IN5550: Neural Methods in Natural Language Processing Sub-lecture 4.2
Using embeddings

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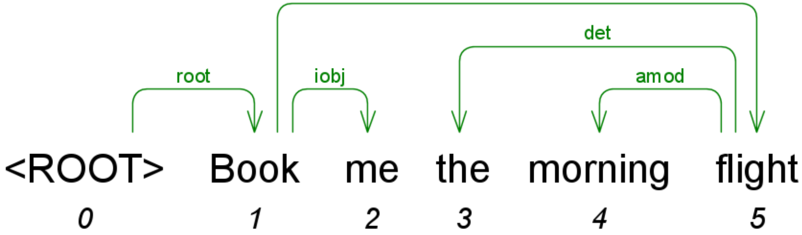
14 February 2023

Contents

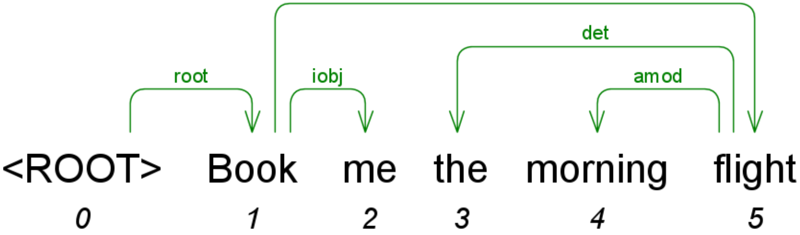
Dense representations (embeddings)



Example of dense features in parsing task

(see also the PoS tagging example in [Goldberg, 2017])

Dense representations (embeddings)



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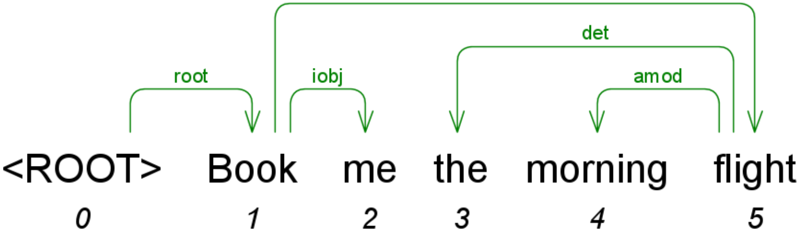

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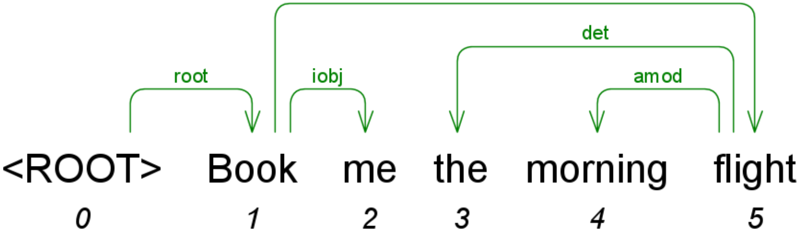

Example of dense features in parsing task

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- Conceptually it is a classic Arc-Standard transition-based parser.
- The difference is in the features it uses:
- Dense embeddings $\boldsymbol{w}, \boldsymbol{t}, \boldsymbol{l} \in \mathbb{R}^{50}$ for words, PoS tags and dependency labels;
  - *nowadays, we usually use $\mathbb{R}^{300}$ (or $\mathbb{R}^{768}$) embeddings for words*

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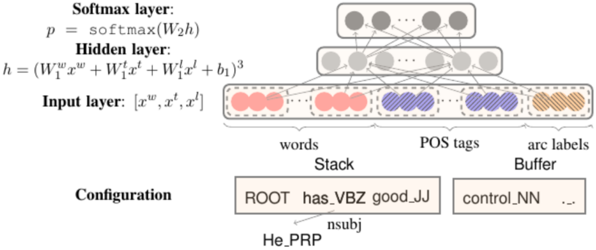

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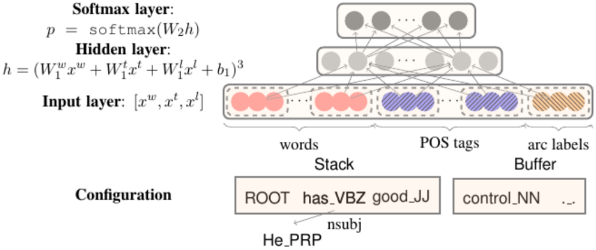

Parsing with dense representations and neural networks (simplified)

- Concatenated embeddings of words (x^w), PoS tags (x^t) and dependency labels (x^l) from the stack are given as input layer.

