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INFORMATION CONCIERGE FOR THE WORLD WIDE WEB

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LI ZHAO

SCHOOL OF COMPUTER ENGINEERING

2006

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Information Concierge for the World Wide Web

Li Zhao

School of Computer Engineering

A thesis submitted to the Nanyang Technological University
in fulfilment of the requirement for the degree of
Doctor of Philosophy

2006

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Abstract

With the rapid growth of information on the Web in today's world, a means to combat information overload is critical. Web data extraction systems have been developed to transform, evaluate, manage and present Web documents on behalf of requirements of various applications. Earlier work described in the literature usually focused on a single phase in the data extraction process, especially the generation of rules to transform Web documents; i.e., wrapper induction. They appeared ad-hoc and difficult to integrate; each phase in the data extraction process was disconnected and did not share a common foundation to make the building of a complete system straightforward.

This thesis focuses on a conceptual study of current concierge systems in the literature and proposes a holistic framework for Web information concierge systems. The principal aspect of this proposal is the notion of document schemata. Document *schemata* are patterns of structures embedded in documents. Queries based on schemata to Web documents are defined. Unlike traditional database schemata, the proposed schemata represent fragments of Web documents, rather than a whole document. Based on the layout of Web documents and appearance of these schemata in Web documents, some attributes of schemata can be exploited to evaluate how sensitive to user requirements the fragments are and how similar multiple documents are. Once document schemata are obtained, the various phases (e.g., training set preparation, wrapper induction, and document classification) can be easily integrated.

The feasibility of the proposed framework depends on two aspects: (1) how integrative the framework is; i.e., whether there is a theoretical basis to facilitate the analysis and integration of related techniques. (2) How efficient the schema generation is. First, we study the relationship among tree language theory, logical program and Web documents, and implement the framework using various techniques to show its flexibility. Next, it is proved that there is no practical algorithm to detect schema in general. The thesis studies a special class of schemata (k-schemata), and proposes some efficient methods to detect k-schemata. First, parsing documents into trees, an $O(n \log n)$ algorithm is introduced to detect frequent structural patterns (k-schemata) from these trees. Second, studying the relation between these structural patterns and flat substrings in original documents, we devise a data structure, called DocItem trees, to store the schemata detected. Linear DocItem tree construction algorithms are presented. Schemata can also be located in DocItem trees in linear time.

The framework and related algorithms in this thesis imply improved efficiency and

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better control over the extraction procedure. Our experimental results confirm this. We also demonstrate an application of the framework — a visual query language similar with QBE query language. Importantly, since a document can be represented as a *vector* of schema, it can be easily incorporated into existing systems based on a vector model of documents as the fabric for integration.

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Acknowledgments

This thesis is the culmination of work in the past three years with the support of other people. I would like to express my gratitude to these people for their kindness.

First I owe a debt of gratitude to **Associate Professor Ng Wee Keong**, my supervisor, for his constructive suggestions and patience. As an advisor, he demonstrated knowledge and patience that I needed as a research student. He went through my work assiduously, and provided the necessary guidance. As the director for Centre for Advanced Information Systems, he provided a conducive environment for my research. His efforts in organizing weekly presentations enriched my knowledge.

Next, I thank **Liu Zehua**, **Li Wenyuan**, **Sun Aixin** three postgraduates, for their assistance in the designing of this research. Also, I thank them for reviewing the paper I wrote.

I also appreciate the support of **Chen Ling**, **Khin Myo Win**, **Erwin Leonadi**, **Myo Myo Naing**, **Ong Kok Leong**, **Wang Yi Da**, **Zhao Qian Kun**, **Yin Ming**, **Li Zhuowei**, postgraduates in our lab. We sit together almost every week to share ideas.

Further, thanks go to my dear wife **Jiang Chang'an**, for all the care, concern and encouragement she gave me during the research and writing of the thesis. Bless you.

Last and most important, my gratitude goes to **my parents**, for their sacrifice and support they gave me in the pursuit of my interest in research.

Thank you all.

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List of Notations

$\alpha, \beta, \alpha_i, \beta_i$ ..... Symbols
Σ ..... Alphabet
$\mathcal{T}(\Sigma)$ ..... Terms over Alphabet Σ
$\mapsto$ ..... Conforma to
t, t_i ..... Terms
n, n_i ..... Nodes in Trees
A, B, A_i, B_i ..... Atoms
$\mathcal{T}(\Sigma)$ ..... Terms
G, G_i ..... Grammars
$L(G)$ ..... The Language generated from G
2^Q ..... Regular Set of Set Q
$dom(t)$ ..... Domain of Term t
DI ..... Data Instance
FO ..... First Order
MSO ..... Second Order
x, y, x_i, y_i ..... Variables Ranging over Elements
X, Y, X_i, Y_i ..... Variables Ranging over Set of Elements
τ ..... Built-in Predicates for Unranked Trees
NTT ..... Non-deterministic Tree Transducer
TA ..... Tree Automata
SQA ..... Strong Query Automata
Q ..... State Set in Tree Automata
q, q_i ..... States in Tree Automata
F ..... Final State in Tree Automata
δ ..... Move Relation in Tree Automata
ω ..... Weight of Schema in a Document

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ξ ..... CharData (Chapter 5)

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Chapter 1

Introduction

1.1 Background to the Study

The advances of information and communication technologies in today's world make it easier than at any other time to deliver data according to our desire. The exponential growth of data online produces a huge variety of information resources. Today we can find airline schedules, weather forecasts, up-to-date news or even the nearest restaurant on the Web. Unfortunately, the information sea surrounding us overloads receptivity of human, thereby making it impossible to absorb all the water in the sea. A pertinent question then arises — what is the essence of producing a stunning quantity of information enthusiastically if we cannot find knowledge or wisdom in it? It is for this reason that John December [1994] observed:

"Without tools and methodologies for gathering, evaluating, managing, and presenting information, the Web's potential as a universe of knowledge could be lost." — *John December [1994].*

From the beginning of the last decade, standards such as HTTP and HTML have been widely adopted and data based on the infrastructure of the Web have been distributed. Users can directly reach these data sources, using browsers such as Mozilla and Internet Explorer. HTML Forms are the tools most frequently used by users to interact with Web service providers and to gather interesting information. Because the quantity of information becomes too huge to gather and process manually, we need alternative Web data process approaches — automatic information collection, collaging, managing and presenting.

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In the past two or three decades, database management systems (DBMS) have been thoroughly studied to manage large volumes of electronic structural data and provide efficient access to data. The success of DBMS in relational data management is based on its key factors such as its solid relational model and convenient query interfaces. As the main problem of Web data process are similar to DBMS (managing large volume data), relevant concepts of DBMS to Web data have been extensively studied in recent years [Florescu et al., 1998]. Although DBMS techniques cannot be expected to solve all problems on the Web, they are valuable complements of other related techniques such as Web data mining, information retrieval (IR), natural language processing (NLP). This thesis focuses on DBMS concepts relevant to information processing on Web: (1) Modeling and querying Web documents, (2) Data Extraction, and (3) Data Integration.

1.2 Information Concierge for the Web

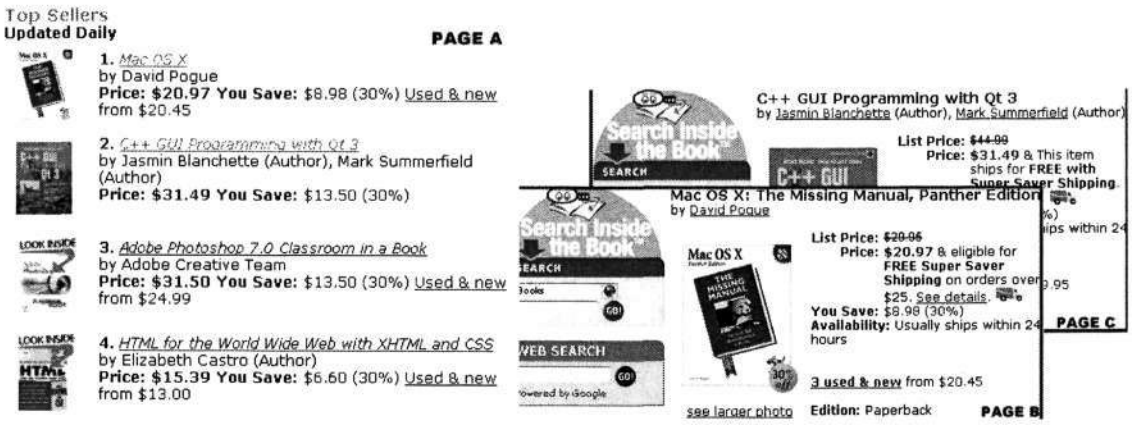
In this section, I briefly describe an information concierge for the Web, highlighting the semantic Web versus concierge for human-centered Web and the challenge for a concierge system.

1.2.1 Semantic Web versus Concierge for Human-centered Web

The Web is not only a human-to-human communication media. Tim Berners-Lee, the designer of the Web argues that the Web should be designed to allow machines to participate and to help the Web to be a repository of information and knowledge. W3C's effort on Semantic Web [Berners-Lee et al., 2001] is a step in this direction. Also, the semantic Web can be viewed as a global database, and Web sites are suggested to be re-engineered to follow Semantic Web specifications. For example, RDF [W3C, 2000] has been successful in some areas.

However, not all enterprises and organizations are willing to disclose their information in an open infrastructure for various reasons. In this situation, only human-friendly Web documents are presented. Thus, we need concierge systems that provide machine-sensitive data accessing of these human-friendly documents. In this thesis, 'concierge', 'information concierge' and 'Web information concierge' are used interchangeably.

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(a) Top Seller Books (b) Book Details

Figure 1.1: Sample Pages

1.2.2 Challenges and Objectives

A concierge system should extract structural data from semi-structural Web documents. The challenges for a concierge system mostly come from the following characteristics of semi-structural Web documents:

- Semi-structural documents have only irregular structures. As the examples in Figure 1.1 show, some books have second hand price while others have none; the same information on a book is presented with different formats.
- Document schemata are hidden from users. In this thesis, a schema is referred to as a structural pattern in Web documents. Even when some documents are generated by regular rules and share common schemata, these schemata usually are hidden from users.
- It is a hard problem to induce hidden schemata from sample documents.

Without restriction on the structure of schemata, we notice that general schema detection problem is hard. Similarly, putting proper restrictions on document structures is important for efficient extraction. Moreover, the problem of how to choose models for Web documents includes:

- There is a tradeoff between the expressive capability and operation efficiency of Web document models.

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- The model chosen should be convenient to build relations with other formalisms and be theoretically analyzable.

Extracted data with common schemata should be integrated, such that a user can query integrated data. Data integration needs to know the similarity among data; and it also needs to choose a data model carefully to guarantee efficiency.

Summarizing the challenges of building a concierge system, we briefly state the objective of this thesis as below: *We need to build a* **concierge system** *between human-centered Web data resources and end-users, which is based on a consistent* **data model** *over* **irregular documents** *with* **implicit schema**, *and provide* **efficient** *and* **extensible** *query interface to other applications.*

1.3 Framework for Web Information Concierge

In this section, we briefly discuss previous research about Web information concierge system, and present a new framework for it.

A Web information concierge system must have the capability to efficiently extract data from the Web. Efficient extraction of data from a given Web document requires building a program, called a wrapper [Kushmerick, 2000a], reading the document and outputting fragments of the documents. The extracted document fragments are named data instances.

At first, wrappers were built using generic programming languages, like Java and C, which are still feasible when the wrapper only needs to extract data from several Web documents. With the coming of Web information concierge systems, more specific programming languages [Gupta et al., 1997] have been invented to analyze Web data structures and to output special parts in a procedural way. However, the wrappers written using these procedural languages are rather ad-hoc and difficult to be compared with each other. Similar to the relationship between procedural database query languages and declarative database query languages, people are inclined to use declarative wrapper generation languages in a unique framework, since it is easier to compare these wrappers and share knowledge to generate wrappers.

Fortunately, recent research on conceptual modeling studies [Liu et al., 2002b, da Silva et al., 2002] of Web data has opened the door to define declarative wrapper generation languages. Usually, Web data are modeled in a two-layer framework: physical layer and logic layer. The physical layer contains data instances to be extracted, while the logic

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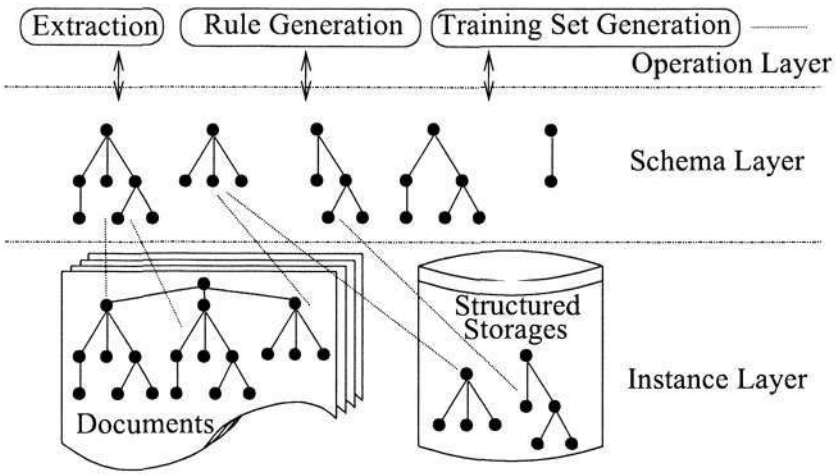


Figure 1.2: Framework for Web Data Extraction

layer contains concepts that describe the syntactic structure of data instances. A declarative wrapper generation language describes abstract concepts of a class of data instances, and an extraction engine then can map these concepts to physical data and undertake real extraction.

Conceptual modeling of Web data and its relationship with wrapper generation languages will be discussed in Chapter 4. In this thesis, concepts corresponding to data instances are denoted as schemata. The term of schema is used to describe both original Web data and extracted data, thus, providing a common basis for a declarative language to access both Web data and extracted data.

The thesis organizes my research work on the conceptual modeling of Web data and how to query Web data in a framework that draws ideas from relational databases. A relational database contains at least a relational data model and relational operations. A relational data model includes *data instances* (2-dimensional tables consisting of sets of tuples) and *schemata* (descriptions of those instances). Relational operations are based on sets; i.e., the inputs and their returned results are tables, instead of individual tuples. Tuples in a relational database may have different structures and can be changed by operations. However, the schema of a table is static. Thus, it is possible to provide a consistent way for all those operations to handle various tuples in a system.

We adapt the relational framework in our Web data extraction framework (Figure 1.2). As our framework works on semi-structured data, it substantially differs from

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the relational framework. Relational schemata only describe linear tuples, while in our framework, schemata describe tree structures. A relational instance is a table with a unique schema, while in our framework, a data instance may be a document, a fragment of a document or a piece of extracted structured data. A document may correspond to multiple schemata, and a schema may correspond to multiple data instances. In Figure 1.2, these dash lines among data instances and schemata represent corresponding relationships among them.

The core of our framework is the *schema layer*. Schemata describe data instances and provide information to the operation layer. To put our framework into practical systems, there are some problems to address. In Chapter 3, these problems will be discussed in detail.

1.4 Organization of Thesis

This thesis is organized as follows. In Chapter 1, we give a brief background about information concierge systems. We also present the key problems in such systems: (1) Discovering the schemata of Web data, and (2) Providing structural query interfaces of Web data. Further, an overview of our framework is described to connect DBMS concepts to concierge systems.

Chapter 2 surveys the related literature that influences our work to build information concierges. It discusses problems in various components of concierge systems, including the key component to extract data and some auxiliary components that facilitate extraction and query on extracted data. Before going on to discuss a unified view of all components in a concierge system, this chapter also provides an introduction to related techniques, and discusses the common and different points among them.

Chapter 3 presents an initial study of the framework introduced in Chapter 1, and discusses some theoretical problems of the framework. Based on the framework, this chapter gives a general definition of schema layer, instance layer and operation layer. The general definition for schema and instance provides a theoretical basis for the following chapters.

In Chapter 4, the details of relationship between schema and instance are discussed regarding the framework. As the selection of expressive power of schema strongly affects the execution complexity of operations, such as automatic schema detection and Web data extraction, Chapter 4 focuses on the comparison of various schema classes, and the

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complexity of corresponding operations. Different characterizations of the framework are demonstrated from various perspectives. The cross-fertilization relationships among these characterizations can facilitate the comparison of schema expressive power and operation complexity. A Web data extraction language (WDEL) that is roughly coinciding with monadic second-order (MSO) logic in terms of expressive power of schema is then proposed.

The purpose of Chapter 5 is to elaborate on the details of the an important operation — schema detection. Although WDEL programs defined in Chapter 4 are easy to generate using visual interface of my system, it is not easy to automatically induce WDEL programs. Thus, Chapter 5 studies two methods to restrict expressive power of schema to reduce the complexity of schema detection. First, a constrained version of schema detection is introduced. By parsing Web documents into trees and schema detection is deduced to a problem of common subtree detection problem. A $O(n \log n)$ algorithm is introduced to solve the problem. Second, by connecting the problem with common substring detection, we devise a data structure, named DocItem tree, which can be constructed in time linear in the document size. As well, DocItem tree can act as a dictionary of schemata that allow schema search in linear time in the schema size.

Chapter 6 demonstrates the flexibility of our framework by touch on how to provide auxiliary operations in the framework, and how to implement visual front-end of WDEL to make Web data extraction easier to use.

In Chapter 7, the experimental details of operations in Chapter 5 and Chapter 6 are presented, and then experiment data are given to show the feasibility of the proposed operations.

Chapter 8 draws the thesis to a close in two key ways. First, it summarizes the key findings of my research as well as the contribution that have been made. Next, it proposes potential areas for further research.

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Chapter 2

Literature Survey

This chapter surveys previous work related to Web information concierge systems. First, a basic wrapper system from Kushmerick [2000a] is studied. This system is analyzed from various aspects. Next, some improvements to each aspect are introduced. And then, techniques that may facilitate tasks of the basic system are discussed. In the end of this chapter, problems of the techniques introduced are presented. It is the motivation of my research in this thesis to overcome these problems.

2.1 Basic Model for Web Data Extraction

The main task of a Web information concierge system is extracting data from Web documents. In this section, we discuss a basic wrapper system that conducts Web data extraction. Most data available on Web are represented using semi-structured data models, such as HTML, XML and LaTeX documents. Unlike free texts written in natural languages, these documents are without obvious structures. Semi-structured documents contain delimiters such as tags in HTML pages, which construct the structure of documents. These structural pieces of information are not perfect, when compared with those in structured data. Data schemata describing the rules of structure organizing usually are hidden from users or do not exist at all. Much unrelated information or noise such as commercial advertisement or wrong handwritten codes may appear in Web documents. Sometimes the delimiters in these documents may be used to define the visual layout displayed in Web browsers, and may not have a relationship with semantic information of the documents.

Due to the complexity of Web data structure, automatically extracting information

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from semi-structured Web documents is not a trivial task. To explain the problems in extraction in detail, we will highlight some aspects of a Web data extraction component, such as how to represent Web documents, schemata and extraction tasks. A class of representations of these aspects is called a Web data extraction model. Such a model should at least consist of five aspects:

- The data model of target Web documents to be extracted,
- The output data model delivered to users,
- The extraction rule model of how to process these target documents and extract data from them,
- The methods to generate extraction rules,
- The methods to execute extraction rules.

2.1.1 Target Document Model

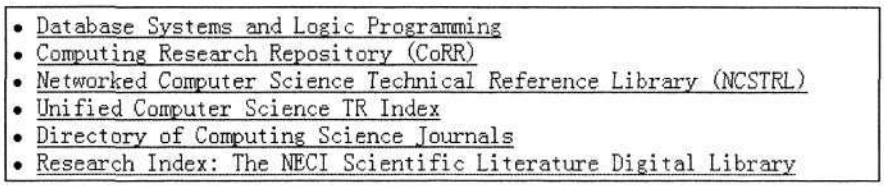
Most Web sites are built based on backend databases [Florescu et al., 1998]. They generate HTML or XML documents with a set of rules on how to map data in structured databases into semi-structured documents. Because these rules are invisible to us, it is essential for us to find the rules inferred from the structures and the contents of documents we can access.

Generally, Web documents can be modeled as directed graphs [Florescu et al., 1998]. However, Kushmerick [2000a] argues that there is a trade-off between the complexity of target document models and complexity of extraction rule induction, thus, Kushmerick [2000a] first suggests a very simple model for Web documents, such that it is possible to induce extraction rules with low complexity. For a simple Web document in Figure 2.1(a) that is rendered from document in Figure 2.1(b), Kushmerick [2000a] suggests a tabular target document model to describe it, described as below:

$$\left\{ \begin{array}{c} \langle b_{1,1}, f_{1,1}, e_{1,1}, \ldots, b_{1,j}, f_{1,j}, e_{1,j}, \ldots, b_{1,n}, f_{1,n}, e_{1,n} \rangle \\ \langle b_{i,1}, f_{i,1}, e_{i,1}, \ldots, b_{i,j}, f_{i,j}, e_{i,j}, \ldots, b_{i,n}, f_{i,n}, e_{i,n} \rangle \\ \langle b_{k,1}, f_{k,1}, e_{k,1}, \ldots, b_{k,j}, f_{k,j}, e_{k,j}, \ldots, b_{k,n}, f_{k,n}, e_{k,n} \rangle \end{array} \right\}$$

In this model, each row is a record in Web documents. Each $f_{x,y}$ is a string in documents to be extracted, and $b_{x,y}$ and $e_{x,y}$ are delimiters around these fragments.

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(a)An HTML page listing several search Web sites

```
01  <LI><A HREF="http://www.informatik.uni-trier.de/~ley/db/index.-
      html">Database Systems and Logic Programming</A>
02  <LI><A HREF="http://xxx.lanl.gov/archive/cs/intro.html">Comput-
      ing Research Repository (CoRR)</A>
03  <LI><A HREF="http://www.ncstrl.org/">Networked Computer Science
      Technical Reference Library (NCSTRL)</A>
04  <LI><A HREF="http://www.cs.indiana.edu:800/cstr/search">Unified
      Computer Science TR Index</A>
05  <LI><A HREF="http://fas.sfu.ca/project...ons/CMPT/cs-journals/">
      Directory of Computing Science Journals</A>
06  <LI><A HREF="http://www.researchindex.com/">Research Index: The
      NECI Scientific Literature Digital Library</A>
```

(b) an HTML text example

Figure 2.1: Example of Web Data

Example 2.1. In the relational model, lines 1 through 6 in Figure 2.1(b) are six records; each record contains information of a search Web search engine including its name and URL. These lines in this simple HTML document are easy to represent using a relational structure. For example, the first line is represented as below:

⟨<LI><A HREF=", http://www.informatik.uni-trier.de/~ley/db/index.html, ", >, Database Systems and Logic Programming,</A>⟩

In this tuple, $b_{1,1}$ is <LI><A HREF=", $f_{1,1}$ is http://www.informatik.uni-trier.de/~ley/db/index.html, $e_{1,1}$ is ", etc.

2.1.2 Output Data Model

The HTML document in Figure 2.1(b) is a string s over a finite alphabet Σ; i.e., $s \in \Sigma*$, where $\Sigma*$ is the application of Kleene closure to Σ. Data extraction components extract

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sub-strings from it. Suppose a user wants to know all engines' names and URLs from the document, these interesting parts in s can be modeled as standard tabular data model. In the tabular model, each relation (or table) is a set of records. Each record is a tuple with fixed arity; i.e., the number of atomic fields in a tuple. A tuple can be denoted as $\langle f_1, f_2, \ldots, f_n \rangle$, where f_1 through f_n are fields in the tuple and n is arity of the tuple. The domain of these fields is the set of sub-strings in s; i.e., each field can be a sub-string in the HTML document.

Based on this model, interesting contents in Figure 2.1(b) can be stored in a table shown in Example 2.2, where each row is a tuple and each column corresponds to a field.

Example 2.2. The table extracted from the HTML document in Figure 2.1(b) is drawn as below:

$$\left\{ \begin{array}{cc} \langle URL_1 & SiteName_1 \rangle \\ \langle URL_2 & SiteName_2 \rangle \\ \langle URL_3 & SiteName_3 \rangle \\ \vdots & \vdots \end{array} \right\}$$

This tabular data model is not enough to describe various kinds of data extracted. For example, a query submitted to *Google* will return an HTML page that is very simple to read by humans. However, it is not easy to resort to a unique table to store all information in it.

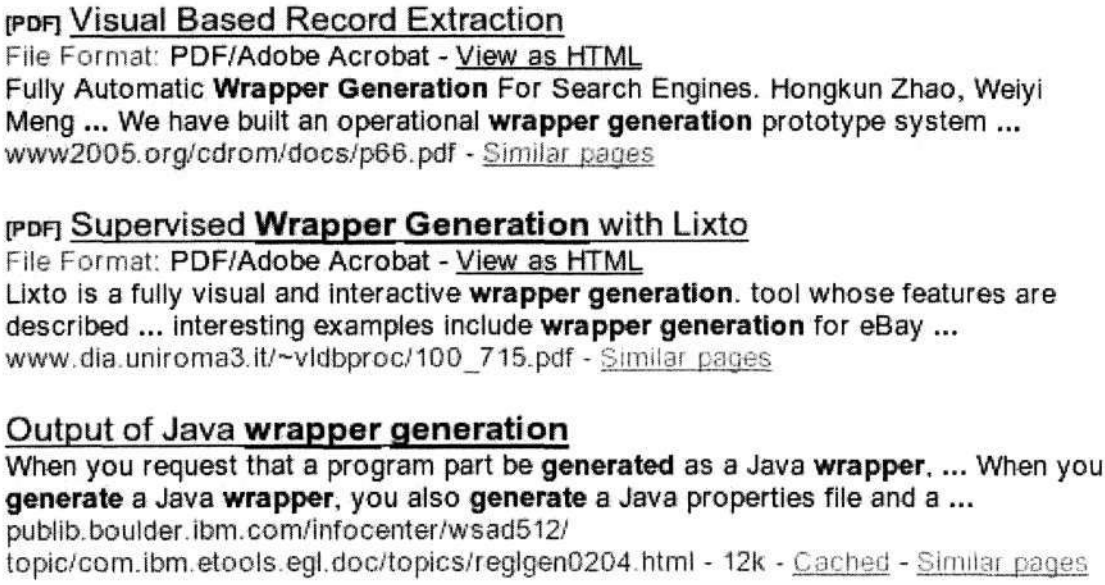
If we submit a query "Wrapper generation" to *Google*, it will return an HTML page like the one in Figure 2.2. This page contains a list of records about online resources related to "wrapper generation". In fact, some records may have fields that are different from others. This page also uses different layouts to organize records describing resources from the same Web site. The information is difficult to model as a tabular structure in Example 2.2. The problem becomes more complex if we represent Web documents as data graphs. These more complicated situations will be discussed in Chapter 4.

2.1.3 Rule Model

In the above sections, tabular model was exploited to describe both target Web documents and extracted data. Kushmerick [1997] defines *wrapper* that fills the gap between target Web documents and extraction data, as below:

Definition 2.1. Given:

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[PDF] Visual Based Record Extraction
File Format: PDF/Adobe Acrobat - View as HTML
Fully Automatic **Wrapper Generation** For Search Engines. Hongkun Zhao, Weiyi Meng ... We have built an operational **wrapper generation** prototype system ...
www2005.org/cdrom/docs/p66.pdf - Similar pages

[PDF] Supervised **Wrapper Generation** with Lixto
File Format: PDF/Adobe Acrobat - View as HTML
Lixto is a fully visual and interactive **wrapper generation**. tool whose features are described ... interesting examples include **wrapper generation** for eBay ...
www.dia.uniroma3.it/~vldbproc/100_715.pdf - Similar pages

Output of Java **wrapper generation**
When you request that a program part be **generated** as a Java **wrapper**, ... When you **generate** a Java **wrapper**, you also **generate** a Java properties file and a ...
publib.boulder.ibm.com/infocenter/wsad512/topic/com.ibm.etools.egl.doc/topics/reglgen0204.html - 12k - Cached - Similar pages

Figure 2.2: Fragment of HTML Page Returned by *Google*

- a set of example Web pages $\mathcal{P} = \{\ldots, P, \ldots\}$,
- a set of *label* $\mathcal{L} = \{\ldots, L, \ldots\}$,

A wrapper W is a function from $\mathcal{P}$ to $\mathcal{L}$.

This is why sometimes Web data extraction components are called wrappers. However, it is more appropriate to divide a wrapper into an extraction rule model and an extraction algorithmic framework that interprets the rule model. The extraction rules represent the mapping relationship between target Web documents and extracted data. Extraction algorithms execute these rules to do real extraction. Defining an independent rule model can highlight the mapping knowledge representation, which is important in comparing various methods, as shown in Chapter 4.

Using the tabular model in Example 2.2, Kushmerick's [1997] basic extraction algorithm can process Web document represented as a list of tuples:

$\langle \ell_1, f_{1,1}, r_1, \ell_2, f_{1,2}, r_2, \ldots, \ell_n, f_{1,n}, \ell_n \rangle \ldots \langle \ell_1, f_{k,1}, r_1, \ell_2, f_{k,2}, r_2, \ldots, \ell_n, f_{k,n}, r_n \rangle$.

That is, the delimiter pairs around the same fields of all tuples are the same. In this example, only the delimiter pairs for the first tuple are needed to do extraction.

The extraction in Kushmerick [1997] is a procedure that locates these delimiter pairs, and output the contents between these delimiters. This procedure is similar to the

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interpreting of XSLT [W3C, 1999], which search Web documents for special nodes that match a given pattern, and then produce output data according to a given template. As well, we can define a extraction rule model similar to XSLT template rules, which contains two parts: (1) a structural pattern matching special parts in Web documents, and (2) a template of output.

In Example 2.1, the extraction rule can be defined as:

```
<RULE>
<Pattern><LI><A HREF=",",>,</A></Pattern>
<Result>contents</Result>
</RULE>
```

When an extraction procedure only needs to write all contents matching the pattern to output, the output template in the corresponding rule can be omitted.

2.1.4 Extraction Procedure Model

Algorithm 1 Extraction

Require: Web Document $P = \langle \ell_1 f_{1,1} r_1 \ell_2 f_{1.2} r_2 \ldots \rangle$
Require: Rules $R = \langle \ell_1, r_1, \ell_2, r_2, \ldots, \ell_n, r_n \rangle$
Ensure: $O = \langle f_{1,1}, f_{1,2}, \ldots f_{1,n} \rangle \ldots$
Ensure:
  while !EOF(P) **do**
    for $i = 1; i \leqslant n;$i++ **do**
      $f_i \leftarrow$ substring between ℓ_i and r_i in P;
    end for
  end while

Extraction rules describe how to map from target documents to extracted data. A tuple $\langle \ell_1, r_1, \ell_2, r_2, \ldots, \ell_n, r_n \rangle$ is the pattern of an extraction rule of the basic extraction rule model. ℓ_i is a text string that marks the left side of ith field f_i, while r_i marks the right side of f_i. The extraction procedure reads target Web document P, and map P to output tuples O. Algorithm 1 is the pseudo-codes of an extraction procedure.

In the extraction rule, each pair of ℓ_i, r_i can be used to locate a text string to be extracted. The extraction procedure starts from the beginning of document P and then locates interesting fragments one by one.

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2.1.5 Rule Generation Model

There are two basic approaches to build rules: *Knowledge Engineering Approach* and *Machine Learning Approach* [Appelt and Israel, 1999]. The former method requires a person called "knowledge engineer" who is familiar with the extraction component to write rules. In contrast, the latter approach does not need require people to deal with the details of the working mechanism of an extraction component and develop rules manually.

Obviously, knowledge engineering approaches are easy to implement if there are experts of Web data extraction. This is the reason why those concierge systems based on these methods [Gupta et al., 1997] can appear years before the systems based on machine learning methods. However, generating rules manually is time-consuming and error-prone. Kushmerick [1997] introduces an initial study about inducing extraction rules based on the models introduced above.

Kushmerick [1997] defines rules generation as a grammar induction problem; i.e., suppose target Web documents are generated from a target grammar; rule generation is meant to formulate some hypotheses of the target grammar based on some training documents selected from target documents.

Algorithm 2 RuleInduction

Require: $\mathcal{P}$ — Training Documents
Require: F — the set of fields in $\mathcal{P}$
Ensure: R — Rule Set
  $R \leftarrow emptyset$
  $E \leftarrow$ all possible rules
  for $e \in E$ **do**
    if $Extraction(\mathcal{P}, e) \neq \emptyset$ **then**
      $R \leftarrow R \cup e$
    end if
  end for

Algorithm 2 is the extraction rule generation procedure based on the extraction model introduced above. It first exploits an oracle to label all fields to be extracted. This oracle can be a person or an intelligent program [Rajaraman and Ullman, 2001]. It then generates all possible extraction rules; i.e., a list of string pairs enclosing each field. Finally, the algorithm tests all these rules using Algorithm 1. If a rule can produce the same output fields as those labeled by the oracle, the rule is inserted into the final rule

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set.

