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ABSTRACT

Web applications are increasingly prominent in society, serving a wide variety of user needs. Engineers seeking to enhance, test, and maintain these applications must be able to understand and characterize their interfaces. Third-party programmers (professional or end user) wishing to incorporate the data provided by such services into their own applications would also benefit from such characterization when the target site does not provide adequate programmatic interfaces. In this paper, therefore, we present methodologies for characterizing the interfaces to web applications through a form of dynamic analysis, in which directed requests are sent to the application, and responses are analyzed to draw inferences about its interface. We also provide mechanisms to increase the scalability of the approach, such as a mechanism based on intelligent request selection. Finally, we evaluate the approach's performance on five well-known, non-trivial web applications.

1. INTRODUCTION

Web applications are among the fastest growing classes of software in use today, providing a wide variety of information and services to a large range of users. Users typically interact with these applications through a web browser, which can render the web pages generated by a web application. As the user navigates or submits data, new requests are sent to the web application through its interface.

Engineers who wish to enhance, test, and maintain web applications must be able to understand and characterize their interfaces, and one way to do this is through the use of invariants that document these interfaces. For example, engineers maintaining a travel support site like Travelocity could leverage invariants that convey what variables must be included in a request to obtain a list of flights (e.g., departure location and date, return date), what variables are optional (e.g., number of children), or whether a particular variable is dependent on the value of other variables (e.g., if the number of adults in a request is 0, then there must be some seniors; if children are present, then their age must be included). Such characterizations could facilitate the engineer's understanding of the potential behavior of the web application. Further, they can be used to help assess the correctness of the web application interface, and to generate test cases and oracles relevant to the application. Such characterizations can also be used to direct maintenance tasks such as re-factoring the web pages. For example, if a certain field cannot be empty, then the input validation code for that field could be migrated over to the client side, where it can operate through scripting languages.

Characterizations of web application interfaces would also be valuable for third party developers (either professional or end-user programmers) attempting to incorporate the rendered data as a part of a web service (e.g., for resource coalitions [15]), or for users making specific queries on a web application without utilizing a browser. Although web applications that are commonly used by clients may provide interface descriptions (e.g., commercial sites offering web services often offer a WSDL-type [3] description), many sites do not currently provide such support mechanisms. In addition, at least one class of users, end user programmers, cannot be expected to learn particular protocols or APIs in order to access applications [4]. Moreover, as briefly exemplified, the characterizations we are pursuing go beyond those that such interface descriptions can offer. Such characterization becomes more challenging in the presence of numerous variables and restrictions on variable values and combinations, which are relatively common for this type of application (the interface of one of the applications we studied had over 29 variables, several of them inter-related).

For these reasons, we have been researching methods for automatically characterizing the properties of and relationships between variables in web application interfaces. Such characterizations can be obtained statically or dynamically. In earlier work [4] we presented static approaches for analyzing HTML and javascript code to identify variable types, and one simple dynamic approach for providing simple characterizations of the values allowed for some variables (e.g., a variable cannot be empty). However, deeper characterizations of web application interfaces, such as those involving variable ranges or dependencies, were not obtainable through the mechanisms that we considered.

In this work we address this lack, presenting a methodology for characterizing the interface of a web application by performing more sophisticated forms of dynamic analysis. Our methodology involves making directed requests to a target web application, and analyzing the application's responses to draw inferences about the variables that can be included in a request and the relationships among those variables. We also provide mechanisms, such as a mechanism based on intelligent request selection, that enhance the scalability of the approach. Finally, we evaluate the approach's performance on five well-known, non-trivial web applications.

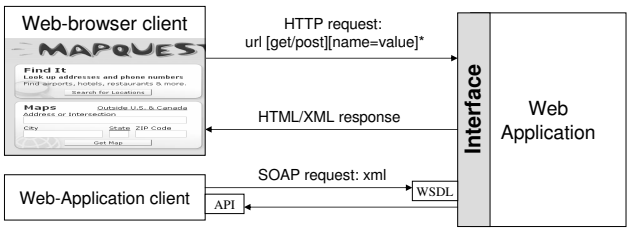


Figure 1: Web Applications

The remainder of the paper is organized as follows. Section 2 provides background information on web applications. Section 3 describes our overall methodology for characterizing web applications, and also provides detailed descriptions of our inferencing and request selection techniques. Section 4 describes an empirical study exploring our methodology's ability to characterize web applications, and the effect of our various request selection techniques. Section 5 discusses related work and approaches, and Section 6 summarizes our contribution and discusses future work.

2. BACKGROUND

Navigating through the WWW can be perceived as performing a sequence of requests to and rendering the responses from a multitude of servers. Browsers assemble such requests as the user clicks on links. Servers generate responses to address those requests, the responses are channelled through the web to the client, and then processed by the browser. Some requests may require additional infrastructure that leads to more complex applications. For example, in an e-commerce site, a request might include both a URL and data provided by the user.

Users provide data primarily through forms consisting of input fields (e.g., radio buttons, text fields) that can be manipulated by a visitor (e.g, click on a radio button, enter text in a field) to tailor a request. These input fields can be thought of as variables. Some of the variables have predefined sets of potential values (e.g., radio-buttons, list-boxes), while others are exclusively set by the user (e.g., text fields). After the client sets the values for the variables and submits the form, these are sent as request parameters known as name-value pairs (input fields' names and their values). For example, in Figure 1 a user populates the form rendered in a browser to obtain directions from MapQuest. After receiving and interpreting the request, Mapquest provides a response (e.g., maps and directions, solicitation for more input data, error message) in the form of a markup language that is again rendered by the browser, and the cycle starts again.

As shown in Figure 1, web applications can also operate in association with other applications through direct data exchanges. For example, sites providing air-travel information often query airlines' sites, exchanging formatted data in the process. Such interactions often occur through programmatic interfaces that have more formal descriptions. For example, the Web Services Description Language (WSDL) [3] and the Really Simple Syndication (RSS) [11], are two popular ways to describe the interfaces between a service provider and the clients invoking the service.

