多 媒 體 系 統
MULTIMEDIA SYSTEM

張家瑋 博士

助理教授

國立臺中科技大學資訊工程系

FOUNDATIONS OF NATURAL LANGUAGE PROCESSING
自然語言處理的原理與應用

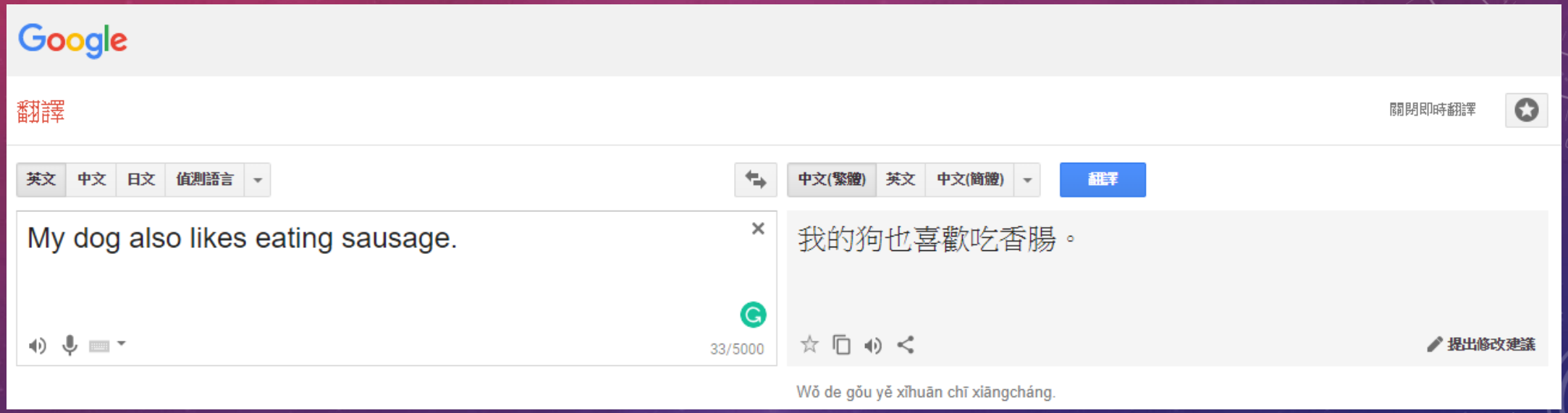
自然語言處理的主要範疇

- 機器翻譯 (Machine Translation)
- 自然語言理解/語意分析 (Natural Language Understanding / Semantic Analysis)
  1. 問答系統 (Question Answering)
  2. 萃取式摘要 (Extractive Summarization)
  3. 文件分類 (Text Categorization)
- 自然語言生成 (Natural Language Generation)
  1. 進階問答系統 (Advanced Question Answering)
  2. 抽象式摘要 (Abstractive Summarization)
  3. 聊天機器人 (Chatbot)
- 語法分析 (Syntactic Parsing)
  1. 中文斷詞 (Chinese word segmentation)
  2. 詞性標註 (Part-of-speech Tagging)
  3. 實體辨識 (Named Entity Recognition)
  4. 詞彙依存 (Typed Dependencies)
  5. 文法樹 (Parse Tree)
- 語音辨識 (Speech Recognition)
- 文字轉語音 (Text to Speech)
- 語音轉文字 (Speech to Text)

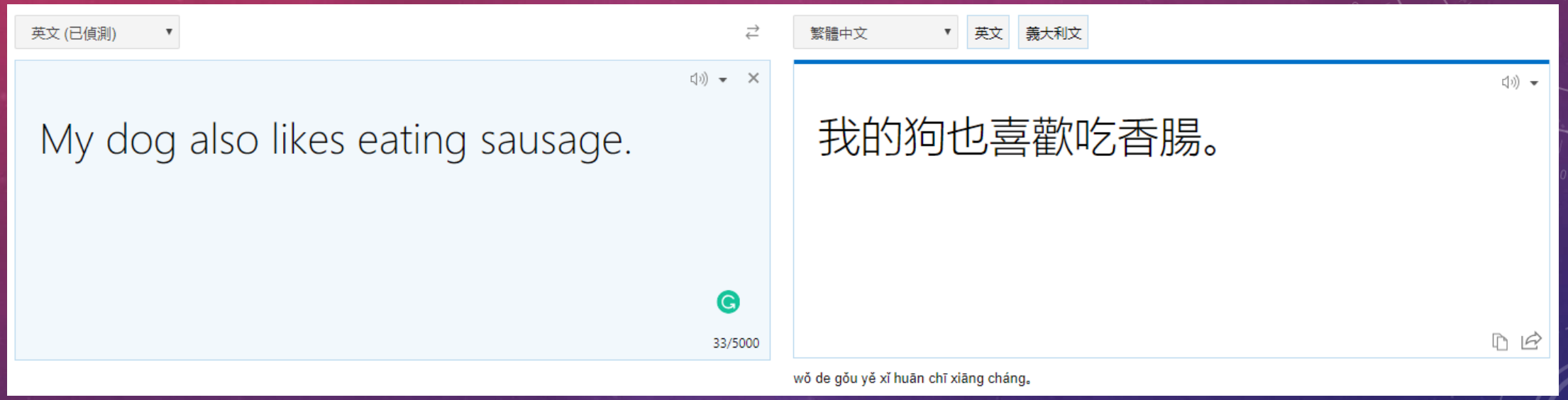
機器翻譯

MACHINE TRANSLATION

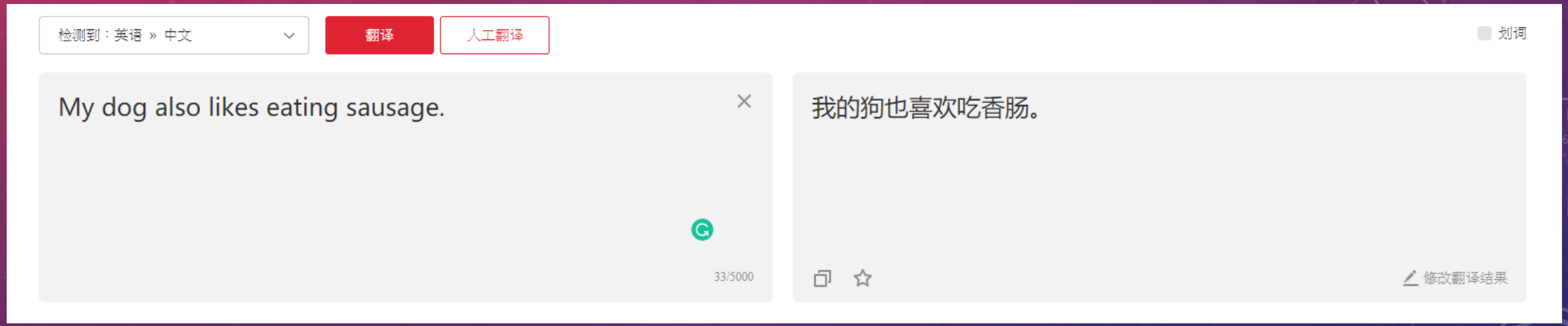
GOOGLE 翻譯


Google
翻譯
關閉即時翻譯
英文
中文
日文
偵測語言
中文(繁體)
英文
中文(簡體)
翻譯
My dog also likes eating sausage.
33/5000
我的狗也喜歡吃香腸。
提出修改建議
Wǒ de gǒu yě xǐhuān chī xiāngcháng.

BING 翻譯

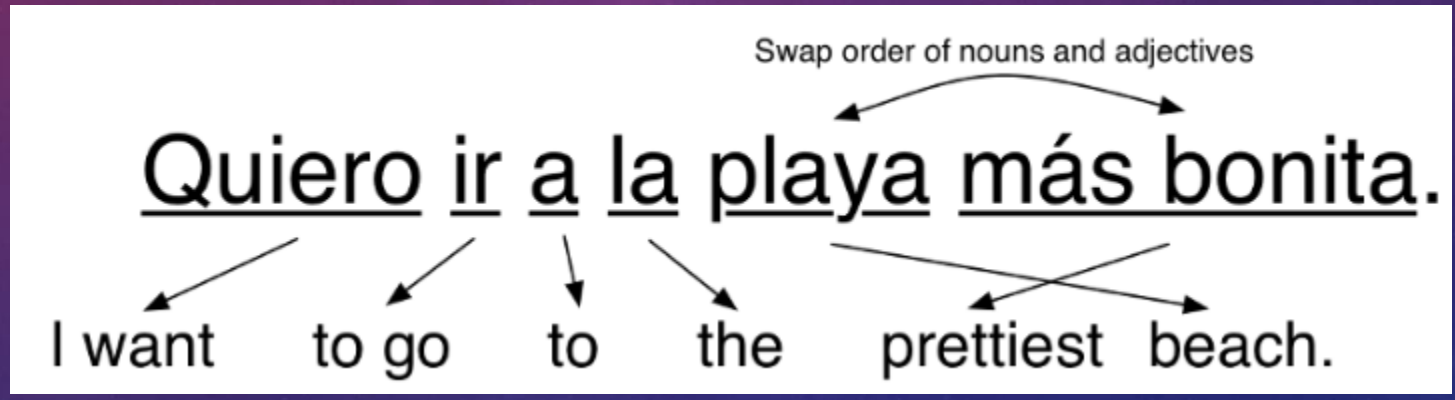

英文 (已偵測)
繁體中文
英文
義大利文
My dog also likes eating sausage.
33/5000
我的狗也喜歡吃香腸。
wǒ de gǒu yě xǐ huān chī xiāng cháng.

有道翻譯


检测到：英语 » 中文
翻译
人工翻译
划词
My dog also likes eating sausage.
33/5000
我的狗也喜欢吃香肠。
修改翻译结果

平行語料

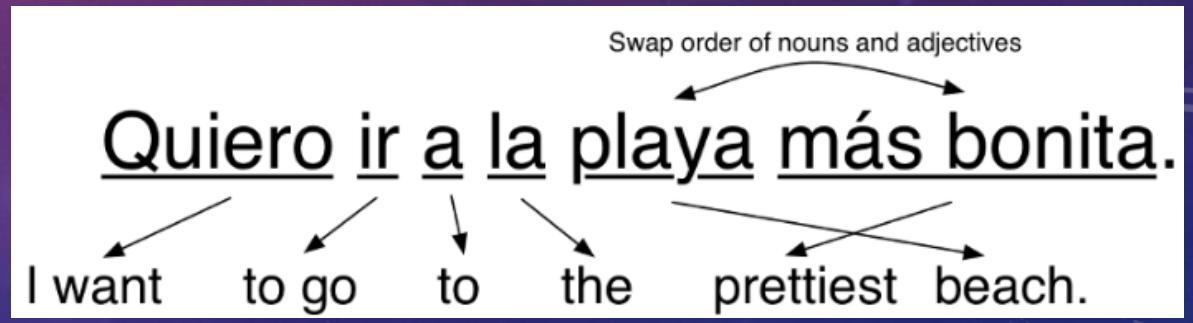

Quiero ir a la playa más bonita.
I want to go to the beach more pretty.
We just replace each Spanish word with the matching English word.


