A Flexible Learning System for “Wrapping” Tables and Lists

or

How to Write a *Really Complicated* Learning Algorithm

Without Driving Yourself Mad

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WhizBang Labs – Research

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Learning “Wrappers”

- A “wrapper” is a program that makes (part of) a web site look like (part of) a database.

  For instance, job postings on microsoft.com might be converted to tuples from a relation:

Job title	*Location*	*Employer*
C# software developer	Seattle, WA	Microsoft
Receptionist	Seattle, WA	Microsoft
Research Scientist	Beijing, China	Microsoft–Asia
...	...	...

Learning "Wrappers"

- Reasons for wanting wrappers:
  - Collect training data for an IE system from lots of websites.
  - IE from not-too-many websites $O(10^2\text{-}10^3)$
  - Boost performance of IE on "important" sites.
- Ways of creating wrappers:
  - Code them up (in Perl, Java, WebL, . . . ,)
  - Learn them from examples

What's Hard About Learning Wrappers

- A good wrapper induction system should generalize across future pages as well as current pages.

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Currently we have offices in two locations:

- Pittsburgh, PA
- Provo, UT

What's Hard About Learning Wrappers

- A good wrapper induction system should generalize across future pages as well as current pages.
- Many generalizations of the first two examples are possible, but only a few will generalize.
- Prior solutions: hand-crafted learning algorithms and carefully chosen heuristics.

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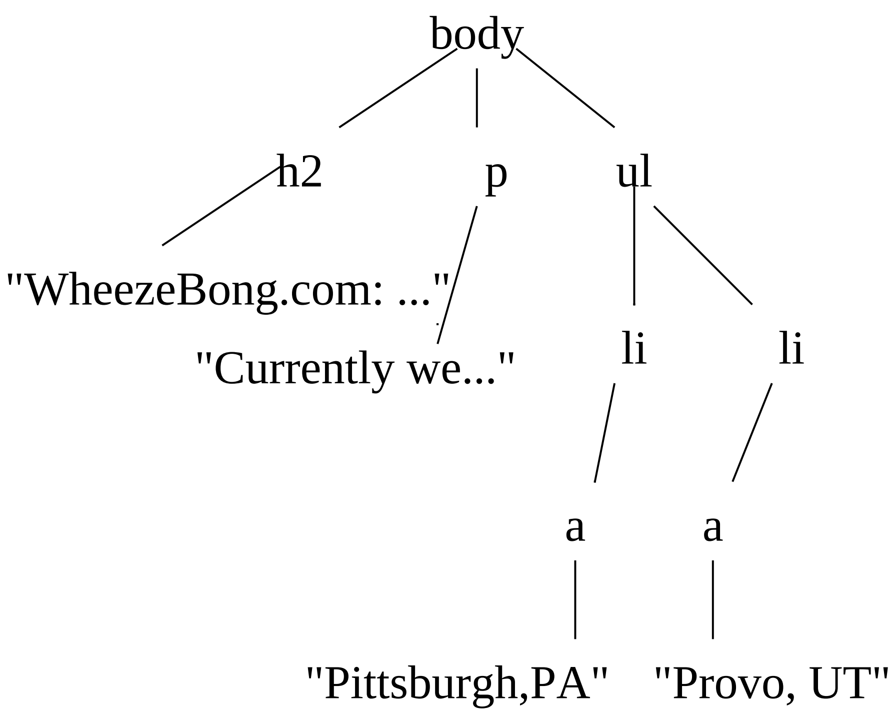
- Provo, UT
- Honolulu, HI

Our Approach to Wrapper Induction

- Premise: A wrapper learning system needs careful engineering (and possibly re-engineering).
  - 6 hand-crafted languages in WIEN (Kushmeric AIJ2000)
  - 13 ordering heuristics in STALKER (Muslea et al AA1999)
- Approach: architecture that facilitates hand-tuning the “bias” of the learner.
  - Bias is an ordered set of “builders”.
  - Builders are simple “micro-learners”.
  - A single master algorithm co-ordinates learning.

Our Approach: Document Representation*



Structured documents (e.g. HTML) are labeled trees (DOMs).

