From Preference into Decision Making

Modeling User Interactions in Recommender Systems

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Recommender Systems

- Most prior research focuses on
  - Learning from user action feedback (e.g., ratings or clicks etc.)

- This work is about
  - Learning from all user browsing (both user action and inaction) activities
Classical Approach: From Explicit/Implicit Feedback to Preference
### Explicit/Implicit Feedback and Preference

What about other (inaction) items?

**Key Missing Factor**
- Within page comparison
- Decision of action vs. inaction

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**Image Description**

- **Add into a wishlist**
- **Not interested**
- **Click to see details**
- **Rating**

*Image Credit: Zhao et al. RecSys’18*
Explicit/Implicit Feedback and Preference

What if this is the 3rd time the user sees this page?

Key Missing Factor
- Temporal dependency to prior browsing

Zhao et al. CSCW’17
Example Impact on User Experience
MovieLens

MovieLens recommends these movies

top picks

The Avengers
2012 PG-13 143 min

Skyfall
2012 PG-13 143 min

Big Hero 6
2014 102 min

Die Hard
1988 R 131 min

Zhao et al. CSCW’17
Again and Again

MovieLens recommends these movies

top picks

- The Avengers
  - 2012
  - PG-13
  - 143 min

- Skyfall
  - 2012
  - PG-13
  - 143 min

- Big Hero 6
  - 2014
  - 102 min

- Die Hard
  - 1988
  - R
  - 131 min

Zhao et al. CSCW’17
Youtube
Interested in two of them

Zhao et al. RecSys’18
Watch one of the two

Zhao et al. RecSys’18
Back to home page…?
Problem

- How to model all user browsing activities jointly?
  - Temporal browsing (viewing recommendation lists and/or searching/filtering) page by page
  - Action (performing actions on recommended items, e.g., clicking, consuming) on a page
  - Inaction (neglecting or skipping recommended items) on a page
Decision Field Theory

Figure 1: The connectionist network representation of DFT.

Busemeyer et al. Psychological Review 1993
Decision Field Theory

Preference is actually the end result of micro-level decision making processes.

Figure 7.1 The decision process for a choice among three actions
The Page-Level RNN Model

- Learn embeddings instead of using attributes
- Weights are estimated from data
- Page view sequence as the deliberation process
- There are actually 24 items because of the page size in MovieLens.
- Contrast layer is a ReLU layer
- Preference accumulation corresponds to a RNN layer
The Page-Level RNN Model

We used $n=24$ because of the page size in MovieLens.
The Page-Level RNN Model
Dataset: MovieLens System Logs

- Jan. 12, 2017 to Jan. 14, 2018
- 60K movies
- 22K users
- 45M movie displays and 1.16M (positive) actions
- Temporal splitting
  - Training: Jan. 12, 2017 to Oct. 31, 2017
  - Testing: Nov. 1, 2017 to Jan. 14, 2018
Classical **User & Preference Models**

- **SVD** (Koren et al. 2009):

- **SVD++** (Koren et al. 2010):

- **RNN** (Wu et al. 2017):
Results

<table>
<thead>
<tr>
<th>User Model</th>
<th>MAP@8</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVD</td>
<td>0.097</td>
</tr>
<tr>
<td>SVD++</td>
<td>0.106</td>
</tr>
<tr>
<td>RNN</td>
<td>0.119</td>
</tr>
<tr>
<td>PL-RNN</td>
<td>0.141</td>
</tr>
</tbody>
</table>

Modeling user actions as a sequence through RNN seems to learn a better user representation compared with SVD or SVD++

Page-level RNN gains substantially better accuracy than RNN.
Classical User & *Preference* Models

- **Independent binary** (logistic; Hu et al. 2008):
  \[ p(r|u, v) = g^r (1 - g)^{1-r} \]

- **Competitive** (softmax; Yang et al. 2011, CCF):
  \[ \hat{p}(a|u, v) = \hat{p}_a(a_i = 1|u, v) = \frac{\exp(f(s, o_i))}{\sum_{k=1}^{\alpha+1} \exp(f(s, o_k))} \]

- **Relative** (pairwise ranking; Rendle et al. 2009):
  \[ p(r_a > r_b|u, v_a, v_b) = g(f(s, o(v_a) - o(v_b))) \]
“Negative” Items

● Negative sampling (Hu et al. 2009)

● Displayed but inaction (Yang et al. 2011; Zhao et al. 2018)
Results (MAP@8)

<table>
<thead>
<tr>
<th>User Model</th>
<th>Preference Model</th>
<th>Displayed but Inaction “Negative”</th>
<th>Sampled “Negative”</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVD</td>
<td>logistic</td>
<td>0.0006</td>
<td>0.104</td>
</tr>
<tr>
<td></td>
<td>softmax</td>
<td>0.0006</td>
<td>0.097</td>
</tr>
<tr>
<td></td>
<td>pairwise ranking</td>
<td>0.114</td>
<td>0.106</td>
</tr>
</tbody>
</table>

Softmax and logistic preference models are sensitive to the choice of negative items.

Pairwise preference models can learn equally well on both types of negative items.
Messages

- Jointly modeling the three aspects (temporal browsing, action and inaction) of user-system interaction in recommender systems has benefits in
  - (this work) offline recommendation accuracy
  - (maybe, future work) online user experience

- Go from simplified preference assumptions into modeling the complex micro-level user decision making processes.
Thanks! Questions?

- **Title:** “From Preference into Decision Making: Modeling User Interactions in Recommender Systems”
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- **Contact:** qzhao2018@gmail.com
Hybrid Based on *Retrieving & Ranking*

- **Retrieving Model**
  - Trained with:
    - Action items as positive
    - Randomly sampled as negative

- **Ranking Model**
  - Trained with:
    - Action items as positive
    - Displayed but inaction as negative
## Results

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</tr>
<tr>
<td>RNN</td>
<td>softmax &amp; pairwise</td>
<td>sampled &amp; displayed but inaction</td>
<td>0.119</td>
</tr>
<tr>
<td>RNN &amp; SVD</td>
<td>softmax &amp; pairwise</td>
<td>sampled &amp; displayed but inaction</td>
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