Supporting Revisitation with Contextual Suggestions

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ABSTRACT

Web browsers provide only little support for users to revisit pages that they do not visit very often. We developed a browser toolbar that reminds users of already visited pages that are relevant to the page they are currently viewing. The toolbar makes use of a recommendation method that combines ranking methods with propagation methods. Our user evaluation shows that, on average, 22.7% of the revisits were triggered by the toolbar, thus accounting for a considerable change in the participants' revisitation routines. In this paper, we discuss the value of the recommendations and the implications derived from the evaluation.

Categories and Subject Descriptors

H.5.4 [**Hypertext/Hypermedia**]: User Issues

General Terms

Experimentation, Human Factors

Keywords

Revisitation, Navigation support, Recommendation

1. INTRODUCTION

Nowadays, millions of people browse the Web every second, navigating from site to site, going back and forth in seemingly chaotic patterns. Modeling their behavior is a complex but crucial task, as many applications rely on regularities in usage patterns - Web search and personalization/recommendation systems, to name but a few. Past research in this area has led to effective user models that are derived from logged, navigational activities [1, 11]. Web usage data also served as a basis for predicting future page requests [3, 7], as well as for recommending relevant pages and queries from earlier sessions [13].

Most Web browsers maintain an extensive log of the pages visited and queries issued, thus building a detailed report of our daily online lives. However, current browser history support - bookmarks, history sidebar, back button, URL auto completion - is targeted to the obvious candidates, the pages that are visited on a very regular basis and the pages that were visited very recently. The long tail of the users' less frequent and less recent activities is still more or less unexploited.

In this paper we introduce the PivotBar, a dynamic browser toolbar that reminds the users of visited pages that are related to the page they are currently viewing. Recommendations on the PivotBar are contextualized and cover a major part of the users' Web history, due to the combination of ranking methods used.

The rest of the paper is organized as follows: after a summary of related work in Sections 2 and 3, we discuss the recommendation methods lying at the core of PivotBar and its experimental evaluation in Section 4. Section 5 continues with a functional description of the toolbar, while Section 6 presents the results of a user evaluation. We conclude the paper in Section 7 together with directions for future work.

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2. STUDIES ON REFINDING

There is a substantial body of research on how people refind and revisit Web pages. In the mid-nineties, Tauscher and Greenberg [15] recognized the Web as a "recurrent system" that follows several regularities. The average probability of a page visit to be a revisit is estimated to be 58%. The majority of these revisits is covered by a small set of frequently used pages as well as recently used pages, mostly triggered by the browser's back button. These sets of most frequently used pages (MFU) and most recently used pages (MRU) both follow a power-law distribution. Such regularities have been confirmed in later studies [1, 11, 16]. However, Obendorf et al [11] discovered, through a client-side clickstream study, that individual browsing behavior might be substantially different from the average numbers. For instance, the usage of multiple browser windows and tabs reduces the usage of the back button.

Adar et al [1] provided more details on why users revisit pages. Apart from backtracking, short-term revisits involve the monitoring of news sites, as well as visits to shopping, search and reference Web sites. Long-term revisits involve specialized sites that are relevant every once in a while, pertaining to travel planning, job searching and weekend activities. Communication sites - Web mail and forums - are represented in both categories. In a follow-up study, Tyler et al [16] analyzed the use of search engines for refinding. Results show that up to 39% of all queries involved refinding; queries for refinding are often used as a substitute for bookmarks. Still, less frequent revisits are not supported sufficiently enough neither by search engines nor by Web browser history mechanisms [11].

3. BROWSER HISTORY MECHANISMS

In current Web browsers, the standard history mechanisms comprise the back and forward buttons, the home button, URL auto-completion, the search toolbar, and the bookmark and history lists [9]. The use of multiple tabs can be considered as an implicit history mechanism. Longer-term revisits are theoretically supported by bookmarks, but bookmark collections tend to be unorganized, overly large or empty. Many search engines currently offer personalized search, which greatly facilitates refinding.

Browsers like Mozilla Firefox and Google Chrome allow users to install extensions for new functionality. Notable extensions that are relevant for this paper include - in no particular order - Delicious (social bookmarking), Infoaxe and Hooeey (full-text history search), WebMynd (history sidebar for search) and ThumbStrips (history visualization).

Academic research delivered several alternative history mechanisms, including gesture navigation [4], "smart" back buttons that recognize waypoints [10] and many types of history visualizations: lists, hierarchies, trees, graphs, 2d and 3d stacks, footprints (see [9] for an overview).

