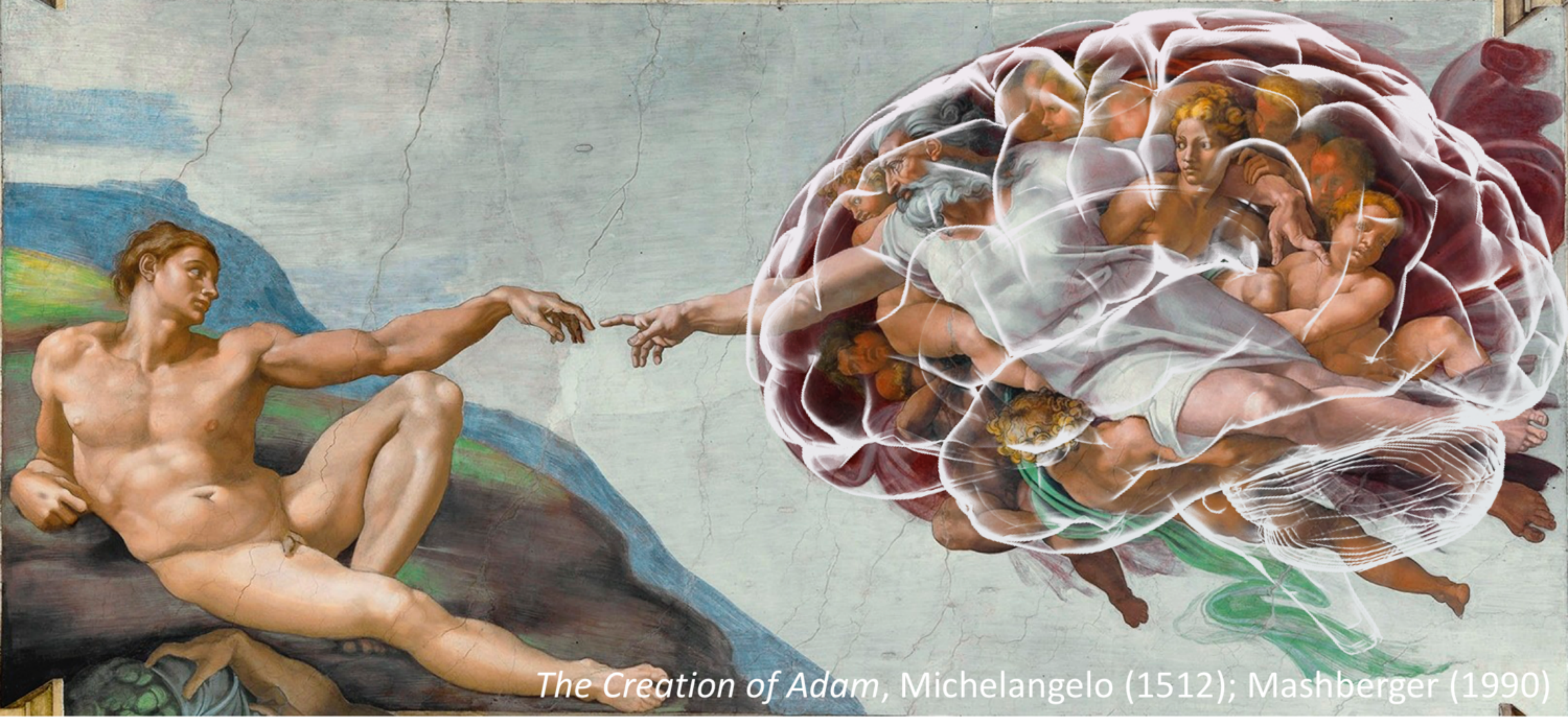

Word Embedding and WordNet based Metaphor Identification and Interpretation

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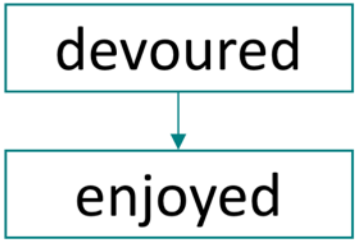
Outline.

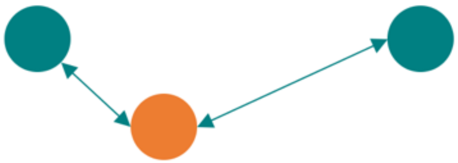
1. Introduction
2. Methodology
   - Word embedding
   - Framework
   - Machine Translation
3. Experiments and Results
4. Conclusion

Novelty.

1. Identify and paraphrase metaphors in whole sentences from unrestricted domains;



2. Using word embedding input and output vectors to model a word and its context co-occurrence;



3. Metaphor processing for Machine Translation.

1. Introduction

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The definition of metaphor.

Linguistically, metaphor is defined as a language expression that uses one or several words to represent another concept, rather than taking their literal meanings of the given words in the context (Lagerwerf and Meijers, 2008).

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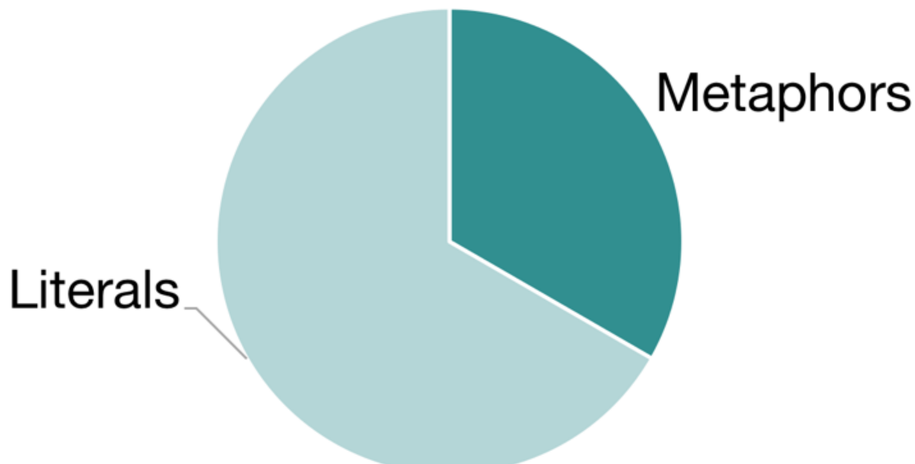
Metaphors are widespread in natural language.

