Wextractor: Follow-up of the evolution of prices in web pages

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Abstract. In the e-commerce world, the follow-up of prices in detail web pages is of great interest for things like buying a product when it falls below some threshold. For doing this task, instead of bookmarking the pages and revisiting them, in this paper we propose a novel web data extraction system, called Wextractor. It consists of an extraction method and a web app for listing the retrieved prices. As for the final user, the main feature of Wextractor is usability because (s)he only has to signal the pages of interest and our system automatically extracts the price from the page.

1 Introduction

Web users are interested in finding the price of an entity in different web sites and in following it up during a certain period of time for different purposes. For example, an user is interested in the price of a pair of shoes in different web sites with the purpose of buying them when they fall below some threshold due, for example, to discounts or special offers.

A manual solution to this problem is to bookmark the pages of interest and to revisit them again and again until the desired price is found. Instead of this boring and repetitive task, we propose to use our web data extraction sytem, called Wextractor, which consists of an extraction method and a web app for listing the retrieved prices. The extraction method takes as input the urls of the pages of interest and, upon user request, it retrieves again the price in all the pages of interest.

Our proposal for extraction fits into the automatic extraction technique as described in [11]. It is composed of two kinds of extraction methods. The first is called from scratch extraction and is applied the first time an extraction is done on a page. It consists of three steps: (1) fragmentation, (2) discarding rule application and (3) automatic pattern creation. In the first step, fragments which contain clues of the prices are found. In the next step, discarding rules previously designed are applied to the fragments. As a result, it is expected that only a fragment containing the price remains. From this fragment, in step three the price is extracted and a pattern for future extractions is obtained. The first
step is inspired in the segmentation of \text{IN} while, to the best of our knowledge, there is no proposal of discarding rules in the literature.

The second kind of extraction method is called \textit{pointing pattern extraction} and uses the pattern determined in the from scratch extraction for retrieving the price. This second method is applied the second and subsequent times an extraction is done on a page. If this extraction does not find any price, the process begins again and a from scratch extraction is applied.

The difficulty of the problem we propose strives in the fact that in the detail web pages there are usually many candidate values from which only one is a true positive and the rest are true negatives. For example, in the page of \textit{The Distant Hours} paperback book in Barnes & Noble, there is one true positive and fifty-six true negatives. Then, the question is: how to find the right discarding rules and the correct order of application so that only the true positive remains? For example, the finding of semantic discarding rules clashes with the problem of meaning. For deciding whether to eliminate a fragment, we would like to identify the concept included in the fragment and, if the concept is not appropriate, the fragment should be discarded. However, the algorithm cannot deal with the concept and only knows how to deal with expressions of the concept. The problem is that there are a great number of expressions of the same concept, so we should codify in the algorithm all the expressions of the concepts which, once found, lead to the algorithm discarding the fragment. Maybe in some special case we are able to identify all the expressions of a concept, but in general we do not know in advance all these expressions. Thus, consider we find an expression of the concept ‘discount’ in a fragment. As a consequence, the fragment must be discarded because we are interested in the concept ‘price’. However, consider the following fragments:

(a) \text{<span>19,95€</span> instead of <span>21€</span>}
(b) \text{<div>Save 1,05€</div>}

One way to identify the concept ‘discount’ is the presence of the word ‘Save’. So, fragment (b) is easily discarded but in fragment (a) it is more difficult to identify the presence of the discount concept.

The contribution of this paper is twofold:

1. We provide a novel method for extracting the prices in web pages based on the use of discarding rules (see Section 4). An analysis of the results of the method is done in Section 6.
2. As for the final user, the main feature of Wextractor is usability. (S)he only has to signal the pages of his/her interest by means of a button of a Chrome extension and to check the extracted prices in a web app (see a more complete description in Section 3). No technical knowledge or programming is required from the user.

The rest of the paper is organized as follows. Section 2 is devoted to the related work. In Section 3 we describe the problem and the solution for extracting prices from web pages. In Section 4 we explain the discarding rules. In Section 5 we detail the algorithms. In the last Sections, we deal with the experimental validation and conclusions and future work.
2 Related Work

There are a lot of works about data extraction from HTML documents and surveys about these works such as [3, 15, 5], so in this short section we can not do justice to all contributions.

We distinguish two kinds of works: commercial tools and research papers. Commercial tools like Mozenda [13], iMacros [8], Visual Web Ripper [14], Lixto [12] offer wrapper generation frameworks for recording user actions and extracting data later on based on the recorded information. In our proposal, the user does not have to install another tool for extracting data, because it is enough to install a Chrome extension.

