IMPLICIT INDICATORS FOR INTERESTING WEB PAGES

Hyoung-rae Kim, Philip K. Chan
Department of Computer Sciences, Florida Institute of Technology, Melbourne, FL. 32901, USA
Email: kim@cs.fit.edu, pkc@cs.fit.edu

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Abstract: A user's interest in a web page can be estimated by unobtrusively (implicitly) observing his or her behaviour rather than asking for feedback directly (explicitly). Implicit methods are naturally less accurate than explicit methods, but they do not waste a user's time or effort. Implicit indicators of a user's interests can also be used to create models that change with a user's interests over time. Research has shown that a user's behaviour is related to his/her interest in a web page. We evaluate previously studied implicit indicators and examine the time spent on a page in more detail. For example, we observe whether a user is really looking at the monitor when we measure the time spent on a web page. Our results indicate that the duration is related to a user's interest of a web page regardless a user's attention to the web page.

1 INTRODUCTION

To help users navigate the web, researchers have been developing intelligent techniques for building user profiles based on web pages that are of interest to individual users (Kim and Chan, 2003; Granka et al., 2004; Goecks and Shavlik, 2000; Chan, 1999). Determining a user's interests can be performed explicitly by asking the user, or implicitly by observing the user's behaviour. Implicit indicators are usually less accurate than explicit indicators (Watson et al., 1998). However, implicit indicators do not require any extra time or effort from the user and can adapt to changes in the user's interests over time. To implicitly measure user interest we need to identify reliable implicit indicators.

One of the major user interest indicators identified by researchers is duration, or the time spent on a web page (Granka et al., 2004; Jung, 2001; Claypool et al., 2001; Resnick et al., 1994; Liberman, 1995; Kim et al., 2001; Oard et al., 1998). However, some research indicate that duration may not be an accurate measure of user interest (Jung, 2001). We suspect that this is because the duration indicator often does not account for the user's absence. For example, a user may leave a web page open while doing something else. Therefore, in this research, a user's duration on a web page is divided into three types depending on if the browser is open (*complete duration*), if the browser is the active application (*active window duration*), and if the user is looking at the screen (*look at it duration*). We also study new implicit indicators (*memo*) that have not been evaluated in previous research. We divided the web pages visited during our evaluation into two groups: (1) web pages that a user visited more than once and viewed for the longest duration, and (2) all web pages that were visited more than once.

The main contributions of this work are:

- Our experiments indicate that *complete duration*, *active window duration*, *look at it duration*, and *distance of mouse movement* are reliable indicators for more users than other indicators – 8 users out of 11;
- The *distance of mouse movement* is often as accurate as indicators based on duration, and it can be the most practical indicator since it is simple to detect and is more robust than *active window duration* against the case of user's absence;
- For the *bookmark*, *save*, *print*, and *memo* indicators, more than 95% of the pages were correctly scored as "interested".

The rest of this paper is organized as follows: Section 2 presents related work on implicit indicators; Section 3 provides a detailed description of implicit indicators studied; Section 4 covers our evaluation of implicit indicators; Section 5 presents and analyzes our results; and Section 6 summarizes our work.

2 RELATED WORK

Jung (2001) developed Kixbrowser, a custom web browser that recorded users' explicit rating for web pages and their actions: *mouse clicks*, *highlight*, *key input*, *size*, *copy*, *rollover*, *mouse movement*, *add to bookmark*, *select all*, *page source*, *print*, *forward*, *stop*, *duration*, the *number of visits* (frequency), and *recency* during users' browsing. He developed individual linear and nonlinear regression models to predict the explicit rating. His results indicate that the *number of mouse clicks* is the most accurate indicator for predicting a user's interest level.

CuriousBrowser (Claypool et al., 2001) is a web browser that recorded the actions (implicit ratings) and explicit ratings of users. This browser was used to record *mouse clicks*, *mouse movement*, *scrolling* and *elapsed time*. The results indicate that the time spent on a page, the amount of *scrolling* on a page, and the combination of time and *scrolling* has a strong correlation with explicit interest.

