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# Scaling invariance in a social network with limited attention and innovation

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ABSTRACT

Competition for limited attention in a social network with innovation is investigated. We consider the case where each piece of information has a fitness as proxy of its quality. The higher is the quality the higher are the chances of being transmitted. We describe the behavior of the diversity of information in a social network as a function of time by using scaling arguments and we demonstrate its scaling invariant with respect of time as well as information load, attention and network sizes. Scaling transformations are used to overlap different curves of diversity, obtained by distinct parameters, onto an universal plot.


## 1. Introduction

The problem of competition for attention has become one of the most thriving topics in the field of information diffusion. With million of people adopting online social medias as their main source of news, associated with their extreme low cost of production, understanding how information propagates is of extreme importance since theses platforms provide the perfect breading ground for the diffusion of low quality information such as misinformation and fake news [1–4]. The term "memes" [5] became popular over the last few years and it is often used to classify any piece of transmissible information. It can be a hashtag on Twitter, a picture on Facebook or even a video on YouTube, most recently also in WhatsApp. In reality, users are exposed to a very large number of memes and, because of the limited attention or limited cognitive capacity [6], they can not consume all the information they are exposed to, and therefore, only a small fraction of them will eventually become popular while the vast majority will simple disappear. There are several cases in which such a behavior is observed. To nominate few of them, the number of hashtags or URL retweet on Twitter [7], video views on YouTube [8], citations [9–11], among many others [12–15]. Normally, people show interest in information with novel and/or popular contents and their intrinsic properties make a huge difference on their popularity and spreading behavior. Aware of this, information producers employ various mechanisms to polish the way they present their product to attract most people attention.

Traditionally, models of information diffusion are based on tools borrowed from theoretical epidemiology where susceptible agents became infected by interaction with infected nodes [16–21]. Over the years a lot of work has been done trying to shed light on the process of competition for attention and what it will take for a meme to attain success. Recently, Weng et al. [22] proposed an agent-based model that, to simulate the limited attention, fixes the amount of time an agent will hold a meme. They showed the combination of network structure and competition for finite attention results in heterogeneity in meme popularity, lifetime and user activity. Hogg and Lerman [23] presented a stochastic processes-based model to predict the popularity of an user-created content via summaries users recent activity. Crane and Sornette [8] employed an epidemic model on a social network to describe the exogenous and endogenous bursts of attention towards a video. Gleeson et al. [24] used a critical branching process to describe the popularity growth of each meme among the competition for attention, and predicted a power-law distribution of popularity with heavy tails. Ratkiewicz et al. [25] proposed a model in which ran-

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dom collective shifts of attention due to exogenous events provide a way to interpret the broad distribution of magnitude in popularity bursts. Bingol [26] proposed a recommendation model where agents can remember and forget, and found that the minimum and maximum popularity of an agent is linear related with the memory size. Cetin and Bingol [27] extended the recommendation by incorporating advertisement and showed this is very effective with small attention capacity relative to the number of items. Besides, there are some research related with the role of intrinsic quality of the meme. For example, Huberman [28] considered content's novelty and popularity as two major factors to get attention and employed prioritization to maximize attention. Wu and Huberman [29] empirically analyzed the dynamics of collective attention and found it fits a dynamical model with the novelty of a story fading with time and also indicated that attention fades over a natural time scale. More recently, Qiu et al. showed that a tradeoff between discriminative power and diversity is possible in a system with limited attention and innovation. However, in realistic conditions, the model predicts that low and high quality information are as just as likely to go viral [30]. Simultaneously, Sreenivasan et al. [31] proposed a model of information cascades on feed-based networks also taking into account the finite attention, innovations and message diffusion. In such a case, the authors estimated the branching factor associated with the cascade process for different attention spans and different forwarding probabilities, and they demonstrated that beyond a certain attention span, cascades tend to become viral. Although several works have been done trying to address to the crucial importance for the problem of competition for attention, there still a lack of a better understanding of how memes behave in on-line social network from the moment they are introduced into the system and start to compete for the user's attention until they are completely forgotten.

