Lack of quality discrimination in online information markets

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Abstract

Online social networks are marketplaces in which memes compete for our attention. While one would expect the best ideas to prevail, empirical evidence suggests that high-quality information has no competitive advantage. Here we investigate this puzzling lack of discriminative power through an agent-based model that incorporates behavioral limitations in managing a heavy flow of information and measures the relationship between the quality of an idea and its likelihood to become prevalent at the system level. We find that both information overload and limited attention contribute to a degradation in the market's discriminative power. A good tradeoff between discriminative power and diversity of information is possible according to the model. However, calibration with empirical data characterizing information load and finite attention in real social media reveals a weak correlation between quality and popularity of information. In these realistic conditions, the model provides an interpretation for the high volume of viral misinformation we observe online.

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1 Introduction

Four centuries ago, the English poet John Milton argued that in a free and open encounter of ideas, truth prevails [31]. Since then the concept of a free marketplace of ideas has been used to support free speech policies and even applied to the study of scientific research [5]. The theory draws analogies to natural selection, where the traits of a species determine its survival, and to economic markets, where the intrinsic value of a good determines its success. Two necessary elements of this theory are the diversity of ideas to which people are exposed and the discriminative power of the marketplace, which we define as its ability to allow better ideas to become more popular.

The recent advent of social media as a major communication platform for the exchange of information and opinions is having a significant impact on the marketplace by broadening participation and facilitating the contribution and sharing of ideas. Through networks such as Twitter and Facebook, users are exposed daily to a large number of transmissible pieces of information, or “memes” [13], that compete to attain success in an “attention economy” [41] [22] [16] [6]. Such information flows have increasingly consequential implications for politics and policy [8] [10] [15], making the questions of discrimination and diversity more important in today’s online information markets than ever before.

In this paper we study discriminative power and diversity in a model information network. We assume the existence of an intrinsic measure of quality for each meme shared online, and explore how two critical factors — the number of competing memes and the finite attention of the participants — affect the system’s ability to select the best memes for survival and diffusion, while sustaining a diverse ecosystem of ideas. We observe a tradeoff between quality discrimination and diversity, in which both can be relatively high when agents have sufficient attention and are not overloaded with information. Calibrating the model to empirical data is difficult because qualities such as value, innovation, reliability, and relevance of information can rarely be measured or even defined a priori, making it difficult to quantify the discriminative power of online information markets. However, it is possible to characterize the distributions of information load and attention from social media data. Unfortunately, these measurements place online information networks in a regime where quality and popularity of information are weakly correlated, far from the optimal tradeoff.

The simple model presented here does not explicitly incorporate behavioral, social, and technological mechanisms that affect discrimination and diversity in the online marketplace of ideas. For example, prior research has studied the role of technology in discriminating between truthful information and misinformation. On the surface, truth is easier to produce and distribute because one can more easily verify truthful sources, making online misinformation expensive to sustain [44]. However, the ease of disseminating misinformation through social media may counter this argument. The “wisdom of the crowd” enabled by social media [48] should also facilitate the discrimination of information based on quality by combining the diverse opinions of many individuals [37]. But when people communicate, their opinions are no longer independent, leading to higher
confidence and lower accuracy [29].

Cognitive and behavioral processes for dealing with opinions that challenge one’s beliefs may decrease our capability to discriminate between high and low quality information [7, 43]. For example, confirmation bias [33] may have evolved as an effective strategy to avoid misinformation, by comparing incoming information to one’s own existing beliefs, and adopting it if it is sufficiently concordant [42]. However, in social media, such a bias easily leads to ineffective discrimination. Confirmation bias may be reinforced online by our limited capacity to cope with the information overload caused by the messages that flood our screens [23] and our consequent need to quickly discard irrelevant information.

The diversity of information present in the market can also be affected by the interplay between behavioral and cognitive factors and algorithmic biases of online social networks. It is easy to rewire our connections and affect the sources of information to which we are exposed [15]. Mechanisms such as triadic closure, facilitated by social media recommendation, may be suboptimal for the discovery of relevant but unfamiliar information [50, 2]. These selection processes may cluster people into a few homogeneous factions [1], often called “echo chambers” [17] or “filter bubbles” [38]. This may further lead to polarization [46, 9, 45, 34]; one group may automatically discount ideas from another [30, 35].

