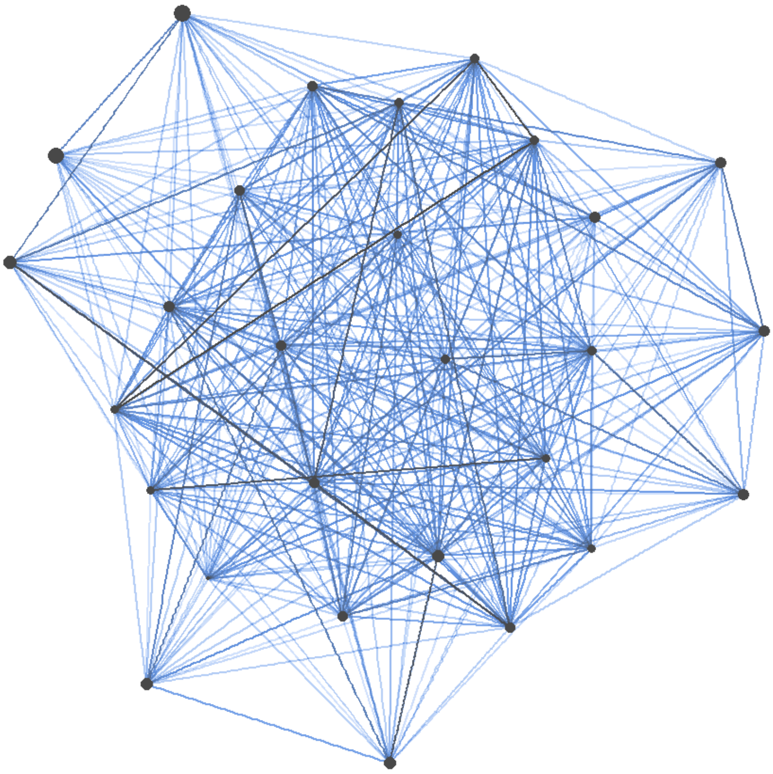

Social Shutdown? Covid-19 lockdown effect on student messaging behavior

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Abstract

The present paper analyses the effects of the covid-19 lockdown in a novel, highly active messaging network of students. We collect anonymised data from Facebook messages and analyse the temporal, directed, weighted network using bayesian analysis to infer the effects of lockdown on the propensity of new connections, and the modulation of lockdown on popularity and connectedness both short-term (within the semester of initial lockdown) and long-term (from september 2019-december 2020). We find a modulating effect of lockdown on the effect of popularity, a big short-term effect of lockdown, and a strong effect of including information about the lockdown on the model performance but find no evidence for lockdown's effect on clustering. Finally, we discuss what could be done to create a more complete dataset. The current dataset and code is openly available on github.

Keywords: Network theory, social network analysis, education, covid-19

Introduction [EJ]

The effects of the covid-19 pandemic have been immense. With social distancing measures and the closing of restaurants, bars and other meeting places, the physical contact between people is greatly reduced to curtail the spread of the virus. The lockdown has also hit schools and universities. With the complete lockdown of most facilities, students across the world have been taught remotely via digital communication technologies and online teaching.

Online teaching has had large effects on students and lecturers and reduced performance and joy of both learning and teaching in Danish higher-level education (Georgsen & Qvortrup, 2021). As physical communication with friends and family has decreased (Nguyen et al., 2021), measures of depression, anxiety, stress and loneliness have also been shown to increase in students as an initial (2-week) effect of the lockdown (Elmer et al., 2020). The long-term mental consequences are still unclear. Long-term, it is also not clear how the interaction between students will be affected.

Covid-19 has also been a source of inequality, e.g. the negative mental health effects have been distributed socioeconomically unequal (Gibson et al., 2021) with similar negative disparities in health between socioeconomic groups in neighbouring Sweden (Burström & Tao, 2020) and ethnoracial minorities and majorities in the U.S. (Mackey et al., 2020). Information is missing whether the epidemic effects have unequally affected social relationships as well.

Social network analysis has shown to be a valuable tool to engage with these types of social and societal effects of the virus (Block et al., 2020; Ortiz-Sánchez et al., 2020; Thurner et al., 2020; Yum, 2020) and as digital communication has increased (Nguyen et al., 2021) and universities have switched to online teaching, data on digital activity has increased similarly with the use of digital communication (Robbins et al., 2020). In the present study, we use 1.5-year longitudinal data of messaging behaviour on both sides of the lockdown start in a dense network at a Danish university course year, expanding the date range of social network data compared with earlier studies (Elmer et al., 2020) and the ecological validity compared with self-report measures due to self-report biases (Choi & Pak, 2004) and the fit of the temporal network to real-world activities. Figure 1 shows the total date range of all 27 participants' messages by week across time.

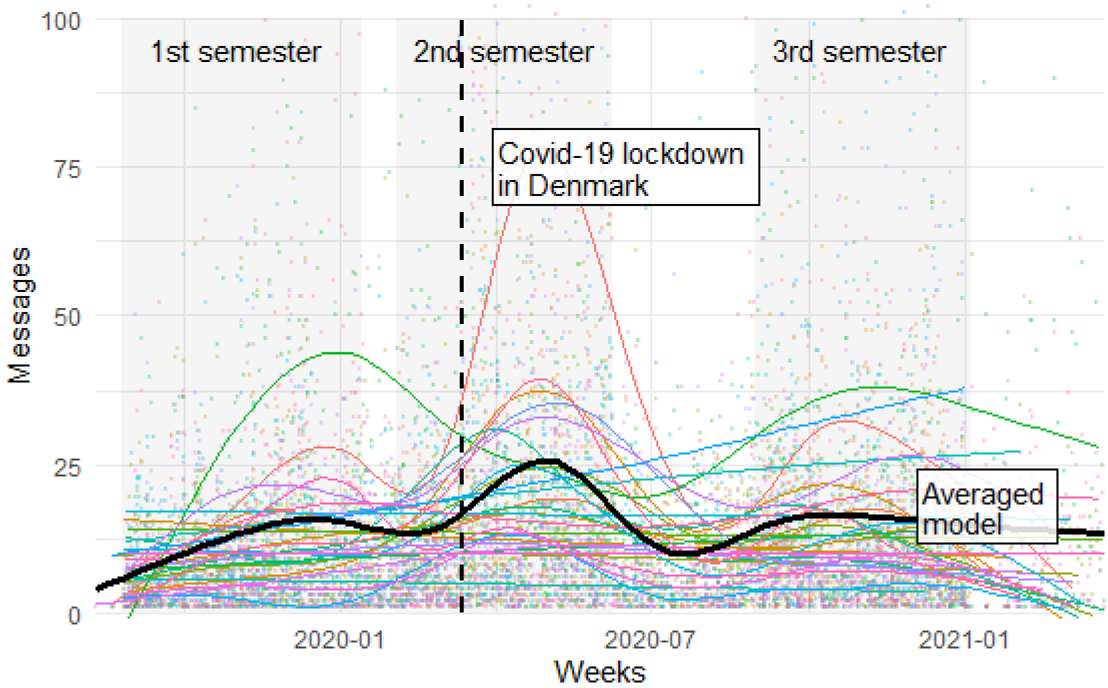

Figure 1: Messages for each node in the Facebook messaging data over time

The main dynamics we are interested in are those concerning new connections. Informally, this is defined as reaching out to drastically increase your communication with another student (we will define this more formally in the "Measures" section). This is an interesting measure as it serves as a proxy for the mobility of the network, i.e. are people holding on to the same group of friends or actively seeking new ones? Having a good proxy for mobility also allows us to investigate the mechanisms of new connections. Here several dynamics come into play.