Those two experiments show some inconsistency. Jung (2001) said *mouse click* is a good indicator, but Claypool et al. (2001) did not. Jung (2001) found that *duration* and *scrollbar movement* are not very predictive of a user's interest, but Claypool et al. (2001) said they are good indicators. In this work, we examine the duration implicit indicator in more detail. We divide the duration into three types: *complete duration*, *active window duration*, and *look at it duration*. Our *complete duration* is different from the duration in Jung's (2001) work. His duration includes the downloading time of a web page, but ours does not. Another difference is that we split the data into two sets, "visits with maximum duration" and "all visits," while Jung (2001) only used "all visits" data set.

Powerize (Kim et al., 2001) is a content-based information filtering and retrieval system that uses an explicit user interest model. They also reported a way to implement the implicit feedback technique of user modelling for Powerize. They also found that observing the printing of web pages along with reading time can increase the prediction rate for detecting relevant documents. Our experiment evaluates a larger number of implicit indicators and divides duration into more detail.

Goecks and Shavlik (2000) proposed an approach for an intelligent web browser that is able to learn a user's interest without the need for explicitly rating pages. They measured *mouse movement* and *scrolling* activity in addition to user browsing activity (e.g., navigation history). We extend these existing implicit interest indicators in this research.

Granka et al. (2004) measured eye-tracking to determine how the displayed web pages are actually viewed. Their experimental environment was restricted to a search results. However, in our experiment we let a user navigate to any web page and do normal tasks such as using chat programs or word processors during the experiment. Another difference is that we use head orientation instead of eye-tracking. Our experiment is also valuable since there are cases where an application does not have devices for tracking a user's eyes.

3 IMPLICIT INTEREST INDICATORS

The time spent on a web page is one of the most intuitive candidates for user interest indicators. This paper thoroughly examines whether duration is related to a user's interest. This section describes duration, as well as other user interest indicators that will be examined. The reason why each indicator is chosen is explained and how each indicator is measured is described.

3.1 Complete Duration

A user may tend to spend more time on pages that he or she finds interesting, so we record the duration spent on a web page. The *complete duration* is defined as the time interval between the time a user opens and leaves a web page. Some web pages contain many images that delay the downloading time, so we start measuring the duration after the entire page is loaded. Thus, the *complete duration* won't be affected by the connection speed, the amount of Internet traffic, or the CPU speed. The *complete duration* for a web page can be calculated by subtracting the time of finishing downloading the current web page from the time of leaving the web page. The *complete duration* is different from the duration used by Jung (2001). His duration includes the downloading time of a web page.

3.2 Active Window Duration

Most modern operating systems allow a user to multitask, or run several applications at the same time. A user may write a report or chat while browsing a web page. Those other applications can be unrelated to the contents of a web page. If a user spent one hour writing a homework paper with a web browser minimized, the *complete duration* of the web page could be one hour. This is very likely to provide erroneous indications of user interest. In order to avoid being affected by this problem, we determine whether a web browser is active or not. The time that a web browser is inactive is subtracted from the *complete duration*. We call this duration *active window duration* since we count the time only when a web browser is active.

3.3 Look At It Duration

Users are not always reading a web page when the web browser is active. They can easily be talking to friends or having a coffee break, while the web browser is active. The *active window duration* can easily be more than 30 minutes if a user leaves the browser active and goes for a coffee break. We may be able to detect the user's absence by detecting the action of mouse movement. However, a better solution is to use a camera that detects a user's face orientation. A camera can even check if a user is looking at the web browser or if his attention is diverted. This duration will be more accurate than the *active window duration* in terms of checking user's attention to a web page. Since this duration counts the time that a user is looking at the web browser, we call it *look at it duration*. The *look at it duration* can be calculated by subtracting the time when a user does not look at the browser from *active window duration*.

