Language Modelling: Advanced Smoothing Models

Niloy Ganguly

CSE, IITKGP

Week 3

Advanced smoothing algorithms

Some Examples

- Good-Turing
- Kneser-Ney

Advanced smoothing algorithms

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- Good-Turing
- Kneser-Ney

Good-Turing: Basic Intuition

Use the count of things we have see once

- to help estimate the count of things we have never seen

N_c: Frequency of frequency c

Example Sentences

<s>I am here </s>
<s>who am I </s>
<s>I would like </s>

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Computing N_c

I	3	
am	2	
here	1	$N_1 = 4$
who	1	$N_2 = 1$
would	1	$N_3 = 1$
like	1	

Good Turing Estimation

Idea

- Reallocate the probability mass of $n-$grams that occur $r+1$ times in the training data to the $n-$grams that occur r times
- In particular, reallocate the probability mass of $n-$grams that were seen once to the $n-$grams that were never seen

Adjusted count

For each count c, an adjusted count c^* is computed as:

$$c^* = \frac{(c+1)N_{c+1}}{N_c}$$

where N_c is the number of $n-$grams seen exactly c times

Good Turing Estimation

Good Turing Smoothing

P^*_{GT}(things with frequency c) $= \frac{c^*}{N}$

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What if $c = 0$

P^*_{GT}(things with frequency c) = $\frac{N_1}{N}$ where N denotes the total number of bigrams that actually occur in training

Complications

What about words with high frequency?

- For small c, $N_c > N_{c+1}$
- For large c, too jumpy

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Simple Good-Turing

Replace empirical N_k with a best-fit power law once counts get unreliable

Good-Turing numbers: Example

22 million words of AP Neswire

$$c^* = \frac{(c+1)N_{c+1}}{N_c}$$

Count c	Good Turing c*
0	.0000270
1	0.446
2	1.26
3	2.24
4	3.24
5	4.22
6	5.19
7	6.21
8	7.24
9	8.25

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It looks like $c^* = c - 0.75$

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But can we do better than using the regular unigram correct?

Kneser-Ney Smoothing

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Instead, $P_{continuation}(w)$: "How likely is w to appear as a novel continuation?"

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- Every bigram type was a novel continuation the first time it was seen

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A frequent word (Francisco) occurring in only one context (San) will have a low continuation probability

Kneser-Ney Smoothing

$$P_{KN}(w_i|w_{i-1}) = \frac{max(c(w_{i-1}, w_i) - d, 0)}{c(w_{i-1})} + \lambda(w_{i-1})P_{continuation}(w_i)$$

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λ is a normalizing constant

$$\lambda(w_{i-1}) = \frac{d}{c(w_{i-1})}|\{w : c(w_{i-1},w) > 0\}|$$

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A general approach is to combine the results of multiple N-gram models.

Backoff and Interpolation

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Interpolation

mix unigram, bigram, trigram

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Estimating $P(w_i|w_{i-2}w_{i-1})$

- If we do not have counts to compute $P(w_i|w_{i-2}w_{i-1})$ estimate this using the bigram probbaility $P(w_i|w_{i-1})$

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- If we do not have counts to compute $P(w_i|w_{i-1})$, estimate this using the unigram probability $P(w_i)$

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- If we do not have counts to compute $P(w_i|w_{i-1})$, estimate this using the unigram probability $P(w_i)$

$P_{bo}(w_i|w_{i-2}w_{i-1})=$

- $\hat{P}(w_i|w_{i-2}w_{i-1})$, if $c(w_{i-2}w_{i-1}w_i) > 0$
- $\lambda(w_{i-1}w_{i-2})P_{bo}(w_i|w_{i-1})$, otherwise

where $P_{bo}(w_i|w_{i-1})$ =

- $\hat{P}(w_i|w_{i-1})$ if $c(w_{i-1}w_i) > 0$
- $\lambda(w_{n-1})\hat{P}(w_n)$, otherwise

Example Problem

In a corpus, suppose there are 4 words, a, b, c, and d. You are provided with the following counts.

n-gram	count	n-gram	count	n-gram	count
aba	4	ba	5	a	8
abb	0	bb	3	b	9
abc	0	bc	0	c	8
abd	0	bd	0	d	7

Use the recursive definition of backoff smoothing to obtain the probability distribution, $P_{backoff}(w_n|w_{n-2}w_{n-1})$, where $w_{n-1} = b$ and $w_{n-2} = a$.
Also assume that $\hat{P}(x) = P(x) - 1/8$.

