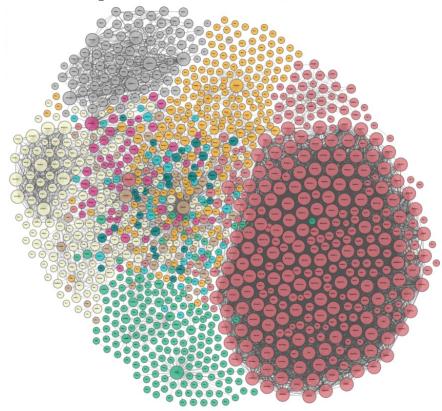


**Heiko Paulheim** 

You've seen this, haven't you?



Linking Open Data cloud diagram 2017, by Andrejs Abele, John P. McCrae, Paul Buitelaar, Anja Jentzsch and Richard Cyganiak. http://lod-cloud.net/

08/22/17

- Knowledge Graphs on the LOD Cloud
- Everybody talks about them, but what is a Knowledge Graph?
  - I don't have a definition either...



08/22/17

- Knowledge Graph definitions
- Many people talk about KGs, few give definitions
- Working definition: a Knowledge Graph
  - mainly describes instances and their relations in a graph
    - Unlike an ontology
    - Unlike, e.g., WordNet
  - Defines possible classes and relations in a schema or ontology
    - Unlike schema-free output of some IE tools
  - Allows for interlinking arbitrary entities with each other
    - Unlike a relational database
  - Covers various domains
    - Unlike, e.g., Geonames

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 -	private
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

# Finding Information in Knowledge Graphs

Find list of science fiction writers in DBpedia



08/22/17

### Finding Information in Knowledge Graphs

#### Results from DBpedia

http://dbpedia.org/resource/A. Lee Martinez http://dbpedia.org/resource/A1 Sarrantonio http://dbpedia.org/resource/Aleksandr Bushkov http://dbpedia.org/resource/Allie Bates http://dbpedia.org/resource/Andy Weir http://dbpedia.org/resource/Angela Steinmüller http://dbpedia.org/resource/Anthony Ryan (writer) http://dbpedia.org/resource/Arinn Dembo http://dbpedia.org/resource/Carrie Vaughn http://dbpedia.org/resource/D. Harlan Wilson http://dbpedia.org/resource/Daniel Warner (artist) http://dbpedia.org/resource/Dave Smeds http://dbpedia.org/resource/David Moles http://dbpedia.org/resource/Deborah Chester http://dbpedia.org/resource/Elaine Corvidae http://dbpedia.org/resource/Elizabeth Chater http://dbpedia.org/resource/Frank Schätzing http://dbpedia.org/resource/Glenda Goertzen http://dbpedia.org/resource/Gregory Benford http://dbpedia.org/resource/Günther Krupkat http://dbpedia.org/resource/H. Rider Haggard http://dbpedia.org/resource/Harriet McDougal http://dbpedia.org/resource/Hiroyuki Morioka http://dbpedia.org/resource/Jacek Sawaszkiewicz http://dbpedia.org/resource/James A. Moore http://dbpedia.org/resource/Jan Weiss http://dbpedia.org/resource/Jason V Brock http://dbpedia.org/resource/Jean Sutton http://dbpedia.org/resource/Jeaniene Frost http://dbpedia.org/resource/Joel Rosenberg (science fiction author) http://dbpedia.org/resource/John Brosnan http://dbpedia.org/resource/K. V. Johansen http://dbpedia.org/resource/Karen Sandler (author)

Arthur C. Clarke?

H.G. Wells?

Isaac Asimov?



# Finding Information in Knowledge Graphs

- Questions in this talk
  - What can we find in different Knowledge Graphs?
  - Why do we sometimes not find what we expect to find?
  - What can be done about this?
- ...and:
  - What new Knowledge Graphs are currently developed?



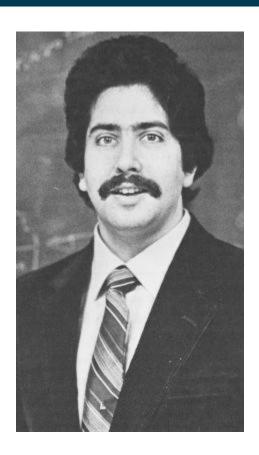
#### **Outline**

- How are Knowledge Graphs created?
- What is inside public Knowledge Graphs?
  - Knowledge Graph profiling
- Addressing typical problems
  - Errors
  - Incompleteness
- New Kids on the Block
  - WeblsALOD
  - DBkWik
- Take Aways



### **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
  - >900 person years
  - Far from completion
  - Used to exist until 2017



### **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)

### **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

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#### **Knowledge Graph Creation**

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



#### **Knowledge Graph Creation: DBpedia & YAGO**

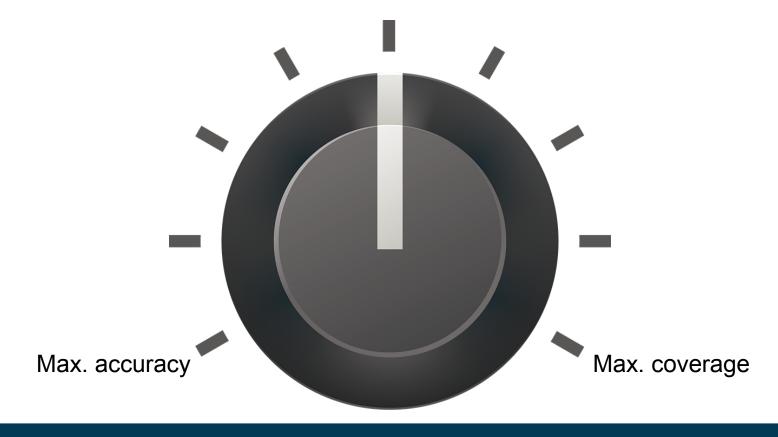
- The 2010s
  - DBpedia: launched 2007
  - YAGO: launched 2008
  - Extraction from Wikipedia using mappings & heuristics
- Present
  - Two of the most used knowledge graphs





