自然語言處理與文字探勘

陳縕儂＆教研處

「版權聲明頁」

課程內容

[講師投影片]
[資料與投影片]
[影片播放列表]
程式碼: ~/courses-tpe/NLP

1. Word Embedding
   - Word Vector
   - Glove
   - gensim API

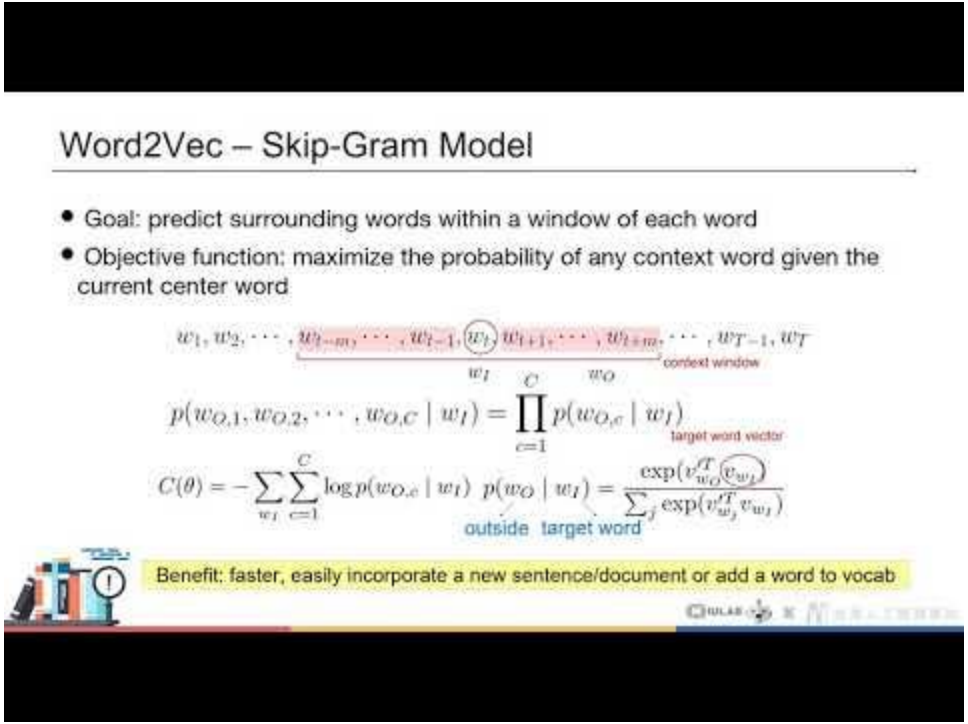
Code / Data 放在 hub 中的 courses 內

- 為維護課程資料，courses 中的檔案皆為 read-only, 如需修改請 cp 至自身的環境中
- 打開 terminal, 輸入
  - [台北班]
    cp -r courses-tpe/NLP/part2 <存放至本機的名稱>
  - [新竹班]
    cp -r courses-hsi/NLP/part2 <存放至本機的名稱>
  - [台中班]
    cp -r courses-txg/NLP/part2 <存放至本機的名稱>

理論教授

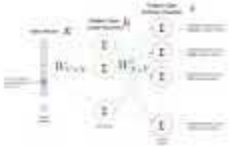
Word Embedding

Word Embedding - Word2Vec



Word Embedding - Word2Vec Training

SGD Update for W



$$\frac{\partial C(\theta)}{\partial w_{ki}} = \frac{\partial C(\theta)}{\partial h_i}\frac{\partial h_i}{\partial w_{ki}}$$

$$\frac{\partial C(\theta)}{\partial h_i} = \sum_{j=1}^{V}\frac{\partial C(\theta)}{\partial s_j}\frac{\partial s_j}{\partial h_i} = \sum_{j=1}^{V}\sum_{c=1}^{C}(y_{jc} - t_{jc}) \cdot w'_{ij}$$

$$\boxed{s_j = {v'_{w_j}}^T \cdot h}$$

Word Embedding - Negative

Negative Sampling

- Idea: only update a sample of output vectors

$$C(\theta) = -\log \sigma({v'_{w_O}}^T v_{w_I}) + \sum_{w_j \in \mathcal{W}_{\text{neg}}} \log \sigma({v'_{w_j}}^T v_{w_I})$$

