補充說明

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

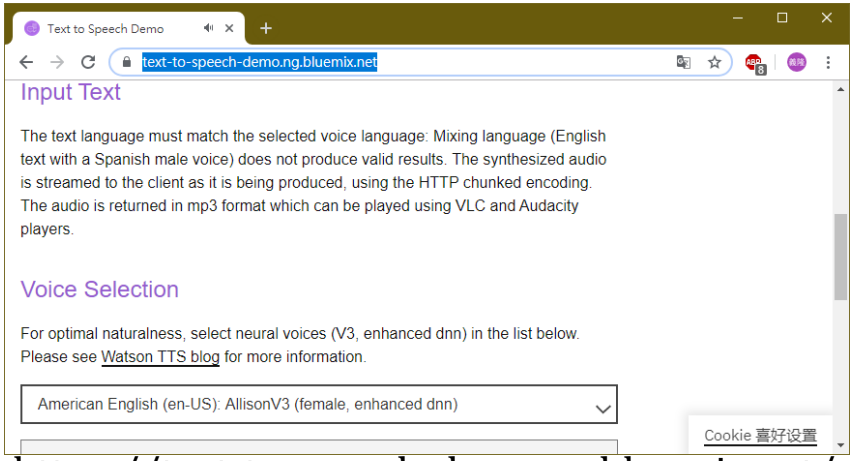
Python 語法

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

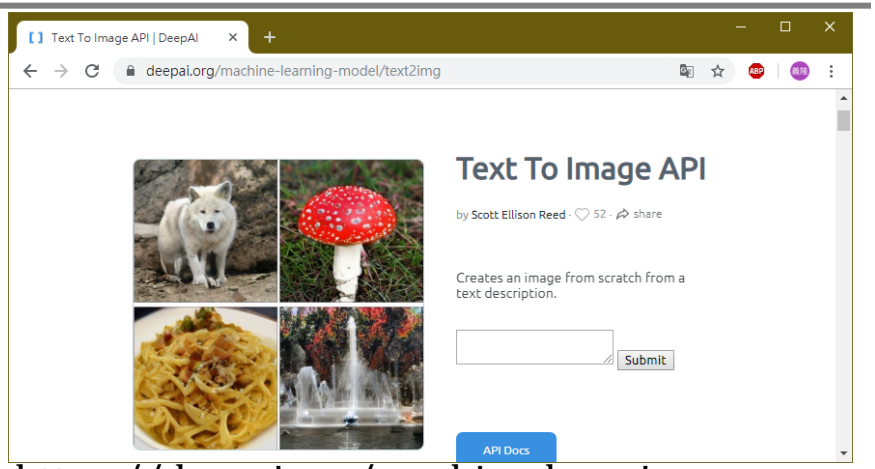
Structured Learning

- Output: Scalar/Class
- Output: Sequence, Matrix, Graph, Tree,…
  - Sequence
    - Machine Translation
    - Speech Recognition
    - Chat-bot
  - Matrix
    - Image to Image
    - Text to Image

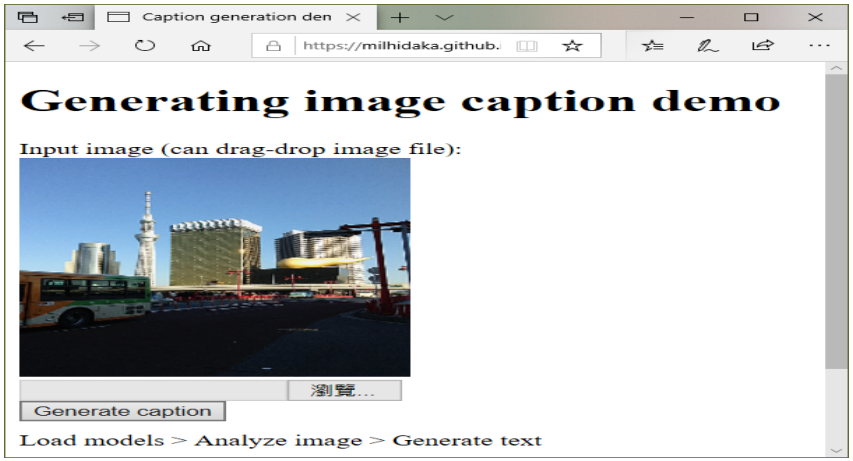
Structured Learning



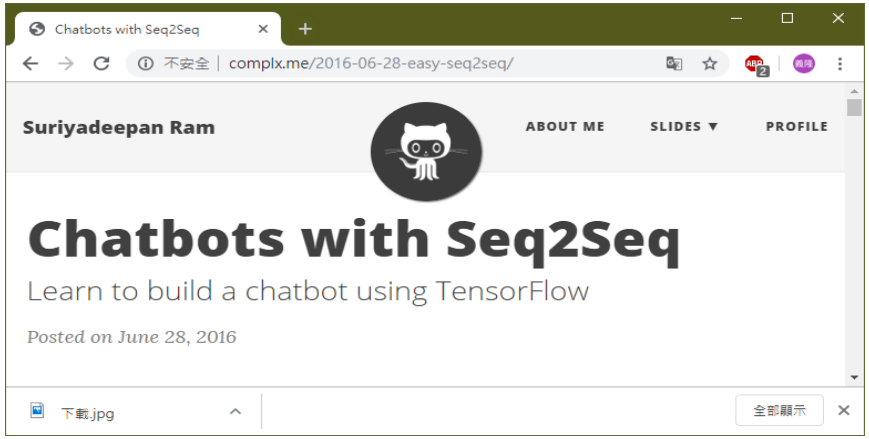
https://text-to-speech-demo.ng.bluemix.net/



https://deepai.org/machine-learning-model/text2img



https://milhidaka.github.io/chainer-image-caption/



http://complx.me/2016-06-28-easy-seq2seq/

Structured Learning

- Output: Matrix
  - Image to Image
  - Text to Image

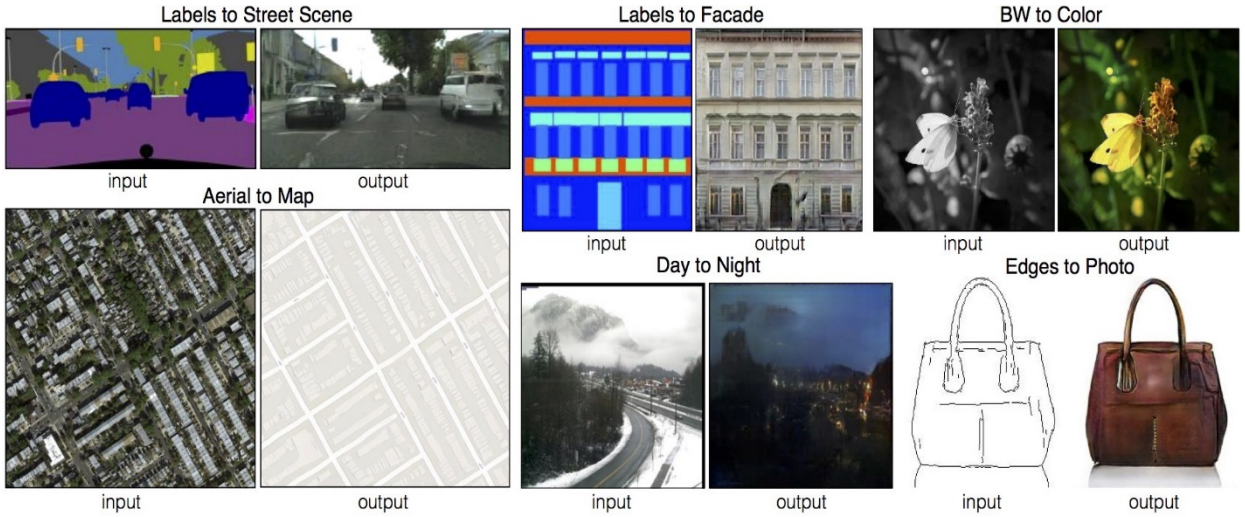
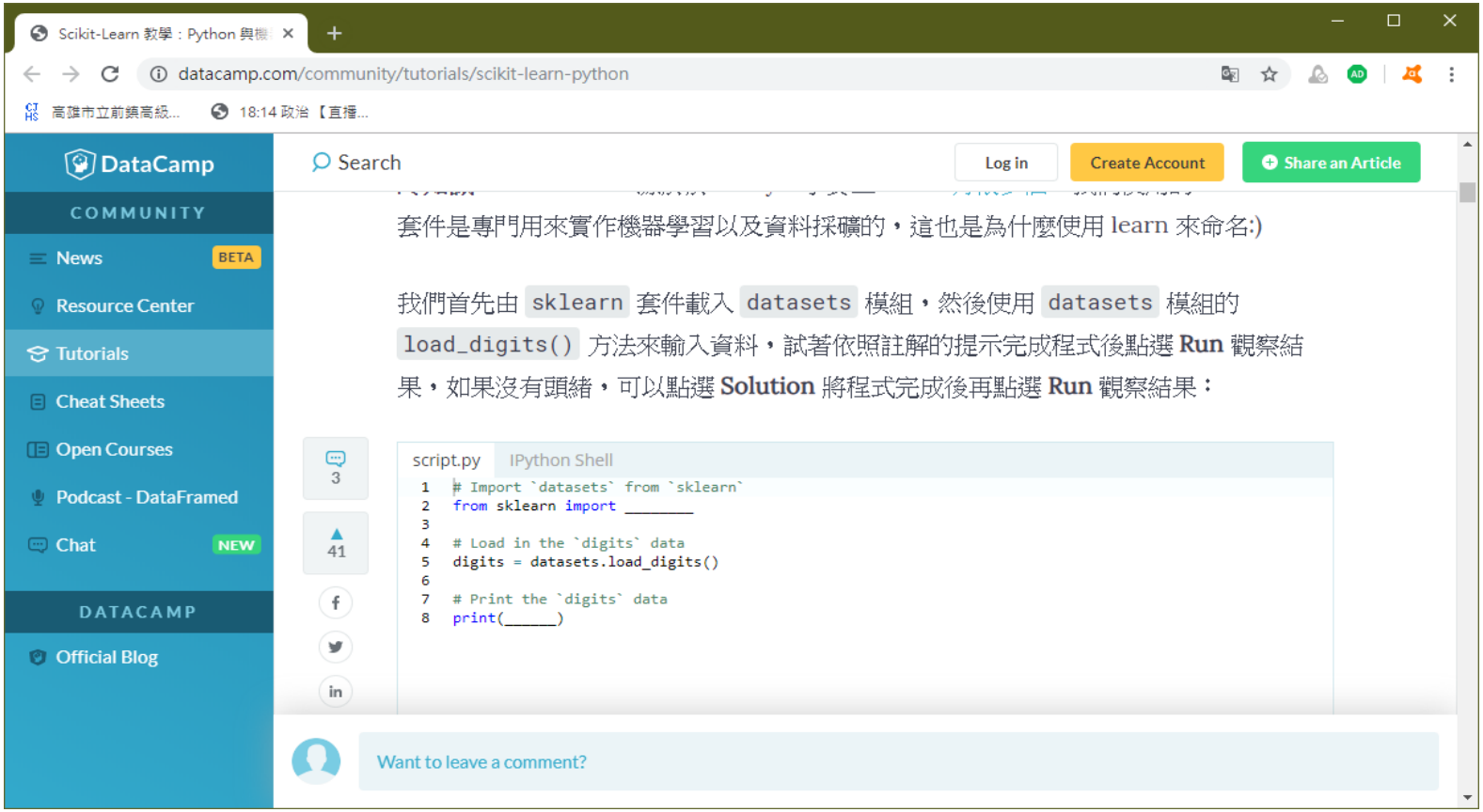