#### **Knowledge Graph Creation**

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

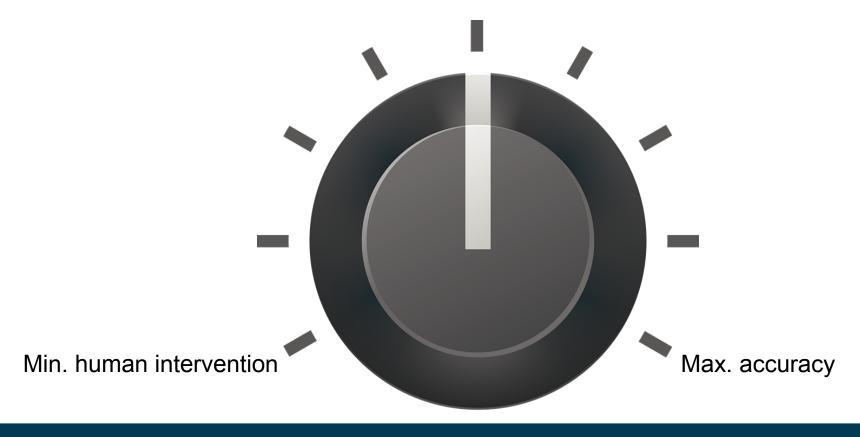


#### **Knowledge Graph Creation: NELL**

- The 2010s
  - NELL: Never ending language learner
  - Input: ontology, seed examples, text corpus
  - Output: facts, text patterns
  - Large degree of automation, occasional human feedback
- Today
  - Still running
  - New release every few days

### **Knowledge Graph Creation**

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



# **Summary of Trade Offs**

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



#### 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

Release cycles



#### Size and density

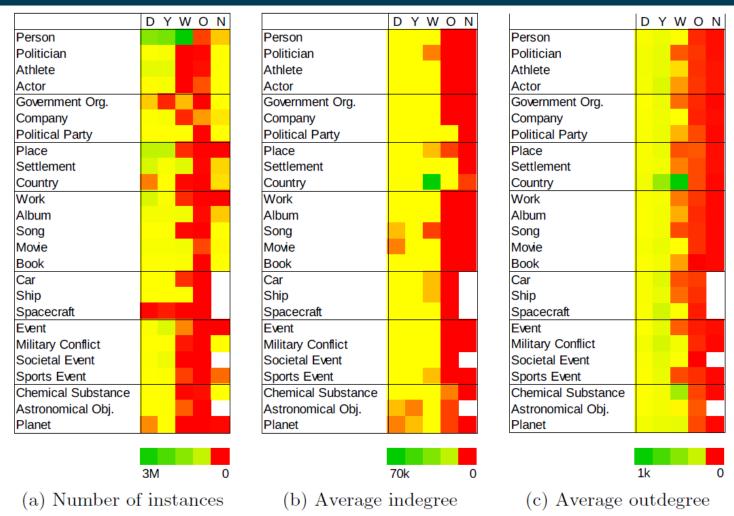
Table 1: Global Properties of the Knowledge Graphs compared in this paper

	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

08/22/17

- 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)



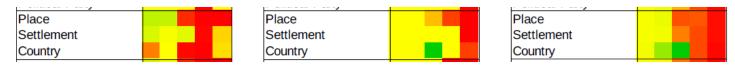
Ringler & Paulheim: One Knowledge Graph to Rule them All? KI 2017

- 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

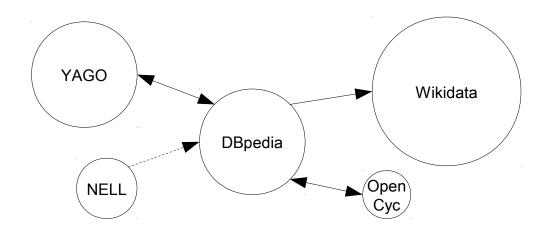
#### **Caveats**

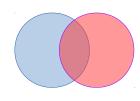
Reading the diagrams right...



- So, Wikidata contains more 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



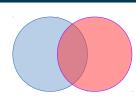


Ringler & Paulheim: One Knowledge Graph to Rule them All? KI 2017

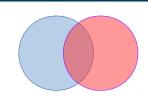
- How largely do knowledge graphs overlap?
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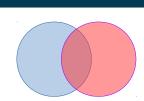
- Links between Knowledge Graphs are incomplete
  - The Open World Assumption also holds for interlinks



- 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:

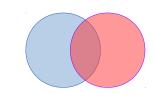
- Given that the link set F is found
- And the (unknown) actual link set would be C



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

Mathematical derivation:

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



- Definition of precision:  $P = \frac{|F_{correct}|}{|F|}$ 

• Resolve both to  $|F_{correct}|$ , substitute, and resolve to |C|

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

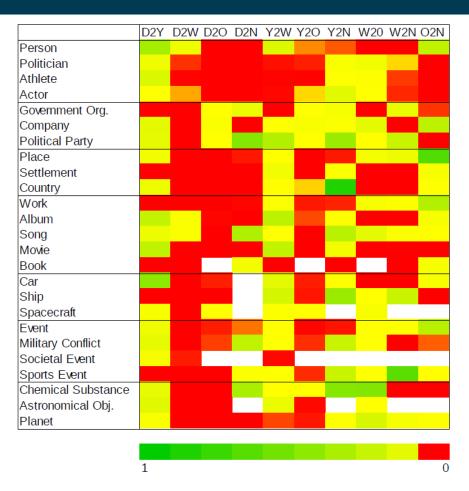
#### Experiment:

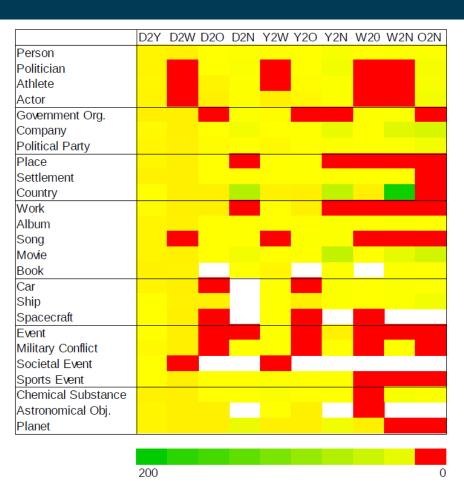
- We use the same 25 classes as before
- Measure 1: overlap relative to smaller KG (i.e., potential gain)
- Measure 2: overlap relative to explicit links (i.e., importance of improving links)



- 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





(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

### **Common Errors in Knowledge Graphs**

- Using DBpedia as an Example
  - ...but most of those hold for other KGs as well
  - ...each KG has its own advantages and shortcomings
- Recap: using mappings & heuristics for extraction from Wikipedia
- Something to keep in mind:
  - Wikipedia is made for humans
  - Not necessarily: for facilitating easy Knowledge Graph creation

### **Common Errors in Knowledge Graphs**

What reasons can cause incomplete results?

- Two possible problems:
  - The resource at hand is not of type dbo: Writer
  - The genre relation to dbr:Science\_Fiction is missing

- Various works on *Knowledge Graph Refinement* 
  - Knowledge Graph completion
  - Error detection
- See, e.g., 2017 survey in Semantic Web Journal

#### Knowledge Graph Refinement: A Survey of Approaches and Evaluation Methods

Editor(s): Philipp Cimiano, Universität Bielefeld, Germany Solicited review(s): Natasha Noy, Google Inc., USA; Philipp Cimiano, Universität Bielefeld, Germany; two anonymous reviewers

#### Heiko Paulheim,

Data and Web Science Group, University of Mannheim, B6 26, 68159 Mannheim, Germany

Abstract. In the recent years, different Web knowledge graphs, both free and commercial, have been created. While Google coined the term "Knowledge Graph" in 2012, there are also a few openly available knowledge graphs, with DBpedia, YAGO, and Freebase being among the most prominent ones. Those graphs are often constructed from semi-structured knowledge, such as Wikipedia, or harvested from the web with a combination of statistical and linguistic methods. The result are large-scale knowledge graphs that try to make a good trade-off between completeness and correctness. In order to further increase the utility of such knowledge graphs, various refinement methods have been proposed, which try to infer and add missing knowledge to the graph, or identify erroneous pieces of information. In this article, we provide a survey of such knowledge graph refinement approaches, with a dual look at both the methods being proposed as well as the evaluation methodologies used.

Keywords: Knowledge Graphs, Refinement, Completion, Correction, Error Detection, Evaluation

#### Paulheim: Knowledge Graph Refinement – A Survey of Approaches and Evaluation Methods. SWJ 8(3), 2017

#### 1. Introduction

Knowledge graphs on the Web are a backbone of many information systems that require access to struc-

by the crowd like Freebase [9] and Wikidata [104], or extracted from large-scale, semi-structured web knowledge bases such as Wikipedia, like DBpedia [56] and YAGO [101]. Furthermore, information extraction

- Missing types
  - Estimate (2013) for DBpedia: at least 2.6M type statements are missing
  - Using YAGO as "ground truth"
- "Well, we're semantics folks, we have ontologies!"

```
- CONSTRUCT {?x a ?t}
WHERE { {?x ?r ?y . ?r rdfs:domain ?t}
UNION {?y ?r ?x . ?r rdfs:range ?t} }
```



38

Bizer & Paulheim: Type Inference on Noisy RDF Data. In: ISWC 2013

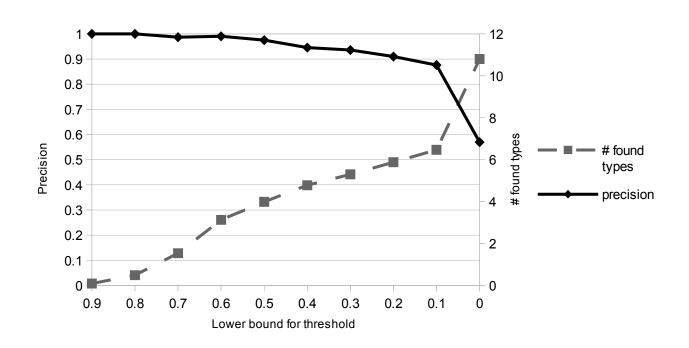
- Experiment of RDFS reasoning for typing Germany
- Results:
  - Place, PopulatedPlace, Award, MilitaryConflict, City, Country, EthnicGroup, Genre, Stadium, Settlement, Language, MontainRange, PersonFunction, Race, RouteOfTransportation, Building, Mountain, Airport, WineRegion
- Bottom line: RDFS reasoning accumulates errors
  - Germany is the object of 44,433 statements
  - 15 single wrong statements can cause those 15 errors
  - i.e., an error rate of only 0.03% (that is unlikely to achieve)

