Self- and Cross-Excitation in Stack Exchange Question & Answer Communities

Tiago Santos[1], Simon Walk[2], Roman Kern[1,3], Markus Strohmaier[4], Denis Helic[1]
[1]Graz University of Technology, [2]Detego GmbH, [3]Know-Center, [4]RWTH Aachen University
tsantos@iicm.edu,s.walk@detego.com,rkern@tugraz.at,markus.strohmaier@cssh.rwth-aachen.de,dhelic@tugraz.at

ABSTRACT

In this paper, we quantify the impact of self- and cross-excitation on the temporal development of user activity in Stack Exchange Question & Answer (Q&A) communities. We study differences in user excitation between growing and declining Stack Exchange communities, and between those dedicated to STEM and humanities topics by leveraging Hawkes processes. We find that growing communities exhibit early stage, high cross-excitation by a small core of power users reacting to the community as a whole, and strong long-term self-excitation in general and cross-excitation by casual users in particular, suggesting community openness towards less active users. Further, we observe that communities in the humanities exhibit long-term power user cross-excitation, whereas in STEM communities activity is more evenly distributed towards casual user self-excitation. We validate our findings via permutation tests and quantify the impact of these excitation effects with a range of prediction experiments. Our work enables researchers to quantitatively assess the evolution and activity potential of Q&A communities.

CCS CONCEPTS

• **Human-centered computing** → *Collaborative and social computing*; • **Mathematics of computing** → *Stochastic processes.*

KEYWORDS

Q&A communities, Excitation effects, Hawkes processes

ACM Reference Format:

Tiago Santos, Simon Walk, Roman Kern, Markus Strohmaier, Denis Helic. 2019. Self- and Cross-Excitation in Stack Exchange Question & Answer Communities. In *Proceedings of the 2019 World Wide Web Conference (WWW'19), May 13–17, 2019, San Francisco, CA, USA.* ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3308558.3313440

1 INTRODUCTION

Why and *how* some Question & Answer (Q&A) communities gain traction and attract activity from large numbers of users—while others do not—are questions of theoretical and practical relevance [31, 38]. Understanding how users become active in such systems, and how user activity evolves over time, can be considered an important stepping stone towards better modeling and shaping of online Q&A communities. This will allow to devise novel approaches to guide and encourage activity [12] and to support community managers in their community building efforts [2, 20].

User excitation. In this paper, we investigate *self-excitation* and *cross-excitation* of users in Q&A communities. Self-excitation reflects how a user's *own* past activity shapes her future activity, while cross-excitation reflects how *other users'* past activity influences future activity of a given user. Modeling temporal traces of user activity informs the inference of excitation effects and thus provides a first step towards deeper causal analysis of user excitation.

In the present work, we adopt point processes [7–9]—in particular Hawkes processes [14]—to leverage temporal traces of user activity as latent indicators of self- and cross-excitation. We empirically analyze 69 Stack Exchange Q&A instances where we fit a multivariate Hawkes process model[1]. With that, we are able to analyze self- and cross-excitation of users across: (i) communities with growing and declining activities, (ii) the topics of the conversations, (iii) activity types (e.g., question, answers), and (iv) activity source (e.g., power user, casual users). Subsequently, we characterize self- and cross-excitation as a function of community age. We then validate, with a range of statistical tests, the excitation effects we uncover, and we quantify their relative importance in the evolution of Q&A communities with a prediction experiment. We illustrate various types of excitation and how they generate user activity in Figure 1.

Findings. Our empirical findings emphasize the need for Q&A communities to maintain a steady core of highly cross-excited power users (i.e. very active users) reacting, particularly in a community's early stages, to the community as a whole. In thriving communities, casual users (less active users) shape each others' activity levels via cross-excitation. This suggests that growing communities are, in general, facilitating and embracing less active and casual users, thereby offering low barriers of entry. Additionally, we observe late-stage domination of self-excitation over cross-excitation, meaning that self-driven activity becomes a crucial factor in successful communities. This effect may serve as a long-term growth indicator, as this self-excitation dominance is most prominent in growing communities. Finally, we observe differences in user participation across distinct topics: Q&A communities dedicated to topics in the humanities (such as languages) are more driven by cross-excitation of power users, whereas those in STEM-related fields are not.

With our work we make the following contributions. First, we model self- and cross-excitation effects in successful and unsuccessful Q&A communities. Second, we empirically show how self- and cross-excitation manifests in communities defined by different levels of success and different topics. Third, our validation provides a foundation for building further predictive models of user activity in Q&A communities. Finally, we provide and illustrate an approach

[1]We make our code available at https://github.com/tfts/Excitation_in_QA.

WWW '19, May 13–17, 2019, San Francisco, CA, USA

ACM ISBN 978-1-4503-6674-8/19/05.
https://doi.org/10.1145/3308558.3313440

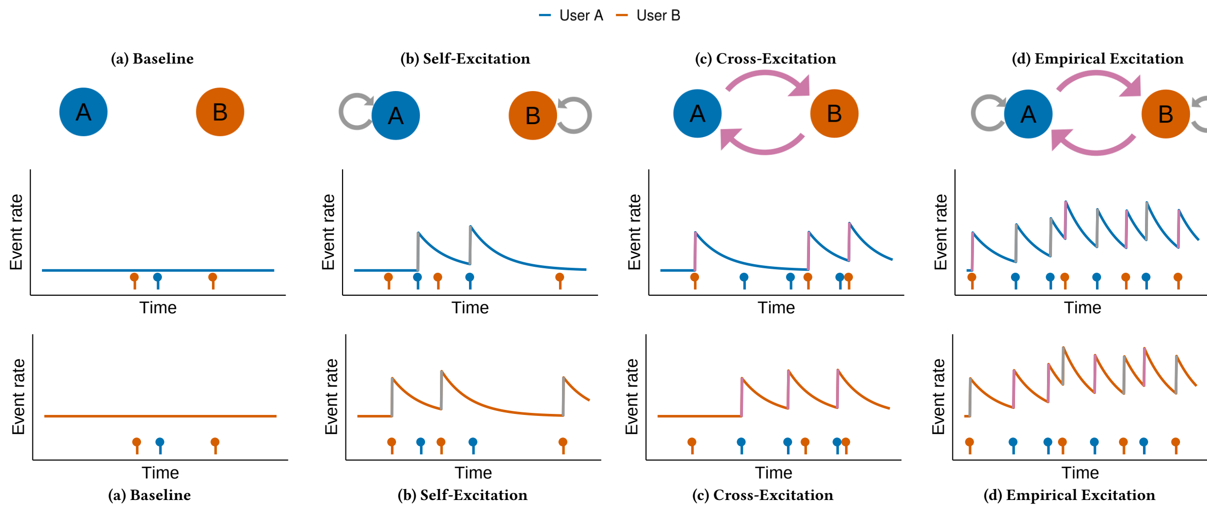


Figure 1: Excitation types. We distinguish between three drivers of user activity excitation: (a) Baseline, a constant base event rate level, (b) Self-Excitation, a proxy for increased propensity by a user to be active in the future following her past activity, and (c) Cross-Excitation, a boost to event rate triggered by activity of other users. The upper row of this Figure depicts the links between users A and B per excitation type, and the two lower rows the corresponding event rate as it reacts to the user's own and others' activity events, marked by the trees below each event rate line and colored by the corresponding user. The first three excitation types cover excitation components which combine to form (d) empirical excitation. This work characterizes and quantifies how each type of excitation manifests itself in Q&A communities and how excitation strength changes over time as a Q&A community develops.

that allows community managers to quantitatively compare long-term dynamics of their online Q&A communities—in terms of user excitation—to well-established ones.

2 HAWKES PROCESSES

A point process can be broadly defined as a collection of points randomly located in some mathematical space. Temporal point processes employ the real line, representing time, as the underlying mathematical space. For the interested reader, the work by Daley and Vere-Jones [8, 9] and by Cox and Isham [7] are comprehensive references on point process theory.

In practice, temporal point processes model the arrival of discrete events over time with the help of a *conditional intensity function* λ^*, a stochastic model for the arrival of the next event given the event history. Hawkes processes [14] are a particular class of temporal point processes, which assume a particular functional form for the intensity function. Specifically, the intensity function of Hawkes processes is in itself a stochastic process and it explicitly encodes *self-excitation*, the increase in intensity caused by past events:

$$\lambda^*(t) = \mu + \sum_{t_i < t} \alpha e^{-\beta(t - t_i)}, \tag{1}$$

where $\mu > 0$ is the baseline intensity independent on the event history, and $\alpha, \beta > 0$ establish the dependence on previous events. In particular, each previous event at time t_i increases the intensity by α, the self-excitation factor. We choose to let the intensity jumps exponentially decay at the rate β, which is a commonly used functional form of intensity decay called an *exponential kernel*.

