

Learning Semantic Descriptions of Web Information Sources

Mark James Carman*

Information Sciences Institute / USC

&

ITC-irst / University of Trento

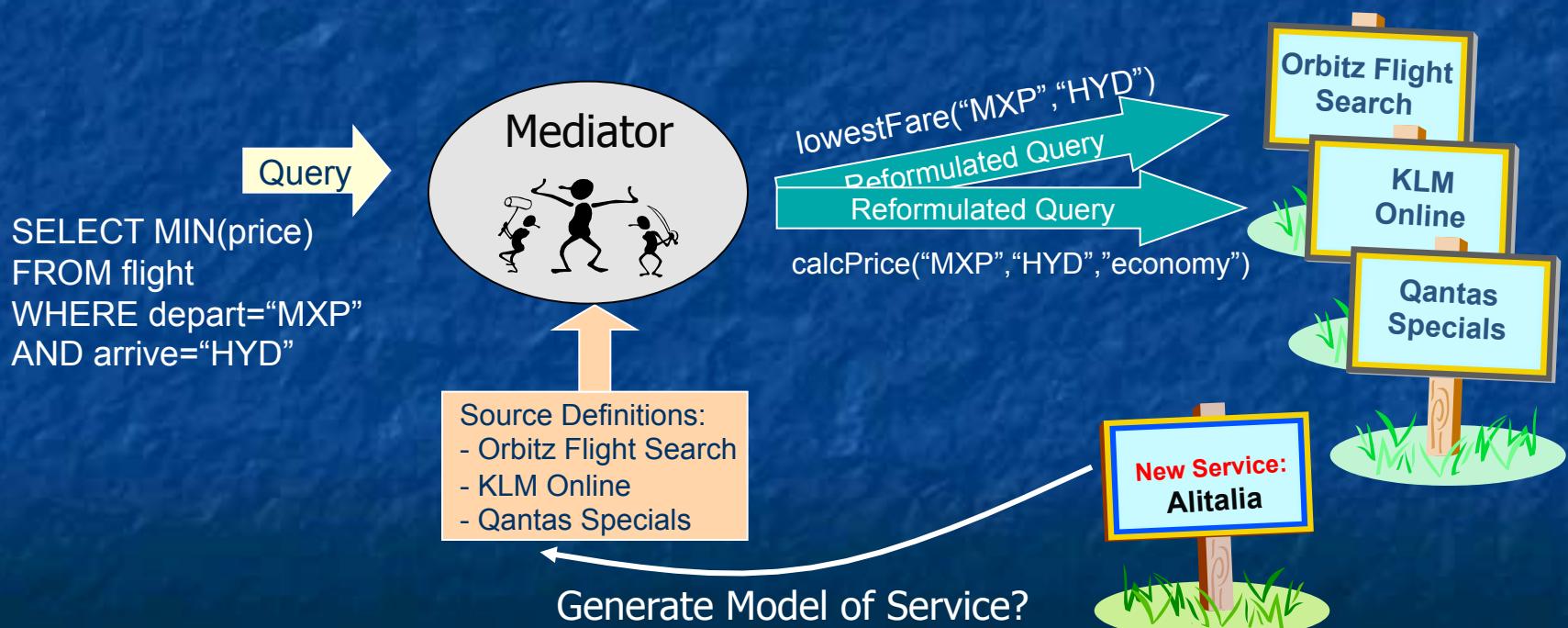
Craig A. Knoblock

Information Sciences Institute / USC

* I am currently seeking a Postdoc position
in Europe somewhere near northern Italy ...

Mediators & Source Definitions

- Explosion of online information sources
- Mediators run queries over multiple sources
- Require declarative source definitions
- New service → model it automatically?



