Public Knowledge Graphs

UNIVERSITY OF MANNHEIM Data and Web Science Group

IE650 Knowledge Graphs



Previously on "Knowledge Graphs"



Principles:

- RDF, RDF-S, SPARQL & co
- Linked Open Data

Today

- A closer look on actually existing knowledge graphs
- Some useful, large-scale resources



Introduction



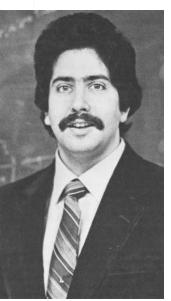
Knowledge Graphs out there (not guaranteed to be complete)

Name	Instances	Facts	Types	Relations	
DBpedia (English)	4,806,150	176,043,129	735	2,813	
YAGO	4,595,906	25,946,870	488,469	77	
Freebase	49,947,845	3,041,722,635	26,507	37,781	public
Wikidata	15,602,060	65,993,797	23,157	1,673	F public
NELL	2,006,896	432,845	285	425	
OpenCyc	118,499	2,413,894	45,153	18,526	
Google's Knowledge Graph	570,000,000	18,000,000,000	1,500	35,000	\Box
Google's Knowledge Vault	45,000,000	271,000,000	1,100	4,469	├ private
Yahoo! Knowledge Graph	3,443,743	1,391,054,990	250	800	

Knowledge Graph Creation: CyC



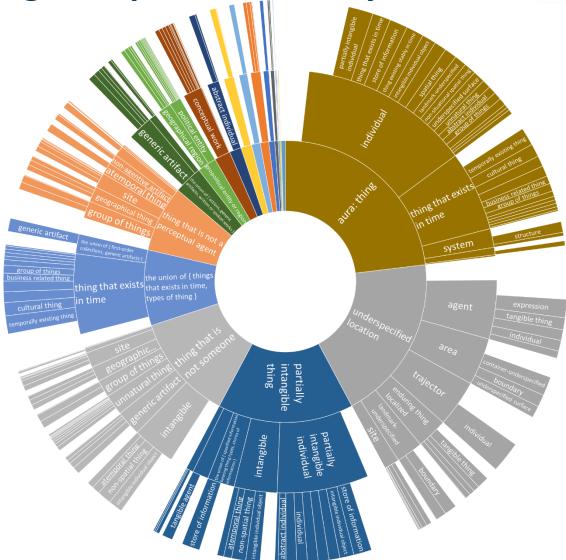
- The beginning
 - Encyclopedic collection of knowledge
 - Started by Douglas Lenat in 1984
 - Estimation: 350 person years and 250,000 rules should do the job of collecting the essence of the world's knowledge



- The present (as of June 2017)
 - ~1,000 person years, \$120M total development cost
 - 21M axioms and rules
 - Used to exist until 2017

Knowledge Graph Creation: CyC





Knowledge Graph Creation



- Lesson learned no. 1:
 - Trading efforts against accuracy



Knowledge Graph Creation: Freebase



- The 2000s
 - Freebase: collaborative editing
 - Schema not fixed



- Present
 - Acquired by Google in 2010
 - Powered first version of Google's Knowledge Graph
 - Shut down in 2016
 - Partly lives on in Wikidata (see in a minute)

coming up soon: was it a good deal or not?

Knowledge Graph Creation: Freebase



- Community based
- Like Wikipedia,
 but more structured

Arnold Schwarzenegger ☐ Discuss "Arnold Schwarzenegger" ☐ Show Empty Fields



- .≡ **Types:** Person (People) US Politician (Government) Film actor (Film) Film producer (Film) Pro Athlete (Sports) Sports Award Winner (Sports)
- .= Also known as: Arnold Alois Schwartzenegger, The Governator
- .≡ Gender: Male
- .≡ Date of Birth: Jul 30, 1947 .≡ Place of Birth: Thal, Austria
- .= Country Of Nationality: United States
- .= Profession: Politician, Bodybuilder, Entrepreneur, Actor
- .≡ Religion: Roman Catholicism
- .≡ Parents: Aurelia Jadrny Schwarzenegger, Gustav Schwarzenegger
- Children: Christopher Schwarzenegger, Patrick Schwarzenegger, Christina Schwarzenegger, Katherine Schwarzenegger
- .= Siblings: Meinhard Schwarzenegger
- .≡ Spouse (or domestic partner): Maria Shriver Apr 26, 1986
- .≡ **Height:** 1.88 m
- IMDB Entry: http://www.imdb.com/name/nm0000216/
- .= Career Start: 1968
 .= Career End: 1980

Knowledge Graph Creation



- Lesson learned no. 2:
 - Trading formality against number of users





The 2010s

- Wikidata: launched 2012
- Goal: centralize data from Wikipedia languages
- Collaborative
- Imports other datasets



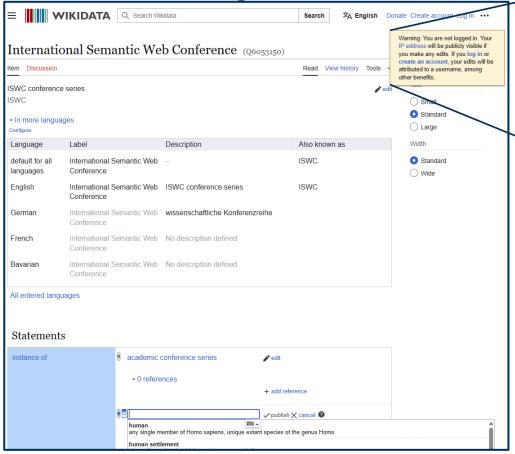
Present

- One of the largest public knowledge graphs (see later)
- Includes rich provenance



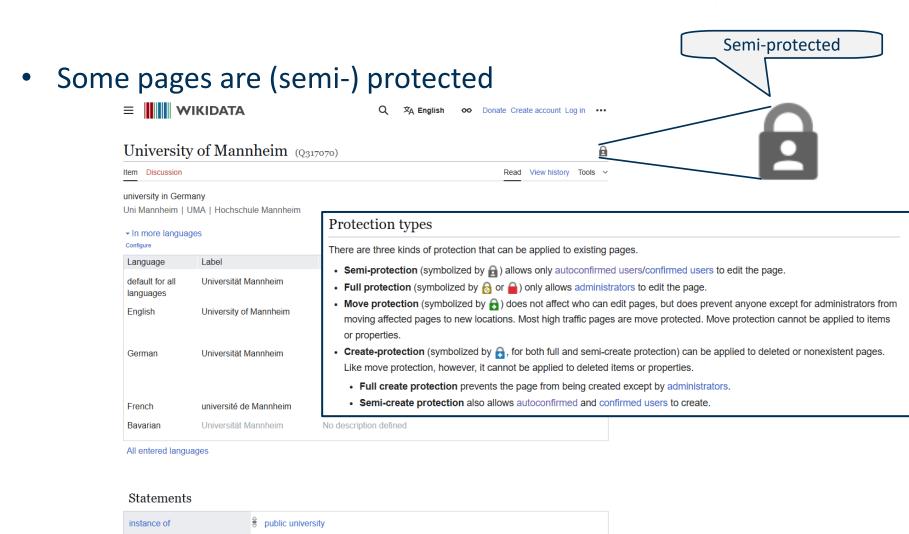
Even without login

Collaborative editing



Warning: You are not logged in. Your IP address will be publicly visible if you make any edits. If you log in or create an account, your edits will be attributed to a username, among other benefits.

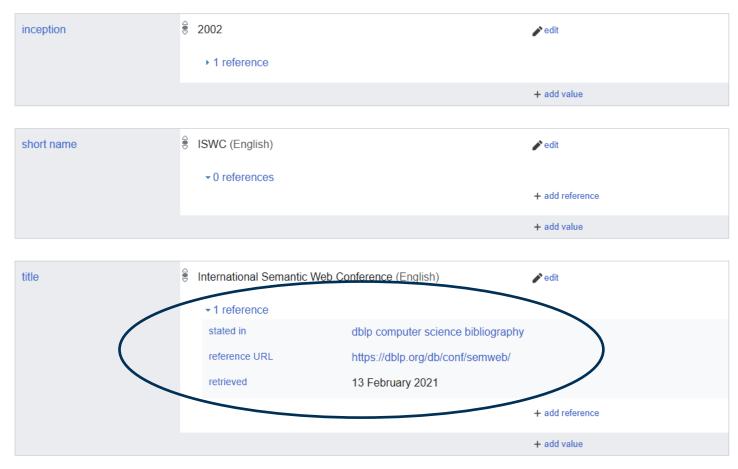




▼ 0 references

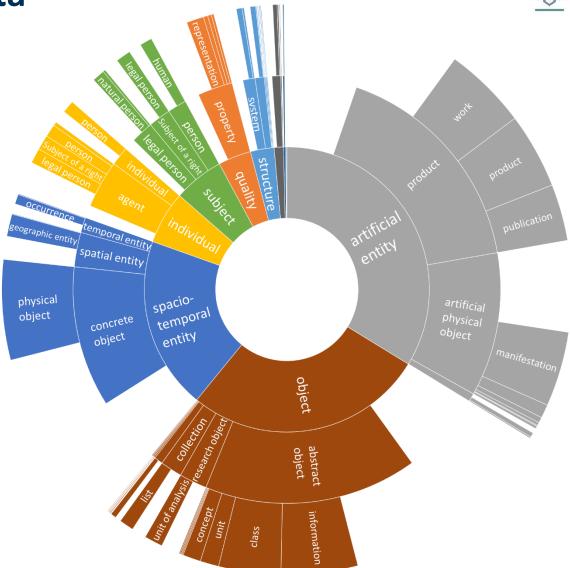


Provenance



Wikidata





Knowledge Graph Creation



- Lesson learned no. 3:
 - There is not one truth (but allowing for plurality adds complexity)



Knowledge Graph Creation: DBpedia & YAGO

- The 2010s
 - DBpedia: launched 2007
 - YAGO: launched 2008
 - Extraction from Wikipedia using mappings & heuristics
- Present
 - Two of the most used knowledge graphs
 - Next to Wikidata