With regard to research papers, the book [11] distinguishes three kinds of extraction: manual, wrapper induction and automatic extraction. In the first, the human programmer writes a program to extract target data. An example is [17] and its main drawback is that it does not adapt well to HTML structure changes. In the wrapper induction approach, a set of extraction rules is extracted from previously labeled pages. Some examples are [9, 16, 10]. Finally, the automatic extraction is an unsupervised approach where patterns are automatically found for data extraction. Some examples are [4, 2]. Our paper adheres to this proposal because it overcomes the two shortcomings of manual labeling effort and of costly wrapper maintenance of the wrapper induction approach.

To the best of our knowledge, the extraction of prices without programming tasks by the users is novel and there are not any other methods to compare with. Also, we have not found papers with method similar to our paper. The first phase is inspired in the segmentation of [18] while, to the best of our knowledge, there is no proposal of discarding rules in the literature. We simplify the follow-up of the price in a detail page of interest because no programming is required from the user and because we concentrate the information in the user account. The majority of papers try to extract all the information of a page. See, for example, [6].

3 The problem and our solution

We state our problem as follows:

Given a detail web page pg of an entity e with url u, extract the price of e of page pg.

An example of the problem is the query (q1): Given the web page http://www.wiggle.co.uk/asics-gel-nimbus-19-shoes/ devoted to the Asics Nimbus 19 shoes, find its price.

Note that when we say detail page, we do not mean that the page contains no other information. In fact, for example, the Asics Nimbus 19 shoes contains twelve more prices of running-related objects apart from the price of the shoes.

Let us explain our solution, the web data extraction system Wextractor. It combines a web app and our method for extracting prices. Before beginning to work, the user has a user account in the web app and a browser extension is
installed to connect with the user account. As a result, the button ‘Follow this price’ appears in the browser. When the user arrives at a page of interest, for example, the page of Asics Nimbus 19 shoes in Wiggle, (s)he clicks the button ‘Follow this price’. Then, the HTML code and the url of the page are taken and sent to the user account.

![Asics Gel-Nimbus 19 Shoes](image)

**Fig. 1.** Fragment of Asics Nimbus 19 shoes web page as of May 2017

Next, the from scratch extraction of our method starts. The fragmentation step consists of detecting fragments of HTML code which contain clues indicating the presence of prices. Examples of clues are € or $. For query (q1), nine fragments are extracted, two of them being:

(f1) `<div class="Wprice">€142.29</div>`
(f2) `<div class="saving">SAVE20%=€57.71</div>`

In the second step, discarding rules are applied to the collected fragments where a discarding rule searches for properties of the fragments which indicate that they do not contain the price of the entity e. An example of a discarding rule, called `semr1`, is ‘discard those fragments which contain the word SAVE’. (f2) is an example of a fragment discarded by the `semr1` discarding rule. After applying the discarding rules, a small number of fragments remain. From these fragments, in the third step, the target price is extracted. In the example, the fragment (f1) is the only non discarded fragment and from it the value 142.29 euros is obtained. This result is shown in the web app as in Figure 2(a).

If the user wanted to check the price of an entity again, we would have two options. One of them is to repeat a from scratch extraction again. The second one is to try to use the information of the from scratch extraction for speeding up the process. As our method relies on detecting HTML fragments and, in general, the web page structure does not change too much with time, we have chosen the second option.

Following the second option, the non-discarded fragments of the from scratch extraction are used for building a pointing pattern, that is, a regular expression that matches the price. For example, after applying the from scratch extraction in query (q1), only the fragment (f1) remains. From this fragment, the pointing pattern `pp1 Wprice">€[0-9]{2,3}\.[0-9]{1,2}` is built for subsequent extractions. It is worth noting that when a new extraction is done with this pattern, the price of 142.29 euros could have fallen below 100 euros. For this reason, the first part of the numeric pattern is `[0-9]{2,3}`, that is, prices of less than 100 euros are also matched by the pattern.
From the side of the user, the second and subsequent times (s)he wants to check the price of the entity, (s)he does not have to visit the page again. Instead of this, (s)he will enter into his/her account and (s)he will click the ‘Find again’ button. For this new extraction, the pointing pattern extraction is used for retrieving the price. For query (q1), the result of the second extraction can be seen in Figure 2(b).

Having explained our general idea, technical details and algorithms are offered in Sections 4 and 5.

### 4 Discarding rules

In this section, we present one of the main contributions of this paper, the discarding rules. Previously, we briefly define the notion of fragment.

