Finding Word Sense Embeddings of Known Meaning

A method for refitting word sense embeddings, using a single example, by application of Bayes' theorem to the language model

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Words don’t only have one meaning

Kid *(Noun)*

1. (a young person of either sex) "she writes books for children"; "they’re just kids"; "‘tiddler’ is a British term for youngster"
2. (English dramatist (1558-1594))
3. (a human offspring (son or daughter) of any age) "they had three children"; "they were able to send their kids to college"
4. (young goat)

George A Miller. “WordNet: a lexical database for English”. In: *Communications of the ACM* 38.11 (1995), pp. 39–41.

Word embeddings represent each word as a single vector

SkipGram Language Model:

- Input a word w_T
- Output probabilities of words appearing in its context $P(w_i \mid w_T)$

$$\overbrace{\overbrace{\texttt{wow}}^{w_1}\ \overbrace{\texttt{the}}^{w_2}\ \overbrace{\texttt{wool}}^{w_3}\ \overbrace{\texttt{from}}^{w_4}\ \overbrace{\texttt{the}}^{w_5}\quad \underbrace{\texttt{kid}}_{\textit{target word}}\quad \overbrace{\texttt{is}}^{w_6}\ \overbrace{\texttt{so}}^{w_7}\ \overbrace{\texttt{soft}}^{w_8}\ \overbrace{\texttt{and}}^{w_9}\ \overbrace{\texttt{fluffy}}^{w_{10}}}^{\mathbf{c}}$$

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Word Embeddings Implementation

- Represent each input word as a vector
- Train a neural network to estimate $P(w_i \mid w_T)$
- Back-prop finds values for the input vector – i.e. good representation for the word

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Word sense embeddings represent each word as a multiple vectors

- Each word has multiple senses $\{u_1, u_2, \dots, u_n\}$
- SkipGram Language Model becomes
  - Input a word sense u_i
  - Output probabilities of words appearing in its context $P(w_i \mid u_j)$

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Many sense embeddings don’t produce human recognisable senses

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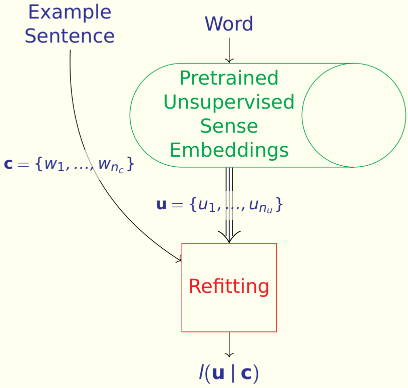
  - Find overly narrow meanings
  - Capture rare jargon uses

Many sense embeddings don't produce human recognisable senses

- Embeddings are learnt by modelling what words occur near the sense
- No control over the meanings of the senses
  - Cover overlapping definitions
  - Find overly narrow meanings
  - Capture rare jargon uses
- Useful, but not interoperable with lexical knowledge bases.

We will solve this by *refitting* them to be for the sense we mean

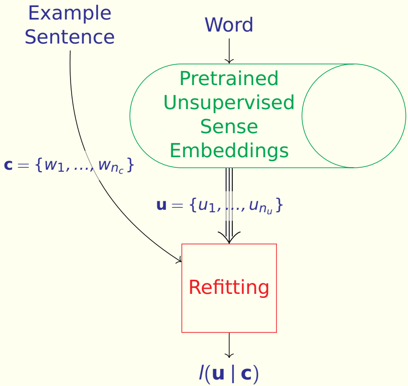
- Refitting constructs new sense embeddings out of the old.
- It uses the probabilities of example sentence occuring.
- The new embedding aligns to the meaning in that sentence.



