Inferring UI Patterns with Inductive Logic Programming

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Abstract—This paper presents an approach to infer UI patterns
dominant in a web application. This reverse engineering process
is performed in two steps. First, execution traces are collected
domestic concerns. Second, the
existing UI patterns within those traces are identified using
Machine Learning inference with the Aleph ILP system. The
paper describes and illustrates the proposed methodology on a
case study over the Amazon web site.

Keywords—Reverse Engineering, Inductive Logic Programming,
Web Application, UI Patterns

I. INTRODUCTION

In the past years, the usage of web applications has been
steadily increasing. This is due to the fact that they are now
capable of handling tasks that were before performed only by
desktop applications. Web applications design and testing are
becoming a major concern, but their lack of standards and
conventions is making development and deployment more
complicated [9].

Some user interface (UI) patterns exist to provide end users
a sense of easiness when using web applications. The time
users are willing to take to learn how a web application works
is very short. Users like conventions and patterns. The less they
have to think how to get the information they need, the better
[14]. UI patterns are recurring solutions that solve common
design problems. They can be commonly found in web
applications. The login form is a good example of it: it
provides a simple way for the user to access his account and
personal data. In the majority of web applications, a login form
is composed by a username, a cyperehed text box for the
password, and a button to trigger the validation of the data.
When this UI pattern is within a web application, the user can
costumedly infer how it is supposed to be used and what is
its functionality. In addition, it is also possible to define
specific techniques to discover UI patterns in existing software
systems to extract behaviour models that may be useful in
several contexts, like software maintenance [17] and
model-based testing [13] [26]. This paper presents an approach
to identify UI patterns from web applications in two steps.

First, execution traces are collected from a dynamic reverse
engineering approach. Second, the traces are input to an ILP
(Inductive Logic Programming) system to infer the UI patterns.

The goal of an ILP system is to construct first-order definite
tabular theories [21] or rules, from examples and background
knowledge. The background knowledge contains all the
necessary predicates encoding the relevant information to infer
the rules from the examples. The examples can be positive
(instances of the target concept) or negative (non-instances of
the target concept, but “close” to the positive examples).

The rest of the paper is structured as follows. Section II
addresses the related work, as well as the tools available to
perform the needed tasks. Section III describes how the system
was implemented. Section IV provides a practical example of
the system proposed. Section V provides the conclusions,
reports some of the problems found and points out the future
work.

II. STATE OF THE ART

Reverse engineering is “the process of analysing the subject
system to, identify the system’s components and
interrelationships and to create representations of the system
in another form or at a higher level of abstraction” [5]. In
reverse engineering, the subject system is not changed. There
are different methods of applying reverse engineering to a
system: the dynamic method, in which the data are retrieved
from the system at run time without access to the source code,
the static method, which obtains the data from the system’s
source code, and the hybrid method, which combines the two
previous methods.

There are many possible approaches to obtain information
from application’s execution traces [4] [31]. Taniguchi [32] has
developed a tool to construct sequence diagrams using dynamic
analysis on JAVA programs. Duarte [10] combined static and
dynamic information to construct behaviour models that can be
used for model checking. Fischer [11] used extraction traces for
tracing the evolution of a software system. Morgado [20]
created a tool to reduce the effort of obtaining models of the
structure and behaviour of Graphical User Interfaces (GUI)
Internet Applications (RIAs) that generates test cases from the applications' execution traces.

Several tools have been created to obtain information from web applications. ReWeb [28] obtains dynamic information from web server logs that helps to find structural and navigational problems in web applications. WARE [27] is a static analyser that creates UML diagrams from the web application source code. Crawjax [29] is a tool that obtains graphical sitemaps, by automatically crawling through a web application and Selenium [15] is an open-source capture-replay tool that saves the users interaction in HTML files.

There also some examples in the literature that use ILP systems in the context of reverse engineering [1] [6] [18]. Cohen [7] uses ILP to recover software specifications from a real-world software system. Flach [12] applies ILP to learn integrity constraints from databases.

There are a significant number of ILP systems available on the Web, such as Progol [22], Golem [23] and Aleph [8]. When an ILP system learns from both types of examples it searches for consistent hypotheses (hypotheses that cover all the positives and none of the negative ones). This is known as predictive induction, and it is commonly used at solving classification and prediction tasks. Descriptive induction uses only positive examples to find the hypotheses. In this type of induction, used to discover regularities or uncovering patterns, there are no negative examples as all the data provided to the ILP can be valid [16].

