AAAI 2018 Tutorial
Building Knowledge Graphs

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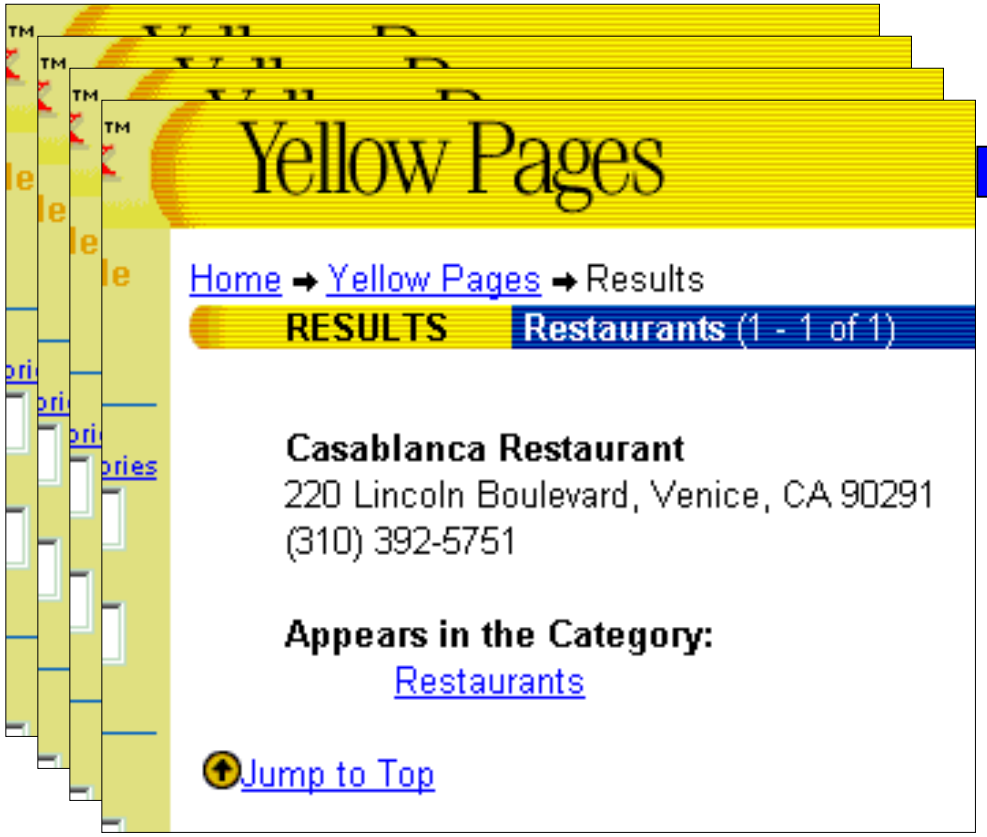
University of Southern California

Wrappers for Web Data Extraction

Extracting Data from Semi-structured Sources



NAME	Casablanca Restaurant
STREET	220 Lincoln Boulevard
CITY	Venice
PHONE	(310) 392-5751

Approaches to Wrapper Construction

- Manual Wrapper Construction
- Learning Wrappers from Labelled Examples
- Grammar Induction for Automatic Wrapper Construction

Grammar Induction Approach

- Pages automatically generated by scripts that encode results of db query into HTML
  - Script = grammar
- Given a set of pages generated by the same script
  - Learn the grammar of the pages
    - Wrapper induction step
  - Use the grammar to parse the pages
    - Data extraction step

RoadRunner

[Crescenzi, Mecca, & Merialdo]

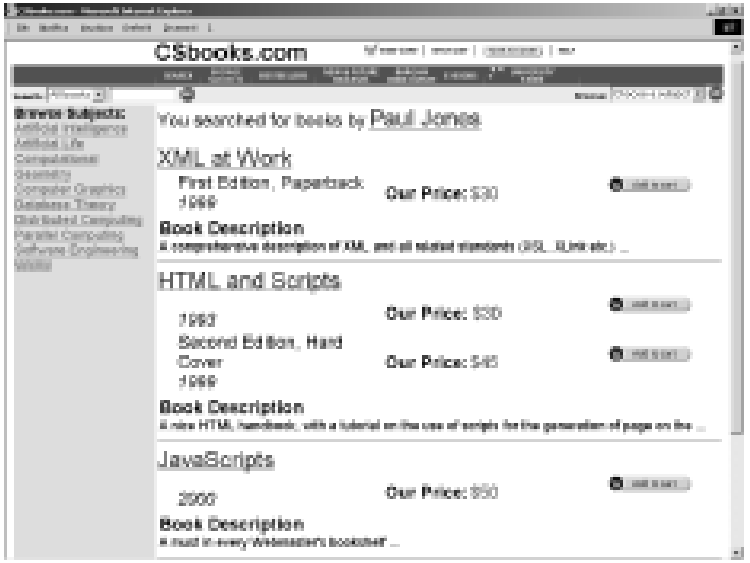
- Automatically generates a wrapper from large web pages
  - Pages of the same *class*
  - No dynamic content from javascript, ajax, etc
- Infers source schema
  - Supports nested structures and lists
  - Extracts data from pages
- Efficient approach to large, complex pages with regular structure

Example Pages

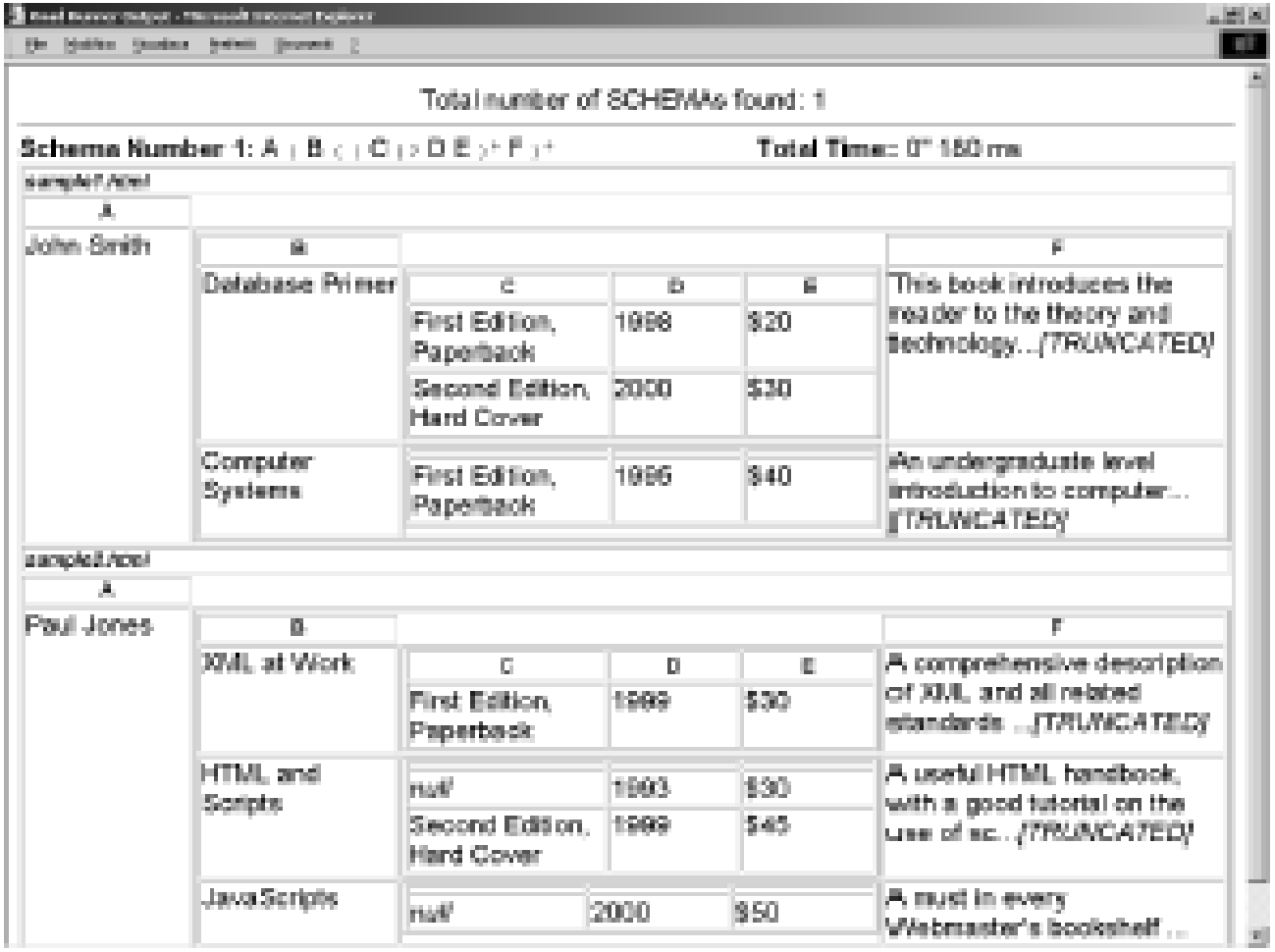
- Compares two pages at a time to find similarities and differences
- Infers nested structure (schema) of page
- Extracts fields

http://www.csbooks.com/author?John+Smith

http://www.csbooks.com/author?Paul+Jones



Extracted Result



Total number of SCHEMAs found: 1

Schema Number 1: A (B (C) D E)* F)* **Total Time:** 0" 180 ms

sample1.html

A					
John Smith	B				F
	Database Primer	C	D	E	This book introduces the reader to the theory and technology...[TRUNCATED]
		First Edition, Paperback	1998	$20	
		Second Edition, Hard Cover	2000	$30	
	Computer Systems	First Edition, Paperback	1996	$40	An undergraduate level introduction to computer... [TRUNCATED]

sample2.html

A					
Paul Jones	B				F
	XML at Work	C	D	E	A comprehensive description of XML and all related standards ...[TRUNCATED]
		First Edition, Paperback	1999	$30	
	HTML and Scripts	null	1993	$30	A useful HTML handbook, with a good tutorial on the use of sc...[TRUNCATED]
		Second Edition, Hard Cover	1999	$45	
	JavaScripts	null	2000	$50	A must in every Webmaster's bookshelf ...

Union-Free Regular Expression (UFRE)

- Web page structure can be represented as *Union-Free Regular Expression* (UFRE)
  - UFRE is Regular Expressions without *disjunctions*
  - If *a* and *b* are UFRE, then the following are also UFREs
    - a.b
    - (a)+
    - (a)?

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  - UFRE is Regular Expressions without *disjunctions*
  - If *a* and *b* are UFRE, then the following are also UFREs
    - a.b → string fields
    - (a)+ → lists (possibly nested)
    - (a)? → optional fields
  - Strong assumption that usually holds

Approach

- Given a set of example pages
- Generate the *Union-Free Regular Expression* which contains example pages
- Find the least upper bounds on the RE lattice to generate a wrapper in *linear time*
- Reduces to finding the least upper bound on two UFREs

Matching/Mismatches

Given a set of pages of the same type

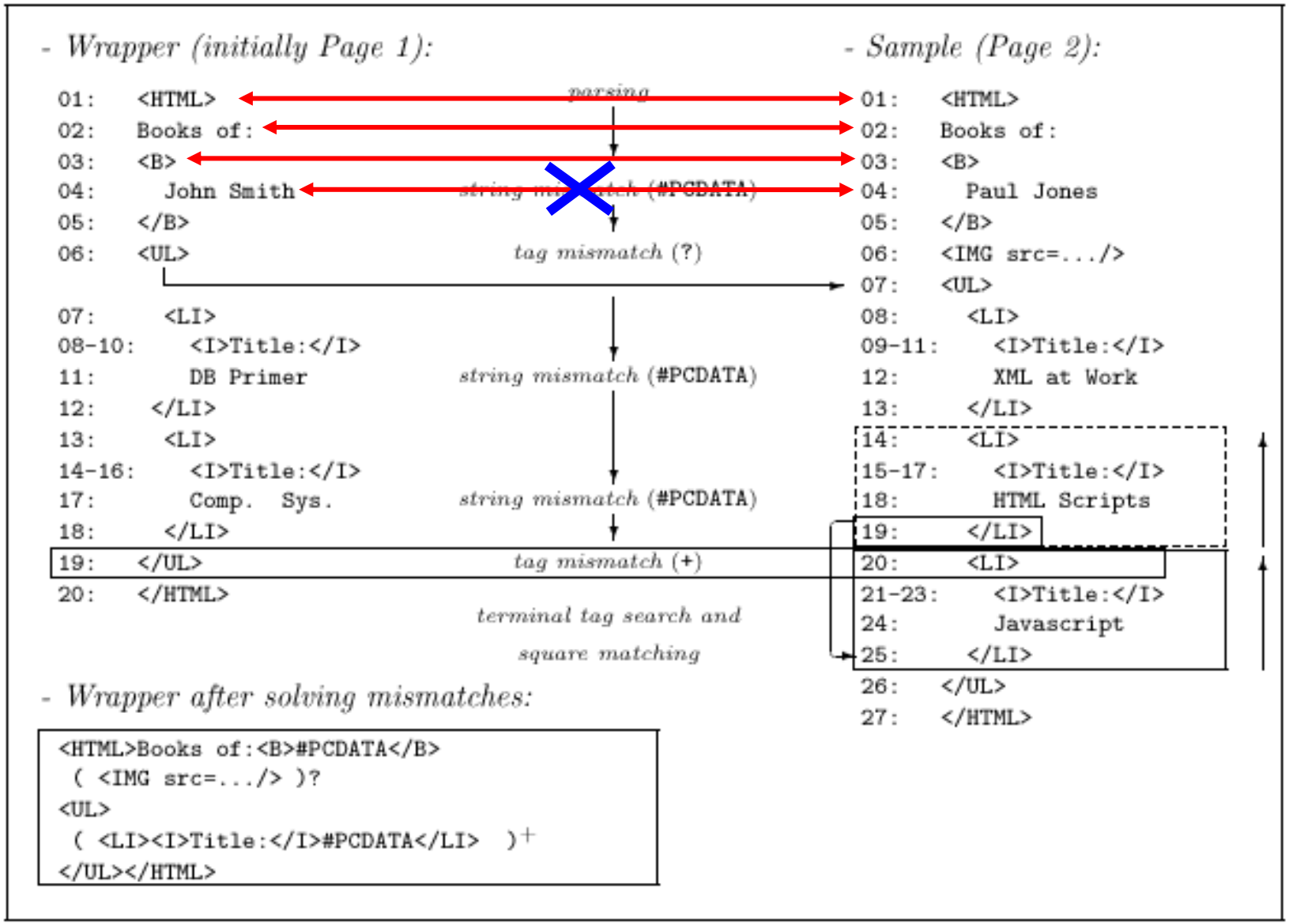
- Take the first page to be the *wrapper* (UFRE)
- Match each successive sample page against the wrapper
- *Mismatches* result in generalizations of wrapper
  - String mismatches
  - Tag mismatches

Matching/Mismatches

Given a set of pages of the same type

- Take the first page to be the *wrapper* (UFRE)
- Match each successive sample page against the wrapper
- *Mismatches* result in generalizations of wrapper
  - String mismatches
    - Discover fields
  - Tag mismatches
    - Discover optional fields
    - Discover iterators

Example Matching



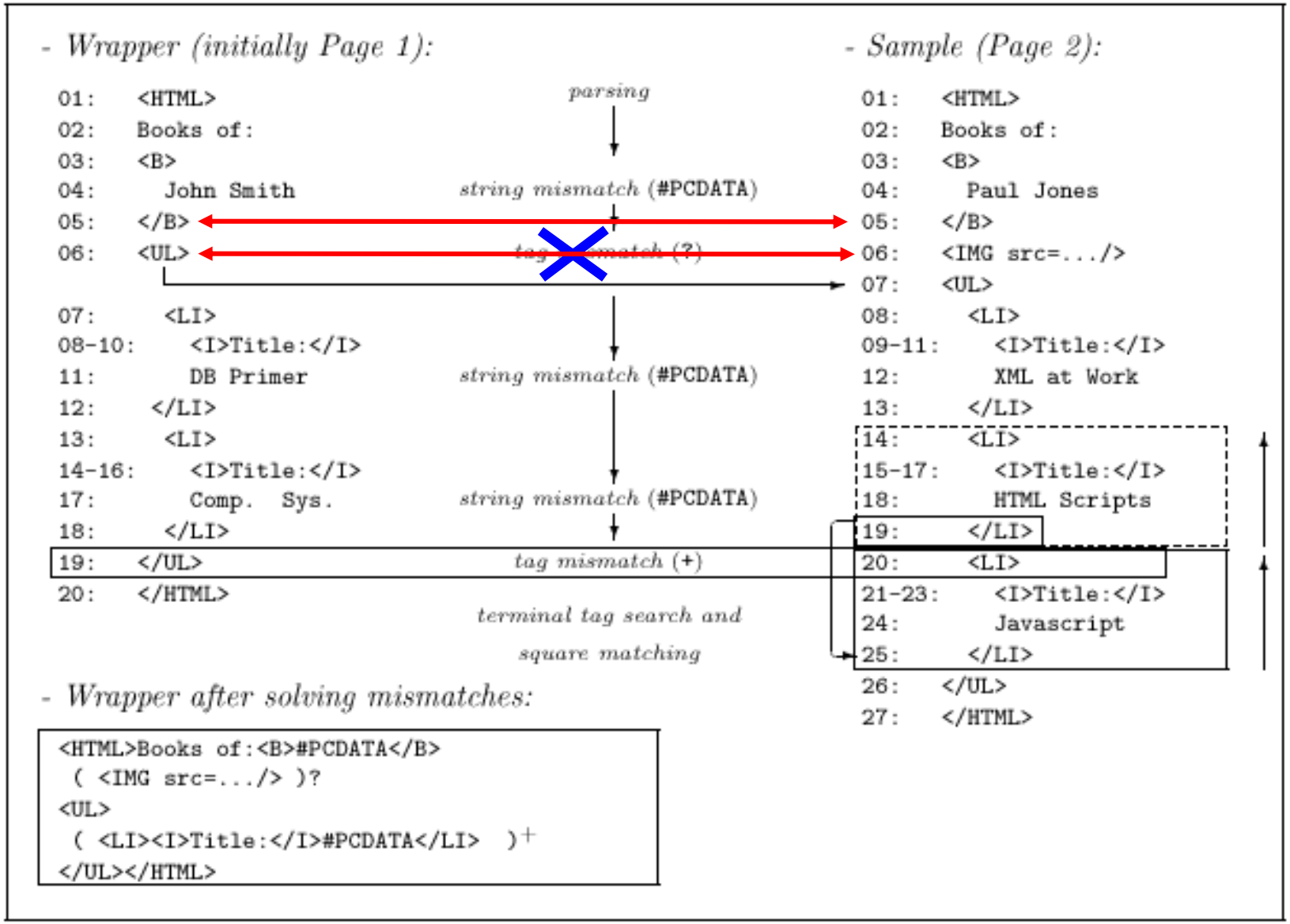
String Mismatches: Discovering Fields

- String mismatches are used to discover fields of the document
- Wrapper is generalized by replacing "John Smith" with #PCDATA

