A Probabilistic Model for Using Social Networks in Personalized Item Recommendation

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ajbc.io/spf
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  - Comparison approaches
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  • Define the model
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  - Results on data
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  • Data overview
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  • Define the model
  • Algorithm for inference
  • Results on data
• Current work: extensions
Personalized Item Recommendation
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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
latent user preferences

latent item attributes

≈

# users

# items
# users \( K \) \# items \( K \)

latent user preferences

latent item attributes

\( \approx \)

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
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- 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

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSTE</td>
<td>Ma et al., Learning to Recommend with Social Trust Ensemble, SIGIR 2009.</td>
<td></td>
</tr>
<tr>
<td>TrustMF</td>
<td>Yang et al., Social Collaborative Filtering by Trust, IJCAI 2013.</td>
<td></td>
</tr>
<tr>
<td>TrustSVD</td>
<td>Guo et al., TrustSVD: Collaborative Filtering with Both the Explicit and Implicit Influence of User Trust and of Item Ratings, AAAI 2015.</td>
<td></td>
</tr>
</tbody>
</table>
Data
# Data

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

[etsy.com](https://etsy.com) and [librec.net/datasets.html](https://librec.net/datasets.html)
Data Curation

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

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- 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 in common 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 in common with friends
Social Poisson Factorization
Social Poisson Factorization

Ratings:

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

User preferences:

\[ \theta_{uk} \sim \text{Gamma}(a_\theta, b_\theta) \]

Item attributes:

\[ \beta_{ik} \sim \text{Gamma}(a_\beta, b_\beta) \]

User influence:

\[ \tau_{uv} \sim \text{Gamma}(a_\tau, b_\tau) \]

\[ \mu = \{a, b\} \]
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

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

- Latent model parameters
- Observed data
- Model hyperparameters
Posterior Distribution

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

- latent model parameters
- observed data
- model hyperparameters

easy to compute
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:

\[ z_{uik}^M \sim \text{Poisson}(\theta_{uk}\beta_{ik}) \]

\[ z_{uv}^S \sim \text{Poisson}(\tau_{uv}\tau_{vi}) \]
Variational Inference for SPF

Auxiliary variables:

\[ z_{uik}^{M} \sim \text{Poisson}(\theta_{uk} \beta_{ik}) \]
\[ z_{uiv}^{S} \sim \text{Poisson}(\tau_{uv} r_{vi}) \]

if \( r \sim \text{Poisson}(a + b) \) then \( r = z_1 + z_2 \)
where \( z_1 \sim \text{Poisson}(a) \) and \( z_2 \sim \text{Poisson}(b) \)
Variational Inference for SPF

Auxiliary variables:

\[ z_{uik}^M \sim \text{Poisson}(\theta_{uk} \beta_{ik}) \]
\[ z_{uiv}^S \sim \text{Poisson}(\tau_{uv} r_{vi}) \]

\[ r_{ui} \mid r_{-u,i} = \sum_{k=1}^{K} z_{uik}^M + \sum_{v=1}^{V} z_{uiv}^S \]

if \( r \sim \text{Poisson}(a + b) \) then \( r = z_1 + z_2 \)
where \( z_1 \sim \text{Poisson}(a) \) and \( z_2 \sim \text{Poisson}(b) \)
Variational Inference for SPF

\[ z_{ui} \mid \theta, \beta, \tau, r \sim \text{Mult} (r_{ui} , \phi_{ui} ) \]

\[ \phi_{ui} \propto \left\langle \theta_{u1} \beta_{i1}, \ldots, \theta_{uK} \beta_{iK}, \tau_{u1} r_{1i}, \ldots, \tau_{uV} r_{Vi} \right\rangle \]
Variational Inference for SPF

\[ \theta_{uk} \mid \beta, \tau, z, r \sim \text{Gam} \left( a_\theta + \sum_i z_{ui k}, b_\theta + \sum_i \beta_{ik} \right) \]

\[ \beta_{ik} \mid \theta, \tau, z, r \sim \text{Gam} \left( a_\beta + \sum_u z_{ui k}, b_\beta + \sum_u \theta_{uk} \right) \]

\[ \tau_{uv} \mid \theta, \beta, z, r \sim \text{Gam} \left( a_\tau + \sum_i z_{ui v}, b_\tau + \sum_i r_{vi} \right) \]
Variational Inference for SPF

