

# Scalable Construction and Querying of Massive Knowledge Bases

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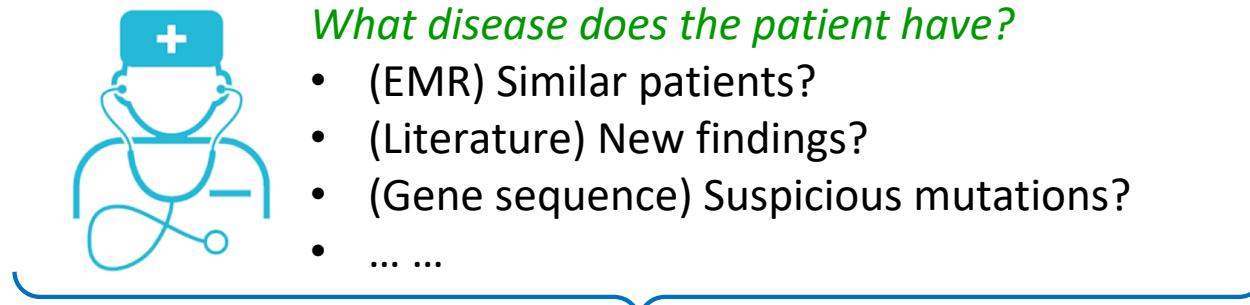


**Tutorial website:**  
[http://usc-isi-i2.github.io/WWW18\\_1/](http://usc-isi-i2.github.io/WWW18_1/)

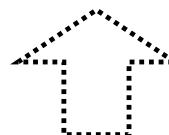
**Slides, code, datasets, references**



# Growing Gap between Human and Data



Ad-hoc information needs for on-demand decision making



Massive, heterogeneous data

86.9% adoption  
(NEHRS 2015)



27M+ papers, >1M  
new/year (PubMed)



\$1000 gene sequencing



24x7 monitoring



# How can AI Bridge the Gap?



Insights  
Discoveries  
Solutions

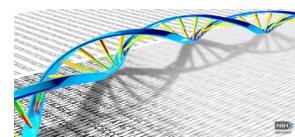
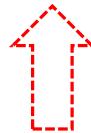
Bottleneck #2: Access



Bottleneck #3: Reasoning



Bottleneck #1: Knowledge

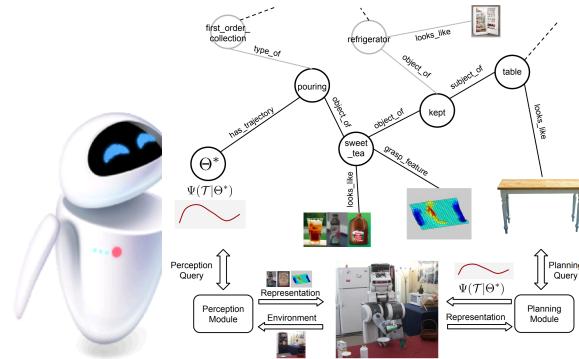


# Broad Applications



“Which cement stocks go up the most when a Category 3 hurricane hits Florida?”

KENSHO

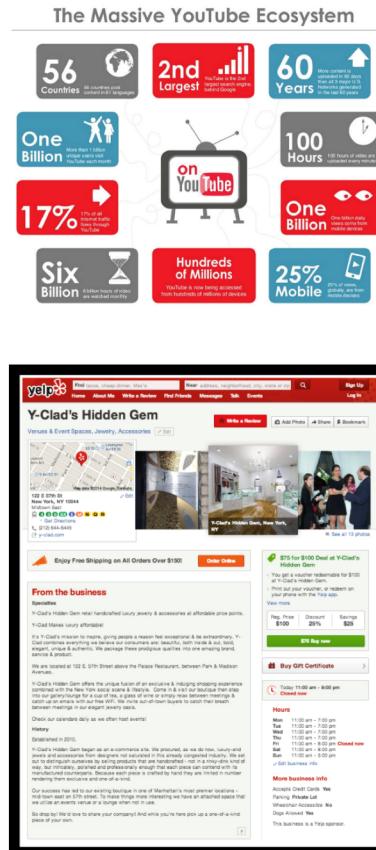


# **Constructing Domain Specific Knowledge Graphs**

**Pedro Szekely**

**Information Sciences Institute,  
University of Southern California**

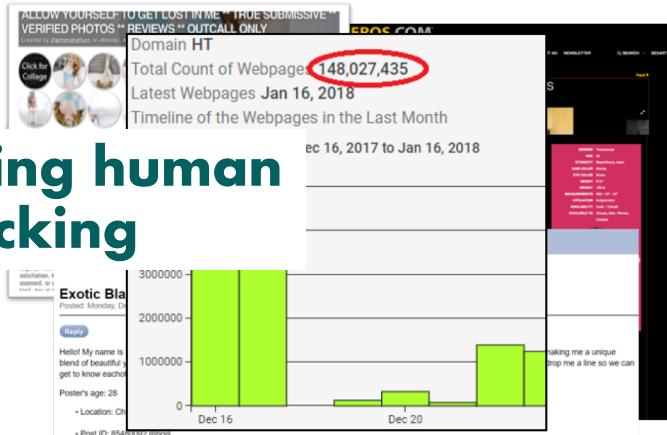
# Domain-specific search (DSS)



