

A Toolbox for the Nearly-Unsupervised Construction of Digital Library Knowledge Graphs at JCDL2021

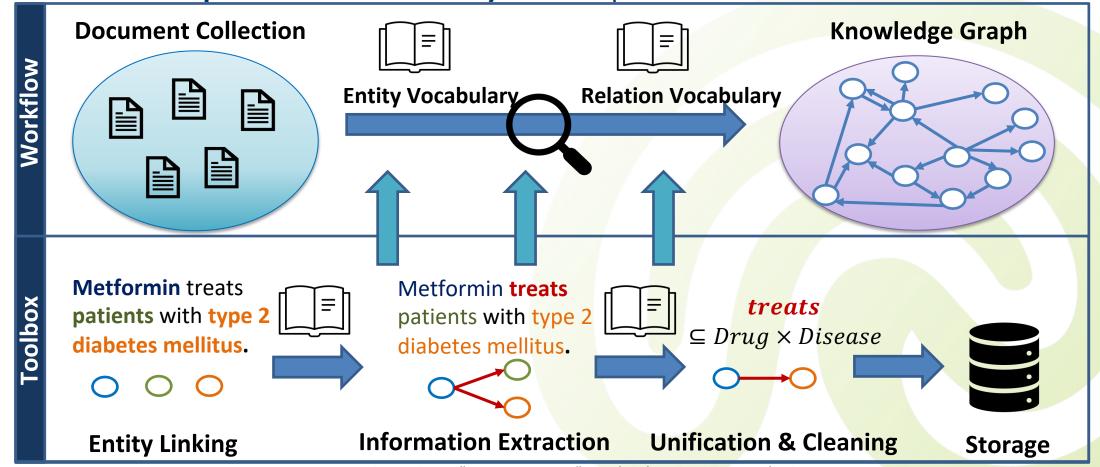
Hermann Kroll, Jan Pirklbauer and Wolf-Tilo Balke

Institut für Informationssysteme
Technische Universität Braunschweig



Toolbox Overview

- Available at:
 - https://github.com/HermannKroll/KGExtractionToolbox
 - Shared as Open Source, written in Python and published with an MIT license





Entity Linking & Recognition

- Dictionary-based **Entity Linker**:
 - Fast and reliable entity linking against a pre-known entity vocabulary
 - Not as precise as domain-specific entity linking
- Domain-specific tool integration:
 - As a demo, we integrated two biomedical tools
- Stanford Stanza (Named Entity Recognition):
 - Detects entities such as persons, events, dates, etc. (18 types)
 - Does not deliver unique entity ids



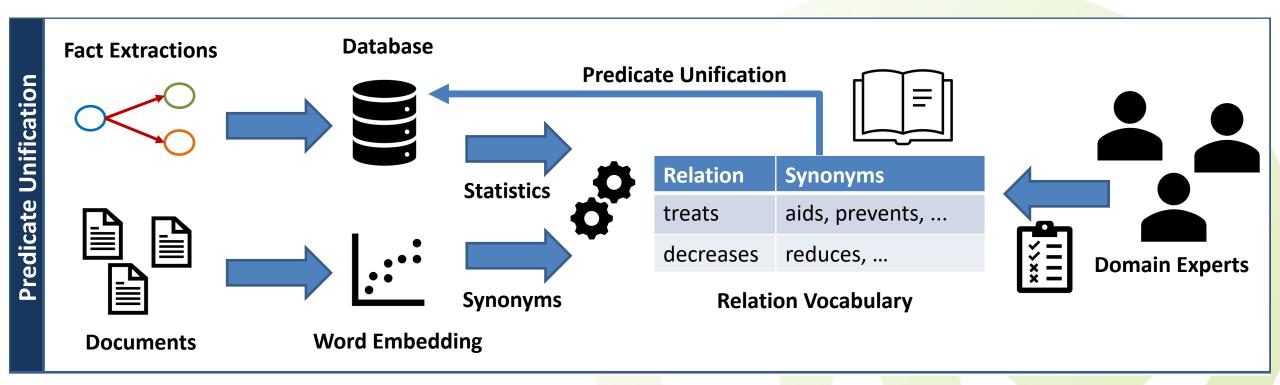
Unsupervised Information Extraction

- Extraction via **Open Information Extraction**:
 - Stanford CoreNLP (fast and reliable)
 - OpenIE 6 (more precise but cost-intensive)
 - Toolbox can filter extractions by detected entities
- Extraction via **PathIE** (Path-based extraction method):
 - A statement is extracted if two entities are connected via a
 verb / keyword on the closest grammatical structure of a sentence
 - PathlE is recall-oriented and requires entity information



