

# Web Wrapper Specification Using Compound Filter Learning

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# Plan

- 1 Introduction
- 2 Defining Wrappers
- 3 Learning Wrappers
- 4 Conclusion

# Web Information Extraction

The screenshot shows a web page for the GRAPPA research group. On the left is a vertical navigation menu with links for English Version, Actualités, Thèmes de recherche actuels, Composition de l'équipe, Publications de l'équipe, Collaborateurs, Automates d'articles, Logiciels, Enseignement, Enseignements liés à la recherche, Soutien et adresse, and Webmail. The main content area has a blue header with the text 'GRAPPA : Groupe de Recherche sur l'Apprentissage Automatique'. Below this is a sub-header 'Composition de l'équipe' with a small link '(Composition, composition)'. A note indicates the last update was on 7/2/05/2005. The next section is 'Liste des membres de de l'équipe' with a sub-header 'Responsable'. A list of members follows, including Rémi Gilleron (responsable), Rémi Coulton, Francesco De Comità, Aurélien Lemay, Joachim Niehren, Philippe Preux, and Isabelle Tellier, each with their email and affiliation.

## Task:

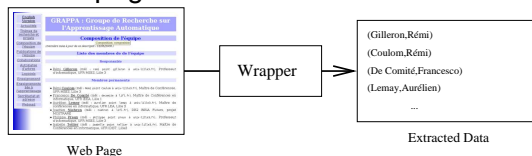
- Automatically access Information available on the Web
- Example: extract member names on labs web sites.

## Difficulty: data organization is

- In a layout description language, not adapted to automatic processing
- Specific to each Web site

# Wrappers

Standard approach: writing wrappers, programs which turn HTML pages into XML or databases.



Wrappers are:

- Specific to a given website
- Specific to a given task

→ Need for an efficient way to write wrappers

# Writing Wrappers

Different ways:

- Using a programming language
  - Generic: Perl, Python...
  - Specialized: XPATH, XSLT
- Using a specification GUI
  - Graphical interface over a wrapper description language
  - Lixto, W4F ...

In both cases, writing wrappers:

- Is time-consuming
- Needs some knowledge from the user

# Learning Wrappers

To solve these problems, we *learn* wrappers:

- The user provides some examples (via mouse clicks in a browser)
- The system *infers* a wrapper from these examples

Advantages:

- Fast
- The user needs no knowledge

Difficulty: the choice of a formalism for wrapper description

- Expressive enough
- Efficiently learnable

# Learning Wrappers: Related Works

Machine learning in wrapper design has been experimented in several works:

- WIEN
  - Delimiters computation
- Stalker
  - Document structure inference
- Roadrunner
  - Sequence matching
- Squirrel
  - Tree automata inference
- ...

# Learning Wrappers in Lixto

We are interested in the integration of wrapper learning in Lixto.

Constraints:

- Constraints of interactive learning:
  - High performances with few examples
  - Very small computing time
- Constraints specific to Lixto
  - Good intelligibility, for human checking and edition.

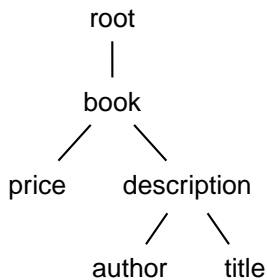


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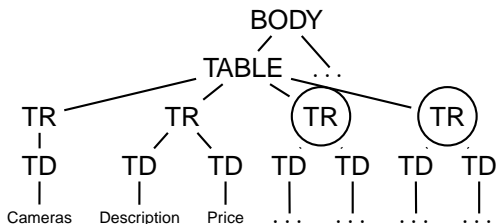
# Framework (1)

- Wrapper: hierarchy of patterns
- Pattern: defines the extraction of one type of elements
- Each pattern is defined independantly



## Framework (2)

- Documents are trees
- Patterns are nodes selection functions in these trees



# Defining patterns

How do we define these functions? Two objects:

- Filters:
  - Simple node selection functions
  - Poorly expressive
  - Very intelligible
- Compound filters:
  - Combination of filters
  - Very expressive
  - Still very intelligible

# Filters

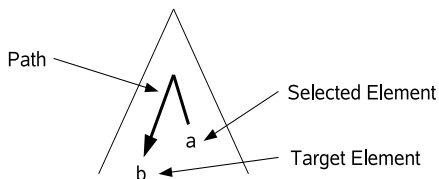
Defined by:

- A path  $p$ 
  - Input a *starting node*
  - Output a set of *target nodes*
- A test  $t$ 
  - Input a *node*
  - Output *true* or *false*

