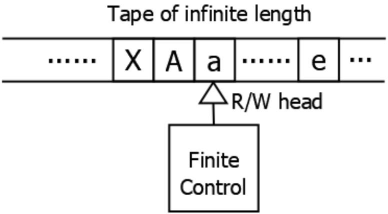
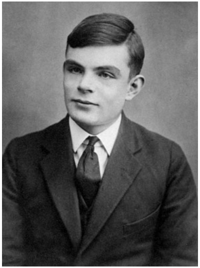
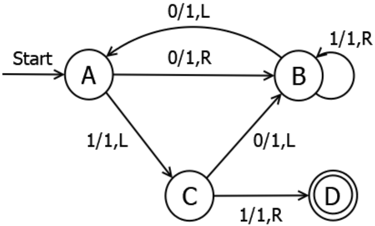
# Turing machine





# Turing machine

A Turing machine consists of: (to be continued)

- A *tape* divided into cells, one next to the other. Each cell contains a symbol from some finite alphabet. The alphabet contains a special blank symbol and some other symbols. The *tape* is assumed to be arbitrarily extendable to the left and to the right.
- A *read/write head* that can read and write symbols on the *tape* and move the *tape* left and right one (and only one) cell at a time.

# Turing machine

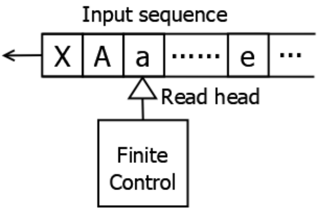
- A Turing machine consists of: (continued)
  - A *state register* that stores the state of the Turing machine, one of finitely many. Among these is the special *start state* with which the state register is initialized.
  - A finite *table* of instructions that, given the *state* the machine is currently in and the symbol it is reading on the *tape*, tells the machine to do the following in sequence:
    - Either erase or write a symbol.
    - Move the *head* to the left or right cell.
    - Assume the same or a *new state* as prescribed.

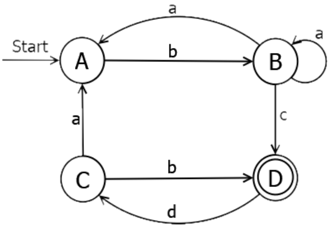
# Linear bounded automaton

A linear bounded automaton is a Turing Machine that satisfies the following three conditions:

- Its input alphabet includes two special symbols, serving as *left and right endmarkers*.
- Its *transitions* may not print other symbols over the *endmarkers*.
- Its *transitions* may neither move to the left of the *left endmarker* nor to the right of the *right endmarker*.

# Finite state automaton / machine (FSA/FSM)



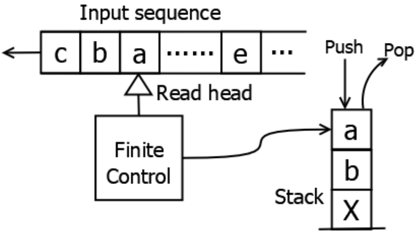



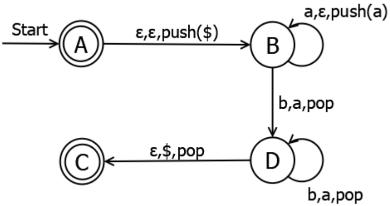
# Finite state automaton / machine (FSA/FSM)

A Finite State Automaton (FSA), or Finite State Machine (FSM), consists of:

- A finite number of *states*, while the FSM can be in one *states* at each given time;
- A *head* which read a symbol from a sequence of symbols as the *input*. The *head* always goes to the next symbol at the next time step;
- A *transition* matrix which determines the next *states* of the FSM according to the current *states* and the current symbol.

# Pushdown automaton (PDA)



# Pushdown automaton (PDA)

- A pushdown Automaton (PDA) is similar to DFA except that it maintains a *stack*:
  - It can use the top of the *stack* to decide which *transition* to take. In each step, it chooses a *transition* by indexing a table by *input symbol*, *current state*, and the *symbol* at the top of the *stack*.
  - It can manipulate the *stack* as part of performing a *transition*. The manipulation can be to *push* a particular symbol to the top of the *stack*, or to *pop* off the top of the *stack*.

