<u>UNIVERSITÄT</u> Mannheim

Knowledge Graphs Public Knowledge Graphs

Heiko Paulheim

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

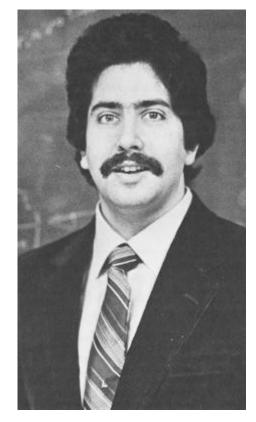
• Knowledge Graphs out there (not guaranteed to be complete)

Name	Instances	Facts	Types	Relations	
DBpedia (English)	4,806,150	176,043,129	735	2,813	public
YAGO	4,595,906	25,946,870	488,469	77	
Freebase	49,947,845	3,041,722,635	26,507	37,781	
Wikidata	15,602,060	65,993,797	23,157	1,673	
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	
Google's Knowledge Vault	45,000,000	271,000,000	1,100	4,469 -	privoto
Yahoo! Knowledge Graph	3,443,743	1,391,054,990	250	800	private

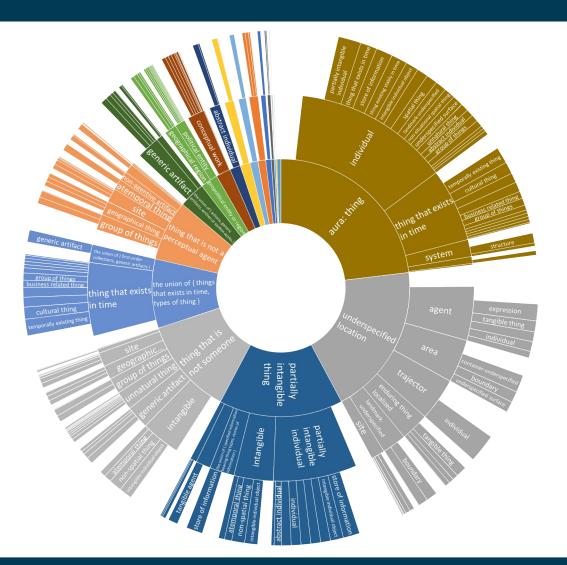
Paulheim: *Knowledge graph refinement: A survey of approaches and evaluation methods.* Semantic Web 8:3 (2017), pp. 489-508

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

Freebase

coming up soon:

was it a good deal or not?

- 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)