$${v'_{w_j}}^{(t+1)} = {v'_{w_j}}^{(t)} - \eta \cdot EI_j \cdot h$$

$$EI_j = \sigma({v'_{w_j}}^T v_{w_I}) - t_j$$

$$v_{w_I}^{(t+1)} = v_{w_I}^{(t)} - \eta \cdot EH^T$$

$$EH = \sum_{w_j \in \{w_O\} \cup \mathcal{W}_{\text{neg}}} EI_j \cdot v'_{w_j}$$

Mikolov et al. "Distributed representations of words and phrases and their compositionality," in NIPS, 2013.

Word Embedding - Word2Vec Variants

Word2Vec Variants

- **Skip-gram**: predicting surrounding words given the target word (Mikolov+, 2013) better

$$p(w_{t-m}, \cdots w_{t-1}, w_{t+1}, \cdots, w_{t+m} \mid w_t)$$

- **CBOW (continuous bag-of-words)**: predicting the target word given the surrounding words (Mikolov+, 2013)

$$p(w_t \mid w_{t-m}, \cdots w_{t-1}, w_{t+1}, \cdots, w_{t+m})$$

- **LM (Language modeling)**: predicting the next words given the proceeding contexts (Mikolov+, 2013) first

$$p(w_{t+1} \mid w_t)$$

Mikolov et al., "Efficient estimation of word representations in vector space," in ICLR Workshop, 2013
Mikolov et al., "Linguistic regularities in continuous space word representations," in NAACL HLT, 2013

Word Embedding - GloVe

GloVe

- The relationship of w_i and w_j approximates the ratio of their co-occurrence probabilities with various w_k

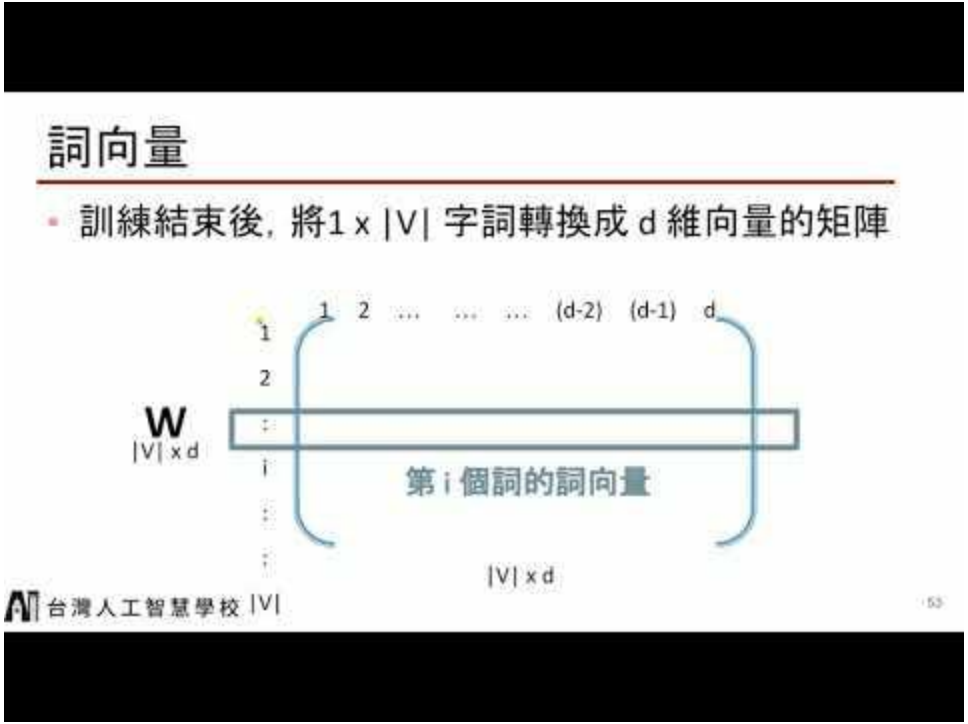
$$F(w_i, w_j, \tilde{w}_k) = \frac{P_{ik}}{P_{jk}}$$

$$F(w_i - w_j, \tilde{w}_k) = \frac{P_{ik}}{P_{jk}}$$

$$F((v_{w_i} - v_{w_j})^T v'_{w_k}) = \frac{P_{ik}}{P_{jk}} \qquad F(\cdot) = \exp(\cdot)$$