Linear Interpolation

Simple Interpolation

$$\tilde{P}(w_n|w_{n-1}w_{n-2}) = \lambda_1 P(w_n|w_{n-1}w_{n-2}) + \lambda_2 P(w_n|w_{n-1}) + \lambda_3 P(w_n)$$

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Lambdas conditional on context

$$\tilde{P}(w_n|w_{n-1}w_{n-2}) = \lambda_1(w_{n-2}, w_{n-1})P(w_n|w_{n-1}w_{n-2})$$

$$+\lambda_2(w_{n-2}, w_{n-1})P(w_n|w_{n-1}) + \lambda_3(w_{n-2}, w_{n-1})P(w_n)$$

Setting the lambda values

Computational Morphology

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Morphology

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---

unladylike

3 morphemes

- un- 'not'
- lady 'well-behaved woman'
- -like 'having the characteristic of'

Allomorphs

Variants of the same morpheme, but cannot be replaced by one another

Example

- opposite: un-happy, in-comprehensible, im-possible, ir-rational

Bound and Free Morphemes

Bound

Cannot appear as a word by itself.
-s (dog-s), -ly (quick-ly), -ed (walk-ed)

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Free

Can appear as a word by itself; often can combine with other morphemes too.
house (house-s), walk (walk-ed), of, the, or

Stems and Affixes

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- Affixes: Bits and pieces adhering to stems to change their meanings and grammatical functions

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Mostly, stems are free morphemes and affixes are bound morphemes

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  Philippines: basa 'read' → b-um-asa 'read'
  English: abso-bloody-lutely (emphasis)
- Circumfixes - precedes and follows the stem
  Dutch: berg 'mountain', ge-berg-te 'mountains'

Content and functional morphemes

Content morphemes

Carry some semantic content

car, -able, un-

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Functional morphemes

Provide grammatical information
-s (plural), -s (3rd singular)

Inflectional and Derivational Morphology

Two different kind of relationship among words

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Grammatical: number, tense, case, gender

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Fairly systematic but some derivations missing: *sincere - sincerity, scarce - scarcity, curious - curiosity, fierce - fiercity?*

Morphological processes

Concatenation

Adding continuous affixes - the most common process:

- hope+less, un+happy, anti+capital+ist+s

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Often, there are phonological/graphemic changes on morpheme boundaries:

- book + s [s], shoe + s [z]
- happy +er $\rightarrow$ happier

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- Phrasal reduplication (Telugu): *pillavāḍu naḍustū naḍustū paḍi pōyāḍu* (The child fell down while walking)

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Suppletion

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Morpheme internal changes

The word changes internally
sing - sang - sung, man - men, goose - geese

Word Formation

Compounding

Words formed by combining two or more words

Example in English:

- Adj + Adj $\rightarrow$ Adj: bitter-sweet

- N + N $\rightarrow$ N: rain-bow

- V + N $\rightarrow$ V: pick-pocket

- P + V $\rightarrow$ V: over-do

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room-temperature: Hindi translation?

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doctor, laboratory, advertisement, dormitory, examination, bicycle, refrigerator

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- Morpheme segmentation: de-nation-al-iz-ation
- Generation: see + verb.past $\rightarrow$ saw

What are the applications?

- Text-to-speech synthesis:
  lead:

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  lead: verb or noun?
  read:

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- Text-to-speech synthesis:
  lead: verb or noun?
  read: present or past?
- Search and information retrieval
- Machine translation, grammar correction

Morphological Analysis

Input	Morphological Parsed Output
cats	cat +N +PL
cat	cat +N +SG
cities	city +N +PL
geese	goose +N +PL
goose	(goose +N +SG) or (goose +V)
gooses	goose +V +3SG
merging	merge +V +PRES-PART
caught	(catch +V +PAST-PART) or (catch +V +PAST)

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Goal

To take input forms like those in the first column and produce output forms like those in the second column.

Output contains stem and additional information; +N for noun, +SG for singular, +PL for plural, +V for verb etc.

Issues involved

boy → boys

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boy → boys
fly → flys → flies (y→ i rule)

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- Getter $\rightarrow$ get + er
- Doer $\rightarrow$ do + er

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- Beer $\rightarrow$ be + er?

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Duck is a possible root, not *duckl*.
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Spelling change rules

Adjust the surface form using spelling change rules

- Get + er → getter

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- Sanskrit: 11 million forms from a lexicon of 170,000 entries, a ratio of 64.7:1

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- English: just 317,477 forms from 90,196 lexical entries, a ratio of 3.5:1
- Sanskrit: 11 million forms from a lexicon of 170,000 entries, a ratio of 64.7:1
- New forms can be created, compounding etc.

One of the most common methods is finite-state-machines

Finite-state methods for morphology

Niloy Ganguly

CSE, IITKGP

Week 3

Finite State Automaton (FSA)
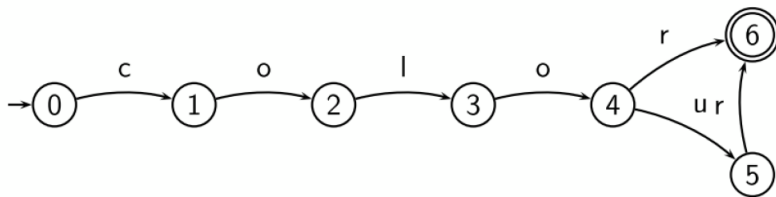
What is FSA?

