Echo chambers in the age of misinformation

Michela Del Vicario *, Alessandro Bessi †, Fabiana Zollo *, Fabio Petroni ‡, Antonio Scala * †, Guido Caldarelli * ‡, H. Eugene Stanley ‡ *, Walter Quattrociocchi *

*Laboratory of Computational Social Science, Networks Dept IMT Alti Studi Lucca, 55100 Lucca, Italy, †IUSS Institute for Advanced Study, 27100 Pavia, Italy, ‡Sapienza University, Rome, Italy, †ISC-CNR Uos “Sapienza”, 00185 Roma, Italy, ‡Boston University, Boston, MA 02115 USA, and * corresponding author walter.quattrociocchi@imtlucca.it

The wide availability of user-provided content in online social media facilitates the aggregation of people around common interests, worldviews, and narratives. Despite the enthusiastic rhetoric on the part of some that this process generates “collective intelligence”, the WWW also allows the rapid dissemination of unsubstantiated conspiracy theories that often elicit rapid, large, but naïve social responses such as the recent case of Jade Helm 15 – where a simple military exercise turned out to be perceived as the beginning of the civil war in the US. We study how Facebook users consume information related to two different kinds of narrative: scientific and conspiracy news. We find that although consumers of scientific and conspiracy stories present similar consumption patterns with respect to content, the sizes of the spreading cascades differ. Homogeneity appears to be the primary driver for the diffusion of contents, but each echo chamber has its own cascade dynamics. To mimic these dynamics, we introduce a data-driven percolation model on signed networks.

misinformation | rumor spreading | collective narratives | crowd dynamics | online social media

The massive diffusion of socio-technical systems and microblogging platforms on the WWW creates a direct path from producers to consumers of content, i.e., allows disintermediation and changes the way users become informed, debate, and form their opinions [11, 12, 13, 14, 15]. This disintermediated environment can foster confusion about causation, and thus encourage speculation, rumors, and mistrust [16]. In 2011 a blogger claimed that global warming was a fraud designed to diminish liberty and weaken democracy [17]. Misinformation about the Ebola epidemic has caused confusion among healthcare workers [18]. Recent research [9, 10, 11] has shown that increasing the exposure of users to unsubstantiated rumors increases their tendency to be credulous.

According to Ref. [12], beliefs formation and revision is influenced by the way communities attempt to make sense to events or facts. Such a phenomenon is particularly evident on the WWW where users, embedded in homogeneous clusters [18, 19, 20], process information through a shared system of meaning [9, 10].

Here we analyze the cascade dynamics of Facebook users when the content is (i) conspiracy theories and (ii) scientific information. Conspiracy theories simplify causation, reduce the complexity of reality, and contain uncertainty [16, 17, 18]. Scientific information disseminates scientific advances and exhibits the process of scientific thinking. The main difference between the two is content verifiability. The generators of scientific information and their data, methods, and outcomes are readily identifiable and available. The origins of conspiracy theories are often unknown and the content of the theories is strongly disengaged from mainstream society and sharply divergent from recommended practices [19], e.g., belief that vaccinations cause autism.

Massive digital misinformation is becoming pervasive in online social media to the extent that it has been listed by the World Economic Forum (WEF) as one of the main threats to our society [20]. To counteract this trend, algorithm-driven solutions have been proposed [21, 22, 23, 24, 25, 26], e.g., Google [27] is developing a trustworthiness score to rank the results of queries. Similarly, Facebook has proposed a community-driven approach where users can flag false contents to correct the news-feed algorithm. This issue is controversial, however, because it raises fears that the free circulation of content may be threatened and the proposed algorithms not be accurate or effective [9, 10, 28]. Often conspiracists will denounce attempts to debunk false information, e.g., the link between vaccination and autism, as acts of misinformation.

