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## A Time Decoupling Approach for Studying Forum Dynamics

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**Abstract** Online forums are rich sources of information about user communication activity over time. Finding temporal patterns in online forum communication threads can advance our understanding of the dynamics of conversations. The main challenge of temporal analysis in this context is the complexity of forum data. There can be thousands of interacting users, who can be numerically described in many different ways. Moreover, user characteristics can evolve over time. We propose an approach that decouples temporal information about users into sequences of user events and inter-event times. We develop a new feature space to represent the event sequences as paths, and we model the distribution of the inter-event times. We study over 30,000 users across four Internet forums, and discover novel patterns in user communication. We find that users tend to exhibit consistency over time. Furthermore, in our feature space, we observe regions that represent unlikely user behaviors. Finally, we show how to derive a numerical representation for each forum, and we then use this representation to derive a novel clustering of multiple forums.

**Keywords** internet forums · conversation dynamics · temporal evolution · reciprocity · visualization

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## 1 Introduction

Online forums are popular websites that allow users to communicate on diverse topics. These forums provide an extensive archive of conversation records over time. Finding temporal patterns in these records can advance our understanding of the dynamics of conversations. Furthermore, forum analysis can facilitate solving practical tasks, such as predicting the future behavior of users; identifying users whose behavior deviates from that of the majority in a given forum; and providing an automated forum categorization that can inform the structural design of forum websites. Accordingly, the temporal analysis of online forum data is of interest to different groups, including sociologists, businesses that run customer support forums, and web designers.

The above-mentioned theoretical and practical advances can be advanced by addressing the following research questions:

1. Are there any trends (e.g., consistency) in the temporal evolution of users in online forums?
2. Is it possible to characterize the normative temporal behavior for a given forum?
3. Can we quantify and categorize forums in terms of the temporal behavior of users?

The main challenges for the analysis of temporal forum data arise from the complexity of the data. Communication records collected from a medium-sized forum website (e.g., *www.boards.ie* or *forumbgz.ru*) for one year may comprise information about thousands of users, with tens of thousands messages sent between different users. Furthermore, there are dozens of features that can be used to describe users and forums (e.g., number of initiated threads, number of connection ties, number of threads in a forum, percentage of “answer people” users [7, 17, 23, 27]). It is not obvious which features to use, and how to define features that evolve over time (e.g., should one consider the number of users’ posts per week or per month?)

Moreover, in order to have a computationally tractable online forum analysis, one may need to select discrete time points for processing. However, it is not obvious which time points to select. Finally, there is the challenge of natural language processing. Different forums can use different languages, and, for a given language, people may mistype words, use slang and non-dictionary words.

Researchers have tried different approaches to forum data analysis, such as focusing on user roles, discussion diversity and growth dynamics. For example, both Viegas and Smith [23] and Welser et al. [27] use visualization to derive structural features of the roles of individual users, thus indicating clear differences between consistent “answer people” and those preferring discussions. Lui and Baldwin [15], and Chan et al. [7] extend this work by categorizing roles and exploring the composition of forums in terms of the diversity of roles. Kumar et al. [11] and Gonzalez-Bailon et al. [8] model growing trees of discussion threads.

These studies tend to assume that users exhibit consistent behavior over time, and that the users can be described using features that are aggregated over the whole time span of the available data (e.g., total number of threads initiated by a user). Studies that look at temporal patterns over time, instead of assuming consistency, tend to be descriptive and difficult to scale. For example, *AuthorLines* [23] show the activity of individual users over time, but with *AuthorLines* it is hard to visualize the evolution of the whole forum. *To the best of our knowledge there has been no forum representation that can be explicitly interpreted in terms of the temporal behavior of individual users.*

To address these limitations, we propose a novel method for studying forum dynamics. By forum dynamics we mean a set of changes in the characteristics of the users participating in the forum over time. We propose to decouple temporal information about users into sequences of user events and inter-event times. Furthermore, we interpret a sequence of user events as a path in a feature space; we represent a forum with a set of paths; and we analyze forums from a geometrical perspective.

In a given forum, we study user paths both individually and as a single interdependent system. This makes our approach unique, because past work on time sequences analysis mostly focuses on pairwise correlation between parts of sequences (e.g., [18]). Moreover, our analysis reveals interesting findings that were not previously reported. This includes a roughly constant ability of users to attract responses (consistency), and existence of user states that are very unlikely to occur (“dead zones” in a feature space). Finally, we propose a forum visualization that allows us to obtain a succinct summary of the behavior of users in forums.

In summary, the main contributions of our paper are as follows.

- A time decoupling approach for finding temporal patterns in online forum data (Section 4.1).
- A new feature space to represent users’ evolution (Section 4.2). A proposed visualization of our feature space allows us to observe users’ characteristics that were not apparent from previous studies (Section 4.3).
- A novel feature representation of forums (Sections 6.1). This has enabled the discovery of a new clustering for one of the previously studied datasets (Section 6.2).
- Discovery of consistent engagement and dead zone patterns (Sections 5.1 and 5.2) and the analysis of inter-event times (Section 5.3).

Prior to giving a detailed description of our methods and results, in the next two sections we first introduce related work and then describe the datasets that we study.

## 2 Related Work

In this section, we start with a review of approaches to study online forum data (Table 1). We then discuss work that studies dynamic processes in related online media, such as online social networks and weblogs.

Chan et al. [7] employ reply graphs, as well as the structure of threads, to derive features for classifying users into different roles (e.g., “taciturn”, “elitist”). In the same work, they study the composition of forums in terms of user roles. Lui and Baldwin [15] classify users by utilizing content based features in addition to structural features. In both works, an implicit assumption is that user roles do not change during the period of observation.

Welser et al. [27] derive features for individual users by means of different visualization techniques. The features are then used for automated identification of “answer people”, a specific type of user. The automated identification is validated by manually inspecting the contents of a selection of user posts. In their study, Welser et al. state that “in many well-defined circumstances, it is generally safe to assume that past behavior will correlate with future behavior”. In our work, we present a framework for assessing this assumption quantitatively by studying the temporal evolution of users.

Viegas and Smith [23] also analyze temporal evolution of users. They propose *AuthorLines* for plotting the number of threads started by a user, as well as the number

**Table 1** Summary of related work on forums. There have been different approaches to study forum data. Some studies focus on individual users, while other studies look at the discussion threads or forums.

References	Objects of study	Involved features	Representing user engagement over time
Lui and Baldwin [15], Welser et al. [27]	users	structural features of reply graph such as proportion of low degree neighbors, content-based features, etc.	not focused on changes over time
Chan et al. [7]	users, forums	number of posts per thread, ratio of in degree to out degree in reply graph, etc.	not focused on changes over time
Viegas and Smith [23]	users, forums	number of initiated threads, number of threads where user participated, etc.	real-time changes in statistics for a user
Xiong and Donath [29]	users, forums	number of messages, time passed since posting, etc.	as a sequence of events (but not quantitative)
Kumar et al. [11], Wang et al. [25]	threads	degree distributions of discussion threads, content based features, etc.	modeling the growths of conversation trees
Morzy [17]	micro-communities, forums	number of communities that sustain longer than certain amount of time, number of communities per user, etc.	user engagement is not represented explicitly
this work	users, forums	number of posts and number of replies over time	as a sequence of events

of threads where the user has participated for a particular week. It is then easy to see, for example, how the number of these threads evolve over subsequent weeks. However, it can be hard to compare the engagement of many (e.g., 50) users at once. Furthermore, Viegas and Smith do not quantify patterns of user evolution. There have been other proposed forum visualizations [23,29], however these visualizations do not define numerical features for describing and comparing the forums automatically.

