Abstract

Recent studies, targeting Facebook, showed the tendency of users to interact with information adhering to their preferred narrative and to ignore dissenting information. Confirmation bias seems to account for user decisions about consuming and spreading content and, at the same time, aggregation of favored information within groups of like-minded people (echo chambers) reinforces selective exposure and group polarization. To gain a deeper understanding of the perspectives of these clustered communities, in this work we analyze the language of users engaged in the echo chambers emerging on Facebook around two distinct and conflicting narratives – i.e., Science and Conspiracy news. Despite the high level of segregation of such communities, we show that users from both the echo chambers adopt very similar vocabularies and use the same word with almost the same frequency in their commenting activity, both at the individual and the collective level. Moreover, zooming in at the conversation level, we observe the emergence of lexical convergence between users who consistently interact with each other through co-commenting activity not only inside, but also across the echo chambers. Thus, the fact that even users with opposite views gradually coordinate their linguistic behavior when joining a discussion, suggests that users always aim to achieve communication when engaging in a conversation.

Introduction

The advent of social media changed the way users consume content and interact. In 2017 the World Economic Forum raised a warning on the potential distortion effect of social media on user perceptions of reality[^1]. Users online tend to join groups of like-minded people around a shared narrative, i.e. echo chambers[^1][^8]. Within these homophilic clusters, users cooperate in framing and reinforcing the shared narrative by paying attention to adhering information and by ignoring dissenting information. Confirmation bias, indeed, seems to account for users’ decisions about consuming and spreading content and, at the same time, aggregation of favored information within those communities reinforces selective exposure[^9] and group polarization[^10][^11].

To gain a deeper understanding of the perspectives of these clustered communities, in this work we analyze the language of users engaged in the echo chambers emerging on Facebook around two distinct and conflicting narratives – i.e., Science and Conspiracy news. Moreover, we investigate the role played by group polarization on the emergence

[^1]: [http://reports.weforum.org/global-risks-2017/acknowledgements/](http://reports.weforum.org/global-risks-2017/acknowledgements/)
of lexical convergence between users who interact with each other through co-commenting activity.

In conversation – the fundamental site of language use – it is known that people achieve shared conceptualizations based on their past references to the same objects \[12\][13]. With repeated references to objects, they tend to reuse the same terms as they coordinate their perspectives, a phenomenon called \textit{lexical entrainment} \[14\]. This process limits and systematizes lexical variability \[15\] in spite of the potential for enormous variations in people’s lexical choices in dialog, dubbed the \textit{vocabulary problem} \[16\][17]. By reflecting conceptual coordination in dialogue \[13\][14], lexical choices give important insight not only about individual processes of language use, but also about distributed ones (i.e. the use of language of a social group).

Here we analyze the lexical choices of two distinct and conflicting Facebook communities by counting the frequency with which words appear in comments of their users, both at individual and collective levels. Zooming in at the level of online dialogues, we also investigate the role of peer influence and polarization in the emergence of lexical entrainment between users who interact with each other through joint commenting activity.

To our aim, we analyze a dataset containing 271,296 posts created by 73 Facebook pages classified according to the kind of information disseminated and their self description in Science news and Conspiracy news \[2\] with more than one million of comments left by 279,972 users over a time span of five years (Jan 2010 - Dec 2014). For further details about the data collection and the dataset refer to \textbf{Materials and methods} Section. Previous works revealed that polarized communities emerge around Science and Conspiracy contents \[18\][19]. Despite the very profound different nature of their contents, it has been shown that engaged users of the two echo chambers consume their preferred information in a similar way in terms of volumes of both likes and comments \[19\]. Here we observe another analogy between these two clustered communities. Namely, we show that the two echo chambers adopt similar vocabularies, with only few words being used with significantly different frequencies, both at individual and collective level.

Moreover, by focusing on the direct interactions among users, we investigate the lexical entrainment of \(\sim 71\)K pairs of co-commenting users in function of the length of their interaction, by performing a comparative analysis of their bags of words \[20\]. In the analysis, we first characterize the polarization of the users with respect to Conspiracy or Science contents by accounting for their liking activity. Then, by defining the joint polarization of two interacting users as the mean of their individual polarization, we differentiate between three types of interaction ("Conspiracy-Conspiracy", "Conspiracy-Science" and "Science-Science") and analyze the corresponding interaction networks.

