On Online Attention Dynamics

Maria Castaldo\textsuperscript{1}, Paolo Frasca\textsuperscript{1}, and Tommaso Venturini\textsuperscript{2}

\textsuperscript{1}Univ. Grenoble Alpes, CNRS, Inria, Grenoble INP, GIPSA-lab, 11 rue des Mathématiques, F-38000, Grenoble, France
\textsuperscript{2}CNRS, CIS-lab, 59 rue Pouchet, F-75017, Paris, France
\textsuperscript{*}Correspondence: maria.castaldo@grenoble-inp.fr

1 Introduction to Attention Economy and Attention Dynamics

This chapter aims to emphasize a number of questions that, although crucial since the early days of media studies, have not yet been the object of the empirical and computational study that they deserve: How does collective attention concentrate and dissipate in modern communication systems? How do subjects and sources rise and fall in public debates? How are these dynamics shaped by media infrastructures? In the perspective of addressing these questions, this chapter provides a review of the literature on the dynamics of online content dissemination: our goal is to prepare the ground for the necessary study, which should comprise empirical investigation, mathematical modeling, numerical simulation, and rigorous system-theoretic analysis.

The interest in dynamics of collective attention is as old as sociology. Already in the 19th century Gabriel Tarde \cite{Tarde, 1890, 1893}, argued that these fleeting dynamics (rather than the more stable structures and norms) should make up the core of social research \cite{Latour, 2002}. Attention dynamics rose again in sociological preoccupations in the ‘70s and ‘80s, when the major problem of the nascent media research was to describe the competition for the limited bandwidth of radio and television broadcasting. Concepts such as “attention cycles” \cite{Downs, 1972, Hilgartner and Bosk, 1988} and “agenda setting” \cite{McCombs and Shaw, 1972, McCombs, 2005} became prominent to investigate media schedules and their consequences on public debate. With the advent of digital media, the interest for collective attention shifted from the supply to the demand side. Vindicating Herbert Simon’s 1971 prophecy \cite{Simon, 1971b}, media scholars (and commercial actors) realized that in an information-rich environment, attention becomes a scarce and therefore valuable resource. This gave rise to many critical reflections on the consequences of the rise of the ‘attention economy’ and its way of transforming collective attention and debates into a marketable commodity \cite{Crogan and Kinsley, 2012, Citton, 2014}.

The research on attention economy is extremely interesting for its effort to conceptualize a very large phenomenon (the way in which collective attention flows through the media system) through the continuous convergence and divergence of a myriad of individual choices \cite{Terranova, 2012}. At the same time, and for the same reason, the literature on attention economy has remained largely theoretical. Until recently, the empirical investigation of the dynamics of collective attention has been hindered by the difficulty to procure data sets broad enough to account for an entire media population, but rich enough to distinguish each fleeting individual choice \cite{Venturini and Latour, 2010, Latour et al., 2012}. In the last few years, however, the massive investments by commercial and governmental actors into the surveillance of media interactions \cite{Zuboff, 2019} have generated the data necessary for the empirical and computational study of the flows of collective attention. And scholars have begun to seize this possibility.

Based on this growing literature, this chapter has the purpose of introducing the “cyber-social” research on attention dynamics, including its conceptualizations and its empirical findings, in the perspective of proposing useful mathematical models on which the instruments of control systems theory can be effectively deployed. Online media feature a tight integration of human and technological (digital) components and involve the participation of large numbers of users: they thus appear to be a socio-technical system with humans-in-multiagent-loops, as per the taxonomy proposed earlier in this book by \cite{Samad, 2022}. We are hopeful that this perspective will help the readers to appreciate the relevance and the challenges of attention dynamics in online media.

The rest of the Chapter is divided into three sections. Section 2 summarizes this emerging field of research by considering seven features that characterize collective attention: (1) its limitation, (2) its skewedness, (3) its sensitivity to novelty and (4) popularity, (5) its burstiness, and (6) its dependency

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on online platforms’ policies and (7) their dynamism. Section 3 considers the latest preoccupation of computational attention studies: how the increasingly sophisticated recommendation systems, introduced by online platforms, interfere with the expression of individual and thus collective attention. To this purpose, we present a simple model, meant to highlight the growing importance of trendiness in recommendation systems and its potential deleterious consequences on public debate. The last section contains some concise final remarks.

