickly. For the platform's productive usage, the user needs to have continuous self-control to stay on the relevant topics and not be lured away into watching irrelevant content - which generally ends up with the user feeling exhausted, inefficient and frustrated with the time lost.

1.2 Literature

Concerns that YouTube's recommendation algorithm funnels people toward content that promotes white supremacy or other forms of bigoted extremism are not a new thing. What is new, however, is a study that curiously claims the platform's algorithm "actively discourages viewers from visiting radicalizing or extremist content." [19a]

These "recommended" videos play one after the other. Maybe you finished a tutorial on how to sharpen knives, but the next one may well be about why feminists are ruining manhood, how vaccinations are poisonous or why climate change is a hoax—or a nifty explainer "proving" the Titanic never hit an iceberg. [Tuf]

The role that YouTube and its behind-the-scenes recommendation algorithm plays in encouraging online radicalization has been suggested by both journalists and academics alike. [LZ20]

"YouTube is an ongoing conversation in my therapy practice, which indicates there's a problem," she said. Over the last five years, she said she has seen a rise in cases of children suffering from anxiety triggered by videos they have watched on YouTube. These children exhibit loss of appetite, sleeplessness, crying fits and fear. [Bil18]

Colloquially known as the YouTube 'Rabbit hole' which describes the process of watching endless YouTube videos but a closer look in the the YouTube recommendation algorithm will reveal how this happens. [Mul19]

1.3 Our experimentation

We conduct a qualitative study on the relevance of videos that are recommended on YouTube to the original video that the user searched for, herein after called the **root video**. This study addresses how rapidly the topic of the video shifts with respect to the topic of the root video as we repeatedly follow the recommendation links, thereby simulating the behaviour of a user going down the rabbit hole.

2 Method

2.1 Implementation details

We developed a web crawler and scraper for gathering video context and recommended links. the following packages were used:

Programming Language: Python
Tools and Libraries:

1. **NumPy** for linear algebra with word vectors

2. **Spacy** for Natural Language Processing tasks - removing non-vocab words, condensing tags, generating word vectors, lemmatization
3. **BeautifulSoup** for scraping static HTML code
4. **Selenium** to run instance of chromium for crawling to extract dynamic HTML code
5. **Matplotlib** for plotting

2.2 Get Data From URL

We use the selenium web driver to run a headless instance of chromium. This function acquires the dynamic HTML loaded in chromium that is then parsed by BeautifulSoup HTML parser. The parser is used to extract the json variable `window["ytInitialPlayerResponse"]`. This json variable stores the tags of the YouTube video in a list under the header `videoDetails>keywords>`.

Links of recommended videos are located under the HTML tag `ytd-compact-video-renderer` that are then extracted and compiled in a list of links.

A list of tags and links is returned.

2.3 Get Relevance

We derive the relevance for two sets of `tags` for two videos respectively by:

1. Splitting the tags into individual words and making a set out of them
2. Lemmatizing the words
3. Reducing the words to spacy's vocabulary
4. Generating word vectors for all words and taking an average over them. Figure1
5. Calculating the cosine similarity between the generated averages. Figure2

2.4 Crawling YouTube

The `getDataFromUrl` function defined in Section 2.2 returns a list of tags and links. A random link is chosen from the list of links and tags are extracted from this link. The `getRelevance` function defined in Section 2.3 is then used to compute relevance between this pair of tags. The result is stored and the random link chosen is crawled on in a recursive fashion.

3 Results

3.1 Experiment findings

We crawled a total of 68 YouTube watch links collected from `algotransparency.org` up to a depth of 16. The relevance of videos at each depth with respect to the corresponding root video was calculated. The results for all root videos were plotted as shown in Figure 3.

We refer to each plot for a root video as a **crawl**.

