

Interfacing the System Evaluation Method LSP with E-commerce Web Sites

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Abstract. For many people faced with a tough purchasing decision, the research tool of choice is a web browser. Search engines solve the general problem of finding relevant data, however it is up to the user to sort, filter, and evaluate it. Decision support methods such as LSP can turn raw data into formal evaluations, but they are generally disconnected from the Web – the most up-to-date, widely-used, and convenient source of data available. This paper demonstrates how LSP can be connected to the Web, so that live data from e-commerce web sites can be used in consumer-oriented system evaluations.

Keywords: Web Information Extraction Systems (WIES); Logic Scoring of Preference (LSP) method.

1. Introduction

Web Information Extraction Systems (WIES) are tools that transform web pages into program-friendly structures that can be used by a variety of web applications and services. A recent WEIS survey [1] provided evaluation and comparison of various information extraction approaches and found that despite the great necessity for WIES the automation degree is generally rather low.

The information extraction automation degree is not constant – it depends on the type of application that uses automatically extracted data. The goal of this paper is to expand the results from [1] by investigating the degree of automatic extraction in detail, using a specific class of service: evaluation of systems using the Logic Scoring of Preference (LSP) method [4]. We selected this class of service because it is a typical e-commerce service that includes evaluation and selection of cars, homes, etc. Therefore, we decided to build WIES for the LSP method and to investigate its applicability in the real estate evaluation case. The goals of our analysis are (1) to provide a detailed survey of information extraction techniques, tools, and problems in this realistic special case, and (2) to provide a reliable quantitative estimate of the

achieved degree of automation. We believe that our results are typical and can be used by WIES designers, planners, and users.

2. LSP method for system evaluation

System evaluation is a process of determining the ability of a system to satisfy user requirements. In the context of e-commerce, it is how we decide what to buy. Evaluations can range from simple feature-by-feature comparisons to full-blown mathematical modeling supported by dedicated decision-support software. The LSP method for system evaluation [4,5,6] falls into the latter category. It is capable of reducing a large and complex set of system attributes into a single overall quality indicator that precisely indicates how well those attributes match against user-specified criteria. This process is illustrated in Fig. 1 where we present both the structure of an LSP criterion and the process of providing inputs for the LSP method if the source of data about evaluated systems is Internet, i.e. an e-commerce web site.

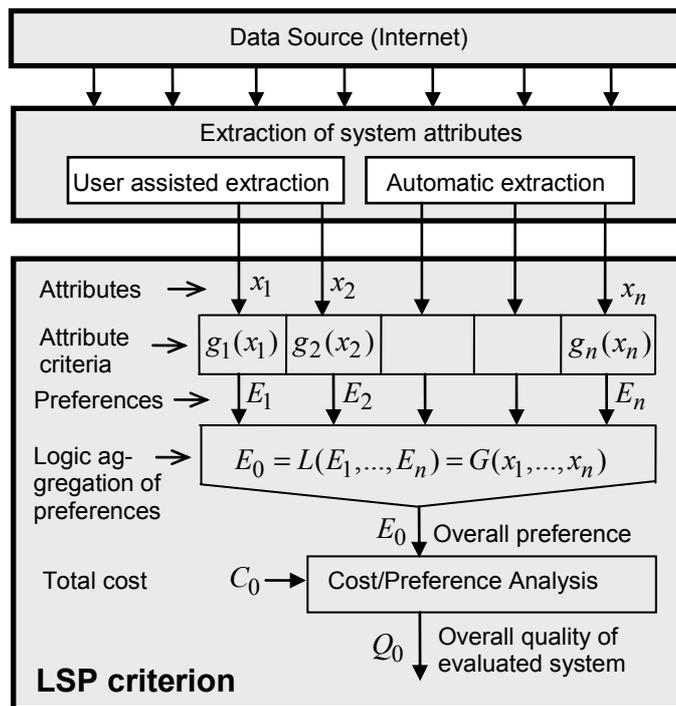


Fig. 1. Extraction of attributes and the structure of LSP criterion

The LSP criterion is a systematically designed complex function that uses input attributes of an evaluated system to compute an overall system quality

indicator. In the case of large and complex systems input attributes are provided by a team of professional evaluators and domain experts. In the case illustrated in **Fig. 1** we consider a simple situation of evaluating an object whose attributes are available on Internet, posted on an e-commerce web site. Of course, the evaluator could manually collect all input data for evaluation and then use them as inputs for the LSP criterion function. On the other hand, it would be much better if the extraction of inputs could be done automatically using a specialized tool. Then the collected data could be automatically forwarded to a tool that implements the LSP criterion. **Fig. 1** shows a realistic situation where automatic extraction of data includes a fraction of total inputs, and remaining inputs are provided by evaluator. Before presenting the problem of automatic data extraction we have to understand the basics of the LSP method.

