

Tokenisation and word segmentation

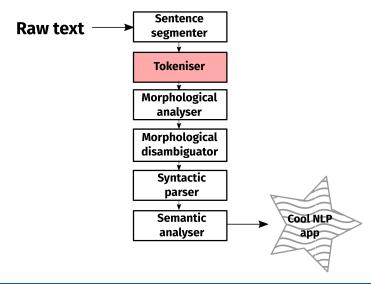
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13 октября 2018 г.





Token separators



ARMA·VIRVMQVE·CANO·TROIAE·QVI·PRIMVS·AB·ORIS ITALIAM·FATO·PROFVGVS·LAVINIAQVE·VENIT LITORA·MVLTVM·ILLE·ET·TERRIS·IACTATVS·ET·ALTO VI·SVPERVM·SAEVAE·MEMOREM·IVNONIS·OB·IRAM

- Peoplecangenerallyreadsentencesevenifthereisnowhitespace, but:
 - The vast majority of languages use some kind of whitespace-based word/token separator

But what is a token?



Some questions:

- Multiword expressions
 - только что от только что?
- Named-entities
 - Нижный Новгород or Нижный∙Новгород?
- Numeral expressions
 - 150 000,0 or 150.000,0

And how about abbreviations:

- Гипотеза была выдвинута Каролем Борсуком в 1933 г.
 - Is there one "here or two?
- В 1933 г. гипотеза была выдвинута Каролем Борсуком.
 - And here?

More questions



Clitics:

- Romance: explicándoselo [explicándo se lo], j'ai [j' ai]
- Germanic: don't [do n't], I'm [I'm], Nastya's [Nastya's]
- Slavic: mógłbym [mógł bym], razumeću [razume ću]
- Finnic: voisiko [voisi ko]
- Turkic: чыгачакмы [чыгачак мы]

Can be ambiguous:

- Nastya's cool \rightarrow Nastya is
- Nastya's broke the record again \rightarrow Nastya has
- Nastya's cat is cute → Nastya's

Is resolving this the job of a tokeniser?



The ideal tokenisation may depend on the task.¹

- Russian–Arabic MT:
 - Split off clitics²
- Dependency parsing
- @@@
- @@@

¹And also on the language (pair)!

²Zalmout and Habash (2017) "Optimizing Tokenization Choice for Machine Translation across Multiple Target Languages"



```
import svs. re
abbr = ['etc.', 'e.g.', 'i.e.']
def tokenise(line, abbr):
        line = re.sub(r'([\(\)"?:!;])', r' \q<1>', line)
        line = re.sub(r'([^0-9]),', r'\q<1>,', line)
        line = re.sub(r',([^0-9])', r', \q<1>', line)
        line = re.sub(r' +' . ' ' . line[:-1])
        output = []
        for token in line.split(' '):
                if token[-1] == '.' and token not in abbr:
                        token = token[:-1] + ' .'
                output.append(token)
        return ' '.join(output)
line = sys.stdin.readline()
while line != '':
        print(tokenise(line.strip('\n'), abbr))
        line = svs.stdin.readline()
```

Split off always-separating punctuation



```
import svs. re
abbr = ['etc.', 'e.g.', 'i.e.']
def tokenise(line, abbr):
        line = re.sub(r'([\(\)"?:!;])', r' \q<1>', line)
        line = re.sub(r'([^0-9]),', r'\q<1>,', line)
        line = re.sub(r',([^0-9])', r', \q<1>', line)
        line = re.sub(r' +' . ' ' . line[:-1])
        output = []
        for token in line.split(' '):
                if token[-1] == '.' and token not in abbr:
                        token = token[:-1] + ' .'
                output.append(token)
        return ' '.join(output)
line = sys.stdin.readline()
while line != '':
        print(tokenise(line.strip('\n'), abbr))
        line = svs.stdin.readline()
```