Bizer & Paulheim: Type Inference on Noisy RDF Data. In: ISWC 2013

- Required: a noise-tolerant approach
- SDType (meanwhile included in DBpedia)
  - Use statistical distributions of properties and object types
    - P(C|p) → probability of object being of type C when observing property p in a statement
  - Averaging scores for all statements of a resource
  - Weighting properties by discriminative power
- Since DBpedia 3.9: typing ~1M untyped resources at precision >0.95
- Refinement:
  - Filtering resources of non-instance pages and list pages

Bizer & Paulheim: Type Inference on Noisy RDF Data. In: ISWC 2013

- Recap
  - Trade-off coverage vs. accuracy



- The same idea applied to identification of noisy statements
  - i.e., a statement is implausible if the distribution of its object's types deviates from the overall distribution for the predicate
- Removing ~20,000 erroneous statements from DBpedia
- Error analysis
  - Errors in Wikipedia account for ~30%
  - Other typical problems: see following slides

Bizer & Paulheim: Improving the quality of linked data using statistical distributions. In: IJSWIS 10(2), 2014

- Typical errors
  - links in longer texts are not interpreted correctly
  - dbr:Carole\_Goble dbo:award dbr:Jim\_Gray

Paulheim & Gangemi: Serving DBpedia with DOLCE – More than Just Adding a Cherry on Top. ISWC 2015



Jim Gray e-Science Award

Notable

- Typical errors
  - Misinterpretation of redirects
  - dbr:Ben\_Casey dbo:company dbr:Bing\_Cosby

Paulheim & Gangemi: Serving DBpedia with DOLCE – More than Just Adding a Cherry on Top. ISWC 2015



- Typical errors
  - Metonymy
  - dbr:Human\_Nature\_(band) dbo:genre dbr:Motown,
  - Links with anchors pointing to subsections in a page
  - First\_Army\_(France)#1944-1945



Paulheim & Gangemi: Serving DBpedia with DOLCE – More than Just Adding a Cherry on Top. ISWC 2015

- Identifying individual errors is possible with many techniques
  - e.g., statistics, reasoning, exploiting upper ontologies, ...
- ...but what do we do with those efforts?
  - they typically end up in drawers and abandoned GitHub repositories

```
Run Result Auto Raw Profile Explorer
@prefix xs: <http://www.w3.org/2001/XMLSchema#>
<http://dbpedia.org/resource/Abraham_lincoln> <http://dbpedia.org/ontology/birthDate> "1809-02-12"^^xs:date ;
 <http://dbpedia.org/ontology/deathDate> "1865-04-15"^^xs:date ;
 <http://www.w3.org/1999/02/22-rdf-syntax-ns#type> <http://xmlns.com/foaf/0.1/Person> ;
 <http://xmlns.com/foaf/0.1/name> "Abraham Lincoln"@en ;
 <http://dbpedia.org/ontology/birthPlace> <http://dbpedia.org/resource/Hardin_County,_Kentucky> ;
<http://purl.org/dc/elements/1.1/description> "16th President of the United States"@en
<http://dbpedia.org/resource/Alexander_Mackenzie> <http://dbpedia.org/ontology/birthDate> "1822-01-28"^^xs:date ;
 <http://dbpedia.org/ontology/deathDate> "1892-04-17"^^xs:date ;
 <http://www.w3.org/1999/02/22-rdf-syntax-ns#type> <http://xmlns.com/foaf/0.1/Person>;
 <http://dbpedia.org/ontology/deathPlace> <http://dbpedia.org/resource/Toronto> ;
 <http://xmlns.com/foaf/0.1/name> "Alexander Mackenzie"@en
 <http://dbpedia.org/ontology/birthPlace> <http://dbpedia.org/resource/Logierait> ,
   <http://dbpedia.org/resource/Perthshire> ,
   <http://dbpedia.org/resource/Scotland>;
 <http://xmlns.com/foaf/0.1/givenName> "Alexander"@en ;
 <http://purl.org/dc/elements/1.1/description> "2nd Prime Minister of Canada (1873-1878)"@en
<http://dbpedia.org/resource/Alan_Turing> <http://dbpedia.org/ontology/birthDate> "1912-06-23"^^xs:date ;
 <http://dbpedia.org/ontology/deathDate> "1954-06-07"^^xs:date ;
 <http://www.w3.org/1999/02/22-rdf-syntax-ns#type> <http://xmlns.com/foaf/0.1/Person>
<http://xmlns.com/foaf/0.1/surname> "Turing"@en ;
 <http://dbpedia.org/ontology/deathPlace> <http://dbpedia.org/resource/Manchester> ;
 <http://xmlns.com/foaf/0.1/name> "Alan Mathison Turing"@en
 <http://dbpedia.org/ontology/birthPlace> <http://dbpedia.org/resource/Paddington> ;
 <http://xmlns.com/foaf/0.1/givenName> "Alan Mathison"@en ;
 <http://purl.org/dc/elements/1.1/description> "Computer scientist, mathematician, and cryptographer"@en
```

