中国科学技术大学

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Incorporating Latent Meanings of Morphological Compositions to Enhance Word Embeddings

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OUTLINE

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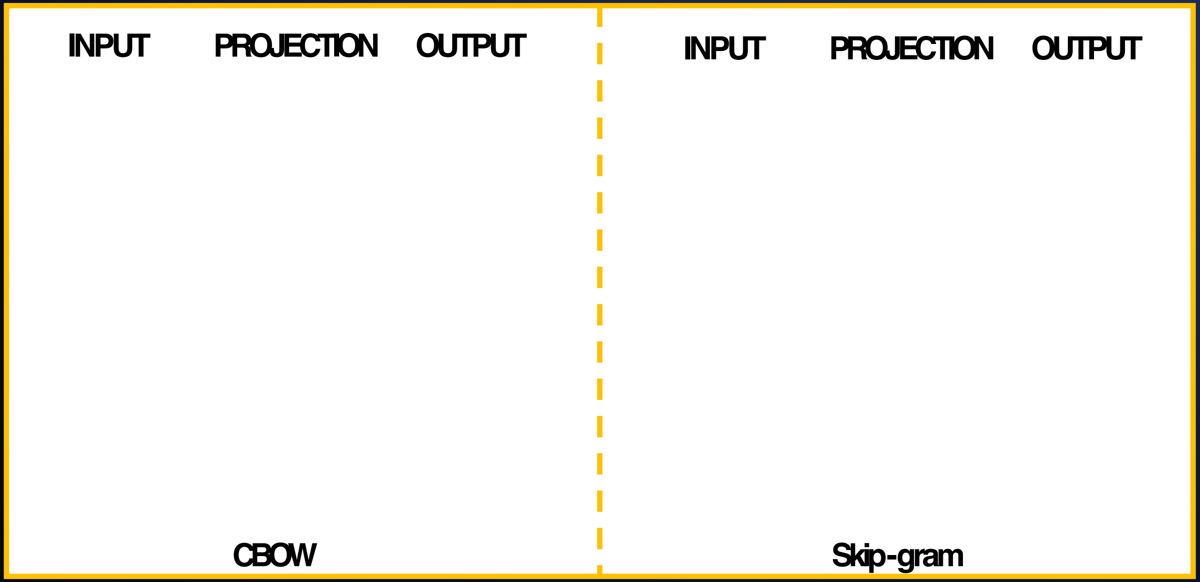
01 Introduction

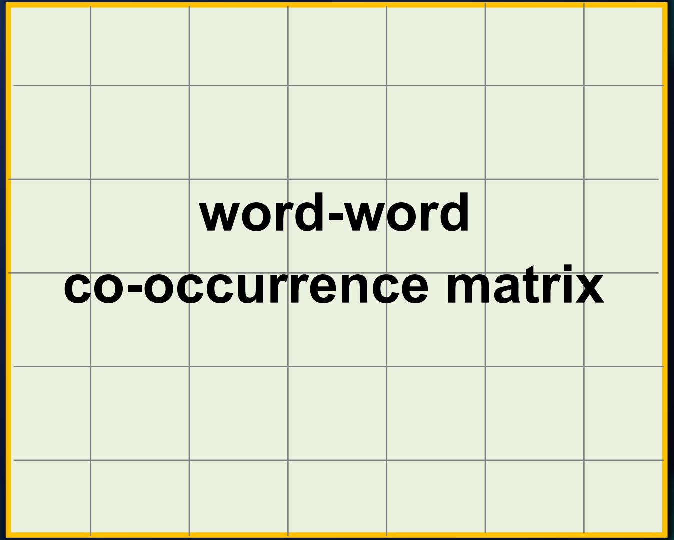
Word-level Word Embedding

01 Neural Network-Based



e.g., CBOW, Skip-gram (Mikolov et al.)

e.g., GloVe (Pennington et al.)



02 Matrix Factorization-Based (Spectral Methods)

Morphology-based Word Embedding

01

Morpheme Embeddings

Prefix + Root + Suffix

$\vec{in-}$ $\vec{cred}$ $\vec{ible}$

+

Word Embeddings

Word

$\overrightarrow{\text{incredible}}$

Training Model

Generated Word Vectors

Generated Word

Generative Model

Morpheme Embeddings

Prefix Root Suffix

02

Our Original Intention

- Word-level models: InputWords;
  Output Word Embeddings

- Morphology-based models: Input Words + Morphemes
  Output Word Embeddings + Morpheme Embeddings

- Our Latent Meaning Models: InputWords + Latent Meanings of Morphemes
  Output Word Embeddings
  (no by-product, e.g., morpheme embedding)

PURPOSE: to not only encode morphological properties into words, but also enhance the semantic similarities among word embeddings

Explicit Models & Our Models

*Note: The lookup table can be derived from morphological lexicons.

