Open Information Extraction: Approaches and Applications

Mausam
Professor, Computer Science.
Head, School of Artificial Intelligence.
Indian Institute of Technology, Delhi

Keshav Kolluru
PhD Scholar
Indian Institute of Technology, Delhi
“The Internet is the world’s largest library. It’s just that all the books are on the floor.”

- John Allen Paulos

~20 Trillion URLs (Google)
Paradigm Shift: from retrieval to reading

Who won Bigg Boss OTT?

What sport teams are based in Arizona?

Phoenix Suns, Arizona Cardinals,...

Divya Agarwal

World Wide Web

Information Food Chain
Paradigm Shift: from retrieval to reading

Quick view of today’s news

Science Report
Finding: beer that doesn’t give a hangover
Researcher: Ben Desbrow
Country: Australia
Organization: Griffith Health Institute

World Wide Web

Google

NASSCOM
Paradigm Shift: from retrieval to reading

Compare Roku vs Fire

- most apps but not iTunes remote
- good UI
- works perfectly needs laptop during travel
- blames router
- connects easily during travel

World Wide Web
Paradigm Shift: from retrieval to reading

Which US West coast companies are hiring for a software engineer position?
Information Systems Pipeline

Data → Information → Knowledge → Wisdom

Text → Facts → Knowledge Base → Applications
Research Overview

- Extraction
- Fact
- KB
- Inference

End-user applications
Downstream NLP Tasks
Research Overview

Extraction → Fact → KB

Inference

End-user applications

Downstream NLP Tasks

Fact
Closed Information Extraction

Extracting information with respect to a given ontology from natural language text.

“Apple’s founder Steve Jobs died of cancer following a...”

Closed IE

\( \text{rel:founder_of}(\text{Apple, Steve Jobs}) \)

- \( \text{rel:founder_of} \) (Google, Larry Page)
- \( \text{rel:founder_of} \) (Apple, Steve Jobs)
- \( \text{rel:founder_of} \) (Microsoft, Bill Gates)

- \( \text{rel:acquisition} \) (Google, DeepMind)
- \( \text{rel:acquisition} \) (Apple, Shazam)
- \( \text{rel:acquisition} \) (Microsoft, Maluuba)

...
Open Information Extraction

Extracting information from natural language text for all relations in all domains in a few passes.

“Apple’s founder Steve jobs died of cancer following a…”

Open IE

(Steve Jobs, be the founder of, Apple), (Steve Jobs, died of, cancer)

(Google, acquired, DeepMind)
(Oranges, contain, Vitamin C)
(Edison, invented, phonograph)

antibiotics (381)
Chlorine (113)
Ozone (61)
Heat (60)
Honey (55)
Benzoyl peroxide (45)
Open Information Extraction

Extracting information from natural language text for all relations in all domains in a few passes.

“Apple’s founder Steve Jobs died of cancer following a...

(Steve Jobs, be the founder of, Apple)
(Steve Jobs, died of, cancer)

Open IE

Extracting information from natural language text for all relations in all domains in a few passes.

(Steve Jobs, be the founder of, Apple)
(Steve Jobs, died of, cancer)

Ontology Free!

(Google, acquired, DeepMind)
(Oranges, contain, Vitamin C)
(Edison, invented, phonograph)

...
Demo

- http://openie.allenai.org
Open Information Extraction

• 2007: Textrunner (~Open IE 1.0)
  – CRF and self-training

• 2010: ReVerb (~Open IE 2.0)
  – POS-based relation pattern

• 2012: OLLIE (~Open IE 3.0)
  – Dep-parse based extraction; nouns; attribution

• 2014: Open IE 4.0
  – SRL-based extraction; temporal, spatial...

• 2017 [@IITD]: Open IE 5.0
  – compound noun phrases, numbers, lists

• 2020 [@IITD]: Open IE 6.0
  – deep neural models
Open Information Extraction

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increasing precision, recall, expressiveness
Fundamental Hypothesis

∃ *semantically tractable* subset of English

- Characterized relations & arguments via POS
- Characterization is compact, domain independent
- Covers 85% of binary relations in sample
ReVerb

Identify Relations from Verbs.

1. Find longest phrase matching a simple syntactic constraint:

\[ V | VP | VW*P \]

\[ V = \text{verb particle? adv?} \]
\[ W = (\text{noun} | \text{adj} | \text{adv} | \text{pron} | \text{det}) \]
\[ P = (\text{prep} | \text{particle} | \text{inf. marker}) \]
Sample of ReVerb Relations

invented

inhibits tumor growth in

has a maximum speed of

gained fame as

was the first person to

acquired by

voted in favor of

died from complications of

granted political asylum to

identified the cause of

has a PhD in

won an Oscar for

mastered the art of

is the patron saint of

wrote the book on
Lexical Constraint

**Problem:** “overspecified” relation phrases

 Obama is offering only modest greenhouse gas reduction targets at the conference.

**Solution:** must have many distinct args in a large corpus

- is offering only modest ...
- Obama the conference \( \approx 1 \)
- is the patron saint of
  - Anne mothers
  - George England
  - Hubbins quality footwear
  - ....

100s \( \approx \)
## Number of Relations (circa 2011)

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Number of Relations</th>
</tr>
</thead>
<tbody>
<tr>
<td>DARPA MR Domains</td>
<td>&lt;50</td>
</tr>
<tr>
<td>NYU, Yago</td>
<td>&lt;100</td>
</tr>
<tr>
<td>NELL</td>
<td>~500</td>
</tr>
<tr>
<td>DBpedia 3.2</td>
<td>940</td>
</tr>
<tr>
<td>PropBank</td>
<td>3,600</td>
</tr>
<tr>
<td>VerbNet</td>
<td>5,000</td>
</tr>
<tr>
<td>WikiPedia InfoBoxes, $f &gt; 10$</td>
<td>~5,000</td>
</tr>
<tr>
<td>TextRunner (phrases)</td>
<td>100,000+</td>
</tr>
<tr>
<td>ReVerb (phrases)</td>
<td>1,500,000+</td>
</tr>
</tbody>
</table>
ReVerb Extraction Algorithm

1. Identify longest relation phrases satisfying constraints

Hudson was born in Hampstead, which is a suburb of London.

