Learning a Subclass of Deterministic Regular Expression with Counting

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Abstract. In this paper, we propose a subclass of single-occurrence regular expressions with counting (cSOREs) and give a learning algorithm of cSOREs. First, we learn a SORE. Then, we construct a *countable finite automaton* (CFA) by traversing the syntax tree of the obtained SORE. Next, the CFA runs on the given finite sample to obtain the minimum and maximum number of repetitions of the subexpressions under the iteration operators. Finally we obtain a cSORE by traversing the syntax tree and introducing the counting operators. Our algorithm not only can learn a cSORE, which is expressive enough to cover more XML data, but also has better generalization ability for smaller sample.

Keywords: Schema inference · Regular expressions · Counting

1 Introduction

The eXtensible Markup Language (XML), which has been widely used on the Web, is the lingua franca for data exchange [1]. The schema languages (such as DTD (Document Type Definitions) and XSD (XML Schema Definitions) recommended by W3C (World Wide Web Consortium) [24]) have advantages for diverse applications such as data processing, automatic data integration, and static analysis of transformations [12,21,22]. However, many XML documents on the Web are not accompanied by a schema [3,23], or valid schema [6,7], therefore, schema inference becomes an essential work.

Schema inference can be reduced to learning regular expressions from sets of positive samples. Using techniques from Gold [16], the class of regular expressions cannot be learned only from positive data. Even Bex et al. proved in [5] that the class of deterministic regular expressions cannot be learned from positive data. Therefore for practical purposes many researchers turned to focus on learning subclasses of deterministic regular expressions [4,5,8,9,13,14,25].

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Deterministic regular expressions [11] require that each symbol in the input word can unambiguously be matched to a position in the regular expression without looking ahead in the word. In practice, there are many applications of the subclass of deterministic regular expressions on the Web, including that of single-occurrence regular expressions (SOREs) [8,9]. However, SOREs, which do not support counting, are defined on standard regular expressions. Regular expressions with counting, which are used in XML Schema [10,15,17–20,25], are extended from standard regular expressions by adding counting [15]. In this paper, we propose a subclass of single-occurrence regular expressions with counting (cSOREs). Our experiments (see Table 1) showed that the proportion of cSOREs is 94.16% for 32,750 real-world XSD files grabbed from Google, Maven, and GitHub, where 378,558 regular expressions were extracted. This indicates the practicability of cSORE. Therefore, it is necessary to study a learning algorithm for cSORE.

For learning regular expressions with counting, we have proposed the class ECsores [25], and the corresponding learning algorithm *InfECsore* [25]. However, although the ECsore learnt by *InfECsore* is a precise representation of any given finite sample, the algorithm *InfECsore* has less generalization ability such that, in some cases, the learnt ECsore covers relatively less XML data[1]. Therefore, a new subclass cSORE and a new method for learning cSORE are proposed. Although the defined cSOREs have more constrains than ECsores, compared with the algorithm *InfECsore*, our algorithm not only can learn a cSORE, which is expressive enough to cover more XML data, but also has better generalization ability (higher precision and recall) for smaller sample.

The main contributions of this paper are as follows. First, we infer a SORE. Then, we present a learning algorithm for cSOREs, where the main steps are as follows: (1) Construct a countable finite automaton (CFA) [25] from the syntax tree of the learnt SORE; (2) The CFA runs on the given finite sample to obtain the minimum and maximum number of repetitions of the subexpressions under the iteration operators; and (3) Generate the cSORE by traversing the syntax tree and introducing the counting operators. Finally, we provide the evaluations in generalization ability about our algorithm.

The paper is structured as follows. Section 2 gives the basic definitions. Section 3 presents the learning algorithm of the cSORE, Sect. 4 presents experiments. Section 5 concludes the paper.

