Accelerating dynamics of collective attention

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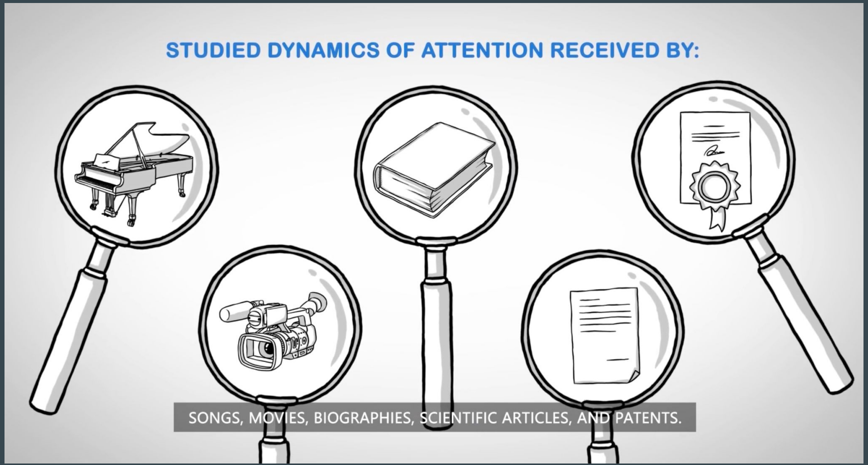
Overview

The accelerating ups and downs of popular content results in a more rapid exhaustion of limited attention resources, which causes growing turnover rates.



Data and data processing

- Dynamical measurements of categorized content as proxies for the amount of collective attention a topic receives
- Measures various forms of population-level content consumption patterns
- Focus on twitter

Source	Timespan	Popularity proxy $L_i(t)$	Res.	Origin
Twitter	2013-2016	hashtag occurrence	daily	`twitter.com`
Books	1870-2004	1- to 5-gram counts/book	yearly	`books.google.com/ngrams`
Movies	1980-2018	weekly gross per theater	weekly	`boxofficemojo.com`
Google	2010-2017	searches/max(searches)	weekly	`trends.google.com`
Reddit	2010-2015	comment counts per post	daily	`reddit.com`
Publications	1990-2015	citation counts per paper	monthly	`journals.aps.org`
Wikipedia	2012-2017	page views per article	daily	`dumps.wikimedia.org/ other/pagecounts-ez/`

Model

- The general nature of the observed development across both, domains and over time.
- The model topics competing for attention, driven by Imitation, and saturation, as a function of communication rates.
- Combining these factors in a minimal mathematical model based on modified Lotka–Volterra, dynamics reproduces the empirical findings surprisingly well.

$$\frac{dL_i(t)}{dt} = \underset{\text{imitation}}{\boxed{r_p L_i(t)}} \left(1 - \underset{\text{saturation}}{\boxed{\frac{r_c}{K} \int_{-\infty}^{t} e^{-\alpha(t-t')} L_i(t')\,dt'}} - \underset{\text{other}}{c \sum_{j=1, j \neq i}^{N} L_j(t)} \right).$$

Result Analysis

The distribution of gains and losses are growing broader.

$$\text{gains } [\Delta L_i^{(g)}/L_i](t) = (L_i(t) - L_i(t-1))/L_i(t-1) > 0$$
$$\text{losses } [\Delta L_i^{(l)}/L_i](t) = (L_i(t) - L_i(t+1))/L_i(t+1) > 0$$

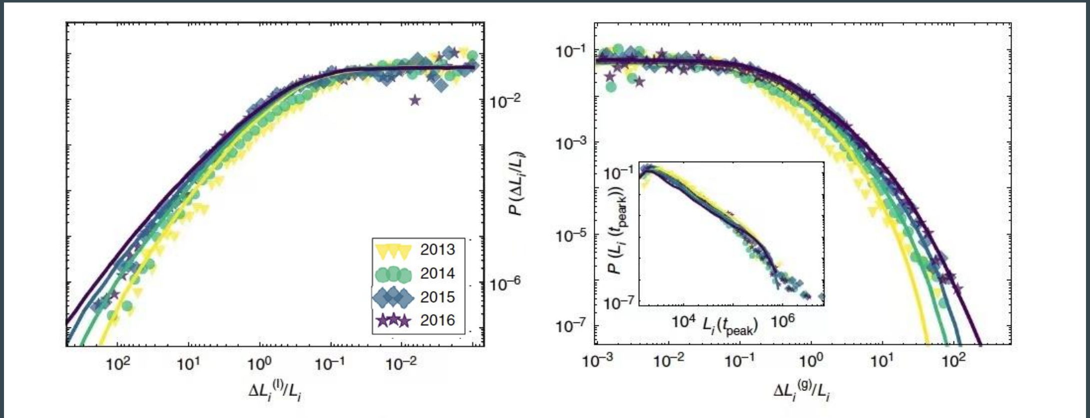


Figure 1: Distribution of losses from the simulations and distribution of gains

Result Analysis

Topics compete for finite collective attention.

