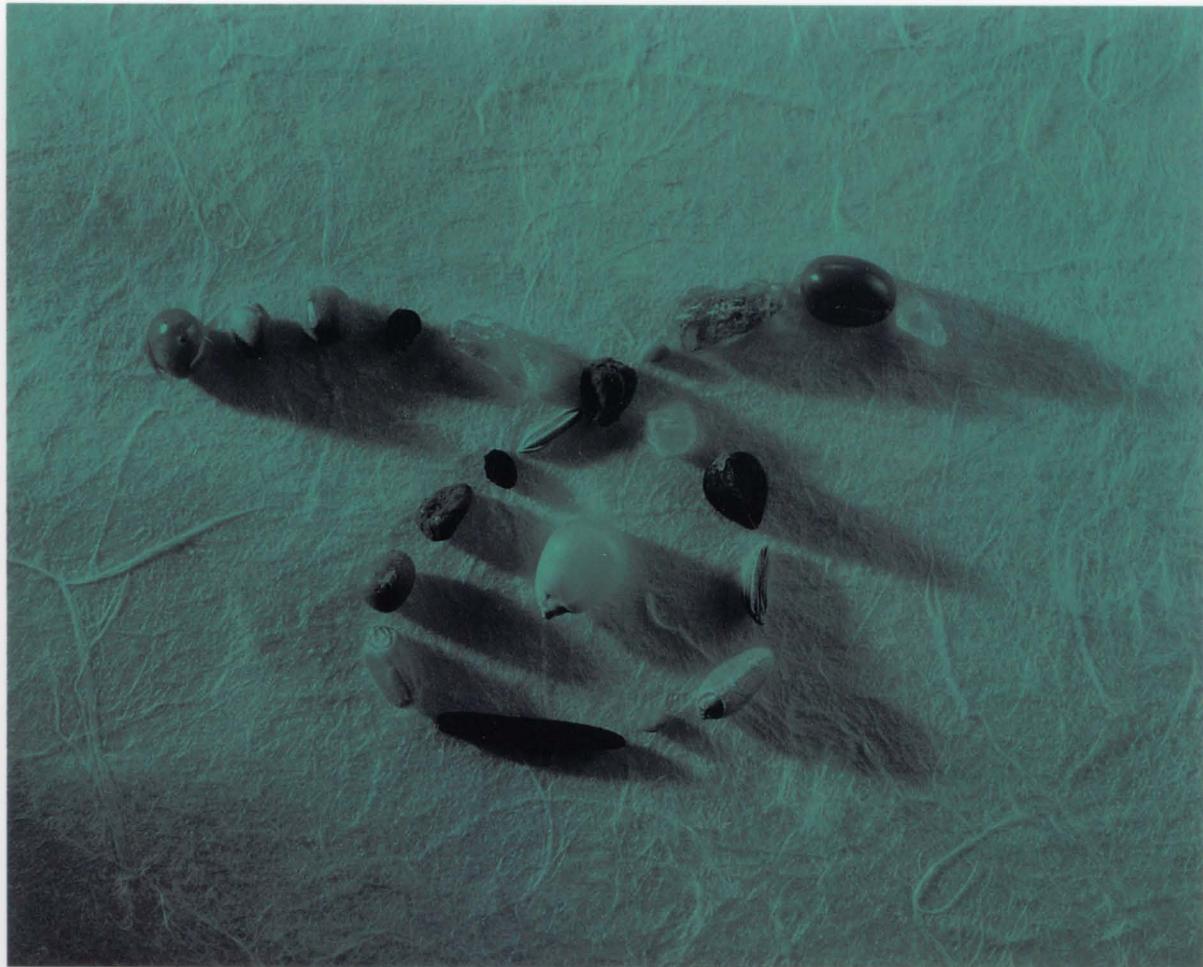


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# Clustering Web Pages into Hierarchical Categories

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## ABSTRACT

*Clustering is well suited for Web mining by automatically organizing Web pages into categories each of which contains Web pages having similar contents. However, one problem in clustering is the lack of general methods to automatically determine the number of categories or clusters. For the Web domain, until now there is no such a method suitable for Web page clustering. To address this problem, we discovered a constant factor that characterizes the Web domain, based on which we propose a new method for automatically determining the number of clusters in Web page datasets. We also propose a new Bidirectional Hierarchical Clustering algorithm, which arranges individual Web pages into clusters and then arranges the clusters into larger clusters and so on until the average inter-cluster similarity approaches the constant factor. Having the new constant factor together with the new algorithm, we have developed a clustering system suitable for mining the Web.*

**Keywords:** *information retrieval; knowledge classification; knowledge discovery; Semantic Web; Web mining*

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## INTRODUCTION

We are interested in cluster analysis that can be used to organize Web pages into clusters based on their contents or genres (Choi & Yao, 2005). Clustering is an unsupervised discovery process for partitioning a set of data into clusters such that data in the same cluster is more similar to one another than

