STEFAN GAMERITH



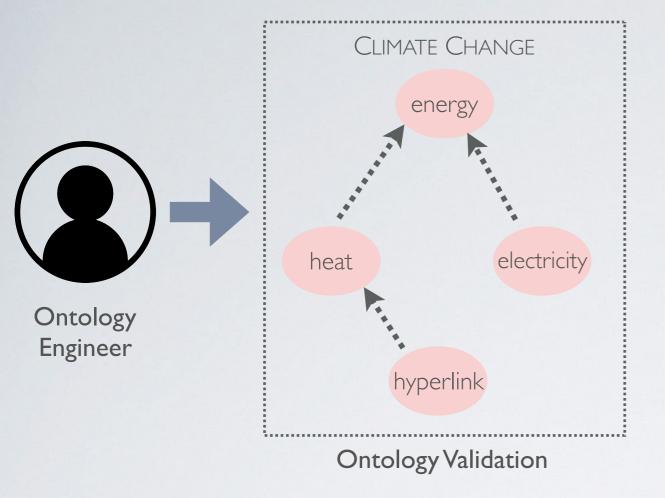
STEFAN GAMERITH

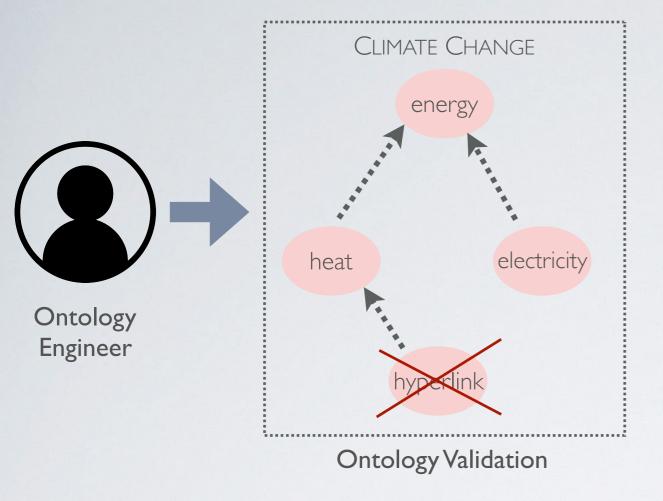


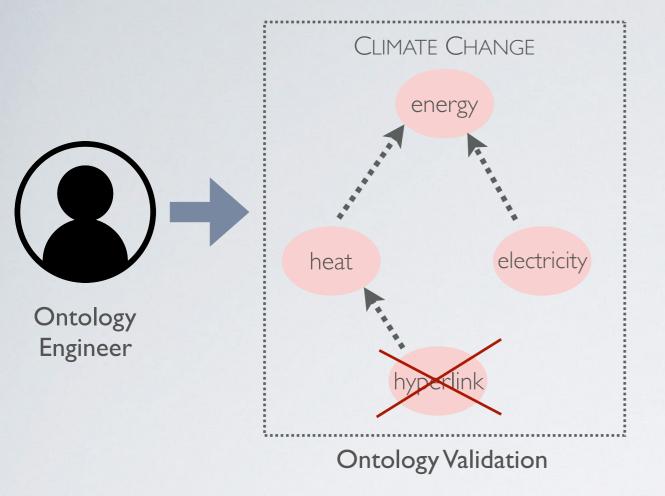
Context Enrichment of Crowdsourcing Tasks for Ontology Validation

Advisor: Ao. Univ. Prof. DI Dr techn. Stefan Biffl

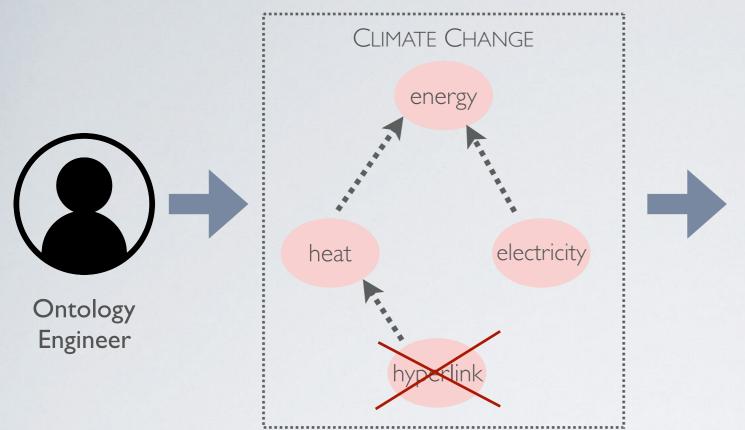
Assistance: Reka Marta Sabou, MSc., PhD







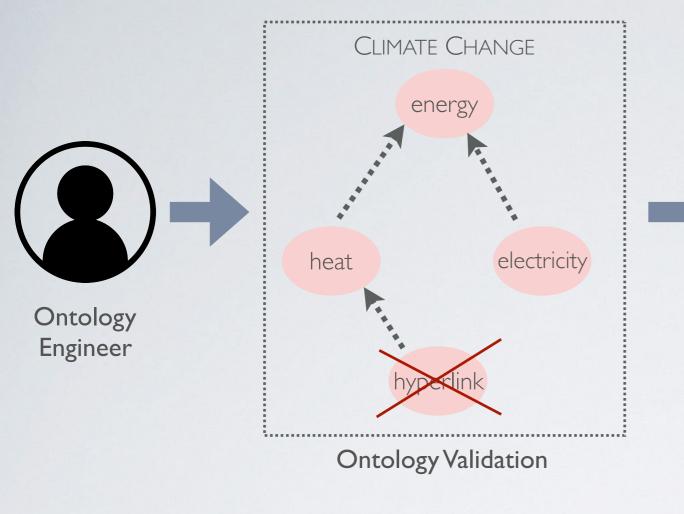
- expert based validation is costly and time consuming
- crowd-based validation is a cost-effective alternative