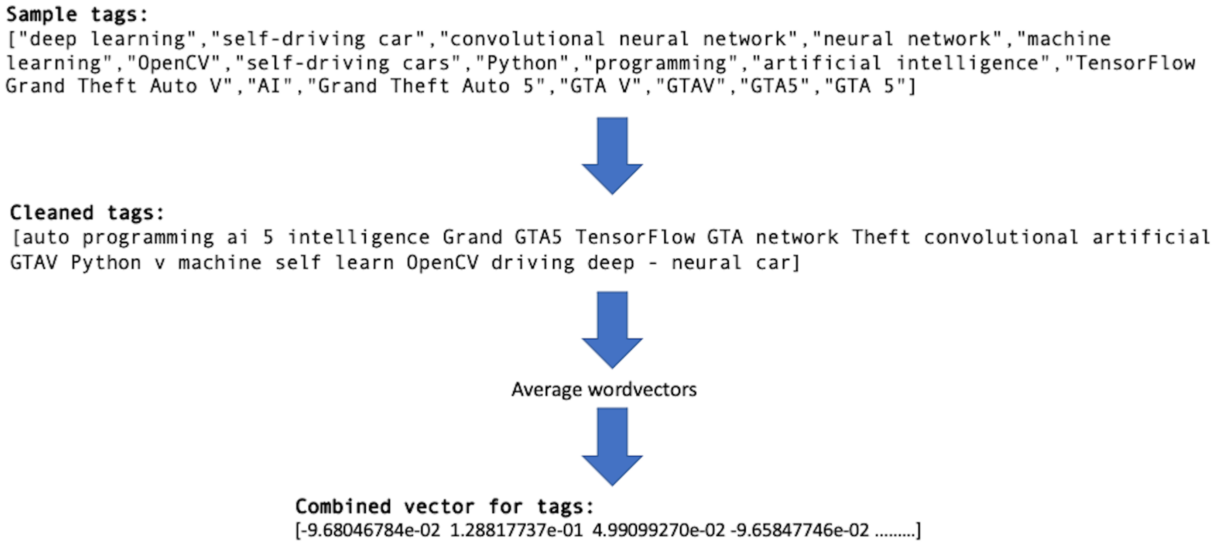

Figure 1: The tags scraped from the HTML are cleaned and converted to individual word vectors. These vectors are then averaged to generate a vector representing the context of the video

3.2 Interpretation of findings

We can observe a gradual downward trend in the plot of the average relevance with respect to the depth. The average relevance even at depth 1, that is the recommendations on the root page start out at around 0.7, which as depicted in Figure 2 represents that the recommended videos share minimum common context with the root to be considered relevant.
We observe that seldom, the relevance jumps to 1.0. This means that the root video shows up in the recommendations.
We can also observe that there are a few trends which start at near zero relevance and fail to reach above the relevance threshold of 0.7. We interpret that the videos in these crawls are purely for short term entertainment and require no relevance whatsoever between the recommendations. We observe 10 out of 68 trends belong to this category
Similarly, we observe that on the opposite end of the spectrum, a few trends never go below the threshold of 0.7. We interpret that these videos belong to tightly knit knowledge communities. We observe 5 out of 68 trends belong to this category
In the histogram of standard deviations 4, we can observe that most crawls tend to have a limited range of relevance. This can be interpreted as, crawls tend to retain the relevance they encounter, although as we interpreted earlier, the crawls do tend to gradually lose this relevance.

The results that we observe correlate with our expectations, specifically, content that YouTube tends to recommend the users is engineered to satisfy the high demands for dopamine that internet users have become accustomed to in the 21st century.

