# **KNOWLEDGE GRAPH COMPLETION PART 3: IDENTITY LINK VALIDATION**

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# LINKED OPEN DATA

Linked Data - Datasets under an open access

- 1,139 datasets
- over 100B triples
- about 500M links
- several domains

Ex. DBPedia : 1.5 B triples



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

- [Halpin et al. 2010] showed that 37% of owl:sameAs links randomly selected among 250 identity links between books were incorrect.
- In [Jaffri et al., 2008], the authors discuss how erroneous use of owl:sameAs in the interlinking of the DBpedia and DBLP datasets has resulted in publications becoming incorrectly assigned to different authors.
- Automatic data linking tools do not guarantee 100% precision, because of:
  - Errors, missing information, data freshness, etc.



Today, the **classical definition** of **identity** has become the **canonical** one on the **Semantic Web** (through **owl:sameAs** predicate).

There are some problems with it,

1 Identity does not hold across modal contexts

Allow Lois Lane to believe that Superman saved her without requiring her to believe that Clark Kent saved her.



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1 Identity does not hold across modal contexts

2 Identity is **context-dependent** [Geach, 1967]

 allowing two medicines to be considered the same in terms of their chemical substance, but different in terms of their price (e.g., because they are produced by different companies).



\* wouterbeek.github.io

Today, the **classical definition** of **identity** has become the **canonical** one on the **Semantic Web** (through **owl:sameAs** predicate).

There are some problems with it,

- 1 Identity does not hold across modal contexts
- 2 Identity is **context-dependent** [Geach, 1967]

**3 Identity over time** poses problems

 since a car may be considered the same car, even though some (or even all) of its original components have been replaced by new ones.



## **OWL:SAMEAS PREDICATE**

- owl:sameAs, indicates that two different descriptions refer to the same entity
- a strict semantics,
  - 1) Reflexive,
  - 2) Symmetric,
  - 3) Transitive and
  - 4) Fulfils property sharing:

 $\forall X \forall Y \text{ owl:sameAs}(X, Y) \land p(X, Z) \Rightarrow p(Y, Z)$ 

#### **IDENTITY PROBLEM: LITERATURE REVIEW**

- 1. Detection of erroneous identity links
- 2. Use of alternate links
- 3. Detection of contextual identity links

Which kind of information to use for detecting erroneous Identity links?



Which kind of information to use for detecting erroneous Identity links?



Content

Content

**Identity Network** 

Which kind of information to use for detecting erroneous Identity links?



Content

**Identity Network** 



Content

**Identity Network** 

**UNA** Which kind of information to use for detecting erroneous Identity links? **Trustworthiness** nbPages nbPages 288 208 owl:sameAs(b1, b2)? b2 **b1 Ontology Axioms:** Func(nbPages) LC(author) Func(title) Disj(Sciencefiction, Memoir), . . .



# INCONSISTENCY-BASED



[Valdestilhas et al., 2017]

### **SOURCE TRUSTWORTHINESS**

Cudré-Mauroux et al. 2009

- Principle: owl:sameAs links published by trusted sources are more likely to be correct. Every pair of URIs coming from the same source are necessary different.
- **idMech:** a probabilistic and decentralized framework for **entity disambiguation**.



### **SOURCE TRUSTWORTHINESS**

#### **Probabilistic Disambiguation**

#### Cudré-Mauroux et al. 2009



- 1) A graph-based constraint satisfaction problem that exploits owl:sameAs symmetry and transitivity.
- 2) Use of iteratively refined trustworthiness of the sources declaring the statements.



**Evaluation on Synthetic Data** 

Cudré-Mauroux et al. 2009

пñП

#### Dataset

 Networks of 50 and 500 entities, 150/3000 links, and a varying fraction of erroneous links (from 0 to 50%)



**Results** 

Proportion of Erroneous Links [%]

- When considering relatively dense networks, cycles up to size 4 and a varying fraction of erroneous links from 0 to 50%:
  - The more erroneous links, the lower the accuracy is.
  - The size of the graph has no impact on the accuracy of the inference.



