6.863J Natural Language Processing
Lecture 5: Finite state machines & part-of-speech tagging

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The Menu Bar

- Administrivia:
  - Schedule alert: Lab1 due next *Weds* (Feb 24)
  - Lab 2, handed out Feb 24 (look for it on the web as laboratory2.html; due the Weds after this – March 5
- *Agenda:*
- Part of speech ‘tagging’ (with sneaky intro to probability theory that we need)
- Ch. 6 & 8 in Jurafsky; see ch. 5 on Hidden Markov models

Two finite-state approaches to tagging

1. Noisy Channel Model (statistical)

2. Deterministic baseline tagger composed with a cascade of fixup transducers

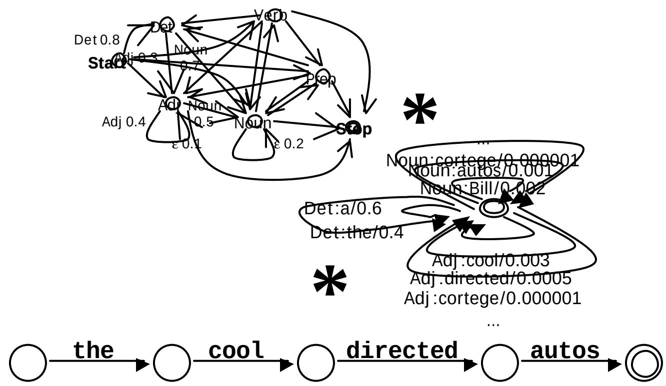
- PS: how do we *evaluate* taggers? (and such statistical models generally?)
- 1, 2, & evaluation = Laboratory 2

The real plan...

$$\mathbf{p(X)}$$
$$*$$
$$\mathbf{p(Y \mid X)}$$
$$*$$
$$\mathbf{p(y \mid Y)}$$
$$=$$
$$\mathbf{p(X, y)}$$

Find x that maximizes this quantity

Cartoon version



$$p(X) * p(Y \mid X) * p(y \mid Y) = p(X, y)$$

transducer: scores candidate tag seqs on their joint probability with obs words; we should pick best path

What's the big picture? Why NLP?

Computers would be a lot more useful if they could handle our email, do our library research, talk to us ...

But they are fazed by natural human language.

How can we tell computers about language? (Or help them learn it as kids do?)

What is NLP for, anyway?

- If we could do it perfectly, we could pass the Turing test (more on this below)
- Two basic 'engineering' tasks – and third scientific one
- Text-understanding
- Information extraction
- ?What about how people 'process' language??? [psycholinguistics]

Some applications...

- Spelling correction, grammar checking ...
- Better search engines
- Information extraction
- Language identification (English vs. Polish)
- Psychotherapy; Harlequin romances; etc.
- And: plagiarism detection - www.turnitin.com
- For code: www.cs.berkeley.edu/~aiken/moss.html
- New interfaces:
  - Speech recognition (and text-to-speech)
  - Dialogue systems (USS Enterprise onboard computer)
  - Machine translation (the Babel fish)

Text understanding is very hard

John stopped at the donut store on his way home from work. He thought a coffee was good every few hours. But it turned out to be too expensive there.

- NL *relies on* ambiguity! (Why?)
- “We haven’t had a sale in 40 years”

What’s hard about the story?

John stopped at the donut store on his way home from work. He thought a coffee was good every few hours. But it turned out to be too expensive there.

To get a donut (spare tire) for his car?

What’s hard?

John stopped at the donut store on his way home from work. He thought a coffee was good every few hours. But it turned out to be too expensive there.

store where donuts shop? or is run by donuts?
or looks like a big donut? or made of donut?
or has an emptiness at its core?

(Think of five other issues...there are lots)

What’s hard about this story?

John stopped at the donut store on his way home from work. He thought a coffee was good every few hours. But it turned out to be too expensive there.

Describes where the store is? Or when he stopped?

What's hard about this story?

John stopped at the donut store on his way home from work. He thought a coffee was good every few hours. But it turned out to be too expensive there.

Well, actually, he stopped there from hunger and exhaustion, not just from work.

What's hard about this story?

John stopped at the donut store on his way home from work. He thought a coffee was good every few hours. But it turned out to be too expensive there.