Knowledge Graph Creation: Freebase

- Community based
- Like Wikipedia, but more structured

Arnold Schwarzenegger -

📿 Discuss "Arnold Schwarzenegger" 🗉 Show Empty Fields



🖣 image 1 of 1 🕨

.= 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



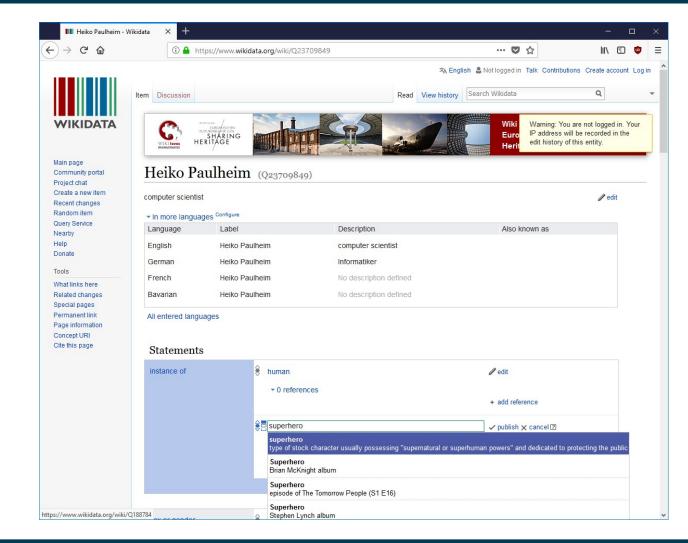
Knowledge Graph Creation: Wikidata

- 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



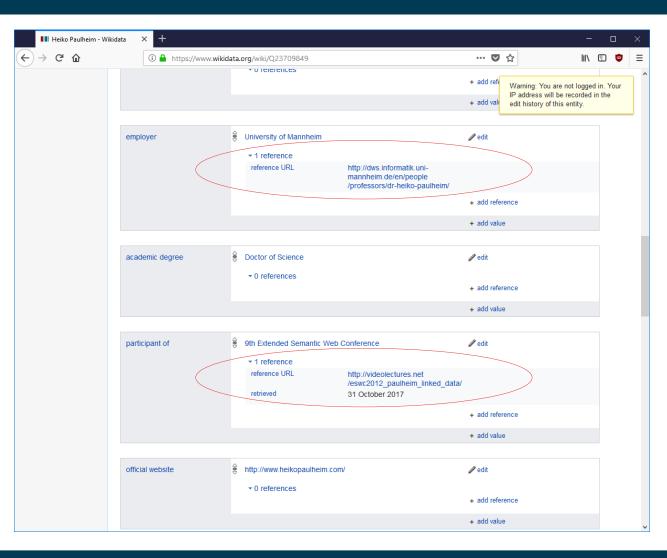
Knowledge Graph Creation: Wikidata

Collaborative
 editing

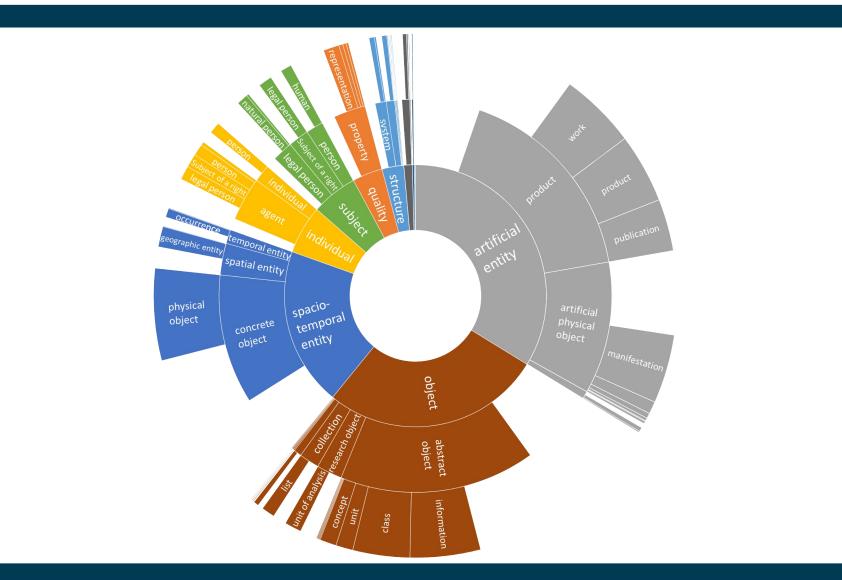


Knowledge Graph Creation: Wikidata

• Provenance

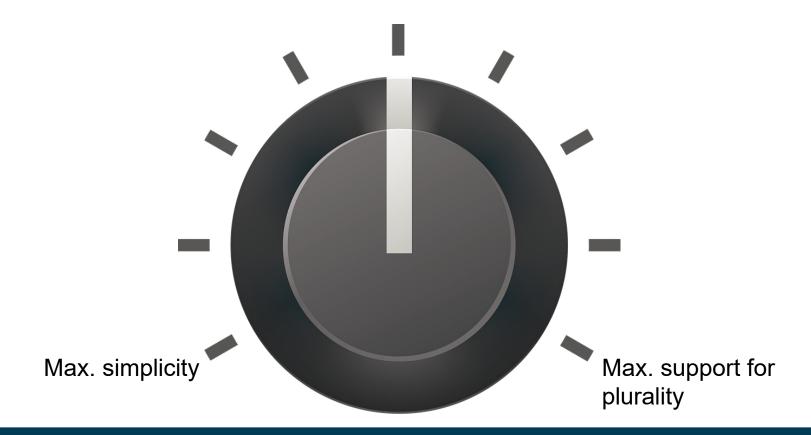


Wikidata



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
 - ...with Wikidata catching up

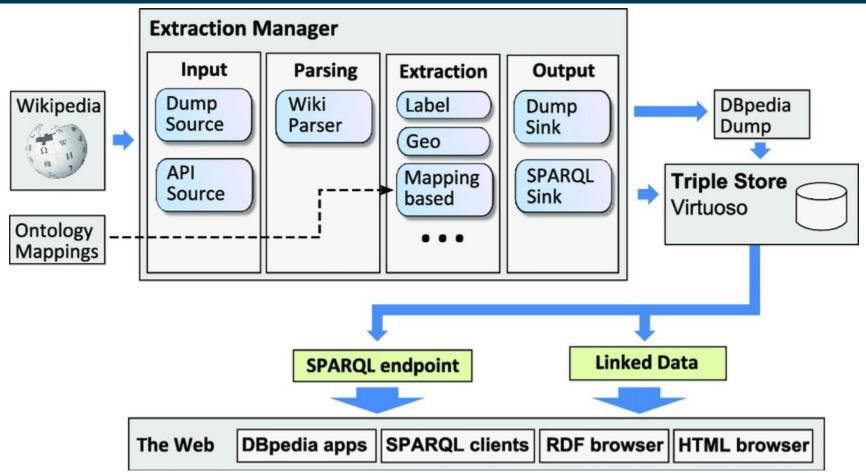




DBpedia

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Doctoral students	249 ^[1]		-Tur.Description-				

DBpedia



Lehmann et al.: DBpedia – A Large-scale, Multilingual Knowledge Base Extracted from Wikipedia. 2014

Mapping en:Infobox film

This is the mapping for the Wikipedia template Infobox film @. Find usages of this Wikipedia template here @. Test this mapping & (or in namespace File & or Creator 장) with some example Wikipedia pages. Check which prog Read more about mapping Wikipedia templates.

Template Mapping (I	nelp)	Ontology	Class:Film				
map to class	Film	This is the definiti	This is the definition of an ontology class.				
Mappings		Show all propertie Show class in cla	s ਲਾ available for this class. ss hierarchy ਲਾ.				
			editing the ontology schema. esult of your edit on DBpedia Live (this is				
Property Mapping (h	elp)	Ontology class (help)				
template property	director	rdfs:label (en)	film				
ontology property	director	rdfs:label (en)	movie				
		rdfs:label (nl)	film				
		rdfs:label (da)	film				
		rdfs:label (de)	Film				
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Property Mapping (h	elp)	rdfs:label (fr)	film				
template property	producer	rdfs:label (ko)	영화				
ontology property	producer	rdfs:label (ja)	映画				
		rdfs:label (ar)	فيلم				
		rdfs:label (pl)	film				
		rdfs:label (ga)	scannán				
		rdfs:label (es)	película				

OntologyProperty:director

This is the definition of an ontology property.

Read more about editing the ontology schema.

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

Ontology object proper	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]
rdte:commont (tr)	Un réalisateur (au féminin, réalisatrice) est une personne qui dirige la fabrication d'une œuvre audio 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	

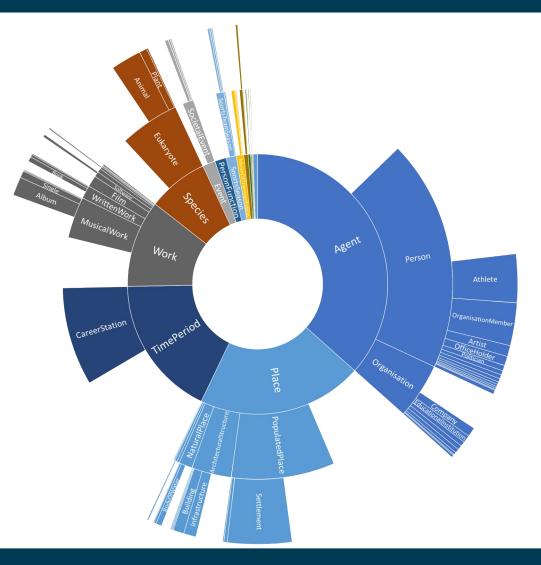
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Work owl:equivalentClass schema:Movie, wikidata:Q11424