This body of work suggests that, paradoxically, our behavioral mechanisms to cope with information overload may make online information markets less meritocratic and diverse, increasing the spread of misinformation [36, 14] and making us vulnerable to manipulation [39, 17]. Anecdotal evidence of hoaxes, conspiracy theories, and fake news in online social media is so abundant that massive digital misinformation has been ranked among the top global risks for our society [25].

Several studies have investigated the role played by network mechanisms affecting the popularity of individual memes. Crane and Sommerte [11] proposed an epidemic model on a social network to describe the exogenous and endogenous bursts of attention toward a video. Ratkiewicz et al. [40] employed a model in which random collective shifts of attention due to exogenous events provide a way to interpret the broad distribution of magnitude in popularity bursts. Bingol [4] proposed a dynamic model where agents can remember and forget, and use recommendation to discover new agents. This model predicts that the popularity of an agent is linearly related to memory size. Huberman [26] studied the effects of the content’s novelty and popularity in attracting attention. Wu and Huberman [51] developed a model with the novelty of a news story fading with time and showed that attention decays over a natural time scale. Lerman and colleagues [24, 27] showed that the combination of competition and position bias (a manifestation of limited attention in social media) affects the visibility of a meme and thus constrains social contagion.

The above literature considers the popularity of pieces of information in isolation. Markets in which many memes compete for the limited attention of social media users have received scarce consideration. A notable exception is the
work of Weng et. al. [49], who used an agent-based model to demonstrate that the combination of social network structure and finite attention of social media users are sufficient conditions for the emergence of viral memes, in the absence of any intrinsic quality difference among memes. Gleeson et. al. [19] formalized this model as a critical branching process, predicting that the popularity of memes follows a power-law distribution with very heavy tails.

These results tell us that quality is not a necessary ingredient to explain popularity patterns in online social networks, but say nothing about the actual importance of information quality. It is reasonable to assume that quality does play a role in individual decisions about information consumption. Yet, the initial empirical evidence presented next shows that higher quality does not imply a larger market share. This motivates our theoretical and empirical analysis to determine whether discrimination of information according to its quality at the individual level can be reflected in discriminative power at the system level, and at what cost in terms of the market’s capability to sustain diversity of information.

2 Results

2.1 Lack of quality discrimination

While it is generally difficult if not impossible to measure the quality of a piece of information that is shared online, proxy measures of quality exist in some cases. We used empirical data from Emergent (see Methods) about posts shared on social media with links to news articles in two groups. One group of articles support claims debunked by fact-checkers or undermine claims verified by fact-checkers. The other group includes articles that fact-check hoaxes or support verified claims. Articles in the first group clearly have lower quality than those in

Figure 1: Distribution of the number of times that news articles in two categories are shared on Facebook. Low-quality articles support false claims or undermine true claims. High-quality articles fact-check false claim or support true claims.
the second. To explore whether high-quality information is more likely to spread widely than low-quality information, as one would expect, we compared the numbers of times articles in these two groups were shared online. As illustrated in Fig. 1, low-quality information is just as likely to go viral. The model and empirical analysis described next are intended to investigate some factors that may help explain such a lack of quality discrimination.

2.2 Effects of information load and finite attention on discriminative power

We aim to examine the conditions in which the “best” ideas are those that capture a greater portion of collective attention, and whether this happens at the expense of the diversity of ideas. To this end, we propose a simple agent-based model inspired by the long tradition of representing the spread of ideas as an epidemic process where messages are passed along the edges of a network [32, 21, 12, 8, 20]. Agents are represented by the nodes of a static, undirected network where the links embody social connections. Each message, or post, carries a “meme” or “idea,” i.e., the unit of information that spreads from person to person [13]. Different messages may carry the same meme.

To examine the discriminative power of the market, we imagine that each meme has a fitness value. The fitness might represent different properties depending on the situation being modeled; the truthfulness of a political claim, the beauty of a picture, and the originality of an idea are valid examples. We assume that the intrinsic qualities of the meme are summarized by this numerical proxy. The higher the fitness, the greater the probability that an agent will pay attention to the meme, sharing it and allowing it to spread.