# Content

# Text segmentation

- In NLP, text is segmented into units of various granularities, which include:
  - Chapters and sections;
  - Paragraphs;
  - Sentences;
  - Clauses;
  - Phrases;
  - Words;
  - Morphemes (stems, suffixes, prefixes).

# Text segmentation

- Text segmentation is not straightforward in many cases:
  - For languages like Chinese, Japanese, Tibetan, Thai, there are no spaces between words;
  - For languages like Thai and Tibetan, the delimiters between sentences, clauses or phrases are not ambiguous, which makes it hard to segment sentences;
  - Even for English, sentence segmentation is not a trivial task, because the full stop mark (.) is also used for abbreviations, decimals, etc., which may or may not terminate a sentence.

# Thai

โลกเราเป็นอะไรหนอในช่วงนี้ ฝั่งหนึ่งของโลกมีอากาศ
อันแปรปรวนวิปริต หนาวเหน็บอย่างไม่เคยเกิดขึ้นมาก่อน
และยังเกิดแผ่นดินพิโรธโกรธาคร่าชีวิตคนไปเป็นเรือนแสน
ส่วนบ้านเรานั้นในปีที่ผ่านมาแทบไม่มีฤดูหนาวให้ชื่นใจกันเลย
อากาศกลับร้อน แถมมีทั้งฝนหลงฤดูในช่วงนี้อีกต่างหาก
ทุกคนพูดว่า เป็นเพราะภาวะโลกร้อนนั่นเองที่ทำให้ทุกอย่าง
ดูไม่เหมือนเดิม ประเทศที่มีอากาศหนาวก็หนาวสุดขั้ว ประเทศ

Spaces are not reliable boundaries between sentences.

# Chinese

西游记 4　真假猴王

师徒四人继续西行。有一天，他们来到一个地方，前面是望不到边的水面，唐僧发愁（chóu）道："这么大的水，怎么过去呢？"

四个人正不知道怎么办，忽然看见远处好像有一个人在河边，于是就走过去，想问一问。

走近了一看，那不是一个人，而是一块石头，石头上写着三个大字"通天河"，旁边还有一行小字——"河宽（kuān）八百里，自古少人行"，意思是这条河有八百里宽，很少有人能通过。

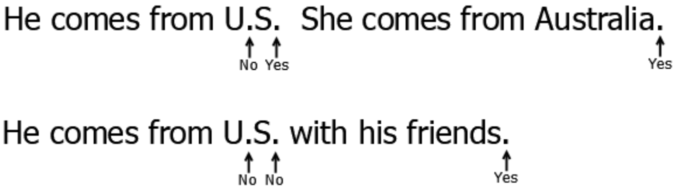
There are not spaces between words.

# English sentence segmentation

- Dot marks (.) are ambiguous:
  - Full stop: *This is an apple.*
  - Decimal: *235.6*
  - Abbreviations: *U.S. Ph.D. etc.*
  - A dot mark can take multiple roles: *He comes from U.S.*
- To segment English text into sentences, we need to determine whether a dot mark is an end of sentence or not.
- It can be solved as a classification problem.

# English sentence segmentation

## — as a classification task



# Chinese word segmentation

| | | |
|---|---|---|
| (a) | 下雨天留客天留我不留 | Unpunctuated Chinese sentence |
| | 下雨、天留客。天留、我不留！ | *It is raining, the god would like the guest to stay. Although the god wants you to stay, I do not!* |
| | 下雨天、留客天。留我不？ 留！ | *The rainy day, the staying day. Would you like me to stay? Sure!* |
| (b) | 我喜欢新西兰花 | Unsegmented Chinese sentence |
| | 我 喜欢 新西兰 花 | *I like New Zealand flowers* |
| | 我 喜欢 新 西兰花 | *I like fresh broccoli* |

http://what-when-how.com/how-to-build-a-digital-library/word-segmentation-and-sorting-digital-library/

Chinese word segmentation may results in different meanings.

