Language Modelling: Advanced Smoothing Models

Pawan Goyal

CSE, IITKGP

Week 3: Lecture 1

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>

N_c: Frequency of frequency c

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Computing N_c

I	3
am	2
here	1
who	1
would	1
like	1

$N_1 = 4$

$N_2 = 1$

$N_3 = 1$

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

Good-Turing numbers: Example

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

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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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

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

Model Combination

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

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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

Use a held-out corpus

Choose λs to maximize the probability of held-out data:

- Find the N-gram probabilities on the training data
- Search for λs that give the largest probability to held-out data

Computational Morphology

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Week 3: Lecture 2

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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- Stems (roots): The core meaning bearing units
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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'*
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- Circumfixes - precedes and follows the stem
  Dutch: berg 'mountain', ge-berg-te 'mountains'

Content and functional morphemes

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Carry some semantic content

car, -able, un-

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Functional morphemes

Provide grammatical information

-s (plural), -s (3^{rd} singular)

Inflectional and Derivational Morphology

Two different kind of relationship among words

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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:

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

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

- book + s [s], shoe + s [z]
- happy +er → happier

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- Sanskrit: ‘pac’ (cook), ‘papāca’ (perfect form, cooked)
- Phrasal reduplication (Telugu): *pillavāḍu naḍustū naḍustū paḍi pōyāḍu* (The child fell down while walking)

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Suppletion

'irregular' relation between the words

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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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- Generation: see + verb.past → 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 $\rightarrow$ boys

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

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- Getter $\longrightarrow$ get + er
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- Beer $\longrightarrow$ 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

Why can't this be put in a big lexicon?

- English: just 317,477 forms from 90,196 lexical entries, a ratio of 3.5:1

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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

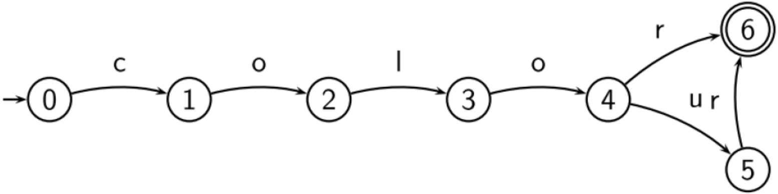
Finite-state methods for morphology

Pawan Goyal

CSE, IITKGP

Week 3: Lecture 3

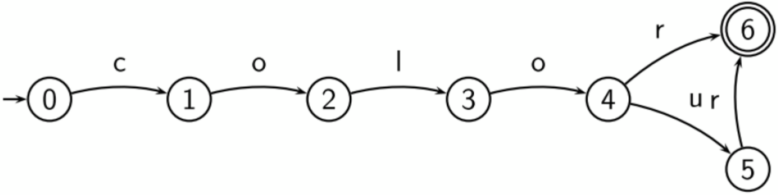
Finite State Automaton (FSA)



What is FSA?

- A kind of directed graph

Finite State Automaton (FSA)



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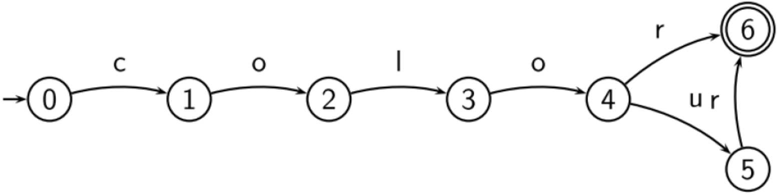

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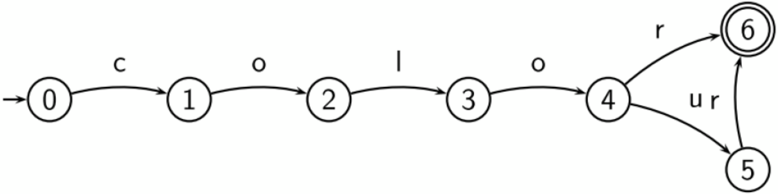
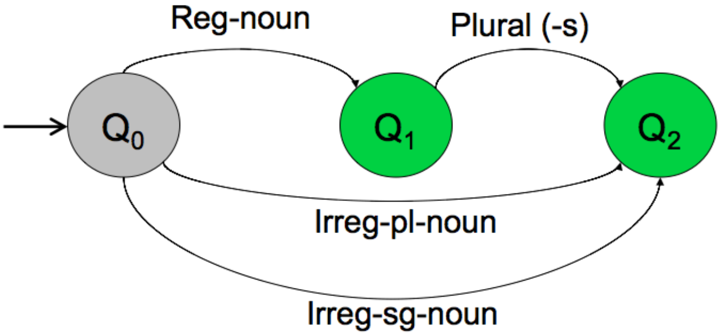


