Cross-Community Influence in Discussion Fora

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Abstract

Online discussion fora have become an important cultural and business asset in the context of many services provided by both non-profit organizations and enterprises. In order to keep and eventually increase the value these systems deliver to their users, it is often necessary to moderate or even manage their dynamics. One way to do this efficiently is to focus primarily on the most influential actors in the system. However, identifying such users becomes increasingly hard with systems where there is a continuously growing large user base. We show that analysis and explanation of influence on the cross-community level is a promising way to provide a coarse-grained picture of a potentially very large system and that it may enable its stakeholders to find groups through which the system can be efficiently influenced, or it can help them to identify and avoid activity considered as malicious. In order to achieve that, we present a novel framework for cross-community influence analysis, which is evaluated on 10 years of data from the largest Irish online discussion system Boards.ie.

Introduction

Online social communities have become an important asset in the context of many services provided by both non-profit organizations and enterprises. Their ascent has been accompanied by a rising research interest of their detection (Fortunato 2010) and dynamics (Spiliopoulou 2011). Online communities often consist of people with shared interests and naturally, some are members of different groups, which causes the communities to *overlap*. The detection of overlapping communities has recently emerged as major research focus and some of the proposed methods determine a degree of membership of each community member, which led to the notion of *fuzzy communities* (Gregory 2011). However, the community structure can also be explicitly given, e.g. in the case of online discussion fora, the set of users participating in a forum acts as a community. The fact that communities overlap often means that they also interact, i.e. one community may affect another one because of their shared users. While some interactions may be beneficial for both sides, e.g. when one community enriches a discourse of another one (McGlohon and Hurst 2009), a community can also get overtaken or isolated.

In this paper we are particularly interested in situations where one forum community has *impact* on another one, i.e. users from one forum, on average, stimulates another forum to have higher activity or replies. For example, Figure 1 shows two discussion communities, $A = \{1, 2, 3, 4\}$ and $B = \{2, 3, 4, 5, 6, 7\}$, in which the nodes represent users connected by their replies. The thickness of the links reflect the number of replies and the shading shows a user's community affiliations, such that the darker the node the more a user is *devoted* to forum A, and the lighter it is, the more it is devoted to forum B.

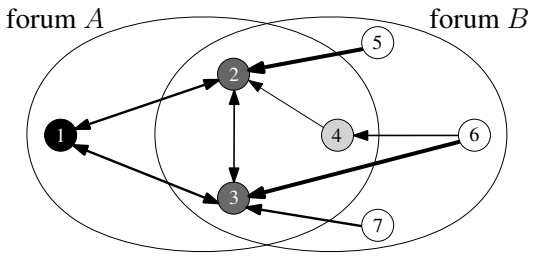


Figure 1: Example of impact from forum A to B. Nodes are users connected by links whose thickness reflects the number of replies. The shading expresses community affiliations, such that the darker (lighter) the node is, the more it is devoted to forum A (B).

In this idealised scenario, we see that users $\{5, 6, 7\}$ in forum B reply frequently to users $\{2, 3\}$ who are mainly devoted to A. And so, while the most devoted members of forum A tend to converse amongst themselves, e.g. as $\{1, 2, 3\}$ do, they also receive a lot of replies from users of forum B, i.e. users from B react more to users who are more devoted to A than B. We further note that users $\{2, 3\}$ are *central* users, in that they receive many replies. So, not only are users $\{2, 3\}$ more devoted to A, they are also the most central users in B. Thus, our intuition is that even though community B has more members than A, A has a high impact on B because the most central users of B are more devoted to A. We may even say that community B lacks a kernel of fully devoted users and that it is *dependent* on A.

The **main hypothesis** of this paper is that the level of mutual impact between communities differ, that there are communities with very high impact on other communities and conversely, that there are also communities whose activity is significantly influenced by others. Analysis and explanation of the cross-community impact is a promising way to provide a coarse-grained picture of a reasonably large system.

It can enable its stakeholders to find groups through which the system can be efficiently influenced (e.g. for assigning local authorities), or it can help them to find and avoid activity considered as malicious (e.g. "flame wars" between rival groups). In particular, we are concerned with the following questions:

- How can we identify communities persistently affecting other communities?
- Given a specific community, which communities are its key influencers? Which communities are dependent on the activity of others?
- Over time, how can we identify that a community is being increasingly influenced or even overtaken by another community?

One conceivable way of tackling these questions is to investigate fora with the highest activity and size, or to first create a community graph (Pollner, Palla, and Vicsek 2006) and use centrality measures like PageRank or betweenness to identify the key fora. We have conducted these experiments and refer on them in the online supplementary material.[1] In short, we found that such centrality measures correlated strongly with the activity of fora and that fora selected on the basis of activity lacked a kernel of strongly devoted users, which in turn misses fora which arguably are the true authorities (such as moderating fora).