The values of attributes x_1, \dots, x_n , $x_i \in \mathbf{R}$, $i = 1, \dots, n$, $n \geq 2$ are inputs for the LSP criterion function. In the case of real estate, examples of input attributes can be the area of a home (x_i), and the home-work distance (x_j). For each attribute we specify requirements in the form of an attribute criterion function $E_i = g_i(x_i)$, $E_i \in [0, 1]$, $i = 1, \dots, n$. For example, we could be perfectly satisfied with the area $x_i \geq A_1$, and the area $x_i \leq A_0$ could be unacceptable. In such a case the elementary attribute criterion could be

$$E_i = \min\{1, \max[0, (x_i - A_0)/(A_1 - A_0)]\}, \quad A_0 < A_1, \quad 0 \leq E_i \leq 1.$$

So, E_i denotes the degree of satisfaction with the area of evaluated home. Similarly, the distance from home to work $x_j \geq D_0$ could be considered unacceptable while the distance $x_j \leq D_1$ could perfectly satisfy the homebuyer. In such a case the criterion could be

$$E_j = \min\{1, \max[0, (D_0 - x_j)/(D_0 - D_1)]\}, \quad D_1 < D_0, \quad 0 \leq E_j \leq 1$$

The resulting values E_1, \dots, E_n are called elementary preference scores. They express the degree of satisfaction of each specific requirement (0 = no satisfaction, 1 = complete satisfaction). The next step is a logic aggregation of preference $E_0 = L(E_1, \dots, E_n)$ that computes the overall preference score E_0 that reflects the overall ability of the evaluated system to satisfy user requirements. The aggregation process is based on graded logic functions, i.e. functions that provide parameterized continuous transition from conjunction to disjunction. The basic preference aggregation function is the generalized conjunction/disjunction (GCD) [7] that is usually implemented using the weighted power mean:

$$e_{out} = \left(\sum_{i=1}^k w_i e_i^r \right)^{1/r}, \quad 0 < w_i < 1, \quad \sum_{i=1}^k w_i = 1, \quad e_i \in [0, 1], \quad e_{out} \in [0, 1], \quad k \geq 2$$

Using stepwise aggregation of groups of related inputs we can make more complex logic functions [8] and organize the tree-like aggregation structure that eventually yields the overall preference indicator E_0 . That indicator reflects the overall capability of evaluated system to satisfy user requirements.

The final evaluation and selection step is to use a cost/preference analysis to compute an overall system quality indicator Q_0 as a function of the overall preference E_0 and the total cost C_0 . Among many possible cost/preference models the simplest is $Q_0 = E_0 / C_0$. We assume that the evaluation is regularly performed as a part of the comparison of multiple alternatives and selection of the best system. In such cases competitive systems are ranked according to decreasing values of the overall quality Q_0 and the system with the highest Q_0 value is proposed for acquisition.

The presented evaluation process critically depends on our ability to extract relevant, up-to-date inputs for the evaluation process. This nontrivial step combines a spectrum of advanced software tools and technologies [3,11,12,13,19], and in some cases generates only partial results. In this paper we identify major problems related to automated attribute extraction and offer several solutions to this problem. It is important to emphasize that system evaluation is only one of many problems where the Web data extraction techniques are indispensable. Therefore, the results of this paper are applicable in a variety of Web-oriented applications.