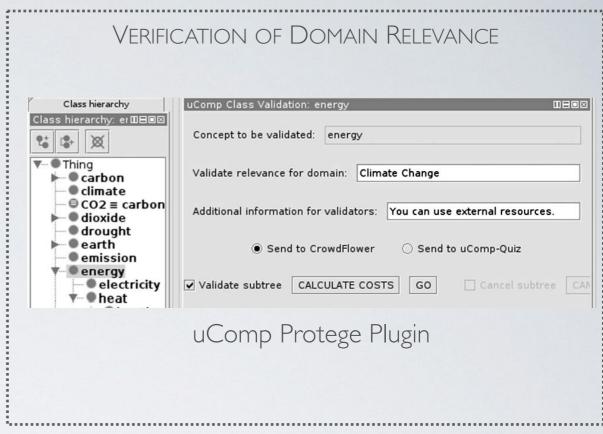


Ontology Validation

- VERIFICATION OF DOMAIN RELEVANCE uComp Class Validation: energ Class hierarchy Concept to be validated: energy Validate relevance for domain: Climate Change carbon climate © CO2 ≡ carbon Additional information for validators: You can use external resources. dioxide drought earth Send to CrowdFlower O Send to uComp-Quiz emission energy electricity ▼ • heat uComp Protege Plugin
 - Crowdsourced Ontology Validation

- expert based validation is costly and time consuming
- crowd-based validation is a cost-effective alternative

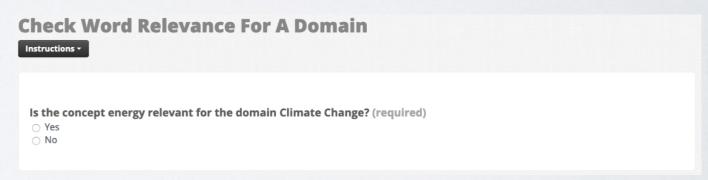




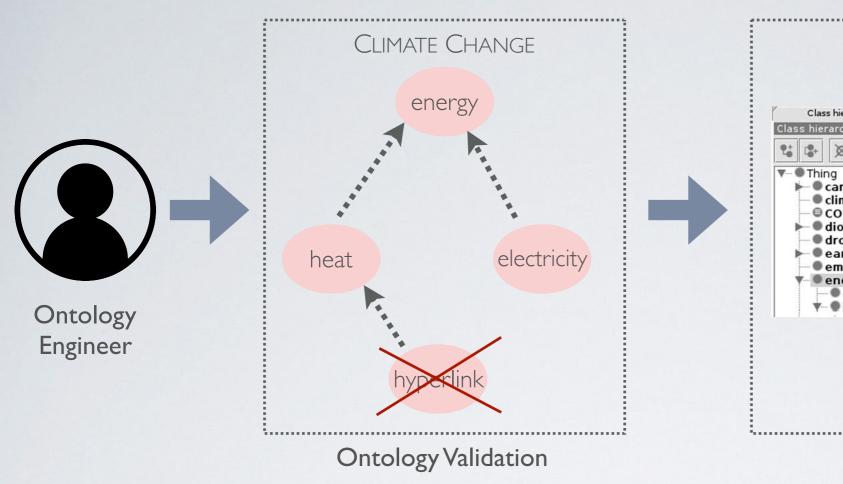
Crowdsourced Ontology Validation

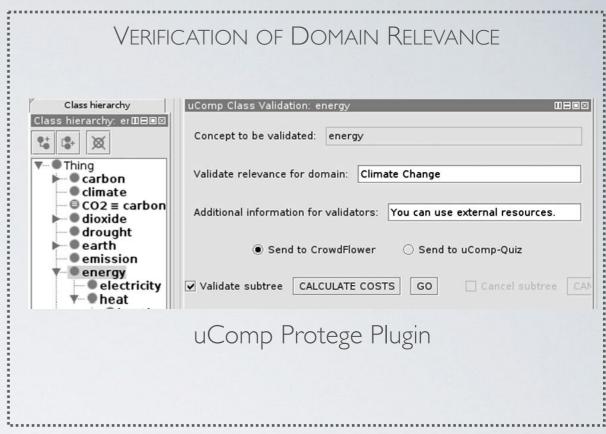


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- crowd-based validation is a cost-effective alternative



Crowdsourcing Task Interface

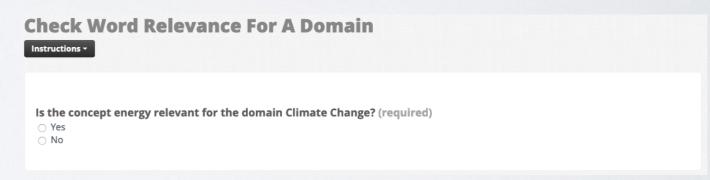




Crowdsourced Ontology Validation



- expert based validation is costly and time consuming
- crowd-based validation is a cost-effective alternative



Crowdsourcing Task Interface

Problem: crowd workers have problems understanding CS tasks because of missing context



MISSON:

Does the crowd perform better on context enriched CS tasks?



MISSON:

Does the crowd perform better on context enriched CS tasks?



What methods can be applied that generate context?

RQ I



MISSON:

Does the crowd perform better on context enriched CS tasks?





What methods can be applied that generate context?

To what extent is it possible to transfer the investigated methods to different datasets?

RQ I

RQ 2



MISSON:

Does the crowd perform better on context enriched CS tasks?







What methods can be applied that generate context?

To what extent is it possible to transfer the investigated methods to different datasets?

Which of the proposed methods works best and what are potential shortcomings?

RQ I

RQ 2

RQ 3

How to define the notion of Context?

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Context refers to any sort of additional information that is supplied with a Crowdsourcing task to improve its understanding in such a way that it positively affects the crowds performance and result quality.

How to define the notion of Context?

