Applying Expert for Recommending Items

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Introduction

Source: www.executivechase.in, www.blu-amp.com
Introduction (cont.)

Collaborative filtering

<table>
<thead>
<tr>
<th></th>
<th>w</th>
<th>x</th>
<th>y</th>
<th>z</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>4</td>
<td>3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>b</td>
<td>4</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>c</td>
<td></td>
<td>3</td>
<td>4</td>
<td></td>
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<tr>
<td>d</td>
<td>2</td>
<td>4</td>
<td></td>
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</tbody>
</table>

Recommender Systems

Source: sal-garcia.com, limn.it
Introduction (cont.)

Friends

Experts

Introduction (cont.)

Social Network

Frequency of Rating

<table>
<thead>
<tr>
<th>User/Movie</th>
<th>Movie 1</th>
<th>Movie 2</th>
<th>Movie 3</th>
<th>Movie 4</th>
<th>Movie 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>User 1</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td>3</td>
</tr>
<tr>
<td>User 2</td>
<td>5</td>
<td>4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>User 3</td>
<td></td>
<td>4</td>
<td></td>
<td></td>
<td>5</td>
</tr>
<tr>
<td>User 4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>4</td>
</tr>
<tr>
<td>User 5</td>
<td></td>
<td></td>
<td>3</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>User 6</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

User Rating

Related Work

• Recommender System
  – Collaborative filtering
  – Content-based filtering
  – Hybrid filtering
• Friends VS Experts
Related Work

• Applying Experts in Recommender system
  – Recommend expert
  – Develop recommender system

• Experts Identification
  – Reputation (Social Network)
  – Himself (Frequency of Rating)
  – Another person (User Rating)
Proposed Approach

- Item Requirement
- Items
- Expert Identification
- Social Network
- User Rating
- Expert Neighbor Filtering
- User-Items Matrix
- Prediction
- Recommended Item

The Eleventh International Symposium on Natural Language Processing SNLP-2016
Proposed Approach (cont.)

Expert Identification

- Item Requirement
- Match Items Requirement
- List of Items Requirement
- Items
Proposed Approach (cont.)

Expert Identification (cont.)

- Social Network
- List of Items Requirement
- Count Indegree
- List of Expert from SN
- User-Items Matrix
Proposed Approach (cont.)

Expert Identification (cont.)

List of Items Requirement → Calculate Item Similarity → User Items Matrix

(Threshold: 0.7, 0.8, 0.9)

User Rating

Calculate User Rating (Like) → List of Expert From User Rating (Like)

Count Rating → List of Expert From Frequency of Rating
Proposed Approach (cont.)

Expert Neighbor Filtering

1. User-Items Matrix
2. List of Expert
3. Calculate Expert Neighbor Similarity (Distance Based)
4. Sort and Filter Expert Neighbor (10% to 90%)
5. List of Expert
Proposed Approach (cont.)

Prediction

\[ p_{a,x} = R_a + \frac{\sum_{b=1}^{n} (Similarity_{a,b} \times (R_{b,x} - R_b))}{\sum_{b=1}^{n} (Similarity_{a,b})} \]

List of Expert \[ \rightarrow \] Predict Result \[ \rightarrow \] Result of Prediction \[ \rightarrow \] Recommended Item

[1, 5]
Proposed Approach (cont.)

Comparison

Evaluation:
- Expert Identification based on Social Network
- Expert Identification based on Frequency of Rating *
- Expert Identification based on User Rating *

* with Item Similarity threshold 0.7, 0.8, 0.9
Proposed Approach (cont.)

Comparison

Consideration:
- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Accuracy (%)
- Precision
- Recall
Experiment

Experimental Setup

- Epinion dataset
  (user 20,355; Item 30,738; Transaction 532,837)
- Divide data 5 folds
- Similarity Measure:
  Distance based Similarity Measure
  (Manhattan, Chebychev, Euclidean, Minkowsky)
Experiment (cont.)

Experimental Results (cont.)
**Experimental Results**

**Experimental Results from Minkowsky Similarity (r=3)**

<table>
<thead>
<tr>
<th>Similarity by Minkowsky (r=3)</th>
<th>ESN</th>
<th>EF (0.7)</th>
<th>EF (0.8)</th>
<th>EF (0.9)</th>
<th>EL (0.7)</th>
<th>EL (0.8)</th>
<th>EL (0.9)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average MAE</td>
<td>0.147</td>
<td>0.146</td>
<td>0.146</td>
<td>0.146</td>
<td>0.148</td>
<td>0.147</td>
<td>0.147</td>
</tr>
<tr>
<td>Average RMSE</td>
<td>0.383</td>
<td>0.382</td>
<td>0.382</td>
<td>0.382</td>
<td>0.384</td>
<td>0.384</td>
<td>0.384</td>
</tr>
<tr>
<td>Average Accuracy (%)</td>
<td>85.297</td>
<td><strong>85.404</strong></td>
<td>85.402</td>
<td>85.402</td>
<td>85.236</td>
<td>85.251</td>
<td>85.268</td>
</tr>
<tr>
<td>Average Precision</td>
<td>0.979</td>
<td>0.984</td>
<td>0.984</td>
<td>0.984</td>
<td>0.978</td>
<td>0.978</td>
<td>0.979</td>
</tr>
<tr>
<td>Average Recall</td>
<td>0.866</td>
<td>0.864</td>
<td>0.864</td>
<td>0.864</td>
<td>0.867</td>
<td>0.867</td>
<td>0.866</td>
</tr>
</tbody>
</table>

* ESN : Expert from SN ,  
EF: Expert from Frequency of Rating ,  
EL : Expert from User Rating (Like)
Experiment (cont.)

Experimental Results (cont.)

![Graph showing experimental results](image-url)
Experiment (cont.)

Experimental Results (cont.)
Conclusion

• The contribution of this research is present an applying expert for recommending items
• Percentage of Accuracy are more than 80%
• The error rate of approximately 0.14
• Experts from frequency of rating method is more accurate than other methods
Conclusion (cont.)

- Future work, combination items category
THANK YOU
for your attention.

Source: www.linkedin.com