

# Chinese Word Segmentation

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unless otherwise stated






# What Is a Word?

- **Phonological word:** e.g.  English words could be defined according to stress
  - Sproat 1992:
    - *SPARK plug*
    - *electrical ENGINEER*
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- **Orthographic word:** roughly between two whitespaces (plus some rules for punctuation)
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  - Differences between languages:
    -  en: *life insurance company employee*
    -  de: *Lebensversicherungsgesellschaftsangestellter*
  -  Chinese (and other languages) does not mark words orthographically
  - Nevertheless, it is desirable to be able to define a word in NLP



- No orthographic word boundary
  - 这个多少钱？ ... simplified Chinese characters
  - *zhè ge duō shǎo qián ?* ... transcription
  - *this piece much little money ?* ... literal character-based



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  - “How much is this?” ... translation
- Character = syllable ~ morpheme
  - Thousands of characters mapped on about 400 possible syllables ⇒ gigantic homonymy!
  - Typical new words are compounds
  - Phonetically approximated loanwords





## Do We Need Words?

- For NLP it is desirable to have words
  - Dictionaries
  - Most NLP applications assume there are words as units of the text
    - Indexing, language modeling, translation modeling
  - Meaning of sequence of characters cannot be always predicted from the meaning of the parts



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- Roosevelt Road (Taipei) = 罗斯福路 = *luō sī fú lù*
  - 罗 *luō* = net for catching birds
  - 斯 *sī* = this, thus, such
  - 福 *fú* = happiness, good fortune, blessing
  - 路 *lù* = road, path, way



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- There are dozens of other characters pronounced *fu*
  - 罗 *luō* = net for catching birds
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  - 蝮 *fù* = venomous snake, viper
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## What Is a Word in Chinese?





- Which sequences should be chosen to become words?
  - 火车站 = *huǒ chē zhàn* = fire vehicle stand = (railroad) station
    - Three, two, or one word?
  - 电话 = *diàn huà* = electric speech = telephone
  - 电脑 = *diàn nǎo* = electric brain = computer
    - Two words or one?
  - 北海 = *běi hǎi* = North Sea:
    - Two words as in  English (*North Sea*) and  Czech (*Severní moře*)?
    - One word as in  German (*Nordsee*) and  Dutch (*Noordzee*)?



## What Is a Word in Chinese?

- A more peculiar case: verb-object constructions
- Transitive verbs have a “default object”
- 吃饭 = *chīfàn* = “to eat” (lit. “eat cooked rice”)
- Used in sentences like “He likes eating” or “She is going to eat”
  - 我们吃饭吧 = *wǒmen chīfàn ba* = lit. “we eat(-cooked-rice) suggest” = “Let’s eat”
- If there is a real object it replaces the default
  - 今天晚上吃中国菜 = *jīntiān wǎnshang chī zhōngguó cài* = lit. “today evening eat China dish” = “We are going to eat Chinese tonight”
- **The confusion:** Is *chīfàn* a morphological form of the verb *chī* or is it two words, *chī* and *fàn*?



- There have been various attempts to standardize words in Chinese
- GB/T 13715-92 (*guóbiāo*, 国标, “National Standard”)
  -  Mainland China (PRC)
- Popular corpora, such as
  -  Academia Sinica Treebank (Taiwan)
  -  Penn Chinese Treebank (University of Pennsylvania)
  -  City University Corpus (Hong Kong)



# Words in Japanese

*I went to a beauty salon in Kyōdō [, Beyond-R.]*

経堂	の	美容室	に	行っ	て	き	まし	た
Kyōdō	no	miyōshitsu	ni	it	te	ki	mashi	ta
経堂	の	美容室	に	行く	て	来る	ます	た
Kyōdō	of	beauty-salon	to	go	CONV	come	will	PAST
<b>PROPN</b>	<b>ADP</b>	<b>NOUN</b>	<b>ADP</b>	<b>VERB</b>	<b>SCONJ</b>	<b>AUX</b>	<b>AUX</b>	<b>AUX</b>

経堂	の	美容室	に	行って	きました
Kyōdō	no	miyōshitsu	ni	itte	kimashita
経堂	の	美容室	に	行く	来る
Kyōdō	of	beauty-salon	to	going	come
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<b>PROPN</b>	<b>NOUN</b>	<b>VERB</b>	<b>VERB</b>



