All Who Wander: On the Prevalence and Characteristics of Multi-community Engagement

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ABSTRACT

Although analyzing user behavior *within* individual communities is an active and rich research domain, people usually interact with *multiple* communities both on- and off-line. How do users act in such multi-community environments? Although there are a host of intriguing aspects to this question, it has received much less attention in the research community in comparison to the intra-community case. In this paper, we examine three aspects of multi-community engagement: the *sequence of communities* that users post to, the *language* that users employ in those communities, and the *feedback* that users receive, using longitudinal posting behavior on Reddit as our main data source, and DBLP for auxiliary experiments. We also demonstrate the effectiveness of features drawn from these aspects in predicting users' future level of activity.

One might expect that a user's trajectory mimics the "settling-down" process in real life: an initial exploration of sub-communities before settling down into a few niches. However, we find that the users in our data continually post in new communities; moreover, as time goes on, they post increasingly evenly among a more diverse set of smaller communities. Interestingly, it seems that users that eventually leave the community are "destined" to do so from the very beginning, in the sense of showing significantly different "wandering" patterns very early on in their trajectories; this finding has potentially important design implications for community maintainers. Our multi-community perspective also allows us to investigate the "situation vs. personality" debate from language usage across different communities.

Categories and Subject Descriptors: J.4 [**Computer Applications**]: SOCIAL AND BEHAVIORAL SCIENCES; H.2.8 [**Database Applications**]: Data Mining

General Terms: Algorithms, Experimentation

Keywords: multiple communities, lifecycle, language, Reddit, DBLP

1. INTRODUCTION

树挪死，人挪活 (*People, unlike trees, thrive on relocation*).
—A Chinese saying

How people behave *within* a given community is a profound and broad question that has inspired work ranging from basic social-science research (e.g., [27]) to the design of online social systems (e.g., [21]). However, many settings offer an array of *multiple* possible interest sub-groups for users to engage in. In the offline world, for example, within the bounds of a single college campus, students can get involved with a variety of clubs, organizations, and social circles. And in the online case, there are many multi-community sites, such as Reddit, 4chan, Wikia, and StackExchange, all of which host a slew of topic-based sub-discussion forums. As the results in this paper show, multi-community settings exhibit many interesting and useful properties that are not manifested in within-community situations, and so *our main goal is to demonstrate that multi-community engagement is an exciting and underexploited research area*: we believe that such work will shed additional light on human behavior and on the design of social-media systems.

To demonstrate, we first tackle a seemingly foregone conclusion: that, analogously to the human life course [5, 14], a person first passes through an "adolescent" phase of trying out many different interests before "settling down". Indeed, the best-paper award at WWW 2013 was given to an excellent within-community study [9] demonstrating (among other things) that users' language use becomes more inflexible and out-of-step with the community's over time. But, contrary to this expectation, we find that even people with long histories of participation in a global community *continually* try out new sub-communities. Figure 1 depicts this for two very different settings: for Reddit and for the universe of computer-science conferences given by DBLP, the latter choice inspired by [3]. Note that despite their very different timescales (one can post to Reddit at any time, but submission deadlines only roll around every so often) and barriers to entry (conferences have gate-keepers, whereas posting on Reddit can be done essentially at will), they exhibit the same qualitative behavior. On average, Redditors post to 5 communities in their first 10 posts and then post to 2.5 *new* communities every 10 posts, while researchers publish at 5 *new* conferences every 10 papers (Fig. 1a and 1b). These exploration trends continue over the users' lifetimes (Fig. 1c, 1d). Thus, while within a single community "all users die old" [9], it seems that a multi-community setting keeps users young by offering them choices to explore as an alternative to opting out entirely.

Having established the prevalence of "wandering" behavior, we are led to investigate a host of related phenomena. *We believe that these phenomena are interesting in their own right, and at times quite surprising. Moreover, we also demonstrate that our findings inspire new kinds of features that are strongly predictive of users' future level of activity.*

Organization, further paper highlights and design implications. In Sections 2 and 3, we investigate three aspects of users' community trajectories: the communities they post to (§3.1), the language they use within a community (§3.2), and the feedback

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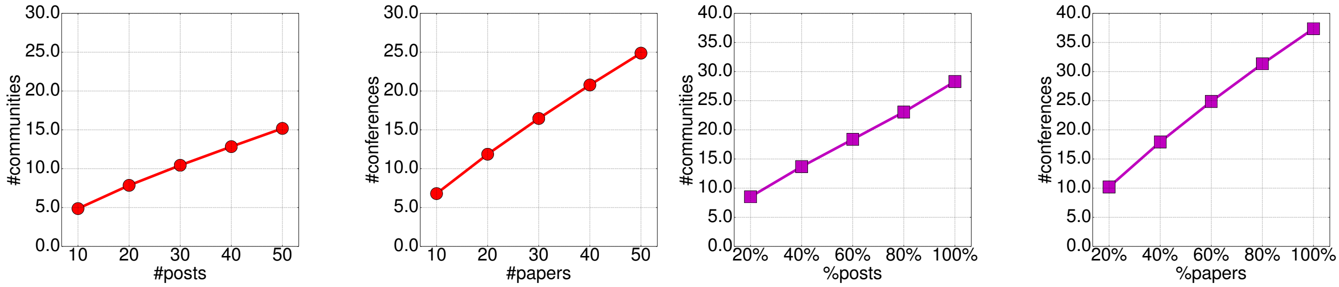


(a) 1^{st} 50, Reddit (b) 1^{st} 50, DBLP (c) lifetime, Reddit (d) lifetime, DBLP

Figure 1: Mean number of **unique** communities (subreddits for Reddit, conferences for DBLP) where people make their temporally first x contributions (left-hand plots) or their first x percent of contributions (right-hand plots), for "long-lived" people (50+ contributions overall). For Reddit (respectively, DBLP), contributions = posts (papers). Standard-error intervals are depicted, but very small, and trends for the median are consistent with the mean. Note that the left-hand plots depict long timespans: the average time to accumulate 50 contributions is 456.0 days on Reddit, 15.6 years on DBLP.

Example of a Redditor's first 50 subreddits, in the order posted to, first-time communities underlined: skyrim, aww, skyrim, aww, pics, aww, aww, pics, WTF, aww, pics, WTF, pokemontrades, funny, pokemontrades, pics, aww, AskReddit, pics, pokemon, fashion, AskReddit, aww, Scotland, fashion, aww, Scotland, pics, keto, keto, Fitness, keto, skyrim, pokemon, cats, aww, aww, pokemon, Scotland, AskReddit, fashion, keto, pokemon, ketouk, Scotland, keto, pics, ketouk, funny, gamecollecting.

