

# Approximate Structural Consistency

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**Abstract.** We consider documents as words and trees on some alphabet  $\Sigma$  and study how to compare them with some regular schemas on an alphabet  $\Sigma'$ . Given an input document  $I$ , we decide if it may be transformed into a document  $J$  which is  $\varepsilon$ -close to some target schema  $T$ : we show that this approximate decision problem can be efficiently solved. In the simple case where the transformation is the identity, we describe an approximate algorithm which decides if  $I$  is close to a target regular schema (DTD). This property is testable, i.e. can be solved in time independent of the size of the input document, by just sampling  $I$ . In the general case, the *Structural Consistency* decides if there is a transducer  $\mathcal{T}$  with at most  $m$  states such that  $I$  is  $\varepsilon$ -close to  $I'$  and his image  $\mathcal{T}(I')$  is both close to  $T$  and of size comparable to the size of  $I$ . We show that Structural Consistency is also testable, i.e. can be solved by sampling  $I$ .

## 1 Introduction

Property Testing [8, 5] considers approximations of decision problems, and is the basis for our approach. Testers for regular trees have been proposed in [6] and in [4] and extended to Data Exchange [3] where predefined constraints are given by a fixed transducer  $\mathcal{T}$  [2]. In this paper we extend the approach when  $\mathcal{T}$  is unknown, and we approximately decide if there exists a  $\mathcal{T}$  which satisfies the Data Exchange condition.

Documents are considered as large labeled, unranked, ordered trees on an alphabet  $\Sigma$  with attributes [7], in some source-schema  $S$  (regular language given by regular expression on word and DTD on trees), and need to be classified. We define a canonical problem, *Structural Consistency*, which decides if a large tree  $\tau_n$  close to some schema  $S$  can be transformed to a tree close to a regular target schema  $T$ . For a regular schema  $S$ , a tree  $\tau_n$  of size  $n$  is  $\varepsilon$ -close to  $S$  for  $0 \leq \varepsilon \leq 1$  if we can find  $\tau' \in S$  such that  $\text{dist}(\tau, \tau') \leq \varepsilon \cdot n$ . We use classical *transducers* on words and trees to transform the documents.

Some specific distance on documents, completely modifies the complexity of the basic questions, when we consider their approximate versions. Our goal is to show that some approximate classification problems can be simplified by the analysis of the statistics of schema and transducers to obtain algorithms with complexity independent of the size of the input structure.

Fix a source schema  $S$ , a target schema  $T$ , parameters  $k = 1/\varepsilon$  (the precision),

$\alpha$  (the ratio) and  $m$  (the number of states of a transducer  $\mathcal{T}$ ), where  $0 < \varepsilon \leq 1$  and  $0 < \alpha \leq 1$ . An input  $I$  is a word  $w_n$  or an unranked ordered tree  $\tau_n$  of size  $n$  following  $S$ .

**Structural Consistency:** Given a large input document  $I_n$  (word  $w_n$  or tree  $\tau_n$ ), decide if there is a transducer  $\mathcal{T}$  with at most  $m$  states and an input  $I'$   $\varepsilon$ -close to  $I$ , such that:  $\alpha \cdot n \leq |\mathcal{T}(I')| \leq n/\alpha$  and  $\mathcal{T}(I')$  is  $\varepsilon$ -close to  $T$ .

The transformed  $I'$  (word or tree) must satisfy two conditions: it must be of size proportional to  $n$  within a factor  $\alpha$ , and  $\varepsilon$ -close to the schema  $T$ . A transducer which satisfies both conditions is called  $\varepsilon, \alpha$  compatible. This problem captures the difficulties of Information Integration and Classification, as given target schemas  $T_1, \dots, T_k$  and an input document  $I$ , we can decide how to classify  $I$ , i.e. decide which schemas are  $\varepsilon, \alpha$  compatible for  $I$ . For simplicity, we first consider words  $w_n$  where the techniques are simpler and generalize them to trees. Our main results are:

**Theorem 4.1.** Structural Consistency is testable on words.

**Theorem 4.2.** Structural Consistency is testable on unranked ordered trees.

We associate to a word  $w_n$  the statistics vector  $\text{ustat}_k(w_n)$ , from which we can approximate any regular property [4]. In this paper we introduce a statistics matrix  $\text{ustat}_k(\tau_n)$ , for an unranked ordered tree  $\tau_n$ , from which we can similarly approximate any regular tree property. Regular schemas such as  $S$  and  $T$  are represented by unions of polytopes in the statistical space. A schema mapping  $\mu$  is a mapping between some summits of a polytope  $H_S$  for  $S$  and some summits of  $H_T$  for  $T$ . A transducer  $\pi$  provides a linear transformation between the source and the target statistics and may be  $\varepsilon, \alpha$  compatible for  $\mu$ . As we can efficiently enumerate all possible  $\varepsilon, \alpha$  compatible transformations, we obtain the results.

In section 2 we recall the basic notions on testers and the statistical embedding of [4] on words and trees. In section 3, we recall the basic results when the transformation is the identity, and in section 4 we study the Structural Consistency on words and trees.

## 2 Preliminaries

We consider classes of finite structures such as words and trees with possible attributes, and schemas are regular languages given by Tree-automata or DTDs. We approximate decision problems on such classes, given a distance between structures. We transform these structures with specific transducers.

**Approximation** The *Edit distance with moves* between two structures  $I$  and  $I'$ , written  $\text{dist}(I, I')$ , is the minimal number of elementary operations on  $I$  to obtain  $I'$ , divided by  $\max\{|I|, |I'|\}$ . An *elementary operation* on a structure  $I$  is either an *insertion*, a *deletion* of a node or of an edge, a *modification* of a letter (tag) or of an attribute value, or a *move*. For trees, a move consists in moving an entire subtree of  $\tau$  into another position; for words, it means moving a consecutive sequence of letter into another position. For simplicity, in this paper we transform structures ignoring attribute values. We say that two structures

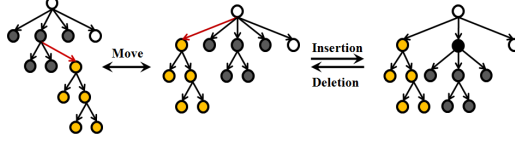


Fig. 1. Edit Distance with Moves: Elementary Operations

$U_n, V_m$  (words or trees), whose domains are respectively of size  $n$  and  $m$ , are  $\varepsilon$ -close if their distance  $\text{dist}(U_n, V_m)$  is less than  $\varepsilon \times \max\{n, m\}$ . They are  $\varepsilon$ -far if they are not  $\varepsilon$ -close. We use a classical weak approximation:

**Definition 1.** Let  $\varepsilon \geq 0$  be a real. An  $\varepsilon$ -tester for a property  $P$  is a randomized algorithm  $A$  such that: (1) If  $I$  satisfies  $P$ ,  $A$  always accepts; (2) If  $I$  is  $\varepsilon$ -far from  $P$ , then  $\Pr[A \text{ rejects}] \geq 2/3$ .