As stated in the introduction, the focus of our research is on the characterization of web application interfaces. Such characterizations will be beneficial when other types of descriptions are not available (e.g., third party developers building on existing web sites without WSDL), are not appropriate (e.g., end user programmers cannot deal with complex APIs), or are not sufficient or are evolving (e.g., developers of a growing and fast changing application).

3. METHODOLOGY

Figure 2 shows the overall architecture for our web application interface characterization methodology, WebAppSleuth, with various processes (sub-systems) in the methodology shown as boxes. The methodology begins with a *Page Analyzer* process, which statically analyzes a target page generated by the web application. The *Page Analyzer* identifies all variables associated with the fields in the form[1] , and then associates a list of potential values with each identified variable. For each pull-down, radio-button, or check-box variable, the *Page Analyzer* obtains values from the possible values defined in the form. For text-type variables, the *Page Analyzer* prompts the user to supply a list of values that may elicit a correct response from the web application. In addition, we also consider the null value to indicate that a variable is not a part of the request.

Next, the *Request Generator* creates a pool of potential requests by exploring all combinations of values provided for each variable. Given this pool of requests, the *Request Selector* determines which request or requests will be submitted to the target application. There are two general request selection modes: *Batch* (requests are selected at once) and *Incremental* (requests are selected one at a time guided by a feedback mechanism). The *Request Submitter* properly assembles the http request and sends it to the target application. The web application response is stored and classified as valid or invalid by the *Response Classifier*. The selected request and the classified response are then fed into the *Inference Engine*, which infers various properties about the variables and the relationships between variables.

The following sections provide details on the two most novel components of this architecture: the *Inference Engine* and the *Request Selector*. Further implementation details on the other components are provided in Section 4.

3.1 The Inference Engine

We have devised a family of inference algorithms to characterize the variables that are part of a web application interface, and the relationships between them. The algorithms operate on the list of variable-value pairs that are part of each submitted request, and on the classified responses (valid or invalid) to those requests.

To facilitate the explanation of the subsequent algorithms we utilize examples that are further elaborated in our study in Section 4. Also, we simplify terminology by defining a *valid request* as one that will generate a valid response from the web application, that is, a response that meets the user's expectation regarding the application behavior. We also define an *invalid request* as one that will generate an invalid response.

3.1.1 Mandatory, Optional, and Mandatorily Absent Variables

It is common for web applications to evolve, deploying additional and more refined services in each new deployment. As an application evolves, it becomes less clear what variables are required by that application, and what variables can be included in a request without being required. Distinguishing between these types of variables is helpful, for example, to anyone planning to access the web application interface, and to developers of the web application who wish to confirm that changes in the application have the expected results in the interface. We define a mandatory variable as a variable that must be in any valid request. An optional variable is one that may be included in a valid request, but is not required.

[1]Although web applications may generate many web pages, at this stage we concentrate on pages that contain forms because they are the most likely to generate complex requests that exercise an important part of the web application interface we intend to characterize.

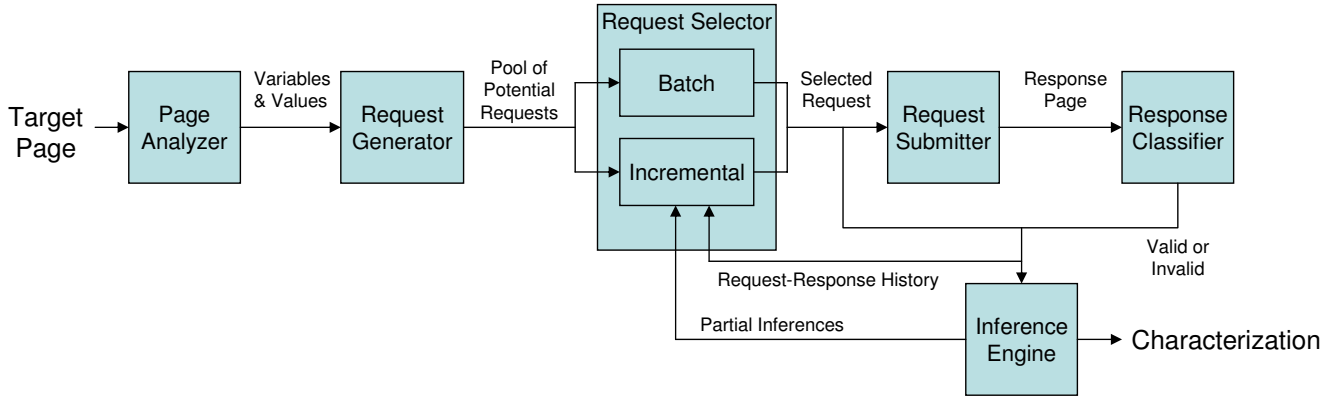


Figure 2: WebAppSleuth architecture.

Request	*name*	*city*	*state*	Response	PresentValid = True	AbsentValid = True	PresentInvalid = True	AbsentInvalid = True	Mandatory	Optional
1	absent	absent	absent	Invalid				name, city, state		
2	present	present	present	Valid	name, state, city			name, city, state	name, city, state	
3	absent	absent	present	Invalid	name, state, city		state	name, city, state	name, city, state	
4	present	absent	present	Valid	name, state, city	city	state	name, city, state	name, state	city

Table 1: Mandatory and Optional Variables in InfoSpace.

