COMP5046

Natural Language Processing

Lecture 2: Word Embeddings and Representation

Dr. Caren Han

Semester 1, 2021
School of Computer Science,
University of Sydney

1

0 LECTURE PLAN

Lecture 2: Word Embeddings and Representation

1. **Lab Info**
2. Previous Lecture Review
   1. Word Meaning and WordNet
   2. Count based Word Representation
3. Prediction based Word Representation
   1. Introduction to the concept 'Prediction'
   2. Word2Vec
   3. FastText
   4. GloVe
4. Next Week Preview

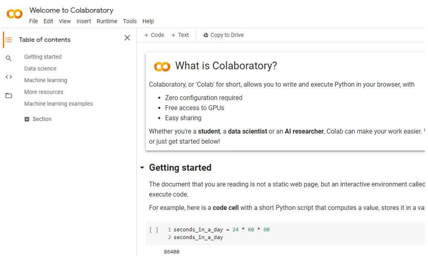
2

1 Info: Lab Exercise

What do we do during Labs?

In Labs, Students will use Google Colab

Colaboratory is a free Jupyter notebook environment that requires no setup and runs entirely in the cloud. With Colaboratory you can write and execute code, save and share your analyses, and access powerful computing resources, all for free from your browser.



3

1 Info: Lab Exercise

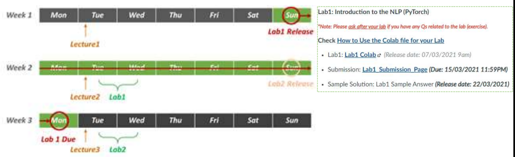
Submissions

How to Submit

Students should submit **"ipynb" file** (Download it from "File" > "Download .ipynb") to Canvas.

When and Where to Submit

Students must submit the Lab 1(for Week2) by ***Week 3 Monday 11:59PM.***



4

0 LECTURE PLAN

Lecture 2: Word Embeddings and Representation

1. Lab Info
2. **Count-based Word Representation**
    1. Word Meaning
    2. Limitations
3. Prediction based Word Representation
    1. Introduction to the concept 'Prediction'
    2. Word2Vec
    3. FastText
    4. GloVe
4. Next Week Preview

5

2 WORD REPRESENTATION

How to represent the meaning of the word?

Definition: meaning (Collins dictionary).

- the idea that it represents, and which can be explained using other words.
- the thoughts or ideas that are intended to be expressed by it.

signifier (symbol) ⟺ signified (idea or thing) = denotation

"Computer"

\x63\x6f\x6d\x70\x75\x74\x65\x72

"Apple"

\x61\x70\x70\x6c\x65

**Unicode (utf-8)*

6

2 COUNT based WORD REPRESENTATION

Problem with one-hot vectors

Problem #1. No word similarity representation

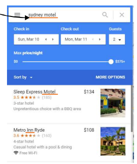
Example: in web search, if user searches for "Sydney motel", we would like to match documents containing "Sydney Inn"

hotel *motel* *Inn*

motel = [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 … 0]

hotel = [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 … 0]

Inn = [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 … 1]



There is no natural notion of similarity for one-hot vectors!

Problem #2. Inefficiency

Vector dimension = number of words in vocabulary

Each representation has only a single '1' with all remaining 0s.

7

2 COUNT based WORD REPRESENTATION

Problem with BoW (Bag of Words)

- The intuition is that documents are similar if they have similar content. Further, that from the content alone we can learn something about the meaning of the document.
- **Discarding word order** ignores the context, and in turn meaning of words in the document (semantics). Context and meaning can offer a lot to the model, that if modeled could tell the difference between the same words differently arranged ("this is interesting" vs "is this interesting").

*S1= I **love** you but you **hate** me*

*S2= I **hate** you but you **love** me*

8

2 COUNT based WORD REPRESENTATION

Limitation of Term Frequency Inverse Document Frequency

$$w_{i,j} = tf_{i,j} \times \log\left(\frac{N}{df_i}\right) \leftarrow 1+df_i$$

$w_{i,j}$ = weight of term i in document j

$tf_{i,j}$ = number of occurrences of term i in document j

N = total number of documents

df_i = number of documents containing term i

- It computes document similarity directly in the word-count space, which may be slow for large vocabularies.
- It assumes that the counts of different words provide independent evidence of similarity.
- It makes no use of ***semantic similarities between words***.

9

2 COUNT based WORD REPRESENTATION

Sparse Representation

With **COUNT based word representation (especially, one-hot vector)**, linguistic information was represented with **sparse representations** (high-dimensional features)

hotel *motel* *Inn*

motel = [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 … 0]

hotel = [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 … 0]

Inn = [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 … 1]

10

2 COUNT based WORD REPRESENTATION

Sparse Representation

With **COUNT based word representation (especially, one-hot vector)**, linguistic information was represented with **sparse representations** (high-dimensional features)

hotel *motel* *Inn*

motel = [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 … 0]

hotel = [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 … 0]

Inn = [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 … 1]

A Significant Improvement Required!

1. How to get the low-dimensional vector representation
2. How to represent the word similarity

maybe a low-dimensional vector?

Can we use a list of fixed numbers (properties) to represent the word?

11

0 LECTURE PLAN

Lecture 2: Word Embeddings and Representation

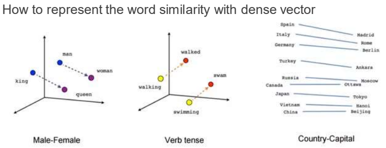
1. Lab Info
2. Previous Lecture Review
   1. Word Meaning and WordNet
   2. Count based Word Representation
3. **Prediction based Word Representation**
   1. Word Embedding
   2. Word2Vec
   3. FastText
   4. Glove
4. Next Week Preview

12

3 Prediction based Word representation

How to Represent the Word Similarity!

