

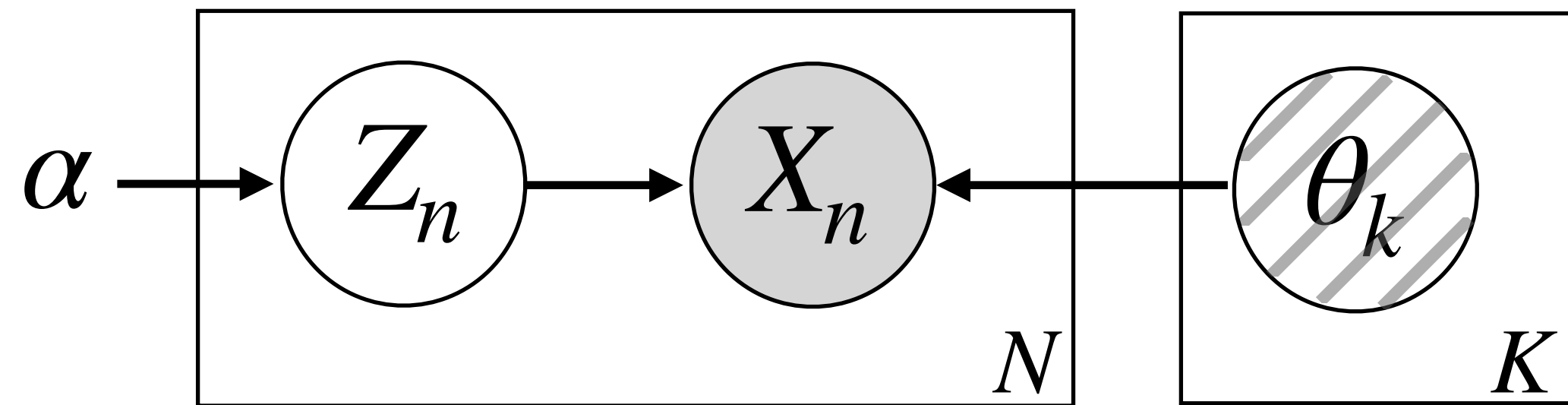
Random Function Priors for Correlation Modeling

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Setup

Model exchangeable data $X = [X_1, \dots, X_N]$



$\theta = (\theta_k)_{k \in K}$ collection of features

$Z_n = [Z_{n1}, \dots, Z_{nk}, \dots, Z_{nK}] \in \mathbb{R}_+^K$

the extent θ_k is used to express X_n .

E.g. Sparse factor models: $Z_n \in \{0,1\}^K$

Topic models: $Z_n \in \Delta^{K-1}$

Problem: model flexible correlations among Z_{n1}, \dots, Z_{nK}

Complexity: $2^{O(K)}$

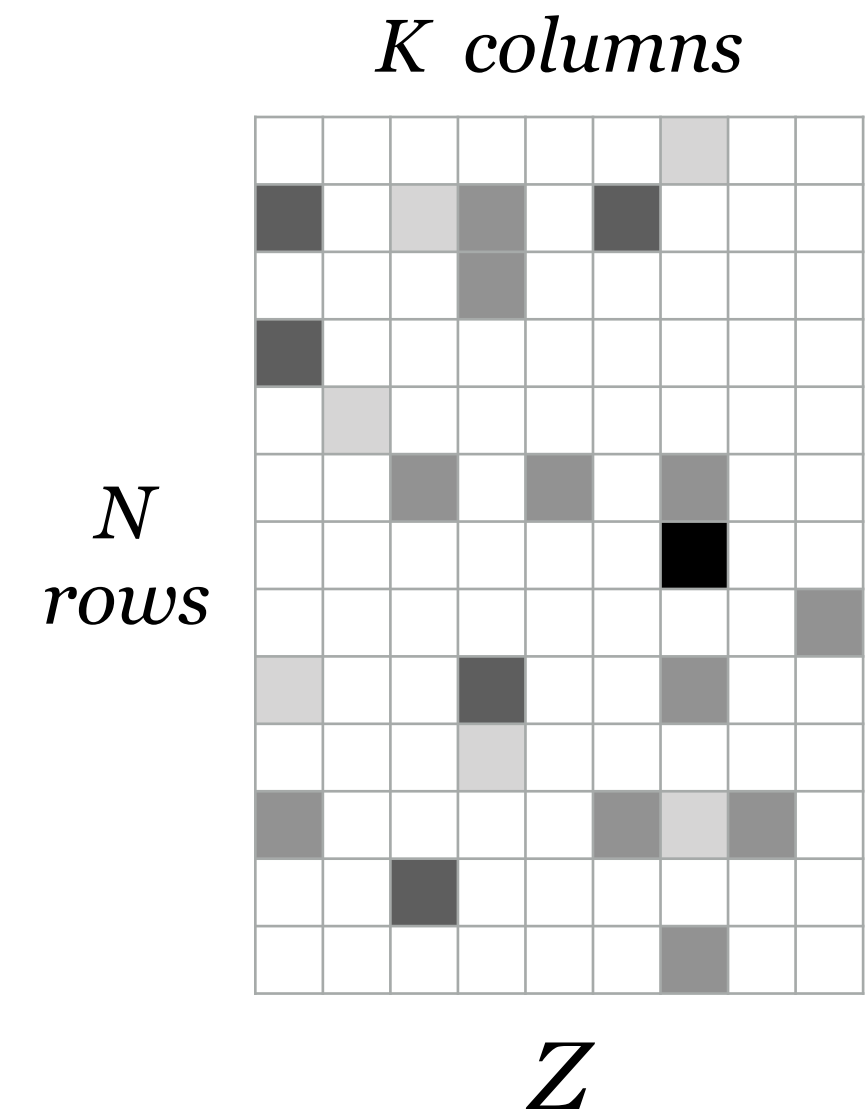
Exponential family?

