Open Information Extraction

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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:
- V | V P | VW* P
- Always choses longest possible match
- Merge ajacent matches together

$$V \mid V P \mid V W^{*} P$$

$$V = \text{verb particle? adv?}$$

$$W = (\text{noun} \mid \text{adj} \mid \text{adv} \mid \text{pron} \mid \text{det})$$

$$P = (\text{prep} \mid \text{particle} \mid \text{inf. marker})$$

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

	Binary Verbal Relation Phrases
85%	Satisfy Constraints
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
	Intro. Phrases: Discovered by Y, X ...
	Relative Clauses: ...the Y that X discovered
3%	Do Not Match 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.

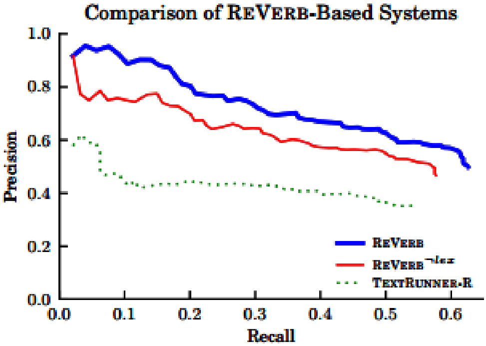
ReVerb Confidence Function

- The Algorithm has a high recall, but low precision
- Now the extracted relation is weighted by a confidence function:

ReVerb Confidence Function

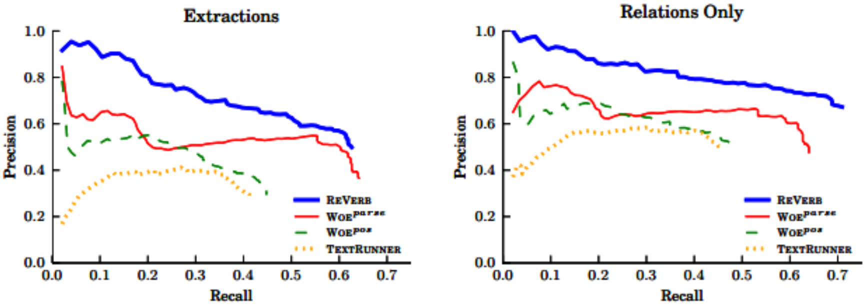
Weight	Feature
1.16	(x, r, y) covers all words in s
0.50	The last preposition in r is *for*
0.49	The last preposition in r is *on*
0.46	The last preposition in r is *of*
0.43	$len(s) \leq 10$ words
0.43	There is a WH-word to the left of r
0.42	r matches VW*P from Figure 1
0.39	The last preposition in r is *to*
0.25	The last preposition in r is *in*
0.23	10 words $< len(s) \leq 20$ words
0.21	s begins with x
0.16	y is a proper noun
0.01	x is a proper noun
-0.30	There is an NP to the left of x in s
-0.43	20 words $< len(s)$
-0.61	r matches V from Figure 1
-0.65	There is a preposition to the left of x in s
-0.81	There is an NP to the right of y in s

Evaluation



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

Why?



Argument extraction is open to improvements

Why?

Evaluating the evaluation:

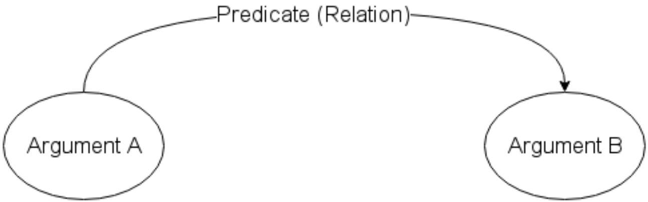
ReVerb - Incorrect Extractions	
65%	Correct relation phrase, incorrect arguments
16%	N-ary relation
8%	Non-contiguous relation phrase
2%	Imperative verb
2%	Overspecified relation phrase
7%	Other, including POS/chunking errors

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

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

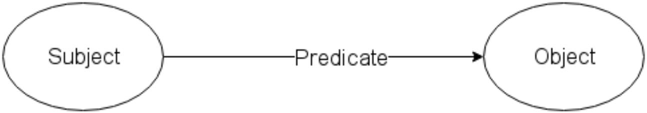
- redundant
- unnormalized
- can only produce binary predicates

