Content-Based Social Recommendation with Poisson Matrix Factorization

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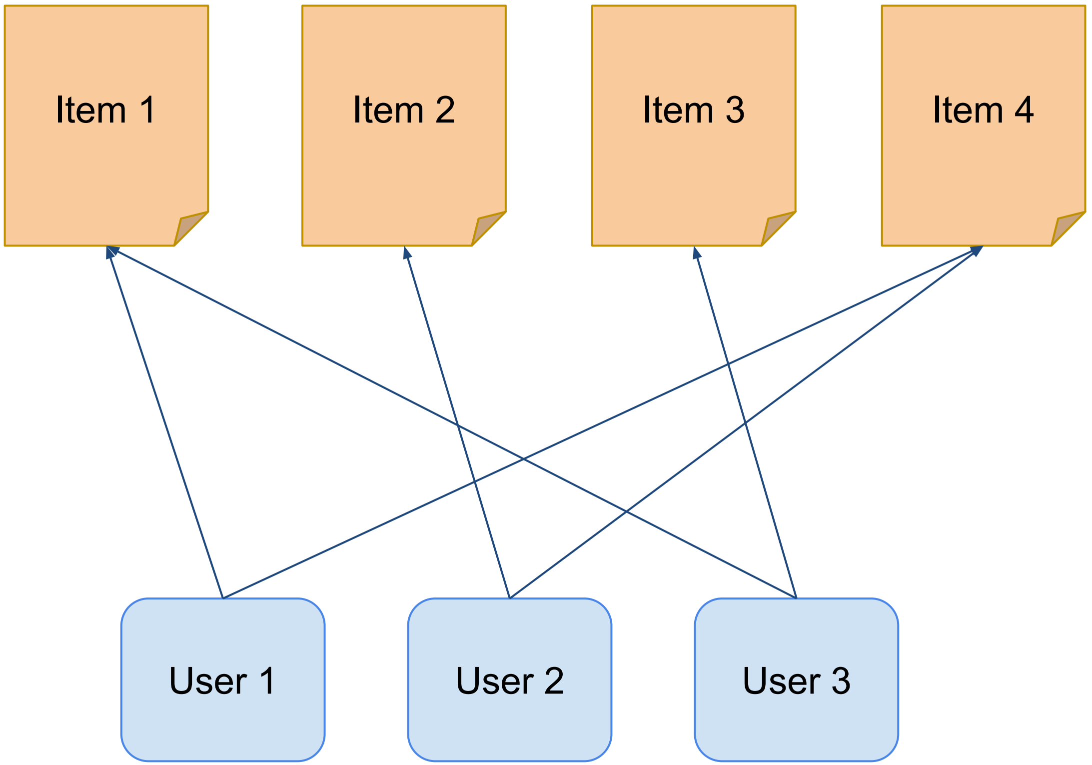
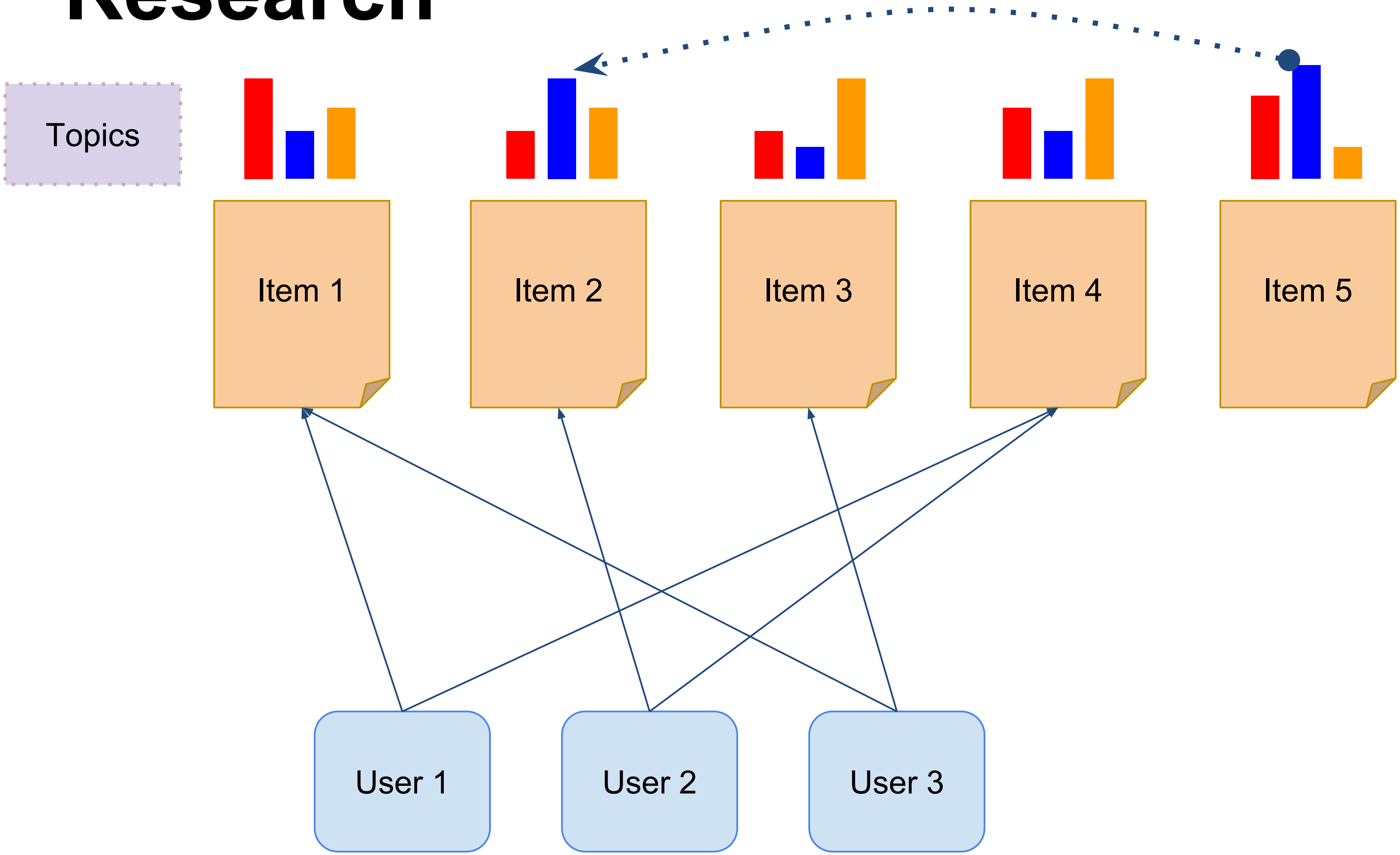
Introduction