First and foremost, there are the general dynamics of a lockdown. Two, possibly conflicting, mechanisms stand out: the lack of (physical) social structures and the potential increase in online communication. Physical social structures such as lectures and Friday bars provide arenas where students can interact, create appointments, and potentially forge new friendships. The absence of these structures potentially makes it more difficult to establish new connections as the initial spark lacks. On the other hand, as online messaging increasingly becomes the only allowed channel of communication (Nguyen et al., 2021), we might see a general increase in messaging (potentially including new connections), as can be seen on the initial period of lockdown on fig. 1.

Secondly, there are the modulating effects of lockdown on existing dynamics. Two particularly interesting dynamics are *popularity* and *clustering*. Popularity is here meant as well-connected, presumably well-liked students (Cillessen & Rose, 2005) - we will provide a more formal definition in later sections. Though popularity helps to establish new connections (Eder, 1985; Scott, 2014), this effect might be amplified as social structures are replaced by unstructured online communication in the lockdown. The effects of clustering, or the propensity of individuals to form groups[1], might also be modulated by lockdown as one might seek out the existing connections of other group members.

Understanding and answering these questions requires a rich tool-set for investigating the dynamics of interpersonal relationships. Here we turn to the methodology of network analysis, which we will discuss in the next section.

Network analysis [EJ]

Network analysis is a tool to study networks and is a highly viable analysis modality for social dynamics in group behaviour with examples ranging from city-wide disaster response (Kim & Hastak, 2018), university student proximity modeling (Sapiezynski et al., 2019), cognition (Baronchelli et al., 2013) and the history of the internet (Pastor-Satorras & Vespignani, 2007).

The basic properties of a network (or graph) are its vertices (nodes, entities, agents) and the edges (connections, links) between them (Albert & Barabási, 2002; Baronchelli et al., 2013), though the basics are not standardised (Barnes, 1969). With these two elements, one can model nearly any interacting, complex system to a high degree of precision with the ability to map data to specific vertices and edges. Many different network types exist (Baronchelli et al., 2013; Radicchi et al., 2020; Will et al., 2020). The network studied in this paper is **weighted**, **directed**, and **temporal**. A weighted network is one where each edge has a weight, indicating the strength of the relationship (Newman, 2004) e.g. the average messages transmitted between two vertices. A directed (or asymmetric) graph is one where edges are directed (Leicht & Newman, 2008), e.g. one node might message another node, who does not write back. A temporal network is a network that exists through time, often defined by the edges having a measure of time and/or date associated with them (Holme & Saramäki, 2012), e.g. a message sent at a specific time point. Many measures have been presented to study these different types of networks (Michail, 2015). We will outline the major measures along with measures used in this paper.

On the node level, measures include **centrality** (including **PageRank** and **betweenness**), **degree**, **clustering coefficient**, and **hubs**. Centrality can be calculated in many ways, but is usually defined by signifying how central a node is to the network, e.g. eigenvector centrality that measures centrality based on the centrality value of the connecting nodes (Bonacich, 1987). PageRank is such an eigenvector centrality measure originally used at Google concerned with how valuable the links (or pages, in Google's terms) from other nodes are, creating a strong measure of directed graph centrality (Page et al., 1999; Xing & Ghorbani, 2004). Betweenness is a class of centrality measures that concerns itself with how many of the shortest possible paths between nodes go through a node (Freeman, 1978). The degree of a node is how many other nodes it is connected to. In directed graphs, this can both be an

[1] This will also be more rigorously defined

in-degree and out-degree, respectively describing the connections towards and outwards from it (Freeman, 1978). The clustering coefficient is a class of measures that concerns the local network of nodes and how dense it is. One definition is defined by dividing the *actual* triangles (links between three nodes) created with neighbouring nodes with the *possible* triangles with neighbouring nodes (Barrat et al., 2004; Wasserman et al., 1994, pp. 243–248). Hubs are the nodes in a network with the highest degree and are also a measure of centrality. Different versions of many of these measures exist for undirected, directed, unweighted, weighted, temporal and static networks.

Edges have a few properties that are often related to the nodes they are connected to, e.g. **shortest path length**, **direction**, **time**, and **weight**. The shortest path length is a measure of how many edges are on the shortest path between two nodes. Direction, time, and weight are related to the network types.

Network **density** describes the average degree of the nodes divided by the highest possible degree. A measure of the network **clustering coefficient** is calculated as the number of open triangles divided by the number of closed triangles (or triads) in the network. Some specific properties often arising in networks is the **small-world effect** and **power-law distributions** (arising from scale-free networks). The small-world effect is that nodes are connected by surprisingly short paths, an effect often arising on the basis of clustered subgraphs connected by a few nodes to other subgraphs in the network, a balance between a **sparse** and a **dense** network. Being scale-free means that the degree distribution of the nodes follows a power law. In this sense, some nodes are highly connected, while most are not well connected.

The network presented in this paper is a weighted, temporal, directed network. Most measures have a version compatible with weighted and directed networks but temporal networks are generally underrepresented in network theory (Baronchelli et al., 2013; Holme & Saramäki, 2012). In this paper, the network measures are made into time series data by splitting it by time units, i.e. weeks, and calculating the relevant measures on a week-by-week basis as if it was a standalone static network. Methods using causality tree network path sampling are some of the more well-developed temporal network types, where the temporal network is transformed into a tree of time-streamed causality of who messages who in the network, resulting in a static network for analysis. It often results in an inordinate amount of vertices and edges since each temporal edge becomes a node and edges represent causality through time.