Solution: random function priors

Model the matrix Z

Joint distribution

$$p(X, Z, \theta) = \underbrace{p(Z)}_{\text{???}} \cdot \prod_{k=1}^K \underbrace{p(\theta_k)}_{\text{i.i.d.}} \cdot \prod_{n=1}^N \underbrace{p(X_n | Z_n, \theta)}_{\text{application dependent}}$$



Workflow to derive $p(Z)$

Exchangeability assumptions on $p(Z)$ $\xrightarrow{\text{representation theorems}}$ $p(Z)$ is a random function model

Representation theorem

Trick: Transform Z (random matrix) to ξ (random measure) on S .

$$\xi = \sum_{n,k} Z_{nk} \delta_{\tau_n, \sigma_k}$$

Assumption: ξ is separately exchangeable.

Proposition. A discrete random measure ξ on S is separately exchangeable, if and only if almost surely,

$$\xi = \sum_{n,k} f_n(\vartheta_k) \delta_{\tau_n, \sigma_k} + \text{trivial terms}$$

Poisson process on \mathbf{R}_+^2
random functions on \mathbf{R}_+

$$Z_{nk} = f_n(\vartheta_k)$$

The power of random function priors

Prototype to applicable models

1. $f_n(\vartheta_k) \rightarrow f(h_n, \vartheta_k)$

└─ learned via inference networks $h_n = g(X_n)$
└─ decoder network

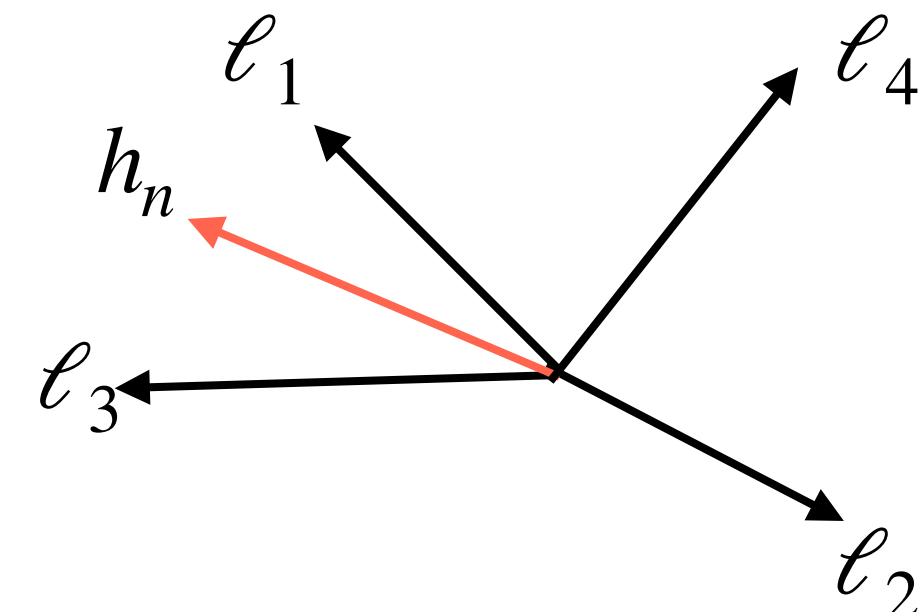
2. $f(h_n, \vartheta_k) \rightarrow f(h_n, \vartheta_k, \ell_k)$