A node  $a$  is selected if and only if there exists a node  $b$  such that:

- $b \in p(a)$  (the path  $p$  leads from  $a$  to  $b$ )
- $t(b)$  ( $b$  satisfies  $t$ )

# Filter: Example

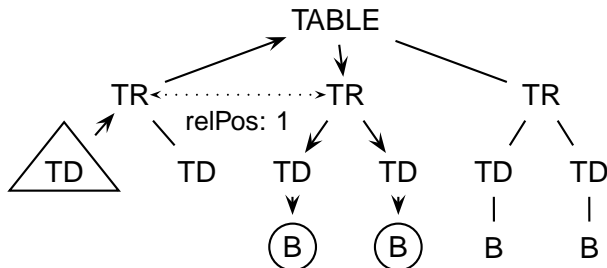


The node  $a$  is selected by the filter  $(p, t)$  iff there exists  $b$  such that  $p$  leads from  $a$  to  $b$  and  $b$  satisfies the test  $t$

# Paths

Describe a way to walk from a node to another, in a way similar to XPATH. Defined by:

- An ascending path (ex: /par::TD/par::TR)
- A relative position (ex: +1, or \*)
- A descending path (ex: /TR[1]/TD/B[1])



# Tests

Output *true* or *false* depending on the properties of input node.  
Different kind of tests:

- |                       |  |
|-----------------------|--|
| Null test:            | Always output <i>true</i>  |
| Text test:            | Output <i>true</i> iff the Text Data of the input node is equal to a given value   |
| Attribute test:       | Output <i>true</i> if the input node contains a given attribute                    |
| Attribute value test: | Output <i>true</i> if the input node contains a given attribute with a given value |



## Example (1)

Selects a node in a list whose left brother contains the string “Price”:

- Path:
  - Ascending: */par :: LI*
  - Relative position:  $-1$
  - Descending: */LI*
- Test:
  - Text test
  - Value: “Price”

## Example (2)

Selects a node which *ID* attribute is equal to “description”:

- Path:
  - Ascending: /
  - Relative position: 0
  - Descending: /
- Test:
  - Attribute value test
  - Attribute: *ID*
  - Value: “description”

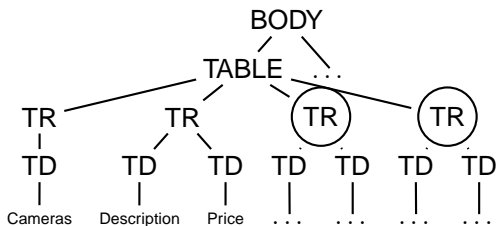
## Example (3)

Selects a node addressed by the XPATH `/HTML/BODY/H1[1]` from the root.

- Path:
  - Ascending: `/par :: H1[1]/par :: BODY/par :: HTML`
  - Relative position: 0
  - Descending: `/`
- Test:
  - Null test

# Compound Filters

Combinations of filters, with operators OR, AND and NOT



$C_1$ : brother of "Cameras"

$C_2$ : second child of its parent

$C_3$ : target of path /BODY/TABLE/TR

Result:  $C_1$  AND  $C_3$  AND (NOT  $C_2$ )

# Defining Wrappers: Conclusion

We have defined objects defining patterns which are:

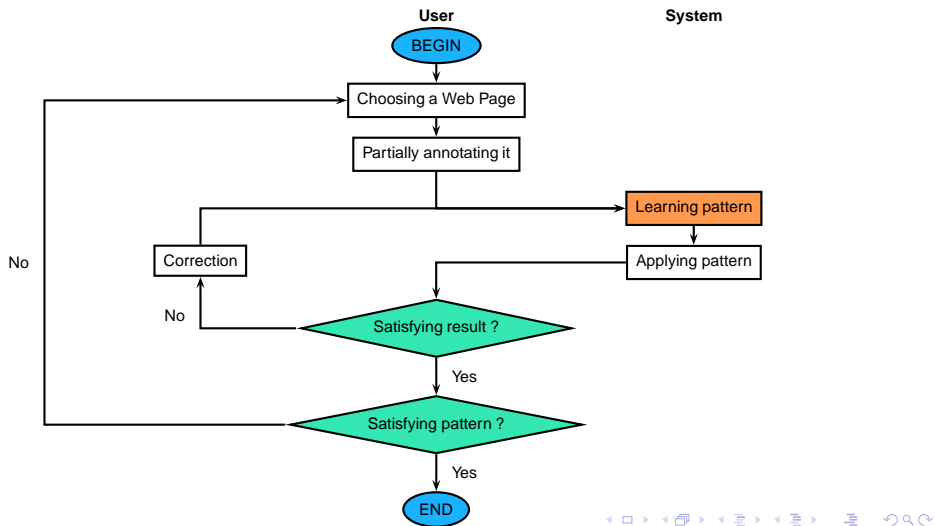
- Intelligible
- Expressive

We show now how to learn these objects from a user interaction.