A property is *testable* if for every sufficiently small  $\varepsilon > 0$ , there exists an  $\varepsilon$ -tester whose time complexity depends only on  $\varepsilon$ .

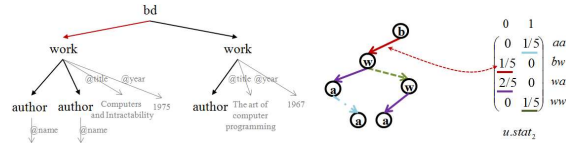
**Statistical embedding on strings.** For a finite alphabet  $\Sigma$  and a given  $\varepsilon$ , let  $k = \frac{1}{\varepsilon}$ . A word  $w$  of length  $n$  is embedded into a vector  $\text{ustat}_k$  of dimension  $|\Sigma|^k$ ;  $\text{ustat}_k(w)[u] \stackrel{\text{def}}{=} \frac{\#u}{n-k+1}$  where  $\#u$  is the number of occurrences of  $u$  (of length  $k$ ) in  $w$ . This embedding is called a  $k$ -gram in statistics, and is related to [1] where the subwords of length  $k$  are called *shingles*.

*Example 1.* For  $\Sigma = \{0, 1\}$ , and  $k = 2$ , let  $w$  be the word 00011111. The statistic of  $w$  written in the lexicographical order is  $\text{ustat}_2(w) = (2/7, 1/7, 0, 4/7)$ .

**Statistical embedding on trees.** We generalize  $k$ -grams on words to trees, using a matrix as in Figure 2. First, we transform an unranked tree with attributes (Fig. 2.(a)) into an extended binary tree<sup>1</sup>, using the classical Rabin encoding<sup>2</sup> (Fig. 2.(b)). In this encoding, paths of length  $k$  can be paths on the right successor, *i.e.* horizontal paths in  $\tau$ , paths on the left successor, *i.e.* vertical paths in  $\tau$ , or zigzags. There are  $2^{k-1}$  types of paths, and for each type we keep the classical  $\text{ustat}_k$  vector. For paths of length  $k$ , we associate their type as a boolean vector of length  $k - 1$ . We use 0 for the left branch and 1 for the right branch. For a tree  $\tau$ , let  $\text{ustat}_k(\tau)$  be the matrix with  $2^{k-1}$  columns and  $|\Sigma|^k$  lines. In column 1, we have the densities of paths of type 0..0, *i.e.* vertical paths in the original unranked tree. The last column describes paths of type 1..1, *i.e.* horizontal paths in the original unranked tree, and all the columns enumerate the  $2^{k-1}$  types. As the matrix is sparse we only enumerate some of the entries with their non zero probabilities.

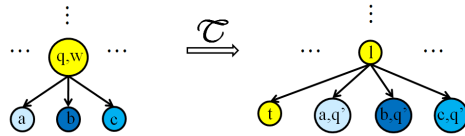
<sup>1</sup> An *extended* 2-ranked tree is a binary tree with a left successor, or a right successor or both.

<sup>2</sup> First child relations in the unranked tree are represented by left successors in the Rabin encoding, and next sibling relations are represented by right successors.



**Fig. 2.** A unranked tree with attributes, its Rabin encoding and its  $ustat_2$  matrix. null entries are not represented; the first line indicates the type of the column; “author” is abbreviated by  $a$ , “bd” by  $b$ , and “work” by  $w$ .

**Transformations** The transformations considered are simple top-down transductions which can be implemented by linear XSLT programs. A transducer in state  $q$  transforms a letter of  $\Sigma_S$  (resp. a labeled node with attributes node, for trees) into a word (resp. a hedge, for trees) and continues the transformation top down, i.e. on the next letter (children, for trees) in another state  $q'$ . For instance, in state  $q$ , a transition on trees, denoted  $(q, w) \rightarrow l(t, \underline{q}')$  transforms a node  $w$  into a node  $l$  with a first child  $\tau$  and outputs the transformation of the children of  $w$  below  $l$ , on the right of  $\tau$ , in state  $q'$ . This corresponds precisely to the linear restriction of a classical model of transduction of [7] and we restrict the study to deterministic transducers without  $\lambda$  transition.



**Fig. 3.** Local transformation  $(q, w) \rightarrow l(t, \underline{q}')$

### 3 Approximate Membership

This section recalls the basic membership testers for words and trees and gives a solution for Approximate Structural Consistency when the Transformation is the identity ( $\mathcal{T} = id$ ). In all the following, let  $\varepsilon$  be fixed and  $k = 1/\varepsilon$ .

The Tester decides Approximate Membership (for words and trees) is based on the following property: if  $I$  is close to some schema  $T$ ,  $I$  can be decomposed on simple loops, and then  $ustat_k(I)$  is  $\varepsilon$ -close to some polytope  $H_i^T$  of  $H_T = \bigcup_i H_i^T$ , i.e.  $\varepsilon$ -close to  $H_i^T = \sum_{t_i \in C} \lambda_i \cdot t_i$ , where  $\sum_i \lambda_i = 1$ , for some  $C \subseteq \{t_1, \dots, t_p\}$  of size at most  $d_T + 1$ , where  $d_T$  is the dimension of the target vectors (Caratheodory theorem). Observe that for  $I$  large enough,  $I$  is  $\varepsilon$ -close to  $I' = \prod_{i \in C} (u_i)^{\lambda_i \cdot n}$  for  $\lambda'_i = \frac{\lambda_i}{|u_i|}$ , as  $\lambda_i$  reflects the density of loops  $u_i$ . In order to obtain  $I'$  from  $I$ , moves have been applied to regroup all identical loops and non loops have been deleted.