At that moment, or habitually?

(*Similarly:* Mozart composed music.)

What’s hard about this story?

John stopped at the donut store on his way home from work. He thought a coffee was good every few hours. But it turned out to be too expensive there.

That’s how often he thought it?

What’s hard about this story?

John stopped at the donut store on his way home from work. He thought a coffee was good every few hours. But it turned out to be too expensive there.

But actually, a coffee only stays good for about 10 minutes before it gets cold.

What’s hard about this story?

John stopped at the donut store on his way home from work. He thought a coffee was good every few hours. But it turned out to be too expensive there.

Similarly: In America a woman has a baby every 15 minutes. Our job is to find that woman and stop her.

What’s hard about this story?

John stopped at the donut store on his way home from work. He thought a coffee was good every few hours. But it turned out to be too expensive there.

the particular coffee that was good every few hours? the donut store? the situation?

What’s hard about this story?

John stopped at the donut store on his way home from work. He thought a coffee was good every few hours. But it turned out to be too expensive there.

too expensive for what? what are we supposed to conclude about what John did?

how do we connect “it” to “expensive”?

Example tagsets

- 87 tags - Brown corpus
- Three most commonly used:

1. Small: 45 Tags - Penn treebank (Medium size: 61 tags, British national corpus
2. Large: 146 tags

Big question: have we thrown out the right info? Impoverished? How?

Current performance

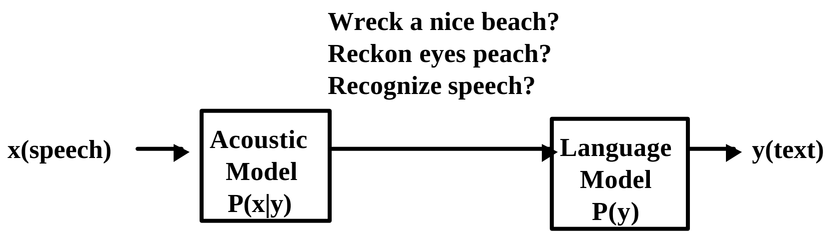
Input: `the lead paint is unsafe`

Output: `the/Det lead/N paint/N is/V unsafe/Adj`

- How many tags are correct?
  - About 97% currently
  - But baseline is already 90%
    - Baseline is performance Homer Simpson algorithm:
    - Tag every word with its most frequent tag
    - Tag unknown words as nouns
- How well do people do?

Knowldege-based (rule-based) vs. Statistically-based systems

A picture: the statistical, noisy channel view



Language models, probability & info

- Given a string *w,* a language model gives us the probability of the string P(*w*), e.g.,
  - *P(the big dog) > (dog big the) > (dgo gib eth)*
  - Easy for humans; difficult for machines
  - Let P(*w*) be called a <u>language model</u>

Language models – statistical view

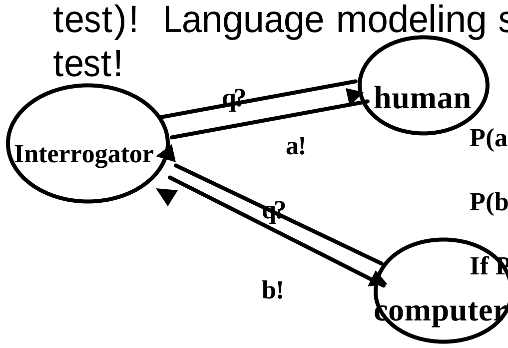
- Application to speech recognition (and parsing, generally)
  - x= Input (speech)
  - y= output (text)
  - We want to find max P(y|x) Problem: we don't know this!
  - Solution: We have an estimate of P(y) [the language model] and P(x|y) [the prob. of some sound given text = an <u>acoustic model</u>]
  - From Bayes' law, we have,

max P(y|x) = max P(x|y) • P(y) = max Pr acoustic model x lang model

(hold P(x) fixed, i.e., P(x|y) • P(y) / P(x), but max is same for both)

Can be generalized to Turing test...!

If we could solve this (the?) NLP problem, we could solve the Turing test.... (but not the Twain test)! Language modeling solves the Turing test!



P(a|q)= pr human answers *q* with *a* = P(q,a)/P(q)

P(b|q)= pr computer answers *q* with *b* = P(q,b)/P(q)

If P(q,a) = P(q,b) then computer successfully imitates human

Some applications...