source: <https://photos.prnewswire.com/prnfull/20151006/274273-INFO>

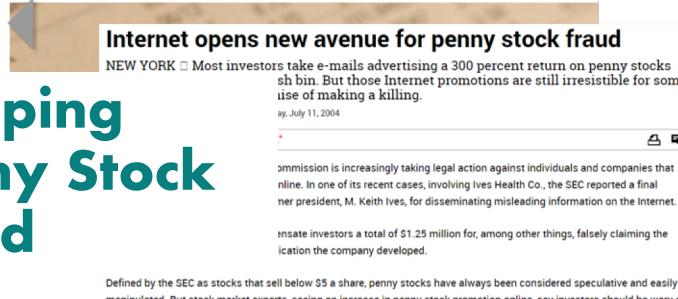
# Emerging opportunities for DSS

## Fighting human trafficking



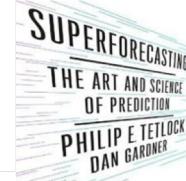
## Penny Stock Fraud Nets Millions

Scheme Mastermind Among Those Sentenced to Prison



## Stopping Penny Stock Fraud

## Predicting cyberattacks



## Accurate geopolitical forecasting



- 1. Forecasters begin by gathering as much information possible.
- 2. Forecasters nurture and develop the habit of thinking in terms of probabilities when exploring the likelihood of specific events.
- 3. Forecasting improves when individuals work in teams.
- 4. Forecasters ensure that they are regularly keeping score of their projections.
- 5. The most successful forecasters are willing to admit error and quickly change course on their projections.

# DARPA/IARPA programs

DARPA Memex

IARPA Hybrid Forecasting  
Competition

DARPA AIDA

DARPA Causal Exploration

DARPA LORELEI

IARPA CAUSE

# DSS is more than keyword search

## Lead Investigation

What is the ad with the earliest post date containing number 7075610282?

## Aggregations/Lists

List all ads in Seattle, WA that include an ethnicity in the ad text. In the answer field, concatenate and list ethnicities

## Indicator Mining

List all ads that have high probability of movement  
List all ads in the Chicago area advertising multiple people at once

## Dossier Generation

Collect and show me all information on the phone number 7075610282

# Google Knowledge Graph

The image displays three examples of Google's Knowledge Graph interface:

- Top Left (Leonardo da Vinci):** A network graph centered on Da Vinci, showing connections to the Mona Lisa, Michelangelo, Italy, and other historical figures.
- Bottom Left (Wonder Woman 2017):** A search result page for the 2017 film. It includes a summary, cast information, and links to IMDB and Wikipedia. A large black oval highlights the "Top stories" section, which features news articles from the Washington Post and Breitbart about the movie's release.
- Right Side (Larry Page):** A detailed knowledge card for Larry Page. It includes his photo, social media links (Google+, LinkedIn, YouTube), and a summary of his life and career. A red box highlights the "Knowledge Graph" section, which shows a grid of small images related to him (Sergey Brin, Eric Schmidt, Larry Ellison, Marissa Mayer, Bill Gates).

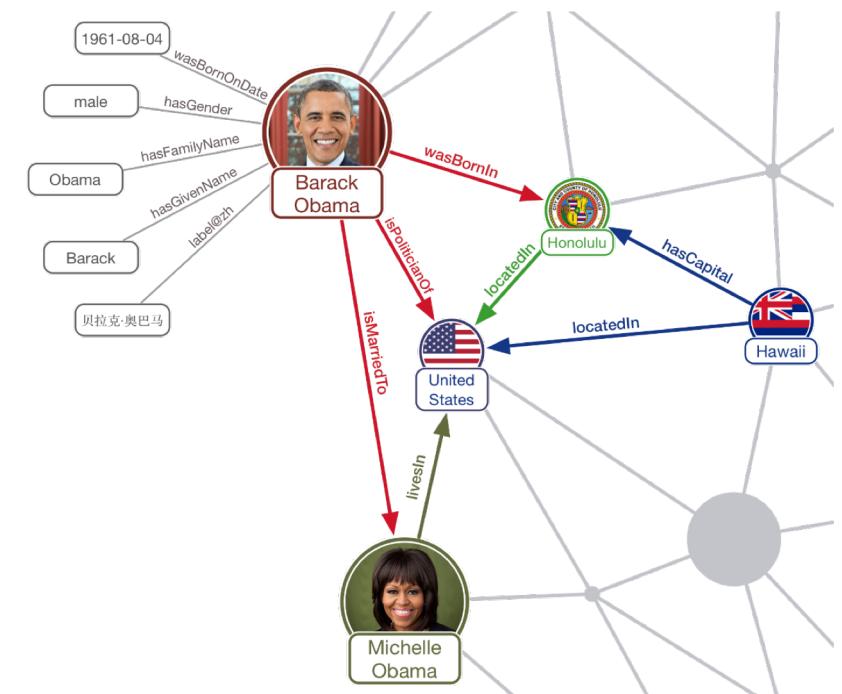
# What is a Knowledge Graph?