2. Heuristically identify arguments for each relation phrase

(Hudson, was born in, Hampstead)
(Hampstead, is a suburb of, London)
ReVerb: Error Analysis

• Steve Squeri, the CEO of American Express, said that a majority of employees will work from home.

• After winning the Superbowl, the Giants are now the top dogs of the NFL.

• Ahmadinejad was elected as the new President of Iran.

**OLLIE: Open Language Learning for Information Extraction**
Open Information Extraction

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Increasing precision, recall, expressiveness

Training data automatically generated
Bootstrapping Approach

- Verb-based relations
- Semantic rels
- Other Syntactic rels
Federer is coached by Paul Annacone.

Diagram:
- Reverb's Verb-based relations
- Other Syntactic rels
- Semantic rels

Bootstrapping Approach
Bootstrapping Approach

Federer is coached by Paul Annacone.

Now coached by Paul Annacone, Federer has ...
Federer is coached by Paul Annacone.

Paul Annacone, the coach of Federer,

Now coached by Paul Annacone, Federer has ...
Federer is coached by Paul Annacone.

Paul Annacone, the coach of Federer, now coached by Paul Annacone, Federer has ...

Federer hired Annacone as his new coach.
Bootstrapping

High Quality ReVerb Ex extractions

Extraction Lemmas (seeds)

Web Sentences

(Ahmadinejad, is the current president of, Iran)

ahmadinejad, president, iran

Ahmadinejad, who is the president of Iran, is a puppet for the Ayatollahs.
Evaluation

[Mausam, Schmitz, Bart, Soderland, Etzioni - EMNLP’12]
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increasing precision, recall, expressiveness
### RelNoun: Nominal Open IE

<table>
<thead>
<tr>
<th>Constructions</th>
<th>Phrase</th>
<th>Extraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Verb1</td>
<td>Francis Collins is the director of NIH</td>
<td>(Francis Collins; is the director of; NIH)</td>
</tr>
<tr>
<td>Appositive1</td>
<td>Francis Collins, the director of NIH</td>
<td>(Francis Collins; [is] the director of; NIH)</td>
</tr>
<tr>
<td>Appositive2</td>
<td>the director of NIH, Francis Collins,</td>
<td>(Francis Collins; [is] the director of; NIH)</td>
</tr>
<tr>
<td>Appositive3</td>
<td>Francis Collins, the NIH director</td>
<td>(Francis Collins; [is] the director [of]; NIH)</td>
</tr>
<tr>
<td>AppositiveTitle</td>
<td>Francis Collins, the director,</td>
<td>(Francis Collins; [is]; the director)</td>
</tr>
<tr>
<td>CompoundNoun</td>
<td><strong>NIH director Francis Collins</strong></td>
<td><strong>(Francis Collins; [is] director [of]; NIH)</strong></td>
</tr>
<tr>
<td>Possessive</td>
<td>NIH’s director Francis Collins</td>
<td>(Francis Collins; [is] director [of]; NIH)</td>
</tr>
<tr>
<td>PossessiveAppositive</td>
<td>NIH’s director, Francis Collins</td>
<td>(Francis Collins; [is] director [of]; NIH)</td>
</tr>
<tr>
<td>AppositivePossessive</td>
<td>Francis Collins, NIH’s director</td>
<td>(Francis Collins; [is] director [of]; NIH)</td>
</tr>
<tr>
<td>PossessiveVerb</td>
<td>NIH’s director is Francis Collins</td>
<td>(Francis Collins; is director [of]; NIH)</td>
</tr>
<tr>
<td>VerbPossessive</td>
<td>Francis Collins is NIH’s director</td>
<td>(Francis Collins; is director [of]; NIH)</td>
</tr>
</tbody>
</table>
Compound Noun Extraction Baseline

- NIH Director Francis Collins

(Francis Collins, is the Director of, NIH)

- Challenges
  - New York Banker Association
  - German Chancellor Angela Merkel
  - Prime Minister Modi
  - GM Vice Chairman Bob Lutz
Continuing with Fundamental Hypothesis

- Rule-based system to characterize relational noun phrases
  - Classifies and filters orgs
  - List of demonyms for location conversion
  - Bootstrap a list of relational noun *prefixes*
    - vice, ex, health, ...
## Experiments

[Pal & Mausam AKBC’16]

<table>
<thead>
<tr>
<th>System</th>
<th>Precision</th>
<th>Yield</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLLIE-NOUN</td>
<td>0.29</td>
<td>136</td>
</tr>
<tr>
<td>RELNOUN 1.1</td>
<td>0.53</td>
<td>60</td>
</tr>
<tr>
<td>+ Compound Noun Baseline</td>
<td>0.37</td>
<td>100</td>
</tr>
<tr>
<td>+ ORG filtering</td>
<td>0.39</td>
<td>100</td>
</tr>
<tr>
<td>+ demonyms</td>
<td>0.52</td>
<td>158</td>
</tr>
<tr>
<td>+ compound relational nouns</td>
<td>0.69</td>
<td>209</td>
</tr>
</tbody>
</table>
Numerical Open IE
[Saha, Pal, Mausam ACL’17]

“Hong Kong’s labour force is 3.5 million.”
**Open IE 4:** (Hong Kong's labour force, is, 3.5 million)
**Open IE 5:** (Hong Kong, has labour force of, 3.5 million)

