文字探勘



(Text Mining) 語意分析和命名實體識別 (Semantic Analysis and Named Entity Recognition; NER)

1082TM09 MBA, BDABI, TKU (E3611) (8480) (Spring 2020) Mon, 7, 8, 9 (14:10-17:00) (B206)



Chichang Jou 周清江 Associate Professor 副教授 cjou@mail.tku.edu.tw



Min-Yuh Day <u>戴敏育</u> Associate Professor 副教授

myday@mail.tku.edu.tw

 Dept. of Information Management, Tamkang University

 淡江大學 資訊管理學系

2020-05-11

課程大綱 (Syllabus)

週次(Week) 日期(Date) 內容(Subject/Topics)

- 1 2020/03/02 文字探勘課程介紹 (Course Orientation on Text Mining)
- 2 2020/03/09 文字探勘基礎:自然語言處理 (Foundations of Text Mining: Natural Language Processing; NLP)

3 2020/03/16 Python自然語言處理 (Python for Natural Language Processing)

4 2020/03/23 處理和理解文本 (Processing and Understanding Text)

5 2020/03/30 文本表達特徵工程 (Feature Engineering for Text Representation)

6 2020/04/06 人工智慧文本分析個案研究 | (Case Study on Artificial Intelligence for Text Analytics I)

課程大綱 (Syllabus)

週次(Week) 日期(Date) 內容(Subject/Topics)

- 7 2020/04/13 文本分類 (Text Classification)
- 8 2020/04/20 文本摘要和主題模型 (Text Summarization and Topic Models)
- 9 2020/04/27 期中報告 (Midterm Project Report)
- 10 2020/05/04 文本相似度和分群 (Text Similarity and Clustering)
- 11 2020/05/11 語意分析和命名實體識別 (Semantic Analysis and Named Entity Recognition; NER)

12 2020/05/18 情感分析 (Sentiment Analysis)

課程大綱 (Syllabus)

週次(Week) 日期(Date) 內容(Subject/Topics)

- 13 2020/05/25 人工智慧文本分析個案研究 II (Case Study on Artificial Intelligence for Text Analytics II)
- 14 2020/06/01 深度學習和通用句子嵌入模型

(Deep Learning and Universal Sentence-Embedding Models)

- 15 2020/06/08 問答系統與對話系統 (Question Answering and Dialogue Systems)
- 16 2020/06/15 期末報告 I (Final Project Presentation I)
- 17 2020/06/22 期末報告 II (Final Project Presentation II)

18 2020/06/29 教師彈性補充教學

Semantic Analysis and **Named Entity Recognition (NER)**

Outline

- Semantic Analysis
 - WordNet
 - Word sense disambiguation
- Named Entity Recognition (NER)

Semantic Analysis

Semantics

-the study of meaning

• Linguistic semantics

-the study of meaning in natural language.

Semantic Analysis and NER

- WordNet and synsets
 - -Analyzing lexical semantic relations
 - -Word sense disambiguation
- Named entity recognition
- Analyzing semantic representations

WordNet A Lexical Database for English

Any opinions, findings, and conclusions or recommendations expressed in this material are those of

the creators of WordNet and do not necessarily reflect the views of any funding agency or Princeton

When writing a paper or producing a software application, tool, or interface based on WordNet, it is necessary to properly <u>cite the source</u>. Citation figures are critical to WordNet funding.

WordNet® is a large lexical database of English. Nouns, verbs, adjectives and adverbs are

freely and publicly available for download. WordNet's structure makes it a useful tool for

computational linguistics and natural language processing.

grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. Synsets

are interlinked by means of conceptual-semantic and lexical relations. The resulting network of

meaningfully related words and concepts can be navigated with the browser @. WordNet is also

😽 PRINCETON UNIVERSITY

What is WordNet?

University.

About WordNet

WordNet A Lexical Database for English

Search...