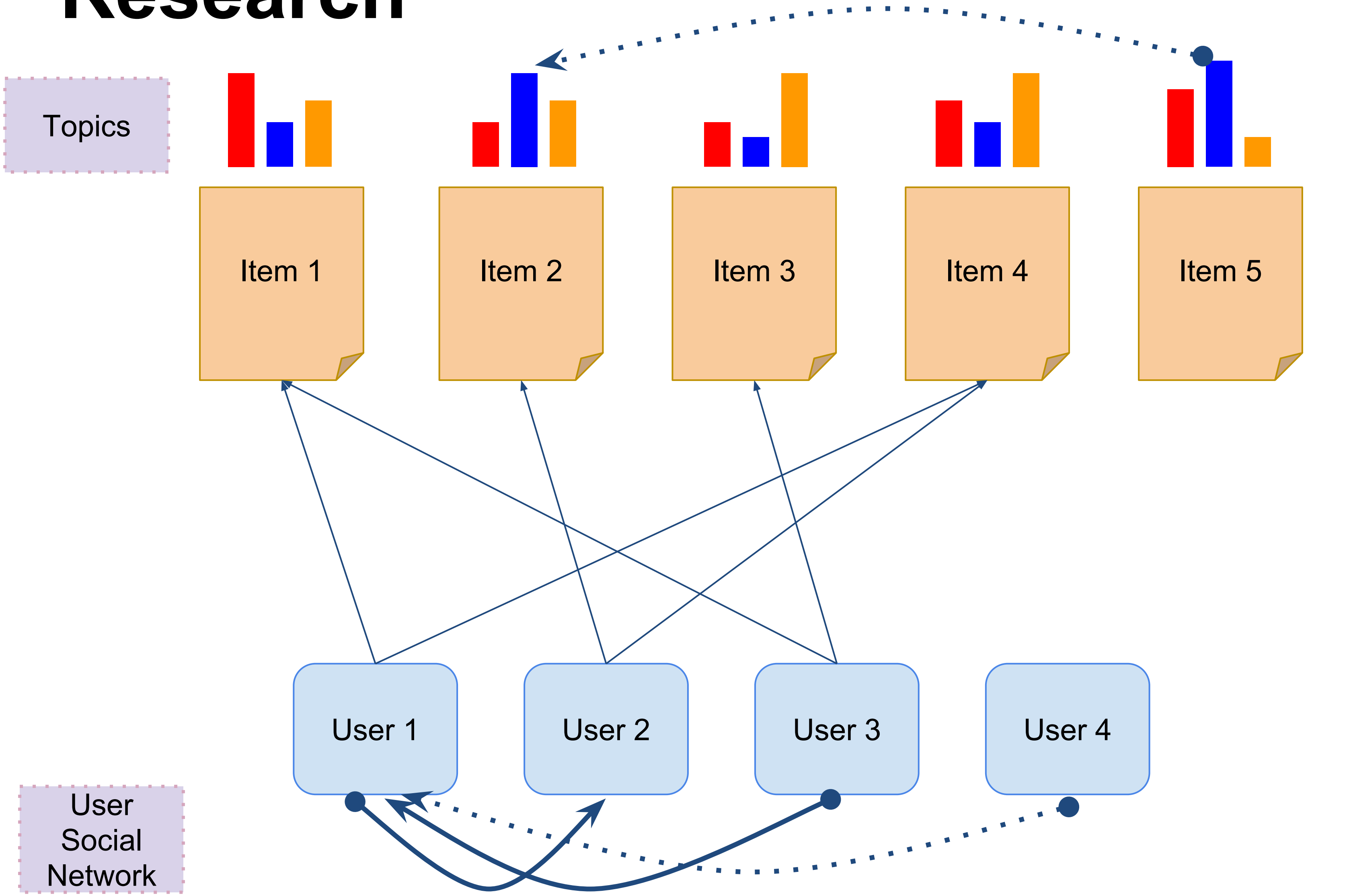
- Basic Problem: Recommendation of items to users given user interaction with some items



