

# A Network Model for Dynamic Textual Communications with Application to Government Email Corpora

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## Abstract

In this paper, we introduce the interaction-partitioned topic model (IPTM)—a probabilistic model of who communicates with whom about what, and when. Broadly speaking, the IPTM partitions time-stamped textual communications, such as emails, according to both the network dynamics that they reflect and their content. To define the IPTM, we integrate a dynamic version of the exponential random graph model—a generative model for ties that tend toward structural features such as triangles—and latent Dirichlet allocation—a generative model for topic-based content. The IPTM assigns each topic to an "interaction pattern"—a generative process for ties that is governed by a set of dynamic network features. Each communication is then modeled as a mixture of topics and their corresponding interaction patterns. We use the IPTM to analyze emails sent between department managers in two county governments in North Carolina; one of these email corpora covers the Outer Banks during the time period surrounding Hurricane Sandy. Via this application, we demonstrate that the IPTM is effective at predicting and explaining continuous-time textual communications.

## 1 Introduction

In recent decades, real-time digitized textual communication has developed into a ubiquitous form of social and professional interaction (see, e.g., Kanungo and Jain, 2008; Szóstek, 2011; Burgess et al., 2004; Pew, 2016). From the perspective of the computational social scientist, this has led to a growing need for methods of modeling networks consisting of text-valued edges that arise in continuous time (e.g., e-mail messages). A number of models that build upon topic modeling through Latent Dirichlet Allocation (Blei et al., 2003) to incorporate link data as well as textual content have been developed in response to this need [ASK HANNA FOR CITES]. The exponential random graph model (ERGM) (Robins et al., 2007; Chatterjee et al., 2013; Hunter et al., 2008), which is the canonical model for network structure as it is flexible enough to account for nearly any pattern of tie formation (Desmarais and Cranmer, 2017), has yet to be adapted to the setting of time-stamped text-valued edges. We build upon recent extensions of ERGM that model time-stamped ties (Perry and Wolfe, 2013; Butts, 2008), and develop the interaction-partitioned topic model (IPTM) to simultaneously model the network structural patterns that govern tie formation, and the content in the communications.

In defining and testing the IPTM we embed three core conceptual properties, in addition to modeling both text and network structure. First, we link the content component of the model, and network component of the model such that knowing who is communicating with whom at what time (i.e., the network component) provides information about the content of communication (i.e., the content component), and vice versa. Second, we fully specify the network dynamic component of the model such that, given the content of the communication and the history of tie formation, we can draw an exact, continuous-time prediction of when and to whom the communication will be sent. Third, we

formulate the network dynamic component of the model such that the model can represent, and be used to test hypotheses regarding, canonical processes relevant to network theory such as preferential attachment [**popularity cites**], reciprocity [**reciprocity cites**], and transitivity [**transitivity cites**]. In what follows we (1) present the generative process for the IPTM, describing how it meets our theoretical criteria, (2) derive the sampling equations for Bayesian inference with the IPTM, and (3) illustrate the IPTM through application to email corpora of internal communications by county officials in North Carolina county governments. [**What predictive comparisons should we run to other models**]?

## 2 Generative Process

Assume we have a collection of documents, consisting of  $D$  number of unique documents. A single email, indexed by  $d \in \{1, \dots, D\}$ , is represented by the four components  $(i^{(d)}, J^{(d)}, t^{(d)}, \mathbf{w}^{(d)})$ . The first two are the sender and receiver of the email: an integer  $i^{(d)} \in \{1, \dots, A\}$  indicates the identity of the sender out of  $A$  number of actors (or nodes) and an integer vector  $J^{(d)} = \{j_r^{(d)}\}_{r=1}^{|J^{(d)}|}$  indicates the identity of the receiver (or receivers) out of  $A - 1$  number of actors (by excluding self-loop), where  $|J^{(d)}| \in \{1, \dots, A - 1\}$  denotes the total number of the receivers. Next,  $t^{(d)}$  is the (unix time-based) timestamp of the email  $d$ , and  $\mathbf{w}^{(d)} = \{w_m^{(d)}\}_{m=1}^{N^{(d)}}$  is a set of tokens that comprise the text of the email. In this section, we illustrate how the words  $\mathbf{w}^{(d)}$  are generated according to the variant of latent Dirichlet allocation (Blei et al., 2003), and then how the rest three components,  $(i^{(d)}, J^{(d)}, t^{(d)})$ , are simultaneously generated from the stochastic intensity and topic assignments of the document. For simplicity, we assume that documents are ordered by time such that  $t^{(d)} < t^{(d+1)}$  for all  $d = 1, \dots, D$ .

### 2.1 Content Generating Process

The content generating process is a simple addition of the interaction pattern assignment to the existing generative process of Latent Dirichlet Allocation Blei et al. (2003). This concept is also very similar to the content-partitioned multinet network embeddings (CPME) model [**ASK BRUCE FOR CITES**], in a way that each topic  $k$  is also associated with a cluster assignment  $c_k$ , where  $c_k$  can take one of  $c = \{1, \dots, C\}$  values.

First we generate the global (corpus-wide) variables. There are two main sets of global variables: those that describe the topics people talk about and those that describe how people interact (interaction patterns). These variables are linked by a third set of variables that associate each topic with the pattern that best describes how people interact when talking about that topic.

There are  $K$  topics. Each topic  $k$  is a discrete distribution over  $V$  word types.

1.  $\phi^{(k)} \sim \text{Dir}(\beta, \mathbf{u})$  [**See Algorithm 1**]
  - A “topic”  $k$  is characterized by a discrete distribution over  $V$  word types with probability vector  $\phi^{(k)}$ . A symmetric Dirichlet prior  $\mathbf{u}$  with the concentration parameter  $\beta$  is placed.

There are  $C$  interaction patterns. Each interaction pattern consists of a vector of coefficients  $\mathbf{b}^{(c)}$  in  $\mathbf{R}^P$  and a vector of  $P$ -dimensional dynamic network statistics for directed edge  $(i, j)$  at time  $t$   $\mathbf{x}_t^{(c)}(i, j)$ ; however, we assume that our generative process is conditioned on these covariates.

2.  $\mathbf{b}^{(c)} \sim \text{Normal}(\mathbf{0}, \sigma^2 I_P)$  [**See Algorithm 2**]:
  - The vector of coefficients depends on the interaction pattern  $c$ . This means that there is variation in the degree of influence from the dynamic network statistics.

The topics and interaction patterns are tied together via a set of  $K$  categorical variables.

3.  $c_k \sim \text{Unif}(1, C)$  [**See Algorithm 3**]:
  - Each topic is associated with a single interaction pattern.

Then, we generate the local variables. We assume the following generative process for each document  $d$  in a corpus  $D$  [**See Algorithm 4**]:

4-1. Choose the number of words  $N^{(d)} = \max(1, \bar{N}^{(d)})$ , where  $\bar{N}^{(d)} \sim \text{Poisson}(\zeta)$

4-2. Choose document-topic distribution  $\boldsymbol{\theta}^{(d)} \sim \text{Dir}(\alpha, \mathbf{m})$

4-3. For  $n = 1$  to  $N^{(d)}$ :

(a) Choose a topic  $z_n^{(d)} \sim \text{Multinomial}(\boldsymbol{\theta}^{(d)})$

(b) if  $\bar{N}^{(d)} > 0$ , choose a word  $w_n^{(d)} \sim \text{Multinomial}(\phi^{(z_n^{(d)})})$

## 2.2 Stochastic Intensity

Here we illustrate how a set of dynamic network features and topic-interaction assignments jointly identify the stochastic intensity of a document, which plays a key role in the generating process in 2.3. Assume that each document  $d \in \{1, \dots, D\}$  has an  $A \times A$  stochastic intensity (or hazard) matrix of  $\boldsymbol{\lambda}^{(d)}(t) = \{\{\lambda_{ij}^{(d)}(t)\}_{i=1}^A\}_{j=1}^A$ , where  $\lambda_{ij}^{(d)}(t) = P\{\text{for document } d, i \rightarrow j \text{ occurs in time interval } [t, t+dt], \text{ given that it has not been sent until time } t\}$ .

To calculate the distribution of interaction patterns within a document, we estimate the (empirical) proportion of the words in document  $d$  which are assigned the topics corresponding to the interaction pattern  $c$  from 2.1:

$$p_c^{(d)} = \frac{\sum_{k: c_k=c} N^{(k|d)}}{N^{(d)}}, \quad (1)$$

where  $N^{(k|d)}$  is the number of times topic  $k$  shows up in the document  $d$ , and  $\sum_{c=1}^C p_c^{(d)} = 1$ .

Now, we define the  $(i, j)^{th}$  element of the stochastic intensity matrix  $\boldsymbol{\lambda}^{(d)}(t)$  forms:

$$\lambda_{ij}^{(d)}(t) = \sum_{c=1}^C p_c^{(d)} \cdot \exp\left\{\lambda_0^{(c)} \cdot \mathbf{b}^{(c)T} \mathbf{x}_t^{*(c)}(i, j)\right\} \cdot 1\{j \in \mathcal{A}_{\setminus i}\}, \quad (2)$$

where  $p_c^{(d)}$  is as defined above,  $\lambda_0^{(c)}$  is the baseline hazards for the interaction pattern  $c$ ,  $\mathbf{b}^{(c)}$  is an unknown vector of coefficients in  $\mathbf{R}^p$  corresponding to the interaction pattern  $c$ ,  $\mathbf{x}_t^{*(c)}(i, j)$  is a vector of the  $p$ -dimensional dynamic network statistics for directed edge  $(i, j)$  at time  $t$  corresponding to the interaction pattern  $c$ , and  $\mathcal{A}_{\setminus i}$  is the predictable receiver set of sender  $i$  within the set of all possible actors  $\mathcal{A}$  (no self-loop). After we include intercept and set  $\mathbf{x}_t^{(c)}(i, j) = (\mathbf{1}, \mathbf{x}_t^{*(c)}(i, j))$ , we rewrite (2) as:

$$\lambda_{ij}^{(d)}(t) = \sum_{c=1}^C p_c^{(d)} \cdot \exp\left\{\mathbf{b}^{(c)T} \mathbf{x}_t^{(c)}(i, j)\right\} \cdot 1\{j \in \mathcal{A}_{\setminus i}\}, \quad (3)$$

where now the first element of  $\mathbf{b}^{(c)}$  corresponds to the baseline intensity of interaction pattern  $c$ . This  $\lambda$  can be seen as the weighted average of stochastic intensities across the interaction patterns. Next, since multicast interactions—those involving a single sender but multiple receivers—are allowed for this model, we expand the rate of interaction between sender  $i$  and the receivers in a set  $J$  by taking the average of  $\mathbf{b}^{(c)T} \mathbf{x}_t^{(c)}(i, j)$  terms across the receivers:

$$\lambda_{iJ}^{(d)}(t) = \sum_{c=1}^C p_c^{(d)} \cdot \exp\left\{\frac{1}{|J|} \sum_{j \in J} \mathbf{b}^{(c)T} \mathbf{x}_t^{(c)}(i, j)\right\} \cdot \prod_{j \in J} 1\{j \in \mathcal{A}_{\setminus i}\}. \quad (4)$$

In case of single receivers ( $|J| = 1$ ), Equation (4) is reduced to Equation (3), thus in the following sections we use the Equation (4) of multicast cases as a general form of the stochastic intensity between the sender and receivers.

