Measuring Platform Effects in Digital Democracy

Pablo Aragón[*†] Vicenç Gómez[*] Andreas Kaltenbrunner[†]

[*] Universitat Pompeu Fabra, Barcelona, Spain [†] Eurecat, Barcelona, Spain

Abstract. Online discussions are the essence of many social platforms on the Internet. Conversations in online forums are traditionally presented in a hierarchical structure. In contrast, online social networking services usually show discussions linearly by sorting messages in chronological order. How discussion networks are affected by choosing a specific view has never been investigated in the literature.
In this article we present an analysis of the discussion threads in Meneame, the most popular Spanish social news platform. In January 2015, this site turned the original linear conversation view into a hierarchical one. Our findings prove that the new interface promoted new discussion network structures. In particular, the hierarchical view increased deliberation and reciprocity based on the rhizomatic structure of discussions.

Keywords:
Digital democracy, Online deliberation, Online discussion, Human-Computer Interfaces, Conversation view

1 Introduction

Online social platforms are playing a key role in the communication of current societies. According to Kemp (2016), more than two billion users are actively participating in social media sites. The interest in online platforms has attracted increasing attention from academia over the last decade and several studies have examined the network structure of a wide array of online digital platforms, e.g. Facebook (Ugander et al., 2011), Twitter (Kwak et al., 2010), Google+ (Magno et al., 2012), Flickr (Cha et al., 2009), Youtube (Mislove et al., 2007), Wikipedia (Laniado et al., 2011), Digg (Lerman and Ghosh, 2010) and Slashdot (Gómez et al., 2008). The relevance of online platforms is not only the massive usage of this sort of communication but also the power and influence that social media have exhibited (Shirky, 2011; Zhang et al., 2009). Conversations in online platforms are already having an impact on the public sphere (Dahlgren, 2005) and some theorists have suggested that information and communication technologies have the potential to originate models of self-organization of distributed intelligence and decision-making (Heylighen, 1999; Surowiecki, 2005; Rheingold, 2007).

A common purpose of many online discussion platforms is the facilitation of deliberative processes among free and equal individuals (Elster, 1998). On the one hand, online platforms are able to involve a much larger number of individuals and, therefore, might reinforce the legitimacy of the debate. On the other hand, these platforms, as any online website, are affected by how information is presented. Technological features such as web and interaction design will have an influence on the structure of arguments that build the dialectical debate. This structure is crucial since decision-making processes will be biased by the way in which people acquire information from the debate.

Although conversations on the Internet are usually presented in conversation threads, there is strong heterogeneity in *conversation views*: the way in which threads are showed to users. Because conversation threads are collections of messages which are posted by users as replies to each other, many platforms like email clients and online forums have adopted a *hierarchical* view, i.e. messages are arranged close to their replies in a tree-like structure. However, the rise of online social networks, like Facebook and Twitter, promoted the usage of *linear* views that show messages regardless of reply relationships. The sorting criteria of messages is commonly chronological to indicate how a discussion thread grows over time. We also note that some other online platforms for question-and-answer features, like Quora and Stack Overflow, apply a popularity sorting criteria, based on the rating scores of comments, in order to better identify the most useful messages.

1.1 Motivation and Research questions

Previous research work has examined benefits and problems of linear and hierarchical views in online platforms. However, as described below, most studies have only focused in platforms with a specific form of view, either linear or hierarchical. The few studies that compared both views are based on small groups of participants in experimental tools. Therefore, there are no comparative analyses of this relevant feature within an online platform with a large and mature community of users. Moreover, these studies presented behavioral analyses but left unexplored how different conversation views affect the network structure of a discussion.

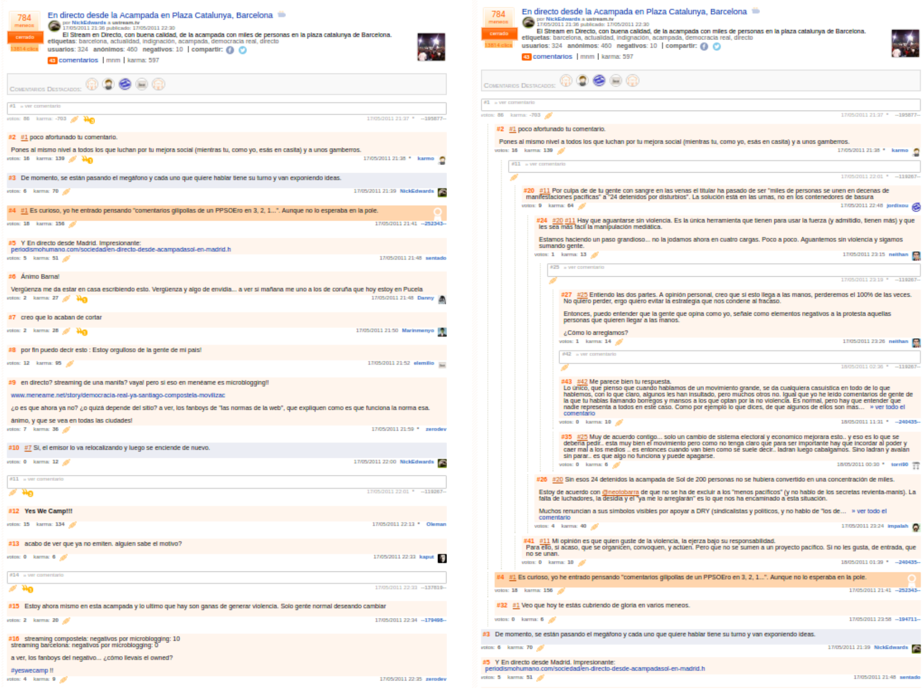
This research gap is the motivation of the present article. In particular we address the following research questions:

- **RQ1**: How are discussion network structures affected by the usage of linear/hierarchical conversation views?

