Learning Semantic Representations for Novel Words: Leveraging Both Form and Context

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Motivation

Why explicitly learn representations for novel words?

- Distributed word representations are a foundational aspect of many natural language processing systems
- Current approaches require many observations of a word for its embedding to become reliable; as a consequence, they struggle with small corpora and infrequent words
- As models are typically trained with a fixed vocabulary, they lack the ability to assign vectors to novel, out-of-vocabulary (OOV) words once training is complete

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$$\begin{aligned}\mathcal{S}_{\mathbf{w}} &= \{\langle s\rangle\text{p}, \text{po}, \text{om}, \text{me}, \text{el}, \text{lo}, \text{o}\langle e\rangle, \langle s\rangle\text{po}, \text{pom}, \text{ome}, \text{mel}, \text{elo}, \text{lo}\langle e\rangle\} \\ &= \{s_1, \dots, s_n\}\end{aligned}$$

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$$\begin{aligned}\mathcal{C} &= \{\text{unlike}, \text{the}, \text{grapefruit}, \text{the}, \text{has}, \text{very}, \text{little}, \dots, \text{marketplace}\} \\ &= \{c_1, \dots, c_m\}\end{aligned}$$

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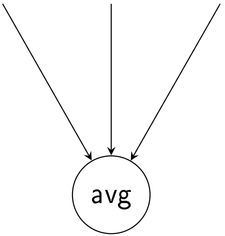

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$e_{\text{ngram}}(s_1) \quad \cdots \quad e_{\text{ngram}}(s_n)$

avg

$v^{\text{form}}_{(\mathbf{w},\mathcal{C})}$

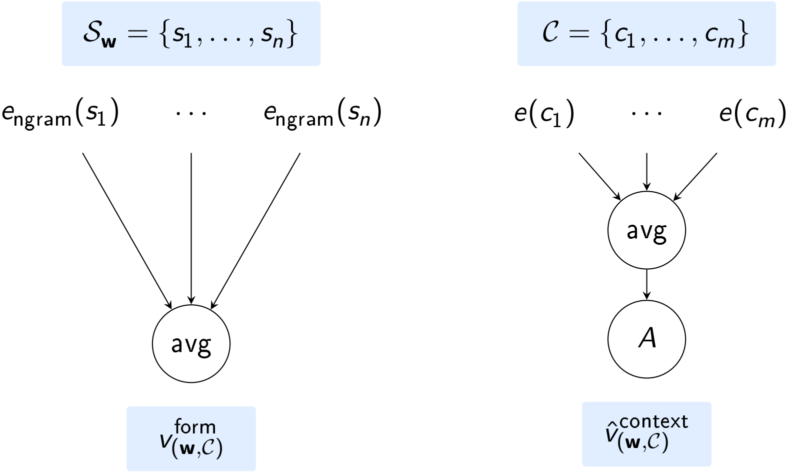
$\mathcal{C} = \{c_1, \ldots, c_m\}$

$e(c_1) \quad \cdots \quad e(c_m)$

avg

$v^{\text{context}}_{(\mathbf{w},\mathcal{C})}$

The Form-Context Model



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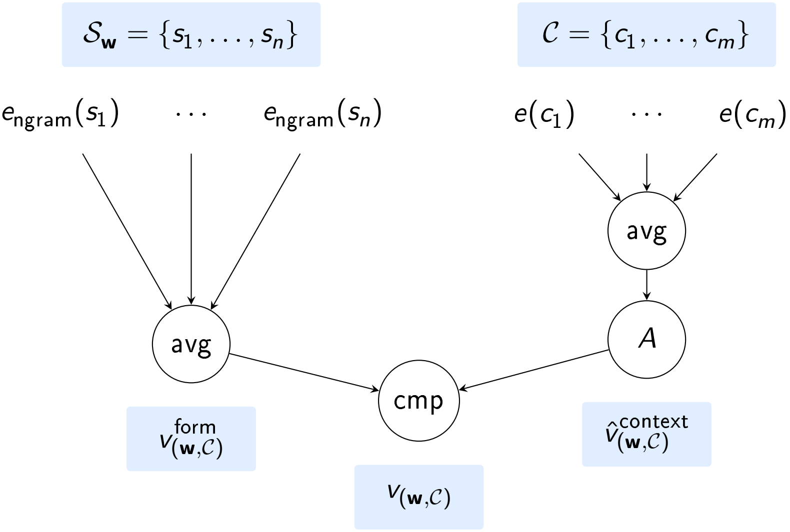

Composition Functions

(i) single-parameter

$$v_{(\mathbf{w},\mathcal{C})} = \alpha \cdot \hat{v}^{\text{context}}_{(\mathbf{w},\mathcal{C})} + (1-\alpha) \cdot v^{\text{form}}_{(\mathbf{w},\mathcal{C})}.$$

with $\alpha \in [0,1]$ being a learnable parameter.