Whether a claim (either substantiated or not) is accepted by an individual is strongly influenced by social norms and the claim’s coherence with the individual’s belief system [29, 30]. Despite some enthusiastic claims about the growth of a collective intelligence [31], many mechanisms animate the flow of false information that generates false beliefs in an individual, which, once adopted, are rarely corrected [32, 33, 34, 35].

We use quantitative analysis to show that homogeneity is the primary driver of content diffusion and generates the formation of homogenous, polarized clusters, i.e., “echo chambers” [9, 10, 36, 37]. We also find that although consumers of scientific information and conspiracy theories exhibit similar consumption patterns with respect to content, the cascade patterns of the two differ. Homogeneity appears to be the preferential driver for the diffusion of content, yet each echo chamber has its own cascade dynamics.

Methods

Ethics Statement. The data collection process has been carried out using the Facebook Graph API [38], which is publicly

SIGNIFICANCE: Using a massive quantitative analysis of Facebook, we show that information related to very specific narratives – conspiracy theories and scientific news – generates homogeneous and polarized communities that have similar information consumption patterns. To account for these features we derive a data-driven percolation model of rumor spreading that demonstrates that homogeneity and polarization are the main determinants for predicting cascade size.

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available. For the analysis (according to the specification settings of the API) we only used publicly available data (thus users with privacy restrictions are not included in the dataset). The pages from which we download data are public Facebook entities and can be accessed by anyone. User content contributing to these pages is also public unless the user’s privacy settings specify otherwise, and in that case it is not available to us.

Data collection. Debate about social issues continues to expand across the Web, and unprecedented social phenomena such as the massive recruitment of people around common interests, ideas, and political visions are emerging. Using the approach described in Ref. [3], we define the space of our investigation with the support of diverse Facebook groups that are active in the debunking of conspiracy theories.

The resulting dataset is composed of 67 public pages divided between conspiracy and science news. A second set, composed of two troll pages, is used as a benchmark to fit our data-driven model. The first category (conspiracy theories) includes the pages that disseminate alternative, controversial information, often lacking supporting evidence and frequently advancing conspiracy theories. The second category (science news) includes the pages that disseminate scientific information. The third category (trolls) includes those pages that intentionally disseminate sarcastic false information on the Web.

For the three sets of pages we download all the posts (and their respective user interactions) across a five-year timespan (2010 to 2014). We perform the data collection process by using the Facebook Graph API [38], which is publicly available and accessible through any personal Facebook user account. The exact breakdown of the dataset is presented in the Supporting Information (SI) Section 1.

Preliminaries and Definitions. A tree is an undirected simple graph that is connected and has no simple cycles. An oriented tree is a directed acyclic graph whose underlying undirected graph is a tree. A sharing tree in the context of our research is an oriented tree made up of the successive sharing of a news item through the Facebook system. The root of the sharing tree is the node that performs the first temporal share. We define the size of the sharing tree as the number of nodes (and hence the number of news sharers) in the tree and the height of the sharing tree as the maximum path length distant from the root.

We define the user polarization $\sigma = 2\rho - 1$, where $0 \leq \rho \leq 1$ is the fraction of “Likes” a user executes on conspiracy related content, and hence $-1 \leq \sigma \leq 1$. From user polarization, we define the edge homogeneity for any edge $e_{ij}$ between nodes $i$ and $j$, as

$$\sigma_{ij} = \sigma_i \sigma_j,$$

with $-1 \leq \sigma_{ij} \leq 1$. Edge homogeneity reflects the similarity level between the polarization of the two sharing nodes. A link in the sharing tree is homogeneous if its edge homogeneity is positive, otherwise it is non homogeneous. We then define a sharing path to be any path from the root to one of the leaves of the sharing tree. A homogeneous path is a sharing path for which the edge homogeneity of each edge is positive, i.e., a sharing path whose edges are all homogeneous links.