- A kind of directed graph

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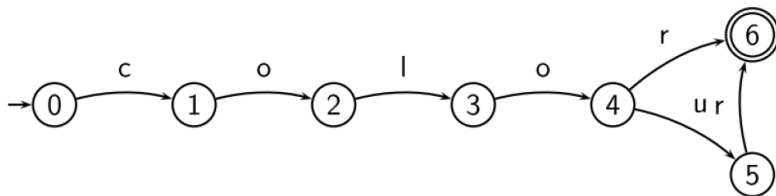
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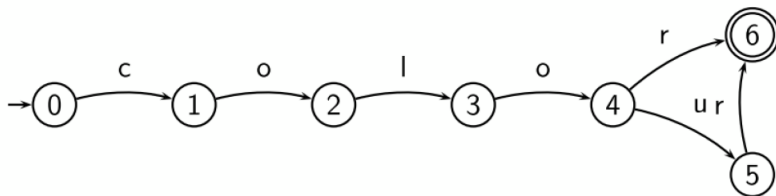
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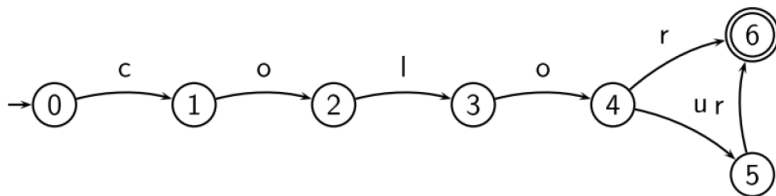
What is FSA?

- A kind of directed graph
- Nodes are called states, edges are labeled with symbols (possibly empty ε)
- Start state and accepting states
- Recognizes regular languages, i.e., languages specified by regular expressions

FSA for nominal inflection in English
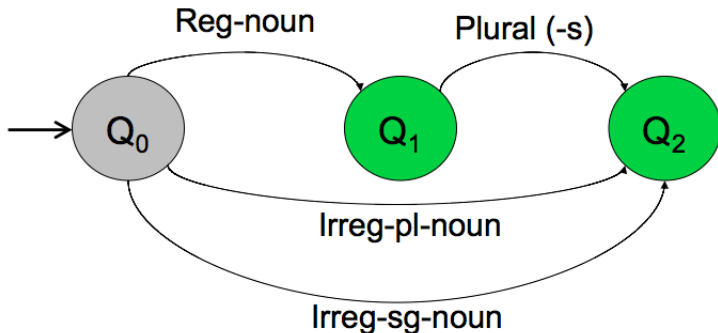
FSA for English Adjectives
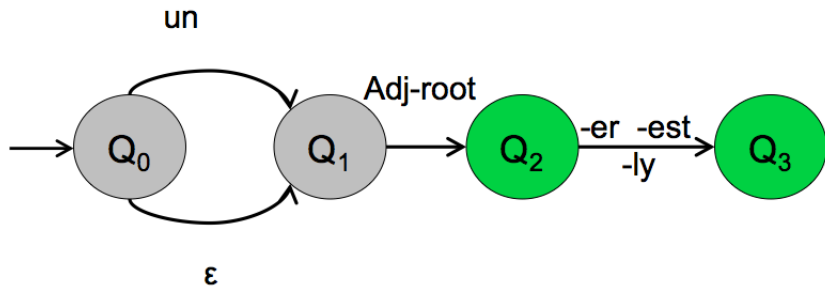
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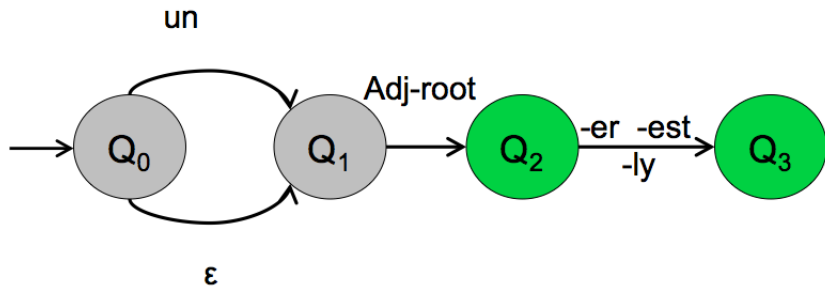
Word modeled

happy, happier, happiest, real, unreal, cool, coolly, clear, clearly, unclear, unclearly, ...

Morphotactics

- The last two examples model some parts of the English morphotactics
- But what about the information about regular and irregular roots?

Morphotactics

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Lexicon

Can we include the lexicon in the FSA?

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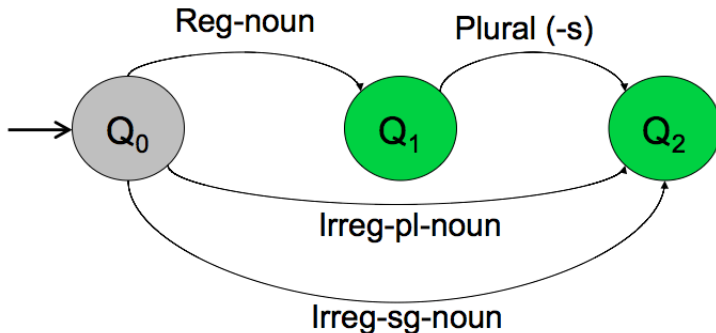
After adding a mini-lexicon
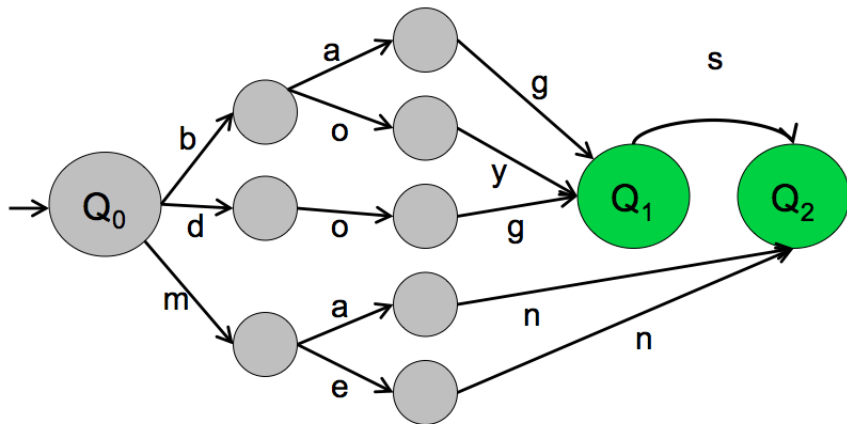
Some properties of FSAs: Elegance

