Activity in Questions & Answers Websites

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Millions of users on the Internet discuss a variety of topics on Question and Answer (Q&A) instances. However, not all instances and topics receive the same amount of attention, as some thrive and achieve self-sustaining levels of activity while others fail to attract users and either never grow beyond being a small niche community or become inactive. Hence, it is imperative to not only better understand but also to distill deciding factors and rules that define and govern sustainable Q&A instances. We aim to empower community managers with quantitative methods for them to better understand, control and foster their communities, and thus contribute to making the Web a more efficient place to exchange information. To that end, we extract, model and cluster user activity-based time series from 50 randomly selected Q&A instances from the StackExchange network to characterize user behavior. We find four distinct types of user activity temporal patterns, which vary primarily according to the users’ activity frequency. Finally, by breaking down total activity in our 50 Q&A instances by the previously identified user activity profiles, we classify those 50 Q&A instances into three different activity profiles. Our categorization of Q&A instances aligns with the stage of development and maturity of the underlying communities, which can potentially help operators of such instances not only to quantitatively assess status and progress, but also allow them to optimize community building efforts.

CCS Concepts:
- Mathematics of computing → Cluster analysis; Time series analysis;
- Information systems → Answer ranking;
- Human-centered computing → Web-based interaction; Computer supported cooperative work;

Additional Key Words and Phrases: Questions & Answers (Q&A) websites; User types in Q&A websites; Temporal activity patterns in Q&A websites; Sustainability of Q&A websites

ACM Reference format:
Tiago Santos, Simon Walk, Roman Kern, Markus Strohmaier, and Denis Helic. 2016. Activity in Questions & Answers Websites. 1, 1, Article 1 (January 2016), 16 pages.
DOI: 0000001.0000001

1 FACTORS OF SUCCESS IN Q&A INSTANCES

Question and answer (Q&A) websites (e.g., StackExchange\textsuperscript{1} or Quora\textsuperscript{2}) are publicly accessible platforms, which are used by millions of users to discuss a variety of topics and problems. For example, the StackOverflow\textsuperscript{3} instance of the StackExchange website deals with topics related to

\textsuperscript{1}http://www.stackexchange.com
\textsuperscript{2}http://www.quora.com
\textsuperscript{3}http://stackoverflow.com/
programming and hosts a flourishing community of more than 6 million users. Another prominent example is Math StackExchange\footnote{\url{http://math.stackexchange.com/}} instances, where a thriving community of mathematical professionals and other users with shared interests pose and solve mathematical questions.

**Problem.** However, not all Q&A instances exhibit the same kind of vibrant, self-sustaining community activity. In fact, the majority of Q&A instances fail to attract and engage enough users to reach self-sustainability in terms of activity. Typically, instance operators provide incentives for users in the form of badges or reputation scores. Although several studies analyzed the effects of such endeavors [3, 17, 21], our research community still lacks the tools to understand, measure, model and predict key factors that influence and drive Q&A communities to sustainable levels of activity. However, without a proper understanding of users, the structures inherent in the communities, as well as the driving mechanisms behind successful Q&A instances, we can not hope to remedy the problems of less successful sites.

**Approach.** In this paper we set out (i) to characterize user activity profiles, (ii) to reveal the compositions of those profiles in various Q&A communities, and (iii) to analyze similarities and differences between highly and less successful Q&A instances.

Although current research on users of online Q&A communities partially uncovers different user roles in these communities [6, 9, 17, 29], we identify a research gap on (i) the composition of activity profiles for communities at different stages of maturity and (ii) specific compositions that ultimately make thriving communities successful.

In this paper, we characterize temporal activity patterns of users, analyze and compare the activity composition of already established and newly created online Q&A instances, and provide actionable information for operators of such instances to assess maturity, improve activity and manage their instances more efficiently. To that end, we randomly pick a total of 50 StackExchange instances, from which we derive time series and features which describe commonly occurring temporal activity patterns. We represent user activity as their total count of posts and replies. Subsequently, we apply K-Means on the extracted features to group users with similar activity profiles and find optimal numbers of clusters by calculating and comparing silhouette coefficients for different values of K. Additionally, we analyze the composition of activity across the obtained clusters for all Q&A instances.

**Contributions.** The main contributions of our work are as follows: First, we find that activity-based time series can be described by only two quantities from the frequency domain: (i) the characteristics of its peaks and (ii) the uniqueness of its non-zero activity values.

Second, we identify typical user activity profiles to describe Activity Archetypes, which represent distinct user engagement levels across all analyzed StackExchange instances. This result helps not only to better understand the different user profiles that operators of Q&A instances need to cater to but also which profiles to include when modeling activity for these instances.

Third, we analyze, compare and categorize the Activity Archetype composition of various StackExchange instances, which allows us to assess the level of maturity in a StackExchange instance’s development towards activity-based self-sustainability. To give an example, we find that thriving instances feature substantial amounts of infrequently active users posing questions. If this group of users is underrepresented, then this affects the instance’s overall activity and development.

