92586 Computational Linguistics

Lesson 13. Word2vec

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Previously

- Introduction to Neural Networks
- First Keras neural network
- Considerations when building/training a network

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Introduction

Introduction

Previously

- Each token represents one dimension (BoW)
- Document- and corpus-based statistics (TF-IDF)
- Dimensional reduction (LSA)

Drawbacks

- Ignoring the (nearby) context of a word
- Ignoring the overall meaning of a statement

Introduction

Word vectors. Numerical vector representations of word semantics, or meaning, including literal and implied meaning (Lane et al., 2019, p. 182)

Math with words

$q =$ "She invented something to do with physics in Europe in the early 20th century"

```
answer_vector = wv['woman'] + wv['Europe'] + \
                wv['physics'] + wv['scientist']
```

Even better:

```
answer_vector = wv['woman'] + wv['Europe'] + \
                wv['physics'] + wv['scientist'] -\
                wv['male'] - wv['man']
```

Word Vectors

Word Vectors

Intuition

Word2vec (Mikolov et al., 2013)

- Learns the *meaning* of words by processing a large corpus[1]
- The corpus is not labeled
- It is **unsupervised**

Can we train a NN to predict word occurrences near a target w?

We don't care about the prediction (that's handy, but not important here). We care about the resulting **internal representation**

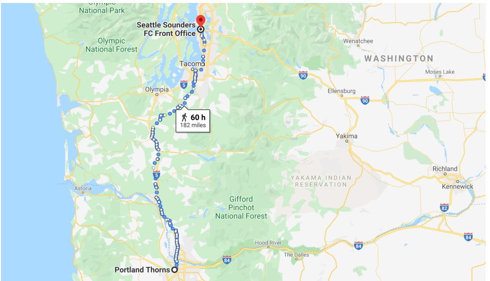
[1]And I mean large; e.g., 100B words from Google News Groups

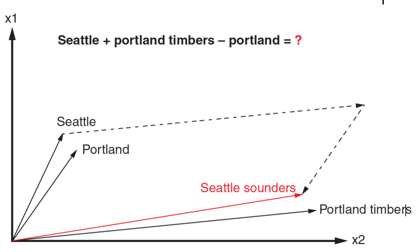
Word Vectors

Vector Algebra (again)

$$\text{Portland Timbers} + \text{Seattle} - \text{Portland} = ?$$

$$ourput\_vector = wv['\text{Seattle}'] + wv['\text{Portland Timbers}'] - wv['\text{Portland}']$$





Word2vec "knows" that

- $dist$(Portland, Portland Timbers $\approx$ $dist$(Seattle, Seattle Sounders)
- The diffs between the pairs of vectors are in roughly the same direction

(Lane et al., 2019, p. 188)

Word Vectors

Vector Algebra (again)

- word2vec transforms token-occurrence vectors into lower-dimensional vectors
- The dimension is usually in the 100s (e.g., 100, 200, 300)

Typical process
Input: Text
Output: Text

1. Compute vectors
2. Do algebra
3. Map back to text

Word Vectors

Some "typical" operations/properties

Gender	king + woman − man → queen
Pl/Sg	$\vec{x}_{coffee} - \vec{x}_{coffees} \approx \vec{x}_{cup} - \vec{x}_{cups} \approx \vec{x}_{cookie} - \vec{x}_{cookies}$
Locations	San Francisco − California + Colorado → Denver
Culture	tortellini − Bologna + Valencia → paella **?**

Computing word2vec representations

Alternatives to Build word2vec Representations

skip-gram

Input one (target) word
Output context words

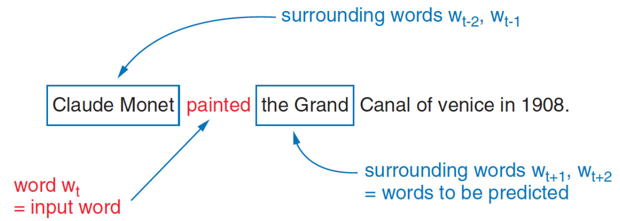
CBOW (continuous bag-of-words)