Our findings reveal the emergence of lexical entrainment between users who consistently interact with each other through co-commenting activity not only inside, but also across the echo chambers. This result suggests that peer influence affects the lexical choices not only during like-minded debates, but also when usual consumers of Science and Conspiracy news meet. However, with regard to this last type of interaction, such lexical convergence is more likely to be due to the necessity of agreeing on a vocabulary to perform the communication rather than to a real opinion convergence. Instead, the role of user polarization seems to be mainly confined upon the choice about the post to interact with – i.e., users polarized towards Science or Conspiracy mostly concentrate their commenting activity on posts from pages of their own community \[21\], and this trend arises as the user polarization increased.

\footnote{Notice that we do not claim that Conspiracy information are false. Our focus is on investigating the frequency with which words are used by communities formed around different and conflicting narratives.}
Materials and methods

Ethics Statement

The entire data collection process has been carried out exclusively through the Facebook Graph API, which is publicly available, and for the analysis (according to the specification settings of the API) we used only public available data (users with privacy restrictions are not included in the dataset). The pages from which we download data are public Facebook entities (can be accessed by anyone). User content contributing to such pages is also public unless the user’s privacy settings specify otherwise and in that case it is not available to us.

Data collection

In this study we address the effects of peer influence and polarization on the emergence of lexical convergence between users who interact on Facebook through joint commenting activity. To this aim, we identified two main categories of pages: Conspiracy news – i.e. pages promoting contents neglected by main stream media – and Science news. The space of our investigation has been defined with the help of Facebook groups very active in debunking Conspiracy theses (Protesi di Complotto, Che vuol dire reale, La menzogna diventa verità e passa alla storia). We categorized pages according to their contents and their self description.

Concerning Conspiracy news, their self description is often claiming the mission to inform people about topics neglected by mainstream media. Pages like Scienza di Confini, Lo Sai or CoscienzaSveglia promote heterogeneous contents ranging from aliens, chemtrails, geocentrism, up to the causal relation between vaccinations and homosexuality. We do not focus on the truth value of their information but rather on the possibility to verify their claims. Conversely, Science news – e.g. Scientificast, Italia unita per la scienza are active in diffusing posts about the most recent scientific advances. The selection of the source has been iterated several times and verified by all the authors. To our knowledge, the final dataset is the complete set of all scientific and conspiracist information sources active in the Italian Facebook scenario. Notice that the dataset used in the analysis is the same used in [10,18,19,22,23].

The pages from which we downloaded data are public Facebook entities (can be accessed by virtually anyone). The resulting dataset is composed of 73 public pages for which we downloaded all the posts and all the likes and comments from the posts over a time span of five years (Jan 2010 - Dec 2014). The exact breakdown of the data is presented in Table 1.

Table 1. Breakdown of Facebook dataset.

|             | Total | Science News | Conspiracy News |
|-------------|-------|--------------|-----------------|
| Pages       | 73    | 34           | 39              |
| Posts       | 271,296 | 62,705       | 208,591         |
| Likes       | 9,164,781 | 2,505,399    | 6,659,382       |
| Comments    | 1,017,509 | 180,918      | 836,591         |
| Likers      | 1,196,404 | 332,357      | 864,047         |
| Commenters  | 279,972  | 53,438       | 226,534         |

The number of pages, posts, likes, comments, likers, and commenters for Science and Conspiracy news.

Likes and comments have a different meaning from the user viewpoint. Most of the times, a like stands for a positive feedback to the post, whereas a comment is the way in
which online collective debates take form. Comments may contain negative or positive feedback with respect to the post.

User and paired polarization

Following previous works \[10\][19][23][24], we label users by means of a simple thresholding algorithm accounting for the percentage of likes on one or the other category. We define user polarization \(\sigma_u = 2\rho_u - 1\), where \(0 \leq \rho_u \leq 1\) is the fraction of likes a user \(u\) puts on Conspiracy-related content, and hence \(-1 \leq \sigma_u \leq 1\). According to the sign of their polarization, users are labelled as Science \((\sigma_u < 0)\) or Conspiracy \((\sigma_u > 0)\) supporters. Note that we here ignore the commenting activity since a comment may be an endorsement, a criticism, or even a response to a previous comment.