Challenges and opportunities in RS Research



Challenges and opportunities in RS Research

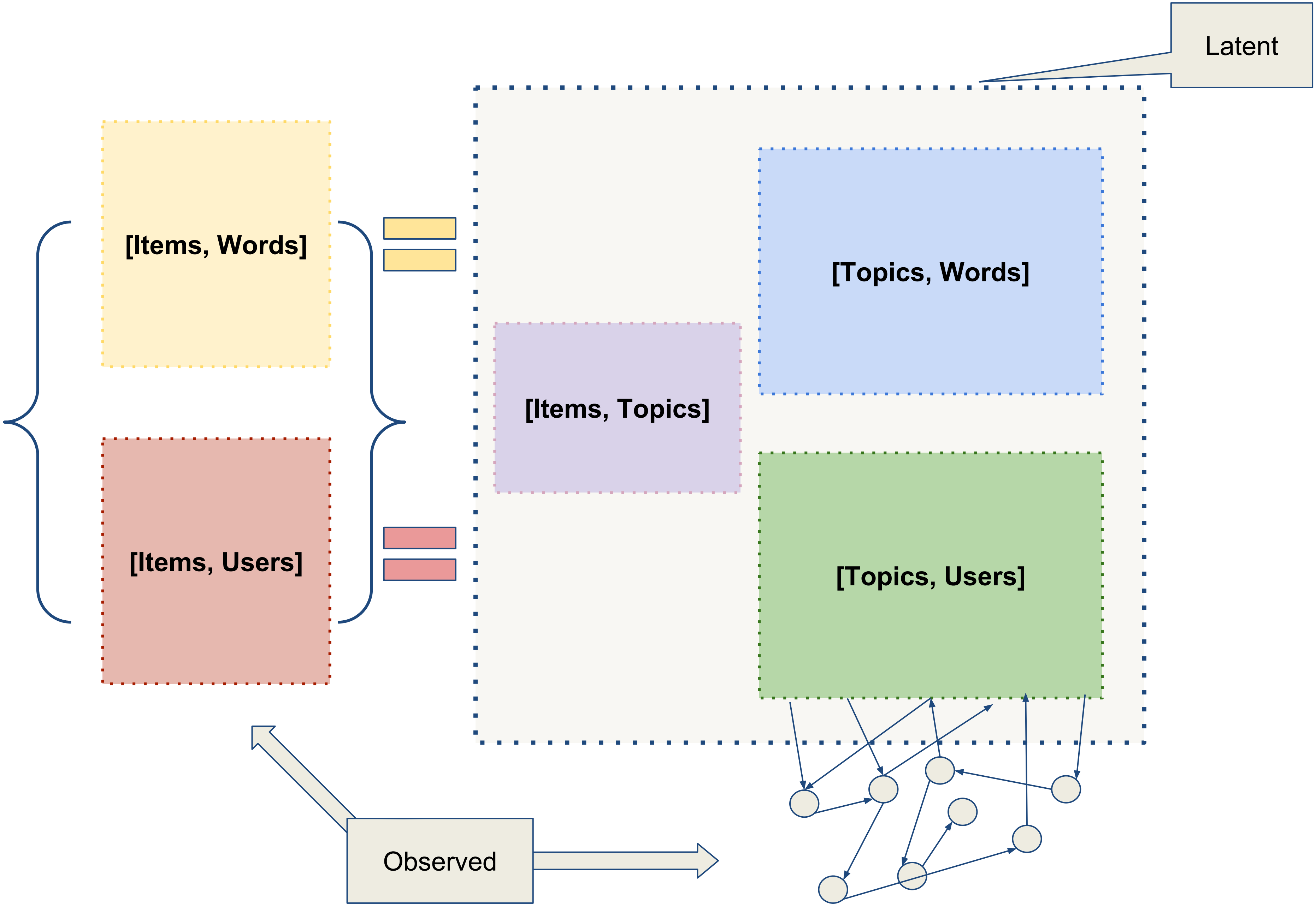


Challenges and opportunities in RS Research

- Incorporate
  - **Social network analysis tools and methods**
  - **Content analysis (topic models, sentiment/intent/mood)**
  - New rich contextual information
    - location, activity, user intent/goal, etc.

