Computer Networks and ISDN Systems 29 (1997) 1157–1166

Syntactic clustering of the Web

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Abstract

We have developed an efficient way to determine the syntactic similarity of files and have applied it to every document on the World Wide Web. Using this mechanism, we built a clustering of all the documents that are syntactically similar. Possible applications include a "Lost and Found" service, filtering the results of Web searches, updating widely distributed web-pages, and identifying violations of intellectual property rights. © 1997 Published by Elsevier Science B.V.

Keywords: Similarity; Duplication; Resemblance; Web search; Fingerprints; Signatures

1. Introduction

The Web has undergone exponential growth since its birth, and this expansion has generated a number of problems; in this paper we address two of these:

(1) The proliferation of documents that are identical or almost identical.
(2) The instability of URLs.

The basis of our approach is a mechanism for discovering when two documents are "roughly the same"; that is, for discovering when they have the same content except for modifications such as formatting, minor corrections, webmaster signature, or logo. Similarly, we can discover when one document is "roughly contained" in another. Applying this mechanism to the entire collection of documents found by the AltaVista spider yields a grouping of the documents into clusters of closely related items. As explained below, this clustering can help solve the problems of document duplication and URL instability.

The duplication problem arises in two ways: First, there are documents that are found in multiple places in identical form. Some examples are:

- FAQ (Frequently Asked Questions) or RFC (Request For Comments) documents.
- The online documentation for popular programs.
- Documents stored in several mirror sites.
- Legal documents.

Second, there are documents that are found in almost identical incarnations because they are:

- Different versions of the same document.
- The same document with different formatting.
- The same document with site specific links, customizations or contact information.
- Combined with other source material to form a larger document.
- Split into smaller documents.

The instability problem arises when a particular

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0169-7552/97/$17.00
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URL becomes undesirable because:

- The associated document is temporarily unavailable or has moved.
- The URL refers to an old version and the user wants the current version.
- The URL is slow to access and the the user wants an identical or similar document that will be faster to retrieve.

In all these cases, the ability to find documents that are syntactically similar to a given document allows the user to find other, acceptable versions of the desired item.

1.1. URNs

URNs (Uniform Resource Names) [6] have often been suggested as a way to provide functionality similar to that outlined above. URNs are a generalized form of URLs (Uniform Resource Locators). However, instead of naming a resource directly — as URLs do by giving a specific server, port and file name for the resource — URNs point to the resource indirectly through a *name server*. The name server is able to translate the URN to the "best" (based on some criteria) URL of the resource.

The main advantage of URNs is that they are location independent. A single, stable URN can track a resource as it is renamed or moves from server to server. A URN could direct a user to the instance of a replicated resource that is in the nearest mirror site, or is given in a desired language. Unfortunately, progress towards URN's has been slow. The mechanism we present here provides an alternative solution.

1.2. Related work

Our approach to determining syntactic similarity is related to the sampling approach developed by Heintze [2], though there are many differences in detail and in the precise definition of the measures used. Since our domain of interest is much larger (his prototype implementation is on a domain 50,000 times smaller) and we are less concerned with plagiarism, the emphasis is often different. Related sampling mechanisms for determining similarity were also developed by Manber [3] and within the Stanford SCAM project [1,4,5].

With respect to clustering, there is a large body of literature related to *semantic clustering*, a rather different concept. Again, clustering based on syntactic similarity (on a much smaller scale) is discussed in the context of the SCAM project.

2. Defining document similarity

To capture the informal notions of "roughly the same" and "roughly contained" in a rigorous way, we use the mathematical concepts of *resemblance* and *containment* as defined below.

The *resemblance* of two documents A and B is a number between 0 and 1, such that when the resemblance is close to 1 it is likely that the documents are "roughly the same". Similarly, the *containment* of A in B is a number between 0 and 1 that, when close to 1, indicates that A is "roughly contained" within B. To compute the resemblance and/or the containment of two documents it suffices to keep for each document a *sketch* of a few hundred bytes. The sketches can be efficiently computed (in time linear in the size of the documents) and, given two sketches, the resemblance or the containment of the corresponding documents can be computed in time linear in the size of the sketches.

