

# Streaming Bayesian Deep Tensor Factorization

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For ICML 2021



## Tensor Data: Widely Used High-Order Data Structures to Represent Interactions of Multiple Objects/Entities



(user, movie, episode)



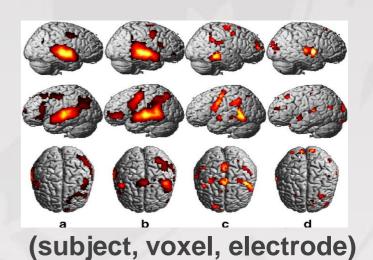
(user, item, online-store)



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(patient, gene, condition)



#### **Tensor Decomposition**

• Traditional methods: Oversimplified multilinear assumptions

$$\mathcal{Y}(i_1, i_2, i_3) = \sum_{j=1}^r \alpha_j \prod_k u_{i_1}^1 u_{i_2}^2 u_{i_3}^3$$
 Tucker
$$\mathcal{Y} = \mathcal{W} \times_1 \mathbf{U}_1 \times_2 \mathbf{U}_2 \times_3 \mathbf{U}_3$$
 CP

Hard to handle fast <u>streaming</u> data!







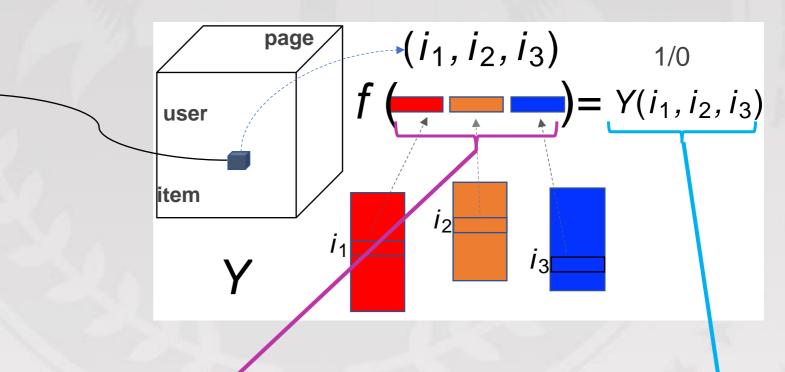
(privacy-demanding applications like Snapchat/Instagram, Data are **NOT** allowed to be stored/revisited)

