Unflattening Knowledge Graphs

Marieke van Erp DHLab KNAW Humanities Cluster Amsterdam, the Netherlands









"A cup of coffee"

"A cup of coffee"



"A cup of coffee"





"A cup of coffee"







"Let's have coffee"







17th Century Coffee House

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https://bgb.resources.huygens.knaw.nl/voyage/49



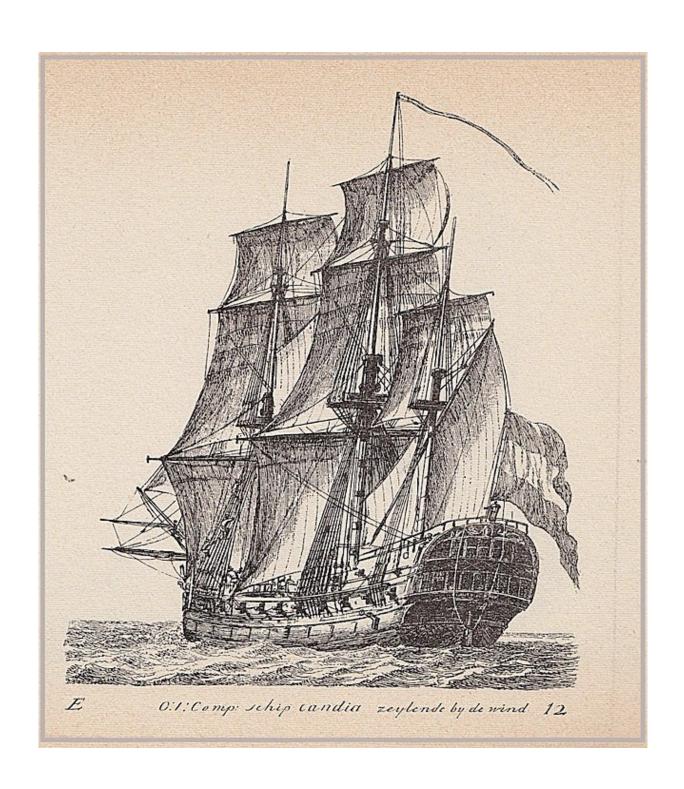


Voyage Details

Number	49	
Book year	1789/1790	
Source	10800	
Folio number	73	
Ship name	Rotterdams Welvaren	
Departure date	18-11-1789	
Departure place and region	Batavia, Batavia	
Arrival date	-	
Arrival place and region	Enkhuizen, Republiek	
Total value Dutch guilders	76.749,15,8	
Total value Indian guilders	-	
Remarks Voyage	Rotterdams Welvaren was wrecked during its voyage to the Cape.	
Voyage in DAS	go to DAS voyage 8269.2	

Cargo details

Quantity		Product	Specification	Value Dutch guilders	Value Indian guilders
616	lb	foelie	macis	304,18,8	
70	lb	moernagel	-	87,11,8	
2.150	lb	nootmuskaat	in soort	354,15	
127.596	lb	peper	zwart geharpt	15.978,12	
3.500	lb	peper	wit	792,16	
4.075	lb	garen	katoenen	2.381,1	
365.500	lb	koffie	Javaans	34.737,2,8	
6.250	lb	kurkuma	-	504,14,8	
2.524	lb	kamfer	Japans	802,12,8	
10.915	lb	calaturshout	Kust	387,9,8	
1.250	lb	indigo	Javaans	1.429,17	
30.000	lb	sapanhout	Bimanees	753.15	



