Universal patterns of online news impact

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Online news can quickly reach and affect millions of people, yet little is known about potential dynamical regularities that govern their impact on the public. By analyzing data collected from two nation-wide news outlets, we demonstrate that the impact dynamics of online news articles does not exhibit popularity patterns found in many other social and information systems. In particular, we find that the news comment count follows a universal exponential distribution which is explained by the lack of the otherwise omnipresent rich-get-richer mechanism. Exponential aging induces a universal dynamics of article impact. We finally find that the readers’ collective attention does “stretch” in the presence of high-impact articles, thus effectively canceling possible competition among the articles. Our findings challenge the generality of widespread popularity dynamics patterns as well as common assumptions of attention economy, suggesting the need to critically reconsider the assumption that collective attention is inherently limited.

INTRODUCTION

Consider a major news, like the results of the presidential elections. In the 80s, we would have discovered it through traditional print and broadcast media. Today, new media and online platforms have disrupted not only the way we discover and consume information, but also the way we form our opinions and attitudes about critical topics for our society like politics [1, 2], science [3, 4], and public health [5]. In particular, to gather information about events in the world, we increasingly rely on online newspapers and social media platforms [6]. Most online newspapers allow users to directly comment on news articles [7], creating a “digital public sphere” where participation is free, recent events are publicly discussed, and comments are visible to everyone [8]. In such a complex information ecosystem, some news articles impact thousands of users who actively discuss and share them in online platforms[9], whereas many others remain little known and quickly forgotten. Therefore, understanding the dynamics of impact of online news articles is vital not only because it deepens our understanding of how information spreads throughout modern societies, but also because it can potentially help to counteract negative side effects of new media like the spreading of misinformation [10, 11] and the amplification of ideological segregation [12].

The unprecedented availability of big data on human online activity has allowed us to uncover and model patterns of human behavior and cultural products’ popularity in diverse contexts [13, 14]. As for online news articles, previous research has unveiled factors that make an online news article more likely to become popular, including story topic [15], content emotion [16], perceived objectivity [17], and format [18]. Yet, little is known about the potential regularities that govern the dynamics of online news articles’ impact. Does the impact of online news articles follow similar patterns as the impact of other types of information items? Are there universal impact patterns for online news articles? How predictable is the dynamics of attention decay for online news articles? Do high-impact articles reduce the impact of other articles by monopolizing the collective attention? To address these questions, we analyze a novel dataset that contains commenting sections of 3,087 articles from the British Broadcasting Corporation (BBC) and a dataset that contains commenting sections of 2,801 articles from the New York Times (NYT).

A growing, interdisciplinary stream of literature has aimed to uncover empirical regularities behind the emergence of popular cultural items in science [19], social media [14], and literature [20], among others. This effort has generated insights that generalize well across domains: popularity and impact typically follow heavy-tailed distributions, leading to the emergence of a small number of “hits” [21] with disproportionate popularity. These successful outliers emerge from a combination of quality (often referred to as fitness) and social amplification mechanisms such as the rich-get-richer phenomenon [22]. In a world where our collective attention is assumed to be inherently limited [23], hits can impact the dynamics of other items by reducing the collective attention that they receive [24–26]. These regularities in popularity dynamics – sometimes referred to as “laws” [27] – have been found to govern the popularity and impact dynamics of cultural items as diverse as scientific papers [22, 28], websites [29], books [20], and patents [30, 31], among others.

Surprisingly, we find none of these regularities in the
impact of online news. Differently from the widespread heavy-tailed distributions of popularity and impact in social systems, news impact (in terms of the number of received comments) is exponentially distributed. Different categories of news have widely different average comment counts, yet their distributions can be collapsed onto a universal exponential distribution. The exponential impact distribution results from the absence or saturation of the widely-studied preferential attachment mechanism. In line with recent findings on the attention decay in science and technology [30, 32], the decay of individual news articles follows a universal exponential form. The impact dynamics of online news articles can be reproduced by a parsimonious model with article-level fitness and exponential aging [33]. Building on this model, we can predict the articles’ long-term impact based on early activity. Finally, we demonstrate that the hits have a negligible effect on the attention received by the other articles in the platform.

Our findings contribute to the literature on popularity dynamics [14, 19, 20, 22, 28, 29] and collective attention [23, 32, 34, 35] by demonstrating that there is a limit to the generality of widely-observed patterns and mechanisms (such as preferential attachment). While previous studies have emphasized the generality of observed patterns of popularity and impact [32], future research might put more emphasis on identifying violations of pervasive patterns and the causes behind the observed violations. Besides, as managing and influencing the spreading of online information is vital for online newspapers and social platforms, our models and methods can be used to inform decisions by newspaper editors and content creators.

RESULTS

News impact is exponentially distributed

By writing comments, the users demonstrate a higher level of engagement compared to only reading the article [7, 17]. Importantly, comments are read also by users who do not actively comment, indicating that they play an important role in how a news article is perceived by the public [36]. The number of comments can be thus considered as a good proxy for the article impact [37]. To study the distribution of article impact, we discard potential multiple comments from a single user on a given news, thus counting the number of unique commenting users. When all comments are used instead, the results do not change qualitatively.

How is the article impact distributed? Impact distributions for creative works are typically found to be heavy-tailed: this is the case for scientific papers [22], patents [38], and books [20], among others. Broad popularity distributions are also typically found for user-generated content in online systems [39]. Based on these findings, one might expect that the article impact follows a heavy-tailed distribution. Surprisingly, we find instead that the distributions exhibit exponential tails for both BBC and NYT data (Fig. 1A, D). Using the exponential distribution $P(c) \sim \exp(-\lambda c)$ for $c \geq c_{\text{min}}$ and following [40], we obtain estimates for the lower bound $c_{\text{min}}$ and the scaling parameter $\lambda$, together with the $p$-value obtained through the Kolmogorov-Smirnov test (see Material and Methods for details).

For BBC, we find 276 articles (9% of all) that belong to the exponential tail of the distribution, i.e., whose comment count reaches the estimated lower bound ($c_{\text{min}} = 438$) of the exponential distribution. The estimated scaling parameter is $\lambda = 262 \pm 16$ and the high $p$-value of 0.72 indicates that the exponential distribution cannot be ruled out. The good fit can be visually appreciated by observing that the empirical distribution lies within the 5th–95th percentile range of synthetic exponentially distributed data generated with the estimated parameters (Fig. 1A). Results are analogous for NYT where $c_{\text{min}} = 845$, $\lambda = 640 \pm 64$, and the $p$-value is 1.00 (see Fig. 1D). A power law distribution yields less accurate fits for both datasets (see Supplementary Information (SI), Sec. S2 for details).

News in both datasets have additional category information provided directly by the news outlets; the most populated categories are football (BBC) and national (NYT); see Tab. S1 in SI for details. Importantly, articles’ comment counts strongly depend on the category of the news (Fig. 1B compares categories with the most articles). The comment count distributions for individual article categories are more accurately fitted by an exponential distribution than the comment count distribution for all the articles. In particular, article impact distributions exhibit remarkably low $c_{\text{min}}$ and high $p$-values for most categories. The low values of $c_{\text{min}}$ indicate that within each category, most of the articles belong to the exponential tail of the distribution. For the BBC data, from the 2,796 articles in the six individually fitted categories, 2,006 belong to the exponential tail of the distributions (93% of all). For the NYT data, 39% of the 1,333 articles in the five most-populated categories belong to the exponential tails; the fraction is 99% for the most popular (by both the number of articles and the average number of comments) category “national” (Fig. 1E).

Inspired by the universality of scientific impact distributions [19, 41], we explore an intriguing possibility: By leveraging the estimated parameters, can we collapse the article impact distributions for different categories on top of each other? We find that this is the case: comment count distributions in different categories collapse on top of each other after the comment counts are transformed as $(c - c_{\text{min}}^X)/\lambda^X$, where $c_{\text{min}}^X$ and $\lambda^X$ are the estimated lower bound and the scaling parameter for category $X$. Fitting results for individual categories are summarized in Section S2 in SI.

In summary, the overall comment count distribution is a superposition of multiple exponential distributions that correspond to different article categories, and a univer-
sal exponential curve emerges when using the estimated (category-level) scaling parameters and lower bounds to transform the comment counts.

**Preferential attachment plays a minor role in the dynamics of impact**

The empirical exponential distributions of article impact inevitably lead us to investigate possible mechanisms behind their emergence. Motivated by existing results on the dynamics of impact for cultural products as diverse as scientific papers [22, 28], patents [30], and bestseller books [20], one expects two main forces shaping the dynamics of news impact [32]: a preferential attachment mechanism and a temporal decay. We start by addressing preferential attachment which implies that the rate at which an article receives new comments, $\Delta c(t, \Delta t)$, is a power-law function (most commonly, a linear function) of the number of already-received comments, $c(t)$.

In contrast with pervasive findings in the popularity dynamics literature, we find that preferential attachment is negligible in the BBC data (Fig. 2A) and exhibits strong sub-linearity and saturation for the NYT data (Fig. 2D). More specifically, in the BBC data, it is possible to explain the weak growth of $\Delta c(t, \Delta t)$ with $c(t)$ in terms of a dynamic model where no preferential attachment is present (see Figure S15 in SI). In the NYT data, the dynamics of $\Delta c(t, \Delta t)$ exhibits an initial growth phase with sub-linear preferential attachment [42]; then it reaches a plateau and becomes independent of $c(t)$. These findings indicate that even though the articles’ comment counts are explicitly reported by the BBC and NYT websites (see Fig. S1 in SI), the impact of preferential attachment on the dynamics of news article impact is limited.

