Towards Complex User Feedback and Presentation Context in Recommender Systems

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User Implicit Feedback

b)

c)

Results

Dwell time: 16.8 sec

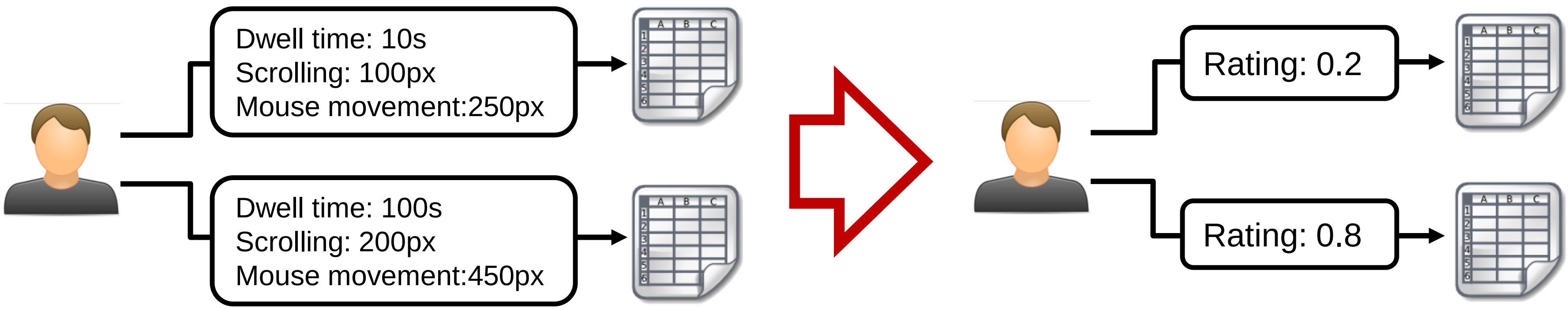
Mouse moving time: 1.8 sec

Travelled distance: 2009px

Software: *Peska, IPIget: The Component for Collecting Implicit User Preference Indicators*

User Feedback – Past Resarch

- 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

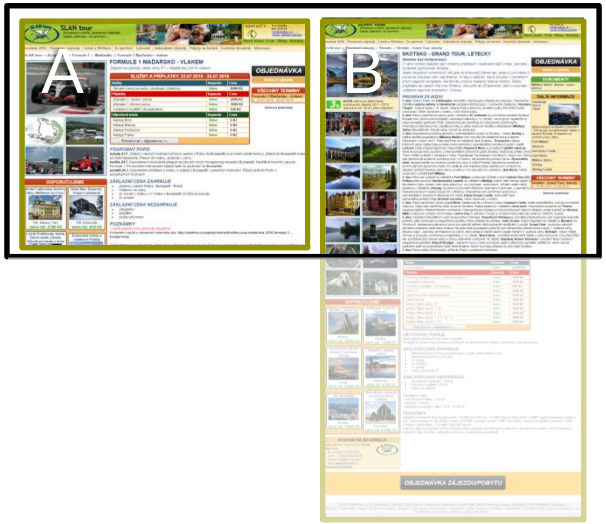
Peska, Vojtas: How to Interpret Implicit User Feedback?
Peska, Eckhardt, Vojtas: Preferential Interpretation of Fuzzy Sets in E-shop Recommendation with Real Data Experiments

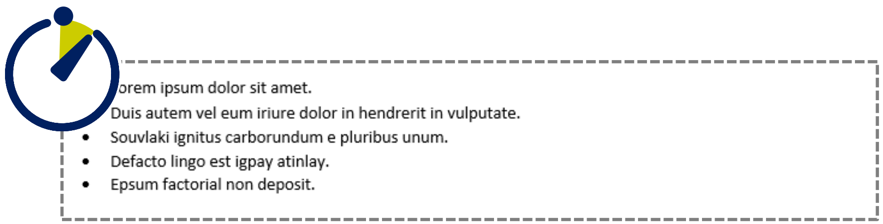
Overview

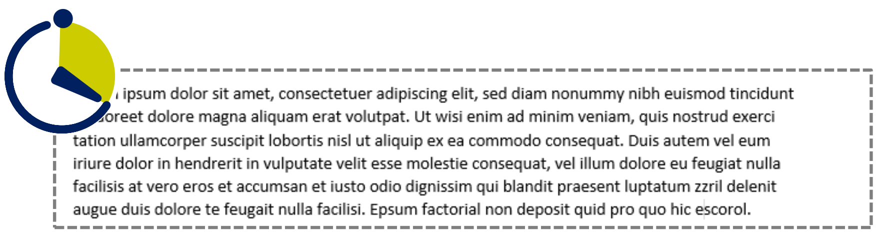
- Context of user feedback – our approach
- Collecting User Behavior
- Estimated Rating from Implicit Feedback
- Employ Context in Rating Estimation
- Evaluation
- Results
- Conclusions, Future Work