Image-to-Image Translation with Conditional Adversarial Nets

Scikit-Learn Packages



https://www.datacamp.com/community/tutorials/scikit-learn-python

中文自然語言

- 他一邊脫衣服，一邊穿褲子。
- 我的其中一只左腳受傷了
- 下班了，爸爸陸陸續續的回家了。
- 我家門前有條水溝很難過。
- 你看什麼看！沒看過啊
- 欣欣向榮榮告白。
- 今天真熱。
- 先生，再見！
- 一列火車經過，況且況且況且況且況且況
- 這個婆娘不是人，九天仙女下凡塵

自然語音處理應用

https://www.youtube.com/watch?v=iqHAL_8Ug2Y

台灣本土AI「雅婷」誕生


PTT創辦人杜奕瑾成功打造人工智慧語音辨識 APP:雅婷逐字稿
42%
PTT 創世神新創舉：台灣本土AI「雅婷」誕生
被鄉民稱為「PTT創世神」的 PTT 創辦人杜奕瑾，日前回到台灣，創辦了台灣人工智慧實驗室（Taiwan AI Labs）。他們推出了 MIT 台灣在地自行開發的AI 人工智慧APP「雅婷逐字稿」。這個 AI「雅婷」可以將語音轉成逐字稿，對於經常需要藉由聽口述而打逐字稿的人，如記者等來說，簡直就是一個福音！這套人工智慧語音辨識 APP 也支援了 Android、iOS 雙平台。
逐字稿聽打 App：雅婷逐字稿辨識推薦
更多影片
播放 (k)
0:55 / 1:04
是Boss就需要SEO!7個理由:3.SEO是免費的
是Boss就需要SEO!7個理由:2.SEO 帶來更高的流量與轉換
是Boss就需要SEO!7個理由:1.為新創業者帶來客戶行為資料
分類
AI課程 (61)
HTML5教學 (37)
Java (1)
photoshop (2)
Python課程 (55)
SEO優化 (25)
前端工程師 (46)
未分類 (33)
程式語言 (4)
網路行銷課程 (24)
設計課程 (45)
達內教育 (4)

Class 02: 自然語言處理

林義隆
義守大學 資訊工程系 副教授

自然語言處理

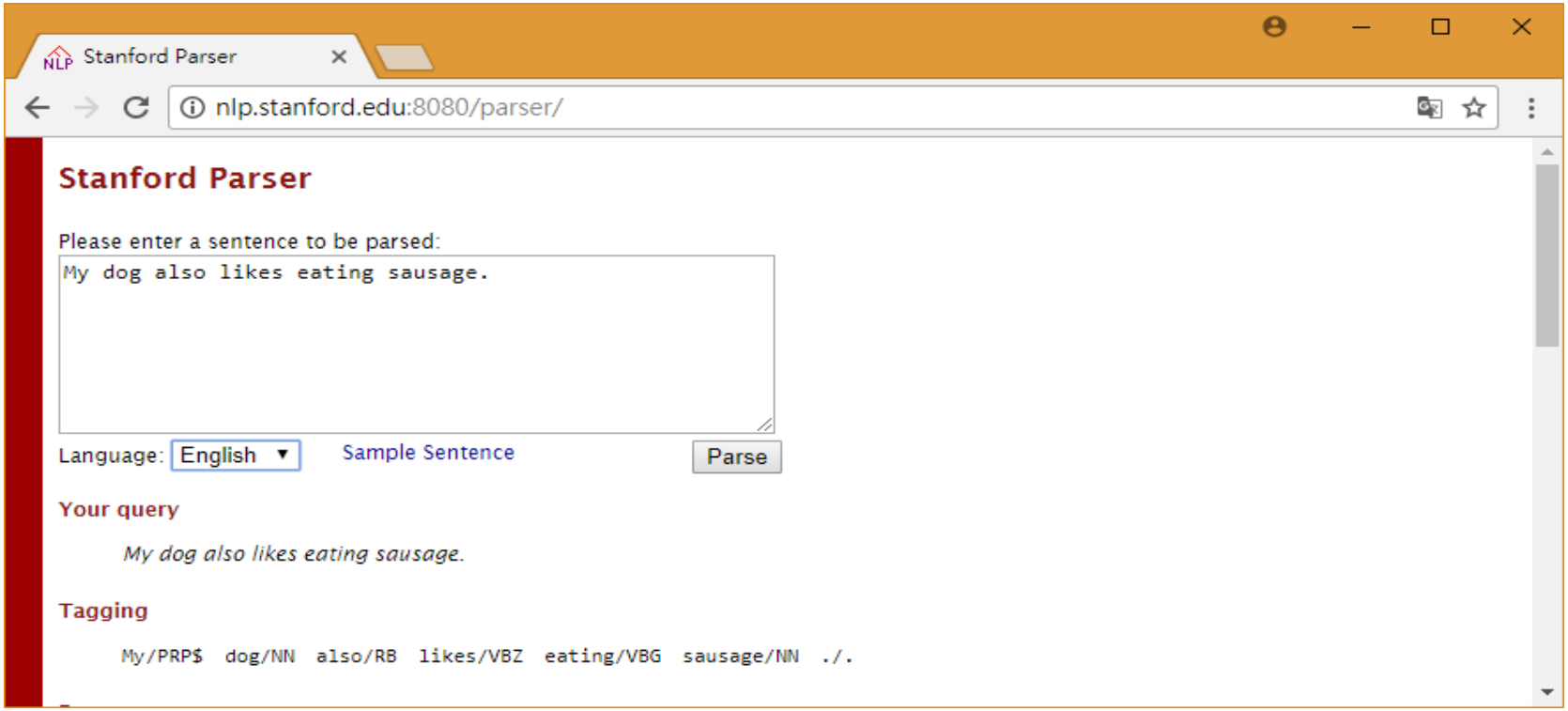
- 問答 Question Answering
- 機器翻譯 Machine Translation
- 摘要 Summarization
- 自然語言推理 Natural Language Inference
- 情感分析 Sentiment Analysis
- 語意角色標註 Semantic Role Labeling
- 關聯萃取 Relation Extraction
- 目標導向對話 Goal-oriented Dialogue
- 語意剖析 Database Query Generation
- 代名詞解析 Pronoun resolution