Wald Test. We use the Wald test to compare the scaling parameters of two power law distributions. We define it as

$$H_0 : \alpha_1 = \alpha_2$$

$$H_1 : \alpha_1 \neq \alpha_2$$

where $\alpha_1$ and $\alpha_2$ are the estimated scaling parameters. The Wald statistic:

$$W = \frac{(\hat{\alpha}_1 - \hat{\alpha}_2)^2}{Var(\hat{\alpha}_1)},$$

follows a $\chi^2$ distribution with one degree of freedom. We reject the null hypothesis $H_0$ and conclude that there is a significant difference between the two scaling parameters if the $p$-value of $W$ is below a given significance level $\alpha$.

Kolmogorov-Smirnov Test. We use the Kolmogorov-Smirnov test to compare the empirical distribution functions of two samples. The Kolmogorov-Smirnov statistic for two given cumulative distribution functions $F_1(x)$ and $F_2(x)$ is

$$D = \sup_x |F_1(x) - F_2(x)|,$$

which measures the maximum punctual distance between the two sample distributions. If $D$ is bigger than a given critical value $D_{c,\alpha}$ we reject the null hypothesis $H_0 : F_1(x) = F_2(x)$ and conclude that there is a significant difference between the two sample distributions.

Results and discussion

Anatomy of Cascades. We begin our analysis by characterizing the statistical signature of cascades as they relate to information type. We analyze the three types—science news, conspiracy rumors, and trolling—and find that size and maximum degree are power-law distributed for all three. The maximum cascade size values are 952 for science news, 2422 for conspiracy news, and 3945 for trolling, and the estimated exponents for the power law distributions are 2.21 for science news, 2.47 for conspiracy theories, and 2.44 for trolling. Tree height values range from 1 to 5, with a maximum height of 5 for science news and conspiracy theories and a maximum height of 4 for trolling. For further information see SI Section 2.1.

Figure 1 shows the probability density function (PDF) of the cascade lifetime (using hours as time units) for science and conspiracy. We compute the lifetime as the length of time between the first user and the last user sharing a post. In both categories we find a first peak at approximately 1–2 hours and a second at approximately 20 hours, indicating that the temporal sharing patterns are similar irrespective of the difference in topic. We also find that a significant percentage of the information diffuses rapidly (24.42% of the science news and 20.76% of the conspiracy rumors diffuse in less than two hours, and 39.45% of science news and 40.78% of conspiracy theories in less than five hours). Only 26.82% of the diffusion of science news and 17.79% of conspiracy lasts more than one day. Kolmogorov-Smirnov test made us reject the hypothesis $H_0$ that the two distributions are equal.

Figure 2 shows lifetime as a function of cascade size. For science news we have a peak in the lifetime corresponding to a cascade size value of $\approx 200$, and higher cascade size values correspond to high lifetime variability. For conspiracy related content the lifetime increases with cascade size.

These results suggest that news assimilation differs according to category. Science news is usually assimilated, i.e., it reaches a higher level of diffusion, quickly, and a longer lifetime does not correspond to a higher level of interest. Conversely,
conspiracy rumors are assimilated more slowly and show a positive relation between lifetime and size. For both science and conspiracy news, we compute size as a function of lifetime and confirm that differentiation in the sharing patterns is content-driven, and that for conspiracy there is a positive relation between size and lifetime. For a more detailed explanation, see SI Section 2.1.

Homogeneous Clusters. We next examine the social determinants that drive sharing patterns and we focus on the role of homogeneity in friendship networks. Figure 3 shows the PDF of the mean edge homogeneity, computed for all cascades of science news and conspiracy theories. It shows that there are homogeneous links between evenly spaced users. In particular, the average edge homogeneity value of the entire sharing cascade is always greater or equal to zero, indicating that either the information transmission occurs inside homogeneous clusters in which all links are homogeneous or it occurs inside mixed neighborhoods in which the balance between homogeneous and non-homogeneous links is favorable towards the former ones. However, the probability of an edge being zero mean edge homogeneity is really small.

