

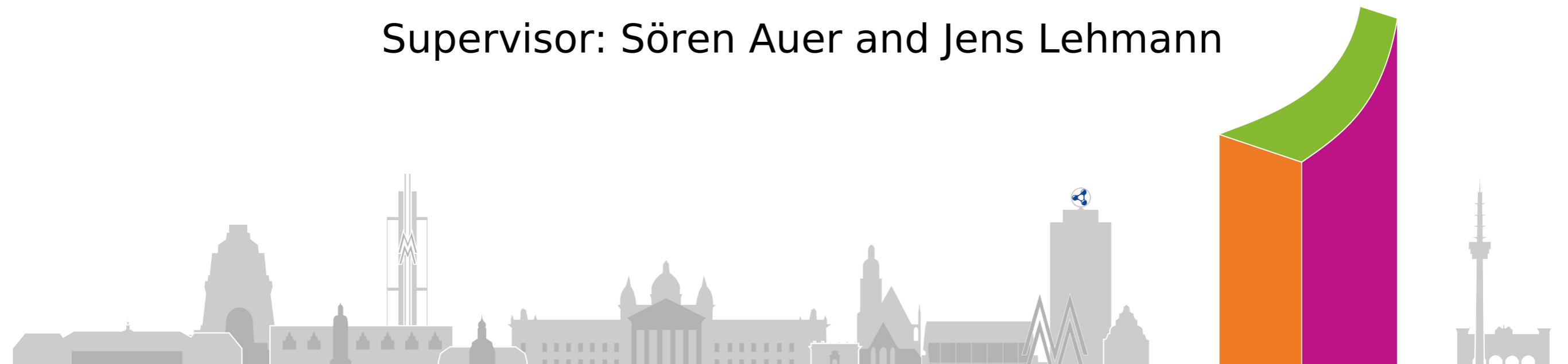
The Semantic Gap of Formalized Meaning

Employment of Semantic Web Technology in the domain of Linguistics and Textmining

Sebastian Hellmann

AKSW, Universität Leipzig

Supervisor: Sören Auer and Jens Lehmann



Content

- **Overview of Areas and Trends**
- **OWL as a Meaning Representation Language**
- **First Results**
- **Evaluation Methodology**

Overview of Areas & Trends

- **Textmining**
 - many available NLP tools
 - poor representation of output, normally Strings only (e.g. POS Tags)

Overview of Areas & Trends

- **Linguistics**

- emerging **Domain Knowledge in OWL**, e.g. by Christian Chiarcos – *Ontologies of Linguistic Annotations*
- hardly any adapted Semantic Web tools to support elicitation, creation and maintenance



Overview of Areas & Trends

- **Ontology Learning**

- fragmented approaches, mostly only one or few NLP methods as input [1, 2]
- preprocessing step can be optimized

1. J. Völker, P. Hitzler, and P. Cimiano. *Acquisition of OWL DL axioms from lexical resources*. In ESWC, 2007.

2. Tamas Horvath and Gerhard Paass and Frank Reichartz and Stefan Wrobel, *A Logic-Based Approach to Relation Extraction from Texts*. ILP 2009