In contrast with classical epidemiological models, messages carrying new memes are continuously introduced into the system in an exogenous fashion. We use the rate \( \mu \) at which this happens as a parameter of the model to regulate the information load of the agents, i.e., the average number of memes received by an agent per unit time.

Agents produce messages containing new memes and reshare messages originated or forwarded by their neighbors. When resharing, an agent is capable to pay attention to only a finite number \( \alpha \) of messages at a time. If we think of messages from neighbors as appearing in, say, reverse chronological order on a social media feed, a user during a session will scroll down the feed to view a finite number of recent posts. Further details about the model are presented in Methods.

Let us investigate how the information load affects the role played by the fitness in the success of a meme. Fig. 2 shows that on average, memes with higher fitness do have a better chance to survive and succeed, but in a way that depends considerably on \( \mu \). A single meme survives in the limit \( \mu = 0 \), typically but not necessarily one with high fitness. For small values of \( \mu > 0 \), very high fitness yields a disproportionally large chance to succeed. For large \( \mu (\mu < 1) \), the relative advantage conferred by a higher fitness is much smaller. In the limit case \( \mu = 1 \), a new meme is introduced at all times and therefore there is
Figure 2: Average popularity of memes as a function of fitness for different values of information load \( \mu \) (left, \( \alpha = 10 \)) and for different values of attention \( \alpha \) (right, \( \mu = 0.1 \)).

no chance for memes to spread, irrespective of fitness. In summary, an increase in information load corresponds to a decrease in discriminative power because fitness has a lesser effect on popularity.

The effect of finite attention on the relationship between fitness and popularity is also illustrated in Fig. 2. The case \( \alpha = 1 \) is special in that agents cannot make any choices based on fitness. Although some memes will go viral for small \( \mu \), fitness plays no role in determining which memes spread, and the network is completely inefficient at promoting quality information. For \( \alpha > 1 \) users can pay attention to more than one meme and have some choice in selecting which memes to share. As expected, the mean popularity grows with fitness: the best memes have much higher chances to win. As the amount of individual attention \( \alpha \) increases, the curves become more concave; the mean popularity grows more slowly except for the highest values of fitness, an indication of increased selective pressure favoring the best memes.

We can summarize the dependency between the quality of memes and their success in a single discriminative power measure by looking at the correlation between fitness and popularity. Since the two quantities are not normally distributed, we employ the Kendall rank correlation coefficient \( \tau \), which is computed by ranking memes according to the two criteria and then counting the number of meme pairs for which the two rankings are concordant or discordant, properly accounting for ties [28]. High \( \tau \) indicates that fitter memes are more likely to win, granting the system discriminative power; in the extreme case \( \tau = 1 \) the two rankings are completely concordant. Small \( \tau \) signifies a lack of quality discrimination by the network. Fig. 3 shows that network discriminative power degrades both with higher information load and with more limited attention.

2.3 Diversity and discriminative power

As discussed above, discriminative power in spreading quality content is a desirable property of a social network. A second desirable property of an ideal
communication system is the preservation of information diversity, i.e., the possibility to have many distinct memes alive simultaneously. As illustrated in Fig. 4, the two goals are in contradiction — the price associated with the capability of the network to let a high-fitness meme prevail is a loss in diversity, with many memes receiving relatively small attention despite their intrinsic quality. Let us therefore explore the tradeoff that results from the competition for attention in the network.

To measure the amount of diversity in the system at the steady state, we start from the entropy $H = -\sum_m P(m) \log P(m)$ where $P(m)$ is the portion of attention received by meme $m$, i.e., the fraction of messages with $m$ across all of the user feeds. The sum runs over all memes present at a given time and is averaged over a long period after stationarity has been achieved (see Methods). The minimum entropy is zero, when all nodes have the same meme ($\mu = 0$). The maximum entropy, obtained in the extreme case $\mu = 1$, depends on $\alpha$.

