Structural Document Similarity for Integrated Crawling and Wrapping*

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Abstract. We propose an architecture which combines crawling and extraction of relevant information from Web pages available on the Web. In this architecture, a primary role played by a distance-based classification methodology is devised. Such a methodology is based on an efficient and effective technique for detecting structural similarities among HTML documents, which significantly differs from standard methods based on graph-matching algorithms. The technique is based on the idea of representing the structure of an HTML document as a time series in which each occurrence of a tag corresponds to a given impulse. By analyzing the frequencies of the corresponding Fourier transform, we can hence state the degree of similarity between documents. Experiments on real data show the effectiveness of the proposed technique.

1 Introduction

The huge amount of information available on the Web offers new perspectives for online applications which can be profitably exploited for various purposes. Information extraction agents can be developed, for investigating and collecting data available from a (set of) Web site(s), in order to effectively exploit such data for business purposes. Typical scenarios include, e.g., competitors monitoring, automatic news filtering, product finding and price comparing, etc.

In order to make Web information effectively available, it is appropriate to manage it through an enterprise information system. When it is *a priori* known which pages the desired information must be collected from, it is possible to use *ad hoc* HTML to XML wrappers [7, 16, 10, 15], to extract information from sets of HTML pages having a similar structure. The extracted information is encoded into XML and then inserted into the enterprise information system. The use of HTML wrappers allows for making high-quality semistructured data available for various purposes, with the major advantage of a low human effort necessary to extract the desired information. Provided with several sets of similarly structured HTML pages, the wrapper designer must generate an HTML/XML wrapper for each set. Once these wrappers have been generated, they can continuously extract information from pages, and it is only necessary to monitor the extraction process in order to handle possible extraction exceptions.

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A main issue arises when it is not *a priori* known which pages contain interesting information to be collected, so it is necessary to crawl the Web, searching for them [14, 13, 18]. In this case, pages collected by crawlers are not necessarily similarly structured, and, as a consequence, they cannot be automatically handled by wrapper programs. Moreover, currently available tools only permit the extraction of textual information (such as, e.g., interesting sentences) [3, 2, 4]. Thus, a company interested in effectively exploiting this information needs to devise a relevant human effort to restructure the available data and detect significant information.

In such a context, data mining techniques can be profitably exploited to classify Web pages made available from a Web crawler. Indeed, the capability of automatically recognizing whether the contents of a Web source can be suitably processed by an available wrapper eases the task of extracting relevant information. Moreover, the capability of automatically detecting and collecting similarly structured pages which do not fit to any available wrapper model, but which may, in principle, contain significant information, can help the expert in building ad-hoc wrappers for them.

In this paper we address the problem of integrating and enhancing crawling and wrapping systems in order to avoid (or reduce) the human effort necessary to deal with the potentially huge amount of pages found by crawlers. The main contribution of this work is twofold:

- we propose an architecture for the extraction of information from the Web and its storage into an enterprise information system, where crawling and wrapping modules with specifically designed document categorization modules are integrated to speed up the wrapping task;
- we develop a technique aimed at HTML document categorization, suitable for both classifying found pages w.r.t. the set of the available wrappers and identifying new sets of similarly structured pages for which new wrappers can be defined.

Particularly relevant in the context of this paper is the technique we adopt for measuring the structural similarity between HTML/XML documents. This technique represents the structure of a document as a time series in which each occurrence of a tag corresponds to a given impulse. By analyzing the frequencies of the corresponding Fourier Transform, we can hence state the degree of (structural) similarity between documents. The efficiency of this approach is compelling when compared to other approaches defined in the literature [17, 8]. Moreover, the technique is particularly attractive also for its effectiveness: e.g., on XML documents [11], the exploitation of some useful properties of the Fourier transform, such as energy concentration or invariance under shifts, allows us to separate both documents belonging to different DTDs, and documents belonging to the same DTDs. As a matter of fact, the exploitation of the Fourier transform to check similarities among time series is not completely new (see, e.g., [5]), and was proven successful. The main contribution of our approach is the systematic development of effective encoding strategies for HTML/XML documents, in a way that makes the use of the Fourier Transform extremely profitable.

2 Wrapping and crawling the Web through structural document categorization

The possibility of automatically processing Web pages permits to reduce the costs of extracting relevant information from them. In the following subsections we first propose an architecture that permits to integrate crawling systems with wrapping ones in order to reduce the human efforts necessary to extract semistructured information from the Web. As this architecture exploits suitable document categorization algorithms to detect structurally similar pages, and to select (or build) a suitable wrapper program to process them, we next introduce the problem of structural document categorization.

2.1 An architecture for integrating crawling and wrapping

The proposed architecture, shown in Fig. 1, is devoted to extract interesting information from the Web and to store it into an enterprise information system. As discussed above, the aim of this architecture is to provide usable semistructured information.

The module which is responsible for finding interesting information on the Web is the *Web crawler*. This module continuously crawls the Web yielding new interesting pages. Once such pages have been found, the *page classifier* module classifies them w.r.t. the available wrapper programs. *Wrappers* are software modules that convert data implicitly stored in (a class of) Web documents into semi-structured data. Each class of similarly structured pages is then forwarded to the chosen wrapper program that translates the information they contain and store them into the enterprise information system.

Obviously, not all the pages found by the crawler can be properly classified. In the proposed architecture, information from unclassified pages can be manually extracted, but such pages can be also used to build new wrappers. To this purpose, this set of pages is also forwarded to the wrapper designer that processes them using the *wrapper designer suite*. During the wrapper design process document categorization techniques are exploited to automatically identify clusters of similarly structured pages that can be handled by the same wrapper. The output of this process is a new set of wrapper definitions that from then on can be used both for classifying new interesting pages and for automatically extracting information.

Observe that, in the proposed architecture, the processes of crawling, classifying and wrapping Web pages are kept separate, and no particular assumption is made about them. Therefore, it is possible to integrate into this architecture any kind of crawling technique [14, 13, 18] and wrapper generation system [10, 7, 16, 15] defined in the literature.

