On Table Extraction from Text Sources with Markups

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Abstract

Table extraction is the task of locating tables in documents and extracting their entries along with the arrangement of the entries inside the tables. The notion of tables applied in this work excludes any sort of meta data, e.g. only the content elements of the tables are to be extracted. We follow a simple unsupervised approach by selecting the tables according to a score that measures the in-column consistency as pairwise similarities of entries where separators columns are also taken into account. Since the average is less reliable for smaller table this score demands a levelling in favor of greater tables for which we make different propositions that are covered by experiments on a test set of HTML documents. In order to reduce the number of candidate tables we use assumptions on the entry borders in terms of markup tags. They only hold for a part of the test set but allow us to evaluate any potential table without referring to the HTML syntax. The experiments show that the discriminative power of the in-column similarities are limited but also considerable given the simplicity of the applied similarity functions.

Contents

1 Introduction

This work is about the task of extracting tables from documents that are given in a markup-language such as HTML. As extraction output we target the entries along with their arrangement in row and columns letting aside any sort of meta data.

In principle, markup-languages allow addressing tables with tools for querying the structure induce by the markups. However, the design of a table extractor is not that simple. In order to formulate queries on the structure we need the definitions of the relevant markups which we might not have at hand. Also, knowing the relevant markups is not sufficient in the sense that the table output we want to obtain cannot always be characterized in terms of markups.

For the approach presented here we do not consider the definitions of the markup-languages. Instead, we confine ourself to inspecting the statistical structure inside a column of a table, where column refers to columns of table entries and columns of entry separators as well. More precisely, we measure the consistency of a column by the pairwise similarity of its elements, where similarity refers to a plug-in string kernel. The basic observation is that the entries in a given column of a table tend to be more similar to each other than to other potential table entries in the document [15],[2]. With this report we want to frame out an extraction algorithm that uses the in-column similarities as single extraction criterion and see to what extend the extraction of tables can draw thereon.

In order to exclude other sources of information as far as possible we would like the algorithm to consider all potential tables in the input likewise searching substrings with certain properties within a string. However, this is not possible because we do not only have to find the substrings of the input covering the tables but also determine therein all substrings representing the entries. If we regard any position in the string after a given position as candidate start point of the next entry, there are far too many candidate tables. For this reason, we consider documents with markup tags such HTML documents. Obviously, the search space for these documents is smaller since the border of a table entry can be assumed to concur with the border of a tag.

Unfortunately, real world documents contain thousands of tags such that the search space still is to big for inspecting it element by element. This means that we either have to use non-exhaustive search, e.g. we evaluate the extraction criterion only for some elements in the space and find or hope to find the most promising candidate nevertheless. Or, we try to further reduce the search space by means of stronger assumptions on the entry borders. We have chosen latter option by applying the assumptions given in section 3 which shrink the search to a moderate size. The drawback of this choice, as reported in the experiments section 5, is that the assumptions hold only for a minority of the documents in the data set we used. We decided to take this loss in relevance of the results because at first we wanted elaborate the extraction criterion itself.

And indeed, there is a principle catch with extraction criteria such as the criterion that specified the second and third subsection of section 4. We intend to evaluate a candidate table by the average in-column similarity of the table entries. However, the reliability of this average score strongly suffers when the candidate table is small and we therefor average over a small number of similarities only. We respond to this problem by deliberately decreasing the chances of smaller candidate table, an procedure to which we refer to as *levelling*. Different proposals for levelling are given in section 4 and covered by the experiments in section 5.

In the remainder of this section we give a more precise description of what we mean by table extraction and discuss some aspects of this task. An unsorted review on related work is given in section 2. Section 3 provides notation and specifies the assumptions for the reduction of the search space. The extraction criterion, called table score, is given in section 4 where we also discuss the levelling. In section 5 we report experimental results based on the set data set from [15] and also provide some plots that illustrate how the extraction criterion applies to a specific document. Section 6 contains conclusions and depicts further work.

1.1 Input

As basis for the input strings we target web pages and well as XML-documents. A self contained XML-document represent a raw-string ready for preprocessing. In contrast, it is not obvious how we should turn a web page into a string. The article [12] analyzes and solves the problems of creating local copies of web pages with respect to visual reproduction demands. Our demands are somehow different. The web pages should be mapped into raw-string and subsequently be preprocessed in order to obtain the *input string* for the table extractor. We want this input string to be a sequences of ASCII symbols ideally of printable and non-whitespace symbols only.

1.2 Output

Following [6],[3] the task of *table extraction* strips downs to two subtasks. For solving the task of *table location* we have to find the exact substring of the input string in which the table is encoded. We speak of *table recognition* when we want to extract the table content and structure out of such a substring having the input string is at hand. Here, a substrings is defined by both, the sequence of character it contains and its *slice* on the string it is taken from that is the start and the end position.

1.2.1 Table Location Task

The output for the table location task is a list of *substrings* that represents the tables in the input string that we are targeting for extraction. We call such substrings *target tables*. For a document given in SGML language we can assume that target tables always given as *table nodes*. In case of HTML-documents a table node is a node with the element name *table*, in other SGML languages a different names are used and even in straight HTML tables can also be given as *div* nodes that refer to some *plug-in extension* of HTML.

Though we can assume target tables to be table nodes, not all table nodes do represent a target table. It is actually not clear how to characterize target tables, also because to some extent it is matter of taste. As a replacement for an explicit specification we can resort to set of examples. The idea of what a target table is might differ for different researchers, such that we should not speak of *the* table location task.

In this work, however, there is only one table location task which is given by the examples set provide by Wang and Hu [15]. Wand and Hu refer to target table as *genuine tables* and they propose a necessary condition for table nodes to be a genuine table: it has to be a *leaf table node* that is a table node that does not contain further table nodes. When we use this example set this does not mean that we perfectly agree with the notion of target table it provides. Still, the understanding of the concept *tables* in this work concurs with above the statement that only leaf nodes can be target tables.

1.2.2 Table Recognition Task

Assume we have given an input string and a substring representing a table. We intend to extract the *table core* that consists of the table entries and the *arrangement* of the entries, while any sort *meta data* is left aside. As meta data we refer to titles, columns headers, separating rows, empty or containing subtitles referring to the following block of rows, or to other descriptions of the entries or of the table itself. Further, we deny concepts such as key column or row headers, they are taken as entries in the first column.

The table arrangement is a nested list. The table is the list of its rows and a row is a list of its entries. No substructures such as blocks or subtables are considered. Note, that this notion of table arrangement allows a reconstruction of an two-dimensional arrangement only if all rows has the same number of entries, since otherwise we do not know to which columns the entries of the shorter rows are to be assigned.

If we know the relevant markups, as it the case for unextended HTML, we can, to some extent, use them for automatically solving recognition problem: there are tags indicating rows and others indicating entries in a row. There are also tags that can be use to mark meta data referring to the tables content but, unfortunately, meta data is often is not declared as such. Instead, the tables can contain *implicit titles* in the top row or *implicit column headers* as plain entries of the top row. Rows are grouped into *table blocks* by using *separating row* that either are empty or contain *in between titles*.

In short, for a simple tool based on the relevant markup the distinction of meta data and content is a problem. Nonetheless, we will use such a simple tool in section 5.2 in order to extend the table locations provided by Wang and Hu to a ground truth on table extraction. The quality of that ground truth will be limited, but we should not be too petty-minded on account to this in face of the low performance of the proposed table extractor as reported in section 5.4.

2 Related Work

2.1 Binary Classification with Content Features

The reference most related to this work is [15]. The authors reduce the table location task to a binary classification problem. First, the leaf table nodes, see section 1.2.1, are marked as candidate target tables. Then, each candidate table is mapped to a feature vector that in turn is the input to a classifier which decides whether the vector represents a target table or not. The feature vector consists of the feature groups for words, layout and content respectively.