One third of sentences in typical corpora contain metaphors.



(Cameron, 2003; Martin, 2006; Steen et al., 2010; Shutova 2016)

Contexts help to find anomalies and identify metaphors.

She devoured his sandwiches.

She devoured his novels.

Anomalies

"devoured" means "enjoyed avidly".

"devoured" and "enjoyed" are different concepts literally.

"devoured" is metaphorical.

Common sense → Interpretation → Identification

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Motivation.

- Many previous metaphor processing methods are domain dependent (Heintz et al., 2013; Strzalkowski et al., 2013).
- Many works simply use input vectors (Shutova et al., 2016; Rei et al., 2017).
- Metaphor processing has rarely been applied to a real-world NLP task, instead mostly reporting accuracy on metaphor identification or interpretation.

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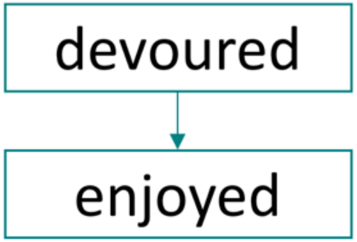
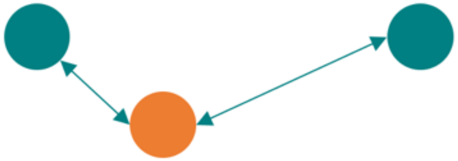
Contribution.

1. Metaphor detection and interpretation in sentences from unrestricted domains.



2. Investigate the effectiveness of input and output vectors of word embedding.



3. Apply metaphor detection and interpretation to improve Machine Translation.

Google Translate

bing Translator

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1. Metaphor detection and interpretation in whole sentence from unrestricted domains.

She devoured his novels.

- enjoyed — Interpretation
- metaphorical — Identification

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1. Metaphor detection and interpretation in whole sentence from unrestricted domains.

Sentence level

Phrase level

This young man knows how to climb the social ladder.

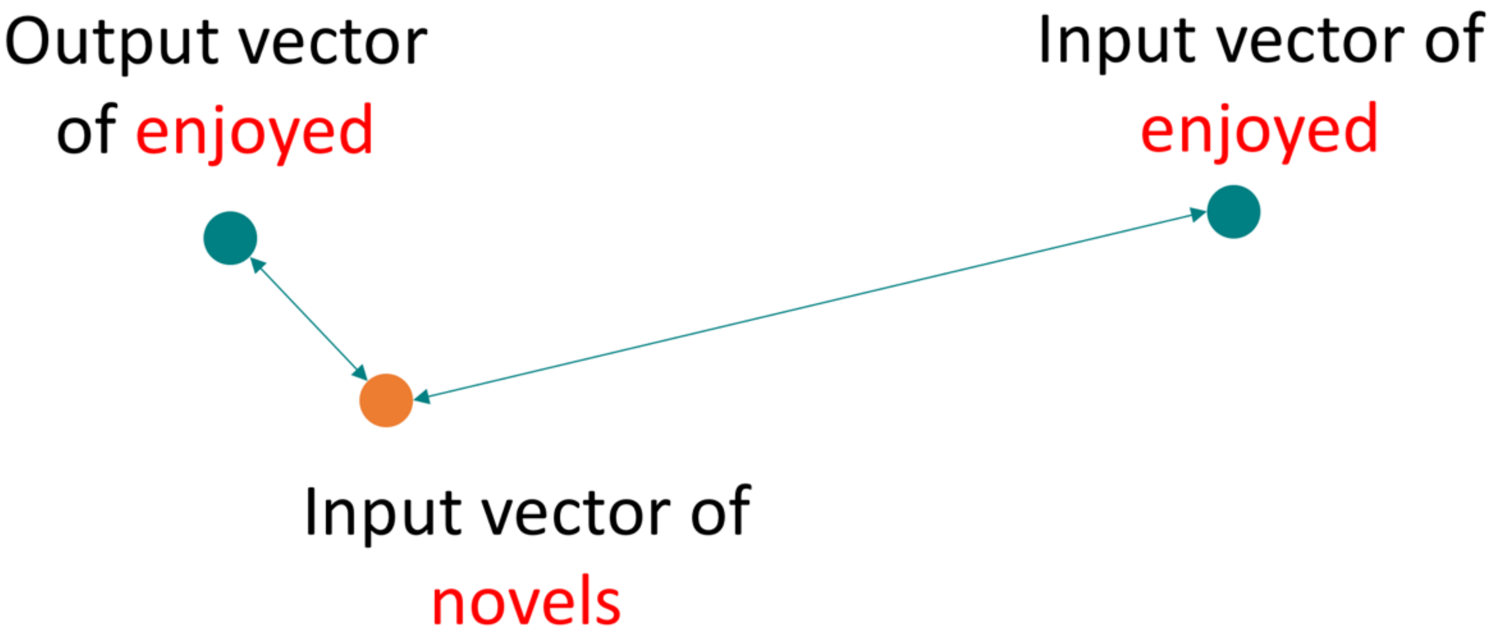
Parsing

climb ladder

Metaphorical

Literal

2. Investigate the effectiveness of input and output vectors of word embedding.



3. Apply metaphor detection and interpretation to improve Machine Translation.

Without metaphor processing

With metaphor processing

2. Methodology

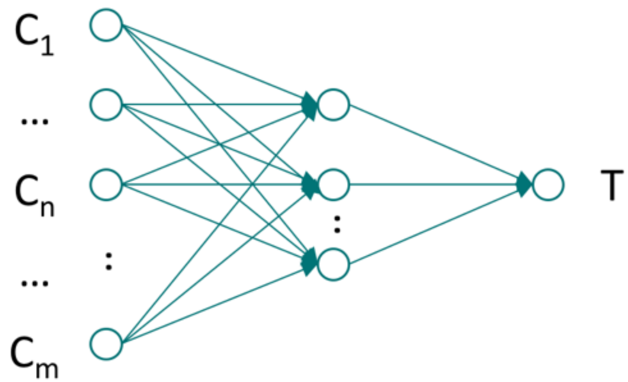
2. Methodology

One of novelties of our work is to model co-occurrence between words with input and output vectors.

