(Open) Information Extraction: Where are we going?
About me

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First-year PhD student

LCL group @ Sapienza

Advisor: prof. Roberto Navigli

Focus (so far): (Open) Information Extraction
Outline

IE and OIE: some background
Outline

IE and OIE: some background

DefIE: OIE from textual definitions
Delli Bovi, Telesca, Navigli: TACL (to appear)
IE and OIE: some background

DefIE: OIE from textual definitions
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KBUnify: KB disambiguation and unification
Delli Bovi, Espinosa-Anke, Navigli: EMNLP 2015
“A process of getting **structured** data from **unstructured** information in the text”
(Jurafsky and Martin, 2009)

“Identification of instances of a particular class of **relationships** in a natural language text, and the extraction of relevant **arguments** for that relationships”
(Grishman, 1997)
Information Extraction

Why?
Information Extraction

Why?

Machine Reading:

“I hereby offer to bet anyone a lobster dinner that by 2015 we will have a computer program capable of automatically reading at least 80% of the factual content across the entire English speaking web, and placing those facts in a structured knowledge base.”

(T. Mitchell. Reading the Web: A Breakthrough Goal for AI. AI Magazine, 2005)
Information Extraction

What?
Information Extraction

What?

Input:
- large corpus of unstructured text
- set of semantic relations
- labelled training data

Output:
- knowledge base of triples
  \langle entity, relation, entity \rangle
Information Extraction

What?

Input:
- large corpus of unstructured text
- set of semantic relations
- labelled training data

Output:
- knowledge base of triples $\langle \text{entity}, \text{relation}, \text{entity} \rangle$

degree of supervision

supervised learning
Information Extraction

What?

**Input:**
- large corpus of unstructured text
- set of semantic relations
- high-precision seeds/examples

**Output:**
- knowledge base of triples
  \( \langle \text{entity, relation, entity} \rangle \)

**degree of supervision**

semi-supervised learning
Information Extraction

What?

Input:
- large corpus of unstructured text
- set of semantic relations

Output:
- knowledge base of triples \( \langle \text{entity}, \text{relation}, \text{entity} \rangle \)
- set of semantic relations

Degree of supervision:
- unsupervised learning
Information Extraction

How?
Information Extraction

How?

degree of supervision

<table>
<thead>
<tr>
<th>semantic information</th>
<th>underlying KB</th>
</tr>
</thead>
<tbody>
<tr>
<td>semi-supervised</td>
<td></td>
</tr>
<tr>
<td>supervised</td>
<td>NER categories</td>
</tr>
</tbody>
</table>

How?
Information Extraction

How?

degree of supervision

“classic” supervision

(Zhao and Grishman, 2005)
Information Extraction

How?

- Weak supervision
  - Bootstrapping from few high-precision seed patterns

- Degree of supervision
  - (Zhao and Grishman, 2005)
  - (Kozareva and Hovy, 2010)
  - (Bunescu and Mooney, 2006)
Information Extraction

How?

- Self supervision
  - (Carlson et al., 2010)
  - (Kozareva and Hovy, 2010)
  - (Bunescu and Mooney, 2006)

Use seed patterns to build a self-labelled training set

Semantic information vs. degree of supervision
Information Extraction

How?

- NELL – Never Ending Language Learning (Carlson et al., 2010)
  - Web-scale self-supervised learning system, running at CMU continuously 24 hours per day
  - Requires an initial ontology with categories and relations, each with 10/15 initial seeds
  - Uses a variety of methods (including human supervision) to extract beliefs from the web

http://rtw.ml.cmu.edu/rtw
Information Extraction

How?

instead of seeds, use a large knowledge base of examples (e.g. Freebase)

semantic information

degree of supervision

distant supervision

(Carlson et al., 2010)

(Kozareva and Hovy, 2010)

(Bunescu and Mooney, 2006)

(Riedel et al., 2010)

(Hoffmann et al., 2011)

(Zhao and Grishman, 2005)

(Riedel et al., 2010)
Information Extraction

How?

