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A Community Ecology Approach for Identifying Competitive and Mutualistic Relationships Between Online Communities

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A growing body of research in social computing has shown how online groups affect each other's group sizes as people, content, and ideas flow between groups. How can researchers and designers understand the relationship between these inter-group interactions and group sizes over time? Inspired by population ecology theory and methods, prior HCI research correlated group size with overlapping content and membership with all other groups. The results yield a puzzling body of evidence suggesting that overlap will sometimes help and sometimes hurt. We suggest that these confusing results are caused by aggregating inter-group relationships into an overall effect of an environment that ignores the rich network of varying relationships between specific online groups. To capture these dynamics, we propose a theoretical framework based on community ecology and propose a method for inferring competitive and mutualistic relationships from time-series participation data. We demonstrate our approach and its benefits for social computing research through analyses of simulated data and of three real networks of groups hosted by Reddit.

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1 INTRODUCTION

Online groups are important places where people collaborate to produce information sources, engage in discussions and participate in culture.[1] Although the fact is frequently ignored in social media scholarship, online groups do not exist in isolation. Indeed, a growing body of HCI scholars have shown how online groups spawn new groups, wage conflicts against each other, compete with each other, and help each other in a range of ways. When people move between groups they transport experience, knowledge, and culture [19, 57, 68]. This emerging body of work has demonstrated that a full understanding of online groups involves understanding how they relate to one another.

[1]We use the term "online group" as interchangeable with "online community" to help avoid confusion with our analytical term "community ecology."

Prior investigations of interdependence between online groups in HCI and social computing draw from ecology [64, 67, 68]. Ecology has been fruitfully applied to human organizations ranging from commercial industries to social movements for over 40 years [5, 30], and is thus a natural approach for understanding interdependence between online groups. However, there remain very few explicitly ecological studies of online groups and those that exist yield a puzzling body of results. This research has shown that groups whose members overlaps with other groups are associated with increased survival in wikis [67], but with increased failure in Usenet groups [64]. In some settings, the relationship between topical overlaps and performance follows theoretical predictions that moderate overlap should lead to the the best outcomes [67], while studies in other settings find weak or theoretically inconsistent relationships [57, 60].

We argue that a path to increased clarity involves first recognizing that there are two distinct strands of ecological theory that may be applicable to social computing but that these strands—called *community ecology* and *population ecology*—have different levels of analysis and make different theoretical predictions [2]. Population ecology considers the dynamics *within a population* such as a biological species or relatively homogenous organizational form like a newspaper. The earliest and most influential works of ecology as applied to human organizations have used the population ecology approach to answer questions such as those about how organizational forms become established or decline [1]. This approach requires treating a population as consisting of entities with similar resource needs while ignoring the distinct roles that individual groups play. Population ecology has framed every ecological analysis of online groups published in social computing venues that we are aware of.

Community ecology is a distinct approach that adopts a higher level of analysis to consider dynamics within an *ecological community* comprised of heterogeneous and interdependent populations [2]. In biology, this might be those organisms inhabiting a lake or valley. In organization science, this might be the network of technology developers, manufacturers, and suppliers in the semiconductor industry [52, 62]. Community ecology is also of considerable influence in organization science [e.g. 2, 4, 46, 48, 52, 54]. To our knowledge, community ecology theories have never been invoked in HCI or social computing research.

However, while ecological studies of online groups like those by Wang et al. [64], Zhu et al. [68], and Zhu et al. [67] are consistently framed in terms *population ecology* theory, their empirical analyses incorporate elements of *community ecology*. Although ecological studies in social computing have focused on overlapping resources like topics and participants, theories of *population ecology* focus on homogenous populations and are thus simply not designed to explain these phenomena. The ultimate result, we believe, is the confusion that ecological studies in social computing are mired in today.

Population ecology studies of resource overlaps in HCI measure the degree to which a groups's participants or topics overlap with every other group is correlated growth or survival. Thus they treat competition and mutualism as environmental forces. While these forces may emerge from relationships between groups, the relationships themselves are obscured through aggregation into overlaps. In this paper, we describe and demonstrate a novel community ecology approach to studying online groups that emphasizes how different online groups have heterogeneous roles and corresponding resources which give rise to competitive or mutualistic relationships between groups. In doing so, we make distinct theoretical and methodological contributions to HCI and social computing scholarship.

First, we contribute to theory by providing a framework that supports a conceptual shift from treating individual online groups as indistinct parts of an ecological environment to treating them as belonging to a ecological community of related entities. Where prior approaches aggregate individual relationships between groups, our approach makes it possible to answer critical questions like "Which are a given online groups strongest mutualists or competitors?." In the process, our theoretical work brings clarity to a confusing set of empirical results in prior research. Our second contribution is to introduce a statistical method for inferring networks of competitive and mutualistic relationships from time-series of participation activity using vector autoregression (VAR) models [13, 38, 55]. We validate our method using simulated data to show that it can identify a full range of ecological relationships and we conduct a series of three case studies of groups hosted on the platform Reddit. Although limited, these analyses make a third contribution in the form of empirical findings that suggest that specific patterns of relationships vary substantially across networks of groups and mutualism appears to be much more common than competition.

2 BACKGROUND

Our contributions build on a body of existing theoretical work from social computing that theorizes online groups as depending on several distinct types of resources as well as a body of ecological research in social computing conducted over the last decade. We briefly summarize both before introducing our conceptual approach.

2.1 Online groups depend on resources

Online groups are important social structures built to serve a wide range of goals [8, 21, 44]. While many online groups are formed, only an extreme minority grow or develop a sizable and sustained group of participants [39, 43]. Understanding why some groups take off while others do not or fall into decline is important because whether an online group can achieve its goals depends on attracting and retaining and pool of contributors [44].

Ecological approaches to explaining the growth of online groups build on a theoretical approach that treats resources contributed by participants such as content, information, attention, or social interactions as playing a role in motivating participation by subsequent participants [10, 64, 66]. Although this dynamic implies a positive feedback loop, groups clearly do not grow forever and increasing costs of participation will eventually limit further growth [10]. While factors such as leadership, organizational practices, network structure, and design decisions can lower costs and benefits of participation in a group [10, 43, 61], institutions intended to improve quality in large groups appear to limit growth. For example, the end of English Wikipedia's growth in early 2007 can be explained by barriers to newcomer participation erected during its growth phase [29] in a pattern observed in other collaborative knowledge production projects [59].