As a further step, we define the paired polarization \(\sigma_{uv}\) of two interacting users \(u\) and \(v\) as the mean of their individual polarization values, i.e. \(\sigma_{uv} = \frac{\sigma_u + \sigma_v}{2}\). We also associate to any pair of interacting users \(u,v\) the label \(\ell_{uv} \in \{\text{Conspiracy-Conspiracy}, \text{Conspiracy-Science}, \text{Science-Science}\}\) for referring to one of the three possible types of interaction. In such a way, we can analyze the network of interactions broken down by interaction type. Obviously, the following holds.

\[
\sigma_{uv} \in \begin{cases} 
[ -1, 0 ] & \text{if } \ell_{uv} = \text{Science-Science} \\
[ -0.5, 0.5 ] & \text{if } \ell_{uv} = \text{Conspiracy-Science} \\
[ 0, 1 ] & \text{if } \ell_{uv} = \text{Conspiracy-Conspiracy}.
\end{cases}
\] (1)

Pairwise user interactions

The most obvious metrics to quantify the amount of interaction between two users who interact through co-commenting activity, like the number of posts co-commented or the total number of comments, may have some counter-intuitive limitations. As an example, let us consider the user pair \(u,v\) co-commenting on post \(p_1, \ldots, p_{10}\) and the user pair \(u',v'\) co-commenting on post \(p'_1, \ldots, p'_5\) according to the following tables:

|     | \(p_1\) | \(p_2\) | \(p_3\) | \(p_4\) | \(p_5\) | \(p_6\) | \(p_7\) | \(p_8\) | \(p_9\) | \(p_{10}\) |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| \(u\) | 3     | 3     | 3     | 3     | 3     | 3     | 3     | 3     | 3     | 3     |
| \(v\) | 3     | 3     | 3     | 3     | 3     | 3     | 3     | 3     | 3     | 3     |

|     | \(p'_1\) | \(p'_2\) | \(p'_3\) | \(p'_4\) | \(p'_5\) |
|-----|-------|-------|-------|-------|-------|
| \(u'\) | 8     | 8     | 8     | 8     | 8     |
| \(v'\) | 16    | 16    | 16    | 16    | 16    |

Here, the cell values of each table correspond to the number of comments a given user makes on a given post. Notice that, since we are considering co-commenting, we are selecting posts for which both users produce at least one comment.

We observe that counting the number of co-commented posts can penalize pairs of users who leave an high number of comments on few posts, while counting the total number of comments two users leave on the same posts does not take into account for unbalanced contributes of the two commenters.

In fact, the number of co-commented posts is 10 for the pair \(u,v\) and 5 for the pair \(u',v'\), even if the first pair shares a lower number of comments (60) with respect to the second pair (that shares 120 comments). On the other hand, the total number of comments by \(u',v'\) on each post is very high (24) even if the activity of \(v'\) is twice the activity of \(u'\).
To overcome these limitations, we define a metric that takes into account not only the number of different posts users interact with, but also the unbalance among users’ comments on single posts. More formally, let \( \mathcal{P} \) be the set of all posts in our dataset and let \( \mathcal{C} \) be the set of all commenters. Denote by \( c_u(p) \) the set of comments that user \( u \) left on \( p \in \mathcal{P} \) and by \( \mathcal{P}_{uv} \) the set of posts with comments from both users \( u \) and \( v \), i.e. \( \mathcal{P}_{uv} = \{ p \in \mathcal{P} \mid c_u(p) \neq \emptyset \text{ and } c_v(p) \neq \emptyset \} \). We define the interaction level between \( u \) and \( v \) as

\[
I_{uv} = \sum_{p \in \mathcal{P}_{uv}} \min_p (|c_u(p)|, |c_v(p)|). \tag{2}
\]

We could think to this measure as a counter of interactions back-and-forth between \( u \) and \( v \). By applying (2) to the user pairs of the previous example, we obtain \( I_{uv} = 30 \) and \( I_{u'v'} = 40 \), respectively, which represent more reasonable values for their amount of interaction.