2.2 Structural Document Categorization

The complexity of wrapper generation systems is strongly related to the structuring level of the Web pages they deal with. Usually, a wrapper is designed for a specific set of Web pages exhibiting inherently similar features. Such features typically define the context in which the relevant information to extract is located. A typical example is

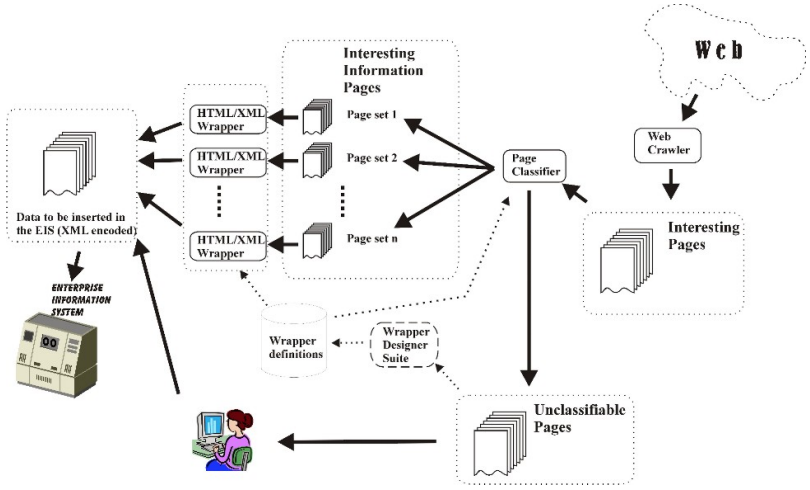


Fig. 1. Architecture of the information extraction system

a set of HTML pages containing details (e.g., price, description, picture, etc.) over a given set of products which can be purchased on-line. If such pages are referred to the same product category (or even if they are extracted from the same service provider), it is likely that the information they provide is structured in a similar way. For example, each product can be represented as a row in a table, in which the first cell contains either the product name or the product picture. Thus, in order to design a wrapper for extracting pricing information from these pages, one has to assume that all the pages under consideration have a similar structure.

The capability of recognizing structures within Web pages is fundamental in the context of the architecture depicted in fig. 1. In particular, the page classifier and of the wrapper design suite are mainly based on the capability of categorizing documents according to their structure, which can be summarized as follows.

Let $\mathbf{w}$ be a wrapper, and $\mathcal{T}_{\mathbf{w}} = \{p_1, \ldots, p_m\}$ the set of Web pages used to generate $\mathbf{w}$ (the training set for $\mathbf{w}$). For a well-defined wrapper, it is assumed that the structural similarity between each pair p_i and p_j is high. The tasks performed by the page classifier and the wrapper generation suite can be described as follows:

1. Given a set $\mathbf{w}_1, \ldots \mathbf{w}_n$ of available wrappers, a new page p is associated with $\mathcal{T}_{\mathbf{w}_i}$ if *(i)* the structural similarity between p and each $q \in \mathcal{T}_{\mathbf{w}_i}$ is acceptable, i.e., it is higher than a given threshold, and *(ii)* no other set $\mathcal{T}_{\mathbf{w}_j}$ exhibits a higher structural similarity. If no $\mathbf{w}_i$ exists such that p can be associated with $\mathbf{w}_i$, p is labelled as *unclassified*.
2. A set $\mathcal{U}$ of unclassified pages is worth further consideration if it is possible to define a partition of $\mathcal{U}$ in k clusters, where each cluster $\mathcal{C}_i$ can be exploited as a training set for learning a new wrapper $\mathbf{w}_{\mathcal{C}_i}$.

Notice that task 1 can be efficiently accomplished by means of k-Nearest Neighbor techniques, while task 2 is mainly a clustering problem, for which many similarity-

based approaches can be defined. Nevertheless, a major issue is the definition of the notion of similarity among Web documents according to the structure they exhibit.

3 Detecting Structural Similarity Among Documents

The concept of structural similarity is difficult to understand by itself. Intuitively, two documents are said to have a similar structure if they correspond in the type of elements they contain and in the way these elements are combined in the two documents. Observe that even if it is easy to detect whether the structure of two documents is exactly the same, this test is not useful for our aims. Indeed we would like to quantify the similarity between the structures of two documents emphasizing the differences that are more relevant in defining a completely different structure. For instance we would like to consider similar two documents that have the same features but with different regularities. In this respect, two HTML documents are similar if it is possible to identify equivalent subparts, even if they appear in the two documents with different frequencies.

The current literature has devoted much attention to the problem of detecting structural similarity between complex objects. In particular, several methods for detecting the similarity of XML documents [9, 17] have been recently proposed. All these methods are based on the concept of edit distance and use graph-matching algorithms to calculate a (minimum cost) edit script that contains the updates necessary to transform a document into another. These techniques are generally computationally expensive, i.e. at least $O(N^2)$, where N is the number of elements of the two documents.

In this section we propose a different approach, which is essentially based on the idea of associating each document with a time series representing its structure (*document encoding*). By exploiting such an encoding, we check the structural similarities of documents by looking at the corresponding time series. As we shall see, this approach is both efficient and effective.

The approach was initially designed to detect structural similarities between XML documents [11]. However, when dealing with Web documents, some issues arise which need to be tackled. In the following subsections, we briefly introduce our technique for encoding and measuring the similarity of XML documents according to their structure. Later in this section we will show how the technique can be adapted to deal with HTML documents. Further details on the encoding techniques for XML and on the similarity measures for time series associated with the documents can be found in [12].

3.1 Document Encoding

An XML document is structured as a tree of elements, where each element is associated with a relevant piece of information. To our purposes, the structure of the tree shall represent the structure of the document, and in this section we define several ways of associating a time series with such a structure. In principle, we would like to flatten the tree structure into a time series which summarizes the relevant features of the original document. Notice that exploiting injective flattenings is not sufficient: since we are interested in directly comparing two time series, we would like to make

this comparison as effective as possible, giving greater weights to the more relevant structural characteristics of the documents.

