XTreePath: A generalization of XPath to handle real world structural variation

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ABSTRACT
We discuss a key problem in information extraction which deals with wrapper failures due to changing content templates. A good proportion of wrapper failures are due to HTML templates changing to cause wrappers to become incompatible after element inclusion or removal in a DOM (Tree representation of HTML). We perform a large-scale empirical analyses of the causes of shift and mathematically quantify the levels of domain difficulty based on entropy. We propose the XTreePath annotation method to captures contextual node information from the training DOM. We then utilize this annotation in a supervised manner at test time with our proposed Recursive Tree Matching method which locates nodes most similar in context recursively using the tree edit distance. The search is based on a heuristic function that takes into account the similarity of a tree compared to the structure that was present in the training data. We evaluate XTreePath using 117,422 pages from 75 diverse websites in 8 vertical markets. Our XTreePath method consistently outperforms XPath and a current commercial system in terms of successful extractions in a blackbox test. We make our code and datasets publicly available online.

1 INTRODUCTION
We address a key problem in information extraction which deals with wrapper failures due to changing content templates. A wrapper is best described by Kushmerick as a "procedure, specific to a single information resource, that translates a [webpage] query response to relational form" [13]. Wrappers are required because much of the desired data on the Internet is presented using HTML templates instead of well formed (XML or JSON) data or unstructured freeform text [6]. Extracting data, such as stock, flight, and product information, from websites that use HTML templates is difficult because wrapper methods have difficulty dealing with changes to HTML structure.

We believe a good proportion of wrapper failures are due to HTML templates changing and cause wrappers to become incompatible after the element inclusion or removal of DOM (Tree representation of HTML). For example, an additional "On Sale" element is included above a product. This shift [3, 19] may require manual retraining of wrappers which is a burden to users. Empirically we find over 50% of our web sample contains shift at various levels and we have a detailed discussion about shift in Section §3.

To handle the problem of shift we need to take in more information from the DOM [2, 4, 7, 11, 15, 19]. Instead of only extracting statistics from the training data we extract an entire sub-tree structure, like Reis [17], and use this during wrapper induction to create a supervised information extraction method.

Figure 1 gives an example of XTreePath. We start by finding the least common ancestor of the nodes of interest (product name, price, etc) and extract a relative XPath as well as the nodes of the DOM for every step of that XPath. We then use this XTreePath with our Recursive Tree Matching method which performs a heuristic graph search in the target DOM to find the most similar sub-trees to those in the training data. Because we are matching sub-trees we can handle large horizontal and vertical shifts as long as some unique traits about the DOM are preserved.

Furthermore, XTreePath is compatible by design, which complements XPath but does not replace it. We only utilize the recursive tree matching lookup process after an XPath has failed, which minimizes runtime. This allows an XPath-based method to adopt XTreePath without sacrificing existing speed or quality. Existing research has discovered many methods to construct robust XPaths a priori. Our presented method can exist in parallel with these methods as they are continually advanced in order to achieve better overall accuracy.
Thus, our main contributions are as follows:

- **Method:** We propose the XTreePath method which is a generalization of XPaths where tree structure is also stored and used during wrapper induction.
- **Algorithm Design:** We propose a Recursive Tree Matching method and a dynamic programming solution to perform wrapper induction.
- **Theoretical Analysis:** We formally define and analyze the problem of shift theoretically and empirically. We mathematically quantify the levels of domain difficulty based on entropy and study a large representative dataset.
- **Robustness:** We evaluate XTreePath using 117,422 pages from 75 diverse websites in 8 vertical markets.
- **Reproducibility:** Our code and data are open-sourced at http://kdl.cs.umb.edu/w/datasets/.

### 2 RELATED WORK

In the field of information extraction there are two primary categories of annotation learning: supervised and unsupervised approaches. We take a supervised approach and combine positional (XPath [1]) and ontological (Tree Structure) concepts [10, 12, 14] together.

In Dalvi and Parameswaran [3, 4, 16] focused on supervised annotation learning algorithms tolerant to noise in the training data. They enumerate many XPath wrappers using a probabilistic ranking system to pick the best one. The output of these methods is XPath annotations which differentiates our method as XTreePath would complement this method and not replace it.

