

Class 02: 自然語言處理

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產學合作計畫

義守大學醫學核心專題研究計畫補助辦法

108 年 08 月 21 日行政會議通過（全文），108 年 08 月 30 日校長核定公告

- 第一條 為鼓勵專任教師積極與醫學相關領域進行多元合作研究，提升醫學院研究能量、跨領域及與新興科技領域結合等合作發展，特訂定「義守大學醫學核心專題研究計畫補助辦法」（以下簡稱本辦法）。
- 第二條 為發展本校醫學特色研究，本辦法補助計畫（以下簡稱專題計畫）區分為以下二類型：
- 一、醫學核心個別型計畫。
 - 二、醫學核心整合型計畫。
- 第三條 醫學核心個別型計畫為與醫學相關之跨領域計畫，主持人應由本校分屬醫學院及非醫學院之二位專任教師共同擔任，並推派一位負責計畫聯絡及經費核銷工作。
- 第四條 醫學核心整合型計畫為與醫學相關之跨領域整合計畫，其中應包含三個以上之子計畫，每一子計畫執行期間為二至三年。子計畫主持人應為本校專任教師，其中至少一個子計畫主持人應為本校醫學院專任教師。
- 第五條 各類型專題計畫提出時間，於每年公告時程向研究發展處學術發展組（以下簡稱學發組）提出申請，每位教師每學年於各類型計畫以申請一件為限。
- 第六條 申請之專題計畫，不得重覆申請同一學年度本校校內專題研究計畫、校內專題產學合作計畫、與義大醫療財團法人研究合

NLP

- Word Segmentation
- Part of Speech Tagging
- Stemming
- Named Entity Extraction
- Parsing
- Text Categorization

課程大綱

- 本課程與自然語言處理之關聯
- 斷辭斷字
- 去停用字
- 詞向量表示
- 詞袋模型

課程重點

- 句子分割
- 去停用字
- 文字編碼
- 詞彙
- 使用Python字典模型建立
 - Index to word
 - Word to index

Python 語法

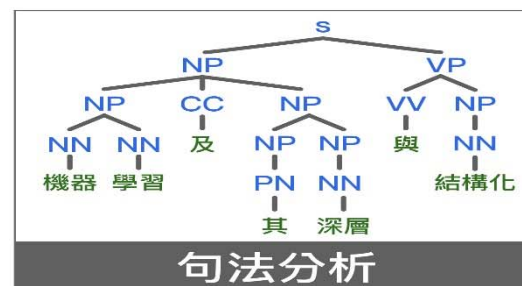
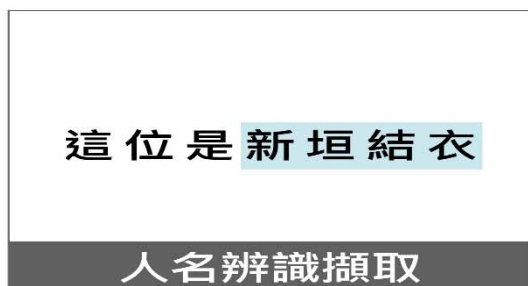
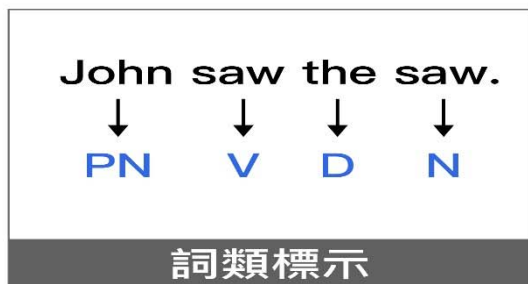
- 套件: NLTK/Scikit-Learn/Keras
- set/dictionary/tuple/list 語法

自然語言處理



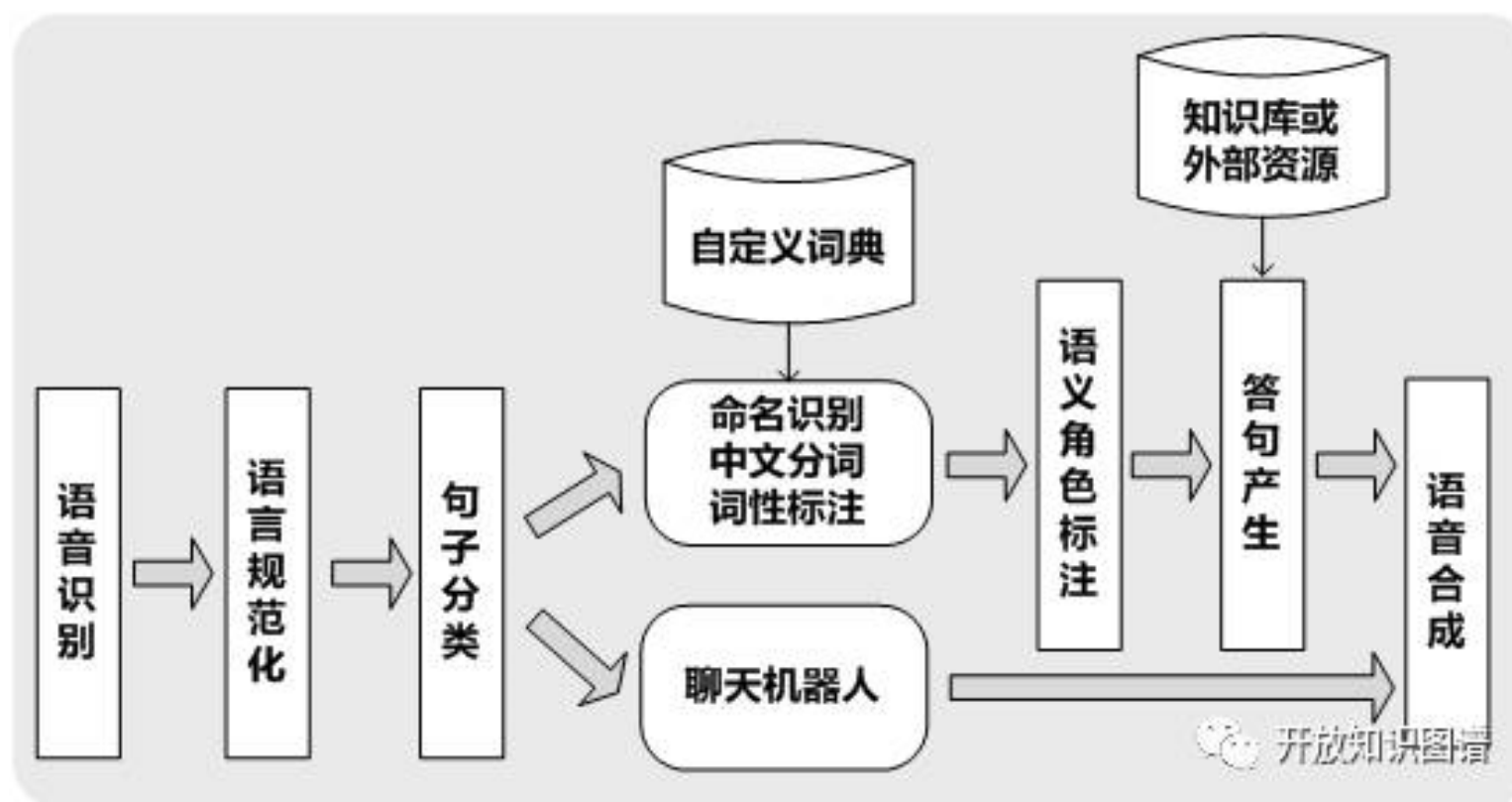
<http://www.gdhcfunds.com/index.php?c=article&id=338>