3. Problems of Web Data Extraction

Whenever we access Web data we are faced with a data that are primarily prepared for visual consumption and consequently pay little attention to facilitating programmatic access. Generally, the difficulties are the consequences of the following:

- Intentional barriers designed to impede extraction of proprietary/reusable data:
 - Client filtering
 - Automation policies
 - Protected/encrypted display formats
 - Authentication/verification
- Unintentional barriers:
 - Lack of website development standards
 - Browser quirks mode
 - Limited expertise of website developers
 - Pages optimized for on-line viewing

Client filtering [10] – Prevents access to content based on the source of the request (usually determined at the IP level). This tactic is a successful barrier against various program-based (“bot”) attacks from common sources.

Automation policies [2] – Directives embedded into web pages that well-behaved programs visiting the site voluntarily obey. This gives site owners a way to declare what data is accessible to bots, and how it should be read.

Protected/encrypted display formats – This may be as simple as shifting content around or heavy-handed such as requiring a browser “plug-in”. This practice can drive traffic away by adversely affecting search engine scores.

Authentication/verification – Restrictions that usually require human involvement, either to enter credentials or to perform a simple task that would be difficult for a program to accomplish (such as CAPTCHA-style puzzles [17]). Most programs are foiled by this type of obstacle.

Lack of website development standards – The same page layout can be coded many different ways using completely different HTML elements, and there are currently no internet-wide standards that govern this.

Quirks mode [12] – Web browsers handle an extraordinary range of coding styles and they can cover up certain serious developer mistakes. This functionality would be difficult to reproduce in a standalone data extraction program without essentially writing a new browser.

Limited experience – The majority of web sites are developed by people with minimal formal programming education [15,16]. No doubt the professionals are concentrated in the e-commerce sector, but the Web is still dominated by a “hobbyist” culture.

Pages optimized for viewing – The web is oriented around free-flowing hyperlinked content. This is nearly opposite the linear, structured format typical of ideal data extraction solutions.

While this is by no means an exhaustive list, it illustrates the magnitude of difficulty involved in designing a general-purpose web data extraction solution, and the fact that there is no single accepted solution for locking down content. In general intentional barriers are easier to overcome than unintentional ones, which tend to result in unpredictable, hard-to-parse pages. It is this random element to site designs more than anything else that complicates any attempt at automated data extraction.

The collective effect of intentional and unintentional barriers results in an overall level of programmatic accessibility called the *cooperation level* of the site, where fully-cooperative means there exists a convenient and efficient means for extracting useful data, and non-cooperative means data extraction is difficult or impossible.

4. Data Extraction and LSP Integration

Given the wide range of data presentation formats and variety of impediments, it would be difficult to construct a 100% automated general-

purpose data retrieval tool without writing a full browser. Any tool that is built around one or several (or even several dozen) specific data sources would miss out on the vast potential of the internet. Therefore, in this project we attempt to bridge the gap by:

1. Providing a tool to collect data specific to the currently-selected LSP project.
2. Providing automated data-collection features where possible, and general data-entry assistance elsewhere.
3. Defining an open standard for storing and moving system attributes.
4. Creating a data repository based on the standard, featuring an interface that is compatible with existing LSP tools.

In short, the goal is to help users find and collect the data more efficiently, and make it easier to share and reuse.

The general solution to collecting data from restricted data sources is to emulate human behavior programmatically as much as possible, and involve human users when it is unavoidable. To avoid having to rewrite most of the functionality that makes browsers so flexible, a browser extension is the logical solution. Browser extensions (also known as “add-ons”) [13] provide a way to leverage the exceptional parsing ability of common browsers and create a seamless connection to the LSP analytic engine running on a remote server.

There are many ways to present the same set of data, but standard conventions and HTML limitations can be used to frame data retrieval and entry services. Extensions have full access to any currently-displayed HTML data, regardless of the source, so it is possible to view, analyze, and attempt to reconcile it against LSP project data. To analyze data on a given page, the contents must be broken down into a navigable set of related low-level components, and there must be some way to navigate this structure and explore relationships between them, both logical and physical (i.e. position).

Although the underlying page code can often be difficult for programs to analyze, humans have little trouble understanding the displayed content. This is because no matter how stylized and embellished the presentation, and no matter how complex the underlying code is, the data is usually arranged in columns, rows, grids, or other conventional publishing layouts. We can make a program analyze a web page more “intelligently” by forcing it to look past the actual structure, and making it consider what the page actually looks like to a user. Not all pages lend themselves to this approach, but enough do to make it a worthwhile endeavor. The technique is as follows:

1. Search for HTML elements that are typically used to display structured data, such as Tables and DIVs.
2. Within those blocks, find the absolute coordinates (starting from the top-left corner of the content window) of the elements contained by the block.