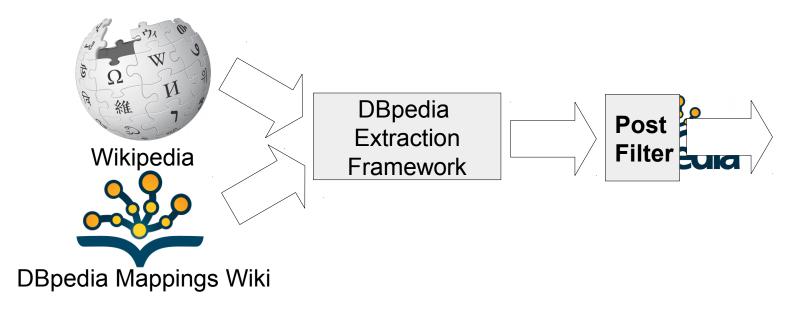


Paulheim & Gangemi: Serving DBpedia with DOLCE – More than Just Adding a Cherry on Top. ISWC 2015

Paulheim: Data-driven Joint Debugging of the DBpedia Mappings and Ontology. ESWC 2017

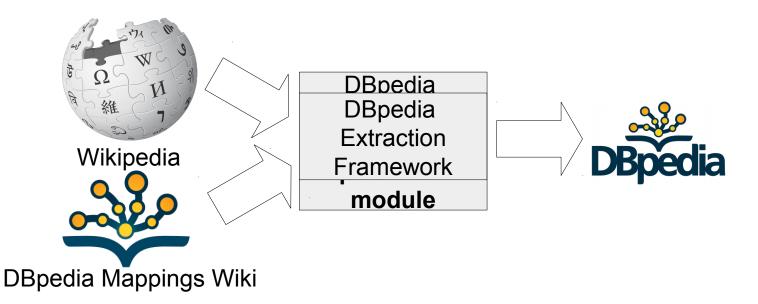
#### **Motivation**

- Possible option 1: Remove erroneous triples from DBpedia
- Challenges
  - May remove correct axioms, may need thresholding
  - Needs to be repeated for each release
  - Needs to be materialized on all of DBpedia

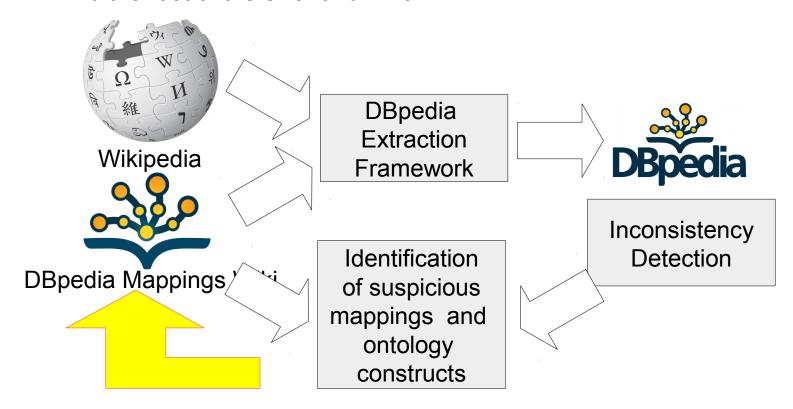


#### **Motivation**

- Possible option 2: Integrate into DBpedia Extraction Framework
- Challenges
  - Development workload
  - Some approaches are not fully automated (technically or conceptually)
  - Scalability



- Goal: a third option
  - Find the root of the error and fix it!



Paulheim: Data-driven Joint Debugging of the DBpedia Mappings and Ontology. ESWC 2017

- Case 1: Wrong mapping
- Example:
  - branch in infobox military unit is mapped to dbo:militaryBranch
    - but dbo:militaryBranch has dbo:Person as its domain
  - correction: dbo:commandStructure
  - Affects 12,172 statements
     (31% of all dbo:militaryBranch)



- Case 2: Mappings that should be removed
- Example:
  - dbo:picture
  - Most of the are inconsistent (64.5% places, 23.0% persons)
  - Reason: statements are extracted from picture caption

```
dbr:Brixton_Academy
    dbo:picture
    dbr:Brixton .

dbr:Justify_My_Love
    dbo:picture
    dbr:Madonna_(entertainer) .
```

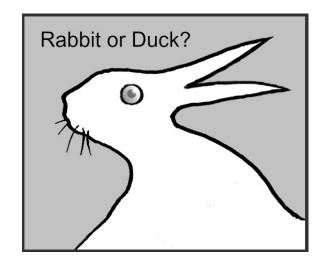




- Case 3: Ontology problems (domain/range)
- Example 1:
  - Populated places (e.g., cities) are used both as place and organization
  - For some properties, the range is either one of the two
    - e.g., dbo:operator (see introductory example)
  - Polysemy should be reflected in the ontology

#### Example 2:

- dbo:architect, dbo:designer, dbo:engineer etc.
   have dbo:Person as their range
- Significant fractions (8.6%, 7.6%, 58.4%, resp.)
   have a dbo:Organization as object
- Range should be broadened



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- Case 4: Missing properties
- Example 1:
  - dbo:president links an organization to its president
  - Majority use (8,354, or 76.2%):
     link a person to the president s/he served for
- Example 2:
  - dbo:instrument links an artist to the instrument s/he plays
  - Prominent alternative use (3,828, or 7.2%):
     links a genre to its characteristic instrument



#### Introductory example:



#### Arthur C. Clarke?

H.G. Wells?

