

Knowledge Graphs: A Practical Introduction across Disciplines

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About me

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E-Commerce

E-Commerce Knowledge Graphs and
Representation Learning



Common Sense Reasoning

Multi-modal Open World Grounded
Learning and Inference



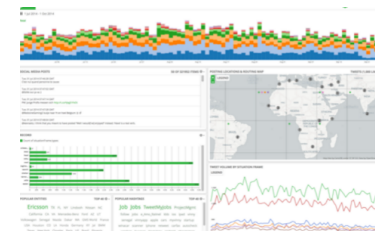
The Human Trafficking Project

The Human Trafficking Project



GNOME

Generating Novelties in Open-world
Multi-agent Environments



AI for Crisis Response

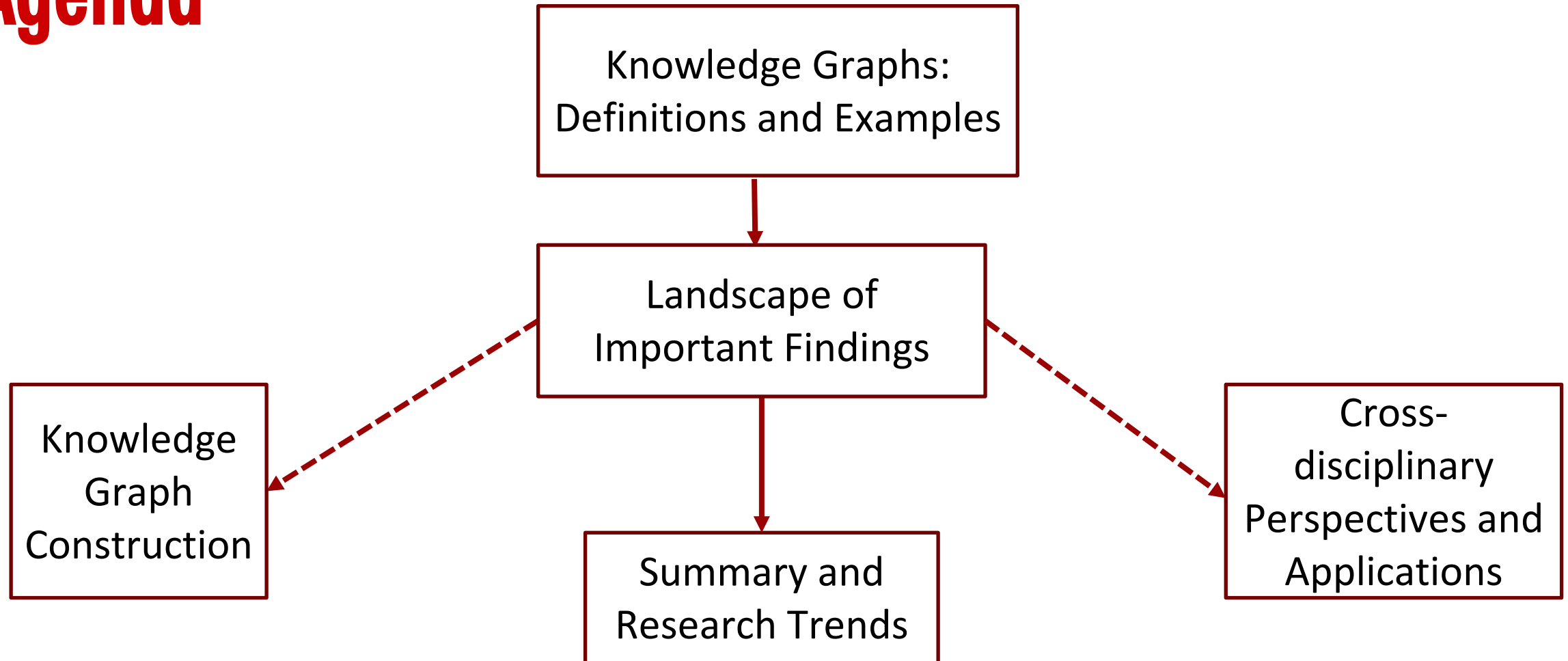
Text-enabled Humanitarian Operations
in Real-time



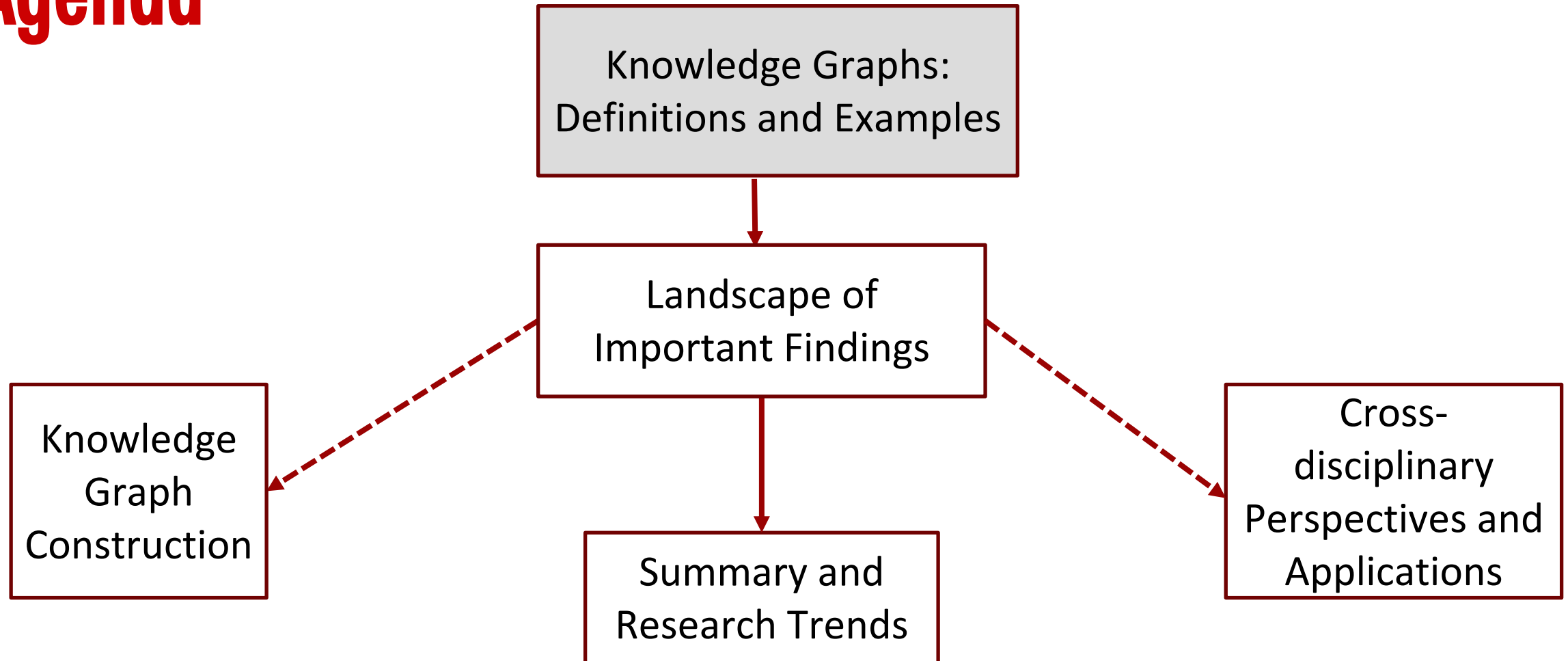
AI, Networks and Society

AI, Networks and Society

Agenda



Agenda



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),

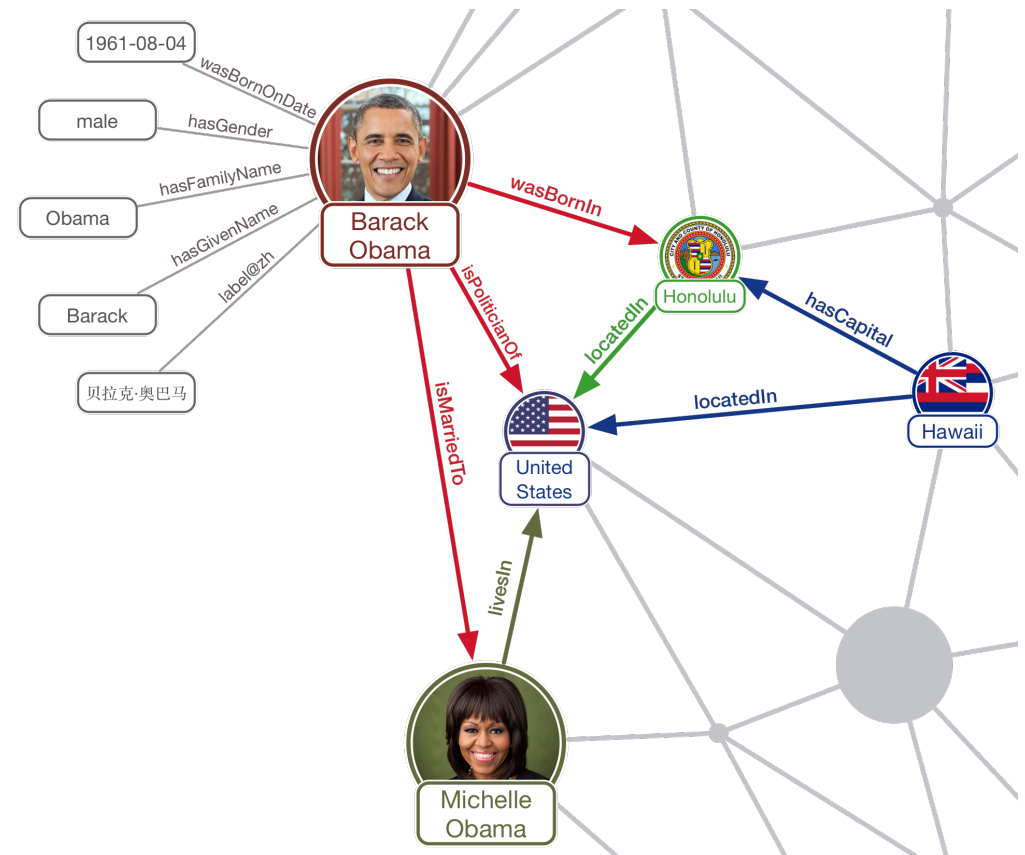
(Barack Obama, hasGender, male),

...

(Hawaii, hasCapital, Honolulu),

...

(Michelle Obama, livesIn, United States)



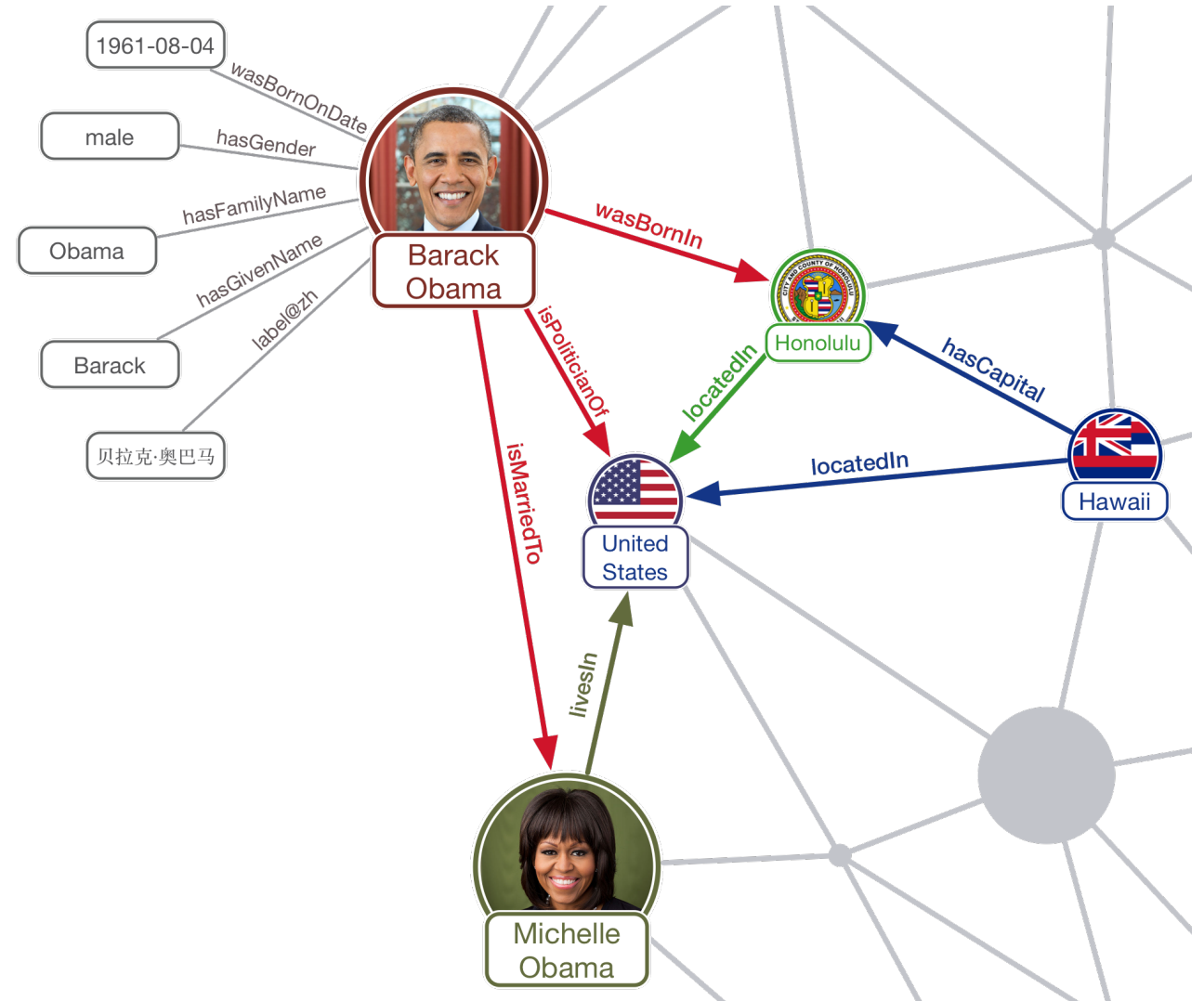
What is a Knowledge Graph?

Technically, a multi-relational directed labeled graph with semantics

Both edges and nodes have labels, but not all labels are equal (literals vs. identifiers)

Where do the semantics come from?

- Complex question, only starting to be understood



More on semantics

Traditionally, semantics are believed to come from ontology

- An ontology is a ‘formal, explicit specification of a shared conceptualization’ (we will go deeper into this in a while)
- In philosophy, an ontology is a ‘study of what there is’ including the study of the ‘most general features of what there is, and how the things there are relate to each other in the metaphysically most general ways’

Source: <https://plato.stanford.edu/entries/logic-ontology/>

More recently, in AI, we have started to recognize a more commonsense view of semantics guided by findings in linguistics and distributional semantics

Have I seen this before?

places to visit san jose

🔍 All 📍 Maps 🖼️ Images 📰 News 🛒 Shopping ⋮ More ⚙️ Settings 🛠️ Tools

About 77,800,000 results (1.02 seconds)

Top things to do in San Jose



Winchester Mystery House
Quirky mansion with odd design details



The Tech Interactive
Interactive displays & an IMAX theater



Mission Peak
Mountain with an iconic summit pole



Happy Hollow Park & Zoo
Animals, activities & conservation focus

☰ More things to do

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Vibrant, diverse and accessible, **San Jose** shines with 300+ days of sunshine that assures indoor and outdoor activities for every inclination. Whether it's nightlife ...

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25 Best Things to Do in San Jose (CA) - The Crazy Tourist

<https://www.thecrazytourist.com> › ... › [United States](#) › [California \(CA\)](#) ▼



25 Best Things to Do in **San Jose (CA)**: Winchester Mystery House: Flickr. Tech Museum Of Innovation: Flickr. Children's Discovery Museum: Flickr. Rosicrucian Egyptian Museum: Flickr. **San Jose Heritage Rose Garden**: wikimedia. Basilica Of St. Joseph: Flickr. Alum Rock Park: Flickr. Happy Hollow Zoo Entrance: Flickr.

THE 15 BEST Things to Do in San Jose - 2019 (with Photos ...

https://www.tripadvisor.com/Attractions-g33020-Activities-San_Jose_Calif... ▼

... **attractions**. Find what to do today, this weekend, or in August. We have reviews of the best **places** to see in **San Jose**. Visit top-rated & must-see **attractions**.

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San Jose

City in California

San Jose is a large city surrounded by rolling hills in Silicon Valley, major technology hub in California's Bay Area. Architectural landmarks, from the 1883 Italianate-style Oddfellows building to Spanish Colonial Revival structures, make up the downtown historic district. The downtown area is also home to the Tech Museum of Innovation, devoted to the exploration of science and technology.

Weather: 64°F (18°C), Wind NW at 10 mph (16 km/h), 85% Humid

Population: 1.035 million (2017)

Plan a trip

- 📍 San Jose travel guide
- 🏨 3-star hotel averaging \$206
- ✈️ 1 h 5 min flight, from \$97

Did you know: San Jose, California has the largest Vietnamese-American population (106,992) among all U.S. cities. [wikipedia.org](#)