2.1.6 Improvements of the Basic Model

The basic data extraction model can handle only tabular structural documents. Using the simple pattern ⟨<LI><A HREF=",",>,</A>⟩, Algorithm 1 can extract from the document in Figure 2.1(b), and produces a table like the one in Example 2.2. As stated in Kushmerick [1997], about half of Web documents can be extracted based on this model. However, it is ineffective in more complicated documents.

Example 2.3. Suppose we insert the following HTML code into the Web documents in Figure 2.1(b) before line 1:

```
<LI><A HREF="http://home/"><B>Information</B></A>
```

The basic extraction model cannot work any more. If the extraction procedure still uses the same rule, it will extract wrong information, i.e., there will be unwanted tags in the name extracted. Moreover, no rule can be generated based on the basic model. In order to deal with such inadequacies, more expressive patterns should be exploited. However, to automatically induce rules with high expressive patterns is not easy. Some enhanced versions of the basic extraction rule models have been introduced [Kushmerick and Thomas, 2002, Sakamoto et al., 2001, Thomas, 1999a], while these rules can be induced efficiently. In this section, we focus on improving the target document model and the corresponding change of the rule model.

Enhanced Tabular Models Target Documents The basic wrapper model can extract data from Web documents with 2-Dimensional tabular structures whose data appear in numerous Web documents. However, the contents surrounding these tabular structures make the situation more complex. Kushmerick [2000a] enhances the basic extraction model to extract more complicated documents, called enhanced tabular documents. The first extension is the Head-Left-Right-Tail (HLRT) model in which extraction rules have two additional delimiters: *Head* and *Tail*. These delimiters are used to locate tabular fragments in documents. For example, to solve the problem in Example 2.3, we define a Head delimiter – </A> to skip the new line, and then process the left lines like the procedure in the basic extraction model. We now change the pattern in the extraction rule to

⟨ </A>,<LI><A HREF=",",>,</A>,</HTML>⟩

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Example 2.4. If we add another line before each record in the Web document in Figure 2.1(b), the HTML document changes as shown below:

```
        ⋮
01  <LI><A HREF="http://xx.xx">icon1</A>
02  <LI><A HREF="http://www.informatik.uni-trier.de/~ley/db/index.
      html">Database Systems and Logic Programming</A>
03  <LI><A HREF="http://xx.xx">icon2</A>
04  <LI><A HREF="http://xxx.lanl.gov/archive/cs/intro.html">Comput-
      ing Research Repository (CoRR)</A>
05  <LI><A HREF="http://xx.xx">icon3</A>
06  <LI><A HREF="http://www.ncstrl.org/">Networked Computer Science
      Technical Reference Library (NCSTRL)</A>
        ⋮
```

Neither a basic model nor a HLRT model can correctly extract information from those Web documents. To deal with this situation, Kushmerick [2000a] has suggested the second extension Open-Close-Left-Right (OCLR). OCLR extraction rule exploits two strings o and c to mark the beginning and end of each record. To extract the above documents, the extraction rule is revised as below:

⟨ </A>,<LI><A HREF=",",>,</A>,</LI>⟩

In this rule, </A> is used to locate the beginning of each record, while </LI> is used to locate the end and each record. Head-Open-Close-Left-Right-Tail (HOCLRT) represents another enhancement of the basic model that combines OCLR and HLRT model to provide more flexibility.

The extraction models introduced in this section extend the basic extraction model by adding some delimiters to locate a regular tabular fragment in Web documents. Though they can be used in more situations on the Web, many Web documents still cannot be represented using enhanced extraction models introduced.

Hierarchical Models for Target Documents It is not easy to describe much information using tabular structured documents, e.g., the contents of a book and the file folders information of a hard disk. Although most relational databases integrate XML storage features, which exploit nested relational tables to store transformed hierarchical XML documents, their performance is not satisfactory enough to store and query large

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```
01 Part I Introduction
02   1 The concept of the C++ Standard Template Library
03     1.1 Genericity of components
04     1.2 Abstract and implicit data types
05     ⋮
06   2 Iterators
07     2.1 Iterator properties
08     ⋮
09 Part II Algorithms
10   1 ···
```

Figure 2.3: Contents of a Book

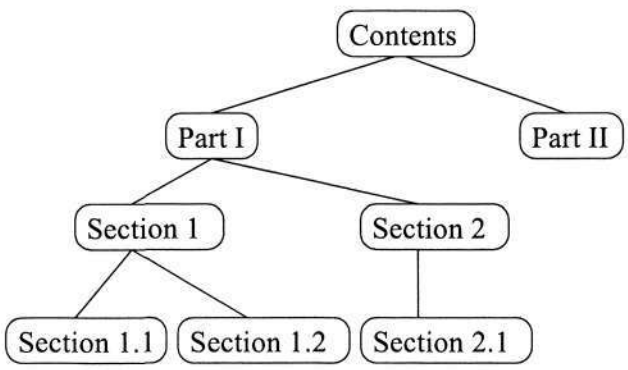


Figure 2.4: Hierarchical Structure of the Contents of a Book

volumes of Web data. We prefer hierarchical structured documents in order to describe such information and to define hierarchical extraction models to extract data from these documents.

Example 2.5. Figure 2.3 is a part of the contents from a book. Unlike the HTML document in Example 2.2, we cannot use the tabular data model to represent this information. The contents have a hierarchical structure shown in Figure 2.4.

Nested-Left-Right (NLR) is an extension of the basic model required to process the above documents. To extract these documents, we can use an extraction rule as below:

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$$\left\{ \begin{array}{ll} \langle \ell_{1,1}, r_{1,1} \rangle & \left\{ \begin{array}{ll} \langle \ell_{1.1.2}, r_{1.1.2} \rangle & \left\{ \begin{array}{l} \langle \ell_{1.1.1.3}, r_{1.1.1.3} \rangle \\ \langle \ell_{1.1.2.3}, r_{1.1.2.3} \rangle \end{array} \right\} \\ \langle \ell_{1.2.2}, r_{1.2.2} \rangle & \langle \ell_{1.2.1.3}, r_{1.2.1.3} \rangle \end{array} \right\} \\ \langle \ell_{2,1}, r_{2,1} \rangle & \{\ldots\} \end{array} \right\}$$

In this rule, each column contains a set of delimiter pairs to locate fields corresponding to nodes in the same layer of the hierarchical structure. For example, $\langle \ell_{1,1}, r_{1,1} \rangle$ and $\langle \ell_{2,1}, r_{2,1} \rangle$ in the first column can locate Part I and Part II.

All these extraction models introduced so far are based on an assumption that there is a common surrounding pair of delimiters for the same fields in each record. While this assumption may be too strong, for some simple Web documents it is true. More expressive models will be introduced in Chapter 4.

We must notice that there exists a tradeoff between the expressive power of extraction rule models and the complexity of automatic rule generation. For example, the NLR model takes time to grow up exponentially in a number of fields, and HOCLRT model requires a much larger training set than that required by OCLR and HLRT models to achieve the same precision. It is important, therefore, to define a compromise model that has "enough" expressive power to represent Web documents and easy to generate extraction rules.

2.2 Variant Formalisms for Target Documents and Rules

We have presented documents that cannot be extracted by the basic extraction model in Example 2.5. Although some enhanced models are introduced, we can find documents fail them. An extraction model that is more expressive and flexible is needed; otherwise, the extraction procedure may be fragile and cannot obtain any information in many situations.

There is a tradeoff between expressive power and learning complexity. The rule learning procedure introduced in the basic extraction model uses an inductive learning method to generate extraction rules. Kushmerick [2000a] compares the rule learning efficiency of the basic wrapper model, NLR, HTLR, OCLR, etc. We notice that the cost in terms of the time of the learning procedure is very expensive. One reason for

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this high cost is Kushmerick [2000a] builds rule generation procedure on PAC-learning model [Valiant, 1984]. We shall introduce other learning models and heuristic methods that can induce acceptable extraction rules. In this section, we elaborate the extraction models that exploit variant target document models and rule models.

2.2.1 Word Language

These extraction rules models we introduced can be analyzed using formal language theory, while documents can be treated as some instances of certain languages. To analyze these rules using formal language theory is important in order to understand them and facilitate their implementation. First, we introduce how to analyze the documents to be extracted using word language theory, Second, tree language and stochastic language are discussed.

Regular Language Many extraction models use grammatical induction techniques to learn extraction rules that roughly coincide with regular languages. In other words, the extraction rules are regular expressions, while documents are treated as regular languages generated by the regular expressions [Chang and Lui, 2001, Crescenzi et al., 2001].

For example, the basic extraction rule $\langle \ell_0, r_0, \ell_1, r_1, \ldots, \ell_n, r_n \rangle$ can be represented as a regular expression $*\ell_0 \perp_0 r_0 * \ell_1 \perp_1 r_1 \ldots \ell_n \perp_n r_n$, where $\perp_i$ and * are symbols that do not appear in target documents. Given a target document and the regular expression, the system will try to match them, where $\perp_i$ can match any strings in documents. If the document and the regular expression are matched, then those strings matching $\perp_i$ are extracted.

For the sake of the strong connection between word language and finite state automata (FSA), it is straightforward to build finite state automata that can match a regular expression to target documents. The regular expression above can be transformed into the finite state automata in Figure 2.5, starting from initial state b, read input ℓ_0, and then search forward for r_0, if r_0 is found, then output strings between ℓ_0 and r_0, and so on.

Some systems [Chidlovskii et al., 2000, Hsu and Chang, 1999, Muslea et al., 2001] exploit finite automata as extraction machines. As the flexibility of regular expressions (e.g., wildcard character '*' can match any string), they can deal with some complex situations. Considering an HTML document of a bookstore Web site, we may encounter the following problems during the data extraction procedure.

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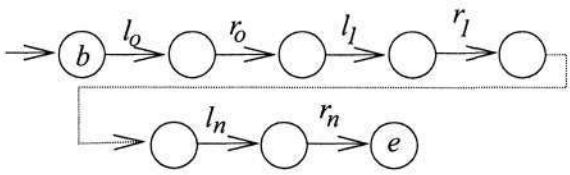


Figure 2.5: Finite State Automata

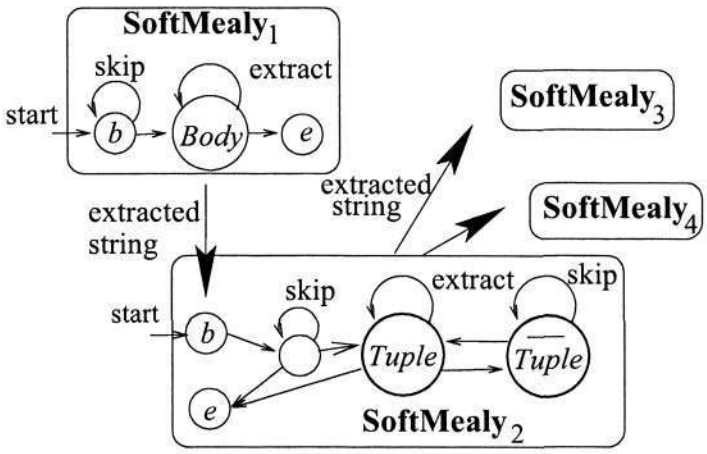


Figure 2.6: Multi-pass SoftMealy Automata

- Missing attributes: A book entry may include an author, publisher, publishing date, and comments. Sometimes, in a document listing a series of books, one book may contain comment information, while another book may not.
- Multi-valued attributes: A book may have more than one author.
- Multiple orderings of attributes: Some book entries put author name before title; some also put the name after the title. Consider another situation, a Web server may send XML documents and the corresponding XSL to a user's Web browser; in this case, the Web browser can decide the ordering of sibling elements according to the XSL. An extraction procedure may not want to interpret the XSL, though it may still need to deal with the possible multiple ordering of these sibling elements.
- Disjunctive delimiters: A document may use different delimiters to mark the same fields of different book entries. For instance, the titles of hot sales may appear in bold format, while other titles may not.

In their extraction model, Hsu and Chang [1999] devise a class of FSA named Soft-

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Mealy Automata to formalize the extraction machine. Figure 2.6 is an example that contains four SoftMealy automata where each circle is a state of SoftMealy, and each edge is a transition. On the one hand, the automata read Web documents as input; one the other hand, the grammar of the automata describes the condition of the transition. During the extraction transition, the automata will write extracted data to output. In this model the extractor can perfectly deal with those complex situations. For example, where the tuples in an HTML document have two kinds of delimiters, SoftMealy_2 can output texts containing tuples and feed other two automata, SoftMealy_3 and SoftMealy_4. Further, these two automata can deal with these two disjunctive delimiters respectively and locate correct tuples.

Context-free Grammar Finite automata have enough expressive capability to process most Web documents. If we still need more powerful extraction models, building a data extraction procedure that can interpret context-free grammar is one plausible choice. For example, we cannot use these finite-state grammars to extract the *middle column* of an HTML table. Indeed, research [Bianchi, 1996, Levy and Joshi, 1978] has been done to discuss how to learn context-free grammar efficiently and use it in data extraction. MINERVA [Crescenzi and Mecca, 1998] is an example of using context-free grammar as its extraction rules. MINERVA especially considers how to deal with errors and exceptions in Web documents. In particular, extraction rules of MINERVA can declare what to do when exceptions occur and recover to normal state.

2.2.2 Tree Language

Compared to various XML schema languages suggested [Lee and Chu, 2000], the basic extraction rule is very naive. As Web documents are mainly HTML and XML documents, and HTML specification today is an XML application, these XML schema languages can be the basis of extraction rule definition. Extraction rules with expressive power less than these XML schema languages are unable to describe all extraction tasks on Web documents conforming to these schema languages.

Murata et al. [2001] analyze the expressive capability of some XML schema languages in a framework based on a kind of formal language theory — tree language theory [Comon et al., 1997]. Their study of these XML schema languages could be a guide to designing extraction rules. They use tree language theory instead of classical formal language theory; given that tree languages are invented to process trees and it

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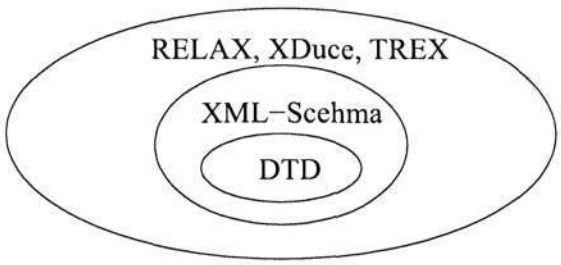


Figure 2.7: Expressive Power of Different Schema Languages

is intuitive to analyze XML schemata that have a hierarchical structure. Murata et al. [2001] define three subsets of regular tree grammars: *local* tree grammar, *single-type* tree grammar, and *restrained-competition* tree grammar. Regular Tree languages can represent all documents represented by context-free word languages. Chapter 4 will introduce more about these grammars, and compare them with other classes of grammars.

In their paper, Murata et al. [2001] prove that these existing XML schema languages can be categorized into the three classes of language grammars. DTD belongs to local tree grammars; XML-Schema belongs to restrained-competition tree grammars and RELAX; XDuce, TREX belong to regular tree grammar. The relationship of their expressive capability is shown in Figure 2.7.

For a Web site, documents usually are generated from some grammars; i.e., the target documents conform to some schemata. Thus, the rule generation process is like a reverse-engineering task meant to find the schemata confirmed by target documents. To extract accurate information from target documents, an intuitive approach is to define an extraction rule model that has the same expressive capability as XML schema languages used by these documents. Some XML parsers provide validators to test whether an XML document conforms to a given schema. Usually, an extraction procedure needs more features than these validators.

2.2.3 Stochastic Language

We have touched on how to improve the flexibility of extraction models so as to deal with complex situations such as missing attributes, and multiple attribute orderings. Some extraction models [Crescenzi and Mecca, 1998] can process errors and exceptions. However, these methods can only make binary decisions; besides, it is not easy to deal with uncertain situations. Sometimes we need deal with uncertain evidence in order to

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extract data.

For example, the Bootstrapping extraction system [Grumbach and Mecca, 1999] matches texts in documents with those field values classified and stored in a repository, then judge which class the parts in documents are, and which parts need to be extracted. So, suppose there are values `"52#, Graduate Hall, NTU"`, `"48#, Nanyang Valley, NTU"` in a repository that are classified into *mail addresses*, then, if they appear in a target document, the Bootstrapping system will extract them. If there is a string "12#, Graduate Hall, NTU" that appears in the document but does not appear in the repository, it will be difficult for the system to decide whether to extract or not. To deal with this situation, DataPro [Lerman and Minton, 2000] devises a stochastic extraction model; its rules can describe the probability of whether or not a text string should be extracted if it has special patterns.

Hidden Markov Model (HMM) is a more general stochastic finite state automata model. In this model, automata states are associated with probability tables with respect to a certain distribution. Transitions also occur according to a fixed distribution. To exploit HMM in Web data extraction, each state is associated with a text pattern that may match strings in documents to be extracted with a probability. For example, `"12#, Graduate Hall, NTU"` has the same pattern `"#num, #name, NTU"` with the other two address strings; a HMM model that accepts strings with this pattern as a mail address with high probability can be constructed. Other studies [Seymore et al., 1999, Leek, 1997, Bikel et al., 1997] have shown how to employ HMM in data extraction. As well there exist efficient algorithms learning HMM. Stochastic context-free grammars (SCFGs) constitute another kind of stochastic automata grammars. Hiemstra and de Vries [2000] discuss the use of SCFG learning techniques to find knowledge from large trees. Also, Church and Mercer [1993] discuss the approaches of applying SCFG to information extraction.

2.3 Auxiliary Components in Concierge Systems

Extraction components are key parts in information concierges. In the previous sections, we introduce how to define extraction models for these components. This section introduces some auxiliary components that aid extraction.

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2.3.1 Pre-processing of Extraction Components

To enhance an information concierge, we have so far highlighted the improvement of extraction models. In other words, we can extend the extraction rules and make them describe more complicated situations. We can also simplify these situations by pre-processing Web documents before passing them to extraction components, as will be discussed presently.

Detecting Informative Parts in Documents Admittedly, there are many redundant contents on the Web, such as mirror sites and identical documents available from different URLs. For a single document, there may be intra-page redundancy; i.e., the data may appear in multiple pages and may not be valuable to a user. If such redundancy is removed, it will be easier for a user to annotate the important parts in Web pages, thereby making them in the preparation of a training set for automatic Web data extraction methods.

A typical Web site includes much intra-page redundant information such as navigator panels, advertisement banners and company logo picture. For example, Figure 2.8 gives a possible layout of Web pages. The top rectangle contains an advertisement banner; the left panel is a navigator area; the right panel contains important information and the bottom panel is an area listing several hyperlinks pointing to related Web documents. Except the right panel, most of the visible areas in this layout contain overlay information that are repeated in many Web documents. But a user usually may not want to extract them multiple times from various documents, although these areas may help a user to browse Web sites and deliver some information.

Usually, Web documents are divided into a set of disjunctive content fragments using some delimiters. For example, Web sites builders used to employ "<TABLE>" to split a Web page into several fragments. It is possible to judge which fragments contain useful information by looking into the distribution of contents in various fragments.

A number of important studies that attempt to deal with the problem of redundant information in Web documents are worth mentioning at this point. As far as I know, Lin and Ho's [2002] work is very insightful. Lin and Ho [2002] introduce a method to detect informative parts in Web documents that are likely interesting to users. It assumes HTML documents to be extracted have multiple "tables", and there exist some similar documents with the same sets of tables. Then, if a table appears in various documents, it compares the contents in each appearance of this table. If contents in this table change

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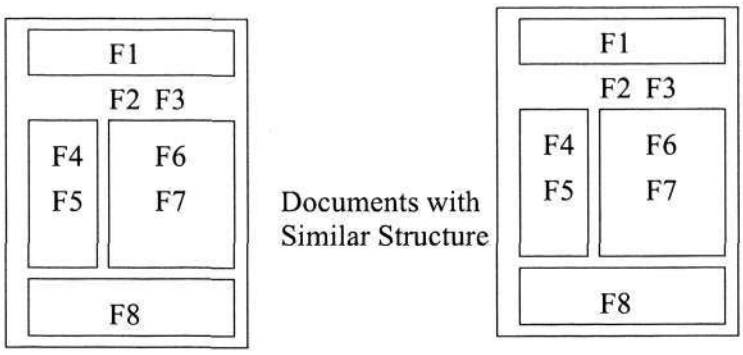


Figure 2.8: Web Page Layout and Feature Distribution

little in almost all these documents and contain similar information, it is reasonable to guess this table becomes a redundant, with little valuable information.

Lin and Ho's [2002] method contains five steps. The first step concerns extracting content blocks (CBs, HTML fragments in HTML documents). In this step HTML documents are divided into several blocks, with each block consisting of a text string inside a table. For example, each of the four rectangles is rendered from a table in Web documents. After extract CBs, the method extracts the most important features of each CB in step 2. There are many algorithms to extract keywords from a fragment of texts; thus the keywords of CBs can be used as a typical class of features. For example, in Figure 2.8, there are six features distributed in four tables and two features outside the tables. In step 3, the method calculates entropy values of all the features extracted using the below formula.

$$H(F_i) = -\sum_{j=1}^{n} w_{ij} \log_2 w_{ij}$$

This formula calculates entropy $H(F_i)$ of each feature F_i. Value w_{ij} is the weight of F_i in document D_j. Here the authors use keywords as features. The weight of a feature is a value used to measure the importance of the keyword in the documents. Step 4 obtains the CB's entropy by summing up all embedded features' entropy values: $H(CB_i) = \sum_{j=1}^{k} H(F_j))$, where CB_i contains k Features: F_1 to F_k. The entropy of CB represents the information embedded. High entropy value shows the CB contains large proportion of redundant or useless data. We can easily categorize these CBs based on their entropy values. If the entropy value of a CB is higher than a threshold we can treat

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this CB as a trivial fragment in documents, otherwise, it is an informative fragment.

While Lin and Ho's [2002] approach may be useful, it only introduces the use of keywords as features. The point though is sometimes a user may have more choices of features. For example, a bookstore Web site usually categorizes books with respect to their contents and provides a category list in most pages in it. Thus, if we only use keywords as a means of classification, the category table becomes obviously redundant and becomes a non-informative fragment in Lin's approach, although sometimes this category list is interesting to a user when he wants to know what kinds of books are provided by this Web site.

Wang et al.'s [2002] paper is insightful for it introduces the use of more kinds of features to classify tables, including layout, content type and word group. Layout features describe the numbers of rows and columns in a table. Content type features refer to the type of information embedded in the tables. Word group features are similar to the features in Lin and Ho's [2002] method. Based on these features, Wang et al. [2002] exploit decision tree and SVM to classify all these tables and ascertain which tables are informative, thus enable classification of tables into finer granularity. In most HTML pages, the tables use a column or a row to show descriptions of categories, and provide hyperlinks to the documents belonging to this category. By combining the features of layout and content type of a table, we can guess which table contains the category list.

It is worth noting that the above two methods both use `<TABLE>` tags to divide Web documents into smaller granularity, although other tags such as *hr, tr, td, a, p, br, h1, h2, strong, b* and *li* can be used to control the page layout of Web documents. In another study, Embley et al. [1999a] introduce a method that uses these tags as features and devise a heuristic algorithm to combine these features to detect which parts in Web documents may contain interesting information.

Automatic Document Annotation Like the basic data extraction model introduced, many systems require users to annotate Web documents as samples to train rule generation components. Although we can select informative fragments first, and ask users to annotate these fragments only, it is still time-consuming to annotate Web documents.

For example, if a company wants to compare all the online information about production items provided by its suppliers, it needs to generate wrappers corresponding to each Web site of suppliers. To generate wrappers, a user needs to annotate the available documents to tell rule generation components which parts are, for example, item names

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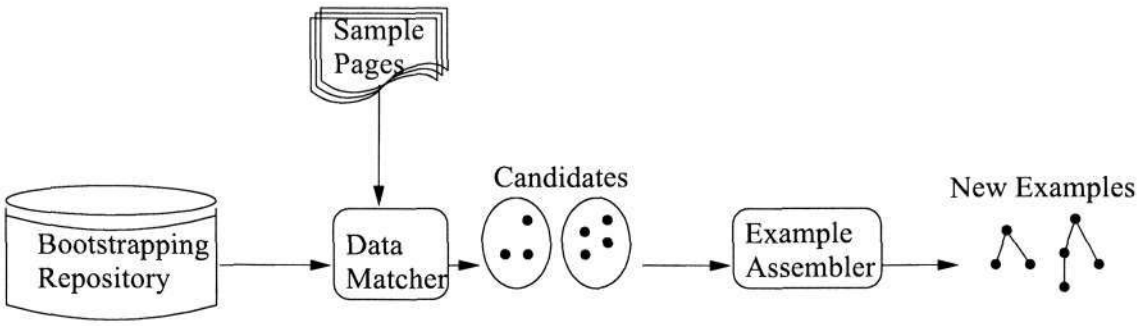


Figure 2.9: Automatic Annotation of Examples

and which parts are prices. If the layout of the Web sites is changed, the user needs to annotate these documents again. A big library to collect information about recent published books will also encounter these problems.

In these two examples, we notice that a library or company may maintain a database of books' information and production items' information. By using these sets of information, we can generate ontological knowledge base and use this knowledge to recognize information fields in documents and annotate them automatically.

Grumbach and Mecca [1999] have devised a method called Bootstrapping to exploit existing knowledge to annotate documents and extract data. Figure 2.9 shows the steps of this method. This method needs a bootstrapping repository containing a set of objects that appear in the Web sites to be extracted. For example, for a company that wants to extract information on production items, the repository should contain some objects of item names. Next *Data Matcher* matches the objects with the text appearing in target documents. Data matcher does not require the objects and text strings in documents match exactly, Grumbach and Mecca [1999] introduce some heuristic methods to judge if they are match when they are similar. For example, "Machado de Assis" and "Jose Maria Machado de Assis" refer to the same person. When there are text strings that match objects in repository, the method is able to extract the text strings.

The first merit of this approach is that it concentrates on extracting interesting data automatically, thereby enabling us to also use it annotate example documents to practice rule generation procedure. Another benefit of this approach is that it can work very well in a situation where various type of objects have seldom overlay parts and the repository is large enough. In this situation, the Data Matcher can generate high precision results. Beyond these strengths of this approach, utilizing more features of Web documents to

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improve precision of Data Matcher can also be an interesting research area.

2.3.2 Post-Process for Extraction Components

So far the techniques discussed relate to building extraction components or aid extraction component construction. After extraction components have been built, two issues remain to be addresses: (1) Are the extracted data the very information we want to extract? (2) Will the extraction rules be still validated when the target Web site changed its layout? Sometimes when we use wrapper techniques to extract information from the Web, we obtain much similar information. Detecting and consolidating similar information are important issues that can help users handle extracted data easily. In this section, we introduce some post-process processes of extraction.

Rule Verification and Maintenance Existing techniques usually generate extraction rules by analyzing structural information of Web documents [Kushmerick, 2000a, Sakamoto et al., 2001] or semantic information [Grumbach and Mecca, 1999]. The extraction rules can describe the structures of data sources and contents embedded in them. Thus, these rules are vulnerable to changes of Web document structures or contents. When the extraction rules fail, we must re-generate and test them.

Example 2.6. Let us back to Example 2.4, this time we want to extract the names of these search engines and the descriptions of these hyperlinks before each search Web site entry. A basic extraction rule's pattern ⟨`xx.xx">,</A>,">,</A>`⟩ can describe how to extract this information. Now if we move the hyperlinks before each search engine to the place after each engine, the HTML document will be changed to below. Obviously, the basic wrapper will fail when it encounters this change.

```
        ⋮
01  <LI><A HREF="http://www.informatik.uni-trier.de/~ley/db/index.
      html">Database Systems and Logic Programming</A>
02  <LI><A HREF="http://xx.xx">icon1</A>
03  <LI><A HREF="http://xxx.lanl.gov/archive/cs/intro.html">Comput-
      ing Research Repository (CoRR)</A>
04  <LI><A HREF="http://xx.xx">icon2</A>
05  <LI><A HREF="http://www.ncstrl.org/">Networked Computer Science
      Technical Reference Library (NCSTRL)</A>
```

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```
06    <LI><A HREF="http://xx.xx">icon3</A>
        ⋮
```

In this situation, verifying whether a wrapper is still validated may not be a big problem. For example, we can imagine that when the wrappers fail, it is very possible that HTML tags will either appear in the extract data or nothing can be extracted. If the number of HTML tags in newly extracted data and historical extracted data varies widely, we can assume the wrapper failed. Based on this assumption, Kushmerick [1999b] suggests a wrapper verification method — RAPTURE.

RAPTURE [Kushmerick, 1999b] is a wrapper verification tool using regression testing techniques to test the validity of wrappers. It counts the number of HTML tags and other features appearing in extracted data. To test the validity of a wrapper, it selects some features r of data extracted, compares r with these features R of historical data extracted using validated wrappers. If r is very similar to R, RAPTURE treats the wrapper as still valid. RAPTURE defines *equal probability* P to measure the similarity of r and R. We can calculate it using the formula below:

$$P[r, \mu_R, \sigma_R] = \frac{1}{\sigma_R\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{r-\mu_R}{\sigma_R})^2}$$

In this formula, μ_R is the mean of R, and σ_R is the standard deviation of R. RAPTURE assumes that these features distributed according to normal distribution; collects all the features of extracted data; calculates the equal probabilities and then combines them to obtain an equal probability v. Using v it is easy to evaluate whether the wrappers are still valid or out-of-date. The features exploited by RAPTURE include: (1) HTML density (the fraction of `"<"` and `">"` characters in extracted data), (2) word count (the number of words in extracted data), and (3) mean word length (average length of extracted words). We have mentioned before that if wrappers (such as OCLR class wrappers) fail it is very possible that the number of HTML tags extracted will change largely. The experiment results of RAPTURE confirmed this assumption. By using the HTML density features of extracted data, we can achieve almost the same or even better veracity, compared with the result of combining several features.

To improve the robustness of wrappers, wrappers need to be more flexible. For example, the basic extraction rule's pattern ⟨`</A>,<LI><A HREF=",",>,</A>,</LI>`⟩ can exactly extract data in Example 2.4. In Example 2.6, some fields appear in various orders, making the wrapper fail. If we use a regular expression as the pattern that means

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these text string can appear in multi-ordering, this situation can be processed. Some research [Chang and Lui, 2001, Davulcu et al., 2000] has been done to improve flexibility of wrappers by transforming fixed string extraction rules to regular expressions.

Some wrapper models such as DataPro [Lerman and Minton, 2000] do not use the exact matching techniques to compare rules and data sources. DataPro first encodes HTML documents to sequences of tokens. For example, a text string `"New York Street 10"` is an address, which can be encoded to `"Cap-Char Street Number"` where `"Number"`, `"Street` and `"Cap-Char"` are three tokens. DataPro calculates the proportion of strings that are encoded to `"Cap-Char Street Number"`. If the proportion is high, then this token sequence is significant and DataPro treats it as an extraction rule.

In these situations, wrapper verification is more complex than that applied in fixed string extraction rules, because changing the layout has little effect on these wrappers. When the wrappers fail, the number of HTML tags may not change as much as the situations in RAPTURE. Whether the verification performance can be improved by combining more features is an interesting issue to be studied.

If the verification result tells us a wrapper is out-of-date, it needs to be re-generated. After it has been regenerated, we can also use verification techniques to test the new wrappers and ascertain whether they are valid.

Data Consolidation Data extracted from heterogeneous resources may have similar structures or overlay contents. For example, news extracted from news Web sites should have news title, detail description, time. Books data extracted from bookstore Web sites should include book title, authors, editor, price, publisher, etc.

Data consolidation consists of two tasks: (1) clustering data with similar structures together, and (2) reducing overlay contents from extracted data. There are two benefits that can be derived from the consolidation of data. The first is that once similar data are clustered together, the efficiency of queries can be improved. Additionally, the queries can be submitted to only restricted clusters. The second is that if the overlay contents are diminished, the size of extracted data will decrease, and the consistency of the extracted data stands to be improved.

As extraction rules describe how to store extracted data, it is natural to find similar structures of output data by investigating the extraction rules. Davulcu et al. [2000] introduce efficient algorithms to find out this kind of information in extraction rules, and define the concept of unambiguous and the maximization of extraction rules that

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can represented by regular expressions. We also hope that wrappers can extract data as accurate as they can. Based on the correct extracted data, we also hope the wrapper rules can process as many data sources as possible. Unambiguous wrapper rules can extract data 100% accurately; maximization wrapper rules are unambiguous rules that can process maximum number of documents. Davulcu et al. have devised an algorithm that can maximize a large class of unambiguous extraction rules. If we find the maximized rules of rules applied to different data source, it is possible to maintain only one set of wrappers in order to extract data from several Web sites; in this case the extracted data will share the common structures.