### 2.3 Tie Generating Process

We assume the following generative process for each document  $d$  in a corpus  $D$ :

1. (Data augmentation) For each sender  $i \in \{1, \dots, A\}$ , create a list of receivers  $J_i$  by applying the Bernoulli probabilities to every  $j \in \mathcal{A}_{\setminus i}$

$$I(i \rightarrow j) \sim \text{Ber}\left(\frac{\delta \lambda_{ij}^{(d)}}{\delta \lambda_{ij}^{(d)} + 1}\right), \quad (5)$$

where the probability is from a inverse log-logit link function ( $= \frac{1}{1 + \exp(-\log(\delta \lambda_{ij}^{(d)}))}$ ) using  $\lambda_{ij}^{(d)}$  evaluated at time  $t_+^{(d-1)}$ , and  $\delta$  is a positive tuning parameter to control the number of recipients. Note that  $_+$  denotes including the timepoint itself, meaning that  $\lambda_{ij}$  is obtained using the history of interactions until and including the timestamp  $t^{(d-1)}$ .

$$\text{(i.e. } \lambda_{ij}^{(d)} = \sum_{c=1}^C p_c^{(d)} \cdot \exp\left\{\mathbf{b}^{(c)T} \mathbf{x}_{t_+^{(d-1)}}^{(c)}(i, j)\right\} \cdot 1\{j \in \mathcal{A}_{\setminus i}\})$$

2. For sender with nonempty receiver sets  $i \in \mathcal{A}_{\setminus J_i = \emptyset}$ , generate the time increments

$$\Delta T_{iJ_i} \sim \text{Exp}(\delta \lambda_{iJ_i}^{(d)}). \quad (6)$$

where  $\delta$  also works as a tuning parameter to controlling the urgency of the document to be sent and  $\lambda_{iJ_i}^{(d)} = \sum_{c=1}^C p_c^{(d)} \cdot \exp\left\{\frac{1}{|J_i|} \sum_{j \in J_i} \mathbf{b}^{(c)T} \mathbf{x}_{t_+^{(d-1)}}^{(c)}(i, j)\right\} \cdot \prod_{j \in J_i} 1\{j \in \mathcal{A}_{\setminus i}\}$  as before.

3. Set timestamp, sender, and receivers simultaneously:

$$\begin{aligned} t^{(d)} &= t^{(d-1)} + \min(\Delta T_{iJ_i}) \\ i^{(d)} &= i_{\min(\Delta T_{iJ_i})} \\ J^{(d)} &= J_{i^{(d)}} \end{aligned} \quad (7)$$

Note:  $i^{(0)} = J^{(0)} = \emptyset$  and  $t^{(0)} = 0$ .

### 2.4 Dynamic covariates to measure network effects

For the network statistics  $\mathbf{x}_t^{(c)}(i, j)$  of Equation (3), we use 9 different effects as components of  $\mathbf{x}_t^{(c)}(i, j)$ , (intercept, outdegree, indegree, send, receive, 2-send, 2-receive, sibling, and cosibling) to measure popularity, centrality, reciprocity, and transitivity. First, we have intercept term to estimate the baseline intensity for each interaction pattern  $c = 1, \dots, C$ :

1. **intercept**<sup>(c)</sup> = 1

Next, following Perry and Wolfe (2013), we introduce binary indicators for all 9 effects as components of  $x_t(i, j)$ . These indicators depend on the sender  $i$ , the receiver  $j$ , and the history of the process at the current time  $t$ . By the shorthand notation  $1\{\text{send}\}$ , we indicates if  $i$  has sent  $j$  a message any time before  $t$ , with the remaining notations ( $1\{\text{receive}\}$ ,  $1\{\mathbf{2-receive}\}$ , etc.) defined similarly.

Moreover, we introduce additional covariates to measure higher-order time dependence with the following form. We partition the interval  $[-\infty, t)$  into  $L = 3$  (or/and  $L = 2$ ) sub-intervals by setting  $\Delta_l = (6 \text{ hours}) \times 4^l$  for  $l = 1, \dots, L - 1$  so that for  $t$  in this range  $\Delta_l$  takes the values 24 hours (=1 day), 96 hours (=4 days), 384 hours (=16 days):

$$\begin{aligned} [-\infty, t) &= [t - \Delta_3, t - \Delta_2) \cup [t - \Delta_2, t - \Delta_1) \cup [t - \Delta_1, t - \Delta_0) \\ &= [t - 384h, t - 96h) \cup [t - 96h, t - 24h) \cup [t - 24h, t - 0), \end{aligned}$$

where  $\Delta_0 = 0$ .

Now define the half-open interval  $I_t^{(l)} = [t - \Delta_l, t - \Delta_{l-1})$ . For the time interval  $l = 1, \dots, L$  and for the interaction pattern  $c = 1, \dots, C$ , the dyadic effects are

$$2. \text{outdegree}_t^{(c|l)}(i) = \sum_{d:t^{(d)} \in I_t^{(l)}} p_c^{(d)} \cdot I\{i \rightarrow \forall j\}$$

$$3. \text{indegree}_t^{(c|l)}(j) = \sum_{d:t^{(d)} \in I_t^{(l)}} p_c^{(d)} \cdot I\{\forall i \rightarrow j\}$$

$$4. \text{send}_t^{(c|l)}(i, j) = \sum_{d:t^{(d)} \in I_t^{(l)}} p_c^{(d)} \cdot I\{i \rightarrow j\}$$

$$5. \text{receive}_t^{(c|l)}(i, j) = \sum_{d:t^{(d)} \in I_t^{(l)}} p_c^{(d)} \cdot I\{j \rightarrow i\}$$

and for the triadic effects involve pairs of messages, for  $l = 1, \dots, L$ ,  $l' = 1, \dots, L$  and  $c = 1, \dots, C$  we define the triadic effects

$$6. \text{2-send}_t^{(c|l,l')}(i, j) = \sum_{h \neq i, j} \left( \sum_{d:t^{(d)} \in I_t^{(l)}} p_c^{(d)} \cdot I\{i \rightarrow h\} \right) \cdot \left( \sum_{d':t^{(d')} \in I_t^{(l')}} p_c^{(d')} \cdot I\{h \rightarrow j\} \right)$$

$$7. \text{2-receive}_t^{(c|l,l')}(i, j) = \sum_{h \neq i, j} \left( \sum_{d:t^{(d)} \in I_t^{(l)}} p_c^{(d)} \cdot I\{h \rightarrow i\} \right) \cdot \left( \sum_{d':t^{(d')} \in I_t^{(l')}} p_c^{(d')} \cdot I\{j \rightarrow h\} \right)$$

$$8. \text{sibling}_t^{(c|l,l')}(i, j) = \sum_{h \neq i, j} \left( \sum_{d:t^{(d)} \in I_t^{(l)}} p_c^{(d)} \cdot I\{h \rightarrow i\} \right) \cdot \left( \sum_{d':t^{(d')} \in I_t^{(l')}} p_c^{(d')} \cdot I\{h \rightarrow j\} \right)$$

$$9. \text{cosibling}_t^{(c|l,l')}(i, j) = \sum_{h \neq i, j} \left( \sum_{d:t^{(d)} \in I_t^{(l)}} p_c^{(d)} \cdot I\{i \rightarrow h\} \right) \cdot \left( \sum_{d':t^{(d')} \in I_t^{(l')}} p_c^{(d')} \cdot I\{j \rightarrow h\} \right)$$

In this setting, if we use  $L = 3$ , the dimension of  $\mathbf{b}^{(c)}$  becomes

$$P = (1 \text{ (intercept)} + 8 \text{ (indicators)} + 4 \times L \text{ (dyadic)} + 4 \times L^2 \text{ (triadic)}) = 57,$$

for each interaction pattern  $c = 1, \dots, C$ .

## 2.5 Joint Generative Process of Document

Below are the joint generative process for each document in a corpus  $D$ , integrating 2.1, 2.2, 2.3, and 2.4. Figure 1 is the corresponding plate notation of IPTM.

