文字探勘實作 - NER

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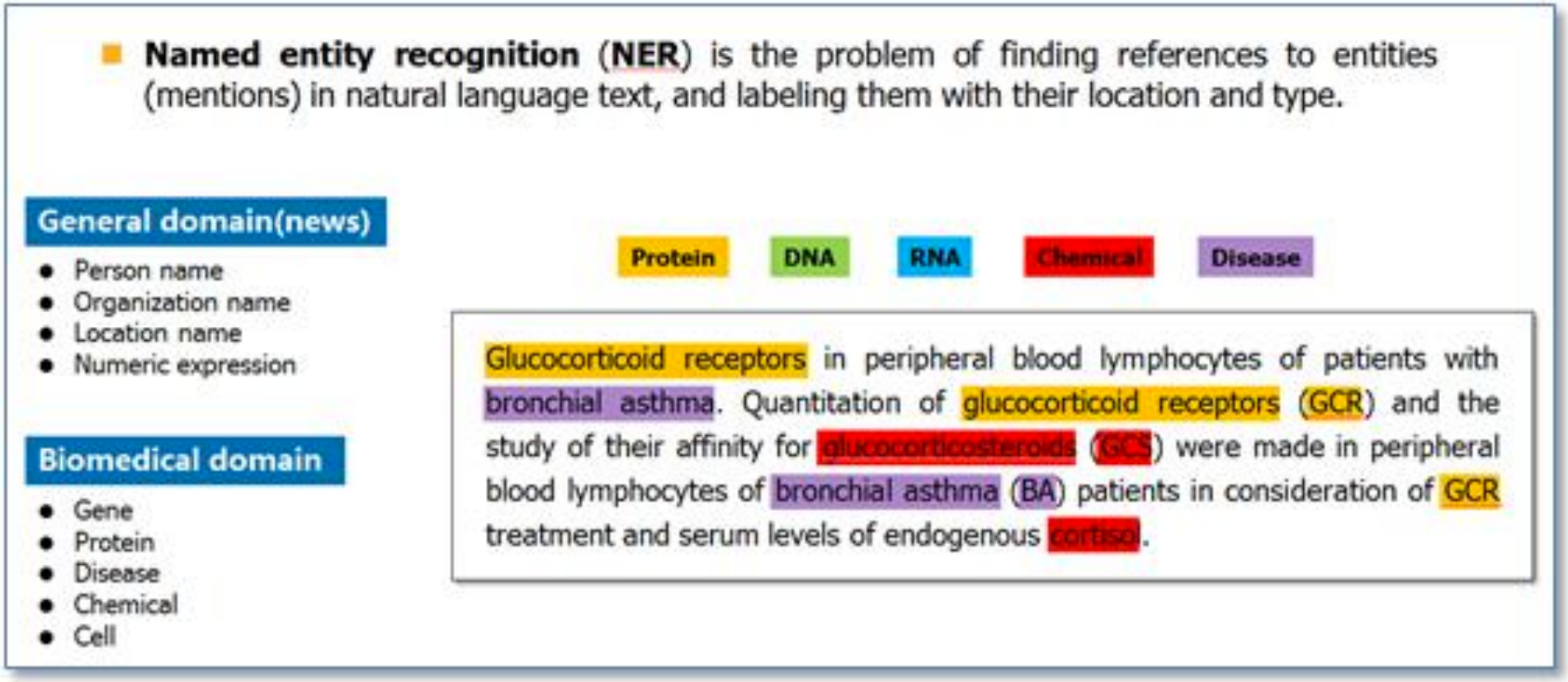
命名實體識別

命名實體識別(Named Entity Recognition)

- 從一段自然語言文本中找出相關實體，並標註出其位置以及類型



為什麼要做 NER?

- 字典比對方法
  - 建立一字典，並比對斷詞過的文章中是否有該關鍵字詞

- 範例

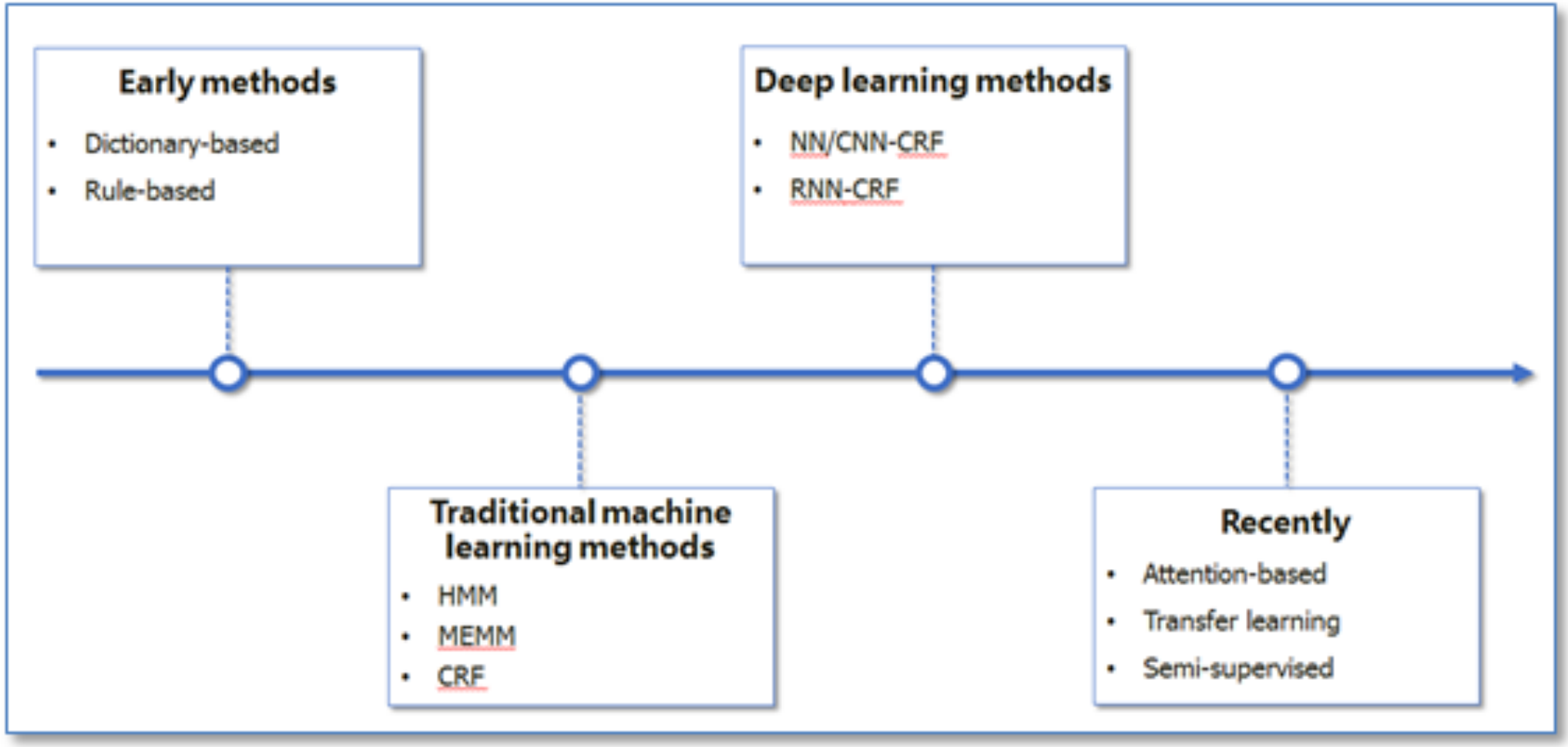
```
org = ['台積電']
import jieba
set(org) & set(list(jieba.cut('今、明年資本支出近兆台積電大擴產商機來了')))
```

但如果有同義詞出現?