These findings led us to the development of a novel framework for cross-community impact analysis, which is based on *purely structural* features, derived from a *dynamic reply-to graph*. Although this framework is flexible and can be extended to exploit other features e.g. content-based ones, this is not necessary, and we find that we can obtain a rich cross-community analysis without it. This is useful for when the data available has little external information, perhaps due to legal reasons or other. Moreover, it is based on a widely known notion of actor centrality which makes its interpretation somewhat easier. We evaluate our framework on 10 years of data from the largest Irish online discussion system Boards.ie[2], and we show that in contrast with activity-based measures, our method can clearly identify communities which are arguably more influential. The **main contributions** of this paper are as follows:

1. We provide a flexible and extensible framework for structural-based analysis of cross-community impact.
2. We extend a notion of centrality of individual actors in a social network to the level of communities.
3. A cross-community analysis of 10 years of Boards.ie was carried out and the key fora were identified, as well as their relations over time.

We note that in this paper we use "influence" and "impact" interchangeably. While the notion of influence in the context of social media analytics refer to the ability of an actor to change behaviour of its neighbours (Sun and Tang 2011), our definition of community influence is specifically tied to the conversational activity.

[1] See http://belak.net/doc/2012/icwsm.html.

[2] See http://www.boards.ie.

The remainder of the paper is organised as follows. In the next section we refer to the related work. The framework itself together with the data-set and its preparation is discussed in Preliminaries. Its evaluation is then presented in Results in which we analyse Boards.ie on different levels, from the level of global patterns of cross-community influence, to the level of individual time-series of impact between pairs of communities. The last section concludes the paper and outlines potential applications and extensions of the framework. Finally, all the data and scripts, along with our previous experiments, are publicly available in the online supplementary material.[3]

Related Work

Online discussions have been extensively researched with respect to the user conversational, grouping, and cross-posting behaviour. In one of the earliest studies, Whittaker et al. (1998) researched three classes of factors influencing conversational dynamics in USENET: conversational strategy, demographic factors, and interactivity represented by reply-to behaviour. A specific feature of USENET is that it is possible to send or forward a message to multiple fora — to *cross-post* it. The authors found that cross-posting leads to higher interactivity and hypothesised that it brings more diversity into the conversation and thus spawns new activity. McGlohon and Hurst (2009) draw on their results and looked closer at the flow of information represented by cross-posting. As a cross-posted message belongs to multiple groups, they developed a thread-ownership model based on the notion of author-group *devotedness* of the users measured by the distribution of their activity. In our analysis we draw on their approach and measure the devotedness in a similar manner. However, although there is no explicit cross-posting in Boards.ie, its users can and do post in multiple fora which are replied to by members of other fora.

The reply-to activity as an atomic element of online interactions has been a subject of multiple studies. For example, Arguello et al. (2006) shed some light onto what influences the likelihood that a user receives a reply from a USENET group. Kumar, Mahdian, and McGlohon (2010) developed several generative models of conversational (thread-like) structures and used these models to e.g. cluster online discussions based on their prevailing characteristics — for example discussions with more "skinny" or "bushy" threads. Sun et al. (2011) evaluate a sidebar mechanism which recommends threads to users based on social influence with the aim of maximising user participation in threads.

In addition, the problem of finding influential actors within a social network has been intensively studied in social network analysis (Wasserman and Faust 2009). For the individual actors a classic approach is to use heuristics like actors' degree or PageRank. Everett and Borgatti (1999) generalised several centrality measures to groups of actors. For instance, they defined *group degree centrality* "as the number of non-group nodes that are connected to group members". Hence the group degree captures relation between a group of actors and the rest of the network but *not* between two

[3] See http://belak.net/doc/2012/icwsm.html.

or more groups. The generalisation to the inter-community level is thus lacking.

In summation, none of the previous work has discussed the mutual impact *between* discussion communities and the aim of this paper is to fill this gap.

Preliminaries

This section presents the framework we have developed for the measurement and exploration of mutual impact of communities and the data we used to evaluated it. First we describe the analysed system and data-set. Then we formally define the notion of cross-community impact and other related measures, which were motivated in particular by two related questions: first, *are there communities with impact on other communities?* and secondly, *how does the impact evolve over time?*

Boards.ie

Boards.ie is structured according to themes into *fora*, optionally further into their subfora, and finally into *threads* of *posts* centred around a particular conversation topic. Each post has its author, who can be either a registered *user* or a guest. Since all the guests' posts are stored with the same user identifier, we omitted them from the analysis. A set of users who have posted at least once to a given forum within a certain time-period form a *community of that forum* in the period. Threads have a tree-like structure as one post can be in *reply to* another one. The set of users linked by the who-replies-to-whom relation thus form a directed dynamic graph weighted by the number of replies each user has replied to another user within a given time period. We particularly looked for communities of users persistently triggering high volume of activity in other communities and we took reply-to behaviour as a measure of such activity. Since the mutual dynamics of communities can be highly volatile in time, we segment the data using a sliding time-window and analyse the changes between the subsequent snapshots of the resulting sequence $s_1, \ldots, s_T$. Table 1 presents some basic statistics of the analysed data.

number of snapshots (T)	448
number of communities	636
mean number of communities per snapshot	159
mean community size (# users) per snapshot	27.52
post count	8,189,148
reply count	7,524,427

Table 1: Elementary statistics about the analysed data-set.

