Recommendation Systems

- Predict items a user may be interested in based on information about the user and the items
- An effective way to help people cope with information overload
- Examples: Amazon, Netflix, Tivo, ...

So How Can We Do It?

- The content-based approach
- The user feedback-based approach

Collaborative Filtering

- Rate items based on the ratings of other users who have similar taste as you

Problem Definitions

- Prediction
  - Given: a user and $k$ items
  - Return: predicted rating for each item
- Recommendation
  - Given: a user
  - Return: $k$ items from the database with the highest predicted rating

Basic Assumptions

- Items are evaluated by users explicitly or implicitly
  - Ratings, reviews
  - Purchases, browsing behaviors
  - ...
- We may map explicit and implicit evaluations to a rating scale, e.g. 1-5.
Heuristic
- People who agreed in the past are likely to agree in the future

Problem Formulation

<table>
<thead>
<tr>
<th>Item</th>
<th>Ken</th>
<th>Lee</th>
<th>Meg</th>
<th>Nan</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>4</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>2</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>3</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>5</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>4</td>
<td>1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>??</td>
<td>2</td>
<td>5</td>
<td></td>
</tr>
</tbody>
</table>

So what would be Ken’s rating for Item 6??

Solving the Problem
- Intuition: Ken’s rating for Item 6 is likely to be high
  - Ken’s ratings are similar to Meg’s
  - Ken’s ratings are opposite of Lee’s
- Develop the algorithm
  1. Quantify rating similarity
  2. Calculate the predicted rating

Similarity Measure
- Pearson Correlation Coefficient
  - A measure of linear correlation of two random variables

Pearson Correlation Coefficient
- Let $x$ and $y$ be two users, and $r_{x,j}$ be the rating of item $j$ by user $x$

$$w_{x,y} = \frac{\text{cov}(x, y)}{\sigma_x \sigma_y} = \frac{\sum (r_{x,j} - \bar{r}_x)(r_{y,j} - \bar{r}_y)}{\sqrt{\sum (r_{x,j} - \bar{r}_x)^2 \sum (r_{y,j} - \bar{r}_y)^2}}$$

So what is $w_{x,y}$?? What’s the range of $w_{x,y}$??

Predict the Rating
- The predicted rating $\hat{r}_{x,j}$ should be a function of
  - The past ratings of user $x$
  - The ratings of other users for item $j$, weighted by their similarity to user $x$
Predicted Rating

\[ P_{x,i} = \bar{r}_x + \frac{\sum_i (r_{x,i} - \bar{r}_x) \times W_{x,i}}{\sum_i |W_{x,i}|} \]

So what is \( p_{x,i} \) ??

Variations and Optimizations

- Similarity measure
- Significance weighting
- Item rating variance
- Neighborhood selection
- Combine neighborhood ratings

Other Similarity Measures ...

- Spearman Correlation
  - Uses ranks instead of raw rating scores
- Cosine similarity
- Mean squared difference
- Entropy-based
- ...

... Other Similarity Measures

- Cosine similarity: \( \cos(X,Y) = \frac{X \cdot Y}{|X||Y|} = \frac{\sum x_i y_i}{\sqrt{\sum x_i^2} \sqrt{\sum y_i^2}} \)
- Mean squared difference: \( \text{msd}(X,Y) = \frac{\sum (x_i - y_i)^2}{N} \)
- Entropy-based association: \( h(X,Y) = -\sum p_{x,i} \ln p_{x,i} \)

Significance Weighting

- Weight users in addition to the similarity measure

\[
w = \begin{cases} 
1 & n \geq 50 \\
\frac{n}{50} & n < 50 
\end{cases}
\]

where \( n \) is the number of items rated by both users.

Item Rating Variance

- Some items are more telling about tastes than others
  - E.g. “Sleepless in Seattle” is more telling about taste than “Titanic”
  - Give more weight to items with high variance in ratings
Neighborhood Selection

- Select a subset of users for better performance and accuracy
  - Correlation threshold
  - Best $n$ neighbors

Combine Neighborhood Ratings

- Deviation from mean
- Weighted average
- Weighted average of z-scores

\[ \text{Mean absolute deviation: } \frac{1}{n} \sum |r_i - \bar{r}| \]

\[ \text{Standardized measurement (z-score): } z_i = \frac{r_i - \bar{r}}{s} \]

Algorithm Quality Metrics

- Coverage – percentage of items for which the system can produce a prediction
- Accuracy
  - Statistical metrics
    - Mean Absolute Error (MAE)
  - Decision-support metrics
- Efficiency
  - Throughput – number of recommendations per second

And The Winners Are

- Similarity measure
  - Pearson Correlation
  - Spearman Correlation
- Significance weighting
- Neighborhood selection
  - Best $n$ neighbors with $n=20$
- Combine neighborhood ratings
  - Deviation from mean

Other Recommendation Algorithms

- Combine collaborative and content-based filtering
- Item-item collaborative filtering
- Bayesian networks
- ...

Collaborative Filtering Libraries

## References