Network Discovery and Recommendation via Joint Network and Topic Modeling

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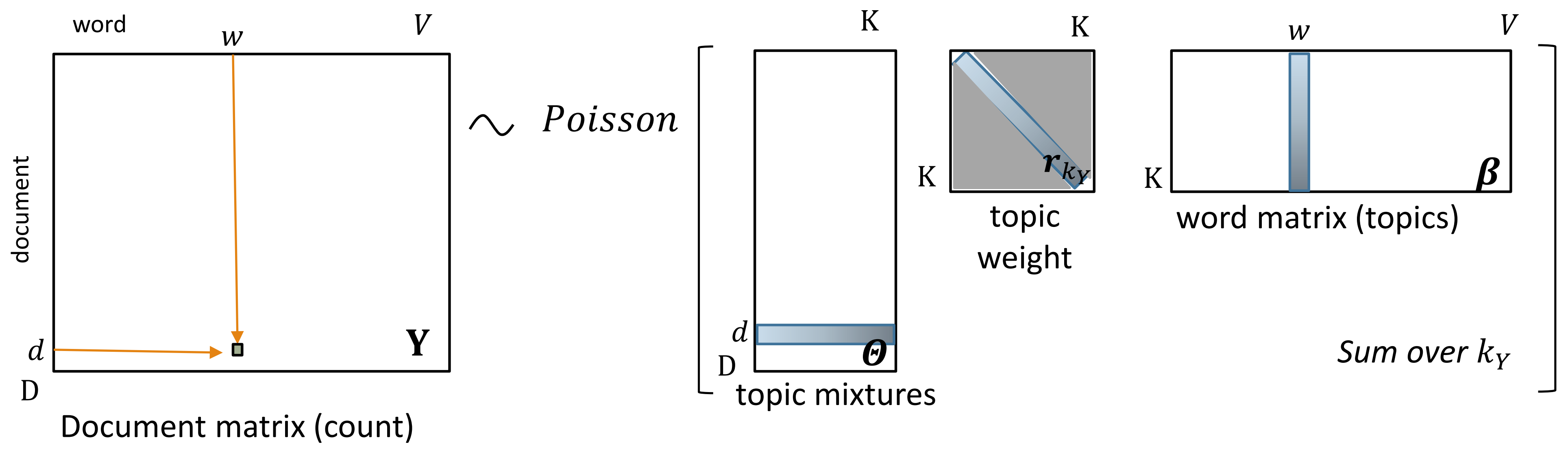
Simultaneous Network Discover and Recommendation

Topic model: Factor groups of items to be recommended from observed user data
Social network model: Factor groups in observed network of users

Propose: a factor for item preferences of groups of users
→ Jointly factor groups of items to be recommended, groups of users

Poisson Factorization for Side Info (C-GPPF)



$$y_{d,w} \sim Pois\left(\sum_{k_Y} r_{k_Y}\theta_{d,k_Y}\,\beta_{w,k_Y}\right)$$

