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 $P(w_i \mid w_T)$
- this results in training a useful vector representation of each word.

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

We can word sense induction method which generate word-sense vectors

- Word sense induction methods discover the senses as it trains.
- They don't need manually annotated training data.
- It is less hand engineered than using some human defined set of senses.
- There exist many methods for vector word sense induction

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For our evaluations we consider two word sense induction models

Greedy

- Model a fixed set of senses vectors
- Assign each training case to the sense that give the highest probability.
- Similar to Neelakantan et al. (2015), but using probability rather than distance.

AdaGram

- Bartunov et al. (2015)
- A Neural-Bayesian approach.
- Models an adaptive number of possible senses.
- A fairly good sense induction method.

Word sense embeddings represent each word as a multiple vectors

- Each word has multiple senses, with one vector per sense $\{u_1, u_2, \ldots, u_n\}$
- SkipGram sense language model
  - Input a word sense u_i
  - Output probabilities of words appearing in its context $P(w_j \mid u_i)$

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- No control over the meanings of the senses
  - Cover overlapping definitions
  - Find overly narrow meanings
  - Capture rare jargon uses

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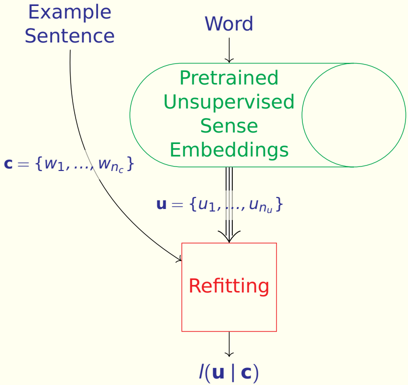
- Embeddings are learnt purely by modelling what words occur near the sense
- No control over the meanings of the senses
  - Cover overlapping definitions
  - Find overly narrow meanings
  - Capture rare jargon uses
- Useful, but not interoperable with lexical knowledge bases. OpenCyc, ImageNet etc.

We want to align these induced senses to a known meaning.

- When people need to clarify a sense, they give just a single example.
  - Kid as in *The fluffy goat kid.*
  - or; Kid as in *My brother is such an annoying kid*
- The hearer immediately knows what sense of the word is meant.
- We want a system that can do that.

We want to *refit* our embeddings to be for the sense we mean

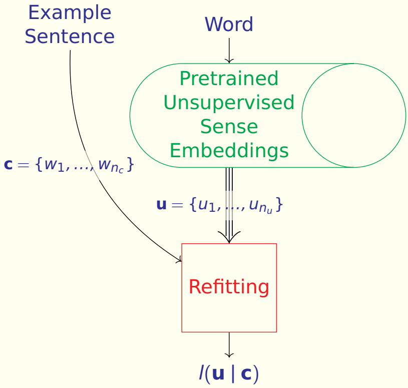
- Refitting constructs new sense embeddings out of the old.
- It uses the probabilities of example sentence occurring.
- The new embedding aligns to the meaning in that sentence.



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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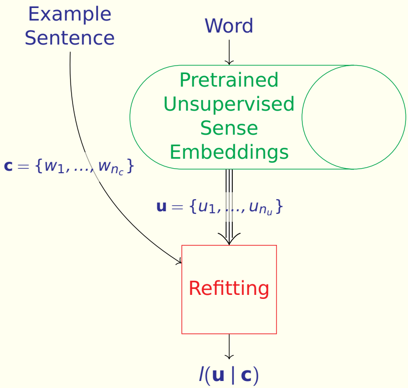
The probabilities are found using Bayes’ theorem

Sense-Language model:
$P(w_j \mid u_i)$



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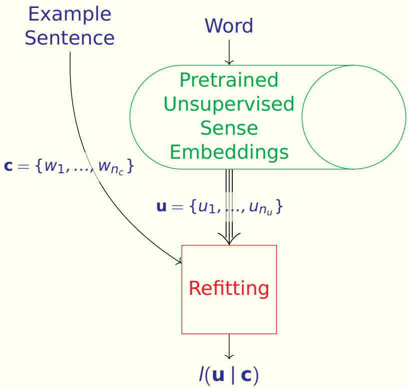
$$P(\mathbf{c} \mid u_i) = \prod_{\forall w_j \in \mathbf{c}} P(w_j \mid u_i)$$