We believe that our analyses represent an important step towards a better understanding of the factors that define and foster success in Q&A instances. With our analyses, we enable Q&A instance operators not only to gauge, quantify and model the status of their communities in comparison to other communities, but also to pinpoint what user groups to focus activity improvement measures on, on the path towards a thriving, self-sustaining community.
We make our code and datasets available at https://github.com/tfts/QA-activity.

2 RELATED WORK

Dynamical Systems for Activity Modeling. Dynamical systems are systems of parametrized equations describing the evolution of numerical quantities over time. They provide mathematical formalizations for activity dynamics models.

Perra et al. [18] model activity in collaboration networks such as publications and references in the Physical Review Letters journal. The authors measure an empirical probability distribution over interactions of agents in a network, model the formation of dynamic networks based on this activity distribution and study resulting dynamical processes. This work influenced other authors modeling activity dynamics as explicit dynamic processes on networks, such as Laurent et al. [14]. Those authors propose an activity-driven model for time varying networks with memory, which captures features of social networks, to analyze mobile call records from an European telecom.

Other approaches to model activity in Q&A instances and networks with dynamical systems focus on a few key variables that drive overall activity dynamics. Ribeiro [19] models activity in membership-based community websites as time series counting the number of active users in such websites. The model includes two main factors, namely active users spontaneously becoming inactive and active users spurring inactive ones to become active. These factors are sufficient to distinguish self-sustaining from non-self-sustaining online communities and to forecast their daily active user numbers. In Walk et al. [27], the authors proposed a dynamical system description for online Q&A instances such as StackExchange instances or Semantic MediaWikis5. Their dynamical system equations allow for (i) forecasting activity levels in those online Q&A communities, and for (ii) assessing the robustness of activity in an online community and if it reached self-sustaining levels of activity. In an extension of Walk et al.’s [27] models, Koncar et al. [13] recently studied the implications of trolling behavior on various StackExchange and Reddit communities.

Much like our previous work [20] on nonlinear characterization of Q&A instances, we contribute a data-driven approach to this body of work using mathematical formalizations to describe activity in online Q&A instances. We empirically identify key driving forces of activity and thus pave the way for new models, which take into account the composition of activity as it changes over time.

Characterization of Activity in Q&A Instances. Literature dealing with dynamics of Q&A instances, such as StackExchange focuses on many different aspects of these types of online communities. Anderson et al. [2] quantify and uncover temporal characteristics of questions which bring (long-term) value to the community. Burel and He [4] measure the maturity of the ServerFault StackExchange instance by its ability to cope with complex questions. Danescu-Niculescu-Mizil et al. [6] characterize user participation in online communities by the evolution of their language, allowing the authors to predict when users depart their communities. Yang et al. [29] examine and correctly identify different types of expert users in the StackOverflow community. Srba et al. [23] aim to incentivize activity on new questions in StackExchange instances with improvements on linking users to unanswered questions by analyzing a larger pool of sources other than the StackExchange portal data itself (like Twitter).

Mamykina et al. [17]’s analysis of the StackOverflow’s design combines a statistical investigation of StackOverflow usage patterns with interviews with StackOverflow’s designers. The goal of that procedure is to understand which user behavior leads to the site’s success. In particular, Mamykina et al. [17] find a set of four different types of user activity behavior, which is similar to the ones we find. Sinha et al. [21] study participation and participation incentives in StackExchange communities. In their work, the authors underline the relevance of a core of highly active users and

5https://www.semantic-mediawiki.org/wiki/Semantic_MediaWiki
of participation incentives for less active users in StackExchange communities. Our work shares most commonalities with Furtado et al. [9]. In that study, the authors extract metrics measuring quality and quantity of activity in StackExchange instances. With those metrics, they describe a set of ten different user profiles obtained with K-Means clustering on those extracted metrics. The authors then study the composition and activity dynamics of users in five StackExchange instances broken down by the user profiles they found. They show that, although users change profiles over time, the overall composition of user profiles of those five instances mostly does not.

We validate the user profile characterization results of Mamykina et al. [17], Sinha et al. [21] and Furtado et al. [9], as our comprehensive analysis of 50 StackExchange instances yields comparable user characterizations. Our paper expands on that body of work as follows: Clustering the user characterizations enables us to uncover previously overseen temporal aspects on the development and maturity of StackExchange instances of varying sizes, ages and activity profiles. In particular, our results, which highlight an instance’s evolving activity composition over time, do not contradict the findings by Furtado et al. [9]. We rather complement the results by Furtado et al. [9], as they analyzed only five similarly sized StackExchange instances, one of which (programmers⁶) we find to be of one of multiple types we identify.

We find that the works by Iriberri and Leroy [12] and by Young [30] qualitatively corroborate our findings. Those authors identify four main life-cycle phases of online communities, namely inception, establishment or growth, maturity and death or self-sustainability or mitosis, which are comparable to the StackExchange instance characterization we derive. In particular, Young [30] also derives a set of recommendations for online health community managers to adapt to their communities’ different life-cycle stages. Similarly to Young, we also propose measures for boosting activity in StackExchange instances at different maturity stages. In the context of the work by these authors, our work complements theirs with quantitative empirical results and with the application domain of online Q&A communities.