**The dynamics of article impact follows an exponential decay**

Existing studies have found various functional forms for the decay of the impact of cultural items, including log-normal [20, 28], exponential [30, 35], stretched exponential [34], and biexponential [32]. To quantify the temporal decay of article impact, for each news $i$, we measure the news’ number of new comments relative to the article’s final comment count, $f_i(t) := \Delta c_i(t, \Delta t)/c_i$, as a function of the article age, $t$. The normalization by the article’s final comment count makes the dynamics of articles of different ultimate impact directly comparable.[43] For each age, $t$, we compute the median of $\Delta c_i(t, \Delta t)/c_i$, as well as the 90th percentile of all comments (679 and 428 comments in BBC and NYT, respectively). To suppress the time-of-day effects, we in-
FIG. 2. The universal dynamics of article impact. (A) The number of new comments in $\Delta t = 10$ min as a function of the current number of comments in the BBC data. The fit up to the comment count 800 yields the slowly-growing dependence proportional to $1 + c/220$. Above 800 comments, the dependence is even weaker above (saturation). (B) The number of new comments of an article, $\Delta c_i(t, \Delta t)$, normalized by its final number of comments, $c_i$, as a function of its age, $t$, for the hit articles (90th percentile by the number of comments). The dotted line indicates the linear fit for age 0–10 hours; its slope corresponds to a representative aging timescale $\Theta = 305$ min. (C) The comment count evolution in terms of the normalized article age $(t - t_i)/\Theta_i$. The dashed line represents the proposed model and its solution given by Eq. (1). The inset shows the distribution of the timescales $\Theta_i$ obtained by minimizing the Kolmogorov-Smirnov statistic. In panels B and C, we limit the time-of-day effects by including only the articles that appear in the morning between 9am and noon. The shaded areas there indicate the 20th–80th percentile range and the solid lines show the median values for the considered articles. (D–F) Same as in (A–C) for the NYT data. As in panels B and C, we restrict here to the articles that appear between 2pm and 5pm GMT. The representative aging timescale determined from panel (E) is $\Theta = 230$ min.

cclude only the articles that start in the morning between 9am and noon—the 10 hour range shown in Fig. 2B is thus a period where the user activity at the BBC website is rather uniform and substantially higher than the night activity (see Fig. S7 in SI).

We find that the articles’ temporal decay follows a universal exponential form (Figs. 2B,E). In particular, the average decay function $f(t)$ can be accurately fitted by an exponential function: $f(t) = e^{-t/\Theta}$ where $\Theta = 305$ min for BBC and $\Theta = 230$ min for NYT. While $f(t)$ decreases exponentially in the BBC data during the whole observed range, it shows a short period (approximately 1 hour) of increase in the NYT data. This is a direct consequence of the preferential attachment that applies for low comment counts—as the number of comments grows, the rate of commenting initially accelerates before aging in combination with sublinear/saturated preferential attachment eventually cause the rate of commenting to decrease.

The observed exponential decay can be interpreted as a limit scenario of the bi-exponential impact decay predicted by a recent work based on a model with communication memory and cultural memory [32]. The reason why such a limit scenario holds for online news needs to be clarified by future research. A plausible hypothesis is that as the comments to online news articles unfold over a narrow time period following a news, we cannot use them to observe the process whereby the communication memory associated with an article is converted into cultural memory. If this is the case, the model in [32] predicts an exponential decay of collective attention, in line with our observed decay functions. More complex patterns of impact decay are likely to emerge when considering more convoluted measures of the impact of a news article on society, potentially including data from social media and references to an article from other articles.

Exponentially-distributed fitness and exponential aging shape the dynamics of article impact

The impact dynamics for scientific papers [22, 28] and bestseller books [20] is typically modeled in terms of preferential attachment, fitness and aging. Building on these studies, a potential model for the commenting dynamics would assume that the probability that an article receives a new comment at time $t$ is $P(t) \sim c_i(t) \eta_i f_i(t-t_i)$, where
$c_i(t)$ is the preferential attachment factor, $\eta_i$ the fitness factor, and $f_i(t - t_i)$ denotes an article-dependent aging function. In line with previous studies [22, 28], article fitness $\eta$ is a hidden intrinsic parameter that quantifies, other factors being equal, how a given article is attractive to the website’s audience. We refer to this model as the PFA model because it includes preferential attachment, fitness and aging. In this model, a narrow exponential distribution of article fitness, $\rho(\eta) = \exp(-\eta)$, leads to the emergence of a power-law distribution of the comment count [22]. In other words, small differences in items’ fitness can lead to wide impact inequalities.

On the other hand, the observed weak preferential attachment and exponential temporal decay suggest a simpler model of the dynamics of article impact where only article fitness and exponential aging play a role. We thus assume that the probability that a news receives a new comment at time $t$ is $P(t) \sim \eta_i f_i(t - t_i)$ where $t_i$ is the appearance time of news $i$; we refer to the resulting model as the FA (fitness-aging) model [33]. To accurately represent the commenting dynamics, we introduce individual aging timescales $\Theta_i$ and the aging factor in the form $f_i(t - t_i) = \exp[-(t - t_i)/\Theta_i]$. The aging timescales $\Theta_i$ are estimated from the empirical data by minimizing the Kolmogorov-Smirnov statistic between the comment count dynamics in the model and in the empirical data (see Materials and Methods). If $\Theta_i \gg 1$, the expected final comment count under the FA model is directly proportional to the product of the article fitness and the aging timescale, $\Sigma \sim \eta_i \Theta_i$. The model further implies that

$$\frac{c_i(t)}{c_i} = 1 - \exp\left(-\frac{t - t_i}{\Theta_i}\right). \tag{1}$$

Motivated by this result, we measure the dynamics of the comment count normalized by the final comment count. We find that Eq. (1) captures the empirical dynamics remarkably well (Fig. 2C,F) and allows us to collapse all article trajectories onto a universal curve. This result demonstrates that the fitness-aging model captures the two essential factors that govern the dynamics of news article impact, and it further confirms that preferential attachment plays a negligible role in the emergence of hit articles.

Since $\Sigma \sim \eta_i \Theta_i$, exponentially distributed $\eta \Theta$ leads to the emergence of an exponential comment count distribution in line with the empirical data. When the aging timescales vary relatively little among the articles, as it is the case for us, the distribution of article fitness alone is approximately exponential. Interestingly, an exponential distribution of $\eta \Theta$ (referred to as relevance therein) was reported in [22] for scientific papers and an exponential distribution of $\eta$ (in a model without aging) was reported in [29] for pages of the World Wide Web.

| $\Delta t$ | $P$ | $AUC$ | $P$ | $AUC$ |
|---|---|---|---|---|
| 1 | 0.33 | 0.69 | 0.31 | 0.62 |
| 2 | 0.51 | 0.81 | 0.51 | 0.75 |
| 5 | 0.60 | 0.87 | 0.64 | 0.89 |
| 10 | 0.63 | 0.89 | 0.73 | 0.92 |
| 60 | 0.69 | 0.92 | 0.81 | 0.96 |
| 240 | 0.77 | 0.94 | 0.83 | 0.98 |
| 1200 | 0.93 | 0.99 | 0.95 | 0.99 |

**TABLE I.** Classification precision and AUC for the hit articles.

**Early activity can be used to predict article impact**

The orderly dynamics demonstrated by the panels of Fig. 2C,F suggests that there might be a high degree of impact based on early activity on the articles. To verify this conjecture, we study a classification problem where we aim to predict whether an will article will become a hit (90th percentile by the final impact). We classify an article as positive if it belongs to the 90th percentile by the number of comments that it has attracted over the first $\Delta t$ minutes, and negative otherwise. We evaluate the classifier using precision and AUC which are both classical information retrieval metrics [44] that range from zero (the worst result) to one (the best result). We find that the proposed simple classifier exhibits high values of precision and AUC even when $\Delta t$ is short: precision exceeds 0.6 after five minutes, for example (see Table I for full results).

The observed predictability is unsurprising given previous results on the correlation between early and late popularity of online content [39, 45, 46]. However, previous studies interpreted the early-stage predictability of the virality of online cascades as a possible manifestation of cumulative advantage [46]. This cannot be the case for online news where preferential attachment is negligible. Taken together, our findings suggest a somewhat simpler scenario: the news that are highly attractive for the public tend to receive more connections throughout their whole lifetime than less attractive news. In this sense, the impact of online news might be seen as more “meritocratic” than that of content in systems with preferential attachment: the news with a truly high fitness are those that eventually succeed, regardless of cumulative advantage effects.

**Hit articles have a negligible effect on the other articles**

As our time and energy are inherently limited, our collective attention is necessarily bounded. This idea is typically reflected in popularity dynamics models by assuming that the existing items compete for a finite amount of attention [22–26, 47]. Under the limited collective attention hypothesis, it is natural to expect that the appear-
ance of a popular article (a breaking news reporting or a major event in the presidential race, for example) leads to a decrease in the attention given to the concurrent news. An alternative hypothesis is that hit items “live on their own”. In this scenario, hits would increase the overall activity on the platform, but they would not significantly affect the commenting dynamics of the other articles. We shall demonstrate that the latter scenario corresponds to the dynamics of online news.

We quantify the effect of the appearance of a new hit article on the system’s dynamics as follows. We measure the number of comments received by articles over two consecutive short time periods of length $\Delta t$ just before and just after a time $t_0$. These comment counts are referred as $\Delta c_i^B(t_0)$ (before $t_0$) and $\Delta c_i^A(t_0)$ (after $t_0$), respectively. In the following, we use $\Delta t = 10$ min; the main conclusions remain the same if a different short $\Delta t$ is chosen. We compare the observed comment counts between two special cases: (1) The baseline scenario where no new articles appear in the period $[t_0 - \Delta t, t_0 + \Delta t]$; (2) The hit scenario where a future hit (i.e., an article that is ranked among the top-10% by the final number of comments) appears at time $t_0$. In the baseline scenario, we expect the number of new comments to decrease, on average, between the two time windows as a manifestation of the aging effects demonstrated by Fig. 2. In a system where items compete for a finite collective attention, the number of new comments to other articles would decrease after the appearance of a future hit at a faster rate than in the baseline scenario.