### 3.1 Word Case

The word embedding associates  $\{\text{ustat}_k(w) : w \in r\}$  to a regular expression  $r$ , a union of polytopes  $H$  in the same space, such that the distance (for the  $L_1$  norm) between a vector and a union of polytopes is approximately  $\text{dist}(w, L(r))$ , as shown in [4]. For a simple regular expression such as  $(001)^*$ , the polytope is a unique summit, the *base vector*, which by definition is  $\lim_{n \rightarrow \infty} \text{ustat}((001)^n)$ . For a more general regular expression, the polytope is the convex hull of the base vectors, associated with compatible *simple loops*, i.e. simple loops for which there is a run which follows them. Consider a word  $w$  as the input  $I$ , and its  $\text{ustat}_k(w)$  vector. The embedding associates with  $T$  a finite set  $H^T$  of polytopes  $H_i^T$ , with summits  $t_1, \dots, t_p$ . Each geometrical summit  $t_i$  is associated with a set  $U_i = \{u_i^j\}$  of loops  $u_i^j$  ( $j$  is an index), and all the  $u_i^j$  have the same  $\text{ustat}$  vectors, i.e. correspond to the same geometrical summit  $t_i$ . Some of these loops  $u_i^j$  may be decomposed as smaller loops: if  $ab$  is a loop for an automaton associated with a schema  $T$ , so is  $abab, ba, \dots$ . For  $k = 2$ , they all have the same statistics. A finite set of loops  $\{u_i^j\}$  for  $i = 1, \dots, p$  is *compatible* if there is an input  $w$  which follows all these loops.

*Example 2.* Let  $k = 2 = 1/\varepsilon$ ,  $w = 000111$ ,  $T = (001)^*.1^*$ . For a lexicographic enumeration of the length 2 binary words,  $\text{ustat}_2(w) = (2/5, 1/5, 0, 2/5)$ . Let  $t = (1/3, 1/3, 1/3, 0)$  the base vector of the regular expression  $(001)^*$ , and similarly  $t' = (0, 0, 0, 1)$  for  $1^*$ . The polytope  $H$  associated with  $T$  is  $\text{Convex} - \text{Hull}(t, t') = \{\lambda.t + (1 - \lambda).t', \lambda \in [0, 1]\}$  and it approximates the set of  $\text{ustat}_2(w)$  when  $w \in T$ . The word  $w$  is at distance  $1/6$  to  $T$  as it requires the removal of the first 0 to yield the corrected word  $001.11 \in T$ .

The  $\text{ustat}_k(w)$  vector can be approximated for the  $L_1$  norm by taking  $N$  random samples to define the random variable  $\widehat{\text{ustat}}_k(w)$  which approximates  $\text{ustat}_k(w)$ . These techniques yield the simple testers of [4] for Membership  $(w, r)$  between a word  $w$  and a regular expression  $r$ . Take  $N \in O(\frac{|\Sigma|^{2/\varepsilon} \cdot \ln|\Sigma|}{\varepsilon^3})$  samples, and let  $\widehat{\text{ustat}}_k(w)$  be the  $\text{ustat}_k$  of the samples. We compute the set of polytopes  $H$  associated with  $r$  in the same space and reject if the geometrical distance from the point  $\widehat{\text{ustat}}_k(w)$  to  $H$  is greater than  $\varepsilon$ . If  $w$  is in  $r$  then  $\widehat{\text{ustat}}_k(w)$  is close to  $H$  and the membership test accepts. On the other hand, if  $w$  is  $\varepsilon$ -far from the regular expression  $r$ , then the tester rejects with high probabilities. This shows that the approximate Membership is testable on words.

### 3.2 Tree Case

**Sampling.** The  $\text{ustat}_k(\tau)$  can be approximated, for the  $L_1$  norm, by taking random samples as follows. Select with the uniform distribution a random node  $i$  of  $\tau$  and let  $\widehat{\text{ustat}}_k(\tau)$  be the random matrix where we add each path of length  $k - 1$  from  $i$  as a unit in the corresponding position (type, labels). After  $N$  samples, we divide by the numbers of units. Observe that  $E(\widehat{\text{ustat}}_k(\tau)) = \text{ustat}_k(\tau)$ , and that a Chernoff bound will determine  $N = O(k^5 \cdot |2\Sigma|^{2k} \cdot \ln(\Sigma))$  with  $k = 1/\varepsilon$ , to insure that  $|\text{ustat}_k(\tau) - \widehat{\text{ustat}}_k(\tau)| \leq \varepsilon$ , with high probabilities.

**DTD Embedding** We now generalize the notion of base loop from words to trees. We associate a set of *base loops*  $\tau_i$  to a DTD  $T$ , i.e. a set of minimal 2-extended tree  $\tau_i$  in a Rabin Encoding with a distinguished leaf *compatible* with the root of  $\tau_i$ , i.e. with the same label and free successors to accept iterations. If the root of  $\tau_i$  has one left successor, the distinguished element of  $\tau_i$  has a free left successor, and similarly for the right successor or both successors. The base loop  $\tau_i$  has at least two nodes and the distinguished element is underlined, for example  $\tau_i = a(b, \underline{a})$  or  $a(., \underline{a})$ . We define  $(\tau_i)^m$  as the  $m$ -th iteration of the tree  $\tau_i$  on the distinguished element. Let  $\tau_a$  be a *terminal tree* with a root labeled  $a$  associated with a DTD, in a Rabin Encoding, i.e. a valid subtree for the label  $a$  and no label occurs twice in a path. For each base loop  $\tau_i$ , a *derived loop* from  $\tau_i$  is a base loop  $\tau_i$  where some terminal trees  $\tau_a$  are connected to possible nodes  $a$  of  $\tau_i$ . There are finitely many distinct terminal trees  $\tau_a$  for each letter  $a$ . With each base loop and derived loop, we associate a *base matrix*  $t_i = \lim_{n \rightarrow \infty} \text{ustat}_k((\tau_i)^n)$ . The set of  $\text{ustat}_k(\tau)$  for  $\tau \in T$  is a union of polytope  $H_i^T$  which is the Convex-Hull  $(\tau_1^*, \dots, \tau_l^*)$  of the base vectors of compatible base loops, restricted to some additional linear constraints. If  $\text{ustat}_k(\tau)$  is  $\varepsilon$ -close to  $H_i$ , then it is also close to  $\sum_{s_i \in C} \lambda_i \cdot \tau_i^*$  where  $C \subseteq \{\tau_1^*, \dots, \tau_p^*\}$  of size at most  $d_T + 1$ , where  $d_T$  is the dimension of the vectors, i.e.  $2^{k-1} \cdot |\Sigma_T|$ .

