### Open Information Extraction

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#### Strukturierung

- Introduction to Information Extraction
- OIE Principles
- 3 Example: LODifier
- 4 OIE Systems in Context
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# Introduction to Information Extraction

#### What is 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

Open Information Extraction

## OIE - Principles Open Information Extraction

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)

Methods

### 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

Methods

#### 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 VP \mid VW^*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

Methods

#### 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.

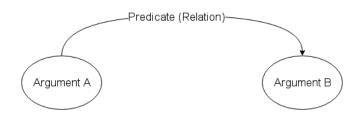
#### ReVerb Confidence Function

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

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	$len(s) \le 10$ 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	$10 \text{ words} < len(s) \le 20 \text{ words}$
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
-0.93	Coord. conjunction to the left of $r$ in $s$

## 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**

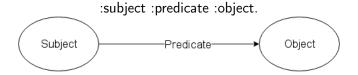
- redundant
- unnormalized
- can only produce binary predicates

#### RDF and Linked Data

#### Resource Description Framework

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

Generates a directed graph



#### 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
- Queries can be searched by querying (eg SPARQL)

#### Vocabularies & Ontologies

Several vocabularies provide useful relations and functionality, eg.:

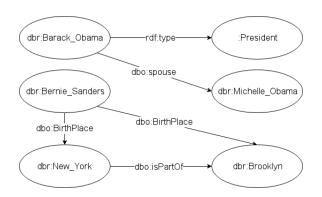
- RDF (rdf:type, ...)
- RDFS (rdfs:subClassOf, rdfs:domain, rdfs:range, ...)
- OWL (owl:sameAs, owl:SymmetricProperty, ...)
- FOAF

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

- DBpedia
- Wikidata
- WordNet

#### RDF Syntax

#### ... as Graph



### Example: LODifier

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

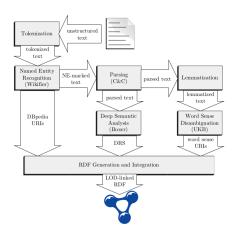
Generate an RDF Graph from unstructured Text

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)
- 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', '0')),
     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', '0'),
          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', '0'))))),
    t(period, '.', '.', '.', '0', '0'))).
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', '0'),
       fa(np:nb.
          t(np:nb/n, 'the', 'the', 'DT', 'I-NP', '0'),
         fa(n.
            t(n/n, 'programming_language', 'programming_language', 'NN', 'I-NP', '0'),
            t(n, 'LISP', 'LISP', 'NNP', 'I-NP', '0')))),
    t(period, '.', '.', '.', '0', '0'))).
```

#### Find Relations - Boxer

Boxer

Creates DRSs from C&C Output

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### Discours Representation Structure (DRS)

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

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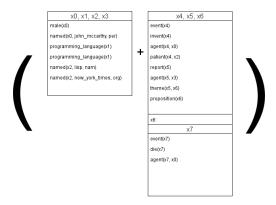
#### Discours Representation Structure (DRS)

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:

- Lemmatization
- 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

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

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- Create a blanknode \_:x for each discourse referent (x0, x1, ...)
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- if NE and DBpedia URI exists create \_:x owl:sameAs dbpedia:URI

# RDF Construction Strategy

- 1 Create a blanknode \_ :x for each discourse referent (x0, x1, ...)
- if NE, then create :x drsclass:named ne:URI
- 3 if NE and DBpedia URI exists create
  - \_:x owl:sameAs dbpedia:URI
- via rdf:type assign closed classes (event, person, ...)
   \_:x rdf:type drsclass:CLOSEDCLASS

# RDF Construction Strategy II

via rdf:type assign open classes (die, programming\_language,
...)
:x rdf:type wn30:OPENCLASS, class:OPENCLASS

4日 → 4周 → 4 章 → 4 章 → 9 9 0

# RDF Construction Strategy II

- via rdf:type assign open classes (die, programming\_language,
  ...)
  \_:x rdf:type wn30:OPENCLASS, class:OPENCLASS

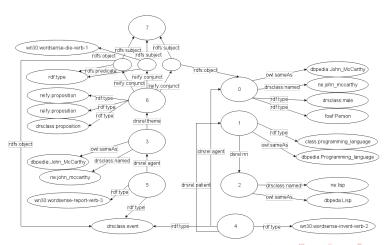
# RDF Construction Strategy II

- via rdf:type assign open classes (die, programming\_language,
  ...)
  - \_:x rdf:type wn30:OPENCLASS, class:OPENCLASS
- recursive reification of embedded propositions (eg. by report or says)

## 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 vork 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 ;
        reifv: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 . ]
         reifv:conjunct [ rdf:subject :var0x7 :
                          rdf:predicate drsrel:agent ;
                          rdf:object _:var0x0 . ]
```

## RDF Construction: Output as Graph



#### Experiments

Example: LODifier Experiments

•000

Conclusions

Example: LODifier Conclusions

0.00

Conclusions

What to draw from this?

0000

#### Conclusions

#### What we liked

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

0000

#### 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

Comparison

# OIE Systems in Context Comparison

Evaluating the Approaches

# OIE Systems in Context Evaluating the Approaches

# Conclusion

DE - Princip 000 00000000 00000000 Example: LODifier 0000 00000000 0000000

OIE Systems in Context

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Problems and Obstacles

# Conclusion Problems and Obstacles

**Future Opportunities** 

# Future Opportunities