Joint modelling of user social network and item topic content

- **User social network**
  - Homophily
  - Item exposure positively influenced by peers (positive “peer-pressure”)
- **Item content analysis**
  - Enrich items latent factors with topic model
  - Cold start items
  - Preferences can be influenced by topics



Latent
[Items, Words]
[Items, Users]
[Items, Topics]
[Topics, Words]
[Topics, Users]
Observed

Poisson Matrix Factorization with Content and Social trust information (PoissonMF-CS)

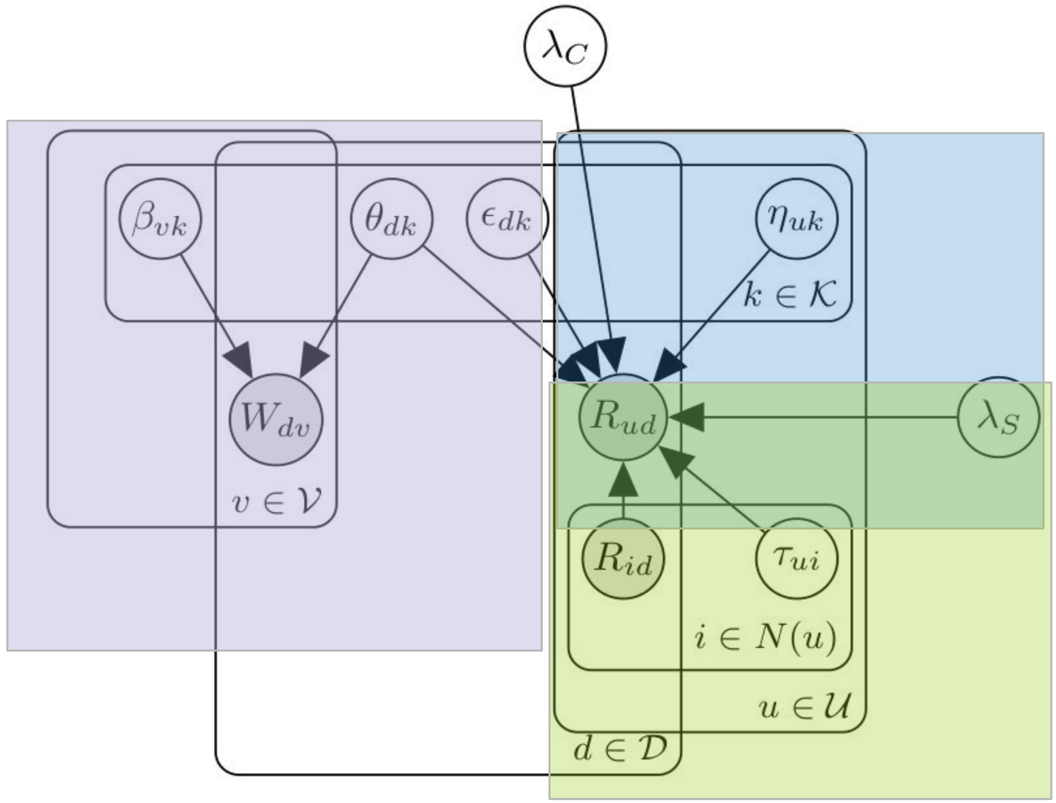
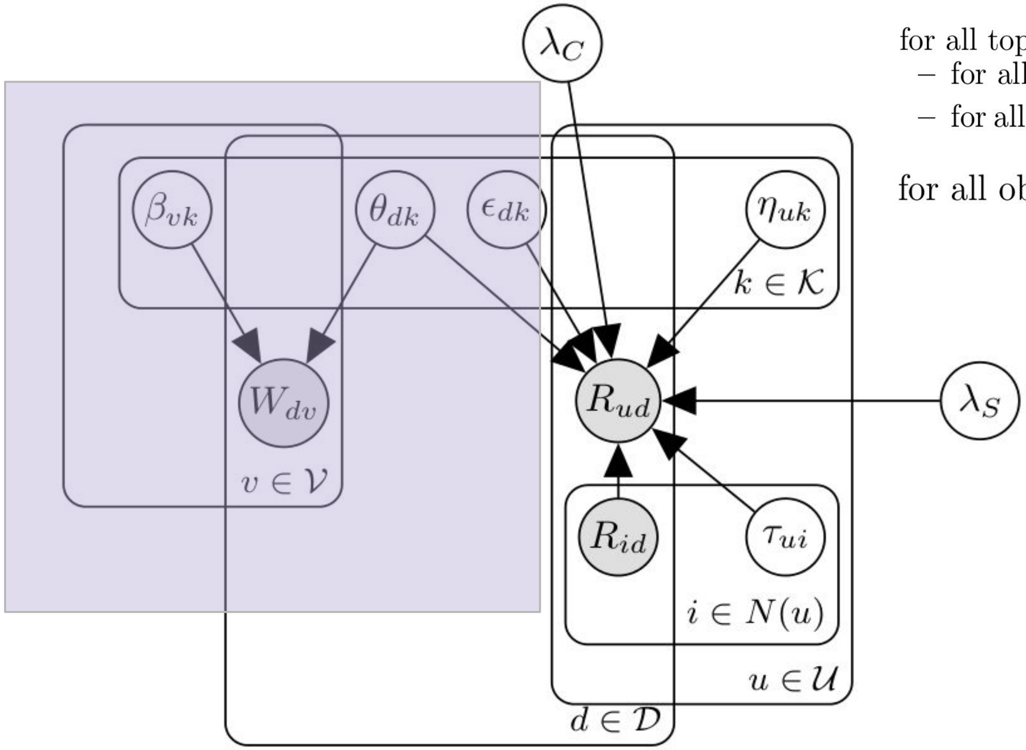