2 Preliminaries

2.1 Regular Expression with Counting

Let Σ be a finite alphabet of symbols. The class of standard regular expressions over Σ is defined in the standard way: ε, $a \in \Sigma$ are regular expressions. For any

[1] For instance, the original schema in XSD can be denoted by $r_0 = (a|b)^+$, given sample $S = \{ba, aa, baabaa\}$, the ECsore learnt by *InfECsore* is $r_1 = (b?a^{[1,2]})^{[1,2]}$. However, an learnt cSORE can be $r_2 = (b?a)^{[1,4]}$, $|\mathcal{L}(r_1)| = 16 < |\mathcal{L}(r_2)| = 30$. Note that $\mathcal{L}(r_0) \supseteq \mathcal{L}(r_2) \supseteq S$ and $\mathcal{L}(r_0) \supseteq \mathcal{L}(r_1) \supseteq S$.

regular expressions r_1 and r_2, the disjunction $(r_1|r_2)$, the concatenate $(r_1 \cdot r_2)$, and the Kleene-star r_1^* are also regular expressions. Usually, we omit concatenation operators in examples. The regular expressions with counting are extended from standard regular expressions by adding the counting [15]: $r^{[m,n]}$ is a regular expression for regular expression r, where $m \in \mathbb{N}$, $n \in \mathbb{N}_{/1}$, $\mathbb{N} = \{1, 2, 3, \cdots\}$, $\mathbb{N}_{/1} = \{2, 3, 4, ...\} \cup \{+\infty\}$, and $m \leq n$. $\mathcal{L}(r^{[m,n]}) = \{w_1 \cdots w_i | w_1, \cdots, w_i \in \mathcal{L}(r), m \leq i \leq n\}$. Note that r^+, $r?$, and r^* are used as abbreviations of $r^{[1,+\infty]}$, $r|\varepsilon$, and $r^{[1,+\infty]}|\varepsilon$, respectively.

2.2 SORE, ECsore and cSORE

SORE is defined as follows.

Definition 1 (SORE [8,9]). *Let Σ be a finite alphabet. A single-occurrence regular expression (SORE) is a standard regular expression over Σ in which every terminal symbol occurs at most once.*

In this paper, for a SORE r, since $\mathcal{L}(r^*) = \mathcal{L}((r^+)?)$, a SORE does not use the Kleene-star operation, and forbids the expressions of forms $(r?)?$, $(r^+)^+$, and $(r?)^+$.

Example 1. $(ab)^+$ is a SORE, while $(ab)^+a$ is not. The expressions $(a?)?$, $(a^+)^+$, and $(a?)^+$ are forbidden.

Definition 2 (ECsore [25]). *Let Σ be a finite alphabet. An ECsore is a regular expression with counting over Σ in which every terminal symbol occurs at most once. For a regular expression r, an ECsore forbids immediately nested counters, expressions of form $(r?)?$ and $(r?)^{[m,n]}$.*

ECsore does not use the Kleene-star and the iteration operations. And ECsores are deterministic by definition.

Definition 3 (cSORE). *Let Σ be a finite alphabet. A cSORE is an ECsore over Σ. For regular expressions r_1, r_2, $\cdots$, r_k ($k \geq 2$), a cSORE forbids expressions of form $(r_1 r_2^{[m_1,n_1]} r_3)^{[m_2,n_2]}$ and $(r_1 (r_2^{[m_1,n_1]})? r_3)^{[m_2,n_2]}$ where $\varepsilon \in \mathcal{L}(r_1)$ and $\varepsilon \in \mathcal{L}(r_3)$, and expressions of form $(r_1?r_2? \cdots r_k?)^{[m,n]}$.*

According to the definition, cSOREs are a subclass of ECsores. ECsores are deterministic regular expressions, so are the cSOREs.

