CHAPTER 8

AUTOMATIC TABLE DETECTION IN HTML DOCUMENTS

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Table is a commonly used presentation scheme for describing relational information. Table understanding on the web has many potential applications including web mining, knowledge management, and web content summarization and delivery to narrow-bandwidth devices. Although in HTML documents tables are generally marked as <table> elements, a <table> element does not necessarily indicate the presence of a *genuine* relational table. Thus the important first step in table understanding in the web domain is to identify the genuine tables. In this chapter we explore a machine learning based approach for automatic table detection in HTML documents. Various features reflecting the layout as well as content characteristics of tables are explored. Two different classifiers, the decision tree classifier and the Support Vector Machines, are investigated. The system is tested on a large database which consists of 1, 393 HTML files collected from hundreds of different web sites from various domains and contains over 10, 000 leaf <table> elements. Experiments were conducted using the cross validation method. The machine learning based approach outperformed a previously designed rule-based system and achieved an F-measure of 95.88%.

1. Introduction

The increasing ubiquity of the Internet has brought about a constantly increasing amount of online publications. As a compact and efficient way to present relational information, tables are used frequently in web documents. Since tables are inherently concise as well as information rich, the automatic understanding of tables has many applications including knowledge management, information retrieval, web mining, summarization, and content delivery to mobile devices. The processes of table understanding in web documents include table detection, functional and structural analysis and finally table interpretation.[1]

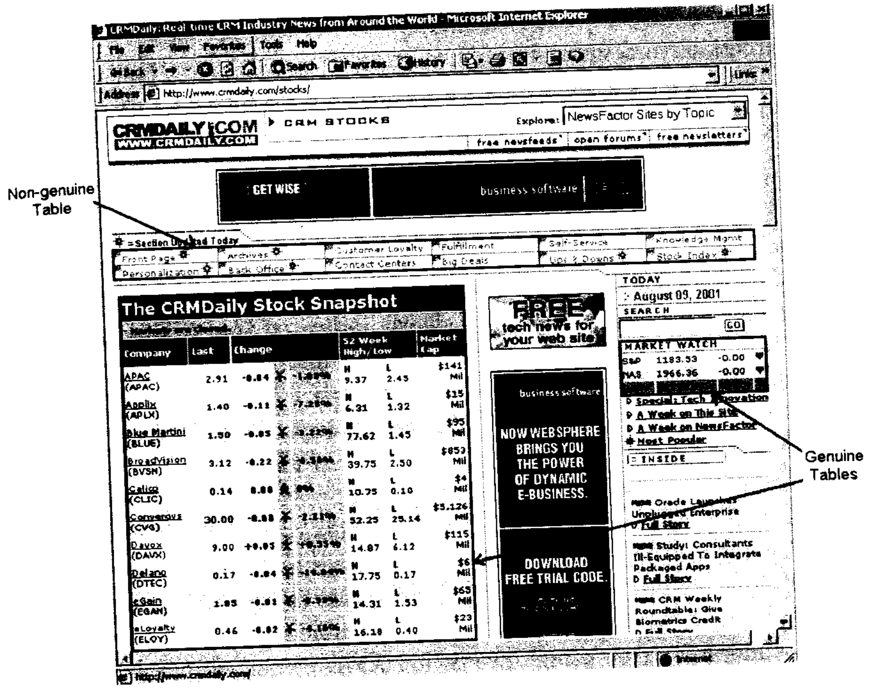
In this chapter, we concentrate on the problem of table detection. The web provides users with great possibilities to use their own style of communication and expressions. In particular, people use the `<table>` tag not only for relational information display but also to create any type of multiple-column layout to facilitate easy viewing, thus the presence of the `<table>` tag does not necessarily indicate the presence of a true relational table. We define *genuine* tables to be document entities where a two dimensional grid is semantically significant in conveying the logical relations among the cells.[2] Conversely, *Non-genuine* tables are document entities where `<table>` tags are used as a mechanism for grouping contents into clusters for easy viewing only. Fig. 1 gives a few examples of genuine and non-genuine tables. While genuine tables in web documents could also be created without the use of `<table>` tags at all, we do not consider such cases in this chapter as they seem very rare from our experience. Thus, in this study, *Table detection* refers to the technique which classifies a document entity enclosed by the `<table></table>` tags as a genuine or non-genuine table.

Several researchers have reported their work on web table detection. Chen *et al.* used heuristic rules and cell similarities to identify tables and tested their algorithm on 918 tables form airline information web pages.[3] Yoshida *et al.* proposed a method to integrate WWW tables according to the category of objects presented in each table.[4] Their algorithm was evaluated on 175 tables.

In our earlier work, we proposed a rule-based algorithm for identifying genuinely tabular information as part of a web content filtering system for content delivery to mobile devices.[2] The algorithm was designed for major news and corporate web site home pages. It was tested on 75 web site front-pages and achieved an F-measure of 88.05%. While it worked reasonably well for the system it was designed for, it has the disadvantage that it is domain dependent and difficult to extend because of its reliance on hand-crafted rules.

To summarize, previous methods for web table detection all relied on heuristic rules and were only tested on a database that is either very small,[2,4] or highly domain specific.[3]

In this chapter, we propose a new machine learning based approach for table detection from generic web documents. While many learning algorithms have been developed and tested for document analysis and information retrieval applications, there seems to be strong indication that good document representation including feature selection is more important than choosing a particular learning algorithm.[5] Thus in this work our emphasis is on identifying features that best capture the characteristics of a genuine table compared to a non-genuine one. In particular, we introduce a set of novel features which reflect the layout as well as content characteristics of tables. These features are then used in classifiers trained on thousands of examples. Two widely used classifiers, the decision tree classifier and the Support Vector Machines (SVM), are investigated for this application.



