2 Word Level Analysis 8

2.1 Tokenization, Stemming, Segmentation, Lemmatization, Edit Distance, Collocations, Finite Automata, Finite State Transducers (FST), Porter Stemmer, Morphological Analysis, Derivational and Reflectional Morphology, Regular expression with types.

2.2 N –Grams, Unigrams/Bigrams Language Models, Corpora, Computing the Probability of Word Sequence, Training and Testing.

https://web.stanford.edu/~jurafsky/slp3/ed3book.pdf

Ambiguity

Find at least 5 meanings of this sentence:

I made her duck

- I cooked waterfowl for her benefit (to eat)
- I cooked waterfowl belonging to her
- I created the (plaster?) duck she owns
- I caused her to quickly lower her head or body
- I waved my magic wand and turned her into undifferentiated waterfowl

Ambiguity is Everywhere

- Lexical category: part of speech
  - Duck can be a Noun or Verb
    - V: *Duck!* I caused her to quickly lower her head or body.
    - N: I cooked waterfowl for her benefit
  - Her can be possessive (of her) or dative (for her)
    - Possessive: I cooked waterfowl belonging to her.
    - Dative: I cooked waterfowl for her benefit
- Lexical Semantics:
  - Make can mean create or cook
    - create: I made the (plaster) duck statue she owns
    - cook: I cooked waterfowl for her benefit

Examples (Challenges)

1. **"Buffalo buffalo Buffalo buffalo buffalo buffalo Buffalo buffalo"**

1. **Will, will Will will Will Will's will?**

1. **Police police Police police police police Police police.**

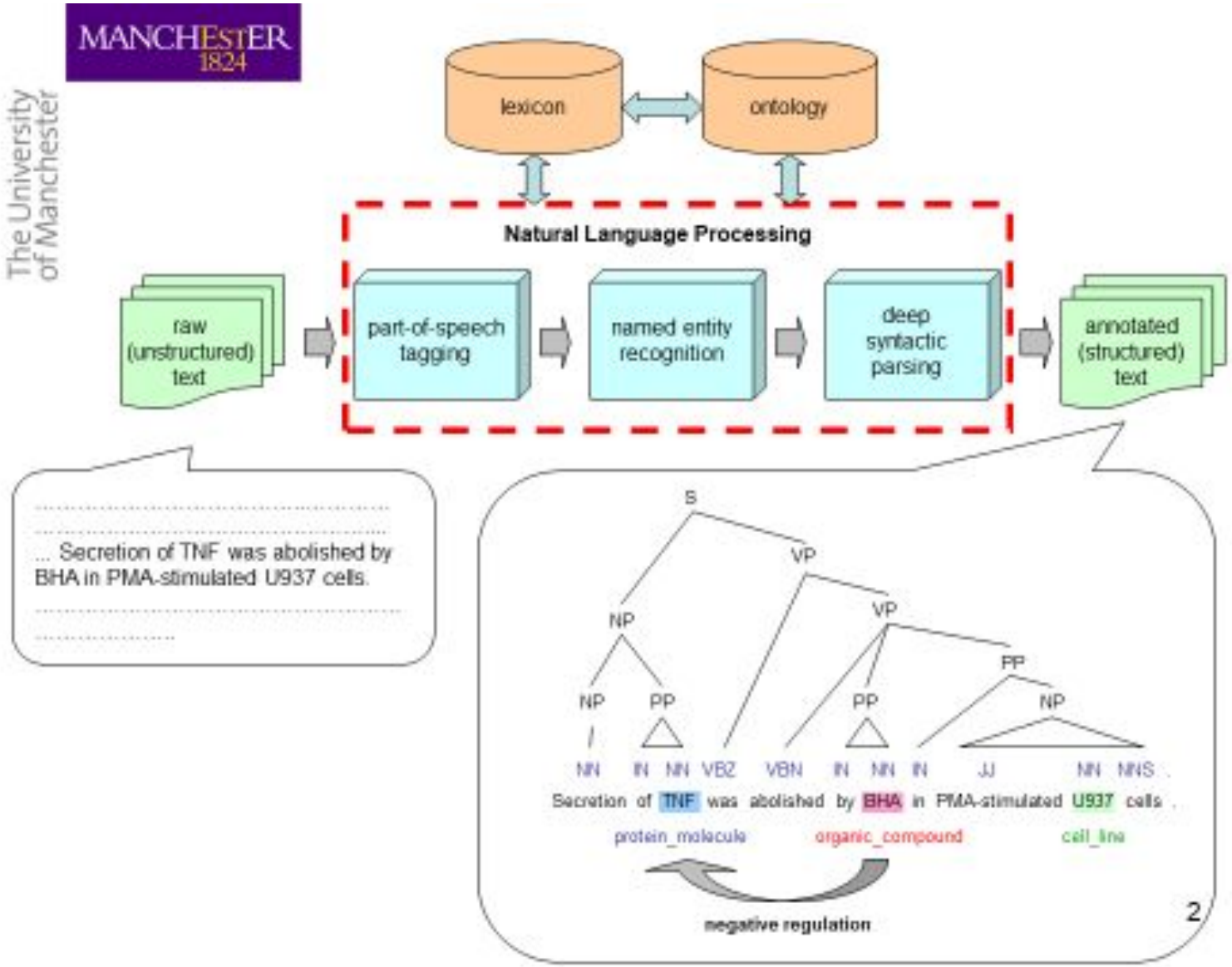
1. **Rose rose to put rose roes on her rows of roses**

1. **Can can can can can can can can can can**

other example

- **Time flies like an arrow; fruit flies like a banana.**
- **Actions speak louder than words.**

NLP fundamentals


MANCHESTER 1824
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lexicon
ontology
Natural Language Processing
raw (unstructured) text
part-of-speech tagging
named entity recognition
deep syntactic parsing
annotated (structured) text
... Secretion of TNF was abolished by BHA in PMA-stimulated U937 cells.
S
VP
NP
VP
NP
PP
PP
NP
PP
NP
NN IN NN VBZ VBN IN NN IN JJ NN NNS .
Secretion of TNF was abolished by BHA in PMA-stimulated U937 cells .
protein_molecule
organic_compound
cell_line
negative regulation
2

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Basic Steps of Natural Language Processing

- Sentence splitting
- Tokenization
- Part-of-speech tagging
- Shallow parsing
- Named entity recognition
- Syntactic parsing
- (Semantic Role Labeling)

User: I am unhappy.
ELIZA: DO YOU THINK COMING HERE WILL HELP YOU NOT TO BE UNHAPPY
User: I need some help, that much seems certain.
ELIZA: WHAT WOULD IT MEAN TO YOU IF YOU GOT SOME HELP
User: Perhaps I could learn to get along with my mother.
ELIZA: TELL ME MORE ABOUT YOUR FAMILY
User: My mother takes care of me.
ELIZA: WHO ELSE IN YOU FAMILY TAKES CARE OF YOU
User: My father.
ELIZA: YOUR FATHER
User: You are like my father in some ways.

Weizenbaum (1966)

Regular Expressions

Regular expressions

- A formal language for specifying text strings
- How can we search for any of these?
  - woodchuck
  - woodchucks
  - Woodchuck
  - Woodchucks

Regular Expressions: Disjunctions

- Letters inside square brackets []

Pattern	Matches
`[wW]oodchuck`	Woodchuck, woodchuck
`[1234567890]`	Any digit

- Ranges `[A-Z]`

Pattern	Matches	
`[A-Z]`	An upper case letter	`Drenched Blossoms`
`[a-z]`	A lower case letter	`my beans were impatient`
`[0-9]`	A single digit	`Chapter 1: Down the Rabbit Hole`

Regular Expressions: Negation in Disjunction

- Negations [^Ss]
  - Carat means negation only when first in []

Pattern	Matches	
[^A-Z]	Not an upper case letter	Oyfn pripetchik
[^Ss]	Neither 'S' nor 's'	I have no exquisite reason"
[^e^]	Neither e nor ^	Look here
a^b	The pattern a carat b	Look up a^b now

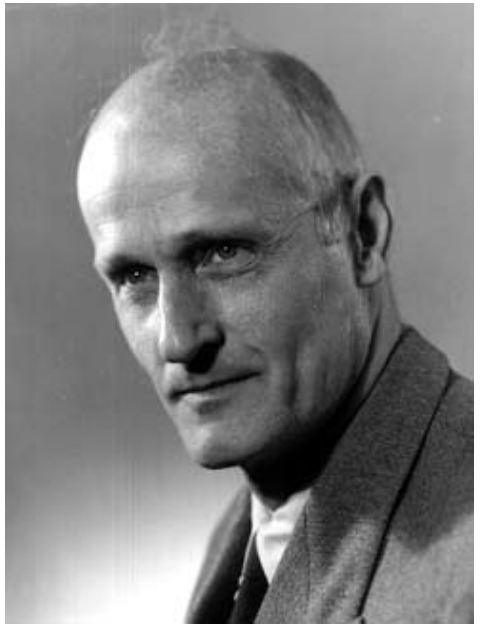
Regular Expressions: More Disjunction

- Woodchucks is another name for groundhog!
- The pipe | for disjunction

Pattern	Matches
`groundhog|woodchuck`	
`yours|mine`	yours mine
`a|b|c`	= [abc]
`[gG]roundhog|[Ww]oodchuck`	

Regular Expressions: ? * + .

Pattern	Matches	
colou?r	Optional previous char	color colour
oo*h!	0 or more of previous char	oh! ooh! oooh! ooooh!
o+h!	1 or more of previous char	oh! ooh! oooh! ooooh!
baa+		baa baaa baaaa baaaaa
beg.n		begin begun begun beg3n



Stephen C Kleene

Kleene *, Kleene +

Regular Expressions: Anchors ^ $

Pattern	Matches
^[A-Z]	Palo Alto
^[^A-Za-z]	1 "Hello"
\.$	The end.
.$	The end? The end!

- ^ – The caret anchor matches the beginning of the text.
- $ – The dollar anchor matches the end of the text.
- \. a period Dr.
- * if u want to match *

Example

- Find me all instances of the word “the” in a text.

```
the
```

Misses capitalized examples

```
[tT]he
```

Incorrectly returns `other` or `theology`

```
[^a-zA-Z][tT]he[^a-zA-Z]
```

-non alphabetical characters before and after the

Errors

- The process we just went through was based on fixing two kinds of errors
  - Matching strings that we should not have matched (there, then, other)
    - False positives (Type I)
  - Not matching things that we should have matched (The)
    - False negatives (Type II)

```
/(^|[^a-zA-Z])[tT]he([^a-zA-Z]|$)/
```

^ begining of line
$ end of line
non alphabetic character

Errors cont.

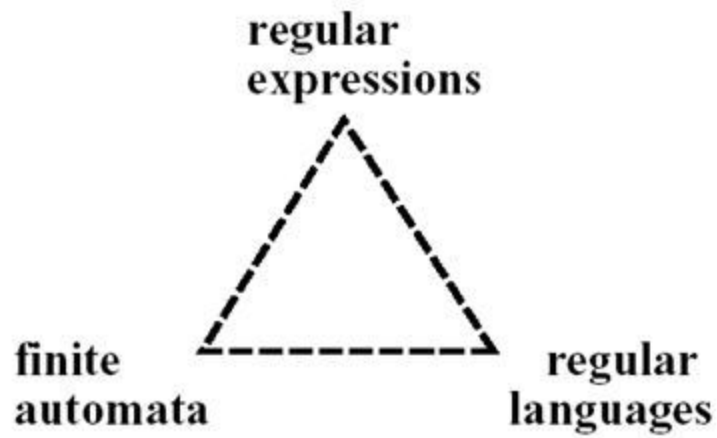
- In NLP we are always dealing with these kinds of errors.
- Reducing the error rate for an application often involves two antagonistic efforts:
  - Increasing accuracy or precision (minimizing false positives)
  - Increasing coverage or recall (minimizing false negatives).

Summary

- Regular expressions play a surprisingly large role
  - Sophisticated sequences of regular expressions are often the first model for any text processing
- For many hard tasks, we use machine learning classifiers
  - But regular expressions can be used as features in the classifiers
  - Can be very useful in capturing generalizations

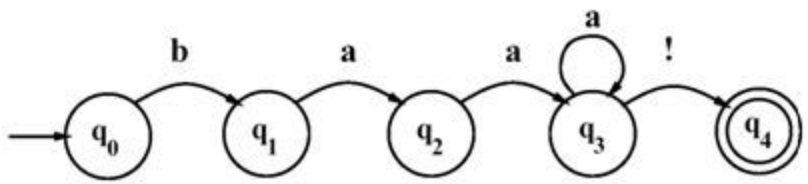
2.2 Finite-State Automata

- An RE is one way of describing a FSA.
- An RE is one way of characterizing a particular kind of formal language called a **regular language**.