Equation 1 describes *univariate* Hawkes processes, as they consider only the effect of past events in future event times of the same event stream. The *multivariate* generalization of univariate Hawkes processes includes not only self-excitation but also *cross-excitation*. Cross-excitation is the intensity increase that an event in one event stream implies in another event stream. More formally, let $\boldsymbol{N}(t) = (N^1(t), N^2(t), \ldots, N^M(t))$ be a simple multivariate point process, where each of the $N^i(t)$ is a counting process in the i-th dimension. An M-variate Hawkes process with an exponential kernel is defined by the following intensity function:

$$\lambda^{*m}(t) \quad = \quad \mu_m + \sum_{n=1}^{M} \sum_{t_i^n < t} \alpha_{mn} e^{-\beta_{mn}(t - t_i^n)}. \tag{2}$$

We write μ_m as the baseline intensity in dimension m, α_{mn} as the cross-excitation on dimension m caused by an event in dimension n and the corresponding decay rate as β_{mn}. In matrix notation, we write $\boldsymbol{\mu} \in \mathbb{R}^M$, $\boldsymbol{\alpha} \in \mathbb{R}^{M \times M}$ and $\boldsymbol{\beta} \in \mathbb{R}^{M \times M}$. Linniger [23] provides a more detailed treatment of multivariate Hawkes process theory.

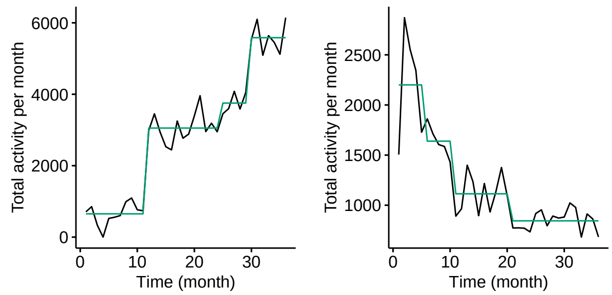
Samples from multivariate Hawkes processes, which can be obtained via Ogata's thinning algorithm [27], generate self-excitation and cross-excitation effects of the kind depicted in Figure 1, where users A and B correspond to two dimensions of a Hawkes process and their event rate to the Hawkes process intensity. We observe, in both dimensions, intensity peaks corresponding to the sampled events, and we note the intensity decays exponentially until converging to the baseline intensity level $\boldsymbol{\mu}$.

Fitting Hawkes processes. Given an observed sequence of events $\{t_i\}$, we fit the parameters of Hawkes processes by maximizing its *log-likelihood*. Closed form expressions for the log-likelihood can be derived for many different types of intensity function kernels, including the exponential kernel that we assume. For a given $\boldsymbol{\beta}$, all other parameters of the process may be estimated by maximizing the log-likelihood via well-known convex optimization methods such as Levenberg-Marquardt [21]. However, fitting $\boldsymbol{\beta}$-s is a challenging task, since the likelihood functions of Hawkes processes with exponential kernels are either flat around the optimal $\boldsymbol{\beta}$ (see, for example, Upadhyay et al. [36]) or, in some other formulations of the kernel function, even non-convex in $\boldsymbol{\beta}$. In this paper, we propose an effective Bayesian hyperparameter optimization step, which allows fitting the decay-related and then the remaining parameters of a Hawkes process. Assuming $\beta_{m,n} = \beta, \forall_{1 \leq m,n \leq M}$ [12, 35], we apply the Tree of Parzen Estimators approach, as described by Bergstra et al. [4], on the convex optimization routine of log-likelihood for a given set of event sequences to estimate β. We perform 15 runs of the Bergstra et al. algorithm and keep the β yielding highest likelihood, since this effectively allows for convergence even in the presence of flat plateaus around local maxima of Hawkes likelihood as a function of β. Finally, using the learned β, we fit $\boldsymbol{\mu}$ and $\boldsymbol{\alpha}$.

Furthermore, practical fitting of Hawkes processes requires the fits to be done on *stationary* [23] periods of the corresponding count time series. Stationarity, in this context, refers to translation-invariance in the Hawkes process distribution, which implies a linear growth in the associated time series of event counts over time. However, in the time series representing activity in the Q&A communities we work with, we observe a range of non-stationary phenomena: exponential growth and decline and other sudden structural changes, such as level jumps. Therefore, we need to restrict the fitting procedure to stationary subsequences of an observed event stream. To that end, we use the time series structural change detection algorithm devised by Zeilis et al. [45]. Given a linear regression model, this algorithm returns optimal points in time for structural change in the regression model's fit to a given input time series. Using a constant regression model allows us to detect level changes in an input event count time series, and thus to segment it into stationary subsequences.

3 EXPERIMENTAL SETUP

We study user self- and cross excitation by empirically analyzing Stack Exchange instances. We distinguish activity in these datasets by two aspects: (i) activity content, which we define as questions and answers (with the latter including answers and comments), and (ii) activity source, meaning whether it originated from highly active (power) or less active (casual) users. Further, we explore the differences in excitation across communities, which we group according to two criteria: (i) growth pattern, and (ii) topical focus.



(a) Growing instance (electronics) (b) Declining instance (cstheory)

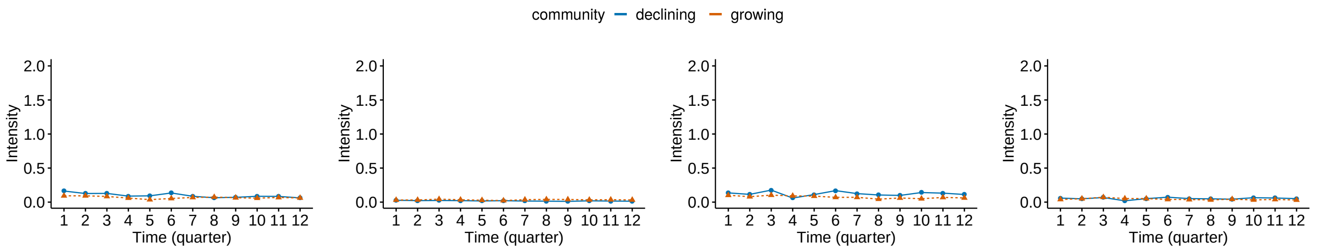
Figure 2: Exemplary *growing* (left) and *declining* (right) Stack Exchange instances. These two curves exemplify the monthly total activity time series of a *growing* (*declining*) instance, electronics (cstheory). Following Zeilis et al., we indicate stationarity in subsequences of both time series with the green lines. Note that *growth* (*decline*) in electronics (cstheory) was, at 757.62% (−61.63%), one of the highest (lowest) among Stack Exchange instances we analysed.

Datasets. Stack Exchange encompasses several Q&A communities, termed Stack Exchange instances, with each dedicated to Q&A on a single topic, such as computer science, the English language or movies. We extract user activity in all 159 Stack Exchange instances[2] (as of June 2017) as the timestamps of users' activity events: posts (i.e. questions) and replies (i.e. answers and comments). In a first step, we consider these instances' complete history, which spans the period from August 2008 to June 2017 and comprises a total of 22 million events. However, our analysis is independent from the calendar date a Stack Exchange instance originated, as we map the inception of each instance to a time scale starting at zero.

[2] The Stack Exchange dataset is available at https://archive.org/details/stackexchange.

Table 1: Dataset characteristics. We show the datasets per group sorted by activity growth (top and bottom three growth percentages per group shown in parenthesis), the total number of datasets per group (#), as well as ranges for a number of descriptive statistics: the activity total as the sum of all questions and answers, the age in years and the total growth as a percentage of the level of the first subsequence found by Zeilis et al.'s algorithm. We observe a clear separation in strongly positive and negative growths (and thus also total activity) in the major distinction we draw between datasets, *growing* vs. *declining*. This distinction is remarkably less pronounced in *STEM* vs. *humanities* instances, which both feature positive and negative growths.

Dataset Group	Datasets	#	Activity total	Age (years)	Growth (%)
Stack Exchange Growing	electronics (757.62%), ru (736.42%), codegolf (510.06%), chemistry, sharepoint, academia, puzzling, tex, codereview, blender, unix, money, gis, ux, crypto, security, stats, salesforce, dba, wordpress (182.28%), opendata (174.69%), askubuntu (169.29%)	22	[7987, 1489384]	[3.08, 7.83]	[169.29, 757.62]
Stack Exchange Declining	boardgames (−28.53%), fitness (−34.56%), sound (−35.01%), productivity, tridion, parenting, pets, craftcms, webapps, spanish, cooking, ham, bricks, gardening, cstheory, expressionengine, pm, skeptics, sustainability, genealogy (−80.26%), ebooks (−81.52%), stackapps (−82.7%)	22	[3301, 117474]	[3, 7.75]	[−82.7, −28.53]
Stack Exchange STEM	electronics (757.62%), chemistry (473.48%), stats (199.18%), biology, datascience, physics, astronomy, cs, space, cogsci, earthscience, engineering, reverseengineering (0.00%), softwareengineering (−21.28%), sound (−35.01%)	15	[15759, 745674]	[2.41, 8.75]	[−35.01, 757.61]
Stack Exchange Humanities	philosophy (122.45%), english (117.76%), chinese (23.17%), music, german, mythology, portuguese, christianity, esperanto, arabic, russian, writers, buddhism (−26.62%), french (−27.91%), spanish (−50.10%)	15	[87, 896631]	[0.17, 6.83]	[−50.10, 127.47]



(a) Baseline of Answers by Power Users **(b) Baseline of Questions by Power Users** **(c) Baseline of Answers by Casual Users** **(d) Baseline of Questions by Casual Users**

Figure 3: Low baseline excitation in *growing* and *declining* communities. Given the Hawkes process dimensions questions and answers per power and casual users, we depict the baseline parameters μ of the Hawkes processes fitted every three months over three years of *growing* (orange lines) and *declining* (blue lines) Stack Exchange instances. Error bars in this Figure and Figures 4 and 5 show bootstrapped 95% confidence intervals, many of which are too small to be visible. Note our use of the same scale in Figures (a)-(d) and throughout Figure 4: The relatively low baseline intensities in comparison to the effects depicted in Figure 4 stress that overall activity is driven by self- or cross-excitation rather than baseline intensity.