We begin by fixing some notation. Given an XML document d, we denote by $tags(d)$ the *tag set* of the document d, i.e. the set of all the tags occurring within d; moreover, $tnames(d)$ denotes the set of all the distinct tag names appearing in d. Furthermore, for an element el of d, we denote by el_s the starting tag of el and respectively by el_e the ending tag of el. Given a tag t with tag name tn the *type* of t is its tag name tn if t is a start tag or $/tn$ if t is an end tag. The *skeleton* of d (denoted by $sk(d)$) is defined as the sequence of tags appearing within d, the sequence $[t_0, t_1, \cdots, t_n]$ such that $t_i \in sk(d) \Leftrightarrow t_i \in tags(d)$ and t_i precedes t_j within d if and only if $i > j$. Intuitively, the skeleton of an XML document represents a description of the sole document structure. In particular, for a tag $t \in sk(d)$, we define $nest_d(t)$ as the set of the start tags el_s in d occurring before t and for which there is no end tag el_e matching el_s and appearing before t. The *path name* of an element el is defined as the concatenation of the names of the element that enclose it in d. We also denote by l_t the nesting level of the tag t, i.e. $l_t = |nest_d(t)|$. Finally, for a given set D of documents, $maxdepth(D)$ denotes the maximum nesting level of tags appearing in a document $d \in D$.

We define a document encoding mainly as a combination of a *tag encoding function* and a *document encoding function*. The effectiveness of the document encoding is strongly influenced by the choices in the functions to adopt. Intuitively, a tag encoding function provides a numerical encoding of a tag appearing in a skeleton of a document, by looking at the "internal" properties of the tag. On the other side, a document encoding function aims at encoding a sequence of tags, by looking mainly at the features of the sequence seen as a whole. In a sense, a tag encoding corresponds to the analysis of the *locality* of a tag, while the nesting of different tags within the whole document provides a *overall* perspective: we look at the document as a globally uniform entity.

Tag Encoding Functions. A tag encoding function is a function that associates a number with each tag appearing in the document.

Definition 1. Given a set D of XML documents, a function γ from $tags(D)$ to $\mathbb{R}$ is a *tag encoding function* for D. γ is said to be *symmetric* iff for each document $d \in D$ and for each element $el \in d$, $\gamma(el_e) = -\gamma(el_s)$. Moreover, it is *null* if $\gamma(el_e) = 0$. □

We can assign a number n to each tag in several different ways: for instance, by generating it randomly, or using a hash function. Obviously, a good tag encoding function should at least ensure to be *injective* w.r.t. tag names. The encoding functions presented in the following mainly differ for their capability to *contextualize* a given tag, i.e., to capture information about its neighbors.

The simplest tag encoding function we consider is named *direct tag encoding* (γ_d) and is defined below. Given a set D of XML documents, we build a sequence of distinct tag names $[tn_1, tn_2, \cdots, tn_k]$ by considering a (randomly chosen) linear order on $tnames(D)$. Given an element el, the direct encoding simply associates each start tag el_s with the position n of the tag name tn of el in the sequence ($\gamma_d(el_s) = n$). We complete the above definition by distinguishing between two possible encoding strategies for end tags: symmetric and null.

A simple extension of the above strategy consists in assigning a value to each tag by relating such value to the subsequent tag in the document. We denote by *cpairs*(D) the pairs of types of tags $< tn_i, tn_{i+1} >$ such that there exists a pair of tags $< t_i, t_{i+1} >$, resp. of type tn_i, tn_{i+1}, that appear consecutively in a document $d \in D$. We associate an integer number $P_{<tn_i,tn_{i+1}>}$ with each pair of types of tags $< tn_i, tn_{i+1} >$ by considering a randomly chosen linear order on *cpairs*(D). Given a pair of tags t_i, t_{i+1} (resp. of type tn_i, tn_{i+1}) appearing consecutively in a document d, the *Pairwise tag encoding* function ($\gamma_{pw}(t_i)$) associates with t_i the number $P_{<tn_i,tn_{i+1}>}$.

The last strategy we propose encodes a tag on the basis of its *path name*. Consider a set of documents D, and let *pnames*(D) be the set of path names associated with the elements appearing in a document $d \in D$. Again, we use a sequence of path names $[pn_1, pn_2, \cdots, pn_k]$ obtained by considering a randomly generated linear order on *pnames*(D), and we associate each path name pn_i with its position i (denoted as $pos(pn_i)$) in the sequence. Given a start tag el_s appearing in a document d with corresponding path name pn, the *Nested tag encoding* function $\gamma_{pt}(t)$ is defined by associating el_s with $pos(pn)$. Again, we distinguish between symmetric and null version of this encoding.

Document Encoding Functions. A document encoding is a function that associates the structure of an XML document with a time series, i.e. a sequence of signal samples. The behavior of the signal corresponds to the structure of the document.

Definition 2. Let D be a set of XML documents. A document encoding is a function *enc* that associates each $d \in D$ with a sequence of real numbers, i.e. $enc(d) = h_0, h_1, \cdots, h_n$. □

In the following we concentrate on three different document encoding functions. Notice that all these functions are defined w.r.t. a tag encoding function that associates tags to numbers. In particular, we assume a set of XML documents D, a document $d \in D$ with $sk(d) = [t_0, \cdots, t_n]$ and a tag encoding function γ.

A *trivial encoding* of d ($tenc(d)$) is a sequence $[S_0, S_1, \cdots, S_n]$, where $S_i = \gamma(t_i)$. This encoding simply applies a tag encoding function to each tag appearing in the skeleton of the document.

A *linear encoding* of d ($lenc(d)$) is a sequence $[S_0, S_1, \cdots, S_n]$, where $S_0 = \gamma(t_0)$ and $S_i = \sum_{k \leq i} \gamma(t_k)$. The main idea underlying this type of encoding is that each element e of the time series associated with a document d should encode more than the information corresponding to a single tag t. Indeed, it computes a *linear* combination of the codes of the tags that appear before t in the document.