Isaac Asimov?



- Incompleteness in relation assertions
- Example: Arthur C. Clarke, Isaac Asimov, ...
  - There is no explicit link to Science Fiction in the infobox
  - i.e., the statement for... dbo:genre dbr:Science Fiction
    - is not generated



Arthur C. Clarke in June 1982

Born Arthur Charles Clarke

16 December 1917 Minehead, Somerset,

England, UK

ed 19 March 2008 (aged 90)

Colombo, Sri Lanka

Pen name Charles Willis

E. G. O'Brien[1][2]

Occupation Writer, inventor

Nationality British

Citizenship United Kingdom

Sri Lanka (resident guest

status)

Alma mater King's College London

Period 1946–2008 (professional

fiction writer)

Genre Hard science fiction

Popular science

Subject Science

- Example for recent work (ISWC 2017):
   heuristic relation extraction from Wikipedia abstracts
- Idea:
  - There are probably certain patterns:
    - e.g., all genres linked in an abstract about a writer are that writer's genres
    - e.g., the first place linked in an abstract about a person is that person's birthplace
  - The types are already in DBpedia
  - We can use existing relations as training data
    - Using a local closed world assumption for negative examples
  - Learned models can be evaluated and only used at a certain precision

Heist & Paulheim: Language-agnostic relation extraction from Wikipedia Abstracts. ISWC 2017

#### Results:

 1M additional assertions can be learned for 100 relations at 95% precision

#### Additional consideration:

- We use only links, types from DBpedia, and positional features
- No language-specific information (e.g., POS tags)
- Thus, we are not restricted to English!

Heist & Paulheim: Language-agnostic relation extraction from Wikipedia Abstracts. ISWC 2017

- Cross-lingual experiment:
  - Using the 12 largest language editions of Wikipedia
  - Exploiting inter-language links

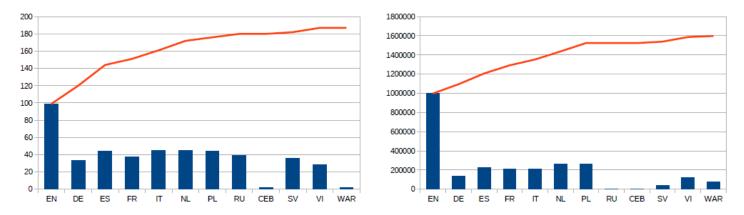
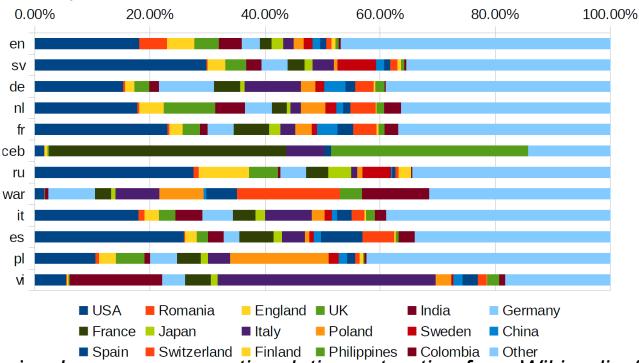


Fig. 3: Number of relations (left) and statements (right) extracted at 95% precision in the top 12 languages. The bars show the number of statements that could be extracted for the given language, the line depicts the accumulated number of statements for the top N languages.

Heist & Paulheim: Language-agnostic relation extraction from Wikipedia Abstracts. ISWC 2017

#### Analysis

 Is there a relation between the language and the the country (dbo:country) of the entities for which information is extracted?



Heist & Paulheim: Language-agnostic relation extraction from Wikipedia Abstracts. ISWC 2017

- So far, we have looked at relation assertions
- Numerical values can also be problematic...
  - Recap: Wikipedia is made for human consumption
- The following are all valid representations of the same height value (and perfectly understandable by humans)

```
- 6 ft 6 in, 6ft 6in, 6'6'', 6'6", 6'6', ...
- 1.98m, 1,98m, 1m 98, 1m 98cm, 198cm, 198 cm, ...
- 6 ft 6 in (198 cm), 6ft 6in (1.98m), 6'6'' (1.98 m), ...
- 6 ft 6 in<sup>[1]</sup>, 6 ft 6 in <sup>[citation needed]</sup>, ...
```

Wienand & Paulheim: Detecting Incorrect Numerical Data in DBpedia. ESWC 2014 Fleischhacker et al.: Detecting Errors in Numerical Linked Data Using Cross-Checked Outlier Detection. ISWC 2014

- Approach: outlier detection
  - With preprocessing: finding meaningful subpopulations
  - With cross-checking: discarding natural outliers
- Findings: 85%-95% precision possible
  - depending on predicate
  - Identification of typical parsing problems

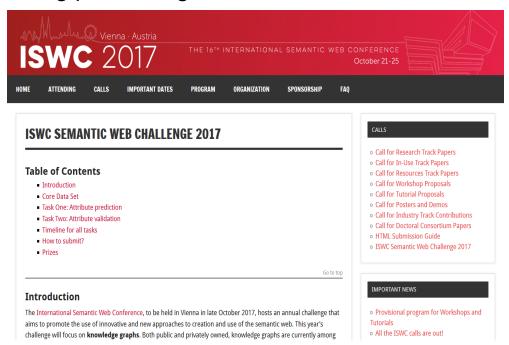
Wienand & Paulheim: Detecting Incorrect Numerical Data in DBpedia. ESWC 2014 Fleischhacker et al.: Detecting Errors in Numerical Linked Data Using Cross-Checked Outlier Detection. ISWC 2014