We start with the observation that the appearance of a hit article dramatically increases the overall activity in the platforms (Fig. 3A,B). However, this increase is solely due to the hit article itself as the average number of new comments to the other existing articles before and after the hit’s appearance are similar, suggesting that the hit’s influence on the other articles’ dynamics is negligible. To validate this hypothesis, we design a maximum-likelihood procedure to gauge the effect of hits on the dynamics of the other existing articles. The procedure assumes that the observed numbers of new comments are random variables drawn from a Poisson distribution with an unknown and article-dependent mean (Figure S16 in SI shows that this is a good approximation) and this mean systematically differs between pairs of consecutive time windows: Denoting the mean of article $i$ in the first time window as $\mu_i$, the article’s mean in the subsequent time window is $\gamma \mu_i$. The previously documented overall decrease of the number of new comments with time suggests that $\gamma$ is typically smaller than one – for this reason, we refer to $\gamma$ as the slow-down factor.

To obtain a robust estimate of the slow-down factor in the baseline and hit scenarios, we consider several pairs of consecutive time windows defined by the dividing time points $t_j$; $\Delta c_i^B(t_j)$ and $\Delta c_i^A(t_j)$ denote the numbers of new comments in the periods $[t_j - \Delta t, t_j]$ and $(t_j, t_j + \Delta t]$, respectively. The hit scenario and the baseline scenario differ in how the dividing time points are selected. In the hit scenario, we choose $t_j$ values that are the appearance times of the hits. To quantify the average slow-down factor in the baseline scenario, we use the same number of time points as in the hit scenario, but we draw them at random. To avoid potential confounding effects of other articles that appear in the analyzed time periods, in both scenarios we exclude the $t_j$ values for which some other articles appear within the period $[t_j - \Delta t, t_j + \Delta t]$.

For a given set $\{t_j\}$ of dividing time points, we show that the maximum likelihood estimate of the slow-down factor (see Materials and Methods) has the form

$$\hat{\gamma} = \frac{\sum_{i,j} \Delta c_i^A(t_j)}{\sum_{i,j} \Delta c_i^B(t_j)}.$$  \hspace{1cm} (2)

In the hit scenario, the summation in Eq. (2) excludes the hit article whose effect we aim to measure. Comparing the slow-down factor estimates between the baseline and hit scenarios allows us to answer the question: Is there an significant difference between the attention given to the other articles before and after the appearance of a hit article?

We find that the average slow-down factor in the hit scenario is smaller than in the baseline scenario by approximately 2% and 5% for BBC and NYT, respectively, indicating that the appearance of a hit is associated with a slightly faster decay of impact for the other articles (see Fig. 3C). However, the difference is not statistically significant ($P = 0.67$ and $P = 0.28$ for BBC and NYT, respectively). We obtained qualitatively similar results by constraining the analysis to articles from a specific article category (Sec. 5.2 in SI). Taken together, these results indicate no robust evidence that the appearance of a hit article affects the dynamics of the other articles in the platforms.

Is the observed lack of effect of hits due to the fact that hits and ordinary articles attract substantially different audiences? To answer this question, we divided both the news articles and the users, respectively, in three groups by their number of received comments and commented articles, respectively. We compared the numbers of comments by each of the three groups of users and the three groups of articles with the values observed in randomized data where individual users’ total activity and articles’ total impact are preserved (see Material and Methods). As shown in Fig. S9, while some significant differences arise (e.g., little-active users comment on little-impact articles more than expected by their activity level), the differences from randomized article-user connectivity are small: up to 5% in the BBC data and up to 10% in the NYT data. This indicates, among other things, that the hits do not reach high impact by activating a pool of little-active users but by nearly-uniformly attracting attention from users of all activity levels.
The effect of hits on the other articles is observable when user attention is not elastic

A possible objection to the presented lack of effect of hits is that the proposed maximum-likelihood procedure might not be able to detect the effect of hits in cases where such an effect is veritably present. To rule out this possibility, we introduce a generalized dynamical model where the level of competition between articles for collective attention is ruled by an elasticity parameter, $\lambda$ (see Materials and Methods) – we refer to this model as the FAE model because it includes fitness, aging, and tunable elasticity. This model allows us to interpolate between two extreme worlds: A world where the collective attention can stretch without limitations in presence of high-impact articles (perfect elasticity, $\lambda = 1$, see Fig. 3D), and a world where the collective attention is fixed and is not influenced by the presence of high-impact articles (no elasticity, $\lambda = 0$, see Fig. 3E). In the perfect elasticity world, in line with our empirical findings, the appearance of a hit has no effect on the other articles (Fig. 3D), whereas in the no elasticity world, the appearance of a hit is associated with a sharp reduction of the attention received by the other articles (Fig. 3E). Can our maximum-likelihood procedure detect the effect of hits in low-elasticity worlds?

To address this question, we calibrate the FAE model on the BBC data and create synthetic datasets for the full range of elasticity values (from no elasticity, $\lambda = 0$, to perfect elasticity, $\lambda = 1$, see Materials and Methods and Sec. 6 in SI). As shown in Figure 3F, the estimated slow-down factor significantly differs between the baseline scenario and the hit scenario for most elasticity values: for $\lambda$ as high as 0.9, the average $z$-score is $-2.8$ corresponding to the $p$-value of 0.005. This demonstrates that the proposed effect measurement has the potential to detect the effect of hits for all elasticity values except for those that are close to $\lambda = 1$. In light of this high sensitivity of the proposed slow-down factor to the elasticity of the system, we conclude that the empirical lack of effect of hits on the other articles suggests that the collective attention is highly elastic in real-world news outlets, deriving directly from the news articles present in the platform.

DISCUSSION

By analyzing data on the comments to online news articles in two major nationwide newspapers, we were able to uncover surprising empirical regularities that charac-
terize the distribution of the impact of online news articles, its dynamics, and the impact of hit articles on the other articles. In particular, we revealed two universal patterns: for both newspapers, the distribution of the number of comments received by articles from various categories collapse onto the a universal exponential curve, and the dynamics of the comment count of different news articles collapse onto a universal curve once appropriate rescaling is applied.

The observed patterns are strikingly different from those that are typically observed in the literature on success and popularity in social systems. Indeed, previous literature has emphasized that success and popularity are usually characterized by heavy-tailed distributions [29, 39, 41], and that preferential attachment plays a key role in shaping the emergence of hits [20, 22, 28, 29]. Our findings illustrate that this is not the case for online news articles, whose impact exhibits a bounded distribution. Such a bounded distribution emerges from a dynamics where preferential attachment plays a negligible role. This indicates that in online newspapers, popularity signals might play a limited role compared to other systems [48]. Additional research is needed to quantify the relative importance of different factors that trigger user engagement in a news article, and how our findings generalize to different cultures and platforms in different languages than English.

The fact that new hit articles attract short after their appearance a large fraction of the users’ cumulative attention gives us the unique possibility to probe the limited attention hypothesis which is one of the pillars of the attention economy [22–26, 47]. If the hypothesis is true, the appearance of a hit must reduce the attention given to the other articles. The absence of such a significant reduction in the studied data can be explained by the users’ collective attention, instead of being fixed, elastically adapting to the supplied articles. These results contradict one of the pillars of the attention economy, namely that users’ collective attention is inherently limited. Future works may examine whether a similar elasticity of individuals’ collective attention can be found for different kinds of cultural products, economic goods, and services. Our result suggests that for publishers, it might be more fruitful to focus on news with a high-potential to resonate with their audience rather than to search for the optimal timing for the release of the news based on the other articles present in the respective news platforms. Experimental studies will be needed to validate this conjecture. More generally, the proposed method to measure the effect of hit articles on the system can be used in a broad range of complex systems where the non-linear system response and a low signal-to-noise ratio make such a measurement difficult.

We quantified the impact of a news article through the number of comments it received from the online newspaper’s readers. Other metrics of impact might be also relevant to news outlets. For example, the overall impact of a news can be quantified as a combination of the impact on the readers of the newspaper and the impact on users who shared or commented the news in different social media and news aggregation platforms. Uncovering the regularities of the news articles’ dynamics by incorporating data from social media and news aggregators is an important direction for future research, given the critical role of these platforms for news dissemination [49, 50].

Although our study focused on news outlets that only include verified news (BBC and NYT), our findings can inspire future studies related to the spreading of misinformation in online systems [10, 11]. Our results could serve as baselines in future studies that consider the commenting dynamics of both verified and false news. Do false news trigger different patterns of impact compared to true news? Is the diffusion of false and true news governed by different fundamental mechanisms? Understanding which mechanisms play a major role in engaging users and triggering their comments might suggest intervention strategies to prevent their impact.

To conclude, new media have disrupted the way we consume and share information, creating new challenges and opportunities for our society. Among the opportunities, the accessibility of online news data allows us to quantify and model empirical regularities behind the spreading of information throughout our society. We hope that our work constitutes the first step toward a comprehensive, quantitative understanding of the mechanisms that govern the impact of online news articles on the public.

**MATERIALS AND METHODS**

**Empirical datasets**

We regularly crawled the sport section of the BBC website (its front page and the pages dedicated to individual sports) and collected the found news articles with commenting sections. From October 1, 2018 to June 30, 2019, we collected 3,087 articles that received 852,400 comments from 67,527 readers. Each article is assigned to a sport category. The most populated categories are Football (1590 articles), Rugby Union (439 articles), Cricket (240 articles), Tennis (162 articles), Formula 1 (139 articles), Golf (123 articles) and Boxing (103 articles). Each comment is time-stamped with the time resolution of one minute. BBC typically closes commenting on the second midnight after the article has been published; most of them are therefore open for 24–48 hours.

