Structural-temporal neighbourhoods of posts to characterize conversations in online forums

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Abstract—**Users of social networks are often characterised by extracting some relevant features from the graphs associated to that network. The structural dynamic of the conversation are usually forgotten due to a lack of proper tools. We present a purely graph-based method to cluster users in online forums.**

I. Introduction

The interactions between users in online forums are often modelled as complex networks. As such, they can be studied from many levels, each of which is represented by a graph where vertices and edges may represent different things. The most studied graph is a graph where vertices represent users and edges represent interactions between users (a post from one user replying to a post from another user). From the point of view of the community, some typically analysed properties are the degree distribution, the clustering coefficient, density, or the diameter of the graph. From the point of view of the individual users, analyses are typically focused either on the centrality of users, on the community structure or in blockmodeling (groups of users that tend to interact with the same other groups) [1]. Another common graph is a tree graph where vertices represent posts (or e-mails) and edges from one vertex to another indicate that the first is a reply to the second. Given the different discussion trees of a forum (a forest) the global analyses include depth distribution, branching factors, or even the time between two posts [2]. Studying discussion trees from the point of view of the users means, since trees are discussions, studying the user at a conversational level. Unfortunately, there is a lack of structural tools to perform this analysis. In this paper, we propose to fill this gap through the concept of *structural-temporal neighbourhood*.

Our goal in this paper is two-fold: on the one hand, to illustrate how structural-temporal neighbourhoods can play the role of triads for conversation trees, in the sense that they show us the local structures or dynamics from which the bigger graph emerges. On the other hand, to show how structural-temporal neighbourhoods can be used for the detection of different types of conversationalists in online forums or any other type of online discussion that is representable by a tree structure (e.g.: e-mails).

The remaining of the paper is as follows. We first discuss about the convenience of the classic neighbourhood definition in dynamic graphs such as discussion trees. Then we introduce our two definitions of structural-temporal neighbourhoods. To illustrate the kind of neighbourhoods that we obtain in a real data, we analyse the neighbourhood census of a Reddit forum. Finally, we apply both neighbourhood definitions to detect clusters of users that tend to appear in the same neighbourhoods. We close the paper with some suggestions of future research.

II. Discussion trees

We represent a discussion thread by a tree graph $G = (V, E)$ where V is a set of n vertices representing the posts (also called messages or comments) and E is a set of $n-1$ directed edges that say which posts replied to which post. Vertices have two attributes namely time and author. If for two given vertices v_i, v_j there exists an edge $e = (v_i, v_j) \in E$ then v_j is called the *parent* of v_i, denoted as $p(v_i) = v_j$. The *root* of the tree is the only vertex with no parent, and corresponds to the post that starts the discussion. We say that two vertices v_i, v_j are *siblings* if and only if $p(v_i) = p(v_j)$. A vertex v_i is an ancestor of a vertex v_j and v_j is descendant of v_i if and only if v_i is in the path from v_j to the root. A *leaf* is a post with no replies. A *branch* is the path between a leaf and the root. Two vertices v_i and v_i are said to be *neighbours* if either $p(v_i) = v_j$ or $p(v_j) = v_i$ or, in other words, if their distance in the undirected version of G is one.

III. Structural neighbourhoods

Extending the classic definition of neighbourhood according to which two vertices are neighbours if the distance between them is one, we start by the following definition of *structural neighbourhood*:

Definition 1: Given a tree graph G, the *structure-based neighbourhood* of radius r of post i, denoted as $\mathcal{N}_i(r)$, is the induced graph composed by all the vertices that are at distance equal or less than r from post i.

In the context of discussion threads, this definition has two limitations. First, the decision on whether to include some

post in the neighbourhood is only based on the structural distance, and therefore two posts that are at distance $d \le r$ are considered neighbours of i regardless of the time when they were written. In conversations, time plays an important role, therefore this is an important limitation. Another consequence of looking only at the structure is that the number of possible neighbourhoods within a radius r is infinite. This poses a problem when trying to categorize conversations since many conversations, while structurally different, can be considered semantically similar.

IV. STRUCTURAL-TEMPORAL NEIGHBOURHOODS

We propose two refinements of the structure-based neighbourhood to take into account the order and time in which posts are written. As we will see, the criteria to choose which posts are neighbours of a post i is not only based on the structural distance but also on the temporal distance to i. In the order-based definition, a new radius is set to include at most the n closest posts in time. In the time-based definition, the new radius is set to include all posts (in the structural-neighbourhood) until the first point where the conversation slows down.

A. Order-based

Definition 2: Given a ordered tree graph G, the *order-based neighbourhood* of radius r and order n of vertex i, denoted as $\mathcal{N}_i^T(r,n)$ is the induced subgraph from its structural neighbourhood composed by the n vertices that are closest to i in time and for which there exists a path to i in $\mathcal{N}_i^T(r,n)$.

An example of order-based neighbourhood is given in Figure 1. This definition has two advantages over the *structural neighbourhood*. First, the temporal aspect of the conversation is better taken into account since the neighbourhood only includes posts that are not only near to i in the structure but also in time. Second, the size of the neighbourhood has an upper bound of $min(|\mathcal{N}_i(r))|, n)$ thus making the space of possible neighbourhood structures finite. The main limitation of this definition is that the we have no *a priori* criteria to choose the proper parameter n other than making it small to capture only the local dynamic of the conversation around the post i.

