Everyday the Same Picture: Popularity and Content Diversity

Alessandro Bessi, Fabiana Zollo, Michela Del Vicario, Antonio Scala, Fabio Petroni, Bruno Gonçcalves and Walter Quattrociocchi

Abstract Facebook is flooded by diverse and heterogeneous content, from kittens up to music and news, passing through satirical and funny stories. Each piece of that vivid production reflects the heterogeneity of the underlying social background and provides sometimes interesting opportunities for the study of social dynamics. Indeed, in Facebook we found an interesting case: a page having more than 40 K followers that every day posts the same picture of a popular Italian singer. We use such a peculiar page as a baseline for the study and modeling of the relationship between content heterogeneity and popularity. In particular, we perform a comparative analysis of information consumption patterns with respect to pages posting heterogeneous content (science and conspiracy news). We conclude the paper by introducing a model mimicking users selection preferences accounting for the heterogeneity of contents.

1 Introduction

Online social networks such as Facebook foster the aggregation of people around common interests, narratives, and worldviews. Indeed, the World Wide Web caused a paradigm shift in the production and consumption of contents that increased both

A. Bessi
Information Sciences Institute, University of Southern California, Los Angeles, CA, USA

F. Zollo · M. Del Vicario · W. Quattrociocchi
IMT Institute for Advanced Studies, Lucca, Italy

A. Scala
ISC CNR, Rome, Italy

F. Petroni
Sapienza University of Rome, Rome, Italy

B. Gonçcalves (✉)
Center for Data Science, New York University, New York, NY, USA
e-mail: bgoncalves@gmail.com

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its volume and heterogeneity. Users can express their attitudes by producing and consuming heterogeneous information—e.g. conspiracists avoid mainstream news and follow their own information sources, whereas debunkers try to inhibit the diffusion of false claims. Images of kittens and pets, political memes, gossip, scandals spread on Facebook. By liking, commenting, and sharing their preferred contents, users express their passions and emotions—with sarcasm being no exception. In particular, pages promoting parody and sarcastic imitations of online social dynamics are common occurrences—e.g., *Ebola and Kittens* [1] or *In favor of chem-trails* [2]—An interesting case in Facebook is a page [3] with more than 40 K followers that posts everyday the exactly alike picture of Toto Cutugno, a famous Italian pop-singer.

In this work, we use this page as a baseline with which to study the effect of content diversity on popularity/virality. Specifically, we analyze user activity and post consumption patterns on the baseline page for a timespan of about 4 months. Through a comparative analysis between two sets of pages producing heterogeneous contents, we show that there are no remarkable differences in user activity patterns, whereas significant dissimilarities between post consumption patterns emerge. Such a comparative analysis allows to model information consumption accounting for the heterogeneity of contents. Hence, we show that the proposed model is able to reproduce the phenomenon observed from empirical data. In particular, we show the effects of different levels of contents' heterogeneity on posts consumption patterns.

The remainder of the paper is structured as follows. Background and Related Work reviews the literature on the study of social dynamics in online social media, stressing the challenges raised by the economy of attention. In Data Description we describe the Facebook dataset we used, whereas in Preliminaries and Definitions we explain some of the statistical tools we use throughout the paper. In Results and Discussion we show some statistical signatures concerning user activity and post consumption patterns, and then we introduce and discuss our data-driven model of information consumption. Finally, Concluding Remarks summarizes our findings.

2 Background and Related Works

A large body of literature addresses the study of social dynamics on socio-technical systems from social contagion to social reinforcement [4, 9, 13–16, 20, 23–25, 30–37, 46]. Among these, one of the most defining topics of computational social science is the understanding of the driving forces behind content popularity [44]. This challenge is typically addressed by analyzing the sentiment of comments, post, and users' attention [7, 19, 22, 27, 28, 38, 42, 45, 49]. However, the mechanisms behind popularity remain largely unexplored [21, 29, 47]: Why do some pieces of content become viral while other, seemingly identical, languish in obscurity? In [40] the authors tackle this question experimentally by measuring the impact of content quality and social influence on the eventual popularity or success of cultural artifacts. The effects of specific contents on the formation of communities of interest, their permeability to false information, and the resistance to changes were recently