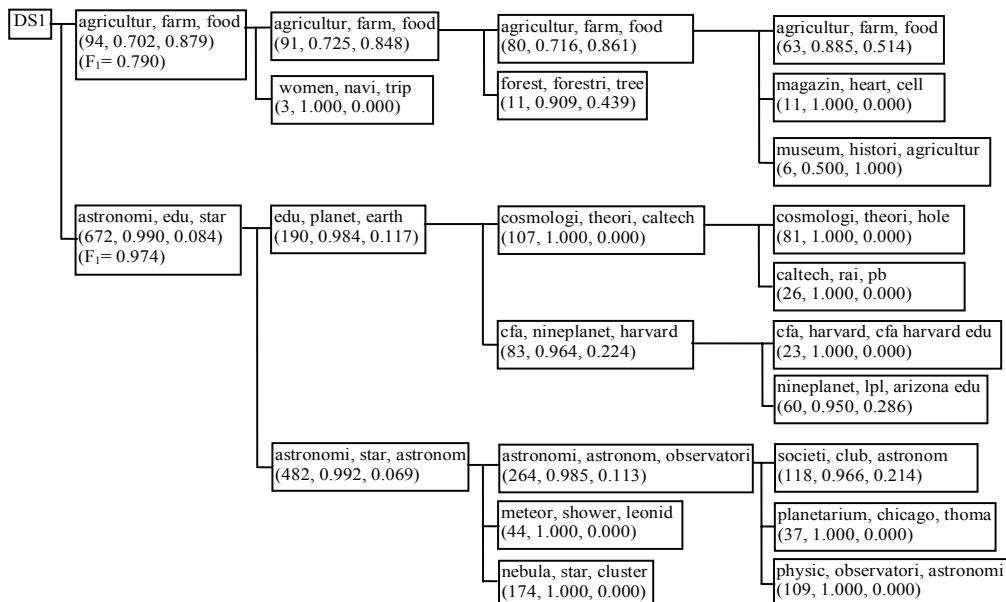
data in other clusters (Berkhin, 2002; Everitt et al., 2001; Jain & Dubes, 1998; Jain et al., 1999). Typical application areas for clustering include artificial intelligence, biology, data mining, information retrieval, image processing, marketing, pattern recognition, and statistics (Berkhin, 2002; Everitt et al., 2001; Jain et al., 1999). Compared to

classification methods, cluster analysis has the advantage that it does not require any training data (i.e., the labeled data), but can achieve the same goal in that it can classify similar Web pages into groups.

The major aspects of the clustering problem for organizing Web pages are: To find the number of clusters  $k$  in a Web page dataset, and to assign Web pages accurately to their clusters. Much work (Agrawal et al., 1998; Dhillon et al., 2001; Ester et al., 1996; Guha et al., 1998a; Guha et al., 1998b; Hinneburg & Keim, 1999; Karypis & Kumar, 1999; Ng & Han, 1994; Rajaraman & Pan, 2000; Sander et al., 1998; Tantrum et

al., 2002; Yao & Karypis, 2001; Zhang et al., 1996; Zhao & Karypis, 1999) has been done to improve the accuracy of assigning data to clusters in different domains, whereas no satisfactory method has been found to estimate  $k$  in a dataset (Dudoit & Fridlyand, 2002; Strehl, 2002) though many methods were proposed (Davies & Bouldin, 1979; Dudoit & Fridland, 2002; Milligan & Cooper, 1985). As a matter of fact, finding  $k$  in a dataset is still a challenge in cluster analysis (Strehl, 2002). Almost all existing work in this area assumes that  $k$  is known for clustering a dataset (e.g., Karypis et al., 1999; Zhao & Karypis, 1999). However in

*Figure 1. The hierarchical structure produced for dataset DS1. Each box in this figure represents a cluster. The format of the description of a cluster is: its top three descriptive terms followed by (#docs, purity, entropy). Only the descriptions of clusters at the top level contain the  $F_1$  scores.*



many applications, this is not true because there is little prior knowledge available for cluster analysis except the feature space or the similarity space of a dataset.

This article addresses the problem of estimating  $k$  for Web page datasets. By testing many existing methods for estimating  $k$  for datasets, we find that only the average inter-cluster similarity (*avgInter*) need to be used as the criterion to discover  $k$  for a Web page dataset. Our experiments show that when the *avgInter* for a Web page dataset reaches a constant threshold, the clustering solutions for different datasets from the Yahoo! directory are measured to be the best. Compared to other criterion, e.g., the maximal or minimal inter-cluster similarity among clusters, *avgInter* implies a characteristic for Web page datasets.

This article also describes our new clustering algorithm called bi-directional hierarchical clustering. The new clustering algorithm arranges individual Web pages into clusters and then arranges the clusters into larger clusters and so on until the average inter-cluster similarity approaches a constant threshold. It produces a hierarchy of categories (see for example Figure 1), in which larger and more general categories locate at the top while smaller and more specific categories locate at the bottom of the hierarchy. Figure 1 shows the result of one of our experiments for clustering 766 Web pages to produce a hierarchy of categories. The top (left-most) category contains all

the Web pages (Dataset 1). The next level consists of two categories, one of which has 94 Web pages and the other has 672 Web pages. Then, each of the two categories has sub-categories and so on, as shown in the figure. This example shows that our new clustering algorithm is able to handle categories of widely different sizes (such as 94 comparing to 672 pages). By using two measures, purity and entropy, this example also shows that more general categories (which have lower purity but higher entropy) locate at the top, while more specific categories (which have higher purity but lower entropy) locate at the bottom of the hierarchy.

The rest of this article is organized as follows. The second section gives background and an overview of related methods. Our new bi-directional hierarchical clustering algorithm is presented in the third section. The fourth section describes the Web page datasets used in our experiments. The fifth section provides the experimental details for the discovery of a constant factor that characterizes the Web domain. The sixth section shows how the constant factor is used for automatically discovering the number of clusters. The seventh section provides the conclusion and future research.

