

Applying a Naive Bayes Similarity Measure to Word Sense Disambiguation

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1. WSD



terminal (n.)

The **passengers** disembarked onto the parking bay in front of a small **terminal** building.

She confirmed the tape recorder was working and examined her **computer terminal** for instructions.

2. The (simplified) Lesk Algorithm for WSD^[1]

The sense whose dictionary gloss has the highest degree of overlap with the context words is chosen as the correct sense.

ter·mi·nal (n.)

- 1 station where transport vehicles load or unload **passengers** or goods.
- 2 electronic equipment consisting of a device providing access to a **computer**.

(WordNet 3.1)



3. Limitations of String Matching

“Lesk’s approach is very sensitive to the exact wording of definitions, so the absence of a certain word can radically change the results.”^[2]

Even for the two most frequent senses of the word *terminal*, only a small number of contexts actually overlap with the corresponding glosses by exact string matching:

<i>terminal</i>	<i>passenger</i> <i>terminal</i>	<i>computer</i> <i>terminal</i>
2,235	143 (6.40%)	317 (14.18%)

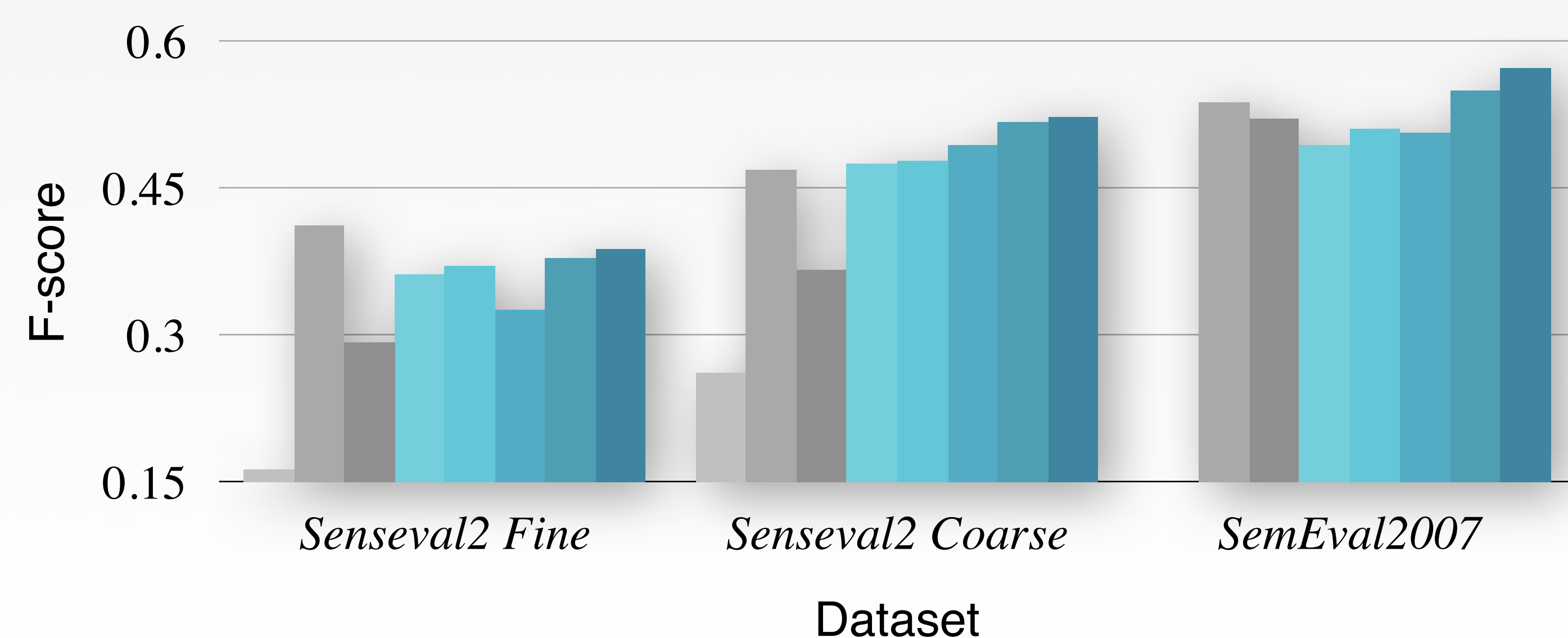
(Counts in the BNC)

4. Experiments

WSD accuracy on three datasets. Our probabilistic model (blue bars) uses gloss and various additional knowledge sources to overlap with context words.

Baselines

- simplified Lesk
- 1st place system*
- 2nd place system*
- gloss only
- gloss+synonyms
- gloss+hyponyms
- gloss+hypernyms
- gloss+all other types



* Senseval/SemEval 1st and 2nd place systems.

5. Conclusions

- Probabilistic matching significantly improves WSD accuracy over exact string matching (blue bars vs. left-most grey bars).
- Combining multiple types of lexical knowledge achieves state-of-the-art accuracy (right-most blue bars).
- Hyponyms are the most effective feature when added to gloss texts for WSD (2nd-to-right-most blue bars).

[1] Adam Kilgarriff and Joseph Rosenzweig. Framework and results for English Senseval. *Computers and the Humanities*, 34(1-2):15–48, 2000.

[2] Roberto Navigli. Word sense disambiguation: A survey. *ACM Computing Surveys*, 41(2):10:1–10:69, 2009.

We therefore propose a “softer” measure of gloss-context overlap using a Naive Bayes model:

$$p(\mathbf{f}|\mathbf{e}) = \prod_j p(f_j|\{e_i\}) = \prod_j \frac{p(\{e_i\}|f_j)p(f_j)}{p(\{e_i\})}$$

$$= \frac{\prod_j [p(f_j) \prod_i p(e_i|f_j)]}{\prod_j \prod_i p(e_i)} \quad (1)$$

Probability estimation:

$$(1) \approx \sum_i \log \frac{c(f_j)}{c(\cdot)} + \sum_i \sum_j \log \frac{c(e_i, f_j)}{c(f_j)} - |\{f_j\}| \sum_j \log \frac{c(e_i)}{c(\cdot)}$$

$$= (1 - |\{e_i\}|) \sum_i \log c(f_j) - |\{f_j\}| \sum_j \log c(e_i)$$

$$+ \sum_i \sum_j \log c(e_i, f_j) + |\{f_j\}| (|\{e_i\}| - 1) \log c(\cdot),$$

where $c(\cdot)$ is the corpus size.