Measuring Collective Attention in Online Content

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In his thesis, Siqi focused on understanding how online content captures collective human attention. He tackled a series of questions, including (a) how does Twitter API's sampling mechanism impact common measurements? (b) why do some YouTube videos keep the users staying longer? (c) how does YouTube recommender system drive user attention? (d) how do liberals and conservatives engage in cross-partisan discussions online? and (e) how does online attention transcend across platforms, across topics, and over time? Altogether, his research explores the collective consumption patterns of human attention in digital platforms. Methods, observations, and software demonstrations from his work can be used by content owners, hosting sites, and online users alike to improve video production, recommender systems, and advertising strategies.

Human attention is a scarce resource. In online platforms, while users have an unprecedented volume of content to choose from, the content in turn competes for limited user attention. Motivated by the MusicLab experiments [Salganik et al. 2006; Krumme et al. 2012], I take an item-centric approach and conceptualize online user behaviors as two steps – the first step is based on the content appeal, measured by the number of clicks or views; the second step is based on the content quality, measured by post-clicking metrics, e.g., dwell time, comments, likes, or shares. Hence, online attention metrics (behaviors) are categorized into two classes: popularity (viewing) and engagement (watching, commenting, liking, or sharing). Intuitively, the notions of popularity and engagement respectively describe the decision to click on an item and the decision to interact after clicking.

In my research, I study collective human behavior online through the lens of YouTube and Twitter, from the perspectives of social data sampling, content engagement, recommendation network, cross-cutting communication, and ideological asymmetries. Methods used and developed in my work are applicable to other media hosting platforms (e.g., TikTok, Spotify). In what follows, I provide a brief summary of each of the perspectives above.

(1) **How does Twitter API's sampling mechanism impact common measurements?** The first question quantifies the effects of data sampling on widely-used measures on social media [Wu et al. 2020]. We build a longitudinal dataset that tracks YouTube URLs on Twitter over a five-year span. Consisting of more than five billion tweets, this dataset is the largest public discourse of YouTube videos on Twitter. Albeit the size is substantial, we find that Twitter API still subsamples the data. To this end, we show how to construct a complete tweet stream and propose a method to estimate the Twitter sampling rate from rate limit messages. Next, we present in-depth measurements on the effects of Twitter data sampling across different timescales and different subjects (entities, networks, and cascades). For counting statistics such as number of tweets per user and per hashtag, we find that the Bernoulli process with a uniform rate is a reasonable approximation. We also build HIPie, an interactive demo that models video viewership on YouTube by promotion tweets on Twitter [Kong et al. 2018].[1]

(2) **Why do some YouTube videos keep the users staying longer?** The second question examines the user watching patterns toward online content [Wu et al. 2018]. We study a set of metrics including time and percentage of a video being watched. We observe that video duration is an important covariate on watching patterns. Longer videos generally make the users stay for a longer time but are less likely to keep them watching till the end. To calibrate the effect of duration, we construct a two-dimensional tool, dubbed *engagement map*, which captures the nonlinear relationship between video duration and watch percentage. Based on it, we propose a new metric – relative engagement – as the watch percentage rank percentile among videos of similar lengths. We show that this metric is closely correlated with recognized notions of quality, stable over time, and predictable even before videos' upload. The result is significant as it separates the concerns for modeling engagement and popularity – the latter is known to be unstable and driven by external promotions.

(3) **How does YouTube recommender system drive user attention?** The third question studies the effects of recommender systems on steering online attention [Wu et al. 2019]. Fig.1 shows an anecdotal example of how YouTube recommender system drives user attention, especially when a blockbuster video is uploaded or when a breaking news event happens. In this work, we study the relation between the structure of video recommendation network and the viewing dynamics of videos. We identify the popularity bias – videos are disproportionately recommended toward more popular videos. This means YouTube recommender system is likely to take random viewers to more popular videos and keep them there, therefore reinforcing the "rich get richer" phenomenon. We also use the bow-tie structure to characterize the recommendation network. We find that its core component (23.1% of the videos), which occupies most of the attention (82.6% of the views), is made out of videos that are mainly recommended among themselves. This is indicative of the connection between video recommendation and the inequality of user attention allocation. Finally, we conduct the task of estimating the attention flow in the video recommendation network and find that network structure is a useful feature in predicting video popularity. We also build AttentionFlow, a new system to visualize networks of time series and the dynamic influence they have on one another [Shin et al. 2021].[2]