For *word features* a bag of words is collected from the text nodes of each candidate table and mapped to a feature vector in a TF.IDF fashion with respect to the set of positive and negative candidate tables in the example set.

The *layout features* are based on counts of rows, columns, cells (leaf text nodes) and the lengths of the cells. Here, rows refer to nodes declared as table rows by HTML-tags. We have not yet understood to what columns refer to in cases where the rows differ in the number of entries. The standard deviation of the number of cells per row is one of the layout features. All normalization are *local* in the sense that they refer to corresponding elements inside the same table.

Another layout feature is called *cumulative length consistency*. It is intended to capture the observation that the lengths of entries for a given column are often similar. The *content-features* transfer this concept to consistency with respect to content types such as *hyperlink, image, alphabetical*. This concept of consistency has also been the initial motivation for our work. While in our work this idea is formalized in terms of pairwise similarities, the consistencies in [15] are computed based on a reference value that is the mean for the lengths and the most frequent value for types. It might be interesting to draw a clear sight on the relation of these two formalizations, but we have not done this.

The authors report experimental results in term of the F_1 score for three different classifiers: decision trees, linear SVM and RBF-SVM. The latter yields a performance as good as for the first, while the performance of linear SVM is below. It is not reported how the choice of parameters for the SVMs had been done. For the decision tree classifier different combination of feature groups are tested. It turns out that the combination of the layout and the content features performs best, while additionally including the word features yield only a small increase of performance.

2.2 Display Models

In order to ease the reading of web pages, the developers of browser invest much effort to translate HTML-files into a clear arrangement one a 2-dimensional display. In [3], see also [4], the authors propose to make use of this arrangement result as provided by the mozilla rendering engine for solving the task of table extraction. We estimate this as a particularly clever approach. Tables can be characterized as boxes that are tiled in a regular manner fulfilling certain constraints. Though the arrangement pattern are of comprehensible complexity the approach yields good results on a large set of web-pages. It works out without any training.

The approach of [4] and the approach presented here are complementary in sense that the first focuses on topological structure of the input without considering the content of the table while the latter inspects the possible entries and separators without explicitly modeling the meaning of the separators for the arrangement. Nonetheless, they also overlap to some extend. Certainly, string similarity of separators is correlated to similar local topology. Also, in [4] congruence in text and background colors is taken into account which has no influence on the topology but on the similarity measures applied here.

2.3 Belief Propagation on Line Sequences

Pinto et. al. consider the problem of table extraction as segmentation of the input string into segments carrying labels such as *table-title lines, data-row lines, non-table lines* [10]. The authors target plain input strings and apply the assumption that segment borders are at line breaks such that entire lines can be used as tokens for linear belief propagation. Under a conditional random field model (CRF) this yields good results on set of documents fulfilling the assumption even with a rather simples feature set. In the provided state, the approach targets the location of the tables and meta-information on its rows but does not reveal the row-column structure of a table. To fix that the authors proposed to apply a 2-dimensional CRF with characters as token. For such a model, however, the optimization is difficult [14].

2.4 What is not Discussed

In this work we do not aim to extract meta-data as table titles or headers ([10]) nor provide additional tags carrying information that could used for further processing of the extracted data. The problem of integration of the extracted data [11] is not considered either, though this work is much inspired by [5] where data integration is a main application.

3 Reduced Output Space

In this section we want get a more formal grip on what the candidate outputs of table extraction are. First, we formally specify the general output space independent of concrete ground truthes and extractors. Then, we formulate assumption made by the table extractor given in section 4. These assumptions only hold for less than one out of six input-output examples from the ground truth we build in section 5 but they allow us to use a reduced output space that is suited to study table extraction by column-wise similarities with reduced technical outlay.

3.1 Table Extraction Formally

For table extraction we want to map an *input string* x over a fixed alphabet Σ to a *list of tables* $y = (t^1, \ldots, t^q)$ of indefinite length q. The k-th *table* in that list is a list of rows $t^k = (r^1, \ldots, r^{n_k})$ where the i-th *row* in turn consists of $m_{k,i}$ entries $r^i = (e^1, \ldots, e^{m_{k,i}})$. An *entry* is a string over Σ.

If $m_{k,i} = m_{k,\bar{i}}$ for all $1 \leq i, \bar{i} \leq n_k$, we say the table t_k is *rectangular*. In this case the tuples $(c^1, \ldots, c^m_k)$ where $c^j = (e^1_j, \ldots, e^{n_k}_j)$ such that $r^i = (e^i_1, \ldots, e^i_{m_k})$ are referred to as *columns* of t_k.

Instead of defining entries as self-contained strings, one can also represent them as substrings or only as slices on the input string [7]. The above representation has the advantages that it is more readable and that it is decoupled from the input and therefore more robust. Nonetheless, we assume that the entries occur in the input x as non-overlapping substrings in the order induced by the table structure (depth first). When we talk about an entry in the following section, we may refer to its proper string, its slice or both, depending on the context.

3.2 Assumptions

In the following we formulate some strong assumptions on the input string and the tables therein. These assumptions characterize the cases to which the proposed approach presented in this paper is restricted to.

The input string is assumed to contain *markup tags* or *tags* in short. Here, a tag is a substring that starts with a *less than* symbol (<) and ends with a *greater than* symbol (>) but has neither of both in-between.

A1 *non-overlapping tags*: There are no overlapping tags in the input string.

A2 *non-empty entries*: A table entry contains at least one non-whitespace character.

We estimate A2 to be rather strong assumption. Though, empty table entries in web-pages are often given as a special string which is not displayed by the browser.

A1 and A2 allow an unambiguous *alternating segmentation* of the input string into *tag segments* and *content segments*. Tag-segments are substrings that consists of tags and whitespace only, starting and ending with a tag, while content segments contain some non-whitespace substring but no tags. The idea is that the content segments are potential entries while tags or groups of tags form potential separators between entries. We therefore refer to content and tag segment also as *entry segments* and *separator segments* respectively.

The alternating segmentation is denoted by G and the separated subsequences of G containing separator segments and entry segments only by G^s and G^e respectively.

$$G = (g^\mathrm{s}_1, g^\mathrm{e}_1, g^\mathrm{s}_2, g^\mathrm{e}_2, \ldots, g^\mathrm{s}_p, g^\mathrm{e}_p),\ G^\mathrm{s} = (g^\mathrm{s}_1, \ldots, g^\mathrm{s}_p),\ G^\mathrm{e} = (g^\mathrm{s}_1, \ldots, g^\mathrm{s}_p) \tag{3.1}$$

If the input does not start with a separator segment we drop the first segment and correspondingly proceed with the last segment.

Table entries can contain tags. But they mostly have formating purpose and surround a single content segment. We therefore define the *peeling function* $\gamma : \Sigma^* \to \Sigma^*$ to take away any prefix and suffix of its string argument that consist of tags and whitespace only.

A3 *entry segments*: Any entry, when peeled by γ, is a content segment.

Of course, entries may contain tags surrounded by content segments. In such cases the A3 does not hold and the algorithm below will fail.

If, on the other hand, the assumption does hold, the extraction of the table entries reduces to the selection of a subsequence of G^e. We further restrict the output space by assuming tables to consist of consecutive content segments.