Plate diagram for PoissonMF-CS model

Items Topic Model



for all topics $k \in \mathcal{K}$:

- for all words $v \in \mathcal{V}$: $\beta_{vk} \sim \text{Gamma}(a^0_\beta, b^0_\beta)$
- for all documents $d \in \mathcal{D}$: $\theta_{dk} \sim \text{Gamma}(a^0_\theta, b^0_\theta)$ and $\epsilon_{dk} \sim \text{Gamma}(a^0_\epsilon, b^0_\epsilon)$

for all observed document–word pairs dv :

$$W_{dv} | \boldsymbol{\beta}_v, \boldsymbol{\theta}_d \sim \text{Poisson}(\boldsymbol{\beta}_{\boldsymbol{v}}^T \boldsymbol{\theta}_{\boldsymbol{d}})$$

Plate diagram for PoissonMF-CS model

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User preference and social factors

– for all users $u \in \mathcal{U}$: $\eta_{uk} \sim \text{Gamma}(a_\eta^0, b_\eta^0)$
- for all user $i \in N(u)$: $\tau_{ui} \sim \text{Gamma}(a_\tau^0, b_\tau^0)$

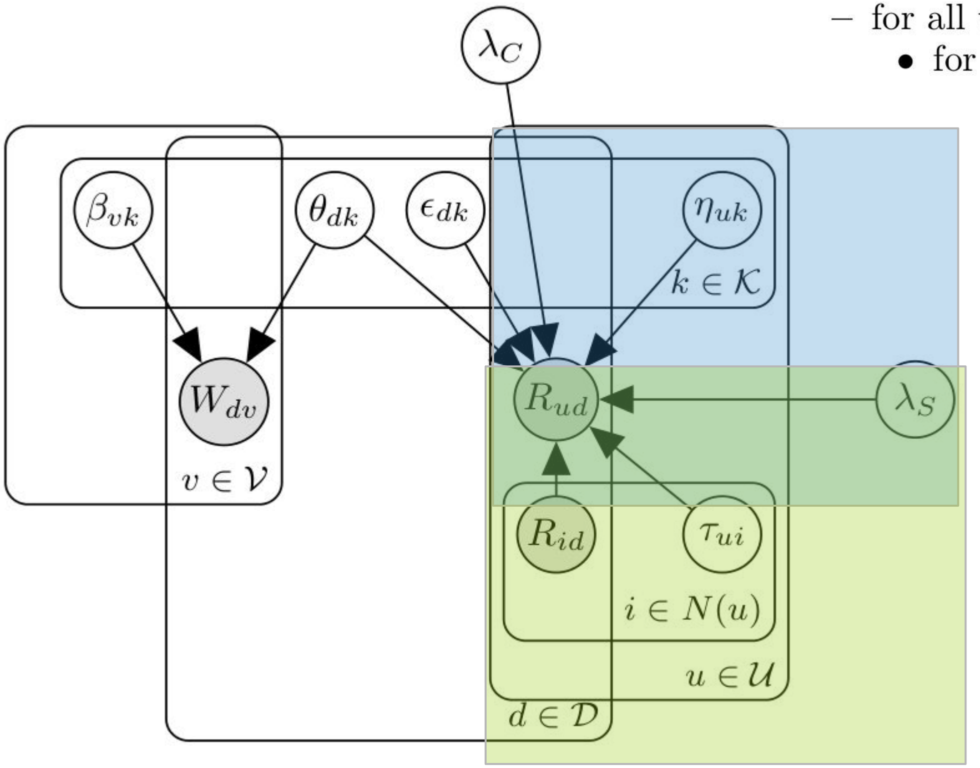


Plate diagram for PoissonMF-CS model

Poisson Matrix Factorization with Content and Social trust information (PoissonMF-CS)

for all observed user–document pairs ud :

$$R_{ud}|\boldsymbol{R_{N(u),d}}, \boldsymbol{\eta_u}, \boldsymbol{\epsilon_d}, \boldsymbol{\theta_d} \sim \text{Poisson}(\lambda_C \boldsymbol{\eta}_u^T \boldsymbol{\theta}_d + \boldsymbol{\eta}_u^T \boldsymbol{\epsilon}_d + \lambda_S \sum_{i \in N(u)} \tau_{ui} R_{id})$$