People also search for

View 15+ m



San Francisco



Santa Clara County



California



San Diego



San Francisco Bay Area

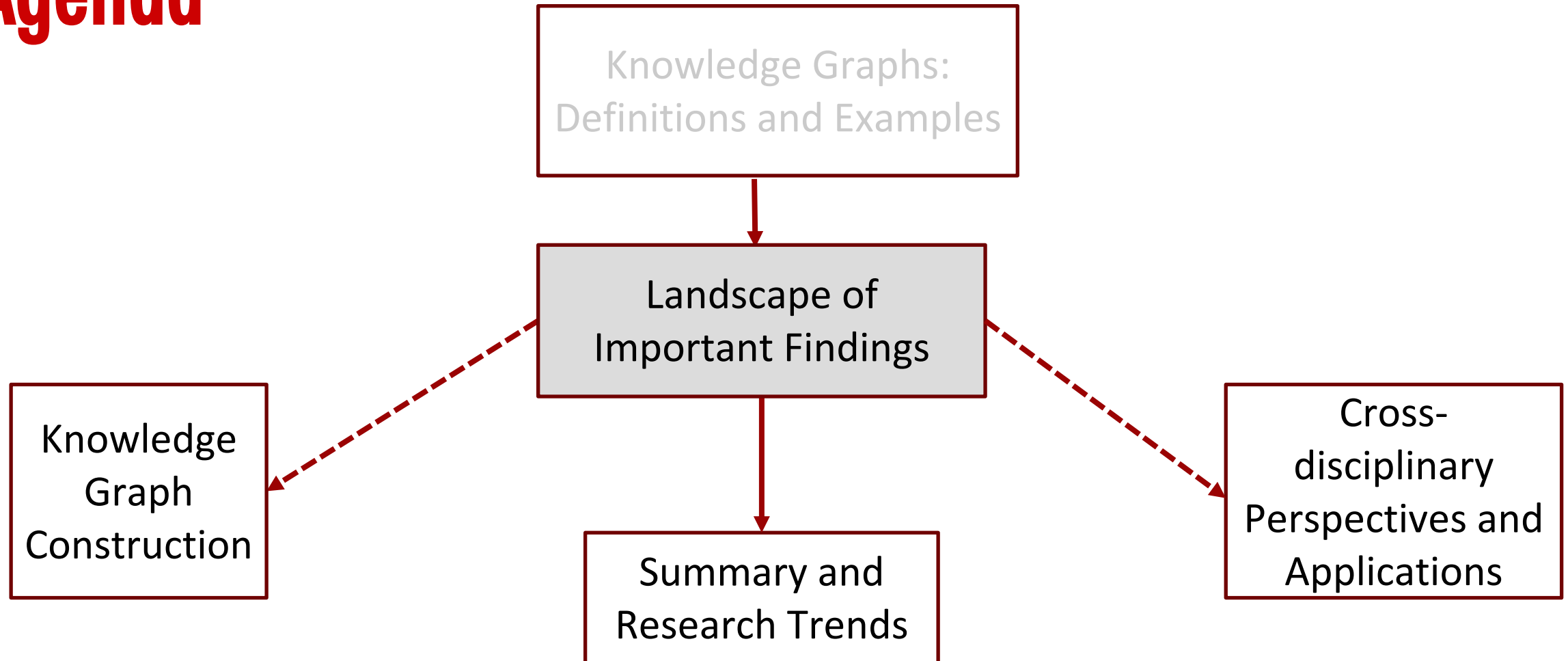
Knowledge panel

Recognition of user intent

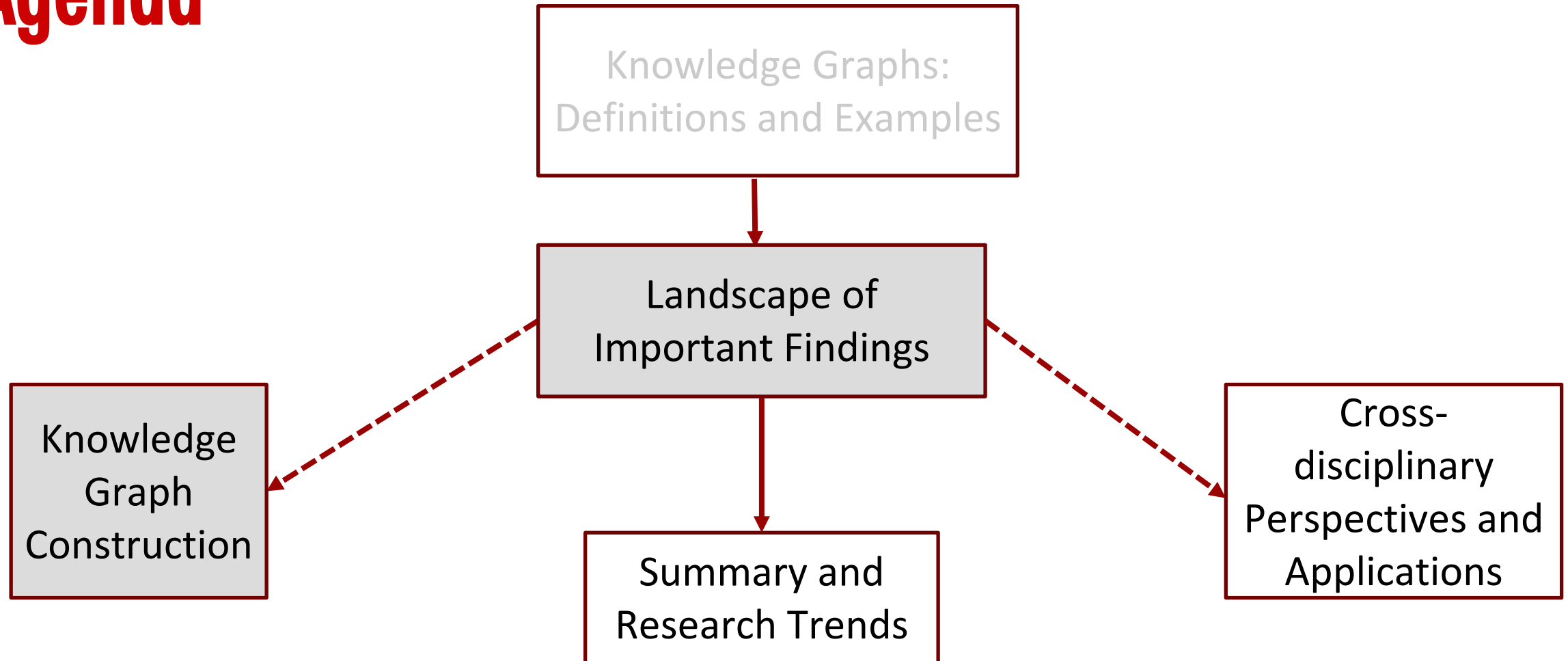
Recommendations

Exploration-suggestions

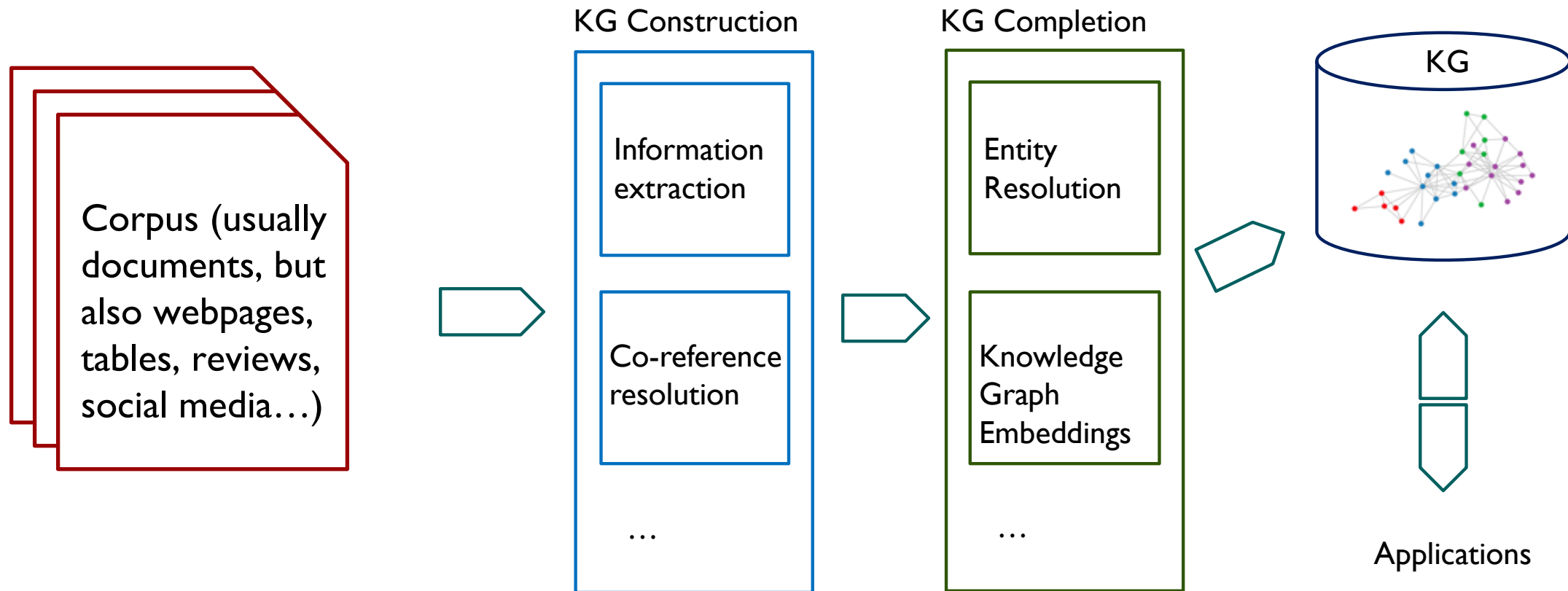
Agenda



Agenda



A typical KGC workflow starts from corpus acquisition and ends with applications



INFORMATION EXTRACTION (IE)

Named Entity Recognition (NER)

contentSkip to site indexPoliticsSubscribeLog InSubscribeLog InToday's PaperAdvertisementSupported **ORG** byF.B.I. Agent **Peter Strzok PERSON**,
Who Criticized Trump **PERSON** in Texts, Is FiredImagePeter Strzok, a top **F.B.I. GPE** counterintelligence agent who was taken off the special counsel
investigation after his disparaging texts about President **Trump PERSON** were uncovered, was fired. Credit**T.J. Kirkpatrick PERSON** for **The New York TimesBy Adam Goldman ORG** and **Michael S. SchmidtAug PERSON**. **13 CARDINAL**, **2018WASHINGTON CARDINAL** — **Peter Strzok PERSON**, the **F.B.I. GPE** senior counterintelligence agent who disparaged President **Trump PERSON** in inflammatory text messages and helped oversee the **Hillary Clinton PERSON** email and **Russia GPE** investigations, has been fired for violating bureau policies, Mr. **Strzok PERSON**'s lawyer said **Monday DATE**.Mr. Trump and his allies seized on the texts — exchanged during the **2016 DATE** campaign with a former **F.B.I. GPE** lawyer, **Lisa Page — in PERSON** assailing the **Russia GPE** investigation as an illegitimate “witch hunt.” Mr. **Strzok PERSON**, who rose over **20 years DATE** at the **F.B.I. GPE** to become one of its most experienced counterintelligence agents, was a key figure in **the early months DATE** of the inquiry.Along with writing the texts, Mr. **Strzok PERSON** was accused of sending a highly sensitive search warrant to his personal email account.The **F.B.I. GPE** had been under immense political pressure by Mr. **Trump PERSON** to dismiss Mr. **Strzok PERSON**, who was removed **last summer DATE** from the staff of the special counsel, **Robert S. Mueller III PERSON**. The president has repeatedly denounced Mr. **Strzok PERSON** in posts on

Source: Named Entity Recognition and Classification with Scikit-Learn. <https://towardsdatascience.com/named-entity-recognition-and-classification-with-scikit-learn-f05372f07ba2>

Demo: displaCy

<https://explosion.ai/demos/displacy-ent>

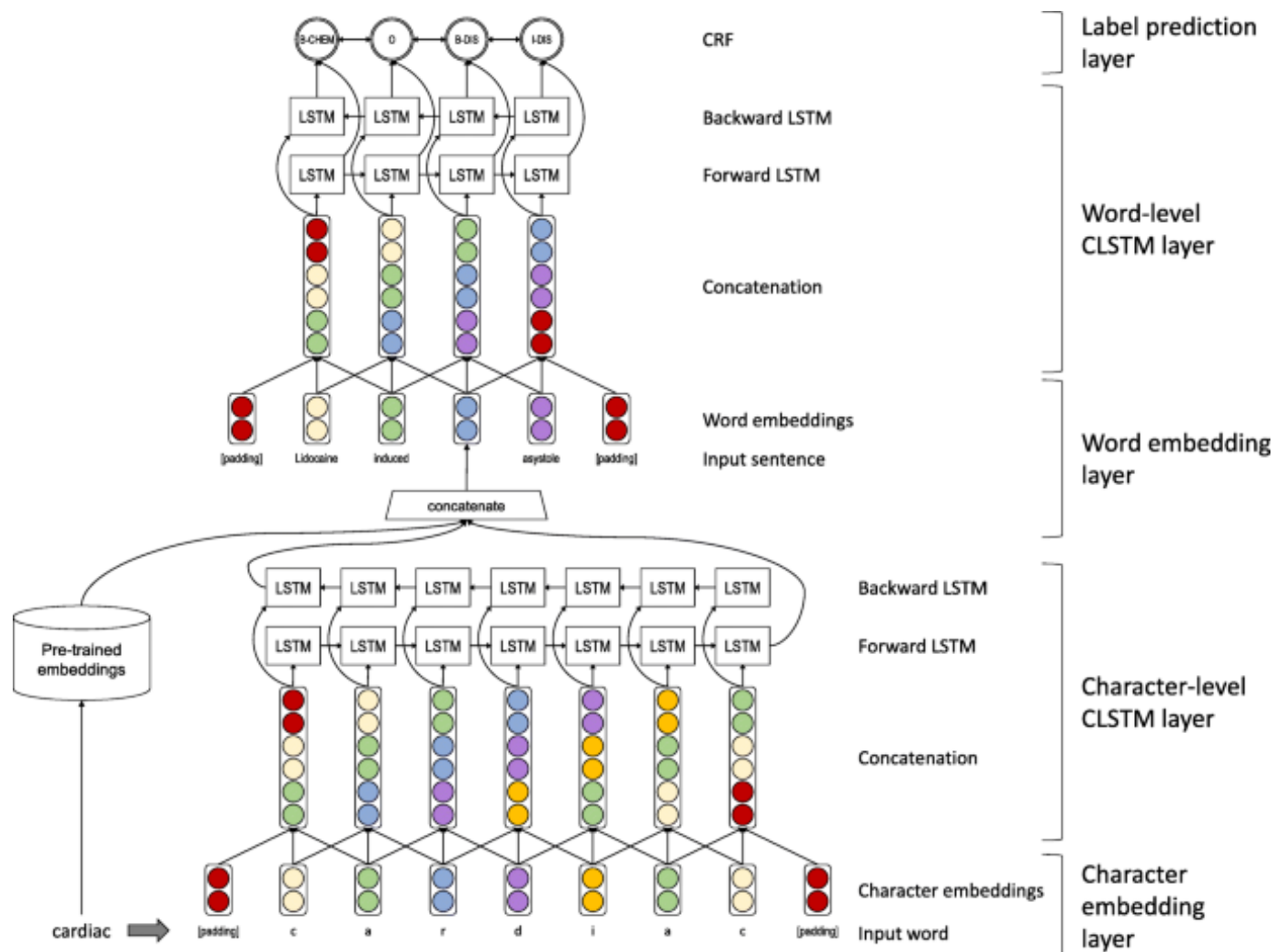
NER workflows

Many methods proposed over the previous 3-4 decades:

- Rule-based
- Dictionary-based
- Simple machine learning
- Sequence labeling (e.g., using conditional random fields or, before that, hidden Markov models)

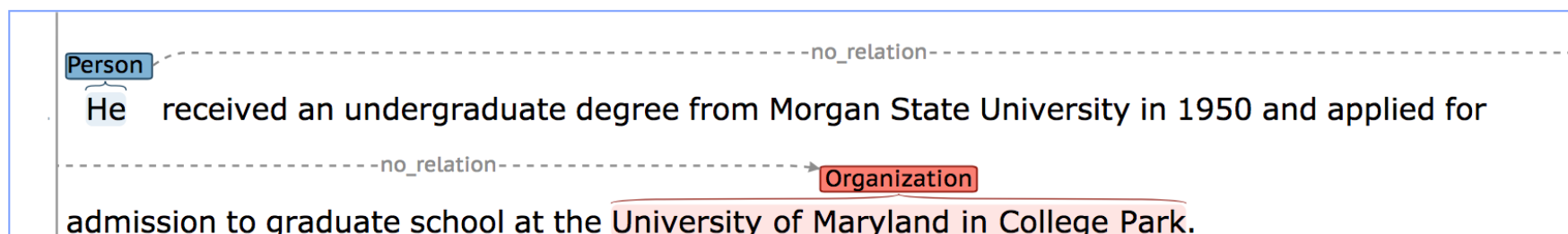
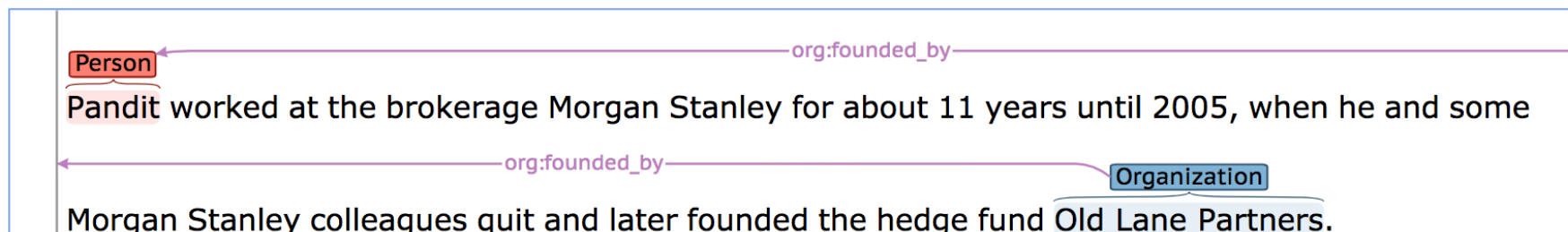
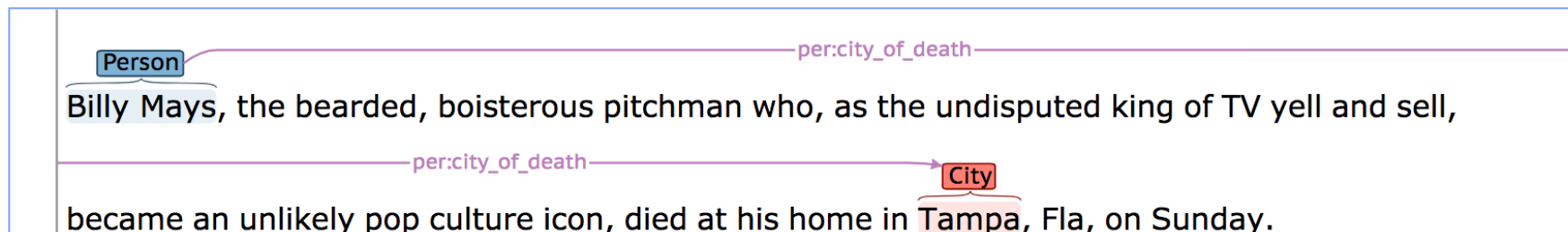
Today, deep learning methods designed for sequences (such as RNNs and, more recently, transformers) are state-of-the-art

Much research still remains (especially for social media!)



Source: Cho, H., and H. Lee. *Biomedical named entity recognition using deep neural networks with contextual information*. BMC Bioinformatics. 2019.

Other kinds of IE: Relation Extraction



Source: Stanford TACRED

Other kinds of IE: Open Information Extraction

ID	Document
1	Your dry cleaner set out from eastern Queens on foot Tuesday morning and now somewhere near Maspeth.
2	Recently, North Korea has begun to allow tourists, including Americans, ..., and South Korean tourists have been able to go to Kaesong on a limited basis.
...	...

Entity 1	Relation Phrase	Entity 2	Human Evaluation
your dry cleaner	set out from	eastern Queens	✓
your dry cleaner	set out from_on	foot	✓
your dry cleaner	is near	Maspeth	✓
North Korea	has begun to allow	tourist	✓
South Korean tourists	to go to	Kaesong	✓
...	
Queens	on	foot	X
Kaesong	on	a limited basis	X

Source: Zhu et al. Open Information Extraction with Global Structure Constraints. ACM WWW Conference. 2018.

Is IE a solved problem?

Table 2: Main Results on Testing Set: F_1 Score (Precision/Recall) (in %)

Method	CoNLL03	Tweet	OntoNote5.0	Webpage	Wikigold
Entity Types	4	10	18	4	4
KB Matching	71.40(81.13/63.75)	35.83(40.34/32.22)	59.51(63.86/55.71)	52.45(62.59/45.14)	47.76(47.90/47.63)
Fully-Supervised (Our implementation)					
RoBERTa	90.11(89.14/91.10)	52.19(51.76/52.63)	86.20(84.59/87.88)	72.39(66.29/79.73)	86.43(85.33/87.56)
BiLSTM-CRF	91.21(91.35/91.06)	52.18(60.01/46.16)	86.17(85.99/86.36)	52.34(50.07/54.76)	54.90(55.40/54.30)
Baseline (Our implementation)					
BiLSTM-CRF	59.50(75.50/49.10)	21.77(46.91/14.18)	66.41(68.44/64.50)	43.34(58.05/34.59)	42.92(47.55/39.11)
AutoNER	67.00(75.21/60.40)	26.10(43.26/18.69)	67.18(64.63/69.95)	51.39(48.82/54.23)	47.54(43.54/52.35)
LRNT	69.74(79.91/61.87)	23.84(46.94/15.98)	67.69(67.36/68.02)	47.74(46.70/48.83)	46.21(45.60/46.84)
Other Baseline (Reported Results)					
KALM [†]	76.00(— / —)	—	—	—	—
ConNET [◇]	75.57(84.11/68.61)	—	—	—	—
Our BOND Framework					
Stage I	75.61(83.76/68.90)	46.61(53.11/41.52)	68.11(66.71/69.56)	59.11(60.14/58.11)	51.55(49.17/54.50)
BOND	81.48(82.05/80.92)	48.01(53.16/43.76)	68.35(67.14/69.61)	65.74(67.37/64.19)	60.07(53.44/68.58)

Source: Liang et al. BOND: BERT-Assisted Open-Domain Named Entity Recognition with Distant Supervision. KDD Conference. 2020.

Other NLP steps: Coreference Resolution, Entity Linking...

"I had no idea I was getting in so deep," says Mr. Kaye, who founded Justin in 1982. Mr. Kaye had sold Capetronic Inc., a Taiwan electronics Maker, and retired, only to find he was bored. With Justin, he began selling toys and electronics made mostly in Hong Kong, beginning with Mickey Mouse radios. The company has grown -- to about 40 employees, from four initially, Mr. Kaye says. Justin has been profitable since 1986, adds the official, who shares [his] office... (nw/wsj/2418)

Sources:

<https://aryamccarthy.github.io/wiseman2016learning/>

([Wiseman, Rush, and Shieber, 2016](#)) at NAACL

The Northern Lights, also called Aurora Borealis, are one of the most spectacular shows on this earth and can frequently be seen in Iceland from September through March on clear and crisp nights.



-----Finding entities belonging to category : place name-----
[0..1) location : Iceland

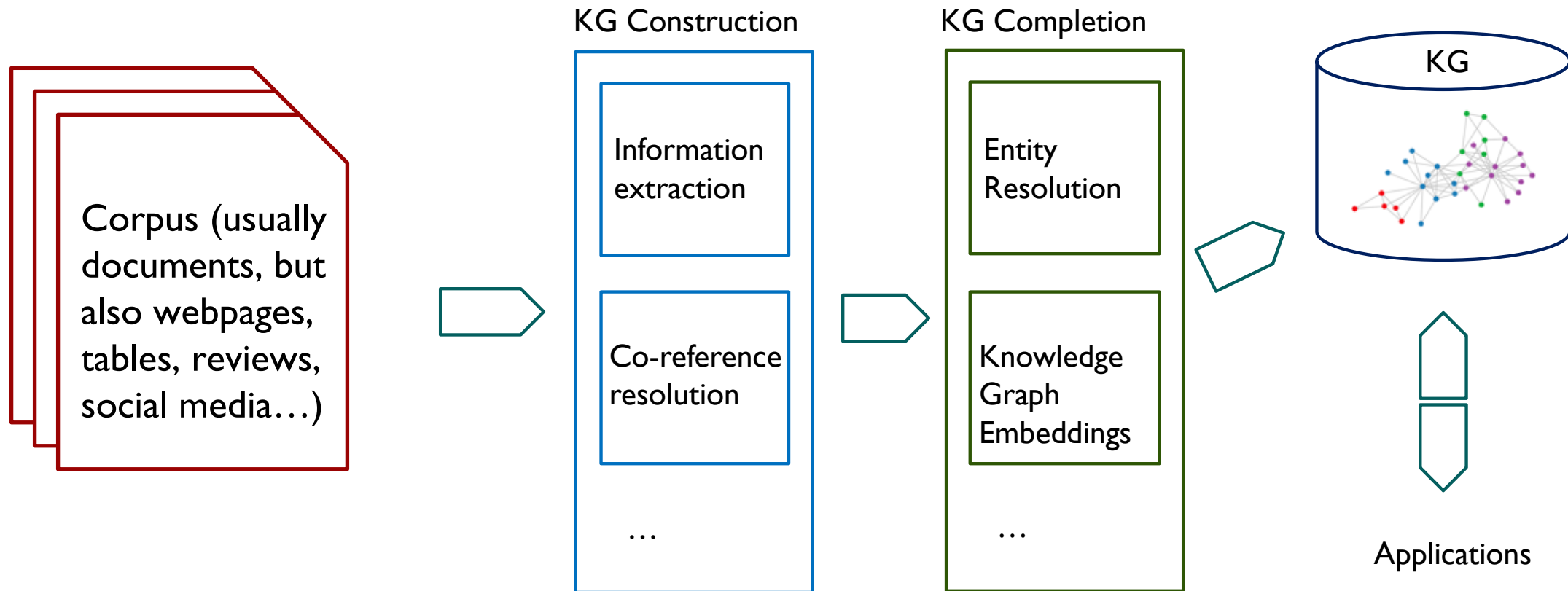


Iceland, California	
From Wikipedia, the free encyclopedia	
Iceland, Nevada	Iceland Lake
From Wikipedia, the free encyclopedia	
Iceland, the south	Iceland
From Wikipedia, the free encyclopedia	
Reference	Hydro
1. The lake	This article is about the country. For other uses, see Iceland (disambiguation).
2.	

Source:

Alokaili and Menai. SVM ensembles for named entity disambiguation. Computing. 2019.

