Class 8: Static Embeddings

Theme: Text

Computational Analysis of Text, Audio, and Images, Fall 2023

Aarhus University

Mathias Rask (mathiasrask@ps.au.dk)

Aarhus University

Today’s Menu

Beyond BoW

Today’s Menu

Beyond BoW

Embeddings

Today's Menu

Beyond BoW

Embeddings

Word2Vec

Today's Menu

Beyond BoW

Embeddings

Word2Vec

Lab

Table of Contents

Recap on Vectorization

Recap on Vectorization

Recap:

Recap on Vectorization

Recap:

1. What's the main reason we need to vectorize text when using machine learning?

Recap on Vectorization

Recap:

1. What’s the main reason we need to vectorize text when using machine learning?
2. Explain the fundamentals of BoW vectorization. How does it work, what’s the assumption?

Recap on Vectorization

Recap:

1. What's the main reason we need to vectorize text when using machine learning?
2. Explain the fundamentals of BoW vectorization. How does it work, what's the assumption?

Example:

	jeg 0	elsker 1	slik 2	chokolade 3	er 4	min 5	favorit 6
$\mathcal{D}_1$	1	1	1	0	0	0	0
$\mathcal{D}_2$	0	0	0	1	1	1	1

Recap on Vectorization

Recap:

1. What's the main reason we need to vectorize text when using machine learning?
2. Explain the fundamentals of BoW vectorization. How does it work, what's the assumption?

Example:

	jeg	elsker	slik	chokolade	er	min	favorit
	0	1	2	3	4	5	6
$\mathcal{D}_1$	1	1	1	0	0	0	0
$\mathcal{D}_2$	0	0	0	1	1	1	1

Two drawbacks:

Recap on Vectorization

Recap:

1. What's the main reason we need to vectorize text when using machine learning?
2. Explain the fundamentals of BoW vectorization. How does it work, what's the assumption?

Example:

	jeg	elsker	slik	chokolade	er	min	favorit
	0	1	2	3	4	5	6
$\mathcal{D}_1$	1	1	1	0	0	0	0
$\mathcal{D}_2$	0	0	0	1	1	1	1

Two drawbacks:

$\rightarrow$ Sparse and inefficient representation

Recap on Vectorization

Recap:

1. What's the main reason we need to vectorize text when using machine learning?
2. Explain the fundamentals of BoW vectorization. How does it work, what's the assumption?

Example:

	jeg 0	elsker 1	slik 2	chokolade 3	er 4	min 5	favorit 6
$\mathcal{D}_1$	1	1	1	0	0	0	0
$\mathcal{D}_2$	0	0	0	1	1	1	1

Two drawbacks:

→ Sparse and inefficient representation

→ Similar words have orthogonal representations

Beyond BoW

Beyond BoW

We want a representation of words that are short and dense which capture meaning and relations

Beyond BoW

We want a representation of words that are short and dense which capture meaning and relations

How can we obtain that?

Beyond BoW

We want a representation of words that are short and dense which capture meaning and relations

How can we obtain that?

⇝ From vectorization of documents to vectorization of words: *word embeddings*

Beyond BoW

We want a representation of words that are short and dense which capture meaning and relations

How can we obtain that?

- ⇝ From vectorization of documents to vectorization of words: *word embeddings*

Word embeddings are widely used in political science nowadays:

Beyond BoW

We want a representation of words that are short and dense which capture meaning and relations

How can we obtain that?

⇝ From vectorization of documents to vectorization of words: *word embeddings*

Word embeddings are widely used in political science nowadays:

1. Learning representations for 'downstream' tasks (e.g. classification)

Beyond BoW

We want a representation of words that are short and dense which capture meaning and relations

How can we obtain that?

- ⇝ From vectorization of documents to vectorization of words: *word embeddings*

Word embeddings are widely used in political science nowadays:

1. Learning representations for 'downstream' tasks (e.g. classification)
2. Learning word usage and meaning (semantics) directly

Table of Contents

Intuition

Intuition

“Embeddings” are designed to represent words in a short and dense format while still maintaining meaning and relations:

Intuition

"Embeddings" are designed to represent words in a short and dense format while still maintaining meaning and relations:

- General term that refers to representing discrete features (e.g. word, document, actors) as a real-valued vector with d-dimensions: $X \in \mathbb{R}^d$

Intuition

"Embeddings" are designed to represent words in a short and dense format while still maintaining meaning and relations:

- General term that refers to representing discrete features (e.g. word, document, actors) as a real-valued vector with d-dimensions: $X \in \mathbb{R}^d$
- From fixed-length vectors of length-$|\mathcal{V}|$ to fixed-length vectors of d-length

Intuition

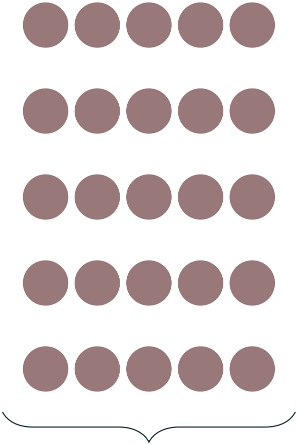
"Embeddings" are designed to represent words in a short and dense format while still maintaining meaning and relations:

- General term that refers to representing discrete features (e.g. word, document, actors) as a real-valued vector with d-dimensions: $X \in \mathbb{R}^d$
- From fixed-length vectors of length-$|\mathcal{V}|$ to fixed-length vectors of d-length

Example I

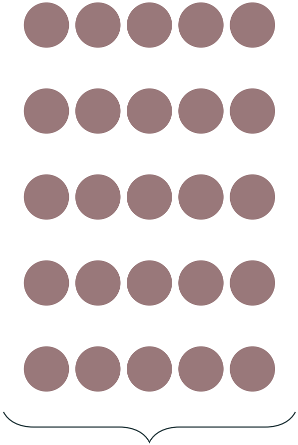
Example I

Example I



Collection of movies

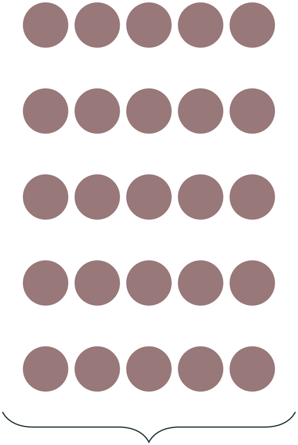
Example I



Collection of movies

Let's say we want to embed movies using $d = 5$ embeddings:

Example I

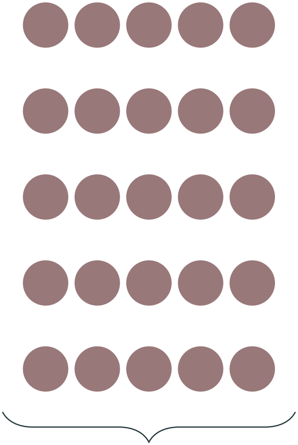


Collection of movies

Let's say we want to embed movies using $d = 5$ embeddings:

1. crime
2. comedy
3. drama
4. horror
5. romance

Example I



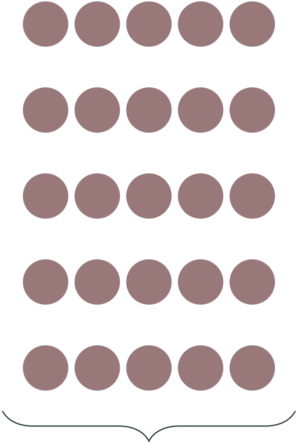
Collection of movies

Let's say we want to embed movies using $d = 5$ embeddings:

1. crime
2. comedy
3. drama
4. horror
5. romance

- The Godfather (1972): $[0.80, 0.20, 0.90, 0.30, 0.20]$

Example I



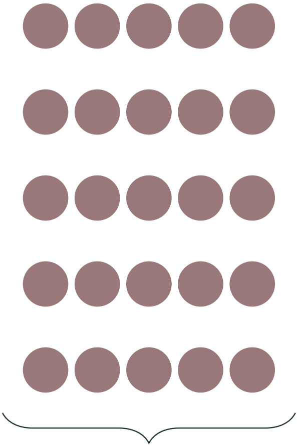
Collection of movies

Let's say we want to embed movies using $d = 5$ embeddings:

1. crime
2. comedy
3. drama
4. horror
5. romance

- The Godfather (1972): $[0.80, 0.20, 0.90, 0.30, 0.20]$
- Dumb and Dumber (1994): $[0.20, 0.90, 0.30, 0.01, 0.40]$

Example I



Collection of movies

Let's say we want to embed movies using $d = 5$ embeddings:

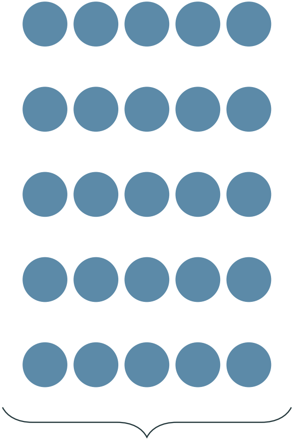
1. crime
2. comedy
3. drama
4. horror
5. romance

- ▷ The Godfather (1972): $[0.80, 0.20, 0.90, 0.30, 0.20]$
- ▷ Dumb and Dumber (1994): $[0.20, 0.90, 0.30, 0.01, 0.40]$
- ▷ *Not* a probability distribution!