“James Valley is nearly 600 metres long.”
**Open IE 4:** (James Valley, is, nearly 600 metres long)
**Open IE 5:** (James Valley, has length of, nearly 600 metres)

“James Valley has 5 sq kms of fruit orchards.”
**Open IE 4:** (James Valley, has, 5 sq kms of fruit orchards)
**Open IE 5:** (James Valley, has area of fruit orchards, 5 sq kms)
Peculiarities of Numerical IE

• Numbers are weak entities

• Units
  – Multiple units for same relation
  – Implicit relations may be expressed via units

• Sentence may express change in quantity

• Relation/argument scoping
  – literacy rate of India
  – rural literacy rate of India
  – literacy rate of South India
Bootstrapping for Numerical Open IE
[Saha, Pal, Mausam ACL’17]
Experiments
[Saha, Pal, Mausam ACL’17]

Open IE 5 achieves 1.5x yield and 15 point precision gain on numerical facts over Open IE 4.2.
"President Biden met the leaders of India and China."

**Open IE 4:** (President Biden, met, the leaders of India and China)

**Open IE 5:** (President Biden, met, the leaders of India)

(President Biden, met, the leaders of China)
“President Biden met (the leaders of India) and (China).”

- President Biden met the leaders of India
- President Biden met China

“President Biden met the leaders of (India) and (China).”

- President Biden met the leaders of India
- President Biden met the leaders of China
Complex Example

"Gates, an American investor and co-founder of Microsoft, stepped down as CEO of Microsoft in January 2000, but remained as chairman and created the position of chief software architect for himself and transferred his duties to Ray Ozzie and Craig Mundie."

<table>
<thead>
<tr>
<th>Extraction</th>
<th>Systems</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. (Gates; stepped down as; CEO of Microsoft)</td>
<td>[OC, O4, C]</td>
</tr>
<tr>
<td>2. (Gates; stepped down as CEO of Microsoft; in January 2000)</td>
<td>[OC, O4]</td>
</tr>
<tr>
<td>3. (Gates; is; an American investor)</td>
<td>[OC]</td>
</tr>
<tr>
<td>4. (Gates; is an investor from; United States)</td>
<td>[OC, O4]</td>
</tr>
<tr>
<td>5. (Gates; is co-founder of; Microsoft)</td>
<td>[OC]</td>
</tr>
<tr>
<td>6. (Gates; is; an American investor and co-founder of Microsoft)</td>
<td>[C]</td>
</tr>
<tr>
<td>7. (Gates; remained as; chairman)</td>
<td>[OC, O4, C]</td>
</tr>
<tr>
<td>8. (Gates; created; the position of chief software architect for himself)</td>
<td>[OC, O4, C]</td>
</tr>
<tr>
<td>9. (Gates; transferred; his duties)</td>
<td>[OC]</td>
</tr>
<tr>
<td>10. (Gates; transferred his duties to; Ray Ozzie)</td>
<td>[OC]</td>
</tr>
<tr>
<td>11. (Gates; transferred his duties to; Craig Mundie)</td>
<td>[OC]</td>
</tr>
<tr>
<td>12. (His; has; duties)</td>
<td>[C]</td>
</tr>
<tr>
<td>13. (Gates; transferred his duties to Ray Ozzie; the position of chief software architect for himself)</td>
<td>[C]</td>
</tr>
<tr>
<td>14. (Gates; transferred his duties to Craig Mundie; the position of chief software architect for himself)</td>
<td>[C]</td>
</tr>
</tbody>
</table>
Experiments
[Saha, Mausam COLING’18]

<table>
<thead>
<tr>
<th></th>
<th>Precision</th>
<th>Yield</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open IE 4.2</td>
<td>79.1</td>
<td>172</td>
</tr>
<tr>
<td>ClausIE</td>
<td>67.2</td>
<td>204</td>
</tr>
<tr>
<td>Open IE 5</td>
<td>81.2</td>
<td>315</td>
</tr>
</tbody>
</table>

Code for Open IE 5 available at https://github.com/dair-iitd/OpenIE-standalone (downloaded over 9000 times)
(Intermediate) Take Home

• **Find a high precision subset**
  – even regular expressions are good for low data
  – significant subset of a language is semantically tractable

• **Bootstrap training data**
  – increase recall while maintaining high precision
  – going down the long tail of syntactic expressions

• **Focus on specific constructions**
  – nested lists, compound nouns, numerical expressions
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increasing precision, recall, expressiveness

taking a stronger ML leap
Primer on Deep Learning for NLP

- **Word2Vec**: Vector representation of words
- **Transformers**: Attention-based models
- **BERT**: Pretrained Representations
- **Seq2Seq**: Encoder-Decoder models
Word2Vec
[Mikolov, et. al., Neurips’13]
Vector representation of words

[0.1, 0.9, ..., -0.8]
Word2Vec
[Mikolov, et. al., Neurips’13]

• \( \text{vec}(\text{King}) - \text{vec}(\text{Man}) + \text{vec}(\text{Woman}) = \text{vec}(\text{Queen}) \)

• A person is known by the ________ he keeps

• A person is known by the company he keeps

• A word is known by the company it keeps
Transformer
[Vaswani, et. al., Neurips’17]

• One static vector per word is very limiting!

• What about words that have multiple meanings?

• Bank – financial institution or river bank

• Transformers:
  Generate context-based word embeddings
Transformer
[Vaswani, et. al., Neurips’17]

I played on the bank today
I withdrew money from the bank today
BERT
[Devlin, et. al., NAACL’18]

• Training model on each task independently
• Requires learn language from scratch
• Tedious approach!

