Junk News Bubbles

Modelling the Rise and Fall of Attention in Online Arenas

Maria Castaldo, Tommaso Venturini, Paolo Frasca

In this paper, we present a type of media disorder which we call "junk news bubbles" and which derives from the effort invested by online platforms and their users to identify and share contents with rising popularity. Such emphasis on trending matters, we claim, can have two detrimental effects on public debates: first, it shortens the amount of time available to discuss each matter; second it increases the ephemeral concentration of media attention. We provide a formal description of the dynamic of junk news bubbles, through a mathematical exploration the famous "public arenas model" developed by Hilgartner and Bosk in 1988. Our objective is to describe the dynamics of the junk news bubbles as precisely as possible to facilitate its further investigation with empirical data.

From filter bubbles to junk news bubbles

Much has been written in the last years about online media and the threat of "selective exposure" (Sears & Freedman, 1967), "echo chambers" (Garrett, 2009) and "filter bubbles" (Pariser, 2011). The argument put forward by communication scholars and observers is that the growing availability of information in online media and the perfecting of filtering and recommendation technologies creates a "situation in which thousands or perhaps millions or even tens of millions of people are mainly listening to louder echoes of their own voices" (Sunstein, 2001, p.16). Reviving a long tradition of homophily and segregation models (Schelling, 1971), this idea has sparked much interest in computational sociology (cf., among others, Colleoni et al., 2014; Barberá et al., 2015; Quattrociocchi et al., 2016; Geschke et al., 2019). Less attention and computational efforts have been dedicated to a different type of media bubbles whose danger comes not from the fragmentation, but from the ephemeral concentration of public attention, in a way that reminds the economic bubbles of financial speculation. Though less studied, these "junk news bubbles" are as dangerous and possibly more dangerous than the filter bubbles (whose impacts may have been overestimated, cf. Flaxman et al. 2016 and Dubois, 2018).

We introduced the term "junk news" in a previous paper (Venturini, 2019) as a replacement for the notion of "fake news" and its excessive focus on deceitfulness (cf., among others, Wardle & Derakhshan, 2017; Zuckerman, 2017; Benkler et al., 2018; Gray et al. 2020). Fabricated news, we argued, are less prevalent and less dangerous than the avalanche of memes, click-baits, trolling provocations and other forms of distractions that prevent online audiences from engaging in a thoughtful public debate. In this paper, we propose a more precise characterization of junk news based on a feature that is often neglected when considering online misinformation – its distinctive temporal profile. In this paper, we thus define junk news as an *adverse media dynamic in which large shares of public attention are captured by items that are incapable of sustaining it for a long time*.

Central in the '70s and '80s, the question of "attention cycles" (Downs, 1972) has lost steam in current media research because of the advent of digital technologies and the extension of the media system that they brought with them. Because of such extension, the question of the occupation of public debate has begun to be formulated in spatial rather than in temporal terms (i.e. where something is discussed rather than when). Temporal dynamics, however, remains crucial for, as in the words of McLuhan, "the 'message' of any medium or technology is the change of scale or pace or pattern that it introduces into human affairs... amplif[ying] or accelerate[ing] existing processes" (McLuhan, 1964, p.8). As noted by scholars working on attention economy (Lanham, 20066; Terranova, 2012; Crogan & Kinsley, 2012), digital technologies are particularly inclined to amplify "media hype" (Vasterman, 2005). Such a partiality for trendiness can be found in the practices of social media users, which are increasingly driven by micro-celebrity strategies (Marwick & Boyd,

2011; Khamis et al. 2017) and vanity metrics (Rogers, 2018). It can also be found in their machine-learning recommendation algorithms and their tendency to reinforce user behaviors (Cardon, 2005; Cardon *et al.*, 2018), particularly when in line with the business model of online advertisement (Braun & Eklund, 2019). As candidly admitted by YouTube engineers: "in addition to the first-order effect of simply recommending new videos that users want to watch, there is a critical secondary phenomenon of boot-strapping and propagating viral content" (Covington *et al.*,2016 p.193, see also Zhao *et al.*, 2019).

