Open Information Extraction

Dominik Both, Tonio Weidler

Proseminar *Text Mining*
Andrea Zielinski

Institut für Computerlinguistik, Universität Heidelberg, 15.07.2016

Papers

Identifying Relations for Open Information Extraction (Fader et al., 2011)

LODifier: Generating Linked Data from Unstructured Text (Augenstein et al., 2012)

Strukturierung

Introduction to Information Extraction

What is Information Extraction?

Information Extraction

Goal of Information Extraction is automatically extracting information from unseen text
Information: entities, relations, events...

To make the dough for a good pizza, we start with putting 1kg of flour into the mixing bowl.
(1kg of flour, put into, mixing bowl)

Problems of Information Extraction

- Named Entity Recognition
- Relationship Extraction
- Coreference Resolution
- Comment Extraction
- many more..

OIE - Principles

OIE - Principles

Open Information Extraction

Open Information Extraction

IE: Extractor for each target relation

Open: No pre-specified extractors

Unsupervised learning of relation phrases

Extraction of information on every given domain

Problems of Open Information Extraction

- **Incoherent extractions:**
  This guide contains dead links and omits sites
  contains omits
- **Uninformative extractions:**
  Faust made a deal with the devil
  (Faust, made, a deal)

OIE - Principles

Methods

Text Runner and WOE

1. *Label:* Automatic sentence labeling by heuristics
2. *Learn:* A relation phrase extractor is learned
3. *Extract:* Identifying NP pairs and searching relations words between

Problems

- Large number of labeled training examples required
- Alternative heuristic labeling leads to huge noise and stacked uncertainty
- Ignores both holistic and lexical aspects

Syntactic constraint

- Limits relations to those matching a certain POS Tag pattern:
- Always choses longest possible match
- Merge ajacent matches together

V | V P | VW* P

V = verb particle? adv?
W = (noun | adj | adv | pron |det)
P = (prep | particle | inf. marker)

Faust made a deal with the devil

Lexical constraint

- Only assume relations that appear in the corpus for a certain amount
- The Obama administration **is offering only modest greenhouse gas reduction targets at** the conference

Limitations of those constraints

- In a set of 300 hand-annotated sentences 85% relations fell into those constraints
- Model is not complete and has its flaws
- Of all relation phrases in the gold standard:
  - 85% satisfied constraints and were found
  - 8% Non-contiguous phrase structure
    Coordination: X is produced and maintained by Y
    Multiple Args: X was founded in 1995 by Y
    Phrasal Verbs: X turned Y off
  - 4% Relation phrase not between arguments
    Introductions: Discovered by Y, X ...
    Relative Cl.: ... the Y that X discovered
  - 3% Not matching POS pattern
    Interrupting Modifiers: X has a lot of faith in Y
    Infinitives: X to attack Y

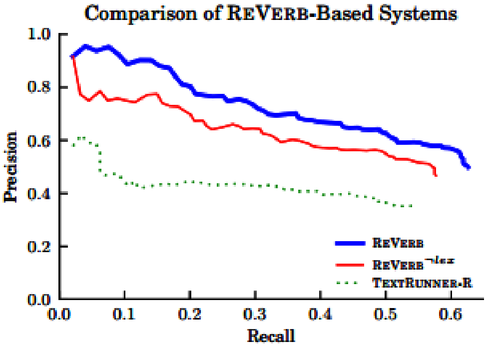
ReVerb Extraction Algorithm

- *Relation Extraction:* Find the longest possible string of words that match the relation constraints, merge adjacents
- *Argument Extraction:* Find the nearest NP left and right to the relation that is not a relativ pronoun, WHO-adverb or existential-there.
- How is the lexical constraint being checked? By creating a list of relational phrases by applying this algorithm on a 500 million Web sentences.

ReVerb Confidence Function

- The Algorithm has a high recall, but low precision
- Now the extracted relation is weighted by a confidence function:
  Examples:
  - 1.16 (x, r, y) covers all words in s
  - 0.50 The last preposition in r is for
  - 0.43 len(s) under 10
  - -0.65 There is a preposition to the left of x in s
  - ...