https://blog.einstein.ai/the-natural-language-decathlon/

自然語言工處理開源套件

- 自然語言工具箱 (NLTK)
- 斯丹福自然語言處理 (Stanford NLP)
- 哈工大語言技術平台 (LTP)
- 台灣中央研究院

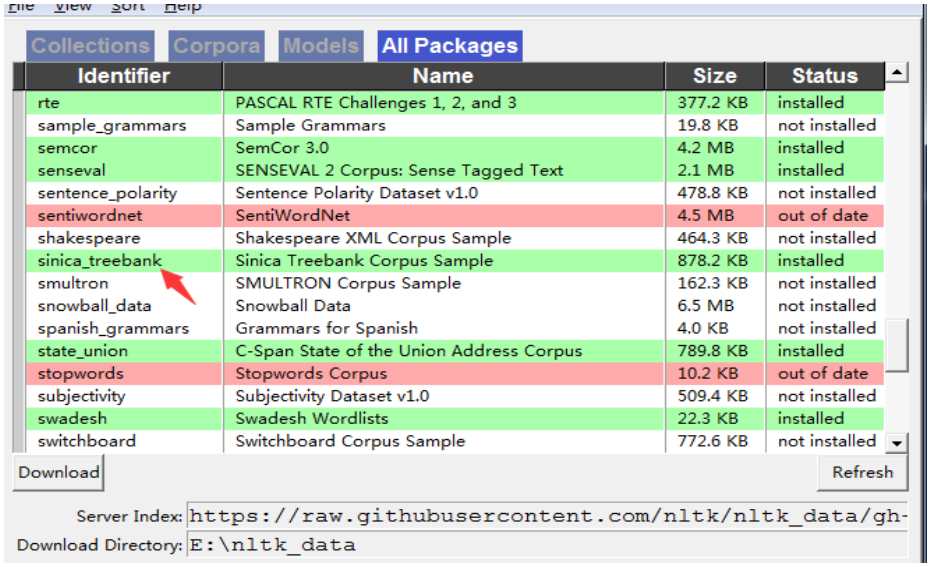
Stanford NLP



http://nlp.stanford.edu:8080/parser/index.jsp

NLTK

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

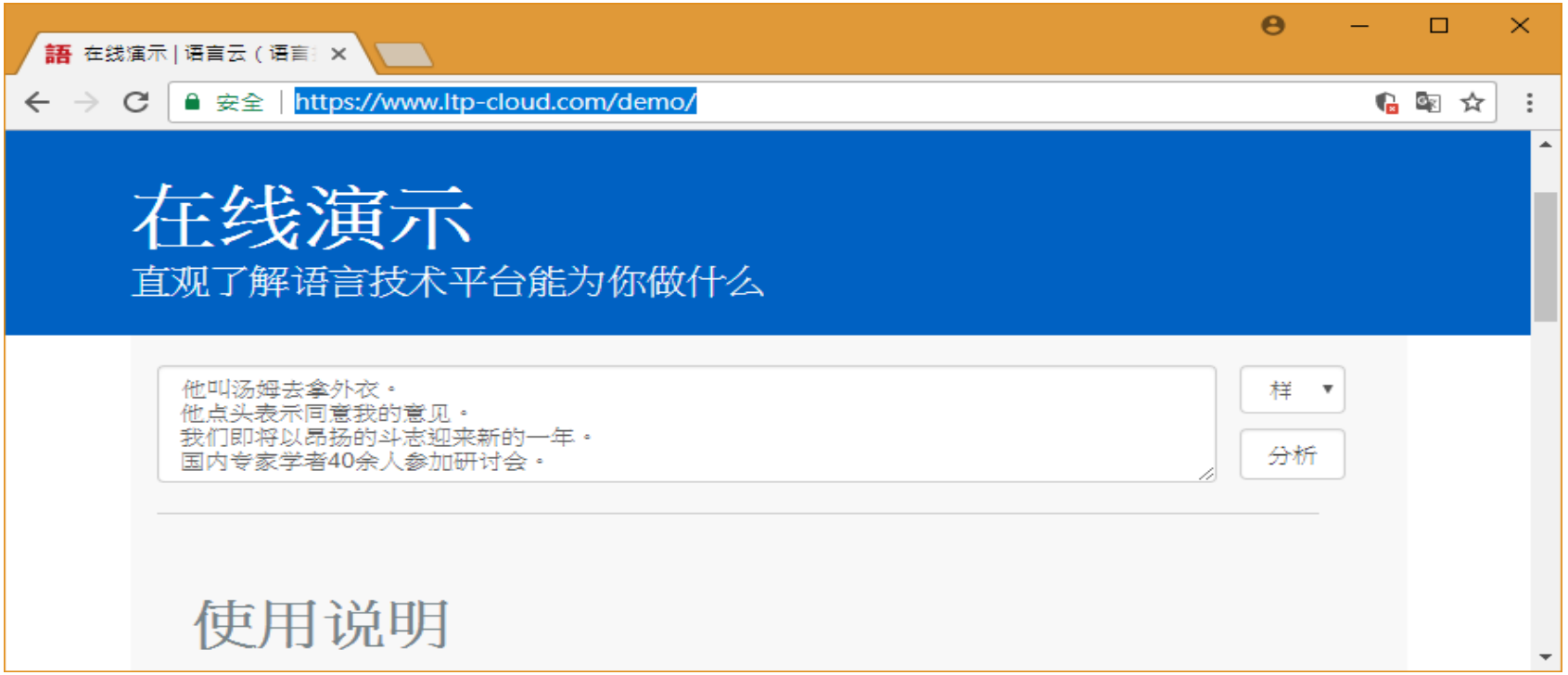


http://www.nltk.org/

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

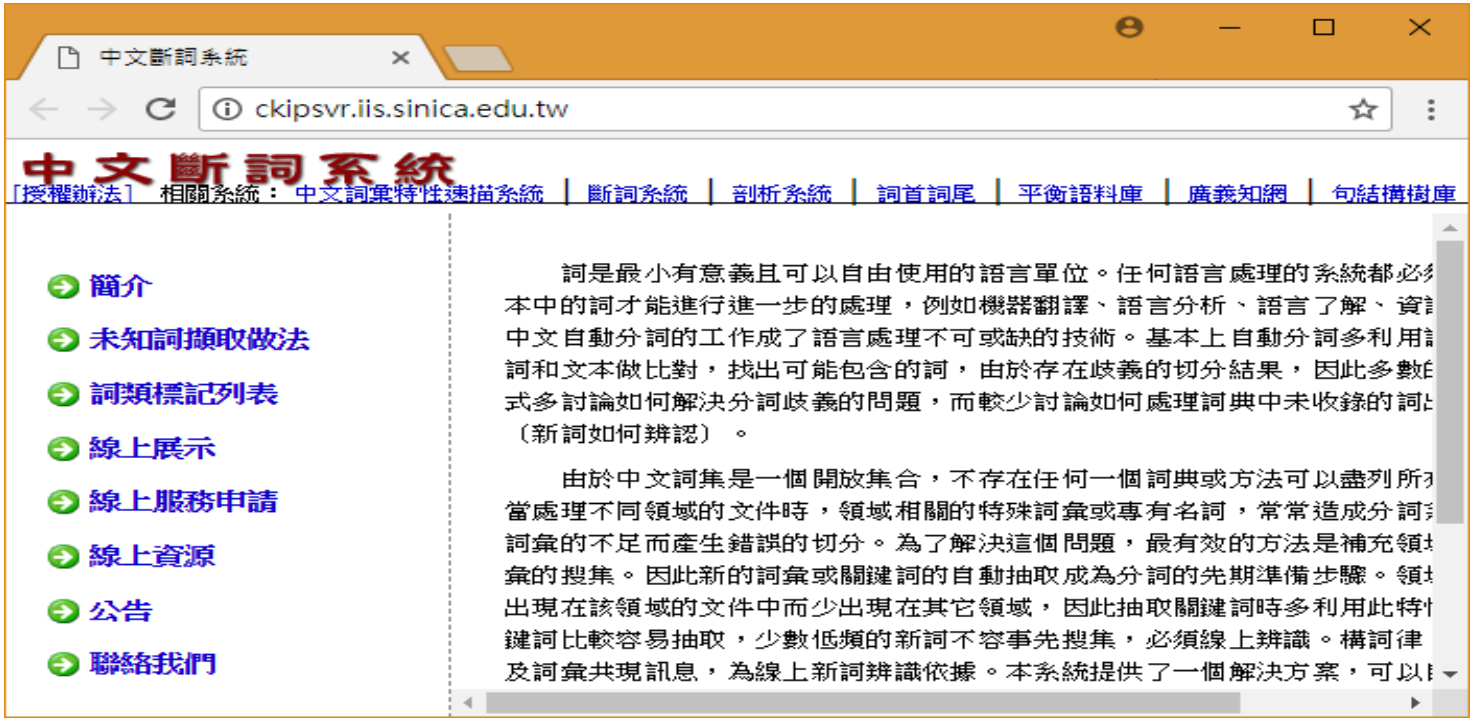
LTP

- 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/

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

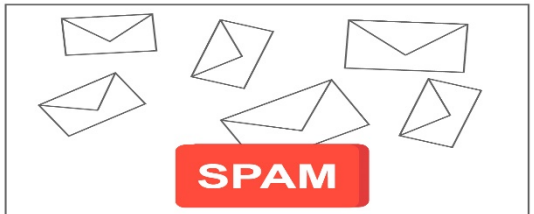
課程重點

- 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 ti index

自然語言處理

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

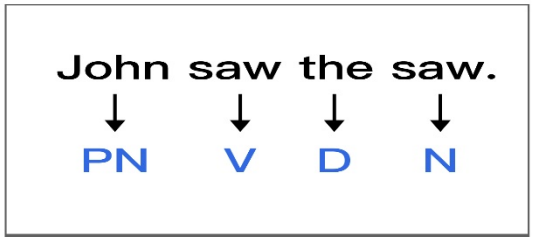