自然語言處理

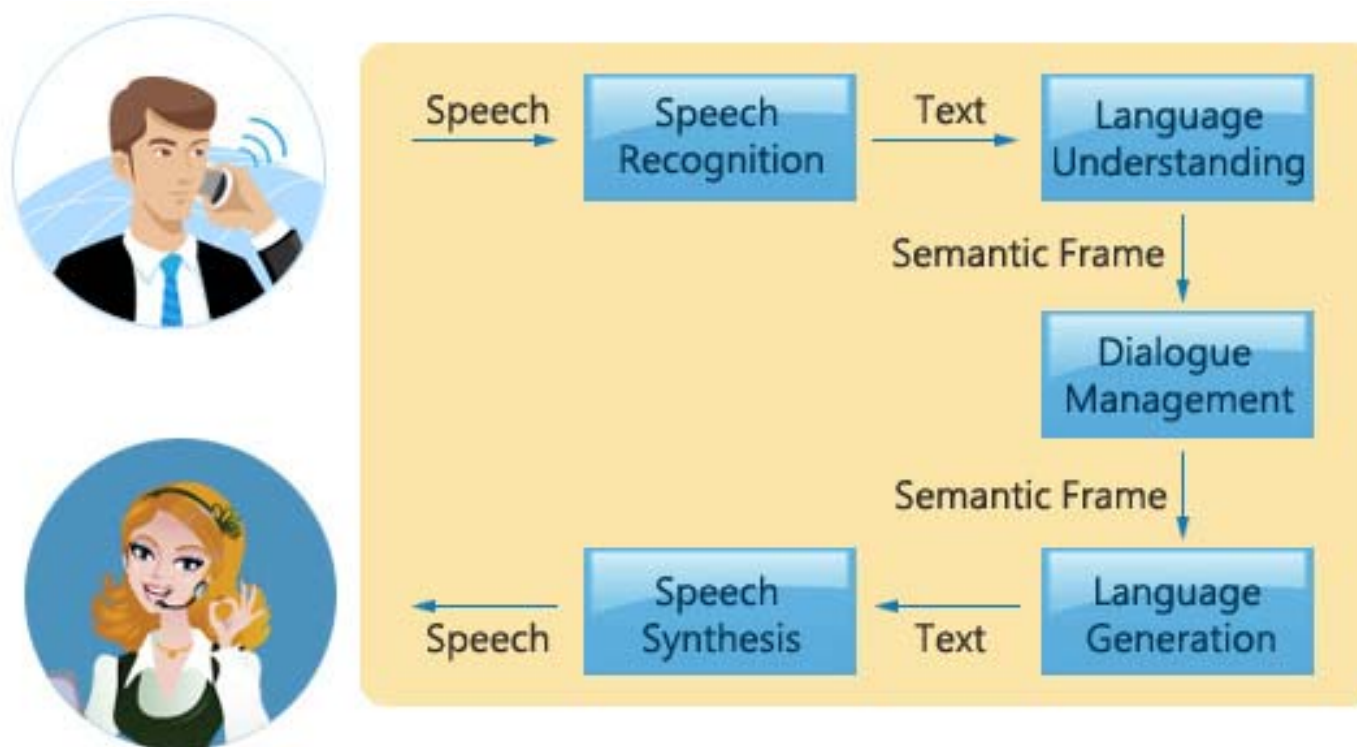


資料來源 | 中研院: 研之有物

對話系統



對話系統

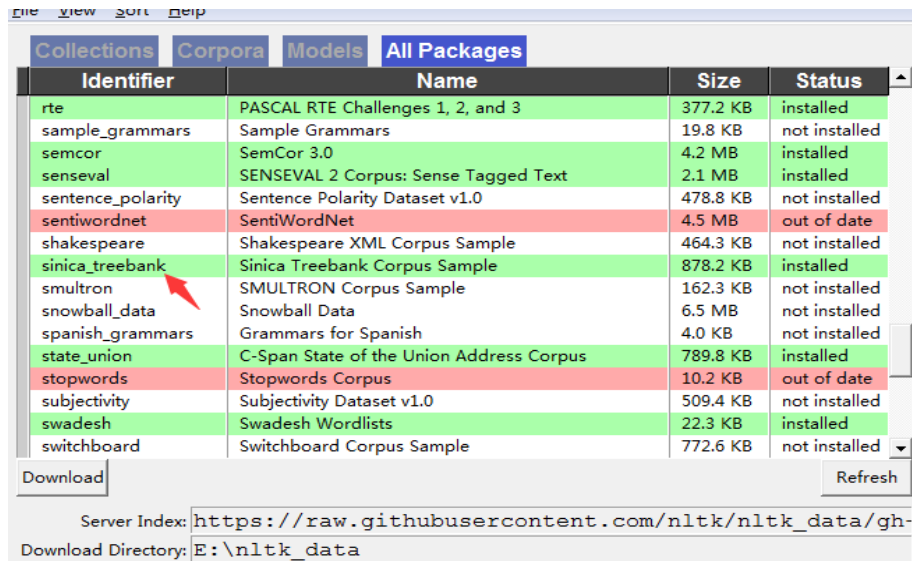


口語對話系統架構示意圖

<http://atc.ccl.itri.org.tw/interaction/conversation.php>

NLTK

```
import nltk
nltk.download()
python -m nltk.downloader all
```



The screenshot shows the NLTK Data application window. It has tabs for 'Collections', 'Corpora', 'Models', and 'All Packages'. The 'Corpora' tab is selected, displaying a table with columns: Identifier, Name, Size, and Status. A red arrow points to the 'sinica_treebank' entry. Below the table are buttons for 'Download' and 'Refresh', and fields for 'Server Index' and 'Download Directory'.

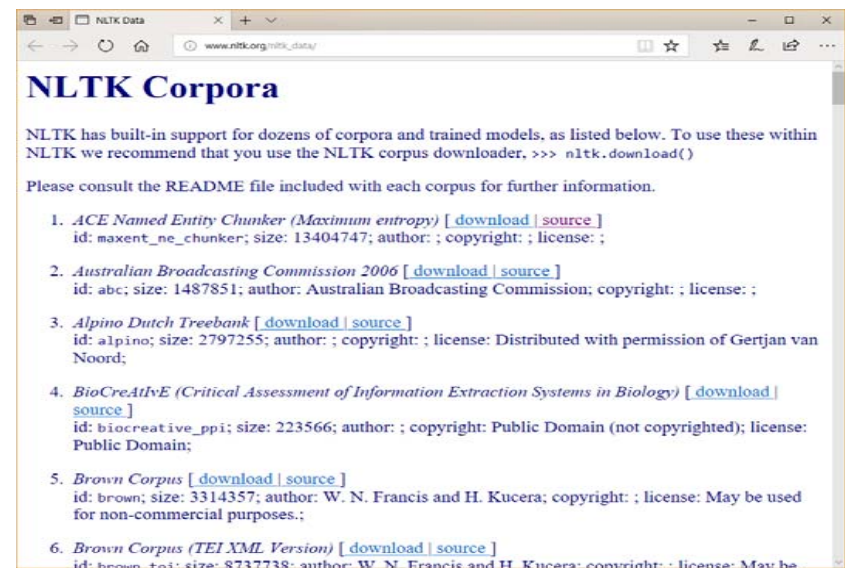
Identifier	Name	Size	Status
rte	PASCAL RTE Challenges 1, 2, and 3	377.2 KB	installed
sample_grammars	Sample Grammars	19.8 KB	not installed
semcor	SemCor 3.0	4.2 MB	installed
senseval	SENSEVAL 2 Corpus: Sense Tagged Text	2.1 MB	installed
sentence_polarity	Sentence Polarity Dataset v1.0	478.8 KB	not installed
sentiwordnet	SentiWordNet	4.5 MB	out of date
shakespeare	Shakespeare XML Corpus Sample	464.3 KB	not installed
sinica_treebank	Sinica Treebank Corpus Sample	878.2 KB	installed
smultron	SMULTRON Corpus Sample	162.3 KB	not installed
snowball_data	Snowball Data	6.5 MB	not installed
spanish_grammars	Grammars for Spanish	4.0 KB	not installed
state_union	C-Span State of the Union Address Corpus	789.8 KB	installed
stopwords	Stopwords Corpus	10.2 KB	out of date
subjectivity	Subjectivity Dataset v1.0	509.4 KB	not installed
swadesh	Swadesh Wordlists	22.3 KB	installed
switchboard	Switchboard Corpus Sample	772.6 KB	not installed

Download Refresh

Server Index: https://raw.githubusercontent.com/nltk/nltk_data/gh-

Download Directory: E:\nltk_data

<http://www.nltk.org/>



The screenshot shows the NLTK Corpora webpage. It lists several corpora with their IDs, sizes, authors, and licenses. Each entry has links for 'download' and 'source'.