2 Online Attention Dynamics

We can summarize the current status of the knowledge about online attention dynamics in some few key ideas:

- collective attention is limited;
- collective attention is distributed in a highly nonuniform way among contents;
- novelty has a fundamental role in directing collective attention;
- previous popularity influences future popularity;
- people take part in the diffusion of content, and their individual activity is bursty, i.e. highly concentrated in time;
- online platforms’ policies and infrastructures have a major influence on the diffusion of content;
- platforms themselves are ever-changing.

In the following sections, we consider each of these ideas separately and discuss the literature that regards them.

2.1 Collective attention is limited

When Herbert A. Simon first theorized the concept of attention economy, he built his reasoning on the statement that human attention can be treated as a scarce commodity. Despite the impressive complexity and processing power of the human brain, it is undeniable that its capacities are limited: we can barely attend to over one object at a time, and we can hardly perform two tasks at once [Marois and Ivanoff, 2005]. Much research in the cognitive science has investigated the limitations of our brain, and we refer the interest reader to [Marois and Ivanoff, 2005]. For our purpose, it suffices to point out that these limitations have become standard assumptions in many works, not only to analyze the patterns of online engagement [Lorenz-Spreen et al., 2019] [Weng et al., 2012] [Qiu et al., 2017] but also in modeling opinion dynamics in social groups [Rossi and Frasca, 2020, Ceragioli et al., 2021b,a]. Crucially for this chapter, these assumptions have become an essential starting point for the research on collective attention, as the scarcity of individual cognitive resources has turned attention into the object of increasingly competitive market, in which attention ceases to be an individual feature and becomes a collective commodity that is consumed online.

2.2 Skewed attention distribution

As a result of the limitedness of individual and collective attention, news items have to compete with each other to gain the consideration of the public. This competition rewards few items which become over-popular, while the vast majority of them remain unnoticed. As largely discussed in the last years, online popularity is highly skewed, with a relatively small number of participants getting most of public attention. The distribution of popularity among online items has often been found to respect the "80-20 rule", also known as the Pareto rule: the 20% of the online content accounts for the 80% of the popularity. Evidence of this have been brought out on many platforms: it turned out to be true for videos on Metacafe, Yahoo!, Dailymotion, Veoh [Mitra et al., 2009] and YouTube [Cha et al., 2007], and for retweets in Twitter [Bild et al., 2015] [Lu et al., 2014].

It is legitimate to wonder what causes this skewness and whether it exists also outside of user-generated content platforms like the ones mentioned above. A first answer to these questions is given by Cha et al. in 2009 [Cha et al., 2009], where they compared the consumption of videos on platforms of User Generated Content (UGC), like YouTube, and Professionally Generated Content (PGC), like Netflix or Yahoo! Movies. They outlined that in UGC platforms attention is less equally distributed among items. More precisely, at that time, on YouTube 10% of the most popular videos were accounting for nearly 80% of the total views, while on-demand videos presented a less skewed distribution of popularity. In practice, while on PGC platform it never happens that a content is left with no public, on YouTube there is a significant quantity of videos that do not receive any view at all. But that is not the only difference between UGC and PGC: the authors also stress an enormous difference in the quantity of content uploaded on the two kinds of platforms, with UGC platform collecting a significantly
higher quantity of material. The massive amount of content present on YouTube, together with the human cognitive limitations and the peer influence, might be the cause of the stressed skewness in UGC platforms: people, only disposing of a limited attention, have to choose among an excessive variety of contents and may end up relying on imitation for their choices. As a result, collective attention is more concentrated and many items cannot arouse the slightest interest.

Acknowledging that the distribution of attention is skewed is crucial not only to conduct research on attention dynamics but also to contextualize previous works in the field: working with empirical data on social platforms often means dealing with a majority of items that received no or very little attention. When aiming at modeling popularity trends, it then becomes important to remove the non-relevant observations. For instance, Crane and Sornette in [Crane and Sornette, 2008] based their model of content diffusion on only the 10% of YouTube videos in their dataset, as the remaining 90% either showed a too low number of views or could be accurately described as (purely random) Poisson processes. Similarly, Kampf et al. in [Kampf et al., 2012] had to perform a significant filtering of their Wikipedia dataset: the vast majority of articles they monitored were rarely accessed and almost never experienced significant bursts of activity. To filter their data, they focused on articles that exhibited a minimum rate of 256 views at least in one hour, over the period of observation. This threshold, that might not seem particularly demanding, was met by only the 0.17% of the Wikipedia articles studied by the authors. Such a low percentage is, again, evidence of the quantity of content available on the web but never or rarely accessed.