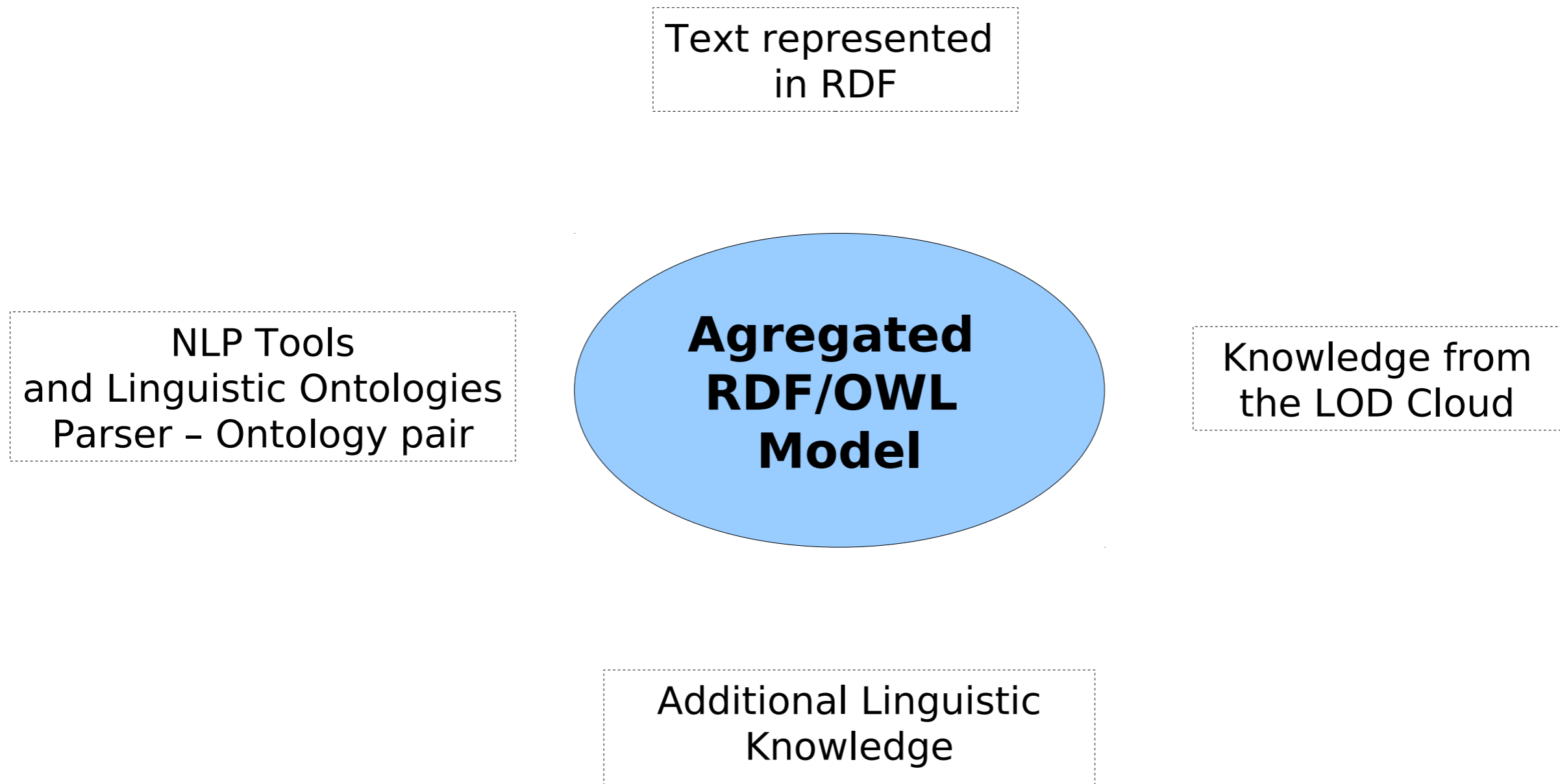
Overview of Areas & Trends

- **LOD cloud**
 - vast amount of structured knowledge
 - concept tagging is only a first step, further enrichment is possible

Goal

- Create a **holistic approach**, that combines techniques and knowledge from all fields.
- Implement a general purpose **preprocessing API** (NLP2RDF)
- **Evaluate** it thoroughly based on available benchmarks and tasks

OWL as an MRL



Semantic Gap

NLP2RDF stack

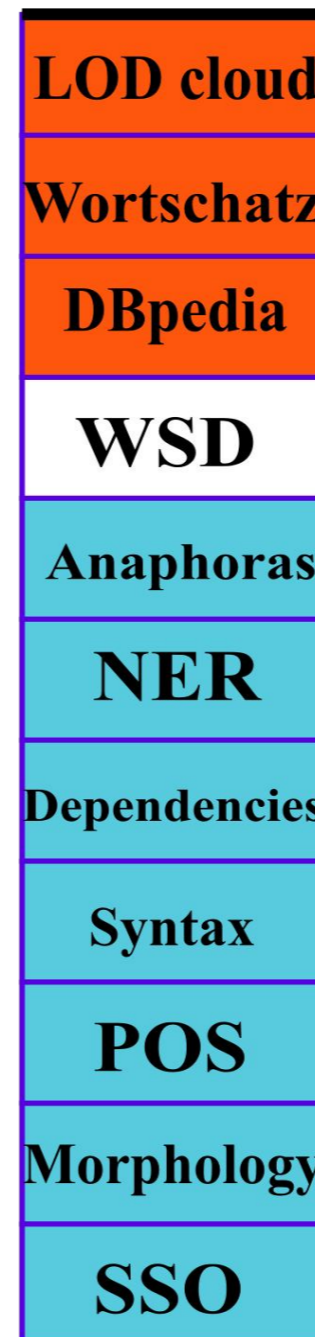
Existing structured knowledge is selected, disambiguated and integrated

