



Web-Based Learning

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Joint work with

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Introduction



Problem

- Web sources and services are designed for people, not machines
- Limited or no description of the information provided by these sources
- This makes it hard, if not impossible to find, retrieve and integrate the vast amount of structured data available
 - Weather sources, geocoders, stock information, currency converters, online stores, etc.

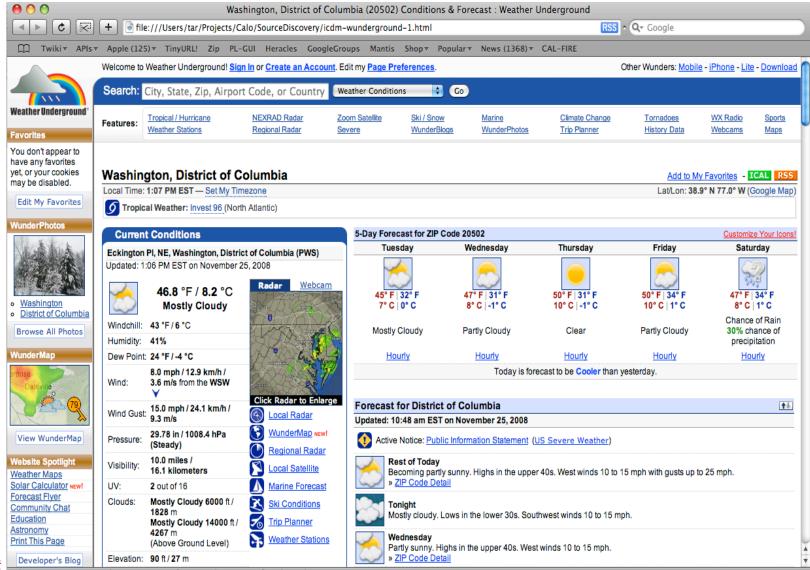
Approach

- Start with an some initial knowledge of a domain
 - Sources and semantic descriptions of those sources
- Automatically
 - Discover related sources
 - Learn the syntactic structure of the sources
 - Build semantic models of the source
 - Validate the correctness of the results