A fragment is an HTML string which contains a price. The string is enclosed between an open and a closed HTML mark. The price is composed of a value and a clue for the price as, for example, $, EUR or €.

Basically, a discarding rule identifies a property which indicates that a fragment does not contain a price. Each discarding rule is applied to all fragments and those fragments verifying the property are marked as deleted, meaning that no right price is available inside it. For example, a discarding rule identifies fragments beginning with the element strike, so that, during the execution of the discarding rule, fragments with this property are discarded.

**Definition** A discarding rule is a Condition-Action rule which rules out fragments as containers of a possible price. Its syntax is:

\[
\text{discardingRule name (HTMLFragment f)}
\]

\[
\text{IF condition THEN action}
\]

Some examples of discarding rules, with their conditions and their meaning are shown in Table 1. There are four types of discarding rules: syntactic, semantic, frequency and threshold. Let us explain each type of rule.

#### Syntactic rules

The syntactic rules are related to the meaning of the HTML elements as well as to the meaning of the styles included in CSS files. Some syntactic rules and the rationale behind them are:

\[
\text{discardingRule syr1(HTMLFragment f)}
\]
Table 1. Some examples of discarding rules

| Name   | Condition                        | Meaning                                                                 |
|--------|----------------------------------|-------------------------------------------------------------------------|
| syr1   | `beginsWith('<strike', f)`      | The fragment f begins with the string `<strike`                          |
| syr2   | `beginsWith('<script', f)`      | The fragment f begins with the string `<script`                         |
| semr1  | `containsNear('Save', f)`       | The fragment f contains the string 'Save' near the price                |
| fr1    | `nPre(f)>=3`                     | The number of fragments with the same pre as f is greater than three    |

IF `beginsWith('<strike', f)` THEN markAsDeleted(f)
Reason for the rule: The mark strike denotes that the price is crossed-out, so it is no longer valid. It can mean, for example, an old price for the entity.

discardingRule syr2(HTMLFragment f)
IF `beginsWith('<script', f)` THEN markAsDeleted(f)
Reason of the rule: A precondition of our extraction is that the HTML page is not generated by Javascript, so, the content of the scripts is not visualized in the page.

Semantic rules The semantic rules are related to the meaning of the words contained in the fragments. An example of semantic rule is:

discardingRule semr1(HTMLFragment f)
IF `containsNear('Save', f)` THEN markAsDeleted(f)
Reason of the rule: The quantity which appears in the fragment corresponds to a discount and not to a price.

Frequency rules These are established according to the repetition of specific strings in the fragments. Some examples of discarding rules and the rationale behind them are:

Rule fr1. For each fragment f, let nPre(f) be the number of fragments whose pre coincides with the pre of f, where the pre is the start tag including attributes.

discardingRule fr1(HTMLFragment f)
IF `nPre(f)>=x` THEN markAsDeleted(h), such that pre(h)=pre(f)
The value of x is obtained by direct observation of real cases. A typical value is x=3.
Reason for the rule: The pre of the fragment which contains the price is very specific. So, if x or more fragments have the same pre, all of them are discarded.

Rule fr2. For each fragment f, let nChar(f, n) be the number of fragments whose first n characters coincide with the first n characters of f.

discardingRule fr2(HTMLFragment f)
IF `nChar(f, n)>=x` THEN markAsDeleted(h), such that substr(h, 1, n)=substr(f, 1, n)
The values of n and x are obtained by direct observation of real cases. Typical values are n=21 and x=3.

Reason for the rule: If there are several fragments with the same beginning, they may be discarded because the beginning of the fragment containing the price is usually very specific.

Threshold rules These rules filters the prices based on limits imposed by the user or limits given by common knowledge. For example, if the entity is a new car, the common knowledge tells us that its price is greater than 6000 euros. Moreover, the user can tell the maximum price (s)he can allow is 12000 euros. So, all cars out of the range 6000-12000 euros must be discarded.

\[\text{discardingRule thresrl(HTMLFragment f, Number min, Number max)}\]
\[\text{IF (value(f)<min or value(f)>max) THEN markAsDeleted(f)}\]

5 The Algorithms

In this section, we present the algorithms which implement our proposal. The from scratch extraction, that is, the first time we search for a price, is implemented by means of the \text{doFromScratchExtraction} algorithm (see Section 5.1). When pointing patterns are available, we do a pointing pattern extraction implemented by the algorithm \text{doPointingPatternExtraction} (see Section 5.2). The main algorithm (see Section 5.3) decides which of the previous algorithms is executed.