The interaction network

Using commenting data of our collection, we construct the interaction network as an undirected graph, where a link exists between a pair of users if they co-commented at least once. More formally, let \( G_I = (\mathcal{C}, \mathcal{P}, E_I) \) be the bipartite network whose vertex parts \( \mathcal{C} \) and \( \mathcal{P} \) denote the set of (even weakly) polarized commenters and the set of posts in our collection, respectively. Here a link \( \{u, p\} \in E_I \) between the user \( u \) and the post \( p \) exists if \( u \) commented \( p \). By projecting on the level of users we obtain the weighted interaction network \( G^C_I \) where the link \( \{u, v\} \) exists if both users \( u \) and \( v \) commented at least once on the same post \( p \) and the link weight equals their interaction level \( I_{uv} \) given by (2).

The resulting interaction network consists of 180,622 users (nodes) and 20,081,023 distinct pairs of interacting users (links). Since we find a strong skew in the interaction level among user pairs, the majority of the user pairs display very little interaction, while only few users are highly interacting in the sense of (2).

For carrying out the analysis on lexical convergence, we focus only on user pairs exhibiting a reasonably significant interaction level instead of consider the interaction network as a whole. Specifically, we discard all links \( \{u, v\} \) such that \( I_{uv} < 3 \). With this restriction, our threshold network \( G^T_I \) contains 17,168 users and 70,920 links. Namely, \( G^T_I \) is composed by 13,272 Conspiracy supporters and 3,896 Science supporters who produced 52,960 and 14,896 homophilic interactions, respectively. The interactions of type Conspiracy-Science are 3,064 generated by 769 users (305 from Conspiracy and 464 from Science) who comment posts from pages of the other community. Furthermore, Conspiracy-Science interactions decrease to \( \sim 0.01\% \) of the total amount of interactions if we consider only users with individual polarization \( \geq 0.9 \) in absolute value. Hence, users polarized towards Science or Conspiracy mainly concentrate their commenting activity on posts from pages of their own community, and this trend arises as the user polarization increased.

Backbone detection algorithm

The disparity filter algorithm is a network reduction technique that identifies the backbone structure of a weighted network without destroying its multiscale nature \cite{25}. We use this algorithm to determine the connections that form the backbones of our interaction network and to produce clear visualization.
Measuring lexical convergence

To test whether more conversation leads to lexical entrainment, we perform a pairwise comparative analysis on the multisets of words used by individuals who interact with each other through co-commenting activity. Specifically, we associate to each user her bag of words (BoW) disregarding grammar and even word order but keeping multiplicity. A user bag of words is a sparse vector of occurrence counts of words – i.e., a sparse histogram over the dataset vocabulary. BoW objects are represented as a Vector Space Model (VSM) [26] with term frequencies as components.

To measure the overlap of two BoWs, we calculate their cosine similarity [27] as normalized dot-product of the two vectors; thus, for positive values, it varies in the range [0,1]. More formally, if \( x_u = (x_{u1}, x_{u2}, \ldots, x_{un}) \) and \( x_v = (x_{v1}, x_{v2}, \ldots, x_{vn}) \) are the term frequency vectors of users \( u \) and \( v \), respectively, their cosine similarity is computed as follows:

\[
\cos(x_u, x_v) = \frac{\sum_{k=1}^{n} x_{uk} \cdot x_{vk}}{|x_u| \cdot |x_v|}.
\]  

(3)

Results and discussion

To gain a deeper understanding of users’ behavior online, in this work we analyze the language of users engaged in the echo chambers emerging on Facebook around two distinct and conflicting narratives – i.e., Science and Conspiracy news. Zooming in at the conversation level, we also aim to test whether users who actively interact with each other on the same content through joint commenting activity, adopt similar lexical choices. Moreover, a characterization of users’ polarization as a continuous variable as well as the presence of co-commenting conversations among users supporting opposite narratives, allow to investigate the role played by user polarization on the emergence of lexical entrainment. For carrying out our analysis on language use, we only consider those interactions whose level satisfies some minimum requirements as defined in Section Pairwise user interactions. Therefore, in the remainder of the paper, unless otherwise specified, we take into account only those users producing such threshold interactions.

Quantifying user polarization

Our analysis starts by defining users’ engagement across Science and Conspiracy contents as a continuous variable. This allows to distinguish different degrees of polarization, in opposition to most common binary measures. Following previous works [10, 19, 23, 24], users are labelled by means of a simple thresholding algorithm accounting for the percentage of likes on one or the other category. Formally, the user polarization is a real number \( \sigma_u \in [-1, 1] \) and users are labelled as Science or Conspiracy supporters according to whether \( \sigma_u < 0 \) or \( \sigma_u > 0 \), respectively (See Section Pairwise user interactions).