Time-Window Selection For the purpose of data segmentation it is necessary to find a suitable size for the time-window. As our methods are based on cross-fora posting activity, the window length should capture as much of that activity as possible, yet still fine enough to uncover changes in users' behaviour. Let $\tau(p)$ be a *minimum* time it took an author of post p to contribute a message in another fora, i.e. a *cross-fora posting waiting time*. If the author has not posted to any other fora, then $\tau(p) = \infty$.

In order to find out a suitable time-window size, we sampled 10,000 posts and investigated the distribution of $\tau(\cdot)$. Table 2 lists values of the empirical distribution function of $\tau(\cdot)$ for some selected times. It turned out that in approximately 84% of the cases a user has posted into another fora within 7 days, while 14 days period covers 88%. This means that doubling the window size would lead to an increase of only 4% in the coverage of cross-fora posting activity, and thus we decided to use a one-week window for our analysis. In total the data was segmented into 521 weekly snapshots. However, as some of the early snapshots were empty, we created a cut-off point from the first 73 weeks and used the next 448 snapshots between Monday 12.7.1999 and Sunday 10.2.2008 for our analysis.

t (days)	1	2	5	7	14
$ecdf_\tau(t)$	0.6806	0.7373	0.8152	0.8416	0.8817

Table 2: Values of the empirical cumulative distribution function $ecdf_\tau(t)$ for selected waiting times.

Mutual Impact of Fuzzy Communities

We want to characterise to what extent one community is influencing another one as depicted in the ideal case in Figure 1. In that scenario, users mostly devoted to B, $\{4, 5, 6, 7\}$, reply mainly to its central users $\{2, 3\}$ who are mostly devoted to A, and therefore A has an impact on B. Thus, any measure of impact between communities should take into account two factors: the degree of *membership* of each user and its *centrality* within each community. In this section we show how to express and combine these factors and how to derive additional measures which are helpful in the interpretation of the cross-community impact. We consider a general case of k communities and n users.

In order to represent which communities and to what extent an actor belongs to, let us define an $n \times k$ **membership** matrix $\mathbf{M} : m_{ij} \in [0, 1], \forall\, i : \sum_{j=1}^{k} m_{ij} = 1$ representing users' affiliations. Columns of $\mathbf{M}$ are fuzzy sets representing the individual communities. $\mathbf{M}$ can be known a priori e.g. from an in-field survey, determined by a community detection algorithm (Fortunato 2010), or from activity traces of users. In our analysis $m_{ij} = \frac{p_{ij}}{\sum_{j=1}^{k} p_{ij}}$, where p_{ij} is the number of posts an i-th user posted to j-th forum. Hence we measure the level of devotedness of a user by its activity in a similar manner to the work of McGlohon and Hurst (2009).

An impact of any given user within its communities can be formalised as an $n \times k$ **centrality** matrix $\mathbf{C}$ with elements c_{ij} representing an impact of i-th user to the other users of j-th community. It can be obtained by some centrality measure of a user, e.g. PageRank, in-degree, closeness, etc. We set c_{ij} as the number of replies a user received in a community, which is an *in-degree* of i-th user in a reply-to graph of j-th community. We chose in-degree for our experiments because the reply behaviour is the cornerstone of the conversational dynamics; it is a well-established heuristic for influence maximisation (Kempe, Kleinberg, and Tardos 2003) and it has a clear interpretation.

The $k \times k$ cross-community impact matrix $\mathbf{J}$ can then be obtained as a product of the two matrices: $\mathbf{J} = \mathbf{M}^{\mathrm{T}}\mathbf{C}$. The

elements $\mathbf{J}_{ij}$ represent weighted sums of centralities of the users of i-th community in j-th community. However, social communities usually have different sizes (Palla et al. 2005), which can bias the impact matrix. A very big community can, from its raw size, accumulate high values in $\mathbf{J}$ despite the fact that its members are not very devoted to it. Therefore we further divide the rows of the impact matrix by the cardinalities (Zadeh 1983) of the sets representing the communities — sums of the columns of the membership matrix — in order to obtain a **normalised impact** matrix:

$$\hat{\mathbf{J}}_{ij} = \frac{\mathbf{J}_{ij}}{\sum_{l=1}^{n} \mathbf{M}_{l,i}} \tag{1}$$

The normalised impact $\hat{\mathbf{J}}_{ij}$ then represents a weighted *mean* of centralities of members of i-th community in j-th community. The diagonal of $\hat{\mathbf{J}}$ contains **independence** values (self-impact), i.e. it measures to what extent the highly devoted members of each community are also central in it. If we subtract the diagonal from $\hat{\mathbf{J}}$, we can obtain a vector of total impact as row sums:

$$\mathcal{I}(\hat{\mathbf{J}}) = \hat{\mathbf{J}}\mathbf{1} - diag(\hat{\mathbf{J}}) \tag{2}$$

where $\mathbf{1}$ is a column vector of ones of length k. We call the total impact computed by $\mathcal{I}(\cdot)$ a community's **importance**, which measure how much impact a community has in total. Similarly, a vector of the column sums contains, at the i-th position, the total impact *other* communities have on the i-th community — a community's **dependence**:

$$\mathcal{D}(\hat{\mathbf{J}}) = \hat{\mathbf{J}}^{\mathrm{T}}\mathbf{1} - diag(\hat{\mathbf{J}}) \tag{3}$$