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

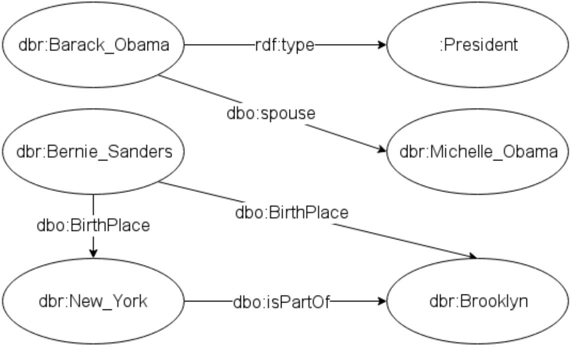
Ontologies are huge RDF Graphs containing many triples, eg.:

- 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

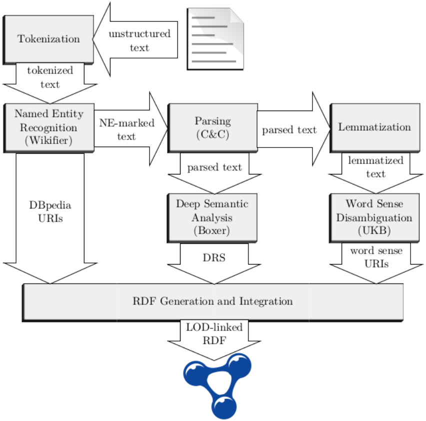
LODifier: Generating Linked Data from Unstructured Text (Augenstein et al., 2012

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



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 (CCG).

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

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Boxer

Creates DRSs from C&C Output

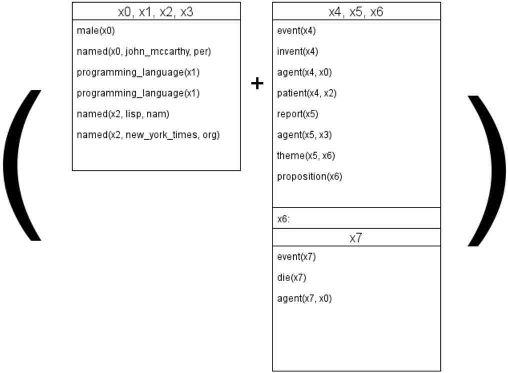
Discours Representation Structure (DRS)

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

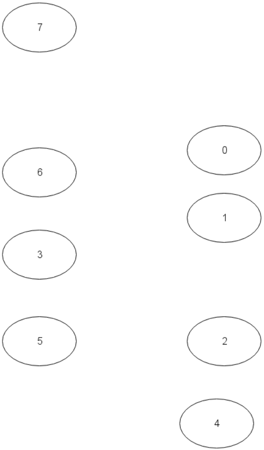
Finally the two ontologies:

- **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, ...)

