

Clustering XML Documents Using Structure and Content based on a New Similarity Function OverallSimSUX

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Abstract. Every day more digital data in semi-structured format are available on the World Wide Web, corporate intranets, and other media. Knowledge management using information search and processing is essential in the field of academic writing. This task becomes increasingly complex and defiant, mainly because collections of documents are usually heterogeneous, big, diverse, and dynamic. To resolve these challenges it is essential to improve management of time necessary to process scientific information. In this paper, we propose a new method of automatic clustering of XML documents based on their content and structure, as well as on a new similarity function OverallSimSUX which facilitates capturing the degree of similarity among documents. Evaluation of our proposal by means of experiments with data sets showed better results than those in previous work.

Keywords. Clustering, XML, structure and content, similarity.

1 Introduction

An XML document is a hierarchical and auto-descriptive entity of information in a semi-structured format, since it incorporates structure and data in the same entity. Such structure of information can be used to retrieve relevant documents [1]. Being expandable, having a structure easy to analyze and process, XML has become the standard format of data exchange among Web applications [2]. Every day more digital data in XML format are available on the Web, corporate intranets, databases, and other media [2], so there is a need to manage these big volumes of data efficiently. Clustering based on

XML structure and/or content [3] allows organizing the information.

A clustering algorithm tries to find natural clusters of data based mainly on similarity, so it is desirable that the objects that belong to the same cluster be as similar as possible and the objects that belong to different clusters be as dissimilar as possible [4].

In this paper, a new method for automatic clustering of XML documents is proposed using their content and structure. Another contribution is a new function of similarity OverallSimSUX which facilitates capturing the degree of similarity among the documents. The rest of the paper is organized as follows. Section 2 describes forms of clustering XML documents and some related papers; in Section 3 a new model of clustering of XML documents is presented using the new similarity function proposed by us. In Section 4 the experimental results are analyzed, and finally, Section 5 presents conclusions.

2 Related Work

Since XML documents are semi-structured, three forms of computing distance or similarity of these exist: (1) considering only the content of documents; (2) considering only the structure of documents; and (3) considering both dimensions of XML documents (structure and content).

The algorithms that consider only the content of documents obviate the advantage of structure which they offer as well. The algorithms that carry out lexical analysis, generally view a document as a bag of words, therefore, all the labels are

Only content	Kurgan, L. <i>Semantic mapping of xml tags using inductive machine learning</i> [7]	Use a variant of VSM.
	Shen, Y. <i>Clustering schemaless xml document</i> [8]	
Only structure	Dalamagas, T. <i>A Methodology for Clustering XML Documents by Structure</i> [2]	Use an XML tree representation to calculate a variant of tree-edit distance.
	Flesca, S. <i>Fast detection of XML structural similarities</i> [5]	
	Lesniewska, A. <i>Clustering XML documents by structure</i> [10]	
	Chawathe, S.S. <i>Comparing Hierarchical Data in External Memory</i> [11]	Consider XML structure based on the use of Edit Graph.
	Costa, G. <i>Hierarchical clustering of XML documents focused on structural components</i> [13]	Propose a new hierarchical approach.
	Aïtelhadj, A. <i>Using structural similarity for clustering XML documents</i> [12]	Follow the two-step approach to clustering XML documents.
	Both structure and content	Kutty, S. <i>Combining the structure and content of XML documents for clustering using frequent subtrees</i> [16]
Yang, W. <i>A semi-structured document model for text mining</i> [17]		Analyze a variant of XML document comparison based on VSM.
Tekli, J.M. <i>A Novel XML Document Structure Comparison Framework based-on Subtree Commonalities and Label Semantics</i> [18]		Propose a framework to deal with both structural and semantic similarity in XML documents, use tree-edit distance.
Pinto, D. <i>BUAP: Performance of K-Star at the INEX'09 Clustering Task</i> [19]		Use the iterative clustering algorithm K-Star in a recursive clustering process.

Fig. 1. Summary of XML clustering algorithms

eliminated and the structural information that the document offers is lost [5].

Following this focus, several authors based their research on the traditional Vector Space Model (VSM) [6] representation [7, 8].