Of course, the nature of particular resources is clearly important to resource-based theories and online group research has been particularly concerned with *rival* resources that becomes unavailable for use by others when used by any one group [8, 45, 51, 53]. Interdependence between online groups can be important to explaining their growth, decline and survival because important rival resources like the time, attention, and efforts of participants are are subject to competition between groups. Although opportunity costs of participation mean that people will not participate in a group if they prefer alternatives like sleep, enjoyment of entertainment, or work [7, 11], participation in a related online group providing the same benefits at lesser costs might be a compelling alternative. In this way, declines in online participation can sometimes be explained in terms of competition over rival resources [64].

On the other hand, not all resources important to online groups will be subject to competition. Some groups produce connective and communal public goods in the form of opportunities to communicate and beneficial information [27] which can be non-rival or even "anti-rival" when their usefulness increases as a result of others using them [45, 65]. For example, the usefulness of a communication network increases as more people join it [27, 41]. Similarly, the usefulness of an information good can increase as more people come to know and depend upon it [45, 65]. For example, awareness of an audience can motivate participation in online groups [66]. If multiple online groups help build the same connective or communal public goods, they may form *mutualistic* relationships with one another such that contributions to one group may "spill over" and motivate participation in related groups [68].

Even though online groups are likely to share or compete over resources, studying interdependence between online groups adds enormous complexity to research projects [36]. Despite the challenges, a growing body of empirical research in social computing has sought to quantify how online groups can share users or topics [19, 20, 34, 58] and how interactions between groups relate to outcomes like the emergence of new groups [57], contributions to peer produced knowledge [63], and the spread of hate speech [17]. In these ways, existing research establishes that online groups interact in important ways. However, few general theories or theoretical frameworks exist with which to understand how forms of interdependence between online groups shape their growth or survival.

2.2 Ecological research in social computing

We follow theoretical approaches to the study of interdependence between online drawing from ecology. While our work focuses on the ecological study of online groups, other social computing scholars like Nardi and O'Day [49] have used the term "ecology" and related concepts like "ecoystem" and "environment" as metaphors denoting assemblages of sites, technologies, or platforms. We use the term in a more narrow sense to refer to the conceptual and mathematical models of ecological dynamics as in biological, social, and communication systems. In particular, our work builds on a tradition rooted in *organizational ecology*. First developed in the late 1970s by sociologists studying interrelatedness between firms, organizational ecology was inspired by and has drawn closely from ecological studies in biology [30].

Because online groups bear many similarities to traditional organizations, organizational ecology provides a theoretical framework for understanding interdependence between online groups and has been adopted by at least three empirical studies of how the resources shared between online groups shape the growth, decline, or survival of online groups [64, 67, 68]. All three take up propositions of density dependence theory which sees competitive or mutualistic forces in a population of groups as a function of *density*. In the earliest and most influential strands of organizational ecology, density is simply the number of members in a *population* [1].

Density dependence theory proposes a trade-off between positive and negative consequences of density such that low levels of density are associated with resource-scarce environments unable to support a large population but high levels of density lead to competition. Low levels of density reflect limited opportunities for mutualistic relationships that contribute to shared non-rival resources like legitimacy, connectivity, or knowledge, but when density is high it becomes difficult to avoid competitive relationships. Thus density aggregates individual relationships.

Models of density dependence theory in population ecology have a similar form to the models of resource dependence described in §2.1. Just as online group growth is thought to be driven by the attraction of new members to the contributions of prior participants, so growth in an organizational population is driven by positive feedback as successful organizations legitimate a business model and attract new organizations to enter the market. In an analagous way, a population of online groups may grow as their platform gains in popularity, as existing groups spin off new ones, and as useful knowledge develops that can be shared between groups [57, 68]. An individual online group's growth may be limited by the ability of their social structures to scale to include more members [10] or due to competition with other groups over members just as firms compete over employees, customers, or financial resources [31]. Similarly, population of online groups may decline if they compete with one another over participants.

While the foundational studies of density dependence in organizational research study density and growth at the population level, ecological studies of online groups model a different notion of density dependence based on the concept of *overlap density*.[2] Rather than the number of groups that exist in a population, overlap density measures the extent to which an individual group's members or topics overlap with all other groups. Thus overlap density is not a property of a population of groups, but a property of the resource environment an individual group faces.

In contrast to biological species, this approach does not assume a population is homogeneous, but comprised of diverse individuals having different *niches* corresponding to their resource needs [1]. This is plausible in the case of online groups sharing a platform with diverse topics [40], norms [18, 24], and user bases [58]. Yet results from studies of overlap density in populations of online groups are inconsistent both with each other and with theoretical predictions of density dependence theory. For example, Wang et al. [64] study user overlaps in Usenet newsgroups and find these are associated with decreasing numbers of participants. Similarly, TeBlunthuis et al. [60] find that topical overlaps between online petitions are negatively associated with participation. By contrast Zhu et al. [68] find that membership overlap is positively associated with increasing survival of new Wikia wikis. Only Zhu et al. [67] find support for the curvilinear relationship predicted by density dependence theory as topical overlaps are associated with increasing activity at low levels of overlap and with decreasing activity at high levels of overlap.

[2]Although it is less common in organizational research, overlap density has also been used by some organizational ecologists [e.g. 22].

3 A COMMUNITY ECOLOGY APPROACH FOR SOCIAL COMPUTING

Now we propose a community ecology approach to the study of online groups defined by the recognition of relationships between online groups and the networks formed of these relationships as a focal object of study. Our focus is on relationships that affect membership sizes of groups and on networks of relationships that make visible the distinctive roles that particular groups play in the the broader ecological community.

Overlap density has been useful for advancing ecological theory and empirical analysis of online groups. It provides a way to characterize the environment that an online group faces in terms of the resources it may share with other groups. As noted above in §2.1, empirical studies of some studies of online groups find that higher levels of of overlap density are associated with decreasing group sizes in some contexts but increasing growth or survival in other contexts. We propose that these puzzling results are due to how overlap density aggregates a group's many relationships into a property of the group's environment.

Consider the example of how Zhu et al. [68] find membership overlap is associated with increasing survival of new Wikia wikis, but in Wang et al.'s [64] study of Usenet groups user overlaps are associated with decreasing group sizes. One possible reasons for these inconsistent findings is that factors other than topic or user overlaps can lead to competitive and mutualistic forces on the growth and survival of online groups. During Zhu et al.'s [68] study period, Wikia was a growing platform and they found a stronger relationship when overlapping members were from more established groups. Perhaps the growth Wikia wikis was limited by knowledge of how to build a Wiki which was provided by more experienced users and user overlaps were correlated with access to such knowledge. While Usenet was a mature platform (in fact it was in decline) during Wang et al.' [64] study period and thus not limited by such resources.

