interactive visualizations of recommendations for social streams

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Plan

• Problem – user satisfaction with recommendations
• Early works
  – Open learner modeling
  – Social navigation
• Visualization and user control of recommendations in streams – 6 approaches
• Analysis and general challenges
Problem

• Most recommender systems are evaluated for **Analytical metrics**, such as **accuracy**, coverage, diversity, novelty

• **User satisfaction** with recommendations is harder to evaluate
  – Depends on user **trust** (Felfering, 2007, Cramer et al, 2008)
  – Trust can be gained with **explanation** of how the system works (Tintrarev & Masthoff, 2007) (Herlocker, et al. 2000)
  – Depends on **user understanding and control** (Knijenburg et al, 2012): “...inspectability and control indeed increase users’ perceived understanding of and control over the system, their rating of the recommendation quality, and their satisfaction of the system”

• So, how to present the system adaptations / suggestions to
  – **Explain** the reasons / mechanism for adaptation and
  – Involve and **Give control** to the user
Historical overview of interactive/visual recommendations

- Intelligent tutoring systems and learning environments
- Open learner models
- Adaptive navigation support
- Social navigation support
- Interactive Recommender systems
Give user control

Visualize other user models – open social

To change rec. process
To change model

Content (Compare with others)
Footprints (Navigation support)

Visualize user model

To explain Recommendation (Brusilovsky)
To stimulate reflection on Content (Kay, Bull, Dimitrova, Zapata Rivera & Greer...)
The idea of “Skillometers”

- Corbett and Anderson, 1995 - APTList Tutor
- …
- …
- …
- …
- …
- …
- …
- …
- …

- Finally now it shows up in the HCI community:

The ideas of opening up the learner model 1994-1995

• Judy Kay with students - 1994 – scrutability of learner /user models
  – To verify it and eventually fix errors
  – But can we trust the learner to change the model?

• Susan Bull – 1995 – focus on open learner models as a tool for reflection
  – Don’t trust learner corrections, store both the learner’s and system’s model of the learner
  – Discuss the differences, involve learner in argument
ELM: Visualization of Rec’s for Navigation in a Course

VisMod – open model to teachers & parents

JD Zapata-Rivera, JE Greer (2000) *Inspecting and visualizing distributed Bayesian student models* Intelligent Tutoring Systems, 544-553
CourseVis: presenting multiple models of students to teachers

Comtella: Visualizing peer contributions: to motivate participation


Comparison with peers

Comparison to peers on a scale:
Social navigation

Brusilovsky & Sosnovsky, 2003
Social Navigation with QuizMap

Peter Brusilovsky, I-Han Hsiao, Yetunde Folajimi (2011) QuizMap: Open Social Student Modeling and Adaptive Navigation Support with Tree Maps. Towards Ubiquitous Learning, Springer
Bostandjev’s layered approach for visualizing hybrid recommendations
Control to the user: Interactive hybrid recommender visualization


• Until 10 yrs ago - recommending in a fairly static context (educational content, music, music, products)

• However the social web (with user-generated content) has brought both opportunities and problems

http://www.citravel.com/blog/meet/?p=94
http://www.ilead.co.za/blog/the-age-of-information-overload-and-how-to-simplify-communication.html
What did we do 2006-now?

• Focused on social environments
  → recommending items of interest in time-based streams of social (user-generated) data

• Different requirements from recommending products or people
  → User satisfaction is crucial (otherwise they won’t use the tool)

→ You don’t want to miss something important; but if something unimportant gets recommended – no problem → Recall is more important than precision
Comtella-D

• Andrew Webster, 2006
• Recommends posts in discussion forum, and threads based on their popularity and rating
• Visualizes highly rated content with visual emphasis (rec. by popularity)
  – Hierarchical propagation of visual emphasis from post to thread
• Visualizes the impact of a single rating on rec.