rdfs:subClassOf

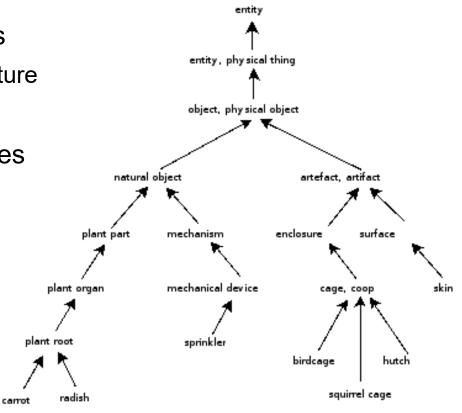
owl:disjointWith

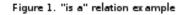
DBpedia



YAGO

- Wikipedia categories for types
 - Plus WordNet as upper structure
- Manual mappings for properties





https://www.cs.princeton.edu/courses/archive/spring07/cos226/assignments/wordnet.html

YAGO

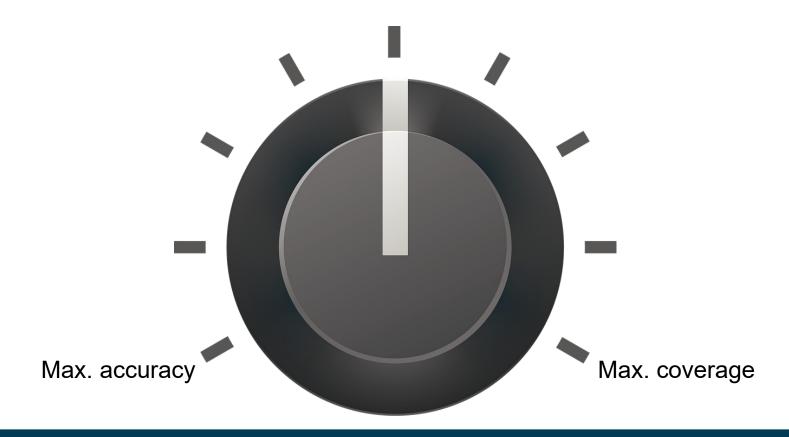
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YAGO



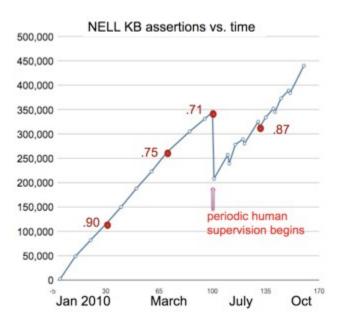
Knowledge Graph Creation

- 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



http://rtw.ml.cmu.edu/rtw/overview

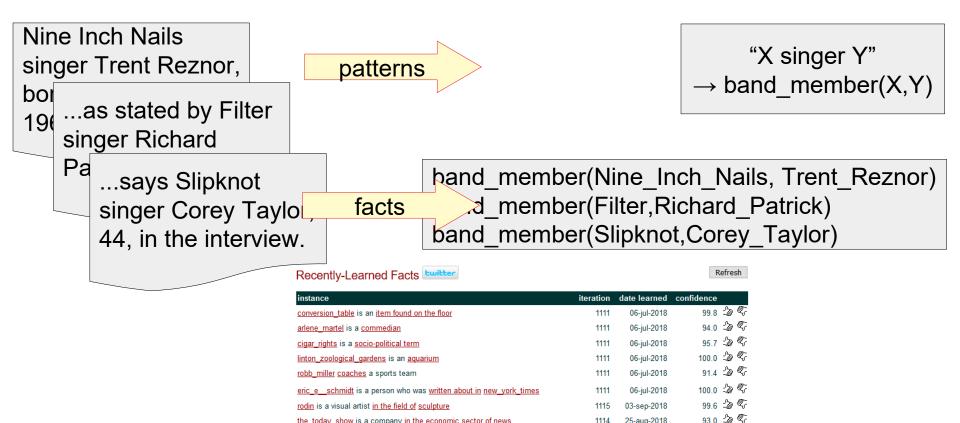
Knowledge Graph Creation: NELL

Extraction of a Knowledge Graph from a Text Corpus ٠

the_today_show is a company in the economic sector of news

jerusalem is a city located in the geopolitical location israe

china is a country located in the geopolitical location other_countries



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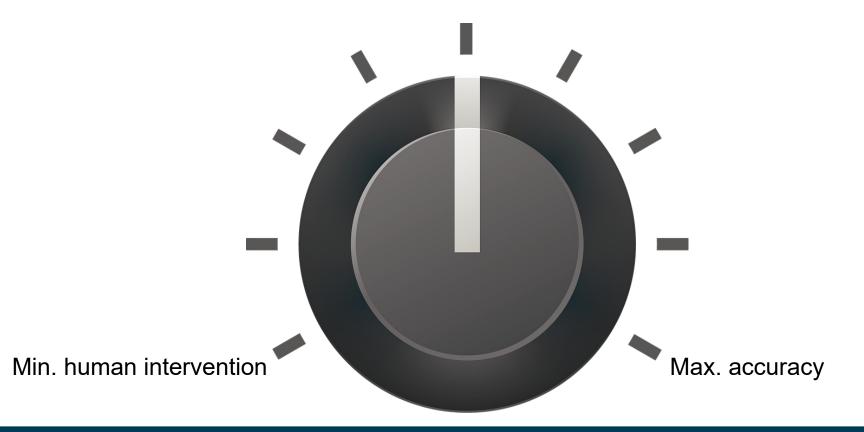
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Knowledge Graph Creation: NELL



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

 \rightarrow all those decisions influence the shape of a knowledge graph!



