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

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1 Tie Generating Process

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

1. For each $i \in \mathcal{A}$, implement rank ordering of the possible receivers $j \in \mathcal{A}_{\setminus i}$:

$$R_i^{(d)} = \text{rank}(\{\lambda_{ij}^{(d)} + \epsilon_{ij}\}_{j \in \mathcal{A}_{\setminus i}}), \tag{1}$$

   where $\epsilon_{ij} \sim N(0, \sigma_\epsilon^2)$.

2. Choose the number of recipients (cutoff point)

$$C_i^{(d)} \sim \text{zero-truncated Binomial}(A-1, \delta_i), \tag{2}$$

   where $A-1$ comes from excluding the sender himself as a possible receiver (self-loop) and δ_i is the sender-specific probability of success. For example, we can use R function

```
library(actuar)
C_i = rztbinom(n = 1, size = 3, prob = 0.1)
```

3. For each $i \in \mathcal{A}$, set the latent receivers with indicator vector $J_i^{(d)}$, by

$$J_i^{(d)} = \{I(R_{ij}^{(d)} <= C_i^{(d)})\}_{j \in \mathcal{A}_{\setminus i}} \tag{3}$$

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

$$\Delta T_{iJ_i}^{(d)} \sim \text{Exp}(\lambda_{iJ_i}^{(d)}), \tag{4}$$

   where $\lambda_{iJ_i}^{(d)}(t) = \sum_{c=1}^{C} p_c^{(d)} \cdot \exp\Big\{\lambda_0^{(c)} + \frac{1}{|J_i|}\sum_{j \in J_i} \boldsymbol{b}^{(c)T}\boldsymbol{x}_t^{(c)}(i,j)\Big\} \cdot \prod_{j \in J_i} 1\{j \in \mathcal{A}_{\setminus i}\}$.

4. Set timestamp, sender, and receivers simultaneously (NOTE: $t^{(0)} = 0$):

$$\begin{aligned} t^{(d)} &= t^{(d-1)} + \min(\Delta T_{iJ_i}), \\ i^{(d)} &= i_{\min(\Delta T_{iJ_i})}, \\ J^{(d)} &= J_{i^{(d)}}. \end{aligned} \tag{5}$$

2 Inference

$$
\begin{aligned}
&P(\mathcal{R}^{(d)}, \mathcal{J}_{\text{a}}^{(d)}, \mathcal{T}_{\text{a}}^{(d)}, i_{\text{o}}^{(d)}, J_{\text{o}}^{(d)}, t_{\text{o}}^{(d)} | \mathcal{I}_{\text{o}}^{(<d)}, \mathcal{J}_{\text{o}}^{(<d)}, \mathcal{T}_{\text{o}}^{(<d)}, \mathcal{Z}, \mathcal{C}, \mathcal{B}, \boldsymbol{\delta}) \\
&= P\Big(\text{Number of recipients}\Big) \times P\Big(\text{Edge generation}\Big) \times P\Big(\text{Time generation}\Big) \times P\Big(\text{choose the observed}\Big) \\
&= \prod_{i\in\mathcal{A}} \Big(R_i^{(d)} \sim \text{ztbinom}(A-1, \delta_i)\Big) \times \prod_{i\in\mathcal{A}} \Big(J_i^{(d)} \sim \text{MWNCHypergeo}\Big(\mathbf{1}_{A-1}, R_i^{(d)}, \{\lambda_{ij}^{(d)}\}_{j\in\mathcal{A}_{\backslash i}}\Big)\Big) \\
&\qquad \times \prod_{i\in\mathcal{A}} \Big(\Delta T_{iJ_i}^{(d)} \sim \text{Exp}(\lambda_{iJ_i}^{(d)})\Big) \times \prod_{i\in\mathcal{A}_{\backslash i_o^{(d)}}} P\Big(\Delta T_{iJ_i}^{(d)} > \Delta T_{i_o^{(d)} J_o^{(d)}}\Big) \\
&= \Big(\prod_{i\in\mathcal{A}} \binom{A-1}{R_i^{(d)}} \frac{\delta_i^{R_i^{(d)}} (1-\delta_i)^{A-1-R_i^{(d)}}}{1-(1-\delta_i)^{A-1}}\Big) \times \Big(\prod_{i\in\mathcal{A}} \text{dMWNCHypergeo}\Big(J_i^{(d)}; \mathbf{1}_{A-1}, R_i^{(d)}, \{\lambda_{ij}^{(d)}\}_{j\in\mathcal{A}_{\backslash i}}\Big)\Big) \\
&\qquad \times \Big(\prod_{i\in\mathcal{A}} \lambda_{iJ_i}^{(d)} e^{-\Delta T_{iJ_i}^{(d)} \lambda_{iJ_i}^{(d)}}\Big) \times \Big(\prod_{i\in\mathcal{A}_{\backslash i_o^{(d)}}} e^{-\Delta T_{i_o^{(d)} J_o^{(d)}}^{(d)} \lambda_{iJ_i^{(d)}}^{(d)}}\Big),
\end{aligned}
\tag{6}
$$

