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Analyzing Bias in Recommender Systems: A Comprehensive Evaluation of YouTube's Recommendation Algorithm

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***Abstract*—Recommender systems play a crucial role in suggesting relevant content to users based on their past activities. They employ a process known as "collaborative filtering" to efficiently navigate extensive content repositories. However, concerns have been raised regarding the potential bias and homogeneity in recommendations, resulting in filter-bubbles and echo-chambers. Detecting and mitigating these biases is crucial for ensuring fair and diverse automated decision-making systems. This study investigates the impact of YouTube's recommendation algorithm on three distinct narratives across multiple dimensions. Our objective is to identify potential biases and gain insights into its decision-making behavior. We applied a multi-method approach to evaluate emotional content, moral foundations, lexical similarity, and social network analysis across 5 depths of YouTube recommendations. The results of our analysis showed diversity in emotions, significant drift in topics, and a push toward non-related, but highly influential videos across multiple recommendation depths. The findings from this study contribute to the understanding of bias in recommender systems. These insights inform the development of strategies to mitigate biases and improve the user experience. Policymakers and platform developers can utilize this knowledge to establish effective guidelines and policies for their recommender systems, enhancing decision-making processes.**

***Index Terms*—Recommender Systems, Bias Detection, Narrative Analysis, Network Analysis, Emotion Analysis, Morality Assessment, Engagement Analysis, Topic Diversity**

I. Introduction

In this study, we examine the behavior of YouTube's recommendation algorithm on competing narratives with the goal of detecting bias and interpreting the decision-making behavior of the algorithm. To achieve this, we examine the effects of the algorithm on videos related to three socio-political issues in the Indo-Pacific region which include the China-Uyghur crisis, Cheng Ho propaganda, and the South China Sea conflict.

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1) China-Uyghur crisis: The China-Uyghur crisis has garnered significant criticism from the organizations across the globe. According to the Council on Foreign Relations [20], more than a million Uyghurs - a Muslim, Uyghur speaking ethnic group, have been detained since 2017 in the China Xinjiang region. The United States and the UN human rights office have described these acts as crimes against humanity. Although international journalists and researchers have reported the ongoing systems of mass detention throughout the region using satellite images and leaked Chinese government documents, individual testimonies from Chinese officials maintain that the rights of Uyghur Muslims have not been infringed upon and government crackdown measures such as re-education camps have been closed since 2019 [8]. According to Silverman, content evoking polarization is propagated faster than non-polarizing content [21]. Therefore, since the emotions attached to our seed videos are negative, we also expect to see more of these emotions propagated through videos across recommendation depths, the sentiments and emotions in videos related to this topic are expected to be negative and sad/fearful.

2) Cheng Ho Propaganda: The Cheng Ho propaganda is a narrative that is believed to have been introduced to inspire confidence and encourage positive sentiments concerning the Chinese government. Created in response to the accusations on China's oppression of Muslims, this propaganda was designed by the Chinese Communist Party to portray China as having Muslim roots in order to dispel negative imagery rising from claims of its discrimination against the predominantly Muslim Uyghur group. The Cheng Ho narrative claims that a Chinese Admiral known for commanding naval voyages in the early 15th century, traveled as a compassionate gift giver, spreading Islam, religious tolerance, and peace. He is often compared to Christopher Columbus but was not known to occupy a single piece of land [22]. The purpose behind promoting this narrative appears to involve addressing the allegations of China's oppression of the Uyghur Muslims and bolstering support for China, as well as supporting its strategic pursuits, which may include the South China Sea conflict. The sentiments and emotions in the videos about this narrative are expected to be positive and joyful.