• BERT pre-training learns language separately
• Frees the model to learn task-specific details
The ___ sat on the mat

The cat is very cute!
Seq2Seq

- NLP tasks often require generating sequences
- *Machine Translation, Summarization, Chatbots*

- Seq2Seq use an **Encoder-Decoder** architecture

- Encoder embeds the input
- Decoder generates the sequence
Seq2Seq

He is a good teacher

वे अच्छे शिक्षक हैं
Neural OpenIE Extraction

*From text:*
1. Generative models ([IMoJIE, ACL’20](#))
2. Labeling models ([OpenIE6, EMNLP’20](#))
3. Multilingual models ([AACTrans, Submitted](#))

*From Knowledge Bases:*
1. Open Knowledge Bases ([CEAR, Submitted](#))
Neural Models

- How to output a set?
  - one at a time: like a sequence

- How to handle large output lengths?
  - output one extraction at a time

- How to ensure model does not repeat same tuple?
  - give all previous extractions as input
IMoJIE: Iterative Memory Based Joint Open IE
[Kolluru, Aggarwal, Rathore, Mausam, Chakrabarti ACL’20]

Terminology
<arg1>, <rel>,
<arg2>
<subj>, <rel>, <obj>
IMoJIE Encoder – Step 1

[CLS] Apple’s founder Steve Jobs died of cancer <SEP>
IMoJIE Decoder – Step 1

Copy Module

Contextualized [CLS] Token

Attention Module

Steve
Jobs
<rel>
is
the
founder

<arg1>
Extraction 1: <arg1> Steve Jobs <rel> is the founder of <arg2> Apple
IMoJIE Encoder – Step 2

[CLS] Apple’s founder Steve Jobs died of cancer <SEP> <arg1>Steve Jobs <rel> is the founder of <arg2>Apple<SEP>

Extraction 1
IMoJIE Decoder – Step 2

Copy Module

Contextualized [CLS] Token

Attention Module

Steve
Jobs
<rel>
died
of
<arg2>

<arg1>

...
Extraction 2: \(<\text{arg1}>\) Steve Jobs \(<\text{rel}>\) died of \(<\text{arg2}>\) cancer
Extraction 1: <arg1> Steve Jobs <rel> is the founder of <arg2> Apple

Extraction 2: <arg1> Steve Jobs <rel> died of <arg2> cancer

Terminology
<arg1>, <rel>, <arg2>, <subj>, <rel>, <obj>
Extraction 1: <arg1> Steve Jobs <rel> is the founder of <arg2> Apple

Extraction 2: <arg1> Steve Jobs <rel> died of <arg2> cancer

Terminology
<arg1>, <rel>, <arg2>, <subj>, <rel>, <obj>
Evaluation using CaRB  
[Bharadwaj, Aggarwal, Mausam EMNLP’19]

• CaRB uses a matching strategy to compare system extractions with reference extractions and produces a precision, recall value

• We compute 3 metrics:
  ○ *Optimal F1*: Maximum F1 value
  ○ *AUC*: Area under the curve
  ○ *Last F1*: F1 at last point in curve
Results

<table>
<thead>
<tr>
<th>System</th>
<th>CaRB F1</th>
<th>CaRB AUC</th>
<th>Speed Sentences/sec.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open IE 4</td>
<td>51.6</td>
<td>29.5</td>
<td>20.1</td>
</tr>
<tr>
<td>RnnOIE</td>
<td>49.0</td>
<td>26.0</td>
<td>149.2</td>
</tr>
<tr>
<td>IMoJIE</td>
<td>53.5</td>
<td>33.3</td>
<td>2.6</td>
</tr>
</tbody>
</table>

- Trade-off between speed and accuracy
- IMoJIE is **4.5 F1** better than RnnOIE 😊
- IMoJIE is **60x slower** than RnnOIE! 😞

- Code, training data, pretrained models at [https://github.com/dair-iitd/imojie](https://github.com/dair-iitd/imojie) downloaded 3500+ times
Labeling for OpenIE

Apple’s founder Steve Jobs died of cancer [is] [of] [from]

ARG2 REL ARG1 ARG1 NONE NONE NONE NONE
REL REL NONE
NONE NONE ARG1 ARG1 REL REL ARG2
NONE NONE NONE
Labeling for OpenIE

Apple’s founder Steve Jobs died of cancer

(Steve Jobs, [be] the founder [of], Apple)
(Steve Jobs, died of, cancer)
IGL – *Iterative* Grid Labeling

[Kolluru, Adlakha, Aggarwal, Mausam, Chakrabarti EMNLP’20]
IGL – *Iterative* Grid Labeling
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IGL – *Iterative* Grid Labeling
IGL – *Iterative* Grid Labeling
IGL – Iterative *Grid* Labeling

<table>
<thead>
<tr>
<th></th>
<th>E4</th>
<th>NONE</th>
<th>NONE</th>
<th>NONE</th>
<th>NONE</th>
<th>NONE</th>
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<th>NONE</th>
</tr>
</thead>
<tbody>
<tr>
<td>E3</td>
<td>ARG1</td>
<td>NONE</td>
<td>REL</td>
<td>REL</td>
<td>REL</td>
<td>ARG2</td>
<td>ARG2</td>
<td>NONE</td>
</tr>
<tr>
<td>E2</td>
<td>ARG1</td>
<td>NONE</td>
<td>REL</td>
<td>REL</td>
<td>NONE</td>
<td>ARG2</td>
<td>ARG2</td>
<td>NONE</td>
</tr>
<tr>
<td>E1</td>
<td>ARG1</td>
<td>ARG1</td>
<td>NONE</td>
<td>NONE</td>
<td>REL</td>
<td>NONE</td>
<td>ARG2</td>
<td>NONE</td>
</tr>
</tbody>
</table>

| w1 | w2 | w3 | w4 | w5 | w6 | w7 | w8 |
## Results

<table>
<thead>
<tr>
<th>System</th>
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<th>CaRB AUC</th>
<th>Speed</th>
</tr>
</thead>
<tbody>
<tr>
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<td>49.0</td>
<td>26.0</td>
<td>149.2</td>
</tr>
<tr>
<td>IMoJIE</td>
<td>53.5</td>
<td>33.3</td>
<td>2.6</td>
</tr>
<tr>
<td>IGL-OIE</td>
<td>52.4</td>
<td>33.7</td>
<td>142.0</td>
</tr>
</tbody>
</table>