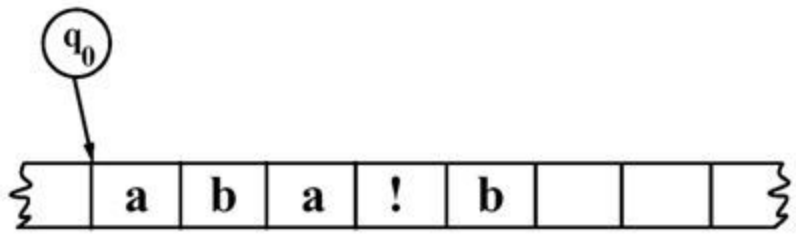


2.2 Finite-State Automata

Using an FSA to Recognize Sheeptalk



/baa+!/



A tape with cells

	Input		
State	b	a	!
0	1	0	0
1	0	2	0
2	0	3	0
3	0	3	4
4:	0	0	0

The transition-state table

- Automaton (finite automaton, finite-state automaton (FSA))
- State, start state, final state (accepting state)

2.2 Finite-State Automata

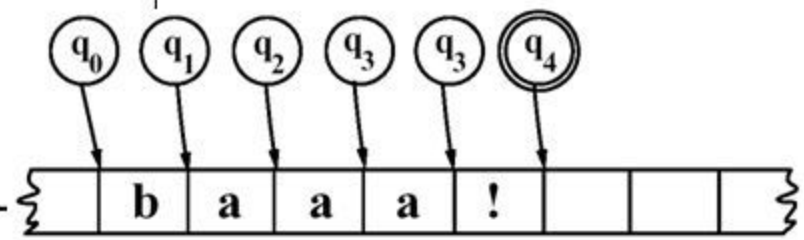
Using an FSA to Recognize Sheeptalk

- A finite automaton is formally defined by the following five parameters:
  - Q: a finite set of N states $q_0, q_1, \ldots, q_N$
  - Σ: a finite input alphabet of symbols
  - q_0: the start state
  - F: the set of final states, $F \subseteq Q$
  - $\delta(q,i)$: the transition function or transition matrix between states. Given a state $q \in Q$ and input symbol $i \in \Sigma$, $\delta(q,i)$ returns a new state $q' \in Q$. δ is thus a relation from $Q \times \Sigma$ to Q;

2.2 Finite-State Automata
Using an FSA to Recognize Sheeptalk

- An algorithm for deterministic recognition of FSAs.

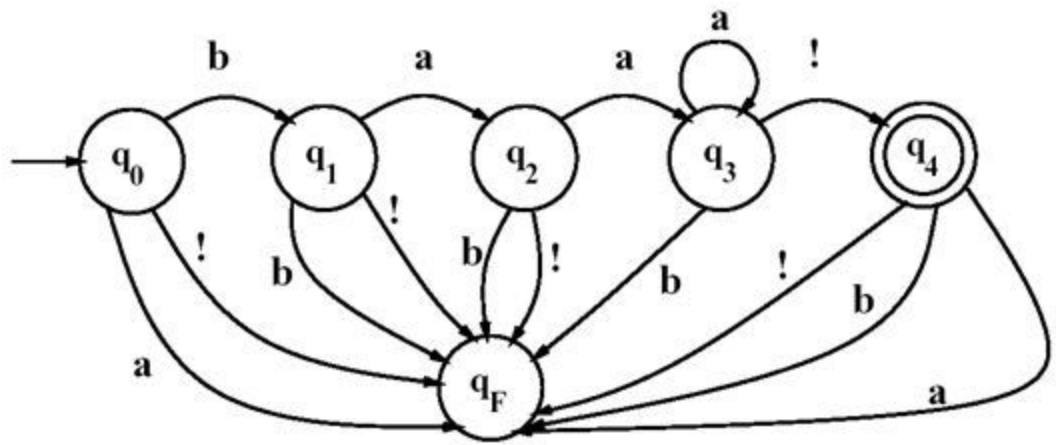
```
function D-RECOGNIZE(tape, machine) returns accept or reject

  index ← Beginning of tape
  current-state ← Initial state of machine
  loop
    if End of input has been reached then
      if current-state is an accept state then
        return accept
      else
        return reject
    elsif transition-table[current-state,tape[index]] is empty then
      return reject
    else
      current-state ← transition-table[current-state,tape[index]]
      index ← index + 1
  end
```



2.2 Finite-State Automata

Using an FSA to Recognize Sheeptalk

- Adding a fail state



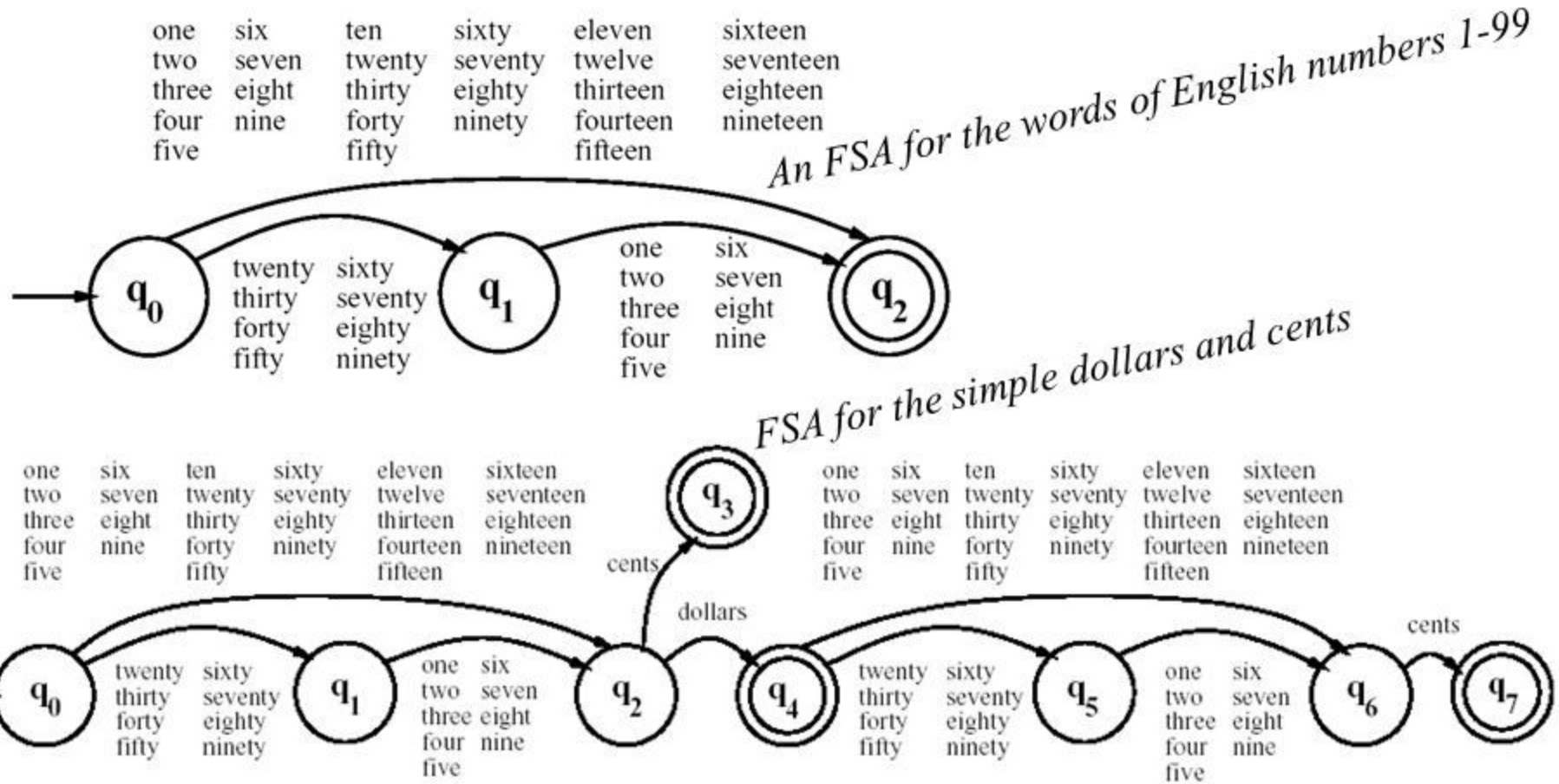
2.2 Finite-State Automata

Formal Languages

- **Key concept #1: Formal Language:** A model which can both generate and recognize all and only the strings of a formal language acts as a *definition* of the formal language.
- A **formal language** is a set of strings, each string composed of symbols from a finite symbol-set call an **alphabet**.
- The usefulness of an automaton for defining a language is that it can express an infinite set in a closed form.
- A formal language may bear no resemblance at all to a real language (natural language), but
  - We often use a formal language to model part of a natural language, such as parts of the phonology, morphology, or syntax.
- The term **generative grammar** is used in linguistics to mean a grammar of a formal language.