A typical KGC workflow starts from corpus acquisition and ends with applications

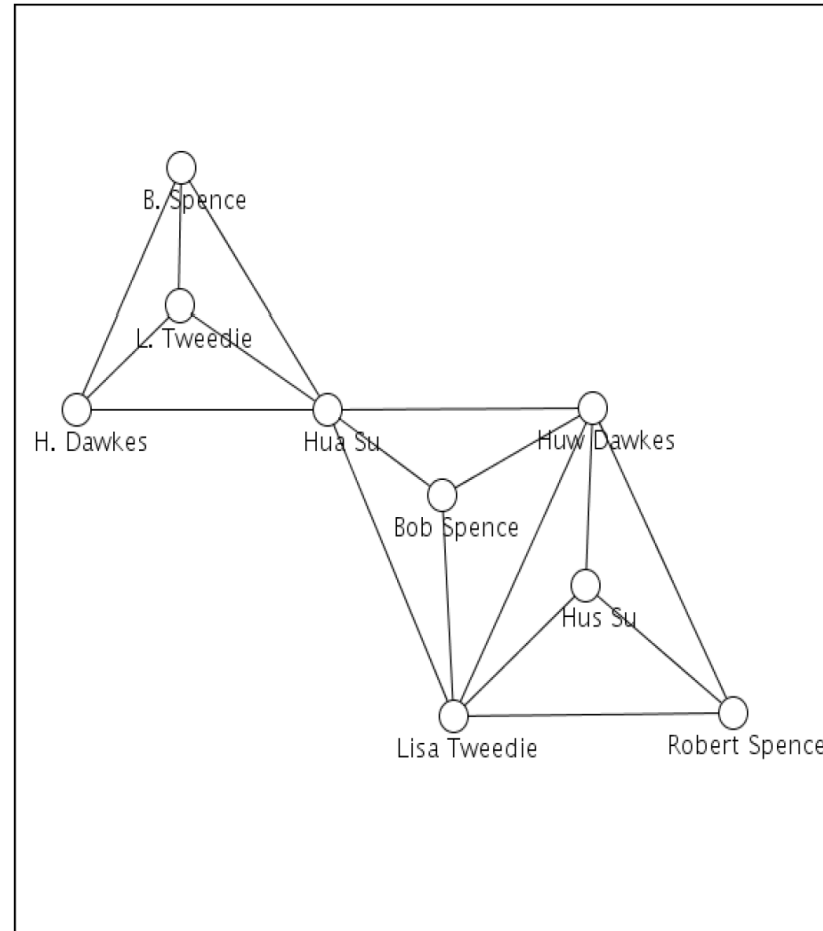


KNOWLEDGE GRAPH COMPLETION

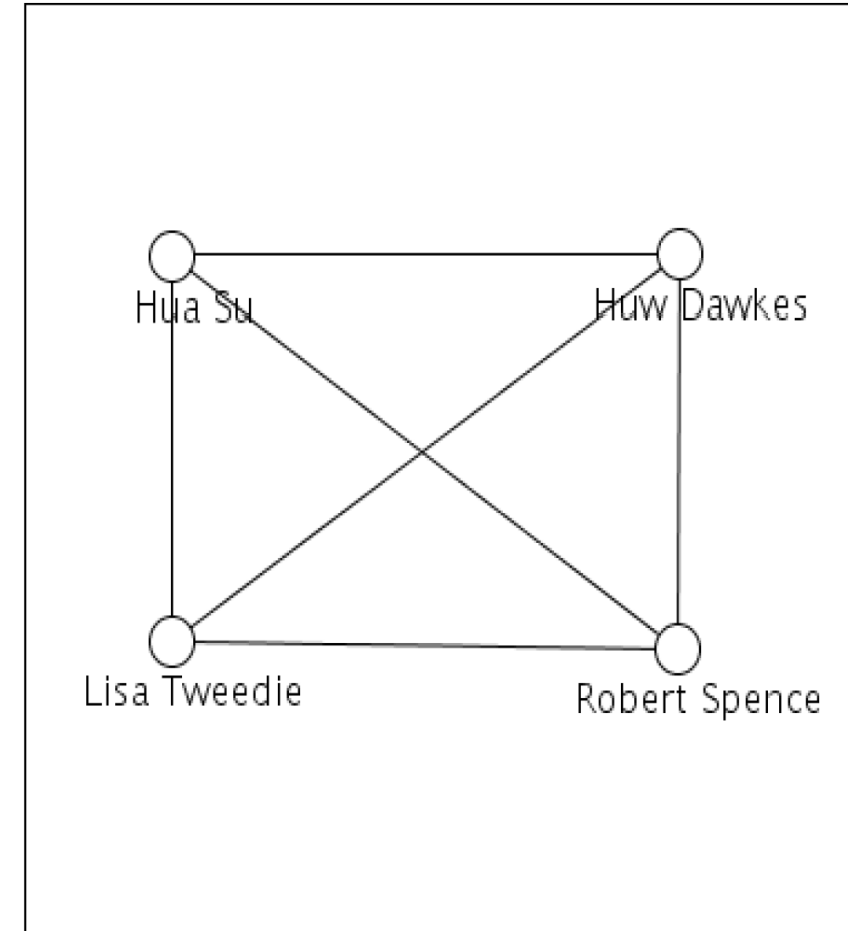
Entity Resolution

Algorithmically identifying and linking/grouping different manifestations of the same real-world object

Problem has existed for 50 years in many communities (databases, graphs, networks, tables...)



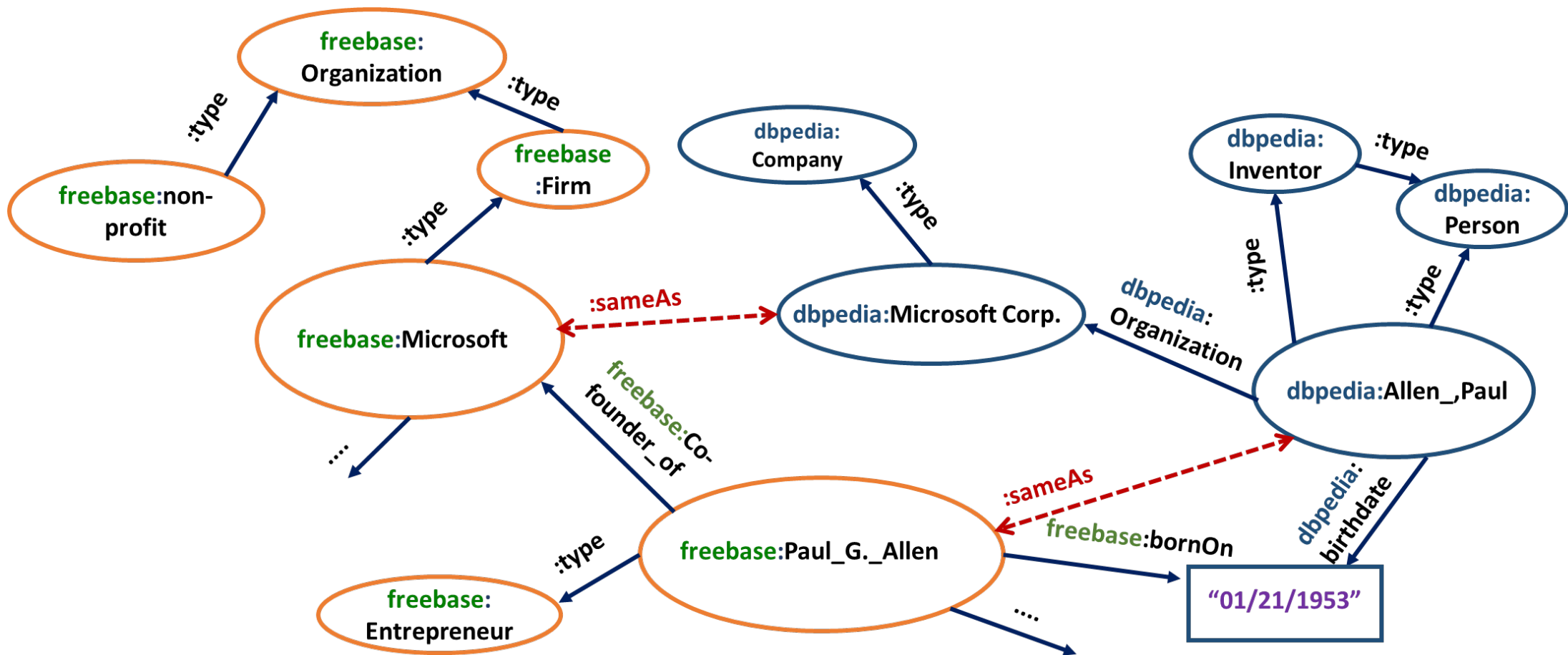
before



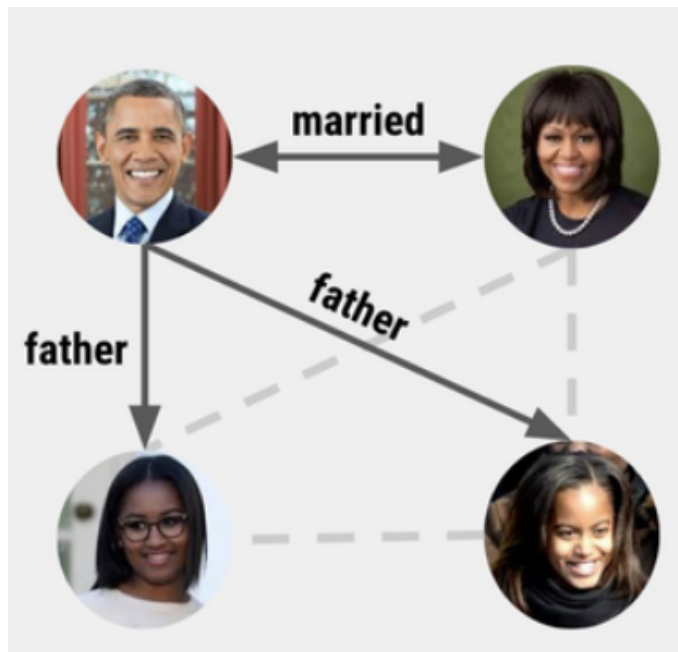
after

Source: Entity Resolution: Tutorial. Getoor and Machanavajjhala. VLDB, 2012

In the world of knowledge graphs

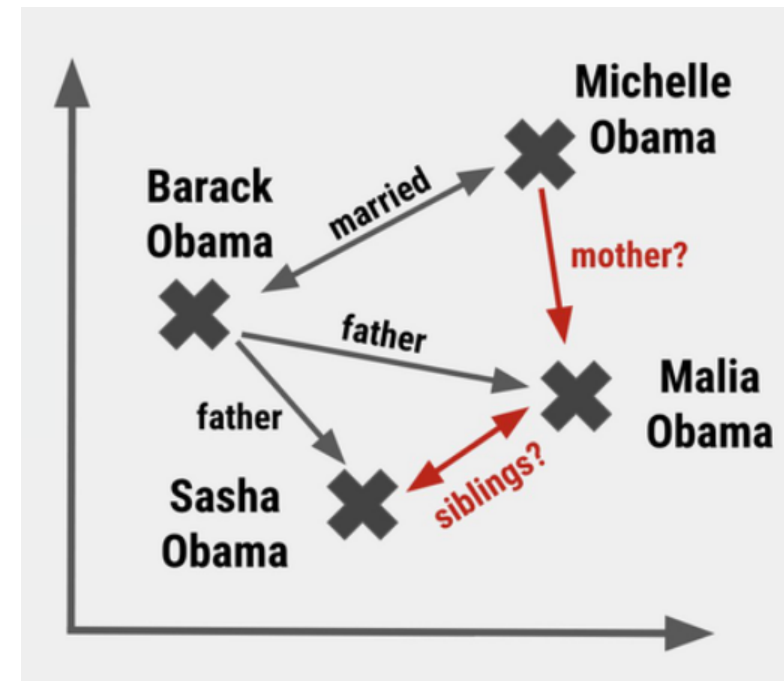


Representation Learning on Knowledge Graphs aka Knowledge Graph Embeddings



Knowledge graph embeddings:

- TransE, H...
- Neural tensor networks
- Graph convolutional networks (or their variants)
- Matrix factorization
- ...



KGEs (results)

Useful resources:

- OpenKE:
<http://139.129.163.161//index/toolkits#pretrained-embeddings>
- StarSpace:
<https://github.com/facebookresearch/StarSpace>
- Recent transformer-based models could potentially be adapted, including BERT and RoBERTa:
<https://ai.facebook.com/blog/roberta-an-optimized-method-for-pretraining-self-supervised-nlp-systems/>

Method	Raw						Filtered					
	WN18			FB15k			WN18			FB15k		
	MR	H@10	MRR	MR	H@10	MRR	MR	H@10	MRR	MR	H@10	MRR
SE (Bordes et al., 2011)	1011	68.5	-	273	28.8	-	985	80.5	-	162	39.8	-
Unstructured (Bordes et al., 2012)	315	35.3	-	1074	4.5	-	304	38.2	-	979	6.3	-
SME (Bordes et al., 2012)	545	65.1	-	274	30.7	-	533	74.1	-	154	40.8	-
TransH (Wang et al., 2014)	401	73.0	-	212	45.7	-	303	86.7	-	87	64.4	-
TransR (Lin et al., 2015b)	238	79.8	-	198	48.2	-	225	92.0	-	77	68.7	-
CTransR (Lin et al., 2015b)	231	79.4	-	199	48.4	-	218	92.3	-	75	70.2	-
KG2E (He et al., 2015)	342	80.2	-	174	48.9	-	331	92.8	-	59	74.0	-
TransD (Ji et al., 2015)	224	79.6	-	194	53.4	-	212	92.2	-	91	77.3	-
lppTransD (Yoon et al., 2016)	283	80.5	-	195	53.0	-	270	94.3	-	78	78.7	-
TranSparse (Ji et al., 2016)	223	80.1	-	187	53.5	-	211	93.2	-	82	79.5	-
TATEC (García-Durán et al., 2016)	-	-	-	-	-	-	-	-	-	58	76.7	-
NTN (Socher et al., 2013)	-	-	-	-	-	-	-	66.1	0.53	-	41.4	0.25
DISTMULT (Yang et al., 2015)	-	-	-	-	-	-	-	94.2	0.83	-	57.7	0.35
Complex (Trouillon et al., 2016)	-	-	0.587	-	-	0.242	-	94.7	0.941	-	84.0	0.692
HolE (Nickel et al., 2016b)	-	-	0.616	-	-	0.232	-	94.9	0.938	-	73.9	0.524
RESCAL (Nickel et al., 2011) [*]	-	-	0.603	-	-	0.189	-	92.8	0.890	-	58.7	0.354
TransE (Bordes et al., 2013) [*]	-	-	0.351	-	-	0.222	-	94.3	0.495	-	74.9	0.463
STransE (Nguyen et al., 2016b)	217	80.9	0.469	219	51.6	0.252	206	93.4	0.657	69	79.7	0.543
rTransE (García-Durán et al., 2015)	-	-	-	-	-	-	-	-	-	50	76.2	-
PTransE (Lin et al., 2015a)	-	-	-	207	51.4	-	-	-	-	58	84.6	-
GAKE (Feng et al., 2016b)	-	-	-	228	44.5	-	-	-	-	119	64.8	-
Gaifman (Niepert, 2016)	-	-	-	-	-	-	352	93.9	-	75	84.2	-
Hiri (Liu et al., 2016)	-	-	-	-	-	-	-	90.8	0.691	-	70.3	0.603
NLFeat (Toutanova and Chen, 2015)	-	-	-	-	-	-	-	94.3	0.940	-	87.0	0.822
TEKE.H (Wang and Li, 2016)	127	80.3	-	212	51.2	-	114	92.9	-	108	73.0	-
SSP (Xiao et al., 2017)	168	81.2	-	163	57.2	-	156	93.2	-	82	79.0	-

Other proposals: knowledge graph identification using probabilistic soft logic

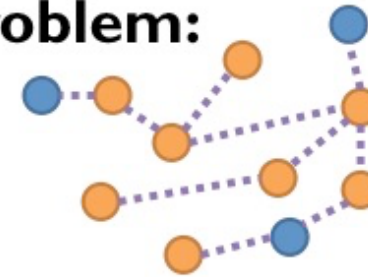
(Pujara et al., ISWC13)

Examples of ontological constraints

1. $DOM(R, L) \tilde{\wedge} REL(E_1, E_2, R) \xRightarrow{w_o} LBL(E_1, L)$
2. $RNG(R, L) \tilde{\wedge} REL(E_1, E_2, R) \xRightarrow{w_o} LBL(E_2, L)$
3. $INV(R, S) \tilde{\wedge} REL(E_1, E_2, R) \xRightarrow{w_o} REL(E_2, E_1, S)$
4. $SUB(L, P) \tilde{\wedge} LBL(E, L) \xRightarrow{w_o} LBL(E, P)$
5. $RSUB(R, S) \tilde{\wedge} REL(E_1, E_2, R) \xRightarrow{w_o} REL(E_1, E_2, S)$
6. $MUT(L_1, L_2) \tilde{\wedge} LBL(E, L_1) \xRightarrow{w_o} \neg LBL(E, L_2)$
7. $RMUT(R, S) \tilde{\wedge} REL(E_1, E_2, R) \xRightarrow{w_o} \neg REL(E_1, E_2, S)$

Knowledge Graph Identification

Problem:

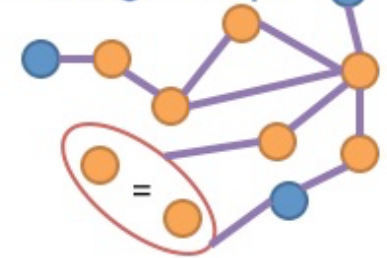


Extraction Graph



Knowledge
Graph
Identification

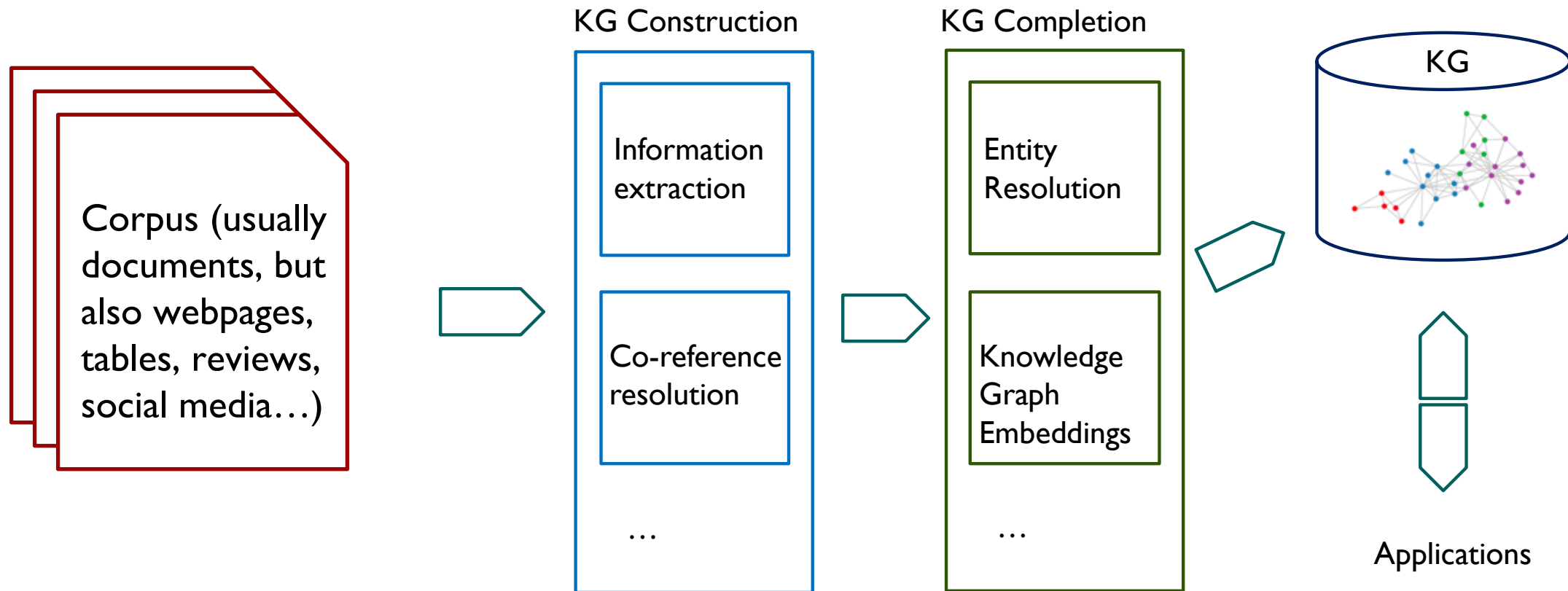
Knowledge Graph



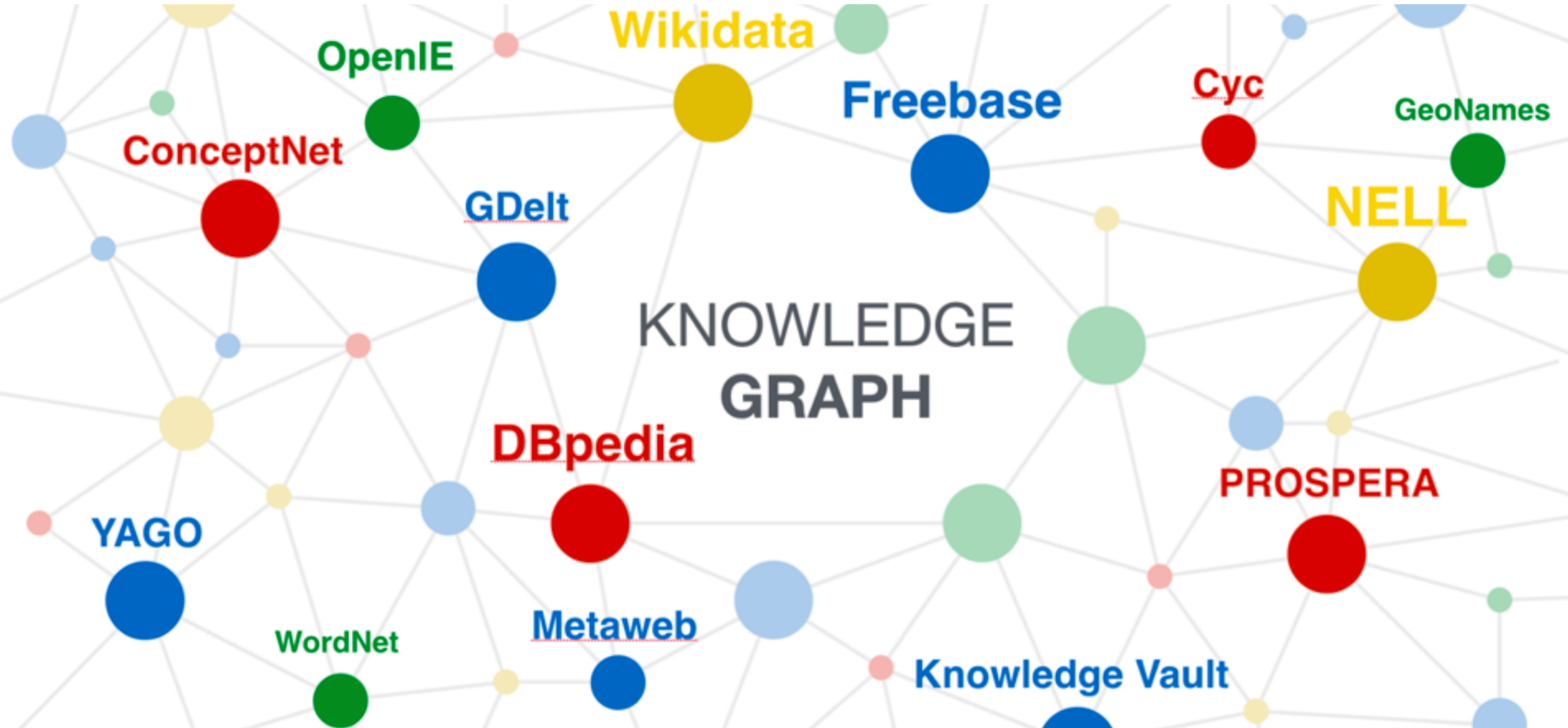
Solution: Knowledge Graph Identification (KGI)

- Performs *graph identification*:
 - entity resolution
 - node labeling
 - link prediction
- Enforces *ontological constraints*
- Incorporates *multiple uncertain sources*