The CRMDaily Stock Snapshot

Company	Last	Change		52 Week High/Low		Market Cap
APAC (APAC)	2.91	-0.04	[illegible]	H 9.37	L 2.45	$141 Mil
Applix (APLX)	1.40	-0.11	-7.25%	H 6.31	L 1.32	$15 Mil
blue Martini (BLUE)	1.50	-0.05	-3.22%	H 77.62	L 1.45	$95 Mil
BroadVision (BVSN)	3.12	-0.22	[illegible]	H 39.75	L 2.50	$853 Mil
Calico (CLIC)	0.14	0.00	0%	H 10.75	L 0.10	$4 Mil
Convergys (CVG)	30.00	-0.88	[illegible]	H 52.25	L 25.14	$5,126 Mil
Davox (DAVX)	9.00	+0.03	[illegible]	H 14.87	L 6.12	$115 Mil
Delano (DTEC)	0.17	-0.04	[illegible]	H 17.75	L 0.17	$6 Mil
eGain (EGAN)	1.05	-0.01	[illegible]	H 14.31	L 1.53	$65 Mil
eLoyalty (ELOY)	0.46	-0.02	[illegible]	H 16.18	L 0.40	$23 Mil

Fig. 1. Examples of genuine and non-genuine tables.

To facilitate the training and evaluation of the table classifiers, we constructed a large web table ground truth database consisting of 1,393 HTML files containing 11,477 leaf `<table>` elements. Experiments on this database using the cross validation method demonstrate a significant performance improvement over the previously developed rule-based system.

The rest of the chapter is organized as follows. We describe our feature set in Section 2, followed by a brief description of the classifiers we experimented with in Section 3. Section 4 explains the data collection process.

xperimental results are then reported in Section 5 and we conclude with iture directions in Section 6.

. Features for Web Table Detection

eature selection is a crucial step in any machine learning based methods. n our case, we need to find a combination of features that together proide significant separation between genuine and non-genuine tables while t the same time constrain the total number of features to avoid the curse f dimensionality. Past research has clearly indicated that layout and content are two important aspects in table understanding.[1] Our features were lesigned to capture both of these aspects. In particular, we developed 16 eatures which can be categorized into three groups: seven layout features, ight content type features and one word group feature. In the first two groups, we attempt to capture the global composition of tables as well as he consistency within the whole table and across rows and columns. With he last feature, we investigate the discriminative power of words enclosed n tables using well developed text categorization techniques.

Before feature extraction, each HTML document is first parsed into a locument hierarchy tree using Java Swing XML parser with W3C HTML 3.2 DTD.[2] A <table> node is said to be a *leaf table* if and only if there are no <table> nodes among its children. Our experience indicates that almost all genuine tables are leaf tables. Thus in this study only leaf tables are considered candidates for genuine tables and are passed on to the feature extraction stage. In the following we describe each feature in detail.

2.1. *Layout Features*

In HTML documents, although tags like <tr> and <td> (or <th>) may be assumed to delimit table rows and table cells, they are not always reliable indicators of the number of rows and columns in a table. Variations can be caused by spanning cells created using <rowspan> and <colspan> tags. Other tags such as <br> could be used to move content into the next row. To extract layout features reliably, we maintain a matrix to record all the cell spanning information and serve as a pseudo rendering of the table. Layout features based on row or column numbers are then computed from this matrix.

Given a table T, we compute the following four layout features:

- (1) and (2): Average number of columns, computed as the average number of cells per row, and the standard deviation.

- (3) and (4): Average number of rows, computed as the average number of cells per column, and the standard deviation.

Since the majority of tables in web documents contain characters, we compute three more layout features based on cell length in terms of number of characters:

- (5) and (6): Average overall cell length and the standard deviation.
- (7): Average *Cumulative length consistency*, CLC.

The last feature is designed to measure the cell length consistency along either row or column directions. It is inspired by the fact that most genuine tables demonstrate certain consistency either along the row or the column direction, but usually not both, while non-genuine tables often show no consistency in either direction. Similar kinds of features have been used successfully in table detection in plain text documents.[6]

To compute this feature, first the average cumulative within-row length consistency, CLC_r, is computed as follows. Let the set of cell lengths of the cells from row i be $\mathcal{R}_i$, $i = 1, \ldots, r$ (considering only non-spanning cells), and the the mean cell length for row $\mathcal{R}_i$ be m_i:

(1) Compute cumulative length consistency within each $\mathcal{R}_i$:

$$CLC_i = \sum_{cl \in \mathcal{R}_i} LC_{cl}.$$

Here LC_{cl} is defined as: $LC_{cl} = 0.5 - D$, where $D = min\{\frac{|cl - m_i|}{m_i}, 1.0\}$. Intuitively, LC_{cl} measures the degree of consistency between cl and the mean cell length, with -0.5 indicating extreme inconsistency and 0.5 indicating extreme consistency. When most cells within $\mathcal{R}_i$ are consistent, the cumulative measure CLC_i is positive, indicating a more or less consistent row.

(2) Take the average across all rows:

$$CLC_r = \frac{1}{r}\sum_{i=1}^{r} CLC_i.$$

After the within-row length consistency CLC_r is computed, the within-column length consistency CLC_c is computed in a similar manner. Finally, the overall cumulative length consistency is computed as $CLC = \max(CLC_r, CLC_c)$.