B. Time-based

In order to take time explicitly into account, one might set fixed time-based boundaries for the neighbourhood and include only those posts whose timestamp t_j is at distance less than τ from the ego post i, $|t_j - t_i| < \tau$. However, the pace at which posts are added to the conversation may be very different between conversation threads (and also within a thread) and we have no *a priori* criteria for a proper choice of τ.

Rather than looking for a fixed time radius, we may instead decide it by looking at changes in the pace how new posts are added to the thread. In statistical analysis, a *changepoint* in a sequence $x_1, ...x_n$ is a point that comes from a different
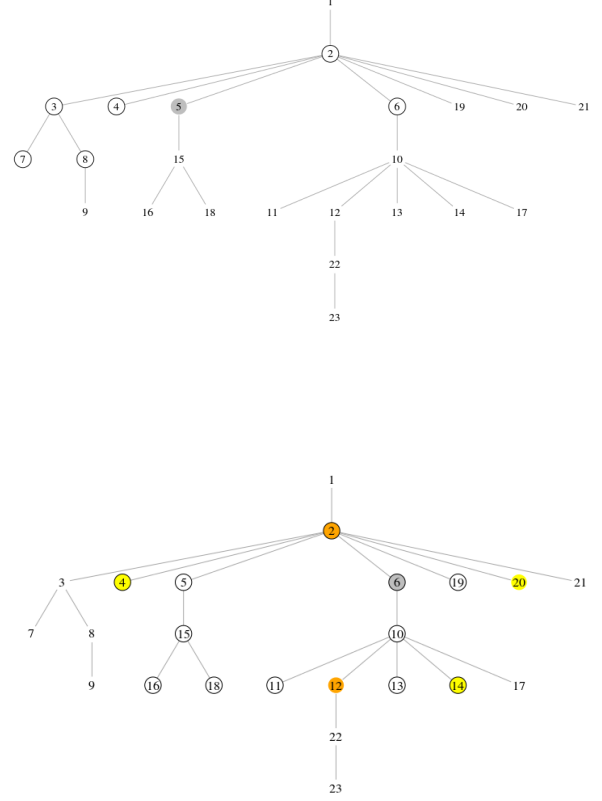

Fig. 1. Illustration of order-based (top) and time-based (bottom) neighbourhoods. Grey nodes represent the ego post. Nodes with circles are those in the neighbourhood. Numbers indicate the order of the post. The order-based neighbourhood has parameters $r = 3$, $n = 6$. The time-based neighbourhood has parameter $r = 3$. In the time-based neighbourhood, horizontal changepoints (yellow) and vertical changepoints (orange) represent posts that are temporally far from their predecessors (siblings or parents) and therefore set the limits of the neighbourhood.

probability distribution than its precedent values. If sequences are timestamps, they are monotonic increasing, therefore the changepoints will correspond to sudden pauses in the conversation. If applied either to the timestamps of posts in a branch (vertical sequence) or to the timestamps of the replies to the same post (horizontal sequence), we say that a sequence posts with timestamps $t_1, ..., t_n$ belong to the same (vertical or horizontal) *local dynamic* if there is no changepoint t_i in the sequence such that $1 < i \le n$. For the detection of changepoints we use the PELT algorithm [3][1]. Now we can introduce our second definition of neighbourhood.

Definition 3: Given a tree graph G, the *time-based neighbourhood* of radius r of vertex i, denoted as $\mathcal{N}_i^T(r)$, is the maximal subgraph of the structural neighbourhood $\mathcal{N}_i(r)$

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[1] An implementation of this algorithm written by its own authors is available in the R library `changepoint`.

where all the vertices belong to the same vertical and horizontal local dynamic than i.

Note that we still have a radius parameter r to guarantee that the resulting structure remains local even if no changepoint is detected near the post i.

Algorithm 1 extracts time-based neighbourhoods of a given post according to the given definition. Since the breakpoints only depend on the tree and not on the particular post we analyse, we previously detect the horizontal and vertical breakpoints in the tree. In the case of multiple branches with some common posts, we consider that a common post is a vertical breakpoint if it is a vertical breakpoint in any of the branches. Once we have the breakpoints we can proceed with the algorithm. First, we extract the structural-neighbourhood. The time-based neighbourhood will be a subset of the later. Then, we look for horizontal and vertical breakpoints, which mark the frontiers of the time-based neighbourhood. There are four possible cases:

- A *vertical breakpoint in the ancestors*: If the breakpoint is in the path between the post and the root, then the breakpoint started the new local dynamic to which the ego post belongs. Thus, we remove the ancestors of the breakpoint, but not the breakpoint.
- A *vertical breakpoint in the descendants*: If the breakpoint is a descendant then it started a new different dynamic and therefore we must remove the descendants of the breakpoint and the breakpoint itself.
- An *horizontal breakpoint either in the older siblings or in the ancestors*: If the breakpoint is among the older siblings, then it started the horizontal dynamic to which the ego post belongs. Similarly, if the breakpoint is among the ancestors, then every older sibling of the breakpoint belongs to a previous local dynamic. In both cases, we remove the older siblings of the breakpoint but not the breakpoint.
- An *horizontal breakpoint elsewhere*: In any other case, the horizontal breakpoint starts a different local dynamic and therefore we remove its younger siblings and the breakpoint.