In general, competition over overlapping resources may have no affect on group growth if growth is limited by something other than the resource subject to competition. Ecologists of biological organisms understand that different populations might consume the same resource (e.g. eating the same food, sharing the same habitat), but if the resource is so abundant that neither population's growth is limited by the resource (instead something else, like a predator or a different resource limits population growth), different populations may not compete over it [62]. Further, those resources that do limit growth may be unobserved. Thus our community ecology approach begins by relaxing the assumption that competition and mutualism are driven by observable resource overlaps.

A second possible reason for prior inconsistent findings is that user and topic overlaps may indicate groups are related to one another, but that the overall amount that a particular groups overlaps with others is a poor proxy for the degree to which its size is limited by a competitive or mutualistic environment. It may simply be that user overlaps indicate that two groups are related and that in Zhu et al.'s [68] context most relationships were mutualistic but in Wang et al.' [64] most were competitive. Also, differences in communication modalities between discussion groups and Wikis are associated with different resource needs and thus different relationships between user overlaps and competitive or mutualistic ties.

The logic of density dependence is that at high levels of resource overlap competitive mechanisms will be more powerful than mutualistic ones. But this argument depends on assumptions of a relatively homogeneous population where all individuals have similar needs for rival resources. However, the inconsistent findings of population ecology analyses in social computing suggest that online groups likely do not have homogenous resource needs. Overlap density takes an indirect approach to understanding competition or mutualism between online groups based on correlating the extent a focal group's users or content overlaps with all other grups with that group's subsequent growth. Importantly, it does not infer whether or not two groups are competitors or mutualists. The community ecology approach we propose opens such relationships up to investigation. While varying conceptions of community ecology are found in the literature on organizational ecology [25], our approach follows Aldrich and Ruef [1] and Hawley [32]. While population ecology analyzes populations, community ecology aims to understand how different groups shape each other's growth, survival, and evolution [1, 2]. In organizational science, this can mean studying relationships between different organizational populations [e.g. 47, 56], or networks relationships between organizations [e.g 46, 52].

Table 1. The five possible commensal relationships between two online groups. Values in the column "A → B" represent the sign of hypothetical group A's effect on group B. Based on table 11.1 from Aldrich and Ruef [1].

A → B	B → A	Relationship type
+	+	Full mutualism
+	·	Partial mutualism
+	−	Predation
−	·	Partial competition
−	−	Full competition

We propose a community ecology approach for social computing that, in an analogous way, seeks to theorize the relationships between different online groups. Our approach follows community ecology in biology and organization science by seeking to understand *commensal* relationships between groups [1]. A commensal relationship is a way groups affect one another through changes in population. A group may have a commensal influence another group in three ways. *Mutualism* is when one group has a positive influence on the second such that growth (decline) in the first group leads to growth (decline) in the second. *Competition*, is where one group has a negative effect on the second such that growth (decline) in the first group leads to decline (growth) in the second. It is of course possible that growth or decline in the first group has no effect on the second group, a situation termed *neutrality*.

There are five possible commensal relationships as described in Table 1. Note that commensal relationships can be reciprocal (as in full mutualism and competition) or not (as in partial mutualism and competition. In our framework "predation" (also called parasitism) refers to cases where a relationship is positive in one direction but negative in the other. With commensalism in view we can seek to explain puzzling results of resource overlap studies by asking questions like "What kinds of resource overlaps between two groups are associated with mutualism or competition?" or "Do groups that overlap more with more other groups have more (or stronger) mutualistic or competitive relationships?"

Ecological dynamics play out through the network of such relationships over time as represented by the *community matrix*. Analysis of the community matrix can reveal indirect relationships between groups and properties of an ecological community like stability [38]. Seeing interdependence between online groups through a community ecology-based network of dynamical relationships can make visible special roles that particular groups play in a community ecology through their many mutualistic or competitive relationships.

Community ecology can provide a bridge between quantitative studies of participation in online groups and broader theories of interconnected information ecologies [49]. While we focus on relationships between groups sharing a platform, one can apply our concepts and methods to understand how interdependent systems of technologies and users give rise to the development of higher levels of social organization such as entire social media platforms [1, 2].

4 METHODS

4.1 Vector Autoregression Models

Here we review the prior work on which we build our methodological approach to inferring competitive and mutualistic relationships between online groups. §4.3 describes our own methodological contributions.

Our goal is to infer the "community matrix" of commensal relationships between groups which is a central analytical object in community ecology both in biological and organizational ecology [1, 50, 62]. Yet limitations of available data and statistical challenges mean that organizational scientists rarely attempt to estimate the full community matrix [e.g. 54, 56].

We take advantage of advances in tools for statistical inference and of granular behavioral trace data from online groups to use vector autoregression (VAR) models, an established approach in biological ecology, to infer ecological networks of commensal relationships. VAR models are a workhorse in biological ecology because VAR(1) models (i.e., VAR models with a single autoregressive term) have a close relationship to Gompertz models of population growth, which are themselves similar to the Lotka-Volterra self-limiting growth models used in Butler's [10] resource dependence framework from social computing [38]. Certain et al. [16] demonstrate using a simulation that even in the presence of unmodeled nonlinearities, VAR(1) models can reliably identify competition or mutualism between species in empirically realistic scenarios.

VAR models have also been widely adopted in the social sciences, particularly in political science and in macroeconomics Box-Steffensmeier [9]. They are flexible enough to model a wide range of systems so long as sufficiently long time-series data are available Sims [55]. They can be intuitively understood as a generalization of a one-dimensional auto-regressive AR models in time series analysis. But while AR models predict state of a single time-series variable as a function of its previous values, VAR models simultaneously predict multiple time series variables as a function of the values of every other variable in the system [13]. A VAR(1) model has the form:

$$Y_t = B_0 + \mathbf{B}X_t + \Phi Y_{t-1} + \epsilon_t \tag{1}$$

Where Y_t is a vector of of length m. The parameter B_0 is a vector of intercept terms. Φ is a matrix where the diagonal elements are intrinsic growth rates for each element of Y and the off-diagonal elements are the influence between different variables. Additional predictors can be included in X_t, and ϵ_t is the error term.