- How to represent the word similarity with dense vector



- Try this with word2vec

Word Algebra

Enter all three words, the first two, or the last two and see the words that result.

shanghai + (australia - sydney) = Get result

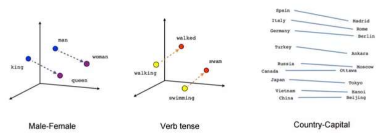
china 0.7477672216910414

Reference: http://turbomaze.github.io/word2vecjson/

13

3 Prediction based Word representation

Let's make the word representation



We need to…

1. Have the fixed low-dimensional vector representation
2. Represent the word similarity

maybe a low-dimensional vector?

What if we use a list of fixed numbers (properties) to represent the word?

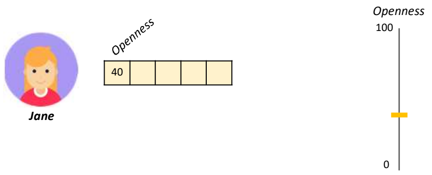
14

3 Prediction based Word representation

Let's get familiar with using vectors to represent things

Assume that you are taking a personality test (the Big Five Personality Traits test)

1)Openness, 2)Agreeableness, 3)Conscientiousness, 4)Negative emotionality, 5)Extraversion



https://openpsychometrics.org/tests/IPIP-BFFM/

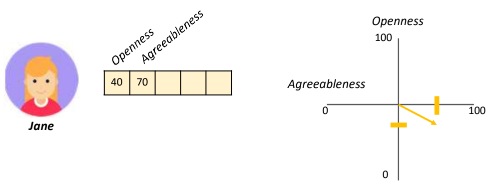
15

3 Prediction based Word representation

Let's get familiar with using vectors to represent things

Assume that you are taking a personality test (the Big Five Personality Traits test)

1)Openness, 2)Agreeableness, 3)Conscientiousness, 4)Negative emotionality, 5)Extraversion



16

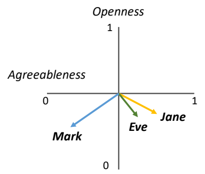
3 Prediction based Word representation

Let's get familiar with using vectors to represent things

Assume that you are taking a personality test (the Big Five Personality Traits test)

1)Openness, 2)Agreeableness, 3)Conscientiousness, 4)Negative emotionality, 5)Extraversion

	Openness	Agreeableness			
Jane	0.4	0.7			
Mark	0.3	0.2			
Eve	0.4	0.6			



17

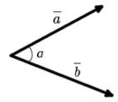
3 Prediction based Word representation

Let's get familiar with using vectors to represent things

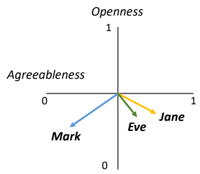
Which of two people (Mark or Eve) is more similar to Jane?

Cosine Similarity

Measure of similarity between two vectors of inner product space that measures the cosine of the angle between them



$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}},$$



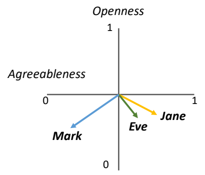
18

3 Prediction based Word representation

Let's get familiar with using vectors to represent things

Which of two people (Mark or Eve) is more similar to Jane?

	Openness	Agreeableness			
Jane	0.4	0.7			
Mark	0.3	0.2			
Eve	0.4	0.6			



$\cos(\underbrace{[0.4, 0.7]}_{Jane}, \underbrace{[0.3, 0.2]}_{Mark}) \approx 0.89$

$\cos(\underbrace{[0.4, 0.7]}_{Jane}, \underbrace{[0.4, 0.6]}_{Eve}) \approx 0.99$

https://onlinemschool.com/math/assistance/vector/angl/
https://scikit-learn.org/stable/modules/generated/sklearn.metrics.pairwise.cosine_similarity.html

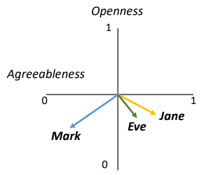
19

3 Prediction based Word representation

Let's get familiar with using vectors to represent things

We need all five major factors for represent the personality

	Openness	Agreeableness	Conscientiousness	NE	Extraversion
Jane	0.4	0.7	0.5	0.2	0.1
Mark	0.3	0.2	0.3	0.7	0.2
Eve	0.4	0.6	0.4	0.3	0.5



With these embeddings,

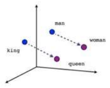
1.Represent things as vectors of fixed numbers!

2.Easily calculate the similarity between vectors

20

3 Prediction based Word representation

Remember? The Word2Vec Demo!

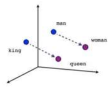


This is a word embedding for the word “king”

21

3 Prediction based Word representation

Remember? The Word2Vec Demo!



This is a word embedding for the word “king”

** Trained by Wikipedia Data, 50-dimension GloVe Vector*

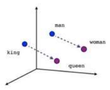
king

[0.50451, 0.68607, -0.59517, -0.022801, 0.60046, 0.08813, 0.47377, -0.61798, -0.31012, -0.066666, 1.493, -0.034173, -0.98173, 0.68229, 0.812229, 0.81722, -0.51722, -744.5.4 1503, -0.55809, 0.66421, 0.1961, -0.1495, -0.033474, -0.30344, 0.41177, -2.223, -1.0756, -0.343554, 0.33505, 1.9927, -0.042434, -0.64519, 0.72519, 0.71419, 0.714319, 0.71419 9159, 0.16754, 0.34344, -0.25663, -0.8523, 0.1661, 0.40102, 1.1685, -1.0137, -0.2155, 0.78321, -0.91241, -1.6626, -0.64426, -0.542102]

22

3 Prediction based Word representation

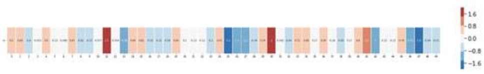
Remember? The Word2Vec Demo!



