Compact Open Information Extraction on Large Corpora

Kiril Gashteovski

University of Mannheim
Data and Web Science Group





Motivation

Making the knowledge from unstructured text more accessible



1

Open Information Extraction

• Extract relations and their arguments from unstructured text in unsupervised manner

"AT&T, which is based in Dallas, is a telecommunication company."



• Common problem: relations/arguments can be overly specific

```
("The great R. Feynman"; "worked jointly with"; "F. Dyson")

("Richard Feynman"; "worked with"; "Freeman Dyson")
```

MinIE - OIE system for minimizing and annotating facts

MinIE: Open Information Extraction System



https://github.com/uma-pi1/minie

MinIE: Minimize by Annotating and Structuring Information

- **Polarity:** is the triple positive (+) or negative (-)?
 - ("H. Clinton"; "is not president of"; "U.S.") ⇒ ("H. Clinton"; "is president of"; "U.S.") (-)
- Modality: is the triple a certainty (CT) or a possibility (PS)?
 - ("Bill Cosby"; "may go to"; "jail") ⇒ ("Bill Cosby"; "go to"; "jail") (PS)
- Attribution: consider the source of information
 - ("D. T."; "said that"; "B. O. may have been born in Kenya") ⇒
 ("B. Obama"; "have been born in"; "Kenya") (+, PS)
 Attribution: (Donald Trump, +, CT)
- Quantities: phrases expressing an amount of something
 - e.g. 9 cats, all cats, almost about 100 cats
 ⇒ QUANT cats

MinIE: Minimize by Dropping Overly Specific Words

```
("The great R. Feynman"; "worked jointly with"; "F. Dyson") ⇒
    ("Richard Feynman"; "worked with"; "Freeman Dyson")
```

- MinIE-S: drop words considered to be safe
 - determiners, adverbs modifying verbs, ...
 - e.g. "the President" ⇒ "President"
- MinIE-D: drop words modifying noun phrases
 - adjectives, adverbs, etc.
 - keep constituents that are found frequently in the corpus
 - additional fuel: enrich dictionary with domain knowledge
 - "very long cold war" ⇒ "cold war"
- MinIE-A: aggressive strategy of dropping of words
 - drop constituents (prepositional attachments, quantities, ...)
 - (J. Cleese; starred as Lancelot in national tour of; Spamalot) ⇒
 (John Cleese; starred in tour of; Spamalot)

MinIE: Comparative Analysis

	MinIE-S	MinIE-D	MinIE-A
precision ^w	0.73	0.72	0.60
precision ⁿ	0.79	0.77	0.68
triple length	7.2 ± 4.2	6.9 ± 4.0	4.7 ± 1.9
$(\mu \pm \sigma)$			

Applications of MinIE

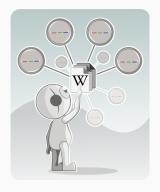
Fact saliance: "generate machine-readable representation of the most prominent info. in text document as a set of facts" (Ponza et al., 2018)

- Top-3 salient facts automatically extracted from a sample of two NYT documents
- Human Summary: Body of Toni Grossi Abrams, widow and Staten Island socialite, is found in warehouse on outskirts of Panama City, Panama, where she had moved to begin career in real estate; Debra Ann Ridgley, one of her tenants, is charged with stabbing Abrams to death in her apartment on April 9.

SallE:

- 1. (Abrams, had been stabbed to death in, apartment)
- 2. (Remains, were discovered beside warehouse at, edge of cinder-topped soccer field on outskirts of Panama City)
- 3. (Apartment, tending wounds at time of, murder)

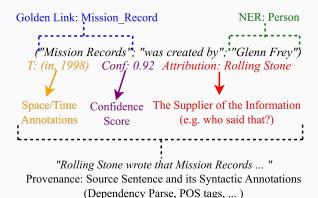
OPIEC: An Open Information Extraction Corpus



https://www.uni-mannheim.de/dws/research/resources/opiec/

OPIEC: An Open Information Extraction Corpus

- The **largest OIE corpus** to date (341M triples)
- Rich with meta-data: many syntactic/semantic annotations
- Ran MinIE-SpaTe on the entire English Wikipedia
 - the original **golden links** from a Wikipedia article are kept



OPIEC: Underspecific Triples



- Large portion of the triples are underspecific ($\sim 25\%$) ("he"; "founded"; "Microsoft") ("this"; "leads to"; "controversy")
- Entity mentions are broken up ($\sim 1\%$) ("Zip"; "Goes"; "a Million")

OPIEC-Clean



- Triple filters
 - entity mentions are broken up \rightarrow e.g. ("Zip"; "Goes"; "a Million")
 - triple has an empty object → e.g. ("Albert Einstein"; "died")
 - are underspecific → e.g. ("He"; "co-founded"; "Microsoft")
- Argument constraints
 - fully linked
 - recognized named entity (person, location, organization, ...)
 - matches a Wikipedia page title (e.g. Super Bowl, biology, ...)