We refer the interested reader to the survey by Srba and Bielikova [22] on previous work on community questions and answers websites for more literature on these topics.

**Time Series Clustering.** Time series clustering aims to group time series with similar shapes or properties together, to ultimately categorize time series, find representative patterns and uncover hidden structures in time series.

A number of authors [7, 8, 11, 15, 26] have applied time series clustering techniques to domains such as finance, sensor data or even warfare analysis. These authors share a common time series clustering approach, which begins with the choice of time series representation to feed to different clustering algorithms. Authors, such as Hautamaki et al. [11], consider time series without any transformation, while others extract features [7, 8] or apply transformations to the time series, such as Discrete Wavelet Transforms and Symbolic Aggregate ApproXimation [15, 26]. The time series clustering approach continues with the selection of a distance metric, which very often is the Euclidean [7, 15, 26] or the Dynamic Time Warping distance [11]. Finally, authors settle on a time series clustering algorithm, with popular choices being K-Means and variations thereof [11, 15, 26], self-organizing maps [8] and hierarchical clustering [11]. We select time series features and apply Euclidean K-Means on them, to cope with the challenge which discrete valued time series data presents. We encourage readers interested in more time series clustering methods and applications to acquaint themselves with the review by Aghabozorgi et al. [1].

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⁶As of February 2017, the programmers StackExchange instance is termed softwareengineering and programmers. stackexchange.com redirects to softwareengineering.stackexchange.com.
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Identifying user types as a time series clustering problem. We start by extracting question-based (and, separately, answers-based) activity time series as the monthly sum of posted questions (respectively answers) of each user in a StackExchange instance. We then extract three features from these time series: two boolean features, describing if an activity time series has peaks of equal height and if it has more than five peaks, and the ratio of unique non-zero values to time series length, a continuous feature varying between zero and one. Finally, we cluster the extracted features with K-Means for $K = 2, \ldots, 10$ and save $K^*$, the value of $K$ which maximizes the average silhouette coefficient. Graphical inspection of the clusters via PCA projection to two-dimensional space yields well-separated and cohesive clusters for $K = 2, 3, 4$. However, in this example, for $K = 2, 3, 4$, we get average silhouette coefficient values of 0.423, 0.563 and 0.871, respectively. Hence, $K^*$ equals four.

3 MATERIALS AND METHODS
3.1 Dataset Characterization
We analyze questions and answers from 50 StackExchange Q&A instances on many diverse topics, such as tex\textsuperscript{7}, english\textsuperscript{7}, gardening\textsuperscript{7} or buddhism\textsuperscript{7}. The observation periods for all instances vary between 4 to 80 months, depending on the inception date of each instance. The final observation month is February 2015.

As different instances originate at different points in time, the communities in each of those instances naturally exhibit different levels of activity and maturity. For example, english started in June 2009 and attracted a total of 37,125 users until February 2017. In contrast, earthscience\textsuperscript{7} managed to attract only 578 users between April 2014 and February 2015. To foster the development of young instances, such as earthscience, the StackExchange community submits, incubates and evaluates proposals for new Q&A instances at a dedicated website called Area 51\textsuperscript{8}. If an Area 51 Q&A instance reaches a significant level of activity, the Area 51 community deems it ready for a live test. Then, its live deployment ensues and the Area 51 community monitors its progress until it reaches a sustainable level of activity.

In this paper, we analyze a total of 50 StackExchange instances consisting of 25 randomly chosen Area 51 datasets and another 25 randomly chosen non-Area 51 datasets (see Table 1).

\begin{table}
\centering
\begin{tabular}{|c|c|c|c|}
\hline
Time series # & Peaks of equal height? & More than 5 peaks? & Ratio of unique non-zero values \\
\hline
1 & Y & N & 0.057 \\
2 & Y & Y & 0.142 \\
3 & N & N & 0.057 \\
4 & Y & N & 0.057 \\
5 & N & Y & 0.4 \\
6 & N & Y & 0.743 \\
7 & Y & Y & 0.343 \\
8 & N & N & 0.057 \\
\hline
\end{tabular}
\caption{Examples of time series features.}
\end{table}
3.2 Feature Engineering

Modeling User Activity as Time Series. We model user activity in StackExchange online Q&A instances as two activity-based time series per user. The first one comprises question counts, and the second one reply and comment counts for a given user per month. We stipulate that a user has zero activity if the user did not post a single question (or answer) in any given month of a portal’s existence. In all of the following, we treat questions-based activity time series separately from answers-based ones.

Comparing Users’ Activity-Based Time Series Directly. We aim to group users with similar activity profiles by clustering similar activity-based time series.