Several works treat an XML document as a tree taking advantage of its hierarchical structure. Examples of this approach are [2, 9, 10] which use a tree representation to calculate the tree-edit distance or some of its variants to compare the documents. The method of Structural Summaries is proposed in [2] to reduce nesting and repetitions which may exist in the trees. Other methods of documents' clustering considering their structure are based on the use of Edit Graph [11]. In [12], a new hierarchical approach is proposed which allows considering multiple forms of structural components to structurally isolate homogeneous clusters of XML documents.

At each level of the resulting hierarchy, clusters are divided by considering some type of structural components which still differentiate structures of

XML documents. In [13] SOS is proposed, a similarity search method based on structures and styles of office documents. SOS needs to compute similarity values between multiple pairs of XML files included in the office documents. The authors also proposed LAX+, which is an algorithm to calculate a similarity value for a pair of XML files by matching leaf nodes of sub-trees in the XML files. A new method for clustering XML documents is proposed in [14], where the goal is to group documents sharing similar structures, following a two-step approach. Firstly they extract automatically the structure from each XML document to be classified. The extracted structure is then used as a representation model to classify the corresponding XML document. The idea behind clustering is that if XML documents share similar structures, they are more likely to correspond to the structural part of the same query.

Most of state of the art research does not use the two dimensions (structure and content) because of their great complexity [15]. However, to

obtain better results in clustering it is essential to use both [16]. A first and very simple option is to mix the content and the labels of a document in a VSM. In [16] the Closed Frequent Sub-Trees method is used to process the structure of documents and then to perform preprocessing of the content of the documents.

Other works developed extensions to the VSM representation called C-VSM and SLVM [17]. However, C-VSM can be seen as a method of “low contribution” since it ignores the semantic relationships among different elements; and SLVM does not consider the relationships among common elements, so it can be seen as a technique of “over contribution”. With the purpose of resolving these problematic issues, in [5] the Proportional Transportation Similarity is proposed, which works with heavy comparisons according to likeness or unlikeness of the elements while comparing pairs of documents. In [18] a framework is suggested to deal with both structural and semantic similarities in XML documents. This framework consists of four main modules for discovering structural commonalities among sub-trees, identifying sub-tree semantic resemblances, computing tree-based edit operation costs, and computing tree- edit distance. In [19] unsupervised classification techniques are used in order to group documents of a given huge collection into clusters. The authors approached this challenge by using the iterative clustering algorithm K-Star [20] in a recursive clustering process over sub-sets of the complete collection. Fig. 1 presents a summary of previous XML clustering algorithms.

3 Clustering Model

This section presents a method of automatic clustering of XML documents, as well as a new similarity function *OverallSimSUX* which facilitates capturing the degree of similarity among the documents.

3.1. OverallSimSUX Similarity Matrix

Meditating shortly on the concept of a document, there can be found multiple types of documents, so it seems more natural to treat them as a set of parts

(i.e. scientific papers, news, etc.). Consequently given a document d , a set of structural units $SU = \{SU_1, \dots, SU_n\}$ can be associated with it. For example, in a scientific paper, structural units will be abstract, introduction, Section 1, etc.

The existent structural relationships among XML documents can contribute to better clustering results when the content is used in function of the relations between their SU . In this paper, for the construction of a similarity matrix, a new measure of similarity is proposed which facilitates capturing the degree of similarity of these documents. In this function the existent relationship among the documents is analyzed, treating SUs simultaneously like independent collections and the documents like indivisible units.

Fig. 2 shows how a similarity matrix *OverallSimSUX* is obtained starting from a collection of XML documents. For the matrix construction, it is necessary to perform three steps: (1) to build a first representation, denominated *Representation I*, using the SU of the documents; (2) to build a second representation, *Representation II*, by considering the whole collection; (3) to carry out clustering using *Representation I*.

a. Representation I (Step 1)

The original collection of documents is divided in n collections, where n is the number of SUs in a document. Definition 1 captures the correspondence between the collection and SU , giving place to the k -collection concept.

Definition 1 (k -collection). Let D be a corpus of XML documents, then the k -collection of the collection D is formed by the group of new documents DSU_k :

$$DSU_k = \{SU_k \in d, \forall d \in D\}, \quad (1)$$

where d is a document of D , SU_k is the k -th SU of d .

