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

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Motivation

- In many networks, ties are attributed with text
  - International treaties
  - International sanctions
  - Legislative cosponsorship
  - Discussion networks on social media
- Network models can't model text
- Models for text either...
  - Are not designed for networks
  - Include simplistic network structure

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?"

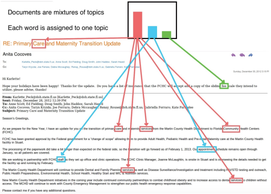
Content Generating Process: LDA (Blei et al., 2003)

- For each topic $k = 1, ..., K$:
  1. Choose a topic-word distribution over the word types
  2. Choose a topic-interaction pattern assignment

Probability

k = 1	k = 2	k = 3
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
⋮	⋮	⋮
IP = 1	IP = 2	IP = 1

- For each document $d = 1, ..., D$:
  - 3-1. Choose a document-topic distribution
  - 3-2. For each word in a document $n = 1$ to $N^{(d)}$:
    - (a) Choose a topic from document-topic distribution
    - (b) Choose a word from topic-word distribution



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)

Model accounts for dyadic, node, structural tendencies to form ties via e-mail sending

- 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

outdegree	$(i \rightarrow \forall j)$	**send**	$(i \rightarrow j)$	**2-send**	$\sum_h (i \rightarrow h \rightarrow j)$	**sibling**	$\sum_h \left(h \begin{smallmatrix} \nearrow i \\ \searrow j \end{smallmatrix}\right)$
indegree	$(i \leftarrow \forall j)$	**receive**	$(i \leftarrow j)$	**2-receive**	$\sum_h (i \leftarrow h \leftarrow j)$	**cosibling**	$\sum_h \left(h \begin{smallmatrix} \swarrow i \\ \nwarrow j \end{smallmatrix}\right)$

Dynamic Network Features (Perry and Wolfe, 2012)

currently implemented statistics

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

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Dynamic Network Features (Perry and Wolfe, 2012)

Conditioning statistics on recency

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

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indegree	$(i \leftarrow \forall j)$	**receive**	$(i \leftarrow j)$	**2-receive**	$\sum_h (i \leftarrow h \leftarrow j)$	**cosibling**	$\sum_h \left(h \begin{smallmatrix} \nwarrow i \\ \swarrow j \end{smallmatrix}\right)$

Tie Generating Process: Receivers

1. For each sender $i \in \{1, ..., A\}$ and receiver $j \in \{1, ..., A\}$ $(i \neq j)$, calculate the stochastic indensity between i and j:

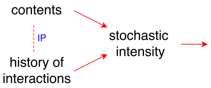
$$\lambda_{ij}^{(d)} = \sum_{c=1}^{C} p_c^{(d)} \cdot \mathsf{exp}\Big\{\boldsymbol{b}_0^{(c)} + \boldsymbol{b}^{(c)T} \boldsymbol{x}_{t^{(d-1)}}^{(c)}(i, j)\Big\},$$

   which is a mixture of contents, baseline interaction rate, and network effects.

2. 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)

$$\mathsf{P}(J_i^{(d)}) \propto \exp\Big\{\sum_{j \in \mathcal{A}_{\setminus i}} (\delta + \mathsf{log}(\lambda_{ij}^{(d)}))J_{ij}^{(d)}\Big\},$$