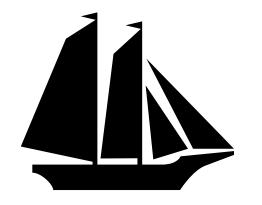






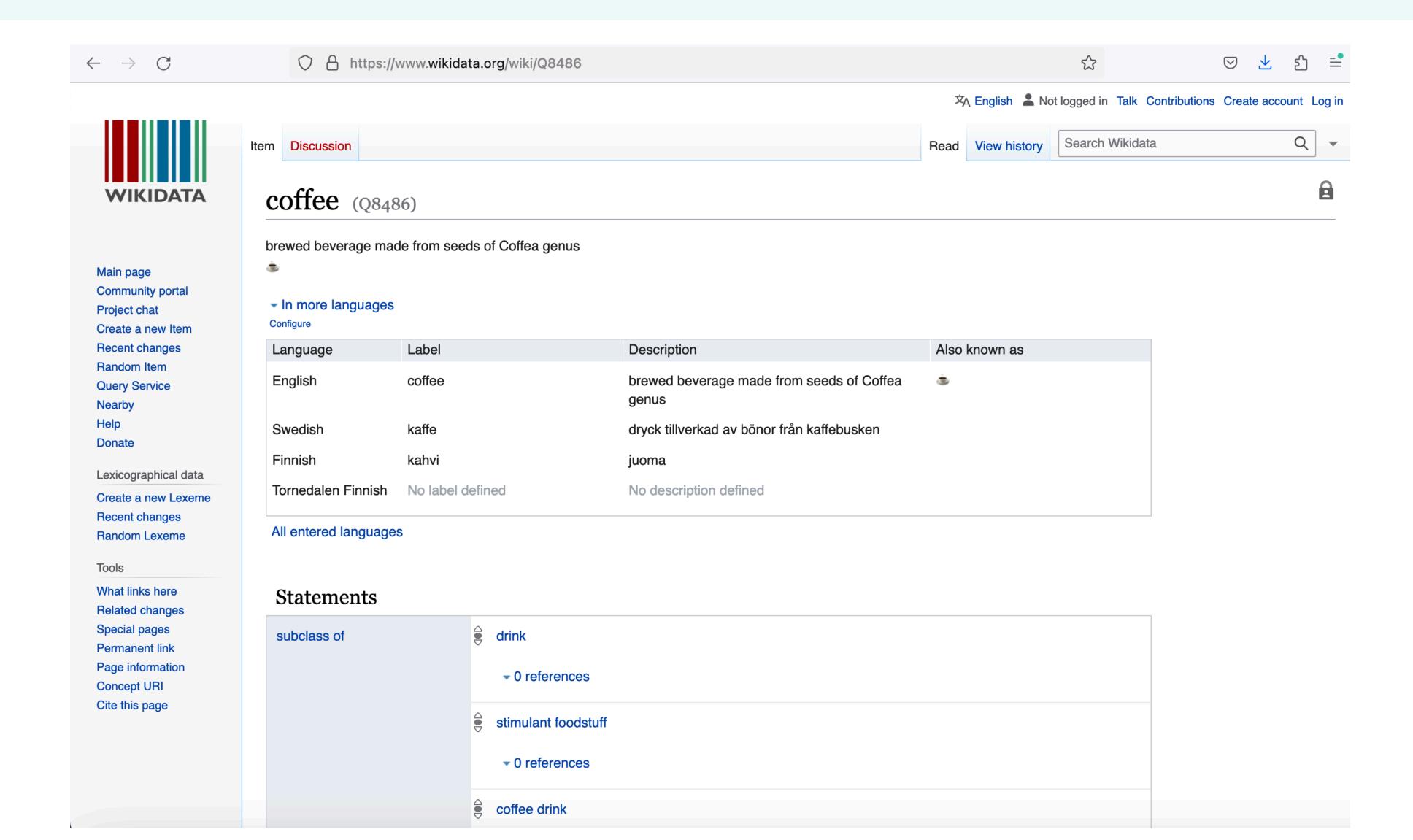


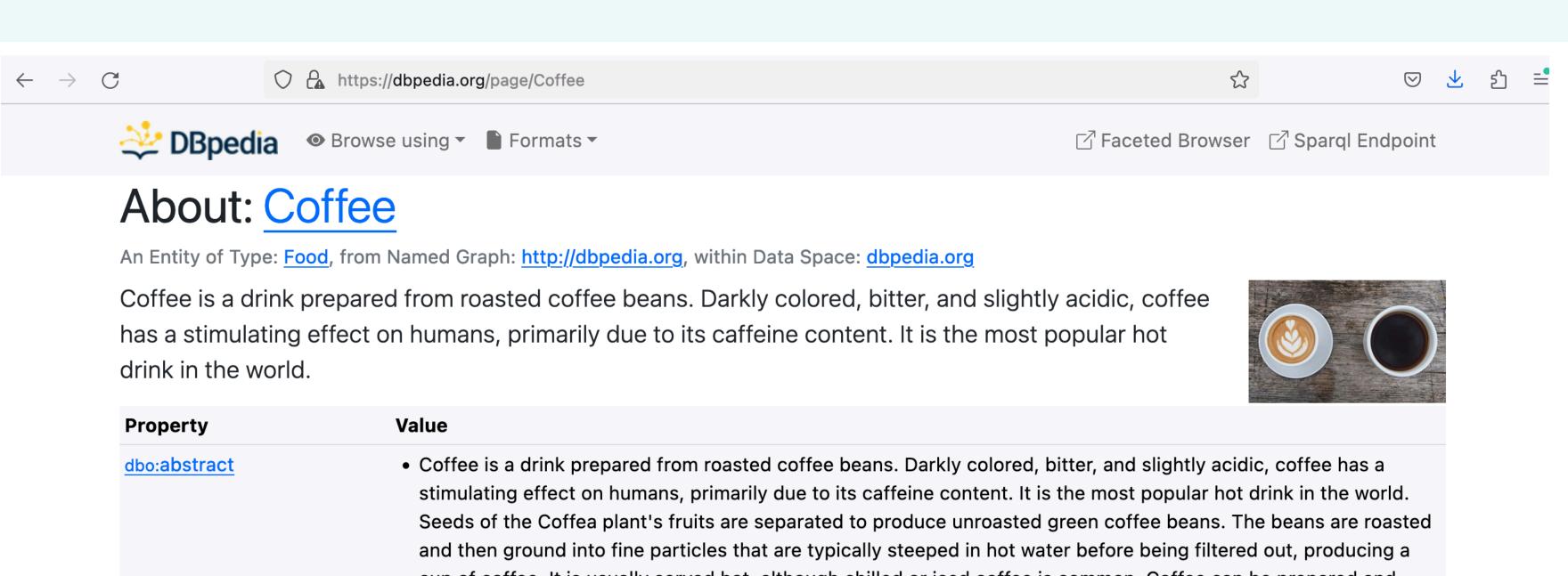
coffee





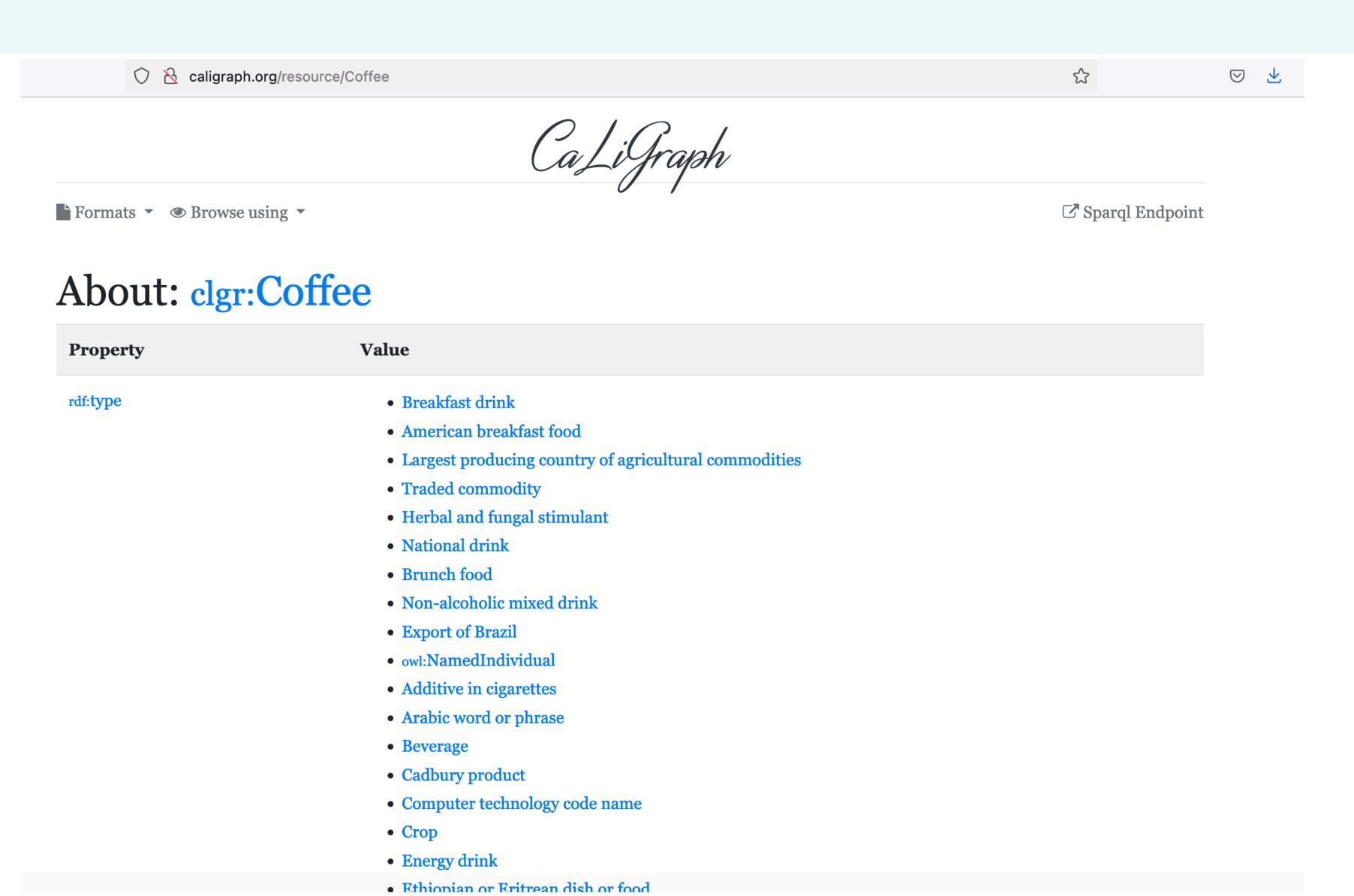






cup of coffee. It is usually served hot, although chilled or iced coffee is common. Coffee can be prepared and presented in a variety of ways (e.g., espresso, French press, caffè latte, or already-brewed canned coffee). Sugar, sugar substitutes, milk, and cream are often used to mask the bitter taste or enhance the flavor. Though coffee is now a global commodity, it has a long history tied closely to food traditions around the Red Sea. The earliest credible evidence of coffee drinking in the form of the modern beverage appears in modern-day Yemen from the mid-15th century in Sufi shrines, where coffee seeds were first roasted and brewed in a manner similar to current methods. The Yemenis procured the coffee beans from the Ethiopian Highlands via coastal Somali intermediaries and began cultivation. By the 16th century, the drink had reached the rest of the Middle East and North Africa, later spreading to Europe. In the 20th century, coffee became a global commodity, creating different coffee cultures around the world. The two most commonly grown coffee bean types are C. arabica and C. robusta. Coffee plants are cultivated in over 70 countries, primarily in the equatorial regions of the Americas, Southeast Asia, the Indian subcontinent, and Africa. As of 2018, Brazil was the leading grower of coffee beans, producing 35% of the world's total. Green, unroasted coffee is the most traded agricultural commodity and one of the most traded commodities overall, second only to petroleum. Despite sales of coffee reaching billions of dollars worldwide, farmers producing coffee beans disproportionately live in poverty. Critics of the coffee industry have also pointed to its and the clearing of land for coffee-growing and water use. (en)







Synonyms

- rt Café (n, food) →
- ar قَهْوَة (n, food)
- cafè (n, food) →
- cafè (n, plant) →
- da kaffe (n, food)
- da mokka (n, food)
- fr café →
- sh kafa →
- sh kahva →
- sh kava →
- en chocolate (n, attribute)
- en coffee bean (n, food) →
- en coffee tree (n, plant)
- en java ^(n, food) →

Types of coffee

- en Arabian coffee (n, plant) →
- en cafe au lait (n, food)
- en cafe noir (n, food)
- en cafe royale (n, food) →
- en cappuccino coffee (n_{English})
- en coffee substitute (n, food)
- en decaffeinated coffee (n, food)
- en drip coffee (n, food) →
- en espresso (n, food)
- en iced coffee (n, food) →
- en instant coffee (n, food)
- en Irish coffee (n, food) →

coffee is a type of...

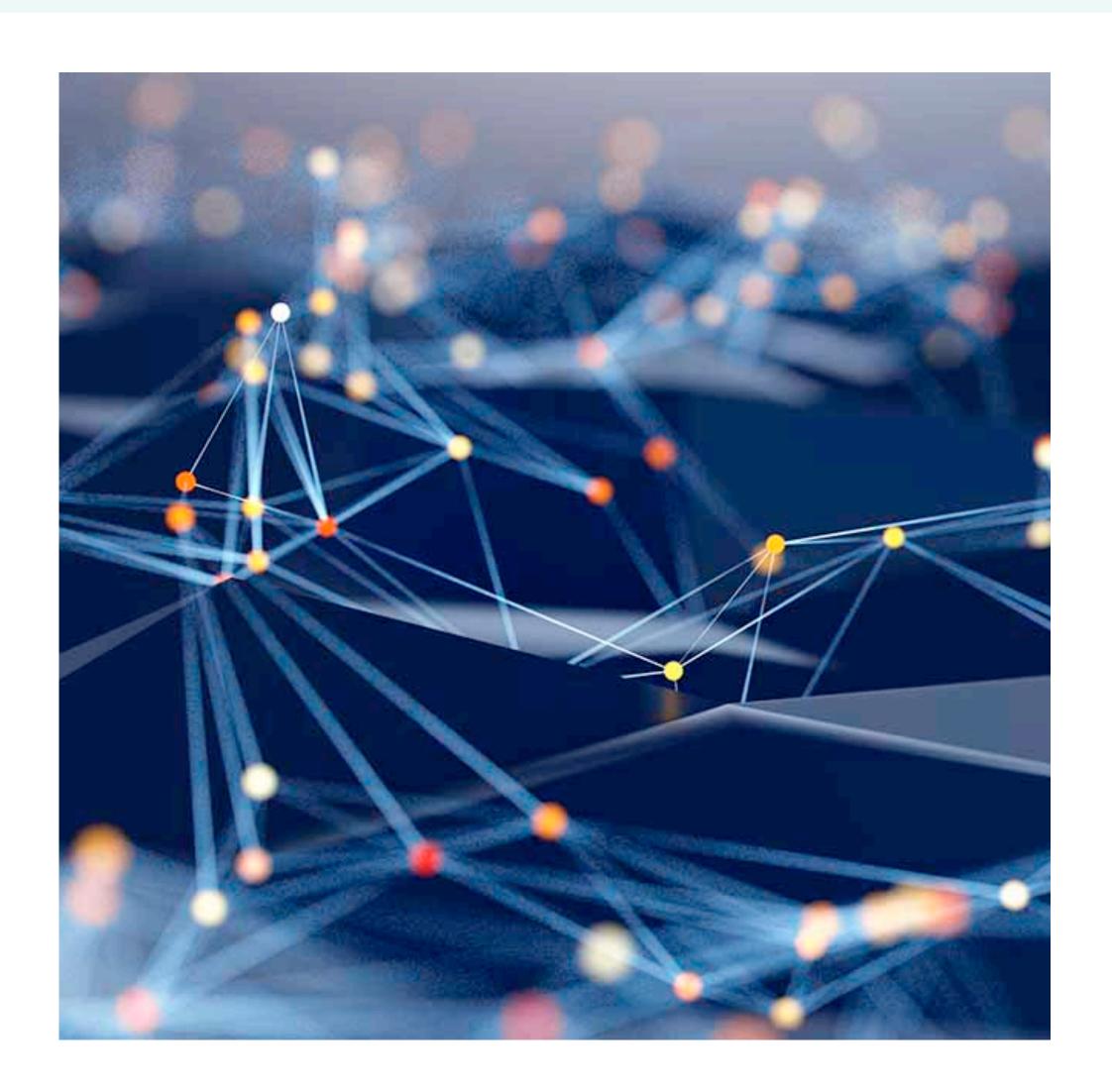
- en a stimulant →
- en an acquired taste →
- en an addictive substance →
- en a beverage →
- en a bushy plant →
- en a good after dinner drink
- en a popular drink →
- en beverage (n, food) →
- en tree (n, plant)
- en a breakfast beverage →
- en gooooooooooooo →
- en a hot beverage →
- en a liquid →

Related terms

- en sugar →
- it moka ⁽ⁿ⁾ →
- sh fildžan ⁽ⁿ⁾→
- sh findžan ⁽ⁿ⁾→
- sh kafa (n) →
- sh kahva ⁽ⁿ⁾ →
- sh kava (n) →
- en mug →
- en break →
- en latte →
- en cafe →
- аь акаҳуа ⁽ⁿ⁾→
- ^{аdy} КЪЭХЬО ⁽ⁿ⁾→
- af koffie (n) →

Why is this a problem

- Entity Linking is often employed in KG creation
- Imprecise links can create imprecise analyses
- Not only an issue for historical use cases