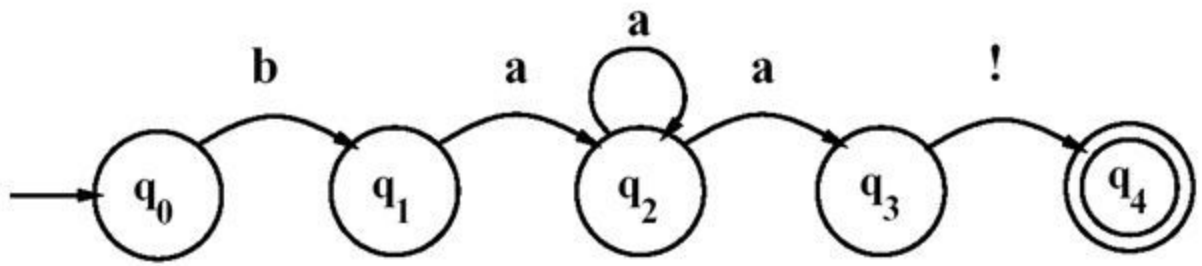
2.2 Finite-State Automata

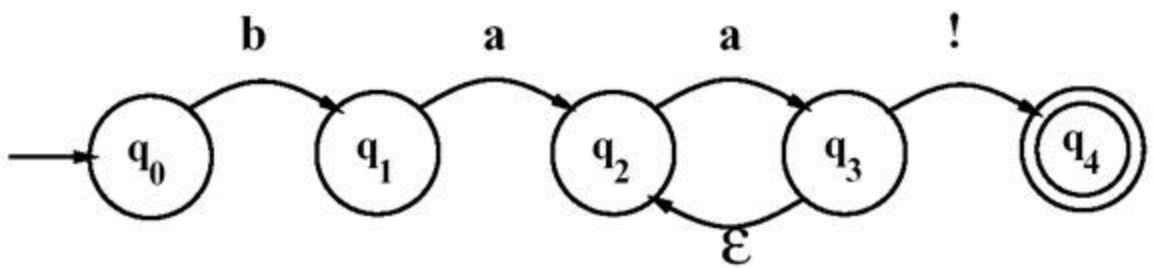
Another Example



2.2 Finite-State Automata

Non-Deterministic FSAs

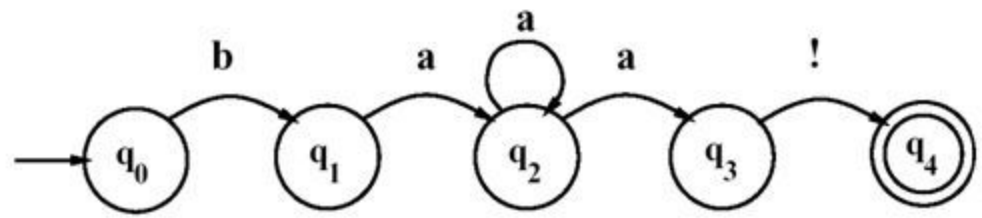




2.2 Finite-State Automata

Using an NFSA to Accept Strings

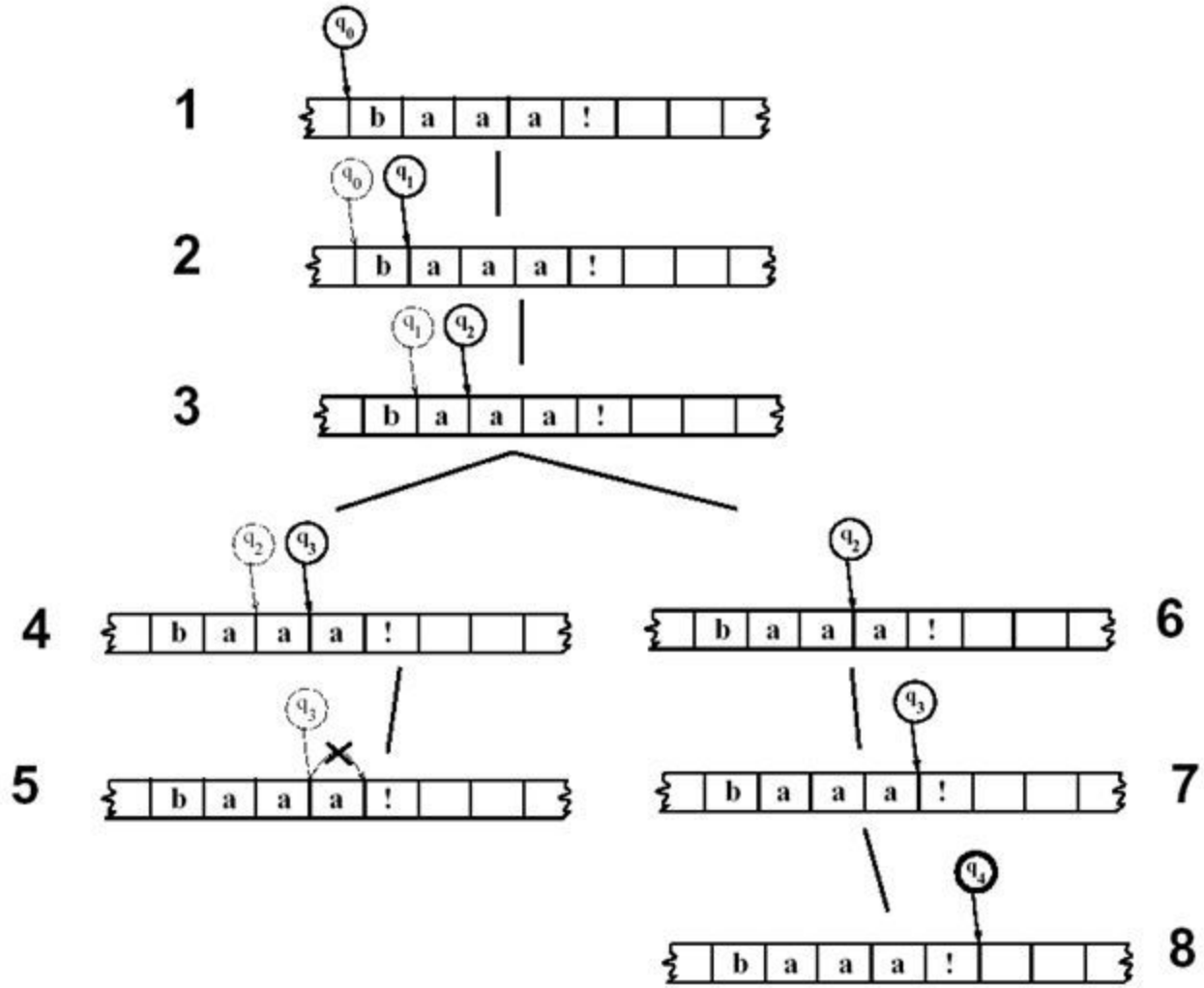
- Solutions to the problem of multiple choices in an NFSA
  - Backup
  - Look-ahead
  - Parallelism



	Input			
State	b	a	!	ε
0	1	∅	∅	∅
1	∅	2	∅	∅
2	∅	2,3	∅	∅
3	∅	∅	4	∅
4:	∅	∅	∅	∅

2.2 Finite-State Automata

Using an NFSA to Accept Strings



2.2 Finite-State Automata

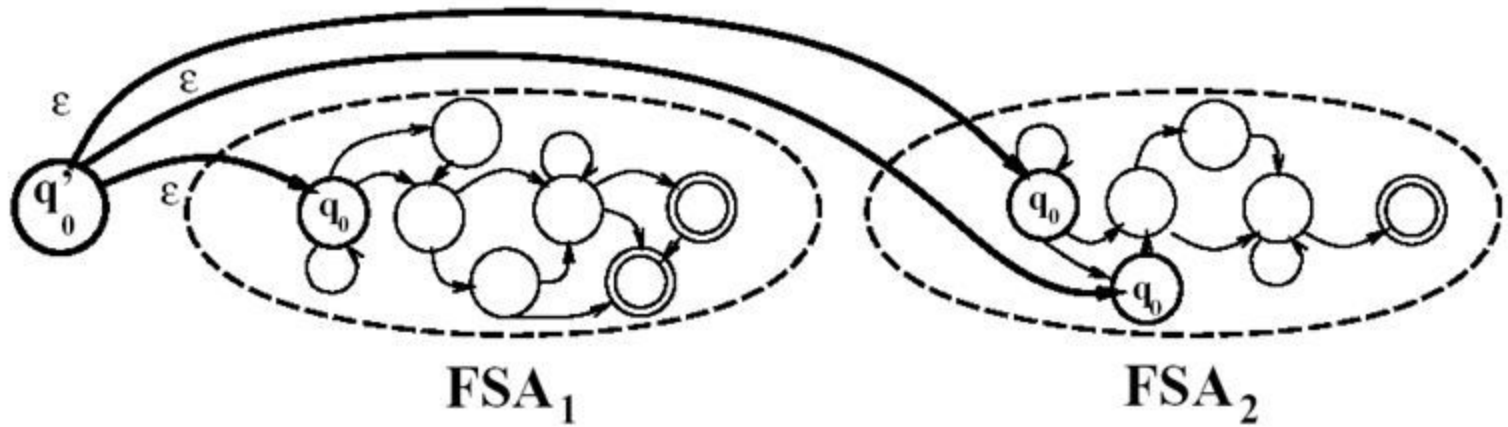
Recognition as Search

- Algorithms such as ND-RECOGNIZE are known as **state-space search**
- **Depth-first search** or **Last In First Out** (**LIFO**) strategy
- **Breadth-first search** or **First In First Out** (**FIFO**) strategy
- More complex search techniques such as **dynamic programming** or **A***

2.3 Regular Languages and FSAs

- The class of languages that are definable by regular expressions is exactly the same as the class of languages that are characterizable by FSA (D or ND).
  - These languages are called **regular languages**.
- The regular languages over Σ is formally defined as:
  1. ϕ is an RL
  2. $\forall a \in \Sigma$, $\{a\}$ is an RL
  3. If L_1 and L_2 are RLs, then so are:
     a) $L_1 \cdot L_2 = \{xy \mid x \in L_1 \text{ and } y \in L_2\}$, the **concatenation** of L_1 and L_2
     b) $L_1 \cup L_2$, the **union** of L_1 and L_2
     c) L_1^*, the **Kleene closure** of L_1

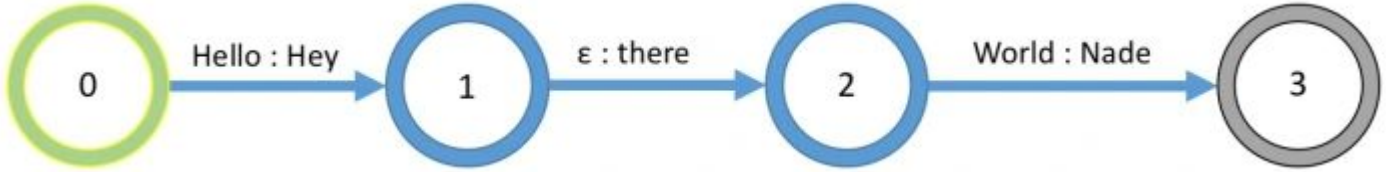
2.3 Regular Languages and FSAs



The union (|) of two FSAs

Finite State Transducers

- **generation mode:** It writes a string of `a`s on one tape and a string `b`s on the other tape. Both strings have the same length.
- **recognition mode:** It accepts when the word on the first tape consists of exactly as many `a`s as the word on the second tape consists of `b`s.
- **translation mode (left to right):** It reads `a`s from the first tape and writes an `b` for every `a` that it reads onto the second tape.
- **translation mode (right to left):** It reads `b`s from the second tape and writes an `a` for every `f` that it reads onto the first tape.



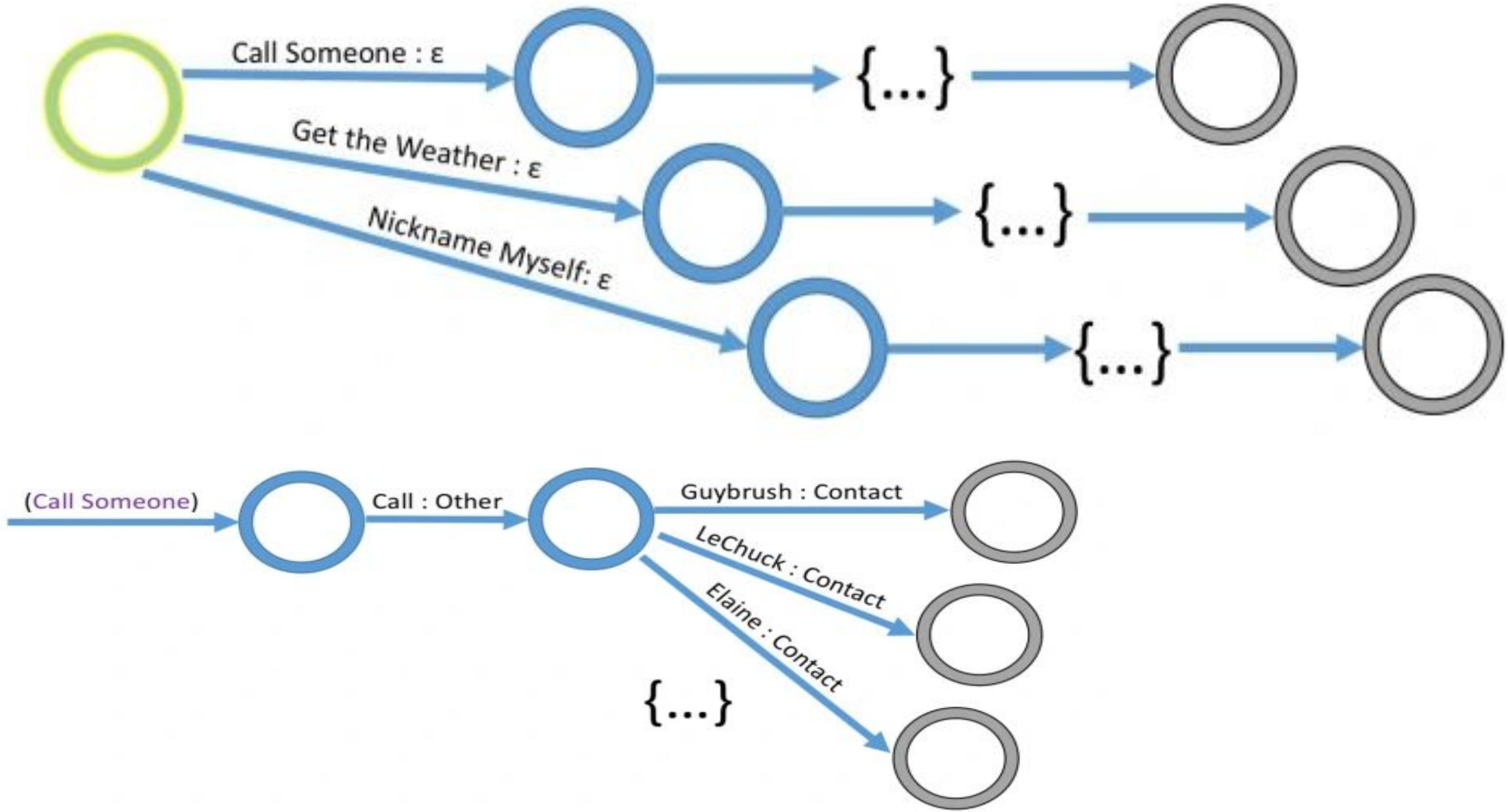
- Edges ("Transitions") have input/output labels
  - Sometimes, labels are "empty" (indicated here as lowercase epsilon **ε**)
- Traversing through to the end of an FST implies the generation (or indication of) a set of string relations
- There is a defined "initial state" (indicated here in **green**) and 1 or more "final states" (indicated here in **gray**)

Applications

FSTs are used for a variety of different applications:

- Word Inflections. For example, pluralizing words (cat -> cats, dog -> dogs, goose -> geese, etc.).
- Morphological Parsing; i.e., extracting the “properties” of a word (e.g., computers -> computer + [Noun] + [Plural])
- Simple Word Translation, e.g., translating US English to UK English.
- Simple commands made to a computer

commands made to a computer



Word tokenization

Text Normalization

- Most NLP tasks need to do text normalization:
  1. Segmenting/tokenizing words in running text
  2. Normalizing word formats
  3. Segmenting sentences in running text

How many words?

- I do uh main- mainly business data processing
  - Fragments, filled pauses
- Seuss's cat in the hat is different from other cats!
  - **Lemma**: same stem, part of speech, rough word sense
    - cat and cats = same lemma
  - **Wordform**: the full inflected surface form
    - cat and cats = different wordforms

How many words?

they lay back on the San Francisco grass and looked at the stars and their

- **Type**: an element of the vocabulary.
- **Token**: an instance of that type in running text.
- How many?
  - 15 tokens ……(or 14)?
  - 13 types ……..(or 12)?

How many words?

N = number of tokens

V = vocabulary = set of types

$|V|$ is the size of the vocabulary

Switchboard is a collection of about 2,400 two-sided telephone conversations among 543 speakers (302 male, 241 female) from all areas of the United States.