**p**3

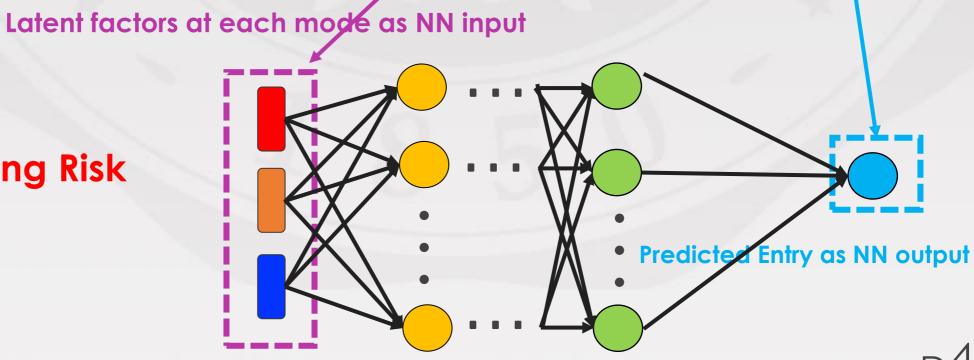


#### Interaction Records

user	item	page	purchase
100	25	35	1
23	21	56	0
100	25	35	1
32	33	46	0



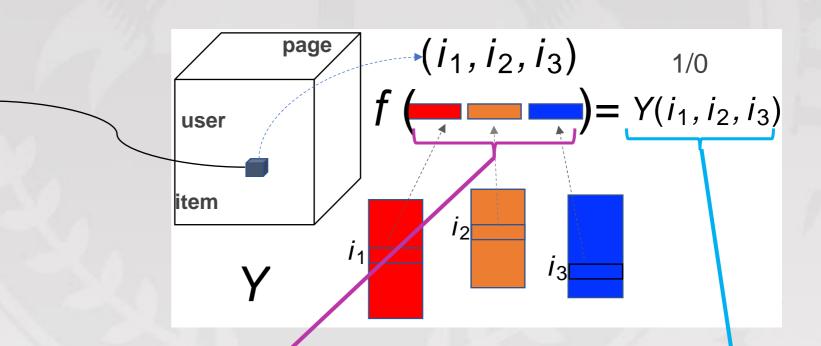
**Problem: Overfitting Risk** 



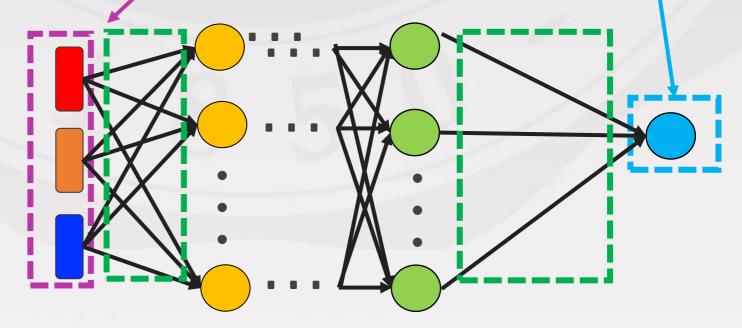


#### Interaction Records

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Predicted Entry as NN output
Latent factors at each mode as NN input

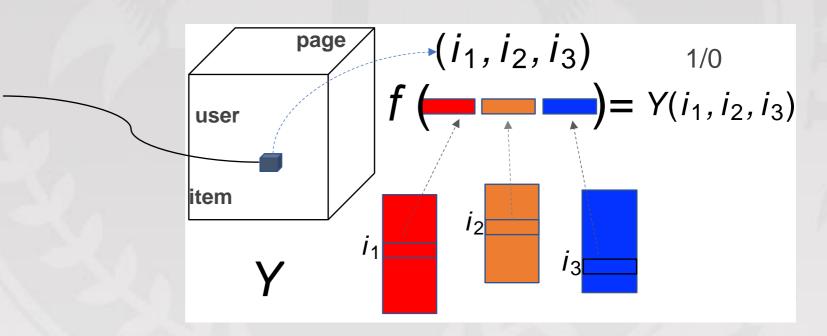


Assign spike & slab priors over each NN weights!



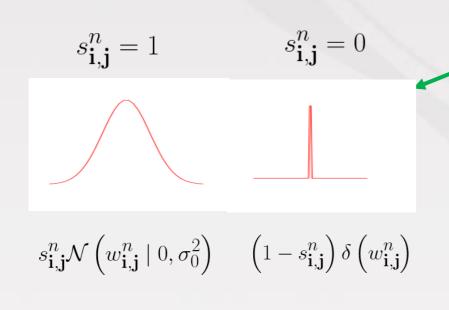
#### Interaction Records

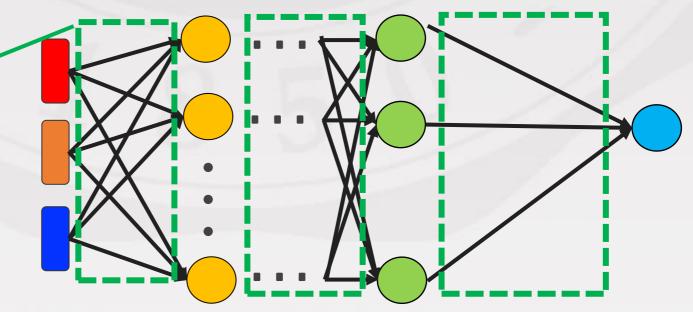
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#### Solution: Build a sparse BNN!

