COMP5046
Natural Language Processing

Lecture 2: Word Embeddings and Representation

Semester 1, 2020

School of Computer Science

The University of Sydney, Australia

THE UNIVERSITY OF SYDNEY

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0 LECTURE PLAN

THE UNIVERSITY OF SYDNEY

Lecture 2: Word Embeddings and Representation

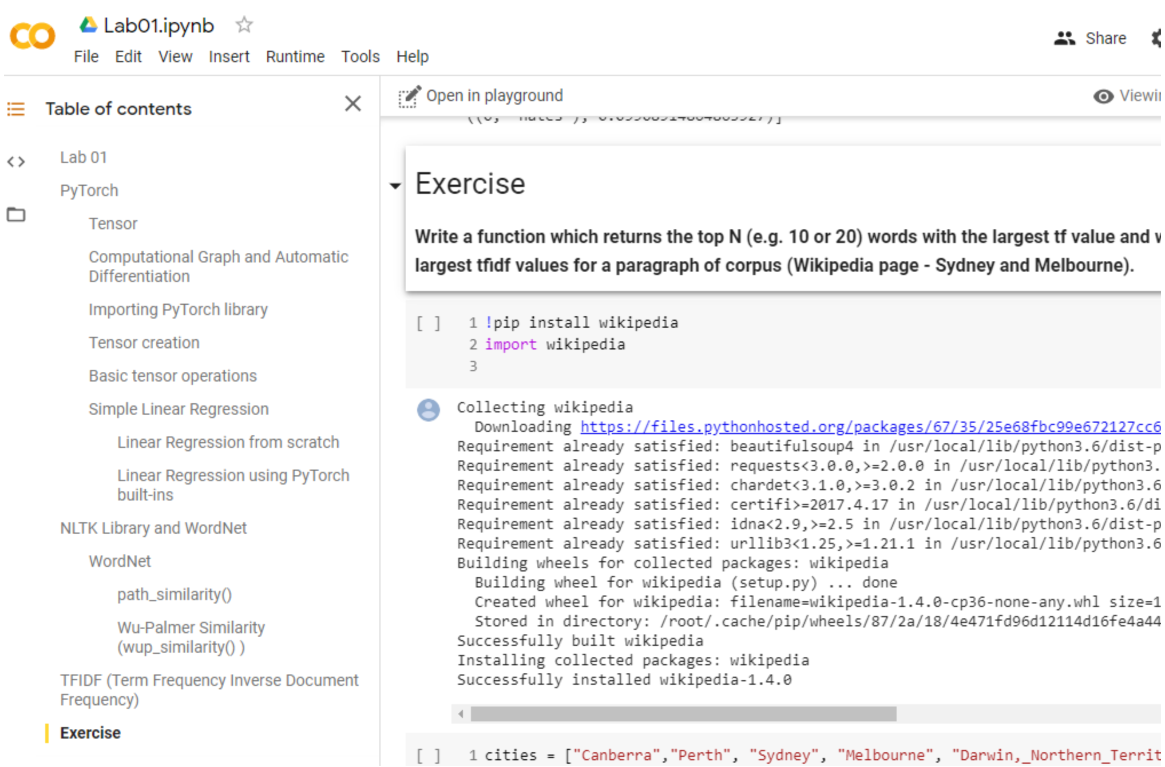
1. **Lab Info**
2. Previous Lecture Review
    1. Word Meaning and WordNet
    2. Count based Word Representation
3. Prediction based Word Representation
    1. Introduction to the concept ‘Prediction’
    2. Word2Vec
    3. FastText
    4. Glove
4. Next Week Preview

1 Info: Lab Exercise

What do we do during Labs?

In Labs, Students will use Google Co Lab

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.



1 Info: Lab Exercise

Submissions

How to Submit

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

When to Submit

Students must submit the Lab 1 in Week2 by the day before 5pm in Week3.

- If you were in **Tuesday 4pm or 5pm or 6pm** Lab, you should submit your lab1 work by **Monday 6pm in week3**.
- If you were in **Wednesday 4pm or 5pm Lab**, you should submit your lab1 work by **Tuesday 6pm in week3**.

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Previous Lecture…

How to represent the meaning of the word?

Definition: meaning (Collins dictionary).

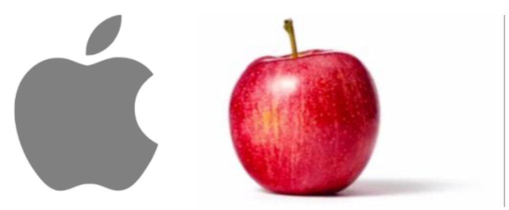
- the idea that it represents, and which can be explained using other words.
- the thoughts or ideas that are intended to be expressed by it.

Commonest linguistic way of thinking of meaning:

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

“Computer”

“Apple”



Previous Lecture…

Problem with one-hot vectors

Problem #1. No word similarity representation

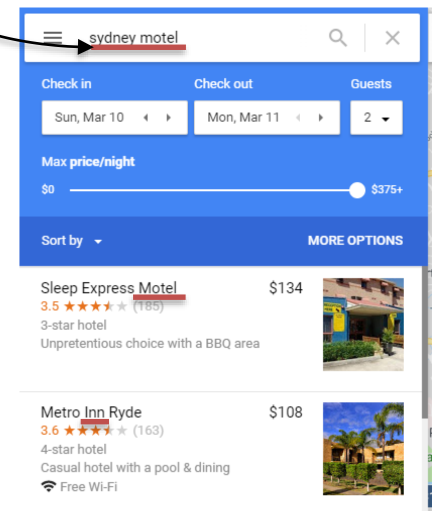
Example: in web search, if user searches for “Sydney motel”, we would like to match documents containing “Sydney Inn”

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.

Previous Lecture…

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*

3 COUNT based WORD REPRESENTATION

Term Frequency Inverse Document Frequency

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

$1+df_i$

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

Document #1: I like apple

Document #2: I like banana

Document #3: Sweet and yellow banana banana

Document #4: Sweet fruit

	and	apple	banana	fruit	I	like	sweet	yellow
D#1	0	0.693147	0	0	0.287682	0.287682	0	0
D#2	0	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0	0
D#3	0.693147	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.287682	0.693147
D#4	0	0	0	0.693147	0	0	0.287682	0

What if we just use Term Frequency?

3 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]

3 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

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

maybe a low-dimensional vector?

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Prediction based Word representation

Let’s get familiar with using vectors to represent things

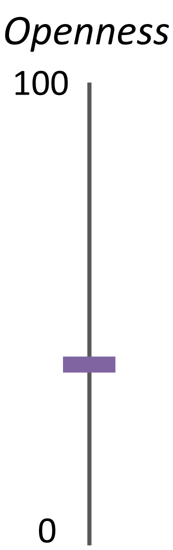
Assume that you are taking a personality test (the Big Five Personality Traits test)

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

Jane

Openness

40				



Prediction based Word representation

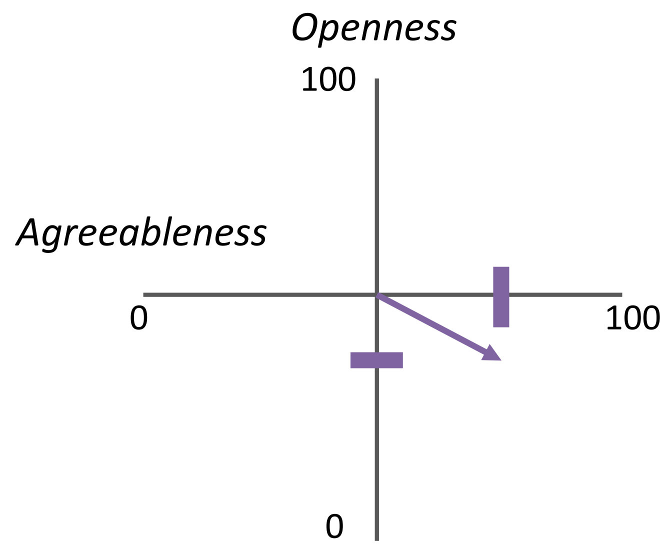
Let’s get familiar with using vectors to represent things

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

Jane

Openness	Agreeableness			
40	70			



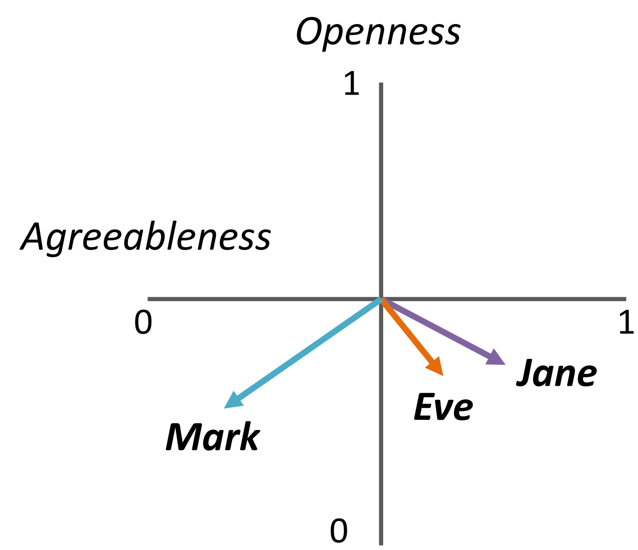
Prediction based Word representation

Let’s get familiar with using vectors to represent things

Assume that you are taking a <u>personality test (the Big Five Personality Traits test)</u>

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			



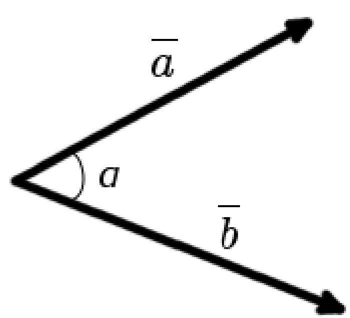
3 Prediction based Word representation

Let’s get familiar with using vectors to represent things

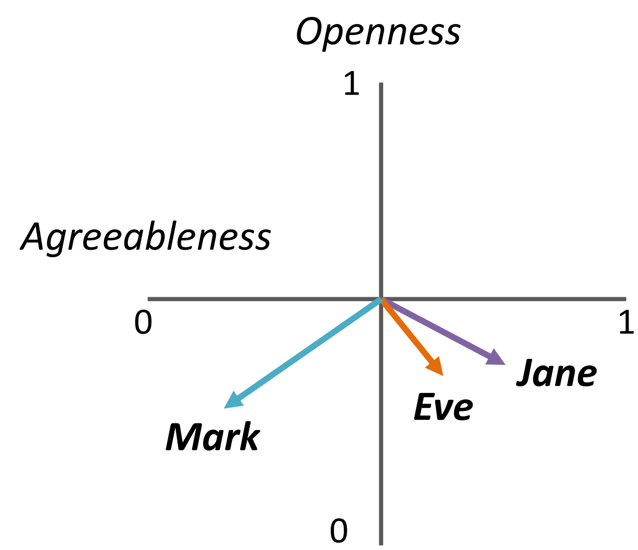
Which of two people (Mark or Eve) is more similar to Jane?