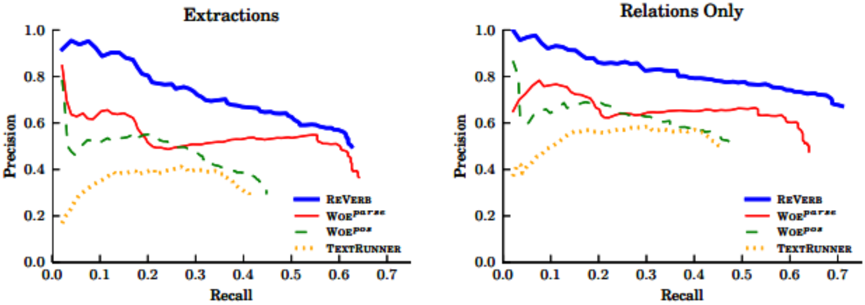
Evaluation



Better results than TextRunner through lexical features, but still low recall.

Source: Fader et al., 2011

Why?



Argument extraction is open to improvements

Source: Fader et al., 2011

Why?

Evaluating the evaluation:

ReVerb - Incorrect Extractions	
65%	Correct relation phrase, incorrect arguments
16%	N-ary relation
8%	Non-contiguous relation phrase
2%	Imperative verb
2%	Overspecified relation phrase
7%	Other, including POS/chunking errors

ReVerb - Missed Extractions	
52%	Could not identify correct arguments
23%	Relation filtered out by lexical constraint
17%	Identified a more specific relation
8%	POS/chunking error

Source: Fader et al., 2011

Conclusion

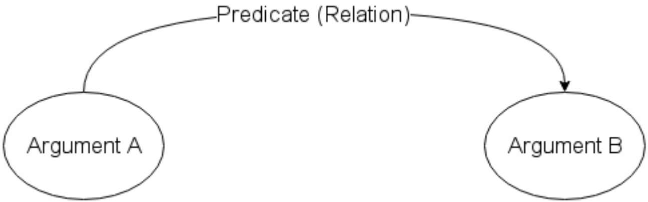
Acceptable results on easy sentences. Fails on more complex sentences. *Possible points of improvement:*

- Does not support n-ary relations
- Relations seem overly specific in many results
- Coordination is not in all cases correctly recognized
- Coreference is not predetected by the system
- Syntactic fixation on S-V-O word order

OIE - Principles

Data Representation

Standard Patterns



Argument A is in a directed **relation** to **Argument B**.

Unnormalized Annotation

(argument_a, predicate_x, argument_b)
(argument_a, predicate_y, argument_c)
(argument_a, predicate_y, argument_d)

Problems

- redundant
- unnormalized
- can only produce binary predicates

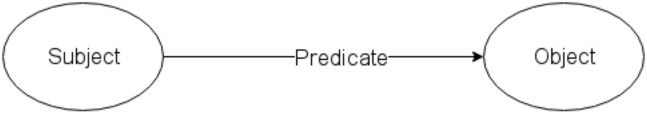
RDF and Linked Data

Resource Description Framework

Models propositions by constructing *triples* including **Subjects**, **Objects** and **Predicates**

Generates a directed graph

:subject :predicate :object.



RDF Concepts and Notation

- **URIs**
  identifies ressources (S, R, O) distinctivly and references further informations (triples)
- **Conclusions**
  allows to draw conclusions using rules
- **Turtle**
  allows syntax abbreviations
- **Blanknodes**
  placeholder for something without a URI
- **Queries**
  can be searched by querying (eg SPARQL)

RDF Reification

Motivation: How can I realize embedded propositions?

Example: Peter said, he watched the movie.

RDF Reification

Motivation: How can I realize embedded propositions?

Example: Peter said, he watched the movie.

Wrong proposition

:Peter :watched :movie

RDF Reification

Motivation: How can I realize embedded propositions?