2.2. *Content Type Features*

Web documents are inherently multi-media and have more types of content than any traditional document. For example, the content within a `<table>` element could include hyperlinks, images, forms, alphabetical or numerical strings, etc. Because of the relational information it needs to convey, a genuine table is more likely to contain alpha or numerical strings than, say, images. The content type feature was designed to reflect such characteristics.

We define the set of content types $\mathcal{T}$ ={Image, Form, Hyperlink, Alphabetical, Digit, Empty, Others}. Our content type features include:

- (1) - (7): The histogram of content type for a given table. This contributes 7 features to the feature set;
- (8): Average *content type consistency*, *CTC*.

The last feature is similar to the cell length consistency feature. First, within-row content type consistency CTC_r is computed as follows. Let the set of cell type of the cells from row i as $\mathcal{T}_i$, $i = 1, \ldots, r$ (again, considering only non-spanning cells), and the dominant type for $\mathcal{T}_i$ be DT_i:

(1) Compute the cumulative type consistency with each row $\mathcal{R}_i$:

$$CTC_i = \sum_{ct \in \mathcal{R}_i} D,$$

where $D = 1$ if ct is equal to DT_i and $D = -1$, otherwise.

(2) Take the average across all rows:

$$CTC_r = \frac{1}{r} \sum_{i=1}^{r} CTC_i.$$

The within-column type consistency is then computed in a similar manner. Finally, the overall cumulative type consistency is computed as: $CTC = \max(CTC_r, CTC_c)$.

2.3. *Word Group Feature*

If we look at the enclosed text in a table and treat it as a "mini-document", table classification could be viewed as a text categorization problem with two broad categories: genuine tables and non-genuine tables. In order to explore the the potential discriminative power of table text at the word level, we experimented with several text categorization techniques.

Text categorization is a well studied problem in the IR community and many algorithms have been developed over the years (e.g., Joachims[7] and Yang.[8]) For our application, we are particularly interested in algorithms with the following characteristics. First, it has to be able to handle documents with dramatically differing lengths (some tables are very short while others can be more than a page long). Second, it has to work well on collections with a very skewed distribution (there are many more non-genuine tables than genuine ones). Finally, since we are looking for a feature that can be incorporated along with other features, it should ideally produce a continuous confidence score rather than a binary decision. In particular, we experimented with three different approaches: vector space, naive Bayes and weighted kNN. The details regarding each approach are given below.

2.3.1. *Vector Space Approach*

After morphing[9] and removing the infrequent words, we obtain the set of words found in the training data, $\mathcal{W}$. We then construct weight vectors representing genuine and non-genuine tables and compare that against the frequency vector from each new incoming table.

Let $\mathcal{Z}$ represent the non-negative integer set. The following functions are defined on set $\mathcal{W}$.

- $df^G : \mathcal{W} \rightarrow \mathcal{Z}$, where $df^G(w_i)$ is the number of genuine tables which include word w_i, $i = 1, ..., |\mathcal{W}|$;
- $tf^G : \mathcal{W} \rightarrow \mathcal{Z}$, where $tf^G(w_i)$ is the number of times word w_i, $i = 1, ..., |\mathcal{W}|$, appears in genuine tables;
- $df^N : \mathcal{W} \rightarrow \mathcal{Z}$, where $df^N(w_i)$ is the number of non-genuine tables which include word w_i, $i = 1, ..., |\mathcal{W}|$;
- $tf^N : \mathcal{W} \rightarrow \mathcal{Z}$, where $tf^N(w_i)$ is the number of times word w_i, $i = 1, ..., |\mathcal{W}|$, appears in non-genuine tables.
- $tf^T : \mathcal{W} \rightarrow \mathcal{Z}$, where $tf^T(w_i)$ is the number of times word w_i, $w_i \in \mathcal{W}$ appears in a new test table.

To simplify the notations, in the following discussion, we will use df_i^G, tf_i^G , df_i^N and tf_i^N to represent $df^G(w_i)$, $tf^G(w_i)$, $df^N(w_i)$ and $tf^N(w_i)$, respectively.

Let N^G, N^N be the number of genuine tables and non-genuine tables in the training collection, respectively and let $C = \max(N^G, N^N)$. Without loss of generality, we assume $N^G \neq 0$ and $N^N \neq 0$. For each word w_i in $\mathcal{W}$, $i = 1, ..., |\mathcal{W}|$, two weights, p_i^G and p_i^N are computed:

$$p_i^G = \begin{cases} tf_i^G log(\frac{df_i^G}{N^G}\frac{N^N}{df_i^N}+1), & \text{when } df_i^N \neq 0 \\ tf_i^G log(\frac{df_i^G}{N^G}C+1), & \text{when } df_i^N = 0 \end{cases} \tag{1}$$

$$p_i^N = \begin{cases} tf_i^N log(\frac{df_i^N}{N^N}\frac{N^G}{df_i^G}+1), & \text{when } df_i^G \neq 0 \\ tf_i^N log(\frac{df_i^N}{N^N}C+1), & \text{when } df_i^G = 0 \end{cases} \tag{2}$$

As can be seen from the formulas, the definitions of these weights were derived from the traditional $tf * idf$ measures used in informational retrieval,[7] with some adjustments made for the particular problem at hand.