02
Latent Meaning Models

CBOW with Negative Sampling

- Sequence of tokens

INPUT PROJECTION OUTPUT

- Objective Function:

$$L = \frac{1}{n}\sum_{i=1}^{n} \log p(t_i \mid Context(t_i))$$

rd)

- Negative Sampling:

(Context Words)

Three Specific Models

01

LMM-A
(Latent Meaning Model-Average)

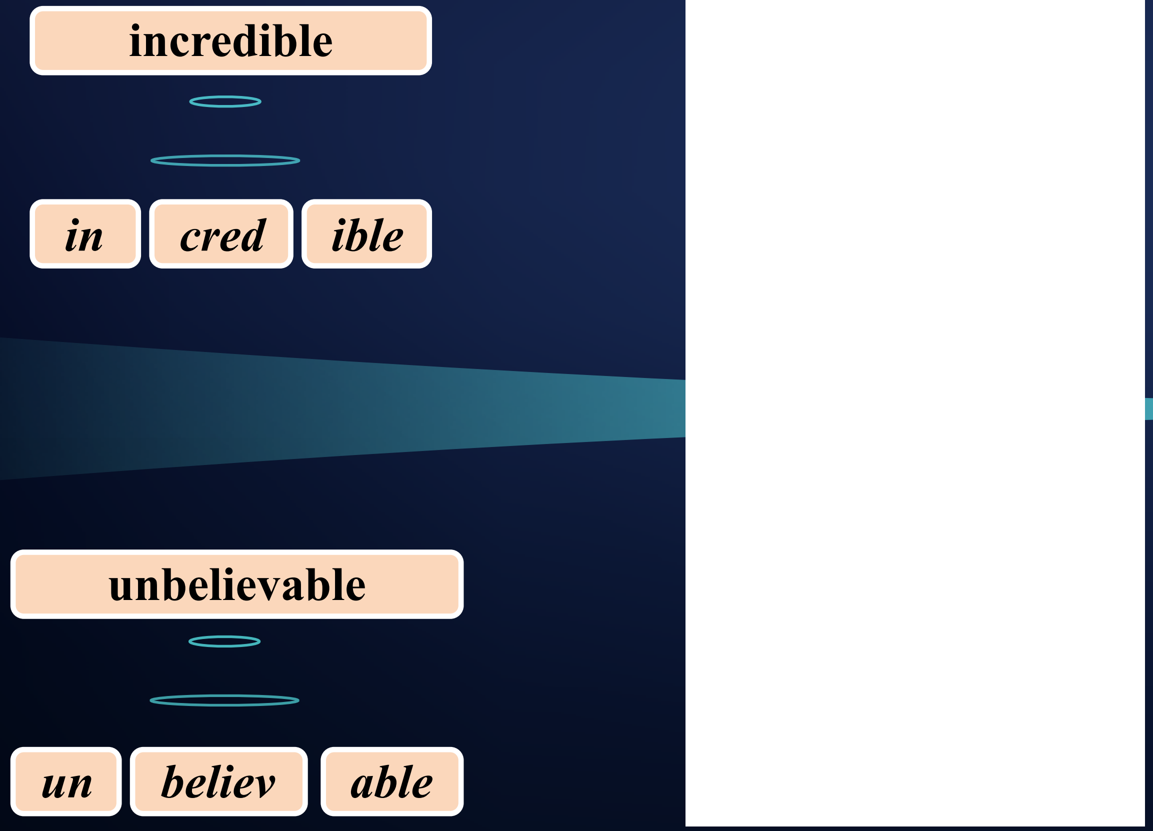
02

LMM-S
(Latent Meaning Model-Similarity)

03

LMM-M
(Latent Meaning Model-Max)

Word Map



Word Map

Word	Prefix		Root	Suffix	
incredible	*in*	*not*	*believe*	*able*	*capable*
unbelievable	*not*		*believe*	*able*	*capable*

#rows = |vocabulary|

*Note: The derivational morphemes, not the inflectional morphemes, are mainly concerned