## **BACKGROUND AND RELATED METHODS**

In this section we first give the necessary background of cluster analysis and then briefly review existing methods

for estimating the number of clusters in a dataset.

The task of clustering can be expressed as follows (Berkhin, 2002; Everitt et al., 2001; Jain et al., 1999). Let  $n$  be the number of objects, data points, or samples in a dataset,  $m$  the number of features for each data point  $d_i$  with  $i \in \{1, \dots, n\}$ , and  $k$  be the desired number of clusters to be recovered. Let  $l \in \{1, \dots, k\}$  denote the unknown cluster label and  $C_l$  be the set of all data points in the  $l$  cluster. Given a set of  $m$ -dimensional data points, the goal is to estimate the number of clusters  $k$  and to estimate the cluster label  $l$  of each data point such that similar data points have the same label. Hard clustering assigns a label to each data point while soft clustering assigns the probabilities of being a member of each cluster to each data point. In the following we present an overview of several common methods for estimating  $k$  for a dataset.

Calinski and Harabasz (1974) defined an index,  $CH(k)$ , to be:

$$CH(k) = \frac{\text{tr}B(k)/(k-1)}{\text{tr}W(k)/(n-k)} \quad (1)$$

where  $\text{tr}$  represents the trace of a matrix,  $B(k)$  is the between cluster sum of squares with  $k$  clusters and  $W(k)$  is the within cluster sum of squares with  $k$  clusters (Mardia et al., 1979). The number of clusters for a dataset is given by  $\arg \max_{k \geq 2} CH(k)$ .

Krzanowski and Lai (1985) defined the following indices for estimating  $k$  for a dataset:

$$\text{diff}(k) = (k-1)^{2/m} \text{tr}W_{k-1} - k^{2/m} \text{tr}W_k \quad (2)$$

$$KL(k) = \frac{|\text{diff}(k)|}{|\text{diff}(k+1)|} \quad (3)$$

where  $m$  is number of features for each data point. The number of clusters for a dataset is estimated to be  $\arg \max_{k \geq 2} KL(k)$ .

The Silhouette width is defined (Kaufman & Rousseeuw, 1990) to be a criterion for estimating  $k$  in a dataset as follows:

$$sil(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))} \quad (4)$$

where  $sil(i)$  means the Silhouette width of data point  $i$ ,  $a(i)$  denotes the average distance between  $i$  and all other data in the cluster which  $i$  belongs to, and  $b(i)$  represents the *smallest* average distance between  $i$  and all data points in a cluster. The data with large  $sil(i)$  is well clustered. The overall average silhouette width is defined by  $\bar{sil} = \sum sil_i / n$  (where  $n$  is the number of data in a dataset). Each  $k$  ( $k \geq 2$ ) is associated with a  $\bar{sil}_k$  and the  $k$  is selected to be the right number of clusters for a dataset which has the largest  $\bar{sil}$  (i.e.  $k = \arg \max_{k \geq 2} \bar{sil}_k$ ).

Similarly, Strehl (2002) defined the following indices:

$$\begin{aligned} \text{avgInter}(k) &= \\ &\sum_{i=1}^k \frac{n_i}{n-n_i} \sum_{j \in \{1, \dots, i-1, i+1, \dots, k\}} n_j \cdot \text{Inter}(C_i, C_j) \end{aligned} \quad (5)$$

$$\text{avgIntra}(k) = \sum_{i=1}^k n_i \text{Intra}(C_i) \quad (6)$$

$$\phi(k) = 1 - \frac{\text{avgInter}(k)}{\text{avgIntra}(k)} \quad (7)$$

where  $\text{avgInter}(k)$  denotes the weighted average inter-cluster similarity,  $\text{avgIntra}(k)$  denotes the weighted average intra-cluster similarity,  $\text{Inter}(C_i, C_j)$  means the inter-cluster similarity between cluster  $C_i$  with  $n_i$  data points and cluster  $C_j$  with  $n_j$  data points,  $\text{Intra}(C_i)$  means the intra-cluster similarity within cluster  $C_i$ , and  $\phi(k)$  is the criterion designed to measure the quality of clustering solution. The  $\text{Inter}(C_i, C_j)$  and  $\text{Intra}(C_i)$  are given by (Strehl, 2002)

$$\text{Inter}(C_i, C_j) = \frac{1}{n_i n_j} \sum_{d_a \in C_i, d_b \in C_j} \text{sim}(d_a, d_b) \quad (8)$$

$$\text{Intra}(C_i) = \frac{2}{(n_i - 1)n_i} \sum_{d_a, d_b \in C_i} \text{sim}(d_a, d_b) \quad (9)$$

where  $d_a$  and  $d_b$  represent data points. To obtain high quality with small number of clusters, Strehl (2002) also designed a penalized quality  $\phi^T(k)$  which is defined as

$$\phi^T(k) = (1 - \frac{2k}{n})\phi(k). \quad (10)$$

The number of clusters in a dataset is estimated to be  $\arg \max_{k \geq 2} \phi^T(k)$ .

It can be noticed that the above methods cannot be used for estimating  $k=1$  for a dataset. Some other methods, e.g., Clest (Dudoit & Fridlyand, 2002), Hartigan (1985), and gap (Tibshirani et al., 2000) were also found in literature.