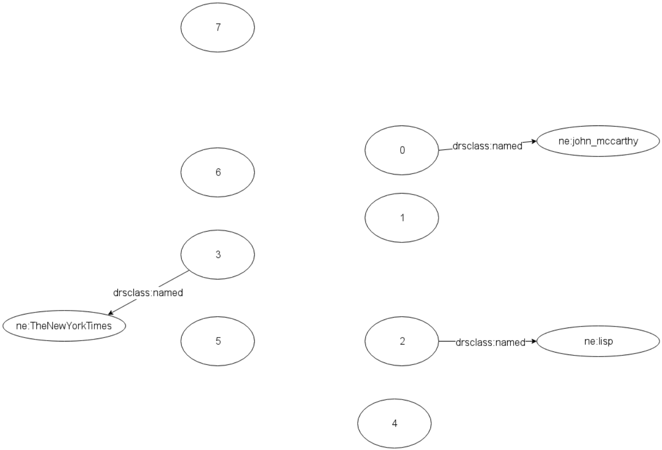
RDF Construction Strategy II



RDF Construction Strategy III

if NE, then create
_:x drsclass:named ne:URI

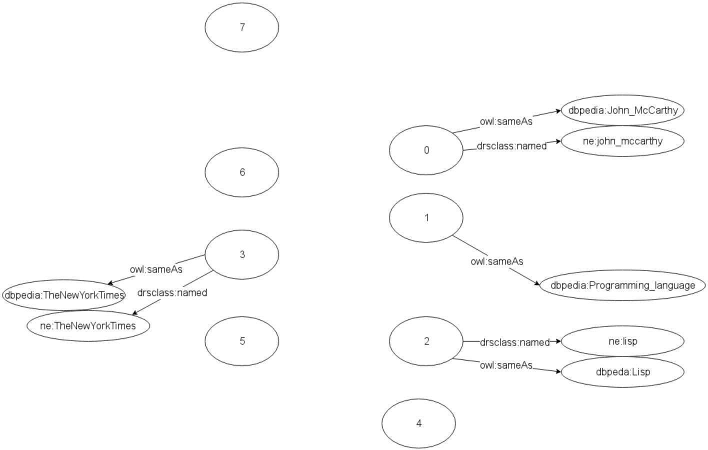
RDF Construction Strategy IV



RDF Construction Strategy V

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

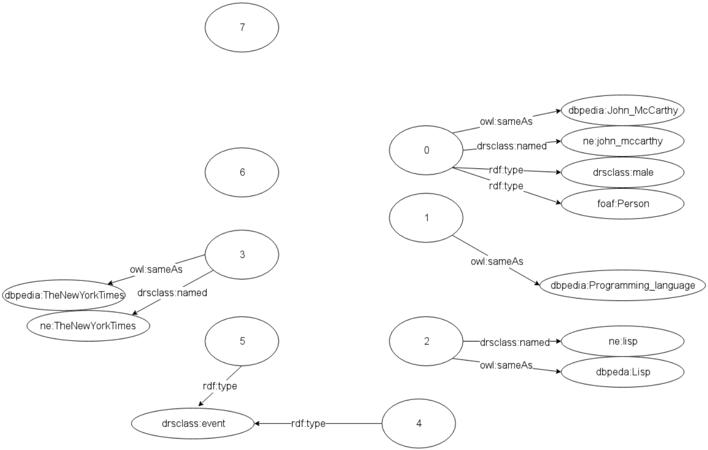
RDF Construction Strategy VI



RDF Construction Strategy VII

via rdf:type assign closed classes (event, person, ...)
_:x rdf:type drsclass:CLOSEDCLASS

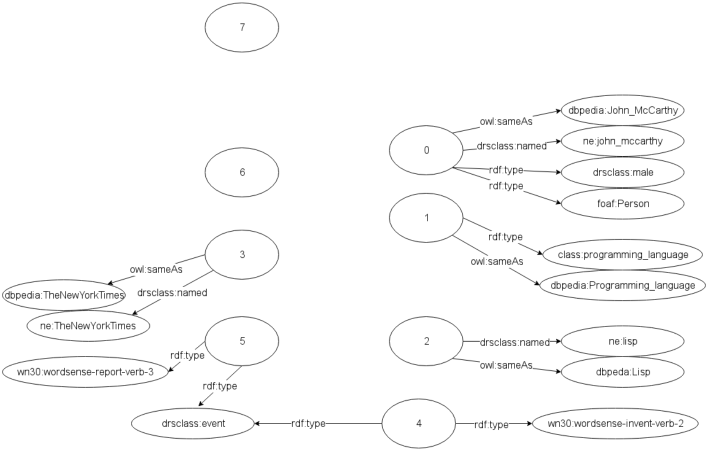
RDF Construction Strategy VIII



RDF Construction Strategy IX

via rdf:type assign open classes (die, programming_language, ...)
_:x rdf:type wn30:OPENCLASS, class:OPENCLASS