Open Information Extraction

no initial set of relations, no training data at all

semantic information

degree of supervision

(Fader et al., 2011)

(Carlson et al., 2010)

(Kozareva and Hovy, 2010)

(Bunescu and Mooney, 2006)

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(Riedel et al., 2010)

(Zhao and Grishman, 2005)

(Bunescu and Mooney, 2006)
Information Extraction

How?

ReVerb (Fader et al., 2011)

For each sentence in the corpus:
- POS tagging and chunking
- Identify relation string as “well formed” sequence of words wrapping a verb
- Find the nearest NPs to the left and right
- Assign a confidence to the extraction

(Carlson et al., 2010)

(Kozareva and Hovy, 2010)

(Bunescu and Mooney, 2006)

(Zhao and Grishman, 2005)
Information Extraction

How?

**Semantically-informed OIE**

- (Nakashole et al., 2012)
- (Moro and Navigli, 2013)
- (Carlson et al., 2010)
- (Kozareva and Hovy, 2010)
- (Bunescu and Mooney, 2006)
- (Hoffmann et al., 2011)
- (Riedel et al., 2010)
- (Zhao and Grishman, 2005)

**explicit disambiguation, semantic analysis of relation strings**

degree of supervision

semantic information
How?

From patterns to **pattern synsets** (clusters of relation phrases that express the same relation)

Each pattern has **syntactic generalizations** and **semantic types** for its arguments:

```plaintext
<Person> 's [ ADJ ] voice * <Song>
```

Patterns are hierarchically organized in a **taxonomy**

---

Information Extraction

---

**PATTY** (Nakashole et al., 2012)

---

(Moro and Navigli, 2013)

---

Carlson et al., 2010

---

Hoffmann et al., 2011

---

Fader et al., 2011

---

Riedel et al., 2010

---

Zhao and Grishman, 2005

---

Bunescu and Mooney, 2006

---

Kozareva and Hovy, 2010

---

Fader et al., 2011
How?

WiSeNet (Moro and Navigli, 2013)

Wikipedia-based Semantic Network: triples in the KB are determined by Wikipedia hyperlinks

Syntactically-grounded relational phrases with Wikipedia categories as semantic types

Relation synsets built using soft clustering techniques

WiSeNet

{techniques to improve, strengthening the}

Natural Language Processing

Adversarial Information Retrieval

Computer Science

Information Retrieval

Software Company

\( (\text{Bunescu and Mooney, 2006}) \)

\( (\text{Kozareva and Hovy, 2010}) \)

\( (\text{Carlson et al., 2010}) \)

\( (\text{Fader et al., 2011}) \)

\( (\text{Zhao and Grishman, 2005}) \)

\( (\text{Nakashole et al., 2012}) \)
(Open) Information Extraction

OIE is great, but...

**Sparsity**: many relation phrases express the same relationship (e.g. synonyms, paraphrases)

**Ambiguity**: arguments (and relation phrases) are ambiguous!
Outline

IE and OIE: some background

DefIE: OIE from textual definitions

Claudio Delli Bovi, Luca Telesca and Roberto Navigli.
Large-Scale Information Extraction from Textual Definitions through Deep Syntactic and Semantic Analysis.
Transactions of the Association for Computational Linguistics (TACL), 2015.

KBUnify: KB disambiguation and unification

Delli Bovi, Espinosa-Anke, Navigli: EMNLP 2015
DefIE: OIE from textual definitions

http://lcl.uniroma1.it/defie

The idea:

instead of targeting massive and noisy corpora (like the web) and then trying to find a smart way to cope with the noise

target smaller but “denser” (and virtually noise-free) corpora of **definitional knowledge**.
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instead of targeting massive and noisy corpora (like the web) and then trying to find a smart way to cope with the noise

target smaller but “denser” (and virtually noise-free) corpora of **definitional knowledge**.

Apply OIE techniques to extract as much information as possible!