*Example 3.* Consider the DTD given by the four rules:  $\{\text{root} : a^*b ; a : c.d ; c : a.f + g ; b : e^*\}$ . The base loops are:  $\tau_1 = a(., \underline{a})$ ,  $\tau_2 = e(., \underline{e})$ ,  $\tau_3 = a(c(\underline{a}(., f), d), .)$ , as the "." indicates the absence of successor. A terminal tree for  $a$  is  $\tau_a = a(c(g, d), .)$  and a terminal tree for  $c$  is  $\tau_c = c(g, .)$ . A derived loop from  $\tau_1$  is  $\tau_4 = a(c(g, d), \underline{a})$ . On the unranked trees, the base loops are equivalent to:  $a^*$ ,  $e^*$  and  $a(c(\underline{a}(., f), d), .)^*$ . The base matrices for  $k = 2$ , with the notation of sparse matrices, are:

$$\begin{array}{|c|c|c|} \hline t_1 & 0 & 1 \\ \hline aa & 0 & 1 \\ \hline \end{array}, \begin{array}{|c|c|c|} \hline t_2 & 0 & 1 \\ \hline ee & 0 & 1 \\ \hline \end{array}, \begin{array}{|c|c|c|} \hline t_3 & 0 & 1 \\ \hline ac & 1/4 & 0 \\ af & 0 & 1/4 \\ ca & 1/4 & 0 \\ cd & 0 & 1/4 \\ \hline \end{array} \quad \text{and} \quad \begin{array}{|c|c|c|} \hline t_4 & 0 & 1 \\ \hline aa & 1/4 & 0 \\ ac & 0 & 1/4 \\ cd & 1/4 & 0 \\ cf & 0 & 1/4 \\ \hline \end{array} \quad \text{for the derived loop } t_4.$$

If  $\tau$  is  $\varepsilon$ -close to the DTD, then  $\text{ustat}_k(\tau)$  is  $\varepsilon$ -close to

$$H = \left\{ \lambda_1 \cdot t_1 + \lambda_2 \cdot t_2 + \lambda_3 \cdot t_3 + \lambda_4 \cdot t_4 \mid \sum_i \lambda_i = 1 \right\}.$$

#### **$\varepsilon$ -Membership Tester.**

1. Sample  $\tau$  (in a Rabin encoding) with  $N \in O\left(\frac{|2\Sigma_S|^{2/\varepsilon} \ln(\Sigma_S)}{\varepsilon^5}\right)$  samples, and let  $\widehat{\text{ustat}}_k(\tau)$  be the estimation of  $\text{ustat}_k(\tau)$ .
2. Enumerate all possible polytope  $H_T$  and Accept if one is  $\varepsilon$ -close to  $\widehat{\text{ustat}}_k(\tau)$ , else Reject.

This shows that Membership is testable on unranked trees. The argument is similar to the case of words and the complexity is  $O(1)$  for the size  $n$  of the tree  $\tau$  but exponential in the size of the DTDs.

## 4 Approximate Structural Consistency

Fix a source schema  $S$ , a target schema  $T$  and parameters  $k = 1/\varepsilon$  (the precision),  $\alpha$  (the ratio) and  $m$  (the number of states of a transducer  $\mathcal{T}$ ). Given an input (word or tree of size  $n$ ) in  $S$ , we decide if there is a transducer  $\mathcal{T}$  with  $m$  states,  $I'$   $\varepsilon$ -close to  $I$  such that  $\mathcal{T}(I')$  is  $\varepsilon$ -close to  $T$  and  $\alpha \cdot n \leq |\mathcal{T}(I')| \leq n/\alpha$ . We approximate the  $k$  statistics of  $I$  by sampling, consider some possible *base mappings* or *schema mappings*  $\mu$  between the summits of  $H_S$  and the summits of  $H_T$ , and some compatible 1-state transducer  $\pi$  associated with  $\mu$ . The important observation is that we can enumerate all possible  $\mu, \pi$  in time independent of  $n$ . We then decide if there are  $m$  input mappings  $\pi_1, \dots, \pi_m$  defining  $\mathcal{T}$  such that  $I$  is  $\varepsilon$ -close to  $I' = I'_1 \cdot I'_2 \cdot \dots \cdot I'_m$  such that  $\mathcal{T}(I') = \pi_1(I'_1) \cdot \dots \cdot \pi_m(I'_m)$  and  $\alpha \cdot n \leq |\mathcal{T}(I')| \leq n/\alpha$ . The total number of operations is independent of  $n$ .

**Sampling and decomposition** The embedding associates with  $S$  a finite set  $H^S$  of polytopes  $H_i^S$ , with summits  $s_1, \dots, s_p$ . Each geometrical summit  $s_i$  is associated with a set  $U_i$  of base loops.  $U_i = \{u_i^j\}$ , and all  $u_i^j$  have the same **ustat** vectors, i.e. correspond to a summit  $s_i^j$  which coincide with the geometrical summit  $s_i$ . These loops cannot be decomposed as smaller loops, and are compatible, i.e. there is an input  $I$  which follows these loops. Similarly for  $T$ , we have a finite set of polytopes  $H_j^T$  with summits  $t_1, \dots, t_q$ . Given an input  $I$  (word  $w_n$  or tree  $t_n$ ) close to some schema  $S$ , we first take  $N$  samples as before, and  $x = \widehat{\text{ustat}}_k(I)$ . We decompose  $x$  on a simplex for some polytope  $H_i^S$  of  $H_S$ , i.e.  $\text{ustat}_k(I)$  is  $\varepsilon$ -close to  $\sum_{s_i \in C} \lambda_i \cdot s_i$ , where  $\sum_i \lambda_i = 1$ , for some  $C \subseteq \{s_1, \dots, s_p\}$  of size at most  $d_S + 1$ , where  $d_S$  is the dimension of the source vectors. Observe that for large enough  $I$ , it is  $\varepsilon$ -close to  $I' = \prod_{i \in C} (u_i)^{\lambda_i \cdot n}$  for  $\lambda'_i = \frac{\lambda_i}{|u_i|}$ , as  $\lambda_i$  reflects the density of loops  $u_i$ . In order to obtain  $w'$  from  $w$ , some *moves* are applied to regroup all identical loops and non loops are deleted. In the decomposition, we can assume that each  $\lambda_i > \frac{\varepsilon}{d_S} = c$ . Otherwise we can find another input  $\varepsilon$ -close to  $I$  by deleting a few symbols and rounding the small coefficient to 0. The symbols are characters for the words and nodes for the trees.

