word2vec



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Seems magical.



"Neural computation, just like in the brain!"

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Seems magical.



"Neural computation, just like in the brain!"

How does this actually work?

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word2vec implements several different algorithms:

Two training methods

- Negative Sampling
- Hierarchical Softmax

Two context representations

Continuous Bag of Words (CBOW)

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Skip-grams

word2vec implements several different algorithms:

Two training methods

- Negative Sampling
- Hierarchical Softmax

Two context representations

- Continuous Bag of Words (CBOW)
- Skip-grams

We'll focus on skip-grams with negative sampling.

intuitions apply for other models as well.

- Represent each word as a d dimensional vector.
- Represent each context as a d dimensional vector.
- Initalize all vectors to random weights.
- ► Arrange vectors in two matrices, *W* and *C*.



While more text:

Extract a word window:

A springer is [a cow or heifer close to calving]. $c_1 \quad c_2 \quad c_3 \quad W \quad c_4 \quad c_5 \quad c_6$

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▶ *w* is the focus word vector (row in *W*).

• c_i are the context word vectors (rows in *C*).

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Extract a word window:

A springer is [a cow or heifer close to calving]. $C_1 \quad C_2 \quad C_3 \quad W \quad C_4 \quad C_5 \quad C_6$

Try setting the vector values such that:

 $\sigma(\mathbf{w} \cdot \mathbf{c}_1) + \sigma(\mathbf{w} \cdot \mathbf{c}_2) + \sigma(\mathbf{w} \cdot \mathbf{c}_3) + \sigma(\mathbf{w} \cdot \mathbf{c}_4) + \sigma(\mathbf{w} \cdot \mathbf{c}_5) + \sigma(\mathbf{w} \cdot \mathbf{c}_6)$

is high

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is high

- Create a corrupt example by choosing a random word w' [a cow or comet close to calving] c₁ c₂ c₃ w' c₄ c₅ c₆
- Try setting the vector values such that:

 $\sigma(\mathbf{w}' \cdot \mathbf{c}_1) + \sigma(\mathbf{w}' \cdot \mathbf{c}_2) + \sigma(\mathbf{w}' \cdot \mathbf{c}_3) + \sigma(\mathbf{w}' \cdot \mathbf{c}_4) + \sigma(\mathbf{w}' \cdot \mathbf{c}_5) + \sigma(\mathbf{w}' \cdot \mathbf{c}_6)$

is **low**

The training procedure results in:

- $w \cdot c$ for **good** word-context pairs is **high**.
- $w \cdot c$ for **bad** word-context pairs is **low**.
- $w \cdot c$ for ok-ish word-context pairs is neither high nor low.

As a result:

- Words that share many contexts get close to each other.
- Contexts that share many words get close to each other.

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At the end, word2vec throws away C and returns W.

Imagine we didn't throw away C. Consider the product WC^{\top}

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The result is a matrix *M* in which:

- Each row corresponds to a word.
- Each column corresponds to a context.
- Each cell correspond to w · c, an association measure between a word and a context.



Does this remind you of something?





Does this remind you of something?

Very similar to SVD over distributional representation:

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