A *multilevel encoding* of d ($mlenc(d)$) is a sequence $[S_0, S_1, \cdots, S_n]$, where $S_i = \gamma(t_i) \times B^{maxdepth(D)-l_{t_i}} + \sum_{t_j \in nest_d(t_i)} \gamma(t_j) \times B^{maxdepth(D)-l_{t_j}}$. This encoding function assumes that the contribution of a tag t to the document encoding must depend on the nesting level of the tag. Intuitively, we encode t according to a basis B which takes into account both its nesting level and the path from the root to t. We usually set $B = |tnames(D)| + 1$ to avoid "mixing" the contributions of different nesting levels.

As an example consider the toy XML document shown below, and representing information about books.

```
<xml>
    <book year="1997">
        <title> A First Course in Database Systems </title>
        <author> Ullman </author>
        <author> Widom  </author>
        <publisher> Prentice-Hall </publisher>
    </book>
</xml>
```

The *tag set* of the XML document shown above is: {<xml>, <book>, <title>, </title>, <author>, </author>, <author>, </author>, <publisher>, </publisher>, </book>, </xml>}.
For the same document *tnames* = {xml, book, title, author, publisher}. Observe that tags with the same name are not considered to be the same object, so that <author> appears twice in the tag set, whereas the set of tag names does not contain duplicates.
Finally, the skeleton of the document is: <xml>, <book>, <title>, </title>, <author>, </author>, <author>, </author>, <publisher>, </publisher>, </book>, </xml>.
Figure 2 shows the output of the three encodings when applied to the toy document shown above. Finally, in Figure 3 is shown the document encoding obtained using the

Tag Name	Enc. value
<xml>	1
<book>	2
<ATTRIB@year>	3
</ATTRIB@year>	-3
<title>	4
</title>	-4
<author>	5
</author>	-5
<publisher>	6
</publisher>	-6
</book>	-2
</xml>	-1

Direct encoding

First Tag Type	Second Tag Type	Enc. value
<xml>	<book>	1
<book>	<ATTRIB@year>	2
<ATTRIB@year>	</ATTRIB@year>	3
</ATTRIB@year>	<title>	4
<title>	</title>	5
</title>	<author>	6
<author>	</author>	7
</author>	<publisher>	8
<publisher>	</publisher>	9
</publisher>	</book>	10
</book>	</xml>	11

Pairwise encoding

Tag Name	Path Name	Enc. value
<xml>	xml	1
<book>	xml.book	2
<ATTRIB@year>	xml.book.ATTRIB@year	3
<title>	xml.book.title	4
...	...	...

Nested encoding

Fig. 2. Tag Encodings Example

encoding functions described above.

3.2 Similarity Measures

Faced with the above definitions, we can now detail the similarity measure for XML documents. Observe that a document encoding function provides us with a particular view of the structure of a document d, like we are visiting the tree-structure of d (in a depth-first, left-to-right way) starting from an initial time t_0. Considering an encoding function, we also assume that each node (tag) is found after a fixed time interval Δ. The total time spent to visit the document is then $t_0 + N\Delta$ (where N is the size

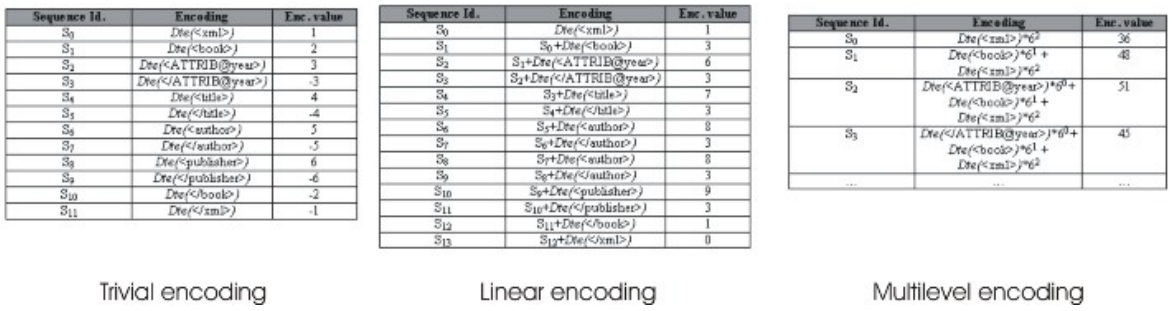
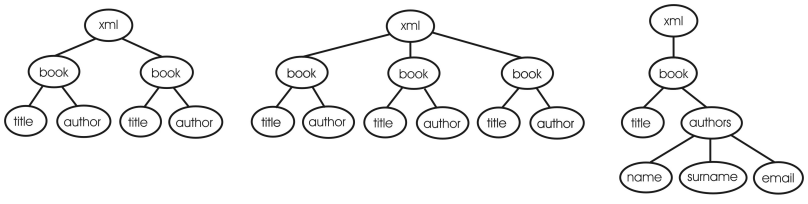


Fig. 3. Document Encodings Example

of $tags(d)$). During the visit, as we find a start-tag, we produce an impulse, that is assumed to stand until we reach the corresponding end-tag, and depends on a given tag encoding e and the overall structure of the document, as it is represented by the selected document encoding *enc*. As a result of the above physical simulation, the visit of the document produces a signal $h_d(t)$, that usually changes its intensity, in the time interval $[t_0, t_0 + N\Delta)$.

Comparing two such signals can be as difficult as comparing the original documents, since *(i)* comparing documents having different lengths requires to costly resizing and alignment operations, and *(ii)* stretching (or narrowing) signals is not a solution, since these operations heavily affect the document structure.

