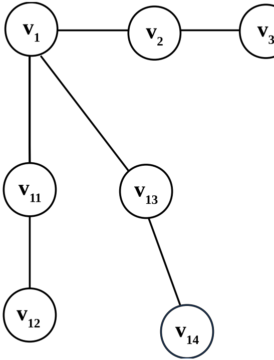
EDS-MEMBED

Multi-sense embeddings based on enhanced distributional semantic structures via a graph walk over word senses [1]



Eniafe Festus Ayetiran*, Petr Sojka, Vít Novotný

ayetiran@mail.muni.cz, sojka@fi.muni.cz, witiko@mail.muni.cz

Faculty of Informatics, Masaryk University

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1. Introduction

- Word embeddings are popular, but conflate word meanings, a.k.a. *polysemy*.
- Multi-sense embeddings (M-SE) tackle polysemy by modeling word senses, not words.
- Existing approaches to M-SE include:

Multi-prototype [2, 3] Unsupervised, based on clustering, and

Sense-inventory-based [4, 5] Semi-supervised, based on knowledge bases, our approach.

Problems

- Sense-annotated corpora are small, a.k.a. *the knowledge acquisition bottleneck*.
- Existing approaches focus on word similarity task, not word sense disambiguation.

Our Contributions

- We propose augmenting sense-annotated corpora using semantic relations.
- We propose new semantic similarity measures for word sense disambiguation.

2. Related work

Existing approaches to M-SE include:
Multi-prototype [6, 2, 3, 7, 8], and
Sense-inventory-based [9, 4, 10, 11, 12, 13, 14, 5, 15, 16].
Existing NLP tasks for M-SE include:

Word similarity [17, 2, 3, 9, 4, 10, 11, 13, 7, 14, 5, 15],

Word sense disambiguation [9, 11, 13, 16],

Relational similarity [4],

Analogical reasoning [10, 7],

Sense clustering [13, 14],

Domain labeling [13],

Synonym recognition [15], and

Outlier detection [15].

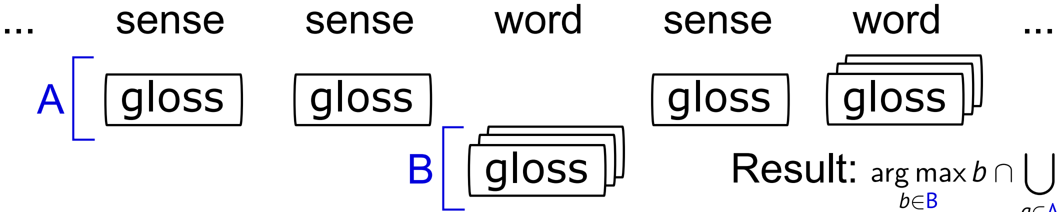
3. & 4. Preprocessing I

- For training our M-SE, we use the following sense-annotated corpora:

Semcor [18] 362 English texts comprising over 200,000 words, and

WordNet Gloss Tags (WNGT) [19] Semi-automatic sense annotations of *all WordNet glosses*.

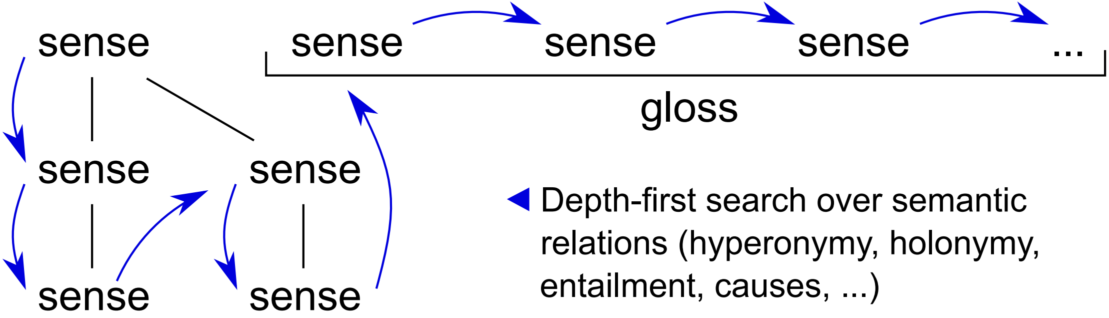
- First, we remove stopwords and we disambiguate unannotated words by maximum overlap of target and context sense glosses from WordNet using a Lesk algorithm [20]:



Result: $\arg\max_{b \in B} b \cap \bigcup_{a \in A} a$

3. & 4. Preprocessing II

- Second, we train M-SE using word2vec [21] and we use our word sense disambiguation algorithm (to be described later) to improve the disambiguation from first step. (MEMBED)
- Third, we augment WNGT using semantic relations from WordNet: (EDS-MEMBED)



◀ Depth-first search over semantic relations (hyperonymy, holonymy, entailment, causes, ...)