	Tokens = N	Types = |V|
Switchboard phone conversations	2.4 million	20 thousand
Shakespeare	884,000	31 thousand
Google N-grams	1 trillion	13 million

https://books.google.com/ngrams/

Simple Tokenization in UNIX

- (Inspired by Ken Church's UNIX for Poets.)
- Given a text file, output the word tokens and their frequencies

```
tr -sc "A-Za-z" "\n" < sample.txt
      | sort
      | uniq -c
```

Change all non-alpha to newlines

Sort in alphabetical order

Merge and count each type

```
1945 A
  72 AARON
  19 ABBESS
   5 ABBOT
 ... ...
```

```
 25 Aaron
  6 Abate
  1 Abates
  5 Abbess
  6 Abbey
  3 Abbot
.... …
```

The first step: tokenizing

```
tr -sc "A-Za-z" "\n" < sample.txt | head
```

```
THE
SONNETS
by
William
Shakespeare
From
fairest
creatures
We
...
```

The second step: sorting

```
tr -sc "A-Za-z" "\n" < sample.txt | sort | head
```

```
A
A
A
A
A
A
A
A
A
...
```

More counting

- Merging upper and lower case

```
tr "A-Z" "a-z" < sample.txt | tr -sc "A-Za-z" "\n" | sort | uniq –c
```

- Sorting the counts

```
tr "A-Z" "a-z" < sample.txt | tr -sc "A-Za-z" "\n" | sort | uniq -c | sort -n -r
```

```
23243 the
22225 i
18618 and
16339 to
15687 of
12780 a
12163 you
10839 my
10005 in
8954  d
```

What happened here?

MANCHESTER 1824

The University of Manchester

A heuristic rule for sentence splitting

sentence boundary

= period + space(s) + capital letter

Regular expression in Perl

```
s/\. +([A-Z])/\.\n\1/g;
```

Issues in Tokenization

- Finland's capital → Finland Finlands Finland's ?
- what're, I'm, isn't → What are, I am, is not
- Hewlett-Packard → Hewlett Packard ?
- state-of-the-art → state of the art ?
- Lowercase → lower-case lowercase lower case ?
- San Francisco → one token or two?
- m.p.h., PhD. → ??

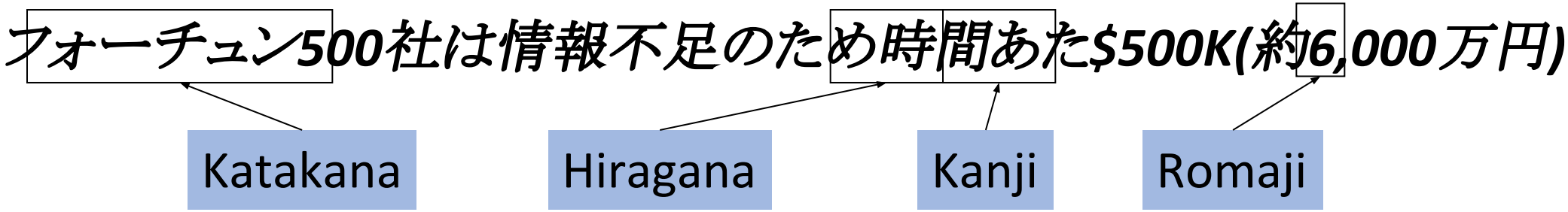
Tokenization: language issues

- French
  - ***L'ensemble*** → one token or two?
    - ***L*** ? ***L'*** ? ***Le*** ?
    - Want ***l'ensemble*** to match with ***un ensemble***

- German noun compounds are not segmented
  - ***Lebensversicherungsgesellschaftsangestellter***
  - 'life insurance company employee'
  - German information retrieval needs **compound splitter**

Tokenization: language issues

- Chinese and Japanese no spaces between words:
  - 莎拉波娃现在居住在美国东南部的佛罗里达。
  - 莎拉波娃 现在 居住 在 美国 东南部 的 佛罗里达
  - Sharapova now lives in US southeastern Florida
- Further complicated in Japanese, with multiple alphabets intermingled
  - Dates/amounts in multiple formats



End-user can express query entirely in hiragana!

Word Normalization and Stemming

Normalization

- Need to “normalize” terms
  - Information Retrieval: indexed text & query terms must have same form.
    - We want to match ***U.S.A.*** and ***USA***
- We implicitly define equivalence classes of terms
  - e.g., deleting periods in a term
- Alternative: asymmetric expansion:
  - Enter: ***window*** Search: ***window, windows***
  - Enter: ***windows*** Search: ***Windows, windows, window***
  - Enter: ***Windows*** Search: ***Windows***
- Potentially more powerful, but less efficient

Case folding

- Applications like IR: reduce all letters to lower case
  - Since users tend to use lower case
  - Possible exception: upper case in mid-sentence?
    - e.g., ***General Motors***
    - ***Fed*** vs. ***fed***
    - ***SAIL*** vs. ***sail***
- For sentiment analysis, MT, Information extraction
  - Case is helpful (***US*** versus ***us*** is important)

Lemmatization

- Reduce inflections or variant forms to base form
  - *am, are, is → be*
  - *car, cars, car's, cars' → car*
- *the boy's cars are different colors → the boy car be different color*
- Lemmatization: have to find correct dictionary headword form
- Machine translation
  - Spanish quiero (‘I want’), quieres (‘you want’) same lemma as querer ‘want’

Morphology

- **Morphemes**:
  - The small meaningful units that make up words
  - **Stems**: The core meaning-bearing units
  - **Affixes**: Bits and pieces that adhere to stems
    - Often with grammatical functions

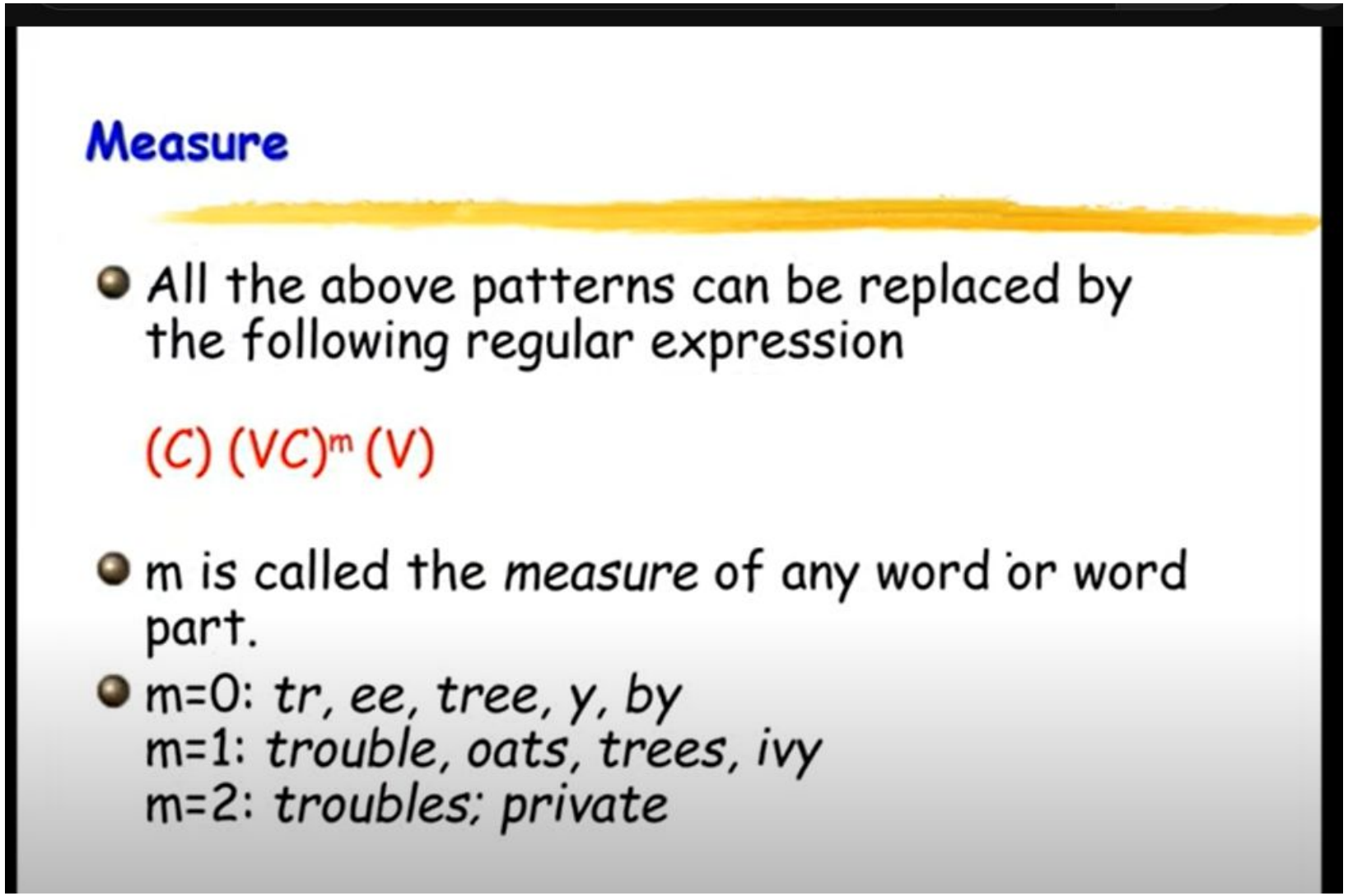
Stemming

- Reduce terms to their stems in information retrieval
- *Stemming* is crude chopping of affixes
  - language dependent
  - e.g., ***automate(s), automatic, automation*** all reduced to ***automat***.

for example compressed and compression are both accepted as equivalent to compress.

for exampl compress and compress ar both accept as equival to compress

Compression word in regular expression



Rules

- Rules for removing a suffix are given in the form

  (condition) S1 → S2

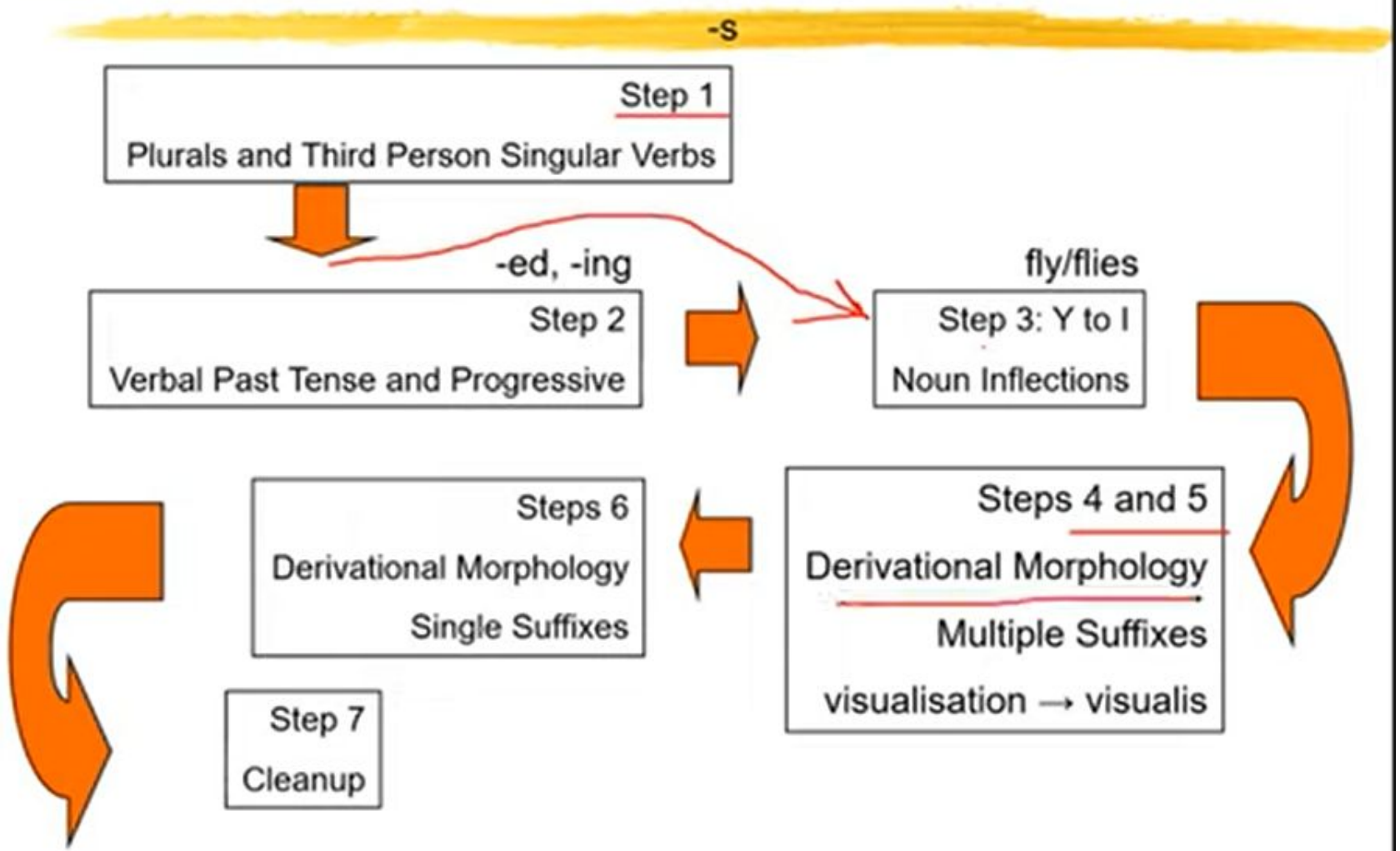
- i.e. if a word ends with suffix S1, and the stem before S1 satisfies the condition, then it is replaced with S2. Example

  (m > 1) EMENT → ε
  Example: Here S1 is 'EMENT' and S2 is null. This would map REPLACEMENT to REPLAC, since REPLAC is a word part for which m = 2

Conditions

- *Z - stem ends with z
- *T – stem ends with t
- *v* - stem contains a vowel
- *d - stem ends with a double consonant
- *o - stem ends cvc, where second c is not *w*, *x* or *y* e.g. –wil, -hop
- In conditions, Boolean operators are possible e.g. (m>1 and (*S or *T))
- Sets of rules applied in 7 steps. Within each step, rule matching longest suffix applies.