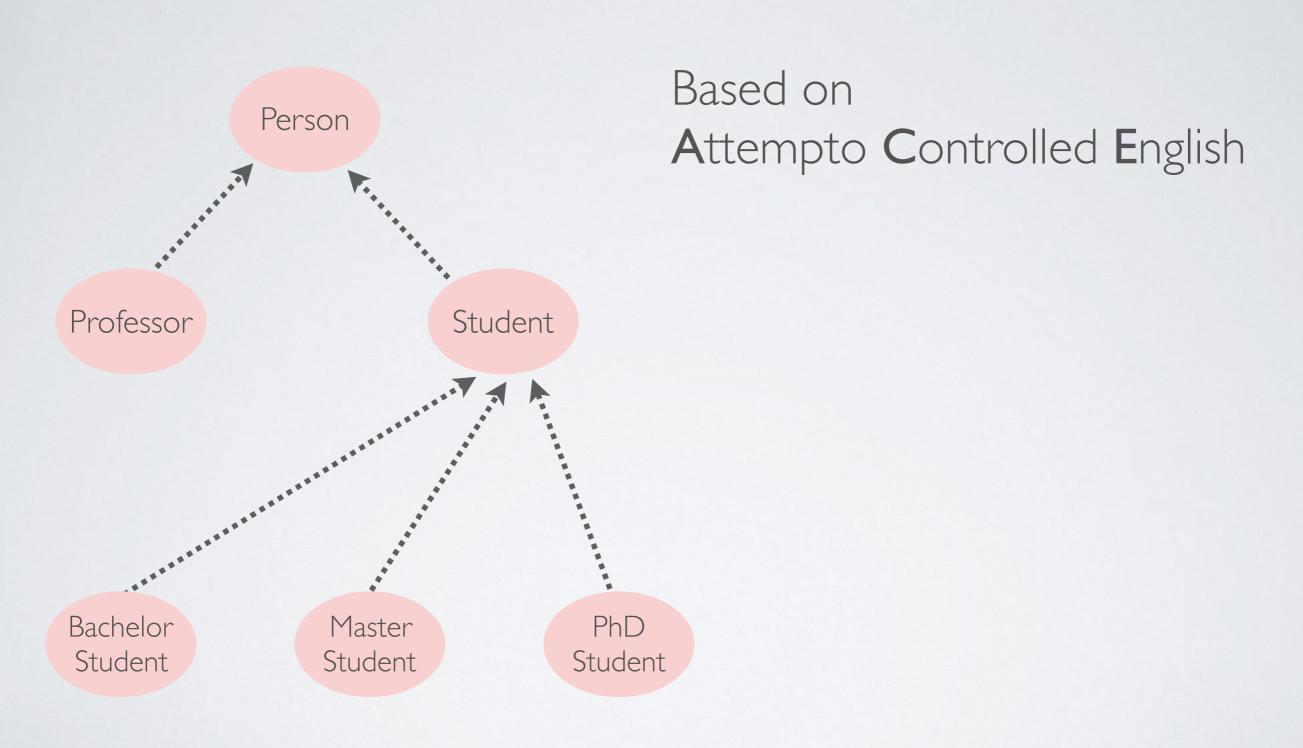
Context refers to any sort of additional information that is supplied with a Crowdsourcing task to improve its understanding in such a way that it positively affects the crowds performance and result quality.

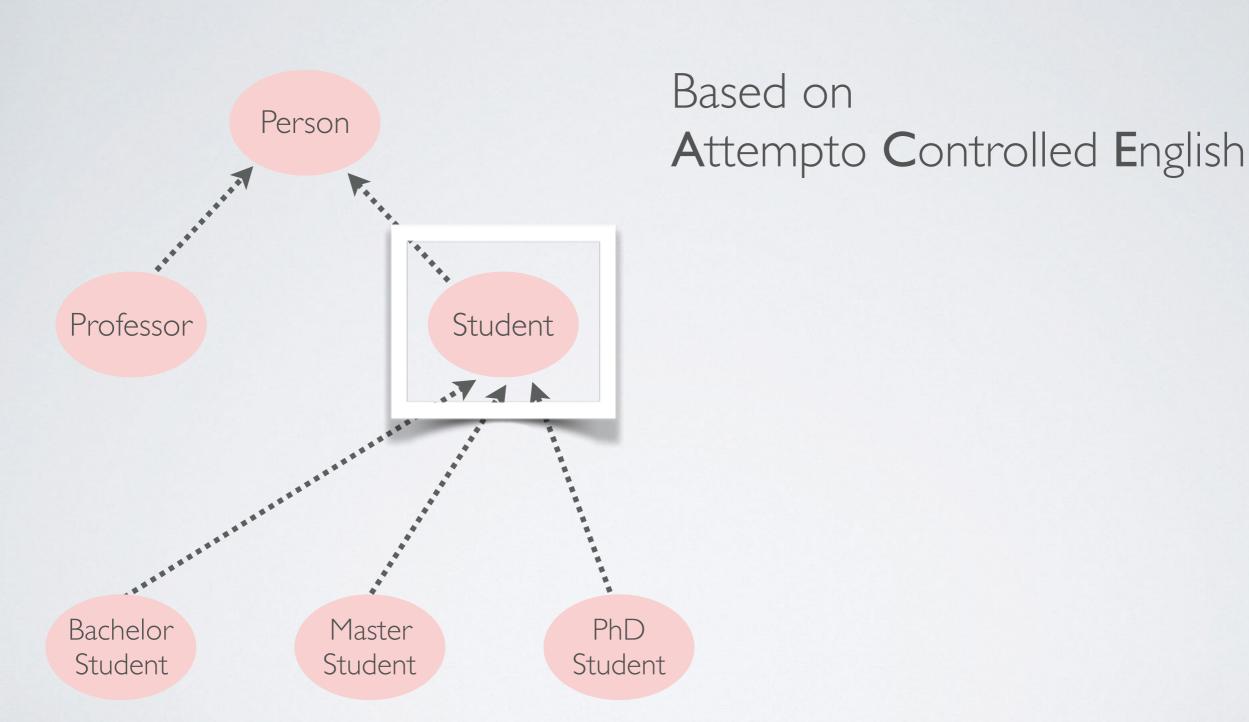
Paper	Evaluated Unit	CONTEXT
Acosta et. al.	RDF Triples Wikipedia Link	
Mortensen et. al.	Ontology Structure	Concept Descriptions
Sabou et. al. Winkler et. al.	Conceptual Model	EER Diagram