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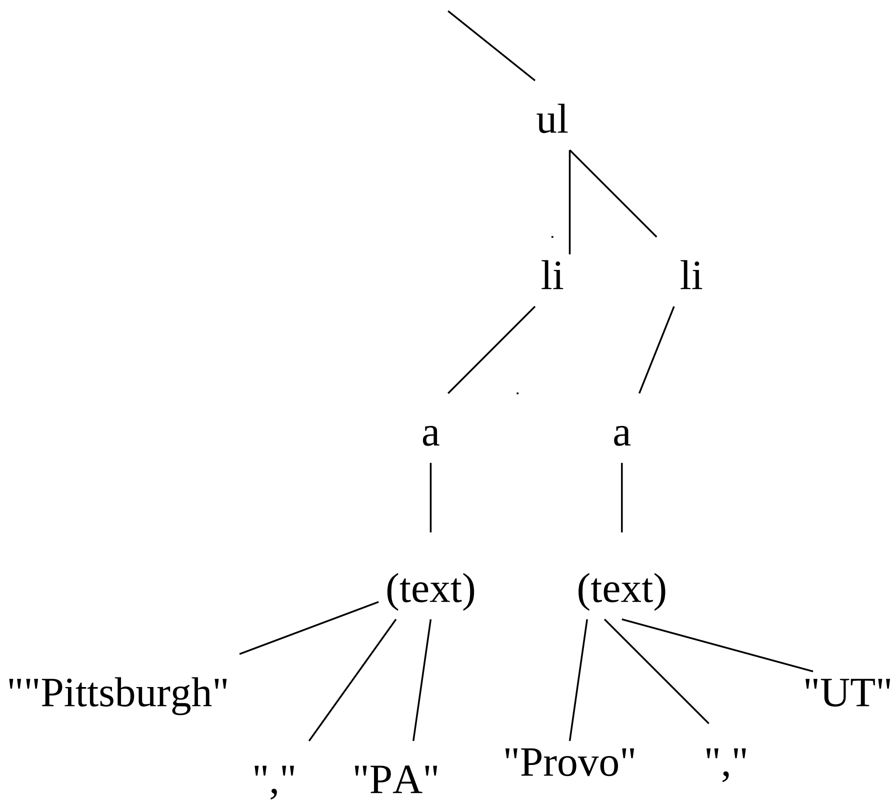
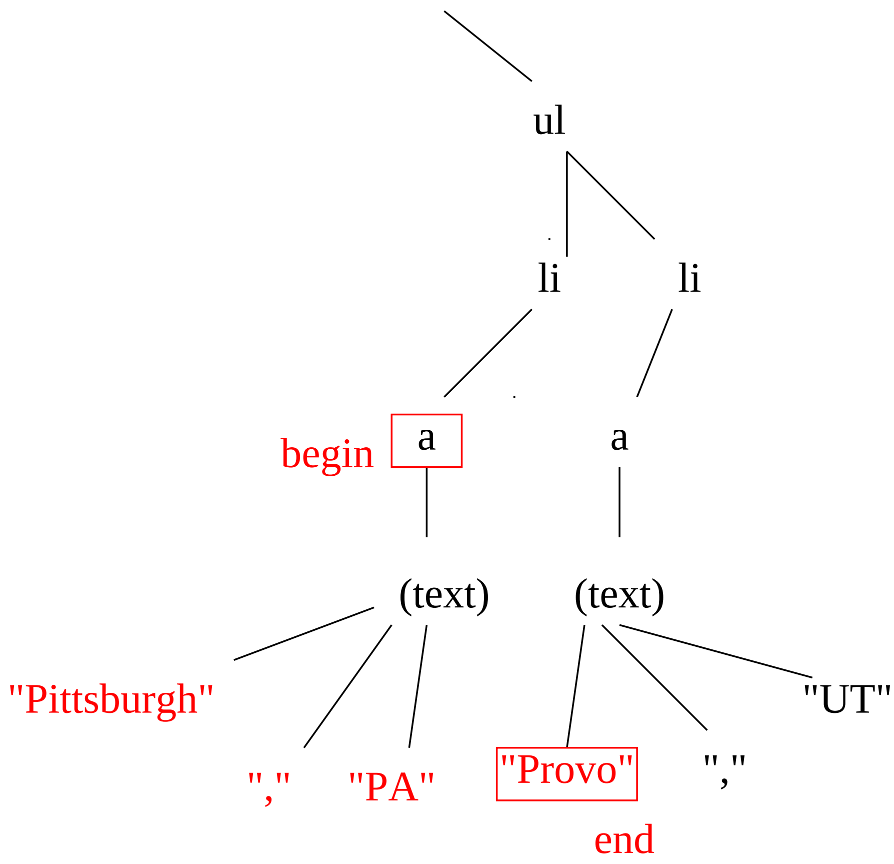
*Slightly over-simplified...