For each k -collection, *Representation I* is built using the classic VSM. In particular, the construction of this matrix was carried out by means of the Term Frequency and Inverse Document Frequency (*TF-IDF*) measure [6]. *TF-IDF* is a statistical measure of weight often used in natural language processing to determine

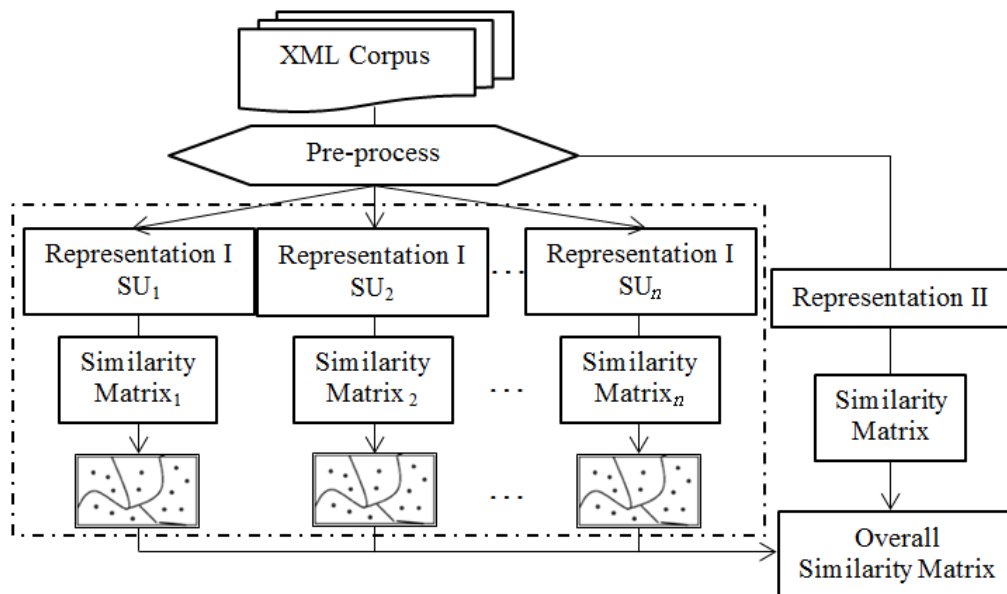


Fig. 2. This diagram shows the methodology to build the OverallSimSUX similarity matrix

how important a term is in a given corpus, by using a vector representation. The importance of each term increases proportionally to the number of times this term appears in the document (frequency), but is offset by the frequency of the term in the corpus.

The tf component of the formula is calculated by the normalized frequency of the term, whereas idf is obtained by dividing the number of documents in the corpus by the number of documents which contain the term, and then taking the logarithm of that quotient. Given a corpus DSU_k and a document d_j ($d_j \in DSU_k$), the $TF-IDF$ value for a term t_i in d_j is obtained by the product between the normalized frequency of the term t_i in the document d_j (tf_{ij} , equation 2) and the inverse document frequency of the term in the corpus ($idf(i)$, equation 3) as follows [19]:

$$tf_{ij} = \frac{frequency(t_i, d_j)}{\sum_{s=1}^{|d_j|} frequency(t_s, d_j)}, \quad (2)$$

$$idf(i) = \log \left(\frac{|D|}{|d: t_i \in d, d \in D|} \right), \quad (3)$$

$$tf_{ij} \cdot idf_i = tf_{ij} \times idf(i). \quad (4)$$

b. Representation II (Step 2)

In this paper the structure of the documents is added to the analysis, therefore, in *Representation II* a modification to the classic VSM is carried out and the frequency will be weighted by the SU that corresponds to the analyzed term. This approach was proposed in [21]. Equation 5 shows how to calculate this frequency in a document j for a term i :

$$tf_{ij} = \sum_{k=1}^n (w_{kj} \times frequency_{ik}), \quad (5)$$

$$w_{kj} = \left(e^{(-L_{SU}/L_{Doc})} \right)^{pot}, \quad (6)$$

where n is the quantity of the SU present in document j , $frequency_{ik}$ is the frequency of term i in SU_k , w_{kj} is the weight calculated for SU_k in the document j , L_{SU} is the length of the SU_k , L_{Doc} is the length of the document j , Pot is a given value. After several experiments, the best results were obtained with a Pot value of 5.

