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半構造データからの縮約可能変数つきタグ木パターンの抽出

宮原　哲浩† 　鈴木　祐介†† 　正代　隆義†† 　内田　智之† 　高橋　健一†
上田　祐彰†

† 広島市立大学 情報科学部　〒731–3194 広島市安佐南区大塚東 3–4–1
†† 九州大学大学院システム情報科学府・研究院　〒816–8580 春日市春日公園 6–1
E-mail: †{miyahara@its, uchida@cs, takahasi@its, ueda@its}.hiroshima-cu.ac.jp,
††{y-suzuki,shoudai}@i.kyushu-u.ac.jp

あらまし　半構造データからの情報抽出がますます重要になってきている．半構造データから意味がある，興味深い内容を抽出するためには，半構造データに共通なパターンを抽出することが必要である．タグ木パターンは，辺ラベルを持つ順序木で，タグの木構造と構造的変数を持つ．辺ラベルはタグがキーワードかワイルドカードであり，変数には任意の木を代入することができる．特に，縮約可能変数は，1頂点だけから成る木を含む，任意の木とマッチする．よって，タグ木パターンは，不定形な半構造データに共通する構造的パターンを表現するのに適している．我々は，与えられたデータを説明する最小に一般化されたタグ木パターンをみつけるアルゴリズムを用いて，不定形な半構造データから特徴的なタグ木パターンを抽出する新しい方法を提示する．本手法を，HTML/XML ファイルからの特徴的タグ木パターンの抽出へ適用した実験結果についても報告する．

キーワード　情報抽出，Web マイニング，半構造データ，HTML/XML ファイル，タグ木パターン

Extraction of Tag Tree Patterns with Contractible Variables from Semistructured Data

Tetsuhiro MIYAHARA†, Yusuke SUZUKI††, Takayoshi SHOUDAI††, Tomoyuki UCHIDA†,
Kenichi TAKAHASHI†, and Hiroaki UEDA†

† Faculty of Information Sciences, Hiroshima City University, Hiroshima 731–3194, Japan
†† Department of Informatics, Kyushu University, Kasuga 816–8580, Japan
E-mail: †{miyahara@its, uchida@cs, takahasi@its, ueda@its}.hiroshima-cu.ac.jp,
††{y-suzuki,shoudai}@i.kyushu-u.ac.jp

Abstract　Information Extraction from semistructured data becomes more and more important. In order to extract meaningful or interesting contents from semistructured data, we need to extract common structured patterns from semistructured data. A tag tree pattern is an edge labeled tree with ordered children which has tree structures of tags and structured variables. An edge label is a tag, a keyword or a wildcard, and a variable can be substituted by an arbitrary tree. In particular, a contractible variable matches any subtree including a singleton vertex. A tag tree pattern is hence suited for representing common tree structured patterns in irregular semistructured data. We present a new method for extracting characteristic tag tree patterns from irregular semistructured data by using an algorithm for finding a least generalized tag tree pattern explaining given data. We report some experiments of applying this method to extracting characteristic tag tree patterns from HTML/XML files.

Key words　Information Extraction, Web based mining, semistructured data, HTML/XML file, tag tree pattern

1. Introduction

Due to the rapid growth of semistructured data such as Web documents, Information Extraction from semistructured data becomes more and more important. In order to extract meaningful or interesting contents from semistructured data, we need to extract common structured patterns from semistructured data. Many semistructured data have irregularities such as missing or erroneous data. In this paper, we present a new method for extracting characteristic tag tree patterns from irregular semistructured data which are considered to be positive data.

Web documents such as HTML files and XML files have no rigid structure and are called semistructured data. According to the Object Exchange Model [1], we treat semistructured data as tree structured data. To represent a tree structured pattern common to such tree structured data, we propose a *tag tree pattern*, which is a rooted tree consisting of ordered children, structured variables and edges labeled with tags, keywords or wildcards. A variable can be substituted by an arbitrary tree.

In the Object Exchange Model, many essential data are represented as leaves or subtrees. We hence introduce a new type of variable, called a *contractible variable*, which is regarded as an anonymous subtree in a tag tree pattern and matches any subtree including a singleton vertex. A usual variable, called an *uncontractible variable*, in a tag tree pattern does not match any singleton vertex.

