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Using Semantic Treemaps to categorize and visualize bookmark files

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ABSTRACT

As more and more information is available on the Internet, search engines and bookmark tools become very popular. However, most search tools are based on character-level matching without any semantic analysis, and users have to manually organize their bookmarks or favorite collections without any convenient tool to help them identify the subjects of the Web pages. In this paper, we introduce an interactive tool that automatically analyzes, categorizes, and visualizes the semantic relationships of web pages in personal bookmark or favorites collections based on their semantic similarity. Sophisticated data analysis methods are applied to retrieve and analyze the full text of the Web pages. The Web pages are clustered hierarchically based on their semantic similarities. A utility measure is recursively applied to determine the best partitions that are visualized by what we call the Semantic Treemap. Various interaction methods such as scrolling, zooming, expanding, selecting, searching, filtering etc. are provided to facilitate viewing and querying for information. Furthermore, the hierarchical organization as well as the semantic similarities among Web pages can be exported and visualized in a collaborative 3D environment, allowing a group of people to compare and share each other's bookmarks.

Keywords: Semantic Treemap, Spring Embedding, semantic similarity, bookmark, cluster, hierarchy, interaction, information visualization

1. INTRODUCTION

The millions of documents on the rapidly expanding World Wide Web further exacerbate the information overload problem. The Web today has no classification system for Web sites, no formal indexing policy or controlled vocabulary, and no systematic way to name Web pages and assigning authorship in a particular catalogue. Currently most Web surfers rely on browser search engines such as Yahoo, Google etc. to find specific information on the Web. A typical search engine allows a user to type in certain keywords and simply retrieves all Web pages containing those words using character-level matching, instead of analyzing the semantic relationships between the query and the retrieved pages. As a result, many irrelevant Web pages may be retrieved, especially in the case of words with different meanings (e.g., bank) or different words with similar meanings (e.g., dad and pa). A big part of the work to identify relevant information is still left to the user and information searching on the Web remains a challenging and often frustrating task. One strategy to deal with this problem is to develop personal information systems consisting of focused subsets of Web sites highly relevant to a particular user. Bookmark or favorite collections are a convenient and popular way to achieve this goal. Most Web browsers nowadays such as Netscape and Internet Explorer provide embedded tools for a user to bookmark his favorite URLs and organize them into folder structures featuring different categories. The efficiency of the categorization is totally up to the user's own archiving experience and knowledge about the Web pages. In many cases the user bookmarks a Web page for later use before having a chance to read it, so it's hard for him to label the category for that page. Another problem is that the bookmark archive management is completely manual: the user has to reorganize the folders himself after he adds, deletes, or changes bookmarks. As the size of the archive grows, pool scalability of the current tools makes it hard to browse and retrieve bookmarks in a deeply nested hierarchy [16].

In this paper, we introduce an interactive tool that aims automatically analyses, categorizes and visually displays collections of Web pages. The tool can take personal bookmark archives or bookmark collections from different individuals and parse all the linked Web pages. Advanced data mining techniques such as Latent Semantic Analysis [1] is used to analyze the semantic similarities between the pages. According to this semantic information, clusters of Web pages are generated and labeled with their semantic topics. Further on, a visualization technique that we call Semantic Treemap is utilized to visualize the bookmark hierarchy in both the generated clustering division and the original folder organization making it easy for users to quickly locate relevant Web pages. To avoid information overflow and improve focusing, zooming and expanding are enabled on any area inside the Semantic Treemap. Besides, various searching and filtering methods are provided to help users quickly identify the Web pages satisfying their requests. Finally, the spatial layout of the Web pages can be exported and utilized to create a visualization of the Web pages in a 3D virtual reality environment that can be shared and collaboratively examined.

The rest of the paper is organized as follows: section 2 introduces related work; section 3 explains the data analysis process for semantic similarity analysis and categorization of Web page collections; section 4 describes the Semantic Treemap used to visualize bookmark hierarchies as well as the various embedded interaction methods to facilitate information viewing and retrieval; section 5 gives some application examples using the Semantic Treemap to visualize bookmark collections; finally, section 6 summarizes the paper and discusses future work.

2. RELATED WORK

Since its first appearance, Latent Semantic Analysis (LSA) [1] has been widely used to induce semantics of textual documents [3], especially in content-based information retrieval [2] and semantic similarity comparison [4]. The technique is explained in section 3.2. To visualize similarity results, Force Directed Placement (FDP) algorithms [5] are frequently used. Kumar etc. implemented a 3D version of FDP [6]. Huang etc. extended FDP in a system that uses a "logical frame" to present a subgraph of an entire graph and smoothly migrates from one frame to another [7]. FDP is used in Pathfinder Network Scaling (PfNet), which is utilized in StarWalker by Chen to layout documents according to their semantic similarity [8]. In StarWalker, the similarity matrix is determined based on co-citation patterns for a large set of papers and the citation networks are displayed as minimal spanning trees that preserve only the most important links.

