#### CS447: Natural Language Processing

http://courses.engr.illinois.edu/cs447

# Lecture 2: Finite-State Methods and Tokenization

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## Today's lecture: all about words!

Let's start simple....:

What is a word?

How many words are there (in English)? Do words have structure?

Later in the semester we'll ask harder questions:

What is the meaning of words?

How do we represent the meaning of words?

Why do we need to worry about these questions when developing NLP systems?

## Dealing with words

# Basic word classes in English (parts of speech)

#### Content words (open-class):

Nouns: student, university, knowledge,...

Verbs: write, learn, teach,...

Adjectives: difficult, boring, hard, ....

Adverbs: easily, repeatedly,...

#### Function words (closed-class):

Prepositions: in, with, under,...

Conjunctions: and, or,...

Determiners: a, the, every,...

Pronouns: I, you, ..., me, my, mine,.., who, which, what, .....

## How many words are there?

Of course he wants to take the advanced course too. He already took two beginners' courses.

This is a bad question. Did I mean:

How many word tokens are there? (16 to 19, depending on how we count punctuation)

How many word types are there?

(i.e. How many *different* words are there? Again, this depends on how you count, but it's usually much less than the number of tokens)

## How many words are there?

Of course he wants to take the advanced course too. He already took two beginners' courses.

The *same* (underlying) word can take different forms: course/courses, take/took

We distinguish (concrete) word forms (take, taking) from (abstract) lemmas or dictionary forms (take) Also: upper vs. lower case: Of vs. of, etc.

Different words may be spelled the same:

course: of course or advanced course

## How many words are there?

How large is the vocabulary of English (or any other language)?

Vocabulary size = nr of distinct word types

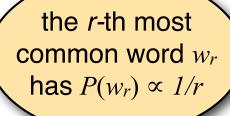
Google N-gram corpus: 1 trillion tokens, 13 million word types that appear 40+ times

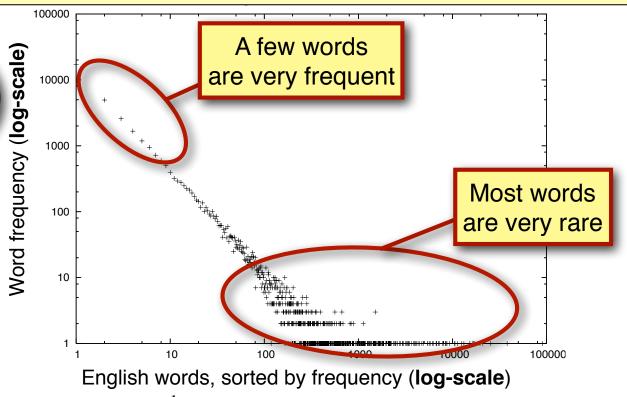
#### If you count words in text, you will find that...

- ...a few words (mostly closed-class) are very frequent (the, be, to, of, and, a, in, that,...)
- ... most words (all open class) are very rare.
- ... even if you've read a lot of text, you will keep finding words you haven't seen before.

## Zipf's law: the long tail

How many words occur once, twice, 100 times, 1000 times?





 $w_1 = the, w_2 = to, ..., w_{5346} = computer, ...$ 

#### In natural language:

- -A small number of events (e.g. words) occur with high frequency
- -A large number of events occur with very low frequency

## Implications of Zipf's Law for NLP

#### The good:

Any text will contain a number of words that are very **common**. We have seen these words often enough that we know (almost) everything about them. These words will help us get at the structure (and possibly meaning) of this text.

#### The bad:

Any text will contain a number of words that are rare.

We know something about these words, but haven't seen them often enough to know everything about them. They may occur with a meaning or a part of speech we haven't seen before.

#### The ugly:

Any text will contain a number of words that are **unknown** to us. We have *never* seen them before, but we still need to get at the structure (and meaning) of these texts.

## Dealing with the bad and the ugly

Our systems need to be able to **generalize** from what they have seen to unseen events.

There are two (complementary) approaches to generalization:

 Linguistics provides us with insights about the rules and structures in language that we can exploit in the (symbolic) representations we use

E.g.: a finite set of grammar rules is enough to describe an infinite language

 Machine Learning/Statistics allows us to learn models (and/or representations) from real data that often work well empirically on unseen data

E.g. most statistical or neural NLP

## How do we represent words?

#### Option 1: Words are atomic symbols

Can't capture syntactic/semantic relations between words

- Each (surface) word form is its own symbol
- Map different forms of a word to the same symbol
  - -Lemmatization: map each word to its lemma (esp. in English, the lemma is still a word in the language, but lemmatized text is no longer grammatical)
  - -Stemming: remove endings that differ among word forms (no guarantee that the resulting symbol is an actual word)
  - -Normalization: map all variants of the same word (form) to the same canonical variant (e.g. lowercase everything, normalize spellings, perhaps spell-check)

## How do we represent words?

Option 2: Represent the **structure** of each word "books" => "book N pl" (or "book V 3rd sg")

This requires a **morphological analyzer** (more later today) The output is often a lemma plus morphological information This is particularly useful for highly inflected languages (less so for English or Chinese)

### How do we represent unknown words?

Systems that use machine learning may need to have a unique representation of each word.

