Moving Down the Long Tail of Word Sense Disambiguation with Gloss Informed Bi-encoders

Terra Blevins and Luke Zettlemoyer

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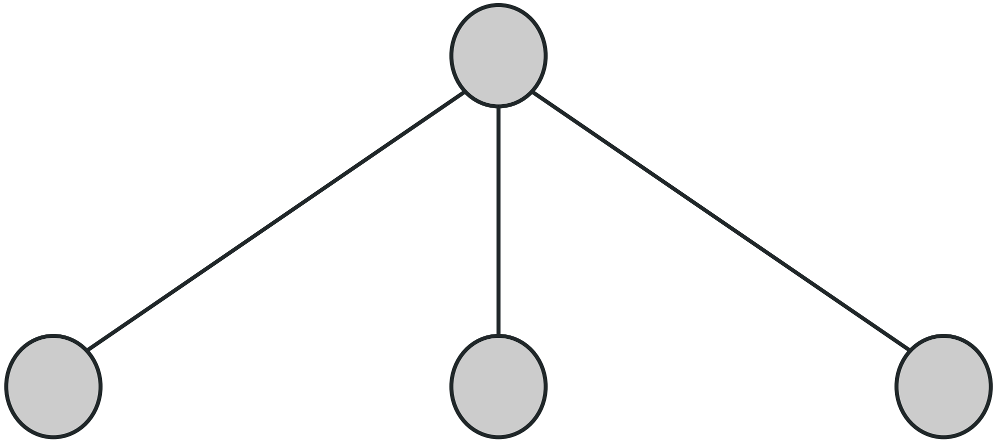
The **plant** sprouted a new leaf.



(n) (botany) a living organism…

(n) buildings for carrying on industrial labor

(v) to put or set (a seed or plant) into the ground

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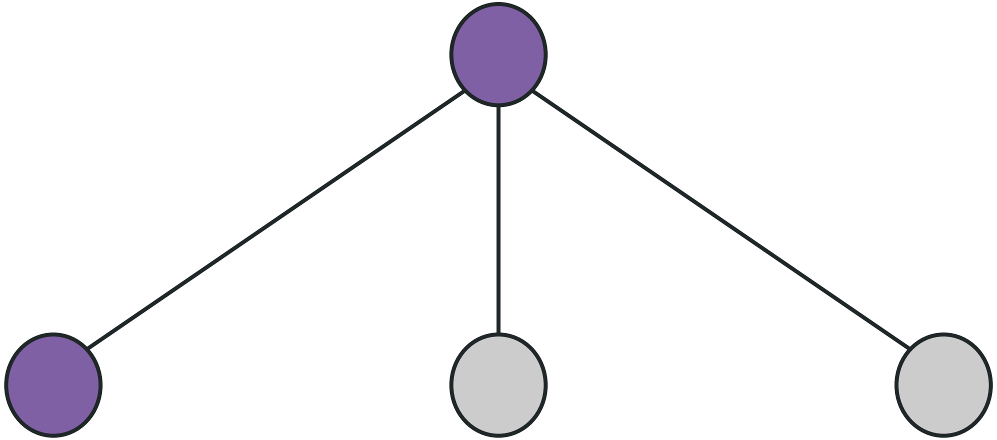

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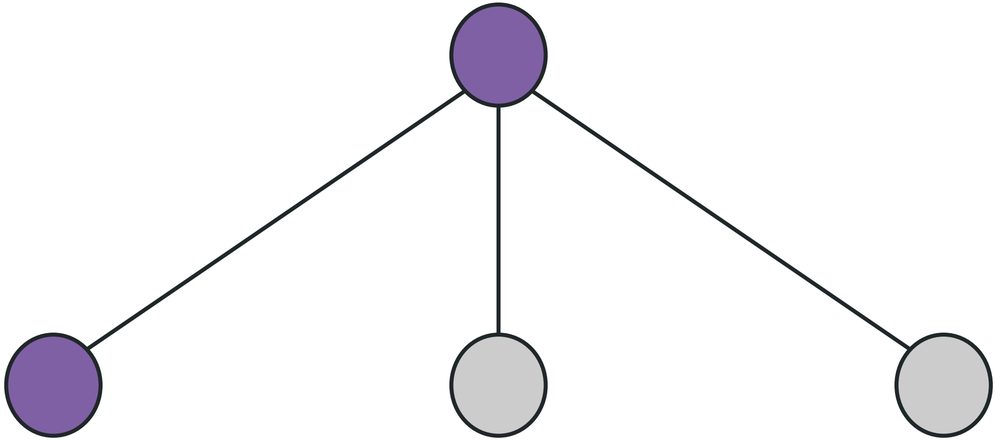
Target Word

Context The **plant** sprouted a new leaf.



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Candidate Senses

Data Sparsity in WSD

- Senses have Zipfian distribution in natural language

Kilgarriff (2004), *How dominant is the commonest sense of a word?*.
Kumar et al. (2019), *Zero-shot Word Sense Disambiguation using Sense Definition Embeddings.*

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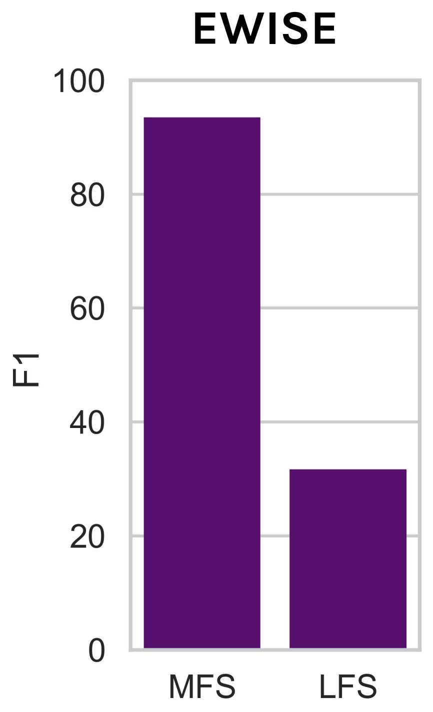
- Data imbalance leads to worse performance on uncommon senses



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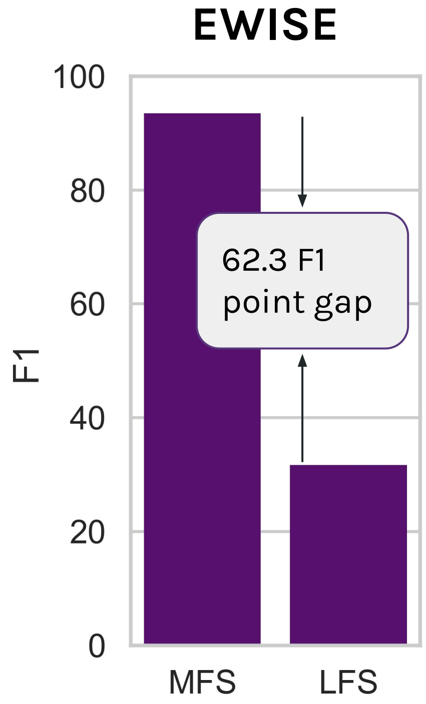