- 台積電也可以被稱作 TSMC, 台積
  - e.g. 台積鉅額交易爆萬張大量

- 解決方案
  - 建立同義辭典(耗工費時)
  - 做命名實體識別(Named Entity Recognition)

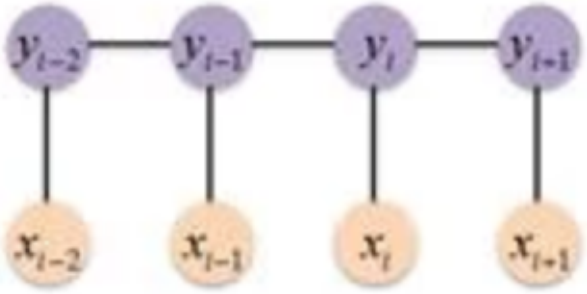
NER研究進展


Early methods
Dictionary-based
Rule-based
Deep learning methods
NN/CNN-CRF
RNN-CRF
Traditional machine learning methods
HMM
MEMM
CRF
Recently
Attention-based
Transfer learning
Semi-supervised

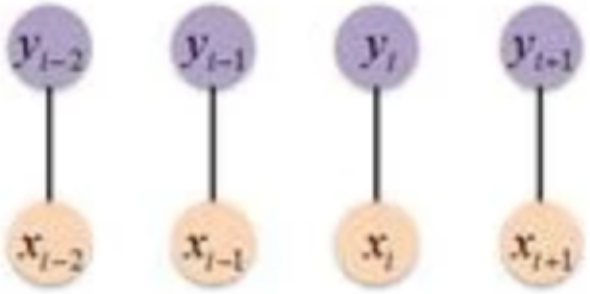
序列標注方法

- 在基於機器學習的方法中，NER被當作是序列標註問題
- 序列標註問題中當前的預測標籤不僅與當前的輸入特徵相關，還與之前的預測標籤相關，即預測標籤序列之間是有強相互依賴關係

序列標注方法



分類方法



序列標注問題

- I come from New York
  - 對應的標註是：O O O B-loc I-loc O
  - New York 標示成 B-loc I-loc，B表示開頭，I表示之後的字，loc代表自己定義entity的類別
- I come from Taiwan
  - 對應的標註是：O O O B-loc O

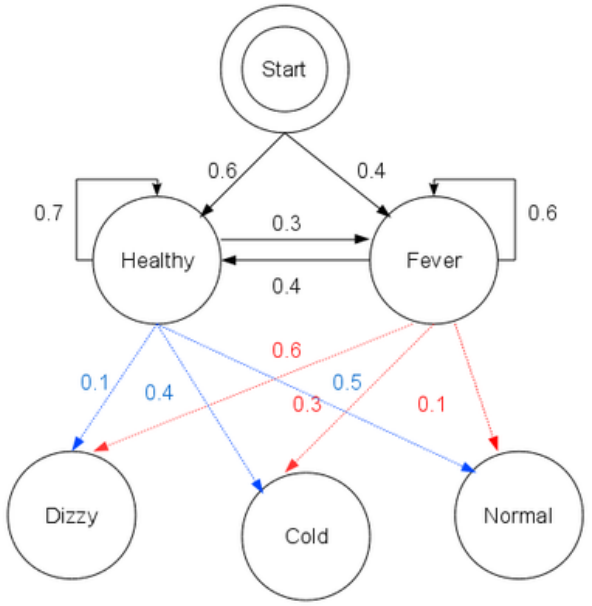
使用者可以自訂所需要的entity

NER 方式

- 任務簡單或訓練資料量很少，用正則表達式或直接比對資料庫
- 如果訓練資料量夠多的話就可以用：HMM或CRF
- HMM 或 CRF 都可以寫成Evaluation 與 Inference 兩個步驟
  - Evaluation:定義F(x,y)，x代表輸入序列，y代表輸出序列，F(x,y)代表好壞程度，值越大代表y越符合我們的需要
  - Inference:在所有可能的y集合裡找到一組y能最大化F(x,y)的值

隱馬爾可夫模型

- 用來描述一個含有隱含未知參數的馬爾可夫過程
- 目的是從可觀察的參數中確定該過程的隱含參數。然後利用這些參數來作斷詞



誰是馬可夫?

- Andrey Markov

(14 June 1856 N.S. – 20 July 1922)

- Calculated letter sequences of the Russian language

問題描述

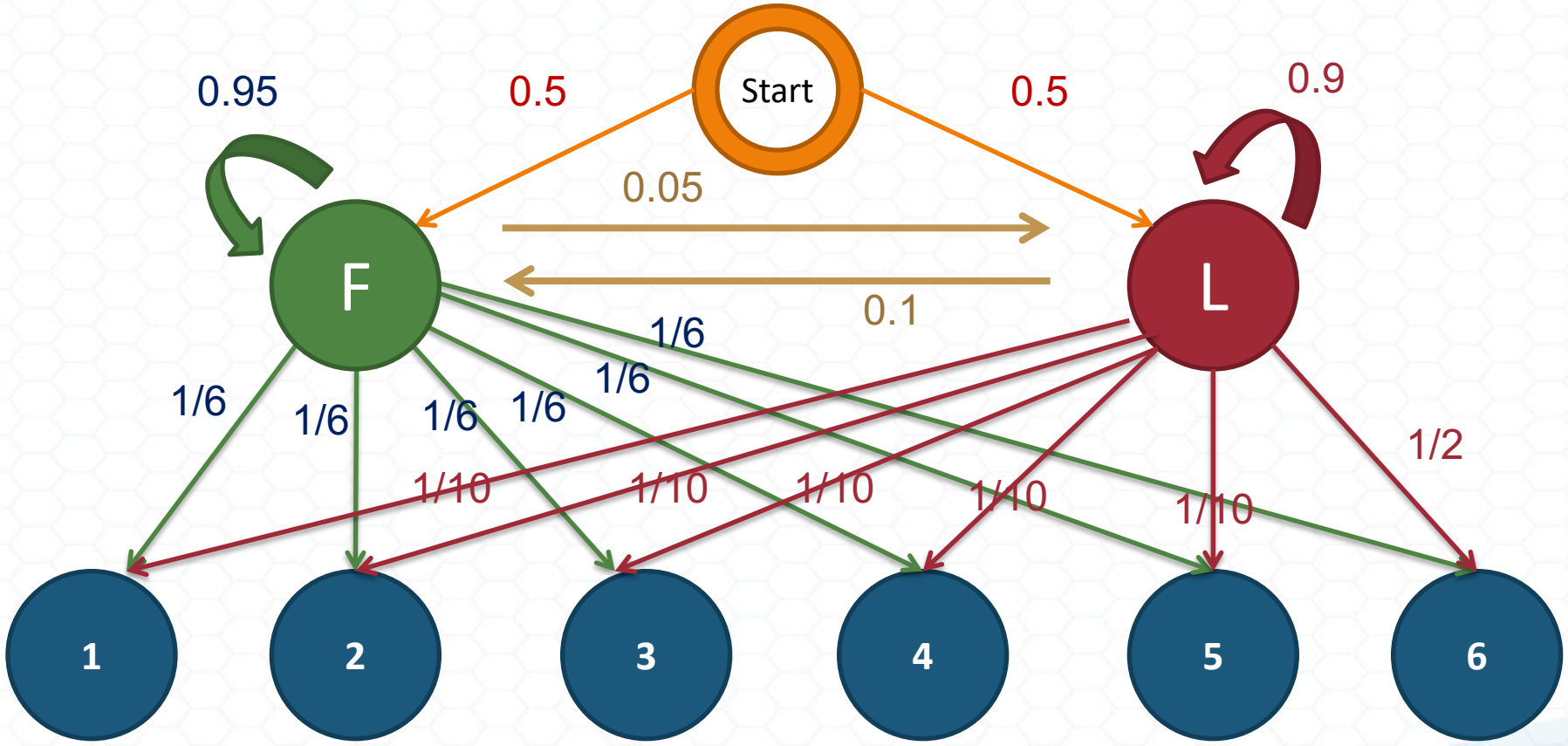
- States -> "F", "L“
- Transition Matrix