We complement the unique BBC dataset with a dataset containing articles with commenting sections from the New York Times (NYT). [51] From January 1, 2017 to May 30, 2017, there are 2,801 articles that received 649,794 comments from 75,118 readers. Also here, each article is assigned to a category. Unlike for BBC, sport articles are a minority in the NYT data: The most populated categories are National (348 articles), Learning (306 articles), Magazine (262 articles), Sports (213
Fitting the comment count distributions

The maximum likelihood estimate (MLE) of the scaling parameter of the exponential distribution is known to be the sample mean, \( \hat{\lambda} = \left( \sum_{i=1}^{n} c_i \right) / n \). As can be seen from Figure 1, the comment count distribution follows an exponential form starting from some lower bound \( \hat{c}_{\text{min}} \). The MLE estimate then changes to \( \hat{\lambda}(\hat{c}_{\text{min}}) = \left[ \sum_{j} (c_j - \hat{c}_{\text{min}}) \right] / n(\hat{c}_{\text{min}}) \) where the summation is over \( j \) for which \( c_j \geq \hat{c}_{\text{min}} \) and \( n(\hat{c}_{\text{min}}) = |\{ j : c_j \geq \hat{c}_{\text{min}} \}| \) is the number of comment counts that match or exceed the lower bound. We assess the estimate uncertainty using non-parametric bootstrap—standard deviation of the MLE estimates is evaluated for 10,000 bootstrap realizations of the comment count data.

To determine \( \hat{c}_{\text{min}} \), we follow the approach suggested by [40]: We choose \( \hat{c}_{\text{min}} \) that minimizes the difference between the comment count distribution and the fitted exponential distribution. While the Kolmogorov-Smirnov (KS) statistic is a common way to measure the difference between probability distributions, we prefer the weighted Kolmogorov-Smirnov statistic which puts more emphasis on differences between the distributions’ tails [40, 52].

A detailed comparison between fitting exponential and power-law distribution to the commenting data, including the log-likelihood test which directly compares the likelihood that the analyzed data has been drawn from the exponential or the power-law distribution, is presented in Sec. S2 in SI.

Measuring the effect of hits on the other articles

Our approach is based on evaluating how the number of new comments received by articles changes with time. In particular, we count the number of new comments received by article \( i \) in the window of length \( \Delta t \) just before time \( t_j \), \( \Delta c_i^B(t_j) \), and the number of new comments in the window of length \( \Delta t \) just after time \( t_j \), \( \Delta c_i^A(t_j) \). In the case of measuring the effect of hits, time \( t_j \) is the time of appearance of a hit article. In the case of measuring the general aging effects, time \( t_j \) is a randomly chosen time point. To avoid possible confounding effects of other articles, we consider only the time points \( t_j \) for which no other article appears in the measurement period \([t_j - \Delta t, t_j + \Delta t]\).

To test the proportionality factor \( \gamma \), we assume that the numbers of new comments are drawn from the Poisson distribution with some unknown value of mean activity \( \mu_i(t_j) \) in the time window before \( t_j \), and mean activity \( \gamma \mu_i(t_j) \) in the time window after \( t_j \). The likelihood of the observed data \( D \) has the form

\[
L(D | \mu, \gamma) = \prod_{i,t_j} P(\Delta c_i^B(t_j) | \mu_i(t_j)) \times P(\Delta c_i^A(t_j) | \gamma \mu_i(t_j))
\]

where the product is over all measurement times \( t_j \) and articles with open commenting sections, \( \mu \) is the vector of all mean activity values and \( P(n | \mu) = \mu^n e^{-\mu} / n! \) (the Poisson distribution).[53] This likelihood function can be maximized analytically, leading to the maximum likelihood estimate \( \hat{\gamma} \) given by Eq. (2). The confidence intervals for \( \hat{\gamma} \) can be estimated by non-parametric bootstrap.

Denoting the standard deviations of the bootstrap estimates as \( \sigma_B \) and \( \sigma_H \) for the baseline and hit scenario, respectively, the significance of the observed difference between \( \hat{\gamma}_B \) and \( \hat{\gamma}_H \) can be assessed by computing its z-score

\[
z = \frac{\hat{\gamma}_B - \hat{\gamma}_H}{\sqrt{\sigma_B^2 + \sigma_H^2}}
\]

and the corresponding two-tailed \( p \)-value. See SI for derivation details, description of the bootstrap procedure, and a comparison of the MLE estimate with other ways to estimate the proportionality factor \( \gamma \).

A. The FAE model with Fitness, Aging, and Elasticity

A synthetic dataset is created in \( T_S \) discrete time steps with each step representing one minute. In each step,
a new article appears with probability $p_n$. Fitness of article $i$, $\eta_i$, is drawn from a given fitness distribution. The expected number of new comments at time $t$ is

$$C(t) = n_0(1 - \lambda) + \lambda X \sum_j \eta_j D_j(t - t_j)$$  \hspace{1cm} (7)

where $n_0$ is chosen so that the average number of comments reaches a desired value at $\lambda = 0$. The elasticity of the collective attention is tuned by $\lambda \in [0, 1]$ where $\lambda = 0$ and $\lambda = 1$ correspond to a non-elastic case and a perfectly elastic case, respectively. The exponential aging factor $D_j(t - t_j) = \exp[-(t - t_j)/\Theta_j]$ is a function of the article aging timescale, $\Theta_j$, and the article appearance time, $t_j$. Finally, the multiplying factor $X$ is set so that $C(t)$ is independent of the elasticity parameter $\lambda$, thus ensuring that varying $\lambda$ leaves the data volume approximately unchanged. The actual number of new comments at time $t$ is drawn from the Poisson distribution with mean $C(t)$. The probability that a single comment at time $t$ is added to article $i$ has the usual form $[22, 28, 29]

$$P(i,t) = \frac{\eta_i D(t - \tau_i)}{\sum_j \eta_j D(t - \tau_j)}$$  \hspace{1cm} (8)

nodes. The choice $\lambda = 0$ in Eq. (7), which we refer to as the non-elastic case, induces the much-studied network dynamics where the articles “compete” for the incoming links. By contrast, the choice $\lambda = 1$, the perfectly elastic case, results in Eqs. (7) and (8) yielding the expected number of new comments of article $i$ in the form $\Delta C_i(t) = X \eta_i D(t - \tau_i)$ which is independent of the other articles’ fitness values and appearance times. Note that we focus here on the article commenting dynamics and avoid modelling the user side (i.e., which user authored an individual comment). This decision is further supported by the found lack of structure in the users’ commenting patterns (see Fig. S9 in SI).

To match the BBC data as closely as possible, we choose the same duration, $T_S = 393,120$ (with additional initial 2,000 steps to equilibrate the simulation), $p_n = 7.9 \times 10^{-3}$, aging timescale values $\Theta_i$ distributed uniformly in the range $[150, 600]$, and $X = 0.85$. The values of $R_i := \eta_i \Theta$ are drawn from a combination of two exponential distributions, $R = \frac{1}{2} \exp(-R/450)/450 + \frac{1}{2} \exp(-R/150)/150$, which represent the more and less popular article categories, respectively. For given $R_i$ and $\Theta_i$, article fitness is obtained as $\eta_i = R_i/\Theta_i$. The underlying user activity $n_0$ changes on a daily basis; we obtain it as $1 + c_1 + c_2$ where $c_{1,2}$ are distributed uniformly in the range $[0, 1]$, thus leading to $\tau_0 = 2$ which is close to the average number of comments per minute (2.2) in the BBC data. These parameters were used to obtain panels D–F in Figure 3. See SI, Sec. S6 for further figures illustrating the model’s behavior for various values of the elasticity parameter $\lambda$.

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| Category  | Articles | Mean comment count | Mean number of unique users (impact) |
|-----------|----------|--------------------|-------------------------------------|
| Football  | 1590     | 361                | 236                                 |
| Rugby Union | 439     | 219                | 130                                 |
| Cricket   | 240      | 213                | 133                                 |
| Tennis    | 162      | 157                | 108                                 |
| Formula 1 | 139      | 338                | 209                                 |
| Golf      | 123      | 117                | 85                                  |
| Boxing    | 103      | 195                | 152                                 |
| National  | 348      | 678                | 563                                 |
| Learning  | 306      | 59                 | 52                                  |
| Magazine  | 262      | 77                 | 72                                  |
| Sports    | 213      | 48                 | 45                                  |
| Foreign   | 204      | 277                | 241                                 |

TABLE II. Categories with the largest number of articles in the BBC data (top) and the NYT data (bottom). Article categories are provided directly by both media outlets.

Supporting Information

S1. DATA DESCRIPTION

S1.1. The BBC article discussion data

We collected a comprehensive dataset of sport news articles with discussions by periodically crawling the BBC Sport website (its front page and the pages dedicated to individual sports). In the time period from October 1, 2018 until June 30, 2019 (273 days), there were 3,087 article discussions open that received 852,400 comments from 67,527 users. The user median and mean number of comments are 2 and 12.6, respectively. The median and mean number of comments of a news article are 155 and 276, respectively. We measure the news article impact by the number of unique users who left a comment in its discussion. The median and mean article impact are 108 and 180, respectively.

Each comment is time-stamped with the time resolution of one minute. BBC typically closes article discussions on the second midnight after the article has been published; most of them are therefore open for 24–48 hours. There are two exceptions in the dataset: one discussion that has been open marginally longer than 48 hours and another discussion that was open for 13 days; it attracted only a few comments after day two, though.

S1.2. The NYT article discussion data

We further support our findings using the New York Times (NYT) commenting data obtained from https://www.kaggle.com/aashita/nyt-comments. Our NYT dataset comprises articles published in January–May 2017. At the NYT, it is possible to comment on a previously written comment (in fact, several levels of response are possible). To measure the article impact, we consider only the top-level comments; responses to comments are neglected as they are driven by the comments to which the responses are made. There are 2,801 articles and 649,794 comments from 75,118 users. The user median and mean number of comments are 1 and 6.0, respectively. The median and mean number of comments of a news article are 38 and 165, respectively. We measure the news article impact by the number of unique users who left a comment in its discussion. The median and mean article impact are 37 and 143, respectively.