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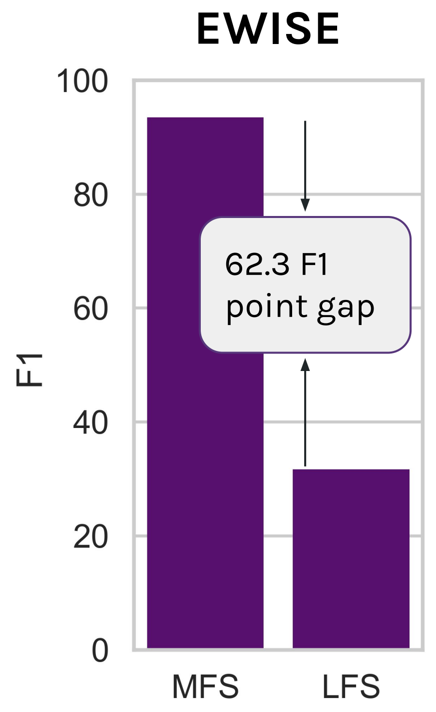
- We propose an approach to improve performance on rare senses with pretrained models and glosses



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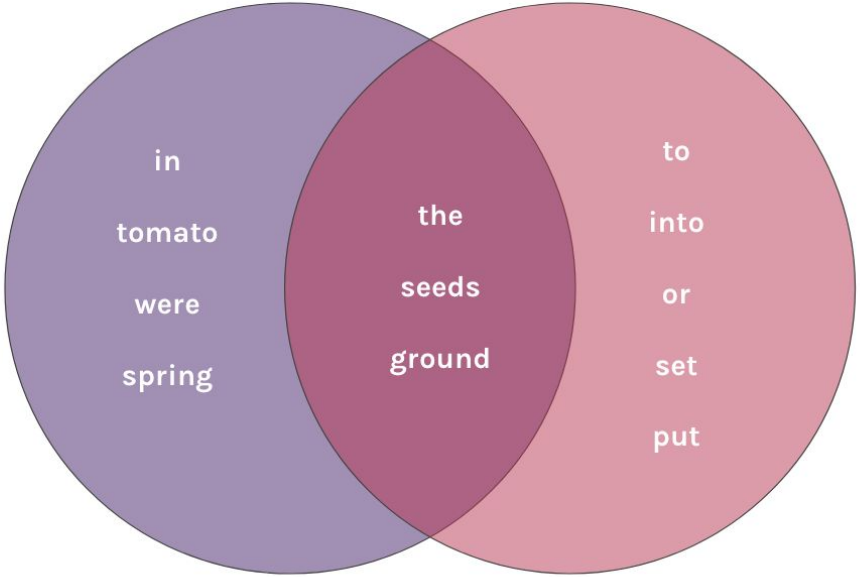
Incorporating Glosses into WSD Models

- Lexical overlap between **context** and **gloss** is a successful knowledge-based approach (Lesk, 1986)



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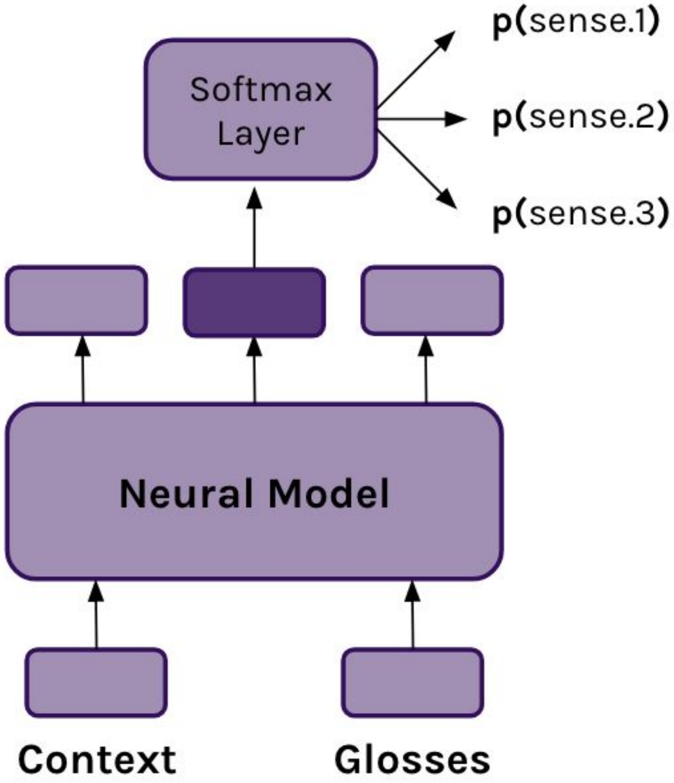

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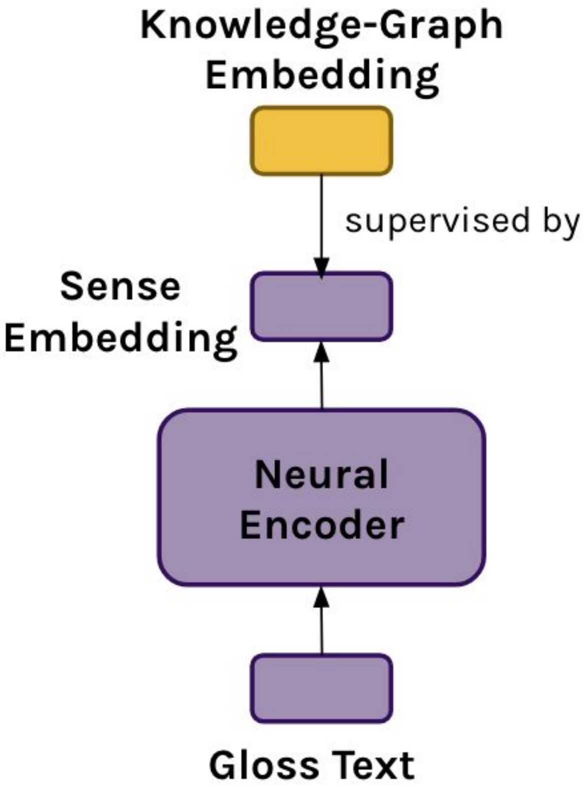
  - Mapping encoded gloss representations onto graph embeddings to be used as labels for a WSD model (Kumar et al., 2019)



Pretrained Models for WSD

- Simple **probing** classifiers on frozen pretrained representations found to perform better than models without pretraining

Hadiwinoto et al. (2019), *Improved word sense disambiguation using pretrained contextualized representations.*
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- **GlossBERT** finetunes BERT on WSD with glosses by setting it up as a sentence-pair classification task

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Our Approach: Gloss Informed Bi-encoder