What is WordNet

People

News

Use Wordnet Online 🗗

Download

Citing WordNet

License and Commercial Use

Related Projects

Documentation

Publications

Frequently Asked

WordNet superficially resembles a thesaurus, in that it groups words together based on their

https://wordnet.princeton.edu/

Note

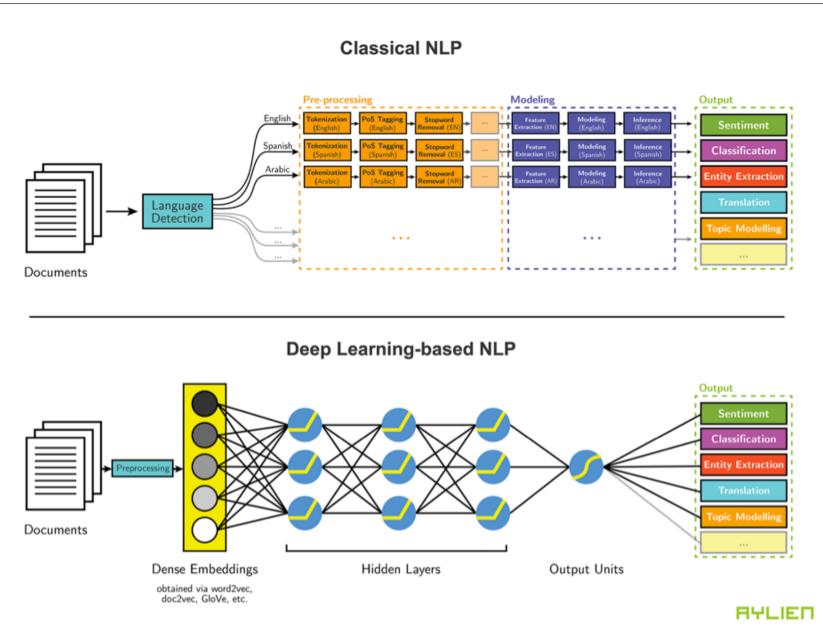
Due to funding and staffing issues, we are no longer able to accept comment and suggestions.

We get numerous questions regarding topics that are addressed on our FAQ page. If you have a problem or question regarding something you downloaded from the "Related projects" page, you must contact the developer directly.

