(Open) Information Extraction: Where are we going?

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About me

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LCL group @ Sapienza
Advisor: prof. Roberto Navigli

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

**BabelNet and friends**: some background
Research work @ LCL Sapienza

**DefIE**: OIE from textual definitions
Delli Bovi, Telesca, Navigli: TACL 2015

**KBUnify**: KB disambiguation and unification
Delli Bovi, Espinosa-Anke, Navigli: EMNLP 2015
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Linguistic Computing Laboratory (LCL) @ Sapienza University of Rome

- Part of the Computer Science Department of Sapienza, focused on Natural Language Processing
- Some projects we have been involved in:
  - **MultiJEDI (1.3M €):** ERC Starting Grant
  - **LIDER (1.5 M €):** EU CSA
  - **Google Focused Research Award (300k $)**
Multijedi
Multilingual joint word sense disambiguation

Project

MultiJEDI is a 5-year ERC Starting Grant (2011-2016) headed by Prof. Roberto Navigli at the Linguistic Computing Laboratory of the Sapienza University of Rome. The project has two main objectives: creating large-scale lexical resources for dozens of languages, and enabling multilingual text understanding. The project has received funding from the European Union’s specific programme ‘Ideas’ implementing the seventh framework programme (FP7-Ideas-ERC) under grant agreement no. 259234.
To the best of our knowledge, the largest multilingual encyclopedic dictionary and semantic network (almost 14M entries in 271 languages and 380M semantic connections)
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Initially created as an integration of Wikipedia and WordNet, now BabelNet is a merger of many different resources (Wiktionary, Wikidata, OmegaWiki, VerbNet, ImageNet, ...)

The integration is performed via an automatic linking algorithm and by filling in lexical gaps with the aid of Machine Translation.
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BabelNet is composed of Babel Synsets, concepts or entities lexicalized ("WordNet-style") in many languages and featuring:

- is-a relations
- domain and categories
- images and definitions
- translations
BabelNet and friends
BabelNet and friends

Babelfy
A graph-based algorithm for multilingual joint Word Sense Disambiguation and Entity Linking, based on BabelNet
BabelNet and friends

Babelfy
A graph-based algorithm for multilingual joint Word Sense Disambiguation and Entity Linking, based on BabelNet

The Wikipedia Bitaxonomy
An iterative algorithm for the automatic creation of a “bitaxonomy” for Wikipedia pages and categories

... and much more!
BabelNet and my research

- BabelNet (especially in its early stages) was conceived as a **lexico-semantic resource** more than an actual **knowledge base**:
  - semantic connections are mostly **lexical relations** from WordNet or unspecified “relatedness edges” derived from Wikipedia hyperlinks
BabelNet and my research

- BabelNet (especially in its early stages) was conceived as a lexico-semantic resource more than an actual knowledge base:
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- Construct from BabelNet a proper knowledge base with labeled relations (X is album by Y, X worked at Y, ...)

- Use Open Information Extraction!
(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!
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DefIE: OIE from textual definitions

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

Apply OIE techniques to extract as much information as possible!
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)
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DefIE: How it works

1. Extracting relation instances

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

Textual definition $d$
DefIE: How it works

1. Extracting relation instances

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

---

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

DefIE: How it works

1. Extracting relation instances

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

Syntactic-Semantic Graph $S^\text{sem}_d$
DefIE: How it works

1. Extracting relation instances
DefIE: How it works

1. Extracting relation instances

\[
X \rightarrow \text{is} \rightarrow \text{album} \rightarrow \text{by} \rightarrow Y
\]

Extraction 1

\[
X = \text{Atom Heart Mother} \quad \text{bn:02070902n}
\]

\[
Y = \text{Pink Floyd} \quad \text{bn:03292767n}
\]
1. Extracting relation instances

**Extraction 1**

\[ X \rightarrow \text{is} \rightarrow \text{album} \rightarrow \text{by} \rightarrow Y \]

\[ X = \text{Atom Heart Mother} \quad \text{bn:02070902n} \]

\[ Y = \text{Pink Floyd} \quad \text{bn:03292767n} \]

**Extraction 2**

\[ X \rightarrow \text{is} \rightarrow \text{Y} \]

\[ X = \text{Atom Heart Mother} \quad \text{bn:02070902n} \]

\[ Y = \text{album} \quad \text{bn:00002488n} \]
DefIE: How it works

1. Extracting relation instances

\[ R_1: \quad X \rightarrow is \rightarrow Y \]

\[ R_2: \quad X \rightarrow is \rightarrow \text{album} \quad bn:00002488n \rightarrow by \rightarrow Y \]
DefIE: How it works