Refitting uses a probability weighted sum

New sense embedding:

$$l(\mathbf{u} \mid \mathbf{c}) = \sum_{\forall u_i \in \mathbf{u}} u_i P(u_i \mid \mathbf{c})$$



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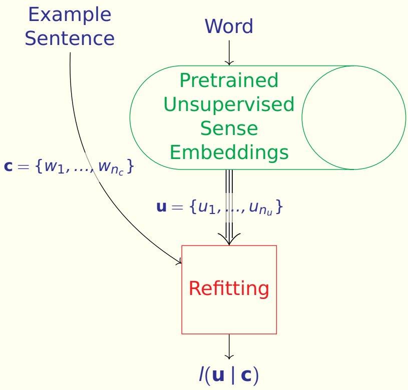
The probabilities are found using Bayes' theorem

Language model: $P(w_i \mid u_i)$



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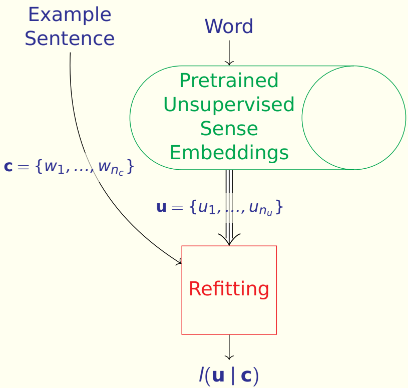
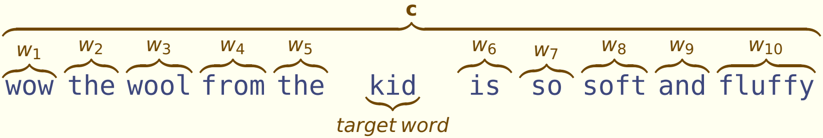
Language model: $P(w_i \mid u_i)$

Conditional Independence:

$$P(\mathbf{c} \mid u_i) = \prod_{\forall w_j \in \mathbf{c}} P(w_j \mid u_i)$$





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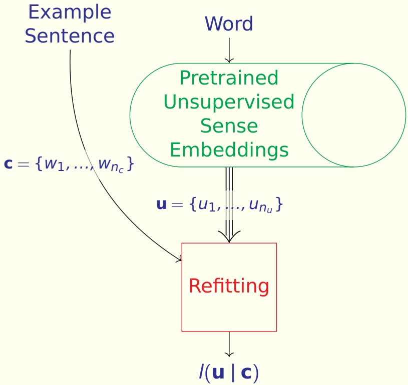
$$P(u_i \mid \mathbf{c}) = \frac{P(\mathbf{c} \mid u_i) P(u_i)}{\sum_{u_j \in \mathbf{s}} P(\mathbf{c} \mid u_j) P(u_j)}$$



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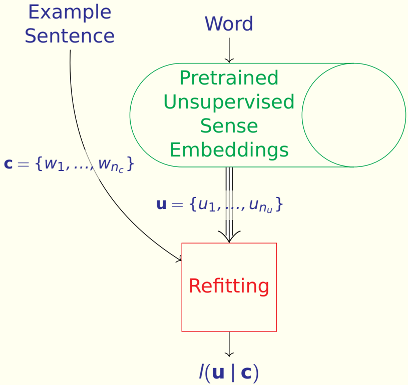
Refitted Sense Embedding:

$$l(\mathbf{u} \mid \mathbf{c}) = \sum_{\forall u_i \in \mathbf{u}} u_i P(u_i \mid \mathbf{c})$$



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The posterior distribution (over senses) is too sharp, so we smooth it

Original:

Context Likelihood:

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Sense Likelihood:

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Context Likelihood:

$$P_S(\mathbf{c} \mid u_i) = \prod_{\forall w_j \in \mathbf{c}} \sqrt[|\mathbf{c}|]{P(w_j \mid u_i)}$$

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Sense Likelihood:

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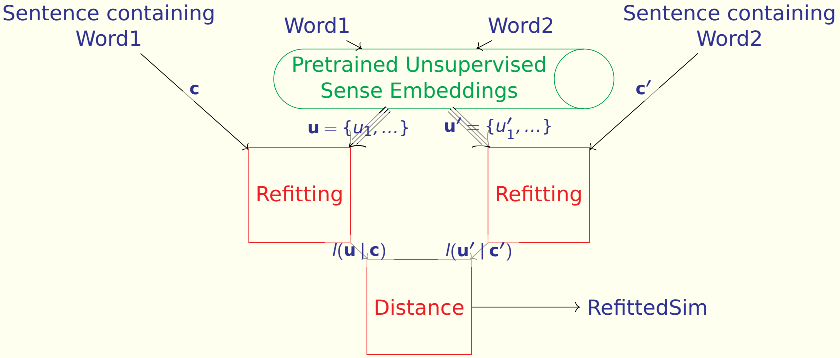
Similarity with context, is the task of ranking how similar a word is, given its usage

$$\overbrace{\overbrace{\texttt{stone}}^{w_1}\ \overbrace{\texttt{axes}}^{w_w}\ \overbrace{\texttt{was}}^{w_3}\ \overbrace{\texttt{a}}^{w_4}\ \overbrace{\texttt{major}}^{w_5}\ \underbrace{\texttt{advance}}_{word\,1}\ \overbrace{\texttt{because}}^{w_6}\ \overbrace{\texttt{it}}^{w_7}\ \overbrace{\texttt{allowed}}^{w_8}\ \overbrace{\texttt{forest}}^{w_9}\ \overbrace{\texttt{clearance}}^{w_{10}}}^{\mathbf{c}}$$

$$\overbrace{\overbrace{\texttt{forces}}^{w'_1}\ \overbrace{\texttt{could}}^{w'_2}\ \overbrace{\texttt{make}}^{w'_3}\ \overbrace{\texttt{no}}^{w'_4}\ \overbrace{\texttt{further}}^{w'_5}\ \underbrace{\texttt{headway}}_{word\,2}\ \overbrace{\texttt{without}}^{w'_6}\ \overbrace{\texttt{resting}}^{w'_7}\ \overbrace{\texttt{and}}^{w'_8}\ \overbrace{\texttt{regrouping}}^{w'_9}\ \overbrace{\texttt{.}}^{w'_{10}}}^{\mathbf{c}'}$$

Huang et al. 2012.

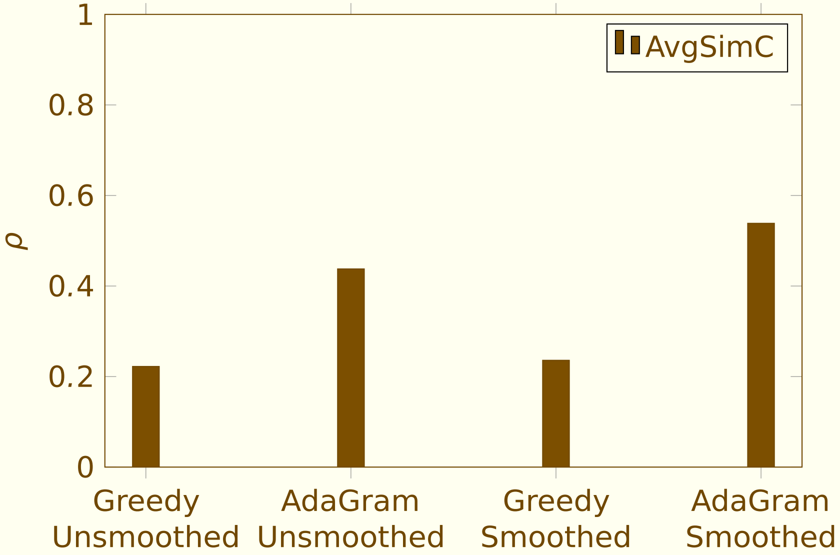
Use for word similarity with context



$$\mathrm{RefittedSim}((\mathbf{u},\mathbf{c}),(\mathbf{u'},\mathbf{c'})) = d(l(\mathbf{u}\mid\mathbf{c}), l(\mathbf{u'}\mid\mathbf{c'}))$$

$$\mathrm{RefittedSim}((\mathbf{u},\mathbf{c}),(\mathbf{u'},\mathbf{c'})) = d\left(\sum_{u_i\in\mathbf{u}} u_i P(u_i\mid\mathbf{c}),\ \sum_{u'_j\in\mathbf{u'}} u_i P(u'_j\mid\mathbf{c'})\right)$$