This is a word embedding for the word “king”

** Trained by Wikipedia Data, 50-dimension GloVe Vector*

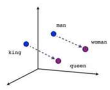
king



23

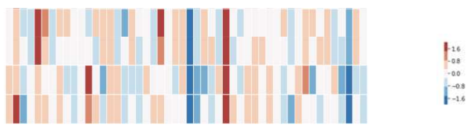
3 Prediction based Word representation

Remember? The Word2Vec Demo!



Compare with Woman, Man, King, and Queen

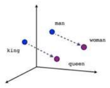
woman
man
king
queen



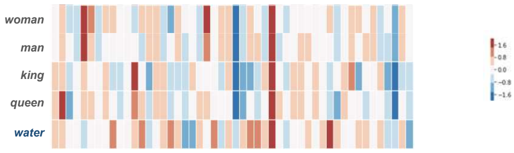
24

3 Prediction based Word representation

Remember? The Word2Vec Demo!



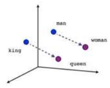
Compare with Woman, Man, King, Queen, and Water



25

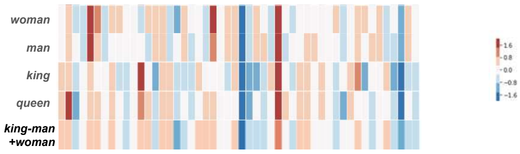
3 Prediction based Word representation

Remember? The Word2Vec Demo!



king – man + woman ≈ queen?

Word Algebra



How to make dense vectors for word representation

26

3 Prediction based Word representation

How to make dense vectors for word representation

Prof. John Rupert Firth

Distributional Hypothesis

"You shall know a word by the company it keeps"
— (Firth, J. R. 1957:11)

*Prof. Firth is noted for drawing attention to the context-dependent nature of meaning with his notion of **'context of situation'**, and his work on **collocational meaning** is widely acknowledged in the field of **distributional semantics**.*

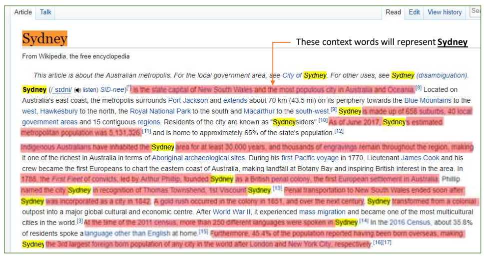
27

3 Prediction based Word representation

Word Representations in the context

When a *word w* appears in a text, its context is the set of words that *appear nearby*

- Use the surrounding contexts of w to build up a representation of w

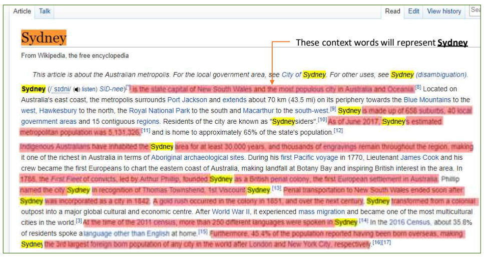


28

3 Prediction based Word representation

How can we train the word representation to machine?

Neural Networks! (Machine Learning)

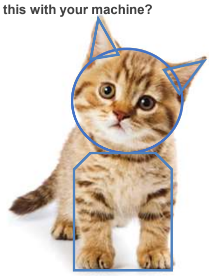


29

Brief in Machine Learning!

Machine Learning

How to classify this with your machine?

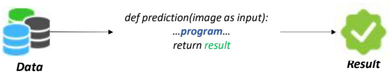


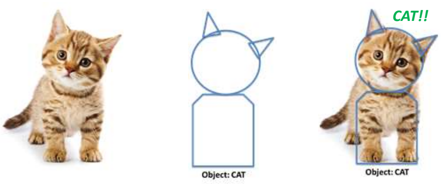
Object: CAT

30

Brief in Machine Learning!

Computer System





31

Brief in Machine Learning!

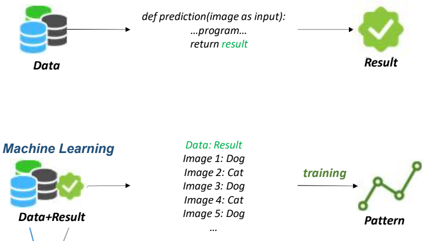
Can we classify this with the computer system?

Object: ??? *Object: ???* *Object: ???*

32

Brief in Machine Learning!

Computer System VS Machine Learning



$\{x_i, y_i\}^N_{i=1}$

xi	Input	words (indices or vectors), sentences, documents, etc.
yi	class	What we try to classify/predict

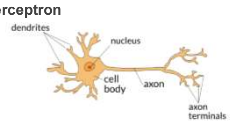
33

Brief in Machine Learning!

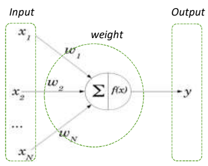
Neural Network and Deep Learning

Neuron and Perceptron

Neuron



Perceptron



NOTE: The detailed neural network and deep learning concept will be covered in the Lecture 3

34

3 Prediction based Word representation

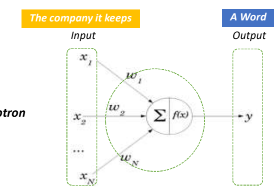
Neural Network and Deep Learning in Word Representation

"You shall know a word by the company it keeps" *(Firth, J. R. 1957:11)*

Why don't we train a word by the company it keeps?

Why don't we represent a word by the company it keeps?