c. k -collection Clustering (Step 3)

Starting from *Representation I*, a similarity matrix is calculated, which compares two documents

using the Cosine measure; this is shown in equation 7. For each k -collection an independent cluster is obtained.

$$S_{Cosine}(d_i, d_j) = \frac{\sum_{r=1}^s (d_{ir} \times d_{jr})}{\sqrt{\sum_{r=1}^s d_{ir}^2 \times \sum_{r=1}^s d_{jr}^2}}. \quad (7)$$

To carry out clustering, the classic K -Star algorithm [20] is used. Nevertheless, the choice of other algorithm does not invalidate the idea of the method proposed in this work. In future work, we will present a comparative study of the performance of our approach against other clustering techniques. K -Star is an iterative clustering method that starts by building a similarity matrix of the documents to be clustered (corpus). This algorithm does not need to know the number of cluster value a priori, instead it automatically proposes a number of clusters in a totally unsupervised way. K -Star is a considerably fast algorithm and also obtains reasonably good results when applied to text corpora [22].

d. OverallSimSUX Matrix Calculation

The considerations exposed before are the starting point to develop the similarity measure *OverallSimSUX*, specified formally by Definition 3. It begins with the results of the clustering carried out for all k -collections and the similarity matrix based on the calculation of the cosine measure using *Representation II*.

Definition 2 (λ -membership). This is a boolean function, i.e. one if both documents (i, j) belong to the same cluster c_n , otherwise it is zero depending on clustering results by using *Representation I*. The λ -membership is formalized in equation 8:

$$\lambda(i, j) = \begin{cases} 1, & \{i, j\} \in c_n \\ 0, & i \in c_n \wedge j \in c_m \mid m \neq n \end{cases} \quad (8)$$

Definition 3 (OverallSimSUX). A normalized measure of similarity among the documents i, j is considered. It is calculated by the function $S_{ossux}(i, j)$, equation (9), and its values are within $[0, 1]$:

$$S_{ossux}(i, j) = \frac{\sum_{k=1}^n (w_k \times \lambda_k(i, j)) + S_g(i, j)}{\sum_{k=1}^n (w_k) + 1}, \quad (9)$$

1. Build the OverallSimSUX similarity function.
2. Estimate similarity thresholds.
3. Apply K-Star clustering method from OverallSimSUX matrix.

Fig. 3. Basic steps to obtain document clustering using K-Star method with OverallSimSUX matrix

Input: Corpus D of XML documents
Output: Set of clusters, cluster quality, the most representative document of each cluster.

Begin

1. Pre-process /* lexical analysis, stop word elimination, stemming... */
2. Build all k -collections (corpus D)
3. **For each** DSU_k
 - Rep-I \leftarrow Make Representation-I (DSU_k) according to TF-IDF
 - Sim_matrix \leftarrow Calculate similarity matrix for Rep-I using Cosine measure
 - Clusters \leftarrow Apply K-Star clustering method to Sim_matrix
- end_for**
4. Rep-II \leftarrow Make Representation-II of entire corpus D using equation (5) for calculating frequency
5. Sim_matrixII \leftarrow Calculate similarity matrix for Rep-II using Cosine measure
6. O_Sim_Matrix \leftarrow Calculate similarity Matrix using OverallSimSUX measure taking into account all the clustering of all DSU_k and Sim_matrixII
7. Make final clustering applying K-Star clustering method to O_Sim_Matrix
- end**

Fig. 4. General procedure

where $S_g(i, j)$ is an element of the matrix S_g calculated by equation (7) from *Representation II*; w_k is the weight of SU_k , n is the quantity of SUs identified in the documents, $\lambda_k(i, j)$ is λ -membership of the documents i, j from the clustering result for *Representation I* of SU_k .

3.2. Final Clustering

To carry out final clustering, the *K*-Star algorithm is used again.