This paper's goal is to provide a *formal* description of these attention dynamics in order to encourage their further study. With a few remarkable exceptions (see in particular Leskovec, Backstrom & Lars, 2009 and Lorenz-Spreen et al., 2019), no large-scale empirical research has been devoted to attention cycles, despite the growing availability of traces produced by digital media (Lazer et al., 2009; Latour et al, 2012; Venturini, Jensen & Latour, 2015). To facilitate such research, we propose a mathematical formalization of one of the most influential accounts of attention dynamics: the "public arenas model" introduced in 1988 by Stephen Hilgartner and Charles Bosk. Despite its clarity and insightfulness, H&B's framework has so far found no mathematical formalization for its complexity and lack of formal description. In this paper, we streamline H&B's model focusing on the rise and fall of attention matters (and ignoring the linkages across different arenas and the actors within each arena). Doing so we propose a ready-to-test (*prêt-à-tester*) version of H&B s model hoping that it will encourage further empirical investigation on junk news bubbles.

Model description

(a) The first ingredient of our model is a **population of "matters of attention"** (or "social problems" as in H&B original formulation) defined self-referentially as the *entities that compete to capture public attention*. The non-essential nature of this definition is crucial for H&B, who contend that "social problems are projections of collective sentiments rather than simple mirrors of objective conditions" (H&B p.54). In other words, matters of attention are defined by their visibility and not the other way around ("we define a social problem as a putative condition or situation that is labeled a problem in the arenas of public discourse and action" p.55). Three corollaries descend from this non-essentialist definition:

- First, *all attention matters are equal before our model* and that their rise and fall depend exclusively on the competition between them and not on any substantial features ("social problems exist in relation to other social problems" p.55).
- Second, *our model focuses on attention dynamics internal to media arenas*, deliberately disregarding the influence of exogenous shocks. This does not mean, of course, that these shocks do not exist (clearly the breaking of a war or of an earthquake will command attention in all attention arenas). Yet, their influence is both classic (Crane & Sornette, 2008) and insufficient to account for all media dynamics can ("if a situation becomes defined as a social problem, it does not necessarily mean that objective conditions have worsened. Similarly, if a problem disappears from public discourse, it does not necessarily imply that the situation has improved" p.58). This is particularly true of the kind of junk news we are interested in, which may occasionally surf the drama of external events, but is more often entirely self-referential. For these reasons, exogenous shocks are deliberately excluded from our model (but empirical applications should, of course, control for them).
- Third and similarly to H&B framework, *our model can be applied to different media and at different scale*. Attentions matters are broadly defined as recognizable units of content in a particular forum of collective debate (the attention arena). Examples could be different videos in a given YouTube channel or different threads in a given Reddit subreddit. To be sure, we are not promising that our model will fit to all media debate but inviting scholars to test it empirically on different phenomena to determine to which it can be fruitfully applied.

(b) The second ingredient of our model are two **competition mechanisms** that favor some attention matters over others. The four different "principles of selection" distinguished by H&B find in our model a formalization in two main mechanisms:

- *Exogenous influences*. Three of the four "principles of selection" distinguished by H&B, "drama" (pp.61-62), "culture and politics" (H&B p.64) and "organizational characteristics" (pp. 65,66) are rendered in a deliberately coarse way in our model. The dramatic value of attention matters as well as the way in which they resonate with the general culture or with the specific organization of the medium are important, but their influence falls outside the self-induced media dynamics that constitute the focus of our model. In our formalization, the influence of these features is thus rendered as a noise which randomly increases or decreases the visibility of each item at each iteration. This solution allows to account for this type of influence (and to explore the effect of its variation) under the assumption that its specific nature does not affect the dynamic of junk news bubble.
- *Endogenous trending*. The last selection principle identified by H&B, "novelty and saturation", is crucial to our model. At each iteration, the model increases or decreases the visibility of each matter, repeating its previous variation, *multiplied by a parameter that accelerates or decelerates such variation*. The model therefore rewards rising items and penalizes declining ones. This mechanism works as a *Matthew effect* (Merton, 1968 and Newman, 2001), but a *dynamic one* which rewards not the most visible matters, but the ones that have increased the most since the previous iteration. This boosting of trendiness is consistent with the way in which online platforms "emphasiz[e] novelty and timeliness… [by] identifying unprecedented surges of activity" and "reward[ing] popularity with visibility" (Gillespie, 2016, p.55&60). Such partiality for trendiness is characteristic of both social media and their users, in a sociotechnical loop in which the visibility granted by platform algorithms both *depends on* and *is influenced by* the number of views generated by different contents.