Any time a vertex is remove we also remove its descendants. The final neighbourhood will be connected induced subgraph from the structural neighbourhood. If there are no changepoints in the structural neighbourhood, the time-base neighbourhood will be exactly the structural neighbourhood.

An example of time-based neighbourhood is given in Figure 1 (right).

Algorithm 1 Extraction of time-based neighbourhood

Input: Posts tree g, vertical breakpoints, horizontal breakpoints, ego post ego
Output: Subgraph of g with all vertices in $V(g)$
  Compute structural neighbourhood $\mathcal{N}_i(r)$
  ancestors $\leftarrow$ ancestors(ego) in $\mathcal{N}_i(r)$
  older_siblings $\leftarrow$ older_siblings(ego) in $\mathcal{N}_i(r)$
  dump $\leftarrow \varnothing$
  for bp $\in$ vertical breakpoints **do**
    if bp $\in$ ancestors **then**
      dump $\leftarrow$ dump $\cup$ ancestors(bp)
    else
      dump $\leftarrow$ dump $\cup$ descendants(bp) $\cup$ bp
    end if
  end for
  for bp $\in$ horizontal breakpoints **do**
    if bp $\in$ (older_siblings $\cup$ ancestors) **then**
      dump $\leftarrow$ dump $\cup$ older_siblings(bp)
    else
      dump $\leftarrow$ dump $\cup$ younger_siblings(bp) $\cup$ bp
    end if
  end for
  $\mathcal{N}_i^{(t)}(r) \leftarrow$ delete(dump_posts $\cup$ descendants(dump_posts)) from $\mathcal{N}_i(r)$

V. NEIGHBOURHOOD COLOURING AND PRUNING

A. Colouring

Even if the structure contains some important information about the type of conversation, there is still some ambiguity left, and two similar neighbourhoods can represent very different types of conversation. We can easily reduce this ambiguity by assigning colors, or labels, to vertices, identifying some relevant property of the post.

In particular, we assign the following colours:
- *Red*: ego post.
- *Orange*: other posts written by the author of ego. It allows to identify re-entries (the same author participating more times in the discussion [4])
- *Yellow*: parent of ego post and other posts written by the same author. It allows to identify, for instance, debates between the ego author (red and orange) and the other author (yellow). We have observed this phenomena in our data, and it is often the cause of long chains.
- *White*: root post. Differentiating the root post from the rest has been proven by previous research on online discussions. For instance, some types of users seem to get more replies than others when they initiate a thread ([5], [6]). Also, in terms of preferential attachment, root posts use to get more replies than the non-roots [7], [8].
- *Black*: none of the above.

Since some posts might correspond to several colors, we perform a sequential assignment of colors given by `black, orange, red, yellow, white`.

We do not claim this choice of labels to be of universal. Indeed, other labellings might also give interesting results
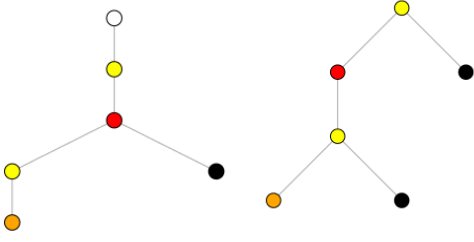
Fig. 2. Illustration of different real structures using different colors for the root (white), the ego (red) and other posts written by the same author (orange) the ego parent and other posts written by the same author (yellow), posts previous to the ego (grey) and posts posterior to the ego.

since they would look at conversations from new points of view (e.g.: a colour for leaf vertices, colours according to the length of the post, or colours to represent the sentiment of the post).

B. Pruning

At this point, we can still find structures whose only difference is that one of them has more leafs hanging from some of the nodes. Thus, we prune every neighbourhood by leaving a maximum of two consecutive siblings of the same color and where neither of them has any children. The reason of setting the limit to two is that it is the minimum necessary to distinguish between *zero*, *one* and *more than one* consecutive occurrences. In other words, we consider that the difference between one and zero replies to a post is relevant, but that five and six replies do not make any difference worth being represented. Figure 2 shows some real examples, from our dataset, of time-based neighbourhoods after colouring and pruning.

VI. APPLICATION TO REDDIT FORUMS

Our data consists of two different forums of Reddit, namely the Podemos dataset [2] and the Game of Thrones dataset[3]. The Podemos forum was conceived in March 2014 as a tool for internal democracy, and forum members used it to debate ideological and organizational principles that were later formalized in their first party congress hold in Madrid the October 18th and 19th 2014. Nowadays, its members use it mainly to share and discuss about political news. The Game of Thrones is a casual discussion forum about the Game of Thrones TV series. The Podemos dataset contains 75,000 posts corresponding to 4,262 threads written by 9,160 users between the April 25th and October 20th 2014. The Game of Thrones dataset contains 75,000 posts corresponding to 5,862 threads written by 18,907 users.

A. Neighbourhood extraction

As a previous step for all further analysis we extract the structure-based ($r = 2$), the order-based ($r = 2, n = 4$) and the time-based ($r = 2$) neighbourhood around every post for

[2]https://www.reddit.com/r/podemos
[3]https://www.reddit.com/r/gameofthrones

the two forums. We label every structure with a unique integer number, where a structure is a coloured graph. Two neighbours have the same structure, and therefore they have the same integer number, if their coloured graphs are isomorphic.

