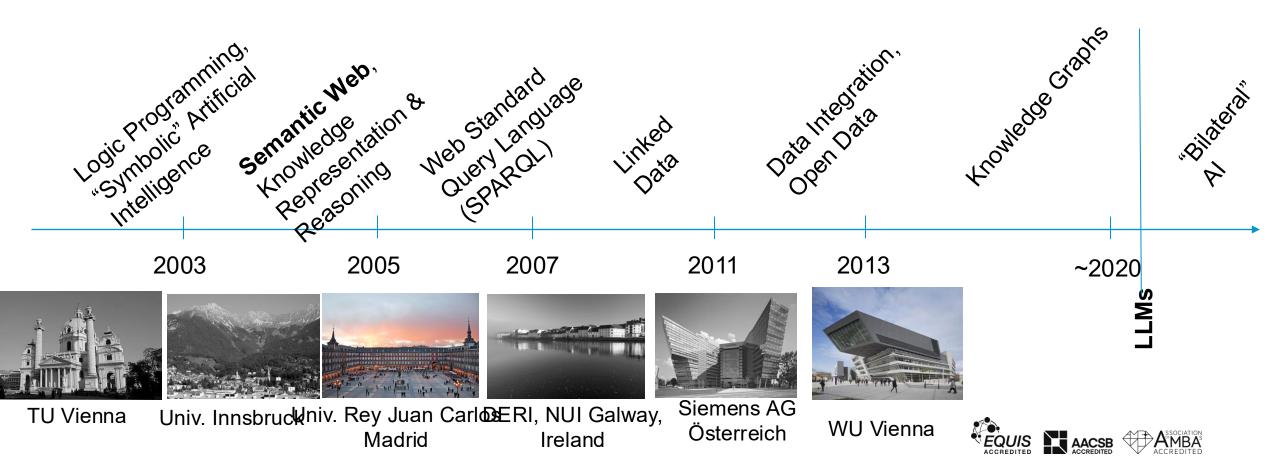


My background...





Instead of its initial focus on agents the "Semantic Web"...



A new form of Web content that is meaningful to computers will unleash a revolution of new possibilities by TIM BERNERS-LEE, JAMES HENDLER and ORA LASSILA

The entertainment system was belting out the Beatles' "We Can Work It Out" when the phone rang. When Pete answered, his phone turned the sound down by sending a message to all the other *local* devices that had a *volume control*. His sister, Lucy, was on the line from the doctor's office: "Mom needs to see a specialist and then has to have a series of physical therapy

Lucy, was on the mention the doctors office. Informaticus to see a specialist and then has to have a series of physical incrapy sessions. Biweekly or something. I'm going to have my agent set up the appointments." Pete immediately agreed to share the chauffeuring. At the annel the going to have my agent set up the appointments. Fere immediately agreed to share the chaumening. At a doctor's office, Lucy instructed her Semantic Web agent through her handheld Web browser. The agent promptly ation about Mom's prescribed treatment from the doctor's agent, looked up several lists of providers. and or very good on trusted rating services. It then began trying to find a match between available appointment nes (supplied by the agents of individual providers through their Web sites) and Pete's and Lucy's busy schedules.

In a few minutes the agent presented them with a plan. Pete didn't like it—University Hospital was all the way across The revenience are agent presented mein with a pian, rece usun tince it—conversity prospital was at the way across town from Mom's place, and he'd be driving back in the middle of rush hour. He set his own agent to redo the search with stricter preferences about location and time. Lucy's agent, having complete trust in Pete's agent in the context of the present task,

"[...] The **agent** promptly

retrieved information about Mom's prescribed treatment from the doctor's agent, looked up several lists of providers,

and checked for the ones in-plan for Mom's insurance within a 20-mile radius of her home and with a rating of excellent or very good on trusted rating services[...]"

- Appointment detection in emails
- Semantic Search
- Ratings of products/services

... has then mostly become the basis for the "Web of Data"...

"If HTML and the Web made all the online documents look like one huge **book**, RDF, schema and inference languages will make all the data in the world look like one huge database"

Tim Berners-Lee, Weaving the Web, 1999

... and its more recent focus on Open Knowledge Graphs...

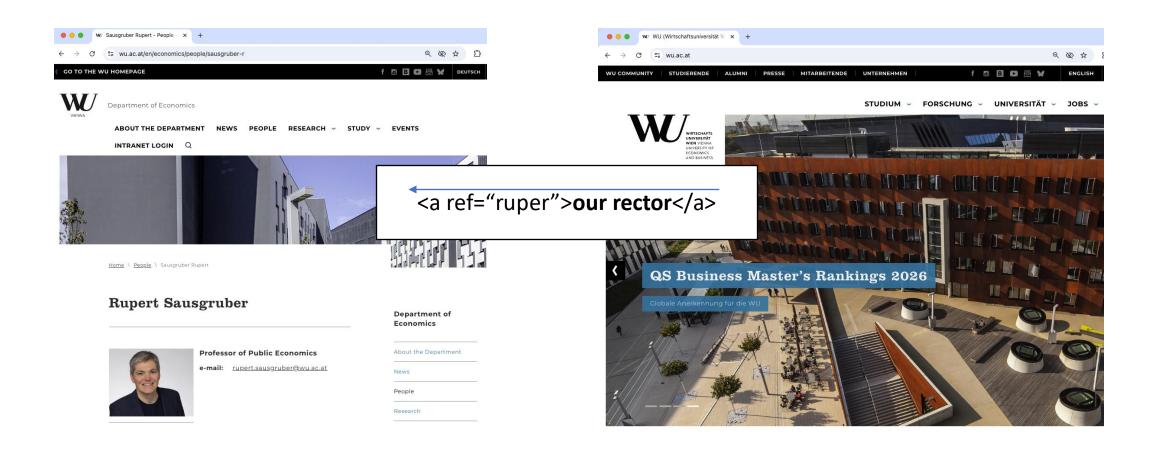
" huge knowledge bases, also known as **knowledge graphs**, have been automatically constructed from web data, and have become a key asset for search engines and other use cases.

Gerhard Weikum, Knowledge Graphs 2021: A Data Odyssey, VDLB 2021



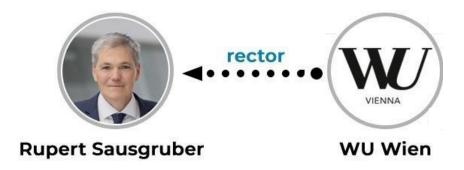
Phase 1: RDF – Linked "Metadata"

• "Typed links" describing Ressources (such as Web pages)



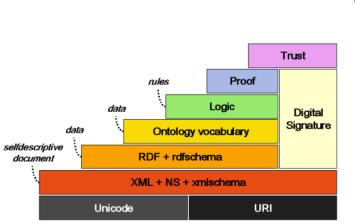
Phase 1: RDF (Ressource Description framework) — Linked "Metadata"

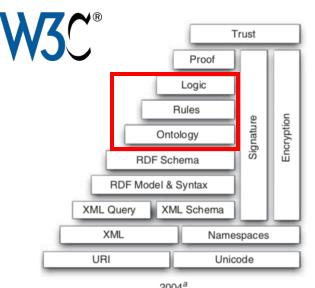
Typed links "triples" describing Ressources (such as Web pages)

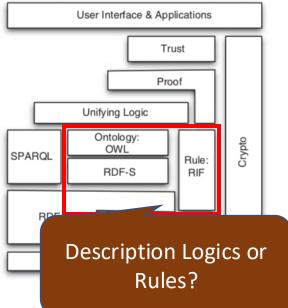


Semantic Web: <u>Standard</u> formats, Reasoning & Logics

• (2000s - ca. 2009)



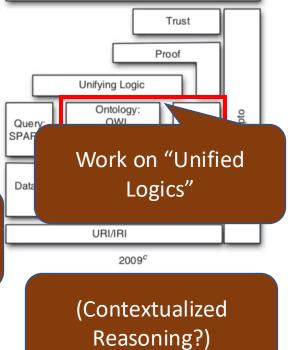




ahttp://www.w3.org/2004/Talks/0319-RDF-WGs/sw_stack. bhttp://www.w3.org/2007/Talks/0130-sb-W3CTechSemWeb/layerCake-4.png

Good news! **Standards** meant a Boost in **KR/AI** research: We know very well which ontological reasoning approaches are decidable and how they scale

→ RDF, OWL, SPARQL Ontology-based Data Access but also: constraint checking (SHACL)