We view each document as a sequence of words, and start by lexically analyzing it into a canonical sequence of tokens. This canonical form ignores minor details such as formatting, html commands, and capitalization. We then associate with every document D a set of subsequences of tokens $S(D, w)$.

A contiguous subsequence contained in D is called a *shingle*. Given a document D we define its w-*shingling* $S(D, w)$ as the set of all unique shingles of size w contained in D. So for instance the 4-shingling of

```
(a,rose,is,a,rose,is,a,rose)
```

is the set

```
{(a,rose,is,a), (rose,is,a,rose),
                        (is,a,rose,is)}
```

For a given shingle size, the resemblance r of two documents A and B is defined as

$$r(A, B) = \frac{|S(A) \cap S(B)|}{|S(A) \cup S(B)|}$$

where $|A|$ is the size of set A.

The containment of A in B is defined as

$$c(A, B) = \frac{|S(A) \cap S(B)|}{|S(A)|}$$

Hence the resemblance is a number between 0 and 1, and it is always true that $r(A, A) = 1$, i.e. that a document resembles itself 100%. Similarly, the containment is a number between 0 and 1 and if $A \subseteq B$ then $c(A, B) = 1$.

Experiments show that these mathematical definitions effectively capture our informal notions of "roughly the same" and "roughly contained".

Notice that resemblance is not transitive (a well-known fact bemoaned by grandparents all over), but neither is our informal idea of "roughly the same"; for instance consecutive versions of a paper might well be "roughly the same", but version 100 is probably quite different from version 1. Nevertheless, the *resemblance distance* defined as

$$d(A, B) = 1 - r(A, B)$$

is a metric and obeys the triangle inequality. (The proof of this, as well as most of the mathematical analysis of the algorithms discussed here are the subject of a separate paper, in preparation.)

3. Estimating resemblance and containment

Fix a shingle size w, and let U be the set of all shingles of size w. Without loss of generality we can view U as a set of numbers. Now fix a parameter s. For a set $W \subseteq U$ define $\mathrm{MIN}_s(W)$ as

$$\mathrm{MIN}_s(W) = \begin{cases} \text{the set of the smallest} & \\ \quad s \text{ elements in } W, & \text{if } |W| \geq s, \\ W, & \text{otherwise} \end{cases}$$

where "smallest" refers to numerical order on U, and define

$$\mathrm{MOD}_m(W) = \text{the set of elements of } W \text{ that are 0 mod } m$$

Theorem. *Let $\pi : U \to U$ be a permutation of U chosen uniformly at random. Let $F(A) = \mathrm{MIN}_s(\pi(S(A)))$ and $V(A) = \mathrm{MOD}_m(\pi(S(A)))$. Define $F(B)$ and $V(B)$ analogously. Then*

- *The value*
$$\frac{|\mathrm{MIN}_s(F(A) \cup F(B)) \cap F(A) \cap F(B)|}{|\mathrm{MIN}_s(F(A) \cup F(B))|}$$
is an unbiased estimate of the resemblance of A and B.
- *The value*
$$\frac{|V(A) \cap V(B)|}{|V(A) \cup V(B)|}$$
is an unbiased estimate of the resemblance of A and B.
- *The value*
$$\frac{|V(A) \cap V(B)|}{|V(A)|}$$
is an unbiased estimate of the containment of A in B.

In view of the above, we can choose a random permutation and afterwards keep for each document D a *sketch* consisting only of the set $F(D)$ and/or $V(D)$. The sketches suffice to estimate the resemblance or the containment of any pair of documents without any need for the original files.

The set $F(D)$ has the advantage that it has a fixed size, but it allows only the estimation of resemblance. The size of $V(D)$ grows as D grows, but allows the estimation of both resemblance and containment.

To limit the size of $V(D)$ we can proceed as follows: for documents that have size between (say) $100 * 2^i$ and $100 * 2^{i+1}$, we store the set $V_i(D) = \mathrm{MOD}_{2^i}(\pi(S(D)))$. The expected size of $V_i(D)$ is always between 50 and 100. On the other hand, we can easily compute $V_{i+1}(D)$ from $V_i(D)$. (We simply keep only those elements divisible by 2^{i+1}.) Thus, if we are given two documents, A and B, and 2^i was the modulus used by the longer document, we use $V_i(A)$ and $V_i(B)$ for our estimates. The disadvantage of this approach is that the estimation of the containment of very short documents into substantially larger ones is rather error prone due to the paucity of samples.