[http://lcl.uniroma1.it/defie](http://lcl.uniroma1.it/defie)
DefIE: OIE from textual definitions

The tools:

- An underlying **inventory/knowledge base** (to which arguments and relation patterns will be connected)

- A **WSD/EL** system (to disambiguate concepts and entity mentions across the input text)

- A **syntactic parser** (to construct meaningful relation patterns and avoid sparsity)
DefIE: OIE from textual definitions

http://lcl.uniroma1.it/defie

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http://lcl.uniroma1.it/defie

http://babelfy.org

unified graph-based approach to **EL** and **WSD**
unsupervised, based on **BabelNet**
DefIE: OIE from textual definitions

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DeflE: How it works

http://lcl.uniroma1.it/defie

I. Extracting relation instances

“Atom Heart Mother is the fifth album by English band Pink Floyd.”

Textual definition $d$
DefIE: How it works

http://lcl.uniroma1.it/defie

I. Extracting relation instances

"Atom Heart Mother is the fifth album by English band Pink Floyd."

Parsing

Dependency graph $G_d$

Disambiguation

Sense mappings $S_d$
“Atom Heart Mother is the fifth album by English band Pink Floyd.”
I. Extracting relation instances
I. Extracting relation instances

\[
\begin{align*}
X & \rightarrow \text{is} \rightarrow \text{album}^1_{bn} \rightarrow \text{by} \rightarrow Y \\
X & = \text{Atom Heart Mother}^1_{bn} \\
Y & = \text{Pink Floyd}^1_{bn}
\end{align*}
\]
1. Extracting relation instances

\[
\begin{align*}
X \rightarrow & \text{ is } \rightarrow Y \\
X = & \text{ Atom Heart Mother}^{1}_{bn} \\
Y = & \text{ album}^{1}_{bn}
\end{align*}
\]

\[
\begin{align*}
X \rightarrow & \text{ is } \rightarrow \text{ album}^{1}_{bn} \rightarrow \text{ by } \rightarrow Y \\
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DefIE: How it works

http://lcl.uniroma1.it/defie

2. Relation typing and scoring
DeflE: How it works

http://lcl.uniroma1.it/defie

2. Relation typing and scoring

For each relation $R$:

Substitute each domain and range argument with its hypernym $h$ (using the BabelNet taxonomy) and generate a probability distribution over semantic types for the two sets.
2. Relation typing and scoring

For each relation $R$:

Substitute each domain and range argument with its hypernym $h$ (using the BabelNet taxonomy) and generate a probability distribution over semantic types for the two sets.

Compute the entropy of $R$ as

$$H_R = - \sum_{i=1}^{n} p(h_i) \log_2 p(h_i)$$
DefIE: How it works

http://lcl.uniroma1.it/defie

2. Relation typing and scoring

For each relation $R$:

Compute the score of $R$ as

$$score(R) = \frac{|S_R|}{(H_R + 1) \cdot length(r)}$$

- Total number of extracted instances for $R$
- Domain and range entropy of $R$
- Length of the relation pattern of $R$
2. Relation typing and scoring

<table>
<thead>
<tr>
<th>Pattern</th>
<th>Score</th>
<th>Entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>X directed by Y</td>
<td>4025.80</td>
<td>1.74</td>
</tr>
<tr>
<td>X known for Y</td>
<td>2590.70</td>
<td>3.65</td>
</tr>
<tr>
<td>X is election district(^1)(_{bn}) of Y</td>
<td>110.49</td>
<td>0.83</td>
</tr>
<tr>
<td>X is composer(^1)(_{bn}) from Y</td>
<td>39.92</td>
<td>2.08</td>
</tr>
<tr>
<td>X is street(^1)(_{bn}) named after Y</td>
<td>1.91</td>
<td>2.24</td>
</tr>
<tr>
<td>X is village(^2)(_{bn}) founded in 1912 in Y</td>
<td>0.91</td>
<td>0.18</td>
</tr>
</tbody>
</table>
DefIE: How it works

http://lcl.uniroma1.it/defie

3. Relation taxonomization
3. Relation taxonomization

Hyponymy Generalization
3. Relation taxonomization

Hyponym Generalization

Hypernym Generalization

Substring Generalization
Dataset:
whole set of English textual definitions in BabelNet 2.5

4 357 327 items from 5 different sources (Wikipedia, WordNet, Wikidata, Wiktionary, OmegaWiki)
## DefIE: Results

![Logo](http://lcl.uniroma1.it/defie)