Social media and network analysis [JE]

Many network studies analyse social media (Adedoyin-Olowe et al., 2013; Singh et al., 2020) because of its rich data on human interaction, something not easily generated from e.g. video material of real-life interaction, which is often used in studies of social cognition (see e.g. Tylén et al., 2012). Network analysis shifts the focus from a focus on content to a focus on the relations between actors. This can reveal powerful insights about the dynamics of behavior spread (Centola, 2010; Centola & Macy, 2007) and ideas (Tremayne, 2014; Wright, 2016).

A central discussion in social network analysis is the relative importance of weak and strong ties (Granovetter, 1973; Krackhardt et al., 2003). *Weak ties* are relations between well-connected groups (Granovetter, 1973). These ties allow for efficient transfer of information in a network making them a key feature of small-world networks such as global friendships (Milgram, 1967; Watts & Strogatz, 1998) and the brain (Bassett & Bullmore, 2006). Newer research has shed doubt on the power of weak ties when it comes to more complex behavior and ideas (Centola & Macy, 2007). Instead, they argue that strong, redundant ties - that is dense clustering - better facilitates this kind of behavior (Centola, 2010).

This discussion is also relevant to the present paper as it embodies the relationship between popularity and clustering. Popularity, as operationalized by centrality-measures, is largely influenced by the amounts of weak ties, whereas clustering signifies the amount of strong ties. Investigating their respective influence on getting new connections, thus allowing us to examine the complexity of getting new connections. The more complex the process, the more we would expect the importance of clustering to increase. Furthermore, we can investigate how these effects were modulated by the pandemic.

A popular platform to study is Twitter (Murthy, 2018) with its easy public data access and presence of highly interacting and influential networks of users (Broniatowski et al., 2014). Analyses of other social platforms exist (Bradbury, 2011; Russell, 2013; Solberg, 2010), but Twitter is overrepresented, because of its ease of access to large amounts of data (Broniatowski et al., 2014). With this study, we focus on private messaging data on Facebook. This is a hitherto unexplored data source, which is probably related to the stringent privacy and ethical standards required to work with it (see “Anonymization”). The reason we use network analysis is that the data is composed of nodes (users) interacting in a variety of ways (edges) to each other (directedness) to differing degrees (weight) over time (temporal). In this way, the networks capture the interactions while not simplifying the data, enabling a higher ecological validity by gaining access to these precise digital social dynamics.

Previous literature [JE]

Due to the recency of the pandemic, it still remains relatively unexplored in the social sciences. However, a few papers have approached the subject from angles related to this paper.

Firstly, Elmer et al. (2020) investigated the mental health of university students in Switzerland from 2018 to April 2020. Thus, they had longitudinal data spanning before and immediately after the lockdown. They found sparser social connections as well as increased levels of fear, loneliness, and anxiety. The methods deployed were primarily survey-based which limits the granularity and also questions the ecological validity (Jack & Roepstorff, 2003). Furthermore, the surveys ended shortly after the lockdown. This leaves out potential long-term consequences, which might be consequential (Mahase, 2020). Thus, we hope to expand on the findings using naturalistic data covering a longer time frame of the lockdown. This might allow us to find more subtle longer-lasting changes.

Secondly, Hung et al. (2020) investigated topics and sentiment of Twitter-conversations about Corona. This has a more content-driven approach than the previous paper as well as ours. The paper found five distinct topics with differing sentiment dynamics, illustrating the power of ML-driven approaches. However, given the fact that Danish and multilingual NLP is inferior to English (Kran & Orm, 2020; Névéol et al., 2018) and due to privacy concerns it is not possible to include content analysis of private Facebook messages.

Lastly, Yum (2020) investigated how information on corona spread on social media, namely Twitter. He argues that knowledge of social media dynamics are key for governments to efficiently target information. Twitter is widely used for studying information dynamics (Anger & Kittl, 2011; Rystrøm, 2020; Wu et al., 2011) because of its importance and ease of access to high-quality data. In contrast to Elmer et al. (2020), however, it focuses on much larger impersonal networks that probably exhibit different dynamics compared to friend networks, where everyone usually knows everyone offline. To our knowledge, this is the first paper to analyse Facebook messaging data which combines both the data amounts of Yum (2020) with the nearness of Elmer et al. (2020).

Hypotheses [JE]

Based on the literature and our dataset, we postulate four hypotheses to test on the networks using Bayesian analysis. *H1: There is a difference in new connections made during lockdowns*, *H2: The effect of popularity on new connections is increased during lockdowns*, *H3: The effect of clustering on new connections is increased during lockdowns*, *H4: Information about lockdowns improves model predictions.*

Methods and data [JE]

Experiment [EJ]

During 1.5 years, 28 students communicated intensely on the social messaging app Facebook as part of the cognitive science bachelor's program at Aarhus University. These students voluntarily gave us their highly anonymized data (see "Anonymization"). In a post-experimental questionnaire, 100% reported that it was their main communication tool in the study group and 86% reported that it was their main communication tool with everyone from the program.

Data [JE]

The data contains a message per observation between two of the 27 users (28 minus 1 dropout). The weight of a message is 1 for a direct message, while a group message is weighted as $1/(n-1)$ where n is the amount of users in the group (the sender inclusive).

Table 1: Summary of the dataset

Metric	Value
Vertices (people)	27
Total edges (messages)	366,013
Median total node in-degree	81,562
Median node in-degree by week	33
Average network density by week	10.3 (sd = 7.25)
First message date	2019-08-22
Last message date	2021-04-01

Demographic [JE]

The 27 participants were all part of the same year of the cognitive science bachelor's program at Aarhus University in Denmark during the data collected. As of writing, the year is 48 people, thereby excluding dropouts during the data period, so the collected data represents 56,25% of the students. The demographic is predominantly WEIRD (Western, Educated, Industrialized, Rich, and Democratic; Henrich et al., 2010), has ages between 18 and 30 years, is 60% female, all students, all white, 90% Danish, 98% European.

Anonymization [JE]

The information present for each message is the date, time and the anonymized ids for the receiver(s) and the sender. The participants downloaded their private messaging data (1-3GB) from Facebook between the 1st of August 2020 and the 1st of January 2021. They personally ran a script that anonymized and extracted the relevant data to create a first-step encrypted dataset using a sha1-hash (Eastlake & Jones, 2001, p. 1) of their name (2-10MB). These were sent to the authors that performed a second-step anonymization using pseudo-random IDs, leaving no connection to the original names.

Finally, we had to deal with students who opted out of the data collection. Though we technically had partial data from them (if they had written with consenting students), we chose to remove these conversations to respect their privacy and informed consent (Corrigan, 2003). For group conversations, we chose to remove the non-consented students but retain the rest of the messages.

Measures [EJ]

To create models from the hypotheses, the network measures of PageRank, weighted local clustering coefficient and new connections were calculated for each node, and the lockdown effect was encoded.