NLTK Corpora

NLTK has built-in support for dozens of corpora and trained models, as listed below. To use these within NLTK we recommend that you use the NLTK corpus downloader, >>> nltk.download()

Please consult the README file included with each corpus for further information.

1. *ACE Named Entity Chunker (Maximum entropy)* [download | source]
id: maxent_ne_chunker; size: 13404747; author: ; copyright: ; license: ;
2. *Australian Broadcasting Commission 2006* [download | source]
id: abc; size: 1487851; author: Australian Broadcasting Commission; copyright: ; license: ;
3. *Alpino Dutch Treebank* [download | source]
id: alpino; size: 2797255; author: ; copyright: ; license: Distributed with permission of Gertjan van Noord;
4. *BioCreAtivE (Critical Assessment of Information Extraction Systems in Biology)* [download | source]
id: biocreative_ppi; size: 223566; author: ; copyright: Public Domain (not copyrighted); license: Public Domain;
5. *Brown Corpus* [download | source]
id: brown; size: 3314357; author: W. N. Francis and H. Kucera; copyright: ; license: May be used for non-commercial purposes.;
6. *Brown Corpus (TEI XML Version)* [download | source]
id: brown_tei; size: 8717738; author: W. N. Francis and H. Kucera; copyright: ; license: May be used for non-commercial purposes.;

http://www.nltk.org/nltk_data/

LTP

- Language Technology Platform (LTP)
- `pip install pyltp`



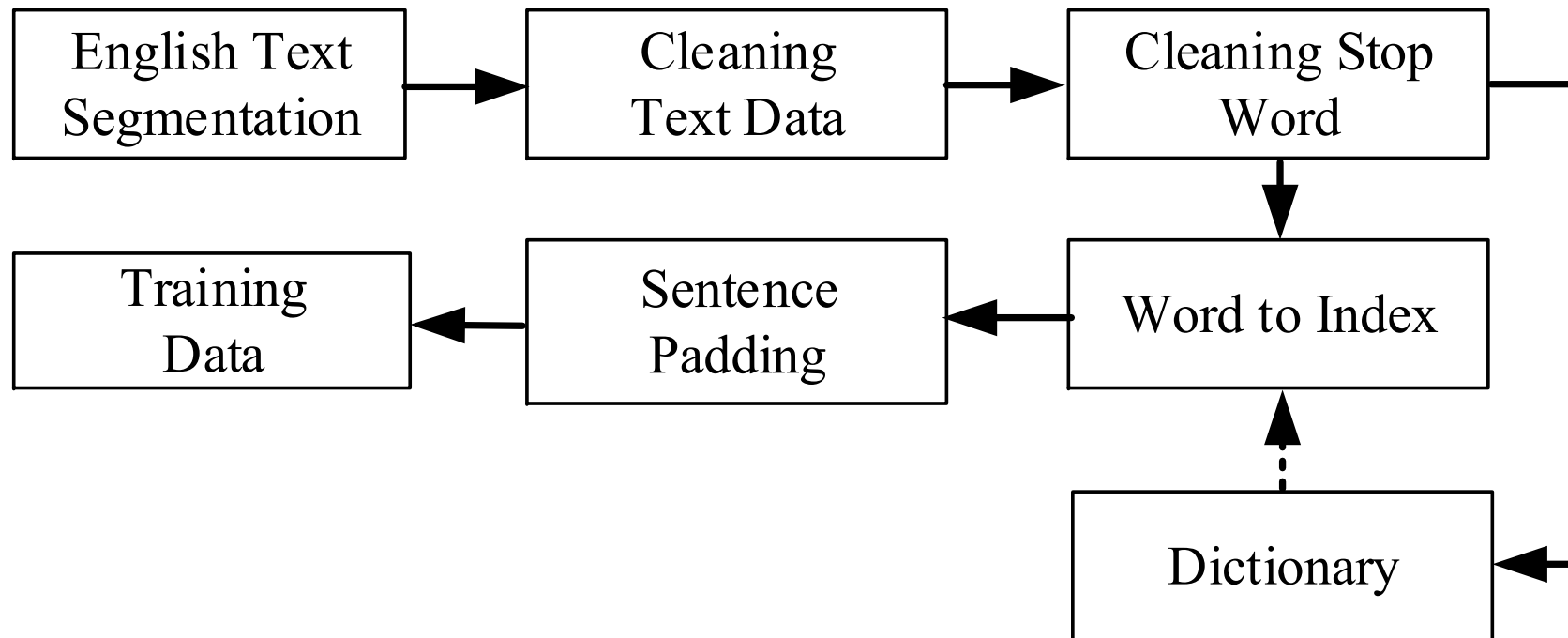
语言技术平台云 <https://www.ltp-cloud.com/demo/>