- See [1, Section 4.2] for hyperparameters and [1, tables 7 and 8] for their ablation study.

3. & 4. Preprocessing III

4.1 Augmentation Example

- In WNGT, the sense *permit.v.01* is defined by the gloss *consent to, give permission*.
- We remove the stopword *to* and disambiguate the gloss to *accept.v.03 give.v.09 permission.n.01*.
- Using WordNet, we expand *permit.v.01* to its hypernym *accept.v.03*.
- Using WordNet, we expand *permit.v.01* to its hyponyms:
  1. *admit.v.02*
  2. *admit.v.03*
  3. *allow.v.10*
  4. *authorize.v.01*
  5. *digest.v.03*
  6. *furlough.v.02*
  7. *give.v.40*
  8. *legalize.v.01*
  9. *privilege.v.01*
  10. *trust.v.02*
- We produce the following augmented sequence:
  permit.v.01 accept.v.03 admit.v.02 admit.v.03 allow.v.10 authorize.v.01 digest.v.03 furlough.v.02 give.v.40 legalize.v.01 privilege.v.01 trust.v.02 accept.v.03 give.v.09 permission.n.01
- Before training M-SE, we convert the senses to ⟨WordNet offset, part of speech⟩:
  00802318v 00797697v 02502536v 02449847v 00802946v 00803325v 00668099v 00748803v 00748972v 02481436v 02453692v 02481819v 00797697v 01629403v 06689297n

5. Experiments I

- We use the following word–word similarity measures:

AvgSim(w, w') [6] `np.mean(`$W \cdot W'^T$`)`, where W, W' are ℓ_2-normalized M-SE matrices for words w, w' and $\cdot$ is dot product, which gives us all pairwise cosine similarities,

MaxSim(w, w') [6] `np.max(`$W \cdot W'^T$`)`, where W, W' as above,

AvgSimC(w, w', c) [6] `np.mean(`$(W \cdot W'^T) \odot S$`)`, where $S = (W \cdot \bar{C}) \otimes (W' \cdot \bar{C})$, C is an M-SE matrix for context words c, $\bar{C} =$ `np.mean(C, axis=0)` is mean context M-SE, $\odot$ is Hadamard product, $\otimes$ is outer product, and W, W' as above,

MaxSimC(w, w', c) [6] `np.max(`$(W \cdot W'^T) \odot S$`)`, $S = (W \cdot \bar{C}) \otimes (W' \cdot \bar{C})$, where W, W', C as above,

globalSim(w, w') [3, 5] $\bar{W} \cdot \bar{W}'$, where W, W' as above.

- We propose the following sense–word similarity measures for word sense disambiguation:

AvgSimS(s, w') `np.mean(`$\vec{s} \cdot W'^T$`)`, where $\vec{s}$ is an M-SE for sense s and W' as above,

SumAvgSimS$(s, \mathbf{w}')$ $\sum_{w' \in \mathbf{w}'}$ AvgSimS(s, w'), where $\mathbf{w}'$ is a set of context words,

MaxSimS(s, w') `np.max(`$\vec{s} \cdot W'^T$`)`, where $\vec{s}, W'$ as above,

SumMaxSimS$(s, \mathbf{w}')$ $\sum_{w' \in \mathbf{w}'}$ MaxSimS(s, w'), where $\mathbf{w}'$ as above.