- **RQ2**: What are the parameters that explain the resulting changes in the discussion network structures?

- **RQ3**: Which conversation view (linear/hierarchical) is more effective to promote deliberation and reciprocity between users?

To answer these questions, we analyze how discussion network structures changed in Meneame[1], the most popular Spanish social news networking service (154^{th} most visited site in Spain according to Alexa[2]). The original conversation view of Meneame presented the comments of a thread linearly in a chronological order. This design changed in January 2015 and now messages are displayed by default hierarchically following the tree structure of the discussion. Therefore, Meneame becomes an unique opportunity to measure how conversation views shape the structure of discussion networks at a large scale. Figure 1 shows the same thread for both interfaces: linear (left), and hierarchical (right).



(a) Linear (b) Hierarchical

Fig. 1: Conversation views in Meneame for an example thread.

[1] https://www.meneame.net/

[2] http://www.alexa.com/siteinfo/meneame.net

2 State of the art

Prior research has exploited conversation threading for different purposes, e.g. visualization of online interactions (Levin et al., 2006; Pascual-Cid and Kaltenbrunner, 2009), refinement of graphical interfaces for e-mail clients (Rohall et al., 2001), online community search (Seo et al., 2011) or the development of information retrieval test collections (Elsas, 2011). Some studies from human-computer interaction have provided specific insights by examining conversation views (either linear or hierarchical) in a diverse range of online discussion platforms.

The functions of the hierarchical view in online forums were explored within an online learning environment (McVerry, 2007). According to the quality of responses in that study, the author reported that threaded discussions were more effective in building communities than traditional talk and, therefore, the hierarchical view gave users the opportunity to easily construct knowledge.

In the context of chat platforms, the research work in Fuks et al. (2006) examined the problems found during the development process of a chat tool. In particular, the authors identified the so-called "co-text loss" problem. This problem was defined by Pimentel et al. (2003) as the inability of readers to "identify which of the previous messages provides the elements that are necessary to understand the message that is being read". That is to say that co-text loss occurs when a user is not able to distinguish the earlier message to which a particular message is replying to. The empirical results in the development of that chat tool indicate that the hierarchical view mitigated such problem. These results are consistent with another experimental study of chat interfaces by Smith et al. (2000) in which authors recruited 70 participants to test a chat tool with a hierarchical view. According to the results, hierarchical view improved coherence within the discussion. Nevertheless, participants reported lower ratings regarding user experience for the hierarchical view than for the linear view.

Conversation views have been also explored for electronic mail services. The experiment conducted by Venolia and Neustaedter (2003) examined the experience of 6 participants reading their mail messages in a hierarchical view and concluded that this alternative provided better local context. That is to say that users can better understand the meaning of each individual message. Whittaker et al. (2011) carried out a field study of 345 long-term users in the platform Bluemail. This platform groups messages in threads but applies a linear view to display the corresponding conversation. According to the authors, this strategy was generally accepted by most users since it represents a way to easily access related messages.

Popular online social networks, platforms like Facebook or Twitter, have been performing significant changes in conversation views over time. For many years Facebook presented comments in a linear view disallowing direct replies to comments. The interface was modified in March 2013[3] when users were able to reply directly to comments. The team responsible of this feature aimed that

[3] https://www.facebook.com/notes/journalists-on-facebook/improving-conversations-on-facebook-with-replies/578890718789613/

conversation threading would improve conversations and be used to start open dialogues with the community. Nevertheless, the depth of trees was constrained to the third level, that is to say that comments to comments were presented at the same level. A survey of this specific Facebook feature concluded that conversation threading favoured participation giving the conversation a rhizomatic structure (Bendor et al., 2012). However, this survey also indicated that Facebook threading approach hides comments to comments by default and, therefore, decreases opportunities for deep conversations. In the case of Twitter, the interface of discussions was also modified in 2013[4] in order to present replies in a linear view. A study of user behavior on Twitter found that previously conversationalist behaviour decreased from 2011 to 2013 (García-Gavilanes et al., 2014), however the effect of the new conversation view has never been analysed.

3 Dataset description

As mentioned in the introduction, the analysis presented in this article relies on a dataset from Meneame, the most popular social news networking service in Spain. Social news websites, like Reddit, Slashdot or Digg, feature user-posted stories which are ranked based on their popularity within the community. Each story has an associated conversation thread. Indeed, the original version of the Meneame was a clone of the Digg platform.Besides the change of the conversation view (from linear to hierarchical), some other reasons make Meneame interesting from a sociological and political perspective:

– The community of Meneame consists of thousands of users who daily debate hundreds of stories (links to news / blog posts) in order to collectively discuss and decide which of them will appear in the front page. The selection process is made by an open source collaborative filtering algorithm.

– The platform was released in 2005 and therefore Meneame is a mature community of users which have developed their own culture of practices. For instance, in 2014 users decided to exclude links to the mass media outlets that promoted a law for demanding copyright fees for incoming links from news aggregators[5].

– Although many links in early years were related to science and technology, the irruption of the Spanish 15M movement in May 2011 (also known as the Indignados movement) turned Meneame into one of the most relevant online platforms in Spain about social and political issues.

We run a crawling process to collect all the stories in the front page from 2011 to 2015 (both years included). We then perform a second crawling process

[4] https://blog.twitter.com/2013/keep-up-with-conversations-on-twitter
[5] https://medium.com/@JulioAlonso/the-story-of-spains-google-tax-5434d746df48

to collect every comment from the discussion thread of each story. From both crawling processes we obtain 72,005 posts and 5,385,324 comments. For each of them, we keep associated metadata such as the id, url, user name, timestamp, text message and received votes. Also, we include the parent id for each comment in order to generate the tree structures.