Our Approach: Document Representation



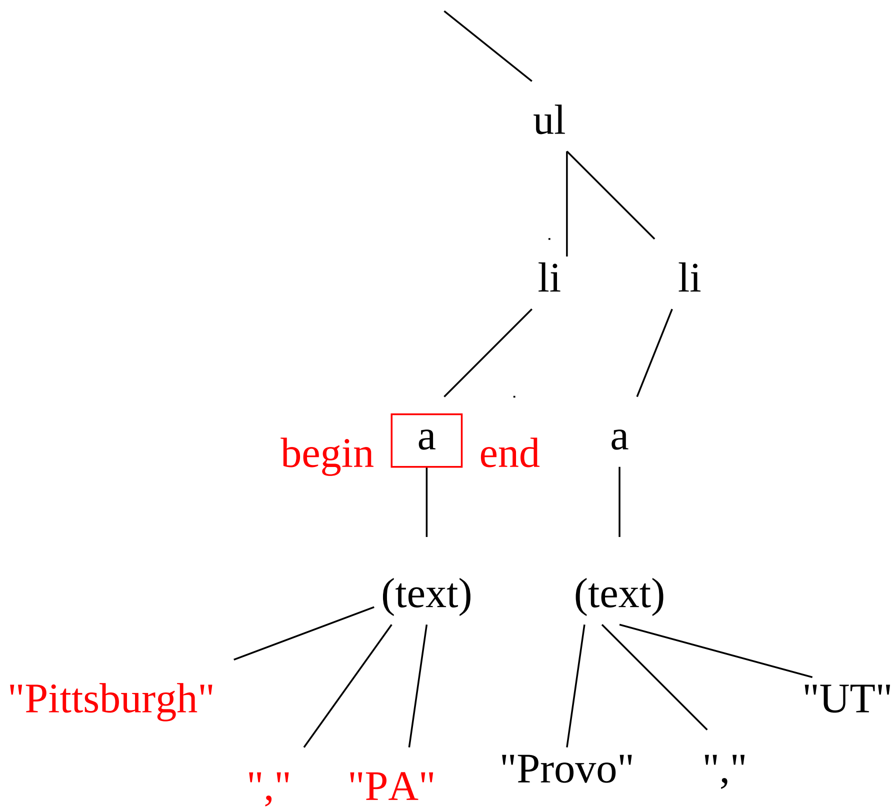
Imagine the DOM extended with a new node for each token of text...

Our Approach: Document Representation



A "span" is defined by a start node and an end node...

Our Approach: Document Representation



...and the start node and end node might be identical (a “node span”).

Our Approach: Representing Extractors

- A predicate is a binary relation on spans: $p(s_1, s_2)$ means that s_2 is extracted from s_1.
- Membership in a predicate can be tested:
  - Given (s_1, s_2), is $p(s_1, s_2)$ true?
- Predicates can be executed:
  - EXECUTE(p,s_1) is the set of s_2 for which $p(s_1, s_2)$ is true.

Example Predicate

Example:

- $p(s_1, s_2)$ iff s_2 are the tokens below an `li` node inside s_1.
- EXECUTE(p,s_1) extracts
  - "Pittsburgh, PA"
  - "Provo, UT"

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Our Approach: Representing Bias

- The hypothesis space of the learner is built up from simple sublanguages.

- L_{bracket}: p is defined by a pair of strings (ℓ, r), and $p_{\ell,r}(s_1, s_2)$, is true iff s_2 is preceded by ℓ and followed by r.

  $\text{EXECUTE}(p_{in,locations}, s_1) = \{$ "two" $\}$

- L_{tagpath}: p is defined by $\texttt{tag}_1, \ldots, \texttt{tag}_k$, and $p_{\texttt{tag}_1,\ldots,\texttt{tag}_k}(s_1, s_2)$ is true iff s_1 and s_2 correspond to DOM nodes and s_2 is reached from s_1 by following a path ending in $\texttt{tag}_1, \ldots, \texttt{tag}_k$.