- Spelling correction, grammar checking ...
- Better search engines
- Information extraction
- Language identification (English vs. Polish)
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- New interfaces:
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What's this stuff *for* anyway? Information extraction

- Information extraction involves processing text to identify selected information:
  - particular types of names
  - specified classes of events.
  - For names, it is sufficient to find the name in the text and identify its type
  - for events, we must extract the critical information about each event (the agent, objects, date, location, etc.) and place this information in a set of templates (data base)

Example – “Message understanding” (MUC)

ST1 -MUC3-0011

SANTIAGO, 18 MAY 90 (RADIO COOPERATIVA NETWORK) – [REPORT] [JUAN ARAYA]
[TEXT]
EDMUNDO VARGAS CARRENO, CHILEAN FOREIGN MINISTRY UNDER SECRETARY, HAS STATED THAT THE BRYANT TREATY WITH THE UNITED STATES WILL BE APPLIED IN THE LETELIER CASE ONLY TO COMPENSATE THE RELATIVES OF THE FORMER CHILEAN FOREIGN MINISTER MURDERED IN WASHINGTON AND THE RELATIVES OF HIS U.S. SECRETARY, RONNIE MOFFIT. THE CHILEAN FOREIGN UNDER SECRETARY MADE THIS STATEMENT IN REPLY TO U.S. NEWSPAPER REPORTS STATING THAT THE TREATY WOULD BE PARTIALLY RESPECTED.

FOLLOWING ARE VARGAS CARRENO'S STATEMENTS AT A NEWS CONFERENCE HE HELD IN BUENOS AIRES BEFORE CONCLUDING HIS OFFICIAL VISIT TO ARGENTINA:

Extracted info – names, events

0. MESSAGE: ID	TST1-MUC3-0011
1. MESSAGE: TEMPLATE	1
2. INCIDENT: DATE	18 MAY 90
3. INCIDENT: LOCATION	UNITED STATES: WASHINGTON D.C. (CITY)
4. INCIDENT: TYPE	ATTACK
5. INCIDENT: STAGE OF EXECUTION	ACCOMPLISHED
6. INCIDENT: INSTRUMENT ID	-
7. INCIDENT: INSTRUMENT TYPE	-
8. PERP: INCIDENT CATEGORY	STATE-SPONSORED VIOLENCE
9. PERP: INDIVIDUAL ID	-
10. PERP: ORGANIZATION ID	"CHILEAN GOVERNMENT"
11. PERP: ORGANIZATION CONFIDENCE REPORTED AS FACT:	"CHILEAN GOVERNMENT"
12. PHYS TGT: ID	-
13. PHYS TGT: TYPE	-
14. PHYS TGT: NUMBER	-
15. PHYS TGT: FOREIGN NATION	-
16. PHYS TGT: EFFECT OF INCIDENT	-
17. PHYS TGT: TOTAL NUMBER	-
18. HUM TGT: NAME	"ORLANDO LETELIER" "RONNIE MOFFIT"
19. HUM TGT: DESCRIPTION	"FORMER CHILEAN FOREIGN MINISTER": "ORLANDO LETELIER" "U.S. SECRETARY" / "ASSISTANT" / "SECRETARY": "RONNIE MOFFIT"
20. HUM TGT: TYPE	GOVERNMENT OFFICIAL: "ORLANDO LETELIER" CIVILIAN: "RONNIE MOFFIT"
21.	

Text understanding vs. Info extraction

- For information extraction:
  - generally only a fraction of the text is relevant; for example, in the case of the MUC-4 terrorist reports, probably only about 10% of the text was relevant;
  - information is mapped into a predefined, relatively simple, rigid target representation; this condition holds whenever entry of information into a database is the task;
  - the subtle nuances of meaning and the writer's goals in writing the text are of at best secondary interest.

Properties of message understanding task

- Simple, fixed definition of the information to be sought.
- Much, or even most, of the text is irrelevant to the information extraction goal.
- Large volumes of text need to be searched.