Once the dataset is built, we make a preliminary exploration of the data in order to examine basic patterns. Figure 2(top) presents the weekly number of stories (top-left), comments (top-center) and users (top-right). We observe that, although the number of stories in the front page decreases over time, the number of comments firs decreases from 2011 to 2014 but then increases from 2014 to 2016. The number of users also decreases from 2011 to 2014 but then remains stable. All time series show a seasonal pattern in which the activity drops on summer and winter holidays.

Figure 2(bottom) shows that the weekly average number of users per thread (bottom-left) and users per thread (bottom-right) grow at the beginning of 2015. This observation is relevant since the conversation view was modified from linear to hierarchical at that time.

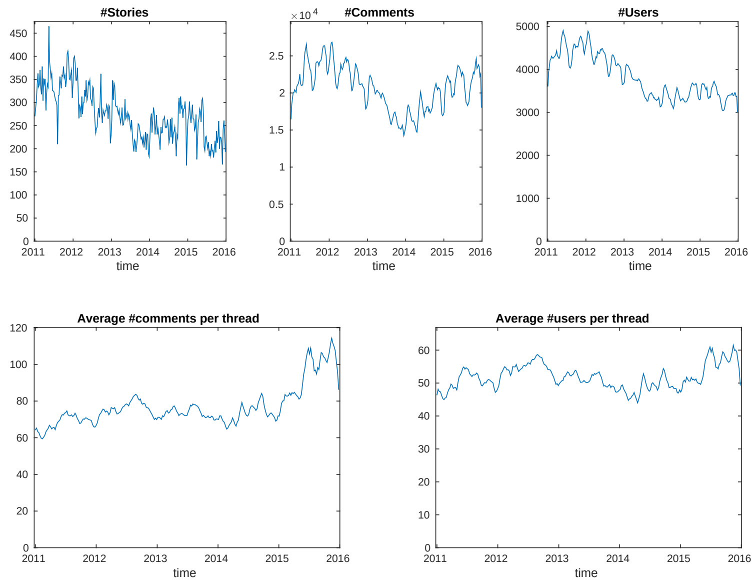


Fig. 2: Weekly number of stories, comments, users (top), and weekly average number of comments and users per thread (bottom).

We then examine the posting and voting activity. Figure 3 presents a scatter plot of the number of stories and the number of votes to stories for every day in the dataset. The plot shows a strong correlation between both variables (Pearson coefficient=0.821) and we identify some days (red markers) with abnormally higher activity than the rest of the days, especially in the number of votes. The inspection of the corresponding stories reveals that these were relevant days in the Spanish 15M movement:

17-19/05/2011: Occupation of the main squares.

27/05/2011: Police eviction the occupation in Barcelona.

25-27/09/2012: Citizen encirclement of the Parliament.

31/01/2013: Podemos (party) anti-austerity rally in Madrid

21/02/2012: 15M Outbreak in Valencia

11/07/2012: Asturian miners' strike

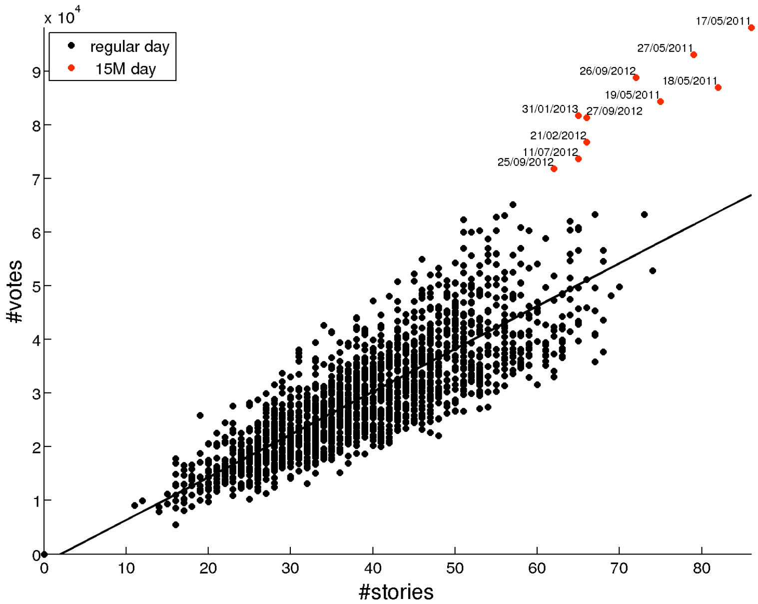
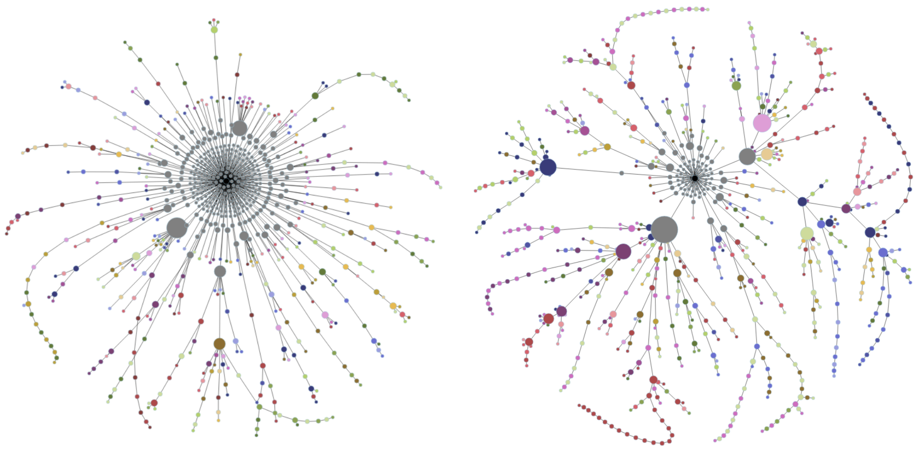


Fig. 3: Number of stories versus number of votes in the front page for every day.