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# Interactive Learning



# Learning from positive and negative example

## Interactive learning

→ Learning from positive and negative examples

Two kind of interactions:

- The user adds a new element  
→ provides a positive example
- The user removes a selected element  
→ provides a negative example

At each interaction, a new pattern is learned from examples provided by all previous interactions.



# Learning algorithm

Goal: given a set of examples, find a compound filter, which:

- is consistent with all examples
- is as small as possible
- is constituted with filters as “simple” as possible

Overview of the algorithm:

- Exhaustive generation of all filters consistent with at least one example
- Selection of a set of optimal filters
- Generation of an optimal combination of filters of this set

# Learning algorithm: filter generation

We generate the set of all filters consistent with at least one example

All filters  $(p, t)$  such that:

- $p$  leads from  $a$  to  $b$ , where  $a$  is an example
- $t$  is satisfied for  $b$

## Learning algorithm: filter selection (1)

Filters are compared considering their behaviour on examples.

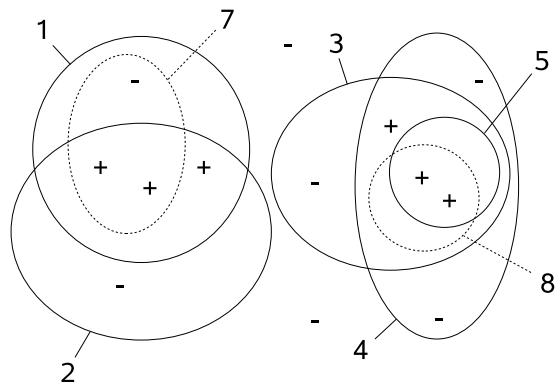
Let:

- $E$  be the set of examples
- $f_1$  and  $f_2$  be two filters
- $E_{f_1}$  and  $E_{f_2}$  be subset of  $E$  satisfied by  $f_1$  and  $f_2$ .

Then:

- If  $E_{f_1} \subsetneq E_{f_2}$ , then  $f_1$  is discarded.
- If  $E_{f_1} = E_{f_2}$ , then  $f_1$  or  $f_2$  is discarded.

## Learning algorithm: filter selection (2)



- 7 is discarded, because  $E_7 \subsetneq E_1$
- 8 (or 5) is discarded, because  $E_5 = E_8$

## Learning algorithm: filter selection (3)

When two filters behave similarly on examples, a choice based on heuristics is done between them.

These heuristics tend to choose the “simplest” filter:

- The shortest path
- The most generic path
- The simplest test. In order of preference:
  - Null test
  - Text test defined on the shortest possible text
  - Attribute test
  - Attribute value test

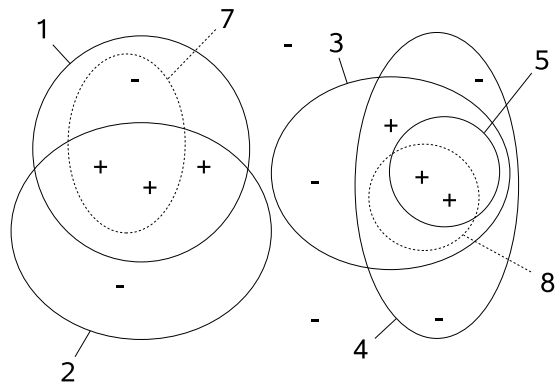
## Learning Algorithm: combination

From the remaining filters, an optimal combination is computed.

This can be reduced to a standard boolean function learning problem:

- Each example  $x$  is a vector of boolean  $(x_1 \dots x_n)$
- Each  $x_i$  is the consistence of  $x$  with filter  $i$ .
- The target function:
  - Inputs a vector  $(x_1 \dots x_n)$
  - Outputs *true* for positive examples, *false* for negative examples

# Learning algorithm: combination



Optimal compound filter: (1 AND 2) OR (3 AND 4)

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# Conclusion

- Work in progress:
  - Integration in Lixto
  - Extensive tests
- Preliminary results:
  - Fast enough for interactive learning
  - Resulting wrappers close to manually written ones in Lixto
  - Very good results on standard benchmarks
- Perspectives:
  - Combination with a textual information extraction system