Swap order of nouns and adjectives
Quiero ir a la playa más bonita.
I want to go to the prettiest beach.

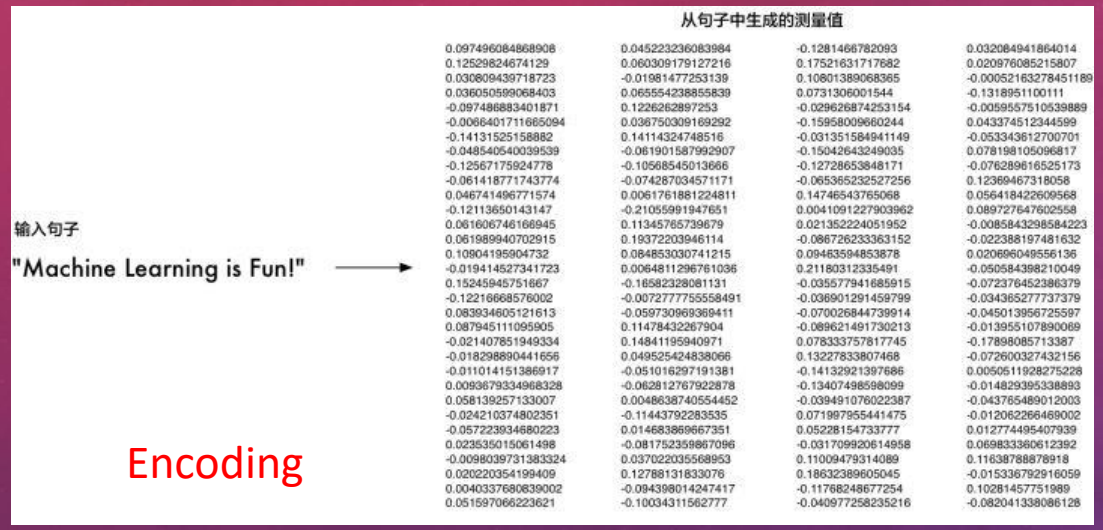
統計式機器翻譯之原理

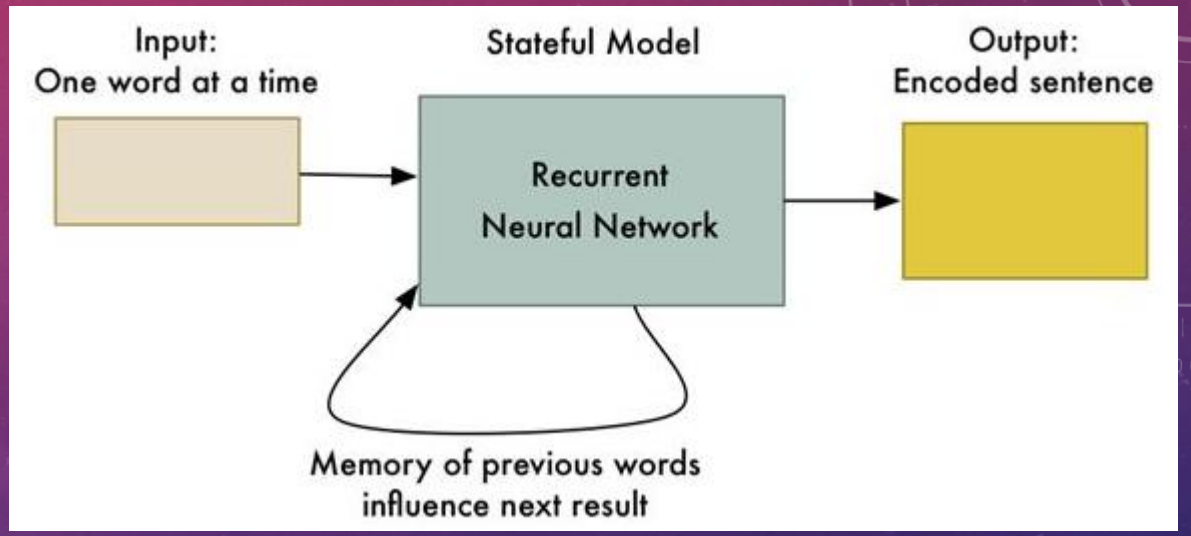

Quiero ir a la playa más bonita.
I want to go to the beach more pretty.
We just replace each Spanish word with the matching English word.

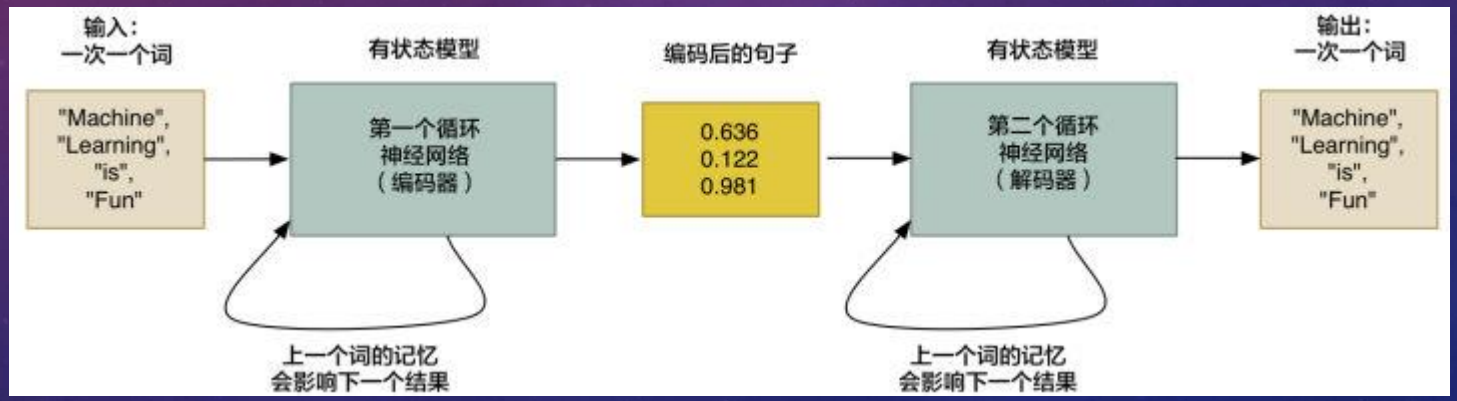

Quiero ir a la playa más bonita.
- I want
- I love
- I like
- I try
- I mean
- to go
- to work
- to run
- to appear
- to be on
- to be
- to leave
- to pass away
- to forget
- to
- at
- per
- the beach
- the seaside
- the open space
- more pretty
- most pretty
- more lovely
- most lovely
- more tidy
- most tidy
Even the most common phrases have lots of possible translations.


Swap order of nouns and adjectives
Quiero ir a la playa más bonita.
I want to go to the prettiest beach.