Organisation



The Porter Stemmer: Step 1

- SSES -> SS
  - *caresses -> caress*
- IES -> I
  - *ponies -> poni*
  - *ties -> ti*
- SS -> SS
  - *caress -> caress*
- S -> ϵ
  - *cats -> cat*

The Porter Stemmer: Step 2a (past tense, progressive)

- (m>0) EED -> EE
  - Condition verified: *agreed -> agree*
  - Condition not verified: *feed -> feed*
- (*V*) ED -> ϵ
  - Condition verified: *plastered -> plaster*
  - Condition not verified: *bled -> bled*
- (*V*) ING -> ϵ
  - Condition verified: *motoring -> motor*
  - Condition not verified: *sing -> sing*

The Porter Stemmer: Step 2b (cleanup)

- (These rules are ran if second or third rule in 2a apply)
- AT-> ATE
  - *conflat(ed) -> conflate*
- BL -> BLE
  - *Troubl(ing) -> trouble*
- (*d & ! (*L or *S or *Z)) -> single letter
  - Condition verified: *hopp(ing) -> hop, tann(ed) -> tan*
  - Condition not verified: *fall(ing) -> fall*
- (m=1 & *o) -> E
  - Condition verified: *fil(ing) -> file*
  - Condition not verified: *fail -> fail*

The Porter Stemmer: Steps 3 and 4

- Step 3: Y Elimination (*V*) Y -> I
  - Condition verified: *happy -> happi*
  - Condition not verified: *sky -> sky*
- Step 4: Derivational Morphology, I
  - (m>0) ATIONAL -> ATE
    - *Relational -> relate*
  - (m>0) IZATION -> IZE
    - *generalization-> generalize*
  - (m>0) BILITI -> BLE
    - *sensibiliti -> sensible*

The Porter Stemmer: Step 7 (cleanup)

- Step 7a
  - (m>1) E -> ϵ
    - *probate -> probat*
  - (m=1 & !*o) NESS -> ϵ
    - *goodness -> good*
- Step 7b
  - (m>1 & *d & *L) -> single letter
    - Condition verified: *controll -> control*
    - Condition not verified: *roll -> roll*

Porter's algorithm
The most common English stemmer

Step 1a

sses	→ ss	caresses	→ caress
ies	→ i	ponies	→ poni
ss	→ ss	caress	→ caress
s	→ ø	cats	→ cat

Step 1b

(*v*)ing	→ ø	walking	→ walk
		sing	→ sing
(*v*)ed	→ ø	plastered	→ plaster

…

Step 2 (for long stems)

ational	→ ate	relational	→ relate
izer	→ ize	digitizer	→ digitize
ator	→ ate	operator	→ operate

…

Step 3 (for longer stems)

al	→ ø	revival	→ reviv
able	→ ø	adjustable	→ adjust
ate	→ ø	activate	→ activ

…

Viewing morphology in a corpus
Why only strip –ing if there is a vowel?

(*v*)ing → ø walking → walk
sing → sing

Viewing morphology in a corpus
Why only strip –ing if there is a vowel?

(*v*)ing → ø walking → walk
sing → sing

```
tr -sc "A-Za-z" "\n" < sample.txt | grep "ing$" | sort | uniq -c | sort -nr
```

```
1312 King
 548 being
 541 nothing
 388 king
 375 bring
 358 thing
 307 ring
 152 something
 145 coming
 130 morning
```

```
 548 being
 541 nothing
 152 something
 145 coming
 130 morning
 122 having
 120 living
 117 loving
 116 Being
 102 going
```

```
tr -sc "A-Za-z" "\n" < sample.txt | grep "[aeiou].*ing$" | sort | uniq -c | sort -nr
```

Dealing with complex morphology is sometimes necessary

- Some languages require complex morpheme segmentation
  - Turkish
  - Uygarlastiramadiklarimizdanmissinizcasina
  - `(behaving) as if you are among those whom we could not civilize'
  - Uygar `civilized' + las `become'
    + tir `cause' + ama `not able'
    + dik `past' + lar 'plural'
    + imiz 'p1pl' + dan 'abl'
    + mis 'past' + siniz '2pl' + casina 'as if'

Minimum Edit Distance

Definition of Minimum Edit Distance

How similar are two strings?

- Spell correction
  - The user typed “graffe”

    Which is closest?
    - graf
    - graft
    - grail
    - giraffe
- Computational Biology
  - Align two sequences of nucleotides

    AGGCTATCACCTGACCTCCAGGCCGATGCCC

    TAGCTATCACGACCGCGGTCGATTTGCCCGAC
  - Resulting alignment:

    –AGG**CTATCAC**CT**GACC**T**C**CA**GG**C**CGA--TGCCC**---

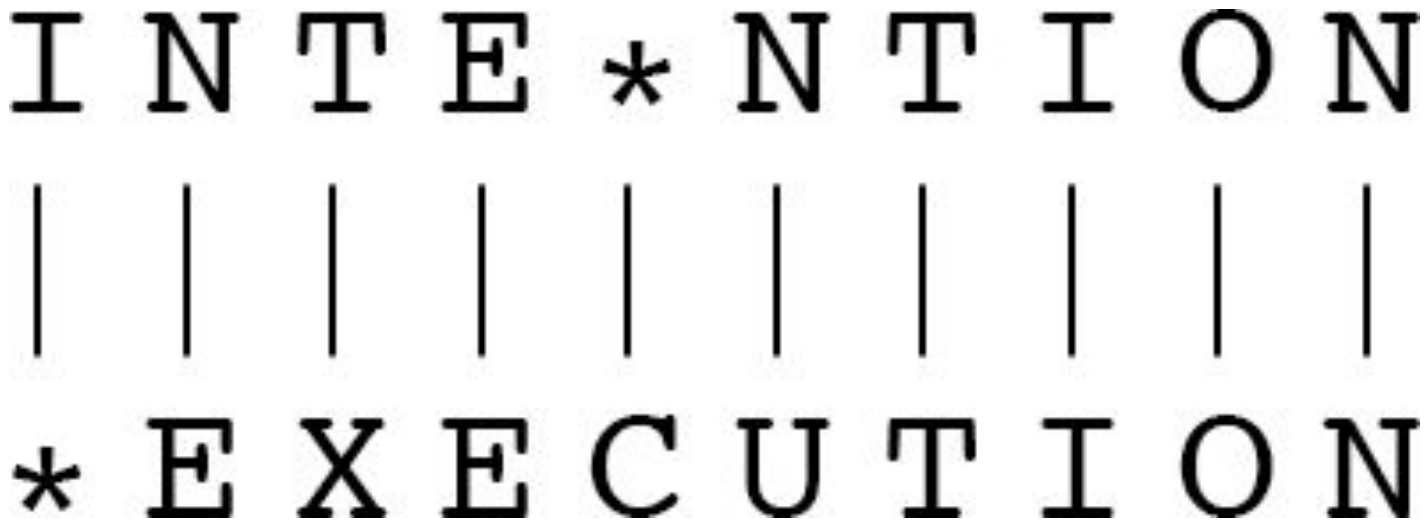
    T**AG–CTATCAC--GACC**G**C--GG**T**CGA**TT**TGCCC**GAC
- Also for Machine Translation, Information Extraction, Speech Recognition

Edit Distance

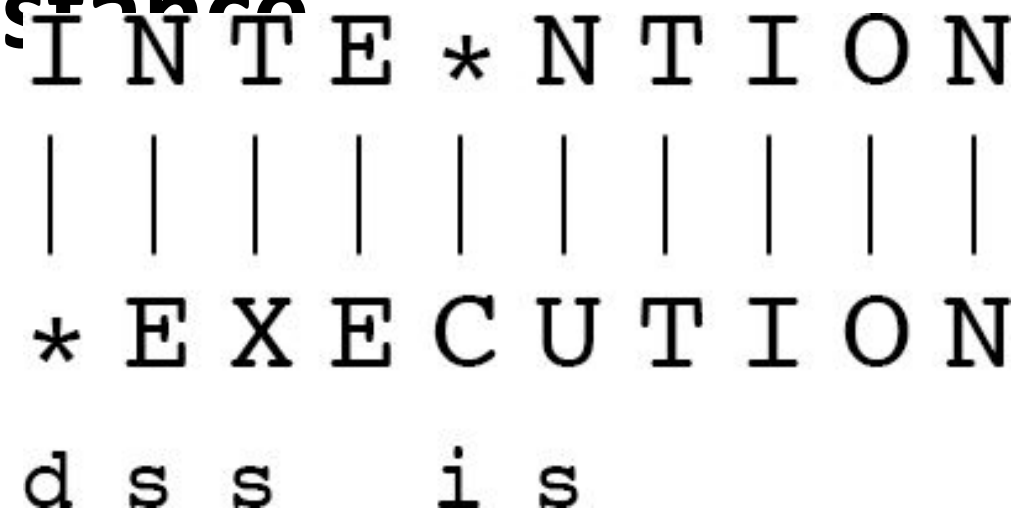
- The minimum edit distance between two strings
- Is the minimum number of editing operations
  - Insertion
  - Deletion
  - Substitution
- Needed to transform one into the other

Minimum Edit Distance

- Two strings and their **alignment**:



Minimum Edit Distance



- If each operation has cost of 1
  - Distance between these is 5
- If substitutions cost 2 (Levenshtein)
  - Distance between them is 8

Alignment in Computational Biology

- Given a sequence of bases

AGGCTATCACCTGACCTCCAGGCCGATGCCC

TAGCTATCACGACCGCGGTCGATTTGCCCGAC

- An alignment:

–AGG**CTATCAC**C**T****GACC**T**C**C**A****GG**C**CGA****––TGCCC****–––**

T**AG****–****CTATCAC****––****GACC**G**C****––****GG**T**CGA**T**T****TGCCC**GAC

- Given two sequences, align each letter to a letter or gap

Other uses of Edit Distance in NLP

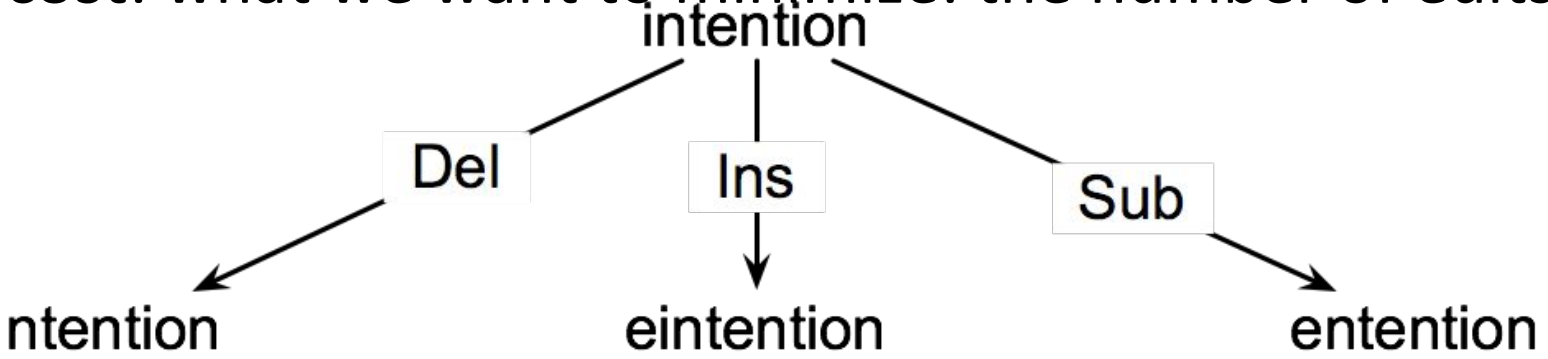
- Evaluating Machine Translation and speech recognition

```
R  Spokesman confirms senior government adviser was shot
H  Spokesman said the senior adviser was shot dead
D                I  S                              I
```

- Named Entity Extraction and Entity Coreference
  - IBM Inc. announced today
  - IBM profits
  - Stanford President John Hennessy announced yesterday
  - for Stanford University President John Hennessy

How to find the Min Edit Distance?