Pennington et al., "GloVe: Global Vectors for Word Representation," in EMNLP, 2014

Word Embedding Conclusion



Why word embedding？

- one-hot representation vs. distributed representation
- one-hot representation
  - 每個詞都是一個維度，彼此 independent
- 但每個單詞彼此 independent 明顯不符合
  - 語義 : girl 和 woman
  - 複數 : word 和 words
  - 時態詞 : buy 和 bought
- 如何轉成 distributed representation？
  - word embedding !!

教電腦從文章中解讀詞意

- word2vec
  - Tomas Mikolov et.al 2013 年於 Google 開發
  - Prediction-based method reference

- Glove
  - Jeffrey Pennington et al. 2015 年開發 (Stanford)
  - Count-based method reference

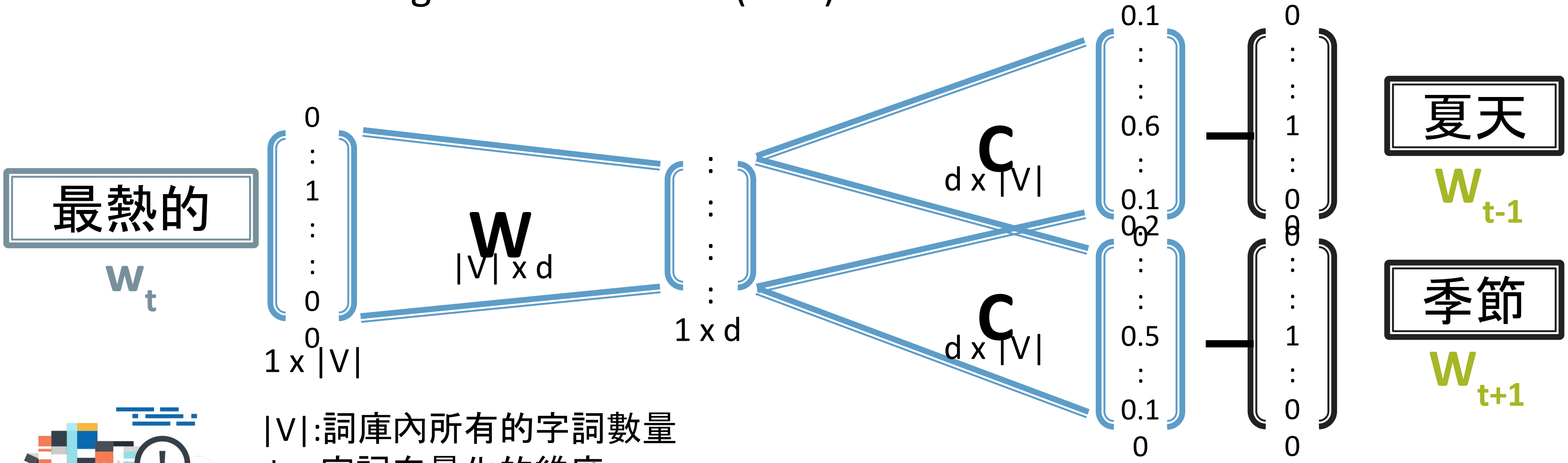
淺談 word2vec

- 語意相近的字較常出現在一起
  - Local window

- 讓電腦玩克漏字填空學習 word embedding
  - Continuous bag of words
  - Skip-gram

Skip-gram 模型

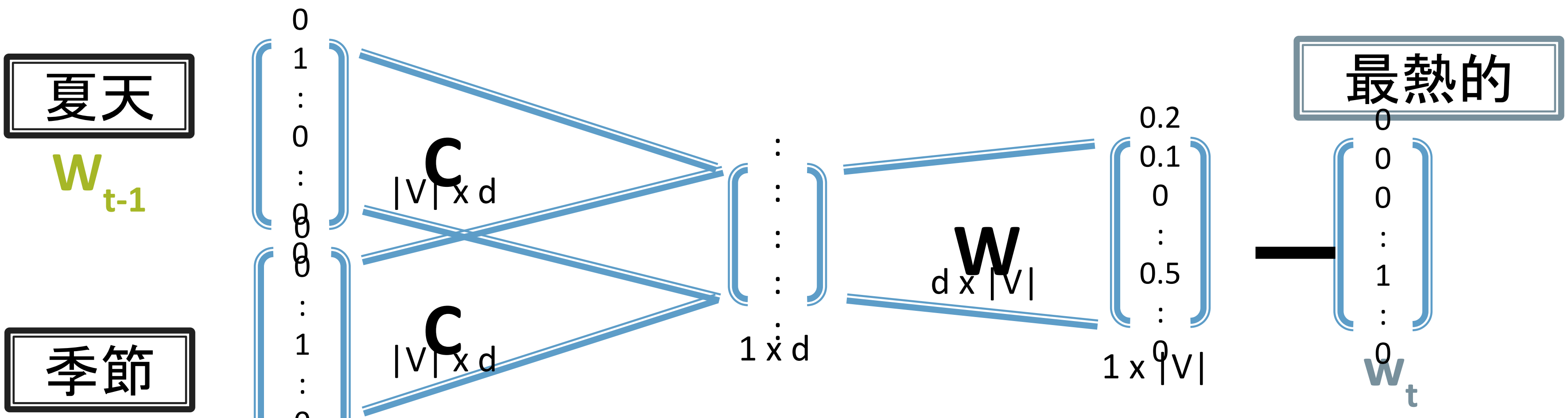
- 藉由 current word 推測 context words
- Neural network model
  - Stochastic gradient descend (SGD)