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### Algorithm 1 Topic Word Distributions

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**for**  $k=1$  **to**  $K$  **do**  
  | draw  $\phi^{(k)} \sim \text{Dir}(\beta, \mathbf{u})$   
**end**

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### Algorithm 2 Interaction Pattern Parameters

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**for**  $c=1$  **to**  $C$  **do**  
  | draw  $\mathbf{b}^{(c)} \sim \text{Normal}(\mathbf{0}, \sigma^2 I_P)$   
**end**

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### Algorithm 3 Topic Interaction Pattern Assignments

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**for**  $k=1$  **to**  $K$  **do**  
  | draw  $C_k \sim \text{Unif}(1, C)$   
**end**

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**Algorithm 4** Document Generating Process
 

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for  $d=1$  to  $D$  do
  draw  $N^{(d)} = \max(1, \bar{N}^{(d)})$ , where  $\bar{N}^{(d)} \sim \text{Poisson}(\zeta)$ 
  draw  $\boldsymbol{\theta}^{(d)} \sim \text{Dir}(\alpha, \mathbf{m})$ 
  for  $n=1$  to  $N^{(d)}$  do
    draw  $z_n^{(d)} \sim \text{Multinom}(\boldsymbol{\theta}^{(d)})$ 
    if  $\bar{N}^{(d)} > 0$  then
      draw  $w_n^{(d)} \sim \text{Multinom}(\boldsymbol{\phi}^{(z_n^{(d)})})$ 
    end
  end
  for  $c=1$  to  $C$  do
    set  $p_c^{(d)} = \frac{\sum_{k: c_k=c} N^{(k|d)}}{N^{(d)}}$ 
  end
  for  $i=1$  to  $A$  do
    for  $j=1$  to  $A$  do
      if  $j \neq i$  then
        calculate  $\mathbf{x}_{t_+^{(d-1)}}^{(c)}(i, j)$ , the network statistics evaluated at time  $t_+^{(d-1)}$ 
        set  $\lambda_{ij}^{(d)} = \sum_{c=1}^C p_c^{(d)} \cdot \exp\left\{\mathbf{b}^{(c)T} \mathbf{x}_{t_+^{(d-1)}}^{(c)}(i, j)\right\} \cdot 1\{j \in \mathcal{A}_{\setminus i}\}$ 
        draw  $I(i \rightarrow j) \sim \text{Ber}\left(\frac{\delta \lambda_{ij}^{(d)}}{\delta \lambda_{ij}^{(d)} + 1}\right)$ 
      end
    end
    draw  $\Delta T_{iJ_i} \sim \text{Exp}(\delta \lambda_{iJ_i}^{(d)})$ 
  end
  set  $t^{(d)} = t^{(d-1)} + \min(\Delta T_{iJ_i})$ ,  $i^{(d)} = i_{\min(\Delta T_{iJ_i})}$ , and  $J^{(d)} = J_{i^{(d)}}$ 
end

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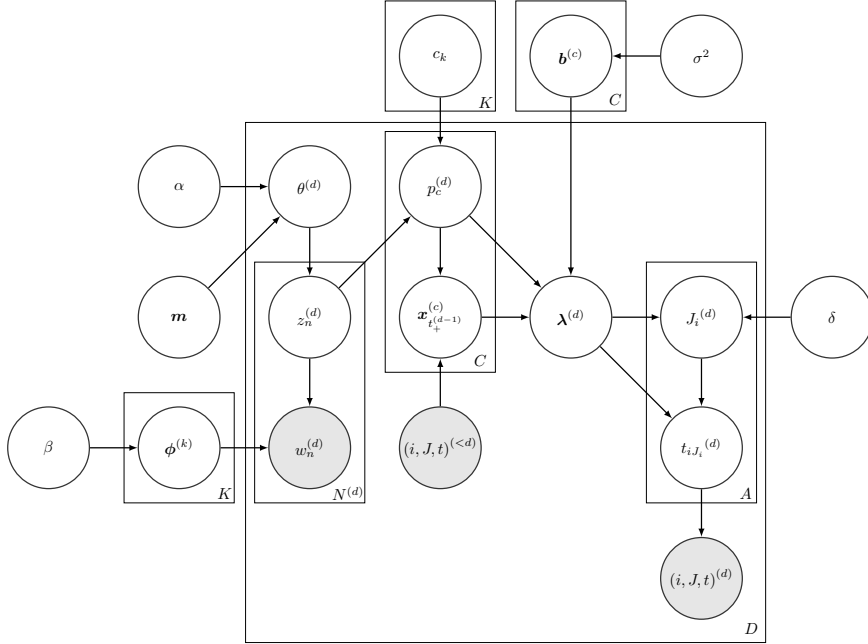


Figure 1: Plate notation of IPTM

### 3 Inference

The joint generative process implies a particular factorization of the joint distribution over the variables  $\Phi = \{\phi^{(k)}\}_{k=1}^K$ ,  $\Theta = \{\theta^{(d)}\}_{d=1}^D$ ,  $\mathcal{Z} = \{z^{(d)}\}_{d=1}^D$ ,  $\mathcal{W} = \{w^{(d)}\}_{d=1}^D$ ,  $\mathcal{C} = \{c_k\}_{k=1}^K$ ,  $\mathcal{B} = \{b^{(c)}\}_{c=1}^C$ ,  $\mathcal{I} = \{i^{(d)}\}_{d=1}^D$ ,  $\mathcal{J} = \{J_i^{(d)}\}_{i=1}^A\}_{d=1}^D$ ,  $\mathcal{T} = \{t_{iJ_i}^{(d)}\}_{i=1}^A\}_{d=1}^D$ , and  $\mathcal{O} = \{(i, J, t)^{(d)}\}_{d=1}^D$  given the observed  $\mathcal{H} = \{(i, J, t)^{(<d)}\}_{d=1}^D$  and the hyperparameters  $(\beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2, \delta)$ :

$$\begin{aligned} & P(\Phi, \Theta, \mathcal{Z}, \mathcal{W}, \mathcal{C}, \mathcal{B}, \mathcal{J}, \mathcal{T}, \mathcal{O} | \mathcal{I}, \mathcal{H}, \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2, \delta) \\ &= P(\Phi | \beta, \mathbf{u}) P(\Theta | \alpha, \mathbf{m}) P(\mathcal{Z} | \Theta) P(\mathcal{W} | \mathcal{Z}, \Phi) P(\mathcal{C}) P(\mathcal{B} | \mathcal{C}, \sigma^2) \\ &\quad \times P(\mathcal{J} | \mathcal{Z}, \mathcal{C}, \mathcal{B}, \mathcal{I}, \mathcal{H}, \delta) P(\mathcal{T} | \mathcal{Z}, \mathcal{C}, \mathcal{B}, \mathcal{J}, \mathcal{I}, \mathcal{H}) P(\mathcal{O} | \mathcal{T}). \end{aligned} \quad (8)$$

We can simplify this further by integrating out  $\Phi$  and  $\Theta$  using Dirichlet-multinomial conjugacy:

$$\begin{aligned} & P(\mathcal{Z}, \mathcal{W}, \mathcal{C}, \mathcal{B}, \mathcal{J}, \mathcal{T}, \mathcal{O} | \mathcal{I}, \mathcal{H}, \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2, \delta) \\ &= P(\mathcal{Z} | \alpha, \mathbf{m}) P(\mathcal{W} | \mathcal{Z}, \beta, \mathbf{u}) P(\mathcal{C}) P(\mathcal{B} | \mathcal{C}, \sigma^2) P(\mathcal{J} | \mathcal{Z}, \mathcal{C}, \mathcal{B}, \mathcal{I}, \mathcal{H}, \delta) P(\mathcal{T} | \mathcal{Z}, \mathcal{C}, \mathcal{B}, \mathcal{J}, \mathcal{I}, \mathcal{H}) P(\mathcal{O} | \mathcal{T}). \end{aligned} \quad (9)$$

Note that since  $p_c^{(d)}$  is a deterministic function of  $(\mathcal{Z}, \mathcal{C})$ ,  $\mathbf{x}_{t_{+}^{(d-1)}}^{(c)}$  is a deterministic function of  $(p_c^{(d)}, \mathcal{I}, \mathcal{H})$  and  $\lambda^{(d)}$  is a deterministic function of  $(p_c^{(d)}, \mathbf{x}_{t_{+}^{(d-1)}}^{(c)}, \mathcal{B})$ , we do not include them as variables in the joint distribution.

What we observe in the data is  $\mathcal{W}$  and  $\mathcal{O}$ . We want to infer the values of all the latent variables  $(\mathcal{Z}, \mathcal{C}, \mathcal{B})$  that most likely would have generated the data we observe, if we believe the generative process. Currently the variables  $(\mathcal{I}, \mathcal{J}, \mathcal{T}, \mathcal{O}, \mathcal{H})$  are redundant, thus we re-define the variables considering the data augmentation:  $\mathcal{I}_a = \{i^{(d)}\}_{i \neq i_o^{(d)}}_{d=1}^D$ ,  $\mathcal{J}_a = \{J_i^{(d)}\}_{i \neq i_o^{(d)}}_{d=1}^D$ , and  $\mathcal{T}_a = \{t_{iJ_i}^{(d)}\}_{i \neq i_o^{(d)}}_{d=1}^D$  of the augmented data and  $\mathcal{I}_o = \{i^{(d)}\}_{d=1}^D$ ,  $\mathcal{J}_o = \{J^{(d)}\}_{d=1}^D$ , and  $\mathcal{T}_o = \{t^{(d)}\}_{d=1}^D$  from the observed data.

Now, our inference goal is to draw samples from the posterior distribution

$$\begin{aligned} & P(\mathcal{Z}, \mathcal{C}, \mathcal{B}, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a | \mathcal{W}, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o, \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2, \delta) \\ &\propto P(\mathcal{Z}, \mathcal{C}, \mathcal{B}, \mathcal{W}, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o | \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2, \delta) \\ &= P(\mathcal{Z} | \alpha, \mathbf{m}) P(\mathcal{C}) P(\mathcal{B} | \mathcal{C}, \sigma^2) P(\mathcal{W} | \mathcal{Z}, \beta, \mathbf{u}) P(\mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o | \mathcal{Z}, \mathcal{C}, \mathcal{B}, \delta) \end{aligned} \quad (10)$$

As mentioned earlier in Section 2.3, we use data augmentation in the tie generating process. Since we should include both the observed and augmented data to make inferences on the related latent variables, the derivation steps for the contribution of tie is not as simple as other variables. Therefore, here we provide the detailed derivation steps for the last term of conditional probability:

$$\begin{aligned} & P(\mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o | \mathcal{Z}, \mathcal{C}, \mathcal{B}, \delta) \\ &= \prod_{d=1}^D P(\mathcal{I}_a^{(d)}, \mathcal{J}_a^{(d)}, \mathcal{T}_a^{(d)}, i_o^{(d)}, J_o^{(d)}, t_o^{(d)} | \mathcal{I}_o^{(<d)}, \mathcal{J}_o^{(<d)}, \mathcal{T}_o^{(<d)}, \mathcal{Z}, \mathcal{C}, \mathcal{B}, \delta). \end{aligned} \quad (11)$$

Note that on the right hand side we have dropped the conditional dependence on  $(\mathcal{I}_a^{(-d)}, \mathcal{J}_a^{(-d)}, \mathcal{T}_a^{(-d)})$  and  $(\mathcal{I}_o^{(>d)}, \mathcal{J}_o^{(>d)}, \mathcal{T}_o^{(>d)})$  as the tie generating process implies independence  $(\mathcal{I}_a^{(d)}, \mathcal{J}_a^{(d)}, \mathcal{T}_a^{(d)}, i_o^{(d)}, J_o^{(d)}, t_o^{(d)}) \perp (\mathcal{I}_a^{(-d)}, \mathcal{J}_a^{(-d)}, \mathcal{T}_a^{(-d)})$  and  $(\mathcal{I}_a^{(d)}, \mathcal{J}_a^{(d)}, \mathcal{T}_a^{(d)}, i_o^{(d)}, J_o^{(d)}, t_o^{(d)}) \perp (\mathcal{I}_o^{(>d)}, \mathcal{J}_o^{(>d)}, \mathcal{T}_o^{(>d)})$ , respectively.