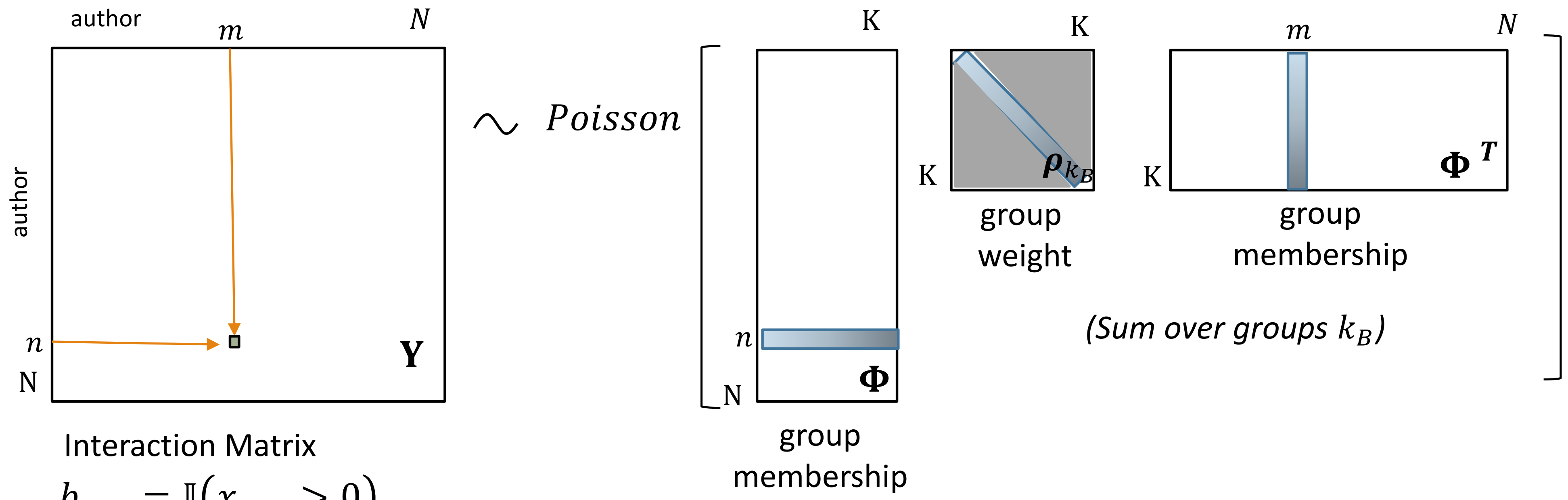
Priors: $\boldsymbol{\beta}_k \sim Dir(\eta)$; $\boldsymbol{\theta}_k \sim \sum_{d=1}^{D} Gamma(a_d, {}^{1}/_{c_d})$; $\boldsymbol{r}_k \sim Gamma({}^{\nu}/_{k}, {}^{1}/_{c})$

Truncated Gamma Process (K topics from ∞)

Inference with Gibbs sampling

Poisson Factorization for Network Associations (N-GPPF)

Network association (blockmodel):



Interaction Matrix

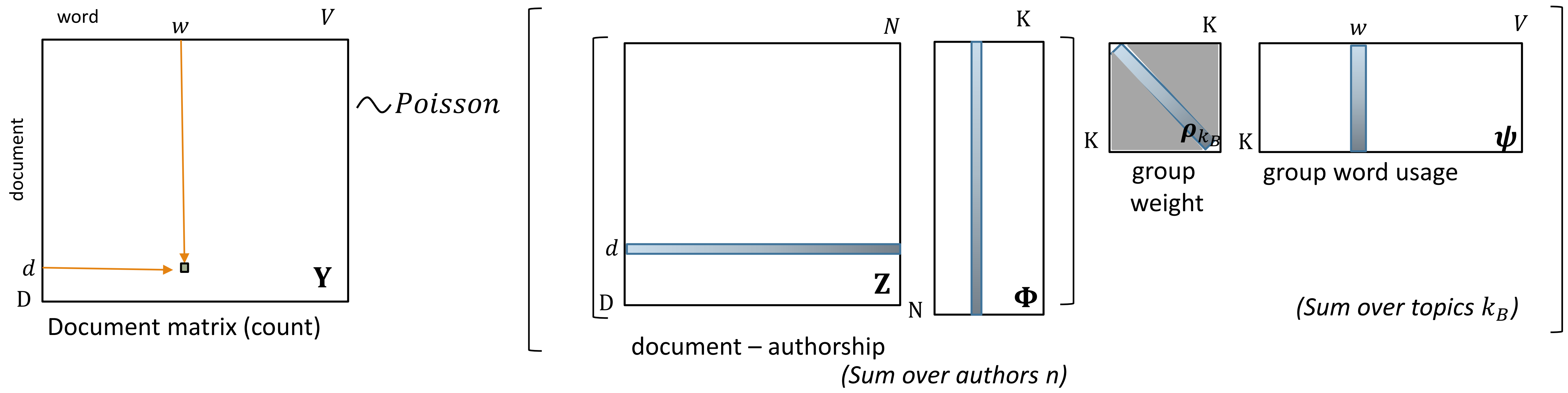
$$b_{n,m} = \mathbb{I}\left(x_{n,m} > 0\right)$$

$$x_{n,m} \sim Pois\left(\sum_{k_B} \rho_{k_B} \phi_{nk_B} \phi_{mk_B}\right)$$

Priors: $\boldsymbol{\phi}_k \sim \sum_{n=1}^{N} Gamma(a_n, {}^{1}/{c_d})$; $\boldsymbol{\rho}_k \sim Gamma({}^{\nu}/{k}, {}^{1}/{c})$