To further characterize the role of homogeneity in sharing cascades, we compute cascade size as a function of mean edge homogeneity for both science and conspiracy news, see Figure 1. In science news, higher levels of mean edge homogeneity in the interval (0.5, 0.8) correspond to larger cascades, but in conspiracy theories lower levels of mean edge homogeneity (∼ 0.25) correspond to larger cascades. Notice that, although viral patterns related to distinct contexts differ, homogeneity is clearly the driver of information diffusion. In other words, different contents generate different echo chambers, characterized by the high level of homogeneity inside them.

The probability density function (PDF) of the edge homogeneity for science news and conspiracy theories, see SI Section 2.1. We record the CCDF of the number of all sharing paths on each cascade with the CCDF of the number of homogeneous paths for science and conspiracy news, and the two together. A Kolmogorov-Smirnov test and Q-Q plots confirm that for all three pairs of distributions considered there is no significant statistical difference (see SI Section 2.2 for a more detailed analysis). In SI Section 2.2 we report also the frequency of maximum length for all sharing paths and homogeneous paths, for both categories of content.

We confirm the pervasiveness of homogeneous paths; but we also find homogeneous paths in which there is a shift of −1 in the path length (with respect to the total path length k). Notice that the first publisher of a news is generally a page, hence the (k − 1)-homogeneous paths are due to a discordant sharing in the first step (i.e., when the product of the first sharer’s user polarization and the sharer page category is negative).

Cascade lifetimes of science and conspiracy news exhibit a probability peak in the first two hours, and that in the following hours they rapidly decrease. Despite the similar consumption patterns, cascade lifetime expressed as a function of cascade size differs greatly for the different content sets. The PDF of the mean edge homogeneity indicates that there is homogeneity in the linking step of sharing cascades. The distribution of the number of total and homogeneous sharing paths are very similar for both content categories.

Viral patterns related to contents belonging to different narratives differ, but homogeneity is clearly the driver of content diffusion.

The Model. We now introduce a percolation model of rumor spreading to account for homogeneity and polarization. We consider n users connected by a small-world network. The model parameter space varies on a rewiring probability r, mimicking the network density, and a news set of size m.

Every node has an opinion ω, i ∈ [1, n] uniformly distributed in [0, 1]. Every news item has a fitness (degree of interest) θj, j ∈ [1, m] uniformly distributed in [0, 1]. At each step the news items are diffused and initially shared by a group of first sharers. After the first step, the news recursively passes to the neighborhoods of previous step sharers, e.g., those of the first sharers during the second step. If a friend of the previous step sharers has an opinion close to the fitness of the news, then she shares the news again.

In particular, when |ωi − θj| ≤ δ, user i shares news j; δ is the sharing threshold.

Because δ by itself cannot capture the homogeneous clusters observed in the data, we model the connectivity pattern as a signed network considering different fractions of homogeneous links and hence restricting diffusion of news only to homogeneous links. We define φHL as the fraction of homogeneous links in the network, M as the number of total links, and nh as the number of homogeneous links, thus we have:

\[ φ_{HL} = \frac{nh}{M}, \quad 0 \leq nh \leq M. \]

Notice that 0 ≤ φHL ≤ 1 and that 1 − φHL, the fraction of non-homogeneous links, is complementary to φHL. In particular, we can reduce the parameters space to φHL ∈ [0, 1] as we would restrict our attention to either one of the two complementary clusters.

The model can be seen as a branching process where the sharing threshold δ and neighborhood dimension z are the key parameters. More formally, let the fitness θj of the jth news and the opinion ωi of the ith user be uniformly i.i.d. between [0, 1]. Then the probability p that a user i shares a post j is defined by a probability \( p = \min(1, \theta_i + \delta - \max(0, \theta_i - \delta) \approx 2\delta \), since θ and ω are uniformly i.i.d. In general, if ω and θ have distributions f(ω) and f(θ), then p will depend on θ:

\[ \gamma = f(\theta) \int_{\max(0, \theta - \delta)}^{\min(1, \theta + \delta)} f(\omega) d\omega. \]

