Collaborative Filtering with Social Local Models

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Recommender System

Inspired by your shopping trends

- Benchmark Bouquets White Elegance, With Vase
  - $37.42
- Benchmark Bouquets Signature Roses and Alstroemeria, With Vase
  - $39.44
- KaBloom Romantic Red Rose Bouquet: 12 Fresh Cut Red Roses...
  - $35.99

See more

Products Recommendation
Recommender System

Questions and Answers Recommendation
Recommender System

Restaurants Recommendation
Recommender System

• Recommender systems (RS) are everywhere.
• They are not only useful for people, but also create huge revenues for companies.

• The most popular RS method is collaborative filtering (CF).
  – User-based CF
  – Item-based CF
  – Matrix Factorization (MF)
Matrix Factorization (MF)

- The assumption is that users’ preferences are controlled by a small number of factors.

\[
\min_{U,B} \frac{1}{2} \sum_{i=1}^{m} \sum_{j=1}^{n} I_{ij} (R_{ij} - u_{ij}b_j)^2 + \frac{\lambda_1}{2} ||U||^2_F + \frac{\lambda_2}{2} ||B||^2_F
\]

[Link to source: https://buildingrecommenders.wordpress.com/2015/11/18/overview-of-recommender-algorithms-part-2/]
Problems of MF

• Sparsity of the rating matrix.
  – More than 99% entries are missing.

• Cold Start.
  – Some users or items have no ratings.

• More importantly, the low-rank assumption may be too restrictive.
  – Lee et.al. relaxed this assumption to propose the local low rank matrix approximation (LLORMA) framework. [Lee et.al. ICML 2013]
LLORMA

• The rating matrix is composed of a number of smaller matrices which are of low rank.
• The rating is then predicted by weighted ensemble of predictions from all submatrices.

\[
R_{ij} = \sum_{t=1}^{q} \frac{\omega_{ij}^t}{\sum_{s=1}^{q} \omega_{ij}^s} \left[ u_i^t (v_j^t)^\top \right].
\]
Problems of LLORMA

• Meaningless of submatrices
  – Randomly select *anchor points* from the rating matrix.
  – Select other points within some distance threshold.

• Inconsistence of submatrices.

\[ d(i_t, k) = \arccos \left( \frac{u_{i_t} u_k}{\| u_{i_t} \| \cdot \| u_k \|} \right) \]

**Lemma III.1.** Given any matrices $U$ and $V$ which are an optimal solution to (2), then $\hat{U} = UQ$ and $\hat{V} = VQ^{-1}$ are also an optimal solution, if matrix $Q$ is invertible.

• Space and computational cost.
  – Need to save pairwise similarities of all points in all submatrices.
Our Work (Social Local Models)

• We are the first to integrate social connections with LLORMA.
  – It can enjoy the advantages of both social recommendation and local low rank assumption.

• Meaningfulness of submatrices.
  – Social communities can explain the local models.

• Social regularization with LLORMA can further improve the recommending performance.
Our Work (Social Local Models)

- Right part is LLORMA.
- Left part motivates our framework.
Framework

• Identify social groups from the social graph and then construct submatrices based on the groups.
• Apply MF to all the submatrices, independently, and obtain multiple groups of user-specific and item-specific latent features.
• Predict the missing ratings using the ensemble of predictions from all submatrices.

$$R_{ij} = \frac{1}{q} \sum_{t=1}^{q} u_i^t (v_j^t)^\top$$
Submatrices Construction

• Heuristic methods.
  – Build the social groups based on the fact that users’ influences to each other can propagate through the networks.
  – Submatrices are constructed by firstly select influential users, called connectors, and their friends within a fixed number of hops.

• Different methods to select connectors.
  – Hub: those with the most friends.
  – Greedy: each time we select a connector, we select from those not yet covered by existing connectors.
Submatrices Construction

• Systematic methods.
  – Overlapping community detections methods can be exploited.
  – BIGCLAM are utilized for its scalability and good performance. [Yang et.al. ICDM 2013]

• After we create social groups, for each group, we select the users and the items they rate to construct a submatrix.
Submatrices Factorization

• Social LOcal Matrix Approximation (SLOMA).
  — Apply MF to each submatrix independently.

• SLOMA++.
  — Add social regularization to each submatrix factorization.

\[
\min_{U,V} \frac{1}{2} \sum_{(i,j) \in \Omega} (O_{ij} - u_i v_j^\top)^2 + \frac{\lambda}{2} (||U||_F^2 + ||V||_F^2) + \frac{\beta}{2} \sum_{i=1}^{m} \sum_{j \in F(i)} S_{ij} ||u_i - u_j||_2^2.
\]
Experimental Results

• Datasets.