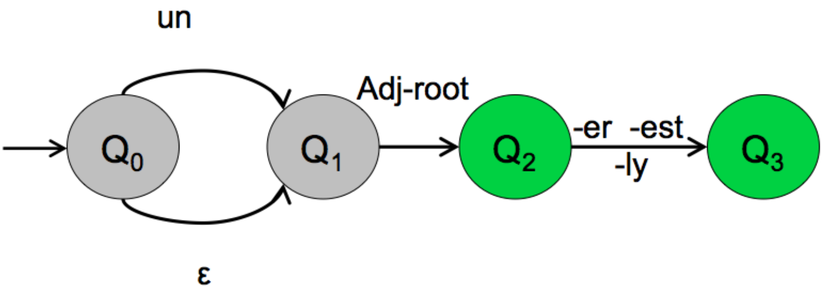
What is FSA?

- 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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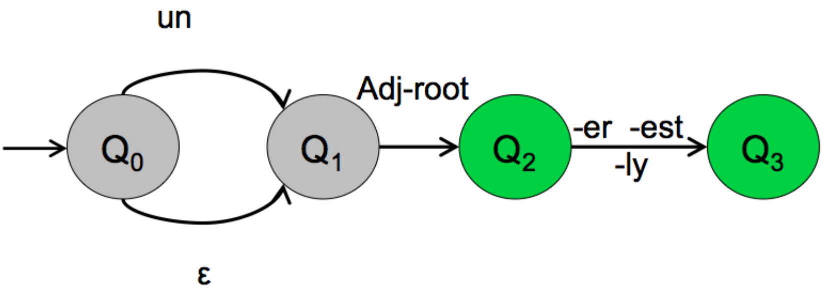

Word modeled

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?

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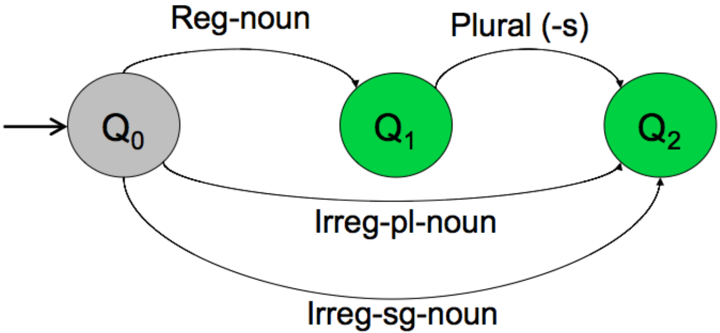
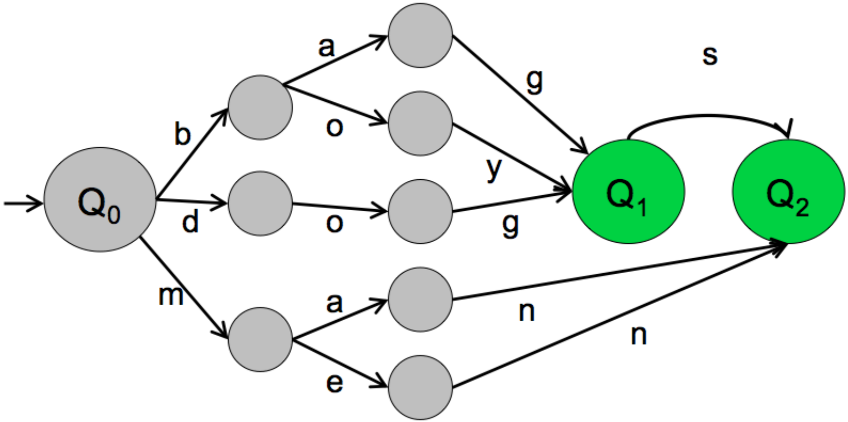
Lexicon

Can we include the lexicon in the FSA?