1. Extracting relation instances

\[ R_1: X \rightarrow \text{is} \rightarrow Y \]

- Domain
- Range

\[ R_2: X \rightarrow \text{is} \rightarrow \text{album} \rightarrow \text{by} \rightarrow Y \]

bn:00002488n

\[ \langle \text{Atom Heart Mother, album} \rangle \]
\[ \langle \text{Pink Floyd, band} \rangle \]
\[ \langle \text{Seattle, city} \rangle \]
\[ \langle \text{Atom Heart Mother, Pink Floyd} \rangle \]
\[ \langle \text{Mutter, Rammstein} \rangle \]
\[ \langle \text{Can’t Get Enough, Barry White} \rangle \]
DefIE: How it works

2. Relation typing and scoring
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**
DefLE: How it works

2. Relation typing and scoring

For each relation R:

Compute the score of R as

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

- Domain and range entropy of R
- Total number of extracted instances for R
- Length of the relation pattern of R
## DefIE: How it works

### 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>
3. Relation taxonomization
3. Relation taxonomization

Hypernym generalization
3. Relation taxonomization

DefIE: How it works

Hypernym generalization

Substring generalization
DefIE: Setup

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

<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>
DefIE: Results

Other evaluations:

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

...
DefIE: Future work

Where from here?

- Relation **clustering** (as in PATTY and WiSeNet)
- **Multilinguality**
- Relational **learning** and KB completion
- Harvest definitions from the web
- Adapt to “**general**” text

...
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KB-Unify: Knowledge base unification via sense embeddings and disambiguation

The idea:

[Diagram showing the flow from Open Information Extraction systems to Linked and Unlinked Resources]

- PATTY
- WiseNet
- NELL
- ReVerb

Linked Resources

Unlinked Resources
KB-Unify: Knowledge base unification via sense embeddings and disambiguation

The idea:

Open Information Extraction system

PATTY
WiseNet
...

NELL
ReVerb
...

Linked Resources

Unlinked Resources

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

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 $S$)
KB-Unify: Knowledge base unification via sense embeddings and disambiguation

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SensEmbed (Iacobacci et al., 2015)
Sense-based embedding model
Popular word2vec architecture (skip-gram) trained on a sense-annotated corpus
KB-Unify: How it works

A bird’s-eye view

Linked Resources $K_D$
- $K_{D1}$
- $K_{D2}$

Unlinked Resources $K_U$
- $K_{U1}$
- $K_{U2}$
KB-Unify: How it works

A bird’s-eye view

- **Linked Resources** $K_D$: $K_{D1}$, $K_{D2}$
- **Unlinked Resources** $K_U$: $K_{U1}$, $K_{U2}$

**Inter-Resource Linking**
- Use BabelNet mappings to redefine each linked resource

**Disambiguation**
- Disambiguate each unlinked resource using BabelNet as sense inventory (more on this later!)
KB-Unify: How it works

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〉
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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).
KB-Unify: How it works

Identifying seed argument pairs

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

\[ \mathbf{v}_g = \{ \mathbf{v}_g^1 \} \]
KB-Unify: How it works

Identifying seed argument pairs

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

\[
\langle \mathbf{v}_d^*, \mathbf{v}_g^* \rangle = \arg\max_{\mathbf{v}_d \in \mathbf{v}_d, \mathbf{v}_g \in \mathbf{v}_g} \frac{\mathbf{v}_d \cdot \mathbf{v}_g}{\|\mathbf{v}_d\| \|\mathbf{v}_g\|}
\]
KB-Unify: How it works

Identifying seed argument pairs

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

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

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

Seed Disambiguation Confidence
KB-Unify: How it works

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

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

Domain/Range
Variances
KB-Unify: How it works

Ranking relations by specificity

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

Domain/Range Centroids

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

Domain/Range Variances

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

High \( \text{Gen}(r) \)

Low \( \text{Gen}(r) \)
KB-Unify: How it works

Disambiguation with Relation Context

unlinked triples → disambiguated seeds → δ_{spec} → general specific

triple-by-triple disambiguation

relation-by-relation disambiguation

Babelfy

specificity ranking
KB-Unify: How it works

A bird’s-eye view

Linked Resources $K_D$

Inter-Resource Linking

Redefined Resources $K^S$

Relation Alignment

Unlinked Resources $K_U$

Disambiguation

represent each relation in the unified vector space $V_s$ and compare them pairwise