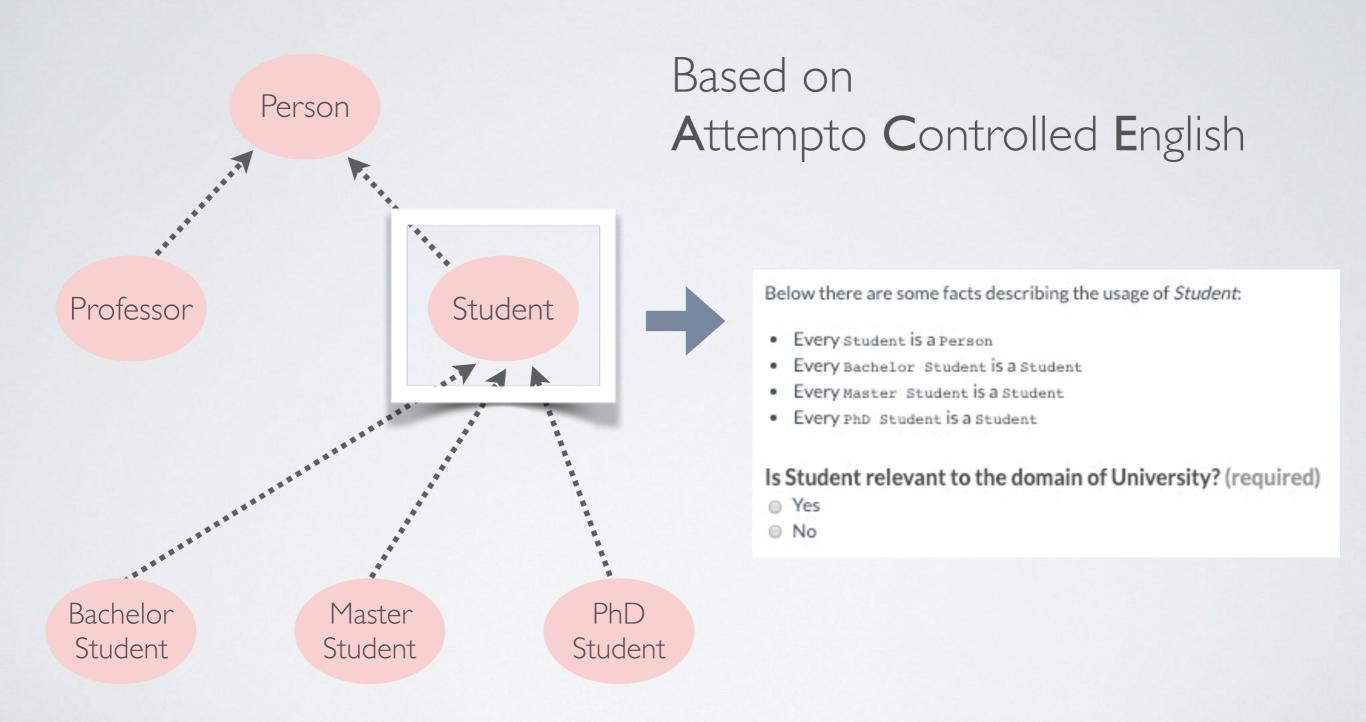
The use of Context in other Ontology Engineering settings

Context Enrichment Methods (RQ I)

Based on Attempto Controlled English







M2: Metadata based Approach

M2: Metadata based Approach

M2: Metadata based Approach



Short Description for 'greenhouse gas':

• greenhouse gas

Detailed Description for 'greenhouse gas':

• Greenhouse gas (GHG) is one of several gases, especially carbon dioxide, that prevent heat from the earth escaping into space, causing the greenhouse effect. Greenhouse gases from human activities are the most significant driver of observed climate change since the mid-20th century.

Is 'greenhouse gas' relevant to the domain of Climate Change? (required)

Yes

O No









Dictionary Lookup







Dictionary Lookup







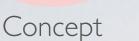


Concept

Dictionary Lookup

```
JSON Response
```











JSON Response



Example Sentences:

• Emerson Process Experts

Marshall described \'chartjunk\' as additional graphics not related to the data in a quest to make the chart more aesthetically pleasing.

Is chartjunk relevant to the domain of Climate Change? (required)

- Yes
- O No

Experimental Evaluation (RQ 2)

Evaluation Datasets

Evaluation Datasets

	Climate Change	Tennis	FINANCE
Classes	101	52	77
Properties	28	34	29
Subclass Relations	84	35	78
Individuals	64	33	47

Evaluation Setup

METHODS

None Meta, Onto, Dict

None Meta, Onto, Dict

None Meta, Onto, Dict

Methods	Ontology
None Meta, Onto, Dict	Climate Change
None Meta, Onto, Dict	Tennis
None Meta, Onto, Dict	Finance

Methods	Ontology	Judgements / Price
None Meta, Onto, Dict	Climate Change	5 / 0.05\$
None Meta, Onto, Dict	Tennis	5 / 0.05\$
None Meta, Onto, Dict	Finance	5 / 0.05\$