characterized in [10–12, 39] while in [5] the authors observe that connectivity patterns of the Facebook social network are prominently driven by homophily of users—i.e., the tendency of individuals to associate with others that are similar to them—towards specific kinds of contents. Microblogging platforms such as Facebook and Twitter [43] have lowered the cost of information production and broadcasting, boosting the potential reach of each idea or meme [8, 17]. Still, the abundance of information to which we are exposed through online social networks and other socio-technical systems is rapidly exceeding our capacity to consume it [48] causing information dynamics to be attention driven more than it had ever been before [18, 26, 41]. We further this debate and study the interlink between content diversity and popularity.

3 Data Description

In this work, we aim at investigating the role of content diversity on the dynamics of information consumption in online social networks. To this end, we use a set of Facebook pages promoting heterogeneous contents and a Facebook page promoting always the same picture. The set of pages promoting heterogeneous contents is composed by 73 public Facebook pages, whereof 34 are about science news and 39 are about conspiracy theories; we refer to the former as *science pages* and to the latter as *conspiracy pages* [11]. Using two significantly different kinds of topics we are also able to control for topical and community variety since there is little overlap between the users of both groups of pages. To further ground this analysis we use a page promoting homogeneous contents. This page, "La stessa foto di Toto Cutugno ogni giorno" ("Everyday the same photo of Toto Cutugno") publishes exclusively the same picture of the Italian singer every day, making it the perfect baseline; we refer to this page as the *baseline page*. We collected all the *likes* and *comments* to every post in each page, as well as the number of *shares*. The dataset includes all activity in the science and conspiracy pages for the period between August 22, 2013 and December 31, 2013, as well as all activity for the baseline page between August 22, 2014 (when the page was created) and December 31, 2014. In total, we collected around 2 M likes and 190 K comments, made by about 340 K and 65 K users, respectively. In Table 1 we summarize the details of our dataset. Likes, shares, and comments have different semantic meanings: a 'like' is a positive feedback on the post; a 'share' expresses approval and the will to divulge it further; while a 'comment' is a form to participate in collective debate and can be both positive or negative.

4 Preliminaries and Definitions

Here we provide some of the basic definitions that we use throughout the overall paper.

Table 1 Dataset statistics. The number of pages, posts, likes, comments, shares, likers, and commenters for science pages, conspiracy pages, and the baseline page

	Total	Science	Conspiracy	Baseline
Pages	74	34	39	1
Posts	49,354	13,028	36,169	157
Likes	2,095,677	614,078	1,184,084	297,515
Comments	192,967	40,608	138,138	14,221
Shares	3,782,480	477,457	3,297,687	7,336
Likers	344,367	162,146	159,524	22,697
Commenters	64,903	18,358	41,666	4,875

Statistical Tools. The Probability Density Function (PDF) of a real–valued random variable is a function f_X that describes the probability of the random variable falling within a given range of values, so that

$$\mathbf{Pr}[a \leq X \leq b] = \int_a^b f_X(x)\, dx.$$

The cumulative distribution function (CDF) of a real–valued random variable X is defined as

$$F_X(x) = \mathbf{Pr}(X \leq x) = \int_{-\infty}^{x} f_X(u)\, \mathrm{d}u.$$

Similarly, the complementary cumulative distribution function (CCDF) is defined as one minus the CDF, so that

$$C_X(x) = 1 - F_X(x) = \mathbf{Pr}(X > x) = \int_x^{\infty} f_X(u)\, \mathrm{d}u.$$

Notice that in order to compare metrics related to pages showing different activity and consumption volumes, we perform the unity–based normalization to bring all values in the range [0, 1].