Two DBLP examples: the set of venues of *James Harland*'s first 50 papers: LPAR, ACE, NACLP, TABLEAUX, DALT, ECOWS, CADE, Australian Joint Conference on Artificial Intelligence, IAT, ICLP, ICSOC, ILPS, "Workshop on Programming with Logic Databases (Book), ILPS", Future Databases, AAMAS, ACSE, EDBT, JICSLP, ACSC, ACAL, SAC, AAMAS (1), PRICAI, Computational Logic, CLIMA, ECAI, AMAST, ISLP, "Workshop on Programming with Logic Databases (Informal Proceedings), ILPS", KR, CATS.

Jure Leskovec's: INFOCOM, HT, AAAI, PKDD, ICDE, ECCV (4), KDD, ICDM, UAI, NIPS, ICML, CHI, VLDB, WWW, EC, WAW, WSDM, ICWSM, PAKDD, CIKM-CNIKM, JCDL, SDM, WWW (Companion Volume).

they receive from other members of the community (§3.3). Consistently, we see that — again, in contrast to the "older people become less adventurous" hypothesis — our users appear to continually seek out new and different communities, and adopt the language characteristics of the new communities. Another interesting point, albeit arguably less surprising, is that they tend to move to smaller communities (a fact noted by Redditors[1]), which might be a signal to site designers to make sure to offer a menu of narrowly-targeted options for users to choose from (or to ensure that sub-groups can arise organically). Finally, a complete surprise is that for users who made at least 50 posts, the patterns exhibited by those who end up departing the site altogether are *already* significantly different from those users who end up staying by *their first 10 posts*. The fact that future abandonment can be detected so early should be of interest to administrators of social-media systems. But, there is an unexpected factor potentially making this discrimination difficult: in our data, the eventually departing users are often most similar *not* to the least active users in our study, but to the *most* active users. We conjecture that our "dying" users are actively striving to remain engaged, but are not quite managing to explore enough to make their overall posting experience satisfactory. A design implication might be to include mechanisms in one's site that more proactively suggest new, diverse sub-communities for posting.

In Section 4, we show that the aforementioned differences in patterns are not "mere" correlations, but do indeed serve as features that are effective at predicting future activity level.

Again, our overall goal is to encourage further work on multi-community settings. As a spur to the imagination, and as a demonstration that this research domain is rich with possibilities, we discuss in sections 5 and 6 two additional questions that arise. First, what makes a user abandon a community and move on to new ones? We see that the positivity of initial feedback correlates with what groups users choose to return to, a finding that contradicts recent results on the power of negative feedback [6], albeit for commenting instead of posting. Second, we make a foray into the "situation vs. personality" debate in psychology [20, 12]: how much of our behavior is determined by fixed personality traits, versus how much is variable and influenced by the specific situation at hand? We consider this question from a linguistic perspective, and determine that *even after topic-specific vocabulary is discarded* (after all, it wouldn't be interesting to find that people use gym-related words at the gym that they don't use at work), users *do* employ different language patterns in different communities. This means that they are able to adapt even into "maturity" — a positive note to end on.

[1]One comment: "the longer you are on reddit, the more you get pulled into smaller subs".

2. EXPERIMENTAL SETUP

In the following, we first describe the data that we use and then propose an analysis framework for capturing the temporal dynamics of multi-community engagement.

2.1 Datasets.

The main dataset used in this paper is drawn from Reddit, a very active community-driven platform for submitting, commenting on, and rating posts[2] [30]. Reddit is organized into thousands of topic-based, user-created discussion forums called "subreddits", which users can post to essentially at will (modulo spam filtering, rate limits, and deletion of posts by moderators). Other users can "upvote" or "downvote" posts; the difference between the number of

[2]A Reddit post consists at a minimum of a title that serves as anchor-text for a link. The link may be to an offsite item ("link post") or to some text that the post's author places on Reddit ("text post"). The dataset with more detailed explanation is available at `https://chenhaot.com/pages/multi-community.html`.

upvotes and the number of downvotes, a difference that we henceforth refer to as *feedback*, is readily available.[3]

Relying primarily on RedditAnalytics[4], in February 2014 we collected all[5] 76.6M posts ever submitted to Reddit since its inception, together with their associated feedback values. We discarded the last month of posts, since their feedback values might not have had sufficient time to converge.

Since we need our users' community trajectories to be long enough to be *able* to exhibit significant wandering (whether or not they actually do), the set of users we consider are those who have made at least 50 posts, following the choice in [9]. We focus on the 157K *50+ posters* who first posted between January 2008 and January 2012 so that we have at least two years' worth (2012-2014) of observations for each of them. We chose to start from January 2008 because users were granted the ability to create their own subreddits at will then. Not only are the 50+ posters good objects of study because we have a lot of data on their behavior, but they also play a major role in determining the character of Reddit because they made 63% of the posts written by users who first posted in the time period under consideration.[6]

In order to ensure that our findings generalize beyond Reddit, we also consider a (more) physical-world multi-community situation: the set of conferences in computer science. Conferences generally correspond to topic areas within CS, and each can be thought of as representing a social group, at least to some degree. In this setting, we take "posting" to mean publishing a paper. We use the DBLP database[7] to find what papers appeared in which conferences, and refer to the resultant dataset as "DBLP". For DBLP, we do not consider an analog of Reddit's feedback, although citation or download counts could be used in future work.

It is important to note that program committees play a huge role in determining an author's conference trajectory. This property makes DBLP a less suitable domain for the questions of user choice that we focus on in this paper. We thus place our DBLP trajectory results in the Appendix (§9).

Statistics on the 50+ posters in Reddit and DBLP are given in Table 1.

Note 1: how we define "posting". In this paper, we use the term *posting* to refer to submitting an item to be voted or commented upon. We distinguish posting from *commenting on posts* for several reasons. First, posting is important for site designers to encourage since the site will presumably die without fresh conversation-starters. Second, posting is not affected by a confounding factor that commenting is subject to: Reddit influences commenting by how it presents potential targets for comments (e.g., by ranking them, or featuring targets on the Reddit home page). Third, the way that comments are presented on Reddit makes scraping the complete commenting history rather difficult. Nonetheless, looking at commenting in multi-community environments is an interesting direction for future research. We conjecture that it would lead to new findings since, for example, we do know that top posters are generally not top commenters, and vice versa.[8]

[3]The actual number of upvotes or downvotes is purposely inaccessible: http://bit.ly/1xrciQY.

[4]http://redditanalytics.com/

[5] Except that we filter out bots and banned users.

[6]Cross-posting (posting the same URL to multiple subreddits, with or without a title change) accounts for only 3% of the posts from the users that we consider in this paper — only 1.77% if we only consider their first 50 posts.

[7]http://dblp.uni-trier.de

[8]http://bit.ly/1tendtD

	Reddit	DBLP
Average number of posts	152.04	86.30
Median	89.	71.
Avg. no. of communities	28.85	38.08
Median	26.	34.
Mean avg. time gap btwn posts	10.47 days	3.36 mos

Table 1: Statistics for 50+ posters (157K in Reddit, 10K in DBLP).

