A Probabilistic Model for Using Social Networks in Personalized Item Recommendation

Allison J.B. Chaney

Princeton University

ajbc.io/spf

A Probabilistic Model for Using Social Networks in Personalized Item Recommendation

A Probabilistic Model for Using Social Networks in Personalized Item Recommendation

- What is personalized item recommendation?

A Probabilistic Model for Using Social Networks in Personalized Item Recommendation

- What is personalized item recommendation?
- Probabilistic matrix factorization models

A Probabilistic Model for Using Social Networks in Personalized Item Recommendation

- What is personalized item recommendation?
- Probabilistic matrix factorization models
- Social networks

A Probabilistic Model for Using Social Networks in Personalized Item Recommendation

- What is personalized item recommendation?
- Probabilistic matrix factorization models
- Social networks
    - Comparison approaches

A Probabilistic Model for Using Social Networks in Personalized Item Recommendation

- What is personalized item recommendation?
- Probabilistic matrix factorization models
- Social networks
    - Comparison approaches
    - Data overview

A Probabilistic Model for Using Social Networks in Personalized Item Recommendation

- What is personalized item recommendation?
- Probabilistic matrix factorization models
- Social networks
    - Comparison approaches
    - Data overview
- Social Poisson Factorization

A Probabilistic Model for Using Social Networks in Personalized Item Recommendation

- What is personalized item recommendation?
- Probabilistic matrix factorization models
- Social networks
    - Comparison approaches
    - Data overview
- Social Poisson Factorization
    - Define the model

A Probabilistic Model for Using Social Networks in Personalized Item Recommendation

- What is personalized item recommendation?
- Probabilistic matrix factorization models
- Social networks
    - Comparison approaches
    - Data overview
- Social Poisson Factorization
    - Define the model
    - Algorithm for inference

A Probabilistic Model for Using Social Networks in Personalized Item Recommendation

- What is personalized item recommendation?
- Probabilistic matrix factorization models
- Social networks
    - Comparison approaches
    - Data overview
- Social Poisson Factorization
    - Define the model
    - Algorithm for inference
    - Results on data

A Probabilistic Model for Using Social Networks in Personalized Item Recommendation

- What is personalized item recommendation?
- Probabilistic matrix factorization models
- Social networks
    - Comparison approaches
    - Data overview
- Social Poisson Factorization
    - Define the model
    - Algorithm for inference
    - Results on data
- Current work: extensions

Personalized Item Recommendation

Personalized Item Recommendation

Personalized Item Recommendation

Anna Karenina

Winter’s Tale

East of Eden

Personalized Item Recommendation

Anna Karenina

Winter's Tale

East of Eden

???