In summary, most existing methods make use of the distance (or similarity) of inter-cluster and (or) intra-cluster of a dataset. The problem is that none of them is satisfactory for all kinds of cluster analysis (Dudoit & Fridlyand, 2002; Stehl, 2002). One reason may be that people have different opinions about the granularity of clusters and there may be several right answers to  $k$  with respect to different desired granularity. Unlike partitional (flat) clustering algorithms, hierarchical clustering algorithms may have different  $k$ 's by cutting the dendrogram at different levels, hence providing flexibility for clustering results.

In the next section we will present our new clustering algorithm which is used to cluster Web pages and to estimate  $k$  for Web page datasets. Throughout this article, we use term "documents" or "Web pages" to denote Web pages, the term "true class" to mean a class of Web pages which contains Web pages labeled with the same class label, and the term "cluster" to denote a group of Web pages in which Web pages may have different class labels.

## Bi-Directional Hierarchical Clustering Algorithm

We present our new bi-directional hierarchical clustering (BHC) system (Yao & Choi, 2003) in this section. The BHC system consists of three major steps:

1. Generating an initial sparse graph,

2. Bottom-up cluster-merging phase, and
3. Top-down refining phase.

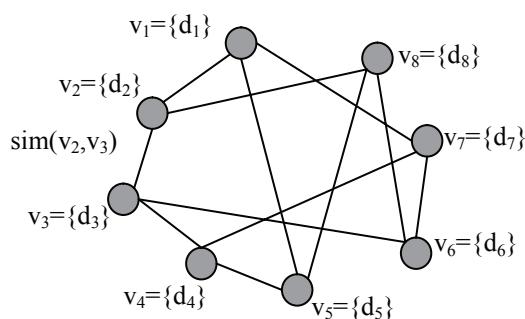
These major steps are described in detail in the following subsections. Here we outline the workings of the entire system. In the first phase, the BHC system takes a given dataset and generates an initial sparse graph (e.g., Figure 2), where a node represents a cluster, and is connected to its  $k$ -nearest neighbors by similarity-weighted edges. The BHC system then creates a hierarchical structure of clusters in the two phases, the bottom-up cluster-merging phase and the top-down refinement phase. During the bottom-up cluster-merging phase, two or more nodes (clusters) are merged together to form a larger cluster. Then, again two or more clusters are merged and so on until a stopping condition is met. During the top-down refinement

phase, the BHC system eliminates the early errors that may occur in the greedy bottom-up cluster-merging phase. It moves some nodes between clusters to minimize the inter-cluster similarities. Thus, these two phases make items in a cluster more similar and make clusters more distinct from each other. The key features of the BHC system are that it produces a hierarchical structure of clusters much faster than the existing hierarchical clustering algorithms, and it improves clustering results using a refinement process, as detailed in the following.

#### *Generating an Initial Sparse Graph*

In this subsection we describe how to arrange a set of Web pages to form a weighted graph (e.g., Figure 2) based on the similarities of Web pages. A Web page is first converted to a vector of terms:

*Figure 2. The initial all- $k$ -nearest-neighbor (Aknn) graph  $G_0$  with  $n$  nodes ( $n=8$  in this case). Each node in this graph contains a single Web page (e.g., node  $v_1$  contains Web page  $d_1$ ) and is connected to its  $k$ -nearest neighbors ( $k$  is 3 in this case). The edge connecting two nodes is weighted by the similarity between the two nodes.*



$$\mathbf{d}_i = (w_{i1}, \dots, w_{ij}, \dots, w_{im}) \quad (11)$$

where Web page  $d_i$  has  $m$  terms (also called features), and the weights of the features are indexed from  $w_{il}$  to  $w_{im}$ . Usually a feature consists of one to three words, and its weight is the number of occurrences of the feature in a Web page. Common methods to determine  $w_{ij}$  are the term frequency-inverse document frequency (tf-idf) method (Salton & Buckley, 1988) or the structure-oriented term weighting method (Peng, 2002; Riboni, 2002). Many approaches (e.g., Rijksbergen, 1979; Strehl et al., 2000) are then used to measure the similarity between two Web pages by comparing their vectors. We choose the cosine (Rijksbergen, 1979) as the metric for measuring the similarity, i.e.,  $\cos(d_i, d_j)$  is the cosine similarity between Web pages  $d_i$  and  $d_j$ . We then define the similarity between two clusters  $u$  and  $v$  as:

$$sim(u, v) = \frac{\sum_{d_i \in u, d_j \in v} \cos(d_i, d_j)}{|u| |v|} \quad (12)$$

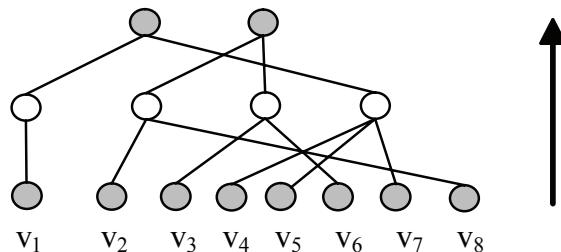
where  $d_i$  is a Web page within cluster  $u$ ,  $d_j$  is a Web page within cluster  $v$ ,  $|u|$  is the number of Web pages in cluster  $u$ .

An initial sparse graph is generated by using the  $sim(u, v)$  to weight the edge between two nodes  $u$  and  $v$ . Figure 2 shows an example. Initially each node in the graph contains only one Web page. Each node does not connect to all other nodes, but only to  $k$  most similar nodes. By choosing  $k$  small in comparison to the total number of nodes, we can reduce the computation time in later clustering processes.