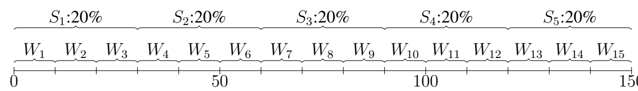


Figure 2: Illustration of windows and stages for window size $w = 10$, number of stages $S = 5$, number of posts $T = 150$, number of windows $T_w = 15$. W_i is a window; S_i is a stage.

2.2 Analysis framework.

We now set up terminology and concepts that facilitate discussion of users' trajectories among communities.

For each post by a given user, we store the timestamp, *time*, and the *community* (sometimes C for short). For Reddit data, we also store the post's *feedback* as of February 2014 and its *words* (the anchor-text plus any text written by the user, all tokenized and part-of-speech tagged using the Stanford NLP package[9]).

Several of the questions we are interested in pertain to properties of subsequences of trajectories. For example, suppose we want to know whether users are visiting a broader set of communities over time; one way to check is to look at how many communities they engaged with in their first w posts versus in their last w posts. Therefore, a basic element in our analysis is a *window*. Let variable t index the posts made by a user u, and suppose u has made T posts altogether. We split the entire index sequence $1, \ldots, T$ into non-overlapping consecutive windows W_i of size w, where i ranges from 1 to $T_w \stackrel{def}{=} \lfloor T/w \rfloor$. For example, in Fig. 2, W_6 would be the integers in the range $[51, 60]$. We use $w = 10$ throughout this paper. Our Reddit results were insensitive to choices of w.

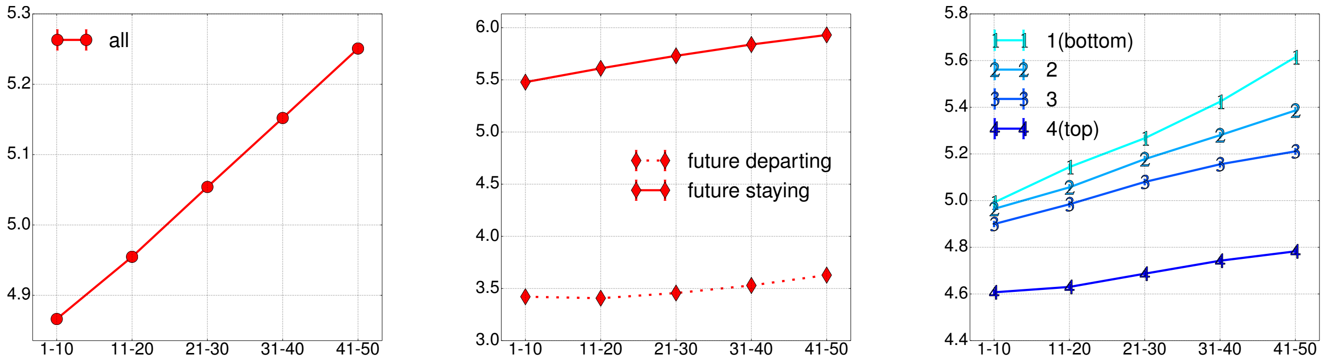
We define functions F on windows W_i to summarize properties of that window and track how these properties change over time. We use two ways to define F. One way is to directly define F based on the entire window, for example, $F(W_i) = |\{C_t : t \in W_i\}|$, the number of unique communities in W_i. The other way is to define a function f for each index t — for example, $f(t)$ could be the number of words in the t^{th} post — and let $F(W_i)$ be induced by f's average value over the indices in W_i, $F(W_i) = \frac{1}{w}\sum_{t \in W_i} f(t)$.

Given a window size w and a function of interest, F, we take two perspectives to track the trajectory of F: a *full-life view (all the user's posts)* and a *fixed-prefix view (50 posts)*. The rationals are as follows:

The first perspective, *full-life*, tracks users' entire lifetimes. Because the value of some functions is affected by choice of window size (e.g., the number of unique communities), we still fix the window size in the full-life view, but set an additional parameter S of the number of life stages that we want to examine, where each life stage contains the same number of windows, as depicted in Fig. 2. For each stage, we compute the average value over the windows in that stage.

A slight problem with the full-life view is that for different users, the value of the same life stage (say, the first 10% of one's life)

[9]http://nlp.stanford.edu/software/corenlp.shtml



(a) Overall trend (b) Future departing status (c) Future activity quartile

Figure 3: Number of unique communities per window. x-axis: each of the first 5 windows. y-axis: number of unique communities appearing in the corresponding window. In Fig. 3b and Fig. 3c, users are categorized by their future state *after* the initial 50 posts. Standard-error intervals are depicted, but very small.

Note 2: y-axes scales, and other considerations regarding subsequent figures. Since many of the figures in Section 3 tend to support the same overall point as in Figure 3, we make the subsequent figures relatively small (labeling the y-axes in the captions), but use the same x-axis, legends, and line styles in all of them.
As in Figure 3, each of the other figures in Section 3 consists of three sub-figures. In each, we scale the y-axes according to the corresponding data's range in order to show significant changes (all figures show standard-error bars, which are tiny). But it should be noted that the lines when averaging over all users (leftmost sub-figure in the figures) would usually look flatter if plotted on the graphs that divide users by departure status (middle sub-figures) or activity quartile (rightmost sub-figures).

may be based on a significantly different number of posts (say, 10 for one user but 100 for another). The full-life view also includes information about the entirety of the user's life, and thus is not appropriate for prediction settings (for example, one does not ordinarily know at the time what percent of one's life has already passed). Thus we also take a *fixed-prefix* view, where *only* the initial 50 posts are examined. (Recall from the caption of Fig. 1 that this encompasses a long time span on average.) Thus, the same amount of data is used for every user and the induced features are valid for predicting future behavior. For space reasons, in the main paper we will focus on the fixed-prefix view, and place some full-life-view results in the Appendix (§9).

Future activity level. We further relate our analysis to users' future activity level, since future activity level is a useful quantity to predict. We employ two different ways to categorize users' future commitment: the two-way classification of whether a user eventually abandons the global community altogether or not, and a 4-way split based on the relative number of posts that a user eventually makes over his/her lifetime, as follows.

- Departing status. To determine which users should be considered to have abandoned the site, we define a date (specifically, 6 months before January 2014) as the start-of-future (SOF). We define *departing* users as those who stopped posting as of SOF; we define *lasting* users as non-departing users who additionally post at least once in the first 3 months and at least once in the second 3 months since SOF, so that they are consistently "active". There are 43,910 departing users and 75,708 lasting users. Note that they all made at least 50 posts before SOF.

- Activity quartile. We split users into four quartiles based on the number of posts that they make in their entire life after the initial 50 posts. (As it happens, the lasting/departing ratio is higher in the the higher-activity quartile.)