Algorithm 1 Inferring Mandatory, Optional, and Mandatorily Absent Variables

for all $V \in Variables$ **do**
  $PresentValid[V] =$ FALSE
  $PresentInvalid[V] =$ FALSE
  $AbsentInvalid[V] =$ FALSE
  $AbsentValid[V] =$ FALSE
for all $R \in SubmittedRequests$ **do**
  for all $V \in Variables$ **do**
    if R.isValid() **then**
      if R.includes(V) **then**
        $PresentValid[V] =$ TRUE
      else
        $AbsentValid[V] =$ TRUE
    else
      if R.includes(V) **then**
        $PresentInvalid[V] =$ TRUE
      else
        $AbsentInvalid[V] =$ TRUE
for all $V \in Variables$ **do**
  if $PresentValid[V] \wedge \neg AbsentValid[V] \wedge AbsentInvalid[V]$ **then**
    V is MANDATORY
  else if $AbsentValid[V] \wedge \neg PresentValid[V] \wedge PresentInvalid[V]$ **then**
    V is MANDATORILY-ABSENT
  else if $PresentValid[V] \wedge AbsentValid[V]$ **then**
    V is OPTIONAL

Although an interface variable should either be mandatory or optional, our inferences also identify a third type of variable that we call mandatorily absent. We define a mandatorily absent variable as one that should never be in a valid request. Finding a mandatorily absent variable implies the presence of an anomaly, since it is reasonable to assume that a variable present in a form should be used in a valid request under some circumstances. There are two potential reasons mandatorily absent variables may be identified: 1) the web page or web application contains a possible error (e.g., a field was left in a form but is not used anymore by the web application), and 2) additional directed requests are needed for the methodology to provide an appropriate characterization of that variable.

Algorithm 1 shows how we find mandatory, optional, and mandatorily absent variables. The algorithm identifies as mandatory any variable that appears in every valid request and that is absent in at least one invalid request. The algorithm identifies as optional any variable that appears in at least one valid request and is absent in at least one valid request. The algorithm identifies as mandatorily absent any variable that is absent in every valid request, but appears in at least one invalid request.

Table 1 illustrates the operation of the algorithm on *InfoSpace*, a web application utilized to locate businesses or people. The form in the page generated by the application has just three main fields (name, city, and state) and we have arbitrarily chosen a sequence of requests that quickly illustrates the application of the algorithm. (As we shall see, usage of the algorithm on web applications with more variables may require thousands of requests to converge.) The algorithm identifies name and state as mandatory, and city as optional. Observe that the algorithm is sound but not precise when reporting optional variables. That is, a variable identified as optional by the algorithm, is optional in the web application interface. However, optional variables may be temporarily identified as mandatory until a valid request without that variable is submitted (e.g., in Table 1: city before the fourth request).

3.1.2 Variable Implication

Sometimes the presence of a variable requires other variables to be present in order to construct a valid request. Identifying such relationships is useful for understanding the impact of application changes on such dependencies, or to avoid sending incomplete requests to the application.

To investigate this type of relationship, we began by defining the notion of implication as a conditional relationship between variables p and q as: if p is present, then q must be present. After examining existing implications on many sites we decided to expand our attention to implications in which the right hand side is in *disjunctive normal form* and does not contain negations or the constant TRUE. This guarantees that our implications are satisfiable but not tautological, and it simplifies the construction of requests that do not satisfy a target implication (which will be useful for re-

Request	$address$	$city$	$state$	zip	Response	Implication	At least one-of
1	absent	absent	present	absent	Valid	$address \implies$ FALSE	TRUE $\implies state$
2	absent	absent	absent	present	Valid	$address \implies$ FALSE	TRUE $\implies state \vee zip$
3	present	absent	absent	present	Valid	$address \implies zip$	TRUE $\implies state \vee zip$
4	present	present	present	absent	Valid	$address \implies zip \vee (city \wedge state)$	TRUE $\implies state \vee zip$
5	present	present	present	present	Valid	$address \implies zip \vee (city \wedge state)$	TRUE $\implies state \vee zip$

Table 2: MapQuest requests and variable implications

quest selection). Further, this type of implication is relatively simple to understand because it can easily be mapped to the expected variables' behavior.

Algorithm 2 explains how we find various types of implications. The algorithm focuses on the implications between optional variables (implications involving mandatory variables would be of little value because they would just be added to the right side of every implication). The algorithm begins by initializing the set *Implications*. In the initial case, the initialization is performed according to Algorithm 3, one implication per optional variable. Then, it iterates through all valid requests, extending each implication with an additional clause (an and'ing of all optional variables in the request) every time the implication is not satisfied by a request. Note that to generate the most general implications, the iterations through the requests progress from those with the fewest variables to those with the most variables.

Algorithm 2 Inferring Variable Implications

```
1: Implications = Init-Implications()
2: Sort requests in SubmittedRequests from smallest to largest
3: for all R ∈ SubmittedRequests do
4:    if R.isValid() then
5:       for all I ∈ Implications do
6:          if ¬I.satisfiedBy(R) then
7:             I.appendClause(R)
```

Algorithm 3 Init-Implications (standard implications)

```
1: Implications = {}
2: for all V ∈ Variables do
3:    if V is optional then
4:       Add implication V ⟹ FALSE to Implications
5: return Implications
```

Algorithm 4 Init-Implications (at least one of)

```
1: return {TRUE ⟹ FALSE}
```

To illustrate how the algorithm works, consider the set of valid requests to MapQuest shown in Table 2, and the inferred implications in the seventh column. MapQuest offers several fields including an address, city, state, and zipcode, each of them optional. For each optional variable v, the starting implication is $v \implies$ FALSE (to keep the table content simple we consider only implications with $address$ on the left-hand side.) The first and second requests in the table do not include variable $address$, therefore the implication $address \implies$ FALSE is satisfied, and nothing needs to be changed. The third request in the table includes $address$, therefore $address \implies$ FALSE is not satisfied, and the implication is updated by adding another clause and'ing all of the other optional variables that are present in the request, in this case zip. For request 4, the implication $address \implies zip$ is false, and needs to be updated by adding the clause $city \wedge state$. For request 5, the implication is satisfied and no further updating is necessary. The algorithm ends up reporting that including a street address requires the user to include either a zip code or a city and state in order for the request to generate a valid response. Note that if we had discovered a request in which $address$ was the only optional variable present, this would have caused the $address$ implication to be removed from the set of implications.

Another type of useful inference that can be obtained through the same algorithm is "at least one of". This is a special case of implication of the form TRUE $\implies$ ..., and can be generated using the same method used for implication, only changing Init-Implications to Algorithm 4. The eighth column of Table 2 provides an example of such an occurrence in MapQuest where either state or zipcode must be selected in order for a request to be valid.

