ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA
CAMPUS DI FORLÌ

91258 / B0385
Natural Language Processing

Lesson 12. word2vec

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Previously

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

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Chapter 6 of Lane et al. (2019)

Introduction

Introduction

Previously

- **BoW** Each token represents one dimension
- **TF–IDF** Document- and corpus-level statistics
- **LSA** Dimensional reduction for a dense representation[1]

[1] Quite superficially

Introduction

Previously

BoW Each token represents one dimension

TF–IDF Document- and corpus-level statistics

LSA Dimensional reduction for a dense representation[1]

Drawbacks

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

[1] Quite superficially

Introduction

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

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Math with words

$q =$ "She was a key physics figure in Europe in the early 20th century"

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

Even better:

```
answer_vector = wv['she'] + wv['physics'] + \
                wv['Europe'] + wv['scientist'] - \
                wv['he'] - wv['America']
```

Word Vectors

Word2vec (Mikolov et al., 2013)

- Learns the *meaning* of words by processing a large corpus[2]

[2] For instance, 100B words from the Google News Groups

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

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Word Vectors
Intuition

Word2vec (Mikolov et al., 2013)

- Learns the *meaning* of words by processing a large corpus[2]
- The corpus is not labeled
  $\rightarrow$ unsupervised

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

We do not care about the prediction (that is handy, but not important here). We care about the resulting internal representation

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

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Typical process
Input: Text
Output: Text

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Typical process

Input: Text

Output: Text

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

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

Word Vectors
Vector Algebra (again)

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

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

Word Vectors

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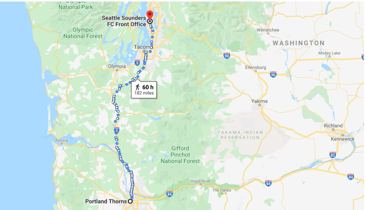

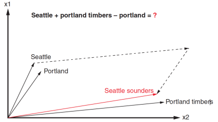

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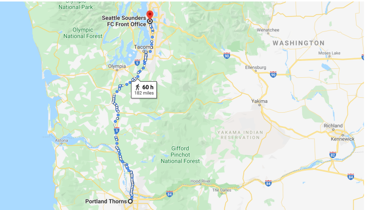

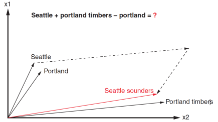

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[a] (Lane et al., 2019, p. 188)

Word2vec "knows" that

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

Word Vectors

Some “typical” operations/properties

Gender $\quad$ king $+$ woman $-$ man $\rightarrow$ queen

Gender	king + woman − man → queen
Pl/Sg	$\vec{x}_{coffee} - \vec{x}_{coffees} \approx \vec{x}_{cup} - \vec{x}_{cups} \approx \vec{x}_{cookie} - \vec{x}_{cookies}$

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Locations	San Francisco − California + Colorado → Denver

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Locations	San Francisco $-$ California $+$ Colorado $\rightarrow$ Denver
Culture	tortellini $-$ Bologna $+$ Valencia $\rightarrow$ paella ?

Computing word2vec representations

The grand canal of Venice (Claude Monet, 1908)

Alternatives to Build word2vec Representations

skip-gram

Input one (target) word

Output context words

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)

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

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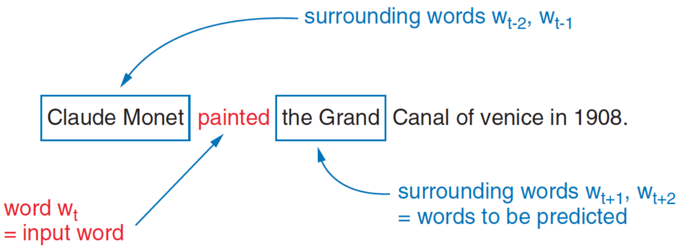
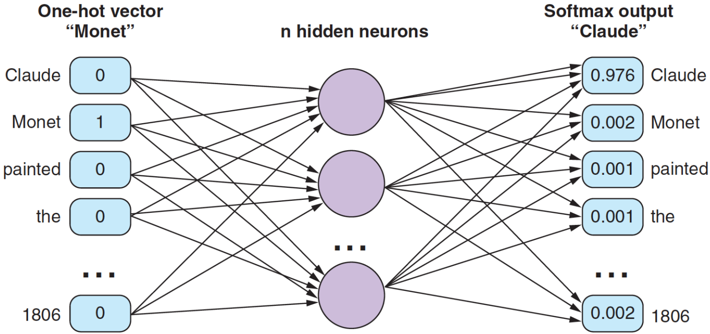


