

Sequence labeling: POS Tagger (+ NLTK Practice)

Knowledge & Language Engineering Lab.

Contents

- Sequence Labeling
 - Introduction
 - Method

- Practice
 - Simple POS tagger using HMM Algorithm
 - Natural Language ToolKit (Open source Platform)

[Relation Extraction]

SEQUENCE LABELING

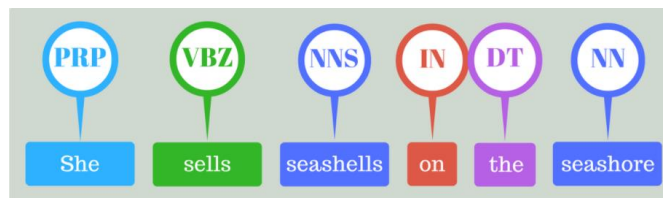
Introduction

- Sequence labeling
 - A pattern recognition task that classifies a categorical label to each member of a sequence elements.
 - In NLP, which deals with sequential data, sequence labeling is one of the major task.
- Tasks or subtasks

Named entity recognition

Automatically find names
of people, places, products,
and organizations in text
across many languages.

Part of speech tagging



Spacing problem

아버지가방에들어가신다.
↓
아버지가 방에 들어가신다.

Introduction

- Sequential Data
 - Data stored in chronological order.
 - Generally, each element is related to each other.
 - E.g.)
 - Video: a sequence of frames
 - Text: a sequence of words
 - Voice: a sequence of signals

Methods

- Sequence labeling methods
 - Vector space model
 - Neural network model
 - Structured SVM
 - Probabilistic model
 - Hidden Markov Model (HMM)
 - Conditional Random Field (CRF)

Methods

- Sequence labeling methods
 - Vector space model
 - Neural network model
 - Structured SVM
 - Probabilistic model
 - **Hidden Markov Model (HMM)**
 - Conditional Random Field (CRF)

Hidden Markov Model

- $y_{1:N}^* = \operatorname{argmax}_{y_{1:N}} P(y_{1:N} | x_{1:N})$

(Bayes rule)

$$= \operatorname{argmax}_{y_{1:N}} P(x_{1:N} | y_{1:N}) P(y_{1:N})$$

$$= \operatorname{argmax}_{y_{1:N}} \prod_{k=1}^N P(x_k | x_{1:k-1}, y_{1:k}) \prod_{k=1}^N P(y_k | y_{1:k-1})$$

(Markov assumption)

$$\approx \operatorname{argmax}_{y_{1:N}} \prod_{k=1}^N P(x_k | y_k) \prod_{k=1}^N P(y_k | y_{k-1})$$

Hidden Markov Model

- $$y_{1:N}^* = \operatorname{argmax}_{y_{1:N}} P(y_{1:N} | x_{1:N})$$

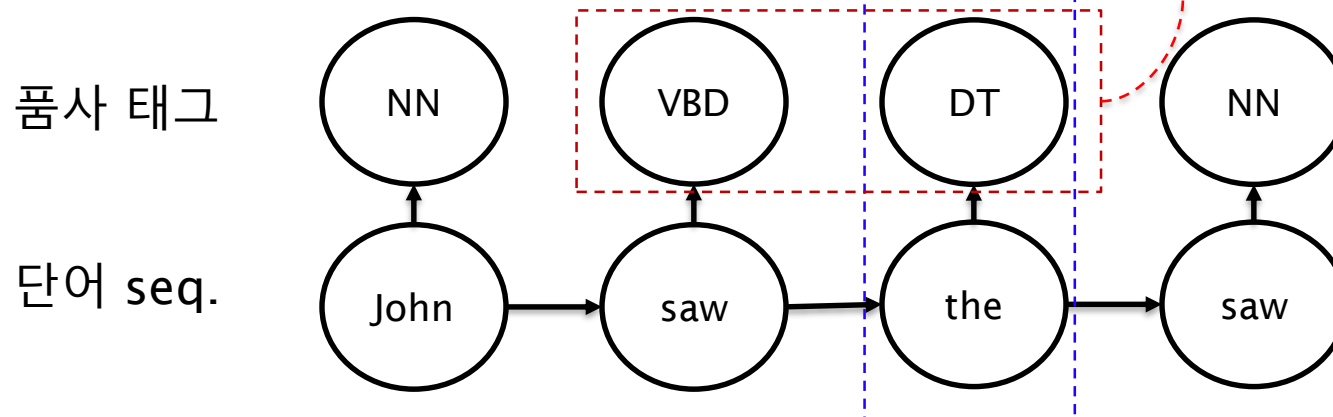
(Bayes rule)