Our approach bears similarities with the concept of dynamic bookmarks, as introduced by Takano and Winograd [14]. We build upon this concept and extend the underlying methods with ranking algorithms and context information. Gamez et al [5] proposed an automatic way to create bookmarks based on temporal information; to our knowledge, the proposed extension has not been evaluated with a substantial dataset or with real users.

4. PREDICTION OF REVISITS

Three kinds of methods are typically employed for predicting revisits: Association Rules (AR), Frequent Sequences (FS) and Frequent Generalized Sequences (FGS). AR are well documented in the literature as a method that effectively identifies pages typically visited together in the same session, but not necessarily in the same order [2]. Mining FS can be considered as equivalent to AR mining over temporal data sets, while FGS introduce sequences that allow wildcards, constituting a more flexible means of modeling users' navigational activity [6].

All three methods were compared by Gery and Haddad on real-world logged data [7], with FS having the best performance. However, their data consists of server side logs, thus providing the prediction methods with a limited pool of pages to choose from. Our goal is to handle an unlimited set of revisited pages, potentially involving the whole Web. In this section we describe the evaluation of the recommendation methods that are used by the PivotBar.

4.1 Recommendation Methods

The revisitation prediction problem we are tackling in this paper can be formally defined as follows:

DEFINITION 1. *Given a collection of Web Pages, $P = \{p_1, p_2, \ldots\}$, that have been visited by a user, u, during her past n page requests, $R_u = \{r_1, r_2, \ldots, r_n\}$, rank them so that the ranking position of the page revisited in the next, $n + 1$, transaction is the highest possible.*

To cope with this task, we introduced in [8] a framework that combines two categories of methods. The first one involves *ranking methods*, which estimate for each web page the likelihood that it will be accessed in the next transaction. These estimations are based on evidence, like the recency or the frequency of earlier visits to this page. We considered the following ranking methods: Most Recently Used (**MRU**), Most Frequently Used (**MFU**) and Polynomial Decay (**PD**), a function that smoothly balances the recency and the frequency of usage of Web pages, as introduced in [12].

The second category covers *propagation methods*. These are techniques that identify groups of pages that are typically visited together, in the same session but not necessarily in a specific order. We considered two kinds of propagation methods: the transition matrix (**TM**) and the association matrix (**AM**). As the name suggests, TM is a two dimensional structure whose rows and columns represent all the Web pages visited so far. Each cell TM(x,y) encapsulates the frequency of the transition $x \rightarrow y$, i.e., the number of times y was visited after x in the same session. In contrast to TM, AM is based on the idea that the order of transitions between pages visited in the same session should be neglected. Thus, these pages should be uniformly connected with each other. AM and TM can be combined with one of the ranking methods through a simple, linear scheme (see [8]).

Method	ARP	P@10
MFU	168 (σ=188)	0.34 (σ=0.11)
MRU	64 (σ=60)	0.71 (σ=0.09)
PD	48 (σ=47)	0.74 (σ=0.07)
PD+TM	30 (σ=27)	0.79 (σ=0.06)

Table 1: Summary of Experimental Results

4.2 Experimental Setup and Results

To evaluate our framework, we conducted an experimental study, making use of a client-side Web usage log of 25 users with a total of 137,737 page requests, gathered in the course of 6 months [11]. The participant pool of the data set consisted of 25 participants, 19 male and 6 female. Their average age was 30.5, ranging from 24 to 52 years. The participants were logged between August, 2004 and March, 2005. Although the dataset is not so recent and may be considered outdated for other purposes, little has changed in navigation dynamics; the browsers already contained tabbed based navigation, bookmarks and URL auto completion.

In Table 1 we summarize the results of the prediction methods. The evaluation metrics that we employed are Average Ranking Precision (**ARP**) and Precision@10 (**P@10**). The former denotes the place a revisited page is found on average in the ranking list of the prediction method, while the latter expresses the percentage of revisitations that involved a web page ranked in one of the predicted top 10 positions. It is clear that the baseline MFU performs much worse than MRU, as revisiting popular sites is less common than backtracking. PD, which is a combination of MFU and MRU, improves upon the latter for all users to a varying but considerable extent, especially for users where MRU pages perform relatively bad. The differences become smaller together with the increase of the recency effect. Most notably, though, PD's performance is significantly enhanced when combined with AM or with TM, with the latter accounting for a higher improvement.