A traditional approach to the comparisons of two such sequences is known in literature as *Time Warping* distance [19], which consists mainly in comparing every possible stretching and narrowing of the two signals, and choosing the best matching. However, such an approach is quite expensive (quadratic in complexity) when dealing with high-dimensional signals. Moreover, the effectiveness of the approach has a serious drawback. The structural similarity of two documents does not necessarily correspond to a similar shape of the associated signals. Consider the documents shown in fig. 4



(a) book1 (b) book2 (c) book3

Fig. 4. Example `book1`, `book2` and `book3` documents

In the multilevel encoding scheme, these documents are associated with the signals reported in fig. 5. Observe that all the signals have different shapes. Notwithstanding,

the only difference between `book1` and `book2` (belonging to the same DTD) stems in the fact that `book1` has two `book` elements, whereas `book2` has three elements. `book3` has the same length as `book1`, but they have a quite different DTD. However, a comparison in the time domain (accomplished using the time-warping distance) will result in a higher similarity between `book1` and `book3` than between `book1` and `book2`.

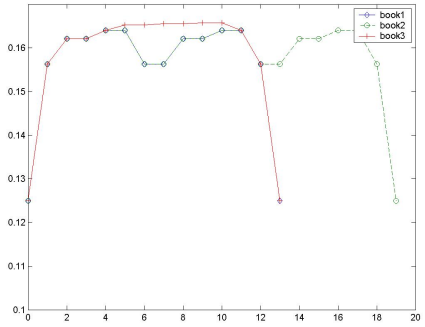


Fig. 5. Signals of `book1`, `book2` and `book3` documents

To avoid these drawbacks, it is convenient to compare the structure of two XML documents by exploiting the Fourier transforms of the signals associated with them, since they reveal much about the distribution and meaning of signal frequencies. Indeed, some useful properties of such transform, namely the concentration of the energy into few frequency coefficients, its invariance of the amplitude under shifts, and especially its efficient computation, make it particularly attractive for the problem at hand. In particular, it is useful to consider a document d as a window on its periodic extension, i.e. $\tilde{d}$ is d repeated infinitely many times. More formally, given an encoding $h_d(t) = enc(d)$ of a document d, we can define a function $\tilde{h}_d(t)$ as the periodic extension of the $h_d(t)$ function. That is, we consider the time series associated with a document as a *window* on the time series $\tilde{h}_d(t)$ associated with the periodic extension of the structure of the document (a document is *repeated* infinitely many times). As a consequence, a comparison between two documents d_1 and d_2 can be accomplished by comparing the frequencies of their periodic extensions $\tilde{h}_{d_1}(t)$ and $\tilde{h}_{d_2}(t)$.

Given a document d, we denote as $\texttt{DFT}(enc(d))$ the Discrete Fourier Transform of the (normalized) time series resulting from its encoding. The overall computation of the dissimilarity between documents can be done as follows. Let d_1, d_2 be two XML documents, and enc be a document encoding, such that $h_1 = enc(d_1)$ and $h_2 = enc(d_2)$. We define the *Discrete Fourier Transform* distance of the documents as an approximation of the squared difference of the magnitudes of the two signals:

$$dist_{\texttt{DFT}}(d_1, d_2) = \left(\sum_{k=1}^{M/2} \left(\left| [\tilde{\texttt{DFT}}(h_1)](k) \right| - \left| [\tilde{\texttt{DFT}}(h_2)](k) \right| \right)^2 \right)^{\frac{1}{2}}$$

where $\tilde{\texttt{DFT}}$ is an interpolation of DFT to the frequencies appearing in both d_1 and d_2 (and M is the total number of points appearing in the interpolation).

Notice that, when comparing two documents with length N, our method requires $O(N \log N)$, since computing their transforms is $O(N \log N)$ that is compelling w.r.t. other approaches (e.g., graph-based approaches).

3.3 Dealing with Web Documents

Providing a general definition for the structure of Web documents, without referring to a precise application context, is quite a hard task. Indeed, even if tags are the basis for detecting the structure of a document, they only express its syntactic structure, disregarding the semantics of the data presented by the document. Finding heterogeneous representations of semantically similar information is a very common situation in the Web. Different tags and different structurings of them could be used to represent similar information sources. Worst, similar markup tags could be used to structure different information sources. Such a problem is even more critical when document are written in HTML, a language specifically designed to address presentation issues and, thus, providing little expressiveness from a semantic point of view.

However, to the best of our knowledge, most wrapper languages [10, 16, 15] use only the syntactic structure of Web pages to define how to extract information, while only a few ones [7] have semantic facilities(actually very limited). Thus, in the following we mainly concentrate on syntactic similarity, as defined by the formatting structure of HTML tags. Despite the limited number of HTML tag names and their lack of explicit semantics, we believe that such a simple approach can be successful in recognizing homogeneous groups of data-intensive HTML documents. As a matter of fact, we experienced that recognizing syntactically homogeneous groups of documents is sufficient for inducing and selecting the most suitable wrappers for handling them. Indeed, a wrapper is able to process only pages that exhibit almost the same syntactic structure, at least in their portion containing relevant data to be extracted. Obviously, the other portions of the pages, for instance those containing advertisements, can exhibit very different syntactic structure. We can nevertheless look at the overall syntactic structure since usually the irrelevant parts of the pages are smaller than the ones containing relevant data. Furthermore, irrelevant parts are likely to have different structure even in unrelated pages.

Finally, notice that the technique proposed in the the previous section looks at the structure of a document as a tree of elements. The tagging structure in well-formed XML documents naturally induces such a kind of representation; HTML pages on the Web, instead, are often not well-formed, i.e. the end tag is not always required to appear. However HTML parsers are able to parse not well-formed documents and represent them as a tree of elements, following the *Document Object Model* [1].

4 Experiments

In this section, we present some experiments we conducted to evaluate the effectiveness of proposed approaches in measuring structural similarity among HTML documents.