Cosign Similarity

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



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



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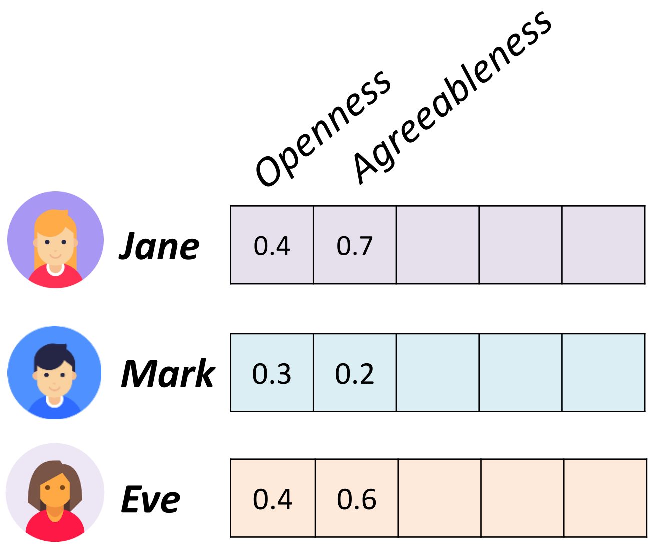
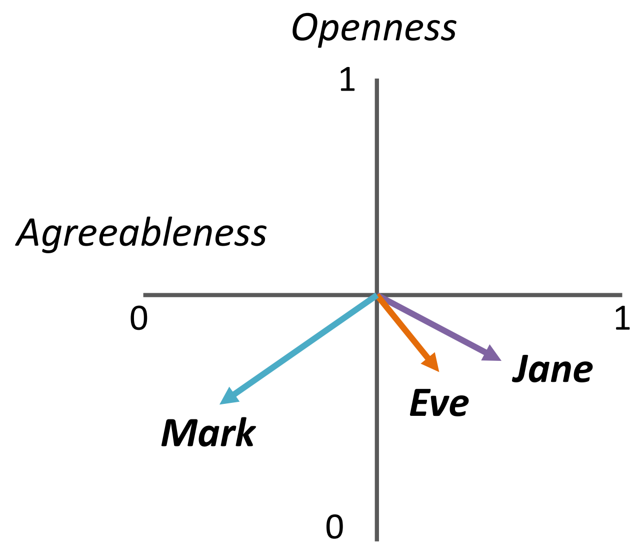
Let’s get familiar with using vectors to represent things

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





$$\cos\left(\overset{Jane}{\begin{bmatrix}0.4 & 0.7\end{bmatrix}}, \overset{Mark}{\begin{bmatrix}0.3 & 0.2\end{bmatrix}}\right) \approx 0.89$$

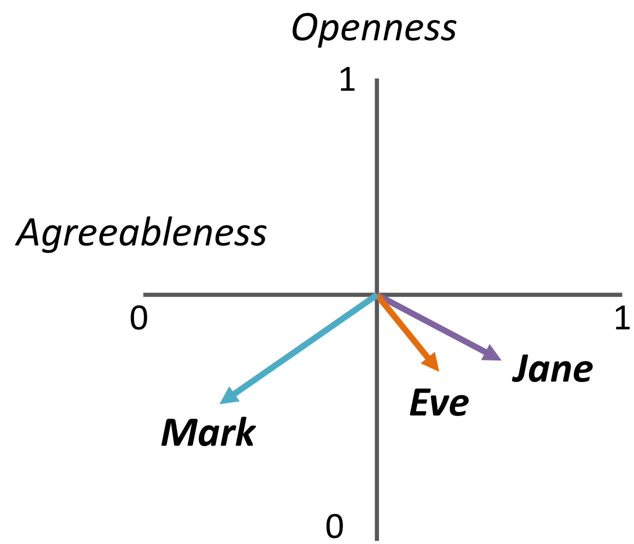
$$\cos\left(\overset{Jane}{\begin{bmatrix}0.4 & 0.7\end{bmatrix}}, \overset{Eve}{\begin{bmatrix}0.4 & 0.6\end{bmatrix}}\right) \approx 0.99$$

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



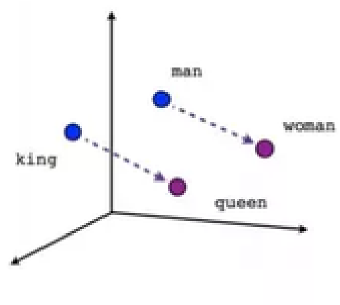
With these embeddings,

1.Represent things as vectors of fixed numbers!

2.Easily calculate the similarity between vectors

3 Prediction based Word representation

Remember? The Word2Vec Demo!

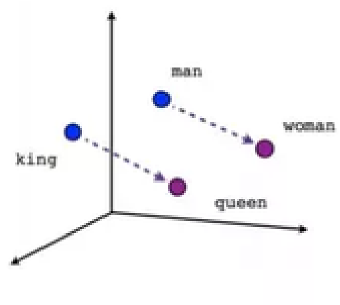


This is a word embedding for the word "king"

3

Prediction based Word representation

Remember? The Word2Vec Demo!



This is a word embedding for the word "king"

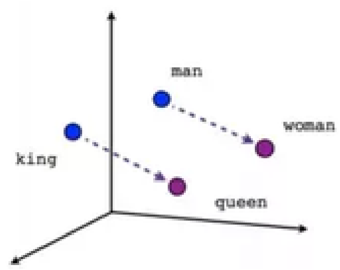
** Trained by Wikipedia Data, 50-dimension GloVe Vector*

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]

Prediction based Word representation

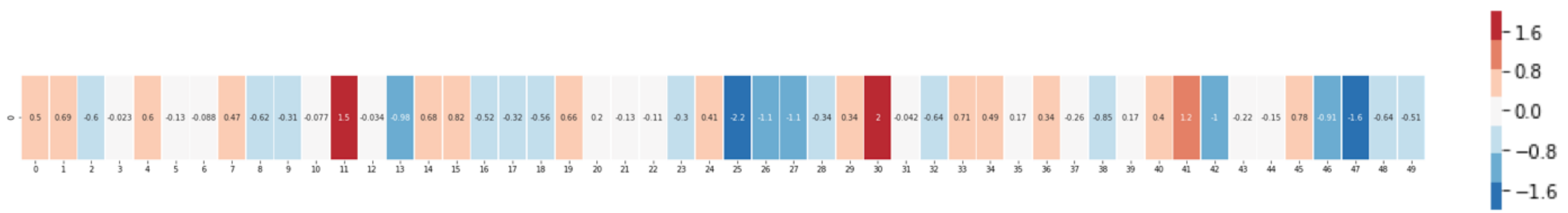
Remember? The Word2Vec Demo!



This is a word embedding for the word "<u>king</u>"

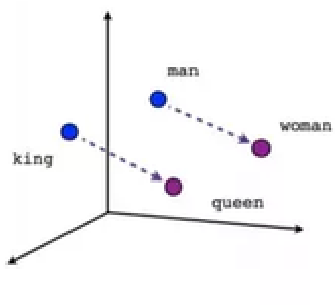
** Trained by Wikipedia Data, 50-dimension GloVe Vector*

<u>king</u>

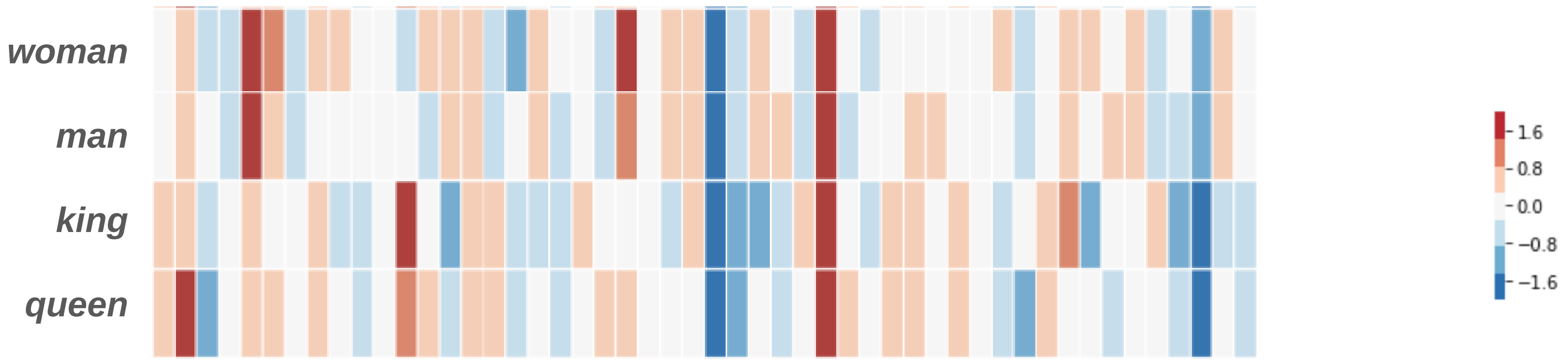


3 Prediction based Word representation

Remember? The Word2Vec Demo!

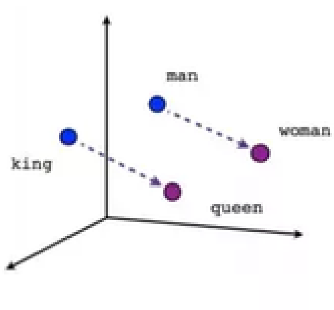


Compare with Woman, Man, King, and Queen

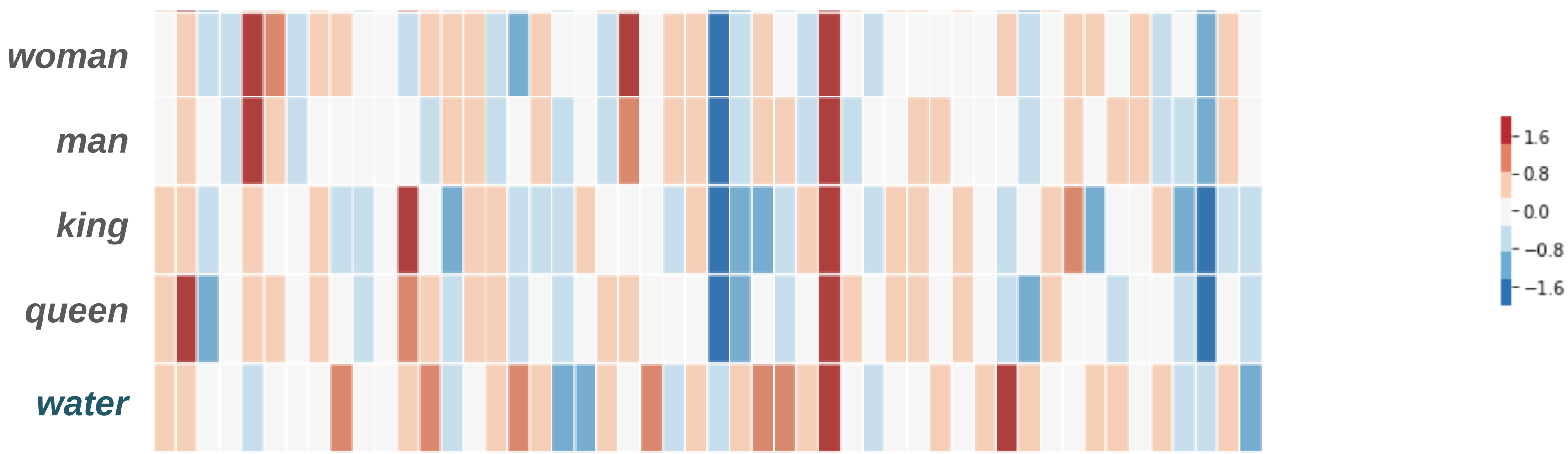


3 Prediction based Word representation

Remember? The Word2Vec Demo!

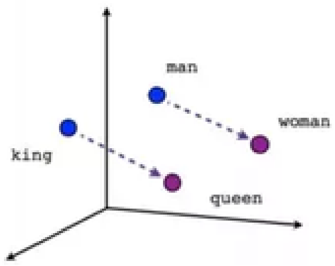


Compare with Woman, Man, King, Queen, and Water



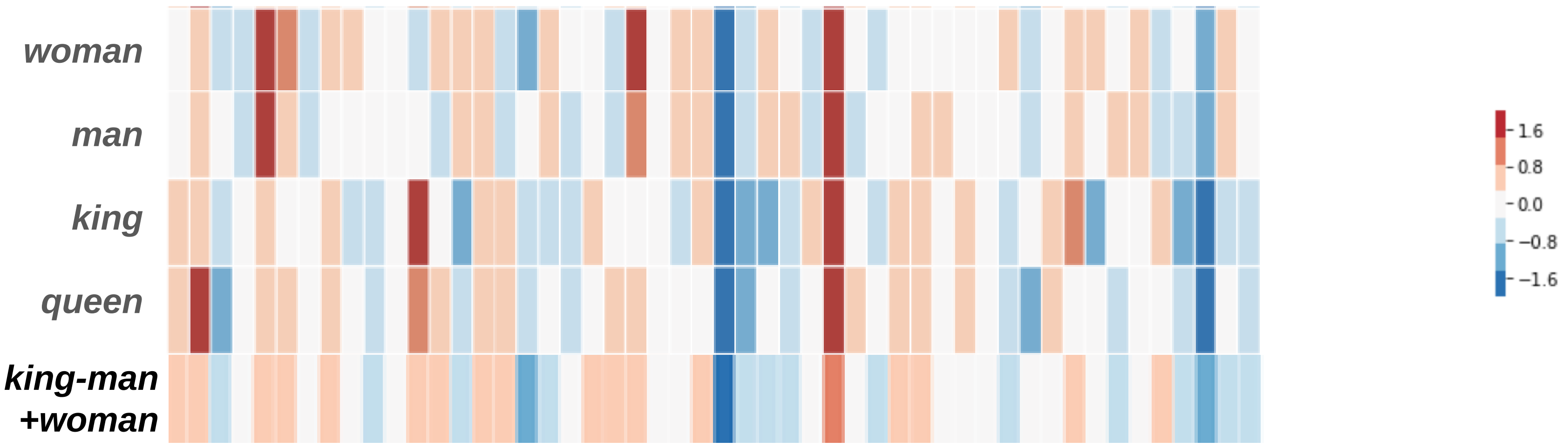
Prediction based Word representation

Remember? The Word2Vec Demo!



king – man + woman ≈ queen?