Since ILP can accept almost any kind of information, as background knowledge, to construct its models and both models and data are described in a very expressive language [24], the number of domains where the use of ILP systems can be advantageous to is quite large. The background knowledge of an ILP system can encode data with structure and can handle numerical computations together with relations. However, for complex applications, ILP systems can become very slow, especially if used for predictive induction.

In this work the Aleph ILP system was used. As typical in predictive ILP systems, Aleph transforms the induction process into a search through an order hypothesis space. In the experimental part of this work, Aleph performs a top-down search of the hypothesis space starting with the most general hypothesis and moving towards the more specific ones. The result of this search is the best hypothesis. If not all positive examples are covered in this search then Aleph removes the ones covered and performs another search using the remaining examples.

This work uses ILP to identify existing UI patterns within a set of execution traces extracted by a dynamic reverse engineering process.

### III. THE METHODOLOGY

The approach described in this paper uses a dynamic method to extract execution traces from which additional information is inferred. An execution trace is the sequence of user actions executed during the interaction with a software system, such as clicks, text inputs and also some information of the system state (e.g., the information that is being displayed).

The execution traces collected are then input to an ILP system for identifying information about the existing UI patterns (from a pre-defined catalogue).

As explained in Section I, the ILP system needs examples and background knowledge to infer rules. In the presented application, the background knowledge has two parts. A first part that is independent of the particular UI being analysed. This part is composed by a set of definitions of UI patterns and some auxiliary/general purpose predicates, all of which are encoded in Prolog. This will allow the ILP system Aleph to be applicable in a wide range of UIs. The second part of the background knowledge is composed by the specific traces. This part is therefore case specific. Finally all traces are encoded as the (positive) examples.

The execution traces are captured using Selenium IDE [22]. While the user navigates through a web application, this capture-replay tool is used to record his steps, such as the text inserted in a specified text box or the ID of a clicked button. Each trace generates a HTML table, such as the one seen in Table 1.

| TRACE1 | 
|---|---|---|
| open | /account/login.php | pbgt |
| type | name=| form_loginname | pbgt |
| type | id= | remember_usernamepwd | pbgt_pass |
| clickAndWait | name=login |  |
| clickAndWait | css=| button[type="button"] |  |
| click | link=Me |  |
| clickAndWait | link=Log Out |  |

The data used by Aleph is encoded in Prolog. As such, a parser was developed to convert the extracted interaction traces (Table 1) to a Prolog structure. An execution trace, identified by TraceID, is a sequence of Actions (with a variable ID and the corresponding input values) and a TraceStep that identifies the position of the Action in the sequence/trace. A transition is encoded as the following:

\[
\text{transition}(\text{Action}(ID, Data), \text{TraceID}, \text{TraceStep})
\]

To code the first interaction within trace 1 regarding the introduction of the text “pbgt” in the textbox with the ID “form_loginname”, the transition would look like:

\[
\text{transition}(\text{enterText}(\text{form_loginname}, \text{pbgt}), \text{trace1}, 1)
\]

So far, four different UI patterns are available for the ILP background knowledge. The goal is to (given the execution traces) identify the patterns in the web application under analysis. The patterns are:

A. Login

The login pattern is commonly found in web applications, especially in the ones that provide specific data that only a certain user (or group) may be able to access. This pattern is encoded as an input text box for the username, a text box
with cyphered characters for the password, and a button that validates the data.

Login pattern was encoded in Aleph considering two cases: the case where both username and password are valid, and the submit action (click of the button) changes the URL page and the case where one of the parameters (or both) is invalid, and the submit action causes an error message to appear.

B. Search

The search UI pattern consists of an input text box, where the user types the content he wants to search for, and a button, that will send the query to the server. The result of the search is shown in a new page.

C. Sort

The sort pattern consists of a set of buttons that organizes a list of data, both in ascending and descending order. This pattern is commonly present in e-commerce applications, where the user can sort the products by different variables such as name and price. At this stage of the research work, the Sort pattern is encoded in a way that only the execution traces containing both of the ordering options (ascending and descending) are considered to be valid sort patterns.