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(ii) gated

As above, except:

$$\alpha = \sigma(w^\top [v^{\text{context}}_{(\mathbf{w},\mathcal{C})} \circ v^{\text{form}}_{(\mathbf{w},\mathcal{C})}] + b)$$

with $w \in \mathbb{R}^{2k}$, $b \in \mathbb{R}$ being learnable parameters.

Training

$$\begin{aligned}\mathcal{B} &= \{(\mathbf{w}_1, \mathcal{C}_1), (\mathbf{w}_2, \mathcal{C}_2), \ldots, (\mathbf{w}_k, \mathcal{C}_k)\} \\ &= \{(\text{pomelo}, \{\text{unlike}, \text{the}, \text{grapefruit}, \ldots\}), (\mathbf{w}_2, \mathcal{C}_2), \ldots, (\mathbf{w}_k, \mathcal{C}_k)\}\end{aligned}$$

$$L_{\mathcal{B}} = \frac{1}{|\mathcal{B}|} \sum_{(\mathbf{w}, \mathcal{C}) \in \mathcal{B}} \| v_{(\mathbf{w}, \mathcal{C})} - e(\mathbf{w}) \|^2$$

Evaluation

We train the form-context model using skipgram embeddings trained on Wikipedia. To construct our training set, we

- consider all words **w** that occur at least 100 times;
- create $\mathcal{C}$ by randomly sampling 20 sentences from Wikipedia in which **w** occurs;
- create $\mathcal{S}_{\mathbf{w}}$ from all 3-, 4- and 5-grams of **w**, considering only *n*-grams that occur in at least 3 different words.

We evaluate the model on two tasks: the **Definitional Nonce Task** and the **Contextual Rare Words Task**.

The Definitional Nonce Task

spies most commonly refers to people who engage in spying, espionage or clandestine operations

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	form	context	frm-ctx
neighbours	pies, cakes, spied, sandwiches	espionage, clandestine, covert, spying	espionage, spying, clandestine, covert
rank	668	8	6

The Definitional Nonce Task

hygiene which comes from the name of the greek goddess of health hygieia is a set of practices performed for the preservation of health

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	form	**context**	**frm-ctx**
neighbours	hygienic, hygiene, cleansers, hypoallergenic	hygieia, goddess, eileithyia, asklepios	hygienic, hygieia, health, hygiene
rank	2	465	4

The Definitional Nonce Task

perception (from the latin percipio) is the organization, identification and interpretation of sensory information in order to represent and understand the environment

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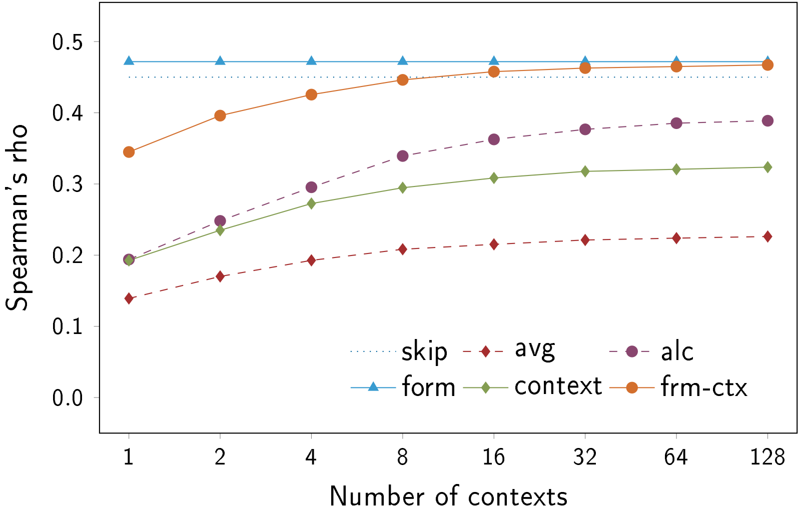
	form	context	frm-ctx
neighbours	interception, interceptions, fumble, touchdowns	sensory, perceptual, auditory, contextual	sensory, perceptual, perception, auditory
rank	115	51	3