FSA for nominal inflection in English



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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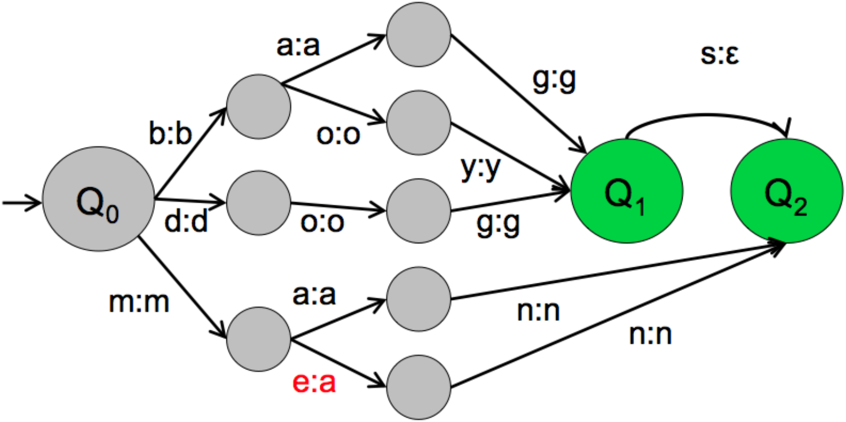
FSAs are language recognizers/generators.
We need transducers to build Morphological Analyzers

Finite State Transducers

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

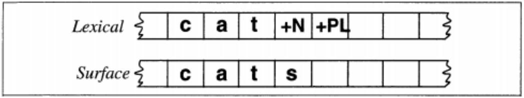
An example FST



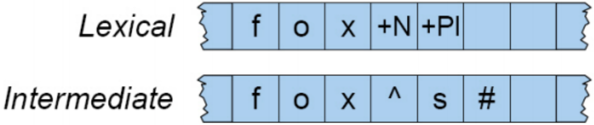
Two-level morphology

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

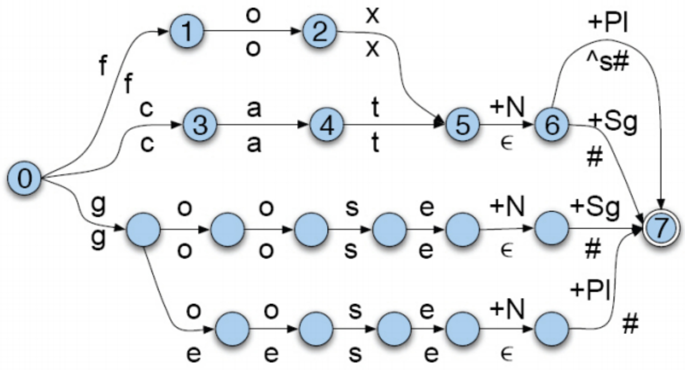
We do this via a version of **two-level morphology**, a correspondence between a lexical level (morphemes and features) to a surface level (actual spelling).



Intermediate tape for Spelling change rules

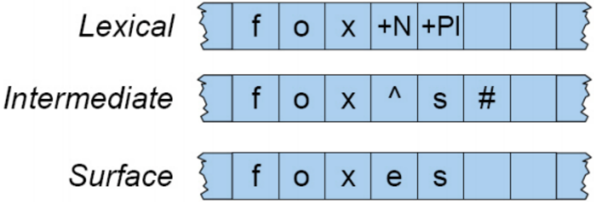


English Nominal Inflection FST



Spelling Handling

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



Rule Handling

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

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

An engineering approach

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

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

Pawan Goyal

CSE, IITKGP

Week 3: Lecture 4

Part-of-Speech (POS) tagging

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Task

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

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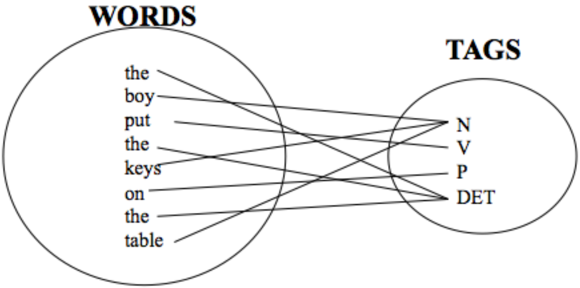

Parts of Speech: How many?