Example II

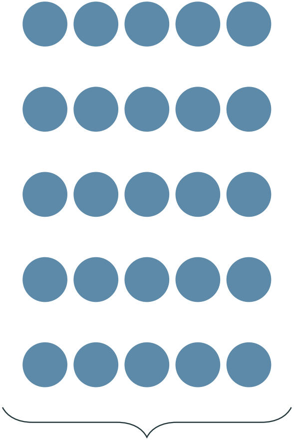
Example II

Example II



Collection of people

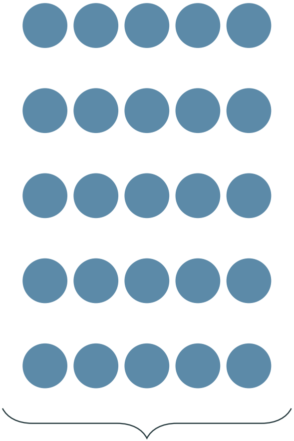
Example II



Collection of people

Person characteristics

Example II

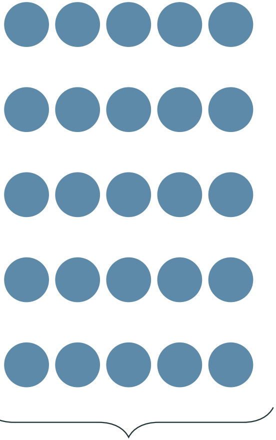


Collection of people

Person characteristics

1. Age
2. Height (cm)
3. Weight (kg)
4. Skin color
5. Hair-color

Example II



Collection of people

Person characteristics

1. Age
2. Height (cm)
3. Weight (kg)
4. Skin color
5. Hair-color

- Embedding: $[28, 184, 79, 0.1, 2]$

The Distributional Hypothesis

The Distributional Hypothesis

The core idea about embeddings is that we want to represent words such that semantically related words are closer to each other

The Distributional Hypothesis

The core idea about embeddings is that we want to represent words such that semantically related words are closer to each other

$\rightsquigarrow$ *The distributional hypothesis*:

The Distributional Hypothesis

The core idea about embeddings is that we want to represent words such that semantically related words are closer to each other

$\rightsquigarrow$ *The distributional hypothesis*:

- Words that occur in *similar contexts* tend to have *similar meaning*

The Distributional Hypothesis

The core idea about embeddings is that we want to represent words such that semantically related words are closer to each other

$\rightsquigarrow$ *The distributional hypothesis*:

- Words that occur in *similar contexts* tend to have *similar meaning*
  - $\rightsquigarrow$ "We know a word by the company it keeps" (Firth, 1957)

The Distributional Hypothesis

The core idea about embeddings is that we want to represent words such that semantically related words are closer to each other

$\rightsquigarrow$ *The distributional hypothesis*:

- Words that occur in *similar contexts* tend to have *similar meaning*
  - $\rightsquigarrow$ "We know a word by the company it keeps" (Firth, 1957)
- Formalizes the very intuitive idea that contexts give meaning to words

The Distributional Hypothesis

The core idea about embeddings is that we want to represent words such that semantically related words are closer to each other

⇝ *The distributional hypothesis*:

- Words that occur in *similar contexts* tend to have *similar meaning*
  - ⇝ "We know a word by the company it keeps" (Firth, 1957)
- Formalizes the very intuitive idea that contexts give meaning to words
  - ⇝ Context $\neq$ co-occurrence

Embeddings in The Social Sciences

Embeddings in The Social Sciences

The semantic similarity conveyed by embeddings is a *powerful* and *flexible* tool:

Embeddings in The Social Sciences

The semantic similarity conveyed by embeddings is a *powerful* and *flexible* tool:

- Semantic changes

Embeddings in The Social Sciences

The semantic similarity conveyed by embeddings is a *powerful* and *flexible* tool:

- Semantic changes
- Semantic differences

Embeddings in The Social Sciences

The semantic similarity conveyed by embeddings is a *powerful* and *flexible* tool:

- Semantic changes
- Semantic differences

$\rightsquigarrow$ The core idea is that the similarity between embeddings is informative about the semantic similarity of the concept we want to measure

Embeddings in The Social Sciences

The semantic similarity conveyed by embeddings is a *powerful* and *flexible* tool:

- Semantic changes
- Semantic differences

⇝ The core idea is that the similarity between embeddings is informative about the semantic similarity of the concept we want to measure

⇝ How can we define similarity?

Embeddings in The Social Sciences

The semantic similarity conveyed by embeddings is a *powerful* and *flexible* tool:

- Semantic changes
- Semantic differences

⇝ The core idea is that the similarity between embeddings is informative about the semantic similarity of the concept we want to measure

⇝ How can we define similarity?

  ▷ Cosine similarity!

Semantic Changes (Hamilton *et al.*, 2016)