- Supervised
  - Vocabulary (manually created or learned from corpus
    - **Main problem: OOV (out-of-vocabulary words)**, i.e. those that do not occur in training data but occur in test data
  - Greedy approach: left-to-right, longest match
    - Backtracking or out-of-vocabulary characters
    - Possible ambiguous readings
  - Viterbi algorithm
    - Score possible segmentation paths using N-gram language model
    - Search for the path with the highest score
- Unsupervised
  - Mutual co-occurrence of characters
  - Explore language regularities similarly to the unsupervised morphemic segmentation

## Example: Nokia Beijing System at the SIGHAN Bakeoff 2007

- List of recurring OOV strings created before the main segmentation process
  - Only OOV strings of 2 or 3 characters are considered as possible words
  - Heuristics: 的 (*de*, possessive particle) is a high-frequency single-character word. Don't consider repeating strings that contain it
- All possible paths of segmentation are considered
- Every candidate word is categorized into certain type
  - Dictionary (lexicon acquired from training data)
  - Factoid (Latin letters, Arabic numbers)
  - Named entities: names of persons and locations. Organizations left for postprocessing.
  - Recurring OOV
  - Other

## Example: Nokia Beijing System at the SIGHAN Bakeoff 2007

- The paths are scored (tag-based N-gram language model)
  - Category transition probability  $P(T_j|T_{j-1})$
  - Word emission probability  $P(W_i|T_j)$
  - Product  $\Rightarrow$  probability of the path
- OOV words detected during postprocessing based on character information
  - Merge two single characters to a new word
  - Combine parts of organization names
- Jiang Li, Rile Hu, Guohua Zhang, Yuezhong Tang, Zhanjiang Song, Xia Wang: NOKIA Research Center Beijing Chinese Word Segmentation System for the SIGHAN Bakeoff 2007. In: Proceedings of the Sixth SIGHAN Workshop on Chinese Language Processing, pp. 86–89, Hyderabad, India, 2008.  
<http://aclweb.org/anthology-new/I/I08/I08-4012.pdf>

- Cache-based model
  - The more times a word is observed, the more likely it is to be proclaimed a word the next time
  - Probability distribution covers infinite number of words
  - Yet shorter words are preferred
- Kevin Knight: Bayesian Inference with Tears. Marina del Rey, CA, USA, September 2009 <http://www.isi.edu/natural-language/people/bayes-with-tears.pdf>

# Word Generation Model

- 1 Word = empty.
- 2 Pick a Chinese character from the uniform distribution ( $1/C$ ).
- 3 Add the chosen character to the end of Word.
- 4 With probability 0.5, go to 2.  
With probability 0.5, quit and output Word.
- 5 E.g. if there are only three characters  $a, b, c$ , all two-character words get the same probability  $P_0 = 1/3 \times 1/2 \times 1/3 \times 1/2 = 1/36 = 0.028$

# Text Generation Model

- 1  $H = 0$ . ( $H$  is the length of the history, the number of decisions taken so far.)
- 2 With probability  $\alpha/(\alpha + H)$ , generate a Chinese word according to the base distribution  $P_0$ .  
With probability  $H/(\alpha + H)$ , generate a Chinese word using the cache of words generated so far.
- 3 Write down the word just chosen.
- 4 With probability 0.99,  $H = H + 1$ ; go to 2.  
With probability 0.01, quit.
- 5 Prior parameters:  $P(\text{quit}) = 0.01$ ;  $\alpha$  (*concentration parameter*). Let's pick  $\alpha = 1$ .

## Probability of a Word from Cache

$$P(w) = \frac{H}{\alpha + H} \times \frac{\text{cacheCount}(w)}{H}$$

$$P(w) = \frac{\text{cacheCount}(w)}{\alpha + H}$$

## Probability of a Word Sequence $w_1 \dots w_n$

$$\prod_{i=1}^n \frac{\alpha \times P_0(w_i) + \text{cacheCount}(w_i)}{\alpha + i - 1} \times 0.99^{n-1} \times 0.01$$



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- Other possible derivation: two words  $a b$ 
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## Example