(c) The third ingredient of our model are the **attention boundaries**. At each iteration, *after* adding (or subtracting) to each attention matter its random variation and its trending acceleration, the model *corrects* the potential visibility of each item to make sure that it remains within two inflexible boundaries:

- *Lower boundary: exclusion of negative visibility*. Because it is impossible to conceptualize such thing as a negative attention, when noise or acceleration push the visibility of a matter of attention below zero, the item is removed from the arena and replaced with a new one with null initial visibility. Because a new attention matter can enter the arena only when old one leaves it, the number of items in the model remains fixed (but some items can have visibility equal to zero).
- *Upper boundary: saturation of the attention capacity*. After having applied noise and acceleration and corrected for negative attention, the model divides the potential visibility of each items by the sum of the potential visibilities of all items. This normalization makes sure that the sum of all computed visibilities remains equal to one. This boundary implements a key ingredient of H&B framework, the idea that each debate arena has a **fixed attention capacity**. (or "carrying capacity", in H&B terms). The fixity of the global "carrying capacity" is crucial to ensure that our model does not converge to a trivial winner-takes-all equilibrium. While raising attention matters are pushed to an increasing visibility by their trendiness, they all end up reaching a point where they exhausted their potential for growth, begin to slow down and are penalized by competition mechanisms.

  The inelasticity of attention capacity also ensures that the visibility gained by one matter of attention is always lost by some other so that "the ascendance of one social problem will… be accompanied by the decline of one or more others" (H&B p.61). While we are, of course, aware that public attention fluctuates with circadian and professional rhythms, we believe that these cyclical fluctuations can be discounted for the sake of simplicity. Following H&B,

we think that good reasons for a fixed attention capacity can be found in the limited staging capacity of media ("the prime space and prime time for presenting problems publicly are quite limited" p.59) and, more importantly, in the limited capacity of the public to attend to public ("members of the public are limited not only by the amount of time and money they can devote to social issues, but also by the amount of 'surplus compassion' they can muster for causes beyond the usual immediate concerns" p.59). While, others (see for example, Cinelli et al., 2019) takes these limitations as a reason for selective exposure and filter bubbles, we believe that they are a crucial ingredient of ephemeral concentration and fake news bubbles.

Model formulation and parameters

(a) We call x_i each item of our **population of matters of attention**, with $i = 1, \ldots, N$, where $N$is the maximum number of items in the population. We call "visibility" or ${\pi^t}_i$ the share of attention captured by x_i at time t. By a mechanism explained below, at each timestep, the sum of ${\pi^t}_i$ for all i is fixed and equal to one. This allow, without loss of generality, to interpret each ${\pi^t}_i$ as the percentage of the total attention captured by each item i at time t

(b) We model the two **competition mechanisms** as follows:

- *Endogenous trending*. At every timestep $t+1$, the visibility ${\pi^{t+1}}_i$ of each item i is modified by adding to its current visibility ${\pi^t}_i$ a term which repeat its previous variation (i.e. $\Delta\pi = {\pi^t}_i - {\pi^{t-1}}_i$) multiplied by a positive factor α, which could be interpreted as a boost of trendiness.
- *Exogenous influences*. In our formalization, we render all external influences on media dynamics as a noise ${\varepsilon^t}_i$which increase or decrease the visibility of item i randomly at timestep t. The noise ${\varepsilon^t}_i$ is a realization of a normal distribution

