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)*

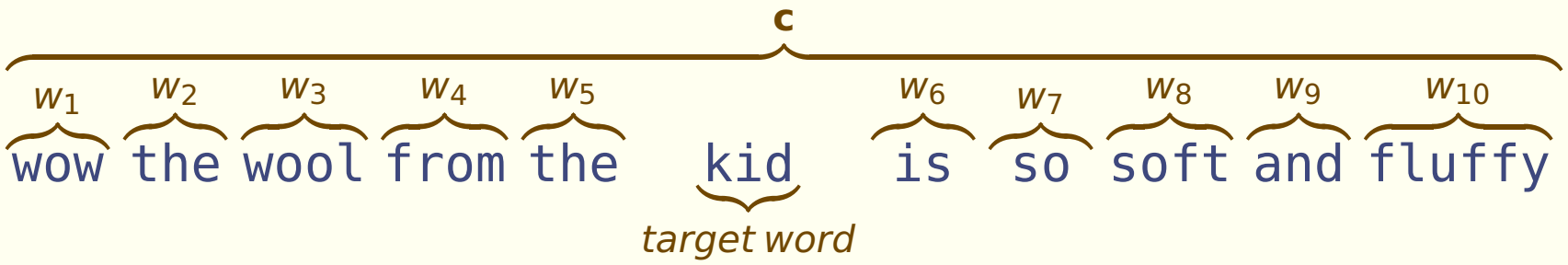
1. (a young person of either sex) "she writes books for children"; "they’re just kids"; "‘tiddler’ is a British term for youngster"
2. (English dramatist (1558-1594))
3. (a human offspring (son or daughter) of any age) "they had three children"; "they were able to send their kids to college"
4. (young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

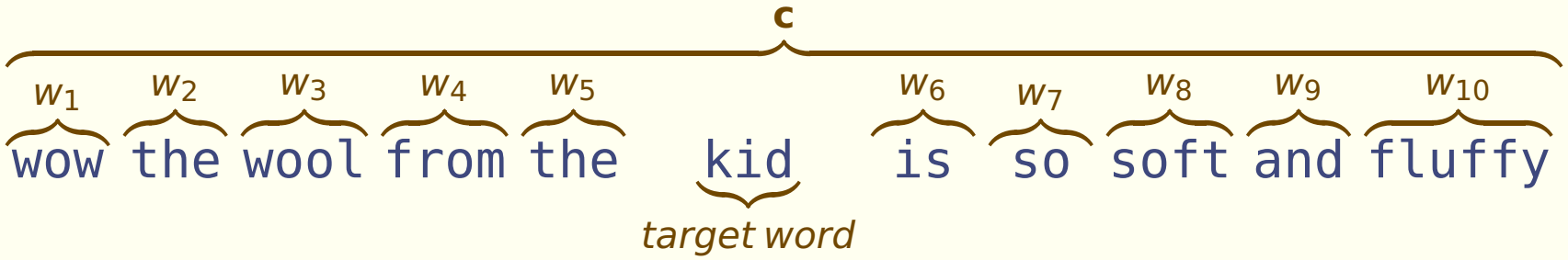
SkipGram Language Model:

- Input: a word w_T
- Output: 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.



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.



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.

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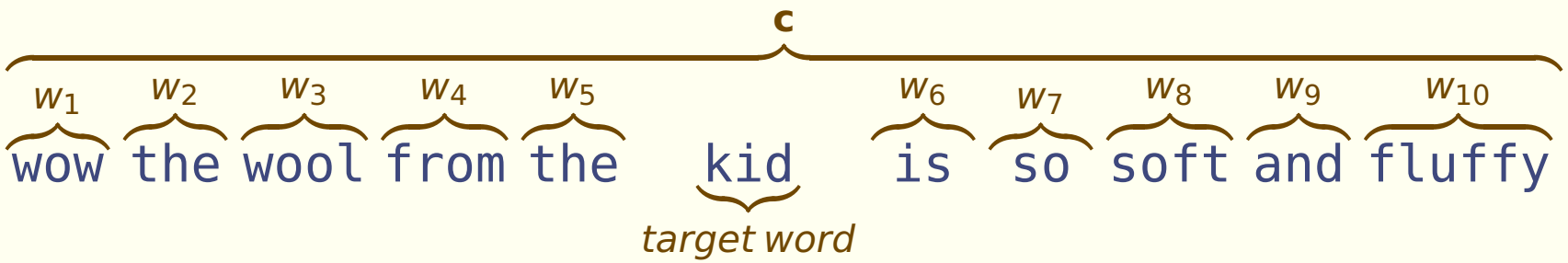
AdaGram

- 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 senselanguage model
  - Input a word sense u_i
  - Output probabilities of words appearing in its context $P(w_j \mid u_j)$



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  - Capture rare jargon uses

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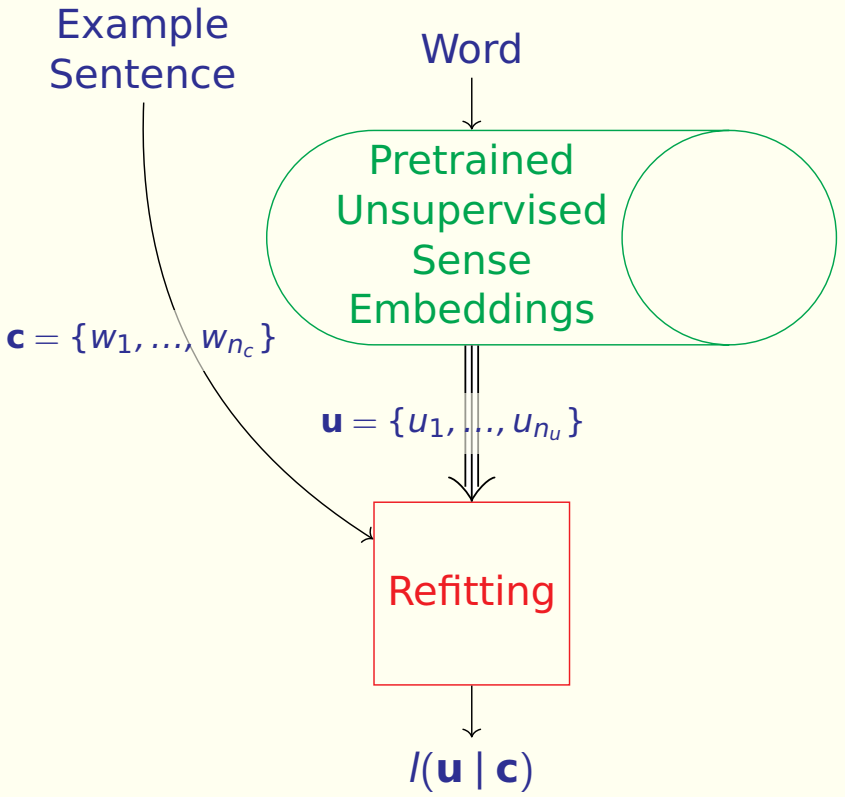
  - Capture rare jargon uses
- Useful, but not interoperable with lexical knowledge bases. OpenCyc, ImageNet etc.