Input context words
Output one target word

Skip-Gram

Definition Skip-grams are *n*-grams that contain gaps (skips over intervening tokens)

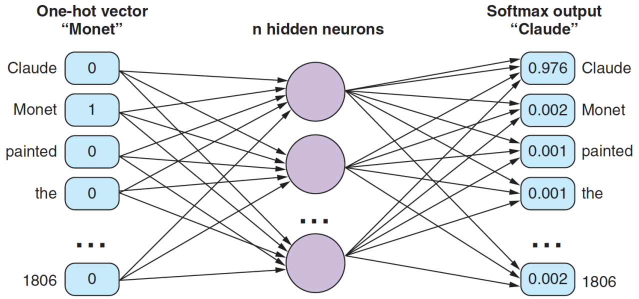
Input: one word
Output: context words



(Lane et al., 2019, p. 192)

Skip-Gram

Neural Network Structure



- n is the number of vector dimensions in the model
- M is the number of input/output neurons; $M = |\text{vocabulary}|$
- The output activation function is a **softmax**
  Typical in multi-class problems; $\sum_M = 1.0$

(Lane et al., 2019, p. 193)

Skip-Gram

Learning the Representations (1/3)

- Window size: 2 words $\rightarrow$ 5-grams
- Input: each token, from left to right
- Output: the context on the left and right (one at a time)

$$s = w_1\ w_2\ w_3\ w_4\ w_5\ w_6\ w_7\ w_8\ w_9\ w_{10}$$

$$[\ldots]\ w_{t-2}\ w_{t-1}\ \underline{w_t}\ w_{t+1}\ w_{t+2}\ [\ldots]$$

Skip-Gram

Learning the Representations (2/3)

Example: "Claude Monet painted the Grand Canal of Venice in 1908."

input	**expected output**			
w_t	w_{t-2}	w_{t-1}	w_{t+1}	w_{t+2}
Claude			Monet	painted
Monet		Claude	painted	the
painted	Claude	Monet	the	Grand
the	Monet	painted	Grand	Canal
Grand	painted	the	Canal	of
Canal	the	Grand	of	Venice
of	Grand	Canal	Venice	in
Venice	Canal	of	in	1908
in	of	Venice	1908	
1908	Venice	in		

(Lane et al., 2019, p. 194)

Skip-Gram

Learning the Representations (3/3)

Training

- Both input and output are a one-hot vector
- $n-1$ iterations when using n-grams:

$$[\ldots]\ w_{t-2}\ w_{t-1}\ \underline{w_t}\ w_{t+1}\ w_{t+2}\ [\ldots]$$

i	input	output	i	input	output	i	input	output
0	w_t	w_{t-2}	4	w_{t+1}	w_{t-1}	8	w_{t+2}	w_t
1	w_t	w_{t-1}	5	w_{t+1}	w_t	9	w_{t+2}	w_{t+1}
2	w_t	w_{t+1}	6	w_{t+1}	w_{t+2}	10	w_{t+2}	w_{t+3}
3	w_t	w_{t+2}	7	w_{t+1}	w_{t+3}	11	w_{t+2}	w_{t+4}

- To simplify the loss calculation, the softmax is converted to one-hot

Skip-Gram

Outcome

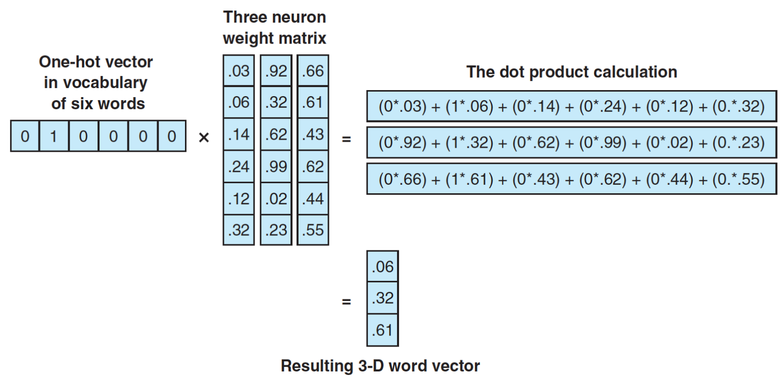
- The output layer can be *ignored*[2]
- Semantically similar words have similar vectors —they were trained to **predict similar contexts**
- The weights from input to hidden layer are used to compute **embeddings**