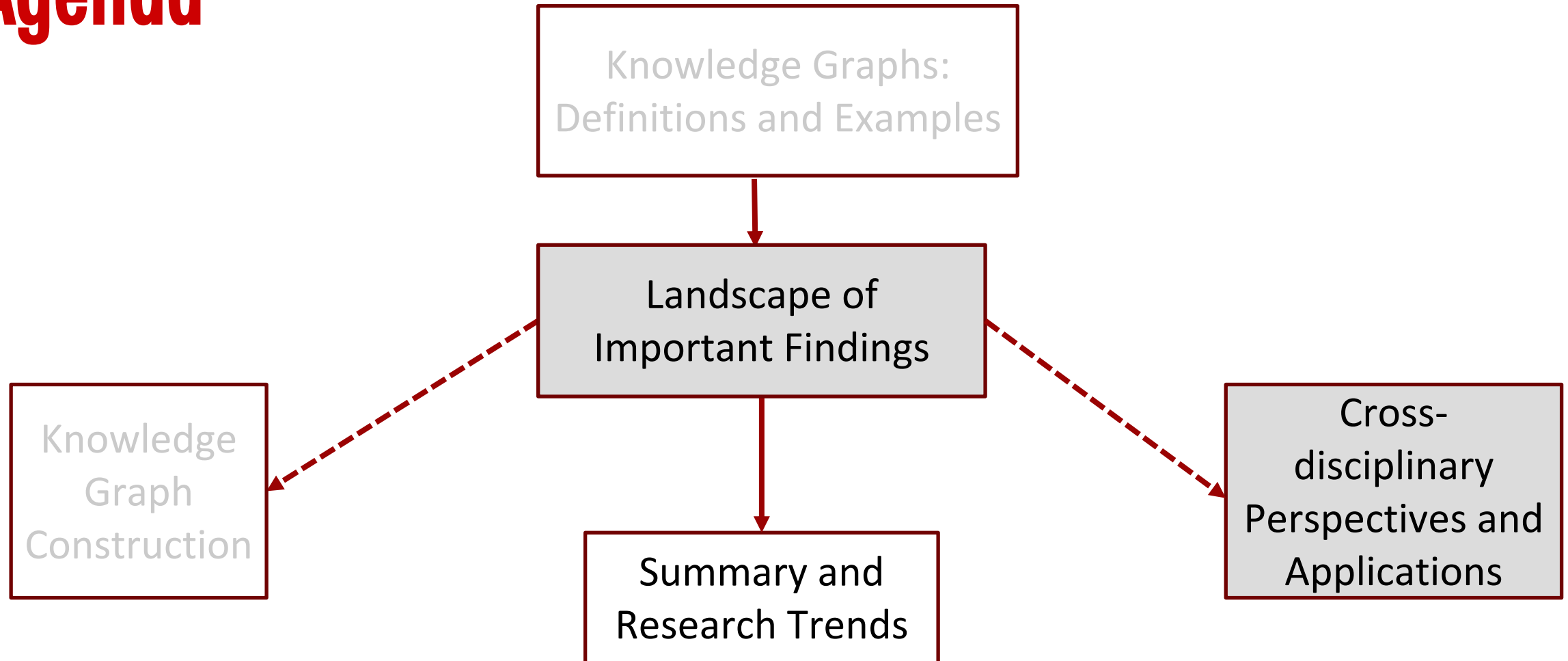
A typical KGC workflow starts from corpus acquisition and ends with applications



Open-source KGs that have been built

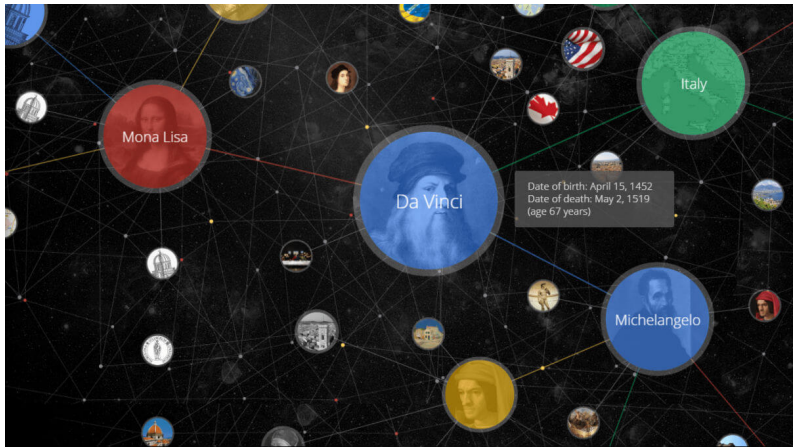


Agenda



CROSS-DISCIPLINARY PERSPECTIVES: WEB AND INFORMATION RETRIEVAL

Google Knowledge Graph



About 36,700,000 results (0.67 seconds)

Wonder Woman (2017) - IMDb

www.imdb.com/title/tt0451279/

★★★★★ Rating: 7.6/10 - 360,568 votes

When a pilot crashes and tells of conflict in the outside world, Diana, an Amazonian warrior in training, leaves home to discover her true destiny.

Full Cast & Crew · Chris Pine · Trivia · Parents Guide

Wonder Woman (2017 film) - Wikipedia

[https://en.wikipedia.org/wiki/Wonder_Woman_\(2017_film\)](https://en.wikipedia.org/wiki/Wonder_Woman_(2017_film))

Wonder Woman is a 2017 American superhero film based on the DC Comics character of the same name, distributed by Warner Bros. Pictures. It is the fourth installment in the DC Extended Universe (DCEU). The film is directed by Patty Jenkins, with a screenplay by Allan Heinberg, from a story by Heinberg, Zack Snyder, ...

Gal Gadot · Patty Jenkins · Elena Anaya · Doctor Poison

Top stories



Oscars voting ends today. Will 'Wonder Woman' finally break the anti-superhero streak?

Washington Post



Fashion War: Wonder Woman Gal Gadot infuriates Lebanese with Dress Design

Breitbart



Gal Gadot Diet and POPSUGAR Fitness Australia

POPSUGAR Australia



Wonder Woman

[PG-13] 2017 · Fantasy/Science fiction film · 2h 21m

Play trailer on YouTube

7.6/10
IMDb

92%
Rotten Tomatoes

90% liked this movie

Google users

Before she was Wonder Woman (Gal Gadot), she was Diana, princess of the Amazons, trained to be an unconquerable warrior. Raised on a sheltered island paradise, Diana meets an American pilot (Chris Pine) who tells her about the massive conflict that's raging in the outside world. Convinced that she c...

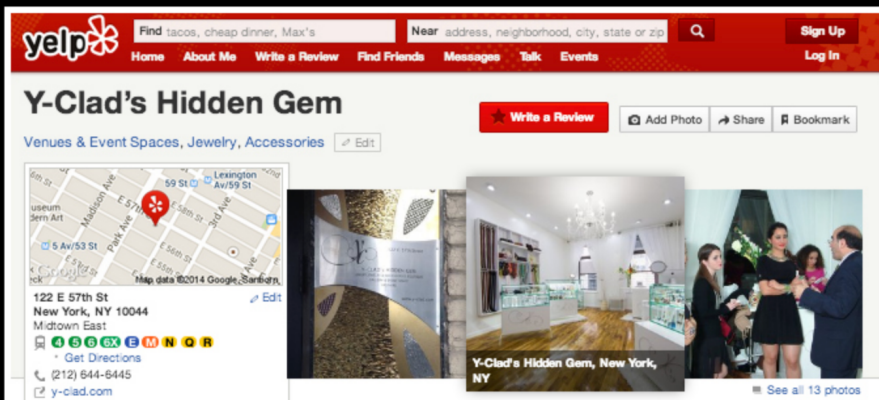
Release date: June 2, 2017 (USA)

Director: Zack Snyder

Google Search results for "Larry Page". The page shows search results for "Larry Page" with a Knowledge Graph on the right. The Knowledge Graph displays a large image of Larry Page and smaller images of other Google founders. The search results include a Wikipedia link, a Forbes link, and a Google+ link. The page also shows a "Recent posts" section with a post about the new Android release.

Domain-specific search (DSS)

The Massive YouTube Ecosystem



BloomReach surveyed

2,000 CONSUMERS*

► Where do consumers start product searches?



44% go directly to Amazon first



34% use top search engines like Google, Bing and Yahoo!



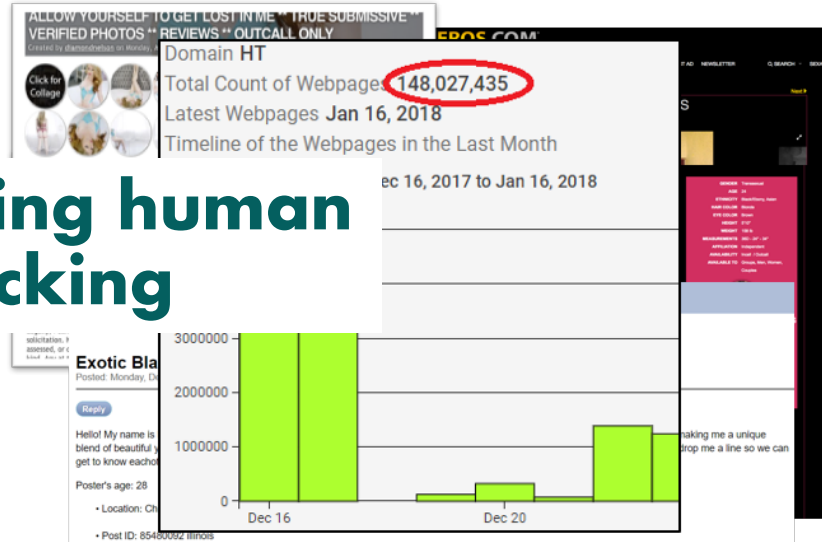
21% start at a specific retailer

To slow Amazon's dominance, retailers must integrate technology that creates frictionless experiences for their customers across channels

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

Emerging opportunities for DSS

Fighting human trafficking



Stopping Penny Stock Fraud

Penny Stock Fraud Nets Millions

Scheme Mastermind Among Those Sentenced to Prison

Internet opens new avenue for penny stock fraud

NEW YORK □ Most investors take e-mails advertising a 300 percent return on penny stocks sh bin. But those Internet promotions are still irresistible for some use of making a killing.

ay, July 11, 2004

ommission is increasingly taking legal action against individuals and companies that nline. In one of its recent cases, involving Ives Health Co., the SEC reported a final ner president, M. Keith Ives, for disseminating misleading information on the Internet.

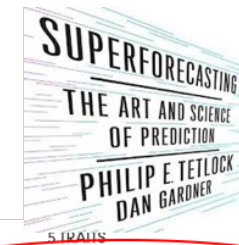
nsate investors a total of \$1.25 million for, among other things, falsely claiming the igation the company developed.

Defined by the SEC as stocks that sell below \$5 a share, penny stocks have always been considered speculative and easily manipulated. But stock market experts, seeing an increase in penny stock promotion online, say investors should be wary of

Predicting cyberattacks



Accurate geopolitical forecasting



- perforecasters begin by gathering as much information possible.
- perforecasters nurture and develop the habit of thinking in terms of probabilities when exploring the likelihood of cific events.
- recasting improves when individuals work in teams.
- perforecasters ensure that they are regularly keeping are of their projections.
- 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

Research Question

General Search

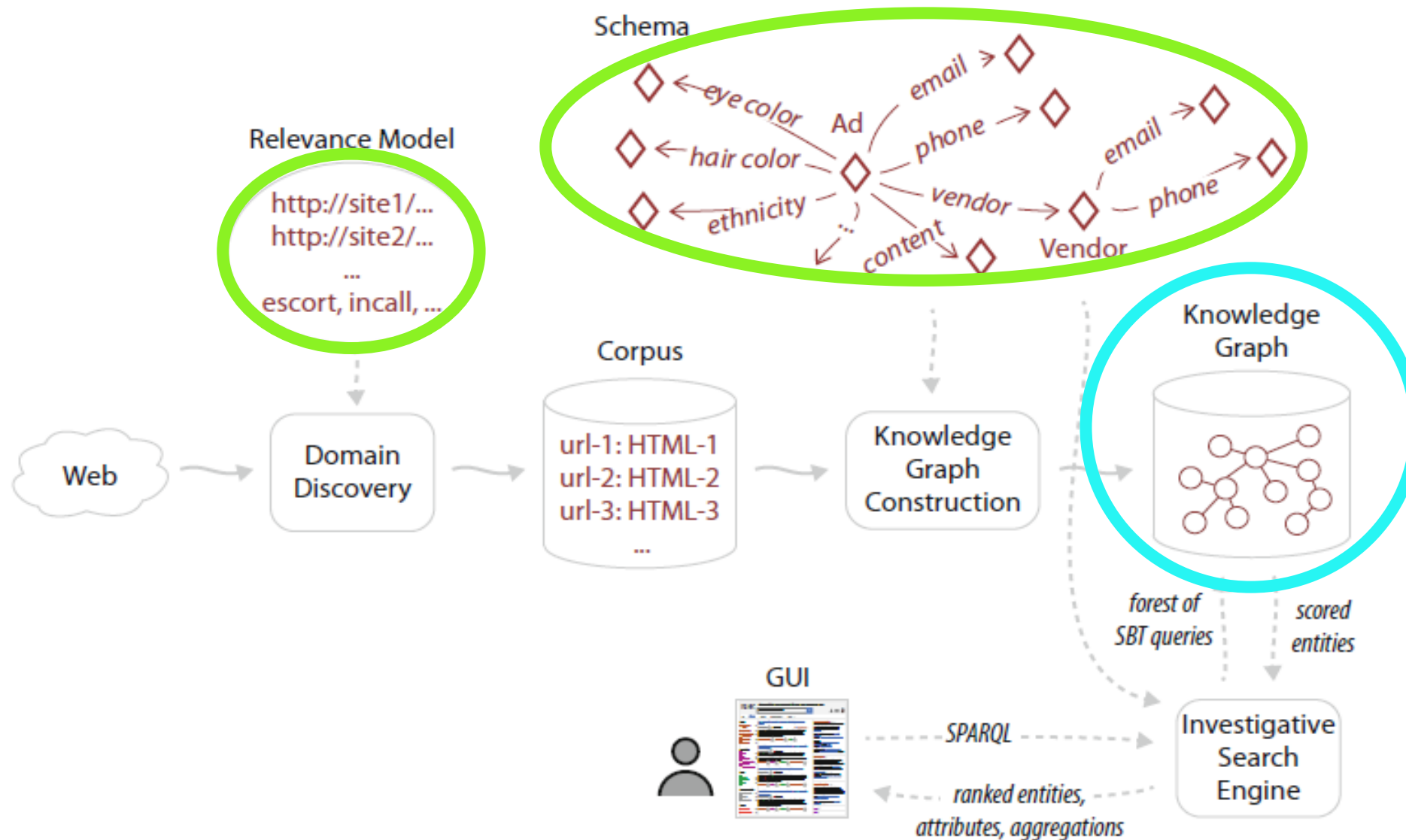
Google Knowledge Graph

DSS

Domain-Specific Knowledge Graphs

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

Knowledge Graphs for DSS



Domain-specific Insight Graphs

Project: atf_firearms_domain

Search Terms

Caliber or Gauge: 9mm X

Model: glock X Model: glock 26 X

Make (Top 10)

View More

Sort By: A-Z

<input type="checkbox"/>	<u>glock</u>	110,530
<input type="checkbox"/>	<u>springfield</u>	50,468
<input type="checkbox"/>	<u>ruiger</u>	47,236
<input type="checkbox"/>	<u>browning</u>	42,122
<input type="checkbox"/>	<u>colt</u>	40,750
<input type="checkbox"/>	<u>smith</u>	40,730
<input type="checkbox"/>	<u>winchester</u>	37,697
<input type="checkbox"/>	<u>walther</u>	37,037
<input type="checkbox"/>	<u>taurus</u>	35,942
<input type="checkbox"/>	<u>smith & wesson</u>	34,298

Model (Top 10)

View More

Sort By: A-Z

<input type="checkbox"/>	<u>glock 19</u>	17,554
<input type="checkbox"/>	<u>glock 17</u>	12,801
<input type="checkbox"/>	<u>desert eagle</u>	9,556
<input type="checkbox"/>	<u>springfield xd</u>	8,926
<input type="checkbox"/>	<u>glock 43</u>	8,644
<input type="checkbox"/>	<u>glock 22</u>	7,314
<input checked="" type="checkbox"/>	<u>glock 26</u>	6,966
<input type="checkbox"/>	<u>glock 23</u>	6,482
<input type="checkbox"/>	<u>glock 27</u>	6,316
<input type="checkbox"/>	<u>springfield xdm</u>	4,710

25 of 461,480 Results [How are search results found?](#)

PLEASE NOTE THAT ONLY THE TOP 10 EXTRACTIONS OF EACH TYPE ARE SHOWN IN THE RESULT LIST.

2.84 **Glock 26**

Calibers or Gauges

☒ 9mm

Emails

☒ gda32570@yahoo.com

Models

☒ glock 26

Social Media Names

☒ facebook

Username

☒ gda32570

Prices

☒ 650

Dates (Any)

☒ Feb 6, 2016

☒ Dec 18, 2015

☒ Oct 25, 2016

☒ Feb 2, 2016

☒ Jan 21, 2016

☒ Oct 24, 2016

☒ Jan 9, 2016

☒ Feb 1, 2016

Cities

☒ pensacola, florida

Makes

☒ Glock

☒ fast

☒ chicago

Model: glock 26
9173 Total Results



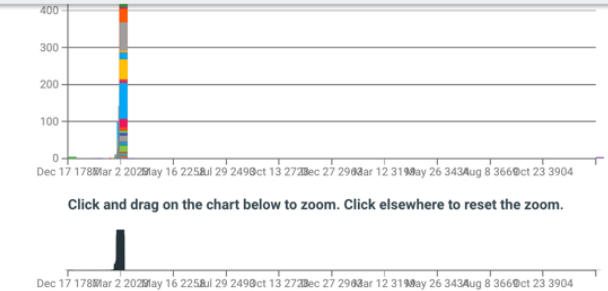
CITY	RESULTS CO-OCCURRING WITH GLOCK 26	RESULTS NOT CO-OCCURRING
<input type="checkbox"/> <u>dallas, texas</u>	1,100	0
<input type="checkbox"/> <u>orange, california</u>	674	0
<input type="checkbox"/> <u>springfield, oregon</u>	539	0
<input type="checkbox"/> <u>david, chiriqui</u>	403	0
<input type="checkbox"/> <u>springfield, massachusetts</u>	287	0
<input type="checkbox"/> <u>springfield, ohio</u>	239	0
<input type="checkbox"/> <u>springfield, missouri</u>	228	0
<input type="checkbox"/> <u>south bend, indiana</u>	171	0
<input type="checkbox"/> <u>pune, maharashtra</u>	97	0
<input type="checkbox"/> <u>phoenix, arizona</u>	95	0

SHOW MORE

4 Calibers or Gauges

CALIBER OR GAUGE	RESULTS CO-OCCURRING WITH GLOCK 26	RESULTS NOT CO-OCCURRING
<input checked="" type="checkbox"/> <u>9mm</u>	19	0
<input type="checkbox"/> <u>9mm, .40, .45</u>	9	0
<input type="checkbox"/> <u>9mm luger</u>	3	0
<input type="checkbox"/> <u>9x19</u>	2	0

Copy



Click and drag on the chart below to zoom. Click elsewhere to reset the zoom.

25 of 9,173 Results

PLEASE NOTE THAT ONLY THE TOP 10 EXTRACTIONS OF EACH TYPE ARE SHOWN IN THE LIST.

6.85 **Sig Sauer P250 For Sale**

Cities

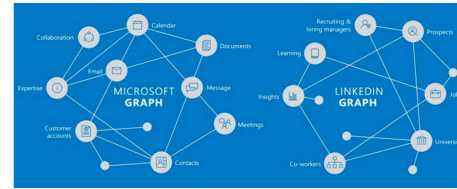
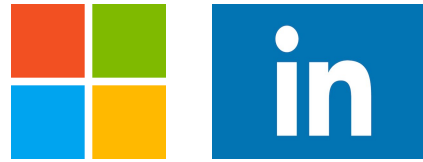
☒ springfield, oregon

Makes

- ☒ pelican
- ☒ walther
- ☒ savage arms
- ☒ colt
- ☒ springfield armory m1a
- ☒ allen
- ☒ bushmaster
- ☒ beretta usa
- ☒ chip mccormick
- ☒ ruiger

Models

TLDs



amazon



Building an Enterprise
Knowledge
Graph @Uber:

Lessons from Reality

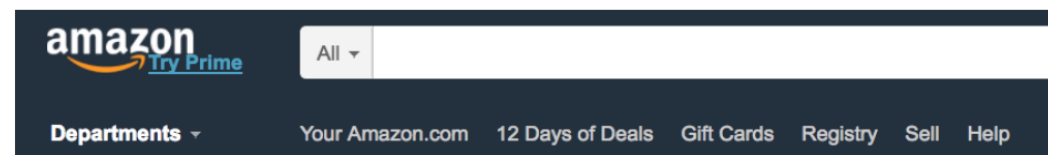
Joshua Shinavier, PhD
Knowledge Graph Conference
May 8th, 2019

Uber

**Many examples in industry
and non-profit**

Commercial domains: Amazon Product Graph

❑ Mission: To answer any question about products and related knowledge in the world



Customers who bought this item also bought



Source: Dong, Luna. Building a Broad Knowledge Graph for Products. Keynote at ICDE. 2019