Bipartite Networks. In our model we consider a bipartite network having as nodes users and posts. A like to a given post determines a link between a user and a post. More formally, a bipartite graph is a triple $\mathscr{G} = (A, B, E)$ where $A = \{a_i \mid i = 1 \ldots n_A\}$ and $B = \{b_j \mid j = 1 \ldots n_B\}$ are two disjoint sets of vertices indicating, respectively, users and posts, and $E \subseteq A \times B$ is the set of edges—i.e. edges exist only between vertices of the two different sets A and B. The bipartite graph $\mathscr{G}$ is described by the matrix M defined as

$$M_{ij} = \begin{cases} 1 & if\ an\ edge\ exists\ between\ a_i\ and\ b_j \\ 0 & otherwise \end{cases}$$

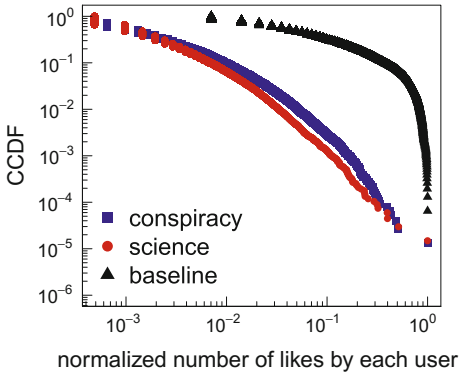

Fig. 1 Users' activity patterns. Complementary cumulative density function (CCDF) for the normalized number of likes by each user

Thus, $M_{ij} = 1$ means that a user $a_i \subset A$ liked a post $b_j \subset B$. It follows that the bipartite projection of users is a network of users in which a user $a_x \subset A$ is linked to a user $a_y \subset A$ if and only if both liked a given post $b_z \subset B$, i.e. if and only if

$$M_{xz} = 1 \wedge M_{yz} = 1.$$

5 Results and Discussion

In this section, we first present the statistical signatures characterizing users activity on pages with diversified content on specific topics (science and conspiracy news) against the case of the page posting every day the same picture (baseline). Then, we derive a model of information consumption mimicking user preferences with respect to contents.

5.1 Content and Users Activity

Let us focus on some regularities concerning users' activity on science pages and conspiracy pages compared with the baseline page. Figure 1 shows the complementary cumulative density function (CCDF) for the normalized[1] number of likes for each user.

In Fig. 2 we show the CCDF of the users' lifetime in terms of their liking activity—i.e. the temporal interval between the first and the last like of the user on a given page.

These figures show that users activity patterns are similar and present heavy–tailed distributions despite the different nature of the contents, and we can not find any

[1] We rescaled the number of likes to bring all values in the range [0, 1].

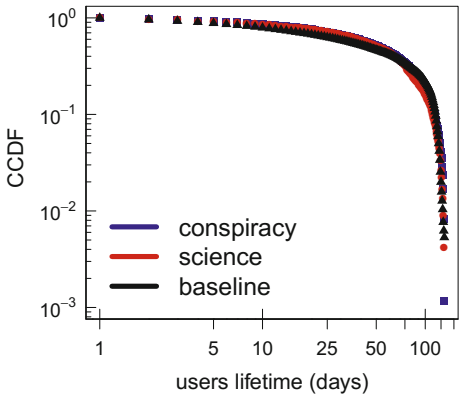

Fig. 2 Users' lifetime. Complementary cumulative density function (CCDF) of the users' lifetime in terms of their liking activity. The CCDF shows a slight difference in the lifetime of the baseline users with respect to science and conspiracy users

significant difference between the users interaction patterns induced by heterogeneous or homogeneous contents.

Conversely, by analyzing consumption patterns related to posts, we find a significant difference in the information consumption dynamics. Figure 3 shows the PDF for the number of likes received by posts belonging to science pages, conspiracy pages, and the baseline page. The number of likes received by posts are heavy–tailed distributed if the posts belong to pages promoting heterogeneous contents (science and conspiracy pages); whereas they are approximately distributed according to a Gaussian if the posts belong to a page promoting homogeneous content (baseline page).

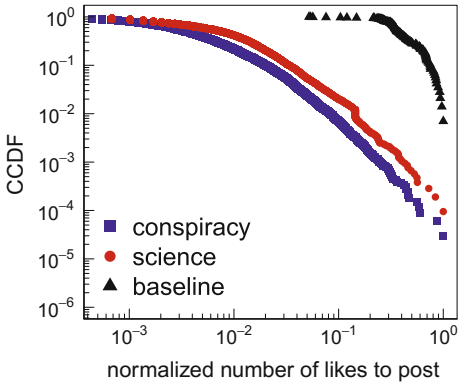

Fig. 3 Posts' consumption patterns. Complementary cumulative density function (CCDF) for the normalized number of likes received by posts belonging to science pages, conspiracy pages, and the baseline page. The CCDFs show remarkable differences between consumption patterns' distributions related to pages promoting heterogeneous contents and those related to the page promoting homogeneous contents