Modeling Sources: an Example

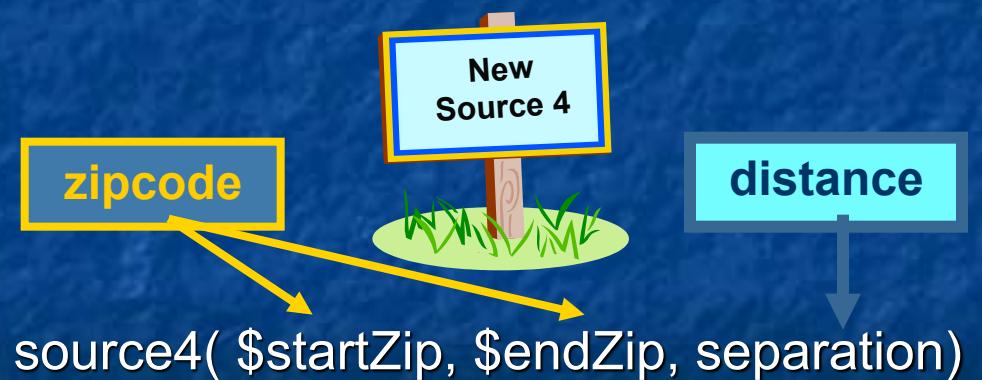


```
source1($zip, lat, long) :-  
    centroid(zip, lat, long).
```

```
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, using:
■ Metadata (labels)
■ Data (content)



Modeling Sources: Step 2



Step 2:
model functionality by:
■ generating plausible
definitions

```
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).
```

```
source4( $zip1, $zip2, dist) :-
```

```
    centroid(zip1, lat1, long1),  
    centroid(zip2, lat2, long2),  
    greatCircleDist(lat1, long1, lat2, long2, dist2),  
    convertKm2Mi(dist1, dist2).
```

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

Modeling Sources: Step 2

Step 2:

model functionality by:

- generating plausible definitions
- comparing the output they produce

```
source4( $zip1, $zip2, dist) :-
```

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

match

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

Summary - Modeling Sources