Given a new incoming table, let us denote the set including all the words in it as $\mathcal{W}_n$. Since we only need to consider the words that are present in both $\mathcal{W}$ and $\mathcal{W}_n$, we first compute the *effective word set*: $\mathcal{W}_e = \mathcal{W} \cap \mathcal{W}_n$. Let the words in $\mathcal{W}_e$ be represented as w_{m_k}, where $m_k, k = 1, ..., |\mathcal{W}_e|$, are indexes to the words from set $\mathcal{W} = \{w_1, w_2, ..., w_{|\mathcal{W}|}\}$. we define the following weight vectors:

- Vector representing the genuine table class:

$$\vec{G_S} = \left(\frac{p_{m_1}^G}{U}, \frac{p_{m_2}^G}{U}, \cdots, \frac{p_{m_{|\mathcal{W}_e|}}^G}{U}\right),$$

where U is the cosine normalization term:

$$U = \sqrt{\sum_{k=1}^{|\mathcal{W}_e|} p_{m_k}^G \times p_{m_k}^G}.$$

- Vector representing the non-genuine table class:

$$\vec{N_S} = \left(\frac{p_{m_1}^N}{V}, \frac{p_{m_2}^N}{V}, \cdots, \frac{p_{m_{|\mathcal{W}_e|}}^N}{V}\right),$$

where V is the cosine normalization term:

$$V = \sqrt{\sum_{k=1}^{|\mathcal{W}_e|} p_{m_k}^N \times p_{m_k}^N}.$$

- Vector representing the new incoming table:

$$\vec{I_T} = \left(tf_{m_1}^T, tf_{m_2}^T, \cdots, tf_{m_{|\mathcal{W}_e|}}^T\right).$$

Finally, the word group feature is defined as the ratio of the two dot products:

$$W_{vs} = \begin{cases} \frac{\vec{I_T}\cdot\vec{G_S}}{\vec{I_T}\cdot\vec{N_S}}, & \text{when } \vec{I_T}\cdot\vec{N_S} \neq 0 \\ 1, & \text{when } \vec{I_T}\cdot\vec{G_S} = 0 \text{ and } \vec{I_T}\cdot\vec{N_S} = 0 \\ 10, & \text{when } \vec{I_T}\cdot\vec{G_S} \neq 0 \text{ and } \vec{I_T}\cdot\vec{N_S} = 0 \end{cases} \tag{3}$$

2.3.2. *Naive Bayes Approach*

In the Bayesian learning framework, it is assumed that text data has been generated by a parametric model, and a set of training data is used to calculate Bayes optimal estimates of the model parameters. Then, using these estimates, Bayes rule is used to turn the generative model around and compute the probability of each class given an input document.

Word clustering is commonly used in a Bayes approach to achieve more reliable parameter estimation. For this purpose we implemented the distributional clustering method introduced by Baker and McCallum.[10] First stop words and words that only occur in less than 0.1% of the documents are removed. The resulting vocabulary has roughly 8000 words. Then distribution clustering is applied to group similar words together. Here the similarity between two words w_t and w_s is measured as the similarity between the class variable distributions they induce: $P(C|w_t)$ and $P(C|w_s)$, and computed as the average KL divergence between the two distributions. (see the paper by Baker and McCallum[10] for more details).

Assume the whole vocabulary has been clustered into M clusters. Let w_s represent a word cluster, and $C = \{g, n\}$ represent the set of class labels (g for for genuine, n for non-genuine), the class conditional probabilities are (using Laplacian prior for smoothing):

$$P(w_s|C = g) = \frac{tf^G(w_s) + 1}{M + \sum_{i=1}^{M} tf^G(w_i)}; \tag{4}$$

$$P(w_s|C = n) = \frac{tf^N(w_s) + 1}{M + \sum_{i=1}^{M} tf^N(w_i)}. \tag{5}$$

The prior probabilities for the two classes are:

$$P(C = g) = \frac{N^G}{N^G + N^N}; \tag{6}$$

$$P(C = n) = \frac{N^N}{N^G + N^N}. \tag{7}$$

Given a new table d_i, let $d_{i,k}$ represent the kth word cluster. Based on the Bayes assumption, the posterior probabilities are computed as:

$$P(C = g|d_i) = \frac{P(C = g)P(d_i|C = g)}{P(d_i)} \tag{8}$$

$$\sim \frac{P(C = g)\prod_{k=1}^{|d_i|} P(w_{i,k}|C = g)}{P(d_i)}; \tag{9}$$

$$P(C = n|d_i) = \frac{P(C = n)P(d_i|C = n)}{P(d_i)} \tag{10}$$

$$\sim \frac{P(C = n)\prod_{k=1}^{|d_i|} P(w_{i,k}|C = n)}{P(d_i)}. \tag{11}$$

Finally, the word group feature is defined as the ratio between the two:

$$W_{nb} = \frac{P(C = g)\prod_{k=1}^{|d_i|} P(w_{i,k}|C = g)}{P(C = n)\prod_{k=1}^{|d_i|} P(w_{i,k}|C = n)} \tag{12}$$

$$= \frac{N^G}{N^N} \prod_{k=1}^{|d_i|} \frac{P(w_{i,k}|C = g)}{P(w_{i,k}|C = n)}. \tag{13}$$

2.3.3. *Weighted kNN Approach*

kNN stands for k-nearest neighbor classification, a well known statistical approach. It has been applied extensively to text categorization and is one of the top-performing methods.[8] Its principle is quite simple: given a test document, the system finds the k nearest neighbors among the training documents, and uses the category labels of these neighbors to compute the likelihood score of each candidate category. The similarity score of each neighbor document to the test documents is used as the weight for the category it belongs to. The category receiving the highest score is then assigned to the test document.