$$= \operatorname{argmax}_{y_{1:N}} P(x_{1:N} | y_{1:N}) P(y_{1:N})$$

$$= \operatorname{argmax}_{y_{1:N}} \prod_{k=1}^N P(x_k | x_{1:k-1}, y_{1:N}) \prod_{k=1}^N P(y_k | y_{1:k-1})$$

(Markov assumption)

$$\approx \operatorname{argmax}_{y_{1:N}} \prod_{k=1}^N P(x_k | y_k) \prod_{k=1}^N P(y_k | y_{k-1})$$



Hidden Markov Model

- $\operatorname{argmax}_{y_{1:N}} \prod_{k=1}^N P(x_k|y_k) \prod_{k=1}^N P(y_k|y_{k-1})$
- $P(x_k|y_k)$: emission probability
 - 각 state(y) 에서 관측 가능한 값(x)의 확률
 - E.g.) 명사(NN) 인 'saw' 가 등장할 확률
 - $P(x_k|y_k) = \frac{P(x_k, y_k)}{P(y_k)}$
- $P(y_k|y_{k-1})$: transition probability
 - State(y) 간의 변화 확률
 - E.g.) 동사(VB) 이후에 명사(NN)가 등장할 확률
 - $P(y_k|y_{k-1}) = \frac{P(y_k, y_{k-1})}{P(y_{k-1})}$

Hidden Markov Model

- $\log(P(NN \ VBD \ DT \ NN | \text{John saw the saw}))$
 $= \log P(\text{John} | NN) + \log P(NN | \langle BOS \rangle)$
 $+ \log P(\text{saw} | VBD) + \log P(VBD | NN)$
 $+ \log P(\text{the} | DT) + \log P(DT | VBD)$
 $+ \log P(\text{saw} | NN) + \log P(NN | DT)$
 $+ \log P(\langle EOS \rangle | NN)$

PRACTICE

KLE tagset

- 부가자료: KLE_Tagset.pdf 파일 참고

preprocessing

- Preprocess each line with a list of tuples.

- $[(word_1, tag_1), (word_2, tag_2), \dots, (word_n, tag_n),$
 $[(word_1, tag_1), (word_2, tag_2), \dots, (word_n, tag_n)$
 \vdots
 $[(word_1, tag_1), (word_2, tag_2), \dots, (word_n, tag_n)]]$

그/CT 도/fjb 강하/YBH ㄴ/fmotg 카리스마/CMC 를/fjco 필요/CMC 하/fph 버니다/fmof ./g
 애플/CMC 이/fjcs 80/CS %/g 로/fjcao 그/SG 뒤/CMC 를/fjco 쫓/YBD 앓/fmb 습니다/fmof ./g
 이제/SBO 참가자들/CMC 이/fjcs 기념촬영/CMC 을/fjco 하/YBD 고/fmoc 있/YA 다/fmof ./g



$[(\text{그}, \text{CT}), (\text{도}, \text{fjb}), (\text{강하}, \text{YBH}), \dots, (\text{버니다}, \text{fmof}), (., \text{g})],$
 $[(\text{애플}, \text{CMC}), (\text{이}, \text{fjcs}), (80, \text{CS}), \dots, (\text{습니다}, \text{fmof}), (., \text{g})],$
 $[(\text{이제}, \text{SBO}), (\text{참가자들}, \text{CMC}), (\text{이}, \text{fjcs}), \dots, (\text{다}, \text{fmof}), (., \text{g})]]$