- IGL-IE 60x faster than IMoJIE
- IGL-IE 1.1 F1 lower than IMoJIE
IGL for OpenIE

Known-tradeoff between Speed & Accuracy

- Full generation is more powerful than labeling
- Full generation is much slower than labeling

Solution: Constraints
[Nandwani, Pathak, Mausam, Singla NeurIPS’19]
What makes a good set of extractions?

“Obama gained popularity after Oprah endorsed him for the presidency”

(Obama, gained, popularity)
What makes a good set of extractions?

“Obama gained popularity after Oprah endorsed him for the presidency”

(Obama, gained, popularity)

(Oprah, endorsed, him)
What makes a good set of extractions?

“Obama gained popularity after Oprah endorsed him for the presidency”

(Obama, gained, popularity)

(Oprah, endorsed him for, the presidency)
What makes a good set of extractions?

“What Obama gained popularity after Oprah endorsed him for the presidency”

(Obama, gained, popularity)

(Obama, gained, popularity)

(Oprah, endorsed, him)

(Oprah, endorsed him for, the presidency)

What changed?
What makes a good set of extractions?

“Oprah”, “endorsed”, “presidency” should have been in the set of extractions

Because they convey information!

POSC Constraints:
All words with POS tags as nouns (N), verbs (V), adjectives (JJ), and adverbs (RB) should be part of at least one extraction.
Constrained Iterative Grid Labeling (CIGL)

<table>
<thead>
<tr>
<th>System</th>
<th>CaRB</th>
<th>Speed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F1</td>
<td>AUC</td>
</tr>
<tr>
<td>RnnOIE</td>
<td>49.0</td>
<td>26.0</td>
</tr>
<tr>
<td>IMoJIE</td>
<td>53.5</td>
<td>33.3</td>
</tr>
<tr>
<td>IGL-OIE</td>
<td>52.4</td>
<td>33.7</td>
</tr>
<tr>
<td>CIGL-OIE</td>
<td>54.0</td>
<td>35.7</td>
</tr>
</tbody>
</table>

- CIGL 0.5 F1 improvement over IMoJIE
- CIGL 60x faster than IMoJIE
“President Biden met the leaders of India and China.”

**Open IE 4:** (President Biden, met, the leaders of India and China)

**Open IE 6:** (President Biden, met, the leaders of India)
(President Biden, met, the leaders of China)
Augmenting OpenIE with Coordination Analysis

OpenIE6

Code, training data, pretrained models at https://github.com/dair-iitd/openie6 downloaded 1500+ times
Take Home

• Find a high precision subset
  – even regular expressions are good for low data
  – significant subset of a language is semantically tractable

• Bootstrap training data
  – increase recall while maintaining high precision
  – going down the long tail of syntactic expressions

• Focus on specific constructions
  – nested lists, compound nouns, numerical expressions

• Constraints in neural models
  – allow AI experts to correct neural models and enable train-test analyze cycles
Multilingual OpenIE

- OpenIE has primarily focused on English

- Extending OpenIE to other languages

- **Challenge:** Creating/Curating training data
  - manual annotation is expensive

- **Solution:** Translate English data
Issues with normal Translation

• Need to translate sentence and extractions

• Independent translation leads to inconsistencies

• Lexical Inconsistencies: *Usage of synonyms*

• Semantic Inconsistencies: *Changes meaning*
# Examples of Inconsistencies

<table>
<thead>
<tr>
<th><strong>Lexical Inconsistency</strong></th>
<th><strong>Semantic Inconsistency</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>English Sentence</strong></td>
<td><em>The discovery was remarkable as the skeleton was almost identical to a modern Kuvasz</em></td>
</tr>
<tr>
<td><strong>English Extraction</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Spanish Sentence</strong></td>
<td><em>Un descubrimiento notable porque fósil era casi idéntica a un Kuvasz moderno</em></td>
</tr>
<tr>
<td><strong>Spanish Extraction (Indp)</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Spanish Extraction (Const)</strong></td>
<td></td>
</tr>
</tbody>
</table>

*The shield of Athena Parthenos, sculpted by Phideoas, depicts a fallen Amazon* |
<s> The shield of Athena Parthenos </s> <r> depicts </r> <o> a fallen Amazon </o> |
El escudo de Atena Parthenos, sculptado por Phideoas, representa un Amazonas fallecido |
<s> El escudo de Atena Parthenos </s> <r> representa </r> <o> un Amazonas caído </o> |
<s> El escudo de Atena Parthenos </s> <r> representa </r> <o> un Amazonas fallecido </o>
## Other Desiderata