Some authors study forums at the level of discussion threads or micro-communities [11,17,25]. Kumar et al. [11] present and evaluate a model of the dynamics of conversations, where adjusting model parameters can lead to the production of “bushy” or “skinny” thread trees. While this model can be adapted to infer the evolution of individual users, this adaptation is not straightforward and is not covered in their paper. Furthermore, this model describes conversations on the level of individual threads, whereas forums often consist of a number of threads. Threads are modeled as trees whereas a forum is generally a forest.

Furthermore, there has been a large body of literature that studies processes in related media spaces such as Facebook, Twitter and weblogs. Many researchers look at the dynamic processes in online media from an information diffusion perspective. With this approach one models the propagation of information among users in a similar manner to modeling the propagation of infection in epidemiology [1,12]. Other approaches to studying evolving online social media include the combined study of the diffusion and evolution of discussion topics [13], modeling user interactions with dynamic graphs [24], and looking at the properties of time series of social interactions [3]. Our work

complements these earlier studies by approaching online forums from the perspective of individual users and the reciprocity of communication.

More generally, time series mining is an established field of data mining [26]. Keogh et al. spell out an intuitive idea that “representation of the data is the key to efficient and effective solutions” [9]. One of the novel contributions of our work is the representation of the history of individual users as two decoupled series: sequence of events and event timings.

In summary, forum data analysis is a field with growing research interest. Clearly participating users constitute the essence of the forums, and users’ behavior eventually determines all the numerical features of the forum data. However, there are several remaining open issues, such as the lack of scalable methods for the representation and analysis of the temporal evolution of individual users, and the lack of a numerical representation for forums in terms of the evolution of users.

### 3 Datasets

In our study, we use data from four Internet forums: *Boards.ie*, *SAP Community Network (SCN)*, *TiddlyWiki*, and *Ancestry.com*. In total, we analyze records for over 30,000 users. We observe similar patterns in all datasets, and in the main text, we focus mainly on results for *Boards.ie*. We present results for the *SCN*, *TiddlyWiki*, and *Ancestry.com* forums in Supplementary Information 1.

*Boards.ie* is a national Irish bulletin board that comprises a variety of forums on different topics, from concert announcements, to dedicated discussions about martial arts and politics. The records for *Boards.ie* were collected over a two year period (2006 and 2007).

We select nine *Boards.ie* forums that represent a variety of topics (Table 2). In each forum, we select users that had registered in 2006. This selection allows us to observe the evolution of users for at least one year. From the users registered in 2006, in each forum, we randomly select 30% of users.

**Table 2** Selected forums from *Boards.ie* covering a variety of topics (#posts is the total number of posts made by all users from the sample; #replies is the total number of replies received by all users from the sample)

Forum name	#Users in sample	#Posts in sample	#Replies in sample	Comments
politics	264	3,867	3,761	topical discussion
soccer	73	4,352	4,215	topical discussion
poker	183	10,542	9,660	topical discussion
martial arts	156	5,444	4,911	topical discussion
personal	586	6,709	6,178	discussion of personal issues
accommodation	236	1,764	1,523	classifieds and discussion
gigs	345	2,141	1,715	musical performance announcements and discussion
weather	56	300	259	forecasts and discussion
development	107	679	590	tech. questions and discussion

Sampling was used in order to speed up the computations. Note that our sample is sufficiently large (there are around 2,000 users in the *Boards.ie* sample) to draw conclusions. Furthermore, we have studied the effect of sampling on two forums from *Ancestry.com* (as these forums have the largest numbers of users), and found that taking a 30% sample of users results in observations similar to those made on the complete set of users. Details on our study of the sampling effect are presented in Supplementary Information 2.

Note that the method presented in this paper operates at the level of forums. The method will be mainly affected by the sizes of individual forums rather than the size of a complete dataset. The size of the forum can be measured, for example, using the average number of posts per day. With respect to this measure, forums in our study appear to be on the same scale with many other forums reported in the literature [11, 17]. This indicates that our study is applicable to a large number of typical Internet forums.

We note that there can exist exceptionally large forums (e.g., with more than 1000 posts per day). On the other hand, we speculate that there is a certain upper limit for the size of a forum. For example, a forum with more than 1000 posts per day may effectively become unreadable for users, as it would be updated much faster than the users can read. Such a forum might have a tendency to split into smaller forums or to lose its participants, which would bring the forum back to a smaller size and a more balanced state.

Finally, it is worth mentioning that *Boards.ie* was previously studied by Chan et al. [7]. This enables us to compare our results. We introduce our methods and results in the next sections.

## 4 Research Methods

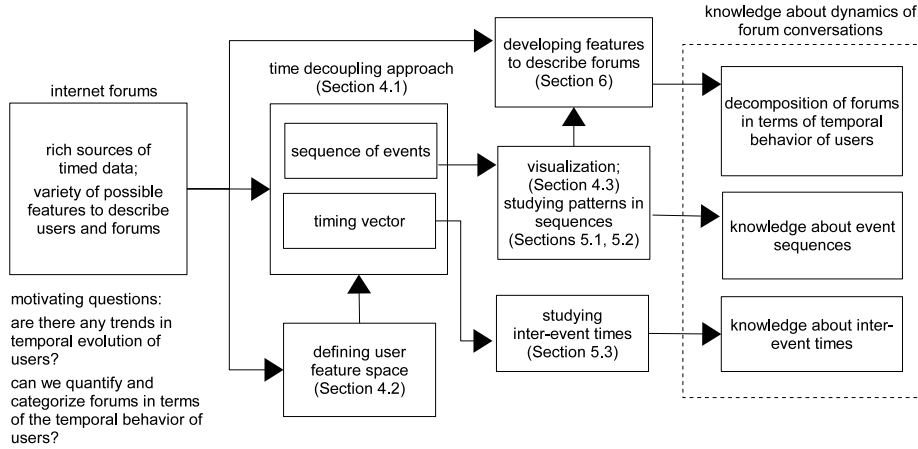
We outline our research methodology in Figure 1. Our goals are (i) to discover temporal patterns in user behavior, and (ii) to use the obtained information to develop a numerical description of forums in terms of the evolution of users. In order to achieve the first goal, we seek a convenient representation of temporal data that allows us to observe and quantify temporal patterns.

Previous work has shown that visualization is a powerful tool in forum data analysis [22, 23, 27]. Therefore, we develop our representation of users with a novel time decoupling approach, and select features in a way that allows us to visualize user evolution. We start with a description of our time decoupling approach in the next section.

### 4.1 Time Decoupling Approach

Consider forum data that spans over time window  $[T_0, T_1]$ , for example from January 2006 till December 2008. Let  $U$  be the set of all users in the forum, and let user  $u \in U$  be registered in the forum at time  $T_0(u) \geq T_0$ . A user feature is some quantity that characterizes the user over time, for example the number of posts the user  $u$  has made by the time  $t$ .

**Definition 1** A user feature  $f(u, t)$  is a function  $U \times [T_0(u), T_1] \rightarrow \mathbb{R}$ .



**Fig. 1** Outline of our research methodology. The goal is to obtain novel knowledge about the temporal evolution of users (on the right). In order to achieve this goal we use a time decoupling approach and a feature construction to represent users with (i) paths in a feature space, and (ii) timing vectors. We then study the paths and vectors separately. Visualization of paths allows us to construct features that can describe forums.

Note that we assume that the feature values are real valued. In practice, many widely used features (e.g., degree of a user in the reply graph, number of posts per thread) can be mapped to real values.

At any time point  $t \in [T_0(u), T_1]$ , the user can be numerically described with a set of features  $F(u, t) = \{f_1(u, t), \dots, f_n(u, t)\}$ . We note that it is generally safe to assume that every user feature  $f_i \in F$  is a piecewise-constant function. This is the case with many features used in practice, e.g., the number of user posts only changes at certain time points, rather than continuously. Under this assumption, we can describe a user with two finite sets defined below.