<HTML>Books of: <B>John Smith

→ <HTML> Books of: <B>#PCDATA

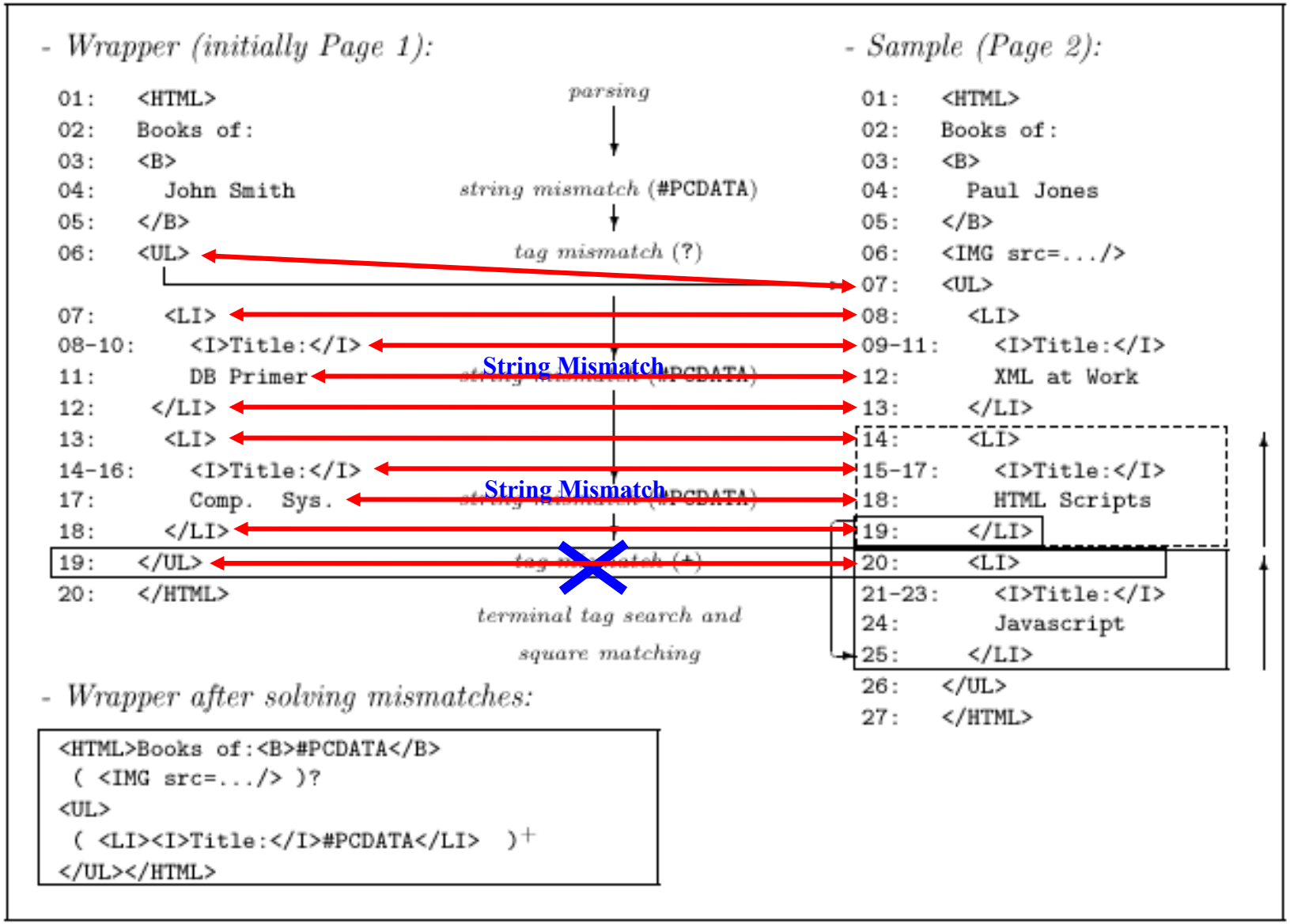
Example Matching



Tag Mismatches: Discovering Optionals

- First check to see if mismatch is caused by an iterator (described next)
- If not, could be an optional field in wrapper *or* sample
- Cross search used to determine possible optionals
- Image field determined to be optional:
  - ( )?

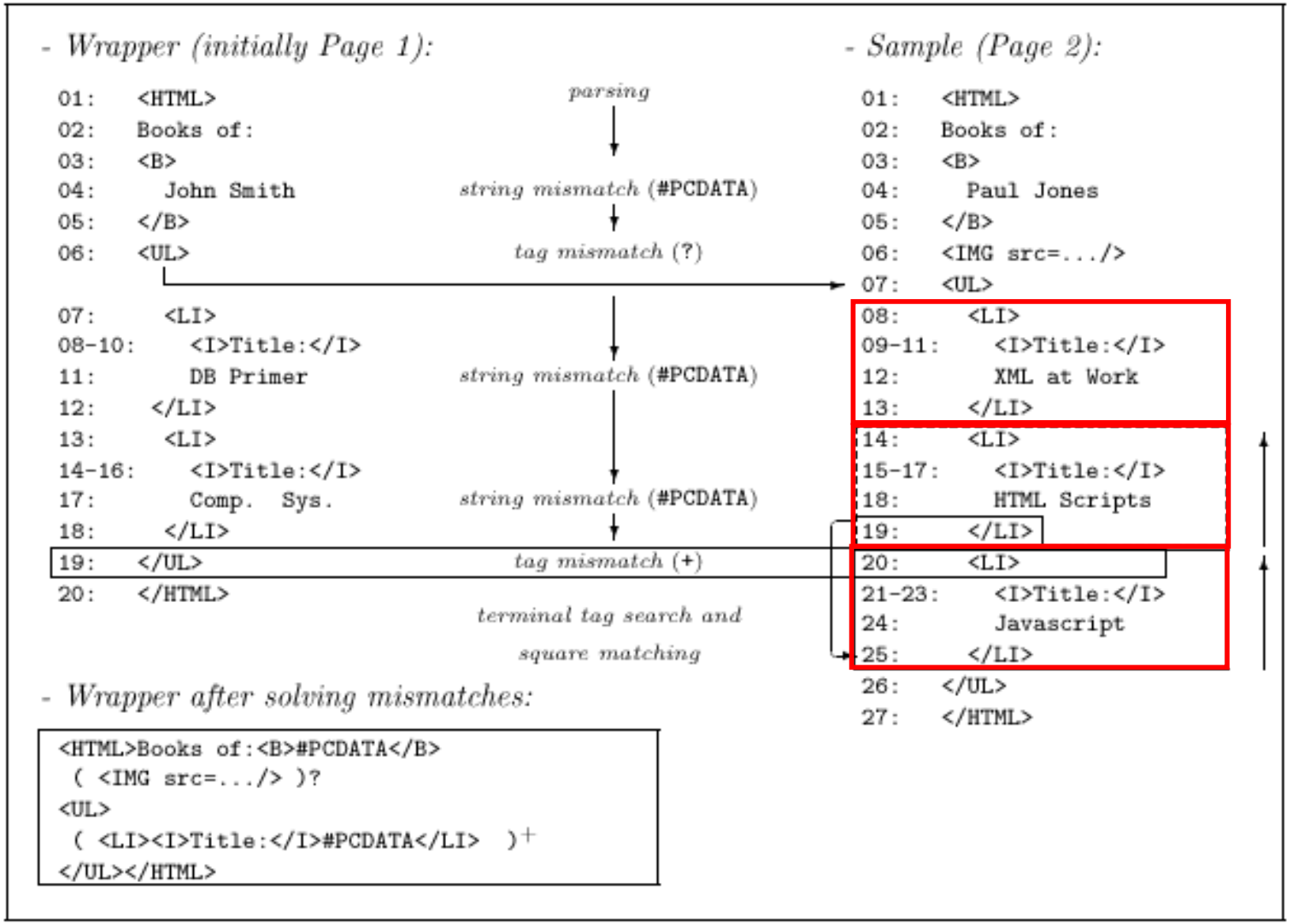
Example Matching



Tag Mismatches: Discovering Iterators

- Assume mismatch is caused by repeated elements in a list
  - End of the list corresponds to last matching token: </LI>
  - Beginning of list corresponds to one of the mismatched tokens: <LI> or </UL>
  - These create possible “squares”
- Match possible squares against earlier squares
- Generalize the wrapper by finding all contiguous repeated occurrences:
  - (<LI><I>Title:</I>#PCDATA</LI>)+

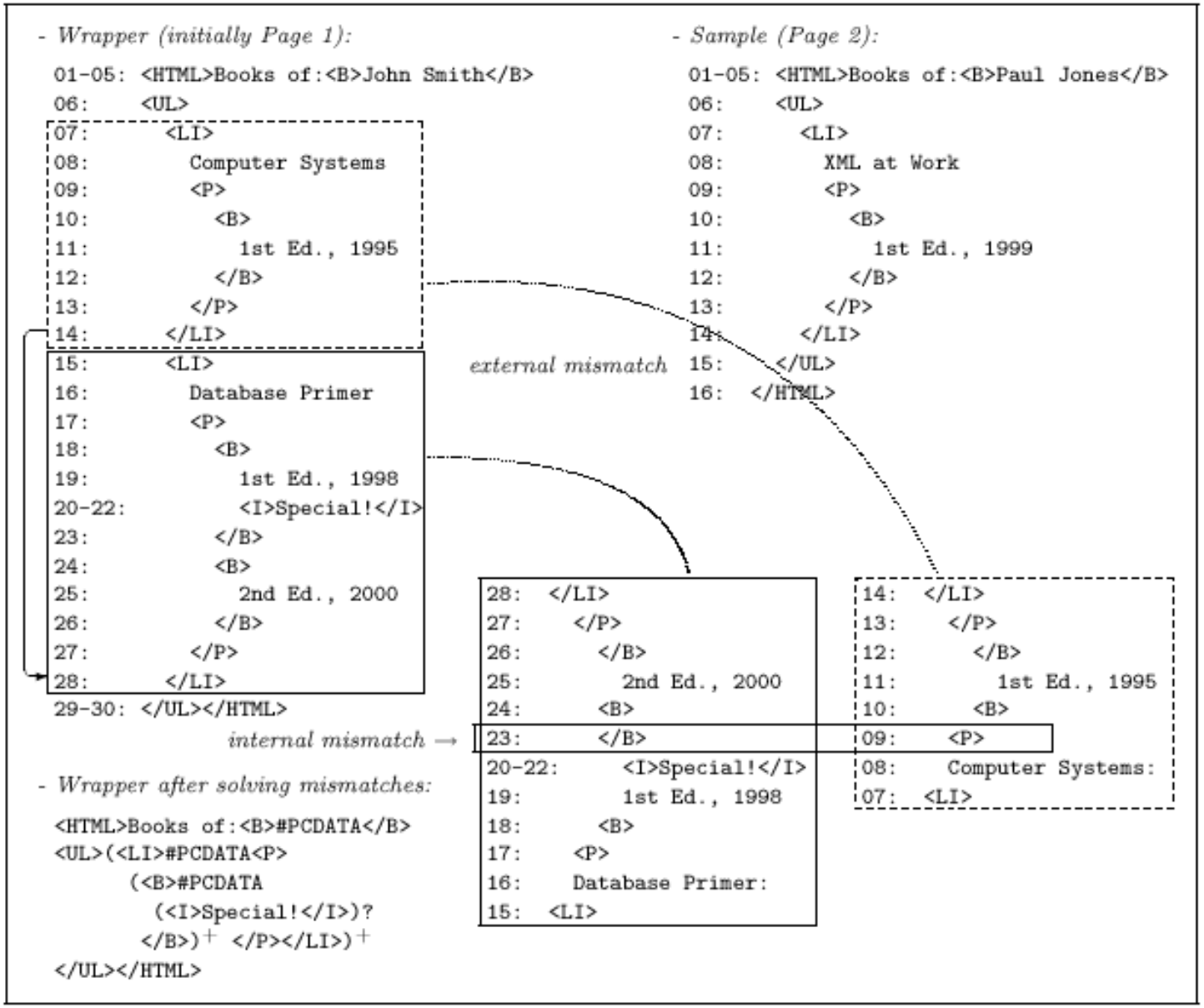
Example Matching



Internal Mismatches

- Generate *internal mismatch* while trying to match square against earlier squares on *the same page*
  - Solving internal mismatches yield further refinements in the wrapper
    - List of book editions
    - <I>Special!</I>

Recursive Example



Discussion

- Assumptions:
  - Pages are well-structured
  - Structure can be modeled by UFRE (no disjunctions)
- Search space for explaining mismatches is huge
  - Uses a number of heuristics to prune space
    - Limited backtracking
    - Limit on number of choices to explore
    - Patterns cannot be delimited by optionals
  - Will result in pruning possible wrappers

Limitations

- Learnable grammars
  - Union-Free Regular Expressions (RoadRunner)
    - Variety of schema structure: tuples (with optional attributes) and lists of (nested) tuples
    - Does not efficiently handle disjunctions – pages with alternate presentations of the same attribute
  - Context-free Grammars
    - Limited learning ability
- User needs to provide a set of pages of the same type

Inferlink Web Extraction Software

Extraction

FOR SALE: STOEGER M3500

post id: 4700468
share:

Price:	$ 500	**Listed On:**	Thursday, September 17, 2015
Seller:	Private Party	**Listed In:**	Shotguns
Account:	Registered on 5/9/2013	**Location:**	Keenesburg, Denver, Colorado - Map
	Listings by this user	**Shipping:**	No

Manufacturer:	Stoeger
Caliber:	12 Gauge
Action:	Semi-automatic
Firearm Type:	Shotgun

Flag | Edit | Favorite

Contact Seller

I have a Stoeger m3500. It is a year old. It has 200 rounds through it from clay shooting. Its in perfect condition. If you have any questions email or text me. 9703427061. I'm asking 500

Contact Seller

Structured Extraction

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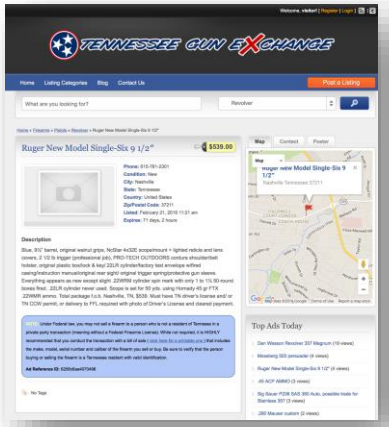
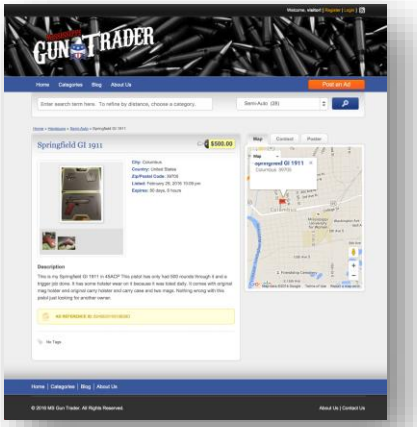
Contact Seller

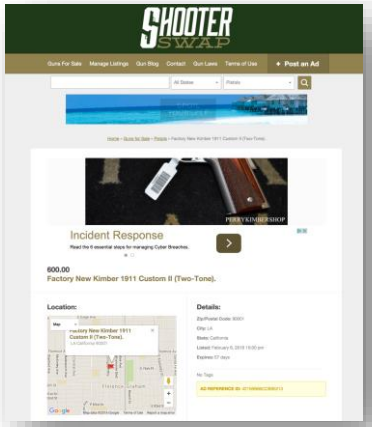
Automated Extraction

[Minton et al., Inferlink]

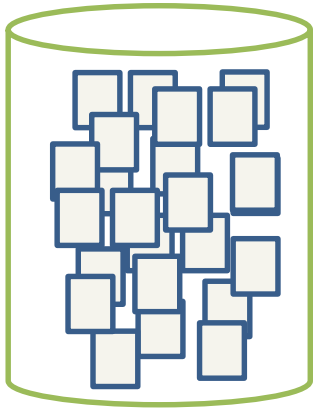
- Title
- Description
- Seller
- Post Date
- Expiry Date
- Price
- Location
- Category
- Member Since
- Num Views
- Post ID