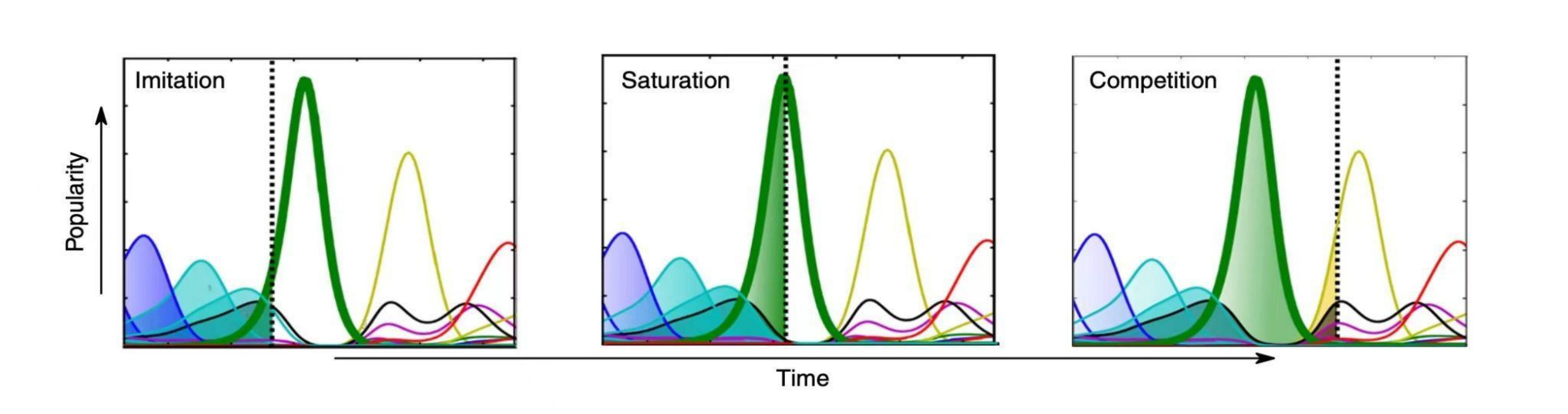


Figure 2: Exemplary details of trajectories

Result Analysis

Faster communication causes temporal fragmentation.

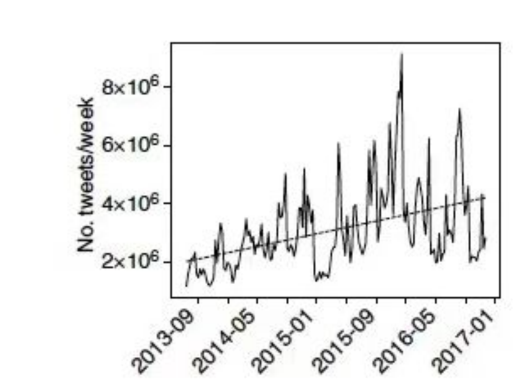
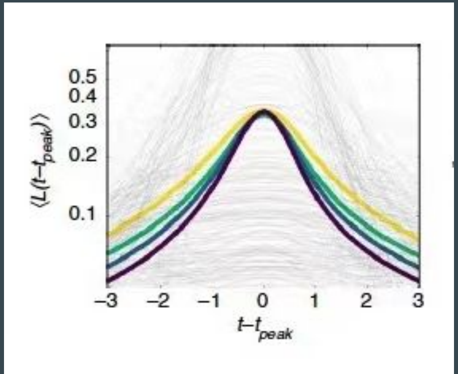
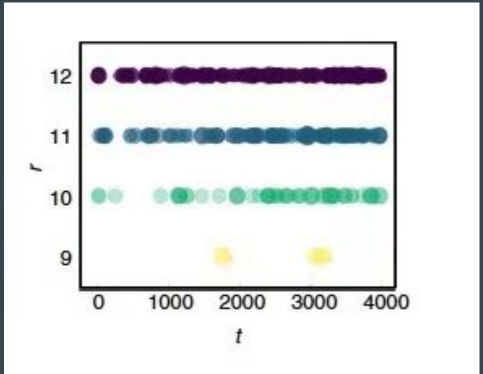