Please note that by definition it is possible that $\hat{\mathbf{J}}_{ij} > 0$ and $\hat{\mathbf{J}}_{ji} > 0$, i.e. i-th community has an impact on j-th *and* j-th has some impact on i-th community as well. However, the values may differ and it is exactly these differences in mutual impact we are interested in because we specifically look for pairs of communities that are in some sort of misbalanced relationship. For instance, if community A has high impact on community B, as idealised in Figure 1, then we find that the most central users of B are mostly devoted to A, rather than B. Using the introduced concepts we formalise this intuition by saying that an impact of i to j is *significant* if it is at least as high as the independence of j, which is expressed by the following function:

$$\psi(i, j, \hat{\mathbf{J}}) = \begin{cases} 1 & \frac{\hat{\mathbf{J}}_{ij}}{diag(\hat{\mathbf{J}})_j} \geq 1 \\ 0 & otherwise \end{cases} \tag{4}$$

While some communities may have impact to a relatively small circle of other communities, others may be broadly influential. For instance, a community of system administrators may have an impact to the whole system. Analogously, a community may be influenced by many other communities or it may be strongly influenced just by few fora. Such feature of a community's importance or dependence can be characterised as an entropy of the respective row or column of $\hat{\mathbf{J}}$. Because some elements of $\hat{\mathbf{J}}$ may be 0, let us define the convention $\log_2(0) = 0$. Further it is necessary to normalise the rows of the matrix in order to obtain probability distributions of impact, i.e. $\hat{\mathbf{J}}^N_{i,j} = \hat{\mathbf{J}}_{i,j} / \sum_{l=1}^{k} \hat{\mathbf{J}}_{i,l}$. The normalised **importance entropy** of i-th community is then defined as

$$\mathcal{H}_I(i, \hat{\mathbf{J}}) = -\frac{\sum_{m=1}^{k} \hat{\mathbf{J}}^N_{im} \log_2 \hat{\mathbf{J}}^N_{im}}{\log_2 k} \tag{5}$$

The **dependence entropy** $\mathcal{H}_D(i, \hat{\mathbf{J}})$ is defined similarly but on the transpose $\hat{\mathbf{J}}^{\mathrm{T}}$. Both measures have range within $[0, 1]$. The more the importance (dependence) of i-th community is equally distributed, the more the entropy value is close to 1. We note that in the case of entropy we *include* the diagonal elements (independences), because in such case it differentiates whether the most of the community's total impact is concentrated *within* that community or not.

For each time-snapshot we computed an importance matrix leading to a sequence $\hat{\mathbf{J}}_S = (\hat{\mathbf{J}}_1, \hat{\mathbf{J}}_2, \ldots, \hat{\mathbf{J}}_{448})$. It is also possible to *aggregate* this sequence e.g. by computing its mean $\langle \hat{\mathbf{J}}_S \rangle$. All the previously defined functions like importance $\mathcal{I}(\cdot)$ or dependence $\mathcal{D}(\cdot)$ can then be defined on the aggregate straightforwardly.

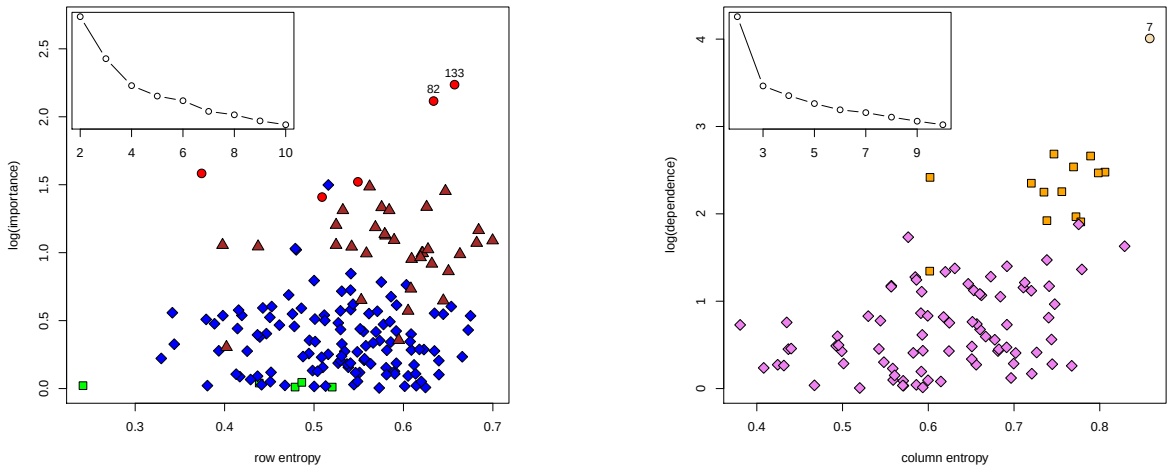
Results

We used the framework to analyse fora in Boards.ie in order to evaluate its suitability to reveal and explain cross-community influence on three different levels. First, we grouped together similar communities according to their impact and dependency relations with other fora in order to get a global overview of what classes of communities emerge, i.e. to show a high-level cross-community impact interaction in the system. Based on that, we further investigated communities identified as highly influential or dependent in time, and finally, we looked even closer to the level of pairs of communities and analysed how one community affected the other over time.