└─ augment the 2d Poisson process (ϑ_k, σ_k)
to higher dimension $(\vartheta_k, \sigma_k, \ell_k)$

Model correlations through arbitrary moments

Assume $Z_{nk} = f(h_n^\top \ell_k)$

Then $\mathbb{E}[Z_{nk_1} Z_{nk_2} \dots Z_{nk_j}] = \mathbb{E}[f(h_n^\top \ell_{k_1}) \dots f(h_n^\top \ell_{k_j})]$



Visualize correlations via paintboxes

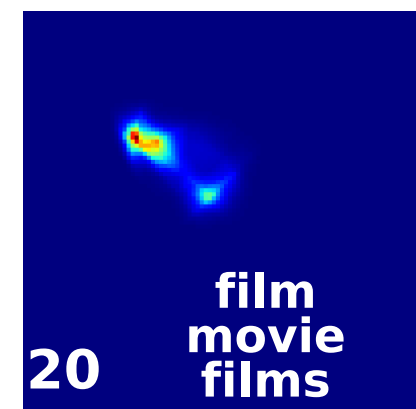
Each paintbox
is a
heatmap.



Visualize correlations via paintboxes

Correlated Topics

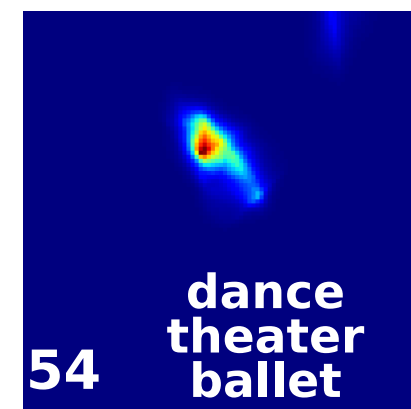
$$Z_{n,20} = f(h_n, \ell_{20})$$



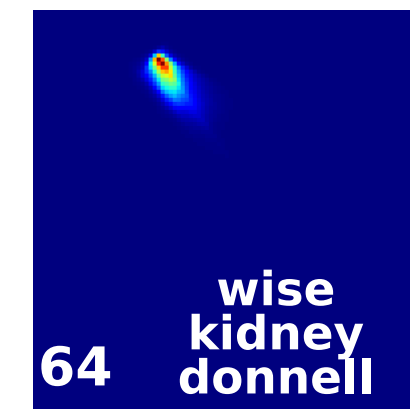
$$Z_{n,47} = f(h_n, \ell_{47})$$



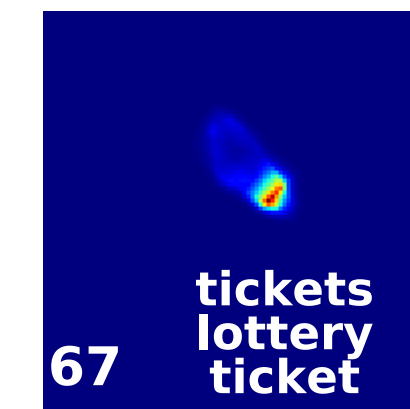
$$Z_{n,54} = f(h_n, \ell_{54})$$



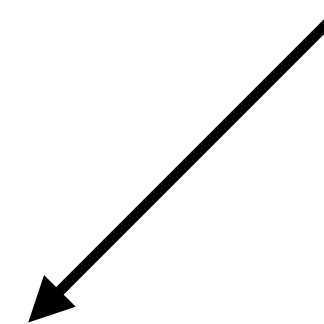
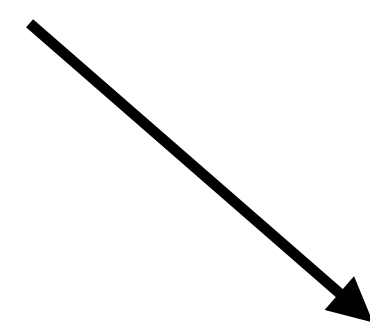
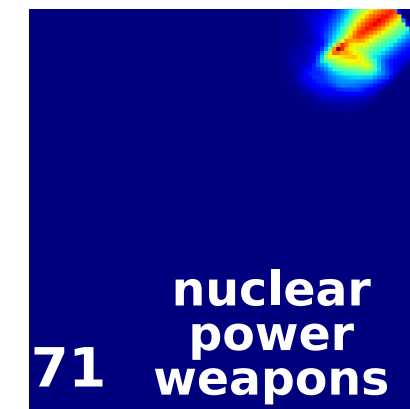
$$Z_{n,64} = f(h_n, \ell_{64})$$



