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# Modelling the Closed Loop Between a Personalised Recommender System and Users' Opinion Dynamics

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**Abstract:** In this abstract, we present a model that allows insight into the interplay between a group of users, content, and a recommender system (RS). The proposed model extends current ones via the addition of an intuitive softmax-type selection process, the ability to set the diversity of content available to users, and the introduction of virality-based filtering. Through a campaign of Monte Carlo simulations, we investigate how the RS performs under different conditions and how it affects its users' opinions. An overview of the model, results, and an exemplar simulation showcase the model and the effects of viral content.

***Keywords:*** *Social media, polarisation, radicalisation*

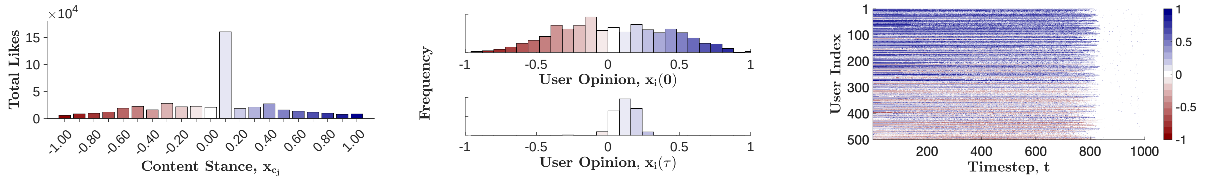
## 1 INTRODUCTION

The ubiquitous nature of personalised content coming from RSs into our daily lives has raised concerns regarding how said content can increase polarisation and the presence of extremist beliefs and behaviours (KGI Expert Working Group on Recommender Systems, 2025). Therefore, ample motivation exists to investigate how RSs affect user behaviours, beliefs and attitudes. Quantitative and qualitative data-driven approaches to analyse online behaviours have been useful in the past. However, collecting said data has become increasingly difficult, with platform providers utilising paywalls and screening to determine who can access the data. An emergent way to study the closed loop dynamics between an RS, the content it recommends, and its users is by constructing mathematical and agent-based models. A seminal model in this field, proposed by Rossi et al. (2021), examined the closed loop between an RS and the dynamics of a user's opinion. The closed loop refers to the loop between an RS and a user, where the RS makes a recommendation to users, which influences their opinion, the user's opinion determines their engagement, which is relayed back to the RS to help formulate future recommendations, thus completing the closed loop. Extending previous models with a more sophisticated RS, accounting for diversity in the recommended content, and many users allows for a model reminiscent of social media platforms today. The proposed model allows further exploration into how user opinions evolve under the influence of a social media's RS, and whether polarisation and radicalisation of user opinions are exacerbated within the closed loop system.

## 2 METHODOLOGY AND RESULTS

***Model.*** We briefly introduce our model and refer the reader to Davidson and Ye (2025) for full details and results. Our model is an extension of the one proposed by Rossi et al. (2021), and explores the interplay between a large group of users, content, and an RS. The model is an abstract representation of the popular "endless scroll" feature used on platforms like TikTok's For You page, YouTube Shorts, or Instagram Reels. There is a population of users, and each user $i$ has an opinion $x_i(t) \in [-1, 1]$. Users are recommended content by the RS, each content has a fixed stance $x_{c_j} \in [-1, 1]$, and users can engage with the content (like, watch). Upon receiving their recommended content at each discrete timestep, users can like or dislike content, or choose not to engage at all, following a stochastic decision-making mechanism that depends on their opinion. We also explicitly model how long users watch or consume the content. The watch rate depends on their current opinion and determines how much the content changes their opinion. After engaging with the content, the engagement decision and the watch rate are relayed to the RS to tailor future recommendations better, and users "scroll on" to their next recommendation. This highlights the closed loop nature of the model, recommendations, opinions and engagement are all shaped by one another. Recommendations are constructed through a combination of content-based filtering (what a user has specifically liked or watched previously (Jannach et al., 2011)) and virality-based filtering (what content is popular in the system). The evolution of users' opinions is determined by a variation of the classical and experimentally-grounded Friedkin–Johnsen Model (Friedkin and Johnsen, 1990)—a convex combination of their initial opinion, their current opinion, and the stance of content they consumed.




(a) Total likes per piece of content at $\tau = 1000$.

(b) Changes in opinion distributions over time.

(c) Content recommendations over time, indexed by $x_i(\tau)$.

**Figure 1. Example output from the model showing one piece of content go viral. Panel (a) total likes per piece of content at the end of the simulation, panel (b) the opinion distributions of users at the start (t = 0) and end ($t = \tau$) of the simulation, and panel (c) the content recommended to each user over time.**

***Overview of Results.*** We now present the exemplar simulation in Fig. 1 that ran for $\tau = 1000$ timesteps with $n = 500$ users, where we can see the effects of a piece of *viral* content. Fig.1c shows the total likes per piece of content; in this case, there are 21 pieces of content equally spaced between $-1$ and 1. We can see that the content with the stance $x_{c_j} = 0.1$ went viral, gaining over one hundred thousand more likes than the next most liked content. Fig. 1b compares the initial opinion distribution to the final, providing insight into how user opinions have changed due to the closed loop system. By the end of the simulation, we can see that user opinions coalesce around the stance of the viral content, $[0, 0.2]$. Fig. 1c shows a contour plot of all recommendations made over the length of the simulation and gives insight into when the RS began recommending the viral content to all users, $t \approx 800$. We found that viral content could be achieved by altering many parameters in our model, but it was consistently effective in lowering polarisation and radicalisation in user opinions. This was because the viral content was always neutral or close-to-neutral in its stance, $x_{c_j}$. Although not observed in our simulations, if an extreme piece of content were to go viral, we expect a radicalised population of users to form. Other key findings include: levels of polarisation and radicalisation in an already polarised population are not exacerbated by the RS, having more diversity in the content available is ineffective in changing user opinions, and when this diversity is lower, offering neutral content is an effective way to bring together user opinions.

## 3 CONCLUSIONS

This abstract presents a mathematical model that allows one to study the interplay between an RS, its many users, and many types of content. Basing the mathematical model on one of the most popular mechanisms used by social media platforms today (the endless scroll feature) has allowed insight into how modern social media platforms influence their users' opinions. There are still many avenues open for future work to broaden this area of research; this includes the addition of collaborative filtering techniques, the adaptation of the model to study the rabbit-hole effect, and comparison with real-world data. This model and future work in this area will contribute to our understanding of how RSs and the content they recommend influence society.

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