In our system, we implement the sketches as follows:

- We canonicalize documents by removing HTML formatting and converting all words to lowercase.
- The shingle size w is 10.
- We use a 40 bit fingerprint function, based on Rabin fingerprints [7], enhanced to behave as a random permutation. (When we refer to a *shingle*

or *shingle value* in the rest of this paper, we will mean this fingerprint value.)
- We use the "modulus" method for selecting shingles with an m of 25.

4. Algorithms

Conceptually, applying this resemblance algorithm to the entire Web is quite simple. We:
- retrieve every document on the Web (this data was available to us from an AltaVista spider run),
- calculate the sketch for each document,
- compare the sketches for each pair of documents to see if they exceed a threshold of resemblance,
- combine the pairs of similar documents to make clusters of similar documents.

While this algorithm is quite simple, a naive implementation is impractical. Our test case is a set 30,000,000 HTML and text documents retrieved from the Web. A pairwise comparison would involve $O(10^{15})$ (a quadrillion) comparisons. This is clearly infeasible.

The magnitude of the input data imposed severe restrictions on the design of our data structures and algorithms. Just one bit per document in a data structure requires 4 Mbytes. A sketch size of 800 bytes per document requires 24 Gbytes. One millisecond of computation per document translates into 8 hours of computation. Any algorithm involving random disk accesses or that causes paging activity is completely infeasible.

In the design of our algorithms, we use a single, simple approach for dealing with so much data — divide, compute, merge. We take the data, divide it into pieces, compute on each piece separately and then merge the results. We choose the piece size m so that the computation can be done entirely in memory. Merging the results is a simple, but time consuming process due to the required I/O. Each merge pass is linear, but $\log(n/m)$ passes are required, so the overall performance of the process is dominated by a $O(n \log(n/m))$ term.

4.1. The clustering algorithm

We perform the clustering algorithm in four phases. In the first phase, we calculate a sketch for every document. This step is linear in the total length of the documents.

In the second phase, we produce a list of all the shingles and the documents they appear in, sorted by shingle value. To do this, the sketch for each document is expanded into a list of <shingle value, document ID> pairs. We sort this list using the divide, sort, merge approach outlined above.

In the third phase, we generate a list of all the pairs of documents that share any shingles, along with the number of shingles they have in common. To do this, we take the file of sorted <shingle, ID> pairs and expand it into a list of <ID, ID, count of common shingles> triplets by taking each shingle that appears in multiple documents and generating the complete set of <ID, ID, 1> triplets for that shingle. We then apply the divide, sort, merge procedure (adding the counts for matching ID–ID pairs) to produce a single file of all <ID, ID, count> triplets sorted by the first document ID. This phase requires the greatest amount of disk space because the initial expansion of the document ID triplets is quadratic in the number of documents sharing a shingle, and initially produces many triplets with a count of 1.

In the final phase, we produce the complete clustering. We examine each <ID, ID, count> triplet and decide if the document pair exceeds our threshold for resemblance. If it does, we add a link between the two documents in a union-find algorithm. The connected components output by the union-find algorithm form the final clusters. This phase has the greatest memory requirements because we need to hold the entire union-find data structure in memory.

4.2. Query support

After we have completed the clustering, we need several auxiliary data structures to make queries more convenient. We produce:
- the mapping of a URL to its document ID:
  - fingerprint each URL and pair it with the document ID,
  - sort the <fingerprint, ID> pairs by fingerprint value,
  - when given a URL, we fingerprint it, find it in the sorted list and output the document ID;
- the mapping of document ID to the cluster containing it

  - this is a inversion of the cluster to document ID mapping, ordered by document ID;
- the mapping of a cluster to the documents it contains
  - this is the output of the clustering algorithm;
- the mapping of a document ID to its URL
  - an array of all the URLs in document ID order.