Car Manufacturers





- •April 2006:
 - •production of Polo from Spain to Eastern-Europe because of social problems in Volkswagen Pamplona and maybe to Volkswagen Vorst in Belgium
- •July 2006:
 - •Polo production in Vorst, no jobs lost in Spain but extra jobs in Belgium.
- •August 2006:
 - •Fewer Golfs produced in Vorst, maybe more Polos. 'If not, we have a problem', says a union representative.....Chances that Vorst will not make any Polos next year are minimal, because the factory invested this year in a special new welding installation specific for Polo cars.
- •November 2006:
 - •Volkswagen stops the production of Golf in Vorst: 3,500 jobs are lost plant renamed to Audi-Brussels
- •November 2009:
 - •Audi plant in Vorst stops the production of Polo: 300 jobs lost

Audi-Brussels present in DBpedia Volkswagen Pamplona linked to Volkswagen

Volkswagen closes Volkswagen Pamplona ≠ dbp:Volkswagen closes dbp:Volkswagen

Commodities



Sugar is an energy source

Sugar is a treat

Sugar caused ecological crises

Sugar enabled enslavement

Sugar is a health hazard



Smells



Jewellery is a status symbol

Jewellery can convey a message

Scented jewellery can ward off disease

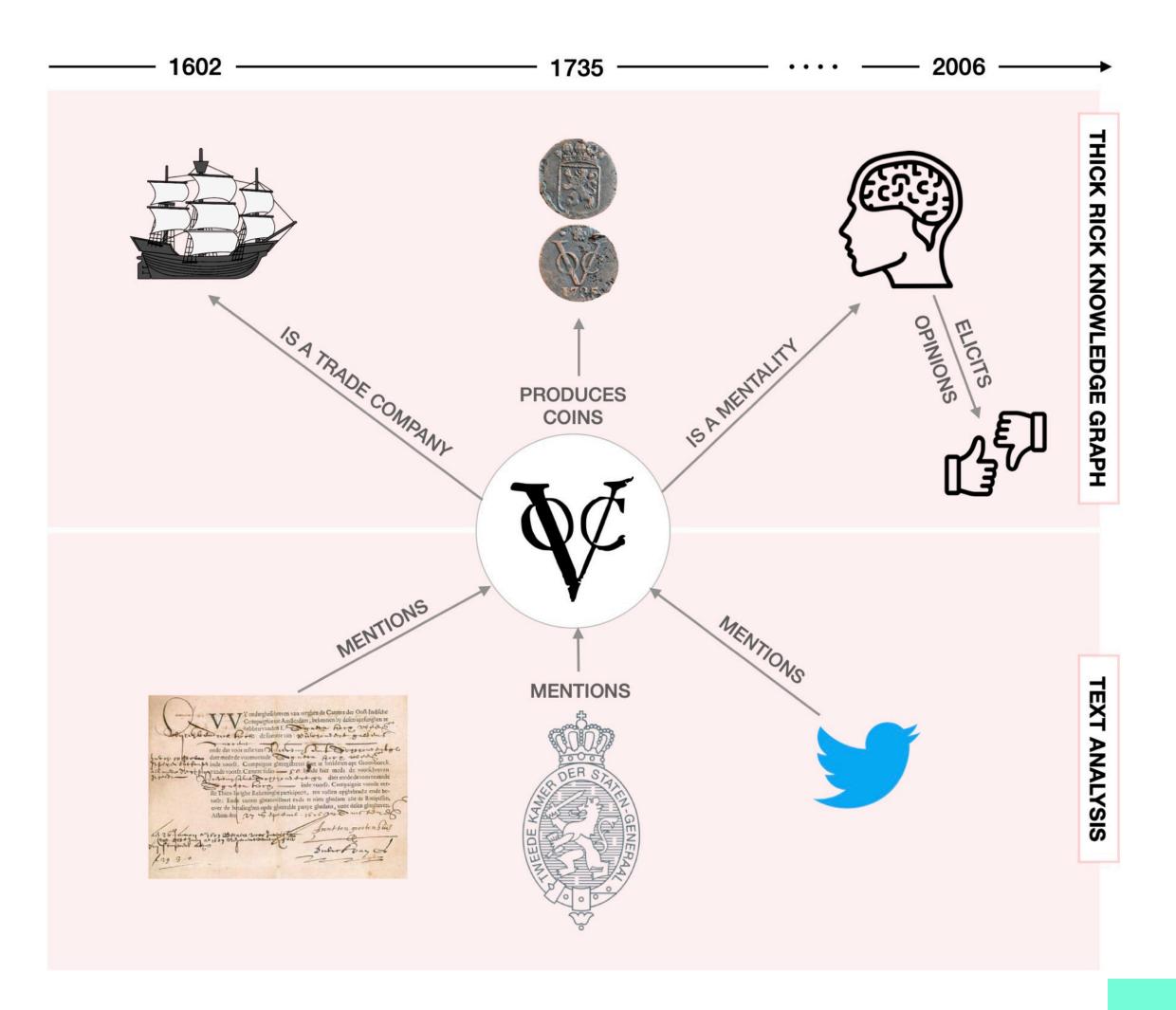


Pasquale Lisena, Daniel Schwabe, Marieke van Erp, Raphaël Troncy, William Tullett, Inger Leemans, Lizzie Marx, and Sofia Colette Ehrich. "Capturing the Semantics of Smell: The Odeuropa Data Model for Olfactory Heritage Information." In *The Semantic Web: 19th International Conference, ESWC 2022, Hersonissos, Crete, Greece, May 29–June 2, 2022, Proceedings*, pp. 387-405. Cham: Springer International Publishing, 2022.

Unflattening KGs

- Identity concepts are multidimensional and have *coreferring*, *non*- and *near*-identity relations to other concepts
- Change concepts evolve over time
- Long tail go beyond popular concepts and entities

Provenance - keep track of where the information comes from



 Co-referring relationship: when two entities are the same (owl:sameAs)





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Bill said Alice would arrive soon, and she did.

 Co-referring relationship: when two entities are the same (owl:sameAs)





Bill said Alice would arrive soon, and she did.

Non-identity: when two entities are distinctly different





 Co-referring relationship: when two entities are the same (owl:sameAs)





Bill said Alice would arrive soon, and she did.

Non-identity: when two entities are distinctly different





Bill said Alice would arrive soon, then Jane arrived.

 Co-referring relationship: when two entities are the same (owl:sameAs)





Bill said Alice would arrive soon, and she did.

Non-identity: when two entities are distinctly different





Bill said Alice would arrive soon, then Jane arrived.

Near-identity: when two entities share most but not all feature values





 Co-referring relationship: when two entities are the same (owl:sameAs)





Bill said Alice would arrive soon, and she did.

Non-identity: when two entities are distinctly different





Bill said Alice would arrive soon, then Jane arrived.

Near-identity: when two entities share most but not all feature values





The United States has officially restored diplomatic relations with Yugoslavia . . . **The White House** said the United States will provide 45 million dollars in food aid.

Identity @ESWC2023

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Refining Large Integrated Identity Graphs using the Unique Name Assumption

SAP-KG: Synonym Predicate Analyzer across Multiple Knowledge Graphs

Shuai Wang¹ \bowtie [0000-0002-1261-9930], Joe Raad² [0000-000] Bloem $^{1[0000-0002-0189-5817]}$, and Frank van Harmelen $^{1[0]}$

Department of Computer Science, Vrije Universiteit Amster {shuai.wang | p.bloem | frank.van.harmelen ² LISN, University of Paris-Saclay, Orsay, Fr joe.raad@lisn.fr

> Abstract. The Unique Name Assumption (UNA) sup terms with distinct id....c

Transformer based Semantic Relation Typing for Knowledge Graph Integration

Sven $\operatorname{Hertling}^{[0000-0003-0333-5888]}$ and $\operatorname{Heiko\ Paulheim}^{[0000-0003-4386-8195]}$

Data and Web Science Group, University of Mannheim, Germany {sven,heiko}@informatik.uni-mannheim.de

 $\operatorname{azmand}^{1,2[0000-0001-8194-8079]}$ and Maria-Esther $Vidal^{1,2,3}[0000-0003-1160-8727]$

tion Centre for Science and Technology, Hannover, Germany eibniz University of Hannover, Germany

Emetis.Niazmand@tib.eu ³ L3S Research Center, Germany Maria.Vidal@tib.eu

emo paper presents SAP-KG, a knowledge graph agtrate the benefits of identifying the synonym predicomplementary information; they are used for query query answer completeness. SAP-KG proposed a he percentage of overlap between pairs of synonym

Entity Typing with Triples using Language \mathbf{Models}

Aniqa Riaz¹, Sara Abdollahi $^{2[0000-0001-7752-146X]}$, and Simon $Gottschalk^{2[0000-0003-2576-4640]}$

¹ Universität Bonn, Germany s6anriaz@uni-bonn.de ² L3S Research Center, Leibniz Universität Hannover, Germany {abdollahi,gottschalk}@L3S.de

Abstract. Entity Typing is the task of assigning a type to an entity in a

NASTyLinker: NIL-Aware Scalable Transformer-based Entity Linker

Nicolas ${\rm Heist}^{[0000-0002-4354-9138]}$ and ${\rm Heiko~Paulheim}^{[0000-0003-4386-8195]}$

Data and Web Science Group, University of Mannheim, Germany ${\tt nico,heiko}{\tt @informatik.uni-mannheim.de}$

Abstract. Entity Linking (EL) is the task of detecting mentions of entities in text and disambiguating them to a reference knowledge base. Most prevalent EL approaches assume that the reference knowledge base is complete. In practice, however, it is necessary to deal with the case of linking to an entity that is not contained in the knowledge base (NIL entity). Recent works have shown that instead of

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Identity



Entity Linking & Entity Spaces

Entity Linking & Entity Spaces

- Germany imported 47,600 sheep from Britain last year, nearly half of total imports.
- German July car registrations up 142 pct yr/yr.
- Australia last won the Davis Cup in 1986, but they were beaten finalists against Germany three years ago under Fraser's guidance.

Entity Linking & Entity Spaces

http://en.wikipedia.org/wiki/Germany

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Germany 1996 Davis Cup Team

Marieke van Erp and Paul Groth. 2020. Towards Entity Spaces. In Proceedings of the Twelfth Language Resources and Evaluation Conference, pages 2129–2137, Marseille, France. European Language Resources Association.

