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)

⇒ **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

b)

c)

Results

Dwell time: 16.8 sec

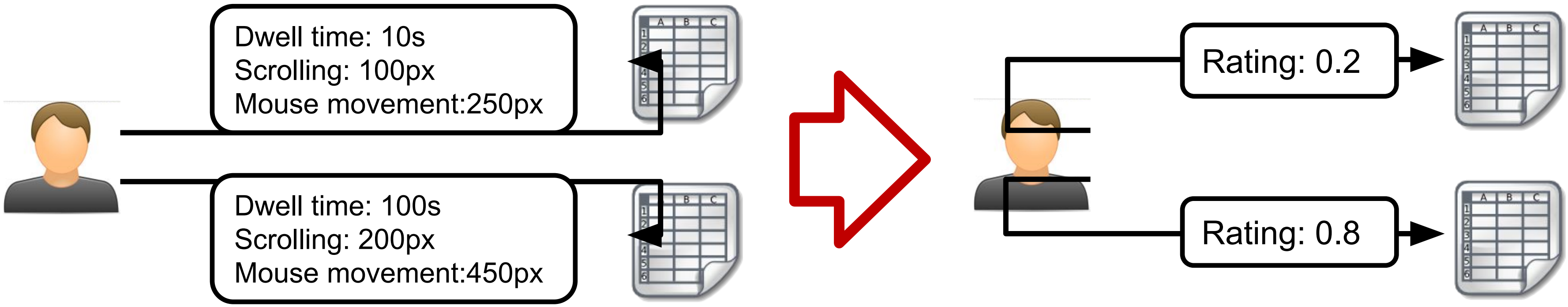
Mouse moving time: 1.8 sec

Travelled distance: 2009px

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

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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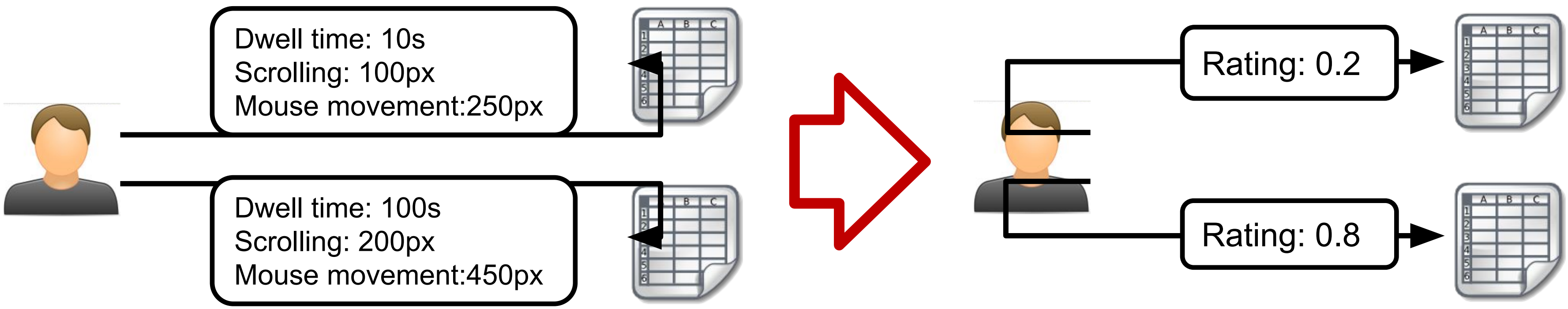


  - Improvements over the usage of simple implicit feedback

Is that all we can do?

Implicit User Feedback

Is that all we can do?

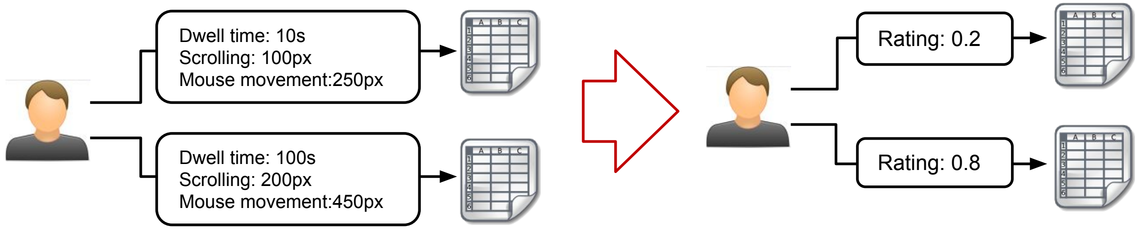
- Negative Implicit Feedback
  - Implicit feedback on object's categories