METHODS	Ontology	Judgements / Price	Worker Selection
None Meta, Onto, Dict	Climate Change	5 / 0.05\$	Level 3 AUS, UK, USA
None Meta, Onto, Dict	Tennis	5 / 0.05\$	Level 3 AUS, UK, USA
None Meta, Onto, Dict	Finance	5 / 0.05\$	Level 3 AUS, UK, USA

Methods	Ontology	Judgements / Price	Worker Selection	Quality Control
None Meta, Onto, Dict	Climate Change	5 / 0.05\$	Level 3 AUS, UK, USA	Quiz
None Meta, Onto, Dict	Tennis	5 / 0.05\$	Level 3 AUS, UK, USA	Quiz
None Meta, Onto, Dict	Finance	5 / 0.05\$	Level 3 AUS, UK, USA	Quiz

Aggregated Results over all Ontologies

Aggregated Results over all Ontologies

METHOD	Precision	RECALL	F-Measure
Metadata based Approach	0,80	0,92	0,85
Ontology based Approach	0,79	0,89	0,83
Dictionary based Approach	0,73	0,90	0,81
None	0,67	0,91	0,78

Conclusions Future Work



MISSON:

Impact on the crowd's performance







Context Enrichment Methods Generalising the Applicability of the proposed Methods

Comparative Analysis of the proposed Methods

RQ I

RQ 2



- the use of context improves the crowd's performance
- · results exhibit relatively high recall
- good alternative to expert-based validation







Context Enrichment Methods Generalising the Applicability of the proposed Methods

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MI: Ontology based

M 2: Metadata based

M 3: Dictionary based

Generalising the Applicability of the proposed Methods

Comparative Analysis of the proposed Methods

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- the use of context improves the crowd's performance
- results exhibit relatively high recall
- good alternative to expert-based validation







MI: Ontology based

M 2: Metadata based

M 3: Dictionary based

MI: Ontology dependent

M 2: Annotation dependent

M 3: Dictionary dependent

Comparative Analysis of the proposed Methods

RQ I

RQ 2



- the use of context improves the crowd's performance
- results exhibit relatively high recall
- good alternative to expert-based validation







- MI: Ontology based
- M 2: Metadata based
- M 3: Dictionary based

MI: Ontology dependent

M 2: Annotation dependent

M 3: Dictionary dependent

MI: works isolated, requires subsumption relations

M 2: best performance, requires preprocessing

M 3: extendable for other providers, sometimes irrelevant results

RQ I

RQ 2

 Evaluate the impact of context for other ontology validation tasks

 Evaluate the impact of context for other ontology validation tasks

Combination of context enrichment methods

 Evaluate the impact of context for other ontology validation tasks

- Combination of context enrichment methods
- Integration of OWL-Verbalizer

- Evaluate the impact of context for other ontology validation tasks
- Combination of context enrichment methods
- Integration of OWL-Verbalizer
- · Evaluation of the methods on a larger scale

Thank you

Any questions?

Backup Slides

What is Crowdsourcing?

What is Crowdsourcing?

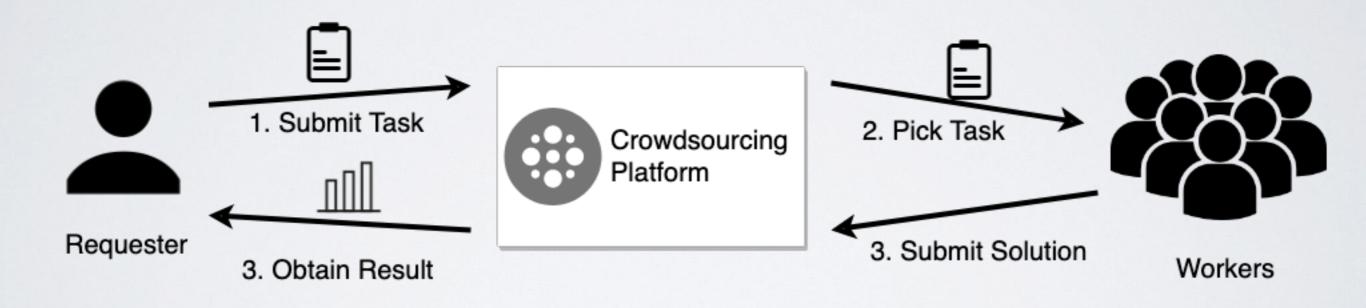
"Crowdsourcing is the act of taking a task traditionally performed by a designated agent and outsourcing it by making an open call to an undefined but large group of people."

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"Crowdsourcing is the act of taking a task traditionally performed by a designated agent and outsourcing it by making an open call to an undefined but large group of people."

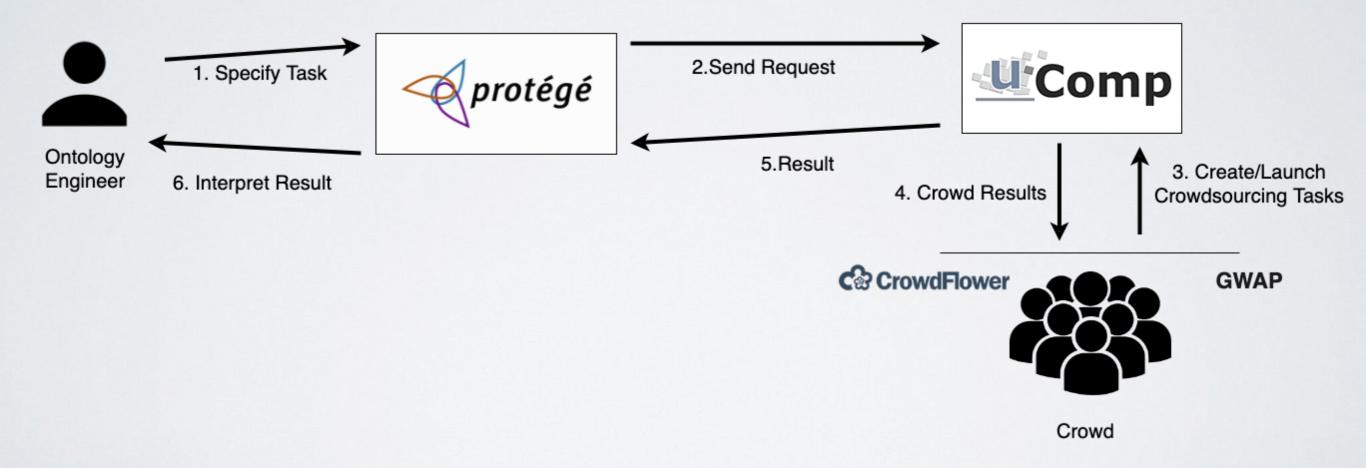
Jeff Howe Wired Magazine - 2006 The Stakeholders of the Crowdsourcing Process