	Fair	Loaded
Fair	0.95	0.05
Loaded	0.1	0.9

- Emission Matrix

	Fair	Loaded
1	1/6	1/10
2	1/6	1/10
3	1/6	1/10
4	1/6	1/10
5	1/6	1/10
6	1/6	½

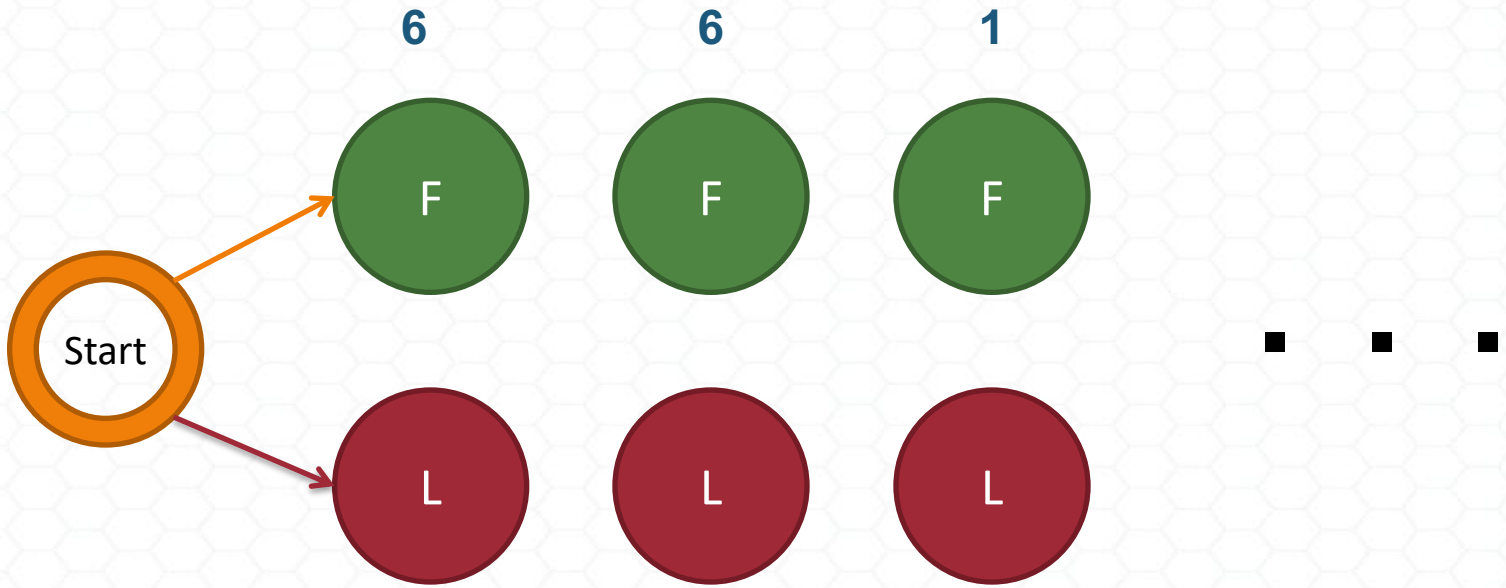
Problem Description



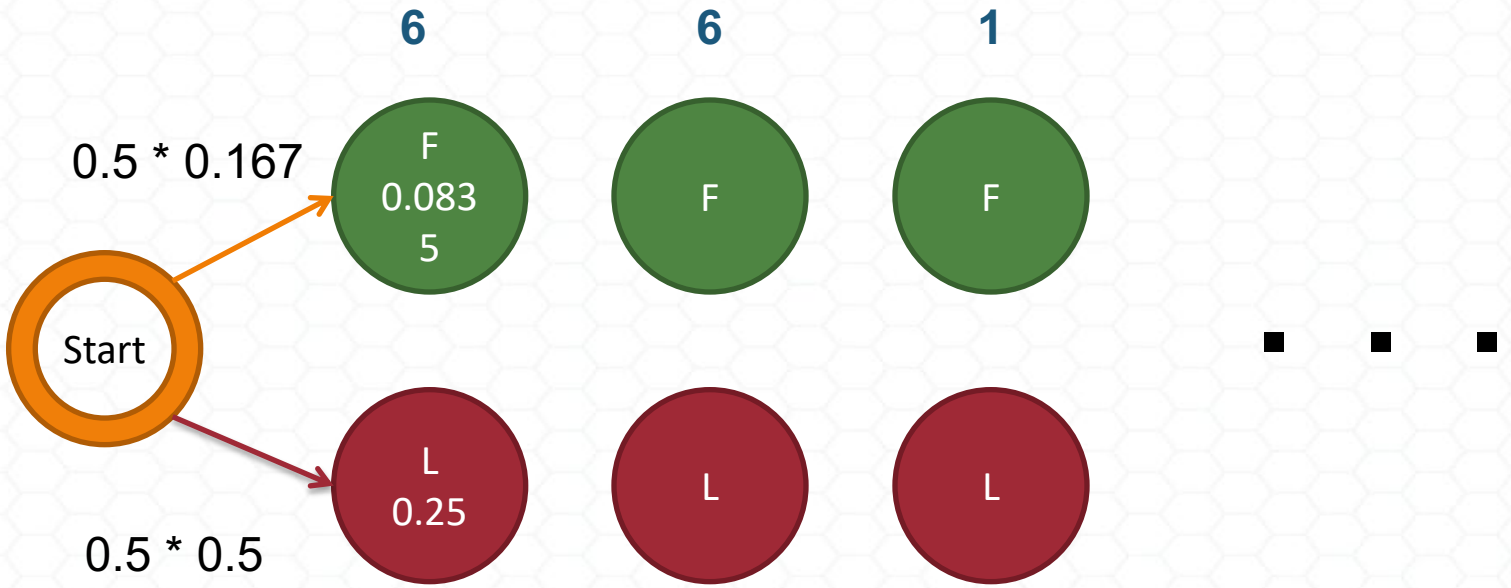
Algorithm

- Given Observable Sequence:

  6,6,1,5,3,2…

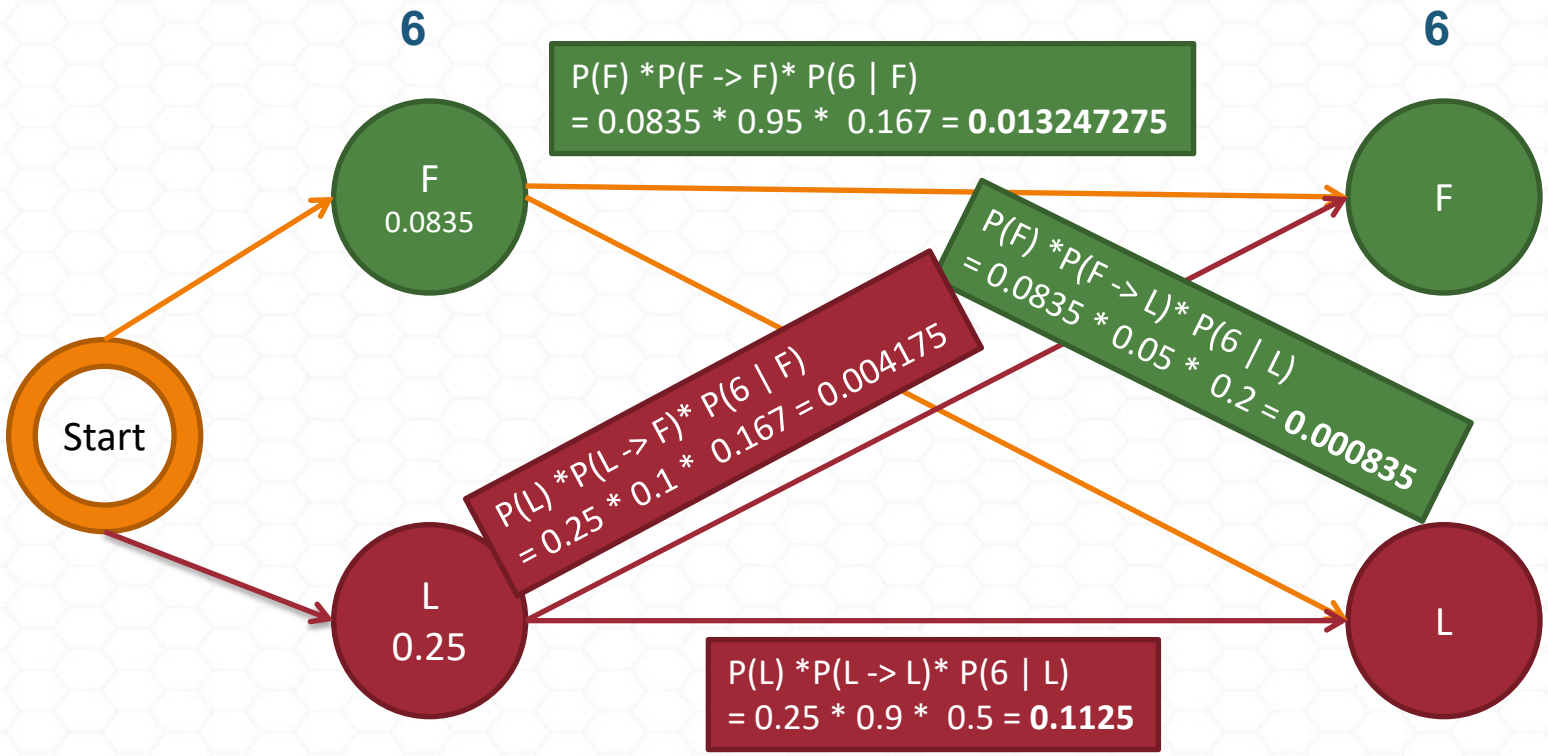


Start to Step 1



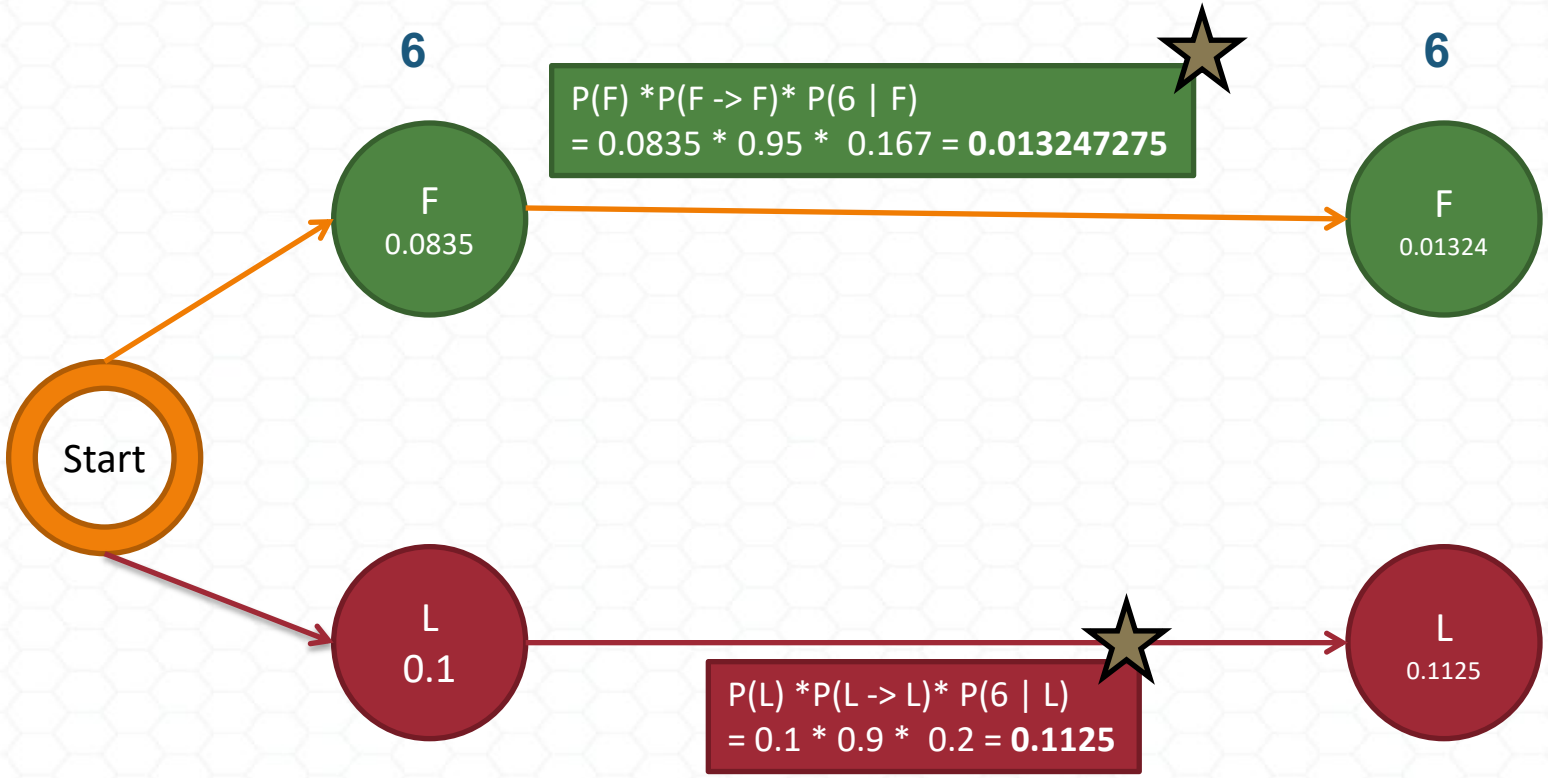
P_Start(State) * P_Observe(6)