**set of triples, where each triple ( $h$ ,  $r$ ,  $t$ ) represents a relationship  $r$  between head entity  $h$  and tail entity  $t$**

(Barack Obama, wasBornOnDate, 1961-08-04),  
(Barack Obama, hasGender, male),

...  
(Hawaii, hasCapital, Honolulu),

...  
(Michelle Obama, livesIn, United States)



**General Search**

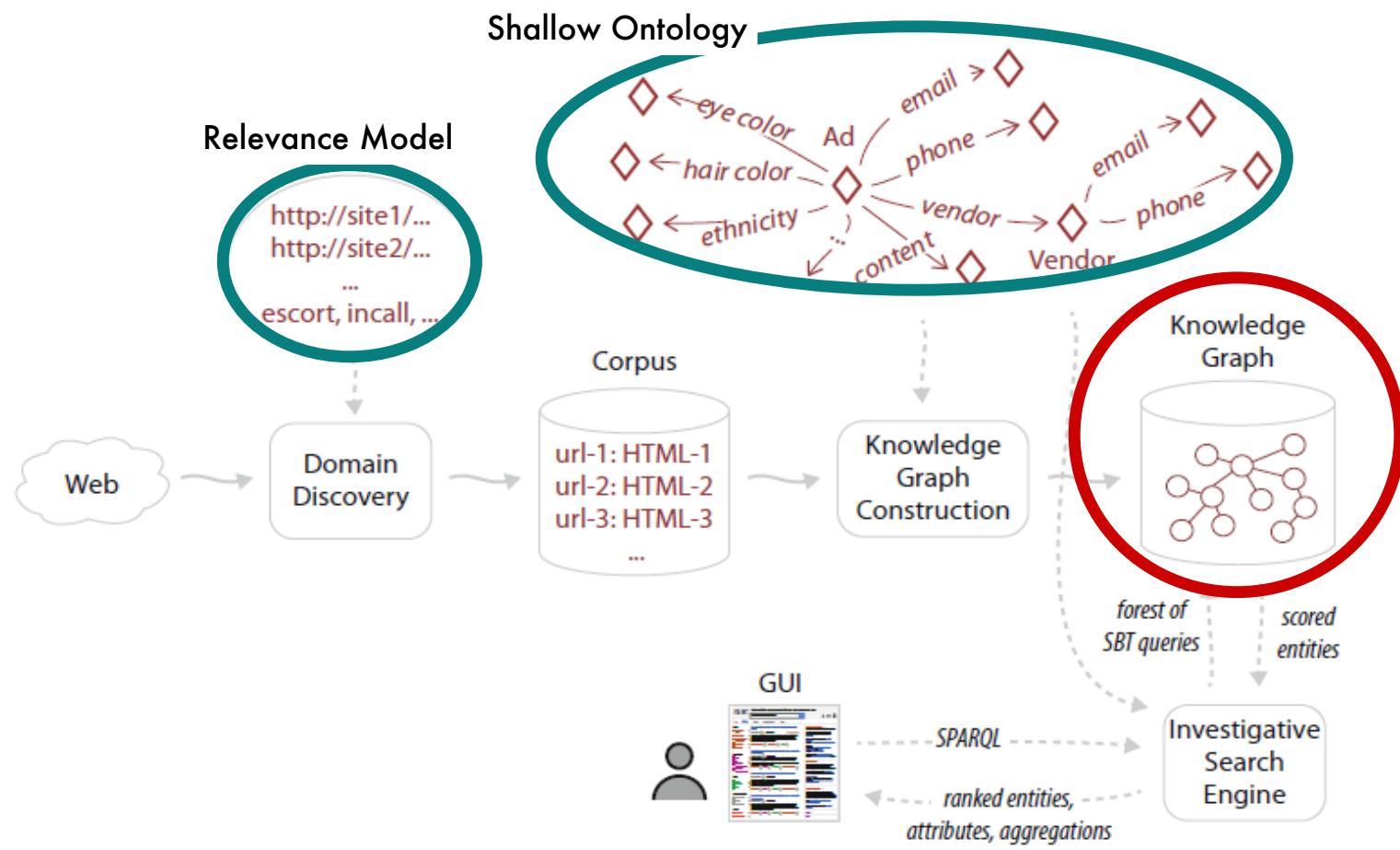
**Google Knowledge Graph**

**DSS**

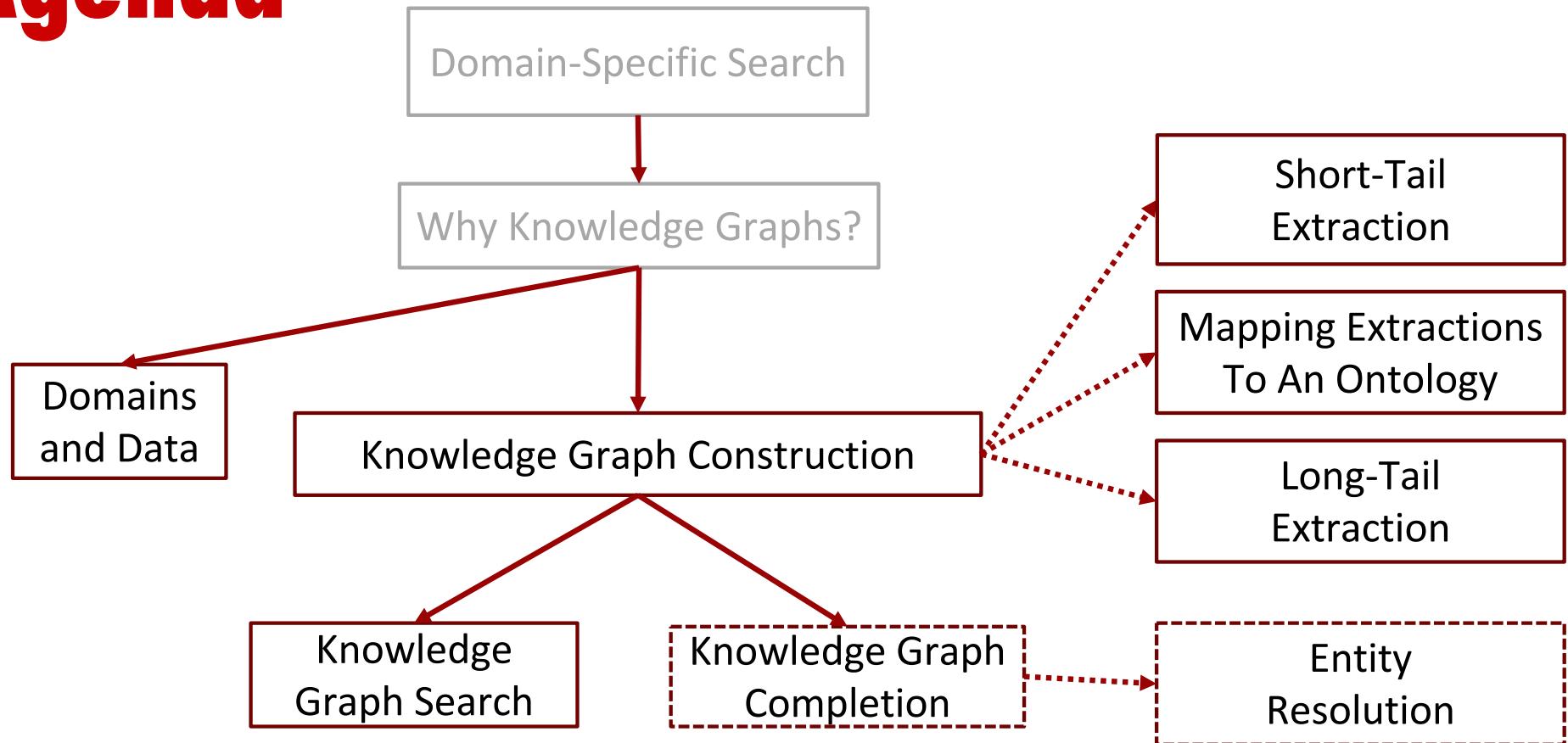
**Domain-Specific Knowledge Graphs**

How do we construct domain specific  
knowledge graphs over web data for  
powerful DSS applications

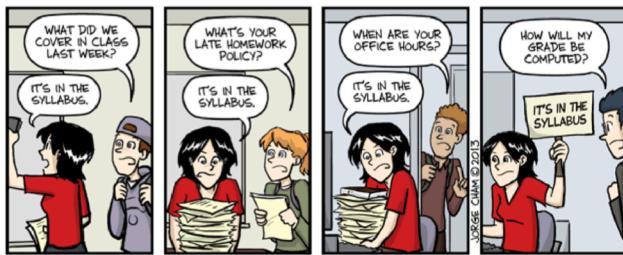
# Knowledge Graphs for DSS



# Agenda

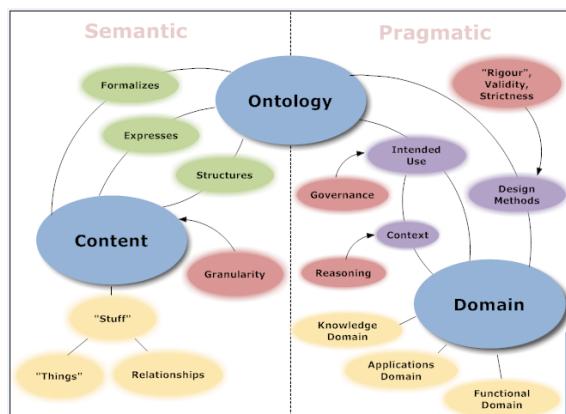


# What is (or even isn't) a domain?



## IT'S IN THE SYLLABUS

This message brought to you by every instructor that ever lived.  
WWW.PHDCOMICS.COM  
*"Piled Higher and Deeper"* by Jorge Cham



## Some dictionary definitions

(Merriam Webster) A sphere of **knowledge, influence or activity**

(Oxford) A **specified sphere of activity or knowledge**

## Specifying the sphere

### Rules

Scope (e.g., the legal system)

Syllabi (for classrooms)

### Examples

## How do domain experts specify the sphere?

### Examples

### Ontology

# Domain-Specific Challenges

- Subject matter
- Complex nature
- Ambiguous
- Obfuscation
- How to adapt off-the-shelf tools?