Word Algebra



How to make dense vectors for word representation

3 Prediction based Word representation

How to make dense vectors for word representation

Prof. John Rupert Firth

"You shall know a word by the company it keeps"

— (Firth, J. R. 1957:11)

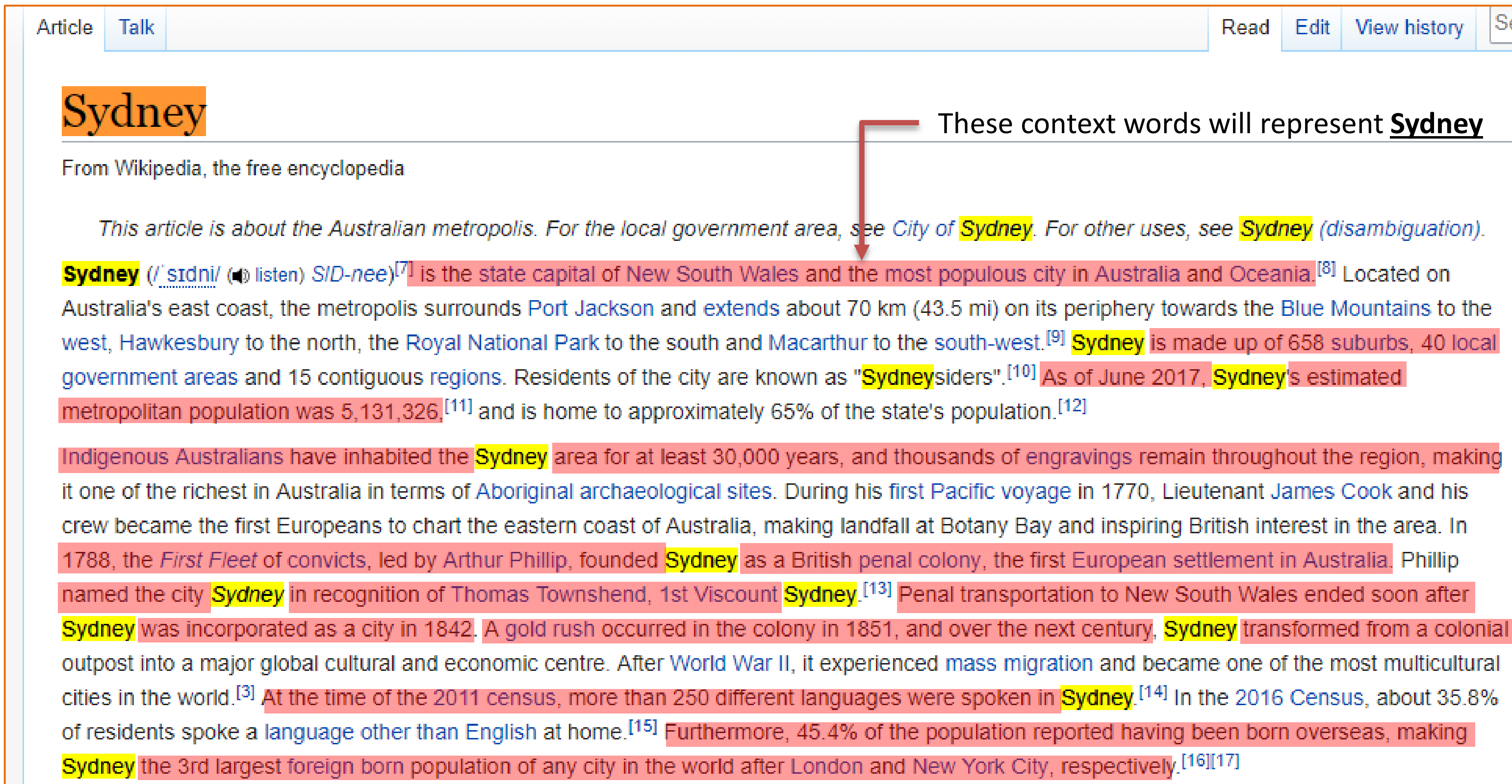
*Prof. Firth is noted for drawing attention to the **context-dependent nature of meaning** with his notion of '**context of situation**', and his work on collocational meaning is widely acknowledged in the field of **distributional semantics**.*

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


Article Talk Read Edit View history

Sydney

These context words will represent **Sydney**

From Wikipedia, the free encyclopedia

This article is about the Australian metropolis. For the local government area, see City of Sydney. For other uses, see Sydney (disambiguation).

Sydney (/ˈsɪdni/ listen) *SID-nee*)[7] is the state capital of New South Wales and the most populous city in Australia and Oceania.[8] Located on Australia's east coast, the metropolis surrounds Port Jackson and extends about 70 km (43.5 mi) on its periphery towards the Blue Mountains to the west, Hawkesbury to the north, the Royal National Park to the south and Macarthur to the south-west.[9] Sydney is made up of 658 suburbs, 40 local government areas and 15 contiguous regions. Residents of the city are known as "Sydneysiders".[10] As of June 2017, Sydney's estimated metropolitan population was 5,131,326,[11] and is home to approximately 65% of the state's population.[12]

Indigenous Australians have inhabited the Sydney area for at least 30,000 years, and thousands of engravings remain throughout the region, making it one of the richest in Australia in terms of Aboriginal archaeological sites. During his first Pacific voyage in 1770, Lieutenant James Cook and his crew became the first Europeans to chart the eastern coast of Australia, making landfall at Botany Bay and inspiring British interest in the area. In 1788, the *First Fleet* of convicts, led by Arthur Phillip, founded Sydney as a British penal colony, the first European settlement in Australia. Phillip named the city *Sydney* in recognition of Thomas Townshend, 1st Viscount Sydney.[13] Penal transportation to New South Wales ended soon after Sydney was incorporated as a city in 1842. A gold rush occurred in the colony in 1851, and over the next century, Sydney transformed from a colonial outpost into a major global cultural and economic centre. After World War II, it experienced mass migration and became one of the most multicultural cities in the world.[3] At the time of the 2011 census, more than 250 different languages were spoken in Sydney.[14] In the 2016 Census, about 35.8% of residents spoke a language other than English at home.[15] Furthermore, 45.4% of the population reported having been born overseas, making Sydney the 3rd largest foreign born population of any city in the world after London and New York City, respectively.[16][17]

3 Prediction based Word representation

How can we train the word representation to machine?

Neural Network! (Machine Learning)

Article Talk Read Edit View history Sea

Sydney

These context words will represent **Sydney**

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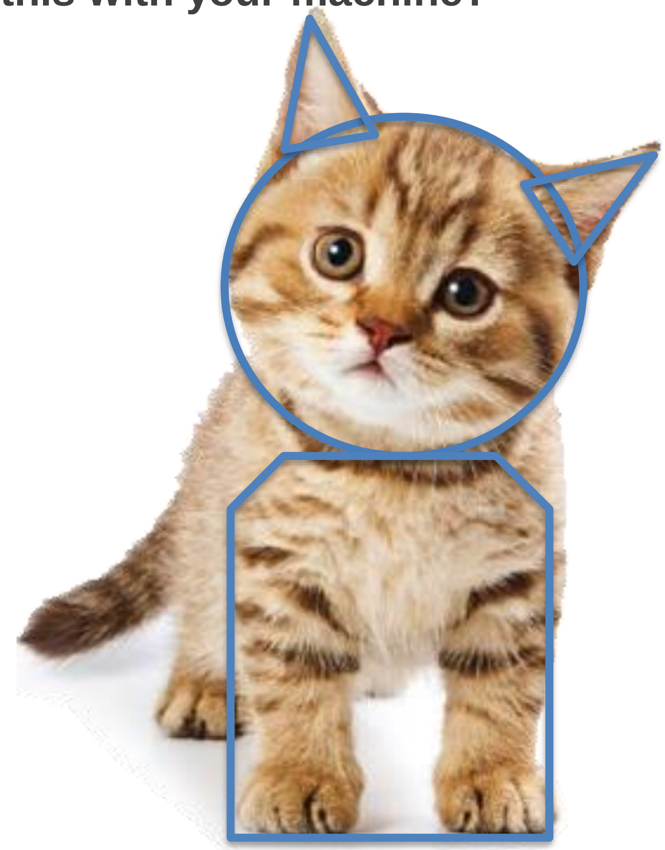
Brief in Machine Learning!

Machine Learning

How to classify this with your machine?



Object: CAT

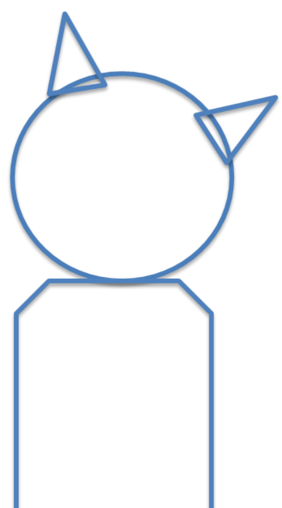
Brief in Machine Learning!

Computer System

Data

def prediction(image as input):
...program...
return result

Result

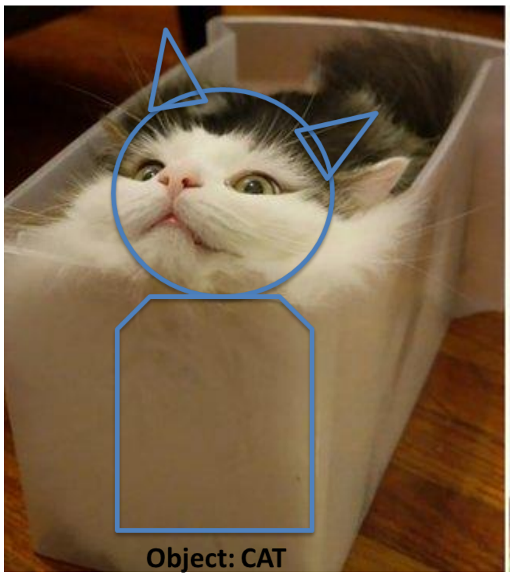


Object: CAT

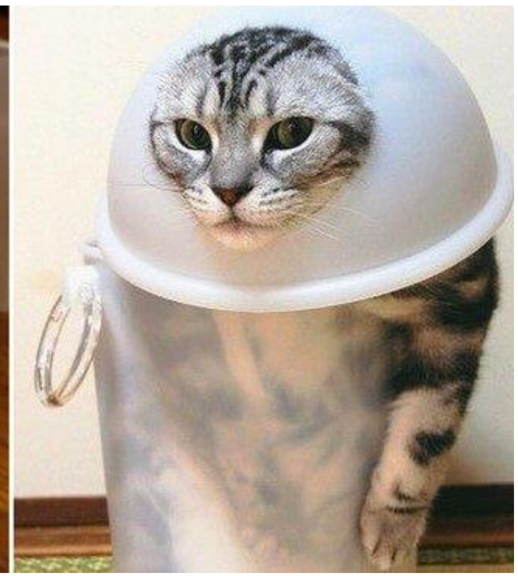
Object: CAT

Brief in Machine Learning!

Can we classify this with the computer system?



Object: ???



Object: ???

Object: ???

Brief in Machine Learning!