The context of nodes has been used to create annotations themselves but not during extraction as our method does. In 2009 Zheng [20] and Fang [5] used a “broom” structure inside the HTML DOM to represent both records and generated wrappers. This work was motivated to capture lists of products instead of creating wrappers tolerant to shift.

Tree similarity has been used in unsupervised information extraction approaches to find common sub-trees in websites by Zhai in 2005 [19] and used as a method to locate lists from web pages by Jindal in 2010 [9]. These methods focus on locating interesting data but not in a way of imposing a label as our method XTreePath would complement this method and not replace it.

A break away from just carrying XPaths forward from the training was discussed by Omari [15]. In this work they would learn a decision tree to predict which XPath fragments should be used at test time.

Moving beyond XPath is not a new concept. There has been work on tree automata induction by [11] which aims to learn a deterministic finite automata which will process the DOM tree and accept nodes which contain the information of interest. The mechanics of this are very different but we can also argue that a DFA does not take the neighborhood of the tree into account when accepting a node.

Possibly the most similar approach to our method was proposed by Reis[17]. Here they use the tree edit distance to determine if a webpage contains a specific type of content (news) based on tree structure. We take this concept and structure it into a generalized XPath representation that can be used for supervised information extraction.

### 3 SHIFT ANALYSIS

A **shift** of a web page occurs when a modification of the page causes the inclusion, removal, or substitution of DOM elements which changes the DOM tree representation. Not all shifts are bad. A shift only becomes a problem when it causes wrappers to become incompatible and return no result or an incorrect result. Here compatibility is defined as whether the DOM structure of a wrapper matches the DOM structure of a web page.

![Vertical Shift](diagram.png)

**Figure 2:** A vertically shift occurs by adding a parent node to the *span* element. The XPath that reaches Name must have a *div* element added to maintain compatibility with the altered HTML tree.

Our method is based on the principle that all shifts can be broken down into a combination of vertical and horizontal shifts. We can take advantage of this by considering all tree permutations. Given a tree \( T \) with nodes \( t \in T \), each node is a sub-tree and has a parent \( t.parent \) and a set of children \( t.children \). A tree contains many paths \( p \) with elements \( p_i \in T \), when the path travels down the tree: \( p_{i+1} \in p_i.children \).

**Definition 3.1.** A **vertical shift** is a tree modification where a node is inserted on the path from the root to the target element. Formally, for some path \( p = \{p_1, \ldots, p_i, p_{i+1}, \ldots, p_n\} \), a vertical shift occurs when some new node, lets call it \( s \), is inserted and

\[
p' = \{p_1, \ldots, p_i, s, p_{i+1}, \ldots, p_n\}
\]

or, if a node is removed,

\[
p' = \{p_1, \ldots, p_i, p_{i+2}, \ldots, p_n\}.
\]

A vertical shift causes an insertion or removal in an XPath, see the example in Figure 2.

**Definition 3.2.** A **horizontal shift** is a tree modification where a sibling element of a node is inserted. Formally, for some path
p = \{p_1, \ldots, p_{i-1}, p_i, p_{i+1}, \ldots, p_n\}, a horizontal shift occurs when some new node, let's call s where s \neq p_i, is inserted

p' = \{p_1, \ldots, p_{i-1}, s, p_{i+1}, \ldots, p_n\}.

p_i may still exist in the tree but a different node now connects the two path segments p_1, \ldots, p_{i-1} and p_{i+1}, \ldots, p_n.

A horizontal shift causes the index of a node to change, see the example in Figure 3.

![Diagram of horizontal shift](image)

Figure 3: A sibling \texttt{div} element is added under the \texttt{html} parent. This is a horizontal shift that affects many XPaths at once due to the change of a child index from \texttt{div[1]} to \texttt{div[2]}.

With formal definition of shifts, we study a large dataset of 117,422 pages from 75 websites in 8 vertical markets described in Section §5 to empirically analyze possible reasons for shifts.