Step 1 to Step 2

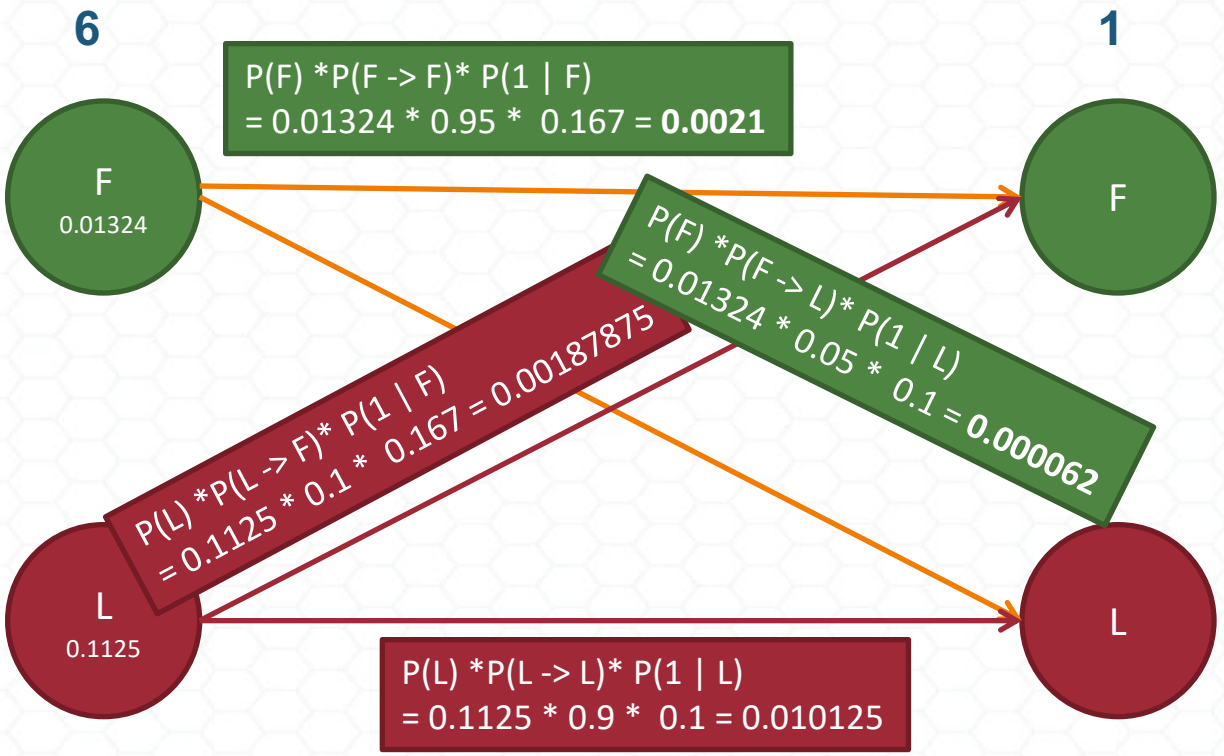


P_OldState(State) *P_Trans(Old_State -> New_State)* P_Observe(6 | New_State)

Most Likely Path

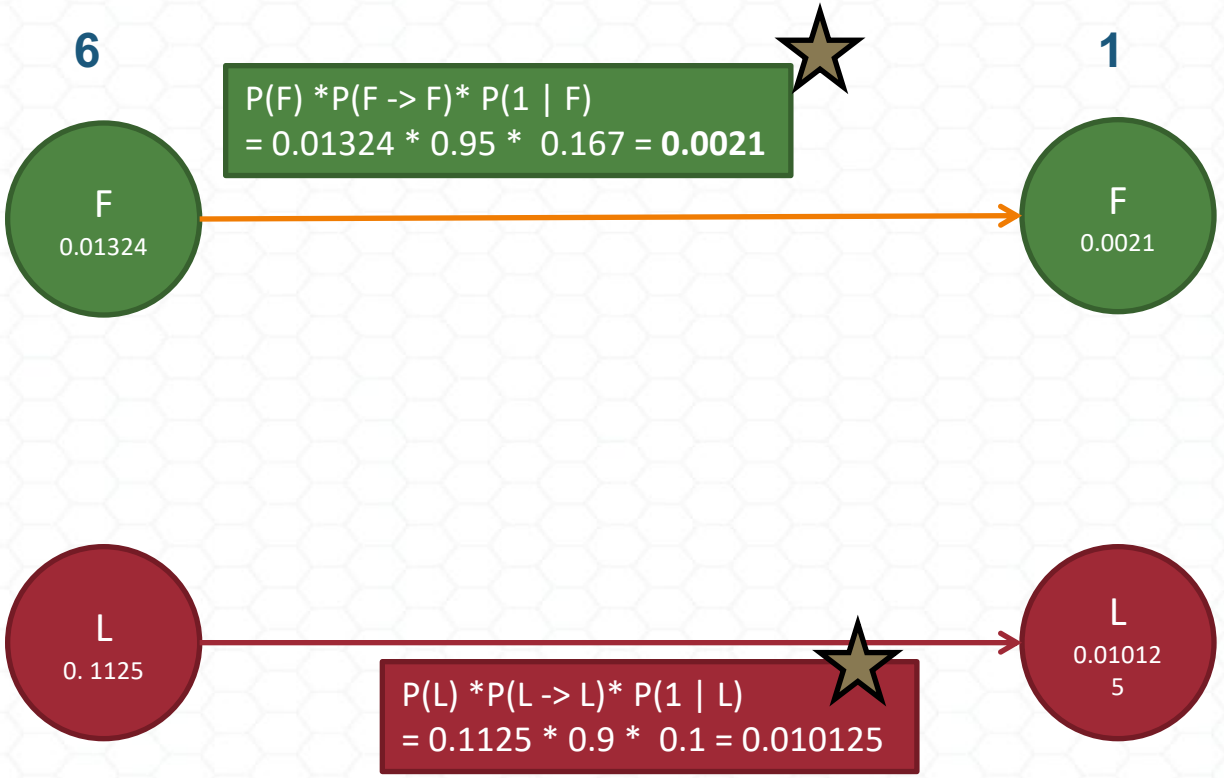


Step 2 to Step 3



P_OldState(State) *P_Trans(Old_State -> New_State)* P_Observe(1 | New_State)