The *K*-Star algorithm uses a similarity threshold for determining the minimum ratio of similarity that must exist between a document and an already formed cluster in deciding whether to incorporate a given document as a member of this cluster. This threshold must be given [19] or calculated using several variants [23]. In this work we calculated the threshold using the means of all similarity values between all pairs of documents.

Fig. 3 shows the basics steps to obtain the final clustering. A complete description of the implemented approach is given in the following section.

3.3 Description of the Approach

Fig. 4 shows the proposed general procedure.

This procedure includes three important steps: (1) preprocessing of the entire collection, identifying each Structural Unit; (2) textual representation using *Representation I* and *Representation II*, and (3) final clustering process.

4. Experimental Results

To check the validity of the obtained results starting from the pattern of the proposed clustering, two experiments were designed and applied to three data sets with the purpose of carrying out a statistical analysis. This analysis allows verifying if significant differences exist between the proposed methodology and other variants of algorithms reported in the literature.

4.1 Case Studies and Experiment Design

- *Case study 1*: documents retrieved from the site of ICT of the Center of Studies on Informatics of the Universidad Central "Marta Abreu" de las Villas (UCLV)¹.

¹ <http://ict.cei.uclv.edu.cu>

- *Case study 2*: summary of documents of the IDE-Alliance repository, provided by the University of Granada, Spain.
- *Case study 3*: summary of Wikipedia documents, published by INEX to evaluate clustering.

We conform 16 corpora of XML documents (corpora 1 to 7 with documents from case study 1; corpora 8 to 11 with documents from case study 2, the rest from case study 3).

We perform two experiments with these 16 corpora for evaluating the results according to our objective.

The first experiment consisted in verifying how our method behaves globally on the three data sets described previously. Other methods used for comparison were the one proposed in INEX [19] broadly used for clustering of XML documents and the *K*-Star algorithm, a predecessor of our proposal. Both approaches, the *K*-Star algorithm and the algorithm proposed in [19], were implemented in a system for clustering scientific papers in XML format (LucXML).

To evaluate the results, we applied an external measure called *Overall F-measure* [24]. This measure is based on *Precision (Pr)* and *Recall (Re)* [25]. *Pr* and *Re* are calculated for a cluster *g* and a class *c* as follows:

$$Pr(c, g) = \frac{n_{cg}}{n_g}, \quad (10)$$

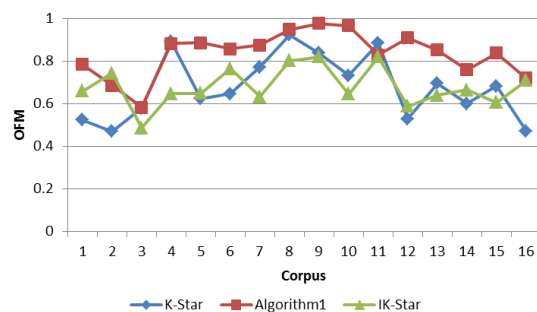


Fig. 5. Overall *F*-measure values of the compared algorithms

Table 1. Values of the Micro-Purity and Macro-Purity measures for INEXK-Star and the Alg1 (our approach)

Corpus	Micro-Purity		Macro-Purity	
	IK-Star	Alg1	IK-Star	Alg1
1.	0.716	0.568	0.792	0.534
2.	0.559	0.451	0.488	0.483
3.	0.3	0.673	0.2	0.759
4.	0.405	0.418	0.405	0.628
5.	0.725	0.418	0.816	0.628
6.	0.459	0.557	0.44	0.643
7.	0.481	0.571	0.481	0.596
8.	0.511	1	0.511	1
9.	0.542	0.545	0.656	0.697
10.	0.636	1	0.627	1
11.	0.463	0.633	0.529	0.71
12.	0.722	0.958	0.792	0.972
13.	0.59	0.597	0.59	0.664
14.	0.552	0.689	0.552	0.806
15.	0.525	0.638	0.524	0.71
16.	0.515	0.461	0.56	0.55

$$Re(c, g) = \frac{n_{cg}}{n_c}, \quad (11)$$

where n_{cg} is the number of objects of class c in cluster g , n_g is the number of objects in cluster g , and n_c is the number of objects of class c . These values are used to calculate F -measure using harmonic means of Pr and Re as shown in formula 12:

$$FM(c, g) = \frac{1}{\alpha \left(\frac{1}{Pr(c, g)}\right) + (1-\alpha) \left(\frac{1}{Re(c, g)}\right)}. \quad (12)$$