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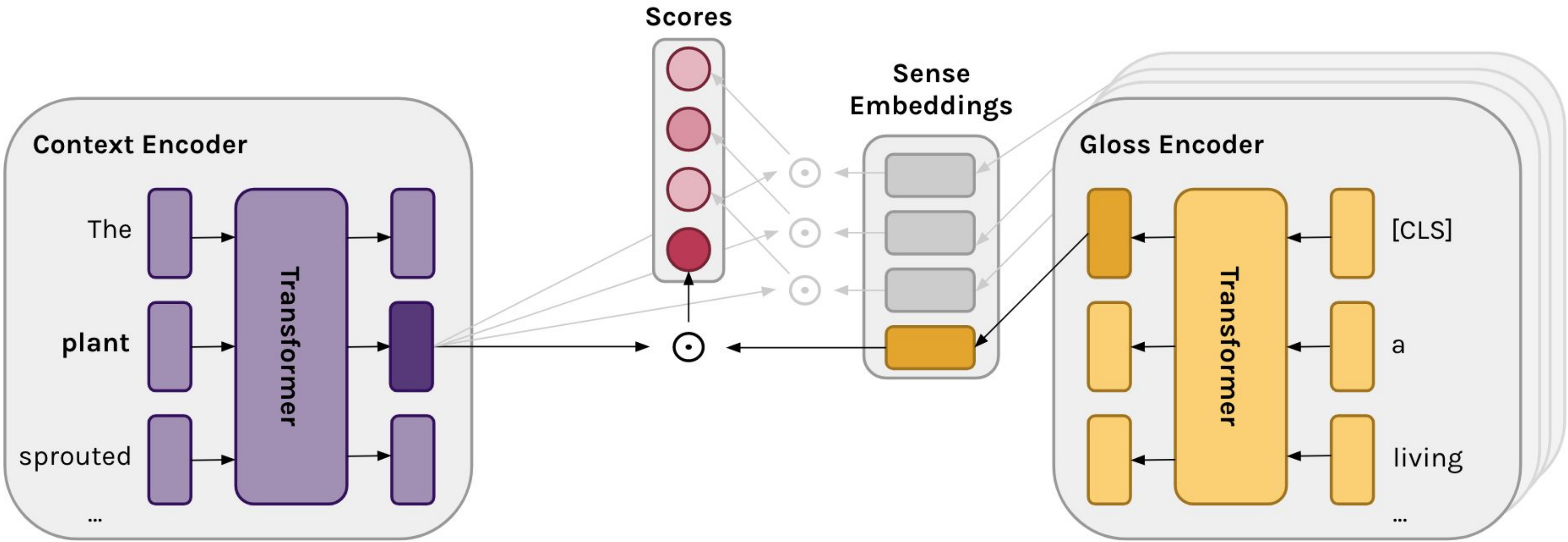
- Encoders initialized with BERT and trained end-to-end, without external knowledge
- The bi-encoder is more computationally efficient than a cross-encoder

Our Approach: Gloss Informed Bi-encoder



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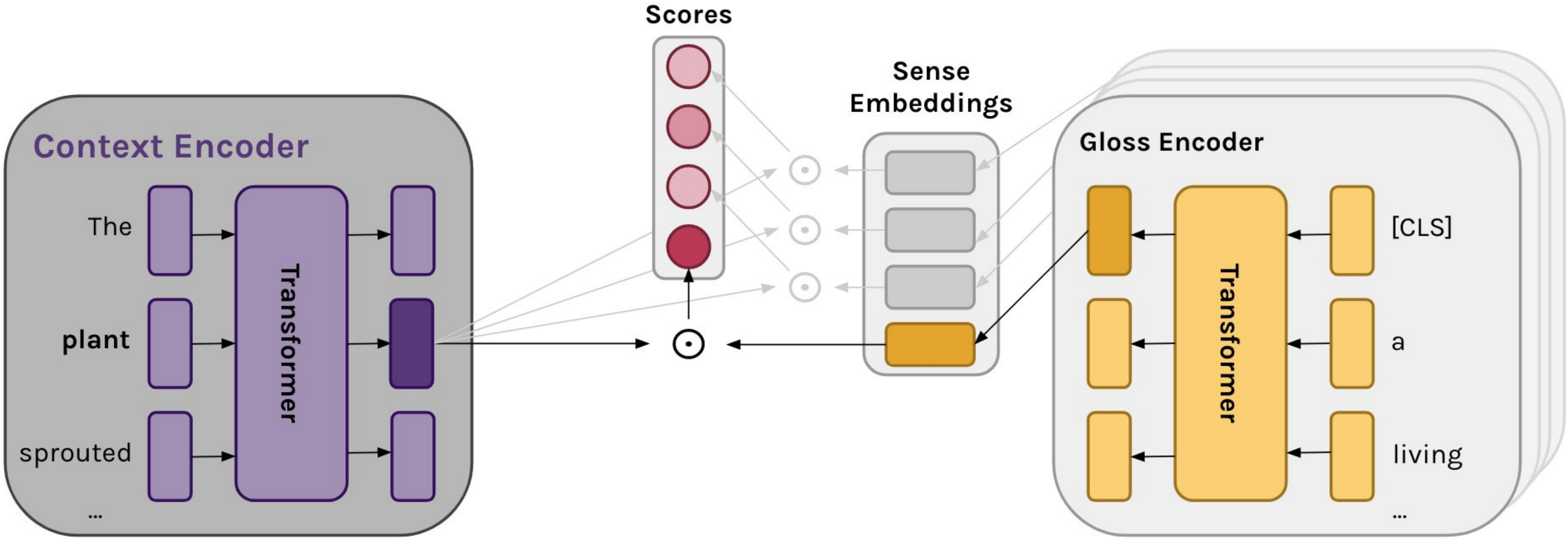

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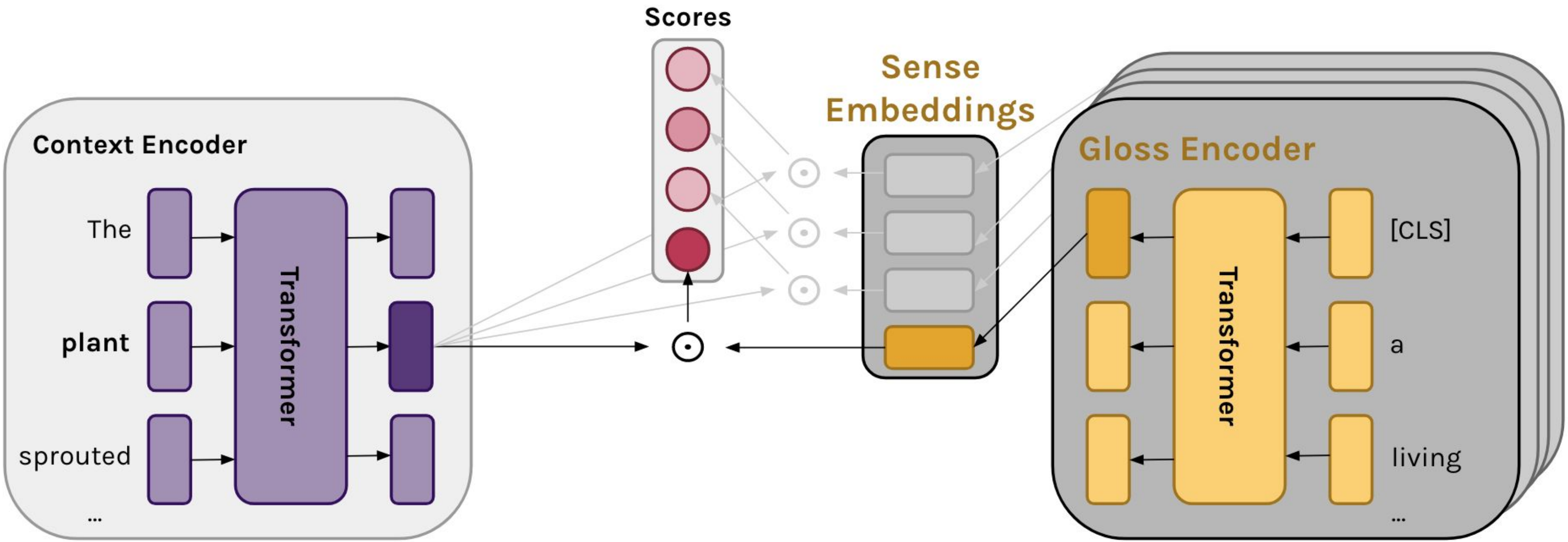