Figure 3: Total amount of tweets





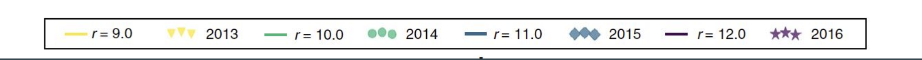
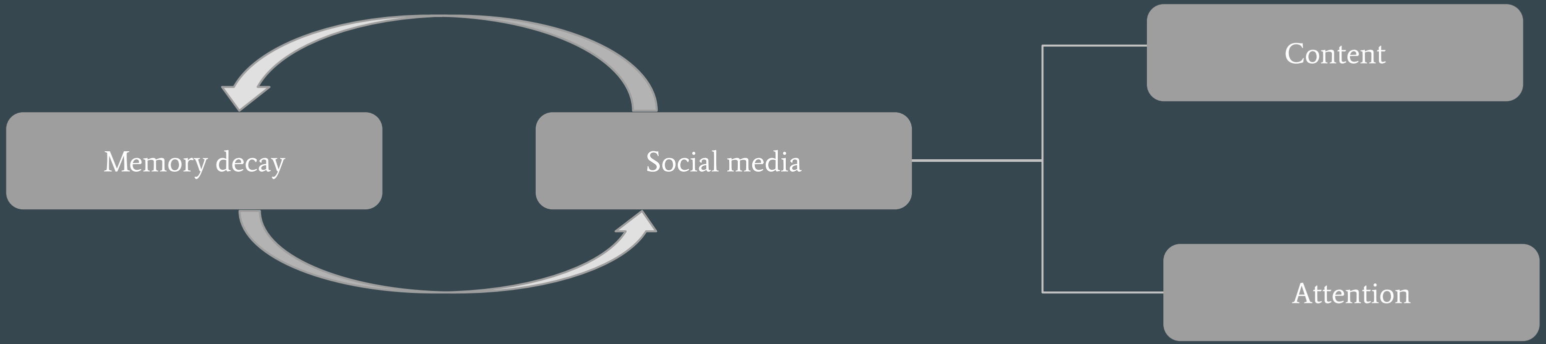


Figure 4: Average trajectories L(t − tpeak)

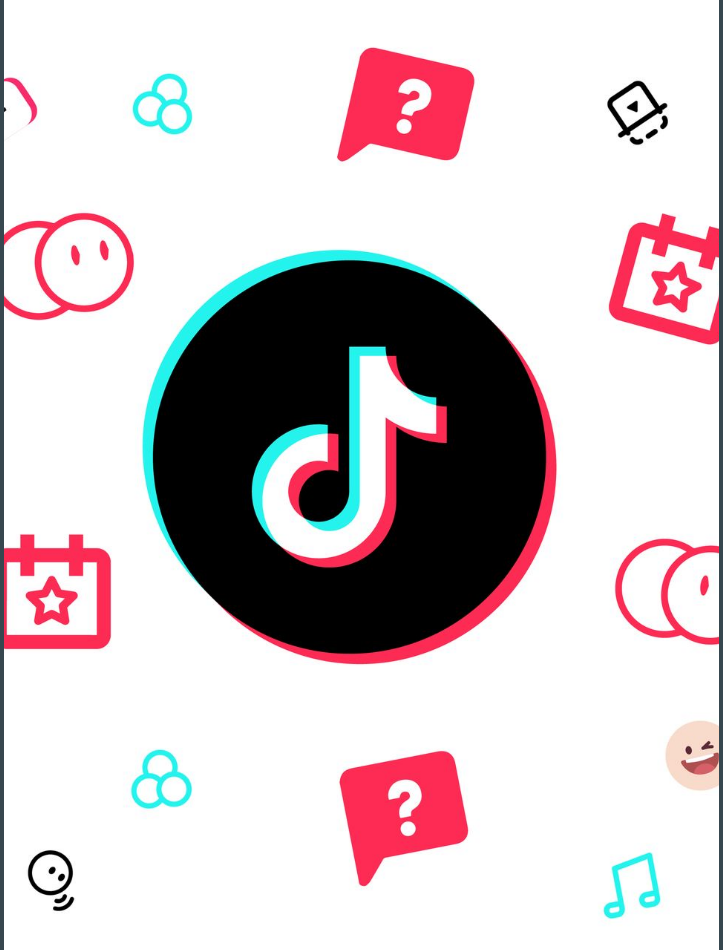
Figure 5: The intensity of bursts and time

Conclusion



Improvements

- More vision analysis, including TikTok, Instagram and Youtube
- Need to consider the “automatic pushed algorithms” in the app
- Divide the information more segmently



Reference

1.Accelerating dynamics of collective attention(Philipp lorenz-Spreen, Bjarke Moorch Monsted, Philipp Hovel,Sune Lehmann)

2.Anderson, J. R. *Cognitive Psychology and its Implications* (New York, NY, US: WH Freeman/Times Books/Henry Holt & Co., 1985).

3.Lazer, D. M. J. et al. The science of fake news. *Science* 359, 1094–1096 (2018).

4.Clauset, A., Shalizi, C. R. & Newman, M. E. J. Power-Law Distribution in Empirical Data *SIAM review*, 51, 661–703 (2009).

5.Lazer, D. M. J., Rubineau, B., Chetkovich, C., Katz, N. & Neblo, M. The coevolution of networks and political attitudes. *Polit. Commun.* 27, 248–274 (2010).

5.Code: https://github.com/philipplorenz/integrator_boringness

Thanks!