Unfortunately, it is not practical to give a number to every theoretically possible structure since, even if we could enumerate all the possible trees up to a given size, a lot of of these trees would not be seen in the data. It appears then a much more practical approach to enumerate only those trees that are seen in the data. In order to share a unique labelling of structures among the two forums and the three types of neighbourhoods (which gives 6 different labellings) we re-label the structures after the extraction for every post is finished. We will call this final labelling a *dictionary* of neighbourhoods.

Given a type of neighbourhood (struture-based, order-based or time-based) we extract the neighbourhood around every post of a forum as follows. A counter for every neighbourhood structure is created the first time it us detected. For every post, we extract its neighbourhood, colour and prune it (Sections III and IV). Then we check whether it is isomorphic to some of the neighbourhoods that we have already seen. If this is the case, then we increment the counter for the neighbourhood previously seen. Otherwise we create a new entry for the current neighbourhood.

Once the six extractions are finished we merge there dictionaries into a global one and sort the labels by frequency of the neighbourhood (1 for the most frequent and so forth). Figure 7 shows some frequent neighbourhoods that will be discussed later.

In the worst case, where every post has a unique neighbourhood, every extracted neighbourhood should be compared against every neighbourhood in already in the dictionary before concluding that it needs a new entry. In this case, the computational cost of this operation is $\mathcal{O}(n^2)$ where n is the number of posts. In practice, however, the bigger the number of posts processed, the less likely that we go through all the dictionary without finding and isomorphism. Moreover, if we keep the dictionary sorted by frequency, a large number of neighbourhoods will find and isomorphism among the first neighbours of the dictionary.

B. Comparing neighbourhood methods

In this section we compare different aspects of our three classes of neighbourhood, namely (a) the size and frequency distribution of the neighbours for each class, (b) the discrepancies between methods when they extract the neighbourhood of a same post, (c) the neighbourhood census obtained for each class in a same forum.

1) Size and frequency distribution: We detected, in the the whole dataset, 3791 different structure-based neighbourhoods, 174 different order-based and 1488 different time-based. which means that the structure-based captures a much wider set of structures. Of course, this is not necessarily and advantage since these extra structures may be just spurious and only occur a very small number of times. Indeed, Figure 3 shows

that around half of the time-based neighbourhoods (41%) and the structure-based neighbourhoods (60%) occur only once, while the number of neighbourhoods that appear more than 100 times (among 150,000 posts) is similar for the three types of neighbourhood. To cover 95% of the posts we need 623 structure-based neighbourhoods, 40 order-based and 155 time-based.

The main reason why the frequency of the order-based neighbourhoods decay faster is that the most frequent neighbourhood (id 1) is much more frequent (upper-left red point in the left plot of figure 3) than the most frequent time-based neighbourhood. This is the main handicap of the order-based neighbourhood since, as we will see later, it avoids finding richer structures.

2) Discrepancies: The divergent number of neighbourhoods between structure-based, order-based and times-based suggests that some neighbourhoods, for instance, in time-based, might be systematically mapped to the same neighbourhoods in order-based. Or similarly, that some structure-base neighbourhoods are systematically mapped into the same time-based neighbourhoods. Figure 4 gives a general overview of these mappings. The left figure shows, for every post, its time-based neighbourhood and its order-based neighbourhood, while the right figure shows the time-based and the structure-based. The points in the diagonal correspond to posts that have been assigned the same neighbourhood by the two compared methods.

The diagonal of the time-based / order-based plot contains 36% of posts. The diagonal of the structure-based / time-based plot contains 40% of the posts. For the order-based / struct-based (not shown) there are 41% of posts in the diagonal. In general, the structures with bigger agreement are among the most frequent. This is comprehensible since the most frequent tend to be also the most simple structures with less room for discrepancy. There is a 30.75% of posts that are assigned the same neighbourhood structure by the three methods.

Rather than looking at where the methods agree, it is even more interesting to see where they disagree, since this will reveal whether one of the methods is incapable of detecting some interesting conversational structure. In Figure 4 some horizontals lines can be spotted specially in the lower part of the plots. These correspond to posts with different time-based neighbourhoods that are assigned the same order-based neighbourhood (left) and different time-based neighbourhoods that are assigned the same order-based neighbourhood (right). Looking for the order-based neighbourhoods that have a correspondence with a larger set of time-based neighbourhoods, we detect that these correspond to neighbourhoods 1 (77 different time-based) and 50 (57 different time-based), 17 and 18. Looking for the time-based neighbourhoods that have a correspondence with a larger set of structure-base neighbourhoods, we detect that these are neighbourhoods 10, 4, 8, 19, 14.

In retrospective, these results are not surprising. What we see is simply that structures that are often captured by one method collapse into another single structure when other method with a smaller space of structures is used. Yet, the three methods mostly agree when they find a frequent neighbourhood. But this might be due to the fact that simpler motifs tend to be in shorter threads, where there is no room for two neighbourhood methods to detect a different structure.

3) Neighbourhood census: Given a set of local structures and a graph under study, a census is a counting of how many times does each structure appear in the graph. In the context of online discussion forums, triad census has been sometimes used in the graph of users interactions are often used (in these graphs, an edge exists from user u to user v if u wrote a post reply to some of the posts written by v in some thread.) [9], [6]. However, triads are poor objects when studying trees since there are only three possible structures with, at most, three nodes: a single vertex, a directed dyad (reply), star (two replies to the same post) and a chain (reply and reply to the reply). On the contrary, our neighbourhoods are potentially richer structures that respect the real structure of conversations.

