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

Lyndon White,
Roberto Togneri, Wei Liu, Mohammed Bennamoun

School of Electical, Electronic and Computer Engineering
The University of Western Australia

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: the 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 their vectors.
- 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.

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

For our evaluations we consider two word sense induction models

Greedy

- Model a fixed number 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.

For our evaluations we consider two word sense induction models

Greedy

- Model a fixed number 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 $P(w_j \mid u_j)$

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

Induced sense embeddings don’t produce standard dictionary senses

- Senses are learnt purely by modelling what words occur near the sense

Induced sense embeddings don't produce standard dictionary senses

- Senses 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

Induced sense embeddings don't produce standard dictionary senses

- Senses 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
- Not certain to have any sense ideal for any particular use.

Induced sense embeddings don't produce standard dictionary senses

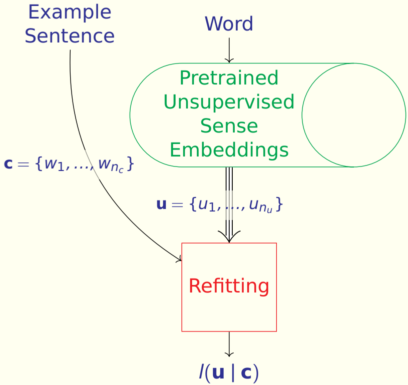
- Senses are learnt purely by modelling what words occur near the sense
- No control over the meanings of the senses.
  - Cover overlapping definitions
  - Find overly narrow meanings
  - Capture rare jargon uses
- Not certain to have any sense ideal for any particular use.
- Not interoperable with lexical knowledge bases. 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 little kid.*
- The listener immediately knows what is meant.
- We want a system that can do that.

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

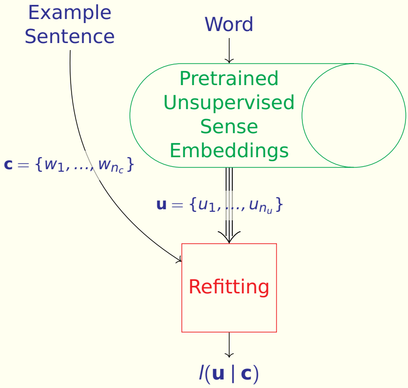
- Refitting constructs new sense embeddings out of the old.
- We use the probabilities of induced senses.
- The new embedding is aligned to the meaning in that sentence.



Refitting uses a probability weighted sum

New sense embedding:

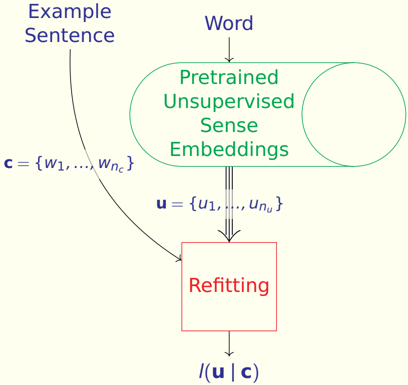
$$l(\mathbf{u} \mid \mathbf{c}) = \sum_{\forall u_i \in \mathbf{u}} u_i P(u_i \mid \mathbf{c})$$



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

The probabilities are found using Bayes’ theorem

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

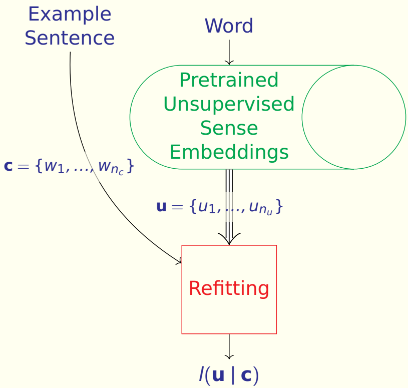


$$\overbrace{\overbrace{\texttt{wow}}^{w_1}\ \overbrace{\texttt{the}}^{w_2}\ \overbrace{\texttt{wool}}^{w_3}\ \overbrace{\texttt{from}}^{w_4}\ \overbrace{\texttt{the}}^{w_5}\ \underbrace{\texttt{kid}}_{\textit{target word}}\ \overbrace{\texttt{is}}^{w_6}\ \overbrace{\texttt{so}}^{w_7}\ \overbrace{\texttt{soft}}^{w_8}\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

The probabilities are found using Bayes' theorem

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

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



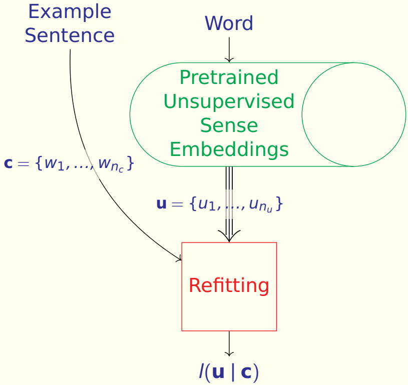
$$\overbrace{\overbrace{\texttt{wow}}^{w_1}\ \overbrace{\texttt{the}}^{w_2}\ \overbrace{\texttt{wool}}^{w_3}\ \overbrace{\texttt{from}}^{w_4}\ \overbrace{\texttt{the}}^{w_5}\ \underbrace{\texttt{kid}}_{\textit{target word}}\ \overbrace{\texttt{is}}^{w_6}\ \overbrace{\texttt{so}}^{w_7}\ \overbrace{\texttt{soft}}^{w_8}\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