Perceptron



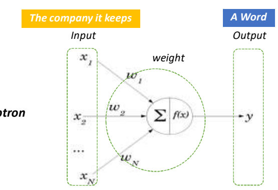
35

3 Prediction based Word representation

Neural Network and Deep Learning in Word Representation

Wikipedia: "Sydney is the state capital of NSW..."

Perceptron

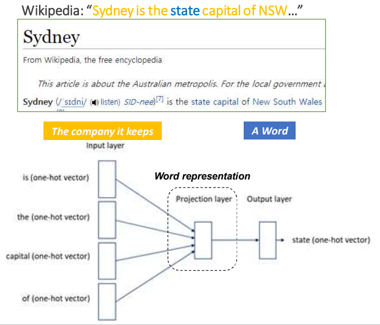


36

3 Prediction based Word representation

Neural Network and Deep Learning in Word Representation

Wikipedia: "Sydney is the state capital of NSW..."

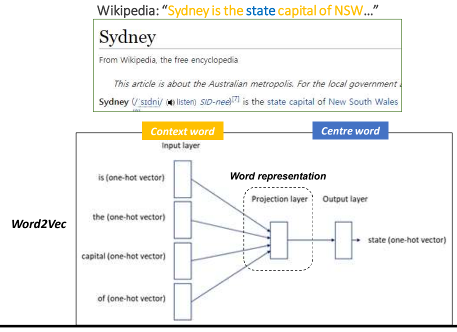


37

3 Prediction based Word representation

Neural Network and Deep Learning in Word Representation

Wikipedia: "Sydney is the state capital of NSW..."



38

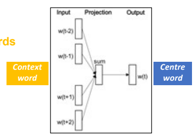
3 Prediction based Word representation

Word2Vec

Word2vec can utilize either of two model architectures to produce a distributed representation of words:

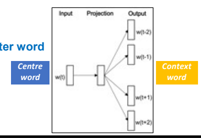
1. Continuous Bag of Words (CBOW)

Predict center word from (bag of) context words



2. Continuous Skip-gram

Predict context ("outside") words given center word



39

3 Prediction based Word representation

Word2Vec with Continuous Bag of Words (CBOW)

Predict center word from (bag of) context words

Sentence: "Sydney is the state capital of NSW"

Aim
- Predict the center word

Setup
- Window size
  - Assume that **the window size is 2**

Sydney	is	the	state	capital	of	NSW
Sydney	is	the	state	capital	of	NSW
Sydney	is	the	state	capital	of	NSW
Sydney	is	the	state	capital	of	NSW
Sydney	is	the	state	capital	of	NSW
Sydney	is	the	state	capital	of	NSW
Sydney	is	the	state	capital	of	NSW

Center word
Context ("outside") word

40

3 Prediction based Word representation

Word2Vec with Continuous Bag of Words (CBOW)

Predict center word from (bag of) context words

Sentence: "Sydney is the state capital of NSW"

Using window slicing, develop the training data

Center word	Context ("outside") word	
[1,0,0,0,0,0,0]	[0,1,0,0,0,0,0], [0,0,1,0,0,0,0]	**Sydney** is the state capital of NSW
[0,1,0,0,0,0,0]	[1,0,0,0,0,0,0], [0,0,1,0,0,0,0], [0,0,0,1,0,0,0]	Sydney **is** the state capital of NSW
[0,0,1,0,0,0,0]	[1,0,0,0,0,0,0], [0,1,0,0,0,0,0] [0,0,0,1,0,0,0], [0,0,0,0,1,0,0]	Sydney is **the** state capital of NSW
[0,0,0,1,0,0,0]	[0,1,0,0,0,0,0], [0,0,1,0,0,0,0] [0,0,0,0,1,0,0], [0,0,0,0,0,1,0]	Sydney is the **state** capital of NSW
[0,0,0,0,1,0,0]	[0,0,1,0,0,0,0], [0,0,0,1,0,0,0] [0,0,0,0,0,1,0], [0,0,0,0,0,0,1]	Sydney is the state **capital** of NSW
[0,0,0,0,0,1,0]	[0,0,0,1,0,0,0], [0,0,0,0,1,0,0] [0,0,0,0,0,0,1]	Sydney is the state capital **of** NSW
[0,0,0,0,0,0,1]	[0,0,0,0,1,0,0], [0,0,0,0,0,1,0]	Sydney is the state capital of **NSW**

Center word
Context ("outside") word

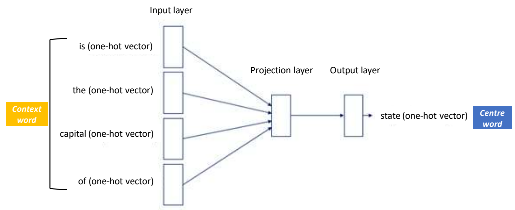
41

3 Prediction based Word representation

CBOW – Neural Network Architecture

Predict center word from (bag of) context words

Sentence: "Sydney is the state capital of NSW"



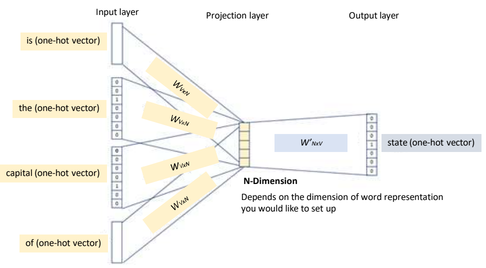
42

3 Prediction based Word representation

CBOW – Neural Network Architecture

Predict center word from (bag of) context words

Sentence: "Sydney is the state capital of NSW"