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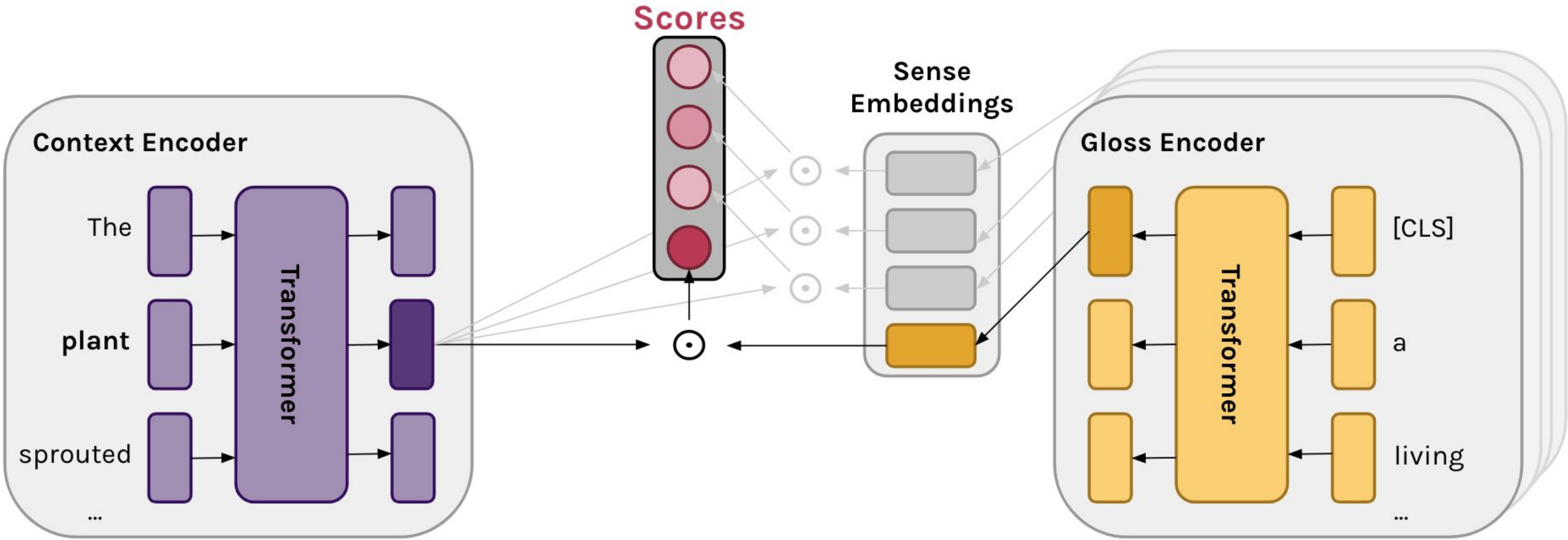

Baselines and Prior Work

Model	Glosses?	Pretraining?	Source
HCAN	✓		Luo et al., 2018a
EWISE	✓		Kumar et al., 2019
BERT **Probe**		✓	**Ours**
GLU		✓	Hadiwinoto et al., 2019
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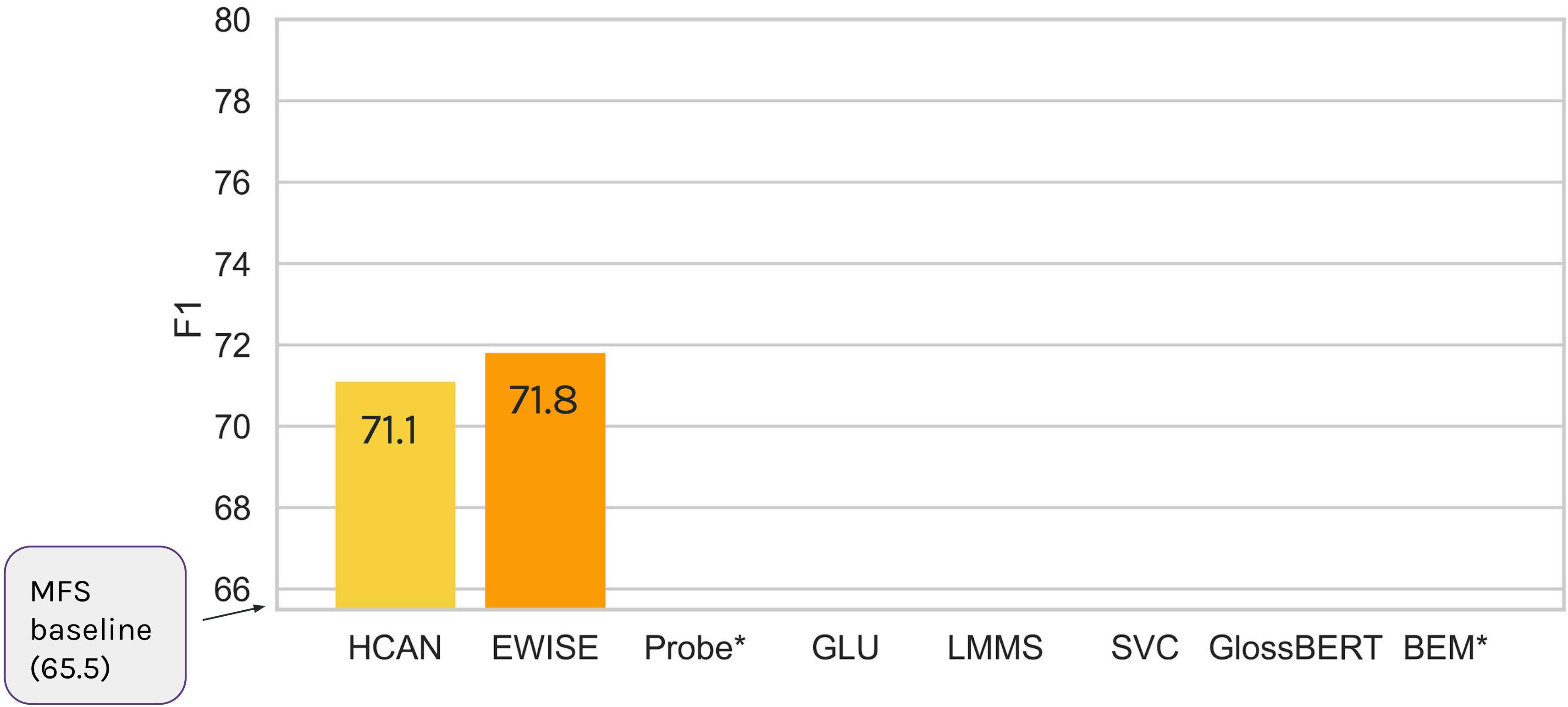
Overall WSD Performance