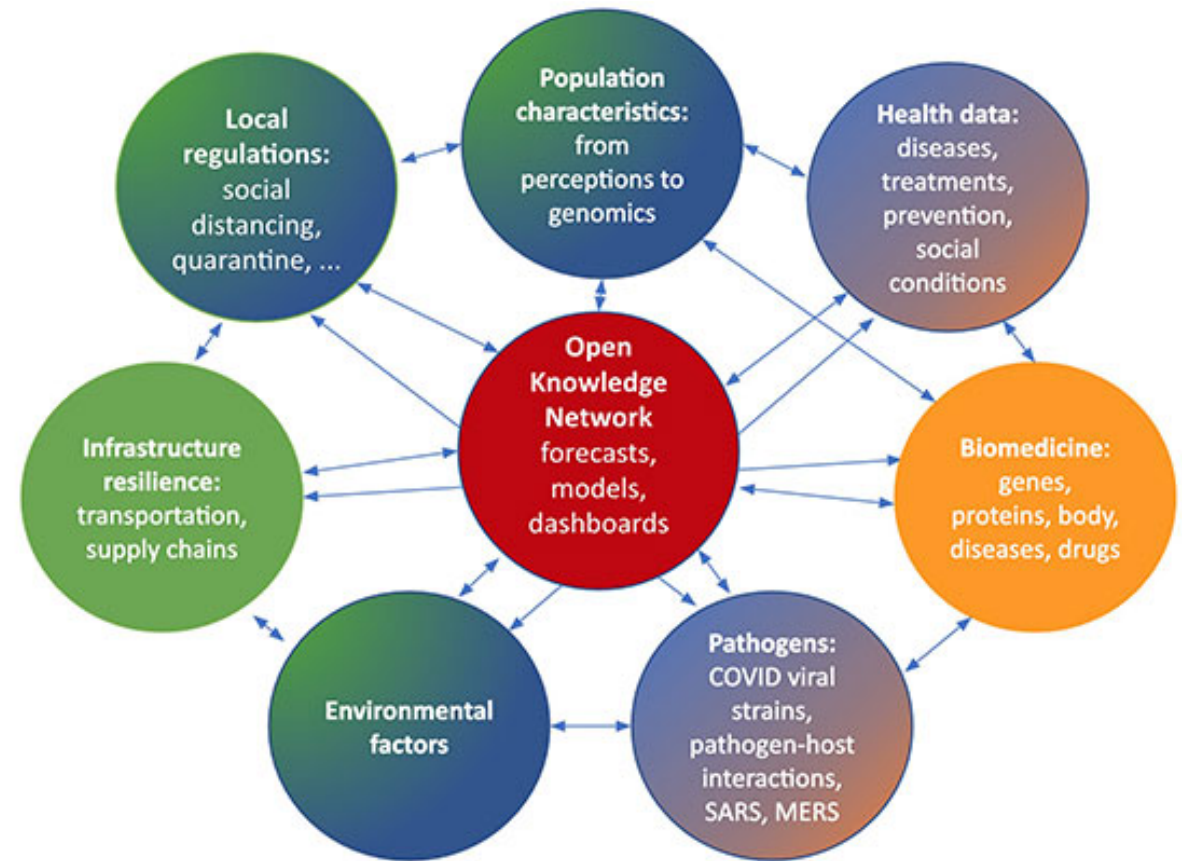
Another example: COVID-19

June 01, 2020 | By Jan Zverina

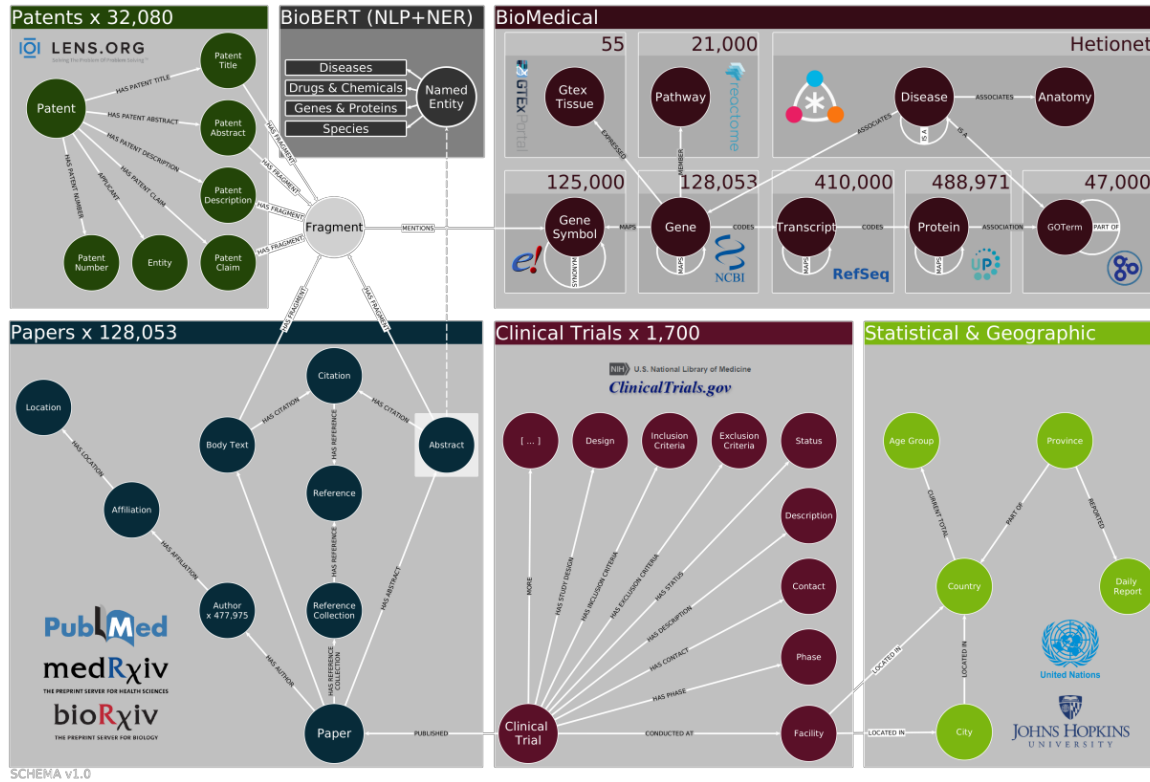
Fighting COVID-19 with Knowledge Graphs

National Science Foundation awards funding for a semantic integration platform

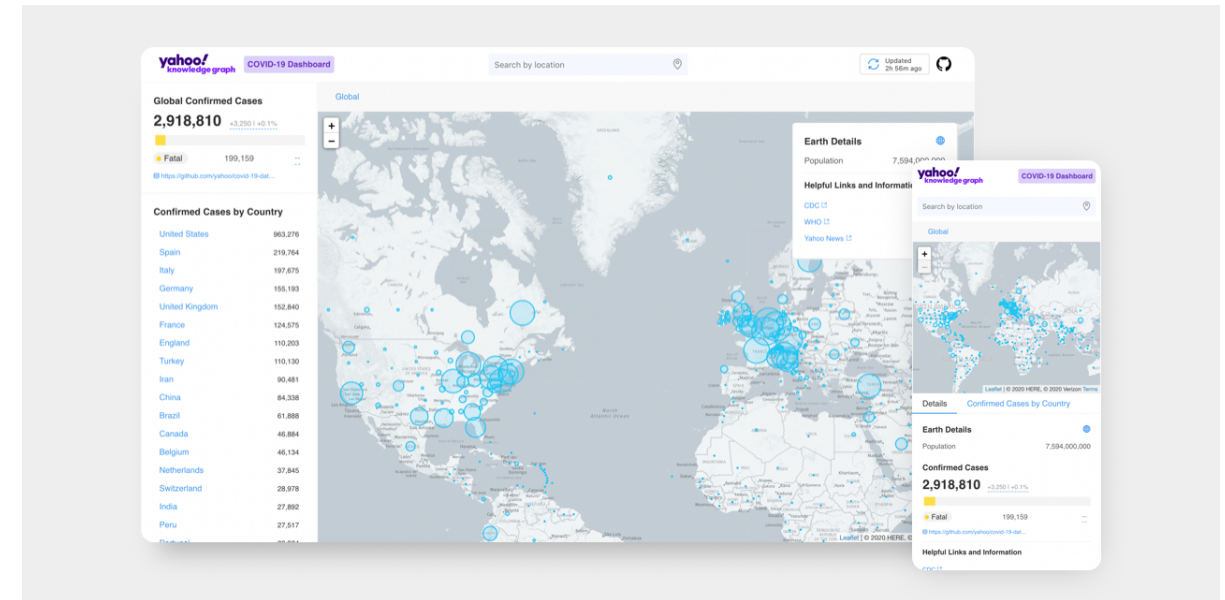
“The project will be based on our knowledge graph prototype linking information about pathogens, health data, and environmental indicators and enabling cross-domain inferencing,” said Peter Rose, director of SDSC’s Structural Bioinformatics Laboratory and principal investigator (PI) for the project, called ‘COVID-19-Net: Integrating Health, Pathogen and Environmental Data into a Knowledge Graph for Case Tracking, Analysis, and Forecasting.’ “Such a graph lets researchers trace the spread of the coronavirus in different geographic conditions, focusing on specific virus strains and transmissions.”



Other COVID-19 KG examples



Source: CovidGraph



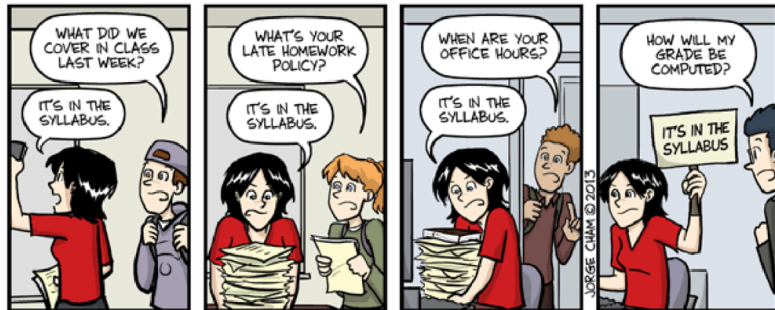
Source: Verizon Media

<https://github.com/yahoo/covid-19-dashboard>

Further reading: Kejriwal, M. (2020). Knowledge Graphs and COVID-19: Opportunities, Challenges, and Implementation. *Harvard Data Science Review*.

CROSS-DISCIPLINARY PERSPECTIVES: SEMANTIC WEB

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

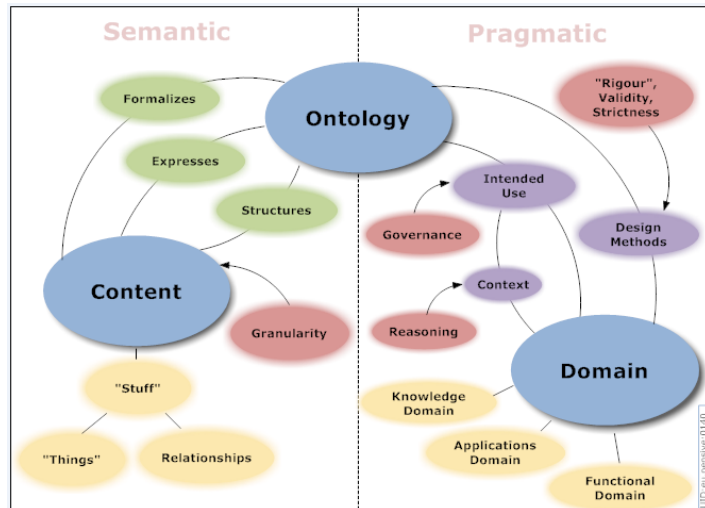


IT'S IN THE SYLLABUS

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

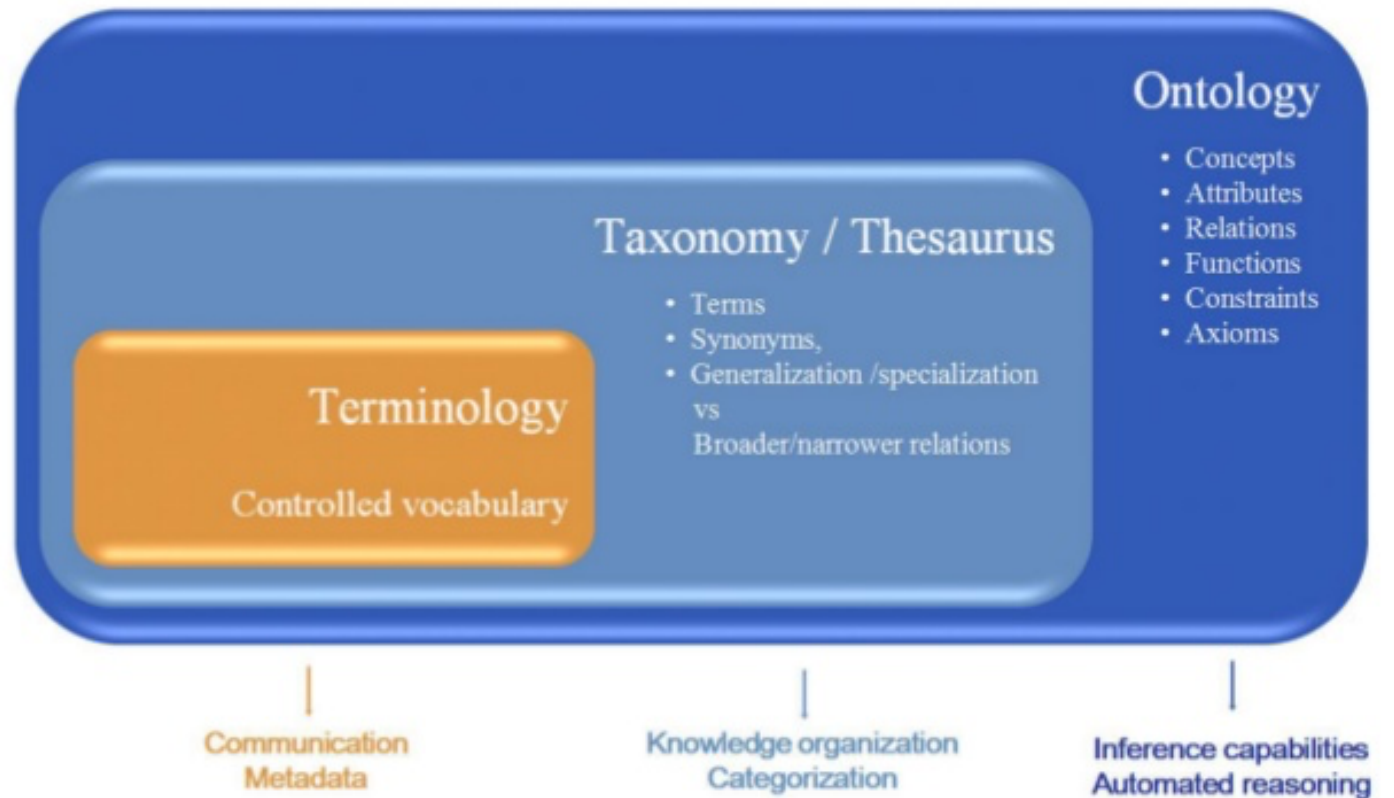
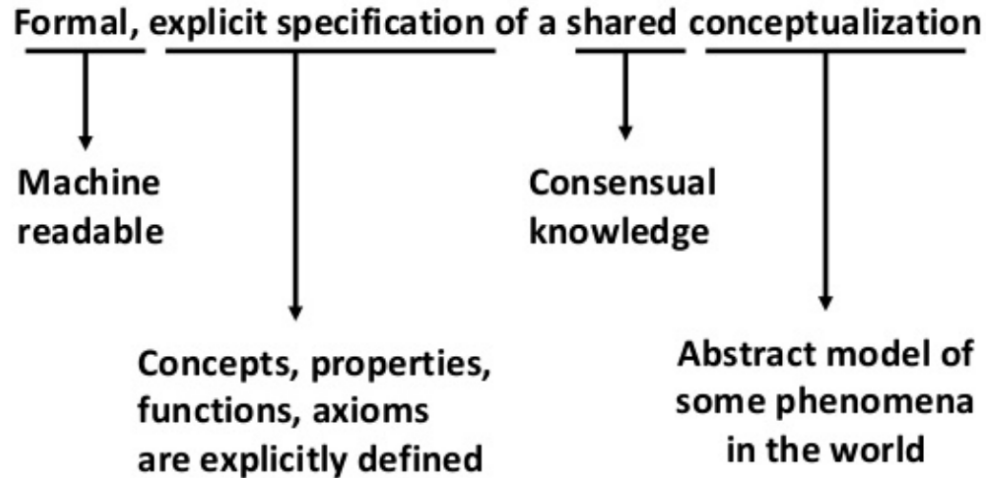
How do domain experts specify the sphere?

Examples

Ontology

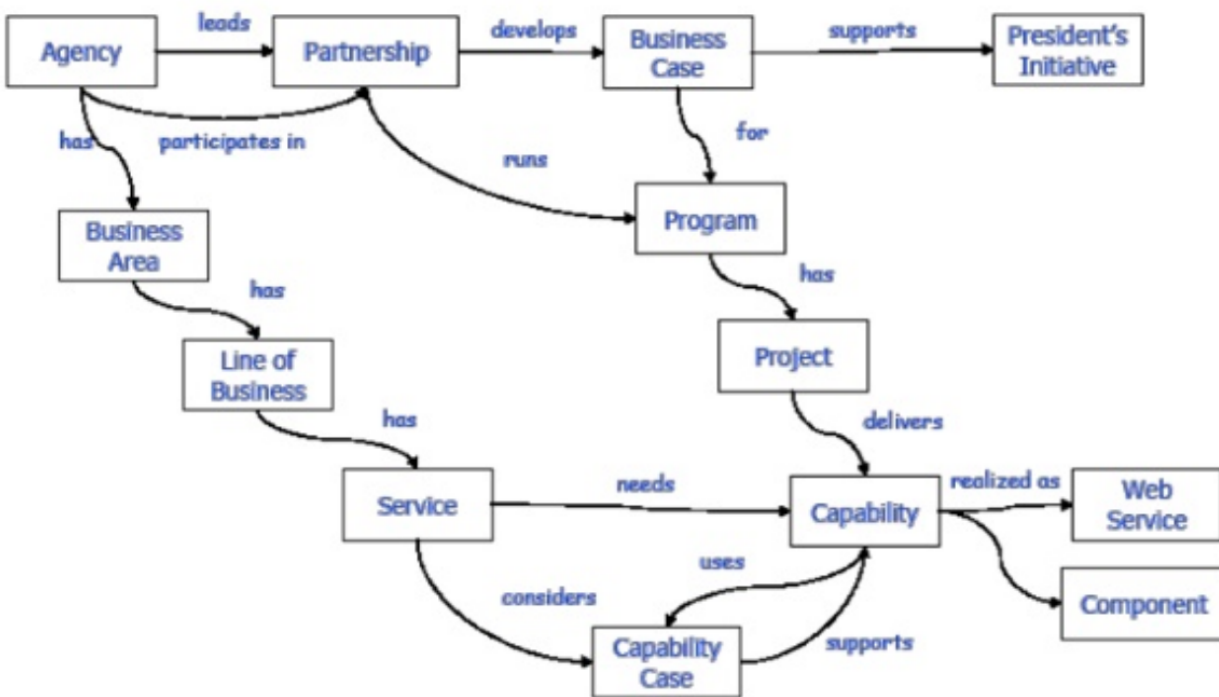
Modeling domains: Ontologies

What is an ontology?

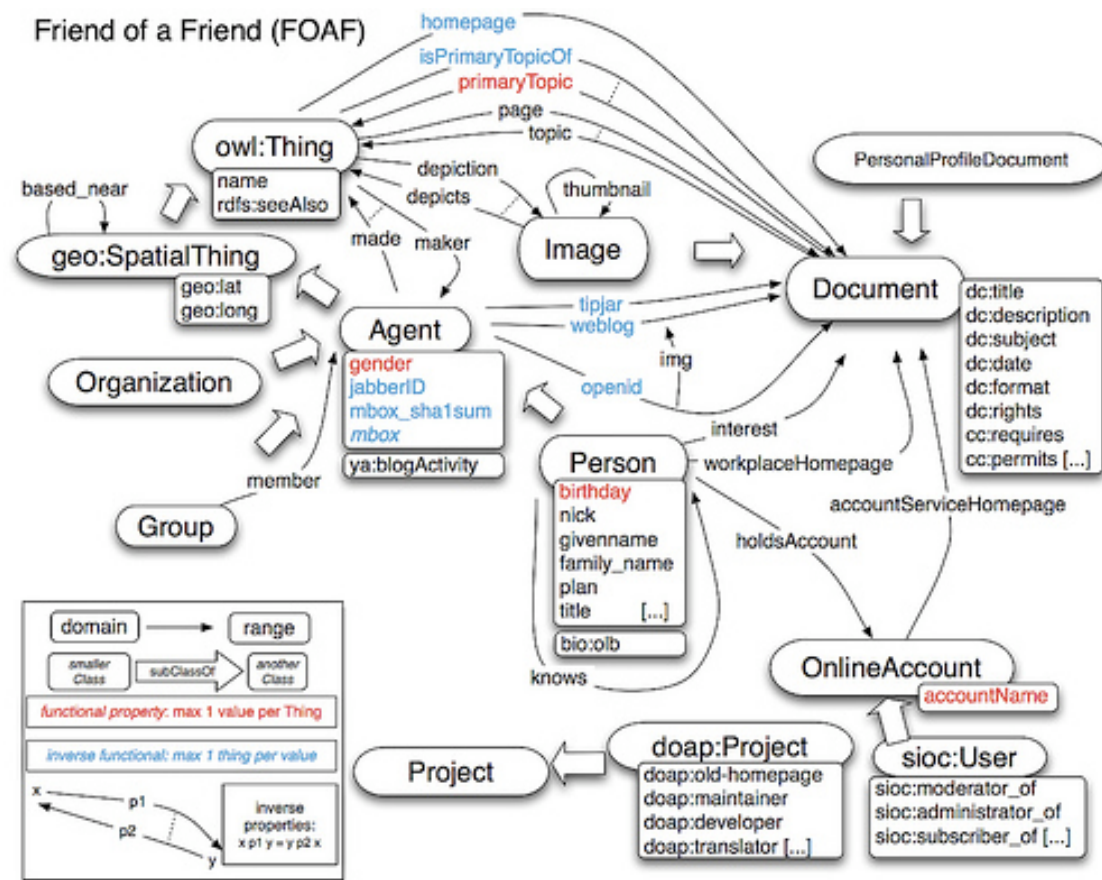


Source: “Ontologies and semantic web.” Stanley Wang. <https://www.slideshare.net/stanleywanguni/ontologies-and-semantic-web>

Examples of ontologies



Agency domain



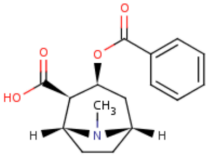
Friend-of-a-friend

Ontologies are big in Science

ChEBI > Main

CHEBI:41001 - ecgonine benzoate

Main ChEBI Ontology Automatic Xrefs Reactions Pathways Models



ChEBI Name **ecgonine benzoate**

ChEBI ID **CHEBI:41001**

Definition A benzoate ester metabolite of cocaine formed by hydrolysis of the methyl ester group, catalysed by carboxylesterase

Stars ★★ This entity has been manually annotated by the ChEBI Team.

Secondary ChEBI IDs CHEBI:3041

Supplier Information [ChemicalBook:CB1217496](#), [eMolecules:535127](#), [ZINC000002572652](#)

Download [Molfile](#) [XML](#) [SDF](#)

[Find compounds which contain this structure](#)

[Find compounds which resemble this structure](#)

[Take structure to the Advanced Search](#)

[more structures >>](#)

Wikipedia

Benzoyllecgonine is the main [metabolite](#) of [cocaine](#).

[Read full article at Wikipedia](#)

Formula	C16H19NO4
Net Charge	0
Average Mass	289.32640
Monoisotopic Mass	289.13141
InChI	InChI=1S/C16H19NO4/c1-17-11-7-8-12(17)14(15(18)19)13(9-11)21-16(20)10-5-3-2-4-6-10/h2-6,11-14H,7-9H2,1H3,(H,18,19)/t11-,12+,13-,14-,15-,16-,17-,18-,19-,20-,21-/m1/s1
InChIKey	GVGYEFKIHTNQZ-RFQIPJRSA-N
SMILES	[H][C@]12CC[C@]([H])([C@H]([C@H](C1)OC(=O)c1ccccc1)C(O)=O)N2C

Roles Classification

[marine xenobiotic metabolite](#)

Any metabolite produced by metabolism of a xenobiotic compound in marine macro- and microorganisms.

[plant metabolite](#)

Any eukaryotic metabolite produced during a metabolic reaction in plants, the kingdom that include flowering plants, conifers and other gymnosperms.

Search GO data

terms and gene products

Search

Enrichment analysis (beta)

Your genes here...

biological process

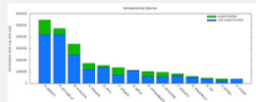
H. sapiens

Submit

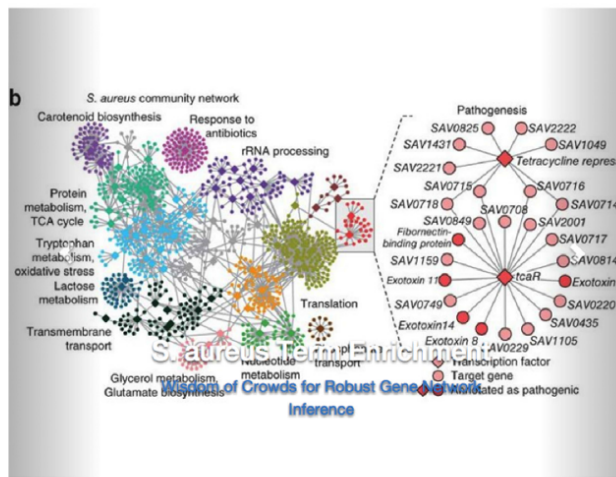
Advanced options

Powered by [PANTHER](#)

Statistics



Gene Ontology Consortium



Highlighted GO term

Representing "phases" in GO biological process

The GOC has recently introduced a new term [biological phase \(GO:0044848\)](#), as a direct subclass of biological process. This class represents a distinct period or stage during which biological processes can occur.