Italian 19 hello guys....My name is <b>charlotte</b> , New to town from <b>kansas</b>
[ GORGEOUS BLONDE beauty] ? FROM <b>Florida</b> ? (Petite) ? [ CURVY ]?
NO DISAPPOINTMENTS. 34C.. <b>Brazilian,ITALIAN</b> beauty....
Hey gentleman im <b>Newyork</b> and i'm looking for generous
Hi guy's this is sexy <b>newyork</b> . & ready to party.
AVAILABLE NOW! ?? - (1 two 1) six 5 six - 0 9 one 2 - 21

# Specifying investigative domains



## Functional

I have some questions I'd like answers to  
Domain is the scope of the answers  
Presents interesting cognitive dilemma!  
I know what I want but can't define it precisely

## Two major functional steps

### Data Acquisition

- Find me the data from a universe aka the Web that can help me answer my questions

### Ontological Specification

- Let me define fields and field properties that will help me unambiguously represent questions and interpret answers

# Specifying investigative domains

## Functional

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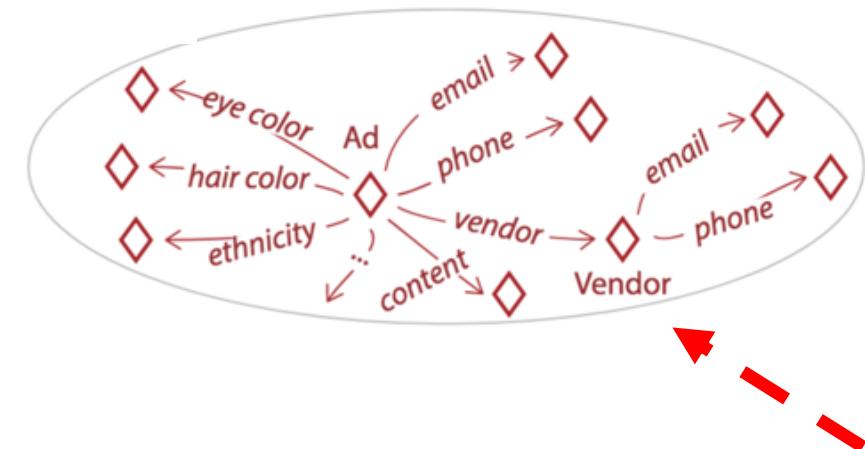
## Two major functional steps

### Data Acquisition

- The data from a universe aka the Web that can help me answer my questions

### Ontological Specification

- The classes and fields that will help me unambiguously represent questions and interpret answers



# In practice...

...investigators think of a domain as a  
**tri-faceted** combination of:

1. Questions

2. Entity types (a shallow ontology)

Ad, Posting Date, Title, Content, Phone, Email, Review

ID, Social Media ID, Price, Location, Service, Hair

Color, Eye Color, Ethnicity, Weight, Height

3. Examples/Annotations

# Crawling Challenges

## Scale, cost, speed

DNS, fetching, parsing/extracting, memory/disk

## Errors, redirects, localization

Need sophisticated software

## Deep web, forms, dynamic pages, infinite scrolling

Identify and fill in forms, render pages while crawling (headless browser)