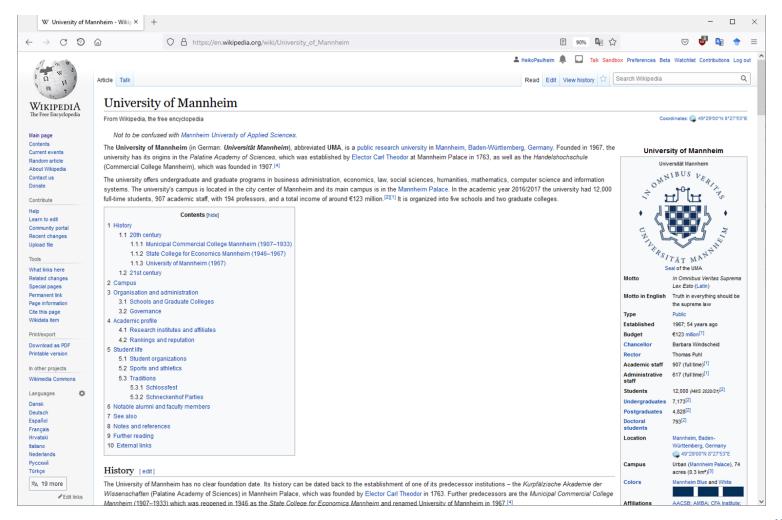






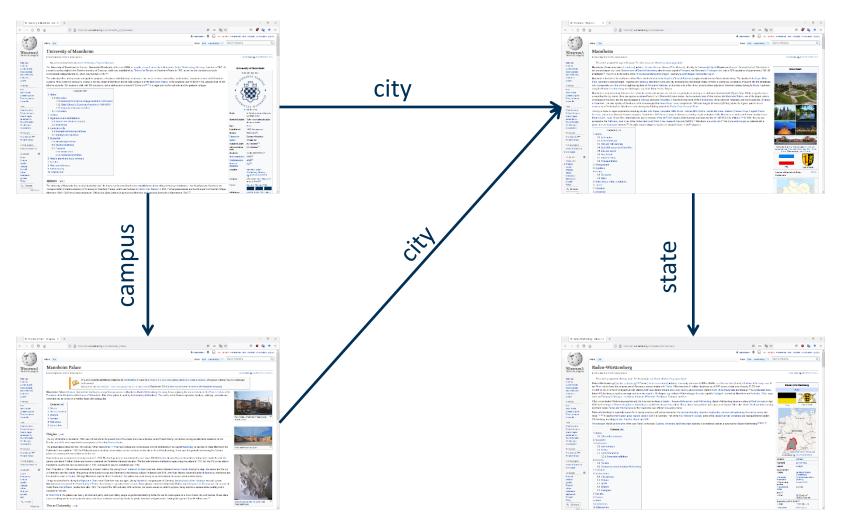
Wikipedia as a Knowledge Graph





Wikipedia as a Knowledge Graph

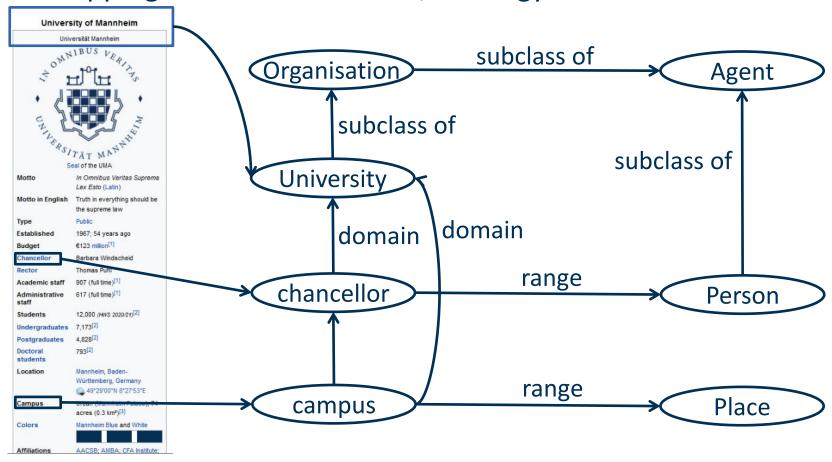




Wikipedia as a Knowledge Graph



Mapping to a central schema/ontology





University of Mannheim



249[1]

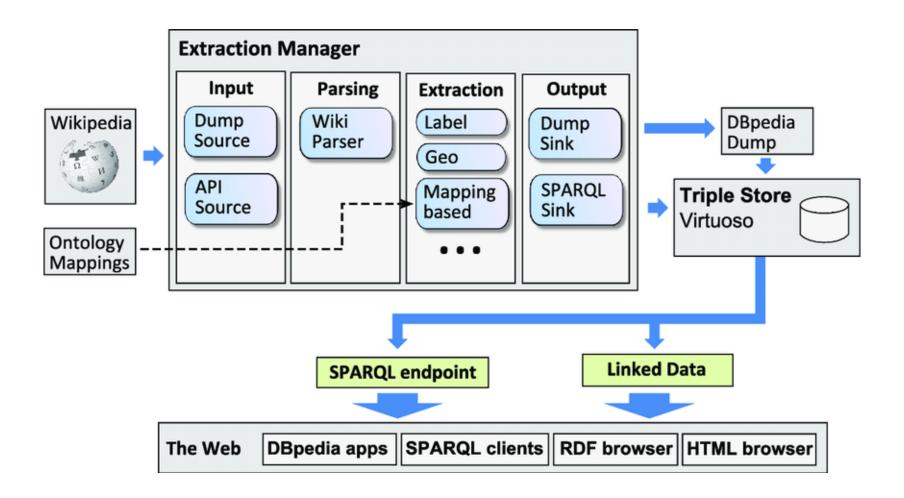
Doctoral

students

```
{{Infobox university
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Imotto
                  = Truth in everything should be the supreme law
Imottoeng
                  =University of Mannheim
Iname
                  =Universität Mannheim
native name
                  =Uni Mannheim Siegel.gif
|image name
                  =[[Seal (emblem)|Seal]] of the UMA
caption
                  =1763: Theodoro Palatinae <br/> 1907: Handelshochschu
lestablished
Itvpe
                  =[[Public University|Public]]
lendowment
                  =€115 [[million]]
|academic staff =800 (full time)
administrative staff = 550 (full time)
Schools
Irector
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chancellor
                  =[[Susann-Annette Storm]]
students
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                  =6,915<ref name="uni-mannheim.de"/>
undergrad
                  =4,965<re: <pre>

</
postgrad
                  =249<ref ! <rdf:Description rdf:about="http://dbpedia.org/resource/University of Mannheim">
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profess
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country
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                                 <dbp:caption xml:lang="en">Seal of the UMA</dbp:caption>
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Icoor
                                 <dbp:colors xml:lang="en">Mannheim Blue and White</dbp:colors>
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                                 <dbp:rector xml:lang="en">Thomas Puhl</dbp:rector>
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                                 <dbp:type rdf:resource="http://dbpedia.org/resource/Public University" />
                                 <dbp:website rdf:resource="https://www.uni-mannheim.de/en/%7C2=www.uni-mannheim.de" />
                                <georss:point>49.4832 8.4647/georss:point>
                              </rdf:Description>
```







Mapping en:Infobox film

This is the mapping for the Wikipedia template Infobox film @. Find usages of this Wikipedia template Test this mapping & (or in namespace File & or Creator &) with some example Wikipedia pages. Che This is the definition of an ontology property.

Template Mapping (help)	
map to class Film		
Mappings		
viappingo		_
Property Mapping (h	ielp)	
template property	director	
ontology property	director	
	,	
Property Mapping (h	ielp)	
Property Mapping (h	producer	

OntologyClass:Film

This is the definition of an ontology class. Show all properties 🗗 available for this class. Show class in class hierarchy 🗗

Read more about editing the ontology schema.

You can see the result of your edit on DBpedia Live (

Ontology class (help)		
rdfs:label (en)	film	
rdfs:label (en)	movie	ŀ
rdfs:label (nl)	film	
rdfs:label (da)	film	
rdfs:label (de)	Film	ŀ
rdfs:label (el)	ταινία	
rdfs:label (fr)	film	
rdfs:label (ko)	영화	
rdfs:label (ja)	映画	
rdfs:label (ar)	فيلم	
rdfs:label (pl)	film	
rdfs:label (ga)	scannán	
rdfs:label (es)	película	
rdfs:subClassOf	Work	
owl:equivalentClass	schema:Movie, wikidata:Q11424	
owl:disjointWith		

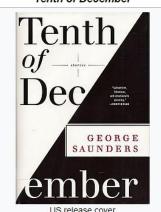
OntologyProperty:director

Read more about editing the ontology schema

You can see the result of your edit on DBpedia Live @ (this is BETA!).

Ontology object prope	rty (help)
rdfs:label (en)	director
rdfs:label (en)	film director
rdfs:label (nl)	regisseur
rdfs:label (da)	instruktør
rdfs:label (de)	regisseur
rdfs:label (ru)	директор
rdfs:label (el)	σκηνοθέτης
rdfs:label (es)	director de cine
rdfs:label (fr)	réalisateur
rdfs:comment (en)	A film director is a person who directs the making of a film. ^[1]
rdfs:comment (fr)	Un réalisateur (au féminin, réalisatrice) est une personne qui dirige la fabrication d'une œuvre audiovisuelle, généralement pour le cinéma ou la télévision. ^[2]
rdfs:domain	Film
rdfs:range	Person
rdf:type	
rdfs:subPropertyOf	dul:coparticipatesWith
owl:equivalentProperty	schema:director, wikidata:P57
owl:propertyDisjointWith	

Tenth of December



Author George Saunders Language English Genre Short story of Publisher

Random Mouse January 8, 2013 **Publication date** United States Publication place

Media type rint (hardcover) Pages 208

ISBN 0812993802 785558855 ₺ OCLC

{{Infobox book name = Tenth of December author = [[George Saunders]] language = English country = United States genre = [[Short story collection]] publisher = [[Random House]] isbn = 0812993802 image = Tenth of December.jpg caption = US release cover release_date = January 8, 2013 media type = Print (hardcover) pages = 208 oclc = 785558855

Mapping en:Infobox book

Book

This is the manping for the Wikipedia template Infobox book . Find usages of this Wikipedia templ Test this mappillg∰ (or in namespace File∰ or Creator∰) with some example Wikipedia pages. Ch Read more about mapping Wikipedia templates.

Template Mapping (help)

map to class

Mappings

Property Mapping (help) template property name foaf:name ontology property

Property Mapping (help) template property genre ontology property literary Genre

Property Mapping (help) template property pages University of Mann ontology property numberOfPages



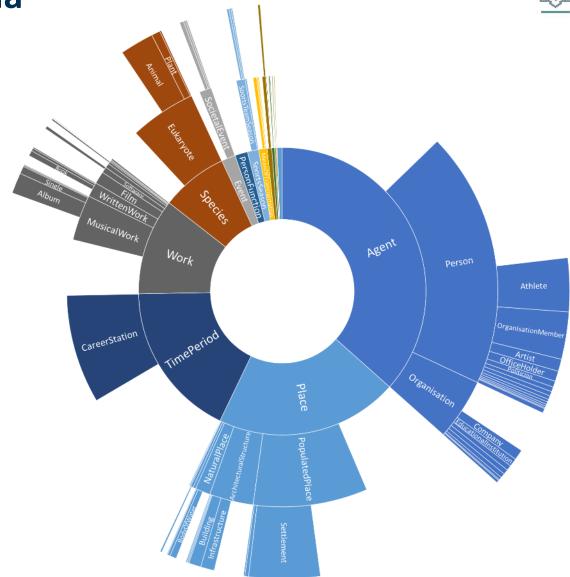
About: Tenth of December: Stories

An Entity of Type: Buch, from Named Graph: http://dbpedia.org, within Data Space: dbpedia.org

Tenth of December is a collection of short stories by American author George Sau magazines between 1995 and 2012. The book was published on January 8, 2013, I was a 2011 Bram Stoker Award finalist. Tenth of December was selected as one of New York Times Book Review. The collection also won the 2013 Story Prize for sho Folio Prize.