5. Experiments II

5.3 Word Sense Disambiguation I

- We disambiguate word w in context $\mathbf{w}'$ as $\arg\max_{s \in w} f(s, \mathbf{w}'), f \in \{\text{SumAvgSimS, SumMaxSimS}\}$.
- For words with no context or negative arg max, we assign the first WordNet sense.
- We evaluate on six datasets, see [1, Section 5.3] for details:
  1. Senseval-2 (SE2) [22]
  2. Senseval-3 English all-words task (SE3) [23]
  3. SemEval-2007 task 17 (SE07-17) [24]
  4. SemEval-2007 task 07 (SE07-07) [25]
  5. SemEval-2013 task 12 (SE13-12) [24]
  6. SemEval-2015 task 13 (SE15-13) [25]
- In our comparison, we distinguish M-SE-based and non-M-SE-based systems.
- In our comparison, we also distinguish four kinds of approaches:

Unsupervised Based on large unannotated corpora, worst performance,

Knowledge-based Based on sense inventories and lexical resources, our approach,

Semi-supervised Based on small sense-annotated corpora and large unannotated corpora,

Supervised Based on small sense-annotated corpora, best performance.

5. Experiments III

5.3 Word Sense Disambiguation II

Table 3

F_1 (%) of EDS-MEMBED in comparison with MEMBED and state-of-the-art embeddings-based WSD systems on the benchmark datasets. Best results for each approach in bold.

Approach	System	SE2	SE3	SE07-17	SE13-12	SE15-13	SE07-07
Supervised	IMS+Word2Vec(OMSTI)	68.3	68.2	**59.1**	–	–	–
	IMS + S-product	66.8	**73.6**	–	–	–	–
Semi-Supervised	Chen et al.(Model S2C)	–	–	–	–		**82.6**
Knowledge-based	+LS	58.4	59.4	–	–	–	–
	Chen et al.(Model S2C)	–	–	–	–	–	75.8
	VecLesk(baroni c)	–	–	–	–	58.0	75.3
	VecLesk(glove)	–	–	–	–	59.0	73.0
	MEMBED$_{AvgS}$	65.7	58.8	47.5	64.2	69.2	78.6
	MEMBED$_{MaxS}$	66.1	58.9	48.4	64.4	70.3	78.9
	EDS-MEMBED$_{AvgS}$	66.3	**60.4**	46.2	65.6	**72.4**	78.5
	EDS-MEMBED$_{MaxS}$	**66.6**	59.9	47.0	**66.7**	71.9	**79.1**

5. Experiments IV

5.3 Word Sense Disambiguation III

Table 4

F_1 (%) of EDS-MEMBED in comparison with MEMBED and state-of-the-art WSD systems on the benchmark datasets. Best results for each approach in bold. † indicates values not given by authors but deduced [48].

Approach	System	SE2	SE3	SE07-17	SE13-12	SE15-13	SE2+SE3+SE07-17+SE13-12+SE15-13					SE07-07
							Nouns	Verbs	Adj.	Adv.	ALL	
Supervised	$LMMS_{2348}$(BERT)	76.3	75.6	68.1	75.1	77.0	–	–	–	–	75.4	–
	HCAN	72.8	70.3	–	68.5	72.8	72.7	58.2	77.4	84.1	71.1	–
	LSTMLP	73.8	71.8	63.5	69.5	72.6	†73.9	–	–	–	†71.5	83.6
	GAS	72.2	70.5	–	67.2	72.6	72.2	57.7	76.6	85.0	70.6	–
	BERT	75.5	73.6	68.1	71.1	76.2	–	–	–	–	74.1	–
	GLOSSBERT	77.7	75.2	72.5	76.1	80.4	79.3	66.9	78.2	86.4	77.0	–
	SemCor+WNGC	**79.7**	**77.8**	**73.4**	**78.7**	**82.6**	**81.4**	**68.7**	**83.7**	**85.5**	**79.0**	**90.4**
	MFS	65.6	66.0	54.5	63.8	67.1	67.7	49.8	73.1	80.5	65.5	78.9
Knowledge-based	KEF	**69.6**	66.1	**56.9**	68.4	72.3	**71.9**	**51.6**	74.0	80.6	**68.0**	–
	Babelfy	67.0	63.5	51.6	66.4	70.3	68.6	49.9	73.2	79.8	65.5	–
	UKB	68.8	66.1	53.0	**68.8**	70.3	–	–	–	–	67.3	–
	WSD-TM	69.0	**66.9**	55.6	65.3	69.6	69.7	51.2	**76.0**	**80.9**	66.9	–
	WN 1st sense	66.8	66.2	55.2	63.0	67.8	67.6	50.3	74.3	**80.9**	65.2	78.9
	$MEMBED_{AvgS}$	65.7	58.8	47.5	64.2	69.2	66.7	47.2	69.3	73.7	62.9	78.6
	$MEMBED_{MaxS}$	66.1	58.9	48.4	64.4	70.3	66.8	48.7	68.8	75.7	63.3	78.9
	$EDS\text{-}MEMBED_{AvgS}$	66.3	60.4	46.2	65.6	**72.4**	68.2	48.4	69.9	74.9	64.2	78.5
	$EDS\text{-}MEMBED_{MaxS}$	66.6	59.9	47.0	66.7	71.9	68.0	49.2	70.3	76.0	64.4	**79.1**