  $N(0, \frac{1}{c*n^2})$ with mean = 0 and standard deviation = $\frac{1}{\sqrt{c}n}$

  where *c* is a positive parameter. We can therefore write the potential visibility of each item after the iteration ${p^{t+1}}_i$ as the output of the two above mechanisms as follows:

$$ {p^{t+1}}_i := {\pi^t}_i + \alpha({\pi^t}_i - {\pi^{t-1}}_i) + {\varepsilon^t}_i \tag{1} $$

(d) At each iteration t, the potential visibility ${p^{t+1}}_i$ is replaced with its corrected version ${\tilde{p}^{t+1}}_i$ to abide by the model's **attention boundaries**:

- *Exclusion of negative visibility*. ${\tilde{p}^{t+1}}_i$ equals ${p^{t+1}}_i$ if ${p^{t+1}}_i$is positive. Otherwise it is set to zero. Hence,

$$ {\tilde{p}^{t+1}}_i = max(0, {p^{t+1}}_i) \tag{2} $$

- *Saturation of the attention capacity*. The limited capacity of an arena is represented by the constraint of having a fixed sum of popularities at each timestep. Therefore, each visibility is obtained from the non-negative ${\tilde{p}^{t+1}}_i$ by normalization.

$$ {\pi^{t+1}}_i = \frac{{\tilde{p}^{t+1}}_i}{\sum_j {\tilde{p}^{t+1}}_j} \tag{3} $$

Initialization. At the first step of the model, the visibility of every i (i.e. ${\pi^1}_i$) is initialized with a random numbers drawn from a uniform distribution between 0 and 1 and normalized to satisfy the constraint $\sum_i {\pi^1}_i = 1$. At the second step, the visibility every i (i.e. ${\pi^2}_i$) is obtained by adding to

${\pi^1}_i$ a noise ${\varepsilon^t}_i$ drawn from the normal distribution $N(0, \frac{1}{c*n^2})$ and normalizing. After the first two steps, the dynamics is self-sustained by evaluating equations (1), (2) and (3) at each iteration.

Inspecting the equations above, it is easy to observe that our model has only three parameters:

- α, trendiness boost, which decides whether the visibility variation at the previous iteration is amplified at the next one and by how much, is the key parameter of our simulation. Conceptually, α can be interpreted as the keenness of media algorithms and media users to identify and promote trendy matters of attention. The bigger is α, the more important is the role played by trendiness in the sociotechnical choices that influence the visibility of media items. High values of trendiness boost thus simulates the attention dynamics occurring in debate arenas prone to junk news bubbles.
- The other two parameter are
    - n, which represent the maximum number of attention matters simultaneously present in the simulation,
    - and c, which represent the size of noise, that is to say the importance of exogenous influences.

  Both n and c are used in the realization of noise and, because they appear in the denominator of the distribution that generate noise, the higher they are, the smaller are the variations due to noise.

Model results and discussion

Despite its simplicity, our model is able to generate patterns comparable with the empirical observations of media systems (Leskovec, Backstrom & Lars, 2009; Lorenz-Spreen, 2019). In particular, our formalization supports the H&B intuition that the "shifting waves of social problems" (H&B p.67) typical of media attention cycle can be explained by the interaction between the push of trendiness and the saturation of the carrying capacity: "if we explore these complex linkages, we find a huge number of positive feedback loops, 'engines', that drive the growth of particular problems. Growth is constrained, however, by the negative feedback produced by the finite carrying capacities of the public arenas, by competition among problems for attention, and by the need for continuous novel drama to sustain growth" (H&B p.67).