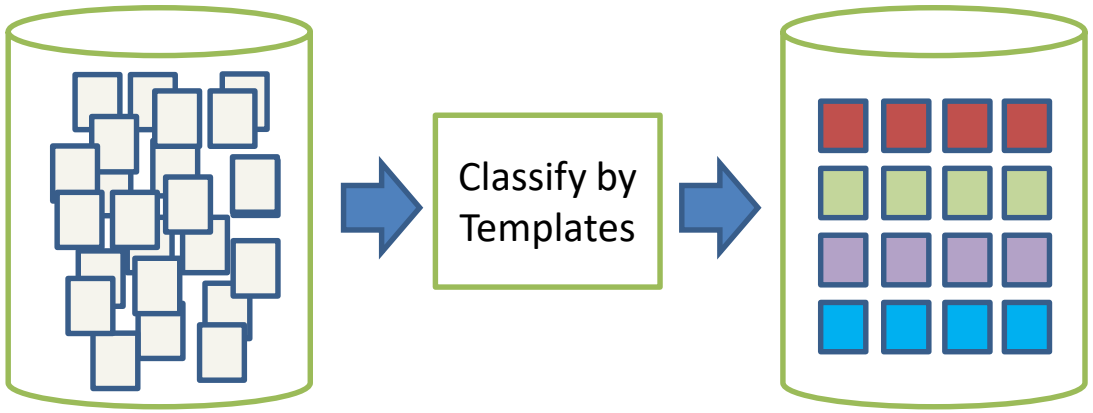


Automated Extraction



Input: A Pile of Pages

Automated Extraction



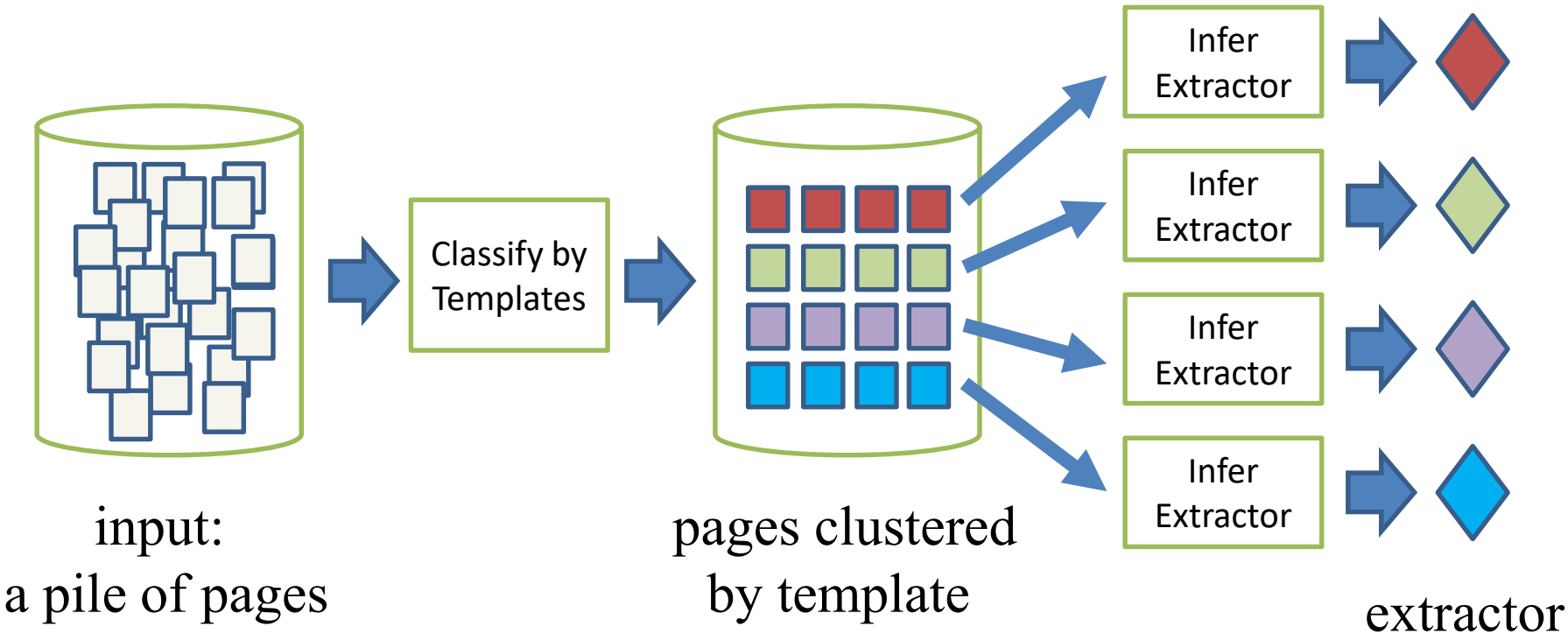
input:
a pile of pages

pages clustered
by template

Clustering

- Cluster
  - Based on the visible text
  - Page is broken into chunks
    - These are continuous blocks of text
  - Search for common visible chunks
    - Remove chunks that occur in all pages
    - Remove those that occur in fewer than 10 pages
  - Greedy algorithm to cluster the pages based on the remaining chunks
    - Sort by the size of the clusters created by each chunk

Automated Extraction



Extractor Learning

- Input: cluster
- Select 5 random pages to build a template
  - Tokenize on space & punctuation
  - Start with n-grams of tuples of size n
    - Find those n-grams that occur on all pages
    - Keep only those n-grams that occur exactly once per page
    - Decompose pages based on these n-grams
    - Run algorithm recursively on decomposed page
  - Repeat above for size n-1 down to n=2
  - Construct template based on the decomposition

Unsupervised Extraction Tool

InferLink {Landmark} | tennesseegunexchange | Markup | Extraction | Downloads

+ Add Page	page_2.html	page_3.html	page_4.html	page_5.html
0036	Winchester model 140	Beretta hand gun for sale	1956 Mossin nagant	Ruger New Model Single-Six 9 1/2″
Code1354	37122	37201	37122	37211
Description1392	Winchester model 140 12 guage semiauto. 28inch ribbed and vented barrel with modified choke. Gun fires and cycles well. Text for pics.	9mm Beretta hand gun for sale at a very good price with a delivery to any interested buyer in the state.contact me at silven2016@yandex.com or text me at	1956 Mossin nagant. 7.62×54 bolt action Russian war rifle. Missing bayonet but rifle fires and cycles well.	Blue, 9½" barrel, original walnut grips, NcStar 4x32E scope/mount + lighted reticle and lens covers, 2 1/2 lb trigger (professional job), PRO-TECH OUTDOORS cordura shoulder/belt holster, original plastic box/lock & key/.22LR cylinder/factory test envelope w/fired casing/instruction manual/original rear sight/ original trigger spring/protective gun sleeve. Everything appears as new except slight .22WRM cylinder spin mark with only 1 to 1½ 50-round boxes fired. .22LR cylinder never used. Scope is set for 50 yds. using Hornady 45 gr FTX .22WMR ammo. Total package f.o.b. Nashville, TN, $539. Must have TN driver's license and/ or TN CCW permit, or delivery to FFL required with photo of Driver's License and cleared payment.
Expires1366	45 days, 23 hours	This ad has expired	46 days, 4 hours	89 days, 7 hours
Facebook2081	2015	2015	2015	2016
Firearms1276	raquo; Shotguns » Winchester model 140	raquo; Pistols » Semi-Auto » Beretta hand gun for sale	raquo; Rifles » Bolt Action » 1956 Mossin nagant	raquo; Pistols » Revolver » Ruger New Model Single-Six 9 1/2″
Group2122	Non-Felon / Legal	Non-Felon / Legal	Non-Felon / Legal	Mentally Capable / Non-Felon / Legal
ID1421	47955db13ce85f8e	930552dc84196efa	8655da9d2455236	6256c6aa4070496

Extraction Evaluation

10 websites, 5 pages each

fields

	Title	Desc	Seller	Date	Price	Loc	Cat	Member Since	Expires	Views	ID
Perfect	1.0 (50/50)	.76 (37/49)	.95 (40/42)	.83 (40/48)	.87 (39/45)	.51 (23/45)	.68 (34/50)	1.0 (35/35)	.52 (15/29)	.76 (19/25)	.97 (35/36)
Including partial and extra data	1.0 (50/50)	.98 (48/49)	.95 (40/42)	.83 (40/48)	.98 (44/45)	.84 (38/45)	.88 (44/50)	1.0 (35/35)	.55 (16/29)	1.0 (25/25)	1.0 (36/36)

Discussion

- Inferlink approach solves some of the key limitations of Roadrunner
  - Pages do not all have to be of the same type
  - Multiple optionals would be treated as different page types
  - Scales well with complex pages

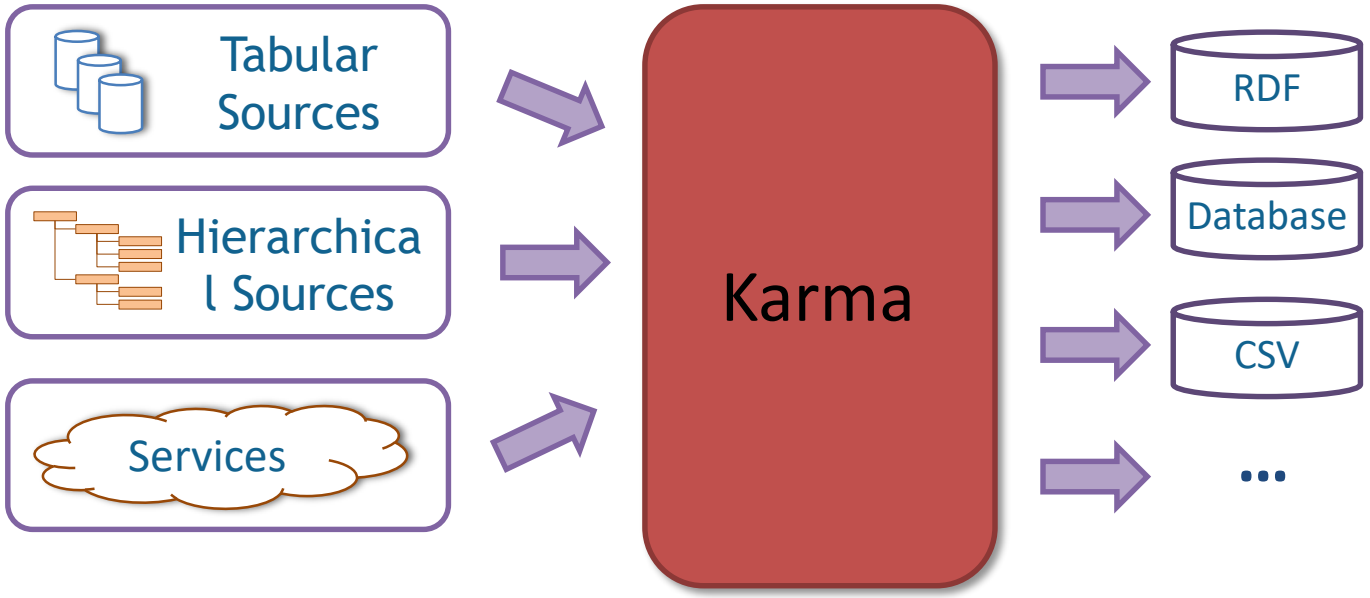
Web Data Extraction Software

- Beautiful Soup
  - http://www.crummy.com/software/BeautifulSoup/
  - Python library to manually write wrappers
- Jsoup
  - http://jsoup.org/
  - Java library to manually write wrappers
- ScrapingHub
  - http://scrapinghub.com/
  - Portia provides a wrapper learner
- Others
  - https://www.quora.com/Which-are-some-of-the-best-web-data-scraping-tools
  - Tell us if you find a good one!

Aligning and Integrating Data in Karma

Karma

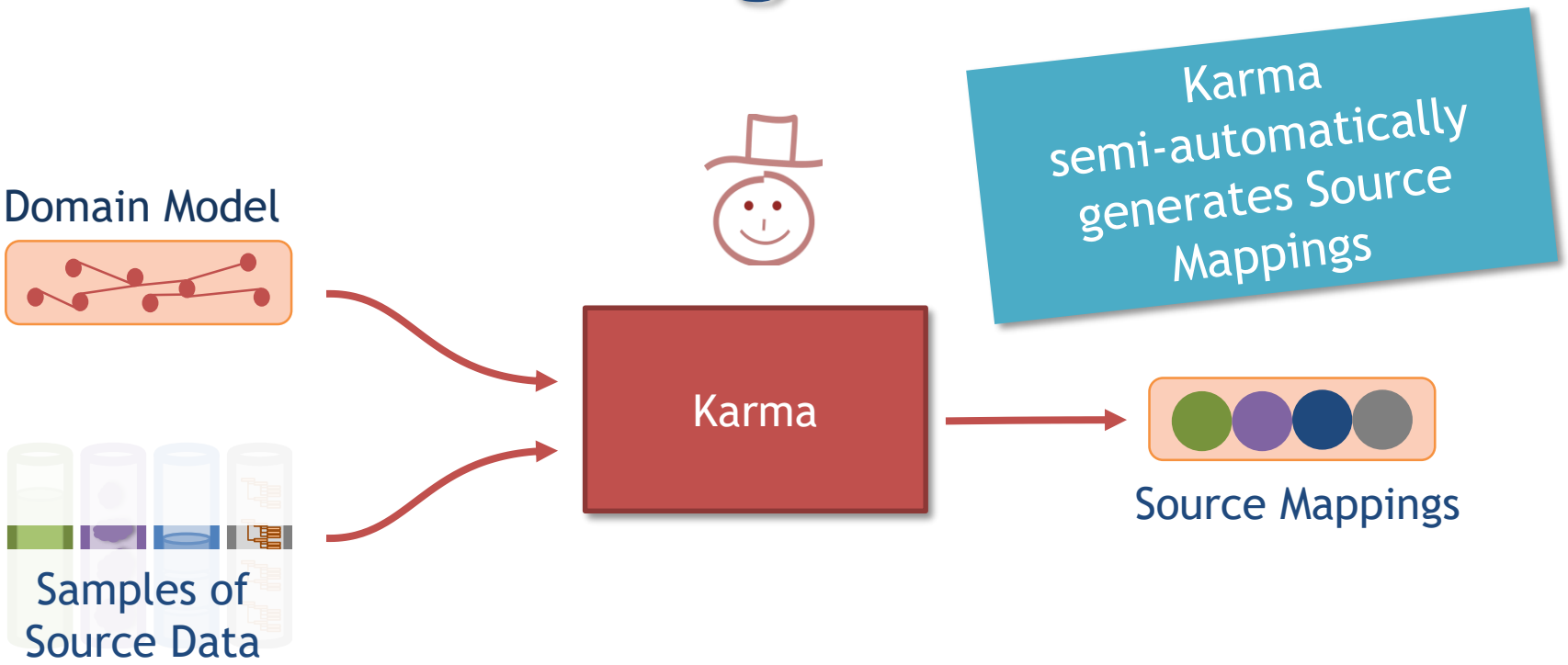
Interactive tool for rapidly extracting, cleaning, transforming, integrating and publishing data