3.4 Distance of Mouse Movement

Many people move their mouse while reading the contents of a web page. Mouse movement can occur while looking at an interesting image, or when pointing at interesting objects. We hypothesize that the more distance a mouse moves, the more a user be interested in the web page. This indicator was also examined by Jung (2001). Our distance is a little bit different from his in a sense of detecting overall mouse movement. He counted on the mouse movement only when the mouse point is inside the active browser. The *distance of mouse movement* is detected by its *x* and *y* coordinates on a monitor every 100 milliseconds. The formula is

$$mouse\_movement(pixels) = \sum_{i=1}^{t-1} Dist(P(t_i) - P(t_{i-1}))$$

where time t is the *active window duration*, the time interval, t_i-t_{i-1}, is 100 milliseconds, $P(t_i)$ is a mouse location with x and y coordinates at time t_i, and the *Dist* function is a Euclidean distance.

3.5 Number of Mouse Clicks

People use "click" to hyperlink to another web page. In addition, clicking can be considered as a habitual behaviour (Jung, 2001). Clicking can be a way of expressing our emotions such as if some people are happy to find a product that they were looking for (e.g., book), then they can click the object several times repeatedly. This indicator was examined in Kixbrowser (Jung, 2001), Curious browser (Claypool et al., 2001), Goeck's browser (Goecks et al., 2000), and Letizia (Liberman, 1995). We use the hypothesis that the greater the *number of mouse clicks* on a web page is, the more a user is interested in it (Jung, 2001). The *number of mouse clicks* is counted every time a mouse button is clicked.

3.6 Distance of Scrollbar Movement

A user can also scroll a web page up and down by dragging a scrollbar. Those dragging events can occur several times while a user is reading a web page. The *distance of scrollbar movement* for an occasion, *E*, can be calculated by measuring the mouse movement every 100 milliseconds. By summing all distances of scrollbar movement for all occasions, the *distance of a scrollbar movement* for a web page can be calculated. The formula is

$$scrollbar\_movement(pixels) = \sum_{j}^{E} \sum_{i=1}^{E(j)-1} \left| P(t_i) - P(t_{i-1}) \right|$$

where E is the number of times the scrollbar is pressed, time $E(j)$ is the duration that the scrollbar is dragged in a single dragging event, and t_i-t_{i-1}, is 100 milliseconds. We hypothesize that greater scrollbar movement is correlated with more user interest in a web page.

3.7 Number of Scrollbar Clicks

The length of many web pages is longer than the height of a monitor. If a user finds a web page interesting, he or she may read further down the web page. A user can scroll down a web page either by clicking or by dragging the scrollbar. Those events are counted separately. The number of scrollbar clicks is counted every time a user clicks scrollbar. As a user scrolls a web page up and down by clicking, the number of scrollbar clicks increases. Jung (2001), Goecks et al. (2000), and Claypool et al. (2001) measured this event and reported that it is a good indicator. We hypothesize that we will also find that the number of scrollbar clicks is correlated with a user's interest in the web page.

3.8 Number of Key UP and Down

When scrolling a web page, some people use the "up" and "down" keys instead of the scrollbar. This indicator is similar to the number of scrollbar clicks and the distance of scrollbar movement. The hypothesis is that the greater the *number of key up and down* presses, the more a user is interested in the web page. This event is measured by increasing the count every time a user strikes up or down keys. Curious browser (Claypool et al., 2001) and Jung (2001) measured keyboard activities. But they did not measure the key up and down for measuring scrollbar movement.