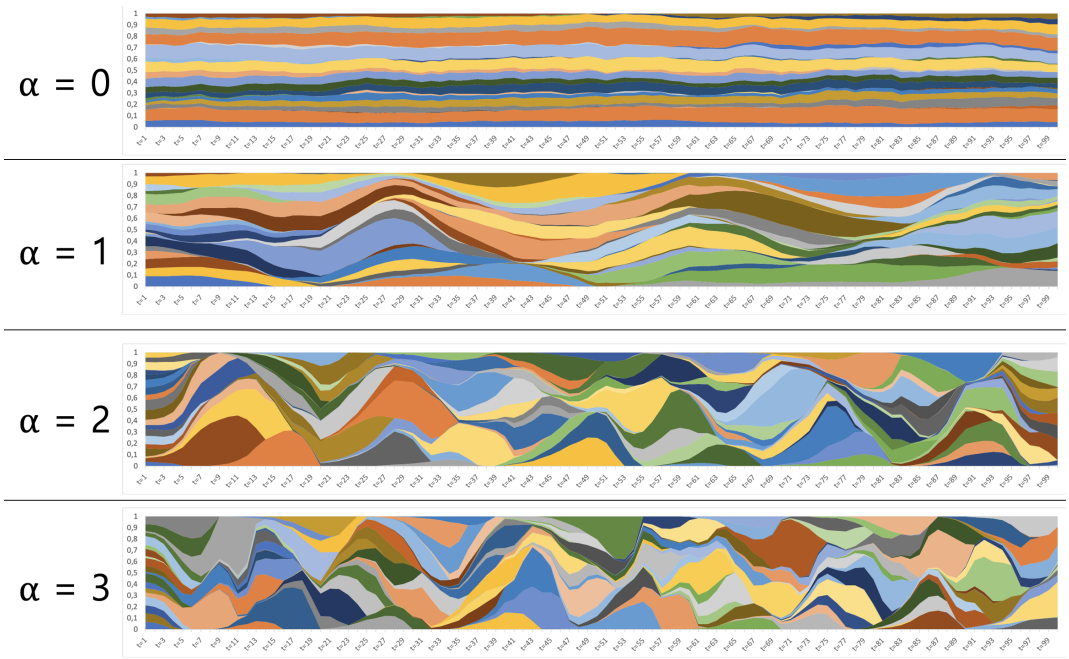


Figure 1. Evolution of our model for trendiness boost = 0, 1, 2, and 3 (with $n = 20$ and $c = 12$). Only the first 100 iterations are shown as the shape of the curves does not change in further iterations

The comparison between the graphs in fig. 1 suggests that, as the boost of trendiness grows, the rise and fall of attention matters becomes steeper. This relation can be tested by computing the mean steepness of attention curves (the absolute increase or decrease by unit of time) and observing that it increases monotonically at the increase of alpha before reaching a plateau (probably due to the upper and lower boundaries of our model and to impossibility of compressing the width of curve beyond a certain point).