[1] `https://hipie.cmlab.dev`
[2] `https://attentionflow.cmlab.dev`

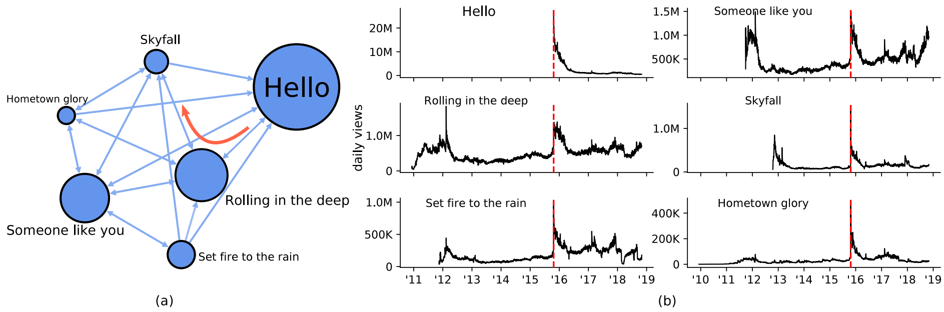

Fig. 1. Observing the impact of the recommendation network on video popularity. (a) A directed network consists of six videos by artist Adele. The node size is proportional to the video's cumulative view counts till Nov 02, 2018. The red arrow highlights one possible route that users can visit "Skyfall" from "Hello" in two hops. (b) View series for the six videos shown in (a). Visually we observe simultaneous spikes across all videos when "Hello" was uploaded on Oct 22, 2015 (red dashed vertical line). The other synchronized spikes in 2012 were triggered by the 54th annual Grammy Awards.

(4) **How do liberals and conservatives engage in cross-partisan discussions online?** The fourth question investigates cross-cutting communication on YouTube [Wu and Resnick 2021], based on a dataset of 274,241 political videos from 973 channels of US partisan media and 134M comments from 9.3M users over eight months in 2020. Contrary to a simple narrative of echo chambers, we find a surprising amount of cross-talk: most users with at least ten comments posted at least once on both left-leaning and right-leaning YouTube channels. Cross-talk, however, is not symmetric. Based on the user leaning predicted by a hierarchical attention model, we find that conservatives are much more likely to comment on left-leaning videos than liberals on right-leaning videos. Secondly, YouTube's comment sorting algorithm makes cross-partisan comments modestly less visible. Lastly, using Perspective API's toxicity score as a measure of quality, we find that conservatives are not significantly more toxic than liberals when users directly comment on the content of videos. However, when users reply to comments from other users, we find that cross-partisan replies are more toxic than co-partisan replies on both left-leaning and right-leaning videos, with cross-partisan replies being especially toxic on the replier's home turf.

(5) **How does online attention transcend across platforms, across topics, over time?** The fifth question measures collective attention across two social platforms – YouTube and Twitter [Lee et al. 2022], centered on online activities surrounding popular videos of three controversial political topics including Abortion, Gun control, and Black Lives Matter over 16 months. We propose several sets of video-centric metrics to characterize how online attention is accumulated for different ideological groups. We find that neither side is on a winning streak: left-leaning videos are overall more viewed, more engaging, but less tweeted than right-leaning videos. The attention time series unfold quicker for left-leaning videos, but span a longer time for right-leaning videos. Network analysis on the early adopters and tweet cascades show that the information diffusion for left-leaning videos tends to involve centralized actors; while that for right-leaning videos starts earlier in the attention lifecycle. Our findings go beyond the static picture of ideological asymmetries in digital spaces.

In conclusion, a better understanding of how digital items attract human attention will provide us with a set of useful tools toward building the next generation of responsible social systems. For content producers, it can help choose engaging topics to create videos, or adjust advertising strategies for higher rewards. For video audiences, it can help filter out low quality content, thus mitigating information overload and avoiding possible misinformation. For hosting sites, it can help prioritize quality content in recommender systems and better allocate limited storage resources. The impacts of my research go beyond quantitative observations. New datasets, research softwares, and real-world applications are developed and released to facilitate future studies on online content.

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