自然語言處理



偵測詐騙郵件

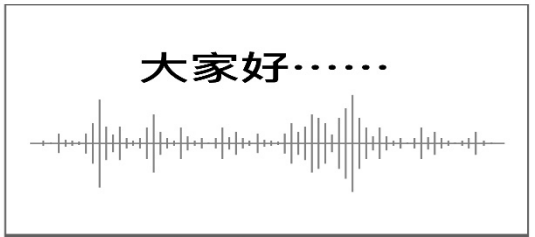
情緒分析

搜尋建議更正

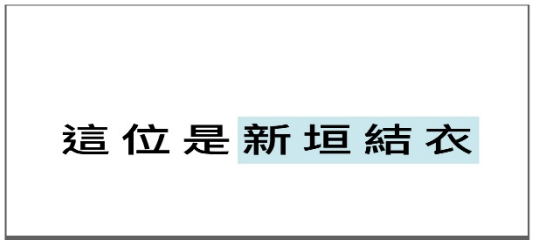


詞類標示

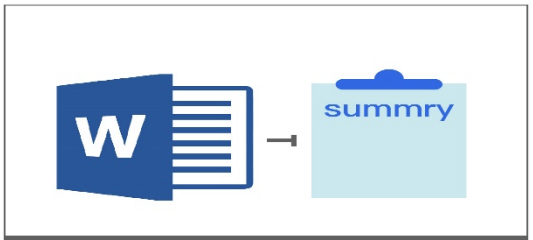
機器翻譯



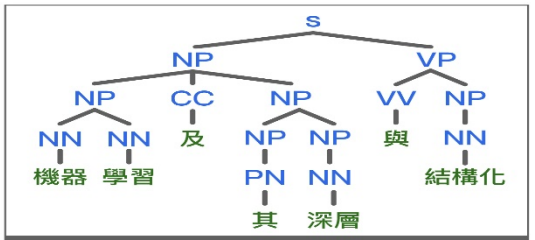
語音辨識



人名辨識擷取



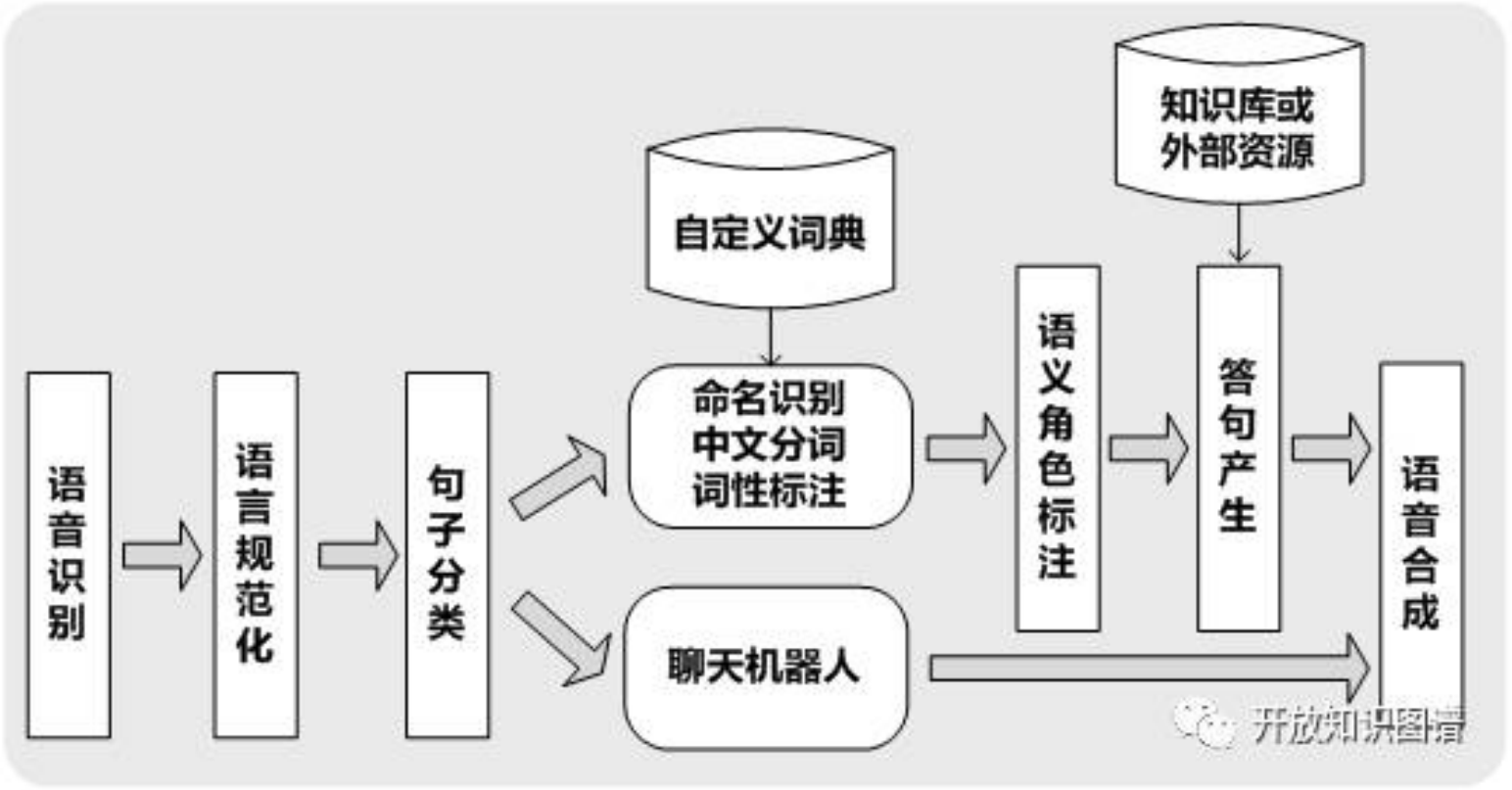
摘要文本大綱



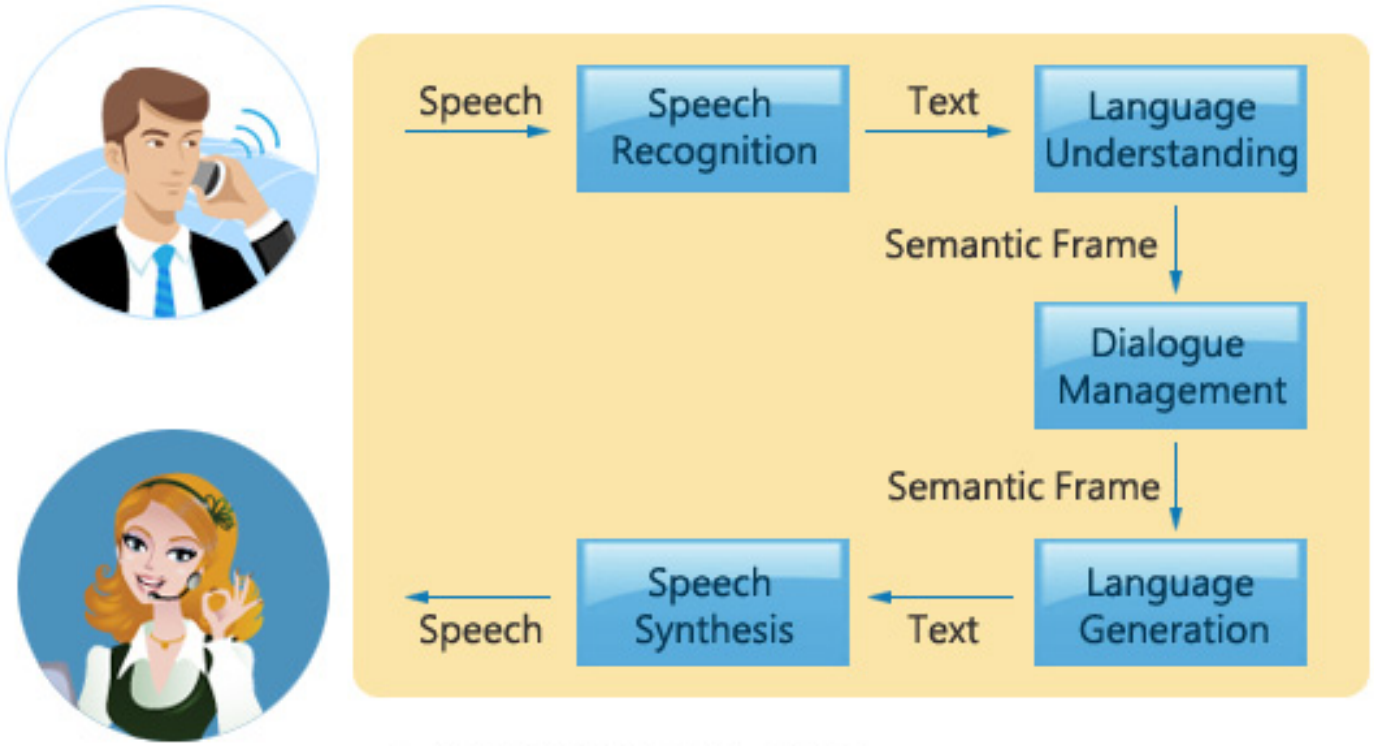
句法分析

資料來源| 中研院: 研之有物

對話系統


知识库或
外部资源
自定义词典
语音识别
语言规范化
句子分类
命名识别
中文分词
词性标注
语义角色标注
答句产生
语音合成
聊天机器人
开放知识图谱

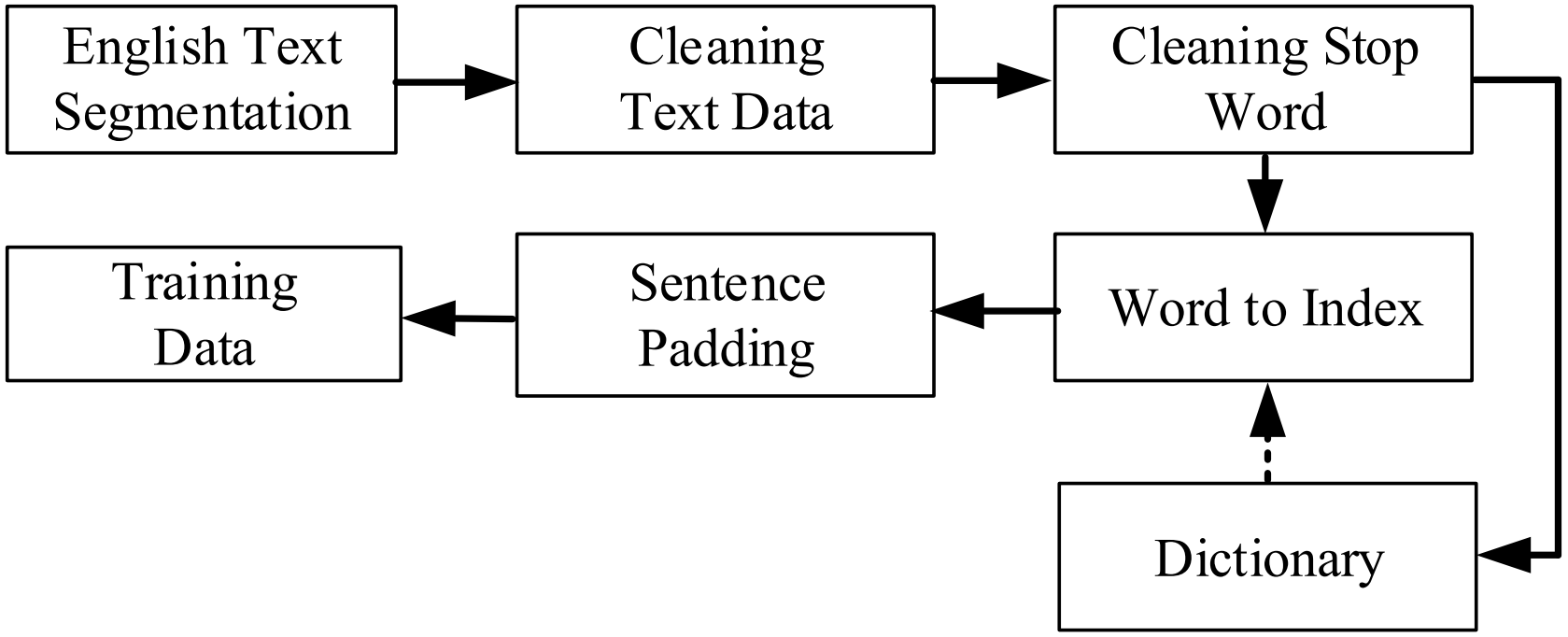
對話系統



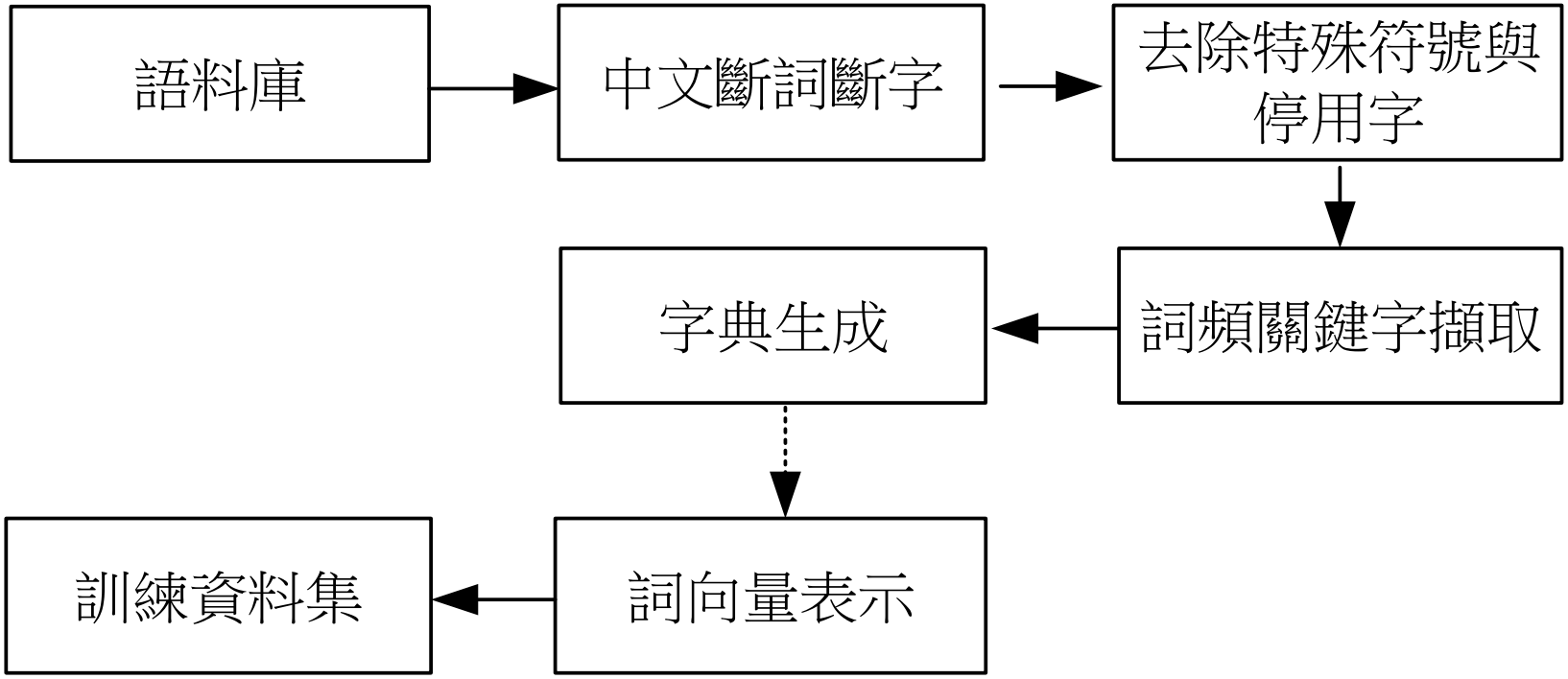
口語對話系統架構示意圖

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

英文前處理


English Text Segmentation
Cleaning Text Data
Cleaning Stop Word
Word to Index
Sentence Padding
Training Data
Dictionary

中文前處理

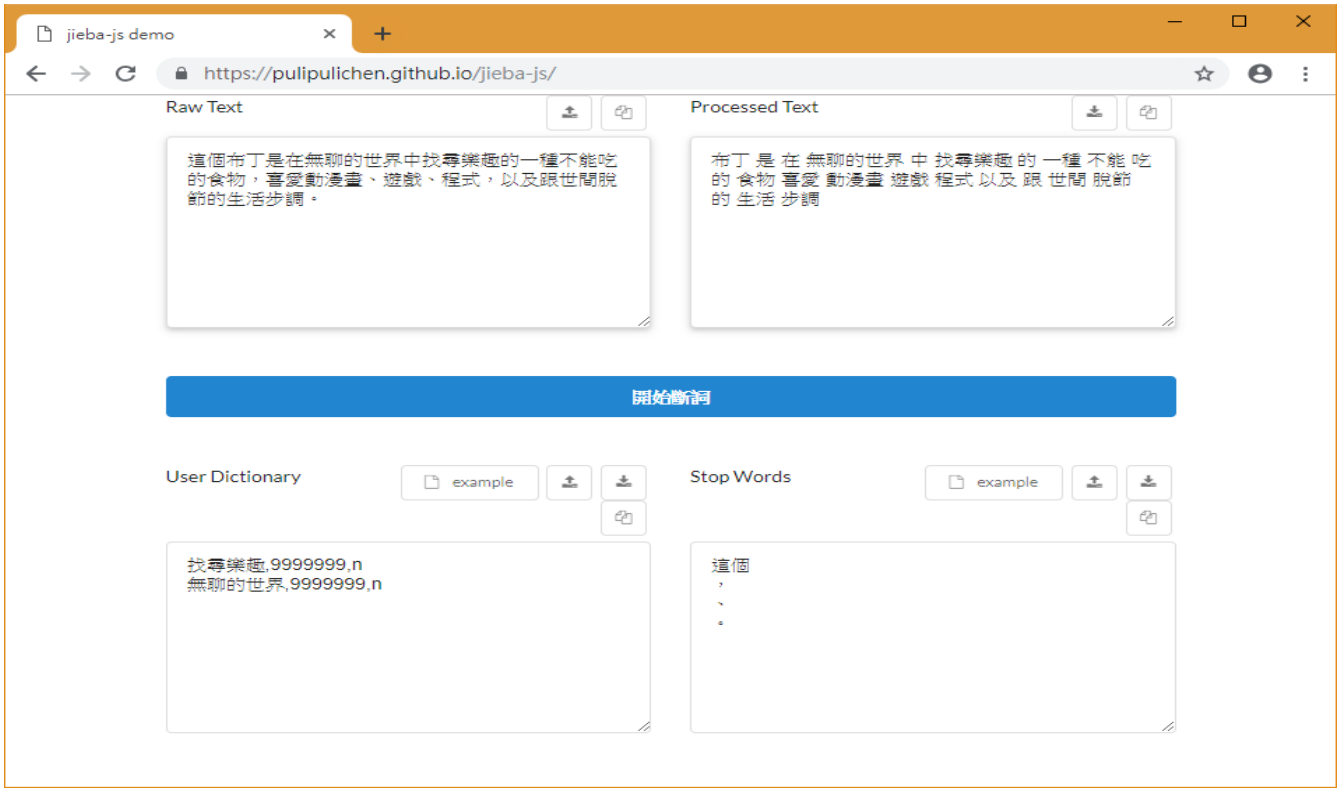


中文分詞器

- 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='丁鈥在哪裡'
cut = jieba.cut(s)
print(','.join(cut))
print([(x.word,x.flag) for x in psg.cut(s)])
```

```
丁,鈥,在,哪裡
[('丁鈥', 'nr'), ('在', 'p'), ('哪裡', 'r')]
```

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

```
我要,找,丁,鈥
[('我', 'r'), ('要', 'v'), ('找', 'v'), ('丁', 'nr'), ('鈥', '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 de ned as the product of the term frequency and the inverse document frequency:

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

Here the tf(t, d) is the term frequency that we introduced in the previous section, and the inverse document frequency *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 *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 de ned 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:

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

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

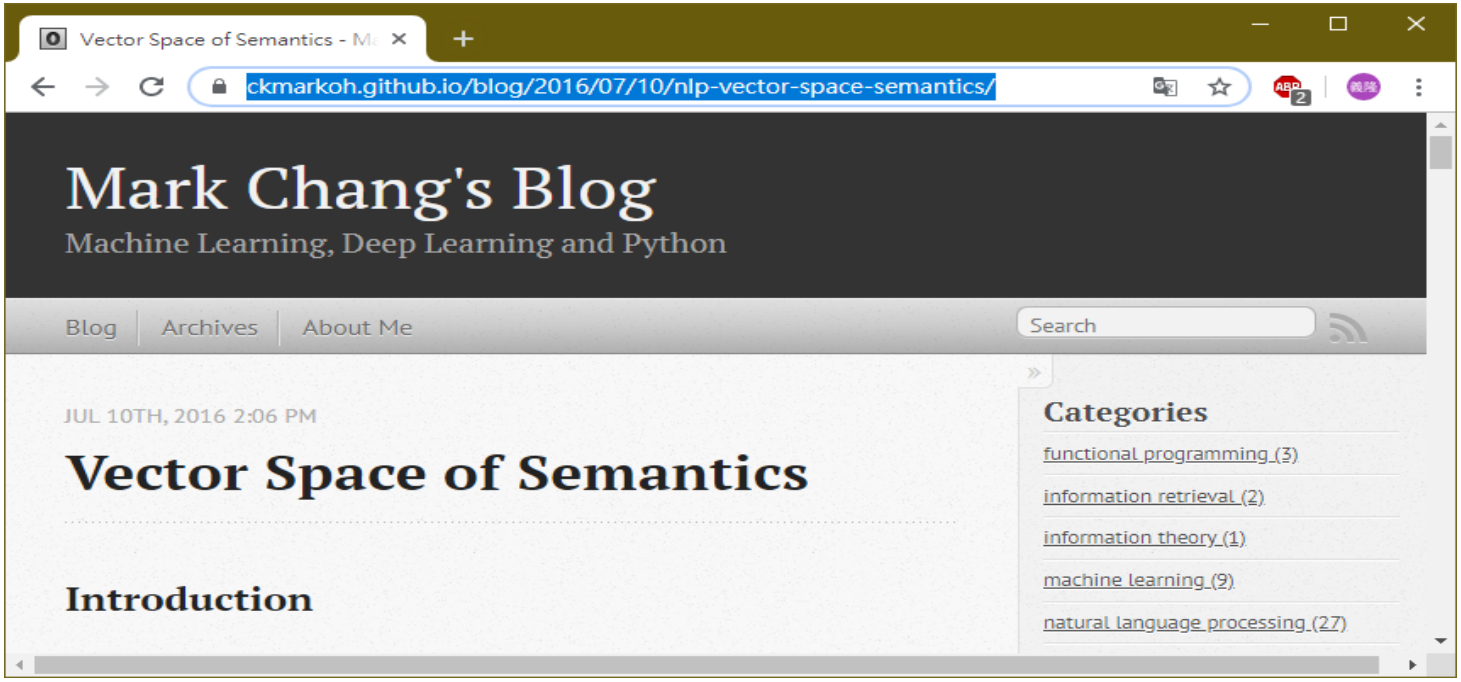
```
import numpy as np
from sklearn.feature_extraction.text import TfidfVectorizer
# list of text documents
text = ["The quick brown fox jumped over the lazy dog.", "The dog.", "The fox"]
# create the transform
vectorizer = TfidfVectorizer()
# tokenize and build vocab
vectorizer.fit(text)
np.set_printoptions(precision=5)
# 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']
[1.69315 1.28768 1.28768 1.69315 1.69315 1.69315 1.69315 1.     ]
(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