The experiments were performed on real HTML documents, gathered from different sources in the Internet. From now on, we will denote any group of documents coming from the same source as a *class*. The documents we used in our tests are about 400 and belong to 16 classes, which can be grouped into the following 4 high-level *categories* (each of them corresponding to a distinct application domain):

- `E-commerce`, a data set containing 102 HTML documents and consisting of 4 classes, named E_1, E_2, E_3 and E_4, corresponding to 4 e-commerce Web sites;
- `Museums`, a data set of 96 HTML documents, coming from 4 classes, named M_1, M_2, M_3 and M_4, corresponding to the Web sites of 4 museums;
- `Newspapers`, a data set of 111 HTML documents, consisting of 4 classes, named N_1, N_2, N_3, N_4, corresponding to the Web sites of 4 newspapers;
- `Universities`, a data set of 94 HTML documents, consisting of 4 classes, named U_1, U_2, U_3, U_4, corresponding to the Web sites of 4 Universities.

The classes we chose are particularly interesting to analyse from an application point of view. Indeed, they offer the following advantages which allow to better evaluate the effectiveness of the proposed approach:

- The general structure of each category is likely to be substantially different from that of different categories. This is mainly due to a different characterization of the information available in the pages, which consequently triggers different perspectives for information extraction and wrapper geneation (price comparison, topic detection, evaluation of course offerings, etc.).
- Many classes, significantly different from a structural point of view, can be found in the same category. This allows to evaluate similarity at different grains of refinement.

The evaluation of the results computed in each test relies on some a priori knowledge about the used data set. In fact, we remember that the data considered in our tests belong to a predefined number of classes, i.e., documents' groups, each of them related to a given data source. The immediate result of each test is a similarity matrix S representing the degree of structural similarity for every pair of documents.

A natural quality measure can be the error rate of a k-Nearest Neighbor classifier. Indeed, for each document, we can measure whether the dominant class of the k most similar elements allows to correctly predict the actual class of the document, and consider the total number of documents correctly predicted as a measure for evaluating the effectivenss of the similarity. This measure can be refined by evaluating the average number of elements, in a range of k elements, having the same class of the document under consideration. Practically, we define q_k, as the average percentage of documents in the k-neighborhood of a generic document which belong to the same class of that document. Formally:

$$q_k(S) = \frac{1}{N} \sum_{i=1}^{N} \frac{|\mathcal{F}_k(i) \cap Cl(i)|}{min(k, |Cl(i)|)}$$

where N is the total number of documents, $Cl(i)$ represents the class associated with the i-th document in the collection, and $\mathcal{F}_k(i)$, is the set of k documents having the

lowest distances from d_i, according to the similarity measure at hand. In principle, a Nearest Neighbor classifier tends to have a good performance when q_k is high, and a poor performance in the opposite case. Furthermore, q_k provides a measure of the stability of a Nearest-Neighbor: high values of q_k make a kNN classifier less sensitive to increasing values k of neighbors considered.

The sensitivity of the similarity measure can also been measured by considering, for a given group of documents x, y, z, the probability that x and y belong to the same class, and z belongs to a different class, but z is more similar to x than y is. We denote this probability by $\varepsilon(S)$, which is estimated as

$$\varepsilon(S) = \frac{1}{N} \times \sum_{i=1..N} \left(\frac{1}{(|Cl(i)| - 1) \times (N - |Cl(i)|)} \times \sum_{\substack{j\,=\,1..N \\ j \neq i \\ Cl(j)\,=\,Cl(i)}} \sum_{\substack{k\,=\,1..N \\ Cl(k) \neq Cl(i)}} \delta_S(i,j,k) \right)$$

where δ_S is defined as follows:

$$\delta_S(i,j,k) = \begin{cases} 1 \text{ , iff } S(i,j) < S(i,k) \\ 0 \text{ , otherwise} \end{cases}$$

4.1 Experimental Results

We examined different combinations of document and tag encoding functions. In the following, we will refer to any of such combinations as *encoding scheme* and we will consider five of them: (i) *Trivial*, which combines the Trivial document encoding function with the Direct tag encoding one, (ii) *Linear*, where the Linear document encoding function uses the Direct encoding function for tag codes, (iii) *Nested*, combining the Trivial document encoding with the Nested tag encoding function, (iv) *Multilevel*, where the Multilevel document encoding function is integrated with the Direct tag encoding function, and (v) *Pairwise*, combining the Multilevel document encoding function with the Pairwise tag encoding function.

Tables 1 and 2 summarize the quality values obtained when using the above defined encoding schemes. To compute q_k, in each test we chose a neighborhood size equal to the minimum class cardinality w.r.t. the classes considered in the test.

In general, the proposed approach has a good performance, whatever encoding scheme is chosen among the ones previously described. A closer look inside any test reveals that all the considered classes are recognized as sufficiently homogeneous from a structural point of view, i.e. the similarities inside any class are generally higher than similarities between documents of that class and the ones of the other classes. We show this with the data set `Newspapers`, which is composed by 4 disjoint document classes, namely N_1, N_2, N_3, and N_4. Each class corresponds to a news Web site and contains the documents extracted from that site.

We recall that the direct result of each test is a similarity matrix S. In order to allow for an immediate feeling of the similarity relation, we visualize the similarity matrix as an image, using a scale of colors which range from white to black through several tones of yellow, first, and red, after. The color tone of each pixel in such an image is

test	*document classes*	*Trivial*	*Linear*	*Nested*	*Multilevel*	*Pairwise*
1	E_1, E_2, E_3, E_4	0.0114	0.0379	0.0067	0.0212	0.0329
2	M_1, M_2, M_3, M_4	0.0442	0.0314	0	0.1218	0.0829
3	N_1, N_2, N_3, N_4	0.0351	0.0021	0	0.0142	0.0430
4	U_1, U_2, U_3, U_4	0.0796	0.0375	0.0515	0.0498	0.0413
5	E_2, M_3, N_2, U_2	0.0148	0.0053	0.0002	0.0167	0.0687
6	E_3, M_2, N_3, U_3	0.0251	0.0165	0.0552	0.0436	0.0349
7	E_4, M_4, N_4, U_1	0.0002	0.0038	0.0318	0.0075	0.0160