One indicator of shifts is when multiple XPaths are needed to extract the same attribute from different web pages of the same website. The probability of a domain requiring multiple compatible XPaths decreases as the number of XPaths increases. Even with this good news, 116 out of the 231 attributes have more than one XPath associated with them. The most difficult domain and attribute are \texttt{barnesandnoble}'s \texttt{title} with 270 unique XPaths required. Inspecting the mean XPaths required for each domain we can observe slight chunks which would imply possible clusters and maybe some similarities between the websites. We identify three main possible reasons for shifts:

- **Inconsistent templates**: A website might present items to a user differently depending on a property of that item. For example, an item on sale may have a graphic inserted which shifts the DOM. In our dataset, collegeboard.com uses different templates for public and private universities that results in shifts.

- **Temporal changes**: Over time the developer may change the site to fix a bug, add a feature, or perform a redesign. Changes can be related to user tracking, advertising, or updated template software.

- **DOM cleaner inconsistencies**: A DOM cleaner (details in Section §5.1) needs to make assumptions when converting semi-structured HTML into XHTML. If the HTML is ambiguous this process will result in a DOM tree that does not match the intended DOM and will appear as a shift.

In our empirical study, we observe large groups of unique XPaths are due to inconsistent templates and small groups of unique XPaths (less than 4) are usually due to DOM cleaner inconsistencies.

Our next step is to mathematically quantify the difficulty in maintaining a wrapper in order to measure the disorder of the domain.

**Definition 3.3. Attribute difficulty** represents the disorder of the attribute locations with respect to XPath annotations in a sample set of pages from a domain. The probability that a particular XPath for an attribute will be compatible with pages from a domain given a sample of pages is formalized as: $p(x) = \frac{\text{compatible pages}}{\text{total pages}}$. We define attribute difficulty in Eq 1:

$$H(\text{attribute}) = - \sum_{xpaths} p(xpath) \log p(xpath)$$

When looking now at Table 1 the attribute difficulty can be used to quantify the difference between the two attributes presented for the domain \texttt{deepdiscount}. Intuitively \texttt{title} appears more difficult than \texttt{author} due to the long list of unique XPaths. Attribute difficulty confirms this with 0.93 for \texttt{title} and 0.65 for \texttt{author}. One strength of the difficulty analysis is that it weights each XPath to take into account outliers that are only compatible with 1 or 2 webpages. This is important because these outliers will not significantly impact accuracy and therefore should not impact the difficulty.

**Definition 3.4. The domain difficulty** is the mean difficulty of it’s attributes.

Inspecting domain difficulty can provide insight into where the current XPath method fails to solve the problem. In Figure 4 we look at the F1-Score (measure for classification accuracy; the higher the better, explained in §5) versus the domain difficulty (a low value means less shifts occur). The plot reinforces the intuition that XPath usually works well on domains with low difficulty. Also we can confirm that when the difficulty is high XPath does not perform as well. This makes sense because higher difficulty means that there is more disorder in the set of XPaths for that domain which causes them to fail.

![Graph of domain difficulty versus F1-Score](image)

Figure 4: The domain difficulty versus the evaluated F1-Score of an XPath wrapper for every domain in our dataset. A linear trend-line is drawn to show the trend of the relationship.
Table 1: The number of compatible pages in each domain for each XPath. For the XPath listed, the “# Compatible” is the number of pages that have data stored at the location specified by that XPath.

| Domain/Attribute | # Compatible | Unique XPath |
|------------------|--------------|--------------|
| 79                | /html/body/div[2]/div[1]/ul/li/ul/li/ul/li/ul/li/span |
| 44                | /html/body/div[2]/div[1]/ul/li/ul/li/ul/li/ul/li/span |
| deepdiscount/title 20 | /html/body/div[2]/div[1]/ul/li/ul/li/ul/li/ul/li/span |
| title 9          | /html/body/div[2]/div[1]/ul/li/ul/li/ul/li/ul/li/span |
| 577              | /html/body/div[2]/div[2]/div/div/div/div/div[1]/div/h1 |
| 1237             | /html/body/div[2]/div/div/div/div[1]/div/div[2]/div[1]/div[2]/div[1]/a |
| deepdiscount/author 738 | /html/body/div[2]/div[2]/div/div/div/div[1]/div/div[2]/div[1]/div[2]/div[1]/div/ul/li[1]/a |
| author 1257      | /html/body/div[2]/div/div/div/div[1]/div/div[2]/div[2]/div/div[1]/div/ul/li[1]/a[1] |

Figure 5: The starting webpage has simulated shift applied by the addition of the words “On Sale!”. The nodes used to add this text are designed to break existing methods. These are identified with dashed borders. The path of nodes from the root to Name node are highlighted in red.

