Open Information Extraction

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Strukturierung

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

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 = verb particle? adv?
W = (noun | adj | adv | pron | det)
P = (prep | particle | 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

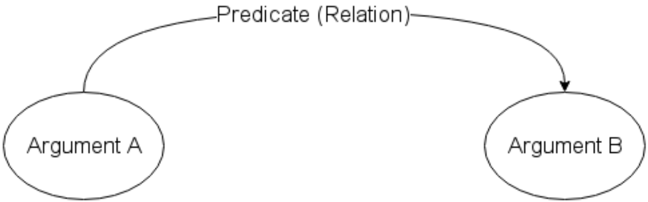
- The Algorithm has a high recall, but low precision
- Now the extracted relation is weighted by a confidence function:

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
-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

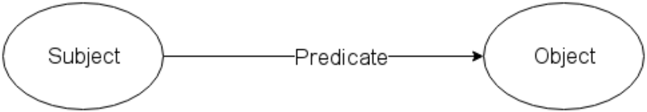
- redundant
- unnormalized
- can only produce binary predicates

RDF and Linked Data

Resource Description Framework

Models propositions by constructing *triples* including **Subjects**, **Objects** and **Predicates**
Generates a directed graph

: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
- **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

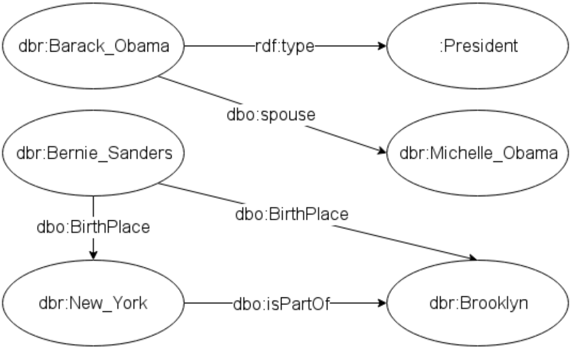
Ontologies are huge RDF Graphs containing many triples, eg.:

- DBpedia
- Wikidata
- WordNet

RDF Syntax

```
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

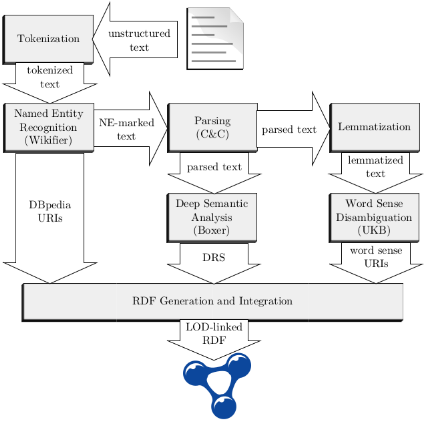
Generate an RDF Graph from unstructured Text

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

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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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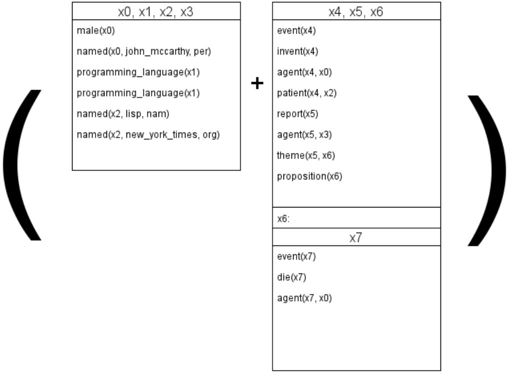
Boxers DRS Relations (Conditions):

- **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:**

Namespaces/Vocabularies

And uses standard namespaces:

- **rdf:** mainly for rdf:type
- **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

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

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RDF Construction Strategy

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

RDF Construction Strategy II

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

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

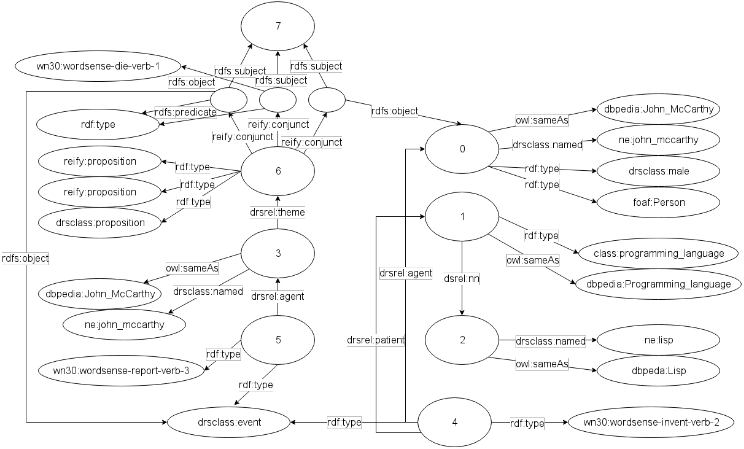
RDF Construction Strategy II

1. via rdf:type assign open classes (die, programming_language, ...)
   _:x rdf:type wn30:OPENCLASS, class:OPENCLASS
2. create triples from binary relations (agent, theme, ...)
   _:x drsrel:RELATION _:y
3. REIFY

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 . ]
```

RDF Construction: Output as Graph



Example: LODifier
Conclusions

OIE Systems in Context

OIE Systems in Context

Comparison

OIE Systems in Context

Evaluating the Approaches

Conclusion

Conclusion

Problems and Obstacles

Conclusion

Future Opportunities