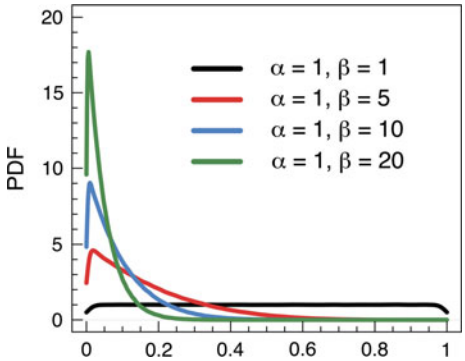

Fig. 4 Beta distribution $\mathscr{B}e(\alpha, \beta)$. Two parameters, α and β, control the shape of the distribution. In particular, for $\alpha = 1$ and $\beta = 1$ the Beta distribution $\mathscr{B}e(\alpha, \beta)$ is equivalent to the Uniform distribution $\mathscr{U}(0, 1)$. Conversely, if $\alpha = 1$ and $\beta \gtrsim 20$, the Beta distribution $\mathscr{B}e(\alpha, \beta)$ is a right heavy–tailed distribution

5.2 *Modeling Contents Consumption*

Here we introduce a model of pattern consumption that exploits the Beta distribution properties to generate different levels of posts' attractiveness, thus varying content–heterogeneity in the simulated collection of posts.

The Beta distribution is a family of continuous probability distributions defined in the interval [0, 1] and characterized by two real parameters, $\alpha > 0$ and $\beta > 0$, which control the shape of the distribution. In particular, for $\alpha = 1$ and $\beta = 1$ the Beta distribution $\mathscr{B}e(\alpha, \beta)$ is equivalent to the Uniform distribution $\mathscr{U}(0, 1)$. Conversely, if $\alpha = 1$ and $\beta \gtrsim 20$, the Beta distribution $\mathscr{B}e(\alpha, \beta)$ is a right heavy–tailed distribution. Figure 4 shows the Beta probability density function with respect to the two shape parameters α and β.

In our model, each post has a value drawn from a Beta distribution $v \sim \mathscr{B}e\,(1, \beta)$, with β ranging between 1 and 1,000,000, indicating its attractiveness. We let the parameter β assume those extreme values in order to obtain different distributions for posts' attractiveness. Indeed, notice that when $\beta = 1$ the Beta distribution $\mathscr{B}e\,(1, \beta)$ is equivalent to a uniform distribution $\mathscr{U}\,(0, 1)$, so that we have a collection of homogeneous–content posts—i.e., each post has the same degree of attractiveness; whereas when $\beta \to \infty$ the Beta distribution $\mathscr{B}e\,(1, \beta)$ is equivalent to a right heavy–tailed distribution, so that we have a collection of heterogeneous–content posts—i.e., there are few posts with a high level of attractiveness, while the vast majority of the posts is characterized by a low level of attractiveness. Moreover, each user is characterized by two parameters randomly drawn from power law distributions: her volume of activity, $a \sim p(x)$; and her fixed–preference about the posts, $b \sim p\,(x)$, where $p\,(x) = x^{-\gamma}$ with $\gamma = 1.5$. Each user can not exceed her assigned volume of activity, a, and she likes a given post if and only if her normalized[2] fixed–preference, b, is smaller than the attractiveness, v, of that post. Note that in our model we do not take into account the users' network: since Facebook network is very

[2]Note that we performed a unity–based normalization in order to bring all values of $b \sim p\,(x) = x^{-1.5}$ in the range [0, 1], so that the fixed–preference of the user is comparable with the attractiveness of the posts.