4 XTREEPATH (XPATH+TREEPATHS)

We now utilize the knowledge gained from our shift analysis that more attribute difficulty means lower performance of XPath annotations. Then we will explain how our Recursive Tree Matching algorithm searches node by node using similarity of sub-trees to train examples to simultaneously accommodate for vertical and horizontal shifts. In order to store the relevant data for searching we first explain tree paths.

4.1 TreePaths

We seek for an efficient wrapper method that can fix incompatible wrappers automatically when shifts happen. In order to have enough information to fix wrappers in an automated way we extract not only the direct indexing into the document but also the context of those elements. Instead of consulting the entire training set to repair a wrapper we store the tree structure immediately surrounding the target data. The algorithm starts building the tree path at the least common ancestor (LCA) of the target elements.

**Definition 4.1. Least common ancestor (LCA) of target elements:** The least common ancestor is an element that exists on every path from the root to each target element. The LCA is unique in that there is no other common element that is closer to every target element.

**Definition 4.2. A tree path** is identified by \( \tau \). It is a sequence of trees in an HTML Document Object Model (DOM) starting from the least common ancestor \( (\tau_0) \) and ending at the target element \( (\tau_n) \) as follows:

\[
TreePath = \tau = (\tau_0, \tau_1, \ldots, \tau_n), \tau_i \in DOM
\]

A tree path is an extension of the XPath concept. With XPath, the elements of the path are tag names that describe the sequence to the target. In contrast, a tree path includes an entire sub-tree starting from each element in the sequence to the target. This is to provide sufficient contextual information from which each element was extracted to aid in the wrapper recovery later. An example tree path of length four is shown in Figure 1.

Extracting tree paths from an HTML DOM is shown in Algorithm 1. First, we find the least common ancestor (LCA) between all the labeled elements. Next, starting from the target element, each element is added to a vector and then it’s parent element and so on until the LCA is reached. Next, we add the LCA because it was
not added in the above loop. Finally the elements are reversed and 
returned so that they start with the LCA and end with the target 
element.

Algorithm 1: Build Tree Path From Training DOM

Input: Training DOM dom
Output: Tree Path \( \tau \)

1. \( \text{dom}_{LCA} = LCA(E, \text{dom}) \)
2. while \( \text{dom}_{LCA} \neq e \) do
3. \( \tau \).add(e) \( e = e \).getParent()
4. \( \tau \).add(e.getLeaf())
5. return \( \tau \)

4.2 Recursive Tree Matching

We learned from analyzing shifts causing incompatibility that the 
majority are composed only a very small number of vertical and 
horizontal shifts. With our proposed Recursive Tree Matching, we 
jump over these shifts by matching sub-trees on each side of the 
shift. The LCA, which is the root of the tree path, provides a starting 
point and allows us to ignore shifts that have occurred outside 
where the target data is. Starting here also allows us to reduce the 
complexity of the search. The proceeding elements of the tree path 
are matched to their most similar nodes in order to align trees that 
existed previously unshifted. The objective function is shown in Eq 
2. Here the maximum matching sequence of \( e \) (DOM elements) to 
the data contained in each \( \tau \) is found. This maximization is iterative 
with constraints which requires two maximization sections.

\[
\max \left( \sum_{\tau_i \in \tau} \{ e_{i+1} = \arg \max e \in E (\text{match}(\tau_i, e)) \} \right)
\]

The algorithmic detail, including the dynamic programming 
heuristic function, of Recursive Tree Matching is shown in Algo-

rithm 2. In this pseudo code a reference to an element of the DOM 
is kept as \( d \) and updated as the search progresses. Line 4 is the 
core where each element of the tree path \( \tau \) is matched to its most 
similar DOM element in \( d \). HTML tree similarity is calculated using 
a modified Simple Tree Matching algorithm [18] which is designed 
to deal with HTML specifically by taking into account the class, 
style, id, name attributes of each node. If a max similarity is 0 then 
the element is considered not found. Using this method we perform a 
heuristic search through the tree using concise information from 
the training data.