To visualize hierarchical data Treemaps have shown great powers in many applications including DiskMapper from Micro Logic Corp, SeeDiff software code viewer from Bell Labs, Honeycomb electronic product catalogs by the Hive Group, as well as SmartMoney's Stock Marketmap and TruePeers's PeopleMap. Many efforts have been made to make the space filling technique more effective. Asahi etc. introduced dynamic queries into the Analytic Hierarchy Process Treemap, allowing users to interactively change and see the influence of different factors [10]. Van Wijk etc. developed Cushion Treemaps to improve the visibility of nesting depth by shadows on cushion-like 3-D mounds [11]. Stasko and Zhang proposed a Focus+Context display and navigation techniques for enhancing radial, space-filling hierarchy visualizations [12]. Bederson etc. proposed Ordered and Quantum Treemaps, which organize the screen space into horizontal-vertical strips with square-like aspect ratio, while at the same time maintaining the original ordering as well as satisfying the need to accommodate fixed shape items [14].

Some empirical studies have been carried out on bookmark usage in the Web information space. A 1996 survey of 6619 Web users [15] reported that over 80% respondents cited bookmarks as a strategy for locating information, and organizing bookmarks became one of the top three Web usability problems. In his survey on 322 Web users [16], Abrams addressed why and how people create, use, and organize bookmarks, as well as the necessity to improve the organization, visualization, representation, and integration of bookmarks. These user studies provide scientific basis for the design of bookmark visualization and management systems.

3. DATA MINING AND CLUSTERING

Our bookmark visualization tool works in two phases: the data analysis phase and the data visualization phase. The first phase is divided into three steps: bookmark file parsing, semantic similarity modeling using LSA, and bookmark clustering and labeling. The second phase is also divided into three steps: bookmark layout with Semantic Treemaps, graphical display, and user interaction. The overall procedure is illustrated in Figure 1 and explained in detail in the following sections.

3.1 Bookmark parsing

Bookmark parsing is the first step of the whole visualization process. The input of the bookmark parser comes from existing bookmark files and the purpose is to set up a folder hierarchy representing the original categorization manifested in those files. There are two formats for the input. The first type contains personal bookmarks organized in a folder archive, usually maintained by their owner through some Web browser and saved as a standard HTML file. For this format our bookmark parser runs a recursive procedure to parse the HTML document and build up a folder tree containing all bookmarks in the document while maintaining the owner's original folder hierarchy. The root of the tree corresponds to the unique top-level folder, each non-leaf node is a subfolder, and all bookmarks are in leaf nodes. Each folder or bookmark has a label, as given by the original owner suggesting his definition of its semantics. A URL link is kept for each bookmark so that the referred Web page can be downloaded for semantic analysis. The folder tree created in this way exactly represents the user's manual organization of his bookmarks.

In the course of collaboration it can be advantageous to share bookmark files. Therefore, we support a second input file format resembling a list of bookmarks collected from different people. Each bookmark has an owner, a name, and a URL link. Since the bookmarks are arranged in a linear order, we need to create a hierarchical structure for the folder tree. We assign the root of the tree to be the bookmark pool containing all bookmarks from the file. In the first level we divide the bookmarks by their owners and for each owner build under the root a subfolder containing all his bookmarks. Next we divide each owner's bookmarks by their URL fields and build a second-level subfolder for each field. For example, URL fields ending with ".edu" are categorized as "Educational", while URLs with ".com" go under "Commercial". We can further develop the folder tree by adding more layers categorized with more fine-grained features. The folder tree generated in this way roughly follows the categorization implied by the bookmarks' features specified in the input file. Both formats of bookmark files can be imported in multiple and combined together, in which case a 'bookmark pool' will be set up for all people's bookmarks and represented as the folder tree root; each owner will have a subfolder under the root and his bookmarks will be categorized either as defined by himself, or by bookmark features when the former is not available.

3.2 Similarity modeling with Latent Semantic Analysis

Next we need to download and parse all Web pages linked from the bookmarks in the folder tree and apply LSA to them. LSA [1] is a variant of the vector space model that converts a representative sample of documents to a term-by-document matrix in which each cell indicates the frequency with which each term (row) occurs in each document (column). In our case, if there are p valid Web pages (documents) and t distinct words (terms) in all pages, this results in a $t \times p$ term-page matrix F, which can also be regarded as p column vectors of t-dimension. LSA extends the vector space by modeling term-page relationships using a reduced approximation for the column and row space computed by singular value decomposition (SVD), as shown in formula (1), where L and R are $t * n$ and $n * p$ respectively, and S is an $n * n$ diagonal matrix with the singular values. Care needs to be taken when choosing an appropriate value for n, which should be ideally large enough to fit the real structure of the data, but small enough so that noise, sampling errors and unimportant details are not modeled. We can sort all singular values and cut them at the point where the value greatly drops, and take the n highest singular values while omitting all others. Thus each Web page is represented as an n-dimensional vector in the $n * p$ matrix F_R, as shown in formula (2). This way, the dimensionality is greatly reduced ($n << t$), and only important and reliable patterns underlying the original data are maintained.