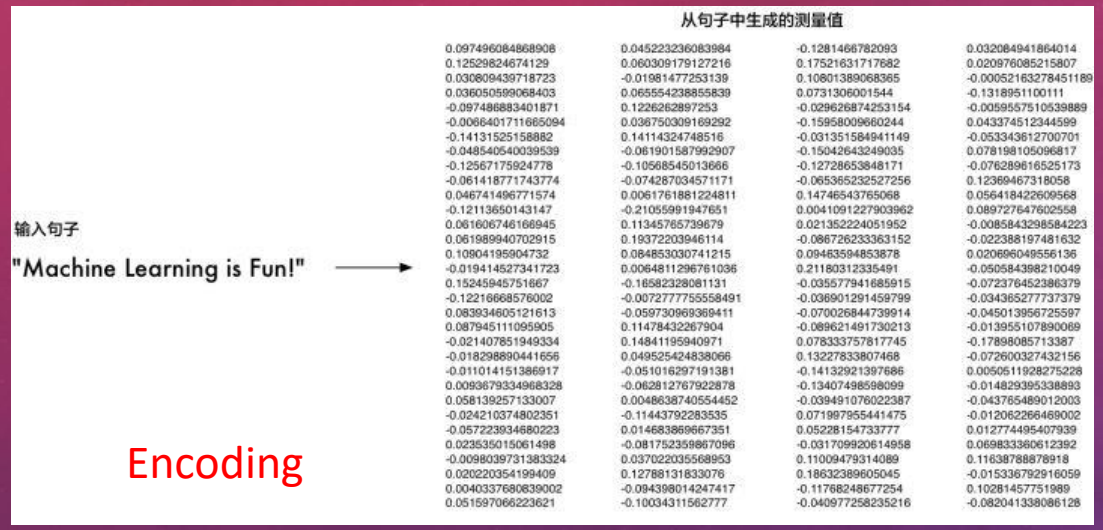
深度學習於機器翻譯之原理

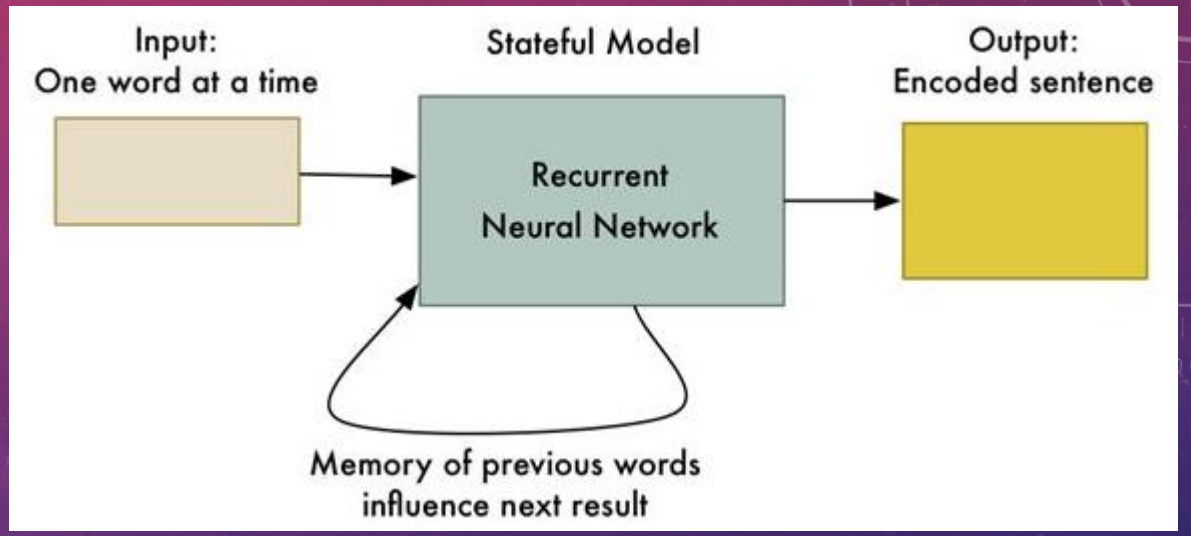


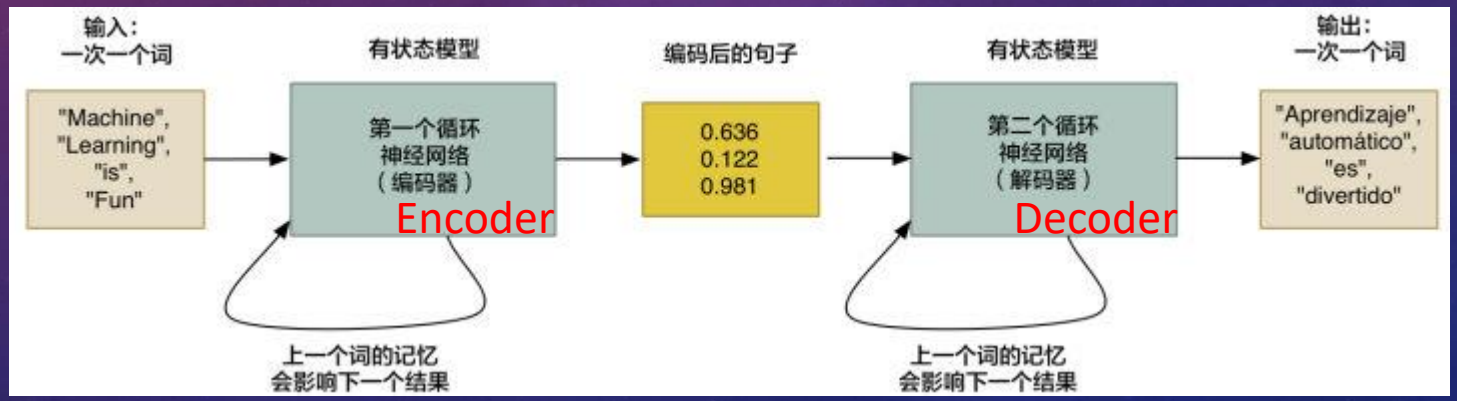




深度學習於機器翻譯之原理







自然語言理解

NATURAL LANGUAGE UNDERSTANDING

WORD-SENSE DISAMBIGUATION

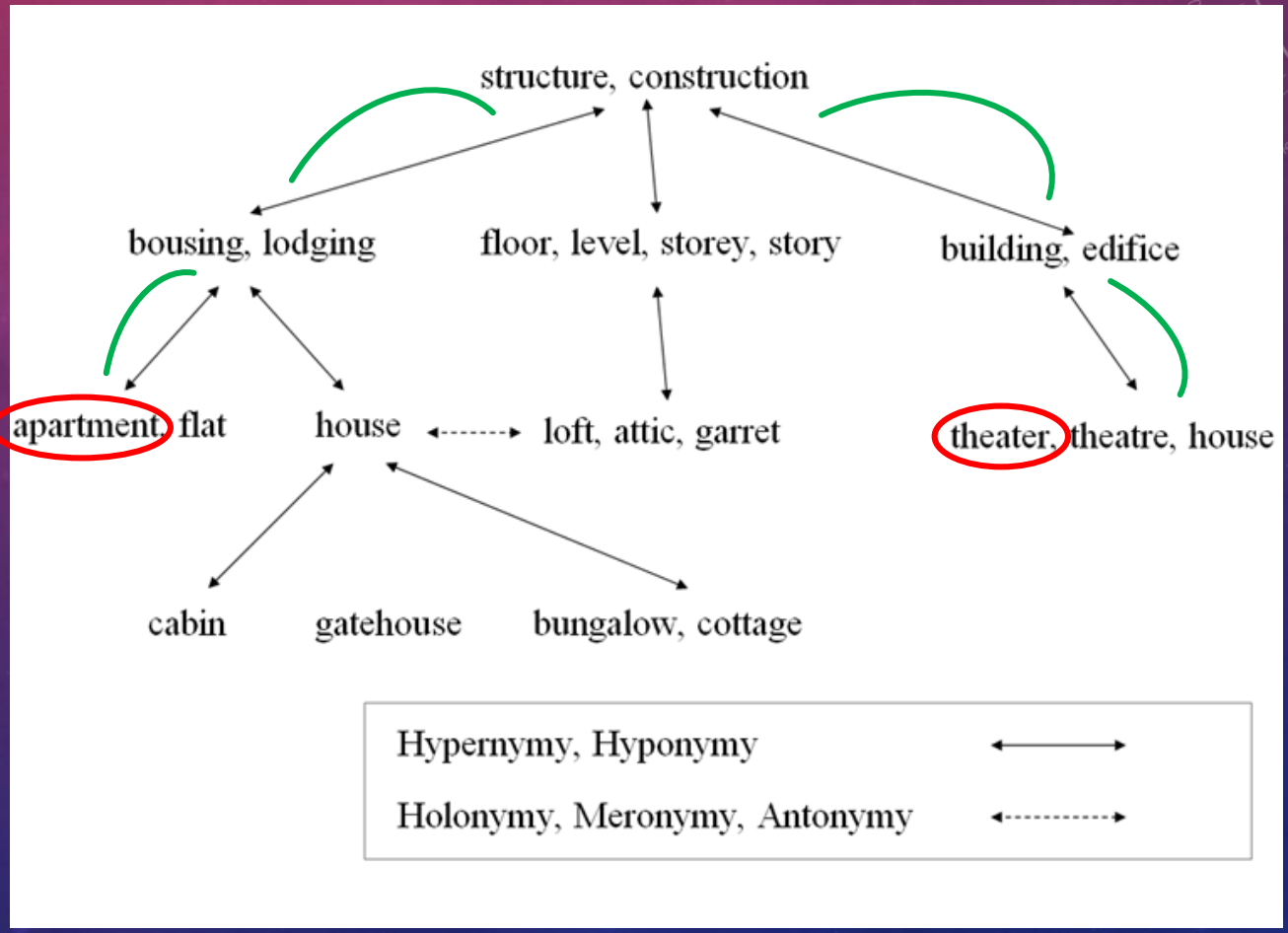
- Ambiguity: a word or phrase with multiple meanings.
  1. “procure” (I will get the drinks)
  2. “become” (she got scared)
  3. “have” (I have got three dollars)
  4. “understand” (I get it)

WORDNET

http://wordnetweb.princeton.edu/perl/webwn

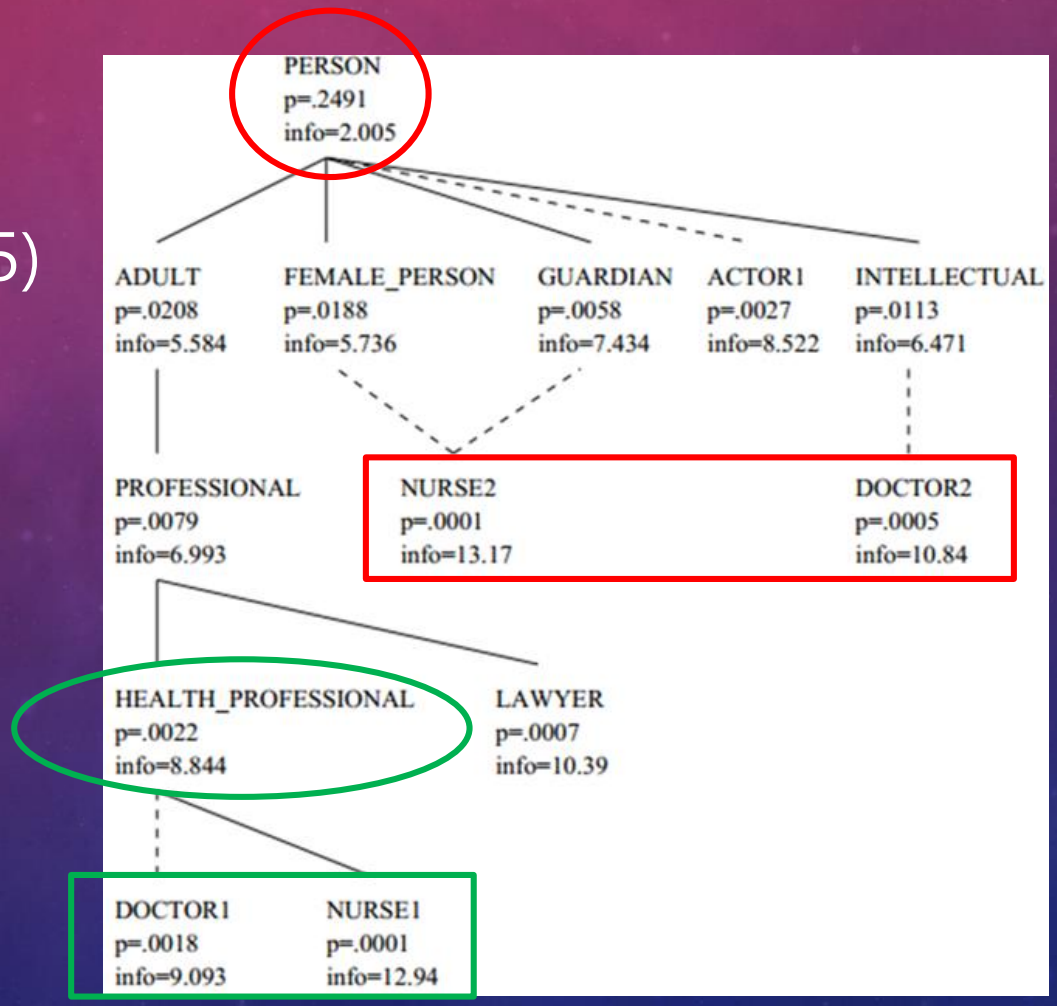
WORD-SENSE DISAMBIGUATION

- Distance-based: PATH (Rada, Mili, Bicknell, & Blettner, 1989)