3) South China Sea Conflict: The South China Sea is of great economic importance as one-third of the world's maritime shipping passes through it yielding about USD3 trillion in trade annually. Also, the sea is believed to contain large quantities of oil and natural gas reserves beneath its seabeds. These features along with lucrative fishery resources make the South China sea of high economic and geostrategic importance. In recent years, it has been discovered that China has made efforts to claim territories in the South China Sea by physically increasing island size as well as creating new islands by dredging sand onto existing reefs [23]. Some other land reclamation activities made by China includes constructing ports, airstrips, and military installations, specifically in Paracel and Spratly Islands, where China has 20 and 7 outposts respectively. These land reclamation activities by China have raised concern over competing territorial claims and maritime rights. In response to China's increasing assertiveness over the South China Sea [25], in July 2016, the Philippines petitioned against China in the Permanent Court of Arbitration at The Hague and won on 14 out of 15 points [27]. This led to a ruling stating that Beijing's "nine-dash line" claim [28] is inconsistent with international law. The current territorial conflict between China and the Philippines is the most recent dispute of the many that have been ongoing for over six decades. The six countries bordering the South China Sea have claimed different parts of three island chains and their associated maritime zones [24]. Beijing's recent reclamation activities over the South China Sea have raised growing concerns as it improves China's ability to influence the global maritime economy by influencing global merchandise export and trade. This dataset is centered around the South China Sea narrative in the Philippines and the effects of China's aggressive endeavors in the South China Sea regions [26].

II. Literature Review

In this section, we discuss previous works related to our study including methodologies around multi-dimension radar chart analysis, recommendation bias and topic shifting. Radar charts are a form of 2D charts which are used to plot multiple quantitative variables (multivariate data). Each variable being analyzed is assigned an axis which begins from the center of the chart. The resulting axes of all variables are arranged radially in an equidistant manner between each other, while maintaining the same scale between all axes. Svenja et al utilized radar graphs to illustrate results from network meta-analysis in cases where the interest lies in the comparison of estimated results or a performance measure to a pre-defined fixed reference value [15]. In this research, the author used radar graphs in visualizing the estimation results or simulation studies on network meta-analysis. By utilizing a radar graph in this research, it was possible to simultaneously visualize contrasts and identify relationships. Also, the type of contrast identified was distinguished by the color and shades of the points. Marina et al utilized radars charts in the visualization of the results of corpus-based text complexity analysis [14]. In this research, the authors explored the possibility of automatically isolating different sections of text complexity across registers of a Swedish corpus in an intuitive and efficient way. Radar charts were used in this study due to its ability to plot polygonal shapes which help emphasize points of similarities and differences across target categories. The authors concluded that the visualization of text complexity facets with radar charts showed a correspondence between linguistic similarity and the similarity of shapes across registers.

Interest in recommender systems bias research has grown in recent years [29], [30]. The goal of such research is to identify and categorize content [16]–[18] to understand its nature, structure, and effects, especially in the area of radicalization, polarization, and spread of misinformation [10]. These studies have explored the generation of homophilic communities through recommendation engines as well as factors which could lead to such homogenous communities [9]. Topic drift is a technique that has been used by many researchers in studying how content evolves and as a result, the possible presence of bias. O' Hare et al. [11] analyzed sentiment-annotated corpus of textual data to determine topic drift among documents within a corpus. Liu et al. developed an LDA (Latent Dirichlet Allocation)-based method for topic drift detection in micro-blog posts [8]. Topal et al. identified and quantitatively studied the effects of topic shift in social media comments [7]. Papakyriakopoulos et al., addressed hyperactive users and their effects on political discussion and recommender systems [6]. According to Papakyriakopoulos, recommendation algorithms favor the interest of hyperactive users, creating significant social influence bias and causing alterations in political opinions. By identifying inherent topics using topic modeling [3], [5], the authors classified content by topic to examine the activities of hyperactive users and determine if engagement distribution diverges.

III. Methodology

Our research involved 2 categories of data; 'seed' videos and depth videos. To begin data collection, we initiated a series of workshops with subject matter experts to generate a list of relevant keywords related to the 3 narratives; the China-Uyghur conflict, the Cheng Ho propaganda and the South China Sea conflict. These keywords were used as search queries on YouTube's search engine to generate 40 seed videos across the 3 narratives sorted by relevance. To ensure that users' search histories did not influence the results and to eliminate personalization bias, we did not log in to the platform. A new browser instance was started for each level of recommendation, and cookies and cache were cleared. The seed videos were used to generate the recommended (depth) videos used in our analysis. China-Uyghur conflict had 10035 videos, Cheng Ho propaganda had 12087 and South China Sea conflict had 10074 videos in total. While they were being collected, they were sorted by relevance. The depth videos used in this research were composed of YouTube's **'watch-next'** videos which are found in the watch-next panel of the platform. These videos were captured via the seed videos using techniques employed in [10]. Drift occurs when there is a deviation from an inital measured metric. In previous research, drift was measured based on select analyses of content such as recommended videos in an effort to track content evolution. In this study, we employ a drift analysis methodology introduced by Okeke et al. to identify and summarize recommendation bias across 3 narratives. For this research we computed and visualized drift in emotions [33], topic and morality [4]. We further conducted network analysis to determine the specific videos which drive recommendations across depths [31], [32]. To find the most influential videos, we isolated and analyzed the top 10 videos with the highest eigenvector centrality score per depth.

