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APATHY: HOW YOUTUBE'S ALGORITHMS FOSTER BINGE-WATCHING BEHAVIOUR

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Abstract. *Our work examines the mechanisms of formation of severe symptoms of psychological dependence on content in YouTube consumers. A technical and psychological analysis of the YouTube platform recommendation algorithm was conducted in order to predict trends in the era of processing large amounts of data. Such phenomena are considered from the point of view of software tricks designed to determine individual customer preferences. Recommendations for overcoming existing difficulties are formulated.*

Key words: *YouTube, algorithm, binge-watching, personalized content.*

Introduction.

Have you ever watched a short YouTube video, just to find yourself hours later in a daze, wondering where time went? This experience is a common factor for content platforms, whose sophisticated algorithms are designed to maximize users' watch time. Specifically, YouTube uses a 'funnel' of two algorithms that work sequentially: while the first gathers 'candidates', the second one - ranks them, which ensures high robustness and precision of recommendations [1]. This paper provides a high-level technical overview of the algorithms' main objective, what is underneath it, and presents ongoing debates regarding psychological implications. To achieve this, it will briefly trace the historic evolution, outline the current state of technology, define and contextualize the binge-watching behaviour, and finally, provide a balanced overview on the algorithm's impact on users.

History

Recommendation systems have been evolving for decades, getting better and better with every published research paper. It is informative to know how it all started. One of the first algorithms used a relatively simple idea: analyzing commonalities between users, grouping them and then trying to fill in the gaps of one another [2, 3]. Amazon was one of the most successful e-commerce websites to benefit from such an algorithm [3, 4]. Then, YouTube featured a similar idea in their early algorithm in 2010 [2]. With associating users between one another by the ‘co-watching’ feature in their datasets and analyzing the viewing patterns they were able to systematically provide recommendations to early users [2]. These algorithms served as a foundation to help develop even more stronger and sophisticated algorithms that social media platforms use nowadays.

However, with the ever-growing userbase, those algorithms faced the challenge: scalability. As early as 2003, Amazon’s computer engineers noticed that comparing millions of their customers between each other and the products they were buying was extremely tedious[4]. The same issue was mentioned in YouTube’s paper in the same context[1]. This recurring challenge has been pushing the industry forward for over two decades now.

The current state of technology

Today, YouTube uses a more nuanced approach, described by its engineers in [1] as a “classic two-stage information retrieval dichotomy”. To put simply, the system employs two distinct deep-learning neural networks, each operating on a different scale, in a funnel-like procedure. The first network filters a massive corpus of YouTube videos, feeding a smaller selection into the second network. This second algorithm then ranks these videos, presenting each user with only a handful of highly relevant options. This design helps overcome the problems that arise from the vastness of videos available on the platform for both sides: users and engineers [1].

The first stage, candidate determination, is responsible for the initial filtering. Its inputs include rich user metrics across an individual account and the platform overall, including watch history, search queries, likes/dislikes, watch time, etc. However, YouTube's engineers emphasize that there is ‘orders of magnitude’ more of ‘implicit’ data, compared to ‘explicit’ data features like thumbs up or down, comments, etc. Nevertheless, such generated candidates remain highly personalised, due to the nature of subsetting from a specific user’s “activity history” [1].

The second stage, ranking, is responsible for taking the output of the first ‘funnel’ in order to rank each video for the user, sort by the highest rank, and then present a handful of recommendations straight to the user. To do so, it uses a much richer set of features that every video has. These two systems, working with one-another are designed to eventually maximize the users' watch time. The authors decided to stick with this metric, rather than the click-through rate, because it did not encourage the behaviour, broadly known as 'click-bait'. Interestingly, click-through rate is a measure of how much users clicked on a video compared to the others who did not do so. Therefore, as the authors argue in [1], using the watch time metric is closer to measuring the true engagement, rather than using CTR or anything else.