 $w^n_{ij}$  Assign spike & slab priors over each NN weights!







### Online moment-match for Streaming inference

#### **Classical ADF**:

- streaming update for BNN weights & involved factors
- integrating entries one by one via moment matching

Closed form
Posterior update
(mean and var)

$$\mu^* = \mu + v \frac{\partial \log Z_n}{\partial \mu}$$

$$v^* = v - v^2 \left[ \left( \frac{\partial \log Z_n}{\partial \mu} \right)^2 - 2 \frac{\partial \log Z_n}{\partial v} \right]$$

#### intractable

$$Z_{n} = \int q_{\text{cur}}(\mathcal{W}, \mathcal{U}, \mathcal{S}) \Phi\left(\left(2y_{\mathbf{i}_{n}} - 1\right) f_{\mathcal{W}}\left(\mathbf{x}_{\mathbf{i}_{n}}\right)\right) d\mathcal{W} d\mathcal{U} d\mathcal{S}$$

For tractable model evidence/analytic posterior update:

- we use <u>delta method</u>
- Expand the BNN output at the mean of U and W (Taylor approx.)

$$f_{\mathcal{W}}\left(\mathbf{x}_{\mathbf{i}_{n}}\right) \approx f_{\mathbb{E}[\mathcal{W}]}\left(\mathbb{E}\left[\mathbf{x}_{\mathbf{i}_{n}}\right]\right) + \mathbf{g}_{n}^{\top}\left(\boldsymbol{\eta}_{n} - \mathbb{E}\left[\boldsymbol{\eta}_{n}\right]\right)$$
 Eliminate when take expectation

II. Get approx. of first & second moments of BNN output

$$\alpha_{n} = \mathbb{E}_{q_{\text{cur}}} \left[ f_{\mathcal{W}} \left( \mathbf{x}_{\mathbf{i}_{n}} \right) \right] \approx f_{\mathbb{E}[\mathcal{W}]} \left( \mathbb{E} \left[ \mathbf{x}_{\mathbf{i}_{n}} \right] \right)$$

$$\beta_{n} = \operatorname{Var}_{q_{\text{cur}}} \left( f_{\mathcal{W}} \left( \mathbf{x}_{\mathbf{i}_{n}} \right) \right) \approx \mathbf{g}_{n}^{\top} \operatorname{diag} \left( \gamma_{n} \right) \mathbf{g}_{n}$$
Moment matching
$$q_{\text{cur}}(\cdot) = \mathcal{N}(\cdot | \alpha_{n}, \beta_{n})$$

III. Tractable model evidence & analytic form update with ADF

$$Z_{n} = \mathbb{E}_{q_{\text{cur}}(\mathcal{W},\mathcal{U},\mathcal{S})} \left[ \Phi \left( \left( 2y_{i_{n}} - 1 \right) f_{\mathcal{W}} \left( x_{i_{n}} \right) \right) \right]$$

$$\approx \Phi \left( \frac{\left( 2y_{i_{n}} - 1 \right) \alpha_{n}}{\sqrt{1 + \beta_{n}}} \right)$$



### Spike & Slab priors: repeated approx. & refinement

Approx. in exponential family: Gaussian + Bernoulli

$$p\left(w_{mjt} \mid s_{mjt}\right) \propto A\left(w_{mjt}, s_{mjt}\right)$$

$$= \text{Bern}\left(s_{mjt} \mid c\left(\rho_{mjt}\right)\right) \mathcal{N}\left(w_{mjt} \mid \mu_{mjt}^{0}, v_{mjt}^{0}\right)$$

Select posterior prob of each NN weight <0.5: unselected <=> sparse

Update with <u>standard EP</u>: analytic form

 Refine it after processing all entries in a coming batch to impose the sparse inducing effect



# Thanks for attention Q&A time

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