#### Option 1: the **UNK** token

Replace all rare words (in your training data) with an UNK token (for Unknown word).

Replace *all* unknown words that you come across after training (including rare training words) with the same UNK token

#### Option 2: substring-based representations

Represent (rare and unknown) words as sequences of characters or substrings

-Byte Pair Encoding: learn which character sequences are common in the vocabulary of your language

## What is a word?

#### A Turkish word

```
uygarlaştıramadıklarımızdanmışsınızcasına
uygar_laş_tır_ama_dık_lar_ımız_dan_mış_sınız_casına
"as if you are among those whom we were not able to civilize
(=cause to become civilized)"
uygar: civilized
_las: become
_tir: cause somebody to do something
ama: not able
_dɪk: past participle
_lar: plural
_imiz: 1st person plural possessive (our)
<u>_dan</u>: among (ablative case)
_mış: past
_siniz: 2nd person plural (you)
```

K. Oflazer pc to J&M

<u>\_casina</u>: as if (forms an adverb from a verb)

# Words aren't just defined by blanks

#### Problem 1: Compounding

"ice cream", "website", "web site", "New York-based"

#### Problem 2: Other writing systems have no blanks

#### **Problem 3: Clitics**

```
English: "doesn't", "I'm",
```

Italian: "dirglielo" = 
$$dir + gli(e) + lo$$

## How many different words are there?

#### Inflection creates different forms of the same word:

Verbs: to be, being, I am, you are, he is, I was,

Nouns: one book, two books

#### Derivation creates different words from the same lemma:

 $grace \Rightarrow disgrace \Rightarrow disgraceful \Rightarrow disgracefully$ 

#### Compounding combines two words into a new word:

cream ⇒ ice cream ⇒ ice cream cone ⇒ ice cream cone bakery

#### Word formation is productive:

New words are subject to all of these processes:

Google ⇒ Googler, to google, to ungoogle, to misgoogle, googlification, ungooglification, googlified, Google Maps, Google Maps service,...

## Inflectional morphology in English

#### Verbs:

Infinitive/present tense: walk, go

3rd person singular present tense (s-form): walks, goes

Simple past: walked, went

Past participle (ed-form): walked, gone

Present participle (ing-form): walking, going

#### Nouns:

Common nouns inflect for number:

singular (book) vs. plural (books)

Personal pronouns inflect for person, number, gender, case:

I saw him; he saw me; you saw her; we saw them; they saw us.

## Derivational morphology in English

#### Nominalization:

V + -ation: computerization

V+ -er: kill<u>er</u>

Adj + -ness: fuzziness

#### Negation:

un-: <u>un</u>do, <u>un</u>seen, ...

mis-: mistake,...

#### Adjectivization:

V+ -able: doable

N + -al: national

### Morphemes: stems, affixes

dis-grace-ful-ly prefix-stem-suffix-suffix

Many word forms consist of a stem plus a number of affixes (*prefixes or suffixes*)

Exceptions: Infixes are inserted inside the stem

Circumfixes (German gesehen) surround the stem

Morphemes: the smallest (meaningful/grammatical) parts of words.

Stems (grace) are often free morphemes.

Free morphemes can occur by themselves as words.

Affixes (dis-, -ful, -ly) are usually bound morphemes.

Bound morphemes *have* to combine with others to form words.

## Morphemes and morphs

The same information (plural, past tense, ...) is often expressed in different ways in the same language.

One way may be more common than others, and exceptions may depend on specific words:

- -Most plural nouns: add -s to singular: book-books, but: box-boxes, fly-flies, child-children
- -Most past tense verbs add -ed to infinitive: walk-walked, but: like-like $\underline{\mathbf{d}}$ , leap-leap $\underline{\mathbf{t}}$

Such exceptions are called *irregular* word forms

Linguists say that there is one underlying morpheme (e.g. for plural nouns) that is "realized" as different "surface" forms (morphs) (e.g. -s/-es/-ren)

Allomorphs: two different realizations (-s/-es/-ren) of the same underlying morpheme (plural)

#### Side note: "Surface"?

This terminology comes from Chomskyan Transformational Grammar.

- Dominant early approach in theoretical linguistics, superseded by other approaches ("minimalism").
- -Not computational, but has some historical influence on computational linguistics (e.g. Penn Treebank)

"Surface" = standard English (Chinese, Hindi, etc.).
"Surface string" = a written sequence of characters or words

vs. "Deep"/"Underlying" structure/representation:

A more abstract representation.

Might be the same for different sentences/words with the same meaning.

# Morphological parsing and generation

## Morphological parsing

```
disgracefully
dis grace ful ly
prefix stem suffix suffix
NEG grace+N+ADJ +ADV
```

## Morphological generation

We cannot enumerate all possible English words, but we would like to capture the rules that define whether a string *could* be an English word or not.

