# *Entity Linking meets Word Sense Disambiguation: a Unified Approach*

*Andrea Moro, Alessandro Raganato, **Tiziano Flati** and Roberto Navigli*


## Abstract

**Entity Linking** (EL) and **Word Sense Disambiguation** (WSD) both address the lexical ambiguity of language. But while the two tasks are pretty similar, they differ in a fundamental aspect: in **EL** the textual mention can be linked to an entity which may or may not contain the exact mention, while in **WSD** there is a perfect match between the word form (better, its lemma) and a suitable sense.

We present a **unified graph-based approach** to EL and WSD based on a **loose identification of candidate meanings** coupled with a **densest subgraph** heuristic which selects high-coherence semantic interpretations.


## The Best of Two Worlds

Our main goal is to **bring together** the two worlds of WSD and EL:

1. Keep the **set of candidate meanings** for a given mention **as open as possible**

2. Provide an effective method for **handling** this **high level of ambiguity**.

A **key assumption** of our work is that **the lexicographic knowledge used in WSD is also useful to tackle the EL task**, and vice versa **the encyclopedic information utilized in EL helps disambiguate nominal mentions in a WSD setting**.

## A joint task

Our task is to **disambiguate and link all nominal and named entity mentions** occurring within a text. The linking task is performed by associating each mention with the most suitable entry of a given knowledge base.

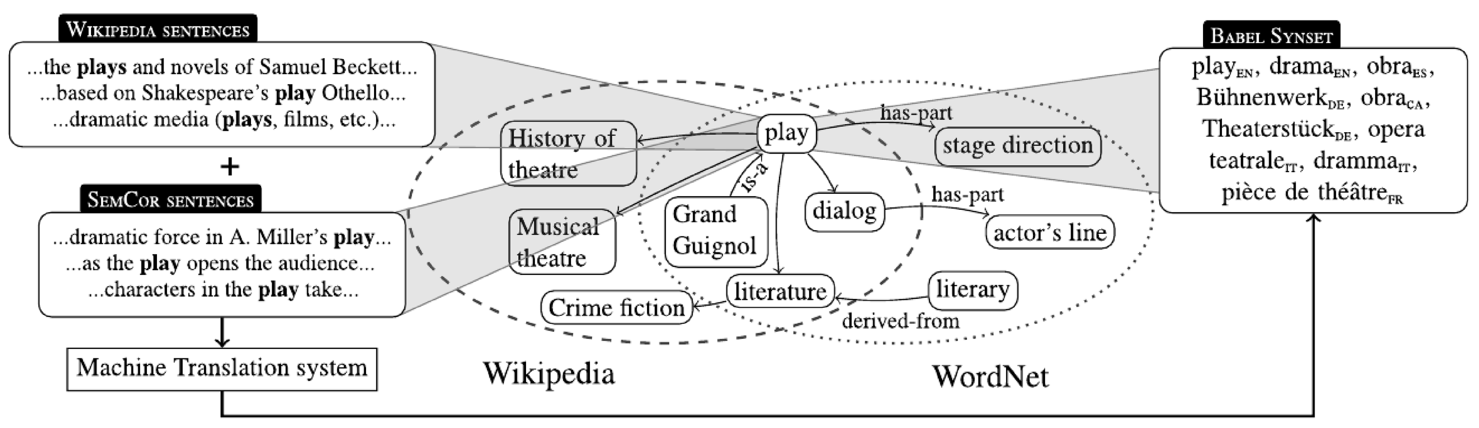
Our definition does not enforce any constraints in terms of what to link, i.e., unlike Wikification and WSD, we can link **overlapping fragments** of text.

**Example.** Given the text fragment: *"Major League Soccer"* we identify and disambiguate several different entity and concept mentions:

*Major League Soccer* *major league* *league* *soccer*

## BabelNet

**BabelNet** is a **multilingual knowledge base** which consists of roughly nine million concepts and named entities together with their lexicalizations in **50 different languages** and 250 million semantic relations. At the core of this resource lies the **integration of encyclopedic**, i.e., from Wikipedia, and **lexicographic knowledge**, i.e., from WordNet, Open Multilingual WordNet and OmegaWiki within a unified, multilingual structured network.




## The method

1. Given a lexicalized semantic network, we associate with each vertex, i.e., either concept or named entity, a **semantic signature**, that is, a set of related vertices. This is a preliminary step which needs to be performed only once, independently of the input text.
2. Given a text, we **extract all the linkable fragments** from the text and, for each of them, list the possible meanings according to the semantic network.
3. We create a **graph-based semantic interpretation** of the whole text by linking the candidate meanings of the extracted fragments using the previously-computed semantic signatures. We then extract a **dense subgraph** of this representation and **select the best candidate** meaning for each fragment.