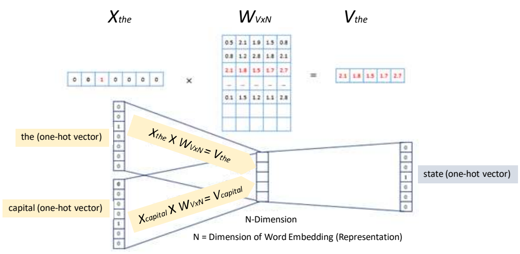
43

3 Prediction based Word representation

CBOW – Neural Network Architecture

Predict center word from (bag of) context words

Sentence: "Sydney is the state capital of NSW"



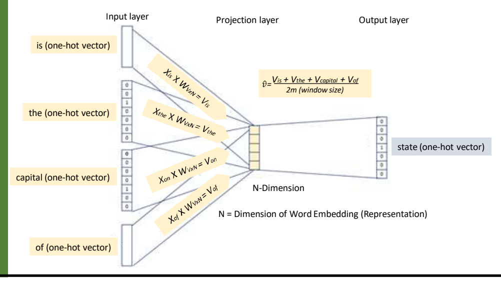
44

3 Prediction based Word representation

CBOW – Neural Network Architecture

Predict center word from (bag of) context words

Sentence: "Sydney is the state capital of NSW"



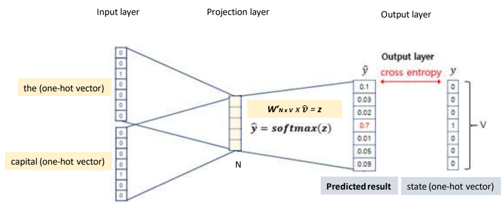
45

3 Prediction based Word representation

CBOW – Neural Network Architecture

Predict center word from (bag of) context words

Sentence: "Sydney is the state capital of NSW"



Softmax: *outputs a vector that represents the probability distributions (sum to 1) of a list of potential outcome*

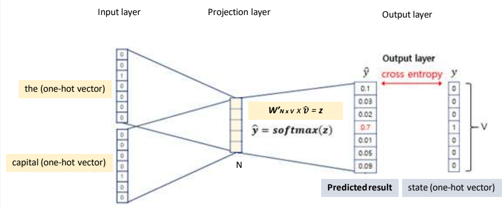
46

3 Prediction based Word representation

CBOW – Neural Network Architecture

Predict center word from (bag of) context words

Sentence: "Sydney is the state capital of NSW"



Cross Entropy: *can be used as a loss function when optimizing classification*

Loss Function (Cross Entropy)

$$H(\hat{y}, y) = -\sum_{j=1}^{|V|} y_j \log(\hat{y}_j)$$

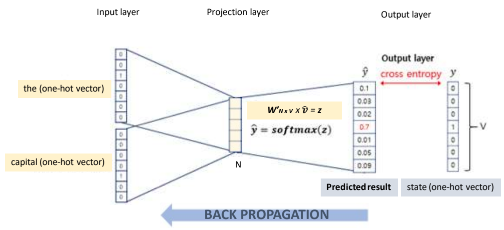
47

3 Prediction based Word representation

CBOW – Neural Network Architecture

Predict center word from (bag of) context words

Sentence: "Sydney is the state capital of NSW"



**This back propagation or optimization function will be learned more details in the lecture 3.*

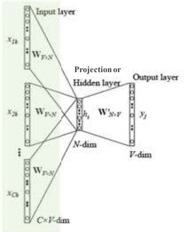
48

3 Prediction based Word representation

CBOW – Neural Network Architecture

Predict center word from (bag of) context words.

Summary of CBOW Training (Review your understanding with equations)



1. Initialise each word in a one-hot vector form.
$\boldsymbol{x_k} = [0,...,0,1,0,...,0]$

2. Use context words (**2m**, based on window size =m) as input of the Word2Vec-CBOW model.
$(\boldsymbol{x^{c-m}}, \boldsymbol{x^{c-m+1}}, \dots, \boldsymbol{x^{c-1}}, \boldsymbol{x^{c+1}}, \dots, \boldsymbol{x^{c+m-1}}, \boldsymbol{x^{c+m}}) \in \mathbb{R}^{|V|}$

3. Has two Parameter Matrices:
1) Parameter Matrix (from Input Layer to **Hidden/Projection Layer**)
$\mathbf{W} \in \mathbb{R}^{V\text{x}N}$

2) Parameter Matrix (to Output Layer)
$\mathbf{W'} \in \mathbb{R}^{N\text{x}V}$

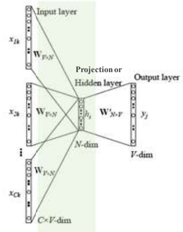
49

3 Prediction based Word representation

CBOW – Neural Network Architecture

Predict center word from (bag of) context words.

Summary of CBOW Training (Review your understanding with equations)



4. Initial words are represented in one hot vector so multiplying a **one hot vector** with $\mathbf{W}_{V\times N}$ will give you a 1 x N (embedded word) vector.

e.g. $[0\ 1\ 0\ 0] \times \begin{bmatrix} 10 & 2 & 18 \\ 15 & 22 & 3 \\ 25 & 11 & 19 \\ 4 & 7 & 22 \end{bmatrix} = [15\ 22\ 3]$

$(\boldsymbol{v_{c-m}} = \mathrm{W}x^{c-m}, \dots, \boldsymbol{v_{c+m}} = \mathrm{W}x^{c+m}) \in \mathbb{R}^{\boldsymbol{n}}$

5. Average those **2m** embedded vectors to calculate the value of the Hidden Layer.

$$\hat{v} = \frac{\boldsymbol{v_{c-m}} + \boldsymbol{v_{c-m+1}} + \dots + \boldsymbol{v_{c+m}}}{2m}$$

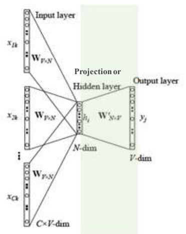
50

3 Prediction based Word representation

CBOW – Neural Network Architecture

Predict center word from (bag of) context words.