In our application the above procedure is modified slightly to generate the word group feature. First, for efficiency purpose, the same preprocessing and word clustering operations as described in the previous section is applied, which results in M word clusters. Then each table is represented by an M dimensional vector composed of the term frequencies of the M word clusters. The similarity score between two tables is defined to be the cosine value ($[0, 1]$) between the two corresponding vectors. For a new incoming table d_i, let the k training tables that are most similar to d_i be represented by $d_{i,j}, j = 1, ..., k$. Furthermore, let $sim(d_i, d_{i,j})$ represent the similarity score between d_i and $d_{i,j}$, and $C(d_{i,j})$ equals 1.0 if $d_{i,j}$ is genuine and -1.0 otherwise, the word group feature is defined as:

$$W_{knn} = \frac{\sum_{j=1}^{k} C(d_{i,j})sim(d_i, d_{i,j})}{\sum_{j=1}^{k} sim(d_i, d_{i,j})}. \tag{14}$$

3. Classification Schemes

Various classification schemes have been widely used in document categorization as well as web information retrieval.[8,11] For the table detection task, the decision tree classifier is particularly attractive as our features are highly non-homogeneous. We also experimented with Support Vector Machines (SVM), a relatively new learning approach which has achieved one of the best performances in text categorization.[8]

3.1. *Decision Tree*

Decision tree learning is one of the most widely used and practical methods for inductive inference. It is a method for approximating discrete-valued functions that is robust to noisy data.

Decision trees classify an instance by sorting it down the tree from the root to some leaf node, which provides the classification of the instance. Each node in a discrete-valued decision tree specifies a test of some attribute of the instance, and each branch descending from that node corresponds to one of the possible values for this attribute. Continuous-valued decision attributes can be incorporated by dynamically defining new discrete-valued attributes that partition the continuous attribute value into a discrete set of intervals.[12]

An implementation of the continuous-valued decision tree described by Haralick and Shapiro[13] was used for our experiments. The decision tree is constructed using a training set of feature vectors with true class labels. At each node, a discriminant threshold is chosen such that it minimizes an impurity value. The learned discriminant function splits the training subset into two subsets and generates two child nodes. The process is repeated at each newly generated child node until a stopping condition is satisfied, and the node is declared as a terminal node based on a majority vote. The maximum impurity reduction, the maximum depth of the tree, and minimum number of samples are used as stopping conditions.

3.2. *SVM*

Support Vector Machines (SVM) are based on the *Structural Risk Management* principle from computational learning theory.[14] The idea of structural risk minimization is to find a hypothesis h for which the lowest true error is guaranteed. The true error of h is the probability that h will make an error on an unseen and randomly selected test example.

The SVM method is defined over a vector space where the goal is to find a decision surface that best separates the data points in two classes. More precisely, the decision surface by SVM for linearly separable space is a hyperplane which can be written as

$$\vec{w} \cdot \vec{x} - b = 0$$

where $\vec{x}$ is an arbitrary data point and the vector $\vec{w}$ and the constant b are learned from training data. Let $D = (y_i, \vec{x_i})$ denote the training set, and $y_i \in \{+1, -1\}$ be the classification for $\vec{x_i}$, the SVM problem is to find $\vec{w}$ and b that satisfies the following constraints:

$$\vec{w} \cdot \vec{x_i} - b \geq +1 \; for \; y_i = +1$$

$$\vec{w} \cdot \vec{x_i} - b \leq -1 \; for \; y_i = -1$$

while minimizing the vector 2-norm of $\vec{w}$.

The SVM problem in linearly separable cases can be efficiently solved using quadratic programming techniques, while the non-linearly separable cases can be solved by either introducing soft margin hyperplanes, or by mapping the original data vectors to a higher dimensional space where the data points become linearly separable.[14,15]

One reason why SVMs are very powerful is that they are very universal learners. In their basic form, SVMs learn linear threshold functions. Nevertheless, by a simple "plug-in" of an appropriate kernel function, they can be used to learn polynomial classifiers, radial basis function (RBF) networks, and three-layer sigmoid neural nets.[15]

For our experiments, we used the SVM^{light} system implemented by Thorsten Joachims.[16]

4. Data Collection and Ground Truthing

Since there are no publicly available web table ground truth database, researchers tested their algorithms in different data sets in the past.[3,2,4] However, their data sets either had limited manually annotated table data (*e.g.*, 75 HTML pages in Penn *et al.*,[2] 175 manually annotated table tags in Yoshida *et al.*[4]) or were collected from some specific domains (*e.g.*, a set of tables selected from airline information pages were used in Chen et al.[3]). To develop our machine learning based table detection algorithm, we needed to build a general web table ground truth database of significant size.

4.1. *Data Collection*

Instead of working within a specific domain, our goal of data collection was to get tables of as many different varieties as possible from the web. At the same time, we also needed to insure that enough samples of genuine tables were collected for training purpose. Because of the latter practical constraint we biased the data collection process somewhat towards web pages that are more likely to contain genuine tables. A set of key words often associated with tables were composed and used to retrieve and download web pages using the Google search engine. Three directories on Google were searched: the business directory and news directory using key words: {`table, stock, bonds, figure, schedule, weather, score, service, results, value`}, and the science directory using key words {`table, results, value`}. A total of 2,851 web pages were downloaded in this manner and we ground truthed 1,393 HTML pages out of these (chosen randomly among all the HTML pages).