Predicate Unification & Constraints

 An iterative predicate unification algorithm maps synonymous predicates to precise relations



• Cleaning by type integrity constraints, e.g., $treats \subseteq Drug \times Disease$



- Our toolbox achieves a **moderate quality** in entity linking and information extraction
 - More details can be found in our paper

TABLE I

ENTITY LINKING QUALITY ON BIOMEDICAL BENCHMARKS: STATE-OF-THE-ART (SOTA) TAGGERS ARE COMPARED TO OUR UNSUPERVISED ENTITY LINKER. THE SOTA-TAGGING QUALITY RESULTS ARE FROM TAGGERONE [10] AND GNORMPLUS [9].

Benchmark	Entity Type	Quality of SOTA Entity Linker			Quality of our Entity Linker			
		Name	Precision	Recall	F-measure	Precision	Recall	F-measure
NCBI Disease [21]	Disease	TaggerOne	82.2%	79.2%	80.7%	74.5%	55.1%	63.3%
BioCreative V CD-R [22]	Disease	TaggerOne	84.6%	82.7%	83.7%	82.8%	62.0%	70.9%
BioCreative V CD-R [22]	Chemical	TaggerOne	88.8 %	90.3%	89.5%	76.6%	78.7%	77.6%
BioCreative II GN [23]	Human Gene	GNormPlus	87.1%	86.4%	86.7%	60.1%	52.4%	56.0%

TABLE III

CDR2015 BENCHMARK EVALUATION [22]. THE TABLE REPORTS THE EXTRACTION QUALITY FOR OPENIE TOOLS, PATHIE AND BASELINES.

Method	Quality			
	Prec.	Rec.	F1	
CoreNLP OpenIE	64.9%	5.8 %	10.6%	
OpenIE6	53.1%	5.5%	10.0%	
PathIE	50.8%	31.7%	39.1%	
PathIE Stanza	51.1%	30.9%	38.5%	
Workshop Best Precision [22]	90.5%	80.8%	85.4%	
Workshop Best Recall [22]	86.1%	86.2%	86.1%	

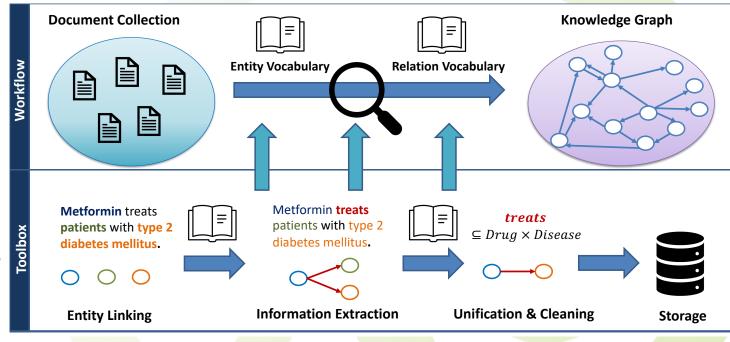
TABLE IV

BIOCREATIVE VI CHEMPROT EVALUATION [25]. THE TABLE REPORTS THE EXTRACTION QUALITY FOR OPENIE, PATHIE AND BASELINES.

Method	Quality			
	Prec.	Rec.	F1	
CoreNLP OpenIE	59.3%	5.1%	9.3%	
OpenIE6	55.9%	6.2%	11.1%	
PathIE	30.3%	55.3%	39.1%	
PathIE Stanza	29.4%	56.6%	38.7%	
Sentence Co-Mention [25]	4.4%	98.0%	0.08%	
Workshop Best Precision [25]	74.4%	55.3%	63.4%	
Workshop Best Recall [25]	56.1%	67.8%	61.4%	
BioBERT [13]	77.0 %	75.9%	76.5%	



- Supervised entity linking and information extraction outperform our toolbox
 - But they require a cost-intensive acquisition of domain-specific training data
- Our toolbox bypasses the need of training data but requires two vocabularies
 - Thus, the **toolbox** can **enable**workflows which are otherwise too cost-intensive to concern





Thank You!







If you have any questions, contact me via:



kroll@ifis.cs.tu-bs.de



@HermannKroll