As few network measures are viable and interpretable as temporal measures, the data was split into weeks and interpreted as separate graphs per week. Weeks were selected because university work was organized by week during the time frame. From these weekly networks, the network measures were calculated to convert each node's measures into a time series format (see figure 5). The measures were calculated by node using R (R Core Team, 2013) and the packages tidygraph (Pedersen, 2020) and igraph (Csárdi & Nepusz, 2006) with additional measures calculated by the authors primarily using dplyr (Wickham et al., 2015) .

PageRank [EJ]

As introduced by Brin and Page (1998), the PageRank algorithm measures the importance of a node in a network based on the relative importance of the connecting nodes. An updated version of this is used, the weighted PageRank, as defined in igraph (Csárdi & Nepusz, 2006):

$$PR(A) = (1-d)/n + d(PR(T_1)/C(T_1) + ... + PR(T_n)/C(T_n))$$

Where node A has directed connections from nodes T_1 to T_n, $PR(A)$ is the PageRank for node A, d is a dampening factor that determines if the walk through the network will restart at a random node, n is the total number of nodes, and $C(A)$ is the number of links going out of node A. igraph weights the connections by the assigned weight of an edge between nodes.

Undirected weighted local clustering coefficient [EJ]

We solve the problem of weighted edges (amount of messages sent between people) being interpreted inaccurately in most clustering coefficients by utilizing the undirected weighted local clustering coefficient of a node in a weighted network, defined as:

$$c_i^w = \frac{1}{s_i(k_i - 1)} \sum_{j,h} \frac{(w_{ij} + w_{ih})}{2} a_{ij} a_{ih} a_{jh}.$$

Where c_i^w is the clustering coefficient for node ***i***, $s_i(k_i - 1)$ is the normalization factor that accounts for the weight of each edge times the maximum number of triplets this weight can participate in, resulting in $0 \leq c_i^w \leq 1$, and w_{ij} are the weights between neighbouring nodes ***i*** and ***j***, and a_{ij} is the adjacency matrix whose elements take the value 1 if an edge connects the node ***i*** to the node ***j*** and 0 otherwise (Barrat et al., 2004).

New connections [JE]

Given our weighting scheme we expect most (if not all) of our pairs of nodes to have a non-zero weight. Thus, we cannot use the existence of an edge as a signal for connections. Instead, we define new connections as:

$$nc(n_i) = \sum_{j^w} m_{ij}^{w=0} >= 2 * \frac{\sum_{w=-1}^{-4} m_{ij}^w}{4}$$

Where $w = 0$ is the current week, $nc(n_i)$ is the new connections of node i, while j^w are the currently connected nodes, and m_{ij}^w are the amount of messages in the week w relative to the current week.

In prose, this equation means that the new connections of a node is calculated as the sum of the connections where the amount of messages is above or equal to twice the average of the last four weeks.

Lockdown [JE]

Lockdown is formalized as a boolean measure where the weeks that are part of the periods `[March 13, 2020; June 8, 2020]` and `[August 31, 2020; January 4, 2021]` are classified as being in lockdown. These periods correspond to the semester time where the lockdown was active. It should be noted that the fall-lockdown was more partial with classes taking place in person and lectures being taught online.

The models [JE]

We define three models. m_0 is our "baseline" model were we don't model the effect of lockdown, so we can compare it to the performance of m_1 and m_2 that includes the lockdown. m_2 is the same as m_1 but its date range is limited within the second semester to avoid noise present in the whole date range (e.g. holidays, exams) at the cost of data:

$$\begin{aligned} m_0 &= connections \sim 0 + time + pagerank + clustering + (1 + time|id) \\ m_2 = m_1 &= connections \sim time + lockdown + pagerank : lockdown + lockdown : clustering \\ &\quad + (1 + time|id) \end{aligned}$$

$$\beta \sim Normal(0, 0.1)$$

$$\sigma \sim Normal(0, 0.1)$$

$$shape \sim \Gamma(0.01, 0.01)$$

$$cor \sim LKJ(1)$$

m_0 assumes fixed effects of time, PageRank and clustering coefficient with a random intercept and slope of time by node ID. Thus, we do not assume an interaction effect between the two measures, mostly for model complexity reasons and the fact that clustering and pagerank are mathematically somewhat independent measures, besides both are causally dependent onconnection count.

m_1 and m_2 assumes an additional main effect of lockdown and two interaction effects between lockdown and pagerank and clustering. These were originally included as random effects but excluded due to the computational complexity. The reason for including all as random effects is due to the individual volatility seen in fig. 5 and 1 for all measures that might show a few people dominating the effects. Having the interaction effects models the assumed modulation of pagerank and clustering coefficient effect by the lockdown.

We have chosen the family of negative binomials as the outcome consists of overdispersed counts thus violating assumptions of poisson distributions. The negative binomial distribution is a discrete probability distribution that models the probability that a binary occurence repeats x times, e.g. a node getting new connections x times. The measure used in this analysis, as seen in fig. 2, is the new connections measure.

We use the default values for the $shape$ and cor priors for negative binomial distributions and select highly informative conservative priors for the β and $sigma$ values to reach inference with our dataset. With the prior-posterior-update plots in fig. 3 and 4, we see that these updated properly (no flat posteriors, no unreasonable update patterns).

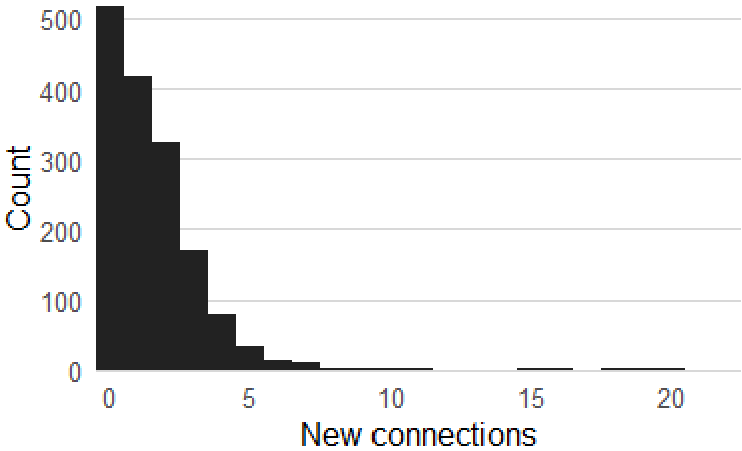

Figure 2: Histogram of the New connections measure

Bayesian workflow [JE]

The main issue of the workflow was finding priors that did not blow up. This problem arose because of the overdispersed nature of the outcome as well as the relative complexity of the model. We solved this by setting highly informative priors (normally distributed with a mean of zero and a standard deviation of 0.1). The sensibility of these priors were tested using prior-predictive checks. The model never settled to a completely reasonable range (it had tails up to ~8000), but it was not as outrageous as early attempts (tails caused overflow errors). This is because of the exponential nature of the log-link function in a negative binomial. This causes even relatively small changes (on the log-scale) to explode, thus making inference highly volatile.