3.1.3 *Value-based extensions*

The previous algorithms have focused on inferences related to the presence or absence of variables, with no attention paid to variable values. Just as the characterization of presence or absence of variables could help maintainers and developers of web applications, so could characterization involving values.

For example, if no requests involving a text variable with a user-provided value generate valid responses, then additional suitable values may be required for a proper characterization. Considering values may also be useful for finding faults associated with variables whose values have been predefined through pull-down, radio-button or checkbox fields. For example, if one field has a value that always produces an invalid request, there is likely a fault in the form (a value in the form that should not be there) or the web application (failure to consider a possible value from the form).

Our algorithms for value-based extensions build on Algorithms 1 and 2. Algorithm 5 presents an extension that infers what ranges of values for a particular variable can be used to generate a valid request. This algorithm keeps track of the values that appear in requests (distinguishing between those that appear in valid or invalid requests). It then reports a list of values that appeared in valid requests for each variable. To reduce the number of falsely reported value-based inferences, this algorithm reports an inference for a variable only after all possible values (values included in the request pool) for that variable have been used at least once. The objective is to observe enough values for a variable before determining what values constitute its valid range. Table 3 illustrates the operation of the algorithm on the $children$ variable from Travelocity (all other variables are assumed to be set to reasonable constant values for all requests).

Algorithm 5 Inferring Relationships Involving Values

```
1: for all V ∈ Variables do
2:    ValidValues[V] = {}
3:    InvalidValues[V] = {}
4: for all R ∈ SubmittedRequests do
5:    for all V ∈ Variables do
6:       if R.isValid() and R.includes(V) then
7:          Add R.valueOf(V) to ValidValues[V]
8:       else if R.includes(V) then
9:          Add R.valueOf(V) to InvalidValues[V]
10: for all V ∈ Variables do
11:    if ValidValues[V] ∪ InvalidValues[V] = V.allValues()
       then
12:       ValidValues[V] appear in valid requests
```

Request	$children$	Response	$ValidValues$	$InvalidValues$	Value-Implication
1	null	Valid	$\{\}$	$\{\}$	
2	0	Valid	$\{0\}$	$\{\}$	
3	1	Invalid	$\{0\}$	$\{1\}$	
4	2	Invalid	$\{0\}$	$\{1,2\}$	
5	3	Invalid	$\{0\}$	$\{1,2,3\}$	Children ϵ $\{0\}$

Table 3: Requests and value-based occurrences for the variable $children$ in Travelocity.

Request	$adults$	$seniors$	Response	Implication
Init-Implications				$(adults = 0) \implies$ FALSE, $(adults = 1) \implies$ FALSE, $(seniors = 0) \implies$ FALSE , $(seniors = 1) \implies$ FALSE
1	1	null	Valid	$(adults = 0) \implies$ FALSE, $(seniors = 0) \implies$ FALSE , $(seniors = 1) \implies$ FALSE
2	null	1	Valid	$(adults = 0) \implies$ FALSE, $(seniors = 0) \implies$ FALSE
3	0	1	Valid	$(adults = 0) \implies seniors$, $(seniors = 0) \implies$ FALSE
4	1	0	Valid	$(adults = 0) \implies seniors$, $(seniors = 0) \implies adults$
5	1	1	Valid	$(adults = 0) \implies seniors$, $(seniors = 0) \implies adults$

Table 4: Requests and value-based implications for $adults$ and $seniors$ on Travelocity.

Algorithm 6 Init-Implications (value based implications)

```
1: Implications = {}
2: for all V ∈ Variables do
3:     for all a ∈ V.allValues() do
4:         Add (V = a) ⟹ FALSE to Implications
5: return Implications
```

Similarly, we extended the implication algorithm. Our extension (Algorithm 6), simply alters Init-Implications to include implications of the form $(V = a) \implies$ FALSE for each variable V and possible value a. Our approach is motivated in part by the frequency with which web pages use radio buttons to determine which other fields might be required in a request. For example, payment forms often have radio buttons to select different payment types, and these payment types have different dependent variables (e.g., card number). We intend to discover this type of implication.

Table 4 illustrates the operation of the algorithm on the $adults$ and $seniors$ variables with possible values 0 and 1 on Travelocity (all other variables are assumed to be held constant at reasonable values). Because the invalid requests have no effect on the implications we consider only valid requests. Request 1 removes the implication with $adults = 1$, because it is alone in the request. Request 2 removes the implication with $seniors = 1$. Request 3 updates the $adults = 0$ implication to include $seniors$ on the right side. Similarly, request 4 updates the $seniors = 0$ implication to include $adults$. Finally, both implications are satisfied by request 9, so they do not need to be updated.

3.2 The Request Selector

As mentioned earlier, one of the fundamental challenges for characterizing a web application through directed requests is to control the number of requests. Larger numbers of requests imply larger amounts of time required to collect request-response data (for Expedia, one of the objects of our studies in Section 4, each request took about 30 seconds) and this slows down the inferencing process. In addition, sites may not be amenable to responding to a large number of requests (for Expedia we received a warning email stating that they suspected we were launching a denial of service attack against their web site).

To address this problem, the *Request Selector* can either select a sample of requests from the pool up-front, or it can operate incrementally by selecting a request based on previous results and continue selecting requests until the user is satisfied or no longer wishes to continue refining the inference set. We have devised two request selection approaches. The first approach simply selects a set of random requests from the pool of requests without repetition.

The second approach is incremental, selecting requests based on the requests already submitted and the inferences already derived. Algorithm 7 shows how we calculate an award value for each unsubmitted request, and choose the request with the highest award value. The award value is computed based on the potential impact of each unsubmitted request on each of the inferences, inversely weighted by the stability of each inference.