<table>
<thead>
<tr>
<th>Sentence Extractions</th>
<th>George Bluth Sr., patriarch of the Bluth family, is the founder and former CEO of the Bluth Company.</th>
</tr>
</thead>
<tbody>
<tr>
<td>English</td>
<td>&lt;s&gt; George Bluth Sr. &lt;/s&gt; &lt;r&gt; is patriarch of &lt;/r&gt; &lt;o&gt; the Bluth family &lt;/o&gt;</td>
</tr>
<tr>
<td></td>
<td>&lt;s&gt; George Bluth Sr. &lt;/s&gt; &lt;r&gt; is &lt;/r&gt; &lt;o&gt; the founder and former CEO of the Bluth Company &lt;/o&gt;</td>
</tr>
<tr>
<td></td>
<td>&lt;s&gt; George Bluth Sr. &lt;/s&gt; &lt;r&gt; is &lt;/r&gt; &lt;o&gt; patriarch of the Bluth family &lt;/o&gt;</td>
</tr>
</tbody>
</table>

| Telugu               | మధ్యగాంధీ నగర సాంస్కర్తిక విద్యాభిషేక అధ్యక్షుడు చన్ని సారి మార్ఫ్ట్ నాయదు ప్రతి ప్రధాన మంత్రి నాయదు ప్రతి ప్రధాన మంత్రి నాయదు ప్రతి ప్రధాన మంత్రి |
| English              | Sharon’s longtime rival Benjamin Netanyahu was elected as leader of Likud |
|                      | <s> మధ్యగాంధీ నగర సాంస్కర్తిక విద్యాభిషేక అధ్యక్షుడు చన్ని సారి మార్ఫ్ట్ నాయదు ప్రతి ప్రధాన మంత్రి నాయదు ప్రతి ప్రధాన మంత్రి <o> రూపాణి సీమల ప్రతి ప్రధాన మంత్రి <r> రూపాణి సీమల ప్రతి ప్రధాన మంత్రి <o> |

| Hindi                | जॉन लंबर्ट ने सरकार के साधन के रूप में जाना जाने वाला एक नया संविधान सामने रखा |
| English              | John Lambert put forward a new constitution known as the Instrument of Government |
|                      | <s> एक नया संविधान </s> <o> सरकार के साधन के रूप में </o> <r> जाना जाता है </r> |
Consistent Translation

• Introduce a new type of translation: AACT

• Alignment-Augmented Consistent Translation

• Two translations are consistent to each other
  – Uses word-alignments b/w English-F translations
Experimental Validation

[Kolluru, Mohammed, Mittal, Chakrabarti, Mausam Unpublished’21]

• Experiments over five languages:

• *Spanish, Portuguese, Chinese, Hindi, Telugu*

• Improvement of **19.5% F1** and **10.6% AUC** over prior multilingual models
Talk Outline

Extraction → Fact → KB

Inference

End-user applications

Downstream NLP/AI Tasks
KB Inference

Knowledge Base

Inference Engine

Larger KB!
OpenIE Inference

• Large-scale inference over Open IE

(iron, is a good conductor of, electricity) →
(iron nail, conducts, electricity)

(David Beckham, was born in, London) →
(David Beckham, was born in, England)
Embeddings for entities/relations

Represent entities (entity pairs) and relations in a continuous $\mathbb{R}^d / \mathbb{C}^d$ space.
Tensor Factorization
(DistMult/ComplEx)

#entity pairs

#relations

\( \approx \)

\( r \rightleftharpoons T \)

\( e_1 \)

\( e_2 \)

(iron nail, conducts, electricity)
CEAR: Cross-Entity Aware Reranker for Knowledge Base Completion
CEAR: Cross-Entity Aware Reranker for Knowledge Base Completion
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CEAR: Cross-Entity Aware Reranker for Knowledge Base Completion
Results on OpenKB

[Kolluru, Chauhan, Nandwani, Singla, Mausam Unpublished’21]

<table>
<thead>
<tr>
<th>Method</th>
<th>H@1</th>
<th>H@10</th>
<th>H@50</th>
</tr>
</thead>
<tbody>
<tr>
<td>ComplEx-LSTM</td>
<td>2.1</td>
<td>7.0</td>
<td>14.6</td>
</tr>
<tr>
<td>ExtremeText</td>
<td>6.4</td>
<td>16.3</td>
<td>26.0</td>
</tr>
<tr>
<td>CEAR (ComplEx-LSTM)</td>
<td>3.8</td>
<td>9.1</td>
<td>14.6</td>
</tr>
<tr>
<td>CEAR (ExtremeText)</td>
<td>7.4</td>
<td>17.9</td>
<td>26.0</td>
</tr>
</tbody>
</table>

Table 3: Link Prediction performance on OLPBENCH.
Overview

Extraction → Fact → KB

Inference

End-user applications

Downstream NLP/AI Tasks
Information Overload

Today a person is subjected to more new information in a day than a person in the middle ages in his entire life!
Extractions: a great way to summarize
## Alzheimer’s Disease Literature

[Tsutsui, Ding, Meng iConference’17]

<table>
<thead>
<tr>
<th>AD</th>
<th>HD</th>
<th>HIV</th>
</tr>
</thead>
<tbody>
<tr>
<td>is the most common cause of</td>
<td>cognitive impairment</td>
<td>is an early symptom of</td>
</tr>
<tr>
<td>are significantly associated with</td>
<td>depression</td>
<td>is common in</td>
</tr>
<tr>
<td>is characterized by</td>
<td>vascular dysfunction</td>
<td>may occur in</td>
</tr>
<tr>
<td>is associated with increased</td>
<td>neuronal death</td>
<td>is also a pathological hallmark in</td>
</tr>
<tr>
<td>is strongly correlated with</td>
<td>the apoe genotype</td>
<td>does not affect the course of</td>
</tr>
<tr>
<td>frequently exhibit</td>
<td>delirium</td>
<td>sometimes accompany</td>
</tr>
<tr>
<td>is the common cause of</td>
<td>dementia</td>
<td>is a common complication of</td>
</tr>
<tr>
<td>affect</td>
<td>neurons</td>
<td>are not infected by</td>
</tr>
<tr>
<td>causes pro-inflammatory effects in</td>
<td>endothelial cells</td>
<td>were not infected with</td>
</tr>
</tbody>
</table>


# Health Claims in News Headlines

[Yuan, Yu COLING Workshop’18]