# UNIQUE NAME ASSUMPTION VIOLATION [de Melo 2013, Valdestilhas et al., 2017]

#### Principle

- Detecting erroneous owl:sameAs links based on Unique Name Assumption (UNA).
- The violation of the UNA is indicative of erroneous identity links.

#### UNA allows to state that

1. Every pair of URIs coming from the same source are necessary different.



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#### UNA allows to state that:

- 1. Every pair of URIs coming from the same source are necessary different.
- 2. Each URI of a source S1 cannot be identical to more than one URI of a source S2.



[de Melo 2013]

- Creates undirected labeled graphs from the existing owl:sameAs links.
- Considers a set of distinctness constraints to account for exceptions.



D<sub>i</sub>({dbpedia:Paul, dbpedia:Paulie(redirect)}, {dbpedia:Paula})

[de Melo 2013]

- Creates undirected labeled graphs from the existing owl:sameAs links.
- Considers a set of distinctness constraints to c account for exceptions.
- Considers the problem of computing the minimum cut (NP-Hard Problem)
- Uses a linear program relaxation algorithm, that aims at deleting the minimal number of edges to cut to ensure the UNA.



D<sub>i</sub>({dbpedia:Paul, dbpedia:Paulie(redirect)}, {dbpedia:Paula})



**Evaluation LOD Data** 

[de Melo 2013]

#### Datasets

	#URI	Relevant Predicates			
		#sameAs	#skos:clos eMatch	#skos:exa ctMatch	#:differentFrom
BTC2011	~4M	~3.5M	125,313	22,398	619
sameas.org 2011	~31M	22.4M			



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#### **Results**

- Several hundred thousand sameAs edges are removed automatically.
- # edges removed < # constraint violations</li>

	BTC2011 +sameas.org	BTC2011	sameas.org
Undirected edges	280,086	32,753	245,987
removed Violations per removed edge	1.85	4.24	1.53

#### [Valdestilhas et al., 2017]



- Erroneous links: detection of resources sharing the same equivalence class and the same dataset.
- Rate of consistent resources inside an equivalence class

$$M1 = \frac{\sum_{P \in \mathcal{P}^-} |P|}{\sum_{P \in \mathcal{P}} |P|}$$

- **P** contains only resources belonging to the same dataset.
- P<sup>-</sup> is the set of consistent resources
- Efficient generation of equivalence classes based on Union Find algorithm



#### [Valdestilhas et al., 2017]

#### **Datasets**

- LinkLion repository ~19.6M links
- µ = ½ (|C| (|C| -1)), C is the set of inconsistent resources
- K1: the knowledge base with more errors (11.5 %)
- K10: the knowledge base with fewer errors (0.06 %)

Label	Knowledge Base
K1	dotac.rkbexplorer.com-eprints.rkbexplorer.com.nt
K2	d-nb.info-viaf.org.nt
K3	dblp.rkbexplorer.com-dblp.l3s.de.nt
K4	linkedgeodata.org-sws.geonames.org.nt
K5	citeseer.rkbexplorer.com-kisti.rkbexplorer.com.nt
K6	wiki.rkbexplorer.com—oai.rkbexplorer.com.nt
K7	www4.wiwiss.fu-berlin.de-dbpedia.org.nt
K8	southampton.rkbexplorer.com-nsf.rkbexplorer.com.nt
K9	rae2001.rkbexplorer.com-newcastle.rkbexplorer.com.nt
K10	lod.geospecies.org-bio2rdf.org.nt

 Data linking algorithms (LIMES, SILK and DBpedia Extraction Framework) have a better consistency index than repositories such as sameas.org (13%).



[Valdestilhas et al., 2017]

# ONTOLOGY AXIOM VIOLATION

[Papaleo *et al.*, 2014] [Hogan et al. 2012]

**Principle**: use of ontology axioms (functionality, local completeness, asymmetry, etc. ) to detect inconsistencies or error candidates in the linked resources descriptions.



#### [Papaleo et al., 2014]

# ONTOLOGY AXIOM VIOLATION

- A logical **ontology-based method** to detect invalid sameAs statements
- Builds a contextual graph «around» each one of the two resources involved in the sameAs by exploiting ontology axioms on:
  - functionality and inverse functionality of properties and
  - local completeness of some properties, e.g., the author list of a book.
- Exploit the descriptions provided in these contextual graphs to eventually detect inconsistencies or high dissimilarities.

