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

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Interaction-Partitioned Topic Model (IPTM)

- Probablistic 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 $k = 1, ..., K$:
    1. Topic-word distribution $\boldsymbol{\phi}^{(k)} \sim \text{Dirichlet}(\beta, \mathbf{u})$
    2. Topic-IP distribution $c_k \sim \text{Uniform}(1, C)$

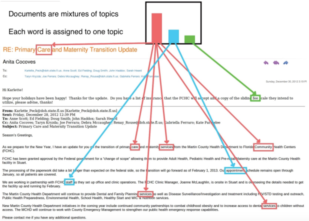
$c_1 = 1$	$c_2 = 2$	$c_3 = 1$
support	services	budget
position	care	funds
fill	child	money
staff	information	budgeted
desk	system	including
service	community	cost
customer	nurse	salary
begin	completed	amount
duties	provided	revenues
vacancy	pregnancy	debt
⋮	⋮	⋮

Probability

- For each document $d = 1, ..., D$:

  3-1. Document-topic distribution:
  $\boldsymbol{\theta}^{(d)} \sim \text{Dirichlet}(\alpha, \boldsymbol{m})$

  3-2. For each word in a document $n = 1$ to $N^{(d)}$:
    - (a) Choose a topic $z_n^{(d)} \sim \text{Multinomial}(\boldsymbol{\theta}^{(d)})$
    - (b) Choose a word $w_n^{(d)} \sim \text{Multinomial}(\boldsymbol{\phi}^{(z_n^{(d)})})$



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

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

Dynamic Network Features (Perry and Wolfe, 2012)

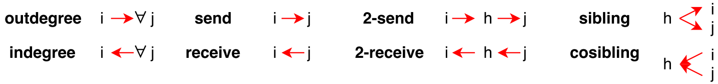
- Partition the past 384 hours (=16 days) into 3 sub-intervals

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

then define the interval-based dynamic network statistics $(l = 1, 2, 3)$

- $\boldsymbol{x}_{t,l}^{(c)}(i, j)$ 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 $i \in \{1, ..., A\}$, choose a binary vector $J_i^{(d)}$ of length $(A-1)$, by applying Gibbs measure (Fellows and Handcock, 2017)

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

where

- $\lambda_{ij}^{(d)} = \sum_{c=1}^{C} p_c^{(d)} \cdot \exp\Big\{\lambda_0^{(c)} + \boldsymbol{b}^{(c)T} \boldsymbol{x}_{t_{(d-1)}}^{(c)}(i,j)\Big\}$ is a stochastic intensity
- δ 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

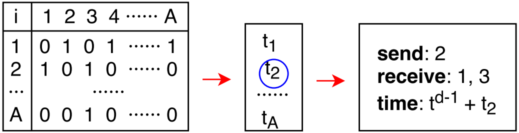
2. For each sender $i \in \mathcal{A}$, generate the time increments

$$\Delta T_{iJ_i} \sim \mathsf{Exp}(\lambda^{(d)}_{iJ_i}),$$

where $\lambda^{(d)}_{iJ_i} = \sum_{c=1}^{C} p^{(d)}_c \cdot \exp\Big\{\lambda^{(c)}_0 + \frac{1}{|J_i|}\sum_{j \in J_i} \boldsymbol{b}^{(c)T}\boldsymbol{x}^{(c)}_{t^{(d-1)}}(i,j)\Big\}.$

3. 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

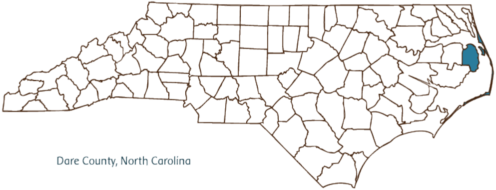
- Bayesian Inference using Markov Chain Monte Carlo (MCMC)

Algorithm 1 MCMC

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 δ via Metropolis-Hastings
end

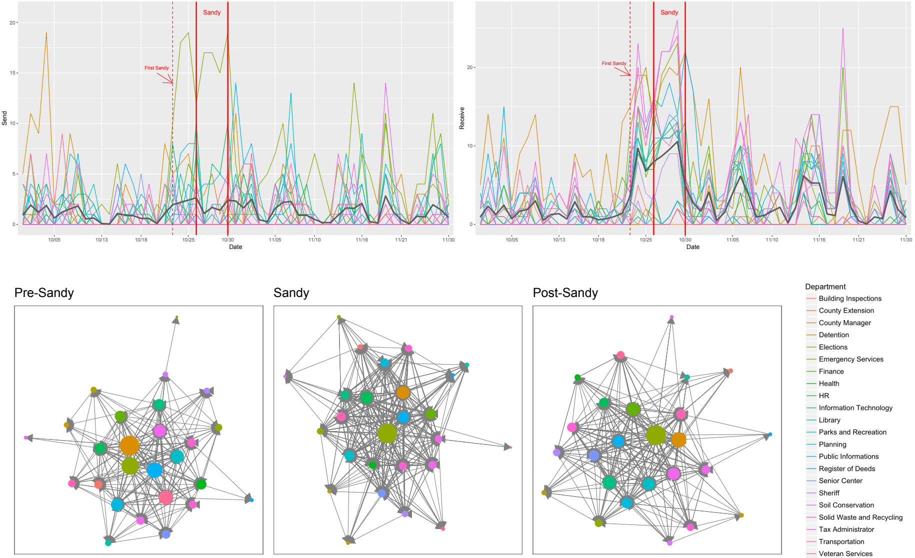
Data: North Carolina Dare county email data

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



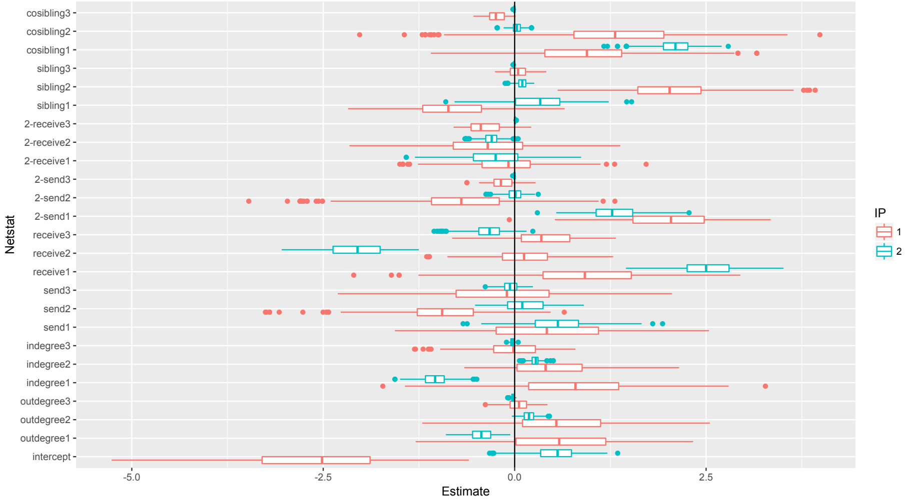
- Hurricane Sandy passed by NC: October 26 - October 30

Effect of Hurricane Sandy on Email Exchange



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