The Stakeholders of the Crowdsourcing Process



Crowd-based Ontology Validation Workflow

Crowd-based Ontology Validation Workflow



What is the problem of the Plugin?

"When it comes to the information to be displayed, a challenging aspect is to identify the minimum amount of **Context** [...] that contributors need to have to accomplish the task correctly."

Sarasua et. al.

Crowdsourcing and the Semantic Web - A Research Manifesto

I. Verification of Domain Relevance

- I. Verification of Domain Relevance
- II. Verification of Relation Correctness

- I. Verification of Domain Relevance
- II. Verification of Relation Correctness
 - i. Subsumption

- I. Verification of Domain Relevance
- II. Verification of Relation Correctness
 - i. Subsumption
 - ii. InstanceOf

- I. Verification of Domain Relevance
- II. Verification of Relation Correctness
 - i. Subsumption
 - ii. InstanceOf
- III. Specification of Relation Type

- I. Verification of Domain Relevance
- II. Verification of Relation Correctness
 - i. Subsumption
 - ii. InstanceOf
- III. Specification of Relation Type
- IV. Verification of Domain and Range

Context Enrichment Methods

Simple Sentences

Simple Sentences

"A customer inserts some cards into a slot."

Simple Sentences

"A customer inserts some cards into a slot."

Composite Sentences

Simple Sentences

"A customer inserts some cards into a slot."

Composite Sentences

"A customer inserts a card and the machine checks the code."

Simple Sentences

"A customer inserts some cards into a slot."

Composite Sentences

"A customer inserts a card and the machine checks the code."

"It is possible that a trusted customer inserts a card."

Simple Sentences

"A customer inserts some cards into a slot."

Composite Sentences

"A customer inserts a card **and** the machine checks the code."

"It is possible **that** a trusted customer inserts a card."

"Every card is inserted by a customer."

Simple Sentences

"A customer inserts some cards into a slot."

Composite Sentences

"A customer inserts a card and the machine checks the code."

"It is possible that a trusted customer inserts a card."

"Every card is inserted by a customer."

"No customer inserts more than 2 cards."

Query Sentences

Query Sentences

"Who inserts a card?"

Query Sentences

"Who inserts a card?"

"Which customer inserts a card?"

Query Sentences

"Who inserts a card?"

"Which customer inserts a card?"

"What does a customer insert?"

Query Sentences

"Who inserts a card?"

"Which customer inserts a card?"

"What does a customer insert?"

"When does a customer enter a card?"

Query Sentences

"Who inserts a card?"

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"When does a customer enter a card?"

"Where does a customer enter a card?"

Query Sentences

"Who inserts a card?"

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Anaphoric References

Query Sentences

"Who inserts a card?"

"Which customer inserts a card?"

"What does a customer insert?"

"When does a customer enter a card?"

"Where does a customer enter a card?"

Anaphoric References

"A customer inserts a code. The ATM accepts the card if the code is valid."

Query Sentences

"Who inserts a card?"

"Which customer inserts a card?"

"What does a customer insert?"

"When does a customer enter a card?"

"Where does a customer enter a card?"

Anaphoric References

"A customer inserts a code. The ATM accepts the card if **the code** is valid."

"If a customer owns a card, he inserts it."

Procedure Generate Description			

Procedure Generate Description

Input: A concept C

Output: A textual description T of C's neighbouring nodes based on subsumption

 $T = \{\}$

Procedure Generate Description

Input: A concept C

Output: A textual description T of C's neighbouring nodes based on subsumption

 $T = \{\}$

for $(c, d) \in C \sqsubseteq D do$

Procedure Generate Description

Input: A concept C

```
T = \{\}
for (c, d) \in C \sqsubseteq D do
T = T \cup \{"Every" \cup name(c) \cup "is a" \cup name(d)\}
```

Procedure Generate Description

Input: A concept C

```
T = {}
for (c, d) ∈ C ⊑ D do

T = T ∪ {"Every" ∪ name(c) ∪ "is a" ∪ name(d)}
for (e, c) ∈ E ⊑ C do
```

Procedure Generate Description

Input: A concept C

```
T = {}
for (c, d) ∈ C ⊑ D do

    T = T ∪ {"Every" ∪ name(c) ∪ "is a" ∪ name(d)}
for (e, c) ∈ E ⊑ C do

    T = T ∪ {"Every" ∪ name(e) ∪ "is a" ∪ name(c)}
```

Procedure Generate Description

Input: A concept C

```
T = {}
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    T = T ∪ {"Every" ∪ name(c) ∪ "is a" ∪ name(d)}
for (e, c) ∈ E ⊑ C do

    T = T ∪ {"Every" ∪ name(e) ∪ "is a" ∪ name(c)}
```

Dublin Core Metadata Set

Dublin Core Metadata Set

Initially contained only 15 terms

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Initially contained only 15 terms