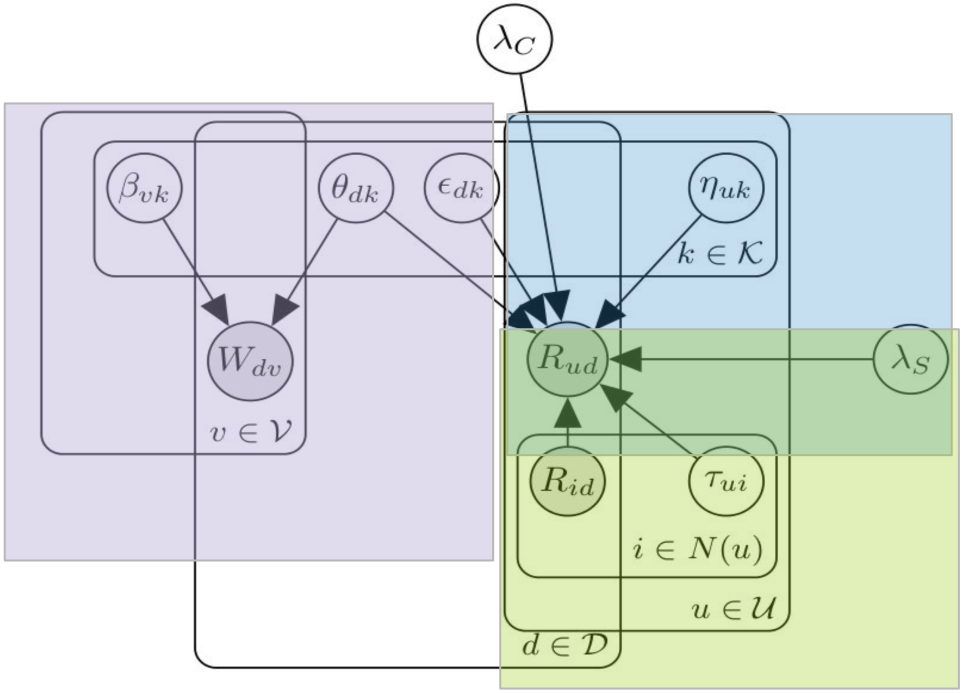


Plate diagram for PoissonMF-CS model

Inference

- Batch variational inference: $\underset{\Psi}{\operatorname{argmin}} \, \mathrm{KL}\{q(\Theta|\Psi), p(\Theta|\boldsymbol{R}, \boldsymbol{W})\}$

- Conjugate model with auxiliary variable "tricky" for each Poisson likelihood term:

$$Y_{dv,k}|\beta_{vk}, \theta_{dk} \sim \mathrm{Poisson}(\beta_{vk}\theta_{dk})$$