$$F \,\tilde{}\, L * S * R \qquad (1)$$

$$F_R = S * R \qquad (2)$$

$$S_M = F_N * F_N', \quad 0 = S_{M(ij)} = 1 \qquad (3)$$

$$D_{S(ij)} = 1 - |S_{M(ij)}|, \quad 1 = i,\ j = n \qquad (4)$$

Similarities between Web pages can be computed using dot products between two column vectors of the reduced matrix, reflecting the degree to which two Web pages have a similar term usage pattern. The formula is given in (3), where S_M is the $n * n$ similarity matrix, and F_N is obtained by normalizing the column vectors in F_R. To simplify clustering and visualization, S_M is converted into the distance matrix D_S by subtracting the absolute value of each element in S_M from 1,as given in formula (4), resulting in a symmetric $n * n$ matrix with all elements in the range [0, 1] and all zeros on the diagonal.

The terms we use for LSA are collected from the textual part of all downloaded Web pages (including the titles and labels of all HTML elements), and only terms with substantial meanings are counted. All punctuations, numbers, and special names are excluded. Besides, we build a small dictionary of stopwords to filter out grammatical or commonly used phrases that tend to appear in almost every document. To speed up text parsing, a hashtable is used to record the frequencies of term occurrences for each Web page. However, not all Web pages are valid. Some bookmarks have mal-formatted URLs, some pages aren't accessible due to network failures, and some just don't contain any useful terms. All invalid bookmarks are recorded with special marks and will not be considered in the semantic analysis. After all Web pages are parsed, the term-page matrix is generated for all valid terms and Web pages.

Other than text, an HTML page may contain various multimedia and executable elements, such as images, audio, video, and applets etc. the semantic analysis of which is beyond the scope of this paper. However, we maintain statistics on the number of audio files, video clips, and applets etc. that are linked from any web page as well as information on its type, size, and access frequency etc. These statistics can be useful for data filtering and searching when users want to hide or highlight Web pages with certain features.

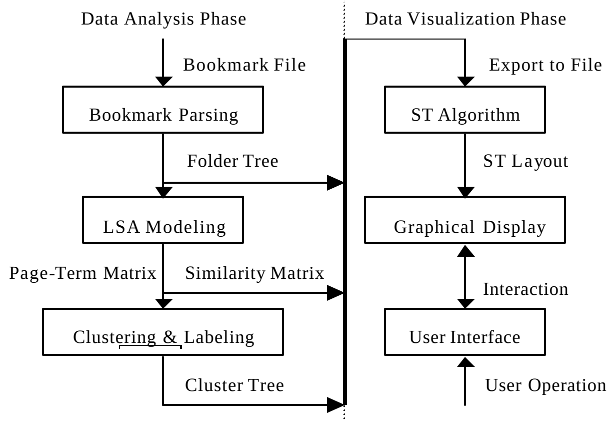


Figure 1. Two phase bookmark visualization

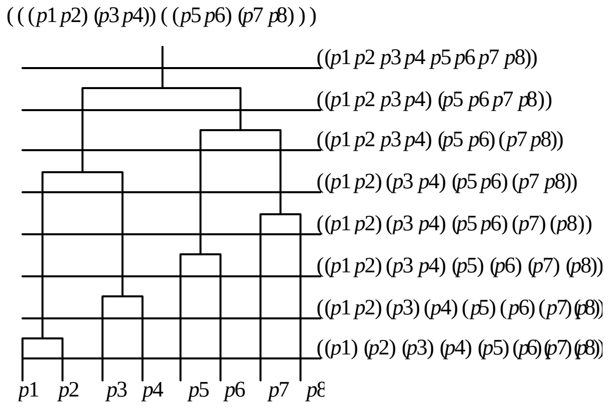

(((p1 p2) (p3 p4)) ((p5 p6) (p7 p8)))
((p1 p2 p3 p4 p5 p6 p7 p8))
((p1 p2 p3 p4) (p5 p6 p7 p8))
((p1 p2 p3 p4) (p5 p6) (p7 p8))
((p1 p2) (p3 p4) (p5 p6) (p7 p8))
((p1 p2) (p3 p4) (p5 p6) (p7) (p8))
((p1 p2) (p3 p4) (p5) (p6) (p7) (p8))
((p1 p2) (p3) (p4) (p5) (p6) (p7) (p8))
((p1) (p2) (p3) (p4) (p5) (p6) (p7) (p8))
p1 p2 p3 p4 p5 p6 p7 p8

Figure 2. Hierarchical clustering of 8 Web pages

3.3 Hierarchical clustering

From the similarity results of LSA we categorize the bookmarks and create a hierarchy of clusters grouping Web pages of similar semantic contents by a nearest-neighbor-based, agglomerative, hierarchical, unsupervised clustering algorithm. Clustering starts with a set of singleton clusters, each containing one Web page. The two most similar clusters over the entire set are merged into a new one that covers both. A complete linkage measurement is applied to determine the distance inside and between clusters based on the distance matrix. Merging of clusters repeats until a single all-inclusive cluster remains and a binary hierarchy of clustering sequence is produced. Figure 2 shows an example of how eight Web pages are clustered. The clustering layers are shown on the left with their corresponding partitions on the right.