~~4.2 Impulse responses~~

The parameter Φ in a VAR(1) model encodes the "community matrix" ~~in community ecology as direct associations between growth in one group and subsequent growth in another~~ [50]. ~~But~~ VAR models ~~also~~ capture "net effects," which include indirect relationships between groups ~~accounting for responses of all groups to one another~~. Consider relationships between three groups (A, B, C) such that A partially competes with B and B partially competes with C but A and C have no direct relationship. A VAR(1) model inferring these relationships will have negative coefficients $\phi_{A,B}$ and $\phi_{B,C}$ and $\phi_{A,C}$ will be nearly zero.

However, This does not mean that groups A and C are independent~~. Rather~~ because an exogenous increase in A will cause a decrease in B and thereby an eventual increase in C. Indirect relationships like these can be inferred by using impulse response functions (IRFs) to interpret a VAR model [9]. ~~Often~~ In large VAR models the great number of parameters can mean that few specific elements of Φ will be statistically significant, ~~but~~ while the cumulation of many weak relationships ~~can~~ might yield a statistically significant impulse response function [13].

4.3 Inferring the community matrix for social computing systems

Most ~~Traditionally~~ VAR models in ~~both~~ macroeconomics and biological ecology are fit using ordinary least squares, an approach which relies on assumptions that will be difficult to sustain the online group settings of our interest. The number of parameters in the model increases quadratically with the number of variables in the system which can lead to over-fitting and estimation difficulties. For models fit using OLS, non-normal errors can lead to bias. A Bayesian vector autoregression approach can overcome such limitations [3, 12]. This allows the use of hierarchical priors which pull estimates towards 0 and thereby help correct for multiple hypothesis tests [28].

We extend equation 1 to include a Poisson link function and a hierarchical Bayesian prior structure. We use a Poisson link function in order to model count data for groups with smaller numbers of participants. In our model Y_t is a ~~distributed~~ count of participants distributed according to a parameter λ_t which has a multivariate normal distribution evolving over time according to a VAR process. The parameter Φ corresponds to the community matrix as described in §4.1 ~~with off-diagonal entries representing competition or mutualism coefficients for commensal relationships between groups and diagonal entries representing intrinsic growth rates~~. We use X_t to account for seasonality in as described ~~one of~~ our case studies.

consistent

We use impulse response functions to quantify how much a group's size will change in response to a ~~an impulse~~ sudden increase in the size of another group represented by Θ_0, which is an identity matrix so our impulses represent a log-unit increase of 1. Our models have a latent VAR process which we ~~and then~~ transform ~~it~~ into a count variable through a Poisson link. a As shown in Equation 2, to interpret IRFs in terms of the number of members of a group, we transform them using a baseline of the median number of participants in a group over the study period, $(\widetilde{Y}_i)$ and exponentiating to obtain Θ_i^*.

$$\Theta_i = \Theta_{i-1}\Phi, i = 1, 2, \ldots \tag{2}$$

$$\Theta_i^* = e^{\Theta_i + \log(\widetilde{Y}_i)}$$

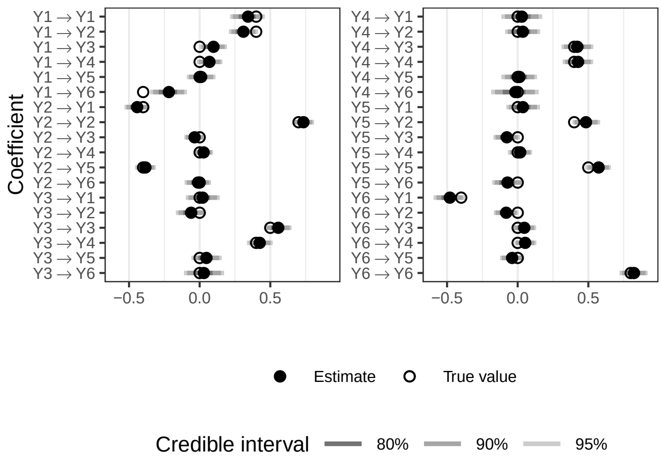


Fig. 1. Results of our simulation study demonstrating that our model can recover true values of Φ with estimated medians and 95% credible intervals (CI). True simulated values are shown as open circles and the median and 95% credible intervals (CI) from our fitted model are solid.

Stationarity is a common assumption in time series analysis [9]. For a VAR(1) model, stationarity means assuming that the eigenvalues of Φ are all less than 1. Practically speaking, this assumes that ~~the system of online groups converges, or in other words, that~~ groups will not grow infinitely ~~nor~~ and that the probabilities of activity in them will go to zero. In developing our model we found that enforcing stationarity through the Heaps prior improved forecast accuracy and helped us fit larger VAR models including more online groups [33]. More information on our models, including our prior specifications is available in Appendix A.

We developed our model using the Stan probabilistic programming language building off of code published by Heaps [33] to add support for intercept terms, account for seasonality, and count data [14]. In our simulation and in all our empirical case studies we report results from Stan models fit using 4 chains that pass Stan's diagnostic checks.

We have included all code and data necessary to reproduce these analyses in the Harvard Dataverse.

5 SIMULATING AN ECOLOGICAL COMMUNITY

Before turning to our empirical analysis, we first present a brief simulation study to demonstrate that our our model can correctly infer all 6 possible commensal relationships included in Table 1 ~~so long as they are sufficiently strong~~. We

Table 2. Summary of data collected for case studies.

Case study	# Groups	Date Range	Time span
Seattle-area	16	2011-06-06—2015-11-30	235 weeks
Wallpaper	15	2014-11-03—2019-10-28	261 weeks
Design humor	10	2014-09-15—2018-04-02	186 weeks

simulated an ecological community consisting of 6 hypothetical groups with every possible commensal relationship over 320 weeks, a length of time similar to that available in our empirical data.

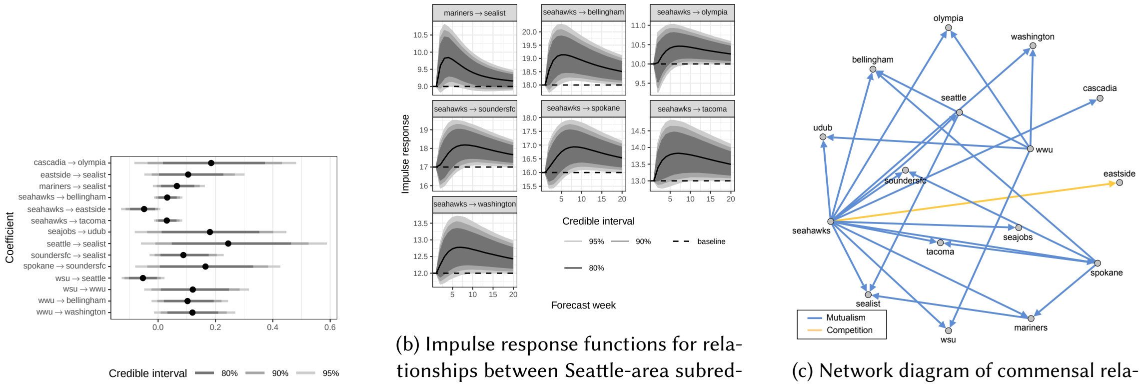
Results from the simulation are shown in Figure 1. For each element of Φ we show the true simulated value along with the median and 95% credible intervals (CI) from our fitted model. In all but 1 case the true parameter value is within the 95% CI and even in this case the correct sign is inferred. We conclude from our simulation that our model can ~~be fit and~~ infer ~~correct~~ commensal relationships from data ~~on online groups~~.