Gamma variables:

\[ \lambda \sim \text{Gamma}(\lambda_a, \lambda_b) \]

\[ \mathbb{E}[\lambda] = \frac{\lambda_a}{\lambda_b} \]
Algorithm 1 Mean field variational inference for social Poisson factorization

1: initialize $E[\theta], E[\beta]$ randomly

2: while $\Delta \mathcal{L} > \delta$ do
   ▷ check for model convergence

3:   initialize global $\beta^a$ to priors for all items

4:   for each user do

5:      while $\Delta E[\theta_{user}] + \Delta E[\tau_{user}] > \delta'$ do
         ▷ check for user convergence

6:         initialize $\theta^a_{user}$ and $\tau^a_{user}$ to priors

7:         $\theta^b_{user} = \text{prior} + \sum_i \beta_i$

8:         $\tau^b_{user} = \text{prior} + \sum_i \tau_i$

9:         initialize local $\beta^a_{item}$ to prior

10:        for each $(\text{item}, \text{rating}) \in \text{ratings}_{\text{user}}$ do

11:           $E[z_{ui}] = \text{rating} \ast \phi_{ui}$

12:           update $\theta^a_{user} += E[z^M_{ui}]$

13:           update $\tau^a_{user} += E[z^S_{ui}]$

14:           update local $\beta^a_{item} += E[z^M_{ui}]$

15:           $E[\theta_{user}] = \frac{\theta^a_{user}}{\theta^b_{user}}$

16:           $E[\tau_{user}] = \frac{\tau^a_{user}}{\tau^b_{user}}$

17:           global $\beta^a_{item} += \text{local} \beta^a_{item}$

18:           $\beta^b = \text{prior} + \sum_u \theta_u$

19:           $E[\beta] = \frac{\beta^a}{\beta^b}$
Recommendation

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

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

\[ \text{recall}(n, \text{user}) = \frac{\# \text{ of held-out items in top } n}{\text{total } \# \text{ of held-out items}} \]
Metrics on held-out data

RMSE / MAE

Precision / Recall

NDCG

\[
DCG(n, \text{user}) = 1[\text{rec}_1 \in \mathcal{H}] + \sum_{i=2}^{n} \frac{1[\text{rec}_i \in \mathcal{H}]}{\log_2(i)}
\]

\[
NDCG(n, \text{user}) = \frac{DCG(n, \text{user})}{\text{ideal } DCG(n, \text{user})}
\]
Metrics on held-out data

RMSE / MAE

Precision / Recall

NDCG

NCRR

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

100 iterations on FilmTrust data
SPF Evaluation

100 iterations on FilmTrust data

![Graph showing the evaluation of different methods. The x-axis represents time (s) and the y-axis represents average NCRR. The methods include SPF, PF, PMF, RSTE, SF, SocialMF, SoRec, BiasedMF, TrustMF, and TrustSVD. SPF has the highest average NCRR at a time of around 15s.]
SPF Evaluation

FilmTrust

![Graph showing SPF Evaluation for FilmTrust with different models: PF, SF, SPF. The graph plots NCRR against degree.](image-url)
SPF Evaluation

Ciao
SPF Evaluation

An Example Etsy User

Training

PF

SPF
SPF Evaluation

ranking shifts for Etsy users

Rating
- light blue: unrated
- red: held out

User A: PF, SPF, Social only
User B: PF, SPF, Social only
User C: PF, SPF, Social only
User D: PF, SPF, Social only
User E: PF, SPF, Social only
User F: PF, SPF, Social only
User G: PF, SPF, Social only
User H: PF, SPF, Social only
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