- By finding those inline elements that fall on the same (or close) x-coordinate, we can programmatically discern what elements will form a column of data to the user's eye, no matter how obfuscated the code is.

Once the column structure is determined, it is possible to make educated guesses about the content based on criteria and system information in the current project. For example, data for a particular system could be discerned by looking at the top-most element in a column (that with the lowest y value) and, assuming it is a column header, match it against system names in the current project (Fig. 2). If a match is found, further steps can be taken to automatically extract the data into the data entry grid.

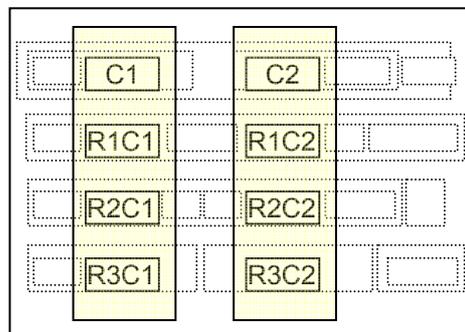


Fig. 2. Inferring Page Structure

Each criterion definition includes a regular expression value for the name and the legal values that apply to it. When combined with structural analysis it becomes possible to programmatically “read” data on a web page.

Label/Value Proximity - Attribute searches closely follow the behavior of a human reader performing the same search. First, the current attribute is searched for by label (using regular expressions). Once found, this cell position is used as an anchor for locating the applicable value. The value search goes left-to-right, top-to-bottom (adjusted appropriately for the current locale settings) as a human reader would behave, and values found closer to the label anchor have a higher probability of being correct. When multiple potential matches are found, the values are presented in decreasing order of proximity, with the most probable value being the default. Many page extraction algorithms follow a similar pattern of emulating human reading habits in the hopes of improving extraction accuracy [1].

Once a user has collected some data they can post an update to the repository directly, either to restore it later for further editing, or to immediately run an LSP evaluation. To post the updates, all of the current system data is bundled into a single XML document and posted to the repository server via asynchronous XML (AJAX) calls. In the realm of information extraction systems, this general approach can be categorized as a “supervised multiple-pass record-level wrapper which relies on regular expressions to extract data

from semi-structured (HTML) content” [1]. The complete design and implementation details for the LSP/data extraction project can be found in [9].

Figure 3. shows the complete process:

1. The evaluation is set up using standard LSP tools such as ISEE [5]
2. Evaluation metadata is imported into the WebForager server.
3. The WebForager browser add-on uses this information to assist data collection in a normal web browsing session.
4. Collected system data is returned to the LSP server and stored in a neutral format in the repository.
5. The system data is exported to standard LSP tools, and the evaluation results are sent via HTTP back to the browser. To the end-user, this simply appears as a comprehensive report in a new tab in their browser.