- Recognizing problem can be solved in linear time (independent of the size of the automaton)
- There is an algorithm to transform each automaton into a unique equivalent automaton with the least number of states
- An FSA is deterministic iff it has no empty (ε) transition and for each state and each symbol, there is at most one applicable transition
- Every non-deterministic automaton can be transformed into a deterministic one

But ...

FSAs are language recognizers/generators.

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We need transducers to build Morphological Analyzers

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We need transducers to build Morphological Analyzers

Finite State Transducers

- Translate strings from one language to strings in another language
- Like FSA, but each edge is associated with two strings

An example FST
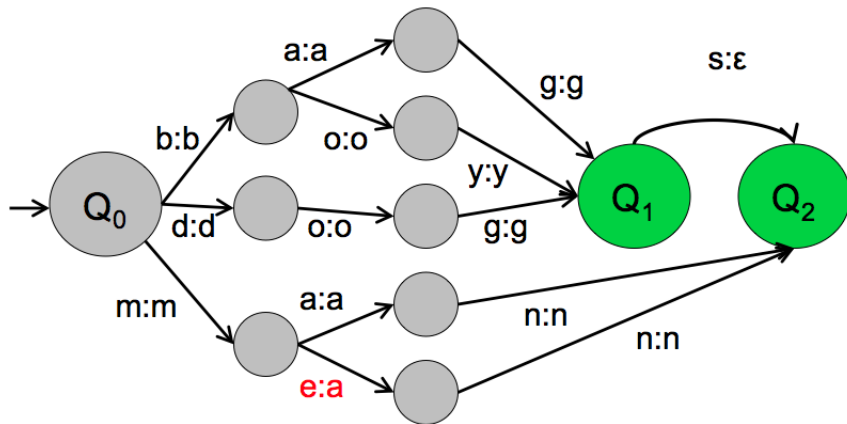
Two-level morphology

Given the input *cats*, we would like to output *cat+N+PL*, telling us that cat is a plural noun.

We do this via a version of **two-level morphology**, a correspondence between a lexical level (morphemes and features) to a surface level (actual spelling).
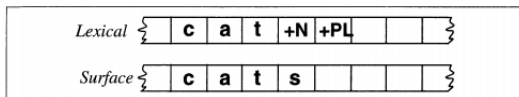
English Nominal Inflection FST
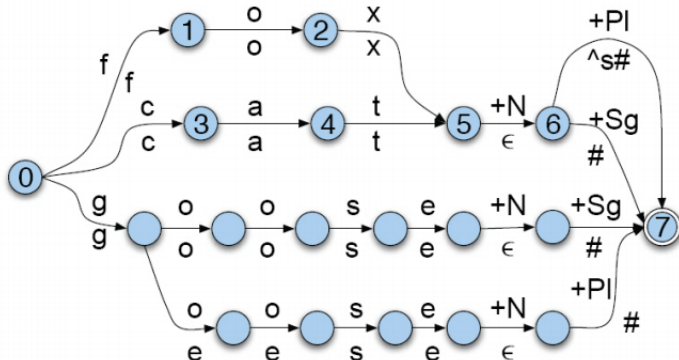
Spelling Handling

A spelling change rule would insert an e only in the appropriate environment.

Rule Handling - Context Sensitive

Rule Notation

$a \rightarrow b/c\_d$: "rewrite a as b when it occurs between c and d."

Morphological Analysis: Approaches

Two different ways to address phonological/graphemic variations

- Linguistic approach: A phonological component accompanying the simple concatenative process of attaching an ending

- Engineering approach: Phonological changes and irregularities are factored into endings and a higher number of paradigms

Different Approaches: Example from Czech

	woman	owl	draft	iceberg	vapor	fly
S1	žen-a	sov-a	skic-a	kr-a	pár-a	mouch-a
S2	žen-y	sov-y	skic-i	kr-y	pár-y	mouch-y
S3	žen-ě	sov-ě	skic-e	kř-e	pář-e	mouš-e
⋮						
P2	žen-0	sov-0	skic-0	ker-0	par-0	much-0

A linguistic approach

$$
žen + \begin{cases} a \\ y \\ ě \\ 0 \end{cases}
\quad sov + \begin{cases} a \\ y \\ ě \\ 0 \end{cases}
\quad skic + \begin{cases} a \\ y \\ ě \\ 0 \end{cases}
\quad kr + \begin{cases} a \\ y \\ ě \\ 0 \end{cases}
\quad pár + \begin{cases} a \\ y \\ ě \\ 0 \end{cases}
\quad mouch + \begin{cases} a \\ y \\ ě \\ 0 \end{cases}
$$