Example 2. $a?b^{[1,2]}(c|d)^{[1,+\infty]}$, $((c|d)^{[1,2]})?$, and $a?b(c|d)e$ are cSOREs, also ECsores, while $a(b|c)^+a$ is not a SORE, therefore neither a cSORE nor an ECsore. $(a^{[3,4]}|b)^{[1,2]}$ and $(a^{[3,4]}b)^{[1,2]}$ are cSOREs, also ECsores. However, the expressions $(a?b^{[1,2]}c?)^{[3,4]}$, $(a?(b^{[1,2]})?c?)^{[3,4]}$ are ECsores, not cSOREs.

Definition 4 (Countable Finite Automaton [25]). *A Countable Finite Automaton (CFA) is a tuple $(Q, Q_c, \Sigma, \mathcal{C}, q_0, q_f, \Phi, \mathsf{U}, \mathsf{L})$. The members of the tuple are described as follows:*

- *Σ is a finite and non-empty alphabet.*
- *q_0 and q_f : q_0 is the initial state, q_f is the unique final state.*
- *Q is a finite set of states. $Q = \Sigma \cup \{q_0, q_f\} \cup \{+_i\}_{i \in \mathbb{N}}$.*
- *$Q_c \subset Q$ is a finite set of counter states. Counter state is a state q ($q \in \Sigma$) that can directly transit to itself, or a state $+_i$. For each subexpression (excluding single symbol $a \in \Sigma$) under the iteration operator, we associate a unique counter state $+_i$ to count the minimum and maximum number of repetitions of the subexpression, respectively.*
- *$\mathcal{C}$ is finite set of counter variables that are used for counting the number of repetitions of the subexpressions under the iteration operators. $\mathcal{C} = \{c_q | q \in Q_c\}$, for each counter state q, we also associate a counter variable c_q.*
- *$\mathsf{U} = \{u(q) | q \in Q_c\}$, $\mathsf{L} = \{l(q) | q \in Q_c\}$. For each subexpression under the iteration operator, we associate a unique counter state q such that $l(q)$ and $u(q)$ are the minimum and maximum number of repetitions of the subexpression, respectively.*
- *Φ maps each state $q \in Q$ to a set of tuples consisting of a state $p \in Q$ and two update instructions. Φ: $Q \mapsto \wp(Q \times ((\mathsf{L} \times \mathsf{U} \mapsto (\boldsymbol{Min}(\mathsf{L} \times \mathcal{C}), \boldsymbol{Max}(\mathsf{U} \times \mathcal{C}))) \cup \{\emptyset\}) \times ((\mathcal{C} \mapsto \{\boldsymbol{res}, \boldsymbol{inc}\}) \cup \{\emptyset\}))$. ($\emptyset$ denotes empty instruction.)*

Definition 5 (Transition Function of a CFA [25]). *The transition function δ of a CFA $(Q, Q_c, \Sigma, \mathcal{C}, q_0, q_f, \Phi, \mathsf{U}, \mathsf{L})$ is defined for any configuration (q, γ, θ) and the letter $y \in \Sigma \cup \{\dashv\}$*

(1) $y \in \Sigma$: $\delta((q, \gamma, \theta), y) = \{(z, f_\alpha(\gamma, \theta), g_\beta(\theta)) | (z, \alpha, \beta) \in \Phi(q) \wedge (z = y \vee ((y, \alpha, \beta) \notin \Phi(q) \wedge z \in \{+_i\}_{i \in \mathbb{N}}))\}$.

(2) $y = \dashv$: $\delta((q, \gamma, \theta), \dashv) = \{(z, f_\alpha(\gamma, \theta), g_\beta(\theta)) | (z, \alpha, \beta) \in \Phi(q) \wedge (z = q_f \vee z \in \{+_i\}_{i \in \mathbb{N}})\}$.

3 Inference of cSOREs

Our learning algorithm works in the following steps.

Step 1: We infer a SORE for a given finite sample, and the SORE is obtained by post-processing the result of the algorithm *Soa2Sore* [14].