Example: Peter said, he watched the movie.

Reification

:Peter :said _:prop.
_:prop rdf:subject :Peter.
_:prop rdf:predicate :watched.
_:prop rdf:object :movie.

Vocabularies & Ontologies

Several vocabularies provide useful relations and functionality, eg.:

- RDF (rdf:type, ...)
- RDFS (rdfs:subClassOf, rdfs:domain, rdfs:range, ...)
- OWL (owl:sameAs, owl:SymmetricProperty, ...)
- FOAF

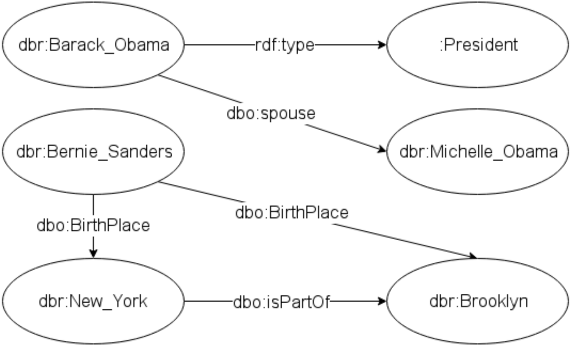
Ontologies are huge RDF Graphs containing many triples, eg.:

- DBpedia
- Wikidata
- WordNet

RDF Syntax

```
dbr:Barack_Obama a foaf:person, :President;
    dbo:spouse dbr:Michelle_Obama.
dbr:Bernie_Sanders dbo:birthPlace dbr:New_York,
                                  dbr:Brooklyn;
dbr:Brooklyn dbo:isPartOf dbr:New_York
```

... as Graph


dbr:Barack_Obama
rdf:type
:President
dbo:spouse
dbr:Bernie_Sanders
dbr:Michelle_Obama
dbo:BirthPlace
dbo:BirthPlace
dbr:New_York
dbo:isPartOf
dbr:Brooklyn

Example: LODifier

LODifier: Generating Linked Data from Unstructured Text (Augenstein et al., 2012

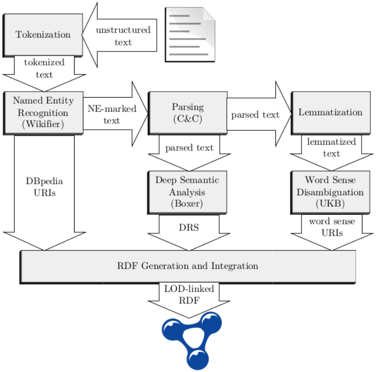
Generate an RDF Graph from unstructured Text

Past Approaches: Use Patterns to trade recall for precision
LODifier: Process the entire text

Example: LODifier

Architecture

Architecture



(Augenstein et al., 2012)

Approach

1. **Parse** the input text (POS, Treetagging, NER)
2. Apply **Deep Semantic Analysis** to get relations
3. Enrich NEs and words with **URIs** (DBpedia and WordNet)
4. Forge an **RDF Graph** of this information

How does it happen?

Lets go through the process step-by-step!

Example Text:
The New York Times reported that John McCarthy died. He invented the programming language LISP.
example taken from Augenstein et al., 2012

Example: LODifier

Preprocessing

Named Entity Recognition - Wikifier

Wikifier

Recognizes NE and replaces them with the Wikipedia Page Link
Disambiguates by comparing links between pages.

Example Text Output:
[The New York Times] reported that [John McCarthy (computer scientist)|John McCarthy] died. He invented the [Programming language|programming language] [Lisp (programming language)|LISP].

Parsing Syntax - C&C

C&C Parser

Syntactical Parser that tags POS and builds Parse Trees in CCG.