# ONTOLOGY AXIOM VIOLATION

[Papaleo et al., 2014]

#### F is the set of RDF facts

enriched by a set of ¬synVals facts in the form

¬synVals(w₁, w₂)

 $w_1$  and  $w_2$ , being literals and different.

Apply Unit Resolution on  $\{F \cup R\}$ . [F set of facts, R set of rules]

EXAMPLES: - notSynVals('231','100') for a functional property *nbPages* 

-notSynVals('New York', 'Paris')
for a functional property cityName

... knowledge from expert or extracted.

# ONTOLOGY AXIOM VIOLATION

[Papaleo et al., 2014]

Apply Unit Resolution on  $\{F \cup R\}$ . [F set of facts, R set of rules]

R the set of rules

#### (inverse) functional properties

- $-R_{1_{FDP}}: sameAs(x, y) \land p_i(x, w_1) \land p_i(y, w_2) \to synVals(w_1) \land$
- $-R_{2_{FOP}}: sameAs(x, y) \land p_j(x, w_1) \land p_j(y, w_2) \rightarrow sameAs(w_1) \land p_k(w_1, x) \land p_k(w_2, y) \rightarrow sameAs(w_1) \land p_k(w_2, y) \rightarrow sameAs(w_1) \land p_k(w_2, y) \land$ 
  - $\mathfrak{h}_{3_{LED}}: SameAs(x, y) \land \mathcal{D}_{k}(w_{1}, x) \land \mathcal{D}_{k}(w_{2}, y) \rightarrow SameAs(y)$

sameAs(x,y)  $\land$  nbPages(x,w<sub>1</sub>)  $\land$  nbPages(y,w<sub>2</sub>)  $\rightarrow$  SynVals(w<sub>1</sub>,w<sub>2</sub>)

#### local complete properties

 $-R_{4_{LC}}: sameAs(x, y) \land p(x, w_1) \rightarrow p(y, w_1)$ 

sameAs(x,y)  $\land$  hasAuthor(x,w<sub>1</sub>)  $\rightarrow$  hasAuthor(y,w<sub>1</sub>)

# ONTOLOGY AXIOM VIOLATION



[Papaleo et al. 2014]

- OAEI 2010 dataset on Restaurants
- Use of the output of different linking tools [1], [2] and [3].



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LM	LM Precision	linkInv precision	LM+linklnv precision	
2	95.55%	37%	98.85%	
1	69.71%	88.4%	95.19%	
3	90.17%	42.30%	100%	
			mprovement in precision	
#### **1. DETECTION OF ERRONEOUS IDENTITY LINKS**



[Valdestilhas et al., 2017]

[Paulheim, 2014]

**Principle**: links follow certain patterns, links that violate those patterns are erroneous.

- A multi-dimensional and scalable outlier detection approach for finding erroneous identity links.
- Projection of links into Vector Space: each link is a point in an n-dimensional vector space



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[Paulheim, 2014]

- Feature Vector: resource types and ingoing/outgoing properties
  - e.g. LHS\_foaf:based\_near and RHS\_foaf:based\_near are distinct features.
- Different strategies of creating vectors: direct types only, all ingoing and outgoing properties, or a combination
- Several outlier detection methods were tested: LOF, CBLOF, LOP, 1-class SVM etc.
- Each method assign a score to each data point indicating the likeliness of being an outlier → incorrect link.



#### [Paulheim, 2014]

		D1		D2	
Dataset	Dataset	Peel Session	DBpedia	DBTropes	DBpedia
	# Links	2,087		4,229	
	# Types	3	31	2	79
	# Properties	4	56	18	124

- **Gold Standard**: 100 randomly sampled links from D1 and D2
- Use of RapidMiner with anomaly detection and LOD extensions (6 methods)



#### [Paulheim, 2014]



- Gold Standard: 100 randomly sampled links from D1 and D2
- Use of RapidMiner with anomaly detection and LOD extensions (6 methods)
- Best performance on D1:
  - CBLOF (F1= 0.537), 1-class SVM (AUC = 0.857)
- Best performance on D2:
  - LOF (F1= **0.5**, AUC = **0.619**)



#### [Paulheim, 2014]



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- Best performance on D2:
  - LOF (F1= 0.5, AUC = 0.619)
- Examples of typical source of errors for D1:
  - Linking of songs to albums with the same name.
  - Linking of <u>different persons</u> of the <u>same name</u>,

e.g., a blues musician named Jimmy Carter to the U.S. president.