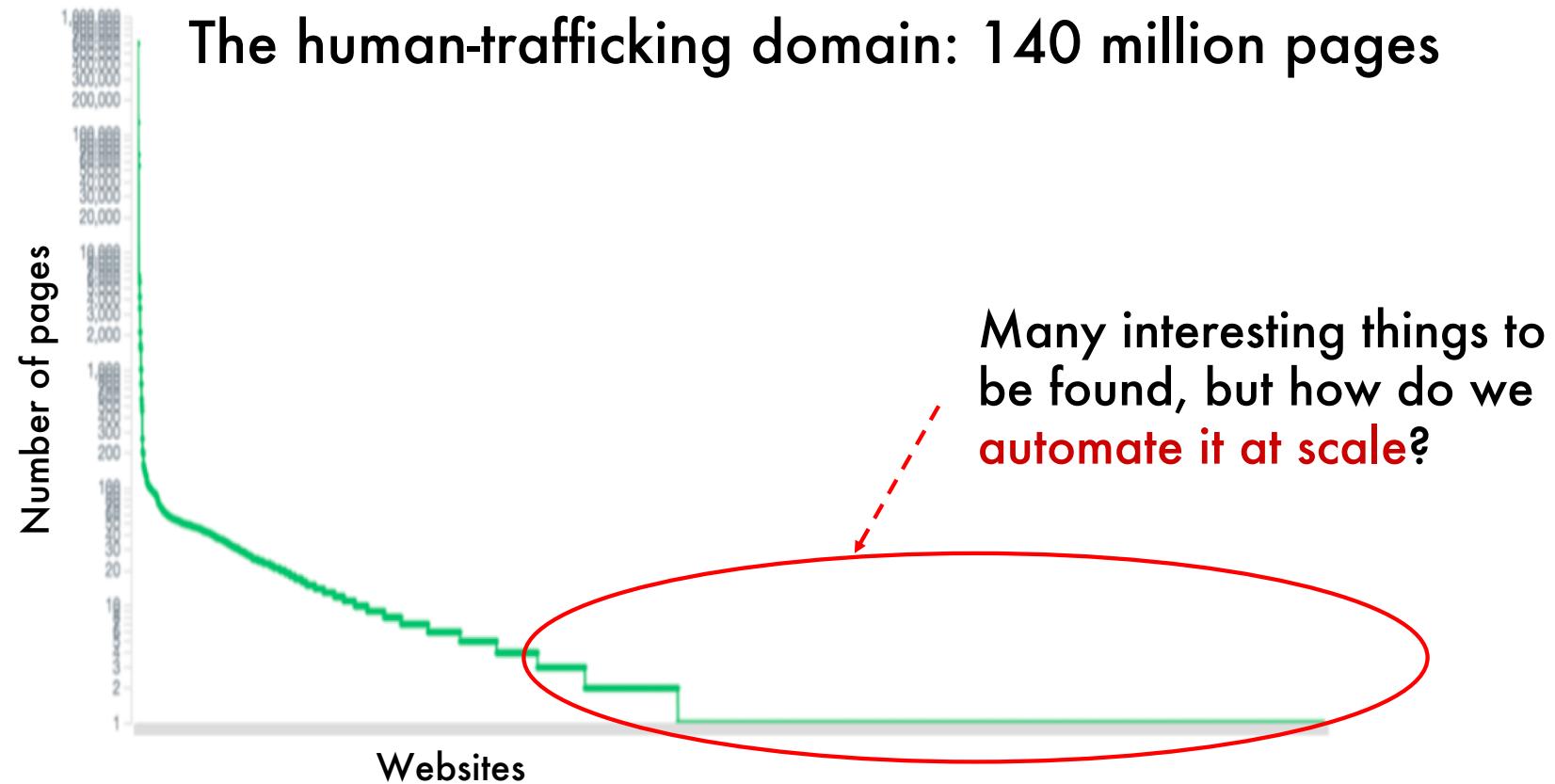
## Counter-crawling measures

Login, captchas, traps, fake errors, banning

## Freshness and deduplication

Identify and re-crawl new content

# Domains have a long tail



# **Schema-agnostic Knowledge Base Querying**

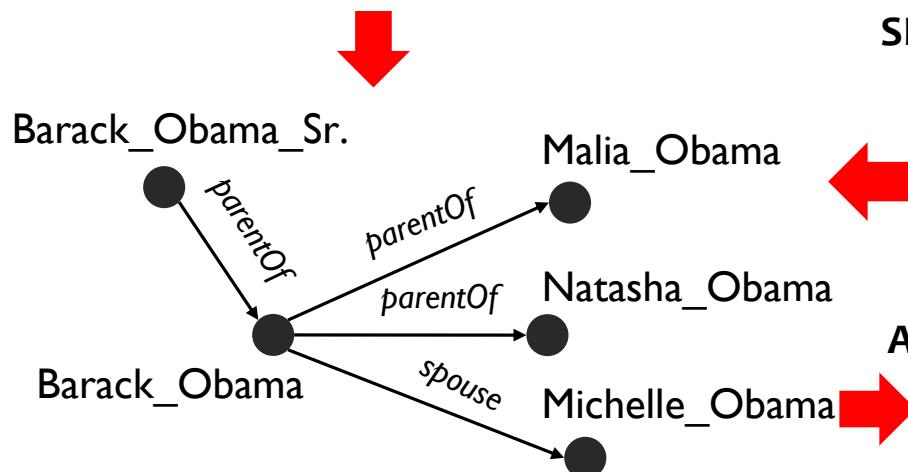
**Yu Su**

**University of California, Santa Barbara**

# Structured Query: RDF + SPARQL

Triples in an RDF graph

Subject	Predicate	Object
Barack_Obama	parentOf	Malia_Obama
Barack_Obama	parentOf	Natasha_Obama
Barack_Obama	spouse	Michelle_Obama
Barack_Obama_Sr.	parentOf	Barack_Obama



SPARQL query

```
SELECT ?x WHERE
{
  Barack_Obama_Sr. parentOf ?y .
  ?y parentOf ?x .
}
```

Answer

```
<Malia_Obama>
<Natasha_Obama>
```

# Why Structured Query Falls Short?

Knowledge Base	# Entities	# Triples	# Classes	# Relations
Freebase	45M	3B	53K	35K
DBpedia	6.6M	13B	760	2.8K
Google Knowledge Graph*	570M	18B	1.5K	35K
YAGO	10M	120M	350K	100
Knowledge Vault	45M	1.6B	1.1K	4.5K

\* as of 2014

**It's more than large: High heterogeneity of KBs**

***If it's hard to write SQL on simple relational tables,  
it's only harder to write SPARQL on large knowledge  
bases***