Before we group Stack Exchange instances according to our two criteria, growth patterns and topical focus, we discard all datasets with less than ten events in any period of three months, which ensures that we have enough events for the fitting procedure.

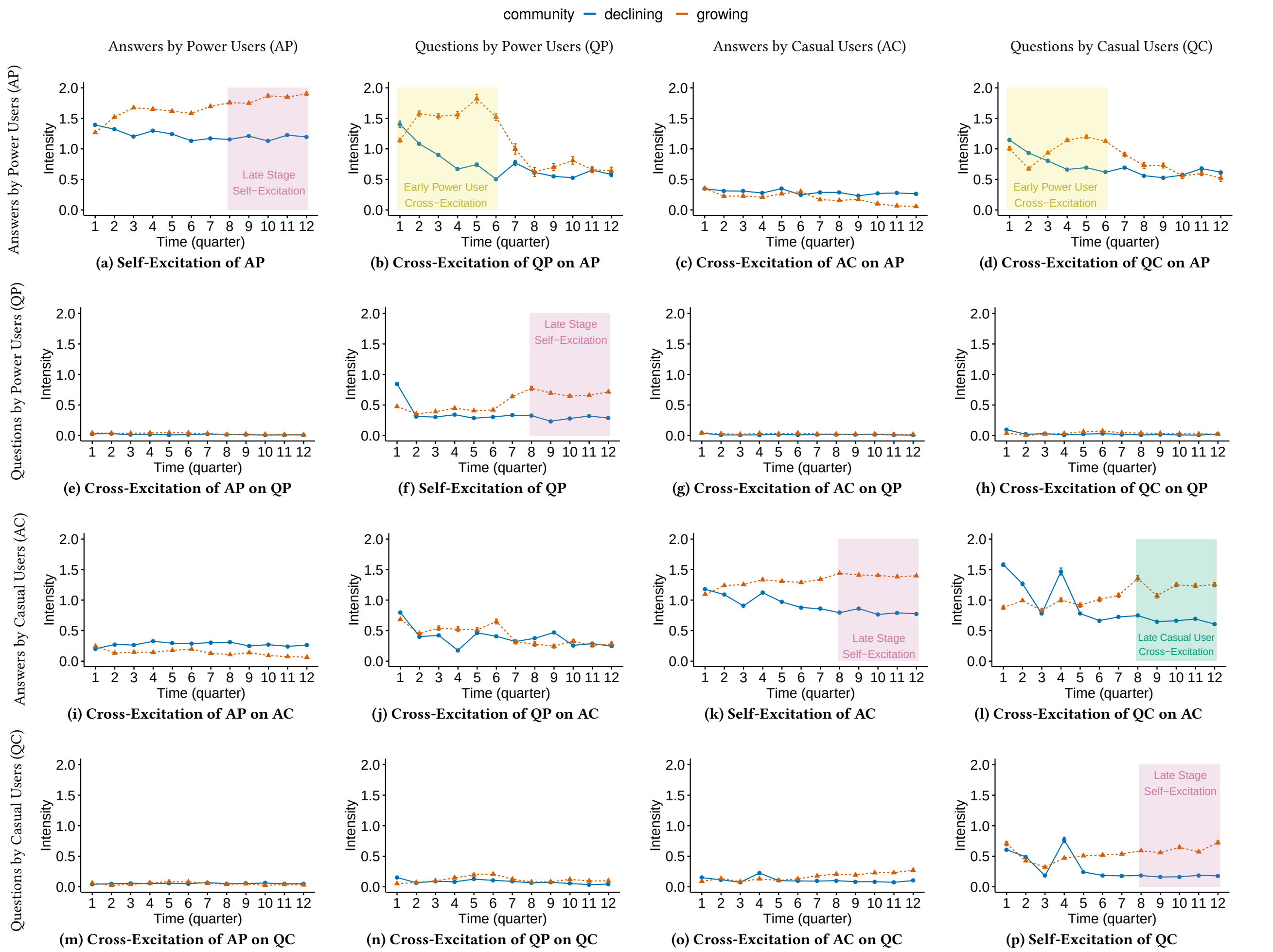
Growth pattern. In our first comparison by growth pattern, we analyze the first three years of existence of Stack Exchange instances, so we exclude datasets with durations shorter than three years. To better distinguish excitation effects driving overall activity increase or decrease in these communities, we then extract, from the remaining datasets, two groups of strongly *growing* and strongly *declining* datasets. The extraction criterion stems from our application of Zeilis et al.'s algorithm to find level structural changes in the time series of total activity count per month: We define a dataset as strongly growing (declining), if the percentage change in structural level from the first fitted window to the last fitted window is in the 80$^{\text{th}}$ (20$^{\text{th}}$) percentile over all datasets. The grouping of Stack Exchange instances into *growing* and *declining* yields two groups of 22 datasets each, of which we provide descriptive statistics in Table 1. Note that the *growing* (*declining*) group only includes instances with strongly positive (negative) growth. We plot the total monthly event counts for a selected dataset from each dataset group in Figure 2 to exemplify their activity curves and the detected structural level changes. Often, there are prolonged periods of stagnancy in one structural level, both in *growing* as well as *declining* datasets. Typically, such periods vary in length.

Topical focus. For the topical comparison, we study Stack Exchange instances dedicated to *STEM* (i.e. science, technology, engineering and mathematics) and *humanities* topics. To that end, we randomly picked a set of 15 Stack Exchange instances we manually classified as STEM topics, and another 15 as humanities. The instances in these two groups vary in size and age, and feature no distinctive growth patterns, although some *humanities* instances are smaller and have shorter overall durations than *STEM* instances (cf. Table 1). In this comparison, we also analyze instances' first three years, but we do not impose a minimum duration, which leads to fewer than 15 instances per group later in time. However, the number of instances per group remains comparable over time and reaches a minimum of nine instances per group by the third year.

Hawkes process application. In the Stack Exchange instances, we distinguish between more active and less active users, which we term *power users* and *casual users.* This definition mainly distinguishes a *core* of remarkably engaged power users typically found in Q&A communities [13, 24, 41] from casual users. Thus, for each dataset individually, we count the total activity per month per user, and per activity type (question or answer) and postulate that power users are those in the 90$^{\text{th}}$ percentile of most active users for that month. This implies that this monthly group of power users is ever-changing, as users join and leave the communities or as the users' intrinsic motivation to contribute content rises and falls over time. Note that our results changed only minimally with different percentile thresholds (i.e., 85$^{\text{th}}$ and 95$^{\text{th}}$) for power user classification. To measure self- and cross-excitation per user and activity event type, we map the event stream of question and answer activity to four Hawkes process dimensions: questions by power users, questions by casual users, answers by power users and answers by casual users. For each such dimension, we work with the corresponding event timestamps at the resolution of a second.

We then follow the procedure outlined in Section 2 to fit four-dimensional Hawkes processes to each dataset group (Stack Exchange instances in the groups *declining* vs. *growing* and *STEM* vs. *humanities*). For each dataset group comparison, we begin by fitting overall β for all datasets over the first three years of their existence. Then, we perform structural level change fits on the total monthly event count, and observe a minimal window length of five months. According to our experimentation with different window lengths, specifically two to six months, we find a window length of three months is long enough to ensure we have enough events per window and do not overfit a particular window, while also short enough to capture granular changes in the evolution of the underlying Hawkes process distribution. Hence, we set the constant window length to three months (a quarter).

To measure variability in the evolution of the fitted models, we bootstrap, with 100 repetitions, the fitting procedure of all Stack Exchange instances per dataset group per window. From the resulting bootstrap distribution, we compute 95% confidence intervals for the mean value of each fitted Hawkes process parameter. We display the confidence intervals as error bars in Figures 3, 4 and 5.