Seed Source

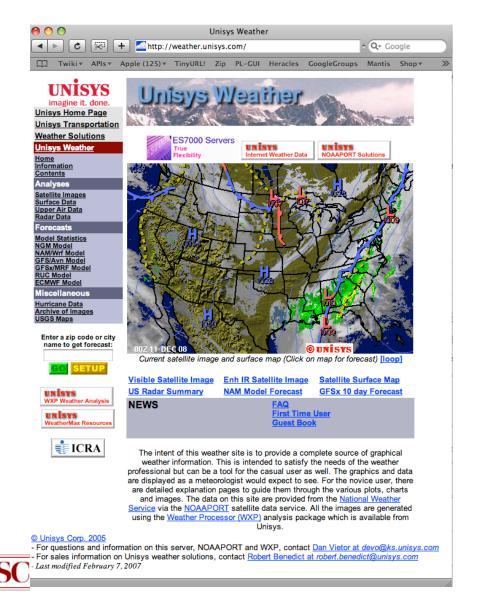


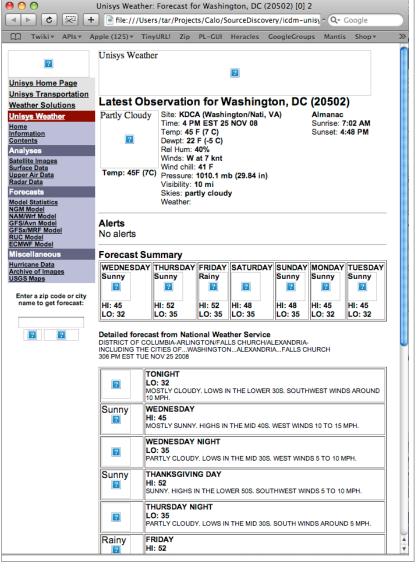




Automatically Discover and Model a Source in the Same Domain

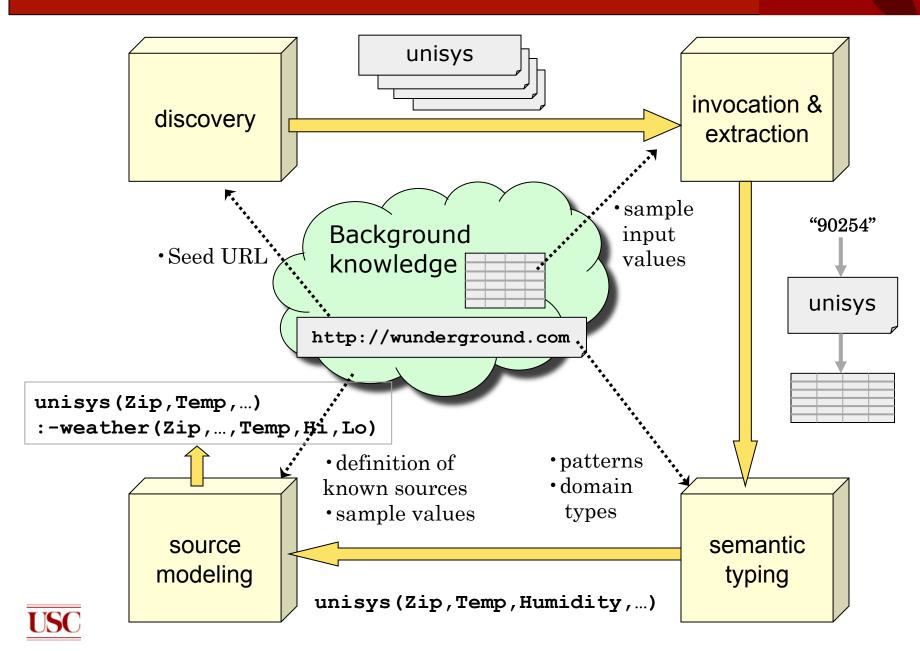






Approach





Outline



- Discovering sources using social annotations
- Discovering the structure of sources
- Learning semantic types of the source data
- Learning semantic models of the sources
- Experimental Results
- Discussion



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Learning Concepts from Social Annotation (Tags)







By sparky2000

By A lion Rohrs

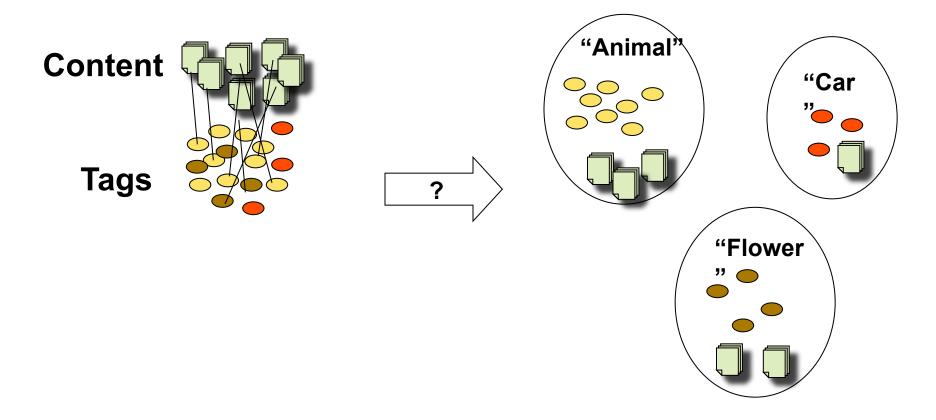
Animal

Car



Goal





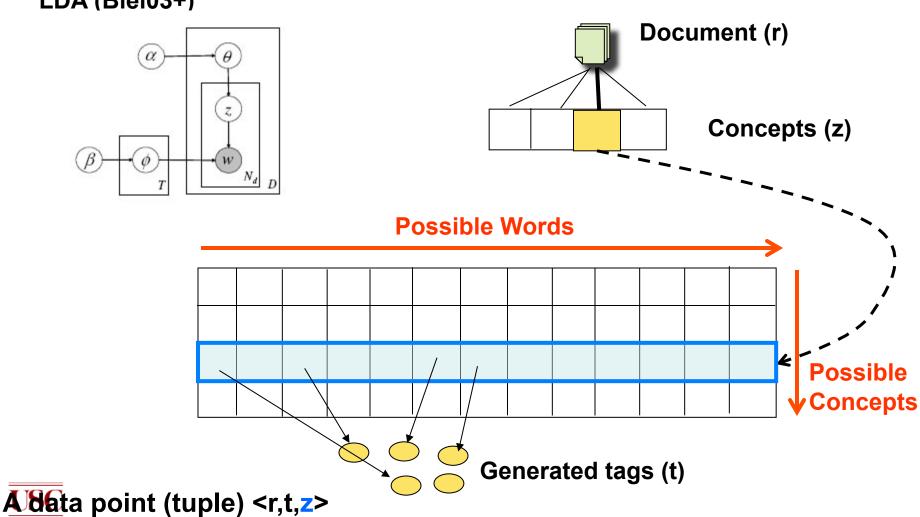
Grouping semantically related tags and content