Train function

- Count the number of (word, tag)
 - Nested dictionary type
 - `pos2words_freq = defaultdict(lambda: defaultdict(int))`
 - `Pos2words[pos][word]_freq`:
 - stores the number (frequency) of (word, tag)
- Count the number of bigram tags (tag_{i-1}, tag_i)
 - Dictionary type
 - Define `trans_freq = defaultdict(int)` for bigrams counts
 - Define `bos_freq = defaultdict(int)` for the bigrams counts containing "BOS"
 - `Trans[(tagi-1, tagi)]` stores the number of bigrams
 - `Bos[tagi]` stores the number of BOS bigrams

Train function

- Example

- pos2words_freq

```
{CMC: {아버지: 10, 올림픽: 15, ..},  
  CMP: {구글: 20, 애플: 15, ..}  
  YBD: {마시: 10, 듣: 20, ...}}
```

- trans_freq

```
{(CMC, fjb): 20, (CMP, fjb): 31, (fjco, fd): 55, ..}
```

- bos_freq

```
{CMP: 100, CMC: 200, CT: 55, ...}
```


Train function

- Frequency -> probability

- pos2words_prob

{CMC: {아버지: 0.1, 올림픽: 0.2, ..},
CMP: {구글: 0.05, 애플: 0.03, ..}
YBD: {마시: 0.1, 듣: 0.2, ...}}

sum = 1.0



- trans_prob

{(CMC, fjb): 0.2, (CMP, fjb): 0.1, (fjco, fd): 0.48, ..}

- bos_prob

{CMP: 0.3, CMC: 0.1, CT: 0.24, ...}

Train function

- Frequency -> probability

- pos2words_prob

{CMC: {아버지: 0.1, 올림픽: 0.2, ..},
 CMP: {구글: 0.05, 애플: 0.03, ..}
 YBD: {마시: 0.1, 듣: 0.2, ...}}

sum = 1.0

- trans_prob

$$P(x_k = \text{애플} \mid y_k = \text{CMP}) = 0.03$$

{(CMC, fjb): 0.2, (CMP, fjb): 0.1, (fjco, fd): 0.48, ..}

- bos_prob

{CMP: 0.3, CMC: 0.1, CT: 0.24, ...}

Train function

Frequency -> probability

pos2words_prob

{CMC: {아버지: 0.1, 올림픽: 0.2, ..},
 CMP: {구글: 0.05, 애플: 0.03, ..}
 YBD: {마시: 0.1, 듣: 0.2, ...}}

sum = 1.0

trans_prob

{(CMC, fjb): 0.2, (CMP, fjb): 0.1, (fjco, fd): 0.48, ..}

$$P(x_k = \text{애플} \mid y_k = \text{CMP}) = 0.03$$

bos_prob

{CMP: 0.3, CMC: 0.1, CT: 0.24, ...}

$$P(y_k = \text{fd} \mid y_{k-1} = \text{fjco}) = 0.48$$

Train function

- Emission probability

- $$P(x_k|y_k) = \frac{P(x_k, y_k)}{P(y_k)} = \frac{\# \text{ of } (word_k, tag_k)}{\# \text{ of } tag_k}$$

- Transition probability

- $$P(y_k|y_{k-1}) = \frac{P(y_k, y_{k-1})}{P(y_{k-1})} = \frac{\# \text{ of } (tag_{k-1}, tag_k)}{\# \text{ of } tag_{k-1}}$$

Inference

- For given input sentences
 - "감기/CMC 는/fjb 줄이/YBD 다/fmof ./g"
 - "감기/fmotg 는/fjb 줄/CMC 이다/fjj ./g"