Latent Meaning Model-Average (LMM-A)

- Sequence of tokens

- The latent meanings of ’s morphemes have **equal** contributions to

- The modified embedding of :

  : a set of latent meanings of ’s morphemes

  : the length of

- is utilized for training

A paradigm of LMM-A

Latent Meaning $Context(t_i)$

Latent Meaning Model-Similarity (LMM-S)

- Sequence of tokens

- The latent meanings of ’s morphemes are assigned with **different weights**:

$$\omega_{<t_j,\, w>} = \frac{\cos\left(v_{t_j}, v_w\right)}{\sum_{x \in M_j} \cos\left(v_{t_j}, v_x\right)}, w \in M_j$$

- The modified embedding of :

: a set of latent meanings of ’s morphemes

A paradigm of LMM-S

Latent Meaning

$Context\left(t_i\right)$

Latent Meaning Model-Max (LMM-M)

- Sequence of tokens

- Keep the latent meanings that have **maximum similarities** to :

$$P_{max}^{j} = \underset{w}{argmax} cos\left(v_{t_j}, v_w\right), w \in P_j$$

$$R_{max}^{j} = \underset{w}{argmax} cos\left(v_{t_j}, v_w\right), w \in R_j$$

$$S_{max}^{j} = \underset{w}{argmax} cos\left(v_{t_j}, v_w\right), w \in S_j$$

- The modified embedding of :

$$M_{max}^{j} = \left\{P_{max}^{j}, R_{max}^{j}, S_{max}^{j}\right\}$$

A paradigm of LMM-M

Latent Meaning $\quad Context(t_i)$

Update Rules for LMMs

- **New Objective Function (After modifying the input layer of CBOW):**

$$\hat{L} = \frac{1}{n}\sum_{i=1}^{n} \log p(v_{t_i} \mid \sum_{t_j \in Context(t_i)} \hat{v}_{t_j})$$

- **All parameters introduced by our models can be directly derived using the word map and word embeddings**

- **Update not just but the embeddings of the latent meanings with the same weights as they are assigned in the forward propagation period**

03
Experimental Setup

Corpus & Word Map

Corpus

- News corpus of 2009 (2013 ACL Eighth Workshop)
- Size: 1.7GB
- ~500 million tokens
- ~600,000 words
- Digits & punctuation marks are filtered

Word Map

- Morpheme segmentation using Morefessor (Creutz & Lagus, 2007)
- Assign latent meanings
- Lookup table
  - ▶ derived from the resources provided by Michigan State University*
  - ▶ 90 prefixes, 382 roots, 67 suffixes

*Resources web link:
https://msu.edu/~defores1/gre/roots/gre_rts_afx1.htm

Baselines & Parameter Settings

Baselines:

- Word-level models: CBOW, Skip-gram, GloVe
- Explicitly Morpheme-related Model (EMM)

A paradigm of EMM

Morphemes

Super-parameter Settings:

- Equal settings to all models
- Vector Dimension: 200
- Context window size: 5
- #Negative_Samples: 20

Evaluation Benchmarks (1/2)

Word Similarity:

Dataset

Name	#Pairs	Name	#Pairs	Name	#Pairs
RG-65	65	Rare-Word	2034	Men-3k	3000
Wordsim-353	353	SCWS	2003	WS-353-Related	252

Gold Standard Datasets — Widely-used Datasets

Syntactic Analogy:

- "a b as c _? (d)_" e.g., Queen King as Woman (Man)
- Microsoft Research Syntactic Analogies dataset (8000 items)

Evaluation Benchmarks (2/2)

Text Classification:

- 20 Newsgroups dataset (19000 documents of 20 different topics)
- 4 text classification tasks, each involves 10 topics
- Training/Validation/Test subsets (6:2:2)
- Feature vector: average word embedding of words in each document
- L2-regularized logistic regression classifier

04
Experimental Results

The Results on Word Similarity

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	CBOW	Skip-gram	GloVe	EMM	LMM-A	LMM-S	LMM-M
Wordsim-353	58.77	61.94	49.40	60.01	62.05	**63.13**	61.54
Rare-Word	40.58	36.42	33.40	40.83	**43.12**	42.14	40.51
RG-65	56.50	62.81	59.92	60.85	62.51	62.49	**63.07**
SCWS	**63.13**	60.20	47.98	60.28	61.86	61.71	63.02
Men-3k	68.07	66.30	60.56	66.76	66.26	**68.36**	64.65
WS-353-Related	49.72	57.05	47.46	54.48	56.14	**58.47**	55.19