|V|:詞庫內所有的字詞數量
d :字詞向量化的維度

Continuous Bag of Words 模型

- 由 context words 推測 current word



詞向量

- 訓練結束後，將1 x |V| 字詞轉換成 d 維向量的矩陣

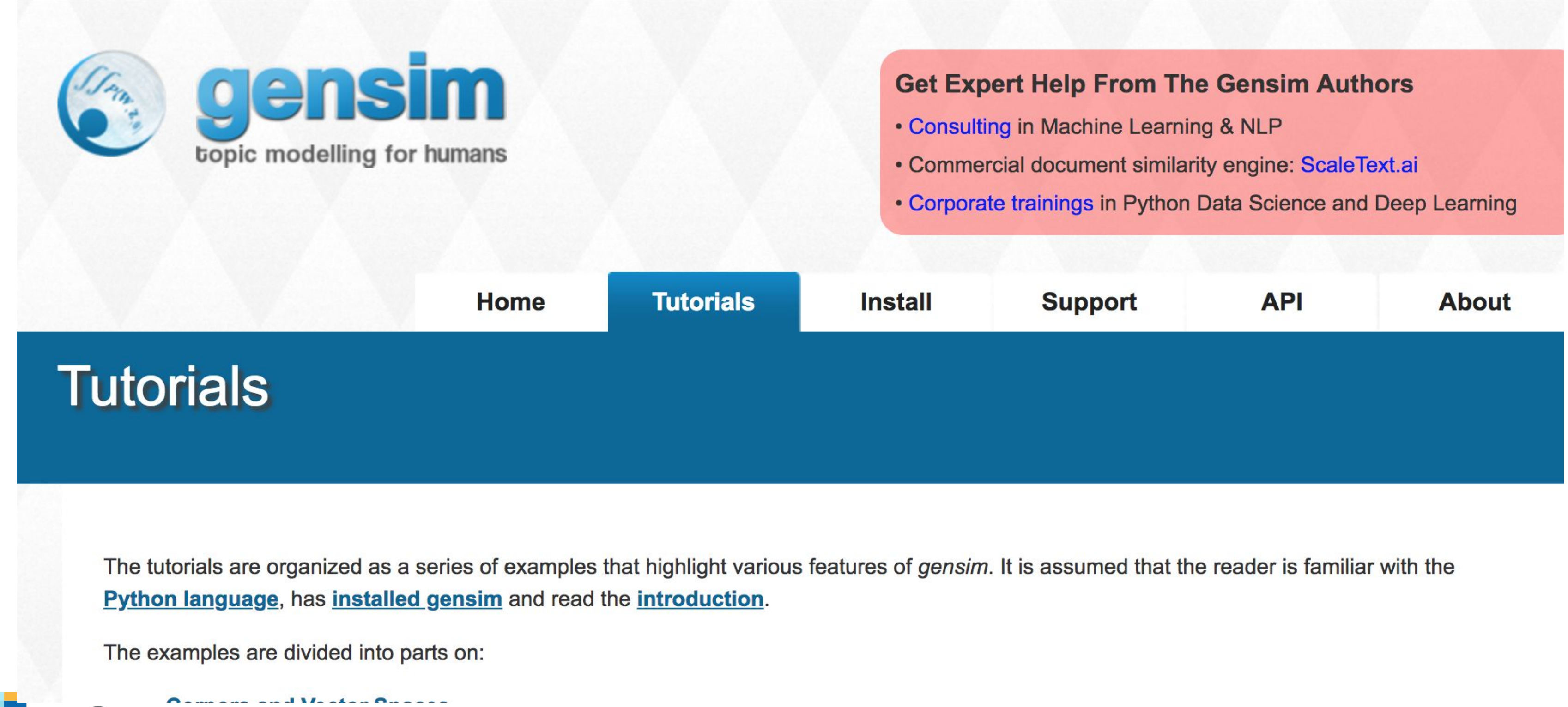
W
|V| x d

$$
\begin{array}{c|cccccccc|}
 & 1 & 2 & \cdots & \cdots & \cdots & (d-2) & (d-1) & d \\
\hline
1 & & & & & & & & \\
2 & & & & & & & & \\
\vdots & & & & & & & & \\
i & & & & & & & & \\
\vdots & & & & & & & & \\
\vdots & & & & & & & & \\
|V| & & & & & & & &
\end{array}
$$

第 i 個詞的詞向量

|V| x d

gensim


gensim
topic modelling for humans
Get Expert Help From The Gensim Authors
• Consulting in Machine Learning & NLP
• Commercial document similarity engine: ScaleText.ai
• Corporate trainings in Python Data Science and Deep Learning
Home
Tutorials
Install
Support
API
About
Tutorials
The tutorials are organized as a series of examples that highlight various features of gensim. It is assumed that the reader is familiar with the Python language, has installed gensim and read the introduction.
The examples are divided into parts on:

gensim 程式範例

- from gensim.models import [word2vec]
- sg 指定要用 CBOW (0) 或 skip-gram (1)

```
model = word2vec.Word2Vec(size=256, min_count=5, window=5, workers=10, sg=0)
```

```
model.build_vocab(data)
```

- 訓練 model

```
for i in range(20):
    random.shuffle(data)
    model.train(data, total_examples=len(data), epochs=1)
```