Different Groups of Important/Dependent Fora

In order to gain some first insights into the cross-community impact behaviour in Boards.ie we wanted to see if we could group similar fora together according to their impact/dependent behaviour. To do this we found groups formed by clustering the communities embedded in the row and column spaces of the impact matrix. Recall that rows represent the impact a community has on other communities, whereas columns express impact *other* communities have on the given community, dependence. To do this we first took the mean $\langle \hat{\mathbf{J}}_S \rangle$ of the whole sequence of snapshots $\hat{\mathbf{J}}_S$ and set the diagonal of the aggregate matrix to 0 so as to focus only on cross-community relations. Next we embedded the communities into row and column spaces of the resulting matrix and obtained importance- and dependence-based clusters using the k-means algorithm.[4] It can be seen in Figure 2 that there are clear clusters in both spaces. The number of clusters was determined by investigating the distribution of within cluster sums of squares, which has a characteristic

[4]We ran k-means with 100 random seeds each with 100 iterations.



(a) overall importance and its entropy

(b) overall dependence and its entropy

Figure 2: Overall logarithmically scaled importance and dependence, and their entropies. The shapes and colours denote clusters of communities embedded in the row (importance), resp. column (dependence) spaces. Circles, squares, diamonds, and triangles represent cluster 1 (I), 2 (II), 3 (III), and 4 respectively. As insets are plotted within cluster sums of squares (y axis) for different number of clusters (x axis) — note the characteristic "elbow" for four (a) and three (b) clusters. Fora FEEDBACK, MODERATORS, and AFTER HOURS are marked with their IDs 82, 133, and 7, respectively. For the sake of clarity only communities with importance (dependence) of at least 1 are plotted and thus large parts of clusters 2 and III are not displayed.

"elbow" in both cases around 4 and 3 for importance- and dependence-based clusters respectively — see the insets of Figures 2a and 2b. The points are individual communities and their shapes and colours denote their clusters. For the sake of clarity only communities with importance (dependence) at least 1 are plotted. [5]

Row-based clustering: Impact The communities in Figure 2a are plotted against their logarithmically scaled importances (see Eq. 2) and the corresponding entropies (Eq. 5) in order to characterise how much was each forum important and whether its influence was distributed equally or not. We found it surprising that although the clusters were obtained by clustering rows of impact matrix only, they clearly follow the importances of the communities *and* their entropies, which was not used for the clustering whatsoever. It suggests that using only the importance and entropy alone may be enough to discriminate different classes of communities with respect to their impact to other communities.

cluster	size	in-degree	# user	# post	import.
1	5	**68.7**	**61.21**	**285.14**	**6.24**
2	**461**	15.6	14.73	42.79	0.3
3	137	29.46	38.9	114.48	1.39
4	33	55.99	58.2	167.6	2.85

Table 3: Number (size) of the importance-based clusters and the average group in-degree, number of active users, number of posts, and importance for each cluster. The maximal values are in bold.

Table 3 lists some statistics for the clusters, which clearly follow the level of the overall importance. The group in-degree is the number of replies received by members of a community from the non-members, and its average was computed from the group in-degrees obtained for each snapshot of the reply-to network. The smallest cluster, 1, consists of five communities MODERATORS, FEEDBACK, THE THUNDERDOME, HUMANITIES, and THE CUCKOO'S NEST, all with very high average metrics as seen in Table 3. In particular, the first two are highly important to a lot of communities which follows from their outstanding position in the top-right corner in Figure 2a. As their titles suggest MODERATORS is a private community comprising of users moderating and facilitating discussion in other fora, while FEEDBACK is a public forum for users to provide feedback to the system maintainers. Therefore, members of both fora should naturally have high authority and impact in other communities. Conversations in THE THUNDERDOME have one main purpose: to provoke and insult other participants under the agreed rules.[6] Since the impact measures the ability of one community to *stimulate* another one, it is no surprise that a community specifically focusing on provocation was recognised as influential.

Clusters 3 and 4 are less-clearly separated and they consist of many general, mid-level fora like PERSONAL ISSUES, FILMS, HUMOUR, AFTER HOURS, etc. which have a relatively high average number of posts suggesting that these clusters represent fora where every-day conversation within Boards.ie happens. For instance, the most popular and biggest forum AFTER HOURS is a general-topic common meeting place for chat (see Table 5 for the list of the

[5] Again, the full listings of the clusters are provided only in the supplementary material.