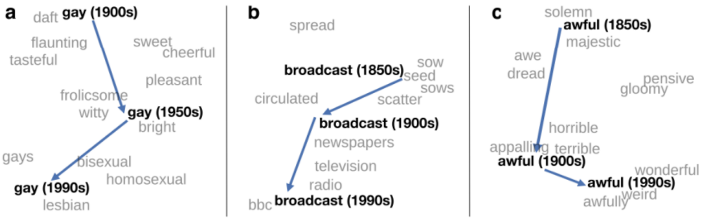
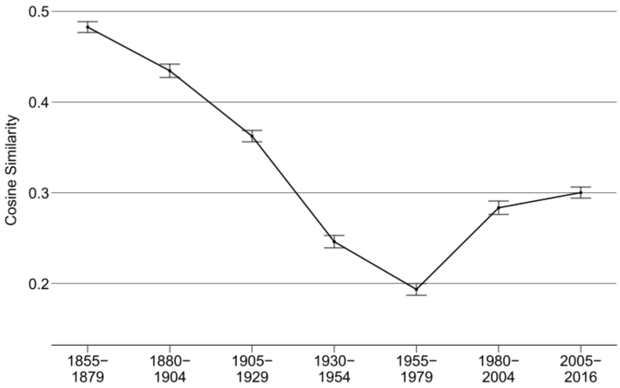
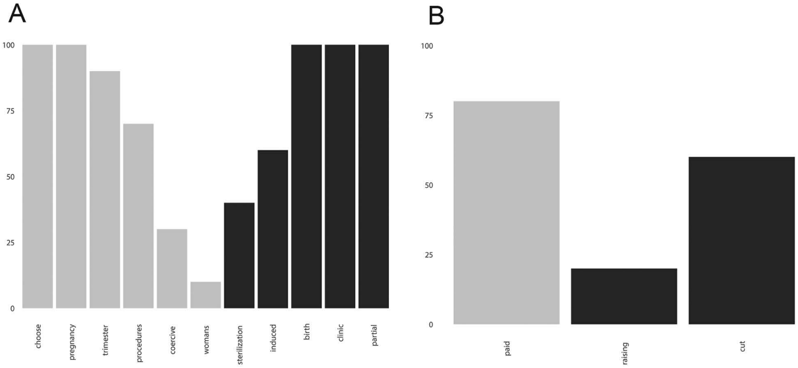


Figure 1: Two-dimensional visualization of semantic change in English using SGNS vectors.[2] **a**, The word *gay* shifted from meaning "cheerful" or "frolicsome" to referring to homosexuality. **b**, In the early 20th century *broadcast* referred to "casting out seeds"; with the rise of television and radio its meaning shifted to "transmitting signals". **c**, *Awful* underwent a process of pejoration, as it shifted from meaning "full of awe" to meaning "terrible or appalling" (Simpson et al., 1989).

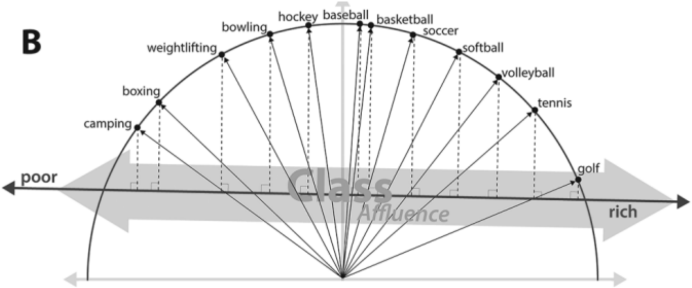
“Equality” - “Social” Cosine Similarity (Rodman, 2020)



Partisan Differences in Word Choice (Rodriguez and Spirling, 2022)

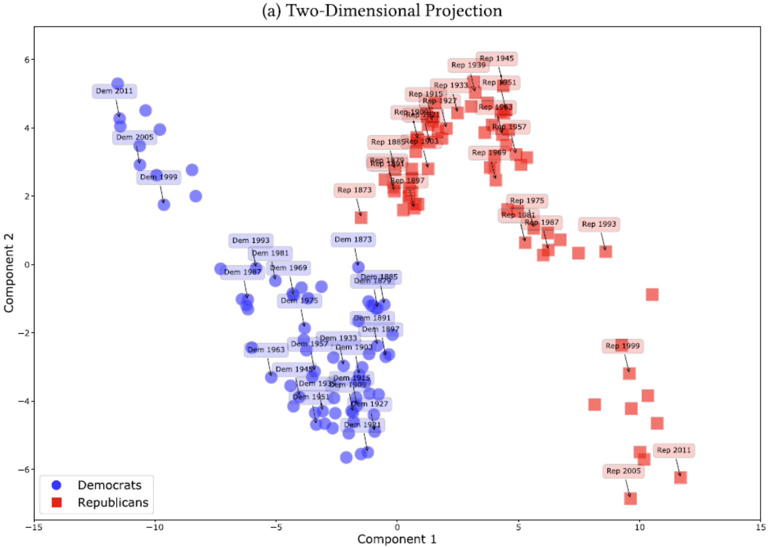


Cultural Dimensions of Word Embeddings (Kozlowski *et al.*, 2019)



Ideology and Word Embeddings (Rheault and Cochrane, 2020)

Ideology and Word Embeddings (Rheault and Cochrane, 2020)



Exercise

Discuss with your neighbors how word embeddings can be combined with dictionaries.