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 litte kid.*
- The hearer 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

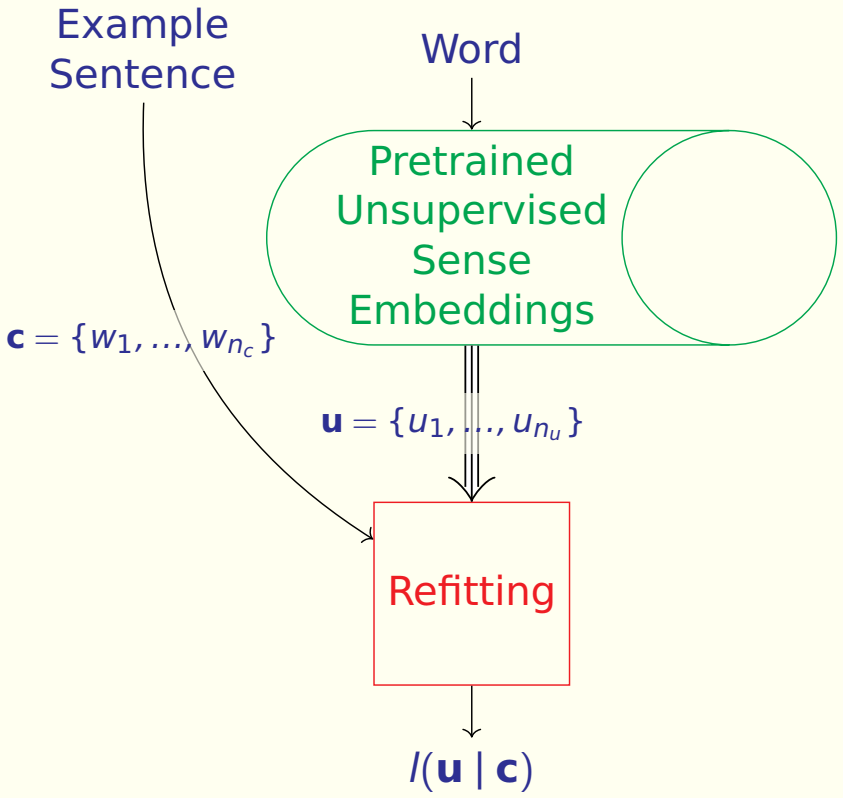
- Refitting constructs new sense embeddings out of the old.
- We uses the probabilities of example sentence occurring.
- The new embedding aligns to the meaning in that sentence.

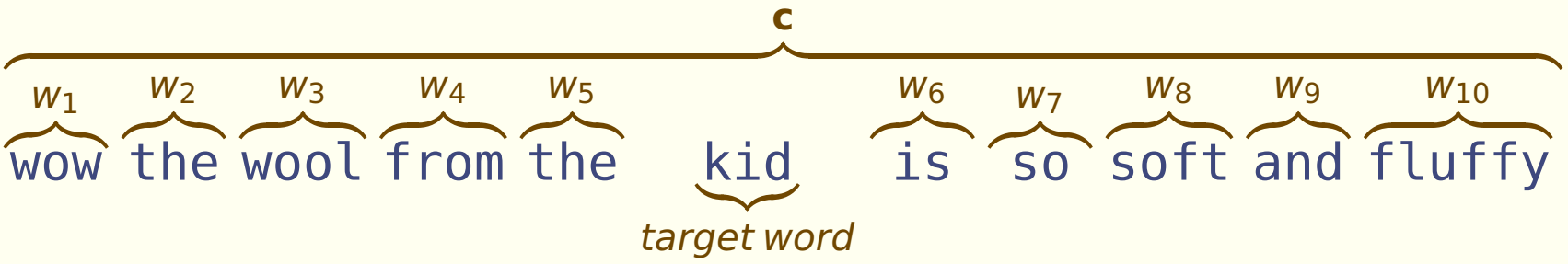


Refitting uses a probability weighted sum

New sense embedding:

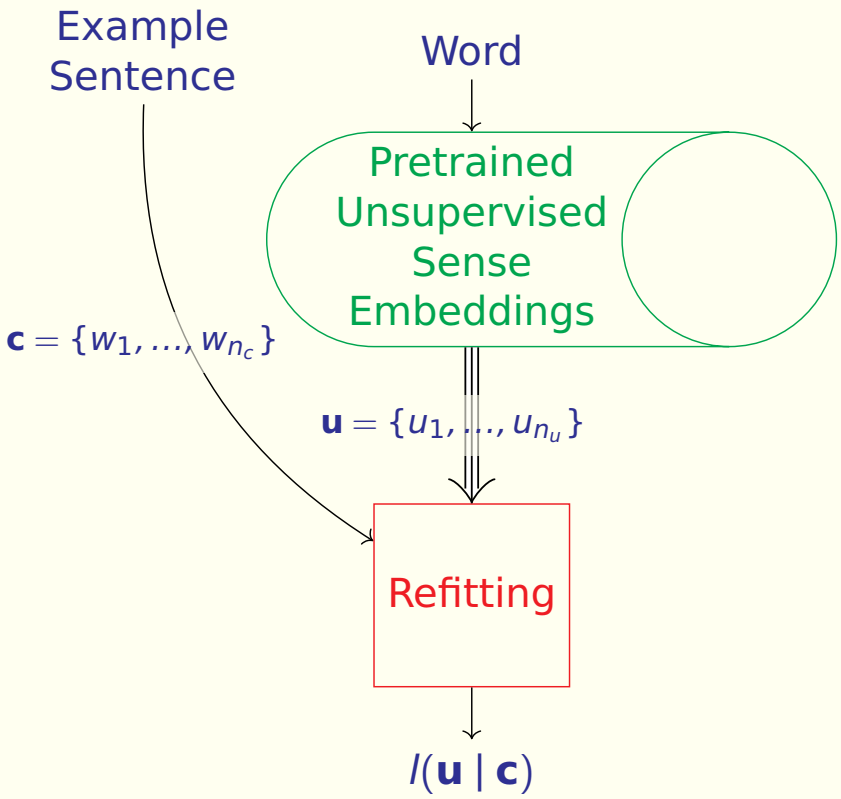
$$l(\mathbf{u} \mid \mathbf{c}) = \sum_{\forall u_i \in \mathbf{u}} u_i P(u_i \mid \mathbf{c})$$