3. TRAJECTORY PROPERTIES

We have established in Fig. 1 that users do constantly "wander around" in multi-community environments. In this section, we apply the framework proposed in §2 to explore three aspects of this wandering process: (§3.1) the communities users post to; (§3.2) the language users employ in each community; (§3.3) the feedback that users receive from other community members. In §4, we will further validate the effectiveness of features based on these properties in prediction tasks.

3.1 Multi-community aspects

We have shown in §1 that users on average consistently post to 2.5 new communities every 10 posts (Fig. 1). But what else characterizes their patterns of movement among communities? The answers to this question have the design implications outlined in §1.

Section summary. *We find that over time, users span more communities every 10 posts, "jump" more, and concentrate less.*[10] *They enter smaller and less similar communities. Eventually-departing users seem consistently less "adventurous" than lasting users even, notably, from the very beginning. Curiously, eventually-departing users act similarly to users in the top activity quartile.*

In the following, we explain the metrics for understanding these properties and discuss related theories.

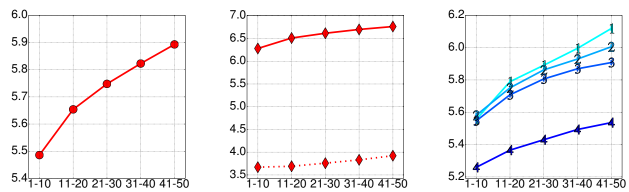
Users span more and more unique communities in a window, but relatively speaking, departing users span fewer unique communities. Figure 3 shows the per-window number of unique communities that users post to. The actual number is interesting: in Fig. 1, users post to 2.5 new communities every 10 posts; here on average, users post to around 5 communities every 10 posts, and thus only around 2.5 of them are ones that they have ever posted to. Given that users have more potential communities to go back

[10] The continual exploration is not simply an effect of the introduction of new communities over time. For instance, although new communities or options also emerge in real life, people seem to settle down and do not explore much.

to over time, this suggests that they do not tend to return to some previous communities. More discussion as to why users return to certain communities will be presented in §5.

Users "jump" between communities more and more "frequently", but departing users do so at around half the "rate". (Fig. 4) To understand how often users "jump", we count the number of "jumps" that users make per window. Formally, define $F(W_i) = \sum_{t,t+1 \in W_i} I(C_t \neq C_{t+1})$, where $I(x)$ is the indicator function: $I(x) = 1$ if x is true, 0 otherwise.

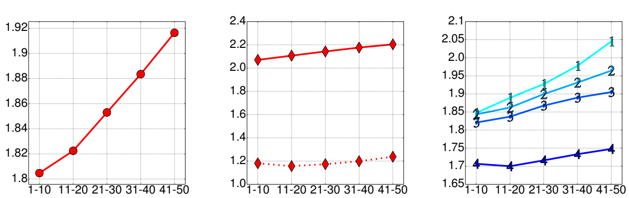
Note that the number of unique communities in a window of 10 does not determine how often users "jump". Given a window size of 10, users can jump as many as 9 times; given that users on average span 5 communities in a window, users can jump as few as 4 times. In fact, users make around 5.8 "jumps" per 10 posts.



(a) Overall trend (b) Departing status (c) Activity quartile

Figure 4: Number of "jumps".

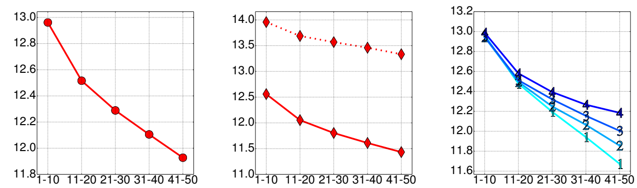
Users spread their posts out more and more evenly, but relatively speaking, departing users focus more. (Fig. 5) We employ entropy as a metric for concentration, following [1]. Entropy is based on the probability of a community appearing in a window W_i, $p_c = \frac{1}{w} \sum_{t \in W_i} I(C_t = c)$, and is defined as $-\sum_c p_c \log_2 p_c$ for W_i. It is an information-theoretic measure that grows as the intra-window community-posting distribution approaches the uniform distribution (minimum concentration) [26]. The same qualitative results hold if we use the Gini-Simpson index $(1 - \sum_c p_c^2)$, a commonly used metric in ecology for species concentration [16, 29].[11]



(a) Overall trend (b) Departing status (c) Activity quartile

Figure 5: Entropy of community-posting distribution.

Users enter smaller-looking communities (fewer posts per month), but relatively speaking, departing users prefer larger communities. (Fig. 6) Engaging with different communities entails a choice between communities of different sizes. A large community can encompass diverse community purposes and member preferences, leading to broader appeal, but at the same time, a large size may dilute personal connection and lead to more conflicts [24]. Or, size might not have any effect at all. To study this question, we set $f(t)$ to log of the number of posts made by the user in the community in month t as a simple metric of how "large" the active portion of a community looks to an incoming user. [12]



(a) Overall trend (b) Departing status (c) Activity quartile

Figure 6: Average $\log_2$(number of monthly posts in communities that a user posts to). Note that it is *not* the case that big subreddits are being abandoned as a whole: despite the availability over time of more and more small subreddits, the number of posts in the popular subreddits continues to increase.

We note that with respect to this metric of community size, the full-life view, shown in the Appendix (Fig. 16a), differs from the fixed-prefix perspective plotted above. In the full-life view, the higher-activity quartile users eventually enter smaller communities than lower-activity quartile users. It seems that they just move more slowly to such communities.

Users post to less similar communities over time, but relatively speaking, departing users prefer more similar ones. (Fig. 7) One hypothesis for how people select new communities is that they explore similar communities to those they have visited in the past, because they want more exposure to topics that they are already interested in. On the other hand, perhaps they choose new communities because their interests have changed, implying that they would choose more different communities.

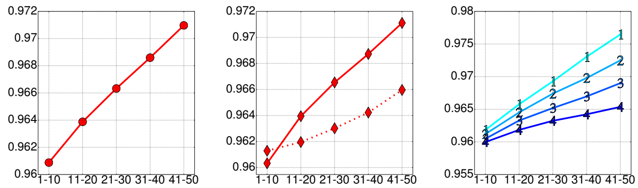
We measure the dissimilarity between communities C_1 and C_2 based on poster overlap, restricting attention to just those communities with at least 1000 posts to ensure sufficient data. Denoting the set of users who ever posted in a community C as U_C, our measure is $1 - \frac{|U_{C_1} \cap U_{C_2}|}{|U_{C_1} \cup U_{C_2}|}$. Note that the dissimilarity between two communities is computed based on their eventual poster set, since we want to capture the "actual", eventual relationship between the two, and so does not change over time. For a window W_i, the overall community dissimilarity $F(W_i)$ is defined as the average of all the pairwise dissimilarities between the communities that the user posted at during that window W_i.