2.3 The role of novelty

Once acknowledged that few items capture most of the public attention, it comes natural to wonder which are the factors that concentrate everyone’s interest on specific items. In the "Attention Economy" literature, novelty is often presented as one of the main factors [Simon, 1971a] [Goldhaber, 1997]. Indeed, as Goldhaber stated, since it is hard to get new attention by repeating exactly what has already been done in the past, a key role in the attention economy is played by novelty.

Online platform managers are well aware of the importance of novelty. Its promotion is expressly sought by platforms and specifically encoded in recommendation systems and in particular in the algorithms that select and suggest content to users, trying to meet their tastes and interests. Covington et al. [Covington et al., 2016], developers at YouTube in 2016, include freshness among the three major needs of YouTube recommendation system. In particular, they acknowledge that, as "many hours' worth of videos are uploaded each second to YouTube", "recommending recently uploaded ("fresh") content is extremely important for YouTube as a product". In fact, they observe that users constantly prefer fresh content and, hence, to keep their engagement high and make them spend time on the platform, YouTube has to satisfy their need for novelty.

The preference for novel content has been observed also in other contexts. In 2012 on Twitter, among the total tweets published in a week, the 45% had never been published before [Weng et al., 2012]. Similarly, according to Roth et al. [Roth et al., 2020] in 2020, two-thirds of the suggestions of YouTube given at a certain moment were not anymore associated with the same video after 2 days. Novelty can thus be listed as a key factor for capturing people’s attention and it should be considered when modeling popularity trends and shifts of collective attention from one topic to another.

2.4 The role of popularity

Various models, stemming from different branches of science, have been adopted to describe the evolution of popularity online. By classifying these models according to research field that generated them, we could distinguish: epidemic models, issued from the tradition of mathematical models describing the spread of infectious diseases, Bass-like diffusion models stemming from the theory of innovation diffusion, and self-exciting processes belonging to the larger family of counting processes in statistics.

Independently from the specific model used, one assumption is recurrent: people influence each other. To describe this occurrence, different terms have been adopted in different fields. When dealing with innovation diffusion models, we usually refer to the tendency of people to be influenced by others as an imitation processes. When adopting epidemic models instead, we usually refer to it as a contagion effect or a word-of-mouth effect. Despite its different names, the concept is the same: when many people are aware of a content, it becomes more likely for an individual to encounter it. We could also talk of popularity effects: the future spread of a piece of information is influenced by its previous success. In the following section, we are going to explain how this popularity effect has been considered by researchers in different contexts.

- Epidemic models. Despite originally designed to model the spread of infectious diseases, epidemic models can effectively describe the propagation of content online. Daley and Kendall [Daley and Kendall, 1964], in 1964, first proposed the analogy between epidemics and the spread of rumors, suggesting the same mathematical model might apply to both fields of study. The foundation of these models resides in partitioning a population into different classes of individuals. Among the most common classes we find Susceptible, Infected and Recovered individuals.
Susceptible individuals are those who still have not been in contact with the disease. Infected individuals have caught the disease and can spread it, while recovered individuals healed from the disease and cannot transmit it anymore. Of course, when adapting these models to attention dynamics, the disease is replaced by a piece of information and healing is replaced by forgetting. We can elaborate on different models, depending on the class of individuals considered. For example, the SI model considers only susceptible or infected individuals. In an SI model, the fraction of infected individuals $I$ evolves in time according to:

$$\dot{I} = \alpha(1 - I)I.$$ 

Here, the fraction of newly infected individuals is given by the probability of a susceptible individual to meet an infected one, multiplied by a transmission rate $\alpha$.