An engineering approach

$$
žen + \begin{cases} a \\ y \\ ě \\ 0 \end{cases}
\quad sov + \begin{cases} a \\ y \\ ě \\ 0 \end{cases}
\quad skic + \begin{cases} a \\ i \\ e \\ 0 \end{cases}
\quad k + \begin{cases} ra \\ ry \\ ře \\ er \end{cases}
\quad p + \begin{cases} ára \\ áry \\ áře \\ ar \end{cases}
\quad m + \begin{cases} oucha \\ ouchy \\ ouše \\ uch \end{cases}
$$

Tools Available

- AT&T FSM Library and Lextools
  http://www2.research.att.com/~fsmtools/fsm/
- OpenFST (Google and NYU)
  http://www.openfst.org/

Introduction to POS Tagging

Niloy Ganguly

CSE, IITKGP

Week 3

Part-of-Speech (POS) tagging
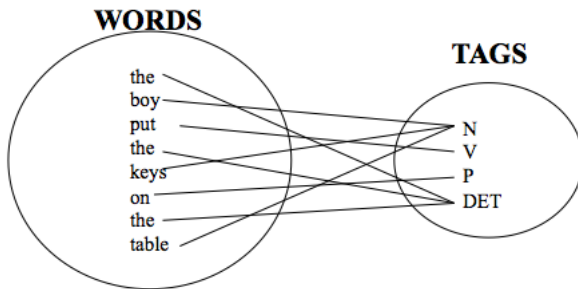
Part-of-Speech (POS) tagging

Task

Given a text of English, identify the parts of speech of each word

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Parts of Speech: How many?

Open class words (content words)

- nouns, verbs, adjectives, adverbs
- mostly content-bearing: they refer to objects, actions, and features in the world
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- nouns, verbs, adjectives, adverbs
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Closed class words

- pronouns, determiners, prepositions, connectives, ...
- there is a limited number of these
- *mostly functional:* to tie the concepts of a sentence together

POS examples

- N — noun — chair, bandwidth, pacing
- V — verb — study, debate, munch
- ADJ — adj — purple, tall, ridiculous
- ADV — adverb — unfortunately, slowly,
- P — preposition — of, by, to
- PRO — pronoun — I, me, mine
- DET — determiner — the, a, that, those

POS tagging: Choosing a tagset

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POS tagging: Choosing a tagset

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A Nice Tutorial on POS tags

https://sites.google.com/site/partofspeechhelp/

UPenn TreeBank POS tag set

Tag	Description	Example	Tag	Description	Example
CC	Coordin. Conjunction	*and, but, or*	SYM	Symbol	*+,%, &*
CD	Cardinal number	*one, two, three*	TO	"to"	*to*
DT	Determiner	*a, the*	UH	Interjection	*ah, oops*
EX	Existential 'there'	*there*	VB	Verb, base form	*eat*
FW	Foreign word	*mea culpa*	VBD	Verb, past tense	*ate*
IN	Preposition/sub-conj	*of, in, by*	VBG	Verb, gerund	*eating*
JJ	Adjective	*yellow*	VBN	Verb, past participle	*eaten*
JJR	Adj., comparative	*bigger*	VBP	Verb, non-3sg pres	*eat*
JJS	Adj., superlative	*wildest*	VBZ	Verb, 3sg pres	*eats*
LS	List item marker	*1, 2, One*	WDT	Wh-determiner	*which, that*
MD	Modal	*can, should*	WP	Wh-pronoun	*what, who*
NN	Noun, sing. or mass	*llama*	WP$	Possessive wh-	*whose*
NNS	Noun, plural	*llamas*	WRB	Wh-adverb	*how, where*
NNP	Proper noun, singular	*IBM*	\$	Dollar sign	*\$*
NNPS	Proper noun, plural	*Carolinas*	#	Pound sign	*#*
PDT	Predeterminer	*all, both*	"	Left quote	*(' or ")*
POS	Possessive ending	*'s*	"	Right quote	*(' or ")*
PRP	Personal pronoun	*I, you, he*	(	Left parenthesis	*([, (, {, <)*
PRP$	Possessive pronoun	*your, one's*	)	Right parenthesis	*( ],), }, >)*
RB	Adverb	*quickly, never*	,	Comma	*,*
RBR	Adverb, comparative	*faster*	.	Sentence-final punc	*(. ! ?)*
RBS	Adverb, superlative	*fastest*	:	Mid-sentence punc	*(: ; ... − -)*
RP	Particle	*up, off*			

Using the UPenn tagset

Example Sentence

The grand jury commented on a number of other topics.

Using the UPenn tagset

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POS tagged sentence

The/DT grand/JJ jury/NN commmented/VBD on/IN a/DT number/NN of/IN
other/JJ topics/NNS ./.

Why is POS tagging hard?

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Words often have more than one POS: back

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POS tagging problem

To determine the POS tag for a particular instance of a word

Ambiguous word types in the Brown Corpus

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- 40% of word tokens are ambiguous
- 12% of word types are ambiguous

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- 40% of word tokens are ambiguous
- 12% of word types are ambiguous
- Breakdown of ambiguous word types:

Unambiguous (1 tag)	35,340
Ambiguous (2–7 tags)	4,100
2 tags	3,760
3 tags	264
4 tags	61
5 tags	12
6 tags	2
7 tags	1 ("still")

How bad is the ambiguity problem?

