



Knowledge Graphs for Cultural Heritage and Digital Humanities

Victor de Boer SUMAC 2023



With input from: Xander Wilcke, Sarah Shoilee, Jacco van Ossenbruggen, Go Sugimoto, Niels Ockeloen, Paul Groth, Oana Inel, Lora Aroyo, Jur Leinenga, Matthias van Rossum, Andrea Bravo Balado, Robin Ponstein, Ronald Siebes, Roderick van der Weerdt, Loan Ho...

More and more structured data available online

Government data

Social web data

Medical data

Museum data

Research data

Development data





The Digital Turn

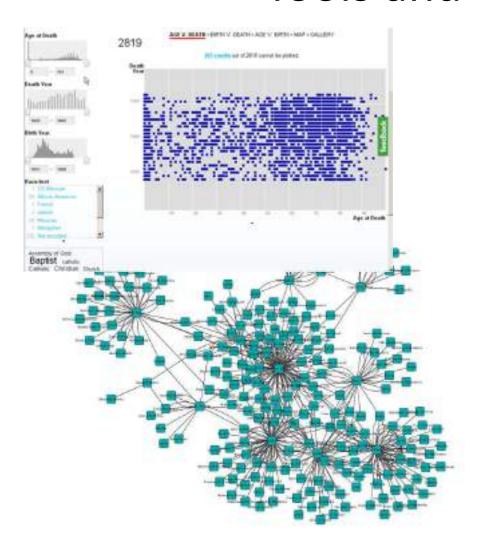
From the physical archives to digital ones

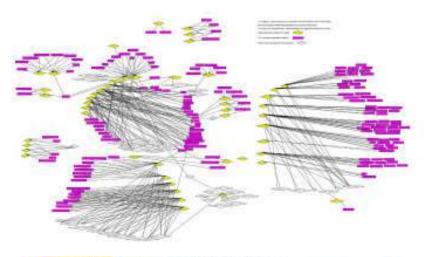


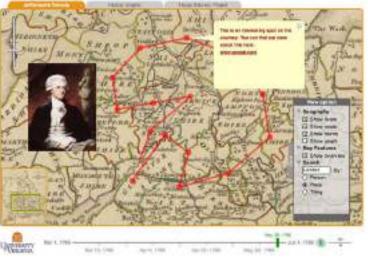


allows for new (types of) research, access

Tools and visualisations

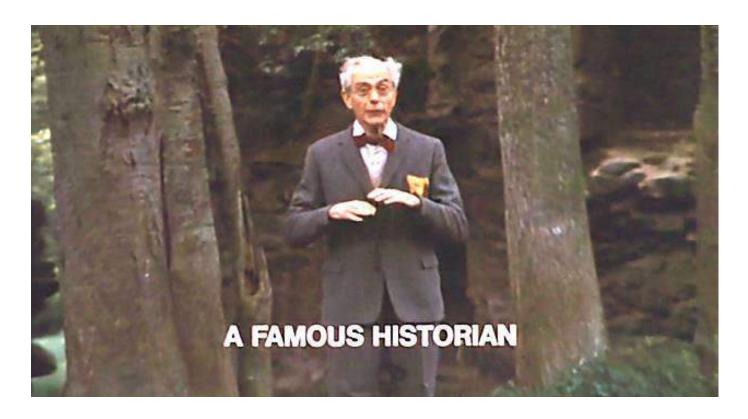






http://armstrongdigitalhistory.org/, http://www.vcdh.virginia.edu/courses/fall07/hius401-f/http://digitalhistory.unl.edu/essays/thomasessay.php, http://www.philipvickersfithian.com/2013/05/gender-in-stacks-on-managing-small.htm

"That is great. I would love that...



...but my research questions are slightly different."

Aging





Data Tool

Data - Centric

Do not bake the data into the tool
Build tools on top of the data.
Allow for integration of various data