The same trends hold if we measure language dissimilarity between communities using the KL-divergence between community language models.

Different activity quartiles. For *all* of the above metrics, users of different *future* activity quartiles manifest significant differences even in their very earliest behavior, although the differences are not as dramatic as those between departing users and lasting users. The curves for the different quartiles always appear in either the

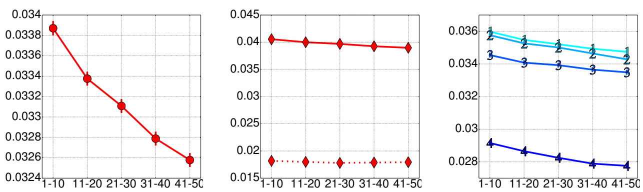
[11] An alternative hypothesis regarding the difference in activity quartiles is that there isn't really a difference, but perhaps users in the higher-activity quartile make several posts in a single community where a lower-activity user makes just one, e.g., $C_1C_1C_1C_2C_2C_2$ vs. C_1C_2. If this were so, we would observe a lower entropy simply due to accidentally choosing a window size that is small relative to the average burst size. However, we verified that this "burstiness" hypothesis does not hold, since the higher-activity users only change communities about 0.5 fewer times than lower-activity ones.

[12] Reddit does not provide directly applicable metrics: the number of subscribers or those "online now" can consist mostly of passive observers. The number of users who posted in a month is not presented at all, but we observe similar trends when extracting that as the metric.



(a) Overall trend (b) Departing status (c) Activity quartile

Figure 7: Community dissimilarity based on poster overlap.



(a) Overall trend (b) Departing status (c) Activity quartile

Figure 8: Percentage of first singular person pronouns.

order 1,2,3,4 or 4,3,2,1, and the highest-activity quartile curves are always the closest to those for departing users.

3.2 Language aspects

The second aspect that we examine is the language that users employ within communities. This examination, and the formulation we apply below, are inspired by [9], which found that in single-community settings, users first pass through an "adolescent" phase where they learn linguistic norms, but after this phase stop adapting to new norms and become increasingly distant from the community. Our results indicate that this is *not* the case in the multi-community setting. Rather, with respect to part-of-speech tags or stopwords, users do not move farther and farther away from the community distribution; and when (frequent) content words are included, users seem to "stay young", continuously growing closer to the community's language. Surprisingly, departing users are better mimics of the community's language than lasting users are. The bulk of this section provides the experimental evidence, based on various forms of cross-entropy, from which we draw these conclusions.

Additionally, we, like [9], find that the usage of 1st-person-singular pronouns (e.g., I, me) declines over time,[13] which has been argued to indicate a greater sense of community affiliation [7, 28]. However, upon closer inspection, the fact that departing posters use these words *less* frequently than those users who end up staying seems problematic for such theories — although one could speculate that the cause is that our departing users start out with strong affiliation needs but become disappointed. These results are shown in Figure 8.

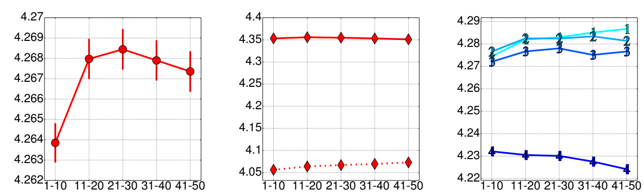
Cross-entropy with vocabulary-varying language models. We use cross-entropy to measure the distance between (a language model constructed from) a user's t^{th} post and a language model built from all the posts in the corresponding community, C, in that same month $m(t)$. Importantly, we will compute these models based on various choices of vocabulary V; this will reveal that although users' topical-word usage grows closer and closer to that of the community's, their usage in part-of-speech tags and stopwords stabilizes in terms of distance from the community's.

The first step of our V-dependent language-model construction is to replace every instance of any word not in V with the new token "<RARE>". Next, we define the community-based language model to be the distribution over $v \in V \cup \{\text{<RARE>}\}$ given by setting p^C to the relative frequency of v in the concatenation $words^{C,m(t)}$ of all the posts in C during the month $m(t)$. Then, we measure the cross-entropy by

$$f(t) = \frac{1}{|words_t|} \sum_{v \in words_t} \log_2 \frac{1}{p^C(v)}.$$

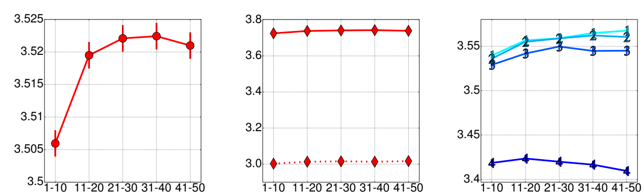
(This equation shows why we do not need to smooth the community language model: since $words_t$ is a component of $words^{C,m(t)}$, $p^C(v) > 0$ for $v \in words_t$.)

With all of this in hand, Figure 9 depicts representative evidence for the conclusions we drew at the beginning of this section. Specifically, the evidence consists of cross-entropy values for V chosen to be 46 parts-of-speech tags, the most frequent 100 words in Reddit, or the most frequent 1000 words in Reddit. Trends for V set to the 500 or 5000 most frequent words are similar to the most frequent 1000 words.



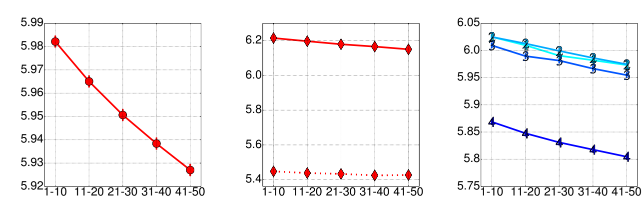
(a) Overall trend (b) Departing status (c) Activity quartile

V = part-of-speech tags



(d) Overall trend (e) Departing status (f) Activity quartile

V = stopwords (the 100 most frequent words in Reddit)



(g) Overall trend (h) Departing status (i) Activity quartile

V = stopwords + content words (1000 most frequent words)

Figure 9: Distance from the community language model. The rows indicate different choices of vocabulary V.