Results on word similarity with context



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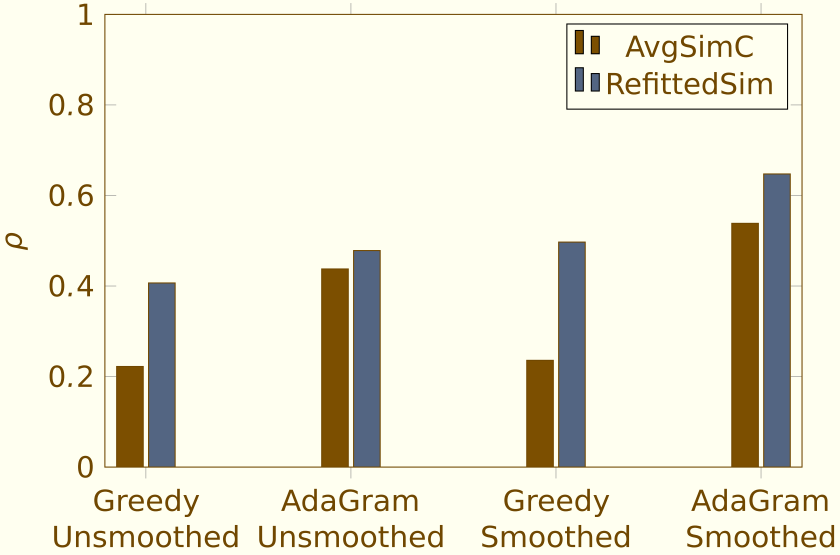

WSD is the task of determining which sense is being used

Kid *(Noun)*

1. (a young person of either sex) "she writes books for children"; "they’re just kids"; "‘tiddler’ is a British term for youngster"
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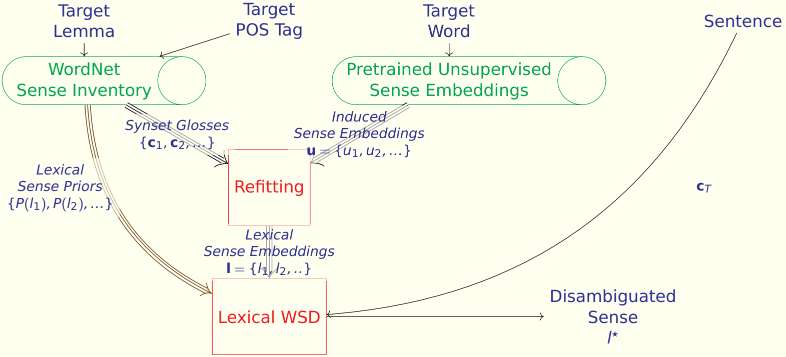
Use of refitted senses for word sense disambiguation