CKIP

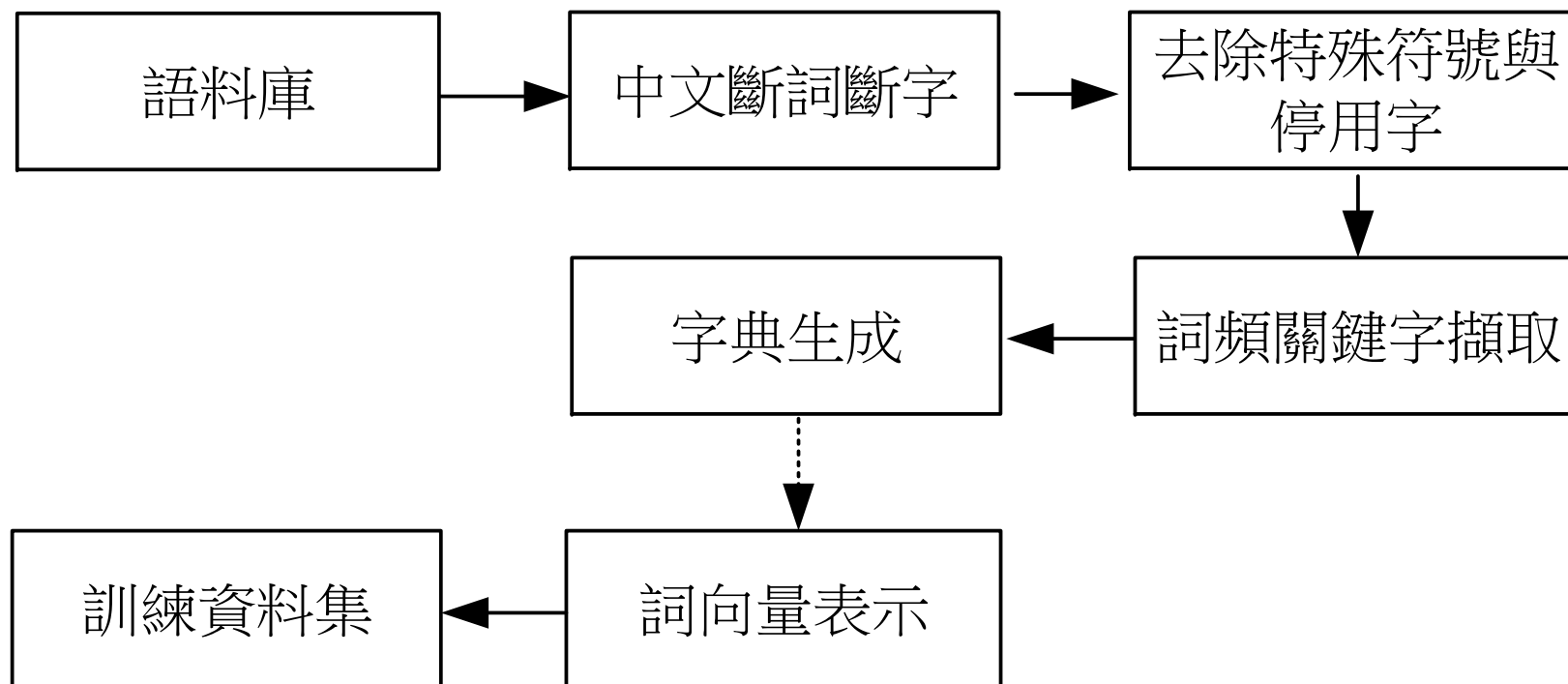


<http://ckipsvr.iis.sinica.edu.tw/>

英文前處理



中文前處理

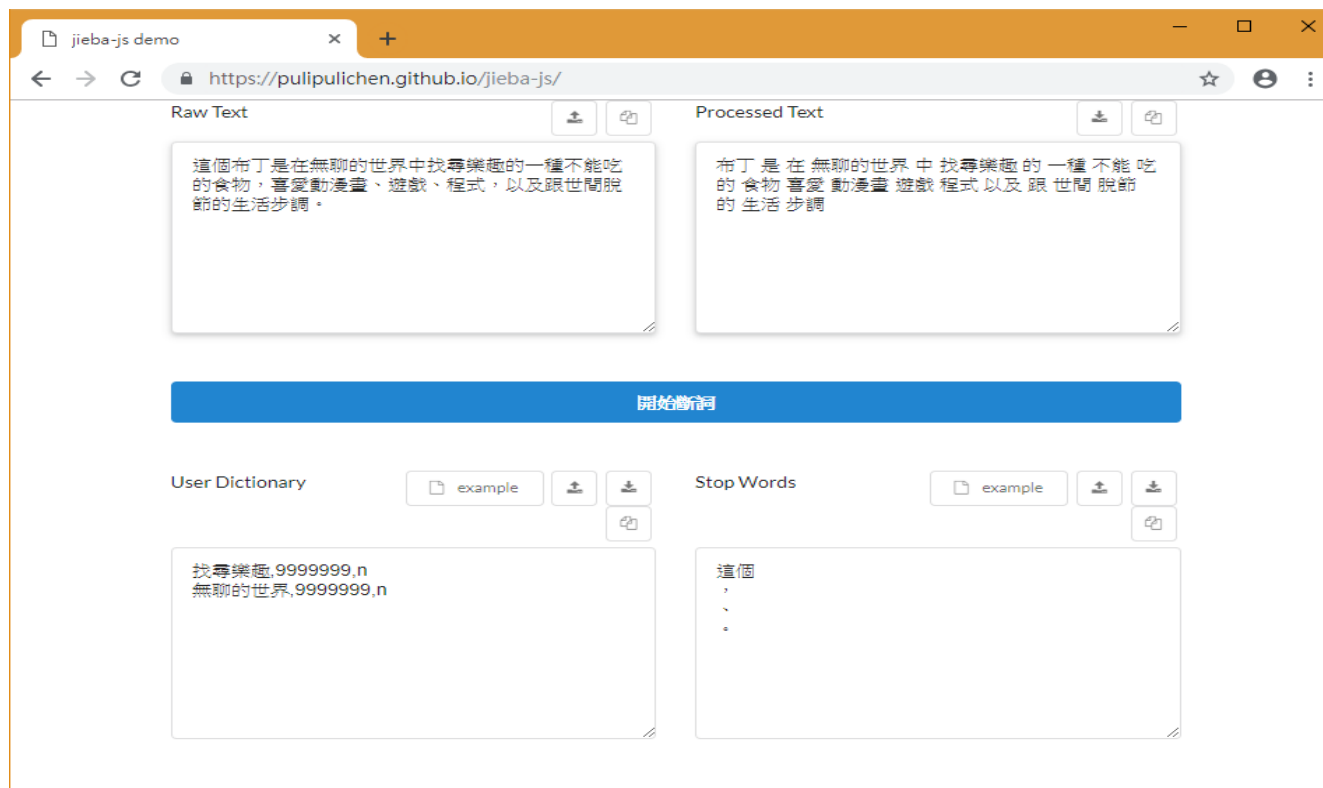


中文分詞器

- KIP: 台灣中研院研發的一款斷詞器，不過並未對外公布技術節。
- HanLP: 這是一個開源的分詞器(java),我在這篇Hanlp自然語言處理器有使用範例
- Ansj: 這也是一個開源的中文分詞器(java)
- jieba: Python 的中文分詞器

中文分詞器

- Jieba Package



<https://pulipulichen.github.io/jieba-js/>

Jieba 中文斷詞器

- Raw Text
- Processed Text
- User Dictionary (user_dict.txt)
- Stop Words (stop_words.txt)

基於Jieba的詞性標註

```
In [9]: import jieba
import jieba.posseg as psg
s='皮膚科在哪裡?'
cut = jieba.cut(s)
print(', '.join(cut))
print([(x.word,x.flag) for x in psg.cut(s)])
```

皮膚科,在,哪裡,?
[('皮膚', 'n'), ('科', 'n'), ('在', 'p'), ('哪裡', 'r'), ('?', 'x')]

```
In [10]: s='陳大義醫師在哪裡?'
cut = jieba.cut(s)
print(', '.join(cut))
```

陳,大義醫師,在,哪裡,?

```
In [11]: s='心臟科在哪裡?'
cut = jieba.cut(s)
print(', '.join(cut))
print([(x.word,x.flag) for x in psg.cut(s)])
```

心臟科,在,哪裡,?
[('心臟科', 'n'), ('在', 'p'), ('哪裡', 'r'), ('?', 'x')]

```
In [12]: cut = jieba.cut(s)
print([(x.word,x.flag) for x in psg.cut(s)])
s='腦外科怎麼走?'
cut = jieba.cut(s)
print(', '.join(cut))
```

[('心臟科', 'n'), ('在', 'p'), ('哪裡', 'r'), ('?', 'x')]
腦,外科,怎,麼,走,?

```
In [14]: print([(x.word,x.flag) for x in psg.cut(s)])
s='腦外科在哪裡?'
cut = jieba.cut(s)
print(', '.join(cut))
```

[('腦', 'zg'), ('外科', 'n'), ('在', 'p'), ('哪裡', 'r'), ('?', 'x')]
腦,外科,在,哪裡,?

```
In [15]: print([(x.word,x.flag) for x in psg.cut(s)])
```

[('腦', 'zg'), ('外科', 'n'), ('在', 'p'), ('哪裡', 'r'), ('?', 'x')]

問題討論

- 使用Python建立字典

基於Jieba的詞性標註

```
In [7]: import jieba
import jieba.posseg as psg
s='周兆明老師在哪裡'
cut = jieba.cut(s)
print(' '.join(cut))
print([(x.word,x.flag) for x in psg.cut(s)])
```