- Context of User Feedback

CONTEXT OF USER FEEDBACK

Context of User Feedback

- Combine multiple implicit feedback features to estimate user rating

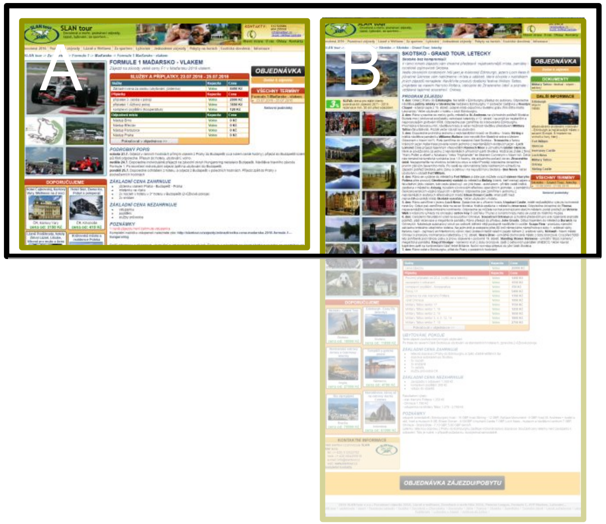


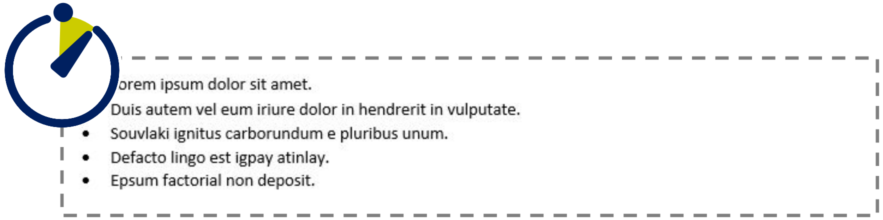
- *Is that all we can do?*

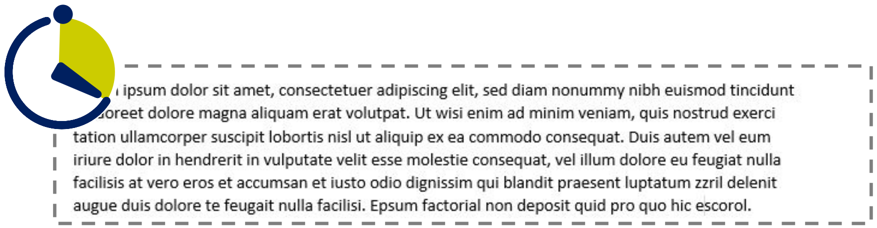
- Pages may substantially vary in length, amount of content etc.
  - This could affect perceived implicit feedback features
  - Leveraging context could be important

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
	View Count
	Dwell Time
	Mouse Distance and Time
	Scrolled Distance and Time
	Clicks count
	Hit bottom of the page
	Purchase

	Contextual features
	Number of links
	Number of images
	Text size
	Page dimensions
	Visible area ratio
	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

  $\hat{R}_u = \{o_1, \ldots, o_k\}$

Our approach

- Several imlicit 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 $\bar{r}_{u,o}$ 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

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

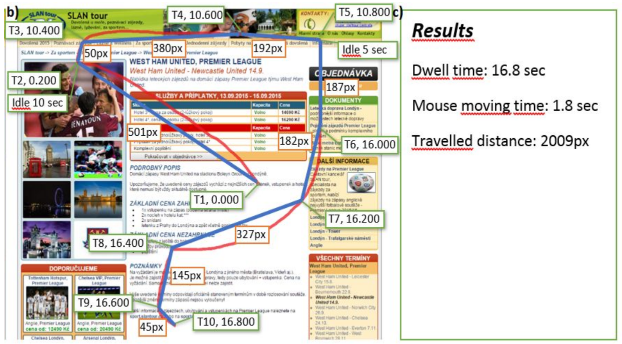
Feedback on Categories and

NEGATIVE IMPLICIT FEEDBACK

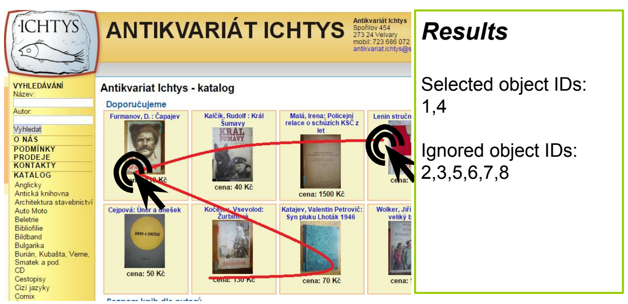
User Feedback

- 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…)