CBOW word2vec
(Mikolov et al, 2013)

Input Hidden Output

Context words



Target words

Input vector

Output vector
Abandoned
(e.g., gensim word2vec
(Rehurek and Sojka, 2010))

POSITIVE
NEGATIVE

Input vec Output vec

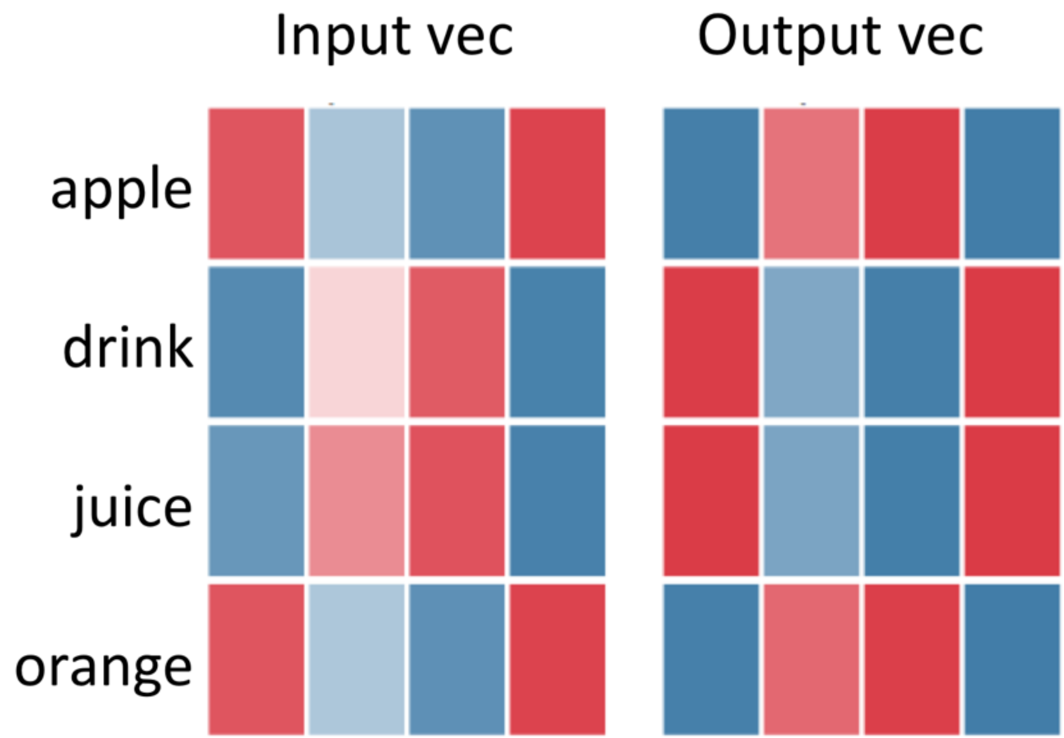
The interaction between input and output vectors represents the co-occurrence of words and contexts.

Training corpus

drink apple juice

drink orange juice

500 iterations on wevi
https://ronxin.github.io/wevi/



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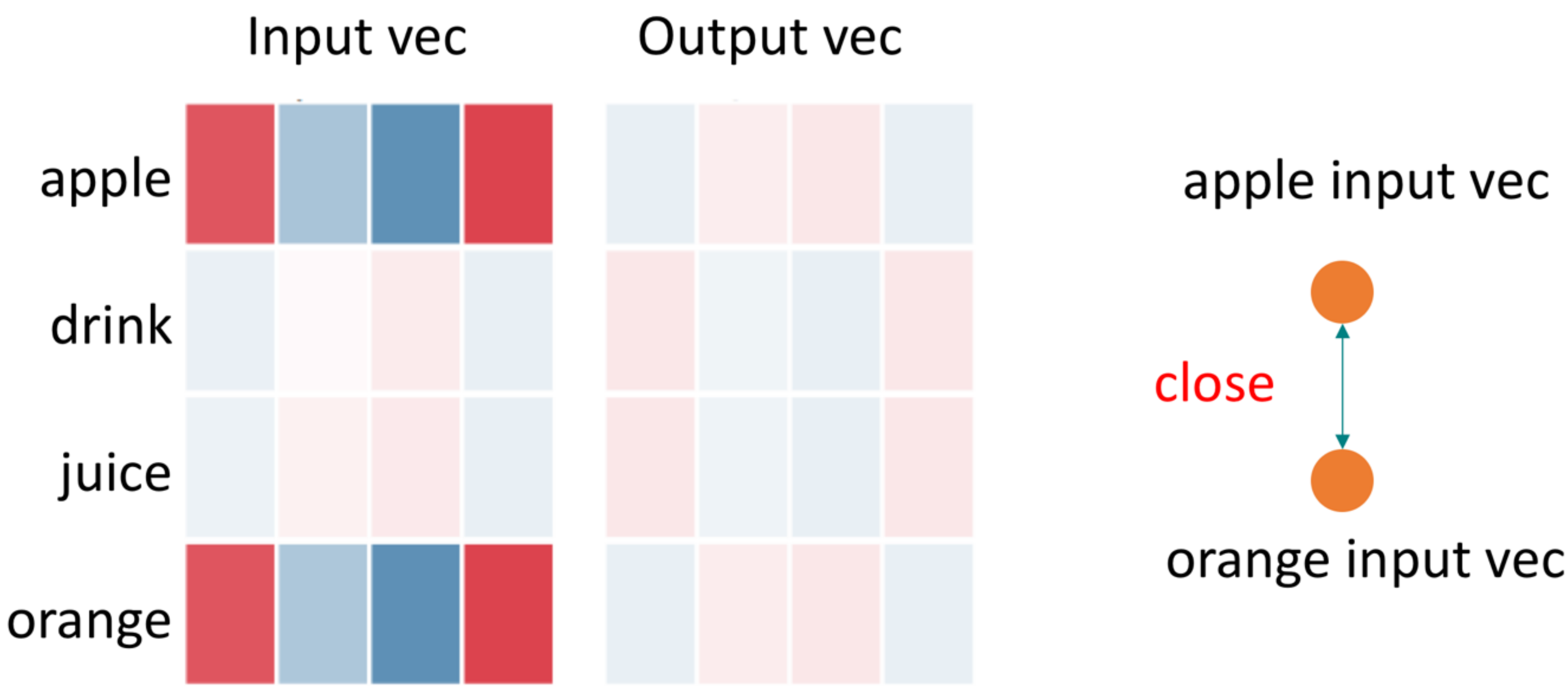
The interaction between input and output vectors represents the co-occurrence of words and contexts.