The probabilities are found using Bayes' theorem

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



$\mathbf{c}$

w_1 wow w_2 the w_3 wool w_4 from w_5 the kid w_6 is w_7 so w_8 soft w_9 and w_{10} fluffy

target word

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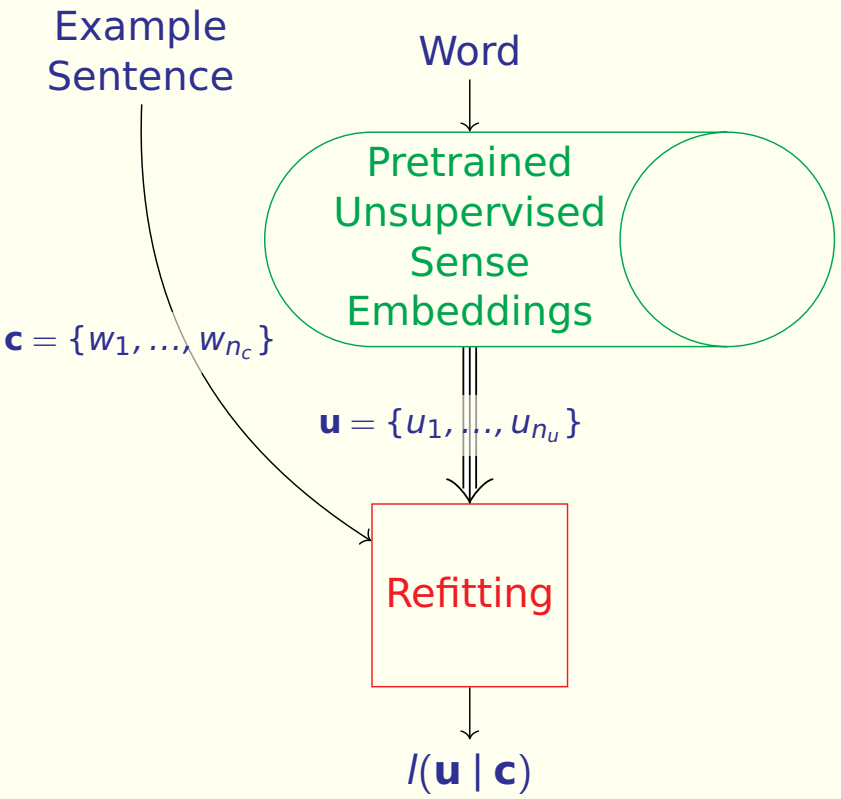
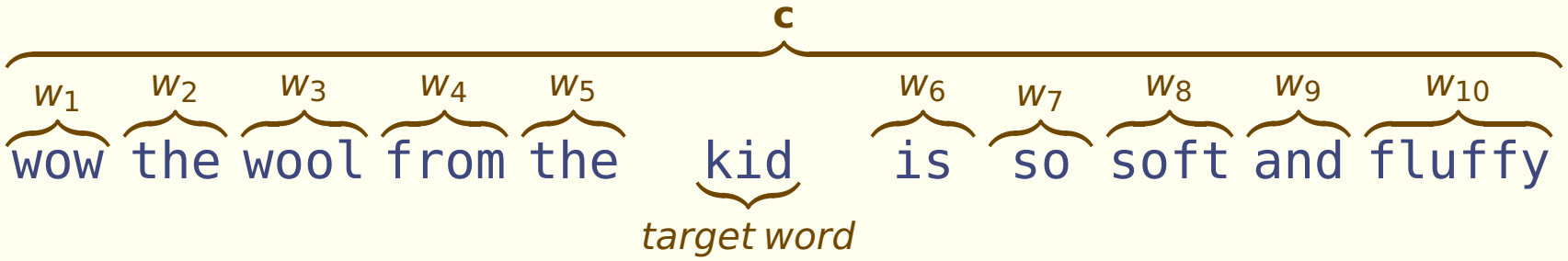
Sense-Language model:
$P(w_j \mid u_i)$

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





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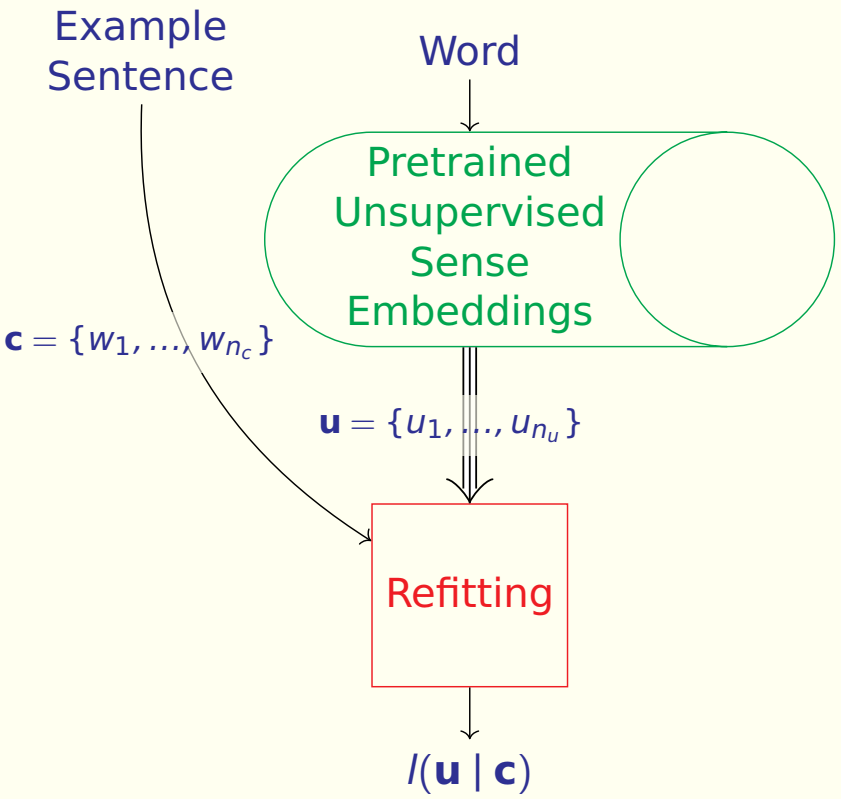

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Refitted Sense Embedding:

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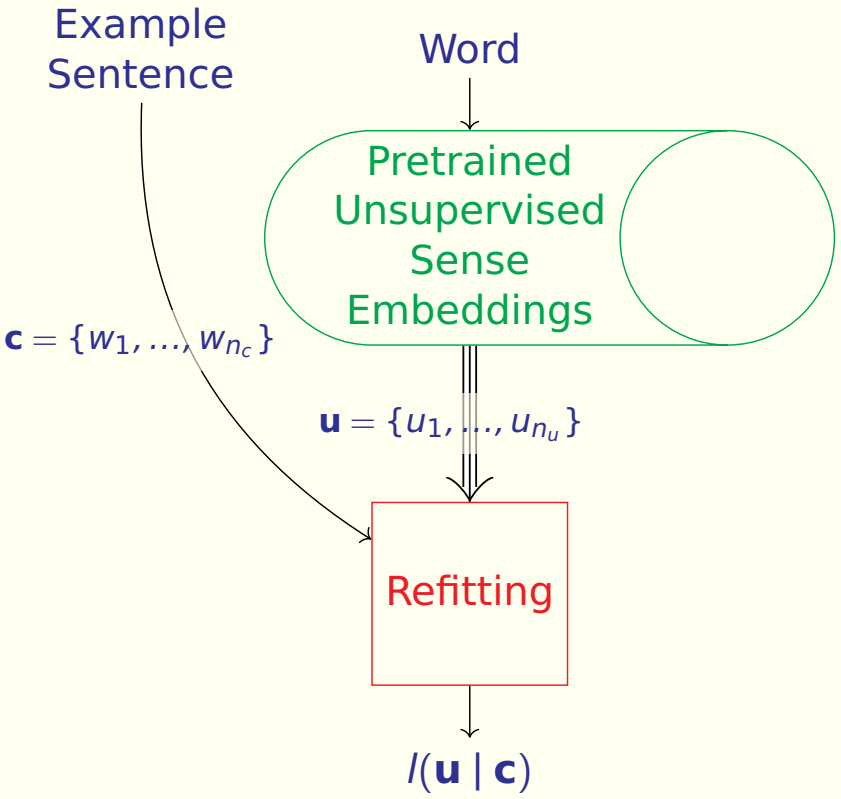

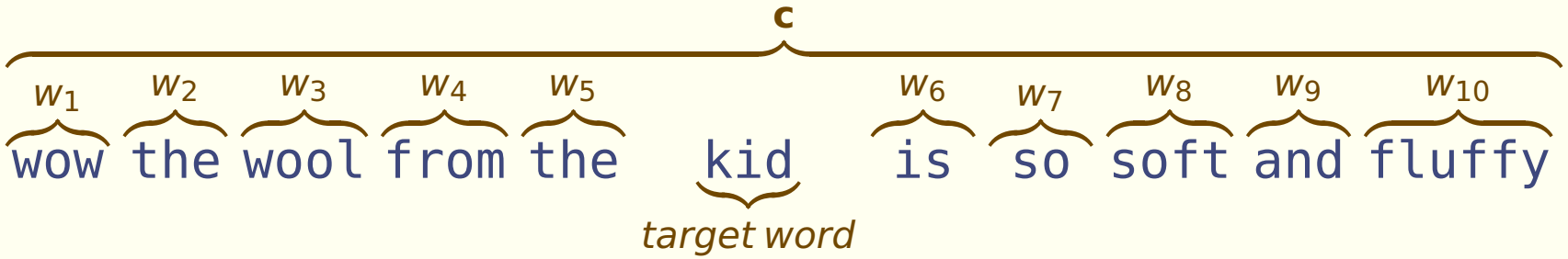

The posterior distribution (over senses) is too sharp, so we smooth it

Original:

Context Likelihood:

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

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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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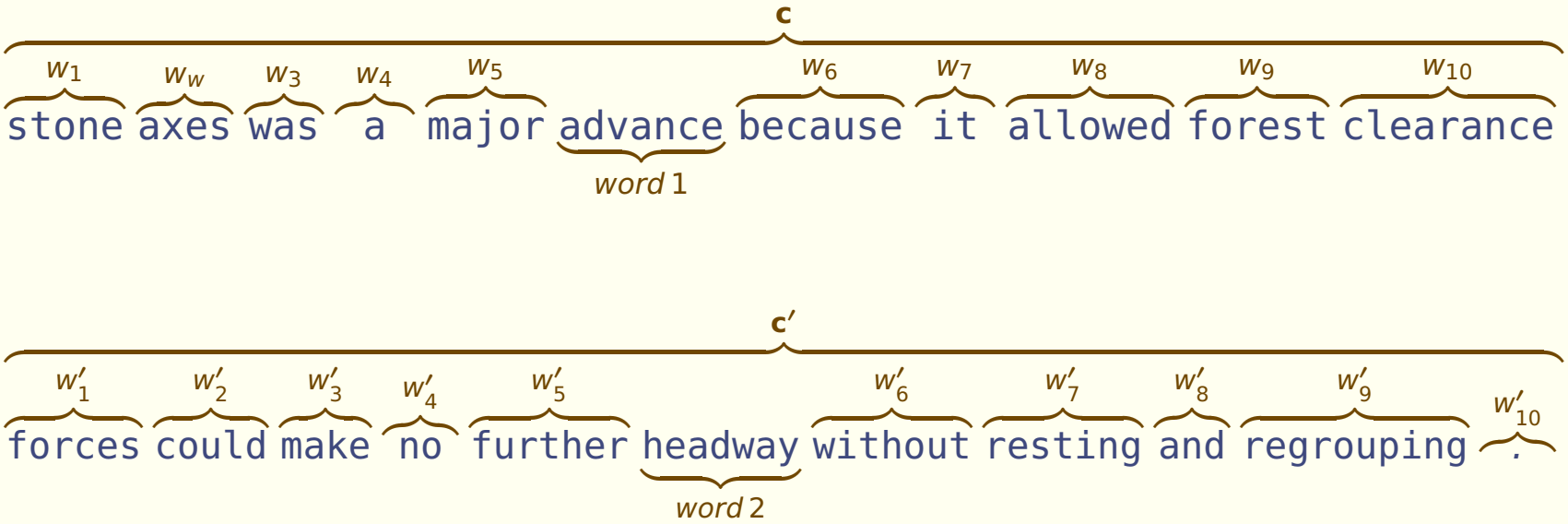
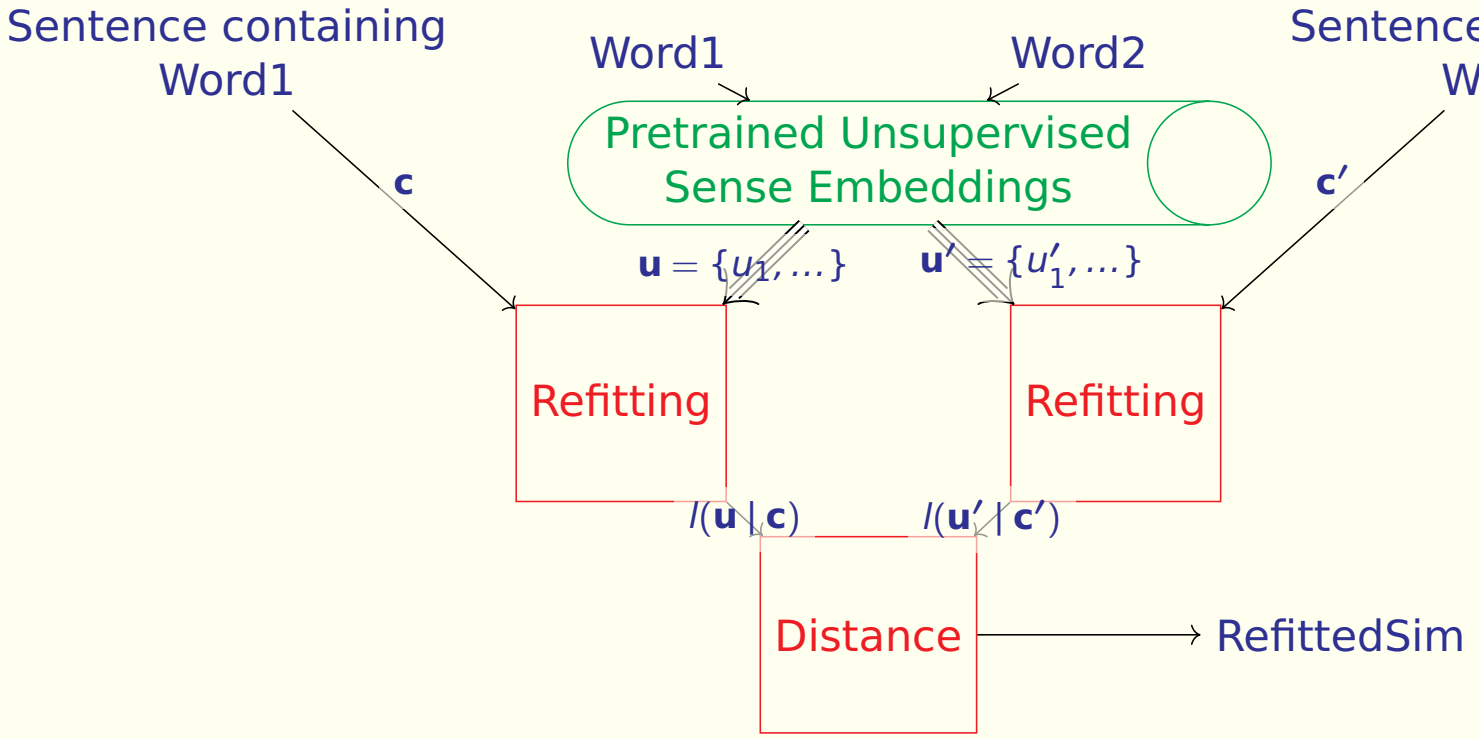
Similarity with Context

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



Huang et al. 2012.

Use for word similarity with context



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

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

RefittedSim vs AvgSimC

RefittedSim

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

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

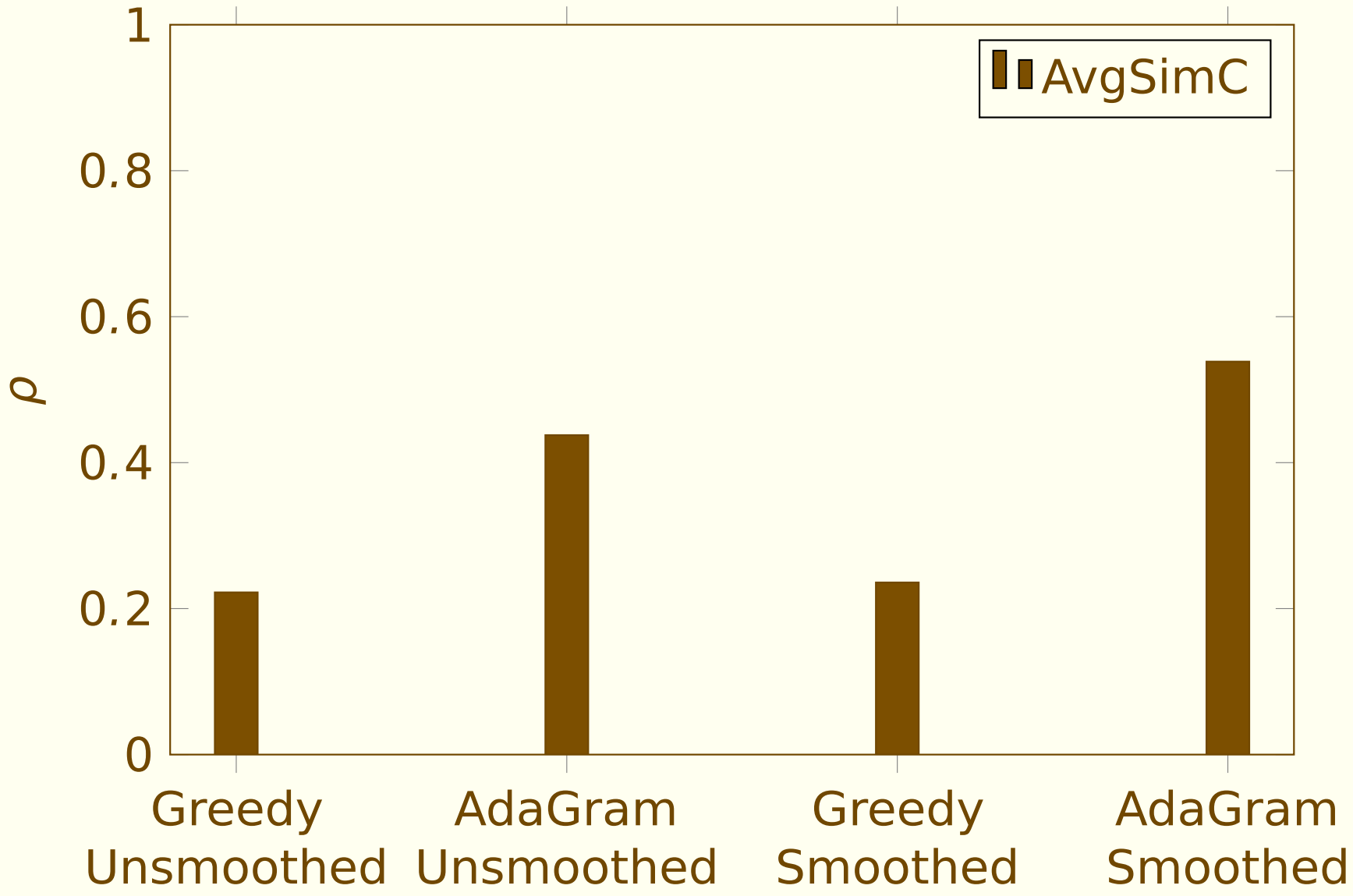
AvgSimC

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

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

Reisinger2010.