New ways of analyzing integrated data

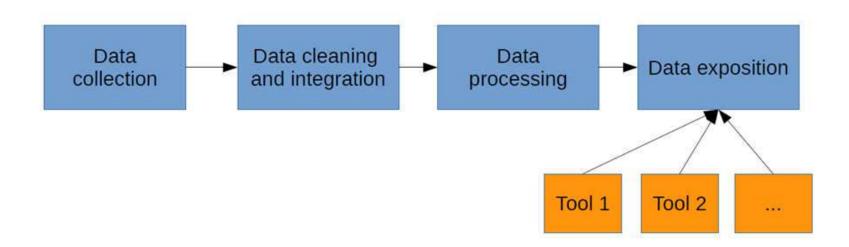


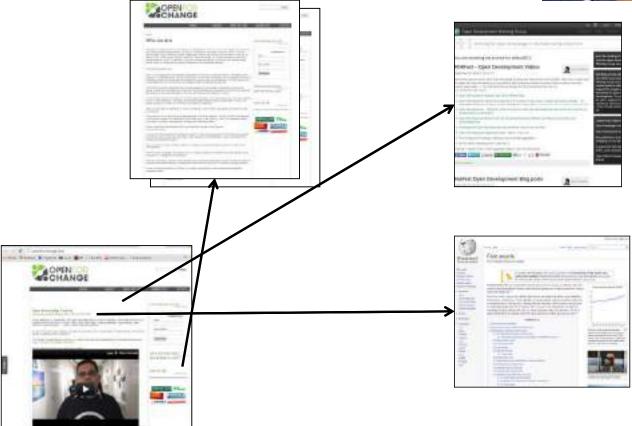
Fig: C. Guéret

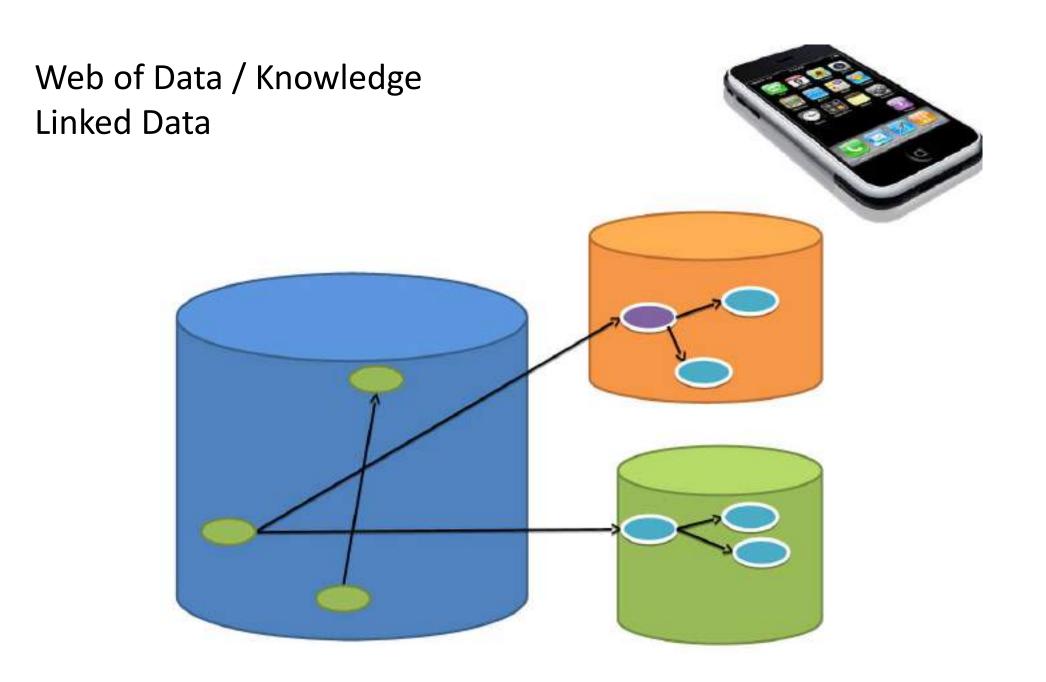




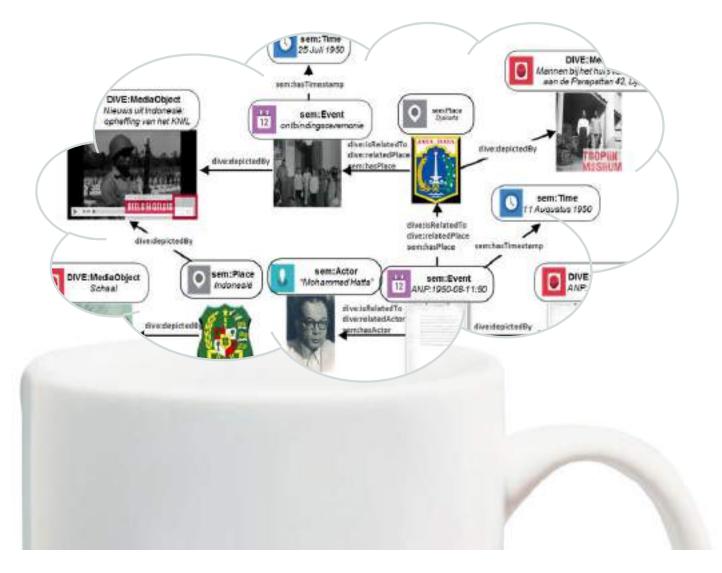
Web of Documents (WWW) Linked Documents







Welcome Knowledge Graphs



Knowledge Graphs

Set of principles and technologies to represent *data*, information and *knowledge*...

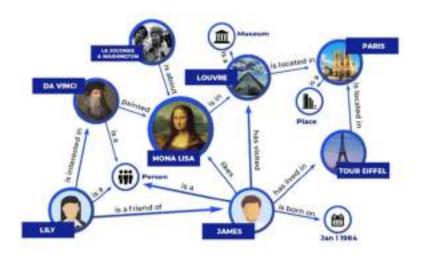
...allowing integration of heterogeneous and distributed data...

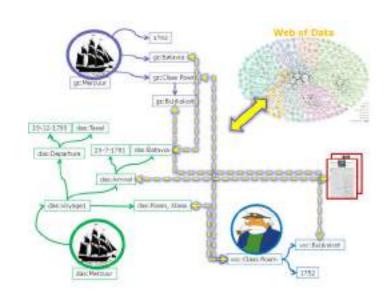
...using Semantic Web standards (RDF, OWL)...

...in the form of networks (graphs)...

...applicable in many domains...

...including Cultural Heritage.





4 proposals for knowledge graphs

- 1. Give all things a name
- 2. Names are addresses on the Web
- 3. Relations between things form Graphs of Data
- 4. Add explicit semantics (formal knowledge) to allow for predictable inferencing



P1 Give all things* a name



"Now! That should clear up a few things around here!"

^{*)} That you want to / can talk about

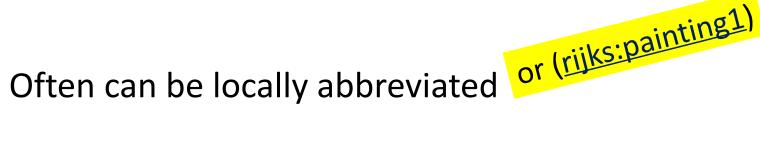
P2: Names are addresses on the Web (HTTP URIs)

Uniform Resource Identifier (URI) is a string of characters used to identify a name of a resource

http://data.rijksmuseum.nl/person/Rembrandt



http://data.rijksmuseum.nl/person/Painting001



P3: Resource Description Framework (RDF)

Semantic Web standard for writing down data, information



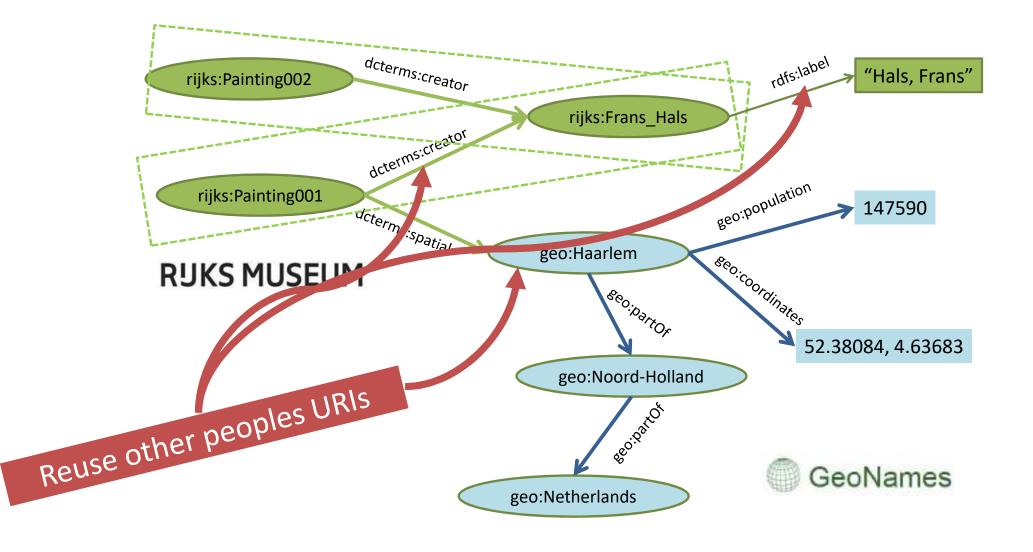
<Painting001> < has_location> <Amsterdam> .