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- Any new approach should be compared against the unigram baseline (assigning each token to its most likely tag)

Deciding the correct POS

Can be difficult even for people

- Mrs./NNP Shaefer/NNP never/RB got/VBD around/_ to/TO joining/VBG.

- All/DT we/PRP gotta/VBN do/VB is/VBZ go/VB around/_ the/DT corner/NN.

- Chateau/NNP Petrus/NNP costs/VBZ around/_ 2500/CD.

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The word itself

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Local context

- Two determiners rarely follow each other
- Two base form verbs rarely follow each other
- Determiner is almost always followed by adjective or noun

POS tagging: Two approaches

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Statistical tagging

- Get a training corpus of tagged text, learn the transformation rules from the most frequent tags (TBL tagger)
- Probabilistic: Find the most likely sequence of tags T for a sequence of words W

TBL Tagger - Transformation Based Learning

Label the training set with most frequent tags

- The can was rusted.

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What gives rise to the two families?

Whether they generate the observed data from hidden stuff or the hidden structure given the data?

Generative vs. Conditional Models

Generative (Joint) Models

Generate the observed data from hidden stuff, i.e. put a probability over the observations given the class: $P(d, c)$ in terms of $P(d|c)$

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Take the data as given, and put a probability over hidden structure given the data: $P(c|d)$

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e.g. Logistic regression, maximum entropy models, conditional random fields

SVMs, perceptron, etc. are discriminative classifiers but not directly probabilistic

Generative vs. Discriminative Models
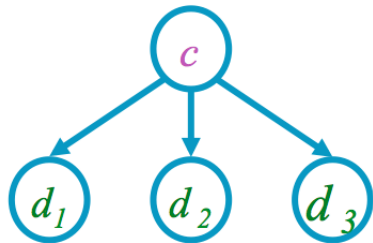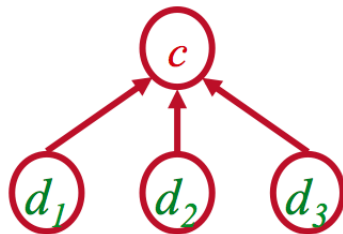
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Logistic Regression

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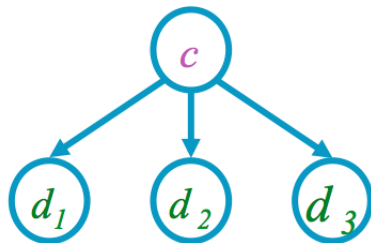
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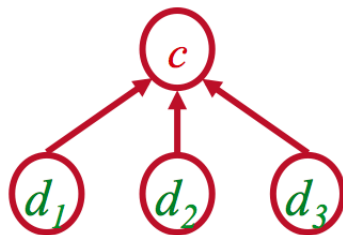
Logistic Regression

Joint vs. conditional likelihood

- A *joint* model gives probabilities $P(d, c)$ and tries to maximize this joint likelihood.

- A *conditional* model gives probabilities $P(c|d)$, taking the data as given and modeling only the conditional probability of the class.

Hidden Markov Models for POS Tagging

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Week 3

Probabilistic Tagging

- $W = w_1 \ldots w_n$ - words in the corpus (observed)
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\end{aligned}
$$

Further simplifications

$$\hat{T} = argmax_T \prod_i P(w_i|w_1 \ldots w_{i-1}, t_1 \ldots t_i) P(t_i|t_1 \ldots t_{i-1})$$

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Further simplifications

$$\hat{T} = argmax_T \prod_i P(w_i|w_1 \ldots w_{i-1}, t_1 \ldots t_i) P(t_i|t_1 \ldots t_{i-1})$$

- The probability of a word appearing depends only on its own POS tag
  $P(w_i|w_1 \ldots w_{i-1}, t_1 \ldots t_i) \approx P(w_i|t_i)$
- Bigram assumption: the probability of a tag appearing depends only on the previous tag
  $P(t_i|t_1 \ldots t_{i-1}) \approx P(t_i|t_{i-1})$
- Using these simplifications:
  $\hat{T} = argmax_T \prod_i P(w_i|t_i) P(t_i|t_{i-1})$

Computing the probability values

Tag Transition probabilities $p(t_i|t_{i-1})$

$$P(t_i|t_{i-1}) = \frac{C(t_{i-1}, t_i)}{C(t_{i-1})}$$

$$P(NN|DT) = \frac{C(DT, NN)}{C(DT)} = \frac{56,509}{116,454} = 0.49$$

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$$P(w_i|t_i) = \frac{C(t_i, w_i)}{C(t_i)}$$