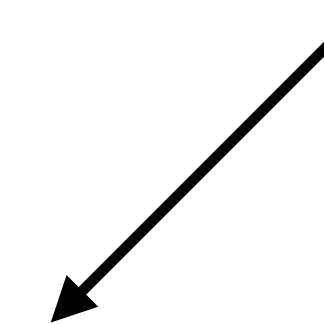
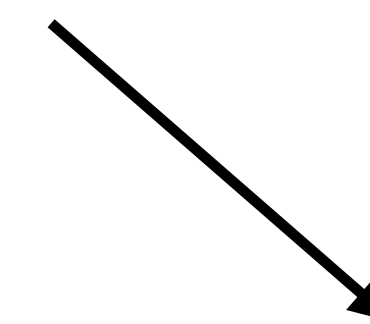
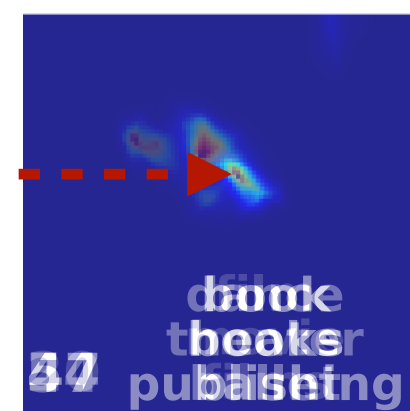
$$Z_{n,67} = f(h_n, \ell_{67})$$



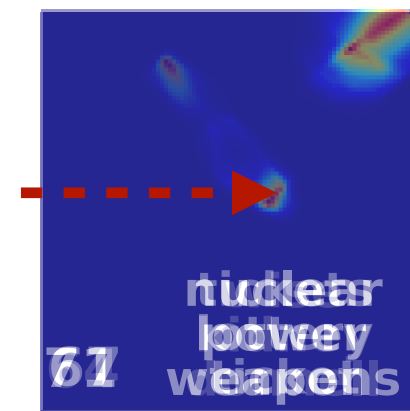
$$Z_{n,71} = f(h_n, \ell_{71})$$



h_n

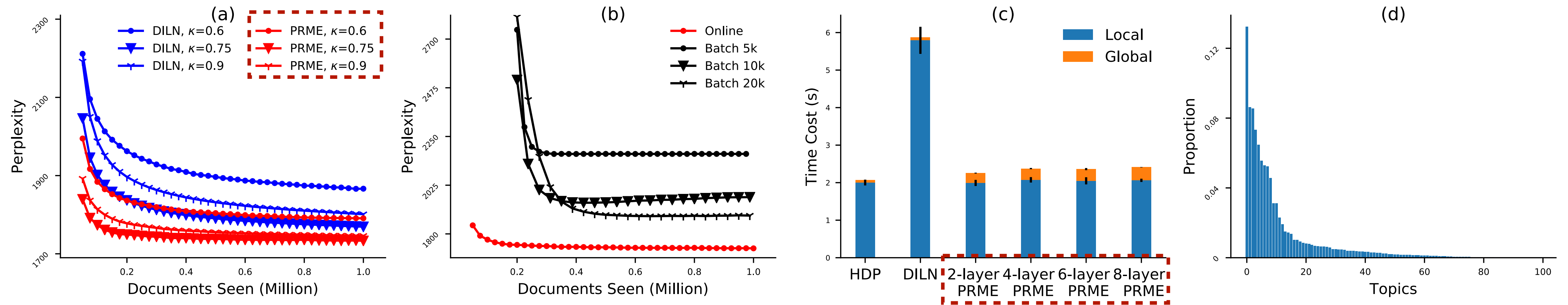


h_n



Model performance

Our model: PRME



Summarize

More details

A representation theorem for correlation modeling.

A deeper understanding of IBP beyond the Beta-Bernoulli process.

A generalization of Kingman's and Broderick's paintbox models.

Connections to random graphs.

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Poster: #222

Code: <https://github.com/zan12/prme>