Breaking Through the 80% Glass Ceiling:

Raising the State of the Art in Word Sense Disambiguation by Incorporating Knowledge Graph Information

Michele Bevilacqua   Roberto Navigli

bevilacqua,navigli@di.uniroma1.it
Sapienza NLP
Department of Computer Science
Sapienza University of Rome

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  - *(baseball) a turn trying to get a hit*
  - *a club used for hitting a ball in various games*



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Supervised WSD Systems

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- structured information (relations between senses or *synsets*).

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    - Kumar et al. [2019, EWISE]: maps a target in context vector to the space of gloss embeddings.

Structured Knowledge

WordNet is not just a sense list, but a **directed graph**. Edges represent lexical (semantic) relations between senses (synsets).

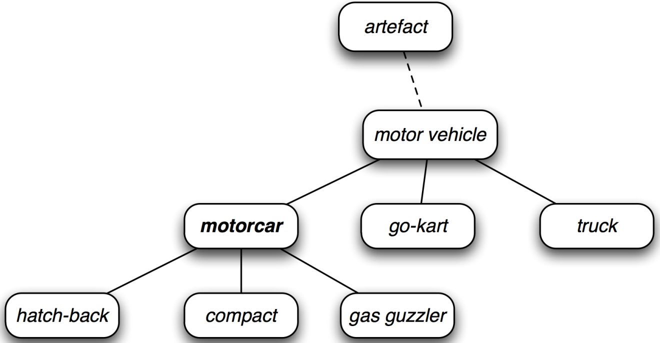

Figure: Image taken from `https://www.nltk.org/book/ch02.html`

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  - Vial et al. [2019]: relations are used to conflate senses into coarser but reversible semantic classes. Information which is specific to a synset is lost.

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  - explicit knowledge, through the incorporation of a WordNet-based adjacency matrix.
- Both techniques are added **on top of a baseline neural classifier**.

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EWISER: Baseline Classifier

- We use a very simple **2-layer feedforward WSD classifier**, taking as input BERT large's hidden states for of the last 4 layers:

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Q &= \boxed{ZA^T} + Z
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Implicit Knowledge ← **Initialize** $\boxed{\mathbf{O}}$ with sense embeddings.

Explicit Knowledge ← Add an additional term to Z **computed via the adjacency matrix** A.

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- we employ sense embeddings that **incorporate gloss information**:
  - LMMS_{2048} [Loureiro and Jorge, 2019];
  - SensEmBERT [Scarlini et al., 2020] + LMMS_{2048}.

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O-thaw*	O-thaw with LR reduced

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- **Test**:
  - **Concatenation of the English datasets** in the framework of [Raganato et al., 2017, **ALL**];
  - **Multilingual datasets** from SemEval 2013 Task 12 [Navigli et al., 2013] and SemEval 2015 Task 13;
  - Results on individual datasets reported in the paper!

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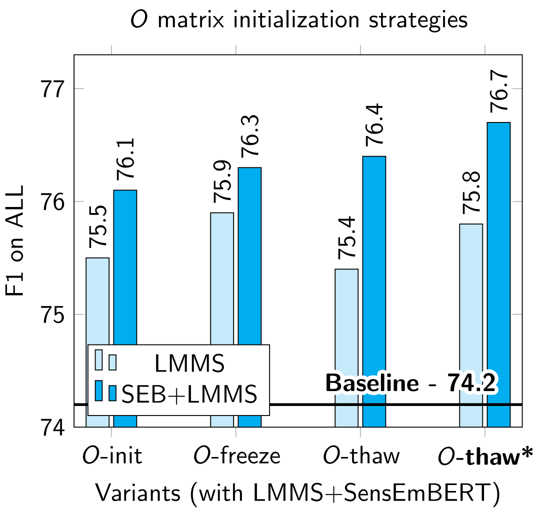
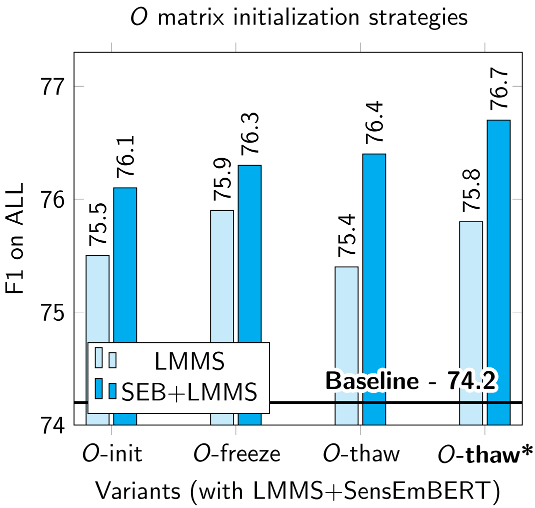
EWISER: Unstructured Knowledge - Results