For threaded discussion forums
Popularity based, not personalized
Comtella-D (2006)

Immediate visual feedback on user actions of rating posts

@work Energy

The quick red fox jumped over the lazy brown dog.
By Andrew

All generalizations are false, including this one.
By Mark Twain

Stored Energy

(*) (*) (*) (*) (*)
Evaluation

While subtle, the visual “heating up” or “cooling down” effect that followed the user’s act of rating was fun, fitted the energy metaphor, and didn’t distract the users’ attention or pose an additional cognitive load. The energy system acted as an implicit recommender function.

<table>
<thead>
<tr>
<th>Label</th>
<th>N</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>C_α</td>
<td>10</td>
<td>Core users (computer science students) who are required to participate and who see the test interface.</td>
</tr>
<tr>
<td>C_β</td>
<td>9</td>
<td>Core users who see a control (standard discussion forum) interface.</td>
</tr>
<tr>
<td>P_α</td>
<td>15</td>
<td>Peripheral users (philosophy students and others) who are not required to participate and who see the test interface.</td>
</tr>
<tr>
<td>P_β</td>
<td>17</td>
<td>Peripheral users who see a control interface.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Group</th>
<th>Threads</th>
<th>Posts</th>
<th>Comments</th>
<th>Evaluations</th>
<th>Logins</th>
<th>Threads</th>
<th>Relavis</th>
</tr>
</thead>
<tbody>
<tr>
<td>C_α</td>
<td>72</td>
<td>326</td>
<td>17</td>
<td>55</td>
<td>66.3</td>
<td>233.6</td>
<td>4</td>
</tr>
<tr>
<td>C_β</td>
<td>60</td>
<td>299</td>
<td>5</td>
<td>11</td>
<td>48.6</td>
<td>180.2</td>
<td>n/a</td>
</tr>
<tr>
<td>P_α</td>
<td>6</td>
<td>10</td>
<td>0</td>
<td>6</td>
<td>15.9</td>
<td>28.1</td>
<td>1.1</td>
</tr>
<tr>
<td>P_β</td>
<td>1</td>
<td>6</td>
<td>1</td>
<td>4</td>
<td>7.9</td>
<td>19.2</td>
<td>n/a</td>
</tr>
</tbody>
</table>

KeepUP

• Andrew Webster, 2007
• Recommends RSS feeds from different streams, semantically annotated (tags, LSA)
• Visualizes the user’s neighbourhood in CF and allows user to manually change the impact of other users over him

Personalized – Collab. Filtering within Channels, Content-Based for Channels
KeepUP Vis – 1st version
KeepUP (2007)

**12 participants, KeepUp**

<table>
<thead>
<tr>
<th>Question</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) How <strong>effective</strong> do you believe KeepUP is at learning your preferences?</td>
<td>0</td>
<td>1</td>
<td>4</td>
<td>6</td>
<td>1</td>
</tr>
<tr>
<td>2) How would you rate your <strong>satisfaction</strong> with KeepUP’s recommendations?</td>
<td>0</td>
<td>1</td>
<td>4</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>3) How <strong>trusting</strong> are you of KeepUP’s ability to make correct recommendations to you?</td>
<td>0</td>
<td>2</td>
<td>5</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>4) How <strong>comfortable</strong> are you with others knowing what articles you like and don’t like?</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>5) How <strong>useful</strong> is the visualization in identifying others who are like-minded to you?</td>
<td>0</td>
<td>1</td>
<td>5</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>6) How <strong>useful</strong> is the tag cloud in identifying others who are like-minded to you?</td>
<td>0</td>
<td>5</td>
<td>1</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>7) How <strong>interested</strong> are you in seeing others who are like-minded to you regarding specific topics?</td>
<td>1</td>
<td>0</td>
<td>3</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>8) How much <strong>difference</strong> in your recommendations did you notice after changing your neighbours’ influence?</td>
<td>0</td>
<td>0</td>
<td>6</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>9) Would having a high level of influence on your neighbours be <strong>important</strong> to you?</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>10) Do you see the service that KeepUP provides as being <strong>useful</strong> to you?</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>5</td>
</tr>
<tr>
<td>11) How often would you <strong>use</strong> KeepUP, given the opportunity?</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>8</td>
<td>3</td>
</tr>
</tbody>
</table>
IBlogVis

• **Indratmo 2008-2010**

• Recommendation by the social interaction history around content (#commenters, #digs) – like social navigation

• For streams, archives, timeline-based data - Visualization of a blog archive

• Interactive visualization allows browsing, zooming time periods...