Property	Value
dbo:abstract	 Tenth of December is a collection of short stories by America 1995 and 2012. The book was published on January 8, 2013, Tenth of December was selected as one of the 10 Best Books the 2013 Story Prize for short-story collections and the inaug
dbo:author	• <u>dbr:George Saunders</u>
<u>dbo:isbn</u>	• 0812993802
<u>dbo:literaryGenre</u>	<u>dbr:Short_story_collection</u>
<u>dbo:numberOfPages</u>	208 (xsd:positiveInteger)
db :oclc	• 785558855
dbo:publisher	• dbr:Random House
dbo:releaseDate	• 2013-01-08 (xsd:date)



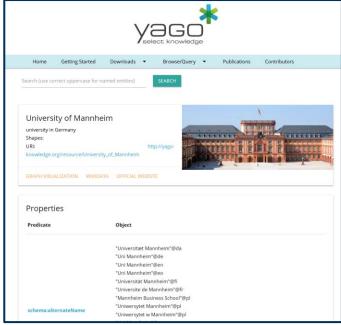


YAGO



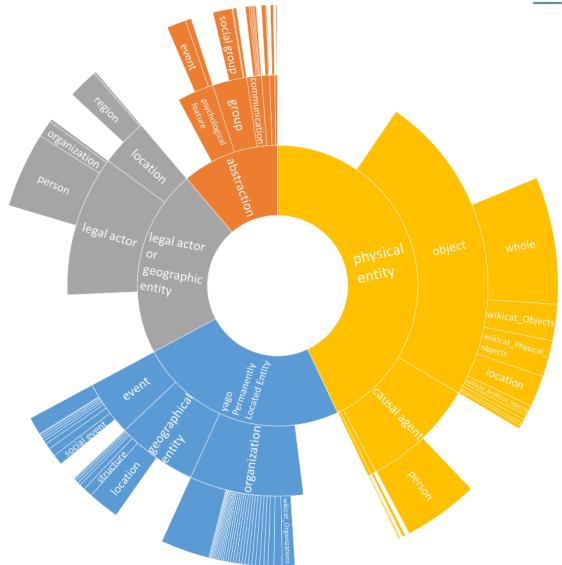
- YAGO 1
 - Wikipedia categories for types
 - Plus WordNet as upper structure
- YAGO 2
 - Anchored in time and space
- YAGO 3
 - Furth improvements + multiple languages
- YAGO 4
 - Based on Wikidata
 - Refines taxonomy and properties by using schema.org





YAGO 3





Knowledge Graph Creation



- Lesson learned no. 4:
 - Heuristics help increasing coverage (at the cost of accuracy)



Knowledge Graph Creation: NELL

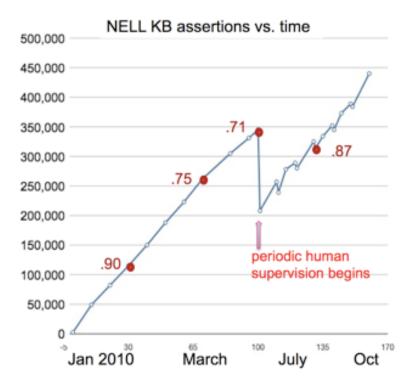


The 2010s

- NELL: Never ending language learner
- Input: ontology, seed examples, text corpus
- Output: facts, text patterns
- Large degree of automation, occasional human feedback

Until 2018

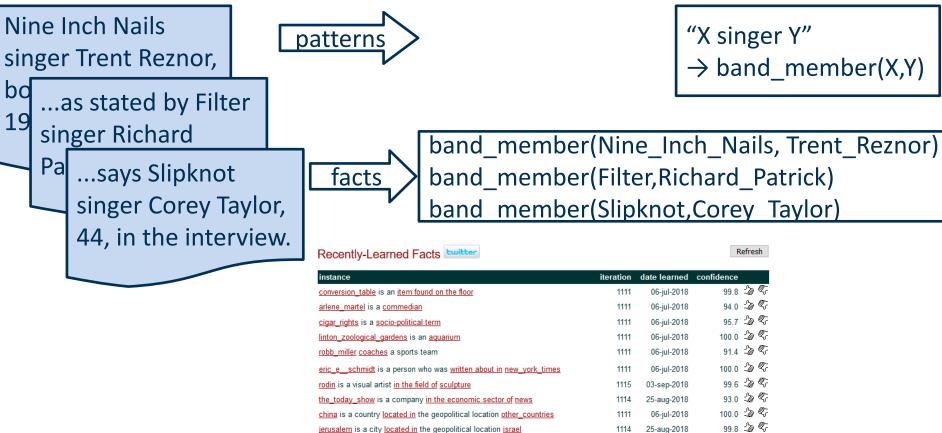
- Continuously ran for ~8 years
- New release every few days



Knowledge Graph Creation: NELL

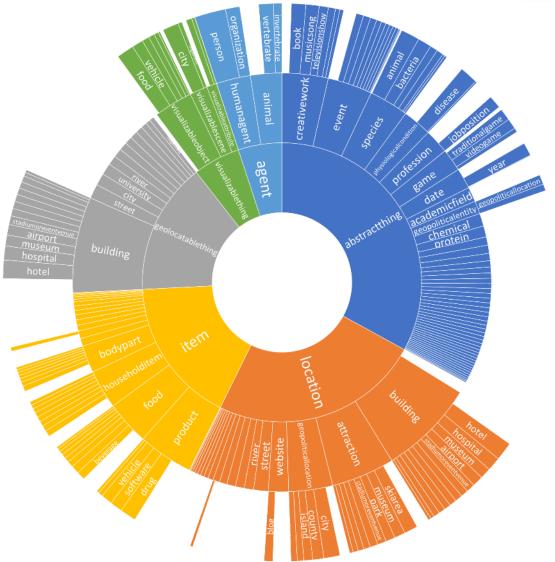


Extraction of a Knowledge Graph from a Text Corpus



Knowledge Graph Creation: NELL

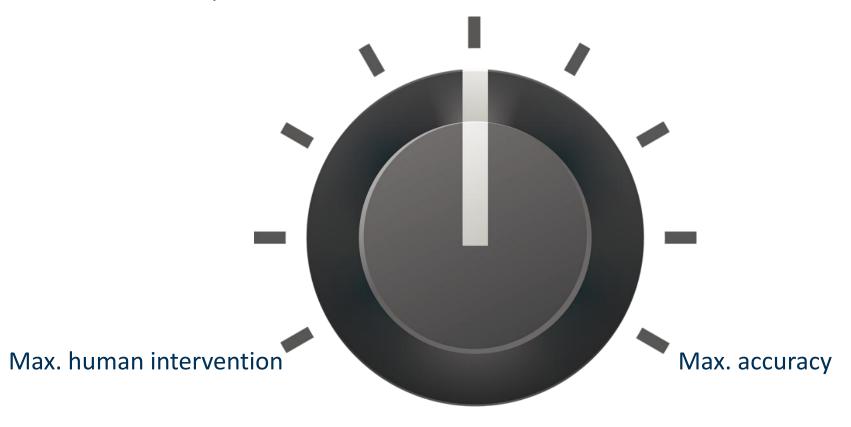




Knowledge Graph Creation



- Lesson learned no. 5:
 - Quality cannot be maximized without human intervention



Summary of Trade Offs



- (Manual) effort vs. accuracy and completeness
- User involvement (or usability) vs. degree of formality
- Simplicity vs. support for plurality and provenance

→ all those decisions influence the shape of a knowledge graph!







Welcome to GPTKB

A large general-domain knowledge base entirely from a large language model

100 million triples 6.1 million entities

10x less cost

Overview

This interface presents **GPTKB v1.5** (Hu et al. arXiv, 2025b), a large general-domain knowledge base (KB) entirely from a large language model (LLM). It demonstrates the feasibility of large-scale KB construction from LLMs, while highlighting specific challenges arising around entity recognition, entity and property canonicalization, and taxonomy construction (Hu et al. ACL, 2025a).

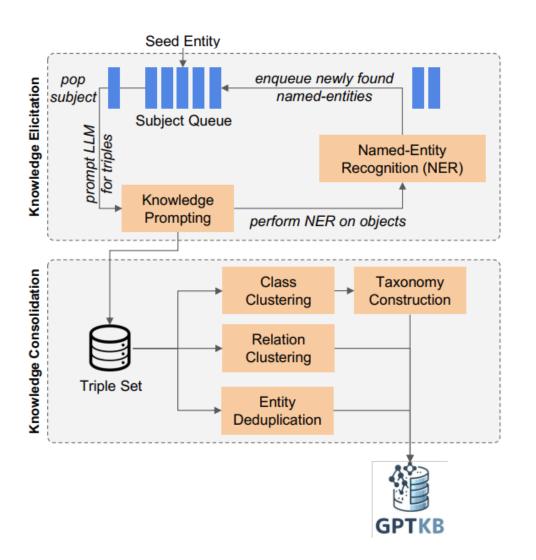
Based on GPT-4.1, **GPTKB v1.5** contains 100 million triples for more than 6.1 million entities, at a cost 10x less than previous KBC projects. We also provide GPTKB v1.1 for download.

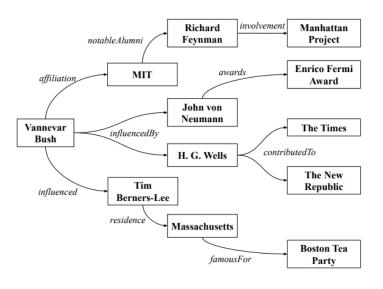
GPTKB is a landmark for two fields:

- · For NLP, for the first time, it provides constructive insights into the knowledge (or beliefs) of LLMs.
- For the Semantic Web, it shows novel ways forward for the long-standing challenge of general-domain KB construction.

Using the search field, you can find entities by name, and browse their triples. Alternatively, you can write SPARQL queries or download the whole KB as a TTL file. Paper and code are also available.









You are a knowledge base construction expert. Given a subject entity, return all facts that you know for the subject as a list of subject, predicate, object triples. The number of facts may be very high, between 50 to 100 or more, for very popular subjects. For less popular subjects, the number of facts can be very low, like 5 or 10.