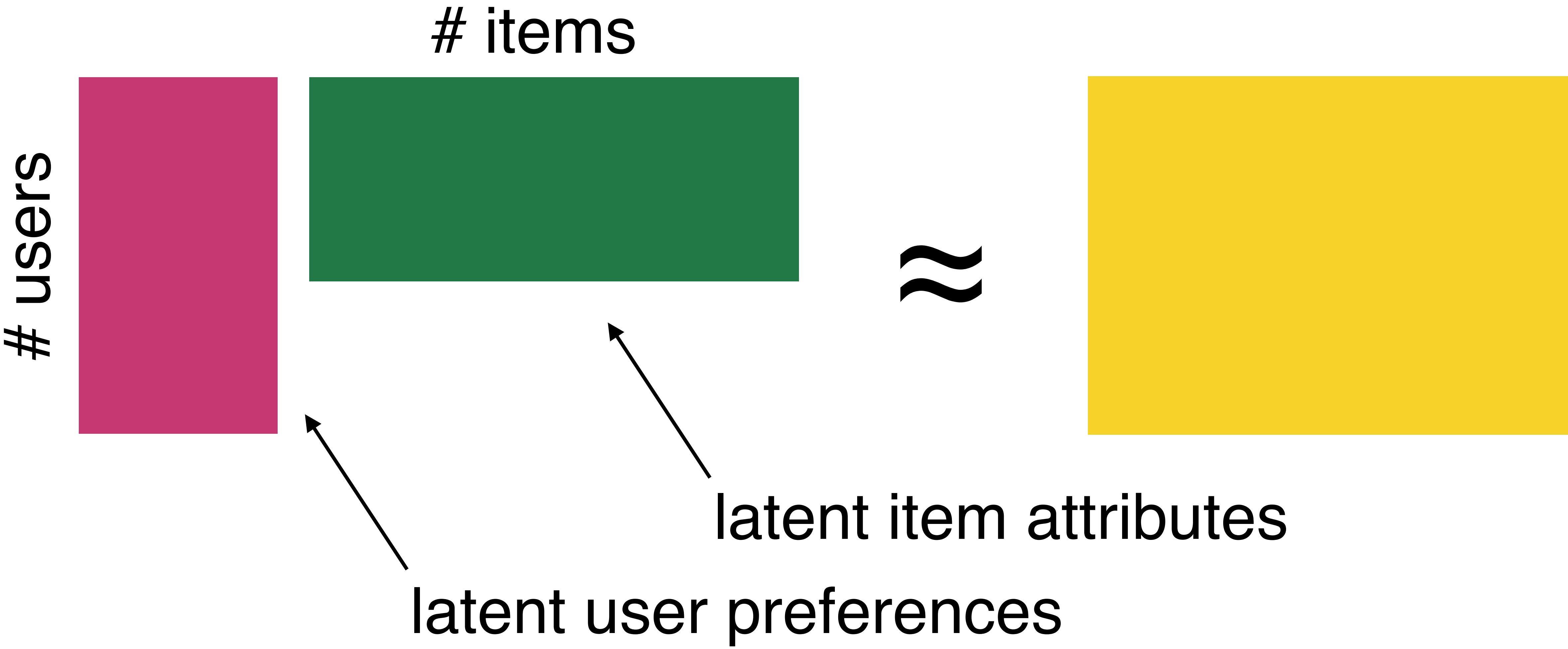
Personalized Item Recommendation

Matrix Factorization

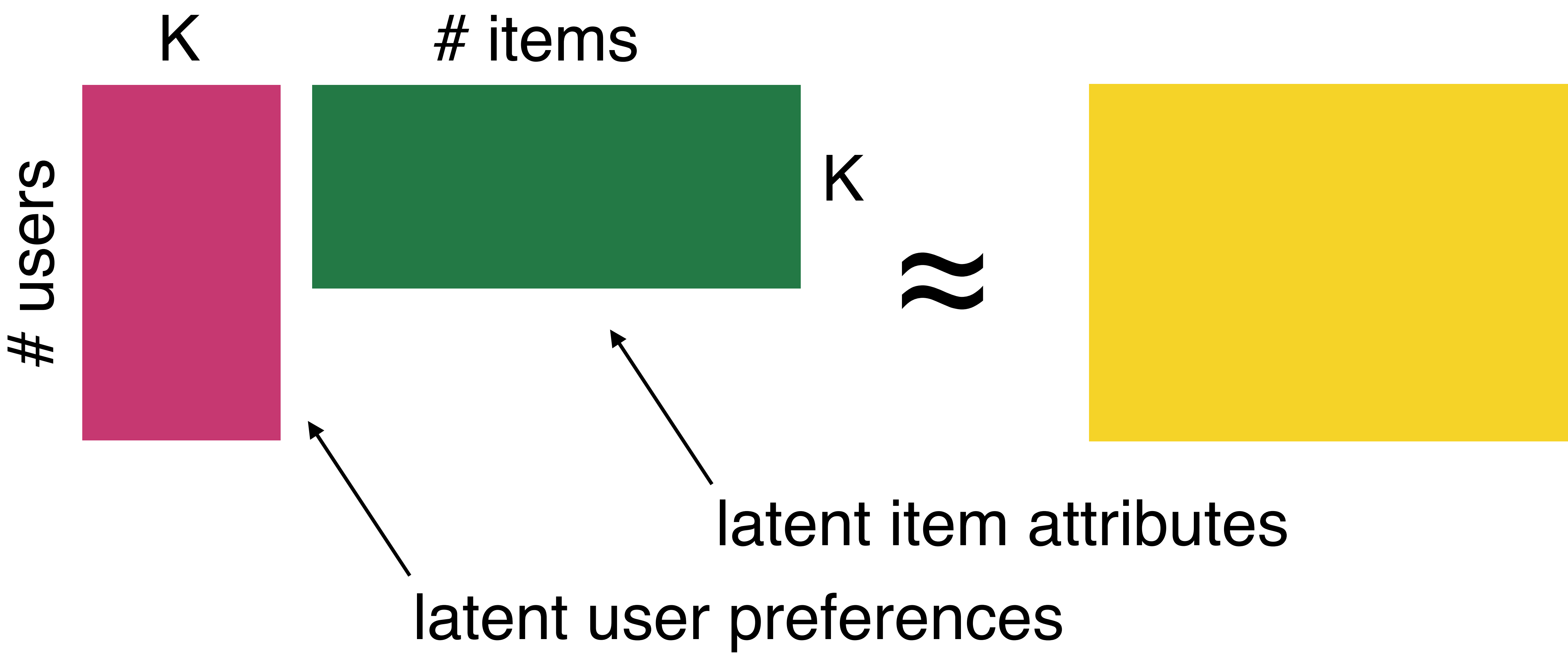
Matrix Factorization

5
4
4
2
5
5
3
4


0
5
4
0
4
2
0
5
5
0
3
4



items
users
≈
latent item attributes
latent user preferences



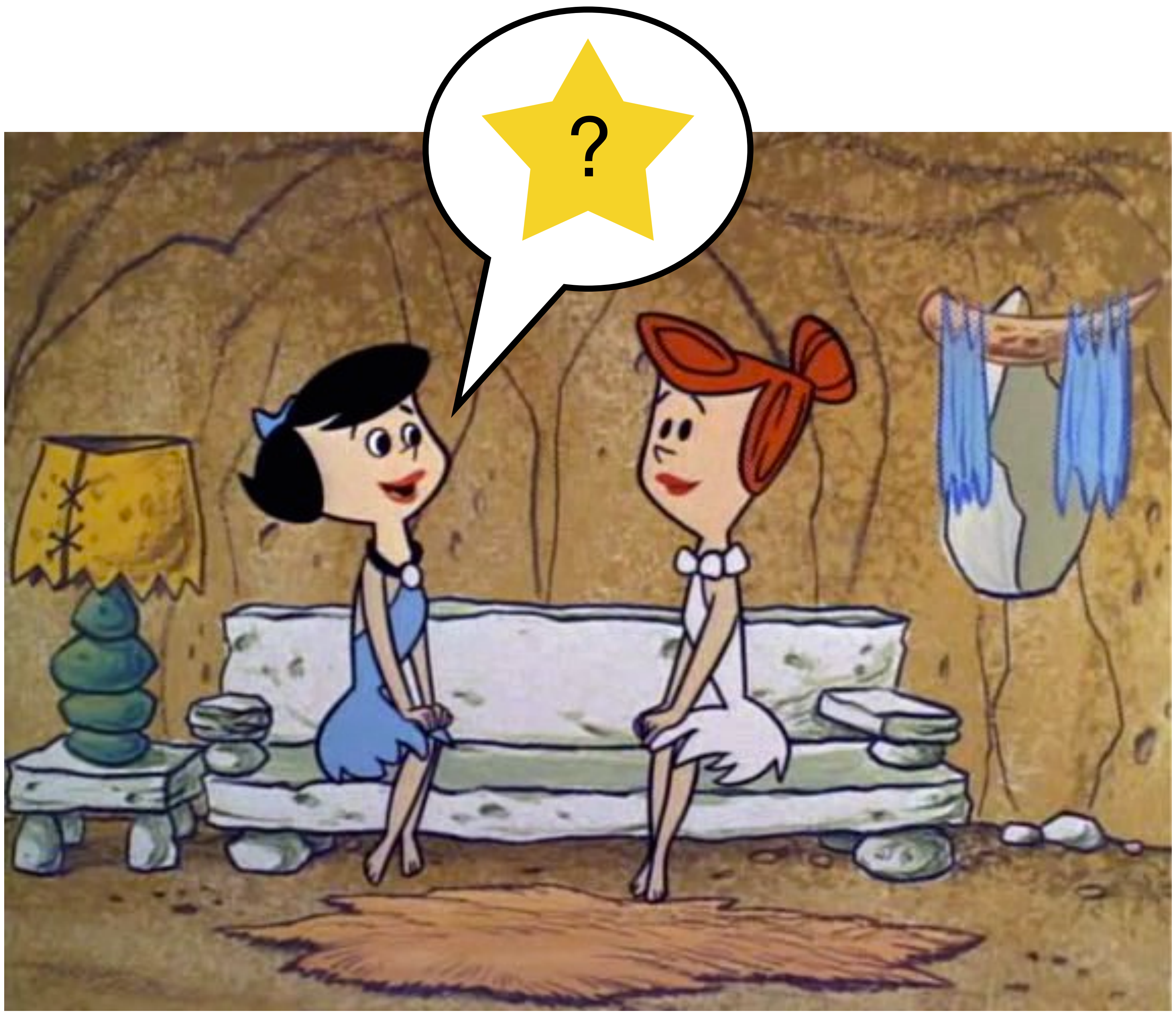
K latent features

Probabilistic matrix factorization

- Scales to large datasets
- Models fit quickly
- Performs well
- Recommendations are interpretable
- Learn about the domain

Including Social Networks

Including Social Networks



Including Social Networks

- Matches our intuition

Including Social Networks

- Matches our intuition
- Choice of K might matter less

Including Social Networks

- Matches our intuition
- Choice of K might matter less
- Introduce explainable serendipity

Including Social Networks

- Matches our intuition
- Choice of K might matter less
- Introduce explainable serendipity
- Improve performance

Including Social Networks

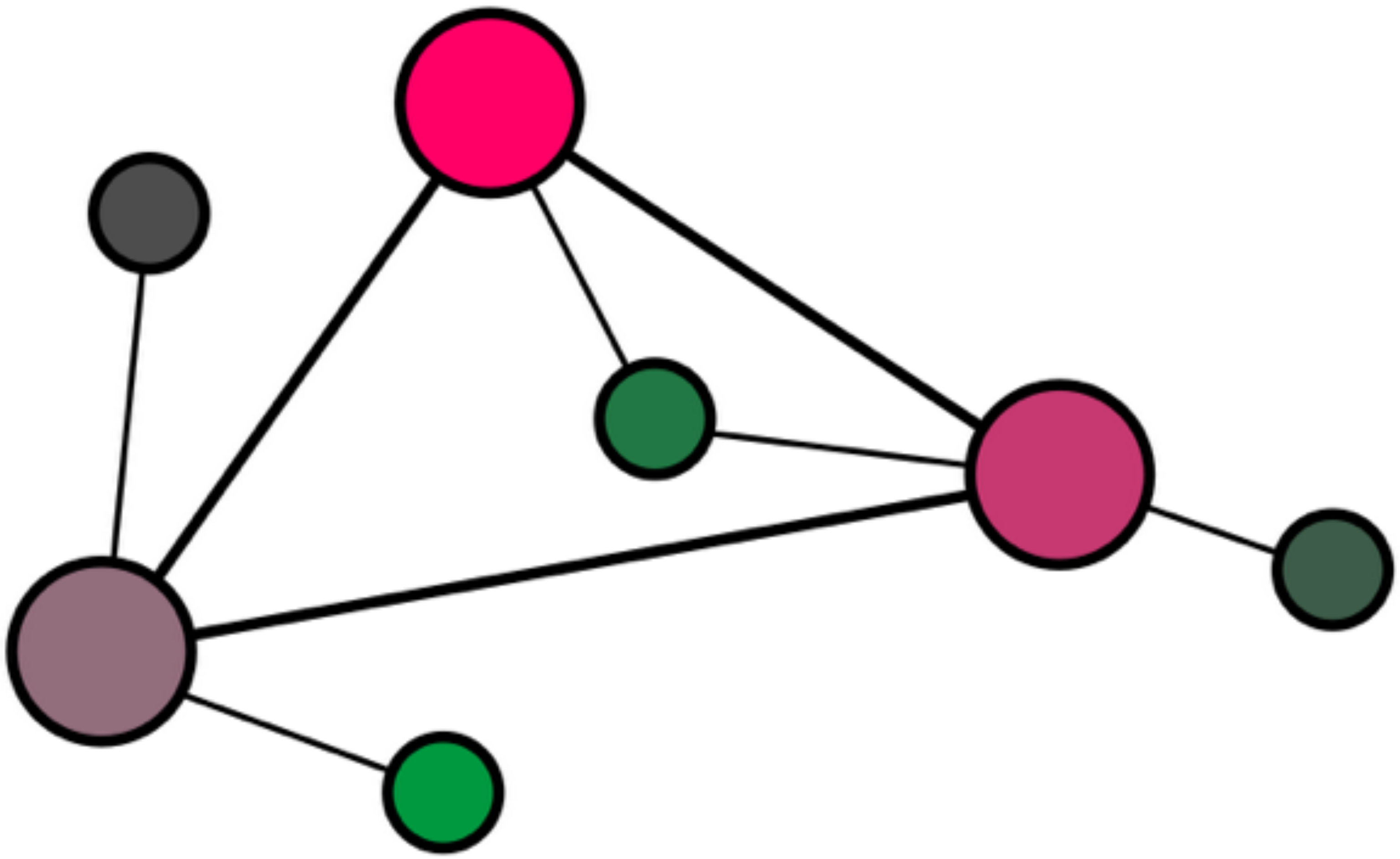
- Matches our intuition
- Choice of K might matter less
- Introduce explainable serendipity
- Improve performance
- Help us learn about the social network