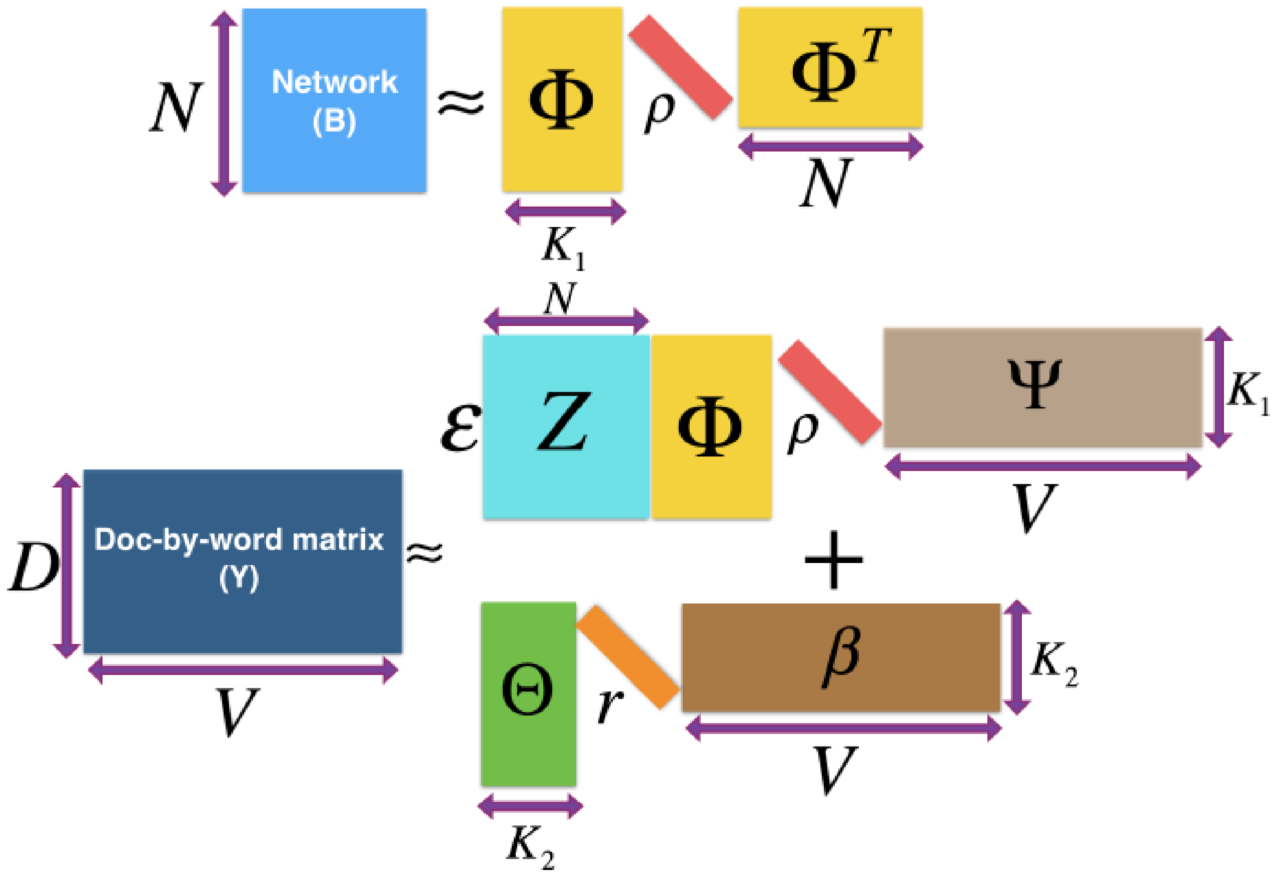
Influence of Community on Topics

How to model Document-Word (observation) matrix from author interaction?