Important:

- If you don't know the subject, return an empty list.
- If the subject is not a named entity, return an empty list.
- If the subject is a named entity, include at least one triple where predicate is "instanceOf".
- Do not get too wordy.
- Separate several objects into multiple triples with one object.

Figure 9: Prompt for knowledge elicitation.

You are an expert on named entity recognition (NER). Your task is to classify if given phrases are named entities (e.g., persons, organizations, works of art), or not (e.g., literals, dates, URLs, verbose phrases). Each phrase is given to you in a line.

Figure 10: Prompt for named-entity recognition (NER).



Entities	2.9M
Triples	101M
Relations	567K (788K before canonicalization)
Classes	4,715 (103K before canonicalization)
Triple objects	37M entities, 64M literals
Avg. triples/entity	35
Avg. label length	21.8 characters
Avg. outlinks	4
Subject-precision*	74% Verifiable, 9% Plausible,
	17% Unverifiable
Subjects in Wikidata*	37% in WD, 63% not in WD
Triple-precision*	31% True, 61% Plausible,
	1% Implausible, 7% False
-1- 1 1	

^{*} as a weighted average across layers.

Non-Public Knowledge Graphs

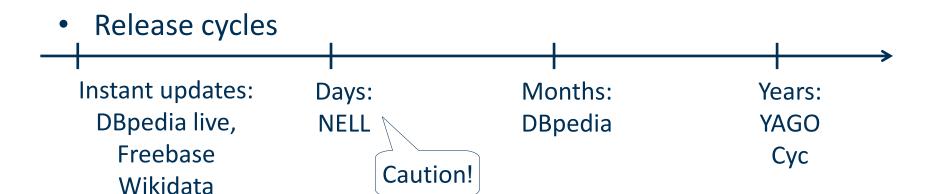


- Many companies have their own private knowledge graphs
 - Google: Knowledge Graph,
 Knowledge Vault
 - Yahoo!: Knowledge Graph
 - Microsoft: Satori
 - Facebook: Entities Graph
 - Thomson Reuters: permid.org (partly public)



However, we usually know only little about them





Size and density

2017

Table 1: Global Properties of the Knowledge Graphs compared in this paper

	_		_	-	
	$\operatorname{DBpedia}$	YAGO	Wikidata	OpenCyc	NELL
Version	2016-04	YAGO3	2016-08-01	2016-09-05	08m.995
# instances	5,109,890	, ,	, ,	,	1,974,297
# axioms	$397,\!831,\!457$	$1,\!435,\!808,\!056$	1,633,309,138	2,413,894	3,402,971
avg. indegree	13.52	17.44	9.83	10.03	5.33
avg. outdegree	47.55	101.86	41.25	9.23	1.25
# classes	754	576,331	30,765	116,822	290
# relations	3,555	93,659	11,053	165	1,334



2020

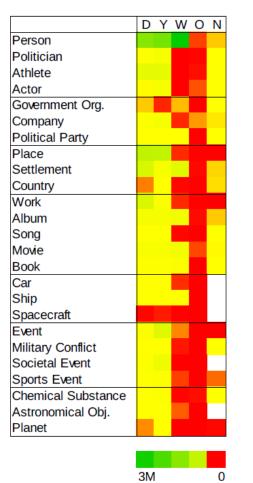
	DBpedia	YAGO	Wikidata	BabelNet
# Instances	5,044,223	6,349,359	52,252,549	7,735,436
# Assertions	854,294,312	479,392,870	732,420,508	178,982,397
Avg. linking degree	21.30	48.26	6.38	0.00
Median ingoing edges	0	0	0	0
Median outgoing edges	30	95	10	9
# Classes	760	819,292	2,356,259	6,044,564
# Relations	1355	77	6,236	22
Avg. depth of class tree	3.51	6.61	6.43	4.11
Avg. branching factor of class tree	4.53	8.48	36.48	71.0
Ontology complexity	SHOFD	SHOIF	SOD	SO

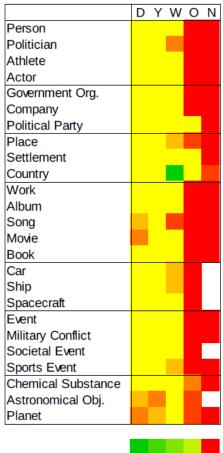
	Сус	NELL	CaLiGraph	Voldemort
# Instances	122,441	5,120,688	7,315,918	55,861
# Assertions	2,229,266	60,594,443	517,099,124	693,428
Avg. linking degree	3.34	6.72	1.48	0
Median ingoing edges	0	0	0	0
Median outgoing edges	3	0	1	5
# Classes	116,821	1,187	755,963	621
# Relations	148	440	271	294
Avg. depth of class tree	5.58	3.13	4.74	3.17
Avg. branching factor of class tree	5.62	6.37	4.81	5.40
Ontology complexity	SHOIFD	SROIF	SHOD	SH

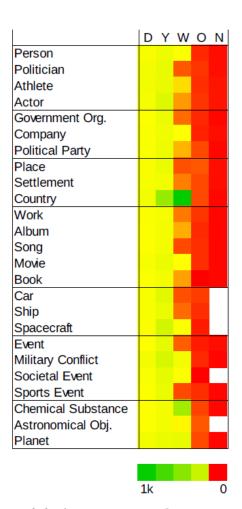


- What do they actually contain?
- Experiment: pick 25 classes of interest
 - And find them in respective ontologies
- Count instances (coverage)
- Determine in and out degree (level of detail)









(a) Number of instances

(b) Average indegree

(c) Average outdegree

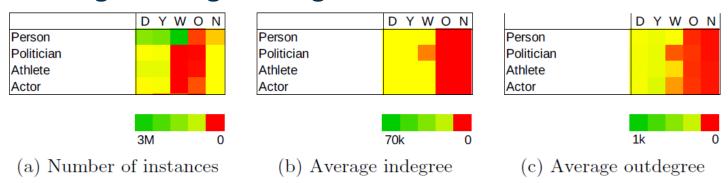


- Summary findings:
 - Persons: more in Wikidata
 (twice as many persons as DBpedia and YAGO)
 - Countries: more details in Wikidata
 - Places: most in DBpedia
 - Organizations: most in YAGO
 - Events: most in YAGO
 - Artistic works:
 - Wikidata contains more movies and albums
 - YAGO contains more songs

Caveats



Reading the diagrams right...

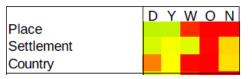


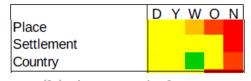
- So, Wikidata contains more persons
 - but less instances of all the interesting subclasses?
- There are classes like Actor in Wikidata
 - but they are hardly used
 - rather: modeled using profession relation

Caveats



Reading the diagrams right... (ctd.)



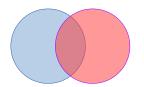




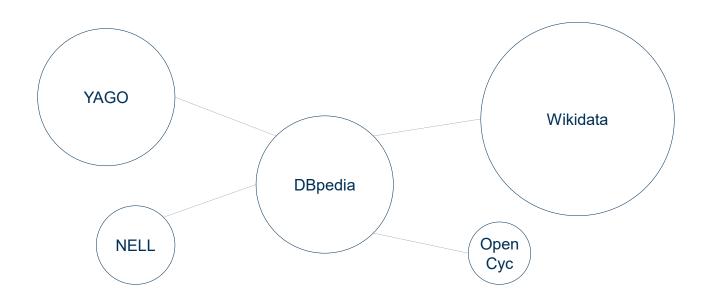
- (a) Number of instances
- (b) Average indegree
- (c) Average outdegree
- So, Wikidata contains more data on countries, but less countries?
- First: Wikidata only counts current, actual countries
 - DBpedia and YAGO also count historical countries
- "KG1 contains less of X than KG2" can mean
 - it actually contains less instances of X
 - it contains equally many or more instances,
 but they are not typed with X (see later)
- Second: we count single facts about countries
 - Wikidata records some time indexed information, e.g., population
 - Each point in time contributes a fact



How largely do knowledge graphs overlap?



- They are interlinked, so we can simply count links
 - For NELL, we use links to Wikipedia as a proxy





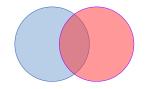
How largely do knowledge graphs overlap?

- They are interlinked, so we can simply count links
 - For NELL, we use links to Wikipedia as a proxy





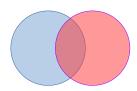
- Links between Knowledge Graphs are incomplete
 - The Open World Assumption also holds for interlinks



- But we can estimate their number
- Approach:
 - Find link set automatically with different heuristics
 - Determine precision and recall on existing interlinks
 - Estimate actual number of links



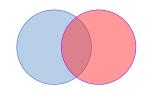
- Idea:
 - Given that the link set F is found
 - And the (unknown) actual link set would be C



- Precision P: Fraction of F which is actually correct
 - i.e., measures how much |F| is over-estimating |C|
- Recall R: Fraction of C which is contained in F
 - i.e., measures how much |F| is under-estimating |C|
- From that, we estimate $|C| = |F| * P * \frac{1}{R}$



- Mathematical derivation:
 - Definition of recall: $R = \frac{|F_{correct}|}{|C|}$ unknown



- Definition of precision: $P = \frac{|F_{correct}|}{|F|}$
- Resolve both to $|F_{correct}|$, substitute, and resolve to |C|

$$|C| = |F| * P * \frac{1}{R}$$

The existing links are used to compute precision and recall



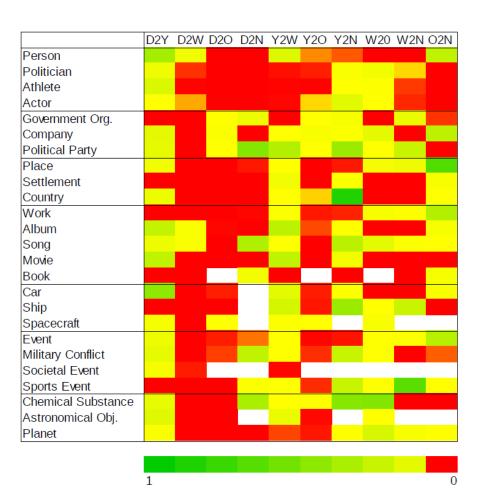
Experiment:

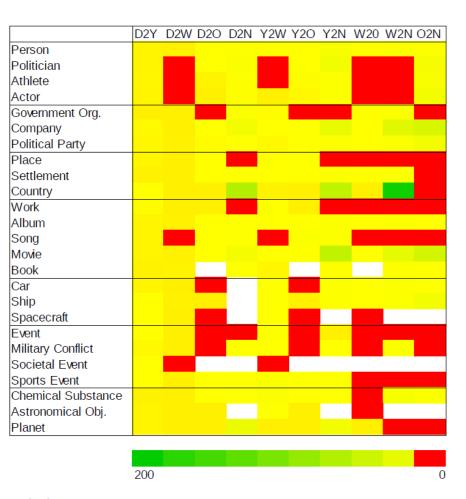
- We use the same 25 classes as before
- Measure 1: overlap relative to smaller KG (i.e., potential gain)
- Measure 2: overlap relative to explicit links
 (i.e., importance of improving links)
- Link generation with 16 different metrics and thresholds
 - Intra-class correlation coefficient for |C|: 0.969
 - Intra-class correlation coefficient for |F|: 0.646

Bottom line:

- Despite variety in link sets generated, the overlap is estimated reliably
- The link generation mechanisms do not need to be overly accurate





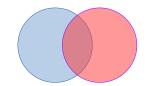


(a) Overlap as potential gain

(b) Overlap relative to existing links



Summary findings:



- DBpedia and YAGO cover roughly the same instances (not much surprising)
- NELL is the most complementary to the others
- Existing interlinks are insufficient for out-of-the-box parallel usage



- There are quite a few metrics for evaluating KGs
 - size, degree, interlinking, quality, licensing, ...