To discount this dependence we measure diversity by the normalized entropy $H/H(\mu = 1)$. Fig. 5 shows that with this normalization, the diversity does not depend in a significant way on the attention $\alpha$. As expected, the diversity increases with information load and is maximized for high $\mu$.

The tradeoffs between discriminative power and diversity are better illustrated in Fig. 6. For any value of finite attention $\alpha > 1$ we observe a transition from high discriminative power and low diversity (low information load) to high diversity and low discriminative power (high information load). The amount of attention $\alpha$ has a significantly effect on the tradeoff: for a given level of diversity the discriminative power improves when people can pay attention to multiple memes, and vice versa the network can sustain a larger diversity without loss in
Figure 4: Illustration of the tradeoff between discriminative power of the system in spreading quality memes and diversity of content in the network. Nodes represent agents, their color represents the last shared meme, and their size indicates the fitness of that meme. When $\mu$ is small, only high-fitness memes are present, with low diversity. As $\mu$ increases we observe higher diversity and lower discriminative power. Here $N = 128$ and $\alpha = 10$.

Figure 5: Diversity $H/H(\mu = 1)$ as a function of intensity of information load and attention.

discriminative power. When $\alpha$ is large, there is a region where the network can sustain very high diversity with relatively small loss in discriminative power.

2.4 Empirical calibration

We have made two simplifying assumption about the agents in our model: that they introduce new memes at the same rate $\mu$ and have the same amount of attention $\alpha$. In the real world, some people may post more new memes, others
Figure 6: Tradeoff between discriminative power $\tau$ and diversity $H/H(\mu=1)$. For each value of the attention $\alpha$, different tradeoffs are obtained by varying $\mu$ between 0 and 1. The light-colored line corresponds to $\alpha = 14$, points in circles correspond to $\mu = 0.75$, and the large filled blue circle marks the case with $\alpha = 14$ and $\mu = 0.75$. The dashed line suggests convergence in the limit for high $\alpha$. The solid line marks the discriminative power of the model where the empirical heterogeneities of $\mu$ and $\alpha$ are taken into account.

may tend to share memes adopted through their connections; some may pay attention to only a handful of messages, others may scroll through social media feeds for prolonged periods. Let us turn to empirical data to calibrate these ingredients of the model.

We counted tweets and retweets by a large sample of Twitter users to estimate the portions of original and reshared memes per user (see Methods). Fig. 7 shows the resulting empirical distribution of the rate of introduction of new memes, which corresponds to the parameter $\mu$ in our model. The information load spans the entire spectrum ($\mu \in [0,1]$) but is skewed toward high values with a peak at $\mu = 1$, corresponding to users who post but do not reshare. The average is quite high ($\langle \mu \rangle \approx 0.75$).

The amount of attention one devotes to assessing information, ideas and opinions encountered in online social media varies not only across persons but also depending on time and circumstance; the same user may be hurried one time and careful another. We counted the number of times that a user stops on a post during a scrolling session on the Tumblr social blogging platform to estimate their finite attention (see Methods). This number corresponds to the parameter $\alpha$ in our model. Fig. 8 shows that the resulting empirical distribution of $\alpha$ is broad, with average $\langle \alpha \rangle \approx 14$.

A naive way to calibrate our model market of ideas to take these data into
account is to set the information load and attention parameters to their empirical averages, $\langle \mu \rangle \approx 0.75$ and $\langle \alpha \rangle \approx 14$, respectively. This yields the values of $\tau$ and $H/H(\mu = 1)$ highlighted in Fig. 6 suggesting that real social media function in a regime of high diversity. The discriminative power is roughly 70% of the maximum $\tau$ obtained in the limit of high $\alpha$. Given this empirical value of attention, the information load in the real world sets us in a region where a significant increase in discriminative power could be obtained with a small loss in diversity.