(a) Self-Excitation of AP (b) Cross-Excitation of QP on AP (c) Cross-Excitation of AC on AP (d) Cross-Excitation of QC on AP

(e) Cross-Excitation of AP on QP (f) Self-Excitation of QP (g) Cross-Excitation of AC on QP (h) Cross-Excitation of QC on QP

(i) Cross-Excitation of AP on AC (j) Cross-Excitation of QP on AC (k) Self-Excitation of AC (l) Cross-Excitation of QC on AC

(m) Cross-Excitation of AP on QC (n) Cross-Excitation of QP on QC (o) Cross-Excitation of AC on QC (p) Self-Excitation of QC

Figure 4: Excitation in *growing* vs. *declining* communities. Given the Hawkes process dimensions questions (Q) and answers (A) per power (P) and casual (C) users, we depict the α matrix of self-excitation (diagonal plots) and cross-excitation (off-diagonal plots) parameters of the Hawkes processes fitted every three months over three years of *growing* (orange lines) and *declining* (blue lines) Stack Exchange instances. The first and second row, respectively, show how answer and question intensities by power users are self- and cross-excited, and the third and fourth the influence on answer and question intensity by casual users as a result of self-excitation and cross-excitation. The yellow highlighted regions (■) of Figures (b) and (d) depict the effects of questions by power and casual users on answers by power users and thus the crucial importance of power user cross-excitation in driving early stage dynamics of *growing* instances. In Figure (l) we observe another difference between the groups: *growing* communities also thrive off interaction between casual users, as shown by long-term cross-excitation of questions by casual users on answers by casual users (cf. green region ■ of Figure (l)). In the long-term, self-excitation (pink highlighted regions ■ of diagonal entries, i.e. Figures (a), (f), (k), and (p)) is the most dominant form of excitation in all four Hawkes process dimensions.

4 EXCITATION EFFECTS

4.1 Comparison by growth pattern

The β value, fitted over 44 datasets in the *growing* vs. *declining* comparison and the whole three year period, is 2.288, corresponding to an intensity half-life of about 0.3 hours (meaning that the intensity jump of magnitude α caused by either self-excitation or cross-excitation decays to $\alpha/2$ after about 18 minutes). With a single constant β, we restrict our model to capture distributional changes in terms of baseline, self- and cross-excitation intensities, allowing us to focus on these factors as direct proxies for the role of different user groups in overall activity intensity over time.

We visualize the evolution of all baseline parameter values for questions and answers by power users and casual users in *growing* (orange) and *declining* (blue) instances in Figure 3. We depict the corresponding self- and cross-excitation parameter values in Figure 4. Note that we employ the same scales throughout both Figures for better comparison.

Low baseline intensities. The Figures 3a through 3d show the baseline intensities ($\boldsymbol{\mu}$) fitted over time. We observe roughly constant baseline intensities throughout the whole period, for both *growing* and *declining* instances. Furthermore, the baseline intensities are rather low, especially in comparison with the self-excitation and cross-excitation effects ($\boldsymbol{\alpha}$) depicted in Figure 4.

Finding: Constant and low baseline intensities suggest Q&A communities thrive off self- and cross-excitation, representing interaction between different user (power and casual) and activity types (questions & answers), rather than featuring constant levels of activity over time, independent from other activity dimensions.

Early Power User Cross-Excitation (■). We continue our analysis with the Hawkes process dimension with the highest intensity values: intensity in answer activity by power users (*first row* in Figure 4, i.e. Figures 4a through 4d). We observe, in the early stages of *growing* instances, high impact of questions by both power as well as casual users on answer activity by power users (see yellow region highlighted in Figures 4b and 4d). In contrast, in *declining* instances, especially in the yellow highlighted region, questions by both types of users elicit declining numbers of answers by power users over time, and self-excitation in answers by power users dominates over all temporal windows. Regarding question activity by power users (*second row* in Figure 4, i.e. Figures 4e through 4h), there is a clear prevalence of self-excitation intensity with respect to other cross-excitation intensities. However, we observe, albeit minor, differences in the short and medium terms between *growing* and *declining* instances, as power users in *growing* instances are more encouraged to participate with new questions as a response to questions by casual users and answers by both (see inlines of Figures 4e, 4g, 4h).

Finding: These observations suggest strong activity by power users, as a response to questions by both power users as well as, crucially, casual users, is related to increased growth in the early stages of Q&A communities. This finding suggests the importance of an active core of users to jumpstart Q&A community development.

Late Casual User Cross-Excitation (■). In Figure 4's *third row* (Figures 4i through 4l), we highlight another type of effect: Answers and discussion by casual users is driven strongly by questions also from casual users, especially in the long-term as highlighted by the green region of Figure 4l. The main difference between *growing* and *declining* instances in this dimension is, besides the intensity magnitude difference, that this cross-excitation effect loses importance in the long-term in the *declining* instances, while overall it does not in *growing* instances. We point out one interesting effect in the *fourth row* (Figures 4m through 4p), which depicts the question intensity dimensions of casual users: In the long term, there is a small increase in questions by casual users after answers also by casual users in *growing* Stack Exchange instances (cf. quarters eight through twelve of Figure 4o).

Finding: Long-term cross-excitation from questions on answers by casual users is a key factor present in *growing* Stack Exchange instances and lacking in *declining* ones. We find contributions by casual users thus attract more participation by casual users, likely helping to sustain and even enhance activity levels. Hence, we identify openness from the community towards casual users in the form of healthy interaction between them as a sign of enduring community growth.

Late Stage Self-Excitation (■). In the diagonal of Figure 4, consisting of Figures 4a, 4f, 4k and 4p, we observe strong and growing self-excitation effects, which dominate over cross-excitation effects in the long-term. We indicate long-term with the pink region marking quarters 8 to 12, the last five quarters we fit. We note this effect is most predominant in *growing* communities. Further, for *growing* instances, notice that, for a given dimension (e.g. answers by power users, Figures 4a through 4d), the timing of the surge in self-excitation coincides in general with a decline in cross-excitation.

Finding: In *growing* Stack Exchange instances, we attribute the phenomenon of higher long-term self-excitation to steadily growing arrivals of questions and answers from power and casual users. As users react to a constantly and regularly growing pool of questions and answers, this makes distinction of direct interaction between single questions and corresponding answers harder over time. The timing of this self-excitation surge may be of particular interest for Q&A community managers, who may be concerned about growth should they not observe this effect by the community's third year.

4.2 Comparison by topic

The comparison between *STEM* and *humanities* instances of Figure 5 shares a few commonalities with our previous findings on the *growing* and *declining* instance comparison: roughly constant and relatively low baseline intensities (not depicted due to limitations in space) and comparatively high long-term self-excitation. In this comparison, we obtained $\beta = 2.067$, which corresponds to an intensity half-life of 0.33 hours. These values are comparable to the ones we obtained previously, which may indicate a universal pattern of user activity decline across Stack Exchange instances.

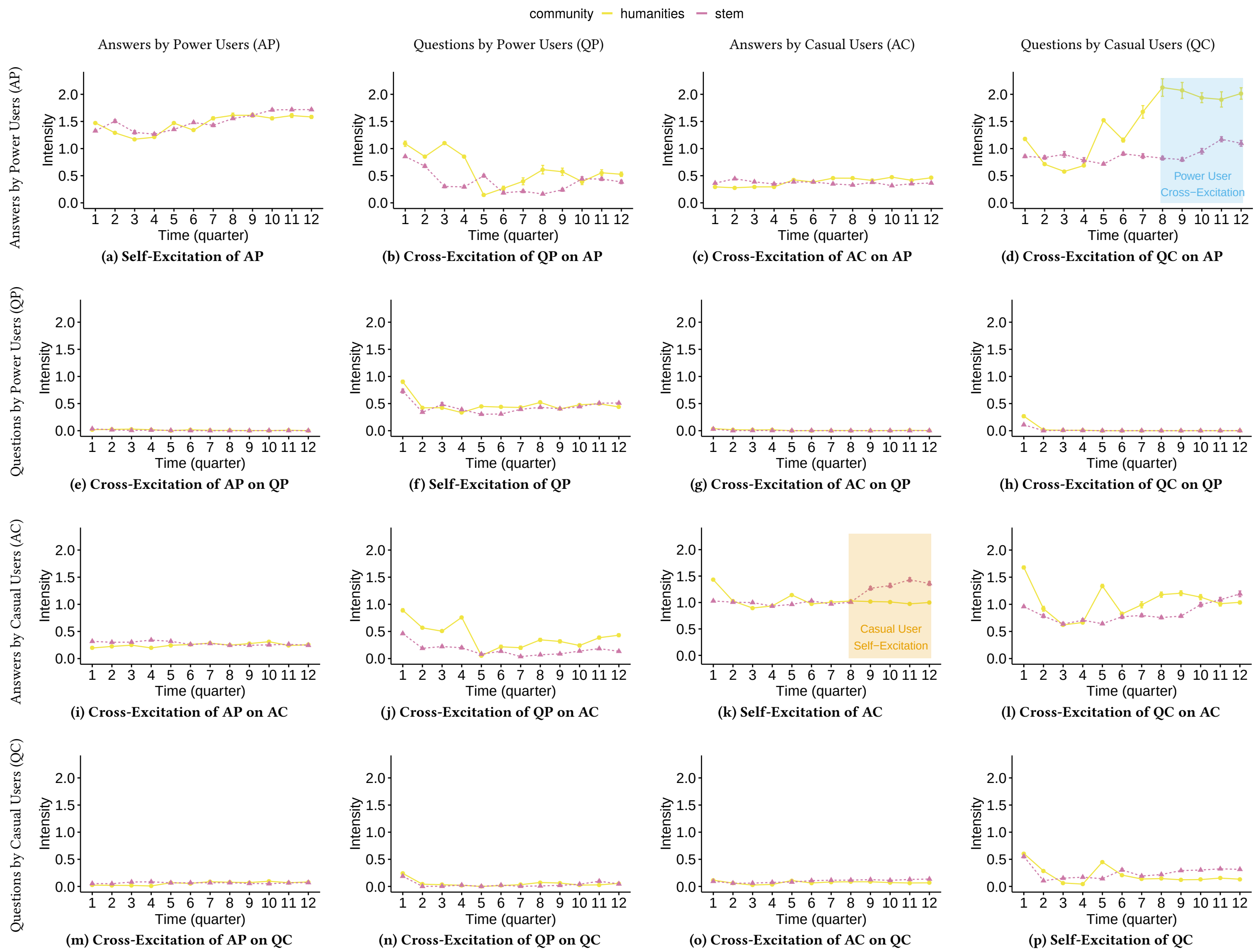
Power User Cross-Excitation (■) vs. Casual User Self-Excitation (■). In the light blue highlighted region of Figure 5d, we stress the notable role of answer activity by power users in *humanities* instances. We observe answers by power users after questions from casual users is notably higher in *humanities* instances than in *STEM* instances (see Figure 5d). With the light orange region of Figure 5k, we underline the counterpart in casual user activity: There are higher long-term intensities in self-excitation of answers by casual users in *STEM* instances as compared to *humanities*.