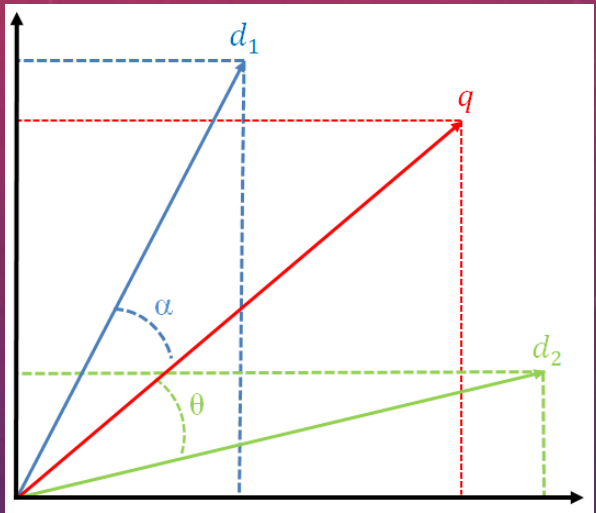


WORD-SENSE DISAMBIGUATION

- Information Content-based: RES (Resnik, 1995)



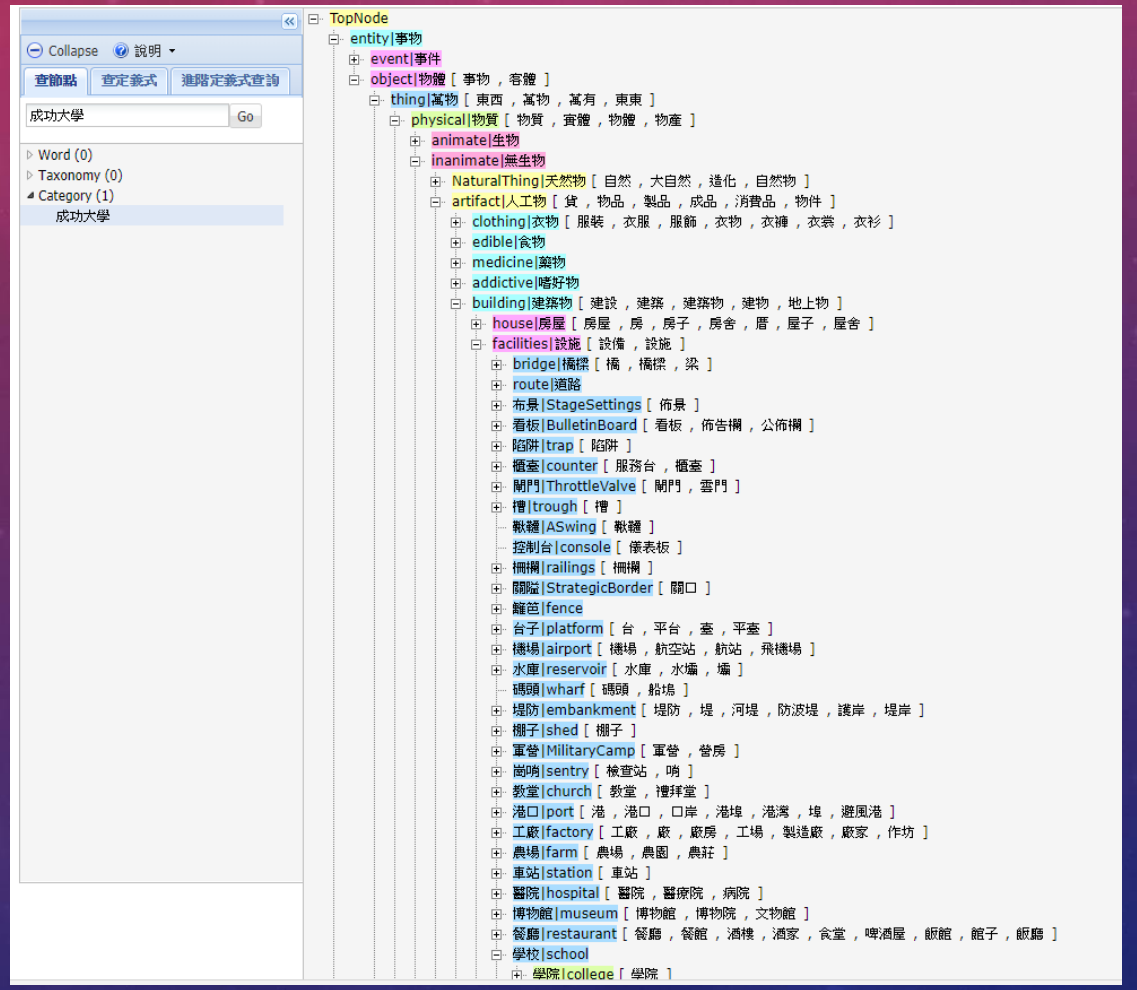
WORD-SENSE DISAMBIGUATION



- Gloss-based: VECTOR (Patwardhan, 2003)

Cute	Cunning
1. attractive especially by means of smallness or prettiness or quaintness	1. attractive especially by means of smallness or prettiness or quaintness
2. obviously contrived to charm	2. marked by skill in deception
	3. showing inventiveness and skill

廣義知網知識本體



http://ehownet.iis.sinica.edu.tw/ehownet.php

VECTOR REPRESENTATION

	w_1	w_2	w_3	..	..	..	w_{n-1}	w_n	label
D_1	0.11	0.23	0	..	..	..	0.57	0	0
D_2	0	0	0	..	..	..	0.29	0.7	1
D_3	0	0.81	0.44	..	..	..	0	0	0
D_4	0	0.37	0	..	..	..	0	0.16	1
..	..	..	..	..	..	..	..	..	..
D_k	..	..	..	..	..	..	..	..	1

TF-IDF

- TF: term frequency: $\mathrm{tf}_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}$
- IDF: inverse document frequency: $\mathrm{idf}_i = \log \frac{|D|}{|\{j : t_i \in d_j\}|}$

where:

- $|D|$: total number of documents in the corpus
- $|\{j : t_i \in d_j\}|$: number of documents where term t_i appears

Then:

- $\mathrm{tfidf}_{i,j} = \mathrm{tf}_{i,j} \times \mathrm{idf}_i$

Document 1

Term	Term Count
this	1
is	1
a	2
sample	1

Document 2

Term	Term Count
this	1
is	1
another	2
example	3

- The calculation of tf–idf for the term "this" is performed as follows:
  - $$\mathrm{tf}(\text{"this"}, d_1) = \frac{1}{5} = 0.2$$
    $$\mathrm{tf}(\text{"this"}, d_2) = \frac{1}{7} \approx 0.14$$

$$\mathrm{idf}(\text{"this"}, D) = \log\left(\frac{2}{2}\right) = 0$$

- So tf–idf is zero for the word "this", which implies that the word is not very informative as it appears in all documents.

$$\mathrm{tfidf}(\text{"this"}, d_1) = 0.2 \times 0 = 0$$
$$\mathrm{tfidf}(\text{"this"}, d_2) = 0.14 \times 0 = 0$$

Document 1

Term	Term Count
this	1
is	1
a	2
sample	1

Document 2

Term	Term Count
this	1
is	1
another	2
example	3

- A slightly more interesting example arises from the word "example", which occurs three times only in the second document:
  - $\mathrm{tf}(\text{"example"}, d_1) = \frac{0}{5} = 0$
  - $\mathrm{tf}(\text{"example"}, d_2) = \frac{3}{7} \approx 0.429$

$$\mathrm{idf}(\text{"example"}, D) = \log\left(\frac{2}{1}\right) = 0.301$$

$$\mathrm{tfidf}(\text{"example"}, d_1) = \mathrm{tf}(\text{"example"}, d_1) \times \mathrm{idf}(\text{"example"}, D) = 0 \times 0.301 = 0$$
$$\mathrm{tfidf}(\text{"example"}, d_2) = \mathrm{tf}(\text{"example"}, d_2) \times \mathrm{idf}(\text{"example"}, D) = 0.429 \times 0.301 \approx 0.13$$

潛藏語意分析(LSA)

- 奇異值分解
  - Singular Value Decomposition (SVD)

Index Words	Titles								
	T1	T2	T3	T4	T5	T6	T7	T8	T9
book			1	1					
dads						1			1
dummies		1						1	
estate							1		1
guide	1					1			
investing	1	1	1	1	1	1	1	1	1
market	1		1						
real							1		1
rich						2			1
stock	1		1					1	
value				1	1				

=

book	0.15	-0.27	0.04
dads	0.24	0.38	-0.09
dummies	0.13	-0.17	0.07
estate	0.18	0.19	0.45
guide	0.22	0.09	-0.46
investing	0.74	-0.21	0.21
market	0.18	-0.30	-0.28
real	0.18	0.19	0.45
rich	0.36	0.59	-0.34
stock	0.25	-0.42	-0.28
value	0.12	-0.14	0.23

*

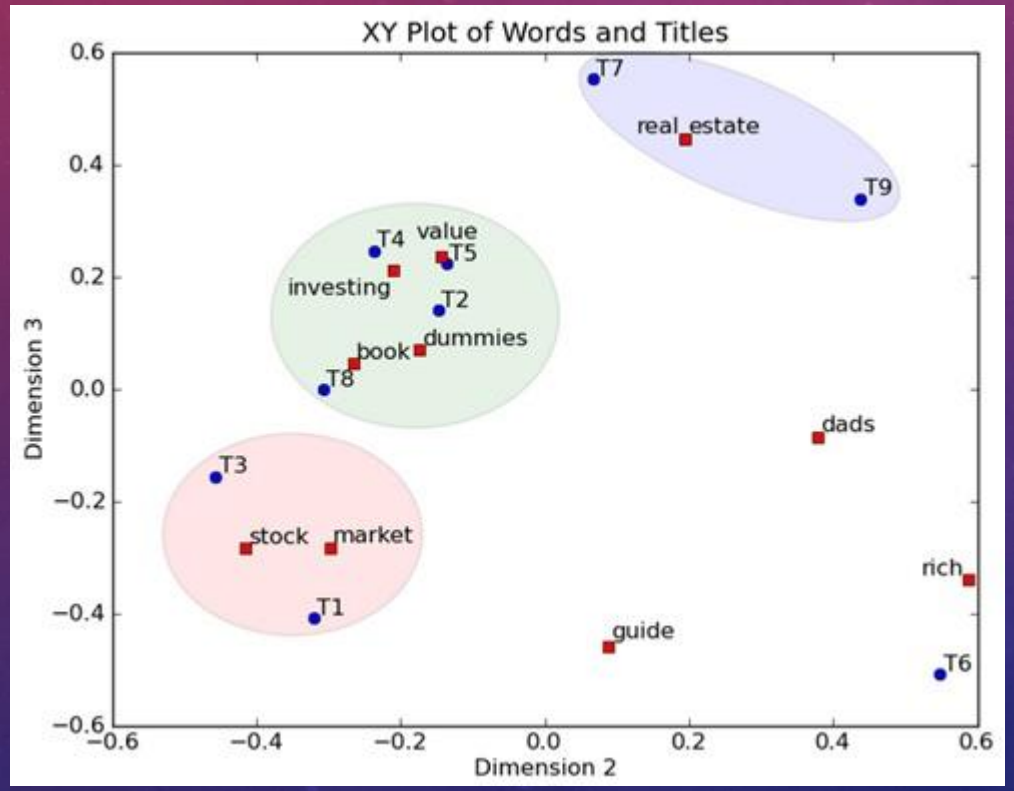
3.91	0	0
0	2.61	0
0	0	2.00

*

T1	T2	T3	T4	T5	T6	T7	T8	T9
0.35	0.22	0.34	0.26	0.22	0.49	0.28	0.29	0.44
-0.32	-0.15	-0.46	-0.24	-0.14	0.55	0.07	-0.31	0.44
-0.41	0.14	-0.16	0.25	0.22	-0.51	0.55	0.00	0.34