Entity Linking & Entity Spaces



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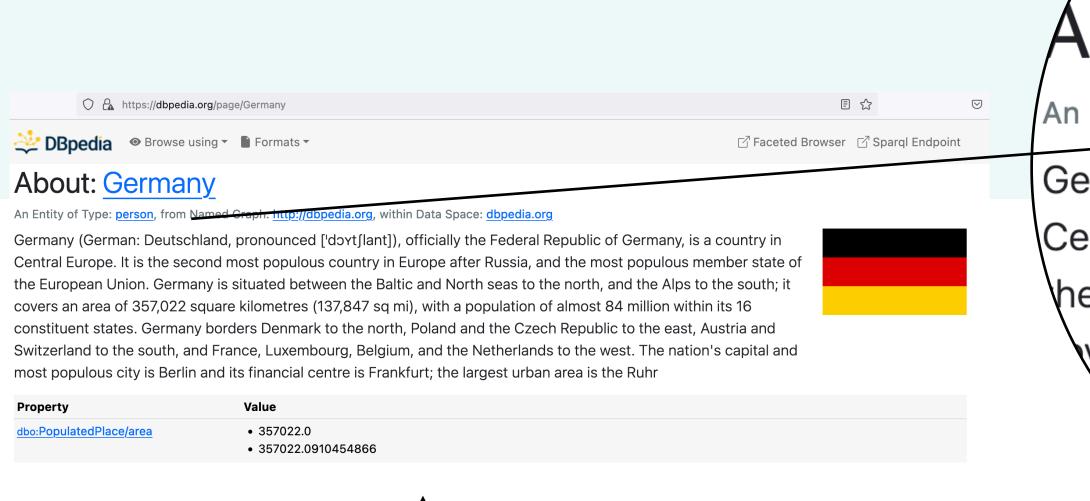
Germany 1996 Davis Cup Team







Germany 1993 Davis Cup Team



About: Germany

An Entity of Type: person, from Named Graph: http://
Germany (German: Deutschland, pronounce Central Europe. It is the second most populo he European Union. Germany is situated by vers an area of 357,022 square kilometry tituent states. Germany borders Deutschland to the south, and France and South and France area of 357,022 square kilometry and to the South, and France and South and South

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http://en.wikipedia.org/wiki/Germany

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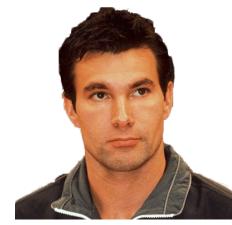
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Germany 1996 Davis Cup Team



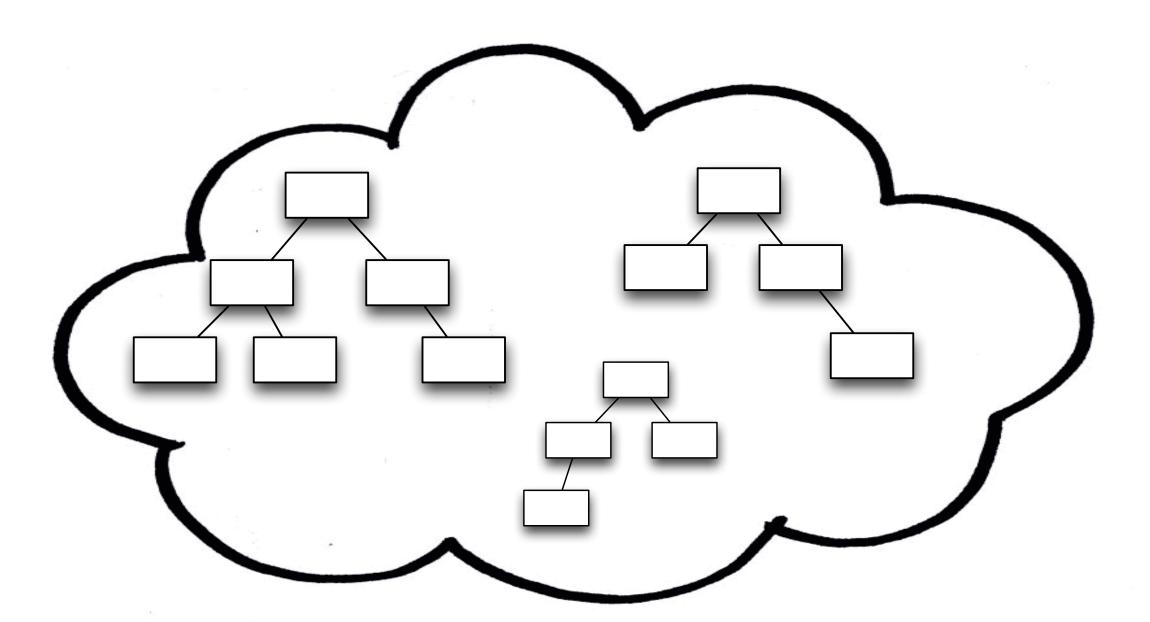




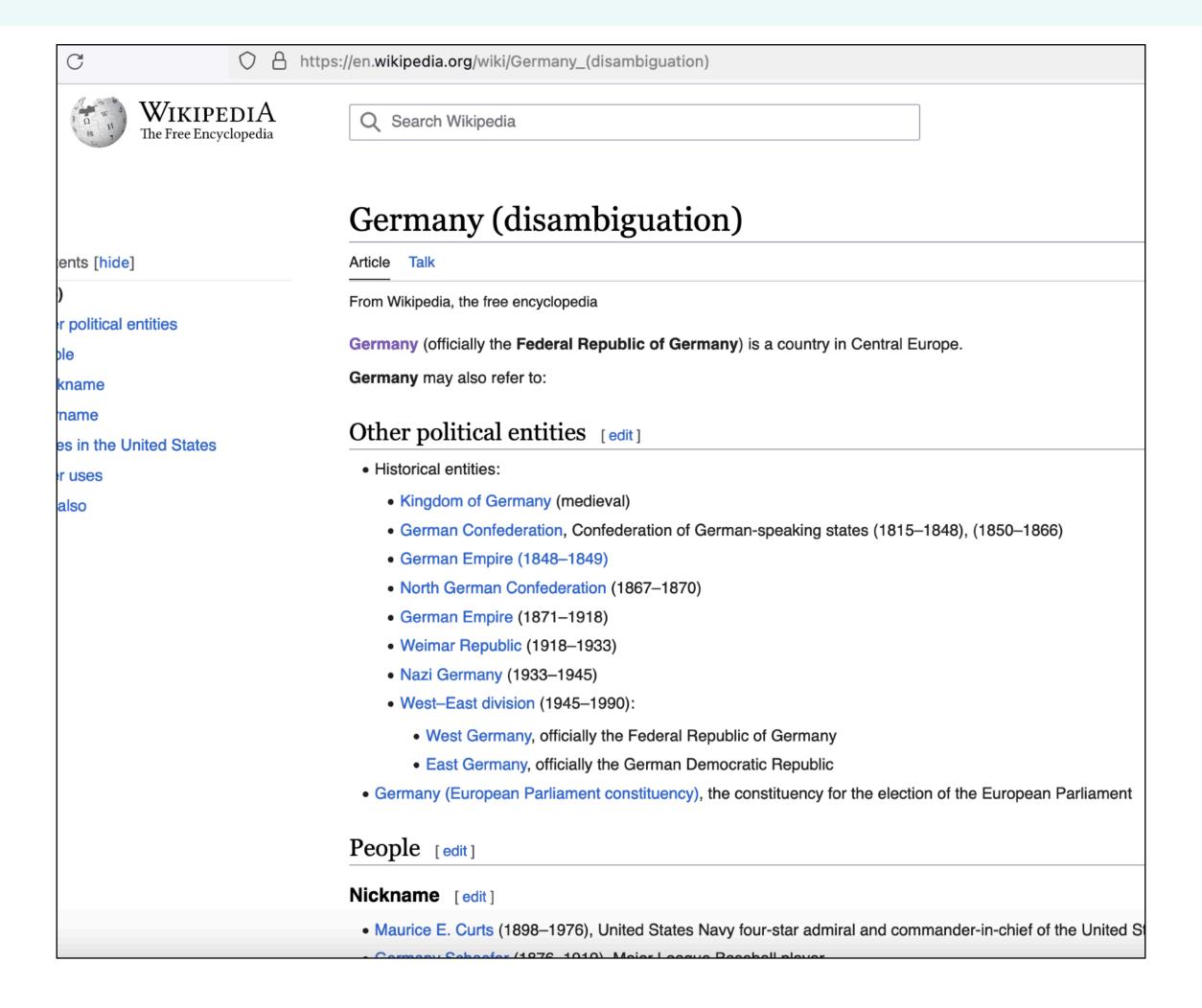
Germany 1993 Davis Cup Team

Entity Spaces

An **Entity Space** is an explicit representation of a set of entities in a knowledge base that have a strong near-identity relationship and whose linguistic labels can be used interchangeably in certain contexts.

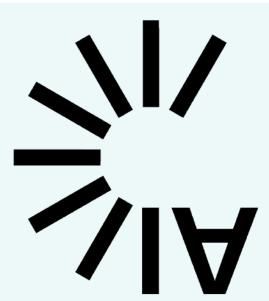


Disambiguation Pages as Entity Space Proxies



Marieke van Erp and Paul Groth. 2020. Towards Entity Spaces. In *Proceedings of the Twelfth Language Resources and Evaluation Conference*, pages 2129–2137, Marseille, France. European Language Resources Association.

Polyvocality



- Multiple dimensions also means multiple perspectives
- All data is biased
- KGs can represent multiple perspectives



Hendrick Cornelis Vroom Een aantal Oostindiëvaarders voor de kust Rijksmuseum SK-A-3108

Words Matter

- GLAMs & society are rethinking their vocabularies
- Change is slow
- What does this mean for SW resources?

The New York Times

A Dutch Golden Age? That's Only Half the Story

Museums in the Netherlands are ditching historical terms and names, and updating their collections as they grapple with the legacy of slavery and colonialism.