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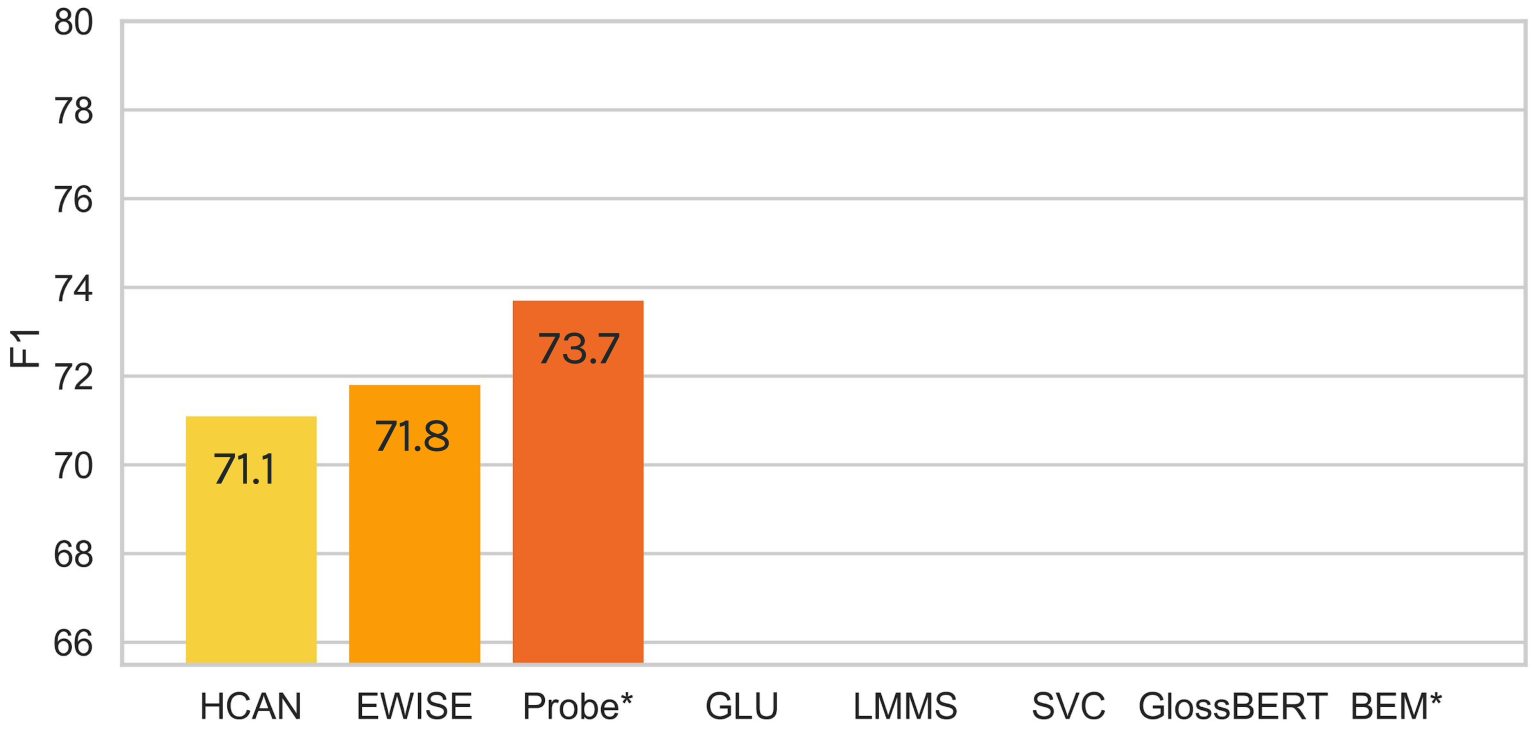

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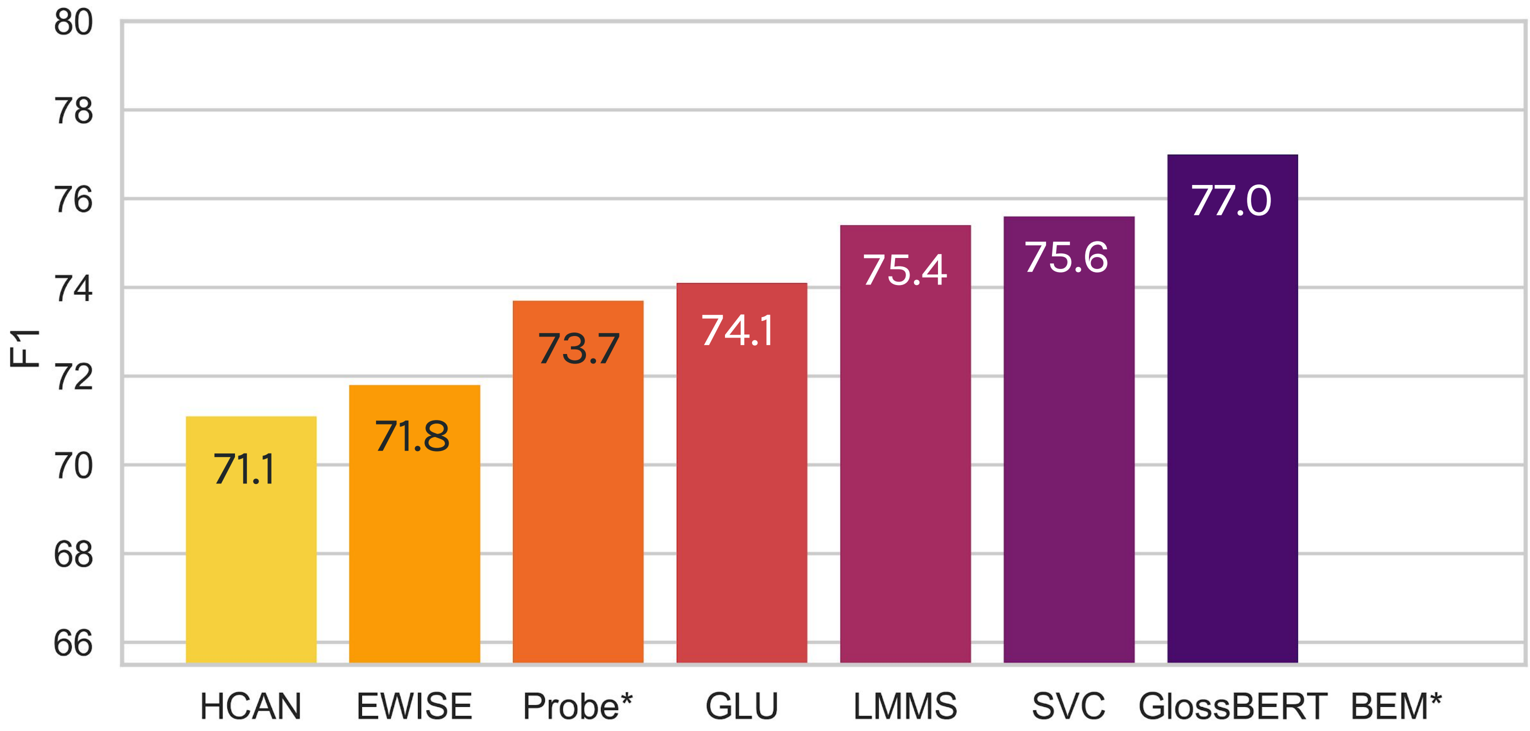