## Semantic Signatures

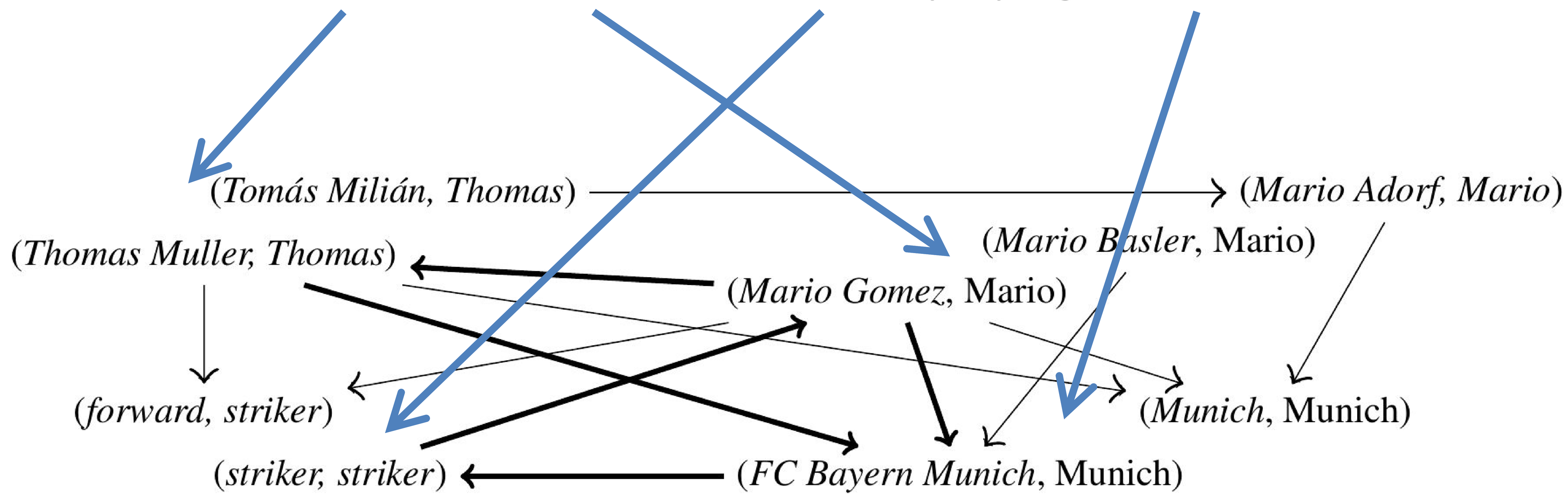
1. We first weight the edges using triangles: $weight(v, v') := |\{(v, v', v'') : (v, v'), (v', v''), (v'', v) \in E\}| + 1$

2. We then run a random walk with restart: $P(v'|v) = \frac{weight(v, v')}{\sum_{v'' \in V} weight(v, v'')}$

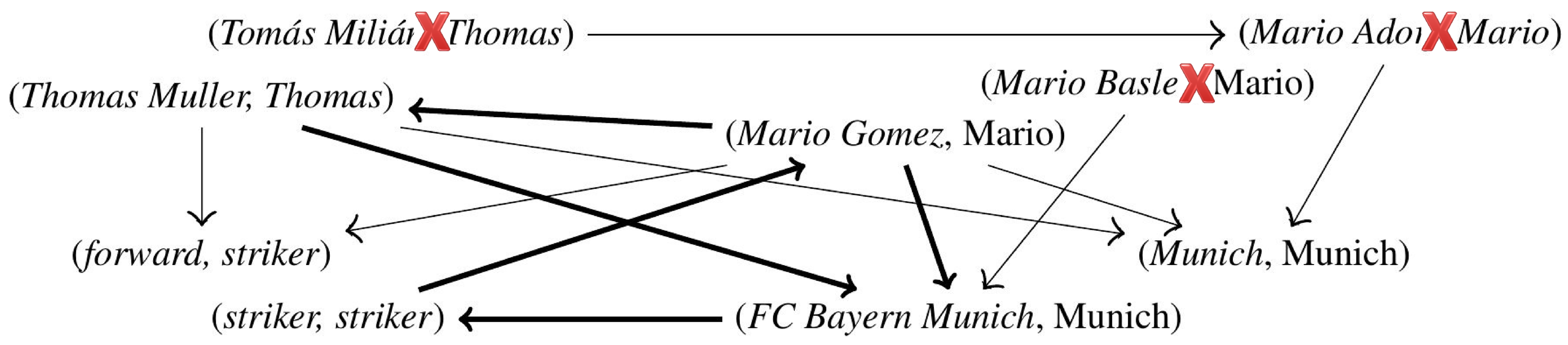
3. The semantic signature of a vertex $v$ is the set of vertices visited at least μ times during the random walk.

