A Fusion Approach to Infer Preference from User Behaviors

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Motivation

- User preference is important, because it is the keystone of many applications:
  - Recommendation System
  - Personalized Search Engine
  - E-Commerce
  - E-Learning
  - …..
- For example, by knowing user preference,
  - A recommendation system could provide particular suggestions for users based on their own interests.
  - A search engine, could return personalized results to match individual's information needs.
- However, the assessment of user preference is a hard problem.

State of the Art (I)

- Explicit rating – the most common method to assess preference:
  - For example, in the Grouplens system (a well-known recommendation system for Usenet news), readers are asked to express their interests explicitly e.g., from 1 (the least) to 5 (the most), for every article they have read. [SKB+98]
- Advantage: it is the simplest solution
- Disadvantage:
  - Cost: it takes users extra efforts
  - Accuracy:
    - Users are observed to read many more articles than they have rated. [SKB+98]
    - Stopping to rate explicitly changes the normal pattern of browsing and reading. [CLWB01]

State of the Art (II)

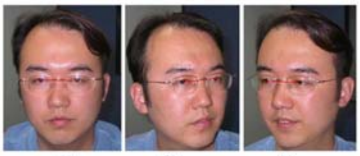
- Implicit feedback indicators:
  - Users just browse and read as normal, and their interests can be unobtrusively inferred from their behaviors.
  - Examples:
    - Reading time; [CLWB01,WRJ02]
    - Number of Scrollings; [CLWB01]
    - Eyeball gaze: attentive systems; [MBCS00]
- "Not all these implicit measures are equally useful and some may only useful in combination with others." – Kelly et. al in [KT03]
- However, as far as we studied, no systematic method has been addressed on the combination of these indicators.

Overview of Our Approach

- Assumption: we can keep track of any user behaviors in the process of the online document reading.
- Goal: unobtrusively assess users' preference on online documents they have browsed as accurate as possible.
- Method: multiple implicit feedback indicators are employed simultaneously. A model based on the Bayesian method is proposed to fuse these indicators for the final assessment of preferences.
- Evaluation: the explicit ratings are used to evaluate the result of the inferences.

Implicit Feedback Indicators

- Reading Time (RT)
  - If users spend longer time on reading a page, it means that they are more interested on it;
  - Normalization: time per 1000 words.
- Number of Scrolling (SC)
  - The scroll either by mouse or PageDown/PageUp key on a page is a signal of interest;
  - Normalization: number per 1000 words.
- Print/Save/Bookmark (PS)
  - Printing/saving/bookmarking a page is a strong signal of interest;
  - Value: true or false.
- Concentration Degree (CD)
  - Concentration Degree is measured by user's eye-gaze captured by web-camera on the top of monitors (shown below), similar to the attentive system in [MBCS00];
  - The Concentration Degree is retrieved periodically (5 sec), the average is computed for each session of page views.



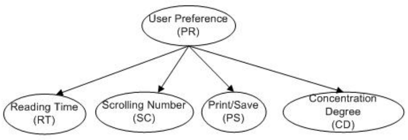
(a) (b) (c)

Figure Concentration Degree retrieved from web camera

(a) r_{cd}=0.87 (b) r_{cd}=0.53 (c) r_{cd}=0.41

Fusion Model

- Four implicit indicators (RT, SC, PS,CR) are fused aiming at a more accurate assessment of preference (PR).
- Naïve Bayesian Network is used because of its simplicity and effectiveness.



$$
\begin{aligned}
& P(PR|RT,SC,PS,CD) \\
= & \frac{P(RT,SC,PS,CD|PR)\cdot P(PR)}{P(RT,SC,PS,CD)} \\
= & \frac{P(RT|PR)\cdot P(SC|PR)\cdot P(PS|PR)\cdot P(CD|PR)\cdot P(PR)}{P(RT,SC,PS,CD)}
\end{aligned}
$$

Experiments

- A customized web browser named *iFusion* has been implemented, which can collect the implicit indicators during web browsing.
- In each session of our experiments, participants are requested to finish the following two steps:
  - Step 1: use *iFusion* browser to do the normal web surfing in a predefined domain for around 30 minutes. Note: participants can do anything as the same as what they do in usual. For example, leaving to get a cup of coffee or chatting with each others.
  - Setp 2: seriously rate the interest on every page they have read in step 1 from 1(the least) to 5(the most).
- Totally 31 participants, around 9000 page views.

Result Analysis: Fusion vs. Single Indicator

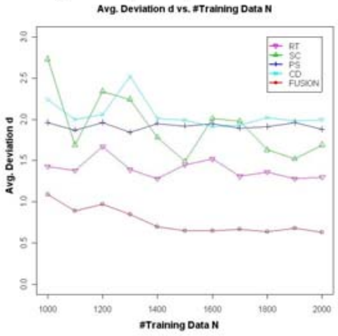
- Assuming that the explicit rating (ER) represents user's real interest, the result of the fusion model (i.e. PR) is evaluated using the average deviation between PR and ER per page view:

$$d = avg \mid PR - ER \mid$$

- Result Analysis:
  - Discretize the implicit indicators RT, SC, CD.
  - Split the test data and training data, and assess the parameters in the fusion model using training data.
  - Apply the fusion model on testing data to compute the PR and the average deviation ***d***.
- Compare the result of the fusion to the result of the each single indicator (shown on the right).
- Conclusion: the fusion of multiple indicators can produce much more accurate results than any single indicators.

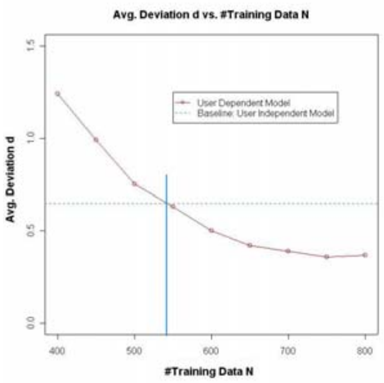
UserId	PageID	RT(sec)	SC	PS	CD	ER
003	00043	54	1	F	0.45	1
003	02021	89	9	F	0.53	4
003	07058	230	3	T	0.60	5
003	01013	105	3	T	0.23	2
...	...	...	...	...	...	...

Figure Sample of Experiment Results



Result Analysis: User Dependent Model vs. User Independent Model

- Feedback Indicators may depend on users, e.g.,
  - Reading Time depends on reading speed.
  - The manner of reading varies.
- User Dependent Model: only use users' own training data to infer their preference.
- For a specific user who has around 1000 page view, results are compared between user dependent model and user independent model (shown on the right).
- Conclusion: user dependent model can produce more accurate result than user independent model.
- Hybrid Model: a threshold is introduced,
  - # training data < threshold: user independent
  - # training data > = threshold: user dependent



Contributions

- A novel approach is proposed which can systematically combine multiple implicit feedback indicators to infer user preference unobtrusively and effectively.
  - Many recent approaches advocate the implicit feedback indicators, however, no one has tried to fuse them for more accurate assessment.
  - It actually leads a new direction to assess user preference.
- Our experiment data is precious resource for further research on user modeling, which we will publish online – Pitt UPMDS (Pitt User Preference Modeling Data Set).
  - It took us two years to collect these data.
  - More complex and accurate model could be built based on them.

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Q&A