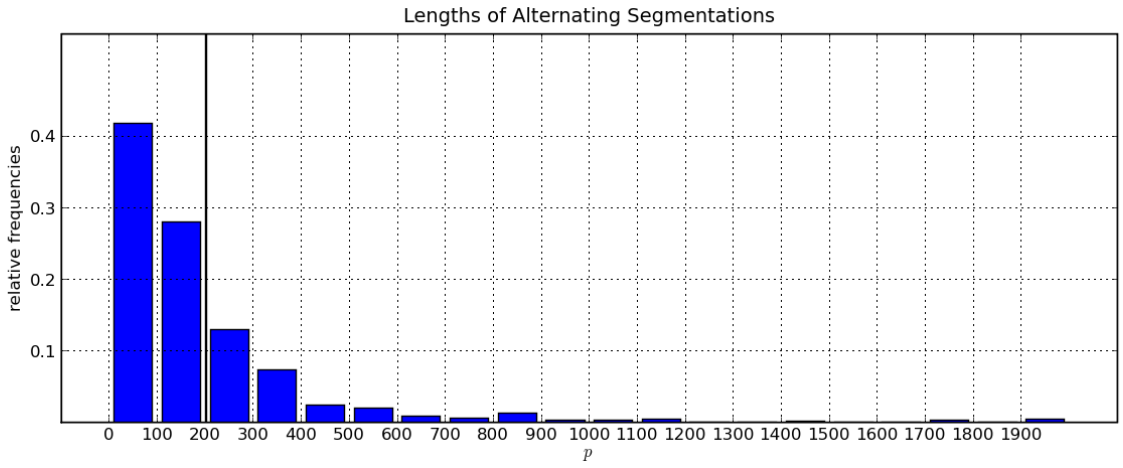


Figure 3.1: The empirical distribution of p based on the collection HTML-documents from [15] (1393 files), summarized to bins of lengths 100. The most right bin is open ended, e.g. it includes all documents with $p \geq 1900$. The solid vertical line indicates the mean at 201.

A4 *rectangular tables*: All rows in a table have the same number of entries.

A5 *compact rows*: There is exactly one tag segment between two consecutive entries of a row.

A6 *compact columns*: There is exactly one tag segment between two consecutive rows in a table.

A6 denies the existence of separating rows and therefore does not hold for a rather big fraction of tables. But, as we will see below, A4–A6 reduce the space of candidate tables to a level that permits exhaustive search.

3.3 Candidate Tables

Applying the above assumption we can specify the output space for given input x in very simple terms. If the alternating segmentation of x has length p any candidate table within x is represented as a triple (a, m, n) where a is the index of its first entry in G^{e}, m the number of columns, and n the number of rows such that $a + mn - 1 \leq p$. Let us denote this space of output tables by $T(G)$.

How many table does $T(G)$ contain? Let $\mathrm{n}^{\mathrm{p}}(a)$ be the number of tables starting at position a, and $\mathrm{n}^{\mathrm{c}}(l)$ the number of tables that can be built from at most l consecutive content segments in G^{e}.

$$|T(G)| = \sum_{a=0}^{p-1} \mathrm{n}^{\mathrm{p}}(a) = \sum_{l=1}^{p} \mathrm{n}^{\mathrm{c}}(l) \tag{3.2}$$

The term $\mathrm{n}^{\mathrm{c}}(l)$ equals the number of ordered pairs that multiply to at most l. On limit average it grows as $\ln l$ as can be seen from the following bounds that hold for any $l \in \mathbb{N} \setminus \{0\}$.

$$l(\ln l - 1) - 2\sqrt{l} \leq \mathrm{n}^{\mathrm{c}}(l) \leq l(\ln l + 2) + 2\sqrt{l} \tag{3.3}$$

The number of candidate tables is therefore bounded from above by $p^2(\ln p + 1)$. In figure 3.1 we depict the empirical distribution of p based on the dataset from [15].

4 Extraction by Column-Wise Similarities

We want to study a simple score based table extraction algorithm. The algorithm is named *CSE*, standing for *column-wise similarity evaluation*, as its selects the output tables according to a table score based on the in-column similarities.

4.1 Iterative Maximization

The proposed table extraction algorithm tries to solve the table location and recognition task in one go by maximizing a *table score* H over the candidate table in T which will be given below. The maximizer $\hat{t}$ of H is one table in the output list $\hat{y}$.

$$\hat{t} = \underset{(a,m,n)\in T(G)}{\operatorname{argmax}} H(a,m,n) \tag{4.1}$$

The other tables in $\hat{y}$ are obtained by incrementally exclude candidate tables that overlap with the tables extracted so far and retrieve the maximizer from the remaining ones. The output list is finally sorted by the position of the first entry a such that the tables appear in the same order as they do in the input string.

We want to assume that true number k of tables is given in addition to the input string. That is, we let aside the problem of detecting where in the sequence of maximizers the entries stop to be tables. In case that the first $l < k$ table already cover the sequence such that no further table can be extracted, the remaining tables are defined as empty tables that are tables with zero rows.

We refer to an input hint such as the number of tables above as *promise* using a notion from complexity theory [1]. More generally, a promise is a string that is added to the input and represents certain information on the true output.

4.2 Table Score

The table score should express how table-like a table is. It is exclusively obtained from scores on the columns of the table, where column here means both, column of entries and column of separator between entries and rows. Row separators are treaded like entry separators. The difference is that in a table there is one row separator less than there are separators between two content columns because we model a table to start with its first entry and to end with its last entry.

A table column is represented by a tuple (u,b,m,n) where $u \in \{\mathrm{e},\mathrm{s}\}$ is its type (content- or separator-segment), b is index of the first entry of the column in G^u, n is the number of its entries and m the number of columns the tables has to that the column belongs to. We denote the score of a column (u,b,m,n) which should express is column-likeness by $h^u(b,m,n)$.

For a given table $(a,m,n) \in T(G)$ the table score is the sum of scores of its columns divided by a normalization term $z(m,n)$.

$$H(a,m,n) = \frac{1}{z(m,n)} \left(h^{\mathrm{e}}(a,m,n) + \sum_{j=1}^{m-1} \left(h^{\mathrm{s}}(a+j,m,n) + h^{\mathrm{e}}(a+j,m,n) \right) + \; h^{\mathrm{s}}(a+m,m,n-1) \right) \tag{4.2}$$

For either type u we aim the score of a column (u,b,m,n) to give a measure of how well the elements of the column $(g_{a+im})_{i=0,\dots n-1}$ in G^{u} fit together. We can model this by the sum of their pairwise similarities. Let $\bar{s}^u : Q^u \times Q^u \to [0,1]$ be a similarity measure where Q^u is the set of possible segments of type u. Then, the score of a column (u,b,m,n) is given by

$$h^u(b,m,n) = \sum_{0\le i<j<n} \bar{s}^u(g_{b+im}, g_{b+jm}). \tag{4.3}$$

The normalize term is the total number of similarities that are taken into account

$$z(m,n) = (2m-1)\binom{n}{2} + \binom{n-1}{2} \tag{4.4}$$

such that H is the average similarity between entries or separators stemming from the same column.

4.3 Entry Similarities

A good design of the similarity functions s^e and s^s is an important factor for the performance of CSE extraction algorithm. This can be seen by trying different similarity functions and/or different parameters of these. We did not undertake systematic studies on this and in this report we neither want to discuss what adequate similarities may be nor to what extend one can expect a good choice of similarities can evaluate the performance. In the following we briefly describe the similarities we applied in our experiments as reported in section 5.

To make sure that a similarity is in the range of 0 to 1 regardless the actual similarity function s^u, the CSE algorithm always uses the normalized variant $\bar{s}^u$.

$$\bar{s}^u(g,\bar{g}) = \frac{s^u(g,\bar{g})}{\sqrt{s^u(g,g)s^u(\bar{g},\bar{g})}} \tag{4.5}$$

For both segment types with apply a similarity with respect the length s^l. Let a and b let us denote the length of a string x by $|x|$. The length similarity evaluates the ratio of the greater length to the smaller one through an exponential decay.

$$s^l(a,b) = \exp(-g(a,b)), \quad g(a,b) = \frac{1+\max(|a|,|b|)}{1+\min(|a|,|b|)} - 1 \tag{4.6}$$

While the similarity of separator segments is reduced to the length similarity, e.g. $s^s = s^l$, the similarity on entry segments additionally checks whether the two string are of the some type where the type of string is either *integer*, *non-integer number*, or *other*. This type similarity $s^t(a,b)$ is 1 if the types of a and b match, and 0 otherwise. The entry similarity is given as product of length and type similarity: $s^e(a,b) = s^t(a,b)s^l(a,b)$.