[more](#)

On the web

Work on Comparative Proteomic Analysis of Supportive and Unsupportive Extracellular...

Integrating information retrieval with distant supervision for Gene Ontology annotation...

The GO was elemental in defining response to cold acclimation in diapause pupae...

a platform for [Gene Ontology](#) annotation of anonymous sequence data

What is the Gene Ontology?

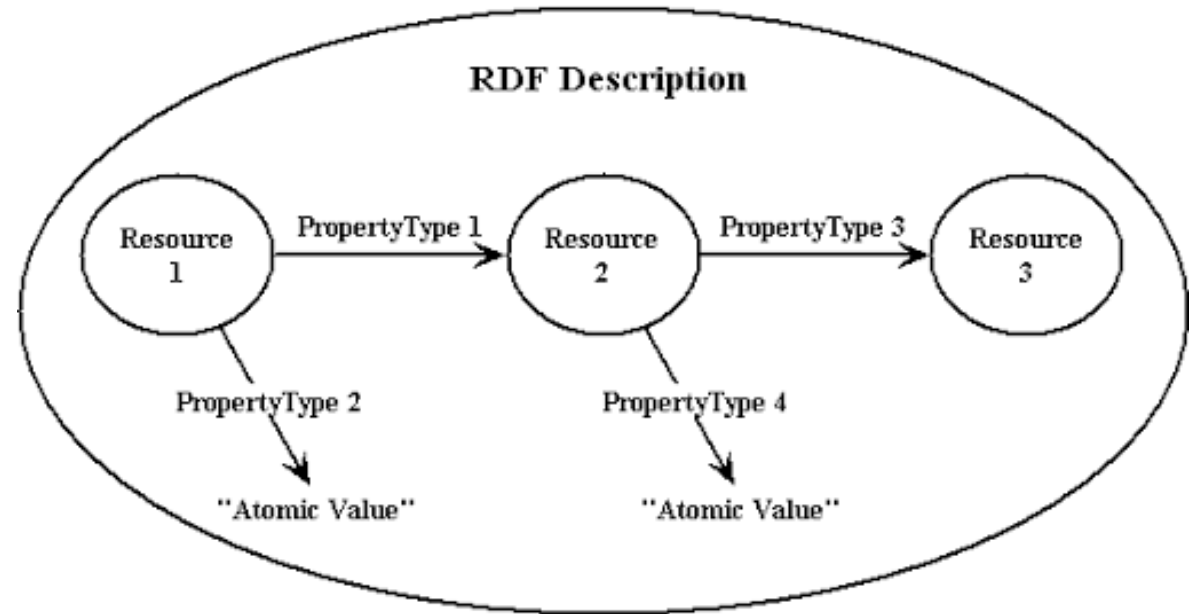
- An introduction to the Gene Ontology
- What are annotations?
- Ten quick tips for using the Gene Ontology **Important**
- Gene Ontology tools
- Enrichment analysis
- Downloads

Representation of knowledge graphs (and ontologies)

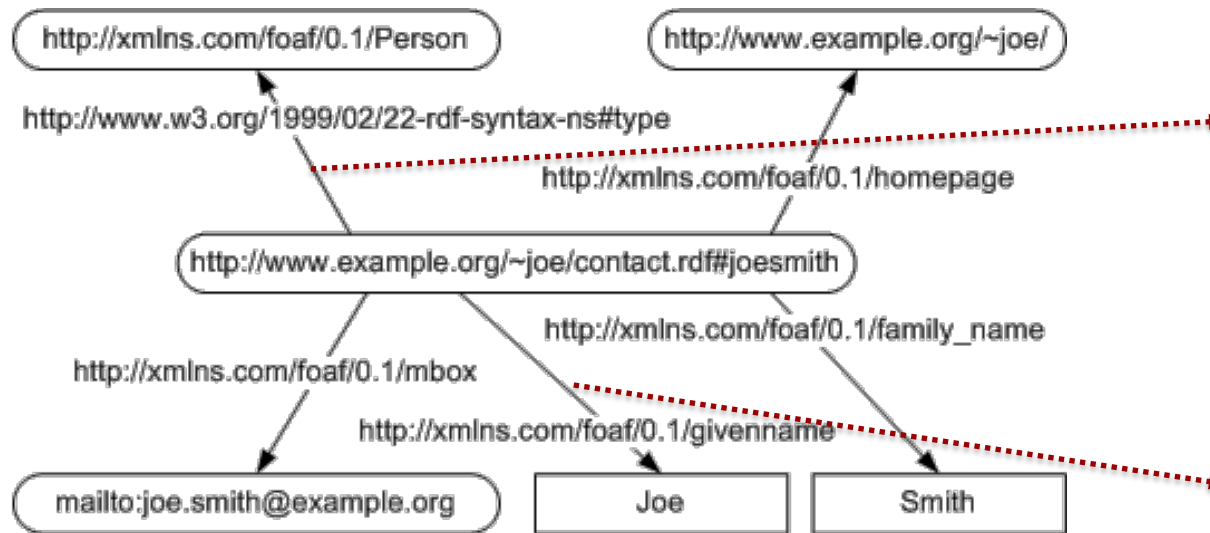
An RDF graph is a set of triples, where each triple is of the form (subject, predicate, object):

- Subjects must be URIs (technically, *internationalized resource identifiers*, in practice, just Uniform Resource Locators)
- Predicates (also called ‘properties’) must be URIs
- Objects can be either URIs or literals (strings, numbers, dates...)

In the Semantic Web, RDF is the ‘building block’ of higher order vocabularies (such as RDF Schema and OWL) that can be used to represent ontologies



Example of RDF KG



As a graph

<http://www.example.org/~joe/contact.rdf#joesmith>
<http://www.w3.org/1999/02/22-rdf-syntax-ns#type>
<http://xmlns.com/foaf/0.1/Person>

...

<http://www.example.org/~joe/contact.rdf#joesmith>
<http://xmlns.com/foaf/0.1/givenname> "Joe"

As a set of triples

Web Ontology Language (OWL)

OWL builds on RDF
(and another layer
called RDF Schema or
RDFS) to provide a
systematic vocabulary
for defining ontologies

Because OWL builds on
RDF, every OWL
ontology is **also** an RDF
graph, but not
necessarily vice-versa

RDF Schema Features:

- [Class \(Thing, Nothing\)](#)
- [rdfs:subClassOf](#)
- [rdf:Property](#)
- [rdfs:subPropertyOf](#)
- [rdfs:domain](#)
- [rdfs:range](#)
- [Individual](#)

Property Restrictions:

- [Restriction](#)
- [onProperty](#)
- [allValuesFrom](#)
- [someValuesFrom](#)

Class Intersection:

- [intersectionOf](#)

Datatypes

- [xsd datatypes](#)

(In)Equality:

- [equivalentClass](#)
- [equivalentProperty](#)
- [sameAs](#)
- [differentFrom](#)
- [AllDifferent](#)
- [distinctMembers](#)

Restricted Cardinality:

- [minCardinality](#) (only 0 or 1)
- [maxCardinality](#) (only 0 or 1)
- [cardinality](#) (only 0 or 1)

Versioning:

- [versionInfo](#)
- [priorVersion](#)
- [backwardCompatibleWith](#)
- [incompatibleWith](#)
- [DeprecatedClass](#)
- [DeprecatedProperty](#)

Property Characteristics:

- [ObjectProperty](#)
- [DatatypeProperty](#)
- [inverseOf](#)
- [TransitiveProperty](#)
- [SymmetricProperty](#)
- [FunctionalProperty](#)
- [InverseFunctionalProperty](#)

Header Information:

- [Ontology](#)
- [imports](#)

Annotation Properties:

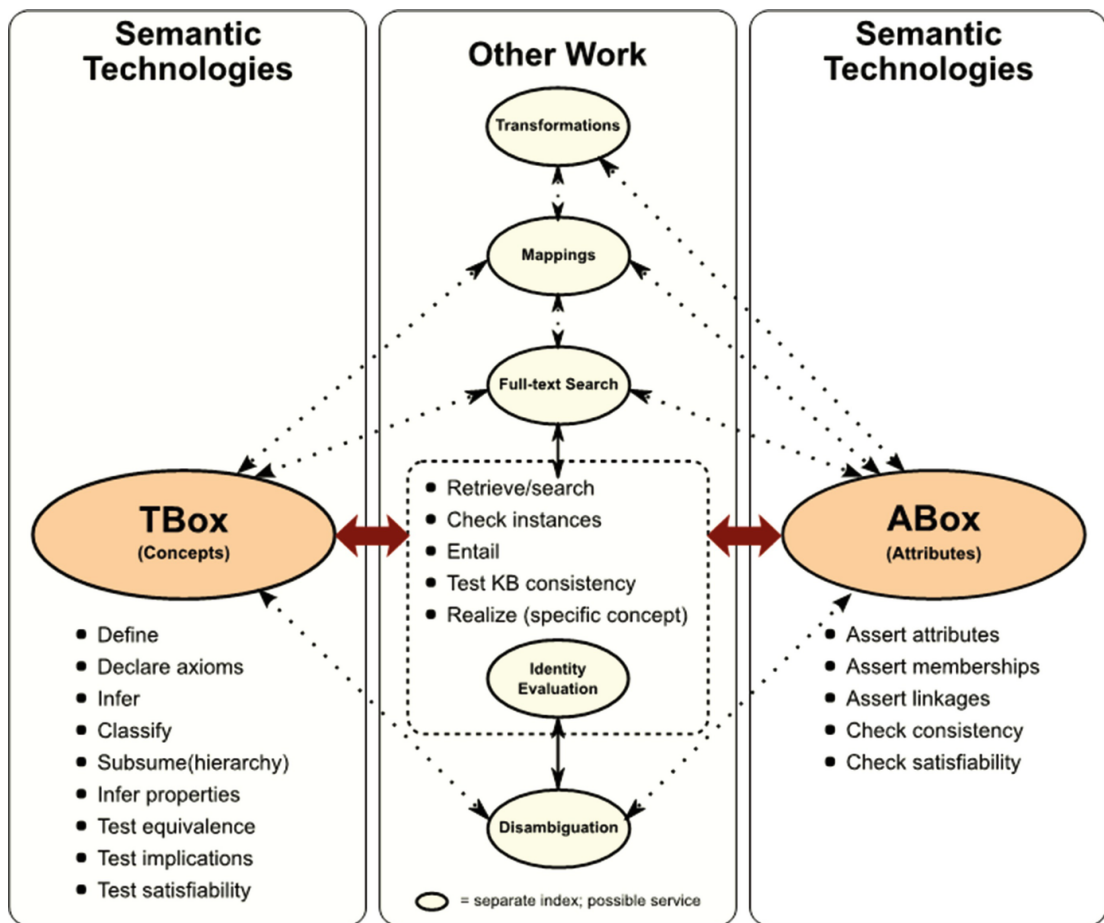
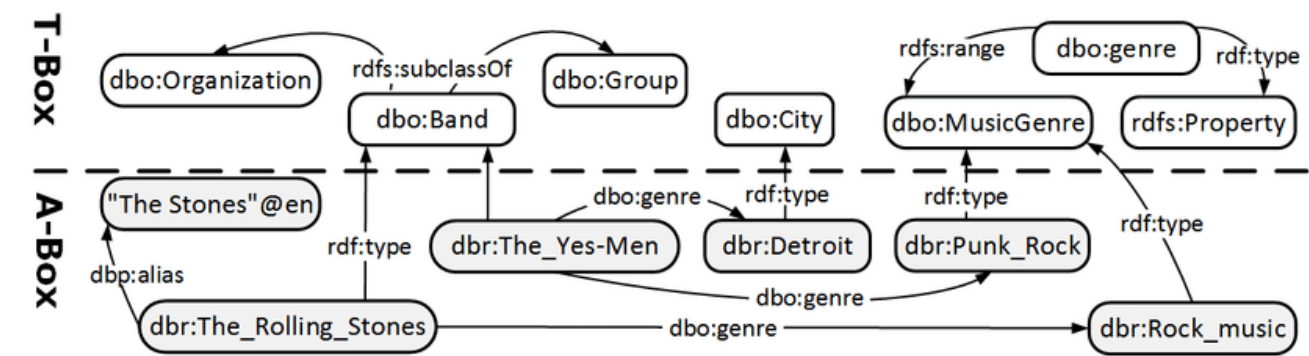
- [rdfs:label](#)
- [rdfs:comment](#)
- [rdfs:seeAlso](#)
- [rdfs:isDefinedBy](#)
- [AnnotationProperty](#)
- [OntologyProperty](#)

<https://www.w3.org/TR/owl-features/>

Reasoning over knowledge graphs

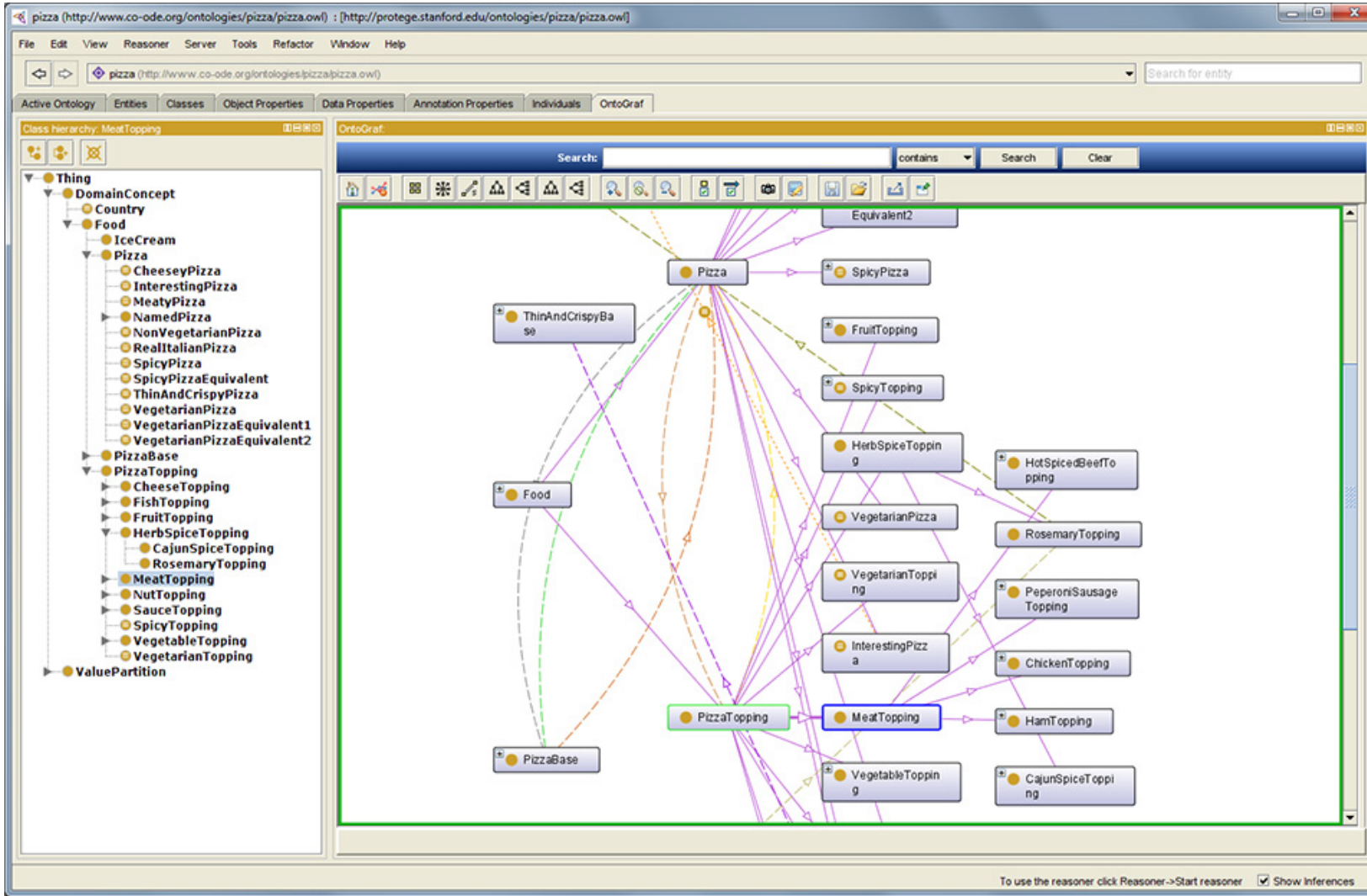
Assertions	DL-axioms
Every animal which can fly has wings	$\varphi_1: Fly \sqsubseteq HasWing$
Every animal which eats fish is a piscivore	$\varphi_2: \exists Eat.Fish \sqsubseteq Piscivore$
tweety is not an abnormal bird or cannot fly	$\varphi_3: (\neg AbnBird \sqcup \neg Fly)(tweety)$
ursidae eats salmon	$\varphi_4: Eat(ursidae, salmon)$
salmon is some fish	$\varphi_5: Fish(salmon)$
ursidae is not a piscivore	$\varphi_6: \neg Piscivore(ursidae)$

<https://doi.org/10.1371/journal.pone.0181056.t001>



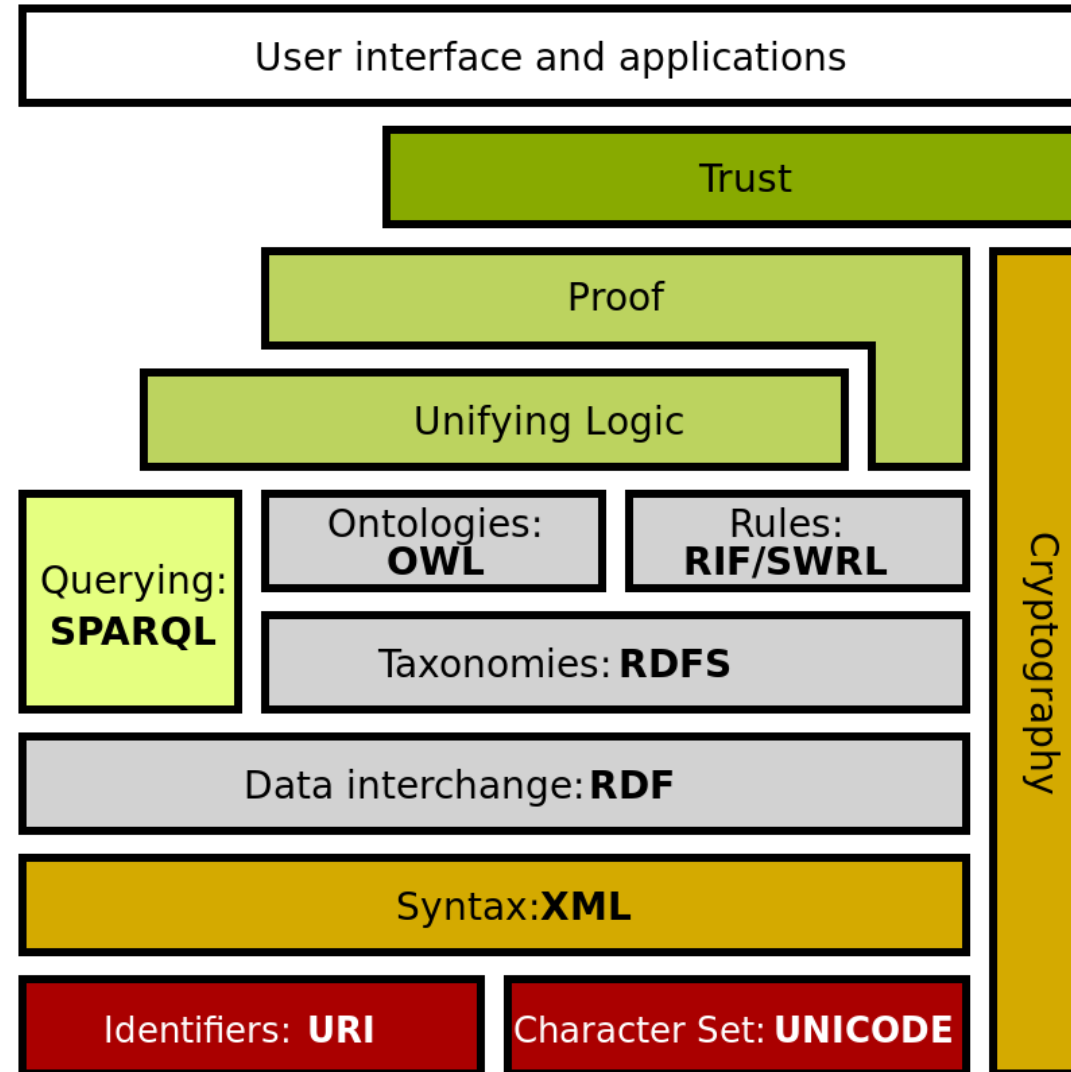
Source: Bergman. Platforms and Knowledge Management. 2018

Example tool for reasoning and ontologies: Protege



Source: <https://protege.stanford.edu/>

Putting it all together: Semantic Web Layer Cake




CROSS-DISCIPLINARY PERSPECTIVES: KNOWLEDGE DISCOVERY & DATA MINING


Knowledge Graph in Personal Assistant

Alexa, play Taylor Swift in the past year




 Taylor Swift > Songs


Love Story
Fearless · 2008




Look What You Made Me...
Reputation · 2017



Shake It Off
1989 · 2014



Delicate
Reputation · 2017



Source: Dong, Luna. Building a Broad Knowledge Graph for Products. Keynote at ICDE. 2019

Others

Scientific Text Mining

Jiang, M., & Shang, J. (2020, August). Scientific Text Mining and Knowledge Graphs. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (pp. 3537-3538).

Question Answering

Hixon, B., Clark, P., & Hajishirzi, H. (2015). Learning knowledge graphs for question answering through conversational dialog. In *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies* (pp. 851-861).

Recommendation Systems

Oramas, S., Ostuni, V. C., Noia, T. D., Serra, X., & Sciascio, E. D. (2016). Sound and music recommendation with knowledge graphs. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 8(2), 1-21.