Finally, we illustrate by means of two examples of representative discussions how the threads differ at a global scale before and after the change of interface. To this end, we adapt an existing thread visualization tool (Aragón et al., 2016). The new version of the tool assigns the size of each comment according to the number of responses. The color of the node is: We present the visualization of a popular thread from 2013[6] (left) and a popular thread from 2015[7] (right) in Figure 4. While both examples of discussions show similar features, such as long chains of two users that alternate messages, there are clear differences. For example, the thread from 2013 contains many more direct comments to the original post than the thread from 2015. Also, in the thread from 2015, comments attract often many replies and originate new sub-discussions within the thread. An effect which is not that pronounce in the previous thread.



(a) Thread from 2013.

(b) Thread from 2015.

Fig. 4: Visualization of popular threads before and after the conversation view was modified. Black: Root of the thread, i.e. the story. Grey: First level comments. Random color: Comments to another comment (every comment written by the same user gets a identical color).

[6] https://www.meneame.net/story/nicolas-maduro-anuncia-muerte-hugo-chavez

[7] https://www.meneame.net/story/cup-dice-plebiscito-no-ha-ganado-descarta-declaracion-unilateral

4 Results

The preliminary data exploration exposed above gives some indication of the change in the threads on Meneame. In this section we analyse how the structure of the discussion networks was affected. Then we propose an adapted version of an existing stochastic generative tree model for information cascades in order to assess changes in the evolution of discussion networks.

4.1 Structure of the discussion threads

In the context of social media and data analysis, the term *platform effect* has been proposed in a recent study (Malik and Pfeffer, 2016) as the "the design and technical features of a given platform which constrain, distort, and shape user behavior on that platform". That study focused on platform effects in datasets from Netflix and Facebook and effectively measured how new features deployed in these two platforms changed patterns of user behavior. We follow the same methodology of that study which consists of applying regression discontinuity (RD) analysis. RD is commonly applied to measure causal effects in cases where an arbitrarily strict cutoff along one covariate exists. In the linear case the regression is:

$$Y_i = \omega_0 + \omega_1 x_i + \omega_2 1(x_i > c) + \omega_3 x_i 1(x_i > c) + \epsilon_i, \tag{1}$$

where i is a seven days bin, x_i is the timestamp of bin i, Y_i is the average rating variable of bin i, ω_i are the coefficients of the regression, ϵ_i is a random error term and c is the cutoff. This analysis fits two different lines, before and after the cutoff, and allows to quantify the difference between both fitted lines at the cutoff. The null hypothesis is that there is no discontinuity (i.e. the platform is not affected by the release of the new conversation view) and, therefore, $\omega_2 = \omega_3 = 0$. In our study, the timestamp of the cutoff is expected to be the time when the conversation view was modified in Meneame. As suggested in Lee and Lemieux (2009), we use the F-test to calculate the most significant point in the time series. Below, the RD results are presented for two rating variables: a metric of online deliberation and a metric of reciprocity.

Online deliberation Several approaches have been proposed in order to define necessary and sufficient conditions for deliberation to take place (Ackerman and Fishkin, 2004; Fishkin and Luskin, 2005; Thompson, 2008; Gutmann and Thompson, 2009). In the context of online discussion, a previous study modeled deliberation through the structural complexity of the discussion threads (Gonzalez-Bailon et al., 2010). In particular, online deliberation was conceived as the conjugation of two prerequisites:

- Representation: Width of the discussion thread.
- Argumentation: Depth of the discussion thread.

This representation of deliberation was then quantified by the *h-index*. This metric was originally defined to rank researchers by their scientific performance, and considers that a scholar with an index of h has published h articles with at least h citations each (Hirsch, 2005). In discussion threads, the h-index is defined by the maximal number h such that there are at least h comments at level h, but not $h+1$ comments at level $h+1$, as suggested in Gómez et al. (2008). Therefore, this metric effectively balances both the width and depth of the discussion thread.

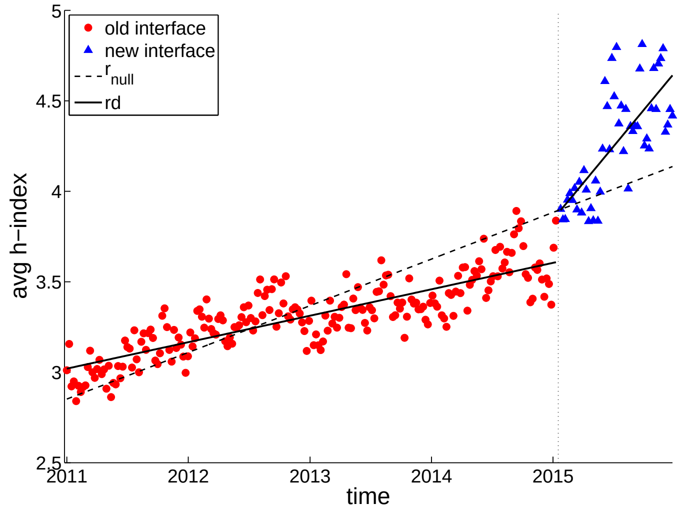
We examine each possible bin as cutoff through the F-test and find the days from 17/01/2015 to 24/01/2015 as the most significant cutoff. For that cutoff, we then plot the local linear regression in Figure 5a and observe that the average h-index increases over time. In particular, the slope of the discontinuous linear regression increases notably at the cutoff from $m = 0.0028$ to $m = 0.0155$, while the slope of the null hypothesis ($m = 0.0049$) does not capture such an effect.