潛藏語意分析(LSA)

- 文件分類/主題探勘
- 語意分析

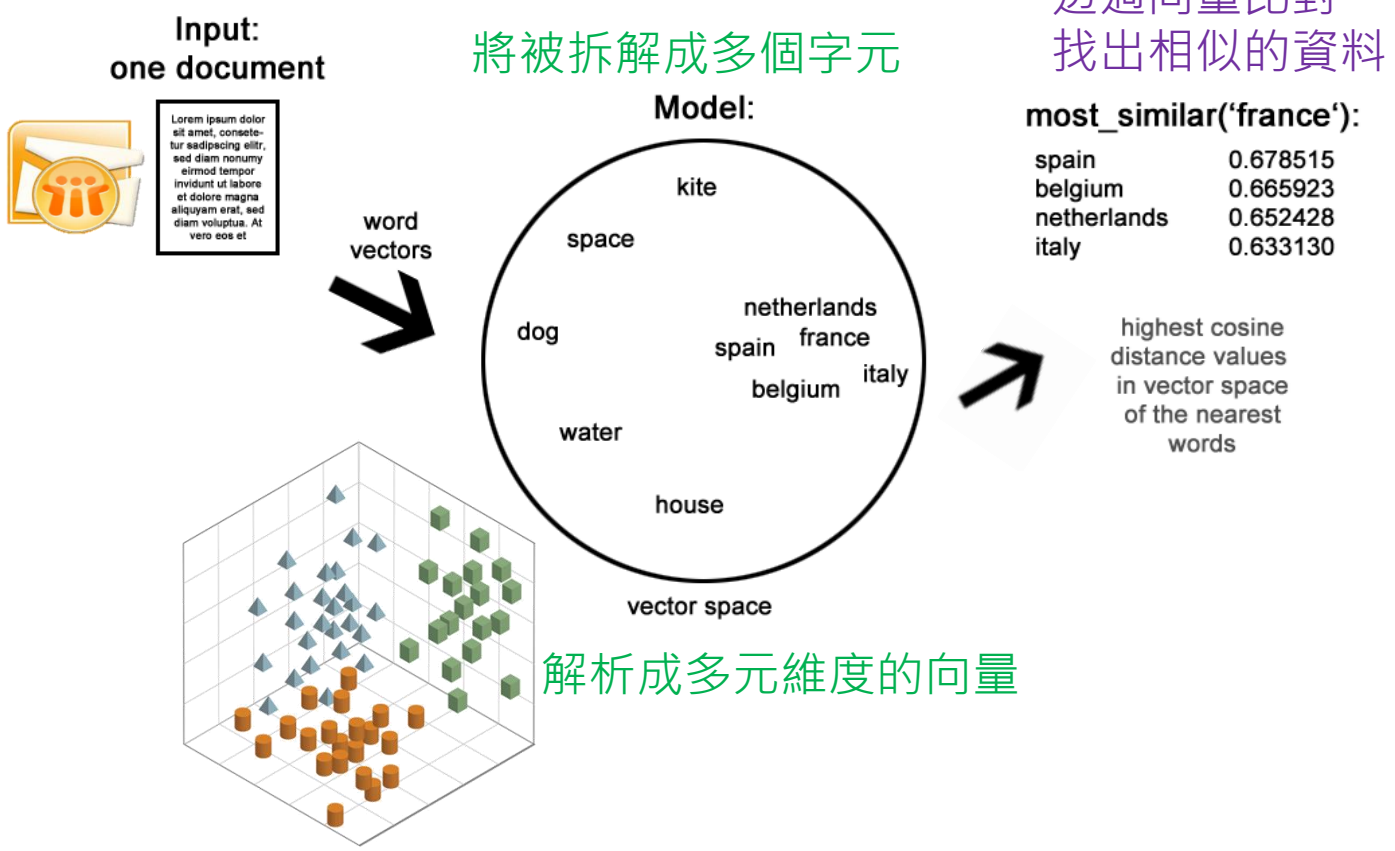


Index Words	Titles								
	T1	T2	T3	T4	T5	T6	T7	T8	T9
book			1	1					
dads						1			1
dummies		1						1	
estate							1		1
guide	1					1			
investing	1	1	1	1	1	1	1	1	1
market	1		1						
real							1		1
rich						2			1
stock	1		1					1	
value				1	1				