Generally, consolidating overlay contents is quite difficult, as the same type of fields in data extracted from different Web sites may have different names. For example, the hottest news is likely to be involved in the homepages of both Web site a and Web site b. The field "news_title" in data from a and the field "article_title" from b talk about the same thing. Here, the different field names make content consolidation difficult. The consolidation of structures of extracted data gives the rationale for consolidating overlay contents. After the structures of the news items extracted are consolidate; i.e., after getting to know that the "news_title" and "article_title" contain the same type of information, it is easier to detect overlay contents by comparing the summary of corresponding fields of data extracted from different Web sites.

2.4 Related Research Area

So far, we have introduced components that may be included in an information concierge system. Some research techniques are strongly related to information concierge. If these techniques can be exploited properly, they can improve components in concierges. These related techniques are briefly discussed in the ensuring sub-sections.

2.4.1 Natural Language Processing (NLP)

In this thesis, when we mention Web data extraction, the target data source is semi-structural Web documents downloaded. Traditional Information Extraction (IE) focuses on free text document and largely depends on Natural Language Processing (NLP) techniques. Figure 2.10 is an architecture [Appelt and Israel, 1999] for transitional IE system focusing on free text extraction. This figure indicates that there is close relationship be-

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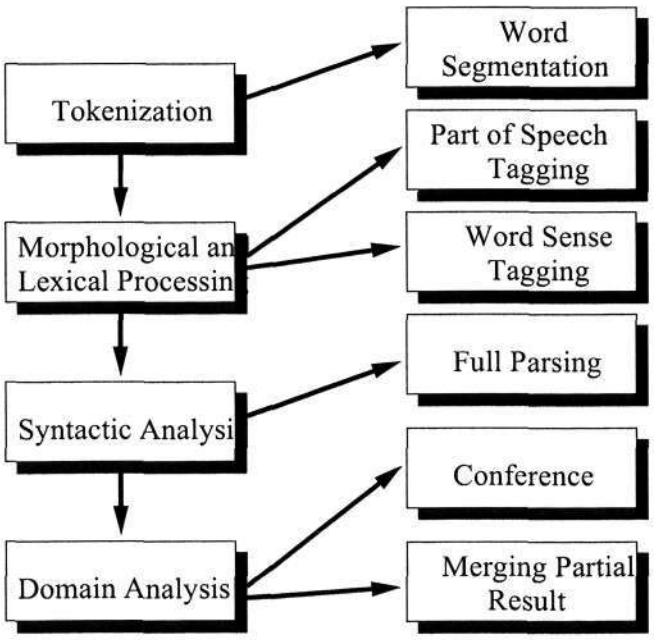


Figure 2.10: Architecture of Free Text Extraction System

tween IE and NLP techniques. Issues in Web data extraction obviously differ from those issues in IE systems.

In free text extraction, tokenization using word segmentation techniques is a prerequisite to execute further processes. To extract Web documents, if long paragraphs are tokenized first, then the extraction can be done at a finer granularity. Morphological analysis and lexical lookup are techniques used to analyze these tokenized text and find the possible semantic information. These techniques are very important in undertaking exact analysis. For example, if a text string is a name and it has not been recognized, there is a big chance of mistaking the meaning of the whole sentence. In most Web data extraction tasks, we do not need to understand the semantic information of documents, but sometimes we can use morphological analysis and lexical lookup techniques. Golgher et al. [2001] discuss how to maintain an object repository and match text appearing in HTML documents with the object attributes in the repository. According to them, the matched text strings can be used as clues to judge which parts of documents are to be extracted. Further, we can employ NLP techniques to improve the performance of such methods.

After word analysis, IE system will analyze the syntax of sentences and use domain

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related knowledge to find out the interesting parts and those to be extracted. This task requires the text to be rendered in full grammatical sentences. It is difficult to ask semi-structured Web documents full of tags meet this requirement. Thus,Soderland [1997] discusses the possibility of using the evidence of the Web page layout to reconstruct HTML documents into grammatical sentences and to apply syntactic analysis techniques to them.

2.4.2 Data Mining

Given that there are so many data available in databases, discovering the full range of knowledge from databases is almost impossible for humans without the aid of computers. The motivation of data mining is to provide methods to find knowledge in large volumes of data in databases. *Classification, Clustering* and *Association Rule mining* constitute the common tasks of data mining.

Web wrappers process Web data and transform extracted data to structured data. These structure data can be stored in database, XML document or other structured storages. The objective of Web data extraction is to provide a middle layer between heterogeneous Web data sources and users, so that users can concentrate on major data collections and find interesting information easily. If there are huge sizes of extracted data, concierges will meet the same problems as those in traditional databases, and data mining techniques can be directly applied to data extracted.

With the rapid growth of information on the Web, mining knowledge from Web documents becomes an interesting area for research. There are three well-known Web mining models *Web content mining, Web usage mining* and *Web structure mining.*

Web content mining is the task of automatically searching and retrieving information from the Web. Unlike traditional Information Retrieval system such as search engine, Web content mining employs domain related knowledge to improve the precision of retrieval results. For example, it can categorize Web data sources by mining users' bookmarks [Maarek and Shaul, 1996]. Web usage mining seeks to analyze user access patterns from Web servers. This kind of information is easy to collect for that Web server can save user access logs. These Web mining methods can help us to choose training samples to train extraction rule generator and help us generate strategy to present extracted data.

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2.4.3 Database Techniques

Database systems are developed to manage information and query them. To manage Web data is really a huge challenge to database techniques and it is impossible to use database techniques to solve all information management problems on the Web. However, because database techniques are mature, there are still many studies in the database community that address problems regarding how to use database systems to manage Web data.

There are three common kinds of database techniques related to Web data management:

- Modeling and Querying the Web
- Information Extraction and Integration
- Web site construction and restructuring

The Web can be viewed as a directed graph where each node is a Web document and edges are the hyperlinks among documents. How to generate queries that can retrieve accurate documents from the Web is a problem. All search engines can only execute simple queries that consist of keywords. Also, many search engines allow users to add more constraints on their queries. Interestingly, these constraints can be related to the content or link relation among documents. For example, *Google* provides an advanced search page that allows users to appoint the language and file format. Web documents can also be viewed in smaller granularity; we can say that the task of Web information concierges is to extract the finer granular data from Web documents. Some databases extend themselves by integrating wrapper system [May et al., 1999] and some databases' main data sources are provided by their internal wrappers [Gupta et al., 1997]. Unlike the main task of Web data concierges, the main task of databases is how to manage the extracted data. Thus, database techniques and Web data mediator techniques can be considered complementary.

2.5 Concierge System Architecture

We now introduce some architecture of Web information concierges. At the outset, it is worth noting that Extraction component is the kernel of information concierges, with various auxiliary components provided according to different application environments.

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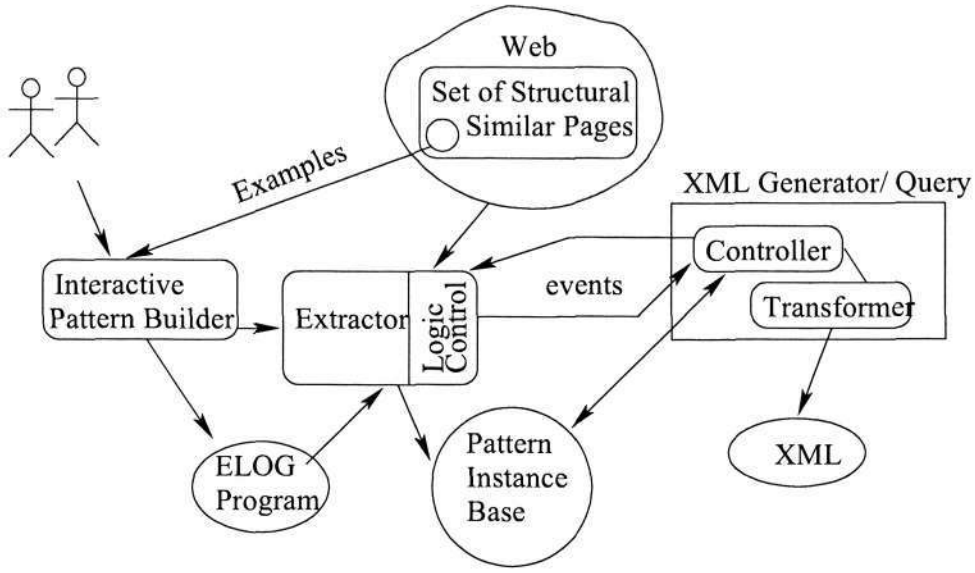


Figure 2.11: Architecture of Lixto

As the systems introduced in this section are oriented to different users, their architecture varies widely. In particular, Lixto [Baumgartner et al., 2001b] focuses on how to build an interactive extraction rule generator and a solid extraction machine. MIA [Beuster et al., 2000] in turn focuses on auxiliary components that can be customized by users, while FLORID [May et al., 1999] concentrates on how to provide a database accessing interface to extraction components to obtain high flexibility.

2.5.1 Extraction Components

Lixto [Baumgartner et al., 2001b] is a Web information concierge system using supervised rule generation techniques to build extraction rules, which are roughly equivalent to monadic second-order logic formulae. Thus, it is possible to exploit those logic program interpreters as extraction machine and use optimization approaches for logic programming.

Lixto considered how to provide visual interfaces to a user to ease extraction rule generation and maintenance. As shown in Figure 2.11, *Interactive Pattern Builder* is the rule generation component with visual interfaces that allows a user to annotate the training samples and the system generate extraction rules based on the sequences of annotation. Learned results are recorded by the internal logic-based declarative language

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— Elog. Users need not understand Elog and deal with it directly, but Elog provides a potential of control extraction tasks by modifying extraction rules manually.

Elog programs generated by the pattern builder are fed to *Extrator* — the extraction machine of Lixto. Web documents are downloaded and fed to the extractor at the same time. Document fragments that match the patterns defined via Elog are extracted after which they are are stored in *Pattern Instance Base*. *XML Generator* transforms the data in pattern instance base into final XML output documents.

Figure 2.11 shows the relationship among these components. Specifically, it provides user interfaces to control whole data extraction process. Lixto stores extracted data in XML documents and provides a simple query interface to users.
Elog [Baumgartner et al., 2001c], a logic based language like Prolog provides a method to store wrapper rules in a familiar way. For example, the following Elog rule tells the system to locate the first table in BBC news Web sites' homepage.

```
tablesq(S,x) ←documents("www.bbc.co.uk"),S),
             subsq(S, (.body,[ ])),(.table,[ ]),x)
```

Though Lixto provides prolific interfaces to control execution, but it is not enough sometimes. Let us imagine an application on the Web: an application service provider (ASP) wants to provide data extraction services to a mobile equipment user. In this application these interfaces are not useful to these end-users. Interfaces of Lixto can assist expert users to define wrappers and control the extraction procedure. Those systems oriented to end-users need to be built on more auxiliary components.

2.5.2 Integration of Auxiliary Components

MIA [Beuster et al., 2000] is Web information concierge system that servers mobile users. It crawls on the Web and extracts data to send them to mobile equipments such as mobile phone and PDA. MIA can collect users' location information and users' preference and present customized data to users. In the architecture provided by MIA, and shown in Figure 2.12, end-users never see the details of extraction rule generation and execution machine.

The Server module provides a gateway through which users can access their mobile equipments. Users' equipments use HTTP and WAP protocols to communicate with the server, while the server collect users' information, tailors the data extracted to correspond to users' information and sends the data to users. Depending on the document type a

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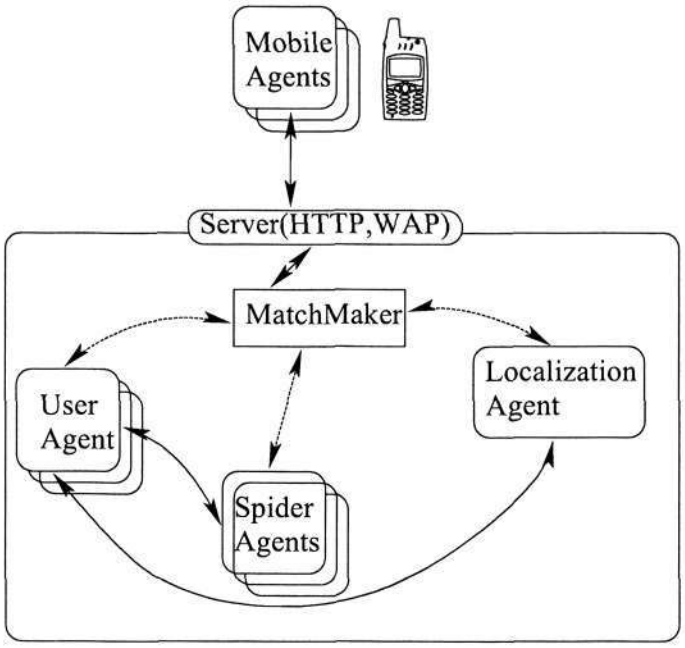


Figure 2.12: MIA Architecture

user appoints, the server can send data in various formats such as HTML, WML or free text.

Users only need to communicate with the gateway, as behind the gateway there are several interacting agents such as user agents, spider agents, and localization agent. Users' operations first analyzed in MatchMaker first and then distributed to different agents. The Spider Agents are the extraction components, as shown in Figure 2.11. It is the responsibility of service providers to define how to use spider agents to extract data from the Web.

Lixto extractor directly extracts data from different Web sites based on extraction rules, while MIA uses another strategy. The spider agents crawl on the Web to extract documents and classify them. Localization Agent detects the current location of users, while User Agents provide interfaces that allow users to define in which type information they are interested. Based on these sets of information, MIA does extraction with finer granularity and sends the final extraction results to users. In this architecture, what the end-users need to do is to select information topics they are interested in.

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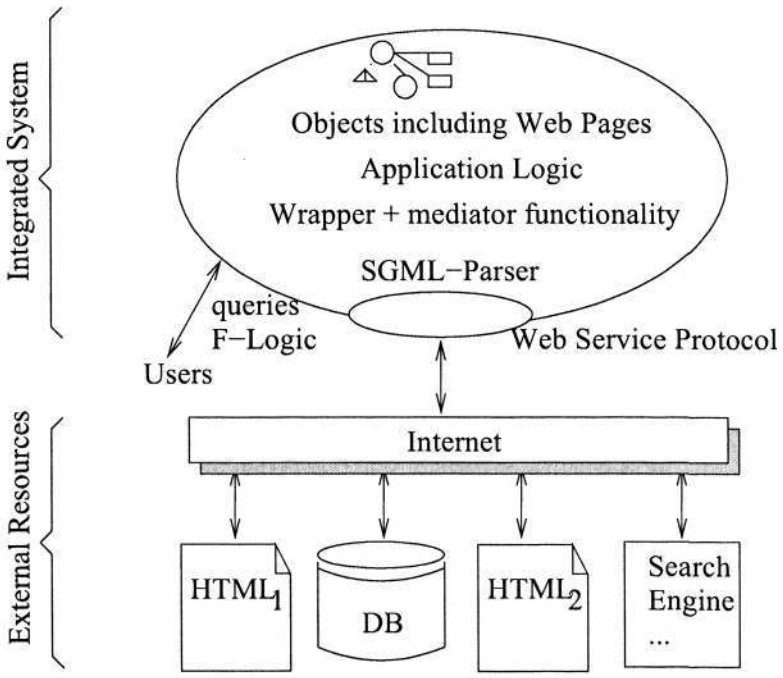


Figure 2.13: Architecture based on Florid

2.5.3 Interface to Database Applications

Although Lixto and MIA provide relative prolific components to support their extraction execution, a further issue remains to be considered: is communication among the various information concierge systems possible? As the ad-hoc formalisms exploited by different systems, the inter-system communication is a problem. For example, while some systems save extracted data in XML documents, some save to relational databases. If two systems use similar storage strategies, it is possible for them to use data extracted by each other, if they can understand schemata of extracted data each other. Thus, it is important to deliver public schemata over data extracted.

Web information concierge systems are still in the process of transformation. The compatibility among different systems had seldom been considered. May et al. [1999] suggest an integrated architecture based on FLORID, shown in Figure 2.13. FLORID is a deductive object-oriented (OO) database system, which employs F-Logic as data definition and query language. Applications that can access objects stored in FLORID can also access Web data extracted. Because OO database techniques are relatively more

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mature and understood by many users, an architecture based on existing databases is easy to use and control for them. This architecture mainly consists of two parts:

- An appropriate modeling of Web documents,
- A formal language and methodology that can handle the model.

From Figure 2.13 we can see the integrated architecture uses SGML-Parser to process Web documents before transforming them to objects in the database, so the details of different Web services and different document structures are hidden from other components. A key advantage of FLORID is that it can maintain comprehensive data models that are suitable to for describing Web data structure. Ludascher et al. [1998] discuss F-Logic, the internal language of FLORID that supports deduction and OO, they argued that it is an excellent tool to handle these models. In this architecture, wrapper definition, execution, user query interface and data presentation are integrated and controlled using F-Logic.

2.6 Summary

As introduced in the beginning of this chapter, Web data extraction is the thrust of information concierge systems, consisting of the following basic constituents: (1) data model for target Web documents, (2) output data model, (3) extraction rule model (4) rule generation mechanism, and (5) extraction execution mechanism. In this chapter, we presented each constituent and discussed its relationship with some auxiliary components in systems including document pre-processing and post-processing technique.

More importantly, by studying the related literature on building information concierge systems, we noted that the knowledge gap in these areas:

- Most studies choose rule generation algorithm, rule model and techniques for other components in a rather ad-hoc way, thereby making the comparison among different systems difficult and the integration of different systems almost impossible.
- Although most automatic rule generation methods need training sets, these sets are assumed to be pre-defined. Given a large set of documents that do not share similar structures, multiple training sets have to be constructed and extraction rules are learnt from these training sets independently. To the best of my knowledge, the automatic construction of training sets has not been addressed.

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- Learnt extraction rules cannot be applied to an incoming target document that is not from a pre-defined target set. That is, mapping between a target document and the corresponding extraction rules cannot be achieved automatically.
- The efficiency of extraction has mostly been studied from a theoretical perspective, or based on relative small corpus.

In the following chapters, we shall discuss how to overcome these weaknesses. In Chapter 3, the framework proposed in Chapter 1 is elaborated on. This framework allows us to integrate the extraction components and auxiliary components. The common layers supporting these components make it easy to analyze their capability and complexity. Then, Chapter 4 will show the flexibility of the framework by demonstrating how it is implemented based on tree language theory and logical program. Further, a practical Web data extraction language is introduced and studied. In Chapter 5, an algorithm with linear time complexity to document size is introduced for both rule generation and data extraction. Chapter 6 will demonstrate some auxiliary operations based on the framework, such as document management and training set preparation.

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Chapter 3

Realization of Web Information Concierge

The concierge framework proposed in Chapter 1 provides a theoretical basis for techniques meant to overcome shortcomings of methods surveyed in Chapter 2. In this chapter, this framework proposed is elaborated on. Specifically, a five-pronged approach is adopted to accomplish this task: (1) Overview of framework, (2) Instance layer, (3) Schema layer, (4) Operation layer, and (5) An example of a concierge system.

3.1 Framework Overview

As stated in Section 2.6, we can analyze a Web data extraction system from five aspects. In Kushmerick's [1997] work, when a more complexity document model is chosen, other aspects need corresponding changing, vice versa. For example, when we use rule generation algorithm from another system, usually, we also must adapt its document model.

In the proposed framework in Chapter 1, we try to devise a mechanism that allows the integration of different approaches from various systems. The basic idea is to use a target document model that can generally represent Web documents and extracted data, while providing a formalism of extraction rules that can describe extraction rules with various expressive powers. Based on this kind of rule formalism, it is possible to compare extraction approaches and rule generation approaches under the same formal framework.

Our framework models both target documents and extracted data as labeled rooted trees, which constitute a common data structure that can represent almost all Web

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documents. An instance layer is built to store cached Web documents and extracted data. The core of the framework is the *schema layer*. *Schemata* describe data instances and provide information to the operation layer. The operation layer contains an extraction component, and a rule generation component that can be extended flexibly. The details of the instance layer are hidden from the operation layer; operations can handle data in instance layer in terms of schemata.

In the rest of this chapter, we first define the components in each layer. Thereafter, a detailed example system based on the framework is demonstrated in Section 3.5.

3.2 Instance Layer

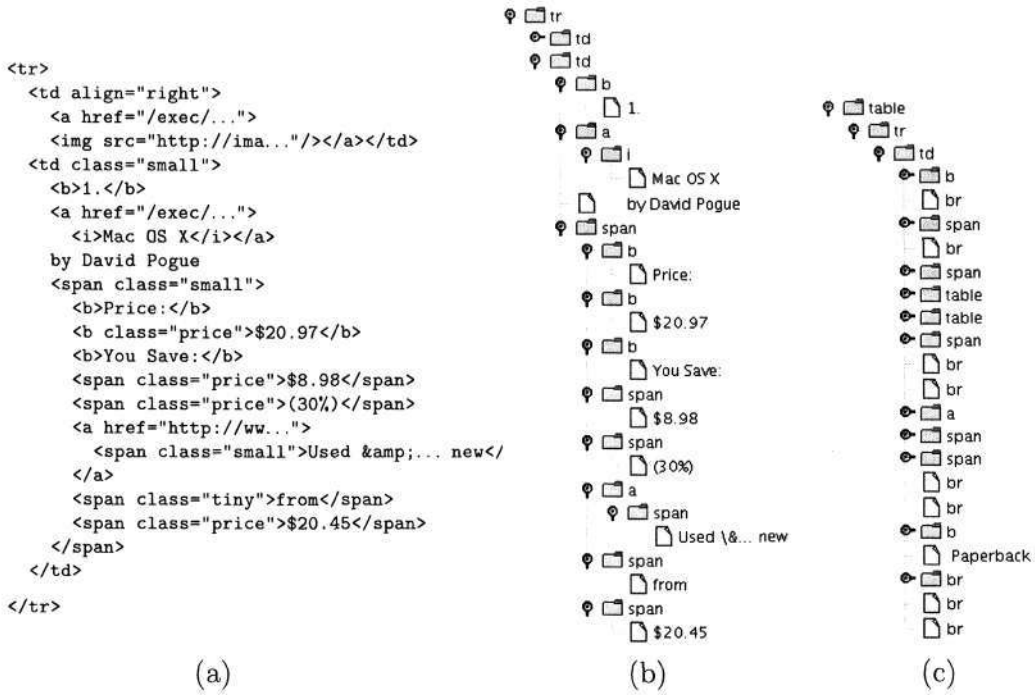
In this section, we propose a model to represent Web documents and extracted data. Based on this representation, the problem of building instance layer is defined.

Semi-structured documents can be generally modeled as directed graphs [Bergholz, 2000, Florescu et al., 1998, Lian and Cheung, 2004]. For example, a HTML document can be parsed into a directed graph — each tag element is parsed to a node; corresponding to each pair of parent-child tag elements, there is a directed edge; and each hyperlink, which describes a non-parent-child link relationship between two tag elements, can be parsed into a directed edge. However, as hyperlinks carry less information in Web data extraction, we do not consider them during the process of parsing in this thesis. Without considering hyperlinks, documents can be parsed into trees. Here are some examples:

Example 3.1. Figure 1.1(a) shows a Web page fragment from the Amazon Web site on 30 Jan 2004. It lists four top sellers of computer books. The topmost seller in this page is rendered from the HTML codes as shown in Figure 3.1(a). DOM (Document Object Model) tree generated from the codes are shown in Figure 3.1(b) (For simplicity, we have not drawn all nodes in the DOM tree; nodes with *folder* icon are non-text nodes and nodes with *paper* icon are text nodes). The right-hand side of pages B and C in Figure 1.1(b) are detailed information about the two topmost popular books respectively. Figure 3.1(c) shows the top four levels of the DOM tree corresponding to the HTML codes for the right-hand side of page B.

In Example 3.1, an element name is mainly used to describe the page layout. However, for some semi-structured documents, especially XML, an element name may contain

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(a) (b) (c)

Figure 3.1: Example of HTML Document Fragment and DOM Tree

important information. Thus, in this thesis, we model semi-structured documents as labeled trees — document tree, as defined below:

Definition 3.1 (Document Tree)**.** A document tree is a rooted, labeled tree that can be defined as a 4-tuple: $t = \langle V, E, r, \gamma \rangle$, where V is the set of nodes corresponding to tag elements, E is the set of edges connecting these nodes, r is the root node, $\gamma : V \rightarrow L$ is a function that assigns each node a string label, where L is the label set of t. An edge e is an ordered 2-tuple (u, v) where $u, v \subseteq V$ and u is the parent node of node v. Root node r has no parent node. Each non-root node u in V has one parent node.

In this thesis, the discussion is restricted to HTML and XML documents so that we can exploit DOM parsers to parse documents into trees. While parsing, we label each non-text node with the name of a corresponding element in the original documents, and label each text node with its value.

The objective of Web data extraction is to extract fragments from document trees that are relevant to a user's requirements. We refer to these fragments as data instances, as defined below:

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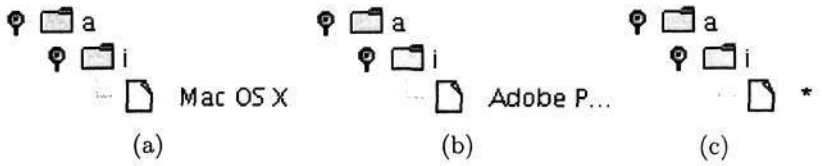


Figure 3.2: Instances and Schemata

Definition 3.2 (Data Instance)**.** Given a document tree $t = \langle V, E, r, \gamma \rangle$, $t_1 = \langle V_1, E_1, r_1, \gamma_1 \rangle$ is a data instance (DI) of t if $V_1 \subseteq V$, $E_1 \subseteq E$ and $\gamma_1 = \gamma$. This relation is denoted as $t_1 \subseteq t$. Given two DIs t_i and t_j, t_i is a sub-DI of t_j if $t_i \subseteq t_j$.

Example 3.2. In Example 3.1, the document tree in Figure 3.1(b) is a DI of the document tree corresponding to Page A in Figure 1.1(a). This instance corresponds to the first book entry in page A. Figure 3.2(a) is a DI of Figure 3.1(b). Figure 3.2(a) corresponds to the title of the first book; while Figure 3.2(b) corresponds to the title of the third book.

Definition 3.2 states that a document tree is also a DI. We, therefore, do not distinguish between semi-structured document, document tree and data instance in the remaining parts of this thesis. Given the definition of *DI*, the problem of *building instance layer* is quite straightforward; i.e., given n Web documents $\mathcal{P} = \{p_1, \ldots, p_n\}$, induce the set of DIs $\mathcal{D} = \{d_1, \ldots, d_n, d_{n+1}, \ldots, d_{n+m}\}$, where d_i is parsed from p_i, and d_{n+j} is a sub-DI of d_k, where $k \in [1, n]$. In our framework, extracted data will be stored in XML documents. Thus, these data can also be modeled as DI.

In Figure 3.1, these repeated contents can be parsed into equivalent DIs, which are substrees that have exactly the same structure. For example, the grey parts in Figure 3.2 are three equivalent DIs. Equivalent relationship is:

Definition 3.3 (Equivalence)**.** Given two DIs $t_1 = \langle V_1, E_1, r_1, \gamma_1 \rangle$ and $t_2 = \langle V_2, E_2, r_2, \gamma_2 \rangle$, t_1 is *equivalent to* t_2, if and only if there exists a bijection $\mathcal{M}$ between V_1 and V_2 such that:

- $\mathcal{M}(r_1) = r_2$;
- $(u, v) \in E_1$ if and only if $(\mathcal{M}(u), \mathcal{M}(v)) \in E_2$;
- $\gamma_1(u) = \gamma_2(\mathcal{M}(u))$.

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This definition does not consider the orders among sibling nodes; i.e., in this thesis, when we compare two document trees, we treat them as unordered trees. For schema detection algorithms introduced in later chapters, an unordered model is more suitable than an ordered model. This statement is based on the observation that if the only difference between two DIs is the order of their sub-DIs, these two DIs usually are generated based on the same schemata. For example, where a table lists top 10 popular sale books, although the order of books may be changed in the table, the table's schema remains unchanged (Chapter 5 discusses this in detail).

3.3 Schema Layer

In this section, we formally define schema and discuss the problems in building a schema layer.

Repeated contents in semi-structured documents are usually prominent and easily raise a reader's attention. Most Web data extraction systems [Arasu and Garcia-Molina, 2003, Chang and Lui, 2001, Crescenzi et al., 2001] assume that repeated contents are important and should to be extracted. For example, in Figure 1.1, all books have similar formats, with most parts of their HTML codes repeated, like those in Figure 3.1.

The two instances in Figures 3.2(a) and (b) are sub-DIs of the DI in Figure 3.1, and are almost the same; except for the labels of two text nodes. If we use a label "$*$" (wildcard character) to replace both labels, the two instances will become Figure 3.2(c). A wildcard character "$*$" is a regular expression that generates any string, denoted as $* \vdash \ell$, where ℓ is a label. We assume "$*$" does not appear in label sets of DIs of document trees to be extracted. As introduced before, schemata are objects describing a set of DIs. Thus, we treat the instance in Figure 3.2(c) as a schema. We define a schema below:

Definition 3.4 (Schema)**.** A schema s is a 2-tuple $\langle D, A \rangle$, where D is a set of DI, and γ functions in these k-subtrees label some text nodes with "$*$". A is a n-tuple $\langle a_1, a_2, \ldots, a_n \rangle$, where a_i is an attribute, $i \in [1, n]$.

Attributes in a schema are important in aiding data extraction and will be discussed in Section 6.1.1. For example, we can assume $A = \langle |s| \rangle$, where $|s|$ denotes the size of a schema s; i.e., the cardinality of the node sets of D. A schema with large size usually is important in HTML documents.

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If after replacing all text nodes with "*", a DI is equivalent to a schemata, then the DI conforms to the schema.

Definition 3.5 (Conformation and Type). A DI $t = \langle V, E, r, \gamma \rangle$ conforms to a schema $s = \langle D, A \rangle$ or s is the schema of t, if and only if there is a DI $\langle V_s, E_s, r_s, \gamma_s \rangle \in D$, and there exists a bijection $\mathcal{M}$ between V and V_s such that:

- $\mathcal{M}(r) = r_s$;
- $(u, v) \in E$ if and only if $(\mathcal{M}(u), \mathcal{M}(v)) \in E_s$;
- $\gamma(u) = \gamma_s(\mathcal{M}(u))$ or $\gamma_s(\mathcal{M}(u)) \vdash \gamma(u)$.

where t conforms to s, denoted as $t \mapsto s$. A set of DIs conforming to the same schema is known as a *type*.

3.4 Operation Layer

As shown in Figure 1.2, extraction and rule generation components are placed in the operation layer. Once the instance and the schema layers are built, we obtain the mapping relationships among DIs and schemata. Both extraction and rule generation can be treated as operations in terms of schemata. We give a simple introduction of these two operations in this section.

Detection of Schemata In our framework, the instance layer contains all Web documents to be extracted. The schema layer contains useful information of DIs in the instance layer. For example, two documents are structurally similar if the sets of schemata corresponding to them are the same. Given a set of n document trees $\{d_1, \ldots, d_n\}$ that contain a set of DIs $\mathcal{D} = \{t_1, \ldots, t_m\}$, *schema detection* is the procedure of inducing the set of schemata $\mathcal{S} = \{s_1, \ldots, s_n\}$, where $s_i \in \mathcal{S}$ if and only if $d_j \in \mathcal{D}$ and $d_j \mapsto s_i$.

The problem of schema detection is to find the set of schemata of all DIs in documents (or subtrees of document trees). This problem can be reduced from the problem of *the largest common subtrees (LCST)* [Akutsu, 1992]. As LCST is P for two trees and NP-hard for more than two trees [Akutsu, 1992], schema detection problem is also NP-hard. The same is applied to the problem of building

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instance layer. Some approximate solutions to similar problems have been proposed by putting some restrictions on the subtrees to be processed; e.g., TreeMiner [Zaki and Aggarwal, 2003] only processes subtrees whose frequency of occurrence exceeds a threshold. (We define a constrained version of this problem in Chapter 4 and an efficient algorithm is proposed to solve it in Chapter 5.)

Extraction in Terms of Schemata Given schemata detected, we can define an extraction as below:

Definition 3.6 (Matching Query)**.** Given a document T, a matching query $M(s) = \{t|t \mapsto s\}$, where s is a schema and t is a DI of T.