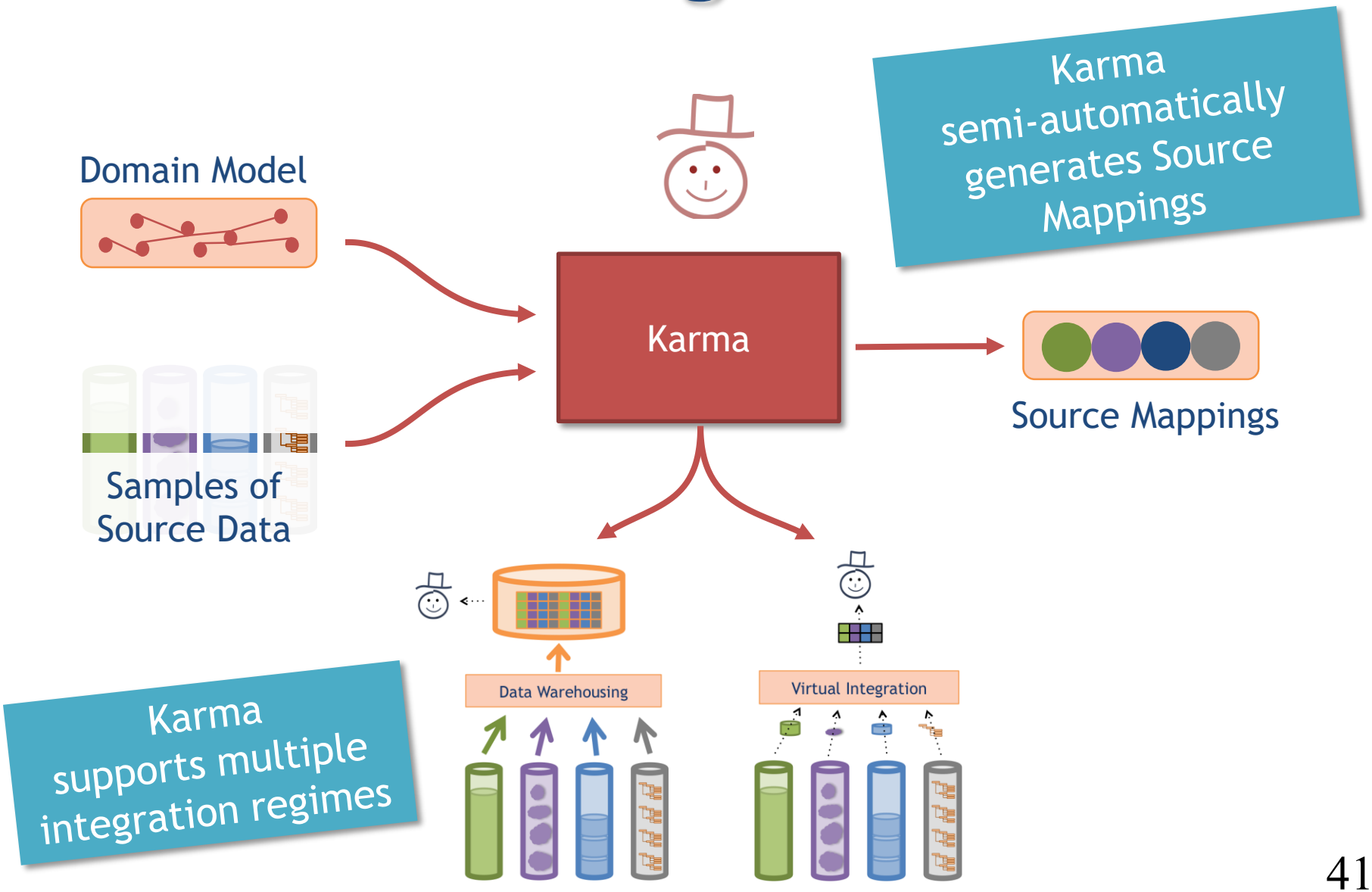
http://www.isi.edu/integration/karma

@KarmaSemWeb

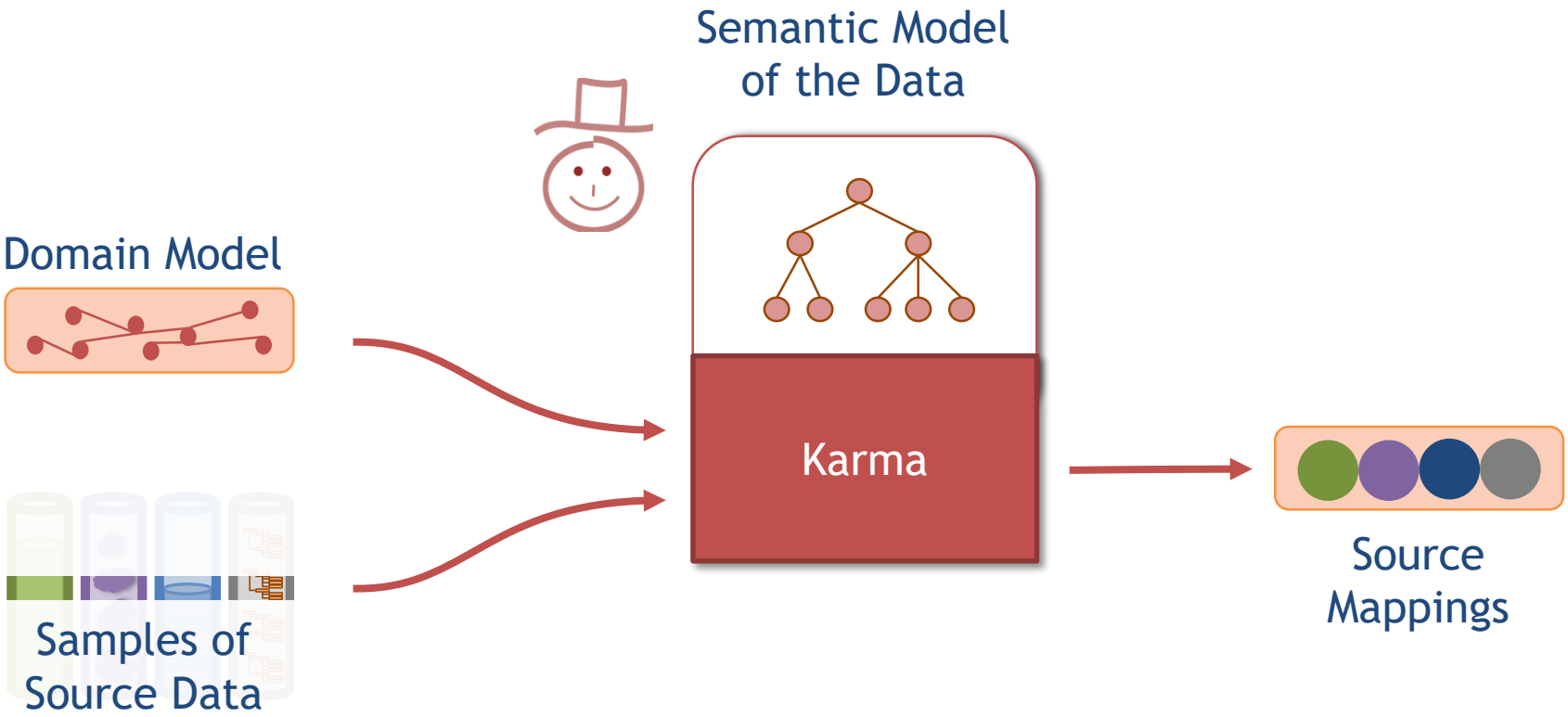
Information Integration in Karma



Information Integration in Karma



Secret Sauce: Karma Understands Your Data



Karma semi-automatically builds a semantic model of your data

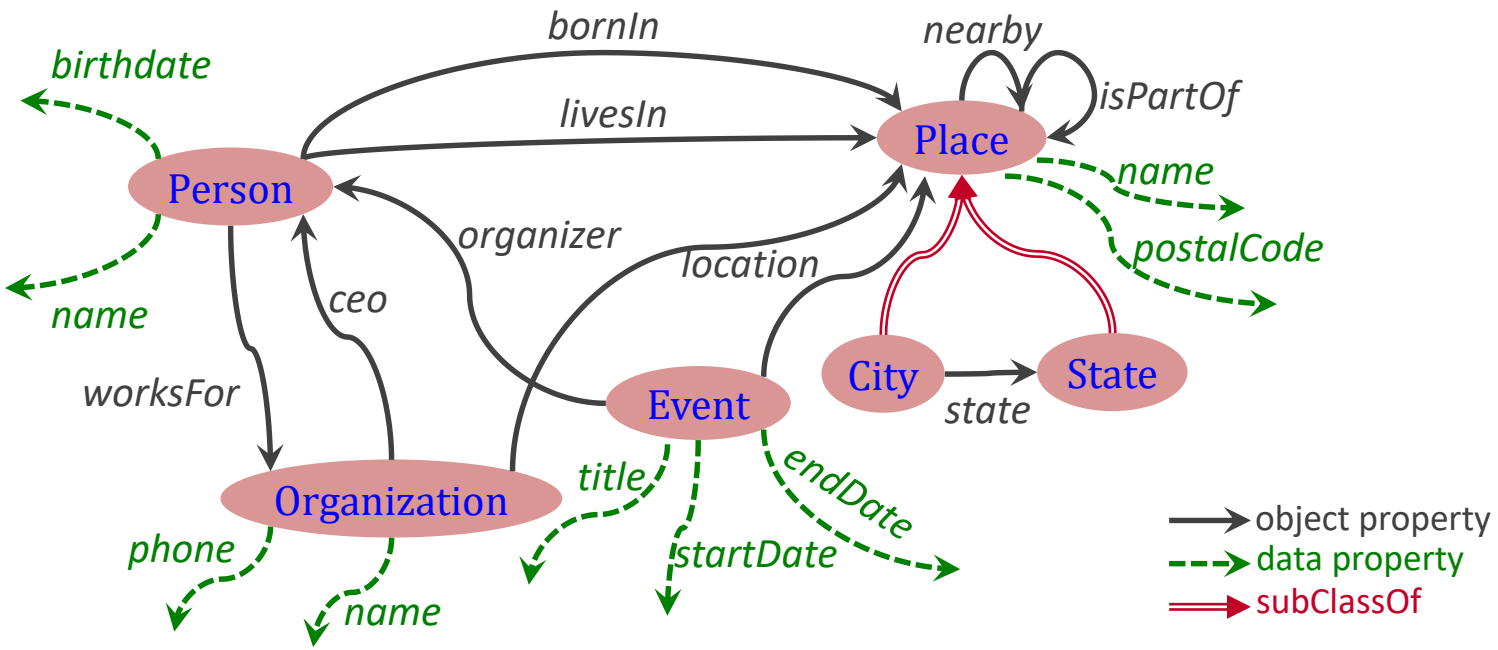
What is a Semantic Model?

Describe sources using classes & relationships in an ontology

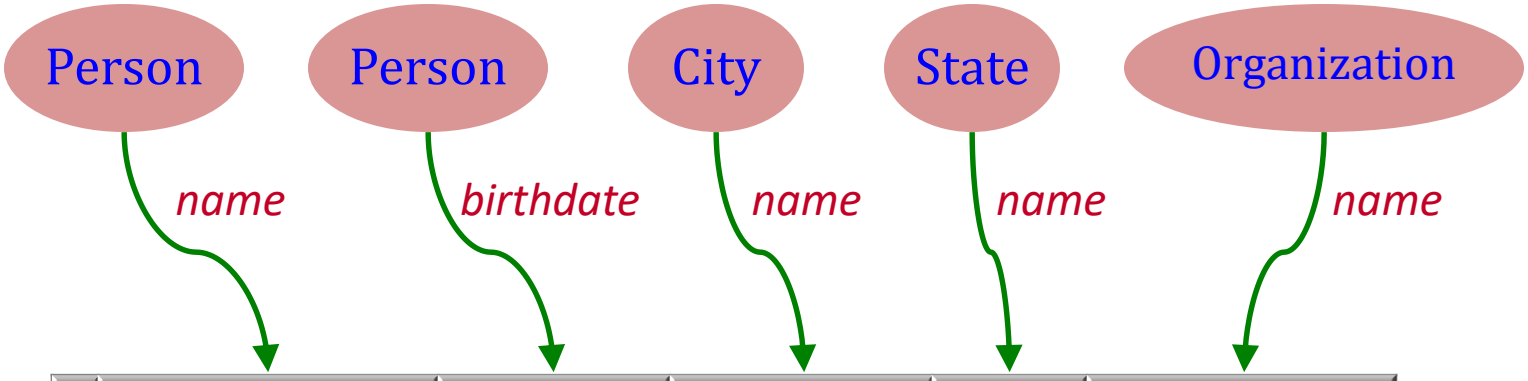
Source

	name	date	city	state	workplace
1	Fred Collins	Oct 1959	Seattle	WA	Microsoft
2	Tina Peterson	May 1980	New York	NY	Google

Domain Model



Semantic Types



	name	date	city	state	workplace
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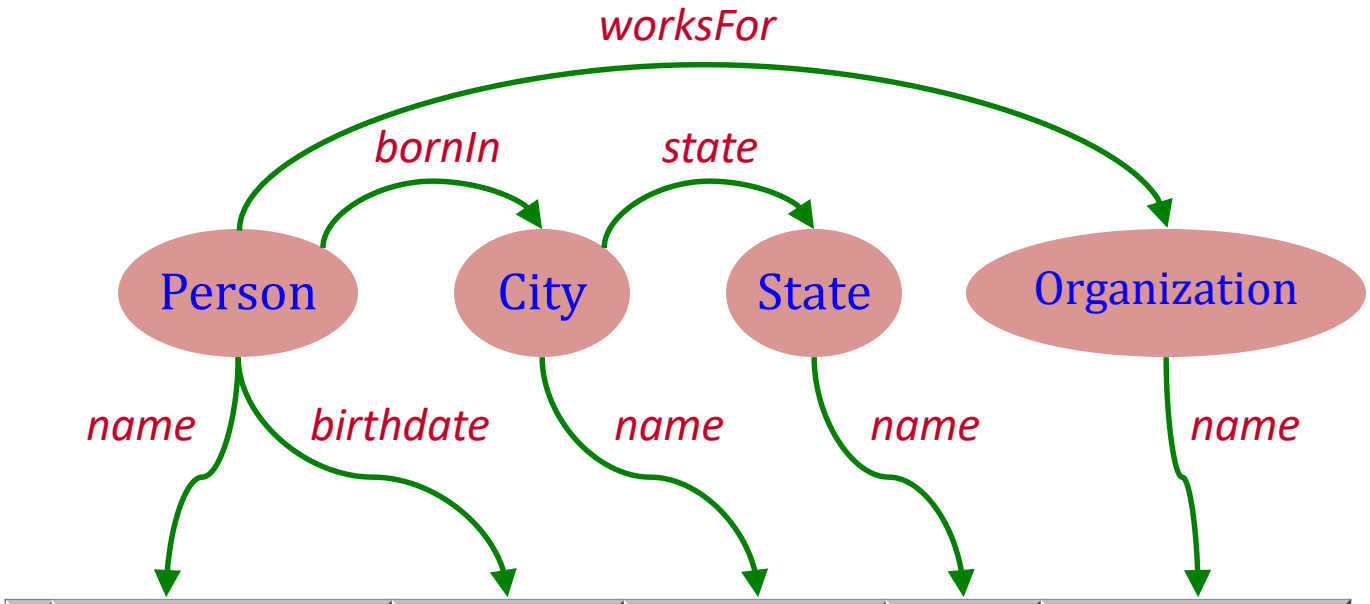
Relationships



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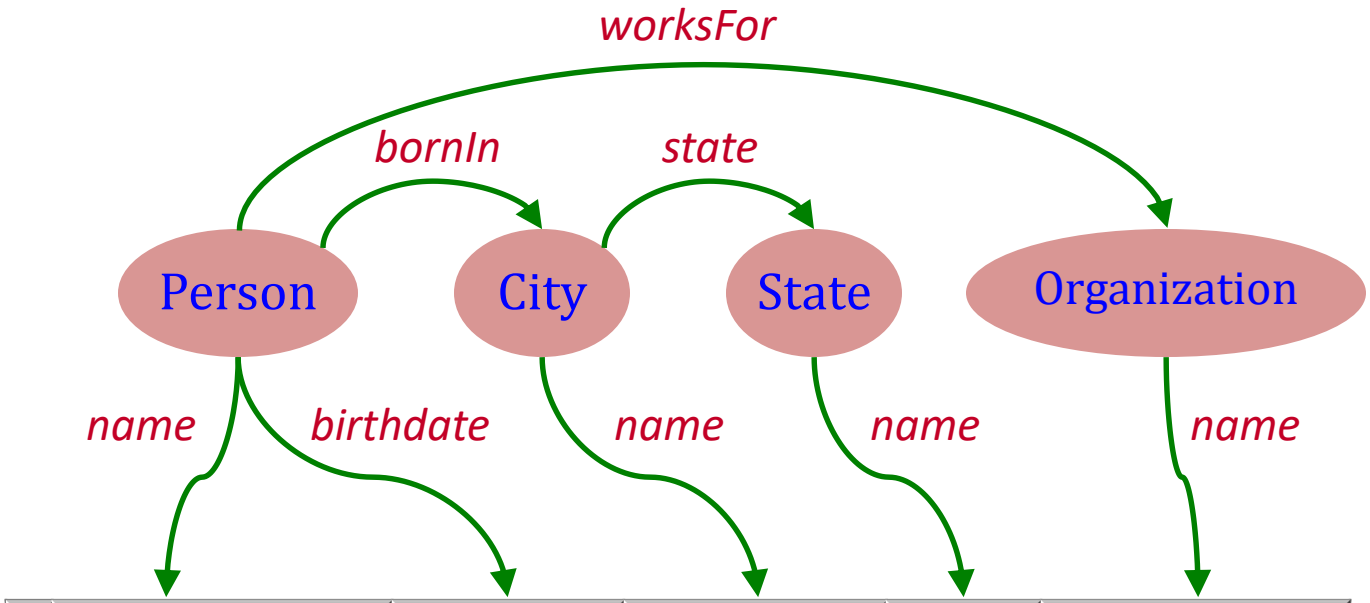
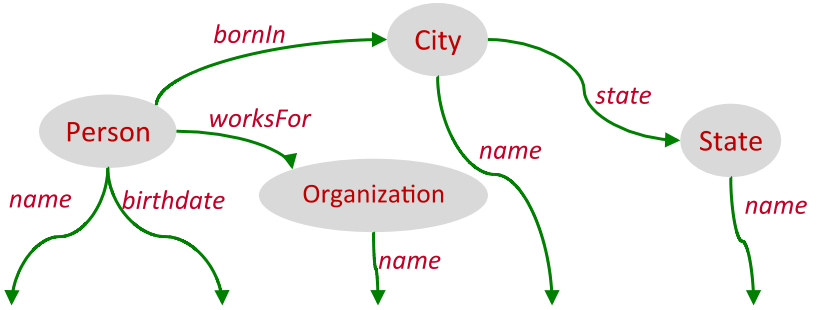


	name	date	city	state	workplace
1	Fred Collins	Oct 1959	Seattle	WA	Microsoft
2	Tina Peterson	May 1980	New York	NY	Google

Semantic models will be formalized as Source Mappings

Key ingredient to automate source discovery, data integration, and publishing semantic data (RDF triples)

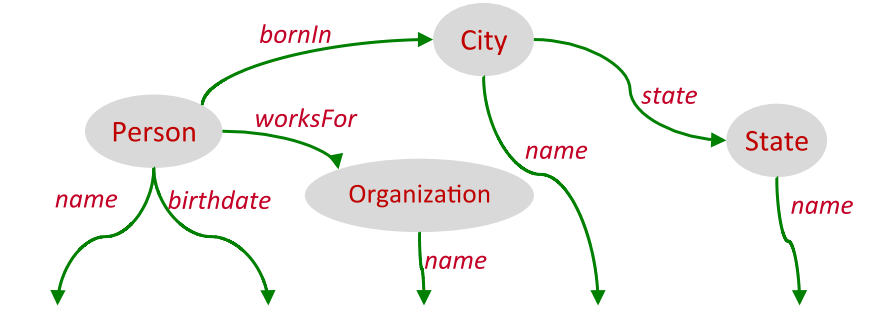


Column 1	Column 2	Column 3	Column 4	Column 5
Bill Gates	Oct 1955	Microsoft	Seattle	WA
Mark Zuckerberg	May 1984	Facebook	White Plains	NY
Larry Page	Mar 1973	Google	East Lansing	MI

Knowledge Graphs

Karma uses semantic models to create knowledge grap

Karma semi-automatically builds semantic models



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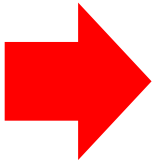
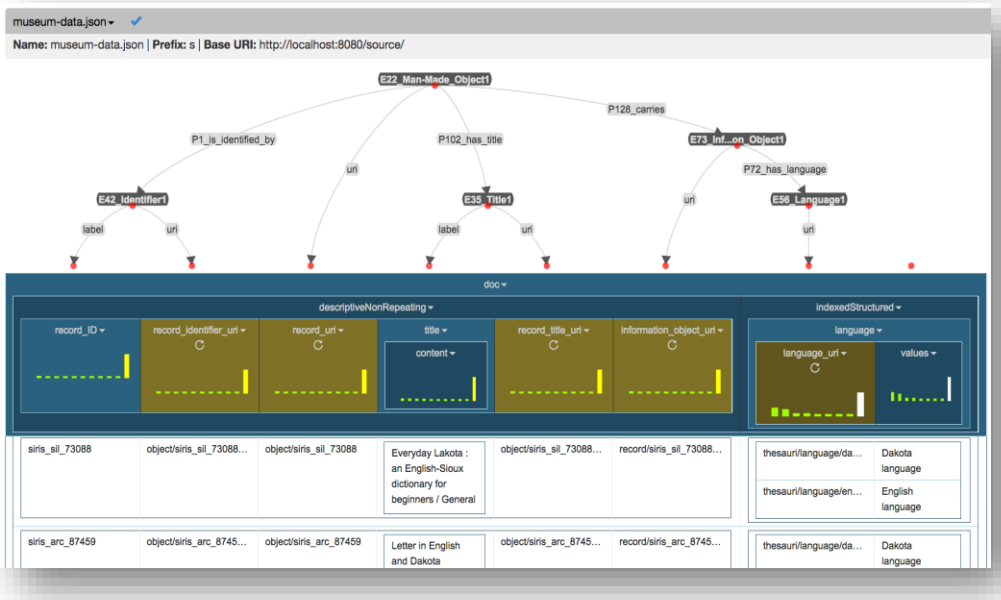