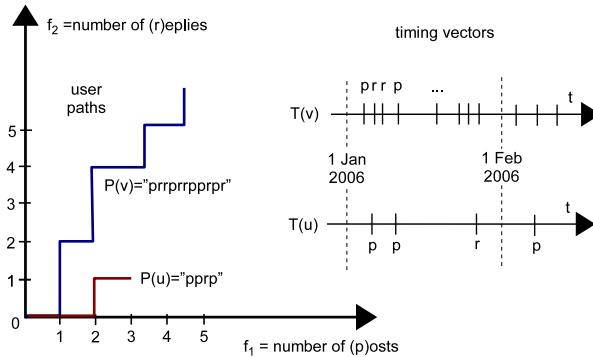
**Definition 2** Given a set of piecewise-constant user features  $f_i(u, t)$ ,  $i = 1, \dots, n$ , a **timing vector** of user  $u$  is the ordered set  $T_{event}(u) = \{T_0(u), t_1, \dots, t_L : T_0(u) \leq t_1 < \dots < t_L \leq T_1\}$ , where  $t_i$  is a time point at which at least one of the features  $f_i(u, t)$  changes its value. A **user path** of user  $u$  is the set  $\mathbb{P}(u) = \{F(u, t) : t \in T_{event}(u)\}$ . A **path length** is the number  $L(u) = |T_{event}(u)| - 1$ .

Note that the user path can be viewed as a sequence of events listed in chronological order, where an event is a change in feature values. We suggest to separate the study of the user paths and the timing vectors. We expect that prominent patterns in user evolution are preserved in user paths with the order of events. On the other hand, time stamps are more noisy, in the sense that they are likely to be influenced by various real world factors that are either not interesting for the study, or very hard to account for (e.g., sickness of a user, weather conditions). Therefore, combining the time stamps with the user paths might obfuscate important patterns.

While this framework is general, in a sense that it can incorporate any number of features, it is particularly convenient to consider a two-feature representation, as it allows us to easily plot the user paths. We propose to represent users with two new features:  $f_1(u, t)$  is the number of posts user  $u$  has made since registration to time  $t$

inclusive, and  $f_2(u, t)$  is the number of replies user  $u$  has received since registration to time  $t$  inclusive.

Figure 2 shows two sample user paths and the corresponding timing vectors. Consider path  $\mathbb{P}(u)$  in the figure. At the registration time, user  $u$  has no posts and no replies, and therefore the path starts from  $(0, 0)$ . User  $u$  then posts twice, receives a reply, and posts again, thus  $\mathbb{P}(u)$  goes to  $(1, 0)$ ,  $(2, 0)$ ,  $(2, 1)$ , and  $(3, 1)$ . There is no more recorded activity for user  $u$ , and so the path stops. We assume that at each point in time, there can be only one post or one reply. The two possible events in this case are incrementing the number of posts (p) and incrementing the number of replies (r). Note that users  $u$  and  $v$  do not necessarily reply to each other. We discuss our choice of user features in the next section.



**Fig. 2** Two sample user paths and the corresponding timing vectors. Two features are used to represent the users. The order of changes in feature values is captured by user paths. The timing of the events is recorded in timing vectors.

## 4.2 User Feature Space

Recall that we aim to represent a user with an interpretable feature set that can be visualized. There are a large variety of previously proposed features to describe users [7, 23, 27], and there are a number of methods for automated feature selection. Broadly relevant feature selection methods can be divided in two groups: feature transformation (such as well known principal component analysis), and unsupervised feature selection (see for example [6, 21]).

Unfortunately, both groups of methods were developed for a setup that differs from the one that we observe in our dataset. Specifically, previous work considers a finite set of objects, where each object is described by a set of numbers. Here, for a given object, a *feature is a number*. In our case, we are interested in the temporal evolution of users. We have a finite set of users, but each user is described by a set of functions of time. We have that for a given user, a *feature is a function* (see Definition 1).

Furthermore, previously proposed features are defined as numbers. For example, the number of initiated threads [7] is counted over the whole time span of the dataset and does not vary with time. We therefore construct new time varying features, instead of selecting from previous features.

As we stated in the previous section, we propose two new user features: the number of posts a user has made since the registration to time  $t$  (inclusive), and the number of replies the user has received since the registration to time  $t$  (inclusive). The two features comprise our feature space. In this space, a user path is constructed as follows. The path starts from point  $(0, 0)$ . Whenever a user makes a post, the path goes one unit to the right. Whenever a user receives a reply the path goes up one unit. We count a self-reply only once as a post, and we assume that at one time point there can be only one post or one reply. Note that the path always starts with a post, as there cannot be replies when there are no posts.

We would like to clarify that a post always belongs to exactly one thread. Within the thread, a post can be the starting post for the thread or it can be a reply to any previous post in the same thread (those posts, can in turn be replies to earlier posts). In some forum settings, one post can even be a reply to more than one previous post in the thread [10]. In all these cases, the post moves its author one unit to the right.

We now discuss the advantages and limitations of the proposed feature space.

### *Advantages of Our Feature Space*

First, our feature space can be visualized and interpreted in terms of persistence and reciprocity of communication (Figure 3). Plickert et al. distinguish two dimensions of reciprocity: one-to-one ( $A \leftrightarrow B$ ) versus network ( $A \rightarrow B, \dots$ , someone  $\rightarrow A$ ), and restricted versus generalized [20]. In the case of the reciprocity in a user path, generalized network exchange is the most appropriate classification: a user contributes to and receives rewards from a network of interlocutors, and the exchange is not restricted (e.g., there is no guarantee that the response will ever be received). At the same time, it is important to understand that a user’s posts and replies are publicly visible. Therefore, every user’s post can be viewed as a contribution to everyone ( $A \rightarrow B$  and everyone else,  $\dots$ , someone  $\rightarrow A$ )<sup>1</sup>.

Second, in our representation we can observe a historical record of reciprocity over time. This allows us to see whether a user first needed to make a few posts (perhaps to establish credibility) in order to start receiving responses, or whether the community started interacting with the user straight away. Furthermore, from this historical record we can obtain the focus of the reciprocity, which is a measure of whether the community is being reciprocal to the individual or is focused on the post. If an individual path has a high deviation from the fitted straight line, then we can consider the community to be more focused on specific posts than the individual. If the deviation is low, it means that the community is interacting more with the individual than with selected posts.

Third, we find that, in our datasets, the user paths in this feature space have strong relations with some widely used structural and temporal properties of users. A *reply graph* [27] is a popular structure, where vertices represent users, and directed edges represent replies made during the time span of the dataset. We find a strong correlation between the path lengths and the total degree of users in the reply graph. In all of our forums we observe Spearman’s  $\rho > 0.9$  and  $p < 0.001$ . We use Spearman’s  $\rho$  because the distribution of path lengths is skewed.

Furthermore, let a *user’s up-time* be the time lapsed between the first and last recorded posts made by a user. We find a strong correlation between the path lengths

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<sup>1</sup> The first posts in a thread are not addressed to anyone in particular, they are often questions. Yet they can be viewed as contributions to the forum in general as they might attract useful responses.

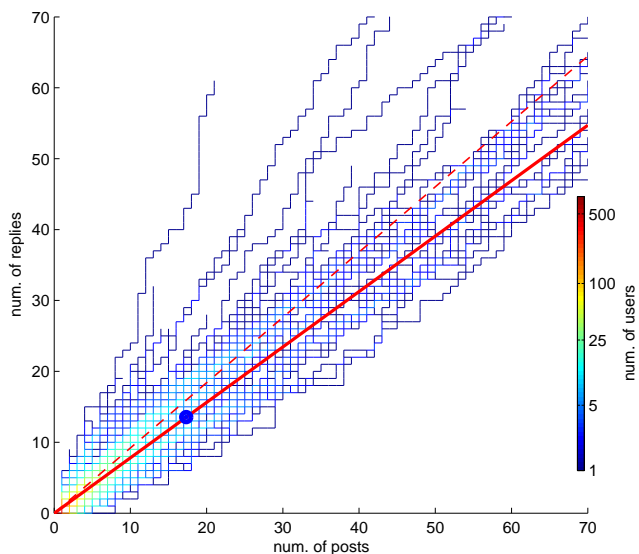


one can use a sequence mining technique as an alternative to the visualization. In this case, a larger number of features can be used. We leave this investigation for future work.