- Calculate the log probability

$$\begin{aligned} & \log(\prod_{k=1}^N P(x_k|y_k) \prod_{k=1}^N P(y_k|y_{k-1})) \\ &= \sum \log P(x_k|y_k) + \log P(y_k|y_{k-1}) \end{aligned}$$

- Results

```
감기/CMC 는/fjb 줄이/YBD 다/fmof ./g: -5.489636
감기/fmotg 는/fjb 줄/CMC 이다/fjj ./g: -14.037157
```

NLTK (Open Source Platform)

Natural Language ToolKit (NLTK)

- NLTK
 - Python Platform for Natural Language Processing
 - Homepage
 - <http://www.nltk.org/>
 - 설치 방법
 - `sudo pip install -U nltk`

Natural Language ToolKit (NLTK)

- NLTK.tagger

- Example

```
>>> import nltk
>>> sentence = "" "At eight o'clock on Thursday morning
... Arthur didn't feel very good.""
>>> tokens = nltk.word_tokenize(sentence)
>>> tokens
['At', 'eight', "o'clock", 'on', 'Thursday', 'morning',
'Arthur', 'did', "n't", 'feel', 'very', 'good', '.']
>>> tagged = nltk.pos_tag(tokens)
>>> tagged[0:6]
[('At', 'IN'), ('eight', 'CD'), ("o'clock", 'JJ'), ('on', 'IN'),
('Thursday', 'NNP'), ('morning', 'NN')]
```


NLTK download

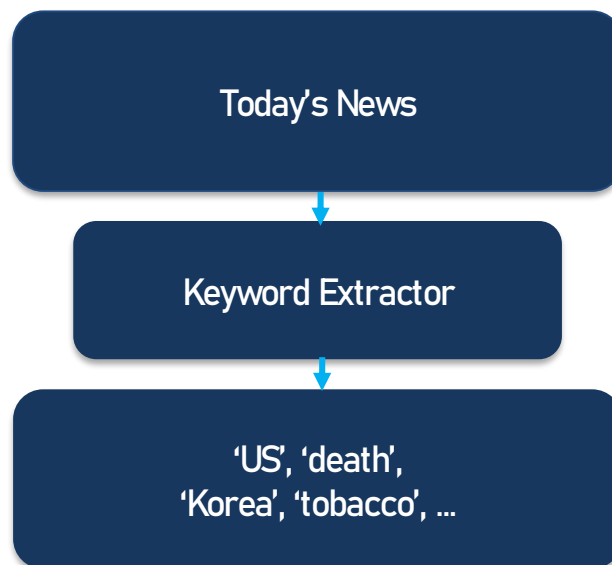
- `$python`
- `import nltk`
- `nltk.download()`

```
>>> import nltk
>>> nltk.download()
NLTK Downloader
-----
d) Download  l) List    u) Update  c) Config  h) Help  q) Quit
-----
Downloader> d

Download which package (l=list; x=cancel)?
Identifier> popular
```

Keyword Extractor

- Keyword Extractor
 - 주어진 문서(document)의 키워드 10개를 추출
- Keyword
 - def. 최대 빈도를 가지는 명사



Keyword Extractor

- Preparation Material
 - 말뭉치 다운로드
 - 말뭉치: endoc1~8.txt

Keyword Extractor

- Guideline
 - Step1. 텍스트 입력 및 형태소 분석
 - Step2. 명사 추출 및 해당 빈도수 저장
 - Step3. 빈도수로 내림차순 정렬
 - Step4. 최대 빈도수 단어 출력