Knowledge Graphs

Karma uses semantic models to create knowledge grap

Karma semi-automatically builds semantic models

… and provides a nice GUI to edit them



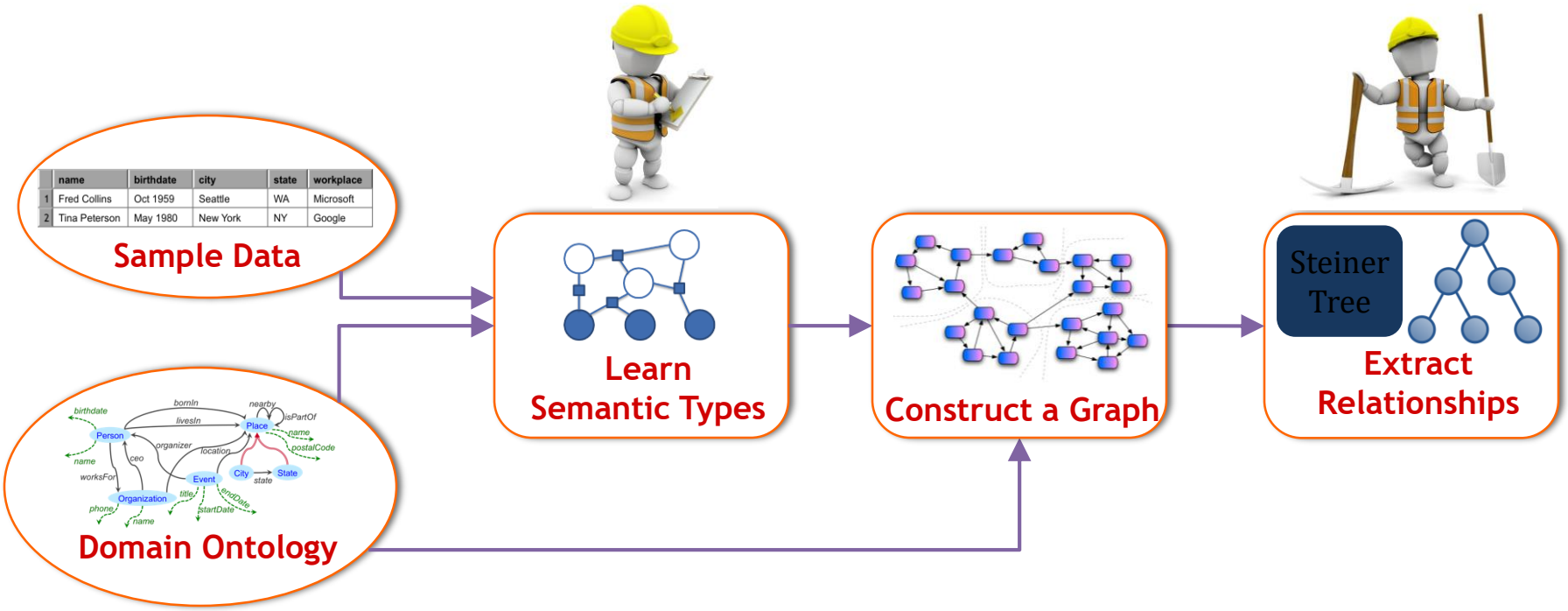
Knowledge Graphs

Karma uses semantic models to create knowledge grap

Semi-automatically Building Semantic Models in Karma

Approach

[Knoblock et al, ESWC 2012]



Example

Source

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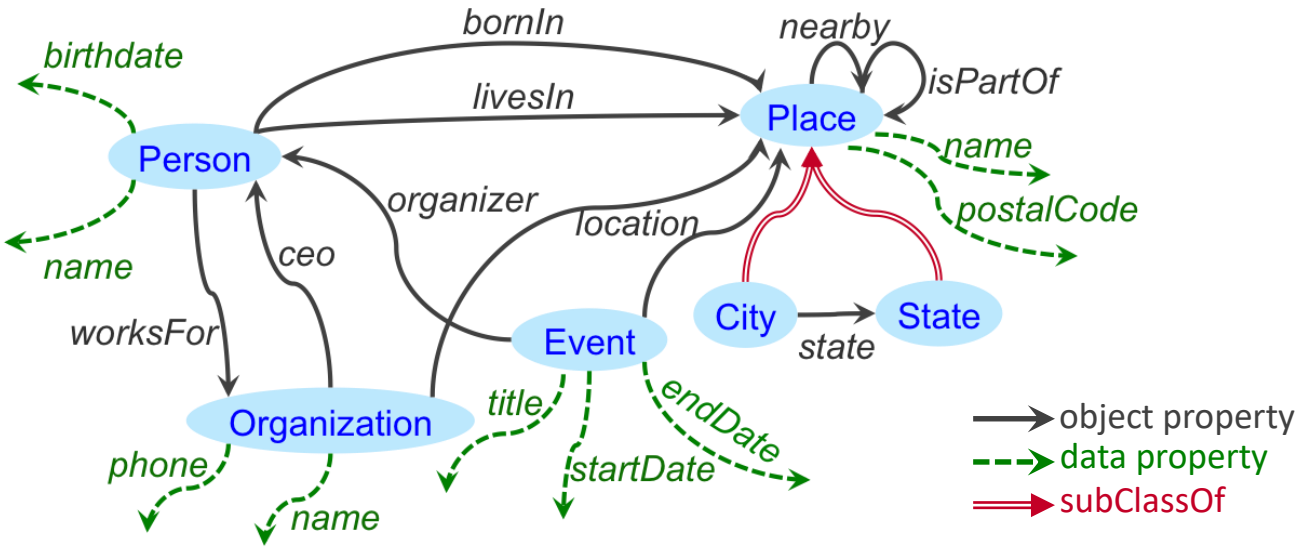
2	Tina Peterson	May 1980	New York	NY	Google

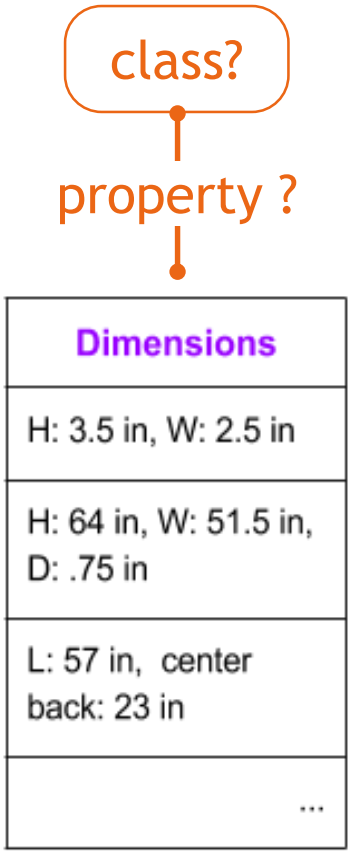
Domain Ontology



Find a semantic model for the source (map the source to the ontology)

Learning Semantic Types

[Krishnamurthy et al., ESWC 2015]



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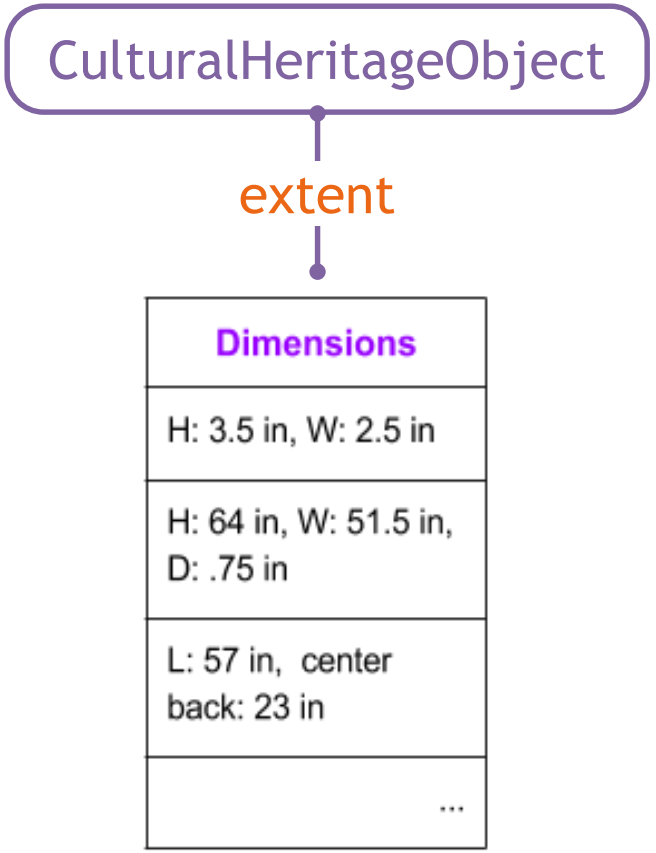
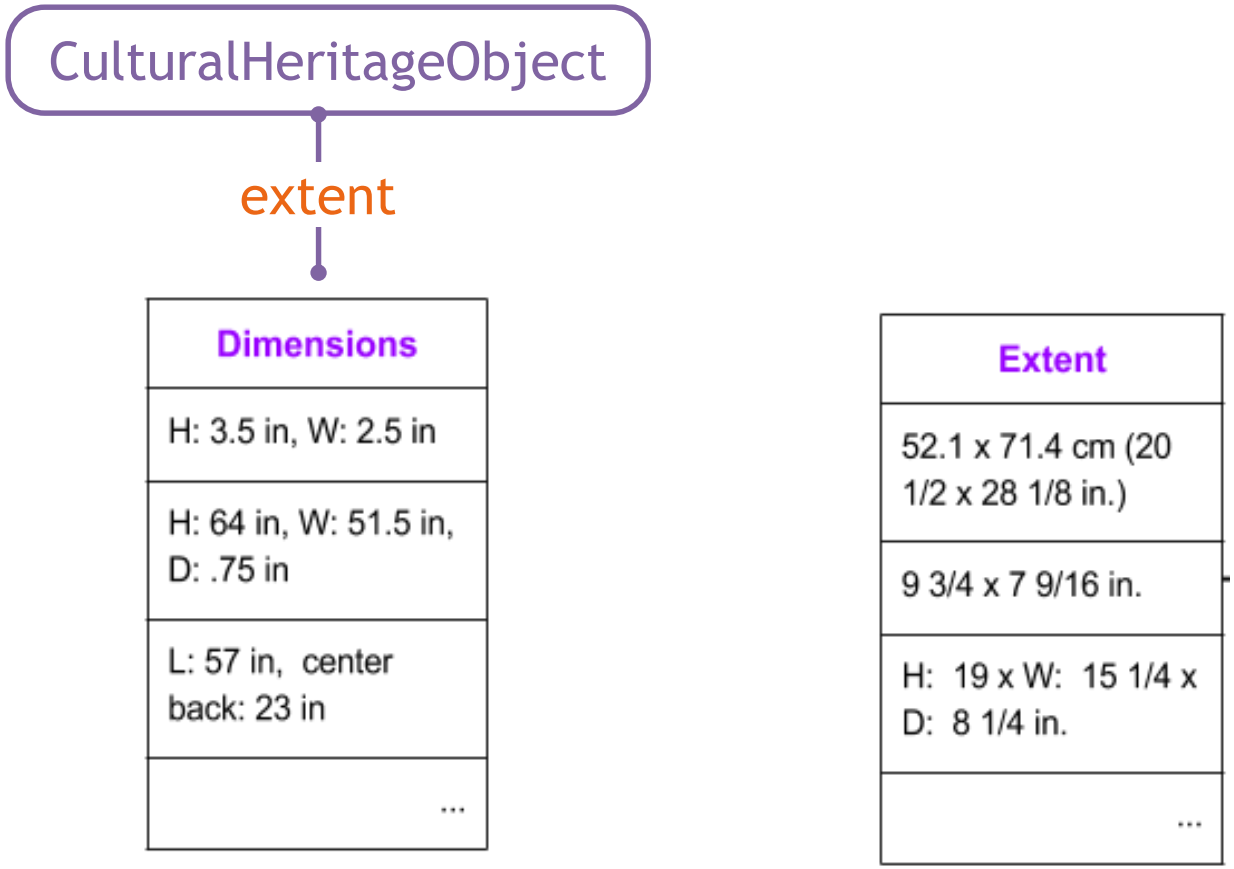


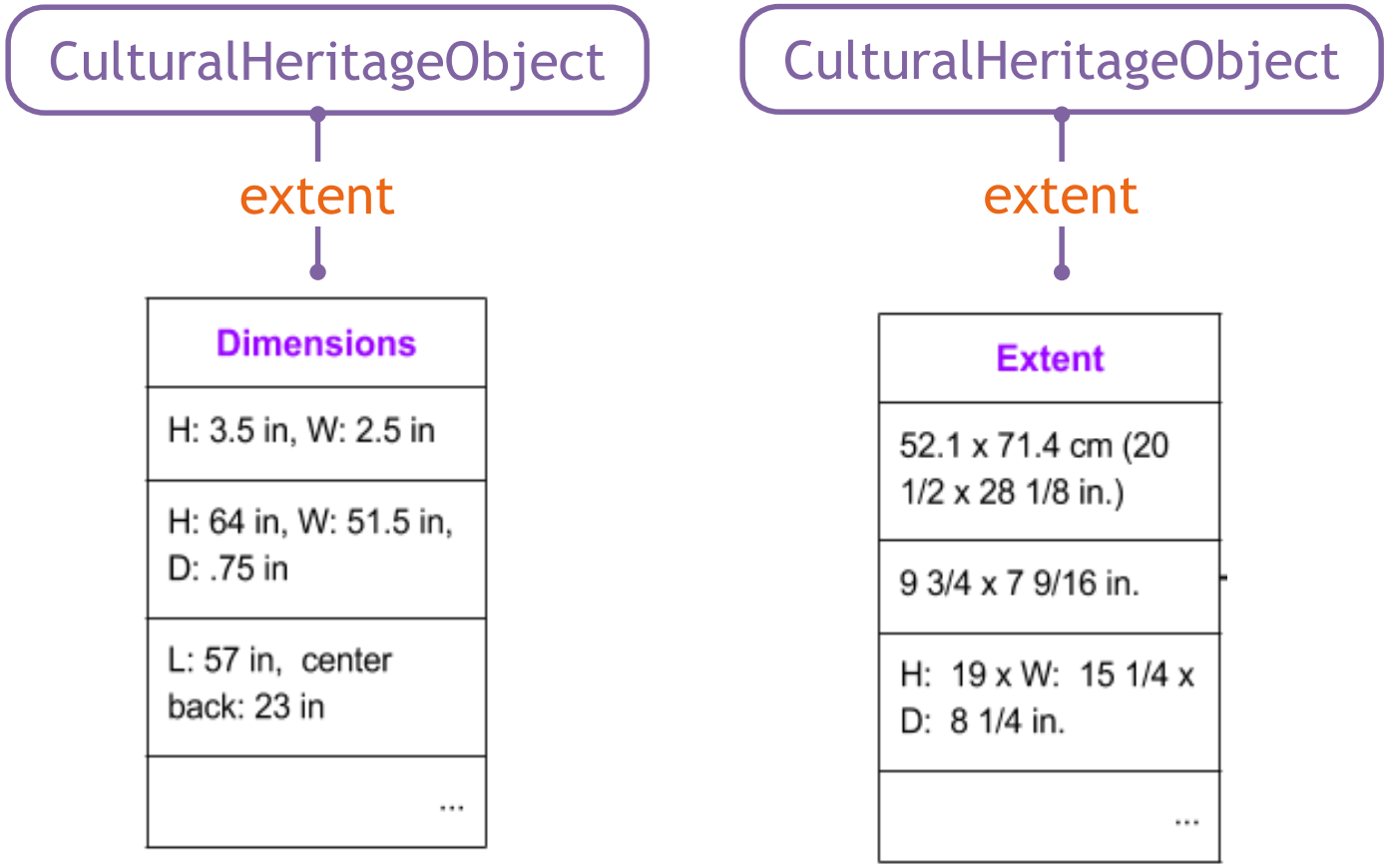
1- User specifies

2- System learns

Learning Semantic Types



Learning Semantic Types



Requirements

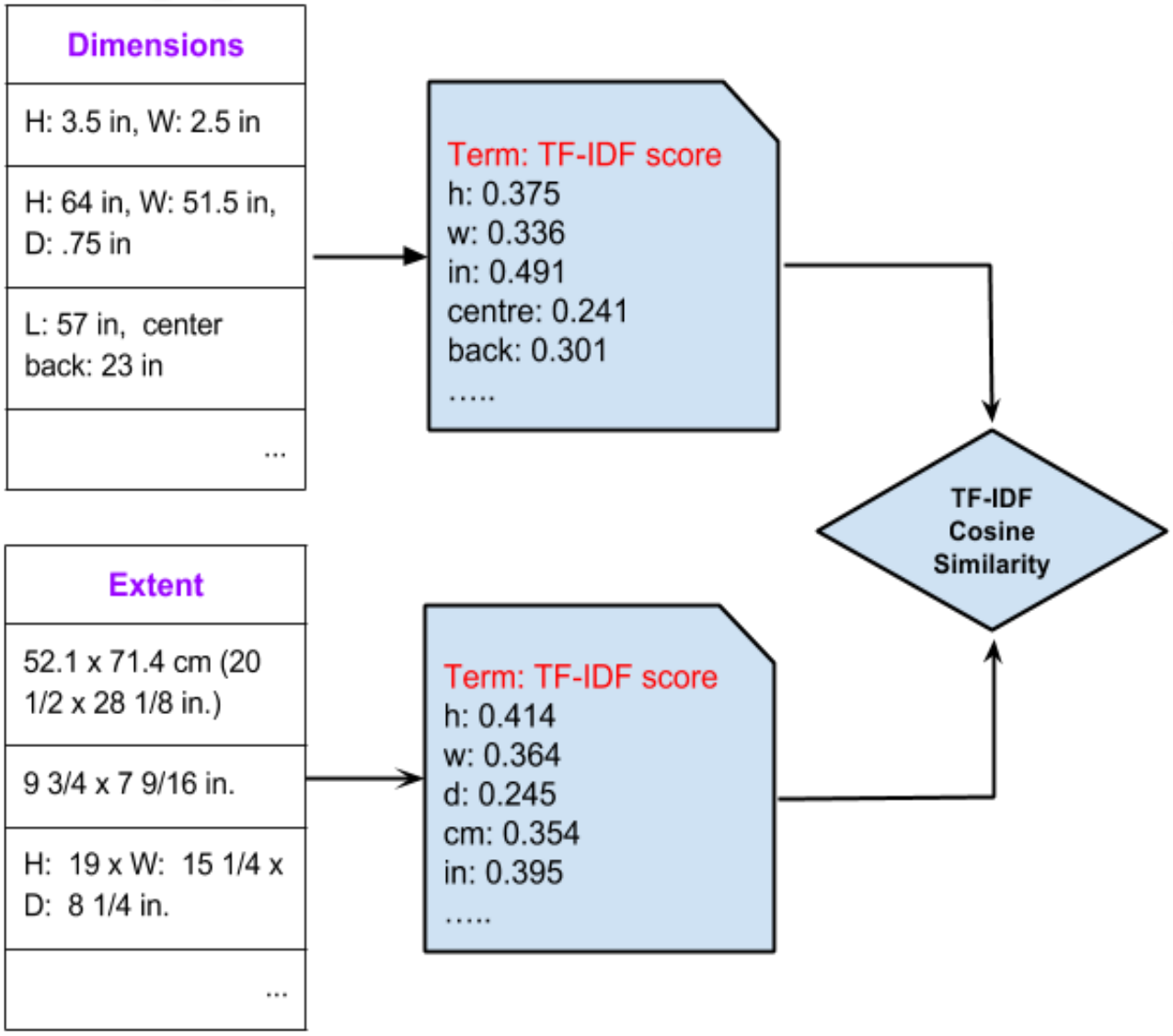
- Learn from a small number of examples
- Work on both textual and numeric values
- Learn quickly and highly scalable to large number of semantic types

Approach for Textual Data

- Document: each column of data
- Label: each semantic type
- Use Apache Lucene to index the labeled documents
- Compute TF/IDF vectors for documents
- Compare documents using Cosine Similarity between TF/IDF vectors

Dimensions
H: 3.5 in, W: 2.5 in
H: 64 in, W: 51.5 in, D: .75 in
L: 57 in, center back: 23 in
...