   where δ is a real-valued intercept controlling the recipient size



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: Sender and Time

3. For each sender $i \in \{1, ..., A\}$, generate the time increments for document d

$$\Delta T^{(d)}_{iJ_i} \sim \text{Exponential}(\lambda^{(d)}_{iJ_i}),$$

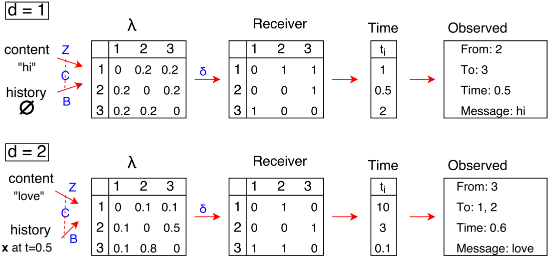
where $\lambda^{(d)}_{iJ_i} = \sum_{c=1}^{C} p^{(d)}_c \cdot \exp\Big\{\lambda^{(c)}_0 + \frac{1}{|J_i|} \sum_{j \in J_i} \boldsymbol{b}^{(c)T} \boldsymbol{x}^{(c)}_{t^{(d-1)}}(i, j)\Big\}$ is the updated sender-specific stochastic intensity given the receivers.

4. Set the observed sender, receivers and timestamp simultaneously:

$$i^{(d)} = i_{\min(\Delta T^{(d)}_{iJ_i})}$$
$$J^{(d)} = J_{i^{(d)}}$$
$$t^{(d)} = t^{(d-1)} + \min(\Delta T^{(d)}_{iJ_i})$$

Joint Generating Process

- Joint Generating Process



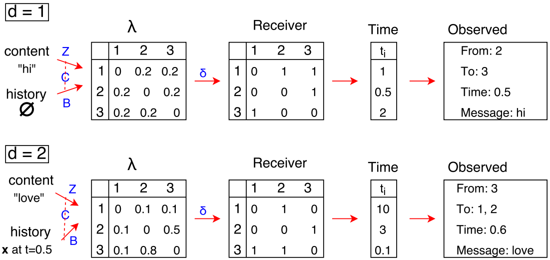
- Bayesian Inference using Markov Chain Monte Carlo (MCMC)

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 receivers $J_{ij}^{(d)}$ via Gibbs sampling
  Sample the topic assignments $\mathcal{Z}$ via Gibbs sampling
  Sample the interaction pattern assignments $\mathcal{C}$ via Gibbs sampling
  Sample the network effect parameters $\mathcal{B}$ via Metropolis-Hastings
  Sample the receiver size parameter δ via Metropolis-Hastings
end

Bayesian Inference

- Joint Generating Process



- Bayesian Inference using Markov Chain Monte Carlo (MCMC)

Algorithm 2 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 receivers $J_{ij}^{(d)}$ via Gibbs sampling
  Sample the topic assignments $\mathcal{Z}$ via Gibbs sampling
  Sample the interaction pattern assignments $\mathcal{C}$ via Gibbs sampling
  Sample the network effect parameters $\mathcal{B}$ via Metropolis-Hastings
  Sample the receiver size parameter δ via Metropolis-Hastings
end

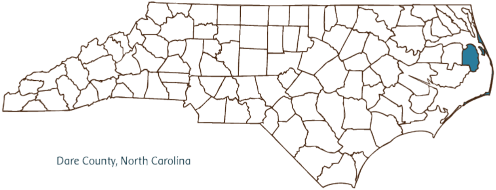
Getting it Right

GiR: Results with full model

GiR: Results with fixed C

Data: North Carolina Dare county email data

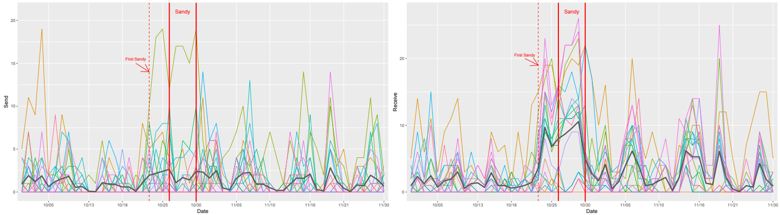
- $D = 1456$ emails between $A = 27$ county government managers, covering 2 month periods (October 1 - November 30) in 2012



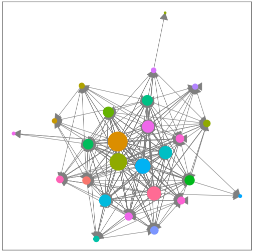
- Hurricane Sandy passed by NC: October 26 - October 30