We first tried to directly base our clustering by directly measuring similarity between users’ activity-based time series with the Euclidean distance. However, using the Euclidean distance fails to discern users with different activity profiles, as it does not account for the misalignment of activity bursts and other activity-affecting events: Notice, for example, the misalignment in the time axis of the activity peak in time series three and eight of Figure 1a. As a counter measure to compare misaligned time series, we employed Dynamic Time Warping (DTW). DTW aligns time series over the time axis before computing their similarity with some measure such as Euclidean distance. However, DTW lead to no improvements in activity-based time series clustering, since it removed valuable information such as the length of the inactivity periods.

Extracting Features Describing Temporal Activity Patterns. Hence, we devised a different approach: We extract time series features summarizing key aspects of temporal user activity patterns occurring in the 50 StackExchange instances. To select time series features, we started with a list of more than 400 different features [5], which comprise descriptive statistics (e.g., mean, auto-correlation or kurtosis), time series models (e.g., auto-regressive coefficients), and other time series transformations (e.g., Fourier).

In general, we observe large numbers of users with sporadic peaks in activity, as well as fewer users who are more active and contribute fluctuating amounts of questions and answers over longer periods of time (cf. examples in Figure 1a). Therefore, we discriminatively chose three activity-based time series features, which capture exactly these kinds of behavior: the ratio of unique non-zero values to time series length, a boolean feature describing if the activity time series has more than five peaks and another boolean feature measuring if the time series has peaks of equal height. We compute activity peaks as values which are larger than other values in their direct neighborhood of the previous and next observations of the activity time series (cf. Figure 1b). Note that, with this definition of a peak, we do not impose a minimum peak height, both in absolute terms, as well as relative to the peak’s neighboring values. For example, assume a user posts a question once in January, responds twice to some other question in February and then asks one other question in March. The activity-based time series corresponding to this user would thus feature one peak in February. We settled on the number five in the feature measuring if an activity-based time series

Table 1. Dataset Characteristics. We present value ranges for the number of users, activity (i.e., aggregated questions, answers and comments) and observation periods (i.e., months) of all datasets per dataset group. Instances listed on Area 51 are typically smaller and younger than those outside Area 51.

| Dataset group | Size | Users   | Activity          | Months |
|---------------|------|---------|-------------------|--------|
| Area 51       | 25   | [473, 6309] | [5023, 47421]     | [4, 47] |
| Non-Area 51   | 25   | [1953, 37125] | [8137, 624166]    | [11, 80] |
has more than five peaks is concerned, as it corresponds to the average 90th quantile of the number of peaks per activity-based time series. This specifically helps to separate a large number of users with few sporadic peaks from the smaller group of users which exhibit more peaks of activity over time.

3.3 Clustering Process

The combination of these three features we propose allows us to derive cohesive, well-separated and interpretable clusters. Each one of the binary features partitions the space of activity-based time series in two sets. Those two features thus yield, when combined, four clusters, since they do not capture the same properties of activity-based time series. The third feature, ratio of unique non-zero values, is continuous and takes values in the interval \([0, 1]\). This continuous feature measures more granular variations in activity frequency than those afforded by having just the two binary features. Using this continuous feature by itself, however, does not separate the space in clusters.

We employ the commonly-used unsupervised clustering algorithm K-Means [16] to group similarly active users. We measure time series similarity with the Euclidean distance on the extracted features. We briefly explain K-Means: The algorithm begins with a random initialization of \(K\) cluster centers, so-called centroids, as \(K\) randomly chosen vectors from an input space. The algorithm labels input vectors with the centroid most similar to each of them. Then, it reassigns all \(K\) cluster centroids to each cluster’s mean vector. These two steps are repeated until convergence [16]. We experimented with variations of K-Means such as bisecting K-Means (see Steinbach et al. [25]), but those efforts yielded similar results.

Selecting the Number of Clusters. The main hyperparameter of K-Means is \(K\), representing the number of clusters, which is often a function of expert knowledge or other external factors. However, we aim to learn a suitable number of clusters directly from the data. Therefore, we automate the estimation of \(K\). The elbow method executes K-Means clustering for a range of values of \(K\) and stores the mean distance of centroids to the clustered input, which is termed the cost function, for each \(K\). The elbow method then selects the optimal \(K\) as the value \(K^*\) where the cost function, plotted as a function of \(K\), brings the best trade-off between low cost and maximum cost reduction with respect to \(K^*-1\)’s cost. Intuitively, this description of \(K^*\) matches the point where the cost function forms an "elbow", hence the method’s name. We employ a purely numeric method to choose the value for \(K\), since we found the elbow method to be inconclusive in practice. Much like the elbow method, we estimate a statistic on the quality of the clustering for a range of values of \(K\). Thus, we pick the value \(K^*\) that maximizes the silhouette coefficient, which combines statistics on the cluster cohesion (intra-cluster) and separation (inter-cluster) into a single value. Cluster cohesion, represented by \(a_i\), captures the mean distance of an element \(i\) in a cluster to other elements in the same cluster. Cluster separation, represented by \(b_i\), denotes the mean distance of an element \(i\) in a cluster to other elements in the closest neighboring cluster. These two factors form the equation for the silhouette coefficient \(s_i = (b_i - a_i)/max(a_i, b_i)\), where \(-1 \leq s_i \leq 1\). A high silhouette coefficient implies that the cluster distance of \(i\) to other elements in its cluster is low, relative to the mean distance to elements in the next nearest cluster, suggesting the correct assignment of \(i\). The opposite holds for low silhouette coefficient values.