Open class words (content words)

- nouns, verbs, adjectives, adverbs
- mostly content-bearing: they refer to objects, actions, and features in the world
- *open class*, since new words are added all the time

Parts of Speech: How many?

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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

- The back door:

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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
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- 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?

- One tag is usually more likely than the others.

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  In the Brown corpus, *race* is a noun 98% of the time, and a verb 2% of the time
- A tagger for English that simply chooses the most likely tag for each word can achieve good performance
- 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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Relevant knowledge for POS tagging

The word itself

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- Some words are ambiguous, e.g. *like, flies*
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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

Rule-based Approach

- Assign each word in the input a list of potential POS tags
- Then winnow down this list to a single tag using hand-written rules

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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

Label the training set with most frequent tags

- The can was rusted.

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- The/DT can/MD was/VBD rusted/VBD.

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- The/DT can/MD was/VBD rusted/VBD.

Add transformation rules to reduce training mistakes

- MD →NN: DT_
- VBD→VBN: VBD_

Probabilistic Tagging: Two different families of models

Problem at hand

We have some data $\{(d, c)\}$ of paired observations d and hidden classes c.

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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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Discriminative (Conditional) Models

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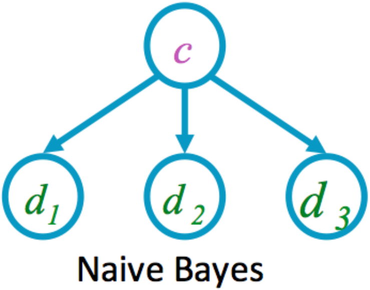
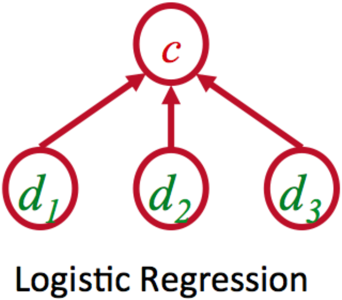
e.g. Logistic regression, maximum entropy models, conditional random fields

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

Generative vs. Discriminative Models





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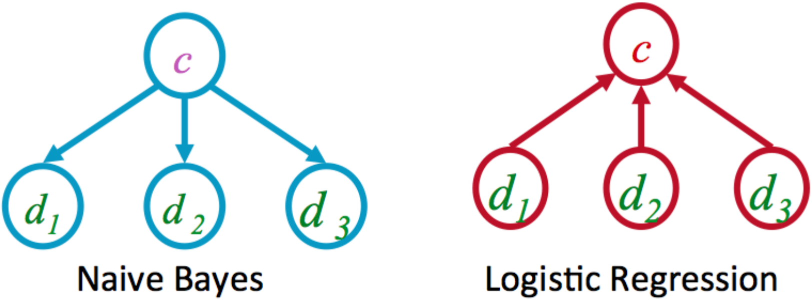

Joint vs. conditional likelihood

- 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

Pawan Goyal

CSE, IITKGP

Week 3: Lecture 5

Probabilistic Tagging

- $W = w_1 \ldots w_n$ - words in the corpus (observed)
- $T = t_1 \ldots t_n$ - the corresponding tags (unknown)

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Find

$$\hat{T} = argmax_T P(T|W)$$

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&= argmax_T P(W|T)P(T) \\
&= argmax_T \prod_i P(w_i|w_1 \dots w_{i-1}, t_1 \dots t_i) P(t_i|t_1 \dots t_{i-1})
\end{aligned}
$$

Further simplifications

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

- The probability of a word appearing depends only on its own POS tag

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  $P(w_i|w_1 \dots w_{i-1}, t_1 \dots t_i) \approx P(w_i|t_i)$
- Bigram assumption: the probability of a tag appearing depends only on the previous tag