Table 2

Data quality metrics related to accessibility dimensions (type QN refers to a quantitative metric, QL to a qualitative one).

Dimension	Abr	Metric	Description	Type
	A1	accessibility of the SPARQL end- point and the server	checking whether the server responds to a SPARQL query [18]	QN
Availability	A2	accessibility of the RDF dumps	checking whether an RDF dump is provided and can be down- loaded [18]	QN
	A3	dereferenceability of the URI	checking (i) for dead or broken links i.e. when an HTTP-GET request is sent, the status code 404 Not Found is not be returned (ii) that useful data (particularly RDF) is returned upon lookup of a URI, (iii) for changes in the URI i.e the compliance with the recommended way of implementing redirections using the status code 303 See Other [18,30]	QN
	A4	no misreported content types	detect whether the HTTP response contains the header field stating the appropriate content type of the returned file e.g. application/rdf+xml [30]	QN
	A5	dereferenced forward-links	dereferenceability of all forward links: all available triples where the local URI is mentioned in the subject (i.e. the de- scription of the resource) [31]	QN
Licensing	L1	machine-readable indication of a license	detection of the indication of a license in the VoID description or in the dataset itself [18,31]	QN
_	L2	human-readable indication of a license	detection of a license in the documentation of the dataset [18, 31]	QN
	L3	specifying the correct license	detection of whether the dataset is attributed under the same license as the original [18]	QN
Interlinking	11	detection of good quality inter- links	(i) detection of (a) interlinking degree, (b) clustering coeffi- cient, (c) centrality, (d) open sameAs chains and (e) description richness through sameAs by using network measures [25], (ii) via crowdsourcing [1,65]	QN
	I2	existence of links to external data providers	detection of the existence and usage of external URIs (e.g. us- ing owl:sameAs links) [31]	QN
	I3	dereferenced back-links	detection of all local in-links or back-links: all triples from a dataset that have the resource's URI as the object [31]	QN
Security	S1	usage of digital signatures	by signing a document containing an RDF serialization, a SPARQL result set or signing an RDF graph [13,18]	QN
	S2	authenticity of the dataset	verifying authenticity of the dataset based on a provenance vo- cabulary such as author and his contributors, the publisher of the data and its sources (if present in the dataset) [18]	QL
	P1	usage of slash-URIs	checking for usage of slash-URIs where large amounts of data is provided [18]	QN
Performance	P2	low latency	(minimum) delay between submission of a request by the user and reception of the response from the system [18]	QN
	P3	high throughput	(maximum) no. of answered HTTP-requests per second [18]	QN
	P4	scalability of a data source	detection of whether the time to answer an amount of ten re- quests divided by ten is not longer than the time it takes to an- swer one request [18]	QN

Zaveri et al.: Quality Assessment for Linked Open Data: A Survey. SWJ 7(1), 2016

Table 14
Framework with an example weighting which would be reasonable for a user setting as given in [30].

Dimension	Metric	DBpedia	Freebase	OpenCyc	Wikidata	YAGO	Example of U Weighting
Accuracy	m_{synRDF}	1	1	1	1	1	1
	m_{synLit}	0.994	1	1	1	0.624	1
	$m_{semTriple}$	1	1	1	1	1	1
Trustworthiness	m_{graph}	0.5	0.5	1	0.75	0.25	1
	m_{fact}	0.5	1	0	1	1	2
	m_{NoVal}	0	1	0	1	0	1
Consistency	$m_{checkRestr}$	0	1	0	1	0	1
	$m_{conClass}$	0.875	1	0.999	1	0.333	1
	$m_{conRelat}$	0.991	0.45	1	0	0.992	1
Relevancy	$m_{Ranking}$	0	0	0	1	0	1
Completeness	$m_{cSchema}$	0.905	0.762	0.921	1	0.952	1
	m_{eCol}	0.402	0.425	0	0.285	0.332	1
	m_{cPop}	0.93	0.94	0.48	0.99	0.89	3
Timeliness	m_{Freq}	0.5	0	0.25	1	0.25	3
	$m_{Validity}$	0	1	0	1	1	1
	m_{Change}	0	1	0	0	0	1
Ease of understanding	m_{Descr}	0.704	0.972	1	0.9999	1	3
	m_{Lang}	1	1	0	1	1	2
	m_{uSer}	1	1	0	1	1	1
	m_{uURI}	1	0.5	1	0	1	2
Interoperability	m_{Reif}	1	0.5	0.5	0	0.5	1
	$m_{iSerial}$	1	0	0.5	1	1	2
	m_{extVoc}	0.61	0.108	0.415	0.682	0.134	2
	$m_{propVoc}$	0.15	0	0.513	0.001	0	1
Accessibility	m_{Deref}	1	0.437	1	0.414	1	2
	m_{Avai}	0.9961	0.9998	1	0.9999	0.7306	2
	m_{SPARQL}	1	0	0	1	1	1
	m_{Export}	1	1	1	1	1	0
	m_{Negot}	0.5	0	0	1	1	1
	m_{HTML_RDF}	1	1	0	1	1	0
	m_{Meta}	1	0	1	0	0	1
Licensing	$m_{macLicense}$	1	0	0	1	0	1
Interlinking	m_{Inst}	0.592	0.018	0.443	0	0.305	2
	m_{URIs}	0.929	0.954	0.894	0.957	0.956	1
Unweighted Average		0.708	0.605	0.498	0.738	0.625	
Weighted Average		0.718	0.575	0.516	0.742	0.646	

Färber et al.: Linked data quality of DBpedia, Freebase, OpenCyc, Wikidata, and YAGO SWJ 9(1), 2018





...but what is the cost of a single statement?



Some back of the envelope calculations...



- Case 1: manual curation
 - Cyc: created by expertsTotal development cost: \$120M

Total #statements: 21M

- \rightarrow \$5.71 per statement
- Freebase: created by laymen
 Assumption: adding a statement to Freebase equals adding a sentence to Wikipedia
 - English Wikipedia up to April 2011: 41M working hours (Geiger and Halfaker, 2013),
 - size in April 2011: 3.6M pages, avg. 36.4 sentences each
 - Using US minimum wage: \$2.25 per sentence

 \rightarrow \$2.25 per statement

acquisition by Google estimated as \$60-300M

(Footnote: total cost of creating Freebase would be \$6.75B)





- Case 2: automatic/heuristic creation
 - DBpedia: 4.9M LOC, 2.2M LOC for mappings software project development: ~37 LOC per hour (Devanbu et al., 1996)

we use German PhD salaries as a cost estimate

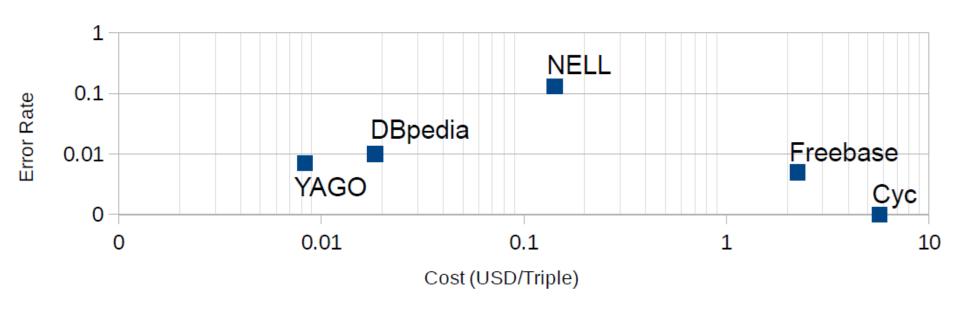


- YAGO: made from 1.6M LOC
 uses WordNet: 117k synsets, we treat each synset like a Wiki page
 - → 0.83c per statement
- NELL: 103k LOC
 - → 14.25c per statement
- Compared to manual curation: saving factor 16-250





- Graph error rate against cost
 - we can pay for accuracy
 - NELL is a bit of an outlier



Enhancing the Coverage of Knowledge Graphs



- Study for KG-based
 Recommender Systems*
 - DBpedia (likewise: YAGO) has a coverage of
 - 85% for movies
 - 63% for music artists
 - 31% for books

Delicious Bookmarks

105,000 bookmarks from 1867 users.

- README.txt
- hetrec2011-delicious-2k.zip

Last.FM

92,800 artist listening records from 1892 users.

- README.txt
- hetrec2011-lastfm-2k.zip

MovieLens + IMDb/Rotten Tomatoes

86,000 ratings from 2113 users.

- README.txt
- hetrec2011-movielens-2k.zip

https://grouplens.org/datasets/

Enhancing the Coverage of Knowledge Graphs



- Only existing pages have categories
 - Lists may also link to non-existing pages

List of intelligent dance music artists

From Wikipedia, the free encyclopedia

This section does not cite any sources. Please help improve this section by adding of Find sources: "List of intelligent dance music artists" - news · newspapers · books · scholar · JSTOR

This is a list of notable music artists who play intelligent dance music (IDM) genre

Contents [hide] 1 # 2 A-K 3 L-Z 4 References

[edit]

- 808 State
- µ-ziq

A-K [edit]

- Actress
- Acustic
- · Air Liquide
- Alarm Will Sound
- Alva Noto
- Amon Tobin

- Andv Stott
- Aphex Twin
- Apparat Arovane
- Atypic
- Autechre

- **Delicious Bookmarks** 105,000 bookmarks from 1867 users
 - README.txt
 - hetrec2011-delicious-2k.zip

Last.FM

92.800 atist listening records from 1892 users.

- README.txt
- hetrec2011-lastfm-2k.zip

MovieLens + IMDb/Rotten Tomatoes

Funkstörung

Gas

Gescom

Goldie

Gridlock

Innovaders

· Global Goon

Zachary Grav^[2]

. The Future Sound Of

Global Communication

86,000 ratings from 2113 users.