With the application of K-Means for \(K = 2, \ldots, 10\) on the extracted features, we look for \(K^*\). We validate separation and cohesion of the \(K^*\) clusters graphically with PCA projections into a two-dimensional space (cf. Figure 1c). Finally, to check the validity of the clustering obtained with K-Means, we compare its performance with a random clustering baseline, which randomly assigns each input vector to one of \(K\) clusters.
Fig. 2. **Activity Archetypes.** We illustrate typical profiles of activity-based time series nearest to K-Means centroid for $K^* = 4$. Users of the Non-Recurring Activity Archetype (a) often feature one single, isolated peak of activity. Users of the Sporadic Activity Archetype (b) typically exhibit a few isolated activity peaks of equal height. Users of the Frequent Activity Archetype (c) show varying but regular activity over time. Finally, repeatedly high levels of activity over time characterize users of the Permanent Activity Archetype (d). In short, we observe that user activity can be grouped into these four activity profiles, which mainly capture different degrees of frequency in user activity.

**Analyzing Cluster Properties.** We analyze the number of clusters we obtain to better understand the activity composition captured by K-Means. To that end, we start by computing basic descriptive statistics on the clusters, such as their size, as measured by the number of users per cluster. Further, we plot the activity-based time series closest to each centroid and thereby visualize typical activity profiles for each cluster. We then visually inspect the sum of the activities in each of the clusters to discern overall cluster group dynamics. We corroborate this visual inspection with a quantification of the relative sizes of the clusters by area-under-the-curve (AUC) values of the sum of the user activity time series per cluster. Finally, we look for commonalities in these patterns between StackExchange instances.

3.4 Clustering Performance

To measure the clustering performance, we first perform random clustering as a baseline. The random clustering yields $K^* = 2$ with average silhouette coefficient values in the interval $[-0.05, 0.02]$. We then cluster activity-based time series of our datasets and obtain significantly better results. For all 50 StackExchange instances we obtain average silhouette coefficient values of at least 0.9 for $K^*$. For 39 of our 50 StackExchange instances $K^* = 4$. The remaining 11 StackExchange instances feature a strictly higher optimal number of clusters between six and ten. Additionally, we investigated two-dimensional projections of the clusters with PCA (not shown due to limitations in space), which all yield clear graphical separation for the $K^*$ clusters in each StackExchange instance.

4 RESULTS

4.1 Activity Archetypes

For all StackExchange instances with $K^* = 4$, we observe four commonly occurring types of temporal user activity patterns, which we term **Activity Archetypes** (see Figure 2). The patterns of these time series are representative of the four Activity Archetypes, which we describe in ascending order of frequency.

In general, users of the **Non-Recurring Activity Archetype** (see Figure 2a) exhibit one prominent peak of activity. They potentially post a question, perhaps follow up on one or two replies to that question or post one or two replies to some other question of interest before becoming inactive again. Prolonged periods of such inactivity, interspersed by rare and short-lived activity bursts, characterize users of the Non-Recurring Activity Archetype.
The **Sporadic Activity Archetype** (see Figure 2b) features more periods of similarly high activity levels compared to the **Non-Recurring Activity Archetype**. Users of the Sporadic Activity Archetype will, in general, post a couple of questions and answers on more than a single topic. However, similar to the **Non-Recurring Activity Archetype**, users of this archetype also take long breaks between posting questions or answers.

We observe significantly more engagement from users of the **Frequent Activity Archetype** (see Figure 2c). They not only answer multiple questions on a broad variety of topics and start discussions with a number of new questions themselves, but also do so on a regular basis. Hence, users of the Frequent Activity Archetype drive and foster activity. The largest gap in activity frequency across all archetypes is in the distinction between users of the Sporadic and Frequent Activity Archetypes.

The most active group of users we identified belongs to the **Permanent Activity Archetype** (see Figure 2d). These are community leaders, who post both questions and answers on a very regular basis. Their activity time series feature regular and repeated high levels of activity over time.

When $K^* > 4$, the **Activity Archetypes** we observe represent more granular variations of the four archetypes we highlight. These variations include, for example, users with more than a few peaks of activity or users with more regular activity than representatives of the Sporadic Activity Archetype but less than the ones from the Frequent Activity Archetype. As we find as many as ten different variations of this kind, we do not characterize them in more detail.

### 4.2 Composition of StackExchange Instances

We break down the composition of total questions and answers by **Activity Archetypes** and categorize each StackExchange instance into one of three types. We term these StackExchange instance types **Sustainable**, **Transitioning** and **Emerging**.