As previously mentioned, we computed and visualized drift in emotions, topic and morality across our 3 target narratives.

1) Emotion Drift Analysis: Emotion drift occurs when there is a deviation from an initially presented emotion. To measure emotion drift, we used the Hugging Face Emotion detection library in python. We analyzed emotions embedded in video text data across 6 emotion levels; joy, anger, sadness, fear, surprise, love across recommended video depths. Each depth represented a traversed hop of recommended videos, starting from the seed videos and going through video recommendations. Once the drift in emotions across depth was computed, the resulting emotion drift was visualized using radar charts.

2) Morality Drift Analysis: Morality describes a system of values which help direct humans on the difference between right and wrong. Using morality assessment, we analyze the inherent morality of a text to determine if the text is morally right or wrong. Using the Moral Foundations Theory [19], we analyzed the drift in morality across depths and across five moral foundations of our 3 narratives; Care/harm (involving intuitions of sympathy, compassion, and nurturance), Fairness/cheating (including notions of rights and justice), Loyalty/betrayal (supporting moral obligations of patriotism and "us versus them" thinking), Authority/subversion (including concerns about traditions and maintaining social order), and Sanctity/degradation (including moral disgust and spiritual concerns related to the body) [12]. The resulting morality diversity in content was also illustrated using radar graphs, with each depth representing a traversed depth of video recommendations.

3) Topic Drift Analysis: The goal of topic drift detection was to determine if recommended videos stayed on the topic of the target narrative as we moved through recommendations or drifted from the conversation of the original seed videos. Topic drift across depths was measured by computing topic similarity using Hellinger distance [12], [13]. The Hellinger score is a probability based distance metric used in estimating distances between probability distributions to determine document similarity. The Hellinger distance metric is comparable to Kullback-Leibler (KL) divergence and is represented as the symmetric midpoint of KL divergence [1], [2]. This distance metric calculates similarity within the range of 0 to 1, where values closer to 0 indicate a smaller distance and therefore larger similarity and vice versa. As with the previous analyses, the topic diversity in content was also illustrated using radar graphs.

IV. Results

In this section we discuss the results of our multi-mode analysis. To simplify the visualization, we focused on the first, middle, and last depths in our radar charts. Each axis of the chart corresponds to a specific categorical value, representing different dimensions of drift. Within the chart, the center point represents the lowest value for each category, labeled as 'zero'. This visual representation aids in understanding the varying drift across each category within the analyzed depths.

1) Emotion Drift Pattern: The distribution of emotions is spread across 6 emotion categories; fear, anger, love, surprise, sadness and joy. The lowest expression occurs at the center of the wheel, while the highest emotion expression occurs at the edge of the wheel. For the Cheng Ho narrative we see that the emotion drift pattern at depth 0, depth 2 and depth 4 are similar in shape and therefore similar in drift pattern, suggesting that the recommendation pattern remains similar across recommendations. We also see that the joy emotion is consistently expressed as the most dominant emotion as we progress across recommendations from depth 0 to depth 4. Considering the South China Sea narrative, the most expressed emotion at depth 0 is anger closely followed by joy. Conversely, the highest expressed emotion at depth 2 and depth 4 is joy which is followed closely behind in their respective depths by anger. This is an interesting pattern as we see that the same emotion distribution trend expressed at depth 0 but in reverse as we approach depth 2 and depth 4. The China-Uyghur narrative tells a different story from the Cheng Ho and South China Sea discussions. On analyzing the emotion distribution at depth 0, we see that the anger emotion is expressed at very high levels with little to no presence of other emotions. At depths 2 and 4, we observe significant expressions of joy with a significantly reduced amount of anger emotion as compared to its levels at depth 0. The results of our analysis suggest that more polarizing narratives show more diversity in the emotions of the recommended videos.