Many variations of this basic model have been proposed in literature with the specific aim of explaining information and rumor diffusion. In 2006 Bettencourt et al. proposed a variation of the SI model (which they called SEIZ model), to fit the spread of the use of Feynman diagrams through the theoretical physics communities in USA, Japan, and USSR in the period immediately after World War II. In their SEIZ model actors can either be susceptible (S), i.e. still unaware of an idea, exposed (E), i.e. having been in contact with the idea, infected (I), i.e. adopters of the idea, or skeptic (Z), namely aware of the idea but unconvinced by it. They prove that introducing exposed individuals consistently increases the capability of the model to fit the data: in fact, inserting a delay between the moment physicists first met Feynman diagrams and the moment they adopted them brought major improvements to the data explanation. Jin et al. later applied the same model to the spread of rumors online, with similar outcomes: they confirmed the improvement due to the introduction of exposed individuals in a simple SI model. Another confirmation of the importance of introducing an exposure delay between the reception and the adoption of an idea comes from the work of Xiong et al. in 2012. The authors proposed a diffusion model with four different states: susceptible (S), contacted (C), infected (I), and refractory (R). Contacted individuals behaved exactly as the exposed individual in the SEIZ model: they acknowledged the information but have not decided yet whether to spread it or not.

Besides the above mentioned variations of the SI model, there also exists some which do not include the addition of new classes of individuals. In Richier et al. 2014, the authors propose different biologically inspired models which proved to fit at least the 90% of videos of a conspicuous YouTube dataset. Among the considered models, we find a variation of the SI model called Gompertz model and governed by:

$$\dot{I} = \alpha I \log(M/I)$$

where $M$ represents the potentially interested public and $I$ represents the number of users that viewed a video. They compared it with a simple exponential model $\dot{I} = \alpha(M - I)$ and with some variations of the Gompertz and the exponential model where the authors added a term $kt$ to the temporal evolution of $I(t)$. While the simple Gompertz and exponential model failed at fitting the majority of the videos, the modified models brought a sensible improvement to the fittings: they explained almost 75% of videos popularity evolution. Even though, adding a term $kt$ to $I(t)$ seems rather contrived and difficult to interpret, we can explain the need of adding a further parameter $k$ as the necessity of higher degrees of freedom when explaining complex dynamics. In this respect, adding a term $kt$ to the evolution of infected individuals, or adding new classes of individuals to the SI model, play the same role.

- **Bass diffusion models.** The Bass diffusion model owns its name to Frank Bass, an academic pioneer of marketing research in the second half of the XX century. It was first introduced in Bass 1969 to model the process of adoption of new products in a market. It is based on a simple classification of individuals into two groups: innovators and imitators. The Bass model found its main application in forecasting innovations or technology sales. The model formulation is the following:

$$\dot{F}(t) = p(1 - F(t)) + qF(t)(1 - F(t))$$

where $F(t)$ is the fraction of adopters in a population at time $t$, $p$ is the coefficient of innovation and $q$ is a coefficient of imitation. As we can see, also in this formulation of the problem, we have a term of contagion $F(t)(1 - F(t))$ that models the influence of users on each other. The analogy between infected individuals in epidemic models and innovators in models of adoption is glaring, and it has been made explicit in many works [Bass 1969; Coleman et al. 1957; Toole et al. 2012]. That is one of the reason why, especially when these models are complemented with additional assumptions, it is hard to make a sharp distinction between adoption models and epidemic models. The main difference relies on the terms used and the community the researchers addressed. Most explanations of real data through the Bass model come from its agent-based extension, that was at first studied in [Rand and Rust 2011]. In this agent based formulation,
the model presents some initially unaware agents connected by relationship links. Over time, agents get the opportunity to become aware of the information through two mechanisms: either by spontaneous adoption, or by influence exerted by their neighbors in the network. In [Rand et al., 2013], Rand et al. apply an agent based Bass model to the diffusion of information in Twitter during four major events happened in the U.S. in 2011-2012. They obtained pretty satisfactory fitting of the increase in time of the number of people talking about each topic. Many other examples can be discussed, e.g. [Chica and Rand, 2017], but, for a complete review on innovation diffusion process, we refer the reader to [Kiesling et al., 2012]. Here, our aim is to highlight the similarities between innovation diffusion processes and epidemic models.