Technical aside: the potentially confounding factor of rare words interacting with community posting volume. We also used a "full" vocabulary that contains all words that appear more than 100 times in Reddit (180K types), but do not show the results here. This is due to the fact that for large vocabulary sizes, what appears to be differences in language matching can actually be merely a side-effect of one class of users posting in more-voluble communities. The argument runs as follows. The full vocabulary allows for many words v' with low frequency in the community — say, 1 — to contribute to the cross-entropy computation. The probability

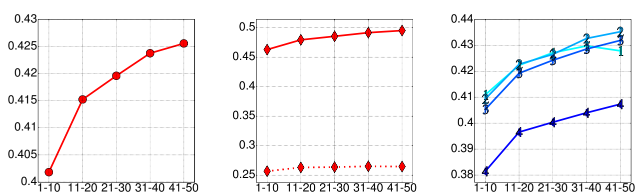
[13] Acronyms such as "TIL" (for "today I learned") were not included.

estimate $p^C(v')$ for such words is $1/|words^{C,m(t)}|$ (where t is chosen appropriately). So, in groups where $|words^{C,m(t)}|$ is large, the contribution of such v' to the cross entropy is bigger than it would be for sub-communities where $|words^{C,m(t)}|$ is small.[14]

3.3 Feedback aspects

A final question that Reddit data allow us to easily answer is, how are users received by other members of the community? For each post, Reddit provides the difference between the number of upvotes and number of downvotes. Because the average value of this difference can vary among different communities, we measure the feedback that users get by the relative position of this difference among all posts in the community that month, i.e., how often the posts made by a user outperform the "median post" in a community. For each index t, we define $f(t)$ as $I(feedback_t > median(C_t, m(t)))$, where $median(C, m)$ represents the median vote difference in community C in month m.

Surprisingly, the feedback that 50+ posters receive is *continually* growing more positive, although the rate slows over time (Fig. 10). However, the growth is small compared to the drastic differences between departing users and lasting users. Even departing users get more-positive feedback over time, but the increase is not as great as for lasting users. Users in the top activity quartile also fare worse, although as shown in the relative perspective (Fig. 16b), they catch up in the later stages of their life. The results are consistent if we measure how often posts outperform 75% of the community's posts.



(a) Overall trend (b) Departure status (c) Activity quartile

Figure 10: Success rate at outperforming the median vote difference.

3.4 Recap

In all three aspects that we examined, users with different future activity levels manifest significant differences in their trajectories of multi-community engagement. Interestingly, users that eventually depart seem "destined" to do so even from the very beginning, since the curves for the departing vs. lasting users generally start out apart and maintain or increase that distance over time. Meanwhile, there are smaller but significant differences in these metrics between users at different activity quartiles. It is important to note that some metrics can be correlated (e.g., number of unique communities and entropy). However, none of the metrics determines another, so we believe discussing each one of them was valuable.

Another interesting phenomenon we consistently observe is that for all our metrics, users in the top activity quartile are the closest to the departing users in the first 50 posts (a direct comparison for language is shown in Fig. 11).

[14] This concern cannot be alleviated simply by sub-sampling a community's posts, since the true root of the problem is rare words, not just the length and number of posts in the community per se.

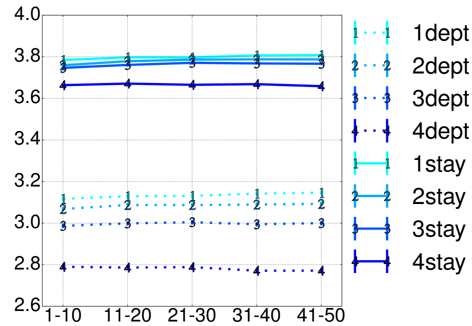


Figure 11: Interplay between departure status and activity quartiles. y-axis: distance from the corresponding monthly language model when setting the vocabulary to the 100 most frequent words. $i$dept refers to departing users in the i-th quartile; $i$stay refers to lasting users in the i-th quartile.

4. PREDICTING DEPARTURE AND ACTIVITY LEVELS

We have now seen many properties of multi-community engagement that correlate with user activity. To examine the effectiveness of these properties in prediction, we set up two different prediction tasks that correspond to how we measure users' future activity level in §2:

- Future departure status. In this task, we predict whether users abandon Reddit in the future. We use F1 for evaluation, with the minority class (departing users, as defined in §2) as the target class. We use weighted L2-regularized logistic regression as classifier.

- Future total number of posts. This is a regression task where the goal is, for a given user, to estimate $\log_2$(future number of posts). We employ L2-regularized support vector regression, and measure performance by root mean squared error (RMSE).

Each instance consists of a user's first 50 posts.

Baseline and features. We consider the following feature sets, where for window-based features we set the window size $w = 10$, thus deriving 50/10 = 5 values.[15]

- Average time-gap between posts. [9] states that this is an effective feature used in prior work on churn prediction [13, 34]. *Thus, this feature by itself serves as our (strong) baseline.*

- Multi-community aspects (henceforth "sub info"). This includes number of unique communities, number of "jumps", entropy, and Gini-Simpson index based on the user's community-posting distribution, as well as mean log "apparent" community size as defined in §3.1. Similarity between communities is not used because information about the future is incorporated in the way we compute it.

- Language aspects ("lang" for short). This includes cross-entropy with the monthly community language model for the following choices of vocabulary: part-of-speech tags; the top 100, 500, 1000, 5000, 10000 most frequent words;

[15] Alternatively, one could set $w = 50$, thus extracting features from all 50 posts in a single batch. This approach turns out to be poorer than using 5 windows because trend information is not captured.

and the full vocabulary as defined in §3.2. Additionally, we include the proportion of 1st-person-singular pronouns and post length in words.

- Feedback aspects. This includes the fraction of posts that outperform 50% and 75% of all of the corresponding month's worth of the community's posts in terms of positivity of feedback. Refer back to §3.3 for more information.

For entropy, Gini-Simpson index, and number of unique communities, we include the value for all 50 posts, since for these features, the values for all 50 posts are not simply the average of the values from 5 windows of 10 posts. We also use the index of the window with the largest value and the smallest value as features, following [9]. All features are linearly scaled to $[0, 1]$ based on training data.

Experiment protocol. In both tasks, we perform 30 randomized trials. In each trial, we randomly draw 20,000 users from our dataset as training data and a distinct set of 5,000 users as testing data. We use 5,000 users from the training data as validation set. We use LIBLINEAR [15] in all prediction tasks. For significance testing, we employ the paired Wilcoxon signed rank test [33].

The standard procedure for generating learning curves would be to only look at the *first* x posts as x varies, $x = 10, 20, 30, 40, 50$. A non-obvious but ultimately fruitful idea we introduce here is to contrast the effectiveness of the information in the early part of each 50-post instance with that of the late part of the 50-post instance. That is, we compare the performance if we use the *first* ("fst" in our plots) x posts with the performance of using the *last* x posts. (One might expect later periods to be more predictive, given that they are more recent. But surprisingly, we will see that when we predict departure status, we find that earlier information is more useful, which again suggests that departing users are "destined" to leave from the very beginning.)

4.1 Predicting departing status

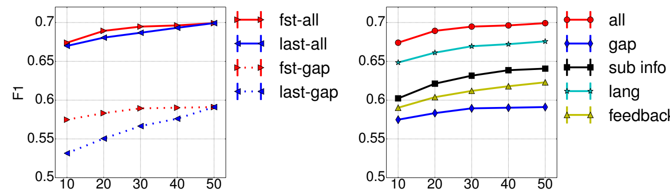
Basic comparisons. (Figure 12a) Using all features outperforms a strong baseline that uses time-gap features by 18.3% — the difference between an F1 of .699 and an F1 of .591 — which shows the effectiveness of features drawn from multi-community engagement.