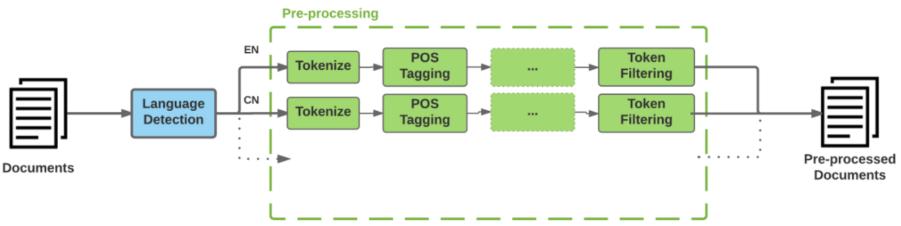
Please note that any changes

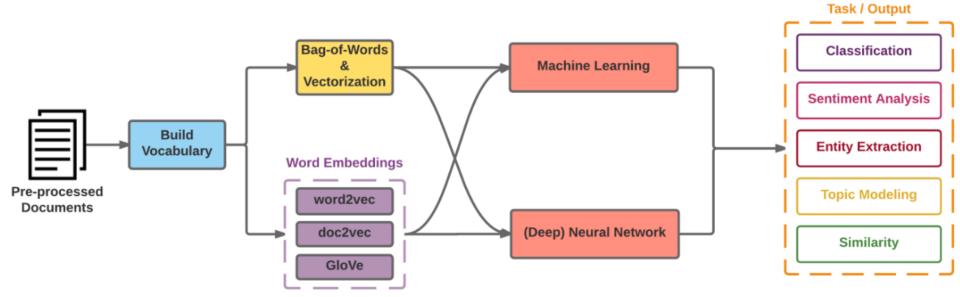
9

NLP



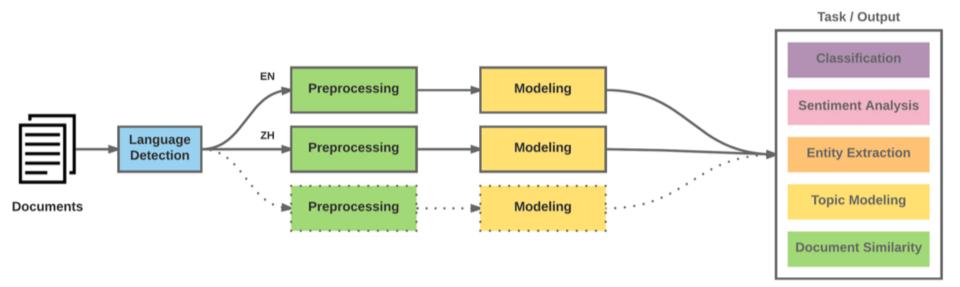
Modern NLP Pipeline



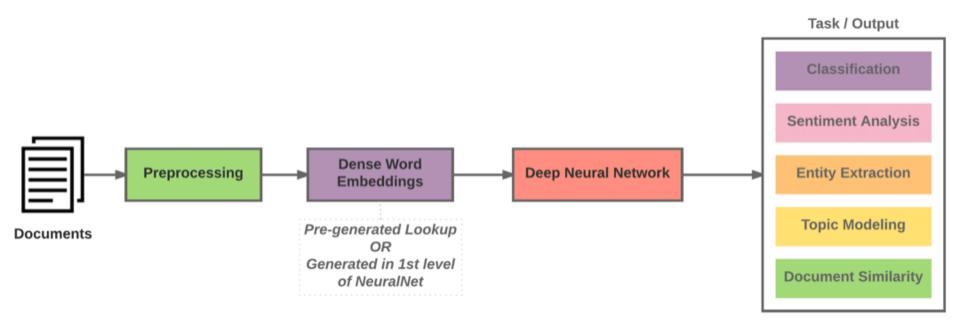


Source: https://github.com/fortiema/talks/blob/master/opendata2016sh/pragmatic-nlp-opendata2016sh.pdf

Modern NLP Pipeline



Deep Learning NLP



Natural Language Processing (NLP) and Text Mining

Raw text

Sentence Segmentation

Tokenization

Part-of-Speech (POS)

Stop word removal

Stemming / Lemmatization

Dependency Parser

String Metrics & Matching

word's stemword's lemma $am \rightarrow am$ $am \rightarrow be$ having \rightarrow havhaving \rightarrow have

Analyzing Lexical Semantic Relationships

- Entailments
- Homonyms and Homographs
- Synonyms and Antonyms
- Hyponyms and Hypernyms
- Holonyms and Meronyms
- Semantic Relationships and Similarity

Word Sense Disambiguation

- Lesk algorithm (Lesk, 1986)
 - leverage dictionary or vocabulary definitions for a word we want to disambiguate in a body of text and compare the words in these definitions with a section of text surrounding our word of interest.
 - The main objective is to return the synset with the maximum number of overlapping words or terms between the context sentence and the different definitions from each synset for the word we target for disambiguation.

Named Entity Recognition (NER)

Named entities

- represent real-world objects
- people, places, organizations
- proper names

Named entity recognition

- Entity chunking
- Entity extraction

NER: OntoNotes 5 Named Entities

SID	ТҮРЕ	DESCRIPTION
1	PERSON	People, including fictional.
2	NORP	Nationalities or religious or political groups.
3	FAC	Buildings, airports, highways, bridges, etc.
4	ORG	Companies, agencies, institutions, etc.
5	GPE	Countries, cities, states.
6	LOC	Non-GPE locations, mountain ranges, bodies of water.
7	PRODUCT	Objects, vehicles, foods, etc. (Not services.)
8	EVENT	Named hurricanes, battles, wars, sports events, etc.
9	WORK_OF_ART	Titles of books, songs, etc.
10	LAW	Named documents made into laws.
11	LANGUAGE	Any named language.
12	DATE	Absolute or relative dates or periods.
13	TIME	Times smaller than a day.
14	PERCENT	Percentage, including "%".
15	MONEY	Monetary values, including unit.
16	QUANTITY	Measurements, as of weight or distance.
17	ORDINAL	"first", "second", etc.
18	CARDINAL	Numerals that do not fall under another type.