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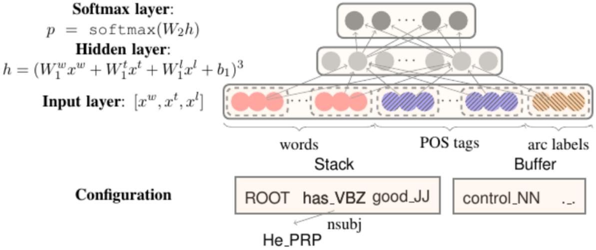

Parsing with dense representations and neural networks (simplified)

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- 200-dimensional hidden layer represents the actual features used for predictions.

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$$L(\theta) = -\sum_{i}^{n} \log(t_i) + \frac{\lambda}{2}\|\theta\| \tag{1}$$

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- Notably, the model employs the unusual cube activation function $g(x) = x^3$

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- More on this next week.

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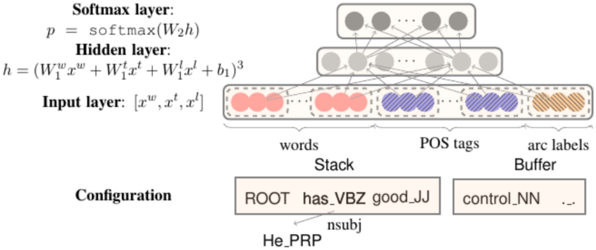
...started the widespread usage of dense representations in NLP.



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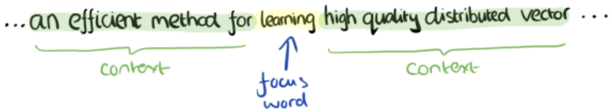
- When using dense inputs outright, we simply make it explicit;
- It is also usually more efficient.

Combining embeddings



Many features, one input vector

- Before feeding embeddings into network, one must somehow combine them.

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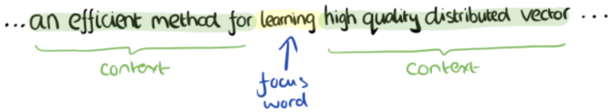

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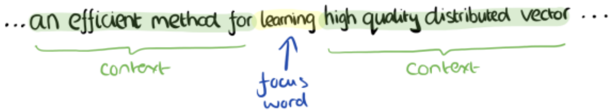

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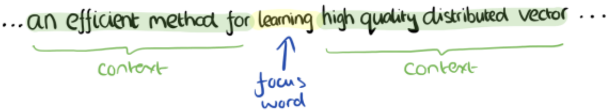

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- Each unique word is assigned a dense vector:
  - '*method*' $\rightarrow \boldsymbol{a}$
  - '*for*' $\rightarrow \boldsymbol{b}$
  - '*high*' $\rightarrow \boldsymbol{c}$
  - '*quality*' $\rightarrow \boldsymbol{d}$

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What can be the input vector x representing 'learning'?

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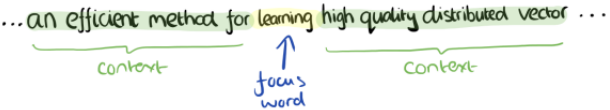

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…an efficient method for learning high quality distributed vector …

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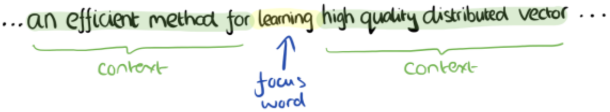

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Question: what information is preserved only by concatenation?

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This is usually not the case :-(. What about unsupervised auxiliary tasks? Here comes language modeling.

References I

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