OPIEC-Clean



PERSON-PERSON		LOCATION-LOCATION		PERSON-LOCATION	
"have" "marry"	(130,019) (49,405)	"be in" "have"	(2,126,562) (40,298)	"be bear in" "die in"	(203,091) (37,952)
"be son of"	(40,265)	"be village in adminis- trative district of"	(9,130)	"return to"	(36,702)
"be daughter of"	(37,089)	"be north of"	(3,816)	"move to"	(36,072)
"be bear to" "be know as"	(29,043) (25,607)	"be suburb of" "be west of"	(3,291) (3,238)	"be in" "live in"	(25,847) (22,399)
"defeat"	(22,151)	"be part of"	(3,188)	"grow up in"	(17,571)

Table 1: Most frequent open relations between persons and locations

OPIEC-Linked



Triples containing only linked arguments

Example



Analysis: OPIEC and KBs

- DBpedia and YAGO: KBs constructed from same resource as OPIEC (Wikipedia)
- KB hit: exploiting the distant supervision assumption
 - for each OIE triple: ("subject", "relation", "object")
 - search for any KB triple (db:subject, db:rel, db:object) or (db:object, db:rel, db:subject)
 - $\bullet~\sim\!30\%$ of OPIEC-Linked has KB hits in either DBpedia or YAGO
- Relation alignment: relation is aligned with db:rel
- Example:

 $("Kachin\ Independence\ Army";\ "has\ headquarters\ near";\ "Laiza")\Leftrightarrow (dbr:Kachin_Independence_Army;\ dbp:headquarters;\ dbr:Laiza)$

Analysis: OPIEC and KBs

- No 1:1 correspondence between open relations and KB relations
- Open relations can be more specific than KB relations
- Although "semantically correlated", open relations may be semantically different than their KB rel. counterparts

loca	tion	associatedMusicalArtist		spouse	
"be in"	(35,754)	"be"	(5,521)	"be wife of"	(1,580)
"have"	(2,500)	"have"	(3,248)	"be"	(980)
"be"	(1,473)	"be guitarist of"	(619)	"marry"	(551)
"be at"	(793)	"be drummer of"	(433)	"be widow of"	(392)
"be of"	(525)	"be feature"	(377)	"be marry to"	(246)
"be historic home located at"	(520)	"be frontman of"	(367)	"have"	(244)

Table 2: Most frequent open relations aligned to DBpedia relations

OPIEC-Linked: Alignment with KBs

- We selected top-100 most freq open rels (38% of OPIEC-Clean)
 - the fraction of KB hits is low (averaging at 14.7%)
 - on average, there are about 40 KB relations per open relation

Open relation	Frequency in OPIEC-Link	# KB hits	# distinct KB rel.s	Top-3 aligned DBpedia rel.	
"be"	1,475,332	162,438 (11.0%)	403	type occupation isPartOf	72,542 12,254 6,776
"have"	216,332	118,625 (54.8%)	320	author director writer	11,678 9,429 8,751
"be in"	1,150,667	734,330 (63.8%)	221	country isPartOf state	269,189 200,851 65,242
"include	" 14,746	1,364 (9.2%)	127	type associatedBand associatedMusical	376 75 Artist 75
"be bear	r in" 7,138	1,478 (20.7%)	31	birthPlace isPartOf deathPlace	1,172 68 60

Take-aways

- Motivation: make natural language text data more structured and useful
- MinIE: OIE System for compact extractions
 - Improve content by adding semantic annotations on extracted triples (polarity, modality, attribution, quantities)
 - Minimize relations and arguments by dropping overly specific words
 - Different levels of minimization: complete, safe, dictionary and aggressive
- OPIEC: the largest OIE corpus to date
 - Aims to spur research in AKBC, open Q&A, ...
 - Rich with meta-data: many syntactic/semantic annotations
 - Multiple sub-corpora from noisy to clean
 - Analyzed and compared with Wikipedia-based KBs