Implicit vs. Explicit Feedback

Challenge

- Recommending for **small e-commerce websites**
  - *Tens of similar vendors, user can choose whichever she likes*
  - (Almost) no explicit feedback

    (No incentives for users)
  - Few visited pages

    (Often usage of external search engines & landing on object details)
  - Low user loyalty

    (New vs. Returning visitors ratio 80:20)

$\Rightarrow$ **Not enough data for collaborative filtering, continuous cold-start problem**

User Feedback

Explicit feedback

- Provided via website GUI
  - Rating an object via Likert Scale

  - Missing in small E-Commerces

Implicit feedback

- Often binary in the literature
  - User visited object
  - User bought object

User Feedback

Explicit feedback

- Provided via website GUI
  - Rating an object via Likert Scale
  - Comparing objects explicitly is not so common
  - *Missing in small E-Commerces*

Implicit feedback

- *Often binary in the literature*
  - *User visited object*
  - *User bought object*
- Virtually any event triggered by user could be a feedback
- Get better picture about user engagement / preference

User Feedback

Explicit feedback

- Provided via website GUI
  - Rating an object via Likert Scale
  - Comparing objects explicitly is not so common
  - *Missing in small E-Commerces*

Implicit feedback

- Virtually any event could be used as feedback
- Tracked via JavaScript
  - Dwell time
  - Number of page views, Scrolling, mouse events, copy text, printing
  - Purchase process etc.

Implicit User Feedback

c)

Results

Dwell time: 16.8 sec

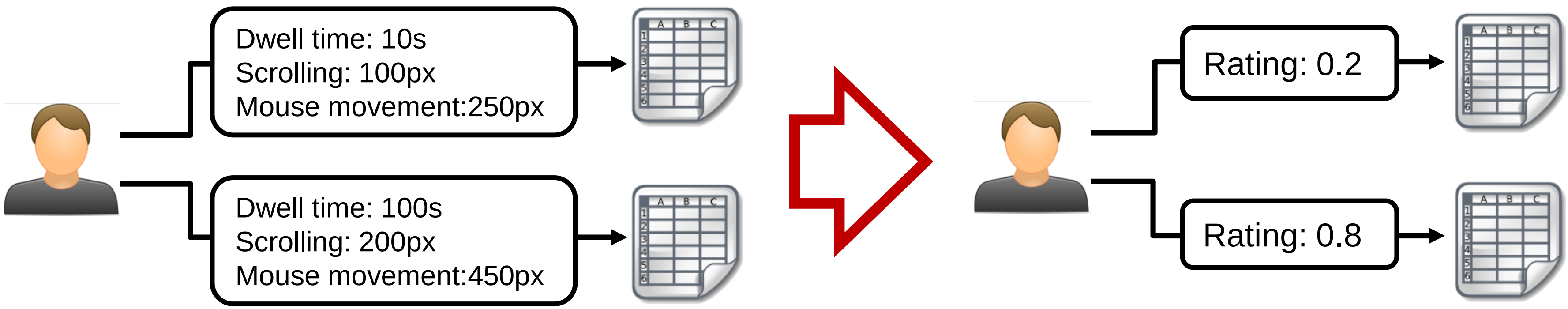
Mouse moving time: 1.8 sec

Travelled distance: 2009px

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

Implicit User Feedback

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



- ***Purchases*** represents fully positive feedback => Std. Machine Learning
- *Otherwise apply „the more the better“ heuristice*
  - *Beware of different range for feedback types -> conjunctive distribution function*

Peska, Vojtas: How to Interpret Implicit User Feedback?