A stochastic process of tag generation



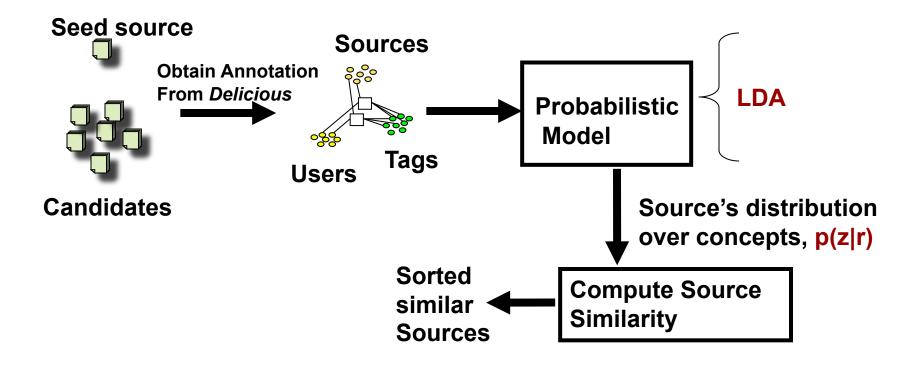
PLSA (Hofmann99); LDA (Blei03+)



Exploiting Social Annotations for Resource Discovery



• Simplified resource discovery task: "given a seed source, find other most <u>similar sources</u>"





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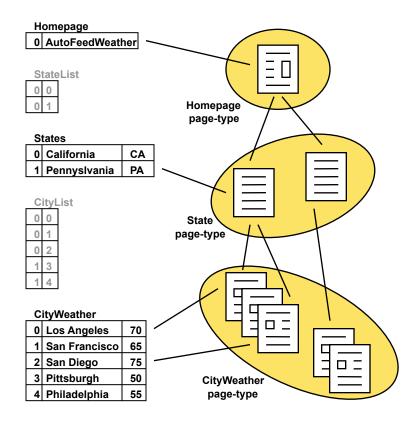


Discovering Web Structure



Goal:

- Model Web sources that generate pages dynamically in response to a query
 - Find the relational data underlying a semi-structured web site
- Generate a page template that can be used to extract data on new pages
- Approach
 - Site extraction
 - Exploit the common structure within a web site
 - Take advantage of multiple structures
 - HTML structure, page layout, links, data formats, etc.