Reciprocity The reciprocity of a directed network indicates the likelihood of nodes to be mutually linked. This metric has been proved informative to understand the structure and formation of social networks, commonly characterized by a high degree of reciprocity (Garlaschelli and Loffredo, 2004; Mislove et al., 2007; Zlatić and Štefančić, 2009; Kumar et al., 2010). Given a directed network, the reciprocity value, between 0 and 1, is defined as the fraction of edges in both directions. By definition, conversations threads are represented as directed trees, i.e. without mutual edges. Therefore, as done in Kaltenbrunner et al. (2011), a directed weighted network is built which comprises a set of nodes (users) and a set of edges (replies between any pair of users). To take into consideration the weighted nature of the network (e.g. the number of times that two users interchange messages within a thread) we apply a reciprocity metric proposed for weighted networks (Squartini et al., 2013):

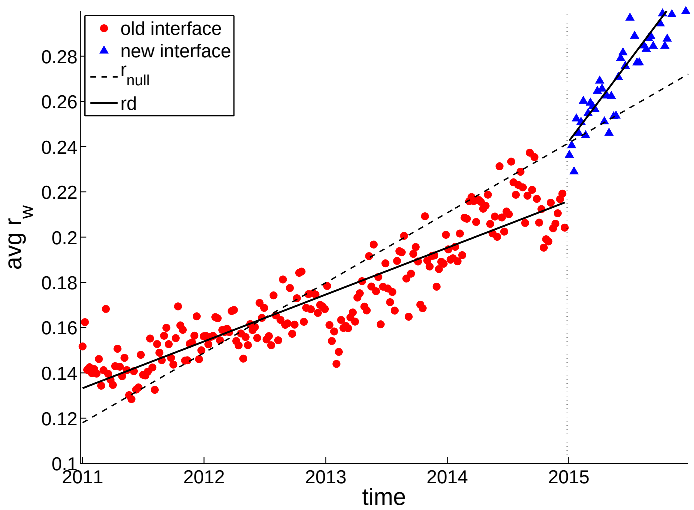
$$r_w = \frac{W^{\leftrightarrow}}{W} = \frac{\sum_i \sum_{j \neq i} w_{ij}^{\leftrightarrow}}{\sum_i \sum_{j \neq i} w_{ij}}, \tag{2}$$

where i,j are nodes, w_{ij} is the weight of the edge from i to j, and $w_{ij}^{\leftrightarrow}$ is the minimum weight between the edge from i to j and the edge from j to i.

As done for online deliberation, we first identified through the F-test which is the most significant bin to be the cutoff. The test detects that the maximum value is at the days from 27/12/2014 to 02/01/2015, a few days before the hierarchical conversation view was released. This might be explained because threads in the analysis are organized according to the timestamp of the initial post but discussions are active for several days. Figure 5b shows discontinuity in the local linear regression for that cutoff. The slope of discontinuous linear regression changed at the cutoff from $m = 0.0004$ to $m = 0.0014$, while the slope of the null hypothesis is $m = 0.0006$.



(a) Average h-index.



(b) Average weighted reciprocity.

Fig. 5: Regression discontinuity (RD) analysis for every seven days. Red circles and blue triangles are the bins before and after the cutoff. Solid lines are the discontinuous linear regression and dashed lines are the continuous linear regression of the null model.

4.2 Evolution of the discussion threads

We now measure the impact of using a hierarchical view by means of a model estimated from data. We build upon the model introduced in Gómez et al. (2013), that has proven to be successful in capturing the structural properties and the temporal evolution of discussion threads present in very diverse platforms, such as Slashdot, Barrapunto, Wikipedia and also Meneame. The original model disregards any content and considers three structural features: the *popularity* α of a comment (number of replies), the *root-bias* β (or tendency to write more comments to the root node) and the *novelty* τ (the elapsed time since it was written). These features are parameterized through the vector $\theta = \{\alpha, \beta, \tau\}$.

The conversation thread at time-step t is represented as a vector of parent nodes $\pi_{1:t} = (\pi_1, \pi_2 \ldots, \pi_t)$. When a new comment arrives to the discussion, the model selects an existing node $j \in 1, \ldots, t$ proportionally to its *attractiveness* function, defined as

$$\begin{aligned} p(\pi_{t+1} = j | \pi_{1:t}; \theta) \propto & \phi_j(\pi_{1:t}; \theta) \\ = & \alpha \deg_j(\pi_{1:t}) + \beta \delta_{j,1} + \tau^{t+1-j}, \end{aligned} \tag{3}$$

where $\deg_j(\pi_{1:t})$ is the degree of node j in the tree $\pi_{1:t}$ and δ is the Kronecker delta function, i.e. β is only relevant for the root node. Parameter estimation is done via maximum likelihood.

Extending the model for authorship In some cases, as noted in (Gómez et al., 2013), the model described in Equation (3) tends to underestimate the depths of the threads. This is actually the case in Meneame, which is characterized by very deep threads with long chains of messages between two alternating users (see Figures 4,6). The original model fails to capture the effect that commenting behaviour tends to be reciprocal, that is, users tend to reply comments that are replies to their previous comments. To incorporate such an effect in the original model, we extend it with an authorship model and introduce a new feature, the reciprocity.