Finding: In comparison with *STEM* Stack Exchange instances, *humanities* Stack Exchange instances are more reliant on cross-excitation by power users to address questions by both types of users. We observe more power user centric interactions in Stack Exchange instances in the *humanities*, while activity in *STEM* Stack Exchange appears more focused on casual users. Higher long-term self-excitation by casual users in *STEM* instances indicates stronger interactions between casual users. In turn, casual user activity is less dependent on power users in these instances. Overall, this finding suggests the existence of topic-dependent user type structures, which can be cast as measurable goals for community managers.

5 EVALUATION

In this section, we assess whether differences in excitation effects we observe in the evolution of *growing* vs. *declining* (*STEM* vs. *humanities*) instances result by chance or if there is some causal link between excitation, as measured with the Hawkes processes, and community growth (topical focus). Moreover, we evaluate the sizes of the observed effects by quantifying their impact on the future user activity.

Comparison of activity distributions. While the comparison of *growing* vs. *declining* instances aims to distinguish excitation effects in instances of increasing vs. decreasing and thus different total



(a) Self-Excitation of AP (b) Cross-Excitation of QP on AP (c) Cross-Excitation of AC on AP (d) Cross-Excitation of QC on AP

(e) Cross-Excitation of AP on QP (f) Self-Excitation of QP (g) Cross-Excitation of AC on QP (h) Cross-Excitation of QC on QP

(i) Cross-Excitation of AP on AC (j) Cross-Excitation of QP on AC (k) Self-Excitation of AC (l) Cross-Excitation of QC on AC

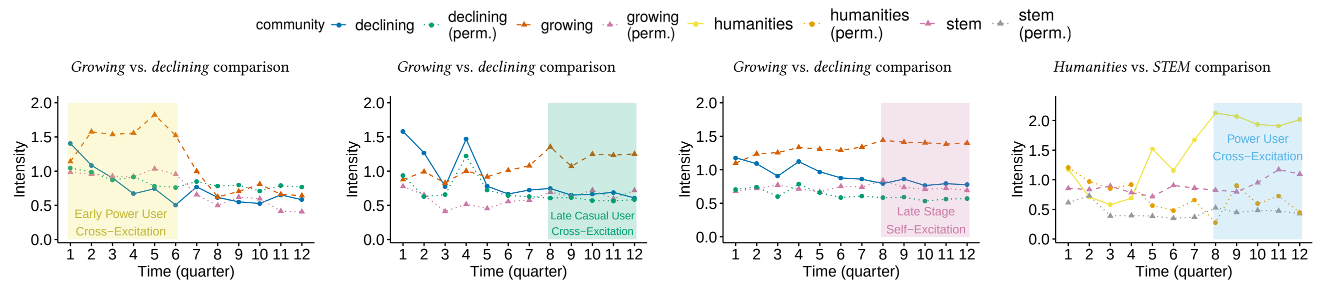
(m) Cross-Excitation of AP on QC (n) Cross-Excitation of QP on QC (o) Cross-Excitation of AC on QC (p) Self-Excitation of QC

Figure 5: Excitation in *humanities* vs. *STEM*. Using the same notation and format as Figure 4, we depict the parameters of the Hawkes processes fitted every three months over three years of Stack Exchange instances dedicated to *STEM* (purple lines) and *humanities* (yellow lines) topics. We observe a more prominent role by power users in *humanities*, as indicated by by the more important role of power user cross-excitation originating from power users answering questions by casual users (cf. blue highlighted region of Figure (d)). Furthermore, regarding casual user activity in *STEM* vs. *humanities* instances, we note the former's casual users feature more prominently in the long-term in the form of higher answer self-excitation (cf. orange highlighted region of Figure (k)).

activity volumes, the *STEM* vs. *humanities* comparison is intended towards providing decoupled effects, which ideally should not be confounded with the excitation effects of *growing* vs. *declining* instances. However, in the *STEM* vs. *humanities* instance comparison, we highlight long-term self-excitation in answers by casual users, an effect which could be similar to the late stage self-excitation of *growing* vs. *declining* instances. Furthermore, if *humanities* instances simply featured overall higher answer-based activity levels by power users than in *STEM* instances, power users would also likely react stronger to questions by casual users, as opposed to them being an inherently more important backbone to questions by casual users.

Hence, we verify if the total answer-based activity distributions of both user types are similar in *STEM* and *humanities* instances. We compare the sample distributions of answers-based activity by power (and separately casual) users in *STEM* vs. *humanities* instances with the Kolmogorov-Smirnov two-sample test for their equality. As this test results in a p-value of 0.3855 (0.2305) for power (casual) users' activity distributions, we conclude there is not enough evidence to reject the null hypotheses of the probability distributions being equal at all usual significance levels. In turn, this test result indicates that the power and casual users' activity distributions are comparable, which supports our finding regarding the importance of the role power (casual) users play in *humanities* (*STEM*) Stack Exchange instances.

Permutation tests. To assess the significance of the excitation effects we conduct the following permutation test. First, we randomly permute the association of event types (questions by power users, questions by casual users, answers by power users and answers by casual users) to the corresponding time stamps per time window.



(a) Permuted Cross-Excitation of Questions by Power Users on Answers by Power Users **(b) Permuted Cross-Excitation of Questions by Casual Users on Answers by Casual Users** **(c) Permuted Self-Excitation of Answers by Casual Users** **(d) Permuted Cross-Excitation of Questions by Casual Users on Answers by Power Users**

Figure 6: Permuting event sources destroys observed excitation effects. We illustrate the temporal evolution of selected cross-excitation effects of multivariate Hawkes process models fitted to both the original (solid lines) as well as the permuted event streams (dashed lines) of the *growing* vs. *declining* and *STEM* vs. *humanities* comparisons of Stack Exchange instances. The permuted event streams in the colored regions of this Figure feature only few of the differences of the original event streams, and, for differences that remain (e.g. of Figure (c)), they are of perceptibly lower magnitude. Hence, the absence of effects in permuted event streams strengthen the significance of our main findings.

This procedure keeps the amount of events per event type constant, but destroys the temporal connection between event types. Then, we refit the multivariate Hawkes processes over windows of these permuted event streams, and we repeat these two steps 100 times. Finally, we compare the difference in mean Hawkes process parameter values fitted on the permuted event streams to the original ones. If there is a notable difference between them, then this indicates that growth (or the evolution of the topical instances) does not come about by chance, but that differences in self-excitation and cross-excitation between *growing* vs. *declining* (*STEM* vs. *humanities*) communities play an important role in their temporal evolution. We depict the result of these permutation tests in Figure 6, in which previously described differences between *growing* vs. *declining* and *STEM* vs. *humanities* Stack Exchange instances are all either remarkably weaker or non-existent. We arrive at similar results with the permutation tests on the other effect not included in Figure 6 (namely casual user self-excitation, in the *STEM* vs. *humanities* comparison). Inspired by Chandrasekharan et al.'s [6] quantification of differences in permutation test distributions, we numerically summarize our permutation tests with a comparison of the absolute difference of *growing* vs. *declining* (*STEM* vs. *humanities*) Hawkes process parameter values fitted on the original event streams with the distribution of absolute differences in parameter values obtained on permuted event streams. If the difference in original values is extreme in relation to the distribution of permuted values in the effects' time spans, then this is further evidence the effects we observe are unlikely to arise by chance. We quantify "extreme" with the p-value, in this case the proportion of values from the permuted difference distribution greater than the original difference. Over the quarters per effect time span, almost all p-values are smaller than or equal to 0.01[3]. Thus, we find the existence of a weak causal link between excitation effects in Stack Exchange instances and their temporal evolution in terms of activity volume.

