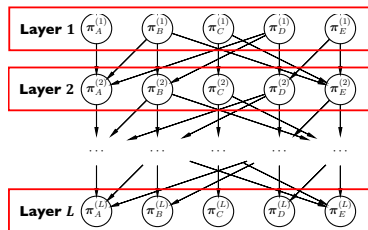


Dirichlet Belief Networks (DirBN)

Applications: topic modeling & relational modeling

$\pi_i^{(l)}$: person i 's categorical distribution at layer l ; β_{ji} : coefficient from person j to i .



- ▶ interpretable units
- ▶ persons' dependencies

$$\pi_i^{(l)} \sim \text{Dirichlet}\left(\sum_j \beta_{ji}^{(l-1)} \pi_j^{(l-1)}\right)$$

$$\pi_i^{(l+1)} \sim \text{Dirichlet}\left(\sum_j \beta_{ji}^{(l)} \pi_j^{(l)}\right)$$

- ▶ $\pi_i^{(l)}$ is involved in **Gamma function** $\Gamma(\cdot)$

$$\begin{aligned} P(\pi_i^{(l+1)} | \{\pi_j^{(l)}, \beta_{ji}^{(l)}\}_j) \\ = \frac{\Gamma(\sum_{jk} \beta_{ji}^{(l)} \pi_{jk}^{(l)})}{\prod_k \Gamma(\sum_k \beta_{ji}^{(l)} \pi_{jk}^{(l)})} \prod_k [\pi_{ik}^{(l+1)}]^{\sum_j \beta_{ji}^{(l)} \pi_{jk}^{(l)} - 1} \end{aligned}$$

- ▶ Forming conjugate models and enabling Gibbs sampling for $\pi_i^{(l)}$ is difficult.

Previous inference method for DirBN

- ▶ Use Chinese Restaurant Table variable to augment the Gamma function ratio.
- ▶ Drawbacks:
 - ▶ information loss in generating Chinese Restaurant Table variable
 - ▶ Similar patterns in $\{\pi_i^{(l)}\}_l$

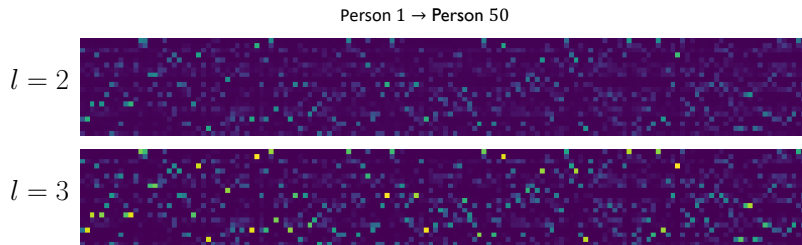


Figure: Visualisations on $\pi_{1:50}^{(2)}, \pi_{1:50}^{(3)}$.

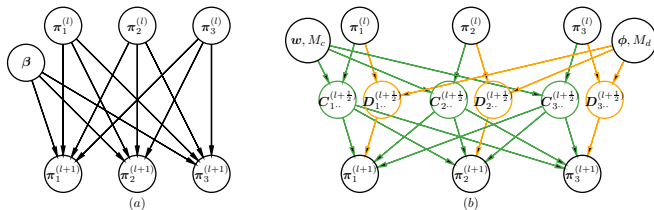
DirBN does not benefit from the deep structure.

Poisson-randomised DirBN

Introduce **augment variables** C, D in the Dirichlet-Dirichlet connection.

$$C_{iki'}^{(l)} \sim \text{Poisson}(M_c \pi_{ik}^{(l)} \omega_{ii'}^{(l)}), D_{ikk'}^{(l)} \sim \text{Poisson}(M_d \pi_{ik}^{(l)} \phi_{kk'}^{(l)})$$
$$\pi_i^{(l+1)} \sim \text{Dirichlet}(\alpha^{(\pi)} + \sum_{i'} C_{i'.i}^{(l)} + \sum_{k'} D_{ik'.})$$

whereas $\omega_{ii'}^{(l)}$: coefficient from person i to person i' , $\phi_{kk'}^{(l)}$: coefficient from component k to component k' , $M_c, M_d, \alpha^{(\pi)}$: hyper-parameters.



Benefits:

- ▶ Layer-wise Gibbs sampling without information loss
- ▶ Component-wise propagation variable D introduce larger mutations

Visualisation on our Pois-DirBN