Approach for Textual Data



$$tf(t,d) = frequency^{1/2}$$

$$idf(t) = 1 + log(\frac{numDocs}{docFreq+1})$$

$$sim(q,d) = \frac{V(q).V(d)}{|V(q)|.|V(d)|}$$

Approach for Numeric Data

- Distribution of values in different semantic types is different, e.g., temperature vs. population
- Use Statistical Hypothesis Testing to see which distribution fits best
- Welch's T-test, Mann-Whitney U-test and Kolmogorov-Smirnov Test

Total Population
107875
47823
60704
81034
.....

Number of people
11070
41542
33039
780058
.....

Approach for Numeric Data

Total Population
107875
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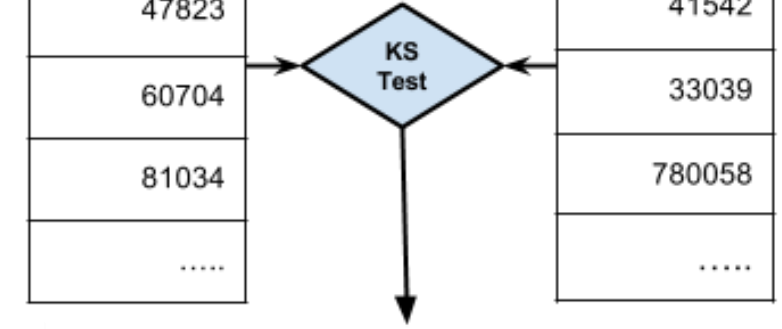
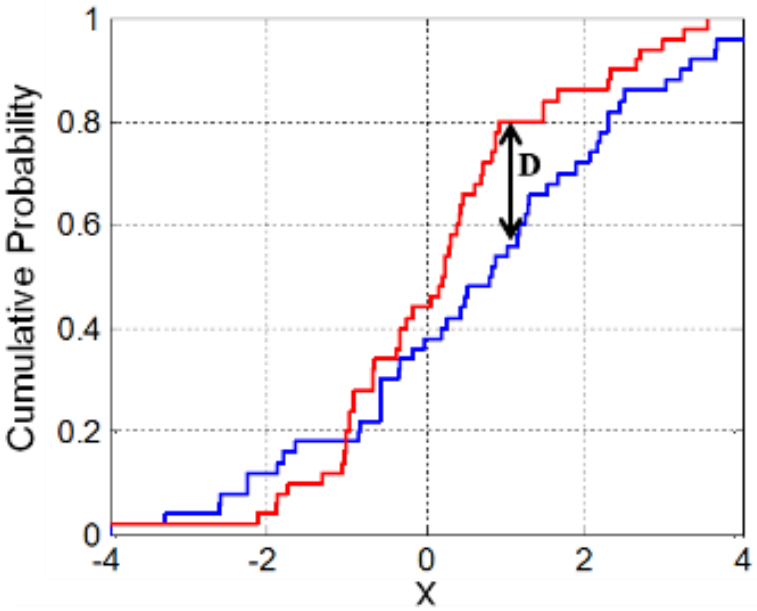
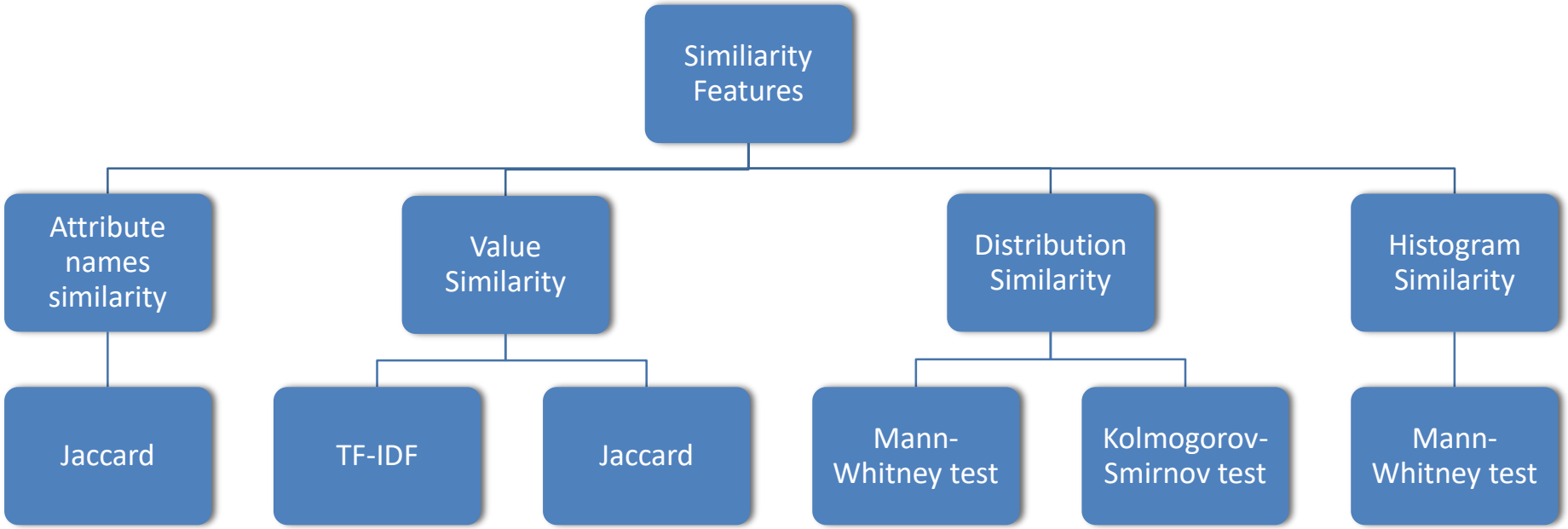


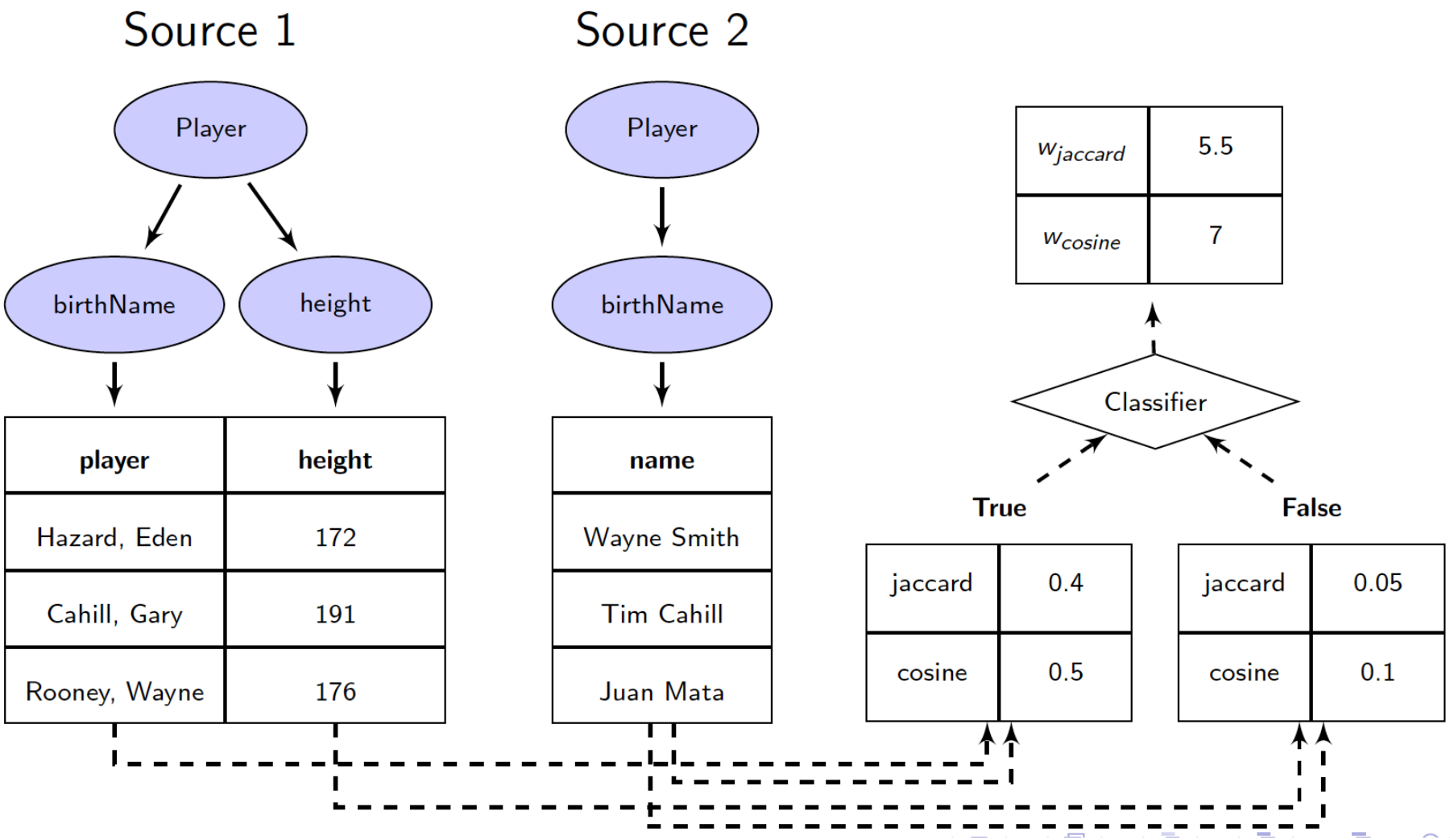


$$D_{N_1,N_2} = \sup_x |F_{1,N_1}(x) - F_{2,N_2}(x)|$$

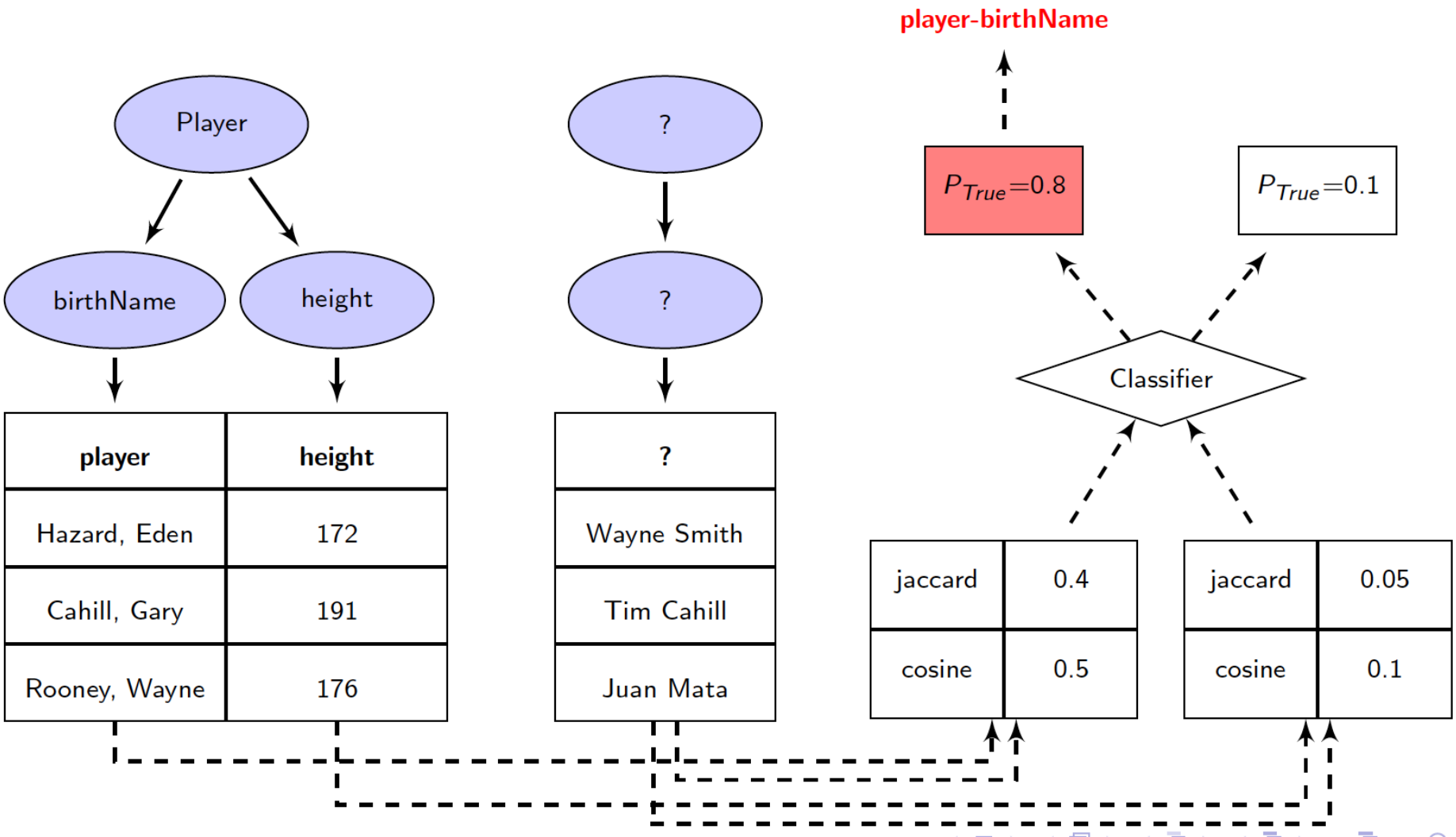
Similarity features



Training machine learning model
[Pham et al., ISWC 2016]

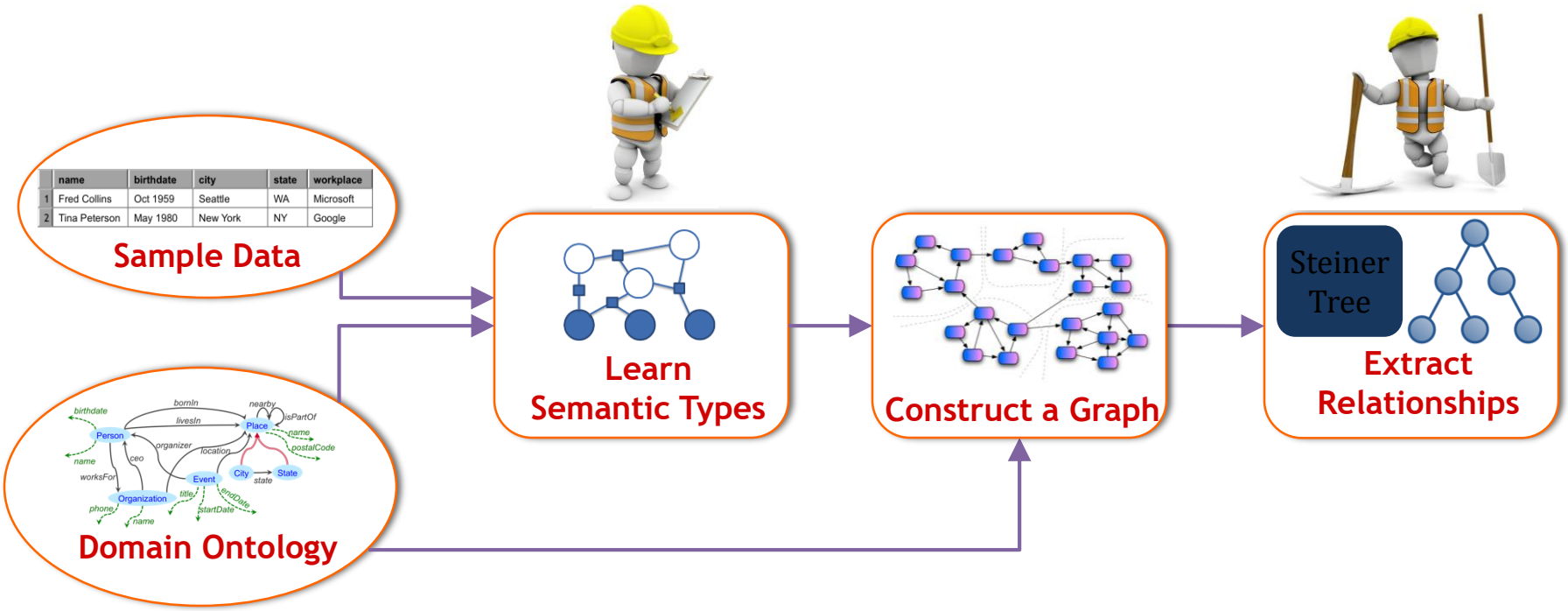


Predicting new attribute



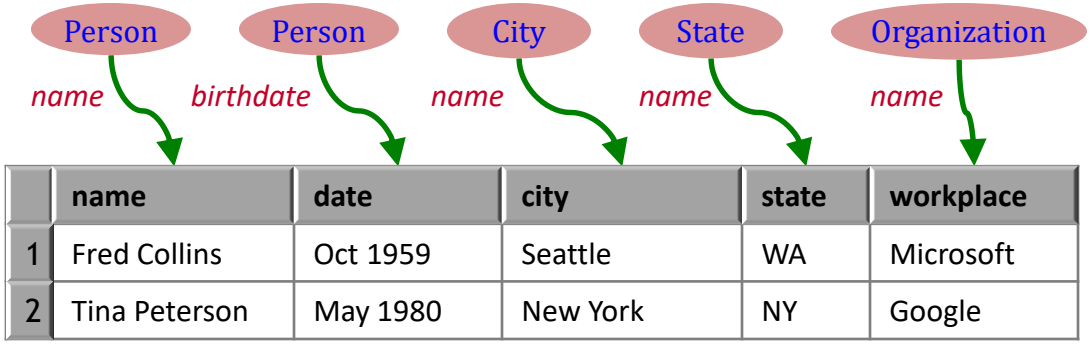
Approach

[Knoblock et al, ESWC 2012]