39 StackExchange instances exhibit $K^* = 4$ when clustering on both questions-based and answers-based time series. Among those 39 we can extract further differences, which are mostly related to the total activity generated by users of the Frequent Activity Archetype. We note that, in some of these 39 StackExchange instances, despite the combined number of users from the Non-Recurring and Sporadic Activity Archetypes being much larger than for the archetypes Frequent Activity Archetype and Permanent Activity Archetype, the latter archetype group accounts for a larger portion of total activity than the former. Therefore, we derive two distinct groups of StackExchange instances by setting the following threshold: If users of the Frequent Activity Archetype account for 90% or more of AUC of answer-based activity time series of Non-Recurring Activity Archetype in a given StackExchange instance, we classify the instance as **Sustainable**, otherwise as **Transitioning**. Using this criteria we identify 26 **Sustainable** StackExchange instances (5 Sustainable instances are still in the Area 51 incubator)\(^9\) and 13 **Transitioning** StackExchange instances (8 Transitioning instances are still in Area 51 incubator)\(^10\).

We compare AUC ratios per **Activity Archetype** of the **Transitioning** and **Sustainable** StackExchange instance types in more detail in Figure 3. We can confirm that the highest proportion of answers-based activity in Sustainable StackExchange instances comes from the Frequent Activity Archetype, whereas the Non-Recurring Activity Archetype generates most answers-based activity in Transitioning StackExchange instances. We draw that conclusion from the relatively higher median

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\(^9\)The 26 Sustainable StackExchange instances are *english*, *unix*, *softwareengineering*, *gaming*, *tex*, *stats*, *wordpress*, *physics*, *mathoverflow*, *sharepoint*, *scifi*, *ux*, *webmasters*, *graphischdesign*, *workplace*, *salesforce*, *cs*, *bicycles*, *skeptics*, *christianity*, *sound*, *history*, *gardening*, *linguistics*, *outdoors* and *tridion*, with *history*, *gardening*, *linguistics*, *outdoors* and *tridion* still being in the Area 51 incubator as of 02/13/2017

\(^10\)The Transitioning group of StackExchange instances consists of *bitcoin*, *chemistry*, *chess*, *codereview*, *cogsci*, *music*, *opendata*, *philosophy*, *poker*, *reverseengineering*, *space*, *sports* and *sustainability*. As of 02/13/2017 chemistry, codereview, music and philosophy have left the Area 51 incubator.
Fig. 3. Distinction between Transitioning and Sustainable StackExchange instances. For the StackExchange instance types Transitioning and Sustainable, we depict the area-under-the-curve (AUC) of the answers-based (Fig. 3a) and questions-based (Fig. 3b) activity time series of users in the Non-Recurring and Frequent Activity Archetypes. In both Figures, we aggregated activity per user archetype and normalized it per StackExchange instance. We highlight the most notable difference between the two instance types: Non-Recurring Activity Archetype users have a larger weight in activity than Frequent Activity Archetype users in Transitioning instances, and the opposite holds for Sustainable instances. This discrepancy is less pronounced in questions-based than answers-based activity.

(and respectively lower) AUC values for users in the Frequent Activity Archetype (and respectively Non-Recurring Activity Archetype) in Sustainable instances compared to Transitioning instances (Figure 3a). Furthermore, we highlight relative importance of the Non-Recurring Activity Archetype in questions-based activity time series (see Figure 3b): Although its dominance is most apparent in Transitioning StackExchange instances, it still plays a significant role in the Sustainable instance type.

We feature a high-level, graphical comparison of instances representative of the three instance types in Figure 4, and we discuss each instance type in more detail.

The Emerging group of StackExchange instances\(^\text{11}\) comprises instances with \(K^* > 4\) for either clustering of questions-based or answers-based activity time series. These StackExchange instances do not exhibit the Activity Archetypes defined in Section 4.1, but instead feature more variations thereof. In general, Emerging instances are among the newest, least active and smallest out of the 50 instances we consider. Furthermore, ten out of eleven Emerging StackExchange instances are still in the Area 51 incubator. Figure 4a illustrates a typical activity profile of Emerging instances, as exemplified by the StackExchange instance tor.

In Transitioning StackExchange instances, users of the Non-Recurring and Sporadic Activity Archetypes generate the most activity. The activity dynamics of Transitioning StackExchange instances exhibit strong oscillations over time and vary considerably in numbers of users and age, as exemplified by the StackExchange instance cogsci in Figure 4b. We note that some of the Transitioning StackExchange instances are among the five smallest datasets in our analysis. However, codereview has one of the largest user bases with 19,140 users and features very high