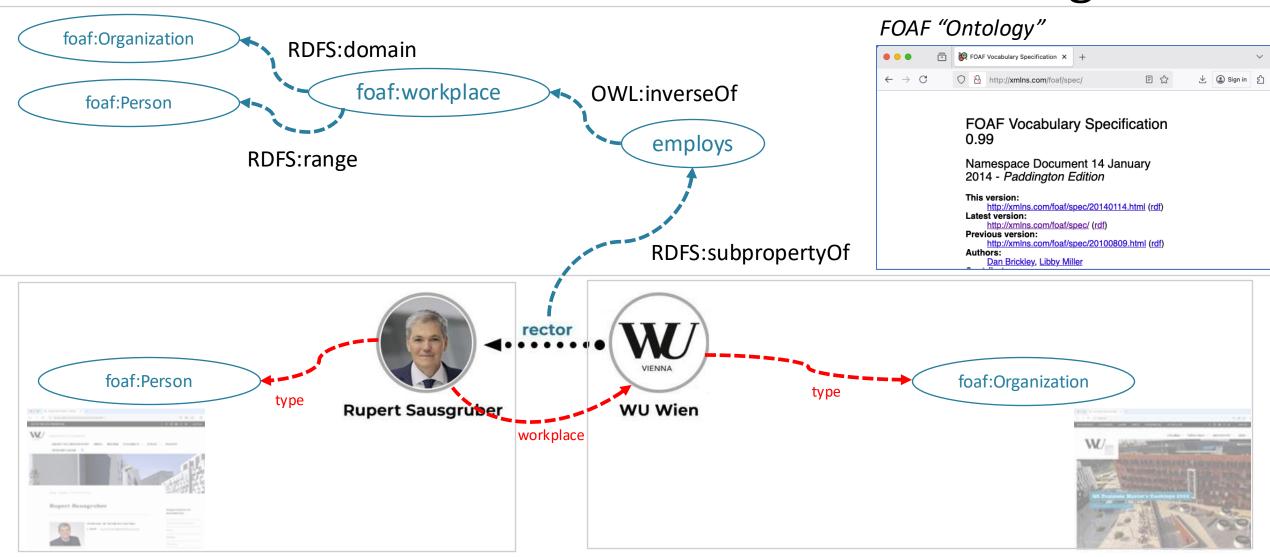
User Interface & Applications

-

x, John-Jules Meyer, and Axel Polleres. Norms, Engineering Review, 28(1):107--116, March 2013.

Phase 2: RDF, RDF Schema, OWL ?P foaf:WorkPlace wu:WUWien. } Linked "Metadata" with Rules and Ontologies.

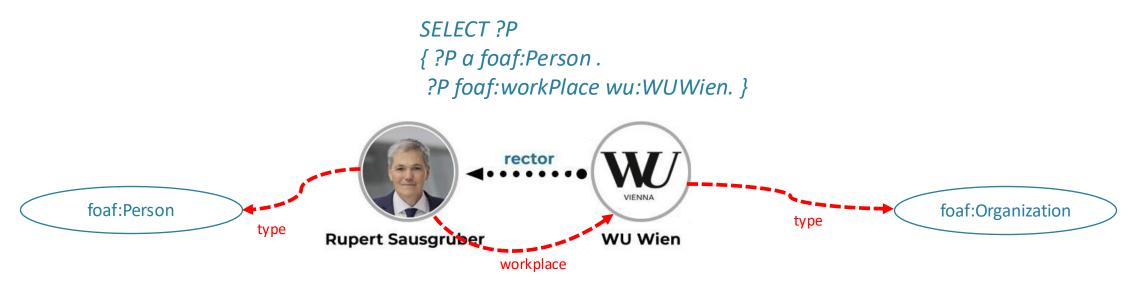
SELECT ?P



Phase 2: RDF, RDF Schema, OWL, *SPARQL* Linked "Metadata" with Rules and Ontologies.

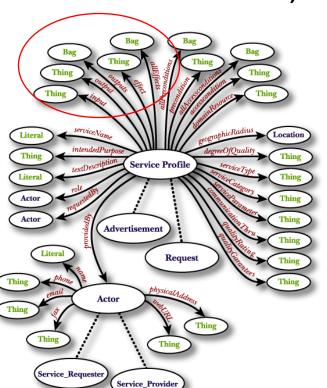
"If HTML and the Web made all the online documents look like one huge **book**, RDF, schema and inference languages will make all the data in the world look like **one huge database**"

Tim Berners-Lee, Weaving the Web, 1999



Phase 2 "interlude"

• Semantic Web Services: We cannot only describe Websites and Metadata, but also Services and APIs! (~2002-2007)



Main Idea:

Describing Services & Agents in a declarative manner

using ontologies...

• ... should enable automated composition, execution

composition by purely symbolic inference ... was time...

On hindsight: automated maybe maybe ahead of its

Mark H. Burstein, Jerry R. Hobbs, Ora Lassila, David L. Martin, Drew V. McDermott, Sheila A. McIlraith, Srini Narayanan, Massimo Paolucci, Terry R. Payne, Katia P. Sycara: DAML-S: Web Service Description for the Semantic Web. ISWC 2002: 348-363

Dumitru Roman, Uwe Keller, Holger Lausen, Jos de Bruijn, Rubén Lara, Michael Stollberg, Axel Polleres, Cristina Feier, Christoph Bussler, **Dieter Fensel**: Web Service Modeling Ontology. Appl. Ontology 1(1): 77-106 (2005)

Focus on Data: Linked Data

- (ca. 2006/7 ca. 2013)
 - Main question: How can I **publish** "Knowledge on the Web" ...



Linked Data Principles

- LDP1: use URIs as names for things
- LDP2: use HTTP URIs so those names can be dereferenced
- LDP3: return useful RDF? information upon dereferencing those URIs
- LDP4: include links using externally dereferenceable URIs.

https://www.w3.org/DesignIssues/LinkedData.html (originally published 2006-07-27)



"A Little Semantics Goes a Long Way" (Jim Hendler)

https://www.cs.rpi.edu/~hendler/LittleSemanticsWeb.html

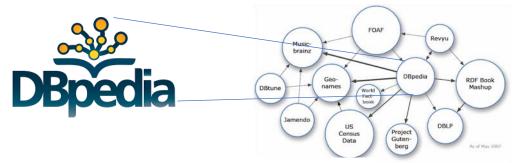


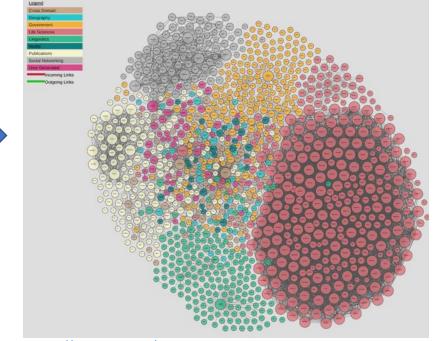
11



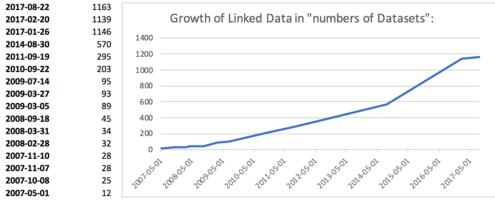
Phase3: From Semantic Web to Linked (Open) Data

- (ca. 2006/7 2012)
 - Main question: How can I publish "Knowledge on the Web" ...
 - Linked **Open** Data... growth slowed down a bit
 - A lot of active developments to publish and link RDF Data
 - also in Enterprises ("Enterprise Linked Data")





http://lod-cloud.net/



Axel Polleres, Maulik R. Kamdar, Javier D. Fernández, Tania Tudorache, and Mark A. Musen. <u>A more decentralized vision for linked data</u>. In *Decentralizing the Semantic Web (Workshop of ISWC2018)*.

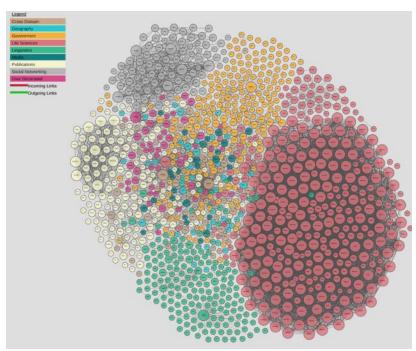


Phase3: From Semantic Web to Linked (Open) Data

- (ca. 2006/7 2013)
 - Main question: How can I publish "Knowledge on the Web" ...
 - Side question(s):

Can deductive symbolic inference and queries scale to a

Reasoning Web. Semantic Technologies for Intelligent Data Access (Reasoning Web 2013) decentralized RDFS & OWL Reasoning for Linked Data International Semantic Web Conference (2014) Web? Strategies for executing federated queries in Axel Polleres¹, Aidan Hogan², Renaud Delbru², and Jürgen Umbrich^{2,3} ¹ Siemens AG Österreich, Siemensstraße 90, 1210 Vienna, Austria Digital Enterprise Research Institute, National University of Ireland, Galway Carlos Buil-Aranda^{1*}, Axel Polleres^{2**}, and Jürgen Umbrich² ³ Fujitsu (Ireland) Limited, Swords, Co. Dublin, Ireland 1 Department of Computer Science, Pontificia Universidad Católica, Chile stract. Linked Data promises that a large portion of Web Data will sable as one big interlinked RDF database against which structured s can be answered. In this lecture we will show how reasoning -DF Schema (RDFS) and the Web Ontology Language (OWL) to obtain more complete answers for such queries over Linked way for exposing RDF data on the Web is by means (first look at the extent to which RDFS and OWL features are or exposing KUF units on une view is my insented the ed on the Web. We then introduce two high-level architecwaves and approvations to query just me ty answering over Linked Data and outline how these can outer returned per query or the

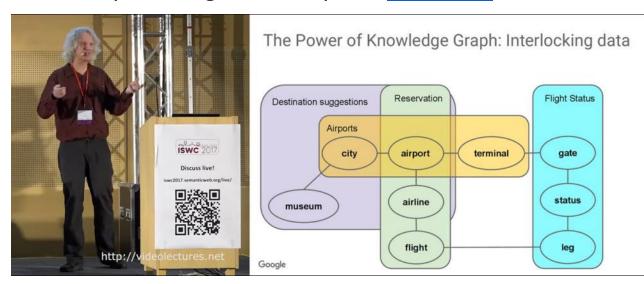


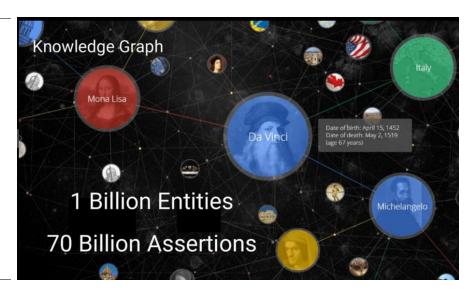
From Linked Open Data to Knowledge Graphs:



2013: Google adopts Semantic Web ideas under a new name

Jamie Taylor, Google, Inc., Keynote <u>ISWC2017</u>





- Actors, Directors, Movies
- Art Works & Museums
- Cities & Countries
- Islands, Lakes, Lighthouses

- Music Albums & Music Groups
- Planets & Spacecraft
- Roller Coasters & Skyscrapers
- Sports Teams

[...]