- Searching for a path (sequence of edits) from the start string to the final string:
  - **Initial state**: the word we're transforming
  - **Operators**: insert, delete, substitute
  - **Goal state**: the word we're trying to get to
  - **Path cost**: what we want to minimize: the number of edits



Minimum Edit as Search

- But the space of all edit sequences is huge!
  - We can't afford to navigate naïvely
  - Lots of distinct paths wind up at the same state.
    - We don't have to keep track of all of them
    - Just the shortest path to each of those revisted states.

Defining Min Edit Distance

- For two strings
  - X of length *n*
  - Y of length *m*
- We define D(*i,j*)
  - the edit distance between X[1..*i*] and Y[1..*j*]
    - i.e., the first *i* characters of X and the first *j* characters of Y
  - The edit distance between X and Y is thus D(*n,m*)

Minimum Edit Distance

Definition of Minimum Edit Distance

Minimum Edit Distance

Computing Minimum Edit Distance

Dynamic Programming for Minimum Edit Distance

- **Dynamic programming**: A tabular computation of D(*n,m*)
- Solving problems by combining solutions to subproblems.
- Bottom--up
  - We compute D(i,j) for small *i,j*
  - And compute larger D(i,j) based on previously computed smaller values
  - i.e., compute D(*i,j*) for all *i* (0 < *i* < n) and *j* (0 < j < m)

Defining Min Edit Distance (Levenshtein)

- Initialization

  $D(i,0) = i$

  $D(0,j) = j$

- Recurrence Relation:

  For each $i = 1 \ldots M = 1 \ldots N$

  For each j

$$D(i,j) = \min \begin{cases} D(i-1,j) + 1 \\ D(i,j-1) + 1 \\ D(i-1,j-1) + \begin{cases} 2; & \text{if } X(i) \neq Y(j) \\ 0; & \text{if } X(i) = Y(j) \end{cases} \end{cases}$$

- Termination:

  $D(N,M)$ is distance

The Edit Distance Table

N	9									
O	8									
I	7									
T	6									
N	5									
E	4									
T	3									
N	2									
I	1									
#	**0**	1	2	3	4	5	6	7	8	9
	#	E	X	E	C	U	T	I	O	N

The Edit Distance Table

N	9									
O	8									
I	7									
T	6									
N	5									
E	4									
T	3									
N	2									
I	1									
#	0	1	2	3	4	5	6	7	8	9
	#	E	X	E	C	U	T	I	O	N

$$D(i,j) = \min \begin{cases} D(i-1,j) + 1 \\ D(i,j-1) + 1 \\ D(i-1,j-1) + \begin{cases} 2; & \text{if } S_1(i) \neq S_2(j) \\ 0; & \text{if } S_1(i) = S_2(j) \end{cases} \end{cases}$$

Edit Distance

$$D(i,j) = \min \begin{cases} D(i-1,j) + 1 \\ D(i,j-1) + 1 \\ D(i-1,j-1) + \begin{cases} 2; & \text{if } S_1(i) \neq S_2(j) \\ 0; & \text{if } S_1(i) = S_2(j) \end{cases} \end{cases}$$

N	9									
O	8									
I	7									
T	6									
N	5									
E	4									
T	3									
N	2									
I	1									
#	**0**	1	2	3	4	5	6	7	8	9
	#	E	X	E	C	U	T	I	O	N

The Edit Distance Table

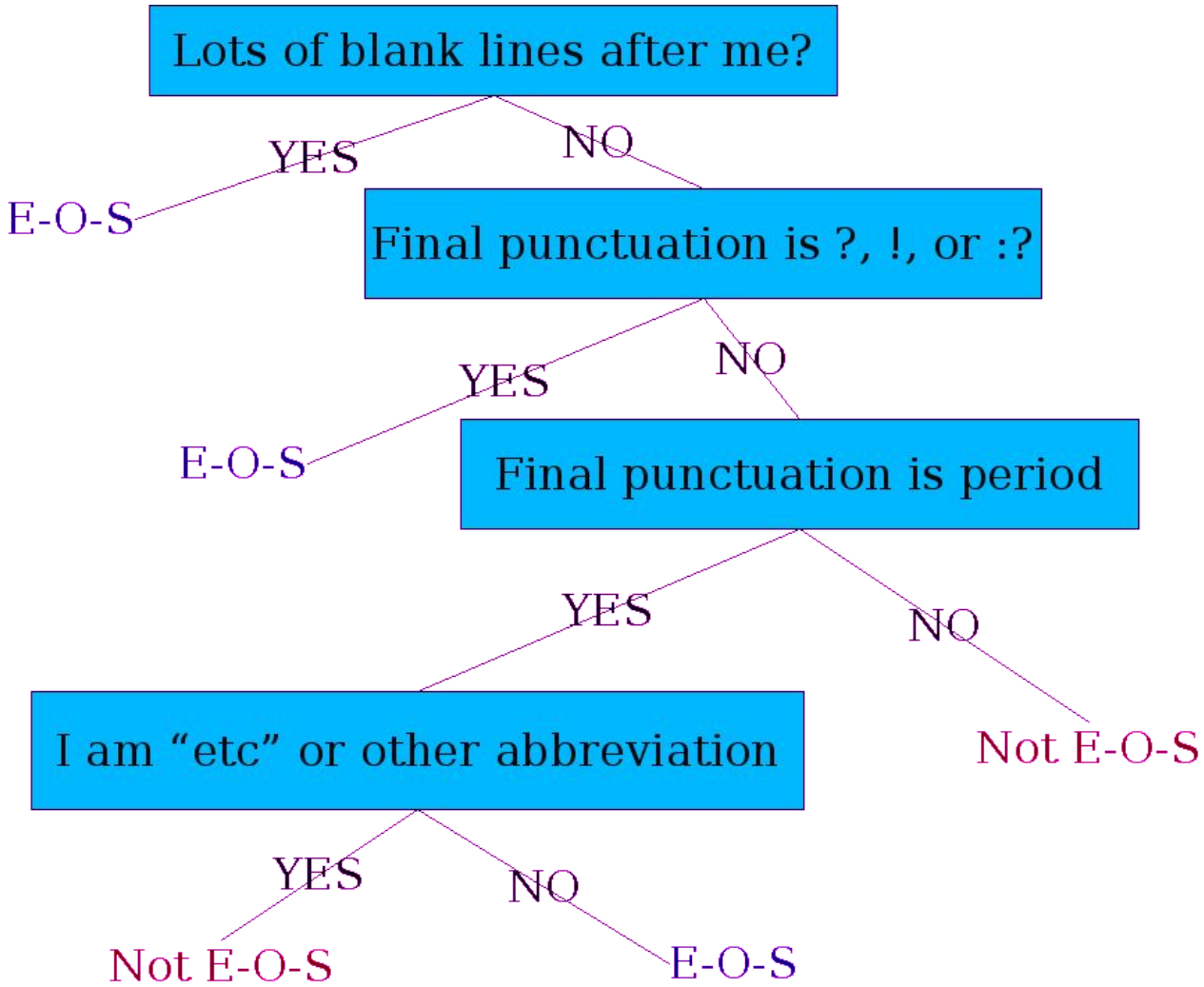
N	9	8	9	10	11	12	11	10	9	**8**
O	8	7	8	9	10	11	10	9	8	9
I	7	6	7	8	9	10	9	8	9	10
T	6	5	6	7	8	9	8	9	10	11
N	5	4	5	6	7	8	9	10	11	10
E	4	3	4	5	6	7	8	9	10	9
T	3	4	5	6	7	8	7	8	9	8
N	2	3	4	5	6	7	8	7	8	7
I	1	2	3	4	5	6	7	6	7	8
#	**0**	1	2	3	4	5	6	7	8	9
	#	E	X	E	C	U	T	I	O	N

Sentence Segmentation and Decision Trees

Sentence Segmentation

- !, ? are relatively unambiguous
- Period “.” is quite ambiguous
  - Sentence boundary
  - Abbreviations like Inc. or Dr.
  - Numbers like .02% or 4.3
- Build a binary classifier
  - Looks at a “.”
  - Decides EndOfSentence/NotEndOfSentence
  - Classifiers: hand-written rules, regular expressions, or machine-learning

Determining if a word is end-of-sentence: a Decision Tree



More sophisticated decision tree features

- Case of word with ".": Upper, Lower, Cap, Number
- Case of word after ".": Upper, Lower, Cap, Number

- Numeric features
  - Length of word with "."
  - Probability(word with "." occurs at end-of-s)
  - Probability(word after "." occurs at beginning-of-s)

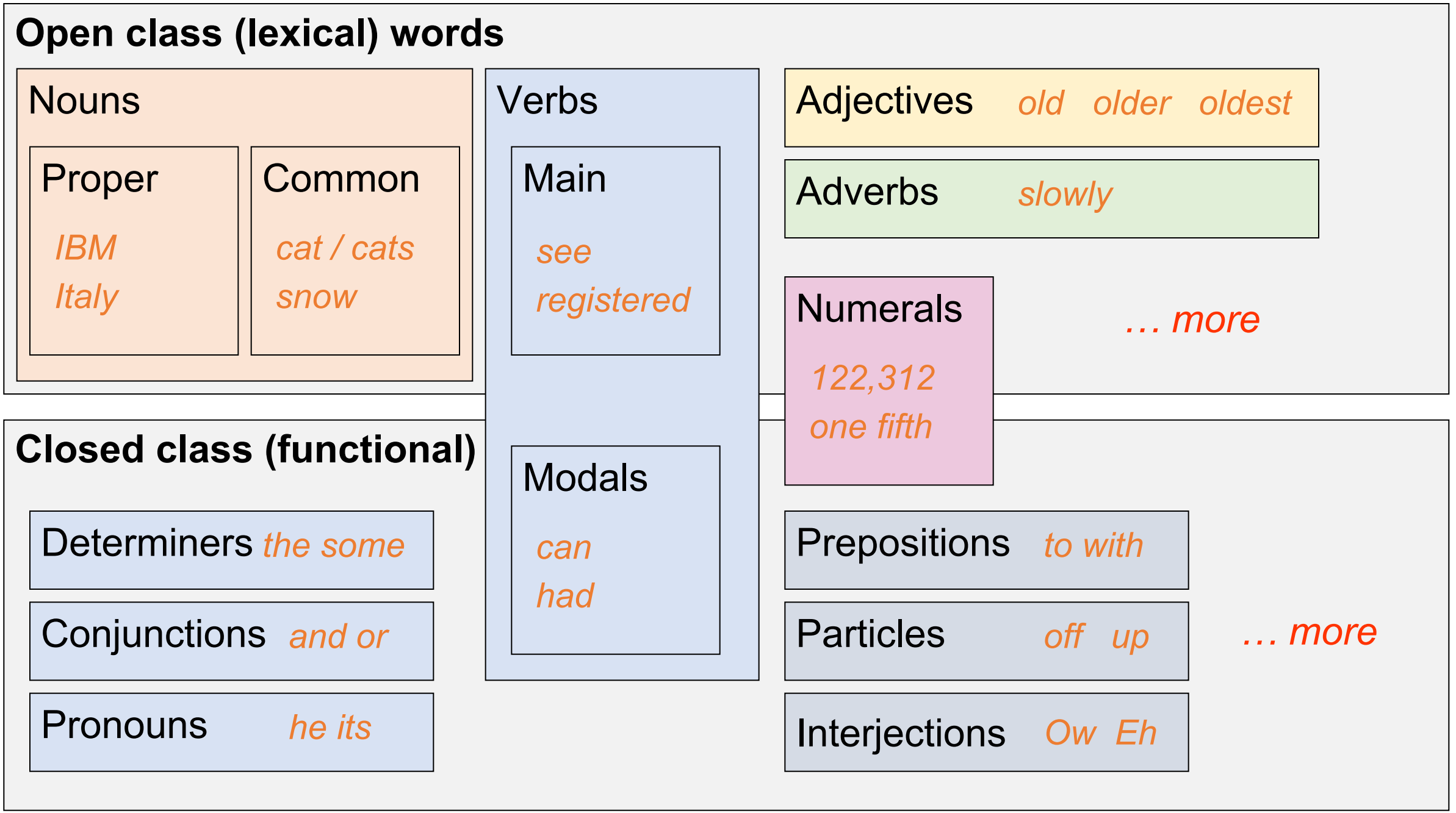
Implementing Decision Trees

- A decision tree is just an if-then-else statement
- The interesting research is choosing the features
- Setting up the structure is often too hard to do by hand
  - Hand-building only possible for very simple features, domains
    - For numeric features, it's too hard to pick each threshold
  - Instead, structure usually learned by machine learning from a training corpus

Decision Trees and other classifiers

- We can think of the questions in a decision tree as features that could be exploited by any kind of classifier:
  - Logistic regression
  - SVM
  - Neural Nets
  - etc.

Part-of-speech (POS) tagging


Open class (lexical) words
Nouns
Proper
IBM
Italy
Common
cat / cats
snow
Verbs
Main
see
registered
Modals
can
had
Adjectives old older oldest
Adverbs slowly
Numerals
122,312
one fifth
… more
Closed class (functional)
Determiners the some
Conjunctions and or
Pronouns he its
Prepositions to with
Particles off up
Interjections Ow Eh
… more

POS Tagging

- Words often have more than one POS: *back*
  - The *back* door = JJ
  - On my *back* = NN
  - Win the voters *back* = RB
  - Promised to *back* the bill = VB
- The POS tagging problem is to determine the POS tag for a particular instance of a word.