Prediction experiment. To quantify the impact of the observed excitation effects on future activity, we design the following prediction experiment. For each three-month time window (quarter) and for each *growing* and *declining* Stack Exchange instance, we fit three variants of the Hawkes process, with the same four dimensions as previously: answers by power users, questions by power

[3]Single exception: Early Power User Cross-Excitation in quarter one (p-value 0.04).

Table 2: Kolmogorov-Smirnov (K-S) distance between predicted and real interevent times, per predicted quarter, effect type, Hawkes process dimension and model variant. Lower K-S values are better. Distance values marked with an asterisk correspond to not rejecting equality of simulated and real interevent times. The Full model produces forecasts with lowest K-S distances and highest number of non-significant distances. Thus, as the Excitation Effects Removed model features higher K-S distances than the Full model, we find all excitation effects are important for prediction. To quantify the importance of each excitation effect, we observe removing Late Stage Self-Excitation (■) in the Excitation Effects Removed model is most detrimental for prediction performance (cf. high values in mid-section of four rightmost columns). Hence, Late Stage Self-Excitation is most important for prediction, followed by Early Power User (■) and Late Casual User (■) Cross-Excitation.

		Early Power User Cross-Excitation					Late Casual User Cross-Excitation				Late Stage Self-Excitation			
	Prediction Quarter	**2**	**3**	**4**	**5**	**6**	**9**	**10**	**11**	**12**	**9**	**10**	**11**	**12**
Baseline	Answers by Power	0.26	0.26	0.29	0.27	0.24	0.24	0.25	0.23	0.24	0.24	0.25	0.23	0.24
	Questions by Power	0.3	0.28	0.25	0.25	0.24	0.23	0.24	0.23	0.24	0.23	0.24	0.23	0.24
	Answers by Casual	0.24	0.22	0.25	0.21	0.21	0.2	0.18	0.17	0.18	0.2	0.18	0.17	0.18
	Questions by Casual	0.23	0.16	0.18	0.13	0.12	0.12	0.14	0.13	0.12	0.12	0.14	0.13	0.12
Excitation Effects Removed	Answers by Power	0.15	0.13	0.14	0.12	0.13	0.1*	0.11*	0.11*	0.12	0.43	0.42	0.41	0.42
	Questions by Power	0.28	0.27	0.27	0.26	0.25	0.22	0.24	0.23	0.25	0.3	0.33	0.3	0.31
	Answers by Casual	0.22	0.12	0.16	0.15	0.16	0.15	0.14	0.13	0.14	0.42	0.4	0.39	0.4
	Questions by Casual	0.24	0.19	0.21	0.17	0.17	0.15	0.16	0.16	0.16	0.190	0.19	0.19	0.19
Full	Answers by Power	0.16	0.12	0.12	0.11*	0.11*	0.1*	0.1*	0.1*	0.11*	0.1*	0.1*	0.1*	0.11*
	Questions by Power	0.28	0.24	0.23	0.23	0.22	0.22	0.24	0.22	0.24	0.22	0.24	0.22	0.24
	Answers by Casual	0.23	0.11*	0.15	0.14	0.15	0.12	0.11*	0.11*	0.11*	0.12	0.11*	0.11*	0.11*
	Questions by Casual	0.25	0.16	0.18	0.13	0.13	0.12	0.13	0.13	0.12	0.12	0.13	0.13	0.12

users, answers by casual users and questions by casual users. The Hawkes process variants we consider are (i) a multivariate baseline model (i.e., a multivariate Poisson process), consisting of only baseline excitation $\boldsymbol{\mu}$ (Baseline in Table 2), (ii) a reduced model where we fit a full Hawkes process model but set the model parameters corresponding to the observed excitation effect to zero for quarters in which we observe a given excitation effect (i.e., we set cross-excitation of power users to zero for quarters one to five to remove the effects of Early Power User Cross-Excitation effect, then we set cross-excitation of casual users to zero for quarters eight to eleven to remove Late Casual User Cross-Excitation effect, and finally we set self-excitation of all users to zero also for quarters eight to eleven to remove the effects of Late Stage Self-Excitation effect) (Excitation Effects Removed), and (iii) a full Hawkes process model as defined in Equation 2 (Full), which we fit in the same manner as when uncovering excitation effects.

Overall, Hawkes process-based models such as ours are suited to forecast event timings, as classical machine learning approaches cannot make such time predictions (cf. e.g. Kurashima et al. [19]). Hence, for each variant of the Hawkes process, each Stack Exchange instance, and for each quarter that we fit, we predict the next quarter's event times by simulating the fitted process 100 times. To assess the model's performance we first compute the distribution of interevent times as well as event counts in all dimensions for each simulated and for given observed event sequences. Then, for each simulated quarter, we compute the mean of the Kolmogorov-Smirnov (K-S) test statistic to compare distributions of interevent times (and the root mean squared error (RMSE) to compare the event counts) between simulated and real events. We list the K-S test distance values for each predicted quarter in Table 2. We highlight, with an asterisk, values of the K-S test distance which correspond to not rejecting the hypothesis of equality of simulated and real interevent times at all usual significance levels.

We observe best K-S distance values overall for the Full model, indicating the overall importance of observed excitation effects at every developmental stage of a Stack Exchange instance for prediction experiments. Moreover, the very poor performance of the Excitation Effects Removed model, at times worse than the Baseline model, reinforces the importance of the effects we found for modeling and prediction. However, there seems to be a difference in the impact of different observed effects on the prediction performance. In particular, removing two cross-excitation effects (i.e., Early Power User Cross-Excitation and Late Casual User Cross-Excitation effect) from the models does not impair the performance of those models as strongly as the removal of Late Stage Self-Excitation effect. In Table 2's columns corresponding to the two Cross-Excitation effects, a comparison of predictions by the Excitation Effects Removed model with the corresponding predictions by the Full model reveals their differences in K-S distances lie in the interval $[-0.01, 0.04]$. In these cases, the Full model has only slightly better performance. On the other hand, the impact of the Late Stage Self-Excitation effect dramatically impairs the performance of the Excitation Effects Removed model. The differences between K-S distances in this case (cf. predictions by the Full model and the Excitation Effects Removed model in the Late Stage Self-Excitation columns of Table 2) range from 0.06 to 0.32, indicating a larger effect size of self-excitation than that of cross-excitation.

To further validate these results we perform another prediction experiment with a fourth variant of Hawkes processes. In this variant, we fit self-excitation only models by setting all cross-excitation parameters to zero. These additional experiments with a self-excitation model confirm previous observations: A model with only self-excitation achieves performances (as measured by the K-S distance and by the event count RMSE) in general on par with those of the Full model and, in the Late Stage Self-Excitation effect, even surpassing its performance slightly.

For all model variants we come to comparable conclusions when measuring the RMSE between simulated and real event counts. Limited by space, we summarize these results: The average RMSE of the Full model is 638.17 events, an improvement of 59.91% (43.09%) upon the Excitation Effects Removed (Baseline) model.

6 LIMITATIONS

Although we experimented with slightly different percentiles in the user type distinction and the instance characterization and obtained qualitatively similar results, we recognize those are arbitrary thresholds, which impact the results if changed significantly. Our results are more robust to changes in window size of the activity event stream of the Q&A communities (e.g. to two, four or five months), since this hyperparameter controls for the granularity of our results. Nevertheless, the Hawkes process model itself could include time-varying parameters, as an alternative to this repeated fitting procedure we apply over fixed time windows.

The effect time spans we propose, namely a one-and-a-half-year-long early stage and a late stage starting in the last quarter of the second year of a Q&A community, stem from our empirical observations of large differences in excitation in specific temporal segments in the community comparisons. Pinpointing exact transition dates is beyond the scope of this work, as we focus on learning temporal user excitation effects.

We acknowledge that mapping each user's questions and answers event streams to a Hawkes process dimension may be a more realistic model. However, we argue that such a model would suffer from sparsity, high dimensionality and higher computational cost. Further, such a model might also not improve the excitation effect characterization, as it would also struggle with distinguishing sources of self- and cross-excitation in high-activity regimes.

Note that we avoid a discussion of how casual users become power users with our characterization of power users as the most active each month, regardless of their histories. We believe engagement reward systems such as badges play an important role in casual user's development in particular and user excitation in general [20], but we leave a detailed investigation of the role of reward systems on excitation effects for future work.