周兆明,老師,在,哪裡
[('周兆明', 'nr'), ('老師', 'n'), ('在', 'p'), ('哪裡', 'r')]

```
In [8]: s='我要找王小明老師'
cut = jieba.cut(s)
print(' '.join(cut))
print([(x.word,x.flag) for x in psg.cut(s)])
```

我要,找,王小明,老師
[('我', 'r'), ('要', 'v'), ('找', 'v'), ('王小明', 'nr'), ('老師', 'n')]

```
In [9]: s='丁鈺在哪裡'
cut = jieba.cut(s)
print(' '.join(cut))
print([(x.word,x.flag) for x in psg.cut(s)])
```

丁,鈺,在,哪裡
[('丁鈺', 'nr'), ('在', 'p'), ('哪裡', 'r')]

```
In [10]: s='我要找丁鈺'
cut = jieba.cut(s)
print(' '.join(cut))
print([(x.word,x.flag) for x in psg.cut(s)])
```

我要,找,丁,鈺
[('我', 'r'), ('要', 'v'), ('找', 'v'), ('丁', 'nr'), ('鈺', 'n')]

詞袋模型簡介

- One-Hot Encoding
- 字母形式/字串形式轉換成數字形式
- Token (字符)
- Vocabulary (詞彙)
 - 整個文件中的字詞(word)
- 文件的特徵
 - 特徵向量
 - 字詞與出現的次數

字詞(word)轉特徵向量

- One Hard Encoding
- 字詞出現的次數(Count)建立詞袋
 - 單元模型(1-gram model或unigram model)
- 詞頻-反向文件詞頻(TF-IDF)
- 詞特徵向量

One-Hot Encoding

- 使用 keras 的 Tokenizer 類別

```
#OneHotEncoder
from sklearn.preprocessing import OneHotEncoder
encoder = OneHotEncoder()
encoder.fit([
    ['A', 'C', 'B', 'L'],
    ['B', 'D', 'F', 'D'],
    ['C', 'D', 'C', 'L'],
    ['B', 'C', 'E', 'D']
])
encoded_vector = encoder.transform(['C', 'D', 'F', 'D']).toarray()
print("\n Encoded vector =", encoded_vector)
```

Encoded vector = [[0. 0. 1. 0. 1. 0. 0. 0. 1. 1. 0.]]

次數詞袋範例說明

- 使用scikit-learn中的 CountVectorizer 類別

```
from sklearn.feature_extraction.text import CountVectorizer
# list of text documents
text = ["The quick brown fox jumped over the lazy dog."]
# create the transform
vectorizer = CountVectorizer()
# tokenize and build vocab
vectorizer.fit(text)
# summarize
print(vectorizer.get_feature_names())
print(vectorizer.vocabulary_)
# encode document
vector = vectorizer.transform(text)
# summarize encoded vector
print(vector.shape)
print(type(vector))
print(vector.toarray())

['brown', 'dog', 'fox', 'jumped', 'lazy', 'over', 'quick', 'the']
{'the': 7, 'quick': 6, 'brown': 0, 'fox': 2, 'jumped': 3, 'over': 5, 'lazy': 4, 'dog': 1}
(1, 8)
<class 'scipy.sparse.csr.csr_matrix'>
[[1 1 1 1 1 1 1 2]]
```

TF-IDF 詞袋

- 使用 scikit-learn 中的 TfidfTransformer

When we are analyzing text data, we often encounter words that occur across multiple documents from both classes. Those frequently occurring words typically don't contain useful or discriminatory information. In this subsection, we will learn about a useful technique called term frequency-inverse document frequency (tf-idf) that can be used to downweight those frequently occurring words in the feature vectors. The tf-idf can be defined as the product of the term frequency and the inverse document frequency:

$$\text{tf-idf}(t, d) = \text{tf}(t, d) \times \text{idf}(t, d)$$

Here the $\text{tf}(t, d)$ is the term frequency that we introduced in the previous section, and the inverse document frequency $\text{idf}(t, d)$ can be calculated as:

$$\text{idf}(t, d) = \log \frac{n_d}{1 + \text{df}(d, t)},$$

where n_d is the total number of documents, and $\text{df}(d, t)$ is the number of documents d that contain the term t . Note that adding the constant 1 to the denominator is optional and serves the purpose of assigning a non-zero value to terms that occur in all training samples; the log is used to ensure that low document frequencies are not given too much weight.

<https://github.com/rasbt/python-machine-learning-book-2nd-edition/blob/master/code/ch08/ch08.ipynb>

TF-IDF 詞袋

- 使用 scikit-learn 中的 TfidfTransformer

However, if we'd manually calculated the tf-idfs of the individual terms in our feature vectors, we'd have noticed that the TfidfTransformer calculates the tf-idfs slightly differently compared to the standard textbook equations that we defined earlier. The equations for the idf and tf-idf that were implemented in scikit-learn are:

$$\text{idf}(t, d) = \log \frac{1 + n_d}{1 + \text{df}(d, t)}$$

The tf-idf equation that was implemented in scikit-learn is as follows:

$$\text{tf-idf}(t, d) = \text{tf}(t, d) \times (\text{idf}(t, d) + 1)$$

While it is also more typical to normalize the raw term frequencies before calculating the tf-idfs, the TfidfTransformer normalizes the tf-idfs directly.

By default (norm='l2'), scikit-learn's TfidfTransformer applies the L2-normalization, which returns a vector of length 1 by dividing an un-normalized feature vector v by its L2-norm:

$$v_{\text{norm}} = \frac{v}{\|v\|_2} = \frac{v}{\sqrt{v_1^2 + v_2^2 + \dots + v_n^2}} = \frac{v}{(\sum_{i=1}^n v_i^2)^{\frac{1}{2}}}$$

To make sure that we understand how TfidfTransformer works, let us walk through an example and calculate the tf-idf of the word is in the 3rd document.

<https://github.com/rasbt/python-machine-learning-book-2nd-edition/blob/master/code/ch08/ch08.ipynb>

TF-IDF 詞袋範例說明

```
import numpy as np
from sklearn.feature_extraction.text import TfidfVectorizer
# list of text documents
text = ["The quick brown fox jumped over the lazy dog.", "The dog.", "The fox"]
# create the transform
vectorizer = TfidfVectorizer()
# tokenize and build vocab
vectorizer.fit(text)
np.set_printoptions(precision=5)
# summarize
print(vectorizer.vocabulary_)
print(vectorizer.get_feature_names())
print(vectorizer.idf_)
vector = vectorizer.transform(text)
# summarize encoded vector
print(vector.shape)
print(vector.toarray())
```