Computer System VS Machine Learning

Data

def prediction(image as input):
...program...
return result

Result

Data+Result

Data: Result
Image 1: Dog
Image 2: Cat
Image 3: Dog
Image 4: Cat
Image 5: Dog
...

training

Pattern

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

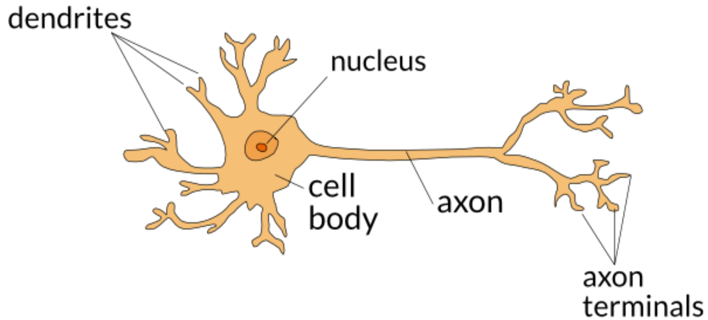
x_i	Input	words (indices or vectors), sentences, documents, etc.
y_i	class	What we try to classify/predict

Brief in Machine Learning!

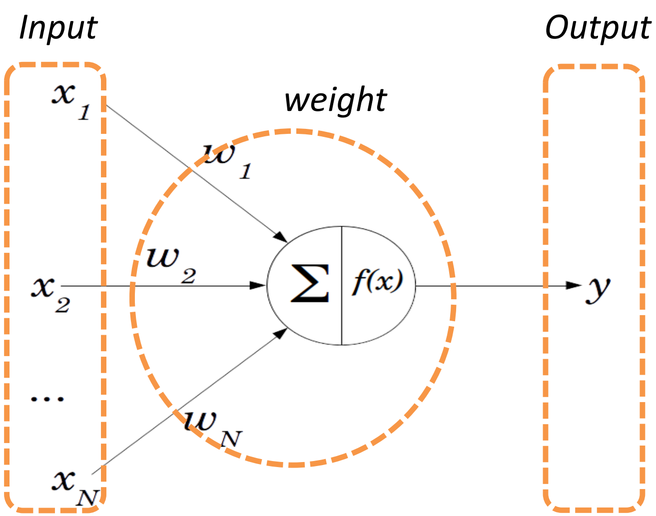
Neural Network and Deep Learning

Neuron and Perceptron

Neuron



Perceptron



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

3 Prediction based Word representation

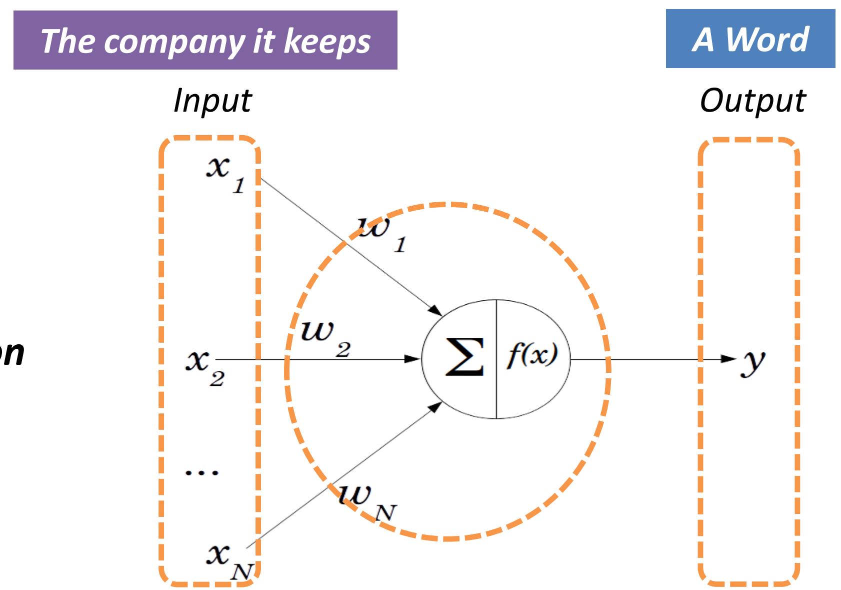
Neural Network and Deep Learning in Word Representation

"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?

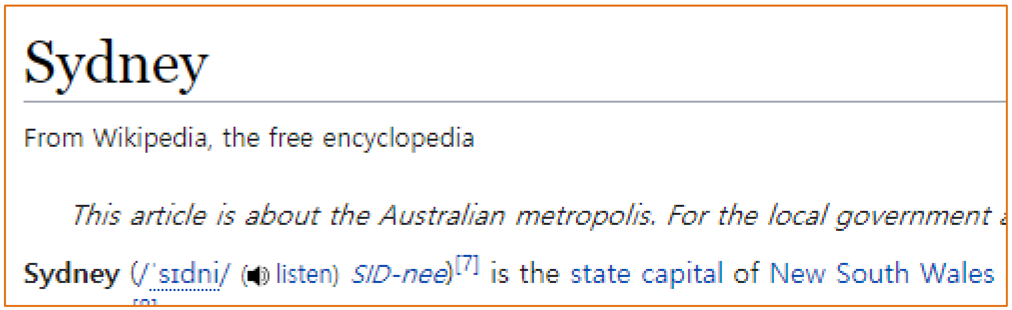
Perceptron



3 Prediction based Word representation

Neural Network and Deep Learning in Word Representation

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


Sydney

From Wikipedia, the free encyclopedia

This article is about the Australian metropolis. For the local government

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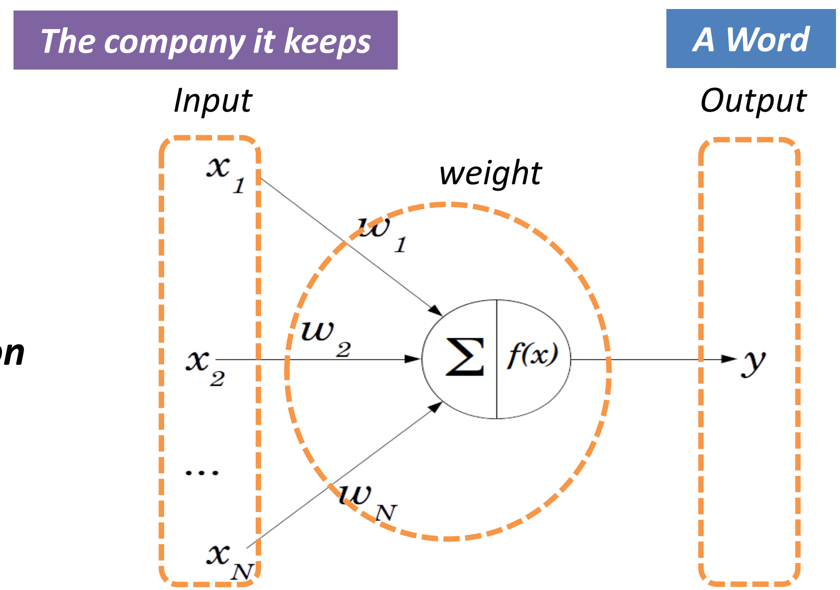

Perceptron

Prediction based Word representation

Neural Network and Deep Learning in Word Representation

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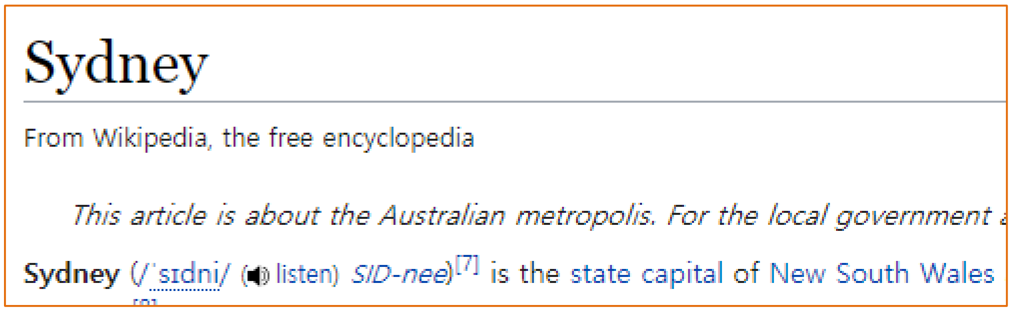
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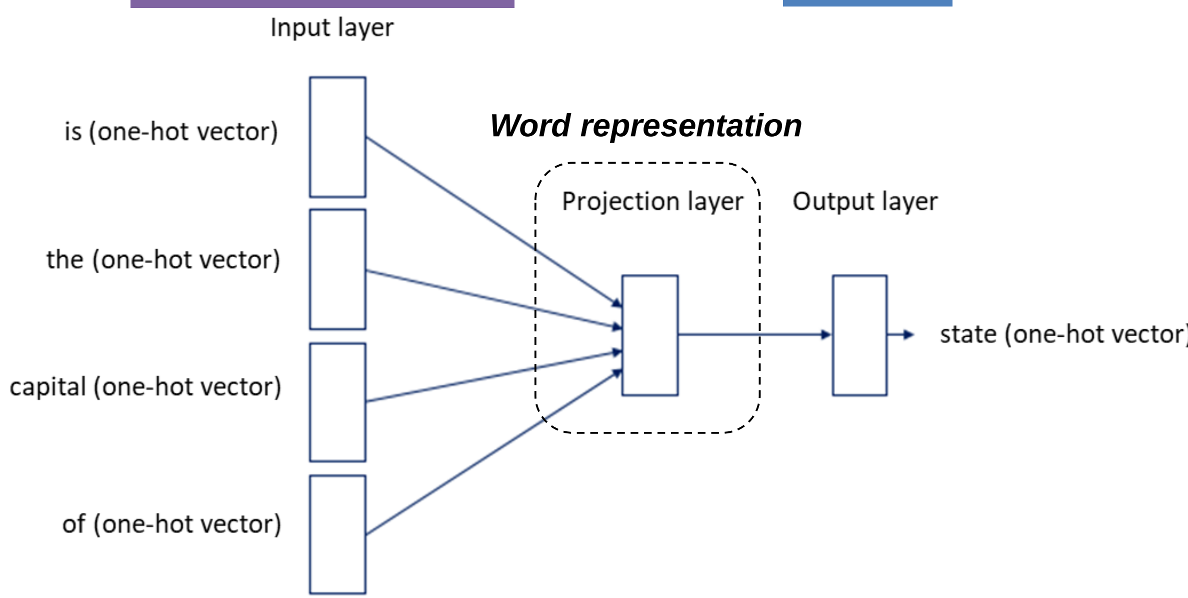
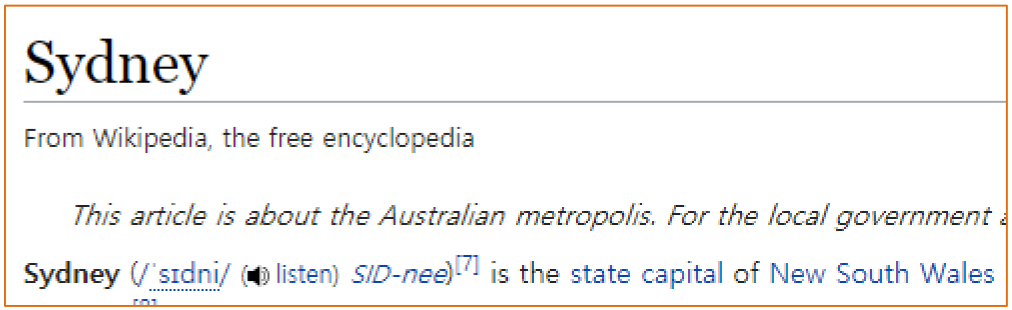
The company it keeps ***A Word***