Based on Definition 3.5, the DIs with the same structure as s will be returned by the matching query. This query is a bit naive, but can be extended easily [Bergholz, 2000]. By defining an extraction as such a query, the schemata can be treated as extraction rules and extraction acts as query in relational databases. Unlike detection of schemata, such a query in terms of schemata can be evaluated [Bergholz, 2000] with polynomial complexity.

Other Operations A DI and its sub-DIs conform to a set of schemata; i.e., it is possible to use a set of schemata to describe a document. (Chapter 6 will discuss how to manage documents based on the set of schemata of DIs appearing in these documents.)

Based on the above introduction, the extraction in terms of schemata can be executed efficiently; though detecting this kind of schemata is hard. We find it frustrating to obtain a single schema model that can both be detected and used to extract efficiently. Thus, in Chapter 4 and 5, our study takes two directions:

- In Chapter 4, we formally define and analyze some classes of schemata that are abstracted from schemata in this chapter. These schemata have higher expressive power, and are hard to be detected automatically, though they can be generated by a person easily.

- Chapter 5 introduces a restricted version of the schemata in this chapter. Detection algorithms of these schemata are given and optimized.

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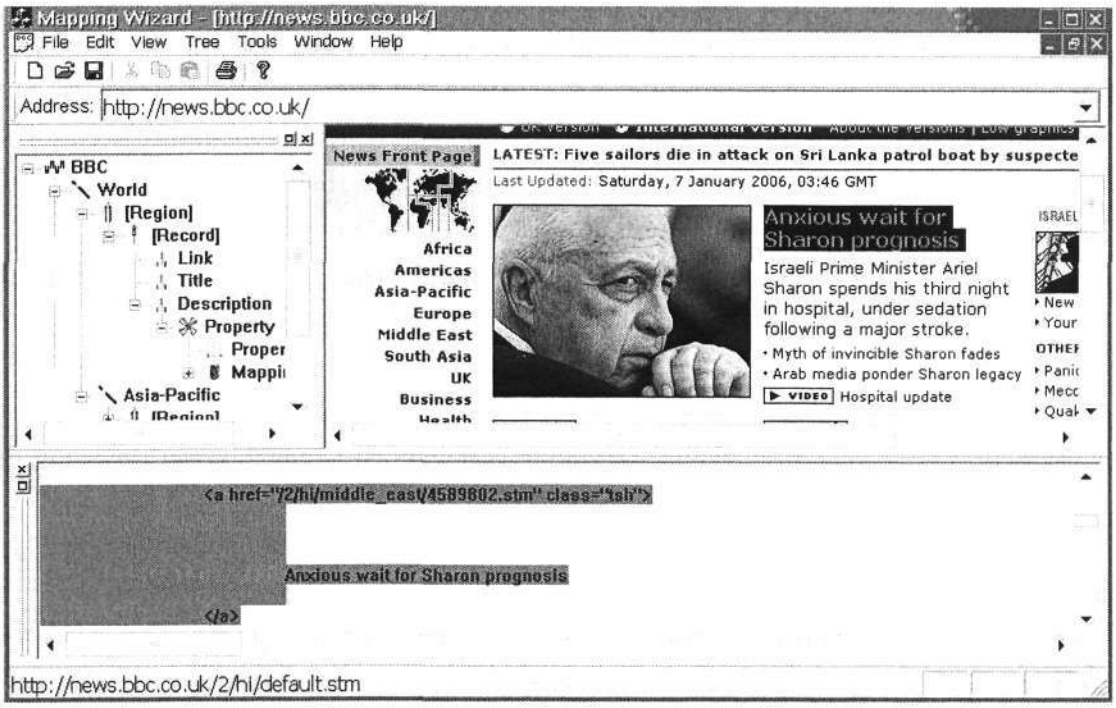


Figure 3.3: Visual Interface of WICCAP

3.5 An Example of a Concierge System

Web Information Collection, Collaging and Programming System (WICCAP), is the Web information concierge system developed at the Centre for Advanced Information Systems (CAIS)[1], on which the thesis is based. This section demonstrates the earlier version of WICCAP [Liu et al., 2002b].

To extract Web data using this system roughly requires three steps: (1) Defining a common logic data structure to store data extracted from Web sites belonging to the same area, e.g., news Web site and product list Web site, (2) Detecting the mapping from physical structures of Web documents to the logic structure, and (3) Scheduling an extraction engine to read Web documents, with the mapping relation between physical structures and logic structures, to extract special parts in documents.

Figure 3.3 is the visual interface of WICCAP that highlights the first two steps. The left panel is the logic data structure editor. In this figure, the logic data structure describes a common view over news Web sites. Usually, a news Web site organize news

[1] http://www.cais.ntu.edu.sg/

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in terms of world areas, i.e., Asia news, Europe news, etc. In each area, there is a list of news entries, with each entry containing news title, news description, etc.

After designing the logic data structure, a user should define the mapping from physical Web documents to the logic structure. In Figure 3.3, the right panel shows Web pages rendered from Web documents. The user can select a node in the logic structure, and then select texts in the right panel corresponding to the logic node. The surrounding texts around the selected text are shown in the bottom windows in Figure 3.3. By recording the surrounding texts with the logic structure, called extraction rules, WICCAP can map the logic structure to the data to be extracted in Web documents. Based on the extraction rules generated, WICCAP engine is scheduled to parse given rules and do real extraction.

In the process described above, a logic data structure can be formalized as a schema defined in Section 3.3. The schema contains only a DI, without any attribute. Web documents can also be formalized as DIs, where each subtree is parsed from texts surrounded by a pair of texts recorded in extraction rules. The extraction engine locates all leave nodes from the DIs and organizes these nodes according to the logic structure.

During the process of applying the WICCAP on real Web environment, we found some weaknesses of this version of WICCAP: (1) Although WICCAP provides a visual interface to aid schemata generation, schemata are essentially detected manually. (2) A schema is corresponds to whole pages only, and it is not easy to do extraction with finer granularity. (3) A schema contains only one DI, and lacks expressive capability; e.g., it is difficult to describe relationships among sibling DIs using a schema. (4) A few operations are provided. Later chapters will introduce further research to overcome these weaknesses.

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Chapter 4

Inside the Concierge Framework

The sample system in Chapter 3 suffers from lack of high expressive schemata, and there is much space to improve the expressive capability of schemata. This chapter discusses the expressive capability, drawing on alternative formalisms of instance layer and schema layer and providing a theoretical framework to compare the expressive capability of schemata. Fortunately, our concierge framework provides a scenario to integrate various techniques. This chapter discusses the cross-fertilization relationships among tree language, logic program and tree automata to: (1) Tree language theory provides a theoretical basis to model DIs and schemata, and to compare schemata expressive power; (2) The logic program provides a declarative perspective of DIs and schemata; (3) Tree automata are natural tools to evaluate tree language and do extraction.

Specifically, Section 4.1 investigates tree language characterization of instances and schemata. Based on logic theory, an alternative formalism of instances and schemata is given in Section 4.2. In Section 4.3, we propose a new class of tree automata as the computational model of extraction components, which can recognize Web documents efficiently. Section 4.4 focuses on a Web data extraction language (WDEL) based on the framework, which is implemented in our Web data extraction system — WICCAP.

4.1 Tree Language Characterization

In this section, characterizations of instances and schemata are described from the perspective of tree language theory. We first study how a set of DIs can be treated as a tree language in Section 4.1.1. Next, the relationships between schemata and tree grammars are explored in Section 4.1.2. Section 4.1.3 discusses schema detection from the

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perspective of grammar induction.

4.1.1 Tree Language and Instance

Given a set of symbols, called the alphabet Σ, a sequence of symbols in Σ is a string. A set of strings is a string language. Given the simple definition of string language, we notice that, if Σ is the character set of HTML and XML, Web documents to be extracted can be treated as string languages. When Web documents are treated as string languages, we also call them flat texts.

In instance layer, instances are stored as XML (or HTML) documents. By modeling XML documents as flat texts, it is natural to exploit automata to process them. However, in the Web world, to treat all documents as flat texts is too simplistic and prone to loss of important information, as a string language is difficult to represent the hierarchical relationship among contents in XML documents. By using tags, XML documents can be parsed into hierarchical trees. Tree automata are machines that process trees, similar to the role of finite automata on string languages.

The basic concepts of tree automata theory include:

- Symbol: A symbol is an atomic item, which usually is a letter. α, β, β_i and α_i are used to represent symbols, where i is a positive integer.

- Alphabet: An alphabet is a set of symbols, denoted as Σ.

- Term: A Term over alphabet Σ is denoted as $\mathcal{T}(\Sigma)$, is inductively defined as below:

  - If $\alpha \in \Sigma$, then α is a term,
  - If $\alpha \in \Sigma$ and t_1 through t_n are terms, then $t = \alpha(t_1, t_2, \ldots, t_n)$ is a term, and t_1 through t_n are child terms of t's root node.

  In this definition, the number of child terms has an upper-bound. These terms are also named ranked terms [Comon et al., 1997]. As in XML specification, there is no limit to the number of child elements. If we want to use terms to model XML documents, it is more natural to define a term as below:

  - If $\alpha \in \Sigma$, then α is a term,

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  - If $\alpha \in \Sigma$, then $\alpha(2^{\mathcal{T}(\Sigma)*})$ is an unranked term, where $2^{\mathcal{T}(\Sigma)*}$ is a regular set of sequences of terms; i.e., strings over $\mathcal{T}(\Sigma)$. This means the sequence of child nodes of α is a regular language over terms.

- Tree Language: A tree language is a set of terms. The language of ranked terms is called ranked tree language, while the language of unranked terms is called an unranked tree language.

A Web document can be represented as a ranked term iff it can be parsed into a document tree. This proposition can be obtained by directly comparing the definition of a document tree and a term. As there is no upper-bound of child elements of an element in XML, we shall therefore insist on treating all data instances as unranked tree languages. We shall use unranked term and document tree interchangeably. A set of trees is also called a *hedge*, following Courcelle [1989], Brüggemann-Klein et al. [2001].

4.1.2 Tree Grammar and Schema

Similar to the role of string grammar in automata theory, a tree grammar is a set of rules that generates a tree language. Formally, a tree grammar is a 5-tuple $\langle \Sigma, S, N, T, P \rangle$ that consists of a set of start symbols S, a set of non-terminal symbols N, a set of terminal symbols T and a set of production rules P. Rules in P have the form of $\mathcal{L} \rightarrow \mathcal{R}$. With different constraints on $\mathcal{L}$ and $\mathcal{R}$, the tree grammars have different expressive capability. We briefly list some classes of tree grammar, with decreasing order of expressive capability.

Context-Free Tree Grammar $\mathcal{L}$, the left side of a production rule in context-free tree grammar has the form of $n(x_1, x_2, \ldots, x_n)$, where $n \in N$, x_1 through x_n are members of the set of variables $\mathcal{X}$, where x_i can be replaced with an element in $N \cup T$ and $\mathcal{X} \cap (N \cup T) = \emptyset$. $\mathcal{R}$ has the form of $\mathcal{T}(N \cup T \cup \{x_1, x_2, \ldots, x_n\})$; i.e., a term over alphabet $N \cup T \cup \{x_1, x_2, \ldots, x_n\}$.

Regular Tree Grammar In a regular tree grammar, $\mathcal{L} \in N$; i.e., only single non-terminal symbol can appear at the left side of a production rule. $\mathcal{R}$ has the form of $t(2^{\mathcal{T}(N \cup T)*})$, where $t \in T$.

Local Tree Grammar In a regular tree grammar, if two production rules sharing the same right hand side cannot have the same left hand side, the grammar is a local tree grammar.

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Given a tree grammar, $G = \langle \Sigma, S, N, T, P \rangle$, a set of terms can be generated according to production rules. A term t_j can be generated from term t_i, denoted as $t_i \rightarrow_G t_j$, if there is a term L appearing in t_i, R appearing in t_j, and $L \rightarrow R \in P$. A term t is generated from a grammar G, if there is a sequence of generation, $s \rightarrow_G t_1, t_1 \rightarrow_G t_2, \ldots, t_i \rightarrow_G t$, denoted as $s \rightarrow_G^+ t$, where $s \in S$. The set of terms belonging to $\mathcal{T}(T)$ that can be generated from G is called the tree languages generated from G, denoted as $L(G)$.

Local tree grammar is strictly less powerful than a regular tree grammar. For example, the language of a(b,c),a(c,b) cannot be generated by a local tree grammar, but is generated by the following regular tree grammar:

Σ={s,a,b,c}, S=N={s}, T={a,b,c} and
P={s→ a(b,c), s→ a(c,b)}

As defined in Definition 3.5, a type is a set of trees conforming to a schema. We loose the restriction to define a type as a set of trees that can be generated by a tree grammar, and say that trees generated from a tree grammar conform to the grammar. As schemata can be viewed as structured patterns used to identify a type, from this perspective, a tree grammar can be treated as a schema.

Murata et al. [2001] proposed a framework based on tree grammar to compare the expressive capability of the six important XML schema languages. In this framework, finer classifications of tree grammars are defined, including a regular tree grammar, restrained competition tree grammar, single-type tree grammar and local tree grammar. The six schema languages are analyzed within this framework. Ranked on expressive capability by Murata et al. [2001], the languages are RELAX, XDuce, TREX, XML-Schema and DTD. As stated in Comon et al. [1997], a context-free tree grammar exceeds a regular tree grammar in term of expressive capability. Thus, most present XML schema languages are strictly less powerful than a context-free tree grammar. As the objectives of studying tree grammar in this research is to obtain methods that describe schemata of Web documents, context-free tree grammars will not be addressed any more.

Based on Definition 3.4, a schema is essentially considered as a set of DIs where some labels are replaced with "*". If the DI set D of a schema s can be generated from a tree grammar G, then the set D_s of all DIs conforming to this schema can also be generated from this tree grammar, with an auxiliary rule $* \vdash \ell$. From this perspective, we can also treat G as the schema of DIs in D_s.

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4.1.3 Schema Detection

The extraction rules are generated before the extraction. Hand-coded extraction rules are used in some practical Web extraction systems [Baumgartner et al., 2001b, Gupta et al., 1997, Li and Ng, 2004]. Convenient visual interfaces are provided in WICCAP [Li and Ng, 2004] and Lixto [Baumgartner et al., 2001b] to facilitate rule generation. However, hand-coded rule generation is very time-consuming. Hence, this section focuses on automatic methods. (In Section 4.4, we shall introduce the process of rule generation, where schema detection is the main task.)

Basically, automatic rule generation can be reduced to schema detection problems. When we model schemata as tree grammars, schema detection is the problem of *grammar induction*, which is a sub-problem of *inductive inference*. Based on materials from Gold [1967] and Mitchell [1997], we conceive inductive inference as a learning problem that consists of four elements: (1) A class of inference objectives, also called target grammars. Target grammars can generate Web documents to be extracted. (2) A method of information presentation about the target grammars, such as some sample Web documents generated from the target grammars. (3) The spaces of hypotheses of target grammars learnt from information presentation. (4) The definition of learnability or performance measurement.

Various information presentations are used in the literature [Gold, 1967] to induce exact grammars. However, only positive examples are available for Web data extraction systems [Crescenzi et al., 2001, Kosala et al., 2003]; i.e., we can obtain information of the target grammars from target Web documents, which are generated from the target grammar. We call these positive examples as the training set or sample documents. Given the nature of training sets, a schema detection procedure gives some hypotheses of the target grammars. Here, the hypothesis spaces can be tree grammars. But the choice of hypothesis spaces in the literature is rather ad-hoc and various formalisms are given [Chang and Lui, 2001, Gottlob and Koch, 2002a, Kushmerick, 2000a]. (We shall introduce logic programs as the hypothesis space in Section 4.2.)

Models of exact learnability such as identification in the limit have been studied in the past decades [Gold, 1967]. Unfortunately, the results concerning practical rule generation methods based on these models are disappointing. Gold [1967] proved it is impossible to identify a target grammar from positive examples only, except the language generated by the grammar is finite. Valiant's [1984] famous approximate learning model *PAC-identification* is exploited by Kushmerick [1997] to generate extraction rules. Although

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his rules are quite simple, the number of samples needed is very large. Sometimes, it is infeasible to prepare such a large training set. Kosala's [2003] work assumes there exist representative documents generated from the grammar that can generate all other documents to be extracted and treat Web documents as k-testable tree languages, which can be identified in the limit from positive examples. This assumption is so strong that the grammars induced are too sensitive to change of structure in documents.

Even when proper training sets are available to induce an exact grammar based on the model of identification in the limit, the typical induction algorithm of identification by enumeration [Gold, 1967, Knuutila, 1994] is burdensome for Web data extraction systems. Further, the extremely restricted schemata are hard to be detected. Fortunately, recent empirical results show that it is possible to construct polynomial heuristic induction algorithms that generate acceptable approximate results. There are some other studies [Arasu and Garcia-Molina, 2003, Chang and Lui, 2001, Crescenzi et al., 2001, Rajaraman and Ullman, 2001] that have detected patterns from documents and heuristically constructed target grammars. Compared to polynomial time complexity of these methods, we shall introduce a class of patterns, named k-subtrees, that can be detected in linear time and that can generate good extraction results. (Chapter 5 will introduce detection algorithms that are more efficient than those in the literature.)

4.2 Logic Characterization

Representing data instances as tree languages provides the possibility of employing tree grammars as schemata. Defining tree grammars as schemata delivers a procedural perspective of DIs; i.e., there is a process that generates DIs from schemata. In this section, we introduce a relational representation of DIs and use logic programs as schemata. The proof-theoretic interpretation [Ullman, 1988] of rules in logic programs provides another procedural perspective of DIs. At the same time, logic programs also provide a declarative perspective over DIs; i.e., a logic program describes the DIs whose corresponding relational structures make all rules in the program true.

4.2.1 Relational Structure and Instance

A node in a tree can be represented by a sequence of positive integers concatenated by a "." character. In $tree_1$ drawn in Figure 4.1, the root node is represented by "1", the first

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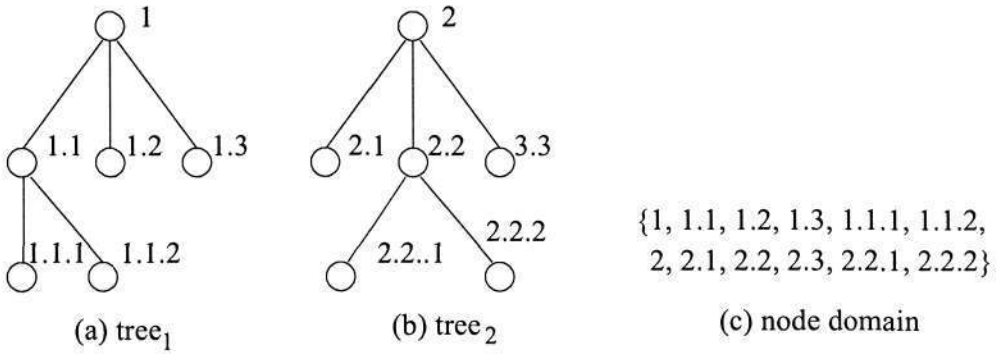


Figure 4.1: Example of Hedge and Node Domain

child of the root is `"1.1"`, the second child is `"1.2"`, and so on. The set of all possible positive integer sequences is called the *universe* of tree nodes. For a hedge, all nodes compose a subset of the universe, called the domain of nodes in the hedge, such that:

- For an empty hedge, the domain is empty, otherwise
- $i \in [1, n]$ is in the domain, if there are n trees in the hedge,
- If $u.j$ is in the domain, then u is also in the domain; if $i < j$, then $u.i$ is also in the domain.

Figure 4.1(c) is the domain of nodes in $tree_1$ and $tree_2$. Given the domain of nodes in a hedge, a relational structure representing the hedge can be built based on parent-child and sibling relationships among nodes as well as the relationship of nodes and labels.

$$\langle dom(T), first_child, next_sibling, label_\alpha \rangle$$

In the structure, $\alpha \in \Sigma$ where Σ is the alphabet, $\langle u, a \rangle \in label_a$ if $u \in dom(T)$ and u is labeled with a, $\langle u, u.1 \rangle \in first_child$ if $u.1 \in dom(T)$, and $\langle u.i, u.j \rangle \in next_sibling$ if $j = 1 + 1$ and $u_i, u_j \in dom(T)$.

4.2.2 Logic and Schema

Because of relational representation of data instances, a logic program can be exploited to represent a set of DIs. We first introduce some basic notations of logic.

Atom An atom is a predicate of the form $P(x_1, x_2, \ldots, x_n)$, where P is a predicate symbol and x_1 through x_n are variables of the predicate. These variables are called

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terms. The syntax of an atom represented using Backus-Naur Form (BNF), is given as below:

<atom>::=<PredicateSymbol>|<PredicateSymbol>(TermList)
<TermList>::=<Term>|<Term>,<TermList>

Term The syntax of a term can be defined in much the same way as a ranked term in a tree language

<Term>::=<Constant>|<Variable>|<FunctionSymbol>$(t_1, t_2, \ldots, t_n)$

The word 'term' in logic and in a tree language has different meanings; when we mention 'terms', they are terms in a tree language. 'Term' in logic will be referred as 'logic term' henceforth.

Literal A literal is an atom or a negative atom, as represented below:

<Literal>::=<Atom>|¬<Atom>

Formula A first-order logic formula is an expression with the following forms:

<Formula>::=<Literal>|¬<Formula>|<Quantifier><Formula>|
<Formula>∨<Formula>|<Formula>∧<Formula>

<Quantifier>::=∀|∃

Before we compare logic and tree grammar in terms of the expressive capability of representing schemata, we briefly introduce the first-order logic (FOL) and monadic second-order logic (MSOL) programs.

FOL FOL formulae are formulae defined above, where a variable is an element in a domain, as in the domain of nodes in trees. Such a variable is also called first-order variable.

MSOL MSOL formulae extend FO logic formulae by allowing a variable to be a set of elements in a domain. These variables ranging over sets are called second-order variables, and will be denoted as uppercase characters (e.g., X, Y).

In a classical knowledge of logic theory, FO logic formulae can be normalized to Skolem normal form:

$$\forall x_1, x_2, \ldots x_n M$$

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M is a conjunctive normal form; i.e., a formula without quantifiers that has the shown below:

$$(A_i \vee A_j \vee \ldots) \wedge (B_i \vee B_j \vee \ldots) \ldots$$

A_i through A_j and B_i through B_j are literals. We only consider closed formulae in which all variables are quantified. As given domain of variables, closed formulae can be evaluated to be true or false, without other requirements. If all variables in M are quantified, the prefix quantifiers of Skolem form can be removed. A closed FO logic formula can then be transformed to a conjunctive normal form, which is a conjunction of a set of disjunctive statements called the logical program of the formula. A FO logical program can be transformed to a Gentzen formula of the form $A_1 \vee \ldots \vee A_k \leftarrow B_1 \vee \ldots \vee B_n$, where A_1 through A_k and B_1 through B_n are atoms. When $k \leqslant 1$, the Gentzen formula is called Horn formula; a horn formula without functions is called a datalog rule, which is usually written in the form $A :\!- B_1, B_2, \ldots, B_n$. It is a classical result that datalog and FO logic have the same expressive power in the sense of querying relational databases.

A MSO formula can be transformed to a monadic datalog in a similar way. Gottlob and Koch [2002b] present an important result:

Proposition 4.1. Given a set of built-in predicate called the signature over unranked trees:

$$\tau = \langle root, leaf, label_\alpha, first_child, last_child, next_sibling \rangle$$

MSO and monadic datalog coincide with each other to represent terms.

As Thomas [1997] has stated, a tree language is regular iff it is definable in MSO. A monadic datalog program can be used to define regular tree languages. From the declarative perspective, that means we can represent all trees belonging to a regular tree language with relational structures. There is also a MSO logic program where all rules are true, given the facts in the structures. Such a set of relational structures of the tree language is called the model of logic program.

Like the relationship between a tree language and grammar, there is also a sequence of process to generate the relational structures from a given logic program, called the *proof-theoretic interpretation* [Ullman, 1988] of the rules in the program. For FO and MSO logic programs, the proof-theoretic interpretation of a logic program is also called the minimal model or the least fixed point (LFP).

Given the data instances represented as relational structures, if these structures compose the minimal model of a logic program, the program can also be treated as schemata

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of these data instances.

Based on the logic and tree language characterizations of the concierge framework, both declarative and computational model for Web data extraction can be devised. Like the cross-fertilization relationships among automata, logic and database [Neven, 2002a], the different characterizations of our framework will enhance further development of concierge systems.

4.3 Extraction Machine

Web data extraction needs to figure out document fragments that conform to given schemata. That means, we need a computational model to compute data instances and schemata; i.e., an algorithm that answers whether or not a data instance conforms to a given schema. In this section, based on the implementation of our framework from the perspective of tree language theory, we shall introduce a computational model, called query automata. The query automata proposed in this section do not only answer whether or not a data instance conforms to given schemata; it can also output transformed data instances.

4.3.1 Tree Automata

Inside the concierge framework, after the schema layer is built, components in the operation layer should have the capability to put query in terms of schemata to instance layer. A tree language is a set of trees. Thus, the data instances embedded in Web documents to be extracted can be viewed as tree languages.

As introduced in the previous section, tree grammars can be used to represent schemata; a query (or extraction) can be treated as the process of recognizing data instances that are generated from a tree grammar. Tree automata are computational models that accept tree languages generated from a tree grammar. They include top-down or bottom-up non-deterministic tree automata (NFTA), top-down or bottom-up deterministic tree automata (DTA) and alternating tree automata [Comon et al., 1997]. Bottom-up NFTA and DFTA can accept tree languages generated from regular tree grammars.

Definition 4.1 (Bottom-Up DTA)**.** A bottom-up deterministic tree automaton is a 4-tuple $\langle Q, \Sigma, \delta, F \rangle$, where Σ is an alphabet, Q is a state set, F is a set of final states, $\delta : \Sigma \times 2^{Q*} \rightarrow Q$ is a move function and 2^{Q*} is a regular language over Q. The δ is

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a function means that with the same $\alpha \in \Sigma$ and regular set 2^{Q*} over Q, $\delta(\alpha, 2^{Q*})$ is a unique state.

Definition 4.2 (Bottom-Up NTA). A bottom-up non-deterministic tree automaton is a 4-tuple $\langle Q, \Sigma, \delta, F \rangle$, where Q, Σ and F have the same meaning as those in Bottom-up NTA, and δ here is a many-to-many relation between $\Sigma \times 2^{Q*}$ and Q.

The definition of tree automata can be intuitively connected with tree languages. A bottom-up tree automaton reads a hedge from leaf to root. When the automaton reads in a leaf node, it will move to a state according to the label of the leaf; when all children of a node are read, the automaton will move to states according to the node's label and states associated with its child nodes. If the automaton transits into a state in F when after it has read the root of a tree, the tree is accepted. If all terms in a hedge are accepted, the hedge is accepted. The hedge containing all terms accepted by an automaton is a tree language.

At any time during the reading of a tree from bottom to up, a tree automaton will be in a set of states. Each state in this set is associated with a node in the tree, which is the set of current nodes. As a node can be associated with a state only after all its child nodes have associated states, a pair of ascendant-descendant nodes will not be in the current node set at the same time.

A possible set of current nodes is a cut of the tree. Formally, a cut of trees and acceptable tree language of an automaton is defined as below:

- A cut of a tree is a set of nodes in the tree, such that there is only one node in the path from root to each leaf. A configuration of the automaton is the set of states associated with nodes in a cut.

- A bottom-up tree automaton reads nodes of a tree from leaves. The set of all leaves is a cut, and the set of states associated with the cut is the initial configuration.

- If the current node set is the cut containing a root only, and the current configuration is in final states, the tree is acceptable to the automaton. If all trees in a hedge are acceptable, the hedge is acceptable.

- The hedge containing all trees acceptable to an automaton is the tree language accepted by the automaton.

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A regular tree language is the language accepted by a bottom-up tree automaton. We do not distinguish non-deterministic and deterministic tree automata, as there is a classical result [Comon et al., 1997, Gottlob and Koch, 2002b]:

Proposition 4.2. Let L be a regular tree language accepted by a bottom-up NTA. Then there exists a bottom-up DTA that accepts it.

The above tree automata are called bottom-up as they recognize trees from leaves. Another class of tree automata, called top-down tree automata, start computing from root node of trees, as defined below:

Definition 4.3 (Top-Down DTA)**.** A top-down deterministic tree automaton is a 4-tuple $\langle Q, \Sigma, \delta, I \rangle$, where I is a set of initial states, $\delta : Q \times \Sigma \rightarrow 2^{Q*}$ is a move function.

The difference between the top-down NTA and DTA is that in a top-down NTA, Σ is a many-to-many relation. From the definition of top-down DTA and local regular tree languages, we notice that they have the same expressive capability.

4.3.2 Tree Transducer

Tree automata provide the mechanism to recognize whether or not hedges are generated from given grammars. This is the basis of extracting Web data, as it is an important step to figure out which subtree in a document hedge contain the needed information. Furthermore, an extraction task usually is not completed at this step. As in Web document trees, many structures are used to describe visual layouts in browsers, and as they are not interesting to extraction tasks, effective approaches are needed to select those nodes sensitive to user requirements from subtrees and to transform these selected nodes to data instances conforming to given schemata.

Suppose the nodes to be extracted are known already, we can exploit a tree transducer to transform these nodes to given structures. We define a class of transducers as below:

Definition 4.4. A bottom-up non-deterministic tree transducer (NTT) is a 5-tuple $\langle Q, \Sigma, \Sigma', \delta, F, \lambda \rangle$, where Q, F have the same meaning as in bottom-up TA, Σ and Σ' are input and output alphabet respectively. $\delta : \Sigma \times 2^{(Q \times \mathcal{T}(\Sigma))*} \rightarrow Q \times \mathcal{T}(\Sigma')*$ is a move relation, $\lambda : \Sigma \times Q \rightarrow \{1, 0\}$ is a function, s.t. $\lambda(a, q) = 1$ is the node associated with q is to be extracted.

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Bottom-up NTT is similar with bottom-up TA, except that there is an output term associated with each state. And when NTT moves from some source states to a target state, the term associated with each source state is passed to the target state. In the final state, the term associated is the transduced form of the trees accepted. As an example, the move relation δ has the form described as below:

$$\alpha \times (q_1 \times t_1)(q_2 \times t_2) \ldots (q_n \times t_n) \rightarrow q \times t$$

Here, t is a hedge and can be a function on α and t_1 through t_n. In this thesis, we only consider a class of simple function with the form $t = \alpha(t_1, \ldots, t_n)$ if $\lambda(\alpha, q) = 1$, or $t = t_1, \ldots, t_n$ if $\lambda(\alpha, q) = 0$, where t_i can be $\varnothing$. With this focus, a transduction process can be treated as a deletion procedure of some unwanted nodes from the original tree accepted by the transducer. In Section 4.3.3, we shall describe nodes which are wanted and those which are not.

4.3.3 Query Automata

In Section 4.3.1, we introduced some tree automata that can accept regular tree languages and have the same expressive capability as MSO logical programs. However, the task of extraction only requires that we select some nodes in the tree, instead of outputting a whole tree. To represent a subset of nodes in a tree, MSOL and monadic datalog are strictly more powerful than regular tree grammar.

As an example, we can build a monadic datalog program to represent a tree, based on the built-in predicate set τ and the following extended predicates:

```
right_sibling(X,X):-
right_sibling(X,Y):-next_sibling(X,Z),right_sibling(Z,Y)
child(X,Y):-first_child(X,Y)
child(X,Y):-first_child(X,Z),right_sibling(Z,Y)
descendant(X,Y):-child(X,Z), descendant(Z,Y)
```

A tree that has more than 2 levels and whose root is labeled with α can be represented, using the following program:

```
root(1):-
label_α(1) :- root(1)
SELECT(x):- descendant(1,x)
```

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Given the rule $SELECT(x) :\!-descendant(1, x)$ in the above program, $\{x|SELECT(x) = true\}$ will be the set of all selected descendant nodes of the root. The program can be treated as a unary query on tree nodes; i.e., query result is a set of nodes. A unary query can also be represented by a tree automaton, if we ask the automaton to output corresponding nodes in specified states. However, there is no such bottom-up tree automaton that can represent the same query represented by the above datalog program. As when the automaton processes descendants of root, the root's label is unknown, while when the automaton goes up to the root, the descendants' information cannot be accessed in the state.

This example shows that although bottom-up tree automata have the same expressive power as monadic datalog to represent a tree structure, it is less powerful in selecting nodes in a tree. Neven and Schwentick [1999] suggest a class of tree automata, also called strong two-way tree automata, that matches with monadic datalog to represent node queries. We use their formalism, defined as below:

Definition 4.5 (Strong Query Automata)**.** A strong query automaton (SQA) is a tuple $\langle Q, \Sigma, \delta_{root}, \delta_{leaf}, \delta_{\downarrow}, \delta_{\uparrow}, \delta_{-}, F, I, \lambda\rangle$, where Q, Σ, I and F have the same meaning as Q, Σ, I and F in bottom-up and top-down TA, $\lambda : Q \times \Sigma \rightarrow \{0, 1\}$ is a select function, $\delta_{\downarrow}$, $\delta_{\uparrow}$ and δ_{-} are down move, up move and stay move functions respectively.