{'the': 7, 'quick': 6, 'brown': 0, 'fox': 2, 'jumped': 3, 'over': 5, 'lazy': 4, 'dog': 1}
['brown', 'dog', 'fox', 'jumped', 'lazy', 'over', 'quick', 'the']
[1.69215 1.28768 1.28768 1.69215 1.69215 1.69215 1.69215 1.69215]
(3, 8)
[[0.36389 0.27675 0.27675 0.36389 0.36389 0.36389 0.36389 0.42983]
 [0. 0.78981 0. 0. 0. 0. 0. 0.61336]
 [0. 0. 0.78981 0. 0. 0. 0. 0.61336]]

the

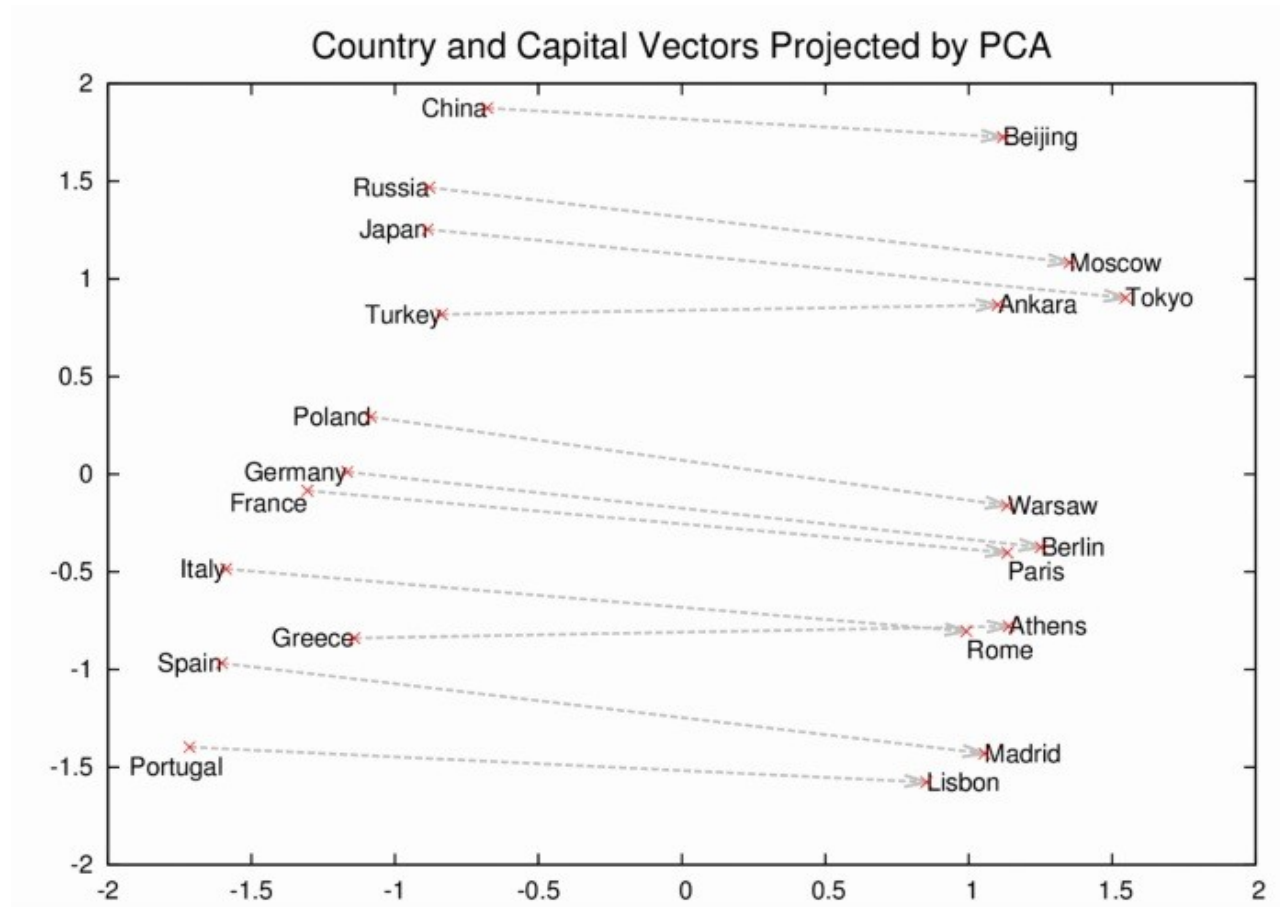
Word Embedding

- Google's **word2vec** [Mikolov et al. 2013]
 - COBW
 - Skip-gram
- **GloVe** [Levy et al. 2014]

<https://code.google.com/archive/p/word2vec/>

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

Word to Vector



Google Open Source Blog

Word to Vec JS Demo

daughter 0.8706230019086026
grandmother 0.8442235585377782
aunt 0.8435924872067456
niece 0.8070082160701633
father 0.7901481870716061
son 0.7683207312810011
sister 0.763335126711493
wife 0.755067714099042
stepmother 0.7531879305425351

Word Algebra

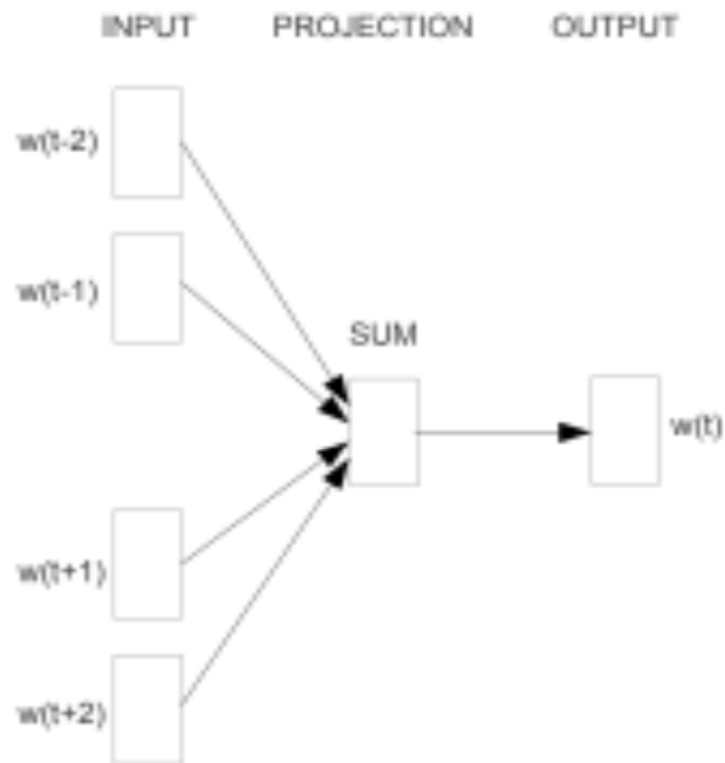
Enter all three words, the first two, or the last two and see the words that result.

father + (daughter - mother) =

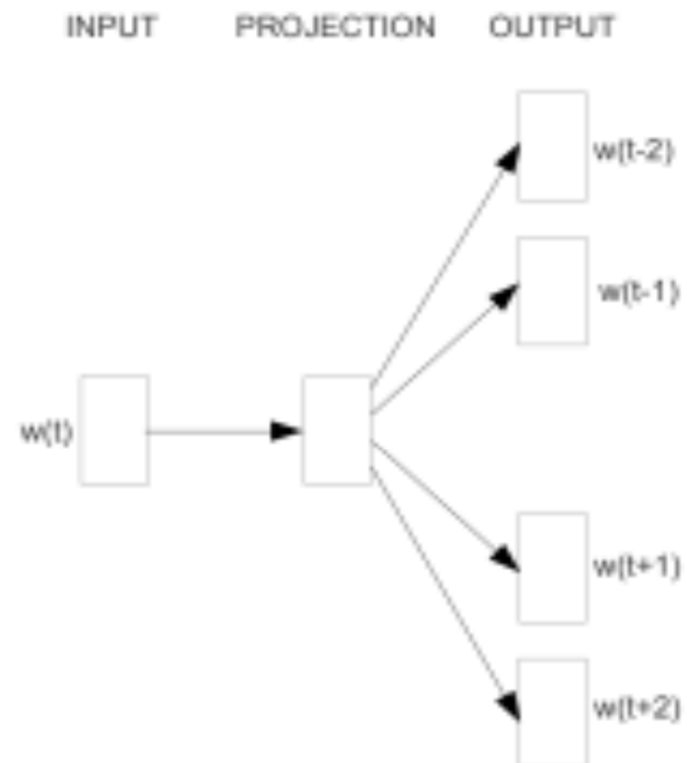
son 0.9048675802514527
father 0.8820846506379102