[6] http://www.boards.ie/vbulletin/forumdisplay.php?f=484

most active communities). The impact measure therefore clearly captures a different quality not expressed by a simple post or member counts. The remaining cluster, 2, contains the majority of all the communities and have low values on all given metrics. This cluster contains many fora of very specific topics like BUDDHISM, SOCIAL MEDIA, or CHESS.

cluster	size	in-degree	# user	# post	depend.
I	1	**67.76**	**317.02**	**1375**	**55.02**
II	13	64.03	110.19	395.18	10.05
III	**622**	24.23	23.79	64.14	0.43

Table 4: Number (size) of the dependence-based clusters and the average group in-degree, number of active users, number of posts, and importance. The maximal values are in bold.

Column-based clustering: Dependence On the contrary, we found that the dependence-based clusters show a different structure. The clusters in Figure 2b show these communities plotted against their logarithmically-scaled dependence and entropy. Please note that again the clusters follow the dependence and its entropy even though the latter was *not* used for the clustering itself. Table 4 contains several statistics characterising the dependence-based clusters. AFTER HOURS was the only member of cluster I with the highest average dependence, which is more than five-times higher than the second highest figure. Moreover, its dependence has high entropy, which means it is influenced by *many other* communities. Hence this community has been identified what it indeed is — a common meeting place of members of disparate communities, while lacking a strong kernel of fully devoted users. The simple activity-based measures thus cannot capture such character, because judging only by activity or user-base volumes AFTER HOURS would be the most influential forum (see Table 5). This raises the question as to whether this community is in fact rather weak, because its users come only to chat, while their true interests lay in other fora.

While the average dependence of cluster III is the lowest, it can be ascribed to the low activity and user base of its communities rather than their particular strength. Cluster III is therefore analogous to the importance-based cluster 2 since it represents the majority of the system. In fact, both clusters are highly overlapping as their Jaccard similarity is 0.74. Many general-topic fora are represented by cluster II: HUMOUR, PERSONAL ISSUES, or FEEDBACK. This means that these communities are not only influencing significantly others as we described in the previous paragraph, but they are also *influenced* significantly. In order to disentangle the concrete mutual impact between these communities and others, it is necessary to drill down in the analysis to the level of time-series of the impact, which is a subject of the next section.

Overall Importance and Dependence over Time

To determine the distribution of impact and dependency over time we plotted fora with the highest importance (dependence) value at each time slot. We expected to uncover emergence of persistently influential communities, or transitions

community	in-deg.	# user	# post
AFTER HOURS	71.97	338.9	1472
THE CUCKOO'S NEST	73.79	89.86	930.1
POKER	38.86	135	903.2
BEER GUTS & RECEDING H.	85.71	98.88	860.4
SOCCER	67.96	144.5	859.3

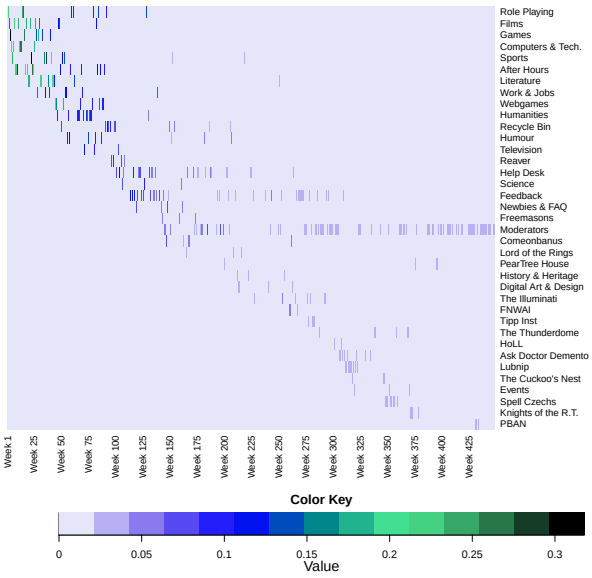
Table 5: The average group in-degree, number of active users, and number of posts for the 5 communities with the highest average post counts.

of a community from e.g. being important to become dependent. At each snapshot, we took the forum with the highest importance (dependence) value and then normalised it by dividing by the total importance/dependence value for that given time. This ensures that the value is comparable over the whole time period and Figure 3 shows the distribution of the fora which have the highest respective values at least three times over the 448 weeks.[7] The ordering is such that the forum whose value was the highest at the earliest available time slot is displayed from top to bottom.