- Errors include
  - Interpretation of imperial units
  - Unusual decimal/thousands separators
  - Concatenation (population 28,322,006)



Wienand & Paulheim: Detecting Incorrect Numerical Data in DBpedia. ESWC 2014 Fleischhacker et al.: Detecting Errors in Numerical Linked Data Using Cross-Checked Outlier Detection. ISWC 2014

- Got curious? Want to get your hands dirty?
  - 2017 Semantic Web Challenge revolves around knowledge graph completion and correction
  - Using permid.org



https://iswc2017.semanticweb.org/calls/iswc-semantic-web-challenge-2017/

#### **New Kids on the Block**



#### **New Kids on the Block**

- 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

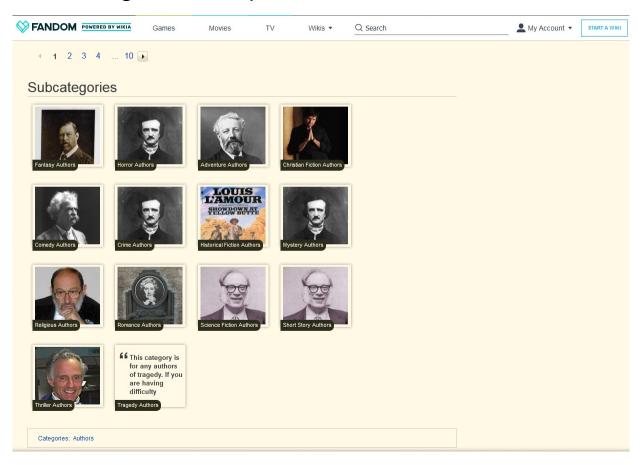


- Why stop at Wikipedia?
- Wikipedia is based on the MediaWiki software
  - ...and so are thousands of Wikis
  - Fandom by Wikia: >385,000 Wikis on special topics
  - WikiApiary: reports >20,000 installations of MediaWiki on the Web

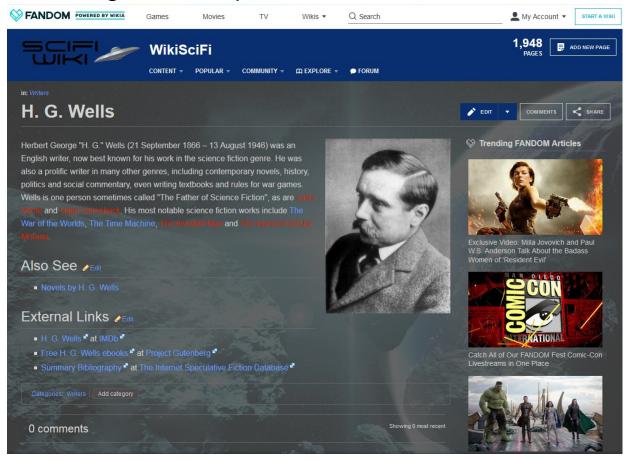




Back to our original example...



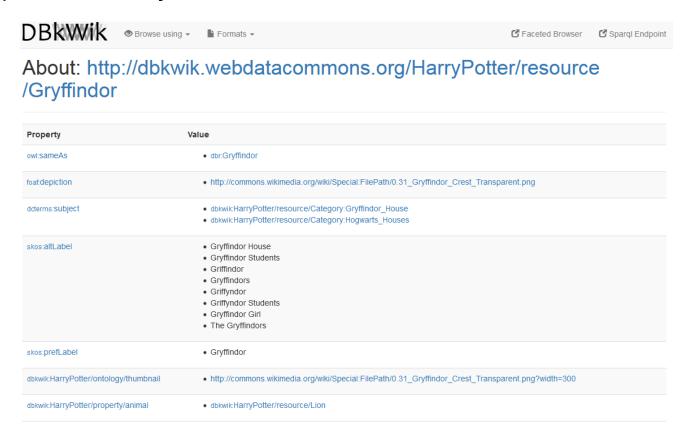
Back to our original example...



- The DBpedia Extraction Framework consumes MediaWiki dumps
- Experiment
  - Can we process dumps from arbitrary Wikis with it?
  - Are the results somewhat meaningful?



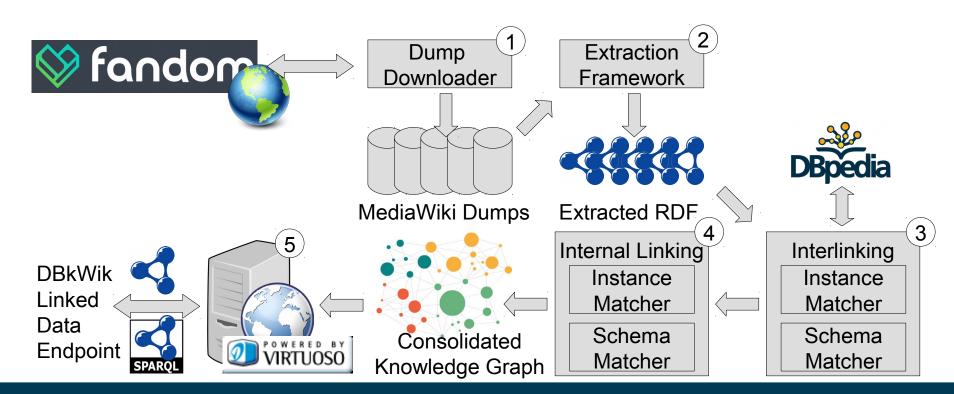
Example from Harry Potter Wiki



http://dbkwik.webdatacommons.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