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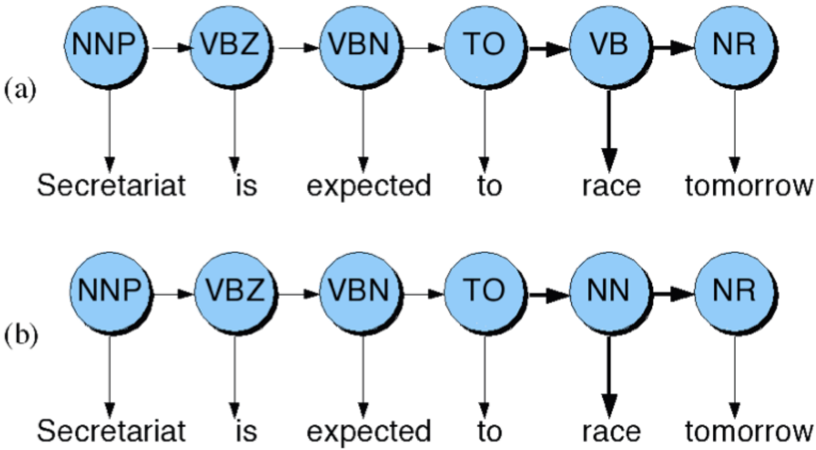
$$P(w_i|t_i) = \frac{C(t_i, w_i)}{C(t_i)}$$

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

Disambiguating "race"



Disambiguating "race"

Difference in probability due to

- $P(VB|TO)$ vs. $P(NN|TO)$
- $P(race|VB)$ vs. $P(race|NN)$
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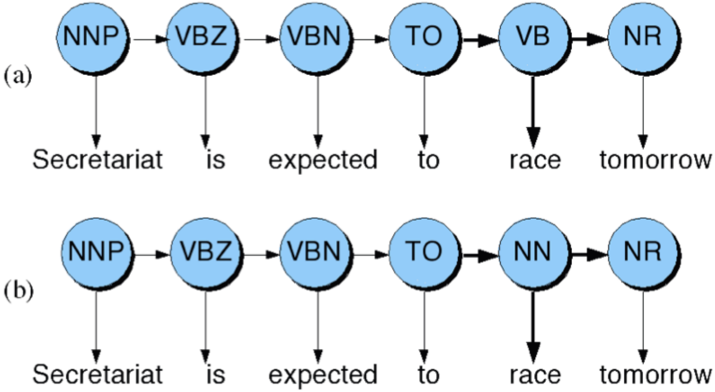
After computing the probabilities

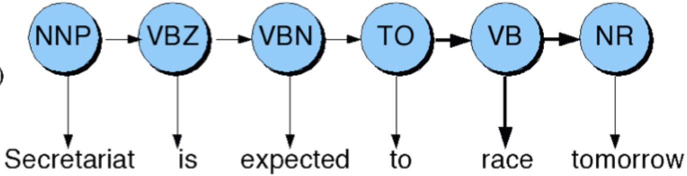
- $P(NN|TO)P(NR|NN)P(race|NN) = 0.0047 \times 0.0012 \times 0.00057 = 0.00000000032$
- $P(VB|TO)P(NR|VB)P(race|VB) = 0.83 \times 0.0027 \times 0.00012 = 0.00000027$

What is this model?

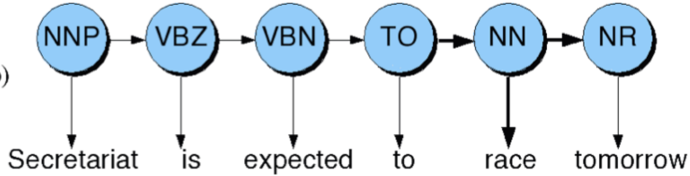


What is this model?

(a)



(b)



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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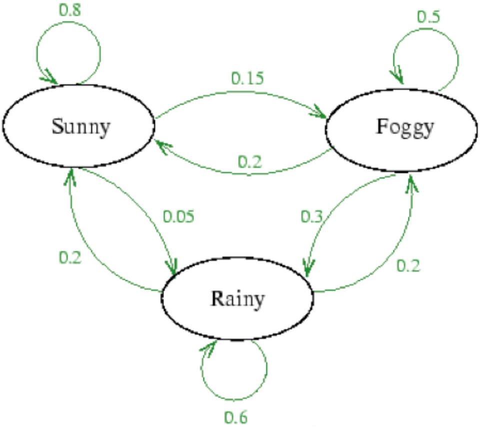
First-order Markov Assumption

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

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



Using Markov Chain

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

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

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$$
\begin{aligned}
&= P(q_3 = rainy | q_2 = sunny, q_1 = sunny) \times P(q_2 = sunny | q_1 = sunny) \\
&= P(q_3 = rainy | q_2 = sunny) \times P(q_2 = sunny | q_1 = sunny) \\
&= 0.05 \times 0.8 \\
&= 0.04
\end{aligned}
$$