2) Topic Drift Pattern: The goal of topic drift analysis is to determine if the recommendations stayed on the topic of the seed videos or drifted away. The distribution of topics in this analysis was spread across 7 different topics. Each collection of 7 topics was unique to the target narrative. Radar charts were used to visualize topic drift across multiple dimensions (7 topics and 4 depths). A depth will be considered to stay 'on-topic' of the seed videos if it shared a similar shape pattern to the depth 0 within a specific narrative. For the Cheng Ho narrative, we see that the 3 depths share a similar dominant topic; topic 5. This suggests that as the algorithm recommends videos from the seed videos of the Cheng Ho narrative, the topics remain relatively similar across depths. On the other hand, for the South China Sea conflict, depth 0 shows 3 dominant topics; topic 3, topic 4 and topic 6. As we approach depth 2 and depth 4, we see they share a dominant topic with depth 0; topic 3. Also, we see that depth 2 and depth 4 are very similar in shape as share the same dominant topics;

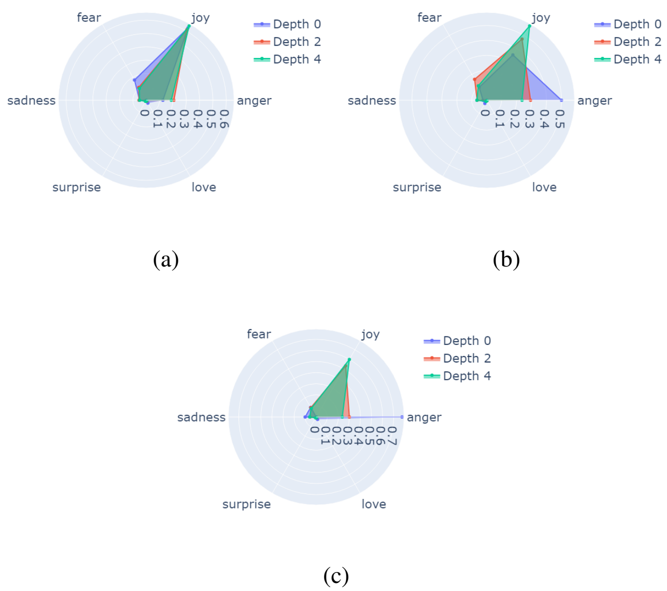


Fig. 1: Radar charts showing emotion diversity across recommendations of videos for (a) Cheng Ho (b) South China Sea (c) China-Uyghur conflict

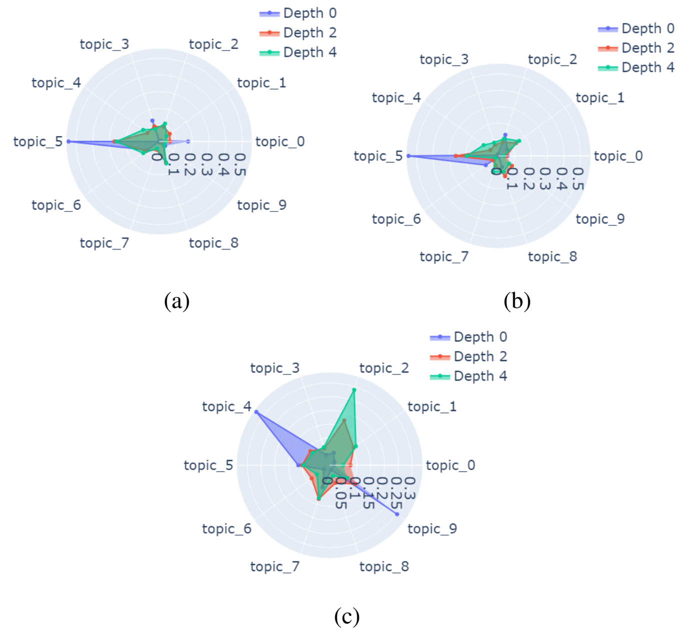


Fig. 2: Radar charts showing topic diversity across recommendations of videos for (a) Cheng Ho (b) South China Sea (c) China-Uyghur conflict