**Example:** SemSign(Hilbert's program) = {Set theory, …, Mathematical proof}

Thomas and Mario are strikers playing in Munich




**We then extract a dense subgraph by iteratively removing loosely connected candidate meanings**




## Experimental Evaluations

Our experiments on **six gold-standard** datasets show the **state-of-the-art performance** of our approach as well as its **robustness across languages**.

| | Sens3 | Sem07 | SemEval-2013 English | | | French | | German | | Italian | | Spanish | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| System | WN | WN | WN | Wiki | BN | Wiki | BN | Wiki | BN | Wiki | BN | Wiki | BN |
| Babelfy | 68.3 | 62.7 | **65.9** | **87.4** | **69.2** | **71.6** | ⋆56.9 | 81.6 | **69.4** | **84.3** | 66.6 | **83.8** | 69.5 |
| IMS | **71.2** | 63.3 | 65.7 | – | – | – | – | – | – | – | – | – | – |
| UKB w2w | ⋆65.3 | ⋆56.0 | 61.3 | – | 60.8 | – | **60.8** | – | 66.2 | – | **67.3** | – | 70.0 |
| UMCC-DLSI | – | – | 64.7 | 54.8 | 68.5 | ⋆60.5 | 60.5 | ⋆58.1 | 62.8 | ⋆58.3 | 65.8 | ⋆61.0 | **71.0** |
| DAEBAK! | – | – | – | – | 60.4 | – | 53.8 | – | 59.1 | – | ⋆61.3 | – | 60.0 |
| GETALP-BN | – | – | 51.4 | – | 58.3 | – | 48.3 | – | 52.3 | – | 52.8 | – | 57.8 |
| MFS | 70.3 | **65.8** | ⋆63.0 | ⋆80.3 | ⋆66.5 | 69.4 | 45.3 | **83.1** | ⋆67.4 | 82.3 | 57.5 | 82.4 | ⋆64.4 |
| Babelfy unif. weights | 67.0 | 65.2 | 65.0 | 87.0 | 68.5 | 71.9 | 57.2 | 81.2 | 69.8 | 83.7 | 66.8 | 83.8 | 70.8 |
| Babelfy w/o dens. sub. | 68.3 | 63.3 | 65.4 | 87.3 | 68.7 | 71.6 | 57.0 | 81.7 | 69.1 | 84.4 | 66.5 | 83.9 | 69.5 |
| Babelfy only concepts | 68.2 | 62.7 | 65.5 | 83.0 | 68.7 | 70.2 | 56.6 | 79.3 | 69.3 | 83.0 | 66.3 | 84.0 | 69.7 |
| Babelfy on sentences | 66.0 | 65.2 | 63.5 | 84.0 | 67.1 | 70.7 | 53.6 | 82.3 | 68.1 | 83.8 | 64.2 | 83.5 | 68.7 |

Table 1: F1 scores (percentages) of the participating systems of SemEval-2013 task 12 together with MFS, UKB w2w, IMS, our system and its ablated versions on the Senseval-3, SemEval-2007 task 17 and SemEval-2013 datasets. The first system which has a statistically significant difference from the top system is marked with ⋆ ($\chi^2$, $p < 0.05$).

| System | F1 |
|---|---|
| (Ponzetto and Navigli, 2010) | **85.5** |
| Babelfy | 84.6 |
| UoR-SSI | 84.1 |
| UKB w2w | 83.6 |
| NUS-PT | ⋆82.3 |
| MFS | 77.4 |
| Babelfy unif. weights | 85.7 |
| Babelfy w/o dens. sub. | 84.9 |
| Babelfy only concepts | 85.3 |
| Babelfy on sentences | 82.3 |

Table 2: F1 score (percentages) on the SemEval-2007 task 7. The first system which has a statistically significant difference from the top system is marked with ⋆ ($\chi^2$, $p < 0.05$).

| System | KORE50 | CoNLL |
|---|---|---|
| Babelfy | **71.5** | 82.1 |
| KORE-LSH-G | 64.6 | 81.8 |
| KORE | 63.9 | ⋆80.7 |
| MW | ⋆57.6 | **82.3** |
| Tagme | 56.3 | 70.1 |
| KPCS | 55.6 | 82.2 |
| KORE-LSH-F | 53.2 | 81.2 |
| UKB w2w (on BabelNet) | 52.1 | 71.8 |
| Illinois Wikifier | 41.7 | 72.4 |
| DBpedia Spotlight | 35.4 | 34.0 |
| Babelfy unif. weights | 69.4 | 81.7 |
| Babelfy w/o dens. sub. | 62.5 | 78.1 |
| Babelfy only NE | 68.1 | 78.8 |

Table 3: Accuracy (percentages) of state-of-the-art EL systems and our system on KORE50 and AIDA-CoNLL. The first system with a statistically significant difference from the top system is marked with ⋆ ($\chi^2$, $p < 0.05$).

## Conclusions

1. We presented a novel, integrated **state-of-the-art approach** to **Entity Linking** and **Word Sense Disambiguation;**
2. Our graph-based approach exploits the semantic network structure to its advantage: two key features of BabelNet, that is, its **multilinguality** and its **integration of lexicographic and encyclopedic knowledge**, make it possible to run our general, unified approach on the two tasks of Entity Linking and WSD in any of the languages covered by the semantic network;
3. At the core of our approach lies the **effective treatment of the high degree of ambiguity** of partial textual mentions by means of a 2-approximation algorithm for the densest subgraph problem;

## References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