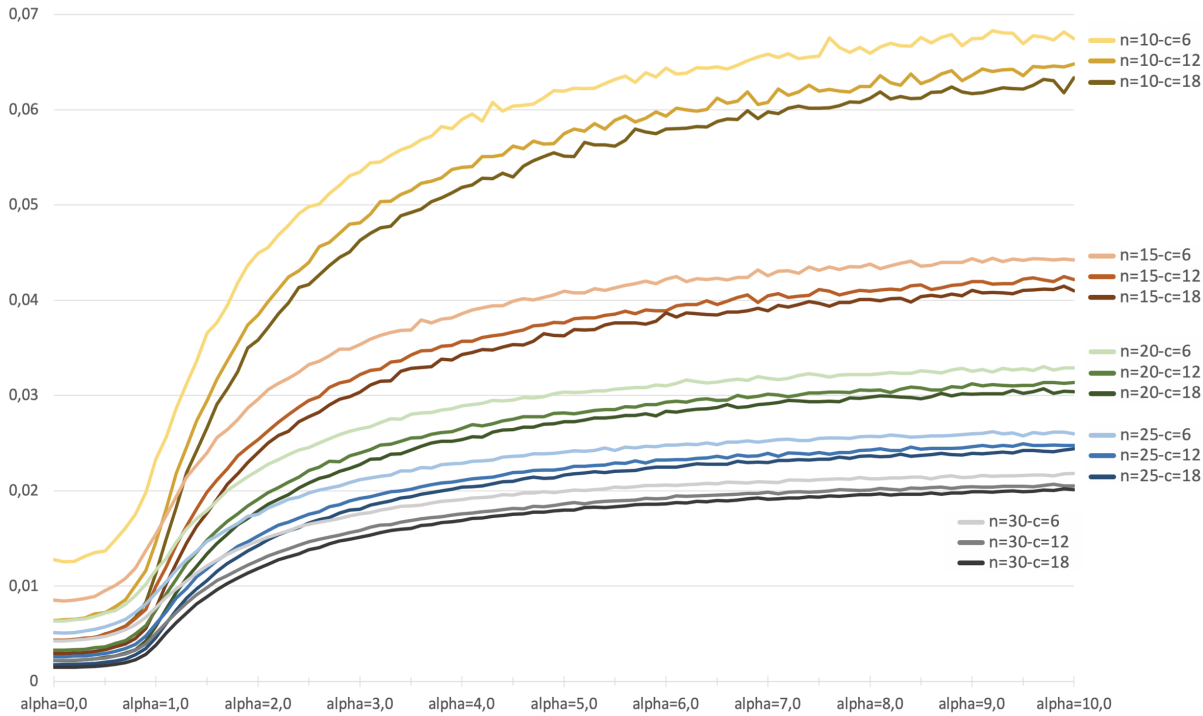
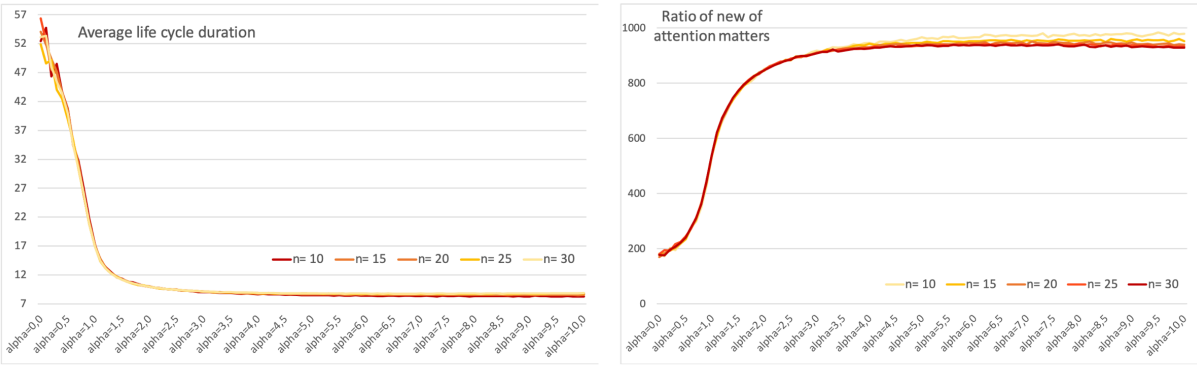


Figure 2. Mean slope of attention curves as function of the trendiness boost (for different values of n and c)

Fig.2 confirms that the relation between the steepness of attention curve and trendiness boost is not substantially transformed by the other parameters of our model. The number of attention matters and the importance of exogenous influences shift the position of the curve, but do not change its shape. Also, because both n and c affect the curve in the same way, only n will be explored in the next figures.

Considering together fig. 1 and 2, it is also interesting to notice that trendiness boost increases rise-and-fall steepness affecting both dimensions of the media cycle: the *height* of attention curves and their *width*. This suggests that junk news bubbles may combine consequences which may appear contradictory.