Simple Knowledge Organization System

Dublin Core Metadata Set

Initially contained only 15 terms

Simple Knowledge Organization System

Defines some of RDF properties and RDFS classes

Procedure Generate Description

Procedure Generate Description

Input: A concept C with embedded metadata $\Phi(C) := \{m_1, m_2, \ldots, m_i\}$

```
Procedure Generate Description
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Input: A concept C with embedded metadata $\Phi(C) := \{m_1, m_2, \ldots, m_i\}$

```
Procedure Generate Description
```

Input: A concept C with embedded metadata $\Phi(C) := \{m_1, m_2, \ldots, m_i\}$

Output: A description T of C's metadata elements

 $T = \{\}$

```
Procedure Generate Description
```

Input: A concept C with embedded metadata $\Phi(C) := \{m_1, m_2, \ldots, m_i\}$

Output: A description T of C's metadata elements

$$T = \{\}$$

for $m_k \in \Phi(C)$ do

```
Procedure Generate Description
```

Input: A concept C with embedded metadata $\Phi(C) := \{m_1, m_2, \ldots, m_i\}$

$$T = \{\}$$
for $m_k \in \Phi(C)$ do
$$T = T \cup m_k$$

Results

$$Precision = \frac{TP}{TP + FP}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F - Measure = 2 \cdot \frac{P \cdot R}{P + R}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F - Measure = 2 \cdot \frac{P \cdot R}{P + R}$$

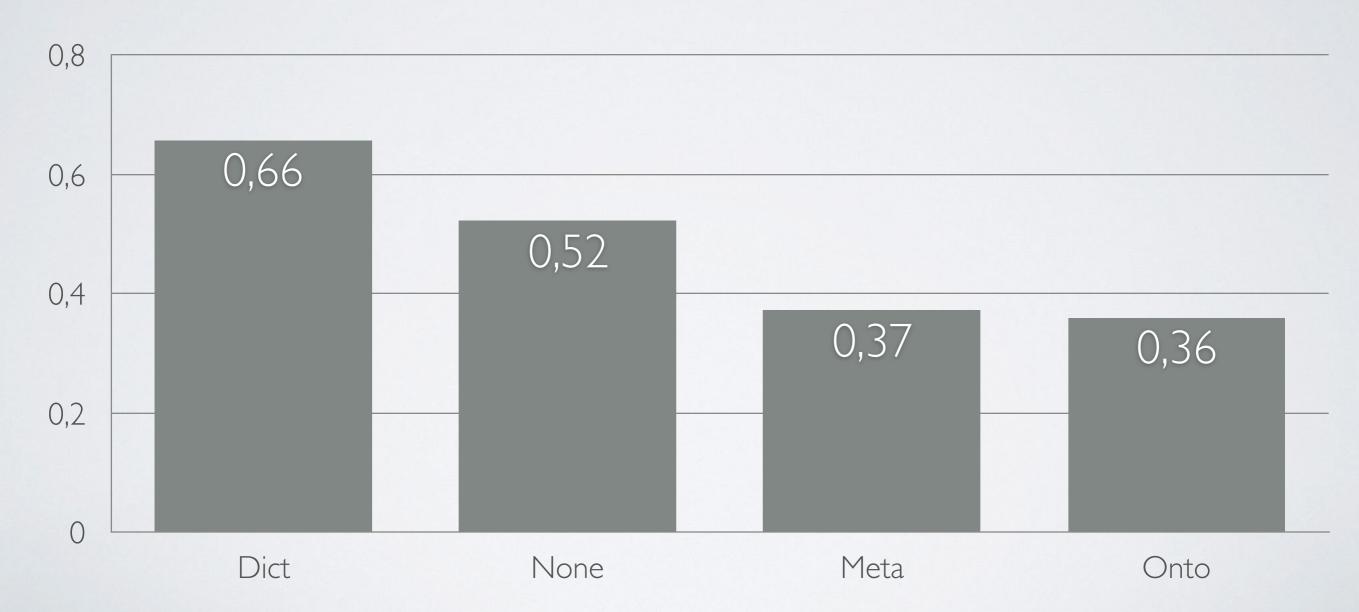
$$Inter-rater \quad Agreement = \frac{\overline{P}-\overline{P_e}}{1-\overline{P_e}}$$

METHOD	Precision		
Ontology based Approach	0,76		
Metadata based Approach	0,73		
Dictionary based Approach	0,72		
None	0,55		

METHOD	Precision	RECALL