5. Clustering performance issues

5.1. Common shingles

Very common shingles (for us, this means shingles shared by more than 1000 documents) are a performance problem during the third phase of our algorithm. As we have discussed, the number of document ID pairs is quadratic in the number of documents sharing a shingle. Overly common shingles can greatly expand the number of the document ID pairs we have to deal with.

When we looked at the most common shingles, we found that they were nearly all mechanically generated. They include:

- HTML comment tags identifying the program that generated the HTML.
- Shared header or footer information on a large number of automatically generated pages (forms or views on databases).
- Extremely common text sequences (the numbers 3–12, ...).
- Mechanically generated pages with artificially different URLs and internal links.

These common shingles either have no effect on the overall resemblance of the documents or they have the effect of creating a false resemblance between two basically dissimilar documents. Therefore, we ignore all very common shingles.

5.2. Identical documents

Identical documents do not need to be handled specially in our algorithm, but they add to the computational workload and can be eliminated quite easily. Identical documents obviously share the same set of shingles and so, for the clustering algorithm, we only need to keep one representative from each group of identical documents. Therefore, for each document we generate a fingerprint that covers its entire contents. When we find documents with identical fingerprints, we eliminate all but one from the clustering algorithm. After the clustering has been completed, the other identical documents are added into the cluster containing the one kept version.

We can expand the collection of identical documents with the "lexically-equivalent" documents and the "shingle-equivalent" documents. The lexically-equivalent documents are identical after they have been converted to canonical form. The shingle-equivalent documents are documents that have identical shingle values after the set of shingles has been selected. Obviously, all identical documents are lexically-equivalent, and all lexically equivalent documents are shingle equivalent.

We can find each set of documents with a single fingerprint. Identical documents are found with the fingerprint of the entire original contents. Lexically-equivalent documents are found with the fingerprint of the entire canonicalized contents. Shingle equivalent documents are found with the fingerprint of the set of selected shingles.

5.3. Super shingles

The second and third phases of our algorithm require a great deal of disk space for the <shingle, ID> pairs and the <ID, ID, count> triplets. We have investigated a method for more directly determining document resemblance from the document sketches.

Sketches are an effective method for estimating the resemblance of two documents because they are easily compared, canonical representations of the documents. Hence, we can estimate the resemblance of two documents with the ratio of the number of shingles they have in common to total number of shingles between them.

Similarly, we can estimate the resemblance of two sketches by computing the *meta-sketch* (sketch of a sketch). We compute *super shingles* by sorting the sketch's shingles and then shingling the shingles. The document's meta-sketch is then determined by its set of super shingles. If two documents have even one super shingle in common, then that means their sketches have a *sequence* of shingles in common.

If the number of shingles in a super shingle is chosen correctly, then it is highly probable that two similar documents will have at least one common super shingle. In addition, the existence of a single common super shingle means it is likely that two documents resemble each other. To compute resemblance with regular shingles, we need to collect and count the common shingles. To detect resemblance with super shingles, we only need to find a single common super shingle. So, super shingles are a simpler and more efficient method of computing resemblance.

A clustering algorithm based on super shingles is:

- Compute the list of super shingles for each document.
- Expand the list of super shingles into a sorted list of <super shingle, ID> pairs.
- Any documents that share a super shingle resemble each other are added into the cluster. (If we want a higher threshold we can compute their actual resemblance.)

So, the entire third phase of the basic algorithm where we generate and merge the document ID pairs is not needed.

Unfortunately, super shingles are not as flexible or as accurate as computing resemblance with regular sketches. First, super shingles do not work well for short documents. Short documents do not contain many shingles and so, even with regular shingles, the error in estimating document resemblance is greater. Super shingles make this problem worse. A super shingle represents a sequence of shingles, and so, shorter documents, with fewer super shingles, have a lower probability of producing a common super shingle.

Second, super shingles cannot detect containment. Suppose we have two documents and the larger one completely contains the smaller one. Then, the sketch of the larger document includes all of the shingles of the smaller document along with additional shingles from its extra material. When we sort the shingles for the larger document and calculate its super shingles, the extra shingles will be interspersed with the common shingles. Therefore, the sequences of shingles — and thus the super shingles — for the larger document will be different than those of the smaller document.

