A Matrix Factorization Technique with Trust Propagation for Recommendation in Social Networks
Outline

- Introduction
- Matrix Factorization Models
  - Basic MF Model
  - Social Trust Ensemble Model
- The SocialMF Model
- Data Sets
- Experiments
- Conclusions
Need For Recommenders

Input Data
- A set of users $U = \{u_1, \ldots, u_N\}$
- A set of items $I = \{i_1, \ldots, i_M\}$
- The rating matrix $R = [r_{u,i}]_{N \times M}$

Problem Definition:
- Given user $u$ and target item $i$
- Predict the rating $r_{u,i}$

Collaborative Filtering Approach

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Introduction (cont.)

- Social Networks Emerged Recently
  - Independent source of information
- Motivation of SN-based RS
  - Social Influence: users adopt the behavior of their friends
- Social Rating Network

- Social Network ➔ Trust Network

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Recommendation in Social Networks

- Memory based approaches for recommendation in social networks
  - [Golbeck, 2005]
  - [Massa et.al. 2007]
  - [Jamali et.al. 2009]
  - [Ziegler, 2005]

A Sample Social Rating Network
Matrix Factorization

- Model based approach
- Latent features for users
  \[ U \in \mathbb{R}^{K \times N} \]
- Latent features for items
  \[ V \in \mathbb{R}^{K \times M} \]

- Ratings are scaled to \([0,1]\)
- \(g\) is logistic function

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Social Trust Ensemble [2009]

\[
\hat{R}_{u,i} = g\left(\alpha U_u^T V_i + (1 - \alpha) \sum_{v \in N_u} T_{u,v} U_v^T V_i\right)
\]

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Issues with STE

- Feature vectors of neighbors should influence the feature vector of \( u \) not his ratings
- STE does not handle trust propagation
- Learning is based on observed ratings only.
Social Influence $\rightarrow$ behavior of a user $u$ is affected by his direct neighbors $N_u$.

Latent characteristics of a user depend on his neighbors.

$$\hat{U}_u = \sum_{v \in N_u} T_{u,v} U_v$$

$T_{u,v}$ is the normalized trust value.
The SocialMF Model (cont.)

\[ p(U, V | R, T, \sigma^2_R, \sigma^2_T, \sigma^2_U, \sigma^2_V) \propto p(R | U, V, \sigma^2_R) p(U | T, \sigma^2_U, \sigma^2_T) p(V | \sigma^2_V) \]

\[ = \prod_{u=1}^{N} \prod_{i=1}^{M} \left[ N \left( R_{u,i} | g(U_u^T V_i), \sigma^2_r \right) \right]_{I_{u,i}}^{R} \]

\[ \times \prod_{u=1}^{N} N \left( U_u | \sum_{v \in N_u} T_{u,v} U_v, \sigma^2_T I \right) \]

\[ \times \prod_{u=1}^{N} N \left( U_u | 0, \sigma^2_U I \right) \times \prod_{i=1}^{M} N \left( V_i | 0, \sigma^2_V I \right) \]
The SocialMF Model (cont.)

\[
p(U, V | R, T, \sigma_R^2, \sigma_T^2, \sigma_U^2, \sigma_V^2) \propto \\
p(R | U, V, \sigma_R^2)p(U | T, \sigma_U^2, \sigma_T^2)p(V | \sigma_V^2)
\]

\[
= \prod_{u=1}^{N} \prod_{i=1}^{M} \left[ \mathcal{N} \left( R_{u,i} | g(U_u^T V_i), \sigma_r^2 \right) \right] I_{u,i}^R \\
\times \prod_{u=1}^{N} \mathcal{N} \left( U_u | \sum_{v \in N_u} T_{u,v} U_v, \sigma_T^2 I \right) \\
\times \prod_{u=1}^{N} \mathcal{N} \left( U_u | 0, \sigma_U^2 I \right) \times \prod_{i=1}^{M} \mathcal{N} \left( V_i | 0, \sigma_V^2 I \right)
\]
The SocialMF Model (cont.)

\[
p(U, V | R, T, \sigma_R^2, \sigma_T^2, \sigma_U^2, \sigma_V^2) \propto
p(R | U, V, \sigma_R^2)p(U | T, \sigma_U^2, \sigma_T^2)p(V | \sigma_V^2)
\]

\[
= \prod_{u=1}^{N} \prod_{i=1}^{M} \left[ \mathcal{N} \left( R_{u,i} | g(U_u^T V_i), \sigma_r^2 \right) \right]^{1_{R_{u,i}}}
\times \prod_{u=1}^{N} \mathcal{N} \left( U_u | \sum_{v \in N_u} T_{u,v} U_v, \sigma_T^2 I \right)
\times \prod_{u=1}^{N} \mathcal{N} \left( U_u | 0, \sigma_U^2 I \right) \times \prod_{i=1}^{M} \mathcal{N} \left( V_i | 0, \sigma_V^2 I \right)
\]

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The SocialMF Model (cont.)

