

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

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Interaction-Partitioned Topic Model (IPTM)

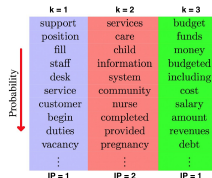
- Probabilistic model for time-stamped textual communications
- Integration of two generative models:
 - Latent Dirichlet allocation (LDA) for topic-based contents
 - Dynamic exponential random graph model (ERGM) for ties

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

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

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

1. Choose a topic-word distribution over the word types
2. Choose a topic-interaction pattern assignment



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

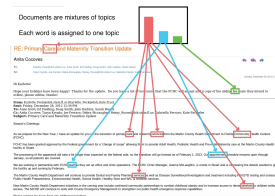
- ### 3-1. Choose a document-topic distribution

- 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:



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

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 ($l = 1, 2, 3$)

- $\mathbf{x}_{t,l}^{(c)}(i, j)$ 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	$\sum_h (h \rightarrow i \rightarrow j)$
indegree	$(i \leftarrow \forall j)$	receive	$(i \leftarrow j)$	2-receive	$\sum_h (i \leftarrow h \leftarrow j)$	cosibling	$\sum_h (h \leftarrow i \leftarrow j)$

Tie Generating Process: Receivers

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

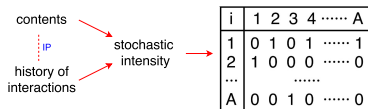
$$\lambda_{ij}^{(d)} = \sum_{c=1}^C p_c^{(d)} \cdot \exp \left\{ \mathbf{b}_0^{(c)} + \mathbf{b}^{(c)T} \mathbf{x}_{t^{(d-1)}}^{(c)}(i, j) \right\},$$

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

2. 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)

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

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



Tie Generating Process: Sender and Time

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

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

where $\lambda_{iJ_i}^{(d)} = \sum_{c=1}^C p_c^{(d)} \cdot \exp\left\{\lambda_0^{(c)} + \frac{1}{|J_i|} \sum_{j \in J_i} \mathbf{b}^{(c)T} \mathbf{x}_{t^{(d-1)}}^{(c)}(i, j)\right\}$ is the updated sender-specific stochastic intensity given the receivers.

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

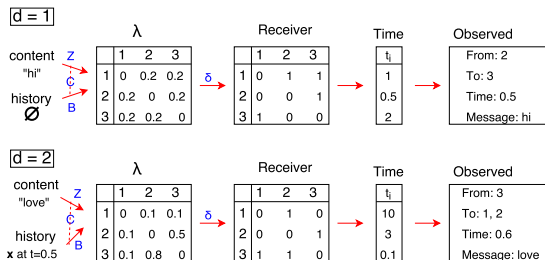
$$i^{(d)} = i_{\min(\Delta T_{iJ_i}^{(d)})}$$

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

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

Joint Generating Process and Bayesian Inference

Joint Generating Process



Bayesian Inference using Markov Chain Monte Carlo (MCMC)

Algorithm 1 MCMC

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

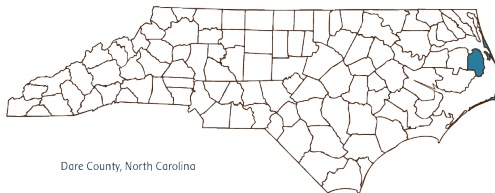
for $o=1$ to O do

- Sample the latent receivers $J_{i,j}^{(d)}$ 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

Data: North Carolina Dare county email data

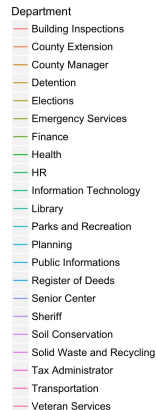
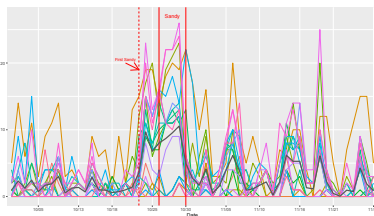
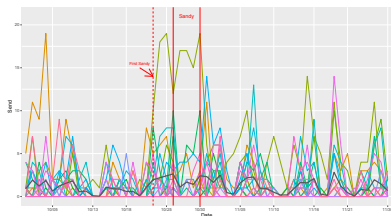
- $D = 1456$ emails between $A = 27$ county government managers, covering 2 month periods (October 1 - November 30) in 2012



Dare County, North Carolina

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

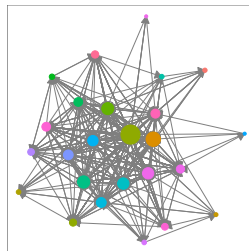
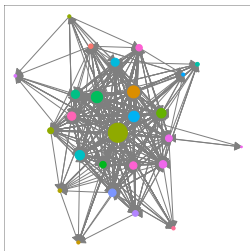
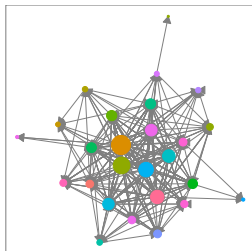
Exploratory Data Analysis: Effect of Sandy



Pre-Sandy

Sandy

Post-Sandy



IPTM Result: Contents

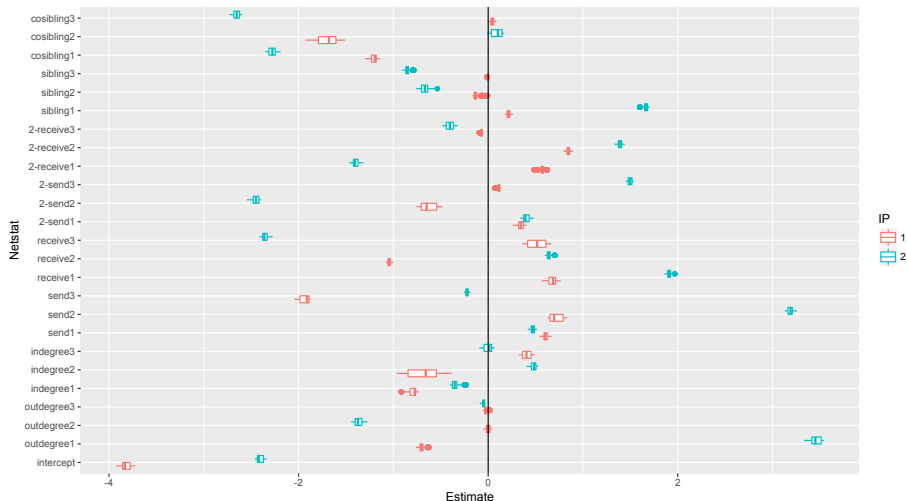
- IPTM result with $C = 2$, $K = 20$ and $O = 20^*$:

IP	1	1	1	2	2	2
Topic	2	13	7	10	9	12
Word	winds flooding policy mph moving outer banks rain will duration monday ocean open heads late	track offices obx shore winds exam area change continues expect curves side east better mile	offices hurricane sandy update force reading contact updates amount northwest tuesday expected good well night	sanitation billed long bill question staff vehicles additional form estimate total doors services tomorrow haterras	marshall human collins phone resources phr drive box fax bridge director monday manteo summary october	morning fema weather ems risks sure tomorrow opening address elections thought minutes starting wrote 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 $O = 20^\dagger$:



[†]Preliminary results with small outer iterations. Model results subject to change.

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'