

# International Conference on Machine Learning (ICML 2019)



## Convolutional Poisson Gamma Belief Network

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### Motivation



#### **Document Representation**

- **□** Basic Lossless Representation
  - ➤ A sequence of one-hot vectors
    - ✓ Preserve all textual information
    - Extremely large and sparse matrices
    - Burdens of calculation and storage
    - Difficult to model directly

#### **Document**

"I love it don't  $\begin{bmatrix} 0 \\ 0 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \end{bmatrix}$  "I love it"  $\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$  it  $\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$  love  $\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$  love  $\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$ 

#### Simplified



One-hot Sequence

#### ☐ Simplified Lossy Representation

- **Bag-of-words** 
  - ✓ Term-document frequency count matrix
  - X Lose word order
- Word embeddings
  - ✓ Project words to low-dimensional vectors
  - \* Require additional large corpora

#### Challenge



Most basic representation



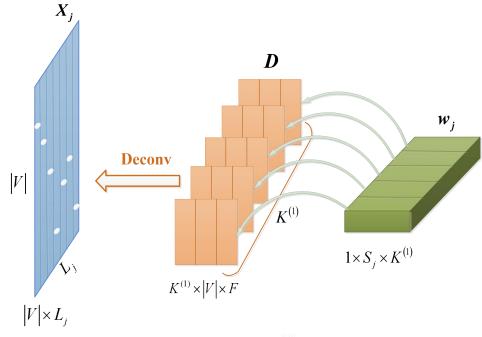


## **Our Contribution**



#### **Convolutional Poisson Factor Analysis**

#### **□** Generative model of CPFA



$$X_j = \mathbf{1}(M_j > 0), \ M_j \sim \operatorname{Pois}(\sum_{k=1}^K D_k * w_{jk}),$$
  
 $w_{jk} \sim \operatorname{Gam}(r_k, 1/c_j), \ D_k(:) \sim \operatorname{Dir}(\eta \mathbf{1}_{|V|F}),$ 

- ✓ Preserve word order information
- / Directly model sparse matrices
- Take advantages of the sparsity
- Support parallel computation
- ✓ Capture pharse-level topics

**Probabilistic Convolutional Layer** 





## **Our Contribution**



#### **Convolutional Poisson Gamma Belief Network**

#### **□** Probabilistic Pooling Layer

$$w_{jks} \sim \text{Gam}(\Phi_{k:}^{(2)}\theta_{j}^{(2)}/S_{j}, 1/c_{j}^{(2)})$$



#### **Equivalent**

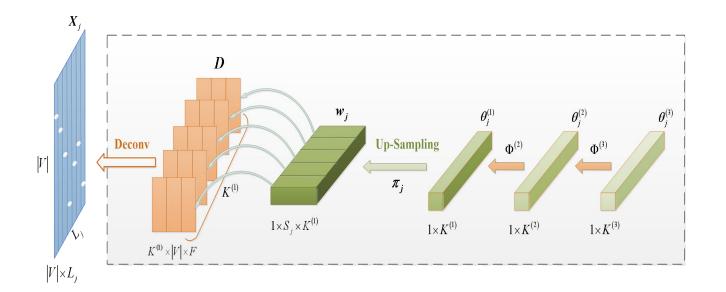
$$\theta_{jk}^{(1)} = \sum_{s=1}^{S_j} w_{jks} \sim \text{Gam}(\Phi_{k:}^{(2)} \theta_j^{(2)}, 1/c_j^{(2)})$$
$$w_{jk} = \pi_{jk} \theta_{jk}^{(1)}, \ \pi_{jk} \sim \text{Dir}(\Phi_{k:}^{(2)} \theta_j^{(2)}/S_j \mathbf{1}_{S_j})$$

#### **☐** Generative model of CPGBN

$$\begin{split} \boldsymbol{\theta}_j^{(T)} &\sim \operatorname{Gam}(\boldsymbol{r}, 1/c_j^{(T+1)}), \\ &\dots, \\ \boldsymbol{\theta}_j^{(t)} &\sim \operatorname{Gam}(\boldsymbol{\Phi}^{(t+1)}\boldsymbol{\theta}_j^{(t+1)}, 1/c_j^{(t+1)}), \end{split}$$

$$\begin{aligned} & \theta_j^{(1)} \sim \text{Gam}(\Phi^{(2)}\theta_j^{(2)}, 1/c_j^{(2)}), \\ & w_{jk} = \pi_{jk}\theta_{jk}^{(1)}, \ \pi_{jk} \sim \text{Dir}(\Phi_{k:}^{(2)}\theta_j^{(2)}/S_j \mathbf{1}_{S_j}), \end{aligned}$$

$$M_j \sim \operatorname{Pois}ig(\sum_{k=1}^{K^{(1)}} D_k * w_{jk}ig),$$



- ✓ Transfer the messages from deeper layers
- ✓ Jointly Train all the other layers
- ✓ Deep extention can boost performance
- ✓ Hierachical pharse-level topic



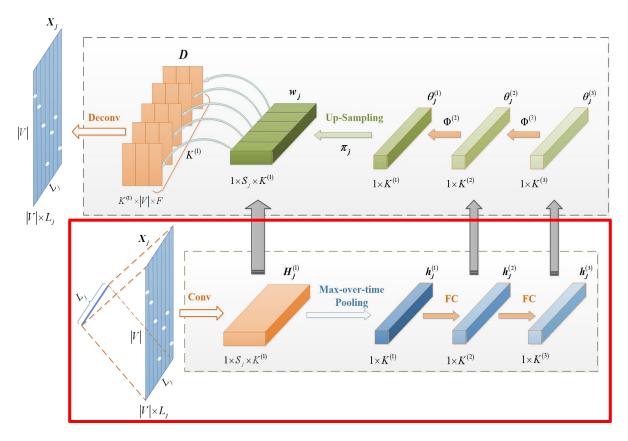


## **Our Contribution**



#### **Hybrid MCMC/Variational Inference**

#### ☐ Convolutional inference network



#### **□** Weibull Reparameterization

Weibull PDF: 
$$P(x \mid k, \lambda) = \frac{k}{\lambda^k} x^{k-1} e^{(x/\lambda)^k}$$
  
 $x = \lambda (-\ln(1-\epsilon))^{1/k}, \ \epsilon \sim \text{Uniform}(0,1)$ 



Gamma PDF: 
$$P(x \mid \alpha, \beta) = \frac{\beta^{\alpha}}{\Gamma(\alpha)} x^{\alpha - 1} e^{-\beta x}$$

- ✓ Fast in out-of-sample prediction
- ✓ Parallel scalable inference
- ✓ Easy extension (e.g., modeling document labels)





## **Experiment**



#### **Phrase-level Topics Visualization**

Table 3. Example phrases learned from TREC by CPGBN.

Kernel Index	Visualized Topic			Visualized Phrase
	1st Column	2nd Column	3rd Column	VISUAIIZEU FIII ase
192th Kernel	how cocktail stadium run	do many much long	you years miles degrees	how do you, how many years, how much degrees
80th Kernel	microsoft virtual answers.com softball	e-mail email ip brothers	addresses addresses floods score	microsoft e-mail address, microsoft email address, virtual ip address
177th Kernel	who willy bar hydrogen	created wrote fired are	maria angela snoopy caesar	who created snoopy, who fired caesar, who wrote angela
47th Kernel	dist all-time wheel saltpepter	how stock 1976 westview	far high tall exchange	dist <b>how</b> far, dist <b>how</b> high , dist <b>how</b> tall

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## Thank you!

Pacific Ballroom #237

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