Combinatory Categorial Grammar (CCG)

Grammatical formalism allows parallel analysis of syntax and semantics

Associates words with categories that can be combined (rule-based) to form a sentence

Syntax via Category Combination, Semantics via lambda calculus

Parsing - Output

```
ccg(1, rp(s:dcl,
    ba(s:dcl,
      lx(np, n,
        t(n, 'The_New_York_Times', 'The_New_York_Times', 'NNS', 'I-NP', 'O')),
      fa(s:dcl\np,
        t((s:dcl\np)/s:em, 'reported', 'report', 'VBD', 'I-VP', 'O'),
        fa(s:em,
          t(s:em/s:dcl, 'that', 'that', 'IN', 'I-SBAR', 'O'),
          ba(s:dcl,
           lx(np, n,
             t(n, 'John_McCarthy', 'John_McCarthy', 'NNP', 'I-NP', 'I-PER')),
           t(s:dcl\np, 'died', 'die', 'VBD', 'I-VP', 'O')))))),
    t(period, '.', '.', '.', 'O', 'O'))).
ccg(2, rp(s:dcl,
    ba(s:dcl,
      t(np, 'He', 'he', 'PRP', 'I-NP', 'O'),
      fa(s:dcl\np,
        t((s:dcl\np)/np, 'invented', 'invent', 'VBD', 'I-VP', 'O'),
        fa(np:nb,
          t(np:nb/n, 'the', 'the', 'DT', 'I-NP', 'O'),
          fa(n,
            t(n/n, 'programming_language', 'programming_language', 'NN', 'I-NP', 'O'),
            t(n, 'LISP', 'LISP', 'NNP', 'I-NP', 'O')))))),
    t(period, '.', '.', '.', 'O', 'O'))).
```

Find Relations - Boxer

Boxer

Creates DRSs from C&C Output

Find Relations - Boxer

Boxer

Creates DRSs from C&C Output

Discours Representation Structure (DRS)

Represents the discourse via *relations* between *entities*
Allows referencing over the entire discourse

Find Relations - Boxer

Boxer

Creates DRSs from C&C Output

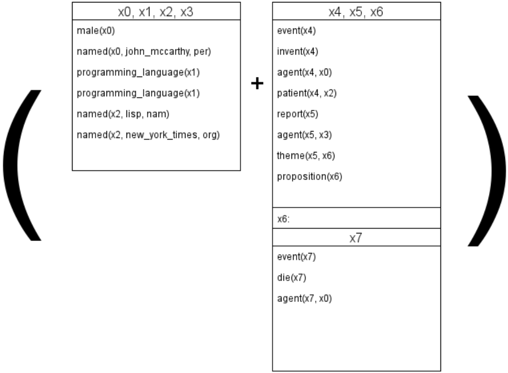
Discours Representation Structure (DRS)

Represents the discourse via *relations* between *entities*
Allows referencing over the entire discourse

Boxers DRS Relations (Conditions):

- **Unary Relations (Classes):** eg. *topic*, *person*, *event*, *male*, ... + all verbs
- **Binary Relations:** agent, patient, ... (semantic roles)

Boxer Output



Assign WordNet URIs

RDF WordNet

WN: Lexicography containing senses linked by semantic relations
RDF WN: LD Representation of WN providing URIs for words

Steps:

1. Lemmatization
2. WSD (UKB)
3. Assign RDF WN URIs to word senses

Preprocessing Result

We now have ...

- URIs for all NEs
- URIs for all (disambiguated) words
- Relations between entities (those URIs)

Example: LODifier

RDF Construction

What now?

Let's now construct the RDF Graph from this information!

Namespaces/Vocabularies

LODifier introduces several namepaces:

- **drsclass:** contains Boxer classes (event, person, ...) and :named relation
- **drsrel:** contains Boxer relations (agent, patient, ...)
- **ne:** contains the named entity URIs
- **reify:** reification (embedding propositions into propositions)

Namespaces/Vocabularies

And uses standard namespaces:

- **rdf:** mainly for rdf:type and reification
- **owl:** for owl:sameAs

Namespaces/Vocabularies

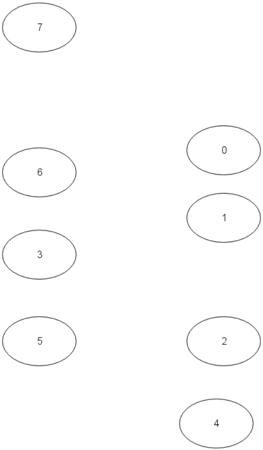
Finally the two ontologies:

- **wn30:** contains all WordNet URIs
- **dbpedia:** contains the dbpedia URIs
- **class:** contains classes not in wn30 nor in dbpedia

RDF Construction Strategy I

Create a blanknode _:*x* for each discourse referent (x0, x1, ...)

RDF Construction Strategy II

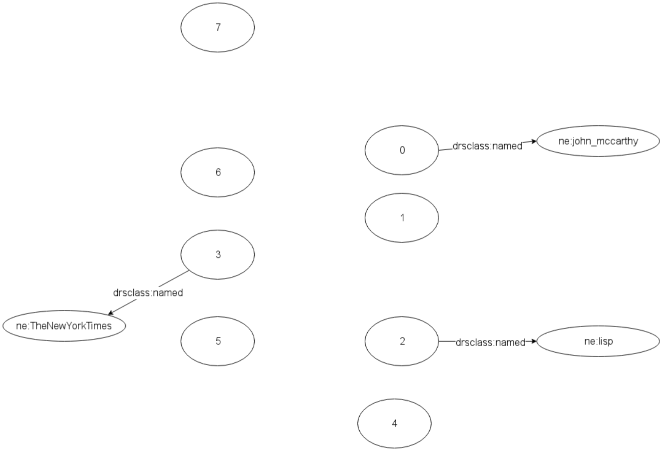


RDF Construction Strategy III

if NE, then create

_ *:x drsclass:named ne:URI*

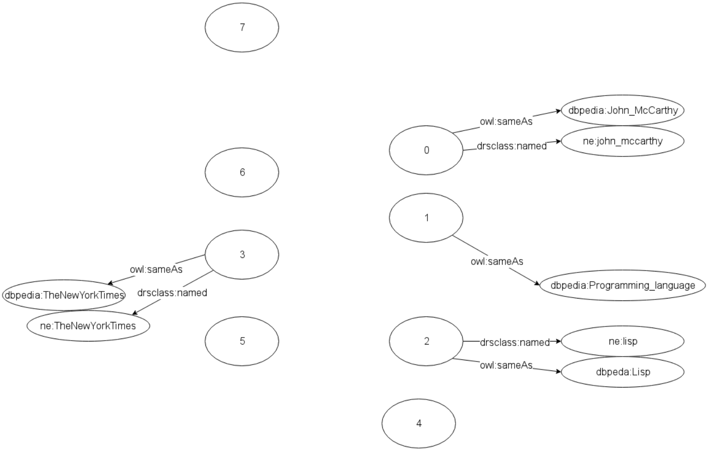
RDF Construction Strategy IV



RDF Construction Strategy V

if NE and DBpedia URI exists create
_:x owl:sameAs dbpedia:URI

RDF Construction Strategy VI

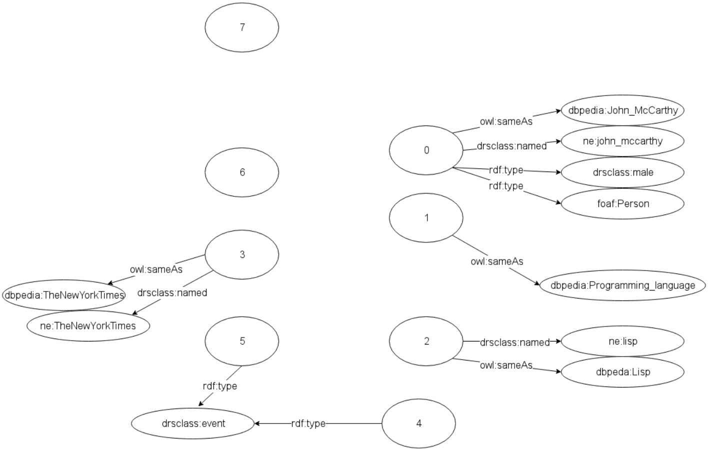


RDF Construction Strategy VII

via rdf:type assign closed classes (event, person, ...)