Painting001

has_location

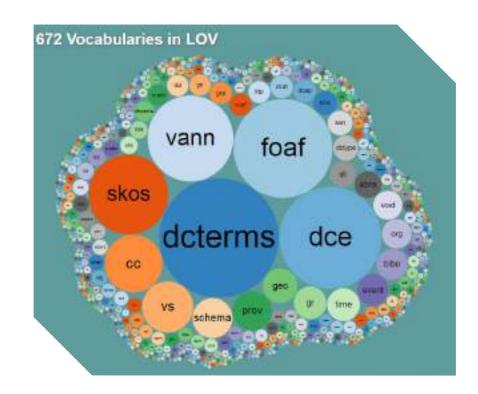
Amsterdam

P3: Triples form **Graphs**



Reuse other URIs: Examples

- RDF and RDFS: basic definitions of objects, properties, classrelations
- OWL: Description logics
- FOAF (Friend of a Friend): People, Organisations, Social Networks
- **schema.org** (Google, Yahoo!, Bing, Yandex): cross-domain, what search engines are interested in
- **Dbpedia/Wikidata** (Wikipedia as LOD): cross-domain
- **Dublin Core** (Bibliographic): publications, authors, media, etc.
- CIDOC-CRM: event-based model for cultural heritage.
- PROV to describe provenance of data





All Greek are men
All men are mortal
All Greek are mortal

All A are B All B are C All A are C

Inferencing is algorithmic manipulation of knowledge to derive new knowledge

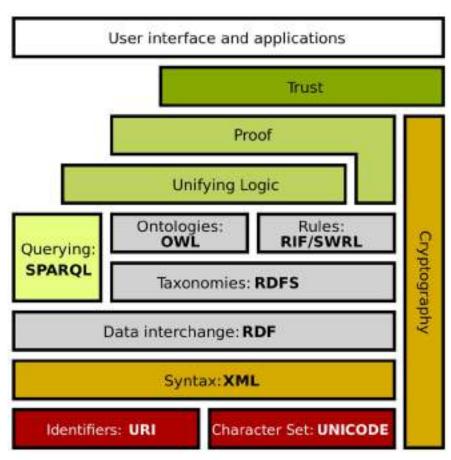
... where the meaning of words is not needed!

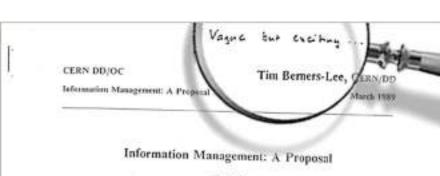
Calculating with Knowledge = inferencing or reasoning

P4: Reserved, standardized symbols with clear formal semantics

- rdf:type
- rdfs:subClassOf
- rdfs:range
- owl:TransitiveProperty
- owl:disjointWith
- owl:sameAs



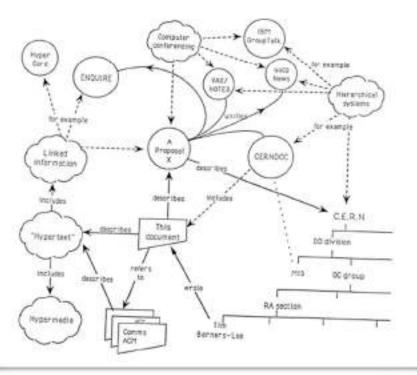




Abstract

This proposal concerns the management of general information about surelevators and experiences at CERN. It discusses the problems of lass of information about complex exotoring systems and derives a solution based on a distributed hypotest, systems.

Keywardz Hyperiesi, Computer conformiting, Discoversi retricust, Information reassignment, Project societal





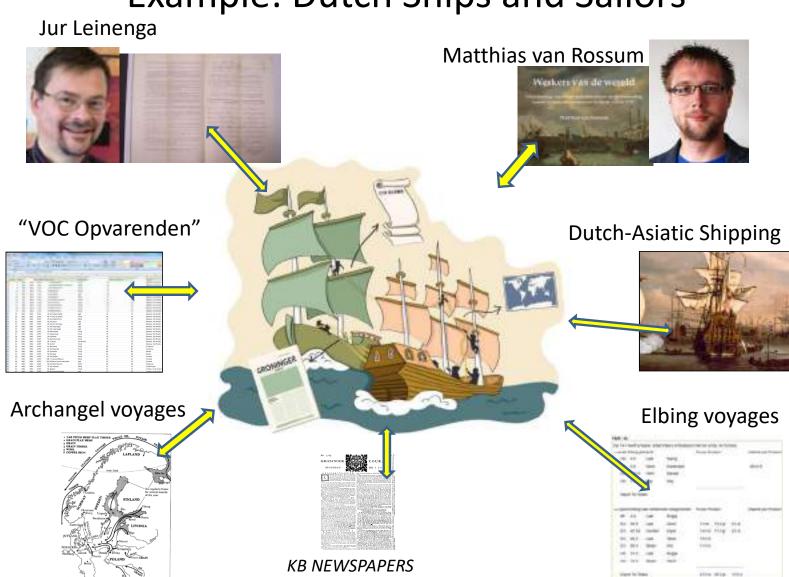
Tim Berners-Lee
The inventor of the (Semantic) Web

http://info.cern.ch/Proposal.html

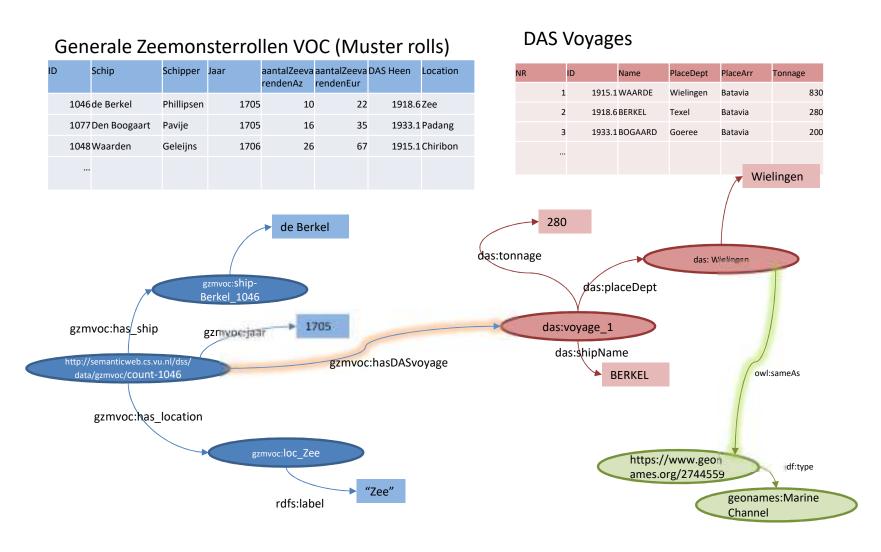
How do you construct it and what would we do with them?