From Linked Open Data to Knowledge Graphs:

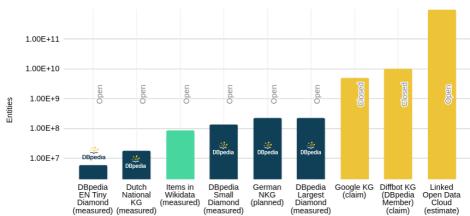
Success stories of mainly monolithic (but huge) Knowledge Graphs rather than a network of Linked small KGs:

Tencent 腾讯

https://www.slideshare.net/Frank.van.Harmelen/adoption-of-knowledge-graphs-late-2019

Google

> Bing



https://www.dbpedia.org 2021

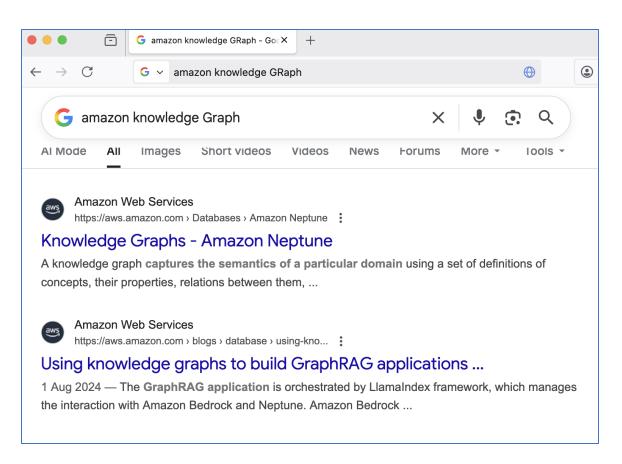


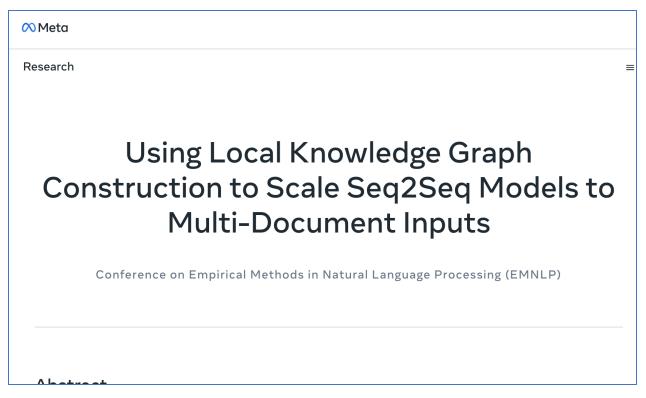




It's not only Search – Oviously... User Recommendation, Language Technologies, ...

Sice then, industry has become a main driver in scaling and using KG Technologies...





Collaborative, Open Knowledge Graphs:

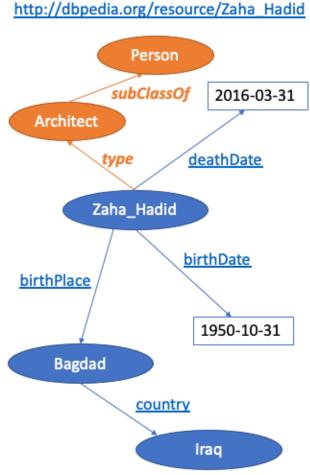


DBpedia generates a graph from links and facts in Wikipedia's Infoboxes:

http://wikipedia.org/wiki/Zaha Hadid





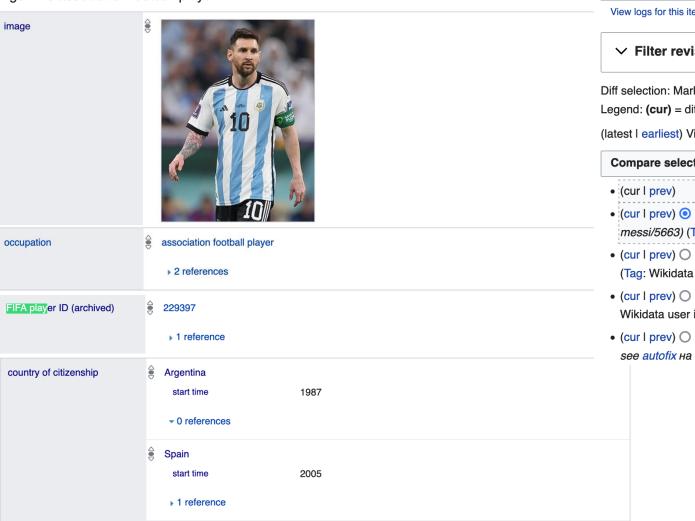


Collaborative, Open Knowledge Graphs:

WIKIDATA

Lionel Messi (Q615)

Argentine association football player



Revision history of "Lionel Messi" (Q615)

Wikidata user interface, Mobile termbox)

see autofix на / on Property talk:P12924)

23:45, 29 November 2024 Mickey Đại Phát (talk I contribs) . . (536,860 bytes) (-

19:47, 27 November 2024 KrBot (talk I contribs) . . (536,877 bytes) (-14) . . (Se

From Linked Open Data to Knowledge Graphs: What's the state of affairs?

- Jamie Large-scale, still data-focused (rather than schema-focused)
 - Often monolithic, rather than linked/decentralised
 - Knowledge extraction rather than Knowledge engineering
 - Collaborative large-scale KGs:
 - Collectively created (automated or curated)
 - Notoriously incomplete
 - (Logical) consistency not a must
- Enterprise KGs: knowledge necessary to power applications
- Ontological expressivity not central BUT: Expressing context is!

Islands, Lakes, Lighthouses

Sports Teams

For instance:

- Provenance
- Temporal context

Let's have a look at practical examples of such collaboratively curated Knowledge Graphs:

DBPedia (since 2007)

VS.

Wikidata (since 2012)

DBpedia



Leipzig University Developer(s)

University of Mannheim

Initial release 10 January 2007 (17 years

ago)

Stable release DBpedia 2016-10 / 4 July 2017

Repository

github.com/dbpedia/ 2 6

Written in Scala Java

Semantic Web - Linked Data Type

GNU General Public License License

dbpedia.org 🗗 🖍 Website

RDF

Standard ontology language (OWL)

SPARQL endpoint

Consistent

Context

Wikidata



Wikimedia Foundation Owner

Editor Wikimedia community

URL www.wikidata.org/wiki

/Wikidata:Main Page 🗹 💣

Commercial No.

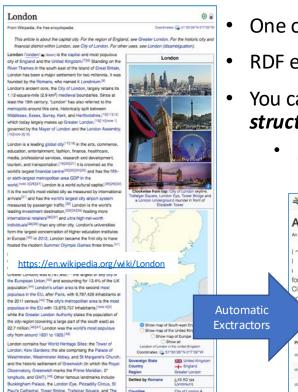
Registration Optional

29 October 2012; 12 years ago[1] Launched

SPARQL: Using KGs to answer questions:

• E.g. from





- One of the central datasets of the Linked Open Data-Cloud
- RDF extracted from Wikipedia-Infoboxes
- You can use a language called SPARQL endpoint (roughly: SQL for RDF) to do structured queries over RDF:
 - "Cities in the UK with more than 1M population":



Structured queries (SPARQL):

https://api.triplydb.com/s/gZZskqRpQ

```
PREFIX: <a href="http://dbpedia.org/resource/">http://dbpedia.org/ontology/</a>
PREFIX dbo: <a href="http://dbpedia.org/class/yago/">http://dbpedia.org/class/yago/</a>

SELECT DISTINCT ?city ?pop WHERE {
    ?city a schema:City .
    ?city dbo:country :United_Kingdom.
    ?city dbo:populationTotal ?pop

FILTER ( ?pop > 10000000 )
}
```

Shard, London is home to numerous museums, calleries.

Renaries, sporting events, and other cultural institutions, including the British Museum, National Gallery, Natural History Museum, Tate Modern, British Library, and West End theatres, 190 The London Underground is the oldest

Knowledge Graphs like Dbpedia are not logically consistent! (3)



Dbpedia Ontology:

dbo:Agent owl:disjointWith dbo:Place.