#### *Bottom-Up Cluster-Merging Phase*

In the bottom-up clustermerging phase we aim at maximizing the intra-similarities of clusters by merging the most similar clusters together (see Figure 3 for example). To achieve this goal,

*Figure 3. Illustration of the bottom-up clustermerging procedure. The nodes at the same level are nodes in a same graph. Some nodes at the lower level are merged to form a single node at the higher level. The two nodes at the top level represent the two final clusters in this example.*



we transform the initial sparse graph  $G_0$  into a sequence of smaller graphs  $G_1, G_2, \dots, G_t$ , such that the number of nodes  $|V_0| > |V_1| > |V_2| > \dots > |V_t|$ , where a stopping criteria is met at  $G_t$ . The nodes in the smallest graph  $G_t$  represent the final clusters for a dataset.

We first define the most similar neighborhood of a node  $v$ ,  $N_v(\delta_i)$ , to be a set of nodes fulfilling the following condition:

$$N_v(\delta_i) = \{u \mid sim(v, u) > \delta_i\} \quad (13)$$

where  $sim(v, u)$  is the similarity between node  $v$  and node  $u$  (see Equation 12), and  $\delta_i$  is an adaptive threshold (e.g.,  $\delta_i = 0.543$ ) and is associated with graph  $G_i$ . The nodes within  $N_v(\delta_i)$  of node  $v$  in  $G_i$  are merged together to become a new node in the smaller graph  $G_{i+1}$  (illustrated in Figure 3). The number of nodes and the number of edges in the smaller graph are reduced, and the number of Web pages in a node in the smaller graph  $G_{i+1}$  is increased, resulting in grouping similar Web pages into nodes (or clusters).

After new nodes in the smaller graph  $G_{i+1}$  are formed, the edges between nodes are built under two conditions: (1) similarity between two nodes is greater than zero and (2) a new node is connected to at most  $k$  most similar nodes. Furthermore, since  $N_v(\delta_i) \subseteq N_v(\delta_{i+1})$  whenever  $\delta_i \geq \delta_{i+1}$ , we design

$$\delta_{i+1} = \delta_i / \beta \quad (14)$$

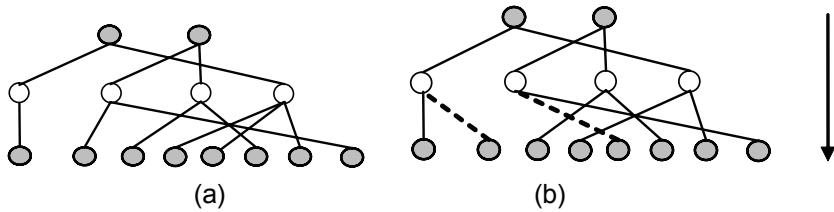
where  $\beta > 1$  is a decay factor (Rajaraman & Pan, 2000), which defines a weaker neighborhood for the smaller graph  $G_{i+1}$  in order to continue to transfer  $G_{i+1}$  into another smaller graph. Therefore this is an iterative procedure to transfer the initial graph  $G_0$  to the sequence of smaller graph  $G_1, G_2, \dots, G_t$  such that  $|V_0| > |V_1| > |V_2| > \dots > |V_t|$ . The decay factor  $\beta$  controls the speed of reducing the value of threshold  $\delta$  in a way that  $\delta_0 = 1/\beta, \delta_1 = \delta_0/\beta, \dots, \delta_t = \delta_{t-1}/\beta$ . The faster the value of  $\delta$  is reduced, the more nodes in the current graph  $G_i$  may be grouped to be a new node in the next smaller graph  $G_{i+1}$ , producing less new nodes in  $G_{i+1}$ . Therefore the decay factor  $\beta$  determines the speed of reducing the number of the sequence of smaller graphs. A larger  $\beta$  will result in a fewer number of levels in the hierarchical structure.

A stopping factor is required to terminate this bottom-up cluster-merging procedure. The details for the discovery of a stopping factor for Web page datasets are provided in the fifth section. This bottom-up cluster-merging phase is a greedy procedure, which may contain errors or fall into local minima. To address this problem, we apply a top-down refinement procedure.

#### *Top-Down Refinement Phase*

The top-down refinement phase refines the greedy clustering results produced by the bottom-up cluster-merging phase (see Figure 4 for example). The objective in this phase is to make clusters more distinct from each other.

*Figure 4. Illustration of top-down refinement procedure. (a) Shows the bottom-up clustering solution, which is used to compare the improvement produced by the top-down refinement procedure. (b) Shows the final clustering solution after the top-down refinement procedure. The dashed lines in (b) indicate the error correction. The hierarchical structure in (b) can be used for users to browse Web pages.*



We first define the term sub-node: a sub-node  $s$  of a node  $u$  in a graph  $G_i+1$  is a node  $s$  in graph  $G_i$ . For instance in Figure 5, node  $x$  is a sub-node of node  $u$ . The top-down refinement procedure operates on the following rule: If a sub-node  $x$  of a node  $u$  is moved into another node  $v$  and this movement results in reduction of the inter-similarity between the two nodes, then the sub-node  $x$  should be moved into the node  $v$ . The reduction of the inter-similarity between two nodes,  $u$  and  $v$ , by moving a sub-node  $x$  from node  $u$  to node  $v$  can be expressed by a gain function which is defined as:

$$gain_x(u, v) = sim(u, v) - sim((u - x), (v + x)) \quad (15)$$

where  $u - x$  means the node after removing sub-node  $x$  out of  $u$ , and  $v + x$  means the node after adding sub-node  $x$  into  $v$ . Although a sub-node is considered to be moved into any of its connected nodes, it is moved only to its connected

node that results in the greatest positive gain. To keep track of the gains, a gain list is used and its implementation can be found in, e.g., Fiduccia and Mattheyes (1982).