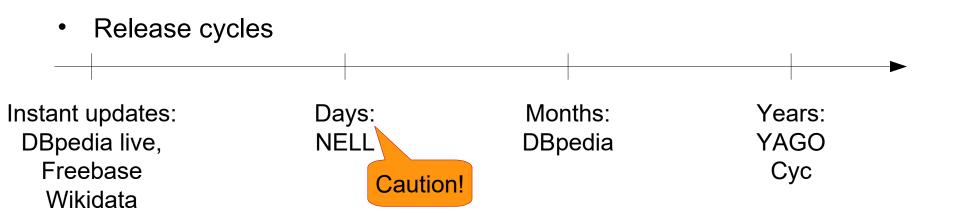
Non-Public Knowledge Graphs

- 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

See: Noy et al. (2019): Industry-scale Knowledge Graphs: Lessons and Challenges: Five diverse technology companies show how it's done



• Size and density

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

	DBpedia	YAGO	Wikidata	OpenCyc	NELL
Version	2016-04	YAGO3	2016-08-01	2016-09-05	08m.995
# instances	5,109,890	$5,\!130,\!031$	17,581,152	118,125	$1,\!974,\!297$
# 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

Ringler & Paulheim: One Knowledge Graph to Rule them All? KI 2017

- 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)

	D	Y	W	0	Ν
Person					
Politician					
Athlete					
Actor					
Government Org.					
Company					
Political Party					
Place					
Settlement					
Country					
Work					
Album					
Song					
Movie					
Book					
Car					
Ship					
Spacecraft					
Event					
Military Conflict					
Societal Event					
Sports Event					
Chemical Substance					
Astronomical Obj.					
Planet					
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Military Conflict					
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(a) Number of instances (b) Average indegree (c) Average outdegree

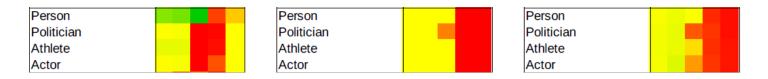
Ringler & Paulheim: One Knowledge Graph to Rule them All? KI 2017

- 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

Ringler & Paulheim: One Knowledge Graph to Rule them All? KI 2017

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

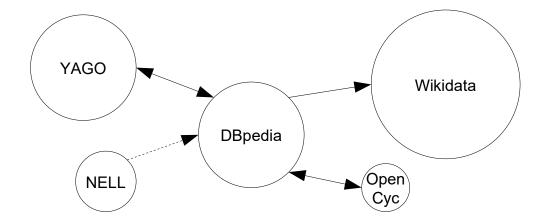
• Reading the diagrams right... (ctd.)



- 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

Overlap of Knowledge Graphs

- 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



Ringler & Paulheim: One Knowledge Graph to Rule them All? KI 2017

- How largely do knowledge graphs overlap?
- They are interlinked, so we can simply count links
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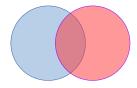
Ringler & Paulheim: One Knowledge Graph to Rule them All? KI 2017

- 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

Ringler & Paulheim: One Knowledge Graph to Rule them All? KI 2017

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

Ringler & Paulheim: One Knowledge Graph to Rule them All? KI 2017



- Mathematical derivation: ٠
 - 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|•

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

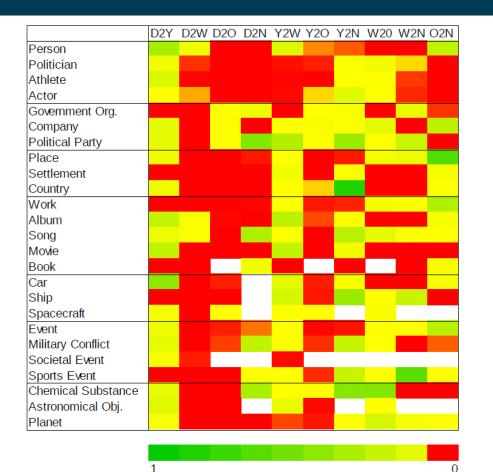
Ringler & Paulheim: One Knowledge Graph to Rule them All? KI 2017

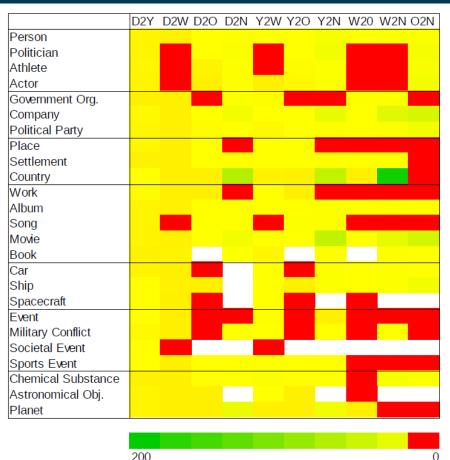
- Experiment:
 - We use the same 25 classes as before
 - Measure 1: overlap relative to smaller KG (i.e., potential gain)
 - Measure 2: overlap relative to explicit links (i.e., importance of improving links)
- Link generation with 16 different metrics and thresholds
 - Intra-class correlation coefficient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

Ringler & Paulheim: One Knowledge Graph to Rule them All? KI 2017

10/17/22 Heiko Paulheim

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(a) Overlap as potential gain

(b) Overlap relative to existing links

Ringler & Paulheim: One Knowledge Graph to Rule them All? KI 2017

- 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

Ringler & Paulheim: One Knowledge Graph to Rule them All? KI 2017

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

Data quality metrics related to accessibility dimensions (type QN refers to a quantitative metric	, QL to a qualitative one).
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Dimension	Abr	Metric	Description	Тур
	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 ber- turned (ii) that useful data (particularly RDF) is returned upon lookup of a URI, (iii) for changes in the URI ic the compli- ance 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	Ll	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 I1	11	detection of good quality inter- links	(i) detection of (a) interlinking degree, (b) clustering coefficient, (c) centrality, (d) open sameAs chains and (e) description richness through sameAs by using network measures [25], (ii) via crowdsourcing [1,65]	QN
	12	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
	13	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	S 1	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
Performance	P 1	usage of slash-URIs	checking for usage of slash-URIs where large amounts of data is provided [18]	QN
	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

Dimension	Metric	DBpedia	Freebase	OpenCyc	Wikidata	YAGO	Example of User Weighting w _i
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 _{cCol}	0.402	0.425	0	0.285	0.332	i
	mcPop	0.93	0.94	0.48	0.99	0.89	3
Timeliness	mFreq	0.5	0	0.25	1	0.25	3
	mValidity	0	1	0	i	1	1
	m _{Change}	Ő	î	Ő	0	0	i
Ease of understanding	m _{Descr}	0.704	0.972	1	0.9999	1	3
	mLang	1	1	0	1	1	2
	muSer	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
	miSerial	1	0	0.5	1	1	2
	mextVoc	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
,	mAvai	0.9961	0.9998	1	0.9999	0.7306	2
	m _{SPARQL}	1	0	0	1	1	1
	mExport	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	mInst	0.592	0.018	0.443	0	0.305	2
2	<i>m</i> 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... Paulheim: How much is a triple?