Since a variable can be replaced by an arbitrary tree, overgeneralized patterns explaining given positive data are meaningless. Then, in order to extract meaningful information from irregular or incomplete tree structured data such as semistructured Web documents, we need to find one of the least generalized tag tree patterns. Consider the examples in Fig. 1. Let T_i' be the corresponding tree which is obtained by retaining the edge labels such as "Sec1" or "SubSec3.1" and ignoring the other edge labels in T_i. The tag tree pattern t_1 explains trees T_1', T_2' and T_3'. That is, T_1', T_2' and T_3' are obtained from t_1 by substituting the variables of t_1 with trees. Further, t_1 is a least generalized tag tree pattern. The tag tree pattern t_2 also explains the three trees. But t_2 explains any tree with two or more vertices. Hence t_2 is overgeneralized and meaningless.

A tag tree pattern is different from other representations of tree structured patterns such as in [2], [13] in that a tag tree pattern has structured variables which can be substituted by arbitrary trees. Recently, Information Extraction has been extensively studied [3], [5]. But most studies are for free-text documents. Information Extraction or wrapper extraction from high-level data such as semistructured data or tables is a hot topic in the field of Web learning or Web mining [4], [12]. Further, many techniques in Information Extraction are based on heuristics. But our extraction method is an polynomial time algorithm which is guaranteed to find a least generalized tag tree pattern from any set of irregular semistructured data. Our extraction method of tag tree patterns is applied to extracting elements or field data from semistructured data. Since a tag tree pattern has a variable which matches a subtree, extracting field data from semistructured data is calculating a subtree which is substituted for a variable. As other methods for extracting characteristics from tree structured data, in [13], Wang and Liu presented the algorithm for finding maximally frequent tree-expression patterns from semistructured data. In [2], Asai et al. presented an efficient algorithm for discovering frequent substructures from a large collection of semistructured data. In our previous works [6], [8], we presented methods of enumerating all maximally frequent tag tree patterns with unordered or ordered children from tree structured data.

This paper is organized as follows. In Section 2, we introduce ordered term trees and tag tree patterns as tree structured patterns and present our extraction method for finding a least generalized tag tree pattern explaining given semistructured data. In Section 3, we report an implementation and some experimental results of our extraction method on HTML/XML files.

2. Tag Tree Patterns and Extraction Method

2.1 Ordered Term Trees

Let $T = (V_T, E_T)$ be a rooted tree with ordered children (or simply a *tree*) which has a set V_T of vertices and a set E_T of edges. Let E_g and H_g be a partition of E_T, i.e., $E_g \cup H_g = E_T$ and $E_g \cap H_g = \emptyset$. And let $V_g = V_T$. A triplet $g = (V_g, E_g, H_g)$ is called a *term tree*, and elements in V_g, E_g and H_g are called a *vertex*, an *edge* and a *variable*, respectively. We assume that every edge and variable of a term tree is labeled with some words from specified languages. A label of a variable is called a *variable label*. Λ and X denote a set of edge labels and a set of variable labels, respectively, where $\Lambda \cap X = \phi$. For a term tree g and its vertices v_1 and v_i, a *path* from v_1 to v_i is a sequence $v_1, v_2, \ldots, v_i$ of distinct vertices of g such that for any j with $1 \leqq j < i$, there exists an edge or a variable which consists of v_j and v_{j+1}. If there is an edge or a variable which consists of v and v' such that v lies on the path from the root to v', then v is said to be the *parent* of v' and v' is a *child* of v. We use a notation $[v, v']$ to represent a variable $\{v, v'\} \in H_g$ such that v is the parent of v'. Then we call v the *parent port* of $[v, v']$ and v' the *child port* of $[v, v']$.