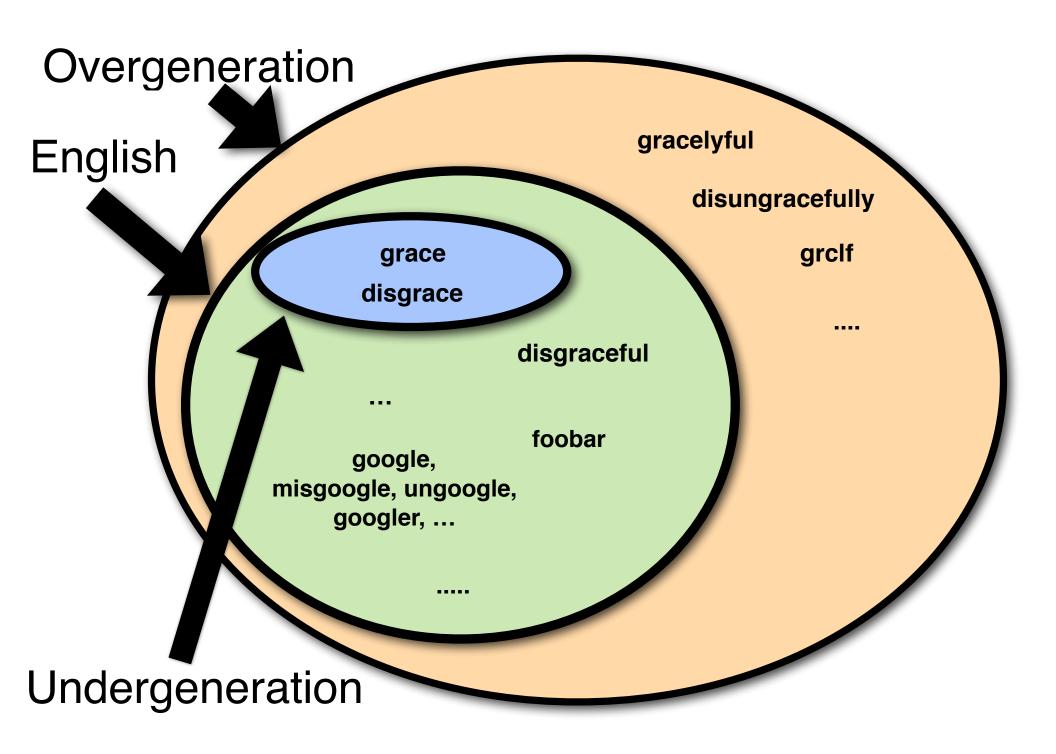
That is, we want a procedure that can generate (or accept) possible English words...

grace, graceful, gracefully disgrace, disgraceful, disgracefully, ungraceful, ungracefully, undisgraceful, undisgracefully,...

without generating/accepting impossible English words \*gracelyful, \*gracefuly, \*disungracefully,...

NB: \* is linguists' shorthand for "this is ungrammatical"

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## Review: Finite-State Automata and Regular Languages

## Formal languages

An alphabet  $\sum$  is a set of symbols:

e.g. 
$$\Sigma = \{a, b, c\}$$

A string  $\omega$  is a sequence of symbols, e.g  $\omega = abcb$ . The empty string  $\varepsilon$  consists of zero symbols.

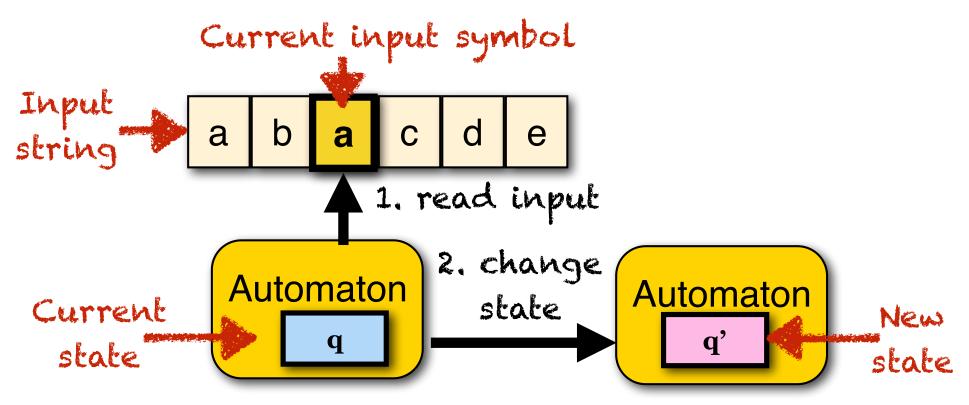
The Kleene closure  $\sum^*$  ('sigma star') is the (infinite) set of all strings that can be formed from  $\sum$ :

$$\sum^*=\{\varepsilon, a, b, c, aa, ab, ba, aaa, ...\}$$

A language  $L \subseteq \Sigma^*$  over  $\Sigma$  is also a set of strings. Typically we only care about proper subsets of  $\Sigma^*$  ( $L \subset \Sigma$ ).