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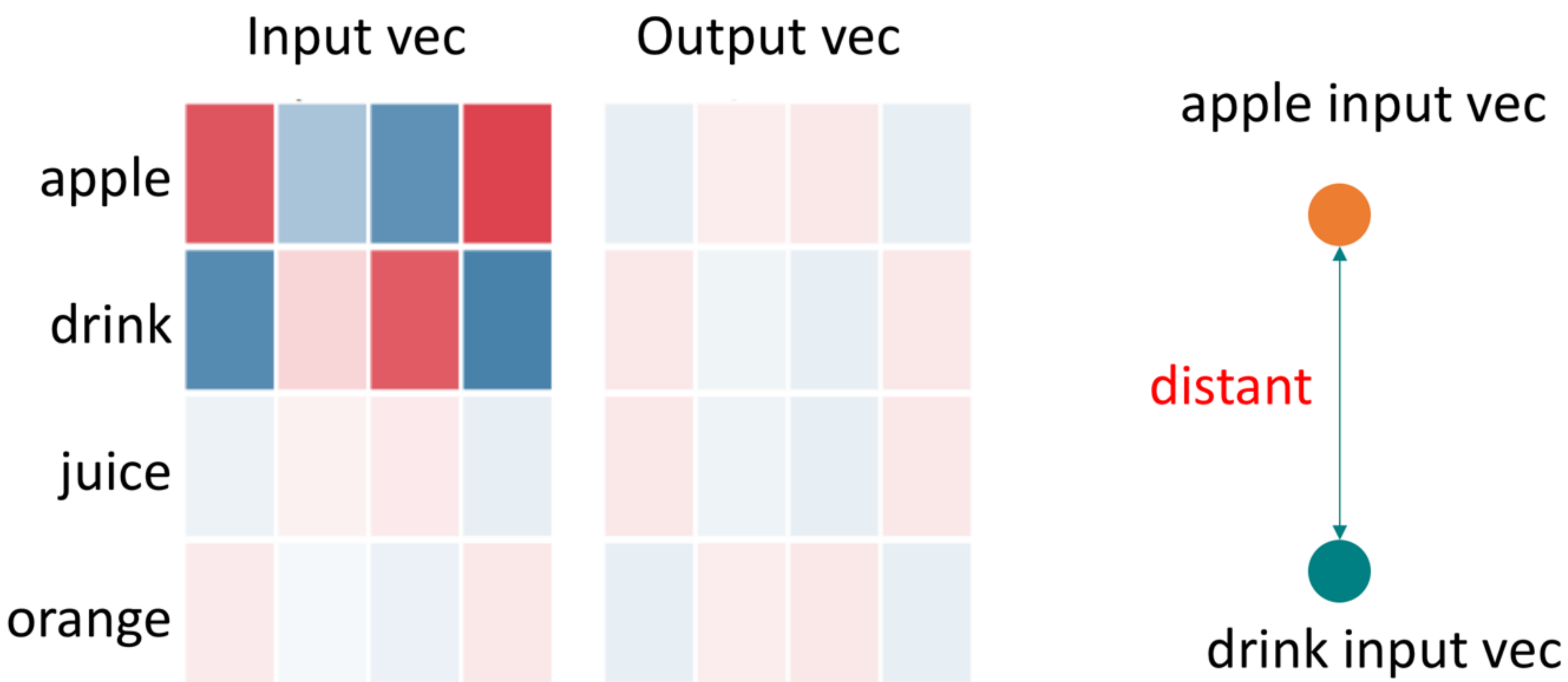
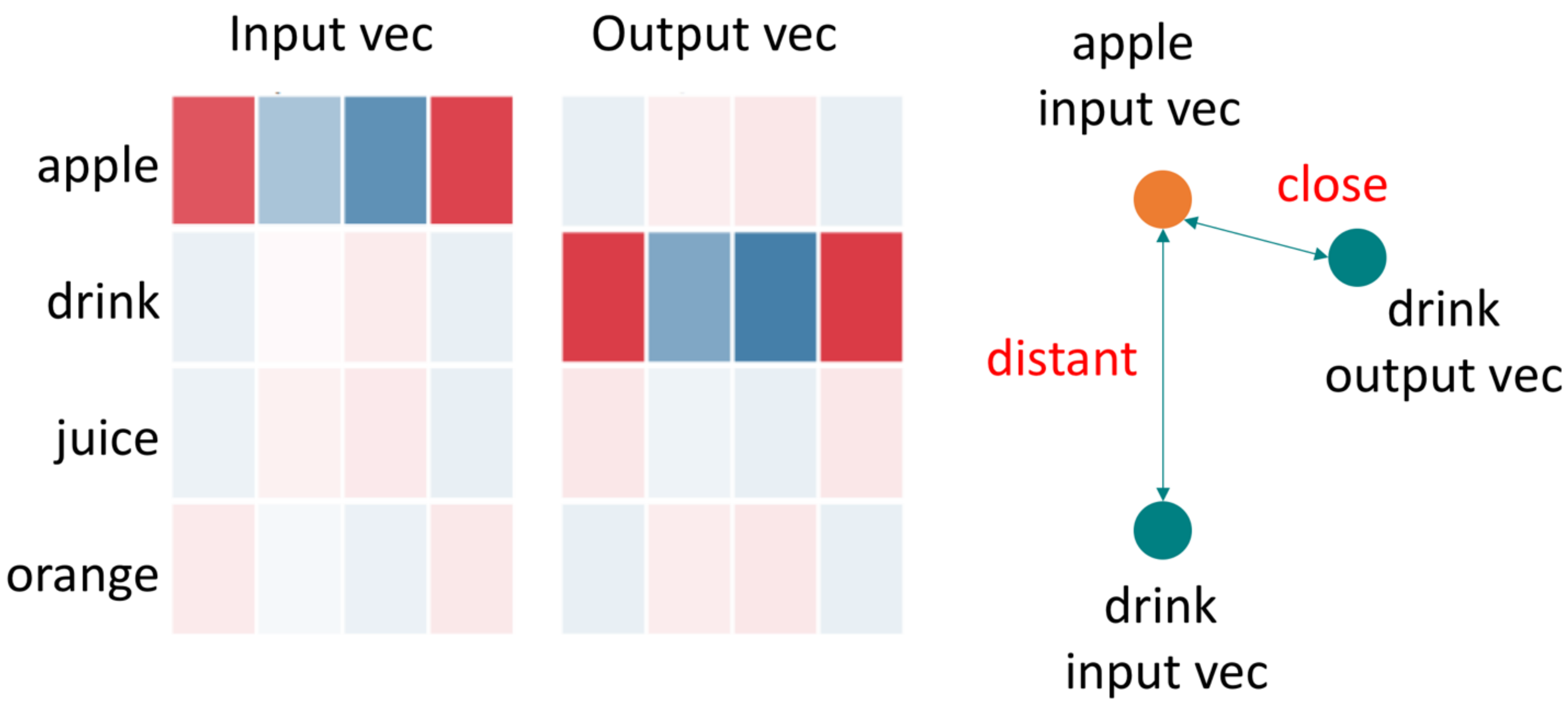
The interaction between input and output vectors represents the co-occurrence of words and contexts.