**Base mappings** Let  $\{s_1, \dots, s_p\}$  the set of summits of  $H_i^S$ , and  $C \subseteq \{s_1, \dots, s_p\}$  of size at most  $d_S + 1$ , where  $d_S$  is the dimension of the source vectors. If  $\text{ustat}_k(w)$  is  $\varepsilon$ -close to  $H_i$ , then it is also close to  $\sum_{s_i \in C} \lambda_i \cdot s_i$  by Caratheodory's theorem, and the  $\lambda_i$  are larger than a fixed value  $c$ . Similarly let  $H_j^T$  be one of the polytopes associated with the schema  $T$  and let  $D \subseteq \{t_1, \dots, t_q\}$  of size at most  $d_T + 1$ , where  $d_T$  is the dimension of the target vectors.

**Definition 2.** A (partial) base mapping  $\mu$  between  $S$  and  $T$  is a partial function  $H_i^S \rightarrow H_j^T$ , only defined on some summits of the polytope, i.e.  $\mu(s_i) = t_j$  for  $s_i \in C$  and  $t_j \in D$ . A 1-state transducer  $\pi$  between  $S$  and  $T$ , is compatible with  $\mu$ , if  $\pi(u_i) = v_j$  if  $\mu(s_i) = t_j$ ,  $s_i = \text{ustat}_k(u_i)$  and  $t_j = \text{ustat}_k(v_j)$ .

In the case of words,  $\pi : \Sigma_S \rightarrow \Sigma_T^*$  and we talk about a  $\pi$  mapping. The domain of  $\mu$  is  $C$  and the range is  $D$ . Each summit  $s_i$  corresponds to a base loop of the regular schema  $S$ , i.e. a minimal word  $u_i$  which can be iterated, and similarly each  $t_j$  corresponds to a base loop  $v_j$  for the regular schema  $T$ . Let  $\alpha_i = \frac{|v_j|}{|u_i|}$  be the ratio between the length of the target loop and the source loop and  $\lambda'_i = \frac{\lambda_i}{|u_i|}$ . A  $\mu$ -compatible mapping  $\pi$  is  $(\varepsilon, \alpha)$ -feasible for the decomposition  $\sum_{i \in C} \lambda_i \cdot s_i$  on  $C$  if there exists  $w' = \prod_{i \in C} (u_i)^{\lambda'_i \cdot n}$ ,  $\varepsilon$ -close to  $w$ , such that  $\alpha \leq \frac{\sum_{s_i \in C} \alpha_i \cdot \lambda'_i}{\sum_{s_i \in C} \lambda'_i} \leq \frac{1}{\alpha}$ .

#### 4.1 Words

Notice that if  $W = \pi(w')$  is the source transformed by  $\pi$ , then  $\alpha \cdot |w| \leq |W| \leq |w|/\alpha$ . An  $(\varepsilon, \alpha)$ -feasible  $\mu$ -compatible mapping  $\pi$  yields directly a 1-state transducer.

**Lemma 1.** If  $w$  is  $\varepsilon$ -close to  $S$  and there exists a  $\mu$ -compatible mapping  $\pi$  which is  $(\varepsilon, \alpha)$ -feasible, there exists an  $(\varepsilon, \alpha)$ -feasible 1-state transducer  $\mathcal{T}$  for  $w, S, T$ .

*Proof.* If there is a  $\mu$ -compatible mapping  $\pi$ , then  $\text{ustat}_k(w)$  is  $\varepsilon$ -close to  $\sum_{s_i \in C} \lambda_i \cdot s_i$ , where  $\sum_i \lambda_i = 1$ , for some  $C \subseteq \{s_1, \dots, s_p\}$  of size at most  $d_S + 1$ . Observe that for  $w$  large enough,  $w$  is  $\varepsilon$ -close to  $w' = \prod_{i \in C} (u_i)^{\lambda'_i \cdot n}$ , as  $\lambda_i$  is the density of loops  $u_i$  in  $w$  and the number of iteration of each loop is  $\lambda'_i \cdot n = \frac{\lambda_i}{|u_i|} \cdot n$  after some rounding. If we erase all the letters of  $w$  which are not loops, and apply moves to regroup all identical loops, we obtain  $w'$   $\varepsilon$ -close to  $w$ . Let  $\mathcal{T}$  the 1-state transducer associated with  $\pi$ , with transitions  $a/\pi(a)$  for  $a \in \Sigma_S$ . By definition,  $\alpha_i$  is the expansion on loop  $u_i$  and the total expansion on  $w'$  is less than  $\alpha$ . Because  $\text{ustat}_k(w') = \sum_{i \in C} \lambda_i \cdot s_i$ ,  $W = \pi(w')$  is such that  $\text{ustat}_k(\pi(w')) = \sum_{i \in C} \lambda_i \cdot \mu(s_i) = \sum_{j \in D} \lambda_j^T \cdot t_j$  where  $\lambda_j^T = \sum_{i \in C, \mu(s_i)=t_j} \lambda_i$ , hence  $\pi(w')$  is  $\varepsilon$  close to  $T$ .