Split off commas not part of numeral expressions



```
import sys, re
abbr = ['etc.', 'e.g.', 'i.e.']
def tokenise(line, abbr):
        line = re.sub(r'([\(\)"?:!;])', r' \q<1>', line)
        line = re.sub(r'([^0-9]),', r'\q<1>,', line)
        line = re.sub(r',([^0-9])', r', \q<1>', line)
        line = re.sub(r' +' . ' ' . line[:-1])
        output = []
        for token in line.split(' '):
                if token[-1] == '.' and token not in abbr:
                        token = token[:-1] + ' .'
                output.append(token)
        return ' '.join(output)
line = sys.stdin.readline()
while line != '':
        print(tokenise(line.strip('\n'), abbr))
        line = svs.stdin.readline()
```

Collapse multiple spaces



```
import sys, re
abbr = ['etc.', 'e.g.', 'i.e.']
def tokenise(line, abbr):
        line = re.sub(r'([\(\)"?:!;])', r' \q<1>', line)
        line = re.sub(r'([^0-9]),', r'\q<1>,', line)
        line = re.sub(r',([^0-9])', r', \q<1>', line)
        line = re.sub(r' +' . ' ' . line[:-1])
        output = []
        for token in line.split(' '):
                if token[-1] == '.' and token not in abbr:
                        token = token[:-1] + ' .'
                output.append(token)
        return ' '.join(output)
line = sys.stdin.readline()
while line != '':
        print(tokenise(line.strip('\n'), abbr))
        line = sys.stdin.readline()
```

Split of full stops not part of abbreviations

Caveats



- Time and numeral expressions:
 - Let's meet at 17:45
- Proper names:
 - I'm surprised that Yahoo! are still solvent
 - Therapy? is one of the best bands from Northern Ireland
- Emoticons:
 - haters gonna hate;_____;

Machine-learning approaches





Space-free languages





- Some languages are written without spaces
- Tokenisation more difficult space is a strong signal
- Issue of ambiguity more than one possible interpretation
- A number of algorithms available

Ambiguity





- Many analyses for each sequence
- How do we choose the correct one(s)?

Graphics by Graham Neubig (NAIST)

(A tale of) two algorithms



Maxmatch:

- Rule-based algorithm
 - Requires some kind of dictionary from wordlist or corpus

Graph-based:

- Statistical algorithm
 - Requires pre-segmented corpus

Maxmatch algorithm



function MAXMATCH(sentence, dictionary) returns word sequence W

```
if sentence is empty
    return empty list
for i ← length(sentence) downto 1
    firstword = first i chars of sentence
    remainder = rest of sentence
    if InDictionary(firstword, dictionary)
    return list(firstword, MaxMatch(remainder, dictionary))
```

```
# no word was found, so make a one-character word
firstword = first char of sentence
remainder = rest of sentence
return list(firstword, MaxMatch(remainder,dictionary))
```

- Start at beginning of string
- Iteratively look up the longest word in the dictionary
- If no word is found, output a single character

Caveats









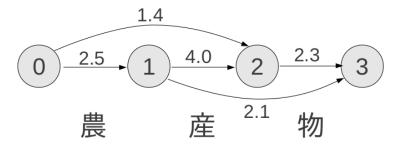
wecanonlyseeashortdistanceahead we canon ly see ash ort distance ahead

Alan Turing

- Works pretty well for some languages (e.g. Chinese)
- Not so great for others
- Why? Length of words

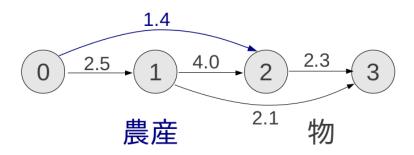
A graph-based approach





A graph-based approach

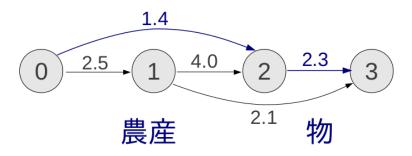




- Each edge is a word (segmentation decision)
- Each edge weight is a unigram probability

A graph-based approach





- Each path is a segmentation
- The path weight is the unigram probability of the sentence

Language model



- P(農産物価格安定法)=4.12*10⁻²³
- P(農産 物価 格安 定法) = 3.53*10⁻²⁴
- P(農産物価格安定法)=6.53*10⁻²⁵
- P(農産物価格安定法)=6.53*10⁻²⁷

. . .