In Figure 8 we show, for every neighbourhood method, the resulting census in the two forums. For each method, the neighbourhoods shown are those among the 30 most frequent in either of the forums. Out of this selection, we checked that no neighbourhood has a frequency higher than 1000 (near a 1.5% of the posts in each forum), which guarantees that we are not missing important information in the plots.

According to the structure-based method, the Podemos census has a bigger presence of 9 and 20, though 9 is also dominant in Game of Thrones. The Game of Thrones has a bigger presence of 10, 11 and 27. The 20 is interesting since it represents chain discussions between two users, which in the context of a political forum suggests a debate. The 11 represents the ego user opening a new discussion but getting only one reply, which means an unsuccessful thread. This structure is much less frequent in Podemos meaning that, for some reason, in Podemos discussions have easier success. The 27 represents a user replying, among others, to the same post which is, in its turn, a reply to another regular post.

According to the order-based method, the Podemos census has a bigger presence of 1, 3, 2, 13, 4 and 18, most of them representing chains. The Game of Thrones has a bigger presence of 1, 12, 9, 3, 11 and 5. Although it captures some of the chain structure in the Podemos forum, the dominance of the motifs 1 clearly deteriorates the census.

Lastly, the time-based method gives the Podemos census a bigger presence of 2,3,4 and 8. The Game of Thrones has a bigger presence of 5, 9, 11 and 25. As seen in the structure-based, 9 and 11 suggest threads that did not attract the attention of the users.

It is clear from the last sections that the order-based does not do a good job on capturing all the richness of the conversational structures. Nevertheless, it is harder to decide between the time-based or the structure-based in terms of the richness of the captured conversations. There are two other reasons to choose the time-neighbourhood over the structure based. First, the time-base has less spurious structures, covering 95% of posts with 155 neighbourhoods, against the 623 neighbours
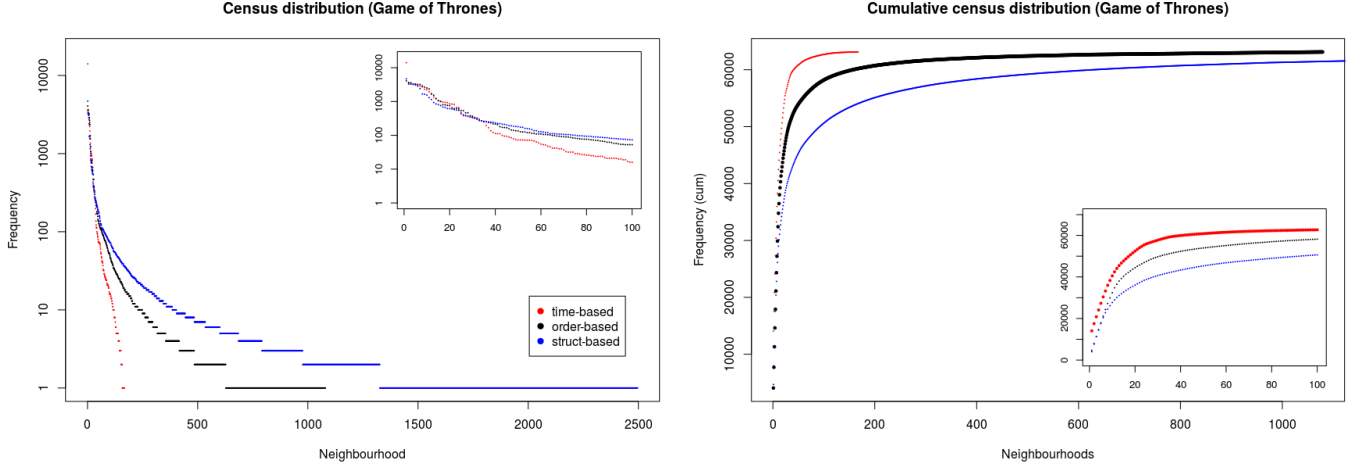
Fig. 3. Comparison of census distributions with order-based and time-based neighbourhoods.
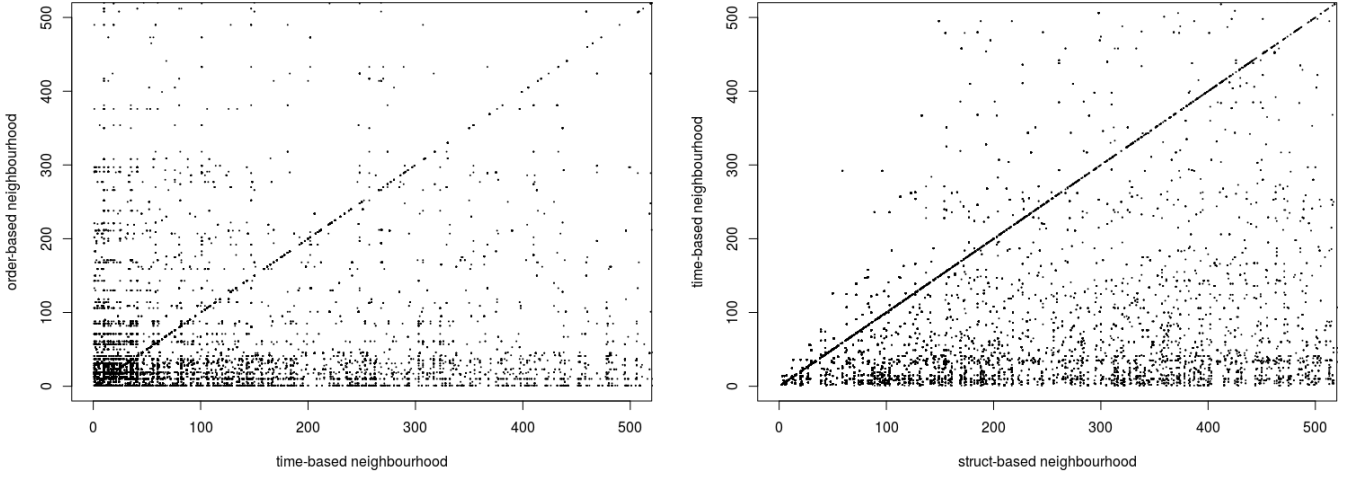