Now we tackle the problem by deriving  $P(\mathcal{I}_a^{(d)}, \mathcal{J}_a^{(d)}, \mathcal{T}_a^{(d)}, i_o^{(d)}, J_o^{(d)}, t_o^{(d)} | \mathcal{Z}, \mathcal{C}, \mathcal{B}, \delta)$  for  $d^{th}$  document. There are three steps involved. First is the generation of the latent receivers  $J_i$  for each  $i$ , which corresponds to the Bernoulli part of tie generation, Equation (5); second is the generation of time increments  $\Delta T_{iJ_i}$  for each  $i$ , which corresponds to the Exponential part of tie generation, Equation (6); and the last is the simultaneous selection process of the observed sender, receivers, and timestamp, Equation (7). Reflecting the three steps, the joint distribution is:

$$\begin{aligned}
& P(\mathcal{I}_a^{(d)}, \mathcal{J}_a^{(d)}, \mathcal{T}_a^{(d)}, i_o^{(d)}, J_o^{(d)}, t_o^{(d)} | \mathcal{I}_o^{(<d)}, \mathcal{J}_o^{(<d)}, \mathcal{T}_o^{(<d)}, \mathcal{Z}, \mathcal{C}, \mathcal{B}, \delta) \\
&= P(\text{latent receivers generation}) \times P(\text{latent time generation}) \times P(\text{choose the observed}) \\
&= P(\text{from Equation (5)}) \times P(\text{from Equation (6)}) \times P(\text{from Equation (7)}) \\
&= \prod_{i \in \mathcal{A}} \prod_{j \in \mathcal{A}_{\setminus i}} \left( I(i \rightarrow j) \sim \text{Ber}\left(\frac{\delta \lambda_{ij}^{(d)}}{\delta \lambda_{ij}^{(d)} + 1}\right) \right) \times \prod_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \left( \Delta T_{iJ_i} \sim \text{Exp}(\delta \lambda_{iJ_i}^{(d)}) \right) \times P(\min_i(\Delta T_{iJ_i}) = \Delta T_{i_o^{(d)} J_o^{(d)}}) \\
&= \left( \prod_{i \in \mathcal{A}} \prod_{j \in \mathcal{A}_{\setminus i}} \left( \frac{\delta \lambda_{ij}^{(d)}}{\delta \lambda_{ij}^{(d)} + 1} \right)^{I(j \in J_i)} \left( \frac{1}{\delta \lambda_{ij}^{(d)} + 1} \right)^{1-I(j \in J_i)} \right) \times \left( \prod_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \delta \lambda_{iJ_i}^{(d)} e^{-(t^{(d)} - t^{(d-1)}) \delta \lambda_{iJ_i}^{(d)}} \right) \\
&\quad \times \left( \prod_{i \in \mathcal{A}_{\setminus J_i = \emptyset, i_o^{(d)}}} e^{-(t^{(d)} - t^{(d-1)}) \delta \lambda_{iJ_i}^{(d)}} \right),
\end{aligned} \tag{12}$$

where the last term is given by the cumulative exponential distributions associated with the respective  $\lambda_{iJ_i}$ . Therefore, we can simplify the above equation as below:

$$\begin{aligned}
& P(\mathcal{I}_a^{(d)}, \mathcal{J}_a^{(d)}, \mathcal{T}_a^{(d)}, i_o^{(d)}, J_o^{(d)}, t_o^{(d)} | \mathcal{I}_o^{(<d)}, \mathcal{J}_o^{(<d)}, \mathcal{T}_o^{(<d)}, \mathcal{Z}, \mathcal{C}, \mathcal{B}, \delta) \\
&= \left( \prod_{i \in \mathcal{A}} \prod_{j \in \mathcal{A}_{\setminus i}} \frac{(\delta \lambda_{ij}^{(d)})^{I(j \in J_i)}}{\delta \lambda_{ij}^{(d)} + 1} \right) \times \left( \prod_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \delta \lambda_{iJ_i}^{(d)} \right) \times \left( e^{-\delta(t^{(d)} - t^{(d-1)}) \left( \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \lambda_{iJ_i}^{(d)} + \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset, i_o^{(d)}}} \lambda_{iJ_i}^{(d)} \right)} \right).
\end{aligned} \tag{13}$$

For implementation, we need to compute these equations in log space to prevent underflow:

$$\begin{aligned}
& \log \left( P(\mathcal{I}_a^{(d)}, \mathcal{J}_a^{(d)}, \mathcal{T}_a^{(d)}, i_o^{(d)}, J_o^{(d)}, t_o^{(d)} | \mathcal{I}_o^{(<d)}, \mathcal{J}_o^{(<d)}, \mathcal{T}_o^{(<d)}, \mathcal{Z}, \mathcal{C}, \mathcal{B}, \delta) \right) \\
&= \sum_{i \in \mathcal{A}} \sum_{j \in \mathcal{A}_{\setminus i}} I(j \in J_i) \cdot \log(\delta \lambda_{iJ_i}^{(d)}) - \log(\delta \lambda_{iJ_i}^{(d)} + 1) \\
&\quad + \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \log(\delta \lambda_{iJ_i}^{(d)}) - \delta(t^{(d)} - t^{(d-1)}) \left( \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \lambda_{iJ_i}^{(d)} + \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset, i_o^{(d)}}} \lambda_{iJ_i}^{(d)} \right).
\end{aligned} \tag{14}$$

To actually perform inference, we therefore want to use Gibbs sampling, where we will sequentially resample the values of each of our latent variables from their posterior distribution, conditional on all of our other variables.

### 3.1 Resampling the augmented data $\mathcal{I}_a, \mathcal{J}_a$

First of all, for each document  $d$ , we update the latent sender and the corresponding receiver set,  $\mathcal{I}_a^{(d)} = \{i^{(d)}\}_{i \neq i^{(d)}}$  and  $\mathcal{J}_a^{(d)} = \{J_i^{(d)}\}_{i \neq i^{(d)}}$ , by accounting for the conditional probability  $P(\text{latent receivers} | \text{latent time} < \text{observed time})$ . To derive this, let  $\Delta T_{i_o^{(d)} J_o^{(d)}}$  be the observed time increment, and  $\Delta T_{i_a J_{i_a}}$  be the latent time increment associated with the document sent by  $i_a$ . We also define  $r_{ij}$  be an indicator of whether sender  $i$  added  $j$  to the latent receivers (i.e.  $j \in J_i$ ), and  $J_i^{(-j)}$  denote the vector of recipient indicators other than  $j$ . Then the conditional probability is:

$$\begin{aligned}
& P(r_{ij} = 1 | (\Delta T_{iJ_i} > \Delta T_{i^{(d)} J^{(d)}}) \cap (J_i^{(-j)})) \\
&= \frac{P((r_{ij} = 1) \cap (\Delta T_{iJ_i} > \Delta T_{i^{(d)} J^{(d)}}) \cap (J_i^{(-j)}))}{P((\Delta T_{iJ_i} > \Delta T_{i^{(d)} J^{(d)}}) \cap (J_i^{(-j)}))} \\
&= \frac{P(\Delta T_{iJ_i} > \Delta T_{i^{(d)} J^{(d)}} | (r_{ij} = 1) \cap (J_i^{(-j)})) P((r_{ij} = 1) \cap (J_i^{(-j)}))}{P((\Delta T_{iJ_i} > \Delta T_{i^{(d)} J^{(d)}}) \cap (J_i^{(-j)}) | r_{ij} = 1) P(r_{ij} = 1) + P((\Delta T_{iJ_i} > \Delta T_{i^{(d)} J^{(d)}}) \cap (J_i^{(-j)}) | r_{ij} = 0) P(r_{ij} = 0)},
\end{aligned} \tag{15}$$



where  $P(\Delta T_{iJ_i} > \Delta T_{i(d)J(d)} | (r_{ij} = 1) \cap (J_i^{(-j)}))$ ,  $P((\Delta T_{iJ_i} > \Delta T_{i(d)J(d)}) \cap (J_i^{(-j)}) | r_{ij} = 1)$ , and  $P((\Delta T_{iJ_i} > \Delta T_{i(d)J(d)}) \cap (J_i^{(-j)}) | r_{ij} = 0)$  are given by the cumulative exponential distributions associated with the respective  $\lambda_{iJ_i}$  and  $P((r_{ij} = 1) \cap (J_i^{(-j)}))$ ,  $P(r_{ij} = 1)$ , and  $P(r_{ij} = 0)$  are given by the Bernoulli equation in Section 2.3. We plug in the equations and update the latent ties  $r_{ij}$  with the probability:

$$\begin{aligned}
& P(r_{ij} = 1 | (\Delta T_{iJ_i} > \Delta T_{i(d)J(d)}) \cap (J_i^{(-j)})) \\
&= \frac{e^{-\delta(t^{(d)} - t^{(d-1)}) \frac{1}{|J_i^{(+j)}|} \sum_{j \in J_i^{(+j)}} \lambda_{ij}^{(d)}} \times \left( \frac{\delta \lambda_{ij}^{(d)}}{\delta \lambda_{ij}^{(d)} + 1} \right) \times \left( \prod_{a \in \mathcal{A}_{i,j}} (\delta \lambda_{ij}^{(d)})^{I(a \in J_i)} / (\delta \lambda_{ij}^{(d)} + 1) \right)}{e^{-\delta(t^{(d)} - t^{(d-1)}) \frac{1}{|J_i^{(+j)}|} \sum_{j \in J_i^{(+j)}} \lambda_{ij}^{(d)}} \times \left( \frac{\delta \lambda_{ij}^{(d)}}{\delta \lambda_{ij}^{(d)} + 1} \right) + e^{-\delta(t^{(d)} - t^{(d-1)}) \frac{1}{|J_i^{(-j)}|} \sum_{j \in J_i^{(-j)}} \lambda_{ij}^{(d)}} \times \left( \frac{1}{\delta \lambda_{ij}^{(d)} + 1} \right)} \quad (16) \\
&= \frac{\left( \prod_{a \in \mathcal{A}_{i,j}} (\delta \lambda_{ij}^{(d)})^{I(a \in J_i)} / (\delta \lambda_{ij}^{(d)} + 1) \right)}{1 + e^{\delta(t^{(d)} - t^{(d-1)}) \left( \frac{1}{|J_i^{(+j)}|} \sum_{j \in J_i^{(+j)}} \lambda_{ij}^{(d)} - \frac{1}{|J_i^{(-j)}|} \sum_{j \in J_i^{(-j)}} \lambda_{ij}^{(d)} \right)} / \delta \lambda_{ij}^{(d)}}.
\end{aligned}$$