2. Methodology

The interaction between input and output vectors represents the co-occurrence of words and contexts.



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Summary.

- Input vectors can better model the similarity between words with similar semantics and syntax;
- Output vector can better model the co-occurrence between words with different Part-of-Speech

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The co-occurrence between a target word and its context is measured by

$$score_{cooccur} = \cos\left(v_T^o, v_{context}^i\right)$$

$$v_{context}^i = \frac{1}{m}\sum_{n=1}^{m} v_{c,n}^i$$

Hypotheses.

H1. Literal sense is more common that metaphorical. (Cameron, 2003; Martin, 2006; Steen et al., 2010; Shutova 2016)

Detect the anomalies

One third of sentences in typical corpora contain metaphors.

H2. A metaphorical word can be identified, if the sense the word takes within its context and its literal sense come from different domains. (Wilks, 1975, 1978)

Identify a metaphor

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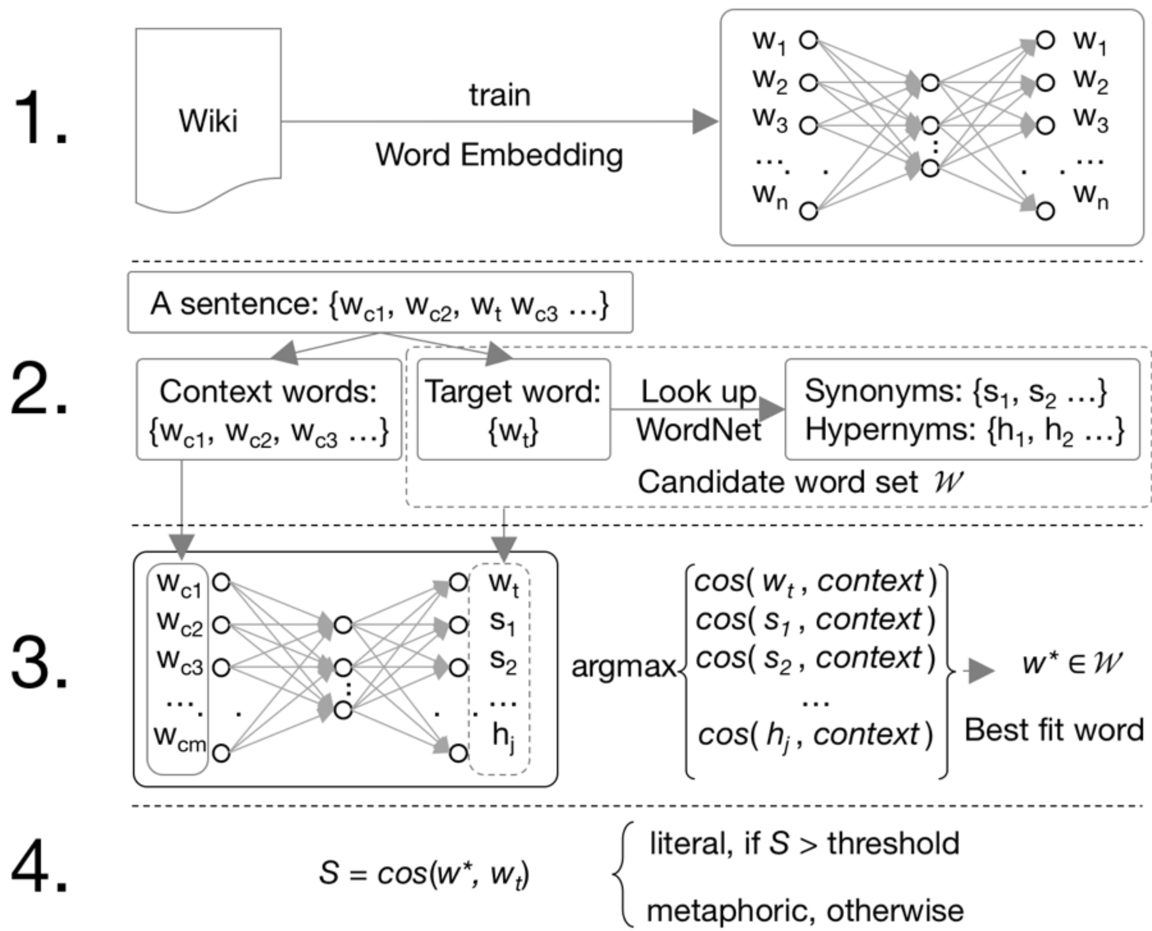
Framework.



