

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

Bomin Kim<sup>1</sup>    Aaron Schein<sup>3</sup>  
Bruce Desmarais<sup>1</sup>    Hanna Wallach<sup>2,3</sup>

<sup>1</sup> The Pennsylvania State University

<sup>2</sup> Microsoft Research NYC

<sup>3</sup> University of Massachusetts Amherst

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# Interaction-Partitioned Topic Model (IPTM)

- Probabilistic model for time-stamped textual communications
- Integration of two generative models:
  - Latent Dirichlet allocation (LDA) for topic-based contents
  - Dynamic exponential random graph model (ERGM) for ties

*“who communicates with whom about what, and when?”*

# Content Generating Process: LDA (Blei et al., 2003)

- For each topic  $k = 1, \dots, K$ :

- Topic-word distribution  $\phi^{(k)} \sim \text{Dirichlet}(\beta, \mathbf{u})$
- Topic-IP distribution  $c_k \sim \text{Uniform}(1, C)$

- For each document  $d = 1, \dots, D$ :

## 3-1. Document-topic distribution:

$$\theta^{(d)} \sim \text{Dirichlet}(\alpha, \mathbf{m})$$

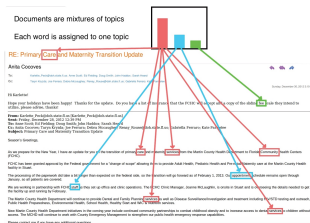
## 3-2. For each word in a document $n = 1$ to $N^{(d)}$ :

- Choose a topic  $z_n^{(d)} \sim \text{Multinomial}(\theta^{(d)})$
- Choose a word  $w_n^{(d)} \sim \text{Multinomial}(\phi^{(z_n^{(d)})})$

## 3-3 Calculate the distribution of interaction patterns within a document:

$$p_c^{(d)} = \left( \sum_{k: c_k = c} N^{(k|d)} \right) / N^{(d)},$$

	$c_1 = 1$	$c_2 = 2$	$c_3 = 1$
Probability	support position fill staff desk service customer begin duties vacancy ⋮	services care child information system community nurse completed provided pregnancy ⋮	budget funds money budgeted including cost salary amount revenues debt ⋮



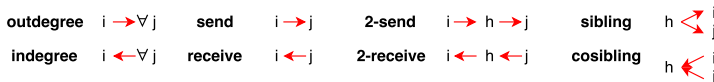
# Dynamic Network Features (Perry and Wolfe, 2012)

- Partition the past 384 hours (=16 days) into 3 sub-intervals

$$[t - 384h, t) = [t - 384h, t - 96h) \cup [t - 96h, t - 24h) \cup [t - 24h, t),$$

then define the interval-based dynamic network statistics

- $\mathbf{x}_t^{(c)}(i, j)$  is the network statistics at time  $t$ , for interaction pattern  $c$ 
  - Degree: outdegree and indegree
  - Dyadic: send and receive
  - Triadic: 2-send, 2-receive, sibling and cosibling



# Tie Generating Process: Latent Edges

1. For each sender  $i \in \{1, \dots, A\}$ , choose a binary vector  $J_i^{(d)}$  of length  $(A - 1)$ , by applying Gibbs measure (Fellows and Handcock, 2017)

$$P(J_i^{(d)}) = \frac{1}{Z(\delta, \log(\lambda_i^{(d)}))} \exp \left\{ \log \left( \mathbb{I} \left( \sum_{j \in \mathcal{A}_{\setminus i}} J_{ij}^{(d)} > 0 \right) \right) + \sum_{j \in \mathcal{A}_{\setminus i}} (\delta + \log(\lambda_{ij}^{(d)})) J_{ij}^{(d)} \right\},$$

where

- $\lambda_{ij}^{(d)} = \sum_{c=1}^C p_c^{(d)} \cdot \exp \left\{ \lambda_0^{(c)} + \mathbf{b}^{(c)T} \mathbf{x}_{t(d-1)}^{(c)}(i, j) \right\}$  is a stochastic intensity
- $\delta$  is a real-valued intercept controlling the recipient size
- $Z(\delta, \log(\lambda_i^{(d)}))$  is the normalizing constant

i	1	2	3	4	.....	A
1	0	1	0	1	.....	1
2	1	0	0	0	.....	0
...					.....	
A	0	0	1	0	.....	0

# Tie Generating Process: Observed

- For each sender  $i \in \mathcal{A}$ , generate the time increments

$$\Delta T_{iJ_i} \sim \text{Exp}(\lambda_{iJ_i}^{(d)}),$$

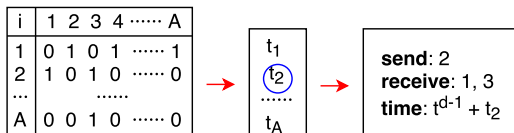
$$\text{where } \lambda_{iJ_i}^{(d)} = \sum_{c=1}^C p_c^{(d)} \cdot \exp\left\{\lambda_0^{(c)} + \frac{1}{|J_i|} \sum_{j \in J_i} \mathbf{b}^{(c)T} \mathbf{x}_{t^{(d-1)}(i,j)}^{(c)}\right\}.$$

- Set timestamp, sender, and receivers simultaneously:

$$t^{(d)} = t^{(d-1)} + \min(\Delta T_{iJ_i})$$

$$i^{(d)} = i_{\min(\Delta T_{iJ_i})}$$

$$J^{(d)} = J_{i^{(d)}}$$



# Inference - Pseudocode

- Bayesian Inference using Markov Chain Monte Carlo (MCMC)