Summary of CBOW Training (Review your understanding with equations)



6. Calculate the score value for the output layer. The higher score is produced when words are closer.
$\boldsymbol{z} = \mathbf{W'} \times \hat{v} \in \mathbb{R}^{|V|}$

7. Calculate the probability using softmax
$\hat{y} = softmax\,(\boldsymbol{z}) \in \mathbb{R}^{|V|}$

8. Train the parameter matrix using **objective function.**

$$\mathrm{H}(\hat{y}, y) = -\sum_{j=1}^{|V|} y_j \, log(\hat{y}_j)$$

* Focus on minimising the value

We use an one-hot vector (one 1, the rest 0) so it will be calculated in only one.
$\mathrm{H}(\hat{y}, y) = -y_j \, log(\hat{y}_j)$

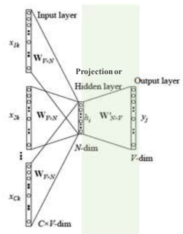
51

3 Prediction based Word representation

CBOW – Neural Network Architecture

Predict center word from (bag of) context words.

Summary of CBOW Training (Review your understanding with equations)



8-1. Optimization Objective Function can be presented:

$$\begin{aligned} minimize J &= -\log P(w_c | w_{c-m}, \dots, w_{c+m}) \\ &= -\log P(u_c | v) \\ &= -\log \frac{exp(u_c^\intercal \hat{v})}{\sum_{j=1}^{|V|} exp(u_j^\intercal \hat{v})} \\ &= -u_c^{intercal} \hat{v} + \log \sum_{j=1}^{|V|} exp(u_j^\intercal \hat{v}) \end{aligned}$$

***This optimization objective will be learned more details in the lecture 3.**

52

ARE WE DONE YET?

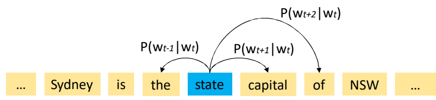
53

3 Prediction based Word representation

Skip Gram

Predict context ("outside") words (position independent) given center word

Sentence: "Sydney is the state capital of NSW"



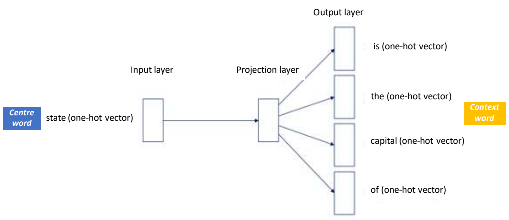
54

3 Prediction based Word representation

Skip Gram

Predict context ("outside") words (position independent) given center word

Sentence: "Sydney is the state capital of NSW"



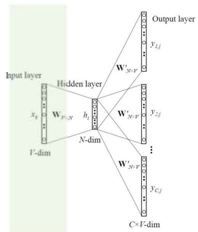
55

3 Prediction based Word representation

Skip Gram – Neural Network Architecture

Predict context ("outside") words (position independent) given center word

Summary of Skip Gram Training (Review your understanding with equations)



1. Initialise the centre word in a one-hot vector form.

$\boldsymbol{x_k} = [0,...,0,1,0,...,0]$

$\boldsymbol{x} \in \mathbb{R}^{|V|}$

2. Has two Parameter Matrices:

1) Parameter Matrix (from Input Layer to Hidden/Projection Layer)

$\mathbf{W} \in \mathbb{R}^{V\text{x}N}$

2) Parameter Matrix (to Output Layer)

$\mathbf{W'} \in \mathbb{R}^{N\text{x}V}$

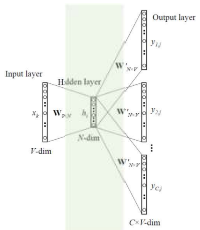
56

3 Prediction based Word representation

Skip Gram – Neural Network Architecture

Predict context ("outside") words (position independent) given center word

Summary of Skip Gram Training (Review your understanding with equations)



3. Initial words are represented in one hot vector so multiplying a **one hot vector** with $\mathbf{W}_{\mathrm{VxN}}$ will give you a 1 x N (embedded word) vector.

e.g. $[0\ \ 1\ \ 0\ \ 0] \times \begin{bmatrix} 10 & 2 & 18 \\ 15 & 22 & 3 \\ 25 & 11 & 19 \\ 4 & 7 & 22 \end{bmatrix} = [15\ \ 22\ \ 3]$

$\boldsymbol{v_c} = \mathbf{W}_{\boldsymbol{x}} \in \mathbb{R}^{\boldsymbol{n}}$ (as there is only one input)

4. Calculate the score value for the output layer by multiplying the parameter matrix **W'**

$\boldsymbol{z} = \mathbf{W'}_{\boldsymbol{v_c}}$

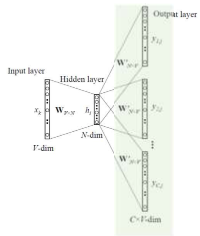
57

3 Prediction based Word representation

Skip Gram – Neural Network Architecture

Predict context ("outside") words (position independent) given center word

Summary of Skip Gram Training (Review your understanding with equations)



5. Calculate the probability using softmax

$\hat{y} = softmax\ (\boldsymbol{z})$

6. Calculate 2m probabilities as we need to predict **2m** context words.

$\hat{y}_{c-m}, \dots, \hat{y}_{c-1}, \hat{y}_{c+1}, \dots, \hat{y}_{c+m}$

and compare with the ground truth (one-hot vector)