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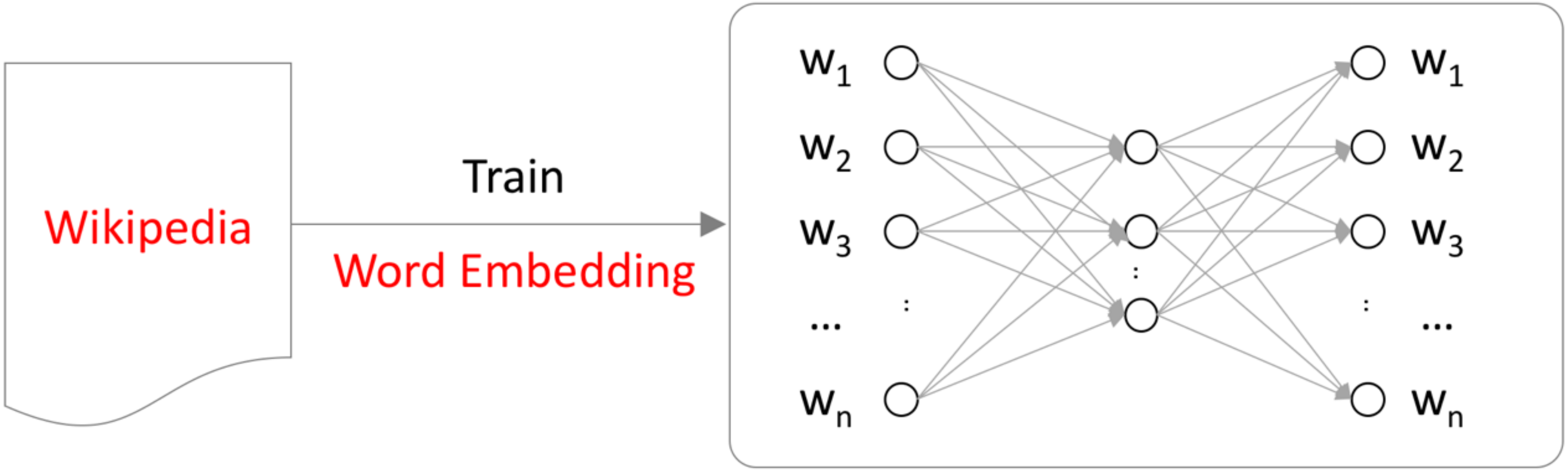
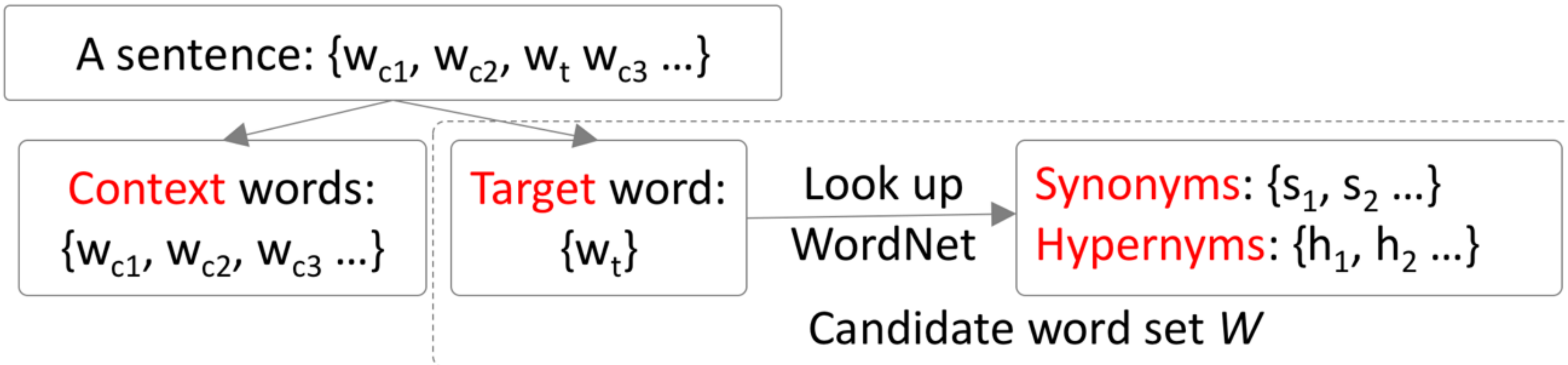
Step 1: training word embedding models on Wikipedia, so that we can model the common expressions.



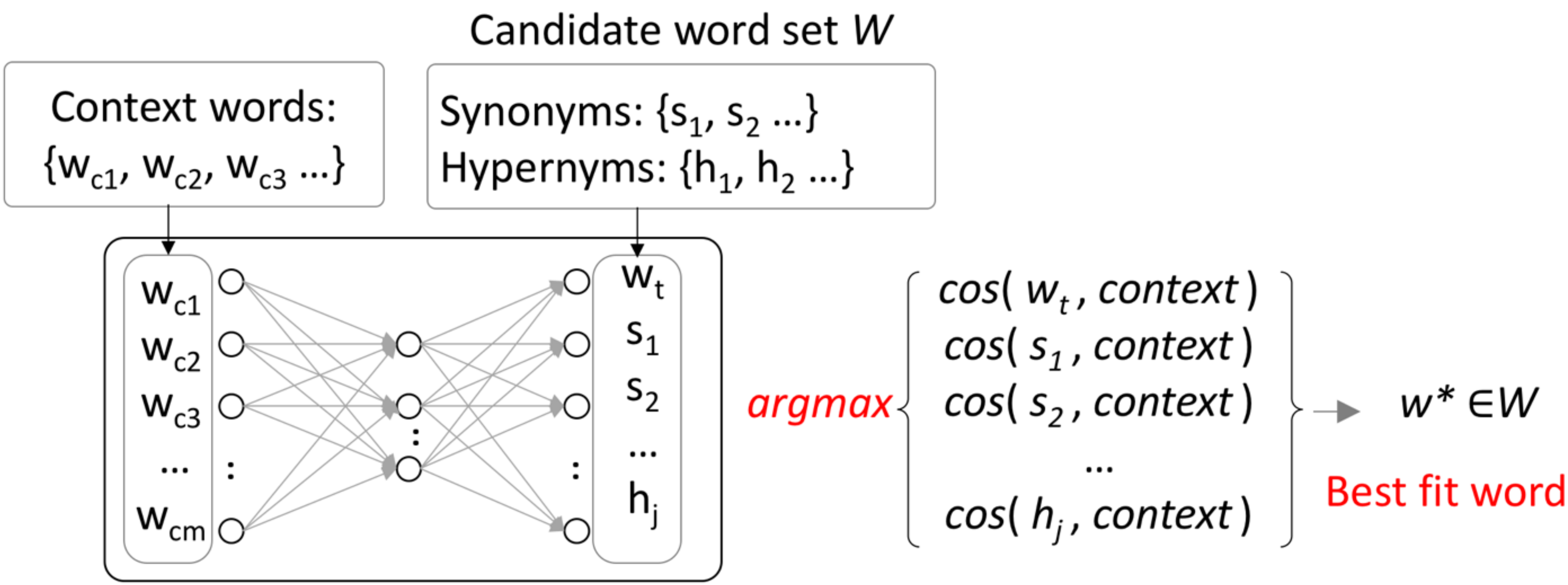
- Wikipedia's language could be more literal.
- We model the literal so that we can identify the anomalies in metaphor in next steps. **(H1)**

Step 2: look up WordNet to list all possible senses of a target word.