## Automata and languages

An automaton is an abstract model of a computer. It *reads* an input string symbol by symbol. It *changes* its internal state depending on the current input symbol and its current internal state.



## Automata and languages

The automaton either accepts or rejects the input string.

Every automaton defines a language (the set of strings it accepts). Input string is in the language b a read accept! **Automaton** reject! Input string is NOT in the language

## Automata and languages

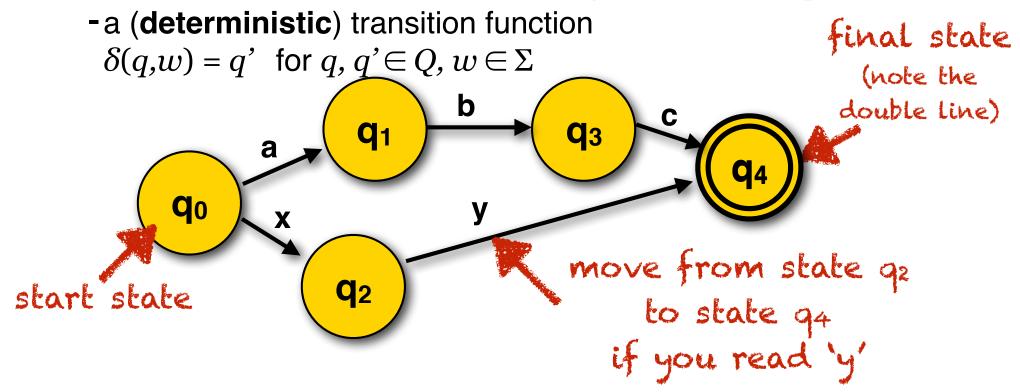
Different types of automata define different language classes:

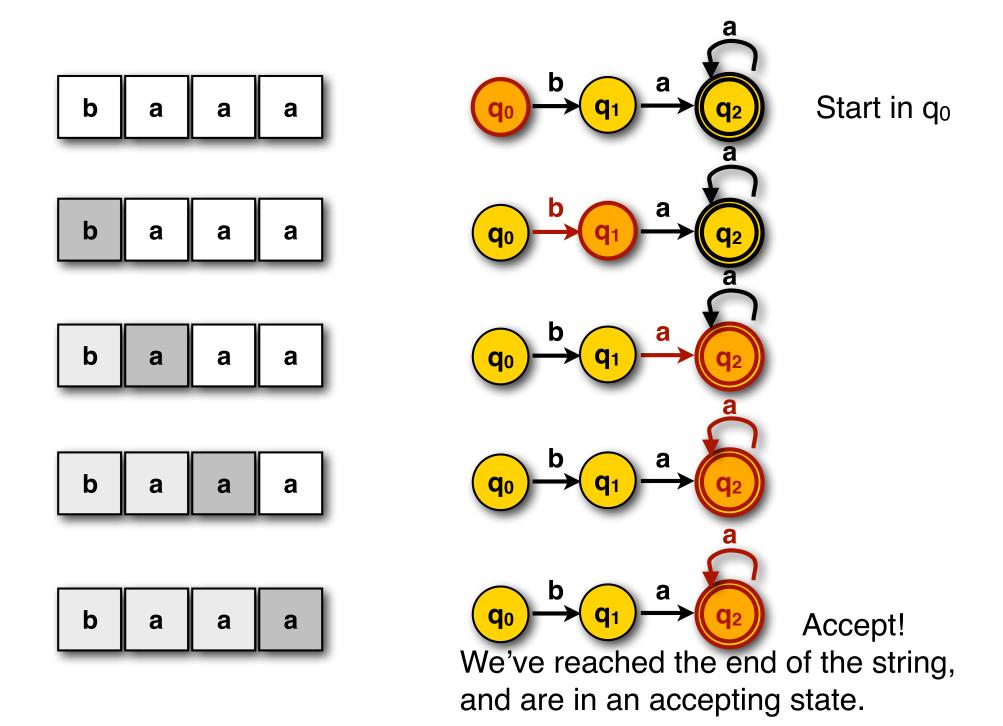
- Finite-state automata define regular languages
- Pushdown automata define context-free languages
- Turing machines define recursively enumerable languages

#### Finite-state automata

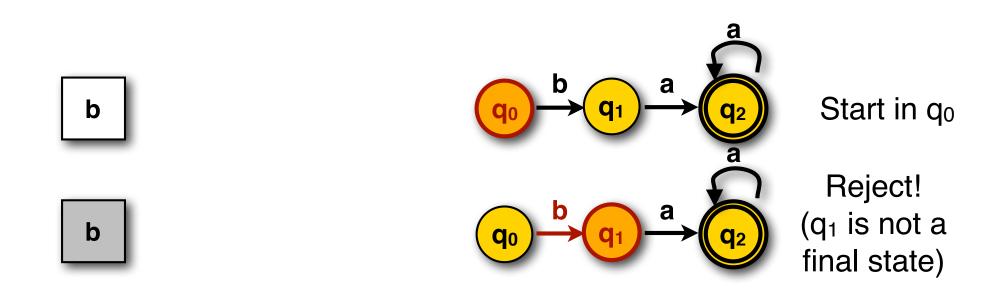
A (deterministic) finite-state automaton (FSA) consists of:

-a finite set of states  $Q=\{q_o....q_N\}$ , including a start state  $q_o$  and one (or more) final (=accepting) states (say,  $q_N$ )

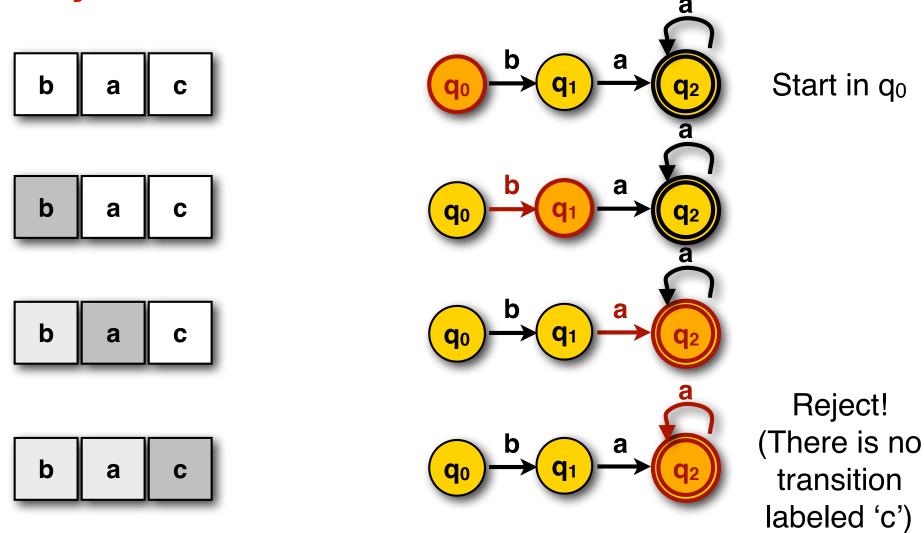




## Rejection: Automaton does not end up in accepting state



Rejection: Transition not defined



## Finite State Automata (FSAs)

#### A finite-state automaton $M = \langle Q, \Sigma, q_0, F, \delta \rangle$ consists of:

- A finite set of states  $Q = \{q_0, q_1,..., q_n\}$
- A finite alphabet  $\Sigma$  of input symbols (e.g.  $\Sigma = \{a, b, c, ...\}$ )
- A designated start state  $q_0 \in Q$
- A set of final states  $F \subseteq Q$
- A transition function  $\delta$ :
  - The transition function for a deterministic (D)FSA:  $Q \times \Sigma \rightarrow Q$   $\delta(q,w)=q$  for  $q, q' \in Q, w \in \Sigma$

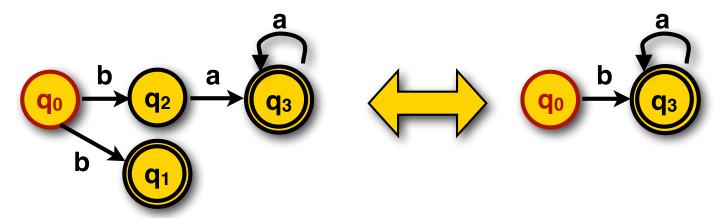
If the current state is q and the current input is w, go to q'

- The transition function for a nondeterministic (N)FSA:  $Q \times \Sigma \rightarrow 2Q$   $\delta(q,w) = Q'$  for  $q \in Q$ ,  $Q' \subseteq Q$ ,  $w \in \Sigma$ 

If the current state is q and the current input is w, go to any  $q' \in Q'$ 

## Finite State Automata (FSAs)

Every NFA can be transformed into an equivalent DFA:



Recognition of a string w with a DFA is linear in the length of w

#### Finite-state automata define the class of regular languages

```
L_1 = \{ a^n b^m \} = \{ ab, aab, abb, aaab, abb, ... \} is a regular language,
```

 $L_2 = \{ a^nb^n \} = \{ ab, aabb, aaabbb, ... \}$  is not (it's context-free).

You cannot construct an FSA that accepts all the strings in  $L_2$  and nothing else.

## Regular Expressions

Regular expressions can also be used to define a regular language.