6. Applications

While we will soon discuss some specific applications related to clustering the Web, we also want to point out that our resemblance and clustering techniques are not limited to text documents. Our general technique only depends on the ability to extract a set of features from objects. Once we are given the set of features for each object, we can then apply the algorithms described above to compute the resemblance of the objects and to cluster groups of similar objects.

For documents and objects other than text, there are many potential features for computing resemblance. An audio message of human speech could have features based on sequences of phonemes. For documents in foreign language, the features could be labels from a multi-lingual concordance. Musical features could be based on Sequences of notes or chords. As techniques are developed for identifying features in other data types, there are no limits on the objects that can be compared for resemblance: images, video sequences, or databases.

6.1. Web-based applications

Now, we will consider some of the Web-related applications of our methods. Once we have the sketches, clusters and auxiliary data structures, we can use them for several interesting applications. As we discuss the different applications, we will consider their storage and performance characteristics. There are two approaches:

(1) Basic clustering

The most straightforward application is a service to locate highly similar alternatives to a given URL. In this case, the user has the URL of a document and for some reason wants to find another document that resembles it. This relationship is exactly what clustering gives us.

Given a complete clustering and the auxiliary files for mapping URLs to document IDs and mapping document IDs back to URLs, we can very efficiently compute all of the URLs for the documents in the cluster.

Unfortunately, clustering must be done with a single fixed threshold for resemblance and we must decide in advance if we want contained and containing documents included in the clusters. We can get around this and produce clusters based on a variety of policies by repeating the final phase of the clustering algorithm for each different policy. This phase is relatively inexpensive and the output clusters are relatively compact.

Another issue is that basic clustering can only support queries about URLs that are part of the input, and the clusters are based on the contents of the URLs at the time they were retrieved. We can solve this problem by computing sketches for new or modified documents on demand.

(2) On the fly resemblance

If we are able to keep the full sketches of every document and the file of sorted <shingle, ID> pairs, then we can perform on the fly resemblance. In this case, the input can be any document; either from a URL or stored locally; whether is was part of the initial clustering or not; whether it has changed or not. The algorithm is as follows:

- Get the sketch of the input document by
  - looking up the sketch for the URL, or
  - computing the sketch from the document itself.
- Look up each shingle from the input document in the sorted <shingle, ID> file.
- For each document that shares a shingle, maintain the count of common shingles.
- Based on the number of shingles in each document, compute the resemblance and contained/containment value.
- Sort, threshold and present the result.

This method requires more space and time, but it offers greater flexibility than precomputed clusters. It also allows any document, even a document that was not part of the original input, to be compared for resemblance. We have found that the performance of this method is quite good (a few seconds) unless the input document is quite big or resembles a large number of documents.

6.2. Lost and found

Everyone is aware that URLs are not good forever. Pages get renamed, pages move, web sites get rearranged, servers get renamed, and users change internet service providers. Every good URL eventually becomes yet another dead link.

Our clustering method can create a World Wide Web lost and found, where we automatically notice that the URL for a page has changed and find its new URL. Instead of just clustering the current contents of the Web, we cluster the contents of the web from multiple sweeps over the web done at different times. As long as any one sweep has found a particular URL, we can find its current location by taking the most recent URL from its cluster. The clustering algorithm remains the same, except that the URLs of the document are also tagged with a date.

Clustering the documents found in a series of sweeps can be made relatively efficient as it is not necessary to perform the entire clustering from scratch each time. Instead, we need only sketch the documents from the last sweep and merge them into the existing clusters. In addition, there will be a large number of identical documents between sweeps and these can be extracted early in the algorithm.

6.3. Clustering of search results

Current search engines like AltaVista try to return the most relevant answers to a query first. Often this means several similar versions of a document are returned as separate entries. Clustering allows us to display this similarity to the user and present the search results more compactly. The user selects the preferred version to retrieve and avoids examining nearly identical copies.