Despite the potential limitations listed above, our feature space allows us to discover novel patterns (e.g., consistency in user behavior) that were not apparent from the previous user representations. Furthermore, our feature space has inspired us to develop a new numerical description of forums. We first summarize our visualization technique, and then present our results in subsequent sections.

### 4.3 Visualization

We propose to visualize forums with superimposed user paths (Figure 4). The paths can cross each other and overlap, and at each point in the plot, color encodes the number of user paths going through that point. The user paths are aligned with respect to the beginning of the users' activity, not in real time. For each path, segment  $(0, 0) - (1, 0)$  corresponds to the first post made by a user since registration, but this first post is made at different times for different users. Such an alignment allows us to compare users as they evolve in the forum.



**Fig. 4** “Personal” forum from *Boards.ie* is visualized with a set of superimposed user paths. At each point, color encodes the number of user paths going through that point. Together the user paths show the trends in conversations specific to the forum. The dashed red line is the baseline that shows the replies to posts ratio. In this forum many paths significantly deviate from the baseline and the mean slope of the forum (solid red line) goes below the baseline.

The overall slope of a forum reflects the reciprocity of communication in the forum. As a reference, we also draw the baseline degree line, which represents the replies to posts ratio in the forum. The mean length of paths represents the persistence of user

engagement in a forum, and the spread of paths in space represents the variety of users. Superimposing paths allows us to reveal the trends in conversations common to users in the given forum.

An advantage of our visualization technique is the scalability in terms of the number of users that can be shown. In principle, this number is not limited. The analogy here is plotting histograms or scatter plots that are capable of showing prominent patterns of populations of arbitrary sizes.

At the same time, we emphasize that visualization is not essential for our numerical analysis methods that we present in the next few sections.

## 5 Patterns in Forum Data

Recall our first and second research questions stated in the introduction.

1. Are there any trends (e.g., consistency) in the temporal evolution of users?
2. Is there a normative temporal behavior for a given forum?

In this section, we address these questions by studying the user paths and timing vectors.

### 5.1 Pattern 1. Consistent Behavior

We plot all forums using our visualization method. The main trend that we observe in the plots is that user paths can be approximated with straight lines at different angles to the x-axis. We quantify this linear dependency by computing Pearson’s correlation coefficient  $r$  between the x and y coordinates of points for individual user paths. That is, for each path we compute the correlation coefficient  $r$  separately. For the *Boards.ie*, *SCN*, *TiddlyWiki*, and *Ancestry.com*<sup>2</sup> datasets the average  $r$  across all users in the corresponding dataset is 0.959, 0.943, 0.937 and 0.921 respectively. The computed correlations are statistically significant ( $p < 0.01$ ). Here we only compute correlation for users whose path contains sufficiently many points. We consider users with path lengths of at least 10. The selection leaves us with 4070 paths across all forums.

We conclude that users tend to exhibit consistency in communication over time. We further investigate this consistency by modeling the user paths.

#### *Modeling User Paths*

We note that the user paths can be represented with strings comprising posts (symbol ‘p’) and replies (symbol ‘r’). Therefore, as a null model for the user paths we use the well-known *coin toss model* (also known as a Bernoulli process). In this model, symbols ‘p’ and ‘r’ are generated sequentially. Our model always starts by producing the symbol ‘p’, because the real paths always start with a post. Then at each step, the symbol ‘p’ is chosen with a fixed probability  $P_{post}$  that describes the ability of a user to elicit replies. Larger values for  $P_{post}$  result in a larger proportion of posts in the path, and this corresponds to a weaker ability to elicit replies. For each user we

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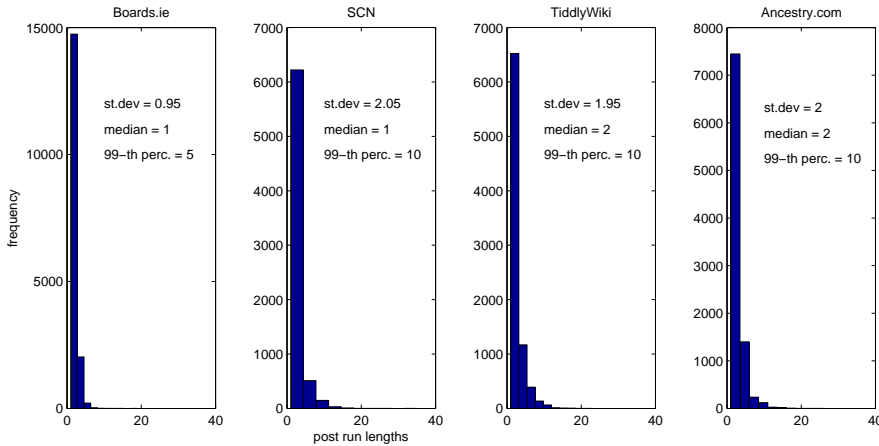
<sup>2</sup> In Section 5.1, for *Ancestry.com* dataset all statistics were obtained from the entire set of users, not a sample.

empirically estimate  $P_{post}$  as  $P_{post} \approx \#posts / (\#posts + \#replies)$ . We evaluate this null model by looking at the distribution of post runs in the data.

By analogy with runs in binary strings, we define a post run as follows.

**Definition 3** Consider a user path  $\mathbb{P}$  represented with a string of posts (symbol 'p') and replies (symbol 'r'). Let the corresponding extended path be the string  $\mathbb{P}' = r\mathbb{P}r$ . In the path  $\mathbb{P}$ , a **post run** is a substring in a form  $rp^+r$  taken from the corresponding extended path  $\mathbb{P}'$ . Here  $p^+$  denotes an arbitrary positive number of posts. A **post run length** is the number of posts in the post run. Where unambiguous, we refer to the post run length as a post run.

We now look at the distribution of post runs in individual user paths. We select users with a path length of at least 20, to ensure that there are several post runs in each path. Figure 5 shows the empirical distributions of post runs aggregated over all tested users in different datasets. We find that post runs and their standard deviations tend to be small compared to the lengths of paths (over 20). This can be a consequence of consistency in user behavior. We are interested in whether the coin toss model is able to reproduce the empirical distribution of post runs for individual users that is present in the data.



**Fig. 5** Empirical distributions of post runs aggregated over all tested users in different datasets. Post runs and their standard deviations tend to be short compared to the lengths of paths (over 20). This can be a consequence of consistency in user behavior.

For each tested user, we estimate  $P_{post}$  and record the path length. We then generate a path of this length using the coin toss model with the estimated parameter  $P_{post}$ . For each user, we then compare the empirical distribution of post runs and the generated distribution using the Kolmogorov-Smirnov (KS) test at a 5% significance level. A user *passes the test* if the KS test fails to reject the null hypothesis that the distributions are different. The number of users that pass the test is shown in Table 3. We conclude that in general, the coin toss model adequately renders the user paths.

At the same time, we find that in the *Boards.ie* dataset about 27% of users fail the test. We hypothesize that in this dataset, users tend to be more consistent (i.e., follow

**Table 3** Results of models evaluation. “Users Tested” shows the number of users with a path length of at least 20 for each of the datasets. Both models are capable of recovering the distributions of post runs for the majority of users. However, in the *Boards.ie* dataset about 27% of users fail the test.