Step 1: Semantic Labeling

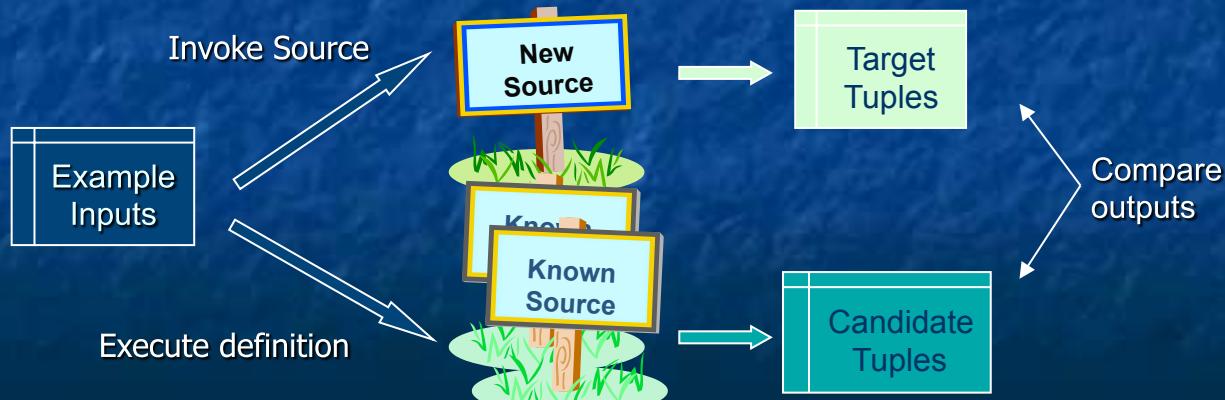
Classify input & output *semantic types*, using:

- Labels: metadata
- Content: output data

Step 2: Functional Modeling

Model the *functionality* of service by:

- Search: generating plausible definitions
- Scoring: compare the output they produce



Summary - Modeling Sources

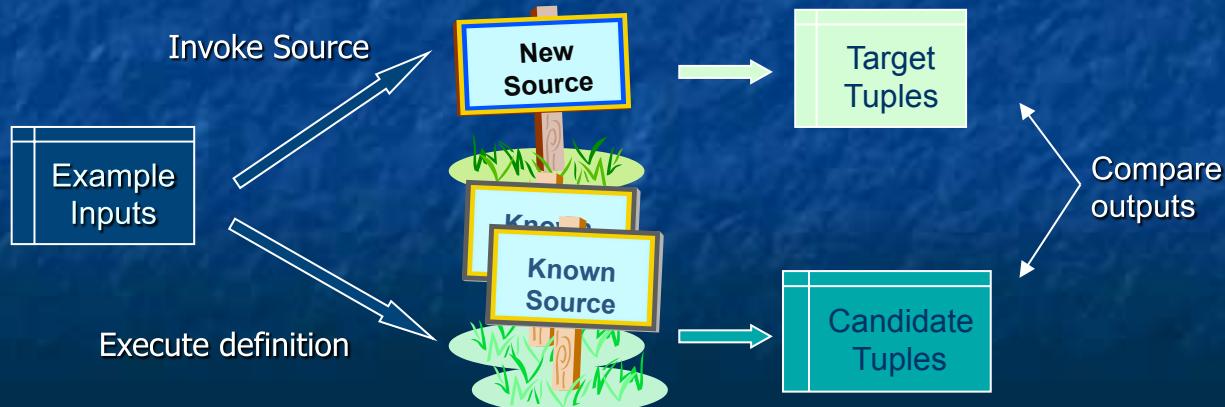
Step 1: Semantic Labeling

Previous Work!
Lerman, Plangprasopchok and Knoblock.
Automatically labeling data used by web services., using:
AAAI'06.

Step 2: Functional Modeling

Model the *functionality* of service by:

- Search: generating plausible definitions
- Scoring: compare the output they produce



Searching for Definitions

- Search space of *conjunctive queries*:

$\text{target}(\underline{X}) :- \text{source1}(\underline{X}_1), \text{source2}(\underline{X}_2), \dots$

Expressive Language
Sufficient for modeling
most online sources

2. Best-first search
through space of
candidate definitions