Keyword Extractor

- Step1. 텍스트 입력 및 형태소 분석
 - 텍스트파일을 입력 받음
 - 입력을 tokenizing
 - 각 token의 형태소 분석

Keyword Extractor

- `os.listdir(path)`

```
pir1@pir1-Precision-Tower-7910:~/NLP/3PosTagger/Practice$ ls Data/
endoc1.txt  endoc3.txt  endoc5.txt  endoc7.txt
endoc2.txt  endoc4.txt  endoc6.txt  endoc8.txt
pir1@pir1-Precision-Tower-7910:~/NLP/3PosTagger/Practice$ python3
Python 3.6.4 |Anaconda, Inc.| (default, Jan 16 2018, 18:10:19)
[GCC 7.2.0] on linux
Type "help", "copyright", "credits" or "license" for more information.
>>> from os import listdir
>>> listdir("./Data")
['endoc1.txt', 'endoc5.txt', 'endoc7.txt', 'endoc3.txt', 'endoc8.txt',
'endoc6.txt', 'endoc2.txt', 'endoc4.txt']
>>> 
```

Keyword Extractor

- Step2. 일반 명사 추출 및 해당 빈도수 저장
 - 형태소 분석 및 품사 태깅된 텍스트에서 명사를 추출
 - dictionary에 단어-빈도수 형태로 저장
 - Nouns = ['NN', 'NNS', 'NNP', 'NNPS']

Document Finder

- Non-alphabet

```
endoc1.txt: China, US, South, Sea, Beijing, systems, mi  
ssile, defense, missiles, region  
endoc2.txt: tobacco, San, Francisco, products, voters,  
American, Reynolds, Association, sales, %  
endoc3.txt: death, method, execution, injection, victim  
, people, seconds, -, man, prison  
endoc4.txt: Russia, North, Korea, Kim, Moscow, Lavrov,  
Korean, US, talks, South  
endoc5.txt: Iran, EU, sanctions, deal, US, business, co  
mpanies, European, EIB, legislation  
endoc6.txt: people, racist, racism, police, part, ideas  
, Americans, Obama, Goff, America  
endoc7.txt: Kennedy, Lewis, years, Robert, America, Cli  
nton, way, hand, John, assassination  
endoc8.txt: US, Afghan, Afghanistan, air, Taliban, Air,  
Force, people, casualties, children
```


Document Finder

- Free Non-alphabet words

```
endoc1.txt: China, US, South, Sea, Beijing, systems, mi  
ssile, defense, missiles, region  
endoc2.txt: tobacco, San, Francisco, products, voters,  
American, Reynolds, Association, sales, Proposition  
endoc3.txt: death, method, execution, injection, victim  
, people, seconds, man, prison, chair  
endoc4.txt: Russia, North, Korea, Kim, Moscow, Lavrov,  
Korean, US, talks, South  
endoc5.txt: Iran, EU, sanctions, deal, US, business, co  
mpanies, European, EIB, legislation  
endoc6.txt: people, racist, racism, police, part, ideas  
, Americans, Obama, Goff, America  
endoc7.txt: Kennedy, Lewis, years, Robert, America, Cli  
nton, way, hand, John, assassination  
endoc8.txt: US, Afghan, Afghanistan, air, Taliban, Air,  
Force, people, casualties, children
```

Document Finder

- `str.isalpha()`

```
str = "this"; # No space & digit in this string  
print str.isalpha()
```

True

```
str = "this is string example....wow!!!";  
print str.isalpha()
```

False

```
for t in tags:  
    if t[1] in Nouns:  
        if t[1] in Nouns and t[0].isalpha():
```

Keyword Extractor

- 형태소 분석 및 품사 태깅된 텍스트
- nltk.word_tokenize
- nltk.pos_tag

```
>>> text = word_tokenize("And now for something completely different")
>>> nltk.pos_tag(text)
[('And', 'CC'), ('now', 'RB'), ('for', 'IN'), ('something', 'NN'),
 ('completely', 'RB'), ('different', 'JJ')]
```

Keyword Extractor

- 명사 추출
- dictionary에 단어(명사)-빈도수 형태로 저장

Keyword Extractor

- Step3. 빈도수로 내림차순 정렬
 - google “sort a Python dictionary by value”!
 - 여기서 value=빈도수, 대응하는 key값은 단어