Analogies

Analogies

Unlike other text representations, word embeddings are capable of solving analogies:

Analogies

Unlike other text representations, word embeddings are capable of solving analogies:

- Son is to father as daughter is to X

Analogies

Unlike other text representations, word embeddings are capable of solving analogies:

- Son is to father as daughter is to X
- Copenhagen is to Denmark what London is to X

Analogies

Unlike other text representations, word embeddings are capable of solving analogies:

- Son is to father as daughter is to X
- Copenhagen is to Denmark what London is to X
- Denmark is to Copenhagen what England is to X

Analogies

Unlike other text representations, word embeddings are capable of solving analogies:

- Son is to father as daughter is to X
- Copenhagen is to Denmark what London is to X
- Denmark is to Copenhagen what England is to X

Textbook example:

Analogies

Unlike other text representations, word embeddings are capable of solving analogies:

- Son is to father as daughter is to X
- Copenhagen is to Denmark what London is to X
- Denmark is to Copenhagen what England is to X

Textbook example:

$$\text{king} + \text{woman} - \text{man} = \text{queen}$$

Analogies

Unlike other text representations, word embeddings are capable of solving analogies:

- Son is to father as daughter is to X
- Copenhagen is to Denmark what London is to X
- Denmark is to Copenhagen what England is to X

Textbook example:

$$\text{king} + \text{woman} - \text{man} = \text{queen}$$

What's the intuition behind this logic?

Analogies

Unlike other text representations, word embeddings are capable of solving analogies:

- Son is to father as daughter is to X
- Copenhagen is to Denmark what London is to X
- Denmark is to Copenhagen what England is to X

Textbook example:

$$\text{king} + \text{woman} - \text{man} = \text{queen}$$

What's the intuition behind this logic?

- The operation (woman − man) captures a gender dimension

Analogies

Unlike other text representations, word embeddings are capable of solving analogies:

- Son is to father as daughter is to X
- Copenhagen is to Denmark what London is to X
- Denmark is to Copenhagen what England is to X

Textbook example:

$$\text{king} + \text{woman} - \text{man} = \text{queen}$$

What's the intuition behind this logic?

- The operation (woman − man) captures a gender dimension
- Starting at king means we are "walking" one step in the vector space along the gender dimension

Analogies

Unlike other text representations, word embeddings are capable of solving analogies:

- Son is to father as daughter is to X
- Copenhagen is to Denmark what London is to X
- Denmark is to Copenhagen what England is to X

Textbook example:

$$\text{king} + \text{woman} - \text{man} = \text{queen}$$

What's the intuition behind this logic?

- The operation (woman – man) captures a gender dimension
- Starting at king means we are "walking" one step in the vector space along the gender dimension
- This means we can consider *directions* and not only *distances*

Exercise

Exercise

Discuss with your neighbor how we can construct neural networks that use the distributional hypothesis to generate embeddings:

Exercise

Discuss with your neighbor how we can construct neural networks that use the distributional hypothesis to generate embeddings:

1. What’s the input?

Exercise

Discuss with your neighbor how we can construct neural networks that use the distributional hypothesis to generate embeddings:

1. What's the input?
2. What's the output?

Exercise

Discuss with your neighbor how we can construct neural networks that use the distributional hypothesis to generate embeddings:

1. What's the input?
2. What's the output?
3. How do we specify d when we implement the net? (recall that d is the dimension of the embeddings)

Exercise

Discuss with your neighbor how we can construct neural networks that use the distributional hypothesis to generate embeddings:

1. What's the input?
2. What's the output?
3. How do we specify d when we implement the net? (recall that d is the dimension of the embeddings)
4. How do we get annotated data? I.e. how can we train a network in a supervised manner?

Exercise

Discuss with your neighbor how we can construct neural networks that use the distributional hypothesis to generate embeddings:

1. What's the input?
2. What's the output?
3. How do we specify d when we implement the net? (recall that d is the dimension of the embeddings)
4. How do we get annotated data? I.e. how can we train a network in a supervised manner?

See tutorial for a hands-on example using PyTorch

Table of Contents

Word2Vec: Overview

Word2Vec: Overview

Word2Vec is one of the possible embedding algorithms that exist: learns *dense* representations that capture word *relations and meaning*

Word2Vec: Overview

Word2Vec is one of the possible embedding algorithms that exist: learns *dense* representations that capture word *relations and meaning*

- Revolutionized NLP – $40,736$ citations – when introduced 10 years ago (Mikolov *et al.*, 2013)

Word2Vec: Overview

Word2Vec is one of the possible embedding algorithms that exist: learns *dense* representations that capture word *relations and meaning*

- Revolutionized NLP – $40,736$ citations – when introduced 10 years ago (Mikolov *et al.*, 2013)
- Learned word vectors/embeddings are typically around $50 - 1000$ with $d \in \mathbb{Z}$ with values $X \in \mathbb{R}^d$

Word2Vec: Overview

Word2Vec is one of the possible embedding algorithms that exist: learns *dense* representations that capture word *relations and meaning*

- Revolutionized NLP – $40,736$ citations – when introduced 10 years ago (Mikolov *et al.*, 2013)
- Learned word vectors/embeddings are typically around $50 - 1000$ with $d \in \mathbb{Z}$ with values $X \in \mathbb{R}^d$
- Individual values can not be interpreted $\rightsquigarrow$ but related words should have vectors closer to each other in the d-dimensional space

Word2Vec: Overview

Word2Vec is one of the possible embedding algorithms that exist: learns *dense* representations that capture word *relations and meaning*