Dataset	Users Tested	Users Passed (Coin)	Users Passed (Sticking)	$P_{harsh}$
<i>Boards.ie</i>	186	135	178	0.8
<i>SCN</i>	112	101	109	0.8
<i>TiddlyWiki</i>	115	97	93	0.6
<i>Ancestry.com</i>	136	120	134	0.7

a straight line more closely, as explained below) than the random users generated by the coin toss model.

We therefore propose another model for the generation of user paths. We call this model the *sticking model*, because in this model users are stuck to a straight line by penalizing deviations. The slope of the straight line is determined by the parameter  $P_{post}$  that is estimated for each user as  $P_{post} \approx \#posts / (\#posts + \#replies)$ . The model is summarized in Algorithm 1. In the model, as soon as the generated path deviates from the straight line, a harsh probability  $P_{harsh}$  (e.g.,  $P_{harsh} = 0.8$ ) forces the model to generate the next symbol in a way such that the balance is restored. Note that the sticking model can only be reduced to the coin toss model in the case when  $P_{harsh} = 0.5$ , which corresponds to the coin toss model with  $P_{post} = 0.5$ .

---

**Algorithm 1** Sticking model

---

**Input:** path length  $L$ , user characteristic  $P_{post}$ , dataset characteristic  $P_{harsh}$ ;

**Output:** string  $\mathbb{S}$ ;

```

1:  $\mathbb{S} \leftarrow 'p'$ ; // real paths always start with posts
2:  $currProp \leftarrow 1$ ; // proportion of posts in the string
3: for each symbol  $currLength = 2 \dots L$ 
4:    $P_{curr} = \begin{cases} P_{harsh}, & P_{post} > currProp \\ 1 - P_{harsh}, & P_{post} < currProp \\ 0.5, & P_{post} = currProp \end{cases}$ 
5:    $currSymb = random(P_{curr}, 'p', 'r')$ ; // select 'p' with probability  $P_{curr}$ ;
6:    $\mathbb{S} \leftarrow \mathbb{S} + currSymb$ ; // append the string
7:    $currProp \leftarrow \#(posts \text{ in } \mathbb{S}) / currLength$ ; // update the proportion
8: end
9: return  $\mathbb{S}$ ;

```

---

We evaluate the sticking model on each user individually, similar to our evaluation of the coin toss model. To simplify and speed-up the calculations, we use the same  $P_{harsh}$  for all users in the same dataset. For each dataset, we find the value that maximizes the number of users that pass the test, using grid search. The results are presented in Table 3. We find that in general the sticking model explains the empirical data better than the coin toss model. The difference in models is especially prominent in the *Boards.ie* dataset. Note that this dataset also has the strongest mean correlation coefficient (Section 5.1), which indicates that users in this dataset have the strongest tendency to adhere to straight lines.

From our modeling experience, we conclude that the consistency of a user can generally be explained by an inherent user property. We expressed this property with a constant parameter  $P_{post}$ . At the same time, small deviations from the parameter are possible, and the amount of this deviation varies in different forums. We can express this freedom to vary by using the parameter  $P_{harsh}$ . For example, in *Boards.ie* users exhibit a stronger consistency than one would expect for a random user modeled with the coin toss model.

## 5.2 Pattern 2. Dead Zones

Another prominent pattern that we observe in our visualizations is that the user paths are not equally distributed in the feature space. We formalize this pattern with the concept of a dead zone.

**Definition 4** A **dead zone** is the set of points  $(x, y)$  with integer coordinates, such that the probability of observing a user in each point  $(x, y)$  is less than some threshold value  $P_{dz}$ .

In order to calculate the empirical probability of user locations, we treat points from all paths in a forum as a single set. We then use a kernel density estimation method by Botev et al. [5]. This method performs an automated selection of kernel bandwidth. However, with the automatically selected bandwidth, the empirical density has a grid patterning, as all our points have integer coordinates. Therefore, we smooth the kernel by increasing the bandwidth in both dimensions to 2. We limit the region for the density estimation to the square that has its lower left corner at point  $(0, 0)$ , and its side equals to the largest coordinate observed among forum points along either the x or y axis. Finally, we set the threshold  $P_{dz}$  to the 5-th percentile of the probabilities of all observed user locations in the forum.

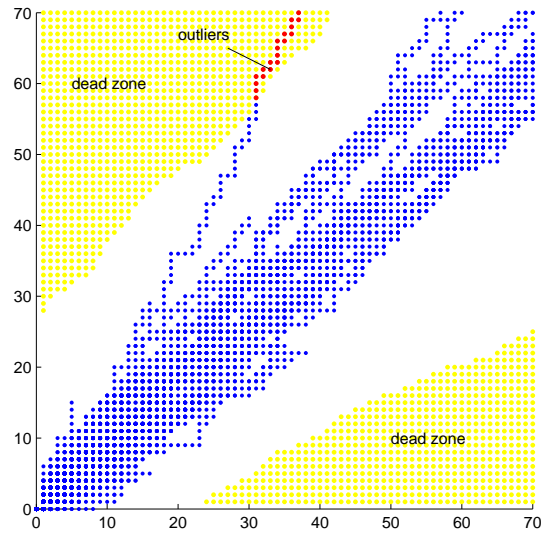
The dead zones for the politics forum from *Boards.ie* are shown in Figure 6. In general, the probability of observing a user in the upper-left or lower-right corners of the plot is low. We observe similar dead zones in all our forums.

The dead zones can be considered as a formal definition of a normative user behavior for a given forum, and user posts found in the dead zones can indicate an 'abnormal' user behavior (see Figure 6). For example, we would expect to find spammers in the zone along the x-axis, and we would expect a user with highly provocative behavior (attracting many replies) along the y-axis.

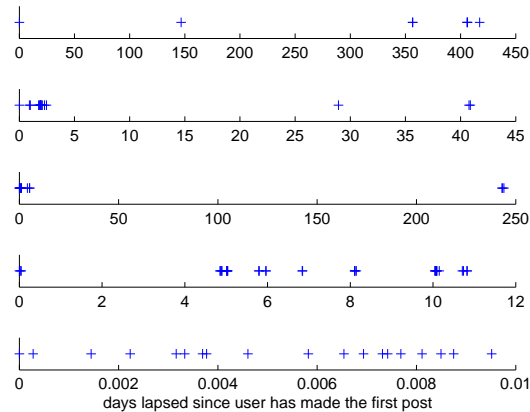
## 5.3 Patterns in Timing Vectors

We now study the second part of our user data model, the timing vectors. We start with plotting events of random users along the time line (Figure 7). In the plot, the x-axis shows the number of days lapsed since the user has made the first post. A cross mark indicates an event (a post or a reply). Although users can have very different time intervals (note the different scales on the x-axes), we note that in general users exhibit bursty behavior: events tend to group together in time.

We confirm this grouping pattern by looking at the distribution of inter-event times. We hypothesize that such a distribution is heavy tailed, with high probability values for a small range of short times and low values for all other times, as short times



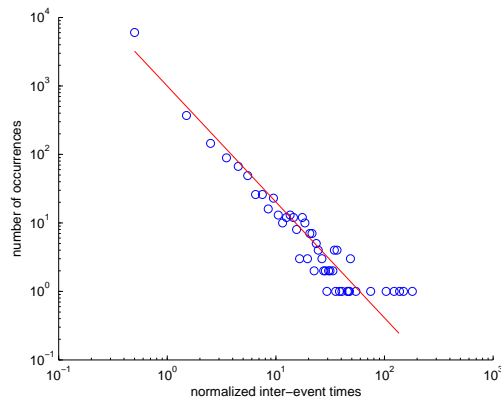
**Fig. 6** Dead zones (shown in yellow) for the politics forum from *Boards.ie*. The blue dots between the two dead zones show empirically observed user locations. Red dots show the outlier locations that can indicate an 'abnormal' user behavior. We observe similar dead zones in all our forums.