Obviously, the display of all the different clusters in this hierarchy in a Treemap would lead to a very cluttered display. We therefore developed a combination of a traditional Treemap and the Spring Embedding algorithm called Semantic Treemap (SM). An SM utilizes a Treemap to display the 'best partitions' of the hierarchical organization of the bookmark categories (clusters or folders) in a slice-and-dice fashion (see Figure 3). Within each subcategory, the Web pages are laid out according to their semantic similarities using the Sping Embedding algorithm. Consequently, similar bookmarks will be positioned close to each other, and bookmarks on similar topics will be clustered under the same category.

To obtain a 'best cluster partitions', we recursively select the partitions that minimize the average intra-cluster distance *AAD* and maximize the average inter-cluster distance *AED*. Starting from the initial singleton clusters, as the cluster merging goes on, the inter-cluster distance between the two merged clusters grows bigger. It's easy to infer from the algorithm described below that *AAD* keeps growing bigger, while *AED* first grows bigger to the maximum and then starts to drop. We define a utility measure *U* as the ratio of *AAD* against *AED*, and the partition with the lowest utility will be selected. In the example shown in Figure 2, layer 6 (the bottom one being layer 0) is selected as the first-level partition. It contains three clusters: (p1..p4)(p5,p6)(p7,p8). We can further partition each cluster in this level by applying the above utility recursively, and eventually build up a cluster tree with the whole bookmark set being the root, each cluster being a non-leaf node, and all bookmarks being the leaf nodes.

Several factors should be considered when deciding whether a cluster should be further partitioned or not. One is the utility measure of the cluster. If its best (minimal) value is still quite small, we'll see that bookmarks inside that cluster still show the tendency to cluster into smaller subclusters, so it makes sense to further partition it. Another factor is the current cluster size, i.e. the number of bookmarks inside that cluster. If the size is too big, the treemap used to visualize it (see section 4) will be very crowded; if the size is too small, then space will not be efficiently used. The third factor is the current depth of the cluster. If the cluster is too deep, the treemap will be divided into too many small areas and it will be hard to identify each individual bookmark. To balance all above factors, we can define a threshold for each of them, while at the same time, give users the option to interactively adjust the level of clustering.

To speed up the clustering procedure, we implement an algorithm that computes the intra/inter-cluster distances iteratively, rather than starting from individual clusters each time. Assume at layer q, we have partition P_q = { C_0, …, C_{p-q-1} }, each cluster C_k contains a set of bookmarks C_k = { …, B_i, … }, the inter-cluster distance AED_{kl} between C_k and C_l and the utility measure U is given as below:

SAD_k = ? d_{ij} for all B_i, B_j ? C_k, i ? j, $\quad$ SAN_k =| C_k | * (| C_k | - 1) / 2, C_k ? P_q (5)

SAD = ? SAD_k & SAN = ? SAN_k for all C_k ? P_q, $\quad$ $AAD = SAD / SAN$ (6)

SED_{kl} = ? d_{ij} for all B_i ? C_k, B_j ? C_l, $\quad$ SEN_{kl} = | C_k | * | C_l |, C_k, C_l ? P_q, k ? l (7)

SED = ? SED_{kl} & SEN = ? SEN_{kl} for all C_k, C_l ? P_q, k ? l, $\quad$ $AED = SED / SEN$ (8)

$AED_{kl} = SED_{kl} / SEN_{kl}$, C_k, C_l ? P_q, k ? l (9) $\quad$ $U_q = AAD / AED$ (10)

SAD_k and SAN_k are the total distance and number of edges inside C_k respectively, d_{ij} is the distance between B_i and B_j, and $|C_k|$ is the size of C_k; SAD and SAN are the total intra-cluster distance and number of edges inside P_q respectively, and AAD is the average intra-cluster distance of P_q; SED_{kl} and SEN_{kl} are the total distance and number of edges between C_k and C_l respectively; SED and SEN are the total inter-cluster distance and number of edges inside P_q respectively, and AED is the average inter-cluster distance of P_q. The algorithm is described as follows:

1. Initialize the bottom-layer partition P_0 = { C_0, …, C_{p-1} }, where C_k = { B_k }, k = 0…p-1, and B_k is any valid bookmark in the bookmark pool. From the above formulas, we have:

   $AED_{kl} = d_{kl}$, C_k, C_l ? P_0, k ? l; $\quad$ $SAD = 0$, $SAN = 0$; $\quad$ SED = ? d_{ij} for all B_i, B_j, $SEN = p * (p – 1) / 2$.