Peska, Eckhardt, Vojtas: Preferential Interpretation of Fuzzy Sets in E-shop Recommendation with Real Data Experiments

Implicit User Feedback

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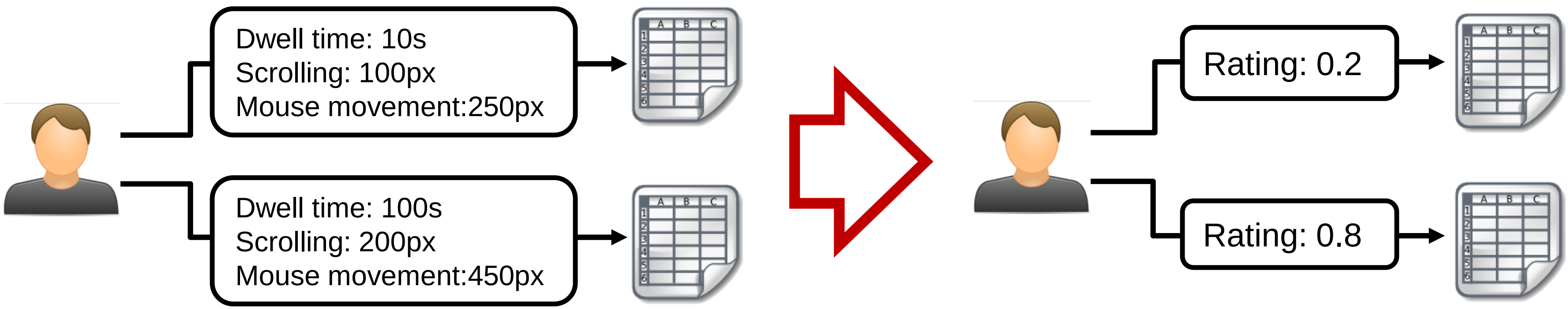


  - Improvements over the usage of simple implicit feedback

Is that all we can do?

Implicit User Feedback

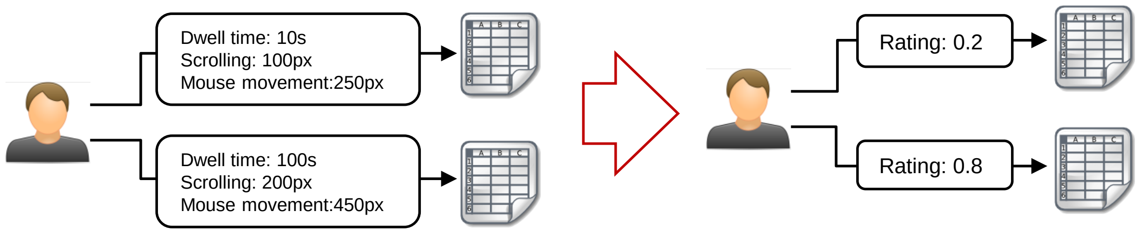
Is that all we can do?

- Negative Implicit Feedback
  - Implicit feedback on object’s categories
- Context of User Feedback