NER: Wikipedia Named Entities

SID TYPE DESCRIPTION PER Named person or family. 1 Name of politically or geographically defined location (cities, provinces, countries, international regions, bodies LOC of water, mountains). 2 Named corporate, governmental, or ORG other organizational entity. 3 Miscellaneous entities, e.g. events, MISC nationalities, products or works of art. Δ

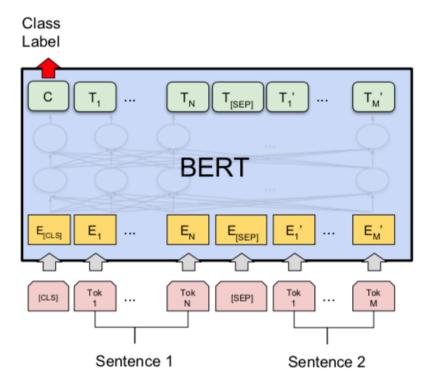
NER IOB Scheme

TAG ID DESCRIPTION "|" 1 Token is inside an entity. **"O"** 2 Token is outside an entity. **"B"** Token begins an entity. 3 1111 0 No entity tag is set (missing value).

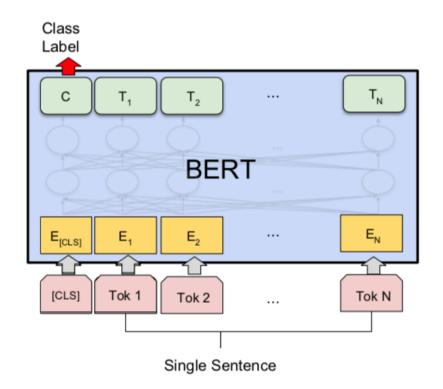
NER BILUO Scheme

TAG	DESCRIPTION
BEGIN	The first token of a multi-token entity.
	An inner token of a multi-token
N	entity.
	The final token of a multi-token
LAST	entity.
UNIT	A single-token entity.
OUT	A non-entity token.