The probabilities are found using Bayes' theorem

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

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

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



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

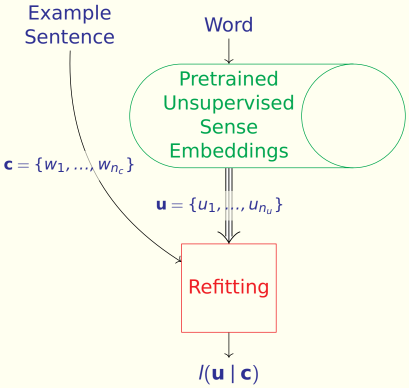
The probabilities are found using Bayes' theorem

Bayes Theorem:

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

Refitted Sense Embedding:

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



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

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:

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

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:

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

Smoothed:

Context Likelihood:

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

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:

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

Smoothed:

Context Likelihood:

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

Sense Likelihood:

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

Similarity with Context

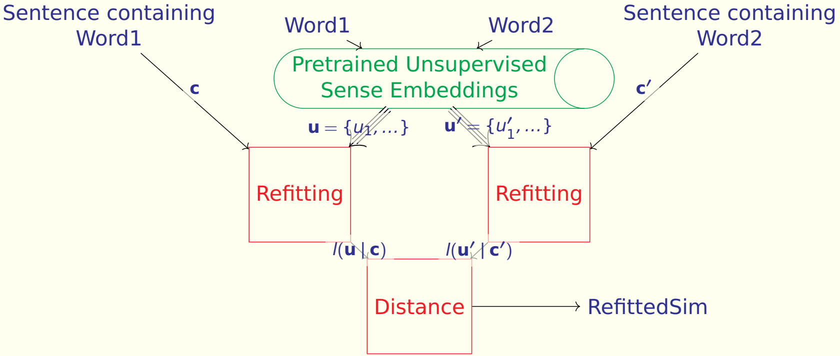
Similarity with context, is the task of ranking how similar a word is, given its usage

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

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

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

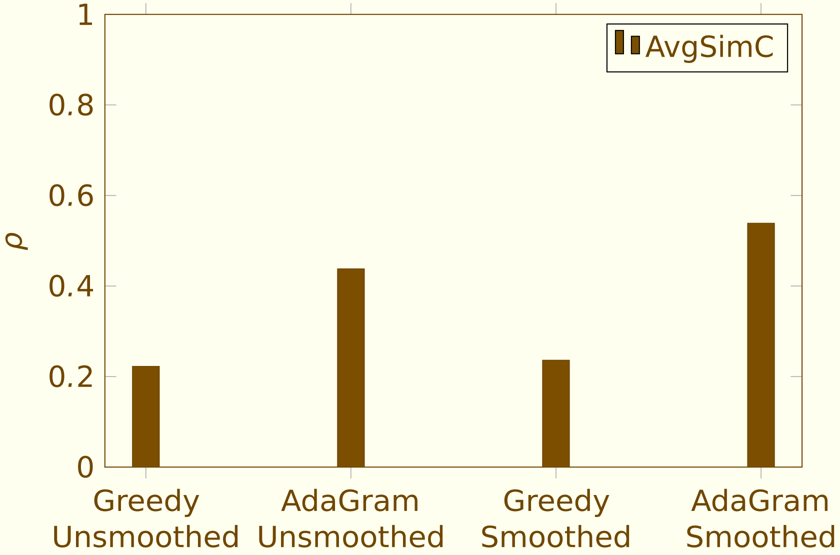
AvgSimC

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

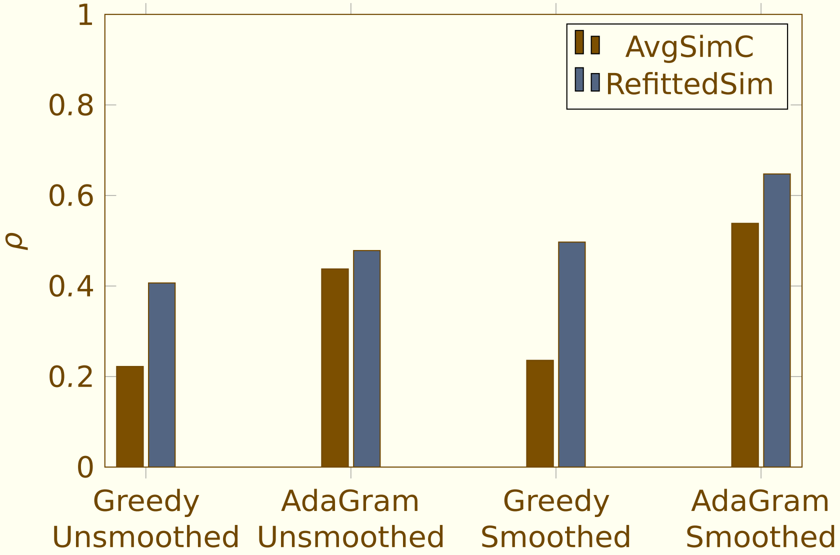
Time Complexity: $O(n\,\|\mathbf{c}\| + n'\,\|\mathbf{c}'\| + n\times n')$

Reisinger and Mooney 2010.