Algorithm 7 Inference-based Request Selection

```
1: for all R ∈ UnsubmittedRequests do
2:     for all I ∈ Inferences do
3:         R.Award = R.Award + I.Impact(R)/I.Stability()
4: Select R with highest award value
   Break ties randomly
```

Algorithm 8 presents the process for determining whether a request impacts an inference. For each of the inferences derived, depending on its type, we check whether the difference between the request being evaluated and any valid submitted request meet the specified criterion (e.g., for mandatory variables the criterion is that the request is the same as a valid request except that the mandatory variable is absent). If the request meets the criterion, then Impact returns 1, otherwise it returns 0.

The criteria are defined to find requests that are similar to submitted valid requests and that, if valid, will cause the inference to be updated. There are two reasons for this. First, the inferences we have considered to date can only be modified by valid requests. Second, we conjecture that a request that is similar to a previously made valid request is more likely to be valid. (Note that no criterion was specified for the "Optional V" type inference because this type of inference is immutable).

Algorithm 8 I.Impact(R)

```
1: Valid = all submitted valid requests
2: if I.type = "Mandatory V" then
3:    if ∃R_v ∈ Valid | R ∼ R_v except ¬R.includes(V) then
4:       return 1
5: else if I.type = "Mandatorily Absent V" then
6:    if ∃R_v ∈ Valid | R ∼ R_v except R.includes(V) then
7:       return 1
8: else if I.type = "V has Values" then
9:    if ∃R_v ∈ Valid | R ∼ R_v except ¬R.valueOf(V)
      ∉ Values then
10:      return 1
11: else if I.type = "V_1 ⟹ (V_2 ∧ V_3) ∨ V_4" then
12:   if ∃R_v ∈ Valid | R ∼ R_v except ¬R_v.includes(V_1)
      ∧R.includes(V_1) then
13:      return 1
14:   else if ∃R_v ∈ Valid | R ∼ R_v except R_v.includes(V_1)
      ∧R.includes(V_1) ∧R does not include one variable from
      each clause in the implication then
15:      return 1
16: else if I.type = "(V_1 = a) ⟹ (V_2 ∧ V_3) ∨ V_4" then
17:   if ∃R_v ∈ Valid | R ∼ R_v except ¬R_v.valueOf(V_1) ≠
      a ∧ R.valueOf(V_1) = a then
18:      return 1
19:   else if ∃R_v ∈ Valid | R ∼ R_v except R_v.valueOf(V_1)
      = a ∧ R.valueOf(V_1) = a ∧ R does not include one variable
      from each clause in the implication then
20:      return 1
21: else if I.type = "(V_2 ∧ V_3) ∨ V_4" then
22:   if ∃R_v ∈ Valid | R ∼ R_v except R does not include one
      variable from each clause in the implication then
23:      return 1
24: return 0
```

Algorithm 9 I.Stability()

```
1: stability = 0
2: for all R ∈ SubmittedRequests do
3:    if R changed I then
4:       stability = 0
5:    else
6:       stability + +
7: return stability
```

Algorithm 9 shows how the stability of each inference is computed. This algorithm gives a higher weight to inferences that are still evolving and may benefit from additional requests in order to converge, and penalizes inferences that have been stable in the presence of recently submitted requests.

4. EMPIRICAL EVALUATION

The goal of our study is to assess whether the proposed methodology can effectively and efficiently characterize real web sites. In particular, we wish to answer the following research questions:

RQ1: What is the effectiveness of the characterization? We would like our characterization to include all the potential valid inferences (of the types specified by the algorithms in Section 3.1) that can be extracted from the responses collected from a web application. We would also like the characterization to include just the inferences that truly characterize a web application.

RQ2: What is the tradeoff between effectiveness and efficiency? Our inferencing algorithms are conservative in that they will not discard an inference unless there is data to reject it (we will validate this conjecture by addressing RQ1). This conservative approach may result in false inferences being reported when only a subset of the requests are submitted and analyzed. A limited request data set may also hinder the inferences we can derive. We wish to explore the effect of request *selection* strategies, aimed at increasing efficiency, on the methodology effectiveness.

4.1 Objects of Analysis

Our objects of analysis (see Table 5) are five popular applications we utilized in previous studies [4] and that are all among the top-40 performers on the web [10]. Expedia and Travelocity are flight travel booking applications, YahooMaps provides driving directions, Infospace is used to search white pages for location information on people and businesses, and MapQuest is used for map lookup.

Table 5 lists the numbers of variables identified by the *Page Analyzer* on the main page produced by each of our target web applications, at the time of this analysis, and the numbers of those that we used for our analysis. Note that for Expedia and Travelocity, we considered only nine of their variables in order to reduce the number of generated requests necessary to obtain the complete data set required by our study (even with such a reduction, we had to make almost 50000 requests to these two sites).

Object	Relevant variables identified *by Page Analyzer*			Variables considered for analysis
	Text Box	List Box	Check & Radio	
Expedia	4	5	2	9
InfoSpace	2	1	0	3
MapQuest	4	0	0	4
Travelocity	4	7	1	9
YahooMaps	4	4	0	8

Table 5: Objects of study.

4.2 Variables and Measures

Our study requires us to apply our inferencing algorithms on a collected data set of requests and responses to characterize the objects of study. Throughout the study we utilize two request selection proceduces, Random and Inference-Guided.

To quantify effectiveness we compute the recall and precision of the characterization generated by the inferencing algorithms on the objects of study. A recall percentage of 100% indicates that all true inferences that characterize an application were reported by the algorithms (this might include false positives). A precision of 100% indicates that all reported inferences are indeed valid (no false positives). Let $ReportedInf$ be the number of inferences reported, let $ReportedCorrectInf$ be the number of correct inferences reported, and let $TotalCorrectInf$ be the total number of correct inferences derivable from the pool of requests, we define recall and precision as follows:

$$Recall = ReportedCorrectInf/TotalCorrectInf;$$
$$Precision = ReportedCorrectInf/ReportedInf;$$

We defined the correct inferences as the set of inferences, of the types specified in Section 3.1, that are derived when the complete pool of requests is submitted. $TotalCorrectInf$ is the cardinality of that set.