This probability will be used when we update the augmented data in every outer iteration. For implementation, we need to compute these equations in log space to prevent underflow:

$$\begin{aligned}
& \log \left( P(r_{ij} = 1 | (\Delta T_{iJ_i} > \Delta T_{i(d)J(d)}) \cap (J_i^{(-j)})) \right) \\
&= \sum_{a \in \mathcal{A}_{i,j}} I(a \in J_i) \cdot \log(\delta \lambda_{ij}^{(d)}) - \log(\delta \lambda_{ij}^{(d)} + 1) \\
& \quad - \log \left( 1 + e^{\delta(t^{(d)} - t^{(d-1)}) \left( \frac{1}{|J_i^{(+j)}|} \sum_{j \in J_i^{(+j)}} \lambda_{ij}^{(d)} - \frac{1}{|J_i^{(-j)}|} \sum_{j \in J_i^{(-j)}} \lambda_{ij}^{(d)} \right) - \log(\delta \lambda_{ij}^{(d)})} \right). \quad (17)
\end{aligned}$$

Here, to protect from numerical underflow and overflow, we use the numerical approximation of  $f(y) = \log(1 + e^y)$  as below:

$$f(y) = \begin{cases} y & y > 35 \\ e^y & y < -10 \\ \log(1 + e^y) & \text{otherwise.} \end{cases}$$

### 3.2 Resampling $\mathcal{Z}$

Second, we are going to resample the topic assignments, one words in a document at a time. The new values of  $z_n^{(d)}$  are sampled using the conditional posterior probability of being topic  $k$  as we derived in APPENDIX C:

$$\begin{aligned}
& P(z_n^{(d)} = k | \mathcal{Z}_{\setminus d,n}, \mathcal{C}, \mathcal{B}, \mathcal{W}, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o, \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2, \delta) \\
& \propto P(z_n^{(d)} = k, w_n^{(d)}, \mathcal{I}_a^{(d)}, \mathcal{J}_a^{(d)}, \mathcal{T}_a^{(d)}, \mathcal{I}_o^{(d)}, \mathcal{J}_o^{(d)}, \mathcal{T}_o^{(d)} | \mathcal{Z}_{\setminus d,n}, \mathcal{C}, \mathcal{B}, \mathcal{W}_{\setminus d,n}, \mathcal{I}_o^{(-d)}, \mathcal{J}_o^{(-d)}, \mathcal{T}_o^{(-d)}, \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2, \delta) \\
& = P(z_n^{(d)} = k | \mathcal{Z}_{\setminus d,n}, \alpha, \mathbf{m}) P(w_n^{(d)} | z_n^{(d)} = k, \mathcal{W}_{\setminus d,n}, \mathcal{Z}_{\setminus d,n}, \beta, \mathbf{u}) \\
& \quad \times P(\mathcal{I}_a^{(d)}, \mathcal{J}_a^{(d)}, \mathcal{T}_a^{(d)}, \mathcal{I}_o^{(d)}, \mathcal{J}_o^{(d)}, \mathcal{T}_o^{(d)} | z_n^{(d)} = k, \mathcal{Z}_{\setminus d,n}, \mathcal{C}, \mathcal{B}, \sigma^2, \delta) \quad (18)
\end{aligned}$$

where the subscript “ $\setminus d, n$ ” denotes the excluision of position  $n$  in  $d^{th}$  document and the subscript “ $\setminus d$ ” and “ $(-d)$ ” denotes the excluision of  $d^{th}$  document. We know that:

$$P(z_n^{(d)} = k | \mathcal{Z}_{\setminus d,n}, \alpha, \mathbf{m}) = \frac{N_{\setminus d,n}^{(k|d)} + \alpha \mathbf{m}_k}{N^{(d)} - 1 + \alpha} \quad (19)$$

which is the well-known form of collapsed Gibbs sampling equation for LDA. We also know that

$$P(w_n^{(d)} | z_n^{(d)} = k, \mathcal{W}_{\setminus d,n}, \mathcal{Z}_{\setminus d,n}, \beta, \mathbf{u}) = \frac{N_{\setminus d,n}^{(w_n^{(d)}|k)} + \frac{\beta}{W}}{N_{\setminus d,n}^{(k)} + \beta}, \quad (20)$$

where  $N^{(w_n^{(d)}|k)}$  is the number of tokens assigned to topic  $k$  whose type is the same as that of  $w_n^{(d)}$ , excluding  $w_n^{(d)}$  itself, and  $N_{\setminus d,n}^{(k)} = \sum_{w=1}^W N_{\setminus d,n}^{(w_n^{(d)}|k)}$ . Finally, in 3.1, we have shown that

$$\begin{aligned} & P(\mathcal{I}_a^{(d)}, \mathcal{J}_a^{(d)}, \mathcal{T}_a^{(d)}, \mathcal{I}_o^{(d)}, \mathcal{J}_o^{(d)}, \mathcal{T}_o^{(d)} | z_n^{(d)} = k, \mathcal{Z}_{\setminus d,n}, \mathcal{C}, \mathcal{B}, \sigma^2, \delta) \\ &= \left( \prod_{i \in \mathcal{A}} \prod_{j \in \mathcal{A}_{\setminus i}} \frac{(\delta \lambda_{ij}^{(d)})^{I(j \in J_i)}}{\delta \lambda_{ij}^{(d)} + 1} \right) \times \left( \prod_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \delta \lambda_{iJ_i}^{(d)} \right) \times \left( e^{-\delta(t^{(d)} - t^{(d-1)}) \left( \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \lambda_{iJ_i}^{(d)} + \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset, i_o^{(d)}}} \lambda_{iJ_i}^{(d)} \right)} \right). \end{aligned} \quad (21)$$

Therefore, if  $\bar{N}^{(d)} > 0$ , then

$$\begin{aligned} & P(z_n^{(d)} = k | \mathcal{Z}_{\setminus d,n}, \mathcal{C}, \mathcal{B}, \mathcal{W}, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o, \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2, \delta) \\ & \propto (N_{\setminus d,n}^{(k|d)} + \alpha \mathbf{m}_k) \frac{N_{\setminus d,n}^{(w_n^{(d)}|k)} + \frac{\beta}{W}}{N_{\setminus d,n}^{(k)} + \beta} \times \left( \prod_{i \in \mathcal{A}} \prod_{j \in \mathcal{A}_{\setminus i}} \frac{(\delta \lambda_{ij}^{(d)})^{I(j \in J_i)}}{\delta \lambda_{ij}^{(d)} + 1} \right) \times \left( \prod_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \delta \lambda_{iJ_i}^{(d)} \right) \\ & \quad \times \left( e^{-\delta(t^{(d)} - t^{(d-1)}) \left( \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \lambda_{iJ_i}^{(d)} + \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset, i_o^{(d)}}} \lambda_{iJ_i}^{(d)} \right)} \right), \end{aligned} \quad (22)$$

and if  $\bar{N}^{(d)} = 0$ , then the first term becomes  $\alpha \mathbf{m}_k$  and disappears because it is a constant. The second term disappears since there are no tokens, thus we just have the last three terms,  $P(\mathcal{I}_a^{(d)}, \mathcal{J}_a^{(d)}, \mathcal{T}_a^{(d)}, \mathcal{I}_o^{(d)}, \mathcal{J}_o^{(d)}, \mathcal{T}_o^{(d)} | z_n^{(d)} = k, \mathcal{Z}_{\setminus d,n}, \mathcal{C}, \mathcal{B}, \sigma^2, \delta)$ , remaining.

$$\begin{aligned} & P(z_1^{(d)} = k | \mathcal{Z}_{\setminus d,1} = \emptyset, \mathcal{C}, \mathcal{B}, \mathcal{W}, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o, \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2, \delta) \\ & \propto \left( \prod_{i \in \mathcal{A}} \prod_{j \in \mathcal{A}_{\setminus i}} \frac{(\delta \lambda_{ij}^{(d)})^{I(j \in J_i)}}{\delta \lambda_{ij}^{(d)} + 1} \right) \times \left( \prod_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \delta \lambda_{iJ_i}^{(d)} \right) \times \left( e^{-\delta(t^{(d)} - t^{(d-1)}) \left( \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \lambda_{iJ_i}^{(d)} + \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset, i_o^{(d)}}} \lambda_{iJ_i}^{(d)} \right)} \right). \end{aligned} \quad (23)$$

### 3.3 Resampling $\mathcal{C}$

The next variable we are going to resample is the topic-interaction pattern assignments, one topic at a time. To obtain the Gibbs sampling equation, which is the posterior conditional probability for the interaction pattern  $\mathcal{C}$  for  $k^{th}$  topic. We can derive the equation as below:

$$\begin{aligned} & P(c_k = c | \mathcal{Z}, \mathcal{C}_{\setminus k}, \mathcal{B}, \mathcal{W}, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o, \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2, \delta) \\ & \propto P(c_k = c, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o | \mathcal{Z}, \mathcal{C}_{\setminus k}, \mathcal{B}, \mathcal{W}, \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2, \delta) \\ & \propto P(c_k = c) P(\mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o | \mathcal{Z}, c_k = c, \mathcal{C}_{\setminus k}, \mathcal{B}, \sigma^2, \delta) \end{aligned} \quad (24)$$

where  $P(c_k = c) = \frac{1}{C}$  so this term disappears. Therefore,

$$\begin{aligned} & P(c_k = c | \mathcal{Z}, \mathcal{C}_{\setminus k}, \mathcal{B}, \mathcal{W}, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o, \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2, \delta) \\ & \propto P(\mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o | \mathcal{Z}, c_k = c, \mathcal{C}_{\setminus k}, \mathcal{B}, \sigma^2, \delta) \\ &= \prod_{d=1}^D \left( \left( \prod_{i \in \mathcal{A}} \prod_{j \in \mathcal{A}_{\setminus i}} \frac{(\delta \lambda_{ij}^{(d)})^{I(j \in J_i)}}{\delta \lambda_{ij}^{(d)} + 1} \right) \times \left( \prod_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \delta \lambda_{iJ_i}^{(d)} \right) \times \left( e^{-\delta(t^{(d)} - t^{(d-1)}) \left( \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \lambda_{iJ_i}^{(d)} + \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset, i_o^{(d)}}} \lambda_{iJ_i}^{(d)} \right)} \right) \right), \end{aligned} \quad (25)$$

with  $c_k = c$  throughout. (Note that in the product over  $d$ , I think we need only consider those emails that actually use topic  $k$ ; the others will have no terms involving  $c_k$ .)