## 2. The model and numerical results

In this work we move a step forward towards the understanding of the mechanism behind the process of spreading of information in a system with limited attention. We revisit the model introduced by Qiu et al. [30] where the authors incorporate an intrinsic property for each meme by assuming that every piece of information possesses a fitness or quality that might represent different properties depending on the situation being modeled. We assume the intrinsic qualities of a meme are summarized by this numerical proxy which is drawn from a uniform distribution at the moment the meme is introduced into the system. Furthermore, the higher the quality, the greater the probability that an agent will pay attention to the meme, therefore re-sharing it and allowing it to spread over the network. Besides, each agent is equipped with a fixed memory size $\alpha$ which means that each agent can pay attention only to a limited amount of information. Furthermore, new memes can be introduced in the system representing the innovation, *e.g.*, users are exposed to a new product or a new idea.

Here, we consider a simple agent-based model inspired by the long tradition of representing the spread of ideas as an epidemic process where information is passed along the edges of a network [32–36]. A Barabasi–Albert network is considered and agents are represented by the nodes of a static, undirected network.[1] The edges embody social connections through which memes can spread. In contrast with classical epidemiological models, new memes are continuously introduced into the system in an exogenous fashion. The rate this happens ultimately determines the amount of competition and diversity the system can support. The

[1] We also considered Erdös–Rényi [37] and Small World [38] networks and the results are shown in the Supplementary Material.

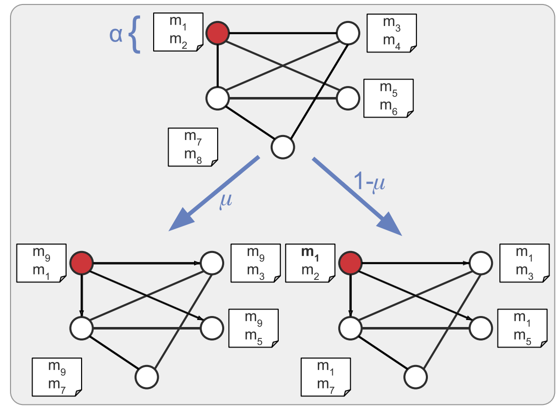


**Fig. 1.** Illustration of the meme diffusion model. At each time step, an agent $i$ is considered (red). The agent chooses to create a new meme with probability $\mu$ and transmit it to all its neighbors. Otherwise, with probability $1-\mu$, the agent copies a meme from its memory and transmit it to all its neighbors. The probability of selecting a meme is proportional to its fitness. The parameter $\alpha$ represents the size of the node's attention and $\mu$ determines the information load and the higher $\mu$, the higher the diversity and the harsher the competition. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

rate of innovation or information load is expressed by a parameter $\mu$ and the higher $\mu$, the harsher the competition. Furthermore, a meme appears spontaneously once and never comes back as soon as it is forgotten by all nodes. We assume at time $t = t_0$ the system is in its state of higher diversity where each node has $\alpha$ unique memes. At every time step a node $i$ is chosen at random and with probability $\mu$ it introduces a new meme in the system and the selected node transmits the meme to all its neighbors, or with probability $1-\mu$ it chooses a meme from its memory (or attention list) and transmits it to all its neighbors. Once all of the neighbors receive the meme, it is placed at the top of their list, and the last meme in each node's list is removed or forgotten. Fig. 1 illustrates the dynamics of the model. The probability that an agent selects a specific meme $m$ from its list to transmit is proportional to the meme's quality $f(m)$. More explicitly, if node $i$ has a set of memes $m(i)$ the probability of meme $m_k$ being selected is

$$P_i(k) = \frac{f(m_k)}{\sum_{j=1}^{\alpha} f_i(m_j)} \,. \qquad (1)$$

It is worth to mention that the copying mechanism represents the adoption of a meme shared by a connection, as is done, *e.g.* through tweets on Twitter, shares on Facebook. The proposed model allows us to study the process behind the competition for limited attention, how the information load and the quality of information affect the chances of a meme to succeed and stay on the network for long times. We start by considering the behavior diversity, $\overline{D}$, as a function of time for different network sizes, different values of the information load $\mu$ and different values for the attention $\alpha$. At time $t = t_0$ the system is in a state of higher diversity with $N \times \alpha$ different memes, where $N$ is the network size and as the competition starts to take place the system converges to a steady state that highly depends on $\mu$, $\alpha$ and the network size.

To investigate how the system changes from high to low diversity due to the competition, we measure the average system diversity $\overline{D}$ of an ensemble of initial conditions. First, we evaluate the average over the time for a single realization and then over an ensemble of initial condition. Thus, we have

$$\overline{D} = \frac{1}{Z}\sum_{i=1}^{Z}\frac{1}{n+1}\sum_{t=0}^{n} D_{i,t} \,, \qquad (2)$$