文字檔案

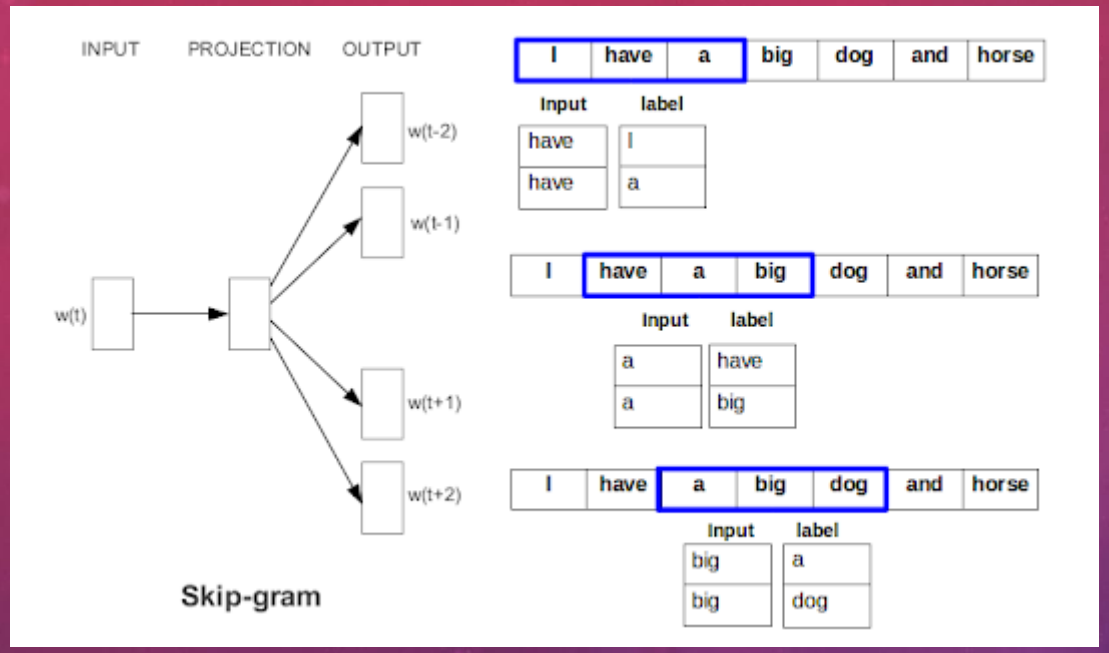
word2vec

透過向量比對
找出相似的資料

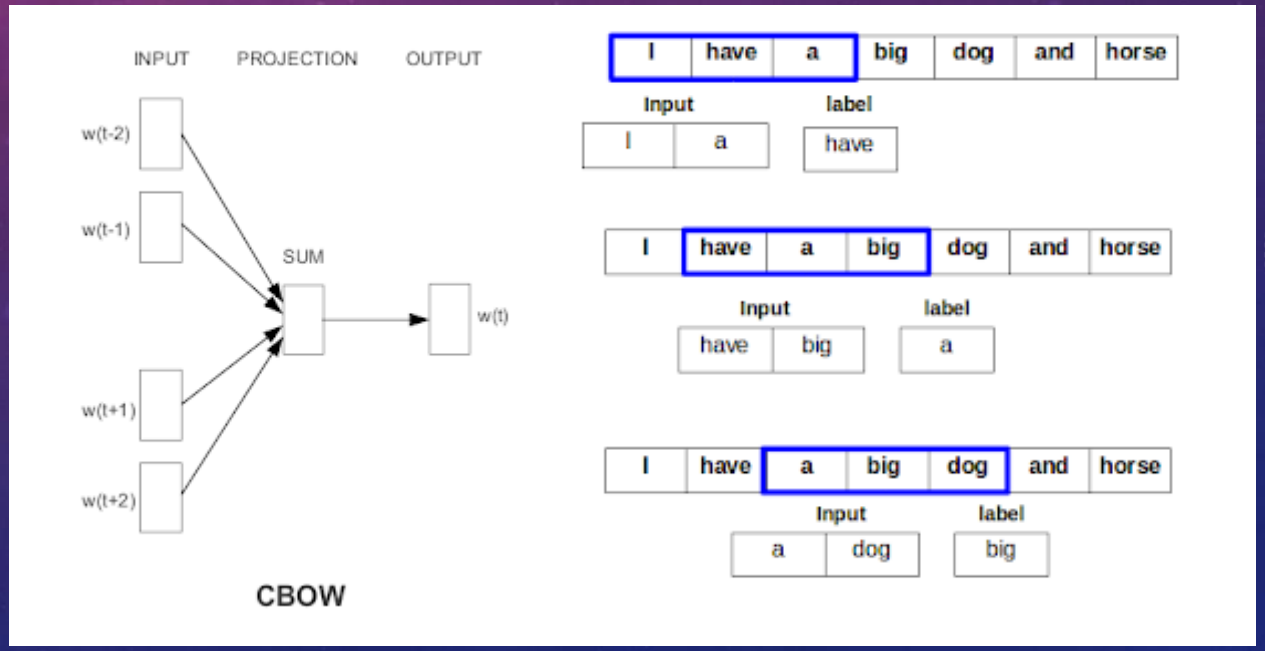


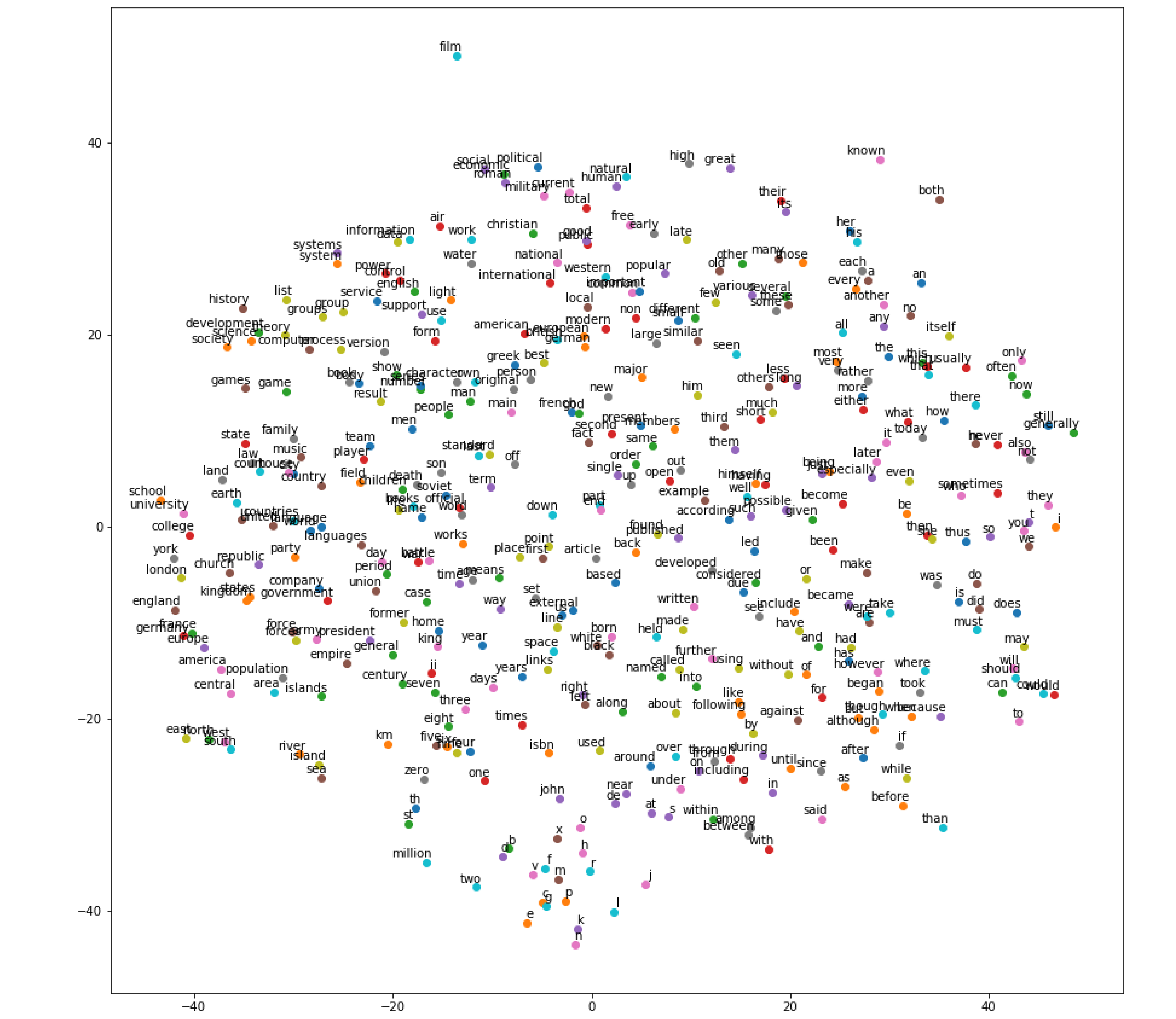
將被拆解成多個字元

解析成多元維度的向量



http://zongsoftwarenote.blogspot.com/2017/04/word2vec-model-introduction-skip-gram.html

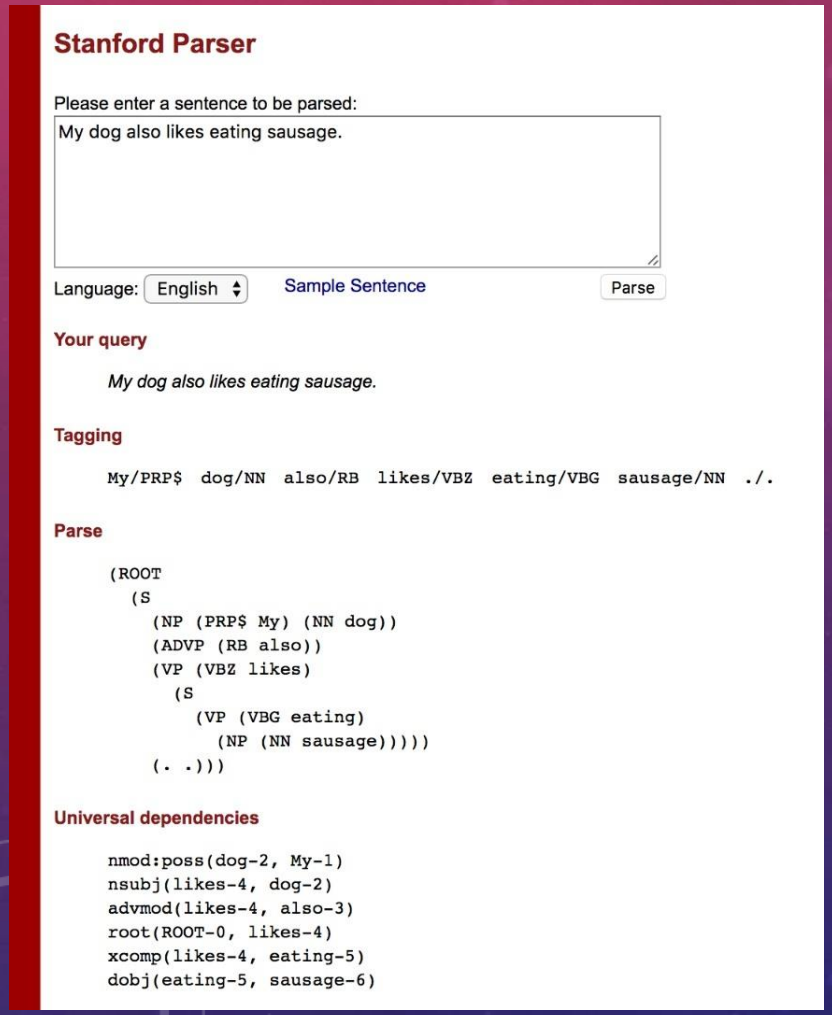




40
20
0
−20
−40
−40
−20
0
20
40
film
social
political
economic
roman
military
current
total
natural
human
high
great
known
both
their
its
her
his
information
data
air
work
christian
good
public
free
early
late
systems
system
water
national
international
western
popular
old
other
many
those
each
a
every
an
another
power
control
english
light
local
important
common
few
various
several
these
some
no
any
history
list
service
groups
group
support
use
non
different
small
modern
all
itself
development
theory
science
society
computer
process
version
form
american
european
british
german
large
similar
seen
the
this
which
that
usually
most
very
only
often
games
game
book
body
show
number
character
own
greek
best
person
original
major
less
others
long
rather
more
either
now
result
man
people
main
french
god
new
him
much
short
there
what
how
still
generally
men
present
second
fact
members
third
same
them
it
today
never
also
not
state
family
team
player
standard
last
off
order
later
law
music
land
country
field
death
children
son
soviet
term
single
up
open
out
example
well
himself
having
being
especially
even
sometimes
who
they
school
university
earth
countries
united
language
world
name
official
part
end
down
according
such
possible
given
become
be
then
see
thus
so
you
t
i
we
college
languages
works
point
place
first
article
found
published
back
led
been
york
london
republic
church
party
day
period
battle
war
time
means
developed
considered
due
or
make
was
do
is
did
does
england
company
government
kingdom
states
union
case
set
external
written
include
became
were
take
are
way
line
see
have
must
france
germany
europe
force
forces
army
president
former
home
born
held
made
had
has
may
empire
general
king
year
space
white
black
further
and
using
without
of
however
where
will
should
can
could
would
america
population
central
area
islands
century
ii
seven
years
days
links
named
called
into
right
left
like
for
began
took
three
along
about
following
against
though
but
when
because
to
east
north
west
south
eight
times
by
although
if
river
island
sea
km
five
six
four
isbn
used
over
through
from
on
during
around
until
since
after
while
including
under
zero
one
near
de
in
as
john
before
th
at
s
within
among
between
said
than
st
o
x
h
with
million
b
d
f
v
m
r
j
two
c
g
p
e
l
k
n

語法分析
SYNTACTIC PARSING

STANFORD PARSER



Stanford Parser

Please enter a sentence to be parsed:

My dog also likes eating sausage.

Language: English Sample Sentence Parse

Your query

My dog also likes eating sausage.

Tagging

```
My/PRP$  dog/NN  also/RB  likes/VBZ  eating/VBG  sausage/NN  ./.
```

Parse

```
(ROOT
  (S
    (NP (PRP$ My) (NN dog))
    (ADVP (RB also))
    (VP (VBZ likes)
      (S
        (VP (VBG eating)
          (NP (NN sausage)))))
    (. .)))
```

Universal dependencies

```
nmod:poss(dog-2, My-1)
nsubj(likes-4, dog-2)
advmod(likes-4, also-3)
root(ROOT-0, likes-4)
xcomp(likes-4, eating-5)
dobj(eating-5, sausage-6)
```

The Stanford Natural Language Processing Group

people publications research blog software teaching local

Software > Stanford Parser

The Stanford Parser: A statistical parser

About | Citing | Questions | Download | Included Tools | Extensions | Release history | Sample output | Online | FAQ

About

A natural language parser is a program that works out the grammatical **structure of sentences**, for instance, which groups of words go together (as "phrases") and which words are the **subject** or **object** of a verb. Probabilistic parsers use knowledge of language gained from hand-parsed sentences to try to produce the *most likely* analysis of new sentences. These statistical parsers still make some mistakes, but commonly work rather well. Their development was one of the biggest breakthroughs in natural language processing in the 1990s. You can try out our parser online.