WSD connects top and bottom

Open source implementation
<http://code.google.com/p/nlp2rdf>

Each NLP layer is augmented with linguistic background knowledge

Backbone ontology



Meaning expressed in OWL

Plain Text

Implicit Meaning

Example

Berlin is bigger than Leipzig.

Berlin | is | bigger | than | Leipzig | .

© Sentence

type

⚠ Berlin is bigger than Leipzig

comment

I

Berlin_is_bigger_than_Leipzig

hasToken

hasToken

hasToken

hasToken

hasToken

I

Berlin

I

is

I

bigger

I

than

I

Leipzig

nextToken

nextToken

nextToken

nextToken

type

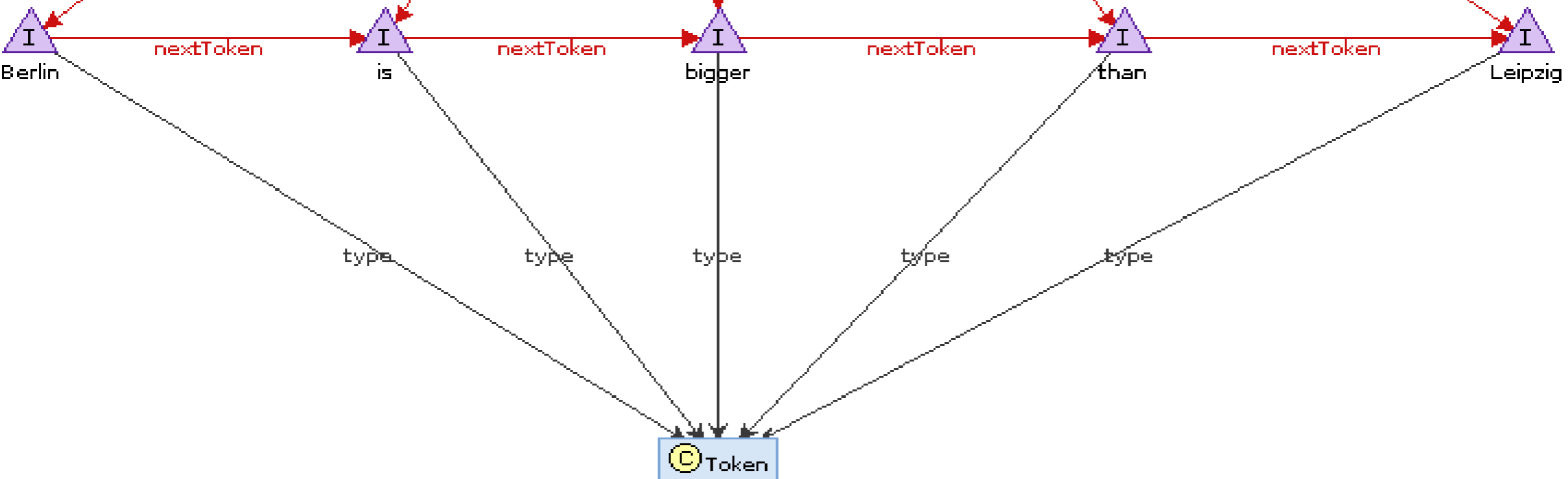
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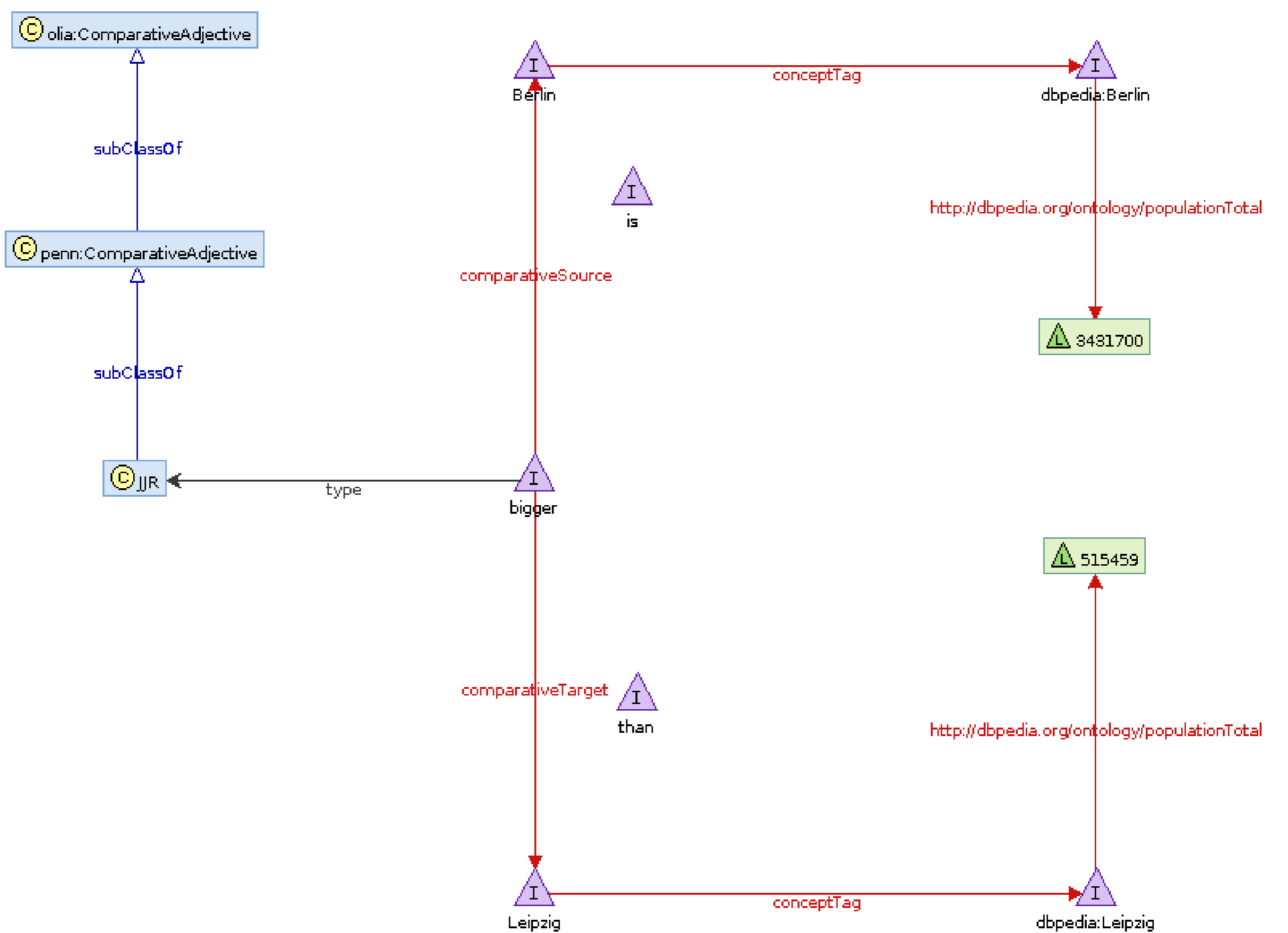
type

type

type

© Token





PREFIX dbpedia: <http://dbpedia.org/>

PREFIX skos: <http://www.w3.org/2004/02/skos/core#>

```
SELECT * WHERE {
<http://dbpedia.org/resource/Berlin> ?p ?o1.
<http://dbpedia.org/resource/Leipzig> ?p ?o2 .
Filter (?o1 < ?o2 || ?o1 > ?o2 ).
Filter (?p LIKE <http://dbpedia.org/ontology/%>) .
Filter (xsd:int (?o1) || xsd:double(?o1))
}
```

Results:

Browse



Go!