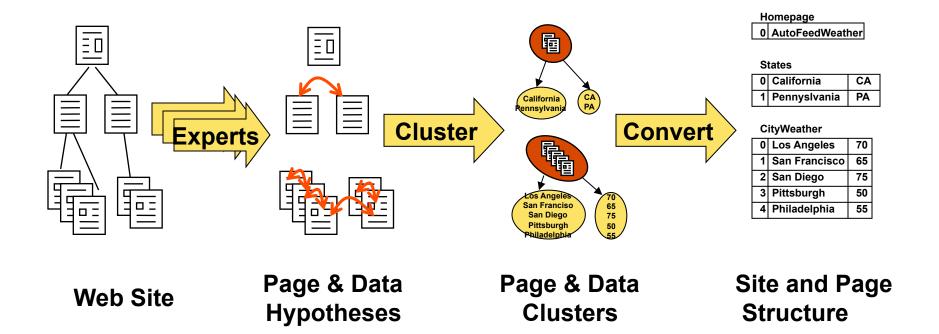






Overview









Sample Experts

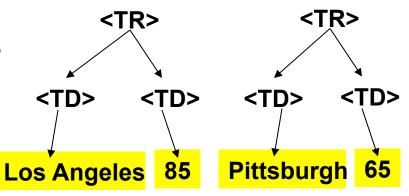


- Page Templates
 - Similar pages contain common sequences of substrings





- HTML Structure
 - List rows are represented as repeating HTML structures



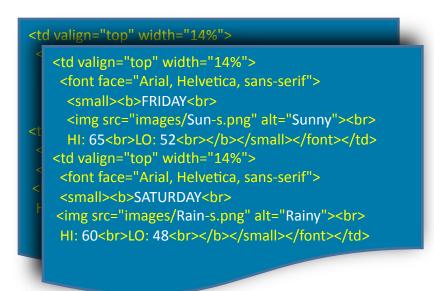




Extracting Data



Pages





Hypotheses

- group_member (FRIDAY, SATURDAY)
- group_member (Sunny, Rainy)
- same_html_context (65, 60)
- vertically_aligned (Sun, Rain)
- two_digit_number (65, 52, 60, 48)
- ...



Clusters

FRIDAY	65 52
SATURDAY	60 48
F	Rainy • Fetch

Extracted Data

FRIDAY	Sun	Sunny	65	52
SATURDAY	Rain	Rainy	60	48





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Learning Patterns to Recognize Semantic Types



- Domain-independent token-level language to represent the structure of data as patterns
 - Token is a string or a general type
 - 90202 is a specific token
 - 5DIGIT number is a general type
 - Pattern is a sequence of tokens
 - E.g., Phone numbers

Sample values	<u>Patterns</u>
310 448-8714	
310 448-8775	[310 448 – 4DIGIT]
212 555-1212	[3DIGIT 3DIGIT – 4DIGIT]

- Efficiently learn patterns from examples of semantic types
- Score the match between a type (patterns) and data



Weather Data Types



Sample values

- PR-TempF
 88 F
 57°F
 82 F ...
- PR-Visibility
 8.0 miles
 10.0 miles
 4.0 miles
 7.00 mi
 10.00 mi
- PR-Zip 07036 97459 02102

Patterns

- PR-TempF
 [88, F]
 [2DIGIT, F]
 [2DIGIT, °, F]
- PR-Visibility

 [10, ., 0, miles]
 [10, ., 00, mi]
 [10, ., 00, mi, .]
 [1DIGIT, ., 00, mi]
 [1DIGIT, ., 0, miles]
- PR-Zip [5DIGIT]



Labeled Columns of Target Source Unisys



Column	4	18	25	15	87
Туре	PR-Zip	PR-TempF	PR- Humidity	PR-Sky	PR-Sky
Score	0.333	0.68	1.0	0.325	0.375
Values	20502	45F	40%	Partly Cloudy	Sunny
	32399	63F	23%	Sunny	Partly Cloudy
	33040	73F	73%	Sunny	Rainy
	90292	66F	59%	Partly Cloudy	Sunny
	36130	62F	24%	Sunny	Partly Cloudy



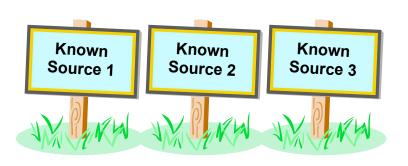
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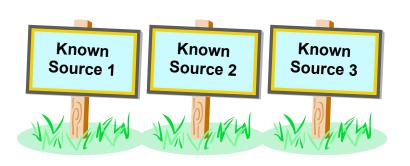
```
source1($zip, lat, long):-
centroid(zip, lat, long).
```

```
source2($lat1, $long1, $lat2, $long2, dist):-
greatCircleDist(lat1, long1, lat2, long2, dist).
```

```
source3($dist1, dist2):-
convertKm2Mi(dist1, dist2).
```







source1(\$zip, lat, long) :centroid(zip, lat, long).

source2(\$lat1, \$long1, \$lat2, \$long2, dist) :greatCircleDist(lat1, long1, lat2, long2, dist).