5.1 The doFromScratchExtraction algorithm

In this extraction, first the clues are detected in the web page. Examples of clues are &euro; EUR € & #8364; In the following steps, fragments containing the clues are detected and discarding rules are applied to these fragments. As a result of applying the discarding rules, there remains a collection of fragments where prices appear. These values are considered possible prices. If n is the total number of distinct found values, these are the results of the algorithm:

- n=0. There is no price on page pg.
- n=1. The price in page pg is the only value found.
- n>1. There are several prices.

In some pages, such as the Asics Nimbus 17 shoes page of Amazon, there can be two values indicating the minimum and maximum price. Our algorithm detects this situation and considers that there is only one value, given by the pair (minimum, maximum).

The complete algorithm can be seen in Table 2.

Algorithm description In line 1, a list of clues previously prepared by the programmer is retrieved and it consists of strings as EUR € & #8364; and so on. In line 2, the discarding rules are loaded. In lines 3 to 6 for each occurrence of
Table 2. Algorithm for doing a from scratch extraction

Algorithm doFromScratchExtraction

Input: HTML code of page pg
Output:
list of candidate prices
pointing pattern, if any

Preconditions:
The page pg is available
The HTML code is explicitly available. It is not generated, for example, by means of Javascript.

Pseudocode

1. listOfClues <-- loadClues()
2. listOfDiscardingRules <-- loadDiscardingRules()
3. for each clue c of listOfClues do
4.   fragments <-- findAssociatedFragments(HTMLCode, c)
5.   listOfFragments <-- add(listOfFragments, fragments)
6. endfor
7. for each discardingRule r of listOfDiscardingRules do
8.   applyDiscardingRule(r, listOfFragments)
9. endfor
10. listOfCandidateFragments <-- getCandidateFragments(listOfFragments)
11. listOfValues <-- extractValues(listOfCandidateFragments)
12. if (#listOfValues=1) then
13.   pp <-- extractPointingPattern(listOfCandidateFragments)
14. end if
15. return (pp, listOfValues)

Each clue in the HTML code, associated fragments to the instances of the clues are found. Next, discarding rules are applied to the fragments (lines 7 to 9). Those fragments which have not been discarded by the application of the rules, make up the list of candidate fragments (line 10). From this list of fragments, the list of prices is extracted (line 11). In lines 12 to 14, a pointing pattern to be used for subsequent extractions is determined. The pointing pattern and the remaining prices are returned as results in line 15.

5.2 The doPointingPatternExtraction algorithm

When a from scratch extraction is done, it is sure that the web page is available because the search is executed just after the user has selected the page. However, when a new search is done on the same page by using the pointing pattern extraction, it can happen that the url no longer points to the page or that the structure of the HTML code of the page has changed so that the pointing pattern does not find any result. We impose as a precondition for this algorithm that the page pg is available. The sketch of the subalgorithm can be seen in Table 3.
Table 3. Algorithm for doing an extraction based on a pattern

| Algorithm doPointingPatternExtraction |
|---------------------------------------|
| Input: HTML code of page pg, pp pointing pattern with which we search the price in page pg |
| Output: list of prices |
| Precondition: The page pg is available |

Pseudocode

1. lstrings<-match(HTMLCode, pp)
2. for each x in lstrings do
3. v<-extractValue(x, pp)
4. lvalues<-add(lvalues,v)
5. end loop
6. return lvalues

Algorithm description In line 1, the strings matched by the pointing pattern pp are retrieved. In lines 2 to 5, for each matched string, the price found in the string is extracted and accumulated into variable lvalues. In line 6, this variable is returned as result of the algorithm.

5.3 The findAttributeValues algorithm

This is the main algorithm and combines the two algorithms we have described in the previous sections. First, a pointing pattern extraction is done (lines 1 to 11). If the extraction does not give the expected results, then a from scratch extraction is done (lines 12 to 19). In particular, the first time an extraction is done, as there are no previously available patterns, a from scratch extraction is always done. The sketch of the subalgorithm can be seen on Table 4.