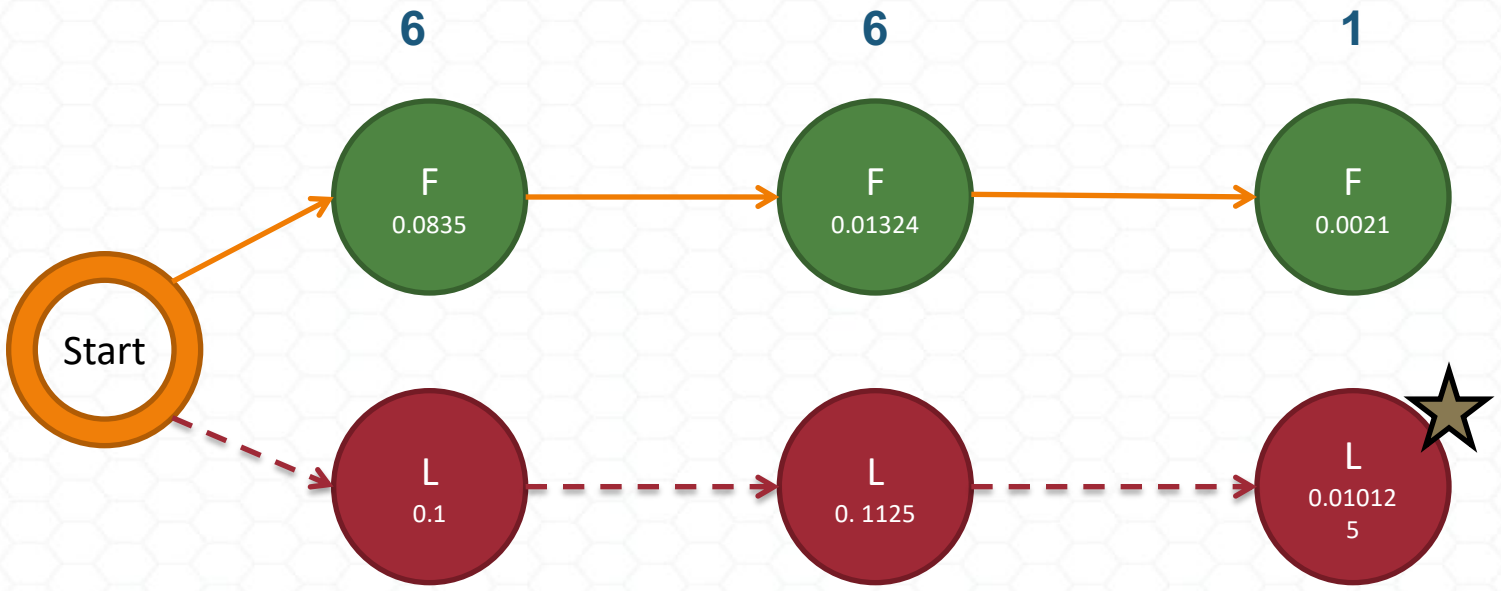
Most Likely Path



P_OldState(State) *P_Trans(Old_State -> New_State)* P_Observe(1 | New_State)

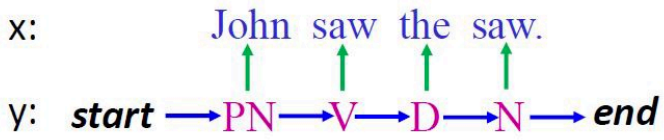
Path Construction

Max(Probability) = 0.010125



State Sequence: Loaded, Loaded, Loaded

HMM



$$P(x,y)=P(y)P(x|y)$$

$$P(y) = P(PN|start) \times P(V|PN) \times P(D|V) \times P(N|D)$$

$$P(x|y) = P(John|PN) \times P(saw|V) \times P(the|D) \times P(saw|N)$$

- P(y)裡的每一項可以由訓練數據統計得到，這裡我們會得到一個N維向量代表Start Probability
- N*N的矩陣代表Transition Probability
- (x|y)代表有了這個標註後，產生這個詞的機率，也可以由統計後得到，寫成N*M的矩陣代表Emission Probability代表有多少種類別標籤

HMM Inference

- 用 Viterbi 演算法窮舉所有的y

$$\tilde{y} = arg \max_{y \in \mathbb{Y}} P(x, y)$$

- 選出最高的 y 當成標注結果

條件隨機域(CRF)

- CRF中的特徵向量，接受四個參數：
  - 句子s（就是我們要標註詞性的句子）
  - i，用來表示句子s中第i個單詞
  - l_i，表示要評分的標註序列給第i個單詞標註的詞性
  - l_i-1，表示要評分的標註序列給第i-1個單詞標註的詞性

- 它的輸出值是0或者1, 0表示要評分的標註序列不符合這個特徵，1表示要評分的標註序列符合這個特徵。

條件隨機域(CRF)

- 定義好一組特徵函數後，我們要給每個特徵函數f_j賦予一個權重λ_j。現在，只要有一個句子s，有一個標註序列l，我們就可以利用前面定義的特徵函數集來對l評分

$$score(l|s) = \sum_{j=1}^{m} \sum_{i=1}^{n} \lambda_j f_j(s, i, l_i, l_{i-1})$$

求每一個特徵函數f_j評分值的和

求句子中每個位置的單詞的的特徵值的和

CRF 範例(1)

$$f_1(s, i, l_i, l_{i-1}) = 1$$

- 當l_i是”副詞”並且第i個單詞以”ly”結尾時，我們就讓f1 = 1，其他情況f1為0

- f1特徵函數的權重λ1應當是正的。而且λ1越大，表示我們越傾向於採用那些把以”ly”結尾的單詞標註為”副詞”的標註序列

CRF 範例(2)

$$f_2(s, i, l_i, l_{i-1}) = 1$$

- 如果i=1，l_i=動詞，並且句子s是以”？”結尾時，f2=1，其他情況f2=0
- λ2應當是正的，並且λ2越大，表示我們越傾向於採用那些把問句的第一個單詞標註為“動詞”的標註序列。

CRF 範例(3)

$$f_3(s, i, l_i, l_{i-1}) = 1$$

- 當l_i-1是介詞，l_i是名詞時，f3 = 1，其他情況f3=0。 λ3也應當是正的，並且λ3越大，說明我們越認為介詞後面應當跟一個名詞

CRF 範例(4)

$$f_4(s, i, l_i, l_{i-1}) = 1$$

- l_i和l_i-1都是介詞，那麼f4等於1，其他情況f4=0。這裡，我們應當可以想到λ4是負的，並且λ4的絕對值越大，表示我們越不認可介詞後面還是介詞的標註序列。