Priors: $\phi_{k_B} \sim \sum_{n=1}^{N} Gamma(a_n, {}^{1}/_{c_d})$; $\psi_{k_B} \sim Dir(\xi)$; $\rho_{k_B} \sim Gamma({}^{\nu}/_{k}, {}^{1}/_{c})$

GPPF for Joint Network and Topic Modeling (J-GPPF)



Characteristics of J-GPPF

- Poisson factorization: $Y_{dw} \sim Pois(\langle\theta_d, \beta_w\rangle)$, samples latent counts corresponding to non-zeros only
- Joint Poisson factorization for imputing a graph
- Hierarchy of Gamma priors for less sensitivity towards initialization
- Non-parametric modeling with closed form inference updates

UT ECE

Negative Binomial Distribution (NB)

- Number of heads seen until r number of tails occurs while tossing a biased coin with probability of head p (or, number of successes before r failures in successive Bernoulli trials): $m \sim \text{NB}(r, p)$
- $m \sim \text{Poisson}(\lambda), \lambda \sim \text{Gam}(r, p)$ – Gamma-Poisson Construction
- $m \sim \sum_{t=1}^{\ell} u_t,\ u_t \sim \text{Log}(p),\ \ell \sim \text{Poisson}(-r \log(1-p))$ – Compound Poisson Construction

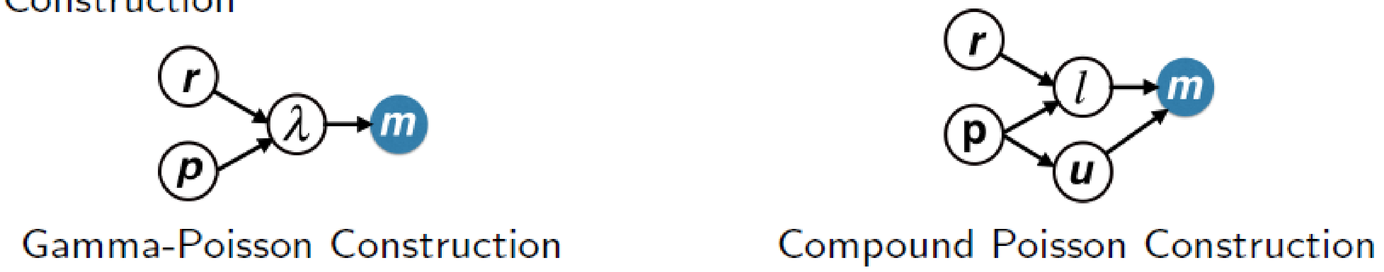
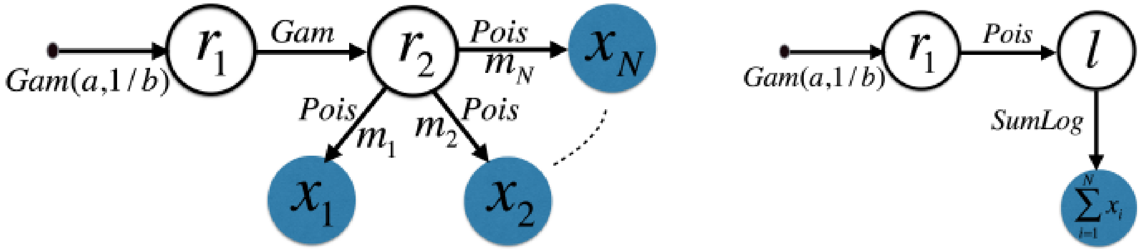


Figure: Constructions of Negative Binomial Distribution

Lemma

If $m \sim NB(r, p)$ is represented under its compound Poisson representation, then the conditional posterior of ℓ given m and r is given by $(\ell | m, r) \sim CRT(m, r)$, which can be generated via $\ell = \sum_{n=1}^{m} z_n, z_n \sim Bernoulli(r/(n-1+r))$.

Inference of Shape Paramenter of Gamma Distribution



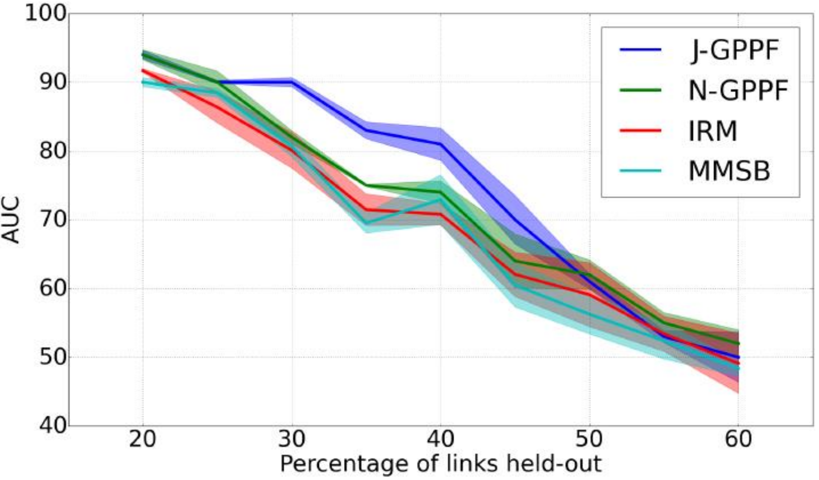
- $x_i \sim \text{Pois}(m_i r_2)\ \forall i \in \{1, 2, \cdots, N\},\ r_2 \sim \text{Gam}(r_1, 1/d),$ $r_1 \sim \text{Gam}(a, 1/b).$