Text understanding

- the aim is to make sense of the entire text;
- the target representation must accommodate the full complexities of language;
- one wants to recognize the nuances of meaning and the writer's goals

MUC 5 - business

Bridgestone Sports Co. said Friday it has set up a joint venture in Taiwan with a local concern and a Japanese trading house to produce golf clubs to be shipped to Japan. The joint venture, Bridgestone Sports Taiwan Co., capitalized at 20 million new Taiwan dollars, will start product ion in January 1990 with production of 20,000 iron and "metal wood" clubs a month.

TIE-UP-1:

Relationship:	**TIE-UP**
Entities:	**"Bridgestone Sports Co."**
	"a local concern“
	"a Japanese trading house"
Joint Venture Company:	**"Bridgestone Sports Taiwan Co." Activity: ACTIVITY-1**
Amount:	**NT$20000000**

ACTIVITY-1:

Activity:	**PRODUCTION**
Company:	**"Bridgestone Sports Taiwan Co."**
Product:	**"iron and `metal wood' clubs"**
Start Date:	**DURING: January 1990**

Applications

- IR tasks:
  - Routing queries to prespecified topics
  - Text classification/routing
- Summarization
  - Highlighting, clipping
  - NL generation from formal output representation
- Automatic construction of knowledge bases from text

Message understanding tasks

Business News:Joint Ventures (English and Japanese),

Labor Negotiations, Management Succession

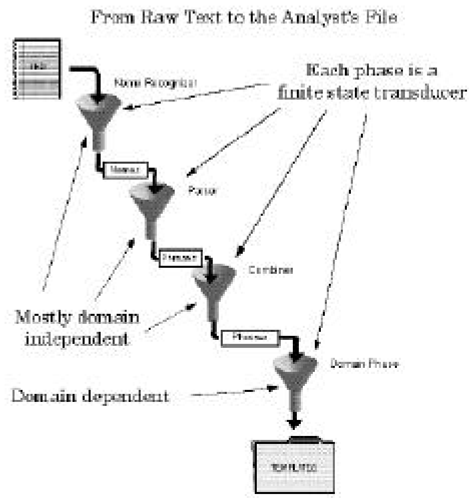
Geopolitical News:Terrorist Incidents

Military Messages:DARPA Message Handler

Legal English:Document Analysis Tool

Integration with OCR

Typical finite-state system – Fastus (SRI)



Name recognition: a fsa task

Bridgestone Sports Co. $_C$ said **Friday** $_D$ it had set up a joint venture in **Taiwan** $_L$ with a local concern and a Japanese trading house to produce golf clubs to be shipped to **Japan**.$_L$

Shallow parsing or 'chunking' – Lab 3

Bridgestone Sports Co.	said	Friday	it	has set up	a joint venture
Company-Name	VG	NG	NG	VG	NG

Complex VG

in	Taiwan	with	a local concern	and	a Japanese trading house
NG	Loc	P	NG	Conj	NG

Complex NG

to produce	golf clubs	to be shipped	to	Japan.
VG(Inf)	NG	VG(Inf,Pass)	P	Loc

Recognizing domain patterns

- Match domain patterns against complex phrase heads
  - <company> <form><joint venture> with <company>
  - <company> capitalized at <currency>

"Bridgestone Sports Co. said Friday it has set up a joint venture in Taiwan with a local concern and a Japanese trading house to produce golf clubs to be shipped to Japan.
"The joint venture, Bridgestone Sports Taiwan Co., capitalized at 20 million new Taiwan dollars, will start production in January 1990."

Relationship:	TIE-UP
Entities:	"Bridgestone Sports Co." "a local concern" "a Japanese trading house"
JV Company:	--
Capitalization:	--

Relationship:	TIE-UP
Entities:	--
JV Company:	"Bridgestone Sports Taiwan Co."
Capitalization:	20000000 TWD

What about part of speech tagging here?

- Advantages
  - Ambiguity can be potentially reduced (but we shall see in our laboratory if this is true)
  - Avoid errors due to incorrect categorization of rare senses e.g., “has been” as noun
- Disadvantages
  - Errors taggers make often those you’d most want to eliminate
  - High performance requires training on similar genre
  - Training takes time

Proper names...