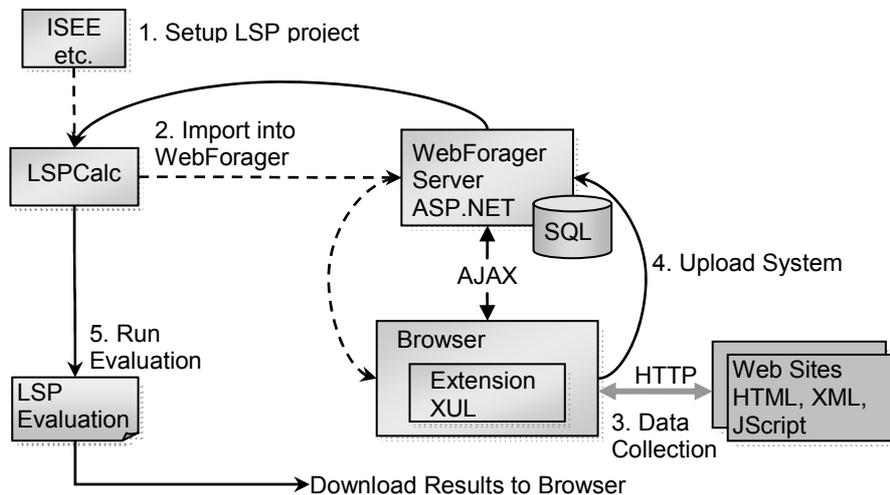


Fig. 3. Lifecycle of a Web-based LSP Evaluation

5. Sample Evaluation: Real Estate

Real Estate is an excellent test subject for exploring system evaluations based on web data. Buying a home is a major life event, in terms of both cost and the amount of effort required for evaluations, so the work required for a proper evaluation is easily justified. The industry is steadily shifting research and selection power to the consumer – via the Internet [14] – and there exist web sites representing the full spectrum of cooperation, from fully-open to fully-closed. Finally, system attributes for home selections are very well-defined and fairly static over time.

Multiple Listing Service (MLS) was created to allow real estate brokers to share listing information in a consistent, centralized, data-driven way, with unique identifiers (MLS numbers) assigned to each property. MLS predates the creation of the Web by decades, but the idea would seem to translate perfectly. Despite this, there are over 900 semi-cooperative local MLS organizations, and consolidation has been slow. The reason for this lack of consolidation is not technical, but most likely grounded in economics [14].

Put simply, MLS data has intrinsic value to the brokers that control it, and it is in their best interest to remain in control. This has the unfortunate effect of dispersing valuable home information, forcing home buyers to either manually consolidate the data themselves, or let their agent determine their “short list” of homes based on some loose criteria. The common sense approach would be exactly opposite: use objective facts to reduce a large list of homes to a short list that all fulfill minimum buyer requirements, then apply the costly and time-consuming in-depth research towards the top-scoring results.

In this case study, we demonstrate how results may be consolidated from several sources, allowing prospective home buyers to run comprehensive LSP evaluations against a list of homes. This can immediately eliminate unqualified homes and highlight those that are most likely to satisfy the buyer.

Data is consolidated from three sources (Fig. 4):

- A (simulated) direct MLS feed.
- A regional “independent” real estate web site (with non-MLs listings).
- Data extracted from the pages of a regional real estate web site featuring searchable MLS-based listings.

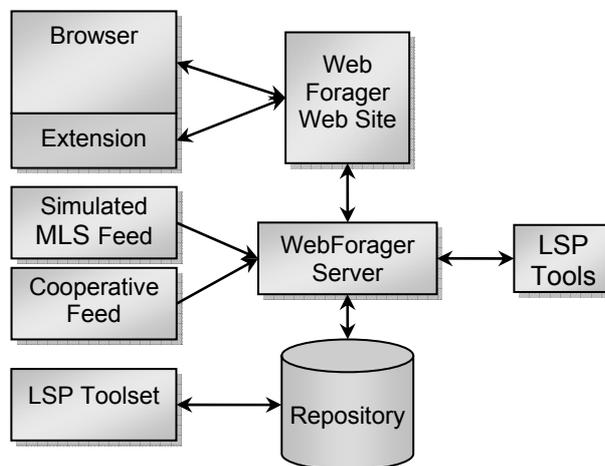


Fig. 4. LSP/Real Estate Data Integration

LSP Project Setup

This example features a trivial LSP evaluation intended to show how data from disparate web-based sources can be consolidated into a single

evaluation. The number of elementary criteria and complexity of the aggregation structure could easily be extended to any size. We are mainly interested in a subset of core home data – information that is found in most MLS records. The attributes are based on three major categories (Table 1):

Layout – this includes physical dimensions, number of rooms, etc. (relative importance 40%)

Amenities – a sampling of typical home features, such as hardwood floors and air conditioning (relative importance 20%)

Location – typically these attributes are specific to a given buyer and not made explicit in MLS (relative importance 40%)

Table 1. Preference Aggregation

Criterion	Operator	Block ID	Operator	Operator	Global Preference
Property Type	50	CA	Layout	40	C+
Bedrooms	30				
Bathrooms	20				
A/C	25	D-	Amenities	20	
Granite	45				
Hardwood	30				
Work Distance	40	C+	Location	40	
School Distance	30				
Shops Distance	30				

These three categories are considered mandatory and the strong partial conjunction aggregator (C+) reflects this requirement [4]. The layout aggregator is the medium partial conjunction CA. All partial conjunction aggregators require simultaneous satisfaction of all inputs and punish systems that are unable to provide the required level of simultaneity. Most house-hunting efforts emphasize the physical dimensions and location of a house, and amenities are considered secondary priorities, the rationale being that it is easier to put in new floors than to add an extra room or relocate the house. This is expressed using appropriate weights. The presented criterion also uses a weak partial disjunction aggregator D-, enabling inputs to easily compensate each other.