Strong query automata's move function can be divided into five categories. Let U and D be two disjunctive set over of $Q \times \Sigma$, and $U_{\uparrow}, U_{-} \in U*$, where $U*$ is a regular set over U and $U_{\uparrow} \cap U_{-} = \emptyset$.

1. $\delta_{leaf} : D \rightarrow Q$ is the move function for leaves. If the SQA is processing a leaf node n associated with state q, and there is $\delta_{leaf}(q, label(n)) = q_1$, then the SQA will associate q_1 with n.

2. $\delta_{\downarrow} : D \times N \rightarrow Q*$ is the down move function, where N is the natural number set, and $\delta_{\downarrow}(q, \alpha, i)$ is a string of length i, and $\{\delta_{\downarrow}(q, \alpha, i)|i \in N\}$ is a regular set. If the SQA is processing a node n associated with state q, and $\delta_{\downarrow}(q, label(n), m) = q_1 q_2 \ldots q_m$, the SQA will leave n and goto process the m child nodes of n and associate state q_i with n_i, where n_i is the ith child node of n.

3. $\delta_{root} : U \rightarrow Q$ is the move function for root. If the SQA is processing the root node n associated with state q, and there is $\delta_{leaf}(q, label(n)) \rightarrow q_1$, then the SQA will associate q_1 with the root node.

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4. $\delta_{\uparrow} : U_{\uparrow} \rightarrow Q$ is a up move function, and $\{\varrho | \delta_{\uparrow}(\varrho) = q\}$ is a regular set. If the SQA is processing node n's child nodes n_1 through n_m, where n_i is associated with state q_i, and there is $\delta_{\uparrow}(\langle q_1, label(n_1)\rangle, \langle q_2, label(n_2)\rangle, \ldots, \langle q_m, label(n_m)\rangle) = q$, the SQA will leave n_1 through n_m to process n, and associate q with n.

5. $\delta_{-} : U_{-} \rightarrow Q*$ is the stay move function, which is computed by a generalized string query automaton (GSQA) [Neven and Schwentick, 1999]. For child nodes of each node, there is at most one stay move.

   If the SQA is processing node n's child nodes n_1 through n_m, where n_i is associated with state q_i, and there is $\delta_{-}(\langle q_1, label(n_1)\rangle, \langle q_2, label(n_2)\rangle, \ldots, \langle q_m, label(n_m)\rangle) = q_{1.1}q_{1.2}\ldots q_{1.m}$, the SQA will stay in n_1 through n_m and associate $q_{1.i}$ with n_i.

.

When a SQA begins to run on a tree t, it is in an initial configuration; i.e., the SQA starts by processing only the root node $root(t)$, and associate a state with the node. According to the move functions defined, the SQA will move to a sequence of configurations. If the SQA move to the final configuration; i.e., if the state associated with $root(t)$ is $q \in F$, then t is accepted by the SQA.

A SQA selects all those nodes n_i, if in some configuration n_i is associated with q_i, and $\lambda(q_i, label(n_i)) = 1$. The set of nodes selected is the results of unary query defined by the SQA. According to Neven and Schwentick [1999], there are two results about the capability of SQA and logic to express unary queries:

Proposition 4.3. A query on strings is expressed by a GSQA iff it is definable in MSO logic.

Proposition 4.4. GSQA coincides with MSO logic to represent unary query over tree nodes.

Strong query automata are used to describe unary queries over tree nodes. In this thesis, our objective is to deliver a machine that can transduce selected nodes to given structures. To archive this objective, the query automata require some revision.

4.3.4 Query Transducer

Definition 4.6 (Query Transducer). A query transducer (QT) is a tuple $\langle Q, \Sigma, \delta_{root}, \delta_{leaf}, \delta_{\downarrow}, \delta_{\uparrow}, \delta_{-}, F, I, \lambda\rangle$, where Q, Σ, I and F have the same meaning as Q, Σ, I and F in

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bottom-up and top-down TA, $\delta_{\downarrow}$, $\delta_{\uparrow}$ and δ_{-} are down move, up move and stay move function respectively.

Query transducer's move function is defined in the same way as those of strong query automata, except for $\delta_{\uparrow}$, which is redefined as below:

$\delta_{\uparrow} : (Q \times \Sigma \times \mathcal{T}(\Sigma)*)* \rightarrow Q \times \mathcal{T}(\Sigma)*$ is an up move function. The value of the function is a tuple, such that $\delta_{\uparrow}(\langle q_1, \alpha_1, t_1\rangle, \ldots, \langle q_m, \alpha_m, t_m\rangle) = \langle q, t\rangle$, where $t = t_{1.1}, \ldots, t_{m.1}$, and $t_{i.1} = \alpha_i(t_i)$ if $\lambda(q_i, \alpha_i) = 1$, else $t_{i.1} = t_i$. If the SQA is processing node n's child nodes n_1 through n_m, where n_i is associated with state q_i, and there is $\delta_{\uparrow}(\langle q_1, label(n_1), t_1\rangle, \ldots, \langle q_m, label(n_m), t_3\rangle) = \langle q, t\rangle$, the SQA will leave n_1 through n_m to process n, associate q with n, and associate t with n.

A QT accepts the same tree language as a corresponding SQA. The difference between QT and SQA is that the terms associated with the root nodes in a final state in QT is the data extracted. These terms are called the extraction result of the QT from a given hedge. The following theorem connects query transducers with MSO logic programs:

Theorem 4.1. An extraction can be defined by MSO logic program, iff it is definable to a query transducer.

Proof: To prove that MSO logical programs can be simulated by query transducers, we only need to prove that all trees satisfying MSO logic formulae can be accepted by a query transducer. From Definition 4.3.4, the extension to query automata does not change the acceptance condition for a tree language. As query automata coincide with MSO logical program, a query transducer can accept those trees described by MSO logic.

We also need to show a query transducer can be simulated by monadic datalog, as monadic datalog coincides with MSO logic to represent unary queries [Gottlob and Koch, 2002b]. Gottlob and Koch [2002b] present the monadic datalog programs simulating query automata, and in this thesis, we do not repeat the overlay programs; i.e., those programs simulating move functions except for $\delta_{\uparrow}$. To simulate $\delta_{\uparrow}$, we need to generate predicates that generate the same tree model as the output of query transducers. For each $q \in Q$, $\alpha \in \Sigma$ and $lambda(q, \alpha) = 1$, the following rule is added:

$\texttt{query}(n) \leftarrow \langle x, q\rangle(n), \texttt{label}_{\alpha}(n)$

For each $x \in Q$, $\alpha \in \Sigma$ and $\lambda(q, \alpha) = 0$, there is a rule:

$\texttt{tmpchild}(n_0, n) \leftarrow \langle x, q\rangle(n), \texttt{label}_{\alpha}(n), \langle x_1, x\rangle(n_0)$

Then, the following rules are added to simulate output:

$\texttt{tmpdescendant}(X, Y) \leftarrow \texttt{tmpchild}(X, Y)$

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$\texttt{tmpdescendant}(\texttt{X}, \texttt{Y}) \leftarrow \texttt{tmpchild}(X, Z), \texttt{tmpdescendant}(Z, Y)$

$\texttt{outChild}(X, Y) \leftarrow \texttt{child}(X, Y), \texttt{query}(X), \texttt{query}(Y)$

$\texttt{outChild}(X, Y) \leftarrow \texttt{child}(X, Z), \texttt{tmpdescendant}(Z, Y), \texttt{query}(X), \texttt{query}(Y)$

It can be inductively proved that the relational model built is the same as the output of the query transducer. ∎

So far, we have introduced a query transducer as the computational model of extraction machine.

4.4 WDEL Language

In this section, Web data extraction language (WDEL) coinciding with monadic datalog program is defined. In the framework introduced, written programs using WDEL contain schemata of Web documents to be extracted. As shown in Figure 3.1(b), a document tree may be so complicated that to perceive real data from the document tree could be painful for a user. The corresponding schemata of these documents may also be very complicated, thus, to handle documents via schemata is not easy. These structures (and schemata) of documents are named *physical structure (schemata)* in this thesis.

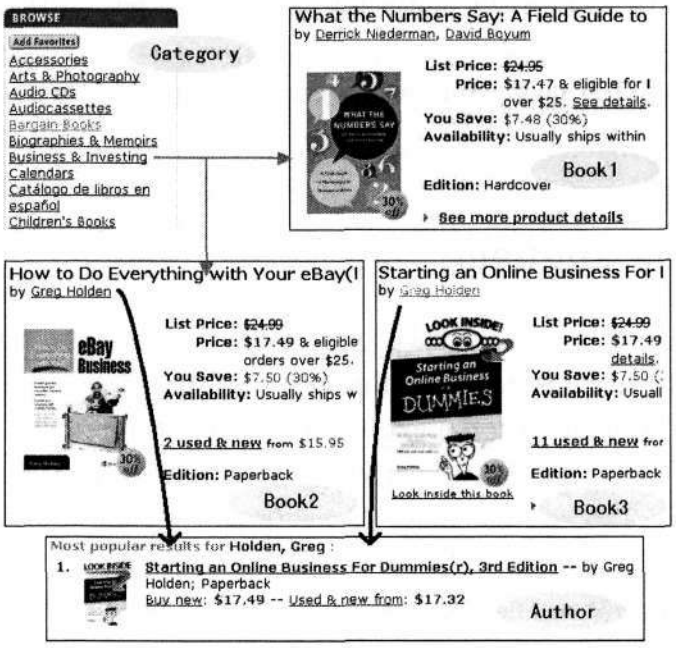
To make accessing Web data easier, we try to derive the logic schemata of the target Web documents and then extract information from the documents based on the schemata. The role of the logic schemata is to relate information from a Web site in terms of a commonly perceived logical structure, instead of physical document structures. The logic schemata here refer to people's perception of the organization of contents in Web documents. Data extracted should conform to the logic of schemata. The logic schemata and the mapping from physical schemata to logic schemata are also defined in WDEL programs.

As the equivalent expressive capability of WDEL, monadic logic program and query transducer, WDEL programs can be further compiled to low-level codes of QT and executed. Based on the logical view over documents and the physical structures of documents, a user can program WDEL to extract data from documents.

4.4.1 WDEL Introduction

Logic Schema and Physical Schema We firstly demonstrate an example that is more complex than Example 3.1. The properties of Web documents in the example

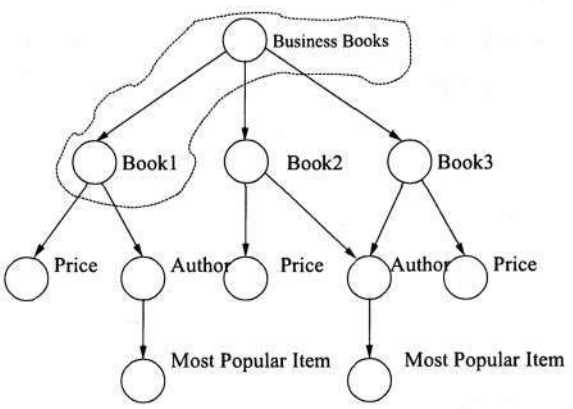
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(a) Web Pages from Amazon

Business	Book1	Price	17.47
		Author	Derrick Niederman
	Book2	Price	17.49
		Author	Greg Holden
	Book3	Price	17.49
		Author	Greg Holden
Arts	...		
...	...		

(b) Output



(c) Logic View

Figure 4.2: Web Pages and Logic View over Web Pages

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motivate the concrete definition of WDEL.

Example 4.1. Figure 4.2 includes fragments selected from five different Web pages. The `"category"` is a part of a navigator panel of Amazon's homepage. `"Book1"` through `"Book3"` are cut from pages linked from `"category"`. `"Author"` is from the author information page, and it is linked by both `"Book2"` and `"Book3"`.

Despite numerous pages and complicated physical structures of Amazon, a user may only care about the information on several books, such as those page fragments in Example 4.1. For such a user, his or her perception of content organization of Amazon usually is much different from the physical structure of Amazon documents. Most users perceive that Amazon consists of book categories, such as Computer book and Children book. Each category contains a list of books, each of which includes information fields regarding price, title, author, etc. This hierarchical content organization is a common view of bookstore Web sites in most users' mind. If we extract data from a bookstore Web site and organize them in this way, a user will be familiar with its structure and can handle the extracted data intuitively. Moreover, as a class of Web sites have the same organization structure in the users' mind, it is possible to organize data extracted from different Web sites with the same structure.

We call the common user perception of a special class of Web sites as their *logic structure*. Figure 4.2(c) is the logic structure of the five pages in Example 4.1, and Figure 4.2(b) is extracted data stored with this structure.

As introduced earlier in our framework, extracted data and target documents share the same data model. Thus, we can also derive schemata of the logic structures. As a logic structure needs not to be restricted in a single Web site, we can organize data extracted from multiple Web sites in the same class with the same logic structure. Besides data extracted from these sites have the same schemata. Thus, a query like *"return all books with schema A"* will return data from various sites. This provides an easy way to integrate Web data.

For a Web information concierge, to fill up the gap between logic schemata and physical schemata is as important as to induce physical schemata. WDEL is a formal language that defines the mapping from physical schemata to logic schemata. In a short word, WICCAP can parse a WDEL program, extract fragments in Web documents conforming to physical schemata in the program, and transform the fragments to data conforming to the logic schemata specified.

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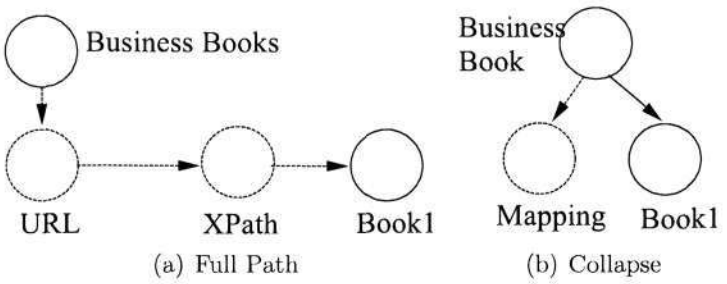


Figure 4.3: Mapping from Physical Structure to Logic View

As an example, Figure 4.3(a) is a physical structure corresponding to the two nodes inside the dash line in logic structure of Figure 4.2(c). When a user extracts Book1 information from the Web, he needs first to follow URL in the `"category"` page by clicking a URL, and then locates the root node of data instance of Book1 by following a path. A WDEL program defines a structure like Figure 4.3(b) to describe schemata corresponding to both the logic structure and physical structure.

The idea of programming WDEL is straightforward. Firstly, a user defines a logic schema corresponding to data extracted and a physical schema corresponding to Web documents. For each pair of parent-child nodes in the logic schema, there should be a pair of ascendant-descendant nodes in a physical schema. By collapsing the path between these ascendant-descendant node pairs, the physical schemata will be the same as logic schema. A WDEL program is then completed by adding a child node to each node in the logic schema that describes the path between a corresponding node pair in a physical schema, shown as Figure 4.3(b).

Thus, WDEL consists of two parts: (1) elements to define logic schemata and (2) elements to define physical paths. The first part, which is called schema elements and the second part named *Mapping Element* are described in the following sections.

Schema Elements A WDEL program is written in a normal XML, conforming to some DTD. The DTD of WDEL is defined later in this section.

schemaElement Schema elements in WDEL are used to define the hierarchical structures of schemata. Schema elements can define both physical schemata and logic schemata. Because that a WDEL program does not directly define physical schemata, in this section, when we mention schemata, we mean logic schemata. Given that

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we use a simple model of data instance to represent schemata, the schema elements to define schemata are also simple. The DTD of schema elements is listed as below:

```
<!ELEMENT schemaElement (Mapping,schemaElement*)>
<!ATTLIST schemaElement Label CDATA "*" #REQUIRED>
<!ATTLIST schemaElement schemaID ID #IMPLIED>
<!ATTLIST schemaElement nextSibling IDREFS #IMPLIED>
<!ATTLIST schemaElement firstChild CDATA "no" #IMPLIED>
    ⋮
```

The schemaElement is a basic construction element of a WDEL program. The XML document tree that conforms to this DTD is a valid schema in Definition 3.4 already, if the first two lines are replaced with the below lines:

```
<!ELEMENT schemaElement (schemaElement*)> <!ATTLIST
schemaElement Label CDATA "*" #REQUIRED>
```

The attributes schemaID, nextSibling and firstChild are added to make WDEL to have the same expressive capability as a monadic datalog. The relationship between a monadic datalog and WDEL is discussed in Section 4.4.2. The above DTD is a minimal definition, and schemaElement can be customized to include more schema attributes. For instance, if a user wants only those DIs with schema that is larger than a certain value *val*, a line can be inserted to the DTD as below:

```
<!ATTLIST schemaElement Size CDATA "[>val]">
```

Mapping Elements Mapping elements included in the above DTDs are used to represent a path in a physical schema. If there is an edge $\langle a_1, a_2 \rangle$ in a logic schema, and b_1,b_2 are corresponding nodes in a physical schema, then the path between b_1 and b_2 is represented by the mapping element of a_2. For Web document trees, an edge between two nodes may be intra-page or inter-page. An intra-page edge allows us to locate any descendant node in the current documents, while an inter-page edge leads to another document from a node in a current page. We first introduce several types of edges in WDEL and then introduce how to use a mapping element to organize these edges to a path.

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PathLoc PathLoc is an element representing an intra-page edge, with DTD as below:

```
<!ELEMENT PathLoc (#PCDATA)>
```

The #PCDATA is a XPath expression. In simple terms, we use a subset of XPath; i.e., a linear expression $[/]b_1.1/b_1.2/\ldots/b_2$, where $b_1.1$ are child node of b_1, $b_1.2$ is a child node of $b_1.1$, and so on. Details of more elements representing intra-page edges can be found in WICCAP [Liu et al., 2002b].

Link Link is an element representing a hyperlink, conforming to the following DTD, where the #PCDATA is a valid URI string.

```
<!ELEMENT Link (#PCDATA)>
```

DynaLink DynaLink is also an element representing a hyperlink. Unlike Link elements that contain static URI strings, a DynaLink contains information on the extraction of URI strings from target documents.

```
<!ELEMENT DynaLink (#PCDATA)>
```

The #PCDATA is a XPath expression that is defined as the one in PathLoc. The element pointed by the path should be a URI string.

Form As there are many dynamic documents generated by submitting a form on the Web, WDEL includes the form elements to represent a form that can return dynamic documents.

```
<!ELEMENT Form (#PCDATA)>
```

In the DTD of form elements, the #PCDATA is the code of a HTML form. During the interpretation of WDEL programs, these #PCDATA will be rendered in browser windows to interact with users and to return dynamic Web documents.

Mapping Given these elements representing edges in Web documents, a Mapping element can organize multiple edges together to compose a path in Web documents, defined as below:

```
<!ELEMENT Mapping ((PathLoc|Link|DynaLink|Form),Mapping?)>
```

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4.4.2 WDEL and Monadic Datalog

So far, we have defined WDEL and introduced the rough process to construct WDEL programs. Before looking into WDEL programming, this section will compare WDEL and the monadic datalog in terms of their expressive power. As stated in Proposition 4.1, monadic datalog has the same expressive power as the monadic second order logic, given the certain predication set. The connection between WDEL and monadic datalog makes it easy to define extraction rules in a declarative way.

Theorem 4.2. An extraction is definable for a monadic datalog program over τ iff it is definable for WDEL with minimal schemaElement definition.

Proof: We need to prove that WDEL programs can be simulated by a monadic datalog program over τ. Given a WDEL program written in XML document, the simulation objective is to define a WDEL extraction using a monadic datalog program over τ, which includes two points: (1) the physical structures of documents to be extracted should be acceptable to a monadic datalog, and (2) the logic structure of output should be computable to a query transducer, so that the query transducer can be simulated by a monadic datalog program. In terms of describing physical structures, any parent-child element pair in a WDEL program contains information about the ascendant node in a physical structure corresponding to the parent element and the descendant node in physical structure corresponding to the child node and the path between these two nodes. Such a pair of nodes can be encoded to the following datalog rule:

$$\texttt{ele}_{desc}(X) \text{:}-\texttt{ele}_{ascd}(Y), \texttt{descendant}_{path}(Y, X)$$
$$\texttt{descendant}_{\alpha.path}(X, Y) \text{:}-\texttt{child}(X, Z), \texttt{label}_{\alpha}(Z), \texttt{descendant}_{path}(Z, Y)$$

The firstChild and the nextSibling attributes can be encoded in a similar way, that done, physical structures described by a WDEL program can be accepted by the datalog program that encodes all parent-child and sibling element pairs.

We also need to simulate monadic datalog programs over τ using WDEL programs. To prove this, we use general strong query automata as auxiliaries. As proven by Gottlob and Koch [2002b], each transition in a GSQA can be simulated by a subset of datalog rules, which can further be simulated by a WDEL program. As GSQA coincide MSO datalog over τ, WDEL programs can simulate monadic datalog programs. ∎

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4.4.3 An Example of WDEL Program

Using Example 4.1 again, this section will illustrate how to program WDEL to execute an extraction task. This task transforms the physical structures of Web documents in Figure 4.2(a) to the logic structure in Figure 4.2(c). Figure 4.4(a) is the WDEL program, which is a valid XML documents that conforms to DTD introduced in Section 4.4.1.

Firstly, let us consider how to define the schema of the logic structure in Figure 4.4(c). The structure is rooted from "Business" book category; there is a list of books belonging to this category; each book has "title", "author" and "price" information. For each book, "title", "author" and "price" appear only once, while the number of books there are in the "Business" category may vary with corresponding Web documents.

The schema of this structure can be represented using a tree grammar, defined as below:

Business $\rightarrow$ Book*
Book $\rightarrow$ Title, Author, Price

This schema can also be defined as the following datalog program:

```
Business(n):- root(n)
Book(X):- Business(Y),child(Y,X)
Title(X):- Book(Y), first_child(Y,X)
Author(X):- Title(Y), next_sibling(Y,X)
Price(X):- Author(Y), next_sibling(Y,X)
```

Corresponding to the five predicates at the left hand side in the above datalog rules are five schema elements in this program: "Business", "Book", "Title", "Author" and "Price". The *first_child*, *next_sibling*, *root* predicates can be simulated by the relationships among schema elements in the XML document of the WDEL program, as shown in Figure 4.4(a). The first datalog rule is simulated by the root element; the second rule is simulated by the schema elements labeled with "Business" and "Book", and so on.

4.5 Summary

In this chapter, we have proposed various perspectives on the implementation of a concierge framework. Given the lack of theoretical framework to compare different Web

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```
1: <schemaElement Label="Business">
2:  <Mapping>
3:    <Link>http://www.amzon.com/</Link>
4:    <Mapping>
5:      <DynaLink>/html/.../a[7]</DynaLink>
6:    </Mapping>
7:  </Mapping>
8:  <schemaElement Label="Book" schemaID="book" nextSibling="book">
9:    <Mapping>
10:     <PathLoc>/html/.../td</PathLoc>
11:   </Mapping>
12:   <schemaElement Label="Title">
13:     <Mapping>
14:       <PathLoc>a[1]/text()</PathLoc>
15:     </Mapping>
16:   <schemaElement Label="Author"
17:       <Mapping>
18:         <PathLoc>text()</PathLoc>
19:       </Mapping>
20:   <schemaElement Label="Price"
21:       <Mapping>
22:         <PathLoc>span/b[1]/text()</PathLoc>
23:       </Mapping>
24:   </schemaElement>
25:  </schemaElement>
26: </schemaElement>
```

(a) A WDEL Program