After checking the validity of convergence (see appendix), we performed hypothesis testing for each of H1-H3. The hypothesis-testing was done using brms (Bürkner, 2017). For one sided hypotheses this is simply the ratio of evidence. For two-sided hypotheses this corresponds to computing the Savage-Dickey evidence ratio (Verdinelli & Wasserman, 1995). Specifically the following tests were performed (all on m_1).

H1: $Lockdown > Open$

H2: $Lockdown : PageRank > Open : PageRank$

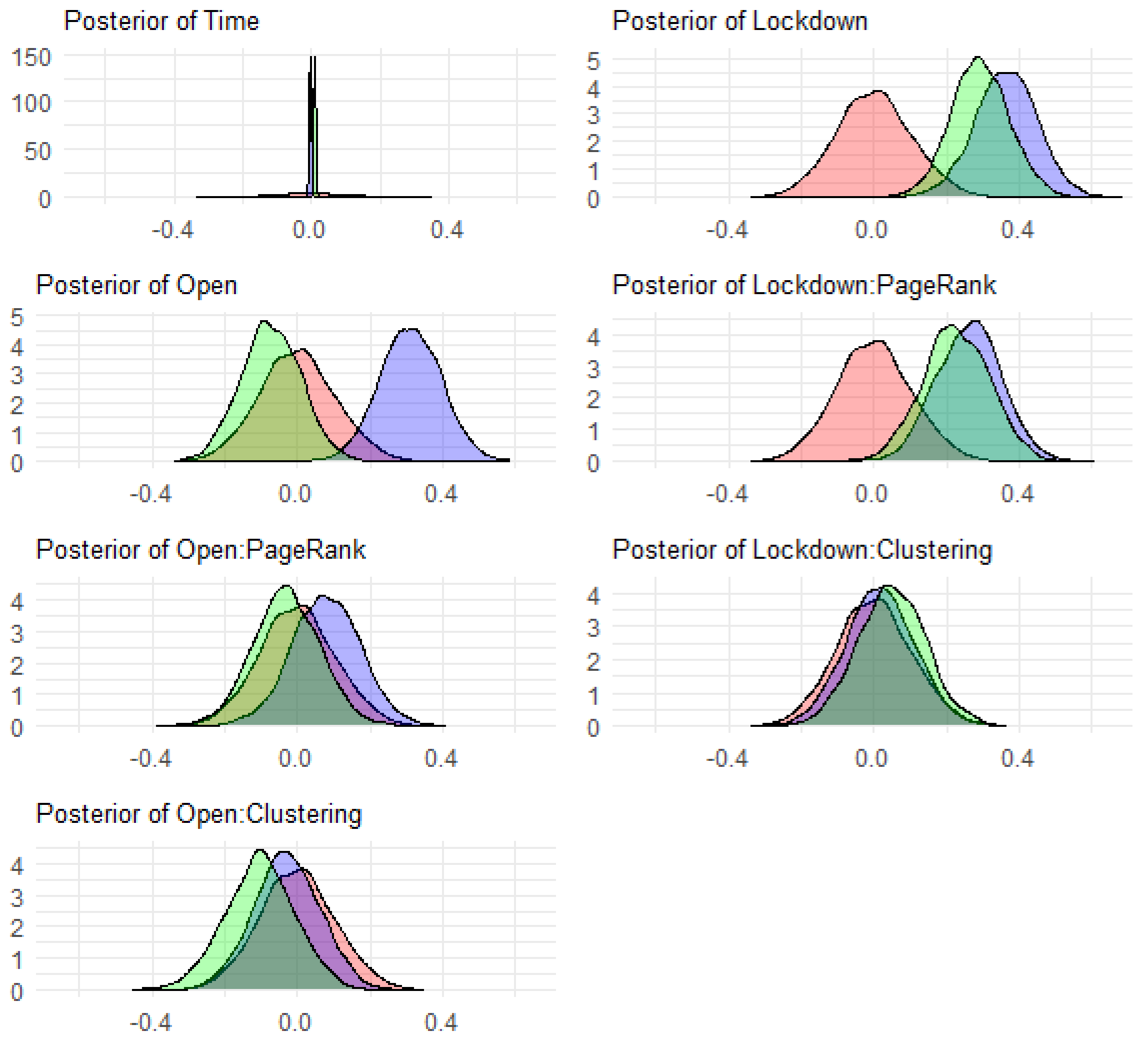

Figure 3: Parameter posteriors for m_1 (blue) and m_2 (green) compared to the priors (red)

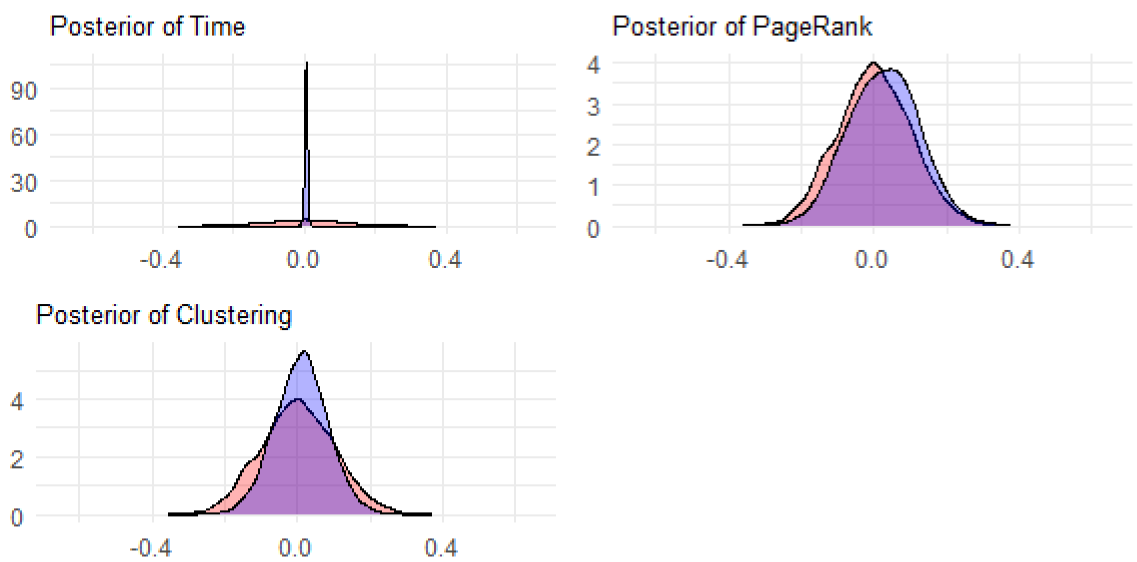

Figure 4: Parameter posteriors (blue) for m_0 with respective priors (red)

H3: $Lockdown : Clustering > Open : Clustering$

Furthermore, we performed marginal two-sided tests for both the effect of PageRank and clustering on new connections:

$$\frac{Lockdown : PageRank + Open : PageRank}{2} = 0$$

$$\frac{Lockdown : Clustering + Open : Clustering}{2} = 0$$

Lastly, we performed a LOO-based model comparison of m_0 and m_1. This would allow us to compare the expected log pointwise predictive density (ELPD). Comparing the relative ELPD of the two models gives us a good estimate of out-of-sample prediction accuracy (Vehtari et al., 2017), which takes into account the balance between over- and underfitting. We also did an analysis of weighing the distributions for the two models, which further allows us to argue for the relative superiority of one over the other.