4.3 Design and Setup

We applied the WebAppSleuth methodology to each of the objects of study. Three particular steps in this process require additional detail.

First, the *Request Generator* utilized all available potential values for each variable (including the null value which indicates that the variable is not present in a request). We used predefined values when possible. For example, for Expedia, we used the values associated with the drop-down box to select the number of "Adults" traveling. For the variables associated with $text$ type fields that

Object	Request Pool Size	Criteria for Valid And Invalid
Expedia	49996	Valid: Available flights are displayed Invalid: More information is requested
InfoSpace	208	Valid: Location information displayed Invalid: Erroneous inputs indicated
MapQuest	16	Valid: Map returned Invalid: No map was returned
Travelocity	49996	Valid: Available flights are displayed Invalid: More information is requested
YahooMaps	256	Valid: Map returned Invalid: No map was returned

Table 6: Request pool size and classification criteria.

have no predefined values, we provided a set of potential values that can be involved in a request that would generate a valid response. For example, for Expedia we provided values for "departing from" and "going to". The second column of Table 6 lists the generated pool size for each of the sites.

Second, since we do not have a specification for each web site's expected behavior, we had to create one so that the *Response Classifier* could determine whether a response was valid or invalid. The third column of Table 6 lists the criteria utilized to make such determination. Once the determination criteria was created for a given web application, we automated the classification process by searching for the specified criteria in the returned response files.

Third, although the methodology is basically a sequential process (with a loop in case of incremental request selection), we investigated the methodology through a slightly different approach. To expedite the exploration of several alternative request selection mechanisms and inference algorithms (without making the same set of requests multiple times), we performed all the requests in the pool at once, and then simulated the application of the different mechanisms and algorithms. We performed this simulation 100 times with each type of *Request Selector* to control for the randomness factor in the selection algorithms.

4.4 Results

We present the results in two steps. First, we show the characterization provided by the methodology for each target web application when the entire pool of requests is utilized. Second, we analyze how the characterization progresses as the requests are submitted and analyzed, utilizing two different request selection mechanisms.

4.4.1 RQ1: Effectiveness of the characterization

Table 7 presents the inferences derived from the requests we made and the responses provided by each of the target applications, grouped according to the types defined in Section 3.1. In Expedia and Travelocity, six variables - $depCity$ (departure city), $arrCity$ (arrival city), $depDate$ (departure date), $retDate$ (return date), $depTime$ (departure time) and $retTime$ (return time) - were identified as mandatory. Indeed, these sites do not provide any flight information unless those fields have been completed. Three variables were optional - $adults$, $seniors$ and $children$ - for both Expedia and Travelocity, which means that their absence did not preclude us from obtaining a valid response from the application.

Both sites also included an "at least one of" inference since either $adults$ or $seniors$ were present in all of the valid requests. Note that this inference is not true in practice since flight information can be obtained when the $children$ variable is present and $adults$ and $seniors$ are absent in a request. However, the available requests

Website	Inferences
Expedia	**Mandatory Variables**: $depCity$, $arrCity$,$depDate$,$retDate$, $depTime$, $retTime$ **Optional Variables**: $adults$, $seniors$, $children$ **At Least One Of**: ($adults \vee seniors$) **Values**: $children \in \{0\}$
InfoSpace	**Mandatory Variables**: $name$, $state$ **Optional Variable**: $city$
MapQuest	**Optional Variables**: $address$, $city$, $state$, zip **At Least One Of**: ($state \vee zip$) **Implications**: $address \implies zip \vee (city \wedge state)$
Travelocity	**All inferences from Expedia** **Value Based Implications**: $(adults = 0) \implies seniors$ $(seniors = 0) \implies adults$
YahooMaps	**Mandatory Variables**: $startCSZ$, $endCSZ$ **Optional Variables**: $startLoc$, $endLoc$, $startAddr$, $endAddr$, $startCountry$, $endCountry$

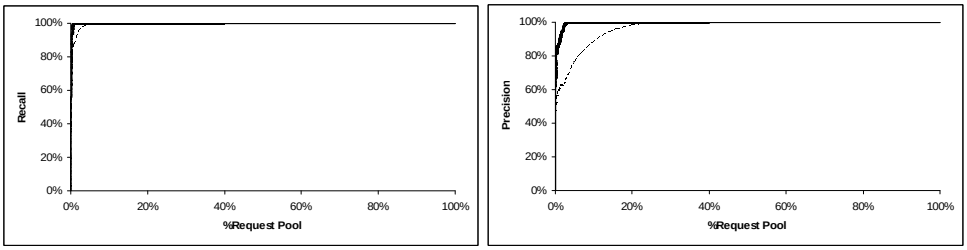
Table 7: Inferences found for each web application

in the pool were insufficient to falsify this inference (our requests including the $children$ variable failed because we did not consider the variable age that is required when $children$ is present). This is the same reason we obtained the inference $children \in \{0\}$. These inferences, although correct within the limitations of the pool of collected data, are an indicator that further requests are needed to provide a more accurate characterization of the site.

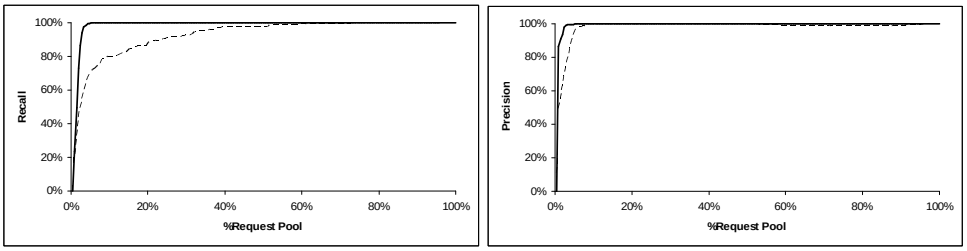
In spite of their similarities, we found an interesting difference between Expedia and Travelocity regarding two additional value-based implications. In Travelocity, if $adults = 0$, then the variable $seniors$ is present, and if $seniors = 0$, then the variable $adults$ must be present. In practice, not having these two inferences implies that Expedia provided flight information even when no passengers were specified. Since flight finding is the first step in Expedia's booking process, and this behavior has been revised in Expedia since our data was collected, this inference is likely to indicate a bug in the earlier version of Expedia.