2. In the current layer partition P_q, select cluster C_m and C_n, where AED_{mn} is the minimum among all AED_{kl}, C_k, C_l ? P_q, and merge them into a new cluster C_h. Calculate the next layer partition:

   $AED_{kl} := AED_{kl}$, where k, l ? m, n, h, $\quad$ $AED_{kh} := (SED_{km} + SED_{kn}) / (SEN_{km} + SEN_{kn})$;

   $SAD := SAD + SED_{mn}$, $SAN := SAN + SEN_{mn}$; $SED := SED - SED_{mn}$, $SEN := SEN - SEN_{mn}$;

   $AAD := SAD / SAN$, $AED := SED / SEN$, $U_{q+1} := AAD / AED$; $P_{q+1} := P_q$ – { C_m, C_n } + { C_h }.

3. Repeat step 2 for p-1 times, until there's only one cluster P_{p-1} = { C }, where C = { B_0, …B_{p-1} } contains all bookmarks in the pool. Now we obtain all layers of partitions.
4. Create the cluster tree with C being the root. Select partition P_o with the optimal (minimal) utility U_o among all U_q, q = 0…p-1, add its clusters as the first-level nodes to the cluster tree.
5. Regard each cluster C_k in P_o as the root of the subtree for C_k, using the knowledge of the partition layers and formulas similar to those in step 2, calculate the optimal utility for subpartitions in C_k, and obtain its next-level subclusters and add them to the cluster tree.
6. Repeat step 5 until one of the thresholds for utility measure, cluster size, or cluster depth is reached.
7. Put all invalid bookmarks in the pool in one cluster, label it as an invalid cluster and add it as a first-level node to the cluster tree. The construction for the cluster tree is now complete.

The purpose of adding all invalid bookmarks into the cluster tree is to keep it consistent with the folder tree so that both contain the complete set of bookmarks. As we can see in step 2, instead of recalculating all cluster distances from scratch for the next layer partition, we reuse the results from the current layer. Besides, only the clusters affected in the merging process need to be recalculated. This greatly reduces the computation complexity.

3.4 Cluster labeling

Each cluster needs a label to represent the semantic category of the Web pages it contains. An ideal label for a cluster would be the keywords that are most popular in all Web pages inside it while not so frequently used outside. To factor out Web page size when we count term frequencies, we normalize the term-page matrix by dividing each element with the norm of its column vector. Each time we label a cluster, we remove that label from the set of selectable terms when we label its subclusters, so that a cluster never uses the same label as its ancestors. Since the root cluster represents the whole bookmark pool, we label it with the same name as the folder tree root, and the set of selectable terms contains all terms in the term-page matrix. Starting from the root, we recursively label all clusters in a top-down order.

Suppose we already have cluster C labeled with term t chosen from term set T (all C's ancestors should have been labeled by now), our next step is to label each subcluster C_k in C. We select from term set $T' = T - t$ the term t_k with the maximum frequency measure (note that all frequencies here are normalized), which is the weighted sum of three factors:

$$M(t_k, C_k) = a * F(t_k, C_k) - b * S(t_k, C_k) - c * F(t_k, C\text{-}C_k) \qquad (11)$$

Here $0 = a, b, c = 1$ are weights, $F(t_k, C_k)$ is the average frequency with which t_k appears in all Web pages in C_k; $S(t_k, C_k)$ is the standard deviation of t_k's frequencies in C_k; $F(t_k, C\text{-}C_k)$ is the average frequency with which t_k appears in all other subclusters in C. The first factor favors terms with a highest overall frequency in C_k. The second factor penalizes terms with uneven frequency distribution in C_k, i.e. terms that are frequent in all Web pages are preferred over those that are only frequent in certain pages. The third factor penalizes terms that also appear frequently outside C_k, so only terms uniquely representative for C_k are chosen, and labels for different subclusters are distinguishable from each other. Among the above three factors, the first one is more important and thus a is usually set bigger than b and c.

4. VISUALIZATION AND INTERACTION

From the data analysis phase we acquire two kinds of bookmark hierarchies, one is based on the original folder structure inherent in the input bookmark files, the other comes from the semantic similarity and clustering results. We use Semantic Treemaps to visualize the tree structure of these two hierarchies as well as the semantic properties of individual bookmarks and the similarities between them.

4.1 Semantic Treemap

Semantic Treemaps are used to visualize the folder tree and the cluster tree respectively. STs use the traditional Treemap [9] space filling technique to represent the tree structure of the best partitions by alternatively dividing rectangles in horizontal and vertical direction, resulting in a set of nested rectangles showing the layers of nodes in the tree. A Spring Embedding also called Force Directed Placement (FDP) algorithm is used to layout the web pages in each Treemap rectangle according to their semantic similarities. By associating the semantic distances between data items with the spring force coefficients similar items will be drawn close to each other and vice versa.

Note that FDP takes a long time to stabilize on large data sets. However, we use a divide-and-conquer strategy: instead of applying the FDP algorithm to the whole data set, we take advantage of the hierarchical data structure and calculate its layout within each subcategory, which is of much smaller size and thus manageable within reasonable amount of time.

In the final visualization, each folder/cluster (both called category) in the tree is represented by a rectangle in the treemap. The nesting of the rectangles represents the relationships among the subcategories. The bottom-level rectangles serve as the containers for web pages, each of which is represented by a small dot inside its corresponding rectangle. The area of each rectangle is in ratio with the size (total number of bookmarks) of that subcategory, which helps maintain an even density among rectangles and avoid over-crowdness in big categories. Inside each rectangle, the semantic similarities between web pages are approximated with their 2D Euclidean distances, with semantically similar ones placed closer.