Each comment is time-stamped with the time resolution of one minute. Unlike the BBC data, article discussions at the NYT remain open for long time. Despite this, the commenting dynamics displays a characteristic aging timescale and the median time to reach 99% of the final comment count is 26 hours.
| Rank | Impact | Category | News title |
|------|--------|----------|------------|
| 1    | 3538   | football | Jose Mourinho: Manchester United sack manager |
| 2    | 2241   | football | Liverpool 4-0 Barcelona (4-3 agg): Jurgen Klopp’s side complete extraordinary comeback |
| 3    | 1931   | football | Chris Hughton: Brighton sack manager after 17th-placed finish in Premier League |
| 4    | 1874   | football | Ajax 2-3 Tottenham (3-3 on aggregate - Spurs win on away goals): Lucas Moura scores dramatic winner |
| 5    | 1697   | football | Champions League: PSG 1-3 Man Utd (agg: 3-3) |
| 6    | 1659   | football | Manchester City 4-3 Tottenham Hotspur (4-4 agg): Spurs stun City on away goals in modern classic |
| 7    | 1575   | football | Liverpool, Tottenham, Chelsea and Arsenal fans criticise Uefa for final ticket numbers |
| 8    | 1417   | football | Ole Gunnar Solskjaer was the wrong choice as Man Utd manager - Jenas |
| 9    | 1342   | tennis   | Andy Murray: Australian Open could be last tournament |
| 10   | 1291   | football | Liverpool beat Spurs 2-0 to win Champions League final in Madrid |
| 1    | 3983   | national | Trump Intensifies Criticism of F.B.I. and Journalists |
| 2    | 3277   | national | Trump Fires Comey Amid Russia Inquiry |
| 3    | 3077   | business | Man Is Dragged From a Full Jet, Stirring a Furor |
| 4    | 2731   | national | G.O.P. Revolt Sinks Bid to Void Health Law |
| 5    | 2692   | national | Judge Blocks Trump Order On Refugees |
| 6    | 2618   | foreign  | Trump Is Said to Expose Ally’s Secrets to Russians |
| 7    | 2572   | national | Britain Furious as Trump Pushes Claim of Spying |
| 8    | 2388   | national | Trump Was Told of Claims Russia Has Damaging Details on Him |
| 9    | 2327   | national | Trump Appealed to Comey to Halt Inquiry Into Aide |
| 10   | 2304   | national | Trump Fires Justice Chief Who Defied Him |

TABLE III. **Discussions with the highest impact as measured by the number of unique commenting users.** The BBC data (top) and the NYT data (bottom).
FIG. S1. Snapshots of the BBC website (top) and the NYT website (bottom). Note that for articles with discussions, the number of comments is indicated for both BBC (icon with number 380 next to it; the other displayed articles do not have discussions) and NYT (labels “238 comments” and “123 comments”).
S2. FITTING EXPONENTIAL DISTRIBUTIONS TO ARTICLE IMPACT DATA

The primary fitting results for the BBC data are shown in Table IV where article impact is measured by the number of unique users who comment on a news article. Our fitting procedure follows the steps described in [40]: We choose the lower bound, \( \hat{c}_{\min} \), that minimizes the chosen statistic. We use two statistics: the standard Kolmogorov-Smirnov statistic as in [40] and the weighted Kolmogorov-Smirnov statistic. We prefer the results obtained with the weighted Kolmogorov-Smirnov statistic which through its weighting has higher sensitivity at the distribution tail (as shown in [52], the standard Kolmogorov-Smirnov statistic can fail to detect a degree distribution cut-off because of its low sensitivity in the distribution tail). The scaling parameter \( \lambda \) is then obtained by maximizing the data likelihood for the exponential model.

\[
\begin{array}{|c|c|c|c|c|c|c|c|c|c|}
\hline
\text{Category} & N & m & O & \hat{c}_{\min} & f_{\min} & \lambda & p\text{-value} & \hat{c}_{\min} & f_{\min} & \lambda & p\text{-value} \\
\hline
\text{All} & 3,087 & 180 & 1 & 438 & 0.09 & 262 & 0.72 & 411 & 0.10 & 255 & 0.83 \\
\text{Boxing} & 103 & 152 & 1 & 9 & 0.97 & 137 & 0.89 & 3 & 0.98 & 142 & 0.86 \\
\text{Cricket} & 240 & 133 & 0 & 23 & 0.97 & 115 & 0.14 & 38 & 0.90 & 107 & 0.58 \\
\text{Football} & 1,590 & 236 & 1 & 10 & 0.99 & 227 & 0.07 & 381 & 0.18 & 270 & 0.96 \\
\text{Formula 1} & 139 & 209 & 0 & 76 & 0.78 & 179 & 0.96 & 42 & 0.94 & 180 & 0.69 \\
\text{Golf} & 123 & 85 & 3 & 2 & 0.97 & 69 & 0.31 & 8 & 0.93 & 66 & 0.97 \\
\text{Rugby-union} & 439 & 130 & 2 & 1 & 0.97 & 117 & 0.21 & 19 & 0.94 & 114 & 0.95 \\
\text{Tennis} & 162 & 108 & 1 & 99 & 0.30 & 129 & 0.83 & 97 & 0.32 & 124 & 1.00 \\
\hline
\end{array}
\]

**TABLE IV.** Results of fitting exponential distributions to the whole dataset and to individual article categories: BBC data, article impact measured by the number of unique commenting users. The displayed characteristics are: the number of articles with a discussion, \( N \), the average number of comments, \( m \), the number of outliers, \( O \), the determined lower bound of the exponential tail, \( \hat{c}_{\min} \), the number of articles that comprise the exponential tail, \( f_{\min} \), the determined scaling parameter, \( \lambda \), and the \( p \)-value of the fit. The last four characteristics \( (\hat{c}_{\min}, f_{\min}, \lambda, \text{and } p\text{-value}) \) are shown twice: first for fits obtained using the weighted Kolmogorov-Smirnov statistic, second for fits obtained using the standard Kolmogorov-Smirnov statistic.

Figure S2(A,B) compares the Kolmogorov-Smirnov statistic (A: weighted KS, B: standard KS) between exponential and power-law fits of the data. As can be seen, the exponential fits reach the lowest KS values earlier (for lower \( \hat{c}_{\min} \)) than the power-law fits do. In addition, the lowest KS values themselves are lower for the exponential fits than they are for the power-law fits. Figure S2(C,D) shows the estimated parameter values (the scaling parameter estimate \( \lambda \) and the power-law exponent estimate \( \alpha \)) as functions of \( \hat{c}_{\min} \). The exponential fits yield \( \lambda \) that varies in the narrow range [250, 300] as \( \hat{c}_{\min} \) increases from the KS-minimizing value. By contrast, \( \alpha \) of the power-law fits grows essentially without interruption: from 3.5 for the KS-minimizing \( \hat{c}_{\min} \) to more than 5. The higher stability of \( \lambda \) as compared to \( \alpha \) is a sign that the exponential fits are more robust (less sensitive to the choice of \( \hat{c}_{\min} \), in particular).

In some cases there are “outliers”: articles that significantly exceed the overall exponential distribution within a given category. Examples of outliers include “Jose Mourinho: Manchester United sack manager” which is the most-discussed article overall and “Andy Murray: Australian Open could be last tournament” which is the most-discussed tennis article. To identify article \( i \) as an outlier, we fit an exponential to the comment counts without article \( i \), and accept the outlier status if the probability to encounter at least \( c_{i} \) comments under the fitted exponential distribution is less than 0.05.

The \( p \)-values in the tables above are obtained by comparing the corresponding Kolmogorov-Smirnov statistic measured on the real data with the Kolmogorov-Smirnov statistic measured on data drawn from the exponential distribution with the previously determined lower bound \( \hat{c}_{\min} \) (which directly influences the sample size represented by the number of article discussions that match or exceed \( \hat{c}_{\min} \)) and the scaling parameter \( \lambda \). Upon generating a large number of exponentially-distributed samples, the \( p \)-value is the fraction of the samples that have a higher Kolmogorov-Smirnov statistic than the value found in the real data. A low \( p \)-value is thus an indication that the artificial exponentially-distributed samples match the fitted exponential distribution better than the real data. \( p \)-values below 0.10 are conventionally understood as an indication that the fit is very good. Needless to say, the \( p \)-values are jointly influenced by the quality of fit and the sample size. As the sample size grows, the same deviation from the exponential distribution results in progressively lower \( p \)-values.

As can be seen in Table IV, the fraction of article discussions that belong to the determined exponential tail of the distribution is considerably lower when all article discussions are fitted at once as compared with fitting respective sport categories individually. An important contributing factor for this observation is that the analyzed sport categories have substantially different popularity among the BBC website visitors. The most commented football articles receive, for example, comments from 236 unique users on average as opposed to the least popular golf articles whose average is only 85. A superposition of exponential distributions with diverse scaling parameters is not an...
FIG. S2. Kolmogorov-Smirnov statistic values and parameter estimates: a comparison between the exponential and power-law distribution, BBC data. The weighted Kolmogorov-Smirnov (KS) statistic, the standard KS statistic, the MLE of the exponential scaling parameter $\lambda$, and the MLE of the power-law exponent $\alpha$ as functions of the fitting lower bound $c_{\text{min}}$ when fitting the complete comment count distribution (for exponential fits, we ignore one outlier with 3,538 comments). For $c_{\text{min}} \gtrsim 500$, the scaling parameter estimate $\hat{\lambda}$ varies little (less than 20%) as opposed to $\hat{\alpha}$ that continually grows through the whole range of $c_{\text{min}}$. This too indicates that the exponential distribution is a good fit to the data whereas the power-law distribution is not. The vertical dashed and dotted line indicate the point of minimum of the weighted and the standard KS statistic, respectively.

When fitting power-law distributions to the data, comparatively higher threshold values are found, indicating that the sample size needs to be further reduced so that the data can be possibly described by a power-law. We complement the $p$-value analysis from Table IV by a direct comparison between the exponential and power-law distribution in

FIG. S3. The fractions of article discussions from respective sport categories as functions of the comment count lower bound $c_{\text{min}}$. BBC data, article impact measured by the number of unique commenting users.
terms of how well they fit the data. This can be done using the log-likelihood test described in [40]. Table V shows the corresponding results for all sport categories where, as we have seen, exponential distributions are good fits for most of the data. Except for the tennis category, all remaining p-values are small—much smaller than customary significance thresholds—which confirms that exponential distributions fit the data better than power-law distributions. For tennis, the positive LR shows that the fitted exponential distribution explains the data better than the fitted power-law distribution but the p-value is high, so the difference is not significant. An important factor in the lack of significance is the “extreme” outlier among the tennis articles: article “Andy Murray: Australian Open could be last tournament” whose 1,342 unique commenting users exceed the second most-successful article by the factor of two (article “Andy Murray: Former British number one has resurfacing surgery on hip” with 654 unique commenting users; Andy Murray is the most successful British tennis player, hence high popularity of BBC articles about him). The impact of this outlier is further magnified by the set of tennis articles being relatively small. The likelihood ratio test p-value would be highly significant without this outlier.