- Revolutionized NLP – $40,736$ citations – when introduced 10 years ago (Mikolov *et al.*, 2013)
- Learned word vectors/embeddings are typically around $50 - 1000$ with $d \in \mathbb{Z}$ with values $X \in \mathbb{R}^d$
- Individual values can not be interpreted $\rightsquigarrow$ but related words should have vectors closer to each other in the d-dimensional space

Word2Vec: Algorithms

Word2Vec: Algorithms

CBOW

Word2Vec: Algorithms

CBOW

- Objective:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c,\, j\neq 0}\log(p(w_t \mid w_{t+j}))$$

Word2Vec: Algorithms

CBOW

- Objective:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c,\, j\neq 0}\log(p(w_t \mid w_{t+j}))$$

Skip-gram

Word2Vec: Algorithms

CBOW

- Objective:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c,\, j\neq 0}\log(p(w_t \mid w_{t+j}))$$

Skip-gram

- Objective:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c,\, j\neq 0}\log(p(w_{t+j} \mid w_t))$$

Word2Vec: Algorithms

CBOW

- Objective:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c,\, j\neq 0}\log(p(w_t \mid w_{t+j}))$$

Skip-gram

- Objective:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c,\, j\neq 0}\log(p(w_{t+j} \mid w_t))$$

- T total number of words
- w_t target word
- c window size
- j is an index within the context window, ranging from $-c$ to c, excluding $j = 0$

Word2Vec: Algorithms

CBOW

- Objective:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c,\, j\neq 0}\log(p(w_t \mid w_{t+j}))$$

Skip-gram

- Objective:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c,\, j\neq 0}\log(p(w_{t+j} \mid w_t))$$

- T total number of words
- w_t target word
- c window size
- j is an index within the context window, ranging from $-c$ to c, excluding $j = 0$
- $p(a \mid b)$ is the conditional probability of observing a given b

Word2Vec: Algorithms

CBOW

- Objective:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c,\, j\neq 0}\log(p(w_t \mid w_{t+j}))$$

Skip-gram

- Objective:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c,\, j\neq 0}\log(p(w_{t+j} \mid w_t))$$

- T total number of words
- w_t target word
- c window size
- j is an index within the context window, ranging from $-c$ to c, excluding $j = 0$
- $p(a \mid b)$ is the conditional probability of observing a given b
  - $p(w_t \mid w_{t+j})$: conditional probability of target word given context words

Word2Vec: Algorithms

CBOW

- Objective:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c,\, j\neq 0}\log(p(w_t \mid w_{t+j}))$$

Skip-gram

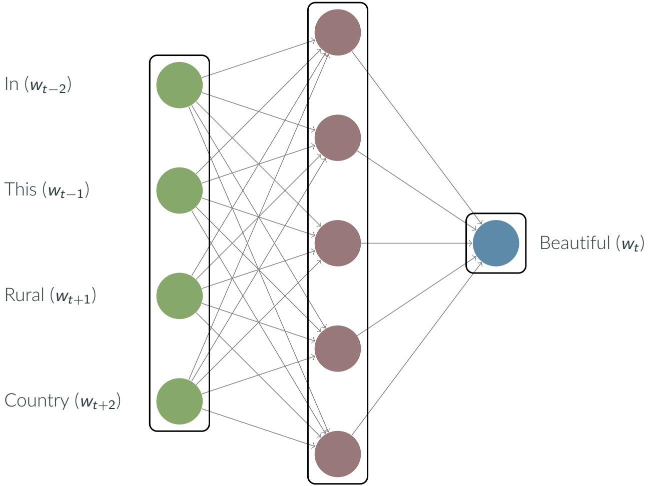
- Objective:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c,\, j\neq 0}\log(p(w_{t+j} \mid w_t))$$

- T total number of words
- w_t target word
- c window size
- j is an index within the context window, ranging from $-c$ to c, excluding $j = 0$
- $p(a \mid b)$ is the conditional probability of observing a given b
  - $p(w_t \mid w_{t+j})$: conditional probability of target word given context words
  - $p(w_{t+j} \mid w_t)$: conditional probability context words given target word