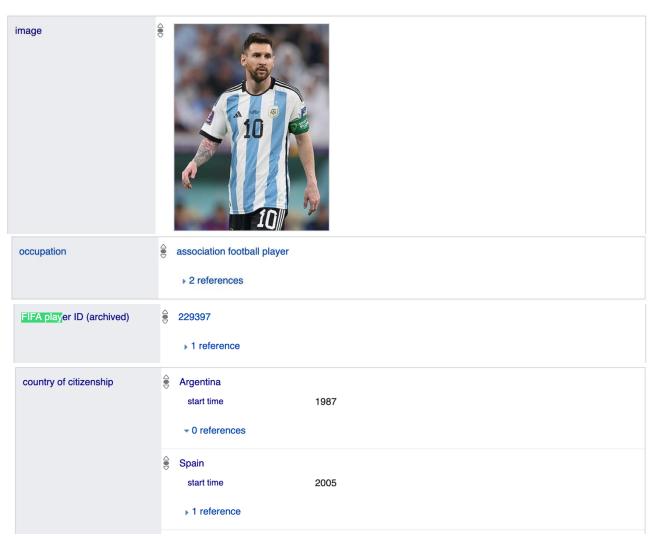
dbo:Country rdfs:subClassOf dbo:Place.

dbo:Organisation rdfs:subClassOf dbo:Agent.



1. Stefan Bischof, Markus Krötzsch, Axel Polleres, and Sebastian Rudolph. Schema-agnostic query rewriting in SPARQL 1.1. In *Proceedings of the 13th International Semantic Web Conference (ISWC 2014)*, Lecture Notes in Computer Science (LNCS). Springer, October 2014. [.pdf]

Wikidata is also not "consistent", but doesn't use OWL



The same question as before in Wikidata:

Note: Wikidata does not even use standard OWL

"Simple" surface <u>query</u>:

Which cities in the UK have more than 1M people?

```
SELECT DISTINCT ?city WHERE {
      ?city wdt:P31/wdt:P279* wd:Q515.
      ?city wdt:P1082 ?population .
      ?city wdt:P17 wd:Q38 .
      FILTER (?population > 1000000) }
```

instance of (P31)

that class of which this subject is a particular example and member. (Subject typically an individual member with Proper Name label.) Different from P279 (subclass of). subclass of (P279)

all instances of these items are instances of those items; this item is a class (subset) of that item. Not to be confused with Property:P31 (instance of).

Note: Wikidata uses numeric IDs

city (Q515)

large and permanent human settlement

population (P1082)

number of people inhabiting the place; number of people of subject

country (P17) sovereign state of this item

United Kingdom (Q145) country in Europe

What's this?

The same question as before in Wikidata:

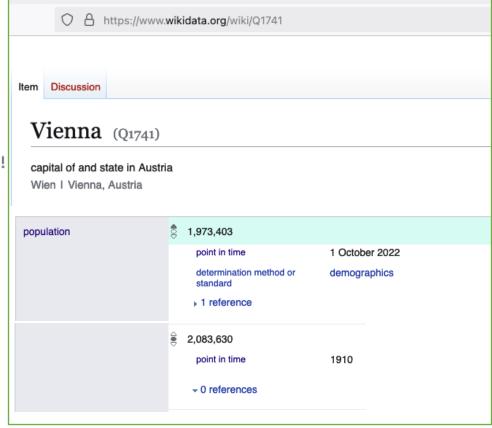
https://w.wiki/BqRX

Which cities in the Austria have more than 1M/2M people?

Note: Wikidata also has such contextual information!!!!

```
SELECT DISTINCT ?City ?Pop
{
    ?City wdt:P17 wd:Q40;
        wdt:P31/wdt:P279* wd:Q515;
        wdt:P1082 ?Pop.
FILTER (?Pop > 1000000)
# note: Vienna historically had more than 2M inhabitants!
# FILTER (?Pop > 2000000)
}
```

So, WHEN did Vienna have 2M inhabitants?



The same question as before in Wikidata:

https://w.wiki/BqRj

Which cities in the Austria have more than 1M/2M people?

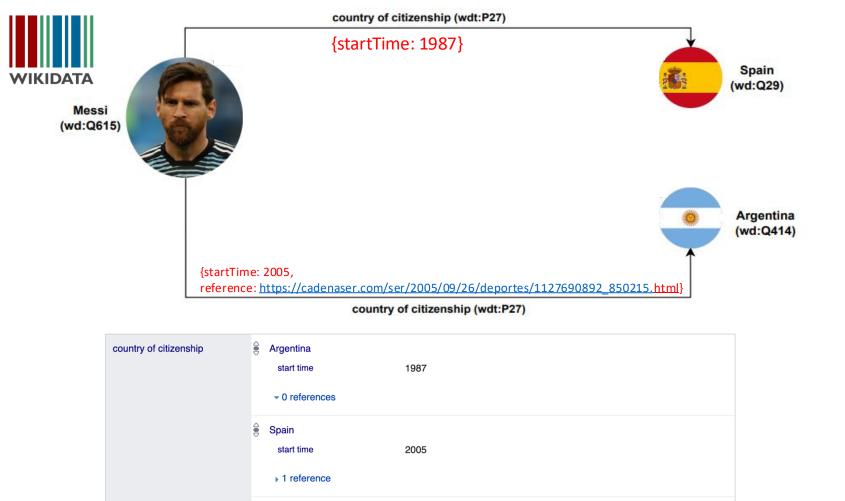
```
SELECT DISTINCT ?City ?Pop ?Timepoint
{
    ?City wdt:P17 wd:Q40;
        wdt:P31/wdt:P279* wd:Q515;
        p:P1082 ?Stmnt.
    ?Stmnt ps:P1082 ?Pop;
        pq:P585 ?Timepoint.
# FILTER (?Pop > 1000000)
# note: Vienna historically had more than 2M inhabitants!
FILTER (?Pop > 2000000)
}
```

So, WHEN did Vienna have 2M inhabitants? Works!!!!

But needs an understanding of Wikidata's proprietary RDF reification model to model context!

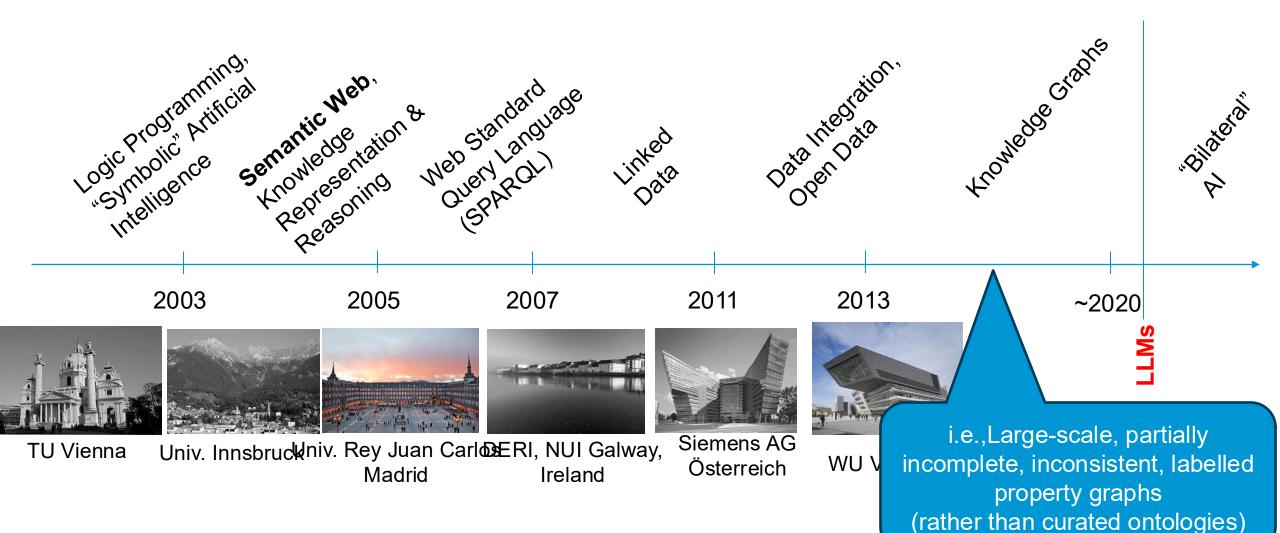
Phase 4: Knowledge Graphs: "(Less Linked) Graph data with Metadata"

• Aka Labelled property graphs



So, what are these KGs actually good for in the age of LLMs

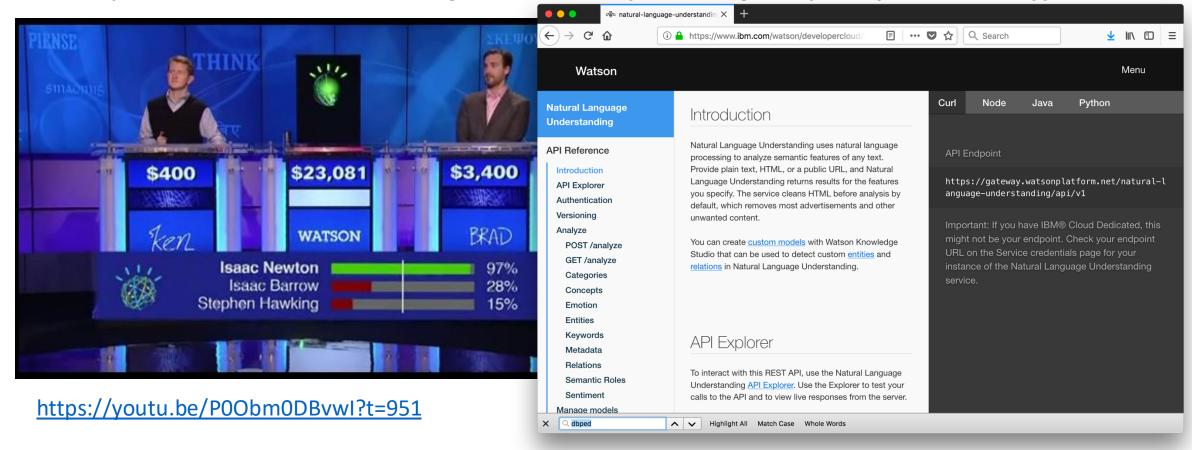




So, for what are these KGs actually good for in the age of LLMs and AI?