POS Tagging

- Input: Plays well with others
- Ambiguity: NNS/VBZ UH/JJ/NN/RB IN NNS
- Output: Plays/VBZ well/RB with/IN others/NNS
- Uses:
  - Text-to-speech (how do we pronounce “lead”?)
  - Can write regexps like (Det) Adj* N+ over the output for phrases, etc.
  - As input to or to speed up a full parser
  - If you know the tag, you can back off to it in other tasks

Penn Treebank POS tags

POS tagging performance

- How many tags are correct? (Tag accuracy)
  - About 97% currently
  - But baseline is already 90%
    - Baseline is performance of stupidest possible method
      - Tag every word with its most frequent tag
      - Tag unknown words as nouns
  - Partly easy because
    - Many words are unambiguous
    - You get points for them (*the*, *a*, etc.) and for punctuation marks!

Deciding on the correct part of speech can be difficult even for people

- Mrs/NNP Shaefer/NNP never/RB got/VBD around/RP to/TO joining/VBG
- All/DT we/PRP gotta/VBN do/VB is/VBZ go/VB around/IN the/DT corner/NN
- Chateau/NNP Petrus/NNP costs/VBZ around/RB 250/CD

How difficult is POS tagging?

- About 11% of the word types in the Brown corpus are ambiguous with regard to part of speech
- But they tend to be very common words. E.g., *that*
  - I know *that* he is honest = IN
  - Yes, *that* play was nice = DT
  - You can't go *that* far = RB
- 40% of the word tokens are ambiguous

Sources of information

- What are the main sources of information for POS tagging?
  - Knowledge of neighboring words
    - Bill saw that man yesterday
    - NNP NN DT NN NN
    - VB VB(D) IN VB NN
  - Knowledge of word probabilities
    - *man* is rarely used as a verb….
- The latter proves the most useful, but the former also helps

More and Better Features Feature-based tagger

- Can do surprisingly well just looking at a word by itself:
  - Word the: the → DT
  - Lowercased word Importantly: importantly → RB
  - Prefixes unfathomable: un- → JJ
  - Suffixes Importantly: -ly → RB
  - Capitalization Meridian: CAP → NNP
  - Word shapes 35-year: d-x → JJ
- Then build a maxent (or whatever) model to predict tag
  - Maxent P(t|w): 93.7% overall / 82.6% unknown

Use of POS tags in downstream NLP tasks

- Features in text classifiers (e.g. spam / not spam)
- Noun-phrase chunking

United Nations

NNP NNP

POS taggers

- Stanford POS tagger
  - https://nlp.stanford.edu/software/tagger.shtml
- Natural Language Tool Kit (NLTK)
  - https://www.nltk.org
- Illinois POS tagger
  - http://cogcomp.org/page/software_view/POS

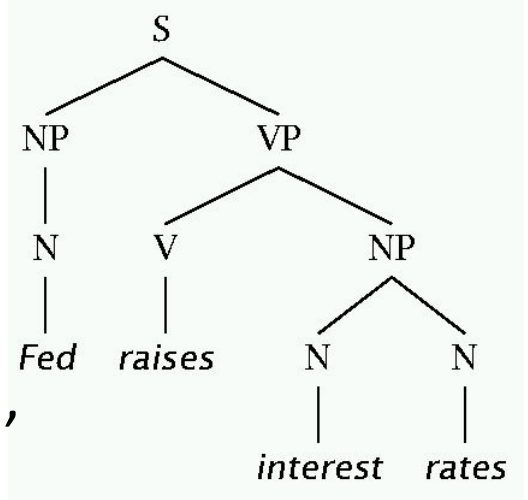
Syntactic parsing

Two views of linguistic structure

1. Constituency (phrase structure)
2. Dependency structure

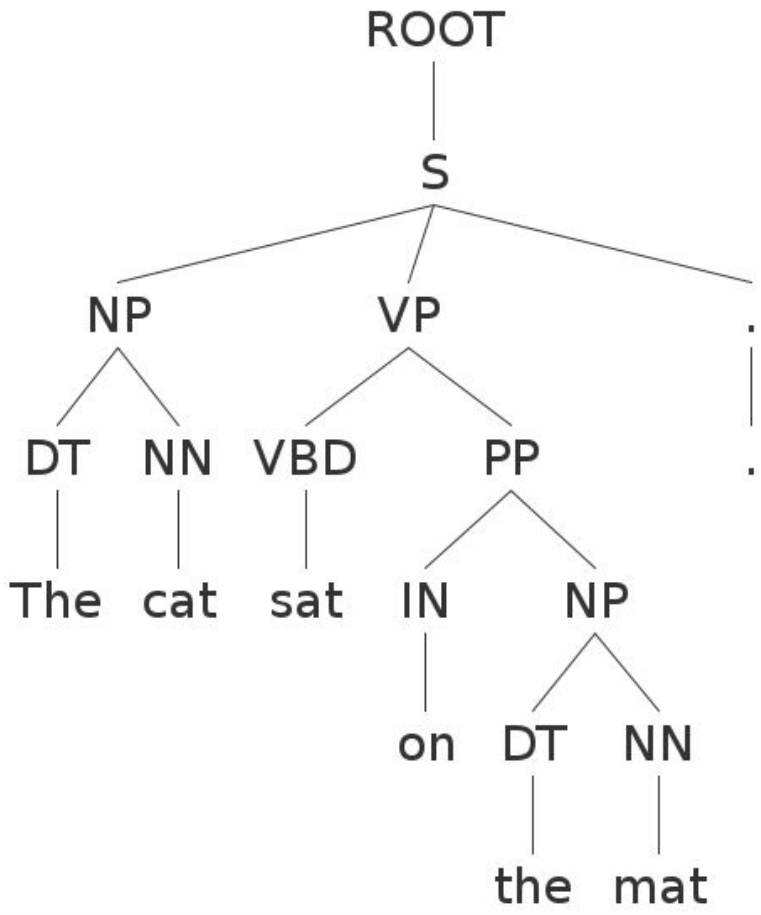
Two views of linguistic structure: 1. Constituency (phrase structure)

- Phrase structure organizes words into nested constituents.
- How do we know what is a constituent? (Not that linguists don't argue about some cases.)
  - Distribution: a constituent behaves as a unit that can appear in different places:
    - John talked [to the children] [about drugs].
    - John talked [about drugs] [to the children].
    - *John talked drugs to the children about
  - Substitution/expansion/pro-forms:
    - I sat [on the box/right on top of the box/there].
  - Coordination, regular internal structure, no intrusion, fragments, semantics, …



Parse Trees

“The cat sat on the mat”



Parse Trees

In bracket notation:

```
(ROOT
  (S
    (NP (DT the) (NN cat))
    (VP (VBD sat)
      (PP (IN on)
        (NP (DT the) (NN mat))))))
```

Grammars

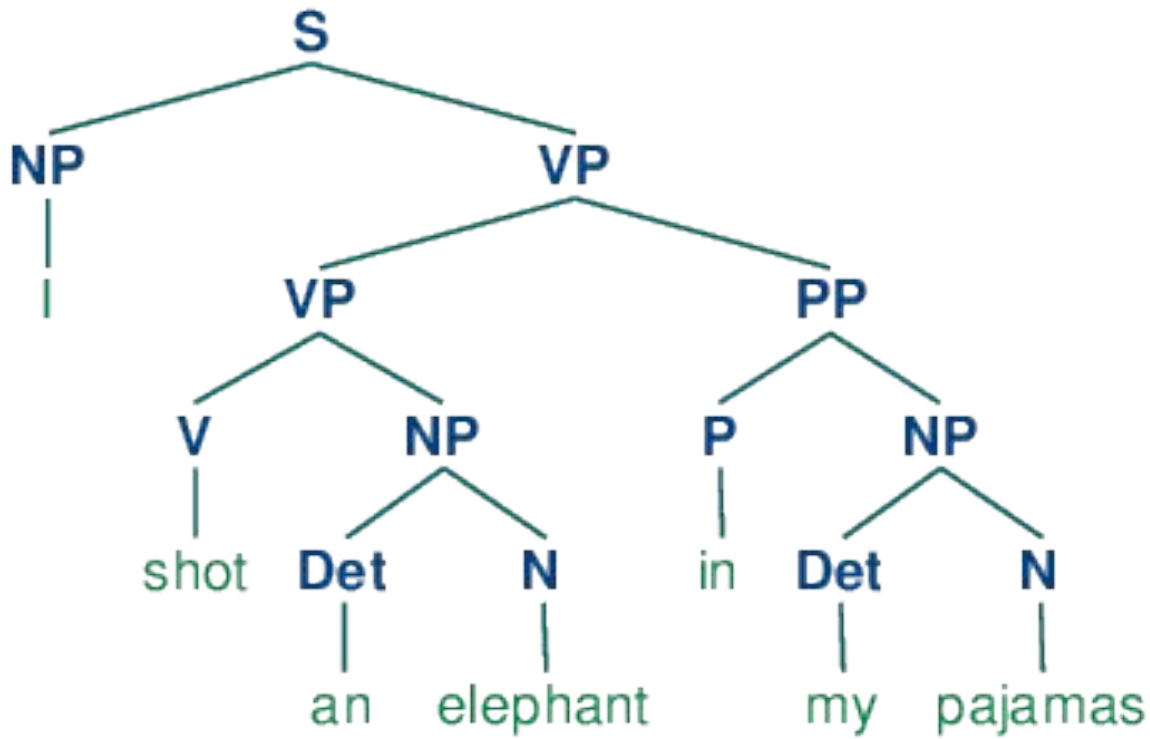
There are typically multiple ways to produce the same sentence. Consider the statement by Groucho Marx:

"While I was in Africa, I shot an elephant in my pajamas"

"How he got into my pajamas, I don't know"

