9^{th} International Conference on Computational Social Science IC^2S^2
July 17-20, 2023, Copenhagen, Denmark

The Impact of Recommender Systems on Cultural Content Consumption on TikTok

recommender systems, personalization, content diversity, social media platforms, TikTok

Extended Abstract

The creation and dissemination of cultural artifacts, such as music, photographs, or videos, depend critically on human interaction that enables learning, collective innovation, and the spread of knowledge [1, 2]. Over the past two decades, an increasing number of such interactions have been taking place online, which resulted in a significant shift from analog to digital cultural content. Especially on social media where individuals can easily produce content and share it with others this led to an explosion of the underlying cultural space. To help users navigate this vast space, most social media platforms have adopted algorithmic recommender systems (RS) that filter content and redirect the flows of information. Although RSs are utilized for various purposes, their primary objective is to suggest content to users that matches their interests and promotes engagement with the platform [3].

TikTok, a video streaming platform with an active user base of approximately 1.2 billion people worldwide, is an example of algorithmic content recommendation taken to the extreme. The platform is designed around an algorithmically curated feed, which provides users with personalized video content, however, deprives them from the ability to spontaneously explore new things on their own. Due to the low level of active control users have over their content and the strong influence of the recommendation system, the question arises whether the incentives of the platform are aligned with those of the users. In particular, can users benefit from the great content diversity on platforms like TikTok to explore new content and come across novel ideas and perspectives? Or is the opposite true, and TikTok aims to keep people engaged by funneling them into very specific content niches?

In order to investigate the impact of TikTok's recommendation algorithm on content consumption, we conduct experiments using bots that imitate real users with distinct interests and interaction patterns on the platform. In particular, each bot is programmed with a specific set of interests that are expressed through its interactions. For instance, we consider bots that are interested in specific topics like "sports" or "politics", or bots that score differently on other dimensions such as sentiment (happy vs sad bots) [4]. These interests are expressed by the interactions that bots perform on the feed. Specifically, if the content matches the interest of a bot it will watch the associated video. Additionally, the bot can like the video or follow the account that has produced it. Otherwise, the video is either skipped or watched only for a fraction of the total video duration.

Our analysis focuses on the trajectories of bots through TikTok's content space. The main goal is to analyze the diversity of videos that bots encounter. Based on the information which is encoded in hashtags and video descriptions, we use word embeddings, language models, and tools from network science to quantify if bots are able to continuously explore and discover new things or if they get trapped in niche content. To exemplify our analysis, in Fig.1, we present the trajectories of two bots with opposing interests - one interested in positive content and the other in negative content. We find that TikTok's recommendation system is capable of identifying bots' preferences quickly, and as a result, it provides them already after a short number of watched videos with diverging content in line with their interests.

Our work contributes to understanding how content personalization on social media impacts content diversity on the individual level. These findings may also have implications on the collective level ranging from decreased rates of cultural innovation to the fragmentation of online society in the digital age [5, 6, 7].

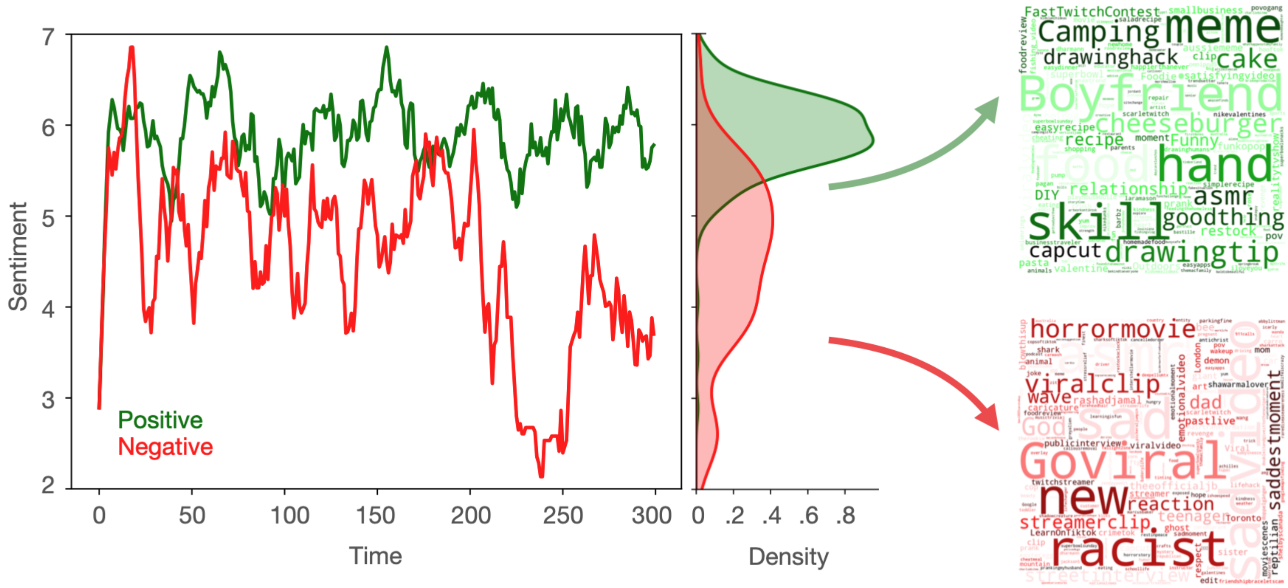

Figure 1: Sentiment scores of content encountered over time by two bots. While one is interested in positive content, the other one prefers negative content.

References

[1] Kevin N Laland. Social learning strategies. *Animal Learning & Behavior*, 32(1):4–14, 2004.

[2] Joseph Henrich and Richard McElreath. The evolution of cultural evolution. *Evolutionary Anthropology: Issues, News, and Reviews: Issues, News, and Reviews*, 12(3):123–135, 2003.

[3] Linyuan Lü, Matúš Medo, Chi Ho Yeung, Yi-Cheng Zhang, Zi-Ke Zhang, and Tao Zhou. Recommender systems. *Physics reports*, 519(1):1–49, 2012.

[4] Peter Sheridan Dodds, Eric M Clark, Suma Desu, Morgan R Frank, Andrew J Reagan, Jake Ryland Williams, Lewis Mitchell, Kameron Decker Harris, Isabel M Kloumann, James P Bagrow, et al. Human language reveals a universal positivity bias. *Proceedings of the national academy of sciences*, 112(8):2389–2394, 2015.

[5] Isaac Waller and Ashton Anderson. Quantifying social organization and political polarization in online platforms. *Nature*, 600(7888):264–268, 2021.

[6] Alberto Acerbi. *Cultural evolution in the digital age*. Oxford University Press, 2019.

[7] Hyejin Youn, Deborah Strumsky, Luis MA Bettencourt, and José Lobo. Invention as a combinatorial process: evidence from us patents. *Journal of the Royal Society interface*, 12(106):20150272, 2015.