Interesting Note - IBM Watson - Jeopardy! (2011)

"Super-human" Question Answering was achieved by Knowledge Graphs before the LLM hype!





- How good or bad can KGs deal with Question answering?
 - By essentially translating Questions to SPARQL queries (Watson)?
 - By other beskpoke techniques such as Message passing:

Svitlana Vakulenko, Javier Fernández, Axel Polleres, Maarten de Rijke, and Michael Cochez. Message passing for complex question answering over knowledge graphs. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management (CIKM2019, pages 1431-1440, Beijing, China, November 2019. ACM.

Idea: use unsupervised message passing to propagate confidence scores obtained by parsing an input question and matching terms in the knowledge graph to a set of possible answers.

2nd hop 1st hop (a) Q: Which hardtop company assembles style cars Broadmeadows, Victoria? C_1^1 dbo:company 1 dbo:assembly 0.9 dbr:Hardtop 1 dbo:Automobile 1 dbr:Broadmeadows, Victoria 0.9 dbp:companyLogo 0.8 • dbp:assembly 0.9 dbr:Car 1 dbo:bodyStyle 0.5 dbo:parentCompany 0.8 (b) dbr:Hardtop dbo:Automobile dbr:Broadmeadows,_Victoria dbo:bodyStyle rdftvpe dbp:assembl dbo:parentCompany dbr:Ford_Falcon_Cobra dbr:Ford_Motor_Company

Figure 1: (a) A sample question Q highlighting different components of the question interpretation model: references and matched URIs with the corresponding confidence scores, along with (b) the illustration of a sample KG subgraph relevant to this question. The URIs in bold are the correct matches corresponding to the KG subgraph.

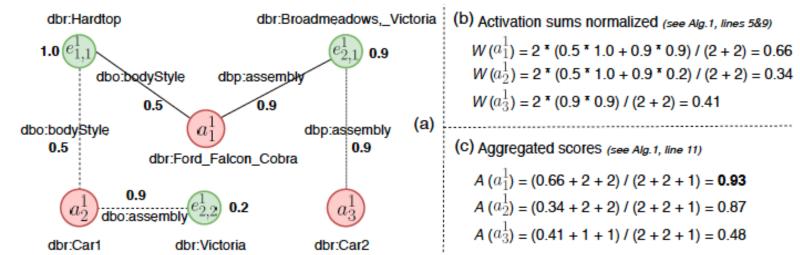


Figure 2: (a) A sample subgraph with three entities as candidate answers, (b) their scores after predicate and entity propagation, and (c) the final aggregated score.

Explanbility "for free"

Some of our own research in this area:

- How good or bad can KGs deal with Question answering?
 - By essentially translating Questions to SPARQL queries (Watson)?
 - By other beskpoke techniques such as Message passing:

Svitlana Vakulenko, Javier Fernández, Axel Polleres, Maarten de Rijke, and Michael Cochez. Message passing for complex question answering over knowledge graphs. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management (CIKM2019, pages 1431--1440, Beijing, China, November 2019. ACM.

How good or bad are LLMs with Question answering compared with KGs?

Gerhard Georg Klager and Axel Polleres. Is GPT fit for KGQA? -- preliminary results. In Proceedings of the International Workshop on Knowledge Graph Generation from Text (Text2KG2023), co-located with Extended Semantic Web Conference 2023 (ESWC 2023), May 2023.

Admittedly things have improved dramatically, since then!

So, for what are these KGs actually good for in the age of LLMs and AI?

No city in Austria has more than 2 million inhabitants. Austria's capital and largest city, Vienna (Wien), has a population of approximately 1.9 million people as of recent estimates. It is the only city in Austria with a population exceeding 1 million. Other cities, such as Graz, Linz, and Salzburg, have much smaller populations, typically below 300,000.

If you're interested in any specific details about Austrian cities, feel free to ask!

Did Vienna ever have more than 2M inhabitants?

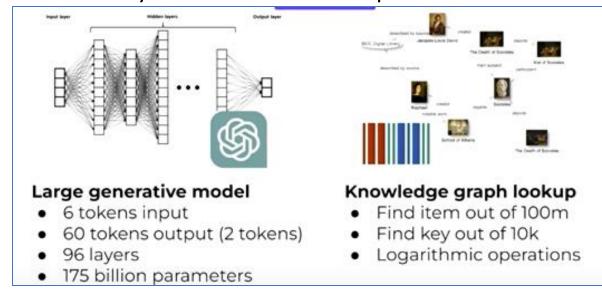
Which cities in Austria have more than 2M inhabitants?

Yes, Vienna once had a population exceeding 2 million. During the early 20th century, particularly around the year 1910, Vienna's population peaked at approximately 2.1 million people. This was during the Austro-Hungarian Empire, when Vienna was a major imperial capital and one of the largest cities in Europe. After World War I and the dissolution of the Austro-Hungarian Empire in 1918, Vienna's population began to decline. This was due to several factors, including changes in national borders, economic challenges, and shifts in urbanization trends. The city's population has been growing again in recent decades but has not yet surpassed 2 million.

今日日日日日日

For instance:

- Explainable answers, fact-checking against hallucinating
- Potentially less resource consumption!

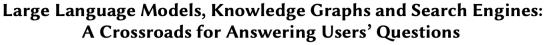


 KGC23 Keynote: "The Future of Knowledge Graphs in a V LLMs — Denny Vrandečić, Wikimedia"

https://www.youtube.com/watch?v=ww99npDh4cg

What's good for what? LLMs, Search Engines, KGs







Denny Vrandečić denny@wikimedia.org Wikimedia Foundation San Francisco, California, USA Xin Luna Dong lunadong@meta.com Meta Reality Labs Redmond, Washington, USA

Gerhard Weikum weikum@mpi-inf.mpg.de Max Planck Institute for Informatics Saarbrücken, Germany