- Proper names are particularly important for extraction systems
- Because typically one wants to extract events, properties, and relations about some particular object, and that object is usually identified by its name

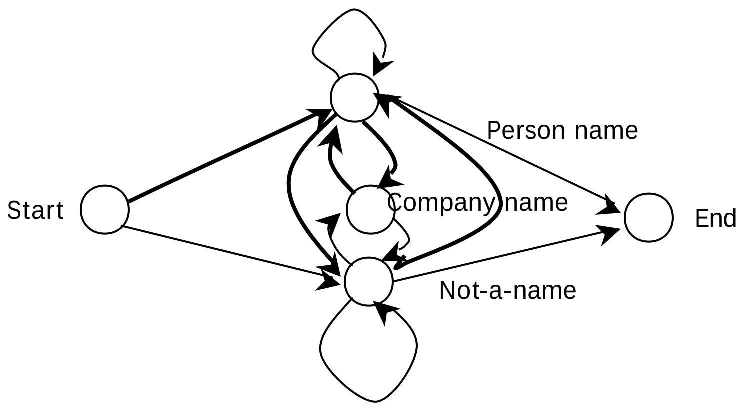
...A challenge...

- Problems though...
  - proper names are huge classes and it is difficult, if not impossible to enumerate their members
  - Hundreds of thousands of names of locations around the world
  - Many of these names are in languages other than the one in which the extraction system is designed

How are names extracted?

- (Hidden) Markov Model
- Hypothesized that there is an underlying finite state machine (not directly observable, hence hidden) that changes state with each input element
- probability of a recognized constituent is conditioned not only on the words seen, but the state that the machine is in at that moment
- "John" followed by "Smith" is likely to be a person, while "John" followed by "Deere" is likely to be a company (a manufacturer of heavy farming and construction equipment).

HMM statistical name tagger



HMM

- Whether a word is part of a name or not is a random event with an estimable probability
- The probability of name versus non-name readings can be estimated from a training corpus in which the names have been annotated
- In a Hidden Markov model, it is hypothesized that there is an underlying finite state machine (not directly observable, hence hidden) that changes state with each input element
- The probability of a recognized constituent is conditioned not only on the words seen, but the state that the machine is in at that moment
- "John" followed by "Smith" is likely to be a person, while "John" followed by "Deere" is likely to be a company (a manufacturer of heavy farming and construction equipment).

HMM construction

- Hidden state transition model governs word sequences
- Transitions probabilistic
- Estimate transition probabilities from an annotated corpus
  - $P(s_j \mid s_{j-1}, w_j)$
  - Based just on prior state and current word seen (hence Markovian assumption)
- At runtime, find maximum likelihood path through the network, using a max-flow algorithm (Viterbi)

How much data is needed?

- System performance bears a roughly log-linear relationship to the training data quantity, at least up to about 1.2 million words
- Obtaining 1.2 million words of training data requires transcribing and annotating approximately 200 hours of broadcast news programming, or if annotating text, this would amount to approximately 1,777 average-length Wall Street Journal articles

If you think name recog is not relevant, then...

- Microsoft announced plans to include "Smart Tags" in its browser and other products. This is a feature that automatically inserts hyperlinks from concepts in text to related web pages chosen by Microsoft.
- The best way to make automatic hyperlinking unbiased is to base it on an unbiased source of web pages, such as Google.

How to do this?

- The main technical problem is to find pieces of text that are good concept anchors… like names!
- So: Given a text, find the starting and ending points of all the names. Depending on our specific goals, we can include the names of people, places, organizations, artifacts (such as product names), etc.
- . Once we have the anchor text, we can send it to a search engine, retrieve a relevant URL (or set of URLs, once browsers can handle multi-way hyperlinks), and insert them into the original text on the fly.

OK, back to the tagging task

- This will illustrate all the issues with name recognition too

Brown/Upenn corpus tags

J. text,
p. 297
Fig 8.6
1M words
60K tag
counts

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	*$*
NNPS	Proper noun, plural	*Carolinas*	#	Pound sign	*#*
PDT	Predeterminer	*all, both*	“	Left quote	(‘ or “)
POS	Possessive ending	*’s*	”	Right quote	(’ or ”)
PP	Personal pronoun	*I, you, he*	(	Left parenthesis	([, (, {, <)
PP$	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*			

Ok, what should we look at?

correct tags

PN	Verb	Det	Noun	Prep	Noun	Prep	Det	Noun
Bill	directed	a	cortege	of	autos	through	the	dunes
PN	Adj	Det	Noun	Prep	Noun	Prep	Det	Noun
Verb	Verb	Noun	Verb					
			Adj					
			Prep					
			...?					

some possible tags for each word (maybe more)

Each unknown tag is **constrained** by its word
and by the tags to its immediate left and right.
But those tags are unknown too ...