Results on word similarity with context



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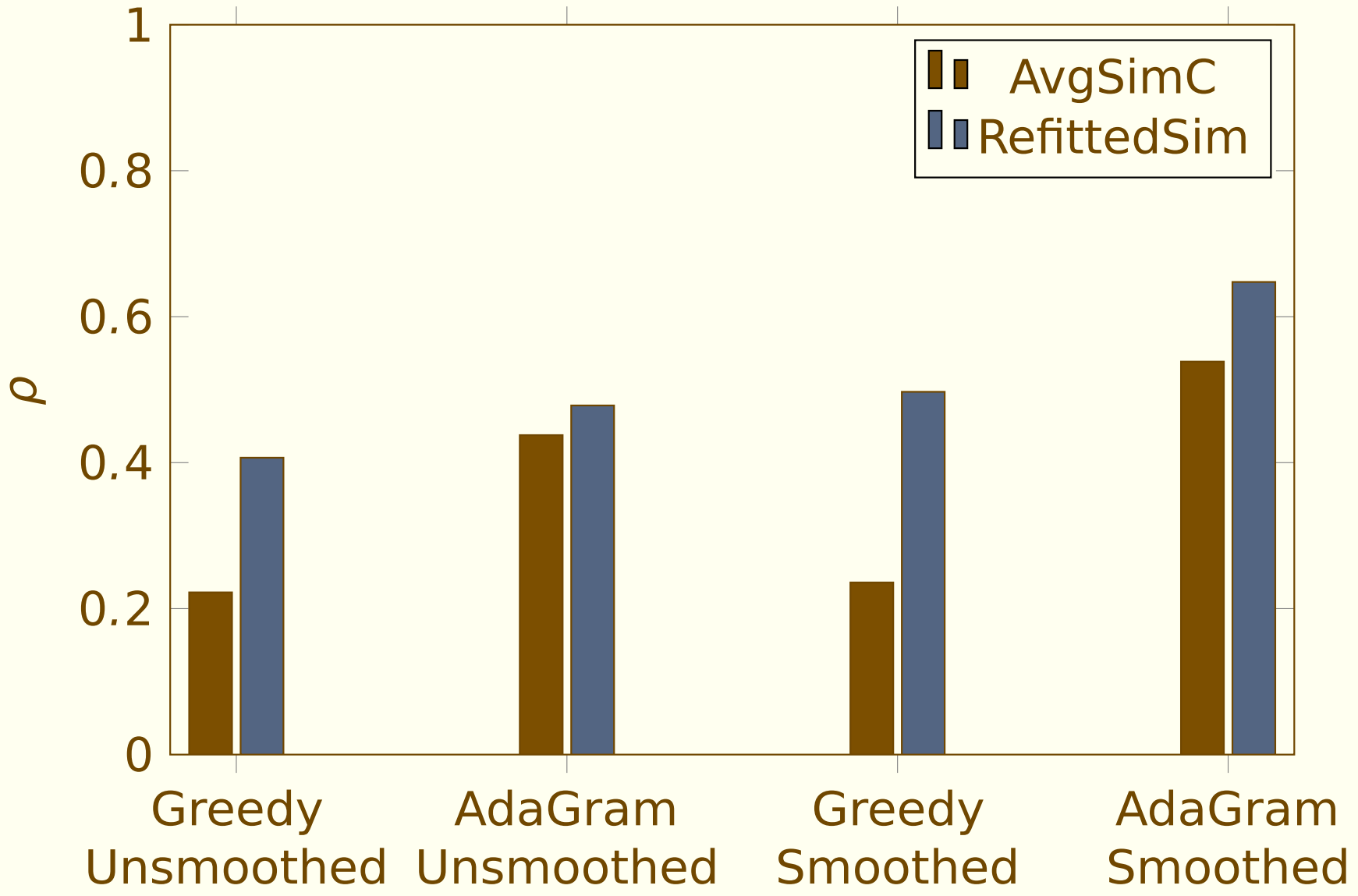