Reset

SPARQL results:

p	o1	o2
dbpedia:ontology/areaCode	"030"@en	"0341"@en
dbpedia:ontology/areaTotal	891820000	297600000
dbpedia:ontology/populationTotal	3431700	515459

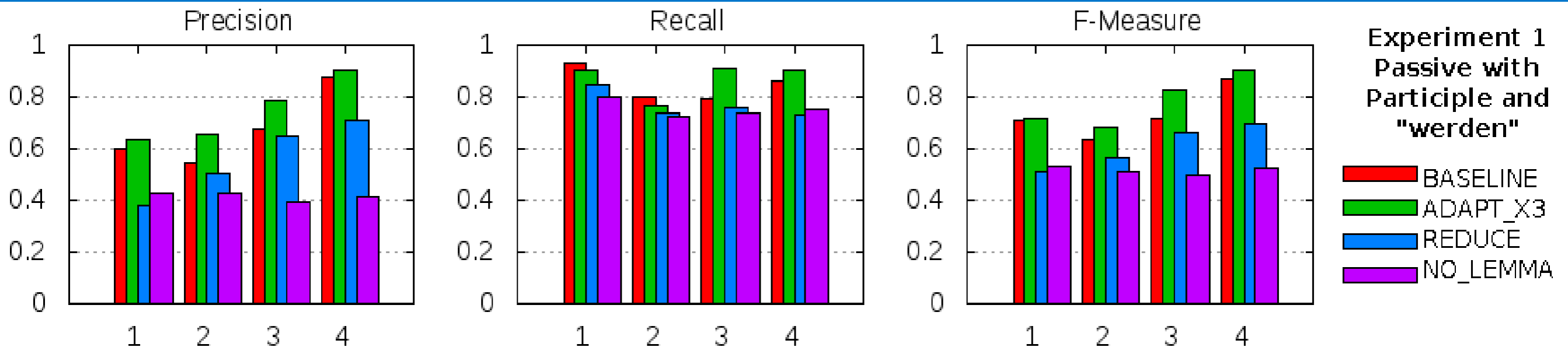
First results

- **Tiger Corpus Navigator**
 - TIGER is a collection of 50,000 German sentences
 - Conversion to RDF yielded 9 Million triples
 - Navigation with Active Machine Learning
 - <http://tigernavigator.nlp2rdf.org/>

Demo Tiger Navigator

<http://tigernavigator.nlp2rdf.org/>

Benchmarking



Find an OWL class description which covers 6300 passive sentences (of 50,000)

currently only POS tags are used

Benchmarking

- Creation of a **benchmark suite** with tasks from Textmining and Ontology Learning (like the 6300 passive sentence)
- NLP2RDF produces **input for machine learning algorithms** such as DL-Learner (as seen in the TCN)
- Which features are necessary for which tasks, how do they need to be represented?
- Improvement can be measured directly.



Next steps

- Planned benchmarks
 - ACE - 2003, Reuters ...
- Conversion of more linguistic corpora
 - Penn, Susanne, **Wiktionary** (DBictionary)
- Implementation of the NLP2RDF stack and framework
 - POS tags, Syntax and Disambiguation partially finished
- Using Ontology Learning on top
 - Integration with LExO (Johanna Völker)



Thank you



Collaboration

- good indicator of right direction
- better and faster results
- Currently:
 - Dr Christian Chiarcos, SFB 632, Potsdam
 - Dr Johanna Völker, KR & KM Research Group, Mannheim
 - Christian Meyer, UKP Darmstadt

Scientific core

- Development of algorithms (including evaluation)
- Creation and collection of benchmarks for Natural Language Engineering



Usefulness

- Creation and Enrichment of Linguistic Resources (Add bubbles to LOD cloud)
- Tools for Linguists (Search and Ontology Engineering)
- Ready-to-use API (NLP2RDF)
- Hopefully improvement on Textmining and Ontology Learning tasks