Our refinement procedure refines clustering solution from the smallest graph,  $G_t$ , at the top level to the initial graph,  $G_0$ , at the lowest level (see Figure 4). Sub-nodes are moved until no more positive gain will be obtained. For the example shown in Figure 4, two sub-nodes are moved to different clusters.

This refinement procedure is very effective in climbing out of local minima (Hendrickson & Leland, 1993; Karypis & Kumar, 1999). It not only finds early errors produced by the greedy clustermerging procedure, but also can move groups of Web pages of different sizes from one cluster into another cluster so that the inter-cluster similarity is reduced.

The nodes in graph  $G_t$  at the top level in the hierarchical structure (see

*Figure 5. Moving a sub-node x into its connected node with the greatest gain*

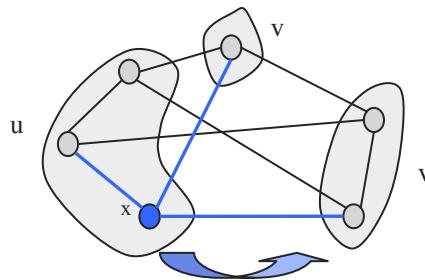


Figure 4) generated after the top-down refinement procedure represent final clusters for a dataset. The resultant hierarchical structure can be used for Web browsing, with larger and more general clusters at higher levels while smaller and more specific clusters are at lower levels.

### **Web Page Datasets for Experiments**

For testing our bi-directional hierarchical clustering algorithm and for discovering a new constant stopping factor, we conducted a number of experiments on Web page datasets. Here we report four Web page datasets taken from Yahoo.com (see Table 1) representing datasets with different sizes and different granularity and we skip other datasets for brevity since their experimental results were found to have similar quality. The first dataset, *DS1*, contains 766 Web pages which are randomly selected from two true classes: *agriculture* and *astronomy*. This dataset is designed to show our method of estimating the number of clusters  $k$

in a dataset which consists of clusters of widely different sizes: The number of Web pages from the *astronomy* true class is about ten times the number of Web pages from the *agriculture* true class. The second dataset, *DS2*, contains 664 Web pages from 4 true classes. The third dataset, *DS3*, includes 1215 Web pages from 12 true classes. In order to show the performance on a more diverse dataset, we produce the forth dataset, *DS4*, which consists of 2524 Web pages from 24 true classes. After we remove stop words and conduct reduction of dimensionality (Yao, 2004), the final dimension for each dataset is listed in Table 1.

### **Discovery of a Constant Factor**

In this section, we outline our experiments for the discovery of a constant factor that characterizes the Web domain and makes our clustering algorithm applicable for clustering Web pages. For all experiments, we use the metric,  $F_1$  measure (Larsen & Aone, 1999; Zhao & Karypis, 1999), which makes use of true class labels of Web

*Table 1. Compositions of four representative Web page datasets*

DS1: true classes = 2, the number of web pages= 766, dimension= 1327

true class (the number of web pages):
agriculture(73) astronomy(693)

DS2: true classes = 4, the number of web pages=664, dimension=1362

astronomy(169) biology(234) alternative(119) mathematics(142)
---

DS3: true classes = 12, the number of web pages = 1215, dimension= 1543

agriculture(108) astronomy(92) evolution(74) genetics(108) health(127) music(103) taxes(80) religion(113) sociology(110) jewelry(108) network (101) sports(91)
---

DS4: true classes = 24, the number of web pages = 2524, dimension= 2699

agriculture(87) astronomy(96) anatomy(85) evolution(76) plants(124) genetics(106) math- ematics(106) health(128) hardware(127) forestry(68) radio(115) music(104) automotive(109) taxes(82) government(147) religion(114) education(124) art(101) sociology(108) archaeol- ogy(105) jewelry(106) banking(72) network (88) sports(146)
--

pages, to measure the quality of clusters in a Web page dataset. The  $F_1$  measure indicates how well a cluster solution matches the true classes in the real world (e.g., the Yahoo! directory). In general, the greater  $F_1$  score, the better clustering solution.

In our experiments we test the existing methods  $CH(k)$ ,  $KL(k)$ ,  $\overline{sil}_k$ ,  $\phi(k)$  and  $\phi^T(k)$  (see the second section) to discover the number of clusters  $k$  for Web page datasets. These five metrics are computed for different  $k$ 's for a Web page dataset. However, none of them works well. Our tests results showed that for any dataset in Table 1 their estimated  $k$  is more than 5 times different from the true number of classes in the Web page datasets and the correspond-

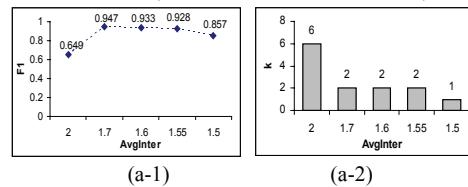
ing cluster solutions have a lower than 0.3  $F_1$  score.

After many trials, we find that  $avgInter(k)$  for any dataset in Table 1 reaches a common threshold of 1.7, when the  $F_1$  measure of the cluster solution for a dataset is greatest. The relation between the thresholds of  $avgInter(k)$  and the  $F_1$  scores of a cluster solution, and the relation between the thresholds of  $avgInter(k)$  and  $k$ 's for the four Web page datasets are illustrated in Figure 6.