We now represent a conversation thread with the parent vector $\pi_{1:t}$ together with a vector of respective authors $a_{1:t} = (a_1, a_2, \ldots, a_t)$. Our author model does not allow two consecutive comments to be written by the same user. Furthermore, a user cannot self-reply a comment made by herself. Let u denote the number of different users that participated in the conversation so far. At time $t+1$, a new comment is originated from a new user $v = u+1$ with probability p_{new}, or otherwise from an existing user v chosen according to how many times user v wrote in the thread, r_v. Our author model is described as

$$p(a_{t+1} = v | a_{1:t}) = \begin{cases} p_{new}, & \text{for } v = u+1 \\ \frac{(1-p_{new}) 2^{r_v}}{\sum_{w=1}^{u} 2^{r_w}}, & \text{for } v \in 1, \ldots, u \end{cases} \tag{4}$$

We set p_{new} empirically to $p_{new} = t^{-1/k}$ and estimate k from the data. Notice that the preferential attachment process that selects authors is multiplicative.

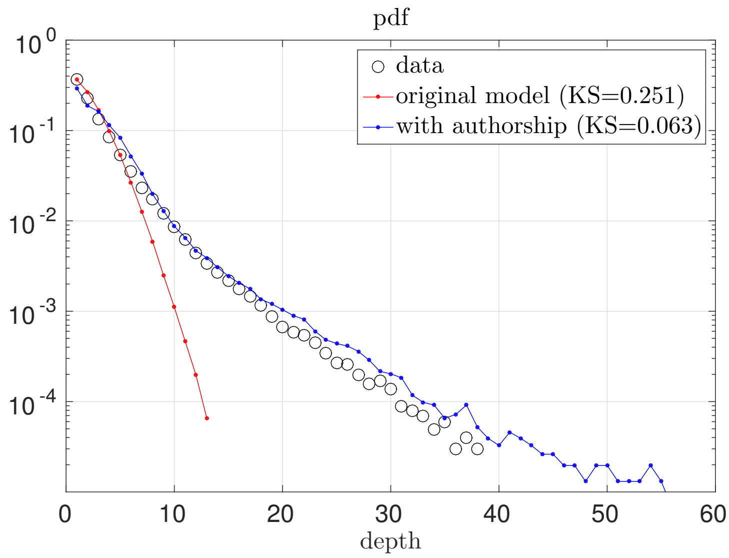


Fig. 6: Probability distribution of the comment's depths. The original model fails to capture the long tail created by reciprocal message chains whereas the proposed model is able to reproduce the data more accurately. The curves where obtained from $2 \cdot 10^3$ threads generated from both models after optimization of their respective parameters. KS indicates Kolmogorov-Smirnov test value (the lower the better).

This is required to capture well the probability distribution of the number of comments per unique author in a thread.

Once the author a_{t+1} is decided, the new comment is attached to an existing comment j according to

$$p(\pi_{t+1} = j | \pi_{1:t}, a_{1:t}; \theta) \propto \kappa \delta_{a_{\pi_j}, a_{t+1}} + \phi_j(\pi_{1:t}; \theta) \tag{5}$$

where $\phi_j(\cdot)$ is the (author-independent) attractiveness function of the original model, Equation (3).

The new parameter κ determines how strong reciprocal comments are weighted. Only those comments which reply to comments authored by the selected author, i.e. $a_{\pi_j} = a_{t+1}$ will contribute to the κ-term. Thus, for $\kappa = 0$ the new feature will play no role evolution of the thread whereas very large values of κ will make all comments of corresponding users reciprocal. The extra parameter κ needs to be optimized together with α, β and τ of the original model.

Compared to the original model, our proposed extended model reproduces better the structural properties. As an example, Figure 6 shows that the extended model (denoted as *with authorship*) can reproduce better the depth distribution of the comments, thanks to the authorship model and the reciprocity feature.

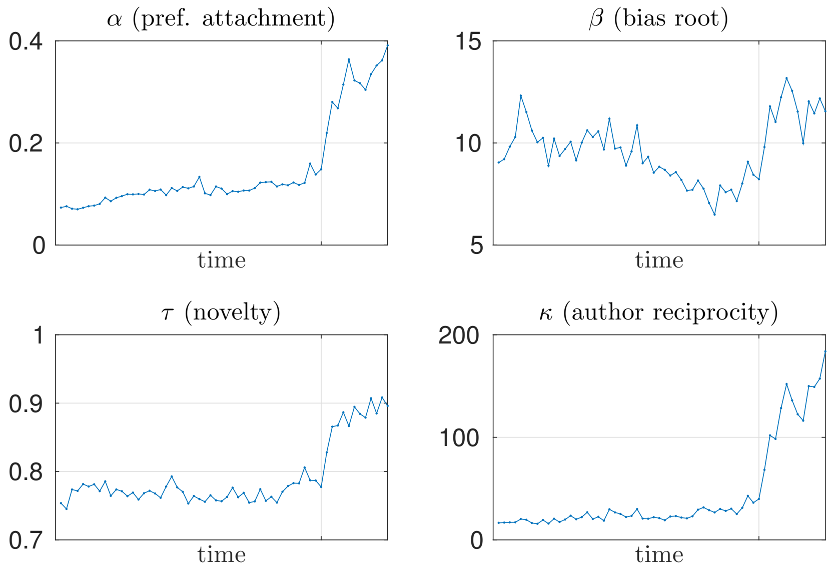


Fig. 7: Temporal profiles of the model parameters. Each point corresponds to one month of discussion threads. The vertical line indicates the change in the interface. All features but the root-bias undergo an notable increase in their corresponding parameter with respect to their previous history.