_:x rdf:type drsclass:CLOSEDCLASS

RDF Construction Strategy VIII

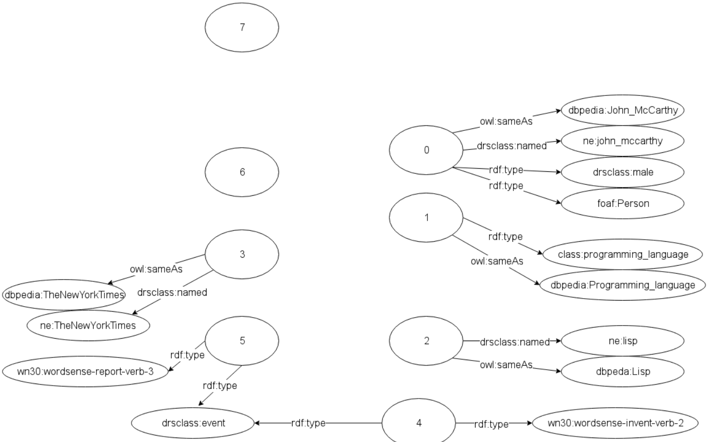


RDF Construction Strategy IX

via rdf:type assign open classes (die, programming_language, ...)

_:x rdf:type wn30:OPENCLASS, class:OPENCLASS

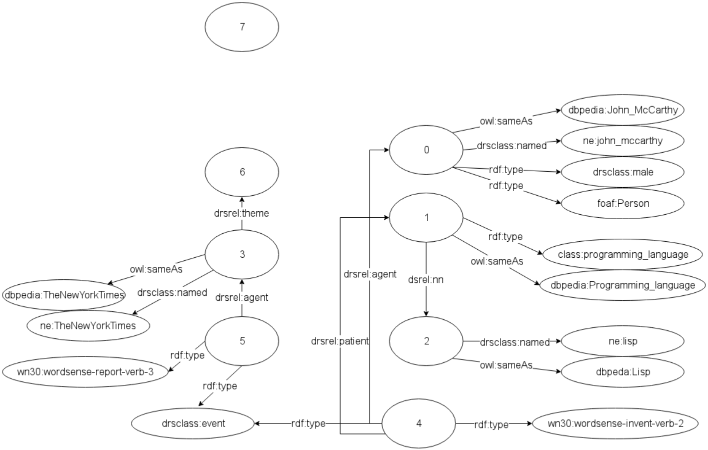
RDF Construction Strategy X



RDF Construction Strategy XI

create triples from binary relations (agent, theme, ...)
_:x drsrel:RELATION _:y

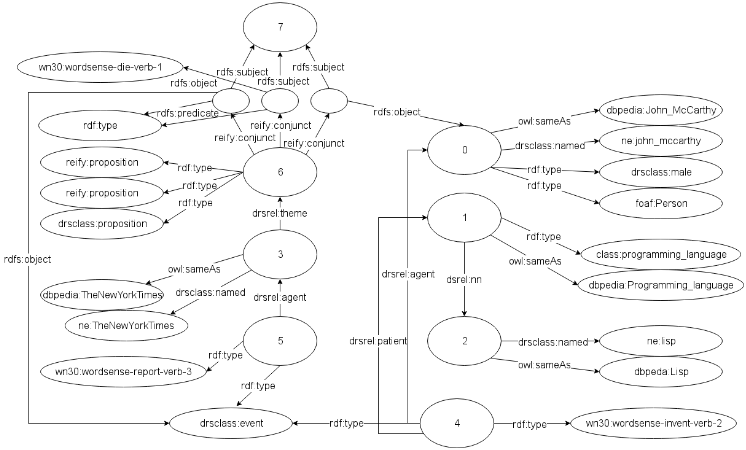
RDF Construction Strategy XII



RDF Construction Strategy XIII

recursive reification of embedded propositions (eg. by *report* or *says)*

RDF Construction Strategy XIV



RDF Construction: Output

```
_:var0x0 drsclass:named ne:john_mccarthy ;
         rdf:type drsclass:male , foaf:Person ;
         owl:sameAs dbpedia:John_McCarthy_(computer_scientist) .
_:var0x1 rdf:type class:programming_language ;
         owl:sameAs dbpedia:Programming_language .
_:var0x2 drsrel:nn _:var0x1 .
_:var0x2 drsclass:named ne:lisp ;
         owl:sameAs dbpedia:Lisp_(programming_language) .
_:var0x3 drsclass:named ne:the_new_york_times ;
         owl:sameAs dbpedia:The_New_York_Times .
_:var0x4 rdf:type drsclass:event , wn30:wordsense-invent-verb-2 .
         drsrel:agent _:var0x0 ; drsrel:patient _:var0x2 .
_:var0x5 rdf:type drsclass:event , wn30:wordsense-report-verb-3 ;
         drsrel:agent _:var0x3 ; drsrel:theme _:var0x6 .
_:var0x6 rdf:type drsclass:proposition , reify:proposition , reify:conjunction ;
         reify:conjunct [ rdf:subject _:var0x7 ;
                          rdf:predicate rdf:type ;
                          rdf:object drsclass:event . ]