<table>
<thead>
<tr>
<th>Information Extractor</th>
<th>Precision</th>
<th>Recall</th>
<th>F-measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>REVERB</td>
<td>.61</td>
<td>.31</td>
<td>.41</td>
</tr>
<tr>
<td>OLLIE</td>
<td>.62</td>
<td>.46</td>
<td>.53</td>
</tr>
<tr>
<td>OPENIE-5.0</td>
<td>.67</td>
<td>.57</td>
<td>.62</td>
</tr>
<tr>
<td>SemRep</td>
<td>.23</td>
<td>.08</td>
<td>.13</td>
</tr>
</tbody>
</table>
Entity Comparisons are Ubiquitous
Extractions: a great way to compare

[Contractor, Mausam, Singla - NAACL’16]

<table>
<thead>
<tr>
<th>Cluster Labels</th>
<th>Granada (Spain)</th>
<th>New York City (U.S.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>art, arch.</td>
<td>moorish architecture</td>
<td>contemporary art</td>
</tr>
<tr>
<td></td>
<td>religious art</td>
<td>modern american art</td>
</tr>
<tr>
<td></td>
<td>fine art</td>
<td>medieval art</td>
</tr>
<tr>
<td></td>
<td>beautiful architecture</td>
<td>egyptian art</td>
</tr>
<tr>
<td>palace, courtyard</td>
<td>brick-walled courtyard</td>
<td></td>
</tr>
<tr>
<td></td>
<td>lovely courtyard area</td>
<td></td>
</tr>
<tr>
<td></td>
<td>nasrid royal palace</td>
<td></td>
</tr>
<tr>
<td></td>
<td>alhambra palace</td>
<td></td>
</tr>
<tr>
<td>museum, finest</td>
<td>alhambra museum</td>
<td>fine art museums</td>
</tr>
<tr>
<td></td>
<td>archaeological museum</td>
<td>guggenheim museum</td>
</tr>
<tr>
<td></td>
<td>world heritage site</td>
<td>islamic art collection</td>
</tr>
<tr>
<td></td>
<td>splendid arabic shops</td>
<td>metropolitan museum</td>
</tr>
<tr>
<td>gardens, park</td>
<td>partial gardens</td>
<td>flushing meadows park</td>
</tr>
<tr>
<td></td>
<td>palace gardens</td>
<td>central park</td>
</tr>
<tr>
<td></td>
<td>pleasant gardens</td>
<td>renowned gardens</td>
</tr>
<tr>
<td></td>
<td>moorish style gardens</td>
<td>natl. recreational area</td>
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## Extractions: a great way to compare

[Contractor, Mausam, Singla - NAACL’16]

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<td>moorish architecture, religious art, fine art, beautiful architecture</td>
<td>contemporary art, modern american art, medieval art, egyptian art</td>
</tr>
<tr>
<td>palace, courtyard</td>
<td>brick-walled courtyard, lovely courtyard area, nasrid royal palace, alhambra palace</td>
<td></td>
</tr>
<tr>
<td>museum, finest</td>
<td>alhambra museum, archaeological museum, world heritage site, splendid arabic shops</td>
<td>fine art museums, guggenheim museum, islamic art collection, metropolitan museum</td>
</tr>
<tr>
<td>gardens, park</td>
<td>partial gardens, palace gardens, pleasant gardens, moorish style gardens</td>
<td>flushing meadows park, central park, renowned gardens, natl. recreational area</td>
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Extractions: a great way to compare

[Contractor, Mausam, Singla - NAACL’16]

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<td>fine art</td>
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<td></td>
<td>beautiful architecture</td>
<td>egyptian art</td>
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<td>central park</td>
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<tr>
<td></td>
<td>pleasant gardens</td>
<td>renowned gardens</td>
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<tr>
<td></td>
<td>moorish style gardens</td>
<td>natl. recreational area</td>
</tr>
</tbody>
</table>
Talk Outline

Extraction → Fact → KB

End-user applications

Downstream NLP/AI Tasks
NLP Applications

• Improving Word Vectors

• Unsupervised KB Construction
  – Event schema induction
  – Multi-document Summarization
  – Complex Question Answering
Lexical Similarity/Analogies
[Stanovsky, Dagan, Mausam, ACL 15]

- We experiment by switching **representations**
  - We compute Open IE based embeddings instead of lexical or syntactic context-based embeddings

<table>
<thead>
<tr>
<th>Target</th>
<th>Lexical</th>
<th>Dependency</th>
<th>SRL</th>
<th>Open IE</th>
</tr>
</thead>
<tbody>
<tr>
<td>John</td>
<td>nsubj_John</td>
<td>xcomp_visit</td>
<td>A0_John</td>
<td>0_John</td>
</tr>
<tr>
<td>to</td>
<td>visit</td>
<td></td>
<td>A1_to</td>
<td>1_to</td>
</tr>
<tr>
<td>refused</td>
<td>visit</td>
<td></td>
<td>A1_visit</td>
<td>1_visit</td>
</tr>
<tr>
<td>Vegas</td>
<td></td>
<td></td>
<td>A1_Vegas</td>
<td>2_Vegas</td>
</tr>
</tbody>
</table>
Why does Open IE do better?

- **Word Analogy**
  - Captures domain and functional similarity
    - \textit{gentlest}: gentler, \textit{loudest}:?

- **Lexical**: higher-pitched
  - \textbf{X} [Domain Similar]

- **Syntactic**: thinner
  - \textbf{X} [Functionally Similar]

- **SRL**: unbelievable
  - \textbf{X} [Functionally Similar?]

- **Open-IE**: louder
  - \textbf{✓}
Unsupervised KB Construction

[Kroll, Pirklbauer, Balke, JCDL’21]

• Manual domain-specific KB construction
• Expensive and Time consuming
• OpenIE can help in automation
A Probabilistic Model of Relations in Text
[Balasubramanian, Soderland, Mausam, Etzioni – AKBC-WEKEX’12]

• **Rel-grams** =
  a model of relation co-occurrence.
  Probability of seeing sequence of Open IE tuples.