(Lane et al., 2019, p. 192)

Skip-Gram

Neural Network Structure



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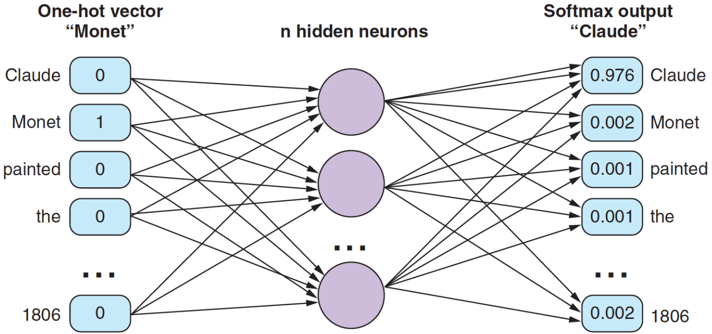

- n is the number of vector dimensions in the model

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Skip-Gram

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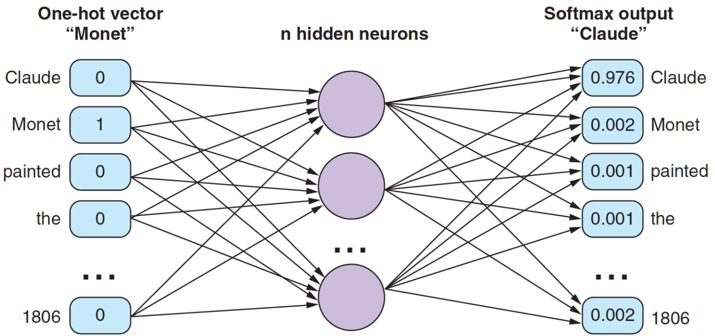
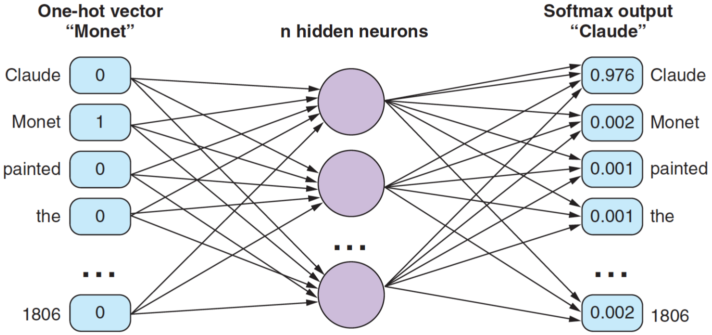


- n is the number of vector dimensions in the model
- M is the number of input/output neurons; $M = |\text{vocabulary}|$

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

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

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- Input: the token at time t: w_t
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$$s = w_1\ w_2\ w_3\ w_4\ w_5\ w_6\ w_7\ w_8\ w_9\ w_{10}$$

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Skip-Gram

Learning the Representations (2/3)

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

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

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input	expected output			
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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
0	w_t	w_{t-2}
1	w_t	w_{t-1}
2	w_t	w_{t+1}
3	w_t	w_{t+2}

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5	w_{t+1}	w_t
6	w_{t+1}	w_{t+2}
7	w_{t+1}	w_{t+3}

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4	w_{t+1}	w_{t-1}
5	w_{t+1}	w_t
6	w_{t+1}	w_{t+2}
7	w_{t+1}	w_{t+3}

i	input	output
8	w_{t+2}	w_t
9	w_{t+2}	w_{t+1}
10	w_{t+2}	w_{t+3}
11	w_{t+2}	w_{t+4}