README.txt

Dopplereffekt

· Chris Douglas

· Eight Frozen Modules

Drexciva

Emptyset

Esem

FaltvDL

Fennesz

The Field

hetrec2011-movielens-2k.z

https://grouplens.org/datasets/

- · Benn Jordan
 - Biosphere

 - Björk^[1]
 - . The Black Dog

 - Blanck Mass
 - · Boards of Canada
 - Bochum Welt Boom Bip
 - Brothomstates
 - Burial Bvdub
 - C418

- · Casino Versus Japan
- · Ceephax Acid Crew
- Cex Christ
- · Chris Clark
- Clocolan
- Cylob Daedelus
- Deadbeat Deepchord
- Deru
- · The Flashbulb Demdike Stare Floating Points
 - · Flying Lotus Forest Swords

- · Himuro Yoshiteru Kim Hiorthøy . I am Robot and Proud
- Kevin Blechdom Kid606

Jon Hopkins^[3]

Jan Jelinek

Jega

Jello

Jlin John Tejada

- Kodomo
- Koreless^[4]

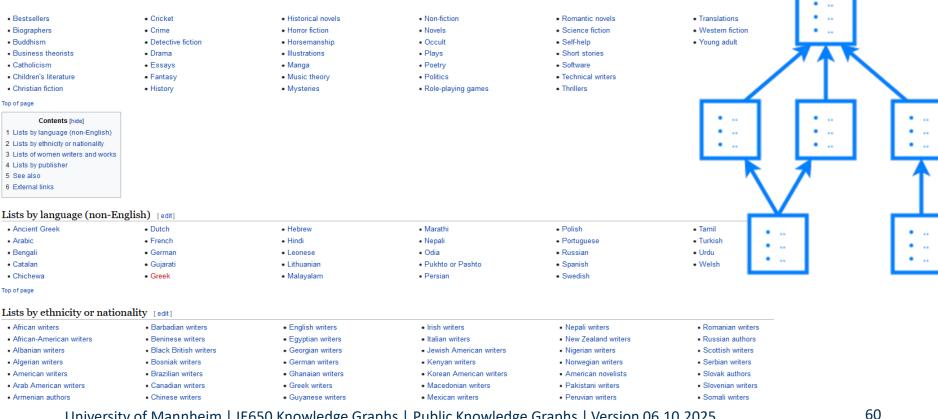
Entity Extraction from List Pages



Lists form (shallow) hierarchies

Lists of writers

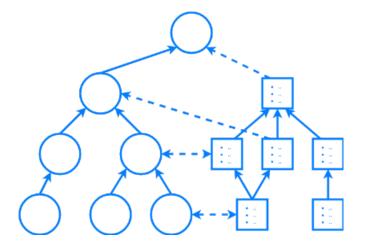
From Wikipedia, the free encyclopedia The following are lists of writers:



Entity Extraction from List Pages



- Idea: Align with category graph
- Equivalence:
 - "List of Japanese Writers"→ Category: Japanese Writers
- Subsumption:
 - "List of JapaneseSpeculative Fiction Writers"
 - → Category:Japanese Writers



Classifying Red Links



- Not all entities on a list page belong to the same category
- Idea:
 - Learn classifier to tell subject entities from non-subject entities
- Distant learning approach
 - Positive examples:
 - Entities that are in the corresponding category
 - Negative examples
 - Entities that are in a category which is disjoint
 - e.g., Book <> Writer

- Patricia Aakhus (1952–2012), The Voyage of Mael Duin's Curragh
- Atia Abawi
- Edward Abbey (1927–1989), The Monkey Wrench Gang
- Lynn Abbey (born 1948), Daughter of the Bright Moon
- Belle Kendrick Abbott (1842-1893), Leah Mordecai
- Eleanor Hallowell Abbott (1872–1958), poet, novelist and short story writer
- · Hailey Abbott, Summer Boys
- Megan Abbott (born 1971), Die A Little
- · Shana Abé. A Rose in Winter
- Louise Abeita (1926–2014), Native American Isleta Pueblo writer, I am a Pueblo Indian Girl
- Robert H. Abel (1941–2017)
- Aberjhani
- Walter Abish (born 1931), How German Is It
- Abiola Abrams (born 1976), TV host, art filmmaker and author, Dare
- Diana Abu-Jaber (born 1960), Arabian Jazz
- · Susan Abulhawa, Mornings in Jenin
- Kathy Acker (1947–1997), Blood and Guts in High School
- · Cherry Adair, Black Magic
- · Alice Adams (1926-1999), Beautiful Girl
- · Victoria Aveyard (born 1990), Red Queen series

Increasing Level of Detail



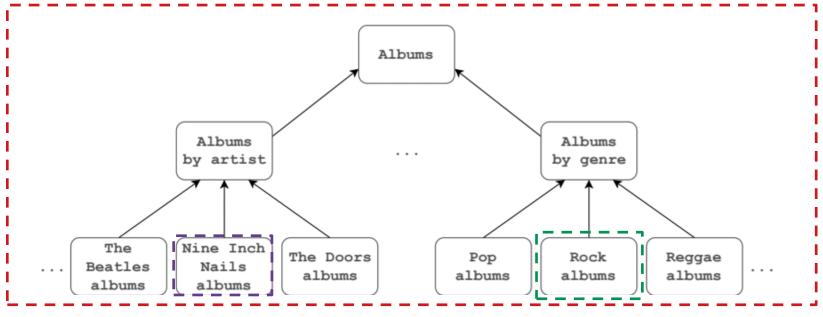
- YAGO uses categories for types
 - e.g., Category: American Industrial Groups
 - but does not analyze them further
- :NineInchNails a :AmericanIndustrialGroup.
 - "Things, not Strings"?

```
    :NineInchNails a :MusicalGroup;
    hometown :United_States;
    genre :Industrial.
```





⊆ dbo:Album

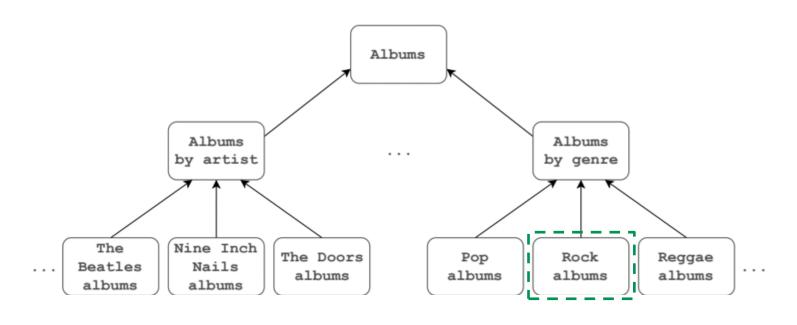


⊆ dbo:artist.{dbr:Nine_Inch_Nails}

⊆ dbo:genre.{dbr:Rock_Music}





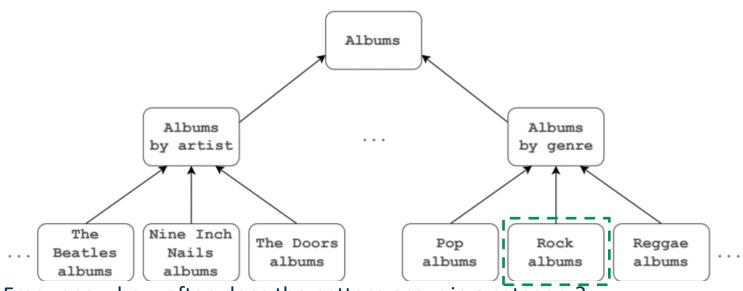


⊆ dbo:genre.{dbr:Rock_Music}

⊆ dbo:genre.{dbr:Rock_(Rapper)}

Cat2Ax: Axiomatizing Wikipedia Categories





- Frequency: how often does the pattern occur in a category?
 - i.e.: share of instances that have dbo:genre.{dbr.Rock_Music}?
- Lexical score: likelihood of term as a surface form of object
 - i.e.: how often is Rock used to refer to dbr:Rock_Music?
- Sibling score: how likely are sibling categories sharing similar patterns?
 - i.e., are there sibling categories with a high score for dbo:genre?

CaLiGraph Example



rdfs:label	• Tiamat
owl:sameAs	* dbr:Tiamat_(band) Category: Musical Groups established
clgo:activeYearsStartYear	• 1987 in 1987
clgo:genre	List of symphonic metal bands
clgo:hometown	Category: Swedish death metal bands List of Swedes in Music

Pushing Entity Coverage Further



Beyond red links (2020)

Title	Running time	Year released	Notes
Amra Ekta Cinema Banabo (The Innocence)	1265 min (21 hr, 5 min)	2019	[31][32]
Resan (The Journey)	873 min (14 hr, 33 min)	1987	[33]
La Flor	803 min (13 hr, 23 min)	2018	[34]
Out 1 (Noli me tangere)	775 min (12 hr, 55 min)	1971	[35]
Evolution of a Filipino Family	593 min (9 hr, 53 min)	2004	[36]
Shoah	566 min (9 hr, 26 min)	1985	[37]
Tie Xi Qu: West of the Tracks	551 min (9 hr, 11 min)	2003	[38]
Death in the Land of Encantos	538 min (8 hr, 58 min)	2007	[39]
Dead Souls	495 min (8 hr, 15 min)	2018	[40]
A Lullaby to the Sorrowful Mystery	485 min (8 hr, 5 min)	2016	[41]
O.J.: Made in America	463 min (7 hr, 43 min)	2016	[42]
Melancholia	450 min (7 hr, 30 min)	2008	[43]
Sátántangó	419 min (6 hr, 59 min)	1994	[44]
La Roue	413 min (6 hr, 53 min)	1923 (Restoration, 2019)	[45]
The Best of Youth	366 min (6 hr, 6 min)	2003	[46]
Century of Birthing	360 min (6 hr)	2011	[47]
Near Death	358 min (5 hr, 58 min)	1989	[48]
Karamay	356 min (5 hr, 56 min)	2011	[49]
Little Dorrit	350 min (5 hr, 50 min)	1987	[50]
Carlos	339 min (5 hr, 39 min)	2010	[51]
Mula sa Kung Ano ang Noon	338 min (5 hr, 38 min)	2014	[52]
Napoléon	332 min (5 hr, 32 min)	1927 (Restoration, 2016)	[53]
1900	317 min (5 hr, 17 min)	1976	[54]
Happy Hour	317 min (5 hr, 17 min)	2015	[55]
Batang West Side	315 min (5 hr, 15 min)	2001	[56]
The Deluge	315 min (5 hr, 15 min)	1974	[57]
Fanny and Alexander	312 min (5 hr, 12 min)	1982	[58]
Tsahal	304 min (5 hr, 4 min)	1994	[59]