詞向量

- 另一種方法來表達詞彙
  - "Word to Vector" or "Word Embedding"



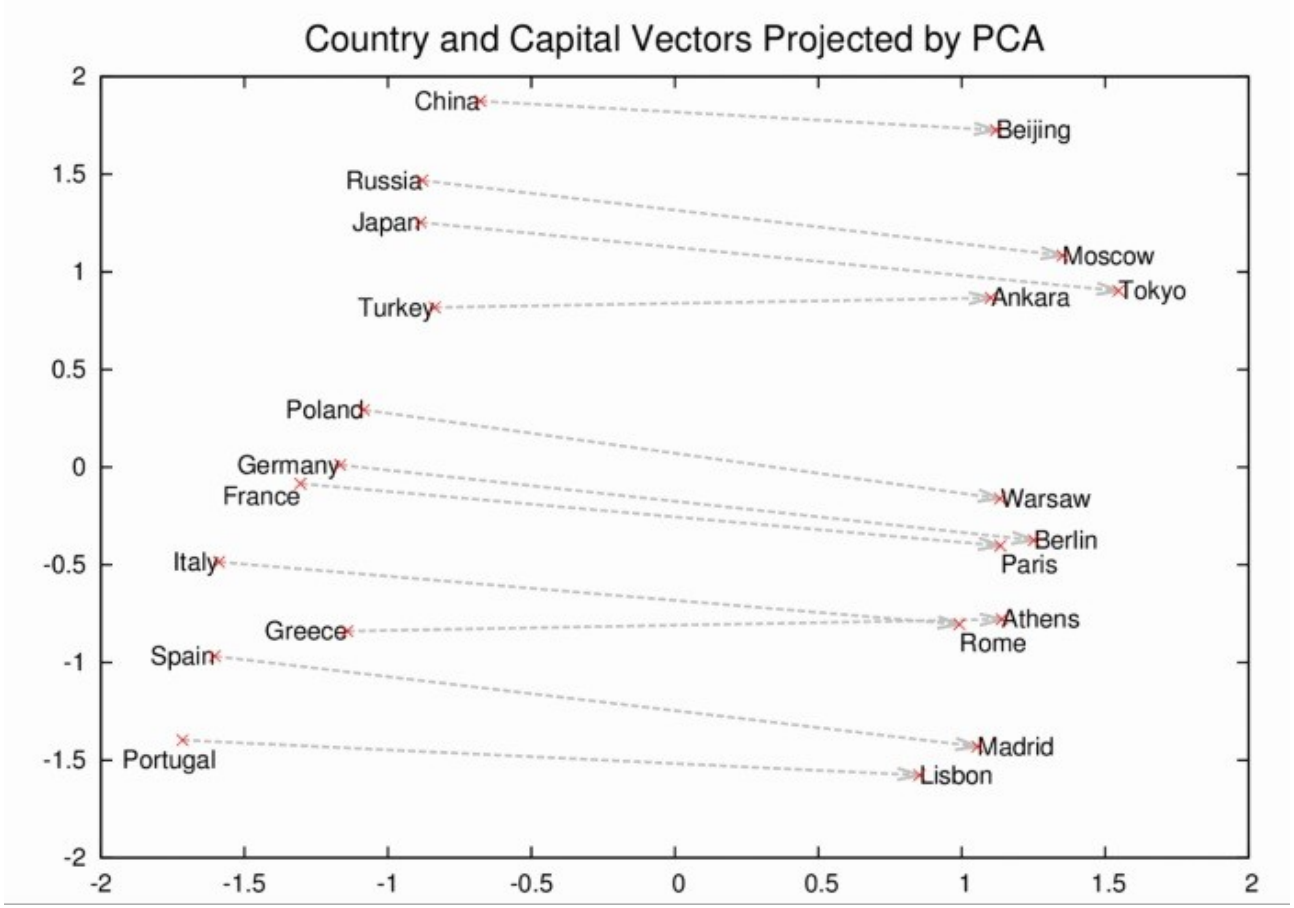
https://ckmarkoh.github.io/blog/2016/07/10/nlp-vector-space-semantics/

Word Embedding

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

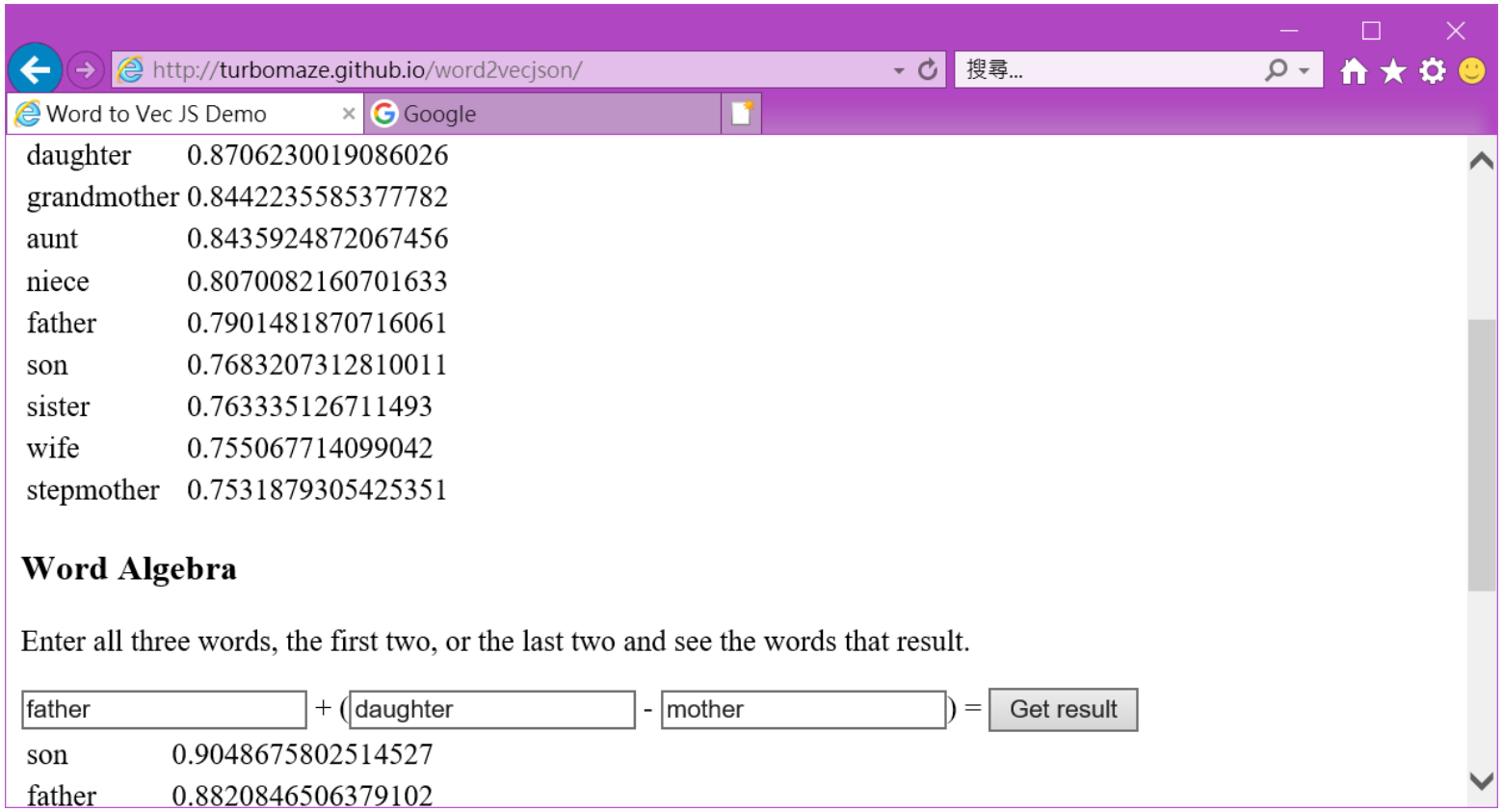
https://code.google.com/archive/p/word2vec/
https://nlp.stanford.edu/projects/glove/

Word to Vector



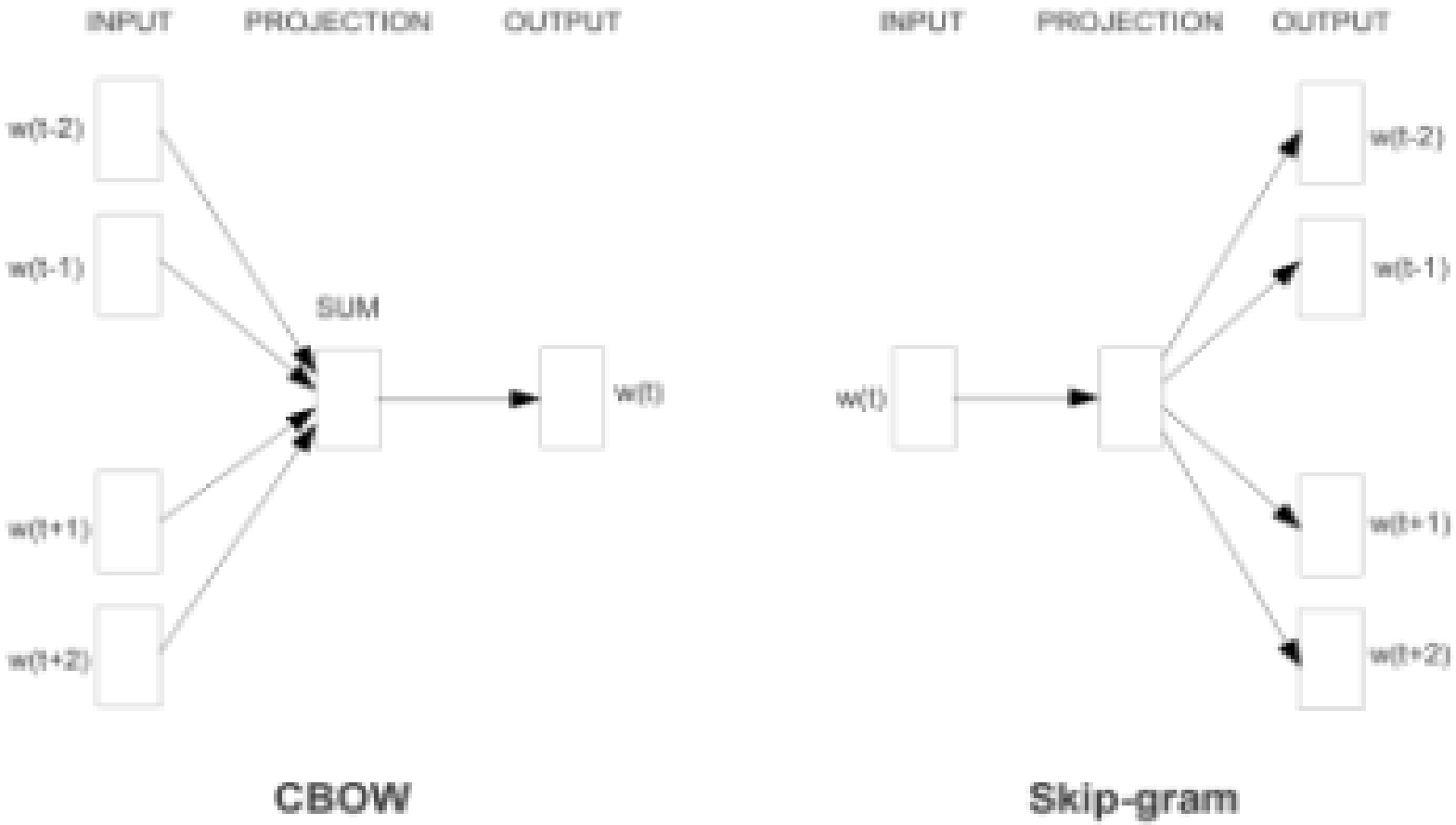
Google Open Source Blog

Word to Vec JS Demo



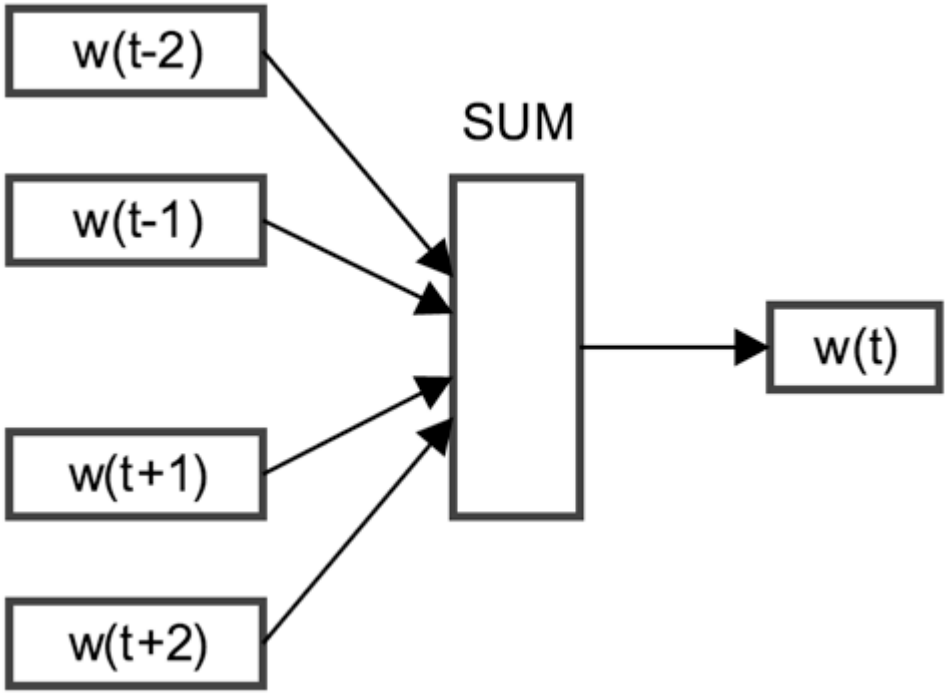
http://turbomaze.github.io/word2vecjson/

BOW & Skip-Gram Models



Bag of Words Model