# Chinese word segmentation

## — as a character tagging task

| S | S | B | E | B | M | E | S |
|---|---|---|---|---|---|---|---|
| 我 | 有 | 一 | 台 | 计 | 算 | 机 | 。 |
| (I) | (have) | (a) | | (computer) | | | (.) |

Wang & Xu, Convolutional Neural Network with Word Embeddings for Chinese Word Segmentation, IJCNLP 2017

Tags:

- **S**: single character word
- **B**: beginning character of a word
- **M**: middle character of a word
- **E**: end character of a word

# English word segmentation - Tokenization

## — A example of Stanford Tokenizer

**Input**

Another ex-Golden Stater, Paul Stankowski from Oxnard, is contending for a berth on the U.S. Ryder Cup team after winning his first PGA Tour event last year and staying within three strokes of the lead through three rounds of last month's U.S. Open. H.J. Heinz Company said it completed the sale of its Ore-Ida frozen-food business catering to the service industry to McCain Foods Ltd. for about $500 million. It's the first group action of its kind in Britain and one of only a handful of lawsuits against tobacco companies outside the U.S.

**Note:** Text in red: change, text in blue: Keep

# English word segmentation - Tokenization

## — A example of Stanford Tokenizer

**Output**

Another ex-Golden Stater , Paul Stankowski from Oxnard , is contending for a berth on the U.S. Ryder Cup team after winning his first PGA Tour event last year and staying within three strokes of the lead through three rounds of last month 's U.S. Open . H.J. Heinz Company said it completed the sale of its Ore-Ida frozen-food business catering to the service industry to McCain Foods Ltd. for about $ 500 million . It 's the first group action of its kind in Britain and one of only a handful of lawsuits against tobacco companies outside the U.S. .

**Note:** Text in red: change, text in blue: Keep

# Morphological analysis

- To break word down into component morphemes and build a structured representation
- A morpheme is the minimal meaning-bearing unit in a language.
  - **Stem**: the morpheme that forms the central meaning unit in a word
  - **Affix**: prefix, suffix, infix, circumfix
    - **Prefix**: e.g., possible $\rightarrow$ impossible
    - **Suffix**: e.g., walk $\rightarrow$ walking
    - **Infix**: e.g., hingi $\rightarrow$ humingi (Tagalog)
    - **Circumfix**: e.g., sagen $\rightarrow$ gesagt (German)

a slide from UW LING 570 by Fei Xia

# Two slightly different tasks

- Stemming:
  - Ex: writing $\rightarrow$ writ + ing (or write + ing)
- Lemmatization:
  - Ex1: writing $\rightarrow$ write +V +Prog
  - Ex2: books $\rightarrow$ book +N +Pl
  - Ex3: writes $\rightarrow$ write +V +3Per +Sg

a slide from UW LING 570 by Fei Xia

# Ambiguity in morphology

- flies $\rightarrow$ fly +N +PL
- flies $\rightarrow$ fly +V +3rd +Sg

a slide from UW LING 570 by Fei Xia

# Language variation

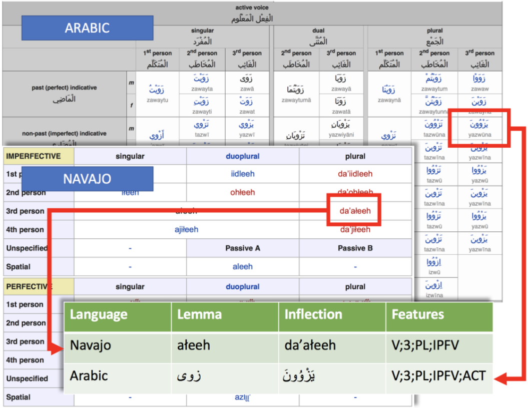
- Analytic languages: e.g., Chinese; English as a language with analytic tendency.
- Synthetic flexive languages: e.g., Russian
- Synthetic agglutinate languages: e.g., Turkish