If we are on a tree of degree z (or on a sparse lattice of degree z + 1), the average number of sharers (the branching ratio) is defined by

\[ \mu = zp \approx 2\delta z \]

with a critical cascade size S = (1 − μ)−1. If we assume that the distribution of the number m of the first sharers is f(m), then the average cascade size is

\[ S = \sum m \cdot f(m) (1 - \mu)^{-1} = \frac{\langle m \rangle_f}{1 - \mu} \approx \frac{\langle m \rangle_f}{1 - 2\delta z} \]

where \( \langle \ldots \rangle_f = \sum \ldots f(m) \) is the average with respect to f. In the simulations we fixed neighborhood dimension z = 8

2Recall that a sharing path is here defined as any path from the root to one of the leaves of the sharing tree. A homogeneous path is a sharing path for which the edge homogeneity of each edge is positive.
since the branching ratio $\mu$ depends upon the product of $z$ and $\delta$ and, without loss of generality, we can consider the variation of just one of them. If we allow a probability $q$ that a neighbor of a user has a different polarization, then the branching ratio becomes $\mu = (1-q)p$. If a lattice has a degree distribution $d(k) = 1 + \delta$, we can then assume a usual percolation process that provides a critical branching ratio and that is linear in $\langle k^2 \rangle_d / \langle k \rangle_d$ ($\mu \approx (1-q) p \langle z^2 \rangle / \langle z \rangle$).

**Simulation Results**. We explore the model parameters space using $n = 5,000$ nodes and $m = 1,000$ news items with the number of first sharers distributed as an (i) inverse Gaussian, (ii) log normal, (iii) Poisson, (iv) uniform distribution, and as the real data distribution (from the science and conspiracy news sample). Parameters are chosen to fit the real data distribution (for details see SI Section 3.1, 3.2). In Table we report the same information as Table 1 for trolling category. Also in this case we notice that the best fit is obtained by the inverse Gaussian ($IG$), shows the best fit for the distribution of first sharers with respect to all the considered statistics.

Along with the first sharers distribution, we vary the sharing threshold $\delta$ in the interval [0.01, 0.05] and the fraction of homogeneous links $\phi_{HL}$ in the interval [0.5, 1]. To avoid biases induced by statistical fluctuations in the stochastic process, each point of the parameter space is averaged over 100 iterations. $\phi_{HL} \sim 0.5$ provides a good estimate of real data values. In particular, consistently with the division of in two echo chambers (science and conspiracy), the network is divided into two clusters in which news items remain inside and are transmitted solely within each community’s echo chamber (see SI Section 3.2 for the details of the simulation results).

In addition to the science and conspiracy content sharing trees, we downloaded a set of 1,072 sharing trees of intentionally false information from troll pages. Frequent troll information, e.g., parodies of conspiracy theories such as chemtrails containing the active principle of Viagra, is picked up by habitual conspiracy theory consumers. In SI Section 3.2 we report the same information as Table 1 for trolling category. Also in this case we notice that the best fit is obtained by the inverse Gaussian distribution.

We computed the mean and standard deviation of size and height of all sharing trees, and reproduced the data using our model. We used fixed parameters from trolling messages (the number of nodes in the system and the number of news items) and varied the fraction of homogeneous links $\phi_{HL}$, the rewiring probability $r$, and sharing threshold $\delta$. See SI Section 3.2 for the distribution of first sharers used and for additional simulation results of the fit on trolling messages.

We simulated the model dynamics with the best combination of parameters obtained from the simulations and the number first sharers distributed as an inverse Gaussian, figure 7 shows the CCDF of size and the CDF of height. A summary of relevant statistics (min value, first quantile, median, mean, third quantile, and max value) to compare the real data size and height distributions with the fitted ones is reported in SI Section 3.2. We notice that the fit is good for all the statistics, with the exception of min and max value of size. For the min value, the presence of a zero is due to the fact that the inverse Gaussian is a real valued distribution function and in simulations we considered the integer part of the number of first sharers, thus producing a number of never shared pieces of information. On the other hand, the high difference in the max value is probably due to the long tail of the data size distribution.