```
1: <Business>
2:   <Book>
3:     <Title>What the Number ...<Title>
4:     <Author>Derrick ...</Author>
5.     <Price>$17.47</Price>
6.   </Book>
2:   <Book>
3:     <Title>How to do ...<Title>
4:     <Author>Greg Holden</Author>
5.     <Price>$17.49</Price>
6.   </Book>
2:   <Book>
3:     <Title>Starting an online ...<Title>
4:     <Author>Greg Holden</Author>
5.     <Price>$17.49</Price>
6.   </Book>
1: </Business>
```

(b) Extraction Results

Figure 4.4: A WDEL Program and its Output

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information concierge systems in the literature, the comparison among these perspectives presents an initial step in integrating different techniques into the framework and aiding further research in Web information concierge systems.

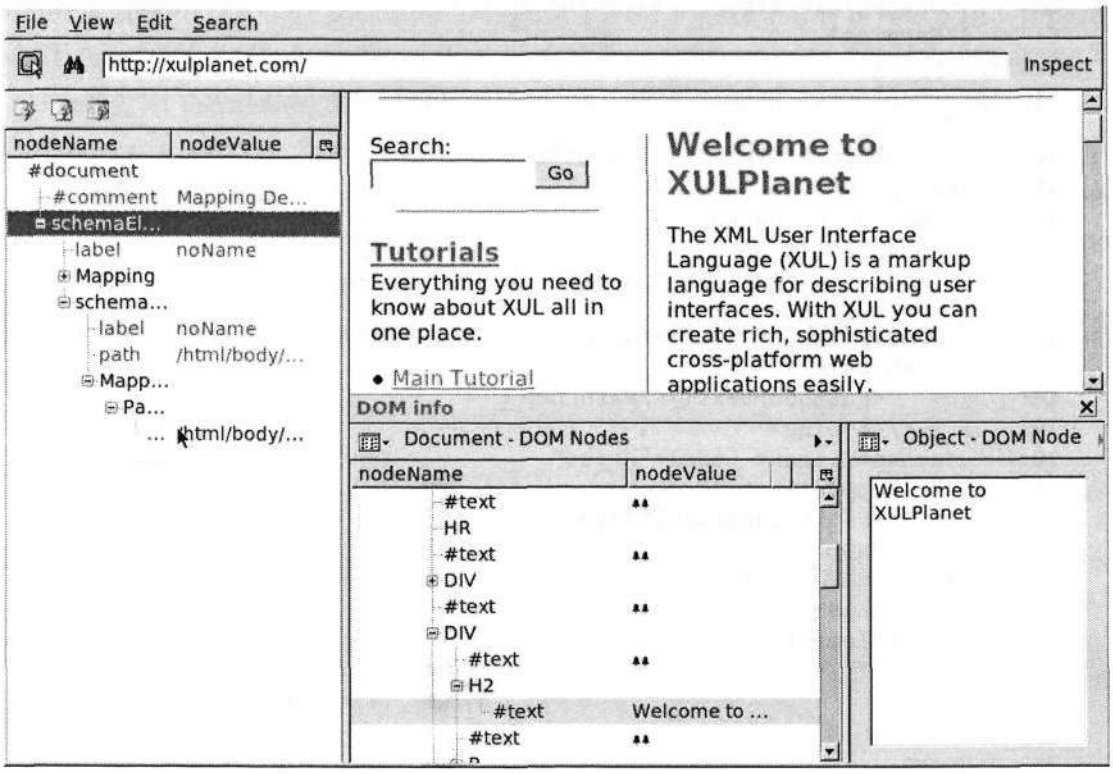


Figure 4.5: Visual Interface to Generate WDEL

WDEL is the language that combines the benefits of both tree language and logic program. WDEL describes Web document structures in a declarative way; it can also be parsed by the tree transducer introduced. Based on techniques discussed in this chapter, we improve the sample system in Chapter 3, with Figure 4.5 as the visual interface to generate WDEL scripts[1]. In this interface, the left panel is the hierarchical structure that corresponds to the WDEL script defined, the upper-right panel is an embedded Web browser and the lower-right panel is the DOM tree and tree node property window corresponding to Web documents in the Web browser.

Compared with the sample system demonstrated in Chapter 3, the main differences are briefly outlined below:

[1]Please refer to http://www.cais.ntu.edu.sg/~lee/wiccap/example-1.html for complete demo.

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1. DIs are simplified DOM trees of Web documents. In Figure 4.5, the lower-right panel replaces the bottom window in Figure 3.3, and contains DOM tree of the Web document.

2. Schemata can describe structures of both Web documents and extracted data.

3. Schemata have the same expressive power as monadic datalog programs.

4. A schema can define structures that corresponds to any fragment of a Web document, instead of the whole document.

With the help of the visual interface, a user can define simple WDEL scripts by clicking on the DOM tree. The extraction engine that parses the scripts to do real extraction. Moreover, if we can devise algorithms that detect important fragments in Web documents, the user may ask the Web browser to show only these fragments, thus generating the schemata automatically and improving efficiency more. The next chapter introduces the algorithms to detect schemata automatically.

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Chapter 5

Efficient Schema Detection

In Chapter 4, WDEL was introduced in order to define extraction rules. The relation between schemata and extraction rules was also presented. Given that extraction rule generation involves detection of schemata, this chapter focuses on efficient detection. To accomplish this task, a five-part structure is adopted: (1) Schema detection and rule generation, (2) Schema detection and inference problems, (3) k-schema, (4) Approximate k-schema detection algorithm, and (5) DocItem tree for k-schema detection.

5.1 Schema Detection and Rule Generation

The basic constituents of WDEL are mechanisms defining schemata of data instances, and the mapping from physical schemata and logic schemata. Thus, a main task of extraction rule generation in our framework is to detect schemata of data instances.

Schema Detection is divided into two parts: (1) physical schema detection, and (2) logic schema detection. As mentioned in Section 4.3.4, logic schemata are restricted to be transformed from physical schema, and problem of logic schema detection can be reduced to select subsets of nodes in physical schemata. We focus how to figure out physical schemata to generate extraction rules.

It is always a straightforward method to ask an expert to observe Web documents in hand, and induce the schemata by hand [Baumgartner et al., 2001b, Gupta et al., 1997, Li and Ng, 2004]. As the manual methods are not scalable, automatic methods are preferred in Web data extraction scenarios. For that physical schemata can be viewed as tree grammars (or equivalent logic rules) that generate data instances in Web documents, grammar induction approaches are exploited in schema detection.

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5.2 Schema Detection and Inference Problem

Schema detection is an inference problem that originated decades ago [Gold, 1967]. Before describing details of schema detection as an inference problem, we need to consider the definition of an inference problem in recent literature. Knuutila [1994] asserts:

The *inference problem* is to find an allowed *algorithm* M that, given an allowable *representation* for (or a sample of) of a language in the *target class* and the possibly present *additional information*, produces a *hypothesis* H from the chosen space $\mathcal{H}$ fulfilling the given definition of learnability.

From the definition above, an inference problem needs to be depicted from at least six aspects: (1) the class of languages to be inferred, that is named target class, (2) the representation of information about target languages, (3) the form of space of hypotheses of target languages, (4) allowable inference algorithms, (5) other additional information that helps inference, and (6) how to measure whether the inference algorithms are successful. Different choices on these aspects produce various models for inference problem.

5.2.1 Models for Schema Detection

The problem of Web document schema detection can be depicted as an inference problem, talking cognizance of the first three aspects: (1) The target languages are Web documents to be extracted; (2) The representation of information is a set of sample documents of the target language; and (3) The hypothesis space consists of Web document schemata. When the schemata in the hypothesis space are represented as language grammars, the inference problem is also called grammar induction.

In a general inference problem, information representation may contain negative examples; i.e., examples that do not belong to a target language. However, in concierge systems, usually only positive examples are available as information representation; i.e., sample documents of the target language [Crescenzi et al., 2001, Kosala et al., 2003]. Although the choice of information representation is limited, various models of target languages and hypotheses can be exploited. As introduced in Chapter 4, target documents can be relational data, local tree languages, regular tree languages, etc. Schemata of documents can be tree grammars introduced before, or be represented as automata, logic programs, and variants in existing work [Chang and Lui, 2001, Gottlob and Koch, 2002a, Kushmerick, 2000a].

Chapter 4 introduced various schemata with different levels of expressive power.

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These included FO logic program, MSO logic program, regular tree grammar and local regular tree grammar. In Web information concierge systems, the following grammar variants are exploited:

- The basic model in Chapter 2 assumes Web documents have tabular structures. The schemata of documents are sequences of delimiter strings and field strings. These sequences can be mapped to relational schemata directly.
- Compared with the simple relational grammar, many systems [Chang and Lui, 2001, Crescenzi et al., 2001] use regular word grammar as document schemata, known to be some regular expressions. Web documents to be extracted are expected to be generated from these expressions.
- Modeling Web documents as trees is more intuitive. Tree patterns are used as schemata in some systems [Arasu and Garcia-Molina, 2003, Rajaraman and Ullman, 2001], although these patterns are explicitly represented as tree grammars. The k-testable tree grammar is a tree grammar with weak expressive power, and is used by Kosala [2003].

5.2.2 Inference Algorithm Evaluation

After choosing models for the first three aspects, the challenge is how to devise inference algorithms and improve the algorithms based on additional information. In this sub-section, we shall present our algorithms for schemata detection. Our implementation includes both offline and online algorithms. Offline algorithms need all available information representation before execution, while online algorithms allow examples fed on-the-fly. Another important point to be considered in inference problem is how to evaluate whether algorithms are successful.

There are many evaluation methods in the literature. Most existing evaluation approaches are not suitable to schema detection. We briefly discuss two of them.

Identification in the limit Suppose there is a sequence of n information representations R_1 through R_n of a target language, and this sequence is fed to inference algorithm one by one, based on the given sequence where n may be infinity, an inference algorithm should constitute a hypotheses. If there exists a number m, such that after R_m is fed, the algorithms will produce no more new hypotheses and the hypotheses obtained coincides

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with the target language, we say that the target language is *identified in the limit* by this algorithm. The algorithm making a target language to be identified in the limit is successful.

The requirements of identification in limit [Knuutila, 1994] are burdensome for Web data extraction systems; even the extremely restricted schemata are hard to detect. When an oracle can answer whether a given example is positive and whether two grammars are equivalent, regular languages can be identified in the limit [Angluin and Smith, 1983]. However, when only positive examples exist, Gold [1967] proved that it is impossible to identify a target grammar, except the language generated by the grammar is finite.

The result of Gold's [1967]'s work is a bit disappointing, as far as inducing schemata in the limit is concerned. More constructive results show that it is possible to identify some languages; e.g., k-testable tree languages [Garcia and Vidal, 1990, Rico-Juan et al., 2000], suitable to be document schemata in the limit based on only positive examples. Kosala [2003] models Web documents as k-testable tree languages, and introduces the polynomial inference algorithms.

Another problem of identification in the limit is the size of example set needed, as we cannot assume there are enough sample documents to make the inference algorithm convergent. This motivates an evaluation method of successful algorithms based on probability theory.

PAC learning model Identification in the limit asks algorithms to give a hypothesis equivalent to the target language. PAC-identification [Valiant, 1984] is a learning model based on probability theory; and it looses the success condition of inference algorithms.

PAC-identification assumes examples are fed randomly to the learning algorithm. Moreover, the success of an algorithm is measured by (1) *error parameter*, and (2) *confidence parameter*. Error parameter is the probability that instances in the hypothesis differ from those in the target language. Confidence is the probability that correct hypotheses are generated. Given the two parameters, an algorithm is successful if it can produce hypotheses with less error and higher confidence.

Kushmerick [1997] exploits PAC learning model to induce extraction rules and analyzes how large the example set is required. Although his rules are quite simple, the number of samples needed is very large. Sometimes, it is infeasible to prepare such a large training set.

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5.2.3 Heuristic Methods for Schema Detection

Based on the evaluation methods above, these exact and probable algorithms are mostly not practical in Web information concierge systems. For example, usually, there are inadequate sample documents; when there are insufficient examples, inducing proper schemata from Web documents may be difficult. For example, Kosala, Kushmerick's [2003, 1997] algorithms will be too fragile if a small set of examples is used to inference; i.e., the grammar learnt cannot generate Web documents with noise data.

Fortunately, recent empirical results [Arasu and Garcia-Molina, 2003, Chang and Lui, 2001, Crescenzi et al., 2001, Rajaraman and Ullman, 2001] have shown that it is possible to construct polynomial heuristic inference algorithms that can generate acceptable extraction results. Unlike using grammars as schemata of the whole Web documents that ask documents to be generated from these grammars, some approaches assume there are frequent patterns that appear in documents and that the schema needs not be the one of a whole document. Those patterns are used as schemata; only those fragments that conform to the patterns should to be extracted. Thus, these algorithms strongly rely on pattern detection techniques.

Compared to the polynomial time complexity of these methods, we shall introduce a class of pattern, called k-subtrees, that can be detected in linear time and generate good extraction results.

5.3 k-Schema: A Class of Simple Schemata

In our concierge framework, instance layer contains data extracted and all those Web documents to be extracted, which may be cached locally. Schema layer contains schemata, which are structural patterns of documents in instance layer and some attributes of these patterns. Operation layer does not directly process items in instance layer; instead, it handles items in schema layer to perform tasks such as extraction and knowledge discovery. Although Web documents are changing, the structures containing interesting data may remain relatively static. Thus, detecting those structural patterns matching with interesting fragments of documents as schemata is more stable than handling data in instance layer.

In this framework, a Web documents is viewed as rooted labeled tree that is a 4-tuple $t = \langle V, E, r, \gamma \rangle$. The set V contains the nodes corresponding to tag elements, E is the set

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of edges connecting these nodes, r is the root node, $\gamma : V \rightarrow L$ is a function that assigns each node a string label, where L is the label set of t. An edge e is an ordered 2-tuple (u, v) where $u, v \subseteq V$ and u is the parent node of node v. Root node r has no parent node. Each non-root node u in V has one parent node.

Data instance (DI) in instance layer includes Web documents and fragments of these documents extracted. A fragment of a document is a data instance if given a document tree $t = \langle V, E, r, \gamma \rangle$, the fragment can be represented by $t_i = \langle V_1, E_1, r_1, \gamma_1 \rangle$ and $V_1 \subseteq V$, $E_1 \subseteq E$ and $\gamma_1 = \gamma$. This relation is denoted as $t_i \subseteq t$, and t_i is a sub-DI of t_j if $t_i \subseteq t_j$. Two DIs $t_1 = \langle V_1, E_1, r_1, \gamma_1 \rangle$ and $t_2 = \langle V_2, E_2, r_2, \gamma_2 \rangle$ are equivalent, iff exists a bijection $\mathcal{M}$ between V_1 and V_2 such that: (1) $\mathcal{M}(r_1) = r_2$. (2) $(u, v) \in E_1$ if and only if $(\mathcal{M}(u), \mathcal{M}(v)) \in E_2$. (3) $\gamma_1(u) = \gamma_2(\mathcal{M}(u))$.

Like the tables in a relational database, which is a set of tuples sharing the same schema, data extracted from Web documents can also be organized as sets corresponding to schemata. In this thesis, a schema also contains DIs, where some nodes are labeled with wildcard char "$*$", and a DI t matches a schema s, denoted as $t \mapsto s$, if t is equivalent to one DI of s, suppose for any node v, $* = \gamma(v)$ is true. The set of all DIs that match a schema is a type.

In a Web document, the data in the same type usually are organized in disjoint subtrees at the bottom. For example, in Amazon Web site, data about each book is represented as a subtree at the bottom of a Web document; those subtrees of different books are disjointed. Based on this observation, we suppose that data to be extracted are those subtrees at the bottom. The set of all subtrees at the bottom of a DI t is denoted as $s = \cup_{j=1}^{n} s_k(t)$, where $s_k(t)$ is the set of subtrees with height k at the bottom. In tree t, whose root has m subtrees from t_1 to t_m, $s_k(t)$ is defined as below:

$$s_k(t) = \cup_{i=1}^{m} s(t_i) \cup \begin{cases} \varnothing & if\ height(t) \neq k \\ t & otherwise \end{cases}$$

The subtrees in $s_k(t)$ are called k-subtrees in document tree t. In the following parts of this chapter, we only consider how to extract those k-subtrees containing user sensitive data. This is an important heuristic that leads to the possibility of efficient schema detection, as the detection of all subtrees from multiple documents is a NP-hard problem, as stated in Li and Ng [2004]. We also observed that the subtrees containing similar contents in the same Web document trend to share the same structure. Empirical data in Li and Ng [2004] confirmed this observation. Thus, it is reasonable to assume that

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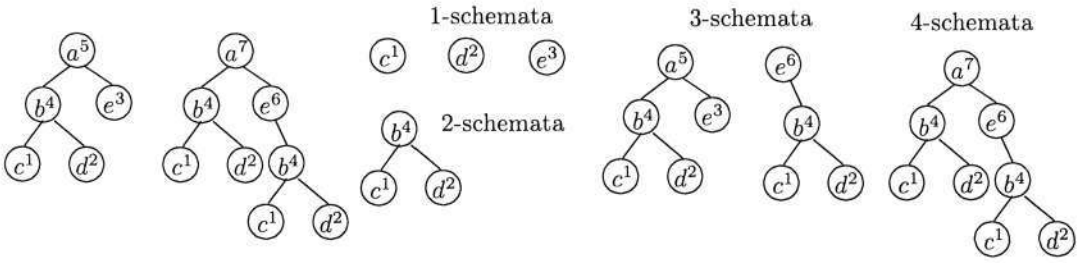


Figure 5.1: Naive Detection

k-subtrees in the same type contain similar contents. As in Web documents, especially HTML documents, data are enclosed in text nodes. We use a structural pattern that is equivalent to subtrees in a type, except those labels of text nodes are "$*$" as the schema of this type. Such a schema of the type of k-subtrees is named k-schema.

Definition 5.1 (k-schema). A k-schema s is a 2-tuple $\langle D, A\rangle$, where D is a set of k-subtrees of Web DIs, and γ functions in these k-subtrees label some text nodes with "$*$". A is a n-tuple $\langle a_1, a_2, \ldots, a_n\rangle$, where a_i is an attribute, $i \in [1, n]$.

Once the schemata of types of interesting data of Web documents are obtained, a user can easily submit a query to a document t; e.g., a query $M(s) = \{t|t \mapsto s\}$, where s is a k-schema and t is a k-subtree of t. The set of all k-schemata is denoted as $S_k(t)$. Figure 5.1 is a sample of a forest including tree t_1, t_2 and these k-schemata in them. In Section 5.4, we shall introduce the details of k-schema detection.

5.4 Approximate k-Schema Detection Algorithm

This section considers only a special class of DIs in document trees based on an observation:

Observation 5.1. Most interesting contents appear near the leaf nodes in many document trees. Text information to be extracted is mainly embedded in text elements, especially for HTML documents.

Based on this observation, we define a class of DIs as follows:

Definition 5.2 (Bottom Data Instance). Given a document hedge T, a bottom data instance (BDI) is a k-subtree of T.

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The only difference between a DI and a BDI is that the leaf nodes of a BDI are also the leaf nodes of the document tree that contains the BDI. Thus, $S_k(t)$ is the schemata of BDIs in document t. In the following parts of this chapter, we consider only BDI and detection of k-schemata. Given this caveat, we shall introduce an algorithm with polynomial time complexity to detect k-schemata. Before introducing the algorithm details, we provide an alternative definition of *conformation* to make our algorithm easier to understand.

Definition 5.3 (Conformation)**.** Given a data instance $t = \langle V, E, r, \gamma \rangle$, its **type vector** is $\varphi(t) = \langle \gamma(r), o_1, \ldots, o_n \rangle$ where o_1 to o_n are sorted schema ID of n child DIs of r. A DI $t = \langle V, E, r, \gamma \rangle$ conforms to a schema $s = \langle V_s, E_s, r_s, \gamma_s, A_s \rangle$ if $\varphi(t) = \varphi(s)$.

(Note that Definition 5.3 is equivalent to Definition 3.5.) From the definition, it is possible to traverse document trees from the bottom to top and to detect all schemata in one traversal.

Unlike schemata introduced in Chapter 4, this kind of schemata are quite simple and can only perform well when document fragments containing the same kind of information can be parsed into the same structure. Unfortunately, the real situation is more complicated. For example, in Figure 1.1(a), the first and the third books in Page A are rendered from document fragments that can be parsed into the same type of DIs. This is ideal; however, the second data instance of book information does not conform to the same schema as the others. Unlike other books, the book titled "*C++ GUI Programming with QT3*" has no second-hand price. There are other properties of semi-structured documents that make data instances describing the same kind of information different and cannot be organized into the same type.

- Missing attributes: Information of a book may include author and price. Sometimes, some books have a second-hand price; while others may not have such information.
- Multi-valued attributes: A book may have more than one author.
- Disjunctive delimiters: A document may use different delimiters to mark the same attribute. For example, the titles of hot sales or the special price may appear in bold format.

To resolve the problem concerning the same kind information embedded in different types, we relax the condition in Definition 5.3 and place two DIs in the same type if most sub-DIs appearing in them are equivalent.

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Algorithm 3 LayerBuilder

Require: a document forest F.

```
initiate a dequeue of nodes 𝒟;
read the schema table 𝒮 from the schema layer, each tuple is [id, s, T];
read the type table 𝒯 from the instance layer, each tuple is [id, T, D];
push all the leaf nodes in F to 𝒟;
while 𝒟 is not empty do
    pop the first node d from 𝒟, t=TreeRootedFrom(d);
    search 𝒮 for 𝒮[i]: φ(t) ≈ 𝒮[i].T;
    if found then
        insert t to 𝒯[i].D;
    else
        let id_d = |𝒮|, s is t's schema;
        insert [id_d, s, φ(t)] to 𝒮;
        insert [id_d, φ(t), {t}] to 𝒯;
    end if
    search sibling nodes of d in 𝒟;
    if failed then
        push the parent node of d to 𝒟;
    end if
end while
```

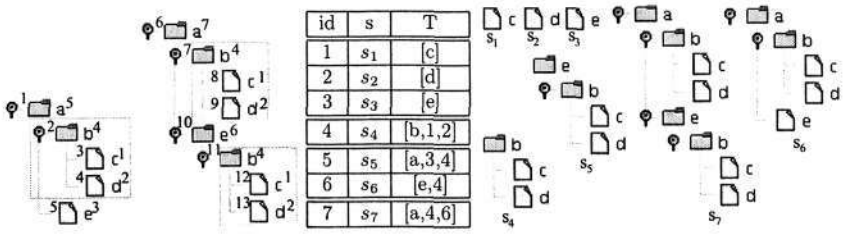
Definition 5.4 (Approximate Equivalence, Conformation and Type)**.** Given a DI $t = \langle V, E, r, \gamma \rangle$, there are m sub-DIs t_1 to t_m rooted from m child-nodes of root r. The DIs t_1 to t_m conform to schemata s_1 to s_k respectively, and $\{s_1, \ldots, s_k\}$ is the child schema set of t, denoted as $\mathcal{S}_c(t)$. Given a DI $s = \langle V_s, E_s, r_s, \gamma_s \rangle$, suppose $\mathcal{S}_{in} = \mathcal{S}_c(t) \cap \mathcal{S}_c(s)$, and $\mathcal{S}_{un} = \mathcal{S}_c(t) \cup \mathcal{S}_c(s)$, type vectors $\varphi(V)$ and $\varphi(V_s)$ are approximate equivalent, if

$$\sum_{s_i \in \mathcal{S}_{in}} |s_i| > r \times \left(\sum_{s_i \in \mathcal{S}_{un}} |s_i| \right) \tag{5.1}$$

denoted as $\varphi(V) \approx \varphi(V_s)$, where $r \in [0, 1]$. DIs t and s are approximate equivalent if $\varphi(V) \approx \varphi(V_s)$, denoted as $t \approx s$. If s is a schema, we say t approximately conforms to s, denoted as $t \succsim s$. We call a set of DIs that approximately conforms to the same schema as an approximate type.

Based on the preliminary information above, we provide a procedure to build the instance layer and schema layer in Algorithm 3. In the schema layer, the schemata detected in each document set are stored in a schema table. Each tuple in a schema

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(a) DI_1 (b) DI_2 (c) Final Status of $\mathcal{S}$ (d) Schema Detected

Figure 5.2: Running Example

table consists of a schema's ID, the schema and its type vector, denoted as $\langle id, s, T\rangle$. In the instance layer, the approximate types detected in each document set are stored in a type table. Corresponding to each approximate type, there is a tuple that consists of the schema ID of this type, its type vector and the list of DIs belonging to this type, denoted as $\langle id, T, D\rangle$. Given a document set, Algorithm 3 first initiates the schema table and type table; then reads nodes from bottom to top, while detecting the schema of the DI rooted from each node. New schemata, DIs and types detected will be appended to the schema table and type table correspondingly. As the schema table and type table of a document set are stored persistently, when the document set is changed (that is, a new document is added), Algorithm 3 only needs to read nodes from changed parts and modify the schema table and type table. We know that DIs in an approximate type may approximately conform to multiple schemata. Line 13 of Algorithm 3 assigns an *id* to an approximate type; this *id* is the same as the *id* of the schema of the first DI inserted into the type. We call this schema the *representative schema* of this approximate type.

In Figure 5.2, we provide a running example of Algorithm *SchemaDetector*. Here, we set r in Equation 5.1 to 1. Figures 5.2(a) and 5.2(b) are input DIs where `"a"`, `"b"`, `"c"`, `"d"`, `"e"` are labels of nodes. The number at the left-upper corner of each node is its pre-order traversal position in the input document forest. The number at the right-upper corner of each node is the *id* of schema to which the DI rooted from the node conforms. The SchemaDetector performs its operation in the following order:

- Detect the schemata of leaf nodes `"c"`, `"d"`, `"e"`, delete corresponding nodes from $\mathcal{D}$, and insert the detected schemata into $\mathcal{S}$; i.e., the first three tuples.

- Detect the schema of the subtree rooted at `"b"` as schemata of all its child nodes

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have been detected, delete node "b" from $\mathcal{D}$, and insert the schema into $\mathcal{S}$; i.e., the fourth tuple.

- Similarly, detect the schema of subtrees rooted at "a" (with pre-order traversal position 1) and "e" respectively; delete the two nodes from $\mathcal{D}$, and insert the detected schemata into $\mathcal{S}$; i.e., the 5th and 6th tuples.

- Detect the schema of the subtree rooted at "a" (with pre-order traversal position 10); delete the node from $\mathcal{D}$; and insert the detected schema into $\mathcal{S}$; i.e., the last tuple.

Figure 5.2(c) is the final status of $\mathcal{S}$.

SchemaDetector accesses each node only once. For a set of DIs containing n nodes, it assigns class id to those nodes in n iterations. In the ith iteration, the complexity of all statements, except line 7 is $O(1)$. Statement 7 searches in a table; its complexity is $O(n)$ in the worst case; i.e., all sub-DIs accessed conform to different schema. Thus, the complexity of SchemaDetector is $O(n^2)$ in the worst case. However, in a large document set, the number of all schemata is often much smaller than the number of nodes. Thus, the complexity of SchemaDetector is near $O(n)$.

5.5 DocItem Tree for k-Schema Detection

In this section, we shall introduce an algorithm with linear time complexity to detect all k-schemata from a given document hedge. The linear algorithm detects only those exact schemata with much higher performance, while the Algorithm 3 detects those approximate schemata. As introduced in Section 5.4, these approximate schemata are more flexible to use in extracting complicated Web documents. A user can choose to apply which algorithm based on a compromise between flexibility and performance.

5.5.1 From k-Schema to DocItem Schema

In previous chapters, documents were modeled as labeled hedge, which is intuitive in representing hierarchical structural data. The k-schemata are tree structure patterns embedded in the hedge. Section 5.4 presented the k-schema detection algorithm and how to exactly match document fragments with a k-schema. Approximate matching

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among k-schemata and document fragments can also be executed efficiently. However, in real implementation, parsing documents into a hedge is rather expensive.

In this section, we treat Web documents as flat texts; i.e., string languages. We shall introduce an algorithm to detect k-schema without parsing documents into a hedge. This algorithm detects string patterns that can be parsed to k-subtrees from flat texts. Firstly, we use a subset of XML specification to model Web documents as sequences of symbols from a given alphabet, described below:

```
CharData = [^<]* - ([^<]* ']]>' [^<]*);
STag = '<' CharData '>';
ETag = '</' CharData '>'.
```

$CharData, STag$ and $ETag$ are atoms of documents.

```
Element = STag Content ETag
Content = CharData?  (Element CharData?)*;
DocItem = CharData | Element;
DocItemList = DocItem*;
```

In the above document model, CharData are strings; those CharData organized by nested tag pairs are elements; each Web document is a DocItem, which is an element or a CharData. Each DocItem in this model can be parsed into a k-tree defined in Section 5.3. If all CharData in a DocItem are replaced with "*", the DocItem can be parsed into a k-schema, called the DocItem schema. Hereafter, when we mention a document, we refer to the document where CharData is replaced with "*".

Unlike modeling Web documents as hedge, one benefit of exploiting DocItem to model documents is that it is possible to build a DocItem schema repository where each schema can be found in linear time. Inspired by the idea of applying trie as an index of word dictionary, we shall introduce a trie data structure containing DocItem schemata. A search in this structure can be done in time linear in the size of DocItem.

Consider that the main workload of Algorithm 3 is brought by searching the schema repository, the complexity of Algorithm 3 can be decreased, if we can search schema more efficiently. The problem is whether the schema repository can be built efficiently, such that the building process does not increase the whole complexity, while the overhead of searching is decreased. We shall present the linear time algorithm to detect k-schemata and to build the schema repository.

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5.5.2 DocItem Trie Construction

Before introducing the algorithm to detect DocItem schemata and build trie of DocItem schemata, we briefly introduce trie for suffix strings of a CharData.

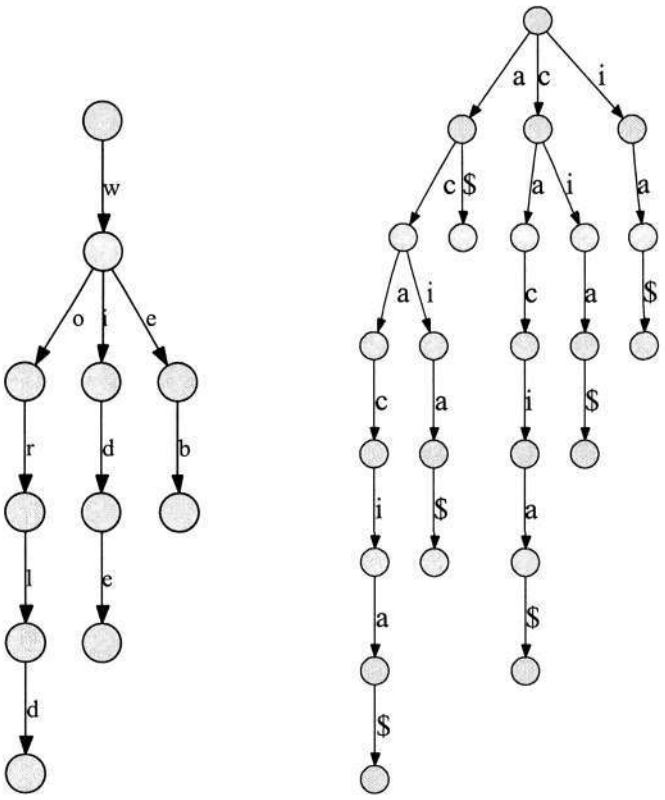


Figure 5.3: Example of Trie

A trie is a ranked tree, where each edge is labeled with a symbol from a given alphabet. Besides, there are no two edges from a node with the same label. Thus the possible maximum degree of a trie of substrings in a CharData is the size of the alphabet of the CharData. The set $\sigma(T)$ denotes the set of sequences of labels from root to each leaf in trie T; i.e., the path labels of leaves. Figure 5.3(a) is a trie T, and $\sigma(T) = \{world, wide, web\}$. We say p is end at l, if a leaf l has path label p.

If $\xi = uvw$ is a CharData, u, v, w are prefix, factor and suffix CharData of ξ respectively. if u, v, w are ElementList, we say they are prefix, factor and suffix elements of ξ.

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If $\sigma(T) = \{w|w$ is a suffix CharData of $\xi\$\}$, T is called the suffix trie of $\xi\$$, where \$ is a symbol does not appear in ξ. Figure 5.3(b) is the suffix trie of `"acacia$"`. The reason to append \$ symbol is appended to make each suffix appear only one time in ξ. Thus, each suffix can end at a leaf node; otherwise, a suffix may end at an internal node. Usually, suffix trie for $\xi\$$ is easier to be read by humans than the one for ξ.

Various linear time suffix trie construction algorithms have been devised by McCreight [1976], Ukkonen [1995], Weiner [1973]. With suffix trie of a CharData, any string pattern can be matched with the CharData in time linear in the pattern size, independent of the size of the CharData size. As introduced in Section 5.5.1, the problem now is whether there is an algorithm for constructing trie for DocItem schemata in linear time.

Basic Idea of Efficient Trie Construction This section introduces preliminary notations for DocItem trie, and a naive algorithm to detect DocItem schemata and construct DocItem tries for Web documents. In later sections, based on this naive algorithm, it is hoped that the application of some tricks will decrease its computational complexity to linear time.

Generally, a Web document is an element. A n-length document D is a string $d_1 d_2 \ldots d_n$. If there is a DocItem start from d_i, d_i is a $SChar$. The atom starts from a SChar is a SAtom. For $1 \leqslant i \leqslant n$, if d_i is a $SChar$, D_i denotes the DocItem start from d_i. For $D_i = d_i, \ldots, d_j$, d_j is named the $EChar$ of D_i, and the atom ended at d_j is an $EAtom$. If a sequence of atoms $\xi_i, \ldots, \xi_j$ is a DocItem, ξ_i and ξ_j are SAtom and EAtom of the DocItem. Given a document D, $\sigma(D) = \{D_i|1 \leqslant i \leqslant n$ and d_i is a $SChar\}$

As introduced in Chapter 3, we can parse Web document into trees. Each DocItem in document D can be parsed into a k-subtree in the DOM tree of D. Thus, detecting all k-subtrees from document trees is reduced to the detection of all DocItem from documents. Hereafter, the set of all DocItem in a document hedge T is denoted as $\sigma(T)$.

In the process of parsing a document D into a document tree T, each symbol in D can be mapped to a node in the T. For a symbol d_i in D, $level(d_i)$ denotes the level of d_i in a corresponding DOM tree, where root node has level 0, and child nodes' level is equal to 1 plus the level of their parent node. The number of atoms in D is denoted as $length(D)$.

Trie is a data structure that is usually used as a dictionary of strings, where a string can be located in linear time. A DocItem trie of a document T is an augmented trie representing $\sigma(T)$, defined as below:

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Definition 5.5. A DocItem trie of document T, denoted as $DTrie(T)$, is a tree that can be defined as a tuple $\langle \Sigma, \mathcal{S}, E, r, \gamma, f, s \rangle$, where Σ is the alphabet of T; $\mathcal{S}$ is a finite set of nodes; E is the set of edges; r is the root node; $\gamma : \mathcal{S} \rightarrow \Sigma*$ is a function that labels each edge with a document atom; $path(x)$ denotes the sequence of edge labels from root to node x; f is transition function $f : \mathcal{S} \times \Sigma* \rightarrow \mathcal{S}$, $f(x, \xi) = y$ if and only if there is a document atom ξ, $path(y) = path(x)\xi$ and $\exists E \in \sigma(T)$ s.t. $path(y)$ is a prefix string of E; s is DocItem link function $s : \mathcal{S} \rightarrow \mathcal{S}$. DocItem link function will be defined in Definition 5.6

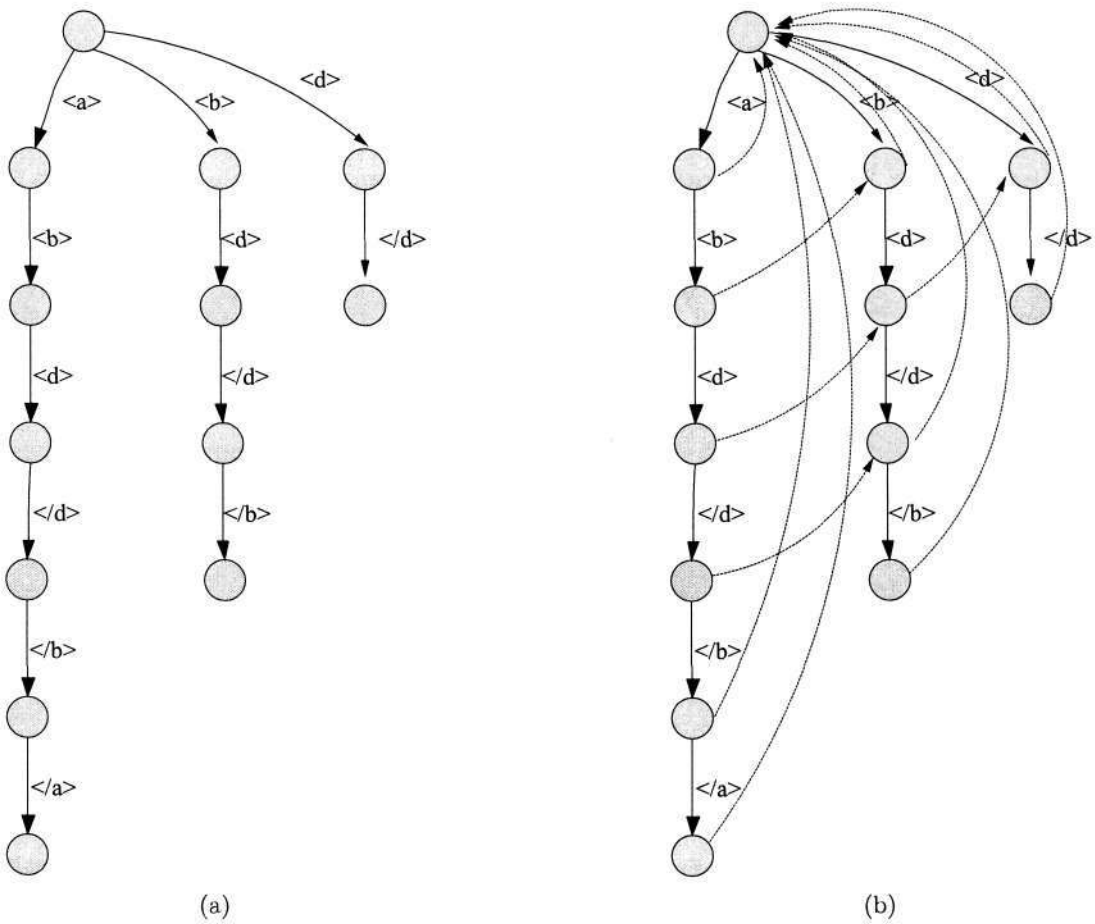


Figure 5.4: Example of DocItem Trie

Figure 5.4(a) is the DocItem trie for document `<a><b><d></d></b></a>`, without DocItem links.

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Ukkonen's well-known algorithm [Gusfield, 1999, Ukkonen, 1995] builds a trie of the set of suffix strings (suffix trie) in linear time to the trie size. Given a string $d_1d_2\ldots d_n$, Ukkonen's algorithm builds a suffix tree $\mathcal{T}_i$ (the suffix trie for $d_1d_2\ldots d_i$) based on $\mathcal{T}_{i-1}$. Given $\mathcal{T}_{i-1}$, suffix strings of $d_1d_2\ldots d_{i-1}$ are already in the trie. To build suffix trie of $d_1d_2\ldots d_i$, the algorithm only needs to check whether there is a transition $f(\eta, d_i)$ from the end point η of each suffix string in $\mathcal{T}_{i-1}$; if no, then create a node η_i and $f(\eta, d_i) \leftarrow \eta_i$.

Algorithm 4 CreateDTree

Require: A document $D = \xi_1, \ldots, \xi_n$, where ξ_i is an atom for $i \in [1, n]$.
Ensure: $\mathcal{T} = DTree(D)$ created.