\(^\text{11}\)The Emerging group of StackExchange instances consists of arduino, buddhism, earthscience, ebooks, freelancing, ham, joomla, lifehacks, puzzling, startups and tor. Only puzzling has left the Area 51 incubator as of 13. February 2017.
We plot total questions-based (bottom) and answers-based (top) activity of three StackExchange instances over time, and break these activity totals down by user archetype. The three selected StackExchange instances are representative of the three instance types we discern: Emerging, Transitioning and Sustainable. A high value of $K^*$, indicating the four user archetypes do not prevail, characterizes Emerging instances like tor (see Figure 4a). Although both Transitioning and Sustainable StackExchange instances feature $K^* = 4$, their activity breakdowns differ: In Transitioning instances such as cogsci, the users of the Non-Recurring Activity Archetype seem to play a larger role in answers-based activity than ones from the Frequent Activity Archetype, and the opposite holds for Sustainable instances such as english (see Figures 4b and 4c). Note that users of the Frequent Activity Archetype are significantly less numerous than those of the Non-Recurring Activity Archetype in both instances. Furthermore, cogsci and tor feature similarly low numbers of users and activity, with cogsci oscillating around positive growth and tor having declining activity. English, however, exhibits the highest number of users and activity levels, as well as the most pronounced growth in activity.

On the other hand, in Sustainable StackExchange instances, the Frequent and Permanent Activity Archetypes generate the most answers-based activity, despite representing at most 10% of the total user base. However, Non-Recurring and Sporadic Activity Archetypes still generate more of the questions-based activity than others. We can observe this in the StackExchange instance english, depicted in Figure 4c. Hence, Sustainable instances rely on Non-Recurring and Sporadic Activity Archetypes to generate the majority of questions and a small core of engaged Frequent and Permanent Activity Archetype community members to address and answer those questions. In general, Sustainable StackExchange instances are among the oldest, most active ones (cf. Table 2), which also exhibit the highest number of users and a steady growth of activity. Note that we estimate activity growth as the slope of a linear regression fitted with ordinary-least-squares, normalized with a min-max transformation (see Table 2). This transformation makes the slope comparable across instances with varying levels of activity.

**Instance type evolution over time.** We count the number of StackExchange instances per...
We count the number of StackExchange instances per type (with “E” standing for Emerging (in green), “T” for Transitioning (in blue) and “S” for Sustainable (in pink)) over the course of the instances’ existence. We start the StackExchange instance categorization when instances are just sixth months old and repeat this categorization every six months until year three. 49 out of 50 StackExchange instances are at least six months old, but only 32 are at least three years old. We observe that Sustainable instances take at least a couple of years to develop, and Emerging instances typically grow to the Transitioning type in less than two years.

Fig. 5. Temporal evolution of StackExchange instance types. We count the number of StackExchange instances per type (with “E” standing for Emerging (in green), “T” for Transitioning (in blue) and “S” for Sustainable (in pink)) over the course of the instances’ existence. We start the StackExchange instance categorization when instances are just sixth months old and repeat this categorization every six months until year three. 49 out of 50 StackExchange instances are at least six months old, but only 32 are at least three years old. We observe that Sustainable instances take at least a couple of years to develop, and Emerging instances typically grow to the Transitioning type in less than two years.

Table 2. Statistics on largest and smallest StackExchange instances. For the top and bottom five StackExchange instances with most and respectively least users, we list a number of statistics, sorted by the number of users: Instance type, number of users, total activity (i.e. sum of questions and answers), age in months and the slope of the trend of total activity per month. The top five StackExchange instances are all of the Sustainable type, and feature a positive growth trend. In contrast to those instances, the bottom five StackExchange instances are either Emerging or Transitioning and have dwindling growths (negative trend slope).

| Instance name | Instance type | Users | Activity | Months | Trend slope |
|---------------|---------------|-------|----------|--------|-------------|
| english       | Sustainable   | 37125 | 522128   | 70     | 0.013       |
| unix          | Sustainable   | 36397 | 390930   | 80     | 0.012       |
| softwareengineering | Sustainable | 35516 | 467234   | 80     | 0.006       |
| gaming        | Sustainable   | 34641 | 321857   | 68     | 0.007       |
| tex           | Sustainable   | 31039 | 624166   | 80     | 0.014       |
| poker         | Transitioning | 594   | 5185     | 39     | −0.002      |
| earthscience  | Emerging      | 578   | 5981     | 12     | −0.040      |
| sustainability| Transitioning | 555   | 5274     | 27     | −0.015      |
| ebooks        | Emerging      | 501   | 3094     | 16     | −0.041      |
| ham           | Emerging      | 473   | 5023     | 18     | −0.037      |
5 DISCUSSION

Features for Modelling Activity. We find that the Activity Archetypes are well-suited to derive well-separated groups of users and help to assess the maturity of Q&A instances. We note that these clusters seem to be representative of the types of temporal user activity patterns typically encountered in online Q&A instances [9, 17, 21].