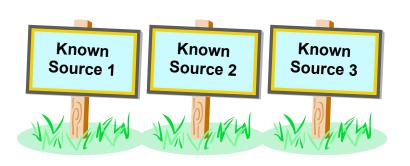
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source4(\$startZip, \$endZip, separation)







source1(\$zip, lat, long):centroid(zip, lat, long).

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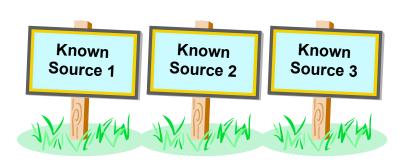
Step 1: classify input & output semantic types



source4(\$startZip, \$endZip, separation)





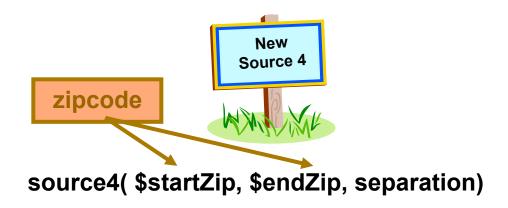


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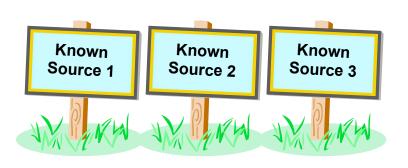
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Step 1: classify input & output semantic types







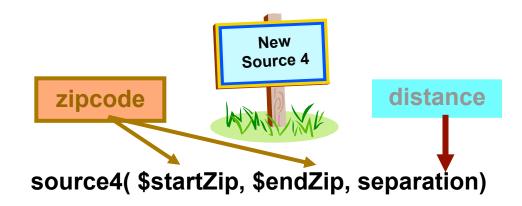


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source3(\$dist1, dist2):convertKm2Mi(dist1, dist2).

Step 1: classify input & output semantic types





Generating Plausible Definition





source1(\$zip, lat, long):centroid(zip, lat, long).

source2(\$lat1, \$long1, \$lat2, \$long2, dist) :greatCircleDist(lat1, long1, lat2, long2, dist).

source3(\$dist1, dist2):convertKm2Mi(dist1, dist2).

- Step 1: classify input & output semantic types
- Step 2: generate plausible definitions

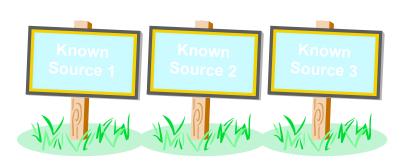


source4(\$zip1, \$zip2, dist)



Generating Plausible Definition





```
source1($zip, lat, long) :-
    centroid(zip, lat, long).
source2($lat1, $long1, $lat2, $long2, dist) :-
    greatCircleDist(lat1, long1, lat2, long2, dist).
source3($dist1, dist2) :-
    convertKm2Mi(dist1, dist2).
```

- Step 1: classify input & output semantic types
- Step 2: generate plausible definitions

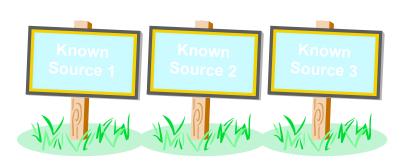
```
source4($zip1, $zip2, dist):-
source1(zip1, lat1, long1),
source1(zip2, lat2, long2),
source2(lat1, long1, lat2, long2, dist2),
source3(dist2, dist).
```

source4(\$zip1, \$zip2, dist)



Generating Plausible Definition





```
source1($zip, lat, long) :-
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source2($lat1, $long1, $lat2, $long2, dist) :-
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- Step 1: classify input & output semantic types
- Step 2: generate plausible definitions

```
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source1(zip1, lat1, long1),
source1(zip2, lat2, long2),
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source3(dist2, dist).
```

```
source4($zip1, $zip2, dist):-
centroid(zip1, lat1, long1),
centroid(zip2, lat2, long2),
greatCircleDist(lat1, long1, lat2, long2, dist2),
convertKm2Mi(dist1, dist2).
```



Invoke and Compare the Definition



- Step 1: classify input & output semantic types
- Step 2: generate plausible definitions
- Step 3: invoke service& compare output

```
source4($zip1, $zip2, dist):-
source1(zip1, lat1, long1),
source1(zip2, lat2, long2),
source2(lat1, long1, lat2, long2, dist2),
source3(dist2, dist).
```