Future prospects

While traditional deep learning algorithms are effective [1], it is crucial to explore new horizons with the progress in large language models research [6]. Zhao et al. detailed some new prospects of using LLMs for 'RecSys' algorithms. With the power of large and diverse data sets, using a more 'generalized' model would mean that it is capable of doing more specific tasks without 'fine-tuning'. Moreover, hence their initial goal, LLMs can be used to provide an explanation for a specific recommendation they see [6]. Even further, it becomes possible for a user to input and modify their preferences with mere text inputs [7].

Another point that is brought up throughout the future 'AI' discussions, is that it is a 'black box': since current LLMs have billions of parameters, it is impossible to reverse-engineer them. As a result, it poses a threat by itself, since we have no understanding of what is happening inside [8]. By allowing those algorithms to work 'from the shade', there is a possibility of unintended consequences we are yet to uncover.

What *was* discovered is the systematic repetition of patterns, including biases: LLMs were to "inadvertently learn and perpetuate biases and stereotypes". Since it is simply any deep-learning model's nature to try to learn and predict, careless, unsupervised and unethical scraping of the whole Internet can lead to disastrous consequences. Speaking of patterns, misinformation and hallucination was on the list too: "language models generate outputs that are plausible-sounding but factually incorrect or not referable in the input data", possibly creating a new rabbit hole of ‘seamless’ misinformation [7].

Overall, it seems like substantial progress is to be made in the newly-emerged LLM field, whose full prospects are yet to be discovered, in combination with the current recommendation algorithms.

Controversy

On the one hand, such algorithms that maximize users’ watch time may by design lead to *excessive* maximization: binge-watching. A review summarizes its definition as “watching multiple episodes [...] in one sitting”. It has been argued that it is not just an innocuous pastime. It is a brain’s systematic coping response to “escape reality and avoid problems or negative emotions” [5]. Therefore, it is a stumbling block for most nowadays recommendation algorithms, as they may be considered to nearly encourage unhealthy patterns of binge-watching or even video platforms addiction.

Critics argue that these algorithms interfere with our receptors in brains in profound ways[9], incorporating ‘psychological hooks’, such as ‘variable rewards’ . Industry experts including Niyal warn that this technique resembles the highly addictive design of slot machines in casinos. By serving a below-baseline content, in terms of engagement and emotional response, and from time to time providing a highly rewarding piece of content, it induces a ‘hunt’ for a next ‘reward’ [10]. Interestingly, in his videos, Dr Alok Kanojia argues that the constant stream of such ‘cheap’ dopamine disencourages brain from seeking rewards from other, not so engaging, but very important activities. This in turn leads to a trans-like drained state where a person experiences an extreme lack of motivation and resources [11]. Therefore, there forms a very strong link between the design of an algorithm, binge-watching and the consequences for a user.

On the other hand, there is an argument towards users’ autonomy and personal responsibility. YouTube’s engineers meticulously picked watch-time as a main metric, above anything else [1]. The argument may further be extended that the metric is close to the ‘ground truth’, therefore almost perfectly matching with what people really like, as a result providing what they needed and would naturally gravitate towards the content they desired.

To reemphasize, it may be argued it should be more up to the user of how they would like to manage their wants and needs.

Summary and conclusions.

In conclusion, this paper has provided a technical and a psychological examination of a YouTube's recommendation algorithm, tracing its evolution and providing insight into what controversy it generates Today. From its origins in collaborative filtering [2,4], to highly sophisticated deep learning 'funnels' maximizing users' watch time, recommendation systems have evolved significantly. While providing highly personalized content to every user [1], they raise some concerns that are worth mentioning and addressing: addiction, binge-watching and other inadvertent behaviours. Future research and developments both in AI and in recommendation systems promise overcoming current struggles and overall look encouraging. Ultimately, the interplay between the two will be of paramount importance for a long time, because humanity is entering the era of Big Data.

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