To compute the Semantic Treemap layout, first we run a recursive procedure to calculate the positions and sizes for all rectangles according to the composition of the hierarchy; then for all innermost rectangles, we calculate their Spring Embedding layouts one by one using a subset of the distance matrix. Even though we might have a huge number of web pages in the pool, there are rather few web pages in each cluster; besides we can limit the cluster size using a threshold (as discussed in section 3.3). As a result we only need to compute the positions of a limited number of nodes during the FDP iterations.

4.2 Visual Cues

Color and size coding is used to visualize some other properties of bookmark folders and clusters. For example, the thickness of the rectangle frame and the size of its header are both in proportion with the rectangle's size, so upper level categories (assuming they are of more importance) will usually have thicker frames and bigger headers and thus are more obvious. Besides, rectangles of different levels are displayed in colors of different brightness, i.e. the further down the nesting level, the darker the color. This gives a much clearer view of the hierarchy than plain rectangles with no frames or color-coding. As for the bookmarks, different dot shapes represent different types of Web pages, and the size of each dot encodes the size of the HTML document. Besides, the popularity (hotness) of a Web page is also modeled by the saturation of its color hue. Naturally, bigger Web pages correspond to bigger dots, while pages more frequently accessed appear in more saturated colors.

When there are many levels in the bookmark hierarchy, the Semantic Treemap might get crowded without enough space for labels, and it could be hard for users to identify the hierarchical structure at one glance. To help users obtain an overview of the hierarchy, we provide an expandable textual node-link tree as a site map on the left side of the Semantic Treemap. Each non-leaf node in the tree represents a subcategory, and each leaf node represents a bookmark. While invalid bookmarks and clusters are not shown in the Semantic Treemap they are shown with special marks in the textual tree, reminding users to delete the obsolete links and reload the temporarily failed ones. To ensure consistency between the textual tree and the Semantic Treemap, any operation on one of them will apply to the other as well. Both views can be chosen to display either the folder or the cluster hierarchy, and the choices are independent of each other, e.g. users can have both views displaying the folder hierarchy, or he can have the textual tree to show folders while the treemap to show clusters. The latter choice can achieve some special query functions as discussed later.

4.3 Interaction Techniques

Various interaction methods are provided to further facilitate the navigation for information, including scrolling, zooming, expanding/collapsing, filtering, searching, and selection. Among these interactions, selection and expanding/collapsing apply to the textual tree and the Semantic Treemap at the same time, scrolling apply to both but are independent, while zooming, filtering, and searching apply only to the treemap.

Both the textual tree and the Semantic Treemap are displayed in a scrollable panel. When the hierarchy is too big to be shown in one frame, a user can scroll horizontally or vertically to move any part into the view port. He can also zoom in/out the treemap to see more details or more overview. An important feature of the Semantic Treemap is that each rectangle is expandable. To avoid over-crowdness, the user can collapse lower-level rectangles and hide them so that the overall structure is clearer. Vice versa, he can expand a path of rectangles to see the internal structure of their subcategories and bookmarks. The user can also expand/collapse nodes in the textual tree and the operation will automatically apply to the treemap as well. If the user opens a dot (bookmark), it will be displayed in a special fill pattern, and a Web browser will be brought up to show the corresponding Web page.