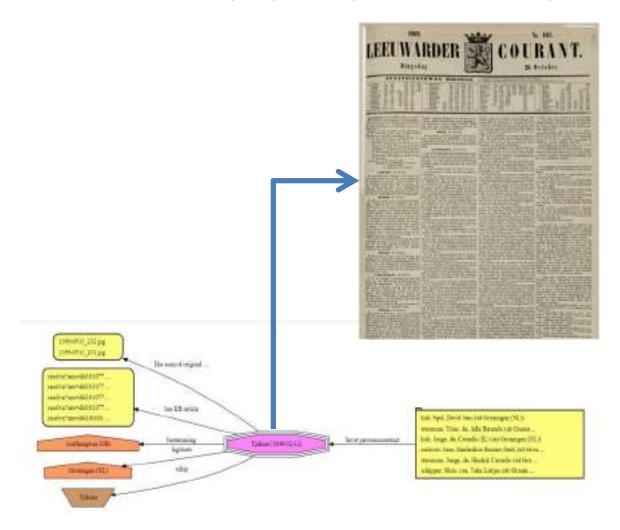
Example: Dutch Ships and Sailors



Building a maritime datahub



Use ML + background knowledge to identify Links to Historical Newspapers published by National Library



Only a few examples to learn from, re-use of background knowledge helps accuracy



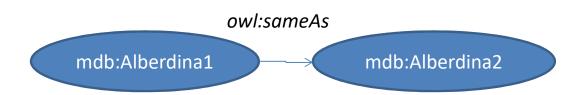
- Andrea Bravo Balado

Use ML+ background knowledge to identify ships

Date	ShipName	ShipType	ShipSize	HomePort	CurrentPort	Captain	
1852-02-27	Alberdiena	kof	NULL	NULL	Noorwegen (N)	Wolkammer	Albert Augustinus
1852-07-31	Alberdina	kof	NULL	Farmsum	Friedrichstadt (D)	Wolkammer	Albert A.
1861-09-30	Alberdina	kof	98	NULL	Gdansk, Danzig (PL)	Wolkammer	Albert Augustinus
1870-03-08	Alberdina	brik	222	NULL	NULL	Wolkammer	Albert Augustinus
1875-09-22	Alberdina	bark	309	NULL	Oostzee	Wolkammer	Augustinus

Only a few examples to learn from, re-use of background knowledge helps accuracy.

Results are clusters of same-as links, retain provenance.



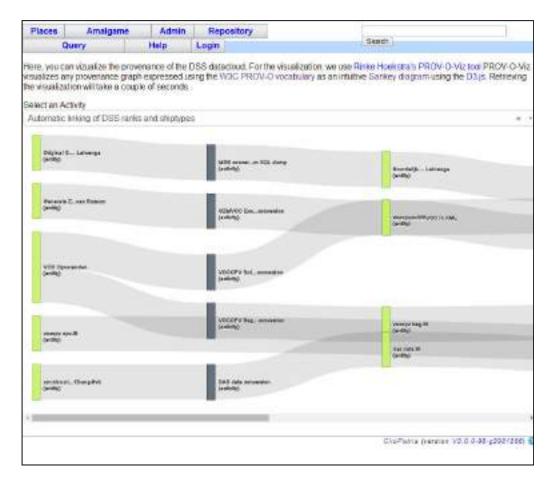


- Robin Ponstein

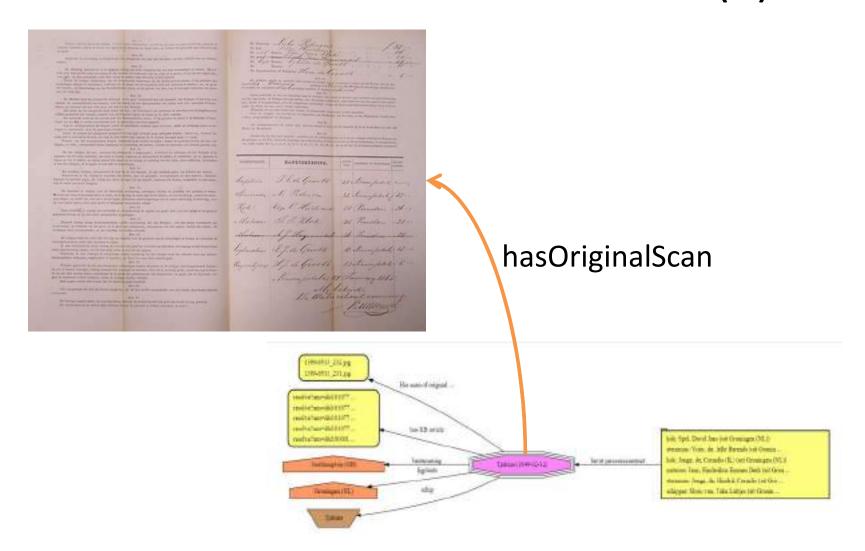
Provenance (1)

Individual named graphs have provenance information

- Who made it
 - Human: Me, historian, crowd
 - Algorithm
 - Hybrid?
- Based on what source
- Content confidence
- Prov vocabulary

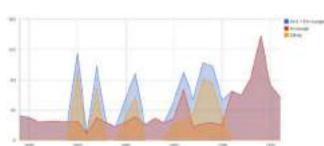


Provenance (2)



Novel data access, analysis and visualisation







Use the textarea below to fire a SPARQL query at the DSS triple store. You can choose adapt that guery if needed before launching it.

Select Query

Find all mdb aanmonsteringen that have a ship and a captain with the last name "Boer"

Give me all ships (across datasets) with the name "Johanna"

Find all mdb aanmonsteringen, and list the last name of the captain of the ship

Find things in DAS and GZMVOC that match the same place in Geonames

Find things in 3 datasets that match the same place in Geonames and also give me the lat/long Places where DAS ships have been

Linked newspaper articles for MDB brikken heading to RIGA

Linked newspaper articles for MDB schoeners with captains name "Veldman"

Links to CEDAR Hiscorical Occupations

Alle KB gelinkte aanmonsteringen met een kapitein met boer in de naam

Personen met "jans" in de naam, aangemonsterd op schip met "kof" in het type

MDB Aanmonsteringen op subtypen van kustvaarders (AAT)

MDB Aanmonsteringen op subtypen van kustvaarders (AAT) in 1815

Alle Vocopy opvar GZM voor links na

SELECT * WHERE {

?record dss:hasOriginalScan ?scan.

