Injecting Knowledge Base Information into End-to-End Joint Entity and Relation Extraction and Coreference Resolution

Severine Verlinden*, Klim Zaporojets*, Johannes Deleu, Thomas Demeester, Chris Develder

Ghent University – imec, IDLab
Ghent, Belgium

Key Ideas

1. End-to-end **document-level information extraction**.
2. Use **span-based** (Lee et al. 2017) architecture to connect each of the textual spans with **candidate entities**.
3. Use candidate entities to inject external knowledge from:
   - Knowledge graphs (Wikidata)
   - Hyperlinked knowledge bases (Wikipedia)
4. Research Wikipedia-derived **prior** and context-based **attention** schemes to weight candidate entities of each of the textual spans.

Introduction

Task: end-to-end named entity recognition, relation extraction, and coreference resolution.

1 Britain's Prince Harry is engaged to [..] partner Meghan Markle [..].
2 [..] the couple are to live in Kensington Palace.
3 [..] Harry's brother Prince William and Kate Middleton, congratulated the couple.
4. "We are very excited for Harry and Meghan"

Coreference Clusters: {"Meghan Markle", "Meghan"}, {"Britain"}, etc.
Entities: Britain (type:country), Harry (type:person,type:royalty,gender:male), etc.
Relations: <Kensington Palace *in* Britain>, <William *spouse_of* Kate Middleton>, etc.

Fig. 1: DWIE: some relations and entity types are not explicitly stated in the text.

Data: DWIE (Zaporojets et al. 2021) and DocRED (Yao et al. 2019).

1. **Document-level**: coreferent entity mentions spread across sentences.
2. Entity and relation annotations on cluster level (**entity-centric**).
3. Annotations (e.g., relations) are not always explicitly stated in the text: model can benefit from **external knowledge**.

Approach:

1. Inject **external knowledge** using **entity representations**.
2. Entity representations derived from **knowledge graph** (Wikidata) and from **hyperlinked textual knowledge base** (Wikipedia).
3. Explore **attention** and **prior**-based weighting of candidate entities for each of the textual spans.

Method

Main components of the proposed architecture:

1. **Text span** i: a span of text in the input document.
2. **Candidate entities** C associated to each of the spans (**EL dictionary**).
3. Wikipedia and Wikidata **KB representations** ξ of entities.
4. **Weighted combination** α of candidate entity representations.