We also caution that our work indicates a *temporal* link between (i) specific community structures in terms of user types and their excitation and (ii) the overall development of activity volume in a Stack Exchange community. This work does not establish causality.

7 RELATED WORK

Research on Q&A communities. There is a considerable amount of authors [1, 10, 13, 24, 33, 41] analyzing the roles different types of users play in Web communities such as Q&A websites. In addition, several authors surveyed the motivation and behaviour of individual users [17, 26] of Q&A communities. While Mamykina et al. [24] and Furtado et al. [13] concentrate on uncovering and studying the roles of user types present in thriving Q&A communities, Danescu-Niculescu-Mizil et al. [10] and Yang et al. [41] explicitly focus on specific user types in Web communities and the user types' static and temporal characteristics. More broadly, Yang et al.'s work is part of a larger body of literature [28, 30, 46] on identifying experts in Q&A websites and characterizing their behavior. Our work leverages a comparable user type characterization to infer properties about the temporal evolution of communities themselves.

In approaches methodologically related to Zhang et al.'s [46], multiple authors [3, 25, 31, 38, 39, 43] study evolution dynamics of Web communities by relying on an explicit description of networks underlying a given Web community, and these networks often serve as a basis for dynamical systems models of the communities. In their study of Quora, another Q&A website, Wang et al. [39] analyze the role different social network structures play in Quora's community growth. Ribeiro [31] and Walk et al. [38] model users and activity in diverse Web communities including Q&A communities, with the former focusing on growth and decline of communities and the latter on the model's implications for self-sustainability in a community's activity. Matsubara et al. [25] and Zang et al. [43] study information diffusion and growth dynamics of Web communities.

Similarly to Matsubara et al.'s, Walk et al.'s and Zang et al.'s work, in this paper we also model growth and interaction dynamics of Q&A communities, but we do not assume an underlying network. We focus rather on excitation between groups of users, which we distinguish not on their expertise but on their overall activity levels. Furthermore, by encoding community lifecycles in Hawkes processes fitted to sequences of time windows, we extend the empirical discussion of Web community lifecycles [15, 42] and the critical mass literature [29, 32] to the Q&A community domain with measurable results.

Applications of Hawkes processes. Hawkes processes and their variations, as models for event streams with unequally spaced events in time, have found wide application in literature on different aspects of Web phenomena [12, 16, 36, 37, 44, 47, 48]. One such topic regards content popularity dynamics, in particular how to predict the influence of internal and external aspects of activity in social networks [12] and reshare popularity of items on the Web [47]. To infer causal links between users and user influence from user activity in social networks, Ver Steeg and Galstyan [37], Iwata et al. [16] and Zhou et al. [48] propose point process-related approaches, which cope with high dimensionality in number of users. Further, Upadhyay et al. [36] model the crowdlearning process of Stack Overflow users and characterize different user types by their expertise and learning curves. The work by Zang et al. [44] models and predicts the growth dynamics of individuals' ties in social networks and predicts its evolution.

Our work draws inspiration and methodological know-how from all above mentioned papers to expand on a topic closely related to Zang et al.'s: the development of not just the relatively small circle of an individual's social ties, but of excitation and interaction of user groups in Q&A communities. Furthermore, we contribute, to the growing body of work on fitting Hawkes process kernels [5, 22, 40, 49], a parsimonious Bayesian hyperparameter optimization method for fitting the decay parameter of exponential kernels in Hawkes processes. Finally, our extension of this fitting method to non-stationary multivariate event streams enables the extraction of temporal excitation effects from Q&A communities.

8 CONCLUSIONS

Summary. In this work, we modeled self- and cross-excitation in Q&A communities along several dimensions, including activity type, user engagement level, growth path and topical focus of a given community. We approached this task by fitting multivariate Hawkes processes to stationary temporal segments of Q&A communities' activity volumes. We found stronger cross-excitation of power (casual) users in early (late) stages of growing communities when compared to communities with declining total activity. Further, in growing communities, we observed self-excitation dominates in the long-term. Moreover, we uncovered strong long-term cross-excitation by power (casual) users in Q&A communities dedicated to topics in the fields of the humanities (STEM). We validated the presence of these excitation effects with statistical and permutation tests and we quantified their strength via prediction tasks.

Implications. Our work can support Q&A community managers in their ambition to promote sustainable community structures. To jumpstart community growth in its first six months, engaging a core of power users, for example in community building efforts, appears to be of crucial importance. In the medium- to long-term, we find community developers should carefully monitor and foster participation rather by casual users. While literature on critical mass in Web communities [29, 32] and studies on the user mix in Wikipedia [18, 34] also support this recommendation, we can afford further advice, as our casual cross-excitation analysis specifically underlines the importance of interaction between casual users. In practice, we believe adjusting reward or badge systems to encourage contributions by casual users, perhaps by welcoming newcomers or by easing their adjustment to community rules, would be of value to community development. Furthermore, community managers, which have not observed a surge in self-excitation by the third year of their communities, may have reason to concern over growth. Such excitation effects should be carefully monitored, as Q&A community growth may come at the cost of other community parameters [11]. Furthermore, our results indicate concrete implementations of these suggestions should depend on community topic, as it impacts excitation effects. Overall, our findings thus highlight the impact of timing in the user mix development.

Future work. Comparing other Q&A communities would allow to further generalize the results we obtained on Stack Exchange communities. Our work can be extended to uncover excitation effects in other domains, such as of Q&A instances in other languages or of other contribution types (e.g. open-ended vs. focused question), as our proposed approach is generic and can be readily extended.

ACKNOWLEDGMENTS

We thank the anonymous reviewers for their valuable feedback on the manuscript. Tiago Santos is a recipient of a DOC Fellowship of the Austrian Academy of Sciences at the Institute of Interactive Systems and Data Science of the Graz University of Technology.

REFERENCES

[1] Lada A. Adamic, Jun Zhang, Eytan Bakshy, and Mark S. Ackerman. 2008. Knowledge Sharing and Yahoo Answers: Everyone Knows Something. In *Proceedings of the 17th International Conference on World Wide Web (WWW'08)*. ACM, 665–674.

[2] Ashton Anderson, Daniel Huttenlocher, Jon Kleinberg, and Jure Leskovec. 2013. Steering User Behavior with Badges. In *Proceedings of the 22nd International Conference on World Wide Web (WWW'13)*. ACM, 95–106.

[3] Roy M Anderson, Robert M May, and B Anderson. 1992. *Infectious Diseases of Humans: Dynamics and Control*. Vol. 28. Wiley Online Library.

[4] James Bergstra, Daniel Yamins, and David Cox. 2013. Making a Science of Model Search: Hyperparameter Optimization in Hundreds of Dimensions for Vision Architectures. In *Proceedings of the 30th International Conference on Machine Learning (ICML'13)*. 115–123.

[5] Qi Cao, Huawei Shen, Keting Cen, Wentao Ouyang, and Xueqi Cheng. 2017. DeepHawkes: Bridging the Gap between Prediction and Understanding of Information Cascades. In *Proceedings of the ACM on Conference on Information and Knowledge Management (CIKM'17)*. ACM, 1149–1158.

[6] Eshwar Chandrasekharan, Umashanthi Pavalanathan, Anirudh Srinivasan, Adam Glynn, Jacob Eisenstein, and Eric Gilbert. 2017. You Can't Stay Here: The Efficacy of Reddit's 2015 Ban Examined Through Hate Speech. In *Proceedings of the 2017 Conference on Computer Supported Cooperative Work (CSCW'17)*. ACM, 31–53.

[7] David Roxbee Cox and Valerie Isham. 1980. *Point processes*. Vol. 12. CRC Press.

[8] Daryl J Daley and David Vere-Jones. 2003. *An Introduction to the Theory of Point Processes: Volume I: Elementary Theory and Methods*. Springer Science & Business Media.

[9] Daryl J Daley and David Vere-Jones. 2008. *An Introduction to the Theory of Point Processes: Volume II: General Theory and Structure*. Springer Science & Business Media.

[10] Cristian Danescu-Niculescu-Mizil, Robert West, Dan Jurafsky, Jure Leskovec, and Christopher Potts. 2013. No Country for Old Members: User Lifecycle and Linguistic Change in Online Communities. In *Proceedings of the 22nd International Conference on World Wide Web (WWW'13)*. ACM, 307–318.

[11] Himel Dev, Chase Geigle, Qingtao Hu, Jiahui Zheng, and Hari Sundaram. 2018. The Size Conundrum: Why Online Knowledge Markets Can Fail at Scale. In *Proceedings of the 2018 World Wide Web Conference (WWW'18)*. ACM, 65–75.

[12] Mehrdad Farajtabar, Nan Du, Manuel Gomez Rodriguez, Isabel Valera, Hongyuan Zha, and Le Song. 2014. Shaping Social Activity by Incentivizing Users. In *Advances in Neural Information Processing Systems (NIPS'14)*. 2474–2482.