The post processes for the SORE derived from algorithm *Soa2Sore* are as follows. Let r_0 denote the SORE inferred by *Soa2Sore*. Every possibly repeated subexpression of r_0 is rewritten to be under iteration ($^+$), and for regular expressions r_1, r_2, $\cdots$, r_k ($k \geq 2$), the expressions of forms $(r_1 r_2^+ r_3)^+$ and $(r_1 (r_2^+)? r_3)^+$ ($\varepsilon \in \mathcal{L}(r_1)$ and $\varepsilon \in \mathcal{L}(r_3)$) are forbidden. And the expressions of form $(r_1? r_2? \cdots r_k?)^+$ are also forbidden.

Step 2: A CFA is constructed by traversing the syntax tree of the SORE obtained from step 1.

First, the state-transition diagram G of a CFA is constructed by traversing the syntax tree of the SORE obtained from step 1. The entire process is similar to the preorder traversal of the binary tree. Then, the detailed descriptions of the CFA are presented such as like in [25]. Note that, the parameter $\Phi(q)$ in transition function of a CFA can be obtained from G.

Step 3: The CFA derived from step 2 runs on the same finite sample used in step 1 to obtain the minimum and maximum number of repetitions of the subexpressions under the iteration operators.

The CFA counts the minimum and maximum number of repetitions of the subexpressions under the iteration operators. Counting rules are given by transition functions of the CFA. We use the algorithm *Counting* proposed in [25] to run the CFA. Let $\mathcal{A}$ denote the constructed CFA and S denote the given finite sample. Let $\mathsf{C}=Counting(\mathcal{A}, S)$, where $\mathsf{C} = \{(l(q), u(q))|q \in \mathcal{A}.Q_c\}$.

Step 4: We obtain a cSORE by traversing the syntax tree constructed in step 2 and replace the iteration operators with corresponding counting operators where the values of the lower bound and upper bound are obtained in step 3.

Note that, C is the set of pairs of the lower bound and upper bound values.

4 Experiments

In this section, first, we present the practical analysis of cSOREs. Then, we provide the evaluations in generalization ability about our algorithm. And all experiments were conducted on a ThinkCentre M8600t-D065 with an Intel core i7-6700 CPU (3.4 GHz) and 8G memory. All codes were written in C++.

4.1 Practicability

The 32,750 real-world XSD files were grabbed from Google, Maven, and GitHub. Table 1 shows that the proportion of cSOREs is 94.16% for the 378,558 regular expressions that were extracted from these XSD files. This indicates the significant practicability of cSOREs.

Table 1. Proportions of SOREs, ECsores and cSOREs.

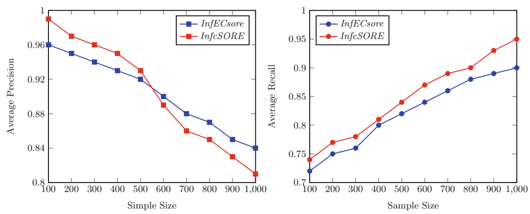
Subclasses	% of XSDs
SOREs	93.74
ECsore	96.53
cSORE	94.16

4.2 Generalization Abilities

We evaluate the algorithms *InfECsore* and *InfcSORE* by computing the precision and recall according to the given sample. We specify that, the learnt expression with higher precision and recall has better generalization ability. The average precision and average recall, which are as functions of sample size, respectively, are averaged over 1000 expressions.