with the probability mass function of dMWNCHypergeo with $\boldsymbol{m} = \mathbf{1}_{A-1}$ given as

$$
\text{dMWNCHypergeo}(\boldsymbol{x}; \boldsymbol{m} = \mathbf{1}_{A-1}, n = R_i^{(d)}, \boldsymbol{\omega} = \{\lambda_{ij}^{(d)}\}_{j\in\mathcal{A}_{\backslash i}}) = \int_0^1 \prod_{i=1}^{A-1} (1 - t^{\omega_i/d})^{x_i} dt,
$$

where $d = \sum_{i=1}^{A-1} \omega_i (1 - x_i)$, $\boldsymbol{x}$ is the $(A-1)$ length vector indicating the receivers, $\boldsymbol{\omega} = (\omega_1, ..., \omega_{A-1})$ is the weight or odds of each receiver to be chosen, and $n = \sum_{i=1}^{A-1} x_i$ is the total number of receivers chosen.

We can simplify this further by integreting out the latent time $\mathcal{T}_{\text{a}}^{(d)} = \{\Delta T_{iJ_i}^{(d)}\}_{i\in\mathcal{A}_{\backslash i_o^{(d)}}}$ in the last two terms:

$$
\begin{aligned}
&\int_0^\infty \cdots \int_0^\infty \Big(\prod_{i\in\mathcal{A}_{\backslash i_o^{(d)}}} \lambda_{iJ_i}^{(d)} e^{-(\Delta T_{iJ_i}^{(d)} + \Delta T_{i_o^{(d)} J_o^{(d)}}^{(d)}) \lambda_{iJ_i}^{(d)}}\Big) d\Delta T_{1J_1}^{(d)} \cdots d\Delta T_{AJ_A}^{(d)} \\
&= \prod_{i\in\mathcal{A}_{\backslash i_o^{(d)}}} e^{-\Delta T_{i_o^{(d)} J_o^{(d)}}^{(d)} \lambda_{iJ_i}^{(d)}} \Big(\int_0^\infty \lambda_{iJ_i}^{(d)} e^{-\Delta T_{iJ_i}^{(d)} \lambda_{iJ_i}^{(d)}} d\Delta T_{iJ_i}^{(d)}\Big) \\
&= \prod_{i\in\mathcal{A}_{\backslash i_o^{(d)}}} e^{-\Delta T_{i_o^{(d)} J_o^{(d)}}^{(d)} \lambda_{iJ_i}^{(d)}} \Big(\Big[-e^{-\Delta T_{iJ_i}^{(d)} \lambda_{iJ_i}^{(d)}}\Big]_{\Delta T_{iJ_i}^{(d)}=0}^{\infty}\Big) \\
&= e^{-\Delta T_{i_o^{(d)} J_o^{(d)}}^{(d)} \sum_{i\in\mathcal{A}_{\backslash i_o^{(d)}}} \lambda_{iJ_i}^{(d)}},
\end{aligned}
\tag{7}
$$

where $\Delta T_{i_o^{(d)} J_o^{(d)}}^{(d)}$ is the observed time difference between d^{th} and $(d-1)^{th}$ document (i.e. $t^{(d)} - t^{(d-1)}$). Therefore, we can simplify Equation (5) as below:

$$
\begin{aligned}
&P(\mathcal{R}^{(d)}, \mathcal{J}_{\text{a}}^{(d)}, i_{\text{o}}^{(d)}, J_{\text{o}}^{(d)}, t_{\text{o}}^{(d)} | \mathcal{I}_{\text{o}}^{(<d)}, \mathcal{J}_{\text{o}}^{(<d)}, \mathcal{T}_{\text{o}}^{(<d)}, \mathcal{Z}, \mathcal{C}, \mathcal{B}, \boldsymbol{\delta}) \\
&= \Big(\prod_{i\in\mathcal{A}} \binom{A-1}{R_i^{(d)}} \frac{\delta_i^{R_i^{(d)}} (1-\delta_i)^{A-1-R_i^{(d)}}}{1-(1-\delta_i)^{A-1}}\Big) \times \Big(\prod_{i\in\mathcal{A}} \int_0^1 \prod_{j=1}^{A-1} (1 - t^{\lambda_{ij}^{(d)} / \sum_{j=1}^{A-1} \lambda_{ij}^{(d)} (1 - J_{ij}^{(d)})})^{J_{ij}^{(d)}} dt\Big) \\
&\qquad \times \Big(\lambda_{i_o^{(d)} J_o^{(d)}}^{(d)}\Big) \times \Big(e^{-\Delta T_{i_o^{(d)} J_o^{(d)}}^{(d)} \sum_{i\in\mathcal{A}_{\backslash i_o^{(d)}}} \lambda_{iJ_i^{(d)}}^{(d)}}\Big),
\end{aligned}
\tag{8}
$$

where this joint distribution can be interpreted as 'probability of choosing the number of recipients from zero-truncated Binomial distribution × probability of choosing the latent receivers from Wallenius' noncenral hypergeometric distribution × probability of the observed time comes from Exponential distribution × probability of all latent time greater than the observed time, given that the latent time also come from Exponential distribution.'