         reify:conjunct [ rdf:subject _:var0x7 ;
                          rdf:predicate rdf:type ;
                          rdf:object wn30:wordsense-die-verb-1 . ]
         reify:conjunct [ rdf:subject _:var0x7 ;
                          rdf:predicate drsrel:agent ;
                          rdf:object _:var0x0 . ]
```

Example: LODifier

Experiments

Method

- Evaluate by testing similarity of two given documents:
- *the problem of deciding whether two randomly selected stories discuss the same news topic* (Augenstein et al., 2012)
- TDT-2 benchmark dataset: 84.000 news documents
- Extract 183 positive and 183 negative pairs (avg. 11.2 per topic)
- Calculate similarity and evaluate the system on the result

Similarity measurements

1. NEs identified by Wikifier and sucessfully disambiguated words in UKB
2. add NEs recognized by Boxer
3. add URIs of unrecognized words

Further add structural features: Measurement of the similarity of the RDF graphs of the two document

Accuracy

Model	normal	extended
Similarity measures without structural knowledge		
Random Baseline	50.0	–
Bag of Words	63.0	–
Bag of URIs (Variant 1)	61.6	75.1
Bag of URIs (Variant 2)	70.6	76.0
Bag of URIs (Variant 3)	**73.4**	**76.4**
Similarity measures with structural knowledge		
$\text{proSim}_{\text{cnt}}$ (k=8, Variant 1)	77.7	77.6
$\text{proSim}_{\text{cnt}}$ (k=8, Variant 2)	79.2	79.0
$\text{proSim}_{\text{cnt}}$ (k=8, Variant 3)	**82.1**	**81.9**

Source: Augenstein et al., 2012

Precision - Recall

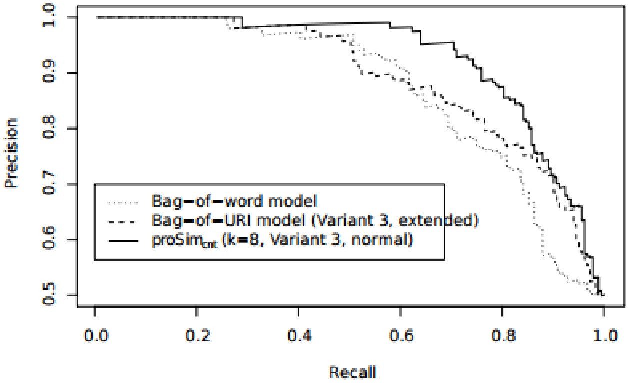


Fig. 5. Precision-Recall-plot for best Story Link Detection models

Example: LODifier
Conclusions

What to draw from this?

