SmallWorlds: Visualizing Social Recommendations

Brynjar Gretarsson, John O’Donovan, Svetlin Bostandjiev, Christopher Hall, Tobias Hollerer
Problema – Dataset

- Usuario activo – en su FB cuenta
- Items – Películas, música
- Acceso restringido
- Visualización y interacción
Human-computer Interaction (HCI)

- User data
- Context data
- Recommendations
Human-computer Interaction (HCI)

- Medium node as extra step
- Arrows = interactions

Fig. 1. Interactive recommender framework.

- User satisfaction
- Trust
- Transparency
- Sense of control

Fig. 2. User mental model of interactive recommender systems.

Interactive recommender systems: A survey of the state of the art and future research challenges and opportunities
Preguntas de investigación

1. Visualización -> transparency + satisfaction
2. Interacción -> sense of control
3. Visualización -> “ambient information”
4. Social connections -> satisfaction + accuracy
Main topics
Interfaz
Interfaz

- Representacion
- Posición
- Visualización
- Interaccion
- Config. inicial
- Algoritmo
Interfaz
Capa 1
Capa 2
Capa 2

- Items de activo
- Weight – float
- Default: 1
- Cambia el dataset
- Dataset dinámica
- Tiene que ajustar todos los pesos
Capa 3
Capa 3

\[
UserSimilarity(x,u) = \frac{UserWeight(u) \cdot TotalWeightOfCommonItems(x,u)}{\sqrt{TotalWeightOfItems(x) \cdot TotalWeightOfItems(u)}}
\]

- Basado en items comunes
- Basado en UserWeight
Capa 3

\[ TotalWeightOfCommonItems(x,u) = \sum_{i \in I} \left( Likes(x,i) \cdot Likes(u,i) \cdot ItemWeight(i) \right) \]

\[ Likes(u,i) = \begin{cases} 1 & \text{caso de éxito} \\ 0 & \text{caso de fracaso} \end{cases} \]

- Basado en items comunes
Capa 3

- Basado en UserWeights
- "tweaking" en tiempo real
- $0 \leq \text{UserWeight} \leq \infty$
- Default: 1
Capa 3

\[
\text{TotalWeightOfItems}(u) = \sum_{i \in I} (\text{Likes}(u, i) \cdot \text{ItemWeight}(i))
\]

\[
\text{UserSimilarity}(x, u) = \frac{\text{UserWeight}(u) \cdot \text{TotalWeightOfCommonItems}(x, u)}{\sqrt{\text{TotalWeightOfItems}(x) \cdot \text{TotalWeightOfItems}(u)}}
\]

• Normalizar
Capa 3

- UserWeight muy alto
- Afuera del rango [0, 1]
- Limite superior

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>UserWeight</td>
<td>30</td>
</tr>
<tr>
<td>Common items</td>
<td>5</td>
</tr>
<tr>
<td>Total items (u)</td>
<td>5</td>
</tr>
<tr>
<td>Total items (x)</td>
<td>5</td>
</tr>
<tr>
<td>UserSimilarity</td>
<td>30</td>
</tr>
</tbody>
</table>

\[
UserSimilarity(x, u) = \frac{UserWeight(u) \cdot TotalWeightOfCommonItems(x, u)}{\sqrt{TotalWeightOfItems(x) \cdot TotalWeightOfItems(u)}}
\]

\[
BoundedUserSimilarity(x, u) = \min(1, UserSimilarity(x, u))
\]
Capa 4
Capa 4

- Recomendaciones
- Conexiones sociales – filtrado
- Score
  - Aristas
  - BoundedUserSimilarity
Capa 4

- Aristas: Likes
- BoundedUserSimilarity

\[ Score(x, i) = \sum_{u \in U} (Likes(u, i) \cdot BoundedUserSimilarity(x, u)) \]
Evaluación

• User study – tasks
  • Facebook (Benchmark)
  • Interfaz arbol
  • Interfaz circulo