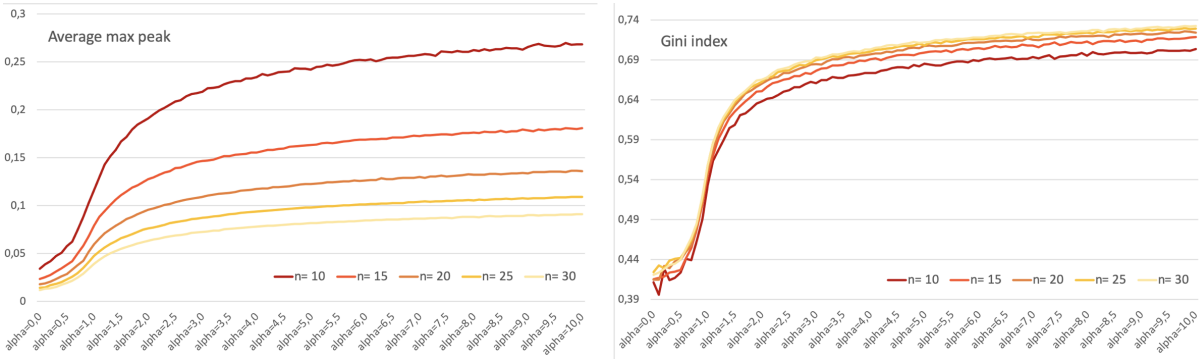
- Regardless of the number of items or the level of noise, the stronger is trendiness boost the shorter is the lifecycle of individual attention matters (fig.3a). Remarkably, this is true for all attention matters: even items that reach very high levels of visibility end up falling as quickly as they rose. As a consequence of the shortening of attention weaves, a higher number of matters enter and exit the arena (fig.3b). Arguably, this may be the reason why online platforms are partial to trendiness: as the barriers to content production lower and volume of content grows, boosting trendiness is an effective way to fit more items in the same attention span.



a. b.

Figure 3. (a) Mean length of attention matters' life cycle and (b) ratio of new attention matters entering the model in its first 10.000 iterations, at the variation of trendiness boost (for different values of n and with c set to 12)

- On the other hand, higher trendiness boost increase the maximum visibility reached by attention matters (fig. 4a) and, most importantly, amplify the difference between successful and unsuccessful attention matters, creating a situation in which, at each iteration, most of the available attention is captured by a minority of over-visible items (fig. 4b). "There is a huge 'population' of potential problems-putative situations and conditions that could be conceived of as problems. This population, however, is highly stratified. An extremely small fraction grows into social problems with 'celebrity' status… [while] the vast majority of these putative conditions remain outside or on the extreme edge of public consciousness" (H&B p. 57).



a. b.

Figure 4. (a) Mean height of the attention curve peaks and (b) Gini index of attention concentration at each iteration of the model, at the variation of trendiness boost (for different values of n and with c set to 12)

Conclusion

Taken alone, none of the consequences of junk news bubbles highlighted by our model is particularly surprising: being an acceleration, trendiness predictably shortens the lifespan of attention matters and, being a positive feedback, it increases their maximum visibility. Their combination, however, is remarkable as it creates a *shoaling* of attention waves which reduces the width *and* increases the height of attention curves. Debate arenas characterized by a stronger focus on trendiness may therefore end up displaying a syncopated rhythm of attention that is at the same time *increasingly dispersed and increasingly concentrated* (as one can easily observe, for example, in YouTube channels or subreddits devoted to buzzing news, memes and viral contents).

Being a simplified formalization of a relatively abstract framework, our mathematical model does not allow substantial claims about actual attention dynamics. It allows, however, to advance a precise hypothesis about the junk news bubbles and their detrimental effects on public debate: the fascination with trendiness of digital platforms and their users may create an over-accelerated public debate in which a disproportionate share of media attention is captured by matters which are incapable to sustain it. As the shoaling of sea waves is associated with the entering in shallower waters, so junk news bubbles may be associated with a shallower public debate, a risk that we believe is as serious as the fragmentation produced by filter bubbles, if not more.

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