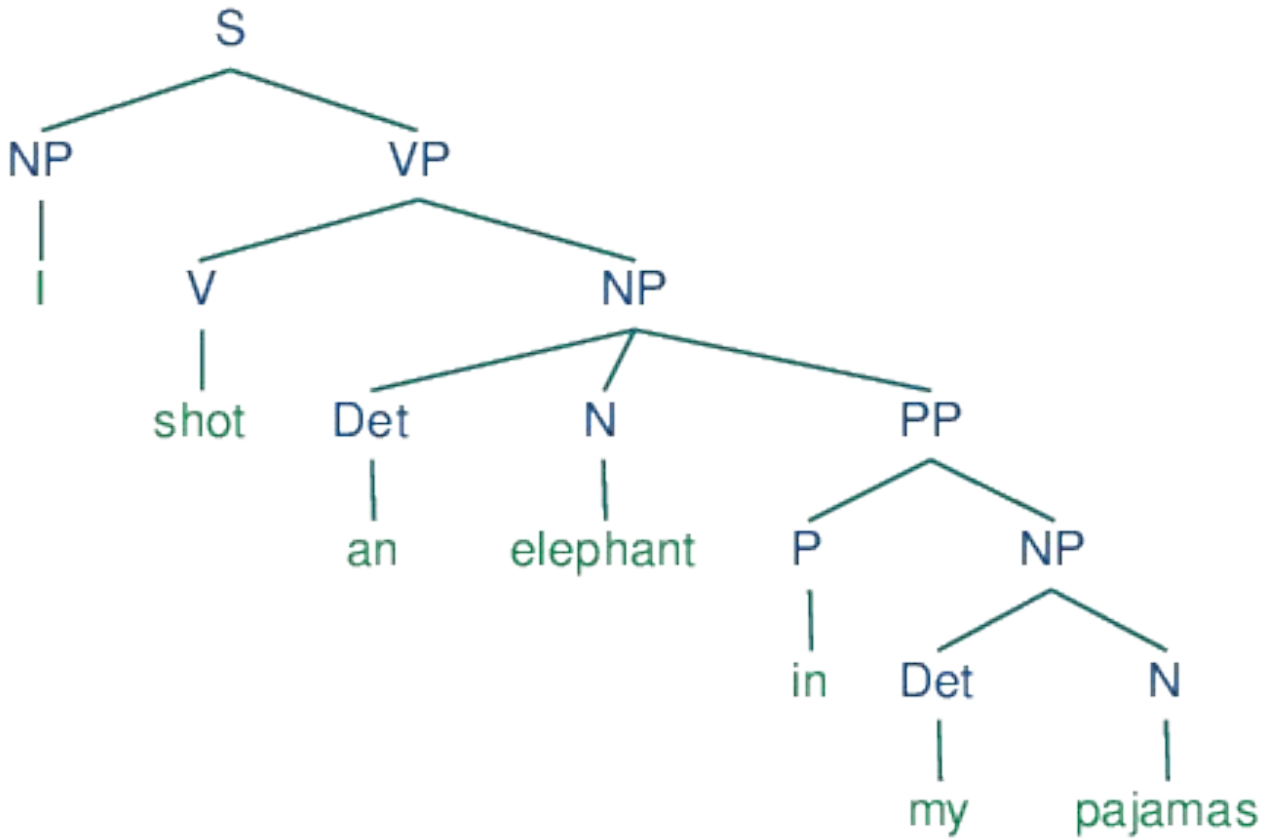
Parse Trees

"…,I shot an elephant in my pajamas" -what people hear first



Parse Trees

Groucho's version



Grammars

Its also possible to have “sentences” inside other sentences…

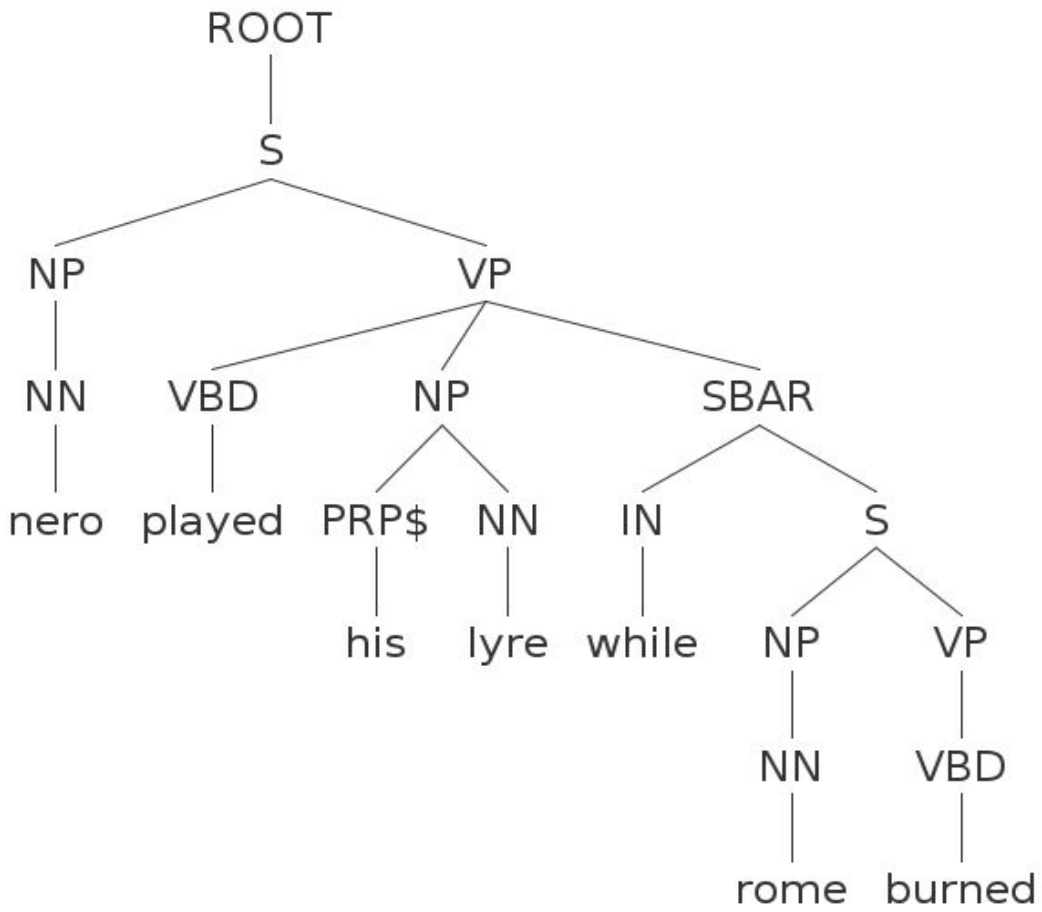
S → NP VP

VP → VB NP SBAR

SBAR → IN S

Recursion in Grammars

"Nero played his lyre while Rome burned".



Headed phrase structure

- VP → … VB* …
- NP → … NN* …
- ADJP → … JJ* …
- ADVP → … RB* …

- SBAR(Q) → S|SINV|SQ → … NP VP …

- Plus minor phrase types:
  - QP (quantifier phrase in NP), CONJP (multi word constructions: *as well as*), INTJ (interjections), etc.

PCFGs

Complex sentences can be parsed in many ways, most of which make no sense or are extremely improbable (like Groucho's example).

Probabilistic Context-Free Grammars (PCFGs) associate and learn probabilities for each rule:

S → NP VP 0.8

S → NP VP PP 0.2

The parser then tries to find the most likely sequence of productions that generate the given sentence. This adds more realistic "world knowledge" and generally gives much better results.

Most state-of-the-art parsers these days use PCFGs.

Systems

- **NLTK:** Python-based NLP system. Many modules, good visualization tools, but not quite state-of-the-art performance.

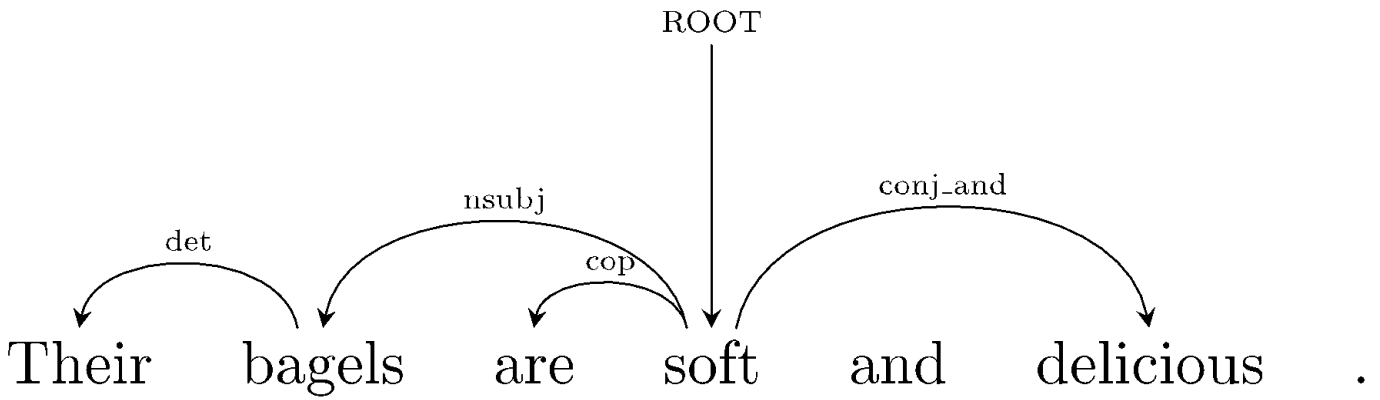
- **Stanford Parser:** Another comprehensive suite of tools (also POS tagger), and state-of-the-art accuracy. Has the definitive dependency module.

- **Berkeley Parser:** Slightly higher parsing accuracy (than Stanford) but not as many modules.

- Note: high-quality dependency parsing is usually very slow, but see: https://github.com/dlwh/puck

Two views of linguistic structure: 2. Dependency structure

Dependency structure shows which words depend on (modify or are arguments of) which other words.



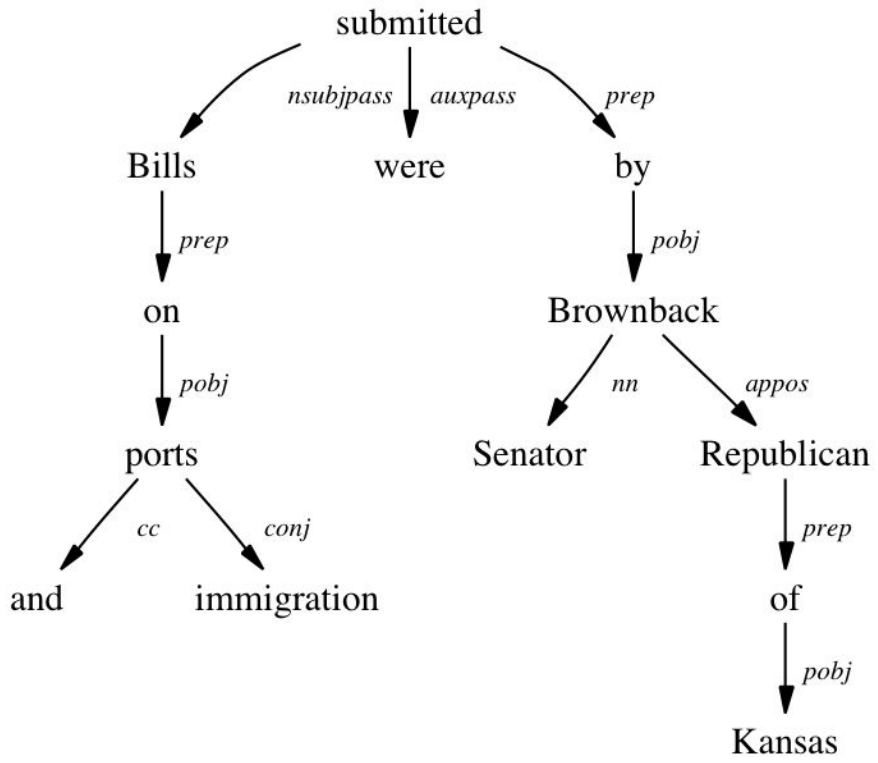
- “Their bagels are soft and delicious.”

  root (ROOT-0 , soft-4)
  nmod:poss (bagels-2 , Their-1)
  nsubj (soft-4 , bagels-2)
  nsubj (delicious-6 , bagels-2)
  cop (soft-4 , are-3)
  cc (soft-4 , and-5)
  conj:and (soft-4 , delicious-6)

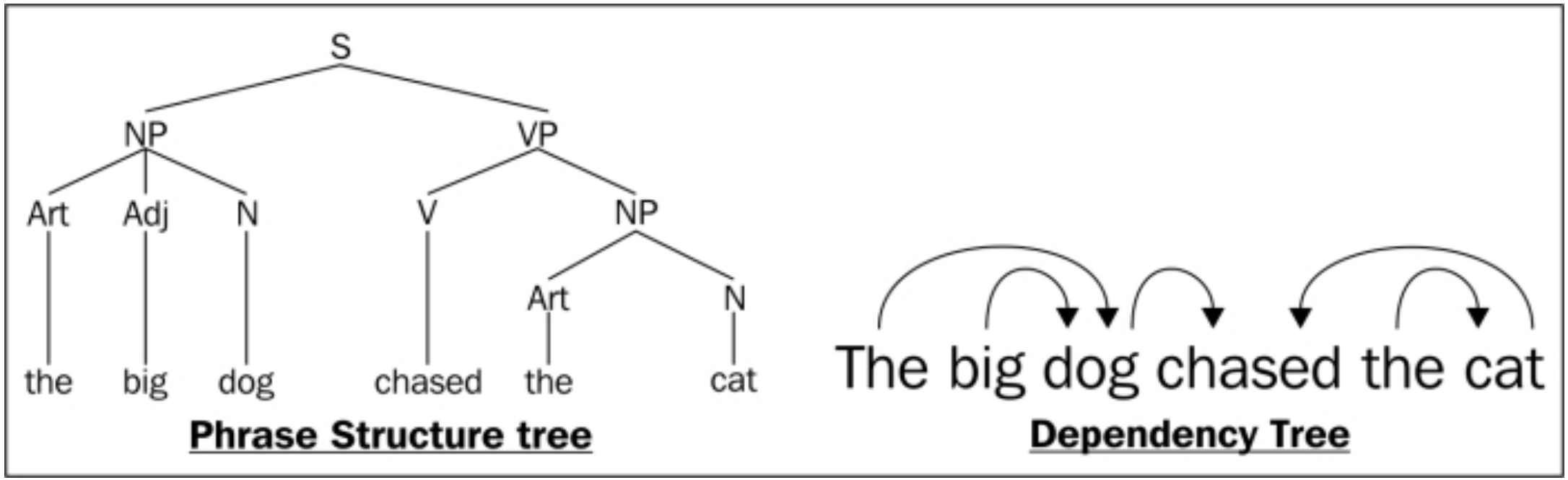
- Typed dependency (relationship) between two words: **head** and **modifier**. Also known as **governor** and **dependent.**

Dependency Parsing

Dependency parses may be non-binary, and structure type is encoded in links rather than nodes:



Comparison between constituent (phrase) and dependency trees



Dependency parser

- Stanford dependency parser

https://nlp.stanford.edu/software/stanford-dependencies.shtml

Statistical parsing applications

Statistical parsers are now robust and widely used in larger NLP applications:

- High precision question answering [Pasca and Harabagiu SIGIR 2001]
- Improving biological named entity finding [Finkel et al. JNLPBA 2004]
- Syntactically based sentence compression [Lin and Wilbur 2007]
- Extracting opinions about products [Bloom et al. NAACL 2007]
- Improved interaction in computer games [Gorniak and Roy 2005]
- Helping linguists find data [Resnik et al. BLS 2005]
- Source sentence analysis for machine translation [Xu et al. 2009]
- Relation extraction systems [Fundel et al. Bioinformatics 2006]

Credits

- Some slides have been adapted from:

https://web.stanford.edu/~jurafsky/NLPCourseraSlides.html