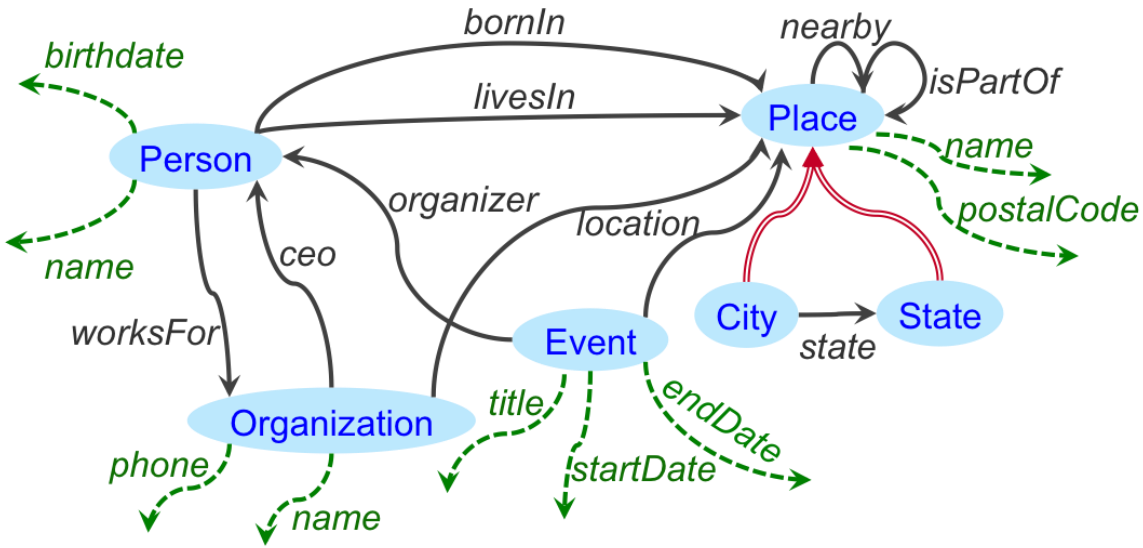


Construct a Graph

Construct a graph from semantic types and ontology

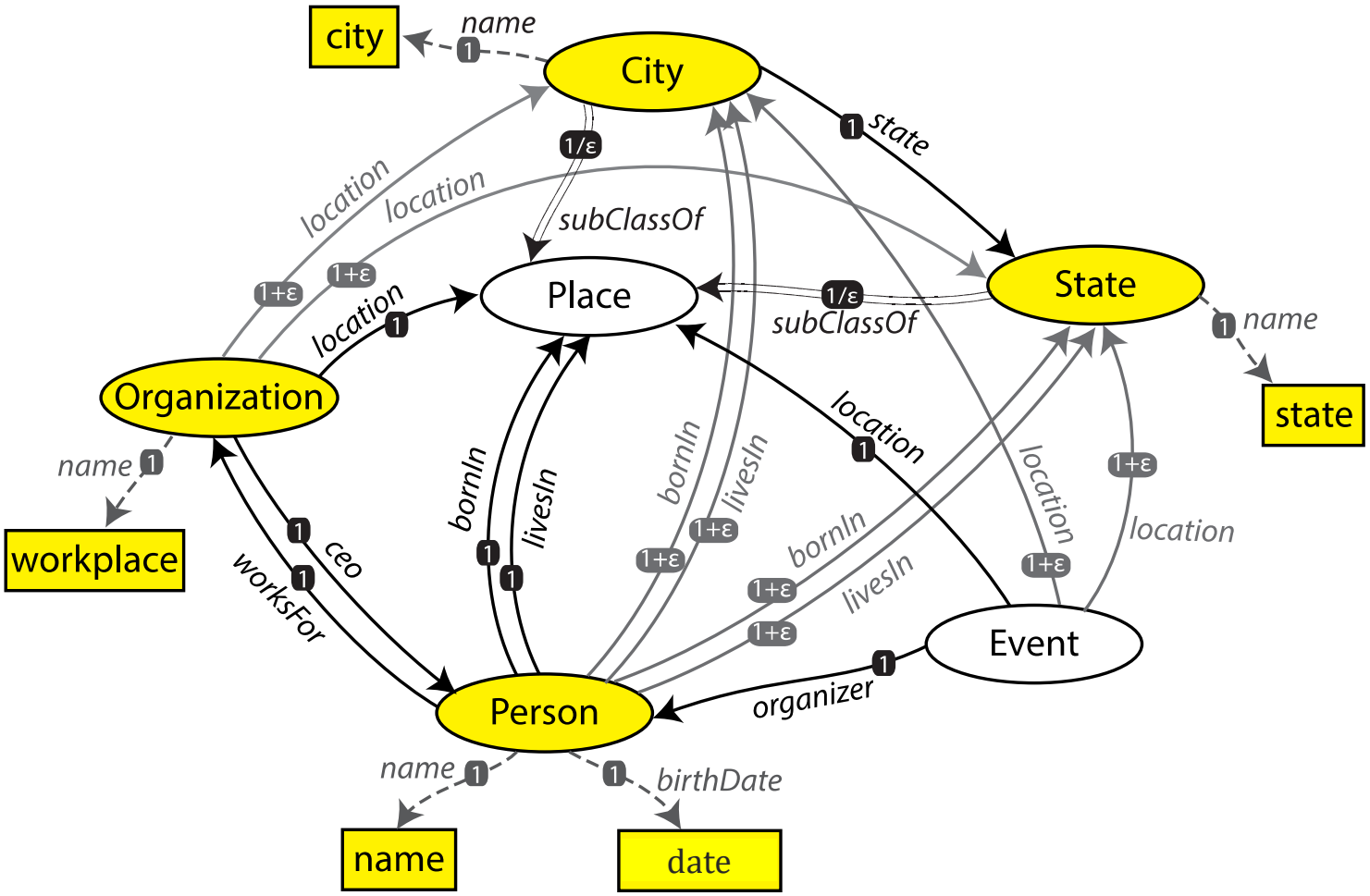


	name	date	city	state	workplace
1	Fred Collins	Oct 1959	Seattle	WA	Microsoft
2	Tina Peterson	May 1980	New York	NY	Google



Construct a Graph

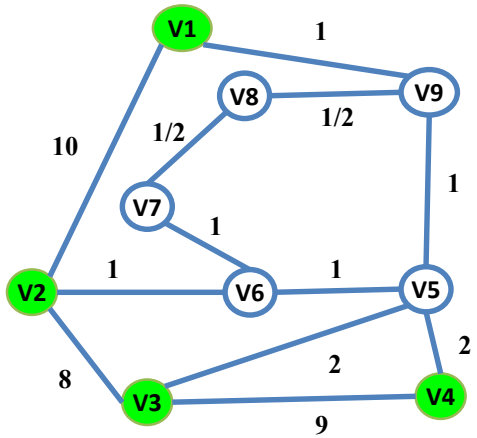
Construct a graph from semantic types and ontology



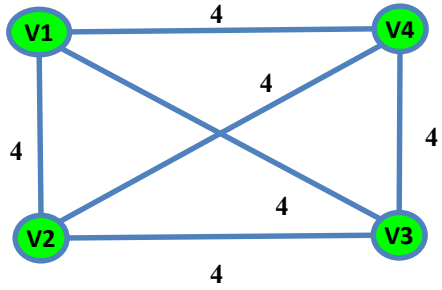
Inferring the Relationships

- Search for minimal explanation
- Steiner tree connecting semantic types over ontology graph
  - Given graph G=(V,E), nodes $S \subset V$, cost c: $E \rightarrow \Re$
  - Find a tree of G that spans S with minimal total cost
  - Unfortunately, NP-complete
- Approximation Algorithm [Kou et al., 1981]
  - Worst-case time complexity: $O(|V|^2|S|)$
  - Approximation Ratio: less than 2

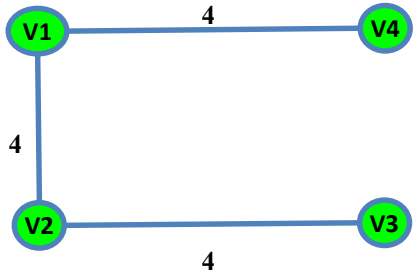
Steiner Tree



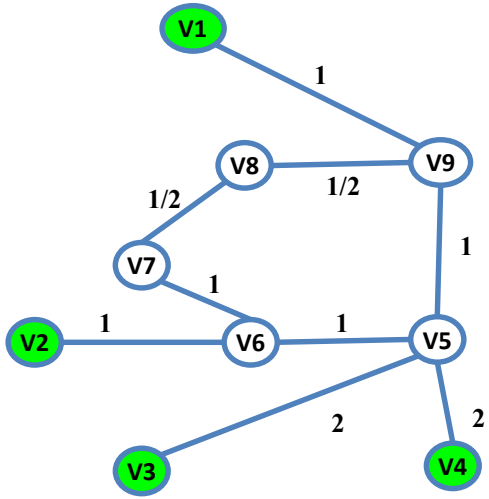
Steiner nodes: {V1, V2, V3, V4}



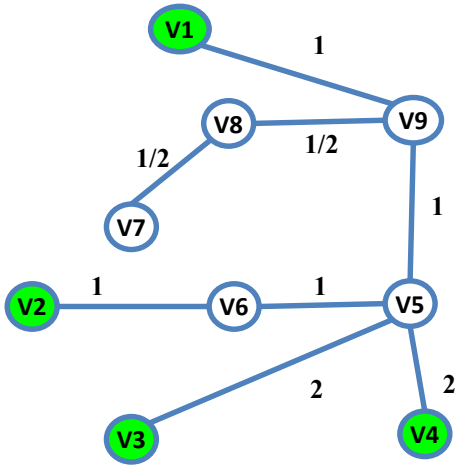
1. construct the complete graph (Nodes: Steiner Nodes, Links Weights: shortest path from each pair in original G)