BERT Sequence-level tasks

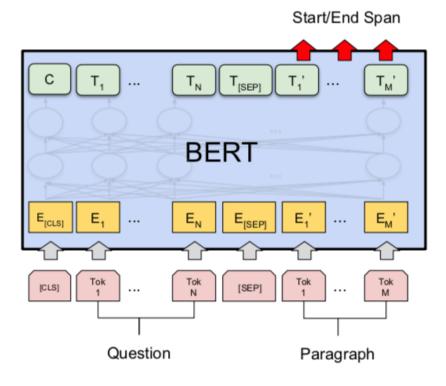


(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

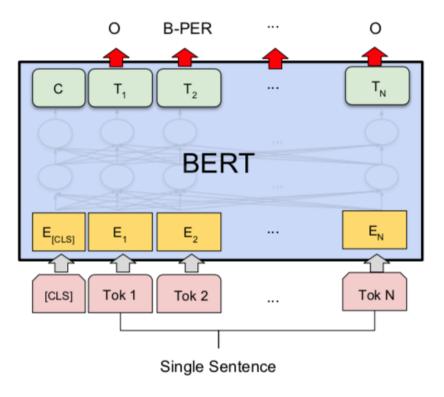


(b) Single Sentence Classification Tasks: SST-2, CoLA

BERT Token-level tasks

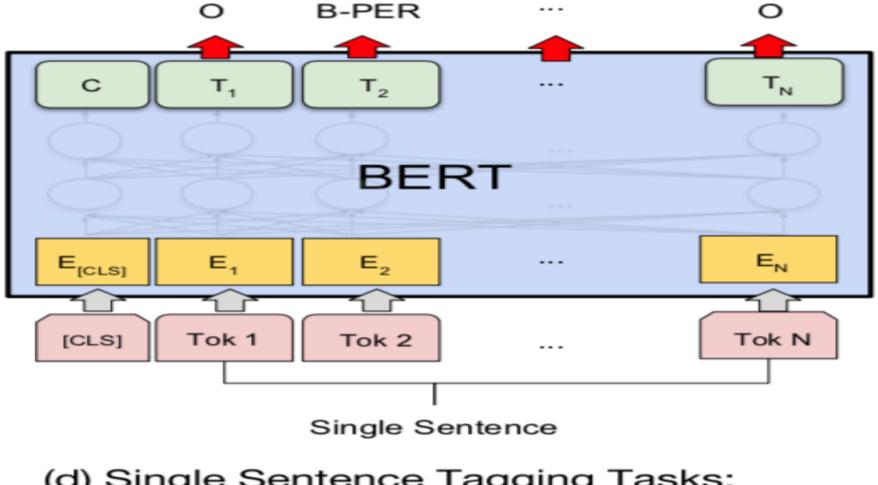


(c) Question Answering Tasks: SQuAD v1.1



(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

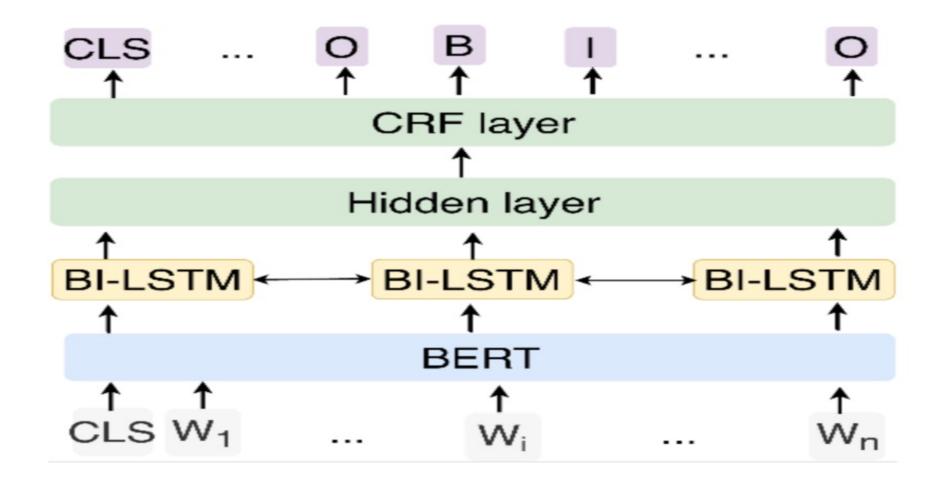
NER: Single Sentence Tagging



(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

Source: Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova (2018). "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." arXiv preprint arXiv:1810.04805

NER: Fine-tuning BERT with Bi-LSTM CRF



Source: Zhang, Xiaohui, Yaoyun Zhang, Qin Zhang, Yuankai Ren, Tinglin Qiu, Jianhui Ma, and Qiang Sun. "Extracting comprehensive clinical information for breast cancer using deep learning methods." International Journal of Medical Informatics 132 (2019): 103985.

Python in Google Colab (Python101)

https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT

CO Apython101.ipynb File Edit View Insert Ru	ntime Tools Help <u>All changes saved</u>	E Comment	👪 Share	\$	A		
	+ Code + Text	V RAM Disk	👻 🧪 Ec	diting	^		
 Text Classification: BBC News Articles Text Summarization and Topic Modeling Text Sumarization Text 	 Semantic Analysis and Named Entity Recognition (NER) Source: Dipanjan Sarkar (2019), Text Analytics with Python: A Practitioner's Guide to Natural Language Processing, Second Edition. APress. <u>https://github.com/Apress/text-analytics-w-python-2e</u> 						
Summarization with Gensim Summarization	- Semantic Analysis						
Topic Modeling Topic Modeling with Gensim LSI model Topic Modeling with Gensim LDA model Topic Modeling with Scikit-learn LDA and NMF Topic Modeling Visualization Text Similarity and Clustering	<pre>[1] 1 import nltk 2 from nltk.corpus import wordnet as wn 3 import pandas as pd 4 nltk.download('wordnet') 5 # WordNet Synsets 6 word = 'fruit' 7 synsets = wn.synsets(word) 8 print('Word:', word) 9 print('Wordnet Synsets:', len(synsets)) 10 df = pd.DataFrame([{'Synset': synset, 11 'Part of Speech': synset.lexname(), 12 'Definition': synset.lexname(), 13 'Lemmas': synset.lemma_names(), 14 'Examples': synset.examples()} 15 for synset in synsets]) 16 df</pre>						
Text Similarity Text Clustering Semantic Analysis and Named Entity Recognition (NER)	<pre>C→ [nltk_data] Downloading package wordnet to /root/nltk_data [nltk_data] Unzipping corpora/wordnet.zip. Word: fruit Wordnet Synsets: 5 Synset Part of Speech Definition Lemmas</pre>	Exa	mples				
Semantic Analysis Named Entity Recognition (NER)	0Synset('fruit.n.01')noun.plantthe ripened reproductive body of a seed plant[fruit]1Synset('yield.n.03')noun.artifactan amount of a product[yield, fruit]		0				