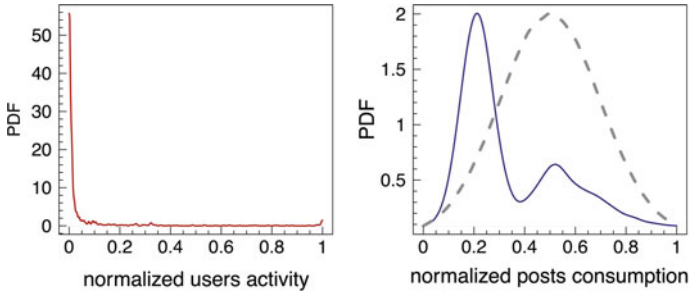

Fig. 5 Users activity and post consumption patterns with extremely heterogeneous–content posts. Probability density function (PDF) of the users activity and the posts consumption patterns generated by a simulation of the model with $\beta = 1{,}000{,}000$. If the content promoted by a page is heterogeneous, the heavy–tailed users' activity resolves in skewed posts consumption's patterns

dense—indeed, the diameter of Facebook social network is just 3.74 [5, 6]—the connections between users are not likely to influence posts' consumption dynamics.

We run simulations for β ranging between 1 and 1,000,000, with $P = 10{,}000$ (posts) and $U = 20{,}000$ (users). Results are averaged over 100 iterations.

Figure 5 shows the probability density function (PDF) of the users activity and the posts consumption patterns generated by a simulation of the model with $\beta = 1{,}000{,}000$—i.e., in the case of extremely heterogeneous–content posts. Observe that users' activity is heavy–tailed, and the distribution of posts' consumption is skewed. Such a result is consistent with empirical data shown in the previous section: if the content promoted by a page is heterogeneous, the heavy–tailed users' activity resolves in skewed posts consumption's patterns.

Figure 6 shows the probability density function (PDF) of the users activity and the posts consumption patterns generated by a simulation of the model with $\beta = 1$—i.e., in the case of homogeneous–content posts. Notice that users' activity is heavy–tailed,

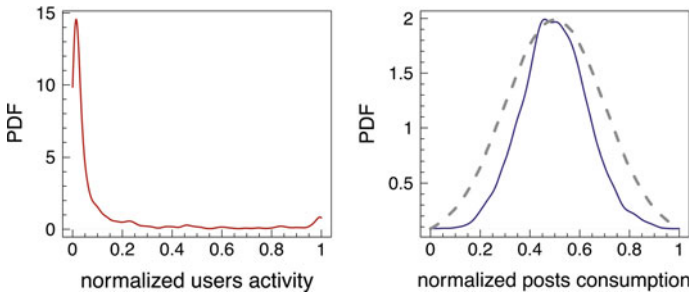

Fig. 6 Users activity and post consumption patterns with homogeneous–content posts. Probability density function (PDF) of the users activity and the posts consumption patterns generated by a simulation of the model with $\beta = 1$. If the content promoted by a page is always the same, the heavy–tailed users' activity resolves in approximately Gaussian posts consumption's patterns

whereas posts' consumption is approximately Gaussian. Such a result is consistent with empirical data shown in the previous section: if the content promoted by a page is always the same, the heavy–tailed users' activity resolves in approximately Gaussian posts consumption's patterns.

6 Concluding Remarks

Facebook is full by different and heterogeneous contents, ranging from the latest news all the way to satirical and funny stories. Each piece of content posted reflects the heterogeneity of the underlying social background of the over 1 Billion Facebook users. Online social networks such as Facebook and Twitter give people an outlet within which to express their attitudes, passions, and emotions by producing, sharing and, consuming heterogeneous information.

In Facebook, we found a fascinating case of contents' homogeneity: a page with more than 40 K followers that every day posts the same picture of Toto Cutugno, a popular Italian singer. In this work, we use such a page as a benchmark to investigate and model the effect that intrinsic contents heterogeneity has on popularity. In particular, we use that page for a comparative analysis of information consumption patterns with respect to pages posting heterogeneous contents related to Science and Conspiracy Theories, two topics with widely different audiences.

Surprisingly, we find that variations in the popularity of individual posts are due mostly to content heterogeneity. Even though there are no remarkable differences in user activity patterns between the Science, Conspiracy and Baseline pages, we observe that post popularity in the baseline page is well approximated by a normal distribution while it is broad tailed in pages promoting heterogeneous content. Finally, we show that these differences can be explained just by content heterogeneity by deriving a conceptually simple model that is able to reproduce our empirical observations.

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