4.2. *Ground Truthing*

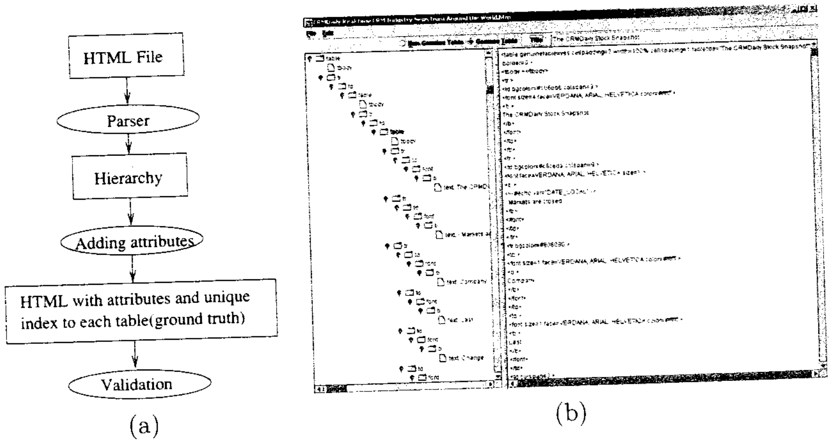

HTML File
Parser
Hierarchy
Adding attributes
HTML with attributes and unique index to each table(ground truth)
Validation
(a)
(b)

Fig. 2. (a) The diagram of ground truthing procedure; (b) A snapshot of the ground truthing interface.

There has been no previous report on how to systematically generate web table ground truth data. To build a large web table ground truth database, a simple, flexible and complete ground truth protocol is required. Figure 4.2(a) shows the diagram of our ground truthing procedure. We created a new Document Type Definition(DTD) which is a superset of W3C HTML 3.2 DTD. We added three attributes for <TABLE> element, which are "tabid", "genuine table" and "table title". The possible value of the second attribute is *yes* or *no* and the value of the first and third attributes is a string. We used these three attributes to record the ground truth of each leaf <TABLE> node. The benefit of this design is that the ground truth data is inside HTML file format. We can use exactly the same parser to process the ground truth data.

We developed a graphical user interface for web table ground truthing using the Java language. Figure 4.2(b) is a snapshot of the interface. There are two windows. After reading an HTML file, the hierarchy of the HTML file is shown in the left window. When an item is selected in the hierarchy, the HTML source for the selected item is shown in the right window. There is a panel below the menu bar. The user can use the radio button to select either genuine table or non-genuine table. The text window is used to input table title.

4.3. *Database Description*

The resulting database is summarized in Table 1. It contains 14,609 <table> elements, out of which 11,477 are leaf <table> elements. Among the leaf <table> elements, 1,740 are genuine tables and the remaining 9,737 are non-genuine tables. Note that even in this somewhat biased collection, genuine tables only account for less than 15% of all leaf table elements.

Table 1. Summary of the database.

<table> elements	Leaf <table> elements	Genuine tables	Non-genuine tables
14,609	11,477	1,740 .	9,737

5. Experiments

A hold-out method was used to evaluate our table classifier. We randomly divided the data set into nine parts. The classifiers were trained on eight parts and then tested on the remaining one part. This procedure was repeated nine times, each time with a different choice for the test part. Then the combined nine part results were averaged to arrive at the overall performance measures.[13]

The output of the classifier is compared with the ground truth and the standard performance measures precision (P), recall (R) and F-measure (F) are computed. Let N_{gg}, N_{gn}, N_{ng} represent the number of samples in the categories "genuine classified as genuine", "genuine classified as non-genuine", and "non-genuine classified as genuine", respectively, the performance measures are defined as:

$$R = \frac{N_{gg}}{N_{gg} + N_{gn}} \qquad P = \frac{N_{gg}}{N_{gg} + N_{ng}} \qquad F = \frac{R + P}{2}.$$

For comparison among different features we report the performance measures when the best F-measure is achieved using the decision tree classifier. The results of the table detection algorithm using various features and feature combinations are given in Table 2. For both the naive Bayes based and the kNN based word group features, 120 word clusters were used ($M = 120$).

Table 2. Results using various feature groups and the decision tree classifier.

	L	T	LT	LTW-VS	LTW-NB	LTW-KNN
R (%)	87.24	90.80	94.20	94.25	95.46	89.60
P (%)	88.15	95.70	97.27	97.50	94.64	95.94
F (%)	87.70	93.25	95.73	95.88	95.05	92.77

L: Layout features only.
T: Content type features only.
LT: Layout and content type features.
LTW-VS: Layout, content type and vector space based word group features.
LTW-NB: Layout, content type and naive Bayes based word group features.
LTW-KNN: Layout, content type and kNN based word group features.

As seen from the table, content type features performed better than layout features as a single group, achieving an F-measure of 93.25%. However, when the two groups were combined the F-measure was improved substantially to 95.73%, reconfirming the importance of combining layout and content features in table detection.

Among the different approaches for the word group feature, the vector space based approach gave the best performance when combined with layout and content features. However even in this case the addition of the word group feature brought about only a very small improvement. This indicates that the text enclosed in tables is not very discriminative, at least not at the word level. One possible reason is that the categories "genuine" and "non-genuine" are too broad for traditional text categorization techniques to be highly effective.

Overall, the best results were produced with the combination of layout, content type and vector space based word group features, achieving an F-measure of 95.88%.