Estimating the Cost of Knowledge Graph Creation, 2018

- Case 1: manual curation
 - Cyc: created by experts
 Total 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

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



acquisition by Google estimated as \$60-300M

- 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

\rightarrow 1.85c per statement

- YAGO: made from 1.6M LOC

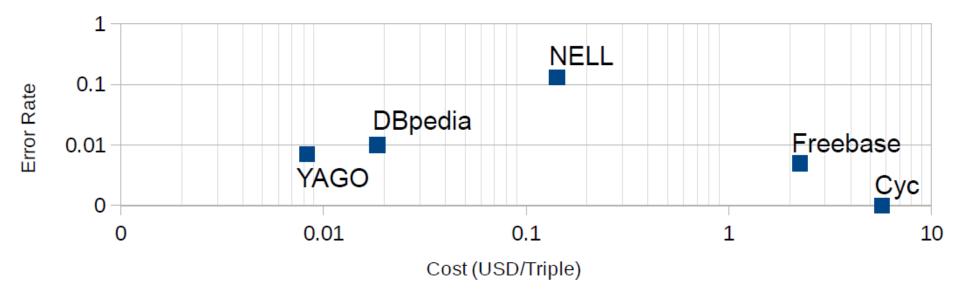
uses WordNet: 117k synsets, we treat each synset like a Wiki page

 \rightarrow 0.83c per statement

- NELL: 103k LOC
 - \rightarrow 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



New Kids on the Block

Subjective age: Measured by the fraction of the audience that understands a reference to your young days' pop culture...

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

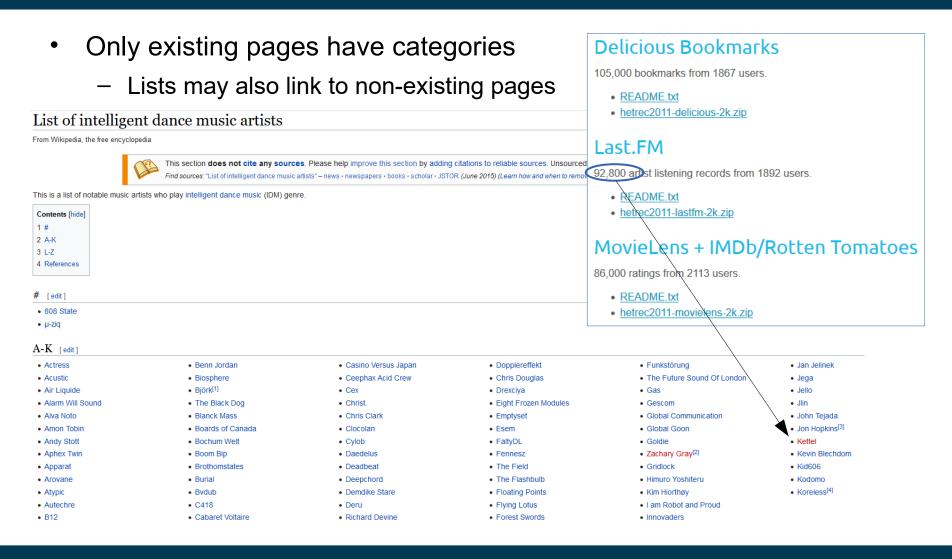
86,000 ratings from 2113 users.

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

https://grouplens.org/datasets/

*) Di Noia, et al.: *SPRank: Semantic Path-based Ranking for Top-n Recommendations using Linked Open Data.* In: ACM TIST, 2016

Enhancing the Coverage of Knowledge Graphs



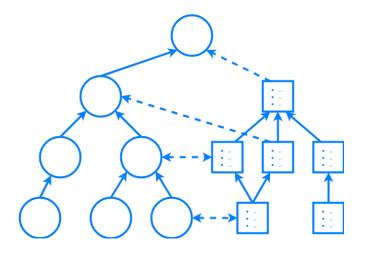
Entity Extraction from List Pages

• Lists form (shallow) hierarchies



Entity Extraction from List Pages

- Idea: align with category graph
- Equivalence:
 - "List of Japanese Writers"
 ↔ Category:Japanese Writers
- Subsumption:
 - "List of Japanese Speculative Fiction Writers"
 - \rightarrow Category:Japanese Writers



Classifying Red Links

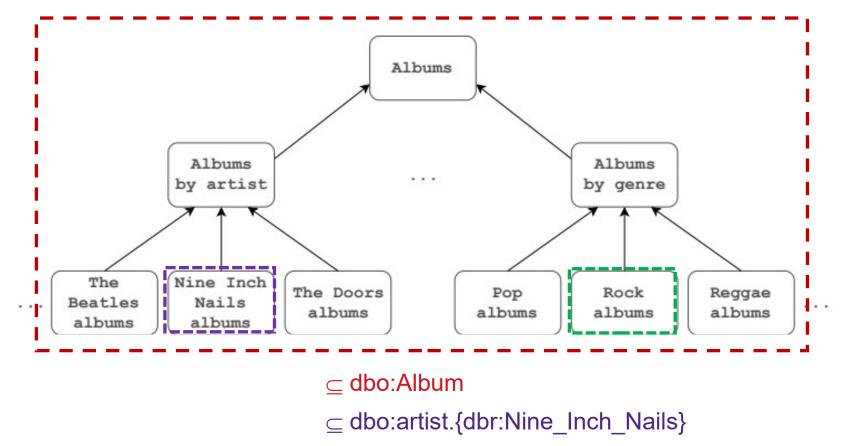
- Not all entities on a list page belong to the same category
- Idea:
 - Learn classifier to tell subject entities from non-subject entities
- Distant learning approach
 - Positive examples:
 - Entities that are in the corresponding category
 - Negative examples
 - Entities that are in a category which 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 .