Keyword Extractor

- `sorted()`
- sort a dictionary by value

```
>>> from operator import itemgetter
>>> dict = {}
>>> dict['a'] = 2
>>> dict['b'] = 1
>>> dict['c'] = 5
>>> print(sorted(dict.items(), key=itemgetter(1), reverse=True))
[('c', 5), ('a', 2), ('b', 1)]
```

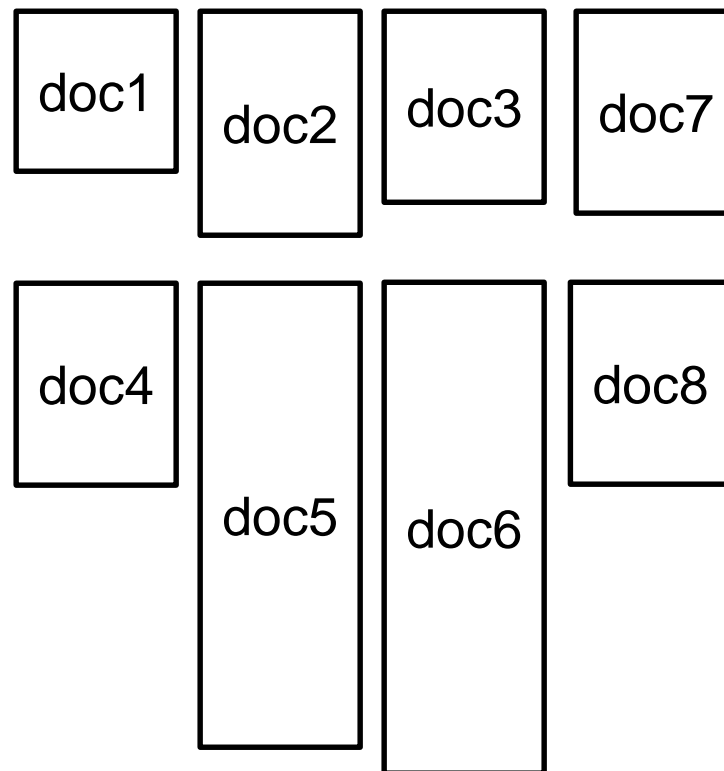
Keyword Extractor

- Step4. 최대 빈도수 단어 출력
 - 정렬한 리스트로부터 top 10개의 단어를 출력

Keyword Extractor

■ 결과물

```
[('US', 42),  
 ('people', 29),  
 ('Russia', 26),  
 ('China', 19),  
 ('Iran', 18),  
 ('North', 18),  
 ('Kennedy', 17),  
 ('years', 16),  
 ('Korea', 16),  
 ('Afghan', 16)]
```



각 뉴스 기사의 길이(# tokens) 반영

Keyword Extractor

- 각 document의 길이를 반영
- Normalized count:
$$1.0 / \text{document_length (\# of words)}$$
- word count 대신 normalized count를 dictionary에 저장