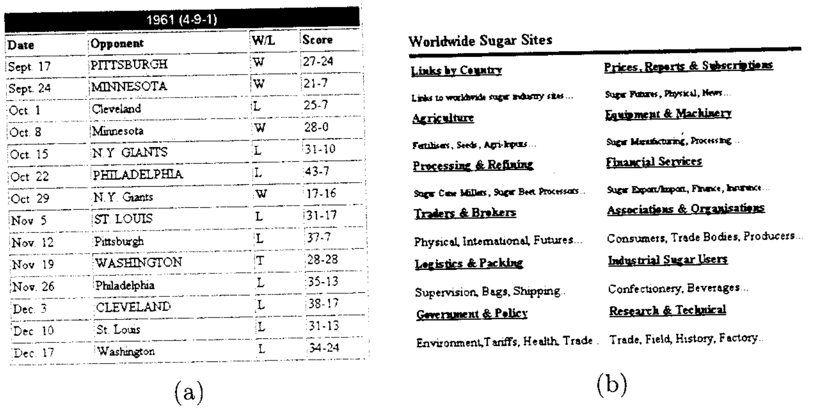
Table 3 compares the performances of different learning algorithms using the full feature set. The leaning algorithms tested include the decision tree classifier and the SVM algorithm with two different kernels – linear and radial basis function (RBF).

Table 3. Experimental results using different learning algorithms.

	Decision Tree	SVM (linear)	SVM (RBF)
R (%)	94.25	93.91	95.98
P (%)	97.50	91.39	95.81
F (%)	95.88	92.65	95.89

As seen from the table, for this application the SVM with radial basis function kernel performed much better than the one with linear kernel. It achieved an F measure of 95.89%, comparable to the 95.88% achieved by the decision tree classifier.

Figure 3 shows two examples of correctly classified tables, where Fig. 3(a) is a genuine table and Fig. 3(b) is a non-genuine table.



1961 (4-9-1)			
Date	Opponent	W/L	Score
Sept 17	PITTSBURGH	W	27-24
Sept 24	MINNESOTA	W	21-7
Oct 1	Cleveland	L	25-7
Oct 8	Minnesota	W	28-0
Oct 15	N Y GIANTS	L	31-10
Oct 22	PHILADELPHIA	L	43-7
Oct 29	N Y Giants	W	17-16
Nov 5	ST LOUIS	L	31-17
Nov 12	Pittsburgh	L	37-7
Nov 19	WASHINGTON	T	28-28
Nov 26	Philadelphia	L	35-13
Dec 3	CLEVELAND	L	38-17
Dec 10	St Louis	L	31-13
Dec 17	Washington	L	34-24

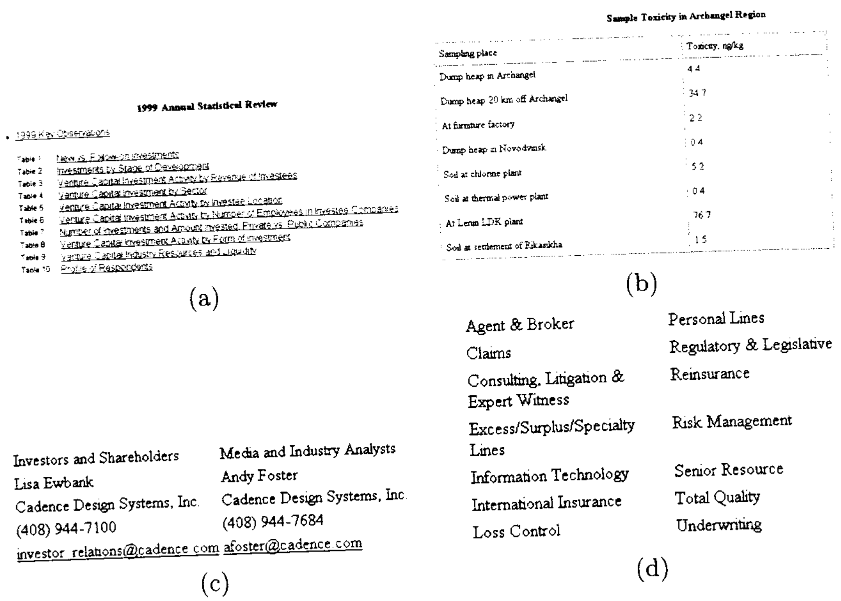
(a)

Worldwide Sugar Sites	
Links by Country	Prices, Reports & Subscriptions
Links to worldwide sugar industry sites ...	Sugar Futures, Physical, News ...
Agriculture	Equipment & Machinery
Fertilisers, Seeds, Agri-Inputs ...	Sugar Manufacturing, Processing ...
Processing & Refining	Financial Services
Sugar Cane Millers, Sugar Beet Processors ...	Sugar Export/Import, Finance, Insurance ...
Traders & Brokers	Associations & Organisations
Physical, International, Futures ...	Consumers, Trade Bodies, Producers ...
Logistics & Packing	Industrial Sugar Users
Supervision, Bags, Shipping ..	Confectionery, Beverages ...
Government & Policy	Research & Technical
Environment,Tariffs, Health, Trade .	Trade, Field, History, Factory ..

(b)

Fig. 3. Examples of correctly classified tables: (a) a genuine table; (b) a non-genuine table

Figure 4 shows a few examples where our algorithm failed. Figure 4(a) was misclassified as a non-genuine table, likely because its cell lengths are highly inconsistent and it has many hyperlinks which is unusual for genuine tables. Figure 4(b) was misclassified as non-genuine because its HTML source code contains only two <tr> tags. Instead of the <tr> tag, the author used <p> tags to place the multiple table rows in separate lines. This points to the need for a more carefully designed pseudo-rendering process.