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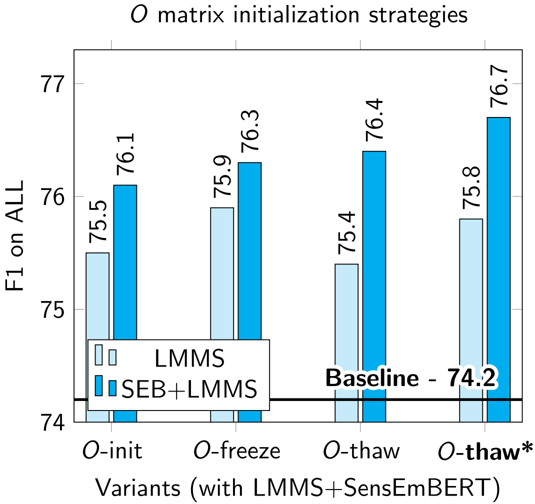

- The **choice of the embeddings is critical** (SEB > LMMS);
- ***O*-thaw*** is a very effective strategy.

EWISER: Structured Knowledge

- Structured knowledge added by a **matrix multiplication** between:
  - Z: logits;
  - A: sparse adjacency matrix.

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- This is equivalent to adding to a synset logit the sum of all the scores for all synsets connected to it, weighted by the edge weight:

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- The adjacency matrix A weights can be **refined with standard backpropagation**!

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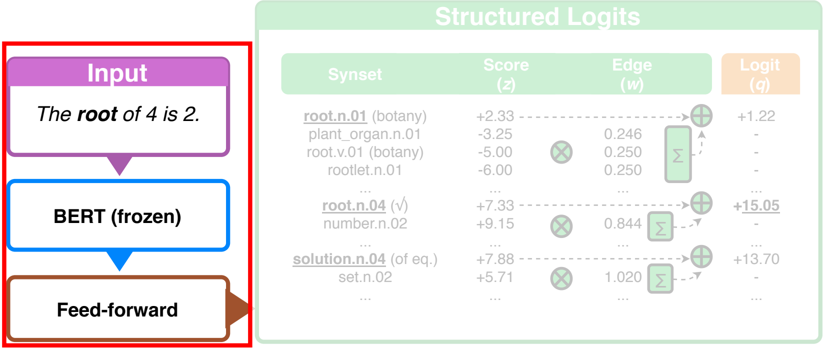

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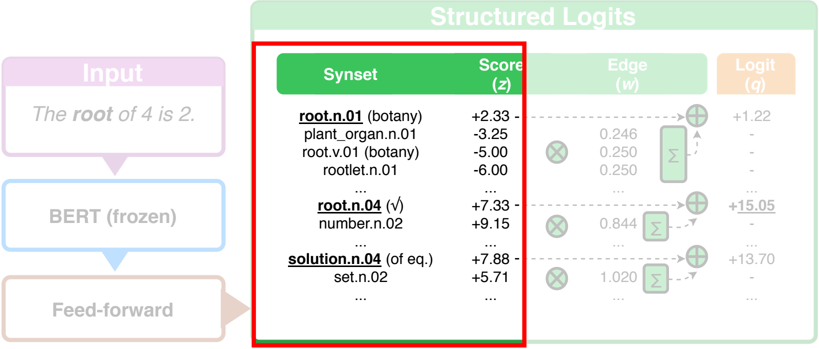