- We observe character sequence *abab*
- *abab*

$$\begin{aligned} P &= \frac{\alpha \times P_0(abab) + 0}{\alpha + 0} \times 0.01 = P_0(abab) \times 0.01 \\ &= (1/3 \times 1/2 \times 1/3 \times 1/2 \times 1/3 \times 1/2 \times 1/3 \times 1/2) \times 0.01 = \underline{0.0000077} \end{aligned}$$

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- *a - b - a - b*

$$\begin{aligned} P &= \frac{\alpha \times P_0(a) + 0}{\alpha + 0} \times 0.99 \times \frac{\alpha \times P_0(b) + 0}{\alpha + 1} \times 0.99 \\ &\times \frac{\alpha \times P_0(a) + 1}{\alpha + 2} \times 0.99 \times \frac{\alpha \times P_0(b) + 1}{\alpha + 3} \times 0.01 \\ &= \frac{1/6}{1} \times 0.99 \times \frac{1/6}{2} \times 0.99 \times \frac{1/6 + 1}{3} \times 0.99 \times \frac{1/6 + 1}{4} \times 0.01 = \underline{0.0000153} \end{aligned}$$



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- *aba - b*

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- *a - b - ab*

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## Search Problem

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- Unfortunately, examining all possible derivations of a long sequence is not tractable
- So how do we find the highest-ranking derivation?

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- Unfortunately, examining all possible derivations of a long sequence is not tractable
- So how do we find the highest-ranking derivation?
  - Enumerating  $\rightarrow$  sampling
  - All derivations  $\rightarrow$  some derivations
    - Selected randomly but in proportion to their probabilities

- 1 Start with some initial sample (e.g., a random segmentation of the sequence)

# Gibbs Sampling

- 1 Start with some initial sample (e.g., a random segmentation of the sequence)
- 2 Make a small change to the sample by **weighted** coin flip
  - Select  $i$ -th position and decide whether there should be a word boundary. 'No change' is also a valid outcome of the coin flip
  - The probability with which we make the change should be proportional to the entire  $P(\text{derivation})$  with the change
    - Before the coin flip, **incrementally** compute probabilities of both derivations with and without word boundary at position  $i$ . Then bias the coin
  - We are more likely to make a change that leads to a better segmentation. Reaching the global optimum is not guaranteed but we are likely to be headed in its general direction

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- 4 Until tired, go to 2. (Next time, change  $(i + 1)$ -th position.)

## Other Languages without Word Boundaries

-  Japanese
  - 語の厳密な定義は各言語によるが、一般に以下の性質がある。
-  Korean written in *hanja* (Chinese characters).  
In *hangul* (Korean script), spaces are used:
  - 다른 낱말이나 낱말의 일부와 합쳐진 낱말은 혼성어를 형성한다.
-  Vietnamese uses Latin script but spaces delimit monosyllabic morphemes, not words
  - *Từ là đơn vị nhỏ nhất, cấu tạo ổn định, mang nghĩa hoàn chỉnh ...*
- Not to be confused with polysynthetic languages (Siberia, Americas)
  - They intricately compose words of many lexical morphemes that are not easily told apart
  - That's why linguists decided not to separate them orthographically
  - One long word may cover a whole sentence
  - Nevertheless, words usually **are** separated. They are just long

## Word Boundaries Are Modern Development

🇬🇷 Greek manuscript from the 4th century:



ποιη εν τη βασιλει-  
α αυτου· και ουτως  
πασαι αι γυναικες  
περιθησουσιν τι-  
μην τοις ανδρασι  
εαυτων απο πτω-  
χου εως πλουσιου·  
και ηρεσεν ο λο-  
γος τω βασιλει· και  
τοις αρχουσιν· και  
εποιησεν ο βασι-  
λευς καθ' α ελαλη-  
σεν ο μαμουχεος·

## Available Segmenters

- CoNLL UD Shared Task 2018 included word segmentation, among other things
- Results:  
[http://universaldependencies.org/conll18/results-words.html#zh\\_gsd](http://universaldependencies.org/conll18/results-words.html#zh_gsd)
- Some of the systems are publicly available, e.g., the Uppsala segmenter:  
<https://github.com/UppsalaNLP/segmenter>
- UDPipe (<https://ufal.mff.cuni.cz/udpipe>) is available as a web service and includes Chinese segmentation. Select a Chinese model at <https://lindat.mff.cuni.cz/services/udpipe/> (use `chinese-gsd` for traditional characters and `chinese-gsdsimp` for simplified characters)