條件隨機域(CRF)

$$score(l|s) = \sum_{j=1}^{m} \sum_{i=1}^{n} \lambda_j f_j(s, i, l_i, l_{i-1})$$

求每一個特徵函數f_j評分值的和

求句子中每個位置的單詞的的特徵值的和

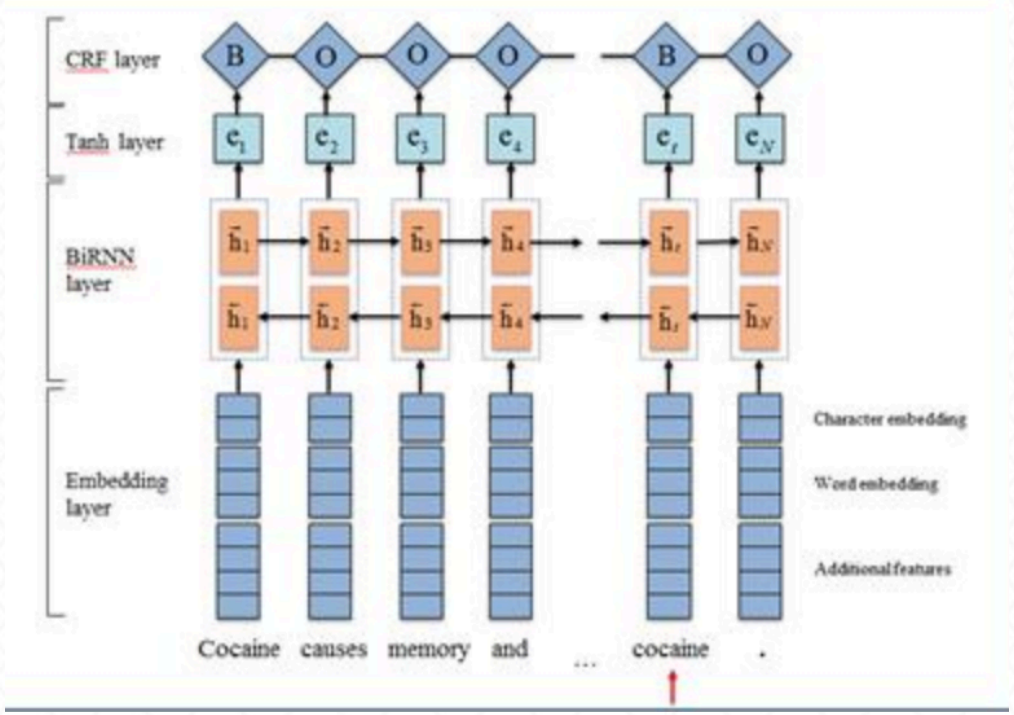
- 建條件隨機場，我們首先要定義一個特徵函數集，每個特徵函數都以整個句子s，當前位置i，位置i和i-1的標籤為輸入。然後為每一個特徵函數賦予一個權重，然後針對每一個標註序列l，對所有的特徵函數加權求和，也可以把求和的值轉化為一個概率值

CRF與HMM的比較

- HMM 可以視為 CRF的特殊類型
- HMM模型中，當前的單詞只依賴於當前的標籤，當前的標籤只依賴於前一個標籤。只能定義局部性的特徵函數
- CRF卻可以著眼於整個句子s定義更具有全局性的特徵函數

神經網路方法

- CRF, HMM 等方法，還是需要定義出特徵，使用深度學習方法可以直接實現End-to-end Learning



深度學習方法與 CRF 方法的比較

- 深度學習方法並沒有一定的優勢

模型/实体类型	地名	组织	人名
BILSTM+softmax	85%	70%	81%
BILSTM+CRF	84%	85%	91%
作者(40轮)	91%	85%	87%
CRF++	91%	85%	86%

NER 實作

NLTK

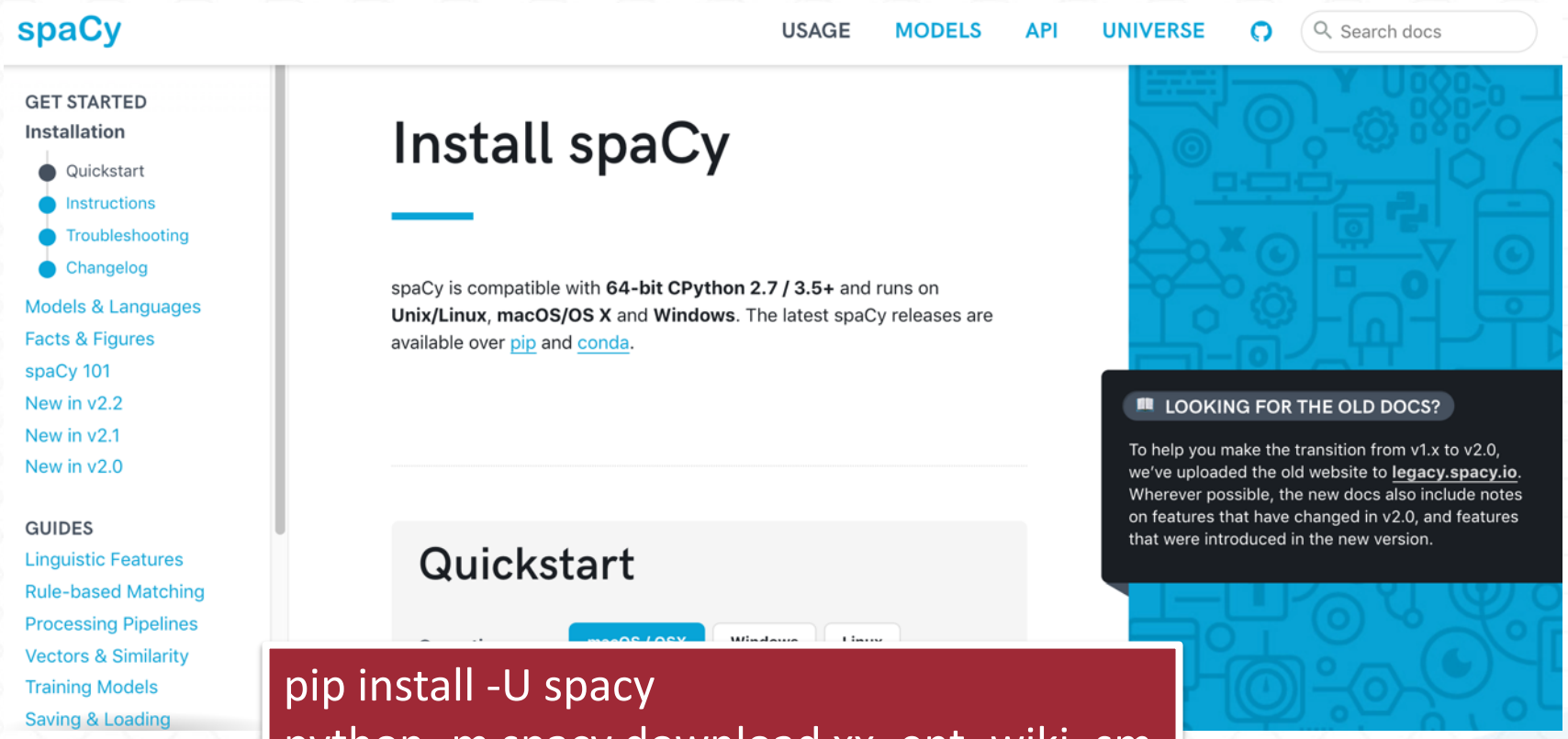
```
import nltk
from nltk.tokenize import word_tokenize
from nltk.tag import pos_tag

sent = nltk.word_tokenize(sent)
sent = nltk.pos_tag(sent)
sent = preprocess(ex)
sent
```