6 EMPIRICAL CASE STUDIES: RELATED SUBREDDITS

Confident that our approach can infer commensal relationships between groups, we turn to the analysis of three sets of related groups on Reddit. These case studies serve to demonstrate ~~the use~~ our method on real online groups ~~, to explore the variety of community ecologies that exist in online platforms, and~~ and to surface empirical findings that may motivate future ~~directions~~ for research.

In each case study, we analyze time series data from a set of related online groups: subreddits related to the Seattle area, subreddits for sharing ~~wallpaper (i.e.,~~ desktop or mobile phone backgrounds~~)~~ or wallpapers, and design and craft humor subreddits. All three studies draw data from the Pushshift archive of Reddit submissions [6]. Table 2 shows the number of groups and time ranges for each study.

In all three case studies our analytic variable is the **number of unique posters** or accounts making submissions to a given subreddit each week. bold?! Compared to alternatives like the number of commenting accounts or the amount of activity in a subreddit, submitting content is a relatively costly form of participation and indicates a relatively high



(a) Estimated VAR(1) model for seattle subreddits. Only coefficients where the 80% CI does not contain 0 are shown.

(b) Impulse response functions for relationships between Seattle-area subreddits. Arrows above each subplot show the direction of the represented relationship. Relationships where the 95% CI does not include the baseline are shown.

(c) Network diagram of commensal relationships among Seattle-area subreddits. Edges represent impulse response functions where the 90% CIs does not include the baseline.

Fig. 2. Results of VAR(1) model for Seattle-area subreddits. Plot (a) shows model coefficients, (b) shows impulse response functions, and (c) shows the network of commensal relationships derived from impulse responses. The community ecology of wallpaper subreddits is relatively dense with several mutualistic relationships.

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degree of involvement ~~in the groups we study~~. ~~The number of unique posters provides a focused assessment of the size of the pool of substantively engaged contributors to a group~~.

In each case study we report all off-diagonal elements of Φ where the 80% CI does not contain 0, impulse response functions where the 95% credible interval (CI) do~~es~~ not include the baseline, and a network of commensal relationships where edges represent impulse response functions where the 90% CI does not include the baseline. Because we are interested not in intrinsic growth, but rather in relationships between groups, we do not show ~~off~~-diagonal elements of Φ~~, IRFs where a group responds to its own impulse, or self-~~ which corresponds to loops in the network. Plots showing our estimates for all our coeffients and all impulse response functions are available in the online supplement.

right?

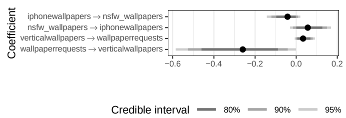
6.1 Seattle-area subreddits

Our first case study looks at subreddits related to Seattle area. We collected a pool of 144 subreddits consisting of all subreddits found in the sidebars and Wikis of the /r/seattle subreddit as of July 20th 2020. In 2016, conflict in /r/seattle led much of the group to migrate to /r/seattlewa. Because this event constitutes a discontinuous shock that will violate assumptions of our model, we restrict our analysis to the period prior to the schism~~:~~ between ~~from~~ June 6~~th~~ 2011 and ~~to~~ November 30~~th~~ 2015. ~~We narrowed our analysis to sufficiently active communities~~. ~~For each subreddit found~~, w~~we~~ examined plots of the time series of the number of unique posters and excluded subreddits ~~that were not active during our study period.~~ ~~We included subreddits with~~ without posts in at least 30% of weeks in each year of the study.

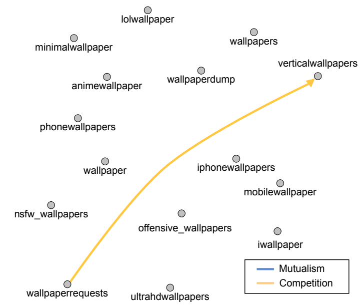
We account for sports-related seasonality in */r/seahawks*, */r/soundersfc*, */r/mariners*, */r/udub* and */r/wsu* using a categorical variable with 5 levels: if a week is during a sports teams' (1) regular season, (2) post-season, (3) if the team has a pre-season game, (4) if they have an off-season friendly or it is the post season and they have not been eliminated from contention, and (5) if their sport is out of season. For the university groups we only account for NCAA American football which is the only sport which appears to drive significant activity. We obtained NFL data from the nflgame-redux python package,[3] MLB data from retrosheets.org, MLS data from the engsoccerdata in R[4] and from Wikipedia articles on SoundersFC seasons, and NCAA football from college football reference.[5] The subreddits */r/udub*, */r/wwu* and */r/wsu* also exhibit seasonality with the academic calendar so we include an additional variable indicating if the university is in session according to historical course calendars and registrar websites.

~~While the resource dependence framework is oriented to the scarcity of participant's time and effort and suggests that such groups may be competitors,~~ our VAR analysis of Seattle-area subreddits reveals a large number of mutualistic relationships. Figure 2a shows median values and credible intervals for elements of the inferred community matrix where the 80% CI does not contain 0. While a handful of coefficients are negative at this credibility level, the vast majority are positive. Figure 2b shows several impulse response functions where the 95% CI ~~is greater than the baseline~~ indicat~~ing evidence of~~ es mutualism. For example, the top-left subplot shows that the commensalism from */r/Mariners* to */r/sealist* is strong enough that, for the median week, a large exogenous increase in the number of unique posters by about 8.6 in */r/Mariners* will most likely drive an ~~a subsequent modest~~ increase ~~in group size~~ in */r/sealist* of almost 1 unique poster per week.