<table>
<thead>
<tr>
<th></th>
<th>Users</th>
<th>Items</th>
<th>Ratings</th>
<th>R_density</th>
<th>S_edges</th>
<th>S_density</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yelp</td>
<td>76,220</td>
<td>79,257</td>
<td>1,352,762</td>
<td>0.022%</td>
<td>647,451</td>
<td>0.022%</td>
</tr>
<tr>
<td>Douban</td>
<td>103,054</td>
<td>57,908</td>
<td>15,129,113</td>
<td>0.254%</td>
<td>753,358</td>
<td>0.028%</td>
</tr>
</tbody>
</table>

• Evaluation metrics.
  – The smaller, the better.

\[
\text{MAE} = \frac{1}{|\Omega|} \sum_{(i,j) \in \Omega} |O_{ij} - R_{ij}|,
\]

\[
\text{RMSE} = \sqrt{\frac{1}{|\Omega|} \sum_{(i,j) \in \Omega} (O_{ij} - R_{ij})^2},
\]
### Experimental Results

<table>
<thead>
<tr>
<th>Datasets</th>
<th>K</th>
<th>Metrics</th>
<th>RegSVD</th>
<th>LLORMA</th>
<th>SocReg</th>
<th>SLOMA</th>
<th>SLOMA++</th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>MAE</td>
<td>0.9478</td>
<td>0.9459</td>
<td>0.9228</td>
<td>0.9362</td>
<td>0.9301</td>
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<tr>
<td></td>
<td></td>
<td>Improve</td>
<td>+1.87%</td>
<td>+1.67%</td>
<td>-0.79%</td>
<td>+0.65%</td>
<td>+0.04%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>RMSE</td>
<td>1.1908</td>
<td>1.1843</td>
<td>1.1802</td>
<td>1.1760</td>
<td>1.1755</td>
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<td>+0.74%</td>
<td>+0.40%</td>
<td>+0.04%</td>
<td>+0.04%</td>
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<tr>
<td>Yelp</td>
<td>20</td>
<td>MAE</td>
<td>0.9499</td>
<td>0.9477</td>
<td>0.9190</td>
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<td>0.9240</td>
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<td>+2.73%</td>
<td>+2.50%</td>
<td>-0.54%</td>
<td>+1.59%</td>
<td>+0.76%</td>
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<tr>
<td></td>
<td></td>
<td>RMSE</td>
<td>1.1918</td>
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<td>+1.85%</td>
<td>+1.38%</td>
<td>+0.48%</td>
<td>+0.76%</td>
<td>+0.76%</td>
</tr>
<tr>
<td>Douban</td>
<td>10</td>
<td>MAE</td>
<td>0.5828</td>
<td>0.5811</td>
<td>0.5662</td>
<td>0.5744</td>
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<td>Improve</td>
<td>+3.86%</td>
<td>+3.58%</td>
<td>+1.04%</td>
<td>+2.45%</td>
<td>+2.07%</td>
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<tr>
<td></td>
<td></td>
<td>RMSE</td>
<td>0.7347</td>
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<td>0.7165</td>
<td>0.7255</td>
<td>0.7105</td>
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<td>+3.29%</td>
<td>+2.80%</td>
<td>+0.84%</td>
<td>+2.07%</td>
<td>+2.07%</td>
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<tr>
<td></td>
<td>20</td>
<td>MAE</td>
<td>0.5803</td>
<td>0.5779</td>
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<td>0.5715</td>
<td>0.5573</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Improve</td>
<td>+3.96%</td>
<td>+3.56%</td>
<td>+1.15%</td>
<td>+2.48%</td>
<td>+2.01%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>RMSE</td>
<td>0.7320</td>
<td>0.7278</td>
<td>0.7142</td>
<td>0.7225</td>
<td>0.7080</td>
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<tr>
<td></td>
<td></td>
<td>Improve</td>
<td>+3.28%</td>
<td>+2.72%</td>
<td>+0.87%</td>
<td>+2.01%</td>
<td>+2.01%</td>
</tr>
</tbody>
</table>

- Our proposed methods outperform baselines consistently, which demonstrates the effectiveness of our framework.
- Comparing SLOMA and LLORAM, the performance gain is obtained by incorporating the social connections.
- Comparing SLOMA++ and SocReg, the performance gain is obtained by the local low rank assumption.
Experimental Results

• Impact of number of local models.
  – When the number is smaller than 10, the performance is weak.
  – When the number is larger, e.g., 50, the performance is consistently good.
Experimental Results

• Impact of number of hops.
  – When the number is smaller than 3, the performance is weak.
  – When the number is larger than 3, the performance is consistently good.
Experimental Results

- **Impact of Connector Selection methods.**
  - Hub and Greedy are the best two methods.
  - Community-based one is the worst.
Conclusion

• We propose social local models to enhance LLORMA.

• Social recommendation and local low rank assumption can both benefit the recommending performance.

• Experimental results have demonstrates the effectiveness of our SLOMA and SLOMA++. 