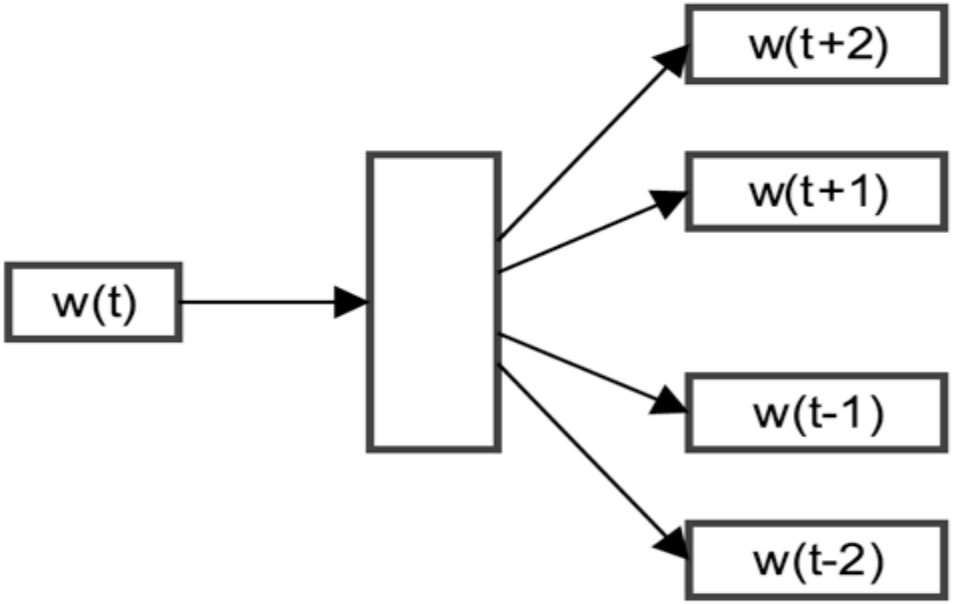
- Predict the surrounding words, based on the current word.



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

Skip-Gram Model

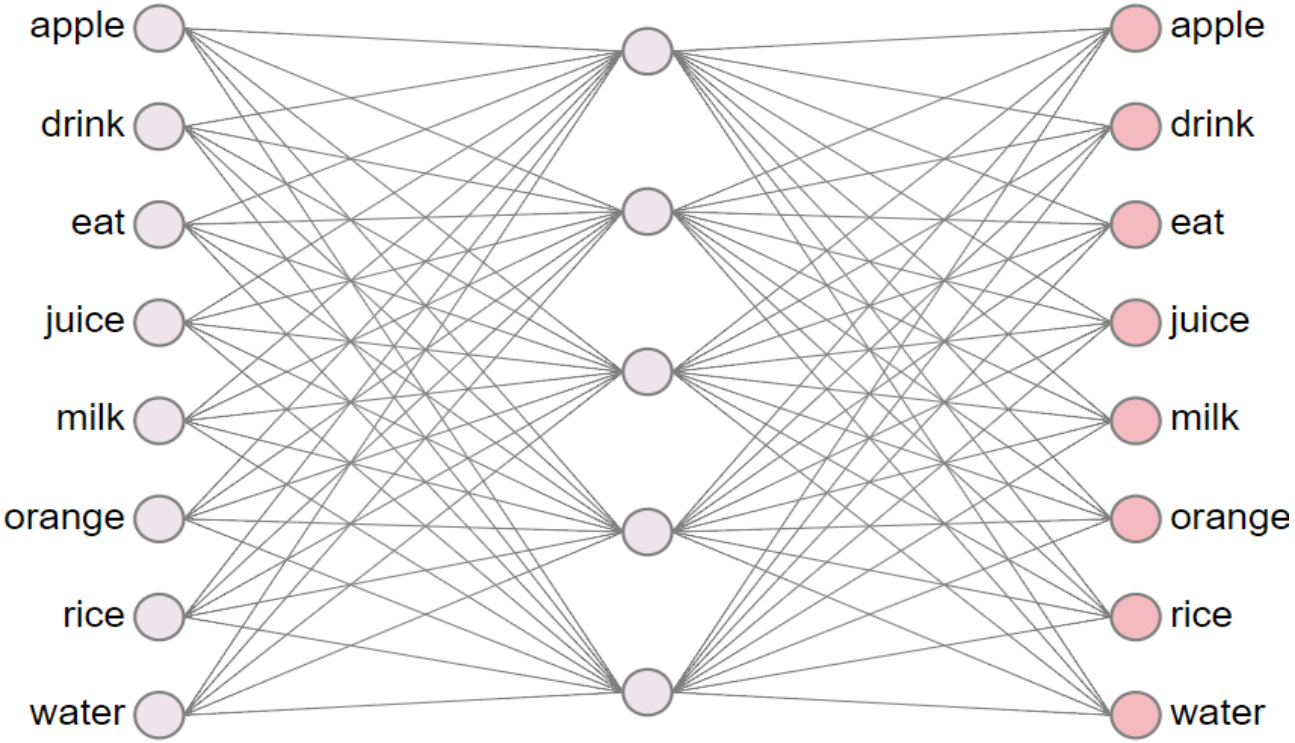
- Predict the surrounding words, based on the current word.



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

Word to Vector

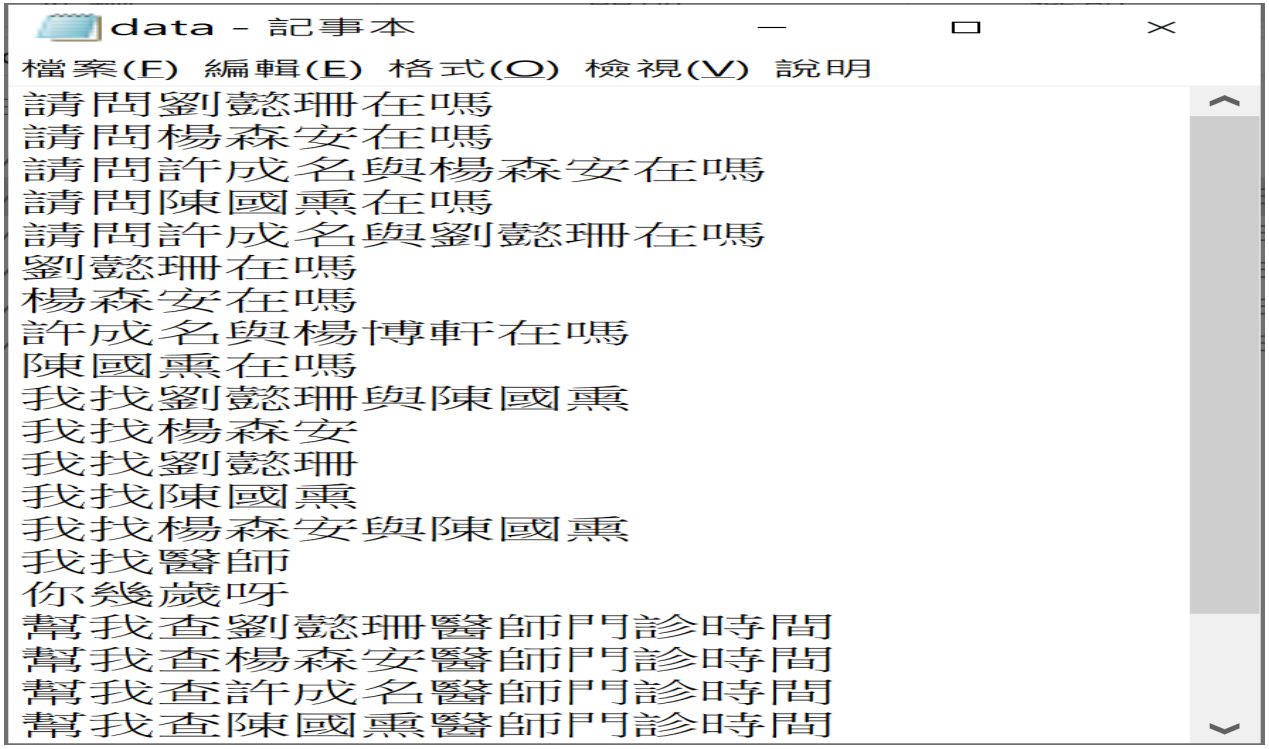
- **WEVI**



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

作業

- 判斷文件中醫師有幾位



作業

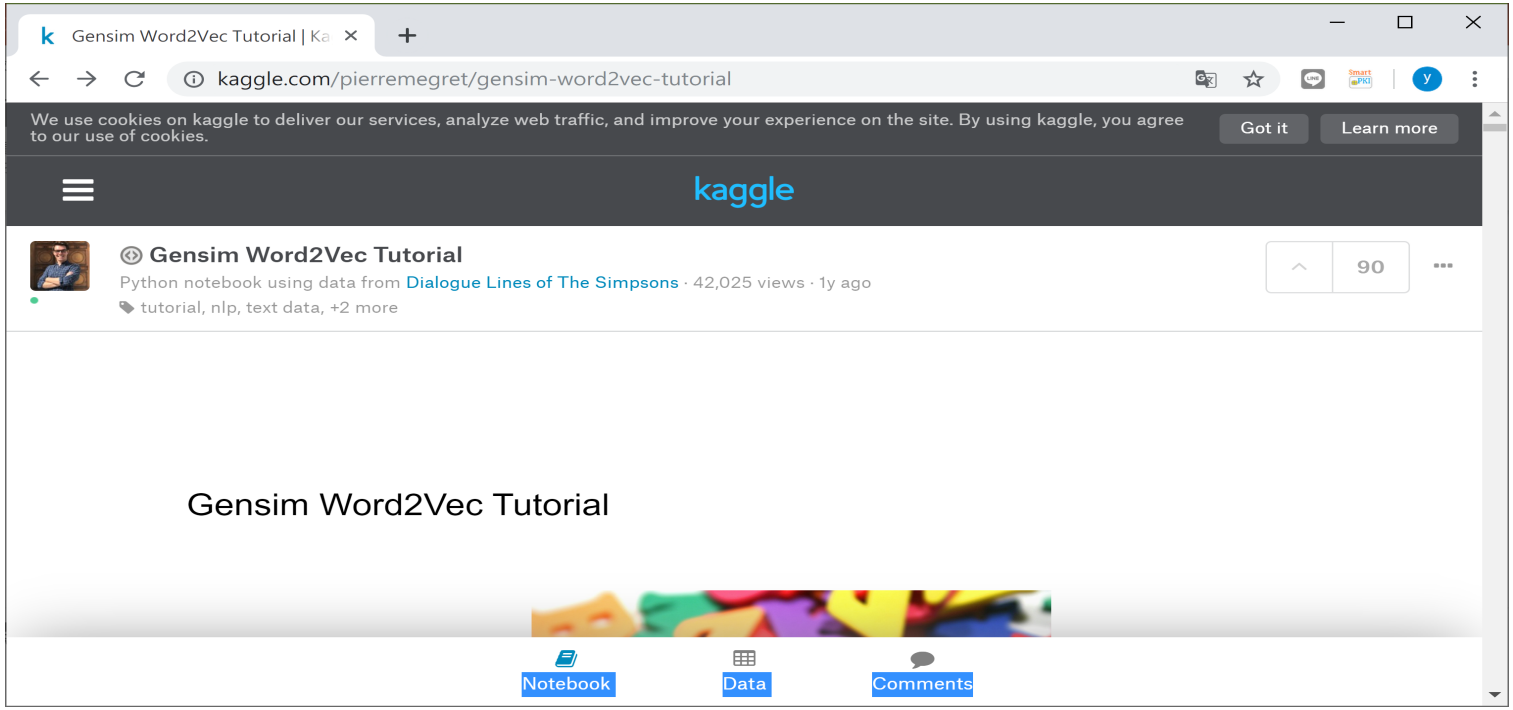
- n -gram model
  - CountVectorizer(ngram_range=(2, 4))
- 解釋說明結果

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