The three features we propose allow for one valid clustering approach out of many different, equally valid ones. Mamykina et al. [17] grouped users by their number of answers and by their activity signatures describing monthly activity levels. Furtado et al. [9], however, employ a total of seven features describing not just activity levels but also the quality of the user contributions. Other features to characterize user activity include directly measuring burstiness and memory effects, as proposed by Goh and Barabási [10] and employed by Jan et al. [28] to distinguish software developer types in GitHub. Burstiness (again, as defined by Goh and Barabási [10]) is a real value ranging in \([-1, 1]\), which captures how regularly activity spikes occur. For example, we often observe similarly negative burstiness (i.e., regular behavior) in users of both Non-Recurring and Permanent Activity Archetypes, as their activity spikes are interspersed by regularly long or regularly short pauses, respectively. Therefore, the use of the burstiness feature would result in users archetypes other than the ones we presented. To sum up, all of these approaches yield, when compared to our approach, different interpretations reflecting different aspects of activity. This also reflects, however, the main limitation of this paper: Although the features we propose achieve high clustering quality and the resulting clusters are interpretable, another combination of features might work even better.

Specifically, our analysis reveals that a simple, small set of features is sufficient for separating temporal user activity patterns. We see these facts as a promising result for future modeling efforts—by using only a small number of parameters, models can be kept simple and interpretable (e.g., we may model user activity as a simple Poisson process), but still effective and accurate. Moreover, empirical estimation of parameters for simple models is typically easy and efficient.

Dynamics of Activity Compositions. We have shown that mature and healthy Q&A communities, typically of the Sustainable type, exhibit a steady flow of activity from numerous users of the Non-Recurring or Sporadic Activity Archetypes, which represent external impulses that stimulate contributions from users of the Frequent and Permanent Activity Archetypes, driving discussions and positively impacting community dynamics. We note that publicly available statistics from Area 51 datasets [24] stress the importance of this core community from the Frequent and Permanent Activity Archetypes, which are akin to experts, community leaders or activists in other literature. While we agree that a core of experts or community leaders is vital to a community’s activity and growth, we add that the community’s ability to attract interest from and react to a stream of users from Non-Recurring and Sporadic Activity Archetypes is key to long-term successful development.

We observe that online Q&A communities of the types Transitioning and especially Emerging generally struggle with overall decreasing activity and/or with a lack of sustained community growth and activity (see Table 2). Further, the dynamics of the four main Activity Archetypes in Emerging StackExchange instances have not formed yet, so other clusters of activity types, not belonging to any of the four archetypes, dominate. We argue that this is a direct consequence of Emerging instances simply lacking users and time required to establish these characteristics.

Practical Implications. Based on the time evolution analysis we propose a series of measures for operators of Q&A instances to focus on as they grow and foster their communities. In early Emerging systems, no feature dominant types of users exist. Hence, as a first priority, operators should promote participation of users from the Non-Recurring and Sporadic Activity Archetypes, as

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12GitHub is an online hosting service and community for software repositories (http://www.github.com).
these users drive activity levels towards Transitioning instances. Measures to entice users from the Non-Recurring and Sporadic Activity Archetypes to engage in Emerging communities should focus on the communities’ ease-of-access and their visibility to the outside world. Managers of Transitioning communities should concentrate on users of the Frequent and Permanent Activity Archetypes to evolve, foster and sustain their communities in the long-term, as these archetypes account for the bulk of activity in Sustainable communities. To enhance activity from users of the Frequent and Permanent Activity Archetypes, we suggest operators reward recurrent participation and try to engage these users in the community building efforts. It is this combination of two key factors that we observe in most successful StackExchange instances: A steady flow of new users, typically of the Non-Recurring and Sporadic Activity Archetypes, engages with a community core of expert users, typically of the Frequent and Permanent Activity Archetypes. Note that the StackExchange instances we analyzed do not become completely inactive. Therefore, we do not consider the death of a StackExchange instance.

6 CONCLUSIONS & FUTURE WORK

In this paper, we uncover temporal activity patterns in 50 StackExchange Q&A instances at both the user and instance levels. To achieve this, we start by representing user activity in those instances as time series, which comprise the total count of users’ questions and answers over time. We extract representative features from these time series to better cluster them and to derive an optimal numbers of clusters. These clusters represent a set of four Activity Archetypes, which characterize users according to the frequency of participation in a Q&A community. Then, we brake down activity in StackExchange instances by the different Activity Archetypes, which allows us to recognize three instance types: Sustainable, Transitioning and Emerging. Sustainable instances have the highest levels of activity and the largest number of active users. Their success correlates with a small but strong backbone of users of the Frequent and Permanent Activity Archetypes, reacting to a steady flow of users from the Non-Recurring and Sporadic Activity Archetypes. We find that Emerging and Transitioning StackExchange instances either completely lack or are in the process of establishing such activity profiles. Our Activity Archetypes and StackExchange instance characterization allow us to measure online Q&A instance health and success. We provide a methodology for community managers of Q&A instances to detect the maturity stage of their communities and we recommend activity structures for them to aim for as their communities mature from one maturity stage to the next one.

Future work includes mathematical modeling of activity in online Q&A communities based on the Activity Archetypes and their activity compositions with the aim of deriving further recommendations for operators to assess and optimize their online presence.

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