The probability density function (PDF) of users’ polarization shows that users are clearly split into two groups with opposite polarization, while few users are weakly polarized or unpolarized (Fig. 1). Indeed, more than 90% of users exhibits a polarization \( |\sigma| \gtrsim 0.9 \), while \( \sigma \sim 0 \) for only the 0.005% of users. This confirms the existence of two well-formed and highly segregated communities around Conspiracy and scientific topics – i.e., users are mainly active in only one category [21]. To better analyze the effects of polarization on the lexical entrainment between interacting users, we discard the few users \( u \) for whom \( \sigma_u = 0 \) – i.e., users who liked the same number of
posts from both the communities. Thus, we focus only on those users who show a preference, even if a small, for one of the two narratives.

Fig 1. User polarization. Probability density function (PDF) of users’ polarization. Notice the strong bimodality of the distribution, with two sharp peaks localized at $-1 \lesssim \sigma \lesssim -0.9$ (Science users) and at $0.9 \lesssim \sigma \lesssim 1$ (Conspiracy users).

As a further step, we also define the paired polarization $\sigma_{uv}$ of two interacting users $u$ and $v$ as the mean of their individual polarization values and we associate to any pair of interacting users $u, v$ the label $\ell_{uv} \in \{\text{Conspiracy-Conspiracy, Conspiracy-Science, Science-Science}\}$ for referring to one of the three possible types of interaction.

Co-commenting interactions

By linking the interaction level to a proxy of interactions back-and-forth, we avoid the pitfalls of considering simple measure of interaction like the numbers of co-commented posts or the total number of comments (see Sec. Pairwise user interactions). Thus, the quantity $I_{uv}$ given by (2) measures the amount of interaction between two users who interact one another through joint commenting activity. Consequently, we investigate the overall distribution of the interaction level across each pair of interacting users, looking at the extent to which certain pairs possess more activity than others. For this, we calculate the empirical complementary cumulative distribution function (CCDF) of the interaction level $I_{uv}$ broken down by interaction type, as represented in a double logarithmic axes plot in Fig. 2, showing that all the three distributions have the same heavy–tailed (possibly power-law) pattern.

Using commenting data of our collection, we also construct the interaction network $G_{IC}$ as an undirected graph, where a link exists between the pair of users $u, v$ if they co-commented at least once and the link weight equals their interaction level $I_{uv}$ (see Section The interaction network). Fig. 3 shows the backbone of $G_{IC}$. The thickness of a line indicates the strength of the link, i.e. the interaction level among the nodes connected by the link.

Words from Science and Conspiracy: faraway so close

Despite the very profound different nature of Science and Conspiracy contents, engaged users of the two clustered communities consume their preferred information in a similar way in terms of volumes of both likes and comments. Through a quantitative analysis of words arranged in terms of their frequencies, here we investigate whether
Fig 2. Interaction level. Empirical complementary cumulative distribution function (CCDF) of users’ interaction level broken down by interaction type. All the distributions are clearly heavy–tailed.

Fig 3. The network of interactions. Backbone of the interaction network with interaction level as link weight. Link colors indicate the interaction type: Conspiracy-Conspiracy in red, Conspiracy-Science in green and Science-Science in blue. Nodes are ordered according to the community membership. Users polarized towards Science or Conspiracy mainly concentrate their commenting activity on posts from pages of their own community, with very few interactions across their respective polarized communities.

users also use similar vocabularies for interacting with their preferred content through commenting activity.

Fig. 4 shows a double logarithmic axes plot of the CCDF of Science and Conspiracy users’ vocabulary size, respectively. Both distributions are indicating a similar lexicon usage. Median and mean vocabulary size of Science users are $\sim 73$ and $\sim 160$ words, respectively. Similarly, median and mean vocabulary size of Conspiracy users are $\sim 88$ and $\sim 166$ words, respectively. Vocabulary sizes are computed after all comments in our dataset have been pre-processed according to the procedure set out in SI Pre-Processing. Pre-processing was necessary for cleaning the text by noise and uninformative parts as well as for letting a word cover all its forms, like *goes, went, gone* for *go*. 
Fig 4. User vocabulary size. Empirical complementary cumulative distribution function (CCDF) of Science and Conspiracy users’ vocabulary size. Both the distributions are indicating similar patterns.