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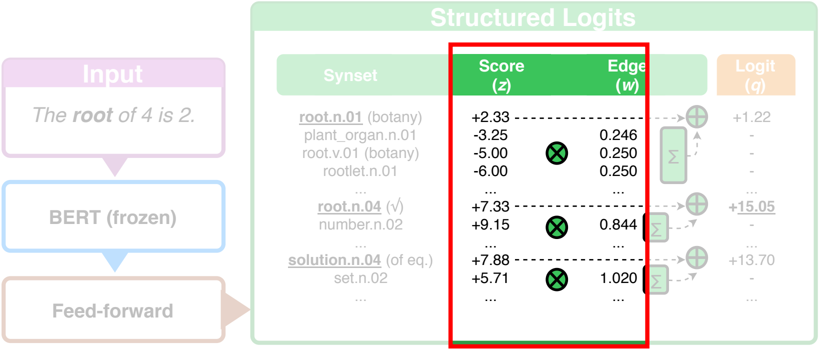

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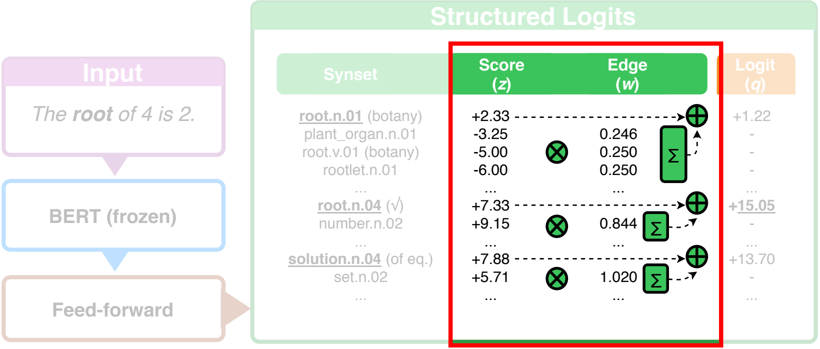

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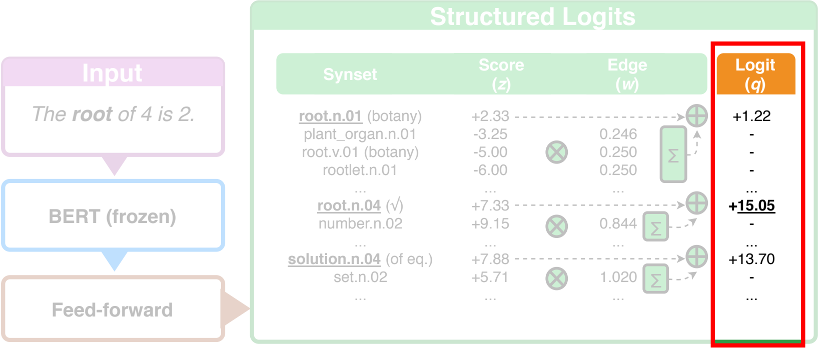

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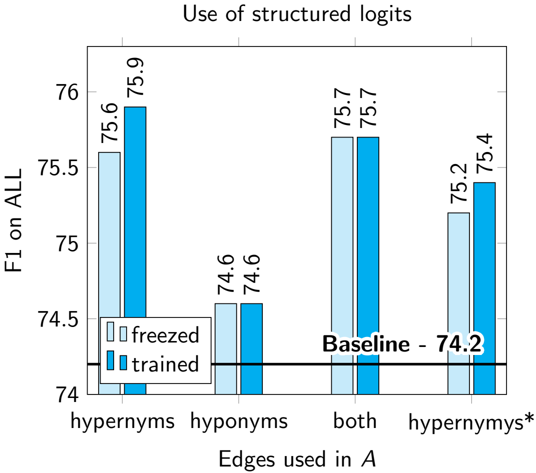