Table 1. Error ε for several data sets and methods

test	*document classes*	*Trivial*	*Linear*	*Nested*	*Multilevel*	*Pairwise*
1	E_1, E_2, E_3, E_4	0.9768	0.9162	0.9808	0.9666	0.9643
2	M_1, M_2, M_3, M_4	0.9501	0.9518	1	0.8300	0.9211
3	N_1, N_2, N_3, N_4	0.9546	0.9914	1	0.9643	0.9287
4	U_1, U_2, U_3, U_4	0.9064	0.9665	0.9144	0.9106	0.9154
5	E_2, M_3, N_2, U_2	0.9640	0.9798	0.9988	0.9786	0.8871
6	E_3, M_2, N_3, U_3	0.9803	0.9857	0.9529	0.9265	0.9578
7	E_4, M_4, N_4, U_1	1	0.9924	0.9271	0.9710	0.9595

Table 2. Quality measure q_k for several data sets and methods

proportional to the value stored in the corresponding cell of the matrix (i.e., darker pixels correspond to higher similarity values). In the case of highly dense subrange of similarity values, suitable distortions will be applied to the color scale, in order to emphasize the differences among such values.

The average values of all the intra-class similarities and inter-class similarities in S can be summarized into a matrix CS to support a simple quantitative analysis. In particular, given a set of documents belonging to n prior classes and a similarity matrix S defined on those documents, an $n \times n$ matrix CS can be produced, where the generic element $CS(i,j)$ is computed as follows:

$$CS(i,j) = \begin{cases} \frac{\sum_{x,y \in C_i, x \neq y} S(x,y)}{|C_i| \times (|C_i|-1)} & \text{iff } i = j \\ \frac{\sum_{x \in C_i, y \in C_j} S(x,y)}{|C_i| \times |C_j|} & \text{otherwise} \end{cases}$$

For each of the encoding strategies under consideration, we show a graphical representation of the similarity matrix, the average of all intra-class and inter-class similarities, and the values obtained for the error ε and the quality measure q_k (with $k = 22$).

Trivial. At a first glance of fig. 6.(a), Trivial encoding seems not to be able to suitably distinguish the prior classes in the data set. In fact, while the classes N_1 and N_4 are clearly recognized, the other ones show a quite low internal similarity.

However, the quantitative results shown in fig. 6 reveal that the Trivial approach performs surprisingly well. Indeed, for all classes the intra-class similarity values are

(a)

	N_1	N_2	N_3	N_4
N_1	0.0608	0.0039	0.0068	0.0094
N_2	0.0039	0.0053	0.0045	0.0039
N_3	0.0068	0.0045	0.0095	0.0065
N_4	0.0094	0.0039	0.0065	0.1536

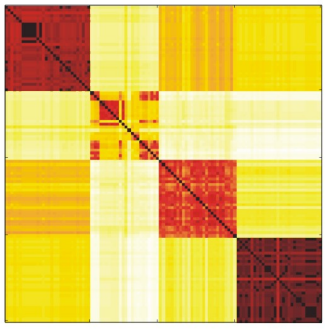
(b)

measure	*value*
ε	0.0351
q_k	0.9546

(c)

Fig. 6. Similarity Matrix (a), Average Similarities (b) and Quality Measures (c) for **Trivial** Encoding Scheme

sufficiently higher than the inter-class ones, thus allowing for separating all classes from each other. In particular, adopting an iterative approach, we can first extract classes N_1 and N_4, which exhibit the highest intra-class similarity. After the removal of these classes, the average similarities lower of about an order of magnitude, allowing the separation of the class N_3 . Finally, the second class, with the lowest intra-class similarity, can be identified.



(a)

	N_1	N_2	N_3	N_4
N_1	0.0650	0.0047	0.0064	0.0056
N_2	0.0047	0.0076	0.0044	0.0042
N_3	0.0064	0.0044	0.0108	0.0051
N_4	0.0056	0.0042	0.0051	0.1779

(b)

measure	*value*
ε	0.0021
q_k	0.9914

(c)

Fig. 7. Similarity Matrix (a), Average Similarities (b) and Quality Measures (c) for **Linear** Encoding Scheme

Linear. The results shown in the right side of fig. 7 demonstrate a slight improvement in recognizing the prior classes which Linear scheme gains with respect to the Trivial one. As in the previous case, the last class has the highest homogeneity , while the second exhibits the minimum average intra-class similarity. The good performance of Linear encoding is supported by the graphical representation of the similarity matrix in fig. 7.(a), where blocks corresponding to the intra-class similarities can be clearly individuated.

(a)

	N_1	N_2	N_3	N_4
N_1	0.0935	0.0023	0.0025	0.0060
N_2	0.0023	0.0055	0.0027	0.0025
N_3	0.0025	0.0027	0.0057	0.0030
N_4	0.0060	0.0025	0.0030	0.1518

(b)

measure	*value*
ε	0
q_k	1

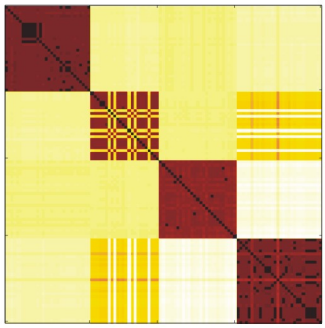
(c)

Fig. 8. Similarity Matrix (a), Average Similarities (b) and Quality Measures (c) for **Nested** Encoding Scheme

Nested. Both the optimal values for the overall similarity measures, shown in fig. 8.(c), and the similarity matrix, depicted in fig. 8.(a), prove the ability of Nested scheme to adequately evaluate structural similarity over the considered data set. Also in this case, the classes N_1 and N_4 can be neatly recognized, while the other ones show lower similarity in their inside, as fig. 8.(c) confirms. It is worth noticing that this scheme emphasizes such a general trend, but it is also able to reduce the inter-class similarities relatively to the intra-class one, thus allowing for better distinguishing the given classes.

Multilevel. The results produced by the Multilevel scheme substantially differ from those presented so far, mainly because all the average similarities in fig. 9.(b) are rather close to the maximum value of similarity allowed.