However, the data provide us with further insight about the mechanisms of the market. In fact, the empirical findings can be explained by a simple extension of the model that takes into account how users scroll through their social media feeds. Rather than assuming a fixed feed depth and a single post or repost per session, imagine that users scroll through their feeds by paying attention to messages and resharing them in sequence, until they decide to stop the session. With some probability $\rho$ the user posts a message with a new meme and stops. Otherwise, with probability $1-\rho$, the user performs a scrolling session. After resharing a message, the user stops with probability $q$. Otherwise, with probability $1-q$, the user scrolls down to view and reshare another message, and so on. Let us further assume that for each session, $q$ is drawn uniformly from an interval $[\langle q \rangle - \sigma, \langle q \rangle + \sigma]$. It can be shown analytically that when $\sigma$ is small, the distribution of $\alpha$ is well approximated by an exponential decay; in the limit $\sigma \to 0$, $P(\alpha) \sim e^{\lambda(\alpha-1)}$ with $\lambda = \ln(1-\langle q \rangle) < 0$. As $\sigma \to \langle q \rangle$, for large $\alpha$ the distribution approaches a power law $P(\alpha) \sim \alpha^{-2}$. The heavy tail indicates that users occasionally scroll through a large number of messages. These behaviors are illustrated in Fig. 8. The parameters $\rho$, $\langle q \rangle$, and $\sigma$ can be tuned to fit the empirical distributions of $\mu$ from Twitter (Fig. 7) or $\alpha$ from Tumblr (Fig. 8). Both distributions can be fit by approximately the same values of $\langle q \rangle$ and $\sigma$, while $\rho$ is different in the two cases.
Figure 8: Empirical distribution of attention $\alpha$ derived from Tumblr. The lines are produced by the scrolling model described in the text, with $\rho = 0.05$ and $\langle q \rangle = 0.1$.

To explore the effect of the attention heterogeneity $\sigma$ on discriminative power, we incorporated the scrolling mechanism into the model to generate $\alpha$ and found that high $\sigma$ leads to a significant decrease in discriminative power. This is due to the fact that although $\alpha$ increases with $\sigma$ on average, large values yield little benefit in discriminative power whereas small values cause serious discriminative power losses. These results suggest that the assumptions of constant $\mu$ and, especially, constant $\alpha$ should be refined in our model market of ideas. We therefore calibrated the model by drawing both $\mu$ and $\alpha$ from the empirical distributions of information load and attention. We repeated the analysis with this modified model and found a significantly lower value of discriminative power, $\tau \approx 0.15$ (Fig. 6). This finding reinforces the notion that the heterogeneous information load and attention of the real world lead to a market that is incapable of discriminating information on the basis of quality.

3 Discussion

The proposed model is quite minimal and relies on few parameters, but it captures salient behavioral features that shape the diffusion of information in online social networks. This allows us to study how information load and limited attention affect the discriminative power of the network, i.e., the likelihood that the best memes will succeed at reaching many people. Our main finding is that the survival of the fittest is far from a foregone conclusion where information is concerned. Both information load and limited attention lead to low discriminative power, so that it becomes very difficult for the best memes to win. Meme diversity can coexist with network discriminative power when we have plenty of attention and are not overloaded with information.

One important direction that is not explored here is the role played by the network structure and size in determining market discriminative power and di-
versity. Our model could be further expanded to capture characteristics derived from empirical social networks, such as large size and high clustering. How the predictions of our model depend on these features remains to be investigated.

Empirical validation of the predictions generated by our model remains a challenge, given the difficulty to measure the intrinsic quality of a meme in the real world. However, it is possible to derive empirical estimations of the key parameters in our model, namely the rate of introduction of new memes and the depth of user attention. According to these calibrations, real social media have heterogeneous levels of information load and attention, and therefore are in a regime of low discriminative power. If prior research had revealed that intrinsic quality is not a necessary ingredient to explain the broad distribution of meme popularity in social media [49, 19], the present results are not much more reassuring. They suggest that better memes do not have a significantly higher likelihood to become popular compared to low quality information. The observation that hoaxes and fake news spread as virally as reliable information in online social media (Fig. 1) is not too surprising in light of these findings.