(Given different models) Spearman's rank correlation (%) on different datasets

The Results on Syntactic Analogy

Question: "a b as c __(d)__"

Answer:

	CBOW	Skip-gram	GloVe	EMM	LMM-A	LMM-S	LMM-M
Syntactic Analogy	13.46	13.14	13.94	17.34	**20.38**	17.59	18.30

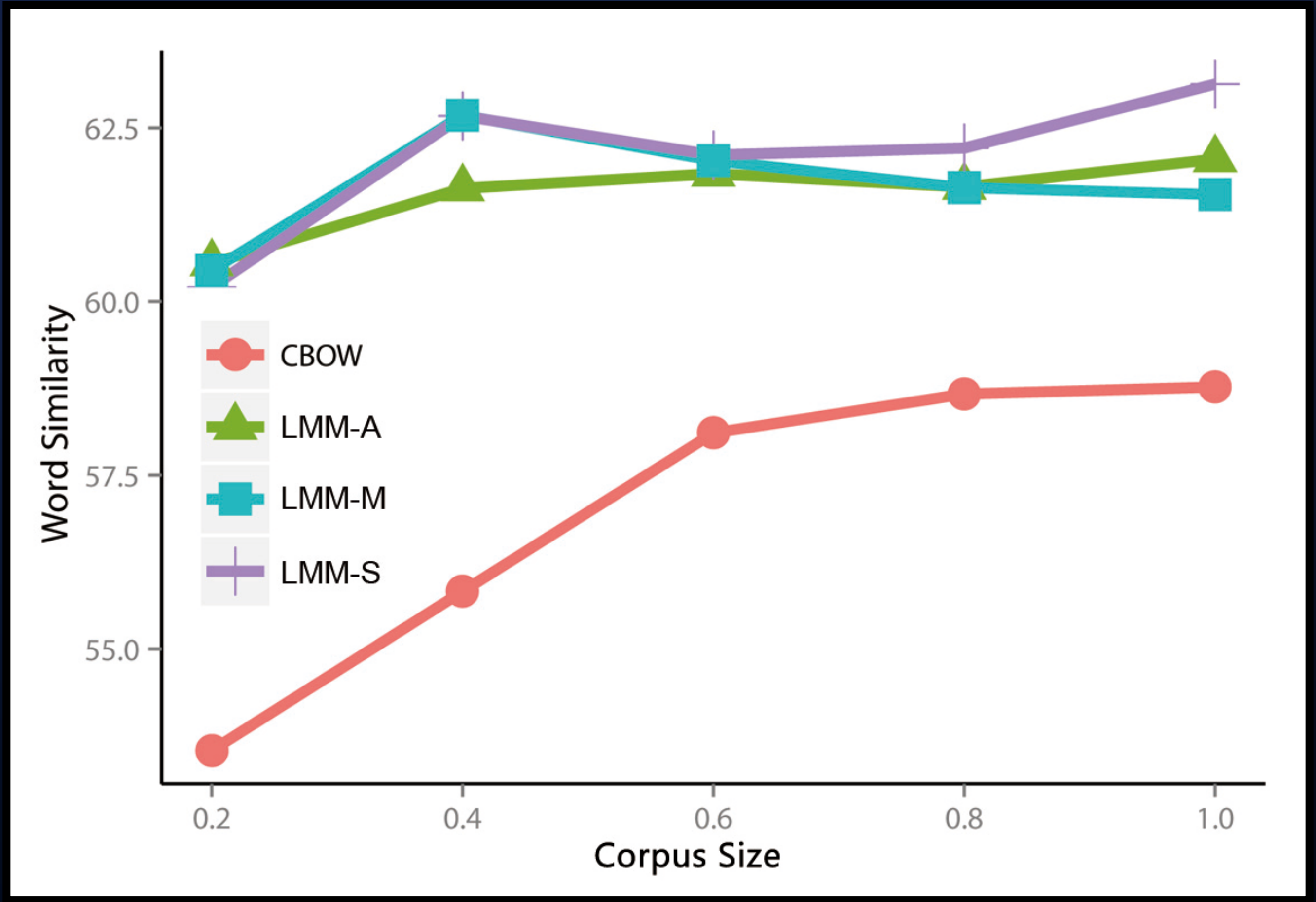
Syntactic analogy performance (%)