  $\text{EXECUTE}(p_{\texttt{ul},\texttt{li}}, s_1) = \{$ "Pittsburgh, PA", "Provo, UT" $\}$

Our Approach: Representing Bias

For each sublanguage L there is a builder $\mathcal{B}_L$ which implements a few simple operations:

- LGG(positive examples of $p(s_1, s_2)$): least general p in L that covers all the positive examples.

  For L_{bracket}, longest common prefix and suffix of the examples.

- REFINE(p, examples): a set of p's that cover some but not all of the examples.

  For L_{tagpath}, extend the path with one additional tag that appears in the examples.

Our Approach: Representing Bias

Builders can be composed: given $\mathcal{B}_{L_1}$ and $\mathcal{B}_{L_2}$ one can automatically construct

- a builder for the conjunction of the two languages, $L_1 \wedge L_2$
- a builder for the composition of the two languages, $L_1 \circ L_2$

  Requires an additional input: how to decompose an example (s_1, s_2) of $p_1 \circ p_2$ into an example (s_1, s') of p_1 and an example (s', s_2) of p_2.

So, complex builders can be constructed by combining simple ones.

Example of combining builders

- Consider composing builders for L_{tagpath} and L_{bracket}.
- The LGG of the locations would be $p_{tags} \circ p_{\ell,r}$

  where

  - $tags$=`ul`,`li`
  - ℓ= "("
  - r= ")"

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- Webmaster (New York). Perl,servlets a plus.
- Librarian (Pittsburgh). MLS required.
- Ditch Digger (Palo Alto). No experience needed.

Limitations of DOMs

- The "real" regularities are at the level of the visual appearance of the document.
- What if the underlying DOM doesn't show the same regularities?

  ⟨b⟩⟨i⟩Provo⟨/i⟩⟨/b⟩ versus ⟨i⟩⟨b⟩Pittsburgh⟨/b⟩⟨/i⟩

Limitations of DOMs

"Actresses"			
Lucy	Lawless	images	links
Angelina	Jolie	images	links
...	...	...	...
"Singers"			
Madonna		images	links
Brittany	Spears	images	links
...	...	...	...

How can you easily express "links to pages about singers"?

Fancy Builders: Understanding Table Rendering

1. Classify HTML tables nodes as "data tables" or "non-data tables".

   On 339 examples, precision/recall of 1.00/0.92 with Winnow and features . . .

2. Render each data table.

3. Find the logical cells of the table.

4. Construct geometric model of table: an integer grid, with each logical cell having co-ordinates on the grid.

5. Tag each cell with (some aspects) of its role in the table.
   - Currently, "cut-in cells".

Fancy Builders: Understanding Table Rendering

“Actresses” cutin,1.1-1.1			
Lucy 2.1-2.1	Lawless 2.2-2.2	images 2.3-2.3	links 2.4-2.4
Angelina 3.1-3.1	Jolie 3.2-3.2	images 3.3-3.3	links 3.4-3.4
“Singers” cutin,4.1-4.1			
Madonna 5.1-5.2		images 5.3-5.3	links 5.4-5.4
Brittany 6.1-6.1	Spears 6.2-6.2	images 6.3-6.3	links 6.4-6.4

Table builders:

Element name + words in last cut-in (e.g., “table cells where the last cut-in contains ‘singers”’)

“Tagpath” builder extended to condition on (x,y) co-ordinates (e.g., “table cells with y-coordinates ‘3-3’ inside . . .)

The Learning Algorithm

Inputs:

- an ordered list of builders $\mathcal{B}_1$, $\mathcal{B}_k$.
- positive examples (s_1, s_2) of the predicate to be learned
- information about what parts of each page have been completely labeled (implicit negative examples)

The Learning Algorithm

Algorithm:

- Compute LGG of positive examples with each builder $\mathcal{B}_i$.
- If any LGG is consistent with the (implicit) negative data, then return it*.
- Otherwise, execute the best* LGG to get explicit negative examples, then apply a FOIL-like learning algorithm, using LGG and REFINE to create "features*".

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* Break ties in favor of earlier builders. With few positive examples there are lots of ties.