Self-exciting processes. The best example of how self-exciting processes can model content diffusion is given by Crane and Sornette [Crane and Sornette, 2008]. The authors provide a model to fit the evolution of videos on YouTube, and they base it on three essential assumptions: (1) the relevance of human interactions in spreading a piece of information, (2) the existence of influences external to social media, and (3) the fact the humans activity follows very specific patterns, which we are going to discuss more in detail in Section 2.5. Crane and Sornette’s model consists of a self-excited Hawkes conditional Poisson process [Hawkes and Oakes, 1974] with an instantaneous rate of views given by:

\[ \lambda(t) = V(t) + \sum_{i,t<\tau} \mu_i \varphi(t - t_i) \]

where the term \( \sum_{i,t<\tau} \mu_i \varphi(t - t_i) \) models the contagion/imitation process, and \( V(t) \) represents and exogenous source of views, which captures all spontaneous engagement not triggered by epidemic effects. The parameter \( \mu_i \) represents the number of potential viewers who will be influenced by person \( i \) that views a video at time \( t_i \). The kernel \( \varphi(t) \) is chosen to be equal to

\[ \varphi(t) = \frac{1}{t^{1+\alpha}} \]  

(2)

and it represents the rate at which individuals consume information. Such formulation stems from a wider literature investigating the rhythms of individual human activity, which, in many contexts, is characterized by power law distribution of waiting times between consequent actions, for instance, between receiving an email and replying to it [Barabási, 2005] [Vázquez et al., 2006] [Oliveira and Vazquez, 2009]. Here, the memory kernel \( \varphi(t) \) describes the distribution of waiting times between acknowledging the existence of a video and actually watching it. We could consider it as another way to model the latency time between acknowledgment and adoption of an idea proposed in the SEIZ model by Bettencourt [Bettencourt et al., 2006]. The rich literature on human interevents [Deschéries and Sornette, 2005] [Johansen and Sornette, 2000] [Johansen, 2001] that justifies Crane and Sornette’s choice of \( \varphi(t) \) will be discussed in the next section.

2.5 Individual activity is bursty

Individual actions online (reading, posting, re-posting or replying) have been the object of a vast literature analysing the temporal patterns of human activity. A consistent number of empirical evidences has outlined that human activities are often inhomogeneous in time: long periods of inactivity are followed by sudden bursts of subsequent events [Karsai et al., 2013]. This behavior affects every task we perform in daily life: the process of editing a scientific paper [Jo et al., 2012] [Mryglod et al., 2012] [Hartonen and Alava, 2013], the loans demanded in a university library [Vázquez et al., 2006], the requests sent to printers [Harder and Paczuski, 2006], messages in a chat system [Dewes et al., 2009], page downloads on a news site [Dezso et al., 2009], e-mails [Johansen, 2004]. Besides being inhomogeneous in time, interevents time share another constant behavior across most of the examples mentioned above: a heavy tailed distribution.

Vázquez et al. extensively analyze the bursts characterizing human activity in [Vázquez et al., 2006]. Among many datasets (the number of clicks by the same user on a Hungarian search engine, the number of emails by the same researcher in a university, the library book checks by the same student, the trade transactions by the same broker) they outline that the interevent time distribution has a power-law tail \( P(x) = x^{-\alpha} \). They recognize two universal classes of exponent \( \alpha = 1 \) and \( \alpha = 3/2 \) in their datasets and proposed two decision based queuing process to explain them. Decision based queuing processes are processes in which tasks get ranked and executed on the basis of some perceived priority. Vázquez et al. proved that when there is no limitation to the number of tasks an individual can handle at any time, the distribution of the waiting time of the individual tasks follows a heavy tail distribution characterized by \( \alpha = 3/2 \). On the other hand, when imposing a limitation on the queue length, the resulting distribution of the waiting time is characterized by \( \alpha = 1 \). Vázquez’s work has been vastly appreciated, even if further studies attenuated the net distinction between the two classes he identified. Nowadays, we know that many other bursty systems can be explained through power laws of various exponents, ranging between 1 and 2. Many other causes of this peculiar distribution
of interevents have been proposed in literature, and we refer the interested reader to [Karsai et al., 2018]. Our general aim here was to provide the reader with the intuition that heavy tailed interevents in human activity are likely to be the outcome of the way individuals process tasks.

Focusing on the implications of bursty activities rather than on their causes, we are confronted with a vast literature, at a first sight partially contradictory. In fact, the effects of heterogeneous interevents times in dynamical processes have been considerably debated in the last ten years. On the one hand, burstiness of interevents seemed to slow down diffusion processes and epidemic spreading [Karsai et al., 2011] [Vazquez et al., 2007]. On the other hand, evidence has been brought to light that, in certain environment, the speed of contagion might be increased by heavy-tailed interevents [Rocha et al., 2011]. A good synthesis of these apparently opposing effects of bursty human activity can be found in Chapter 5 of [Karsai et al., 2018]. Here, Karsai explains that "heterogeneous inter-event times may have different effects when considering the early and late time behavior of a dynamical process". Summarizing his analysis, we could say that bursty activity on networks has an opposite effect when considering the early stages of the diffusion or the later ones: in the first case, in fact, it speeds up the spread, while, in the second case, it slows it down. Given the evidence that bursty activity can influence the outcome of a diffusion process, it is important to acknowledge their existence and their universality. Mean field models like the basic SI model defined in (1) fail in representing users’ individual activity. The need for adding a delay to slow down the spread of information in the SEIZ model can be justified by the slowdown bursty individual activity causes in latter stages of a diffusion process.