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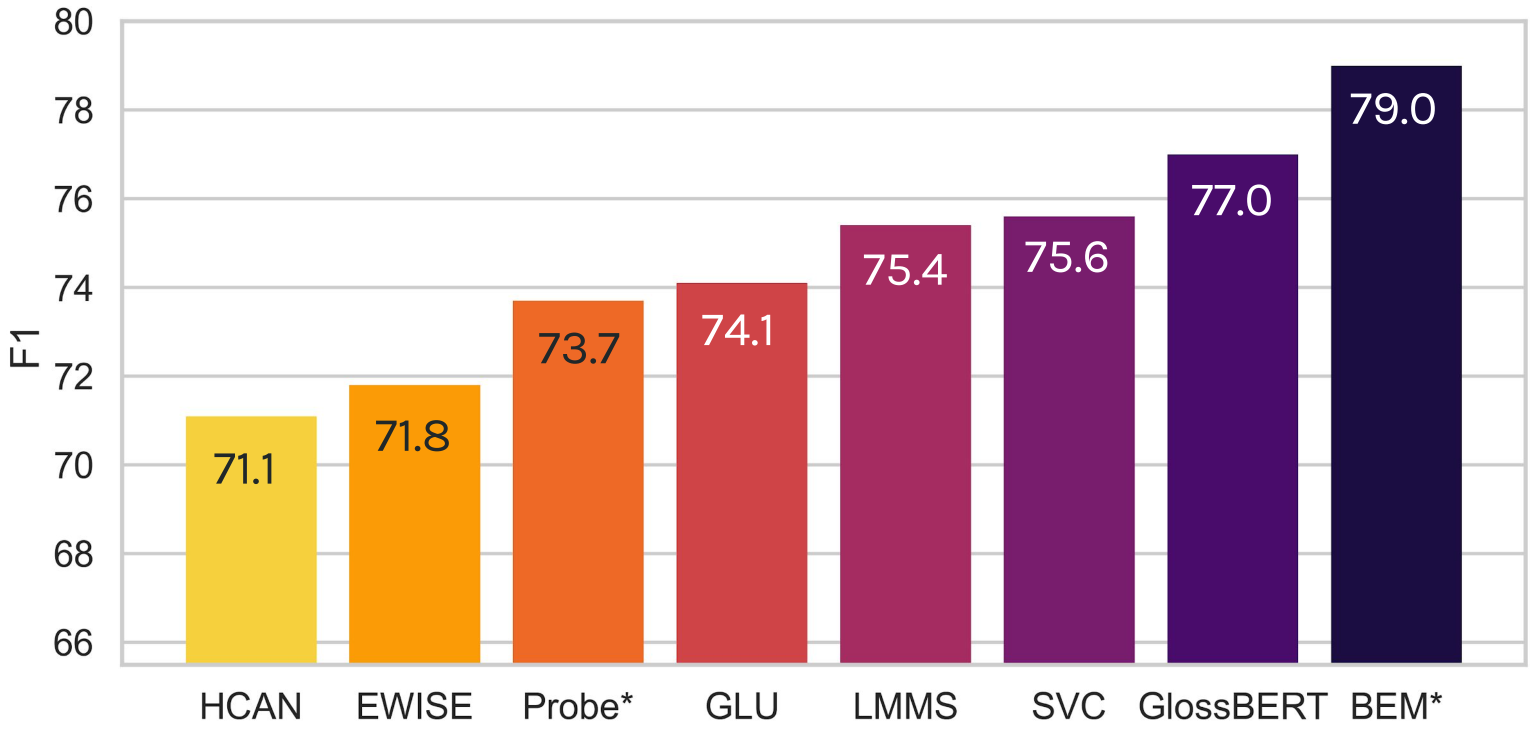

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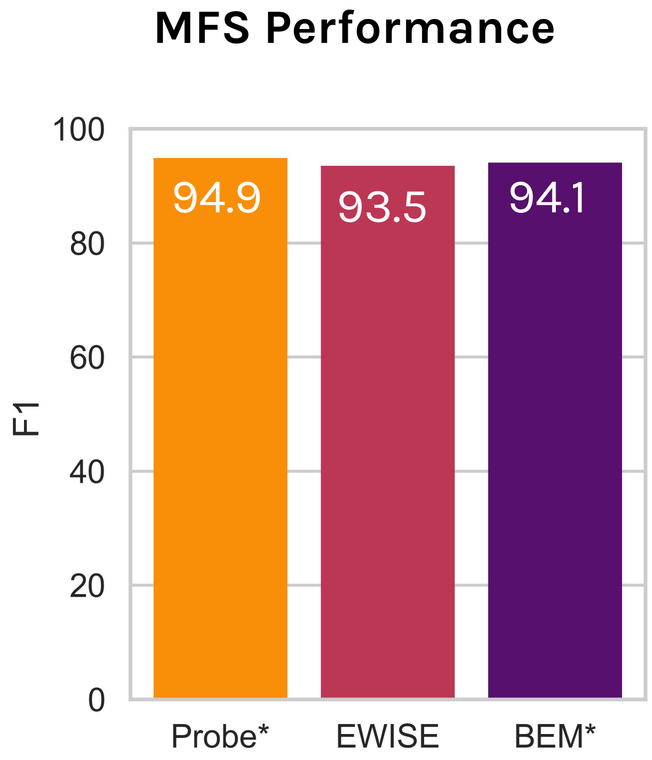