Impact of threading view on the learned features We now analyse how the platform change affected the communication habits that can be captured by the previous model. For that, we fit the extended model to data from different periods of time. Figure 7 shows the temporal profiles of the estimated parameters, each of them corresponding to one of the features. Globally, we observe notable increases in almost all the parameters after the platform change. The most noticeable change corresponds to the reciprocity κ. Once the threaded view is active, users behave significantly more reciprocally and tend to engage more in dialogues. Besides, both the preferential attachment α and the novelty τ also show an abrupt increase after the platform change. Although both increases appear in part as a compensation for the large increase of the reciprocity κ, they also indicate higher relevance of both features. The reason is that the reciprocity is only relevant at the later stages of the discussions, where comments are written from existing authors that have already been replied. Finally, the root-bias does not show any notable change if compared to the whole time history. Since the other features have more weight, this means that relatively, the root-bias is less relevant after the change.

5 Conclusion

In this study we have analysed how the discussion threads on Meneame were affected by the change of the conversation view.

Regression discontinuity analysis was applied to answer our first research question (RQ1). Results show that, once the linear conversation view was replaced by a hierarchical one, the discussion networks acquired more rhizomatic structures by the emergence of sub-discussions in threads. This new network topology of thread is associated with higher levels of deliberation and exhibits reciprocity between users to a greater extent.

To explore our second research question (RQ2), the model-based analysis gave a deeper understanding of the evolution of discussion networks and the parameters affected by the new conversation view. Thus, according to our model, we can conclude that the hierarchical view:

- induces more reciprocal activity,
- makes popular comments to attract more replies,
- slows down the decay of novelty, i.e. comments take longer to be ignored.

The first observation is consistent with the findings from the regression discontinuity analysis. The two last effects might be explained by the fact that the hierarchical view first presents the comments who belong to the first branches of the thread.

All these results allow us to answer the third research question (RQ3) which deals the kind of conversation view that better promotes deliberation and reciprocity. The results are clear: both deliberation and reciprocity notably increase with the hierarchical view. On the one hand, the h-index approach for deliberation, as suggested by Gonzalez-Bailon et al. (2010), might reflect argumentation and representation. However, we should note that there are some other approaches that define necessary conditions for deliberation. For instance, according to Fishkin and Luskin (2005), deliberative discussion must be balanced, conscientious, substantive, comprehensive. All these conditions can not be fully assessed through the structural properties of the discussion network. Therefore, future work might explore features from the content of comments to verify if these other conditions are met. On the other hand, we should note that the hierarchical view gives preference to comments according to the branches they belong. Thus, new messages in large discussions may encounter difficulties in being visible if they do not reply messages from the first branches of the discussion tree. This platform design is crucial for bringing innovation to discussion platforms because new contributions with no connection with previous arguments will be nearly invisible to the community.

All these findings have relevant social and political implications, in particular, in platforms for citizen democracy. Spanish city councils are currently deploying online platforms, like Decide Madrid[8], where citizens are able to discuss and decide the city model through debates and citizen proposals. Although discussions in Decide Madrid have always been presented in a hierarchical view, the sorting criteria for branches did change: branches were originally sorted by the date of the initial comment but now branches are sorted by the number of votes to the initial comment. This change could trigger new forms of discussions, as the change of the conversation view did on Meneame. Therefore, future work should also apply our analysis in this relevant context in order to bring complementary insights on how platform design and algorithms influence the performance of digital democracy.

Acknowledgments

This work is supported by the Spanish Ministry of Economy and Competitiveness under the Maria de Maeztu Units of Excellence Programme (MDM-2015-0502) and the EU project D-CENT (FP7/CAPS 610349).

[8] `http://decide.madrid.es/`

Bibliography

Ackerman, B. A. and Fishkin, J. S. (2004). *Deliberation day.* Yale University Press.

Aragón, P., Gómez, V., and Kaltenbrunner, A. (2016). Visualization Tool for Collective Awareness in a Platform of Citizen Proposals. In *ICWSM-16 - 10th International AAAI Conference on Web and Social Media*. The AAAI Press.

Bendor, R., Lyons, S. H., and Robinson, J. (2012). Whats There Not to Like? Sustainability Deliberations on Facebook. *JeDEM-eJournal of eDemocracy and Open Government*, 4(1):67–88.

Cha, M., Mislove, A., and Gummadi, K. P. (2009). A measurement-driven analysis of information propagation in the flickr social network. In *Proceedings of the 18th international conference on World wide web*, pages 721–730. ACM.

Dahlgren, P. (2005). The internet, public spheres, and political communication: Dispersion and deliberation. *Political communication*, 22(2):147–162.

Elsas, J. L. (2011). Ancestry. com online forum test collection. Technical report, Technical Report CMU-LTI-017, Language Technologies Institute, School of Computer Science, Carnegie Mellon University.

Elster, J. (1998). *Deliberative democracy*, volume 1. Cambridge University Press.

Fishkin, J. S. and Luskin, R. C. (2005). Experimenting with a democratic ideal: Deliberative polling and public opinion. *Acta Politica*, 40(3):284–298.

Fuks, H., Pimentel, M., and De Lucena, C. J. P. (2006). RU-Typing-2-Me? Evolving a chat tool to increase understanding in learning activities. *International Journal of Computer-Supported Collaborative Learning*, 1(1):117–142.

García-Gavilanes, R., Kaltenbrunner, A., Sáez-Trumper, D., Baeza-Yates, R., Aragón, P., and Laniado, D. (2014). Who are my audiences? a study of the evolution of target audiences in microblogs. In *International Conference on Social Informatics*, pages 561–572. Springer.

Garlaschelli, D. and Loffredo, M. I. (2004). Patterns of link reciprocity in directed networks. *Physical review letters*, 93(26):268701.

Gómez, V., Kaltenbrunner, A., and López, V. (2008). Statistical analysis of the social network and discussion threads in slashdot. In *Proceedings of the 17th international conference on World Wide Web*, pages 645–654. ACM.