**Fig. 7** Timing of events of five randomly selected users. The x-axis shows the number of days lapsed since the corresponding user has made the first post. Note the different scales on the x-axes.

correspond to times between events in a burst, and long times correspond to times between bursts. This supposition is confirmed when we look at empirical distributions of the inter-event times collected for individual users in our forums. For each user (with at least 10 events) we collect a set of inter-event times and divide the numbers by the mean value. This results in normalization of the inter-event times across users. We then combine the sets of the normalized inter-event times for all users in a forum and fit a power-law curve. A representative result of such a fit is shown in Figure 8. We

observe a similar distribution in every forum that we study with the fitted characteristic exponents of about  $-1.7$ .



**Fig. 8** The distribution of normalized inter-event times of users in politics forum. The plot shows about 7,000 points in a log-log scale.

This bursty behavior is a well-studied phenomenon in domains such as collaborative tagging [30], and there have been effective models defined for this behavior [16]. The model of Malmgren et al. [16] for inter-event times complements the models that we introduce in Section 5.1 for user paths. Together these models summarize a user’s behavior over time.

There can be cases when studying user paths together with event timings is important. However, we note that combining the two parts can obfuscate otherwise prominent patterns (see Figure 9). This is consistent with our motivation for using a time decoupling approach.

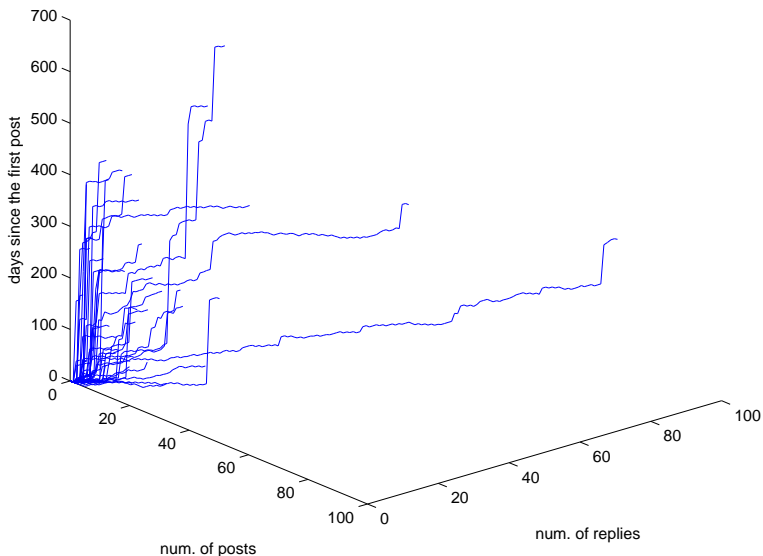
## 6 Describing Forums

In this section, we address our third research question: “Can we quantify and categorize forums in terms of the temporal behavior of users?” We start with the development of a concise numerical description of forum visualizations such as that shown in Figure 10 (see also Supplementary Information 3).

**Definition 5** Let a **forum archive**  $\mathbb{A}$  denote a set of user paths  $\mathbb{A} = \{\mathbb{P}(u)\}$  observed in a forum within the time span of the dataset. A **forum feature** is a function defined on the forum archives  $f : \mathbb{A}^* \rightarrow \mathbb{R}$ , where  $\mathbb{A}^*$  is the set of all possible forum archives.

### 6.1 Deriving Forum Features

One possible way of deriving the forum features is to fit each path independently with a straight line and then use the mean length and slope of the paths. However, using the mean slope is not straightforward. Paths with different lengths have different influence



**Fig. 9** Plotting user paths in 3D with the numbers of posts and replies and timings of events. The consistency in user behavior is not apparent anymore. There is a staircase pattern in the temporal dimension, but this is a consequence of the bursty behavior that we discussed in this section.

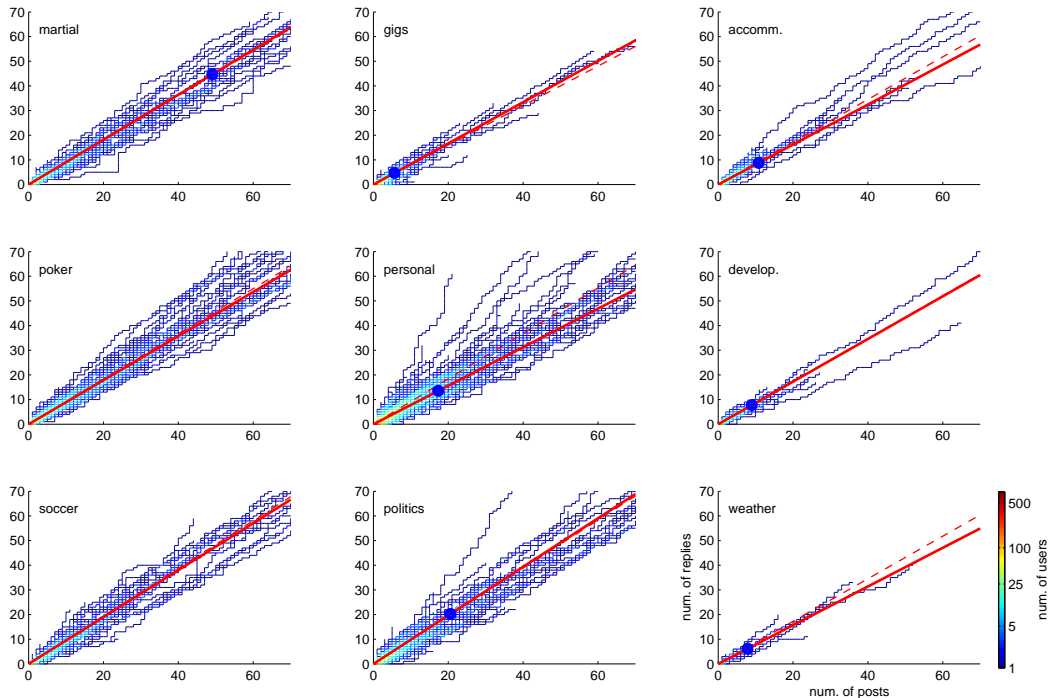
on the overall shape of the forum. Further, different paths have different RMSE when fit with a line. It is not obvious how to weight the paths appropriately. Therefore, we take a different approach. We treat points from all paths as a single set, and define forum features using this set.

#### *Forum Slope and Spread*

Our first feature is called the slope feature  $\tilde{\beta}$ . This feature is derived as follows. We fit a straight line to all points in the forum, and compute the angle between the fitted line and the x-axis. Recall that in a forum, for each user  $u \in U$ , the path with length  $L$  is the set of points  $\mathbb{P}(u) = \{(0, 0), (x_{u1}, y_{u1}), \dots, (x_{uL}, y_{uL}), \}$ . Let  $\mathbb{Q}$  be the union of points from all paths  $\mathbb{Q} = \cup_{u \in U} \mathbb{P}(u)$ . The RMSE of fitting a line to the forum is defined as

$$ERR(\beta) = \sqrt{\frac{\sum_{(x,y) \in \mathbb{Q}} (y - \beta \cdot x)^2}{|\mathbb{Q}|}}. \quad (1)$$

Here  $\beta$  is the parameter of the line that is estimated by the fitting process. Note that we force the fitted line to pass through the point  $(0, 0)$ . This allows us to reduce the number of fitting parameters to one ( $\beta$ ). Also note that points from different paths are considered as different elements, e.g.,  $\mathbb{Q}$  may contain several points  $(1, 1)$  from different



**Fig. 10** Visualization of forums from *Boards.ie*. Each line is a user path. At each point, the color encodes the number of paths going through the point. The dashed red line is the baseline that reflects replies to posts ratio, the solid red line shows the average slope of the forum. The blue dot shows the average length of user paths for the forum measured along the slope line (for the soccer and poker forums the average length is above 50). Differences in forum appearance (different mean length or slope) indicate differences in the nature of communication in the corresponding forums.

users. This introduces an implicit weighting of user paths, because paths that have more points have more influence on the statistic. In every forum that we study, the majority of users have short paths (one or two posts). Without the weighting these short paths will suppress the slope in each forum, leaving almost no room for variation across forums.