- Separate context words and a target word.
- A candidate word set consists of hypernyms and synonyms of the target word, which represents all possible senses of the target word.

Step 3: identify the most likely sense from the candidate set.



- Compute the most likely word appearing in the context.
- The best fit word is interpreted as the sense that metaphor takes. **(H1)**

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Step 4: identify the metaphoricity of a target word.

$$S = cos(w^*, w_t) \quad \begin{cases} \text{literal, if } S > \text{threshold} \\ \text{metaphoric, otherwise} \end{cases}$$

- A metaphor could be identified as the real sense and its literal sense come from different domains. **(H2)**

An example in Step 2.

She devoured his novels.

Context words: {She, his, novels}

Target word: {devoured}

Candidate word set:{

{devour, devoured, devours, devouring}

Sense 1: {destroy, ruin, …}

Sense 2: {enjoy, bask, …}

Sense 3: {demolish, down, …, eat up, finish}

…

}

WordNet

A Lexical Database for English

(Fellbaum, 1998)

HYPERNYMS

SYNONYMS

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An example in Step 3.

$$v^{i}_{context} = \frac{1}{m}\sum_{n=1}^{m} v^{i}_{c,n} = \frac{1}{3}\left(v^{i}_{She} + v^{i}_{his} + v^{i}_{novels}\right)$$

$$\arg\max \left\{ \begin{array}{l} \cos\left(v^{o}_{devoured}, v^{i}_{context}\right) = -0.01 \\ \cos\left(v^{o}_{destroyed}, v^{i}_{context}\right) = -0.04 \\ \cos\left(v^{o}_{ruined}, v^{i}_{context}\right) = -0.01 \\ \cos\left(v^{o}_{enjoyed}, v^{i}_{context}\right) = 0.02 \\ \ldots\ldots \end{array} \right\}$$

Best fit word = enjoyed

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An example in Step 4.

$$S = cos(v^{i}_{enjoy}, v^{i}_{devour})$$

Best fit word   Target word

$$\begin{cases} \text{literal, if } S > \text{threshold} \\ \text{metaphoric, otherwise} \end{cases}$$

S = -0.04 < threshold = 0.6

Metaphoric

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Different setups in Step 3.

(1) $\text{SIM-}CBOW_I = \cos\left(v^{i}_{k,cbow}, v^{i}_{context,cbow}\right)$

(2) $\text{SIM-}CBOW_{I+O} = \cos\left(v^{o}_{k,cbow}, v^{i}_{context,cbow}\right)$

(3) $\text{SIM-}SG_I = \cos\left(v^{i}_{k,sg}, v^{i}_{context,sg}\right)$

(4) $\text{SIM-}SG_{I+O} = \cos\left(v^{o}_{k,sg}, v^{i}_{context,sg}\right)$

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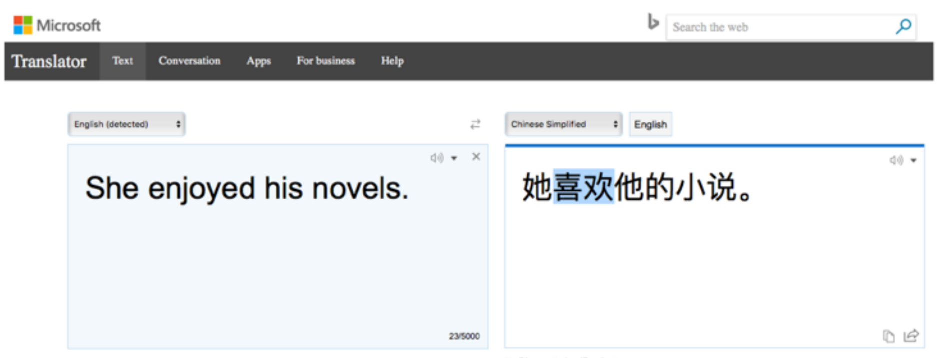
Examine on Machine Translation (before paraphrasing).

- She (physically) swallowed his novels.

- She voraciously wrote novels.

Examine on Machine Translation (after paraphrasing).

- She enjoyed his novels.



- She enjoyed his novels.

3. Experiments and Results

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Experiment setup.

Metaphor identification:

- Sentence level: inputs are original sentences
- Phrase level: inputs are parsed phrases

Metaphor interpretation:

- Machine Translation

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Dataset and baselines.

Mohammad et al. (2016)

- 10 annotators
- 409 metaphors
- 1,230 literals

Sentence evaluation

- 212 meta.
- 212 lite.

Mao et al. (2018)

Phrase evaluation

- 316 meta.
- 331 lite.

Shutova et al. (2016), Rei et al. (2017)

Phrase evaluation baselines:

- Shutova et al. (2016) used Skip-gram input vectors to model the similarity between two component words.
- Rei et al. (2017) used sigmoid function, projecting Skip-gram input vectors into another space, then training a deep neural network based classifier.

Sentence evaluation baseline:

- Melamud et al. (2016) used LSTM trained context embeddings to predict the center word.

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Metaphor identification results.

	Method	P	R	F1
Phrase	Shutova et al. (2016)	0.67	0.76	0.71
	Rei et al. (2017)	**0.74**	0.76	**0.74**
	SIM-CBOW$_{I+O}$	0.66	0.78	0.72
	SIM-SG$_{I+O}$	0.68	**0.82**	**0.74***
Sent.	Melamud et al. (2016)	0.60	0.80	0.69
	SIM-SG$_{I}$	0.56	**0.95**	0.70
	SIM-SG$_{I+O}$	0.62	0.89	0.73
	SIM-CBOW$_{I}$	0.59	0.91	0.72
	SIM-CBOW$_{I+O}$	**0.66**	0.88	**0.75***

Table 1: Metaphor identification results. NB: * denotes that our model outperforms the baseline significantly, based on two-tailed paired t-test with $p < 0.001$.