\[ p(U, V | R, T, \sigma_R^2, \sigma_T^2, \sigma_U^2, \sigma_V^2) \propto \]

\[ p(R | U, V, \sigma_R^2) p(U | T, \sigma_U^2, \sigma_T^2) p(V | \sigma_V^2) \]

\[ = \prod_{u=1}^{N} \prod_{i=1}^{M} \left[ \mathcal{N} \left( R_{u,i} \mid g(U_u^T V_i), \sigma_r^2 \right) \right]_{I_{u,i}}^R \]

\[ \times \prod_{u=1}^{N} \mathcal{N} \left( U_u \mid \sum_{v \in N_u} T_{u,v} U_v, \sigma_T^2 \mathbf{I} \right) \]

\[ \times \prod_{u=1}^{N} \mathcal{N} \left( U_u \mid 0, \sigma_U^2 \mathbf{I} \right) \times \prod_{i=1}^{M} \mathcal{N} \left( V_i \mid 0, \sigma_V^2 \mathbf{I} \right) \]
The SocialMF Model (cont.)

\[
\frac{\partial \mathcal{L}}{\partial U_u} = \sum_{i=1}^{M} I_{u,i} V_i g' \left( U_u^T V_i \right) (g(U_u^T V_i) - R_{u,i}) + \lambda_U U_u + \lambda_T (U_u - \sum_{v \in N_u} T_{u,v} U_v)
\]

\[-\lambda_T \sum_{\{v | u \in N_v\}} T_{v,u} \left( U_v - \sum_{w \in N_v} T_{v,w} U_w \right)\]

\[
\frac{\partial \mathcal{L}}{\partial V_i} = \sum_{u=1}^{N} I_{u,i} U_v g' \left( U_u^T V_i \right) (g(U_u^T V_i) - R_{u,i}) + \lambda_V V_i
\]

\[
\lambda_U = \frac{\sigma_R^2}{\sigma_U^2}, \quad \lambda_V = \frac{\sigma_R^2}{\sigma_V^2}
\]

and \[
\lambda_T = \frac{\sigma_R^2}{\sigma_T^2}
\]

\[
\lambda_U = \lambda_V
\]

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Properties of SocialMF

- Trust Propagation
- User latent feature learning possible with existence of the social network
  - No need to fully observed rating for learning
  - Appropriate for cold start users
Data Sets

- Epinions – public domain
- Flixster
  - Flixster.com is a social networking service for movie rating
  - The crawled data set includes data from Nov 2005 – Nov 2009
  - Available at http://www.cs.sfu.ca/~sja25/personal/datasets/
General Statistics of Flixster and Epinions

Flixster: 1M users, 47K items
- 150K users with at least one rating
- Items: movies
- 53% cold start

Epinions: 71K users, 108K items
- Items: DVD Players, Printers, Books, Cameras, ...
- 51% cold start
Positional strategy

- 5-fold cross validation
- Using RMSE for evaluation
- Comparison Partners
  - Basic MF
  - STE
  - CF
- Model parameters
  - SocialMF: $\lambda_U = \lambda_V = 0.1$
  - STE: $\alpha = 0.4$
Results for Epinions

- Gain over STE: 6.2% for K=5 and 5.7% for K=10
SocialMF gain over STE (5%) is 3 times the STE gain over BasicMF (1.5%)
Sensitivity Analysis on $\lambda_T$

![Graph showing Sensitivity Analysis for Epinions]

Sensitivity Analysis for Epinions
Sensitivity Analysis on $\lambda_T$

Sensitivity Analysis for Flixster
Experiments on Cold Start Users

RMSE values on cold start users (K=5)

Epinions

CF  BaseMF  STE  SocialMF

1.4  1.3  1.2  1.1  1.0
Experiments on Cold Start Users

RMSE values on cold start users (K=5)

<table>
<thead>
<tr>
<th>Method</th>
<th>RMSE Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>CF</td>
<td>1.25</td>
</tr>
<tr>
<td>BaseMF</td>
<td>1.2</td>
</tr>
<tr>
<td>STE</td>
<td>1.15</td>
</tr>
<tr>
<td>SocialMF</td>
<td>1.05</td>
</tr>
</tbody>
</table>

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Experiments on Cold Start Users

RMSE Gain of SocialMF over STE

<table>
<thead>
<tr>
<th></th>
<th>Flixster</th>
<th>Epinions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cold Start Users</td>
<td>8.50%</td>
<td>11.50%</td>
</tr>
<tr>
<td>All Users</td>
<td>5%</td>
<td>6.20%</td>
</tr>
</tbody>
</table>

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Analysis of Learning Runtime

- SocialMF: \( O(N\bar{r}K + N\bar{t}^2 K) \)
- STE: \( O(N\bar{r}\bar{t}^2 K) \)
- SocialMF is faster by factor \( \frac{\bar{r}t^2}{\bar{r} + \bar{t}^2} \)

<table>
<thead>
<tr>
<th>N</th>
<th># of Users</th>
</tr>
</thead>
<tbody>
<tr>
<td>K</td>
<td>Latent Feature Size</td>
</tr>
<tr>
<td>( \bar{r} )</td>
<td>Avg. ratings per user</td>
</tr>
<tr>
<td>( \bar{t} )</td>
<td>Avg. neighbors per user</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>Epinions</th>
<th>Flixster</th>
</tr>
</thead>
<tbody>
<tr>
<td>SocialMF</td>
<td>2.8 sec</td>
<td>29 sec</td>
</tr>
<tr>
<td>STE</td>
<td>37 sec</td>
<td>27 min</td>
</tr>
</tbody>
</table>
Conclusion

- A model based approach for recommendation in social networks based on matrix factorization
- Handling Trust Propagation
- Appropriate for cold start users
- Fast Learning phase
- Improved quality for experiments on two real life data sets.
Thank you!