If $\alpha=1$, then $FM(c, g)$ coincides with Pr value; if $\alpha=0$, $FM(c, g)$ coincides with Re value. So $\alpha=0.5$ means that Pr and Re have equal weight. Finally, the Overall F -measure is calculated using expression 13:

$$OFM = \sum_{i=1}^k \frac{n_c}{n} \max\{FM(c, g)\}. \quad (13)$$

Results obtained for the Overall F -measure are shown in Fig. 5 where the method of [19] is denoted as IK-Star and our approach is denoted as Algorithm1.

In the second experiment it was verified how our proposal behaves globally on 16 corpora of the three data sets described previously. Here we compared our method with the method of INEX'09 [19] using a technique based on the *Micro-Purity* and *Macro-Purity* measures described in [26]. This will show the quality of the groups obtained in each clustering. *Purity* is measured as the ratio of the number of documents with the majority label in a given cluster to the number of documents in this cluster. *Macro-* and *Micro-* *Purity* of the entire clustering solution is obtained as a weighted sum of the individual cluster purity. In general, the larger the value of purity, the better the clustering solution is. Table 1 presents these values.

Equations 15 and 16 show expressions for *Micro-Purity* and *Macro-Purity*, respectively:

Table 2. Wilcoxon test statistics of results for OFM of Alg1 and OFM of K-Star

<i>Experiment1</i>		N	Mean Rank	Sum of Ranks	Alg1 - K-Star	
ofm_Algl - ofm_K-Star	Negative Ranks	2 ^a	3.00	6.00	Z	-3.206 ^a
	Positive Ranks	14 ^b	9.29	130.00	Aymp. Sig (2-tailed)	0.001
	Ties	0 ^c				
	Total	16				

(a. Alg1 < K-Star b. Alg1 > K-Star c. Alg1 = K-Star) a. Based on positive ranks)

Table 3. Wilcoxon test statistics of results for OFM of IK-Star and OFM of Alg1

<i>Experiment1</i>		N	Mean Rank	Sum of Ranks	IK-Star - Alg1	
ofm_IK-Star - ofm_Algl	Negative Ranks	15 ^a	8.87	133.00	Z	-3.361 ^a
	Positive Ranks	1 ^b	3.00	3.00	Aymp. Sig (2-tailed)	0.001
	Ties	0 ^c				
	Total	16				

(a. IK-Star < Alg1 b. IK-Star > Alg1 c. Alg1 = IK-Star) a. Based on positive ranks)

Table 4. Wilcoxon test statistics of results for MicroPurity of IK-Star and MicroPurity of Alg1

<i>Experiment2</i>		N	Mean Rank	Sum of Ranks	IK-Star - Alg1	
microP_IK-Star - microP_Algl	Negative Ranks	12 ^a	8.96	107.50	Z	-2.043 ^a
	Positive Ranks	4 ^b	7.13	28.50	Aymp. Sig (2-tailed)	0.04
	Ties	0 ^c				
	Total	16				

(a. IK-Star < Alg1 b. IK-Star > Alg1 c. Alg1 = IK-Star) a. Based on positive ranks)

$$Purity(q) = \frac{NDMLC_q}{NDC_q}, \tag{14}$$

$$Micro - Purity(q) = \frac{\sum_{q=0}^n Purity(q) \times TFC(q)}{\sum_{q=0}^n TFC(q)}, \tag{15}$$

$$Macro - Purity(q) = \frac{\sum_{q=0}^n Purity(q)}{TotalofCategories}, \tag{16}$$

where *NDMLC* is the number of documents with the majority label in a cluster, *NDC* is the number of documents in the cluster, *TFC* is the total number of documents found by class, *TotalofCategories* is the number of clusters found by the clustering algorithm.

In general, best results were achieved by Algorithm 1 (our proposal) in both experiments.

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