Algorithm description In line 1, the existence of the page pg is checked. If the page is not available, the value (false, -1) is returned (line 21). Otherwise, in line 2, the code of the page is retrieved. For each pointing pattern of the extraction kit, an extraction is done (lines 4 to 8), beginning with the latest pointing pattern, by means of the algorithm doPointingPatternExtraction (see Section 5.2). When an extraction finds a price, the extraction finishes. At the end, the variable $s$ stores the prices found for the first pointing pattern which has found prices. Then, if $s$ has only one element, this element is returned as result(line 9). If $s$ has more than one element, the value (false, -2) is returned, indicating that there are many prices. If $s$ has no elements, this means that the pointing pattern extraction did not find any solution. This can be for many reasons as, for example, (1) it is the first time the extraction is done and there are no patterns, or (2) there can be patterns but the structure of the page has changed so that no old pattern finds the correct price. In any case, the existing patterns are not deleted because they can be used again later. As the extraction did not find any solution, then a from scratch extraction is done (line 12).
Table 4. Algorithm for finding the price of a detail page

Algorithm findAttributeValues

Input: extraction kit sk, composed of the url of the page and of pointing patterns
Output:
(false, -1) the page pg is not available
(false, -2) there are many prices found in page pg
(false, 0) there are none price found in page pg
(true, v) v is the unique price found in page pg

Pseudocode

1. if existsPage(sk.u) then
2.  HTMLcode<--findHTMLCode(sk.u)
3.  s <-- empty
4.  pp<-- lastpp(sk)
5.  while s is empty AND pp is not empty
6.   s<--doPointingPatternExtraction(HTMLCode, pp)
7.   pp<--nextpp(sk, pp)
8.  endwhile
9.  if #s=1 then return (true, s[1])
10. elsif #s>1 then return (false, -2)
11. else
12.   (pp, s)<--doFromScratchExtraction(HTMLCode)
13.   if #s=0 then return (false, 0)
14.   elsif #s>1 then return(false, -2)
15.   else
16.    addPointingPatternToExtractionKit(pp, timestamp, sk)
17.    return (true, s[1])
18.  end if
19.  end if
20. else
21.  return (false, -1)
22. end if

As a result of this extraction, no price is found and the value (false, 0) is returned (line 13) or more than one price is found and the value (false, -2) is returned (line 14) or exactly one price is returned (line 17). Before returning this value, a pointing pattern is determined (line 12) and will be used in subsequent pattern based extractions. For this purpose, the pattern and its timestamp are added to the extraction kit (line 16).

6 Experimental validation

In this section we present the empirical evaluation of the Wextractor method. To evaluate the effectiveness of our solution, we searched for (1) price trackers and (2) adequate datasets on the web. With respect to the former, we found price trackers in the web with the same goal as Wextractor. However, all the trackers we have visited (slickdeals, pricegrabber, camelcamelcamel) are able to track a
limited number of sites, unlike Wextractor, which can track prices in any site. So, we searched for adequate datasets on the web. After an extensive search, we only found the dataset of paper [7], composed of around 124K pages collected from 80 websites. The websites are related to 8 vertical, including autos, cameras or books. For each vertical, 10 popular websites were identified by issuing queries to search engines. For each website, 200-2000 detail web pages were downloaded.

This dataset is also insufficient because only the camera and the auto verticals include the attribute price. So, we decided to create our own dataset. For this purpose, we gathered sites the page myalerts.com (now trackif.com) claimed to be able to track. They are the most active e-commerce sites on the web. For these sites, we selected those which accomplished the following properties: (1) were accessible on the web, (2) offered detail pages and (3) the prices of the objects in the detail pages were available in the HTML code (not in script code). Finally, we have worked with 444 sites. The complete dataset can be downloaded at [1].

For each of these sites, we selected one detail page and we annotated, by direct inspection, the price of the corresponding entity. Then, we executed Wextractor for each page and we compared the results. We evaluated our method against our dataset by using precision and specificity. As there are many true negatives and only one true positive, we have chosen the specificity to measure the true negative rate. In general, the experimental results show that our algorithm discovers prices in different web sites. In average, it achieves 80.00% precision and 97.00% specificity. It returns perfect results (100% precision and specificity) for 342 out of 444 websites of the dataset. It returns 100% precision for 342 out of 444 (77%) of the websites of the dataset. It returns 100% specificity for 387 out of 444 (87%) of the websites of the dataset.

We have implemented Wextractor by means of the Oracle database 11g and the PL/SQL programming language. Packages like UTL_HTTP have been of great help in this task.

7 Conclusions and Future work

In this paper we have presented a web extractor system, called Wextractor, whose purpose is doing a follow-up of prices in web pages. Several questions arise from this work and will be dealt with in future papers: Could our three steps method be extended to other problems as defined in [15], namely, entity extraction or binary relationship extraction? Could our proposal be generalized to other attributes different from the attribute price?

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