Theoretical expectations

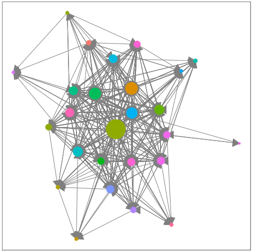
Exploratory Data Analysis: SMALL COUNTY



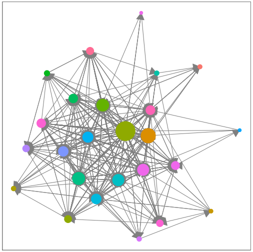
Pre-Sandy



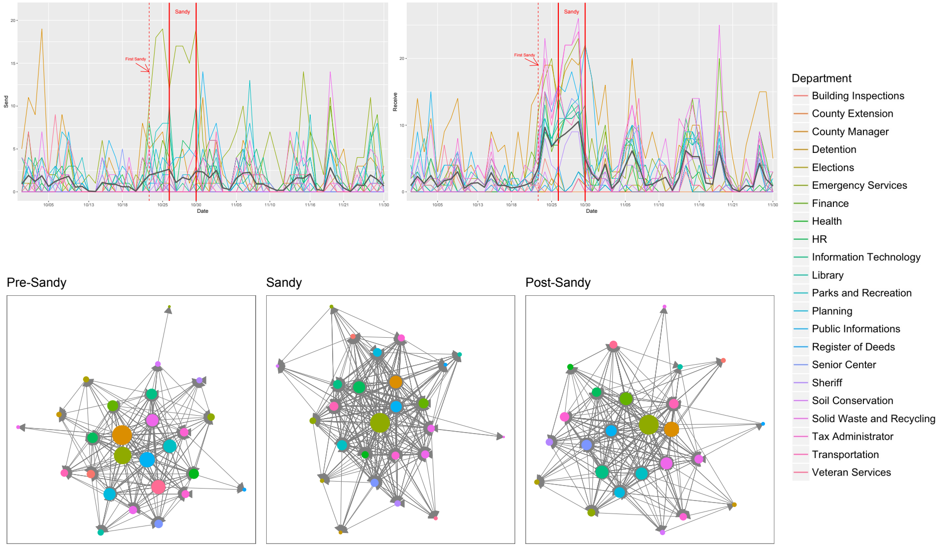
Sandy



Post-Sandy



Exploratory Data Analysis: DARE COUNTY



IPTM Result: Contents

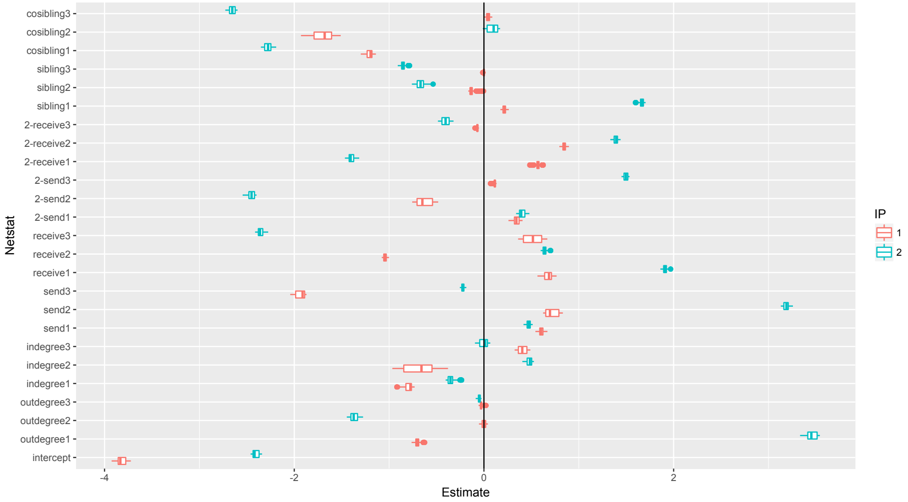
- IPTM result with $C = 2$, $K = 20$ and $O = 20^*$:

IP	1	1	1	2	2	2
Topic	**2**	**13**	**7**	**10**	**9**	**12**
Word	winds	track	offices	sanitation	marshall	morning
	flooding	offices	hurricane	billed	human	fema
	policy	obx	sandy	long	collins	weather
	mph	shore	update	bill	phone	ems
	moving	winds	force	question	resources	risks
	outer	exam	reading	staff	phr	sure
	banks	area	contact	vehicles	drive	tomorrow
	rain	change	updates	additional	box	opening
	will	continues	amount	form	fax	address
	duration	expect	northwest	estimate	bridge	elections
	monday	curves	tuesday	total	director	thought
	ocean	side	expected	doors	monday	minutes
	open	east	good	services	manteo	starting
	heads	better	well	tomorrow	summary	wrote
	late	mile	night	haterras	october	operation

*Preliminary results with small outer iterations. Model results subject to change.

IPTM Result: Dynamic Network Effects

- IPTM result with $C = 2$, $K = 20$ and $O = 20^{\dagger}$:



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IPTM Result: Contents DARE

- IPTM result with $C = 2$, $K = 20$ and $O = 20^{\ddagger}$:

IP	1	1	1	2	2	2
Topic	**2**	**13**	**7**	**10**	**9**	**12**
Word	winds	track	offices	sanitation	marshall	morning
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	policy	obx	sandy	long	collins	weather
	mph	shore	update	bill	phone	ems
	moving	winds	force	question	resources	risks
	outer	exam	reading	staff	phr	sure
	banks	area	contact	vehicles	drive	tomorrow
	rain	change	updates	additional	box	opening
	will	continues	amount	form	fax	address
	duration	expect	northwest	estimate	bridge	elections
	monday	curves	tuesday	total	director	thought
	ocean	side	expected	doors	monday	minutes
	open	east	good	services	manteo	starting
	heads	better	well	tomorrow	summary	wrote
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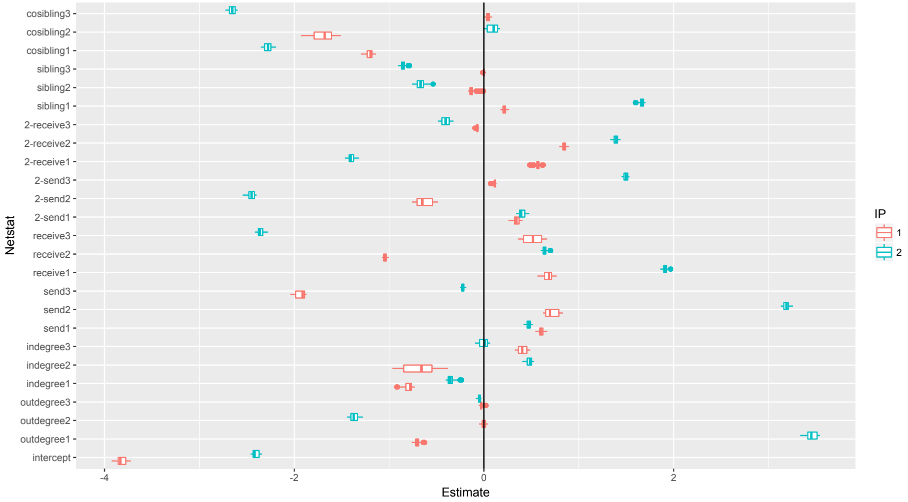
IPTM Result: Dynamic Network Effects DARE

- IPTM result with $C = 2$, $K = 20$ and $O = 20^{\S}$:



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Showing MCMC convergence

Predictive experiment design

Conclusion

- Joint modeling of ties (sender, receiver, time) and contents
- Allowance of multicast – single sender and multiple receivers
- Possible application to various political science data
- Developement of R package 'IPTM'