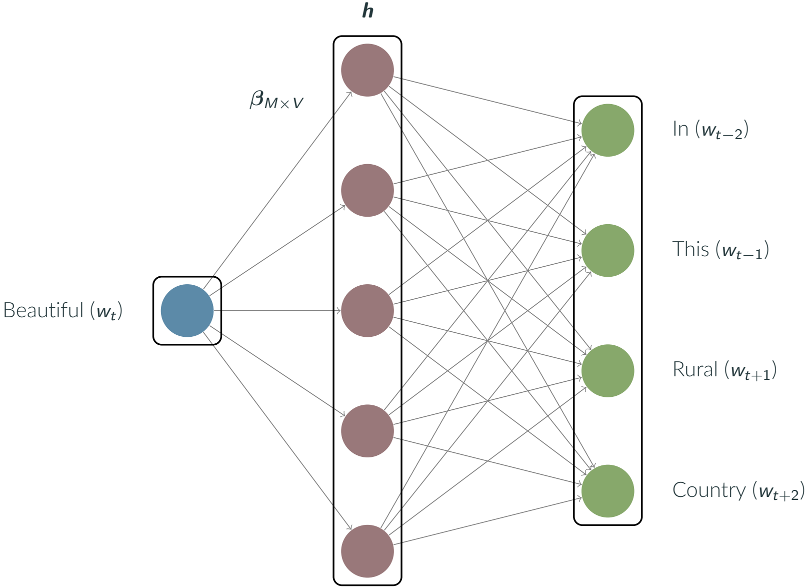
CBOW

CBOW



Skip-Gram

Skip-Gram



$\boldsymbol{h}$
$\beta_{M \times V}$
Beautiful (w_t)
In (w_{t-2})
This (w_{t-1})
Rural (w_{t+1})
Country (w_{t+2})

Skip-Gram Mechanics

Skip-Gram Mechanics

Sentence: “I A mener vi altså ikke at skattelettelser og velfærd er modsætninger”
Window size: 2

Skip-Gram Mechanics

Sentence: “I A mener vi altså ikke at skattelettelser og velfærd er modsætninger”

Window size: 2

$\underbrace{\boxed{\text{I}}}_{t-1}$ $\underbrace{\boxed{\text{A}}}_{\textit{target}}$ $\underbrace{\boxed{\text{mener vi}}}_{t+1,t+2}$ altså ikke skattelettelser og velfærd er modsætninger.

Skip-Gram Mechanics

Sentence: “I A mener vi altså ikke at skattelettelser og velfærd er modsætninger”

Window size: 2

$\underbrace{\boxed{\text{I}}}_{t-1}\ \underbrace{\boxed{\text{A}}}_{\textit{target}}\ \underbrace{\boxed{\text{mener vi}}}_{t+1,t+2}$ altså ikke skattelettelser og velfærd er modsætninger.

I A mener vi altså $\underbrace{\boxed{\text{ikke at}}}_{t-2,t-1}\ \underbrace{\boxed{\text{skattelettelser}}}_{\textit{target}}\ \underbrace{\boxed{\text{og velfærd}}}_{t+1,t+2}$ er modsætninger.

Skip-Gram Mechanics

Sentence: “I A mener vi altså ikke at skattelettelser og velfærd er modsætninger”

Window size: 2

$\underbrace{\boxed{\text{I}}}_{t-1}\ \underbrace{\boxed{\text{A}}}_{\textit{target}}\ \underbrace{\boxed{\text{mener vi}}}_{t+1,t+2}$ altså ikke skattelettelser og velfærd er modsætninger.

I A mener vi altså $\underbrace{\boxed{\text{ikke at}}}_{t-2,t-1}\ \underbrace{\boxed{\text{skattelettelser}}}_{\textit{target}}\ \underbrace{\boxed{\text{og velfærd}}}_{t+1,t+2}$ er modsætninger.

I A mener vi altså ikke at $\underbrace{\boxed{\text{skattelettelser og}}}_{t-2,t-1}\ \underbrace{\boxed{\text{velfærd}}}_{\textit{target}}\ \underbrace{\boxed{\text{er modsætninger}}}_{t+1,t+2}$

Skip-Gram Mechanics

Sentence: “I A mener vi altså ikke at skattelettelser og velfærd er modsætninger”

Window size: 2

$\underbrace{\boxed{\text{I}}}_{t-1}\ \underbrace{\boxed{\text{A}}}_{\textit{target}}\ \underbrace{\boxed{\text{mener vi}}}_{t+1,t+2}$ altså ikke skattelettelser og velfærd er modsætninger.

I A mener vi altså $\underbrace{\boxed{\text{ikke at}}}_{t-2,t-1}\ \underbrace{\boxed{\text{skattelettelser}}}_{\textit{target}}\ \underbrace{\boxed{\text{og velfærd}}}_{t+1,t+2}$ er modsætninger.

I A mener vi altså ikke at $\underbrace{\boxed{\text{skattelettelser og}}}_{t-2,t-1}\ \underbrace{\boxed{\text{velfærd}}}_{\textit{target}}\ \underbrace{\boxed{\text{er modsætninger}}}_{t+1,t+2}$

I A mener vi altså ikke at skattelettelser og $\underbrace{\boxed{\text{velfærd er}}}_{t-2,t-1}\ \underbrace{\boxed{\text{modsætninger}}}_{\textit{target}}$

Negative Sampling

Negative Sampling

I A mener vi altså $\underbrace{\boxed{\text{ikke at}}}_{t-2,t-1}$ $\underbrace{\boxed{\text{skattelettelser}}}_{\textit{target}}$ $\underbrace{\boxed{\text{og velfærd}}}_{t+1,t+2}$ er modsætninger.

Negative Sampling

I A mener vi altså $\underbrace{\boxed{\text{ikke at}}}_{t-2,t-1}$ $\underbrace{\boxed{\text{skattelettelser}}}_{\textit{target}}$ $\underbrace{\boxed{\text{og velfærd}}}_{t+1,t+2}$ er modsætninger.