Lexical Word Sense Disambiguation

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"
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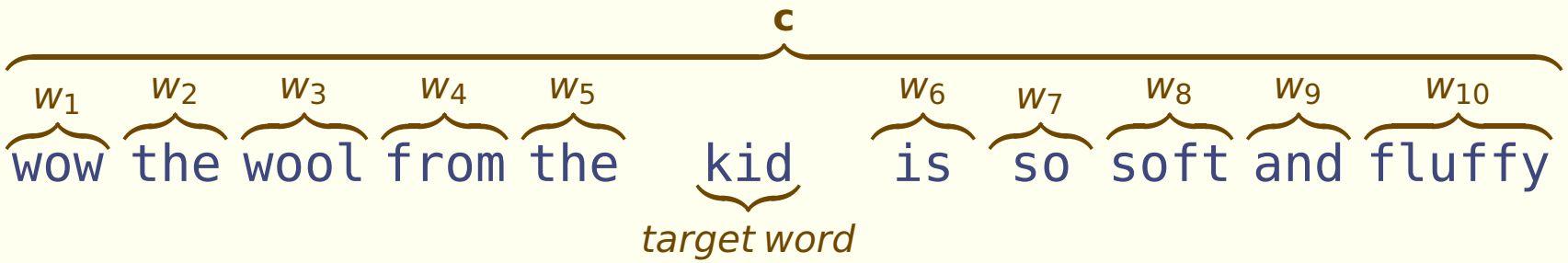
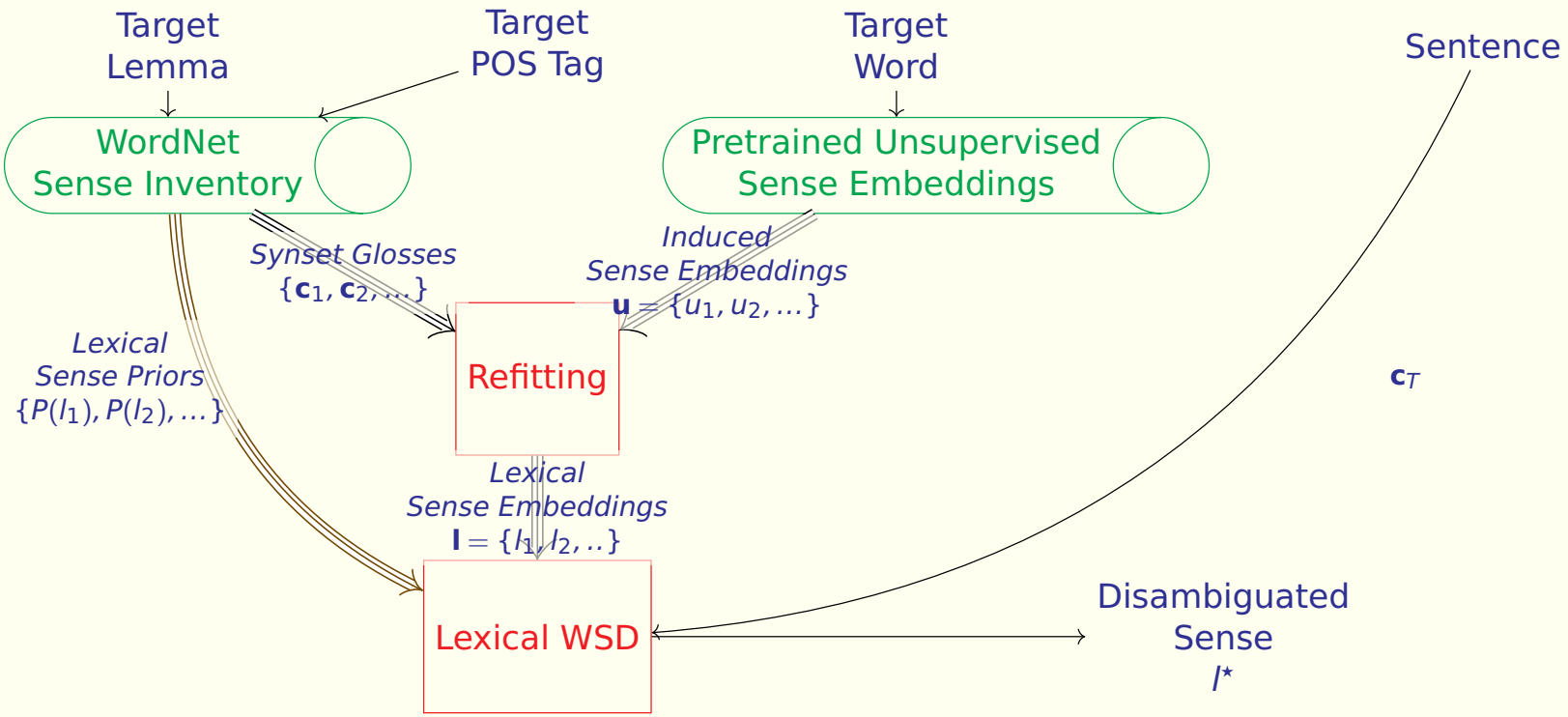


Use of refitted senses for word sense disambiguation

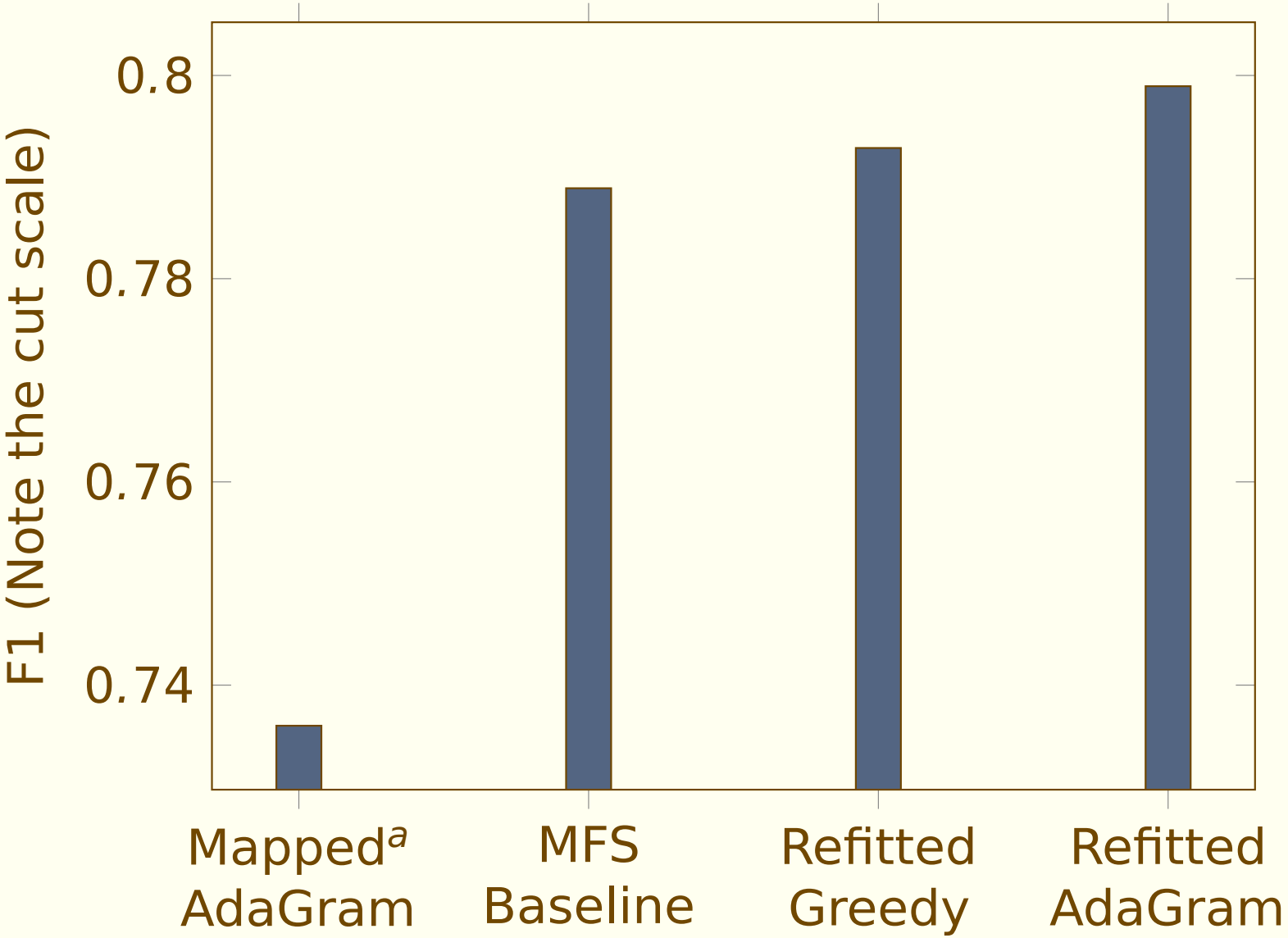


$$l^\star(\mathbf{l}, \mathbf{c}_T) = \arg\max_{\forall l_i \in \mathbf{l}} P(l_i|\mathbf{c}_T)$$