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- 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

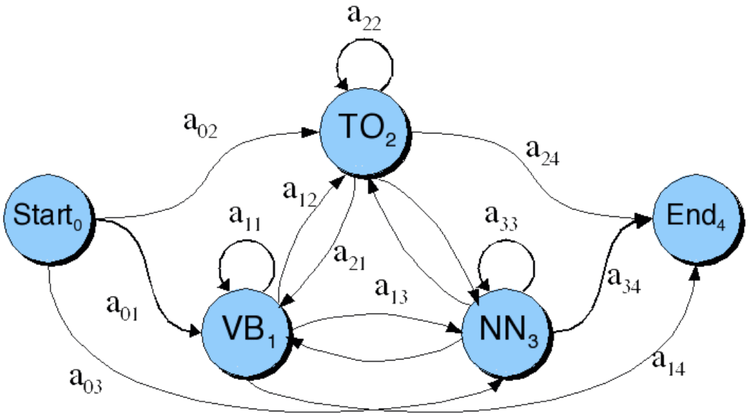
Hidden Markov Models (HMMs)

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 $p(w_i|t_i)$)

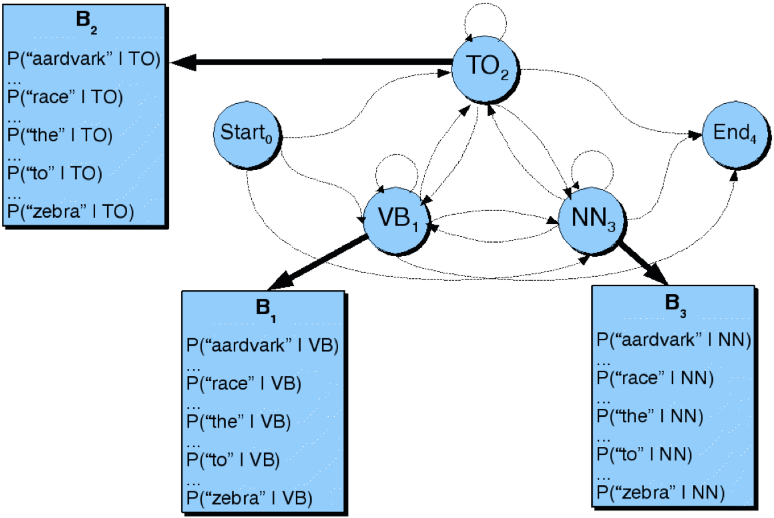
Graphical Representation

When tagging a sentence, we are walking through the state graph:

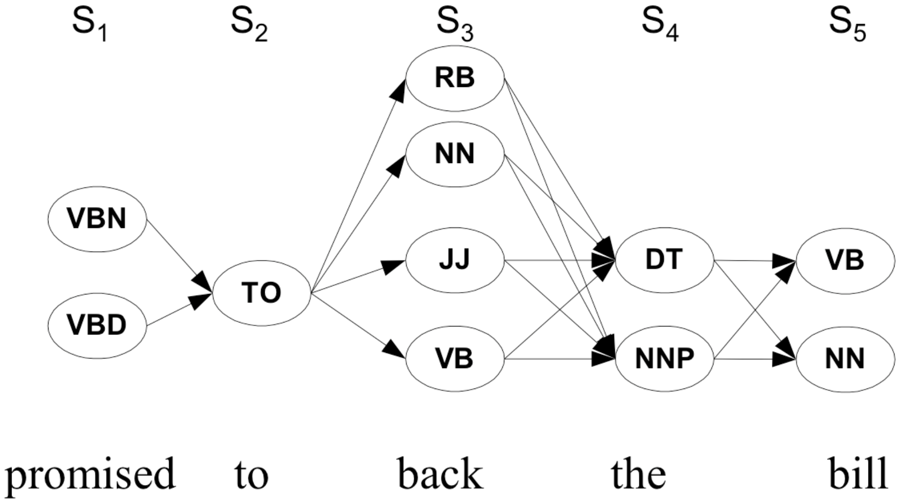


Edges are labeled with the state transition probabilities: $p(t_n|t_{n-1})$

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



Walking through the states: best path



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