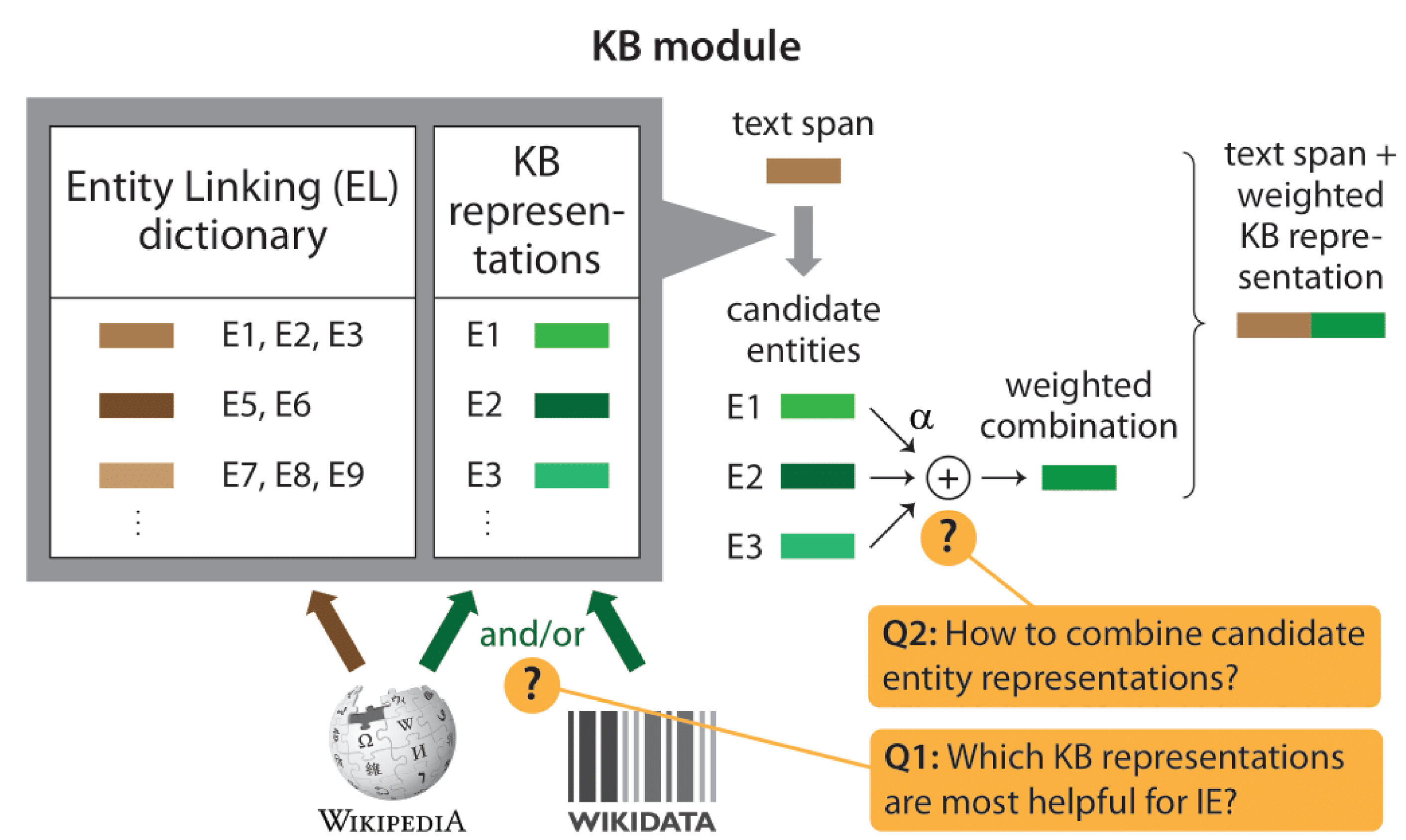


Fig. 2: Sketch of the proposed architecture.

Entity representation for span i:

$$\mathbf{e}_i^{\kappa} = \sum_{c_{ij} \in C_i} \alpha_{ij} \cdot \boldsymbol{\xi}_{\kappa}(c_{ij})$$

To answer Q1 (see Fig. 2) → sources of **external knowledge** κ:

1. Wikidata (**KB-graph**)
2. Wikipedia (**KB-text**)
3. Concatenation of both (**KB-both**).

To answer Q2 (see Fig. 2) → weighted combination α for a span i:

1. **Prior** p_{ij} ($P(e_j|m_i)$ as per Yamada et al. 2016, §3): $a_{ij} = p_{ij}$
2. **Uniform**: $\alpha_{ij} = 1/|C_i|$
3. **Attention**: $\alpha_{ij} = \mathcal{F}_A([\mathbf{g}_i; \boldsymbol{\xi}_{\kappa}(c_{ij})])$
4. **AttPrior**: $\alpha_{ij} = \mathcal{F}_{AP}([\mathbf{g}_i; \boldsymbol{\xi}_{\kappa}(c_{ij}); p_{ij}])$

$\}$ $\mathcal{F}_*$ is a feed-forward neural network, $\mathbf{g}_i$ is the representation of span i.