<http://turbomaze.github.io/word2vecjson/>

BOW & Skip-Gram Models



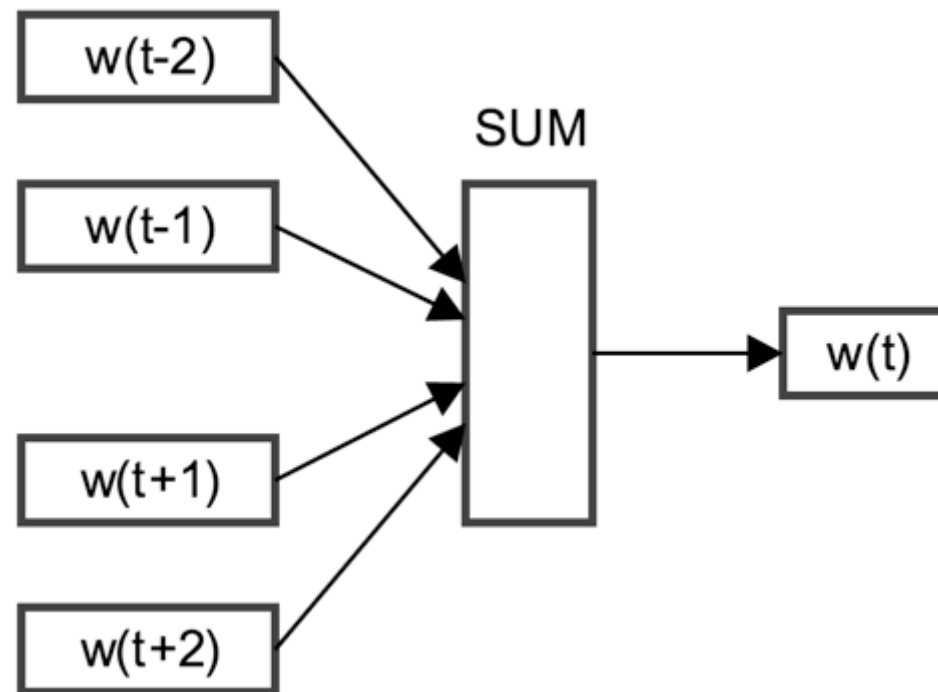
CBOW



Skip-gram

Bag of Words Model

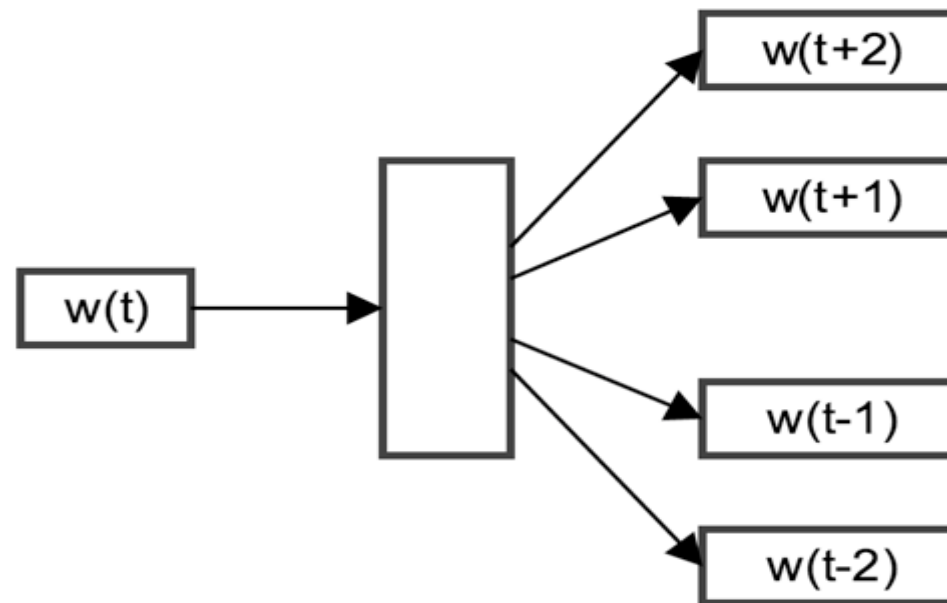
- Predict the surrounding words, based on the current word.



Mikolov et. al. 2013. Efficient Estimation of Word Representations in Vector Space.

Skip-Gram Model

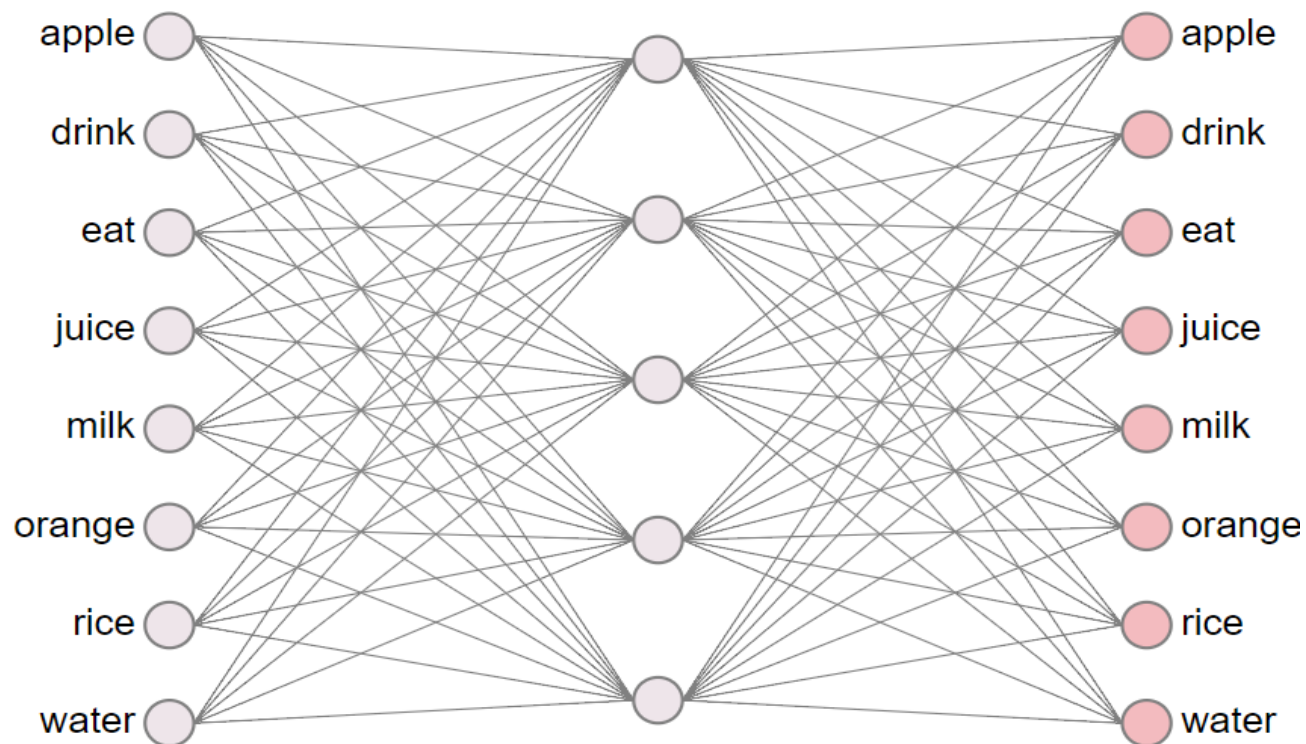
- Predict the surrounding words, based on the current word.



Mikolov et. al. 2013. Efficient Estimation of Word Representations in Vector Space.