3 Prediction based Word representation

Neural Network and Deep Learning in Word Representation

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

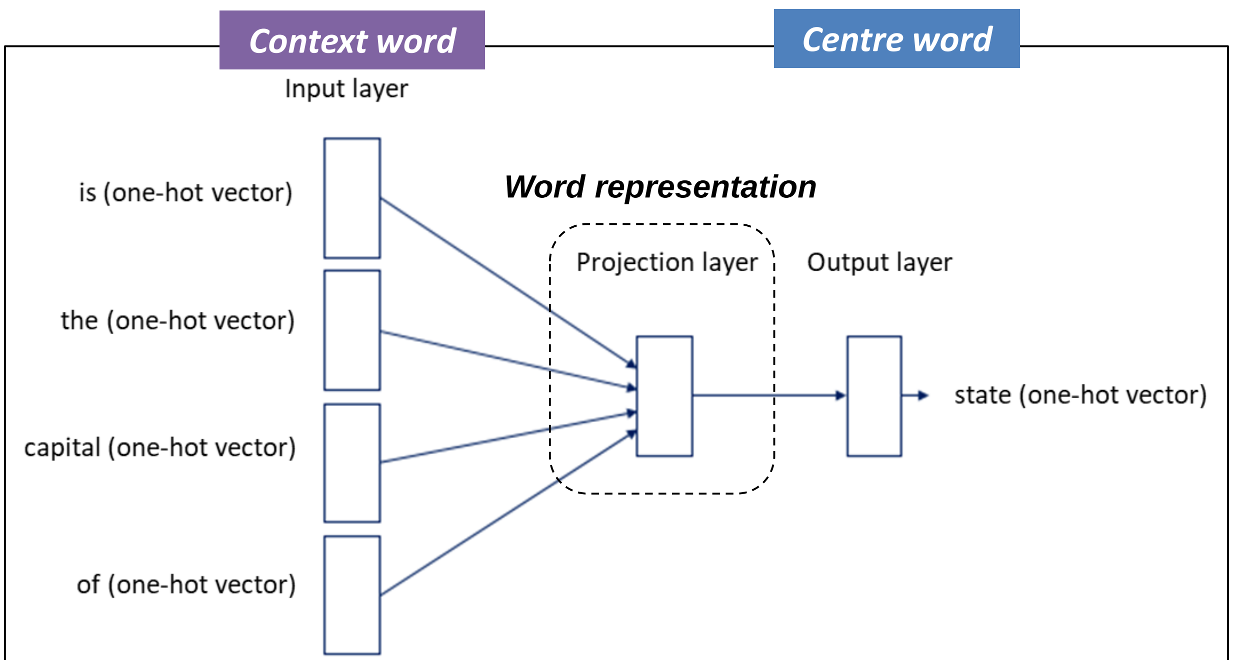

Sydney

From Wikipedia, the free encyclopedia

This article is about the Australian metropolis. For the local government

Sydney (/ˈsɪdni/ listen) *SID-nee*)[7] is the state capital of New South Wales

Word2Vec



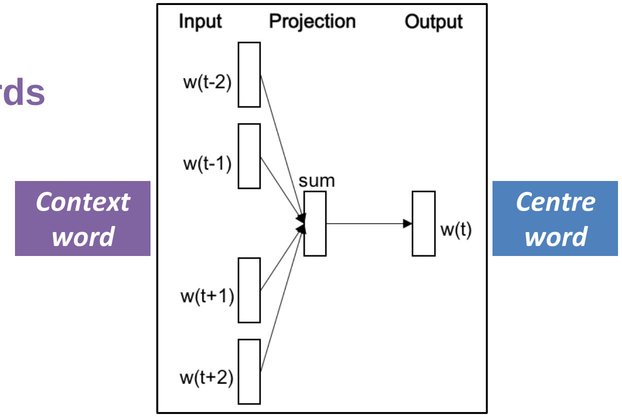
3 Prediction based Word representation

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**



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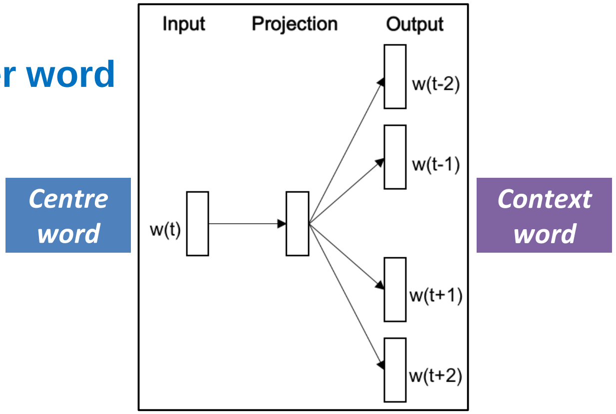
2. Continuous Skip-gram

Predict **context ("outside") words** **given** **center word**



Prediction based Word representation

Word2Vec with Continuous Bag of Words (CBOW)

Predict center word from (bag of) context words

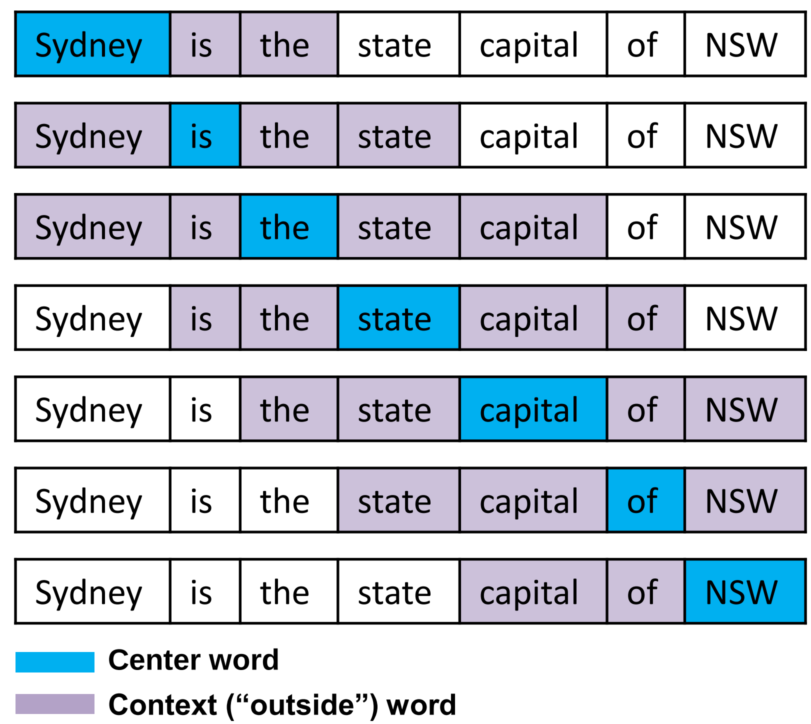
Sentence: “Sydney is the state capital of NSW”

Aim

- Predict the center word

Setup

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



4 Prediction based Word representation

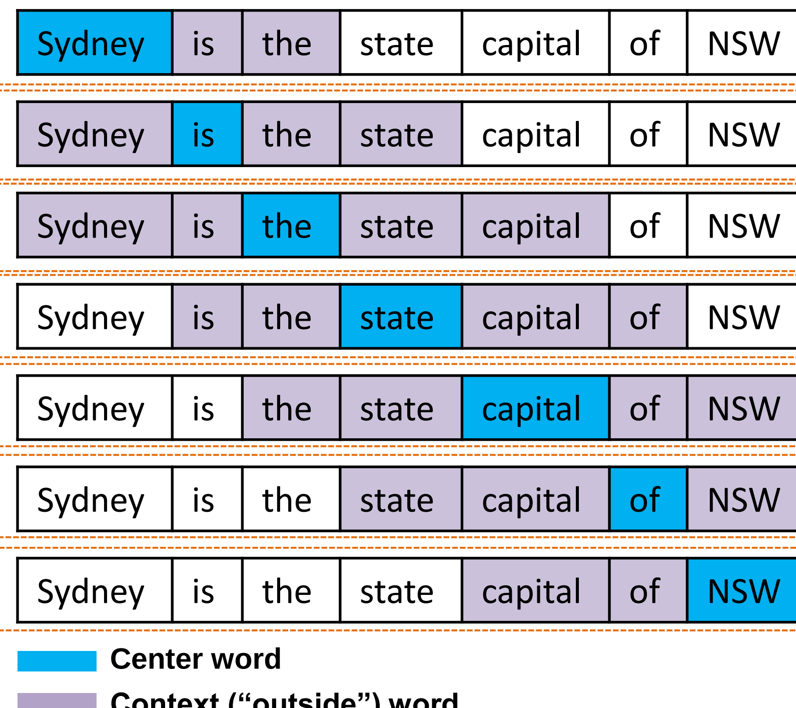
Word2Vec with Continuous Bag of Words (CBOW)

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]
[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]
[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]
[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]
[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]
[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]
[0,0,0,0,0,0,1]	[0,0,0,0,1,0,0], [0,0,0,0,0,1,0]