2.1 Inference on $\boldsymbol{\delta}$

We can assign Beta prior on each δ_i. Does Beta-Binomial conjucacy still hold for zero-truncated Binomial case? I don't think so... (due to the additional denominator) should we use M-H instead?

2.2 Inference on the augmented data $\mathcal{J}_{\mathbf{a}}$

Given the observed sender of the document $i_o^{(d)}$, we sample the latent receivers for each sender $i \in \mathcal{A}_{\backslash i_o^{(d)}}$. Here we illustrate how each sender-receiver pair in the document d is updated.

Define $J_i^{(d)}$ be the $(A-1)$ length vector of indicators (0/1) representing the latent receivers corresponding to the sender i in the document d. For each sender i, we are going to resample the receiver vector $J_i^{(d)}$, one at a time. For a latent sender $i \in \mathcal{A}_{\backslash i_o^{(d)}}$, we derive the conditional probability:

$$\begin{aligned}
&P(\mathcal{J}_i^{(d)} = J_i^{(d)} | \mathcal{R}^{(d)}, i_{\mathrm{O}}^{(d)}, J_{\mathrm{O}}^{(d)}, t_{\mathrm{O}}^{(d)}, \mathcal{I}_{\mathrm{O}}^{(<d)}, \mathcal{J}_{\mathrm{O}}^{(<d)}, \mathcal{T}_{\mathrm{O}}^{(<d)}, \mathcal{Z}, \mathcal{C}, \mathcal{B}, \boldsymbol{\delta}) \\
&\propto P(\mathcal{J}_i^{(d)} = J_i^{(d)}, i_{\mathrm{O}}^{(d)}, J_{\mathrm{O}}^{(d)}, t_{\mathrm{O}}^{(d)} | \mathcal{R}^{(d)}, \mathcal{I}_{\mathrm{O}}^{(<d)}, \mathcal{J}_{\mathrm{O}}^{(<d)}, \mathcal{T}_{\mathrm{O}}^{(<d)}, \mathcal{Z}, \mathcal{C}, \mathcal{B}, \boldsymbol{\delta}) \\
&\propto \Big(\int_0^1 \prod_{j=1}^{A-1} (1 - t^{\lambda_{ij}^{(d)} / \sum_{j=1}^{A-1} \lambda_{ij}^{(d)} (1 - J_{ij}^{(d)})})^{J_{ij}^{(d)}} dt \Big) \times \Big(e^{-\Delta T^{(d)}_{i_o^{(d)} J_o^{(d)}} \sum_{i \in \mathcal{A}_{\backslash i_o^{(d)}}} \lambda^{(d)}_{i J_i^{(d)}}} \Big),
\end{aligned} \tag{9}$$

where we replace typical use of $(-d)$ to $(< d)$ on the right hand side of the conditional probability, due to the fact that $d^{(th)}$ document only depends on the past documents, not on the future ones.

No idea how to choose the proposal distribution for the indicator vector $J_i^{(d)}$. Possibly sample each element $J_{ij}^{(d)}$ as we did before, using M-H sampling with the choice of univariate Wallenius' distribution as the proposal density which relies on approximation (Fog, 2008).

2.3 Inference on $\mathcal{Z}$

same as before but edge probability part changed to $\Big(\prod_{i \in \mathcal{A}} \text{dMWNCHypergeo}\Big(J_i^{(d)}; \mathbf{1}_{A-1}, R_i^{(d)}, \{\lambda_{ij}^{(d)}\}_{j \in \mathcal{A}_{\backslash i}}\Big)\Big)$

2.4 Inference on $\mathcal{C}$

same as before but edge probability part changed to $\Big(\prod_{i \in \mathcal{A}} \text{dMWNCHypergeo}\Big(J_i^{(d)}; \mathbf{1}_{A-1}, R_i^{(d)}, \{\lambda_{ij}^{(d)}\}_{j \in \mathcal{A}_{\backslash i}}\Big)\Big)$

2.5 Inference on $\mathcal{B}$

same as before but edge probability part changed to $\Big(\prod_{i \in \mathcal{A}} \text{dMWNCHypergeo}\Big(J_i^{(d)}; \mathbf{1}_{A-1}, R_i^{(d)}, \{\lambda_{ij}^{(d)}\}_{j \in \mathcal{A}_{\backslash i}}\Big)\Big)$