Parameter posteriors [EJ]

Figure 3 and 4 show the parameter values for the models m_0, m_1, and m_2. This allows us to see how they have updated on their own and to which extent this was limited by the priors.

As the figures 3 and 4 show, some parameters did not change much. This might indicate that they are not relevant for the outcome. These effects include all effects of m_0(fig. 4) as well as the clustering effects of m_1 and m_2 (fig. 3).However, it can be seen that the effects of lockdown and PageRank in m_1 and m_2 (fig. 3) have moved quite a bit beyond the prior. Given our relatively large dataset this has probably not had a big effect on the estimates (especially since this is more of a covariate than a variable of interest.

Results [EJ]

Time series visualizations [EJ]

Figure 1 shows time series visualizations of the messages sent and received per node and figure 5 shows the three graph measures calculated by week.

Model results [EJ]

For H1, we get an estimate for m_1 of 0.073 (-0.11; 0.26) and for m_2 of 0.41 (0.25; 0.59) for the exponentiated difference of an open and a lockdown university being larger than zero. This results in an evidence ratio of `2.93 and ∞ respectively`. This can be seen visually on figure 6.

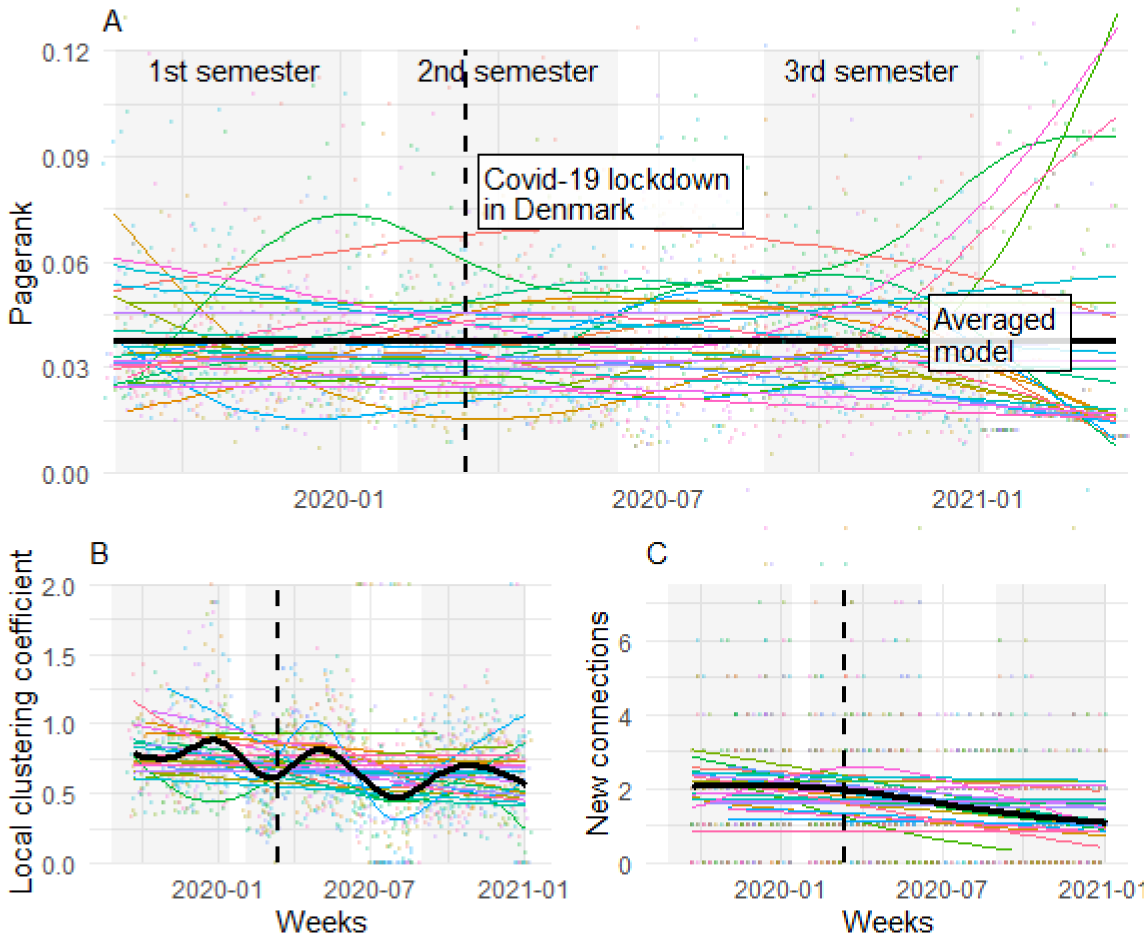

Figure 5: (A) the PageRank of each user by week, (B) the local clustering coefficient for each node by week, (C) the new connections for each node by week

For H2 (the interaction of popularity and lockdown) we have an estimate for m_1 of 0.22 (-0.01; 0.45) and for m_2 of 0.29 (0.07; 0.51). This gives an evidence ratio of 16.78 and 50.28. This can also be seen on figure 6. The marginal effect of pagerank has an estimate for the null for m_1 of 0.17 (0.03; 0.31) and for m_2 of 0.1 (-0.04; 0.23) with an evidence ratio of 0.06 and 0.34.

H3 (the interaction of clustering and lockdown) has an estimate for m_1 of 0.05 (-0.17, 0.26) and for m_2 of 0.15 (-0.06; 0.37). The evidence ratios are 1.72 and 6.69, respectively. This can also be seen in the blue density in figure 6. The marginal effect of clustering is estimated for the null for m_1 at -0.01 (-0.14; 0.13) and for m_2 of -0.3 (-0.16; 0.1) with an evidence ratio of 1.06 and 0.93.