Word to Vector

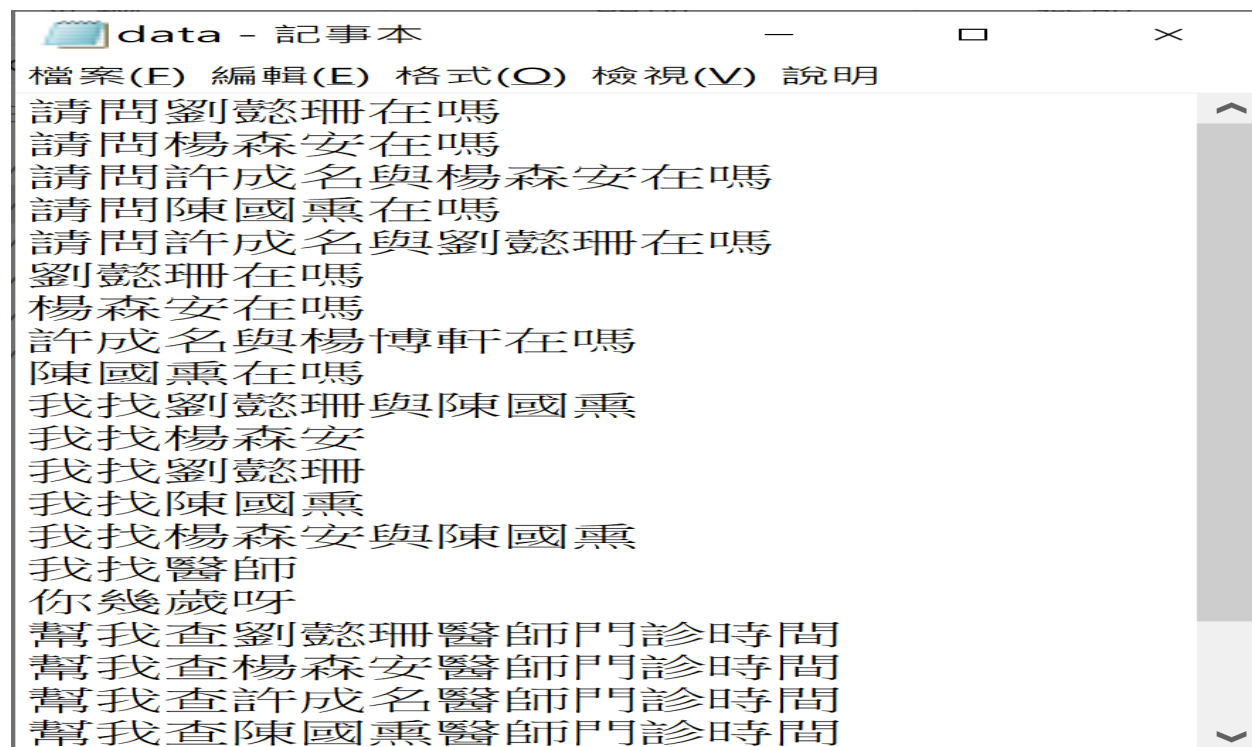
- **WEVI**



<https://ronxin.github.io/wevi/>

作業

- 判斷文件中醫師有幾位



data - 記事本

檔案(E) 編輯(E) 格式(O) 檢視(V) 說明

請問劉懿珊在嗎
請問楊森安在嗎
請問許成名與楊森安在嗎
請問陳國熏在嗎
請問許成名與劉懿珊在嗎
劉懿珊在嗎
楊森安在嗎
許成名與楊博軒在嗎
陳國熏在嗎
我找劉懿珊與陳國熏
我找楊森安
我找劉懿珊
我找陳國熏
我找楊森安與陳國熏
我找醫師
你幾歲呀
幫我查劉懿珊醫師門診時間
幫我查楊森安醫師門診時間
幫我查許成名醫師門診時間
幫我查陳國熏醫師門診時間

作業

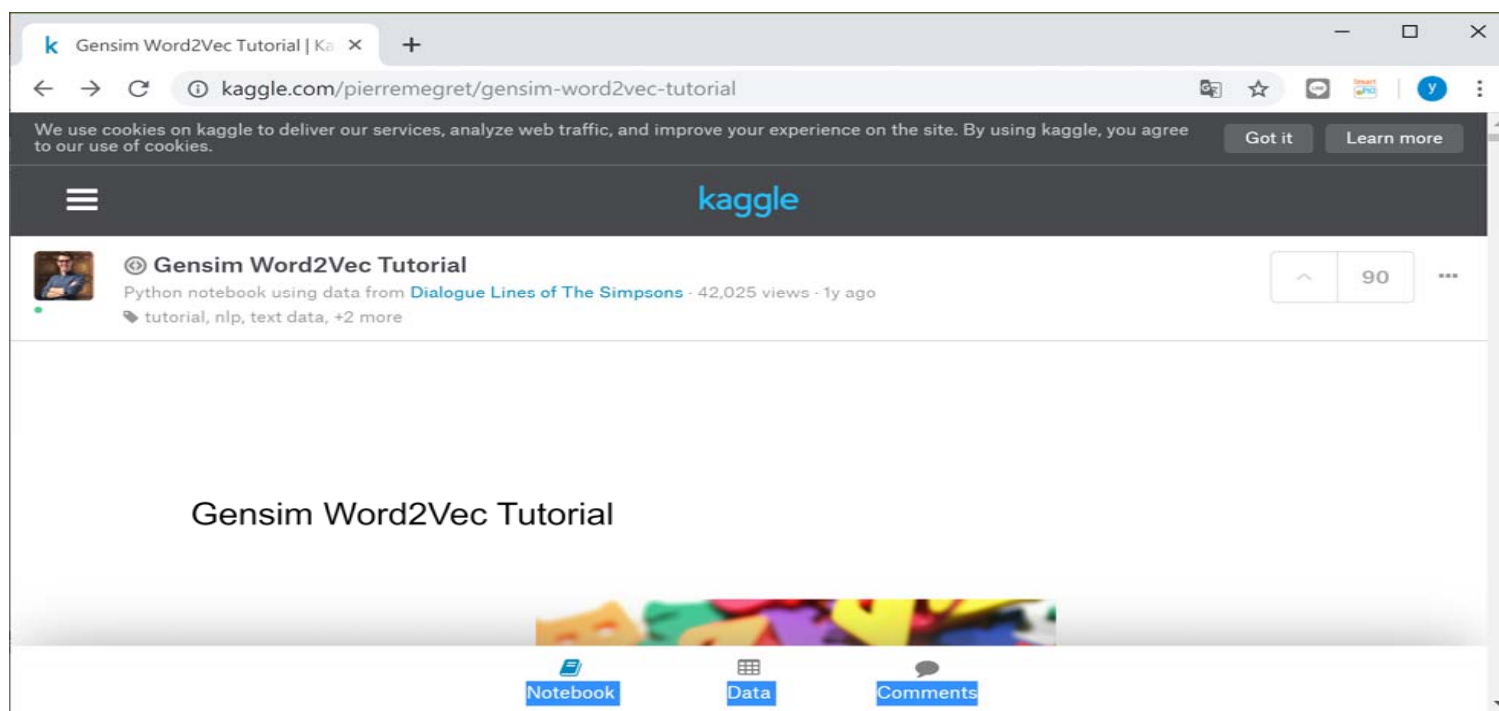
- n -gram model
 - `CountVectorizer(ngram_range=(2, 4))`
- 解釋說明結果

作業

- 使用 The 在計數與TF-IDF 詞袋差別
 - 詞彙總長度 vs 出現次數
 - 詞彙總長度 vs ?
- 為何取 TFIDF 要取 log 函數
- 說明 The 在三個文件中都有出
 - 文件一: 0.42983
 - 文件二: 0.61336
 - 文件三: 0.61336
- 計算文件一的TF-IDF

作業

- 實作練習



<https://www.kaggle.com/pierremegret/gensim-word2vec-tutorial>