5. Experiments V

5.4 Word Similarity I

- For words w, w', we compute similarity as $f(w, w'), f \in \{\text{AvgSim, MaxSim, globalSim}\}$.
- For words w, w' in context c, we use $f(w, w', c), f \in \{\text{AvgSimC, MaxSimC, globalSim}\}$.
- We evaluate on five datasets, see [1, Section 5.4] for details:
  1. RG65, MC28, MEN [26, 27, 28]
  2. SimLex999 [29]
  3. WordSim-353 [30]

Table 5
Spearman's correlation coefficient ($\rho \times 100$) of models on the RG65, MC28, and MEN datasets. Best performing models in bold.

Model	RG65			MC28			MEN		
	AvgSim	MaxSim	globalSim	AvgSim	MaxSim	globalSim	AvgSim	MaxSim	globalSim
GloVe	–	–	82.9	–	–	83.6	–	–	–
Retro	–	–	84.2	–	–	–	–	–	75.9
Word2Vec	–	–	75.4	–	–	–	–	75.0	–
SENSEMBED	87.1	89.4	–	–	88.0	–	**80.5**	77.9	–
MSSA	82.8	87.8	85.9	84.5	88.8	87.5	78.5	74.4	79.5
DeConf	–	**89.6**	–	–	–	–	–	78.6	–
SW2V	–	74.0	–	–	–	–	–	76.0	–
MEMBED	64.4	85.0	83.6	70.2	86.3	81.7	55.2	67.9	58.3
EDS-MEMBED	77.1	**89.6**	86.9	83.2	**89.6**	88.4	63.3	68.4	64.3

5. Experiments VI

5.4 Word Similarity II

Table 6
Spearman's correlation coefficient ($\rho \times 100$) of models on SimLex999 and WordSim-353. Best performing models in bold.

Model	SimLex999			WordSim-353		
	AvgSim	MaxSim	globalSim	AvgSim	MaxSim	globalSim
GloVe	–	–	–	–	–	75.9
Retro	–	–	–	–	–	61.2
Word2Vec	–	39.0	–	–	–	–
SENSEMBED	–	–	–	**77.9**	71.4	–
Huang et al.	–	–	–	64.2	–	22.8
Pruned-TF–IDF	–	–	–	–	–	73.4
MSSG	–	–	–	68.6	–	69.1
MSSA	46.9	38.5	43.9	73.0	66.2	73.7
DeConf	–	51.7	–	–	–	–
SW2V	–	47.0	–	–	71.0	–
Chen et al.	–	43.0	–	–	–	–
MEMBED	37.0	47.6	33.2	45.6	54.0	44.6
EDS-MEMBED	48.0	**53.7**	46.4	59.5	59.6	58.2

5. Experiments VII

5.6 Computational Complexity

Table 9

Training data size, training time, dimension of the models and the hardware environment.

Model	Data size (tokens)	Training time	Dimension	Hardware
Huang at al.	990 million	168 h	50	–
MSSG	990 million	6 h	300	–
SENSEMBED	3 billion	–	400	–
MSSA	540 million	–	1000	–
Word2Vec	783 million	24 h	300	–
GloVe	840 billion	85 m/6 billion	300	Intel CPU @ 2.1 GHz $\times$ 32
MEMBED	1,302,549	12 m:19 s	100	Intel CPU @ 1.60 GHz $\times$ 4, 11.7 GiB RAM
EDS-MEMBED	1,590,998	16 m:26 s	200	Intel CPU @ 1.60 GHz $\times$ 4, 11.7 GiB RAM

Conclusion

- Word embeddings suffer from polysemy.
- Multi-sense embeddings (M-SE) solve polysemy, but suffer from lack of training data.
- We propose an approach that covers all word senses using WordNet.
- We also adapt existing word similarity measures to word sense disambiguation.
- Our approach is *efficient* and *competitive* on word similarity and word sense disambiguation.

Thank You for Your Attention!

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