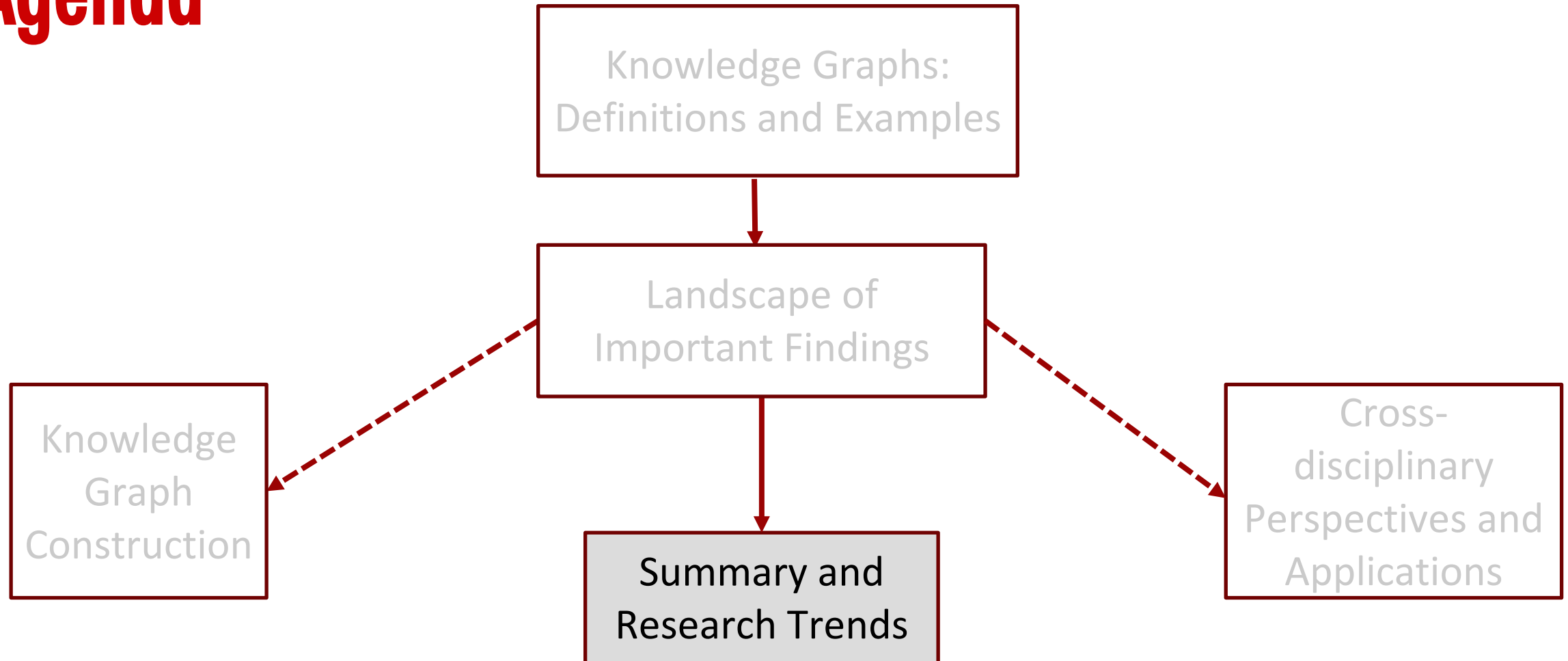
Summarization

Gunaratna, K., Yazdavar, A. H., Thirunarayan, K., Sheth, A., & Cheng, G. (2017, August). Relatedness-based multi-entity summarization. In *IJCAI: proceedings of the conference* (Vol. 2017, p. 1060). NIH Public Access.

Truth/fact-checking

Shiralkar, P., Flammini, A., Menczer, F., & Ciampaglia, G. L. (2017, November). Finding streams in knowledge graphs to support fact checking. In *2017 IEEE International Conference on Data Mining (ICDM)* (pp. 859-864). IEEE.

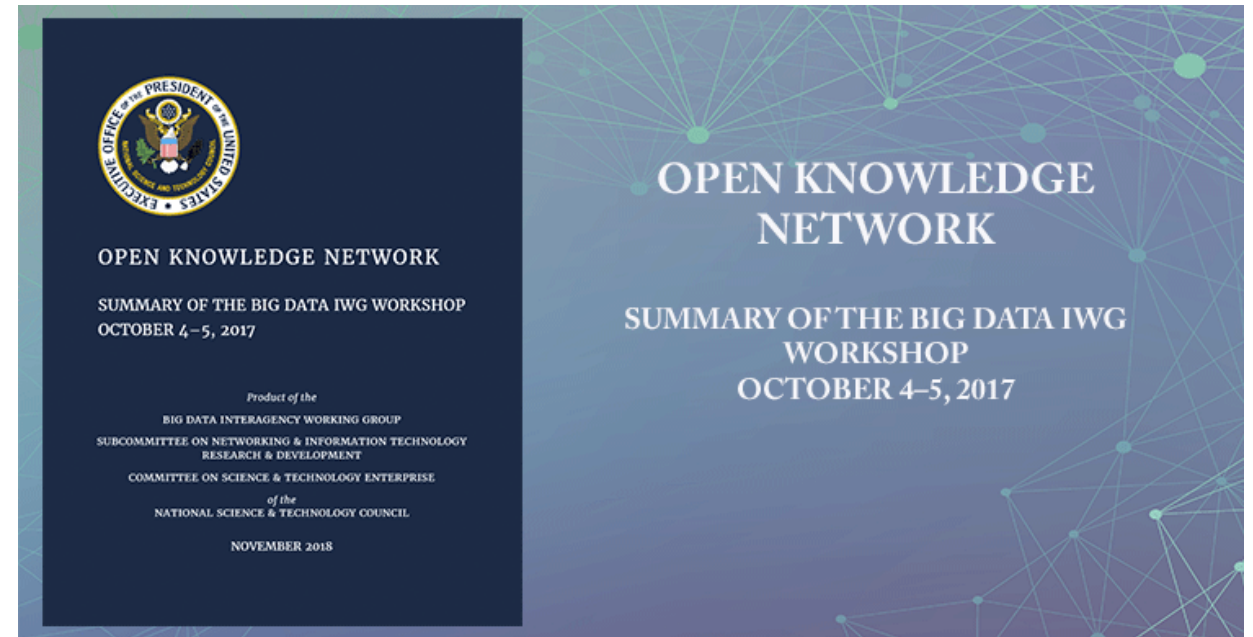
Agenda



Open Knowledge Network (OKN)

Technology companies develop **proprietary knowledge networks** as key business technologies today. However, because these networks are proprietary and expensive to construct, government, academia, small businesses, and nonprofits do not have access to them. In contrast, an open knowledge network (OKN) would be available to all stakeholders, including the researchers who will help push this technology further. An OKN requires a nonproprietary, public–private development effort that spans the entire data science community and will result in an **open, shared infrastructure**.

<https://www.nitrd.gov/pubs/Open-Knowledge-Network-Workshop-Report-2018.pdf>



<https://www.nitrd.gov/news/Open-Knowledge-Network-Workshop-Report-2018.aspx>



Knowledge Graphs for Social Good (KGSG)

Best Practices, Methods, and Challenges – Held May 4th, 2020 at KGC 2020

accenture

Technology Innovation

Applying knowledge graphs for social good

JUNE 26, 2020

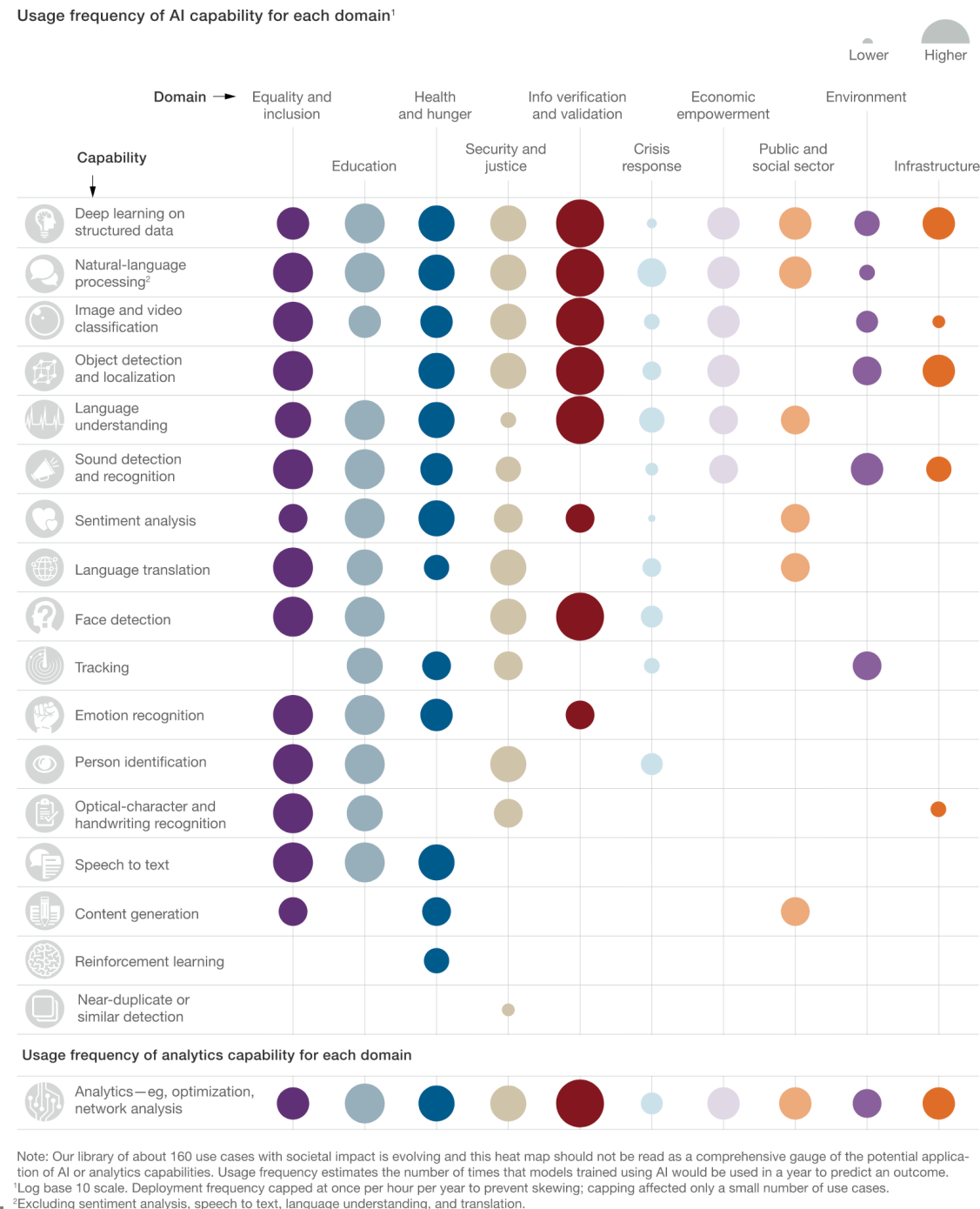
Knowledge Graphs for Social Good: An Entity-centric Search Engine for the Human Trafficking Domain

Publisher: IEEE

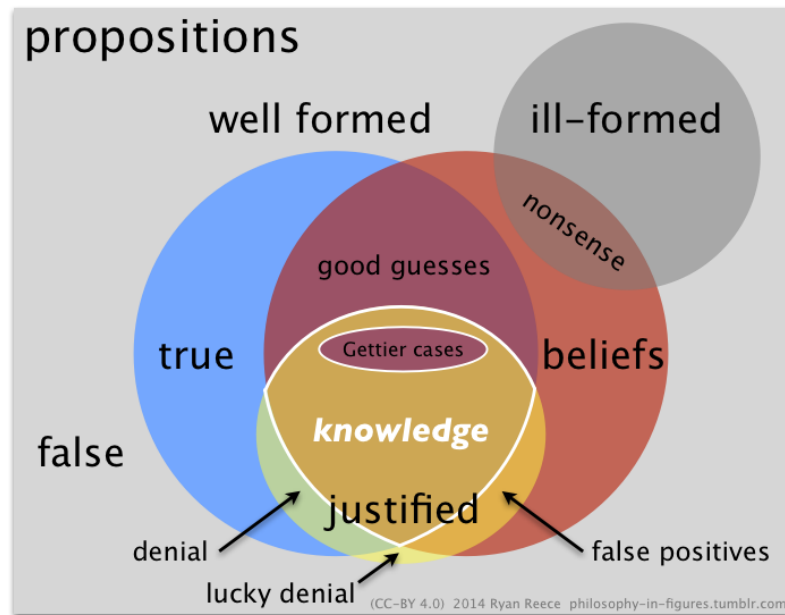
Cite This

PDF

Mayank Kejriwal ; Pedro Szekely All Authors



Knowledge, semantics and context: what are they and how do we better define/represent them?



— *Three quarks for Muster Mark!*
Sure he hasn't got much of a bark
And sure any he has it's all beside the mark.
But O, Wreeneagle Almighty, wouldn't un be a sky
To see that old buzzard whooping about for uns sl
And he hunting round for uns speckled trousers a
stown Park?

Quark, one of the most influential of modern Ferengi thanks to his location at Deep Space Nine when the Bajoran wormhole was discovered, owns Quark's Bar on DS9's Promenade, but hates being called a "barkeep," preferring "host" instead as he fancies himself an empathetic dispenser of advice as well as a goodwill ambassador and legitimate entrepreneur extraordinaire.

Quarks and [Leptons](#) are the building blocks which build up matter, i.e., they are seen as the "elementary particles". In the present standard model, there are six "flavors" of quarks. They can successfully account for all known [mesons](#) and [baryons](#) (over 200). The most familiar baryons are the [proton](#) and [neutron](#), which are each constructed from up and down quarks. Quarks are observed to occur only in combinations of two quarks (mesons), three quarks (baryons). There was a recent claim of observation of particles with five quarks ([pentaquark](#)), but further experimentation has not borne it out.

Quark is similar to French [fromage blanc](#), Indian [paneer](#), and the [queso fresco/queijo fresco](#) made in the Iberian Peninsula and in some Latin American countries. It is distinct from Italian [ricotta](#) because ricotta ([Italian](#) "recooked") is made from scalded [whey](#). Quark is somewhat similar to [yogurt cheeses](#) such as the South Asian [chak\(k\)a](#), the Arabic [labneh](#), and the Central Asian [suzma](#) or [kashk](#), but while these products are obtained by straining [yogurt](#) (milk fermented with [thermophile](#) bacteria),

Explainable AI

On The Role of Knowledge Graphs in Explainable AI

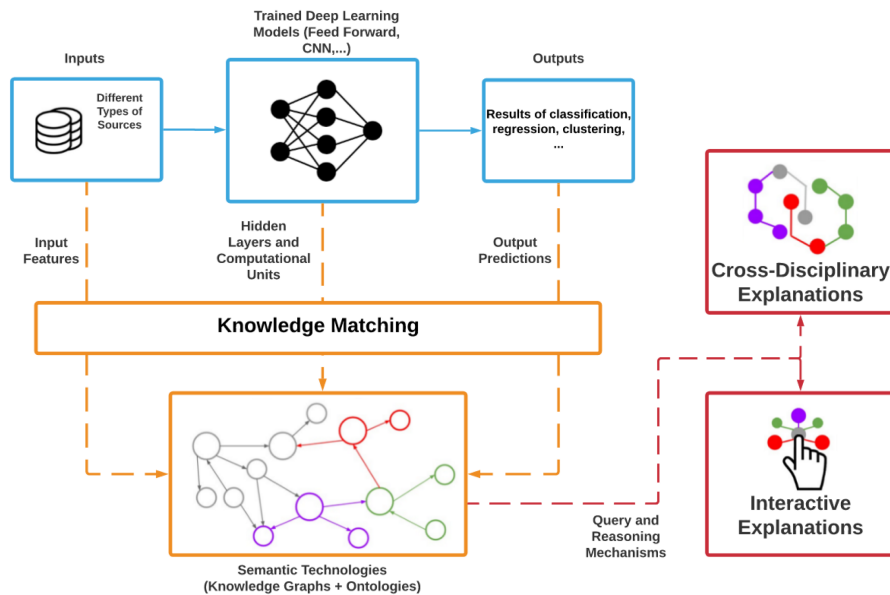
Freddy Lecue^{a,b}

^a CortAIx, Thales, Montreal, Canada

E-mail: freddy.lecue@inria.fr

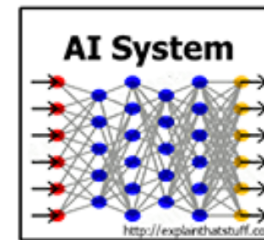
^b WIMMICS, Inria, Sophia Antipolis, France

E-mail: freddy.lecue@thalesgroup.fr



Explainable Artificial Intelligence (XAI)

Dr. Matt Turek



- We are entering a new age of AI applications
- Machine learning is the core technology
- Machine learning models are opaque, non-intuitive, and difficult for people to understand

DoD and non-DoD Applications

Transportation
Security
Medicine
Finance
Legal
Military

User

- Why did you do that?
- Why not something else?
- When do you succeed?
- When do you fail?
- When can I trust you?
- How do I correct an error?

Source: Knowledge Graphs For eXplainable AI. On the Integration of Semantic Technologies and Symbolic Systems into Deep Learning Models for a More Comprehensible Artificial Intelligence.

<https://towardsdatascience.com/knowledge-graphs-for-explainable-ai-dcd73c5c016>

WRAPUP

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),

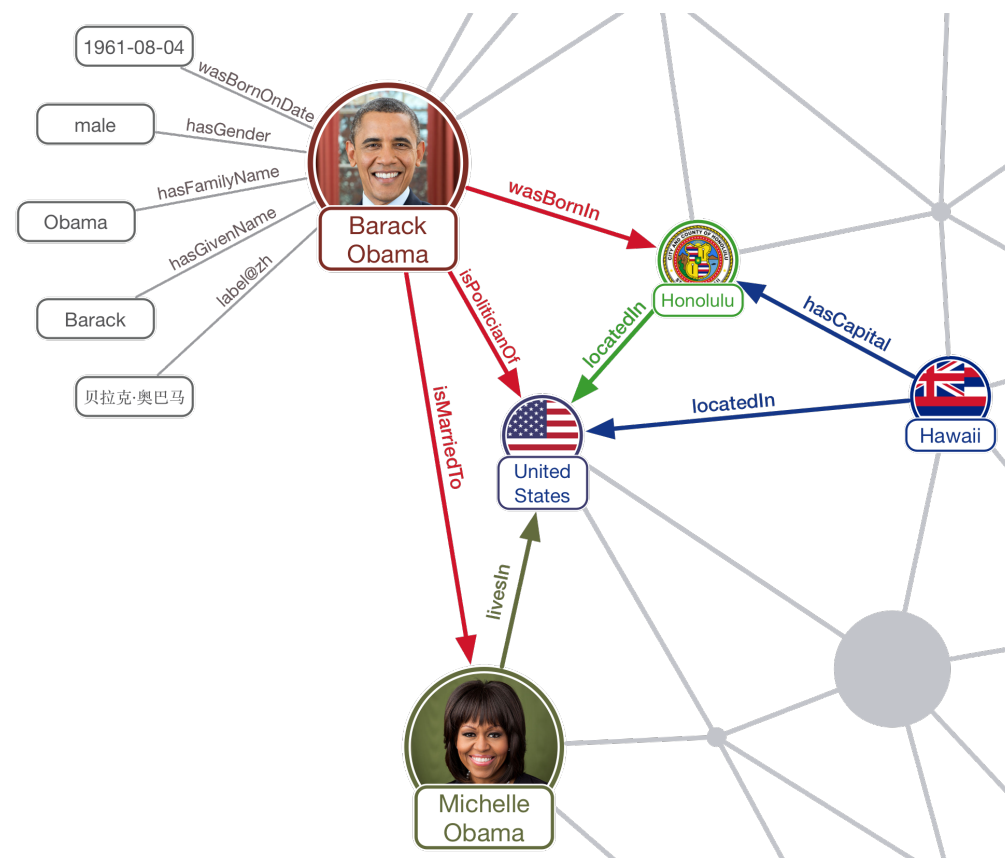
(Barack Obama, hasGender, male),

...

(Hawaii, hasCapital, Honolulu),

...

(Michelle Obama, livesIn, United States)



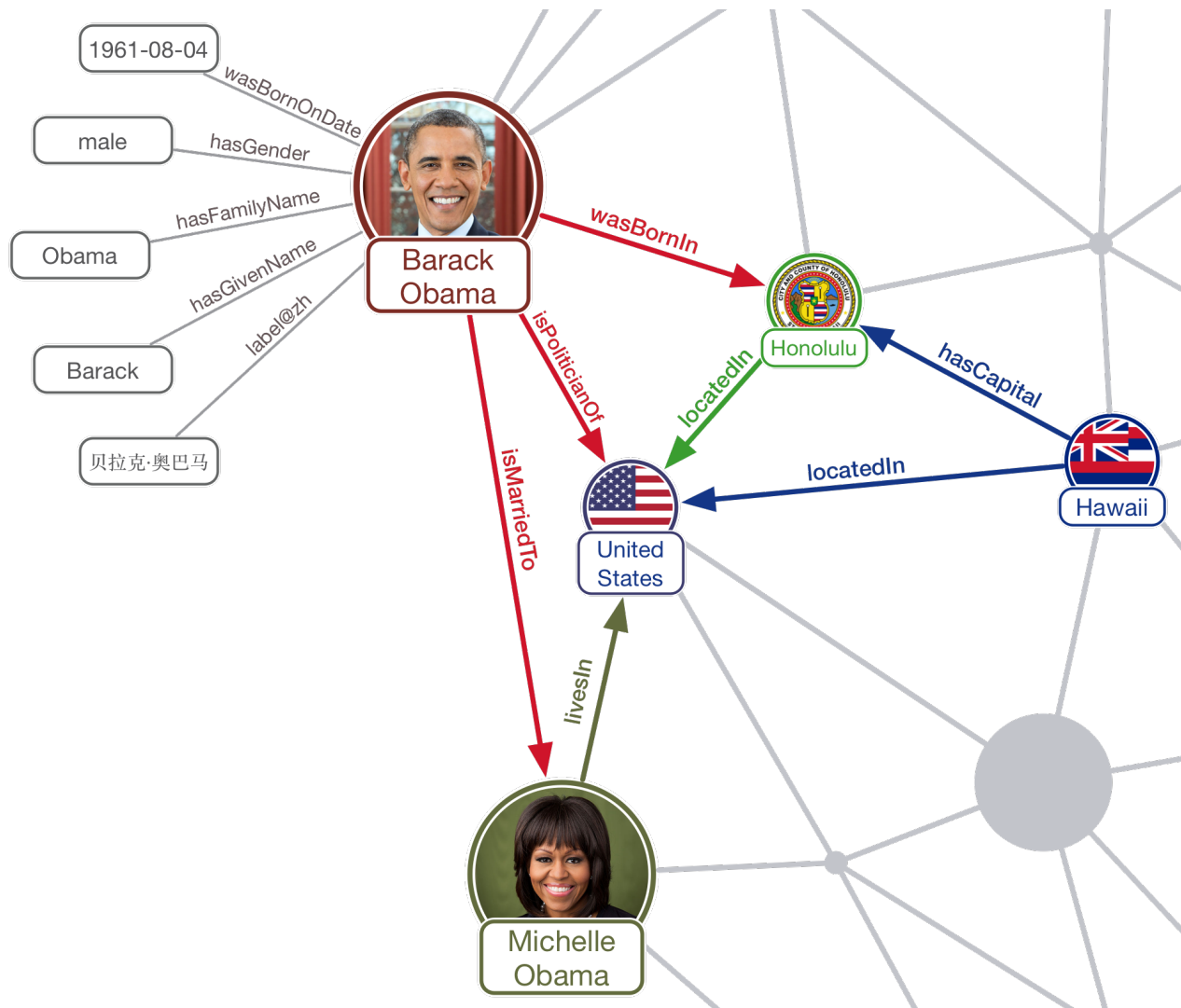
What is a Knowledge Graph?

Technically, a multi-relational directed labeled graph with semantics

Both edges and nodes have labels, but not all labels are equal (literals vs. identifiers)

Where do the semantics come from?