$y^{(c-m)}, \dots, y^{(c-1)}, y^{(c+1)}, \dots, y^{(c+m)}$

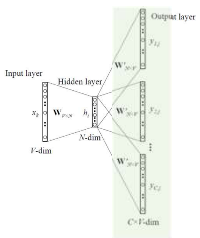
58

3 Prediction based Word representation

Skip Gram – Neural Network Architecture

Predict context ("outside") words (position independent) given center word

Summary of Skip Gram Training (Review your understanding with equations)



8. As in CBOW, use an objective function for us to evaluate the model. A key difference here is that we invoke a Naïve Bayes assumption to break out the probabilities. It is a strong naïve conditional independence assumption. Given the centre word, all output words are completely independent.

$$\begin{aligned}
\text{minimize } J &= -\log P(w_{c-m}, \dots, w_{c-1}, w_{c+1}, \dots, w_{c+m} | w_c) \\
&= -\log \prod_{j=0, j\neq m}^{2m} P(w_{c-m+j} | w_c) \\
&= -\log \prod_{j=0, j\neq m}^{2m} \frac{\exp(u_{c-m+j}^{\intercal} v_c)}{\sum_{k=1}^{|V|} \exp(u_k^{\intercal} v_c)} \\
&= -\sum_{j=0, j\neq m}^{2m} u_{c-m+j}^{\intercal} v_c + 2m \log \sum_{k=1}^{|V|} \exp(u_k^{\intercal} v_c)
\end{aligned}$$

****This optimization objective will be learned more details in the lecture 3.***

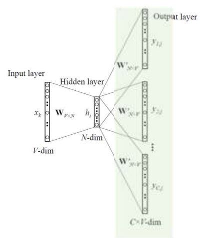
59

3 Prediction based Word representation

Skip Gram – Neural Network Architecture

Predict context ("outside") words (position independent) given center word

Summary of Skip Gram Training (Review your understanding with equations)



8-1. With this objective function, we can compute the gradients with respect to the unknown parameters and at each iteration update them via Stochastic Gradient Descent

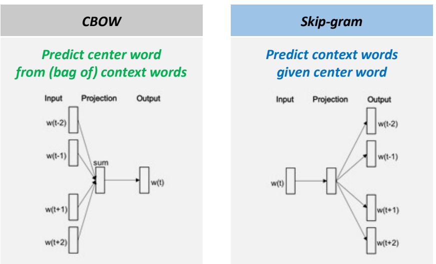
$$\begin{aligned}
J &= -\sum_{j=0, j\neq m}^{2m} \log P(u_{c-m+j} | v_c) \\
&= \sum_{j=0, j\neq m}^{2m} H(\hat{y}, y_{c-m+j})
\end{aligned}$$

****This Stochastic Gradient Descent will be learned details in the lecture 3.***

60

3 Prediction based Word representation

CBOW vs Skip Gram Overview



61

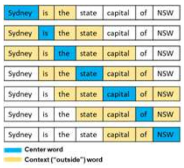
3 Prediction based Word representation

Key Parameter (1) for Training methods: Window Size

Different tasks are served better by different window sizes.

Smaller window sizes (2-15) lead to embeddings where high similarity scores between two embeddings indicates that the words are interchangeable.

Larger window sizes (15-50, or even more) lead to embeddings where similarity is more indicative of relatedness of the words



62

3 Prediction based Word representation

Key Parameter (2) for Training methods: Negative Samples

Note that the summation over |V| is computationally huge!

Negative samples to our dataset – samples of words that are not neighbors

Negative sample: 2

Input word	*Output word*	*Target*
eat	mango	1
eat	exam	0
eat	tobacco	0

**1= Appeared, 0=Not Appeared*

Negative sample: 5

Input word	*Output word*	*Target*
eat	mango	1
eat	exam	0
eat	tobacco	0
eat	pool	0
eat	supervisor	0

The original paper prescribes **5-20 as being a good number of negative samples**. It also states that **2-5 seems to be enough when you have a large enough dataset**.

63

3 Prediction based Word representation

Key Parameter (2) for Training methods: Negative Samples

The number of negative samples is another factor of the training process.

Negative samples to our dataset – samples of words that are not neighbors

Negative sample: 2

Input word	*Output word*	*Target*
eat	mango	1
eat	exam	0
eat	tobacco	0

**1= Appeared, 0=Not Appeared*

Negative sample: 5

Input word	*Output word*	*Target*
eat	mango	1
eat	exam	0
eat	tobacco	0
eat	pool	0
eat	supervisor	0

How to select the Negative Sample?

The "negative samples" are selected using a "unigram distribution", where more frequent words are more likely to be selected as negative samples.

$$P(w_i) = \frac{f(w_i)}{\sum_{j=0}^{n}(f(w_j))}$$

The probability for picking the word (w_i) would be equal to the number of times (w_i) appears in the corpus, divided the total number of word occurs in the corpus.

64

3 Prediction based Word representation

Word2Vec Overview

Word2vec (Mikolov et al. 2013) is a framework for learning word vectors

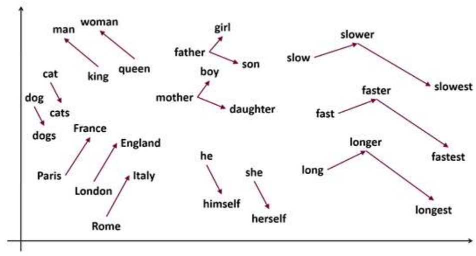
Idea:

- Have a large corpus of text
- Every word in a fixed vocabulary is represented by a vector
- Go through each position *t* in the text, which has a center word *c* and context ("outside") words *o*
- Use the similarity of the word vectors for c and o to calculate the probability of o given c (or vice versa)
- Keep adjusting the word vectors to maximize this probability

65

3 Prediction based Word representation

Let's try some Word2Vec!