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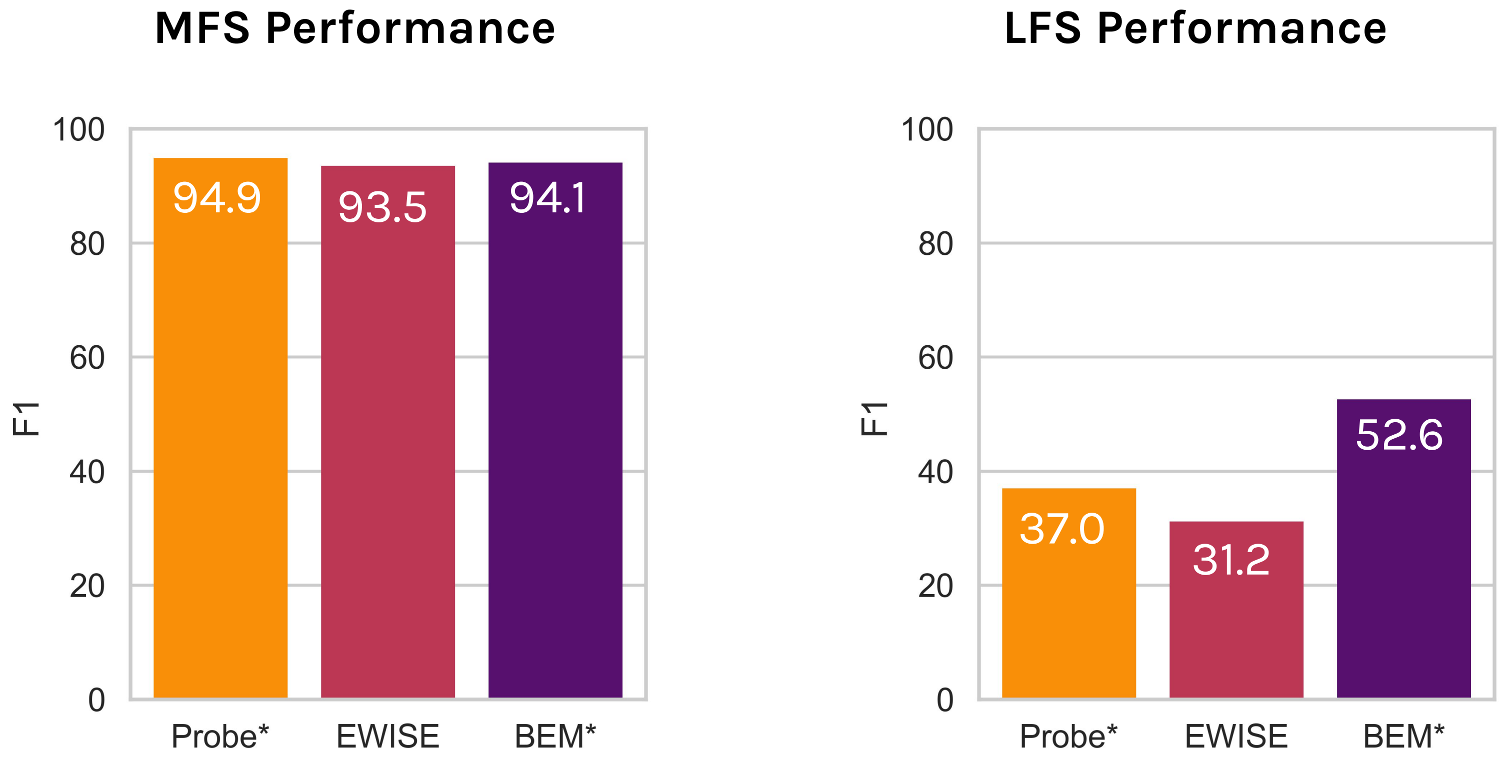

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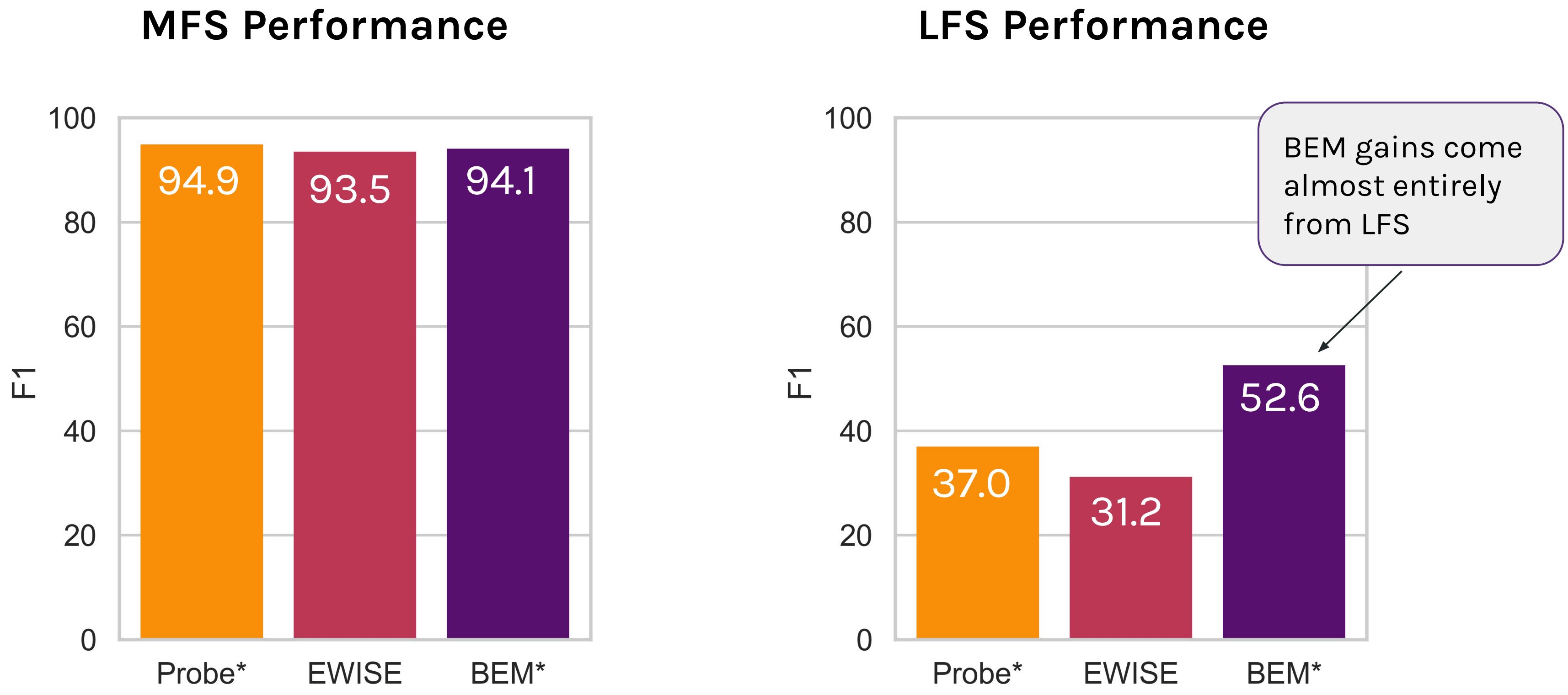

Zero-shot Evaluation

- BEM can represent new, unseen senses with gloss encoder and encode unseen words with the context encoder
- Probe baseline relies on **WordNet back-off**, predicting the most common sense of unseen words as indicated in WordNet