- Avoiding O(n²) internal linking:
  - Match to DBpedia first
  - Use common links to DBpedia as blocking keys for internal matching



08/22/17

- 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)

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



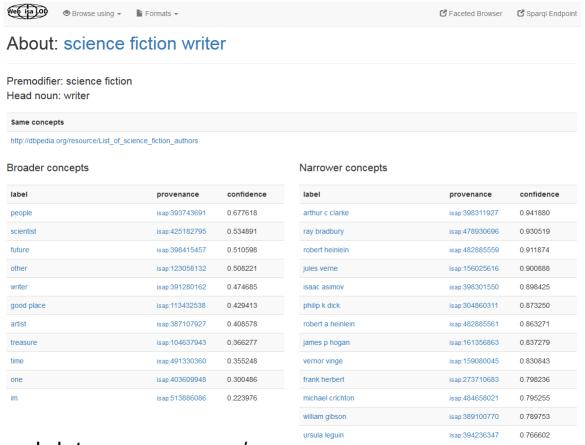
- Extraction of type information using Hearst-like patterns, e.g.,
  - T, such as X
  - X, Y, and other T
- Text corpus: common crawl
  - ~2 TB crawled web pages
  - Fast implementation: regex over text
  - "Expensive" operations only applied once regex has fired
- Resulting database
  - 400M hypernymy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

Common Crawl

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

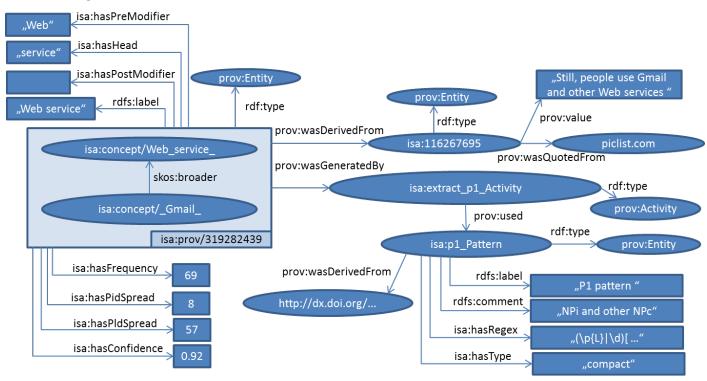
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Back to our original example...



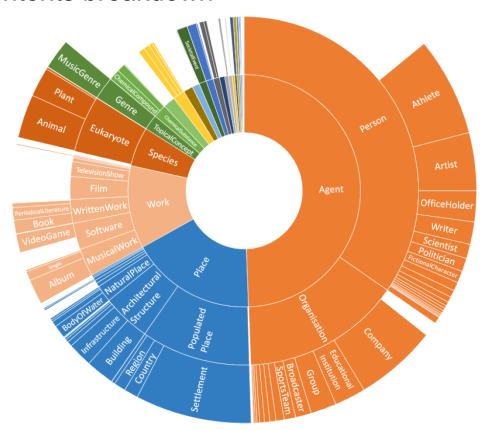
http://webisa.webdatacommons.org/

- 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)</li>
  - 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

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

- 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)

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

### **Take Aways**

- Knowledge Graphs contain a massive amount of information
  - Various trade offs in their creation
- We can find it if...
  - ...it is in there
  - ...the clues we need to find it are in it and correct
- Various methods exist for
  - ...completing knowledge graphs
  - ...identifying errors
  - ...lately also: identifying the roots of errors
- New kids on the block
  - DBkWik and WeblsALOD
  - Focus on long tail entities



#### **Credits & Contributions**



























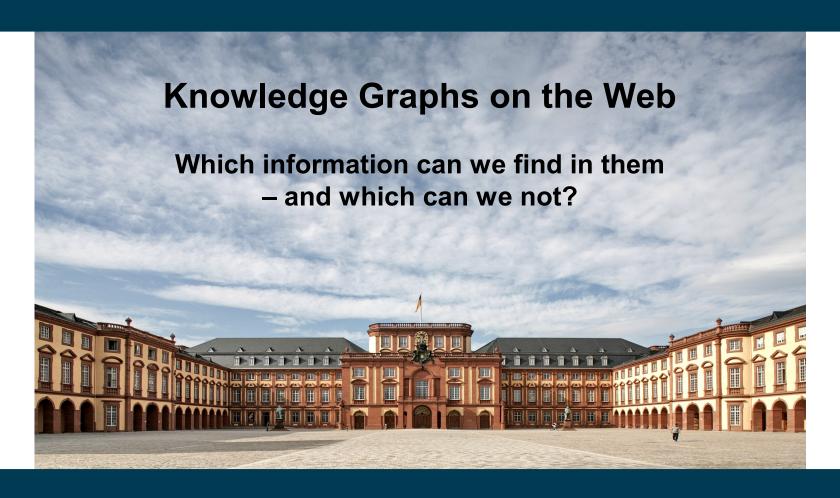












**Heiko Paulheim**