Results on word similarity with context



Results on word similarity with context



Lexical Word Sense Disambiguation

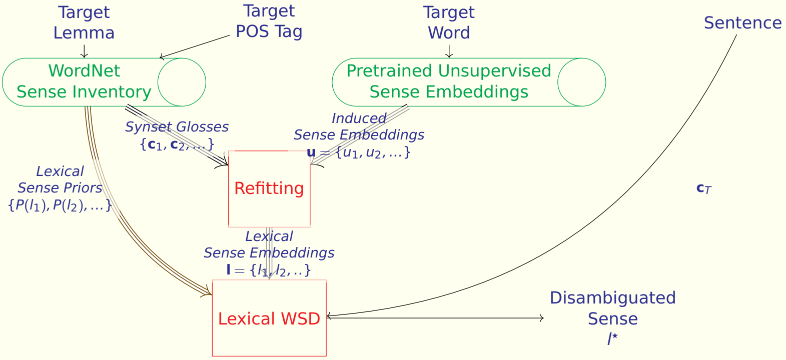
WSD is the task of determining which sense is being used

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"
4. (young goat)

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

Use of refitted senses for word sense disambiguation

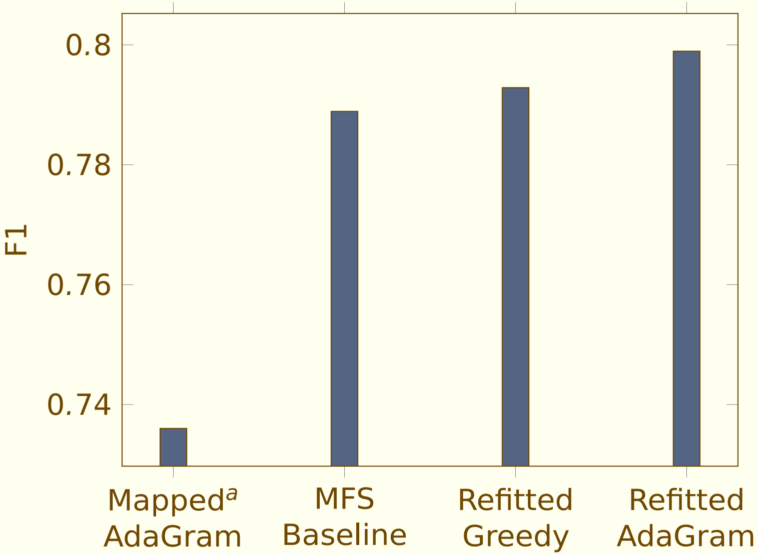


$$l^\star(\mathbf{l}, \mathbf{c}_T) = \underset{\forall l_i \in \mathbf{l}}{\arg\max}\, P(l_i | \mathbf{c}_T)$$

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

Results for word sense disambiguation

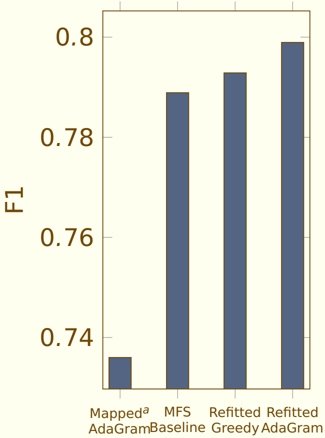
SemEval 2007 Task 7



[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).



[a] Agirre et al. 2006

Conclusion

- Refitting constructs new sense embeddings using a single example.
- RefittedSim, is faster and has 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.

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

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.
- Applications for similarity with context, and lexical tasks, such as Word Sense Disambiguation.

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

References

Eneko Agirre et al. “Evaluating and optimizing the parameters of an unsupervised graph-based WSD algorithm”. In: *Proceedings of the first workshop on graph based methods for natural language processing*. Association for Computational Linguistics. 2006, pp. 89–96.

Sergey Bartunov et al. “Breaking Sticks and Ambiguities with Adaptive Skip-gram”. In: *CoRR* abs/1502.07257 (2015).

Eric H Huang et al. “Improving word representations via global context and multiple word prototypes”. In: *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Long Papers-Volume 1*. Association for Computational Linguistics. 2012, pp. 873–882.

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

Arvind Neelakantan et al. “Efficient non-parametric estimation of multiple embeddings per word in vector space”. In: *arXiv preprint arXiv:1504.06654* (2015).

Joseph Reisinger and Raymond J Mooney. “Multi-prototype vector-space models of word meaning”. In: *Human Language Technologies: The 2010 Annual Conference of the*