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

- The output layer can be *ignored*[2]

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

Skip-Gram
Outcome

- The output layer can be *ignored*[2]
- Semantically similar words end up with similar vectors
  —they were trained to predict similar contexts

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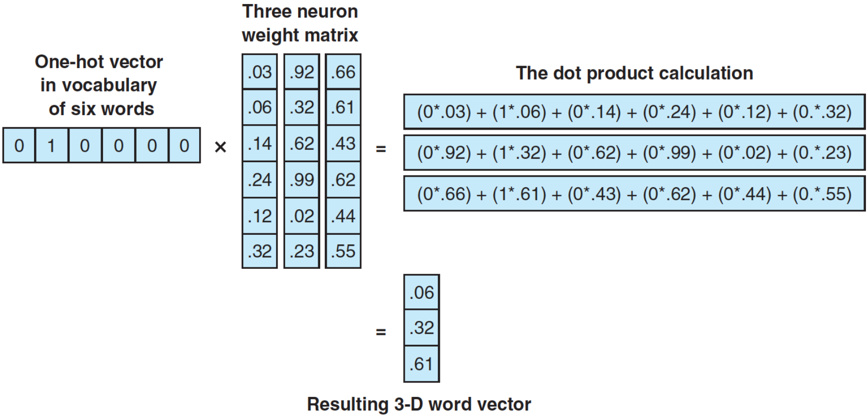
$$wv_w = dot(one\,hot_w, W)$$

[2]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)

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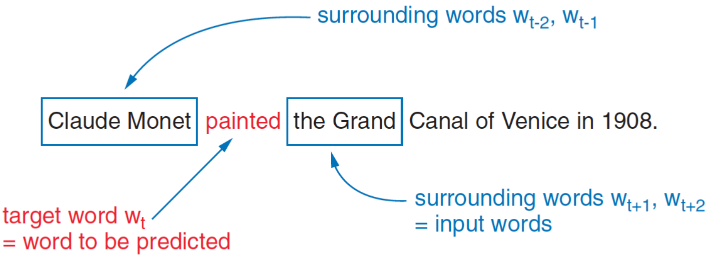

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Learning the Representations (1/3)

Window size: 2 words $\rightarrow$ 5-grams

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

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

CBOW

Learning the Representations (2/3)

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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

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

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Claude	Monet	the	Grand	painted
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	Claude	painted	the	Monet
Claude	Monet	the	Grand	painted
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painted	the	Canal	of	Grand
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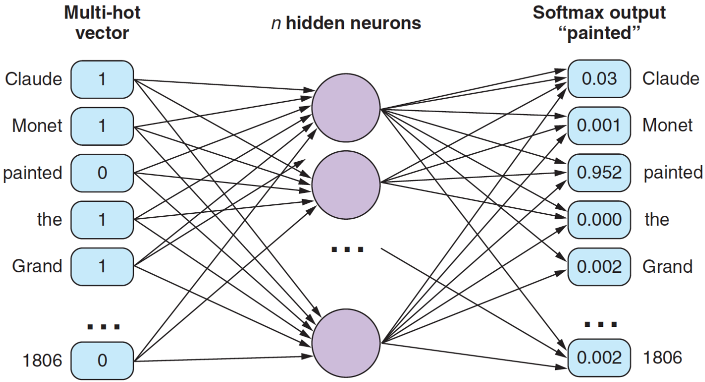
Canal	of	in	1908	Venice
of	Venice	1908		in
Venice	in			1908

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

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 Remarks

Skip-gram

- Works well with small corpora
- High-frequency $[2, 3]$-grams can be added as single terms (e.g., New_York, Atlanta_Braves)
- 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)

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CBOW

- Higher accuracy for frequent words
- Much faster to train

References

Lane, H., C. Howard, and H. Hapkem
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Mikolov, T., K. Chen, G. Corrado, and J. Dean
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