The slope feature  $\tilde{\beta}$  is then defined as  $\tilde{\beta} = \arg \min_{\beta \in (0, \infty)} ERR(\beta)$ . This feature can be estimated with least squares fitting. The slope feature  $\tilde{\beta}$  is essentially a tangent of the angle between the fitted line and the x-axis. Note that this is not the same as taking the mean of the slopes of individual path fits.

Our slope feature  $\tilde{\beta}$  can be interpreted in terms of the reciprocity of communication. For example, the soccer forum has a slope that is closer to one than the slope of the weather forum (Figure 10). This indicates that users in the soccer forum tend to be involved in balanced conversations, and receive replies to almost all posts, whereas in the weather forum, users tend to post more than they receive replies.

Our second feature characterizes the spread or variation in user paths. This feature is called the spread feature and it is defined as the fitting error  $ERR(\tilde{\beta})$  by Equation 1. For example, the poker forum has a larger fitting error  $ERR(\tilde{\beta})$  than the soccer forum,

and this indicates that there is greater diversity of user paths in the poker forum. This can be visually confirmed in Figure 10.

### *Slope, Baseline and Offset*

The slope feature reflects the averaged reciprocity of communication in a forum, whereas on the individual level, the slope reflects “one-to-many” reciprocity where a user contributes to a public domain, but can expect some reward from the public domain.<sup>3</sup>

On the level of the forum, the slope feature can give an overall impression of the type of communication in forums, and we plot the forum slope in our visualizations. However, the slope can be split down further in two components. The first component is the overall ratio of the number of replies to the number of posts in the forum during the period of observation. We call this ratio a baseline feature  $\beta_0 = \#replies/\#posts$ . Recall that a post can also be a thread starter, in which case, it is not a reply to any other post. Therefore, our baseline feature effectively reflects the average number of threads per forum compared to the average thread length. The baseline feature is an aggregated statistic over the whole period of observation, and it is not sensitive to the shapes of the user paths as they evolve over time.

On the other hand, the slope feature itself is sensitive to the ordering of events in paths. Therefore, our second component of the slope is the offset feature, which is a signed difference  $d = \tilde{\beta} - \beta_0$ . The offset feature shows the variance in conversation structure that cannot be captured by the baseline feature.

Consider two fragments of user paths, one with five posts and five replies and another one with five replies and five posts. The baseline for both paths is the same, whereas the slopes and hence the offsets differ. The offset is negative for the first path and positive for the second. This reflects the fact that the second user has always been in a position of a “response-attractor”: at each point of his career he has more or the same number of replies as posts, whereas the first user has never been in that position.

### *Number of Users and Length of Paths*

Other important properties of a forum are the number of participating users  $N = |U|$  (this is called the size feature) and the average length of user paths  $L_{avg} = \frac{1}{N} \sum_{u \in U} L(u)$  (called the length feature).

$N$  can reflect the popularity or the generality of a forum topic, and  $L_{avg}$  can reflect the relative persistence of users in the forum. For example, within the same period of observation, the martial arts forum has a much larger  $L_{avg}$  than the accommodation forum, which indicates that users in the martial arts forum are more persistent (tend to post more) whereas users in the accommodation forum tend to leave after making a small number of posts.

We note that in Section 5.1 we studied the patterns in individual user paths and we omitted short paths. However, in the calculation of our forum features, we used all paths.

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<sup>3</sup> There is also a hidden reward, because even without receiving replies, reading the forum can be a rewarding experience. However, the reading counts are usually difficult to account for numerically. We do not have these counts for our datasets.

We summarize our forum features for nine *Boards.ie* forums in Table 4. We compute the four features as we described above, with the exception of one user from the gigs forum (see Supplementary Information 3). Note that the baseline accounts for a large part, but not all of the variation in the forum slopes. The Pearson correlation between the slope and baseline features is 0.67.

**Table 4** Summary of forum features for nine forums from *Boards.ie*

Name	Size	Length	Slope	Base	Offset	Spread
politics	881	28.89	0.98	0.97	+0.01	11.55
soccer	243	117.36	0.95	0.97	-0.01	13.56
poker	610	110.39	0.89	0.92	-0.03	38.59
martial	520	66.38	0.91	0.90	+0.01	21.57
personal	1952	21.99	0.79	0.92	-0.13	9.86
accomm.	787	13.93	0.81	0.86	-0.05	7.85
gigs	1151	7.32	0.84	0.80	+0.04	2.03
weather	186	9.98	0.78	0.86	-0.08	1.87
develop.	355	11.86	0.86	0.87	-0.01	3.93

## 6.2 Automated Categorization of Forums

We next use our forum features as the basis for performing a hierarchical clustering of forums. We then show how this clustering allows us (i) to validate the proposed forum features, and (ii) to demonstrate the utility of the features.

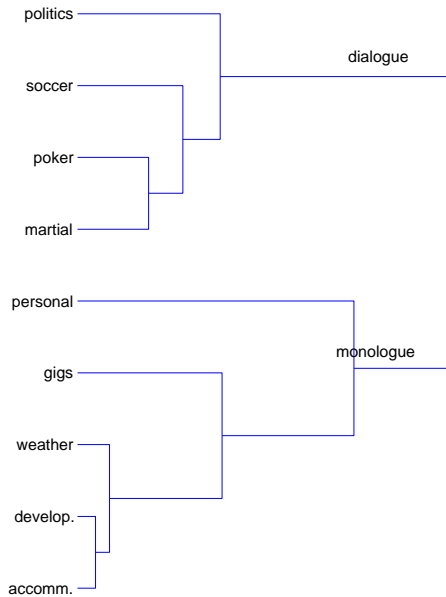
Prior to the clustering, we normalize each feature by its variance, because otherwise some feature values are orders of magnitude larger than others, and hence have a much higher impact on the clustering. The slope feature was not used in the clustering, because it is included as the baseline and offset features. The baseline and offset features were normalized by the variance of the baseline feature, because these two features are on the same scale with dominating baseline values. There is no need to align the features to zero mean, because we use Euclidean distance for the similarity between points, and hence only the difference between values matters.

We do not have a predefined number of clusters, and therefore we use hierarchical clustering. We use agglomerative hierarchical clustering with Ward’s linkage method and the Euclidean distance. We also tried other approaches such as single linkage or average linkage, but observed similar groupings. We report the clustering where the grouping is most prominent. We use Euclidean distance because it is widely used and it is compatible with different linkage strategies. We do not use cosine similarity, since this measure is not sensitive to the magnitude of feature vectors. We discuss our clustering results below.

### *Hierarchical Clustering*

The resulting hierarchical clustering is shown in Figure 11. A prominent feature of the clustering is the presence of two distinct groups that we have labeled with the terms monologue and dialogue. The forums in the monologue branch tend to have slopes closer to the x-axis than the forums from the dialogue branch. That is, the users in monologue forums tend to post more than they receive replies, whereas the

users in dialogue forums tend to have more balanced conversations in terms of the numbers of posts and replies. This justifies the choice of labels for the two branches. Alternatively, monologue forums can be viewed as announcement or classified forums, whereas dialogue forums can be viewed as discussion forums.



**Fig. 11** Hierarchical clustering of forums. A prominent feature of the clustering is the presence of two distinct groups that we labeled with the terms monologue and dialogue. The users in monologue forums tend to post more than they receive replies, whereas the users in dialogue forums tend to have more balanced conversations in terms of the numbers of posts and replies.