2.6 Recommendation systems are the main gateways for information

Knowing how human behave in their daily activities can help us understand their way of posting, forwarding or liking content on social media and hence better describe the process of diffusion and consumption of information. However, when dealing with online attention dynamics, we have to keep in mind that influence from neighbors and word of mouths spreading are not the only way people get into contact with information. On the contrary, in many online platforms, they appear to be rather marginal when compared to recommendation systems.

Many investigations have been carried out to understand the ratio of content diffused by algorithmic and human recommendation. Already in 2010, Zhou et al. [Zhou et al., 2010] confirmed that the related video recommendation on YouTube was the main source of views for most of the videos on YouTube. Furthermore, the authors reveal that there is a strong correlation between the view count of a video and the average view count of its suggested "videos to watch next". This implies that a video has a higher chance of becoming popular when it is placed on the related video recommendation lists of popular videos. In 2014, Fugueiredo et al. [Figueiredo et al., 2011] confirmed that the most likely way to get to watch a video on YouTube is either the related video list, which displays a list of 20 videos and the average view count of its suggested "videos to watch next". This very day, YouTube itself, on its official blog, declares that "recommendations drive 32%, 43% of the total views. On the other hand, external sources like links to the video in other social media, or suggestions made by friends, account for only the 8%-16% of the total views of a video. This very day, YouTube itself, on its official blog, declares that "recommendations drive a significant amount of the overall viewership on YouTube, even more than channel subscriptions or search". In 2018 YouTube Chief Product Officer Neal Mohan admitted that, for over the 70 percent of the time users spend watching videos on the platform, they are lured in by one of the service’s AI-driven recommendations [Solsman].

2.7 Change is the only constant

Given the relevance of platforms suggestions in shaping what people watch, it is important to get a better understanding of their evolution, in order to contextualize researches conducted in different periods. Despite being created and designed relatively recently, online platforms have an incredibly rich history in terms of updates and enhancements: the evolution of their policies, their design and their functionalities is a fast, never-ending process. By keeping in mind that Facebook was created in 2004, YouTube in 2005, Twitter in 2006 and Instagram in 2010, the extent these social media reached in only less than two decades is impressive. Nowadays, over 300 hours of videos get uploaded every minute on YouTube and the platform gathers over 30 million visitors per day. In October 2021, Facebook had 2.910 billion monthly active users [met]. Twitter had 206 million daily active users [kil]. Instagram had 500 million daily active users [met].

Along their way to success, these platforms and their engineers had to face constant challenges. For instance, as already discussed, they had to confront the need for sorting unprecedented quantities of user-generated content and ranking it in a personalized way for each user. The tools used to meet this requirement, recommendation systems, are constantly updated, and undergo continuous improvements to keep up with the latest discoveries in artificial intelligence. Some of the changes that recommendation systems have undergone in the last years have been documented by developers [Covington et al., 2016] [Zhao et al., 2019] [Naumov et al., 2019] [Cheng et al., 2016] [Gupta et al., 2013] [Solsman]. They always aimed at enhancing the efficiency of recommendations, increasing the engagement of the public and the time
they spent online.

Among the other arduous challenges platforms had to face, those maybe most known by the wide public concern ethics. Platforms have been accused, over the years, of promoting the diffusion of fake news, of disseminating hate speech, and of polarizing people by suggesting extremist contents. To cite one of the major and earlier events that rose these concerns, we could name the 2016 US Presidential elections: Buzzfeed reported that false news stories at that time outperformed real news on Facebook [Silverman]. Throughout the years, platforms have changed their policies to overcome these ethical issues. Videos about discrimination, segregation or exclusion have been banned by YouTube [Wojcicki], and creators can no longer monetize videos using inappropriate language or dealing with controversial content [of Service]. Facebook does not allow objectionable or violent content and hate speech [Meta, a] and the same holds for Instagram [Meta, b]. Ethical concerns have hence contributed to shape platform policies and did affect the kind of content diffused online.