Positive Samples

Negative Sampling

I A mener vi altså $\underbrace{\boxed{\text{ikke at}}}_{t-2,t-1}$ $\underbrace{\boxed{\text{skattelettelser}}}_{\textit{target}}$ $\underbrace{\boxed{\text{og velfærd}}}_{t+1,t+2}$ er modsætninger.

Positive Samples

- (ikke, skattelettelser)
- (at, skattelettelser)
- (og, skattelettelser)
- (velfærd, skattelettelser)

Negative Sampling

I A mener vi altså $\underbrace{\boxed{\text{ikke at}}}_{t-2,t-1}$ $\underbrace{\boxed{\text{skattelettelser}}}_{\textit{target}}$ $\underbrace{\boxed{\text{og velfærd}}}_{t+1,t+2}$ er modsætninger.

Positive Samples

- (ikke, skattelettelser)
- (at, skattelettelser)
- (og, skattelettelser)
- (velfærd, skattelettelser)

Negative Samples

- (???, skattelettelser)

Negative Sampling

I A mener vi altså $\underbrace{\boxed{\text{ikke at}}}_{t-2,t-1}$ $\underbrace{\boxed{\text{skattelettelser}}}_{target}$ $\underbrace{\boxed{\text{og velfærd}}}_{t+1,t+2}$ er modsætninger.

Positive Samples

- (ikke, skattelettelser)
- (at, skattelettelser)
- (og, skattelettelser)
- (velfærd, skattelettelser)

Negative Samples

- (???, skattelettelser)
- (kørekort, skattelettelser)
- (fodbold, skattelettelser)
- (zoo, skattelettelser)

Negative Sampling

I A mener vi altså $\underbrace{\boxed{\text{ikke at}}}_{t-2,t-1}$ $\underbrace{\boxed{\text{skattelettelser}}}_{target}$ $\underbrace{\boxed{\text{og velfærd}}}_{t+1,t+2}$ er modsætninger.

Positive Samples

- (ikke, skattelettelser)
- (at, skattelettelser)
- (og, skattelettelser)
- (velfærd, skattelettelser)

Negative Samples

- (???, skattelettelser)
- (kørekort, skattelettelser)
- (fodbold, skattelettelser)
- (zoo, skattelettelser)

The positive and negative samples constitute the training set – no labeling required! $\leadsto$ *self-supervision*

Practical Issues

Practical Issues

Working with embeddings in practice involves choosing between four "hyperparameters" (Rodriguez and Spirling, 2022):

Practical Issues

Working with embeddings in practice involves choosing between four "hyperparameters" (Rodriguez and Spirling, 2022):

1. Window size (depends on the length of input text)

Practical Issues

Working with embeddings in practice involves choosing between four “hyperparameters” (Rodriguez and Spirling, 2022):

1. Window size (depends on the length of input text)
2. Dimensionality size (d)

Practical Issues

Working with embeddings in practice involves choosing between four "hyperparameters" (Rodriguez and Spirling, 2022):

1. Window size (depends on the length of input text)
2. Dimensionality size (d)
3. Locally vs. pretrained (fixed or fine-tuned) embeddings

Practical Issues

Working with embeddings in practice involves choosing between four "hyperparameters" (Rodriguez and Spirling, 2022):

1. Window size (depends on the length of input text)
2. Dimensionality size (d)
3. Locally vs. pretrained (fixed or fine-tuned) embeddings
4. Preprocessing (huge debate!)

Practical Issues

Working with embeddings in practice involves choosing between four "hyperparameters" (Rodriguez and Spirling, 2022):

1. Window size (depends on the length of input text)
2. Dimensionality size (d)
3. Locally vs. pretrained (fixed or fine-tuned) embeddings
4. Preprocessing (huge debate!)

Table of Contents

See you next week!

Theme: Text

Computational Analysis of Text, Audio, and Images, Fall 2023

Aarhus University

References i

[1] W. L. Hamilton, J. Leskovec, and D. Jurafsky, "Diachronic word embeddings reveal statistical laws of semantic change," *arXiv preprint arXiv:1605.09096*, 2016.

[2] E. Rodman, "A timely intervention: Tracking the changing meanings of political concepts with word vectors," *Political Analysis*, vol. 28, no. 1, pp. 87–111, 2020.

[3] P. L. Rodriguez and A. Spirling, "Word embeddings: What works, what doesn't, and how to tell the difference for applied research," *The Journal of Politics*, vol. 84, no. 1, pp. 101–115, 2022.

[4] A. C. Kozlowski, M. Taddy, and J. A. Evans, "The geometry of culture: Analyzing the meanings of class through word embeddings," *American Sociological Review*, vol. 84, no. 5, pp. 905–949, 2019.

References ii

[5] L. Rheault and C. Cochrane, "Word embeddings for the analysis of ideological placement in parliamentary corpora," *Political Analysis*, vol. 28, no. 1, pp. 112–133, 2020.

[6] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, "Distributed representations of words and phrases and their compositionality," *Advances in neural information processing systems*, vol. 26, 2013.