H4 (information about lockdown improves model performance) was tested using a loo model comparison, where m_1 outperformed m_0 with a difference of epld of -12.9 (se: 2.9) and m_2 outperformed an m_0 restricted within the same date range with a difference of elpd of -32.3 (se: 5.5). Furthermore, a model-weight comparison gave all the weight to m_1 and m_3 respectively.

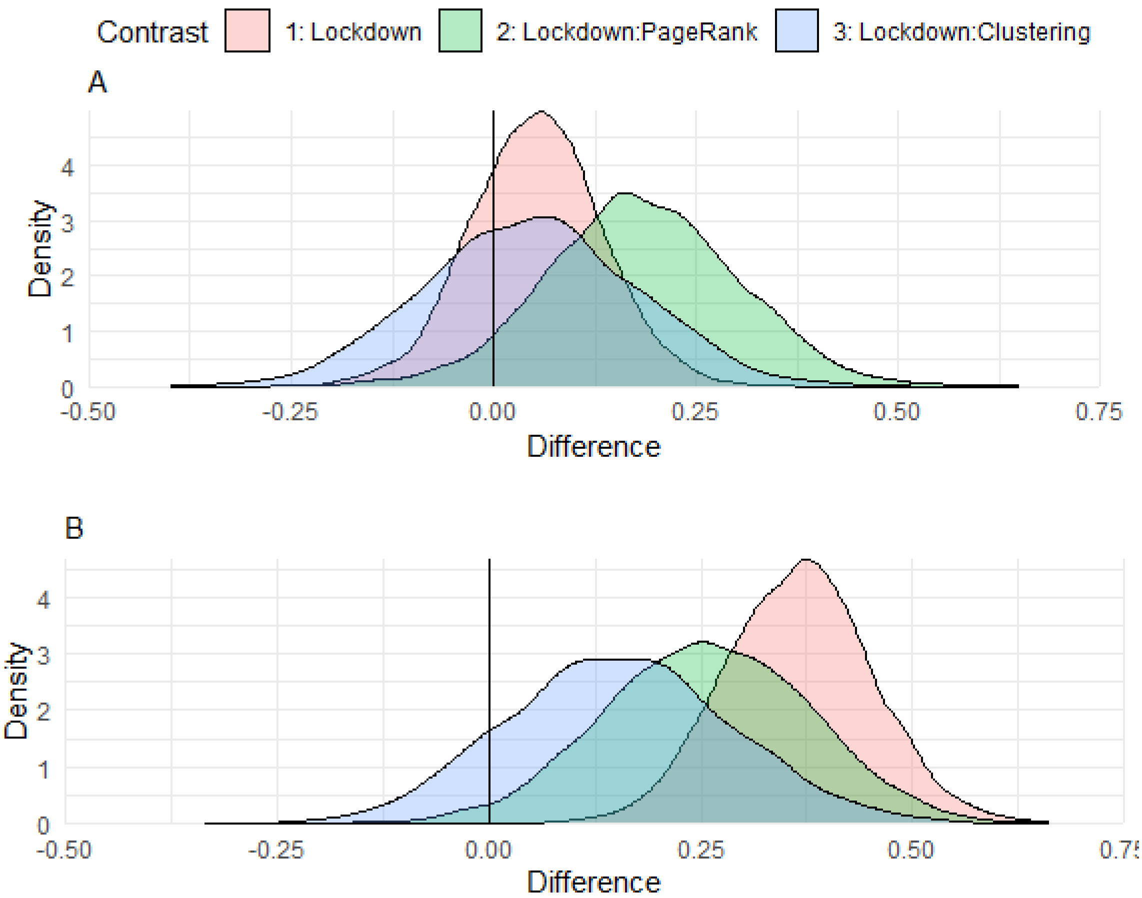

Figure 6: Difference plots for hypotheses 1-3 for an open versus a lockdown university for the long-term dynamics (A: m_1, B: m_2)

Discussion [EJ]

For H1 (that lockdown has a direct effect on the number of new connections), we find extremely strong evidence for the short term effects, but very weak evidence for the long term effects. This implies that lockdown might have acted as a disruptor in the short term radically changing the modes of communication and social structures. In the long term the weakness of the direct effect implies that the effect might be more complex than can be summarized by a simple linear effect. This can be both because of the heterogeneity of the lockdown severity (it was total in spring, whereas it was only partial in the autumn) as well as the general complexity in human communication and the included noise from the holidays where student interaction was different.

For H2 (that lockdown increases the effect of popularity), we find very strong evidence for the short-term effects and also moderately strong long-term effects. The results imply that lockdown created a kind of "winner takes more"-dynamic (Zinoviev & Duong, 2009). As the social life increasingly moved online, a higher PageRank might have made it easier for popular students to establish new connections as they had more intermediate connections

(Granovetter, 1973). This could act as a substitute for offline social structures such as Friday bars making it comparatively harder for less socially-apt students to establish new connections and friends. Furthermore, the strength of the short-term effects imply that being centrally connected allows you to more easily establish new connections.

H3 (that lockdown increases the effect of clustering) doesn't have any strong evidence as can be seen by the blue distribution on figure 6 which is close to fifty-fifty symmetric on zero for the long-term. For the short-term the effect was larger but not substantial. The marginal effects also lacked evidence. Being part of a strong local cluster thus did not seem to have any effect on getting new connections. An implication of this is that new friendships are not a "complex contagion" (Centola & Macy, 2007) and possibly more dependent on weak ties (Granovetter, 1973).

Lastly, for H4 (that lockdown gives important information to a model), both the comparison of ELPD and the model-stacking approach clearly show that lockdown information provides a predictive advantage. One might argue that this is purely a matter of overparameterization. However, this is unlikely as LOO-based methods optimize for out-of-sample predictions (by imitating cross-validation) which balances over- and underfitting (Vehtari et al., 2017).

Still, the possible modalities of friendship were much larger pre-lockdown (e.g. you could meet up in an after-school club or Friday bar). Therefore, the meaning of the target variable ("new connections") might change post-lockdown, as messaging suddenly became the only possible modality,

We can thus be relatively certain that lockdown provides useful information for models predicting new connections. Though our model cannot explain the whole difference, it seems that weak links are more important than robust links. This is especially true after the lockdown where the effects of popularity seems to have been amplified.

The choice of naturalistic data created important trade-offs between experimental control and ecological validity. On the one hand, naturalistic data gives access to real world interactions without observer bias or authority bias (Mahtani et al., 2018; Milgram & Gudehus, 1978). This comes at the cost of experimental control: It becomes difficult to isolate variables of interest and disentangle causal structures without explicit manipulation. Though large social media platforms can covertly do both (Kramer et al., 2014), it is against fundamental research ethics (Israel & Hay, 2006). Thus, social cognition research often faces this dilemma. The naturalistic focus of the present paper is based on the notion that this facet is currently underexplored compared to its experimental counterpart (Armitage & Conner, 2000), though the validity of the latter has been questioned (Adair, 1991).