3.9 Size of Highlighting Text

While reading a web page, if a user copies some contents of the web page it probably means that the user is interested in the web page. Furthermore, a user can also habitually highlight portions of the page that they are interested in, which is a sign that the user is interested in the page. We assume that the more a user highlights in a web page, the more a user is interested in that web page. A user can highlight several different sentences in a web page for several different occasions. We sum all highlighted contents at the end. Jung (2001) examined this indicator. He used the Euclidean distance between two points of pressing and releasing. The weakness of his measure resides in neglecting the texts highlighted horizontally when the mouse moves vertically. In order to solve this problem, we assumed a character is 5 pixels, each line has 80 characters, and distance between two lines is 20 pixels on average. The formula is

$$highlighting\_text = \sum_{j}^{E} DistY_j / 20 \times 80 + DistX_j / 5$$

where E is the number of occasions when highlighting occurs, *DistY* is the vertical distance between two points, and *DistX* is the horizontal distance between two points.

3.10 Other Indicators

We also measure other less-frequently-used events such as *bookmark*, *save*, *print*, and *memo*. A user usually bookmarks web pages in order to visit them later again. We assume those bookmarked web pages are interesting to a user (Li et al., 1999; Maarek and Ben-Shaul, 1996). This can be measured by detecting bookmarking activities during the experiment. Users save important/interesting web pages in their hard drive by using the "Save As" command. This also implies that those saved web pages are interesting to users (Liberman, 1995). This indicator is also counted by detecting saving activities during the users' browsing. Most web browsers allow users to print web pages. These printed web pages are likely to be interesting to users (Kim et al., 2001). The Memo box is a new feature added in our system. It allows a user to write down a short description on a web page. When the user visits the web page again, the message shows up on the Memo box automatically. We assume that if a user is interested in a web page, then s/he will write a note about the web page.

4 EXPERIMENTS

4.1 Experimental Data and Procedures

For our experiments, we built a web browser that can record the indicators described above from user's behaviour and used a camera to record images for identifying face orientation. 11 data sets were collected from 11 different users. Of the 11 human subjects, 4 were undergraduate students, 6 were graduate students, and 1 was a Ph.D. student. In terms of major, 7 were Computer Sciences, 2 were Aeronautical Sciences, 1 was Chemical Engineering, and 1 was Marine Biology. Each subject was asked to spend a total of 2 hours at the computer. Volunteers were allowed to leave the computer and do other non-computer work. All volunteers were encouraged to behave as normal as possible. To get a variety of behaviours, we asked the volunteers to divide their activities into multiple sessions, each of which does not exceed 1 hour.

In the browser used in our experiment, most of the functions in Microsoft Explore 6.0 were implemented. The popup windows were disabled initially, but our browser allowed a user to change the option to able them. We asked users to bookmark more than 10 pages, save more than 5 pages, print more than 5 pages, use Memo on more than 5 pages. The browser had Memo box so that users can write small note on a web page. Our web browser takes a picture of a user every 2 seconds. Every time a user leaved a web page, the web browser asked the user how much they are interested in the web page – there were 5 scales between "not interested" (1) and "very interested" (5).

The interests were subjective to each user. The system had a "rescore" button to allow changing the score marked in the previous visit. The browser was written in Visual Studio .NET and ran on a Pentium 4 CPU. The Operating System was Windows XP.

4.2 Evaluation Criteria

Two evaluation criteria are used: how accurate an indicator could predict a user's interest and how many users an indicator can accurately predict their interests. Instead of mixing all users' data sets together, each individual data set was analysed separately so that we could clearly observe whether some indicator predicted certain individual's interests more accurately than other indicators. An indicator that could predict the score with a lower variance is a more accurate indicator. In order to evaluate each indicator to see which one is more predictable, we use ANOVA (Analysis of Variance). Jung (2001) treated the scale as numeric scale and applied linear regression, multiple linear regression, etc. methods. We, however, consider the interest scores as discrete values and check if the indicator values are significantly different among the five different interest scores provided by the user. For ANOVA, we use a confidence level of 95% to indicate statistical significance. If the difference is significant, indicator values can predict interest scores. As a second criterion, we count the number of users predicted accurately by an indicator. This criterion indicates how reliable the indicator is across different users.