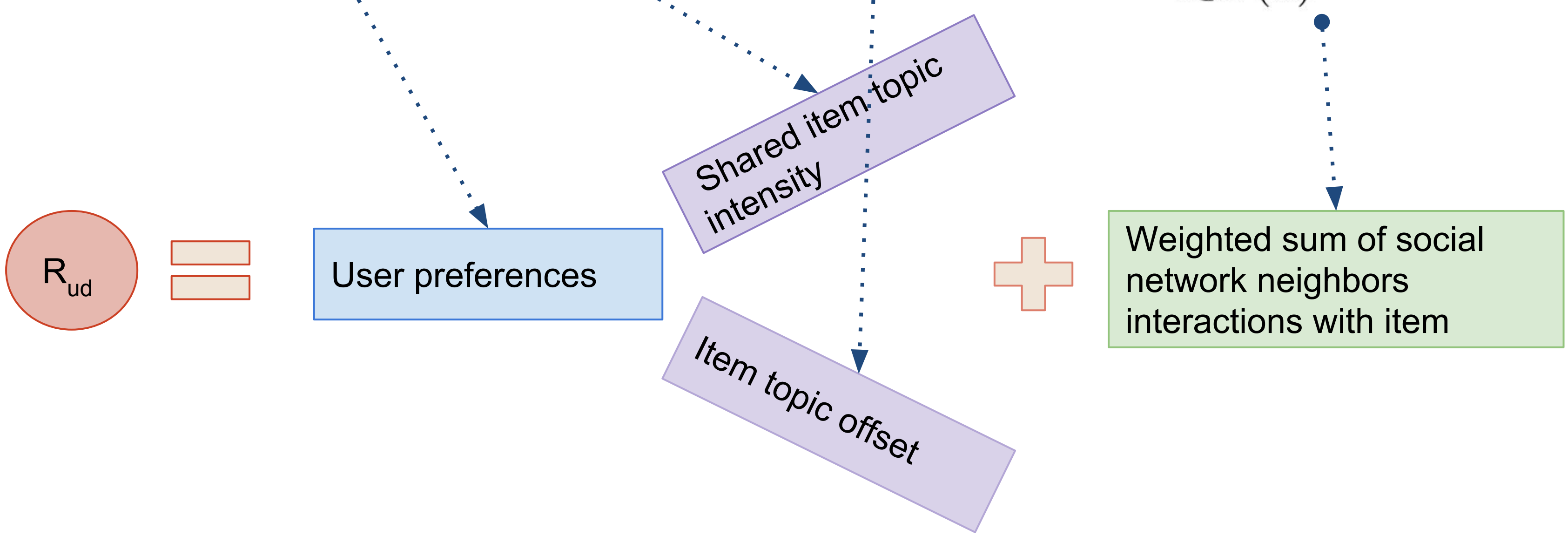
$$\sum_k Y_{dv,k} = W_{dv}$$

- Running time for each iteration depends on the sparse observations:
  - *O(K(obs_W + obs_R + obs_S + U + D + W))*

Item Recommendations

- Top-M items for each user:
  – Approximate expected value of user-item matrix for each unseen item for ranking

$$\mathrm{E}[R_{ud}] \approx \mathrm{E}_q[\eta_u]^T(\mathrm{E}_q[\lambda_C]\,\mathrm{E}_q[\theta_d] + \mathrm{E}_q[\epsilon_d]) + \mathrm{E}_q[\lambda_S] \sum_{i\in N(u)} \mathrm{E}_q[\tau_{ui}] R_{id}$$



Application

Artist recommendation (Last-fm dataset):

- User-artist interactions counts
- User-user social network
- Artist-tags counts

Dataset size:

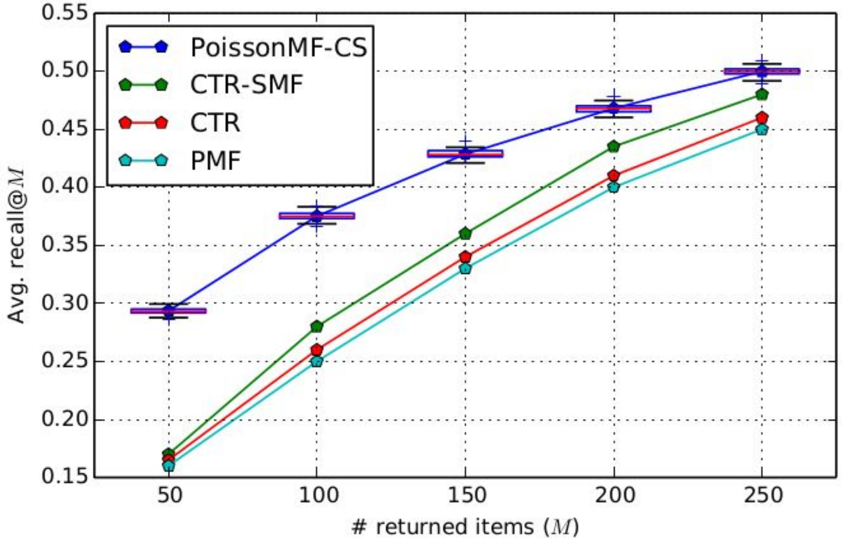
- 1892 users, 17632 artists, 11946 tags
- 25434 user–user connections, 92834 user–items interactions, and 186479 user–tag–items entries.

Results

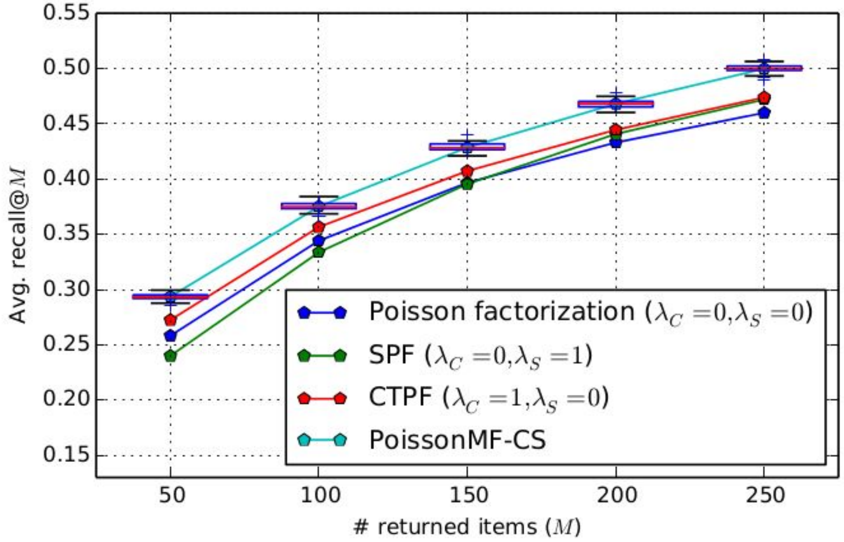
- Avg. Recall Metric:
- Compare with previous work:
  - Collaborative Topic Regression (CTR)
  - Collaborative Topic Regression with Social Matrix Factorization (CTR-SMF)
  - Collaborative topic Poisson factorization (CTPF)
  - Social Poisson Factorization (SPF)

$$\text{recall@}M = \frac{\text{number of items the user likes in Top } M}{\text{total number of relevant items for the user}}$$