**Even harder on automatically constructed KBs with a loosely-defined schema**

# Not Everyone Can Program...



*“find all patients diagnosed with eye tumor”*

```
WITH Traversed (cls,syn) AS (
  SELECT R.cls, R.syn
  FROM XMLTABLE ('Document("Thesaurus.xml")'
    /terminology/conceptDef/properties
    [property/name/text()="Synonym" and
    property/value/text()="Eye Tumor"]
    /property[name/text()="Synonym"]/value'
  )  

  COLUMNS
  cls CHAR(64) PATH './parent::*/parent::*'
    '/parent::*/name',
  tgt CHAR(64) PATH'.' AS R)
UNION ALL
  (SELECT CH.cls,CH.syn
  FROM Traversed PR,
  XMLTABLE ('Document("Thesaurus.xml")'
    /terminology/conceptDef/definingConcepts/
    concept[./text()=$parent]/parent::*/parent::*/
    properties/property[name/text()="Synonym"]/value',
  PASSING PR.cls AS "parent"
  )  

  COLUMNS
  cls CHAR(64) PATH './parent::*/'
    parent::*/parent::*/name',
  syn CHAR(64) PATH'.' AS CH))
SELECT DISTINCT V.*
FROM Visit V
WHERE V.diagnosis IN
  (SELECT DISTINCT syn FROM Traversed)
```

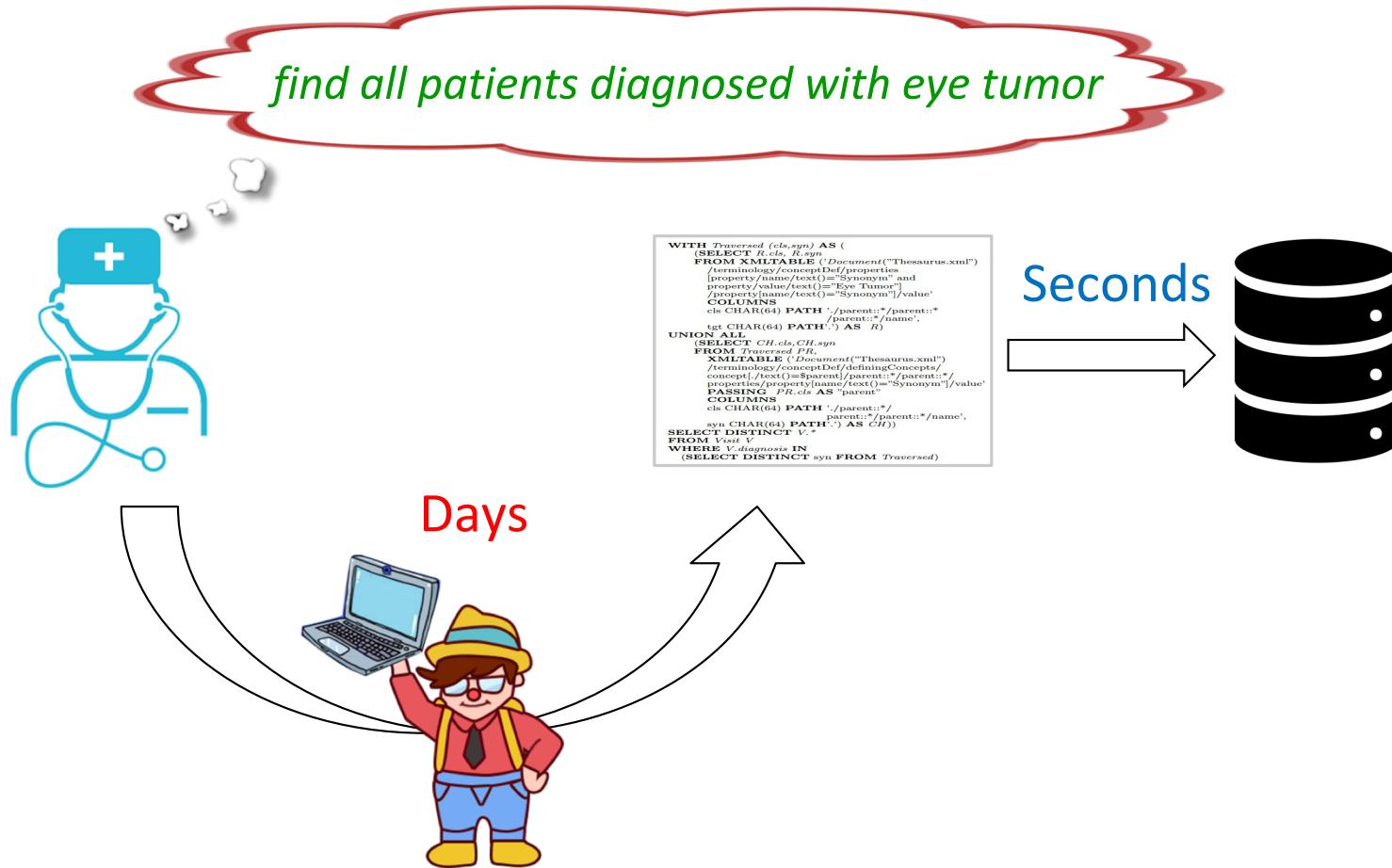
**NCI**thesaurus

“Semantic queries by example”,

Information Sciences Lim et al., EDBT (2014)