Fig. 4. Neighbourhood of posts from the point of view of order-based and time-based. Neighbourhoods with the same label in the order-based and the time-based axes are isomorphic. The points in the diagonal correspond to posts to whom the two methods assign exactly the same neighbourhood. Horizontal rows of points correspond to posts that are assigned many different time-based neighbourhoods but the same single order-based neighbourhood.

necessary to cover that amount with the structure-based. Second, the time-based neighbourhood has more grounded criteria to decide where the neighbourhood ends, while the structure-based has no criteria at all.

C. Conversation-based clustering of users

In this section, we cluster users in the Podemos dataset based on the neighbourhoods of their posts. Our intuition is that some users like participating in some kind of discussion rather than other. Certainly, most part of the information necessary to understand the nature of a discussion in in its textual content. However, due to the huge diversity of topics, vocabulary, and the difficulty of current algorithms to capture the language subtleties such as humour, irony, or context, we turn our attention towards the structure of the discussions,

which can also contain some information. We work under the hypothesis that the structural-neighbourhoods in which a user post in embedded reflect the kind of conversation in that part of the thread.

Our dataset contains a set of 100 *active users* who wrote more than 100 posts. For those users, we create an initial feature matrix $U \times N$ where U is the number of users and N is the number of neighbourhoods in the census, and where the the position (u, n) is a counter of the number of times that a post written by user u has a neighbourhood isomorphic to n. We drop those feature columns that are zero for every user (these are neighbourhoods seen only around posts of users with low-level activity). To make the feature vector of a user independent on the number of posts, we transform the counts into percentages. And since some features have much

