

# Recommendation of content to mitigate the echo chamber effect

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We introduce a novel method to mitigate the echo chamber effect within online social platforms. It consists in finding optimal recommendations tailored to each user in order to increase the diversity of content they're exposed to. This is done through solving a budgeted quadratic optimisation problem with linear constraints. The problem relies on a theoretical model that describes the flow of content throughout the network [2]. User to user propagation implies that recommendations made to an individual will in the long term affect others. We demonstrate the effectiveness of our method on a Twitter dataset related to the 2017 French presidential elections [1]. Even for low budgets the algorithm is able to significantly increase the diversity of content on the newsfeeds, thus decreasing the overall echo chamber effect. Moreover the diffusion aspect encapsulated by the model is shown to be of primary importance, as the impact of recommending content is significantly lower without propagation.

The dataset contains tweets related to the 2017 French presidential elections, and users are manually annotated with their political affiliation—*i.e.* the party they support. These are restricted to  $S = 5$  main ones. We highlight the existence of echo chambers in terms of exposure to content from like-minded sources. This exposure depends on the social connections of the users. It is 73% on average and higher than 90% for roughly a third of the users, indicating a strong exposure bias.

To mitigate this phenomenon we seek to increase the diversity of content presented to the users. We propose the following metric to measure this diversity:

$$\Phi_n \stackrel{\text{def}}{=} \frac{S}{S-1} \sum_{s=1}^S p_s^{(n)} (1 - p_s^{(n)})$$

where  $p_s^{(n)}$  is the average proportion of content supporting party  $s$  that user  $n$  is exposed to. The diversity is maximal ( $\Phi_n = 1$ ) when this exposure is equally shared between all parties, and minimal ( $\Phi_n = 0$ ) when  $n$  is exposed to content from only one single party.

Our method to increase diversity of content takes the platform's perspective. We find individual recommendation policies, that describe how frequently should content supporting a given party be presented to each user. To do so we solve an optimisation problem of the form

$$\operatorname{argmax}_{x,p} \frac{1}{N} \sum_n \Phi_n$$

with  $x$  the recommendation policies. The objective is quadratic and the amount of recommendation per user is restricted by linear budget constraints. In addition there are

linear constraints to quantify the dependency of  $p$  on  $x$ . They are derived from an existing model [2] that describes the flow of content throughout the platform depending on the connections between users as well as their activity. We show that the model can provide good estimates for the values of  $p$ .

Being quadratic with linear constraints, the optimisation problem can be efficiently solved. Even for low budgets we find a significant increase in the diversity  $\Phi$  and a significant decrease in the exposure to like-minded content (Fig. 1). We observe that increasing the budget has diminishing returns and that augmenting the frequency of recommendations quickly becomes less effective. Finally we highlight the importance of the diffusion process, as ignoring it resulted in barely any improvement of diversity from the recommendations.

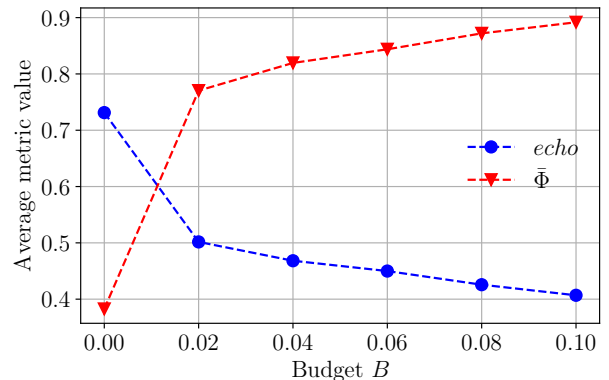


Fig. 1: Optimisation results for various budgets. Average exposure to like-minded content (*echo*) and average diversity  $\Phi := \frac{1}{N} \sum_n \Phi_n$ . The budget  $B$  constrains the frequency of recommendations so that no user is exposed to more than a proportion  $B$  of recommended content. Budget  $B = 0$  corresponds to initial estimates of the values before optimisation.

[1] O. Fraiser, G. Cabanac, Y. Pitarch, R. Besançon, and M. Boughanem. #Élysée2017fr: The 2017 French Presidential Campaign on Twitter. In *Proceedings of the 12th International AAAI Conference on Web and Social Media*, 2018.

[2] A. Giovanidis, B. Baynat, C. Magnien, and A. Vendeille. Ranking online social users by their influence. *IEEE/ACM Transactions on Networking*, 29(5):2198–2214, 2021.