Comparison Approaches

SoRec	Ma et al., SoRec: Social Recommendation Using Probabilistic Matrix Factorization, SIGIR 2008.
RSTE	Ma et al., Learning to Recommend with Social Trust Ensemble, SIGIR 2009.
SocialMF	Jamali and Ester, A Matrix Factorization Technique with Trust Propagation for Recommendation in Social Networks, RecSys 2010.
TrustMF	Yang et al., Social Collaborative Filtering by Trust, IJCAI 2013.
TrustSVD	Guo et al., TrustSVD: Collaborative Filtering with Both the Explicit and Implicit Influence of User Trust and of Item Ratings, AAAI 2015.

librec.net

Data



Data

source	# users	# items	# ratings (% matrix)	# edges (% matrix)
FilmTrust	1,483	1,786	28,468 (1.07%)	982 (0.04%)
Ciao	7,375	92,184	249,834 (0.04%)	43,002 (0.08%)
Epinions	37,826	122,147	651,302 (0.01%)	135,473 (0.01%)
Etsy	39,862	5,201,879	18,650,632 (0.01%)	4,761,437 (0.30%)

etsy.com and librec.net/datasets.html

Data Curation

- Thresholding: set a minimum # of items per user and/or # of users per item

Data Curation

- Thresholding: set a minimum # of items per user and/or # of users per item

- Cull the network to only include network connections with items in common

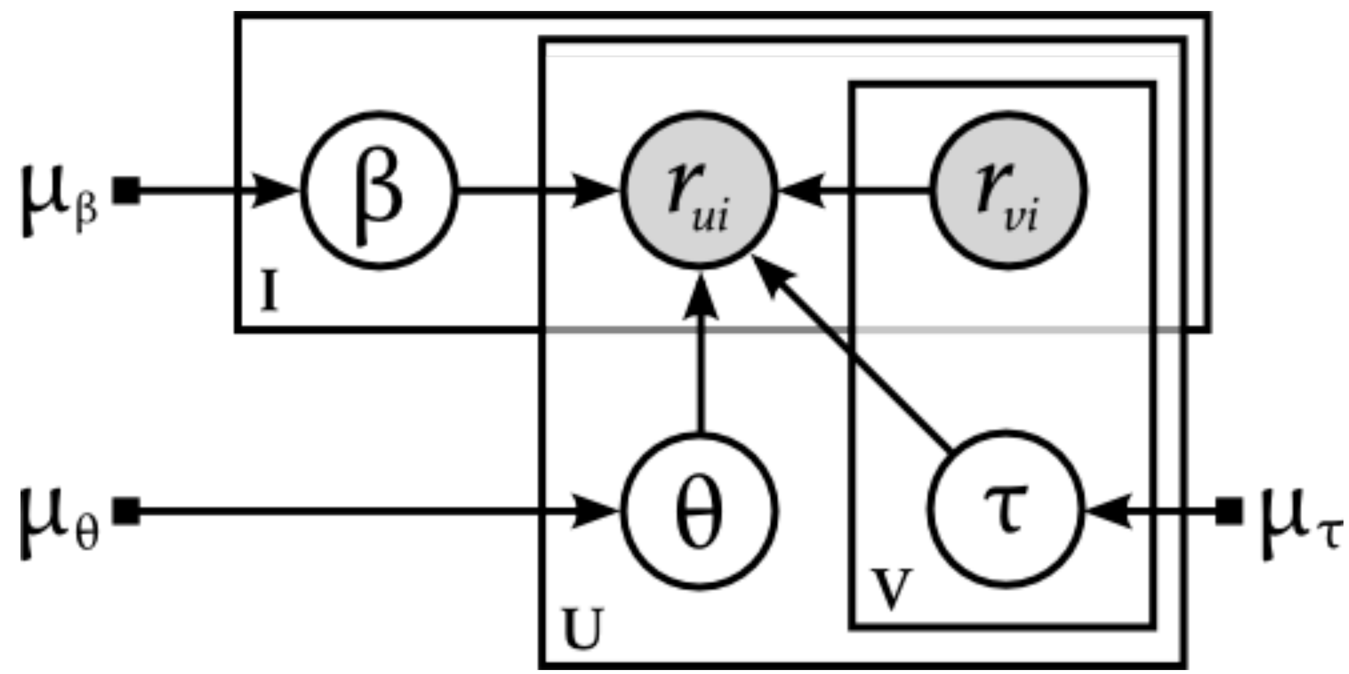
Data Curation

- Thresholding: set a minimum # of items per user and/or # of users per item
- Cull the network to only include network connections with items in common
- Threshold users to only include users who have at least a certain % of items shared with friends

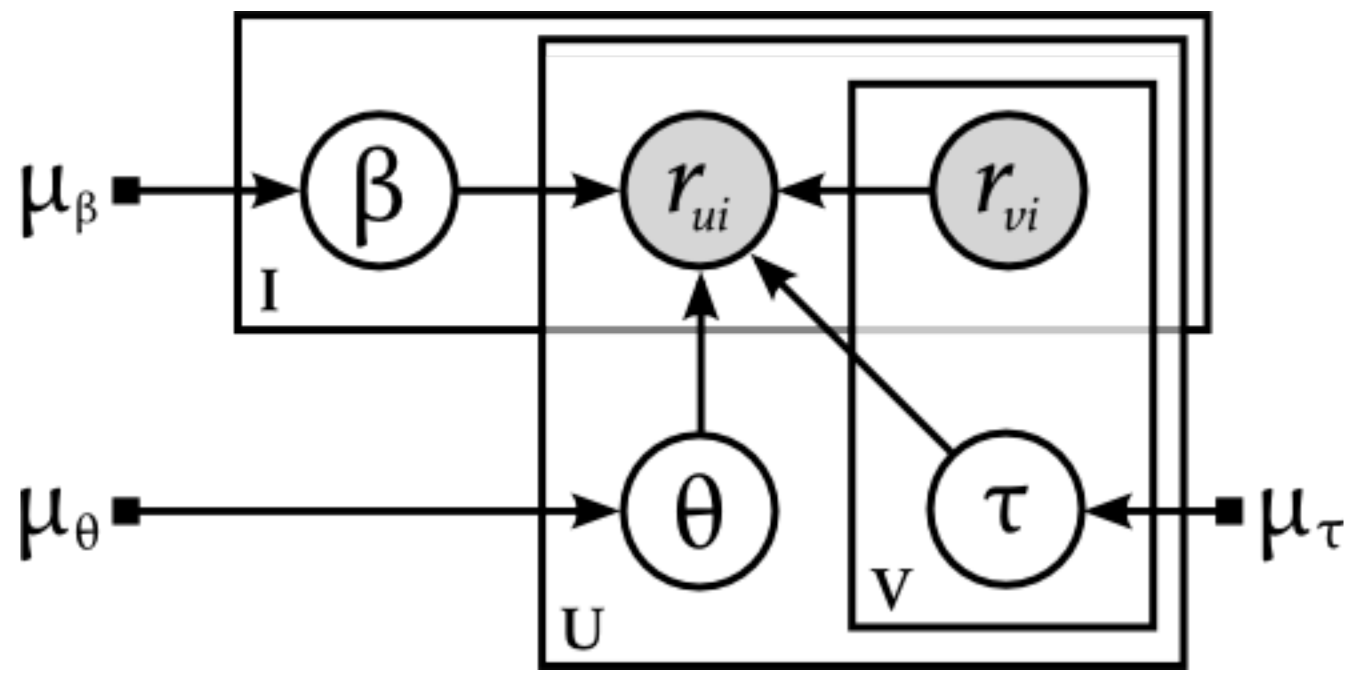
Data Curation

- Thresholding: set a minimum # of items per user and/or # of users per item
- Cull the network to only include network connections with items in common
- Threshold users to only include users who have at least a certain % of items shared with friends

Social Poisson Factorization



Social Poisson Factorization



Ratings:

$$r_{ui} \,|\, r_{-u,i} \sim \text{Poisson}\left(\theta_u^\top \beta_i + \sum_{v \in N(u)} \tau_{uv} r_{vi}\right)$$

Social Poisson Factorization

User preferences:

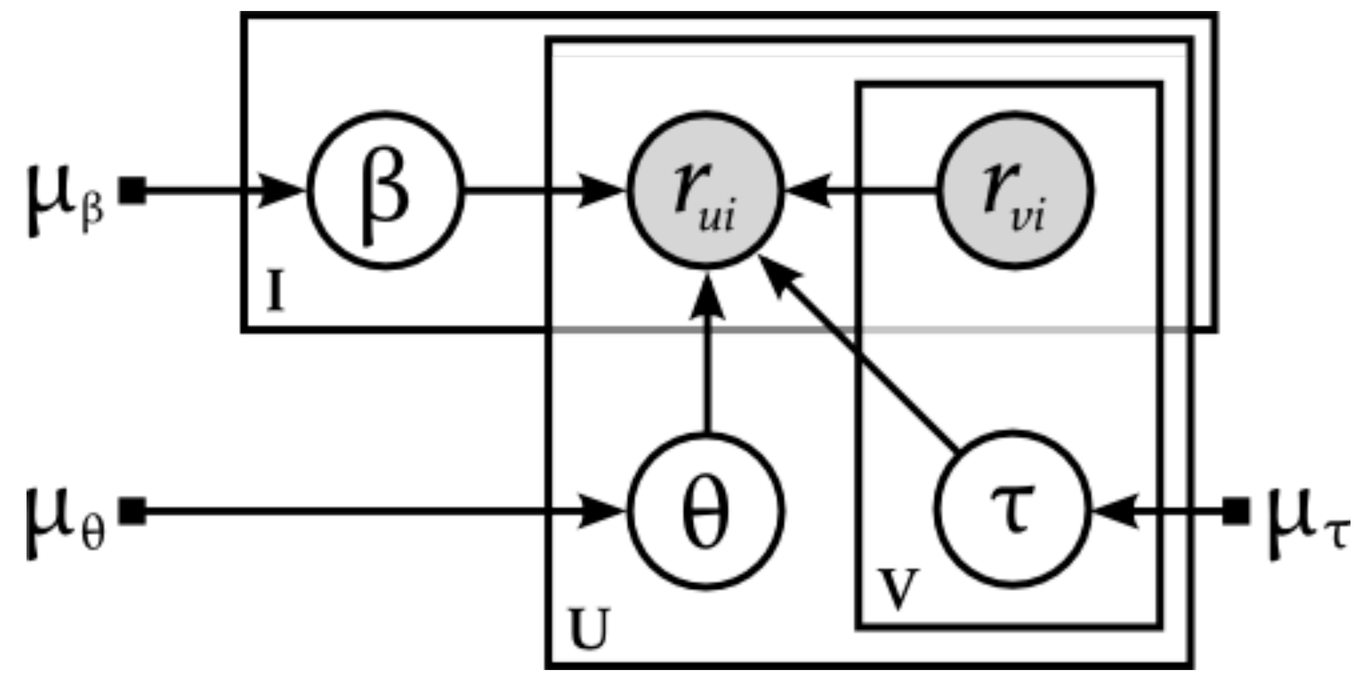
$$\theta_{uk} \sim \mathrm{Gamma}(a_\theta, b_\theta)$$

Item attributes:

$$\beta_{ik} \sim \mathrm{Gamma}(a_\beta, b_\beta)$$

User influence:

$$\tau_{uv} \sim \mathrm{Gamma}(a_\tau, b_\tau)$$



The Problem of Inference:
How do we go from a generative model to finding the values of the variables that best fit our data?

Posterior Distribution

latent model parameters

$$p(z \mid x, \alpha) = \frac{p(z, x \mid \alpha)}{\int_z p(z, x \mid \alpha)}$$

observed data

model hyperparameters

Posterior Distribution

latent model parameters

easy to compute

$$p(z \mid x, \alpha) = \frac{p(z, x \mid \alpha)}{\int_z p(z, x \mid \alpha)}$$

observed data

model hyperparameters

intractable
for most interesting models

Mean Field Variational Inference

- Pick a family of distributions q over the latent variables with its own **variational parameters**
- Optimize q to approximate the posterior p
- To choose q, we use the **mean field assumption**: each variable is independent, allowing q to factorize
- Use coordinate ascent: iteratively optimize each variable, holding the others fixed

Coordinate Ascent:

How do we update each variable?

Variational Inference for SPF

Variational Inference for SPF

Auxiliary variables:

$$z_{uik}^{M} \sim \mathrm{Poisson}(\theta_{uk}\beta_{ik})$$

$$z_{uiv}^{S} \sim \mathrm{Poisson}\left(\tau_{uv} r_{vi}\right)$$

Variational Inference for SPF

Auxiliary variables:

$$z_{uik}^{M} \sim \mathrm{Poisson}(\theta_{uk}\beta_{ik})$$

$$z_{uiv}^{S} \sim \mathrm{Poisson}\left(\tau_{uv} r_{vi}\right)$$

$$\text{if } r \sim \mathrm{Poisson}(a+b) \text{ then } r = z_1 + z_2$$
$$\text{where } z_1 \sim \mathrm{Poisson}(a) \text{ and } z_2 \sim \mathrm{Poisson}(b)$$

Variational Inference for SPF

Auxiliary variables:

$$z^M_{uik} \sim \mathrm{Poisson}(\theta_{uk}\beta_{ik})$$

$$z^S_{uiv} \sim \mathrm{Poisson}\left(\tau_{uv} r_{vi}\right)$$

$$r_{ui} \,|\, r_{-u,i} = \sum\nolimits_{k=1}^{K} z^M_{uik} + \sum\nolimits_{v=1}^{V} z^S_{uiv}$$

if $r \sim \mathrm{Poisson}(a+b)$ then $r = z_1 + z_2$
where $z_1 \sim \mathrm{Poisson}(a)$ and $z_2 \sim \mathrm{Poisson}(b)$

Variational Inference for SPF

$$z_{ui} \mid \theta, \beta, \tau, r \;\sim\; \mathrm{Mult}\left(r_{ui}, \phi_{ui}\right)$$

$$\phi_{ui} \;\propto\; \left\langle\; \theta_{u1}\beta_{i1},\;\; \cdots\;,\; \theta_{uK}\beta_{iK}, \tau_{u1}r_{1i},\;\; \cdots\;,\; \tau_{uV}r_{Vi} \right\rangle$$

Variational Inference for SPF

$$\theta_{uk} \mid \beta, \tau, z, r \;\sim\; \mathrm{Gam}\left(a_\theta + \sum_i z^M_{uik},\; b_\theta + \sum_i \beta_{ik}\right)$$

$$\beta_{ik} \mid \theta, \tau, z, r \;\sim\; \mathrm{Gam}\left(a_\beta + \sum_u z^M_{uik},\; b_\beta + \sum_u \theta_{uk}\right)$$

$$\tau_{uv} \mid \theta, \beta, z, r \;\sim\; \mathrm{Gam}\left(a_\tau + \sum_i z^S_{uiv},\; b_\tau + \sum_i r_{vi}\right)$$

Variational Inference for SPF

Gamma variables:

$$\lambda \sim \mathrm{Gamma}(\lambda_a, \lambda_b)$$

$$\mathbf{E}[\lambda] = \lambda_a / \lambda_b$$

Algorithm 1 Mean field variational inference for social Poisson factorization

initialize $\mathbf{E}[\theta], \mathbf{E}[\beta]$ randomly
while $\Delta\mathcal{L} > \delta$ **do** ▷ check for model convergence
  initialize global β^a to priors for all items
  for each *user* **do**
    while $\Delta\mathbf{E}[\theta_{user}] + \Delta\mathbf{E}[\tau_{user}] > \delta'$ **do** ▷ check for *user* convergence
      initialize θ^a_{user} and τ^a_{user} to priors
      $\theta^b_{user} = \text{prior} + \sum_i \beta_i$
      $\tau^b_{user} = \text{prior} + \sum_i r_i$
      initialize local β^a_{item} to prior
      for each $(item, rating) \in ratings_{user}$ **do**
        $\mathbf{E}[z_{ui}] = rating \ * \ \phi_{ui}$
        update θ^a_{user} += $\mathbf{E}[z^M_{ui}]$
        update τ^a_{user} += $\mathbf{E}[z^S_{ui}]$
        update local β^a_{item} += $\mathbf{E}[z^M_{ui}]$
      $\mathbf{E}[\theta_{user}] = \theta^a_{user} / \theta^b_{user}$
      $\mathbf{E}[\tau_{user}] = \tau^a_{user} / \tau^b_{user}$
    global β^a_{item} += local β^a_{item}
  $\beta^b = \text{prior} + \sum_u \theta_u$
  $\mathbf{E}[\beta] = \beta^a / \beta^b$

Recommendation

$$\mathbf{E}[r_{ui}] = \mathbf{E}[\theta_u]^\top \mathbf{E}[\beta_i] + \sum_{v \in N(u)} \mathbf{E}[\tau_{uv}] r_{vi}$$

Evaluation:

How do we know if our model is doing a good job?