word vector 結果範例

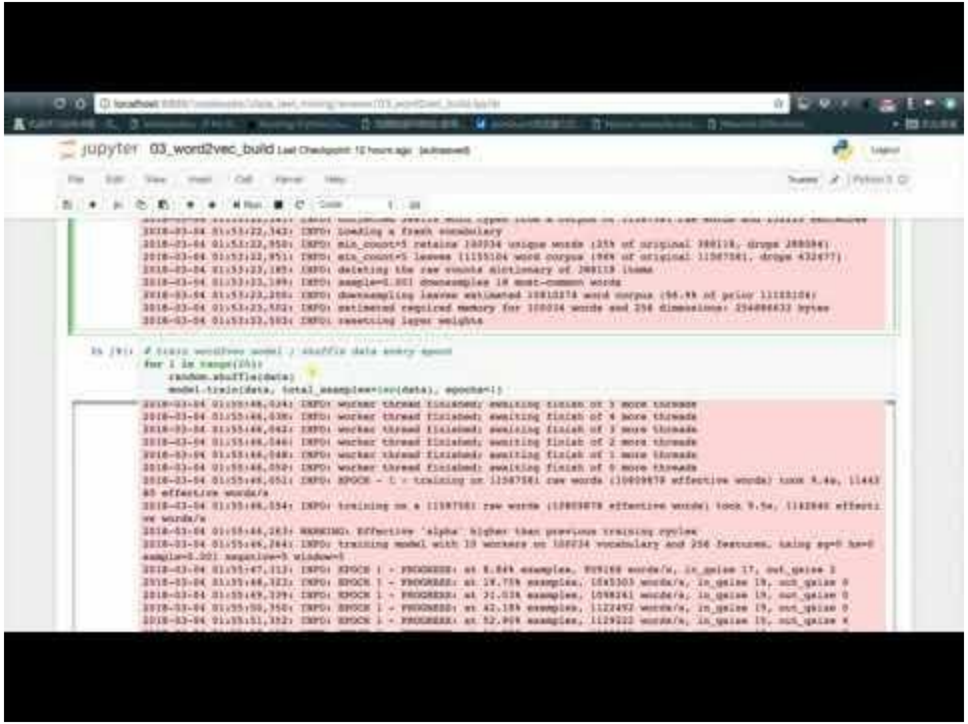
```
model.wv['人工智慧']
```

```
array([ 1.21915638,  0.52043217, -2.32643938,  1.93117321, -0.31237838,
       -0.43847397, -0.76746583, -1.06985056, -0.68717992,  1.39475644,
       -0.11933862,  0.90467405, -0.35574436, -0.03045041,  0.29790911,
       -1.29267919, -1.00543356, -0.44228384, -0.27932352, -0.68174565,
        0.25357905, -1.25369298,  1.50645053, -0.76435697, -1.02407789,
        0.47269911,  2.20226884, -1.1822176 , -0.62692398,  0.53827405,
       -1.1203531 , -0.4413209 ,  2.0929935 , -1.50965261,  0.42474991,
       -0.23208205, -0.2567476 , -0.59872675, -0.76463807, -1.24145818,
       -0.23847748,  1.37008536, -0.15632166, -1.79567409,  1.53807354,
       -1.03542709, -1.40078819,  0.67201942,  1.68245482, -0.19959871,
       -0.74226034, -0.12889996, -1.0839591 , -1.04049397,  0.2660369 ,
        0.0702365 ,  0.0289956 , -0.04043816, -1.18576312, -0.55347919,
       -0.67061466,  0.68260211, -0.2225527 ,  0.20782772, -0.53322947,
       -0.44461682, -1.5774188 ,  0.82782865, -0.91934246,  0.29894483,
       -1.03293765,  1.17304862,  1.46772027,  0.62551779, -2.06187868,
        1.13207734, -0.80871838,  0.35943773, -1.12879944, -0.01194098,
        0.5731349 ,  1.48613763,  0.68320924,  0.14039512,  1.14049029,
       -0.08283772,  0.62286341,  0.73727089, -1.9068346 , -0.63660204,
       -0.18024929, -0.95840788,  0.54120874,  0.80851376,  1.08375335,
        0.20484021, -0.56473464, -1.69883382, -1.25609303, -0.13403395,
        0.70849288, -0.15233018, -1.70290852, -1.39674747, -0.81129694,
       -0.17469636,  0.66630858, -0.563559  , -0.02490964,  0.38999739,
        0.24147406,  0.26629636, -0.87350655,  0.0266343 , -0.05054072,
        0.60931027, -1.26577628, -0.79294878,  0.58070451,  0.92532027,
       -0.17163102,  0.52050233, -1.31764424, -0.25275663, -0.46012133
```

程式練習時間

- 03_word2vec_build.ipynb
    - 執行 Word2Vec 範例
    - 嘗試理解及調整參數 , e.g. 改成 skip-gram

程式解說


jupyter 03_word2vec_build
for i in range(25):
random.shuffle(data)
model.train(data, total_examples=len(data), epochs=1)