The vocabulary of the purged dataset consists of 83,615 unique terms, whereas the words used in Science and Conspiracy communities are 56,743 and 62,830, respectively. Moreover, Science users and Conspiracy users share 38,258 words, which, counted with their multiplicity, represent \( \sim 97\% \) of the total words used in both the communities. Hence, even if the two communities have vocabularies that differ by \( \sim 30\% \) of their words, users of the two clustered communities resort mostly on the remaining \( \sim 70\% \) common words for commenting their preferred content.

Fig. 5 shows lin-log plots of the normalized average frequency of each word by Science and Conspiracy user (left panel), and the normalized word frequency by echo chamber (right panel).

At collective level, we observe a strong correlation between the word frequencies in Science and Conspiracy – i.e, the same word is used with nearly equal frequency in both the communities with very few significant exceptions. Indeed, the Pearson’s correlation coefficient – i.e., the covariance of two variables (in this case word frequencies) divided by the product of their standard deviations – is \( r = 0.94 \). Furthermore, only 3\% of words with frequency \( \gtrsim 0.35 \) from both the communities are used with a frequency difference of at least 30\% from one community to the other.

At the individual level, the average frequency of the same words exhibits more significant differences from one community to the other, especially regarding the most frequent words of Science. The Pearson’s coefficient between average word frequency by Science and Conspiracy user is \( r = 0.89 \), whereas 20\% of the words with average frequency \( \gtrsim 0.35 \) by Science user is used on average 30\% less by Conspiracy user. This suggests that Science supporters use some favorite words for expressing their opinion which are not so essential for the Conspiracy users.

Comparing the lexical choices of interacting users inside and across echo chambers

Here we want to test the hypothesis that users actively interacting on Facebook on the same content through co-commenting activity, with repeated references to objects, tend to reuse the same words as they coordinate their perspectives. Moreover, the definition of users’ polarization as a continuous variable and the presence of interactions across the two echo chambers, allow us to characterize the lexical entrainment between interacting
Fig 5. Word frequencies. Normalized average frequency of each word by Science and Conspiracy user (left panel), and normalized word frequency by echo chamber (right panel). At collective level, the same word is used with nearly equal frequency in both the communities with very few significant exceptions. At the individual level, the average frequency of the same words exhibits more significant differences from one community to the other, especially regarding the most frequent words of Science.

users not only in function of their interaction level, but also with respect to the value of their paired polarization. Namely, we also want to investigate whether an high involvement within the same echo chamber of both the two interacting users is a necessary condition for their BoWs (see Section Measuring lexical convergence) to overlap.

To this aim we perform a pairwise comparative analysis on the multisets of words used by co-commenting individuals by calculating the cosine similarity of their BoWs. Formally, we compare the term frequency vectors of about 71K pairs of interacting users who made more than 480K comments in a time span of 5 years. Fig. 6 shows a lin-log scatterplot of interaction level versus lexical convergence for any of the three possible types of interactions. Points are colored according to the corresponding paired polarization. Plots also display the regression curve obtained via locally weighted polynomial (LOESS) fitted by the vector of the means of the cosine measurements for each interaction level.

With regard to homophilic interactions, only user pairs with paired polarization $> 0.5$ in absolute value, reach an interaction level $> 20$ (Fig. 6—left and right panels). This indicates that the more two users are polarized towards the same content, the more they are likely to interact consistently. Furthermore, Fig. 6 clearly shows that the more two users interact the more their lexical choices are similar, both inside (left and right panels) and across (central panel) echo chambers. Regardless of the interaction type, we measure cosine values of $\sim 0.75$ between the term frequency vectors of the most active user pairs. This result suggests that the emergence of lexical convergence is mainly affected by peer influence, whereas user polarization is mostly confined upon the choice of post to interact with.

For testing our hypothesis we performed a randomization test generating 1000 replicates of the actual dataset broken down by interaction type (pseudosamples). Specifically, for any of the three types of interaction, pseudosamples are generated by randomly permuting the user bags of words and by repeating the cosine measurements between the corresponding randomized term frequency vectors. The permutation test shows that the observed data are statistically significant with a p-value $p < 10^{-3}$. 
Fig 6. Interaction level versus lexical convergence broken down by interaction type. Points colored according to the corresponding paired polarization show that the more two users are polarized towards the same content, the more they are likely to interact consistently (left and right panel). Moreover, the more two users interact the more their lexical choices are similar, both inside (left and right panel) and across (central panel) echo chambers.