Unified Resource KB$^*$
KB-Unify: How it works

Relation alignment
Relation alignment

For each relation pair $\langle r_i, r_j \rangle$:

$$\begin{align*}
\mu_{D_i} & \quad \mu_{G_i} \\
\mu_{D_j} & \quad \mu_{G_j}
\end{align*}$$
KB-Unify: How it works

Relation alignment

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

- \( r_i \) \( \mu_{D_i}, \mu_{G_i} \) Relations
- \( r_j \) \( \mu_{D_j}, \mu_{G_j} \) Centroids

Compare domain and range centroids pairwise:

\[
S_k = \frac{\mu_{r_i}^T \cdot \mu_{r_j}}{\| \mu_{r_i} \| \cdot \| \mu_{r_j} \|}
\]

Relation Centroid Similarity
Relation alignment

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

\[
\frac{1}{2} (s_D + s_G) \geq \delta_{\text{align}} \quad \text{Align } r_i \text{ and } r_j \text{ and merge them in the same cluster}
\]
KB-Unify: How it works

Relation alignment

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

$$\frac{1}{2} (s_D + s_G) < \delta_{\text{align}} \quad \text{?}$$

Leave $r_i$ and $r_j$ in separate clusters
KB-Unify: Experiments

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

Disambiguation

Seed Precision:

<table>
<thead>
<tr>
<th>Model</th>
<th>Precision</th>
<th>Precision</th>
<th>Precision</th>
<th>Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>PATTY</td>
<td>0.98</td>
<td>0.96</td>
<td>0.99</td>
<td>0.98</td>
</tr>
<tr>
<td>WiSeNet</td>
<td>0.97</td>
<td>0.96</td>
<td>0.95</td>
<td>0.94</td>
</tr>
<tr>
<td>NELL</td>
<td>0.95</td>
<td>0.93</td>
<td>0.95</td>
<td></td>
</tr>
<tr>
<td>ReVerb</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

$\zeta_{dis}$

Coverage:

<table>
<thead>
<tr>
<th>Model</th>
<th>$\delta_{spec}$</th>
<th>$\delta_{spec}$</th>
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</tr>
</thead>
<tbody>
<tr>
<td>PATTY</td>
<td>0.62</td>
<td>0.52</td>
<td>0.51</td>
<td>0.41</td>
</tr>
<tr>
<td>WiSeNet</td>
<td>0.61</td>
<td>0.41</td>
<td>0.51</td>
<td>0.45</td>
</tr>
<tr>
<td>NELL</td>
<td>0.53</td>
<td>0.53</td>
<td>0.77</td>
<td>0.51</td>
</tr>
<tr>
<td>ReVerb</td>
<td>0.41</td>
<td>0.41</td>
<td>0.41</td>
<td>0.13</td>
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</table>
Specificity ranking

For each ranked relation compute $Gen(r)$ against the average argument similarity $\bar{s}$:
KB-Unify: Experiments

Specificity ranking

For each ranked relation compute \( \text{Gen}(r) \) 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 $\delta_{\text{align}}$ manually evaluated (in terms of paraphrasing) by two human judges.
### KB-Unify: Experiments

#### Cross-resource relation alignment

Some examples:

<table>
<thead>
<tr>
<th>Patty-WeSeNet</th>
<th>Patty-ReVerb</th>
<th>Nell-Patty</th>
<th>Nell-ReVerb</th>
</tr>
</thead>
<tbody>
<tr>
<td>portrayed</td>
<td>language in</td>
<td>worksfor</td>
<td>bookwriter</td>
</tr>
<tr>
<td>’s character</td>
<td>is spoken in</td>
<td>was hired by</td>
<td>is a novel by</td>
</tr>
<tr>
<td>debuted in</td>
<td>mostly known for</td>
<td>riveremptiesintoriver</td>
<td>personleadscity</td>
</tr>
<tr>
<td>first appeared in</td>
<td>plays the role of</td>
<td>tributary of</td>
<td>is the mayor of</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>Nell-WiSeNet</td>
<td>Nell-WiSeNet</td>
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### Cross-resource relation alignment

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### Cross-resource relation alignment

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KB-Unify: Future work

Where from here?

- Less “naïve” relation alignment procedure
- Iterative algorithm for disambiguation and alignment (EM-style)
- Unify OIE-based KBs with hand-curated resources (Wikidata, DBpedia, etc.)

...
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...
Wrap up and Conclusion

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

Take-home message(s):

Web-scale OIE is absolutely great, but...

1. **Definitional knowledge is important**: sometimes it is worth just stepping back and analyzing 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
Thank you!

xkcd, “Extended Mind”