The Results on Text Classification

	CBOW	Skip-gram	GloVe	EMM	LMM-A	LMM-S	LMM-M
Text Classification	78.26	79.40	77.01	80.00	80.67	80.59	**81.28**

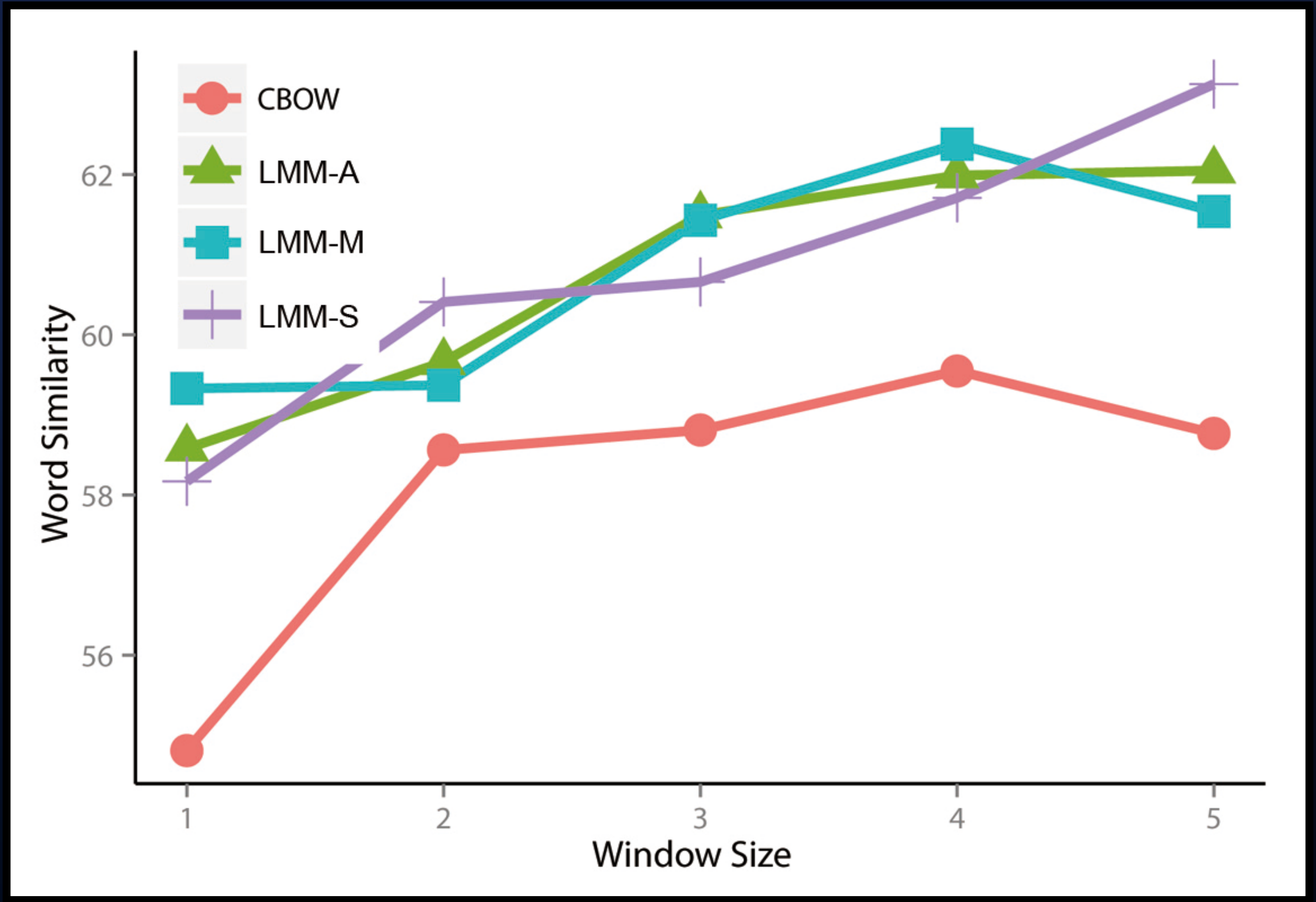
Average text classification accuracy across the 4 tasks (%)