The performance of the first x posts is always above that of the last x posts. This suggests that the initial information is more predictive of eventual departure. Note that for 50+ posters, departure is quite "far away" from the initial posts. In fact, using all features drawn from only the first 10 posts outperforms time-gap features extracted from all 50 posts. Thus it may be very important for designers of social systems to make sure that users start well, perhaps through positive feedback or by recommending communities to post in (which can differ from the communities one might recommend that a user reads).

Feature-set analysis. (Figure 12b) In predicting departure, it is most useful to know how well users match a community's language. The second most useful features are the patterns of community visitation. Language-matching, community-trajectory, and community-feedback features all outperform time-gap information, which suggests that how users interact with different communities is more predictive than activity rate in predicting whether 50+ users will leave.

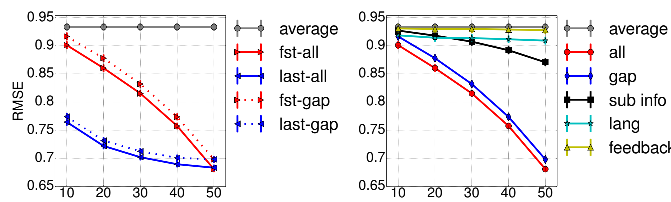
4.2 Predicting activity quartile

Comparisons with the baseline. (Figure 13a, 13b) In contrast to the case just discussed of predicting departure status, time-gap between posts is a much stronger feature in predicting future total



(a) Window comparison (b) Feature comparison

Figure 12: Results for predicting departing status. y-axis: F1 measure. In Fig. 12a, the dashed lines show the performance of the baseline, timing-based features; the solid lines show the performance of using all features. Red lines show the performance using the first x posts, while blue lines show the performance using the last x posts. Fig. 12b: performance of different feature sets. All differences for 50 posts are statistically significant according to the Wilcoxon signed rank test ($p < 0.001$).



(a) Window comparison (b) Feature comparison

Figure 13: Results for predicting $\log_2$(future total number of posts). y-axis: RMSE, the smaller the better. The line styles are the same as in Fig. 12. "Average" shows a baseline that always predits the mean value in the training data. All differences for 50 posts are statistically significant according to the Wilcoxon signed rank test ($p < 0.001$).

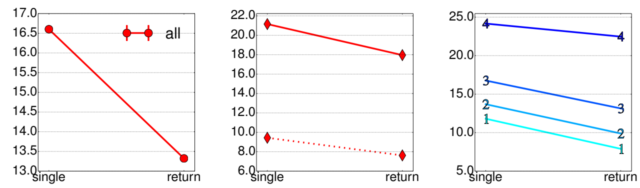
number of posts. This is plausible because for these 50+ posters, time-gaps in posting determine how many posts that people can physically make. However, adding all the features based on multi-community engagement still improves the performance over timing information to a statistically significant degree. Prior work has shown that adding language features can lead to big improvements over timing-based features [9]; the relatively small improvement in our experiment may be due to the fact that the datasets in [9] have a longer history than ours.

Also, using the last x posts is much more effective than using the first x posts. There thus seems to be different factors affecting 50+ posters with respect to deciding whether to remain in a community versus deciding to be highly active in it.

5. WHEN DO USERS ABANDON THEIR POSTS?

We have already seen that (our) users constantly try out new communities, but we have not yet addressed a related question of practical importance to community maintainers, as well as of inherent social-scientific interest: how much and why do users *abandon* communities?

We can frame the "how much" issue succinctly by asking the following question. Suppose we partition the set of communities a user visits into (1) those that he or she abandons after just a single post, and (2) those that he or she posts at least twice to. Which set — the single-post communities or multiple-posts communities, is larger, on average? We claim that the answer is not a priori obvious[16]. But the data shows that users rack up more abandoned communities than return engagements, as depicted in the figure below. This suggests that although users are constantly willing to post to new groups, they are often only giving these new groups one shot.

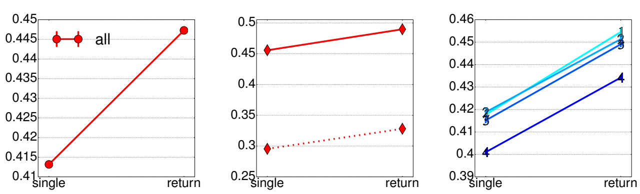


(a) Overall (b) Departing status (c) Activity levels

Figure 14: Comparison of the average number of communities where a user posts only once vs. more than once.

What is happening in the single-post communities that causes a user to stop posting in them immediately? We find that positivity of feedback (in Reddit, the difference in upvotes and downvotes) may play a substantial role, as shown by the figure below. Figure 15 is based on the *very first* post that a user makes in every community they posted in; it plots the percentage of such first posts that received a feedback score above that of the median feedback score in the respective community.

The reason that this is interesting to note is that our results contrast with previous findings of the power of *negative* feedback for predicting repeated commenting [6]; we conjecture that the difference is due to different impulses driving posting vs. commenting behavior.



(a) Overall (b) Departing status (c) Activity levels

Figure 15: Users get better feedback for the first post in the communities that they eventually returned to than for the communities that they ended up making only a single post in. y-axis: average fraction of a user's post with feedback score better than the community's median. We exclude users that have only single-post communities or only multiple-posts communities, thus controlling for individual-user characteristics to some extent. All differences between connected points are statistically significant according to the paired t-test ($p < 0.001$).

6. DO USERS SPEAK DIFFERENTLY IN DIFFERENT COMMUNITIES?

So far we have revealed interesting and sometimes arguably counterintuitive properties of multi-community engagement, and demonstrated that they are effective cues in predicting a user's future activity level. But an additional fascinating and orthogonal question is: when users participate in multiple communities, to what degree are their actions stable *across* settings? To look at this question is to contribute another piece of evidence to the "situation vs. personality" debate [20, 12]: how much of our behavior is determined by fixed personality traits, versus how much is variable and influenced by the specific situation at hand? Or, to put it a bit more dramatically, are you fundamentally the same person at work as you are at the gym?

Here, we study the question with respect to language use. The overall message is, *even after topic-specific vocabulary is discarded* (after all, it wouldn't be interesting to find that people use gym-related words at the gym that they don't use at work), individuals *do* employ different language patterns in different communities. The way we determine this is conceptually straightforward: we check whether it's possible to tell which community a user's posts come from based just on the distribution of stopwords or non-content-words within their posts.

The rest of this section gives a quick sketch of our experiments. (Space constraints preclude a full discussion of the details.)