SEARCH ENGINES ASSUME BOTH HUMANS AND MACHINES ARE STUPID

: WIDELY USED AND WIDELY USEFUL





KNOWLEDGE GRAPHS ASSUME MACHINES ARE STUPID AND HUMANS SMART

∴ BARELY USED AND BARELY USEFUL



LARGE LANGUAGE MODELS ASSUME MACHINES ARE SMART AND HUMANS STUPID

∴ WIDELY USED AND BARELY USEFUL



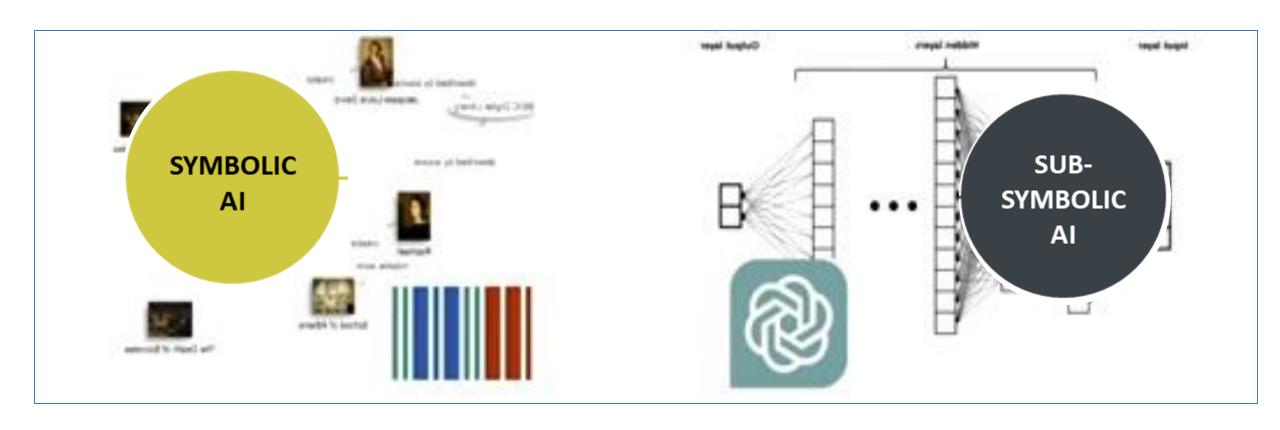






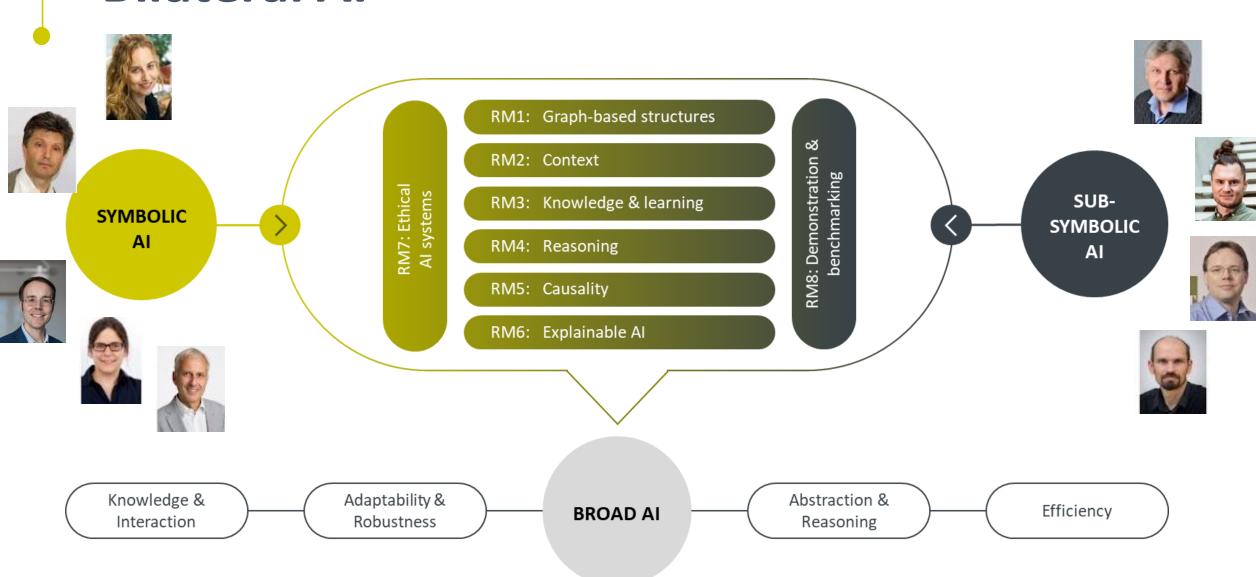
Dimension	\mathbf{SE}	KG	$\mathbf{L}\mathbf{M}$
Precision	+ stores corpus - noisy content	+ stores corpus + precise operators	abstracts corpushallucinations
Coverage	+ broad coverage	+ domain specific - patchy coverage	+ broad coverage - poor long tail
Freshness	+ quick updates + news often text	+ deprecation - structure lag	slow updatescold start
Generation	- no generation	+ ontologies/rule + graph learning	+ text generation
Synthesis	no integrationno synthesis	+ data integration + synthesis	+ text integration + synthesis
Transparency	+ provenance - opaque ranks	+ algorithmic + provenance	black boxno provenance
Determinism	+ deterministic	+ deterministic	unstable resultsrandomness
Curation	+ curatable - opaque ranks	+ curatable	indirect curationunpredictable
Fairness	+ content as-is - bias in ranks	+ content as-is - bias in coverage	generative biasesneeds safeguards
Usability	+ natural language + simple queries	structuredcomplex queries	+ natural language + conversational
Expressivity	simple queriesambiguity	+ complex queries - lacks nuance	+ complex queries - ambiguity
Efficiency	+ retrieval-based + simple queries	+ retrieval-based - complex queries	inference-basedcostly training
Multilingual	- lang. dependent	+ lang. agnostic - manual labels	+ multilinguality - variable results
Context	limited contextnot interactive	limited contextnot personalizable	+ in-context learn. + personalizable

So, let us better combine KGs and LLMs!



Bilateral Al





Bilateral Al

STA Institute of Science and Technology



Christoph Lampert
Machine Learning
Trustworthy Learning



 Machine Learning and Computer Vision group

> TECHNISCHE UNIVERSITÄT

• ELLIS Unit ISTA





Martina Seidl Symbolic AI SAT Solving Formal methods



Sepp Hochreiter

Machine Learning LSTM Vanishing gradient

- Institute for Machine Learning
- ELLIS Unit Linz
- LIT AI Lab
- Institute for Symbolic Artificial Intelligence





Gerhard Friedrich Symbolic Al Model-based reasoning

 Institute for Artificial Intelligence and Cybersecurity





Robert LegensteinMachine Learning
Computational Neuroscience

 Institute of Machine Learning and Neural Computation



Agata Ciabattoni Logic Reasoning



Thomas Eiter Symbolic Al Knowledge representation

• Institute for Logic and Computation





Axel Polleres Knowledge Graphs

 Institute for Data Process and Knowledge Management

FWF Österreichischer Wissenschaftsfonds



around
60 key
researchers

around
60 PhD students
and PostDocs





BILATERAL AI – First results and plans from our Institute and other BILAI partners...













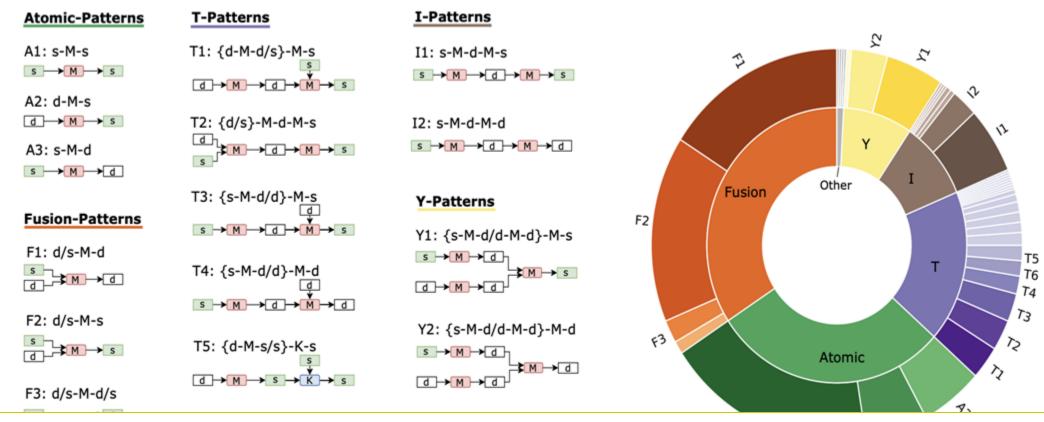
39

What's next?





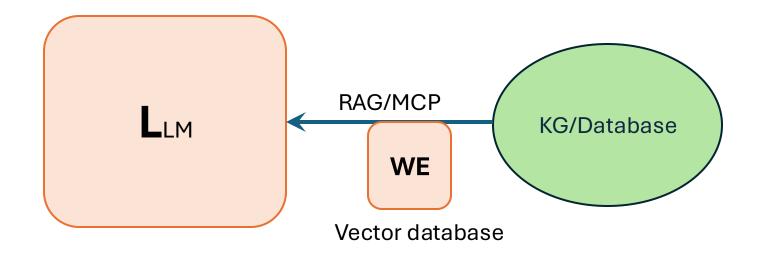
Ingredient1: We have a pretty good understanding of Engineering **Neuro-Symbolic Systems...**



A. Breit, L. Waltersdorfer, F.J. Ekaputra, M. Sabou, A. Ekelhart, A. Iana, H. Paulheim, J. Portisch, A. Revenko, A. ten Teije, and F. van Harmelen. 2023. Combining Machine Learning and Semantic Web: A Systematic Mapping Study. ACM Computing Survey. March 2023.



One such architecture... For instance:









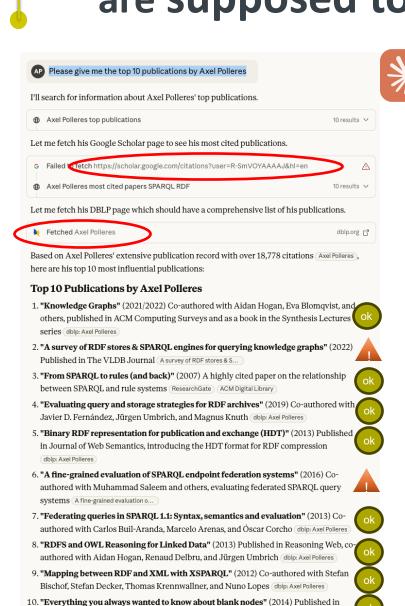






LLMs get better ... but still (plausibly) hallucinate "are supposed to be PhD level"





Journal of Web Semantics with Aidan Hogan, Marcelo Arenas, and Alejandro Mallea

Here are 10 influential publications by Axel Polleres, including papers, book-chapters, and working documents. These are among his most cited or otherwise important contributions. If you want, I can also fetch full download links or more recent ones.

Top 10 Publications by Axel Polleres	
--------------------------------------	--

1	Web Service Modeling Ontology (WSMO)	Jos de Bruijn, Dieter Fensel, Uwe Keller, Holger Lausen, Rubén Lara, Michael Kifer, Martin Hepp, Birgitta König-Ries, Jacek Kopecky, Dumitru Roman, John Domingue, Eyal Oren + Axel Polleres etc. (W3C Member Submission, 2005)
2	Binary RDF representation for publication and exchange (HDT)	Javier D. Fernández, Miguel A. Martínez-Prieto, Claudio Gutiérrez, Axel Polleres, Mario Arias (Journal of Web Semantics, 2013) repositorioslatino_ +4
3	From SPARQL to Rules (and back)	Axel Polleres (WWW 2007) st.acm.org +2
1	SPARQL1.1: New Features and Friends (OWL2, RIF)	Axel Polleres (in Web Reasoning and Rule Systems (RR 2010), Lecture Notes in Computer Science) link.springer.com +2
5	A General Framework for Representing, Reasoning and Querying with Annotated Semantic Web Data	Antoine Zimmermann, Nuno Lopes, Axel Polleres, Umberto Straccia (2011)
	Are We Better Off With Just One Ontology on the Web?	Armin Haller, Axel Polleres (Semantic Web Journal, 2020) wu wirtschaftsu +2
,	Evaluating Query and Storage Strategies for RDF Archives	Javier David Fernández García, Jürgen Umbrich, Axel Polleres, Magnus Knuth (Date ~ 2015) WU Wirtschaftsu +1
3	Serializing RDF in Compressed Space (HDT++)	Antonio Hernández-Illera, Miguel A. Martínez-Prieto, Javier David Fernández, Axel Polleres www.wrschattsu_ +1
9	How (Well) Do Datalog, SPARQL and RIF Interplay?	Axel Polleres (in Datalog 2.0 2012, LNCS) link.springer.com +1

Co-authors / Where / When

Inspired by Georg Gottlob's SEMANTiCS2025 keynote

Heng Ji's SEMANTiCS202 5 keynote

"Larger models are not necessarily better!"