# Ways to combine morphemes to form words

- Inflection: stem + gram. morpheme → same class
  - Ex: help + ed → helped
- Derivation: Derivation: stem + gram. morpheme → different class
  - Ex: civil + -zation → civilization
- Compounding: multiple stems
  - Ex: cabdriver, doghouse
- Cliticization: stem + clitic
  - Ex: they'll, she's (*I don't know who she is)

a slide from UW LING 570 by Fei Xia

# UniMorph 2.0: Universal Morphology



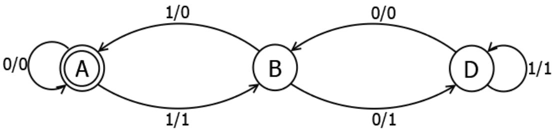

| Language | Lemma | Inflection | Features |
|---|---|---|---|
| Navajo | ałeeh | da'ałeeh | V;3;PL;IPFV |
| Arabic | زوى | يَزْوُونَ | V;3;PL;IPFV;ACT |

Kirov et al., UniMorph 2.0: Universal Morphology, LREC 2018

# Finite state transducers (FSTs)

- Finite State Transducers are an extension to Finite State Machines, where an output symbol will be given for each input symbol.
- FSTs are commonly used tools for morphological analysis.
- A FST can be used in a inverse direction with the input and the output swapped.

# Finite state transducers (FSTs)




| input | output |
|---|---|
| 0 | 0 |
| 11 | 01 |
| 110 | 010 |
| 1001 | 0011 |
| 1100 | 0100 |
| 1111 | 0101 |
| 10010 | 00110 |

# English morphology

- Affixes: prefixes, suffixes; no infixes, no circumfixes.
- Inflectional:
  - Noun: -s
  - Verbs: -s, -ing, -ed, -ed
  - Adjectives: -er, -est
- Derivational:
  - Ex: V + suf $\rightarrow$ N
    computerize + -ation $\rightarrow$ computerization
    kill + er $\rightarrow$ killer
- Compound: pickup, database, heartbroken, etc.
- Cliticization: 'm, 've, 're, etc.

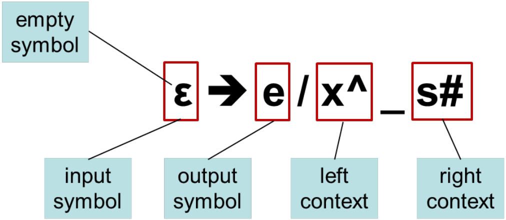
a slide from UW LING 570 by Fei Xia

# Three components

- Lexicon: the list of stems and affixes, with associated features.
  - Ex1: book: N
  - Ex2: -s: +PL
- Morphotactics:
  - Ex: +PL follows a noun
- Orthographic rules (spelling rules): to handle exceptions that can be dealt with by rules.
  - Ex3: $\epsilon \rightarrow$ e / x ˆ _ s#