再利用詞性萃取出專有名詞

Spacy

- 工業級文字處理工具




```
pip install -U spacy
python -m spacy download xx_ent_wiki_sm
```

Spacy

- SpaCy的命名實體識別已經在OntoNotes 5語料庫上進行了訓練，它支持以下實體類型

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

Entity(命名)

```
import spacy
from spacy import displacy
from collections import Counter
import en_core_web_sm
nlp = en_core_web_sm.load()

doc = nlp('European authorities fined Google a record $5.1 billion on Wednesday for abusing its power in the mobile phone market and ordered the company to alter its practices')
pprint([(X.text, X.label_) for X in doc.ents])
```

列出標記

```
pprint([(X, X.ent_iob_, X.ent_type_) for X in doc])
```

TAG	DESCRIPTION
`B EGIN`	The first token of a multi-token entity.
`I N`	An inner token of a multi-token entity.
`L AST`	The final token of a multi-token entity.
`U NIT`	A single-token entity.
`O UT`	A non-entity token.

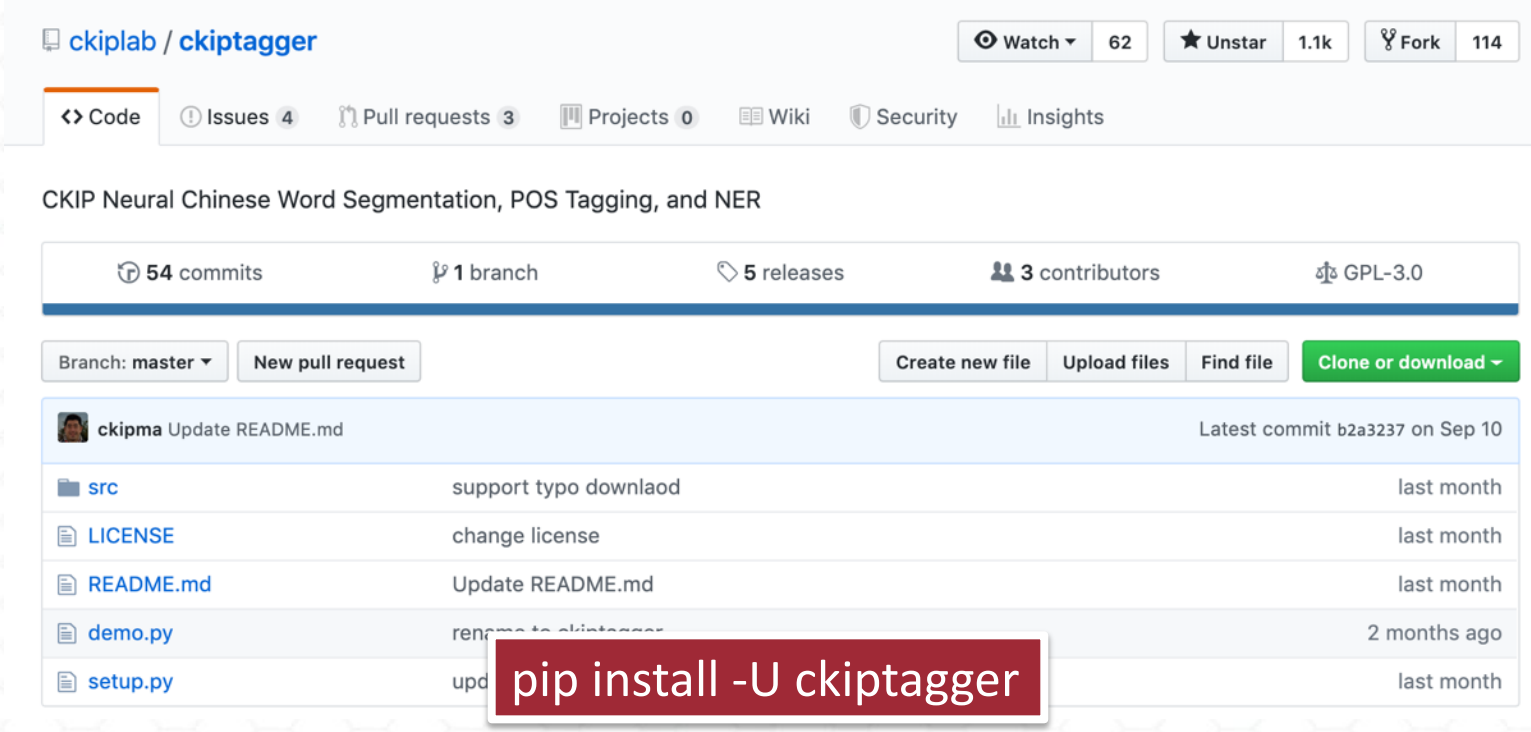
視覺化呈現標記

```
displacy.render(nlp(str(sentences[20])), jupyter=True, style='ent')
```

Firing Mr. Strzok PERSON , however, removes a favorite target of Mr. Trump PERSON from the ranks of the F.B.I. GPE and gives Mr. Bowdich PERSON and the F.B.I. GPE director, Christopher A. Wray PERSON , a chance to move beyond the president's ire.

ckiptagger

- 中研院開源出來的切詞套件
  - https://github.com/ckiplab/ckiptagger



ckiptagger

- 切詞準確度最高

Tool	(WS) prec	(WS) rec	(WS) f1	(POS) acc
CkipTagger	97.49%	97.17%	97.33%	94.59%
CKIPWS (classic)	95.85%	95.96%	95.91%	90.62%
Jieba-zh_TW	90.51%	89.10%	89.80%	--

- 支援 POS, 切詞與NER 功能
- GNU General Public License v3.0

Ckiptagger 範例

```
from ckiptagger import data_utils, construct_dictionary, WS, POS, NER
ws = WS("./data")
pos = POS("./data")
ner = NER("./data")
sentence_list = [
    "全聯福利中心強力推出「PX Pay」行動支付後，更進一步開放8家銀行的實體信用卡、33家金融機構金融卡、3大電子票證、3大國際行動Pay與台灣Pay等交易。同時釋出8大銀行刷卡優惠，其中聯邦卡首刷500元送1,000點福利點最高，平日則以國泰世華天天消費滿500元送300點最強。",
]

word_sentence_list = ws(
    sentence_list,
)
pos_sentence_list = pos(word_sentence_list)
entity_sentence_list = ner(word_sentence_list, pos_sentence_list)
```

需要先下載資料

THANK YOU