We randomly extracted the 1000 expressions from XSDs, which were grabbed from Google, Maven, and GitHub. Each one of the 1000 expressions does not contain the iteration operators ($^+$), but contains the counters, where the upper bounds are less than 10. To learn each extracted expression e_0, we randomly generated corresponding XML data by using ToXgene [2], the samples are extracted from the XML data, each sample size is that listed in Fig. 1. And we define precision (p) and recall (r). Let positive sample (S_+) be the set of the all strings accepted by e_0, and let negative sample (S_-) be the set of the all strings not accepted by e_0. Let e_1 be the expression derived by *InfECsore* or *InfcSORE*. A true positive sample (S_{tp}) is the set of the strings, which are in S_+ and accepted by e_1. While a false negative sample (S_{fn}) is the set of the strings, which are in S_+ and rejected by e_1. Similarly, a false positive sample (S_{fp}) is the set of the strings, which are in S_- and accepted by e_1. While a true negative sample (S_{tn}) is the set of the strings, which are in S_- and rejected by e_1. Then, let $p = \frac{|S_{tp}|}{|S_{tp}|+|S_{fp}|}$ and $r = \frac{|S_{tp}|}{|S_{tp}|+|S_{fn}|}$. Note that $\mathcal{L}(e_0)$ and $\mathcal{L}(e_1)$ are finite languages, and we can construct counter automata [15] (receptors) for e_0 and e_1, respectively. Then we can obtain $|S_{tp}|$, $|S_{fp}|$ and $|S_{fn}|$.

The plots in Fig. 1(a) show that, for a smaller sample (sample size ≤ 500), the precision for the expression derived by *InfcSORE* is higher than that for the expression learnt by *InfECsore*. But for a larger sample (sample size ≥ 600), the precision for the expression derived by *InfcSORE* is lower than that for the expression learnt by *InfECsore*. However, the plots in Fig. 1(b) illustrate that, the recall for the expression derived by *InfcSORE* is consistently higher than that for the expression learnt by *InfECsore*. The reason is that, although the cSOREs are a subclass of the ECsores, for the same sample, the learnt cSORE can have more constrains than the learnt ECsore such that some subexpressions without numerical constrains in the learnt cSORE. This will lead to that the learnt cSORE is expressive enough to cover more XML data. In general, for a smaller sample, *InfcSORE* has better generalization ability such that its result has higher precision and recall.



(a) (b)

Fig. 1. (a) and (b) are average precision and average recall as functions of the sample size for each algorithm, respectively.

5 Conclusion

This paper proposed an inference algorithm for learning a subclass of deterministic regular expressions: cSOREs. The main strategies include: (1) Construct a CFA from the syntax tree of the learnt SORE; (2) The CFA runs on the given finite sample to obtain the counting operators; and (3) Generate the cSORE by traversing the syntax tree and introducing the counting operators. Compared with previous work, for any given finite language, our algorithm not only can learn a cSORE, which is expressive enough to cover more XML data, but also has better generalization ability for smaller sample. A future work is extending the SORE with counting and interleaving, studying the practical issues and the learning algorithms.