Ok, what should we look at?

correct tags

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correct tags

PN Verb Det Noun Prep Noun Prep Det Noun

Bill directed a cortege of autos through the dunes

PN Adj Det Noun Prep Noun Prep Det Noun

Verb Verb Noun Verb

Adj

Prep

...?

some possible tags for each word (maybe more)

Each unknown tag is **constrained** by its word
and by the tags to its immediate left and right.
But those tags are unknown too ...

Ok, what *should* we look at?

correct tags

PN Verb Det Noun Prep Noun Prep Det Noun

Bill directed a cortege of autos through the dunes

PN Adj Det Noun Prep Noun Prep Det Noun

Verb Verb Noun Verb

Adj

Prep

...?

some possible tags for each word (maybe more)

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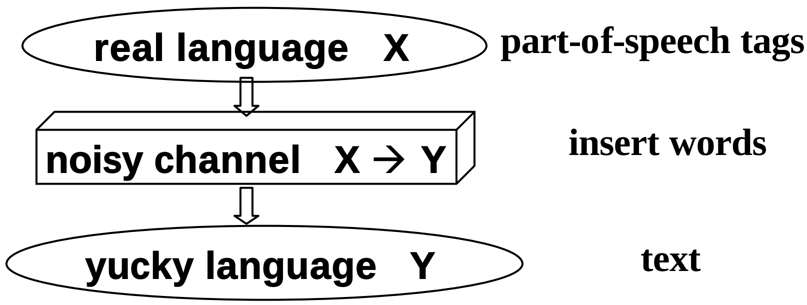
But those tags are unknown too ...

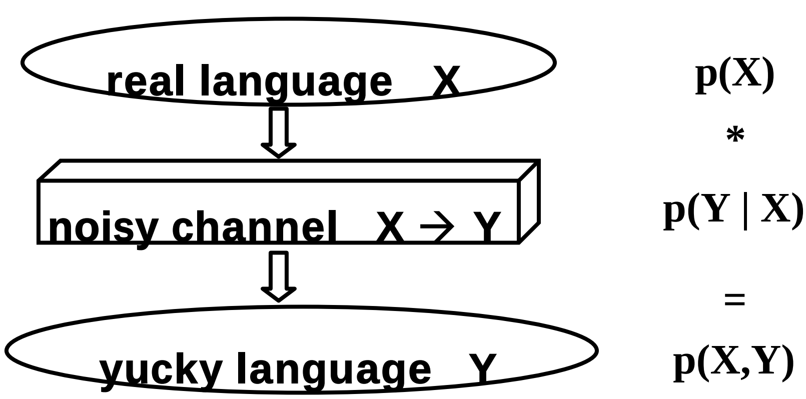
Finite-state approaches

- Noishy Chunnel Muddle (statistical)



want to recover X from Y

Noisy channel – and prob intro



choose sequence of tags X that *maximizes* p(X | Y)
[oops… this isn't *quite* correct… need 1 more step]

Two approaches

- Fix up Homer Simpson idea with more than unigrams – look at tag sequence
- Go to more powerful Hidden Markov model

What are unigrams and bigrams?

- Letter or word frequencies: 1-grams
  - useful in solving cryptograms: ETAOINSHRDLU…
- If you know the previous letter: 2-grams
  - “h” is rare in English (4%; 4 points in Scrabble)
  - but “h” is common after “t” (20%)
- If you know the previous 2 letters: 3-grams
  - “h” is really common after “ ” “t”

    etc. …

In our case

- Most likely word? Most likely tag *t* given a word *w?* = P(tag|word)
- Task of predicting the next word
- Woody Allen:

  "I have a gub"

In general: predict the N^{th} word (tag) from the preceding N-1 word (tags) aka N-gram

Homer Simpson: just use the current word (don't look at context) = unigram (1-gram)

Where do these probability info estimates come from?