Semantic Web Languages and

Application Areas for Answer Set

Semantic Web Services as



Axel Polleres (Dagstuhl Seminar Proceedings, 2005) drops.dagstuhl.de +1





ok

ChatGP⁷







General Data managenemt issue, not KG-specific!



But are KGs (& Databases) actually better?

Google asks it's users to manually correct/merge results

DBLP or scopus attempt to curate ambiguities by constraints (not always successful..)



Axel Polleres /

Vienna University of Economics and Business (WU - Wirtschaftsuniversität Wien) Verified email at wu.ac.at - Homepage

Data & Knowledge Manage... Artificial Intelligence Logic Programming Semantic Web

Knowledge Graphs

Merged citations

 Knowledge graphs A Hogan, E Blomqvist, M Cochez, C d'Amato ACM Computing Surveys (CSUR) 54 (4), 1-3

Web service modeling ontology

D Roman, U Keller, H Lausen, J De Bruijn, R Applied ontology 1 (1), 77-106

Enabling semantic web services: the D Fensel, H Lausen, J de Bruijn, M Stollberg Springer Berlin Heidelberg

Web service modeling ontology (wsn J De Bruijn, C Bussler, J Domingue, D Fense W3C member submission

The web service modeling language J De Bruijn, H Lausen, A Polleres, D Fensel European semantic web conference, 590-604 This "Cited by" count includes citations to the following articles in Scholar. The ones marked * may be different from the article in the profile.

2591 Knowledge graphs A Hogan, E Blomqvist, M Cochez, C d'Amato, GD Melo, C Gutierrez, ... ACM Computing Surveys (Csur) 54 (4), 1-37, 2021

Anisa Rula, Lukas Schmelzeisen, Juan F. Sequeda, Steffen Staab, and Antoine

A Hogan, E Blomqvist, M Cochez, C d'Amato, G De Melo, C Gutierrez, ... Knowledge graphs, 2020

Knowledge graphs

H Aidan, E Blomgvist, M Cochez, C d'Amato, G de Melo, C Gutiérrez, ... Mines Saint-Etienne, 2020

Knowledge graphs. CoRR abs/2003.02320 (2020) A Hogan, E Blomqvist, M Cochez, C d'Amato, G de Melo, C Gutiérrez, ...

URL: https://arxiv. org/abs/2003.02320, 2003

[+] Search dblp @

powered by CompleteSearch, courtesy of Hannah Bast, University of Fr

cience bibliography

> Home

[-] Author search results

Exact matches

- Thomas Müller disambiguation page
- Thomas Müller 0001

TU Munich, Faculty of Computer Science, Germany

■ Thomas Müller 0002

Eastphalia University of Applied Sciences, Braunschweig/Wolfe büttel, Germany

Thomas Müller 0003

Friedrich Schiller University Jena, Institute of Computer Science, Germany

■ Thomas Müller 0004

Fraunhofer Institute for Optronics, System Technologies and Image Exploitation (IOSB), Karlsruhe, Germany

show all

Likely matches

■ Thomas Müller 0013 ©

NVIDIA Research, Zürich, Switzerland

Thomas Müller-Gronbach

University of Passau, Germany

■ Thomas Müller 0009 © Google Research

■ Thomas Müller 0007 🗇

Department of Philosophy, University of Konstanz, Germany



21 *

13 *

















But are KGs actually better?

Example from Wikidata...





▼ In more languages

Configure

Language	Label	Description	Also known as
default for all languages	No label defined	_	
English	Tilikum	dugout canoe	
British English	Tilikum	No description defined	
American English	No label defined	No description defined	
German	Tilikum	Segelboot	















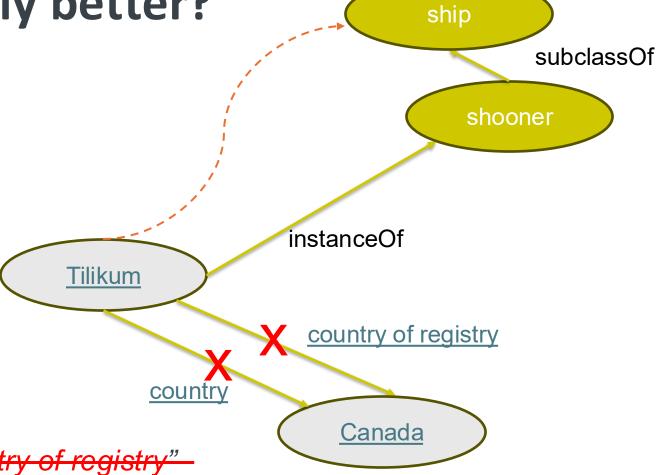
But are KGs actually better?



Ontologies +
Constraints,
such as:

"country conflicts with country of registry"

"i.e., an entity should not have both a "country" and a "country of registry"



















Why KGs can't (scalably) be correct:



Collaborative Editing

Multi-sourced Automatic Extraction

Knowledge is distributed and evolving!

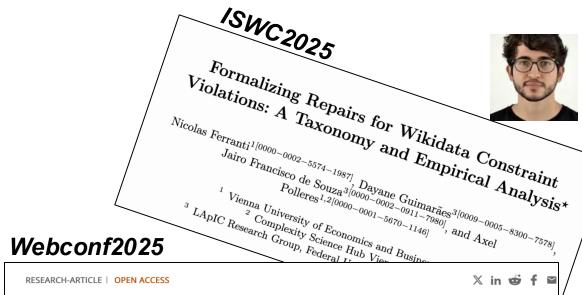
- Remote changes affect consistency
- Ontologies & Constraints evolve as well

What can we do about it?

- Best of both worlds needs **Bilateral Al** approaches!
 - **Symbolic** methods to repair inconsistencies

Forthcoming...

- **Subsymbolic** methods to resolve inconsistencies
 - **LLM**s & **KG** embeddings for resolving inconsistencies
 - **GNNs** for *learning* repairs (*from historical data*, from users' repairs)
 - Iterative **RAG** and **Agent-based** pipelines to fix and construct KGs from text























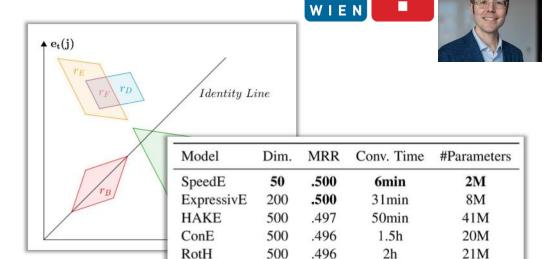
Further starting points in BILAI:

Notably, in BILAI, colleagues from TU Vienna (Sallinger, Pavlovic) work on KG Embeddings that can capture (certain) rules and constraints already:

- Similar to Word embeddings and LLMs, *Knowledge Graph* **Embeddings** allow to
 - predict missing edges in incomplete KGs
 - predict inconsistencies & possible repairs

- **Open Problems:**
 - Scaling KG Embeddings to full, decentralized KGs ...
 - ... but (1) *modularization* might help here, relation to the
 - (2) corresponding trend to LLMs-based "multi-agent frameworks"





		1				
Logical Rule	ExpressivE	RotatE	TransE	BoxE	ComplEx	DistMult
Symmetry: $r_1(X,Y) \Rightarrow r_1(Y,X)$	/	1	X	/	/	✓
Anti-symmetry: $r_1(X,Y) \Rightarrow \neg r_1(Y,X)$	1	/	/	/	/	X
Inversion: $r_1(X,Y) \Leftrightarrow r_2(Y,X)$	/	/	/	/	/	X
Comp. def.: $r_1(X,Y) \wedge r_2(Y,Z) \Leftrightarrow r_3(X,Z)$	/	/	/	X	X	X
Gen. comp.: $r_1(X,Y) \wedge r_2(Y,Z) \Rightarrow r_3(X,Z)$	/	X	X	X	×	X
Hierarchy: $r_1(X,Y) \Rightarrow r_2(X,Y)$	/	X	X	/	/	1
Intersection: $r_1(X,Y) \wedge r_2(X,Y) \Rightarrow r_3(X,Y)$	/	/	/	/	×	X
Mutual exclusion: $r_1(X,Y) \wedge r_2(X,Y) \Rightarrow \bot$	✓	✓	✓	✓	✓	✓











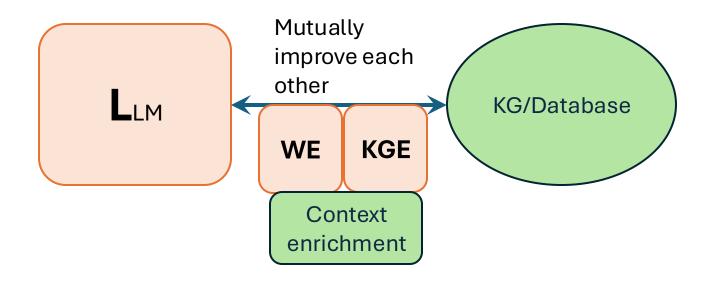








So we actually need this?