https://tinyurl.com/imtkupython101

Python in Google Colab (Python101)

https://colab.research.google.com/drive/1FEG6DnGvwfUbeo4zJ1zTunjMqf2RkCrT

C	Python101.ipynb File Edit View Insert Ru	ntime Tools Help <u>All changes saved</u>	Comment	🐇 Sh	are 🏚	A
	File Edit View Insert Ru	<pre>+ Code + Text November with the intention of hearing from Zuckerberg. Since the Cambridge Analytica scandal be has only appeared in front of two legislatures: the American Senate and House of Representative Facebook has consistently rebuffed attempts from others, including the UK and Canadian parliame He added that an article in the New York Times on Thursday, in which the paper alleged a patter to "delay, deny and deflect" negative news stories, "raises further questions about how recent dealt with within Facebook." re.sub: Three more countries have joined an "international grand committee" of parliaments, add text_nlp: Three more countries have joined an "international grand committee" of parliaments, add text_nlp: Three more countries in article 2 ner_tagged = [(word.text, word.ent_type_) for word in text_nlp]</pre>	es, and the Eur ents, to hear f en of behaviour data breaches ling to calls f	ebook cl ropean p from Zuc r from I were a for Face	parliam ckerber Facebool llegedly ebook's	ent. g. k y boss,
	with Gensim LSI model Topic Modeling with Gensim LDA model Topic Modeling with Scikit-learn LDA and NMF	<pre>3 print(ner_tagged) [+ [('Three', 'CARDINAL'), ('more', ''), ('countries', ''), ('have', ''), ('joined', ''), ('an', '] [] 1 from spacy import displacy 2 # visualize named entities 3 displacy.render(text_nlp, style='ent', jupyter=True)</pre>	'), (' <i>"</i> ', ''),	, ('inte	ernation	nal', '
	Topic Modeling Visualization Text Similarity and Clustering Text Similarity Text Clustering Semantic Analysis and Named Entity Recognition (NER) Semantic Analysis Named Entity Recognition (NER)	Three CARDINAL more countries have joined an "international grand committee" of parliaments, adding to calls for Facebook give evidence on misinformation to the coalition. Brazil GPE , Latvia GPE and Singapore GPE bring the total to eight the world, with plans to send representatives to London GPE on 27 November DATE with the intention of hearing from Analytica scandal broke, the Facebook ORG chief has only appeared in front of two CARDINAL legislatures: the America Representatives ORG , and the European NORP parliament. Facebook has consistently rebuffed attempts from others, include NORP parliaments, to hear from Zuckerberg GPE . He added that an article in the New York Times ORG on Thursda pattern of behaviour from Facebook ORG to "delay, deny and deflect" negative news stories, "raises further questions about with within Facebook ORG ."	ht CARDINAL diff	ferent par . Since t and Ho ape and the pap	liaments a the Camb ouse of Canadi er alleged	across ridge an d a

https://tinyurl.com/imtkupython101



- Semantic Analysis
 - WordNet
 - Word sense disambiguation
- Named Entity Recognition (NER)

References

- Dipanjan Sarkar (2019), Text Analytics with Python: A Practitioner's Guide to Natural Language Processing, Second Edition. APress. <u>https://github.com/Apress/text-analytics-w-python-2e</u>
- Benjamin Bengfort, Rebecca Bilbro, and Tony Ojeda (2018), Applied Text Analysis with Python, O'Reilly Media. <u>https://www.oreilly.com/library/view/applied-text-analysis/9781491963036/</u>
- HuggingFace (2020), Transformers Notebook, https://huggingface.co/transformers/notebooks.html
- The Super Duper NLP Repo, https://notebooks.quantumstat.com/
- Min-Yuh Day (2020), Python 101, https://tinyurl.com/imtkupython101