[13] Adabriand Furtado, Nazareno Andrade, Nigini Oliveira, and Francisco Brasileiro. 2013. Contributor profiles, their dynamics, and their importance in five q&a sites. In *Proceedings of the 2013 Conference on Computer Supported Cooperative Work (CSCW'13)*. ACM, 1237–1252.

[14] Alan G Hawkes. 1971. Spectra of some self-exciting and mutually exciting point processes. *Biometrika* (1971), 83–90.

[15] Alicia Iriberri and Gondy Leroy. 2009. A life-cycle perspective on online community success. *ACM Computing Surveys (CSUR)* 41, 2 (2009), 11.

[16] Tomoharu Iwata, Amar Shah, and Zoubin Ghahramani. 2013. Discovering Latent Influence in Online Social Activities via Shared Cascade Poisson Processes. In *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD'13)*. ACM, 266–274.

[17] Jiahua Jin, Yijun Li, Xiaojia Zhong, and Li Zhai. 2015. Why Users Contribute Knowledge to Online Communities: An Empirical Study of an Online Social Q&A Community. *Information & management* 52, 7 (2015), 840–849.

[18] Aniket Kittur, Ed Chi, Bryan A. Pendleton, Bongwon Suh, and Todd Mytkowicz. 2007. Power of the Few vs. Wisdom of the Crowd: Wikipedia and the Rise of the Bourgeoisie. In *Proceedings of the Alt.CHI Conference on Human Factors in Computing Systems (Alt.CHI'07)*.

[19] Takeshi Kurashima, Tim Althoff, and Jure Leskovec. 2018. Modeling Interdependent and Periodic Real-World Action Sequences. In *Proceedings of the 2018 World Wide Web Conference (WWW'18)*. ACM, 803–812.

[20] Tomasz Kusmierczyk and Manuel Gomez-Rodriguez. 2018. On the Causal Effect of Badges. In *Proceedings of the 2018 World Wide Web Conference (WWW'18)*. ACM, 659–668.

[21] Kenneth Levenberg. 1944. A method for the solution of certain non-linear problems in least squares. *Quarterly of applied mathematics* 2, 2 (1944), 164–168.

[22] Sha Li, Xiaofeng Gao, Weiming Bao, and Guihai Chen. 2017. FM-Hawkes: A Hawkes Process Based Approach for Modeling Online Activity Correlations. In *Proceedings of the ACM on Conference on Information and Knowledge Management (CIKM'17)*. ACM, 1119–1128.

[23] Thomas Josef Liniger. 2009. *Multivariate Hawkes Processes*. Ph.D. Dissertation. ETH Zurich.

[24] Lena Mamykina, Bella Manoim, Manas Mittal, George Hripcsak, and Björn Hartmann. 2011. Design Lessons from the Fastest Q&A Site in the West. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI'11)*. ACM, 2857–2866.

[25] Yasuko Matsubara, Yasushi Sakurai, B Aditya Prakash, Lei Li, and Christos Faloutsos. 2012. Rise and Fall Patterns of Information Diffusion: Model and Implications. In *Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD'12)*. ACM, 6–14.

[26] Meredith Ringel Morris, Jaime Teevan, and Katrina Panovich. 2010. What Do People Ask their Social Networks, and Why?: A Survey Study of Status Message Q&A Behavior. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI'10)*. ACM, 1739–1748.

[27] Yosihiko Ogata. 1981. On Lewis' Simulation Method for Point Processes. *IEEE Transactions on Information Theory* 27, 1 (1981), 23–31.

[28] Aditya Pal, Shuo Chang, and Joseph A Konstan. 2012. Evolution of Experts in Question Answering Communities. In *Proceedings of the Sixth International Conference on Web and Social Media (ICWSM'12)*. 274–281.

[29] Daphne R Raban, Mihai Moldovan, and Quentin Jones. 2010. An Empirical Study of Critical Mass and Online Community Survival. In *Proceedings of the 2010 Conference on Computer Supported Cooperative Work (CSCW'10)*. ACM, 71–80.

[30] Fatemeh Riahi, Zainab Zolaktaf, Mahdi Shafiei, and Evangelos Milios. 2012. Finding expert users in community question answering. In *Proceedings of the 21st International Conference on World Wide Web (WWW'12)*. ACM, 791–798.

[31] Bruno Ribeiro. 2014. Modeling and Predicting the Growth and death of membership-based websites. In *Proceedings of the 23rd International Conference on World Wide Web (WWW'14)*. ACM, 653–664.

[32] Jacob Solomon and Rick Wash. 2014. Critical Mass of What? Exploring Community Growth in WikiProjects. In *Proceedings of the Eight International Conference on Web and Social Media (ICWSM'14)*. 476–484.

[33] Ivan Srba and Maria Bielikova. 2016. A Comprehensive Survey and Classification of Approaches for Community Question Answering. *ACM Transactions on the Web (TWEB)* 10, 3 (2016), 18.

[34] Bongwon Suh, Gregorio Convertino, Ed H Chi, and Peter Pirolli. 2009. The Singularity Is Not Near: Slowing Growth of Wikipedia. In *Proceedings of the 5th International Symposium on Wikis and Open Collaboration*. ACM.

[35] Behzad Tabibian, Isabel Valera, Mehrdad Farajtabar, Le Song, Bernhard Schölkopf, and Manuel Gomez-Rodriguez. 2017. Distilling Information Reliability and Source Trustworthiness from Digital Traces. In *Proceedings of the 26th International Conference on World Wide Web (WWW'17)*. ACM, 847–855.

[36] Utkarsh Upadhyay, Isabel Valera, and Manuel Gomez-Rodriguez. 2017. Uncovering the Dynamics of Crowdlearning and the Value of Knowledge. In *Proceedings of the Tenth ACM International Conference on Web Search and Data Mining (WSDM'17)*. ACM, 61–70.

[37] Greg Ver Steeg and Aram Galstyan. 2012. Information Transfer in Social Media. In *Proceedings of the 21st International Conference on World Wide Web (WWW'12)*. ACM, 509–518.

[38] Simon Walk, Denis Helic, Florian Geigl, and Markus Strohmaier. 2016. Activity Dynamics in Collaboration Networks. *ACM Transactions on the Web (TWEB)* 10, 2 (2016), 11.

[39] Gang Wang, Konark Gill, Manish Mohanlal, Haitao Zheng, and Ben Y Zhao. 2013. Wisdom in the Social Crowd: An Analysis of Quora. In *Proceedings of the 22nd International Conference on World Wide Web (WWW'13)*. ACM, 1341–1352.

[40] Hongteng Xu, Mehrdad Farajtabar, and Hongyuan Zha. 2016. Learning Granger Causality for Hawkes Processes. In *Proceedings of the 33rd International Conference on Machine Learning (ICML'16)*. 1717–1726.

[41] Jie Yang, Ke Tao, Alessandro Bozzon, and Geert-Jan Houben. 2014. Sparrows and Owls: Characterisation of Expert Behaviour in StackOverflow. In *User Modeling, Adaptation, and Personalization*. Springer, 266–277.

[42] Colleen Young. 2013. Community Management that Works: How to Build and Sustain a Thriving Online Health Community. *Journal of Medical Internet Research* 15, 6 (2013).

[43] Chengxi Zang, Peng Cui, and Christos Faloutsos. 2016. Beyond Sigmoids: The Nettide Model for Social Network Growth, and its Applications. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD'16)*. ACM, 2015–2024.

[44] Chengxi Zang, Peng Cui, Christos Faloutsos, and Wenwu Zhu. 2017. Long Short Memory Process: Modeling Growth Dynamics of Microscopic Social Connectivity. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD'17)*. ACM, 565–574.

[45] Achim Zeileis, Christian Kleiber, Walter Krämer, and Kurt Hornik. 2003. Testing and Dating of Structural Changes in Practice. *Computational Statistics & Data Analysis* 44 (2003), 109–123.

[46] Jun Zhang, Mark S Ackerman, and Lada Adamic. 2007. Expertise Networks in Online Communities: Structure and Algorithms. In *Proceedings of the 16th International Conference on World Wide Web (WWW'07)*. ACM, 221–230.

[47] Qingyuan Zhao, Murat A Erdogdu, Hera Y He, Anand Rajaraman, and Jure Leskovec. 2015. Seismic: A Self-Exciting Point Process Model for Predicting Tweet Popularity. In *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD'15)*. ACM, 1513–1522.

[48] Ke Zhou, Hongyuan Zha, and Le Song. 2013. Learning Social Infectivity in Sparse Low-Rank Networks Using Multi-Dimensional Hawkes Processes. In *Artificial Intelligence and Statistics*. 641–649.

[49] Ke Zhou, Hongyuan Zha, and Le Song. 2013. Learning triggering kernels for multi-dimensional hawkes processes. In *Proceedings of the 30th International Conference on Machine Learning (ICML'13)*. 1301–1309.