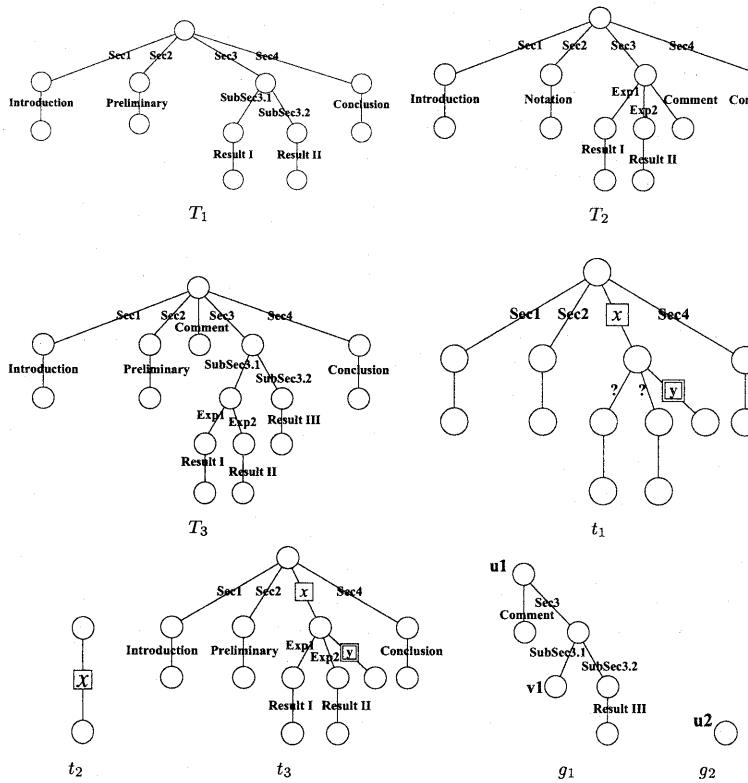


Fig. 1 Tag tree patterns t_1, t_2 and t_3 and trees T_1, T_2 and T_3. An uncontractible (resp. contractible) variable is represented by a single (resp. double) lined box with lines to its elements. The symbol "?" is a wildcard of an edge label. The label inside a box is the variable label of the variable.

Let X^c be a distinguished subset of X. We call variable labels in X^c *contractible variable labels*. A contractible variable label can be attached to a variable whose child port is a leaf. We call a variable with a contractible variable label a **contractible variable**, which is allowed to substitute a tree with a singleton vertex, as stated later. We call a variable which is not a contractible variable an uncontractible variable. For a variable $[v, v']$, when we pay attention to the kind of the variable, we denote by $[v, v']^c$ and $[v, v']^u$ a contractible variable and an uncontractible variable, respectively.

A term tree g is called *ordered* if every internal vertex u in g has a total ordering on all children of u. The ordering on the children of u is denoted by $<_u^g$. An ordered term tree g is called *regular* if all variables in H_g have mutually distinct variable labels in X.

An ordered term tree with no variable is called a **ground ordered term tree**, which is a standard ordered tree. $\mathcal{OT}_\Lambda$ denotes the set of all ground ordered term trees whose edge labels are in Λ. $\mathcal{OTT}_\Lambda^c$ denotes the set of all ordered term trees which have contractible or uncontractible variables, and edge labels in Λ. In this paper, we treat only regular ordered term trees with contractible or uncontractible variables. Therefore we call them **term trees** simply.

Let $f = (V_f, E_f, H_f)$ and $g = (V_g, E_g, H_g)$ be term trees. We say that f and g are *isomorphic*, if there is a bijection φ from V_f to V_g such that the following conditions (i)-(iv) hold: (i) The root of f is mapped to the root of g by φ. (ii) $\{u, v\} \in E_f$ if and only if $\{\varphi(u), \varphi(v)\} \in E_g$ and the two edges have the same edge label. (iii) $[u, v] \in H_f$ if and only if $[\varphi(u), \varphi(v)] \in H_g$. In particular, $[u, v]^c \in H_f$ if and only if $[\varphi(u), \varphi(v)]^c \in H_g$. (iv) For any internal vertex u in f which has more than one child, and for any two children u' and u'' of u, $u' <_u^f u''$ if and only if $\varphi(u') <_{\varphi(u)}^g \varphi(u'')$.