Gensim: https://radimrehurek.com/gensim/models/word2vec.html
Resources: https://wit3.fbk.eu/
https://github.com/3Top/word2vec-api#where-to-get-a-pretrained-models

66

3 Prediction based Word representation

Limitation of Word2Vec

Issue#1: Cannot cover the morphological similarity

- Word2vec represents every word as an independent vector, even though many words are morphologically similar, like: teach, teacher, teaching

Issue#2: Hard to conduct embedding for rare words

- Word2vec is based on the Distribution hypothesis. Works well with the frequent words but does not embed the rare words.

(same concept with the under-fitting in machine learning)

Issue#3: Cannot handle the Out-of-Vocabulary (OOV)

- Word2vec does not work at all if the word is not included in the Vocabulary

67

3 Prediction based Word representation

FastText

- Deal with this Word2Vec Limitation
- Another Way to transfer *WORDS* to *VECTORS*

fastText

- FastText is a library for learning of word embeddings and text classification created by Facebook's AI Research lab. The model allows to create an unsupervised learning or supervised learning algorithm for obtaining vector representations for words.

- Extension to Word2Vec
  - Instead of feeding individual words into the Neural Network, FastText breaks words into several n-grams (sub-words)

https://fasttext.cc/

68

3 Prediction based Word representation

FastText with N-gram Embeddings

- N-grams are simply all combinations of adjacent words or letters of length n that you can find in your source text. For example, given the word *apple*, all 2-grams (or "bigrams") are ***ap, pp, pl***, and ***le***
- The tri-grams (n=3) for the word apple is ***app, ppl***, and ***ple*** (ignoring the starting and ending of boundaries of words). The word embedding vector for apple will be the sum of all these n-grams.

apple → **ap** **pp** **pl** **le**

apple → **app** **ppl** **ple**

- After training the Neural Network (either with skip-gram or CBOW), we will have word embeddings for all the n-grams given the training dataset.
- Rare words can now be properly represented since it is highly likely that some of their n-grams also appears in other words.

https://fasttext.cc/

69

3 Prediction based Word representation

Word2Vec VS FastText

Find synonym with Word2vec

```
from gensim.models import Word2Vec
cbow_model = Word2Vec(sentences=result, size=100, window=5, min_count=5, workers=4, sg=0)

a=cbow_model.wv.most_similar("electrofishing")
pprint.pprint(a)
```

Find synonym with FastText

```
from gensim.models import FastText
FT_model = FastText(sentences=result, size=100, window=5, min_count=5, workers=4, sg=0)

a=FT_model.wv.most_similar("electrofishing")
pprint.pprint(a)
```

electrofishing

https://fasttext.cc/

70

3 Prediction based Word representation

Global Vectors (GloVe)

- Deal with this Word2Vec Limitation

*"Methods like skip-gram may do better on the analogy task, but they poorly utilize the statistics of the corpus since they train on separate local context windows instead of on **global co-occurrence counts**."*

(PeddingLon et al., 2014)

- Focus on the Co-occurrence

Probability and Ratio	$k = solid$	$k = gas$	$k = water$	$k = fashion$
$P(k\|ice)$	1.9×10^{-4}	6.6×10^{-5}	3.0×10^{-3}	1.7×10^{-5}
$P(k\|steam)$	2.2×10^{-5}	7.8×10^{-4}	2.2×10^{-3}	1.8×10^{-5}
$P(k\|ice)/P(k\|steam)$	8.9	8.5×10^{-2}	1.36	0.96

e.g. P(k | i) *k=context words, i =centre words*

https://nlp.stanford.edu/projects/glove/

71

3 Prediction based Word representation

Limitation of Prediction based Word Representation

- I like ______

apple *banana* *fruit*

- Training dataset reflect the word representation result
  - The word similarity of the word 'software' the model learned by Google News corpus can be different from the one from Twitter.

https://nlp.stanford.edu/projects/glove/

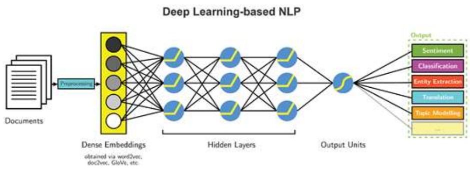
72

4 NEXT WEEK PREVIEW…

Word Embeddings

- Finalisation!

Machine Learning/ Deep Learning for Natural Language Processing



73

/ Reference

Reference for this lecture

- Deng, L., & Liu, Y. (Eds.). (2018). Deep Learning in Natural Language Processing. Springer.
- Rao, D., & McMahan, B. (2019). Natural Language Processing with PyTorch: Build Intelligent Language Applications Using Deep Learning. " O'Reilly Media, Inc.".
- Manning, C. D., Manning, C. D., & Schütze, H. (1999). Foundations of statistical natural language processing. MIT press.
- Manning, C 2017, Introduction and Word Vectors, Natural Language Processing with Deep Learning, lecture notes, Stanford University
- Images: http://jalammar.github.io/illustrated-word2vec/
- Goldberg, Lewis R. 1992, "The development of markers for the Big-Five factor structure." Psychological assessment 4.1: 26.

Word2vec

- Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781.
- Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. In Advances in neural information processing systems (pp. 3111-3119).

FastText

- Bojanowski, P., Grave, E., Joulin, A., & Mikolov, T. (2017). Enriching word vectors with subword information. Transactions of the Association for Computational Linguistics, 5, 135-146.
- Mikolov, T., Grave, E., Bojanowski, P., Puhrsch, C., & Joulin, A. (2017). Advances in pre-training distributed word representations. arXiv preprint arXiv:1712.09405.

74