Results

Ablation study:

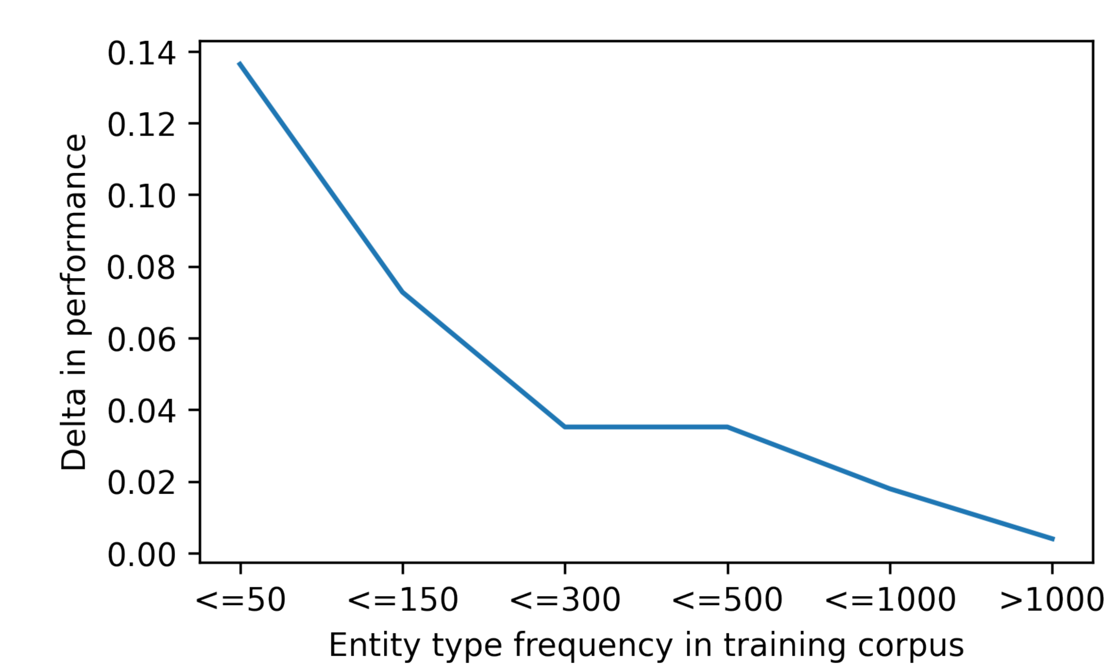
Model	Avg. F1	Δ
Baseline	63.77	-
External Knowledge		
+KB-text	65.55	+1.78
+KB-graph	66.08	+2.31
+both	**66.61**	**+2.84**
Weighting Scheme		
+Prior	65.65	+1.88
+Uniform	65.68	+1.91
+Attention	66.10	+2.33
+AttPrior	**66.61**	**+2.84**

Tab. 1: Average performance.

Q1: Complementarity of *both*, Wikidata and Wikipedia knowledge sources.

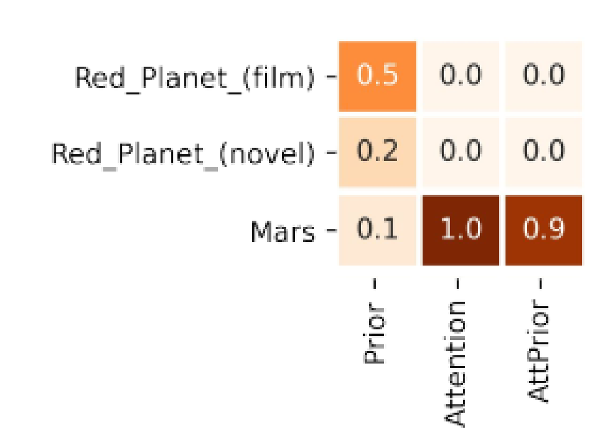
Q2: Best result for attention+prior (AttPrior) weighting scheme.

Performance on rare entity types: external knowledge boosts the performance for entities whose types appear less frequently in the corpus:



Qualitative analysis of weighting schemes → for text snippet:

"NASA's Mars rover, "Curiosity" will [...] continue exploring the surface of the Red Planet."



Attention-based schemes assign highest weight to correct entity (*Mars*).

Attention-based schemes are able to capture the textual context.

Contact Information

Severine Verlinden
severine.verlinden@outlook.be
Klim Zaporojets
klim.zaporojets@ugent.be
klimzaporojets.github.io

*Equal contribution

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[a] https://www.projectcpn.eu/