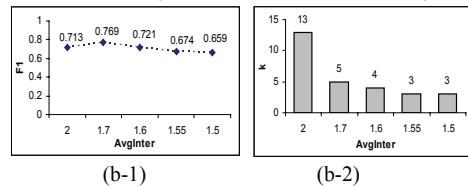
In Figure 6 (a-1), (b-1), (c-1) and (d-1), the  $F_1$  scores of cluster performances for the four datasets reach the maximal values when the threshold of  $avgInter$  is 1.7, and further increasing or reducing the threshold of  $avgInter$

*Figure 6. The impact of avgInter on clustering performances for four representative Web page datasets*

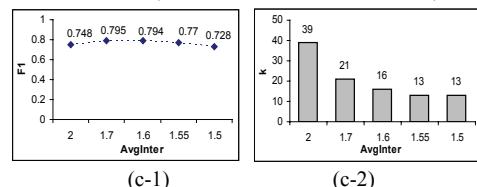
For dataset DS1 (the number of true classes is 2):



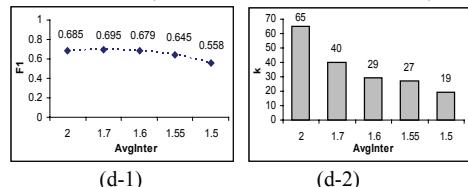
For dataset DS2 (the number of true classes is 4):



For dataset DS3 (the number of true classes is 12):



For dataset DS4 (the number of true classes is 24):



would only worsen the  $F_1$  scores for the datasets *DS1*, *DS2*, *DS3* and *DS4*. In other words, once the weighted average inter-cluster similarity (*avgInter*) reaches the common threshold, 1.7, the cluster solution is found to be best for a Web page dataset. This shows that, unlike other metric such as  $CH(k)$ ,  $KL(k)$ ,  $\overline{sil}_k$ , or  $\phi^T(k)$ , *avgInter* implies a common characteristic in different Web page datasets.

Figure 6 (a-2), (b-2), (c-2) and (d-2) show the  $k$ 's for four Web page datasets produced by setting different thresholds for *avgInter*. In Figure 6 (a-2) it is shown that the *avgInter* method is able to find  $k=1$  while many existing methods are unable to do so. As shown in the figure, when *avgInter* reaches 1.7, the best estimated values for  $k$  is found to be 2 for *DS1*, 5 for *DS2*, 21 for *DS3* and 40 for *DS4*.

The estimated  $k$  is usually greater than the number of true classes in a Web page dataset because outliers are found and clustered into some small clusters, and a few true classes are partitioned into more than one cluster with finer granularity. This situation is exactly shown in Table 2, which shows the clustering solution for the most diverse dataset, *DS4*, obtained when the threshold of *avgInter* is 1.7. The naming for a newly formed cluster is by selecting the top three descriptive terms. The ranking of descriptive terms for a cluster is conducted by sorting the  $tf'_{lj}/df_j$  values of terms in the cluster ( $tf'_{lj}$  is defined to be the number of Web pages containing term  $t_j$  in cluster  $C_l$  and  $df_j$  is the document frequency (Yang & Pedersen, 1997) of  $t_j$ ). It can be noted that for most true classes, a true class has a dominant cluster in Table 2. For

*Table 2. The clustering solution for dataset DS4.*

cluster	The number of web pages	the majority's true class label	purity	$F_1$	top 3 descriptive terms
C <sub>1</sub>	106	Astronomy	0.840	0.881	moon, mar, orbit
C <sub>2</sub>	29	Agriculture	0.793	0.397	pest, weed, pesticid
C <sub>3</sub>	24	Agriculture	0.917		crop, wheat, agronomi
C <sub>4</sub>	64	Anatomy	0.906	0.779	anatom, muscl, blood
C <sub>5</sub>	64	Evolution	0.750	0.686	evolut, darwin, erectu
C <sub>6</sub>	116	Plants	0.776	0.750	plant, flower, garden
C <sub>7</sub>	161	Genetics	0.565	0.682	genom, genet, clone
C <sub>8</sub>	101	Mathematics	0.782	0.763	mathemat, math, algebra
C <sub>9</sub>	94	Health	0.649	0.550	mental, therapi, health
C <sub>10</sub>	32	Health	0.875		grief, bereav, heal
C <sub>11</sub>	115	Hardware	0.452	0.430	font, px, motherboard
C <sub>12</sub>	21	Hardware	0.857		keyboard, pc, user
C <sub>13</sub>	83	Forestry	0.675	0.742	forest, forestri, tree
C <sub>14</sub>	86	Radio	0.709	0.607	radio, broadcast, fm
C <sub>15</sub>	70	Music	0.800	0.644	guitar, music, instrum
C <sub>16</sub>	13	Music	1.000		drum, rhythm, indian
C <sub>17</sub>	86	Automotive	0.849	0.749	car, auto, automot
C <sub>18</sub>	20	Automotive	0.800		motorcycl, bike, palm
C <sub>19</sub>	120	Taxes	0.633	0.752	tax, incom, revenu
C <sub>20</sub>	155	Government	0.806	0.828	congressman, hous, district
C <sub>21</sub>	108	Religion	0.824	0.802	christian, bibl, church
C <sub>22</sub>	92	Education	0.761	0.648	montessori, school, educ
C <sub>23</sub>	43	Education	0.767		homeschool, home school, curriculm
C <sub>24</sub>	60	Art	0.833	0.621	paint, canva, artist
C <sub>25</sub>	89	Sociology	0.831	0.751	sociologi, social, sociolog
C <sub>26</sub>	59	Archaeology	0.864	0.622	archaeologi, archaeolog, excav
C <sub>27</sub>	18	Archaeology	0.722		egypt, egyptian, tomb
C <sub>28</sub>	120	Jewelry	0.817	0.867	jewelri, bead, necklac
C <sub>29</sub>	91	Banking	0.659	0.736	bank, banker, central bank
C <sub>30</sub>	92	Network	0.565	0.578	network, dsl, storag