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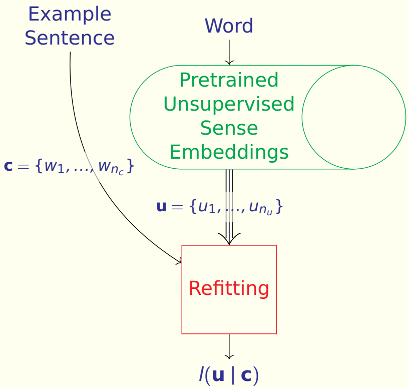

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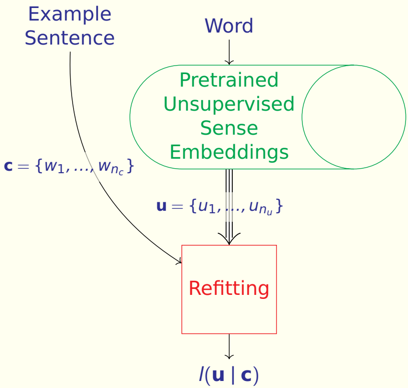
Refitted Sense Embedding:

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



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

Original:

Context Likelihood:

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

Sense Likelihood:

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

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Smoothed:

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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Context Likelihood:

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

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Sense Likelihood:

$$P_S(s_i \mid \mathbf{c}) = \frac{\sqrt[|\mathbf{c}|]{P(\mathbf{c} \mid u_i)P(u_i)}}{\sum_{u_j \in \mathbf{u}} \sqrt[|\mathbf{c}|]{P(\mathbf{c} \mid u_j)P(u_j)}}$$

Similarity with Context

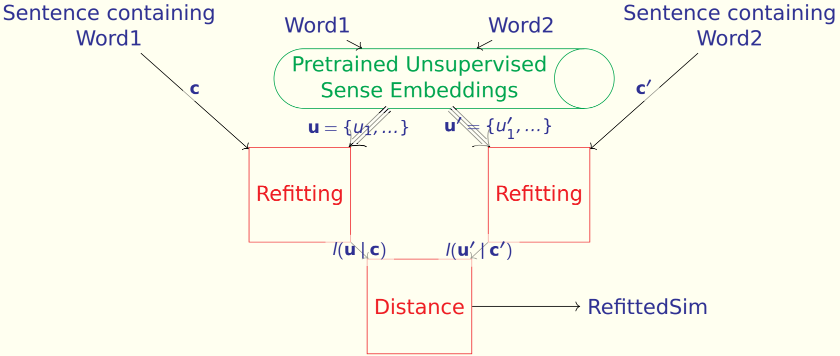
Similarity with context, is the task of ranking how similar a word is, given its usage

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

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

Huang et al. 2012.

Use for word similarity with context



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

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

RefittedSim vs AvgSimC

RefittedSim

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

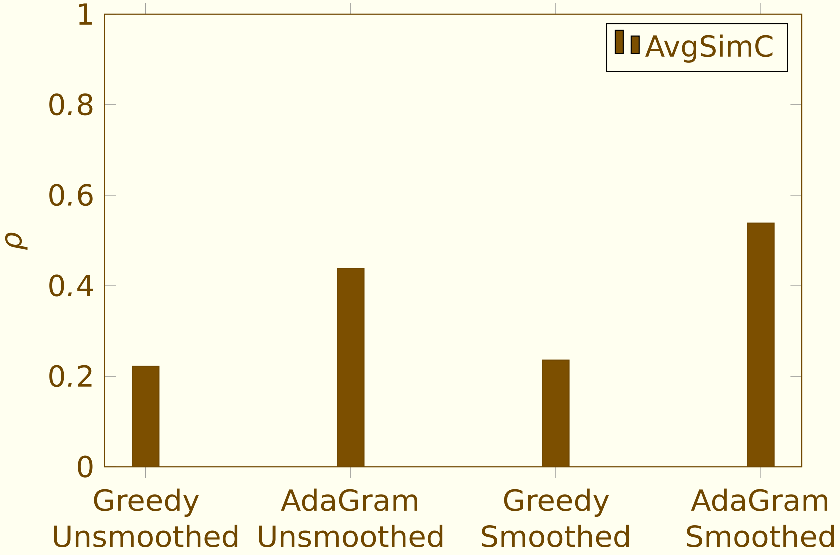
Time Complexity: $O(n\,\|\mathbf{c}\| + n'\,\|\mathbf{c}'\|)$