Experimental results

Problem#	WIEN(=)	STALKER(≈)	WL^2(=)
S1	46	1	1
S2	274	8	6
S3	∞	∞	1
S4	∞	∞	4

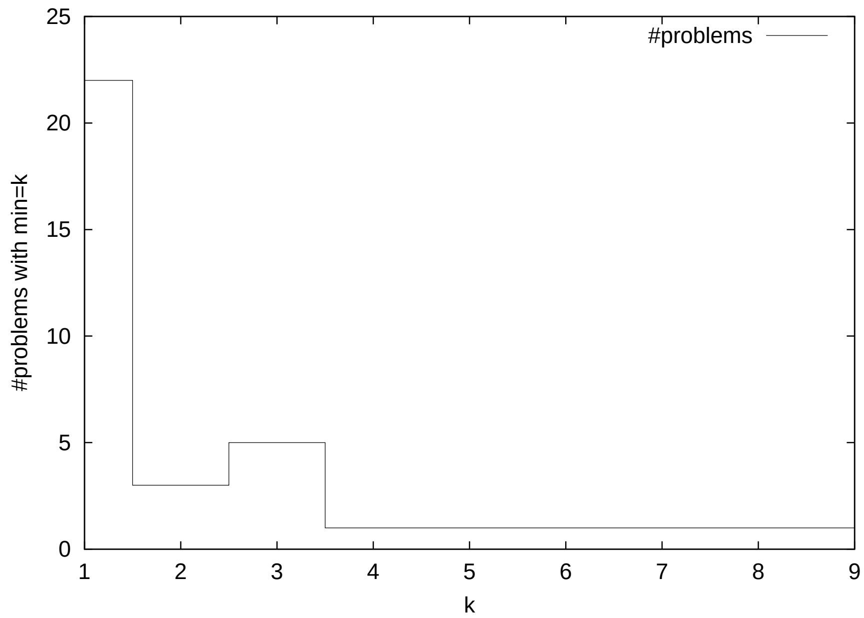
Examples needed to learn accurate extraction rules for all parts of a wrapper for WIEN (Kushmerick '00), STALKER (Muslea, Minton, Knoblock '99), and the WhizBang Labs Wrapper Learner (WL^2).

Experimental results

Problem	WL^2	Problem	WL^2
JOB1	3	CLASS1	1
JOB2	1	CLASS2	3
JOB3	1	CLASS3	3
JOB4	2	CLASS4	3
JOB5	2	CLASS5	6
JOB6	9	CLASS6	3
JOB7	4		
median	2	median	3

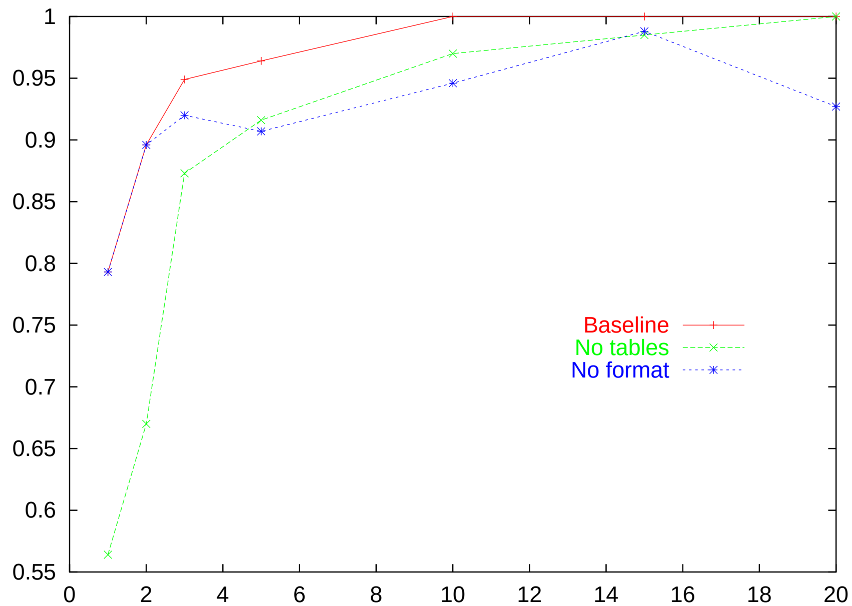
WL^2 on representative real-world wrapping problems.

Experimental results



WL^2 on representative real-world wrapping problems.

Experimental results



Variants of WL^2 on real-world wrapping problems:

average accuracy versus number of training examples.

Conclusions/Summary

- Wrapper learners need tuning. Structuring the bias space provides a principled approach to tuning.
- "Builders" let one mix generalization strategies based on different views of the document:
  - as DOM
  - as sequence of tokens
  - as sequence of rendered fragments of text
  - as geometric model of table
  - ...
- Performance seems to be better than previous systems.