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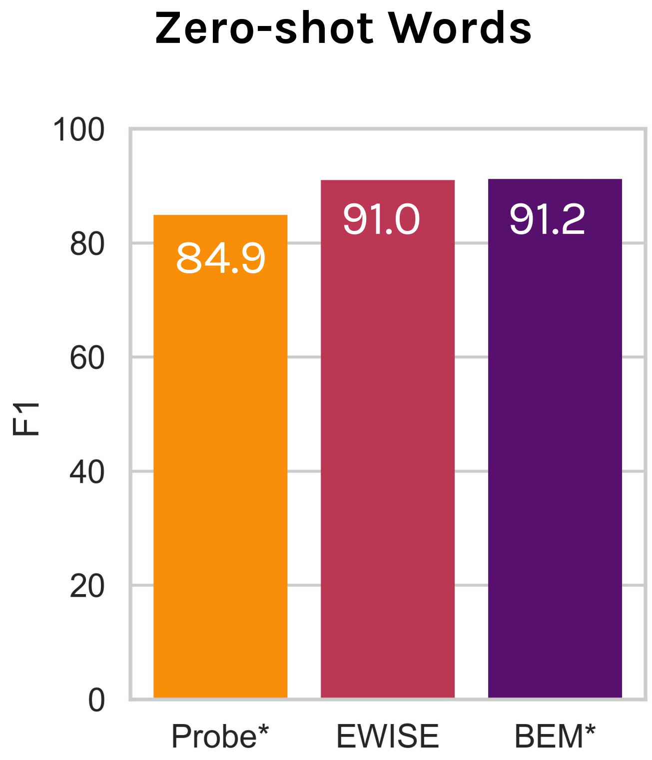

Zero-shot Evaluation

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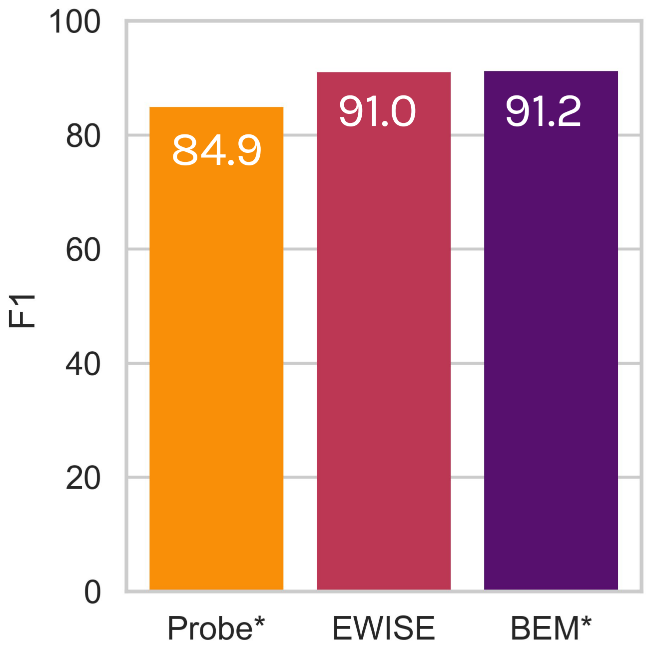
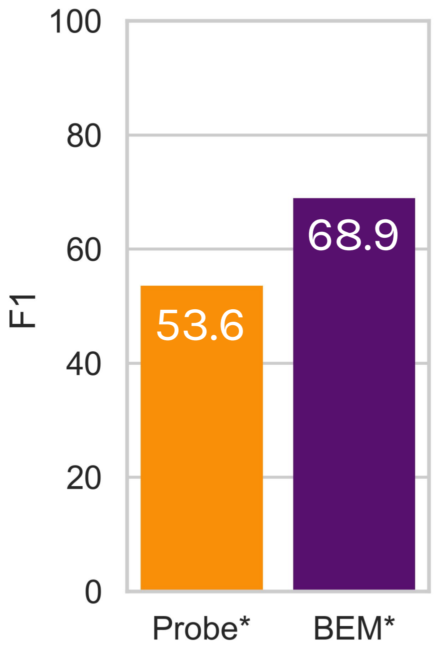


Zero-shot Senses



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Train BEM (and frozen probe baseline) on subset of SemCor, with (up to) **k** examples of each sense in the training data

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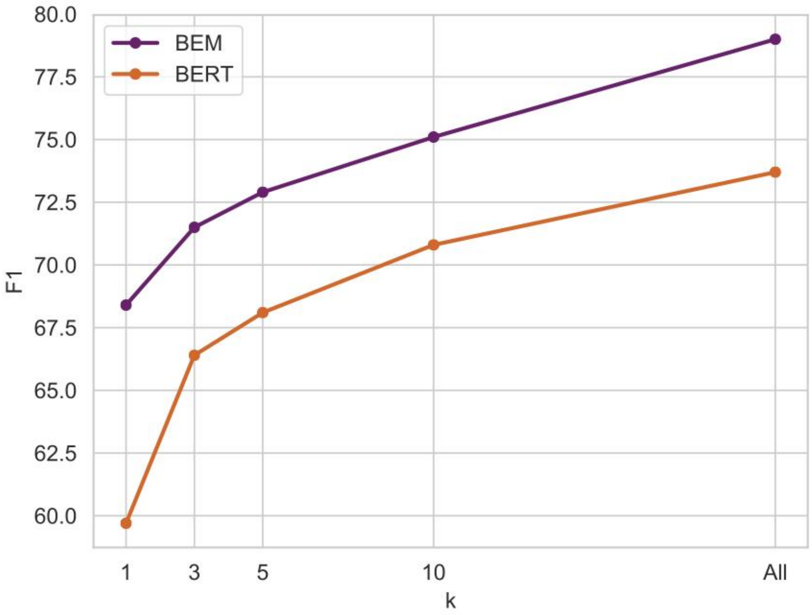

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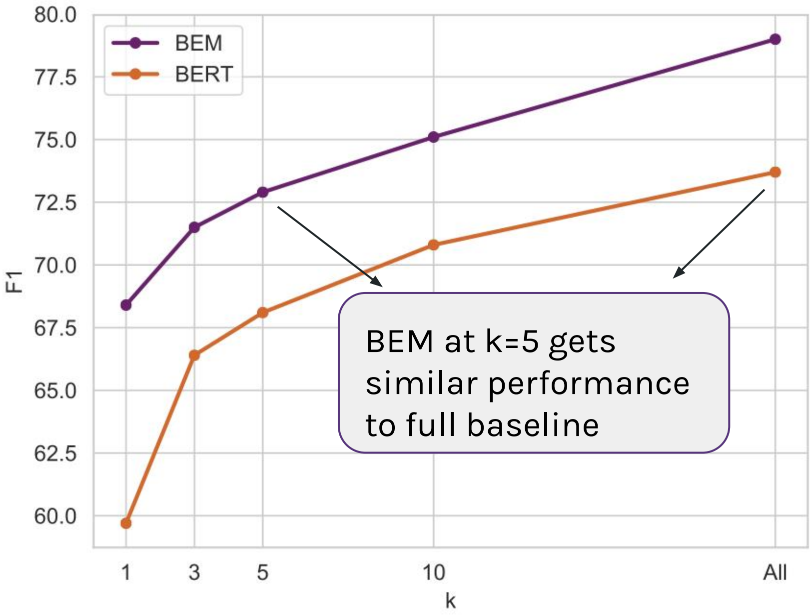

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Questions?

https://github.com/facebookresearch/wsd-biencoders

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