#### Simple patterns:

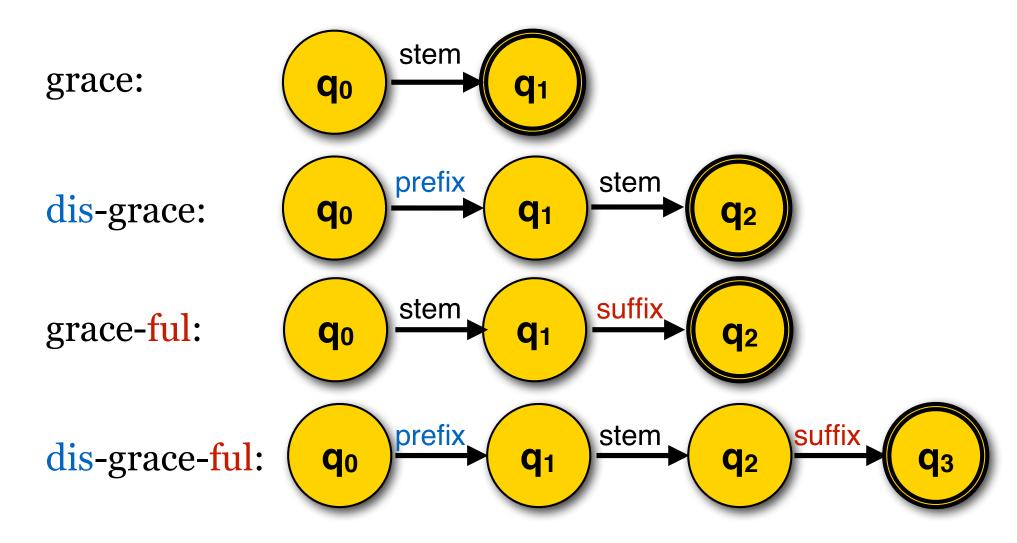
- -Standard characters match themselves: 'a', '1'
- -Character classes: '[abc]', '[0-9]', negation: ' $[^aeiou]$ ' (Predefined:  $\slash s$  (whitespace),  $\slash w$  (alphanumeric), etc.)
- -Any character (except newline) is matched by '.'

#### Complex patterns: (e.g. $^{A-Z}([a-z])+\s$ )

- -Group: '(...)'
- -Repetition: 0 or more times: '\*', 1 or more times: '+'
- -Disjunction: '... | ... '
- -Beginning of line '\' and end of line '\'

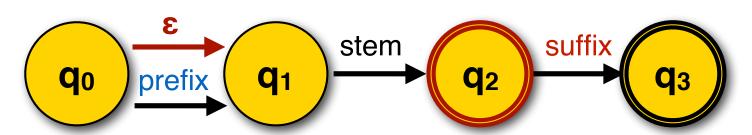
# Finite-state methods for morphology

## Finite state automata for morphology

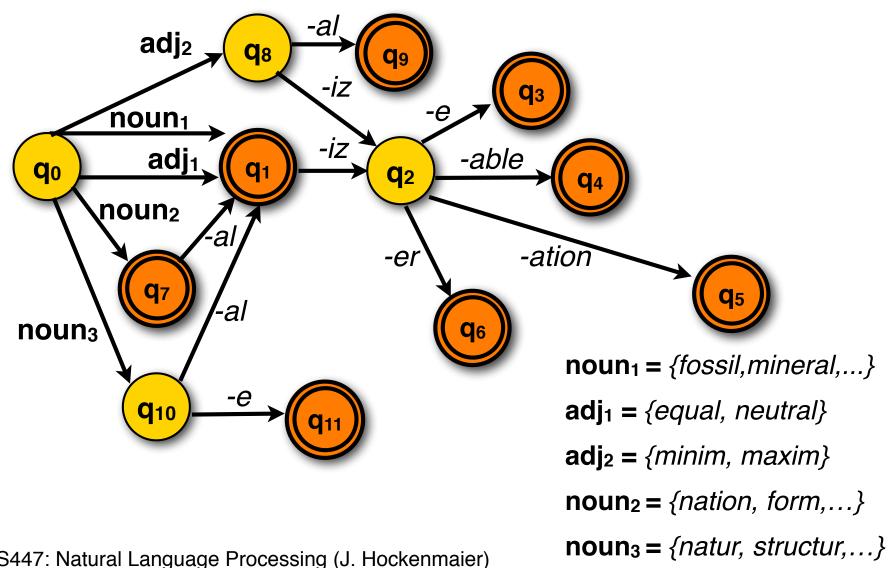


## Union: merging automata

grace, dis-grace, grace-ful, dis-grace-ful



## FSAs for derivational morphology

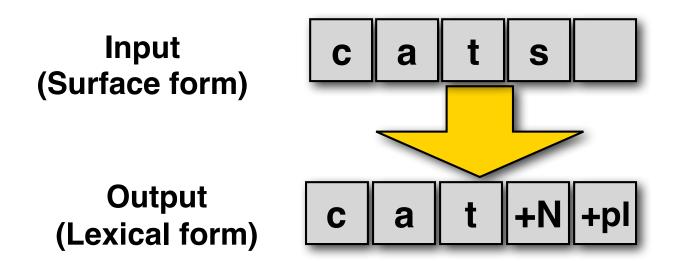


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## Recognition vs. Analysis

FSAs can recognize (accept) a string, but they don't tell us its internal structure.