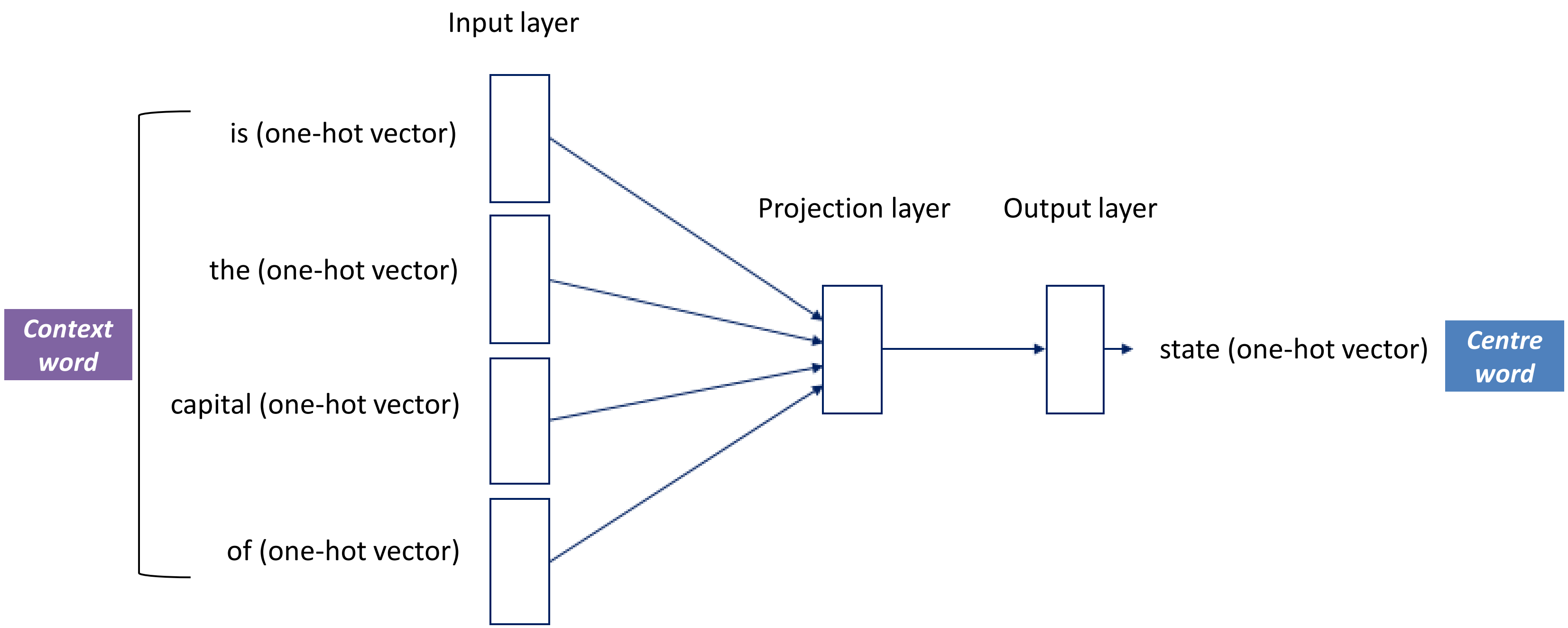


Prediction based Word representation

CBOW – Neural Network Architecture

Predict center word from (bag of) context words

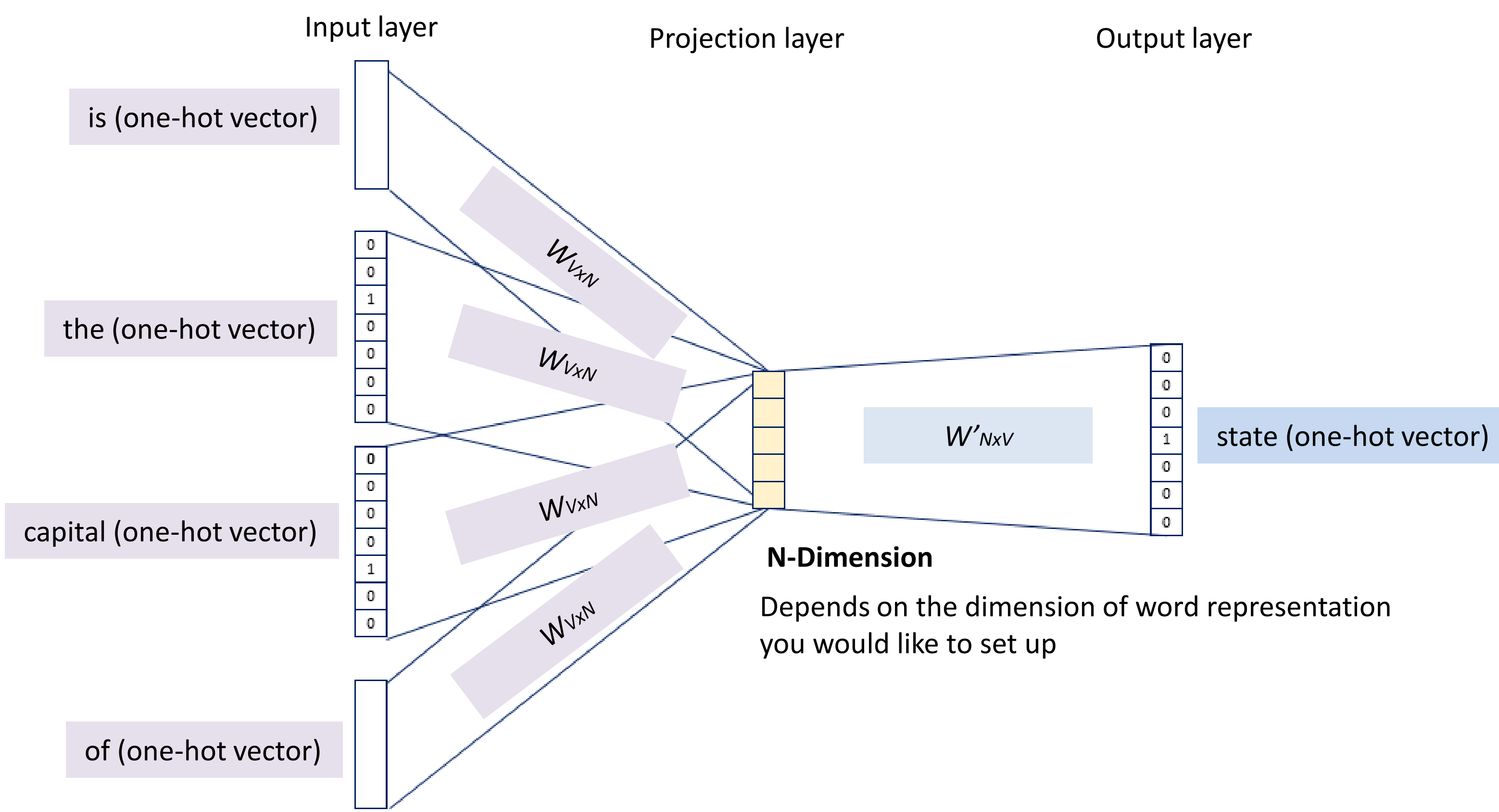
Sentence: "Sydney is the state capital of NSW"



CBOW – Neural Network Architecture

Predict center word from (bag of) context words

Sentence: "Sydney is the state capital of NSW"

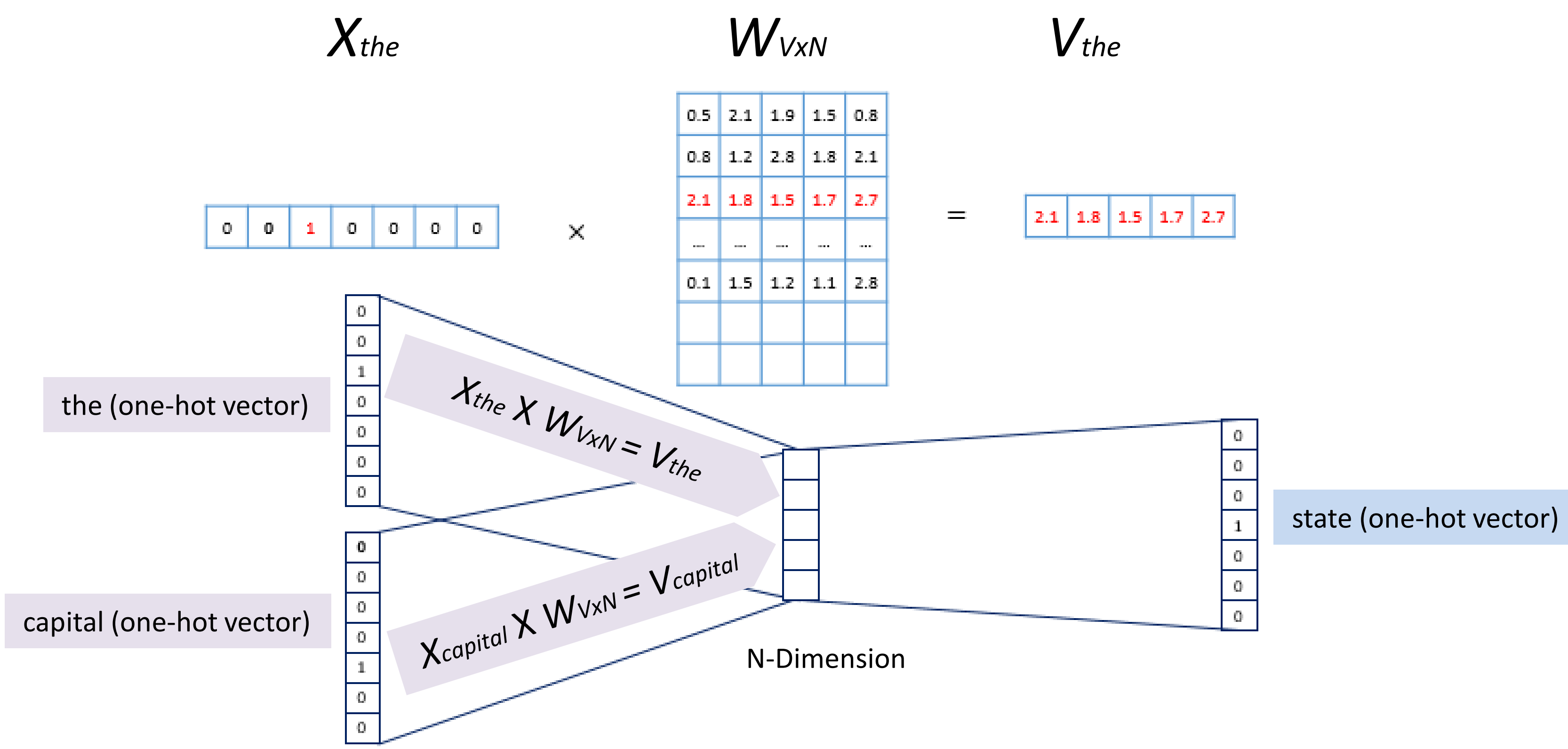


4 Prediction based Word representation

CBOW – Neural Network Architecture

Predict center word from (bag of) context words

Sentence: “Sydney is the state capital of NSW”

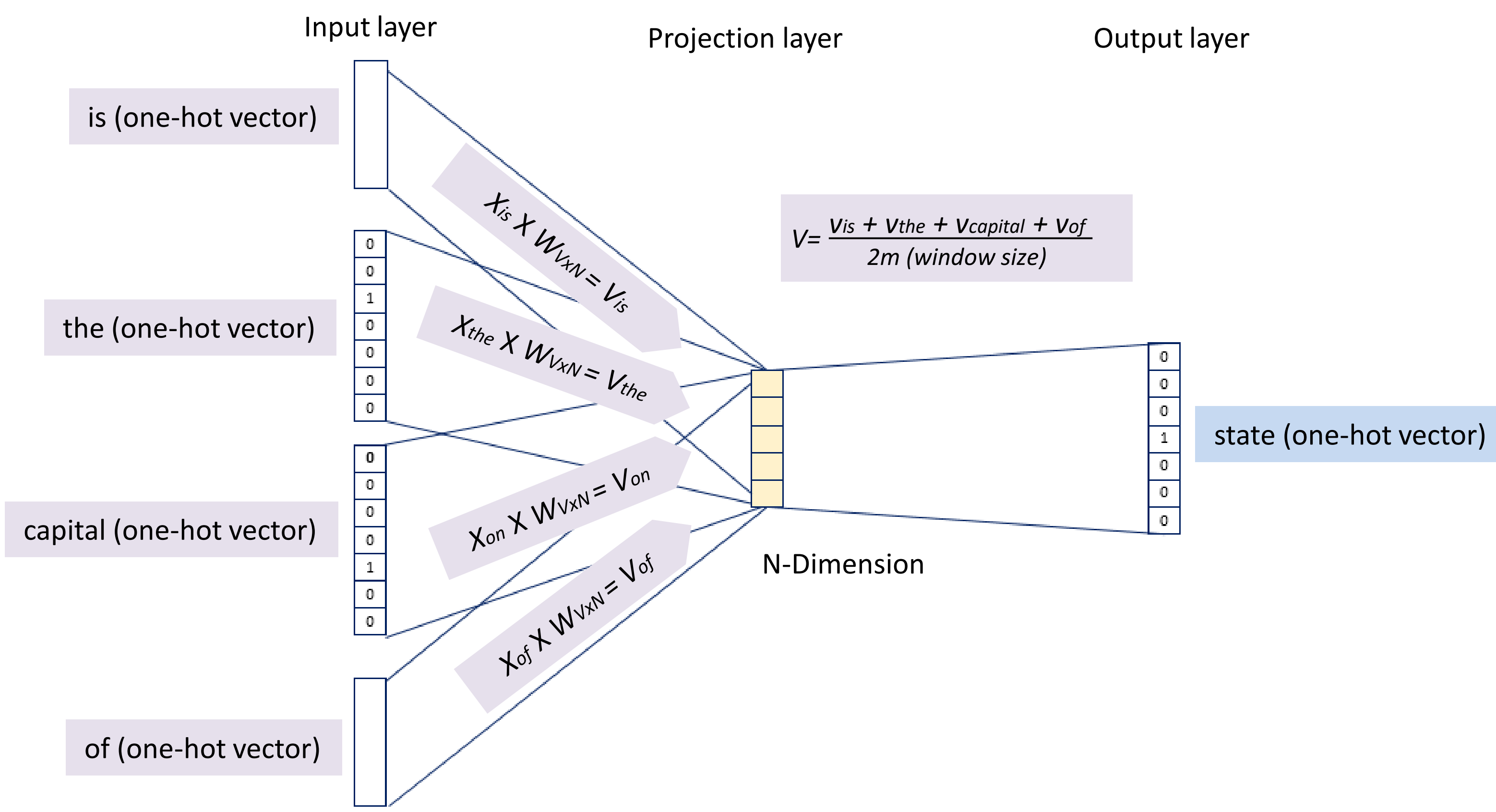


Prediction based Word representation

CBOW – Neural Network Architecture

Predict center word from (bag of) context words

Sentence: "Sydney is the state capital of NSW"