Bias @ESWC2023

Structural Bias in Knowledge Graphs for the Entity Alignment Task

Nikolaos Fanourakis¹, Vasilis Efthymiou¹, Vassilis Christophides², Dimitris Kotzinos², Evaggelia Pitoura³, and Kostas Stefanidis⁴

¹ FORTH-ICS, Greece

{fanourakis, vefthym}@ics.forth.gr ² Lab. ETIS, CY Cergy Paris University, ENSEA, CNRS UMR 8051, France Vassilis.Christophides@ensea.fr, Dimitrios.Kotzinos@cyu.fr ³ University of Ioannina, Greece pitoura@uoi.gr ⁴ Tampere University, Finland

konstantinos.stefanidis@tuni.fi

Abstract. Knowledge Graphs (KGs) have recently gained attention for representing knowledge about a particular domain and play a central role in a multitude of AI tasks like recommendations and query answering. Recent works have revealed that KG embedding methods used to implement these tasks often exhibit direct forms of bias (e.g., related to gender, nationality, etc.) leading to discrimination. In this work, we are interested in the impact of indirect forms of bias related to the structural diversity of KGs in entity alignment (EA) tasks. In this respect, we propose an exploration-based sampling algorithm, SUSIE, that generates challenging benchmark data for EA methods, with respect to structural diversity. SUSIE requires setting the value of a single hyperparameter, which affects the connectivity of the generated KGs. The generated samples exhibit similar characteristics to some of the most challenging real-world KGs for EA tasks. Using our sampling, we demonstrate that state-of-the-art EA methods, like RREA, RDGCN, MultiKE and PARIS,

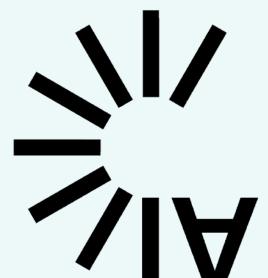
Evaluating Language Models for Knowledge Base Completion

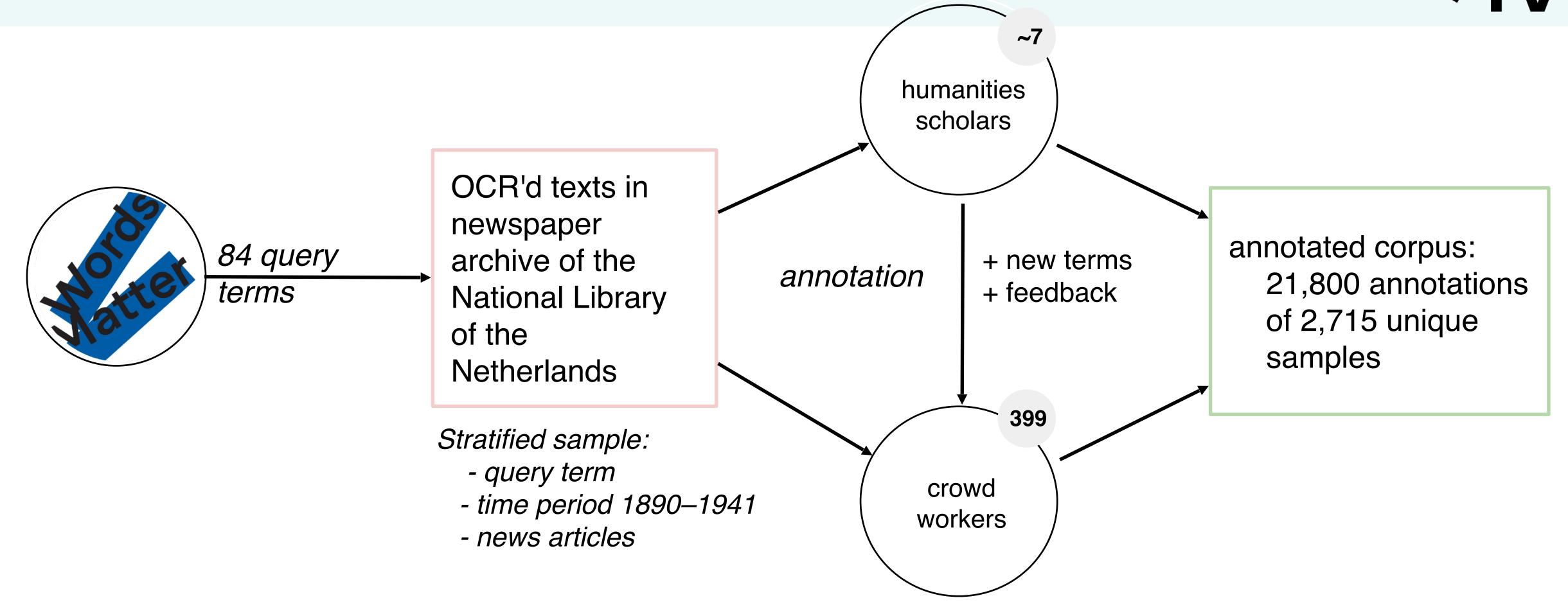
Blerta Veseli¹, Sneha Singhania¹, Simon Razniewski², and Gerhard Weikum¹

¹ Max Planck Institute for Informatics ² Bosch Center for AI

Abstract. Structured knowledge bases (KBs) are a foundation of many intelligent applications, yet are notoriously incomplete. Language models (LMs) have recently been proposed for unsupervised knowledge base completion (KBC), yet, despite encouraging initial results, questions regarding their suitability remain open. Existing evaluations often fall short because they only evaluate on popular subjects, or sample already existing facts from KBs. In this work, we introduce a novel, more challenging benchmark dataset, and a methodology tailored for a realistic assessment of the KBC potential of LMs. For automated assessment, we curate a dataset called WD-Known, which provides an unbiased random sample of Wikidata, containing over 3.9 million facts. In a second step, we perform a human evaluation on predictions that are not yet in the KB, as only this provides real insights into the added value over existing KBs. Our key finding is that biases in dataset conception of previous benchmarks lead to a systematic overestimate of LM performance for KBC. However, our results also reveal strong areas of LMs. We could, for example, perform a significant completion of Wikidata on the relations native Language, by a factor of ~ 21 (from 260k to 5.8M) at 82%precision, and citizenOf by a factor of ~ 0.3 (from 4.2M to 5.3M) at 90% precision. Moreover, we find that LMs possess surprisingly strong generalization capabilities: even on relations where most facts were not directly observed in LM training prediction or

Constructing ConConCor





How did crowd workers annotate the word "exotic"?

"De vrouw tegenover hem was nog maar een meisje, twintig naar schatting.

Een nauwsluitend zwart manteltje en rok, witte satijnen blouse, een kleine, chique, zwarte toque, modieus gedragen op één oor.

Ze had een mooi, **exotisch** gezichtje, mat-witte huid, groote bruine oogen, git-zwart haar.

Ze rookte een sigaret in een langen houder.

Haar gemanicuurde handen hadden donkerroode nagels."

"The woman opposite him was a mere girl—twenty at a guess.

A tight-fitting little black coat and skirt, white satin blouse, small chic black toque perched at the fashionable outrageous angle

She had a beautiful **foreign-looking** face, dead white skin, large brown eyes, jet black hair.

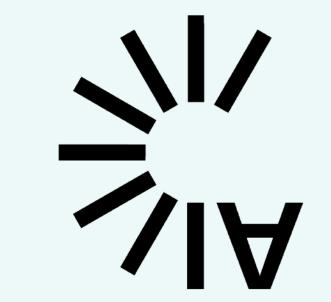
She was smoking a cigarette in a long holder.

Her manicured hands had deep red nails."

7 or 8 annotators per sample

4: contentious, 3: not contentious, 1: I don't know

Lessons learned



Inter-rater agreement is low

- α = 0.54 among experts
- α = 0.31 for crowd workers

but can be improved (to $\alpha = 0.50$)

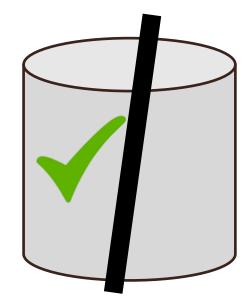
by filtering out underperforming annotators:

- using control questions?
- using pairwise agreement between annotators?

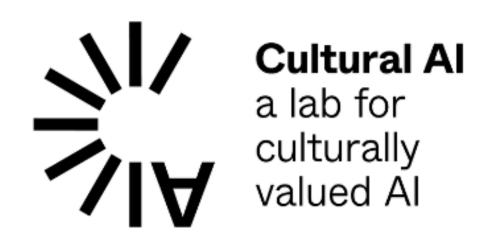
First experiments demonstrate that the corpus can be used to train a model to predict contentiousness

baseline: balanced accuracy = [0.54-0.55] model: balanced accuracy = [0.76-0.78]

Multiple annotators helps to get reliable data: on half of the samples, over 80% of annotators agreed with each other.



Context is necessary to judge contentiousness: most words are sometimes contentious and sometimes not contentious.











A knowledge graph of contentious terminology for inclusive representation of cultural heritage

Andrei Nesterov

Laura Hollink

Marieke van Erp

Jacco van Ossenbruggen

Thursday 1 June
Thursday 1 June
Thursday 1 June
Orpheas
The Extended
Semantic Web Conference
Hersonissos, Greece
June 1st 2023

Sneak Peek

- Characterising charged terms
- Identifying similarly behaving terms

Accepted to: LDK 2023, 12-15
 September, Vienna, Austria

Contextual Profiling of Charged Terms in Historical Newspapers

Ryan Brate and Marieke van Erp KNAW Humanities Cluster, DHLab Oudezijds Achterburgwal 185 1012 DK Amsterdam, Netherlands {ryan.brate, marieke.van.erp}

Antal van den Bosch Utrecht University Institute for Language Sciences

Utrecht, the Netherlands a.p.j.vandenbosch@uu.nl

Abstract

We extract nouns and corresponding cooccurrent targeted context features from a large corpus of Dutch language newspaper articles, from 1950s through the 1990s. Applying a well-established approach for scoring context feature and centre word associativity, we explored using the scores in the task of identifying key characteristics of known-charged terminology. Then use these features to draw parallels between known-charged and other terms. In the context of the very current decolonisation efforts amongst museum institutions, such approaches offer an opportunity to condense large quantities of data into the mostsignificant, salient information for digestion by heritage professionals. The methods were found to indeed yield insights into known and candidate charged terms.

Disclaimer: This paper contains derogatory words and phrases. They are provided solely as illustrations of the research results and do not reflect the opinions of the authors or their organisations. In-text examples of derogatory and potentially offensive are presented in "quotes, boldfaced and italicised".

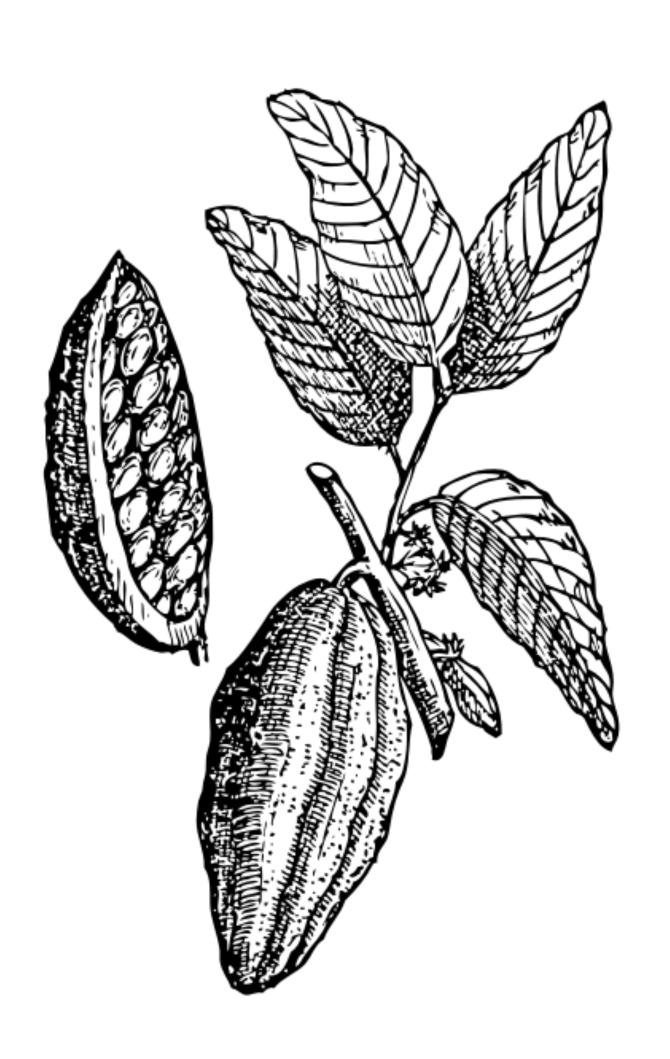
1 Introduction

Museums of the World, a database of cultural her-

Many museum collections originate from the colonial period, with metadata and object portrayals stemming from the particular world of the time. There is now a growing movement of decolonisation in western museums aimed at the acknowledgement and accommodation of previously marginalised voices to combat biases propagated by the advancement of narrow viewpoints (Odumosu, 2020). Part of the decolonisation effort centres around greater sensitivity and reconsideration of the terminology and language used in item metadata. This is more complicated than wholesale removal of terminology from metadata and items from collections. To handle the complexities properly, there needs to be greater contextual understanding of a term's implied characterisation in context. For instance, many terms nowadays considered problematic are ambiguous, also in their contentiousness: calling a plant exotic is different from calling a person the same.