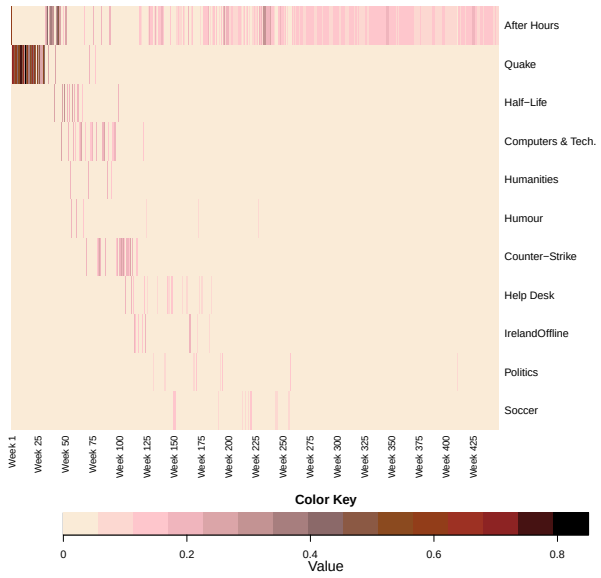
As seen in Figure 3a the maximal impact was quite unstable in the beginning, while few persistently influential communities like HELP DESK, FEEDBACK, and MODERATORS had emerged later on. In the early periods of the system computer- and game-related fora like ROLE-PLAYING, GAMES, WEBGAMES, and COMPUTERS & TECHNOLOGY had a very high impact. Taking into account that Boards.ie was originally set-up as a discussion system for players of computer games, it is natural these communities appeared as highly influential. Over the time, however, the maximal importance appeared lower in general as indicated by the transition from green to violet in the heatmap. In fact, the mean maximal impact of the upper part of the heatmap (early periods) from fora ROLE-PLAYING to REAVER was 0.15, compared with 0.03 of the lower part (later periods) from THE ILLUMINATTI to PBAN. Considering that the values are normalised, it indicates the impact have become more distributed over the time. The emergence of the persistently influential fora HELP DESK (weeks 100–310), FEEDBACK (110–448), and MODERATORS (140–448) suggests that in fact they were established by highly influential users from the early important communities like WEBGAMES or COMPUTERS & TECHNOLOGY. However, in order to test that hypothesis, it is necessary to investigate activity of individual users, which is beyond the scope of this paper.

Figure 3b shows a less dispersed picture, with initially QUAKE having high dependency values but with AFTER HOURS clearly dominating from about week 25. This suggests that one of the first forum of the system altogether, QUAKE, served not only as a place to discuss the at the time popular computer game, but that its highly central users were participating a lot in other communities as well. In contrast with the early weeks the maximal dependence values decreased later on to the mean value about 0.12 from week 325 onwards, when AFTER HOURS emerged as the most de-

[7] Graphs with the full list of fora which have had highest respective values at least once can be found in the supplementary material.



(a) most important fora over time



(b) most dependent fora over time

Figure 3: Heatmaps of fora with highest importance and dependence over time.

pendent forum. Similarly to the distribution of importance, it means that dependency became more dispersed over time. Moreover, whereas the average ratio of dependence (Eq. 3) and independence (self-impact) for QUAKE was 2 between weeks 1–25, the same figure was more than six-times higher for AFTER HOURS in weeks 25–448. Therefore, it suggests QUAKE had a stronger core of its members in contrast with the over-arching AFTER HOURS, which emerged as a popular meeting point for users of many different communities. We can also see that a once important community can increasingly become dependent as in the case of COMPUTERS & TECHNOLOGY, which was 6 times the most influential between weeks 5–26, but then was identified 18 times as the most dependent between weeks 47–122.

Cross-Community Influence over Time

So far we have investigated which fora are similar with respect to their overall importance (dependence), or how the most influential (dependent) communities emerged over the time; but, we can drill down even more to the level of concrete pairs of communities and inspect which communities were influencing a given community the most and at what time. To first get an idea of which pairs were highly related with respect to the high influence one community had on the other, we took an aggregate matrix $\mathbf{\Psi}$ whose elements express how many times i-th community had a significant impact (see Eq. 4) on j-th over the full time span:

$$\mathbf{\Psi}_{i,j} = \sum_{t=1}^{448} \psi(i, j, \hat{\mathbf{J}}_t) \tag{6}$$

Table 6 shows the top four impact counts from $\mathbf{\Psi}$. It can be seen that this reflects our initial findings that MODERATORS and THE THUNDERDOME were amongst the most influential fora, and that AFTER HOURS and PERSONAL ISSUES were the ones which receive the most impact from other fora. We also see, that while MODERATORS was affecting primarily REPORTED POSTS which was concerned with malicious behaviour of the users, THE THUNDERDOME was primarily affecting AFTER HOURS. Recall that THE THUNDERDOME is centred around mutual insults of its participants, and apparently these users successfully trigger high activity in other fora like AFTER HOURS.

# impact ($\mathbf{\Psi}_{i,j}$)	**from** (i)	**to** (j)
29	MODERATORS	REPORTED POSTS
22	FNWAI	POKER
17	THE THUNDERDOME	AFTER HOURS
14	PI MODS	PERSONAL ISSUES

Table 6: Top 4 counts from the aggregate impact matrix $\mathbf{\Psi}$.

One of the highly influenced communities listed in Table 6 is PERSONAL ISSUES. Apart from the highly influencing PI MODS consisting of moderators dedicated particularly to that community, other fora like PARENTING, SEX & SEXUALITY, or MODERATORS were also found to be influential, but less frequently. PERSONAL ISSUES is arguably of high importance for many users because it offers them a discreet opportunity to seek advice or help in many difficult real-life situations like alcoholism, domestic violence, or unemployment. Clearly, such discussion needs to be protected from unhelpful comments. Therefore it is natural that we have observed five significant impact values (see Eq. 4) from MODERATORS between weeks 151 and 246, as illustrated by Figure 4. From week 247 onwards there were no further significant impact values identified which means that influence of MODERATORS on PERSONAL ISSUES lowered. However, that does not mean the forum stopped to be mod-

erated, because a specifically-dedicated community of moderators PI MODS was found to have a significant impact in 14 cases from week 299 until the end of the analysed data.