Quite some work at current ISWC2025, e.g. RAGE-KG workshop is looking into such extensions...

















What's next? Where should this go?

Caveat: Our data and knowledge is typically:

- Distributed/decentralized and
- not always sharable with a central (API) model

→ we need decentralized solutions!

"Our knowledge will never go into a central LLM" – BILAI industry network keynote Stefan Rohringer (Infineon)



Catalog











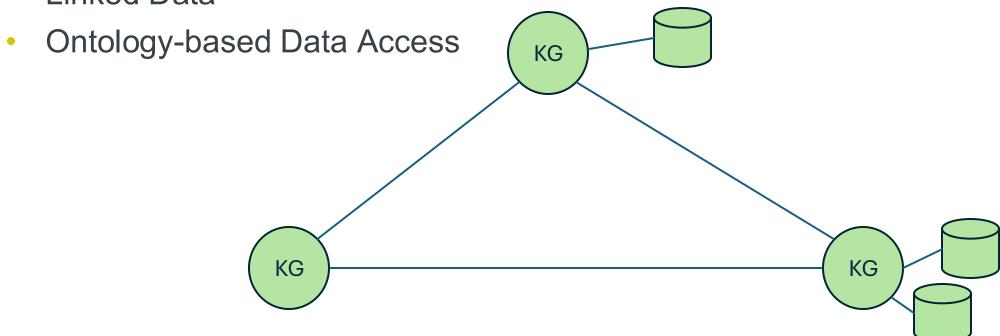




What's next? Where should this go?

Ingredient 2: Expertise on (Symbolic) Data Integration and Repair. Before the LLM hype, we long worked on *purely symbolic* solutions to integrating *decentralised* Knowledge

Linked Data









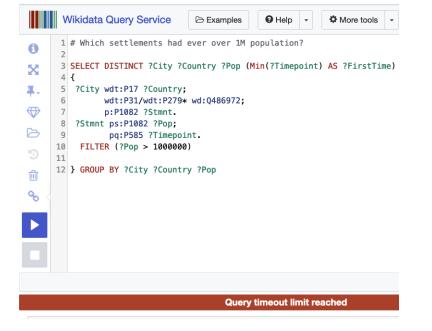






Scalable data access to decentralized KGs:

- Starting Points:
 - graph partitioning and splitting processing between clients and SPARQL endpoints the performance, the problems of central query endpoints can be significantly alleviated
 - Investigating how the asynchronous evolution of KGs affects consistency
- Interesting Open Problems:
 - E.g. Synchronisation/Updates/Repairs in Polyglott Databases









Isn't there something missing?



Ora Lassila (Keynote ISWC2024) https://www.lassila.org/publications/2024/ lassila-iswc2024-keynote.pdf

The realization of autonomous agents minimally requires these:

- 1. KR & reasoning
- 2. Planning
- 3. Ability to converse with the agents

LLMs will give you #3, but not #1 or #2

- (despite what you hear)
- "agentic", "agentive", ... huh?
- good news: we already have #1 and #2

The Semantic Web

A new form of Web content that is meaningful to computers will unleash a revolution of new possibilities

by TIM BERNERS-LEE, JAMES HENDLER and ORA LASSILA

The entertainment system was belting out the Beatles' "We Can Work It Out" when the phone rang. When Pete answered, his phone turned the sound down by sending a message to all the other *local* devices that had a *volume control*. His sister, Lucy, was on the line from the doctor's office: "Mom needs to see a specialist and then has to have a series of physical therapy sessions. Biweekly or something. I'm going to have my agent set up the appointments." Pete immediately agreed to share the chauffeuring. At the

doctor's office, Lucy instructed her Semantic Web agent through her handheld Web browser. The agent promptly retrieved information about Mom's prescribed treatment from the doctor's agent, looked up several lists of providers, and checked for the ones *in-plan* for Mom's insurance within a 20-mile radius of her home and with a rating of excellent or very good on trusted rating services. It then began trying to find a match between available appointment times (supplied by the agents of individual providers through their Web sites) and Pete's and Lucy's busy schedules. (The emphasized keywords indicate terms whose semantics, or meaning, were defined for the agent through the

In a few minutes the agent presented them with a plan. Pete didn't like it—University Hospital was all the way across with stricter preferences about location and time. Lucy's agent, having complete trust in Pete's agent in the context of the present task, town from Mom's place, and he'd be driving back in the middle of rush hour. He set his own agent to redo the search automatically assisted by supplying access certificates and shortcuts to the data it had already sorted through.

Knowledge Graphs

"Agentic" Models ... and maybe a revival?

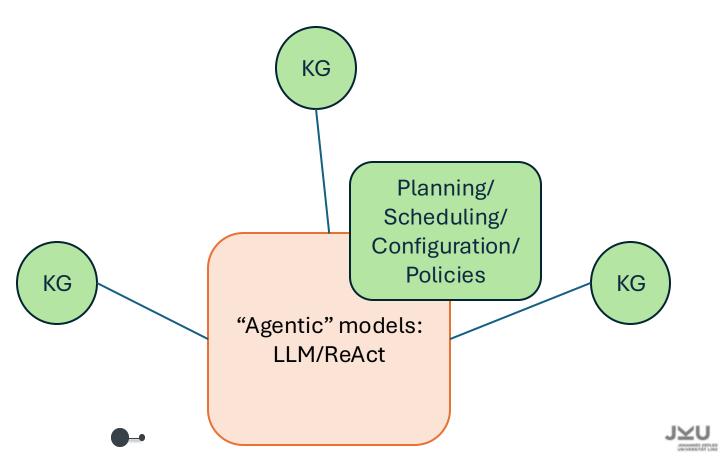
LLMs





What's next? Where should this go?

Ingredient3: <u>Combinations</u> of LLMs and decentral KGs via RAG and Agent frameworks are one example of such Neuro-symbolic architectures:



Example: Federated querying of KGs via agents (work in progress):

Prompt: "Write a federated SPARQL query that queries all of Tim Berners-Lee's publications from DBLP the DOIs of which also appear on Wikidata"

```
PREFIX dblp:
               < http://dblp.org/rdf/schema#>
PREFIX bibo:
               <http://purl.org/ontology/bibo/>
               <http://www.wikidata.org/prop/direct/>
PREFIX wdt:
SELECT DISTINCT ?dblpPub ?title ?doi ?wikidataItem
WHERE {
   SERVICE < https://dblp.org/sparql > {
    ?dblpPub a bibo:Article ;
             dblp: author ?author ;
             dblp:title ?title;
             bibo: doi ?doi .
             ?author dblp: name "Tim Berners-Lee" .}
   SERVICE <https://query.wikidata.org/sparql> {
    ?wikidataItem wdt:P356 ?doi . } }
```

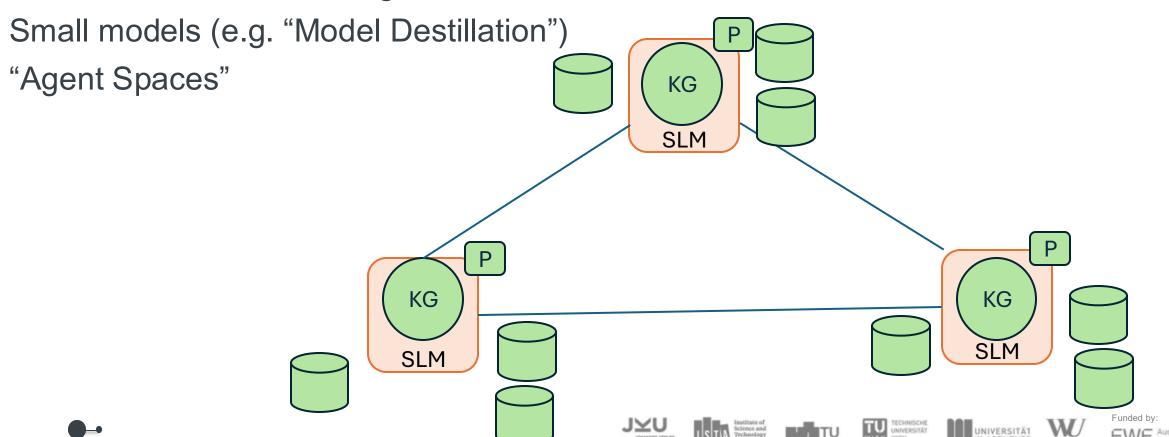


What's next? Where should this go? What is a solution we should jointly work towards?



Neuro-symbolic agents

Trustable Decentralized Agents



Thanks!



Austrian National "Cluster of Exellence" BILAI:

- Broad Al
- (Knowledge) Graph-Based Al plays a key role in BILAI

Knowledge Graphs are symbolic Al with "features" of LLMs:

- Large-scale
- Not always consistent

Ingredient1:
Neurosymbolic
Architectures

Ingredient2:
 scalable
 distributed,fed
 erated data
 symbolic
 processing

(**Dezentralized**) Agents, KGs and LLM combined, could realize BILAI's vision of a broad, *robust* AI, and change the way we access and manage Data

Currently running!





https://www.bilateral-ai.net/