Beyond explicit lists (2021)

Members [edit]

- Jürgen Engler vocals, guitar, keyboards, synthesizers and programming, metallic percussion (1980-1985, 1989-1997, 2005-present)
- Ralf Dörper keyboards, synthesizers and programming (1980–1982, 1985, 1989–1997, 2005–present)
- Marcel Zürcher guitar, keyboards (2005–present)
- · Nils Finkeisen guitar (2015-present)
- · Paul Keller drums (2018-present)

Former members [edit]

- . Bradley Bills live drums (2013-2014)
- Rüdiger Esch bass guitar (1989–1997, 2005–2011)
- . Christoph "Nook" Michelfeit drums, electronic percussion
- Bernward Malaka bass guitar (1980-1982)
- Hendrik Thiesbrummel live drums (2016–2018)
- · Frank Köllges drums
- . Eva Gossling saxophone (1981)
- · Christina Schnekenburger keyboards
- · Walter Jäger ?
- . Christopher Lietz programming, samples (1995-1997)
- Lee Altus guitar (1992–1997)
- . Darren Minter drums (1993)
- . George Lewis drums (1997)
- Oliver Röhl drums
- Achim Färber drums
- Volker Borchert drums (1992, 2015-2016)

Discography [edit]

Albums [edit]

- Stahlwerksynfonie (1981)
- Volle Kraft Voraus! (1982)
- Entering the Arena (1985)
- / (1992)
- II The Final Option (1993)
- The Final Remixes (1994)
- III Odyssey of the Mind (1995)
- Paradise Now (1997)
- . The Machinists of Joy (2013)
- V Metal Machine Music (2015)
- Stahlwerkrequiem (2016)
- Live Im Schatten Der Ringe (2016)

Entity Extraction from List Pages



- Red and grey links
 - Red links point to entities
 that do not exist
 - "Grey links"
 - Are actually not links
 - i.e., entities to be discovered

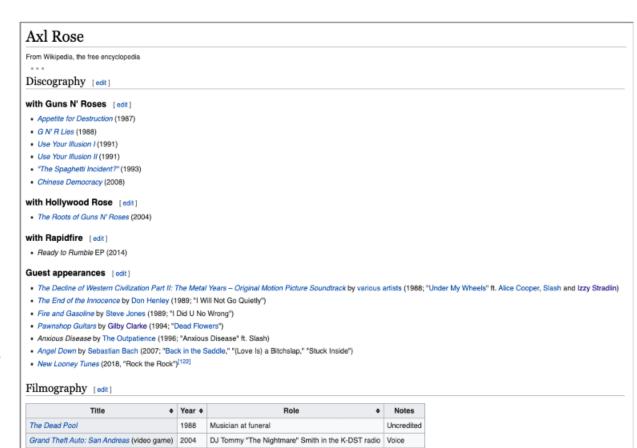
Official Control

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Beyond List Pages



- Many pages contain list-like constructs
- Usually
 - Small
 - Same type
 - Same relation to page entity
 - More grey links



Voice

Voice

New Looney Tunes (TV show)[123]

That Metal Show

Jimmy Kimmel Live!

Scooby-Doo and Guess Who? (Tv Show)

Himself

Himself

Himself

Himself

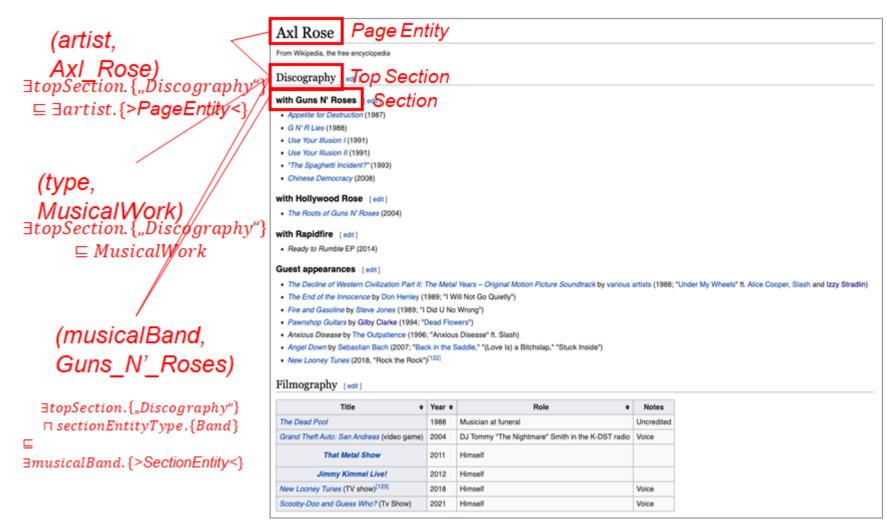
2011

2012

2018

Beyond List Pages





Beyond List Pages



- Learning descriptive rules for listings, e.g.
 - topSection("Discography") → artist.{PageEntity}
 - Learning across pages to mitigate small data problems

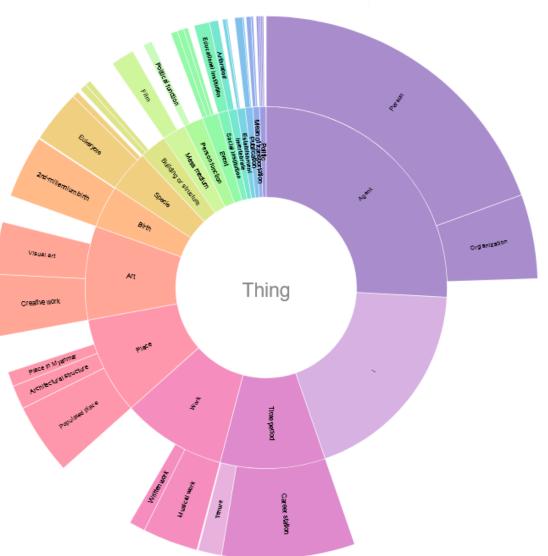
Metrics:

- Support: no. of listings covered by rule antecedent
- Confidence: frequency of rule consequent over all covered listings
- Consistency: mean absolute deviation of overall confidence and listing confidence
 - i.e., does the rule work equally well across all covered listings

CaLiGraph at a Glance



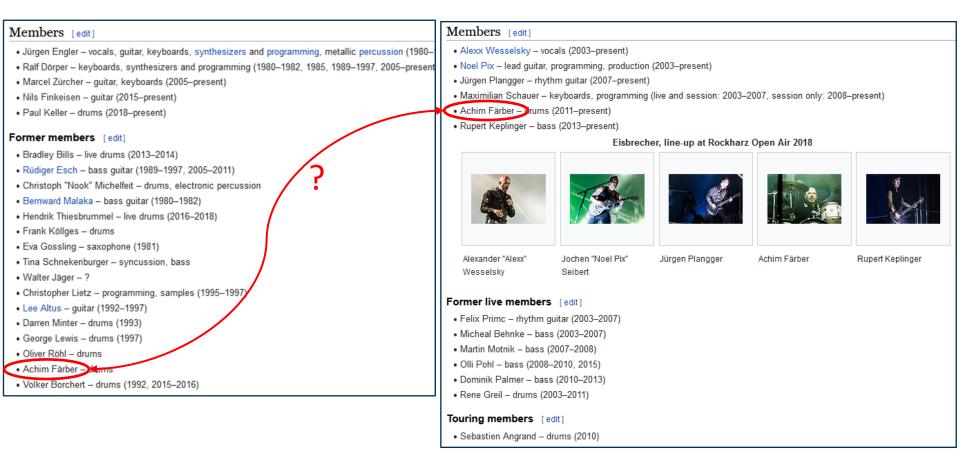
- Latest version 2.1
 - 15M entities
 - incl. 8M from listings
 - Caveat:
 - Disambiguation!



Entity Disambiguation



Examples: Wikipedia pages of Die Krupps and Eisbrecher



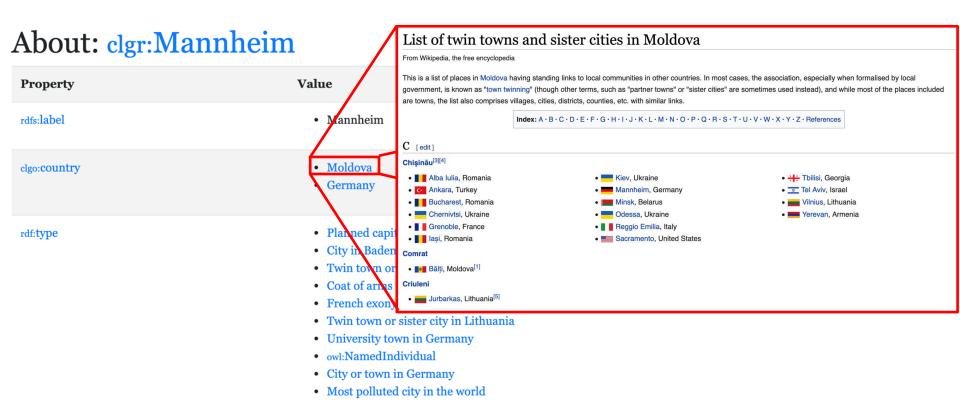
CaLiGraph Glitches



CaLiGraph

Formats

Sparql Endpoint



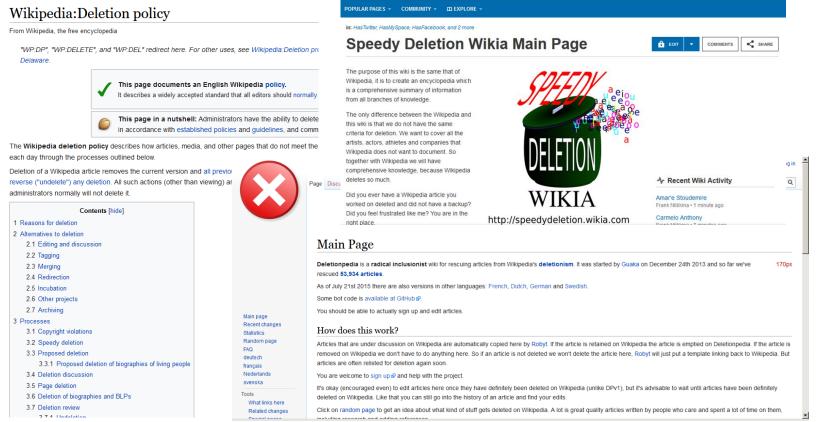


- Wikipedia-based Knowledge Graphs will remain an essential building block of Semantic Web applications
- But they suffer from...
 - ...a coverage bias
 - ...limitations of the creating heuristics





- One (but not the only!) possible source of coverage bias
 - Articles about long-tail entities become deleted