If we fix some vocabulary V of non-content words, then we can create classification instances from the 227K triples that exist in our data consisting of (1) a user u, (2) words of u's first 25 posts in some community C_1, and (3) words of u's first 25 posts in a different community C_2. Then, we compute the cross entropy of each post against the corresponding monthly language models, over the restricted vocabulary V, constructed from each of the two communities C_1 and C_2.[17] Add-1/|V| smoothing is applied to all language models concerned. We then use these non-content-word cross-entropies as features to guess which of (2) and (3) came from community C_1.

We run experiments for several choices of V: parts-of-speech, the 100 most frequent words in Reddit, and the 500 most frequent words in Reddit. The first two choices definitely do not include topic-specific words, and the latter will not include many (there are 180K words in the full Reddit vocabulary), and so these choices may be taken to represent a user's language *style* [2, 8]. If the user's style does not change from community to community, then the cross-entropy features mentioned above will not be helpful for determining that item (1) comes from C_1 and not C_2; thus, accuracy at matching language model to community would be 50%. But, as shown below, the average accuracies, utilizing logistic classification, of 30 random-split experiments (10K tuples for training and development, 2500 for testing) for each choice of V are (statistically) significantly above 50%:

V	accuracy
parts of speech	62.5%
most frequent 100 words	56.0%
most frequent 500 words	61.4%

7. RELATED WORK

Anthropologists, psychologists and sociologists have looked at some questions regarding multi-community engagement, often in the context of interaction with new social circles or cultures [5, 17, 4]. Recently, computer scientists have turned to examining multi-community engagement data available online [3, 1, 31, 32, 22]. Our work differs by focusing on the following specific problems: (a) characterizing full community-trajectory sequences, as opposed to looking at pairwise community transitions [3, 31, 32]; (b) revealing how properties of these trajectories correlate with a user's

[16] Recall the title of Duncan Watts' recent book "Everything Is Obvious: *Once You Know the Answer".

[17] Actually, we divide these 25 posts into windows of 5 posts and take the average cross entropy in each window, in order to be more robust and potentially capture trends, but it simplifies exposition to think of just a single post.

future cross-community activity — we incorporate but also go beyond language-based features, as inspired by previous within-community work [9, 25], and timing-based features [13]; (c) considering the effect of each community's positive and negative feedback, which may shed light on why users choose some communities over others.

Researchers have also been working on predicting users' survival (also known as churn prediction) [10, 13, 34] and activity level [11, 37]. They focus on the single-community setting. A number of studies examined community-level evolution or the success of individual communities (often websites) [18, 19, 23, 35, 36], whereas our work focuses on the life cycle of users.

8. CONCLUDING DISCUSSION

Summary. We have investigated properties of multi-community engagement; this is a setting that has not received much computational research attention before, and yet is important because it encompasses many online and physical situations. In this first large-scale study of the phenomenon, we have found a number of sometimes counterintuitive but robust properties — some involving choice of community, some involving language use within communities, and some involving feedback from communities — revolving around the discovery that users "wander" and explore communities to a greater extent than might have been previously suspected.

Limitations and further directions. We focused on posting, but commenting and other related behaviors are very interesting subjects for future study. Our study is quantitative and observational. Qualitative studies, or controlled experiments regarding the design implications in §1, can further improve our understanding.

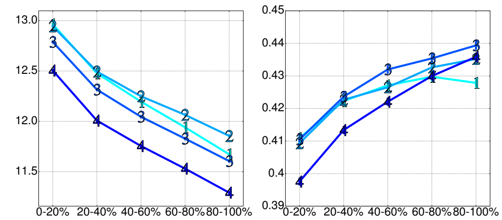
It is important to note that our study is limited to "50+ posters" so that we would have enough history per user to observe a relatively long trajectory. This is an unusually engaged group of users that comprises 5.9% of our users. We have not addressed the question of how multi-community engagement is exhibited by users who are not as active.

The notion of considering users to exist in a multi-community setting can in principle be extended to looking at user behavior across multiple websites or apps. With the advent and adoption of multiple-website services such as OpenID, observing users at that scale of multi-community engagement may well become quite important in the future.

There are many more challenging questions that arise from taking a multi-community perspective. For example, are the particularly nomadic treated differently? What is multi-community engagement like in real life, considering the cost of switching? How can we extend current theories and principles in community design to a multi-community setting? Further understanding of these questions is crucial for on- and off-line community design and an exciting direction for future work.

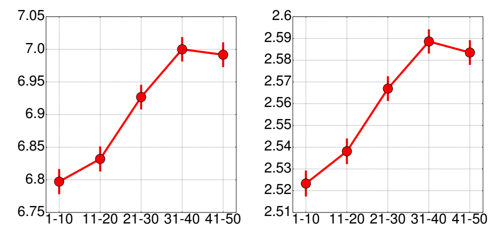
9. APPENDIX

Full-life view for users in Reddit. In general, the overall trends and differences between departing users and staying users are the same as in the fixed-prefix view. But in terms of activity quartiles, there are some interesting differences. For example, the ordering of the activity quartiles with respect to mean $\log_2$(number of posts that month) completely reverses itself (compare Fig. 16a to Fig. 6c). For feedback, as users receive better feedback over time, users in the top activity quartile receive worse feedback in the beginning and catch up later in their life (Fig. 16b). These results are natural



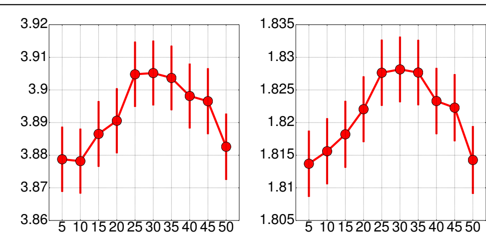
(a) (b)

Figure 16: Comparison of different Reddit activity quartiles from the full-life perspective. (a): mean $\log_2$(monthly number of posts). (b): fraction of posts that outperform the median value of feedback positivity in the corresponding month and community.



(a) (b)

Window size of 10.



(c) (d)

Window size of 5.

Figure 17: Fixed-prefix view for researchers in DBLP. (a,c): number of unique conferences per window. (b,d): entropy of the conference publishing distribution per window.

consequences of the trend developing over time. This suggests that the trends that we observe are robust over user life.

Fixed-prefix view for researchers in DBLP. In DBLP, authors span more conferences per window over time (Fig. 17a) in an increasingly scattered fashion (Fig. 17b), but in contrast to Reddit, there is saturation in the last two windows. Perhaps this suggests that as researchers become very senior, they publish more papers in some favorite set of venues.

When a very small window size is considered (w=5), the number of unique conferences and within-window entropy first increase and then decrease (Fig. 17c and 17d). But, changing the window size does *not* affect our central observation in Fig. 1 that 50+ researchers are publishing in new conferences at a relatively consistent rate over the years.

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