5 RESULTS AND ANALYSIS

This section analyzes the data collected from the users who participated in our experiment. There are two data sets: "visits with maximum duration" and "all visits". For web pages that a user visited more than once, the score might be the same, but all other information (the durations or number of mouse clicks etc.) may be different. The "visits with maximum duration" data set contains only page views where the user stayed for the longest period of time. The maximum duration is determined using *complete duration*, which is described in Section 3.1. The "all visits" data set contains all page views collected in our experiment. We believe that the "visits with maximum duration" data set is more useful than "all visits", because users do not tend to read the web page again if they know about a web page before (Billsus and Pazzani, 1999). On average, users had 182 visits in the "visits with maximum duration" data set, and users had 291 visits in the data set of "all visits". Jung (2001) only used the "all visits" data set.

5.1 Visits with Maximum Duration

Table 1 shows the experimental results with "visits with maximum duration" data set. The table summarized which indicator is reliable for which volunteer. The first column is users, the second column is *complete duration* (*Complete*), the third column is *active window duration* (*Active*), the rest columns are for *look at it duration* (*LookAtIt*), *distance of mouse movement* (*MousMove*), *number of mouse clicks* (*MousClk#*), *distance of scrollbar movement* (*ScrolMov*), *number of scrollbar clicks* (*ScrolCk#*), *number of key up and down* (*KeyUpDn#*), and *size of highlighting text* (*Highligh*). They are implicit indicators examined. The "√" mark means that the hypothesis for the indicator is statistically significant and "x" means that it was not. The mark "?" means it was unavailable to apply statistical methods to the data due to various reasons such as limited data. The last row indicates how many users' interests can be predicted by that indicator – the number of "√" mark for each column.

The Indicators *Complete*, *Active*, *LookAtIt*, and *MousMove* were able to classify 8 users' interests towards web pages (73%). The indicator of *MousClk#* was the next best indicator, which was recognized as the best in (Jung, 2001). Indicators of *KeyUpDn#* and *Highligh* were able to distinguish the lowest number of users' interests – *KeyUpDn#* was significant to only 1 user and *Highligh* was significant to only 3 users. No indicator could predict User 5's interest. The indicator *Highligh* could predict User 7, but no other indicators could do his interest. Indicator of *ScrolMov* was also valid only to User 4. These results indicate that there was no indicator that was valid to all of the users. Depending on users, an indicator may or may not be valid.

We expected that the *LookAtIt* would be the most accurate indicator, but the result did not turn out as we expected. We suspect that this was because they did not move around much and looked at the monitor most of the time while browsing. In practice, a user can use a browser longer period.

Table 1. ANOVA test with “visits with maximum duration” data set

Users	Complete	Active	LookAtIt	MousMove	MousClk#	ScrolMov	ScrolCk#	KeyUpDn#	Highligh
User 1	√	√	√	√	√	×	×	?	×
User 2	√	√	√	√	√	√	√	√	√
User 3	√	√	√	√	√	√	√	?	√
User 4	×	×	×	×	×	√	×	?	×
User 5	×	×	×	×	×	×	×	?	×
User 6	√	√	√	√	×	×	√	×	×
User 7	×	×	×	×	×	×	×	×	√
User 8	√	√	√	√	√	×	×	×	×
User 9	√	√	√	√	×	×	×	×	×
User 10	√	√	√	√	√	√	√	×	×
User 11	√	√	√	√	×	×	×	×	×
Sum	**8**	**8**	**8**	**8**	**5**	**4**	**4**	**1**	**3**

Table 2. ANOVA test with the data set of “all visits”