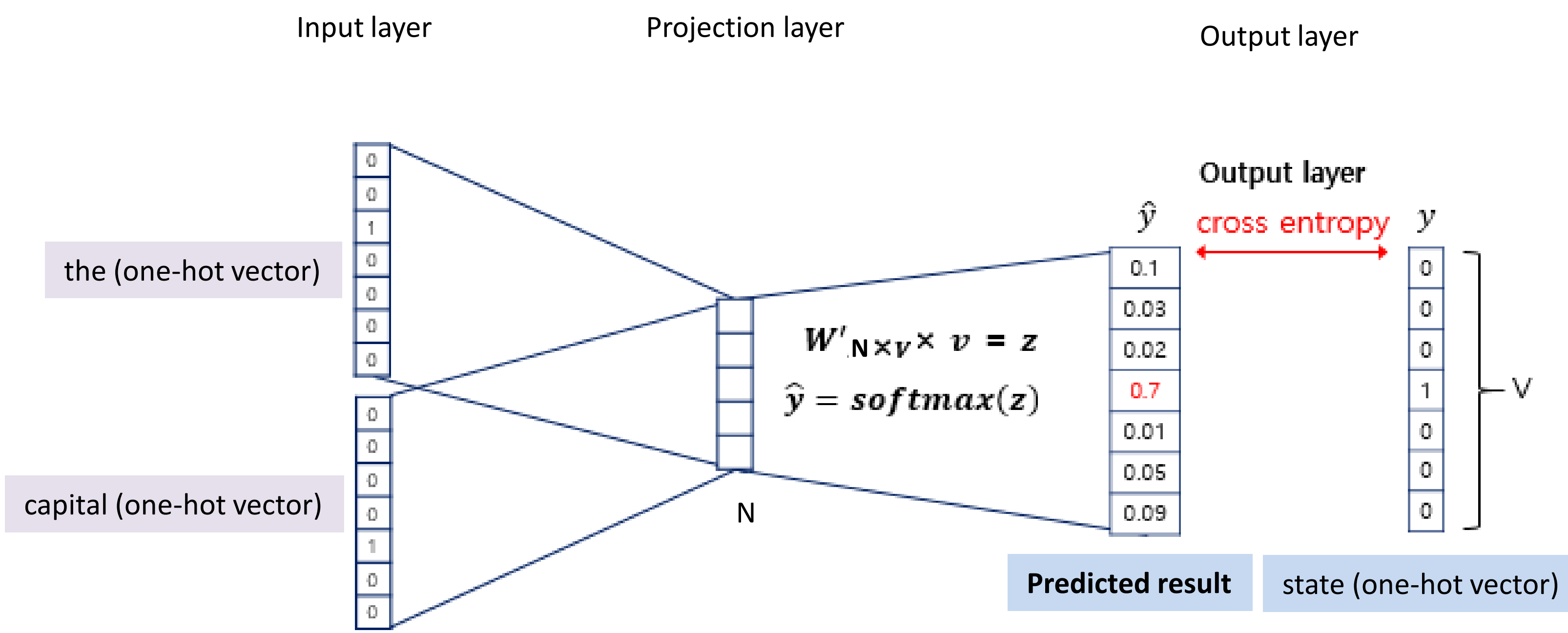


4 Prediction based Word representation

CBOW – Neural Network Architecture

Predict center word from (bag of) context words

Sentence: "Sydney is the state capital of NSW"



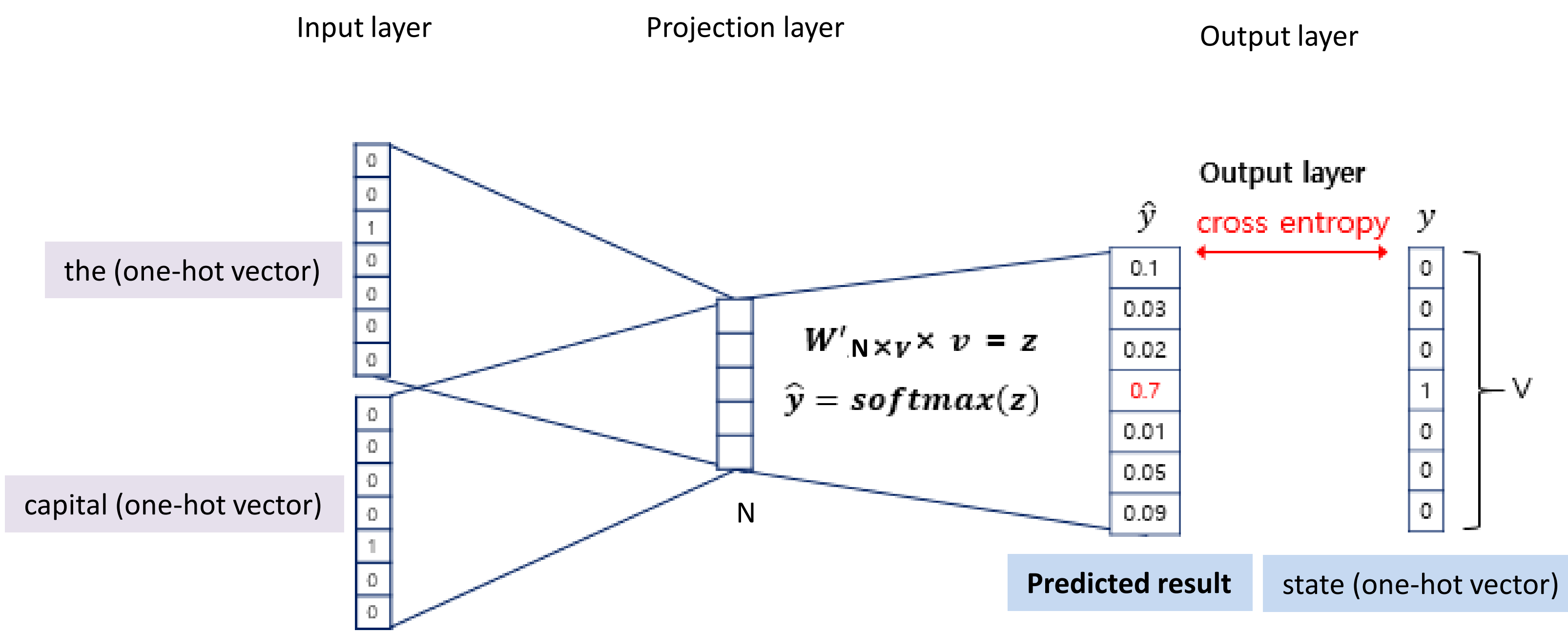
Softmax: *outputs a vector that represents the probability distributions (sum to 1) of a list of potential outcome*

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*

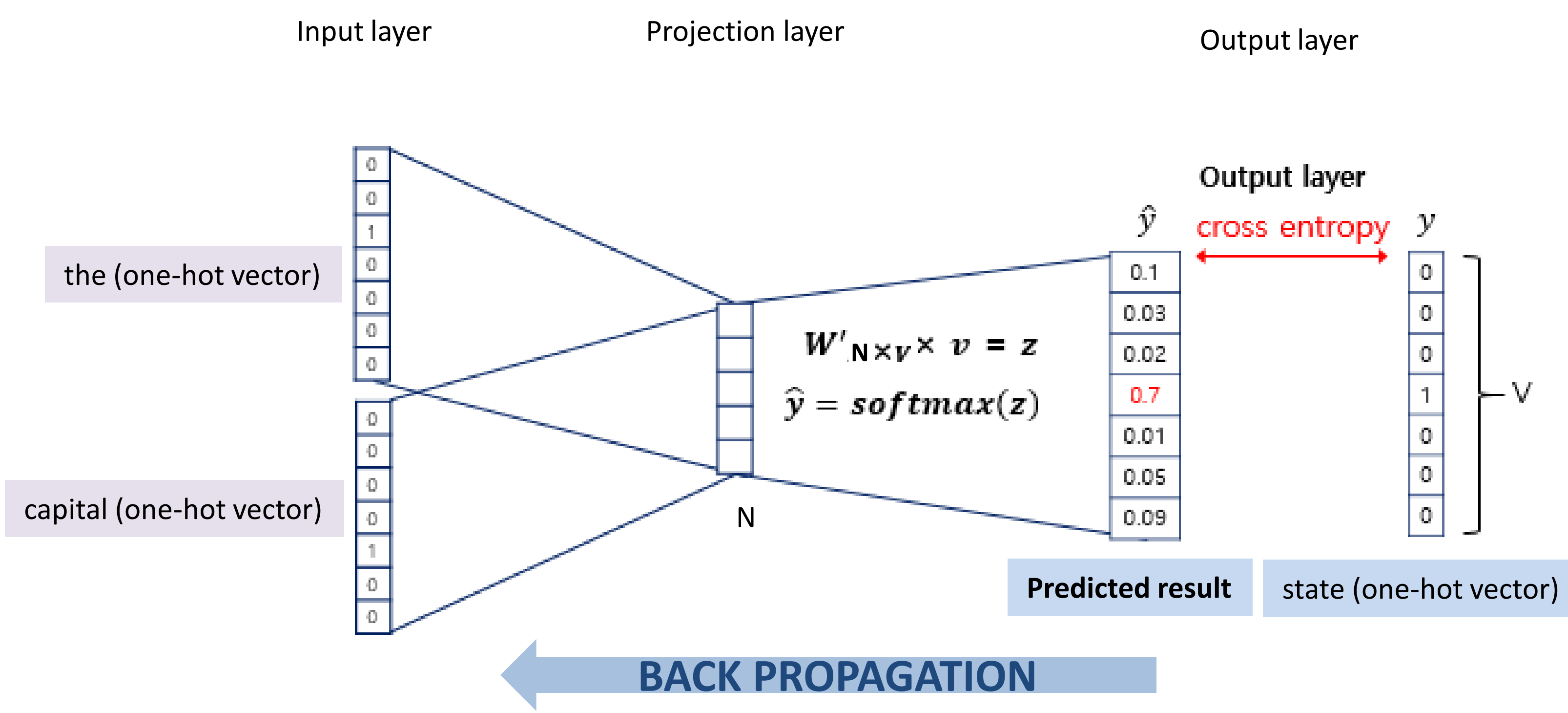
Loss Function (Cross Entropy)

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

CBOW – Neural Network Architecture

Predict center word from (bag of) context words

Sentence: "Sydney is the state capital of NSW"



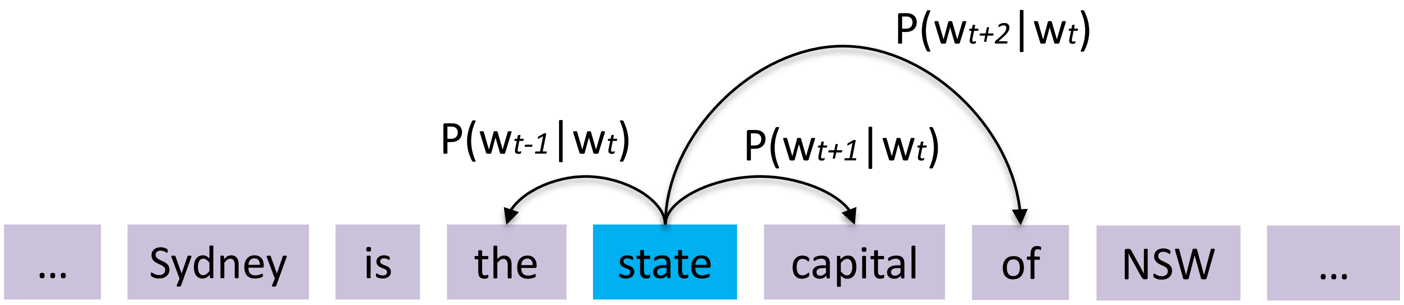
ARE WE DONE YET?