### 3.4 Resampling $\mathcal{B}$ and $\delta$

Finally, we update  $\mathcal{B} = \{\mathbf{b}^{(c)}\}_{c=1}^C$  simultaneously with the hyperparameter  $\delta$ . For this, we use the Metropolis-Hastings algorithm with a proposal density  $Q$  being the multivariate Gaussian distribution, with a diagonal covariance matrix multiplied by  $\sigma_Q^2$  (proposal distribution variance parameters

set by the user), centered on the current values of  $\mathcal{B} = \{\mathbf{b}^{(c)}\}_{c=1}^C$  and  $\delta$ . Then we draw a proposal  $\mathcal{B}' = \{\mathbf{b}'^{(c)}\}_{c=1}^C$  and  $\delta'$ . Under symmetric proposal distribution (such as multivariate Gaussian), we cancel out Q-ratio and then accept the new proposal probability equal to:

$$\text{Acceptance Probability} = \begin{cases} \frac{P(\mathcal{B}', \delta' | \mathcal{Z}, \mathcal{C}, \mathcal{W}, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o, \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2)}{P(\mathcal{B}, \delta | \mathcal{Z}, \mathcal{C}, \mathcal{W}, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o, \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2)} & \text{if } < 1 \\ 1 & \text{else} \end{cases} \quad (26)$$

After factorization, we get

$$\begin{aligned} & \frac{P(\mathcal{B}', \delta' | \mathcal{Z}, \mathcal{C}, \mathcal{W}, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o, \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2)}{P(\mathcal{B}, \delta | \mathcal{Z}, \mathcal{C}, \mathcal{W}, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o, \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2)} \\ &= \frac{P(\mathcal{Z}, \mathcal{C}, \mathcal{B}', \mathcal{W}, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o | \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2, \delta')}{P(\mathcal{Z}, \mathcal{C}, \mathcal{B}, \mathcal{W}, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o | \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2, \delta)} \\ &= \frac{P(\mathcal{B}' | \mathcal{C}, \sigma^2) P(\delta') P(\mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o | \mathcal{Z}, \mathcal{C}, \mathcal{B}', \sigma^2, \delta')}{P(\mathcal{B} | \mathcal{C}, \sigma^2) P(\delta) P(\mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o | \mathcal{Z}, \mathcal{C}, \mathcal{B}, \sigma^2, \delta)}, \end{aligned} \quad (27)$$

where  $P(\mathcal{B} | \mathcal{C}, \sigma^2)$  is calculated from the product of  $\mathbf{b}^{(c)} \sim \text{Normal}(0, \sigma^2 I_P)$  (as defined in Section 2),  $\delta \sim \text{Beta}(1, 10)$  and  $P(\mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o | \mathcal{Z}, \mathcal{C}, \mathcal{B}', \sigma^2, \delta)$  is Equation (25). Again, we take the log and obtain the log of acceptance ratio:

$$\begin{aligned} & \sum_{c=1}^C \log(\text{dmvnorm}(\mathbf{b}'^{(c)}; \mathbf{0}, \sigma^2 I_P)) - \sum_{c=1}^C \log(\text{dmvnorm}(\mathbf{b}^{(c)}; \mathbf{0}, \sigma^2 I_P)) \\ &+ \log(\text{dbeta}(\delta'; 1, 10)) - \log(\text{dbeta}(\delta; 1, 10)) \\ &+ \sum_{d=1}^D \left\{ \sum_{i \in \mathcal{A}} \sum_{j \in \mathcal{A}_{\setminus i}} I(j \in J_i) \cdot \log(\delta \lambda_{ij}^{(d)}) - \log(\delta \lambda_{ij}^{(d)} + 1) \right. \\ &\quad \left. + \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \log(\delta \lambda_{iJ_i}^{(d)}) - \delta(t^{(d)} - t^{(d-1)}) \left( \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \lambda_{iJ_i}^{(d)} + \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset, i_o^{(d)}}} \lambda_{iJ_i}^{(d)} \right) \text{ given } \mathbf{b}' \text{ and } \delta' \right\} \\ &- \sum_{d=1}^D \left\{ \sum_{i \in \mathcal{A}} \sum_{j \in \mathcal{A}_{\setminus i}} I(j \in J_i) \cdot \log(\delta \lambda_{ij}^{(d)}) - \log(\delta \lambda_{ij}^{(d)} + 1) \right. \\ &\quad \left. + \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \log(\delta \lambda_{iJ_i}^{(d)}) - \delta(t^{(d)} - t^{(d-1)}) \left( \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset}} \lambda_{iJ_i}^{(d)} + \sum_{i \in \mathcal{A}_{\setminus J_i = \emptyset, i_o^{(d)}}} \lambda_{iJ_i}^{(d)} \right) \text{ given } \mathbf{b} \text{ and } \delta \right\}, \end{aligned} \quad (28)$$

where dmvnorm is the multivariate normal density and dbeta is the beta density. Then the log of acceptance ratio we have is:

$$\log(\text{Acceptance Probability}) = \min((28), 0) \quad (29)$$

To determine whether we accept the proposed update or not, we take the usual approach, by comparing the log of acceptance ratio we have to the log of a sample from uniform(0,1). Also, note that in the sum over  $d$ , we need only consider those emails that actually use topics corresponding to interaction pattern  $c$ .

### 3.5 Pseudocode

To implement the inference procedure outlined above, we provide a pseudocode for Markov Chain Monte Carlo (MCMC) sampling. Note that we use two loops, outer iteration and inner iteration, in order to avoid the label switching problem (Jasra et al., 2005), which is an issue caused by the nonidentifiability of the components under symmetric priors in Bayesian mixture modeling. When summarizing model results, we will only use the values from the last  $I^{th}$  outer loop because there is no label switching problem within the inner iteration.

---

**Algorithm 5** MCMC

---

set initial values  $\mathcal{Z}^{(0)}, \mathcal{C}^{(0)}$ , and  $(\mathcal{B}^{(0)}, \delta^{(0)})$

**for**  $i=1$  to  $I$  **do**

    optimize  $\alpha$  and  $\mathbf{m}$  using hyperparameter optimization in Wallach (2008)

**for**  $d=1$  to  $D$  **do**

**for**  $i \in \mathcal{A}_{\setminus i^{(d)}}$  **do**

            sample the augmented data  $(i, J_i)$

**end**

**end**

    fix  $\mathcal{C} = \mathcal{C}^{(i-1)}$  and  $\mathcal{B} = \mathcal{B}^{(i-1)}$

**for**  $n=1$  to  $n_1$  **do**

**for**  $d=1$  to  $D$  **do**

**for**  $n=1$  to  $N^{(d)}$  **do**

                calculate  $p^{\mathcal{Z}} | \text{others} = (p_1, \dots, p_K)$  using Equation (20) or Equation (21)

                draw of  $z_n^{(d)} \sim \text{multinomial}(p^{\mathcal{Z}})$

**end**

**end**

**end**

    fix  $\mathcal{Z} = \mathcal{Z}^{(i)}$  and  $\mathcal{B} = \mathcal{B}^{(i-1)}$

**for**  $n=1$  to  $n_2$  **do**

**for**  $k=1$  to  $K$  **do**

            calculate  $p^{\mathcal{C}} | \text{others} = (p_1, \dots, p_C)$  using Equation (23)

            draw  $C_k \sim \text{multinomial}(p^{\mathcal{C}})$

**end**

**end**

    fix  $\mathcal{C} = \mathcal{C}^{(i)}$ ,  $\mathcal{Z} = \mathcal{Z}^{(i)}$ , and  $\mathcal{B}^{(0)} = \text{last value } (n_3^{th}) \text{ of } \mathcal{B}^{(i-1)}$

**for**  $n=1$  to  $n_3$  **do**

        sample  $\mathcal{B}$  and  $\delta$  from proposal distribution

        accept-reject using Equation (26)

**end**

**end**

summarize the results using:

the last value of  $\mathcal{C}$ , the last value of  $\mathcal{Z}$ , and the last  $n_3$  length chain of  $(\mathcal{B}, \delta)$

---

## 4 Application to North Carolina email data

To see the applicability of the model, we used the North Carolina email data using two counties, Vance county and Dare county, which are the two counties whose email corpus cover the date of Hurricane Sandy (October 22, 2012 – November 2, 2012). Especially, Dare county geographically covers the Outer Banks, so we would like to see how the communication pattern changes during the time period surrounding Hurricane Sandy. Here we apply IPTM to both data and demonstrate the effectiveness of the model at predicting and explaining continuous-time textual communications.

### 4.1 Vance county email data

Vance county data contains  $D = 185$  emails sent between  $A = 18$  actors, including  $W = 620$  vocabulary in total. We used  $K = 10$  topics and  $C = 2$  interaction patterns. MCMC sampling was implemented based on the order and scheme illustrated in Section 3. We set the outer iteration number as  $I = 1000$ , the inner iteration numbers as  $n_1 = 3, n_2 = 3$ , and  $n_3 = 3300$ . First 100 outer iterations and first 300 iterations of third inner iteration were used as a burn-in, and every  $10^{th}$  sample was taken as a thinning process of third inner iteration. In addition, after some experimentation,  $\delta_B$  was set as 0.5, to ensure sufficient acceptance rate. MCMC diagnostic plots are attached in APPENDIX D, as well as the geweke test statistics.