*Example 4.* Let  $k = 2 = 1/\varepsilon$  and  $S = (001)^* \cdot (01)^* \cdot 1^* \cdot (011)^*$  with  $\Sigma_S = \{0, 1\}$  as in the previous example, with summits  $\{s_0, s_1, s_2, s_3\}$  associated with the simple loops  $u_0 = (001), u_1 = (01), u_2 = 1, u_3 = (011)$  and  $d_S = 2^2$ . Let  $T = (ab)^* \cdot a^* \cdot (abc)^*$  with  $\Sigma_T = \{a, b, c\}$ ,  $d_T = 3^2$ , and  $H_T$  be the polytope with summits  $\{t_0, t_1, t_2\}$  associated with the simple loops  $v_0 = ab, v_1 = a$  and  $v_2 = abc$ . Let  $w_1 = 0101111 = (01)^2 \cdot 1^3 \in S$ . Let  $\mu(s_1) = t_0, \mu(s_2) = t_1$  as in figure ?? and let  $\pi(0) = b, \pi(1) = a$ , which is  $\mu$ -compatible as  $\pi(u_1) = \pi(01) = ba, \pi(u_2) = \pi(1) = a$ , and  $\text{ustat}_2(\pi(u_1)^*) = \text{ustat}_2((ba)^*) = \text{ustat}_2((ab)^*) = \text{ustat}_2((v_0)^*)$  and  $\text{ustat}_2(\pi(u_2)^*) = \text{ustat}_2((v_1)^*)$ . In this case, the 1-state transducer  $\mathcal{T}$  is such that  $\mathcal{T}(0) = b$  and  $\mathcal{T}(1) = b$ , and  $(0, 1)$ -feasible for  $w_1$ , i.e.  $\alpha = 1$ , and  $\varepsilon = 0$ . If we consider  $w = 000111$ ,  $1/6$ -close to  $w' = 00111 \in S$ ,  $\mathcal{T}(w') = bbaaa$ , at distance  $2/5$  from  $T$  and  $\alpha = 5/6$ . Therefore  $\mathcal{T}$  is  $(2/5, 5/6)$ -feasible for  $w$ .



We now generalize to transducers with  $m$  states and consider  $m$  distinct base mappings  $\mu_1, \dots, \mu_m$ , and  $\mu$ -compatible mappings  $\pi_1, \dots, \pi_m$  for the same  $H_i^S$  and  $H_j^T$ . We first describe a Verification Algorithm, which given  $\pi_1, \dots, \pi_m$ ,  $C$  a subset of summits of  $H_i^S$ ,  $D$  a subset of summits of  $H_j^T$ , such that  $\text{ustat}_k(w)$  is  $\varepsilon$ -close to  $\sum_{s_i \in C} \lambda_i \cdot s_i$ , where  $\sum_i \lambda_i = 1$ , decides if there is an  $(\varepsilon, \alpha)$ -feasible transducer  $\mathcal{T}$  with  $m$  states for  $w, C, D$ . We can find  $w'$   $\varepsilon$ -close to  $w$ , such that  $w' = \prod_{i \in C} (u_i)^{\lambda_i \cdot n}$  for  $\lambda_i = \frac{\lambda_i}{|u_i|}$  and can also decompose  $w'$  into  $m$  components  $w'_1, \dots, w'_m$ , i.e.  $w'' = w'_1 \dots w'_m = (\prod_{i \in C} (u_i)^{\lambda_i^{1 \cdot n}})_1 \dots (\prod_{i \in C} (u_i)^{\lambda_i^{m \cdot n}})_m$  such that  $\sum_{j=1 \dots m} \lambda_i^j = \lambda_i$ . We divide each  $\lambda_i$  into positive  $\lambda_i^j$  associated with the mapping  $\pi_j$  for  $j = 1, \dots, m$  and some of the  $\lambda_i^j$  are 0. Each  $\pi_j$  gives an expansion  $\alpha_i^j$  for each loop  $u_i$  such that  $s_i \in C$ . The general expansion on  $u_i$  is  $\alpha_i = \frac{\sum_{j=1 \dots m} \lambda_i^j \cdot \alpha_i^j}{\lambda_i}$  and the global expansion is  $\alpha_g = \frac{\sum_{s_i \in C} \lambda_i \cdot \alpha_i}{\sum_{s_i \in C} \lambda_i}$  which is either larger or smaller than 1. We can then write two Linear programs with positive variables  $\{\lambda_i^j, \alpha_i, \alpha_g\}$ , whereas  $\lambda_i, \lambda_i$  and  $\alpha_i^j$  are constants, and  $s_i \in C$ , one for the case  $\alpha_g \leq 1$  and the other for the case  $\alpha_g \geq 1$  :

**Linear Programs**  $P(C, \lambda_i)$

$$\text{Min } (1 - \alpha_g) \geq 0 \text{ [case of } \alpha_g \leq 1]$$

$$\text{Min } (\alpha_g - 1) \geq 0 \text{ [case of } \alpha_g \geq 1]$$

$$\alpha_i = \frac{\sum_{j=1 \dots m} \lambda_i^j \cdot \alpha_i^j}{\lambda_i}, \quad \alpha_g = \frac{\sum_{s_i \in C} \lambda_i \cdot \alpha_i}{\sum_{s_i \in C} \lambda_i}, \quad \lambda_i = \frac{\lambda_i \cdot n}{|u_i|}, \quad \sum_{j=1 \dots m} \lambda_i^j =$$

$\lambda_i$ .

Let  $\mathcal{T}_m$  be the transducer with  $m$  states operating on  $w''$ ,  $\varepsilon$ -close to  $w$ , i.e. applying  $\pi_j$  on  $w'_j$  in state  $j$ , for  $j = 1, \dots, m$ . We solve both linear systems and compare the parameter  $\alpha_g$  to  $\alpha$  to decide if the transducer  $\mathcal{T}_m$  is  $(\varepsilon, \alpha)$ -feasible.

**Lemma 2.** *If the solution of the linear programs  $P$  is such that  $\alpha \leq \alpha_g \leq 1$  or  $1 \leq \alpha_g \leq \frac{1}{\alpha}$ , then  $\mathcal{T}_m$  is  $(\varepsilon, \alpha)$ -feasible for large enough inputs.*

*Proof.* Notice that  $w$  is  $\varepsilon$ -close to  $w' = \prod_{i \in C} (u_i)^{\lambda_i}$  for  $\lambda_i = \frac{\lambda_i}{|u_i|}$  and to

$$w'' = w'_1 \dots w'_m = (\prod_{i \in C} (u_i)^{\lambda_i^{1 \cdot n}})_1 \dots (\prod_{i \in C} (u_i)^{\lambda_i^{m \cdot n}})_m \text{ such that } \sum_{j=1 \dots m} \lambda_i^j = \lambda_i.$$

The solution of the linear program, if it exists, insures that the expansion factor is within  $\alpha$  but may yield non integer values to the  $\lambda_i^j$ . We round to the closest integer modifying slightly  $w''$  into  $w'''$ , which is still  $\varepsilon$ -close to  $w$ . By construction the image  $\mathcal{T}_m(w''')$  is in  $T$  and the transducer  $\mathcal{T}_m$  is  $(\varepsilon, \alpha)$ -feasible.