1999 Annual Statistical Review

- 1999 Key Observations

Table 1	New vs. Follow-on Investments
Table 2	Investments by Stage of Development
Table 3	Venture Capital Investment Activity by Revenue of Investees
Table 4	Venture Capital Investment by Sector
Table 5	Venture Capital Investment Activity by Investee Location
Table 6	Venture Capital Investment Activity by Number of Employees in Investee Companies
Table 7	Number of Investments and Amount Invested, Private vs. Public Companies
Table 8	Venture Capital Investment Activity by Form of Investment
Table 9	Venture Capital Industry Resources and Liquidity
Table 10	Profile of Respondents

(a)

Sample Toxicity in Archangel Region

Sampling place	Toxicity, ng/kg
Dump heap in Archangel	4 4
Dump heap 20 km off Archangel	34 7
At furniture factory	2 2
Dump heap in Novodvinsk	0 4
Soil at chlorine plant	5 2
Soil at thermal power plant	0 4
At Lenin LDK plant	76 7
Soil at settlement of Rikasikha	1 5

(b)

Investors and Shareholders	Media and Industry Analysts
Lisa Ewbank	Andy Foster
Cadence Design Systems, Inc.	Cadence Design Systems, Inc
(408) 944-7100	(408) 944-7684
investor_relations@cadence.com	afoster@cadence.com

(c)

Agent & Broker	Personal Lines
Claims	Regulatory & Legislative
Consulting, Litigation & Expert Witness	Reinsurance
Excess/Surplus/Specialty Lines	Risk Management
Information Technology	Senior Resource
International Insurance	Total Quality
Loss Control	Underwriting

(d)

Fig. 4. Examples of misclassified tables: (a), (b) genuine tables misclassified as non-genuine; (c), (d) non-genuine tables misclassified as genuine

Figure 4(c) shows a non-genuine table misclassified as genuine. A close examination reveals that it indeed has good consistency along the row direction. In fact, one could even argue that this is indeed a genuine table, with implicit row headers of *Title*, *Name*, *Company Affiliation* and *Phone Number*. This example demonstrates one of the most difficult challenges in table understanding, namely the ambiguous nature of many table instances (see the paper by Hu *et al*[17] for a more detailed analysis on that).

Figure 4(d) was also misclassified as a genuine table. This is a case where layout features and the kind of shallow content features we used are not enough – deeper semantic analysis would be needed in order to identify the lack of logical coherence which makes it a non-genuine table.

For comparison, we tested the previously developed rule-based system[2] on the same database. The initial results (shown in Table 4 under "Original Rule Based") were very poor. After carefully studying the results from ıe initial experiment we realized that most of the errors were caused by a ıle imposing a hard limit on cell lengths in genuine tables. After deleting ıat rule the rule-based system achieved much improved results (shown in able 4 under "Modified Rule Based"). However, the proposed machine arning based method still performs considerably better in comparison. his demonstrates that systems based on hand-crafted rules tend to be rittle and do not generalize well. In this case, even after careful manual djustment in a new database, it still does not work as well as an automat-:ally trained classifier.

Table 4. Experimental results of the rule based system.

	Original Rule Based	Modified Rule Based
R (%)	48.16	95.80
P (%)	75.70	79.46
F (%)	61.93	87.63

A direct comparison to other previous results[3,4] is not possible currently ɔecause of the lack of access to their system. However, our test database is :learly more general and far larger than the ones used in Chen *et al.*[3] and Yoshida et al.,[4] while our precision and recall rates are both higher.

6. Conclusion and Future Work

We presented a machine learning based table detection algorithm for HTML documents. Layout features, content type features and word group features were used to construct a feature set. Two well known classifiers, the decision tree classifier and the SVM, were tested along with these features. For the most complex word group feature, we investigated three alternatives: vector space based, naive Bayes based, and weighted K nearest neighbor based. We also constructed a large web table ground truth database for training and testing. Experiments on this large database yielded very promising results and reconfirmed the importance of combining layout and content features for table detection.

Our future work includes handling more different HTML styles in pseudo-rendering and developing a machine learning based table interpretation algorithm. We would also like to investigate ways to incorporate deeper language analysis for both table detection and interpretation.

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CHAPTER 9

A WRAPPER INDUCTION SYSTEM fOR COMPLEX DOCUMENTS, AND ITS APPLICATION TO TABULAR DATA ON THE WEB

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A program that makes an existing website look like a database is called a *wrapper*. *Wrapper learning* is the problem of learning website wrappers from examples. We present a wrapper-learning system called WL^2 that can exploit several different representations of a document. Examples of such different representations include document-object model (DOM)-level and token-level representations, as well as two-dimensional geometric views of the rendered page (for tabular data) and representations of the visual appearance of text as it will be rendered. The learning system described is part of an "industrial-strength" wrapper management system. Controlled experiments show that the learner has broader coverage and a faster learning rate than earlier wrapper-learning systems.

1. Introduction

Many websites contain large quantities of highly structured, database-like information. It is often useful to be able to access these websites programmatically, as if they were true databases. A program that accesses an existing website and makes that website act like a database is called a *wrapper*. *Wrapper learning* is the problem of learning website wrappers from examples.[1,2]

In this chapter we will discuss some of the more important representational issues for wrapper learners, focusing on the specific problem of extracting text from web pages. We argue that pure document-object model (DOM) or token-based representations of web pages are inadequate for the