Note that these findings go beyond the recent claim of power-laws being rare [54] where log-normal distributions, also a class of broad distributions, are considered as an alternative to power-laws. We go further by showing that for online articles, a “narrow” exponential distribution is in fact the best fit to the data.

| Category     | Power-law fit | Likelihood ratio test |
|--------------|---------------|-----------------------|
|              | N  | \( \hat{c}_{\text{min}} \) | \( f_{\text{min}} \) | \( \hat{\alpha} \) | \( LR \) | p-value |
| Boxing       | 103 | 0.24 | 3.89 | 50.4 | 1.1 .10^{-10} |
| Cricket      | 240 | 0.32 | 3.15 | 75.8 | 5.0 .10^{-20} |
| Football     | 1590 | 0.07 | 4.09 | 934.2 | 4.2 .10^{-20} |
| Formula 1    | 139 | 0.55 | 2.67 | 19.9 | 1.3 .10^{-05} |
| Golf         | 123 | 0.45 | 2.48 | 89.2 | 4.5 .10^{-20} |
| Rugby union  | 439 | 0.36 | 2.78 | 195.0 | 3.3 .10^{-38} |
| Tennis       | 162 | 0.17 | 3.08 | 2.7 | 4.9 .10^{-01} |

TABLE V. The likelihood ratio test to compare the exponential and the power-law distributions. We measure article impact by the number of unique users who have commented on it and use the weighted Kolmogorov-Smirnov statistic for the fitting analysis. For information, we show the results of the power-law fitting (the estimated lower bound, the fraction of article discussions that comprise the estimated tail, and the estimated power-law exponent) as well as the likelihood test results (the likelihood ratio, \( LR \) that measures the difference in how well the fits agree with the data and the corresponding p-values that estimates how likely it is to see \( LR \) as high or higher by chance). To allow for a fair comparison, we do not exclude any outliers here as that would put the power-law hypothesis in a disadvantage.

As shown in Table VI, fits are comparably good when article impact is measured by the number of comments (the average impact values, the lower bounds of the exponential fits, and the scaling parameters are then naturally higher).

| Category     | Weighted KS | Standard KS |
|--------------|-------------|-------------|
|              | N  | m  | O  | \( \hat{c}_{\text{min}} \) | \( f_{\text{min}} \) | \( \lambda \) | p-value | \( \hat{c}_{\text{min}} \) | \( f_{\text{min}} \) | \( \lambda \) | p-value |
| All          | 3,087 | 277 | 1 | 1 | 0.14 | 412 | 0.76 | 444 | 0.18 | 397 | 0.59 |
| Boxing       | 103 | 198 | 1 | 0.97 | 176 | 0.97 | 0 | 0.99 | 182 | 0.86 |
| Cricket      | 240 | 213 | 1 | 28 | 0.97 | 186 | 0.22 | 31 | 0.96 | 184 | 0.31 |
| Football     | 1,590 | 362 | 1 | 507 | 0.22 | 442 | 0.90 | 428 | 0.28 | 429 | 0.65 |
| Formula 1    | 139 | 338 | 0 | 31 | 0.98 | 314 | 0.97 | 31 | 0.98 | 314 | 0.69 |
| Golf         | 123 | 123 | 3 | 1 | 0.98 | 97 | 0.38 | 9 | 0.93 | 94 | 0.98 |
| Rugby-union  | 439 | 223 | 3 | 8 | 0.99 | 200 | 0.29 | 4 | 0.99 | 203 | 0.21 |
| Tennis       | 162 | 159 | 1 | 142 | 0.30 | 202 | 1.00 | 132 | 0.33 | 196 | 0.92 |

TABLE VI. Results of fitting exponential distributions to the whole dataset and to individual article categories: BBC data, article impact measured by the number of comments. Notation as in Table IV.

We applied the same steps to the NYT data where the article impact is measured by the number of unique commenting users at the top commenting level (see Section S1 for details). Table VII summarizes the results of exponential fitting using the weighted and standard Kolmogorov-Smirnov statistic. Figure S4 visualizes the statistics values and the estimated parameters as functions of \( \hat{c}_{\text{min}} \). Table VIII summarizes the results of likelihood ratio tests for individual article categories.
TABLE VII. Results of fitting exponential distributions to the whole dataset and to individual article categories: NYT data, article impact measured by the number of unique users. Notation as in Table IV.

FIG. S4. Kolmogorov-Smirnov statistic values and parameter estimates: a comparison between the exponential and power-law distribution, NYT data. The weighted Kolmogorov-Smirnov (KS) statistic, the standard KS statistic, the MLE of the exponential scaling parameter $\lambda$, and the MLE of the power-law exponent $\alpha$ as functions of the fitting lower bound $\hat{c}_{\text{min}}$ when fitting the complete comment count distribution (no outliers were used for exponential fits). The lowest KS values achieved for the exponential fits are substantially lower than they are for the power-law fits. For $\hat{c}_{\text{min}} \gtrsim 800$, the scaling parameter estimate $\hat{\lambda}$ varies little as opposed to $\hat{\alpha}$ that continually grows through the whole range of $\hat{c}_{\text{min}}$. This too indicates that the exponential distribution is a good fit to the data whereas the power-law distribution is not. The vertical dashed and dotted line indicate the point of minimum of the weighted and the standard KS statistic, respectively.

FIG. S5. The fractions of article discussions from respective sport categories as functions of the comment count lower bound $\hat{c}_{\text{min}}$. The NYT data with article impact measured by the number of unique commenting users.
TABLE VIII. The likelihood ratio test to compare the exponential and the power-law distributions, NYT data. We measure article impact by the number of unique users who have commented on it and use the weighted Kolmogorov-Smirnov statistic for the fitting analysis. For information, we show the results of the power-law fitting (the estimated lower bound, the fraction of article discussions that comprise the estimated tail, and the estimated power-law exponent) together with the likelihood test results (the likelihood ratio, $LR$ that measures the difference in how well the fits agree with the data and the corresponding $p$-values that estimates how likely it is to see $LR$ as high or higher by chance).

\begin{tabular}{llllll}
\hline
category & $N$ & $c_{\text{min}}$ & $f_{\text{min}}$ & $\hat{\alpha}$ & $LR$ & $p$-value \\
\hline
Foreign & 204 & 90 & 0.57 & 1.86 & 8.5 & $1.04 \cdot 10^{-2}$ \\
Learning & 306 & 7 & 0.53 & 1.64 & 8.8 & $4.34 \cdot 10^{-4}$ \\
Magazine & 262 & 23 & 0.61 & 1.90 & 5.2 & $7.92 \cdot 10^{-3}$ \\
National & 348 & 580 & 0.37 & 2.80 & 385 & $1.59 \cdot 10^{-122}$ \\
Sports & 213 & 73 & 0.20 & 2.76 & 5.1 & $5.90 \cdot 10^{-2}$ \\
\hline
\end{tabular}

S3. ELEMENTARY ANALYSIS OF THE SYSTEM’S DYNAMICS

We present here basic characteristics of the commenting dynamics in the BBC and the NYT data: the daily and hourly profiles of user activity and the distributions of user activity (Figures S6–S8). Finally, we present here also an evaluation of the linking patterns between users and articles divided in groups by their activity/popularity (Figure S9).

FIG. S6. Variations of the daily commenting activity. (Top row, BBC data) There are 3,109 new comments a day on average, the standard deviation is 1,215. There are 11.3 new article discussions a day on average, the standard deviation is 4.8. (Bottom row, NYT data) There are 3,007 new comments a day on average, the standard deviation is 1,347. There are 18.4 new article discussions a day on average, the standard deviation is 8.2.
FIG. S7. Variations of the normalized commenting activity during the day. The value of one corresponds to 1/24 of the day’s comments arriving in a given hour. (Left, BBC data) The activity is low from 1am to 6am and relatively constant between 8am and midnight. The shaded area shows the time of day that we use for the analysis of the commenting dynamics: These articles have a long period of approximately uniform website activity before the night arrives and the activity drops. (Right, BBC data) Due to the time difference, the commenting activity is lower between 5am and noon. The shaded area again shows the “morning articles” that are used for the analysis of new dynamics.

FIG. S8. The distributions of various measures of user activity. (Top, BBC data) The indicative dashed lines have the slopes of 0.7 and 1.9, respectively. (Bottom, NYT data) The indicative dashed lines have the slopes of 0.9 and 2.4, respectively. All three distributions have an initial power-law part with a cut-off at higher activity values.
FIG. S9. **Link propensity between users and articles of various degree.** Both users and articles are divided in three groups by their degree (with 1 and 3 having the lowest and highest degree users/articles, respectively). We then compute the number of links between respective user and article groups and normalize it with respect to the average number of links observed in the randomized data (to randomize the bipartite user-article network, we use the classical configuration model). A displayed number greater than one indicates that the links between users and article from given groups are in the real data *more common* than they are in the considered null model. The left and right panel show the results for the BBC data and the NYT data, respectively. While some deviations from the null model can be observed (except for the 1.00 entry in the BBC table, all results have absolute z-scores above 3), none of them is larger than 10% either way.

The values are particular close to 1 for the links from the least active users (group 1) to the most popular articles (group 3). If the bottom row values are all one, comments to the most-popular articles arrive evenly from the three user groups. The values 1.02/1.01 for the least active users and the most-popular articles hence indicate that the most popular articles receive not 33% but 34% of their comments from the least active users. The results thus demonstrate, among other things, that the most popular articles do not owe their popularity to little active users who become active only when a hit article appears.