topic 3, topic 5 and topic 9. These patterns suggest that as recommendations are generated by YouTube's algorithm from the South China Sea videos, they partially deviate in topic from the seed videos (depth 0) but stay relatively similar as indicated by their respective polygon shapes (depth 2 and depth 4). The China-Uyghur analysis shows a completely different deviation pattern. The respective polygon shapes at each depth show that depth 2 and depth 4 share no dominant topic with depth 0. This suggests that depth 2 and depth 4 have dominant topics; topic 2 and topic 7 have drifted significantly from the topic of conversation at depth 0 which has the dominant topics; topic 4 and topic 9.

3) Engagement Metrics Analysis: To examine the significance of these pattern drifts, we conducted an analysis of user interaction with the videos using engagement metrics across different depths. The objective of this analysis was to determine whether more popular videos were being recommended as users delved deeper into the content . In our experiment, a video was considered popular if it had a considerably high number of views and received high positive engagement in the form of likes.

To calculate user engagement, we focused on two key metrics: views and likes. Figure 3 illustrates the trends we observed. As we progressed through recommendation depths, both the view counts and like counts exhibited an increase. Notably, the median number of likes for the recommended videos was significantly higher when compared to the seed videos. Additionally, we observed a substantial number of outliers in the final depth (depth 4).

Based on our engagement analysis, it is evident that the recommended videos contain a higher proportion of popular content. This finding offers an explanation for the widespread presence of positive emotions and virtues in the higher depths of recommendations.

4) Network Analysis: Network analysis was performed on each depth of recommended videos using a recommendation network. For each depth, every video was ranked using its eigenvector centrality measure to determine its influence in the network.

Nodes are sized by eigenvector centrality in the graph in Figure 4. To find the most influential videos, we isolated and analyzed the top 10 videos with the highest eigenvector centrality score per depth. The mean eigenvector centrality score for the top 10 videos per depth was found and videos which had an eigenvector centrality score above the resulting mean were filtered out and categorized as 'above-average' influential videos. We infer from the analysis that these 'above-average' influential videos were responsible for driving the recommendations of videos across depths and determined how the conversation across depths evolved.

To verify content divergence of above-average videos from our seed videos after depth 3, we performed content analysis on the entire dataset to generate the latent topics present in the recommendations and assigned each video a topic community. For this research, we defined a topic community as a number which categorizes a collection of content within a specific topic. Topic modelling was done using BERTopic, to visualize the content of our 'above-average' influential videos and track the movement of influential topic communities as we moved across recommended videos (see Figure 4). Our results