In principle we can plug-in any string kernel as similarity function on segments, but it should be noted that the evaluation of the similarities must have moderate costs because any two segments of the same type are to be compared.

4.4 Score Levelling

Unfortunately, simply averaging over the relevant similarities is not an option because of two reasons. To the first we refer as *subtable problem*. Consider two tables, where one table is a subtable of the other both having approximately the same elevated score. In such a case we prefer the greater table, because we assume that a wrong extension of a complete table decreases the score while false dropping of rows does not so.

The second issue is the problem of *winning by variance*. The smaller the table shape, e.g. the less candidate entries are taken into account, the less reliable is the table score as selection criterion. The distribution of scores is less concentrated for smaller shapes than for larger ones because we average over fewer similarities and because the candidate tables have less average overlap to each other. Also, there are more non-overlapping candidates in absolute numbers. These properties make them more likely to erroneously exceed the score of the correct target tables.

The two issues differ in their scope. The subtable problem refers to preferences among certain outputs having similar score H. In other settings we might use a similar score although no or other preferences exists. In contrast, the winning by variance problem is not related to the input-output distribution but refers to the different predictive qualities of the scores due to the score structure.

The framework to approach these issues is to apply a*score levelling* that maps the score H of a candidate table to a leveled score $\bar{H}$. The levelling *increasing with the shape* that is the original score is decreased the more the smaller m and n are. We confine ourself to *linear levellings* that have the form below. For better reading, a single term s is used to denote the shape (m,n).

$$\bar{H}_G(a,s) = \frac{H_G(a,s) + b_G(s)}{c_G(s)} \tag{4.7}$$

One may try a reasonable guess for c and b and use it as *ad hoc levelling* or fit the levelling from a broader class of functions using a training set. In the subsequent subsections we discuss instead ways to tackle the problem of winning by variance by levellings of the form (4.7) directly. In contrast, we do not respond to the subtable problem explicitly. We assume that all levellings that do not increase to slowly will sufficiently solve it. If the subtable is much smaller, the the score of the supertable is decreased much decreased much less. If, on the other hand, the subtable only misses a few rows, then its score is unlikely to be much greater since it contributes the main part to the score of the supertable.

In the following we try to give a better idea of the levelling approach and therefore use simplified setting: we assume the input-output pairs $Z = (G,K)$ are drawn from a distribution P which only supports segmentations G that have a given length p and contain exactly one true table denoted by K. We say P has *input length* p and *output length* 1.

Let l be a *score loss* on candidate tables, for instance the 01-loss $l_Z(t) = [\![H_G(t) > H_G(K)]\!]$ or the *hinge-loss* $l_Z(t) = \max(0, H_G(t) - H_G(K))$. The *risk of the score* $\mathrm{R}_P(H)$ is the expected sum of losses over all candidate table in $T(G)$.

$$\mathrm{R}_P(H) = \mathrm{E}_{Z\sim P} \sum_{t\in T(G)} l_Z(t) \tag{4.8}$$

We want to decompose that risk along the shapes. Let S_p be the set of *feasible shapes* and $A_p(s)$ the set of *feasible positions* given the shape s and let $e(s) = \mathrm{E}_{G\sim P}(e_G(s))$ with $e_G(s) = \sum_{a\in A_p(s)} l_Z((a,s))$ be the *risk at shape* s.

$$\mathrm{R}_P(H) = \sum_{s\in S_p} e(s). \tag{4.9}$$

The approach of shape levelling assumes that independently of P but due to the structure of H the risk e is greater for certain shapes such that reducing the chances of a such an s reduces $e(s)$ more than it increases the risk at other shapes and therefore leads to a smaller total risk which in turn is assumed to correspond to a better extraction performance.

Note that we do not further discuss that notion of risk nor the choice of the underlying score loss. Here, they are only used in order to explain the concept of levelling but they are not directly taken into account when discuss ways to choose an levelling below.

4.4.1 Fair Levelling

The idea of *fair levelling* is to design the levelling such that the score maximization scheme does not favor any shapes when the segmentation can be assumed to contain no tables.

Let P be of input length p and output length 0. The segmentations drawn according to P do not contain any tables and we therefor call to such a P *table-less*. Given a table-less distribution P, we say that the table score is *fair with respect to* P if the shape s^* of the maximizer of H_G has uniform distribution over S_p.

A sufficient condition for obtaining a fair score is that that distribution of the maximum does not dependent on the shape. Since this goal is overstated, we propose a rough approximation thereof by setting the expectation of the maxima for different shapes to one level. Let $\mu_p = \mathrm{E}_{G\sim P}\mu_G$ be the expected average score over S_p and $A_p(s)$ and let $\nu_p(s) = \mathrm{E}_{G\sim P}\nu_G(s)$ be the expected maximum of the scores over $A_p(s)$.

$$\mu_G = \operatorname*{avg}_{s\in S_p, a\in A_p(s)} H_G(a,s) \quad \nu_G(s) = \max_{a\in A_p(s)} H_G(a,s) \tag{4.10}$$

With the following levelling, we approximate a fair levelling by standardizing the expected maxima given the shape, e.g. we set $\mathrm{E}_{G\sim P} \max_a \bar{H}_G(a,s) = 1$ for all s in S_p.

$$\bar{H}_G(a,s) = \frac{H_G(a,s) - \mu_G}{\nu_p(s) - \mu_p} \tag{4.11}$$

In praxis, we have to use estimations of μ_p, $\nu_p(s)$ that we obtain in our experiments in section 5 simply by averaging $\nu_G(s)$ and μ_G over a set of segmentations drawn from some P. The term $-\mu_G$ in the nominator in (4.11) is irrelevant for the maximization but it accents the standardization character of the levelling.

4.4.2 Table-Less Models

The approach of approximated fair levelling demands that we have a table-less distribution P, to which we now refer as *segmentation model*, at hand. We discuss a few simple table-less models.

The first model, called *Bernoulli model*, is a simply *iid model* where we draw the segments independently and with equal chances from $\{0,1\}$. The similarity of two segments is 1 if they are equal and 0 otherwise. This model has little to do with the segmentation from which we want to extract tables but still might be sufficient to design a effective levelling as it does capture the structure of the table scores.

The second model, which is named *shuffling model*, is an iid model as well. A segmentation is drawn from an example set and then we sample the segments for the new segmentation according to the distribution of segments in the sampled segmentation. At least with high probability we can assume that we do not find any table in a segmentation that is drawn according to either of these iid models.

Last, we consider the *empirical model* where a set of example segmentations containing no tables as taken as empirical distribution. From one segmentation of length p we obtain sample value of $\nu_p(s)$ for any $s \in S_p$. But contrary to the iid

models, we only get empirical evidence for some p and therefor need a more elaborate smoothing technique than for the iid models where we can generate segmentation for any p. On the other hand, we assume the levelling to be monotone in each of its the arguments m, n and p what strongly decreases the data demand. Nonetheless, the definition of such a smoothing remains future work.

The empirical model as as well as the shuffling model amount, strictly speaking, to supervised table extraction since we only want to sample segmentation not containing tables. On the other hand, this binary labeling is very cheap compared to the actual extraction of tables.