```
1: Create T_1
2: for i = 2 to length(D) do {/*phase loop*/}
3:    T_i ← T_{i-1}
4:    for j = 1 to i and k ⩾ i do {/*extension loop*/}
5:       if ξ_j is a SAtom then {/*ξ_k is the EAtom of ξ_j*/}
6:          search node v with path ξ_j, ..ξ_{i-1}
7:          new node u and f(v, ξ_i) ← u if f(v, ξ_i) is not defined
8:       end if
9:    end for
10: end for
```

Differing from Ukkonen's [1995] algorithm, we need to build a trie of DocItem in a document hedge. Despite the difference, we share similar ideas with Ukkonen. Algorithm 4 depicts the procedural framework of our approach, which does not consider DocItem links yet. The basic idea of Algorithm 4 is to build DocItem trie $\mathcal{T}_i$ of $d_1d_2\ldots d_i$ from $\mathcal{T}_{i-1}$. All paths start from SChar d_j to d_{i-1} should be included in $\mathcal{T}_{i-1}$, thus, given $\mathcal{T}_{i-1}$, Algorithm 4 only needs to check whether there is a transition $f(v, d_i)$, if no, a transition is created.

Using concepts from Gusfield [1999], we call each time of outer loop in Algorithm 4 a phase, and each time of inner loop as an extension. The Statements 6-7 inside the extension loop will be executed $O(i^2)$ times; in each extension, Statement 6 locates a path in $O(i)$ time. Statement 7 only needs to add a transition to the trie in constant time. Thus, the complexity of the naive algorithm is $O(i^3)$. How to exploit some tricks to improve its performance will be introduced step by step.

DocItem Trie Construction Linear to Trie Size In Algorithm 4, most overheads are brought by Statement 6; thus, it is intuitive to decrease the complexity of Statement 6

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to improve Algorithm 4. Inspired by Ukkonen's use of suffix links that guarantees suffix strings can be located in a suffix tried in constant time, we exploit DocItem links to make Statement 6 done in constant time.

Definition 5.6. Let $\mu v \xi$ denote an arbitrary string, where μ is a STag, v is an DocItemList (maybe empty), ξ is a sequence of document atoms inside a DocItem (maybe empty), a DocItem link is a pointer from the node x with path $\mu v \xi$ to the node y with path ξ, denoted as $s(x) = y$, where y is root node, if ξ is empty.

Figure 5.4(b) is the complete DocItem trie for document `<a><b><d></d></b></a>`.

To search a path in a trie without DocItem links, Statement 6 in Algorithm 4 needs to match edge labels form root one by one. With DocItem links, the search can be done in constant time. In ith phase, the first node added definitely is labeled $\xi_1, \ldots, \xi_i$, we can store the node with label $\xi_1, \ldots, \xi_{i-1}$ in $(i-1)$th phase to save the time in searching $\xi_1, \ldots, \xi_{i-1}$, i.e; Statement 6 can be done in constant time. For the following extensions, Statement 6 can be done in constant time, as guaranteed by the lemma below:

Lemma 5.1. In each phase, the DocItem link that starts from the node with path p_i found in an extension points to the node with path p_j to be searched in the next extension.

Proof: Suppose current extension needs to search $p_i = \xi_i, \ldots, \xi_k$. Based on the definition of DocItem trie and Algorithm 4, p_i is a prefix of a DocItem. Thus $\xi_i, \ldots, \xi_k = \xi_i, \xi_{i+1}, \ldots, \xi_j, \xi_{j+1}, \ldots, \xi_k$, where ξ_i is a STag; $\xi_{i+1}, \ldots, \xi_j$ is a DomItemList and $\xi_{j+1}, \ldots, \xi_k$ is a sequence of document atoms inside a DocItem. Next extension will search $\xi_{j+1}, \ldots, \xi_k$, as j is the only position that fulfills conditions in Statement 4. Based on Definition 5.6, the lemma is held. ∎

Now, the problem is how to obtain the DocItem link function, and whether there always exists a DocItem link starting from node v located in the current extension. To solve this problem, we add a DocItem link pointing to the node created in the current extension from the node created in the previous extension. More details about adding DocItem links are depicted in Algorithm 5.

In this algorithm, we need not complete all extensions. If in the jth extension of nth phase, the path $\xi_j, \ldots, \xi_n$ is already in the DocItem trie, the phase can be completed, as based on the definition of DocItem trie, the paths to be added in the following extensions are already in the trie.

Based on the information above, Algorithm 5 enables DocItem trie construction procedure.

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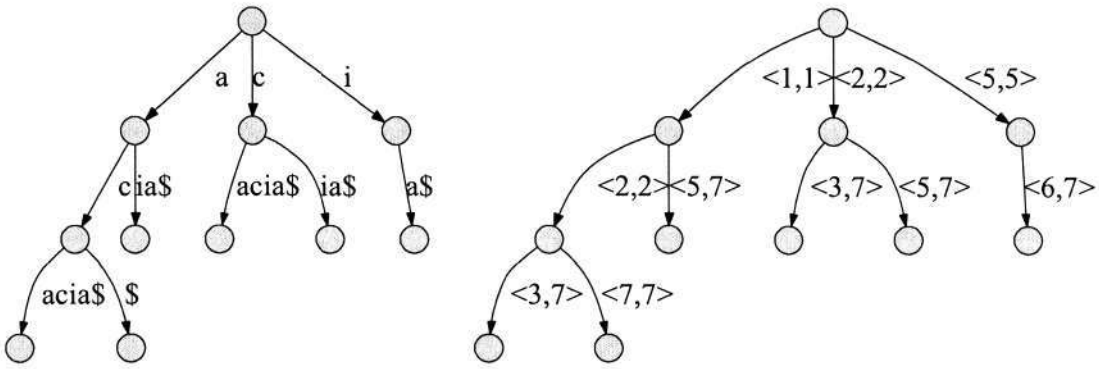


Figure 5.5: Example of Suffix Tree

Theorem 5.1. Algorithm 5 is linear in the size of the trie.

Proof: For each node newly created, only constant time is needed. ∎

The size of a DocItem trie of a document T is $O(|T|^2)$, as the number of DocItems is $O(T)$; for each DocItem, there is a path in the DocItem trie, which contains $O(T)$ nodes. Thus, with Theorem 5.1, we know the complexity of Algorithm 5 is $O(|T|^2)$. In the next section, we shall compact DocItem trie to obtain a data structure, called DocItem tree, while a construction algorithm with linear complexity to the size of documents is introduced.

5.5.3 DocItem Tree Construction Linear to Document Size

This section first introduces a data structure of compact DocItem trie — DocItem tree, whose size is linear in the size corresponding documents. Some tricks are then exploited to further decrease the complexity of Algorithm 5.

Compact DocItem Trie to DocItem Tree As the output trie size Algorithm 5 is $O(|T|^2)$ and an algorithm cannot be less complex than its output size, there is no other DocItem trie construction algorithm that can produce lower complexity. Fortunately, it is possible to compact a trie, without losing important information. For example, the trie in Figure 5.3(b) can be compacted to Figure 5.5(a), where a trie path without a branch is replaced with an edge. The edge label is the concatenation of labels on the trie path. This compacted trie has only $O(|T|)$ nodes; however, its edge labels still has $O(|T|^2)$ size. As each edge label is a substring in document T, it can be replaced by the start position

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and end position of the substring in T; e.g., Figure 5.5(a) is changed to Figure 5.5(b). As edge labels in Figure 5.5(b) have $O(|T|)$ too, the trie has $O(|T|)$ size. Such a compact DocItem trie is also called DocItem tree hereafter. These nodes left in the DocItem tree are called explicit nodes in the original trie, and those nodes that are removed are called implicit nodes.

In a DocItem tree, the transition function should be redefined as $f : \mathcal{S} \times N \times N \rightarrow \mathcal{S}$, $f(x, \langle r, l \rangle) = y$ if and only if there is a list of atoms $\xi = \xi_r, \ldots, \xi_l$, s.t. $path(y) = path(x)\xi$.

The problem now is what information is lost in the process of compacting a DocItem trie to a DocItem tree. The following lemma states the targets of DocItem links from explicit nodes will not be removed in the compact process.

Lemma 5.2. The target of DocItem links from an explicit node is also an explicit node.

Proof: An explicit v has at least two outgoing edges; thus, $path(v)$ is a prefix of at least two different substrings in the original document T. From Definition 5.6, $path(s(v))$ is a suffix of $path(v)$, thus, $path(s(v))$ is also a prefix of at least two different substrings of T, which means there are at least two outgoing edges from $s(v)$, and $s(v)$ is an explicit node. ∎

Thus, we know only these DocItem links among implicit nodes are lost in the compacting process.

The DocItem Tree Construction Algorithm As a path in a DocItem trie may be collapsed to an edge in the corresponding DocItem tree, Algorithm 5 cannot directly construct a DocItem tree. There are four main different points between constructing a DocItem trie and DocItem tree.

1. In a DocItem trie, $path^{-1} : P \rightarrow S$ is a function, and $path^{-1}(p) = v$ if $path(v) = p$; i.e., a path can be identified by a node. As those implicit nodes in DocItem trie are removed, a path cannot be identified by a node in DocItem tree. Instead, we can use a node and a position in its outgoing edge to identify those implicit nodes, i.e. $f'(v, \langle r, j \rangle)$ denotes a prefix of DocItem $p = \xi_i, \ldots, \xi_j$. Thus, in a DocItem tree, a path can be identified as $f'(v, \langle r, j \rangle)$.

2. A DocItem prefix in a DocItem tree may not end at a node. For example, in Figure 5.5(a), the end of `"acaci"` is not an explicit node. Thus, in i-th extension of j-th phase, if $p' = \xi_i, \ldots, \xi_{j-1}$ is located and $p = \xi_i, \ldots, \xi_j$ is not defined in

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DocItem tree, whether and how to create a new node identifying p depends on some conditions:

(a) If p' is identified by an explicit node v and v is a leaf node, then we only need to replace $f(u, \langle r, j-1\rangle) = v$ with $f(u, \langle r, j\rangle) = v$, instead of creating a new node.

(b) Else, if p' is identified by an explicit node v and v is not a leaf node, then we will have to create a leaf node w and let $f(v, \langle j, j\rangle) = w$.

(c) Else, if p' is identified by an implicit node $f'(v, \langle r, j-1\rangle)$, and there is a transition $f(v, \langle o, m\rangle) = u$, then we need to create a new internal node v' and a leaf node w, replace $f(v, \langle o, m\rangle) = u$ with $f(v, \langle r, j-1\rangle) = v'$, let $f(v', \langle j, j\rangle) = w$ and $f(v', \langle (o+j-r), m\rangle) = u$.

Summarizing these differences, Algorithm 6 can be seen is the procedure to create new nodes.

3. Like the building process of a DocItem trie, if in the i-th extension of the j-th phase, the path $p = \xi_i, \ldots, \xi_j$ is in the DocItem tree already, this phase can be completed. In $(j+1)$-th phase, the i-th extension is the first extension that may need to create a new node.

4. In Algorithm 5, DocItem links were used to help search strings in the following extension in constant time. In the DocItem tree, a path found in the current extension may be an implicit node without a DocItem link, starting from it. To search the node in the next extension, we need to exploit DocItem links from explicit nodes. Algorithm 7 gives the pseudocodes of the procedure to locate a node.

Lemma 5.3. Overhead of *LocateNode* is $O(|T|)$ in whole execution process of Algorithm 8.

Proof: In each running, *LocateNode* first traces back to the parent node from a current node, follows DocItem link to the target node from the parent node, and then searches from the target node in the direction to leaf nodes. In the next running, *LocateNode* treats this target node as a current node and repeats the process. Thus, we know all the nodes accessed by *LocateNode* cannot be more than the height of the DocItem tree. As the height of the DocItem tree is $O(|T|)$, the execution time of *LocateNode* cannot be larger than $O(|T|)$. ∎

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Summarizing these different points, Algorithm 8 is the modified algorithm that builds DocItem tree of a given document.

Theorem 5.2. The complexity of Algorithm 8 is linear in the size of T.

Proof: In Algorithm 8, to create each node in a DocItem tree, each statement will be completed in constant time, except for Statement *LocateNode*. As indicated in Lemma 5.3, we know Statement *LocateNode* spends only $O(n)$ in the running process of Algorithm 8. Thus, the complexity of Algorithm 8 is linear in the size of T. ∎

5.6 Summary

This chapter has presented an enhanced schema detection and extraction component in a comprehensive framework of Web data extraction systems introduced in previous chapters. Algorithms for both schema detection and extraction that are linear in the size the documents to be extracted have been demonstrated. Although the theory upper-bound the algorithms is improved from $O(n \log n)$ to $O(n)$ only, the improvement of real implementation is quite significant. This is because the previous work needed to parse documents into trees, unlike our approach which treats documents as linear symbol sequences. The detected schemata are stored in a data structure like suffix tree, which can acts as a dictionary of schemata. As locating any schemata in this dictionary need only linear time, it is possible to be exploited by other applications more efficiently.

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Algorithm 5 CreateDTree1

Require: A document D
Ensure: $\mathcal{T} = DTree(D)$ created.

1: Create $\mathcal{T}$ {init}
2: $r_{init} \leftarrow root$
3: $\{/*path(r_{init}) = \xi_j, \ldots */\}$
4: **for** $i = 2$ to $length(D)$ **do**
5: $r \leftarrow r_{init}\{/*path(r) = \xi_j, \ldots */\}$
6: **while** $f(r, \xi_i) = nil$ and $k \geqslant i$ **do** $\{/*\xi_k$ is the EAtom of $\xi_j */\}$
7: **if** ξ_j is a SAtom **then**
8: Create r'
9: $f(r, \xi_i) \leftarrow r'$
10: **if** $r \neq r_{init}$ **then**
11: **if** $level(\xi_i) \geqslant level(\xi_i') - 1$ **then** $\{\xi_{i'}$ is the first atom in $path(r')\}$
12: $s(oldr') \leftarrow root$
13: **else**
14: $s(oldr') \leftarrow r'$
15: **end if**
16: **end if**
17: $oldr' \leftarrow r'$ {a virtual node linked from root is added}
18: **if** $r \neq$ root **then**
19: $r \leftarrow s(r)$
20: **end if**
21: **end if**
22: **end while**
23: **if** $r \neq$root **then**
24: $s(oldr') \leftarrow f(r, \xi_i)$
25: **else**
26: $s(oldr') \leftarrow$ root
27: **end if**
28: $r_{init} \leftarrow f(r_{init}, \xi_i)$
29: **end for**

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Algorithm 6 CreateNewNode

Require: node $v \in \mathcal{T}$ identifying path $p = \xi_i, \ldots, \xi_j - 1$
Require: ξ_j
Ensure: $newLeafNodeCreated$ and $newIntNodeCreated$ are set according to whether there are leaf or internal nodes created
  if $p\xi_{j+1} \in \mathcal{T}$ **then** {$\mathcal{T}$ is the DocItem tree in construction}
    newIntNodeCreated $\leftarrow$ nil;
    newLeafNodeCreated $\leftarrow$ nil;
  else if $v = f(u, \langle r, j-1\rangle)$ is a leaf **then**
    replace $f(u, \langle r, j-1\rangle)$ with $f(u, \langle r, j\rangle)$
    newLeafNodeCreated $\leftarrow$ nil;
  else if $v = f(u, \langle r, j-1\rangle)$ is NOT a leaf **then**
    create node w and $f(v, \langle j, j\rangle) \leftarrow w$
    newLeafNodeCreated $\leftarrow w$;
  else if v is an implicit node **then**
    create node v' and w
    replace $f(v, \langle o, m\rangle) = u$ with $f(v, \langle r, j-1\rangle) = v'$
    $f(v', \langle j, j\rangle) \leftarrow w$ and $f(v', \langle (o+j-r), m\rangle) \leftarrow u$
    newIntNodeCreated $\leftarrow v$; newLeafNodeCreated $\leftarrow w$;
  end if

Algorithm 7 LocateNode

Require: node $v \in \mathcal{T}$
Ensure: node u pointed by DocItem link starting from v in corresponding DocItem trie
  if v is an explicit node **then**
    $u \leftarrow s(v)$
  else {/*$v = f'(v', \langle r, j\rangle)$*/}
    $nodeV \leftarrow s(v')$
    $k \leftarrow j - r$
    while $k > y - x$ **do** {/*$f(nodeV, \langle x, y\rangle)$ is defined and $\xi_x = \xi_r$*/}
      $nodeV \leftarrow f(nodeV)$
      $k \leftarrow k - y + x$
    end while
    $u \leftarrow f'(nodeV, \langle j - k, j\rangle)$
  end if

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Algorithm 8 CreateCompactDTree

Require: A document D
Ensure: $\mathcal{T} = CDTree(D)$ created.