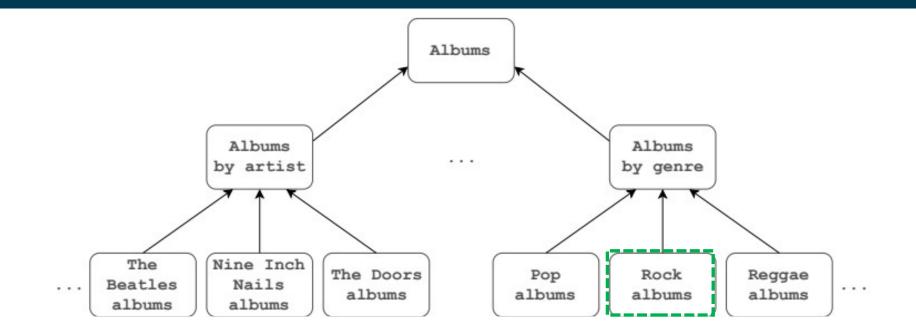
Cat2Ax: Axiomatizing Wikipedia Categories



 \subseteq dbo:genre.{dbr:Rock_Music}

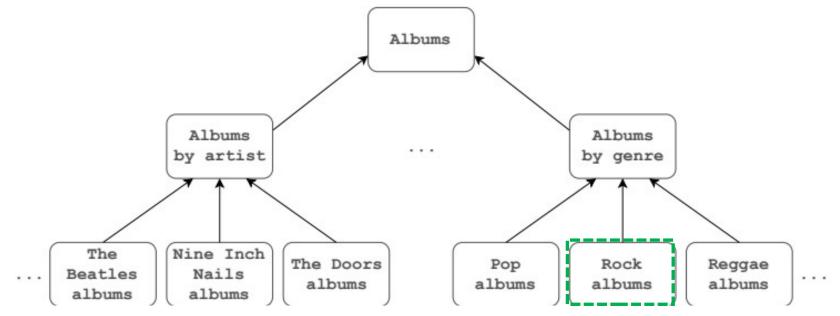
Heist & Paulheim (2019): Uncovering the Semantics of Wikipedia Categories

Cat2Ax: Axiomatizing Wikipedia Categories



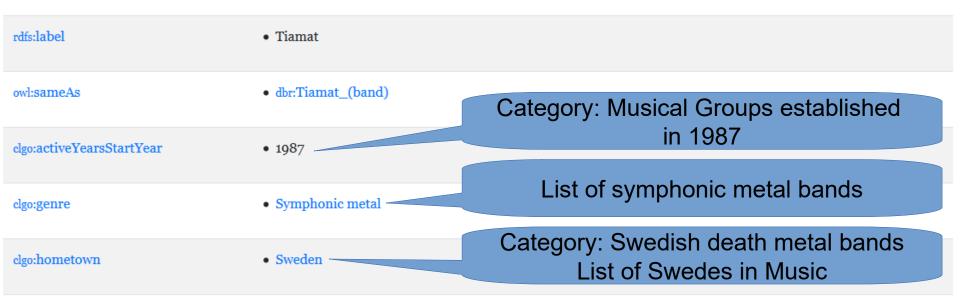
 \subseteq dbo:genre.{dbr:Rock_Music} ? \subseteq dbo:artist.{dbr:Rock_(Rapper)} ?

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



Pushing Entity Coverage Further

• Beyond red links (2020)

Cinematic films						
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

Title	Running time	Year released	Notes	
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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

Axl Rose

From Wikipedia, the free encyclopedia

....

Discography [edit]

with Guns N' Roses [edit]

- Appetite for Destruction (1987)
- G N' R Lies (1988)
- Use Your Illusion I (1991)
- Use Your Illusion II (1991)
 "The Spaghetti Incident?" (1993)
- Chinese Democracy (2008)

with Hollywood Rose [edit]

• The Roots of Guns N' Roses (2004)

with Rapidfire [edit]

Ready to Rumble EP (2014)

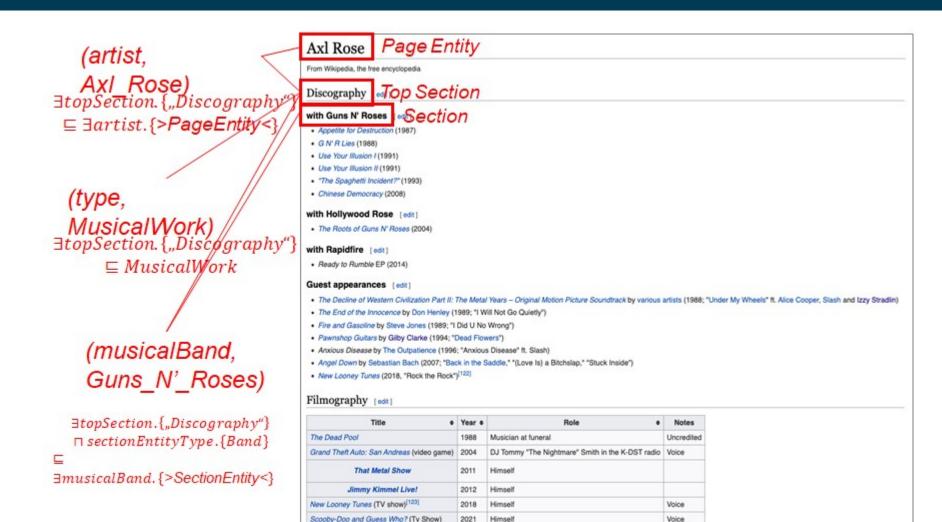
Guest appearances [edit]

- The Decline of Western Civilization Part II: The Metal Years Original Motion Picture Soundtrack by various artists (1988; "Under My Wheels" ft. Alice Cooper, Slash and Izzy Stradlin)
- The End of the Innocence by Don Henley (1989; "I Will Not Go Quietly")
- Fire and Gasoline by Steve Jones (1989; "I Did U No Wrong")
- Pawnshop Guitars by Gilby Clarke (1994; "Dead Flowers")
- Anxious Disease by The Outpatience (1996; "Anxious Disease" ft. Slash)
- Angel Down by Sebastian Bach (2007; "Back in the Saddle," "(Love Is) a Bitchslap," "Stuck Inside")
- New Looney Tunes (2018, "Rock the Rock")^[122]