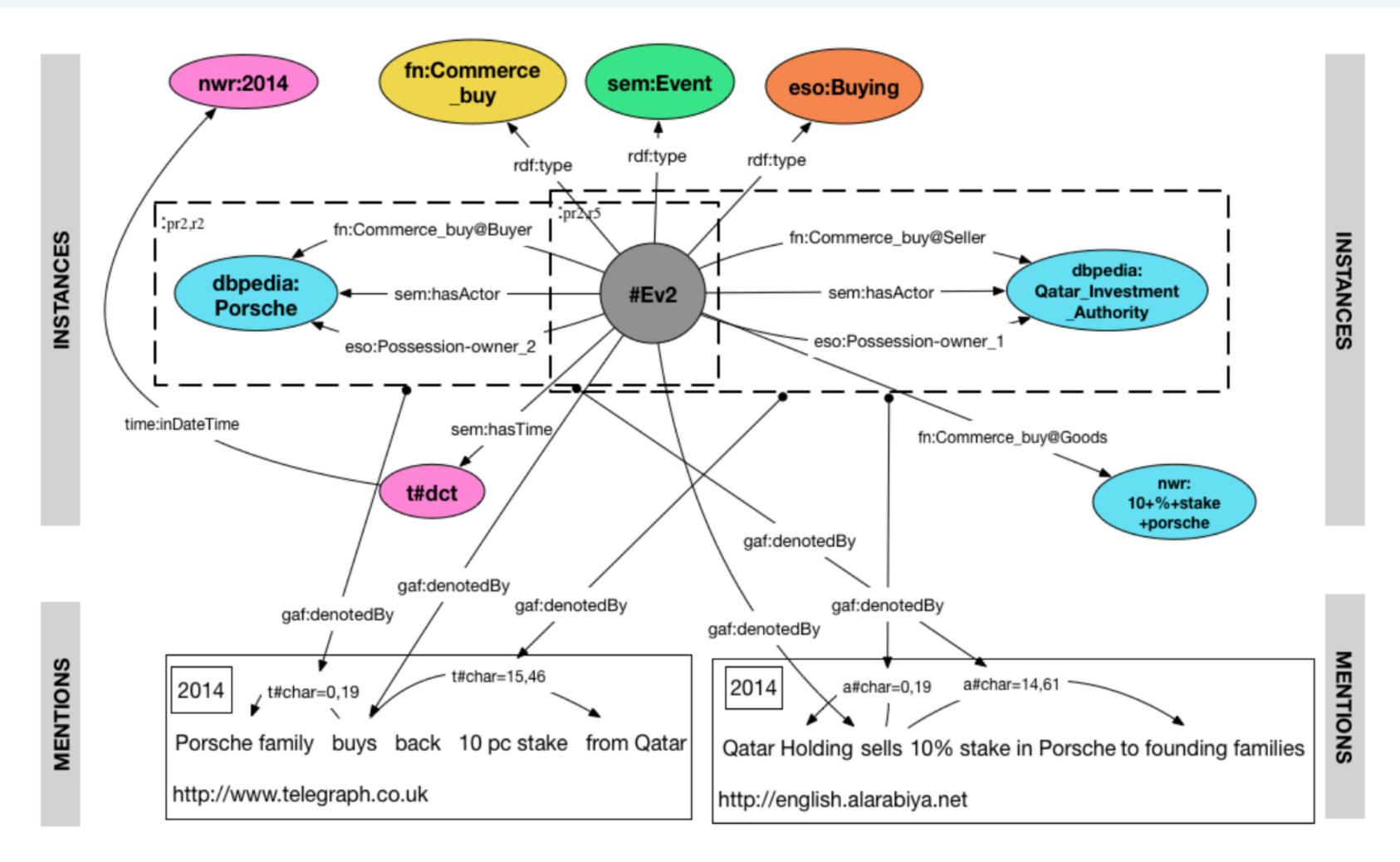
In this paper, we aim to explore the contextual profiles of a reference set of known charged collective nouns, reflective of some people group and identify the contextual features that distinguish them. Specifically, we consider four complementary context feature types: verbs for which the noun is the agent, verbs for which the noun is the patient, adjectives, and compound word modification.

Change



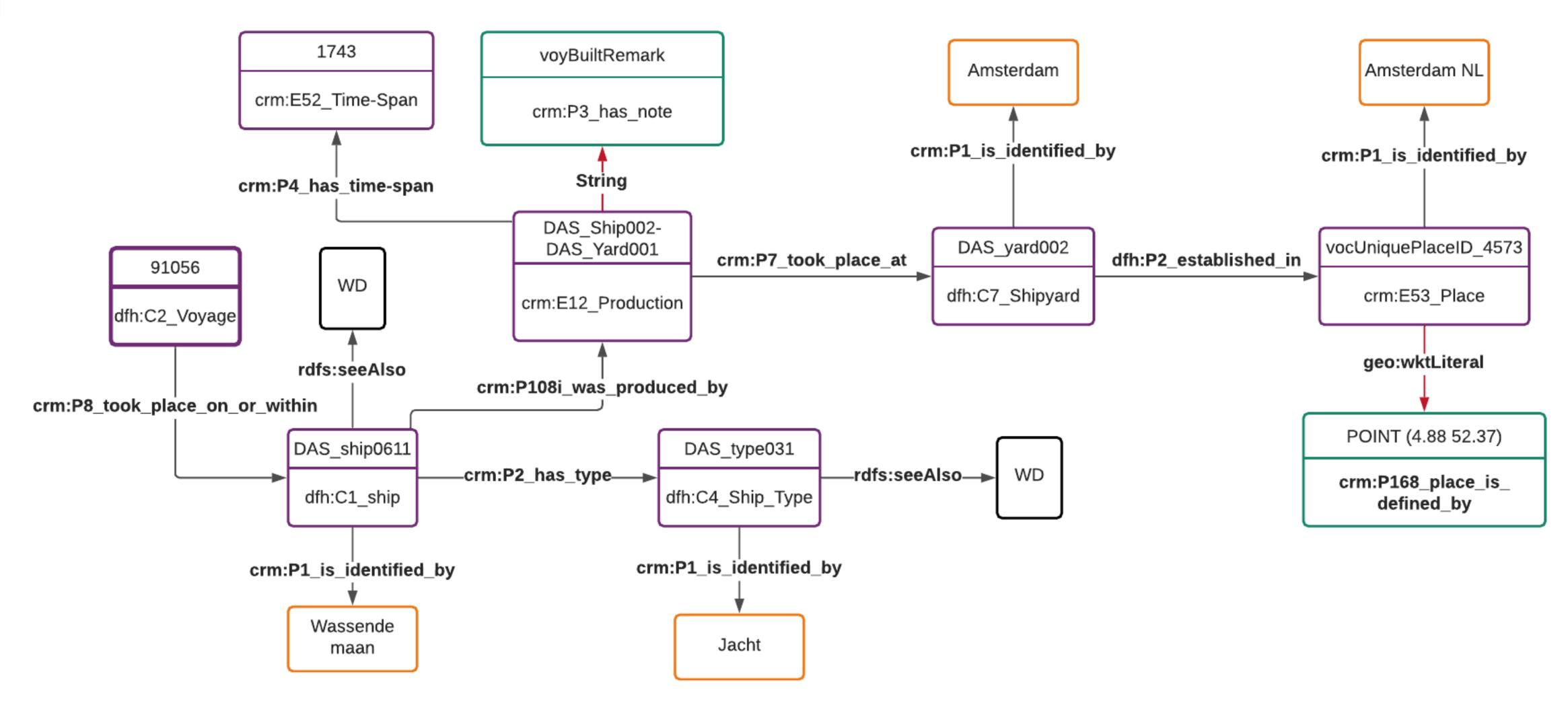
Event-Centric KGs





Marco Rospocher, Marieke Van Erp, Piek Vossen, Antske Fokkens, Itziar Aldabe, German Rigau, Aitor Soroa, Thomas Ploeger, and Tessel Bogaard. "Building event-centric knowledge graphs from news." Journal of Web Semantics 37 (2016): 132-151.