- Why stop at Wikipedia?
- Wikipedia is based on the MediaWiki software
 - ...and so are thousands of Wikis
 - Fandom by Wikia: >385,000 Wikis on special topics
 - WikiApiary: reports >20,000 installations of MediaWiki on the Web

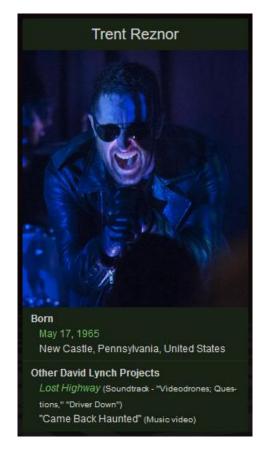




Collecting Data from a Multitude of Wikis







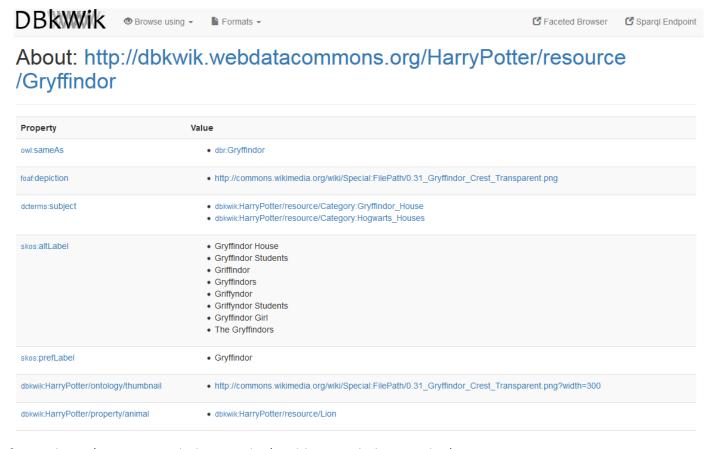


- The DBpedia Extraction Framework consumes MediaWiki dumps
- Experiment (started as team project 2017)
 - Can we process dumps from arbitrary Wikis with it?
 - Are the results somewhat meaningful?





Example from Harry Potter Wiki

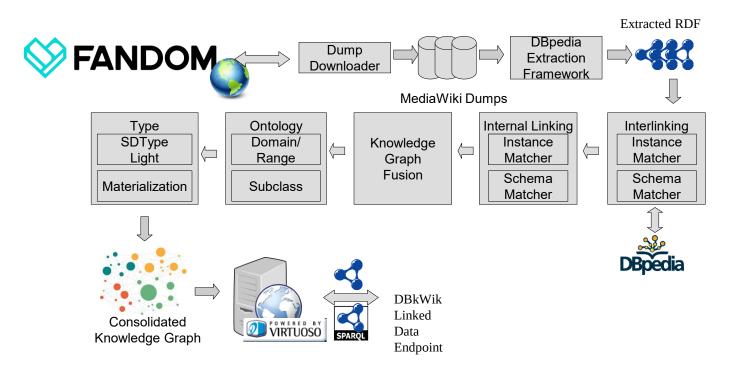




- Differences to DBpedia
 - DBpedia has manually created mappings to an ontology
 - Wikipedia has one page per subject
 - Wikipedia has global infobox conventions (more or less)
- Challenges
 - On-the-fly ontology creation
 - Instance matching
 - Schema matching



- Heuristics
 - Ontology induction
 - Instance/Schema Matching





- Downloaded ~15k Wiki dumps from Fandom
 - 52.4GB of data, roughly the size of the English Wikipedia
- Prototype: extracted data for ~250 Wikis
 - 4.3M instances, ~750k linked to DBpedia
 - 7k classes, ~1k linked to DBpedia
 - 43k properties, ~20k linked to DBpedia
 - ...including duplicates!
- Link quality
 - Good for classes, OK for properties (F1 of .957 and .852)
 - Needs improvement for instances (F1 of .641)



- Scalability of matching:
 - Pairwise matching does not scale
 - 300k Wikis, 1 minute for each pair \rightarrow 171k years
- Iteratively match and merge
 - 300k Wikis, 1 minute for each match&merge run \rightarrow 200 days
- Tree-shaped execution plan
 - Parallelizable
 - Hierarchical clustering by topic
 - Whole run under a week



- Background: Web table interpretation
- Most approaches need typing information
 - DBpedia etc. have too little coverage on the long tail
 - Wanted: extensive type database

Rank ¢	Country/Territory \$	Capital +	Population +	Year +	Percent of Population
1	China	Beijing	20,693,000[1]	2012	1.52%
2	India	New Delhi	16,787,949[2]	2014	0.90%
3	Japan	Tokyo	13,189,000 ^[3]	2011	10.32%
4	≥ Philippines	Manila	12,877,253 ^[4]	2015	12.44%
5	Russia	Moscow	11,541,000 ^[5]	2011	8.07%
6	≡ Egypt	Cairo	10,230,350	2012	11.10%
7	- Indonesia	Jakarta	10,187,595[6]	2011	4.18%
8	☑ Democratic Republic of the Congo	Kinshasa	10,125,000[7]	2012	12.30%
9	South Korea	Seoul	9,989,795[8]	2015	20.47%
10	Bangladesh	Dhaka	8,906,000 [9]	2011	5.56%
11	■•■ Mexico	Mexico City	8,851,080 ^[10]	2010	7.51%
12	<u></u> Iran	Tehran	8,846,782	2014	9.91%
13	United Kingdom	London	8,630,100[11]	2015	13.25%
14	Peru	Lima	8,481,415 ^[12]	2012	28.29%
15	Thailand	Bangkok	8,249,117 ^[13]	2010	12.42%
16	Colombia	Bogotá	7,613,303 ^[14]	2011	16.17%
17	▼ Vietnam	Hanoi	7,587,800 ^[15]	2014	8.22%
18	Hong Kong (China)	Hong Kong	7,298,600 ^[16]	2015	100%
19	<u></u> Iraq	Baghdad	7,216,040 ^[17]		21.59%
20	Singapore	Singapore	5,535,000 ^[18]	2015	100%
21	C- Turkey	Ankara	5,150,072	2014	6.72%
22	L Chile	Santiago	5,084,038[19]	2012	29.12%
23	Saudi Arabia	Riyadh	4,878,723 ^[20]	2009	18.20%
24	Germany	Berlin	3,520,000[21]	2012	4.38%
25	— Syria	Damascus	3,500,000		15.32%
26	■ Algeria	Algiers	3,415,811		8.45%
27	Spain	Madrid	3,233,527[22]	2012	6.84%
28	North Korea	Pyongyang	3,144,005		12.63%
29	Maristan Afghanistan	Kabul	3,140,853		10.28%
30	Kenya	Nairobi	3,138,369	2010	7.67%



- Extraction of type information using Hearstlike patterns, e.g.,
 - T, such as X
 - X, Y, and other T
- Text corpus: common crawl
 - ~2 TB crawled web pages
 - Fast implementation: regex over text
 - "Expensive" operations only applied once regex has fired
- Resulting database
 - 400M hypernymy relations



WebIsALOD



Example:

About: fiction writer

Premodifier: fiction Head noun: writer

Same concepts

http://dbpedia.org/resource/Fiction

Broader concepts

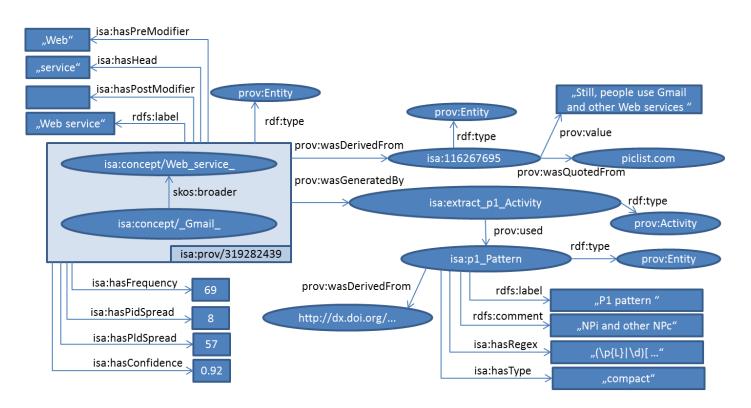
label	provenance	confidence
writer	isap:391280092	0.799331
great idea	isap:493244047	0.672180
several magazine	isap:104101164	0.655684
category	isap:104762336	0.477191
artist	isap:387107910	0.471280
blog	isap:492616562	0.458511
writers	isap:439522913	0.427701
story	isap:122402598	0.306667
group	isap:115379219	0.299656
poet	isap:492284397	0.287519

Narrower concepts

label	provenance	confidence
george orwell	isap:386468501	0.662121
science fiction	isap:275868279	0.635886
franz kafka	isap:159147340	0.602015
steve almond	isap:392552636	0.581515
dan brown	isap:157209267	0.574584
james joyce	isap:159394667	0.561794
stephen king	isap:306753456	0.557354
flannery oconnor	isap:266705231	0.555096
alice munro	isap:162537618	0.552608
ayn rand	isap:301402665	0.526857



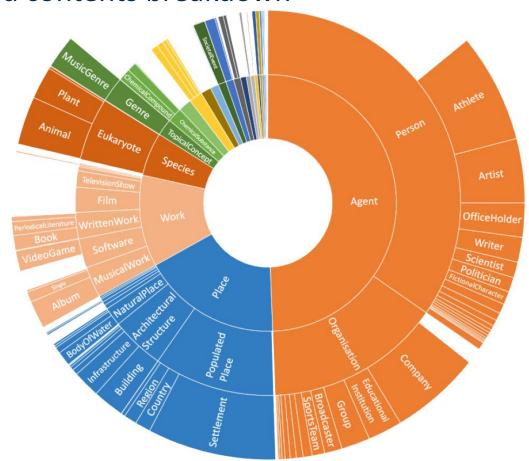
- Initial effort: transformation to a LOD dataset
 - including rich provenance information



WebIsALOD



Estimated contents breakdown





Main challenge

- Original dataset is quite noisy (<10% correct statements)
- Recap: coverage vs. accuracy
- Simple thresholding removes too much knowledge

Approach

- Train RandomForest model for predicting correct vs. wrong statements
- Using all the provenance information we have
- Use model to compute confidence scores

Current ongoing research

Using transformers and a larger training set



- Current challenges and works in progress
 - Distinguishing instances and classes
 - i.e.: subclass vs. instance of relations
 - Splitting instances
 - Bauhaus is a goth band
 - Bauhaus is a German school
 - Knowledge extraction from pre and post modifiers
 - Bauhaus is a goth band → genre(Bauhaus, Goth)
 - Bauhaus is a German school → location(Bauhaus, Germany)

Summary



- We have seen a couple of Knowledge Graphs
 - How they are built
 - What they contain
- For your project
 - Have a look at the fit for your domain
 - Try different options
- For a master's thesis later
 - Work on recent developments in our group

Questions?