4 Prediction based Word representation

Skip Gram

Predict context (“outside”) words (position independent) given center word

Sentence: “Sydney is the state capital of NSW”

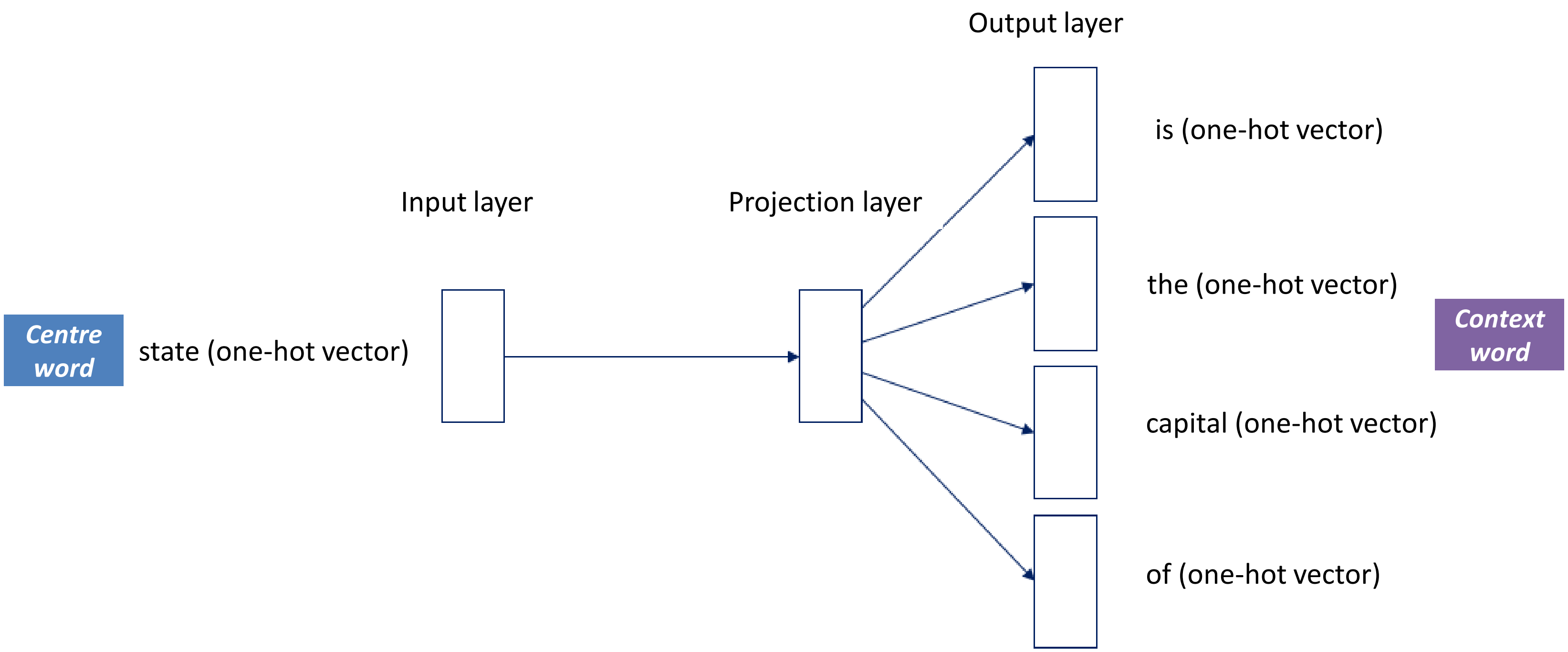


4 Prediction based Word representation

Skip Gram

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

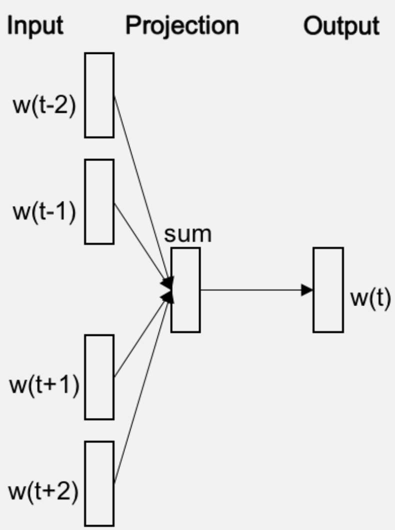
Sentence: "Sydney is the state capital of NSW"

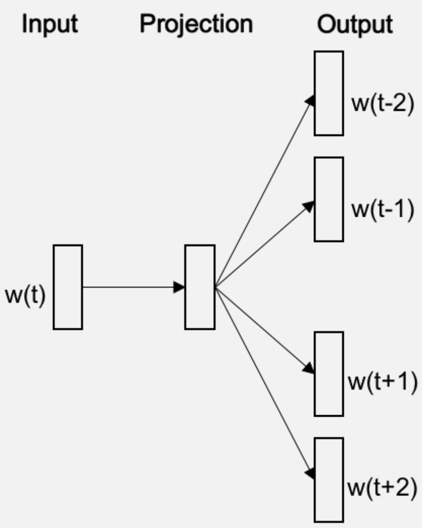


4 Prediction based Word representation

CBOW vs Skip Gram Overview

CBOW	***Skip-gram***
Predict center word from (bag of) context words	*Predict context words given center word*





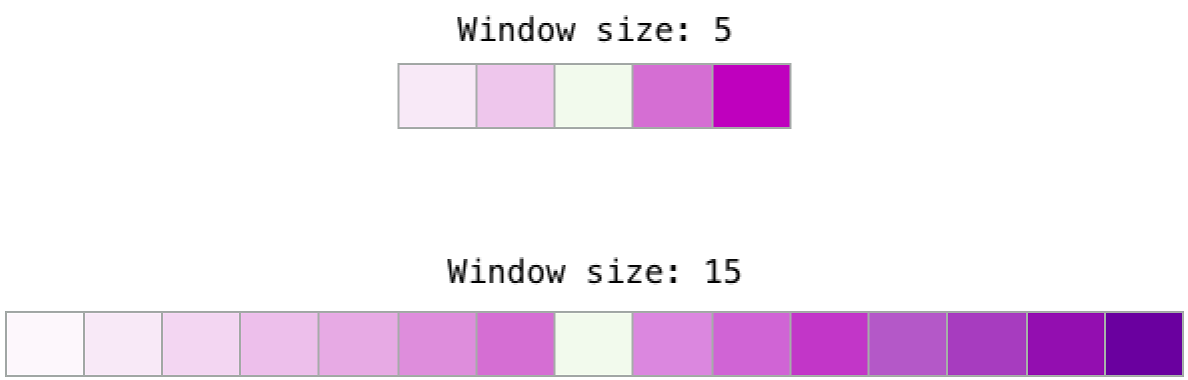
4 Prediction based Word representation

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



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

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**.

Prediction based Word representation

Word2Vec Overview

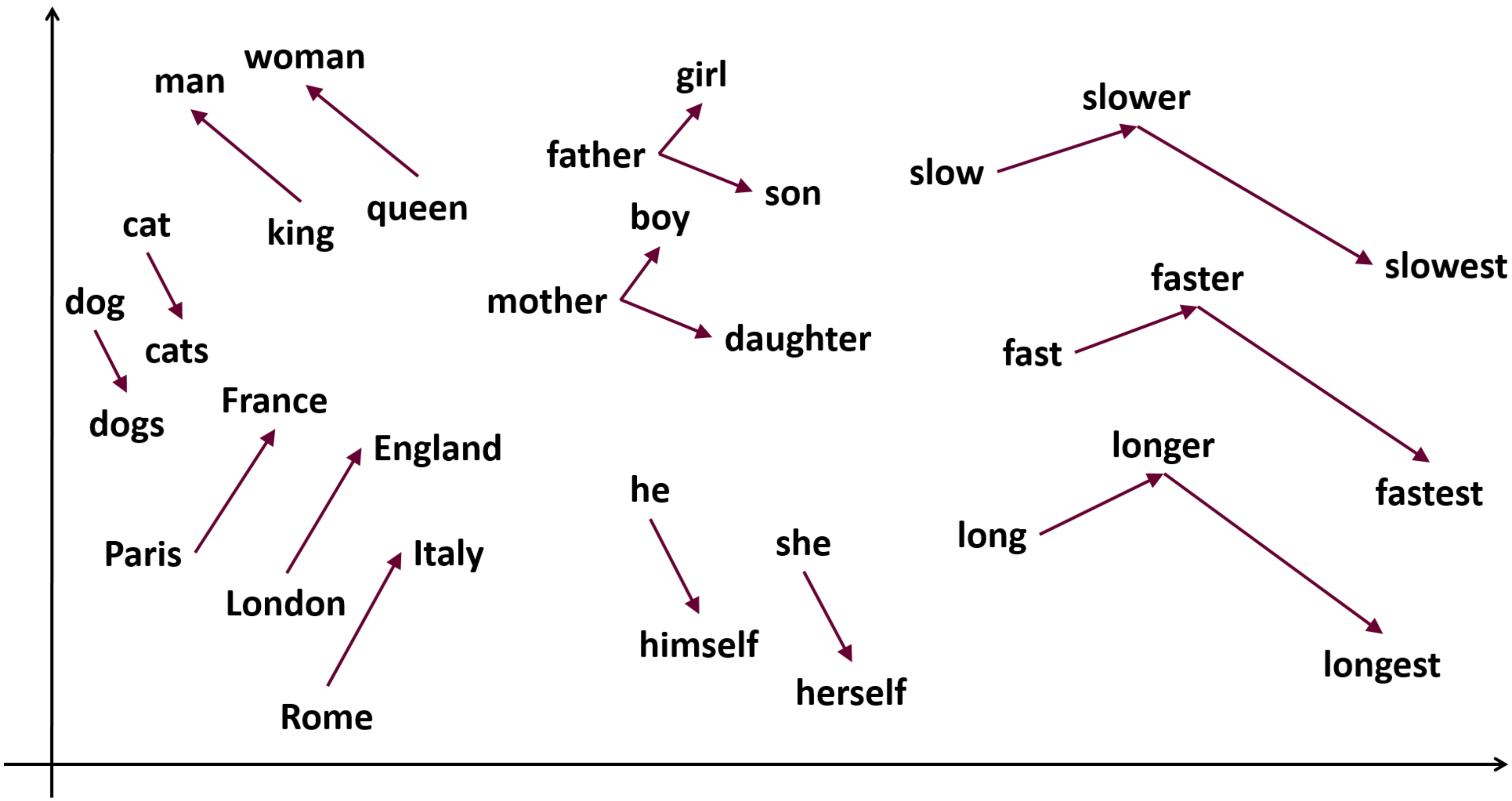
Word2vec (Mikolov et al. 2013) is a framework for learning word vectors

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

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

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

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/

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.

- 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/

4 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)
```

https://fasttext.cc/

Prediction based Word representation

Global Vectors (GloVe)

- Deal with this Word2Vec Limitation

*"Methods like skip-gram may do better on the analogy ask, 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

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

4 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.

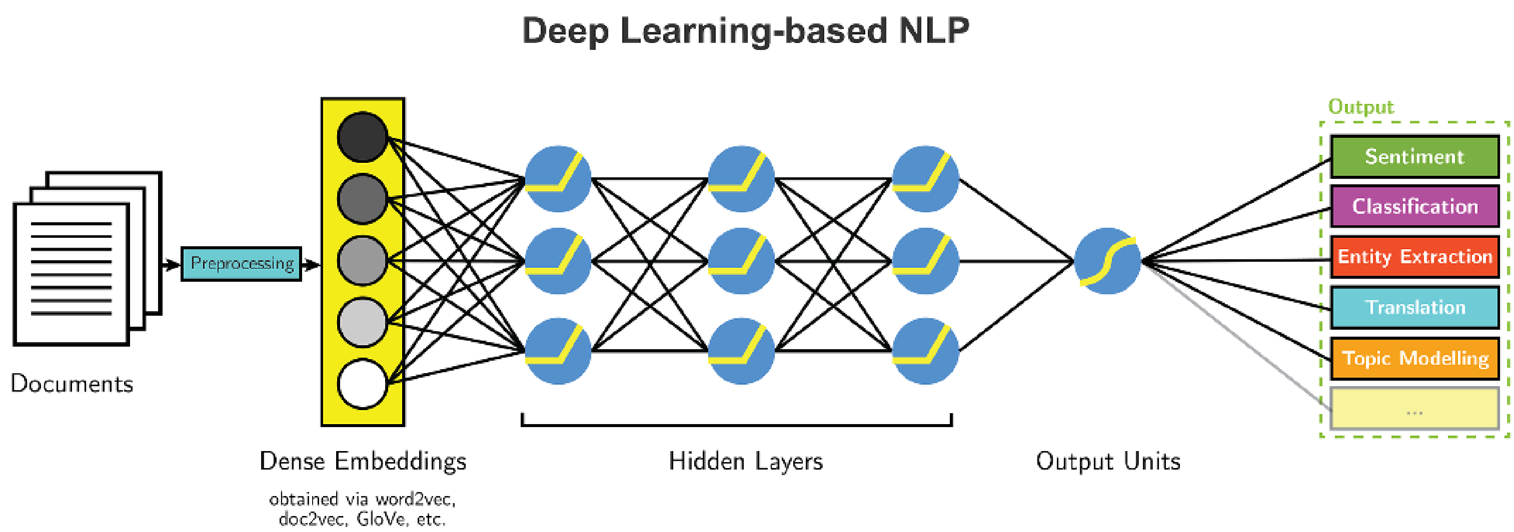
https://nlp.stanford.edu/projects/glove/

0 NEXT WEEK PREVIEW…

Word Embeddings

- Finalisation!

Machine Learning/ Deep Learning for Natural Language Processing



Reference

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FastText

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