The personal forum stands apart, mostly because it has the largest offset between the baseline and slope. In the visualization, this fact is reflected with the presence of user paths that deviate significantly from the baseline. Furthermore, in each branch, the politics and gigs forum stand apart because they have the largest number of users in the corresponding group.

The automated categorization of forums demonstrates the utility of our forum features. The categorization can be used by forum administrators to select different management policies for different categories of forums. Further, the categorization of forums can inform the structural design of forum websites.

It is hard to define the ground truth clustering for forums, and researchers often have to appeal to intuitive categorizations of forum names [7, 17]. Therefore, we validate our clustering, and hence our forum features, indirectly. We note that the hierarchical clustering aligns with a possible manual clustering of visualizations (Figure 10), as well as with a possible intuitive grouping of forums (e.g., the soccer and martial arts forums group together). Furthermore, the interpretable clustering of forums that we were able to produce demonstrates potential value of our forum features.

Moreover, given the explanatory nature of unsupervised clustering, a misalignment with respect to a hypothetical ground truth or with respect to the intuition is not

necessarily a negative result. We note that our clustering reveals new information. For example, it might not be obvious beforehand that the personal forum should be put in the monologue category, or that the accommodation and development forums comprise the most similar pair of forums. We further highlight the novelty of our clustering by comparing it to a result from previous work.

#### *Comparison with Previous Work*

As mentioned in Section 1, we depart from past work on roles by exploring the stability of user patterns over time, rather than assuming a stable behavioral role within an ecology of participatory roles. Moreover, we provide simplified statistics for assessing roles compared to factor analytic approaches [7, 8] or multi-metric assessments [27].

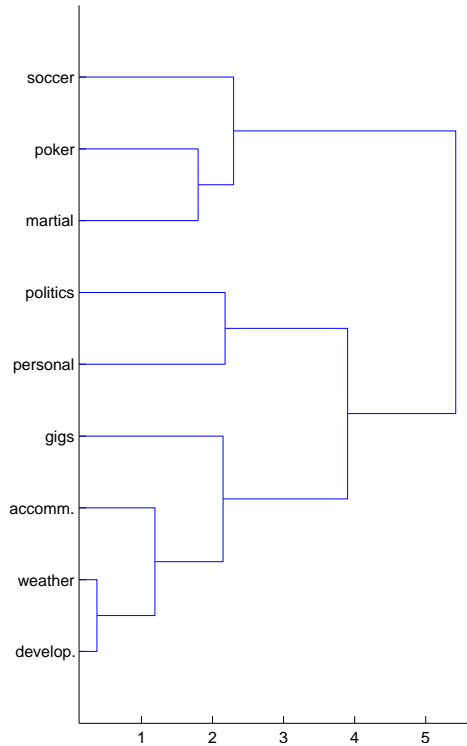
Using this technique we also gained new insights on old data: The categorization of *Boards.ie* by Chan et al. [7] produced an interesting if unexpected series of similarities across boards. For example, ‘Politics’ and ‘Accommodation’ appeared very similar in role composition. Given the unexpected nature of these findings, it made theorization difficult. Also, past work on thread structure has shown that discussion structure tends to map on to expected notions of discussion intensity [8]. To this end, the hierarchical clustering we have shown in this paper has face validity, despite requiring no knowledge of the content of the forums. This is not to undermine earlier work, but to point towards techniques that reinforce existing expected similarities and draw upon behaviors that we consider to be especially salient. We assert that persistence in the board and tendency to reciprocate are salient features. The politics forum consists of highly persistent users and reciprocal communication, whereas the accommodation forum exhibits less reciprocal communication and ephemeral users. Additionally, looking at the role composition of the personal forum, one can suggest that most people are quiet, whereas our study reveals that there are a notable minority of users who are able to consistently generate a lot of attention, probably as a means of garnering social support.

Rather than stating that only one of the methods is correct, we conclude that our approach is complementary to previous work, as it provides an alternative view on the forums. However, three of the advantages of our method are its computational simplicity, its focus on metrics known to be of relevance to forum participants, and its capacity to provide both micro-level statistics about users and global statistics on interactions over time.

#### *Alternative Clustering: Baseline Only*

Recall that the baseline feature accounts for a large part of variation of the slope feature. In this section, we study the effect of replacing the slope feature with the baseline feature. We produce a hierarchical clustering as described above but without the offset feature (Figure 12). We observe that, despite the baseline and slope features being correlated, the clustering results differ.

A prominent effect from ignoring the difference between the baseline and slope features, is that the personal and politics forums appear to be relatively similar and form a cluster. However, as can be seen in Figure 10 (see also Section 3 in Supplementary Information) a certain portion of paths in the personal forum asymmetrically diverges from the baseline, whereas the paths in the politics forum tend to follow the baseline more closely. The baseline feature alone was not able to capture this specific trend,



**Fig. 12** Alternative hierarchical clustering that ignores the difference between the baseline and slope features. This clustering differs from the main clustering. For example, the alternative clustering is less balanced.

and we suggest using both the baseline and the offset features as they encompass more information about the user behavior.

### 6.3 Influential Users in the Personal Forum

We observe a high heterogeneity of user paths in the Personal forum. A few user paths in the upper left part of the plot (Figure 4) deviate from the majority of paths. Therefore we look closely into this group of users and contrast them with the majority of paths in this forum. To this end, we visually identify a group of 7 users that show prominent variation along their paths, and as a result strongly deviate from the average forum behavior, i.e., we take the first 7 paths encountered while moving to the right from point  $(0, 50)$ . We then compare the original slope for the Personal forum (0.79) with the slopes obtained after removing these users (0.77) and the slope calculated only for these users (1.26). We find that individuals in this group are characterized by a high response-to-posts ratio. Interestingly, without these users the Personal forum becomes even more monologue-based and even more distinct from the other forums. Our findings suggest that our user representation has the potential to identify groups of users, which can complement previous studies [7]. A more systematic user categorization is left for future work.

Furthermore, we study effects that individual users makes on averaged forum statistics. We define the *slope influence* of a user as a signed difference between the slope estimated with the user path included and the slope estimated without the path. We find that individually users do not have a noticeable effect on the slope: 99% of the individual slope influences fall in the interval  $[-0.002; 0.001]$ . This suggests that the forum slope is reliable to outliers, while there can be heterogeneous groups within a forum.

## 7 Conclusions

Forum data provide numerous potential avenues for analysis and visualization, many of which we have mentioned above. Our contribution to this area has been to focus on mechanisms that past work have considered salient (reciprocity and persistence) and that can be employed in a time decoupling approach. In our approach, we decoupled timing information into user paths and timing vectors, and studied these parts separately. We constructed user paths using two new features: the number of a user’s posts and the number of replies to the user over time.

We studied the paths of over 30,000 users from four forum websites, and found that users tend to exhibit consistency in communication over time. We proposed to model the user paths with coin toss and stickiness models and found that in certain forums, users tended to be more consistent than one would expect for a random user modeled with the coin toss model. We also found zones in the feature space where users were unlikely to be located. Furthermore, we studied the timing vectors for these users and observed bursty behavior, a well-known phenomenon in other domains.

We used our results to represent forums in terms of the temporal behavior of users, and validated our forum features with a hierarchical clustering of forums. We proposed a number of applications for our results, such as predicting whether a user is likely to be involved in conversations in the future based on past observations, and identifying the normative behavior for a given forum.

In addition to our main results, we wish to emphasize the flexibility and generality of our approach, since it can be applied to other domains, such as email or phone communications. This leads to potential future work in expanding this technique. One expansion would be to consider different media, such as a call graph, where posts and replies are replaced with patterns of initiation between calling partners. Another direction for future work is identification forum leaders from a time-series mining perspective as was previously proposed for some other domains [28].

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