4.4.3 Variance Levelling

A simple variant of the fair levelling is *variance levelling* where we standardize the score in the classical sense with respect to some table-less distribution P. That is, we divide the score by the standard deviation that the tables of shape s are expected to have when we run over the feasible positions.

$$c(s)^2 = \mathrm{E}_{G\sim P} \operatorname*{avg}_a (H_G(a,s) - \mu_G)^2 \tag{4.12}$$

With an iid model we can explicitly compute the values $c(s)$ from two parameters of the underlying segment distribution. For simplicity, we now include the separator subsequent to the last entry segment into the table such the table score is the sum of $2m$ independent identically distributed columns scores. Let H be the score of some candidate table in $G \sim P$ with shape (m,n) and let C be the score of a column in G having n entries. Taking the column score as U-statistic for a binary kernel, we have

$$\begin{aligned} \mathrm{V}(H) &= \frac{1}{2m}\mathrm{V}(C) && (4.13)\\ &= \frac{1}{mn(n-1)}\left((n-2)\sigma_1^2 + \sigma_2^2\right) && (4.14) \end{aligned}$$

where $\sigma_1^2 = \mathrm{V}_X(\mathrm{E}_Y(s(X,Y)))$ and $\sigma_2^2 = \mathrm{V}_{X,Y}(s(X,Y))$, see for instance [8]. For the Bernoulli model the parameters σ_2^1 and σ_2^2 can easily obtained from success probability q. In case of the shuffled model we have to estimate them by sampling.

5 Experiments

For testing the general performance of the CSE algorithm and for comparing the different levellings presented above we run experiments on the Wang and Hu data set that was used in [15].

5.1 Preprocessing

In general, we do not know the encoding of the input-file which defines the exact translation of the sequence of bits in the file into a sequence of characters. This is problematic because each tool that is involved in the extraction process may have its own encoding policy such that the output table entries of two extractors may differ only because at some point they used a different encoding translation.

To solve this problem, we use a tool that tries to detect the encoding and then translate the file into a string of ASCII-character where non-ASCII symbols are replaced by a substitution string such as *•*. The goal of obtaining an input ASCII-string where all non-printable and white-space characters are substituted as well, see section 1.1, was dropped, because it implied additional work. Instead, we substitute the carriage return only, which was necessary for the reasons pointed out above.

In a second preprocessing step we removed the comments from the HTML-code. If we do not do so, assumption A1 will often fail to hold because comments are tags (at least according to section 3.2) and are often used to comment out other tags. Removing comments, however, amounts to the additional assumption that we can detect them.

5.2 Building the Test Set

The Wang and Hu set consists of HTML-documents in which all target tables are marked using a special boolean attribute in the table node. This makes the set a ready-to-use ground truth for the table location task. Since CSE tries to solve the table recognition task as well, we have to extend the ground truth provided by Wang and Hu by additionally solving the recognition of table cores.

We decided to do this automatically with another table extractor, named *RE extractor* or *REE* in short, that uses regular expressions based on the relevant element names of HTML. Attempts to use the parsing of the document tree failed for too many documents where we tried three freely available parsers including the lxml-library [9].

REE uses a pattern for genuine tables based on the element name *table* and the additional attribute in order to get the substrings that represent the content of a genuine table. To solve the recognition task it applies an entry pattern (element name *td*) on the content of the matches of the row pattern (element name *tr*), which in turn is applied on the substrings of genuine table contents. Matches of the row pattern that contain matches for headers (element name *th*) are ignored.

REEs capability for solving the table recognition task is limited. One minor problem is broken HTML in the inspected substrings. The main issue is meta data that is not declared as such, see section 1.2.2. Still, we belief that the output of REE is sufficient for our experiments since extraction capability of CSE is low anyway.

In the following we specify two versions of the ground truth. Both are based on the output of REE but they apply filters of different strength. While the for the *full set* only weak filtering is applied, *feasible set* contains those cases only that fulfill the assumption made by CSE.

5.2.1 Full Set

The Wang and Hu data set contains a total of 1393 documents. For the *full set* we only include the examples that contain at least one genuine table. CSE gets the number of tables k as promise and therefor has nothing to do if the promise is 0. Further, we bound the segmentation length to be not greater than 900. Documents with $p > 900$ are rare but they take a rather big fraction of the total runtime.

As a third filter criterion we demand that the extraction by REE is *successful* in the following sense: each extracted table should contain at least one row and any extracted row should have at least one entry. We hope that most cases where the table recognition by REE does not work as intended are detected by this criterion, while not to many table that are extracted as intended by REE fail to fulfill it. Table 5.1 shows the number of examples passing the filters discussed so far plus an additional filter discussed below.

5.2.2 Feasible Set

The feasible set is restricted to those documents from the full set in which all tables provided by the RE extractor fulfill the assumptions given in section 3.2. Though CSE may extract some of the table or part of tables from a document not in the feasible set, it is not possible that its output is entirely correct. The feasible is useful to analyze the discriminative power of in-column similarities as used by CSE and variants of the algorithm.

In order fulfill assumptions a table has to be rectangular and it has to *fit in the content sequence* of the document. The latter means that the sequence of the entries in the table is a consecutive subsequence of the content part G^{e} of the alternating segmentation modulo the mapping γ. The conjunction of this two criteria is necessary for the assumptions to hold, but unfortunately it is not sufficient because of the implicit column headers. However, this problem can only be solved by human inspection and we therefor prefer to the use the above criteria as approximation. The number of documents under *hold assumptions* in table 5.1 refers to this approximation.

Although the problem of implicit column headers remains, the fraction of documents from which REE erroneously extract meta data should be lower in the feasible set because the rectangularity condition filters out cases with implicit titles or separating rows that are as rows with one or no entry. That is, as side effect of restricting is examples that are feasible for CSE the ground truth has a higher quality with respect to output specification made in section 1.2.2.

Independently of CSE, one may try to use the numbers of entries per row to design a heuristic for detecting rows that contain meta data only for improving the quality of the automatic table recognition for HTML.

total	$k > 0$	$p \leq 900$	RE successful	hold assumptions
1393	774	727	700	162

Table 5.1: The number of examples in the Wang and Hu set that passed the filters in conjunction from the left to right up to the filter heading the column.

5.3 Performance Measure

For the evaluations of an extractors we need a loss function L^{y} that compares its outputs to the output provided as ground truth and encodes the comparison as a value in $[0,1]$. The definition of the loss goes along the hierarchical structure of the outputs them self: L^{y} is an extension of a loss on tables L^{t} that is an extension of a loss on rows L^{r} which in turn is an extension of a loss on entries L^{e}.

We say that an extension is *strict* if the resulting loss is 1 whenever the two arguments do not have the same number of components and otherwise is given as aggregation of the *component losses* that are the losses on the pairs of one components from each of the two arguments having an identical index. The *average extension* is a strict extension which aggregate by the mean and the also strict *maximum extension* takes the maximum as aggregation. For instance, we obtain the 01 *loss* that checks whether its arguments are equal down to their entries by applying the maximum extension at any level of the hierarchy. Here, we want use a loss on table list which is more soft to several regards as we define in the following in a bottom-up manner.

The loss L^{e} on two entries is the 01 loss L^{s} on strings applied to the entries reduced by the peeling function γ introduced in section 3.2.

$$L^{\mathrm{e}}(e,\bar{e}) = L^{\mathrm{s}}\left(\gamma(e),\gamma(\bar{e})\right) \tag{5.1}$$

While the row loss L^{r} is given as strict maximum extension of the loss on entries, we want to use a soft table loss L^{t} such that dropping rows at the beginning or the end of a table results only in a gradual increase of loss.

Therefor, we define the table loss L^{t} not as a strict extension but as *best overlap extension* of the row loss. This extension searches an optimal way to match consecutive subsequence of component indexes of the argument with the smaller number components to the longer one. For every component of the longer argument that is not matched a loss of 1 is taken into account.