Industry ideal: A/B testing

Industry ideal: A/B testing

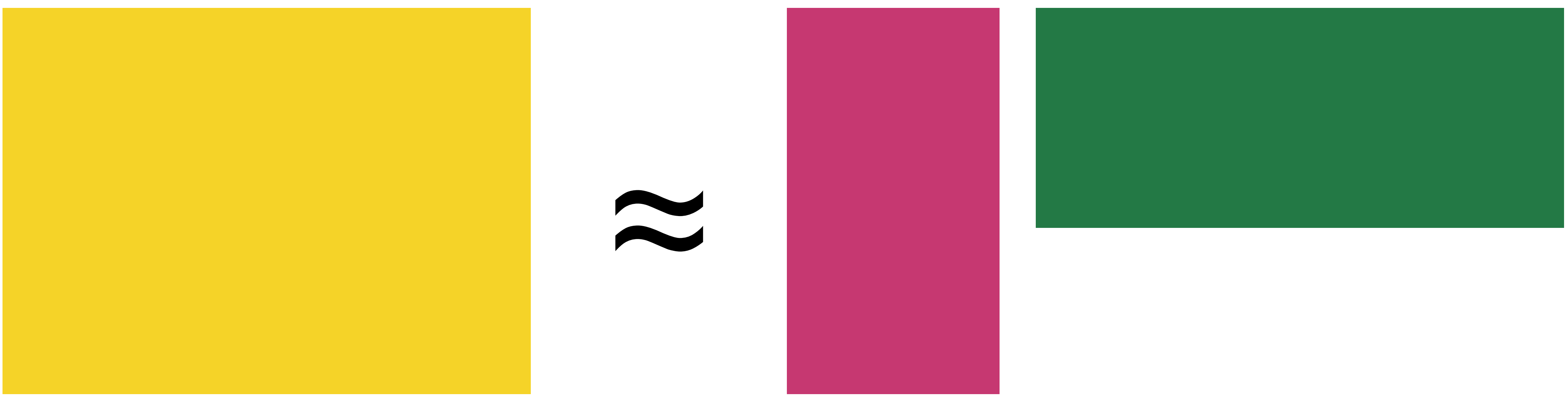
Academic setting: held-out data

Industry ideal: A/B testing

Academic setting: held-out data

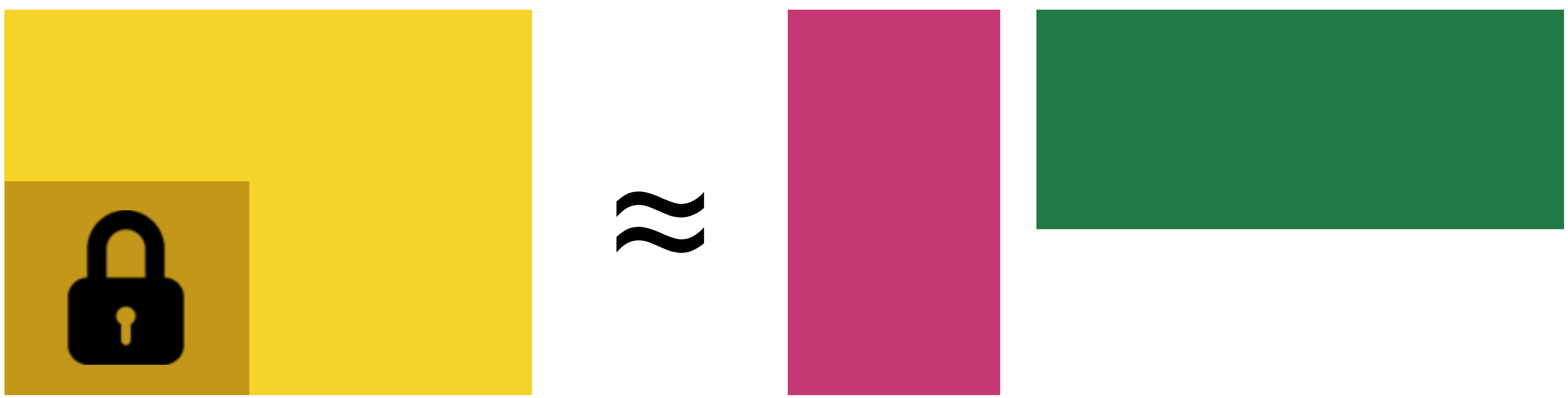
Industry ideal: A/B testing

Academic setting: held-out data



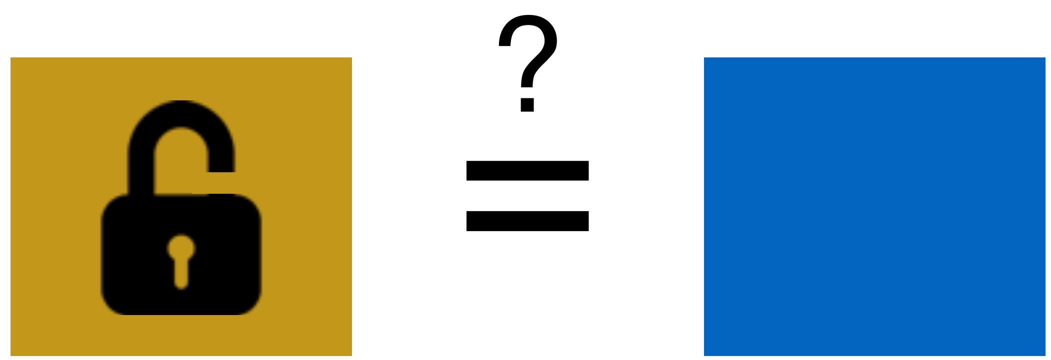
Industry ideal: A/B testing

Academic setting: held-out data



Industry ideal: A/B testing

Academic setting: held-out data



Metrics on held-out data

Metrics on held-out data

RMSE / MAE

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(\hat{r}_{ui} - r_{ui})^2}$$

$$MAE = \frac{1}{N}\sum_{n=1}^{N}|\hat{r}_{ui} - r_{ui}|$$

Metrics on held-out data

RMSE / MAE

Precision / Recall

$$precision(n, user) = \frac{\text{\# of held-out items in top } n}{n}$$

$$recall(n, user) = \frac{\text{\# of held-out items in top } n}{\text{total \# of held-out items}}$$

Metrics on held-out data

RMSE / MAE

Precision / Recall

NDCG

$$DCG(n, user) = \mathbf{1}[rec_1 \in \mathcal{H}] + \sum_{i=2}^{n} \frac{\mathbf{1}[rec_i \in \mathcal{H}]}{\log_2(i)}$$