Data Collection

After the initial LSP project setup and WebForager import, the two external feeds were incorporated (Fig. 4), providing the user with a starting point for comparisons. The remaining records were gathered in an interactive browsing session and uploaded to join the existing data.

MLS Feeds - Real estate agents who wished to provide LSP as a service to their customers would likely provide listing data to WebForager in the form of raw MLS records. The format is highly structured and easily imported into relational tables (see Fig. 5) using a simple data transformation script. Once uploaded, this data can be included in any LSP report.

Non-standard Feeds - A growing number of alternatives allow buyers and sellers to bypass MLS entirely. These companies could conceivably adopt the XML-based system attribute exchange schema used by the WebForager system. The advantage would be twofold, as they would benefit from a common data exchange, and system data would be directly usable in LSP evaluations.

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ListID|PropType|AgentID|AgentName|AgentPhone|OfficeID|Offi...
21234321|SFR|23322112|Bob Smith|555-555-5555|23423432|Real...
21211131|SFR|12233432|Bob Smith|555-555-5555|23423432|Real...
23332111|SFR|73311172|Alice Jones|555-555-5555|23423432|Re...
28733221|SFR|23322112|Alice Jones|555-555-5555|23423432|Re...
26543221|SFR|23322112|Ed Lee|555-555-5555|23423432|Mortgag...
    
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Fig. 5. Sample MLS Data Feed

Extracted Page Data – Some sites allow simple queries, but only a limited number of records are displayed at one time, and there is no mechanism for downloading data for off-line use. To allow this data to be compared against data gathered from other sources, it is extracted and uploaded via the WebForager browser extension (Fig. 6).

The screenshot shows a browser window with a simulated real estate listings page and a comparison table. The listings page displays several property cards with details like Price, MLS Number, Address, Bedrooms, Full Bathrooms, Sq. Ft., and Lot Sq. Ft. The comparison table below has columns for Criteria and five MLS numbers (555550, 555551, 555552, 555553, 555554). The criteria include Property Type, Number of Bedrooms, Number of Bathrooms, Interior Area, Exterior Area, Air Conditioning, and Granite Counters.

Criteria	555550	555551	555552	555553	555554
Property Type [1 2 3 4 5 6]	true	true	true	true	true
Number of Bedrooms [1 2 3 4 5 6 7]	3	2	4	5	3
Number of Bathrooms [1 2 3 4 5 6 7 8 9]	2	4	3	2	2
Interior Area [1 2 3 4 5 6]	2144	1870	2100	2655	2094
Exterior Area [1 2 3 4 5 6]	0.601	0.136	0.138	0.179	0.116
Air Conditioning [1 2 3]		true			true
Granite Counters			true		

Fig. 6. Browser Extension with Simulated Real Estate Listings

After the various records were imported and extracted, an LSP evaluation was run directly from the browser with ten candidate homes, including three from the MLS feed (MLS prefix), four from the direct feed (REP), and three from data extracted by the browser extension (WFB). The final LSP ranking is listed in Table 2.

The top three selections were close to each other, while the middle three differed significantly enough to possibly drop them out of contention, and the bottom four were clearly not worth consideration. The overall preference scores are then used as inputs for the cost/preference analysis. This approach gives a buyer and agent the ability to focus on only those homes that are most likely to be satisfactory, and given the time-critical nature of real estate, this could be a tremendous advantage.

Table 2. LSP Preference Ranking

Rank	Overall Preference Score	Identifier
1	74.29%	REP003
2	72.23%	WFB001
3	70.83%	REP001
4	60.61%	REP002
5	60.22%	MLS002
6	60.09%	MLS003
7	53.72%	REP004
8	51.06%	WFB003
9	0%	WFB002
10	0%	MLS001

6. Conclusions

Search engines do an effective job of categorizing and indexing the Web, but the actual data must generally be gathered and analyzed manually. Connecting LSP to live data provided by e-commerce web sites allows it to be used in a wider range of selection problems, and it creates a way to harness the growing volume of data available on the web. Creating this integration entailed solving three basic problems: (1) extracting and transforming data from non-cooperative sites, (2) importing data from cooperative sites, and (3) building a web-server interface to the predominantly single-user-oriented LSP tools.