For InfoSpace and YahooMaps our characterization resulted in the identification of optional and mandatory variables. All valid responses from these web applications included two variables, which led to their classification as mandatory. In the case of YahooMaps, however, the mandatory variables $startCZS$ and $endCZS$ include $city$ and $state$ or zip information within the same text field. This clearly limits the inferences that we can make on the application since it compounds several types of input into one field.

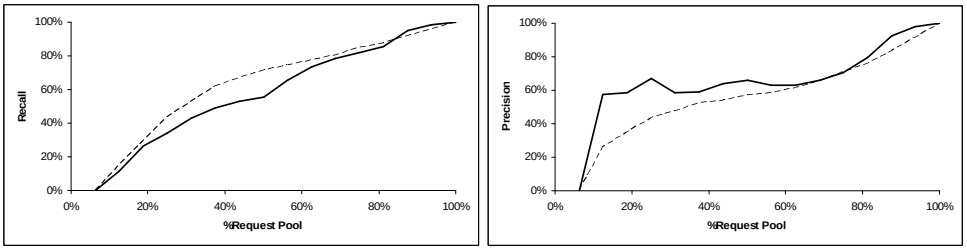
Last, MapQuest was unique in that we did not identify any mandatory variables in it. This application can provide a valid response through the utilization of many variable combinations as long as it includes either zip or $state$. In addition, we found that if $address$ was present and zip was absent then $city$ was required to obtain a valid response.



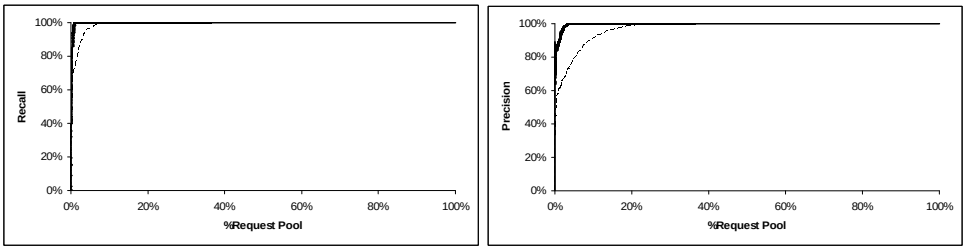
(a) Expedia



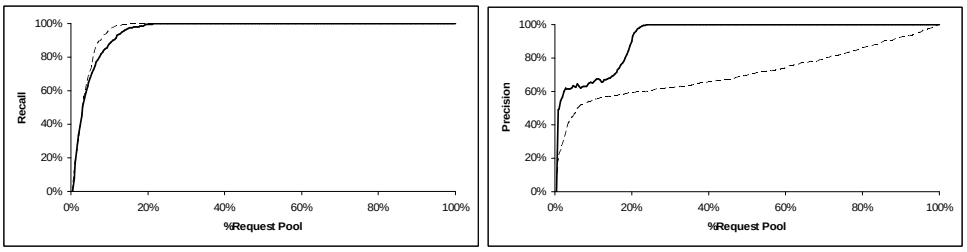
(b) InfoSpace



(c) MapQuest



(d) Travelocity



(e) YahooMaps

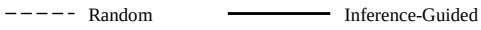
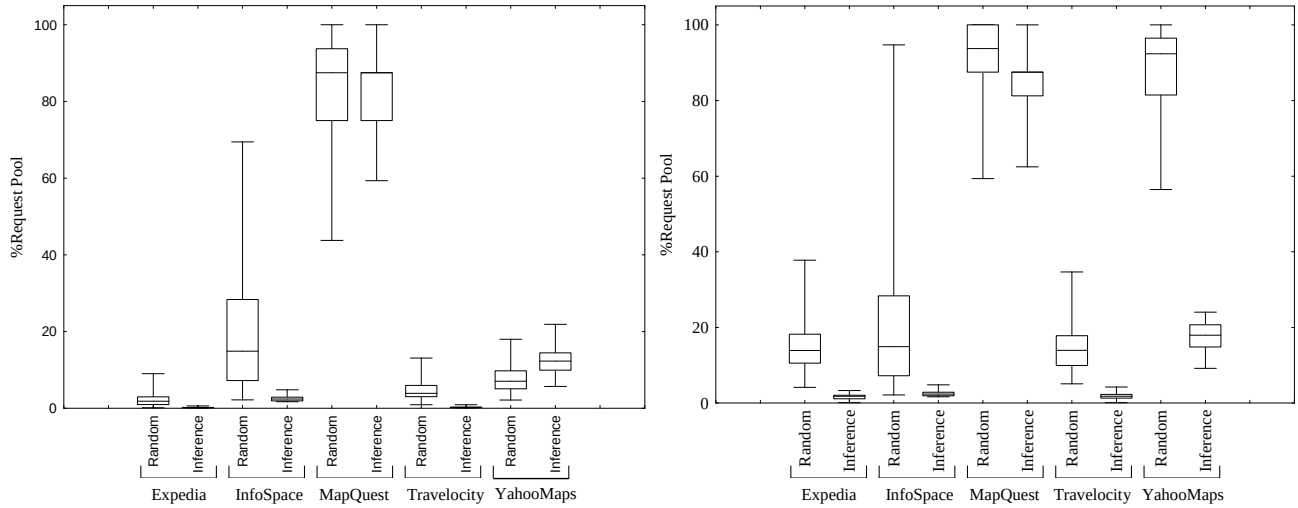


Figure 3: Recall and Precision vs percent of Requests Submitted



(a) Recall (b) Precision

Figure 4: Variation Across Runs for Recall and Precision

4.4.2 RQ2: Effects of Request Selection

Figure 3 presents our results for each of the web applications with respect to both Inference-Guided and Random request selection techniques. In each of the graphs, the x-axis represents the percentage of requests selected from the pool, and the y-axis represents the average recall or precision over the 100 runs.