In a nutshell, online platforms are ever-changing, under the combined forces of technological progress and ethical and political criticism. No man ever steps in the same platform twice. For it’s not the same platform and he’s not the same man. That’s how we could rephrase Heraclitus to stress that this continuous evolution of platform should be kept in mind when considering the previous literature, to better contextualize the findings and avoid improper generalizations.

3 The new challenge: Understanding recommendation systems effect in attention dynamics

So far, we discussed the main features that should be taken into consideration when dealing with online content diffusion. When considering these features together with the models used in literature (discussed in section 2.4), it becomes self-evident that one key variable has been left out when modeling online information spread: the role of recommendation systems.

As we have seen, many models [Crane and Sornette, 2008] include in their formulation an exogenous source of popularity. We do believe this analysis to be potentially superficial as, by calling "exogenous" everything not explained by a mechanism of contagion/imitation, we risk including in the term both what is effectively triggered by events external to the platform, and recommendations made by social networks, hiding the potential role of platforms in influencing information spreads. When studying online content diffusion, we cannot avoid considering the means on which information circulates: online platforms.

Even though much has been written in the last years about online media, we claim that not much has been done to investigate how they shape the speed of content diffusion and whether they have a responsibility in accelerating our collective attention dynamics [Lorenz-Spreen et al., 2019]. Most of the literature about online media has rather focused on other potentially dangerous implications of their use. "Selective exposure" [Sears and Freedman, 1967], "eco chambers" [Garrett, 2009], and "filter bubbles" [Pariser, 2011] fall within the best known threats of social media. To briefly summarize these concerns: social media may create environments in which "thousands or perhaps millions or even tens of millions of people are mainly listening to louder echoes of their own voices" [Sunstein, 2001]. This idea has sparked much interest in computational sociology [Ciccone et al., 2014] [Geslake et al., 2019] and computer science [Nguyen et al., 2014] despite evidence of a possible overestimation of its impact [Bakshy et al., 2015] [Dubois and Blank, 2018]. Recent work includes both mathematical modelling [Jiang et al., 2019] [Rossi et al., 2021] and empirical data analysis, with a focus on e-commerce services [Ge et al., 2020] [Anderson et al., 2020].

Instead of focusing on the kind of content suggested to users and on the possible distortion of reality induced by social media, in this chapter we would like to provide a formal example of how content diffusion might depend on platforms’ policies. Our models is built on few features and assumption and our aim is, through a simplification of recommendation systems, to investigate the effect they might have on the speed of content diffusion.

3.1 Model description

The first ingredient of our model is a population of matters of attention defined as the entities that compete to capture public attention. They can represent tweets on Twitter, posts on Facebook or videos on YouTube.

The second ingredient of our model is a platform in which attention matters live. On this platform we assume attention to be limited, given the evidence already discussed in Section 2.1. For the sake of simplicity, we do not account for circadian or weekly rhythms that affect the attention availability on platforms. Hence, as discussed in Section 2.1 considering a sufficiently small time window on the life of a platform we can avoid considering the arrival of new users and consider the attention fixed. The third ingredient of our model is a representation of the recommendation system that prizes trendiness. In other words, an item that grew fast in popularity in the previous interval of time is more likely to be suggested and viewed by other users in the next future. This boosting of trendiness is consistent with
the way in which online platforms “emphasiz[e] novelty and timeliness... [by] identifying unprecedented surges of activity” and “reward[ing] popularity with visibility” [Gillespie, 2016]. The model therefore should reward rising items and penalize declining ones.

To shape these features into a formal model, we define a set of $x_i, \{i \in 1, \ldots, n\}$ attention matters and we name $\pi^t_i$ the share of attention captured by $x_i$ at time $t$. At every time step the recommendation system rewards rising attention matters according to

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

(3)

where $\varepsilon$ is a random variable drawn from a normal distribution with mean 0 and standard deviation $1/(\sqrt{c+n})$, where $c$ controls the noise. The crucial variable of our model consists of $\alpha$. It represents how much weight is given to trendiness when promoting a content on a platform. It is the boost induced by trendiness.