a slide from UW LING 570 by Fei Xia

# Rewrite rules



# An example

Task: foxes ➔ fox +N +PL

Surface: foxes

Orthographic rules

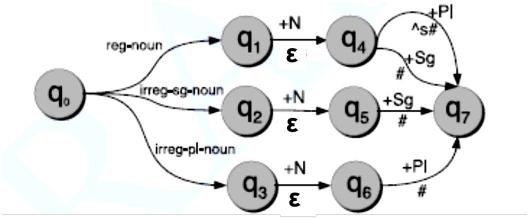
Intermediate: fox ^s

Lexicon + morphotactics

Lexical: fox +N +pl

a slide from UW LING 570 by Fei Xia

# An FST

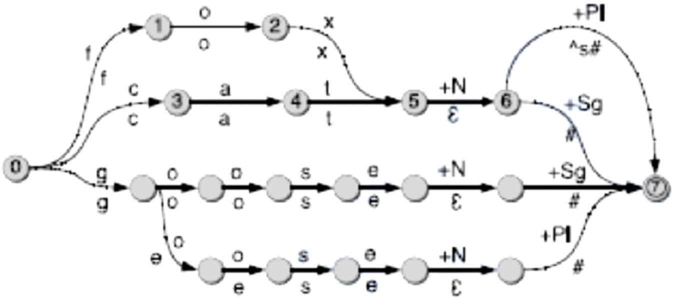



cat +N +PL → cat ˆs #

cat +N +Sg → cat #

a slide from UW LING 570 by Fei Xia

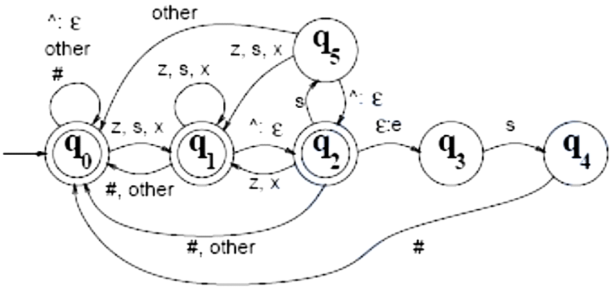
# Expanding FST




fox +N + Pl → fox ˆ s #
cat +N + Pl → cat ˆ s #
goose +N +Sg → goose #
goose +N +Pl → geese #

a slide from UW LING 570 by Fei Xia

# Representing orthographic rules as FSTs




$\epsilon \rightarrow$ e / (s|x|z) ˆ _ s #

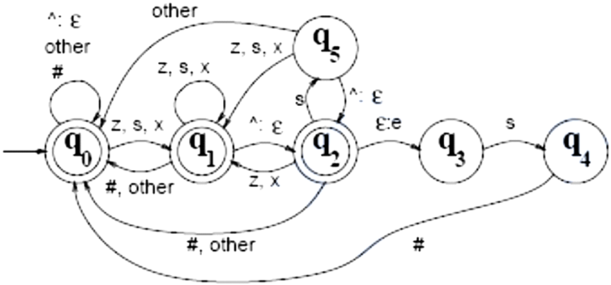
Input: ...(s|x|z) ˆs # immediate level

Output: ...(s|x|z)es # surface level

To reject (fox ˆs, foxs)

a slide from UW LING 570 by Fei Xia

# Representing orthographic rules as FSTs




(fox, fox): q0, q0, q0, q1

(fox#, fox#): q0, q0, q0, q1, q0

(foxˆz#, foxz#), q0, q0, q0, q1, q2, q1, q0

(foxˆs#, foxes#): q0, q0, q0, q1, q2, q3, q4, q0

(foxˆs, foxs): q0, q0, q0, q1, q2, q5

a slide from UW LING 570 by Fei Xia

# Further reading on morphological analysis

- Fei Xia, slides on morphological analysis

  https://www.powershow.com/viewfl/6a39a-ZDc1Z/Morphological_analysis_powerpoint_ppt_presentation
- Mans Hulden (2011), Morphological analysis with FSTs

  https://fomafst.github.io/morphtut.html

# Content

# Top 5000 words in American English

| Rank | Word | Part of speech | Frequency | Dispersion |
|---|---|---|---|---|
| 1 | the | a | 22038615 | 0.98 |
| 2 | be | v | 12545825 | 0.97 |
| 3 | and | c | 10741073 | 0.99 |
| 4 | of | i | 10343885 | 0.97 |
| 5 | a | a | 10144200 | 0.98 |
| 6 | in | i | 6996437 | 0.98 |
| 7 | to | t | 6332195 | 0.98 |
| 8 | have | v | 4303955 | 0.97 |
| 9 | to | i | 3856916 | 0.99 |
| 10 | it | p | 3872477 | 0.96 |


| Rank | Word | Part of speech | Frequency | Dispersion |
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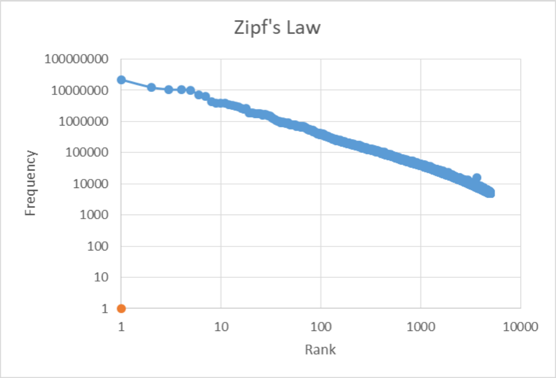
Statics from Corpus of the Contemporary American English