<table>
<thead>
<tr>
<th></th>
<th>DefIE</th>
<th>NELL</th>
<th>PATTY</th>
<th>ReVerb</th>
<th>WiSeNet</th>
</tr>
</thead>
<tbody>
<tr>
<td># Relations</td>
<td>255 881</td>
<td>298</td>
<td>1 631 531</td>
<td>664 746</td>
<td>245 935</td>
</tr>
<tr>
<td>Avg. extractions</td>
<td>81.68</td>
<td>7 013.03</td>
<td>9.68</td>
<td>22.16</td>
<td>9.24</td>
</tr>
<tr>
<td># Extractions</td>
<td>20 352 903</td>
<td>2 089 883</td>
<td>15 802 946</td>
<td>14 728 268</td>
<td>2 271 807</td>
</tr>
<tr>
<td># Entities</td>
<td>2 398 982</td>
<td>1 996 021</td>
<td>1 087 907</td>
<td>3 327 425</td>
<td>1 636 307</td>
</tr>
<tr>
<td># Edges in the taxonomy</td>
<td>44 412</td>
<td>-</td>
<td>20 339</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
Other evaluations:

- **Precision** and **coverage** of relations
- **Novelty** of information
- Quality of relation **taxonomization**
- Quality of **entity linking/disambiguation**
- **Impact** of definition sources

...
DefIE: Results

http://lcl.uniroma1.it/defie

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Data and output soon available for download on the website!
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Claudio Delli Bovi, Luis Espinosa-Anke and Roberto Navigli.
Knowledge Base Unification via Sense Embeddings and Disambiguation.
KB-Unify: Knowledge base unification via sense embeddings and disambiguation

The idea:

Open Information Extraction system

PATTY
WiseNet
...

NELL
ReVerb
...

Linked Resources

Unlinked Resources

〈Armstrong, has worked at, NASA〉

〈Armstrong, works for, NASA〉

http://lcl.uniroma1.it/kb-unify
KB-Unify: Knowledge base unification via sense embeddings and disambiguation

The idea:

Open Information Extraction system

PATTY
WiseNet
...

NELL
ReVerb
...

Linked Resources

Unlinked Resources

Unified Resource

\( Armstrong, r_{work}, NASA \)

\( r_{work} = \{ \text{has worked at, works for, employed at, ...} \} \)
KB-Unify: Knowledge base unification via sense embeddings and disambiguation

http://lcl.uniroma1.it/kb-unify

The tools:

- A WSD/EL system (to disambiguate unlinked resources)

- A unified sense inventory $S$ (to make the various resources “speak to each other”)

- A unified vector space $V_S$ (to associate a vector with each item of $S$)
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SensEmbed
(lacobacci et al., 2015)
Sense-based embedding model
Popular word2vec architecture (skip-gram) trained on a sense-annotated corpus
KB-Unify: How it works

http://lcl.uniroma1.it/kb-unify

A bird’s-eye view
KB-Unify: How it works

http://lcl.uniroma1.it/kb-unify

A bird’s-eye view

use BabelNet mappings to redefine each linked resource

disambiguate each unlinked resource using Babelnet as sense inventory (more on this later!)
KB-Unify: How it works

http://lcl.uniroma1.it/kb-unify

Disambiguation
Disambiguation

Two basic intuitions:

1. Among all triples in target knowledge base, some of them (even if ambiguous) will be easier to disambiguate;

   e.g. 〈 Armstrong, works for, NASA 〉
Disambiguation

Two basic intuitions:

1. Among all triples in target knowledge base, some of them (even if ambiguous) will be **easier to disambiguate**;
   
   e.g. 〈 Armstrong, works for, NASA 〉

2. In general, the disambiguation strategy should vary according to the **degree of specificity** of each relation.
Disambiguation

Group the set of unlinked triples by relation

For each relation \( r \):

- Extract and disambiguate a subset of high-confidence seed argument pairs for \( r \);
- Estimate the specificity of \( r \) by looking at the distribution of its disambiguated seeds in the vector space \( V_S \);
- Disambiguate the remaining argument pairs of \( r \) with Babelfy either triple-by-triple (if \( r \) is general) or all at once (if \( r \) is specific).
Identifying seed argument pairs