#### **1. DETECTION OF ERRONEOUS IDENTITY LINKS**



4

[Guéret *et al.*, 2012] [Raad *et al.*, 2018, UR]

#### Principle

- The quality of a link can be determined based on how connected a node is within the network in which it appears.
- Use of network metrics and structures can help to detect erroneous links?



Centrality



#### Modularity and communities



#### [Guéret et al., 2012]

- Use of network metrics can help to detect erroneous links?
- Changes in quality of the Web of Data with the introduction of new links between datasets.
- It is based on the use of
  - three classic network metrics: clustering coefficient, centrality and degree
  - two Linked Data-specific ones: owl:sameAs chains, and description richness

#### [Guéret et al., 2012]



- The approach selects a set of resources and constructs a local network for each resource by querying the Web of Data.
- After analysis, i.e., measuring the different metrics, each local network is extended by adding new edges and analyzed again.
- The result coming from both analyses are compared to ideal distribution for the different metrics.



#### Dataset

- The European project LOD Around the Clock (LATC) aims to enable the use of the Linked Open Data cloud for research and business purposes.
- LATC created a set of linking specifications (link specs) for Silk engine
  - 6 link sets are selected containing more than 50 correct and incorrect links
    - e.g., geonames-linkedGeodataMountain, linkedct-pubmedDisease, ...
- Samples taken from the generated links are manually checked
  - Two reference sets containing all the positive (correct, good) and negative (incorrect, bad) links of the sample.



#### **Evaluation questions**

- Do positive linksets decrease the distance to a metric's defined ideal, whereas negative ones increase it?
  - If that is the case, it would allow us to distinguish between link sets having high and low ratios of bad links.
- Is there a correlation between outliers and bad links?
  - If so, resources that rank farthest from the ideal distribution of a metric would relate to incorrect links from/to them.



- Recall = 0.68
- Precision = 0.49
- Conclusion:
  - Common metrics such as centrality, clustering, and degree are insufficient for detecting quality.
  - Description Richness and Open SameAs Chain metrics look more promising, especially at detecting good and bad links, but they report too many false positives.

[Raad *et al.*, 2018, under review]



- Considers the identity network build from the explicit identity network of sameAs links: removing of symmetric and reflexive links.
- Uses of Louvain community detection algorithm to detect subgraphs in the identity network that are highly connected.
- Defines a ranking score for each (intra-community and inter-community) identity link based on the density of the community.

[Raad *et al.*, 2018, under review]

#### **Ranking of identity links**

intra-community erroneousness degree

a) 
$$err(e_C) = \frac{1}{w(e_C)} \times \left(1 - \frac{W_C}{|C| \times (|C| - 1)}\right)$$

inter-community erroneousness degree

b) 
$$err(e_{C_{ij}}) = \frac{1}{w(e_{C_{ij}})} \times \left(1 - \frac{W_{C_{ij}}}{2 \times |C_i| \times |C_j|}\right)$$





#### Dataset

- LOD-a-lot dataset [Fernandez et al. 2017]: a compressed data file of 28B triples from LOD 2015 crawl
- An explicit identity network of 558.9M edges (links) and 179M nodes (resources)
- Identity network of 331M edges and 179M nodes: after removing symmetric and reflexive links.