- Complex question, only starting to be understood



More on semantics

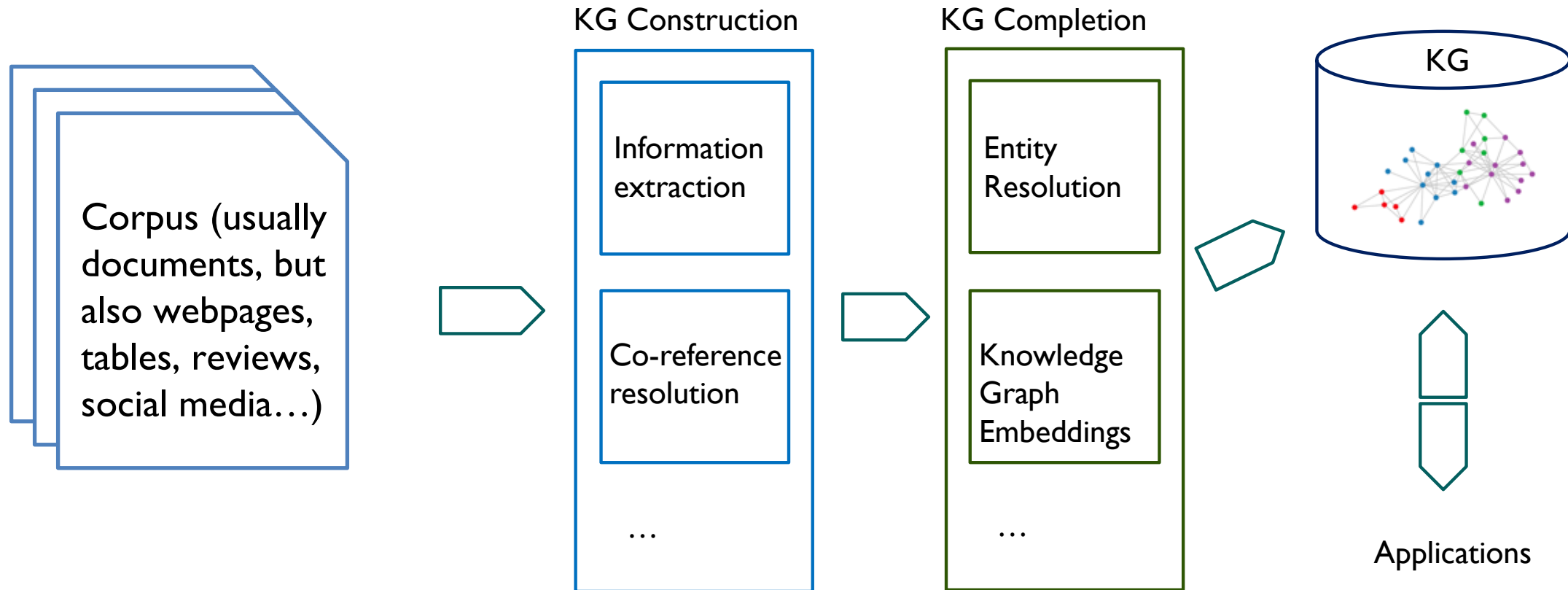
Traditionally, semantics are believed to come from ontology

- An ontology is a ‘formal, explicit specification of a shared conceptualization’ (we will go deeper into this in a while)
- In philosophy, an ontology is a ‘study of what there is’ including the study of the ‘most general features of what there is, and how the things there are relate to each other in the metaphysically most general ways’

Source: <https://plato.stanford.edu/entries/logic-ontology/>

More recently, in AI, we have started to recognize a more commonsense view of semantics guided by findings in linguistics and distributional semantics

A typical KGC workflow starts from corpus acquisition and ends with applications

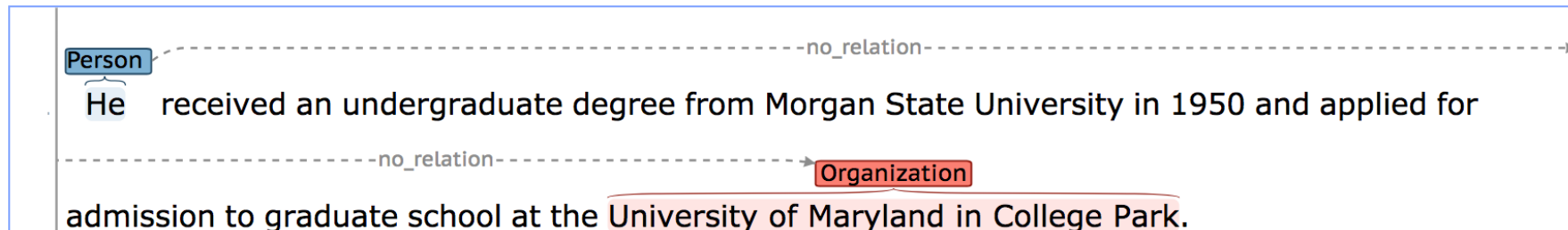
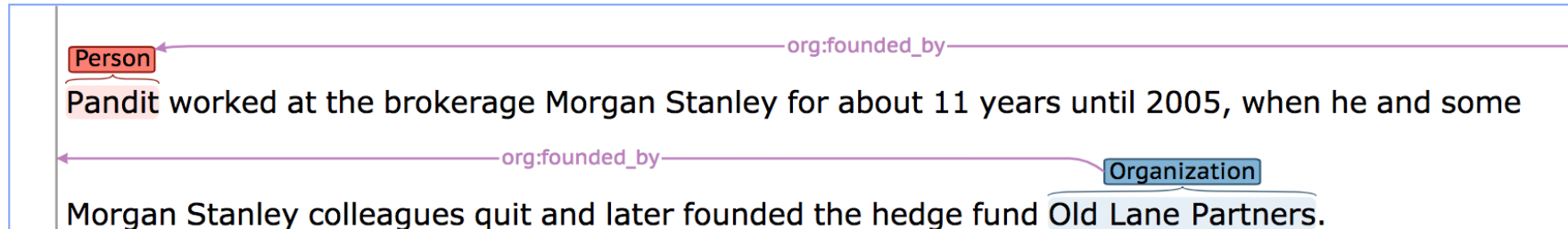
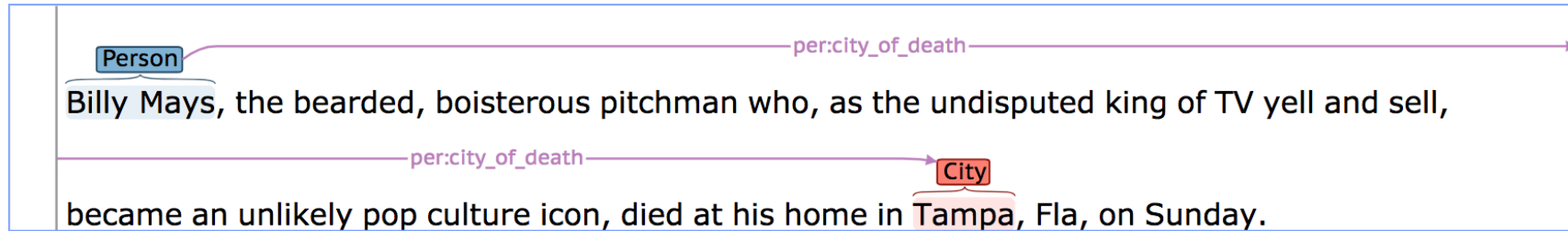


Named Entity Recognition (NER)

contentSkip to site indexPoliticsSubscribeLog InSubscribeLog InToday's PaperAdvertisementSupported **ORG** byF.B.I. Agent **Peter Strzok PERSON**,
Who Criticized Trump **PERSON** in Texts, Is FiredImagePeter Strzok, a top **F.B.I. GPE** counterintelligence agent who was taken off the special counsel
investigation after his disparaging texts about President **Trump PERSON** were uncovered, was fired. Credit**T.J. Kirkpatrick PERSON** for **The New York TimesBy Adam Goldman ORG** and **Michael S. SchmidtAug PERSON**. **13 CARDINAL**, **2018WASHINGTON CARDINAL** — **Peter Strzok PERSON**, the **F.B.I. GPE** senior counterintelligence agent who disparaged President **Trump PERSON** in inflammatory text messages and helped oversee the **Hillary Clinton PERSON** email and **Russia GPE** investigations, has been fired for violating bureau policies, Mr. **Strzok PERSON**'s lawyer said **Monday DATE**.Mr. Trump and his allies seized on the texts — exchanged during the **2016 DATE** campaign with a former **F.B.I. GPE** lawyer, **Lisa Page — in PERSON** assailing the **Russia GPE** investigation as an illegitimate “witch hunt.” Mr. **Strzok PERSON**, who rose over **20 years DATE** at the **F.B.I. GPE** to become one of its most experienced counterintelligence agents, was a key figure in **the early months DATE** of the inquiry.Along with writing the texts, Mr. **Strzok PERSON** was accused of sending a highly sensitive search warrant to his personal email account.The **F.B.I. GPE** had been under immense political pressure by Mr. **Trump PERSON** to dismiss Mr. **Strzok PERSON**, who was removed **last summer DATE** from the staff of the special counsel, **Robert S. Mueller III PERSON**. The president has repeatedly denounced Mr. **Strzok PERSON** in posts on

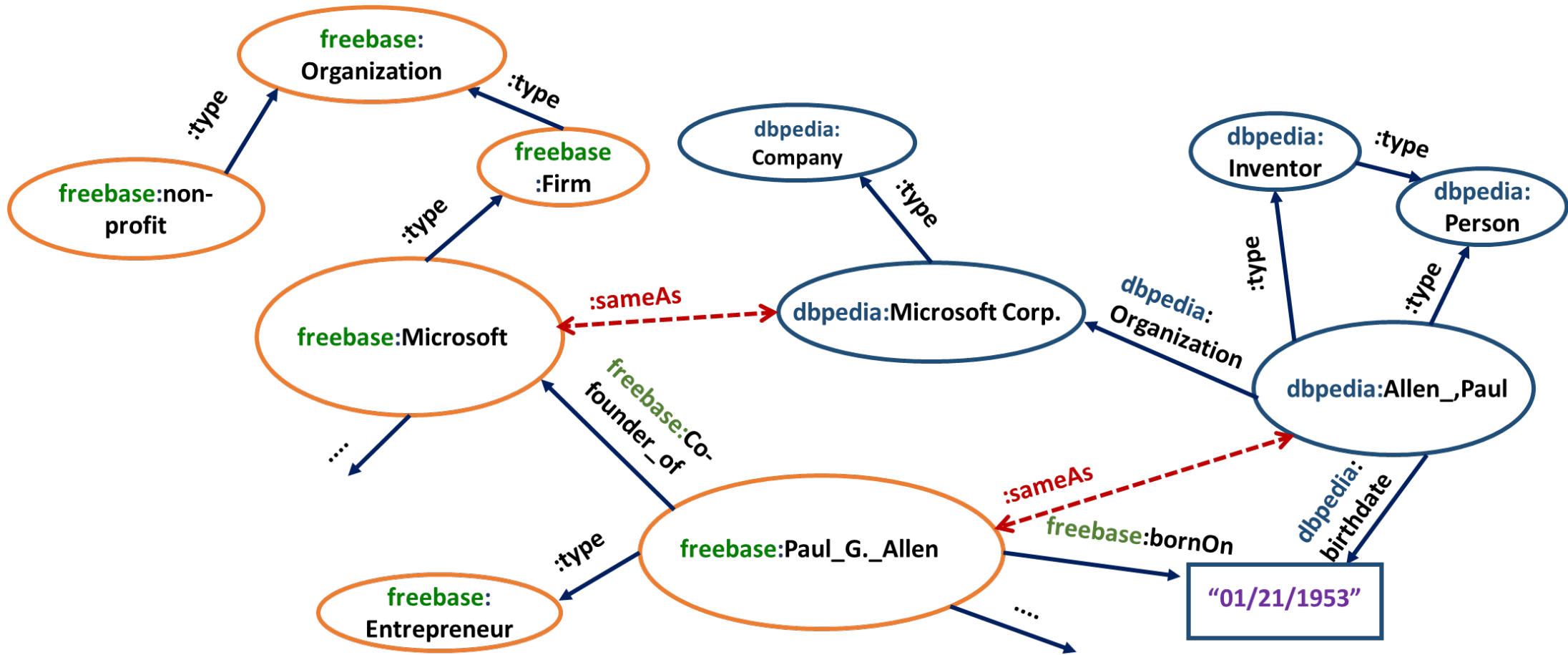
Source: Named Entity Recognition and Classification with Scikit-Learn. <https://towardsdatascience.com/named-entity-recognition-and-classification-with-scikit-learn-f05372f07ba2>

Other kinds of IE: Relation Extraction



Source: Stanford TACRED

In the world of knowledge graphs



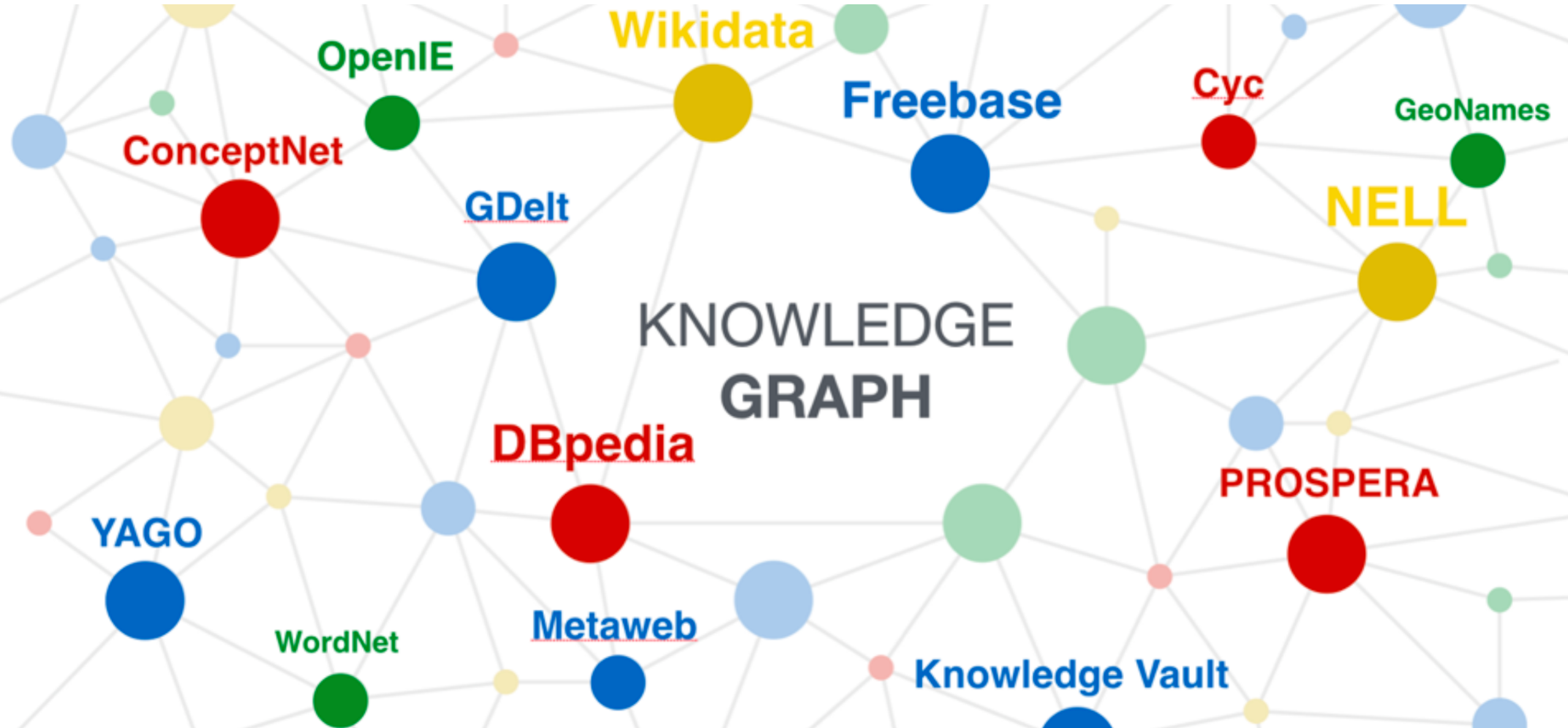
KGEs (results)

Useful resources:

- OpenKE:
<http://139.129.163.161//index/toolkits#pretrained-embeddings>
- StarSpace:
<https://github.com/facebookresearch/StarSpace>
- Recent transformer-based models could potentially be adapted, including BERT and RoBERTa:
<https://ai.facebook.com/blog/roberta-an-optimized-method-for-pretraining-self-supervised-nlp-systems/>

Method	Raw						Filtered					
	WN18			FB15k			WN18			FB15k		
	MR	H@10	MRR	MR	H@10	MRR	MR	H@10	MRR	MR	H@10	MRR
SE (Bordes et al., 2011)	1011	68.5	-	273	28.8	-	985	80.5	-	162	39.8	-
Unstructured (Bordes et al., 2012)	315	35.3	-	1074	4.5	-	304	38.2	-	979	6.3	-
SME (Bordes et al., 2012)	545	65.1	-	274	30.7	-	533	74.1	-	154	40.8	-
TransH (Wang et al., 2014)	401	73.0	-	212	45.7	-	303	86.7	-	87	64.4	-
TransR (Lin et al., 2015b)	238	79.8	-	198	48.2	-	225	92.0	-	77	68.7	-
CTransR (Lin et al., 2015b)	231	79.4	-	199	48.4	-	218	92.3	-	75	70.2	-
KG2E (He et al., 2015)	342	80.2	-	174	48.9	-	331	92.8	-	59	74.0	-
TransD (Ji et al., 2015)	224	79.6	-	194	53.4	-	212	92.2	-	91	77.3	-
lppTransD (Yoon et al., 2016)	283	80.5	-	195	53.0	-	270	94.3	-	78	78.7	-
TranSparse (Ji et al., 2016)	223	80.1	-	187	53.5	-	211	93.2	-	82	79.5	-
TATEC (García-Durán et al., 2016)	-	-	-	-	-	-	-	-	-	58	76.7	-
NTN (Socher et al., 2013)	-	-	-	-	-	-	-	66.1	0.53	-	41.4	0.25
DISTMULT (Yang et al., 2015)	-	-	-	-	-	-	-	94.2	0.83	-	57.7	0.35
Complex (Trouillon et al., 2016)	-	-	0.587	-	-	0.242	-	94.7	0.941	-	84.0	0.692
HolE (Nickel et al., 2016b)	-	-	0.616	-	-	0.232	-	94.9	0.938	-	73.9	0.524
RESCAL (Nickel et al., 2011) [*]	-	-	0.603	-	-	0.189	-	92.8	0.890	-	58.7	0.354
TransE (Bordes et al., 2013) [*]	-	-	0.351	-	-	0.222	-	94.3	0.495	-	74.9	0.463
STransE (Nguyen et al., 2016b)	217	80.9	0.469	219	51.6	0.252	206	93.4	0.657	69	79.7	0.543
RTransE (García-Durán et al., 2015)	-	-	-	-	-	-	-	-	-	50	76.2	-
PTransE (Lin et al., 2015a)	-	-	-	207	51.4	-	-	-	-	58	84.6	-
GAKE (Feng et al., 2016b)	-	-	-	228	44.5	-	-	-	-	119	64.8	-
Gaifman (Niepert, 2016)	-	-	-	-	-	-	352	93.9	-	75	84.2	-
Hiri (Liu et al., 2016)	-	-	-	-	-	-	-	90.8	0.691	-	70.3	0.603
NLFeat (Toutanova and Chen, 2015)	-	-	-	-	-	-	-	94.3	0.940	-	87.0	0.822
TEKE.H (Wang and Li, 2016)	127	80.3	-	212	51.2	-	114	92.9	-	108	73.0	-
SSP (Xiao et al., 2017)	168	81.2	-	163	57.2	-	156	93.2	-	82	79.0	-

Open-source KGs that have been built



Many applications and open research areas!

Information retrieval

Semantic Web

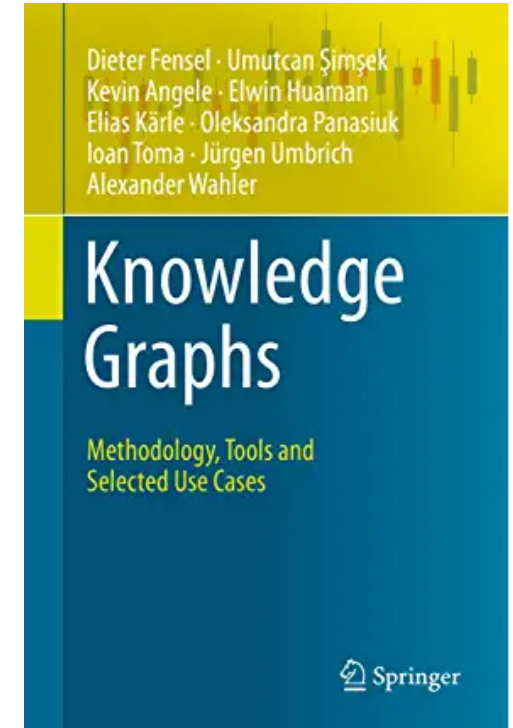
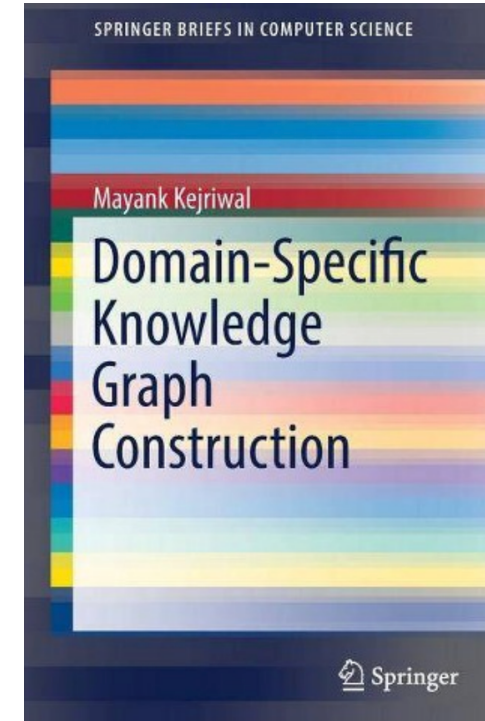
Recommender systems

Knowledge discovery/data mining

?

Numerous surveys, some more technical/field-specific

- Ehrlinger, L., & Wöß, W. (2016). Towards a Definition of Knowledge Graphs. *SEMANTiCS (Posters, Demos, SuCCESS)*, 48, 1-4
- Noy, N., Gao, Y., Jain, A., Narayanan, A., Patterson, A., & Taylor, J. (2019). Industry-scale knowledge graphs: lessons and challenges. *Queue*, 17(2), 48-75
- Nickel, M., Murphy, K., Tresp, V., & Gabrilovich, E. (2015). A review of relational machine learning for knowledge graphs. *Proceedings of the IEEE*, 104(1), 11-33.
- Ji, S., Pan, S., Cambria, E., Marttinen, P., & Yu, P. S. (2020). A survey on knowledge graphs: Representation, acquisition and applications. *arXiv preprint arXiv:2002.00388*.
- Paulheim, H. (2017). Knowledge graph refinement: A survey of approaches and evaluation methods. *Semantic web*, 8(3), 489-508.



Upcoming:

Knowledge Graphs: Fundamentals, Techniques, and Applications (Adaptive Computation and Machine Learning series). *Kejriwal, Knoblock and Szekely*.



Center on Knowledge Graphs

Information Sciences Institute



Q & A

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