```
Create T_1
r ← root
for i = 2 to length(D) do
  oldIntNode ← nil
  while f(r, ⟨i, i⟩) = nil and k ⩾ i do {/*here, we do not distinguish f and f'*/}
    if ξ_j is a SAtom then
      CreateNewNode(r, ξ_i)
      if newIntNodeCreated ≠ nil and oldIntNode ≠ nil then
        if level(oldIntNode) ⩾ level(ξ'_i) − 1 then
          s(oldIntNode) ← root
        else
          s(oldIntNode) ← newIntNodeCreated
        end if
        oldIntNode ← newIntNodeCreated
      end if
      r ← LocateNode(r)
    end if
  end while
  if oldIntNode ≠ nil then
    s(oldIntNode) ← r
  end if
end for
```

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Chapter 6

Auxiliary Operations in Framework

As introduced in Chapter 1 and 3, one objective of the concierge framework proposed in the study is to provide a method of conceptual modeling over Web data and various operations. Chapter 4 gave a closer study of how to model Web documents and extraction operation. Extraction is a principal component of operation layer. However, a practical system may need the support of more auxiliary components. Thus, in this Chapter, we shall conduct an initial study on how to integrate more components into our framework.

6.1 Document Management

Based on operations introduced in the concierge framework, Figure 6.1 presents a typical Web data extraction process consisting of three phases:

- Phase 1: Documents in a training set are parsed to structural representations such as graphs, trees, etc. A training set is a set of documents sharing similar structures.
- Phase 2: Extraction rules are induced from the training set. These extraction rules

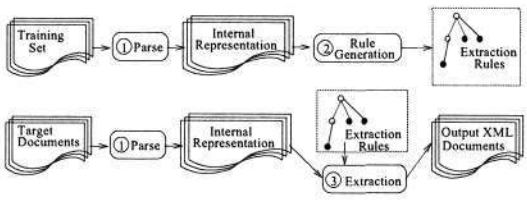


Figure 6.1: Web Data Extraction Process

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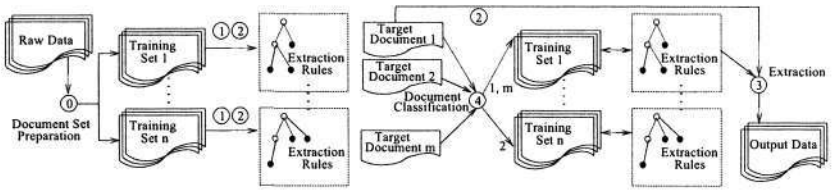


Figure 6.2: Enhanced Web Data Extraction Process

include knowledge about structural patterns appearing in these documents.

- Phase 3: Given the target set consisting of documents to be extracted, parts in these documents matching with structure patterns are extracted and transformed into a structured format. Documents in the target sets are assumed to have similar structures with documents in the training set.

This process suffers from two main problems. Firstly, the training set and the target set are assumed to be pre-defined. Given a large set of documents that do not share similar structures, multiple training sets have to be constructed and extraction rules are learnt from these training sets independently. To the best of my knowledge, automatic construction of training sets has not been addressed. Secondly, the learnt extraction rules cannot be applied to documents that are not from the pre-defined target set. That is, mapping between a document and the corresponding extraction rules cannot be achieved automatically.

This section introduces some operations of document preparation and document classification processes. With the aid of these operations, the Web data extraction process is enhanced and formalized as shown in Figure 6.2. In this enhanced process, phase 0 automatically clusters documents with similar structures together to construct multiple training sets. Given a new document, phase 4 finds the most similar structural training set, using classification techniques. The extraction rules learnt from the set are then used to extract data from the document.

As introduced in Chapter 5, the purpose of schema detection is to induce grammars of a training document set. Documents in a training set should share large number of common structures. Usually, the training set is prepared using manual methods, which are time-consuming. This section introduces how to automatically prepare training sets by clustering documents that are similar in terms of embedded schemata. Document classification operation that classifies a document to a training set is also introduced.

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This operation can help to decide which extraction rules should be applied to a document automatically. These two operations significantly improve efficiency of Web data extraction.

The basic idea of measuring structural similarity of two documents is to collect some attributes of schemata shared by both documents; if these attributes are similar, then we treat these two documents as similar. In this section, we first propose some attributes for schemata; second, we introduce how to measure structural similarities among documents, followed by the details of training set preparation and document classification.

6.1.1 Schema Attributes

Some Web data extraction systems [Arasu and Garcia-Molina, 2003, Chang and Lui, 2001] assume large structural patterns that match large number of structures in documents are important; contents that match these patterns are then extracted. Similarly, we compute schema weight to measure the importance of the corresponding DIs based on two observations.

Observation 6.1. A type including a large number of DIs in documents is usually important, as well as its corresponding schema.

Observation 6.2. A schema with large size is usually important in documents.

There are two factors that influence the weight of a schema — the cardinality of its corresponding type and its size. Given a document tree t, a type T and a schema s, if DIs in T confirm to s, the *weight* of s in the document is:

$$\omega(s) = \ln \|T\| \times |s| \tag{6.1}$$

where $\|T\|$ is the cardinality of T, also known as the *document frequency* of s in this thesis.

The weight of a schema provides an important evidence to decide which DIs should be extracted. However, it is not enough to decide which DIs should be extracted based on only the schema weight. One property of semi-structured documents is irregularity — DIs that conform to the same schema may encode different kinds of content. Another property of semi-structured documents is that there are redundant contents, as in advertisement bars appearing in many HTML pages. In this section, attributes of schemata that provide

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additional information other than the schema weight are introduced. Users may control extraction operations based on these attributes.

Given a document set $\mathbb{C}$, we notice the following attributes of a schema:

- Size, Document Frequency (DF) and Weight.
- Set Frequency (SF): Given a set of documents $\mathbb{C}$, if s is the a schema of DIs in type T, SF of s in $\mathbb{C}$ is $\|T\|$.

All documents are organized into clusters, where each cluster is a set of similar documents. Given these clusters, we may identify more attributes of a schema.

Inverse Set Frequency (ISF) of a schema s is denoted with $I(s)$, and $I(s) = log\frac{N}{n}$, where N is the number of document sets and n is the number of document sets containing DIs conforming to s.

Suppose a document set $\mathbb{C}$ contains types T_1 to T_n, the weight of the schema s of DIs in type T_i is $\varpi(s) = \|T_i\|/max_{j=1}^{n}\|T_j\|$ (ϖ is a temporary variable used to calculate Set Weight, and is different from document weight ω), the *Set Weight (SW)* of a schema s is:

$$W(s) = \varpi(s) \times ISF(s) \tag{6.2}$$

To be easily accessed by users, Web documents often include much redundant information. For instance, the same navigation bar may appear in many pages. An entropy measurement of fragments in Web documents was suggested in Lin and Ho [2002] to detect redundant information; only fragments with small entropy should be extracted. Inspired by this idea, we calculate the entropy of schemata and restrict it to only DIs that conform to schemata with entropy smaller than a threshold will be extracted. Given n document sets, *entropy* of a schema s is:

$$Ent(s) = -\sum_{i=1}^{n} \varpi(s) log \varpi(s) \tag{6.3}$$

Usually, a type of DIs that appears closely and regularly is likely to be interesting. Based on this observation, we define two attributes of a schema – mean distance (MD) and standard deviation of distance (SDD) to measure how close and regular those DIs in a type are. To compute MD and SDD, we need to know the distance and the order relation among DIs and orders among DIs.

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Distance between DIs t_i and t_j in a document tree is the number of nodes in the shortest path between root nodes of t_i and t_j. If t_i and t_j belong to different document trees, the distance between them is 1.

Given a set of document trees $\{d_1, \ldots d_n\}$, a node r_0 is added as the parent node of these trees; the tree rooted from r_0 is denoted as T. The *position* of a DI t is $\theta(t) = m$ if the root of t is the mth nodes accessed in the pre-order traversal of T. An *Order Relation* between a pair of DIs is denoted with $t_i \preceq t_j$. We say $t_i \preceq t_j$ if $\theta(t_i) \leqslant \theta(t_j)$.

Given a type T, we sort all DIs in T, such that $t_i \preceq t_{i+1}$. We say that t_i and t_{i+1} are adjacent DIs. *Mean Distance (MD)* of the schema s of DIs in T, $\mu(s)$, is the mean value of distance between each pair of adjacent DIs belonging to T.

$$\mu(s) = \frac{\sum_{i=1}^{n-1} d(t_i, t_{i+1})}{n-1} \tag{6.4}$$

Standard Deviation of Distance (SDD) of s is defined as below:

$$\sigma(s) = \sqrt{\frac{\sum_{i=1}^{n-1} (d(t_i, t_{i+1}) - \mu(s))^2}{n-1}} \tag{6.5}$$

We store all attributes detected in a schema s in a tuple $\langle$ *Size*, *DF*, *Weight*, *SF*, *ISF*, *SW*, *MD*, *SDD* $\rangle$.

An important property of semi-structured documents is sectional; i.e., contents in different parts of a document may contain different information. Usually, DIs belonging to the same type appear in the same part in a document. Thus, if most DIs belonging to the same type appear in a part and a DI is far away from this part, this DI may be an outlier and will not need to be extracted. We define *Distance Offset* of a DI t_i as:

$$\Delta(t_i) = \frac{d(t_{i-1}, t_i) + d(t_i, t_{i+1})}{2\mu(C)} - 1 \tag{6.6}$$

Based on some intuitive observations, we proposed some attributes of schemata. In Section 6.1.2, weight attribute is used to measure structural similarity among documents. This use of weight attribute is an initial study of exploiting schema attributes in concierge systems. We also noticed that the use of schema attributes is not limited in concierge systems. In fact, Cai et al. [2004] exploit physical location attributes to improve PageRank and HITS. Besides the studies presented in this thesis, how to exploit these attributes to aid concierge systems still needs further investigation. Chapter 7 presents some statistic

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DI_1=[1 1 1 1 0 1 0]
DI_2=[1 1 1 1 1 0 1]
(a)Documents

$$M = \begin{bmatrix} 1 & 1 & 1 & 1 & 0 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 & 0 & 1 \end{bmatrix}$$
(b)Document Space

Figure 6.3: Vector Space of Document

results of the relationship between schemata and their attribute in Web documents.

6.1.2 Document Similarity Measurement

To measure similarity among documents, we try to compare the attributes of schemata shared by these documents. In this section, we consider only the weight of schema. How to measure document similarity based on other attributes is left for future study. We represent documents as vectors of schema weights and compute document similarities by computing the similarity among these vectors. Corresponding to each schema embedded in a DI is an item in the vector that records the weight of the schema. Suppose the weight of a schema is 1 if the schema appears in a document tree, and 0 if it does not appear; the vectors of DI_1 and DI_2 in Figure 5.2 are shown in Figure 6.3(a). So far, we can represent all documents in a vector space. For example, DI_1 and DI_2 can be represented using the matrix in Figure 6.3(b).

Given two documents t_1 and t_2, suppose there are n representative schemata, we represent $t_1 = \langle \omega_1(s_1), \ldots, \omega_1(s_n) \rangle$ and $t_2 = \langle \omega_2(s_1), \ldots, \omega_2(s_n) \rangle$, where $\omega_i(s_j)$ is the weight of s_j in t_i. The similarity between t_1 and t_2 can be computed, using Equation 6.7.

$$\Omega_C(t_1, t_2) = \frac{\sum_{i=1}^{k} (\omega_1(s_i) \times \omega_2(s_i))}{\sqrt{\sum_{i=1}^{k} \omega_1(s_i)^2 \times \sum_{i=1}^{k} \omega_2(s_i)^2}} \tag{6.7}$$

6.1.3 Document Set Preparation and Document Classification

Given the structural similarity among documents, we now introduce how to solve problems in the phases of document set preparation and document classification.

Document Set Preparation We prepare training sets by clustering similar documents together. In the similarity calculation phase, we can obtain similarity square matrix $\mathbb{M}_{m \times m}$, where m is the number of document trees and $\mathbb{M}_{i,j}$ is the similarity between document t_i and document t_j. Given the similarity matrix, we choose bisecting

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k-means clustering algorithm that clusters documents into k clusters (k is predefined by a user), from $\mathbb{C}_1$ to $\mathbb{C}_k$, such that the maximum value of the following formula is obtained:

$$\sum_{i=1}^{k} \sqrt{\sum_{t_1,t_2 \in \mathbb{C}_i} \mathbb{M}(t_1, t_2)} \tag{6.8}$$

Document Classification As introduced before, we may detect schema attributes in terms of document sets, and extract data based on those attributes. Given a new document, there is an issue of how to exploit the known attributes to extract data. We propose to classify the new document into an existing training set and to apply extraction rules learnt from the set on this document. We referred to XRules [Zaki and Aggarwal, 2003] for some initial work of documents classification based on the tree structure of documents. XRules mines rules like $T \Rightarrow \mathbb{C}$, which describe the relationship between the appearance of a tree structure t in a document and the document belonging to class $\mathbb{C}$. During the classification phase, XRules combine the evidence of structures appearing in a document and suggest a class to the document. However, XRules does not consider the occurrence frequency of structure t in the documents to be classified. Here, we suggest a more general approach to classify document trees. From the results of the document set preparation phase, we use a vector $\mathbb{W}_\mathbb{C} = \langle \omega_\mathbb{C}(s_1), \ldots, \omega_\mathbb{C}(s_n) \rangle$ to represent a training set where $\omega_\mathbb{C}(s_i)$ is the weight of a representative schema s_i in training set $\mathbb{C}$. Previously, we had introduced how to represent a document tree using a weighted vector. Assume that $\mathbb{W}_t = \langle \omega_t(s_1), \ldots, \omega_t(s_n) \rangle$ is the weight vector of document tree t, the similarity between a document tree and a document set is:

$$\Omega_S(t, \mathbb{C}) = \frac{\sum_{i=1}^{k} (\omega_t(s_i) \times \omega_\mathbb{C}(s_i))}{\sqrt{\sum_{i=1}^{k} \omega_t(s_i)^2 \times \sum_{i=1}^{k} \omega_\mathbb{C}(s_i)^2}} \tag{6.9}$$

We may classify a document tree t to the training set that is most similar if the similarity value is larger than a threshold; otherwise, t should be treated as an outlier.

6.2 WDEE: Web Data Extraction by Example

Web data extraction systems are the key components of concierge systems between users and Web data resources. In the beginning, the main purpose of Web data extraction systems was to transform semi-structured Web documents into relational databases [Gupta et al.,

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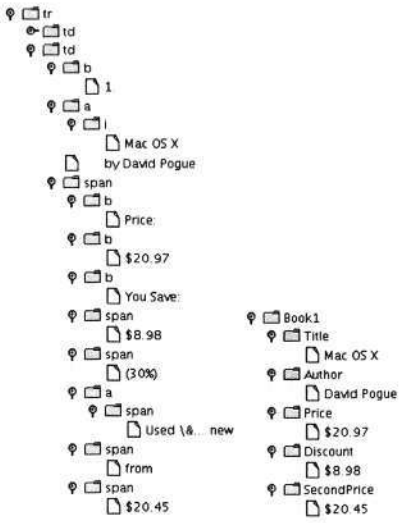
1997] or object-oriented databases [May et al., 1999]. These systems need users to code by hand using formal languages to extract data from Web documents. We also defined WDEL as an extraction language in Chapter 4.

Those formal extraction languages provide a firm basis for Web data extraction. However, manually programming is always time-consuming and error-prone. The appearance of automatic extraction rule generation techniques partially solved this problem. Kushmerick [Kushmerick, 2000a] presented a method, using grammar induction techniques to learn extraction rules. His method assumed documents to be extracted are organized like relational tables. IEPAD [Chang and Lui, 2001], RoadRunner [Crescenzi et al., 2001] use various approaches to learn regular expressions as extraction rules. Those methods treated documents as flat texts. Thus, it was easy to lose structural information. ExAlg [Arasu and Garcia-Molina, 2003] and Skeleton [Rajaraman and Ullman, 2001] can detect tree patterns, which are more intuitive and accurate. WICCAP [Liu et al., 2002b] and Lixto [Baumgartner et al., 2001b] proposed supervised learning approaches based on visual interface to generate an extraction program. Chapter 5 introduced our heuristic algorithms to facilitate automatic extraction rule generation.

Although extraction efficiency can be improved obviously using these methods, extracted data are still not easy to be accessed. To exploit extracted data, a user needs to program, instead of browse, the easy-to-read original document because of two reasons: (1) It is difficult to reverse visual effect from patterns detected by them; (2) There is a lack of management of documents, schemata and extracted data. Wang and Liu [2000] took the first step to use structured patterns in semi-structured documents to manage them. In recent years, more detailed structure-based document management techniques have been devised. XRules [Wang and Liu, 2000] can effectively classify semi-structured documents based on embedded subtrees. Some papers have aslo discussed how to measure similarity among XML documents [Flesca et al., 2002, Nierman and Jagadish, 2002]. Much of this research indicates that it is easy to cluster documents based on their similarity. Further, these approaches provide new ideas of semi-structured document management. However, the structural patterns considered by them are not easy to render in Web browsers and to generate examples like those in our system. Moreover, there is still no literature addressing how to exploit those techniques to facilitate Web data extraction.

In this section, we shall introduce a method called Web data extraction by example (WDEE) based on our concierge framework, which provides mapping relationships among data instances and schemata. As an example, the first book in page A in Figure 1.1(a)

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(a) Codes of Book1 (b) Extracted Data

Figure 6.4: Web Page and Logic View over Web Page

is rendered from the HTML codes in Figure 6.4(a). The corresponding data instances extracted are drawn in Figure 6.4(b). The concierge framework can maintain the mapping relationship between these two data instances. Similarly, the mapping among data instances, Web document schemata and extracted data schemata, can also be maintained.

To illustrate the use of these relationships, we first consider how to generate a query to instance layer without these relationships. As introduced before, a schema describes a type of DIs. A user may write a simple query like "select * from *schemaA*" returns all DIs matching with *schemaA*. Thus, a schema itself can be treated as a query that will return all data instances that match it. However, this kind of queries require a user to handle schemata directly.

These mapping relationships are to be used to generate queries to the instance layer in a manner that resembles the browsing of Web pages. Inspired by query languages like QBE [Zloof, 1977] and QEByE [da Silva et al., 2002], WDEE is devised. As there are mapping relationships among Web documents, document schemata and data instances extracted, when a user wants to query some instances, WDEE will generate visual examples of Web documents corresponding to these instances. By handling these visual examples, queries are generated to handle these corresponding schemata.

Unlike QBE and QEByE that prepare examples w.r.t. the relational query and the nested table query [da Silva et al., 2002] respectively, the schema defined here allows us

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to generate hierarchical examples.

6.2.1 Query Operations by Schema Matching

In this section, we introduce the query language of WDEE. The WDEE language consists of a set of enhanced schemata based on Definition 3.4, whose expressive capability is less than WDEL. These schemata may be used to represent *selection* and *projection* queries. The WDEE language is augmented with set oriented features: union and difference.

We begin by defining a matching query, followed by its extensions:

Definition 6.1 (Matching Query). Given an extracted document T, a matching query $M(s) = \{t | t \mapsto s\}$, where s is a schema and $\eta(t)$ is a DI of T.

Based on Definition 3.4, DIs that have the same structure as s will be returned by the matching query. This query is a bit naive; thus we draw ideas from Bergholz [2000] to improve the expressive capability of the query by augmenting the schema with predicates, as defined below:

Definition 6.2 (Schema and Matching). A schema s is a 4-tuple $\langle V, E, r, \gamma \rangle$, where $\langle V, E, r, \gamma \rangle$ is a DI and γ labels each node with a predicate formula $P(x)$. A DI $t = \langle V_t, E_t, r_t, \gamma_t \rangle$ match with s, denoted as $t \mapsto s$, if $\langle V, E, r \rangle = \langle V_t, E_t, r_t \rangle$ and $P(v)$ is true for $v \in V$.

There are three types of predicates supported by WDEE

$x = c$ where x is the label of corresponding node in a DI, c is a constant string; e.g., `"David Pogue"`.

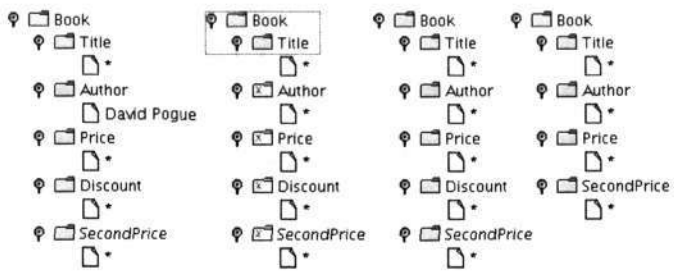
$e \vdash x$ where e is a regular expressive and e can generate x. We allow this type of predicates to appear on only leaf nodes, such that Definition 6.2 is equivalent to Definition 3.4 when e is `"*"`, where `"*"` is a wildcard generating any string label.

$x = X$ where x is the label of a corresponding node in a DI and X is a variable name.

In the following part of this section, we show how to use a matching query to represent these query operations: *selection*, *project*, *union* and *difference*.

Selection (σ) Selection is an unary operation on a schema, denoted as $\sigma_{condition}(s)$. It returns all DIs that match the schema and fulfills the given condition.

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(a) Sel (b) Proj (c) Union

Figure 6.5: Examples for Query Operations

Suppose *Book* is a schema of the DI in Figure 6.4(c), $\sigma_{author="DavidPogue"}(Book)$ is a select operation that returns all data of books in Figure 6.4(a) with author "David Pogue". To represent this operation, we use a matching query with the schema in Figure 6.5(a). The constant string label c in the figure is the short form of $x = c$ and a regular expression label e is the short form of $e \vdash x$. This schema matches with the first DI corresponding to the first book in Figure 6.4(a). Thus, the matching query will return the first DIs.

Projection (π) Projection is also an unary query operation on a schema, denoted as $\pi_{\langle fieldlist \rangle}(s)$.

The $\langle fieldlist \rangle$ is a list of fields with a syntax of *field*:=*path*'.'*schema*, *path*:=*item*'.'...'.'*item*, *item*=*regexp*|*regexp*'['*idx*']', where *regexp* is a regular expression over node labels, *idx* is a natural number and $l[i]$ means the i-th child nodes with label l of a node.

Definition 6.3. A schema $s_p = \langle V_p, E_p, r_p, \gamma_p \rangle$ is a projection schema of $s = \langle V, E, r, \gamma \rangle$, iff $\eta(s_p) = s$; i.e., s_p maps to s. A projection $\pi_{\langle path_1.s_1,...,path_n.s_n \rangle}(s)$ return a set of DIs $\{t | t \mapsto s_p\}$, where $e_p = \langle v_i, v_j \rangle \in E_p$ iff $\langle v_m, v_n \rangle \in E$, or v_m and v_n is connected by $path_i$ in E, v_m is root of s and the tree rooted from v_n match s_i.

Suppose the schema for the book DI in Figure 6.4(c) is s_B and the schema for book title is s_T, a projection $\pi_{\langle Book.s_T \rangle}(s_B)$ will return DIs containing only the book's titles. The schema in the gray box of Figure 6.5 represents this query.

The selection and projection operations are both matching queries. WDEE distinguishes them by the schemata to be processed. A selection or a projection operation returns a set of DIs matching with the given schema. We define two set-oriented operations below:

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Union ($\cup$) Union is a binary query operation on two schemata, denoted as $s_1 \cup s_2$.

A union operation merges two DI sets returned by $M(s_1)$ and $M(s_2)$. It may be represented as shown in Figure 6.5(c) and consists of two schemata corresponding to two types of DIs about book information. If s_1 and s_2 match with each other, the two sets are *union compatible*. If two DI sets are union compatible sets of DIs, the union operation needs to detect overlay DIs to merge them; otherwise, the union operation will simply copy the two sets DIs together.

Difference ($-$) Difference is a binary query operation, denoted as $s_1 - s_2$.

A difference operation asks s_1 and s_2 to match with each other; it simply removes overlay DIs from the DI set returned by $M(s_1)$. The difference operation introduced below may also be represented using schemata like those in Figure 6.5(c). As the two set operations cannot be distinguished only based on the schemata, a user needs to explicitly choose the type of operation. We have shown that with different schemata, we may execute various query operations on extracted documents. By parsing the schemata of extracted DIs into trees like those in Figure 6.5, a user can easily modify these trees and generate schemata to query extracted documents.

6.2.2 WDEE Running Example

In this section, we show how to build examples corresponding to WDEE query operations. An example in WDEE consists of two parts: *tree skeletons* and a *browser view*. A tree skeleton is a visualized schema. To submit a query to an extracted document, a user may give some conditions inside the skeleton, while the browser view presents a sample of Web documents where the document is extracted from.

The principle merit of the WDEE language is that a WDEE program may be generated within a specific Web browser. When a user chooses to query an extracted document, a corresponding Web document will be rendered in the Web browser. Given the Web page shown, a user may generate a WDEE program by selecting texts that are interesting to him or her.

Specifically, generating a WDEE program by visual interface consists of three phases. The first is to select schemata extracted documents to be queried; obtain a sample of the original Web documents to which the schemata map and generate a document tree whose text nodes can be modified by a user, called a tree skeleton. The Web page rendered from

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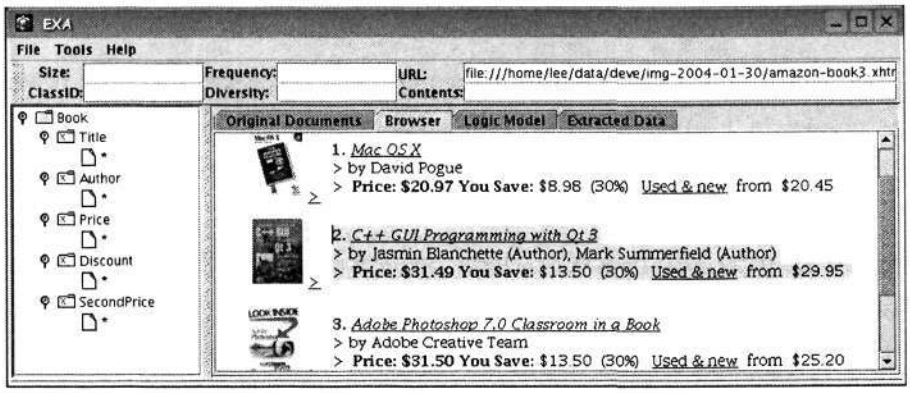


Figure 6.6: WDEE Example 1

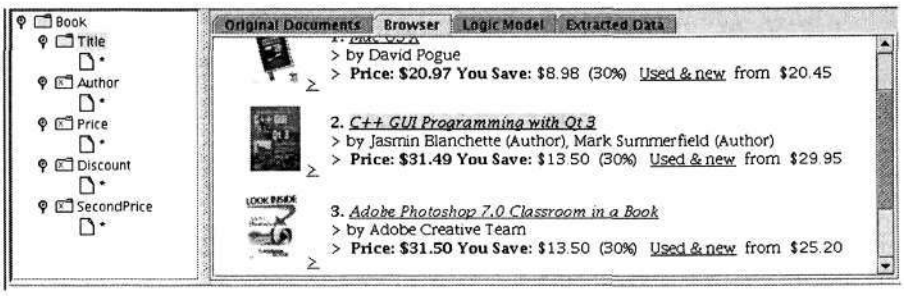


Figure 6.7: WDEE Example 2

the sample Web document and the skeleton together is called an example. The second phase is to generate a basic WDEE program by selecting texts in the Web browser. The third phase is to input conditions in text nodes of tree skeleton to refine the WDEE program.

As an instance, we show how to generate a WDEE program for an example query, as described below:

QueryBook Return book title, price and discount of the books written by `"David Pogue"`.

The detailed operations follow the 3-phase WDEE program generation procedure, as described below:

1. A user may select a schema, using the menu. Suppose the schema *book* is selected, a tree skeleton of this schema will be shown, as in the left panel of Figure 6.6.

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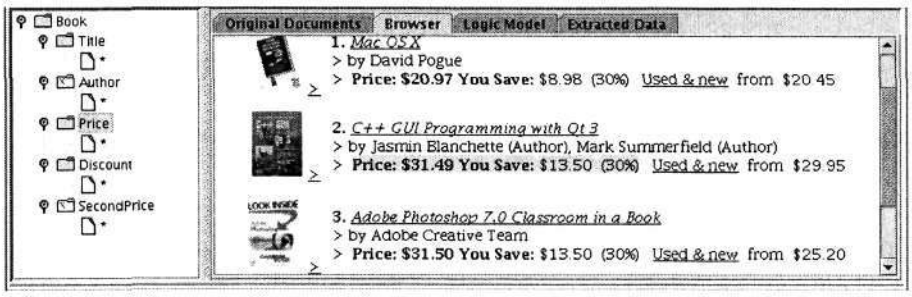


Figure 6.8: WDEE Example 3

A schema of Web documents $\eta(book)$ will be obtained by searching the mapping relation. In turn, a random original Web document containing this Web schema is selected and shown in the Web browser, as shown in the right panel of Figure 6.6. The two panels constitute an example.

2. The Web page contains some information on books. A user may denote which parts of a book should be returned, by selecting texts in the page. Here, book title, price and discount are data to be returned. Initially, all nodes in the tree skeleton are unselected (denoted as white folder icons). After a user selects the book title by a mouse in the Web browser, as indicated in Figure 6.7, corresponding parts in the tree skeleton are selected (those gray folder icon). If the text selection covers more than one field in the given schema, as in Figure 6.8, multiple nodes in the tree skeleton will be selected. So far, the schema corresponding to the skeleton can be used to generate a projection query.

3. After a user selects all texts that are interesting, he or she can give conditions that must be fulfilled by the returned DIs. Here, a user may input `"David Pogue"` in the tree skeleton, like the one in Figure 6.5(a). The schema corresponding to the modified skeleton can be used to generate a selection query.

The skeletons generated in the above steps may be directly saved as a WDEE query program. However, only a subset of the WDEE query language can be generated, using the visual interfaces. For example, in Step 2, the fields generated contain only strings of labels and will not contain regular expression; i.e., the syntax of *item* of $field$ defined in Section 6.2.1 will be changed to $item{:=}labelstring|labelstring`['idx`]'$. To generate a WDEE program with full features, a user may modify or exploit some techniques [Chang and Lui,

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2001] to post-process a generated WDEE query program.

6.2.3 Expressive Capability and Evaluation Complexity

The objective of WDEE is not to provide a general XML query language like XPath or XQuery. WDEE's expressiveness of selection and projection operations is strictly less than XPath. However, by introducing the concept of schema into WDEE, it is easier for a user to generate a query program quickly in the majority of situations of the Web. Besides the efficiency of query generation, how to improve the efficiency of a query execution is another consideration of WDEE.

The evaluation of a WDEE query is a computational process that interprets WDEE query and returns special parts in Web documents. To evaluate a WDEE query, we can translate WDEE selection and projection operations to location paths of XPath in linear time. As shown by Gottlob et al. [2003], location paths of XPath can be evaluated in polynomial time in the size of a query. Thus, the upper bound to evaluate WDEE selection and projection query evaluation is at most polynomial time. As introduced in Section 6.2.1, the union and difference query can both be evaluated in linear time. As the size of a DI set is less than a node number, WDEE queries can be evaluated in polynomial time.

The limited form of WDEE generated by the visual interface can be translated to Monadic Datalog over the signature introduced in [Gottlob and Koch, 2002a]: $\tau_r = \langle root, leaf, (child_k)_{k \leqslant K}, (label_a)_{a \in \sum} \rangle$ in linear time. Thus, the evaluation complexity of a limited form WDEE query is $O(|D| \times |Q|)$, where D is the size of documents to be queried and Q is the size of query.

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Chapter 7

Experiments

In this chapter, we present and analyze results of the experiment. As introduced in the previous chapters, the objective of this study is to produce a comprehensive Web information concierge system. Experiments were conducted to study whether the techniques we discussed can help.

Here, the experiments basically consist of four parts: (1) performance of schema detection and extraction, (2) accuracy of extraction rules generated using introduced inference algorithms, (3) accuracy of document clustering based on schema information, and (4) accuracy of document classification based on schema information. We also conduct an initial study about the distribution of schema attributes. For each part of the experiments, our techniques are also compared with existing systems.

7.1 Performance of Schema Detection and Extraction

This section describes the experiment that compares the performance of Algorithm 3 and those of two recent tree structure miners — TreeFinder and TreeMiner. The objective of Algorithm 3 is to detect frequent sub-structure from document trees. This objective is similar with that of structural mining. The reason for choosing them is that structural mining is a relatively new research area, with TreeFinder [Termier et al., 2002] and TreeMiner [Zaki and Aggarwal, 2003] being two important methods in this area.

The data sets used by TreeFinder and TreeMiner are not available for public use; thus, we try to generate similar data sets. As the two structural miner use XML documents

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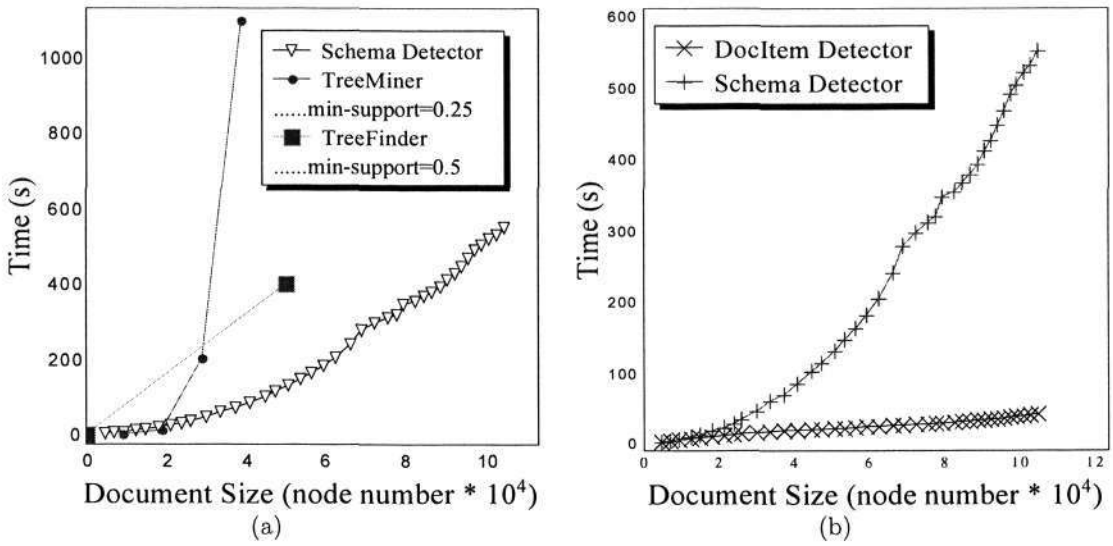


Figure 7.1: Performance Comparison

with small size, we generated the **ETC** (Equivalent Tree Class) data set that is larger and more complicated than those of TreeFinder and TreeMiner. Web pages in ETC data set were crawled from Amazon. All these downloaded pages were then transformed to the XHTML format using HTMLTidy toolkit. The average size of these documents is 550K bytes, and the number of nodes in the document trees is about 110 thousands. ETC data set is also used in the following experiments, and will be introduced later.

We evaluated the complexity of SchemaDetector on ETC dataset, by conducting experiment on a PIII933 laptop with 512M memory, which is similar with the experiment platform of TreeMiner. In Figure 7.1, we drew the complexity of these three algorithms. The results of TreeFinder and TreeMiner were obtained from previous studies [Termier et al., 2002, Zaki and Aggarwal, 2003]. The document size of TreeMiner was measured by the string length of documents, not measured by the number of nodes. We plotted the point of TreeMiner there because in ETC data set the string length of documents containing 50K nodes is about 1M, which is approximately equal to the size of the data set used by TreeMiner.

TreeMiner and TreeFinder will discard structures that appear fewer times than a minimum support value. When the value decreases their complexity increases rapidly. It is easy to see from Figure 7.1(a) that our algorithm outperformed them when the minimum support is set to small value as in TreeFinder (5%) and TreeMiner (0.25%).

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The analysis show that when the number of schemata is much smaller than the number of subtrees, the complexity of SchemaDetector is near linear; otherwise, its worst complexity is $O(n^2)$. The empirical results from the diagram verify that. When the data set is small, the number of schemata is large compared with the number of DIs; thus, the complexity grows quickly. With the increase in size of the data set, the complexity is near linear, as the number schemata is smaller compared with the number of DIs.

The performance of DocItem detector is also compared with SchemaDetector's. Figure 7.1(b) shows the running time of both algorithms on the ETC data set. The complexity of DocItem detector is linear to the size of documents. The result from the experiment supports our complexity analysis in Chapter 5. DocItem detector largely improves the performance of schema detection, compared with SchemaDetector; this is a big step towards detecting schemata efficiently. As DocItem detector can also be used as an extraction engine, Figure 7.1(b) can represent the performance of Web data extraction.

7.2 Clustering Accuracy

Given the similarity between each pair of documents, we chose bisecting K-means method to cluster them. Clustering results based on structural information are then compared with results from CLUTO (a famous software package for clustering high-dimensional datasets) [Karypis, 2002, Steinbach et al., 2000], which also uses bisecting k-means method, and is very suitable to cluster free-text documents, according to experiment data compared with other methods [Steinbach et al., 2000]. The difference is that CLUTO does not consider the structural information in documents.

The comparison between our method and CLUTO focuses on their accuracy. The input to these methods is a set of documents, where each document is assigned a class ID, which is unknown for the methods; and the output is a subset of the document set. The accuracy of clustering results is the rate of the number of documents with the same document ID clustered into the same subset to the number of all documents.

We use the datasets taken from previous literature listed in Table 7.1. With these datasets, we can easily assign class ID to documents based on their original datasets. To evaluate clustering methods, we combine documents from various categories to generate **MIX** dataset. For RoadRunner, we randomly choose 4 documents from each of its 12 categories. We randomly choose 5 documents from each of the 6 categories in RISE (Repository of Online Information Sources Used in Information Extraction Tasks), 4

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Name	URL
IEPAD	http://140.115.156.70/iepad/
RoadRunner	http://www.dia.uniroma3.it/db/roadRunner/index.html
RISE	http://www.isi.edu/info-agents/RISE/
WIEN	http://www.cs.ucd.ie/staff/nick/home/research/wrappers/
ExAlg	http://www-db.stanford.edu/~arvind/extract/

Table 7.1: Data Sets

DataSet	E1	E2	W	R1	R2	Average
Our Method(%)	90	100	100	100	89.6	95.7
CLUTO(%)	47.5	100	72.5	66.7	70.8	71.2

Table 7.2: Clustering Accuracy

documents from each of the 10 categories in WIEN. ExAlg provided 3 categories and 132 documents, except some documents from RoadRunner. We chose 50 documents from 3 categories of ExAlg.

Table 7.2 lists comparison results obtained on MIX dataset including documents selected from several datasets. Row 1 indicates these datasets: E1 (ETC), E2 (ExAlg), W (WIEN), R1 (RISE), R2 (RoadRunner). CLUTO also uses bisecting K-means method but only considers texts in documents. CLUTO is very suitable to cluster free-text documents [Steinbach et al., 2000]. From this table, we can see that except for documents from ExAlg, our method was much better than CLUTO. The reason is that CLUTO only performed well when documents contain long free-text paragraphs such as documents in ExAlg. However, our method delivered good results consistently.

7.3 Classification Accuracy

We used the same dataset introduced in Section 7.2 and generated the **ETC** (Equivalent Tree Class) dataset that is more complicated than the above datasets. The Web pages in ETC dataset which were crawled from Amazon, have been classified by Amazon into categories so that we can easily verify clustering and classification results. To generate ETC dataset, we only follow hyperlinks in the category list on the left side of the homepage of Amazon. Each hyperlink is linked to a homepage of a category of commodities. We randomly chose 10 hyperlinks in this area, and in the homepage of each category, we downloaded 3 to 4 pages, following the hyperlinks in the navigation area.

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DataSet	E1	E2	W	R1	R2	Average
Our Method(%)	97.5	100	100	100	100	99.5
Rainbow(%)	77.08	86.78	89.58	89.58	87.66	86.14

Table 7.3: Classification Accuracy

We exploited a 4-fold cross validation strategy to evaluate our classification method. That is, we divided each dataset into 4 parts, each time we chose 3 of them as training sets and one as a test set. After training with the training sets, the method tried to assign each document in the test set to a training set. The accuracy of each time is the rate of the number of documents classified into the right set to the number of all documents. The final result is the average accuracy of results in four times. Our method is compared with Rainbow from CMU[1]. In fact, the comparison shows that our methods are better on semi-structured document sets.

Table 7.3 lists the comparison results of Rainbow and our classification method. The accuracy results obtained by Rainbow vary from 77.08% to 89.58%. Our method classifies documents based on Formula 6.9. It delivers 100% accuracy on all dataset except ETC, with the average accuracy of our method being about 13% higher than Rainbow. On the ETC dataset including documents with complicated structure, Rainbow's accuracy is low, although in other datasets it can receive accuracy higher than 85%. Our method is almost not affected by the difference among datasets. On the **ETC** dataset, one page was wrongly classified by our methods. This could be attributed to the fact that the page is a page linking other sub-categories, making it difficult to judge to which class it belongs.

7.4 Extraction Accuracy

We evaluated our extraction method on IEPAD dataset including Web documents returned by 10 search engines listed in the first column of Table 7.4. We first manually annotated DIs in these documents. The method was quite straightforward; in other words, each entry returned by those searches was treated as a DI. The numbers of hand-annotated DIs ("RecNum") are listed in the second column in Table 7.4.

We executed SchemaDectector to assign schema ID to each DI in document trees parsed from documents of IEPAD. As a result, most annotated DIs from the same search

[1] http://www-2.cs.cmu.edu/~mccallum/bow/

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DataSet	RecNum	Extracted	Accuracy
Alta	100	90	0.9
Cora	100	70	0.7
Excite	100	100	1
Galaxy	200	199	1
Hotbot	100	95	0.95
L.A. Weekly	81	76	0.94
Magellan	100	92	0.92
Metacrawler	200	179	0.9
Northenlight	100	97	0.97
Openfind	200	185	0.93
SavvySearch	150	140	0.93
StptCom	100	97	0.97
Webcrawler	250	141	0.56
Total	1781	1561	0.88

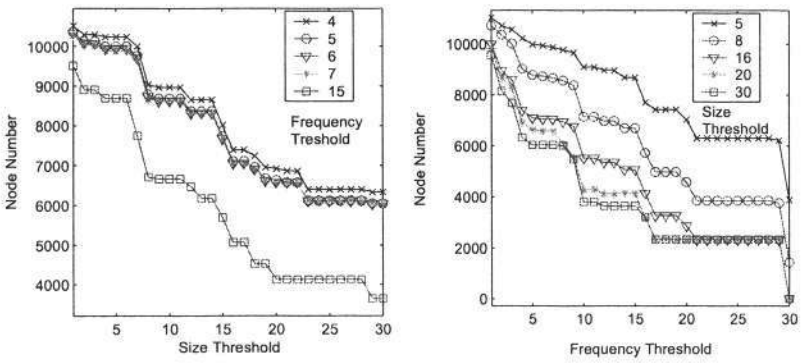
Table 7.4: Extraction Accuracy

engine were assigned with the same schema ID. In Table 7.4, the second column ("Extracted") is the number of annotated DIs belonging to the type that contains the largest number of annotated DIs. We observed that our method accurately identified these important contents in documents. The accuracy values in column 3 are the rate of "Extracted" to "RecNum". For document trees returned by most search engines, our accuracy rate is greater than 90%. The reason for receiving poor accuracy results in documents from "Cora" and "WebCrawler" is that these search engines highlighted some of their search results, using various formats. If we consider the type that contains the second largest set of DIs, the accuracy values will exceed 90% too.

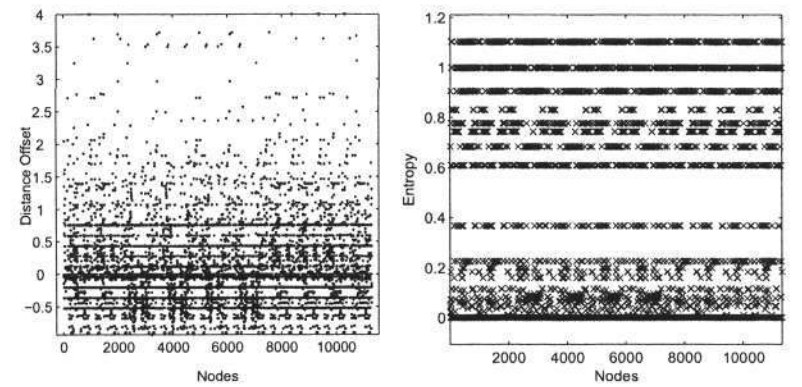
7.5 Discussion on Schema Attributes

As introduced before, we adjusted parameters to select which types and DIs should be extracted. Figure 7.2(a) shows the relation between the size threshold and the number of nodes extracted. Only those DIs conforming to schema with size larger than the threshold were extracted. As the threshold increases, the number of extracted nodes decreases. In some ranges, the changes are very slow. For example, when the size threshold changes from 25 to 28, the number of extracted nodes almost does not change, since there are many DIs belonging to the same schema that has 28 nodes. In Figure 7.2(b), when we

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(a) Size (b) DF



(c) Offset (d) Entropy

Figure 7.2: Distribution of Schema Attributes

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change the DF threshold from 0 to 30, the number of extracted nodes changes, as shown in Figure 7.2(a). In Figure 7.2(c), we plot the distance offset of each DI. The X-axis is the position of their root nodes in traversal and the Y-axis corresponds to distance offset. Most offsets are located from -1 to 1.5. Empirically, those DIs with a large offset are noise. As introduced before, high entropy also means noise sometimes. Figure 7.2(d) shows that DIs that conform to schemata with a low entropy is very easily distinguished from those with a high entropy. We may control extraction results by combining the parameters. For example, in the AltaVista documents of **IEPAD**, when we set the size threshold to 6 and frequency threshold to 89, most child-DIs of the root node in extracted XML document are those DIs we annotated in the original documents. Figures 7.2(a) and (b) show the effect of combining two parameters.

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Chapter 8

Conclusion and Future Work

Information overload motivates the development of concierge systems. A Web information concierge provides a structural accessing interface to Web data resources for end users. The complexity and expressive power of concierge systems are the main concerns of this research. In this chapter, the contributions of this research are summarized and discussed. Some suggestions for the improvement of our systems are offered for further study.

8.1 Summary of Thesis

Much research has been conducted to optimize the performance of Web data extraction, improve extraction accuracy, and deliver formatted results. However, the lack of a generic conceptual modeling over Web documents, extraction methods and extraction rule generation methods make communication among different systems and extension of the current systems difficult. The conceptual framework for information concierge system proposed in this thesis is meant to overcome this problem.

The proposed framework contains three layers, which correspond to the physical models of Web data, logic models of Web data and models of the possible operations a user can use to handle Web data. Unlike those ad-hoc methods, our framework separates research issues and puts them in their due perspectives. Similar with the organization of relational database, the separation of physical Web data and logic view over Web data (schema) provides an abstract layer between operations and physical data. A simple example is presented in Chapter 3 to demonstrate the relationships among different layers.

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The success of relational databases can partially be attributed to the solid theoretical basis of relationship schema. Chapter 4 presented various perspectives on Web data and schemata, and proposes some classes of schemata with different expressive power. The subtle classification of the schema based on the proposed framework provides a basis to compare various systems in the literature.

Other than the theoretical analysis of Web data and their schemata, Chapter 5 concentrates on how to improve the performance of kernel operations in the proposed framework. Some promising results are presented in Chapter 5. To show the flexibility of the framework, some auxiliary operations are introduced in Chapter 6.

8.2 Significance of this Study

This section highlights the main contributions of the thesis:

Flexible Concierge Framework This thesis presents a comprehensive framework for a Web data extraction system that provides a consistent view of various operations in Web data extraction. Operations including document set preparation, document classification and data extraction are all conducted in a schema-based representation of Web documents. To support these operations, similarity measurements for semi-structured documents based on schema are proposed. In our experiments on real world dataset, compared with the methods that do not consider document structures, much better clustering results were achieved using schema-based representation in terms of clustering accuracy. Moreover, better document classification results using schema-based representation are obtained.

WDEL and Query Transducer The proposed framework is investigated from various perspectives, including its characteristics of tree language, logic program and tree automata. Based on these characteristics, the expressive capability of extraction rules, the construction of extraction engines and the model of Web documents are analyzed from a unique viewpoint. A Web data extraction language — WDEL that is roughly equivalent to MSO logic is defined. WDEL is encoded in XML documents to present an intuitive hierarchical view over Web documents, and can be easily generated via a visual interface implemented in WICCAP. Due to the connection between automata and language, a kind of automata — query transducer is introduced to interpret WDEL and extract data from Web documents. WDEL has high

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expressive capability and can be easily generated manually with aid from visual interface.

WDEL Generation Algorithm Manually coded WDEL programs are accurate to extraction contents, as a user can adjust them in a modify-test-modify way. Despite this benefit, manual methods are time-consuming. We compromised the expressive capability of WDEL and devised some algorithms to generate a subset of WDEL. Two types of algorithms are introduced. The first type parses Web documents to trees and detects frequent tree patterns from them. These patterns can be encoded to WDEL programs. The second type shares similar ideas like those suffix tree construction algorithms, and need not to parse documents to trees. In addition, it can detect some substring patterns that can be parsed to trees and transformed to WDEL. We presented Algorithms with time complexity linear to document size. In general, the first type is less efficient than the second one, though it can produce programs to extract more complicated documents. In contrast, the second type over-performs the present pattern detection algorithms, due to its linear complexity.

Auxiliary Components Besides the main components of extraction engine and extraction rule generator, some auxiliary components inside the concierge framework are introduced to show the flexibility of the framework. Based on these structural patterns very efficiently detected, we introduced methods to measure document similarity as well as cluster and classify documents. The clustering and classification results are compared with other methods based on structural information. A visual interface like QBE is also demonstrated.

8.3 Future Work

This thesis has discussed the techniques about various aspects of Web information concierge systems. All the work in this thesis is purely based on structural information embedded in Web documents. The experiment results also showed that structural information is not only very important in processing Web documents, but also strongly related to the semantic information of Web documents. However, whether exploiting semantic information can improve our work is not addressed in this thesis. In future, how to combine semantic and structural information needs to be studied.

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As WDEL introduced in the thesis is oriented to XML documents, and there is a trend in using XML documents as databases of complex data; e.g., bioinformatic data, the application WDEL may be extended to these databases. Due to the high overlay information in such complex data, how to exploit structural information with semantic information to detect redundant data is worth investigating in a future research.

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