- Language model to choose sequence with highest probability
- Requires an existing tokenised corpus
- Maximum likelihood estimation (MLE):
 - Probability of a word: frequency / number of tokens in corpus

Combinatorial explosion



農産物価格安定法 産物価格安定法 物価格安定法 産 物価格安定法 価格安定法 価格安定法 価格安定法 価格安定法 農産物価 格安定法 格安定法 物価 格安定法 農 産 物価 格安定法

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Высшая школа экономики

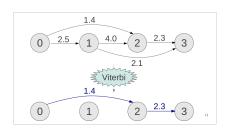
幕座 物価格安 定法 暴産 物価格安 定法 農産物 依接中 宝法 農 産物 価格安 定法 農産 物 価格安 定法 農産物 価格安 定法 農産物価 格安 定法 農産 物価 格安 定法 磨產物 価 格安 定法 幕座 物 佰 格安 定法 暴產 数 街 格史 宝宝 農産物価格 安 定法 農産 物価格 安 定法 暴虐 物価格 安 宝油 悬座物 価格 安 定法 農産物 価格安 定法 農産 物 価格 安 宝法 農産物 価格 安定法 悬座物価 格 安 定法 農産物価格安定法 農産物価格安定法 農産物価格安定法 悬座物価格安定 法 農 産物価格安定 法 農産 物価格安定 法 農産 物価格安定 法 悬座物 価格安定 法 農 產物 価格安定 法 農産 物 価格安定 注 農産物 価格安定 法 悬度物值 格安定 法 農産 物体 核安全 法 農産物 佰 格安定 油 農産物 佰 格安定 法 勝座 物 佰 格安定 法 悬座物 価格安定法

幕 產物価格安 定法

(how many?)

Finding the best segmentation





Viterbi algorithm:

- Forward step:
 - Search the graph left-to-right, picking the highest prob arc at each step,
 - leaving a pointer to the previously visited node
- Backward step:
 - Follow the pointers back to read off the path

[Algorithm covered in Lecture 3 Morphological disambiguation.]

Unknown words



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19/23

What to do with out-of-vocabulary (OOV) items?

Smoothing:

- Add-one smoothing³, basically just add 1 to every count
 - Assigns too much probability mass to unknown words
- Use the Good-Turing method (see Manning and Schütze, p.212)

³If you do this, avoid a man called Ken Church.

A note on encodings



Watch out for characters other than space (U+0020):

- Non-breaking spaces (U+2060, U+FEFF, ...)
- Soft-hyphen (U+00AD)
- En quad (U+2000)
- En space (U+2002)

Plus 20 or so other characters.



Extra-spaces format:

```
Крайняя западная точка расположена в районе Фленсбурга (9°10' в.д.). \downarrow Крайняя западная точка расположена в районе Фленсбурга ( 9°10' в.д.) .
```

- Widely used
- Basically just add in (extra) spaces to indicate tokenisation
- Easy to process
- Loses original text



CoNLL-U:

- More complex to process
- Original text can be reconstructed
- universaldependencies.org/format.html



Most common evaluation method is Word Error Rate (WER):

- Number of edits divided by number of tokens in the reference
 - Edits: insertions (I), deletions (D), substitutions (S)
- Implemented with Levenshtein distance

wecanonlyseeashortdistanceahead

```
REF: we can only see a short distance ahead HYP: we canon l y see ash ort distance ahead EVA: S S I S S
```

WER:
$$\frac{5}{8} = 62.5\%$$



Implement the maxmatch algorithm and test it on Japanese:

- Extract surface form dictionary from the training corpus
- Run the algorithm with the dictionary on the test corpus
- Write script to calculate WER for the segmentation.
 - Feel free to use a library or existing code for this

https://github.com/UniversalDependencies/UD_
Japanese-GSD