( $F_1$  scores are given only for 24 clusters because those clusters represent true classes in dataset DS4. The purity (Strehl et al., 2000) and the top three descriptive terms are given for each cluster.)

*Table 2. cotinued*

C <sub>31</sub>	159	Sports	0.824	0.859	soccer, footbal, leagu
C <sub>32</sub>	1	Religion	1.000		struggl, sex, topic
C <sub>33</sub>	8	Religion	0.250		domain, registr, regist
C <sub>34</sub>	10	Plants	0.300		florida, loui, ga, part, pioneer,
C <sub>35</sub>	1	Archaeology	1.000		guestbook, summar, screen
C <sub>36</sub>	3	Genetics	0.333		pub, patch, demo
C <sub>37</sub>	3	Music	0.333		bell, slide, serial
C <sub>38</sub>	1	Sociology	1.000		relief, portrait, davi
C <sub>39</sub>	2	Music	0.500		ontario, predict, archaeolog
C <sub>40</sub>	4	Music	0.250		unix, php, headlin
overall	2524		0.740	0.698	

(*F*, scores are given only for 24 clusters because those clusters represent true classes in dataset DS4. The purity (Strehl et al., 2000) and the top three descriptive terms are given for each cluster.)

instance, the dominant clusters for true class *astronomy*, *anatomy* and *evolution* are cluster C<sub>1</sub>, C<sub>4</sub> and C<sub>5</sub>, respectively. We can see several true classes have been partitioned more precisely into more than one cluster; e.g., true class *automotive* has been separated into cluster C<sub>17</sub>, which is more related to *car* and *auto*, and cluster C<sub>18</sub> more related *motorcycle* and *bike*, as indicated by their top descriptive terms. Similar situation happens to true class *agriculture*, *health*, *education* and *archaeology*, each of which has been partitioned into two clusters. As shown in Table 2, outliers, which have low purity scores, can be found as cluster C<sub>32</sub>, C<sub>33</sub>, ..., and C<sub>40</sub>.

### Discovering the Number of Clusters

The constant factor described in the last section can be used to estimate

the number of clusters in a clustering process. The number of clusters *k* for a Web page dataset is estimated to be:

$$\arg \max_k (\text{avgInter}(k) \leq 1.7) \quad \text{where } 1 \leq k \leq n. \quad (16)$$

The *avgInter(k)* is computed for different *k*'s. The *k* that results in *avgInter(k)* as close to (but less than) the threshold 1.7 is selected to be the final *k* for a Web page dataset.

For our bi-directional hierarchical clustering system, we determine the number of clusters by using the constant as the stopping factor in the clustering process. Our hierarchical clustering process starts by arranging individual Web pages into clusters and then arranging the clusters into larger clusters and so on until the average inter-cluster similarity

$avgInter(k)$  approaches the constant. As clusters are grouped to form larger clusters the value of  $avgInter(k)$  is reduced. This grouping process (bottom-up cluster-merging phase) is stopped when  $avgInter(k)$  approaches 1.7. The final number of clusters is automatically obtained as the result.

## CONCLUSION AND FUTURE RESEARCH

Although many methods of finding the number of clusters for a dataset have been proposed, none of them is satisfactory for clustering Web page datasets. Finding the number of clusters for a dataset is often treated as an ill-defined question because it is still questionable how well a cluster should be defined. By recognizing this status, we preferred hierarchical clustering methods, which allow us to view clusters at different levels with coarser granularity at the higher level and finer granularity at the lower level. For Web mining in particular, our Bidirectional Hierarchical Clustering method is able to arrange Web pages into a hierarchy of categories that allows users to browse the results in different levels of granularities.

Besides proposing the new Bi-directional Hierarchical Clustering algorithm, we investigated the problem of estimating the number of clusters,  $k$ , for Web page datasets. After many trials, we discovered that the average inter-cluster similarity ( $avgInter$ ) can be used as a criterion to estimate  $k$  for Web page datasets. Our experiments showed that when the  $avgInter$  for a

Web page dataset reaches a threshold of 1.7, the clustering solutions achieve the best results. Compared to other criteria,  $avgInter$  implies a characteristic for Web page datasets. We then use the threshold as a stopping factor in our clustering process to automatically discover the number of clusters in Web page datasets.

Future work includes the investigation of using our  $avgInter$  method on datasets from domains other than Web pages. Having the new stopping factor for the Web domain together with the new bi-directional hierarchical clustering algorithm, we have developed a clustering system suitable for mining the Web. We plan to incorporate the new clustering system into our information classification and search engine (Baberwal & Choi, 2004; Choi, 2001; Choi & Dhawan, 2004; Choi & Guo, 2003; Choi & Peng 2004; Yao & Choi, 2003; Yao & Choi, 2005).

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