• User study – evaluar recomendaciones
  • SmallWorlds
  • MovieLens 100K dataset con CF (MovieLens) [MAL*03]

• Automated accuracy test – leave-one-out cross validation
  • SmallWorlds
  • MovieLens 1M (10K items) dataset con MovieLens QuickPick [Gro09]
User study - results

- **S5**
- Sense of control ✅

<table>
<thead>
<tr>
<th>#</th>
<th>Question Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>effective for finding commonalities in taste</td>
</tr>
<tr>
<td>S2</td>
<td>item popularity easily discoverable</td>
</tr>
<tr>
<td>S3</td>
<td>interesting items easily discoverable</td>
</tr>
<tr>
<td>S4</td>
<td>was easy to use</td>
</tr>
<tr>
<td>S5</td>
<td>was intuitive overall</td>
</tr>
<tr>
<td>S6</td>
<td>was clumsy overall</td>
</tr>
<tr>
<td>S7</td>
<td>was informative overall</td>
</tr>
<tr>
<td>S8</td>
<td>helped you to explore the given topic</td>
</tr>
<tr>
<td>S9</td>
<td>helped you to build your movie profile</td>
</tr>
</tbody>
</table>
User study – other results

<table>
<thead>
<tr>
<th>Method</th>
<th>MovieLens</th>
<th>SW-Tree (interactive)</th>
<th>SW-Tree</th>
</tr>
</thead>
<tbody>
<tr>
<td>Satisfaction</td>
<td>4.25</td>
<td>4.19</td>
<td>3.78</td>
</tr>
</tbody>
</table>

Table 2: Satisfaction ratings of item predictions for Movielens and for SmallWorlds with and without user interactions.

Figure 6: Relation between satisfaction with recommendations and number of Facebook friends.
Conclusion & future work

Interactive recommender systems: A survey of the state of the art and future research challenges and opportunities

<table>
<thead>
<tr>
<th>Approaches</th>
<th>Metrics</th>
<th>Data collection methods</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>SmallWorlds (Figure 4)</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Comparison with baseline without recommendations</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Comparison with baseline without user control or visualization</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Comparing different visualizations</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Comparing different recommendation algorithms</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>Asking users to explore freely</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>

- User satisfaction ✓
- Transparency ✓
- Sense of control ✓
Referencias


Demo video

- Por el cambio de Facebook API, ya no funciona SmallWorlds
- [https://vimeo.com/21060974](https://vimeo.com/21060974)
Web based architecture

• Procesamiento en el servidor
• Captura los movimientos del raton
User study – 7 tasks

1. Task 1: Familiarization (5 mins, supervised)
2. Task 2: Find popular items in your peer-group.
3. Task 3: Find your 3 most similar peers
4. Task 4: Find your 3 least similar peers
5. Task 5: Get recommendations through layout only
6. Task 6: Get recommendations through layout and interaction
7. Task 7: Get recommendations through layout and interaction, with layer 4 (candidate-set) items hidden.

- 17 participantes
- 50 – 1200 amigos (mediano 215)
User satisfaction evaluation

1. For each participant, a list of recommendations are generated by SW or MovieLens.
2. The participants then rate these items on a 5 point rating scale.
3. The ratings are subtracted from 5 (assumed ground truth) as the MAE.
Automated accuracy test

Leave one out analysis
1. Train using $n-1$ items in the profile (Layer 2)
2. Aim to have the left out item in the top 12 recommendations of SW and MovieLens
3. Record for each user the number of times the left out item is included in the list (iteration depends on n), e.g. User X has 10 items, left out item is recommended 2 times in the 10 iterations.
4. Compute the average per user per system: 1.94 items (SW) 0.82 items (MovieLens)
5. Top 5: 1.00 (SW) 0.65 (MovieLens)

Winner-loser analysis
1. The same as above but compare between the two, the number of times each system had the removed item ranked higher than the other.
2. 1.88 items SW ranked higher than MovieLens, 0.65 items MovieLens ranked higher.

Note: MovieLens have much more data.