?record dss:has kb link?kblink.

?record mdb:schip ?schip.

?schip mdb:scheepstype ?shiptype.

?shiptype skos:exactMatch ?em.

?em skos:broader* aat:kustvaarders.

Lessons learned

- KGs are great for integrating datasets
 - Without the need to force everything into one datamodel
 - Guided by domain experts
 - Enriched by hybrid methods
 - Retain original model and intent, reuse another day
 - New research questions



- Re-use background knowledge
- Provenance fits very well to make source, enrichments transparent
 - Accessible to end-users
- Linked Data is the (technically) best way to do FAIR data publishing

Knowledge graphs for heterogenous, multimodal heritage data



DIVE+



Collections and Vocabularies



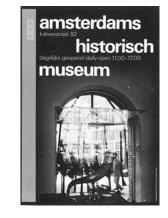
OPENIMAGES.EU

3,220 news broadcasts

Netherlands Institute for Sound & Vision
GTAA thesaurus







AMSTERDAM MUSEUM

73,447 cultural heritage objects





National library of the Netherlands

DELPHER.NL

197,199 Scans of Radio bulletins

1937 - 1984

TROPENMUSEUM

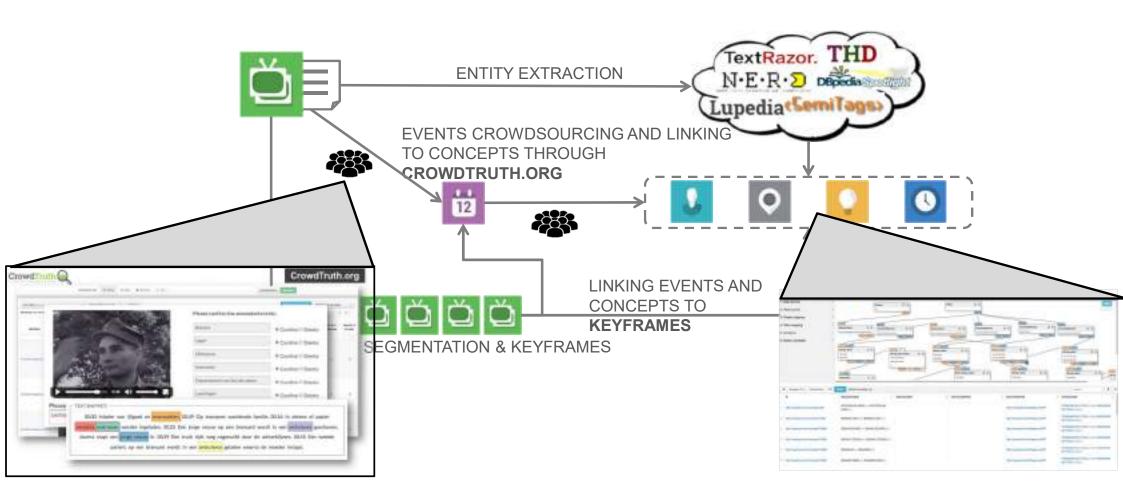
78,270 cultural heritage objects

SVNC

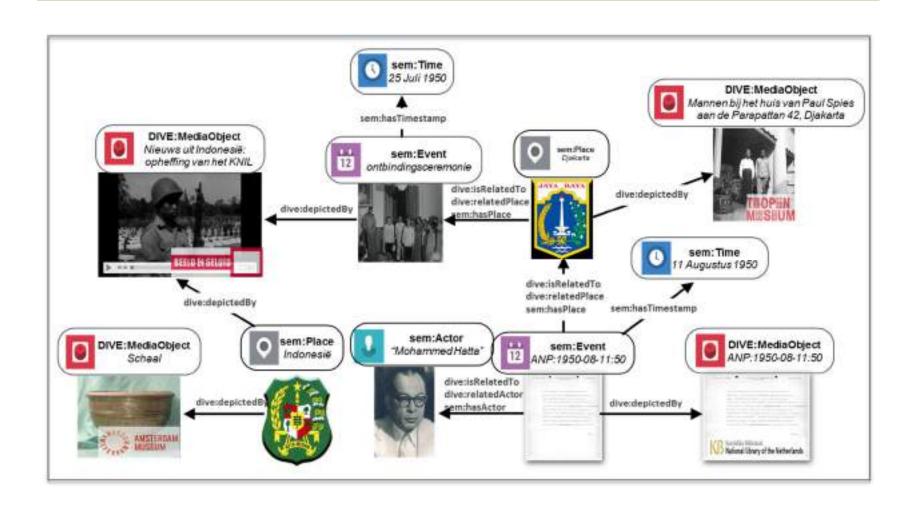


u:

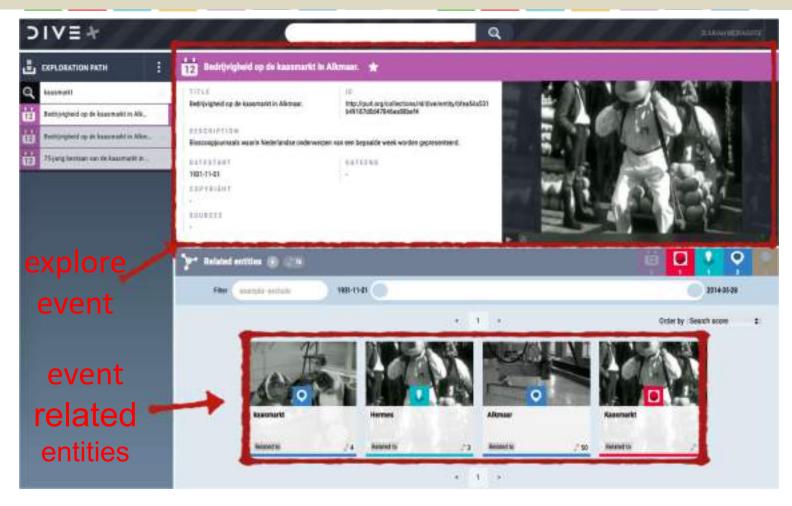
Hybrid Enrichment Pipeline: Text Analysis, Crowdsourcing, Alignment



Cultural Heritage/ Media Knowledge Graph



Exploratory event-based browsing



Lessons learned

- KGs are great for integrating multimodal datasets
 - Use RDFS to map to one shared datamodel
 - Guided by domain experts (interactive alignment)
 - Enriched by hybrid methods (ML + Crowdsourcing)
 - Retain original model and intent, reuse another day
 - New research questions and exploratory browsing



- Re-use background knowledge
- Provenance fits very well to make source, enrichments transparent
 - Accessible to end-users

How about Machine Learning and Knowledge Graphs



Learning and Reasoning

Reasoning

Deductive

Based on formal *logic*al rules

If <x rdf:type A> and <A rdfs:subClassOf B> then <rdf:type B>

RDFS, OWL, other

Learning

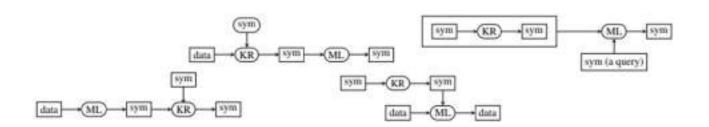
Inductive

Based on statistics

If <x rdf:type A> and <x hasSize 100> and <y rdf:type A> then maybe <y hasSize ~100>?