Let $t = (r^1,\ldots,r^n)$ and $\bar{t} = (\bar{r}^1,\ldots,\bar{r}^{\bar{n}})$ be two tables that are to be compared where we assume without loss of generality that $n \leq \bar{n}$. In order to simplify the below definition of the loss L^{t} on the tables, we extend the shorter table t to $\tilde{t} = (\tilde{r}^1,\ldots,\tilde{r}^{\bar{n}+n+\bar{n}})$ by adding $\bar{n}$ *false rows* to either end of t. A false row is a row r such that $L^{\mathrm{r}}(r,\bar{r}) = 1$ for any row $\bar{r}$.

$$L^{\mathrm{t}}(t,\bar{t}) = \min_{d=0,\ldots,n+\bar{n}} \frac{1}{\bar{n}} \sum_{i=1}^{\bar{n}} L^{\mathrm{r}}\left(\tilde{r}^{d+i},\bar{r}^{i}\right). \tag{5.2}$$

The minimization is needed because we want to define a loss depending only on the outputs decoupled from the input as pointed out in 3.1. If we toke the entry slices on the input string into account, we could use them to match the rows directly.

Finally, the table loss is expanded to a loss on table lists L^y by applying the average extension. The strictness of the extension is not an issue here because the CSE extractor uses promises on the number of tables. We refer to output loss L^y as *best row overlap loss* or *BRO loss* in short.

5.4 Results

We evaluated the performance of the CSE extractor by comparing its output to the REE-ground-truth discussed in subsection 5.2 in terms of best row overlap loss defined subsection 5.3. The CSE extractor gets the number of tables obtained from REE as promise. To simplify the implementation we let CSE look only for tables with $n \leq 80$, $m \leq 20$, other candidate tables were ignored.

In section 4.4 we pointed out that one has to adjust the scores depending on the shape of the candidate table in order to make the extraction by average entry similarities work. The discussed levellings try to do this adjustment in a specific, roughly motivated way. Alternatively, one may pass on the motivation and try to make a good guess on a function of m and n and use this as *ad hoc levelling*. For instance, one might multiply the scores by

$$\frac{1}{c(m,n)} = \gamma + n^{\beta} m^{\alpha\beta} \tag{5.3}$$

for some α, β and γ. Of course, we do not know a priory how to these parameters. One can fit using a training set, but we not try this possibility for this work. Still, we used the above class of ad hoc levellings for two purposes. First, by varying the parameters we get a rough impression on the impact of chances in the levelling. Second, we consider it as base line in the sense that the results yielded by levelling from section 4.4 should be comparable to this ad hoc levelling at least if the chosen parameters had not seriously been fitted to the test set. As a matter of fact, it was not difficult to find parameters for the ad hoc levelling in (5.3) that give better result than the more elaborated levellings discussed in section 4.4.

In general, the extraction performance of CSE with features from section is rather poor: the BRO losses are 0.825 and 0.613 for the full set and feasible set respectively using ad hoc levelling with $\alpha = \beta = \gamma = 0.5$. More details on the distributions of the losses are given in figure 5.1. Results on the feasible set for fair and variance levelling based on Bernoulli sampling with different success probabilities q, for fair levelling with shuffled sampling, as well as for one ad hoc levelling are given in table 5.2, the corresponding details on the distribution of losses in figure 5.3.

The Parameters for the levelling in 5.2 were chosen as follows. For ad hoc levelling the result refers to optimal values where we tested all combination with $\alpha = 0.2, 0.4, 0.6, 0, 08, \beta = 0.2, 0.3, \ldots, 1.4$ and $\gamma = 0, 1, 2, 8, 32$. The success probability for the iid Bernoulli segment sampling was tested at $q = 0.1, 0, 2, 0.3, 0.4, 0.5$ and the values that yielded the best and the worst performance respectively are in given in the table. Therefor, neither of those performances can be stated as performance for respective type of levelling as the parameters are fitted to the test set. The fair levelling with shuffled sampling is based on samples that are also taken from the Wang and Hu set but do not belong to the test set as they contain no tables.

Figure 5.2 shows the BRO losses for ad hoc levelling with $\gamma = 1$. The corresponding plots for other values of γ have similar shapes where with increasing γ the low loss region shifts towards greater values of β and the graphs for different α approaches to each other.

5.5 One Document Plots

In order to get better picture of a the score function H we build some plots containing candidate table scores for a fixed input document. The document (www.sugarinfo.co.uk.index.html from the Wang and Hu set) contains a single target table (genuine table) according to the labeling by Wang and Hu. This example also demonstrates the ambiguity of the notion *table*.

From eye inspection one may identify three areas that have a table-like look, letting aside the lists (one column tables) positioned at the left and right sides of the rendered page. The first *maybe-table*, titled *Sugaronline News Headlines*, has

Ad Hoc	Fair Bern. $q = 0.5$	Fair Bern. $q = 0.2$	Fair Shuffled	Var. Bern. $q = 0.1$	Var. Bern. $q = 0.4$
0.598	0.655	0.617	0.623	0.664	0.628

Table 5.2: BRO losses of CSE using different type of levelling measured on the feasible set. The parameters for the ad hoc levelling in the first column are $\alpha = 0.4, \beta = 0.6$ and $\gamma = 0$ yielding the lowest among all tested combinations. For fair and variance levelling the two given values of q yielded the worst and the best result among five tested values from 0.1 to 0.5.

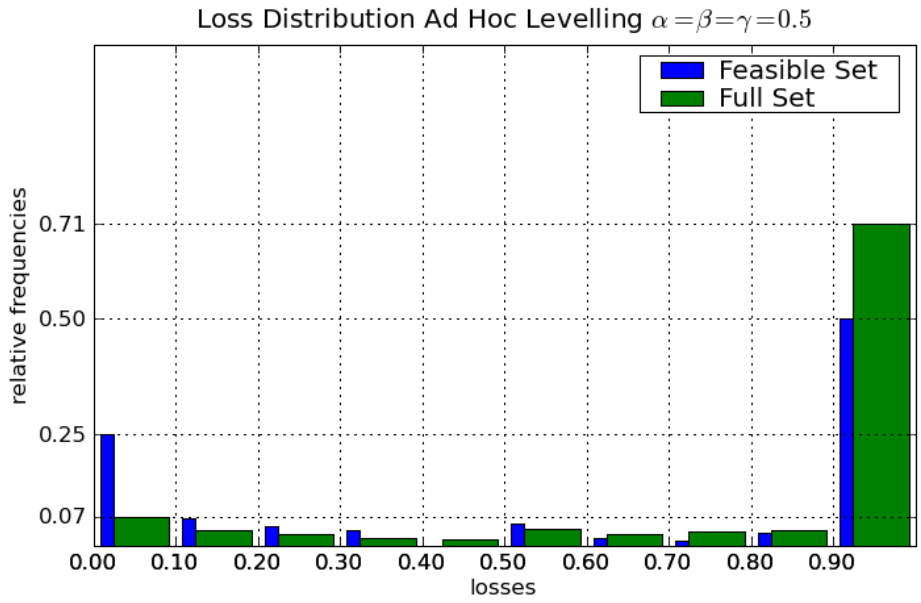


Figure 5.1: Distribution of best row overlap losses that CSE attained on the full set (700 documents) and on the feasible set (162 documents) using ad hoc levelling at $\alpha = \beta = \gamma = 0.5$. By coincidence the frequency of the last bin of the feasible set is exactly $\frac{1}{2}$ while the value of the first bin is only close to $\frac{1}{4}$.

rows each of which are distributed over two lines. We would label this as a table but Wang and Hu did not mark it as a genuine table. The second, titled *Current Enquirers on the Sugar Trading Service* is a straight table with three columns and 12/13 one-line rows. This is one that is is marked as genuine. The REE ground truth says that columns headers belong to the table while CSE would rather extract the 12 rows below only.