Limitations [JE]

Despite the temporal granularity and ecological validity of the data, it nevertheless had several limitations that might have threatened the validity and robustness of the findings.

First of all, there are intrinsic limitations to the type of naturalistic messaging data used. The first of these is that messaging data does not capture all aspects of friendship and communication. There is no such thing as “raw” data (Gitelman & Jackson, 2013), especially when it comes to human interaction.

The second limitation was that we did not have access to every student’s data. Because the data collection was voluntary, approximately half the students did not send their data. The reasons for not participating varied from technical difficulties, to privacy concerns and non-response. These reasons might provide systematic bias in the data we were able to collect (e.g. a person with strong privacy concerns might react differently to increased lockdown induced online communication than a person with weaker privacy concerns). Furthermore, bugs in early versions of the script failed to collect data from some consenting students (n=4). With more time and effort we might have been able to solve most technical and non-response problems and thus get more data. Nevertheless, this would not have alleviated the bias caused by privacy-concerned students.

Next, our study did not have a control group. A control group would have allowed us to make stronger inferences about the effects of lockdown, which would strengthen our confidence in the validity of our hypotheses (or lack thereof). An obvious control group would be to collect data from older students, who didn’t experience lockdown as early in their study, or younger students, who have only studied during lockdown. However, this data was implausible to collect for several reasons. For one, there are time and resource constraints as it takes a while to individually help people troubleshooting, explain the anonymization procedure, establish trust etc. Lastly, there are ethical issues with the power dynamics regarding the younger students as both authors were introduction-week tutors and one of the authors was a teaching assistant. This might have made it harder for the students to decline to participate (Milgram & Gudehus, 1978).

Furthermore, our anonymization procedure obviously limited the information in the data. There were primarily two kinds of limitations in the anonymization process: Limitations in structure and limitations in content. Limitations in structure meant that we lacked information about any existing social structures outside of the messages. The most important of these is probably study groups as all students use messenger for study-group communication.

Implications and further research [EJ]

With the strength of our findings in mind, we can look at their implications. Lockdown and the resulting digitalization of social life has removed social structures that normally facilitate new connections. This has led to some “winner-takes-most”-dynamics (Prakash et al., 2012). To replace these social structures with online counterparts might require more active effort from the study administration. At Cognitive Science, Aarhus University, there has already been some efforts by supporting the (primarily student-led) construction of the online space “Cogwarts” on the platform gather.town (*Gather*, n.d.), which has been used for parties (Mikkelsen & Øvlisen, 2021) though the platform still has some difficulties in comparison to meeting physically (Samiei et al., 2020).

Further research could feasibly investigate these hypotheses with even more complete data. Ideally, this would both include full data on the target-semester (who experienced lockdown) and full data on a control-semester (who did not experience lockdown). It would also be beneficial to incorporate offline social structures such as study groups, though one should make sure to maintain the anonymity of the participants. Furthermore, it would be interesting to do cross-degree comparisons to see if the discovered patterns are idiosyncratic to cognitive science or if they generalize across the population.

Conclusion

This paper investigated the social effects of lockdown using data from Facebook messenger. We hypothesized that lockdown would have a direct effect on new connections, that it would increase the effect of popularity (operationalized with pagerank) and clustering, and provide useful information for models. We investigated both the short-term dynamics (within the semester with the initial lockdown) and longer-term dynamics (using data from September 2019 - December 2020). For the short-term dynamics we found strong effects for the general effects of lockdown and its effect on popularity, whereas the effects on clustering were somewhat weaker. For the long-term effects the pattern of the findings were similar, though the evidence was weaker. These findings imply that being broadly well-connected rather than having robust local clusters is increasingly important as communication is moving online.

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Appendix

Bayesian workflow: Expanded

Because of the volatility of the model, it was especially important to make sure the model had converged properly. We performed four kinds of checks: Check of rhat-values, prior-posterior-update checks, checks of chain mixing and the posterior predictive check. The rhat values were 1 for every variable, which is a good sign of convergence.

Posterior update checks

The posterior update checks can be seen in an equivalent format in fig. 3 and 4 in the main text.

Mixing plots

As an additional check, the chain plots show stability, good mixing and convergence as seen by the plot in figure a.1.

Figure a.1: Trace plots for all four chains per predictor

Mixing plots

Furthermore, we perform a posterior predictive check that shows good fit. We both see the gradual decay with spikes and a reasonable max (the "theoretical" max is 26 new connections).

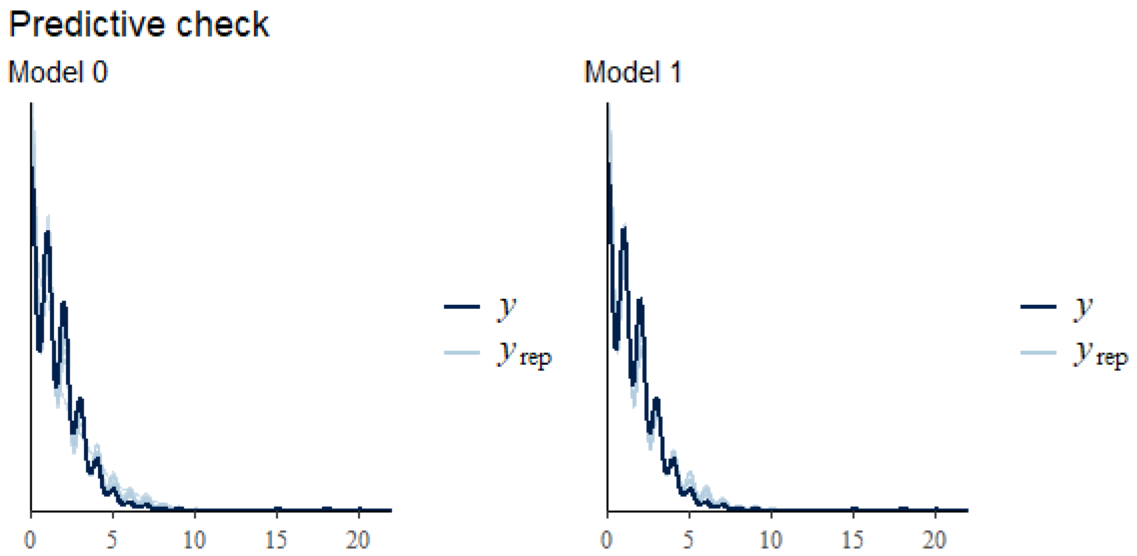

Figure a.2: Posterior predictive check for model 0 and model 1