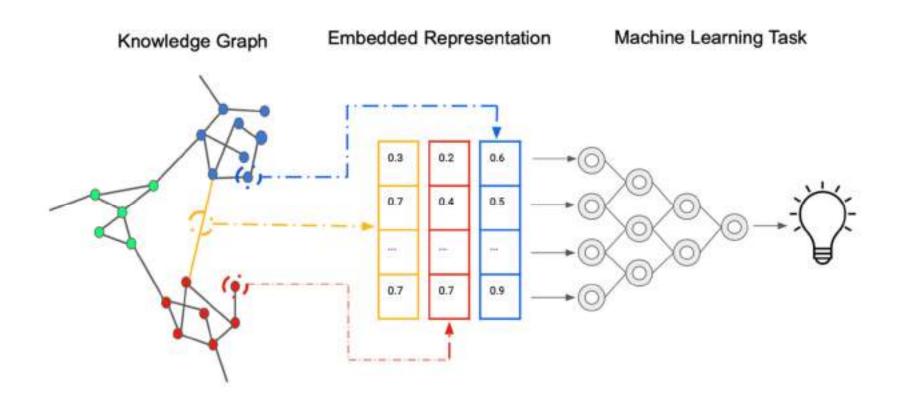
Rule mining, Embedding methods, Deep methods

Many Hybrid Approaches

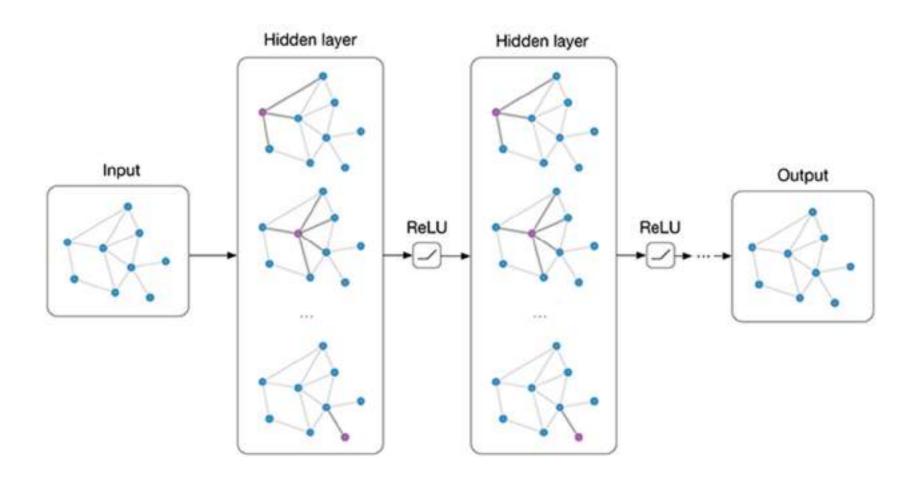


A Boxology of Design Patterns for Hybrid Learning and Reasoning Systems- van Harmelen, ten Teije (2019)

Knowledge Graph Embedding methods (RDF2VEC, TransE, DistMult,...)

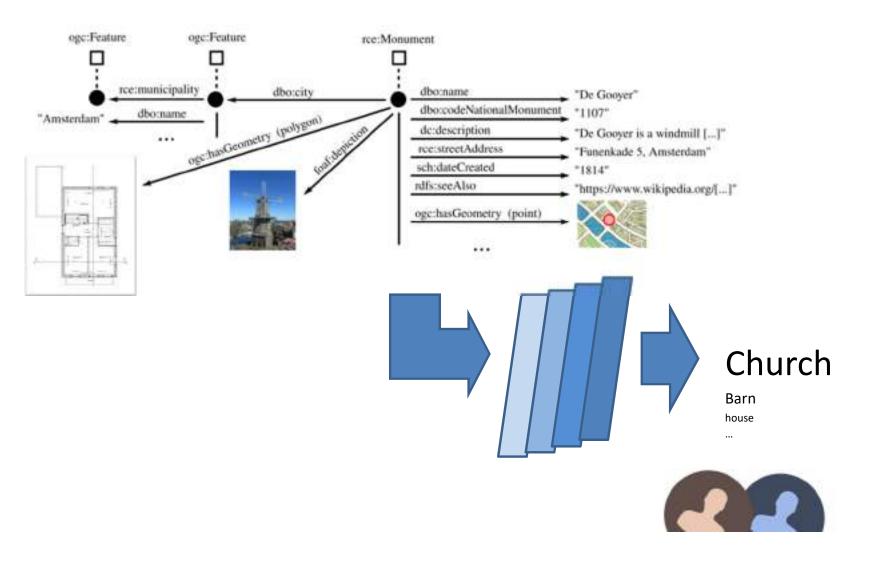


(Knowledge) Graph convolutional methods





End-to-end learning on multimodal knowledge graphs

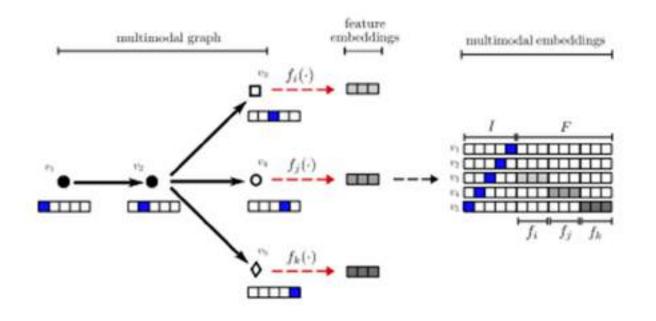




Xander Wilcke

Can be derived from RDF literal datatypes

Extend GCNs



Modules for:

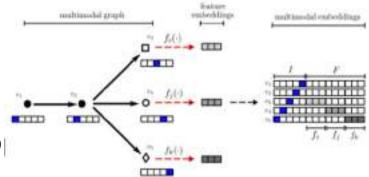
- Numbers (int/float)
- Temporal information (months, days etc)
- Text (CNN)
- Visual information (CNN)
- Spatial information (van het Veer et al)
- RGCN message passing for nodes

gitlab.com/wxwilcke/mrgcn

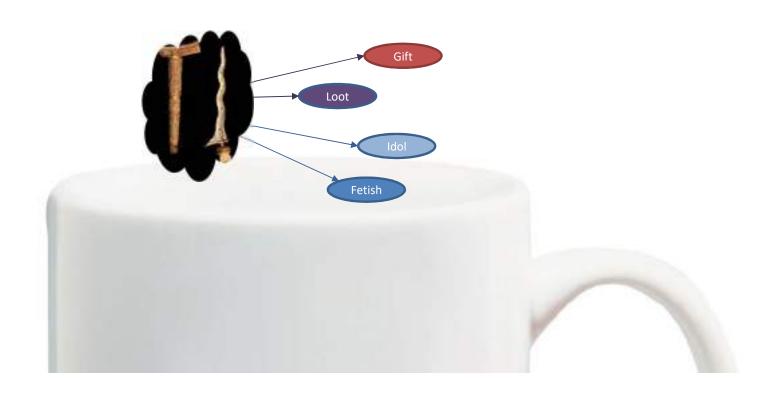
Lessons learned

- KGs are great for integrating multimodal datasets
 - Excellent as "default" data model for ML
- End-to-end (Deep) Machine Learning offers great op
 - Link prediction
 - Classification
 - Message passing methods to learn embedding of graph extended with modality-specific modules
- Various challenges to resolve

Dealing with 1) implicit 2) incomplete 3) differently-structured 4) multi-modal knowledge



Knowledge Graphs and Polyvocality





Integration of four national biographical KGs (Austrian, Dutch, Finnish, Slovenian)

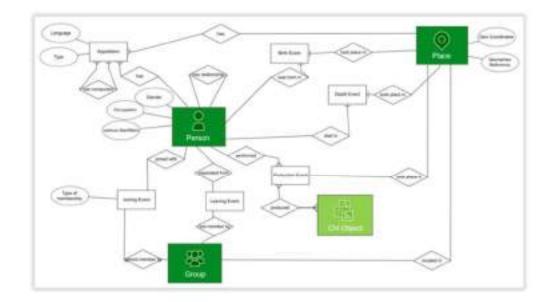
Shared data model (CIDOC-CRM + BIOCRM)

But individual richness intact

Tool suite for DH researchers, educators etc.

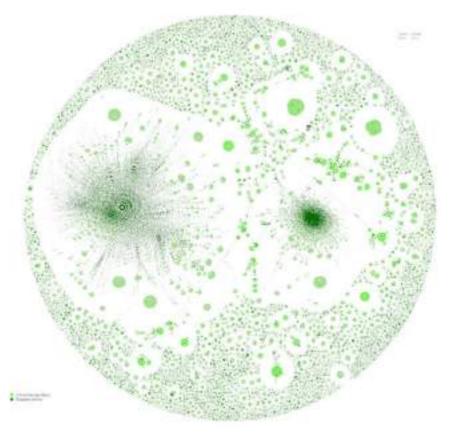
https://intavia.eu/

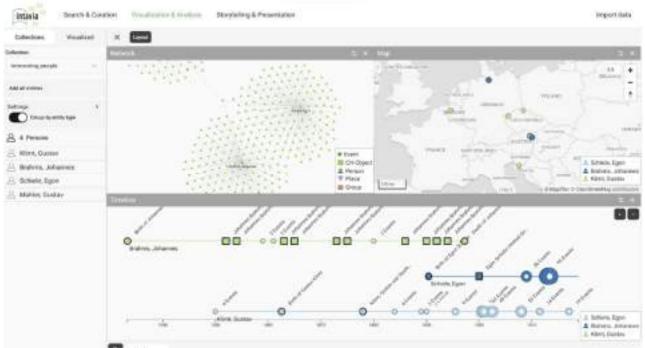




Response: Development of the IDM-RDF data model







Polyvocality

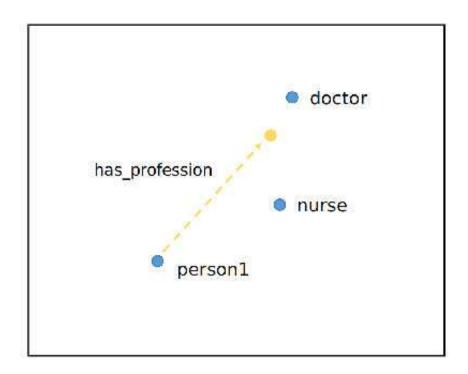
Knowledge graphs, especially those based on historical, cultural data are sure to contain

Biased
Univocal
Single-view
Culturally sensitive

information, based on the majority-view.

This poses the danger of perpetuating gender-/class- etc. biased, colonial-view data.

Bias



https://www.amazon.science/blog/mitigatingsocial-bias-in-knowledge-graph-embeddings

Perspective



Metadata enrichment and bias detection of colonial architecture Roz Sabir

Towards polyvocal Knowledge Graphs

Identifying and acquiring polyvocality knowledge

- Identify existing voices
- Elicit information from polyvocal sources

Representation of polyvocality: models, patterns

- Represent disagreement on categorisation, provenance, etc.

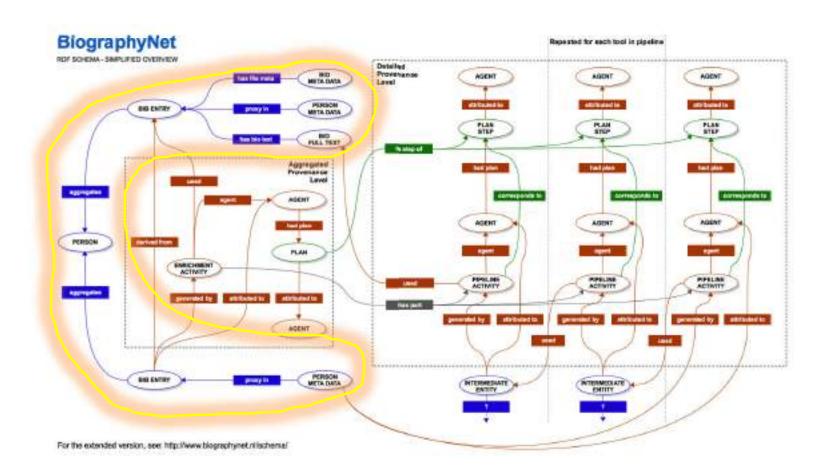
Presentation of polyvocal knowledge

 present it to variety of users, including researchers
 heritage professionals general public
 'source communities'