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Evaluation with different thresholds.

τ	Sentence			Phrase	
	P	R	F1	$\mathbf{F1}_{\text{SIM-CBOW}_{I+O}}$	$\mathbf{F1}_{\text{SIM-SG}_{I+O}}$
0.3	0.75	0.60	0.67	0.56	0.46
0.4	0.69	0.75	0.72	0.65	0.63
0.5	0.67	0.82	0.74	0.71	0.72
0.6	0.66	0.88	**0.75**	**0.72**	**0.74**
0.7	0.64	0.88	0.74	0.72	0.73
0.8	0.63	0.89	0.74	0.72	0.73
0.9	0.63	0.89	0.74	0.71	0.73
1.0	0.50	1.00	0.67	0.65	0.65

Table 2: Model performance vs. different threshold (τ) settings. NB: the sentence level results are based on SIM-CBOW_{I+O}.

Experiment design for Machine Translation evaluation.

Sample Questionnaire

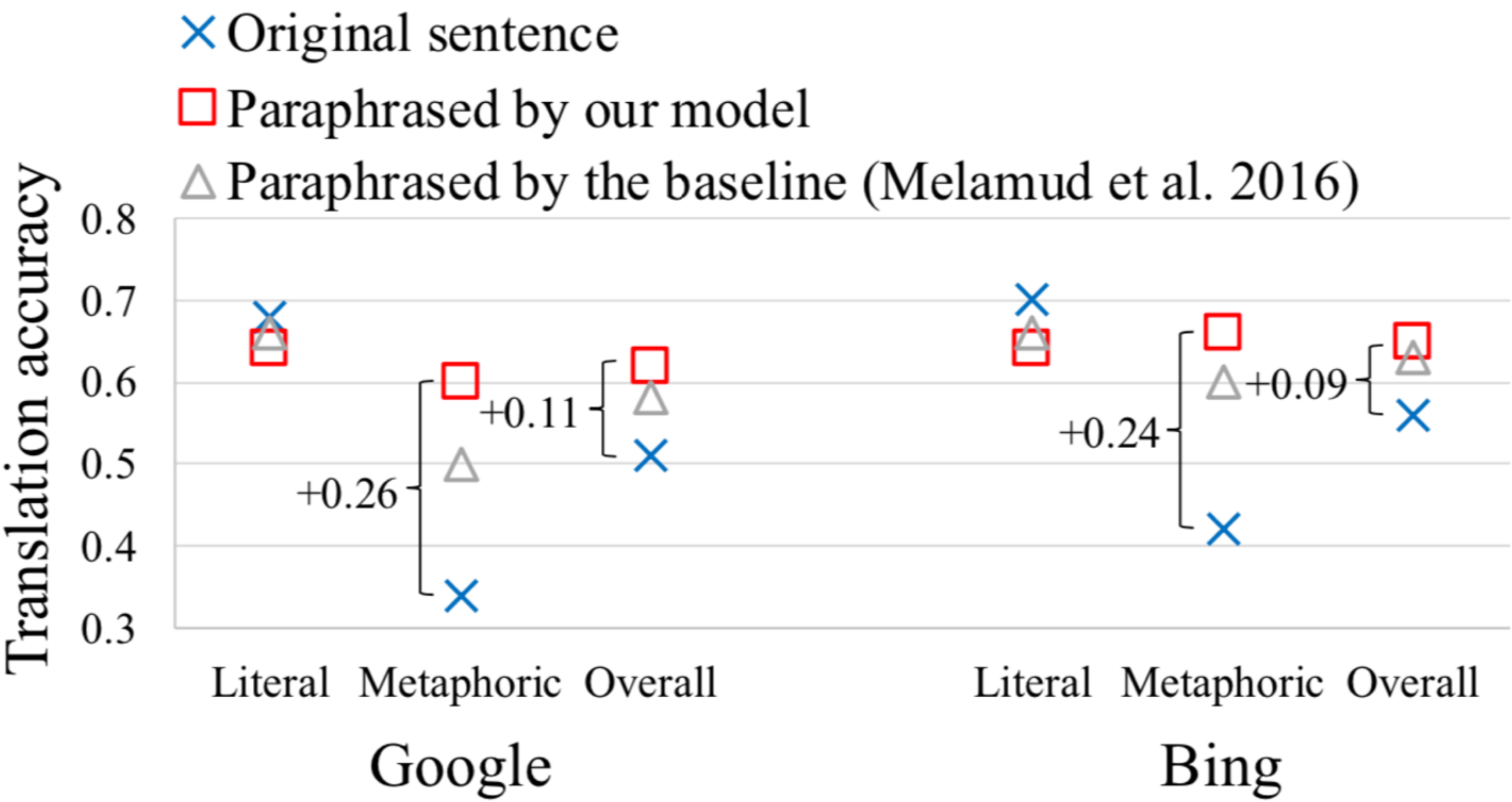
The ex-boxer's job is to **<u>bounce</u>** people who want to enter this private club.

bounce: eject from the premises

	Good	Bad
1. 前拳击手的工作是**反弹**人谁想要进入这个私人俱乐部。	☐	☐
2. 前拳击手的工作是让想要进入这个私人俱乐部的人**弹跳**。	☐	☐
3. 前拳击手的工作是**拒绝**谁想要进入这个私人俱乐部的人。	☐	☐
4. 前拳击手的工作是**拒绝**那些想进入这个私人俱乐部的人。	☐	☐
5. 前拳击手的工作是**打**人谁想要进入这个私人俱乐部。	☐	☐
6. 前拳击手的工作是**打击**那些想进入这个私人俱乐部的人。	☐	☐

1. Google translation on the **original** sentence.
2. Bing Translation on the **original** sentence.
3. Google translation on **our model** paraphrased sentence.
4. Bing Translation on **our model** paraphrased sentence.
5. Google translation on **Context2Vec** paraphrased sentence.
6. Bing Translation on **Context2Vec** paraphrased sentence.

Metaphor interpretation results.



4. Conclusion

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Takeaway.

- A novel model for metaphor identification and interpretation on sentence level.
- A metaphor could be identified by its interpretation.
- Input and output vectors could better model the co-occurrence between two words.
- Effective paraphrasing of metaphors could improve Machine Translation.

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