Users	Complete	Active	LookAtIt	MousMove	MousClk#	ScrolMov	ScrolCk#	KeyUpDn#	Highligh
User 1	√	√	√	√	√	√	√	?	×
User 2	√	√	√	√	√	×	√	√	×
User 3	√	√	√	√	√	√	√	?	√
User 4	×	×	×	×	×	×	√	×	×
User 5	×	×	×	×	×	×	×	×	×
User 6	√	√	√	√	√	×	√	×	×
User 7	×	×	×	×	×	×	×	×	√
User 8	√	√	√	√	√	×	×	×	√
User 9	√	√	√	√	√	×	×	×	×
User 10	×	×	×	×	×	√	×	√	×
User 11	√	√	√	√	×	√	×	√	×
Sum	**7**	**7**	**7**	**7**	**6**	**4**	**5**	**3**	**3**

5.2 All Visits

Table 2 shows the experimental results with the data set of “all visits”. The table summarized which indicator is reliable for which volunteer. The implicit interest indicators *Complete*, *Active*, *LookAtIt*, and *MousMove* were able to predict the interests of 7 users (64%) that participated in the study. This means that when we used “visits with maximum duration” we could predict more number of users – 8 users. This result notifies that the “visits with maximum duration” data set is more useful in predicting users’ interests more accurately than the data set of “all visits”.

The indicator of *MousClk#* was the next best indicator and was able to predict the interests of 6 users. User interest was more accurately predicted by the *MousClk#* implicit indicator in the “all visits” data set, but this was less predictable than the 4 indicators above. This result is similar to the findings of Jung (2001), who also used the “all visits” data set, and where *MouseClk#* was found to be the best indicator. No indicator could predict User 5’s interest. User 4’s interest could be predicted only by *ScrolCk#* and User 7’s interest could be predicted only by *Highligh*. These results also indicate that different indicators can predict different people.

5.3 Other Indicators

The implicit interest indicators *bookmark*, *save*, *print*, and *memo* had lower usage than the other indicators mentioned above. Users bookmarked or printed only a few web pages while surfing web. Users did not bookmark all interesting web pages, so if used alone they cannot be used to identify all of the pages that a user finds interesting. However, these indicators have a very high accuracy when they are used, and they can be used together with other more frequently used indicators.

The results for the *bookmark*, *save*, *print*, and *memo* indicators are listed in Table 3. The first column is the indicator, the second column is the score (1-“not interested”, 3-“interested” and 5-“very interested”); the third column is the sum of the usages for the specified indicator across 11 volunteers. The rest of the columns are detailed usages for each user. The value in each cell is the number of times that the indicator was used. The number of times each indicator was used varied significantly between each individual. For instance, for some users the *bookmark* indicator was a clearer indicator than other ones – user 5; for some other users *save* was a clearer indicator – user 10.

Table 3. Results of *bookmark*, *save*, *print*, *memo* indicators

Indicator	Score	User1	User2	User3	User4	User5	User6	User7	User8	User9	User10	User11	Sum
bookmark	1	0	0	0	0	0	0	0	0	0	0	0	**0**
	2	0	1	0	0	0	0	1	2	0	0	1	**5**
	3	2	6	1	2	1	0	2	5	0	2	3	**24**
	4	2	3	0	1	6	4	1	2	3	7	2	**31**
	5	5	7	6	1	9	1	3	1	2	6	0	**41**
save	1	0	0	0	0	0	0	0	0	0	0	0	**0**
	2	0	0	0	0	0	0	0	1	0	0	0	**1**
	3	0	8	1	0	0	1	0	2	0	0	0	**12**
	4	0	4	3	5	0	1	0	0	0	2	0	**15**
	5	0	10	6	0	1	3	0	1	2	6	0	**29**
print	1	0	0	0	0	0	0	0	0	0	0	0	**0**
	2	0	0	0	0	0	0	0	0	0	0	0	**0**
	3	0	2	0	1	0	1	5	2	0	0	1	**12**
	4	0	4	1	2	0	1	0	0	0	2	1	**11**
	5	0	15	7	1	3	4	2	1	4	3	0	**40**
memo	1	0	0	0	0	0	0	0	0	0	0	0	**0**
	2	0	0	0	0	0	0	0	0	1	0	0	**1**
	3	0	3	0	1	0	1	2	1	0	0	0	**8**
	4	0	1	2	2	1	0	0	0	3	1	2	**12**
	5	0	9	10	0	2	0	0	1	1	7	0	**30**

Of the web pages that were bookmarked, 95% of them were scored more than or equal to "interested" (3). The sum of bookmarked web pages across 11 volunteers tells us that users rarely bookmarked uninteresting web pages – no bookmarked web pages were scored as "not interested". User 1 and 5 showed a tendency of book-marking more web pages as the web pages became more interesting. These results indicate that *bookmark* was a good indicator.