$$NDCG(n, user) = \frac{DCG(n, user)}{\text{ideal } DCG(n, user)}$$

Metrics on held-out data

RMSE / MAE

Precision / Recall

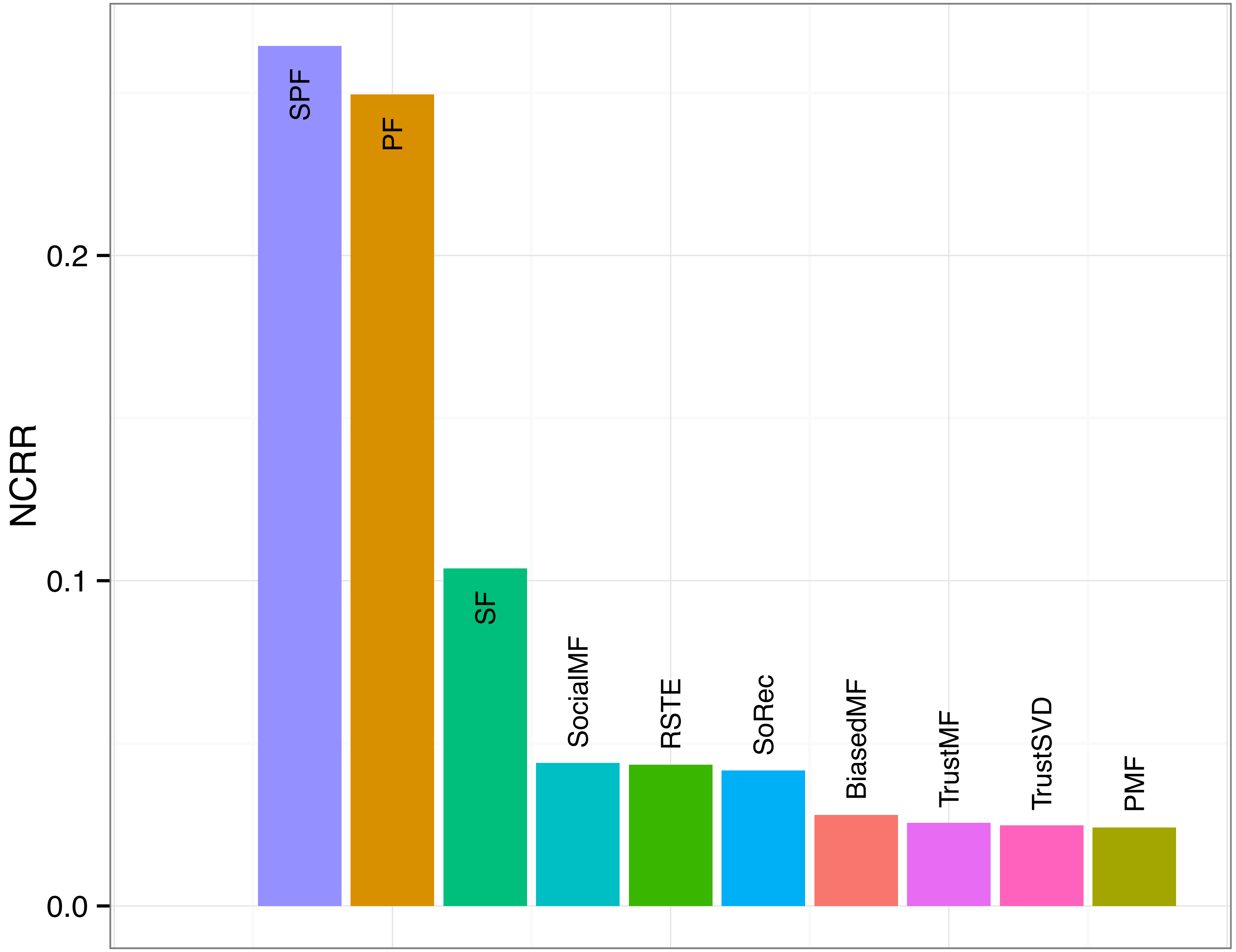
NDCG

NCRR

$$CRR(user) = \sum_{n=1}^{N} \frac{\mathbf{1}[rec_n \in \mathcal{H}]}{n} = \sum_{i \in \mathcal{H}} \frac{1}{rank(i)}$$