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



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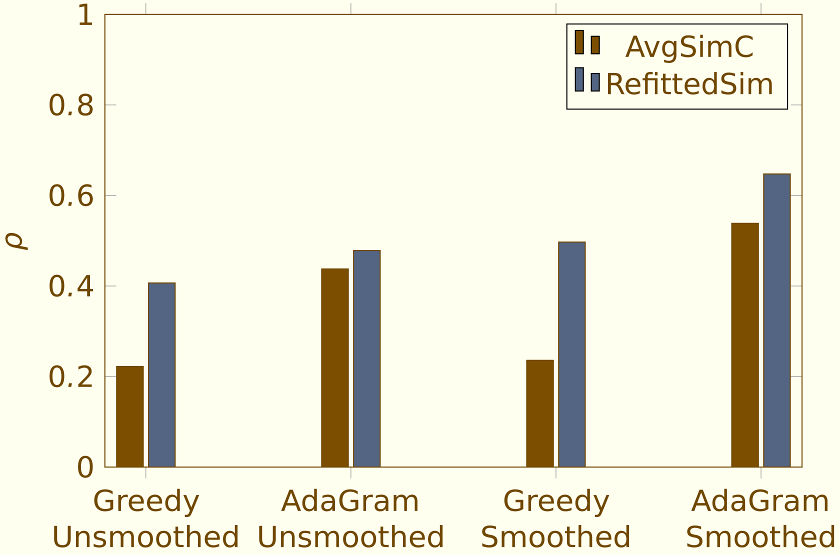

Lexical Word Sense Disambiguation

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"
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"
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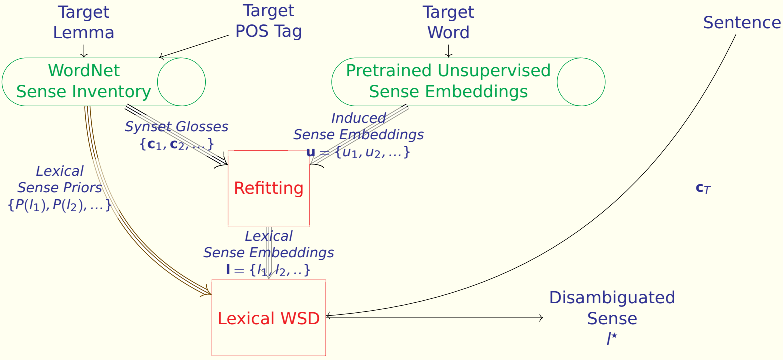
Use of refitted senses for word sense disambiguation

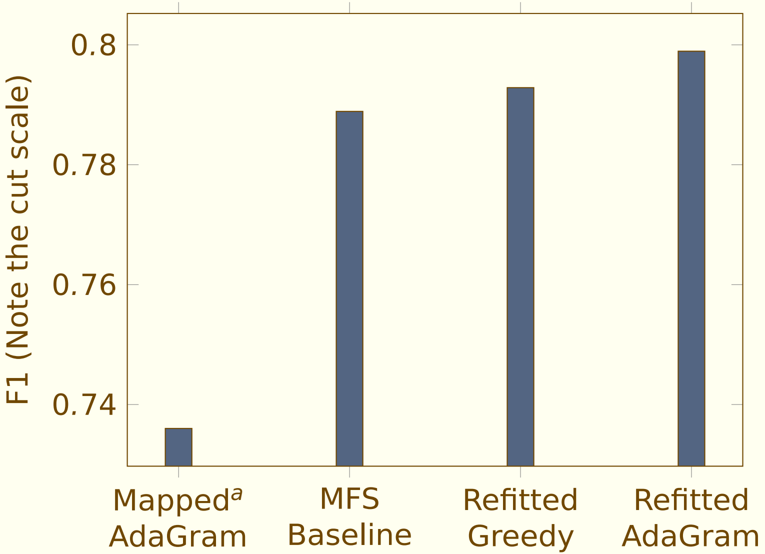


$$l^\star(\mathbf{l}, \mathbf{c}_T) = \underset{\forall l_i \in \mathbf{l}}{\arg\max} P(l_i | \mathbf{c}_T)$$

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

Results for word sense disambiguation

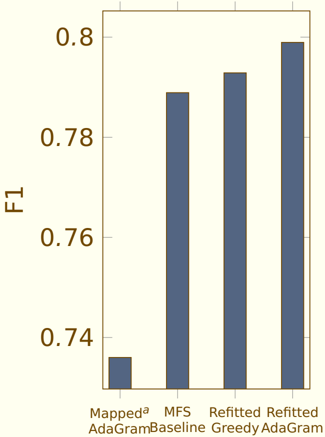
SemEval 2007 Task 7



[a] Agirre et al. 2006

Discussion of the WSD results

- Results are not great: an improvement of $\sim 1\%$ 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 refitting is not competitive with supervised methods.
- This problem of aligning induced senses to lexical senses is important, and worth further research.

Appendix

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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