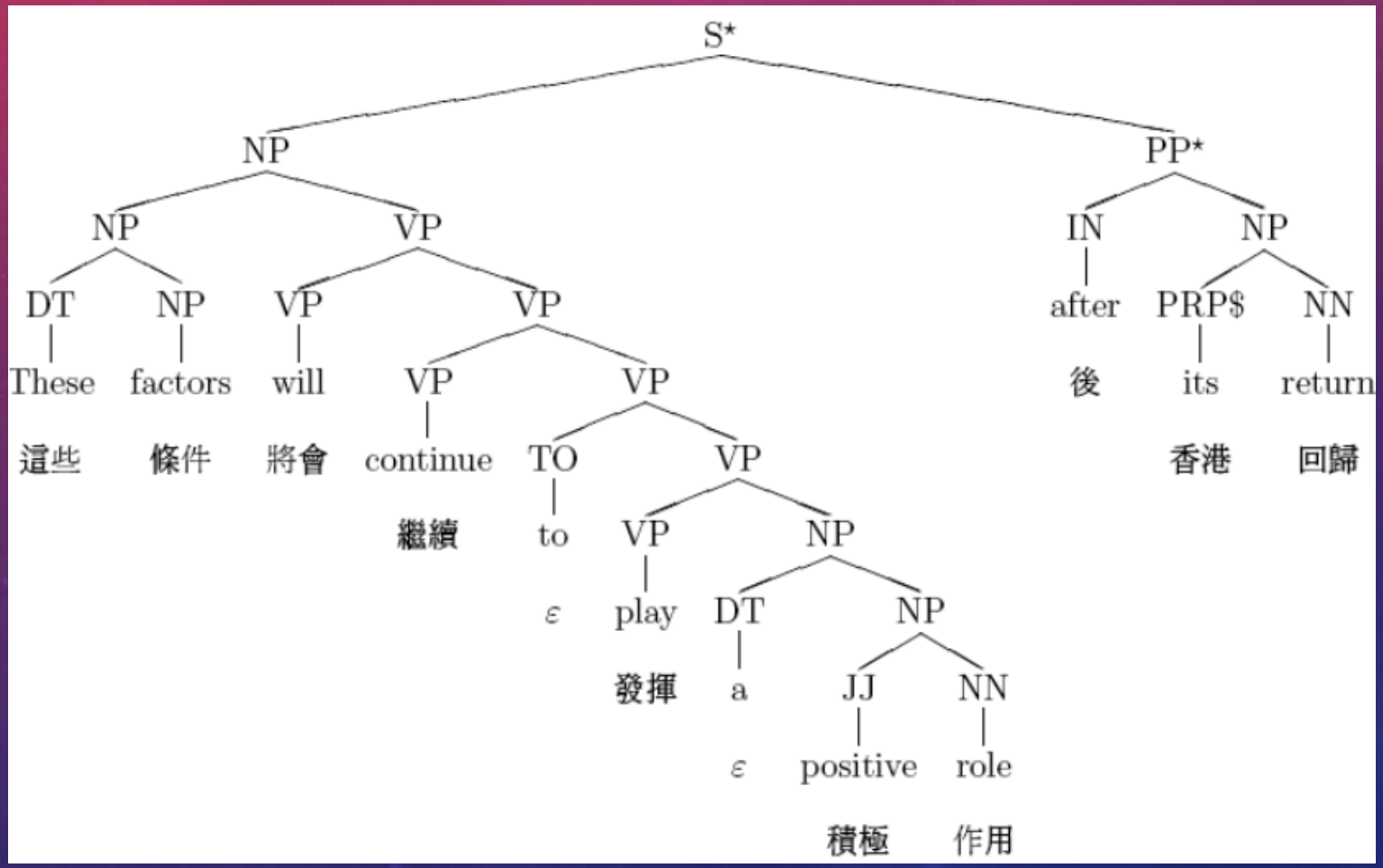
Package contents

This package is a Java implementation of probabilistic natural language parsers, both highly optimized PCFG and lexicalized dependency parsers, and a lexicalized PCFG parser. The original version of this parser was mainly written by Dan Klein, with support code and linguistic grammar development by Christopher Manning. Extensive additional work (internationalization and language-specific modeling, flexible input/output, grammar compaction, lattice parsing, *k*-best parsing, typed dependencies output, user support, etc.) has been done by Roger Levy, Christopher Manning, Teg Grenager, Galen Andrew, Marie-Catherine de Marneffe, Bill MacCartney, Anna Rafferty, Spence Green, Huihsin Tseng, Pi-Chuan Chang, Wolfgang Maier, and Jenny Finkel.

The lexicalized probabilistic parser implements a factored product model, with separate PCFG phrase structure and lexical dependency experts, whose preferences are combined by efficient exact inference, using an A* algorithm. Or the software can be used simply as an accurate unlexicalized stochastic context-free grammar parser. Either of these yields a good performance statistical parsing system. A GUI is provided for viewing the phrase structure tree output of the parser.

- http://nlp.stanford.edu:8080/parser/

PARSE TREE

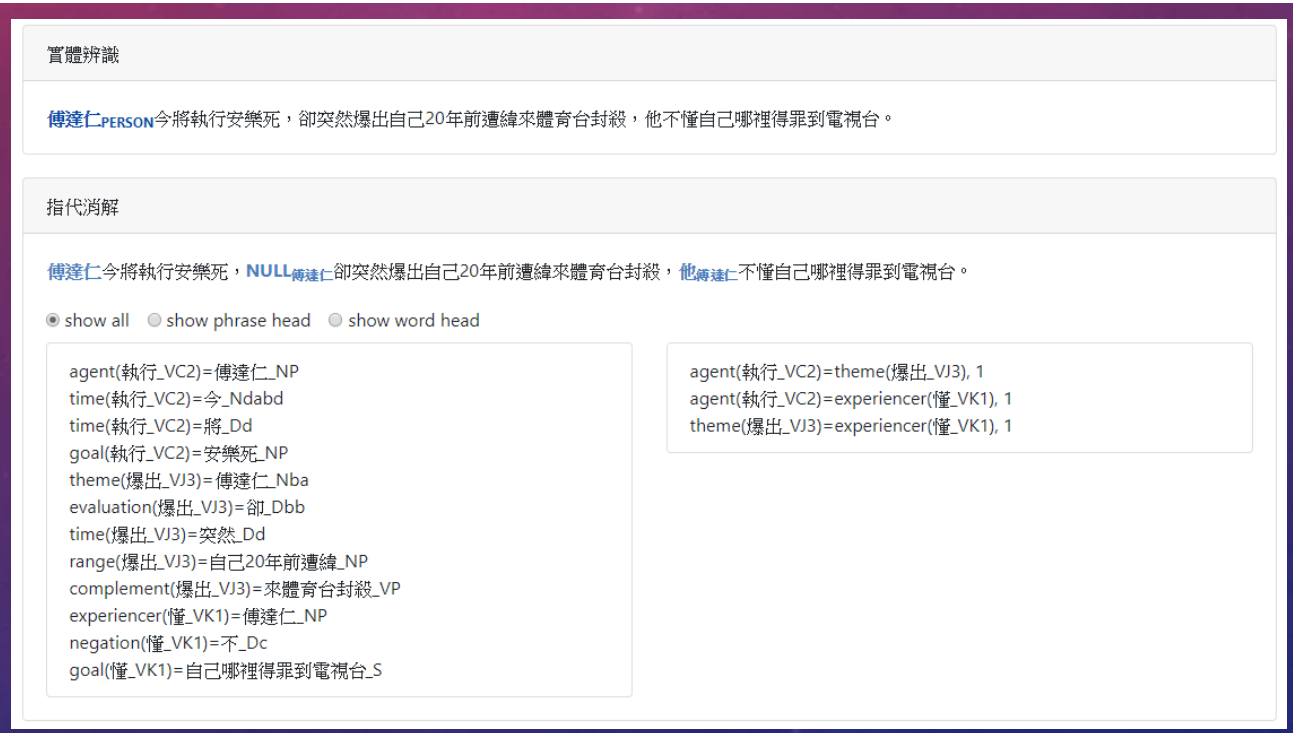

S*
NP
PP*
NP
VP
IN
NP
DT
NP
VP
VP
after
PRP$
NN
These
factors
will
VP
VP
後
its
return
這些
條件
將會
continue
TO
VP
香港
回歸
繼續
to
VP
NP
ε
play
DT
NP
發揮
a
JJ
NN
ε
positive
role
積極
作用

中研院

傅達仁(Nb) 今(Nd) 將(D) 執行(VC) 安樂死(Na) ，(COMMACATEGORY)

卻(D) 突然(D) 爆出(VJ) 自己(Nh) ２０(Neu) 年前(Nd) 遭(P) 緯來(Nb) 體育台(Nc) 封殺(VC) ，(COMMACATEGORY)

他(Nh) 不(D) 懂(VK) 自己(Nh) 哪裡(D) 得罪(VC) 到(P) 電視台(Nc) 。(PERIODCATEGORY)