Let $\sigma = [u, u']$ be a list of two vertices in g where u is the root of g and u' is a leaf of g. The form $x := [g, \sigma]$ is called a *binding* for x. If x is a contractible variable label in X^c, g may be a tree with a singleton vertex u and thus $\sigma = [u, u]$. It is the only case that a tree with a singleton vertex is allowed for a binding. A new term tree $f\{x := [g, \sigma]\}$ is obtained by applying the binding $x := [g, \sigma]$ to f in the following way. Let $e = [v, v']$ be a variable in f with the variable label x. Let g' be one copy of g and w, w' the ver-

tices of g' corresponding to u, u' of g, respectively. For the variable $e = [v, v']$, we attach g' to f by removing the variable e from H_f and by identifying the vertices v, v' with the vertices w, w' of g', respectively. If g is a tree with a singleton vertex, i.e., $u = u'$, then v becomes identical to v' after applying the binding. A *substitution* θ is a finite collection of bindings $\{x_1 := [g_1, \sigma_1], \ldots, x_n := [g_n, \sigma_n]\}$, where x_i's are mutually distinct variable labels in X. The term tree $f\theta$, called the *instance* of f by θ, is obtained by applying the all bindings $x_i := [g_i, \sigma_i]$ on f simultaneously.

For example, let t_3 be a term tree described in Fig. 1 and $\theta = \{x := [g_1, [u_1, v_1]], y := [g_2, [u_2, u_2]]\}$ be a substitution, where g_1 and g_2 are trees in Fig. 1. Then the instance $t_3\theta$ of the term tree t_3 by θ is isomorphic to the tree T_3 in Fig. 1.

2.2 Tag Tree Patterns

Let Λ_{Tag} and Λ_{KW} be two languages which consist of infinitely or finitely many words, where $\Lambda_{Tag} \cap \Lambda_{KW} = \emptyset$. We call words in Λ_{Tag} and Λ_{KW} a **tag** and a **keyword**, respectively. A **tag tree pattern** is a term tree such that each edge label on it is any of a tag, a keyword, and a special symbol "?", which is a wildcard of an edge label. A tag tree pattern with no variable is called a **ground tag tree pattern**.

For an edge $\{v, v'\}$ of a tag tree pattern and an edge $\{u, u'\}$ of a tree, we say that $\{v, v'\}$ *matches* $\{u, u'\}$ if the following conditions (i)-(iii) hold: (i) If the edge label of $\{v, v'\}$ is a tag, then the edge label of $\{u, u'\}$ is the same tag or a tag which is considered to be identical under an equality relation on tags. (ii) If the edge label of $\{v, v'\}$ is a keyword, then the edge label of $\{u, u'\}$ is the same keyword. (iii) If the edge label of $\{v, v'\}$ is "?", then we don't care the edge label of $\{u, u'\}$.

A ground tag tree pattern $\pi = (V_\pi, E_\pi, \emptyset)$ *matches* a tree $T = (V_T, E_T)$ if there exists a bijection φ from V_π to V_T such that the following conditions (i)-(iv) hold: (i) The root of π is mapped to the root of T by φ. (ii) $\{v, v'\} \in E_\pi$ if and only if $\{\varphi(v), \varphi(v')\} \in E_T$. (iii) For all $\{v, v'\} \in E_\pi$, $\{v, v'\}$ matches $\{\varphi(v), \varphi(v')\}$. (iv) For any internal vertex u in π which has more than one child, and for any two children u' and u'' of u, $u' <_u^\pi u''$ if and only if $\varphi(u') <_{\varphi(u)}^T \varphi(u'')$. A tag tree pattern π **matches** a tree T if there exists a substitution θ such that $\pi\theta$ is a ground tag tree pattern and $\pi\theta$ matches T. Then the *language* $L_\Lambda(\pi)$, which is the descriptive power of a tag tree pattern π, is defined as $L_\Lambda(\pi) = \{\text{a tree } T \text{ in } \mathcal{OT}_\Lambda \mid \pi \text{ matches } T\}$ where $\Lambda = \Lambda_{Tag} \cup \Lambda_{KW}$.