```
Invoke target with set of random inputs;  
Add empty clause to queue;  
while (queue not empty)  
   $v :=$  best definition from queue;  
  forall ( $v'$  in Expand( $v$ ))  
    if ( Eval( $v'$ ) > Eval( $v$ ) )  
      insert  $v'$  into queue;
```

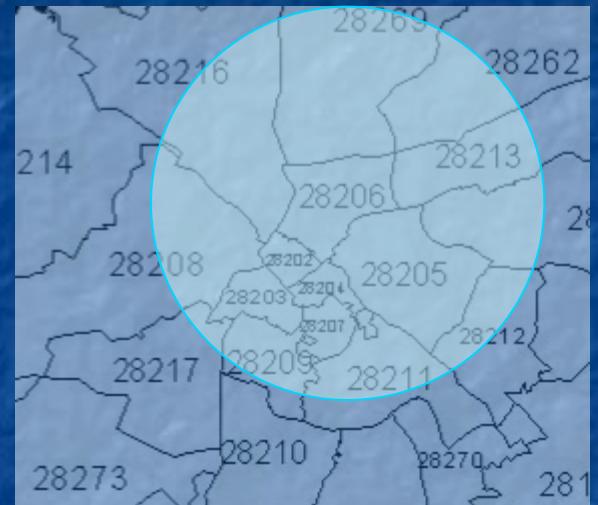
1. Sample the
new source

Invoking the Target



Invoke source with randomly generated tuples

- Use distribution if available
 - If no output is produced try invoking other sources



<u>Input</u> $\langle \text{zip1}, \text{dist1} \rangle$	<u>Output</u> $\langle \text{zip2}, \text{dist2} \rangle$
$\langle 07307, 50.94 \rangle$	$\{ \langle 07097, 0.26 \rangle,$ $\quad \langle 07030, 0.83 \rangle,$ $\quad \langle 07310, 1.09 \rangle, \dots \}$
$\langle 60632, 10874.2 \rangle$	$\{ \}$

randomly generated input tuples

Non-empty Result

Empty Result

Top-down Generation of Candidates

Start with empty clause & specialize it by:

- Adding a predicate from set of sources
- Check that definition is not redundant

`source5(__, __, __, __).`

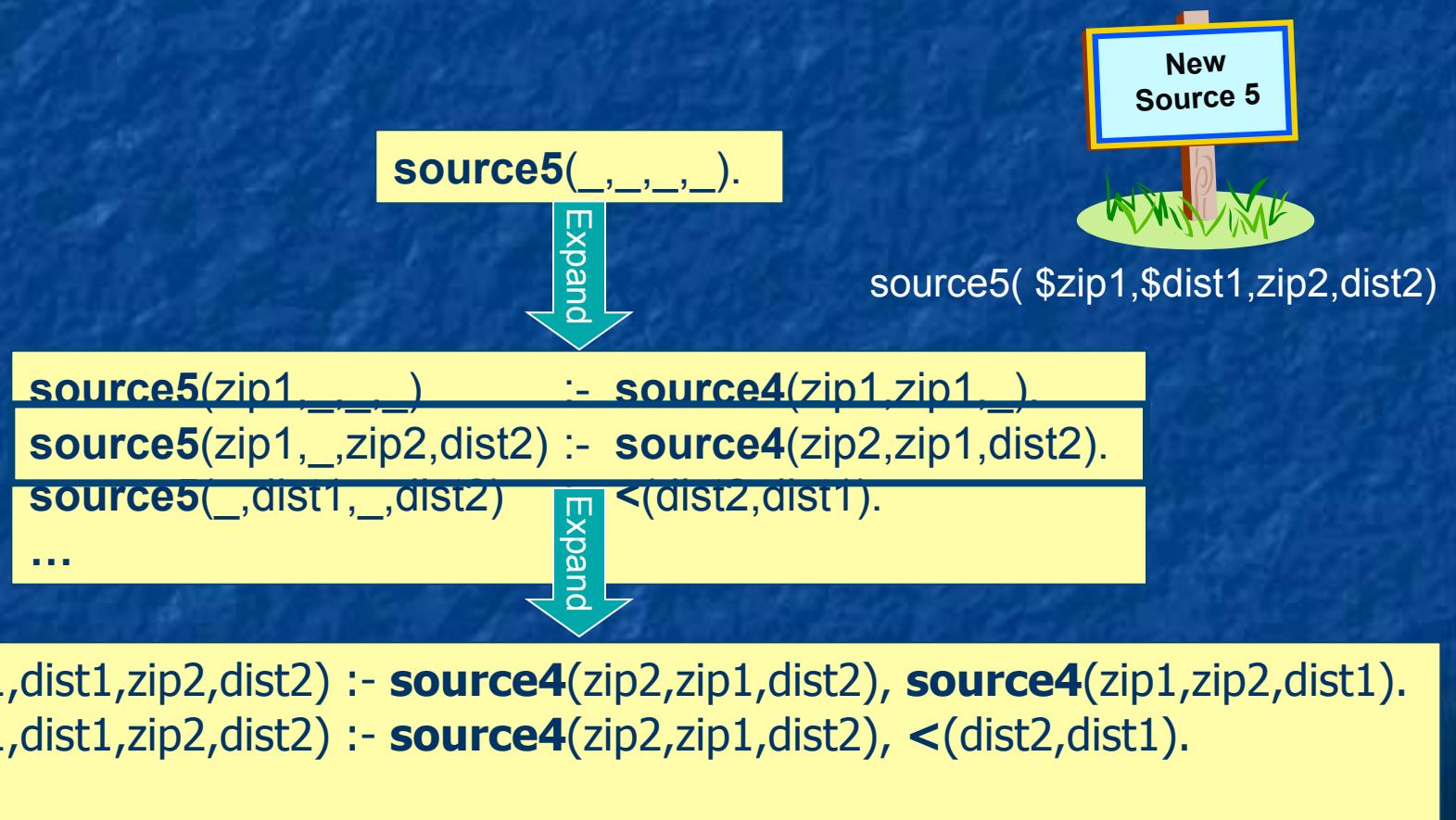


`source5($zip1,$dist1,zip2,dist2)`