Saved web pages were scored more than or equal to "interested" 98% of the time. This means that users rarely saved uninteresting web pages. Saved web pages were never scored as "not interested." All users, except user 8, only saved pages that they found interesting. Users 3, 6, and 10 showed a tendency of saving more web pages as the web pages became more interesting. These results indicate that *save* is a good implicit indicator.

All of the printed web pages were scored more than or equal to "interested". This result tells us that users did not print uninteresting web pages. User 2, 3, 6, and 10 showed a tendency of saving more web pages as the web pages were getting more interesting. These results indicate that *print* is a good indicator.

Nearly all (98%) of the memoed web pages were scored more than or equal to "interested." No memoed web pages were scored as "not interested." No user other than user 9 memoed on web pages for which he was less than "interested." User 1 did not used the *memo*, but user 3, 5, and 10 showed a tendency of saving more memos as the web pages became more interesting. These results also indicate that *memo* is a good indicator.

6 CONCLUSION

This paper identifies several implicit indicators that can be used to determine a user's interest in a web page. This paper evaluates both previously studied implicit indicators and several new implicit indicators. All indicators examined were *complete duration*, *active window duration*, *look at it duration*, *distance of mouse movement*, *number of mouse clicks*, *distance of scrollbar movement*, *number of scrollbar clicks*, *number of key up and down*, and *size of highlighting text*. The data was 11 users' implicit indicator data and a 1-5 interest rating of each page. During our experiment volunteers were encouraged to behave normally.

Two evaluation criteria were used: (1) how accurately an indicator can predict users' interests and (2) how many users' interests an indicator can predict. We used two data sets: "visits with maximum duration" and "all visits". We believe that "visits with maximum duration" is more useful for prediction than "all visits", because users did not tend to read a web page again, once users read about the web page (Billsus and Pazzani, 1999). Over the data set containing "visits with maximum duration", the implicit interest indicators *Complete*, *Active*, *LookAtIt*, and *MousMove* were able to predict 8 users' interests towards web pages, but over the data set of "all visits" the indicators were able to predict only 7 users' interests. These facts also notified that the "visits with maximum duration" data set is more useful in predicting users' interests more accurately than the data set of "all visits".

The experimental results told us that *MousMove* could be the most practical indicator because this event is simple to detect and has less risk than *Active*. If a user leaves a web page open and leaves the room, the *MousMove* indicator will not be affected. The indicator of *MousClk#* was the next best indicator, which was recognized as the best in (Jung, 2001). Our results indicate that there was no indicator that was valid for all users. Depending on the user, an indicator may or may not be valid.

We also evaluated less-frequently-used indicators of user interest: *bookmark*, *save*, *print*, and *memo*. When we divided the data set less than "interested" and more than or equal to "interested", "95% of the bookmarked web pages, 98% of the saved web pages, 100% of the printed web pages, and 98% of the memoed web pages belonged to the score of more than or equal to "interested".

We expected that the *LookAtIt* indicator would be more accurate than the *Complete* and *Active* indicators, but the results for all three were similar. We believe that this was because volunteers did not move around much and looked at the monitor most of the time while browsing. Perhaps a longer evaluation would give more accurate results for the *LookAtIt* indicator, since users would act more naturally after more than 1 or 2 hours of surfing. We can combine this indicator to an application for personalized web search results in the future. The collected interesting web pages for a user can be used for building a user interest hierarchy.

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