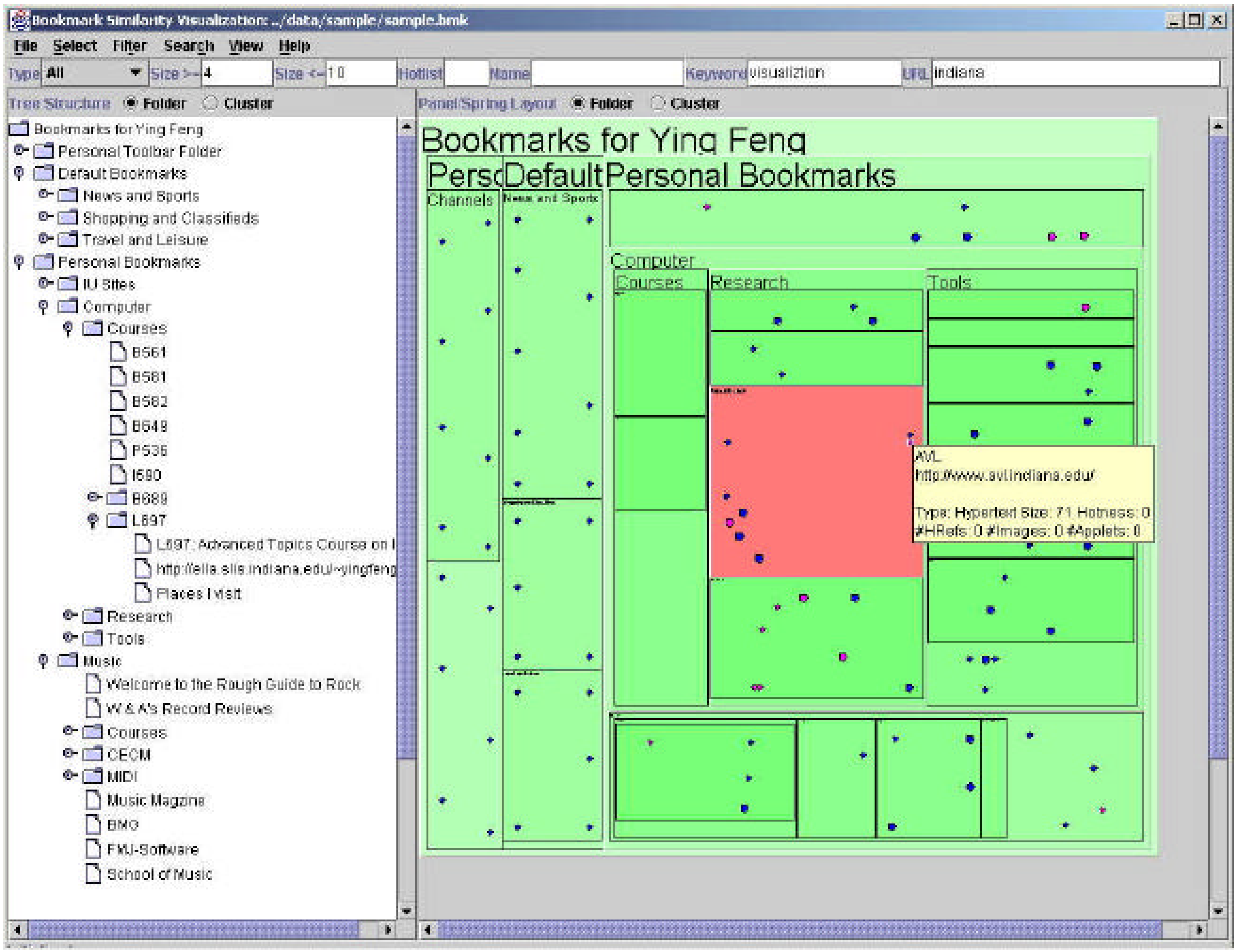
When a rectangle in the Semantic Treemap is pointed at (by mouse), its path (the sequence of its ancestors from itself up to the root) will be highlighted and its detailed information will be popped up next to its header. When a node is selected either in the tree or the treemap, it will be highlighted in the tree and its path will be highlighted in the treemap. When a user wants to see only the bookmarks within a certain range, he can use filters to hide the unwanted ones. Three kinds of filters are provided to select web pages based on domain type, size, or hotness. These filters can be used either separately or conjunctly. For example, the user can filter to see only pure-text Web pages under 10MB among the top ten hottest Web pages. The user can also use searching tools to find certain bookmarks with certain features. There are also three ways for searching: by names, by keywords (terms that appear most frequently in a Web page), and by URL links. For example, the user can type in the name of a folder and retrieve all the bookmarks in that folder; he can also search by keywords that may represent a cluster, or he can directly type in a URL. The bookmarks retrieved from the search will be highlighted. The search is "tolerant" in the sense that partial matching is used so that the user doesn't need to know the exact whole string. Of course, the more complete input the user submits, the more accurate result he will get.

An interesting way to combine selecting with searching in the two bookmark hierarchy views can help a user evaluate how accurate he organizes his bookmarks. This can be achieved in the following way. First the user can show the cluster hierarchy in the textual tree and the folder hierarchy in the Semantic Treemap. Then he can select any cluster in the tree and issue a special "Search Selection" command, which will enable all bookmarks in the selected cluster to be retrieved in the treemap. From the distribution of the highlighted bookmarks, the user can find out how much his own folder organization matches the computed semantic clustering. Vice versa, he can show the folders in the tree and the clusters in the treemap, and test how accurate the automatic categorization match the original manual one.

To enable input and output of data, the tool also provides file operations. A user can import bookmark files from URLs or local file systems, and export the Semantic Treemap layout into a specially formatted text file. He can also reload updated Web pages or broken links due to network failures. Finally, the bookmark trees as well as the interaction status of their Semantic Treemaps can be saved into a binary file enabling users to resume a particular visualization session at a later point in time.

5. APPLICATION EXAMPLES

Figure 3 shows a screen shot visualizing the lead author's personal bookmark archive. The left-side view gives the cluster hierarchy in a link-node tree structure, which is partly expanded displaying the names of some subclusters. The right-side view is the Semantic Treemap for the folder hierarchy. Under the root "Bookmarks for Ying Feng" we can see three folders represented as three light green rectangles. Inside the first folder "Personal Tool Bar" there is a subfolder with smaller header "Channels" at the top of a darker green rectangle, inside which there are several bookmarks represented as small blue dots. Some folders are collapsed, such as "Personal Bookmarks / Computer / Course", whose subfolders inside are hidden; some are expanded, such as subfolder "Research" just to the right, as we can see, its four subfolders are shown. Among them the one called "Visualization" is selected and highlighted in pink. Inside it the bookmark "AVL" is currently pointed at, and a small yellow dialog window is popped up near by showing its detailed information, while all its parent folders are highlighted with white borders showing its path to the root. From the toolbar near the top of the screen, we can see that only Web pages with size between 4KB and 10KB are shown, while all others are filtered out and hidden. On the other hand, all links at Indiana University that are related to visualization are highlighted in purple, as a result of the search by keywords "visualization" and URL link "Indiana".