The third, titled *Worldwide Sugar Sites*, optically has two columns where each entry consists of a link an a short explanation placed below. The two optical column do not correspond to logical columns. Instead they are used to make the list of links more compact. One might declare it as table with the columns link text and explanation but this is mater of taste.

In figure 5.4 the table scores for several shapes a plotted over the the start start position a. The start of all three maybe-table are clearly indicated as peaks provided one chooses the right shape. If the the number of row is too small we observe an plateau instead of sharp peak, because then score remains high as long as the candidate table is a subtable of the true table. Correspondingly, there is a plateau at lower level for n that is too great: whether we add wrong rows at the end or and the beginning is of little importance compared to the score contribution of the true rows in the middle part.

The plots in figures 5.5 and 5.6 show the scores where the number of column and the number of rows is in the x-axis respectively. Corresponding to the plateau of a too short shape $(3, 10)$ in figure 5.4, we observe in figure 5.5(a) a plateau of maxima up to the $n = 12$.

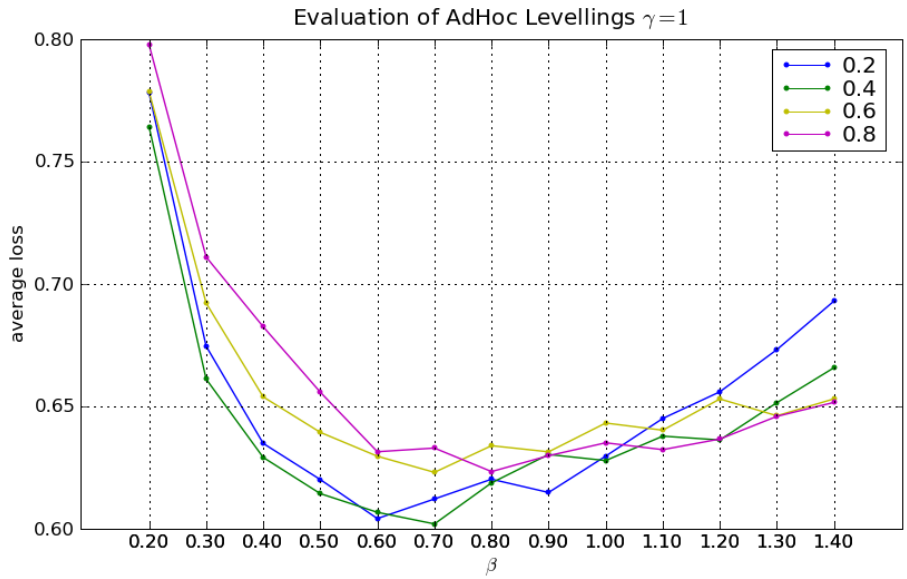


Figure 5.2: The mean BRO loss obtained by CSE with ad hoc levelling for different values of α and β measured on the feasible set. Different values of α are plotted with different colors while β runs along the x-axis.

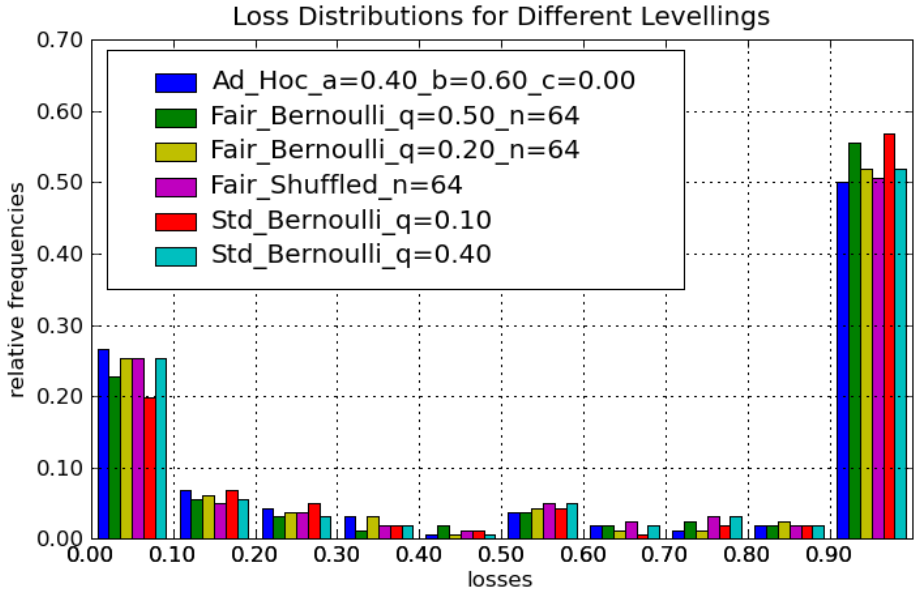
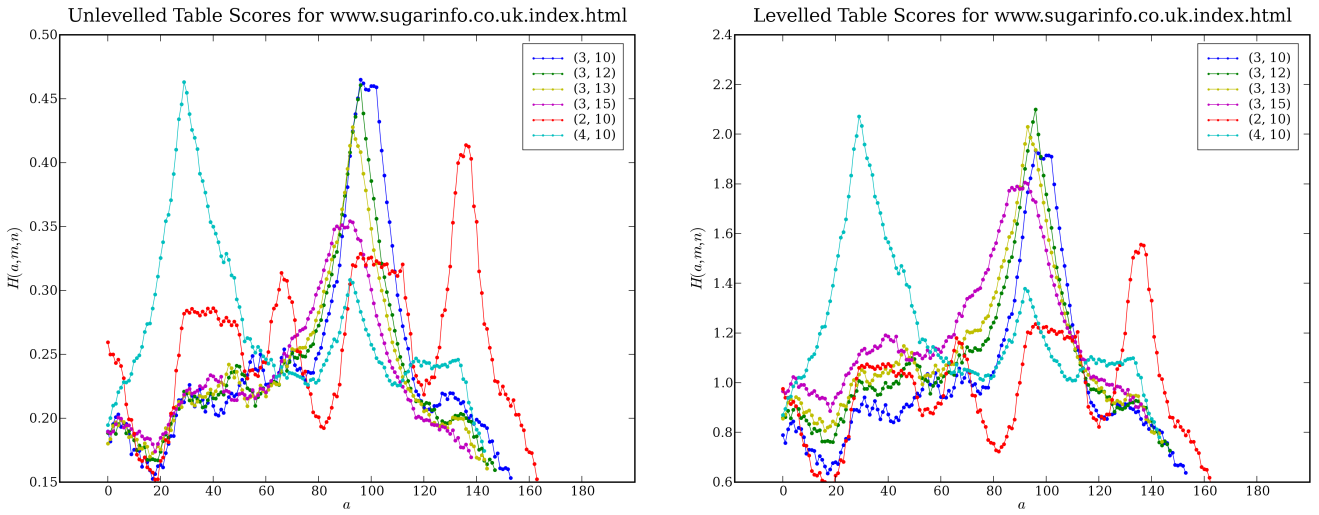
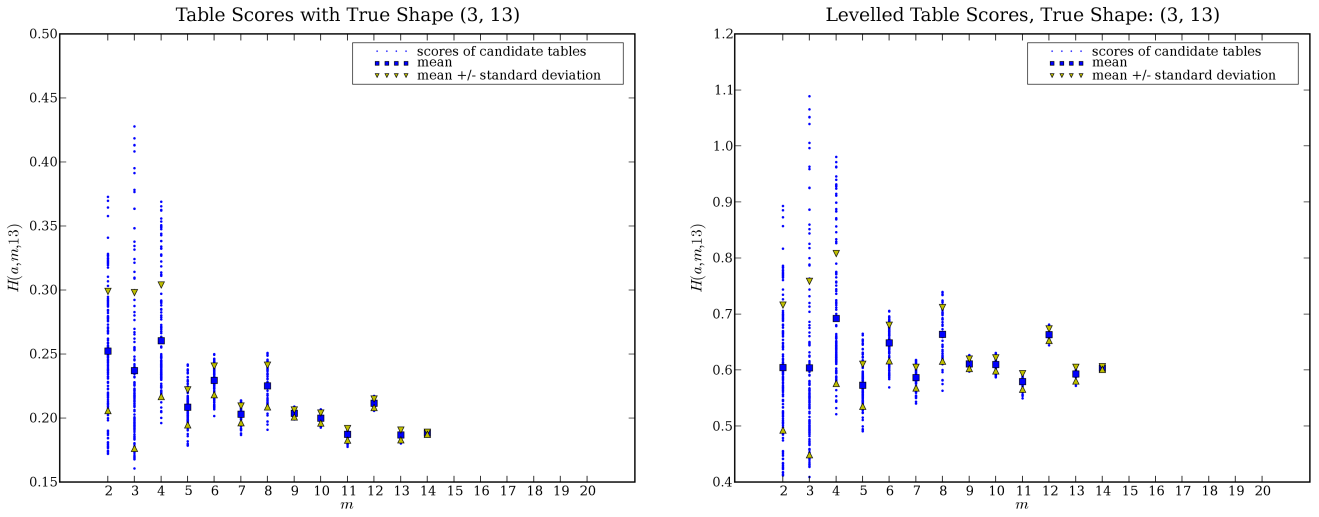