$$P(is|VBZ) = \frac{C(VBZ, is)}{C(VBZ)} = \frac{10,073}{21,627} = 0.47$$

Disambiguating "race"
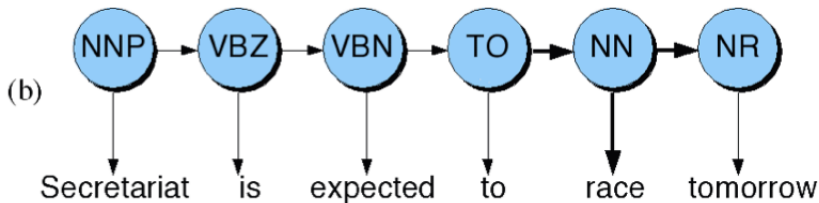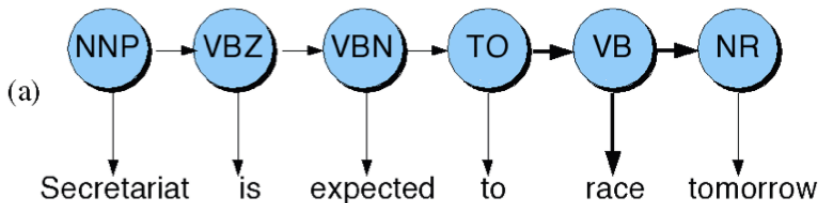
Disambiguating "race"

Difference in probability due to

- $P(VB|TO)$ vs. $P(NN|TO)$
- $P(race|VB)$ vs. $P(race|NN)$
- $P(NR|VB)$ vs. $P(NR|NN)$

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After computing the probabilities
- $P(NN|TO)P(NR|NN)P(race|NN) = 0.0047 \times 0.0012 \times 0.00057 = 0.00000000032$
- $P(VB|TO)P(NR|VB)P(race|VB) = 0.83 \times 0.0027 \times 0.00012 = 0.00000027$

What is this model?

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(a) NNP → VBZ → VBN → TO → VB → NR
Secretariat / is / expected / to / race / tomorrow

(b) NNP → VBZ → VBN → TO → NN → NR
Secretariat / is / expected / to / race / tomorrow
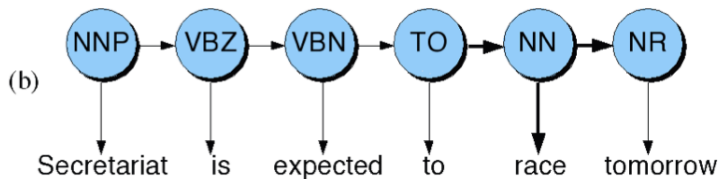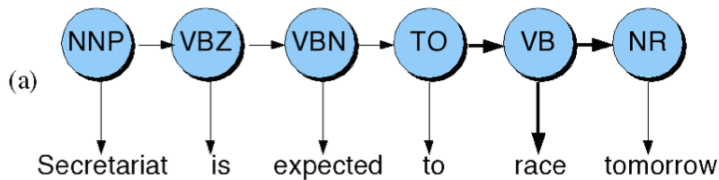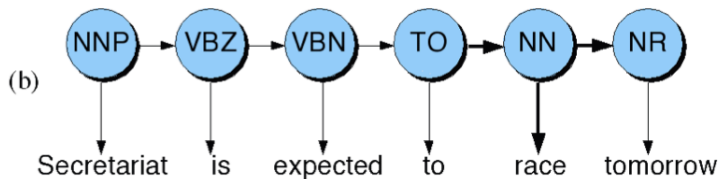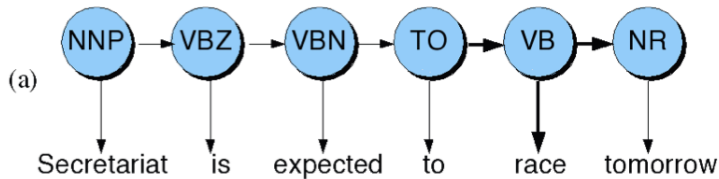
This is a Hidden Markov Model

Hidden Markov Models

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Hidden Markov Models

- Tag Transition probabilities $p(t_i|t_{i-1})$
- Word Likelihood probabilities (emissions) $p(w_i|t_i)$
- What we have described with these probabilities is a hidden markov model.
- Let us quickly introduce the Markov Chain, or observable Markov Model.

Markov Chain = First-order Markov Model

Weather example

- Three types of weather: *sunny, rainy, foggy*

Markov Chain = First-order Markov Model

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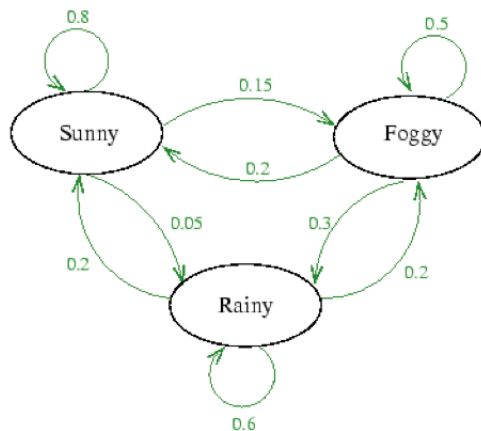
$$P(q_n|q_{n-1}, q_{n-2}, \ldots, q_1)$$

First-order Markov Assumption

$$P(q_n|q_{n-1}, q_{n-2}, \ldots, q_1) = P(q_n|q_{n-1})$$

Markov Chain Transition Table

Table 1: Probabilities $p(q_{n+1}|q_n)$ of tomorrow's weather based on today's weather

	Tomorrow's weather		
Today's weather	☀	❄	☁
☀	0.8	0.05	0.15
❄	0.2	0.6	0.2
☁	0.2	0.3	0.5

- Given that today the weather is sunny, what is the probability that tomorrow is sunny and day after is rainy?