Results

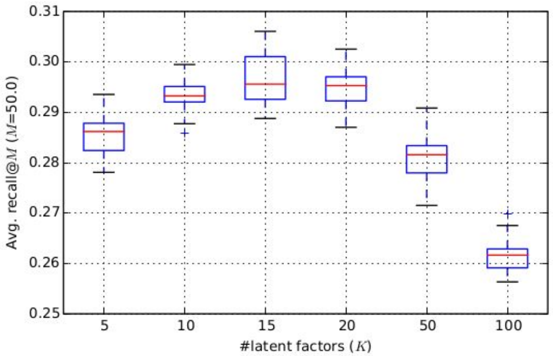


PoissonMF-CS (K =10) and Gaussian-based models

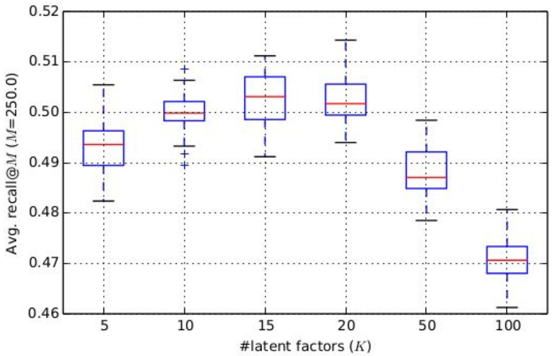


PoissonMF-CS (K =10) and other Poisson factorization models

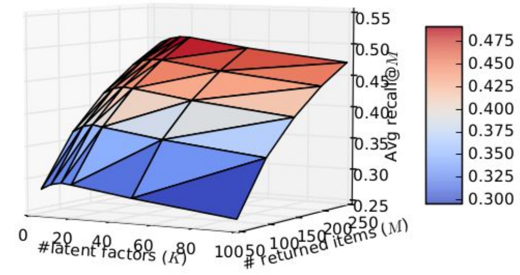
Results



(a) M=50



(b) M=250



(c) 3D visualization

Impact of the number of latent variables (K) parameter on the Av. Recall@M metric for different number of returned items (M). Each subplot is the result of running the PoissonMF-CS recommendation algorithm over 30 random splits of the dataset with K varying in (5,10,15,20,50,100)

Conclusion

- Model including social and topic information in Poisson matrix factorization using coupled latent factors
- Inference is computationally efficient with variational inference
- Future work:
  - Non-negative relational learning
  - Non-parametric extensions
  - Scalable inference (SVI)

Questions?

https://github.com/zehsilva/poissonmf_cs

Content-based Social Poisson Factorization for recommendation

1. Latent parameter distributions:
   (a) for all topics $k \in \mathcal{K}$:
      - for all words $v \in \mathcal{V}$: $\beta_{vk} \sim \text{Gamma}(a^0_\beta, b^0_\beta)$
      - for all documents $d \in \mathcal{D}$: $\theta_{dk} \sim \text{Gamma}(a^0_\theta, b^0_\theta)$ and $\epsilon_{dk} \sim \text{Gamma}(a^0_\epsilon, b^0_\epsilon)$
      - for all users $u \in \mathcal{U}$: $\eta_{uk} \sim \text{Gamma}(a^0_\eta, b^0_\eta)$
        - for all user $i \in N(u)$: $\tau_{ui} \sim \text{Gamma}(a^0_\tau, b^0_\tau)$

   (b) Content weight: $\lambda_C \sim \text{Gamma}(a^0_C, b^0_C)$
   (c) Social weight: $\lambda_S \sim \text{Gamma}(a^0_S, b^0_S)$
2. Observations probability distribution:
   (a) for all observed document–word pairs dv :

$$W_{dv} | \boldsymbol{\beta}_v, \boldsymbol{\theta}_d \sim \text{Poisson}(\boldsymbol{\beta}_{\boldsymbol{v}}^T \boldsymbol{\theta}_{\boldsymbol{d}})$$

   (b) for all observed user–document pairs ud :

$$R_{ud} | \boldsymbol{R}_{\boldsymbol{N(u),d}}, \boldsymbol{\eta}_{\boldsymbol{u}}, \boldsymbol{\epsilon}_{\boldsymbol{d}}, \boldsymbol{\theta}_{\boldsymbol{d}} \sim \text{Poisson}(\lambda_C \boldsymbol{\eta}_u^T \boldsymbol{\theta}_d + \boldsymbol{\eta}_u^T \boldsymbol{\epsilon}_d + \lambda_S \sum_{i \in N(u)} \tau_{ui} R_{id})$$