CONTEXT OF USER FEEDBACK

Context of User Feedback

- Combine multiple implicit feedback features to estimate user rating

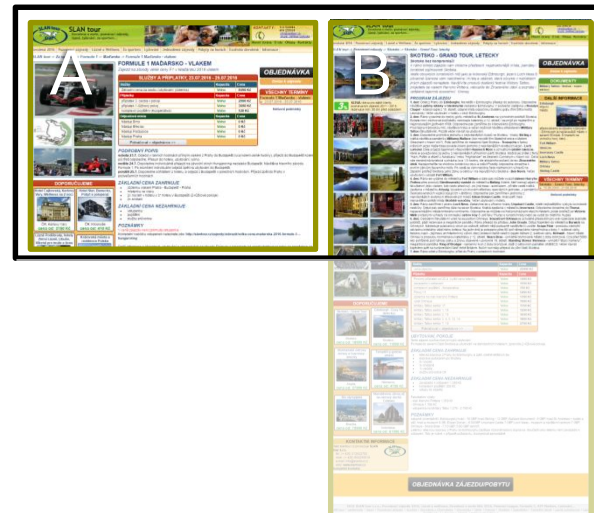


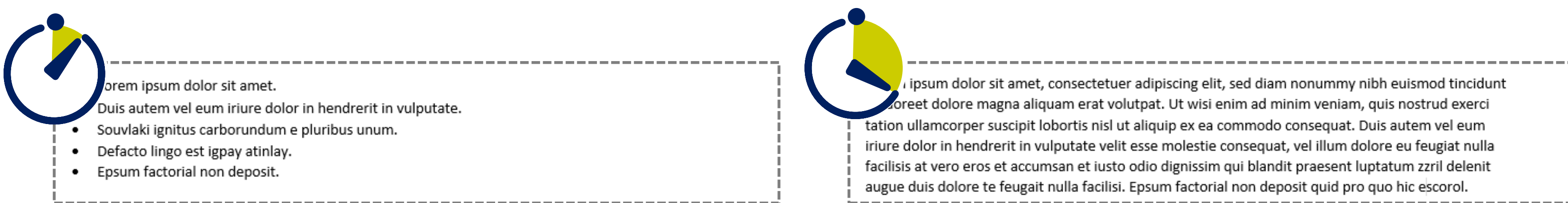
- *Is that all we can do?*

- Pages may substantially vary in length, amount of content etc.
  - This could affect perceived implicit feedback features
  - Leveraging context could be important

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*





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

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 imlicit 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 $\bar{R}_u \rightarrow \hat{r}_{u,o'} : o' \in \boldsymbol{O}$

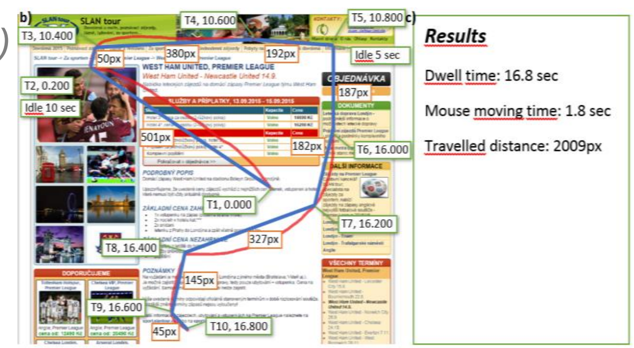
Feedback on Categories and

NEGATIVE IMPLICIT FEEDBACK

User Feedback

- Explicit feedback *(provided via website GUI)*
  - Rating an object via Likert Scale
  - Comparing objects explicitly is not so common

- Implicit feedback *(Virtually any JS event could be used)*
  - Actions related to evaluation of a single object
    - Dwell time on the object detail page
    - Number of page views
    - Scrolling, mouse events
    - Select / copy text, printing, purchase process etc.



  - Actions related to evaluation of a list of objects
    - Analyze user behavior on the category pages, search results etc.

  - Search related actions etc.

Negative Implicit Feedback on Object

- *(The best proxy we have so far)*
  - No (not enough) feedback is negative
    - Visit only for 10 seconds
    - Saw only a half of the video
    - Did not read the text up to the end…
  - **Where is the threshold?**

(Negative) Feedback on Categories

- List of objects, some not visible
- Use browse through the page, by scrolling makes some other visible as well
- User may click on some of the objects
- However, user knows nothing about objects outside of the browser window (o6, o7)

Our Working Hypothesis

- Users are often ***evaluating lists of objects***
  - Search results, category pages, recommended items etc.

- If user ***selects*** some objects from the list, we take it as an ***evidence of*** his/her positive ***preference***.
  - User prefers selected object(s) more, than other displayed & ignored objects
  - We can form preference relations:
    IPR_{rel} (*selected obj.* > *ignored obj.*)
  - We can extend such relations along the content-based similarity of objects

- Some objects could be ignored, because user ***was not aware of them***, not becouse he/she did not like them
  - E.g. they were displayed below the visible area

Possible Approaches

- Negative preference on ignored objects
- Preference relation on selected vs. ignored objects
- ? Extend the preference over some axis? (spreading activation / CB or CF similarity…)