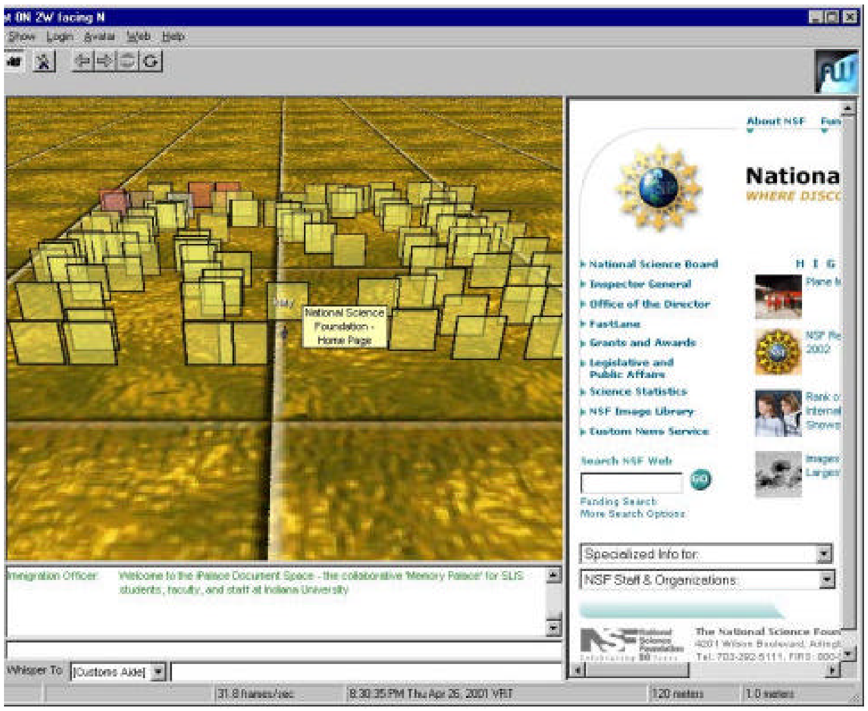


Type: All Size >= 4 Size <= 10 Hotlist Name Keyword visualiztion URL indiana

Tree Structure (● Folder ○ Cluster) Panel/Spring Layout (● Folder ○ Cluster)

AVL
http://www.avl.indiana.edu/
Type: Hypertext Size: 71 Hotness: 0
#HRefs: 0 #Images: 0 #Applets: 0

Figure 3. Visualization of a personal bookmark file



Integration Officer: Welcome to the iPalace Document Space - the collaborative 'Memory Palace' for SLIS students, faculty, and staff at Indiana University

Figure 4. A shared 3-D collaborative bookmark space

To enable sharing and collaborative browsing, web page collections can be exported and visualized in a 3D desktop virtual reality environment such as the ActiveWorlds browser as shown in Figure 4. Each bookmark is represented by a small frame that is linked to the original Web page. The horizontal layout of the web pages is identical to the layout in Figure 3, i.e., bookmarks on similar topics are close in space. Users can enter this virtual bookmark landscape collaboratively, navigate freely, click on the frame to display the corresponding web page in the web browser, or answer questions and give advice using the in-built chat facility [17].

6. CONCLUSIONS AND FUTURE WORK

Today, bookmark and favorite collections are used to create personal Web information spaces that help people remember and retrieve interesting Web pages. This paper introduced and applied Semantic Treemaps to support users to better organize and view their bookmark space as well as to maintain a large bookmark pool for mutual sharing among user groups. Taking advantage of both the Spring Embedding and the Treemap algorithm, Semantic Treemaps make efficient use of limited screen resource and make it possible to display large hierarchical bookmark sets while showing the semantic similarities between individual bookmarks at the same time. The user interface facilitates both browsing and retrieving.

There are several aspects that need to be improved in the future. Squarified [11] or variable-shaped [13] Treemaps can be applied to avoid long narrow areas, so that Spring Embedding layouts can be better displayed in approximate squares. Currently our Semantic Treemaps can visualize inter-cluster hierarchies and intra-cluster similarities. We hope to further develop them to visualize inter-cluster similarities as well. This may be achieved by applying Spring Embedding at the cluster level, and accommodate a layout similar to Bubblemaps [14], instead of following strictly the slice-and-dice layout. Eventually we want to bring the bookmark visualization tool online, so that users can submit and modify their bookmarks and browse the bookmark pool through the Internet, achieving free sharing among communities in the real sense.

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