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**Algorithm 1** MCMC

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

**for**  $o=1$  to  $O$  **do**

    Sample the latent edge  $J_{ij}^{(d)}$  via Gibbs sampling

    Sample the topic assignments  $\mathcal{Z}$  via Gibbs sampling

    Sample the interaction pattern assignments  $\mathcal{C}$  via Gibbs sampling

    Sample the interaction pattern parameters  $\mathcal{B}$  via Metropolis-Hastings

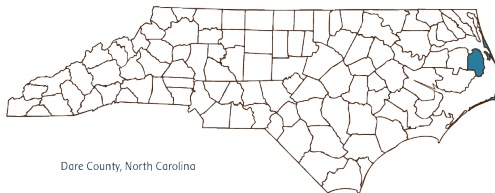
    Sample the receiver size parameter  $\delta$  via Metropolis-Hastings

**end**

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# Data: North Carolina Dare county email data

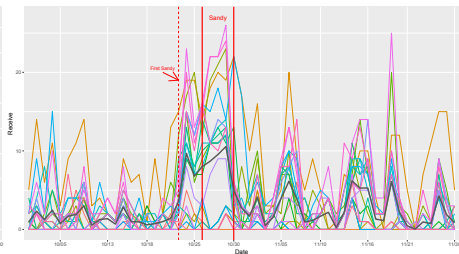
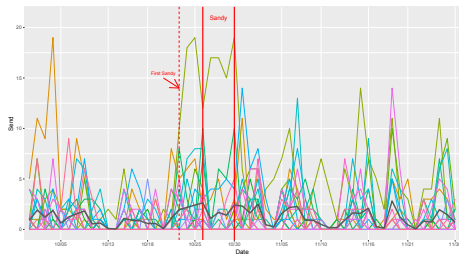
- $D = 1456$  emails between  $A = 27$  county government managers, covering 2 month periods (October 1 - November 30) in 2013



- Hurricane Sandy passed by NC: October 26 - October 30



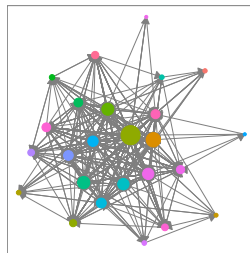
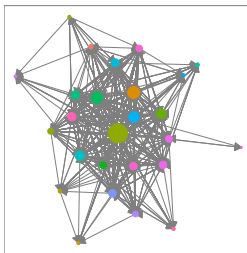
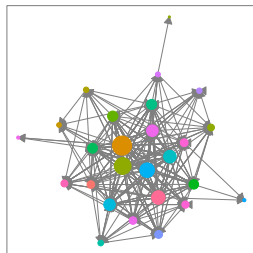
# Effect of Hurricane Sandy on Email Exchange



Pre-Sandy

Sandy

Post-Sandy

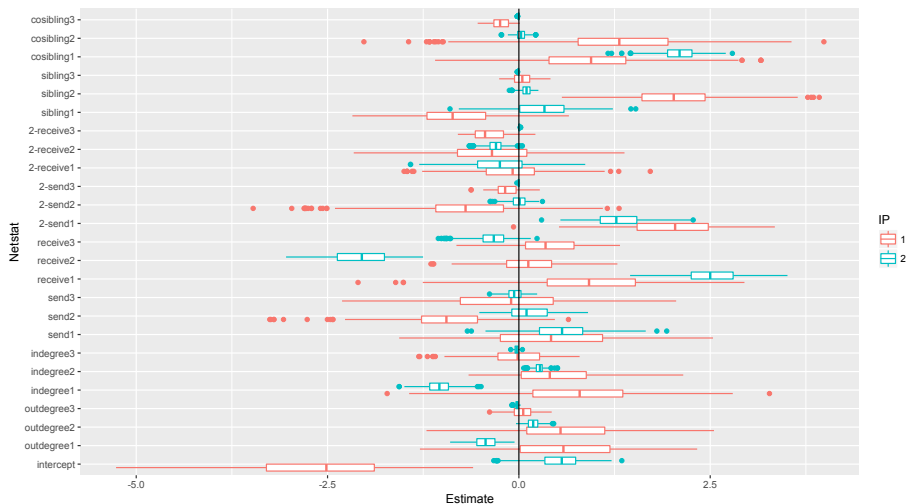


Department

- Building Inspections
- County Extension
- County Manager
- Detention
- Elections
- Emergency Services
- Finance
- Health
- HR
- Information Technology
- Library
- Parks and Recreation
- Planning
- Public Informations
- Register of Deeds
- Senior Center
- Sheriff
- Soil Conservation
- Solid Waste and Recycling
- Tax Administrator
- Transportation
- Veteran Services

# IPTM Result: Dynamic Network Effects

- IPTM result with  $C = 2$ ,  $K = 5$  and  $O = 20$ :



# IPTM Result: Contents

- IPTM result with  $C = 2$ ,  $K = 5$  and  $O = 20$ :

IP	2	2	1	2	2
Topic	5	1	2	3	4
Word	tim request services report tax northwest michelle evans tonnage coastal	forecast force today rip race moderate app summary operations late	updates amount mph exam machine esi view dangerous curves north	parcels billed real ocean continues watched duration early situation wash	overtime east scheduled library comp count expected human period administrative

# Conclusion

- Joint modeling of ties (sender, receiver, time) and contents
- Allowance of multicast – multiple senders and/or receivers
- Possible application to various political science data