We find that the inverse Gaussian is the distribution that best fits the data results both for science and conspiracy news, and for troll messages. For this reason, we performed one more simulation using the inverse Gaussian as distribution of the number of first sharers, 1,072 news items, 16,889 users, and the best parameters combination obtained in the simulations. The CCDF of size and the CDF of height for the above parameters combination, as well as basic statistics considered, fit the real data ones from the trolling category.

**Conclusions**. Digital misinformation has become so pervasive in online social media that it has been listed by the World Economic Forum (WEF) as one of the main threats to human society. Whether a news item, either substantiated or not, is accepted as true by a user may be strongly affected by social norms or by how much it coheres with the user’s system of beliefs [29,30]. Despite enthusiastic claims that social media is generating a vast “collective intelligence” available to all [31], many mechanisms cause false information to gain acceptance, which in turn generate false beliefs that, once adopted by an individual, are highly resistant to correction [32,33,34]. Using extensive quantitative analysis we show that social homogeneity is the primary driver of content diffusion, and one frequent result is the formation of homogeneous, polarized clusters (often called “echo chambers”). We also find that although consumers of science news and conspiracy theories show similar consumption patterns with respect to content, their cascades differ. Social homogeneity appears to be the primary driver of content diffusion, and each echo chamber has its own cascade dynamics. To mimic these dynamics, we introduce a data-driven percolation model of signed networks, i.e., networks composed of signed edges. Our analysis shows that for science and conspiracy news a cascade’s lifetime has a probability peak in the first two hours followed by a rapid decrease. Although the consumption patterns are similar, cascade lifetime as a function of the size differs greatly. The PDF of the mean edge homogeneity indicates that homogeneity is present in the linking step of sharing cascades. The distribution of the number of total sharing paths and homogeneous sharing paths are similar in both content categories. Viral patterns related to distinct contents are different but homogeneity drives content diffusion. We simulate our data-driven percolation model by fixing the number of users and news items downloaded from troll pages and varying the other parameters. We compare the simulated results with the data and find a high level of similarity.

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Fig. 1. Probability density function (PDF) of Lifetime computed on science news and conspiracy theories, where the lifetime is here computed as the temporal distance (in hours) between the first and last share of a post. Both categories show a similar behavior, with a peak in the first two hours and another around 20 hours.

Fig. 2. Lifetime as a function of the cascade size for conspiracy news (left) and science news (right). We note a contents-driven differentiation in the sharing patterns. For conspiracy the lifetime grows with the size, while for science news there is a peak in the lifetime around a value of the size equal to 200, and a higher variability in the lifetime for larger cascades.

Fig. 3. Mean edge homogeneity for science (solid orange) and conspiracy (dashed blue) news. The mean value of edge homogeneity on the whole sharing cascades is always greater or equal to zero.
Fig. 4. Cascade size as a function of mean edge homogeneity for science (solid orange) and conspiracy (dashed blue) news.

Fig. 5. Complementary cumulative distribution function (CCDF) of size (left) and cumulative distribution function (CDF) of height (right) for the best parameters combination that fits troll data values, $(\phi_{IG}, r, \delta) = (0.56, 0.01, 0.015)$, and first sharers distributed as $IG(18.73, 0.63)$. We note that it is indeed a good fit of trolling data.

Table 1. Summary of relevant statistics for the first sharers distributions.

|       | Data | IG  | LN  | Poi |
|-------|------|-----|-----|-----|
| Min   | 1    | 0.36| 0.10| 20  |
| 1st Qu.| 5    | 4.16| 3.16| 35  |
| Median | 10   | 10.45| 6.99| 39  |
| Mean  | 39.34| 39.28| 13.04| 39.24|
| 3rd Qu.| 27   | 31.59| 14.85| 43  |
| Max   | 3033 | 1814| 486.10| 66  |