The results are qualitatively the same when the recently introduced Dynamic Configuration Model [55] is used to randomize the data. This model first divides the network into consecutive time-defined layers and randomizes each layer separately, thus preserving the time structure of the network. Due to the quick aging that we observe in the commenting datasets, we chose the number of layers to be the same as the number of days in each respective dataset.
S4. THE COMMENTING DYNAMICS

FIG. S10. The degree trajectories of the 20 highest impact articles in the BBC data. To suppress the time-of-the-day effects during the displayed 10-hour period, we select only the articles that appear in the morning (as in Figure 2 in the main text). Changing an article’s position at the website has the potential to influence its exposure to the users and, in turn, the rate at which the article receives new comments. The individual trajectories do not exhibit substantial changes of the commenting rates which indicates that the effect of changing the articles’ positions is minor and can be neglected in the scope of our analysis of commenting dynamics.

S4.1. Modeling the commenting dynamics

Based on the results presented in the main text, we see that the commenting dynamics of article discussions is influenced by the following principal factors:

1. Exponential aging.
2. Absence of preferential attachment.
3. Individual articles evolve independently of each other.

These three points can be summarized in the following equation for the number of comments growth rate

\[
\frac{dc_i(t)}{dt} = f_i \exp\left[\frac{- (t - \tau_i)}{\Theta}\right]
\]

(S1)

where \(c_i(t)\) is the number of comments of article \(i\) at time \(t\), \(\tau_i\) is the time when the news article was published (and its discussion opened), \(f_i\) is the fitness of article \(i\) which reflects how attractive it is to the users, and \(\Theta\) is the aging timescale. A similar model was proposed in [33] which explores the relation between fitness and preferential attachment. The initial condition for all articles is \(c_i(\tau_i) = 0\). Besides the simplified continuum dynamics, Eq. (S1) can be rewritten in terms of comment count increments drawn from a Poisson distribution with the mean \(f_i \exp\left[\frac{- (t - \tau_i)}{\Theta}\right] \Delta t\) (see Figure S15 for an indication of the Poisson nature of commenting) or, when the time step \(\Delta t\) is sufficiently short and the resulting increments small, probability \(P(i, t)\) of article \(i\) receiving a new comment at time \(t\) as we do in the main text. These three descriptions (the rate equation, Poissonian increments, and the commenting probability) are equivalent.

In the NYT data, Figure 2 shows that articles with small comment counts are to some extent affected by preferential attachment. Preferential attachment can be readily introduced in Eq. (S1) as

\[
\frac{dc_i(t)}{dt} = f_i F(c_i) \exp\left[\frac{- (t - \tau_i)}{\Theta}\right]
\]

(S2)

where \(F(c_i) = 1 + \alpha c_i\) for \(c_i \leq C\) and \(F(c_i) = 1 + \alpha C\) otherwise. Here \(\alpha\) quantifies the preferential attachment strength and \(C\) is the comment count at which preferential attachment ceases to influence the commenting dynamics. In [22], this model was proposed to model the citation dynamics of scholarly papers (without considering a preferential attachment cut-off). The presence of a preferential attachment cut-off implies that the tail of the comment count distribution does not benefit from its effect, hence the distribution tail is expected to be exponential (in the case of exponentially distributed fitness \(f_i\)). This intuition is confirmed by Figure S11 which compares the comment count
distribution in settings with unlimited preferential attachment, preferential attachment with cut-off, and no preferential attachment.

As can be seen in Figure 2 in the main text, Eq. (S1) fits the BBC data well. As shown in Figure S12, the fit further improves when we determine the timescale individually for each article (we do so by choosing the timescale that minimizes the Kolmogorov-Smirnov statistic between the real course of \( c_i(t) \) and the theoretically expected curve given by Eq. (S1). The lowest mean KS is achieved with the general timescale of 300 minutes which agrees with the timescale obtained by fitting the aging curve in Figure 2B in the main text; the mean KS static is then 0.18 and 9 articles (out of the 39 used to obtain the figure) have the KS statistic below 0.1. With individually-fitted timescales, the mean Kolmogorov-Smirnov statistic reduces by the factor of two to 0.08 and 34 articles have the KS statistic below 0.1.

For the NYT data, the lowest mean KS is achieved with the general timescale of 330 minutes; the mean KS is then 0.23 and 5 article discussions out of 46 have the KS statistic below 0.1 (the values are 0.29 and 4 for the timescale 230 obtained by fitting the aging curve in Figure 2E in the main text). With individually-fitted timescales, the mean KS reduces to 0.12 and 30 articles have the KS statistic below 0.1. The improvement from fitting against Eq. (S2) which includes preferential attachment is minor both in terms of the mean KS as well as the number of articles with KS below 0.1. To summarize, the commenting dynamics described by Eq. (S1) fits the empirical data well even when some limited effects of preferential attachment can be observed in the NYT data.

FIG. S12. Commenting dynamics in the BBC data. (A) As in Figure 2 in the main text; the dashed line corresponds to the aging timescale \( \Theta = 305 \text{ min.} \) The solid line shows the median fraction of the final popularity at given article age; the shaded region shows the 20th–80th percentile range of the observed popularity fraction values. (B) As panel (A) but time is rescaled with the individual aging timescale \( \Theta \) for each article. (C) The distribution of the individual aging timescales among the articles.
S5. THE IMPACT OF HITS

Before analyzing the impact of hits in detail, Figure S14 shows the relative change of the number of comments between two consecutive time windows when hit articles (90th percentile by the comment count) appear. We additionally show the relative change of the number of comments where the comments given to the hit articles themselves are not taken into account. While the latter quantity is centered at zero (in agreement with the Poisson distribution hypothesis which is further examined in Figure S15), the former quantity demonstrates a substantial increase of user activity upon the appearance of a hit.

FIG. S14. The number of comments before and after appearance of a hit. Focusing on the top 10% most popular articles, we compare the total number of comments arriving 10 minutes before and 10 minutes after appearance of these hits, \( n^B \) and \( n^A \), respectively. The solid blue line shows the distribution of \( \log_{10}(n^A/n^B) \) with the comments given to the hit and the dashed orange line is the same without the comments given to the hit. The latter distribution’s sharp peak at zero (mean is 0.02 for both the BBC and NYT data) indicates that when the comments that the hit itself attracts are not taken into account, the overall website activity shows no visible change. For the BBC data (left panel), the former distribution has the average of 0.48 which corresponds to an activity increase by the factor of three \( (10^{0.48} \approx 3.0) \). For the NYT data (right panel), the average is 0.29 which corresponds to an activity increase by the factor of two \( (10^{0.29} \approx 2.0) \).

S5.1. How to measure the slow-down factor \( \gamma \)

The maximum likelihood estimate of the slow-down factor \( \gamma \) between two consecutive time windows has the form

\[
\hat{\gamma} = \frac{\sum_{i,j} a_i(t_j)}{\sum_{i,j} b_i(t_j)}.
\]  

(S3)

where \( t_j \) are the time points between the time windows, \( b_i(t_j) \) is the number of new comments for active article discussion \( i \) in the window before \( t_j \) and \( a_i(t_j) \) is the number of new comments for active article discussion \( i \) in the window after \( t_j \). Both time windows have length \( \Delta T \).

The derivation of the MLE estimate assumes that each article has some underlying commenting activity which then drives the actual number of new comments through a Poisson distribution. In Figure S15, we illustrate that the Poisson distribution is indeed a good approximation by studying the number of new comments that article discussions
receive in two consecutive time windows. The results are grouped by the total number of comments an article discussion receives in the two time windows and we plot the difference of the number of comments between the two time windows. This distribution is then compared with the distribution of differences observed when the comments counts are drawn from a Poisson distribution. As can be seen in Figure S15, the empirical distributions are indeed similar with the distributions produced by Poisson-distributed comment counts.

The uncertainty of the MLE estimate can be computed using bootstrap: If \( \hat{\gamma} \) is computed from \( n \) data points, we choose \( n \) data points from them at random (with repetition) and obtain an estimate on bootstrap data. In the random choice, we do not choose separately from \( \{a_i(t_j)\} \) and separately from \( \{b_i(t_j)\} \), as this would neglect the high correlation between \( a_i(t_j) \) and \( b_i(t_j) \) and in turn lead to a high variation of bootstrap estimates. Instead, we choose data points from \( \{a_i(t_j)\} \) at random, and choose the corresponding data points from \( \{b_i(t_j)\} \). We repeat this procedure 1,000 times and use the 10th percentile and 90th percentile of the obtained estimates on bootstrap data as the estimate uncertainty. Results of this estimation procedure are illustrated in Figure S16.

To assess the performance of Eq. (S3), we compare it with other possible estimation methods. Motivated by Figure S16, a least squares estimate is a natural first choice (in the estimate, we fix the intercept to be zero, so only the slope is to be determined). Since least squares estimation is sensitive to outliers, we evaluate also a robust least squares variant which uses the soft \( L_1 \) loss function \( \rho(z) = 2(\sqrt{1 + z^2} - 1) \).

We use two different kinds of synthetic data that are both calibrated on our commenting datasets:

1. Generate \( N = 5000 \) points by drawing the activity \( \mu_i \) from the exponential distribution with a given mean (this \( N \) is similar to the number of data points in the hit impact estimation in the studied real datasets). Values \( b_i \) are Poissonian with mean \( \mu_i \), values \( a_i \) are Poissonian with mean \( \mu_i \gamma_i \). The noisy proportionality factor \( \gamma_i \) is drawn from the normal distribution \( N(\gamma^T, \sigma) \).

2. Generate \( N = 5000 \) points by drawing the number of comments \( \mu_i \) from the exponential distribution with a
given mean, and set \( b_i = [\mu_i] \) and \( a_i = [\mu_i \gamma_i] \) where \( \gamma_i \) is the same noisy proportionality factor as before (\( \lfloor x \rfloor \) is \( x \) rounded to the closest integer).