5. PIVOTBAR

PivotBar is a browser toolbar that looks quite similar to the bookmark toolbar, containing favicons and links to pages previously visited (see Figure 1). However, in contrast to the bookmark toolbar, PivotBar is dynamic, as it provides contextual recommendations (i.e. pages related to the page currently visited by the user). The list of pages in the bar changes upon each navigation action or tab change.

The design of the toolbar is kept minimalistic, in order not to consume too much of the screen's real-estate. PivotBar is not designed for extensive search into the history - an activity that users hardly undertake anyway -, but for automatically reminding users of past visits that might be relevant in the current context. For example, when planning a train ride, the user might want to visit his

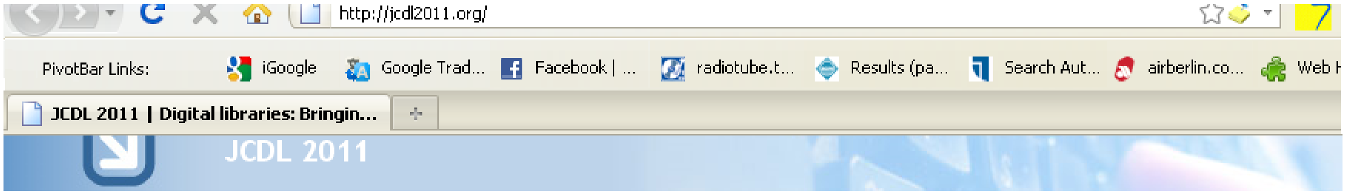

Figure 1: PivotBar recommendations

favorite hotel booking site. The dynamic character of the list ensures that the user's attention will be caught, but only in the periphery and just for a short time period - unless the user chooses to follow a recommendation.

For the first implementation of the PivotBar, we chose Mozilla Firefox as the host browser, since it constitutes a freely available and platform-independent browser that provides developers with clear-cut documentation and transparent access to client data. The PivotBar Add-On makes use of the existing user history in the browser database and all computations take place on the client-side.

For the prediction method we took the best performing algorithm of the previous section: PD+TM. After some initial testing, we deemed some further tuning necessary. First, we filtered out all results that stem from the same host as the current page - our goal is not to uplift the flaws in the hypertext structure of Web sites. Second, visited pages are grouped by host (i.e. Web site) and represented by the page with the highest ranking position. Thus, a user accessing a Web site **A** will not get more than one recommendation from Web site **B**. Both adaptations happen in the interface level and do not influence the real ranking computation.

6. USER EVALUATION

The quality of the recommendations provided by the PivotBar has already been evaluated over a fairly large dataset in Table 1. However, this does not guarantee that the PivotBar will be actually used and appreciated; for example, the history sidebar covers many of the user's (short-term) revisits, but it is hardly used [11].

We conducted a small scale user study in order to obtain quick feedback on whether the combination of a good prediction method and a simple user interface can result in a usable and efficient application. The user study focused on answering the following questions: will users actually click on recommendations (i.e., will the toolbar be used); what would be the user's appreciation of a dynamic toolbar; what could be directions for further improvement of the recommendations.

We asked 11 participants (8 male, 3 female), aged 28 on average, to install the toolbar, either on their business computer or on their private one. Eight opted for the former choice and the remaining three for the latter. The participants were not the same from the extracted log used in the experiments and all were PhD students of computer science. The participants did not have previous experience with the toolbar. It is worth noting that before the evaluation, only six participants had the bookmarks bar visible all the time (in the remaining 5 configured Firefox to hide the bookmarks toolbar). This indicates that our participants, who can be considered 'power users', are likely to be rather skeptical with respect to new tools. The participants were provided with a brief introduction to the tool and some instructions for the experiment[1]. Finally, we asked them to keep the tool installed for at least a period of five working days.

[1]The exact instructions given to the participants were: "PivotBar automatically generates suggestions based on the current page you are accessing. You can use them simply by clicking on a link in order to be redirected to the target page. Feel free to use them or not."

Participant	Total Visits	Revisits	PivotBar	PB%
1	541	264	104	39.4
2	596	248	38	15.3
3	352	147	49	33.3
4	828	424	49	11.6
5	321	63	10	15.9
6	567	283	39	13.8
7	259	137	20	14.6
8	179	102	40	39.2
9	183	75	19	25.3
10	312	149	14	9.4
11	423	145	46	31.7

Table 2: Click data during the evaluation period.

After this period of time, we collected the click-data of each participant for the quantitative results, while qualitative feedback was elicited through an open-ended interview.