Programs intended to automatically extract data from web pages must overcome a wide range of technical impediments – some intentionally created, and some not. The general solution for circumventing these barriers is to create algorithms that emulate human reading patterns. Due to the combined “randomizing” effect that the various impediments have on website structures, general automated extraction tools can only hope to achieve partial success in most cases. In this case, “success” is measured in terms of the level of automation achieved.

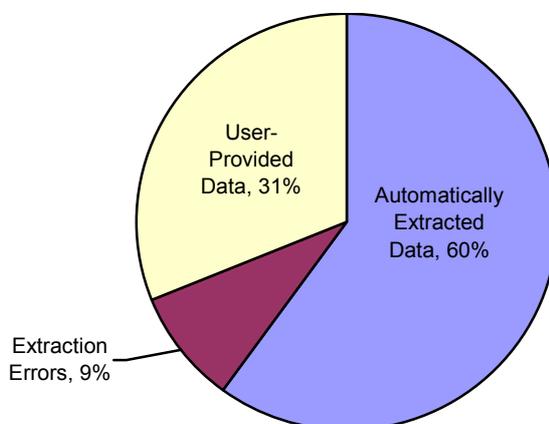


Fig. 7. Typical industry-specific extraction rates

The actual success rate depends on how tightly the tool is tied to the target sites. According to our experiments, a tool that has been tuned for use in a particular industry – automotive sites for example – might experience a 70% - 90% extraction rate on certain specific sites, but overall the typical success rate will be in the 50% - 60% range, leaving users to manually transpose much of the data (Fig. 7). These success rates are not a property of the LSP method, but of information extraction solutions within the e-commerce problem domain. Similar results may be expected in a spectrum of other applications that depend on similarly-structured Web data outside of e-commerce.

An important point to consider in these results is that many website data extraction problems are completely avoidable. Certainly the intentional barriers can be removed at the whim of the site owners, but even the unintentional ones – the most difficult class of problems – are mostly the result of mere habit or lack of standardization.

There are initiatives that seek to address some of these issues, but the burden remains on website developers to embrace them. XHTML [20] attempts to formalize HTML into a stricter syntax, and “Really Simple Syndication” (RSS) provides a standard means for sharing certain types of content. Web Services presents a widely-supported standard which solves many technical issues related to remote data access, but it is first and foremost a developer resource, meaning that both content producers and consumers must embrace the standard on a technical level. Perhaps the most ambitious project is the Resource Description Framework (RDF) [18], which provides a general framework for describing data on the web. To date, RDF has not gained widespread acceptance, and in general research in the area of automated website data sharing/extraction remains surprisingly underdeveloped outside of academia.

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Jozo J. Dujmović was born in Dubrovnik, Croatia, and received the Dipl. Ing. degree in electronic and telecommunication engineering in 1964, and the M.Sc. and Sc.D. degrees in computer engineering, in 1973 and 1976 respectively, all from the University of Belgrade, Serbia.

Since 1994 he has been Professor of Computer Science at San Francisco State University, where he served as Chair of Computer Science Department from 1998 to 2002. His teaching and research activities are in the areas of soft computing, software metrics and computer performance evaluation. In 1973 he introduced the concepts of andness and orness and logic aggregators based on continuous transition from conjunction to disjunction. He is the author of approximately 130 refereed publications, including 13 books and book chapters. Before his current position at San Francisco State University, he was Professor of Computer Science at the University of Belgrade, University of Florida (Gainesville), University of Texas (Dallas), and Worcester Polytechnic Institute. In addition, he was teaching in the graduate Computer Science programs at the National Universities of San Luis and Jujuy (both in Argentina). At the University of Belgrade, where he was teaching from 1968 to 1992, he also served as Chairman of Computer Science Department, and as founding Director of the Belgrade University Computing Center. His industrial experience includes work in the Institute "M. Pupin" in Belgrade, and consulting in the areas of decision methods, performance evaluation, and software design.

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