Towards Complex User Feedback and Presentation Context in Recommender Systems

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User Implicit Feedback

Results

Dwell time: 16.8 sec
Mouse moving time: 1.8 sec
Travelled distance: 2009px
User Feedback – Past Research

- Combine multiple implicit feedback features to estimate user rating
- Standard CB / CF recommender systems can be used afterwards

- Improvements over the usage of simple implicit feedback

Peska, Vojtas: How to Interpret Implicit User Feedback?
Peska, Eckhardt, Vojtas: Preferential Interpretation of Fuzzy Sets in E-shop Recommendation with Real Data Experiments
Overview

- Context of user feedback – our approach
- Collecting User Behavior
- Estimated Rating from Implicit Feedback
- Employ Context in Rating Estimation
- Evaluation
- Results
- Conclusions, Future Work
Context of User Feedback

- Context of the user
  - Location, Mood, Seasonality...
  - *Can affect user preference*
  - *Out of scope of this paper*

- Context of device and page
  - Page and browser dimensions
  - Page complexity (amount of text, links, images,...)
  - Device type
  - Datetime
  - *Can affect perceived values of the user feedback*
Outline of Our Approach

Traditional recommender

- User rates a sample of objects
  \[ r_{u,o} : o \in S \subset O; \quad r_{u,o} \in [0,1] \]
- Preference learning computes expected ratings of all objects
  \[ R_u \rightarrow \hat{r}_{u,o} : o' \in O \]
- Top-k best rated objects are recommended
  \[ \hat{R}_u = \{o_1, \ldots, o_k\} \]

Our approach

- Several implicit feedback and contextual features are collected:
  \[ F_{u,o} = [f_1, \ldots, f_i] \quad C_{u,o} = [c_1, \ldots, c_j] \]
- Learn estimated rating \( \tilde{r}_{u,o} \) for visited objects based on feedback and context
  \[ F_{u,o}, C_{u,o} \rightarrow \tilde{r}_{u,o} : o \in S \]
  \[ „The more the better“ heuristics (STD, CDF) \]
  \[ Machine learning approach (J48) \]
- Incorporate context
  \[ As further feedback features (FB+C) \]
  \[ As baseline predictors (AVGBP, CBP) \]
- Learn rating on all objects as in traditional recommenders
  \[ \tilde{R}_u \rightarrow \hat{r}_{u,o} : o' \in O \]
Collecting User Behavior

- IPIget component for collecting user behavior

<table>
<thead>
<tr>
<th>Implicit Feedback Features</th>
<th>Contextual features</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_1$ View Count</td>
<td>$c_1$ Number of links</td>
</tr>
<tr>
<td>$f_2$ Dwell Time</td>
<td>$c_2$ Number of images</td>
</tr>
<tr>
<td>$f_{3,4}$ Mouse Distance and Time</td>
<td>$c_3$ Text size</td>
</tr>
<tr>
<td>$f_{5,6}$ Scrolled Distance and Time</td>
<td>$c_4$ Page dimensions</td>
</tr>
<tr>
<td>$f_7$ Clicks count</td>
<td>$c_5$ Visible area ratio</td>
</tr>
<tr>
<td>$f_8$ Hit bottom of the page</td>
<td>$c_6$ Hand-held device</td>
</tr>
<tr>
<td>$r$ Purchase</td>
<td></td>
</tr>
</tbody>
</table>

IPIget component download: http://ksi.mff.cuni.cz/~peska/ipiget.zip
Estimated Rating from Implicit Feedback

- „The more the better” heuristics
  - Various feedback features are not comparable in general
    - Dwell time (sec) vs. Distance travelled by mouse (pixels)
    - Transform feedback features on comparable scale and average
  - Use standardization (STD) of feedback features

- Use cumulative distribution (CDF) of each feedback feature

\[ \mu = 0 \quad \sigma = 1 \]
Estimated Rating from Implicit Feedback

- Machine learning approach
  - J48 decision tree
  - *Purchases* are golden standard
    - The only feedback which is a true indicator of positive preference
  - Predict *purchases* based on other feedback features
  - Use probability of purchase as estimated rating $\tilde{r}_{u,o}$
Employ Context in Rating Estimation

- Use context in the same way as feedback \((FB+C)\)
  - Leave the decision about usage of context on the underlined model
  - Plausible strategy for e.g. decision trees or rule mining learning approaches

- Use context as a baseline predictor of feedback
  - Calculate estimated value of feedback feature for particular context value \(\bar{f}_i(c_j)\)
  - Subtract the estimation from the actual value \(f_{i,u,o}^{bp} = f_{i,u,o} - \bar{f}_i(c_j)\)
    - Use feedback with baseline estimators instead of the original one
  - Either employ average baseline predictor over all context features (AVGBP)
  - Or use Cartesian product of feedback features and baseline predictors based on each context feature (CBP)
Preference Learning and Recommendations

- Collaborative filtering not applicable
  - Continuous cold-start problem

- Use combination of content-based and non-personalized
  - VSM (vector space model) content-based recommendation
    - Vector of object features (TF-IDF)
    - User is represented as weighted sum of visited object’s features
    - Resulting score is a cosine similarity of user and object vectors
  - Most popular non-personalized algorithm
    - Based on estimated ratings $\tilde{r}_{u,o}$

- Final score $\hat{r}_{u,o}$ is a multiplication of VSM score and most popular score
Evaluation

- Czech travel agency dataset
  - 3 variants of rating estimation (STD, CDF, J48)
  - 3 variants of context incorporation (FB+C, AVGBP, CBP)
  - 2 baselines (use raw feedback, use binary visits)

- Leave-one-out on purchased objects
  - Ranking prediction
  - nDCG, recall@top-10
### Results

<table>
<thead>
<tr>
<th>Processing method</th>
<th>Feedback and Context composition</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Binary</td>
</tr>
<tr>
<td>STD + popVSM</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.255*</td>
</tr>
<tr>
<td>CDF + popVSM</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.255*</td>
</tr>
<tr>
<td>J48 + popVSM</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.255*</td>
</tr>
<tr>
<td>J48 + objects popularity</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.180**</td>
</tr>
<tr>
<td>J48 + VSM</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.222*</td>
</tr>
</tbody>
</table>

- Results of nDCG, (*) = significant improvement of the best method
- J48 decision tree with both feedback and context on its input performs the best
- Using „the more the better“ heuristics (CDF) with properly processed feedback (AVGBP, CBP) also performs quite well
Conclusions, Future Work

Key outcomes
- Implicit feedback could be more than just a binary variable
- Observed feedback should be considered with respect to the context of page and device
  - Doing so could improve the quality of the recommended objects

Future work, Open Problems
- Better models of context employment and purchase prediction methods
- Further evaluation scenarios
  - Recommending on the beginning of a new session
- More refined feedback?
  - E.g. feedback on object’s attributes?
- On-line deployment and evaluation
Thank you!

Questions, comments?

Supplementary materials: http://bit.ly/2g79VVO