〈 Armstrong, 
  works for, 
  NASA 〉
Identifying seed argument pairs

\[ \mathbf{v}_d = \{ v_d^1, v_d^2, v_d^3 \} \]

\[ \mathbf{v}_g = \{ v_g^1 \} \]

\[ \langle v_d^*, v_g^* \rangle = \arg\max_{v_d \in v_d, v_g \in v_g} \frac{v_d \cdot v_g}{||v_d|| \cdot ||v_g||} \]
Identifying seed argument pairs

\[
v_d = \{ v_d^1, v_d^2, v_d^3 \}
\]

\[
v_g = \{ v_g^1 \}
\]

\[
\langle v_d^*, v_g^* \rangle \rightarrow \zeta_{\text{dis}}
\]

Seed Disambiguation Confidence

Armstrong, works for, NASA
KB-Unify: How it works

http://lcl.uniroma1.it/kb-unify

Ranking relations by specificity

$$\mu_k = \frac{1}{|v_k|} \sum_{v \in v_k} \frac{v}{\|v\|}, \quad k \in \{D, G\}$$

Domain/Range Centroids

$$\sigma^2_k = \frac{1}{|v_k|} \sum_{v \in v_k} (1 - \cos(v, \mu_k))^2$$

Domain/Range Variances
KB-Unify: How it works

http://lcl.uniroma1.it/kb-unify

Ranking relations by specificity

\[ \mu_k = \frac{1}{|v_k|} \sum_{v \in v_k} \frac{v}{||v||}, \quad k \in \{D, G\} \]

Domain/Range Centroids

\[ \sigma_k^2 = \frac{1}{|v_k|} \sum_{v \in v_k} (1 - \cos(v, \mu_k))^2 \]

Domain/Range Variances

\[ Gen(r) = \frac{\sigma_D^2 + \sigma_G^2}{2} \]

Specificity threshold: \( \delta_{\text{spec}} \)

High \( Gen(r) \) (> \( \delta_{\text{spec}} \))

Low \( Gen(r) \) (≤ \( \delta_{\text{spec}} \))
Disambiguation with Relation Context

unlinked triples → disambiguated seeds → specificity ranking → \( \delta_{\text{spec}} \) → general → triple-by-triple disambiguation

specific → relation-by-relation disambiguation

KB-Unify: How it works

http://lcl.uniroma1.it/kb-unify
A bird’s-eye view

Linked Resources $K_D$

- $K_{D1}$
- $K_{D2}$

Unlinked Resources $K_U$

- $K_{U1}$
- $K_{U2}$

Inter-Resource Linking

Redefined Resources $K^S$

- $K_{D1}^S$
- $K_{D2}^S$
- $K_{U1}^S$
- $K_{U2}^S$

Disambiguation

Relation Alignment

represent each relation in the unified vector space $V_S$ and compare them pairwise
KB-Unify: How it works

 Relation alignment

http://lcl.uniroma1.it/kb-unify
Relation alignment

For each relation pair \( \langle r_i, r_j \rangle \):

- \( r_i \) \( \mu_{D}^{r_i} \) \( \mu_{G}^{r_i} \) Relations \( \mu_{D}^{r_j} \) \( \mu_{G}^{r_j} \) \( r_j \) Centroids
Relation alignment

For each relation pair \( \langle r_i, r_j \rangle \):

\[
\begin{align*}
\mu^r_{D} & \\ \\
\mu^r_{G} & \\ \\
\mu^r_{D} & \\ \\
\mu^r_{G} & \\
\end{align*}
\]

Compare domain and range centroids pairwise:

\[
S_k = \frac{\mu^r_{k} \cdot \mu^r_{k}}{\| \mu^r_{k} \| \cdot \| \mu^r_{k} \|}
\]