Popularity-based rec (not personalized)
Evaluation

• Lab study
  – 19 students, predefined exploratory tasks (overview, browsing, social navigational), followed by questions (closed and open-ended)

• Results:
  – Error rate 0-3 out of 16 tasks, avg. 6.25%
  – User satisfaction

*iBlogVis* can be used as a collaborative filter.

<table>
<thead>
<tr>
<th>QUIS Category</th>
<th>Mean</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>7.67</td>
<td>7.22 - 8.12</td>
</tr>
<tr>
<td>Screen</td>
<td>7.86</td>
<td>7.30 - 8.43</td>
</tr>
<tr>
<td>Terminology</td>
<td>8.32</td>
<td>7.99 - 8.64</td>
</tr>
<tr>
<td>Learning</td>
<td>8.43</td>
<td>8.09 - 8.78</td>
</tr>
<tr>
<td>Capabilities</td>
<td>8.08</td>
<td>7.69 - 8.48</td>
</tr>
</tbody>
</table>
IBlogVis-2 (2009)

Evaluation

• Summative – within subjects design
  – Independent variable: type of vis – 3 values: List, TimeVis, and SocialVis
  – Dependent variables: interest score, perception of support, wasted effort, user satisfaction, and overall preference
  – 30 participants, different ages and background

<table>
<thead>
<tr>
<th>Measures</th>
<th>List</th>
<th>TimeVis</th>
<th>SocialVis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interest score</td>
<td>5.58 ± 1.00</td>
<td>5.86 ± 1.13</td>
<td>6.48 ± 1.09</td>
</tr>
<tr>
<td>Perception of support</td>
<td>5.00 ± 2.49</td>
<td>6.07 ± 1.91</td>
<td>7.47 ± 1.20</td>
</tr>
<tr>
<td>Wasted effort</td>
<td>0.24 ± 0.17</td>
<td>0.19 ± 0.17</td>
<td>0.11 ± 0.14</td>
</tr>
<tr>
<td>User satisfaction</td>
<td>6.45 ± 1.43</td>
<td>6.38 ± 1.42</td>
<td>7.55 ± 0.77</td>
</tr>
</tbody>
</table>
SocConnect

- Yuan Wang and Jie Zhang, 2009-2010
- Recommends social updates in social network aggregator – content based (LSA), machine learning
- Visualization of recommendations via emphasis in the stream
- User can filter - from which SSN and which friends to see updates, and what tags/topics

Personalized – content based
SocConnect Evaluation

• Field study
  – 11 valid participants (out of 21 recruited on FB and Twitter); using SocConnect for 2 weeks

• Usage data analysis and final questionnaire to evaluate user satisfaction with the new

- Only half of the participants found the use of color to highlight recommendations intuitive
- Often recommended items buried down in the stream
- Participants split in their awareness and satisfaction with the new functionalities to control the filtering (blend, group)

Details at:
Rings

• Shi Shi, 2011
• Recommends what to read on Facebook – overview first – details on demand; “Big-Bang” timeline vis.
• Prolific and reputable users and popular posts are emphasized visually
• User can interact by filtering by users, by time period (but no influence on the recommendations)
• Mostly used to avoid the filter bubble of Facebook

Popularity-based rec (not personalized)
**Evaluation**

- **Field study**

  - 21 users, need to use Rings 5 times over 3 weeks, after 5 min usage prompted to answer 5 questions.