Event-Centric KGs



Stijn Schouten,, Victor De Boer, Lodewijk Petram, and Marieke Van Erp. "The wind in our sails: developing a reusable and maintainable Dutch maritime history knowledge graph." In Proceedings of the 11th on Knowledge Capture Conference, pp. 97-104. 2021

Event-Centric KGs



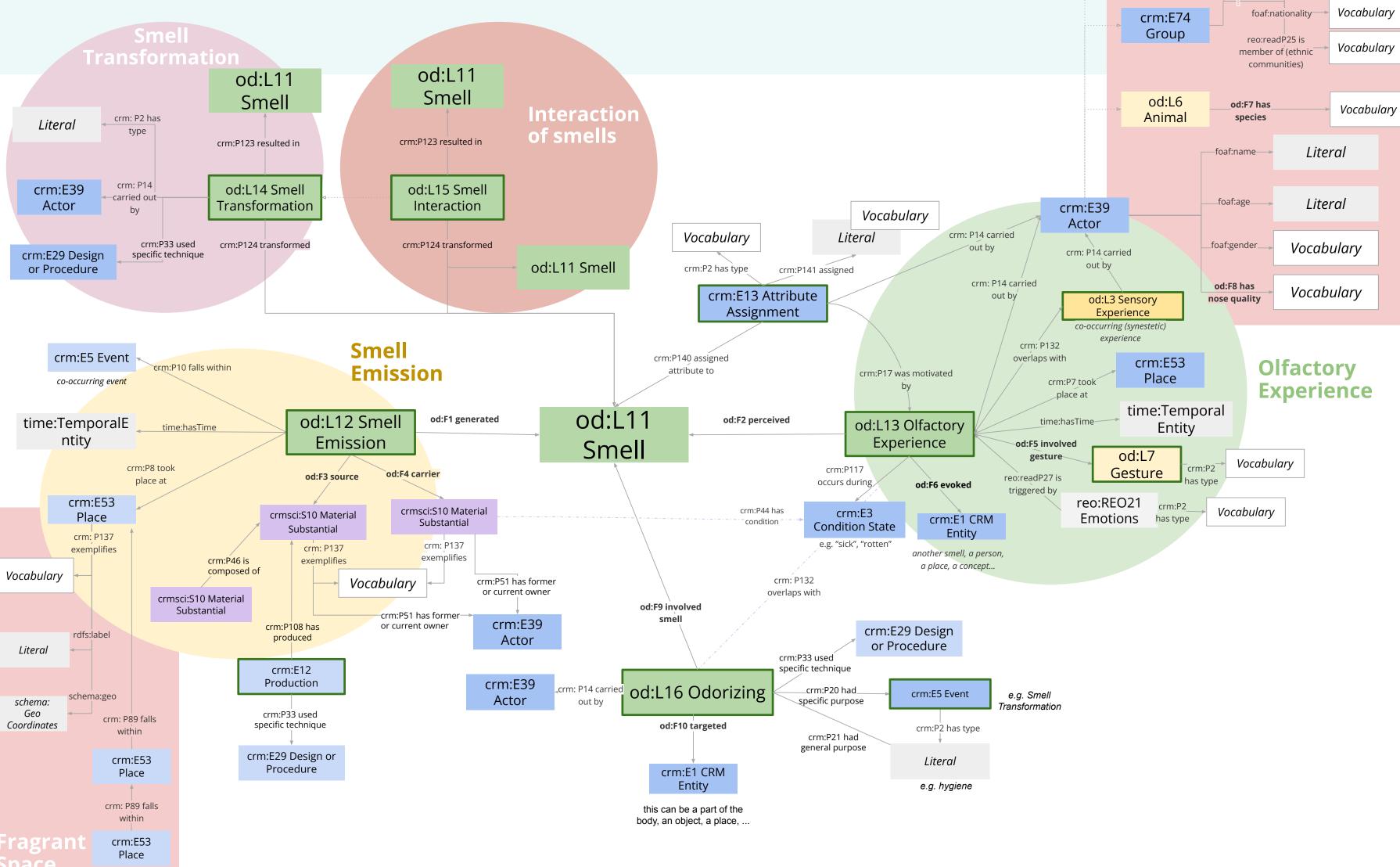
reo:readP1 has

occupation

Vocabulary

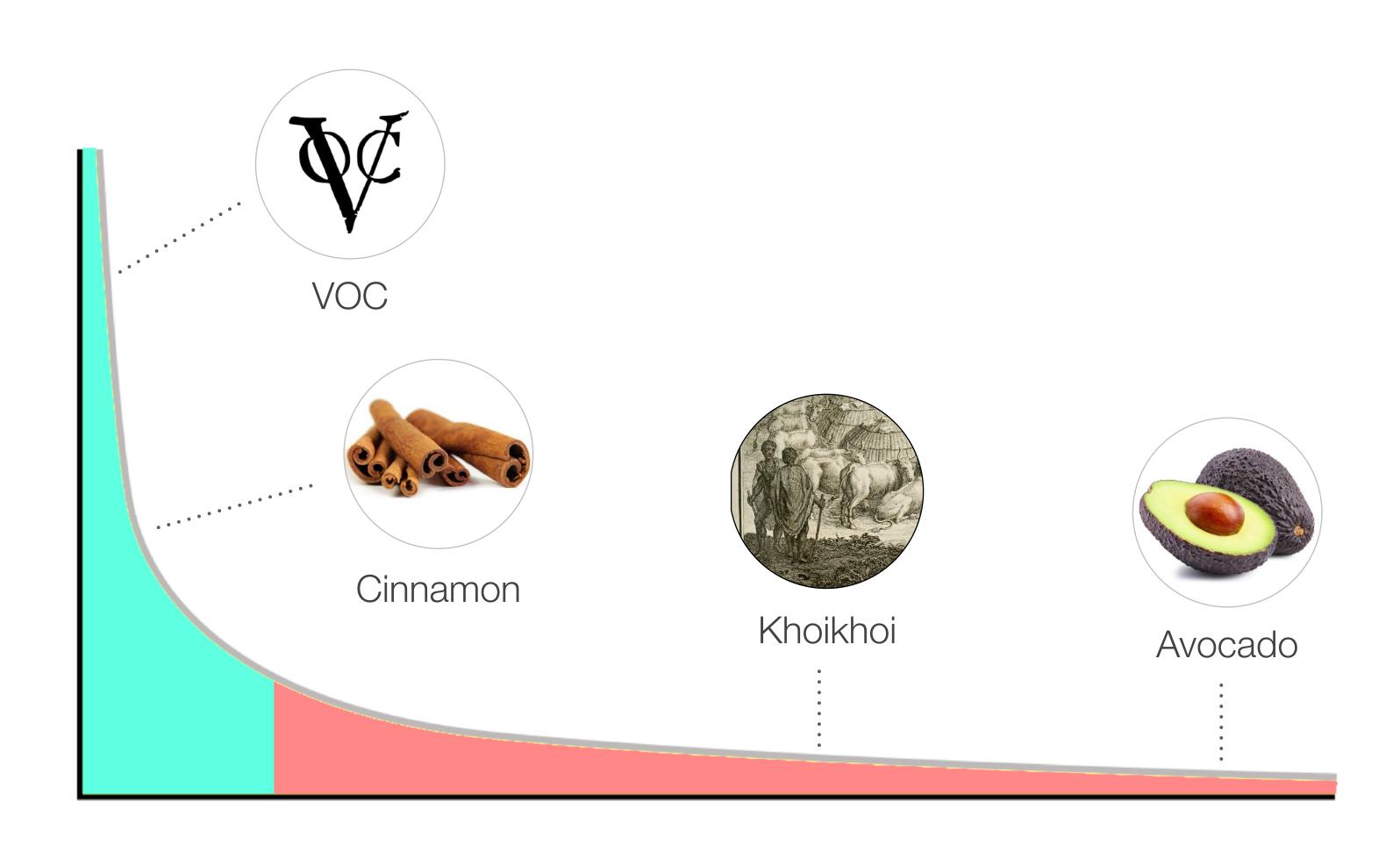
crm:E21

Person



Pasquale Lisena, Daniel Schwabe, Marieke van Erp, Raphaël Troncy, William Tullett, Inger Leemans, Lizzie Marx, and Sofia Colette Ehrich. "Capturing the Semantics of Smell: The Odeuropa Data Model for Olfactory Heritage Information." In *The Semantic Web: 19th International Conference, ESWC 2022, Hersonissos, Crete, Greece, May 29–June 2, 2022, Proceedings*, pp. 387-405. Cham: Springer International Publishing, 2022.

The Long Tail



Datasets

Dataset	Type	Domain	Doc length	Format	Encoding	License
AIDA-YAGO2	news	general	medium	TSV	ASCII	Agreement
2014/2015 NEEL	tweets	general	short	TSV	ASCII	Open
OKE2015	encyclopaedia	general	long	NIF/RDF	UTF8	Open
RSS-500	news	general	medium	NIF/RDF	UTF8	Open
WES2015	blog	science	long	NIF/RDF	UTF8	Open
WikiNews	news	general	medium	XML	UTF8	Open

Marieke van Erp, Pablo N. Mendes, Heiko Paulheim, Filip Ilievski, Julien Plu, Giuseppe Rizzo, and Jörg Waitelonis. "Evaluating Entity Linking: An Analysis of Current Benchmark Datasets and a Roadmap for Doing a Better Job."

Entity Overlap

Proportion of entities present in one dataset that are also present in other datasets

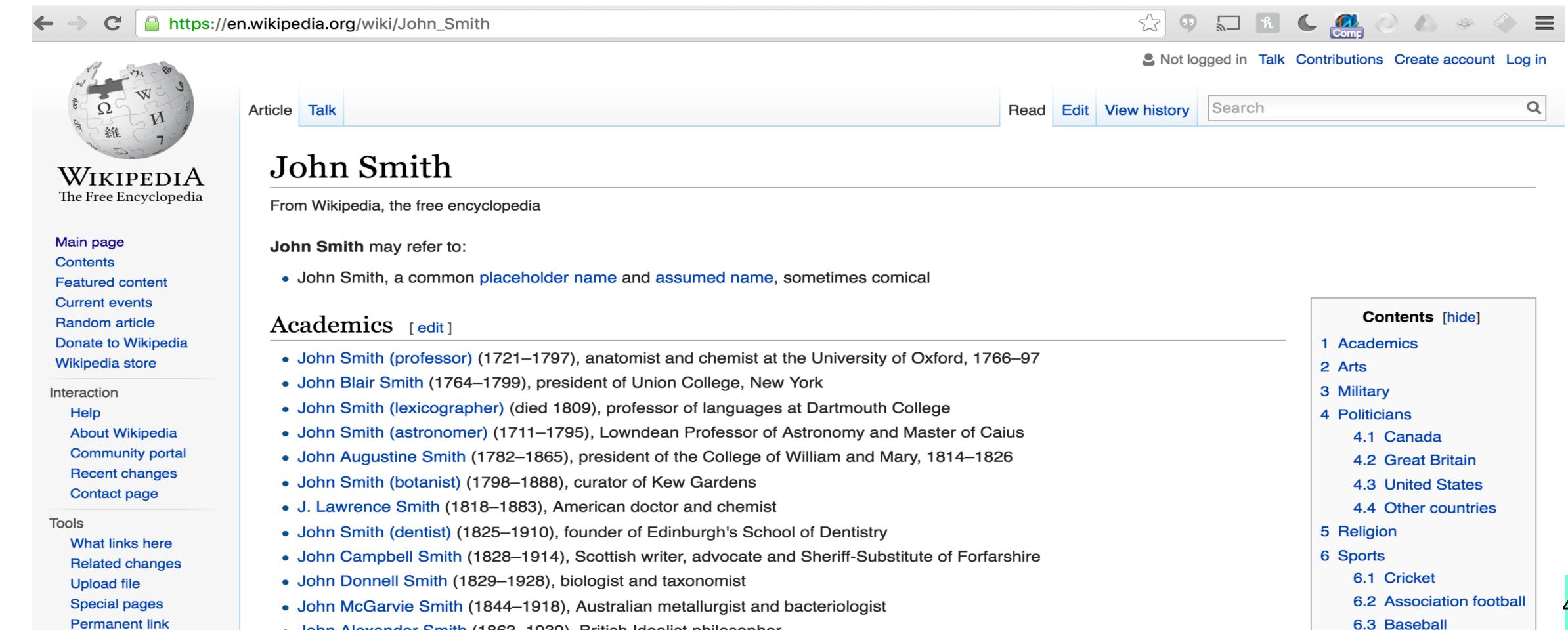
	AIDA-YAGO2	NEEL2014	NEEL2015	OKE2015	RSS500	WES2015	Wikinews
AIDA-YAGO2 (5,596)		5.87%	8.06%	0.00%	1.26%	4.80%	1.16%
NEEL2014 (2,380)	13.73%		68.49%	2.39%	2.56%	12.35%	2.82%
NEEL2015 (2,800)	16.11%	58.21%		2.00%	2.54%	7.93%	2.57%
OKE2015 (531)	0.00%	10.73%	10.55%		2.44%	28.06%	3.95%
RSS500 (849)	8.24%	7.18%	8.36%	1.53%		3.18%	1.88%
WES2015 (7,309)	3.68%	4.02%	3.04%	2.04%	0.16%		0.66%
Wikinews (279)	23.30%	24.01%	25.81%	7.53%	5.73%	17.20%	