#### **Barack Obama's Equality Set**





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#### Precision on a randomly chosen set identity links from LOD

	0-0.2	0.2-0.4	0.4-0.6	0.6-0.8	0.8-1	total
same	35(100%)	22(100%)	18(85.7%)	7(77.7%)	15(68.1%)	97(88.9%)
related	0	0	2	2	(2)	6
unrelated	0	0	1	0	5	6
related + unrelated	0(0%)	0(0%)	3(14.2%)	2(22.2%)	7(31.8%)	<b>12</b> (11%)
can't tell	5	18	19	31	18	91
Total	40	40	40	40	40	200

- Scales up to a graph of 28.3 billion triples: 12 hours
- Validates correct owl:sameAs links
  - 100% of owl:sameAs with an erroneousness degree <0.4 are correct</p>
- Can invalidate a large set of owl: sameAs links on the LOD:
  - **1.26M** owl:sameAs have an erroneousness degree in [0.99, 1]

## ERRONEOUS LINK DETECTION: SUMMARY

#### **Positive points**

- Different approaches relaying on different kinds of information (constraints, axioms, content and network)
- Good scalability of the approaches: up to 28.3 Billion triples
- Evaluations on real data on the LOD

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- Evaluations on real data on the LOD

#### Limitations

- Qualitative evaluation often missing or conducted on only insignificant number of links (max= 200 over 331M)
- Some assumptions can be assumed on only few datasets on the LOD: UNA and provenance information.
- Ontology axioms are not always available: how to ensure their validity in every dataset. Is the LocatedIn is functional for every museum?
- **Difference** relationships are rarely available: useful for inconsistency checking

## ERRONEOUS LINK DETECTION: SUMMARY

"Data linking algorithms "Due to the subjectivity of "common metrics such as SILK near-identity and similarity, we (LIMES, and centrality, clustering, and that additional Extraction DBpedia suggest degree are insufficient for Framework) have a better properties be used to describe detecting quality . . . consistency index the exact nature of the than Description Richness and relationship" repositories such **Open SameAs Chain metrics** as sameas.org (13%) " look promising, more especially at detecting good and bad links, respectively, they report too many false positives for reference sets" [de Melo 2013] [Valdestilhas et al., 2017] [Gueret et al., 2012] J Need for alternate links Need for more controlled Need for hybrid approaches link publication protocols

## 2. USE OF ALTERNATE LINKS

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Use of weaker alternative links to express relatedness between resources/concepts.

- UMBEL<sup>1</sup> vocabulary introduces umbel:isLike "to assert a link between similar individuals who may be believed to be identical"
- Vocab.org<sup>2</sup> introduces similarTo to be used when having two things that are not the owl:sameAs
- [de Melo, 2013] introduces lvont:nearlySameAs and lvont:somewhatSameAs, two predicates for expressing near-identity in the Lexvo.org<sup>3</sup>
- Use of domain-specific identity relations:
  - ex:sameBook to express identity between two books

## **2. USE OF ALTERNATE LINKS**

• [Halpin et al., 2010] proposed a similarity ontology (SO) in which they hierarchically represent 13 different predicates including 8 new ones.



		Transitive	Non-transitive	
Reflexive	Symmetric	so: identical	so:similar	
	Non-Symmetric	so: claims Identical	so: claims Similar	
Non-Reflexive	Symmetric	so:matches	so:related	
	Non-Symmetric	so: claims Matches	so: claims Related	

Reflexivity, Symmetry and Transitivity properties for the 8 new predicates.

# **3. CONTEXTUAL**<br/> **IDENTITY LINKS**

- Weaker kinds of identity can be expressed by considering a subset of properties with respect to which two resources can be considered to be the same.
- Identity is context-dependent [Geach, 1967]
  - allowing two medicines to be considered the same in terms of their chemical substance, but different in terms of their price (e.g., because they are produced by different companies).



[Beek et al., 2016]

- Propose an approach that allows the characterization of the context in which an identity link is valid
- A context is a subset of properties for which two individuals must have the same values
- Contextual identity link preserves equivalence relation, w.r.t. a subset of the properties

[Beek et al., 2016]

 All the possible subsets of properties organized in a lattice using the set inclusion relation.





[Beek et al., 2016]

- Evaluation on a dataset in the instance matching track of the OAEI2012 : a variant of the IIMB datasets.
- The obtained identity subrelations



[Raad et al., 2017]

- New predicate :<u>identiConTo</u> for expressing contextual identity relation
- An algorithm for automatic detection of the most specific contexts in which two instances (resources) are identical
  - the detection process can further be guided by a set of semantic constraints that are provided by domain experts.
- Contexts are defined as a sub-ontology of the domain ontology
- All the possible contexts are organized in a lattice using an order relation.