Structure-based

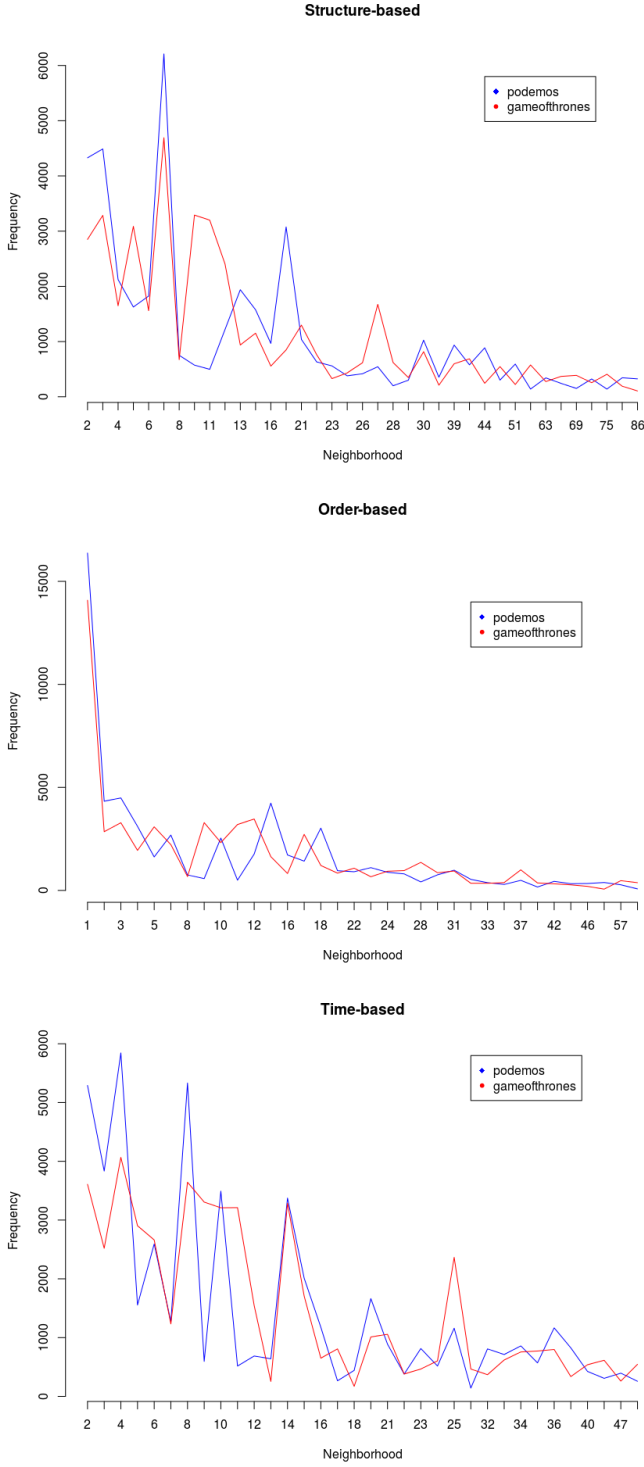**Order-based**

Time-based

Fig. 5. Comparison of neighbourhood census obtained by each type of neighbourhood in two different forums. Order-based is more similar across forums since its most frequent neighbourhood dominates the census.
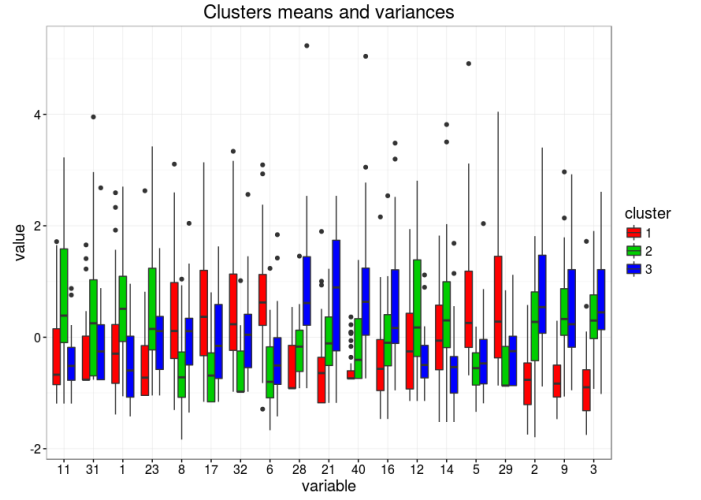
Clusters means and variances

Fig. 6. Whiskers plots in the most relevant features (time-based)

higher percentages than others for most users, we scale and normalize the matrix so that every feature has mean 0 and variance 1. To avoid non-significant scores, we remove also the feature column corresponding to neighbourhoods that have a frequency less than 50 among the active users.

We use k-means to find the clusters, though one can use any other clustering method. Since the plot over the Within-Cluster Sum of Squares for $k = 1, ...20$ did not show any clear elbow we chose $k = 3$ clusters so that clusters are easier to interpret. We did the clustering over a feature matrix with order-based neighbourhoods and another feature matrix with time-based neighbourhoods.

Since the set of feature dimension is relatively large, we show in Figure 6 how the users in a cluster are distributed for each feature. The features shown are the ones that have an bigger absolute value (in mean) for each cluster.

- The green cluster (attraction for X, X, repulsion XXX) correspond to users that...
- The red cluster...
- The blue cluster...

VII. CONCLUSIONS

We presented a method to characterise conversations of users in online threads. Due to the tree nature of online threads, traditional patters such as triads are not able to capture much of relevant dynamics of a conversation. Our defined order-based and temporal-based neighbourhoods are able to capture a very rich variety of structures. We used this neighbourhoods to characterise users in terms of the structure of the conversations they participate in and showed that, indeed, there are different types of structural conversationalists

The concept of structural-temporal neighbourhood opens the door to some interesting paths of research. One might wonder whether other pruning are more pertinent than the proposed here. Also, even after pruning some neighbourhoods suggest the same type of conversation, so a manual merge might be

convenient. Maybe sociologists can help to merge the found neighbourhoods in a meaningful way.

VIII. FUTURE WORK

In this paper we focused on the comparative analysis between three kind of neighbourhoods in order to demonstrate that the time-based neighbourhoods are able to capture relevant structures that other definitions of neighbourhood cannot. We also showed that it can be used to characterise users according to the kind of conversation in which they participate.

We can see many applications of this kind of neighbourhood.

- Caracterise reactions to user posts: instead of capturing the neighbours all around a post, we can limit we neighbourhood to the descendants. This would allow to cluster users from a slightly (but maybe important) point of view.
- The boundaries of our time-based neighbourhood are decided by the changepoint algorithm PELT. How sensible is time-based neighbourhood to the choice of the algorithm?
- Merge more neighbourhoods with sociological criteria.
- Use different coulours to represent different phenomena.