The first kind of synthetic data directly corresponds to the assumptions behind the maximum likelihood estimate of \( \gamma \); we assume here some underlying commenting activity, of which \( a_i \) and \( b_i \) are manifestations. The second kind of synthetic data is substantially different as it has no Poissonian distribution for the observed comment counts \( b_i \) and \( a_i \). Except for the variations of \( \gamma \) among the articles, controlled by the \( \sigma \) parameter, this model has no intrinsic randomness, so it essentially evaluates how well are the methods able to discover the underlying \( \gamma^T \) that, on average, connects \( b_i \) and \( a_i \).

In the simulations, we choose the true proportionality factor to be \( \gamma^T = 0.9 \) (the exact value is of little importance). The slow-down factor randomness \( \sigma \) varies between 0 to 0.2 (as \( \sigma \) increases, it becomes further difficult to estimate the average slow-down factor \( \gamma^T \) as the differences between individual articles are large). For the average activity, we use either 10 (which corresponds to a time window of approximately 30 minutes in the BBC and NYT data) or 2 (which corresponds to a time window length of 10 minutes). We run 100 independent realizations for each synthetic data model. The estimates’ uncertainty is estimated for all estimation methods in the same way: using bootstrap.

Figure S17 reports the performance of various ways to estimate \( \gamma \) as a function of \( \sigma \). We focus here on the mean absolute error (left), width of the estimated confidence intervals (middle), and the fraction of realizations in which \( \gamma^T \) lies in the determined confidence interval (right). We see that the MLE estimate yields the smallest mean absolute error of all methods (for given average comment count). As the average comment count increases, the mean absolute error decreases and so do the confidence range widths. The mean absolute error values are generally smaller for model 2 where there is less space for randomness because \( b_i \) and \( a_i \) are not affected by the Poisson distribution. Furthermore, the MLE estimate yields the smallest confidence range estimates of all methods and the estimated confidence ranges have coverage of around 0.8 as expected for a confidence range based on the 10th and 90th percentile. In summary, MLE is the best way to infer \( \gamma \) from observed \( \{b_i\} \) and \( \{a_i\} \).

**FIG. S17.** A comparison of methods for estimating the slow-down factor \( \gamma \) on synthetic data. Top row: model 1. Bottom row: model 2. Solid lines show results for the average number of new comments 10 and the dashed lines show results for the average number of new comments 2; see the text for other simulation parameters. The confidence range was determined as the 10th–90th percentile range of bootstrapped estimates. The fraction in the confidence range (right-most panels) is the number of data estimation realizations in which the true value lies in the determined confidence range. Here the fraction of 0.8 is the desired value indicating the estimates are unbiased and the confidence range estimation works correctly.
S5.2. Significance analysis of the effect of hits

Our aim is to compare the effect of hits between the baseline scenario (when no new articles appear) and the hit scenario (when hit articles appear). For the hit scenario, we choose the “observation times”, $t_j$, to be the appearance times of the articles whose final comment count is above the 90th percentile (the thresholds are 679 and 428 for the BBC and NYT data, respectively); we reject those times for which other articles appear in the range $t_j - \Delta t, t_j + \Delta t$ as their appearance might interfere with the observation. For the baseline scenario, we choose the “observation times” $t_j$ at random and reject those for which other articles appear in the range $t_j - \Delta t, t_j + \Delta t$. The number of used random time points is the same as the number of appearance times used in the hit scenario measurement.

Eq. (1) in the main text can be then used to obtain the slow-down factor estimates in each scenario, $\hat{\gamma}_B$ for the baseline scenario and $\hat{\gamma}_H$ for the hit scenario. The uncertainty of these estimates is obtained using non-parametric bootstrap [56]: Assuming that $n$ time points are used to estimate $\gamma$, we draw $n$ of them at random with repetition and thus obtain one bootstrap estimate. By repeating this procedure, we can obtain a large number of bootstrap estimates (in Figure 3 in the main text, we use 10,000 bootstrap estimates) and use them to compute the corresponding standard deviation or confidence intervals for $\hat{\gamma}$. Denoting the standard deviations of the bootstrap estimates as $\sigma_B$ and $\sigma_H$ for the baseline and hit scenario, respectively, the significance of the observed difference between $\hat{\gamma}_B$ and $\hat{\gamma}_H$ can be assessed by computing its $z$-score

$$z = \frac{\hat{\gamma}_B - \hat{\gamma}_H}{\sqrt{\sigma_B^2 + \sigma_H^2}} \quad (S4)$$

and the corresponding two-tailed $p$-value.
S6. SYNTHETIC DATA WITH TUNABLE ELASTICITY OF USER DEMAND

The standard way how preferential attachment-based network models are formulated [22, 57] is through the probability that node \(i\) (in our case article \(i\)) attracts a new link at time \(t\) in competition of all other nodes,

\[
P(i, t) = \frac{f_i F(c_i) D(t - \tau_i)}{\sum_j f_j F(c_j) D(t - \tau_j)}.
\]  

(S5)

Here \(D(t - \tau_i)\) is a general aging function and \(F(c_i)\) is a general preferential attachment term as in Figure S11. In agreement of the findings of little importance of preferential attachment for the modeling of the commenting dynamics, we set \(F(c_i) = 1\) from here on. The derivation below holds also for general \(F(c_i)\) as well as for further more complicated forms of \(P(i, t)\) (such as those producing a growing networks with a community structure as in [58]).

In our case of modeling a bipartite user-item network, the source nodes of the links are the users and each link represents a user commenting on an article. Since the user side is not our focus here, we neglect it and concentrate on the article comment counts \(c_i(t)\) and their dynamics. If \(C(t)\) links are created at time \(t\), the expected number of new links of node \(i\) is \(\Delta c_i(t) = P(i, t)C(t)\). In network models, \(C(t)\) is typically chosen constant or it grows with time to represent, for example, an accelerated network growth. Importantly, \(C(t)\) is chosen independently of the nodes (their fitness, age, and so forth) that are currently in the system.

The basic premise of Eq. (S5) is that the nodes compete with each other for links, their dynamics is therefore generally coupled. However, there is a way how to preserve Eq. (S5), yet remove the coupling. If the number of links created at time \(t\) is

\[
C(t) = \sum_j f_j D(t - \tau_j),
\]

it then follows immediately that the expected number of links received by article \(i\) at time \(t\) is \(\Delta c_i(t) = f_i D(t - \tau_i)\) which is the same uncoupled comment count dynamics as we explored before in Section S4.4.1.

We thus see that a fixed \(C(t)\) yields a competitive case where the articles/nodes directly compete for comments/links against the pool of all articles/nodes. In the other case, \(C(t)\) given by Eq. (S6) yields a non-competitive case where the comment count dynamics of an article/node is uncoupled from the rest of the system. To explore the whole range between these two extremes, we propose the simple interpolation

\[
C(t) = n_0 (1 - \lambda) + \lambda X \sum_j f_j D(t - \tau_j)
\]

(S7)

which is shown as Eq. (7) in the main text. Here \(n_0\) is a fixed number of new links and \(\lambda \in [0, 1]\) is the elasticity parameter as it quantifies how much does the number of new links, in our case the number of new comments, depends on the available articles/nodes. When \(\lambda = 0\), \(C(t)\) is independent of the available articles/nodes and the perfectly competitive case ensues. When \(\lambda = 1\), \(C(t)\) is directly proportional to the “attractiveness” of the available nodes and a non-competitive uncoupled case ensues. Note that we have introduced an additional multiplying factor \(X\) in Eq. (7). Its purpose is to help achieve a desired average number of new links when \(\lambda > 0\) and, in our subsequent simulations of synthetic datasets with various \(\lambda\) values, ensure that the average number of links is approximately independent of \(\lambda\).

We choose the model parameters to closely match the BBC commenting data. As specified also in the main text (in Materials and Methods): We grow synthetic data over \(T_S = 393,120\) step (with additional initial 2,000 steps to equilibrate the simulation), \(p_n = 7.9 \cdot 10^{-3}\), aging timescale values \(\Theta_i\) distributed uniformly in the range \([150, 600]\), and \(X = 0.85\). The values of \(R_i := \eta_i \Theta_i\) are drawn from a combination of two exponential distributions,

\[
\rho(R) = \frac{1}{2} \exp(-R/450)/450 + \frac{1}{2} \exp(-R/150)/150,
\]

which represent the more and less popular article categories, respectively. For given \(R_i\) and \(\Theta_i\), article fitness is obtained as \(\eta_i = R_i/\Theta_i\). The underlying user activity \(n_0\) changes on a daily basis; we obtain it as \(1 + c_{1.2}\) where \(c_{1.2}\) are distributed uniformly in the range \([0, 1]\), thus leading to \(\eta_0 = 2\) which is close to the average number of comments per minute (2.2) in the BBC data. These parameters were used to obtain panels D–F in Figure 3 as well as Figures S18 and Figures S19 here. Figure S18 shows that increasing \(\lambda\) (i.e., making the collective attention more elastic) makes the distribution of article impact more heterogeneous. Figure S19 is a direct counterpart of Figure 2 in the main text. Panel (A) shows that despite preferential attachment being absent in the model, \(\Delta c_i(t)\) shows a similar slow growth with \(c_i(t)\) as we found for the BBC data in Figure 2A in the main text. Panel B is again similar to Figure 2B in the main text. The slope of the linear fit corresponds to the aging timescale 297 minutes which too is close to the fit in Figure 2B. Finally, fitting individual aging timescales to each considered article allows us to collapse all article trajectories onto a universal curve.
FIG. S18. The distributions of article impact in synthetic data for various values of the elasticity parameter $\lambda$. The maximal grows with $\lambda$ because elastic collective attention allows hit articles to achieve higher impact. The convex shape of the degree distribution, best visible for $\lambda = 1$, is a consequence of using a superposition of two exponential distributions (one with mean 150, another with mean 450) to generate the “total relevance” $R_i$ for each article ($R_i = \eta_i\Theta_i$).

FIG. S19. Commenting dynamics in the synthetic data. As Figure 2 in the main text but for the synthetic data obtained at the specified model parameters.