Gómez, V., Kaltenbrunner, A., and López, V. (2008). Statistical analysis of the social network and discussion threads in slashdot. In *WWW '08: Proceeding of the 17th international conference on World Wide Web*, pages 645–654, New York, NY, USA. ACM.

Gómez, V., Kappen, H. J., Litvak, N., and Kaltenbrunner, A. (2013). A likelihood-based framework for the analysis of discussion threads. *World Wide Web*, 16(5-6):645–675.

Gonzalez-Bailon, S., Kaltenbrunner, A., and Banchs, R. E. (2010). The structure of political discussion networks: a model for the analysis of online deliberation. *Journal of Information Technology*, 25(2):230–243.

Gutmann, A. and Thompson, D. (2009). *Why deliberative democracy?* Princeton University Press.

Heylighen, F. (1999). Collective intelligence and its implementation on the web: algorithms to develop a collective mental map. *Computational & Mathematical Organization Theory*, 5(3):253–280.

Hirsch, J. E. (2005). An index to quantify an individual's scientific research output. *Proceedings of the National academy of Sciences of the United States of America*, 102(46):16569–16572.

Kaltenbrunner, A., Gonzalez, G., Ruiz De Querol, R., and Volkovich, Y. (2011). Comparative analysis of articulated and behavioural social networks in a social news sharing website. *New Review of Hypermedia and Multimedia*, 17(3):243–266.

Kemp, S. (2016). Digital, social & mobile worldwide in 2016. *We are social*.

Kumar, R., Novak, J., and Tomkins, A. (2010). Structure and evolution of online social networks. In *Link mining: models, algorithms, and applications*, pages 337–357. Springer.

Kwak, H., Lee, C., Park, H., and Moon, S. (2010). What is twitter, a social network or a news media? In *Proceedings of the 19th international conference on World wide web*, pages 591–600. ACM.

Laniado, D., Tasso, R., Volkovich, Y., and Kaltenbrunner, A. (2011). When the wikipedians talk: Network and tree structure of wikipedia discussion pages. *The AAAI Press,[2011]. p. 177-84*.

Lee, D. S. and Lemieux, T. (2009). Regression discontinuity designs in economics. Technical report, National Bureau of Economic Research.

Lerman, K. and Ghosh, R. (2010). Information contagion: An empirical study of the spread of news on digg and twitter social networks. *ICWSM*, 10:90–97.

Levin, J., Kim, H., and Riel, M. (2006). Analyzing instructional interactions on electronic message networks.

Magno, G., Comarela, G., Saez-Trumper, D., Cha, M., and Almeida, V. (2012). New kid on the block: Exploring the google+ social graph. In *Proceedings of the 2012 ACM conference on Internet measurement conference*, pages 159–170. ACM.

Malik, M. M. and Pfeffer, J. (2016). Identifying Platform Effects in Social Media Data. In *Proceedings of the Tenth International AAAI Conference on Web and Social Media, ICWSM-16*.

McVerry, J. G. (2007). Forums and functions of threaded discussions. *New England Reading Association Journal*, 43(1):79.

Mislove, A., Marcon, M., Gummadi, K. P., Druschel, P., and Bhattacharjee, B. (2007). Measurement and analysis of online social networks. In *Proceedings of the 7th ACM SIGCOMM conference on Internet measurement*, pages 29–42. ACM.

Pascual-Cid, V. and Kaltenbrunner, A. (2009). Exploring asynchronous online discussions through hierarchical visualisation. In *Information Visualisation, 2009 13th International Conference*, pages 191–196. IEEE.

Pimentel, M. G., Fuks, H., and de Lucena, C. J. P. (2003). Co-text loss in textual chat tools. In *Modeling and Using Context*, pages 483–490. Springer.

Rheingold, H. (2007). *Smart mobs: The next social revolution.* Basic books.

Rohall, S. L., Gruen, D., Moody, P., and Kellerman, S. (2001). Email visualizations to aid communications. In *Proceedings of InfoVis 2001 The IEEE Symposium on Information Visualization, IEEE*, volume 12, page 15.

Seo, J., Croft, W. B., and Smith, D. A. (2011). Online community search using conversational structures. *Information Retrieval*, 14(6):547–571.

Shirky, C. (2011). The political power of social media: Technology, the public sphere, and political change. *Foreign affairs*, pages 28–41.

Smith, M., Cadiz, J. J., and Burkhalter, B. (2000). Conversation trees and threaded chats. In *Proceedings of the 2000 ACM conference on Computer supported cooperative work*, pages 97–105. ACM.

Squartini, T., Picciolo, F., Ruzzenenti, F., and Garlaschelli, D. (2013). Reciprocity of weighted networks. *Scientific reports*, 3.

Surowiecki, J. (2005). *The wisdom of crowds.* Anchor.

Thompson, D. F. (2008). Deliberative democratic theory and empirical political science. *Annu. Rev. Polit. Sci.*, 11:497–520.

Ugander, J., Karrer, B., Backstrom, L., and Marlow, C. (2011). The anatomy of the facebook social graph. *arXiv preprint arXiv:1111.4503*.

Venolia, G. D. and Neustaedter, C. (2003). Understanding sequence and reply relationships within email conversations: a mixed-model visualization. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 361–368. ACM.

Whittaker, S., Matthews, T., Cerruti, J., Badenes, H., and Tang, J. (2011). Am I wasting my time organizing email? A.

Zhang, W., Johnson, T. J., Seltzer, T., and Bichard, S. L. (2009). The revolution will be networked: The influence of social networking sites on political attitudes and behavior. *Social Science Computer Review.*

Zlatić, V. and Štefančić, H. (2009). Influence of reciprocal edges on degree distribution and degree correlations. *Physical Review E*, 80(1):016117.