Filmography [edit]

Title 🔶	Year ¢	Role ¢	Notes
The Dead Pool	1988	Musician at funeral	Uncredited
Grand Theft Auto: San Andreas (video game)	2004	DJ Tommy "The Nightmare" Smith in the K-DST radio	Voice
That Metal Show	2011	Himself	
Jimmy Kimmel Live!	2012	Himself	
New Looney Tunes (TV show)[123]	2018	Himself	Voice
Scooby-Doo and Guess Who? (Tv Show)	2021	Himself	Voice

Beyond List Pages

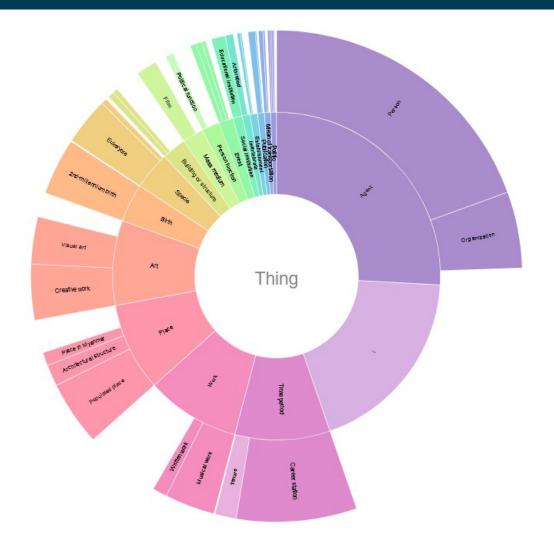


Beyond List Pages

- Learning descriptive rules for listings, e.g.
 - topSection("Discography") \rightarrow 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

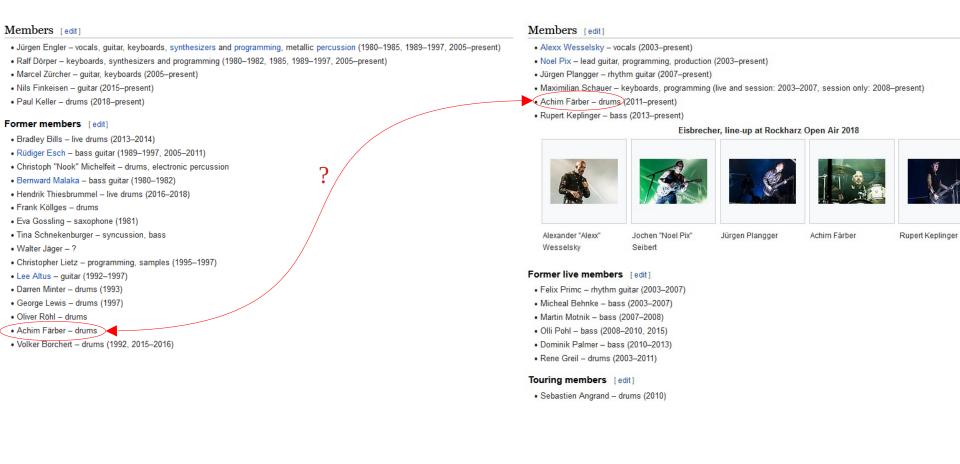
CaLiGraph at a Glance

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

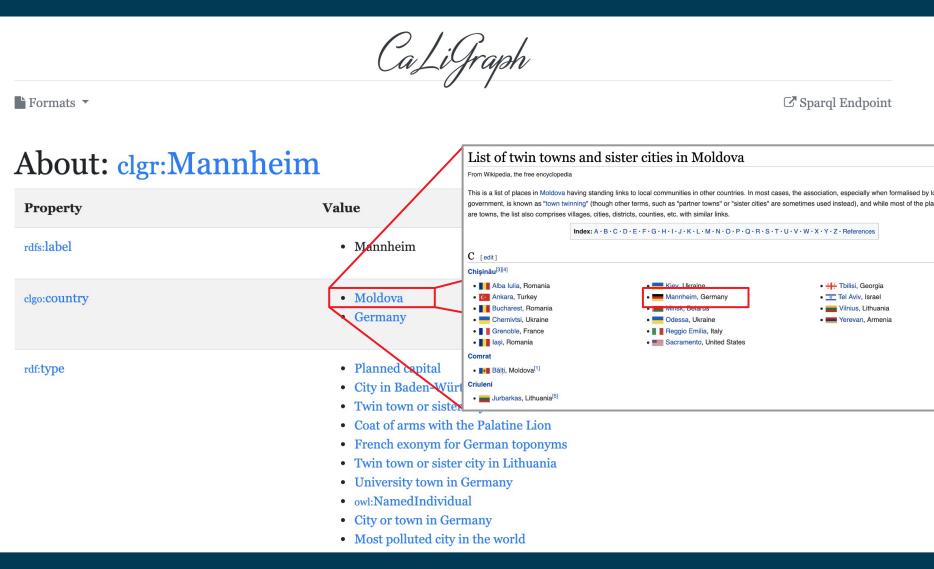


Entity Disambiguation

• Examples: Wikipedia pages of Die Krupps and Eisbrecher



CaLiGraph Glitches



- 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



2.7.1 Undele

Heiko Paulheim

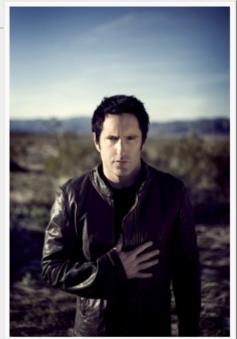
- Why stop at Wikipedia?
- Wikipedia is based on the MediaWiki software
 - …and so are thousands of Wikis
 - Fandom by Wikia: >385,000 Wikis on special topics
 - WikiApiary: reports >20,000 installations of MediaWiki on the Web





• Collecting Data from a Multitude of Wikis

Trent Reznor



Instruments: Vocals, Guitar, Keyboards, Bass, Marimba, Saxophone, Small Percussion Years: 1988-present Tours: VIVIsectVI-present