http://www.wordfrequency.info/

# Top 5000 words in American English

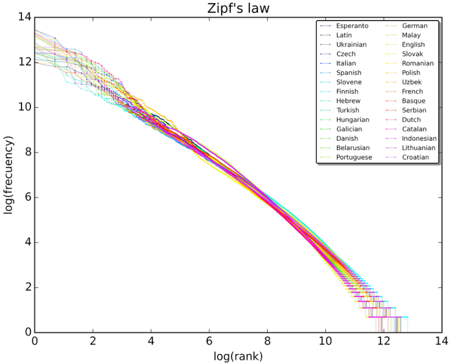


# Zipf's Law

The frequency of any word is inversely proportional to its rank in the frequency table:

$$p(w_r) \propto \frac{1}{r}$$

# Zipf's law




A plot of the rank versus frequency for the first 10 million words in 30 Wikipedias (dumps from October 2015) in a log-log scale.

(By SergioJimenez - Own work, CC BY-SA 4.0, from Wikipedia)

# Collocation or multi-word expression (MWE)

- A COLLOCATION is an expression consisting of two or more words that correspond to some conventional way of saying things.
- The words together can mean more than their sum of parts
  - The Times of India, disk drive
  - hot dog, mother in law

# Collocation or multi-word expression (MWE)

- Examples of collocations
  - noun phrases like *strong tea* and *weapons of mass destruction*
  - phrasal verbs like to *make up*, and other phrases like the *rich and powerful*.
- Valid or invalid?
  - *a stiff breeze* but not a *stiff wind* (while either a *strong breeze* or a *strong wind* is okay).
  - *broad daylight* (but not bright daylight or narrow darkness).

Manning & Schütze, Fundamentals of Statistical Natural Language Processing, 1999

# Criteria for collocations (or MWE)

- Typical criteria for collocations:
  - non-compositionality
  - non-substitutability
  - non-modifiability.
- Collocations usually cannot be translated into other languages word by word.
- A phrase can be a collocation even if it is not consecutive (as in the example *knock ... door*).

Manning & Schütze, Fundamentals of Statistical Natural Language Processing, 1999

# Non-Compositionality

- A phrase is compositional if the meaning can be predicted from the meaning of the parts.
  - E.g. new companies
- A phrase is non-compositional if the meaning cannot be predicted from the meaning of the parts
  - E.g. *hot dog*

Manning & Schütze, Fundamentals of Statistical Natural Language Processing, 1999

# Non-Compositionality

- Collocations are not necessarily fully compositional in that there is usually an element of meaning added to the combination.
  - E.g. *strong tea*
- Idioms are the most extreme examples of non-compositionality
  - E.g. *to hear it through the grapevine*

Manning & Schütze, Fundamentals of Statistical Natural Language Processing, 1999

# Non-Substitutability

- We cannot substitute near-synonyms for the components of a collocation.
- For example
  - We can't say *yellow wine* instead of *white wine* even though *yellow* is as good a description of the color of *white* wine as white is (it is kind of a yellowish white).

Manning & Schütze, Fundamentals of Statistical Natural Language Processing, 1999

# Non-Substitutability

- Many collocations cannot be freely modified with additional lexical material or through grammatical transformations (Non-modifiability).
  - E.g. *white wine*, but not *whiter wine*
  - E.g. *mother in law*, but not *mother in laws*

Manning & Schütze, Fundamentals of Statistical Natural Language Processing, 1999

# Metrics for Collocation or MWE Extraction

- Frequency
- Mean and Variance of Distances between Words
- Hypothesis Testing
  - *t*-test
  - $\chi^2$ test
  - likelihood ratio test
- Mutual Information
- Left and Right Context Entropy
- C-Value

# Further reading on collocation and MWE

- Manning & Schütze, Fundamentals of Statistical Natural Language Processing, 1999, Chapter 3 (A general introduction to collocation)
- Katerina T. Frantzi, Sophia Ananiadou, Junichi Tsujii, The C-value / NC-value Method of Automatic Recognition for Multi-word Terms, ECDL 1998: Research and Advanced Technology for Digital Libraries pp 585-604 (proposed the C-value metric)
- Zhiyong Luo, Rou Song, An integrated method for Chinese unknown word extraction, SIGHAN 2004. Barcelona, Spain. (proposed the context entropy method)

# Content