6.4. Updating widely distributed information

Some important information is widely disseminated and quoted throughout the Web, with slight local changes. For instance there are many slightly reformatted, full or partial copies of an FTC (Federal Trade Commission) ruling regarding consumer credit. If this ruling were to change, one would hope that FTC would try to notify all the sites with any version of this document. The cluster containing the original ruling would assist in producing the list of contacts. In contrast, with a search engine a query wide enough to cover all the variations would result in a large number of irrelevant hits that would have to be filtered out.

6.5. Characterizing how pages change over time

In addition to updating URLs, we can use the technique of comparing sketches over time to characterize the behavior of pages on the web. For instance, we can observe a page at different times and see how similar each version is to the preceding version. When we have this information for many web pages, we can answer some basic questions about the Web:

- How often do pages change?
- How much do they change per time interval?
- How often do pages move? Within a server? Between servers?
- How long do pages live? How many are created? How many die?

A better understanding of these issues will make it possible to build better proxies, search engines, directories and browsers.

6.6. Intellectual property and plagiarism

One final application is the detection of illegal copies or modifications of intellectual property. Given a source document we can detect if all or parts of it have been substantially copied or if small changes were made to documents that were supposed to be left unchanged (eg license agreements). However, the security of our approach is rather limited, since we have a single, static sketching policy. The approach taken by Heintze [2] whereby a new set of samples is selected from a larger stored set, is more secure at the cost of a substantial storage penalty.

7. Status

We have implemented the sketching, clustering and clustering on the fly algorithms and produced a working demonstration system.

We tested our algorithms on a collection of 30,000,000 HTML and text documents from a walk of the web performed by AltaVista in April of 1996. The total input data was 150 Gbytes (an average of about 5k per document). The file containing just the URLs of the documents took up 1.8 Gbytes (an average of 60 bytes per URL). We sketched all of the documents with 10 word long shingles to produce 40 bit (5 byte) shingle fingerprints. We kept 1 in 25 of the shingles found.

There were about 600M shingles so the raw sketch files took up 3 Gbytes (5 bytes per shingle). During the first phase of the clustering algorithm, this expanded to about 5.5 Gbytes (9 bytes per entry — 5 bytes for the shingle and 4 bytes for the document ID). At the maximum, we required 10 Gbytes of storage because we need two copies of the data during the merge operation.

In the third phase — the creation of <ID, ID, count> triples — the storage requirements grew to about 20 Gbytes. (We save some space because there are shingles that only appear in one document, but we lose on the quadratic expansion of document ID lists to document ID pairs. The maximum storage reflects the fact that the document ID pairs are initially duplicated in each separate file. However, they are gradually combined together as the files are merged.) At the end of the third phase, the sorted file of <ID, ID, count> triples took up 6 Gbytes.

The final clustering phase is the most memory intensive phase since we want the entire union-find data structure to be in memory. The final file containing the list of the documents in each cluster took up less than 100 Mbytes.

We calculated our clusters based on a 50% resemblance. We found 3.6 million clusters containing a total of 12.3 million documents. Of these, 2.1 million clusters contained only identical documents (5.3 million documents). The remaining 1.5 million clusters contained 7 million documents (a mixture of exact duplicates and similar). Here is how the processing time for the different operations breaks down (if an operation is parallelizable, then much of it — usually all but the final merge — can be performed independently on many machines at once):

Phase	Time (CPU-days)	Parallelizable
Sketching	4.6	YES
Duplicate elimination	0.3	
Shingle merging	1.7	YES
ID–ID pair formation	0.7	
ID–ID merging	2.6	YES
Cluster formation	0.5	
Total	~10.5	

8. Conclusions

We believe that our system provides new functionality for dealing with the sea of information on the Web. It allows users to find syntactically related documents anywhere on the World Wide Web. It allows search engines to better present results to their clients. And, it allows for new services to track URLs over time, and detect and fix links to moved URLs.

We also believe that our techniques can generalize to other problem domains. Given any technique that extracts a set of features from an object, we can measure the similarity of any two objects or cluster the sets of similar objects from a large number of objects.

Acknowledgments

We wish to thank Greg Nelson for helping to develop the ideas behind the resemblance definition and computation.

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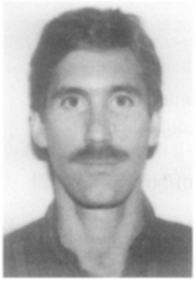

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