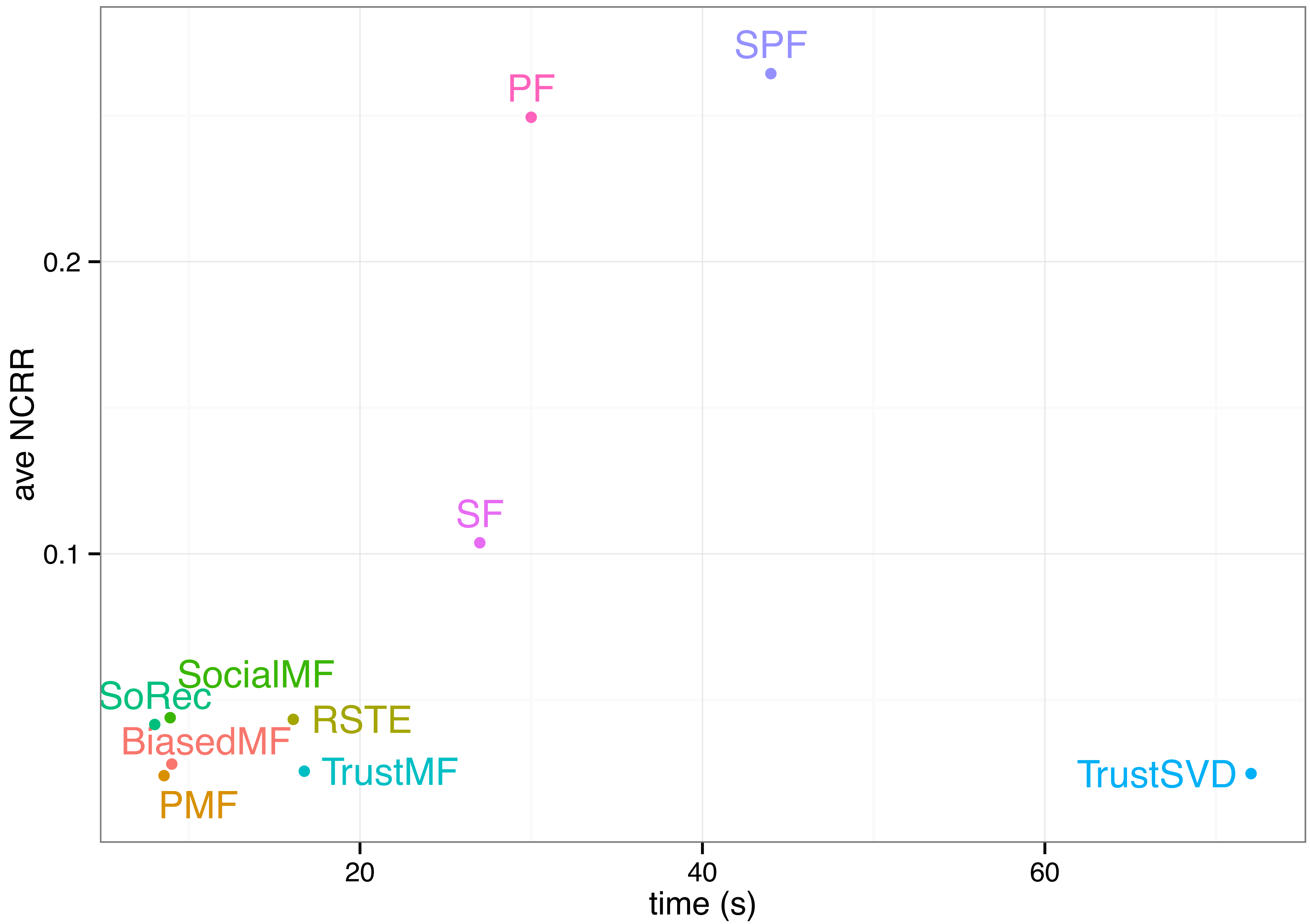
SPF Evaluation

100 iterations on FilmTrust data



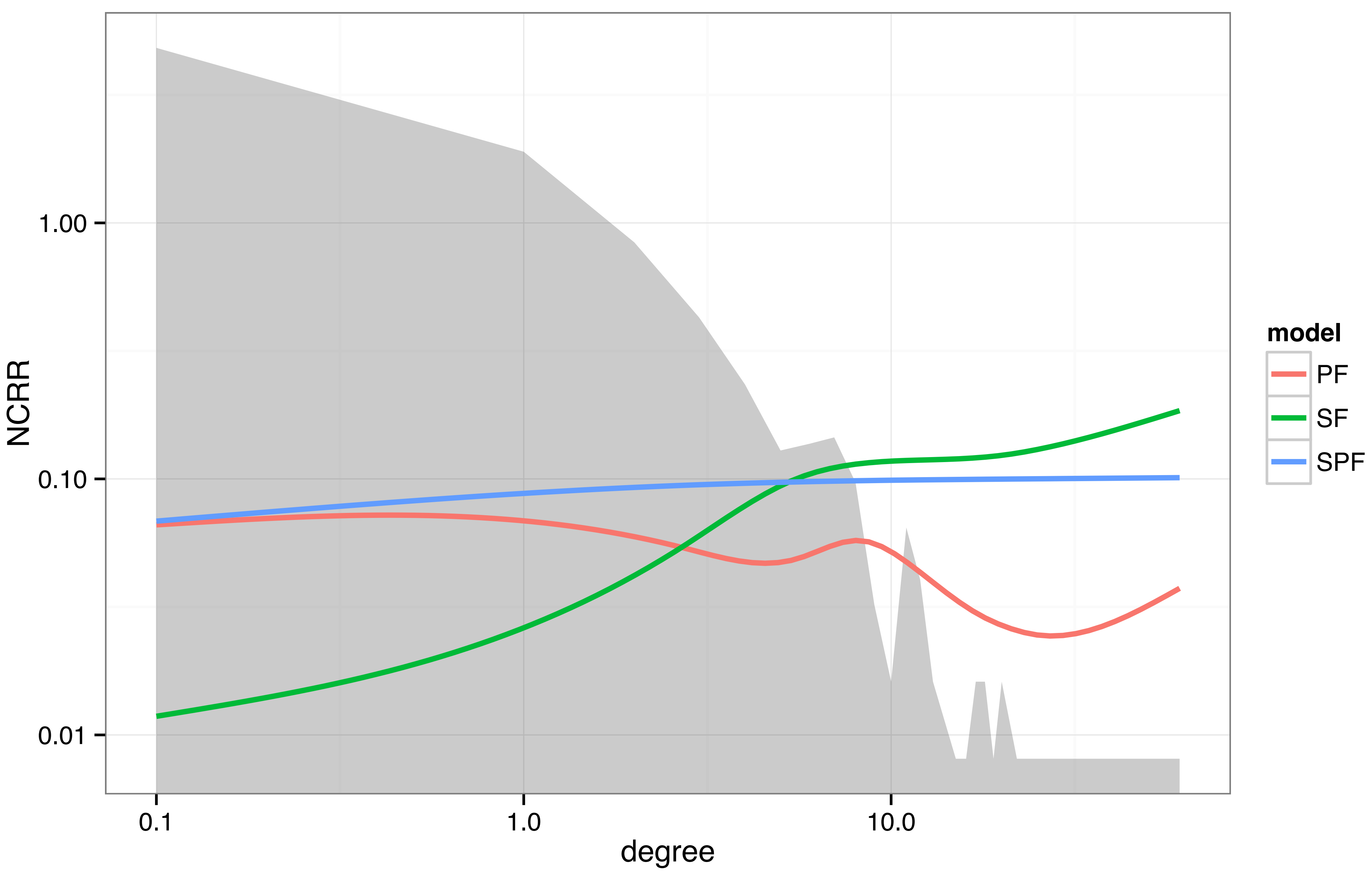
SPF Evaluation

100 iterations on FilmTrust data



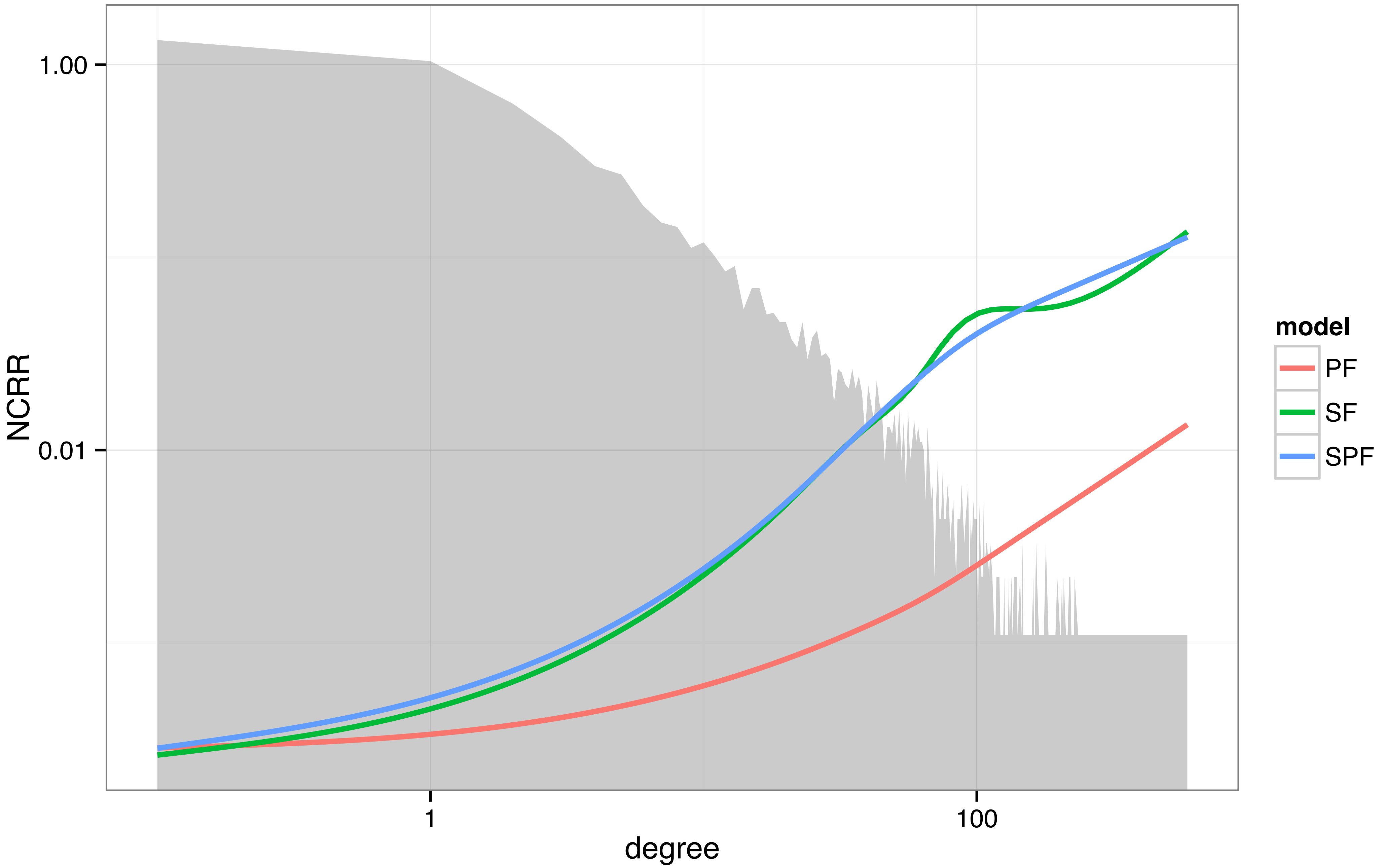
SPF Evaluation

FilmTrust



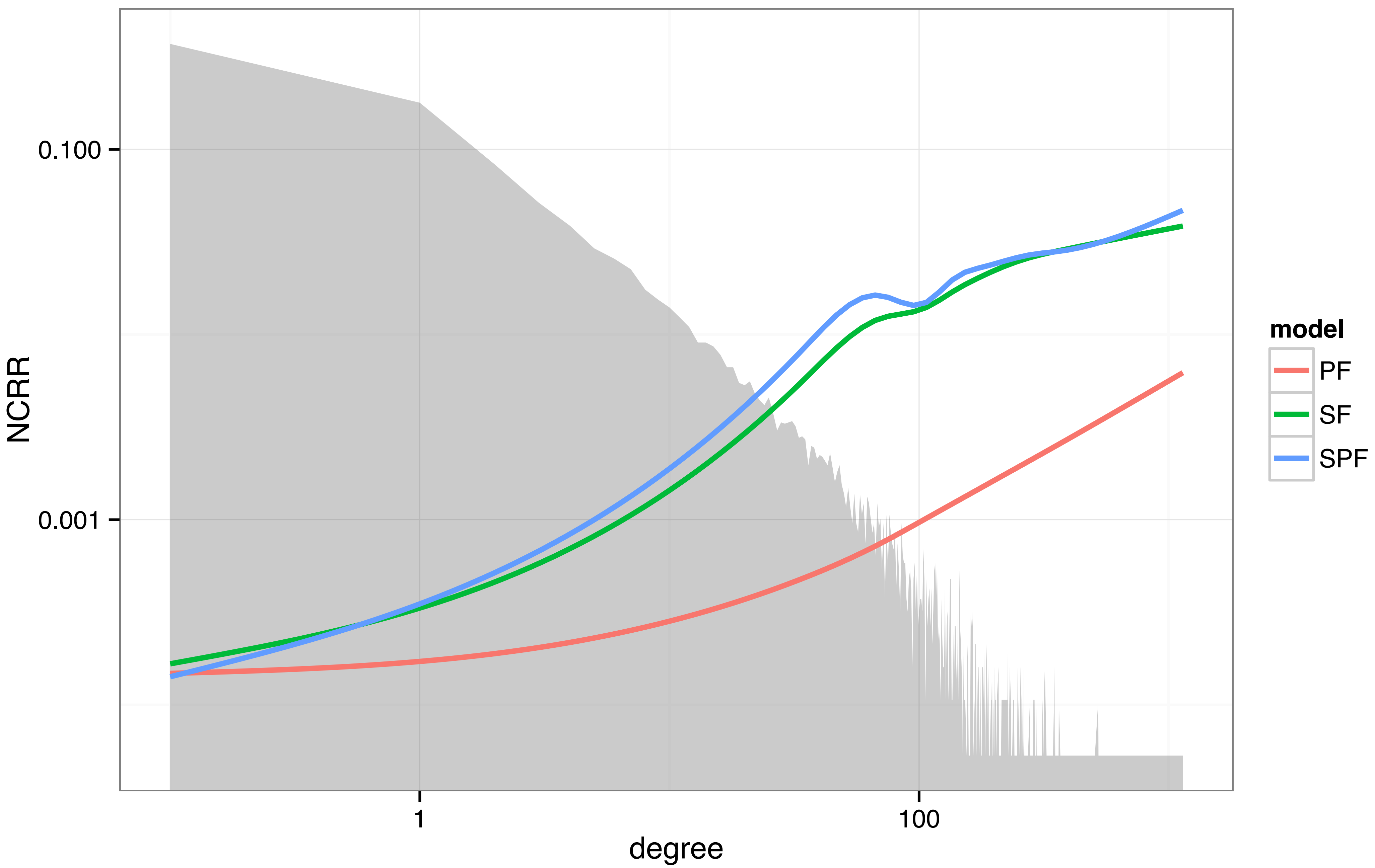
SPF Evaluation

Ciao



SPF Evaluation

Epinions



SPF Evaluation

An Example Etsy User

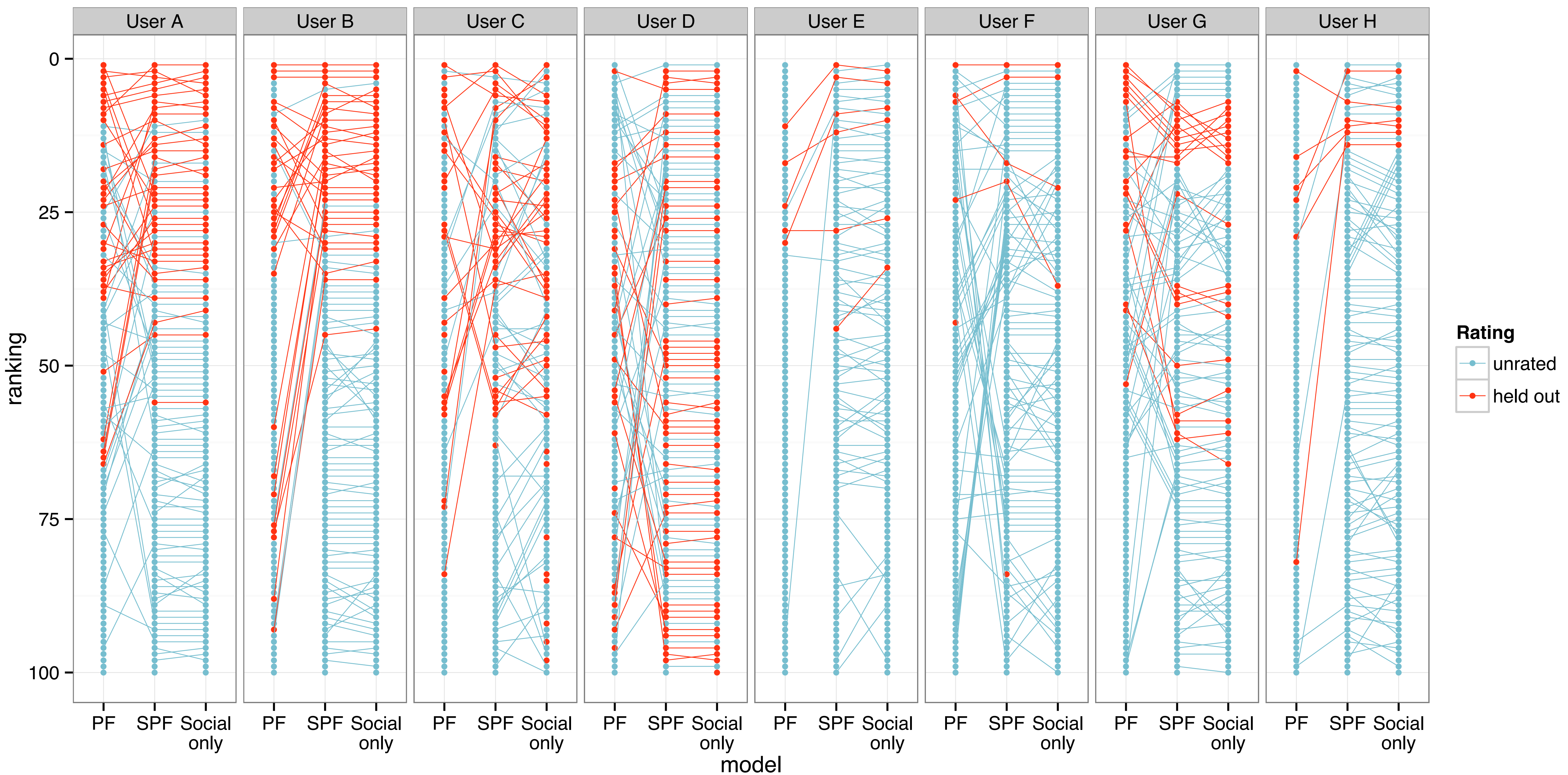
Training

PF

SPF

SPF Evaluation

ranking shifts for Etsy users



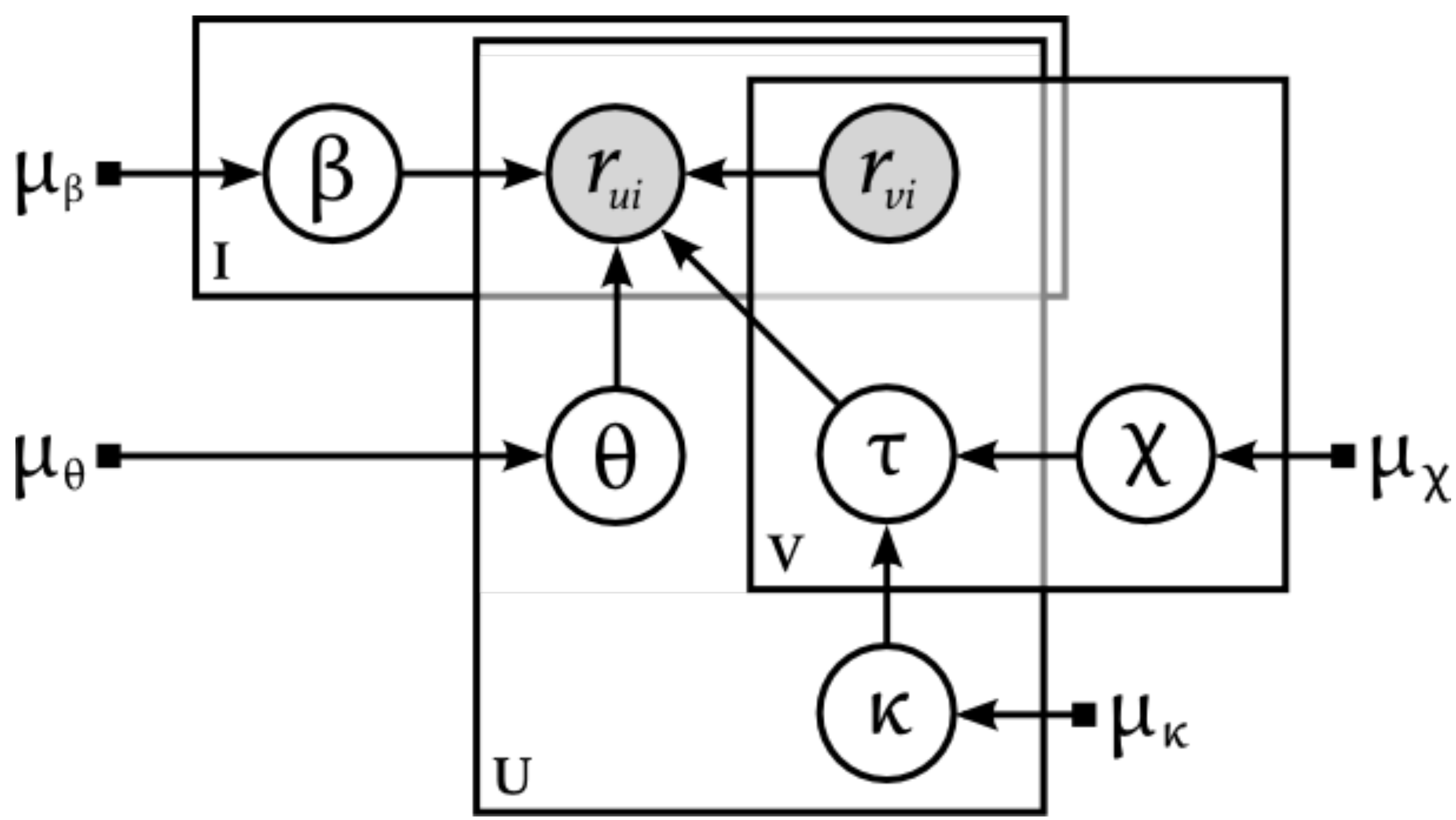
Conclusions

What do we learn from all this?

- Domain makes a difference in how a social network impacts personalized item recommendation
- SPF shows performance improvement on users with even just one friend
- Since the majority of users have a low number of friends, modeling general preferences is important
- No model is universally the best for all users

Current Work

Extensions to SPF include hierarchical influence (user credulity, friend credibility) and topical influence.



Acknowledgements

David Blei, advisor

Tina Eliassi-Rad, Prem Gopalan

Guibing Guo (LibRec creator)

Blei Lab colleagues

Thank You

Questions, ideas, and suggestions welcome!

ajbc.io/spf