2.3 Extraction of Least Generalized Tag Tree Patterns

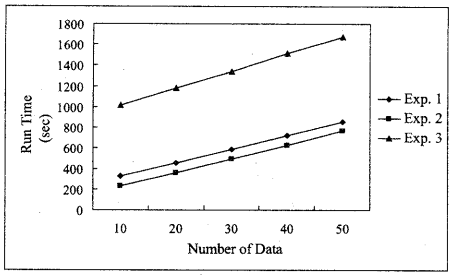
We propose a new method for extracting characteristic tag tree patterns from irregular semistructured data which are considered to be positive tree structured data. A tag tree pattern π is a **least generalized tag tree pattern** explaining a given set S of trees which are considered to be positive data, if (i) $S \subseteq L_\Lambda(\pi)$ (π explains S) and (ii) there is no tag tree pattern π' satisfying that $S \subseteq L_\Lambda(\pi') \subsetneq L_\Lambda(\pi)$. The problem for finding a least generalized tag tree pattern for a given set of trees is discussed as the minimal language problem (MINL for short) in the field of computational learning theory [9], [11].

Our extraction method finds a least generalized tag tree pattern explaining a given set of trees S, by using a polynomial time algorithm for solving the MINL problem [11]. First, the algorithm finds a least generalized tag tree pattern t which consists of only uncontractible variables and explains S. Secondly, it finds a tag tree pattern t' which is obtained from t, by replacing a variable in t with an edge labeled with an edge label or a wildcard, or a contractible variable, if the obtained tag tree pattern t' explains S. The algorithm then repeatedly applies the replacing to the tag tree pattern until no more replacing is applicable. Finally it outputs the resulting tag tree pattern. The extraction method uses a polynomial time matching algorithm for deciding whether or not a given tag tree pattern matches a given tree for hypothesis checking [11]. The matching algorithm is an extension of the polynomial time matching algorithms [9], [10].

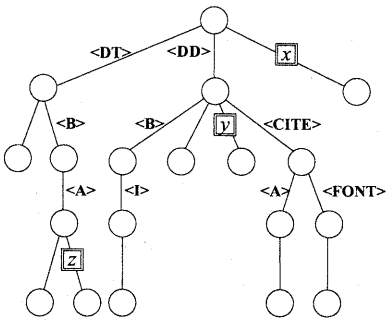
3. Implementation and Experimental Results

We have implemented the extraction method in Section 2.3, which finds a least general tag tree pattern explaining the given semistructured data. The implementation is in GCL2.2 and on a Sun workstation Ultra-10 clock 333MHz. In Fig. 2 we report some experiments on sample files of semistructured data. In these experiments, an input tree represents a subtree of a parsed tree of an HTML/XML file. The tree structure and HTML/XML tags in a parsed tree are preserved in the corresponding input tree. Attributes and their values are ignored. No equality relation on tags is assumed. All string data in a parsed tree are converted to the same dummy keyword, in order to pay attention to structures of tags in a parsed tree.

In Exp. 1 to 3 , we made samples of artificial HTML files in order to evaluate our method. The input file for Exp. 1 consists of trees with about 40 vertices. The input file for Exp. 2 consists of 90 % of trees with about 40 vertices and 10 % of trees with about 20 vertices. The input file for Exp. 3 consists of 90 % of trees with about 40 vertices and 10 % of trees with about 70 vertices. The graphs for Exp. 1 to 3 show the running time of the method with varying the number of data for the three experiments. The numbers of vertices of



Experiments 1-3



Experiment 4

Fig. 2 Experimental results of extracting least generalized tag tree patterns from semistructured data.

the obtained tag tree patterns of the method are almost same for the three experiments. This shows that the method has robustness for irregularities of sample semistructured data.

In Exp. 4, the sample HTML file is a result of a search engine of a web site with a local search function (http://www.ael.org). The sample file consists of 10 trees with about 18 vertices. A tree in the sample file is a record of bibliographic data. The obtained tag tree pattern in Fig. 2 (Exp. 4) is a least generalized tree pattern explaining the sample file. An edge with no edge label represents an edge with the dummy keyword. The obtained tag tree pattern is considered to be a wrapper for such tree structured data.

We have also experiments on a sample XML file which is from the DBLP bibliographic database (http://dblp.uni-trier.de/xml/dblp.xml). The experiments show that a small number of data are sufficient for the method to extract a characteristic tag tree pattern from such bibliographic data.