[3] https://pypi.org/project/nflgame-redux/
[4] https://cran.r-project.org/web/packages/engsoccerdata/index.html
[5] obtained from https://gamethread.redditcfb.com/gamedb.php



(a) Estimated VAR(1) model for wallpaper subreddits. Relationships where the 80% CI does not include the baseline.



(b) Network diagram of commensal relationships among wallpaper sharing subreddits. Edges represent impulse response functions where the 90% CI does not contain zero.

Fig. 3. Results of VAR(1) model for wallpaper subreddits. Plot (a) shows model coefficients, and (b) shows the network of commensal relationships derived from impulse responses. We do not show impulse response functions because in no case does the 95% CI exclude the baseline. The ecological community of wallpaper subreddits is sparse with few commensal relationships between different groups.

As shown in Figure 2c, the commensal network of Seattle-area subreddits is dense with mutualistic relationships revealing a tightly connected ecological community characterized by positive spill-overs ~~of activity between groups~~. From the network we can also see how certain groups ~~can~~ play outsized roles ~~in an ecological community~~. The growth of */r/Seahawks* in particular is strongly associated with growth of a number of other subreddits, especially smaller regional subreddits like */r/Bellingham*, */r/Oympia* and */r/Spokane*. Though we do not measure the trajectories of individual accounts, the network suggests people may ~~often~~ be drawn to ~~the ecological community of~~ Seattle-area subreddits by way of /r/Seahawks ~~and then come to participate in other local communities~~. For example, it may be relatively common for Seahawks fans from Bellingham to come to Reddit to discuss the Seahawks but then find that activity on the Bellingham subreddit is relavent to their ~~other~~ interests. Influxes of sports fans from communities like */r/Seahawks* also appear to promote the growth of ~~a wider array of regional subreddits like /r/Bellingham and /r/Olympia as well as~~ sports subreddits like */r/SoundersFC*.

While The mutualistic relationships associated with sports fan groups are those most confidently inferred by our model, ~~but~~ many ~~more~~ additional mutualistic relationships are ~~seen~~ visible in the network in Figure 2c. ~~Another~~ One intersting example is */r/wwu*, associated with Western Washington University in the town of Bellingham. From Figure 2a, we see that a direct relationship from */r/wwu* to */r/Bellingham* is plausible. The network suggests that when posters become active in */r/wwu* they may later become posters to */r/Bellingham*~~,~~ and in the state-wide */r/Washington* subreddit. ~~Perhaps University students attract their friends to groups related to other universities (*/r/udub*, */r/wsu*) or other college towns in Washington (e.g. */r/Olympia*)~~.

6.2 Wallpaper sharing subreddits

background images

Our second case study looks at a set of subreddits for sharing wallpaper. The wallpaper sharing groups are interesting because ~~on the surface~~ many seem superficially very similar. For example */r/wallpaper* and */r/wallpapers* are both general purpose desktop wallpaper subreddits and ~~similarly~~ */r/mobilewallpaper* and */r/phoneallpapers* both ~~have~~ are based around wallpapers for mobile devices. The high degree of similarity between the content shared in these groups suggests that they ~~may be~~ compete~~itors~~.

Using

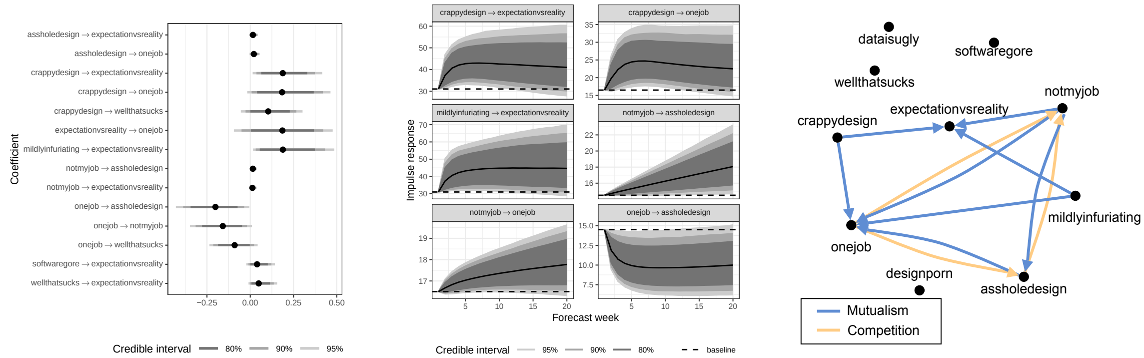
by

We selected ~~wallpaper subreddits beginning~~ with all 898 subreddits including "wallpaper" in their names ~~in the~~ Pushshift submissions data. As with Seattle area subreddits, ~~above~~ we excluded groups with lower levels of activity requiring posts in at least 40% of weeks in each year of our analysis. We chose a lower level of activity as our threshold in our study of Seattle because we were interested in the role of some smaller subreddits like */r/seajobs* in the community ecology of Seattle area subreddits. We ~~chose the time period from~~ collected data from between June 6~~th~~ 2011 to November 30~~th~~ 2015 ~~because all the wallpaper communities in our analysis were active~~.

footnote

While in ~~the case of~~ Seattle-area subreddits we found many mutualistic relationships, our analysis of wallpaper-sharing subreddits reveals very few commensal relationships at all. Only three out of the 210 non-diagonal elements of Φ shown in Figure 3a have an 80% CI that does not contain 0. In only one case does the 90% CI of the raw impulse response functions not contain 0 and in this case the 95% CI does. Even though the content shared in these groups is similar, they have little influence on each other's membership size over time.

This shows that even among groups with apparently similar content, commensal relationships ~~need~~ May not ~~be strong or even~~ exist. Even though this case study covered the longest time period and had fewer groups than our study of



(a) Estimated VAR(1) model for design and craft humor subreddits. Only coefficients where the 80% CI does not include 0 are shown.

(b) Impulse response functions for design and craft humor subreddits. Relationships where the 95% CI does not include the baseline are shown.

(c) Network diagram of commensal relationships among humorous design and craft humor subreddits. Edges represent IRFs where the 90% CI does not include the baseline.

Fig. 4. Results of VAR(1) model for design and craft humor subreddits. Plot (a) shows model coefficients, (b) shows impulse response functions, and (c) shows the network of commensal relationships derived from impulse responses. This ecological community is characterized by a mix of mutualistic and competitive relationships.

— resulting in

Seattle-area subreddits~~, and thus should have~~ more statistical power~~,~~ we found only weak evidence of three commensal relationships.