Figure 5.3: Distributions of BRO losses for CSE with levellings on the feasible. The legend uses Latin letters for the parameters of the ad hoc levelling instead of Greek ones.



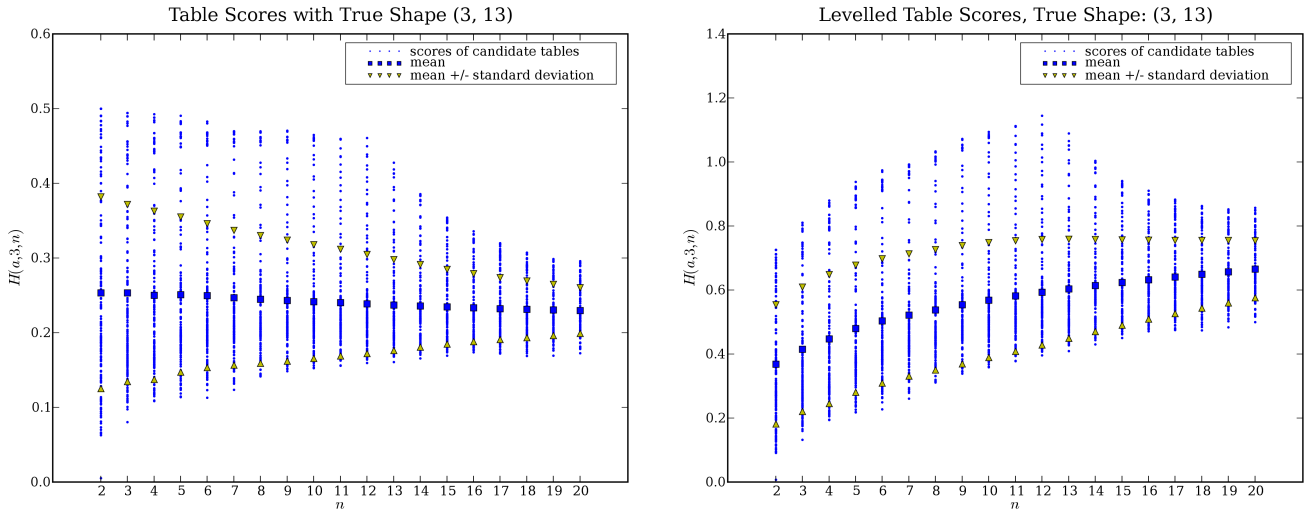
(a) (b)

Figure 5.4: Plot (a) depicts the scores for a given document where start positions a runs along the x-axis. Different colors represent different values of the shape (m, n). For each value of $m = 2, 3, 4$ there is one area in the document containing a table like structure that has m columns. For $m = 3$, the graphs with $n = 12$ (including column headers $n = 13$) fails to be the top scores in the area. With levelling, figure (b), it does attain the highest peak. Note that this example is particularly easy for the CSE algorithm and should not be taken as typical case.



(a) (b)

Figure 5.5: Each small blue dot in plot (a) and (b) corresponds to one candidate table in a given document where the number of rows is fixed to the number $n = 13$ and the number of columns runs along the x-axis. The plots (a) and (b) show shows scores without and with levelling respectively.



(a) (b)

Figure 5.6: Without levelling (plot (a)) smaller number of rows get higher maxima. The true number of rows is $n = 13$ according to REE but the first row turns out to contain column headers. See figure 5.5 for more explanation.

6 Conclusion

We investigated in a simple approach to the task of table extraction: first, we reduce the output space such that we can afford to inspect any candidate output, then, we select a given number of candidates with high average in-column similarities. The inspection of a set of HTML documents revealed that the proposed reduction of the output space cannot be applied in too many cases. Experiments on the remaining cases gave a first impression on the discriminative power of in-column similarities: even with more elaborated entry similarities than the simple ones applied here, it is presumably to weak to sufficiently solve the extraction task. On the other hand, given the simplicity of the applied similarities, we find that the extraction performance is on a level that justifies deeper investigation how we can effectively use the information that lies in similarities of column entries. In the following we revisit some issues of the this approach and indicate proposals for future work.

6.1 Alternating Segmentations

In section 3.2 we defined the input segmentation in terms of SGML tags but the concept of alternating segmentation is more general. Instead of tag-segments vs non-tag-segments on texts with markups, one might consider other input types with other alternating segmentations. A sufficient condition for an alternating segmentation in general terms is that no suffix of a separator-segment is a prefix of a content-segment *or* vice versa. Further, we can build different alternating segmentations and jointly maximize over the contained candidate tables, provided that the scores functions yield comparable values.

6.2 Restrictive Assumptions

The assumptions formulated in section 3.2 are too restrictive. Only one out four documents from the full set does fulfill them. Partially this caused by meta data rows in the ground truth provided by REE but we believe that that fraction would not increase to reasonable level even if we cleaned the example output by hand. It should be noted that most relaxations cause a exponential blowup of the search space. For instance, if we replace A6 by the rule that rows have to be separated by one or two separator segments instead of exactly one, the number of candidate table starting at given position grows exponentially in the number of rows at least as long as there are segments left in the segmentation. It is not obvious how to solve the maximization efficiently under such a relaxation. We cannot apply standard dynamic programming along the sequence of segments, because the column scores as given in section 4.2 does not factorize along this sequence.

6.3 Evaluation of Levellings

Except for levelling with shuffled sampling, all levellings that have been applied in our experiments are parametrized. As long as we do not provide algorithms for pre-test determination of the parameters a comparison of levellings schemes based on the obtained performances is delicate. But we might say that fair and variance levelling as proposed in section 4.4 do not provide a adequate technique for boosting the performance of CSE compared to ad hoc levelling since competitive parameters can easily be found for the later. The proximate way to make comparison between parametrized levellings is to fit each of the levellings with respect to a training set. This will also give us an idea to what extend the performances differ on disjoint test sets which is important to know when we decide on the effort to put in the selection of the levelling.

6.4 Training of Similarity Functions

The definition of the kernels given in sections 4.3 were made ad hoc. We belief that more elaborated similarities can improve the performance of the CSE algorithm. Instead of building improved similarities by hand, we may adapt the kernels with respect to the extraction task using training examples. The table score H is linear in any linear parameterization of the similarities for instance linear combinations of fixed kernels. Provided such a parametrization we can apply

generic training schemes for linear models as the one proposed in [13]. However, for sake of linearity are restricted to documents that contain on table only. Further, we depend on a fast convergence since the evaluation of H is expensive.

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