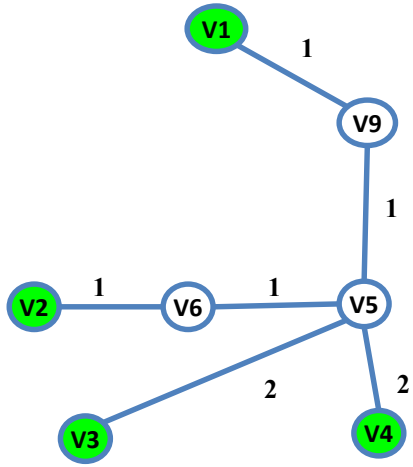
2. Compute MST



3. replace each link with the corresponding shortest path in original G



4. Compute MST

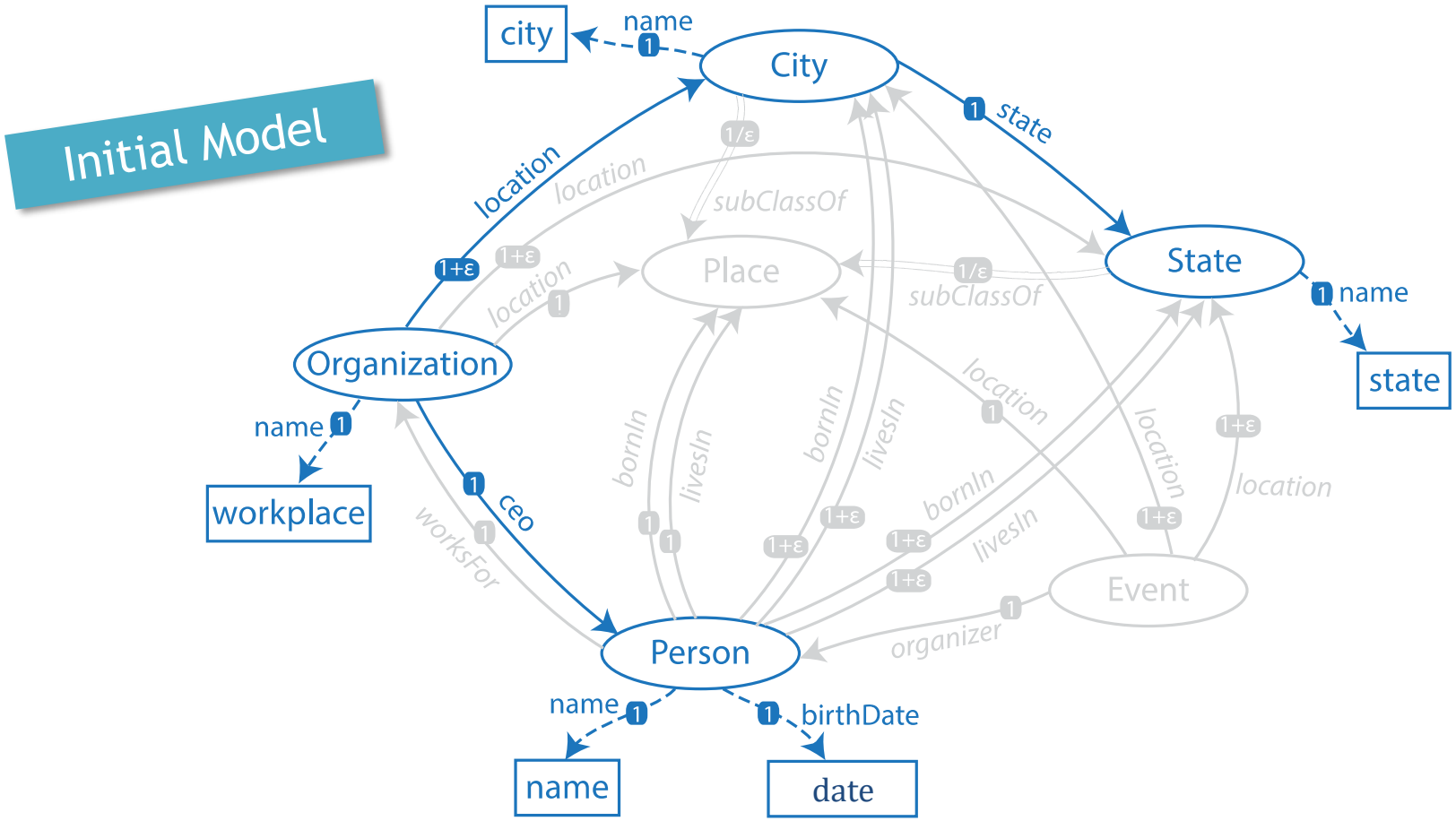


5. remove extra links until all leaves are Steiner nodes

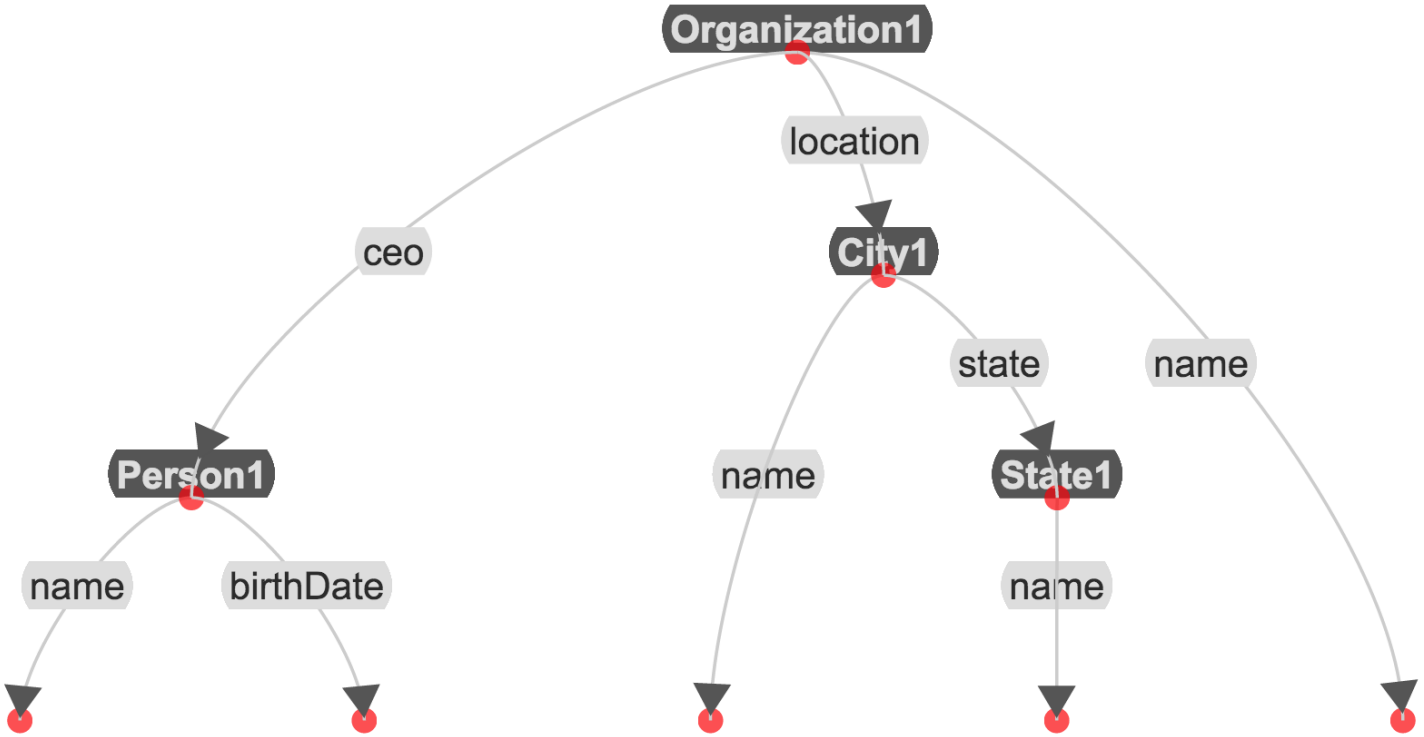
Inferring the Relationships

Select minimal tree that connects all semantic types

- A customized **Steiner tree algorithm**



Result in Karma

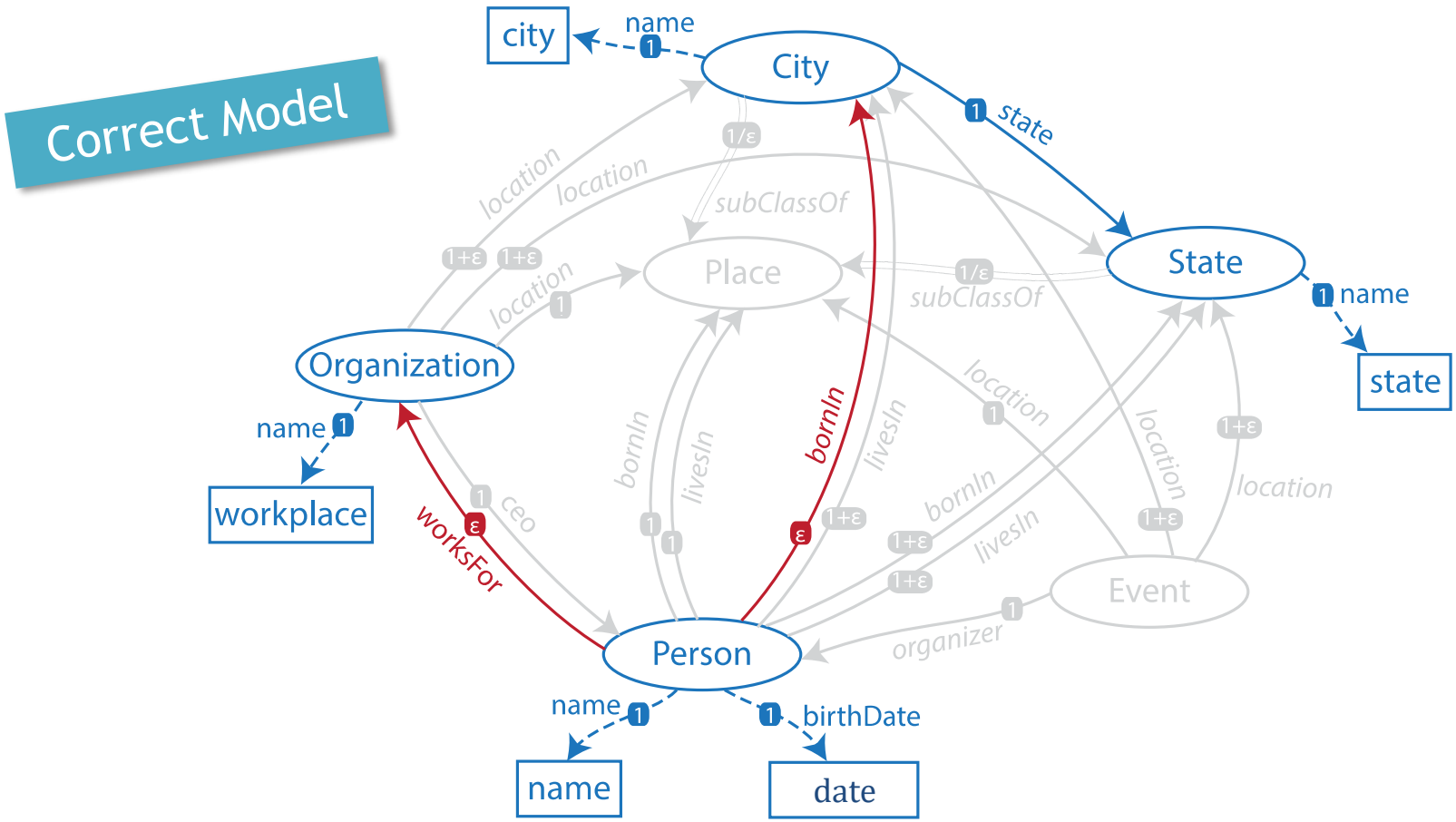


name	birthdate	city	state	workplace
Fred Collins	Oct 1959	Seattle	WA	Microsoft
Tina Peterson	May 1980	New York	NY	Google
Richard Smith	Feb 1975	Los Angeles	CA	Apple

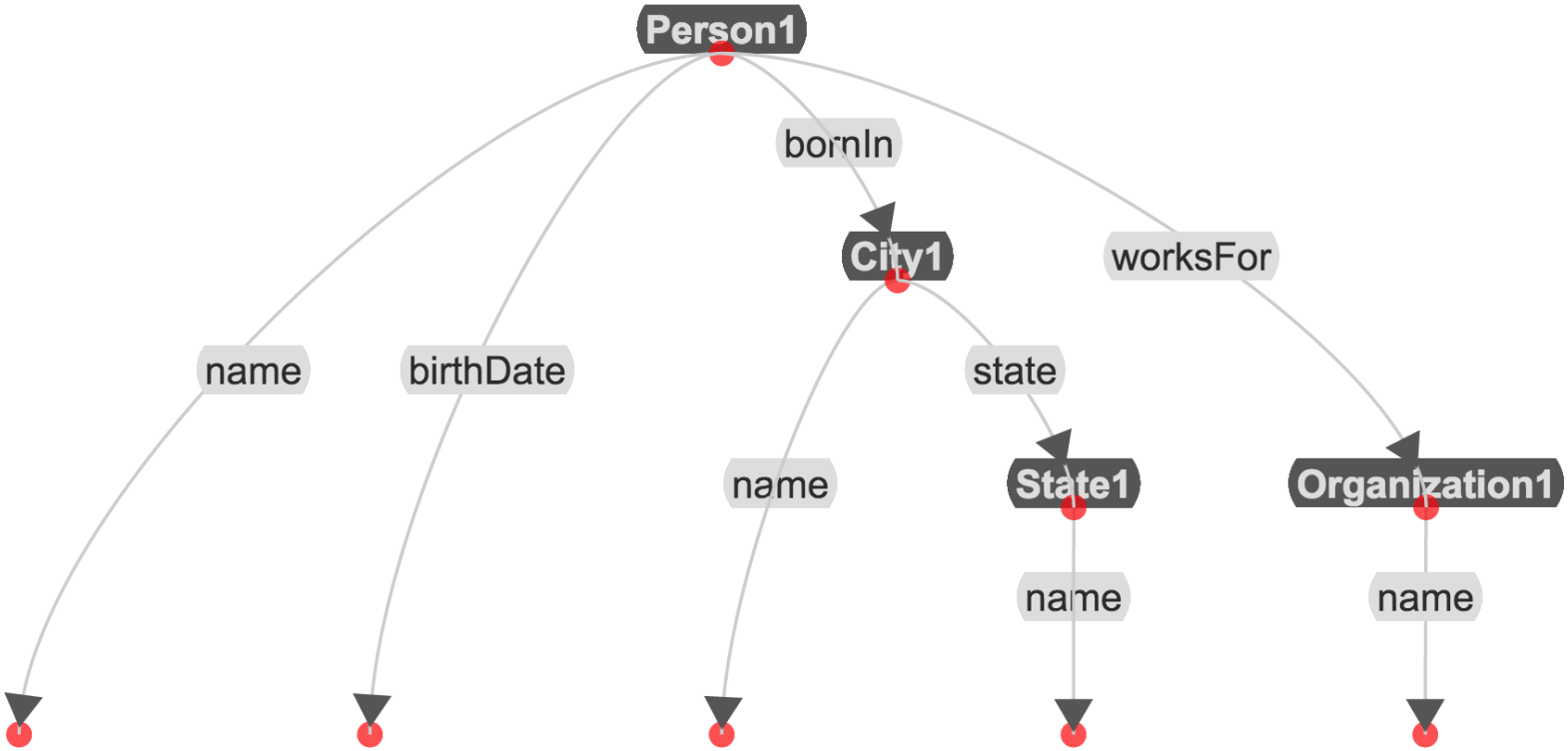
Refining the Model

Impose constraints on Steiner Tree Algorithm

- Change weight of selected links to ε
- Add source and target of selected link to Steiner nodes



Final Semantic Model



name	birthdate	city	state	workplace
Fred Collins	Oct 1959	Seattle	WA	Microsoft
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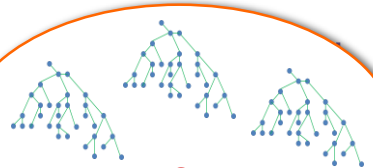
Karma Learns the Source Models

Taheriyan et al., ISWC 2013, ICSC 2014

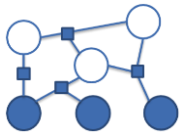
	name	birthdate	city	state	workplace
1	Fred Collins	Oct 1959	Seattle	WA	Microsoft
2	Tina Peterson	May 1980	New York	NY	Google

Sample Data

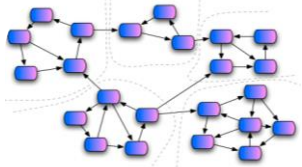
Domain Ontology



Known Semantic Models



Learn Semantic Types



Construct a Graph

Generate Candidate Models

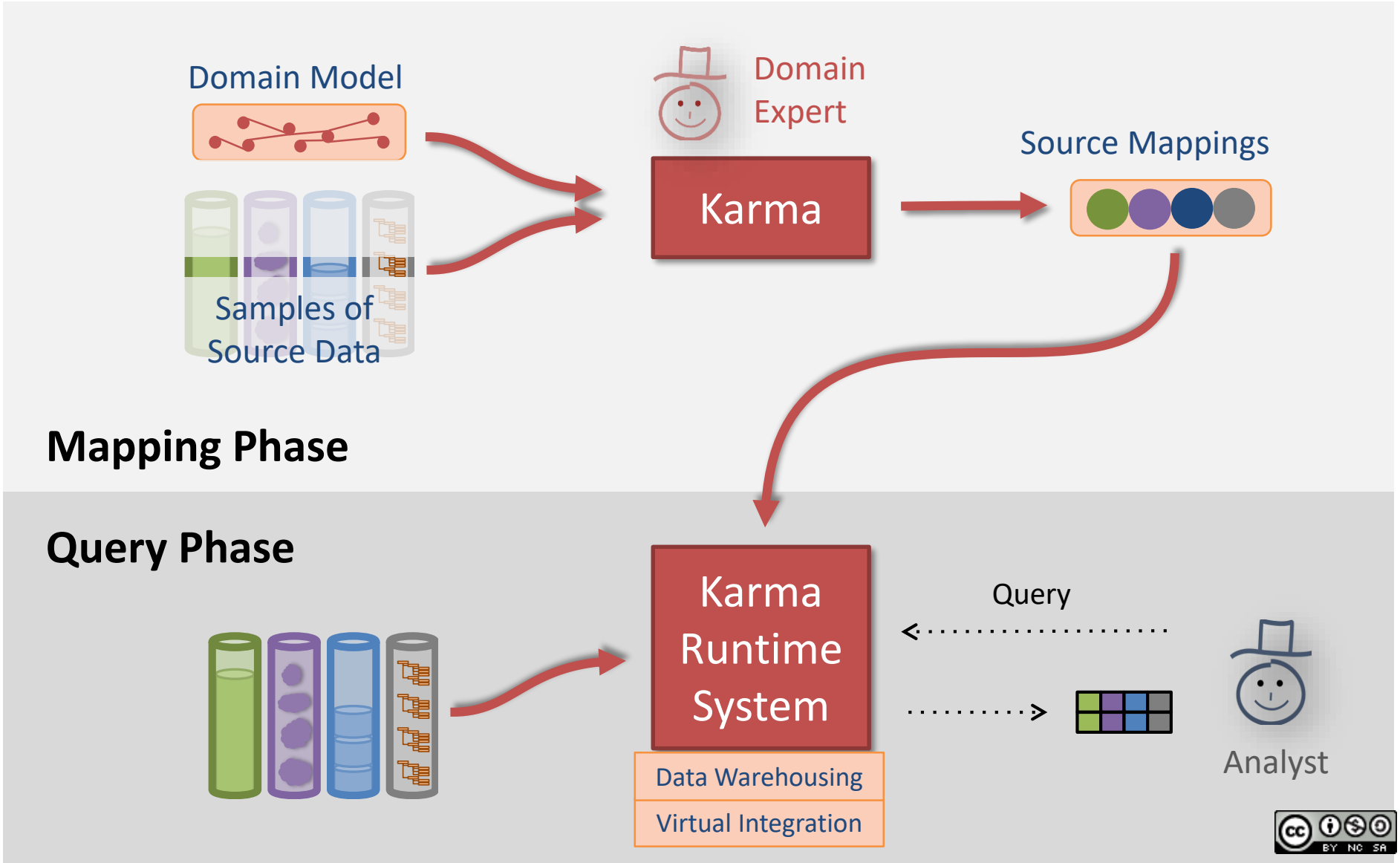
Rank Results

Karma Use Cases

Source Mapping Phase

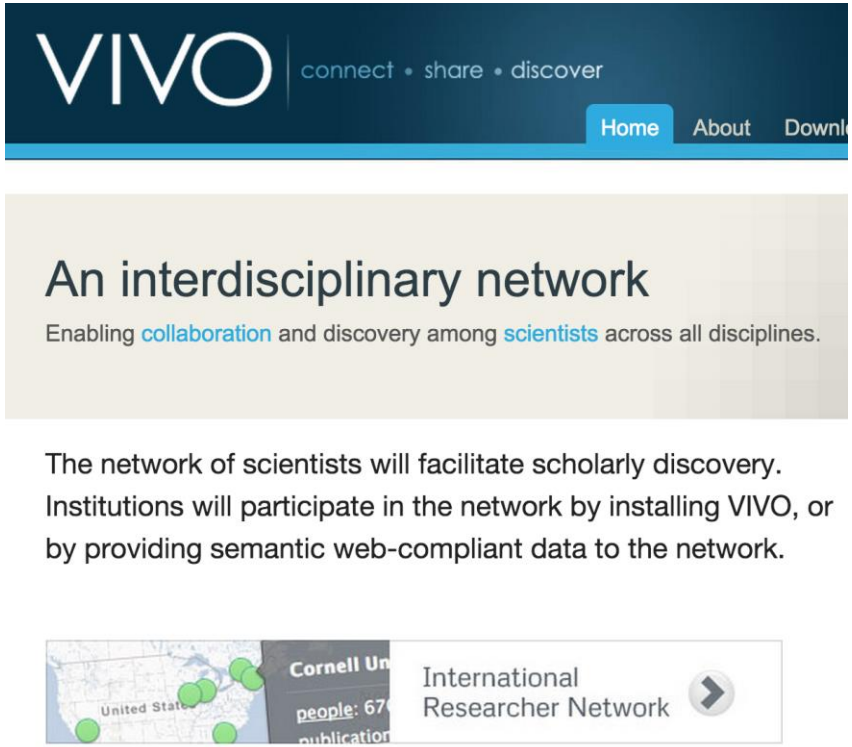
Mapping Phase

Source Mapping and Query Time



VIVO

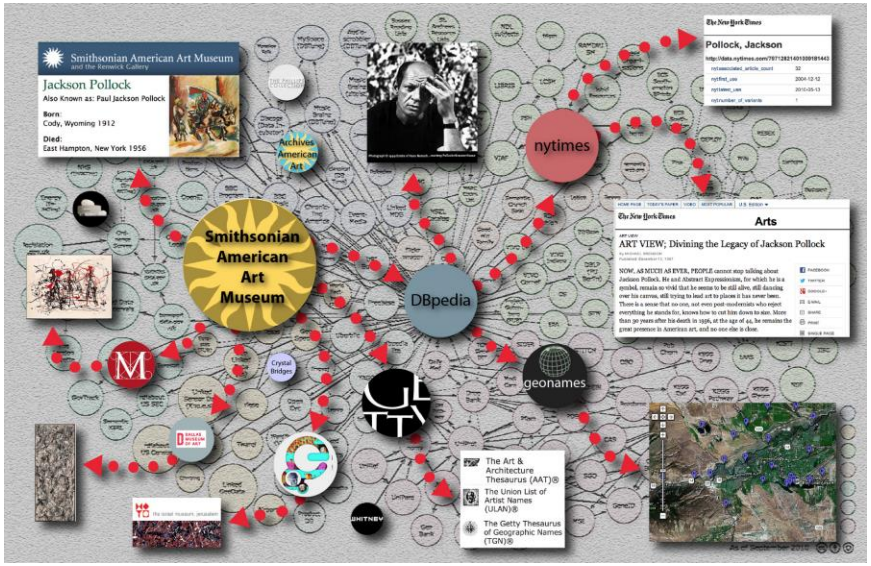
- VIVO is a system to build researcher networks across institutions
- Used Karma to map the data about USC faculty to VIVO ontology and publish it as RDF
- VIVO ingest the RDF data
- Video



American Art Collaborative

[Knoblock et al., ISWC 2017]

- Used Karma to convert data of 13 American Art Museums to Linked Open Data
- Modeled according to CIDOC-CRM Ontology
- Linked the generated RDF to DBPedia and ULAN
- Video



Using Karma to map museum data to the CIDOC CRM ontology

https://www.youtube.com/watch?v=h3_yiBhAJIc

Discussion

- Automatically build rich semantic descriptions of data sources
- Exploit the background knowledge from (i) the domain ontology, and (ii) the known source models
- Semantic descriptions are the key ingredients to automate many tasks, e.g.,
  - Source Discovery
  - Data Integration
  - Service Composition

More Info

karma.isi.edu