Relation Centroid Similarity
Relation alignment

Fix a similarity threshold $\delta_{align}$:

$$\frac{1}{2} (s_D + s_G) \geq \delta_{align}?$$

Align $r_i$ and $r_j$ and merge them in the same cluster.
Relation alignment

Fix a similarity threshold $\delta_{align}$:

$$\frac{1}{2} (S_D + S_G) < \delta_{align} \quad ? \quad \text{Leave } r_i \text{ and } r_j \text{ in separate clusters}$$
KB-Unify: Experiments

http://lcl.uniroma1.it/kb-unify

Evaluation

Experimental setup:

Linked Resources $K_D$:

- PATTY: 1,631,531 relations, 15,802,946 triples
- WiSeNet: 245,935 relations, 2,271,807 triples

Unlinked Resources $K_U$:

- NELL: 298 relations, 2,245,050 triples
- ReVerb: 1,299,844 relations, 14,728,268 triples
KB-Unify: Experiments

http://lcl.uniroma1.it/kb-unify

Disambiguation

Seed Precision:

<table>
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<th>ReVerb</th>
</tr>
</thead>
<tbody>
<tr>
<td>ζ_{dis}</td>
<td>0.98</td>
<td>0.96</td>
<td>0.99</td>
<td>1</td>
</tr>
</tbody>
</table>

Coverage:

<table>
<thead>
<tr>
<th></th>
<th>PATTY</th>
<th>WiSeNet</th>
<th>NELL</th>
<th>ReVerb</th>
</tr>
</thead>
<tbody>
<tr>
<td>δ_{spec}</td>
<td>0.51</td>
<td>0.54</td>
<td>0.53</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Languages:
PATTY
WiSeNet
NELL
ReVerb
Specificity ranking

For each ranked relation compute $Gen(r)$ against the average argument similarity $\bar{s}$:
Specificity ranking

For each ranked relation compute $Gen(r)$ against the average argument similarity $\bar{s}$:
**Specificity ranking**

For each ranked relation compute $Gen(r)$ against the average argument similarity $\bar{s}$:
Cross-resource relation alignment

Samples of 150 candidate alignments for different alignment thresholds $\delta_{align}$ manually evaluated (in terms of paraphrasing) by two human judges.
## KB-Unify: Experiments

Cross-resource relation alignment

Some examples:

<table>
<thead>
<tr>
<th><strong>PATTY-WiSENet</strong></th>
<th>$\zeta_{align}$</th>
<th><strong>NELL-PATTY</strong></th>
<th>$\zeta_{align}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>portrayed</td>
<td>'s character</td>
<td>worksfor</td>
<td>0.72</td>
</tr>
<tr>
<td>debuted in</td>
<td>first appeared in</td>
<td>riveremptiesintoriver</td>
<td>0.89</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>PATTY-ReVerB</strong></th>
<th>$\zeta_{align}$</th>
<th><strong>NELL-WiSENet</strong></th>
<th>$\zeta_{align}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>language in</td>
<td>is spoken in</td>
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<td>teamehometadium</td>
<td>play their home games at 0.88</td>
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</table>

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<th>$\zeta_{align}$</th>
<th><strong>REVerB-WiSENet</strong></th>
<th>$\zeta_{align}$</th>
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</thead>
<tbody>
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<td>has a selection of</td>
<td>0.82</td>
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<td>personleadscity</td>
<td>is the mayor of</td>
<td>had grown up in</td>
<td>0.85</td>
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Wrap up and Conclusion
**DefIE:** A full-fledged OIE pipeline targeted to textual definitions, with explicit semantic characterization of both arguments and relation patterns
Wrap up and Conclusion

**DefIE**: A full-fledged OIE pipeline targeted to textual definitions, with explicit semantic characterization of both arguments and relation patterns.

**KB-Unify**: An approach to knowledge base disambiguation and unification based on a shared sense inventory and a sense-based vector space model.
Wrap up and Conclusion

Take-home message(s):

Web-scale OIE is absolutely great, but…

1. **Definitional knowledge is important**: sometimes it is worth it to just step back and analyze from where valuable information is extracted (quality vs. quantity)

2. **Making sense of the output is important**: semantic analysis can be used to let different OIE outputs “speak to each other” and benefit from mutual enrichment
Thanks!

¡Gracias!

Gràcies!

Grazie!

When Wikipedia has a server outage, my apparent IQ drops by about 30 points.