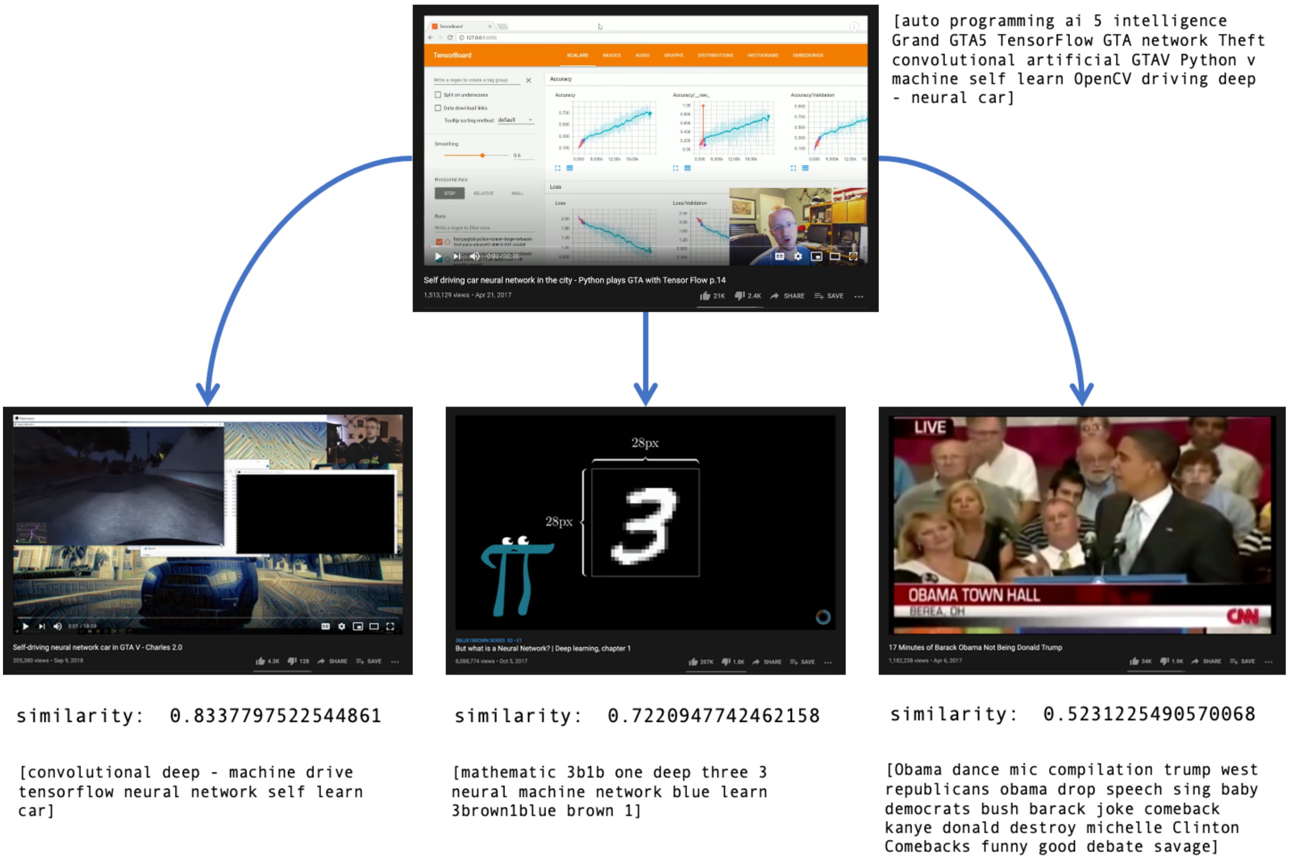

Figure 2: Visual representation of tags for 3 videos sampled from the recommendations of the root video being used to compute the similarity. It is evident that similarity scores 0.8+ are relevant, 0.7+ are at least related through some topic, and scores of 0.6- represent videos that are irrelevant to the context of the root video

4 Conclusion

Our major takeaway from this study is that the YouTube rabbit hole phenomena is real. We support our claims with qualitative analyses of different sorts. We develop a simple method to compare the context of two YouTube videos in form of a similarity metric. The relevance depicted by the similarity metric helps us to present the gradual decline in relevance of links with respect to the root video as we go deeper. All the code used in the implementation and conduction of this study can be found at the repository at this link `github.com/heylakshya/youtubeRabbitHole`