The Definitional Nonce Task

Model	Type	Median Rank	MRR
Mimick	form	85573	0.00006
Skipgram	context	111012	0.00007
Additive	context	3381	0.00945
Nonce2Vec	context	623	0.04907
A La Carte	context	165.5	0.07058
surface-form	form	404.5	0.12982
context	context	184	0.06560
single-parameter	both	55	0.16200
gated	both	**49**	**0.17537**

The Contextual Rare Words Task



The Gated Model

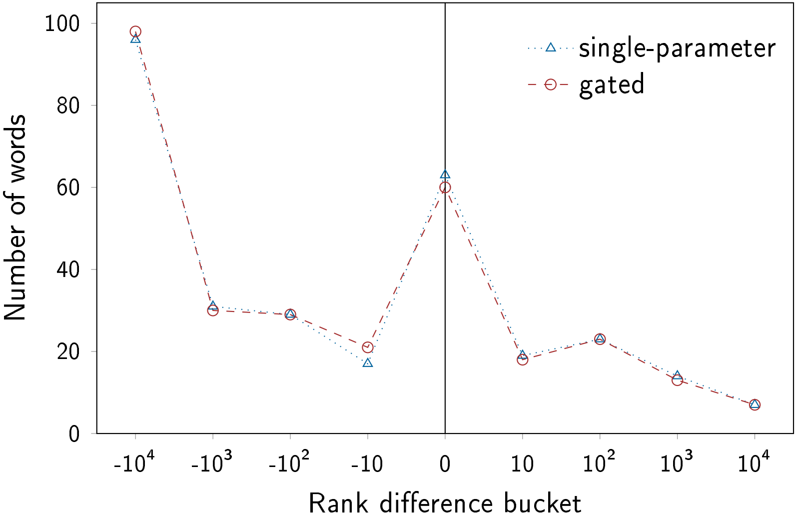
Words with high form weights:

cookstown, feltham, sydenham, wymondham, cleveland, banbury, highbury, shaftesbury

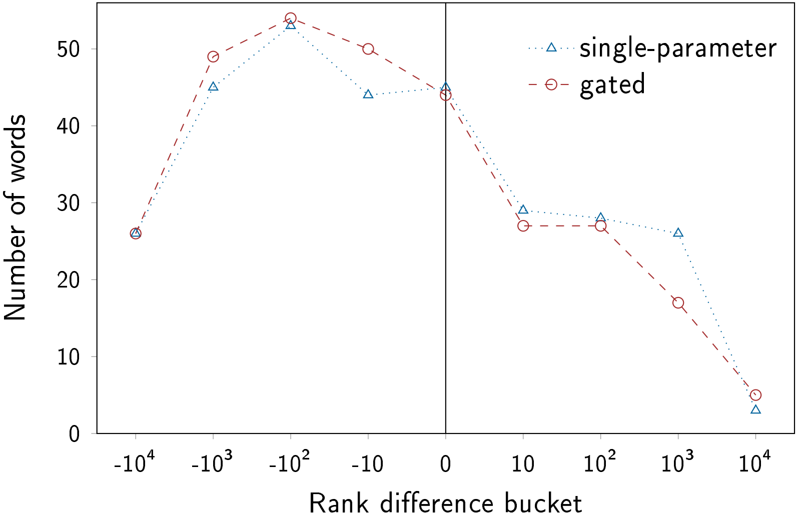
Words with high context weights:

poverty, hue, slang, flax, rca, bahia, atari, snooker, icq, bronze, esso

Adding Context Information



Adding Subword Information



Related Work

Bojanowski, P.; Grave, E.; Joulin, A.; and Mikolov, T. 2017. **Enriching word vectors with subword information**. *Transactions of the ACL*

Herbelot, A., and Braoni, M. 2017. **High-risk learning: acquiring new word vectors from tiny data**. In *Proceedings of the 2017 Conference on EMNLP*

Khodak, M.; Saunshi, N.; Liang, Y.; Ma, T.; Steward, B.; and Arora, S. 2018. **A la carte embedding: Cheap but effective induction of semantic feature vectors**. In *Proceedings of the 56th Annual Meeting of the ACL*

Pinter, Y.; Guthrie, R.; and Eisenstein, J. 2017. **Mimicking word embeddings using subword RNNs**. In *Proceedings of the 2017 Conference on EMNLP*

Conclusion and Future Work

The **form-context model** is capable of inferring high-quality representations for novel words by processing both the word's internal structure and words in its context.

Possible directions for future work include:

- investigating the model's performance for other languages;
- incorporating the number and informativeness of all available contexts into the composition function;
- using more complex ways than averaging to obtain surface-form and context embeddings.