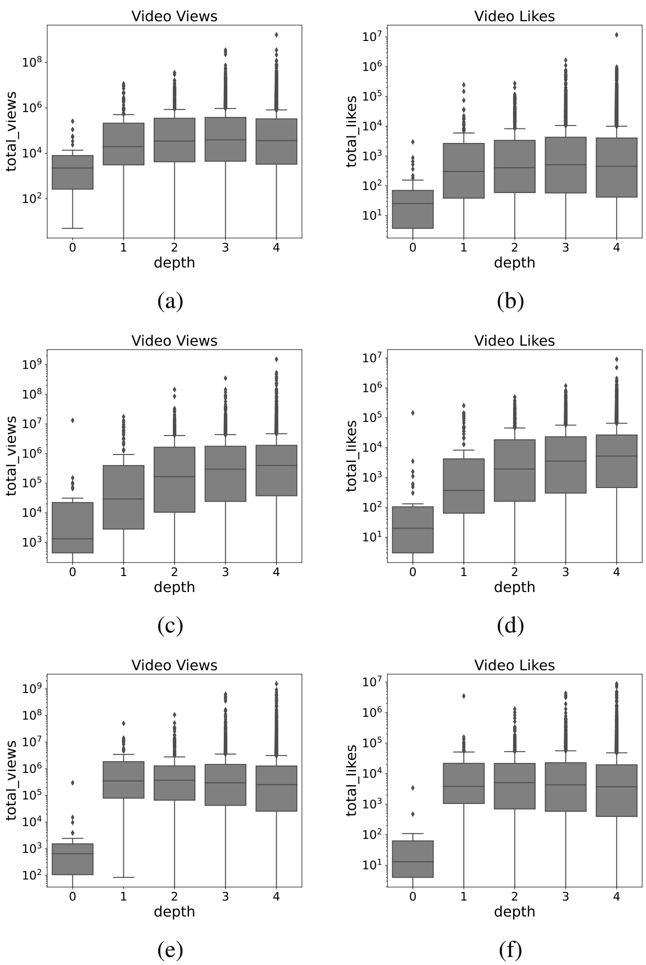


Fig. 3: Video engagement across recommendations of videos for Cheng Ho Video Views (a) and Video Likes (b), South China Sea Video Views (c) and Video Likes (d), China-Uyghur Video Views (e) and Video Likes (f).

showed that seed videos of the South China Sea and Uyghur dataset belonged to one topic community, while the seed videos for the Cheng Ho propaganda narrative belonged to six topic communities. From Table 1 we see that for the South China Sea narrative, the highly-influential video at depth 1 is unrelated to our seed videos as it belongs to a topic community about a Blizzard hitting California on the west coast of the US. As we progress through the recommendations, videos related to our seed videos, became present again in depths 2 and 4, but were filtered out from the recommendations at depth 3. On the other hand, for the Cheng Ho narrative, which is less popular, and less polarizing, we saw that content related to the seed videos are present across all recommendation depths in the Cheng Ho recommendations. The difference in video suggestions between the South China Sea and Cheng Ho stories shows how YouTube's suggestions can change what people see and think. This is why network analysis is crucial, it helps us understand these patterns and their impact better.

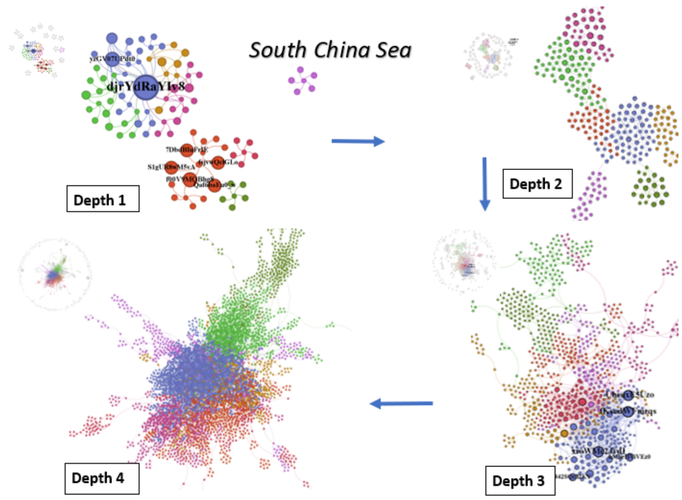


Fig. 4: Recommendation network across depths for South China Sea Dataset

TABLE I: Influential videos in each depth of the South China Sea narrative and their respective topics.

Depth	VideoID	Eigen value	Topic
1	djrYdRaYIv8	1	Blizzard warning California
2	bzF6e5b3YjM	1	anti-capitalism, new social order
	CgxgatA-q5s	0.683	environment damage during warfare
	FgcsvQgYXJs	0.683	nuclear war, disarmament
3	fKsedWFmzqs	1	California winter storm
	xroWMc2JvdI	0.962	California winter storm
	-UheuxE5Uzo	0.949	California winter storm
	hMbeHViVEz0	0.652	private video
	842SQzfl2KY	0.600	northern California Storm
4	rEc5hsWNsCQ	1	US Navy Buildup in China
	uNdnlrkx-wg	0.817	Population Boom, China birth rate
	EXYiUh6AKFw	0.675	NASA Mars, Space exploration