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 percieved values of the user feedback*







Outline of Our Approach

Traditional recommender

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

Our approach

- Several implicit feedback and contextual features are collected:
  $F_{u,o} = [f_1, \dots, f_i]$ $C_{u,o} = [c_1, \dots, c_j]$
- Learn estimated rating $\bar{r}_{u,o}$ for visited objects based on feedback and context
  - $F_{u,o}, C_{u,o} \rightarrow \bar{r}_{u,o}: o \in \boldsymbol{S}$
  - „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
  $\bar{R}_u \rightarrow \hat{r}_{u,o'} : o' \in \boldsymbol{O}$

Collecting User Behavior

- IPIget component for collecting user behavior

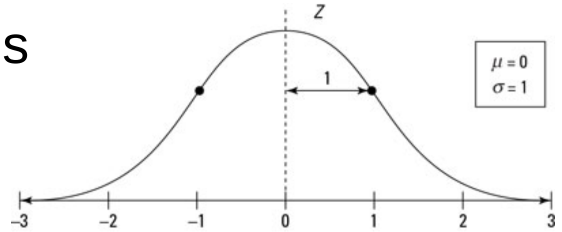
Implicit Feedback Features	
f_1	View Count
f_2	Dwell Time
$f_{3,4}$	Mouse Distance and Time
$f_{5,6}$	Scrolled Distance and Time
f_7	Clicks count
f_8	Hit bottom of the page
r	**Purchase**

Contextual features	
c_1	Number of links
c_2	Number of images
c_3	Text size
c_4	Page dimensions
c_5	Visible area ratio
c_6	Hand-held device

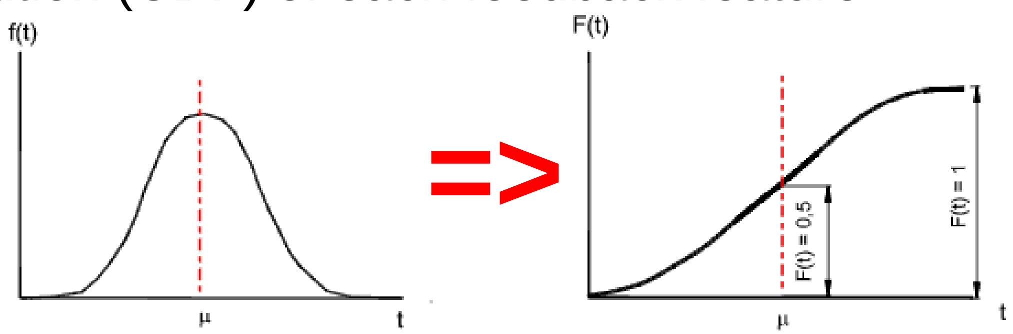
IPIget component download: http://ksi.mff.cuni.cz/~peska/ipiget.zip

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 cummulative distribution (CDF) of each feedback feature



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 $\bar{r}_{u,o}$

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 $\overline{f_i}(c_j)$
  - Subtract the estimation from the actual value $f_{i.u.o}^{bp} = f_{i,u,o} - \overline{f_i}(c_j)$
    - 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 $\bar{r}_{u,o}$

  - 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

Processing method	Feedback and Context composition				
	Binary	*FB*	FB+C	AVGBP	CBP
STD + popVSM	*0.255**	*0.174**	0.197*	0.161*	0.158*
CDF + popVSM	*0.255**	*0.257**	0.253*	0.258*	0.257
J48 + popVSM	*0.255**	*0.256**	**0.274**	0.240*	0.247*
J48 + objects popularity	*0.180***	*0.205**	*0.211**	*0.168**	*0.186**
J48 + VSM	*0.222**	*0.224**	*0.233*	*0.225**	*0.224**

- 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