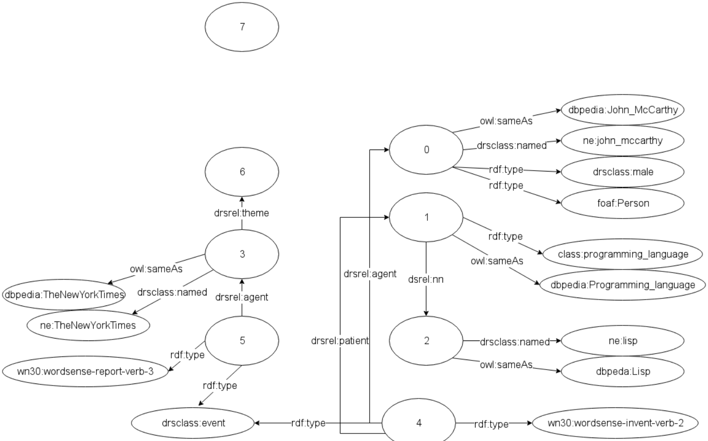
RDF Construction Strategy X



RDF Construction Strategy XI

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

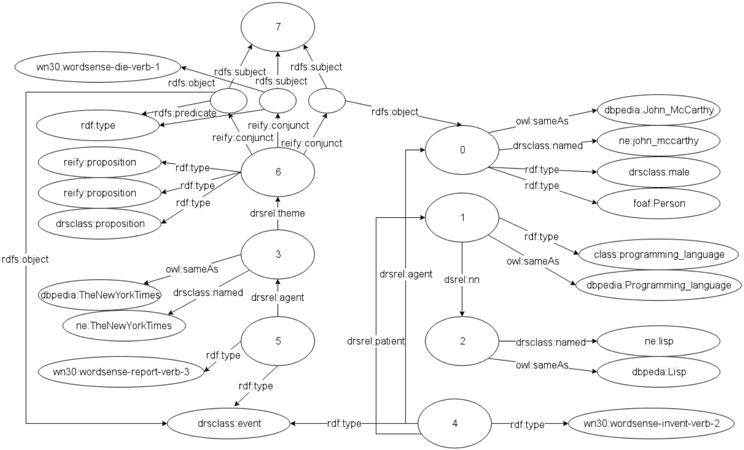
RDF Construction Strategy XII



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

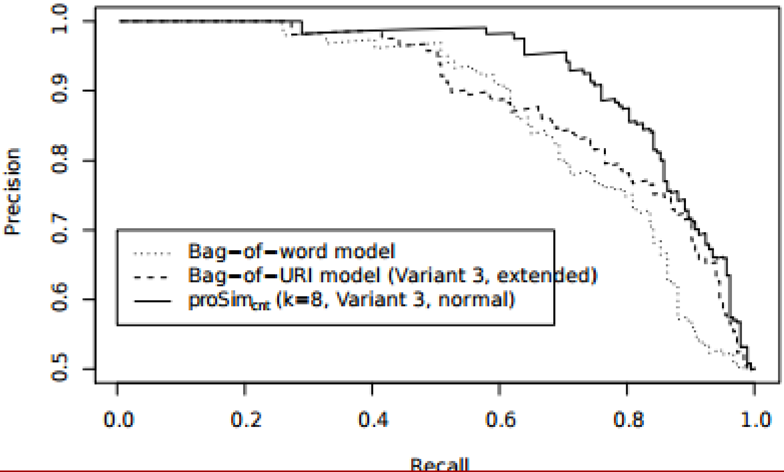
- TDT-2 benchmark dataset: 84.000 news documents

Accuracy

Table 1. Accuracy on Story Link Detection Task

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=6, Variant 1)	79.0	78.9
$\text{proSim}_{\text{cnt}}$ (k=6, Variant 2)	80.3	80.3
$\text{proSim}_{\text{cnt}}$ (k=6, Variant 3)	81.6	81.6
$\text{proSim}_{\text{cnt}}$ (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**
$\text{proSim}_{\text{len}}$ (k=6, Variant 3)	81.5	81.4
$\text{proSim}_{\text{len}}$ (k=8, Variant 3)	80.3	80.1
$\text{proSim}_{\text{len}}$ (k=10, Variant 3)	80.0	79.8
$\text{proSim}_{\text{sqlen}}$ (k=6, Variant 3)	80.4	80.4
$\text{proSim}_{\text{sqlen}}$ (k=8, Variant 3)	81.1	80.9
$\text{proSim}_{\text{sqlen}}$ (k=10, Variant 3)	80.5	80.4

Precision - Recall



Example: LODifier

Conclusions

What to draw from this?

What we liked

- full-text OIE
- relations arent overspecified
- TO BE EXTENDED

What we didnt like

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

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

OIE Systems in Context

OIE Systems in Context

Comparison

OIE Systems in Context

Evaluating the Approaches

Conclusion

Conclusion

Problems and Obstacles

Conclusion

Future Opportunities