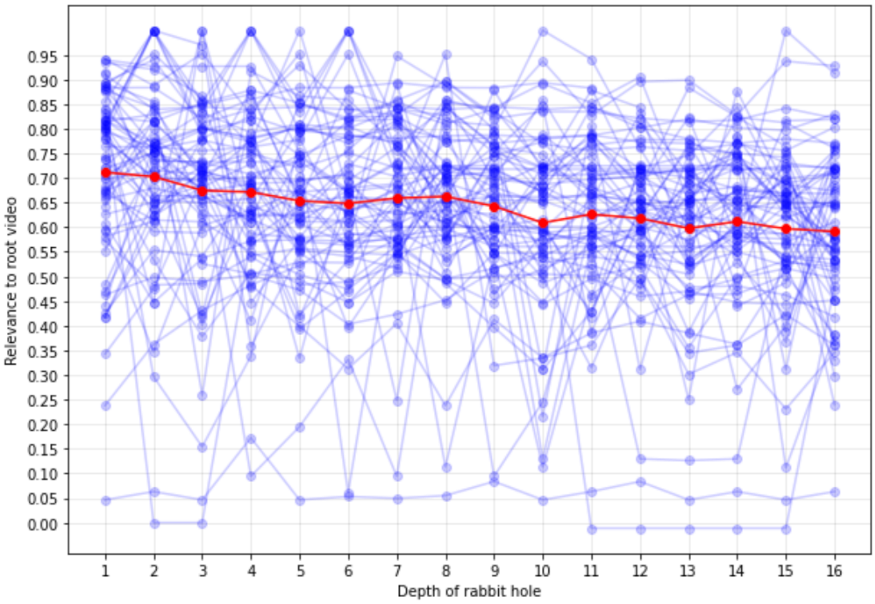

Figure 3: Plot of relevance to root video at different depths

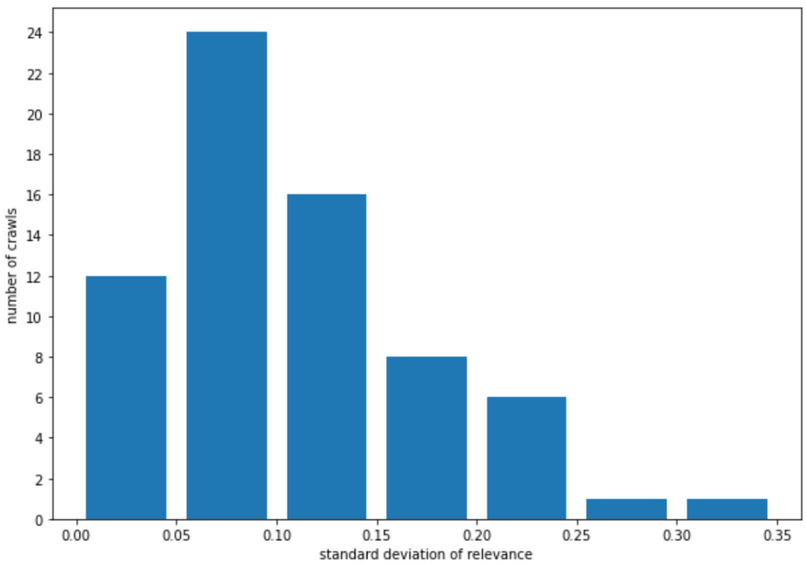

Figure 4: Histogram of standard deviations of crawls

4.1 Future Work

This work can be succeeded by development of an extension that monitors the similarity metric while browsing on YouTube. This tool would notify the user that they have ventured off topic from their initial search.

4.2 Team Work

We believe in a well-organized team's strength, and hence we preferred to work in a planned manner. For the smooth flow of the work, we defined our clear roles and divided our work.
First of all, we worked out the project's clear goals, which will help us develop individuals' skills and utilize each other's abilities.

The work division was as follows:

- Supriya performed the literature analysis to examine the depth of the problem, its adverse effects, and the limitations of the existing solutions.
- Lakshya worked on building the web crawler and web scraper for the collection of the data for analysis. He also performed the various experiments to find the relevance of the recommended videos with respect to the root video.
- The observations drawn from the experiment were analyzed and discussed by both of us to reach a common conclusion.
- While writing the report, based on the previous analysis and experiment, Supriya wrote the Abstract, Introduction, Literature, Problem statement, and Implementation details. Furthermore, Lakshya wrote the experimental details, method followed, interpretations, and the experiment's conclusion.

Coming to what we have been done differently, We think the Data collection process was slow and could have been more efficient. This would have enabled us to study a much larger corpus of YouTube links The similarity measure can also be much more precise if we used neural models like BERT to compare the context of any two videos.

References

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