<table>
<thead>
<tr>
<th>#</th>
<th>Strongly Disagree</th>
<th>Disagree</th>
<th>Neutral</th>
<th>Agree</th>
<th>Strongly Agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>32%</td>
<td>68%</td>
</tr>
<tr>
<td>2</td>
<td>2%</td>
<td>9%</td>
<td>6%</td>
<td>62%</td>
<td>21%</td>
</tr>
<tr>
<td>3</td>
<td>0</td>
<td>0</td>
<td>2%</td>
<td>15%</td>
<td>83%</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>2%</td>
<td>9%</td>
<td>40%</td>
<td>49%</td>
</tr>
<tr>
<td>5</td>
<td>2%</td>
<td>11%</td>
<td>15%</td>
<td>36%</td>
<td>36%</td>
</tr>
</tbody>
</table>

http://ecommons.usask.ca/handle/10388/ETD-2011-09-139
MADMICA

• Sayooran Nagulendra (2013, 2014)

• Filters away posts from friends about things which are not of common interest with the user (Content-based overlaid over Social network)

• Visualization creates awareness of what is being filtered away from each friend (in what category of interest)

• User can interactively change the way the recommender works

Personalized (content-based, social)
MADMICA (2013)

http://prezi.com
Evaluation

- Crowd-sourced lab study
  - M-turk with 326 participants (2 equal-size groups, one with embedded help and one without help)
  - Working bubble visualization incorporated in a questionnaire with equal-sized 25 tasks each
  - Metrics for visualization understandability based on International Standards for Software Quality Evaluation

![Graph showing comparison between Group 1 (no help) and Group 2 (with help) in terms of Awareness, Explanation, Control, and Overall Understandability.]
Analysis of our approaches-1

• Application area: recommending **stream data**
  – Threaded discussion forums: **Comtella-D**
  – RSS feed aggregators: **KeepUP**
  – Digg (archives): **iBlogVis**
  – Social network aggregators: **SocConnect**
  – Social network streams
    • Centralized (FB): **Rings**
    • Decentralized: **Madmica**

• **Purposes** of using visualization
  – Support exploratory browsing: **Comtella-D, iBlogVis, Rings**
  – Explaining the recommendation process to increase user trust: **Comtella-D, KeepUP, SocConnect**
  – Avoiding the filter bubble: **Rings, Madmica**
Analysis of our approaches-2

• Two main kinds of recommenders exploited
  – Popularity-based / social interaction history (not personalized): Comtella-D, iBlogVis, Rings
  – Personalized:
    • Collaborative Filtering + Content-based + Social: KeepUP,
    • Content-Based + Social NW-based: SocConnect
    • Content-Based + Social NW-based: Madmica

• Two types of adaptations exploited
  – Visual emphasis: Comtella-D, iBlogVis, Rings, Madmica
  – Filtering of non-recommended items: KeepUp, SocConnect, Madmica
Analysis of our approaches-3

- **Interactivity dimensions**
  - provide immediate feedback to user actions
  - User rating actions: Comtella-D → Visual effects on increasing/decreasing “hotness” of item
  - User adjusting strength of influence from other users: KeepUP, SocConnect, Madmica → Changing the recommended set of items in the user’s stream
  - Allow user to explore the data interactively: iBlogVis, Rings
  - allow user to change the recommendation algorithm variables: KeepUP, Madmica
General Challenges

- Unconstrained design space for visualization - finding good patterns?
- Evaluation challenges in field studies
  - Hard to isolate the effect of the visualization and interactive functions from the recommender algorithm
  - Rec. sys. for social streams need many users and long time to work well ...
    - Difficulty in recruiting large number of participants
    - Difficulty ensuring participation in loner-term studies
    - Bias towards studies on large social networks (need insider connections)
    - Hard for academics to publish small scale studies
References

• **Comtella-D:**

• **KeepUP:**

• **IBlogVis-1**

• **IBlogVis-2**

• **SocConnect**

• **Rings**

• **MADMICA**