- deep sementic analysis can work for OIE
- combining several existing NLP Systems provides a well functioning extraction system
- information gained by unsupervised OIE can already improve real world tasks

What we liked

- full-text OIE

What we liked

- full-text OIE
- uses many strengths of RDF

What we liked

- full-text OIE
- uses many strengths of RDF
- relations arent overspecified

What we liked

- full-text OIE
- uses many strengths of RDF
- relations arent overspecified
- extendable/improvable by improving/swapping Systems in the architecturesh

What we liked

- full-text OIE
- uses many strengths of RDF
- relations arent overspecified
- extendable/improvable by improving/swapping Systems in the architecturesh
- part of the LOD-Cloud

What we liked

- full-text OIE
- uses many strengths of RDF
- relations arent overspecified
- extendable/improvable by improving/swapping Systems in the architecturesh
- part of the LOD-Cloud
- results in standardized notation

What we liked

- full-text OIE
- uses many strengths of RDF
- relations arent overspecified
- extendable/improvable by improving/swapping Systems in the architecturesh
- part of the LOD-Cloud
- results in standardized notation
- domain-independent

What we didnt like

- Redundant processes like NER

What we didnt like

- Redundant processes like NER
- BlankNode Massacre

What we didnt like

- Redundant processes like NER
- BlankNode Massacre
- confusing boxer relations not simplified for RDF (will be hard to search through)

What we didnt like

- Redundant processes like NER
- BlankNode Massacre
- confusing boxer relations not simplified for RDF (will be hard to search through)

- Paper scratches only the surface of the system

What we didnt like

- Redundant processes like NER
- BlankNode Massacre
- confusing boxer relations not simplified for RDF (will be hard to search through)

- Paper scratches only the surface of the system
- Some points are unclear / not even described

Conclusion

Weaknesses and Strengths of OIE

- trades precision for recall

Weaknesses and Strengths of OIE

- trades precision for recall
- OIE > IE if no sepcial task/domain is defined

Weaknesses and Strengths of OIE

- trades precision for recall
- OIE > IE if no sepcial task/domain is defined
- theory independent

Weaknesses and Strengths of OIE

- trades precision for recall
- OIE > IE if no sepcial task/domain is defined
- theory independent
- relations may be redundant/overspecified/unintended

Weaknesses and Strengths of OIE

- trades precision for recall
- OIE > IE if no sepcial task/domain is defined
- theory independent
- relations may be redundant/overspecified/unintended
- restricted usability of results due to low precision

Future Opportunities

- better subsystems

Future Opportunities

- better subsystems
  - Coreference Resolution

Future Opportunities

- better subsystems
  - Coreference Resolution
  - NER

Future Opportunities

- better subsystems
  - Coreference Resolution
  - NER
  - Disambiguation

Future Opportunities

- better subsystems
  - Coreference Resolution
  - NER
  - Disambiguation
- improve semantic analysis

References I

A. Fader, S. Soderland, O. Etzioni. Identifying relations for open information extraction. Proc. of the Conf. on Empirical Methods in Natural Language, 2011

Augenstein, Isabelle, Sebastian Padó, and Sebastian Rudolph. Lodifier: Generating linked data from unstructured text.The Semantic Web: Research and Applications. Springer Berlin Heidelberg, 2012. 210-224.

References II

James R. Curran, Stephen Clark, and Johan Bos. 2007. Linguistically motivated large-scale NLP with C&C and boxer. In Proceedings of the 45th Annual Meeting of the ACL on Interactive Poster and Demonstration Sessions (ACL '07). Association for Computational Linguistics, Stroudsburg, PA, USA, 33-36.

Unpublished draft of Andreas Harths Linked Data"Book (Version February 2016) as provided in his Linked Data lecture at Heidelberg University.