**Verification Algorithm**  $A(w, C, D, \pi_1, \dots, \pi_m)$ .

1. Decompose  $\widehat{\text{ustat}}_k(w)$  (which approximates  $\text{ustat}_k(w)$ )  $\varepsilon$ -close to  $\sum_{i \in C} \lambda_i \cdot s_i$ , otherwise reject.

2. Solve the linear programs  $P(C, \lambda_i)$ .
3. If  $\alpha \leq \alpha_g \leq 1$  or  $1 \leq \frac{1}{\alpha_g} \leq \frac{1}{\alpha}$ , accept else reject.

**Tester for the Existence of an  $(\varepsilon, \alpha)$ -feasible transducer:**  $TE(w, S, T, \varepsilon, \alpha, m)$ .

1. Sample  $w$  with  $N \in O(\frac{|\Sigma_S|^{2/\varepsilon} \cdot \ln|\Sigma_S|}{\varepsilon^3})$  samples, and let  $\widehat{\text{ustat}}_k(w)$  be the estimation of  $\text{ustat}_k(w)$ .
2. Choose a possible polytope  $H_S$ ,  $\varepsilon$ -close to  $\widehat{\text{ustat}}_k(w)$ .
3. Enumerate all possible  $C, D$ , all possible base mappings  $\mu$ , and all  $\mu$ -feasible  $\pi$ . Accept if one  $A(w, C, D, \pi_1, \dots, \pi_m)$  accepts, else Reject.

**Theorem 1.** *If there exists an  $(\varepsilon, \alpha)$ -feasible transducer with at most  $m$  states, then  $TE(w, S, T, \varepsilon, \alpha, m)$  accepts. If  $w$  is  $\varepsilon$ -far from any  $w'$  such that there exists an  $(\varepsilon, \alpha)$ -feasible transducer with at most  $m$  states, then  $TE(w, S, T, \varepsilon, \alpha, m)$  rejects with high probabilities.*

*Proof.* If there exists an  $(\varepsilon, \alpha)$ -feasible transducer for  $w$ , it must transform a simple loop of  $S$  into a simple loop of  $T$ . Otherwise if  $w = (u_i)^j$ , its image may be far from  $T$ . Therefore each state corresponds to some base mapping  $\mu$  and to some  $\mu$ -compatible mapping  $\pi$ . We generate all possible mappings for  $m$  states. Because each  $\lambda_i > c$ , the number of possible mappings  $\pi$  is independent of  $n$ , and only depends on  $\varepsilon$  and the dimensions. For the right choice, the Verification will accept and so will do the Tester  $TE$ . If  $w$  is  $\varepsilon$ -far from any  $w'$  for which there exists an  $(\varepsilon, \alpha)$ -feasible transducer for  $w$ , then either  $\text{ustat}_k(w)$  is  $\varepsilon$ -far from any polytope  $H_S$  and this condition is detected with high probability from  $\widehat{\text{ustat}}_k(w)$ , or  $\text{ustat}_k(w)$  is  $\varepsilon$ -close to a polytope  $H_S$  and to some  $\sum_{i \in C} \lambda_i \cdot s_i$  but no mapping can map simple loops of  $s_i$  to simple loops of  $t_j$ . This last condition is detected as we analyze all possibilities.

## 4.2 Trees

Recall that we associate a union of polytopes to a DTD. Let  $C \subseteq \{s_1, \dots, s_p\}$  be a polytope described by its summits. To each summit  $s_i$  corresponds a set of base loops  $\tau_i$ , i.e. extended binary trees (in a Rabin encoding) which can be iterated, with the same statistics. As in definition 2, a (partial) base mapping  $\mu$  between two schemas  $S$  and  $T$  is a partial function  $H_i^S \rightarrow H_j^T$ , only defined on some summits of the polytopes, i.e.  $\mu(s_i) = t_j$  for  $s_i \in C$  and  $t_j \in D$ . A 1-state transducer  $\pi$  between  $S$  and  $T$ , is *compatible with*  $\mu$ , if  $\pi(\tau_i) = \tau_j$  if  $\mu(s_i) = t_j$ ,  $\text{ustat}_k(\tau_i) = s_i$  and  $\text{ustat}_k(\tau_j) = t_j$ . In this case  $\pi$  transforms trees. We follow an approach similar to the word case. We first estimate  $\widehat{\text{ustat}}_k(\tau)$  which approximates  $\text{ustat}_k(\tau)$ . If  $\tau$  is close to  $S$ , then  $\text{ustat}_k(\tau)$  has a decomposition on a polytope  $H^S$ , i.e.  $\text{ustat}_k(\tau)$  is close to  $\sum_{i \in C} \lambda_i \cdot s_i$  for some summits  $C$  of  $H$ , where  $s_i$  are the base matrices. The tree  $\tau$  is close to  $\tau' = \prod_{i \in C} (t_i)^{\lambda'_i \cdot n}$  for  $n$  large enough, where each base or derived loop  $\tau_i$  is iterated  $\lambda'_i \cdot n$  times after some

rounding, as we regroup similar loops with moves and erase the other subtrees, for  $\lambda'_i = \frac{\lambda_i}{|t_i|}$ . For a given  $\pi$ , let  $\alpha_i = \frac{|t'_i|}{|t_i|}$  the ratio between the length of the target loop and the source loop. A  $\mu$ -compatible mapping  $\pi$  is  $\varepsilon, \alpha$ -feasible for the decomposition  $\sum_{i \in C} \lambda_i \cdot s_i$  on  $C$  if there exists  $\tau'$   $\varepsilon$ -close to  $\tau$  such that  $\frac{\sum_{s_i \in C} \alpha_i \cdot \lambda'_i}{\sum_{s_i \in C} \lambda'_i} \leq \alpha$  and  $\alpha \cdot |\tau| \leq |\pi(\tau')| \leq |\tau|/\alpha$ .