We need is a machine that maps (transduces) the input string into an output string that encodes its structure:



#### Finite-state transducers

A finite-state transducer  $T = \langle Q, \Sigma, \Delta, q_0, F, \delta, \sigma \rangle$  consists of:

- A finite set of states  $Q = \{q_0, q_1,..., q_n\}$
- A finite alphabet  $\Sigma$  of **input symbols** (e.g.  $\Sigma = \{a, b, c,...\}$ )
- A finite alphabet  $\Delta$  of **output symbols** (e.g.  $\Delta = \{+N, +pl,...\}$ )
- A designated start state  $q_0 \in Q$
- A set of **final states**  $F \subseteq Q$
- A transition function  $\delta: Q \times \Sigma \to 2Q$  $\delta(q,w) = Q'$  for  $q \in Q, Q' \subseteq Q, w \in \Sigma$
- An output function  $\sigma: Q \times \Sigma \to \Delta^*$

$$\sigma(q, w) = \omega$$
 for  $q \in Q$ ,  $w \in \Sigma$ ,  $\omega \in \Delta^*$ 

If the current state is q and the current input is w, write  $\omega$ .

(NB: Jurafsky&Martin define  $\sigma: Q \times \Sigma^* \to \Delta^*$ . Why is this equivalent?)

#### Finite-state transducers

An FST  $T = L_{in} \times L_{out}$  defines a relation between two regular languages  $L_{in}$  and  $L_{out}$ :

```
L_{in} = \{ \mathbf{cat}, \mathbf{cats}, \mathbf{fox}, \mathbf{foxes}, ... \}
L_{out} = \{ cat + N + sg, cat + N + pl, fox + N + sg, fox + N + pl ... \}
T = \{ \langle \mathbf{cat}, cat + N + sg \rangle, \\ \langle \mathbf{cats}, cat + N + pl \rangle, \\ \langle \mathbf{fox}, fox + N + sg \rangle, \\ \langle \mathbf{foxes}, fox + N + pl \rangle \}
```

## Some FST operations

#### Inversion *T-1*:

The inversion  $(T^{-1})$  of a transducer switches input and output labels.

This can be used to switch from parsing words to generating words.

#### Composition ( $T \circ T'$ ): (Cascade)

Two transducers  $T = L_1 \times L_2$  and  $T' = L_2 \times L_3$  can be composed into a third transducer  $T'' = L_1 \times L_3$ .

Sometimes intermediate representations are useful

## English spelling rules

Peculiarities of English spelling (orthography)

The same underlying morpheme (e.g. *plural-s*) can have different orthographic "surface realizations" (-s, -es)

This leads to spelling changes at morpheme boundaries:

E-insertion: fox + s = foxes

E-deletion: make + ing = making

## Intermediate representations

```
English plural -s: cat \Rightarrow cats \quad dog \Rightarrow dogs
but: fox \Rightarrow foxes, bus \Rightarrow buses buzz \Rightarrow buzzes
```

We define an intermediate representation to capture morpheme boundaries (^) and word boundaries (#):

```
Lexicon: cat+N+PL fox+N+PL

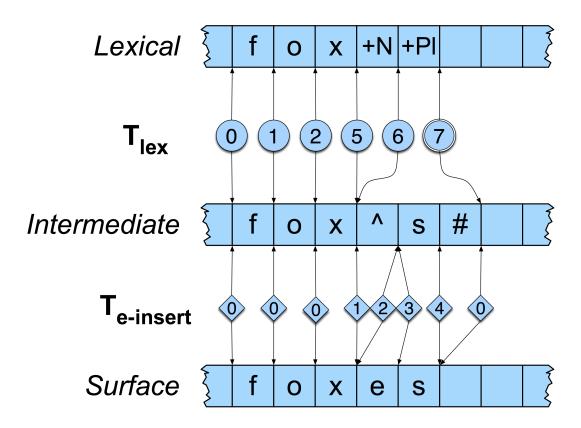
⇒ Intermediate representation: cat^s# fox^s#
```

⇒ Surface string: cats foxes

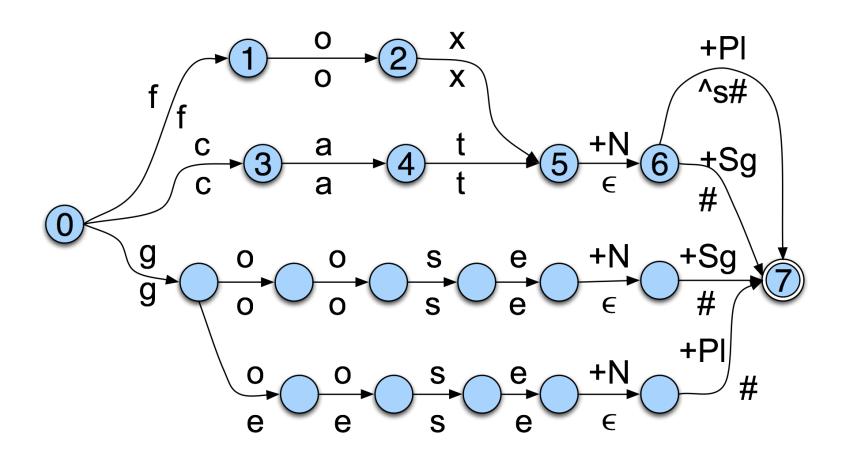
#### Intermediate-to-Surface Spelling Rule:

If plural 's' follows a morpheme ending in 'x', 'z' or 's', insert 'e'.