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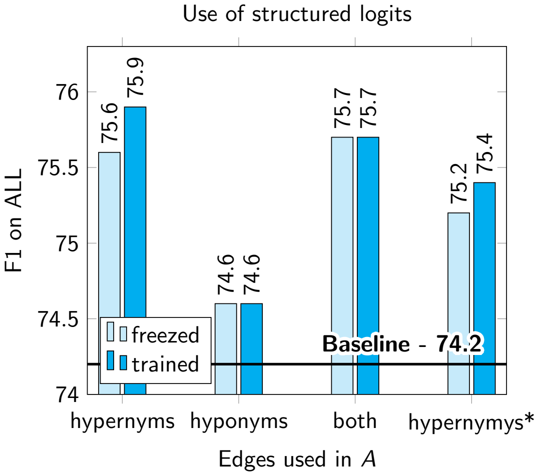

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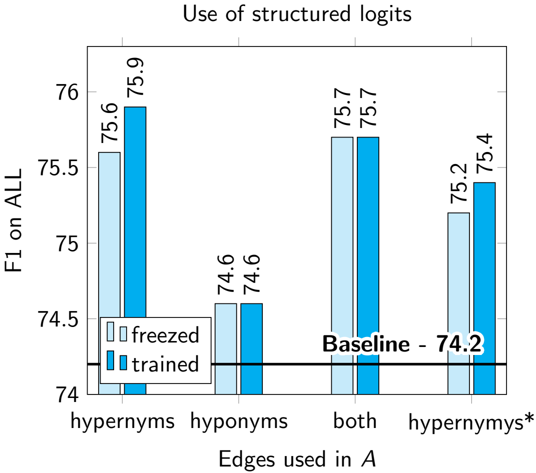
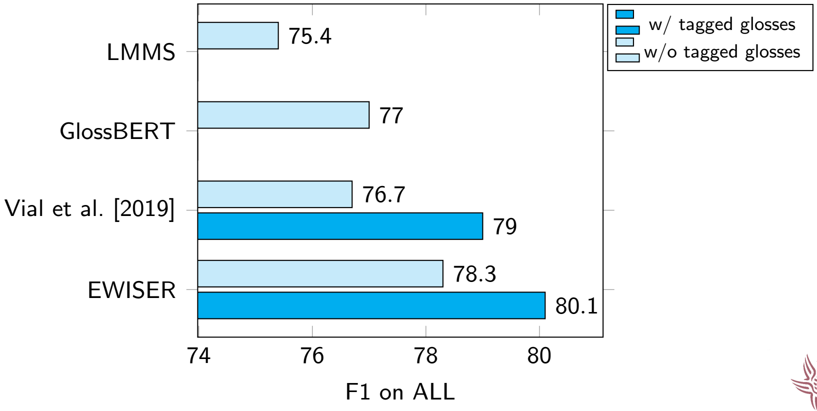


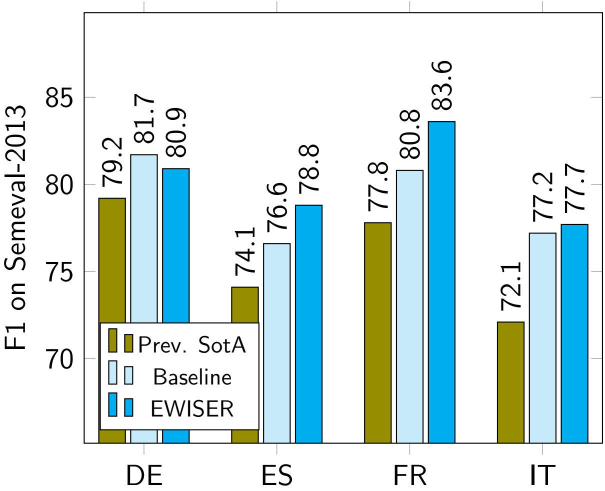
- **hypernymy edges** must be used;
- **training the edge weights** results in a small improvement.

EWISER: Bringing Everything Together

The improvements can be stacked, with **SotA results** on the concatenation of the standard evaluation datasets!



The results are also **strong in a cross-lingual setting**, with the model **trained only on English**.



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- we **surpass for the first time the 80% figure** (upper bound on human annotator agreement on WSD) on the standard English benchmarks;
- performances **scale gracefully to the multilingual** setting.

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Thank you!

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