Below are the summary of IP-topic-word assignments. Each interaction pattern is paired with (a) posterior estimates of dynamic network effects  $\mathbf{b}^{(c)}$  corresponding to the interaction pattern, (b) the top 3 topics most likely to be generated conditioned on the interaction pattern, and (c) the top 10 most likely words to have generated conditioned on the topic and interaction pattern. By

	IP1 (54 emails)	IP2 (107 emails)	IP3 (108 emails)
<b>intercept</b>	0.515 [-0.523, 1.546]	-0.364 [-2.108, 1.934]	-1.230 [-1.948, 0.194]
<b>send</b>	1.916* [1.130, 2.937]	2.843* [1.969, 3.885]	2.531* [1.595, 3.568]
<b>receive</b>	0.158 [-1.126, 1.098]	3.068* [2.427, 4.509]	1.067* [0.488, 1.781]
<b>triangles</b>	1.483 [-0.507, 2.558]	-1.478* [-2.038, -0.918]	-1.787* [-3.062, -0.958]
<b>outdegree</b>	0.514 [-0.570, 1.377]	0.492 [-0.804, 1.665]	0.771 [-1.152, 2.544]
<b>indegree</b>	2.166* [1.534, 2.895]	1.397* [0.720, 2.187]	2.464* [1.840, 3.327]

Table 1: Summary of posterior estimates of  $\mathbf{b}^{(c)}$  for Vance county emails

Figure 2: Posterior distribution of  $\mathbf{b}^{(c)}$  for Vance county emails

examining the estimates in Table 2 and their corresponding interpretation, it seems that there exist strong effects of dynamic network covariates. That is, whether the sender and receiver previously had dyadic or triangle interaction strongly increase the rate of their interactions. Moreover, to see the differences across the interaction patterns more clearly, we compared the posterior distribution using the boxplots in Figure 2 and it seems that there exists notable differences in dynamic network covariates across the interaction patterns. For example, IP2 has the highest send and receive effect and IP3 has the highest outdegree and indegree effect, while its baseline intensity (i.e. intercept) or triangle effect are not as high as other interaction patterns. Later, multiple hypothesis testing could be applied in order to test the significance of the differences in  $\mathbf{b}^{(c)}$  across the  $C$  number of interaction patterns.

Next, we scrutinize the topic distributions corresponding to each interaction patterns in Figure 3. There is some distinctive differences in the topic distributions  $\mathcal{Z}$ , given the assignment of interaction patterns to the documents  $\mathcal{C}$ . Specifically, each interaction pattern has different topics as the topic with highest probability.

Figure 3: Posterior distribution of  $\mathcal{Z}$  for Vance county emails, with (upper) and without (lower) considering IP

Furthermore, we look at the distribution of words given the topics, which corresponds to Algorithm 4 in the generative process. Since the topic-word distribution  $\phi$  does not depend on the interaction patterns as previous cases, Table 3 lists top 10 topics with top 10 words that have the highest probability conditioned on the topic. In addition, this time we try to check the interaction pattern-word distribution by listing top 10 words that have the highest probability conditioned on the interaction pattern. It seems that the words are not significantly different, having several words like ‘director’, ‘phones’, ‘department’, ‘description’, or ‘henderson’ (county seat of Vance county) appeared repetitively across the most of the topics or interaction patterns. The word ‘will’ was ranked the top in most of the lists, probably because it was not deleted during the text mining process while other similar type of words like ‘am’, ‘is’, ‘are’, or ‘can’ are all removed.

## 4.2 Dare county email data

Dare county data contains  $D = 2247$  emails between  $A = 27$  actors, including  $W = 2907$  vocabulary in total. Again, we used  $K = 10$  topics and  $C = 3$  interaction patterns. MCMC sampling was implemented based on the order and scheme illustrated earlier. We set the outer iteration number as  $I = 1000$ , and inner iteration numbers as  $n_1 = 3$ ,  $n_2 = 3$ , and  $n_3 = 3300$ . In addition, after some

<b>IP1</b> (54 emails)	<b>IP2</b> (107 emails)	<b>IP3</b> (108 emails)
K=2 (0.40), K=4 (0.17), K=9 (0.15)	K=8 (0.38), K=5 (0.24)	K=1 (0.31), K=3 (0.17), K=6 (0.15)
message, electronic, records time, response, ncgs department, hereto, attachments heads, finance, director request, financial, operations manager, system, work pursuant, additional, office chapter, class, helped public, local, internal subject, communications, reporting	phones, phone week, department system, rest october, advised training, jail cutting, send cutover, center folks, tuesday instructions, monday dss, thursday	henderson, street, description latest, fax, church planning, suite, emergency attached, director, center extension, goldvance, seal, improved, jordan, phone development, phase, morning e-mail, board, email good, rural, excel young, funds, lease list, turn, form

Table 2: Summary of top 5 topics with top 10 words that have the highest probability conditioned on the topic (Symmetric)

experimentation,  $\delta_B$  was set as 0.02, to ensure sufficient acceptance rate. In our case, the average acceptance rate for  $\mathbf{b}$  was 0.277. As demonstrated in Algorithm 5, the last value of  $\mathcal{C}$ , the last value of  $\mathcal{Z}$ , and the last  $n_3$  length chain of  $\mathcal{B}$  were taken as the final posterior samples. Among the  $\mathcal{B}$  samples, 300 were discarded as a burn-in and every  $10^{th}$  samples were taken. After these post-processing, MCMC diagnostic plots are attached in APPENDIX D, as well as geweke test statistics.

## APPENDIX

### APPENDIX A: Notations in IPTM

Sender of the $d^{th}$ document	$i^{(d)}$	Scalar
Receivers of the $d^{th}$ document	$J^{(d)}$	$ J^{(d)} $ -dimensional vector
Individual receiver of the $d^{th}$ document	$j^{(d)}$	Scalar
Time of the $d^{th}$ document	$t^{(d)}$	Scalar
Authors of the corpus	$\mathcal{A}$	Set
Number of authors	$A$	Scalar
Number of documents	$D$	Scalar
Number of words in the $d^{th}$ document	$N^{(d)}$	Scalar
Number of topics	$K$	Scalar
Vocabulary size	$W$	Scalar
Number of interaction patterns	$C$	Scalar
Number of words assigned to word and topic	$N^{WK}$	Scalar
Interaction pattern of the $k^{th}$ topic	$C_k$	Scalar
Tuning parameter in tie generative process	$\delta$	Scalar
Poisson parameter for number of words $N^{(d)}$	$\zeta$	Scalar
Words in the $d^{th}$ document	$\mathbf{w}^{(d)}$	$N^{(d)}$ -dimensional vector
$n^{th}$ word in the $d^{th}$ document	$w_n^{(d)}$	$n^{th}$ component of $\mathbf{w}^{(d)}$
Topic assignments in the $d^{th}$ document	$\mathbf{z}^{(d)}$	$N^{(d)}$ -dimensional vector
Topic assignments for $n^{th}$ word in the $d^{th}$ document	$z_n^{(d)}$	$n^{th}$ component of $\mathbf{z}^{(d)}$
Dirichlet concentration prior for document topic distribution	$\alpha$	Scalar
Dirichlet base prior for document topic distribution	$\mathbf{m}$	$K$ -dimensional vector
Dirichlet concentration prior for topic word distribution	$\beta$	Scalar
Dirichlet base prior for topic word distribution	$\mathbf{u}$	$W$ -dimensional vector
Variance of Normal prior	$\sigma^2$	Scalar
Probabilities of the words given topic $k$	$\phi^{(k)}$	$W$ -dimensional vector
Probabilities of the topics given the $d^{th}$ document	$\theta^{(d)}$	$K$ -dimensional vector
Coefficient of the intensity process given interaction pattern $c$	$\mathbf{b}^{(c)}$	$p$ -dimensional vector
Network statistics for $(i, j)$ at time $t$ given interaction pattern $c$	$\mathbf{x}_t^{(c)}(i, j)$	$p$ -dimensional vector
Stochastic intensity of document $d$ at time $t$	$\lambda^{(d)}(t)$	$A \times A$ matrix
Stochastic intensity of $(i, j)$ in document $d$ at time $t$	$\lambda_{ij}^{(d)}(t)$	Scalar
Proportion of topics in document $d$ corresponding to interaction pattern $c$	$p_c^{(d)}$	Scalar
Time increments associated to $(i, J)$ pair	$\Delta T_{iJ}$	Scalar

Table 3: Symbols associated with IPTM, as used in this paper

### APPENDIX B: Integrating out $\Phi$ and $\Theta$ in latent Dirichlet allocation

$$\begin{aligned}
& P(\Phi, \Theta, \mathcal{Z}, \mathcal{C}, \mathcal{B}, \mathcal{W}, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o | \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2, \delta) \\
& \propto P(\mathcal{Z}, \mathcal{C}, \mathcal{B}, \mathcal{W}, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o | \Phi, \Theta, \sigma^2, \delta) P(\Phi, \Theta | \beta, \mathbf{u}, \alpha, \mathbf{m}) \\
& \propto P(\mathcal{Z} | \mathcal{W}, \Theta) P(\mathcal{C} | \mathcal{B}, \sigma^2) P(\mathcal{W} | \Phi) P(\Phi | \beta, \mathbf{u}) P(\Theta | \alpha, \mathbf{m}) P(\mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o | \mathcal{Z}, \mathcal{C}, \mathcal{B}, \delta) \\
& = \left[ \prod_{d=1}^D \prod_{n=1}^{N^{(d)}} P(z_n^{(d)} | w_n^{(d)}, \theta^{(d)}) \right] \times \left[ \prod_{k=1}^K P(C_k) \right] \times \left[ \prod_{c=1}^C P(\mathbf{b}^{(c)} | \sigma^2) \right] \times \left[ \prod_{d=1}^D \prod_{n=1}^{N^{(d)}} P(w_n^{(d)} | \phi_{z_n^{(d)}}) \right] \times \left[ \prod_{k=1}^K P(\phi^{(k)} | \beta, \mathbf{u}) \right] \\
& \quad \times \left[ \prod_{d=1}^D P(\theta^{(d)} | \alpha, \mathbf{m}) \right] \times \left[ \prod_{d=1}^D P(\mathcal{I}_a^{(d)}, \mathcal{J}_a^{(d)}, \mathcal{T}_a^{(d)}, i_o^{(d)}, J_o^{(d)}, t_o^{(d)} | \mathcal{I}_o^{(<d)}, \mathcal{J}_o^{(<d)}, \mathcal{T}_o^{(<d)}, \mathcal{Z}, \mathcal{C}, \mathcal{B}, \delta) \right]
\end{aligned} \tag{30}$$