4. Conclusions

In this paper, we have studied Information Extraction from semistructured data. We have proposed a new method for extracting characteristic tag tree patterns from irregular semistructured data. We have also reported some experiments of applying this method to extracting least generalized tag tree patterns from HTML/XML files.

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特殊化による仮説の融合を用いた分散型知識発見環境の構築

菊池　敏幸†　　山本　章博†

† 北海道大学 工学研究科・知識メディアラボラトリー　〒060-8628 北海道札幌市北区北13条西8丁目
E-mail: †{kikuchi,yamamoto}@meme.hokudai.ac.jp

あらまし　本研究の目標は, 機械学習や知識発見の分野においてこれまで開発された様々な知識発見システムを利用して, 分散された位置に蓄積された大量の情報から有意義な知識を引き出せるようにするためのソフトウェア環境を構築することである. 本稿では, まず分割されたデータから個別に規則を求め, そして得られた規則を特殊化によって一つに融合する手法を提案し, その手法を用いた分散型知識発見環境 Distributed EVLD(Distributed Environment for Various Logics of Discovery) の構築について述べる.

キーワード　帰納論理プログラミング, 分散処理, 特殊化

Distributed Knowledge Discovery based on Merging Hypotheses

Toshiyuki KIKUCHI† and Akihiro YAMAMOTO†

† MemeMedia Laboratory, Hokkaido University　N 13 W 8, Sapporo 060-8628 JAPAN
E-mail: †{kikuchi,yamamoto}@meme.hokudai.ac.jp

Abstract　In this paper we propose a method for knowledge discovery from distributed data on distributed computers. Each of the computers is assumed to have a knowledge discovery system which searches hypotheses from general ones to specific ones. We also assume that each hypothesis can be represented as a logic program. Then the discovery method is to correct hypotheses generated by the computers and then merge them. For the merge of hypotheses we use the most general specialization of clauses. We also validate each clause in the merged hypotheses. We implement our method on the EVLD system, which we developed previously, and call it Distributed EVLD (Distributed EVLD). In the paper we report how our method works well with a well-known data set.

Key words　inductive logic programming, distributed processing, specialization

1. はじめに

本研究の目標は, 機械学習や知識発見の分野においてこれまで開発された様々な知識発見システムを利用して, 分散された位置に蓄積された大量の情報から有意義な知識を引き出せるようにするためのソフトウェア環境を構築することである. そのプロトタイプとして本稿では, Distributed EVLD(Distributed Environment for Various Logics of Discovery) を構築し, 知識を引き出したい情報がすべて同じ位置に存在していなくても知識を引き出すことが可能であることを確かめる.

従来, 知識発見のような大規模または複雑な解析は計算サーバーを用いていた. 一方, 近年パソコンやワークステーションの発展と普及に伴い, 高性能のプロセッサが安価に入手可能となり, これを複数台高速のネットワークで結合して, 計算を行わせる分散処理技術に注目が集まっている. 従って知識発見プロセスも分散化する必要が生じている.

さらに分散が必要なのは, データ収集である. 例えば全国に支店の存在するような店の POS データは支店ごとにそれぞれで収集が行われる.

それらのデータからデータマイニングを行う場合, 発見プロセス, 特にトップダウン型の発見プロセスでは与えられたすべてのデータを用いたある基準に従って適切な仮説を生成していくため, 発見プロセス中はすべてのデータを読みとれる状態にしておかなくてはいけない. そのため, 一般的には一度本店でデータを集計してから仮説を生成する. この場合データを転送する際ネットワークの帯域がボトルネックとなり, またネットワーク上をデータそのものが流れてしまうためセキュリティ上にも問題が生じる.

そこで本稿では, 発見プロセスでの計算を並列に処理さるのではなく, データを分割して並列に計算させ, そして得られた仮説を融合することで最終的に一つの仮説を得る手法を提案する. この手法を用いることで既存の機械学習・知識発見システムをそのまま分散処理に適用させることが可能となり, データの分割および発見プロセス計算の並列化に関しての問題も解決