The Impact of Corpus Size



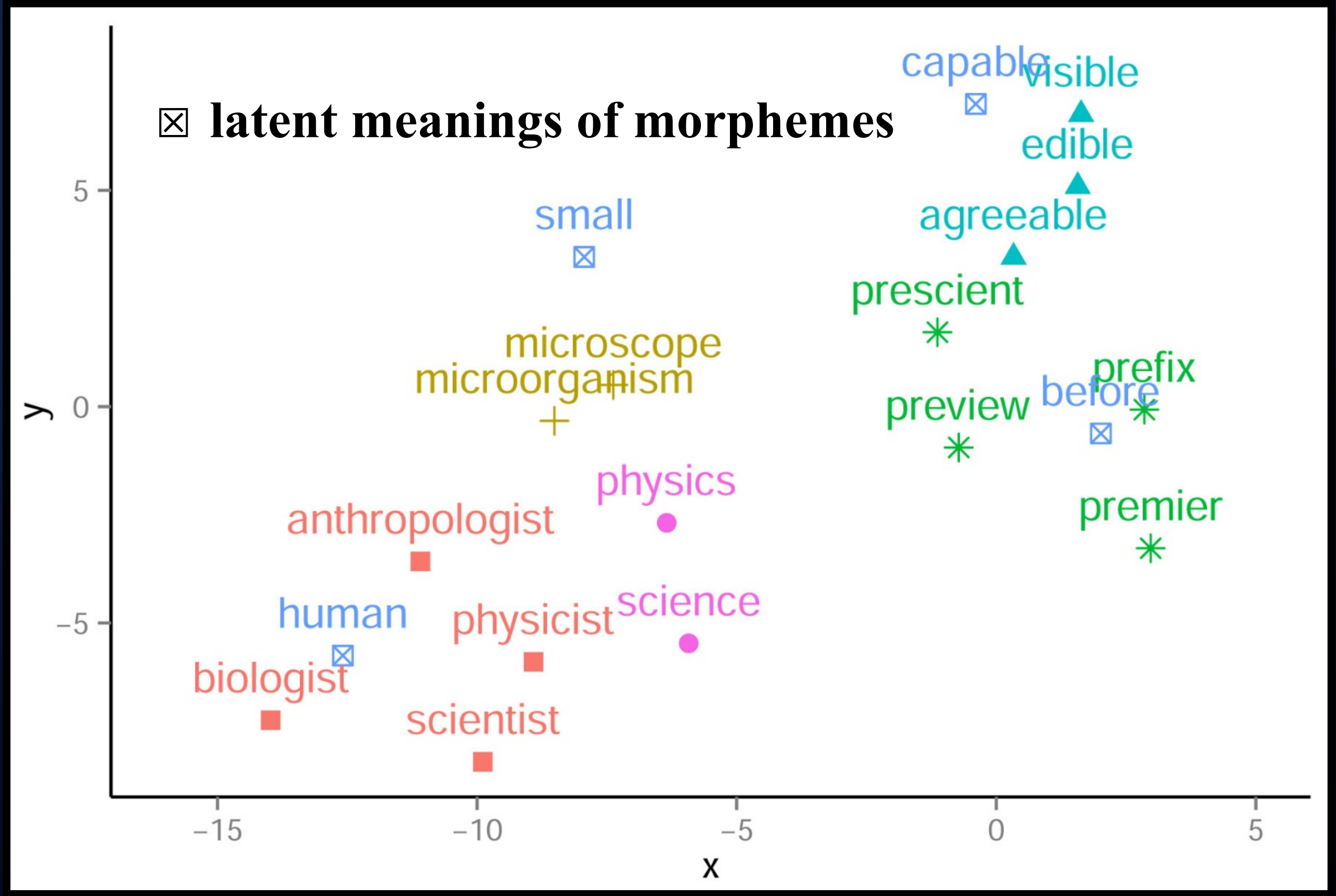
Results on Wordsim-353 task with different corpus size

The Impact of Context Window Size



Results on Wordsim-353 task with different context window size

Word Embedding Visualization



Visualization of word embeddings based on PCA

05 Conclusions

Conclusions

- Employ latent meanings of morphemes rather than the internal compositions themselves to train word embeddings
- By modifying the input layer and update rules of CBOW, we proposed three latent meaning models (LMM-A, LMM-S, LMM-M)
- The comprehensive quality of word embedings are enhanced by incorporating latent meanings of morphemes
- In the future, we intend to evaluate our models for some morpheme-rich languages like Russian, German, etc.

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Thank you!

Questions?