Dropping the terms independent of tokens out, we further rewrite the equation (28) as below:

$$\begin{aligned}
& \propto \left[ \prod_{d=1}^D \prod_{n=1}^{N^{(d)}} P(z_n^{(d)} | w_n^{(d)}, \boldsymbol{\theta}^{(d)}) \right] \times \left[ \prod_{d=1}^D \prod_{n=1}^{N^{(d)}} P(w_n^{(d)} | \phi_{z_n^{(d)}}) \right] \times \left[ \prod_{k=1}^K P(\boldsymbol{\phi}^{(k)} | \beta, \mathbf{u}) \right] \times \left[ \prod_{d=1}^D P(\boldsymbol{\theta}^{(d)} | \alpha, \mathbf{m}) \right] \\
& \propto \left[ \prod_{d=1}^D \prod_{n=1}^{N^{(d)}} \phi_{w_n^{(d)} z_n^{(d)}} \right] \times \left[ \prod_{d=1}^D \prod_{n=1}^{N^{(d)}} \boldsymbol{\theta}_{z_n^{(d)}}^{(d)} \right] \\
& \quad \times \left[ \prod_{k=1}^K \left( \frac{\Gamma(\sum_{w=1}^W \beta u_w)}{\prod_{w=1}^W \Gamma(\beta u_w)} \prod_{w=1}^W \phi_{wk}^{\beta u_w - 1} \right) \right] \times \left[ \prod_{d=1}^D \left( \frac{\Gamma(\sum_{k=1}^K \alpha m_k)}{\prod_{k=1}^K \Gamma(\alpha m_k)} \prod_{k=1}^K (\boldsymbol{\theta}_k^{(d)})^{\alpha m_k - 1} \right) \right] \\
& \propto \left[ \frac{\Gamma(\sum_{w=1}^W \beta u_w)}{\prod_{w=1}^W \Gamma(\beta u_w)} \right]^K \times \prod_{d=1}^D \left[ \frac{\Gamma(\sum_{k=1}^K \alpha m_k)}{\prod_{k=1}^K \Gamma(\alpha m_k)} \right] \times \left[ \prod_{k=1}^K \prod_{w=1}^W \phi_{wk}^{N_{wk}^{WK} + \beta u_w - 1} \right] \times \left[ \prod_{d=1}^D \prod_{k=1}^K (\boldsymbol{\theta}_k^{(d)})^{N_{k|d} + \alpha m_k - 1} \right]
\end{aligned} \tag{31}$$

where  $N_{wk}^{WK}$  is the number of times the  $w^{th}$  word in the vocabulary is assigned to topic  $k$ , and  $N_{k|d}$  is the number of times topic  $k$  shows up in the document  $d$ . By looking at the forms of the terms involving  $\Theta$  and  $\Phi$  in Equation (21), we integrate out the random variables  $\Theta$  and  $\Phi$ , making use of the fact that the Dirichlet distribution is a conjugate prior of multinomial distribution. Applying the well-known formula  $\int \prod_{n=1}^M [x_m^{k_m-1} dx_m] = \frac{\prod_{n=1}^M \Gamma(k_m)}{\Gamma(\sum_{n=1}^M k_m)}$  to (22), we have:

$$\begin{aligned}
& P(\mathcal{Z}, \mathcal{C}, \mathcal{B}, \mathcal{W}, \mathcal{I}_a, \mathcal{J}_a, \mathcal{T}_a, \mathcal{I}_o, \mathcal{J}_o, \mathcal{T}_o | \beta, \mathbf{u}, \alpha, \mathbf{m}, \sigma^2, \delta) \\
& = \text{Const.} \int_{\Theta} \int_{\Phi} \left[ \prod_{k=1}^K \prod_{w=1}^W \phi_{wk}^{N_{wk}^{WK} + \beta u_w - 1} \right] \left[ \prod_{d=1}^D \prod_{k=1}^K (\boldsymbol{\theta}_k^{(d)})^{N_{k|d} + \alpha m_k - 1} \right] d\Phi d\Theta \\
& = \text{Const.} \left[ \prod_{k=1}^K \int_{\phi_{:k}} \prod_{w=1}^W \phi_{wk}^{N_{wk}^{WK} + \beta u_w - 1} d\phi_{:k} \right] \times \left[ \prod_{d=1}^D \int_{\boldsymbol{\theta}_{:d}} \prod_{k=1}^K (\boldsymbol{\theta}_k^{(d)})^{N_{k|d} + \alpha m_k - 1} d\boldsymbol{\theta}_{:d} \right] \\
& = \text{Const.} \left[ \prod_{k=1}^K \frac{\prod_{w=1}^W \Gamma(N_{wk}^{WK} + \frac{\beta}{W})}{\Gamma(\sum_{w=1}^W N_{wk}^{WK} + \beta)} \right] \times \left[ \prod_{d=1}^D \frac{\prod_{k=1}^K \Gamma(N_{k|d} + \alpha m_k)}{\Gamma(N_{\cdot|d} + \alpha)} \right].
\end{aligned} \tag{32}$$

## APPENDIX C: Conditional probability of $\mathcal{Z}$

$$\begin{aligned}
& P(\mathbf{w}^{(d)}, \mathbf{z}^{(d)} | \mathcal{W}_{\setminus d}, \mathcal{Z}_{\setminus d}, \beta, \mathbf{u}, \alpha, \mathbf{m}) \\
& \propto \prod_{n=1}^{N^{(d)}} P(z_n^{(d)} = k, w_n^{(d)} = w | \mathcal{W}_{\setminus d, n}, \mathcal{Z}_{\setminus d, n}, \beta, \mathbf{u}, \alpha, \mathbf{m})
\end{aligned} \tag{33}$$

To obtain the Gibbs sampling equation, we need to obtain an expression for  $P(z_n^{(d)} = k, w_n^{(d)} = w | \mathcal{W}_{\setminus d, n}, \mathcal{Z}_{\setminus d, n}, \beta, \mathbf{u}, \alpha, \mathbf{m})$ . From Bayes' theorem and Gamma identity  $\Gamma(k+1) = k\Gamma(k)$ ,

$$\begin{aligned}
& P(z_n^{(d)} = k, w_n^{(d)} = w | \mathcal{W}_{\setminus d, n}, \mathcal{Z}_{\setminus d, n}, \beta, \mathbf{u}, \alpha, \mathbf{m}) \\
& \propto \frac{P(\mathcal{W}, \mathcal{Z} | \beta, \mathbf{u}, \alpha, \mathbf{m})}{P(\mathcal{W}_{\setminus d, n}, \mathcal{Z}_{\setminus d, n} | \beta, \mathbf{u}, \alpha, \mathbf{m})} \\
& \propto \frac{\prod_{k=1}^K \frac{\prod_{w=1}^W \Gamma(N_{wk}^{WK} + \beta u_w)}{\Gamma(\sum_{w=1}^W N_{wk}^{WK} + \beta)}}{\prod_{k=1}^K \frac{\prod_{w=1}^W \Gamma(N_{wk, \setminus d, n}^{WK} + \beta u_w)}{\Gamma(\sum_{w=1}^W N_{wk, \setminus d, n}^{WK} + \beta)}} \times \frac{\prod_{k=1}^K \frac{\Gamma(N_{k|d} + \alpha m_k)}{\Gamma(N_{\cdot|d} + \alpha)}}{\prod_{k=1}^K \frac{\Gamma(N_{k|d, \setminus d, n} + \alpha m_k)}{\Gamma(N_{\cdot|d, \setminus d, n} + \alpha)}} \\
& \propto \frac{N_{wk, \setminus d, n}^{WK} + \frac{\beta}{W}}{\sum_{w=1}^W N_{wk, \setminus d, n}^{WK} + \beta} \times \frac{N_{k|d, \setminus d, n} + \alpha m_k}{N^{(d)} - 1 + \alpha}
\end{aligned} \tag{34}$$

Then, same as for LDA, we also know that the topic assignment  $z_n^{(d)} = k$  is obtained by:

$$P(z_n^{(d)} = k | w_n^{(d)} = w, \mathcal{W}_{\setminus d, n}, \mathcal{Z}_{\setminus d, n}, \beta, \mathbf{u}, \alpha, \mathbf{m}) \propto \frac{N_{k|d, \setminus d, n} + \alpha m_k}{N^{(d)} - 1 + \alpha} \tag{35}$$



In addition, the conditional probability that a new word generated in the document would be  $w_n^{(d)} = w$ , given that it is generated from topic  $z_n^{(d)} = k$  is obtained by:

$$P(w_m^{(d)} = w | z_m^{(d)} = k, \mathcal{W}_{\setminus d, n}, \mathcal{Z}_{\setminus d, nm}, \beta, \mathbf{u}, \alpha, \mathbf{m}) \propto \frac{N_{wk, \setminus d, n}^{WK} + \frac{\beta}{W}}{\sum_{w=1}^W N_{wk, \setminus d, n}^{WK} + \beta} \quad (36)$$

NOTE: Using Equation (28), the unnormalized constant we use to check the model convergence and the corresponding log-constant is,

$$\begin{aligned} & \prod_{d=1}^D \prod_{n=1}^{N^{(d)}} P(z_n^{(d)} = k, w_n^{(d)} = w | \mathcal{W}_{\setminus d, n}, \mathcal{Z}_{\setminus d, m}, \beta, \mathbf{u}, \alpha, \mathbf{m}) \\ & \propto \prod_{d=1}^D \prod_{n=1}^{N^{(d)}} \frac{N_{w_n^{(d)} z_n^{(d)}, \setminus d, n}^{WK} + \frac{\beta}{W}}{\sum_{w=1}^W N_{w z_n^{(d)}, \setminus d, n}^{WK} + \beta} \times \frac{N_{k|d, \setminus d, n} + \alpha m_{z_n^{(d)}}}{N^{(d)} - 1 + \alpha}, \end{aligned} \quad (37)$$

$$\begin{aligned} & \sum_{d=1}^D \sum_{n=1}^{N^{(d)}} \log \left( P(z_n^{(d)} = k, w_n^{(d)} = w | \mathcal{W}_{\setminus d, n}, \mathcal{Z}_{\setminus d, n}, \beta, \mathbf{u}, \alpha, \mathbf{m}) \right) \\ & \propto \sum_{d=1}^D \sum_{n=1}^{N^{(d)}} \log \left( N_{w_n^{(d)} z_n^{(d)}, \setminus d, n}^{WK} + \frac{\beta}{W} \right) - \log \left( \sum_{w=1}^W N_{w z_n^{(d)}, \setminus d, n}^{WK} + \beta \right) \\ & \quad + \log \left( N_{k|d, \setminus d, n} + \alpha m_{z_n^{(d)}} \right) - \log \left( N^{(d)} - 1 + \alpha \right) \end{aligned} \quad (38)$$

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