Since we observe that users that have interacted much do also share a similar lexicon, it could be that users with similar lexicon are more eager to interact with each other. On the other hand, lexical entrainment could be simply due to the fact that to discuss of a subject people must agree on a common vocabulary. To understand whether this second mechanism could be at work, for each user-user interaction we measure how lexical similarity evolves over time. To make our analysis not dependent on the physical time, we measure the time in terms of the interaction level $I_{uv}$; moreover, to be consistent with the analysis of fig. 6 we start measuring lexical similarity after two users co-commented 3 times.

Fig. 7 shows the temporal evolution of the lexical entrainment between user pairs $u, v$ such that $I_{uv} > 7$. This allows to investigate the effects of peer influence on lexical choices through at least five consecutive interactions. Plots display a strong correlation between number of interactions and lexical convergence.

Fig 7. Emergence of lexical convergence. Evolution over time of lexical entrainment between most interacting users. We consider consecutive interactions as temporal units. In the plots we observe a strong correlation between number of interactions and lexical entrainment.

In Table 2 we also report the Pearson’s correlation between the users’ interaction level ($I_{uv} > 7$) and the difference between their first and last cosine measurement. The positive correlation between such quantities indicates that co-commenting users tend to achieve lexical entrainment as their level of interaction increases over time.

However, in accordance to the high levels of segregation of the two echo chambers (see Section The interaction network), the interactions of type Conspiracy-Science represent only a small fraction of the total ones and the statistical significance of the
Table 2. Pearson’s correlation for interaction level and cosine growth.

|                | Science-Science | Conspiracy-Science | Conspiracy-Conspiracy |
|----------------|-----------------|--------------------|-----------------------|
|                | 0.7246068       | 0.7771097          | 0.5698901             |

Pearson’s coefficient for the interaction level of user pairs and the corresponding difference between their first and last cosine measurement, broken down by interaction type.

corresponding Pearson’s coefficient may be affected by lack of observations.

**Conclusion**

In this work we analyzed the language of users engaged in the echo chambers emerging on Facebook around two distinct and conflicting narratives – i.e., Science and Conspiracy news.

Despite the high level of segregation of such communities, we showed that users from both the echo chambers adopt very similar vocabularies and use the same word with almost the same frequency in their commenting activity, both at the individual and the collective level. Moreover, zooming in at the dialogue level, we investigated the role of peer influence and polarization in the emergence of lexical convergence between users who consistently interact with each other through co-commenting activity. To such an aim, we first characterized users’ polarization with respect to Science and Conspiracy contents by accounting for their liking activity. We then measured the paired polarization of co-commenting users and differentiated between three types of interaction: “Conspiracy-Conspiracy”, “Conspiracy-Science” and “Science-Science” in order to analyze the interaction network broken down by interaction type. Finally, by performing a comparative analysis on the bags of words (BoW) of about 17K users who made more than 480K comments in a time span of five years, we studied the BoWs overlap of co-commenting users from both the static and dynamic point of view.

Our findings reveal the emergence of lexical entrainment between users who consistently interact with each other through joint commenting activity not only inside, but also across the two echo chambers. However, as indicated by the results of previous studies [21], such lexical convergence is more likely to be due to the necessity of agreeing on a vocabulary to perform the communication rather than to a real opinion convergence. Instead, the role of user polarization seems to be mainly confined upon the choice about the post to interact with – i.e., users polarized towards Science or Conspiracy mostly concentrate their commenting activity on posts from pages of their own community, and this trend arises as the user polarization increased.

**Supporting information**

S1 Pre-Processing. All comments in our collection are pre-processed by removing punctuation marks and special characters except apostrophes and by lemmatising the remaining words, i.e., by reducing them into their lemma or dictionary form. The resulting texts are converted to lower case and split on whitespace, leaving only tokens with no whitespace, and no empty tokens. Tokens appearing on our stopword list are removed, as are tokens consisting of a sequence of digits. The result of this processing is a user-term matrix consisting of 83,615 unique terms and populated with the numbers of times each user uses each token. Note that in order to improve the statistical significance of the analysis, no verbs (except auxiliaries) neither adjectives are included.
in our stopword list.

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