These results can be explained by taking into account the nature of the names and positions of tags inside HTML documents, as well as the strategy of the Multilevel document encoding function, which associates each tag with a linear combination of the codes related to all the tags enclosing it. In particular, the weight associated with each tag in such a combination is a power function, where the basis is the number of distinct tag codes globally generated by the tag encoding function and the exponent



(a)

	N_1	N_2	N_3	N_4
N_1	0.9993	0.9930	0.9932	0.9808
N_2	0.9930	0.9969	0.9932	0.9940
N_3	0.9932	0.9932	0.9990	0.9921
N_4	0.9808	0.9940	0.9921	0.9993

(b)

measure	*value*
ε	0.0142
q_k	0.9643

(c)

Fig. 9. Similarity Matrix (a), Average Similarities (b) and Quality Measures (c) for **Multilevel** Encoding Scheme

depends on the nesting level of the tag in an inverse manner. This eventually causes higher weights to be associated with external tags. On the other side, external tags tend to be quite the same in all HTML documents: typically, tags such as `html`, `head` and `body` are used. Therefore, when Multilevel scheme is applied to HTML documents the obtained time series tends to have roughly similar shapes, thus motivating the high values of similarity detected among every couple of documents.

The above described phenomenon can also explains that high-precision digits can be used to actually evaluate the similarity among documents. Indeed, the quality measures shown in fig. 9.(c) prove that the performances of Multilevel scheme are good enough: in the same figure we can observe that the intra-class similarities are yet higher than the inter-classes ones and allows for separating the classes, as confirmed by the image in fig. 9.(a).

Pairwise. The similarity matrix in fig. 10.(a) looks rather similar to the one produced by the Multilevel encoding scheme. Furthermore, high similarities among a most of the documents can still be noticed, even when they belong to different classes. This behavior is essentially due to the Multilevel document encoding, where each tag occurrence is associated with a linear combination of the codes assigned by a given tag encoding function to the tags enclosing that occurrence. Further, since the Pairwise tag encoding strategy considers all the distinct pairs of consecutive tags, it is likely to produce a high number tag codes, so emphasizing the differences in the weights that tags at different levels are assigned to. Combining the Multilevel document encoding and the Pairwise tag encoding functions, hence, makes the similarity between two generic documents essentially depend on how they appear in most external elements, which we have noticed to be nearly invariant over HTML documents.

However, even in this case the results are globally satisfactory since all the classes can be distinguished from each others, in spite of the high inter-classes similarities and

(a)

	N_1	N_2	N_3	N_4
N_1	1.0000	0.9997	0.9998	0.9997
N_2	0.9997	0.9998	0.9996	0.9997
N_3	0.9998	0.9996	0.9999	0.9995
N_4	0.9997	0.9995	0.9996	0.9999

(b)

measure	*value*
ε	0.0430
q_k	0.9287

(c)

Fig. 10. Similarity Matrix (a), Average Similarities (b) and Quality Measures (c) for **Pairwise** Encoding Scheme

the quite low homogeneity of the class N_2, which yet exhibits the minimum average intra-class similarity.

4.2 Remarks

In general, the proposed encoding schemes provide good performances, even in consideration that HTML tag names belong to a rather little set of predefined terms, and do not have a semantics meaning.

The dissimilar behaviors of the encoding schemes mainly depends on the different ways they deal with the context of a tag when encoding the skeleton of a document into a time series. As a matter of fact, very good results are obtained by Nested and, surprisingly enough, by the rather simple schemes Trivial and Linear. In particular, Nested tends to perform best when applied to classes from the same category. On the contrary, the encoding schemes based on Multilevel document encoding function (i.e. Multilevel and Pairwise) do not exhibit as brilliant results as they do over pure XML documents [12]. In a few cases (see test 2 for Multilevel and test 5 for Pairwise, in tables 1 and 2) they perform yet worse than other encoding techniques. This behavior essentially comes from the fact that the multilevel document encoding function, used in both these two schemes, mainly focuses on structural differences localized at most external levels, which tend to be rather similar in HTML documents. In order to remedy, we could straightforwardly improve these approaches by decreasing their dependence on the first levels of the document structure. However, due to space limitations and considering the overall satisfactoriness of the results achieved even by these encoding schemes, we will omit further investigations on this issue.

5 Conclusions

In this paper we proposed an architecture for integrating crawling and wrapping of Web pages, by exploiting structural document categorization. Document categorization is possible thanks to a notion of structural similarity developed and analyzed throughout the paper. The technique, originally developed for XML documents, was successfully adapted to HTML documents, allowing for a "syntactic" structural similarity analysis. Indeed, in specific application domains, the technique has been proved effective in collecting homogeneous structures for wrapper induction.

It is worth mentioning alternative approaches, such as, e.g., *Cosine* or *Jaccard* similarity, or *Edit* distance [17]. In general, Cosine and Jaccard similarity fail in capturing structural information in HTML docs. Indeed, they only could allow to compare frequencies of tags: as already mentioned, in HTML documents tag names and frequencies are likely to be quite invariant. Approaches based on Edit distance have the main drawback of high complexity (quadratic w.r.t. the size of a document). Moreover, as already mentioned in section 3.2, we believe that the effectiveness of the approach is sensitive to the frequency of similar structures in different documents. We still plan a more detailed experimental comparison on HTML documents in a future extension of the paper. Neverthless, early comparisons over XML documents [12] confirm our hypothesis and show that our technique outperforms, e.g., the approach proposed in [17].

Notice that the proposed technique can be further strengthened by enriching the characterization of the document structure with semantic information. For example, a viable solution can be the "annotation" of HTML tags with further data extracted from the context in which the tag appear. Contextualizing a tag can greatly improve the similarity analysis of documents. In particular, text analysis techniques [6] can be easily adapted to add further specificity to an element, according to the textual information appearing between its start and end tag. Some preliminary experiments are very encouraging: we plan to devote further attention to this issue in the future developments of the technique.

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