Using Markov Chain

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$P(q_2 = sunny, q_3 = rainy | q_1 = sunny)$

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$$= 0.05 \times 0.8$$
$$= 0.04$$

Hidden Markov Model

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  'sunny' weather is both observable and state

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Hidden Markov Model

- For Markov chains, the output symbols are the same as the states
  'sunny' weather is both observable and state
- But in POS tagging
  The output symbols are words
  But the hidden states are POS tags
- A Hidden Markov Model is an extension of a Markov chain in which the output symbols are not the same as the states
- We don't know which state we are in

Hidden Markov Models (HMMs)

Elements of an HMM model

- A set of states (here: the tags)
- An output alphabet (here: words)
- Initial state (here: beginning of sentence)
- State transition probabilities (here $p(t_n|t_{n-1})$)
- Symbol emission probabilities (here $p(w_i|t_i)$)
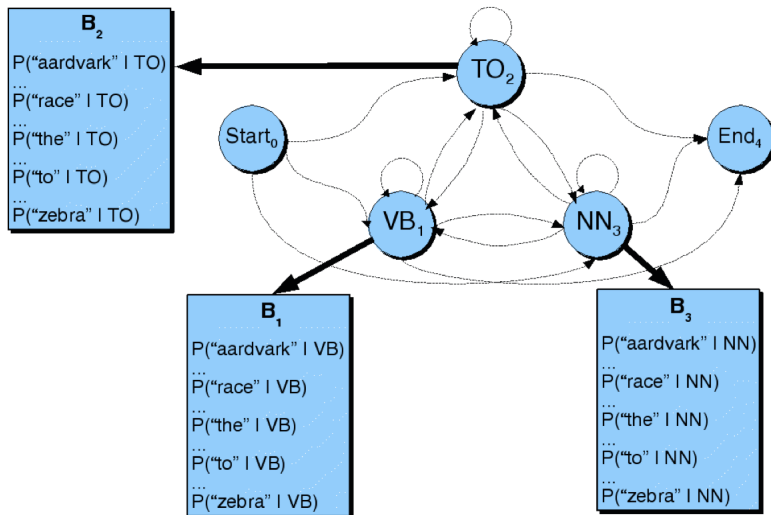
Graphical Representation

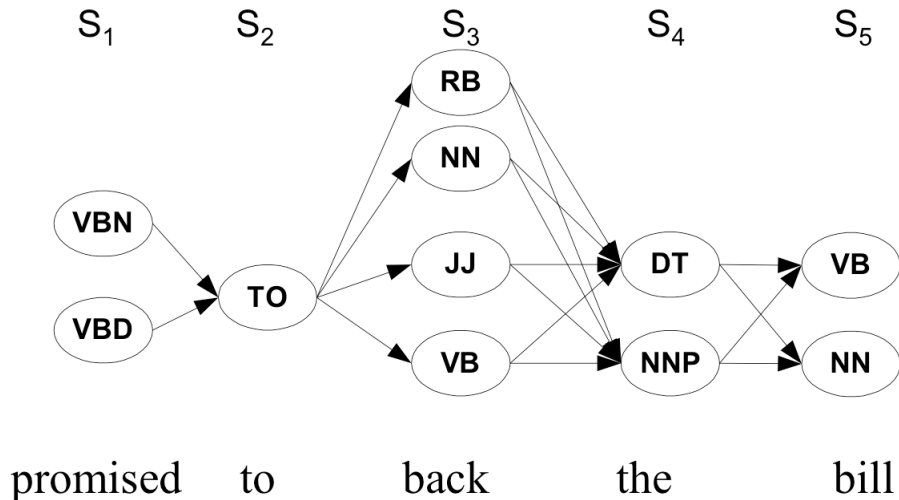When tagging a sentence, we are walking through the state graph:
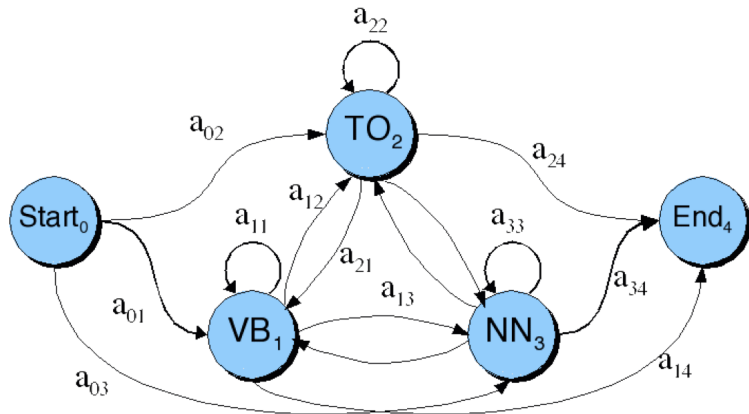
Edges are labeled with the state transition probabilities: $p(t_n|t_{n-1})$

Graphical Representation

At each state we emit a word: $P(w_n|t_n)$

Walking through the states: best path

| S₁ | S₂ | S₃ | S₄ | S₅ |

promised   to   back   the   bill

Walking through the states: best path