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

Results for word sense disambiguation

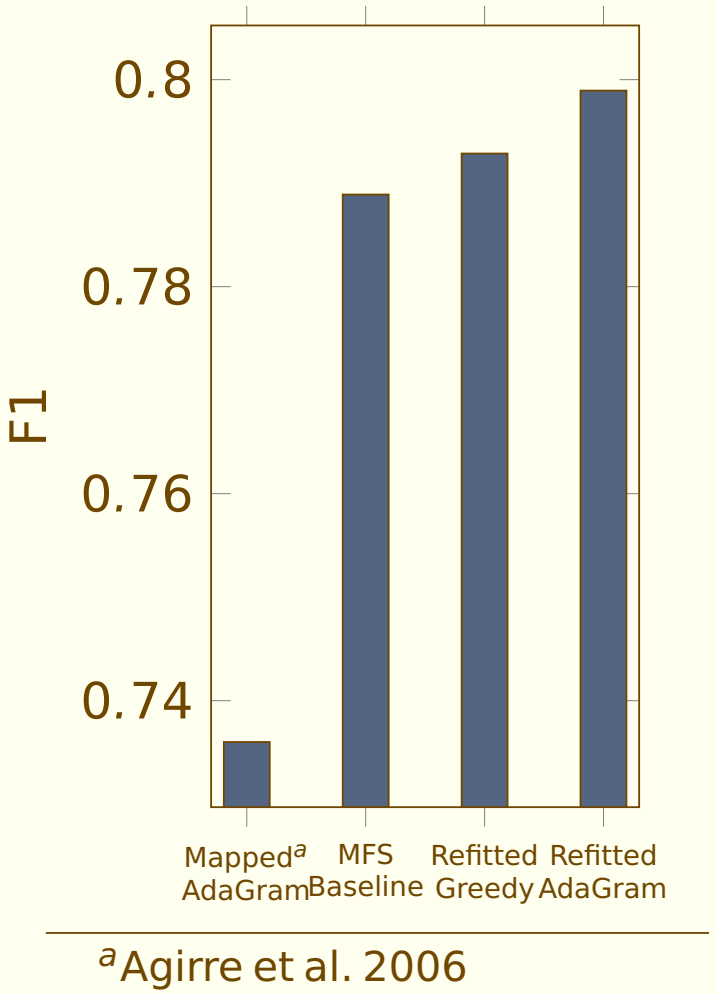
SemEval 2007 Task 7



[a] Agirre et al. 2006

Discussion of the WSD results

- Results are not great: an improvement of $\sim 1\%$ 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.

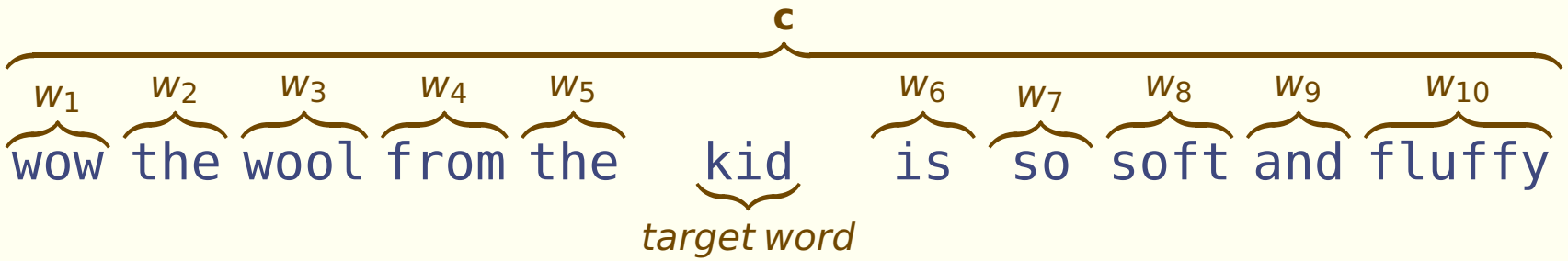
Appendix

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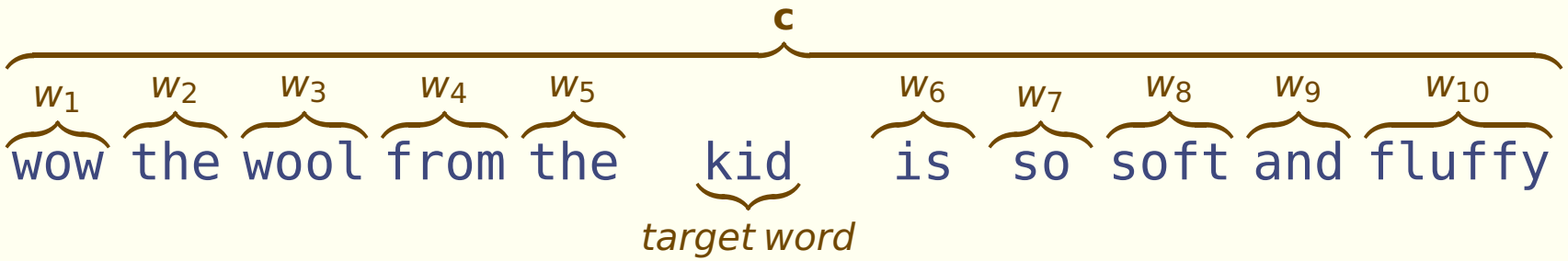
- New embeddings are defined as a as a weighted sum of unsupervised embeddings.
- The weights are determined using the langauge model, with a example sentence.
- This lets us find embedding for the sense of the word in that sentence.
- Applications for similarity with context, and lexical tasks, such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



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

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