References

1. Abiteboul, S., Buneman, P., Suciu, D.: Data on the Web: From Relations to Semistructured Data and XML. Morgan Kaufmann, Burlington (2000)
2. Barbosa, D., Mendelzon, A.O., Keenleyside, J., Lyons, K.: ToXgene: an extensible template-based data generator for XML. In: WebDB (2002)
3. Barbosa, D., Mignet, L., Veltri, P.: Studying the XML web: gathering statistics from an XML sample. World Wide Web **9**(2), 187–212 (2006)
4. Bex, G.J., Gelade, W., Neven, F., Vansummeren, S.: Learning deterministic regular expressions for the inference of schemas from XML data. In: Proceedings of the 17th International Conference on World Wide Web, pp. 825–834. ACM (2008)
5. Bex, G.J., Gelade, W., Neven, F., Vansummeren, S.: Learning deterministic regular expressions for the inference of schemas from XML data. ACM Trans. Web **4**(4), 1–32 (2010)
6. Bex, G.J., Martens, W., Neven, F., Schwentick, T.: Expressiveness of XSDs: from practice to theory, there and back again. In: Proceedings of the 14th International Conference on World Wide Web, pp. 712–721. ACM (2005)
7. Bex, G.J., Neven, F., Van den Bussche, J.: DTDs versus XML schema: a practical study. In: Proceedings of the 7th International Workshop on the Web and Databases: Colocated with ACM SIGMOD/PODS 2004, pp. 79–84. ACM (2004)
8. Bex, G.J., Neven, F., Schwentick, T., Tuyls, K.: Inference of concise DTDs from XML data. In: International Conference on Very Large Data Bases, Seoul, Korea, pp. 115–126, September 2006
9. Bex, G.J., Neven, F., Schwentick, T., Vansummeren, S.: Inference of concise regular expressions and DTDs. ACM Trans. Database Syst. **35**(2), 1–47 (2010)
10. Boneva, I., Ciucanu, R., Staworko, S.: Schemas for unordered XML on a DIME. Theor. Comput. Syst. **57**(2), 337–376 (2015)
11. Brüggemann-Klein, A., Wood, D.: One-unambiguous regular languages. Inf. Comput. **142**(2), 182–206 (1998)
12. Che, D., Aberer, K., Özsu, M.T.: Query optimization in XML structured-document databases. VLDB J. **15**(3), 263–289 (2006)
13. Freydenberger, D.D., Kötzing, T.: Fast learning of restricted regular expressions and DTDs. In: Proceedings of the 16th International Conference on Database Theory, pp. 45–56. ACM (2013)
14. Freydenberger, D.D., Kötzing, T.: Fast learning of restricted regular expressions and DTDs. Theor. Comput. Syst. **57**(4), 1114–1158 (2015)
15. Gelade, W., Gyssens, M., Martens, W.: Regular expressions with counting: weak versus strong determinism. SIAM J. Comput. **41**(1), 160–190 (2012)
16. Gold, E.M.: Language identification in the limit. Inf. Control **10**(5), 447–474 (1967)

17. Hovland, D.: Regular expressions with numerical constraints and automata with counters. In: Leucker, M., Morgan, C. (eds.) ICTAC 2009. LNCS, vol. 5684, pp. 231–245. Springer, Heidelberg (2009). https://doi.org/10.1007/978-3-642-03466-4_15
18. Kilpeläinen, P., Tuhkanen, R.: Towards efficient implementation of XML schema content models. In: Proceedings of the 2004 ACM Symposium on Document Engineering, pp. 239–241. ACM (2004)
19. Kilpeläinen, P., Tuhkanen, R.: One-unambiguity of regular expressions with numeric occurrence indicators. Inf. Comput. **205**(6), 890–916 (2007)
20. Latte, M., Niewerth, M.: Definability by weakly deterministic regular expressions with counters is decidable. In: Italiano, G.F., Pighizzini, G., Sannella, D.T. (eds.) MFCS 2015. LNCS, vol. 9234, pp. 369–381. Springer, Heidelberg (2015). https://doi.org/10.1007/978-3-662-48057-1_29
21. Manolescu, I., Florescu, D., Kossmann, D.: Answering XML queries on heterogeneous data sources. In: VLDB, vol. 1, pp. 241–250 (2001)
22. Martens, W., Neven, F.: Typechecking top-down uniform unranked tree transducers. In: Calvanese, D., Lenzerini, M., Motwani, R. (eds.) ICDT 2003. LNCS, vol. 2572, pp. 64–78. Springer, Heidelberg (2003). https://doi.org/10.1007/3-540-36285-1_5
23. Mignet, L., Barbosa, D., Veltri, P.: The XML web: a first study. In: Proceedings of the 12th International Conference on World Wide Web, pp. 500–510. ACM (2003)
24. Thompson, H., Beech, D., Maloney, M., Mendelsohn, N.: XML Schema Part 1: Structures, 2nd edn. W3C Recommendation (2004)
25. Wang, X., Chen, H.: Inferring deterministic regular expression with counting. In: Trujillo, J.C., et al. (eds.) ER 2018. LNCS, vol. 11157, pp. 184–199. Springer, Cham (2018). https://doi.org/10.1007/978-3-030-00847-5_15