Lemma

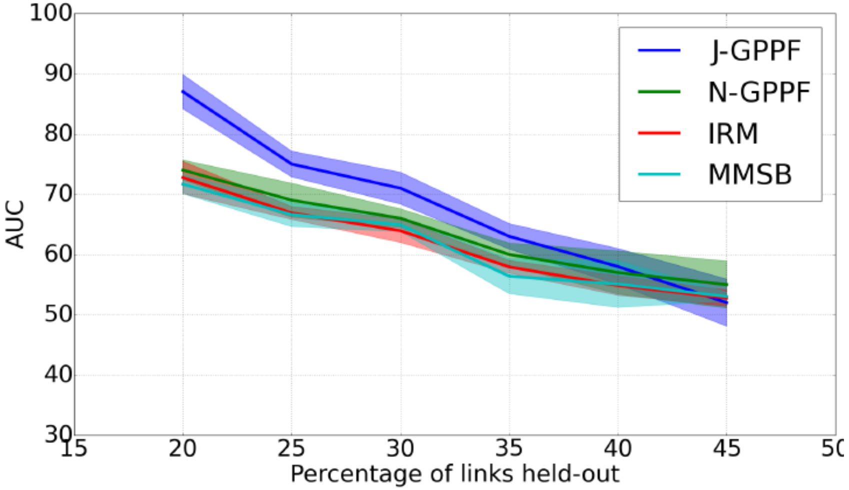
If $x_i \sim Pois(m_i r_2)\ \forall i,\ r_2 \sim Gam(r_1, 1/d),\ r_1 \sim Gam(a, 1/b),$ *then* $(r_1|-) \sim Gam(a + \ell, 1/(b - log(1 - p)))$ *where* $(\ell|\{x_i\}_i, r_1) \sim CRT(\sum_i x_i, r_1), p = \sum_i m_i/(d + \sum_i m_i).$

J-GPPF: Online Data Results

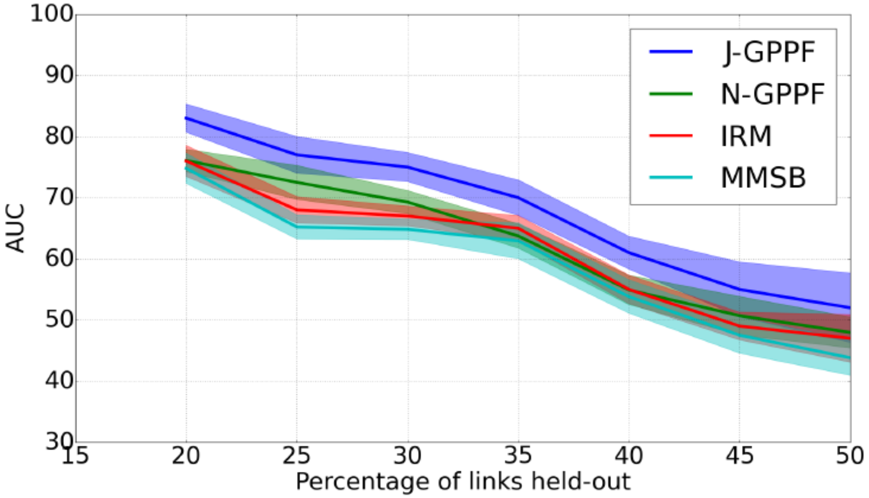
AUC



NIPS



Goodreads



Twitter

Data Source	Authors	Interaction Network Sparsity	Documents	Document Word Sparsity
NIPS	234	0.02	1165	0.01
Goodreads	84	0.03	3241	0.07
Twitter	670	0.01	670	0.02

J-GPPF: Online Data Results

NIPS

Goodreads

AUC

MAP