6.3 Design and craft humor subreddits

The final case study is a set of subreddits for humorous sharing of design and crafts. Subreddits typically place boundaries around the kind of content that is appropriate for their groups in rules posted in their sidebars or Wikis [18, 24]. Often these rules suggest alternative subreddits for submitting content that is not a good fit for a particular subreddit. We are interested in how such boundaries and links may lead to commensal relationships between groups so we collected design and craft humor subreddits from a thread in */r/assholedesign* discussing a flowchart for deciding where to post content.[6] We extended our search for related subreddits by reading the Wikis and sidebars of */r/assholedesign* and */r/crappydesign*. This search yielded 13 subreddits. We excluded 3 subreddits that were created much later than the rest and analyze the period from September 15th 2014 to April 2th 2018 during which all the remaining subreddits had submissions~~, but the excluded subreddits did not~~.

[6]https://www.reddit.com/r/assholedesign/comments/a02ezp/meta_is_it_asshole_design_a_handy_flowchart/

Note: might want to mention multiple stat tests explicitly.

Similar to our analysis of Seattle-area subreddits, our analysis of design and craft humor subreddits reveals a number of commensal ties. ~~Yet~~ However, the portrait of the ecological community that emerges is quite different from ~~the previous~~ both other cases. A shown in Figure 4a~~, in addition to positive coefficients,~~ we ~~also~~ estimate a number of negative coefficients indicating the existence of competitive relationships. Figure 4b shows transformed impulse response functions for relationships inferred by our model where the 95% CI does not include the baseline. The bottom-right plot in Figure 4b shows how, according to our model~~,~~ in a median week~~,~~ a sudden large increase of about 98 unique posters in */r/onejob* can be expected to drive a decrease of about 5 unique posters in */r/assholedesign*.

Seems like a weird #

Figure 4c shows the network of commensal relationships between the 10 design and craft humor subreddits. As with the Seattle-area subreddits, we find relatively few reciprocal ~~fully~~ competitive or ~~fully~~ mutualistic relationships where one group ~~benefits from~~ is helped (harmed) by growth in another and the second also benefits (suffers) from the first. Interestingly, while the network contains more mutualistic ties than ~~commensal~~ competitive ? ones, it contains ~~a~~ three of predatory relationships where one group benefits from an increase in the size of the other~~, but~~ while the other group is hurt by an increase in the first. The subreddit */r/onejob* is a predator of */r/assholedesign* as increases in the size of */r/onejob* predict subsequent decreases in the size of */r/assholedesign* even as increases in the size of */r/assholedesign* predict increases in the size of */r/onejob*. Similarly, */R/onejob* is predator of */r/notmyjob* and also of */r/assholedesign*.

It is interesting that we do not find commensal relationships between the three groups that were most visibly differentiated in ~~posted~~ guidelines about what kind of content belongs in each group (*/r/assholedesign*, */r/mildlyinfuriating*, and */r/crappydesign*). That we do not find competition between these communities is consistent with the prediction of ecological theory that partitioning of resources (here topics or styles of content) between groups may reduce competition [1, 15].

7 THREATS TO VALIDITY

Our work is subject to several important threats to validity ~~that are worth foregrounding~~. The method we propose for identifying commensal relationships between online groups has limitations common to all time-series analysis of observational data. While our community ecology approach assumes that commensal relationships drive dynamics in the size of groups over time and ~~thereby~~ caus~~ing~~e groups to grow or decline, drawing ~~making~~ causal inference~~s~~ using our method would depend on untestable ~~and unlikely~~ assumptions. For example, we do not consider ~~additional~~ groups—including groups on other our ability to infer causal relationship might be limited if platforms—~~that we did not include in our analysis~~ may play a role in an ecological community. Therefore we refrain from claiming ~~that we have demonstrated~~ causal ity ~~relationships~~. Potential omitted variables might also ~~may~~ include additional time lags of group size~~s~~. We chose to use only VAR(1) models with only 1 time lag for simplicity but future work can improve upon our approach and model more complex dynamics ~~using models~~ with additional lags. Our results are offered as limited temporal associations consistent with inferred commensal relationships ~~in the ecological communities we have measured~~.

Like most other time series analysis, our analysis assumes stationarity. Doing so implies that dynamics in the community ecologies of online groups that we study have a single equilibrium. This is difficult to evaluate empirically and may not be realistic ~~in many settings~~ [13]. We selected case studies and restricted our analysis to time spans in ways that sought to avoid obvious violations of these assumptions that ~~research has shown~~ are common in populations of online groups ~~—like the creation of new groups and coordinated migrations [23]~~. Future work might relax these assumptions using more complex models with time-varying VAR parameters or state space models [9]. These types of approaches may also be useful for investigating how commensal relationships change over time, ~~and we~~ W hope to explore these techniques in future work.

Finally, our three cases studies are limited in that they can offer only a proof-of-concept analysis and an enticing hint at ~~a~~ more comprehensive future analyses with more rigorously defined populations of online groups. Although we found varying results in the three ecological communities we selected, these case studies can provide little explanation for when one should expect to find different forms of commensalism in ~~communities of~~ online groups. Our hope is that these initial results can point in new directions for research ~~into interdependence in online groups and provide a method to do so.~~ As is true in all case study research, there is little reason to expect findings from any one of our case studies to generalize to any specific other set of ~~other~~ contexts.

8 DISCUSSION

Prior ecological studies ~~of online groups~~ in social computing use overlap in participants or topics to characterize the resource environment faced by particular online groups [64, 67, 68]. However, they yield a puzzling set of empirical results about the relationship between resource overlaps and growth, decline and survival ~~of groups~~. Observing that the use of overlap density in these studies potentially aggregates many varying kinds of relationships, we propose a community ecology approach as a first step toward resolving ~~the~~ this puzzle ~~in terms of commensal relationships that mediate competitive and mutualistic forces.~~

We set out to infer networks of commensal relationships between groups directly from time series of membership sizes. Applying our method ~~to~~ in three case studies reveals three qualitatively different ecological communities. In an ecological community ~~related by geography~~ focused on Seattle, we find a great number of mutualistic relationships ~~yet~~. Among groups for sharing wallpaper images, we found almost no commensal relationships at all. In design and craft humor subreddits we find many mutualistic ties, but also predation, and ~~we find~~ no commensal ties between those groups where visibly posted norms ~~clarified the distinctive~~ clearly distinguish between content appropriate for sharing in each group.