1 Nomination / 1 Win Role Composer Born May 17, 1965 Mercer, Pennsylvania, USA



Born May 17, 1965 New Castle, Pennsylvania, United States

Other David Lynch Projects Lost Highway (Soundtrack - "Videodrones; Questions," "Driver Down") "Came Back Haunted" (Music video)

- 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

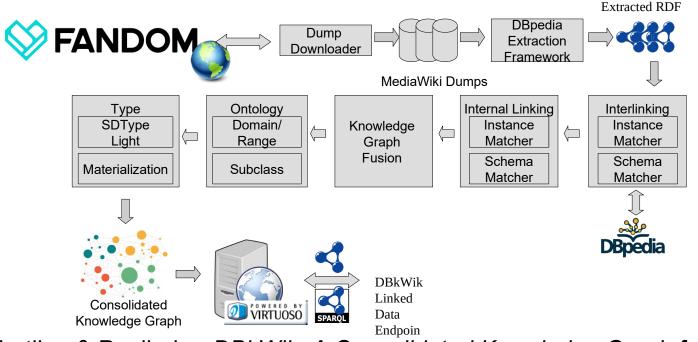
DBKWIK ® Browse us	ing 🗸 📲 Formats 👻	C Faceted Browser	ピ Sparql Endpoint
About: http://dbkv /Gryffindor	wik.webdatacommons.org/HarryPo	tter/resourc	e
Property	Value		
owl:sameAs	dbr.Gryffindor		
foaf.depiction	http://commons.wikimedia.org/wiki/Special:FilePath/0.31_Gryffindor_Crest_Tra	insparent.png	
dcterms:subject	dbkwik:HarryPotter/resource/Category:Gryffindor_House dbkwik:HarryPotter/resource/Category:Hogwarts_Houses		
skos:altLabel	 Gryffindor House Gryffindor Students Griffindor Gryffindors Griffyndor Griffyndor Students Gryffindor Girl The Gryffindors 		
skos:prefLabel	• Gryffindor		
dbkwik:HarryPotter/ontology/thumbnail	http://commons.wikimedia.org/wiki/Special:FilePath/0.31_Gryffindor_Crest_Tra	insparent.png?width=300	
dbkwik:HarryPotter/property/animal	dbkwik:HarryPotter/resource/Lion		

http://dbkwik.org/

- 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

Hertling & Paulheim: *DBkWik: A Consolidated Knowledge Graph from Thousands of Wikis.* ICBK 2018

- Heuristics
 - Ontology induction
 - Instance/Schema Matching



Hertling & Paulheim: *DBkWik: A Consolidated Knowledge Graph from Thousands of Wikis.* ICBK 2018

- 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	Токуо	13,189,000 ^[3]	2011	10.32%
4	Market 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	Z 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	💳 Iran	Tehran	8,846,782	2014	9.91%
13	🙀 United Kingdom	London	8,630,100[11]	2015	13.25%
14	Peru 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	🚾 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	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	C Spain	Madrid	3,233,527[22]	2012	6.84%
28	North Korea	Pyongyang	3,144,005		12.63%
29	a Afghanistan	Kabul	3,140,853		10.28%
30	Kenya	Nairobi	3,138,369	2010	7.67%

Hertling & Paulheim: WebIsALOD: Providing Hypernymy Relations extracted from the Web as Linked Open Data. ISWC 2017

- Extraction of type information using Hearst-like 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

Common Crawl

Seitner et al.: A large DataBase of hypernymy relations extracted from the Web. LREC 2016

• Example:

About: fiction writer

Premodifier: fiction

Head noun: writer

Same concepts

http://dbpedia.org/resource/Fiction

Broader concepts

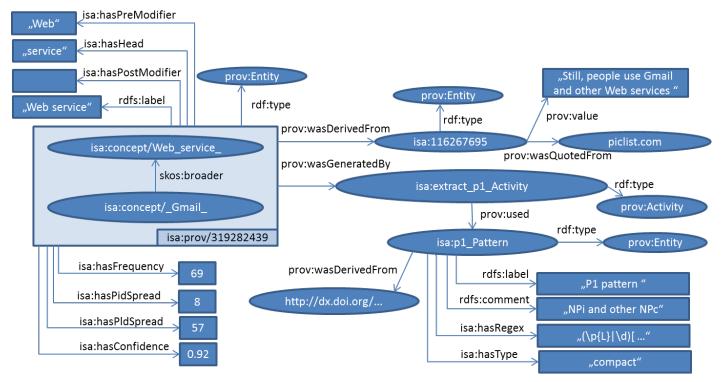
label	provenance	confidence
writer	isap:391280092	0.799331
great idea	isap:493244047	0.672180
several magazine	isap:104101164	0.655684
category	isap:104762336	0.477191
artist	isap:387107910	0.471280
blog	isap:492616562	0.458511
writers	isap:439522913	0.427701
story	isap:122402598	0.306667
group	isap:115379219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

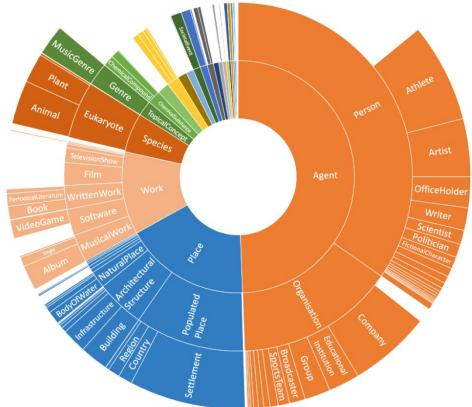
http://webisa.webdatacommons.org/

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



Hertling & Paulheim: WebIsALOD: Providing Hypernymy Relations extracted from the Web as Linked Open Data. ISWC 2017

Estimated contents breakdown



Hertling & Paulheim: WebIsALOD: Providing Hypernymy Relations extracted from the Web as Linked Open Data. ISWC 2017

- 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

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- 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 \rightarrow genre(Bauhaus, Goth)
 - Bauhaus is a German school \rightarrow location(Bauhaus, Germany)

Hertling & Paulheim: WebIsALOD: Providing Hypernymy Relations extracted from the Web as Linked Open Data. ISWC 2017

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?