中研院CKIP Lab – 繁體中文剖析工具
http://ckip.iis.sinica.edu.tw:8080/demo/

FUDANNLP

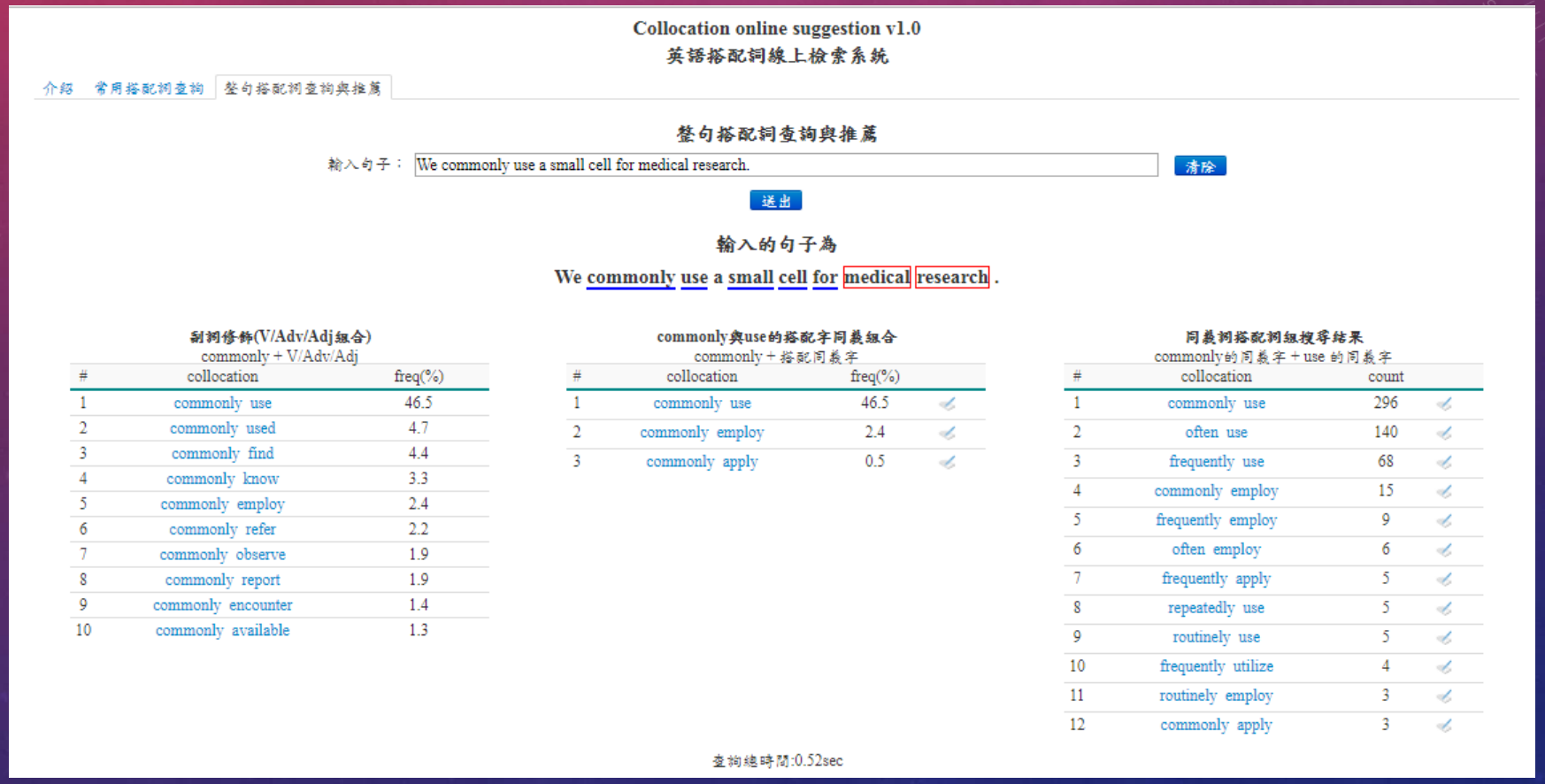
```
D:\fnlp>java -Xmx1024m -Dfile.encoding=UTF-8 -classpath "fnlp-core/target/fnlp-c
ore-2.1-SNAPSHOT.jar;libs/trove-3.1a1.jar;libs/commons-cli-1.4.jar" org.fnlp.nlp
.cn.tag.POSTagger -s models/seg.m models/pos.m "周杰伦出生于台湾，生日为79年1月1
8日，他曾经的绯闻女友是蔡依林。"
周杰伦/人名 出生于/动词 台湾/地名 ，/名词 生日/名词 为/介词 79年/时间短语 1月/时
间短语 18日/时间短语 ，/动词 他/人称代词 曾经/形容词 的/结构助词 绯闻/名词 女友/
名词 是/动词 蔡依林/人名 。/标点
```



```
D:\fnlp>java -Xmx1024m -Dfile.encoding=UTF-8 -classpath "fnlp-core/target/fnlp-c
ore-2.1-SNAPSHOT.jar;libs/trove-3.1a1.jar;libs/commons-cli-1.4.jar" org.fnlp.nlp
.cn.tag.NERTagger -s models/seg.m models/pos.m "詹姆斯·默多克和丽贝卡·布鲁克斯
鲁珀特·默多克旗下的美国小报《纽约邮报》的职员被公司律师告知，保存任何也许与电
话窃听及贿赂有关的文件。"
<美国=地名，纽约=地名，詹姆斯·默多克=人名，鲁珀特·默多克=人名，丽贝卡·布鲁克
斯=人名>
```


復旦NLP - 簡體中文剖析工具
https://blog.csdn.net/hhu_lyc/article/details/79179619

以語言學習輔助工具為例



Collocation online suggestion v1.0
英語搭配詞線上檢索系統

介紹　常用搭配詞查詢　整句搭配詞查詢與推薦

整句搭配詞查詢與推薦

輸入句子： We commonly use a small cell for medical research.　清除

送出

輸入的句子為

We commonly use a small cell for medical research .

副詞修飾(V/Adv/Adj組合)
commonly + V/Adv/Adj

#	collocation	freq(%)
1	commonly use	46.5
2	commonly used	4.7
3	commonly find	4.4
4	commonly know	3.3
5	commonly employ	2.4
6	commonly refer	2.2
7	commonly observe	1.9
8	commonly report	1.9
9	commonly encounter	1.4
10	commonly available	1.3

commonly與use的搭配字同義組合
commonly + 搭配同義字

#	collocation	freq(%)
1	commonly use	46.5
2	commonly employ	2.4
3	commonly apply	0.5

同義詞搭配詞組搜尋結果
commonly的同義字 + use 的同義字

#	collocation	count
1	commonly use	296
2	often use	140
3	frequently use	68
4	commonly employ	15
5	frequently employ	9
6	often employ	6
7	frequently apply	5
8	repeatedly use	5
9	routinely use	5
10	frequently utilize	4
11	routinely employ	3
12	commonly apply	3

查詢總時間:0.52sec

以語言學習輔助工具為例

	computer	data	pinch	result	sugar
aprocot	0	0	1	0	1
pineapple	0	0	1	0	1
digital	2	1	0	1	0
information	1	6	0	4	0

$$P(x = information, y = data) = \frac{6}{19} = 0.32$$

$$P(x = information) = \frac{6+4+1}{19} = \frac{11}{19} = 0.58$$

$$P(y = data) = \frac{6+1}{19} = \frac{7}{19} = 0.37$$

$$pmi(x = information, y = data)$$
$$= log \frac{P(x = information, y = data)}{P(x = information) \times P(y = data)}$$
$$= log 1.49$$
$$= 0.57$$

THINKING TIME

POTENTIAL APPLICATIONS

OPEN DATASETS

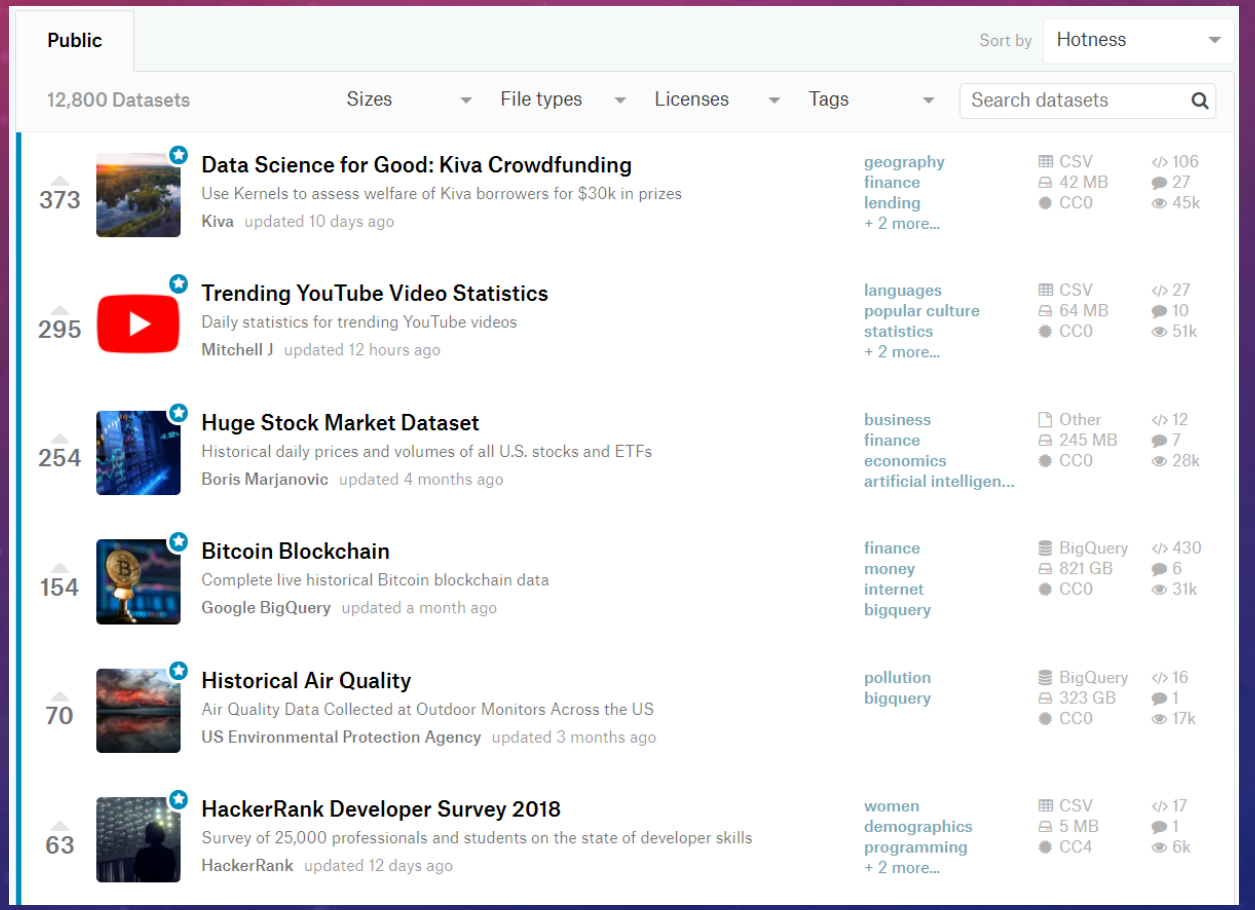
UC IRVINE MACHINE LEARNING REPOSITORY

- http://archive.ics.uci.edu/ml/datasets.html

Name	Data Types	Default Task	Attribute Types	# Instances	# Attributes	Year
Abalone	Multivariate	Classification	Categorical, Integer, Real	4177	8	1995
Adult	Multivariate	Classification	Categorical, Integer	48842	14	1996
Annealing	Multivariate	Classification	Categorical, Integer, Real	798	38	
Anonymous Microsoft Web Data		Recommender-Systems	Categorical	37711	294	1998
Arrhythmia	Multivariate	Classification	Categorical, Integer, Real	452	279	1998
Artificial Characters	Multivariate	Classification	Categorical, Integer, Real	6000	7	1992
Audiology (Original)	Multivariate	Classification	Categorical	226		1987
Audiology (Standardized)	Multivariate	Classification	Categorical	226	69	1992
Auto MPG	Multivariate	Regression	Categorical, Real	398	8	1993
Automobile	Multivariate	Regression	Categorical, Integer, Real	205	26	1987
Badges	Univariate, Text	Classification		294	1	1994

KAGGLE DATASETS

- https://www.kaggle.com/datasets



臺南市開放資料

- http://data.tainan.gov.tw/dataset

THANK YOU