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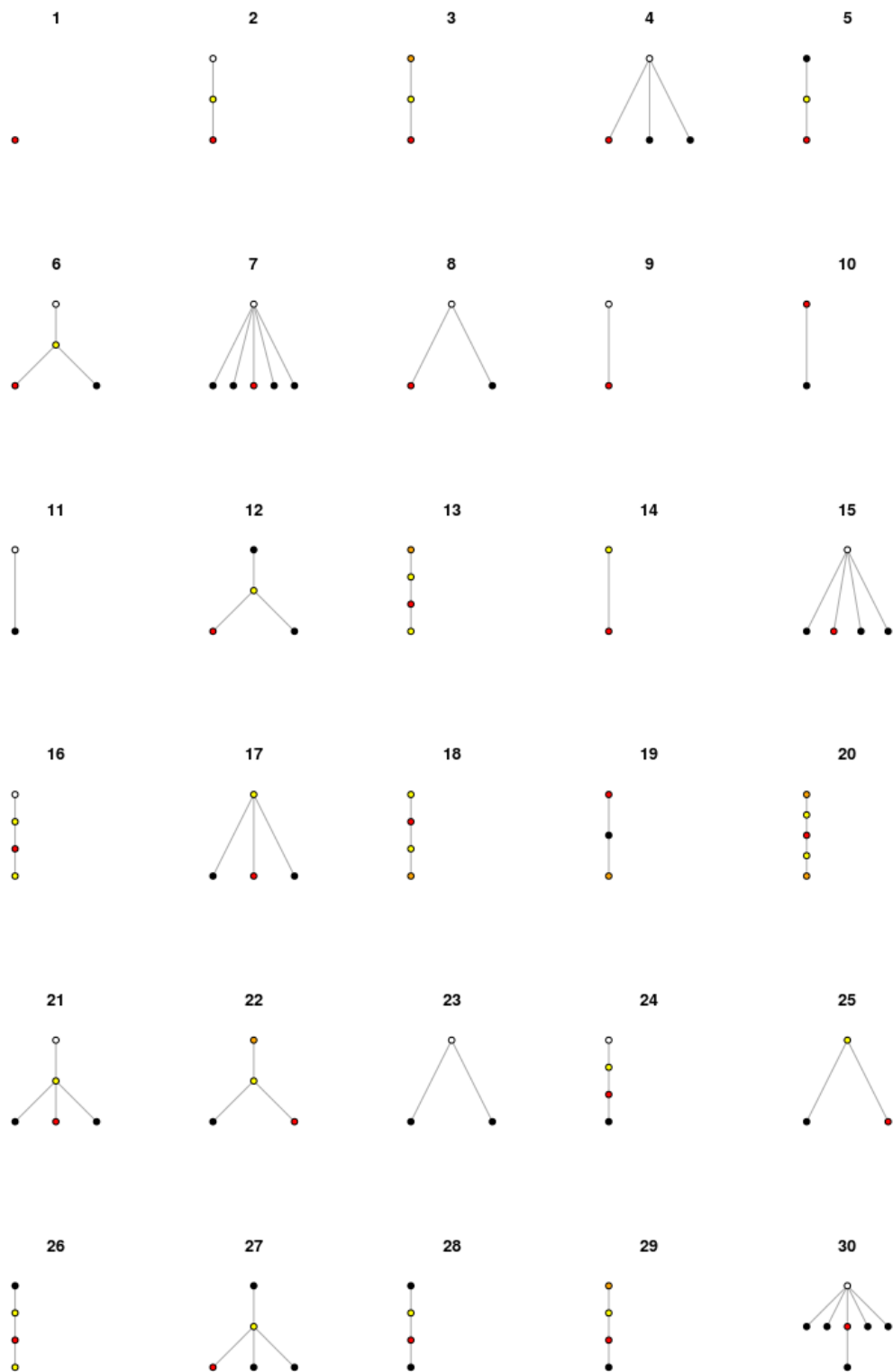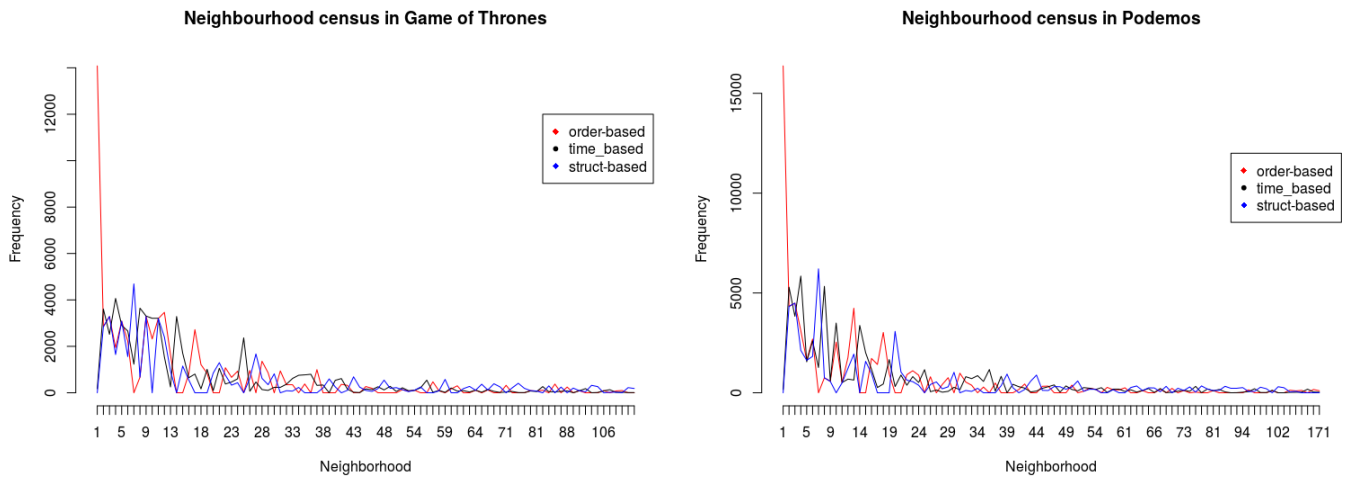
Fig. 7. Neighbourhoods reference list

Fig. 8. Comparison of census for two different forums. POUR BERTRAND. WE CANT SEE ANYTHING HERE

Fig. 9. Most frequent order-based neighbourhoods with $r = 2$ and $n = 4$ (Podemos)

Fig. 10. Most frequent time-based neighbourhoods (Podemos)

Fig. 11. Most popular time-based neighbourhoods (up) and how they are mostly detected in order-based neighbourhood (down).

Fig. 12. PCA projections of the order-based (above) and time-based (below) neighbourhood features