Confusability

• The number of meanings a surface form (mention) can have

Confusability

• The number of meanings a surface form (mention) can have



Confusability

Corpus	Average	Min	Max	5
AIDA-YAGO2	1.08	1	13	0.37
2014 NEEL	1.02	1	3	0.16
2015 NEEL	1.05	1	4	0.25
OKE2015	1.11	1	25	1.22
RSS500	1.02	1	3	0.16
WES2015	1.06	1	6	0.30
Wikinews	1.09	1	29	1.03

Dominance

Corpus	Dominance	Min	Max	σ
AIDA-YAGO2	.98	1	452	0.08
2014 NEEL	.99	1	47	0.06
2015 NEEL	.98	1	88	0.09
OKE2015	.98	1	1	0.11
RSS500	.99	1	1	0.07
WES2015	.97	1	1	0.12
Wikinews	.99	1	72	0.09

Change @ESWC2023

A Geological Case Study on Semantically Triggered Processes

Yuanwei Qu, Eduard Kamburjan, and Martin Giese

SIRIUS Center, University of Oslo, Norway quy, eduard, martingi@ifi.uio.no

Abstract. We present an approach to connect semantic situations to program-based descriptions of processes. T anism is a semantically formalised trigger that initiates demonstrate the viability of the approach by modelling processes in petroleum geoscience.

Semantic technologies are designed to build graph-based reason about static relationships between entities and to represent dynamic behavior and changes. Although on formalisation of the concept of change [6] and top-l to describe processes [1], there is still limited support fo e.g. in simulations, to build conditionals and loops to described by the knowledge representations.

The distinction between utilizing semantic techn edge of dynamic processes and programming languag ics remains pronounced. The current work of [3] inti language called 'Semantic Micro Object Language'

HHT: An Approach for Representing Temporally-Evolving Historical Territories

W. Charles¹, N. Aussenac-Gilles¹, and N. Hernandez¹ IRIT - Université de Toulouse name.surname@irit.fr

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LauNuts: A Knowledge Graph to identify and compare geographic regions in the European Union*

Adrian Wilke and Axel Ngonga

DICE group, Department of Computer Science, Paderborn University adrian.wilke@uni-paderborn.de, axel.ngonga@upb.de https://dice-research.org/

Abstract. The Nomenclature of Territorial Units for Statistics (NUTS) is a classification that represents countries in the European Union (EU). It is published at intervals of several years and organized in a hierarchical system where geographical areas are subdivided according to their population sizes. In addition to NUTS, there is a further subdivided hierarchy level, named Local Administrative Units (LAU), whose data are updated annually by EU member states. While both datasets are published by Eurostat as Excel files, an additional RDF dataset is available for NUTS up to the 2016 scheme. With this work, we provide the Linked Data community with an up-to-date Knowledge Graph in which NUTS and LAU data are linked and which contains population numbers as well as area sizes. We also publish an Open Source generator software for future released versions that will naturally arise due to changes in population numbers. These contributions can be used to enrich other datasets and allow comparisons among regions in the European Union. All resources are available at https://w3id.org/launuts.

he notion of territory plays a major role in human and Representation of this spatio-temporal object and comtackled in various ways. historic/ tric dat ories, w

GLENDA: Querying RDF Archives with full

 $\begin{array}{c} \text{Olivier Pelgrin}^{1[0000-0002-1025-9687]}, \text{Ruben Taelman}^{2[0000-0001-5118-256X]}, \\ \text{Luis Gal\'arraga}^{3[0000-0002-0241-5379]}, \text{and Katja } Hose^{1,4[0000-0001-7025-8099]}, \end{array}$

Aalborg University, Denmark, {olivier, khose}@cs.aau.dk Ghent University, ruben.taelman@ugent.be

3 Inria, France, luis.galarraga@inria.fr 4 TU Wien, Austria, katja.hose@tuwien.ac.at

Abstract. The dynamicity of semantic data has propelled the research Abstract. The dynamicity of semantic data has propened the research on RDF Archiving, i.e., the task of storing and making the full history of on KDF Archiving, i.e., the task of storing and making the null instory of large RDF datasets accessible. However, existing archiving techniques fail to scale when confronted with very large RDF datasets and support only simple SPARQL queries. In this demonstration we theref GLENDA, a system that can run full QDA DOL 1 based storage archi

Towards polyvocal & contextualised KGs

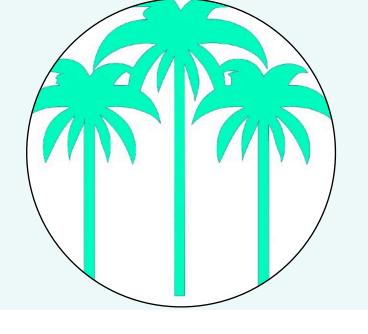
- KGs have come a long way
- More dimensions, change, and including the long tail are the next frontier
- Benchmark datasets need fixing

This is a community effort

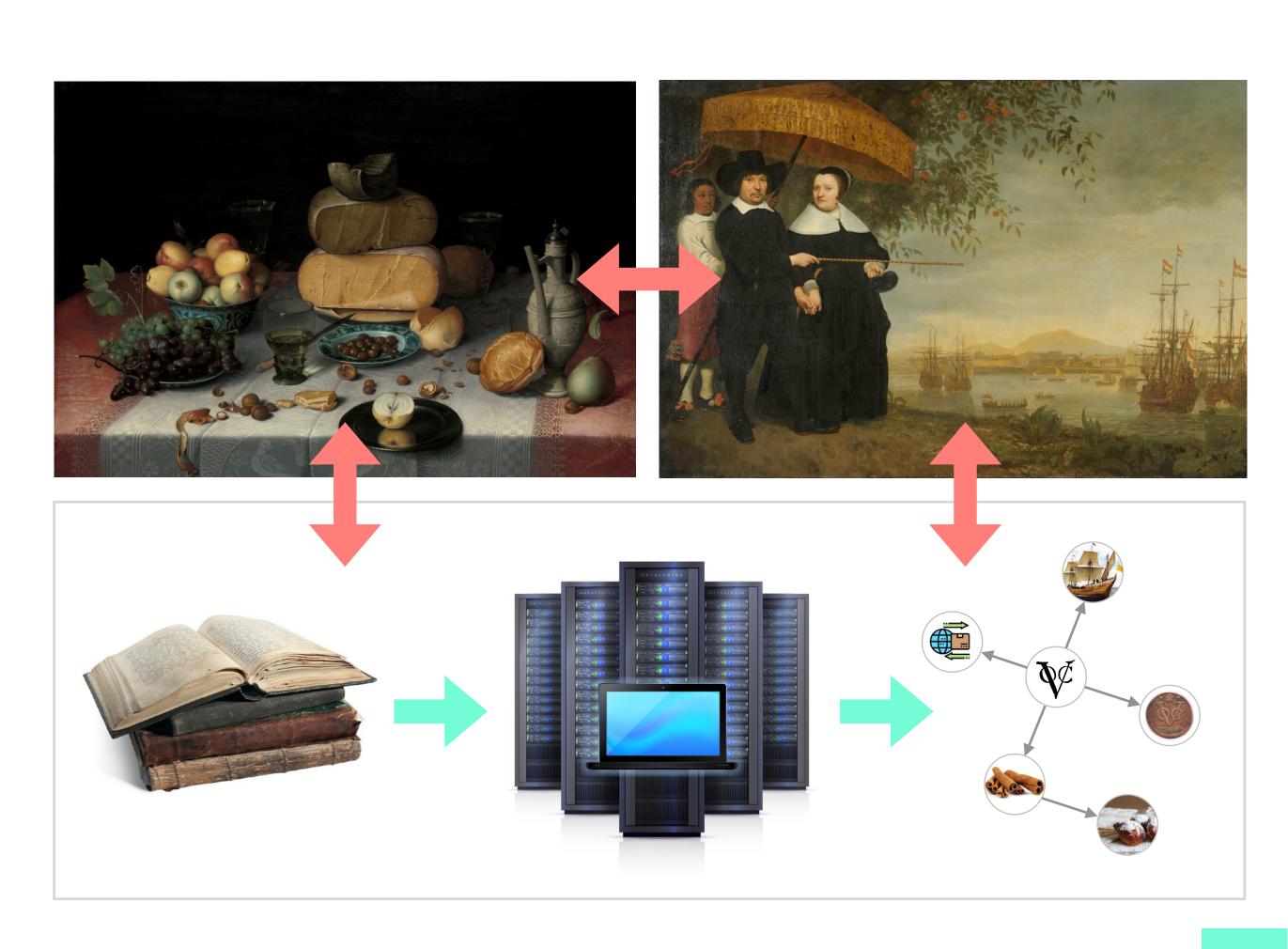


Olfert Dapper (1680) Naukeurige beschryving van Asie

TRIFECTA: Capturing Identity, Change, and the Long Tail in Knowledge Graphs



- Tracing contentious entities and concepts in food and maritime history
- Combining language and semantic web technology to unflatten knowledge graphs
- Strengthening computational data-driven humanities research



Thank you



NewsReader, Odeuropa and TRIFECTA have received funding from the European Union's FP7, Horizon 2020 and Horizon Europe research and innovation programmes under grant agreement No 316404, 101004469, and 10188548. Cultural AI has received funding from the Dutch Research Council (NWO), the Dutch Digital Heritage Network (NDE) and Europeana.









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Slide 28: https://www.nytimes.com/2019/10/25/arts/design/dutch-golden-age-and-colonialism.html

Slide 48: Olfert Dapper (1680) Naukeurige beschryving van Asie https://books.google.nl/books?id=-iGqvQEACAAJ&hl=nl&pg=RA2-

PA62#v=onepage&q&f=false