4 Methods

4.1 Model of online information market

The basic setting for our model is a set of agents connected by an arbitrary network. Fig. 9 illustrates the dynamics of the model. Each agent holds a feed of the $\alpha$ most recent messages produced by their neighbors. At each time step one agent $i$ is chosen at random. With probability $\mu$, $i$ produces a message carrying a new meme. The meme’s fitness is drawn uniformly at random from the unit interval. Alternatively, with probability $1 - \mu$, $i$ selects one of the messages in its feed. The probability that an agent selects a specific message $m$ from its feed is proportional to the meme’s fitness $f(m)$. More explicitly, let $M_i$ be the feed of $i$ ($|M_i| = \alpha$). The probability of message $m \in M_i$ being selected is $P(m) = f(m)/\sum_{j \in M_i} f(j)$ where $f(m)$ is the fitness of the meme carried by $m$. The message is added to the feeds of $i$’s neighbors; if a feed exceeds $\alpha$ messages, the oldest is forgotten. This mechanism represents how finite attention is allocated to information posted by one’s social connections.

The two parameters of the model allow us to explore how the intensity of the information load ($\mu$) and the attention depth ($\alpha$) interact with the intrinsic value of an idea and affect its chances to win.

We analyze the behavior of the model by simulating the diffusion and information load process on synthetic scale-free networks (see below). As the competition takes place, some of the memes die fast while others live longer and infect a large fraction of the network. Such a process continues until the system reaches a steady state in which the average number of distinct memes remains roughly constant. This number depends on $\mu$.

The popularity of a meme can be defined by the cumulative attention it gathers across the network. In practice, we measure popularity by counting
Figure 9: Illustration of the meme diffusion model. At each time step, an agent is considered (shaded). The agent chooses to create and share a new meme ($m_9$) with probability $\mu$. Otherwise, with probability $1 - \mu$, the agent reshares one of $\alpha$ messages in its feed, to which it is currently paying attention ($m_6$). The message is transmitted to the agent’s neighbors and appears on the top of their feeds.

The number of times a meme is shared or reshared. The measurements occur at steady state. The distribution of meme popularity, shown in Fig. [10], depends on $\mu$. For high $\mu$, the distribution is exponentially narrow and no memes go viral. As the information load becomes lighter ($\mu < 0.2$), our model is consistent with the broad distribution from the empirical data, indicating that a few memes spread virally through the population.

The scale-free synthetic network used in our experiments was built with the preferential attachment (BA) model, with $N = 10^3$ nodes and average degree $\langle k \rangle = 20$.

For each experiment and set of parameter values, we simulated the dynamics of the model on the synthetic network. Once the system reached the steady state, we performed measurements to determine the success of a meme. To this
end we considered only memes that were introduced after the system reached the steady state. We followed each of these memes from the moment it was first shared until it completely disappeared from the network, recording its fitness as well as its popularity. During each simulation, we monitored 100,000 memes that were introduced and forgotten after the system reached the steady state. We ran each simulation 20 times, so that our analyses of popularity took $2 \times 10^6$ memes into consideration. Measurements of discriminative power and diversity were averaged across runs.

### 4.2 Data

Data about Facebook shares of articles supporting or debunking true and false claims was collected from Emergent ([emergent.info](https://emergent.info)), a rumor tracking project active between September 2014 and March 2015. The Emergent API provided data about 464 articles supporting 56 true claims, 278 articles fact-checking 72 false claims, 10 articles undermining 3 true claims, and 373 articles spreading 90 false claims.

Twitter data was obtained from a sample of public posts provided by the Twitter streaming API. We extracted the empirical rate $\mu$ from $10^6$ Twitter users based on a random sample of messages collected in 2014. We counted their tweets ($n_t$) and retweets ($n_r$), then measured each user’s rate as $\mu = n_t/(n_t+n_r)$.

We extracted the empirical attention data from approximately $10^7$ mobile scrolling sessions on Tumblr during two weeks in 2016. We consider a session

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**Figure 10:** Distribution (PDF) of meme popularity $p$. We compare the model predictions ($\alpha = 10$) with an empirical distribution obtained by counting the number of occurrences of hashtags in a sample of approximately 10% of public tweets collected in 2014. This empirical data is consistent with a power-law distribution $P(p) \sim p^{-\beta}$ with exponent $\beta \approx 1.9$ (see guide for the eye).
ended when there is no interaction for 30 minutes or longer. During a session, we record the number of times that a user scrolls at least 500 pixels through the feed and then stops for at least one second. This number is used as a proxy for $\alpha$.

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