$$wv_w = dot(one\_hot_w, W)$$

[2] Well, Tweaking this procedure could result in a language model

Skip-Gram

Embedding Computation

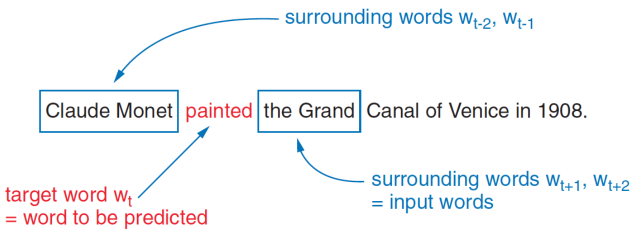


CBOW

Definition Continuous bag-of-words

Input: context words

Output: target (centre) word



(Lane et al., 2019, p. 196)

CBOW

Learning the Representations (1/3)

Window size: 2 words → 5-grams

Input: multi-hot vector (sum of all one-hot vectors)

Output: one-hot vector

$$s = w_1\ w_2\ w_3\ w_4\ w_5\ w_6\ w_7\ w_8\ w_9\ w_{10}$$

$$[\ldots]\ \underline{w_{t-2}\ w_{t-1}}\ w_t\ \underline{w_{t+1}\ w_{t+2}}\ [\ldots]$$

CBOW

Learning the Representations (2/3)

Example: "Claude Monet painted the Grand Canal of Venice in 1908."

input				**expected output**
w_{t-2}	w_{t-1}	w_{t+1}	w_{t+2}	w_t
		Monet	painted	Claude
	Claude	painted	the	Monet
Claude	Monet	the	Grand	painted
Monet	painted	Grand	Canal	the
painted	the	Canal	of	Grand
the	Grand	of	Venice	Canal
Grand	Canal	Venice	in	of
Canal	of	in	1908	Venice
of	Venice	1908		in
Venice	in			1908

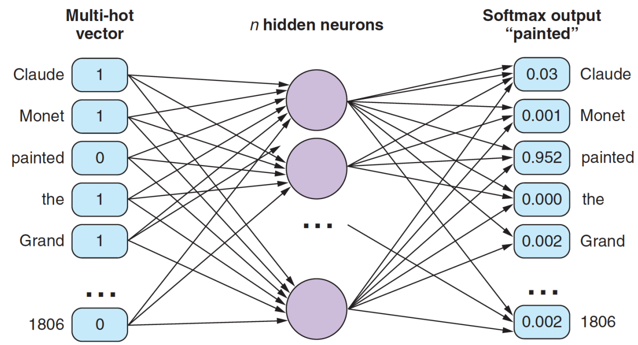
(Lane et al., 2019, p. 194)

CBOW

Learning the Representations (3/3)

Training

- The input is a multi-hot vector: $w_{t-2} + w_{t-1} + w_{t+2} + w_{t+2}$
- The output is a one-hot vector w_t



Final Comments

Skip-gram

- Works well with **small** corpora
- High-frequency $[2, 3]$-grams can be added as single terms (e.g., New_York, Chicago_Bears)
- High-frequency tokens are subsampled ($\sim$ to IDF over stopwords)
- Negative sampling. Not all weights are updated given a pair, just a few negative samples (much cheaper, roughly the same result)

CBOW

- Higher accuracy for frequent words
- Much faster to train

Next time

- Hands on word embeddings

References

Lane, H., C. Howard, and H. Hapkem
2019. *Natural Language Processing in Action*. Shelter Island, NY: Manning Publication Co.

Mikolov, T., K. Chen, G. Corrado, and J. Dean
2013. Efficient estimation of word representations in vector space. In *Arxiv*.