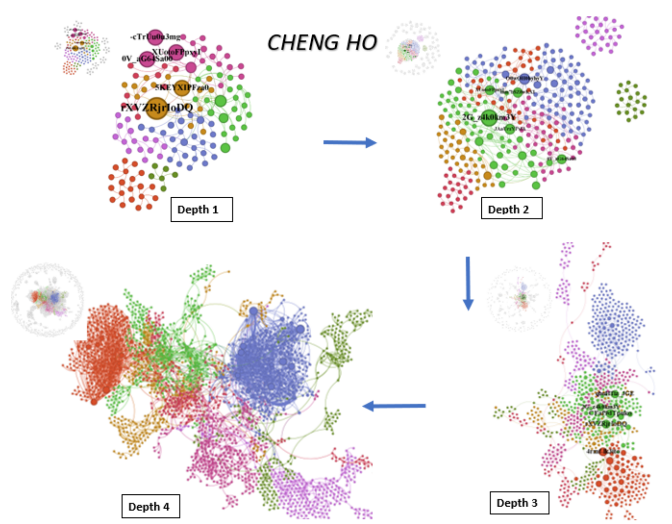


Fig. 5: Recommendation network across depths for Cheng Ho Dataset

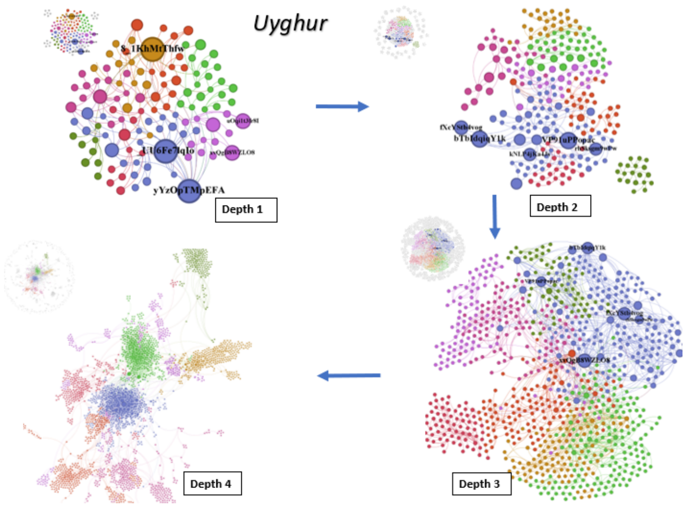


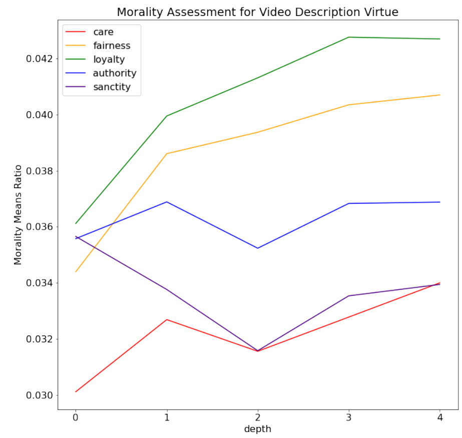
Fig. 6: Recommendation network across depths for Uyghur Conflict Dataset

5) Morality Virtue Diversity Across Depths: In Figure 7 below, we see the lowest occurring virtue for the China-Uyghur narrative is loyalty. As we progressed through each depth, we see that this virtue becomes the highest recorded across recommendations. The sanctity virtue remained low through recommendation depths. For the Chengo Ho narrative, care remains the lowest virtue from depths 0 to 4, while the loyalty virtue is recorded as the highest virtue across depths. The graph also shows that the morality virtues distributed across depths remain relatively stable in pattern. For the South China Sea narrative, we see that at depth 0, the highest virtue recorded is authority while the lowest occurring virtue is care. At depth 4, authority becomes the lowered while care increases but not to a relevant degree. Loyalty shows to be stable across all depths, while fairness shows a similar pattern to authority across all depths.

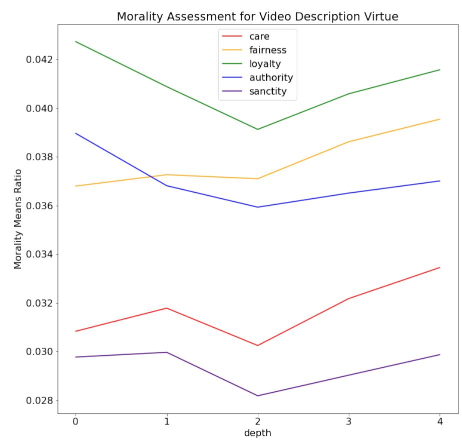
6) Morality Vice Diversity Across Depths - Video Titles: From the Figure 8, we see that the Uyghur narrative shows that at depth 0, the highest occurring vice was harm which steadily decreases across recommendation depth. Conversely, the lowest occurring vice was seen as both subversion and degradation. The occurrence of vices were highest at depth 0 and seen to reduce to plateau at depth 4. This pattern seem to behave differently in the Cheng Ho where depth 0 shows the lowest occurrence of all measured vices. Within this narrative, there is a gradual increase across depths after which the measured vices plateau at depth 4. This morality drift trend is also similar in the South China Sea narrative, where harm is the highest moral vice amongst the morality distribution across depths. We also observe a plateau of morality occurrences at depth 4 but this trend seems steeper in the South China Sea narrative as compared to the Cheng Ho dataset.