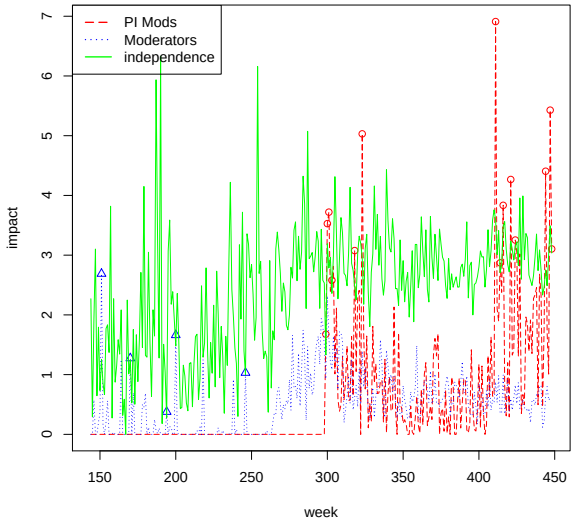


Figure 4: Impact of MODERATORS and PI MODS on PERSONAL ISSUES, and its independence (self-impact) over the time. The significant impact from MODERATORS and PI MODS are emphasised by triangles and circles respectively.

The time-series of cross-community impact thus clearly identified which were the key influencers and how they impacted a given community over time. We have investigated other relations between fora from Table 6, like the impact from FNWAI (Fold, No, Wait, All In) to POKER, and since the time-series evolve similarly, we omit them for space reasons.

Conclusion

We have formalised a flexible and scalable framework for the analysis of cross-community influence. We have demonstrated its efficacy on the Boards.ie data-set to determine communities that are highly *influential* to other communities, or, conversely, communities highly *dependent* on others. We demonstrated cross-community influence phenomena such as global patterns of influence/dependence obtained by a cluster analysis and individual communities with strong mutual influence over time.

However, we believe that this is just a first step towards a fully systematic analysis of cross-community influence. For instance, we believe that the measures of cross-community influence and its entropy can be used for selection of target communities in order to maximise the spread of influence/information (Kempe, Kleinberg, and Tardos 2003).

Another fertile direction is to enrich the structural influence analysis with complementary information like topics or sentiment mined from the content associated with the communities. This may enable the identification of important communities with respect to a particular topic. It may also shed some light on whether there is such a phenomenon as influence polarity or whether influence from one community to another may be beneficial or negative and disruptive.

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References

Arguello, J.; Butler, B.; Joyce, E.; Kraut, R.; Ling, K.; Rosé, C.; and Wang, X. 2006. Talk to me: Foundations for successful individual-group interactions in online communities. In *Proceedings of the SIGCHI conference on Human Factors in computing systems*, 959–968. ACM.

Everett, M., and Borgatti, S. 1999. The centrality of groups and classes. *Journal of Mathematical Sociology* 23(3):181–201.

Fortunato, S. 2010. Community detection in graphs. *Physics Reports* 486(3-5):75–174.

Gregory, S. 2011. Fuzzy overlapping communities in networks. *Journal of Statistical Mechanics: Theory and Experiment* 2011:P02017.

Kempe, D.; Kleinberg, J.; and Tardos, É. 2003. Maximizing the spread of influence through a social network. In *Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining*, 137–146. ACM.

Kumar, R.; Mahdian, M.; and McGlohon, M. 2010. Dynamics of conversations. In *Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining*, 553–562. ACM.

McGlohon, M., and Hurst, M. 2009. Community structure and information flow in USENET: Improving analysis with a thread ownership model. In *International Conference on Weblogs and Social Media (ICWSM)*.

Palla, G.; Derényi, I.; Farkas, I.; and Vicsek, T. 2005. Uncovering the overlapping community structure of complex networks in nature and society. *Nature* 435(7043):814–818.

Pollner, P.; Palla, G.; and Vicsek, T. 2006. Preferential attachment of communities: The same principle, but a higher level. *EPL (Europhysics Letters)* 73:478.

Spiliopoulou, M. 2011. *Social Network Data Analytics*. Springer. chapter Evolution in Social Networks: A Survey, 149–175.

Sun, J., and Tang, J. 2011. *Social Network Data Analytics*. Springer. chapter A survey of models and algorithms for social influence analysis, 177–214.

Sun, T.; Chen, W.; Liu, Z.; Wang, Y.; Sun, X.; Zhang, M.; and Lin, C. 2011. Participation maximization based on social influence in online discussion forums. In *International Conference on Weblogs and Social Media (ICWSM)*.

Wasserman, S., and Faust, K. 2009. *Social network analysis: Methods and applications*. Cambridge University Press.

Whittaker, S.; Terveen, L.; Hill, W.; and Cherny, L. 1998. The dynamics of mass interaction. In *Proceedings of the 1998 ACM conference on Computer supported cooperative work*, 257–264. ACM.

Zadeh, L. 1983. A computational approach to fuzzy quantifiers in natural languages. *Computers & Mathematics with Applications* 9(1):149–184.