```
source5(zip1, __, __, __)      :- source4(zip1, zip1, __).  
source5(zip1, __, zip2, dist2) :- source4(zip2, zip1, dist2).  
source5(__, dist1, __, dist2)   :- <(dist2, dist1).  
...
```

Best-first Enumeration of Candidates

Evaluate clauses & expand the best one



Limiting the Search

Extremely Large Search space!

- Constrained by use of Semantic Types
- Limit search by:
 - Maximum Clause length
 - Maximum Predicate Repetition
 - Maximum Number of Existential Variables
 - Definition must be Executable
 - Maximum Variable Repetition within Literal

Standard
techniques

Non-standard
technique

Scoring Candidates

Need to score candidates to direct best-first search

- Score definitions based on overlap

<u>Input</u> $\langle \$zip1, \$dist1 \rangle$	<u>Target Output</u> $\langle zip2, dist2 \rangle$	<u>Clause Output</u> $\langle zip2, dist2 \rangle$	
$\langle 60632, 874.2 \rangle$	$\{\}$	$\{ \langle 60629, 2.15 \rangle,$ $\langle 60682, 2.27 \rangle,$ $\langle 60623, 2.64 \rangle, \dots \}$	No Overlap
$\langle 07307, 50.94 \rangle$	$\{ \langle 07097, 0.26 \rangle,$ $\langle 07030, 0.83 \rangle,$ $\langle 07310, 1.09 \rangle, \dots \}$	$\{ \}$	No Overlap
$\langle 28041, 240.46 \rangle$	$\{ \langle 28072, 1.74 \rangle,$ $\langle 28146, 3.41 \rangle,$ $\langle 28138, 3.97 \rangle, \dots \}$	$\{ \langle 28072, 1.74 \rangle,$ $\langle 28146, 3.41 \rangle \}$	Overlap!

Scoring Candidates II

Sources may return multiple tuples and not be complete:

- Use Jaccard similarity as fitness function
- Average results across different inputs

forall (tuple in **InputTuples**)

$T_{target} = \text{invoke}(\text{target}, \text{tuple})$

$T_{clause} = \text{execute}(\text{clause}, \text{tuple})$

if not ($|T_{target}|=0$ and $|T_{clause}|=0$)

At least half of input tuples are non-empty invocations of target

$$\textit{fitness} = \frac{|T_{target} \cap T_{clause}|}{|T_{target} \cup T_{clause}|}$$

Average results only when output is returned

Jaccard similarity

return average(*fitness*)

Approximating Equality

Allow flexibility in values from different sources

- Numeric Types like *distance*

$10.6 \text{ km} \approx 10.54 \text{ km}$

Error Bounds (eg. +/- 1%)

- Nominal Types like *company*

$\text{Google Inc.} \approx \text{Google Incorporated}$

String Distance Metrics (e.g. JaroWinkler Score > 0.9)

- Complex Types like *date*

$\text{Mon, 31. July 2006} \approx 7/31/06$

Hand-written equality checking procedures.

Experimental Setup

- 25 problems
- 35 known sources
- All real services
- Time limit of 20 minutes

Inductive search bias:

- Max clause length: 7
- Predicate repetition: 2
- Max variable level: 5
- Executable candidates
- No variable repetition

Equality Approximations:

- 1% for *distance, speed, temperature & price*
- 0.002 degrees for *latitude & longitude*
- JaroWinkler > 0.85 for *company, hotel & airport*
- hand-written procedure for *date*.

Actual Learned Examples

- 1 **GetDistanceBetweenZipCodes(\$zip0, \$zip1, dis2):-**
GetCentroid(zip0, lat1, lon2), GetCentroid(zip1, lat4, lon5),
GetDistance(lat1, lon2, lat4, lon5, dis10), ConvertKm2Mi(dis10, dis2).
- 2 **USGSElevation(\$lat0, \$lon1, dis2):-**
ConvertFt2M(dis2, dis1), Altitude(lat0, lon1, dis1).

Distinguished forecast
from current conditions
- 3 **YahooWeather(\$zip0, cit1, sta2, , lat4, lon5, day6, dat7, tem8, tem9, sky10) :-**
WeatherForecast(cit1,sta2,,lat4,lon5,,day6,dat7,tem9,tem8,,,sky10,,,),
GetCityState(zip0, cit1, sta2).

current price = yesterday's close + change
- 4 **GetQuote(\$tic0,pri1,dat2,tim3,pri4,pri5,pri6,pri7,cou8,,pri10,,,pri13,,com15) :-**
YahooFinance(tic0, pri1, dat2, tim3, pri4, pri5, pri6, pri7, cou8),
GetCompanyName(tic0,com15,,),Add(pri5,pri13,pri10),Add(pri4,pri10,pri1).
- 5 **YahooAutos(\$zip0, \$mak1, dat2, yea3, mod4, , , pri7,) :-**
GoogleBaseCars(zip0, mak1, , mod4, pri7, , , yea3),
ConvertTime(dat2, , dat10, ,), GetCurrentTime(, , dat10,).

Experimental Results

Overall Results:

- Average Precision: 88%
- Average Recall: 69%

Results for different domains:

Problem Domain	# of Problems	Avg. # of Candidates	Avg. Time (s)	Avg. Precision	Avg. Recall
Geospatial	9	136	303	100%	84%
Financial	2	1606	335	56%	63%
Weather	8	368	693	91%	62%
Hotels	4	43	374	90%	60%
Cars	2	68	940	50%	50%

Related Work

Semantic Labeling:

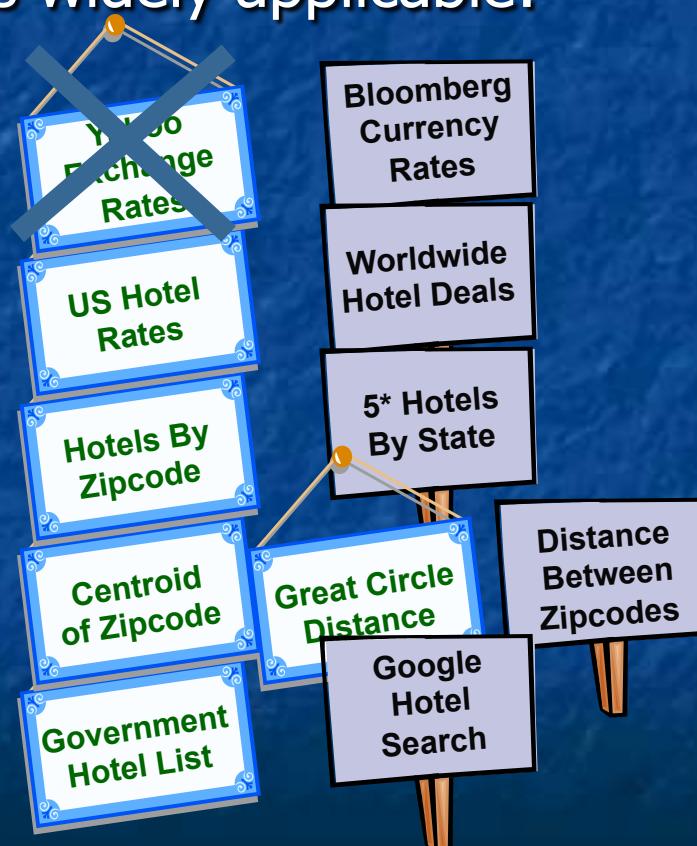
- Metadata-based service classification (Hess & Kushmerick, '03)
- Woogle: Web Service clustering (Dong et al, 2004)
 - Neither system produces sufficient information for integration

Functional Modeling:

- Category Translation (Perkowitz & Etzioni 1995)
 - Less complicated (single input, single output) definitions.
- iMAP: Complex schema matcher (Dhamanka et. al. 2004)
 - Many-to-1 not many-to-many mappings
 - Type-specific search algorithms
 - Not designed for live information sources

Conclusions

- Assumption: overlap between new & known sources
- Technique is nonetheless widely applicable:
 - Redundancy
 - Scope or Completeness
 - Binding Constraints
 - Composed Functionality
 - Access Time



Conclusions

- Integrated approach for learning:
 - *How to invoke a web service (inputs & outputs)*
 - *A definition of what the service does*
- Provides an approach to generate source descriptions for the Semantic Web
 - Little motivation for providers to annotate services
 - Instead we generate metadata automatically
- Provides approach to discover new sources of data automatically