#### **Contextual Identity Link Example**

Π<sub>a</sub>(Juice) = { (Juice, {rdf:Type, expiryDate}, {isComposedOf}), (Banana, {rdf:Type}, {isComposedOf <sup>-1</sup>}), (Strawberry, {rdf:Type}, {hasAttribute, isComposedOf <sup>-1</sup>}), (Weight, {rdf:Type, hasValue, hasUnit}, {hasAttribute<sup>-1</sup>}) }

#### identiConTo<(Tailor))</pre>(juice1, juice2)

<b>Π</b> <sub>a</sub> (Juice) = { (Juice, {rdf:Type, expiryDate}, {isComposedOf}),			
	(Banana, {rdf:Type}, {isComposedOf -1}),		
	(Strawberry, {rdf:Type}, {hasAttribute, isComposedOf <sup>-1</sup> }),		
	(Weight, {rdf:Type, hasValue, hasUnit}, {hasAttribute <sup>-1</sup> }) }		

[Raad et al., 2017]

Π<sub>c</sub>(Juice) = { (Juice, {rdf:Type, expiryDate}, {isComposedOf}), (Banana, {rdf:Type}, {isComposedOf<sup>-1</sup>}), (Strawberry, {rdf:Type}, {isComposedOf<sup>-1</sup>}) }

Π <sub>a</sub> (Juice) = { (Juice, {rdf:Type, expiryDate}, {isComposedOf}),			
(Banana, {rdf:Type}, {isComposedOf <sup>-1</sup> }),			
(Strawberry, {rdf:Type}, {hasAttribute, isComposedOf <sup>-1</sup> }),			
(Weight, {rdf:Type, hasValue, hasUnit}, {hasAttribute <sup>-1</sup> }) <b>}</b>			

[Raad et al., 2017]

Π<sub>b</sub>(Juice) = { (Juice, {rdf:Type, expiryDate}, {isComposedOf}), (Banana, {rdf:Type}, {hasAttribute, isComposedOf<sup>-1</sup>}), (Strawberry, {rdf:Type}, {hasAttribute, isComposedOf<sup>-1</sup>}), (Weight, {rdf:Type, hasUnit}, {hasAttribute<sup>-1</sup>}) }

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each local context in  $\Pi_c$ (Juice) is less specific or equal to its corresponding local context in  $\Pi_a$ (Juice)

[Raad et al., 2017]

# It automatically detects and adds these contextual identity links in the knowledge graph





[Raad et al., 2017]





	Experiment 1	Experiment 2
	Mixture	Step
# Instances	1,187	581
# Possible pairs	703,891	168,490
# Distinct Global Contexts	2 232	718
# Contextual identity links	1, 279,376	348,017
# Contextual identity links per pair	1.81	2.06





Detect for each context **GC**<sub>i</sub>, the measures **m**<sub>i</sub> where

 $\label{eq:identiConTo_{GCi}} \begin{array}{l} (i_1,\,i_2) \cap \textit{observes}(i_1,\,m_1) \rightarrow \textit{observes}(i_2,\,m_2) \\ & \text{with } m_1 \simeq m_2 \end{array}$ 

 $identiConTo_{<GCi>}(i1, i2) \rightarrow same(m_i)$ 

#### **Detection of 38 844 rules**

Règle	Taux d'erreur	Support
$identiConTo_{}(x, y) \\ \rightarrow same(pH)$	6.19 %	57
$identiConTo_{< GC_3>}(x, y) \\ \rightarrow same(Dureté)$	1.86 %	66
$identiConTo_{}(x, y) \\ \rightarrow same(Friabilité)$	4.52 %	647

The domain experts has evaluated the plausibility of the best **20 rules** (in termes of error rate and support)

[Raad et al., 2017]

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The domain experts has evaluated the plausibility of the best **20 rules** (in termes of error rate and support)



The error rate decreases of 12% when a global context is replaced by a more specific global context

[Raad et al., 2017]

Different kinds of identity relationship



Different kinds of identity relationship



Different kinds of identity relationship



- Different kinds of identity relationship
- Need of hybrid methods



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What is about the

distinctness relation?

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