Equation (3) provides us with a potential visibility of item $x_i$ at time $t$. Its actual visibility is given by a normalization of the overall attention on the platform and eventual rounding of negative potential visibilities to zero. The resulting model is fully defined by the following set of equations:

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

(4)

$$\pi^{t+1}_i = \hat{p}^{t+1}_i \sum_j \hat{p}^{t+1}_j$$

Figure 1: Evolution of our model for trendiness boost = 0, 1, 2, and 3 (with $N = 20$ and $c = 12$). Each color area corresponds to the attention received by an item. The first 100 iterations are shown.

3.2 Results and discussion

Our interest lies in understanding the effects of the $\alpha$ parameter modeling a potential recommendation system. When simulating system 4 some typical outcomes, shown by Figure 1, can be observed.

The comparison between the graphs in Fig 1 suggests that, as the boost of the trendiness grows, the rise and fall of attention matters become steeper. This relation can be tested by computing the mean increment by unit of time and observing that it increases with $\alpha$, as analyzed in Figure 2. This behavior is independent on the level of noise and on the number of items populating the platform.

Overall, from Figure 1 emerges that prizing trendiness accelerates the dynamics of collective attention. Without the need of a complex representation of recommendation systems we obtain different regimes of content diffusion depending on the platform policy. Moreover, not only we obtain different regimes, but also we could claim that some of them are healthier than others. To make this point clearer Figure 3a shows the relation between the parameter $\alpha$ and some key metrics of an attention dynamics. The first one is the average life cycle of an item, namely the time from its first view and its latest one. As a consequence of faster rise and decay of interest in news items, the attention waves
shortens. As a consequence a higher number of attention matters enter and exit the arena, as shown by Figure 3d. We recall that our model allows an arena to contain a maximum number of \( n \) items, some of which might not be active (i.e. with \( \pi_t^i = 0 \)). When an item loses public attention and does not receive any for several epochs we consider it as extinguished and substitute it with a new one with a starting popularity equal to 0. Hence, when the rhythm of collective attention accelerates, the number of items receiving attention in a given time-window increases. One closing observation should be made concerning the concentration of collective attention on different items. At every epoch of our simulations we can evaluate the Gini index of how popularity is distributed among different attention matters. Being the Gini index an index of inequality, the higher its value, the higher the concentration of popularity on few items. Figure 3c shows how the average instant Gini index changes with \( \alpha \). Higher trendiness boost amplifies the difference between successful and unsuccessful attention matters, creating a situation in which, at each iteration, most of the available attention is captured by a minority of over-visible items.

Regimes characterized by few items capturing the majority of the attention but incapable of sustaining it for a long time might not be able to raise structured and constructive debate.
In previous work we analyzed this kind of accelerated rhythms under the name of junk news bubbles \cite{Castaldo2021} and discussed the potential harm for the public debate coming from this syncopated rhythm of attention that is at the same time increasingly dispersed and increasingly concentrated.

Here we would primarily stress that recommendation systems, given their enormous impact in diffusing content, should definitely be included in models considering online content diffusion as, otherwise, those models could be mis-interpreted.

4 Conclusion

In the last several years, the control systems community has been drawn towards working on social dynamics. Most attention has been devoted to mathematical models to describe decision-making and the evolution of opinions or beliefs: this focus is testified by surveys \cite{Proskurnikov2018, Jia2015} and is confirmed by the contributions to this book, which include a chapter on social diffusion \cite{Zino2022}. Some of these models have taken into account the concurrent evolution of interpersonal appraisals or individual susceptibilities \cite{Mei2017, Amelkin2017, Bizyaeva2020} or the role of discrete actions such as voting and deliberations \cite{Varma2017, Ceragioli2018, Mei2019}. In several cases, this research has nicely combined theoretical investigation and data analysis \cite{Friedkin2016, Fontan2021}. Despite the growing scope of this research, the community should be aware that the field of potential questions in the social and economic sciences is even broader, including marketing, innovation dynamics, and information diffusion in social media.

In this chapter, we have argued about the importance of attention dynamics in social media, by focusing on the important case study of YouTube. We have provided a review of the relevant literature, emphasizing key facts that shape this dynamics, like the boundedness of collective attention and the role that novelty and popularity play in the diffusion of contents online. We have highlighted how recommendation systems function as gateways of information (and thus, conversely, of attention) and we have described a simple dynamical model of collective attention. We hope that this introduction can foster the interest of the control system community into these problems and contribute to expand the research in cyber-social systems.

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