D. Master Detail

The master detail pattern is present when selecting an element from a set results in filtering/updating another related set accordingly. For example, consider a web application where you can select a course from a set and according to that, the web application shows the students enrolled in that course. To infer this pattern, Aleph compares the content of a UI control before and after a user interaction.

Since interaction data (for instance, the text input) is encoded within the transitions, Aleph needs to backtrack in order to access information, for instance, to compare previous with current variable values. For instance, to identify a Login pattern, Aleph needs to look for the last assigned login and with current variable values. For instance, to identify a Login order to access information, for instance, to compare previous encoded within the transitions, Aleph needs to backtrack in or invalid data. To encode the valid login pattern in Aleph, the traces do not qualify as good or bad examples, they are all searched for the UI patterns (the hypothesis). The execution provided, the Aleph system must be configured in order to test if the pair username/password is valid. Therefore, Aleph must be configured to use only positive examples with the parameter setting:

:- set(evalfn, posonly).

The “set” predicate is used to configure all of Aleph parameters. Among the most used parameters is “nodes” that limits the number of clauses Aleph constructs during the search for the best hypothesis.

Aleph [30] must also be told which predicates, from the background knowledge, to use in the construction of the hypotheses. This is achieved by the use of “determinations”:

:- determination(traceOk/1, existPatterns/2).

In this way, Aleph knows that it shall provide rules that cover the higher number of examples with the predicate “existPatterns”. This particular predicate provides a list containing all types of patterns the system recognises. Aleph will then, trace by trace, verify which patterns are present and return a list with the used ones. At the end of the execution, the rules shall reveal the UI patterns found and the steps it needed to infer each one.

IV. AN ILLUSTRATIVE EXAMPLE

The approach proposed was tested on the Amazon [3] web application. This web application was chosen due to its widespread use in the world. The first step was to collect a significant number of execution traces so Aleph could have a reasonable degree of certainty when inferring the rules.

The execution traces were captured using Selenium IDE. While most of the information was captured automatically when the user navigated through the web application, some of the information had to be manually input. Since it is unfeasible to save all the web page information (due to memory limitations) at each state, the user had to select the most relevant one to save on the execution trace. It is intended to automate the extraction of execution steps by interacting automatically with the web application and without the intervention of the user. However, for the purpose of current experiments, and to assess the feasibility of the approach, it is, for now, a manual step. After the execution traces captured, the JAVA tool converted the execution traces (15 total) to Prolog code that Aleph can interpret. An example of a trace can be seen below:

```
transition(clickButton(id=twotabsearchtextbox),trace1,1).
transition(enterTextBox(id=tabsearchbox,cds),trace1,2).
transition(clickButton(css=input.submit-input),trace1,3).
transition(changePage(link=Software),trace1,4).
transition(enterTextBox(id=tabsearchbox,office),trace1,5).
transition(changePage(link=Software),trace1,6).
transition(clickButton(id=tabsearchbox),trace1,7).
transition(enterTextBox(id=tabsearchbox,office),trace1,8).
transition(clickButton(css=input.submit-input),trace1,9).
transition(changePage(css=input.submit-input),trace1,10).
```

This trace describes two searches performed in the Amazon web site, as it can be seen in the enterTextBox transitions. Aleph then inferred the rules from the set of traces.

[Rule 1] [Pos cover = 7 Rand cover = 37] patterns(A) :-
existPatterns(A,[loginUserPass,searchPattern]).

[Rule 2] [Pos cover = 4 Rand cover = 45]
patterns(A):-
existPatterns(A,[sortPattern]).

[Rule 3] [Pos cover = 12 Rand cover = 22]
patterns(A):-
eexistPatterns(A,[searchPattern]).

The rules show that the search pattern was found in 12 of the 15 traces. This result is obvious since most of the people use Amazon to search for the products they want. The login pattern and the search pattern appear together in 7 traces. The sort pattern was found in 4 traces.

V. CONCLUSIONS

This paper proposed a new method to identify recurrent behaviour present in web applications, by identifying UI patterns.

Aleph ILP system successfully discovered the UI patterns in the execution traces obtained by navigation through the Amazon website. Aleph was configured to use only positive examples, as described in [25]. Inferring the rules proved to be time costly, since the process took 573 seconds, roughly under 10 minutes. As future work, there is the need to improve the estimation method, making it less lengthy; to continue the automation of the whole process, including the web application navigation and execution trace extraction; and to enlarge the set of UI patterns to identify.

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