For three of the five objects of study (Expedia, InfoSpace, and Travelocity), Inference-Guided request selection had equal or better average recall than Random request selection regardless of the number of requests selected (left-side graphs in Figure 3). Of the other two, MapQuest was such a small example (only 16 requests) that request selection is of little help with it at all (for both Random and Inference-Guided selection it could take up to all of the requests to achieve 100% recall). On the other hand, YahooMaps had a larger request pool but it had only one value supplied for each input (all the others had at least one input with multiple values) and most of its inferences were about optional variables.

For all of the web applications, Inference-Guided request selection had equal or better average precision than Random request selection throughout the request selection process (right-side graphs in Figure 3). One of the most noticeable improvements is for YahooMaps where the Inference-Guided selection seems to zero-in on the useful requests more quickly.

These results are encouraging because they show that we can dramatically reduce the number of requests required, while still reporting most correct inferences and few incorrect inferences. In particular, for the two applications with approximately 50000 requests in the pool (Expedia and Travelocity) we need fewer than 2500 requests (5% of the pool) to achieve 100% recall and precision with the Inference-Guided request selection, and 18121 requests (36% of the pool) with Random request selection.

We now explore in greater detail the percentage of requests required by both the Random and the Inference-Guided selection to reach 100% recall and precision for all the web applications. Figure 4 presents box-plots on the percentage of requests required to reach 100% recall and precision. Although the overall tendencies per application remain consistent with the previous observations, Figure 4 shows that the worst case performance for Inference-Guided selection to reach 100% recall and precision for Expedia, InfoSpace and Travelocity is comparable to the best performance of the Random approach. Also, the variation across the 100 simulated runs for the Random selection algorithm is constantly greater than the Inference-Guided selection, indicating that the performance of Inference-Guided is more consistent.

5. RELATED WORK

There has been a great deal of work to help identify deficiencies in web sites such as broken structures, bottlenecks, non-compliance with usability or accessibility guidelines, or security concerns, to provide information on users's access patterns, and to support testing of web applications [2, 5, 6, 13, 12, 16, 17, 18]. Among these tools, our request generation approach resembles the approach used by load testing tools, except that our goal is not to investigate the web application's responses to extreme loads, but rather to generate a broad range of requests that help us characterize the variables in the web application interface. There are also tools that automatically populate forms by identifying known keywords and their association with a list of potential values (e.g., zipcode has a defined set of possible values, all with five characters). This approach is simple but often produces incorrect or incomplete requests, so we refrained from using it in our studies to avoid biasing the inferencing process.

Our work also relates to research efforts in the area of program characterization through dynamic analysis [1, 7, 8, 9, 14, 19]. These tools provide approaches for inferring program properties based on the analysis of program runs. These approaches, however, target more traditional programs or their byproducts (e.g., traces) while our target is web application interfaces. Targeting web applications implies that the set of properties of interest to us are different, that the total number of variables to consider simultaneously to make even the simplest of inferences can be enormous, and that we are making inferences on the program interface instead of on the program internals. The most far-reaching difference between our approach and existing inference approaches, however, is that our approach integrates the dynamic analysis and inferencing procedure with the generation of inputs (requests), to accelerate the convergence toward a set of valid inferences.

These differences aside, we did explore the application of one inferencing tool, Daikon [7], to a targeted subset of Expedia vari-

ables, and we did discover some interesting invariants such as: $retDate \geq depDate$, $depDate > requestDate$ and $retDate > requestDate$. We were also able to identify mandatory and optional variables and the range of valid values for the $children$ variable. Applying Daikon in this context, however, required several adaptations of the problem and transformations of the data. First, with the original pool of requests, the only inferences Daikon was able to make were for mandatory and optional variables and the range of valid values for $children$. We then collected an additional 1296 requests to explore the relationships between the date and time variables. Second, we needed to find ways to separately map valid and invalid requests to some form that Daikon could differentiate. Tools such as Daikon are designed to characterize all behaviors of the application of interest without discriminating between correct and faulty outcomes. This makes the mapping of our context to Daikon's approach difficult, and limits the opportunities for making inferences that take into account both valid and invalid requests. Finally, Daikon requires type information for each variable, to determine the invariants to be generated. This implies that either the user must specify (perhaps erroneously, particularly in the case of end user programmers) type information for each variable, or that additional inference steps be taken to estimate variables' types.

6. CONCLUSION

We have presented and quantified what we believe to be the first methodology for semi-automatically characterizing web application interfaces. This methodology directs requests to exercise a web application, and analyzes the responses to make inferences about the variables and variable relationships that must be considered to obtain a valid response when constructing a request to the application. As part of the methodology we have introduced an inference guided mechanism for directing requests more efficiently. Further, the results of an empirical study of five popular web applications indicate that, given a rich enough pool of requests, the methodology can effectively derive interesting inferences with an affordable number of requests.

These results suggest several directions for future work. First, further studies are needed to determine the usefulness and scalability of the methodology. To that end, we will conduct similar studies targeting a larger number of applications and building richer request pools. Also, we will target web applications on which we have some degree of control such that we can assess the methodology's potential in-vivo. Such assessments will also provide insights into how best to incorporate the methodology into existing web programming and authoring environments.

Second, we will develop further support for the non-fully automated steps of the methodology. For example, we currently solicit a classification criterion to distinguish valid from invalid responses. When invalid responses are not uniquely identifiable, this task can become cumbersome and fault prone. We are exploring the use of clustering devices with which to, for example, solicit user participation only when the response cannot be automatically classified.

Finally, we will explore additional families of inferences. This exploration will consider types of inferences that are not currently present in our library (e.g., inferences involving temporal relationships), and also the application of existing inferences to other elements on the site (e.g., labels associated with the fields) and on the application (e.g., inferences on sequences of requests).

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