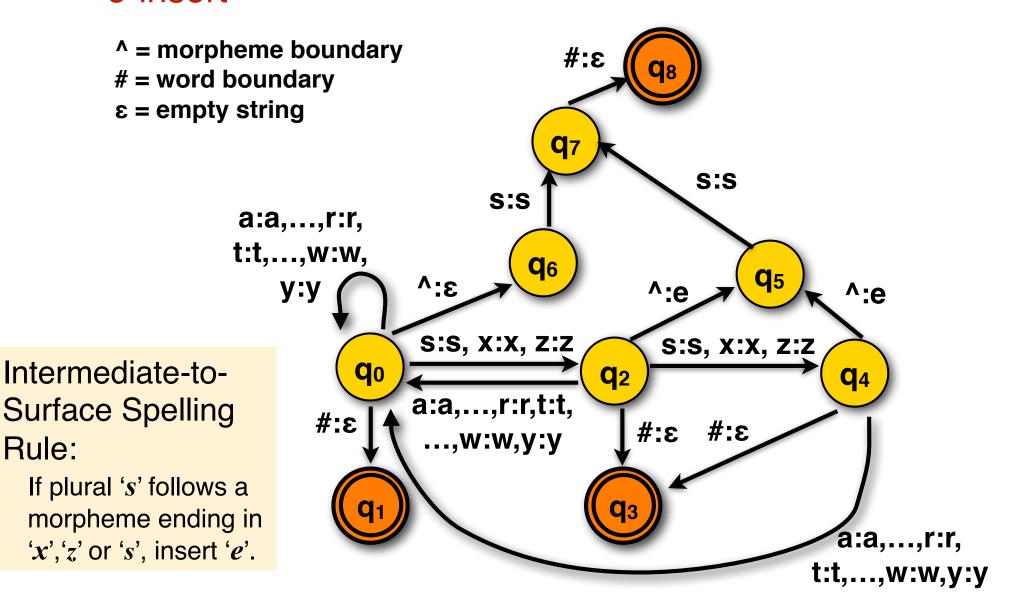
## FST composition/cascade:



## T<sub>lex</sub>: Lexical to intermediate level



## T<sub>e-insert</sub>: intermediate to surface level



## Dealing with ambiguity

book: book +N + sg or book +V?

Generating words is generally unambiguous, but analyzing words often requires disambiguation.

We need a nondeterministic FST.

- Efficiency problem: Not every nondeterministic FST can be translated into a deterministic one!

We also need a scoring function to identify which analysis is more likely.

- We may need to know the context in which the word appears: (I read a book vs. I book flights)

## Other applications of FSTs

## A computer therapist?

**Computer: TELL ME MORE ABOUT YOUR FAMILY** 

**Human:** My mother takes care of me.

Computer: WHO ELSE IN YOUR FAMILY TAKES CARE OF YOU

**Human:** My father.

**Computer:** YOUR FATHER

**Human:** You are like my father in some ways.

**Computer: WHAT RESEMBLANCE DO YOU SEE** 

Human: You are not very aggressive but I think you don't want me

to notice that.

Computer: WHAT MAKES YOU THINK I AM NOT VERY

**AGGRESSIVE** 

**Human:** You don't argue with me.

Computer: WHY DO YOU THINK I DON'T ARGUE WITH YOU

Human: You are afraid of me.

Weizenbaum (1966), ELIZA.

## ELIZA as a FST cascade

Human: You don't argue with me.

Computer: WHY DO YOU THINK I DON'T ARGUE WITH YOU

- 1. Replace **you** with *I* and *me* with *you: I don't argue with you.*
- 2. Replace <...> with Why do you think <...>:

  Why do you think I don't argue with you.

What about other NLP tasks?

Could we write an FST for machine translation?

## What about compounds?

Semantically, compounds have hierarchical structure:

```
(((ice cream) cone) bakery)
not (ice ((cream cone) bakery))

((computer science) (graduate student))
not (computer ((science graduate) student))
```

We will need context-free grammars to capture this underlying structure.

## Today's key concepts

Morphology (word structure): stems, affixes Derivational vs. inflectional morphology Compounding Stem changes Morphological analysis and generation

Finite-state automata
Finite-state transducers
Composing finite-state transducers

## Today's reading

This lecture follows closely Chapter 3.1-7 in J&M 2008

Optional readings (see website)

<u>Karttunen and Beesley '05, Mohri (1997)</u>, the <u>Porter stemmer</u>, <u>Sproat et al. (1996)</u>