```
source4($zip1, $zip2, dist):-
  centroid(zip1, lat1, long1),
  centroid(zip2, lat2, long2),
  greatCircleDist(lat1, long1, lat2, long2,dist2),
  convertKm2Mi(dist1, dist2).
```

	match	
Г		
Ļ		

\$zip1	\$zip2	dist (actual)	dist (predicted)
80210	90266	842.37	843.65
60601	15201	410.31	410.83
10005	35555	899.50	899.21



Source Modeling for Weather



- Given a set of known sources and their descriptions
 - wunderground(\$Z,CS,T,F0,S0,Hu0,WS0,WD0,P0,V0):weather(0,Z,CS,D,T,F0,__,_,S0,Hu0,P0,WS0,WD0,V0)
 - convertC2F(C,F) :- centigrade2farenheit(C,F)
- Learn a description of a new source in terms of the known sources
 - unisys(\$Z,CS,T,F0,C0,S0,Hu0,WS0,WD0,P0,V0):wunderground(Z,CS,T,F0,S0,Hu0,WS0,WD0,P0,V0), convertC2F(C0,F0)



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Experimental Evaluation

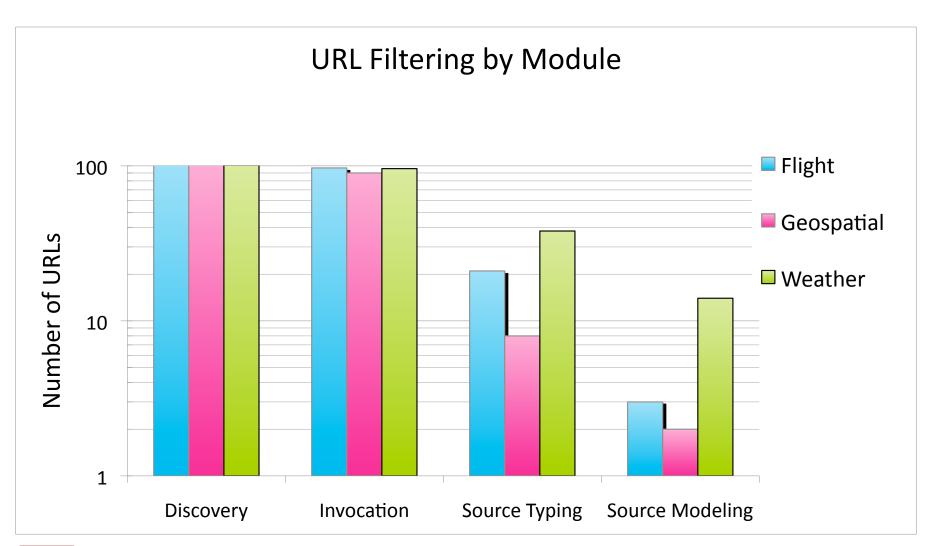


- Experiments in 3 domains
 - Geospatial
 - Geocoder that maps street addresses into lat/long coordinates
 - Weather
 - Produces current and forecasted weather
 - Flight Status
 - Current status for a given airline and flight
- Evaluation:
 - 1) Can we correctly learn a model for those sources that perform the same task
 - 2) What is the precision and recall of the attributes in the model



Candidate Sources after Each Step







Evaluation of the Models



	Recall	Precision	F-measure
geospatial	86	100	92
weather	29	64	39
flight	35	69	46



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Related Work



- ILA & Category Translation (Perkowitz & Etzioni 1995)
 - Learn functions describing operations on internet
- iMAP (Dhamanka et. al. 2004)
 - Discovers complex (many-to-1) mappings between DB schemas
- Metadata-based classification of data types used by Web services and HTML forms (Hess & Kushmerick, 2003)
 - Naïve Bayes classifier
- Woogle: Metadata-based clustering of data and operations used by Web services (Dong et al, 2004)
 - Groups similar types together: Zipcode, City, State



Discussion



- Integrated a diverse set of learning and reasoning techniques
 - Discover new sources
 - Discover the template for a source
 - Find the semantic types of source data
 - Learn a definition of what a source does
- Provides an end-to-end completely automatic approach to discover and build models of sources