While our case studies reveal variation in networks of commensal relationships between related groups, ~~of course,~~ case studies alone cannot resolve the puzzle of why resource overlaps appear related to competition in some circumstances [e.g 60, 64] but in others appear related to mutualism [67, 68]. ~~Yet they~~ However, our results provide strong support our ~~intuition~~ for claim that relationships between similar communities might be competitive or mutualistic depending on factors other than content or topical overlaps.

We believe that ~~propose~~ a search for conditions leading to the emergence of different forms of commensalism is a good ~~such as resource overlaps as a~~ next step toward resolving the puzzle.

Within a large platform like Reddit there are a great number of sets of related groups that can be studied. This is ~~, making~~ it possible to eventually construct and test generalizable theories about when and how different types of ecological communities are constructed. However, ~~But~~ interest groups often use platforms with distinctive affordances for different purposes [42]. Since our method relies only on time series data ~~alone~~, it can ~~plausibly~~ be applied to study ecological communities spanning different social media platforms.

While Competitive relationships are defined by how they decrease the size of groups subject to competition ~~them, but~~ they can also be important to the functioning of the broader ecological community. Exit to an alternative group can be an avenue for political change in response to grievances and poor governance [26, 37]. ~~For example, in our case study of Seattle-area subreddits our model assumptions were violated by the 2016 migration of many *\/r/Seattle* participants to *\/r/SeattleWA* in response to grievances against an *\/r/Seattle* moderator~~. The existence of a sufficient diversity of alternative institutions is likely to lead to competition, but might also make the expression of voice more compelling to moderators [37]. Future studies should investigate such aspects of the dynamics between governance and commensalism.

Finally, we propose that future work investigates higher-level properties of ecological communities. The motivation for community ecology is not only to better describe relationships between online groups, but also to better understand how groups shape one another as well as ~~and ultimately~~ higher order social structures like social media platforms and technological cultures. One direction toward such ends is to analyze stability dynamics of VAR models to investigate conditions giving rise to relatively stable or unstable ecological communities ~~in social computing systems~~ [38].

consider cutting

8.1 Implications for Design

In their final chapter of their book on *Building Successful Online Communities*, Kraut et al. [44] advise managers of online groups to select an effective niche and beware of competition. But these recommendations are based on little direct evidence from studies of online groups and offer almost no concrete advice on what a designer or group should do differently based on either piece of advice. We provide a framework for online group managers to think about ecological constraints on group size in terms of dyadic relationships. While Intuition suggests that online community managers might want to seek out mutualistic relationships and avoid competitive ones, ~~but~~ it is often not obvious ~~just from resource overlaps~~ whether a related community is a competitor or mutualist. Our method provides a ~~tool~~ way for group mangers to solve this problem ~~by inferring competitive and mutualistic relationships~~.

Competitors have a negative impact on growth, but ecological theory suggests that specialization is an adaptive strategy in response to competition [1, 15, 44, 52]. For example, the growth of Wikipedia caused other online encyclopedia projects to shift their focus [35]. Our method provides a tool by which group managers might identify competitors limiting the growth of their groups. With knowledge from this analysis in hand, they might be able to escape a competitive dynamic, perhaps by differentiation through unique design, policies, or governance practices.

~~Mutualism has a positive impact on growth and~~ Groups looking to increase activity should desire to seek out ~~these~~ mutualistic relationships. We suggest that designers of online platforms can do so ~~seek to support mutualistic relationships between groups~~ through ~~design.~~ Features such as meta-~~reddits~~ groups, ~~group~~ search, ~~and~~ recommendation engines, and practices like linking related ~~subreddits in wikis and sidebars~~ groups may help lower boundaries between ~~subreddits~~ groups and ~~thereby~~ support ~~commensal~~ mutualistic relationships. However, it is not obvious to what extent ~~this~~ particular features will ~~supports~~ support competition, mutualism, or both. Using ~~tools like~~ our method, community managers may be able to better understand how such design features give rise to mutualism or competition.

9 CONCLUSION

Explanations for the rise or decline of ~~important~~ online groups often look to internal mechanisms. For example, structural barriers to newcomers are ~~proposed to drive~~ Wikipedia's decline appear to ~~generalize to other knowledge~~ have been caused by created by Wikipedia.

~~peer production projects~~ [29, 59]. ~~Yet, new forms of online participation like Facebook and other social media proliferated during Wikipedia's long period of decline~~. Do ~~Does~~ competition with emerging groups like Facebook also limit Wikipedia's growth?

Ecological approaches provide a path toward answering ~~settling~~ such questions. ~~Yet~~ while prior ecological work in HCI and social computing has shown that online groups influence each others ~~membership sizes~~, they aggregate many varying relationships between groups into resource overlaps and yield puzzling results. The framework of community ecology we introduce narrows the focus to the ~~those~~ dyadic commensal relationships between groups that matters ~~shaping their sizes~~. Networks of commensal relationships between online groups can be inferred directly from time-series data and analyzed to reveal distinctive roles groups play in their ecological communities. Our three case studies yield qualitatively different ecological communities that suggest promising directions for future work investigating when and how commensal relationships form.

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A BAYESIAN POISSON VECTOR AUTOREGRESSION MODEL SPECIFICATION

Below is the full prior specification of our model. Y_t is Poisson distributed with parameter λ_t having a multivariate normal distribution which evolves over time according to a VAR process. More information on our models, including our prior specifications is available in the online supplement. We use a weakly informative hierarchical prior for the elements of B_0.

In developing our model we found that enforcing stationarity through the Heaps prior improved forecast accuracy and helped us fit larger VAR models including more online groups [33] We use the Heaps exchangeable prior over stationary values of Φ , which places separate hierarchical normal priors on the diagonal and off-diagonal elements of an unconstrained matrix that is homeomorphic to Φ. Our choice of hyperparameters follows the recommendations of [33], but we chose a modestly more diffuse hyperprior for the means to increase the sensitivity of our model.

$$
\begin{aligned}
Y_t &\sim \text{Poisson}(e^{\lambda_t}) & \lambda_t &\sim \text{MVN}(\mu_t, \Sigma) \\
\mu_t &= B_0 + \Phi\mu_{t-1} & \Phi &\sim \text{Heaps}(1, \sqrt{3}, 0, \sqrt{3}, 2.1, \frac{1}{3}) \\
\Sigma &\sim IW(m+3, I(m)) & B_0 &\sim \text{N}(\mu_{B_0}, \sigma_{B_0}) \\
\mu_{B_0} &\sim \text{N}(0, 7) & \sigma_{B_0} &\sim \Gamma(4, 3) \\
\mathbf{B} &\sim N(0, 2)
\end{aligned}
\tag{3}
$$