6.1 Results

All participants claimed to use the computer for about 6 to 8 hours per day. They all said that they usually use the auto completion feature for revisitation, while a mere 50% uses bookmarks actively. Further, they indicated that they often use search engines to refind a known page. The revisitation rate during the evaluation reached an average of 44.2% (σ=10.4), lying at the same levels indicated by previous studies [4, 11].

Table 2 summarizes the usage of the PivotBar for each participant. The second column indicates the total number of visited pages. The third column represents the number of revisits among all page requests (including revisits to pages visited before the evaluation). The fourth column corresponds to the number of revisits that were initiated through the PivotBar. The fifth column shows the percentage of revisits covered by the PivotBar.

The average percentage of revisits triggered through the PivotBar was 22.7% (σ=11.4), reaching a peak of 39.3% for participant 1. This number is surprisingly high - even if we take the novelty effect into account: as a comparison, [11] observed that the back button covered 31% of all revisits; bookmarks, the history list and the homepage button together were responsible for only 13.2% of all revisits.

We further examined whether the take-up of the tool has been caused by the novelty effect and/or the fact that the suggestion is present in the toolbar. For the former issue, Figure 2 illustrates a more or less linear growth of clicks per day for each user. This demonstrates that the clicks on the bar were equally distributed among the days of the evaluation and, thus, the high amount of clicks cannot be justified by the novelty effect alone. As for the latter issue, one may argue that a user might click on a suggest link just because it is present in the toolbar. In other words, without the toolbar, a user may have no intention of re-visiting a given URL at a point in time. Nevertheless, that is one of the main purposes of providing suggestions and as a counter-argument, it is reasonable to assume that a user will not click on suggestions that are not useful.

We collected further qualitative feedback via open-ended interviews. When asked about the usage of the toolbar, one of the par-

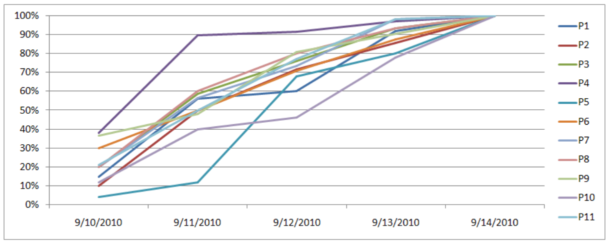

Figure 2: Growth of clicks on the PivotBar per day for each participant.

ticipants explicitly commented: "*I actually scan the shortcuts automatically when they change. The movement attracts my attention but it is not too distracting*". Another participant said: " *It's nice that I can see the pages that I usually access*"; at the same time, he acknowledged that his routine behavior was hard to change: he still tended to automatically open a new tab and directly type the address of a page using auto-complete (note that the lowest usage percentage of the toolbar is still 9.4%).

Although the participants were quite positive about the recommendations in general, they provided several suggestions for improvement. Most importantly, it was mentioned that the toolbar should recommend (portal pages of) sites instead of recommending (specific) pages. Conversely, some participants thought the recommendations should be based on the currently visited site instead of the page. Other remarks suggested that the recency effect recommendations could be further reduced.

The feedback about site-level recommendations instead of page-level recommendations can be explained by the growing importance of revisits to service-oriented sites and the monitoring of news sites [1]. At the same time, site-level recommendations would ignore the informational value of specific news articles, blogs and other listings. We hypothesize that the balance between generic site recommendations and specific page recommendations can be further adjusted by taking the sites' access profiles into account (c.f. [11], who show that search engines invoke different revisitation behavior than project sites or news sites).

7. CONCLUSIONS

In this paper we discussed the design and evaluation of the PivotBar, which reminds users of visited pages that are related to the page they are currently visiting. The contextual page recommendations are generated by a combination of ranking and propagation methods, which was experimentally verified to produce good results. A user study showed that the toolbar and its recommendations were appreciated by the users; 22.7% of the revisits were initiated through the PivotBar.

From the results we can draw several conclusions. First, the usage statistics suggest that the concept of a dynamic toolbar with useful links has an impact on users' page revisits. Further, we have shown that post-hoc experiments on an existing Web usage log provide valuable information for the design of Web history tools. At the same time, results from the user study with the PivotBar suggest that good predictions do not necessarily make good recommendations: further tuning with respect to - among others - site-level vs. page level recommendations and recency vs. serendipity based on usage data and user feedback is needed.

These and other issues will be addressed in future work, once a sufficiently large body of usage data is collected. The data will also help in understanding which browser functionality the PivotBar is replacing and how many clicks and how much time it saves.

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