*Example 5.* Consider the following source **S**, target **T** DTDs and  $\varepsilon = \frac{1}{2}$  fixed, i.e.

```

k = 2. S <!ELEMENT bd (work*)>
        <!ELEMENT work (author+)>
        <!ATTLIST work title CDATA year CDATA>
        <!ELEMENT author (EMPTY)>
        <!ATTLIST author name CDATA #REQUIRED>
T <!ELEMENT bib (livre*,editeur)>
        <!ELEMENT livre (titre, auteur+)>
        <!ELEMENT auteur #PCDATA>
        <!ELEMENT titre #PCDATA>

```

We use the standard abbreviations of the tags, where *bd* and *bib* are abbreviated by *b*. Let  $\tau$  be a large tree of **S** and assume that sampling  $\tau$  gives us a matrix:  $\widehat{\text{ustat}}_2(\tau)$ . Let us explicit a  $(1/2, 3/4)$ -feasible one state transducer. The loops of the schema  $S$  are  $\tau_1 = w(a, \underline{w})$  and  $\tau_2 = a(\cdot, \underline{a})$ . For  $k = 2$ , their statistical representation are  $s_1$  and  $s_2$ . The schema **T** has two loops:  $l(t(\cdot, a), \underline{l})$  and  $a(\cdot, \underline{a})$ , whose statistical representations are  $t'_1$  and  $t'_2$  :

$$\begin{array}{c}
s_1 \left| \begin{array}{cc} 0 & 1 \\ 1/2 & 0 \\ 0 & 1/2 \end{array} \right. , \quad s_2 \left| \begin{array}{cc} 0 & 1 \\ 0 & 1 \end{array} \right. , \quad \widehat{\text{ustat}}_2(\tau) \left| \begin{array}{cc} 0 & 1 \\ \text{aa} & 0.59 \\ \text{bw} & 0.01 \quad 0 \\ \text{wa} & 0.2 \quad 0 \\ \text{ww} & 0 \quad 0.2 \end{array} \right. , \quad t'_1 \left| \begin{array}{cc} 0 & 1 \\ \text{ll} & 0 \quad 1/3 \\ \text{lt} & 1/3 \quad 0 \\ \text{ta} & 0 \quad 1/3 \end{array} \right. \quad \text{and} \quad t'_2 \left| \begin{array}{cc} 0 & 1 \\ \text{aa} & 0 \quad 1 \end{array} \right. .
\end{array}$$

Take the base mapping  $\mu(s_1) = t'_1$  and  $\mu(s_2) = t'_2$ . A possible admissible one state transducer  $\pi$  compatible with  $\mu$  given below by the transition rules in a compact formalism :  $(q, b) \rightarrow b(q, \cdot)$  ;  $(q, w) \rightarrow l(t, \underline{q})$  ;  $(q, a) \rightarrow a, \underline{q}$ . Since the nodes 'bd', 'bib' and 'editeur' have a small impact on the statistics for big trees of **S** and **T**, only loops are considered. Decomposed over  $H_S$ ,  $\widehat{\text{ustat}}_2 \approx 0.6 \cdot s_1 + 0.4 \cdot s_2$ . The distortion produced by the second rule is  $3/2$  and the third rule preserves size i.e. the total distortion is  $0.6 \times \frac{3}{2} + 0.4 \times 1 = 1.3$  and it's inverse ( $\approx 0.76923$ ) is higher than  $3/4$ .

The generalization to transducers with  $m$  states is similar to the case of words. We consider  $m$  distinct base mappings  $\mu_1, \dots, \mu_m$ ,  $\mu$ -compatible mappings  $\pi_1, \dots, \pi_m$  and decompose the tree  $\tau$  into a forest with  $m$  components  $\tau'_1, \dots, \tau'_m$ , i.e.  $\tau'' = \tau'_1, \dots, \tau'_m = (\prod_{i \in C} (t_i)^{\lambda'_i})_1 \dots (\prod_{i \in C} (\tau_i)^{\lambda'_i})_m$  such that  $\sum_{j=1 \dots m} \lambda'_i{}^j = \lambda'_i$ . The forest  $\tau''$  is  $\varepsilon$ -close to  $\tau$ , as we apply a limited number of moves. We use a linear program  $P'(C, \lambda_i)$  to decide if we can find the  $\lambda'_i{}^j$ , and a verification algorithm  $A'(t, S, T; C, \pi_1, \dots, \pi_m)$ , as in the case of words. We can use the same Verification algorithm and the Tester but for  $N \in O\left(\frac{|2\Sigma_S|^{2/\varepsilon} \cdot \ln(|\Sigma_S|)}{\varepsilon^5}\right)$  samples. The number of possible  $C$  is bounded by the dimension  $|\Sigma_S|^k \cdot 2^{k-1}$ , and the number of possible  $\mu$  is also bounded. We need to bound the number of possible  $\pi$ , as in the case of words by the following lemma:

**Lemma 3.** *If there exists an  $\varepsilon, \alpha$ -feasible  $\mu$ -compatible mapping  $\pi$ , then  $|\pi(a)| \leq \frac{1}{c \cdot \alpha}$  for each letter  $a \in \Sigma_S$ .*

*Proof.* Recall that as in the case of words, the  $\lambda_i$  coefficients of the decomposition can be supposed greater than a constant  $c < 1$ . If the expansion  $|\pi(a)|$  was larger than  $\frac{1}{c\alpha}$ , the global expansion would be larger than  $\alpha$ .

We can finally state our main result:

**Theorem 2.** *If there exists an  $(\varepsilon, \alpha)$ -feasible transducer with at most  $m$  states, then  $TES(\tau, S, T, \varepsilon, \alpha, m)$  accepts. If  $\tau$  is  $\varepsilon$ -far from any  $\tau'$  such that there exists an  $(\varepsilon, \alpha)$ -feasible transducer with at most  $m$  states, then  $TES(\tau, S, T, \varepsilon, \alpha, m)$  rejects with high probabilities.*

## 5 Conclusion

The approximate embedding of trees and tree languages proposed in this paper gives an efficient solution to decide Approximate Structural Consistency, as the complexity of the algorithms only depends on the accuracy parameters. The methods are also robust to some noise ratio, as the statistics matrices are close on close inputs. We did not specify the exact complexity of the algorithms as a function of the size of the DTD and leave it as an open problem. Structural Consistency can also be applied to documents which do not have a schema, such as data words or streams but an input schema guarantees a much smaller number of potential mappings. General problems in formal languages and rewriting systems are often hard in their exact versions and approximate solutions are natural.

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