Ontology based Approach	0,76	0,81
Metadata based Approach	0,73	0,83
Dictionary based Approach	0,72	0,82
None	0,55	0,84

METHOD	Precision	RECALL	F-Measure
Ontology based Approach	0,76	0,81	0,78
Metadata based Approach	0,73	0,83	0,78
Dictionary based Approach	0,72	0,82	0,77
None	0,55	0,84	0,66

Agreement

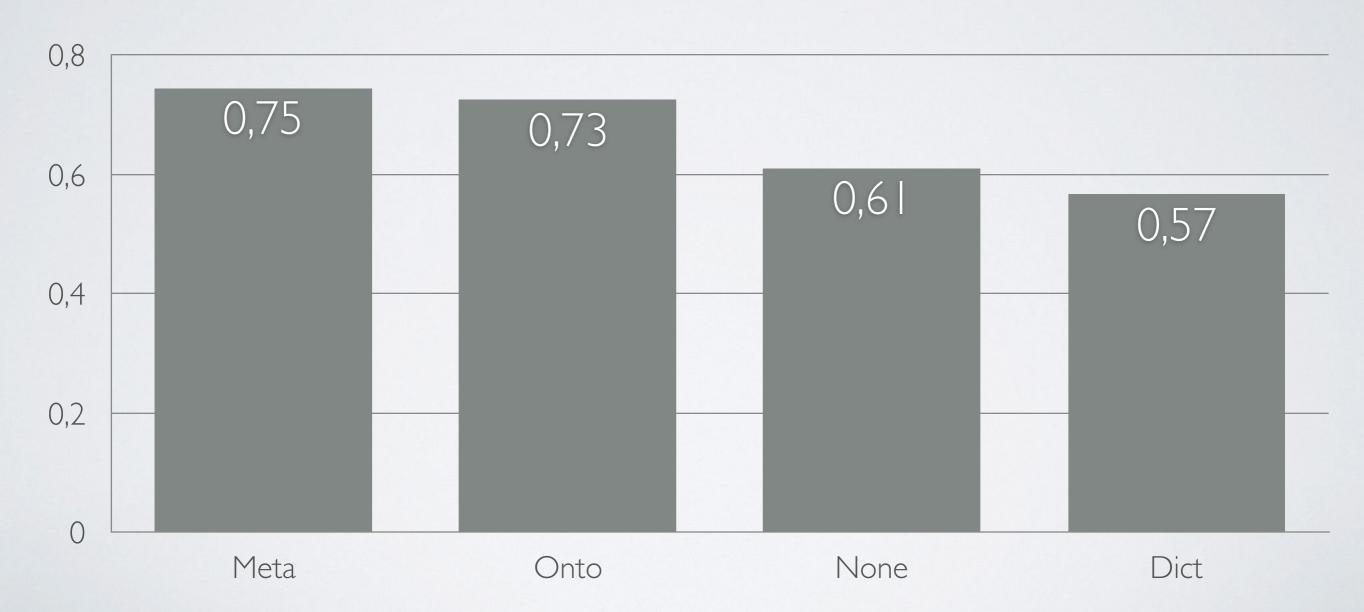


METHOD	Precision		
Metadata based Approach	0,80		
Dictionary based Approach	0,79		
Ontology based Approach	0,76		
None	0,73		

METHOD	Precision	RECALL
Metadata based Approach	0,80	0,99
Dictionary based Approach	0,79	0,94
Ontology based Approach	0,76	0,95
None	0,73	0,96

METHOD	Method Precision Recall		F-Measure
Metadata based Approach	0,80	0,99	0,88
Dictionary based Approach	0,79	0,94	0,86
Ontology based Approach	0,76	0,95	0,84
None	0,73	0,96	0,83

Agreement

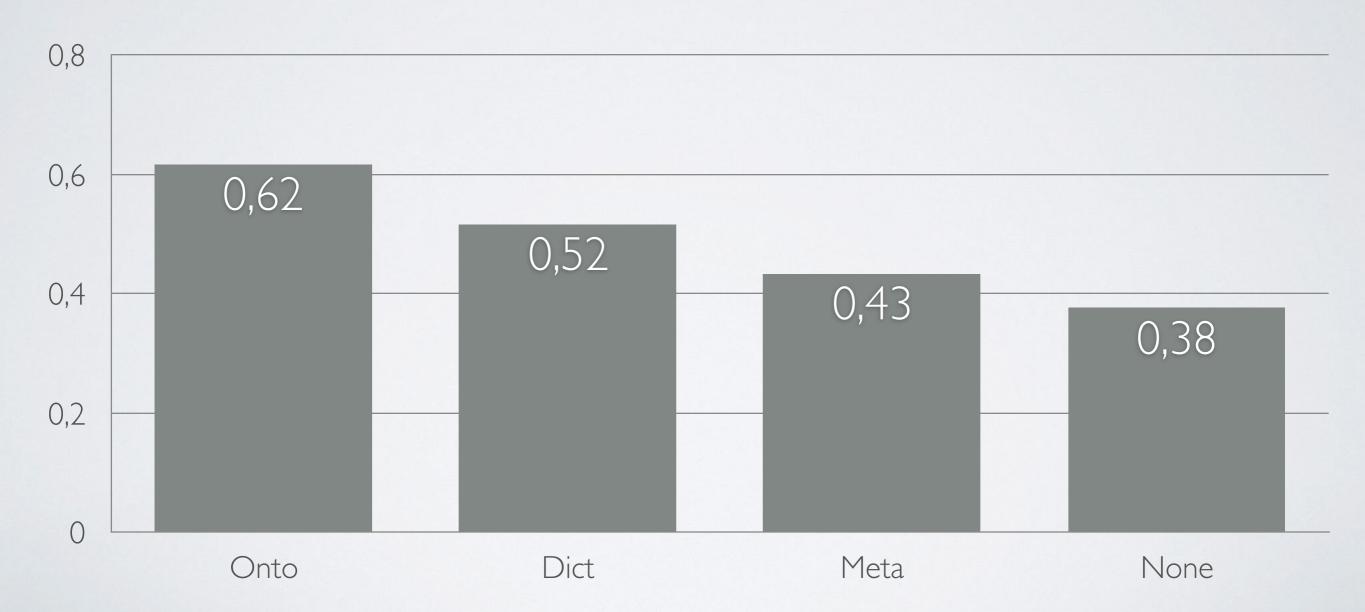


METHOD	Precision		
Metadata based Approach	0,90		
Ontology based Approach	0,87		
None	0,78		
Dictionary based Approach	0,65		

METHOD	Precision	RECALL
Metadata based Approach	0,90	0,98
Ontology based Approach	0,87	0,94
None	0,78	0,93
Dictionary based Approach	0,65	0,98

METHOD	Precision	RECALL	F-Measure
Metadata based Approach	0,90	0,98	0,93
Ontology based Approach	0,87	0,94	0,91
None	0,78	0,93	0,85
Dictionary based Approach	0,65	0,98	0,78

Agreement



For which Concepts were the Crowd wrong?

Concept	META	ONTO	DICT	None	TOTAL
sceptic	0/5	0/5	0/5	0/5	0/20
greenhouse	0/5	1/5	0/5	0/5	1/20
pipeline	0/5	0/5	1/5	0/5	1/20
consensus	2/5	0/5	0/5	0/5	2/20
denier	2/5	0/5	0/5	0/5	2/20
production	1/5	1/5	0/5	0/5	2/20

Inter-rater Agreement over all Ontologies