• A resource with **27 million entries**, compiled from
  **1.8 million news articles**

Available at relgrams.cs.washington.edu
High probability tuples following (X, treat, disease):

(Y, develop, drug)
(Y, cause, disease)
(Y, used to treat, condition)

| First Tuple (f)          | Second Tuple (s)         | $P(R_{i+10}=s|R_i=f)$ | #($R_i=f, \ldots, R_{i+10}=s$) | #($R_i=f, \ldots, R_{i+10}=$) |
|-------------------------|--------------------------|------------------------|---------------------------------|-------------------------------|
| (X, treat, disease)     | (Y, develop, drug)      | 0.017                  | 4.0                             | 221.0                         |
| (X, treat, disease)     | (Y, cause, disease)     | 0.017                  | 4.0                             | 221.0                         |
| (X, treat, disease)     | (Y, use to treat, condition) | 0.013                  | 3.0                             | 221.0                         |
| (X, treat, disease)     | (Y, trigger response from, muscle) | 0.013                  | 3.0                             | 221.0                         |
| (X, treat, disease)     | (Y, treat, patient)     | 0.013                  | 3.0                             | 221.0                         |
| (X, treat, disease)     | (Y, show that, protease inhibitor) | 0.013                  | 3.0                             | 221.0                         |
| (X, treat, disease)     | (Y, reach by, e-mail)   | 0.013                  | 3.0                             | 221.0                         |
| (X, treat, disease)     | (Y, know, it)           | 0.013                  | 3.0                             | 221.0                         |
Personalized PageRank over RelGram Graph
Personalized PageRank over RelGram Graph

- (person, use, drug)
- (person, use, substance)
- (person, suspended by, org)
- (person, suspended for, time)
- (person, suspended for, activity)
- (person, be member of, org)
- (person, be director of, org)
### Extract Actors ➔ Event Schemas

[Balasubramanian, Soderland, Mausam, Etzioni – EMNLP’13]

<table>
<thead>
<tr>
<th>Actor</th>
<th>Rel</th>
<th>Actor</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1:&lt;person&gt;</td>
<td>failed</td>
<td>A2:test</td>
</tr>
<tr>
<td>A1:&lt;person&gt;</td>
<td>was suspended for</td>
<td>A3:&lt;time period&gt;</td>
</tr>
<tr>
<td>A1:&lt;person&gt;</td>
<td>used</td>
<td>A4:&lt;substance, drug&gt;</td>
</tr>
<tr>
<td>A1:&lt;person&gt;</td>
<td>was suspended for</td>
<td>A5:&lt;game, activity&gt;</td>
</tr>
<tr>
<td>A1:&lt;person&gt;</td>
<td>was in</td>
<td>A6:&lt;location&gt;</td>
</tr>
<tr>
<td>A1:&lt;person&gt;</td>
<td>was suspended by</td>
<td>A7:&lt;organization, person&gt;</td>
</tr>
</tbody>
</table>

**Actor Instances:**
- A1: {Murray, Morgan, Governor Bush, Martin, Nelson}
- A2: {test}
- A3: {season, year, week, month, night}
- A4: {cocaine, drug, gasoline, vodka, sedative}
- A5: {violation, game, abuse, misuse, riding}
- A6: {desert, Simsbury, Albany, Damascus, Akron}
- A7: {Fitch, NBA, Bud Selig, NFL, Gov Jeb Bush}
Multi-document Summarization

[Fan, Gardent, Braud, Bordes, EMNLP’19]

• Use OpenIE to create dynamic Knowledge Graphs from multiple documents

• Use graph summarization

**QUESTION**
What is Albert Einstein famous for?

**WEB INFORMATION**

**DOCUMENT 1**
Albert Einstein, a German theoretical physicist, published the **theory of relativity**.
The **theory of relativity** is one of the two pillars of modern physics.

**DOCUMENT 2**
Albert Einstein (March 14, 1879 to April 18, 1955) developed the theory of relativity.
He won the **Nobel Prize**.
The great prize was for his explanation of the photoelectric effect.

**GRAPH CONSTRUCTION**

Albert Einstein

published \(\rightarrow\) the theory of relativity

developed \(\rightarrow\) the Physics Nobel Prize

won \(\rightarrow\) one of the two pillars of modern physics

\(\rightarrow\) for Albert Einstein explanation of the photoelectric effect

**LINEARIZATION**

\(<\text{sub}>\) Albert Einstein <\text{obj}> the theory of relativity <\text{pred}> published <\text{s}>
developed <\text{obj}> the Physics Nobel Prize <\text{s}>
won

\(<\text{sub}>\) the theory of relativity <\text{obj}> one of the two pillars of modern physics <\text{pred}> is

\(<\text{sub}>\) the Physics Nobel Prize <\text{obj}> for his explanation of the photoelectric effect <\text{pred}> was
Complex Question Answering

[Khot, Sabharwal, Clark, ACL’17]

• Science Questions are often complicated and require background knowledge

• OpenIE converts background knowledge into tuples to help answer the question

Figure 1: An example support graph linking a question (top), two tuples from the KB (colored) and an answer option (nitrogen).
Conclusions

• Populating a KB: starting to achieve some maturity
  – still many phenomena waiting to be modeled

• KBs adds tremendous value to end-user apps
  – summarization, data exploration, q/a
  – Complex QA, dialog

• KBs valuable for downstream NLP tasks
  – event schema induction
  – sentence similarity
  – text comprehension
  – vector embeddings

• Exciting research challenges in inference, QA, dialog space
Thanks
THANK YOU