A demonstration of the recursive tree matching process is shown 
in Figure 6. The shifted HTML DOM presented in Figure 5 is 
searched using the Recursive Tree Matching method with the tree 
path we extracted from original DOM in Figure 5 shown in Figure 
1. We first start by trying to directly look up the target data using 
the original sequence of elements. This results in a failure causing 
the algorithm to perform wrapper recovery.

Recovery starts by searching every element in the HTML DOM 
for the sub-tree that has the highest similarity to \( \tau_0 \) (the LCA),

Algorithm 2: Wrapper Induction (Recursive Tree Matching)

Input: Tree path \( \tau \)
Output: Resulting data

1. \( d \leftarrow \text{dom} \)
2. for \( \tau_i \in \tau \) do
3. for \( e \in d \) do
4. \( d = \arg \max e (\text{html_tree_match}(\tau_i, e)) \)
5. //If match is 0 then not found
6. return \( d \)
7. \( \text{html_tree_match}(a, b) \):
8. if \( a \) and \( \tau_i \) contain distinct symbols then
9. return 0
10. else
11. \( m \leftarrow \text{the number of first-level sub-trees of } a \)
12. \( n \leftarrow \text{the number of first-level sub-trees of } b \)
13. \( M[i, 0] \leftarrow 0 \) for \( i = 0, \ldots, m \)
14. \( M[0, j] \leftarrow 0 \) for \( j = 0, \ldots, n \)
15. for \( i = 1 \) to \( m \) do
16. for \( i = 1 \) to \( n \) do
17. \( x \leftarrow M[i, j - 1] \)
18. \( y \leftarrow M[i - 1, j] \)
19. \( z \leftarrow M[i - 1, j - 1] + \text{html_tree_match}(a_i, b_j) \)
20. \( M[i, j] \leftarrow \max (x, y, z) \)
21. for \( \text{attr} \in \{ \text{class}, \text{style}, \text{id}, \text{name} \} \) do
22. if \( a_{\text{attr}} == b_{\text{attr}} \) then
23. \( \text{attrMatch} \leftarrow \text{attrMatch} + 0.25; \)
24. return \( M[m, n] + (\text{attrMatch} + 0.5) + 1 \)

In Figure 6 the element /div has a similarity score of 7 which is 
higher than all other sub-trees. The similarity is calculated using 
the \( \text{html_tree_match} \) method. The score of 7 is calculated as the 
maximum overlap of one tree with the other given the liberty of 
horizontal shifts.

Once we have focused on /div[1], this sub-tree is now searched 
using the second element of the tree path. A similarity score of 5 
yields /div[2] as the most similar sub-tree. Next, the algorithm will 
find a most similar sub-tree by jumping over the element /div[1] 
to find /div[1]/div has a higher similarity. This search will result in the 
/span element being located and the wrapper successfully 
repaired. This example showcases the power of Recursive Tree 
Matching method in dealing with addition of identical trees and 
the extension of trees.

4.3 Complexity

The worst case complexity of the recursive tree matching method 
is \( O(|\tau|n_1n_2) \) where \( n_1 \) and \( n_2 \) are the number of elements in the 
training and test DOM trees. This is derived from the Simple Tree 
Matching (STM) complexity, which is reduced using dynamic pro-
gramming, being \( O(n_1n_2) \). There are \(|\tau| \) iterations of the algorithm, 
each needing to perform an STM search. The cost at each iteration
5 EVALUATION

In this section we aim to show that XTreePaths can be utilized to complement and outperform the existing dominant method XPath. The method presented has no parameters that require tuning. Our goal is to design robust and practical method which can be easily extended under different scenarios.