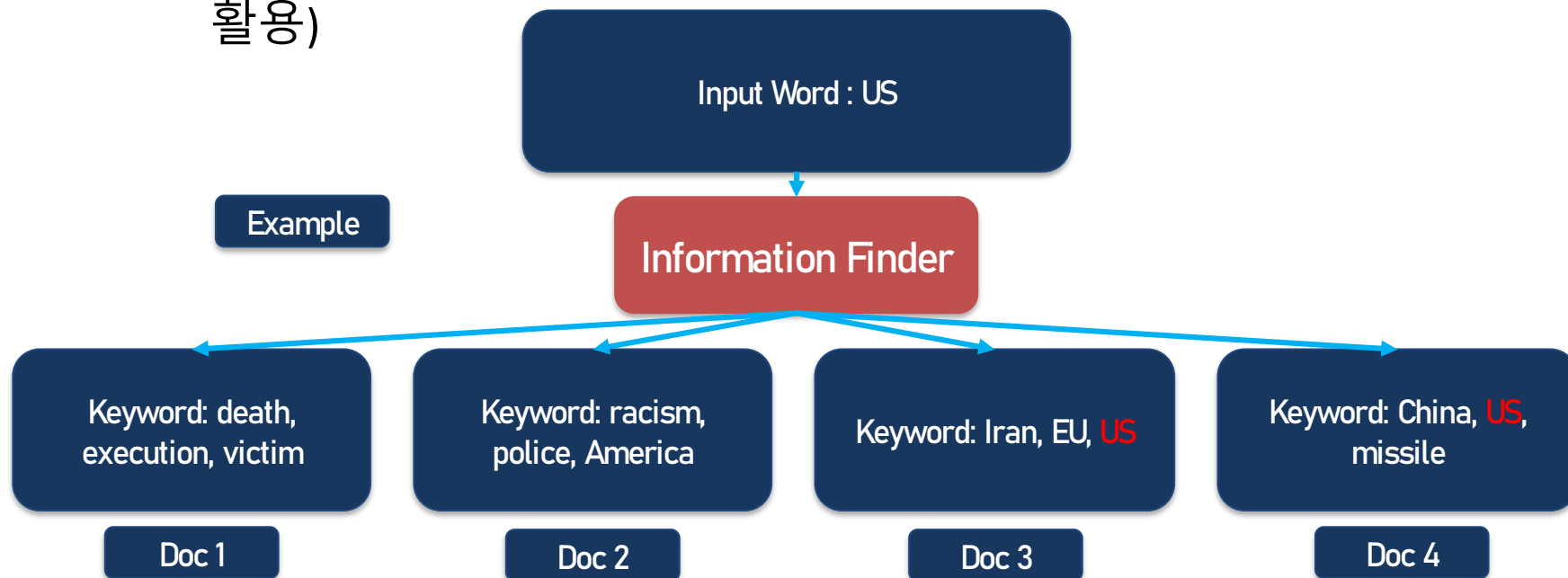
Keyword Extractor

- 결과물

```
[('US', 0.041482327565602065),  
(('Iran', 0.028081123244929798),  
(('China', 0.026340824887495645),  
(('Russia', 0.02146452100122221),  
(('tobacco', 0.019736842105263157),  
(('people', 0.019091525518264874),  
(('EU', 0.0171606864274571),  
(('Kennedy', 0.014808362369337977),  
(('South', 0.014200721051400883),  
(('North', 0.013938257653585369))]
```

Document Finder

- Document Finder
 - 입력된 단어와 가장 관련된 문서를 출력
- 가장 관련된 문서
 - Def. Keyword가 해당 단어와 일치하는 문서 (Keyword Extractor 활용)



Document Finder

■ Guideline

- Step 1. 텍스트 입력 및 형태소 분석
- Step 2. 명사 추출 및 빈도수로 내림차순 정렬
- Step 3. 최대 빈도를 가지는 10 개의 명사들 따로 저장
- Step 4. 각 문서에 대해 Step 1~3 반복

=====

- Step 5. <키워드:해당 문서들> 의 형태로 dictionary 에 저장

=====

- Step 6. 사용자에게 키워드 입력 받음
- Step 7. 입력받은 키워드가 dictionary에 있으면 해당 문서 출력

Document Finder

- Step 5. {키워드:해당 문서들} 의 형태로 dictionary 에 저장

```
dic={}
for intxt in files:
    keywords = keywords_per_doc[intxt]
```

Document Finder

- Step 6. 사용자에게 키워드 입력 받음
- `input()`
- 사용 예시:
- `query = input().strip()`

Document Finder

- Output

```
type keyword (q:to exit)
US
endoc1.txt, endoc4.txt, endoc5.txt, endoc8.txt
type keyword (q:to exit)
Korea
endoc4.txt
type keyword (q:to exit)
people
endoc3.txt, endoc6.txt, endoc8.txt
type keyword (q:to exit)
Lebanon
no such document
type keyword (q:to exit)
q
pir1@pir1-Precision-Tower-7910:~/NLP/3PosTagger/
```

END