Polyvocality and **cultural context** in Biographical knowledge graphs





Niels Ockeloen



Go Sugimoto





Argumentation for **explainable** inconsistency resolving in **polyvocal** knowledge graphs



Loan Ho

```
Consider \mathcal{K}_1 = \{\mathcal{R}_1, \mathcal{C}_1, \mathcal{F}_1\} where:
```

 $\mathcal{R}_1 = \{R : \forall x Person(x) \rightarrow \exists y has Death date(x, y)\},\$

 $\mathscr{C}_1 = \{C : \forall x, y, z Person(x) \land hasDeathdate(x, y) \land hasDeathdate(x, z) \rightarrow y = z\},\$

 $\mathcal{F}_1 = \{f_1 : Person(Thorbecke), f_2 : hasDeathdate(Thorbecke, 14/10/1860),$

 f_3 : hasDeathdate(Thorbecke, 10/10/1860)}

 $A_2 = (\{Person(Thorbecke)\}, \{hasDeathdate(Thorbecke, 10/10/1860)\})$

 $\forall x, y, z Person(x) \land hasDeathdate(x, y) \land hasDeathdate(x, z) \rightarrow y = z$

 $A_1 = (\{Person(Thorbecke)\}, \{hasDeathdate(Thorbecke, 14/10/1860)\})$



User: Why not hasDeathdate(Thorbecke, 10/10/1860) given that A₂? ⁸

User: I understood "why 10/10/1860 is not Thorbecke's death date" Reasoner: Because hasDeathdate(Thorbecke, 10/10/1860) 9 the following constraint is violated: $\forall x, y, z Person(x) \land hasDeathdate(x, y) \land hasDeathdate(x, z) \rightarrow y = z$,





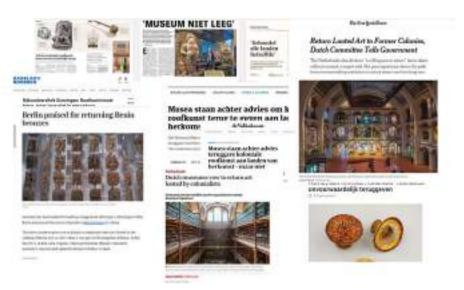
Rethinking colonial heritage collections

Modes of Acquisition

- 1. Scientific (including Expeditions)
- 2. Involuntary dispossession (violent)
- 3. Trade (diplomatic exchanges and legal sales)
- 4. Voluntary dispossession (Missionary)





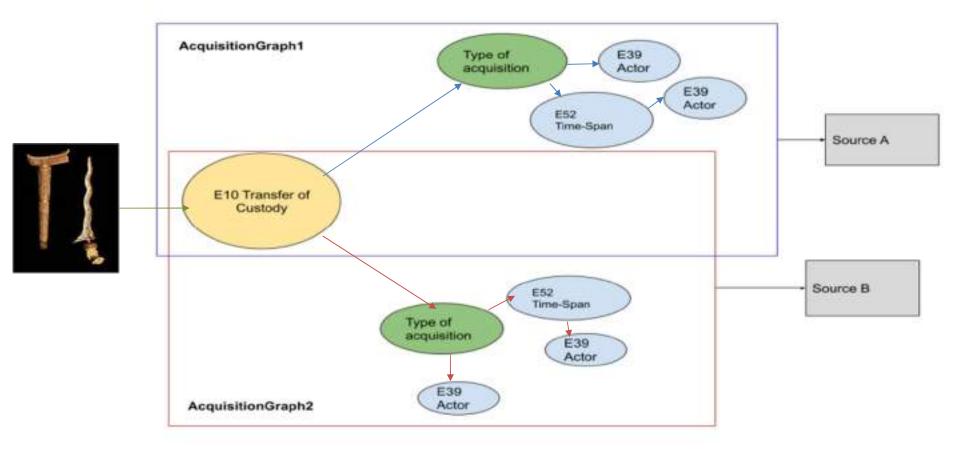








Using provenance to represent multiple views in colonial heritage knowledge graphs

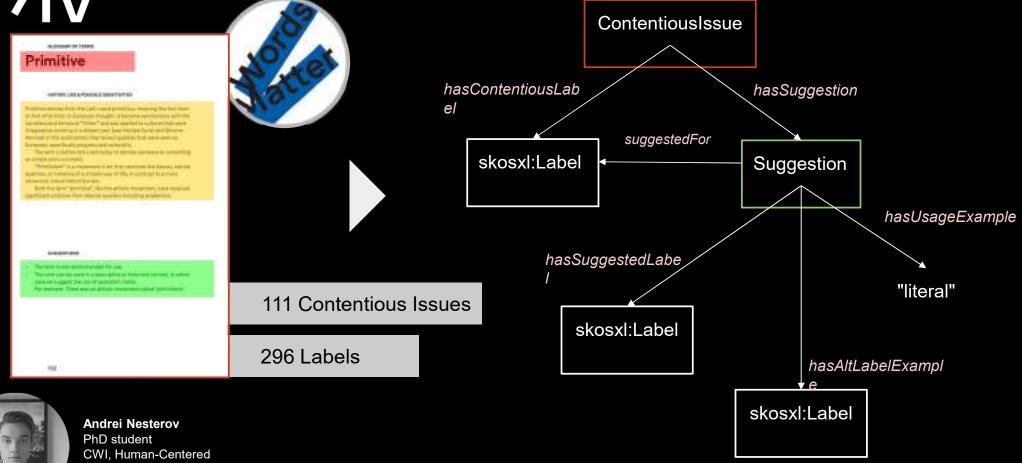




Sarah Shoilee

cultural-ai.nl

Contentious terms in the cultural sector: From expert knowledge to linked data



Cultural Al Lab (culturalai.nl) Steven Claeyssens



Bias **Ethics** Cultural differences Perspectives



Lessons learned

- KGs provide means for integrating datasets
 - Keeping multiple perspectives on data in tact
 - Guided by domain experts





- Provenance is key
- Patterns allow for transparent analysis by end-users

- Cultural Heritage Organisations are becoming more *Open,* Smart, Connected
- Knowledge Graphs to integrate heterogeneous and multimodal knowledge, information and data, with attention for provenance and transparency
 - For a variety of users (internal / experts, external experts, DH experts, toolbuilders, data scientists, laypersons)
 - Through query environments, raw-data access, purposeful tools
- Re-use and re-usability
- Logical Reasoning and Statistical Learning to both enrich and analyse the KGs. Including simple methods, deep learning,
- Challenges around polyvocality, bias, provenance

Take home



Thank you

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cultural-ai.nl