In order to test the robustness of the methods, the percentage of the dataset used for training is varied. This allows a comprehensive comparison between the following three methods:

- **XPath**: Each training example has an XPath to be the target node that is combined into a set of possible paths. Each path is attempted on the testing examples until there is a valid path.
- **XTreePath**: Firstly XPaths are attempted. If it is not successful then a tree paths is used to attempt recovery.
- **TreePath**: Only a tree path is used without XPath. A tree path is extracted from each training example starting from the LCA of the target elements for that domain. Then Recursive Tree Matching is used to search the DOM tree.

- **ScrapingHub**: The web service offered at scrapinghub.com is used as a blackbox to evaluate the state of the art offered commercially by industry. (No authors are affiliated with ScrapingHub)

To compare XTreePath and XPath we use a large dataset built by Qiang Hao [8] to benchmark per-vertical wrapper repair instead of per-domain. This dataset contains a total of 117,422 pages from 75 diverse websites in 8 vertical markets that covers a broad range of topics from university rankings to NBA players. The composition is displayed in Table 2. For each vertical market a set of (3-5) common attributes are labelled on every page. We make our data and code available for comparison at http://kdl.cs.umb.edu/w/datasets/.

5.1 Working With Data

It is important to document the difficulties of dealing with datasets in this field in order to ensure that the benchmark datasets used here can be utilized by other researchers.

The main issue is that HTML in the wild does not always map to the same DOM representation, it is highly dependent on the HTML Cleaner used. There is no standard mapping to convert HTML into...
a properly formatted XHTML file. There are common algorithms used by browsers but there is no agreed specification of how they convert HTML to XHTML. Different cleaners convert HTML in different ways leading to an incompatibility of XPath annotations. A training set made with one cleaning engine will not work using another engine.

The libraries used for our work were chosen as the most reliable and competent methods after a comparative study on major libraries was performed. The complete list of libraries we evaluated are labeled in Table 3 as having the following properties:

- **Cleaning** - These are used to convert from a non-standard HTML file to an XHTML file. The corrections include tag closing, name-space filtering, and tag nesting. This is required because most HTML on the Internet is non-standard.
- **Representation** - This library provides things such as DOM traversal, insertion, and removal. This library is used to build sub-trees and represent namespaces. Most of these libraries are not tolerant to non-standard HTML and require cleaning before they can turn HTML into a DOM.
- **Query** - These methods can include XPath, XQuery, XML-GL, or XML-QL.

In this paper, our research is done using the well supported open source libraries JTidy and Dom4j. These libraries are written in Java and support multi-threading. JTidy’s performed consistently for cleaning and intergraded cleanly into Dom4j. Dom4j has a clean query interface to lookup using XPath as well as a clean Representation interface for implementing tree paths and recursive tree matching. Other Java libraries such as JSoup and TagSoup are designed for their own query language instead of XPath and exposing a DOM.

A few pages today retrieve their content using JavaScript once the page is loaded. This means the HTML retrieved with the initial GET request does not contain the full product information. A way to solve this problem is to use a library that will run the JavaScript code. It is better to get JavaScript out of the way during scraping due to the need to make AJAX calls to retrieve data that may be missing at a later date. For this reason we retrieve the pages using the FireFox web browser which will evaluate JavaScript as expected by the web developer.

We use the standard machine learning metrics precision, recall, and F1-score as the evaluation metrics. In this domain, a true positive (tp) is an extraction of the correct data (verified using labeled data), a false positive (fp) is an extraction that resulted in the wrong data (something other than the correct data), and a false negative (fn) is an extraction that resulted in an error or “not found”. Errors are caused by the lookup reaching a dead end. The following formulae are used: $\text{precision} = \frac{tp}{tp+fp}$, $\text{recall} = \frac{tp}{tp+fn}$, and $F1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$.

### 5.2 Difficulty Correlation

Using our new domain entropy measurement introduced in Section §3 we plot the entropy per domain over all vertical markets in Figure 7 for XPath and XTreePath. As the entropy increases XTreePath is able to maintain performance while XPath degrades. The higher a domain entropy value is, the more changes in HTML elements occur. XTreePath is more robust than XPath when dealing with shifts.

