On Polarization Dynamics in the Age of Information Overload

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Abstract

The paper discusses a recently proposed stochastic model of evolution of human beliefs that demonstrates how today's sheer volume of accessible information (and, thus, information overload), combined with consumers' confirmation bias and asymmetric preference for outlying content, result in increased polarization. It suggests that escaping the polarizing forces in the age of information overload is a particularly challenging problem.

Introduction

We posit the possibly controversial claim that *increased access to information (e.g., made possible by social media platforms, the Web, and online services that facilitate real-time publishing) leads to increased societal polarization*. The general challenges brought about by information overload were first discussed by the authors in earlier work (Abdelzaher 2019). This abstract is grounded in results (by the authors) that recently appeared in arXiv preprints (Xu et al. 2020; Abdelzaher et al. 2020).

The idea that increased access creates polarization is not new. For example, it was shown that the production of the interstate highway system in the US increased socio-economic disparity and geographic polarization in metropolitan areas (Nall 2015); the ease of commute facilitated urban sprawl, allowing communities to self-segregate into more homogeneous geographic neighborhoods (in an analogy with social echo-chambers) of significantly different character (e.g., suburban versus downtown). Similar observations apply to information access; the mere availability of larger volumes of more accessible information allows individuals to find and settle in more homogeneous "ideological neighborhoods" (echo-chambers) with other like-minded sources. Volume (i.e., overload) makes them less likely to explore other ideological neighborhoods. More specifically, volume increasingly necessitates information filtering, as recipients must make consumption choices. The existing customized filtering aided by algorithmic curation services tailored to consumer biases (to maximize engagement and revenue) essentially reinforces these biases. Bias reinforcement gradually erodes the common ground for dialogue among communities of different beliefs, thus triggering the paradox: *ideological fragmentation as a consequence of improved global access and sharing*. Moreover, ingrained asymmetric preferences for less moderate (i.e., more *outlying*) content, creates asymmetry that continues to push in the direction of increasing polarization. Below, we mathematically support these intuitions.

A Model of the Information Ecosystem

Consider set, $\mathcal{X}$, that denotes a society of individuals. Let each individual $a_i \in \mathcal{X}$ be represented as a particle in a belief space, where distance from the origin denotes departure from neutrality, whereas the direction denotes the particular ideology. We denote the position of individual a_i in the belief space at time t by $x_i(t) \in \mathbb{R}^K$. Finally, let $\mathcal{Y}$ denote the set of content producers. One can think of a producer as a source with a broadcast portal that publishes their point of view. We denote the position published by producer, $a_j \in \mathcal{Y}$, at time t by $y_j(t) \in \mathbb{R}^K$. Three equations can now be derived to describe dynamics of belief.

Democratized production

In the age of social media, anyone can be a content producer. Thus, we assume that, on a fully democratized medium, every individual is *both* a content consumer and producer who publishes their current belief. Accordingly:

$$\mathcal{Y} = \mathcal{X} \tag{1}$$

We henceforth use $x_i(t)$ and $y_i(t)$ interchangeably to denote the belief of an individual and the position of the content they generate.

Customized Curation and Confirmation Bias

Aside from other random influences, we assume that an individual, a_i, located at position $x_i(t)$ at time t, will engage with a subset of producers, $\mathcal{Y}^{(i)}(t) \subset \mathcal{Y}$, that match this individual's own belief; a phenomenon known in opinion dynamics literature as *bounded confidence* (Lorenz 2007). Accordingly, for each consumer, a_i, we assume that a visibility radius ϵ_i limits how ideologically distant the producers, a_j, they engage with might be. Thus:

$$\mathcal{Y}^{(i)}(t) = \{a_j | \|x_i(t) - y_j(t)\| \leq \epsilon_i\} \tag{2}$$

Consumer Preference for Outlying Content

In the age of overload, our attention is increasingly hijacked by more statistically anomalous news (Varshney 2019), arguably biasing our collective attention towards more extreme content. Accordingly, an item in $\mathcal{Y}^{(i)}(t)$, that espouses location y in the belief space, has an influence weight $\eta_0(y)$ that generally increases with distance $\|y\|$ from the (neutral) origin. However, beyond a certain $\|y\|$, influence decreases again, when the espoused beliefs become "too extreme". To model social influence, we further assume that a consumed item in $\mathcal{Y}^{(i)}(t)$, that lies at location, y, in the belief space, has a component of influence that increases exponentially with the density of sources around y. Let the *density* of sources at location, y, and time, t, be denoted by $\rho_s(y,t)$. Thus, content influence increases with $e^{\kappa\rho_s(y,t)}$. The total influence weight of an item at location y in the belief space, within consumer a_i's neighborhood set, $\mathcal{Y}^{(i)}(t)$, is then given by:

$$\eta(y,t) = \eta_0(y)e^{\kappa\rho_s(y,t)} \tag{3}$$

where $\eta_0(y)$ increases with distance $\|y\|$ from the neutral origin up to a point, until the beliefs become too extreme, then declines.

The Paradox of Information Access

The above three equations lead to the following theorem, whose proof of is detailed in our arXiv preprint (Xu et al. 2020):

> *Theorem 1:* In a population, $\mathcal{X}$, featuring (i) democratized content production, described by Equation (1), (ii) confirmation bias, described by Equation (2), and (iii) social influence with preference for outlying content, described by Equation (3), the equilibrium distribution of population density, ρ_x, in the belief space is given by the solution to the following nonlinear partial differential equation:
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> $$D\partial_x^2\rho_x + \mu\partial_x(\rho_x\partial_x V_x) - \frac{1}{2}\kappa\mu\partial_x^2(\rho_x^2) = 0$$

where D and μ are constants, and $V_x = -\ln\eta_0(x)$. The above expression is a particle diffusion-drift equation where ρ_x is the steady state local density of particles, D is a diffusion constant, V_x is a virtual potential applied (where particles tend to converge to positions of lower potential), and κ can be interpreted as a strength of attraction among the particles.

Observations on Natural Belief Dynamics

Solving the equation in Theorem 1 for ρ_x computes the steady state outcome (namely, density distribution) according to the modeled social dynamics. Of specific interest in this case is to determine if the steady state distribution is bimodal (i.e., polarized) or not. The bifurcation is measured as visibility of the two potential bifurcated peaks:

$$Q = \frac{peak - valley}{peak + valley} \tag{4}$$

where $peak = max_x(\rho_x)$ and $valley = min_x(\rho_x)$ in the bimodal distribution of ρ_x. If bifurcation occurs, then Q approaches 1 as the degree of bifurcation become higher. The minimum value of Q is zero. We use $\eta_0(x)$ that peaks at distance 0.5 from the origin then declines reaching zero around distance 1 (Xu et al. 2020).

The key effect is shown in Figure 1. Specifically, bifurcation in the belief space increases with population size, N. Moreover, the higher the nonlinear effect of social influence, κ, the more pronounced the belief bifurcation.

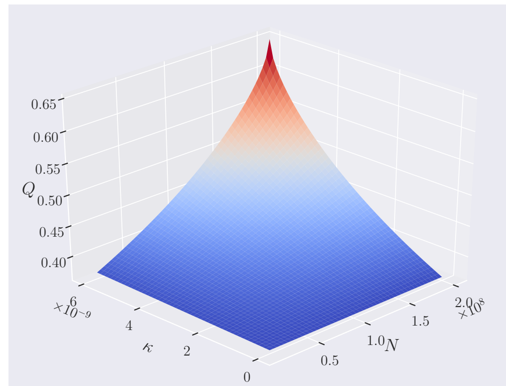

Figure 1: Joint effect of population size, N, and social influence coefficient, κ. $\sigma = 2.3$, $\mu = 1.0$.

Conclusions

The paper explains a social phenomenon caused by the age of democratized access; namely, growing ideological fragmentation exacerbated by information overload. Our model suggests that one of the biggest factors impacting polarization stems from *content volume*. The paper is a call for solutions that may ameliorate this effect.

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