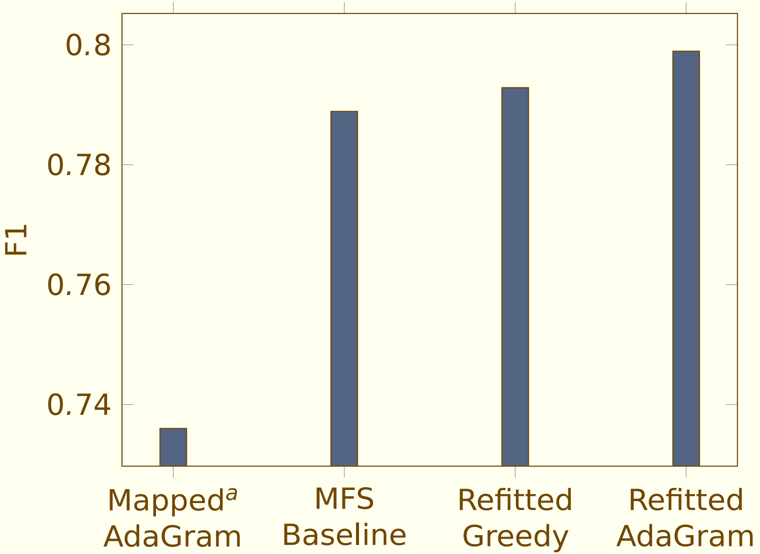


$$l^\star(\mathbf{l}, \mathbf{c}_T) = \operatorname*{arg\,max}_{\forall l_i \in \mathbf{l}} P(l_i | \mathbf{c}_T)$$

$$l^\star(\mathbf{l}, \mathbf{c}_T) = \operatorname*{arg\,max}_{\forall l_i \in \mathbf{l}} \frac{P(\mathbf{c}_T \mid l_i) P(l_i)}{\sum_{\forall l_j \in \mathbf{l}} P(\mathbf{c}_T \mid l_j) P(l_j)}$$

Results for word sense disambiguation

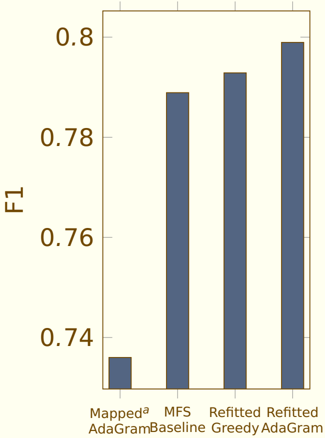
SemEval 2007 Task 7



[a] Agirre et al. 2006

Discussion of the WSD results

- Results are not great: an improvement of a few percent over the baseline.
- With that said, this is an almost unsupervised method.
- The *geometric smoothing* to an extent trades-off between he prior (which is linked to MFS).



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Conclusion

- RefittedSim, faster and higher correlation with human judgement than AvgSimC.
- WSD results using refitted not competitive with supervised methods.
- This problem of aligning induced senses to lexical senses is important.

Appendix

RefittedSim vs AvgSimC

RefittedSim

$$\mathrm{RefittedSim}((\mathbf{u},\mathbf{c}),(\mathbf{u}',\mathbf{c}')) = d\left(\sum_{u_i\in\mathbf{u}} u_i P(u_i \mid \mathbf{c}),\ \sum_{u'_j\in\mathbf{u}'} u_i P(u'_j \mid \mathbf{c}')\right)$$

Time Complexity: $O(n\,\|\mathbf{c}\| + n'\,\|\mathbf{c}'\|)$

AvgSimC

$$\mathrm{AvgSimC}((\mathbf{u},\mathbf{c}),(\mathbf{u}',\mathbf{c}')) = \frac{1}{n\times n'}\sum_{u_i\in\mathbf{u}}\sum_{u'_j\in\mathbf{u}'} P(u_i \mid \mathbf{c})\,P(u'_j \mid \mathbf{c}')\,d(u_i,u'_j)$$

Time Complexity: $O(n\,\|\mathbf{c}\| + n'\,\|\mathbf{c}'\| + n\times n')$

Results on word similarity with context

Method	Geometric Smoothing	Use Prior	AvgSimC	RefittedSim
AdaGram	T	T	**53.8**	64.8
AdaGram	T	F	36.1	**65.0**
AdaGram	F	T	43.8	47.8
AdaGram	F	F	20.7	24.1
Greedy	T	F	23.6	49.7
Greedy	F	F	22.2	40.7

Refitting sense-embeedings allows us to know the sense

- New embeddings are defined as a as a weighted sum of unsupervised embeddings.
- The weights are determined using the langauge model, with a example sentence.
- This lets us find embedding for the sense of the word in that sentence.

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- New embeddings are defined as a as a weighted sum of unsupervised embeddings.
- The weights are determined using the langauge model, with a example sentence.
- This lets us find embedding for the sense of the word in that sentence.
- Applications for similarity with context, and lexical tasks, such as Word Sense Disambiguation.

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