V. Conclusion

In this research, we collected videos from four recommendation stages, using relevant seed videos related to the



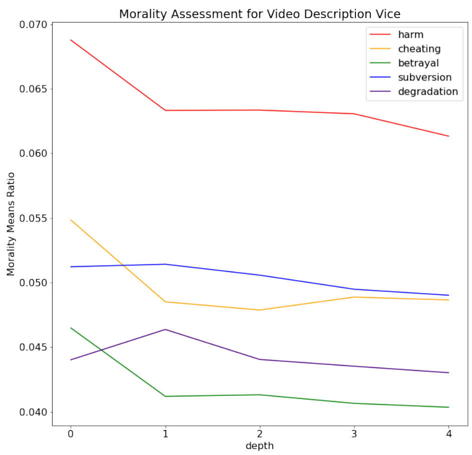
(a)



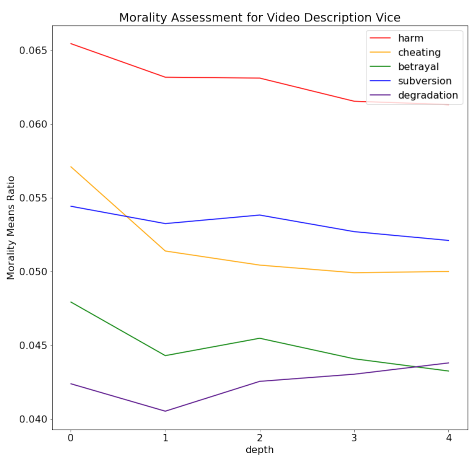
(b)

(c)

Fig. 7: Variation in moral foundation -'virtue' (video titles) across recommendations of videos for (a) Cheng Ho (b) South China Sea (c) China-Uyghur conflict



(a)



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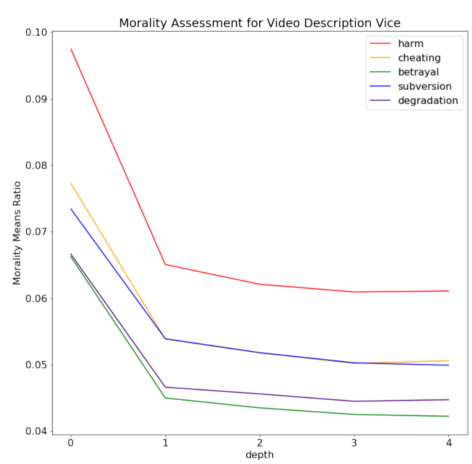

(c)

Fig. 8: Variation in moral foundation -'vice' (video descriptions) across recommendations of videos for (a) Cheng Ho (b) South China Sea (c) China-Uyghur conflict

China-Uyghur crisis, Cheng Ho propaganda, and the South China Sea conflict. Results from our multi-method analysis demonstrate that emotional, moral, and topic similarity vary over YouTube's recommended videos. The data also suggests that this inherent bias could be narrative dependent, with more polarizing content showing more diversity across our measurements, while less polarizing or less popular content such as the Cheng Ho movement experiences smaller impacts from bias. We also see that highly influential videos at each depth act as attractors to gently draw recommendations away from content relate to our seed videos in a pendulum-like motion. In future research, we are developing a framework which serves to methodologically compare content across various discourses and exploring the effects of the YouTube algorithms on these various narratives. The insights from our analysis can be used to help policymakers and platform developers enhance their decision-making processes and inform the development of strategies to mitigate biases.

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