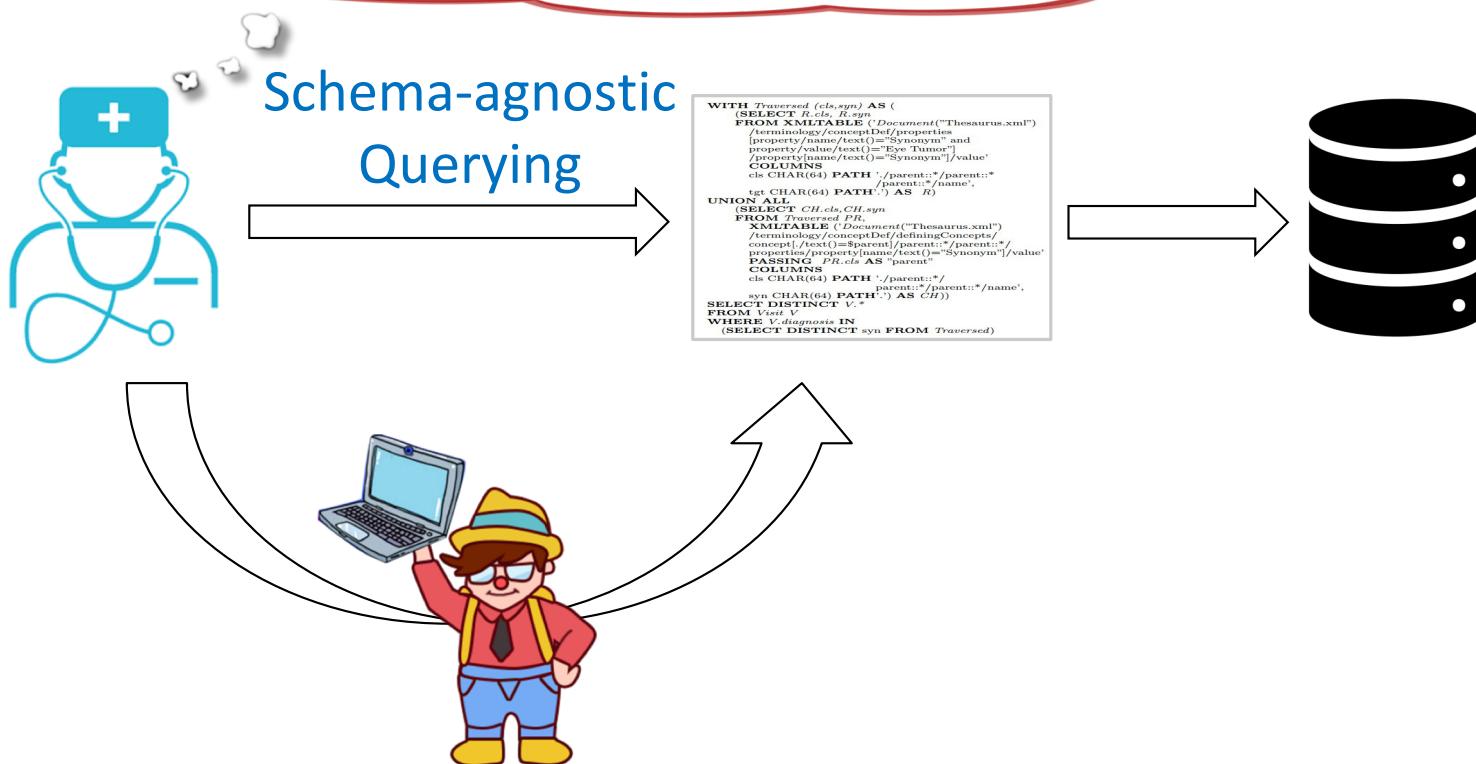
USC Viterbi

# In Pursue of Efficiency



# In Pursue of Efficiency

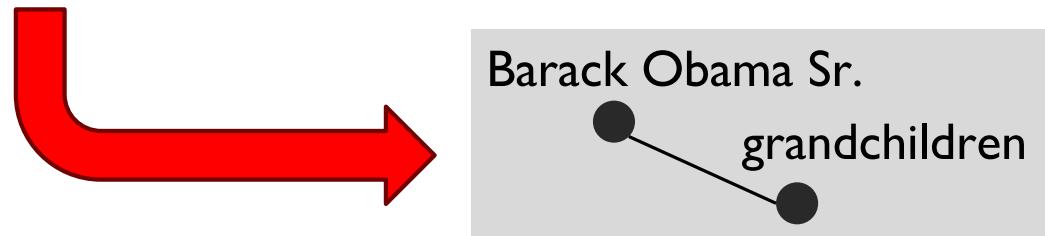
*find all patients diagnosed with eye tumor*



# Schema-agnostic KB Querying

*“Barack Obama Sr. grandchildren”*

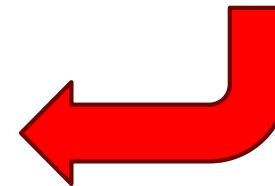
**Keyword query:** query like search engine



**Graph query:** add a little structure

*“Who are Barack Obama Sr.’s grandchildren?”*

**Natural language query:** the holy grail



# **Tutorial Outline**

## **Introduction**

## **Part I: Domain-specific KB Construction**

Lunch Break

## **Part II: Schema-agnostic KB Querying**

## **Summary & Future Directions**