### 5.3 Limiting Training Examples

We evaluate the ability to recover from shift on each domain by splitting the pages of each domain into training and testing sets.
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Figure 7: The entropy of the domains is plotted against the F1-score of XTreePath and XPath. Linear trendlines are shown.

at various percentages. The pages of each domain are chosen randomly to simulate the different possible situations that could be encountered.

In the following experiments each method is trained on a percentage of the dataset. In these experiments; 10% percentage trained means that only 10% of the pages from a domain are used in training to build XPaths and XTreePaths. These are used to extract data from the remaining 90% of the pages.

In Figure 8 the aggregate recall is plotted against the percentage trained. This analyses how many wrappers are saved from needing to be relearned by using the different methods. We can observe the combination of XPath and tree paths as XTreePath achieves a significant increase which confirms they are complementing each other. This is important because these methods do not directly replace each other and together are able to provide a more robust data extraction pipeline. Also, it is important to note the largest increase is with a lower percentage of training data. This is desired because the algorithm can perform even if a small number of pages have been collected which is often the case. This is because every annotated training page is a cost to the system. Also, some data sources will increase in size over time causing the trained percentage will shrink over time.

Figure 8: Recall is not high when evaluating the TreePath alone. However, for XTreePath, when tree paths are used after XPath fails we are able to obtain a higher recall overall.

Next we evaluate the aggregate precision in Figure 9. The most interesting result here is that as the training percentage is increased, the precision is reduced for XPath and tree paths. As more examples are learned, XPath and tree path have more data to try which results in higher false positives. When the methods are combined in XTreePath the same number of false positives exists but the number of true positives increases and allows the precision formula to grow.

Figure 9: Tree paths, by themselves, perform poorly but because there is only a small intersection between successful XPath and tree path extractions the true positives outweigh the false positives and drive the precision up.

The aggregate F1-Score is shown in Figure 10. Here the F1-Score of XTreePath consistently outperform XPath and tree paths alone. The advantage of XPath in precision is countered by it’s low recall.

Figure 10: XPaths and tree paths have slightly decreasing results due to precision. When combined they complement each other and increase as the training set size is increased because they perform better for recall.

5.4 Performance Per Vertical

We are interested to know how the proposed XTreePath perform in vastly different web domains. In Figure 11 we analyze the mean F1-score of XPath and XTreePath in each vertical market. XTreePath performs consistently well against XPath in all vertical markets. We can draw from this analysis that book websites have more stable structure which allows XPaths to work consistently. We can also draw that restaurant and university sites have more dynamic structures with slight changes that can easily be accommodated for by XTreePath.

5.5 Industry Baseline

Finally, we compare our method to a current commercial solution, ScrapingHub, that tackles the same problem. This method is treated
as a black box and we do not know how it works. In this evaluation both methods are trained on the same single example. Each method is then evaluated on the remaining examples from the domain.

Figure 12 shows the comparison using 17 randomly selected domains. XTreePath ties or beats ScrapingHub on 12/17 domains. For the domain *embark* the problems arise from two faults happening at the same time. First, an XPath fails when locating the address (a span[6] is shifted to a span[8]). XTreePath recovers this broken XPath but then fails on the phone number attribute (for which the learned XPath would have worked but the system was already trying to recover the wrapper). The weakness is that when all the children look the same the tree similarity doesn’t work. This happened to be a perfect storm for XTreePath but would easily be fixed by adding another training example.

The *abebooks* results are identical. Why can’t we improve this result? The weakness is that tree paths cannot deal with the shift in this site because it is confused with matching tree structure. The shifted site only has it’s data rearranged but the tree structure has not changed. Even with using the node attributes it cannot repair the wrappers because they are also the same.

6 CONCLUSION

We have presented the XTreePath algorithm which is composed of XPath and tree paths together. Tree paths contain contextual information from training examples and are used by the recursive tree matching search algorithm. We have shown that with a simple data structure, the tree path, we can conquer shifts in webpages and reduce manual retraining. We evaluate our method on a massive and publicly available dataset where XTreePath consistently outperforms XPath alone.

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