- Use tagged corpus e.g. "Brown corpus" 1M words (fewer token *instances*); many others – Celex 16M words
- Use counts (relative frequencies) as estimates for probabilities (various issues w/ this, these so-called Maximum-Likelihood estimates – don't work well for low numbers)
- Train on texts to get estimates – use on new texts

General probabilistic decision problem

- E.g.: data = bunch of text
  - label = language
  - label = topic
  - label = author
- E.g.2: (sequential prediction)
  - label = translation or summary of entire text
  - label = part of speech of current word
  - label = identity of current word (ASR) or character (OCR)

Formulation, in general

$$Label = \arg\max_{Label} \Pr(Label \mid Data)$$

How far should we go?

- "*long distance*___"
- Next word? *Call?*
- p(w_n|w
- Consider special case above
- Approximation says that

  | long distance call|/|distance call| ≈ |distance call|/|distance|
- If context 1 word back = bigram

But even better approx if 2 words back: *long distance*___

Not always right: long distance runner/long distance call

Further you go: *collect long distance*_____

Bigrams, fsa's, and Markov models – take two

- We *approximate* p(tag| all previous tags) Instead of

  p(rabbit|Just then the white...) we use:

  P(rabbit|white)
- This is a *Markov assumption* where past memory is limited to immediately previous state – just 1 state corresponding to the previous word or tag

Forming classes

- "*n-gram*" = sequence of n "words"
  - **unigram**
  - **bigram**
  - **trigram**
  - **four-gram**
- In language modeling, the conditioning variables are sometimes called the "history" or the "context."
- The Markov assumption says that the prediction is conditionally independent of ancient history, given recent history.
- I.e., we divide all possible histories into equiv. classes based on the recent history**.**

3-gram

```
[Genmetheyesse orils of Ted you doorder [6], the Grily
Capiduatent pildred and For thy werarme: nomiterst halt i,
 what production the Covers, in calt cations on wile ars,
was name conch rom the exce of the man, Winetwentagaint up,
and and Al1. And of Ther so i  hundal panite days th the
res of th rand ung into the forD six es, wheralf the hie
soulsee, frelatche rigat. And the LOperact camen
unismelight fammedied: and nople,
```

4-gram

```
[1] By the returall benefit han every familitant of all thou
 go? And At the eld to parises of the nursed by thy way of
 all histantly be the ~aciedfag   . to the narre gread abrasa
of thing, and vas these conwuning clann com to one language;
all Lah, which for the greath othey die. -
```

5-gram

```
[Gen 3:1] In the called up history of its opposition of
bourgeOIS AND Adam to rest, that the existing of heaven; and
land the bourgeoiS ANger anything but concealed, the land
whethere had doth know ther: bury thy didst of Terature their
faces which went masses the old society [2] is the breaks out
of oppressor of all which, the prolETARiat goest, unto German
pleast twelves applied in manner with these, first of this
polities have all
```

3-word-gram

`[Gen 4:25] And Adam gave naines to ail feudal, patriarchal, idyllic relations. It bas but –established new classes, new conditions of oppression, new forme of struggle in place of the West? The bourgeoisie keeps more and more splitting up into two great lights; the greater light to rule the day of my house is this Eliezer of Damascus.`

How far can we go??

Shakespeare in lub...
The unkindest cut of all

- Shakespeare: 884,647 words or *tokens* (Kucera, 1992)
- 29,066 *types* (incl. proper nouns)
- So, # bigrams is $29{,}066^2$ > 844 million. 1 million word training set doesn't cut it – only 300,000 difft bigrams appear
- Use *backoff* and *smoothing*
- So we can't go very far...

Reliability vs. discrimination

“large green ___________”

tree? mountain? frog? car?

“swallowed the large green ________”

pill? broccoli?

Reliability vs. discrimination

- larger n: more information about the context of the specific instance (greater discrimination)
- smaller n: more instances in training data, better statistical estimates (more reliability)

Choosing *n*

Suppose we have a vocabulary (V) = 20,000 words

n	**Number of bins**
2 (bigrams)	**400,000,000**
3 (trigrams)	**8,000,000,000,000**
4 (4-grams)	**1.6×10^{17}**

Statistical estimators

Example:

Corpus: five Jane Austen novels

N = 617,091 words

V = 14,585 unique words

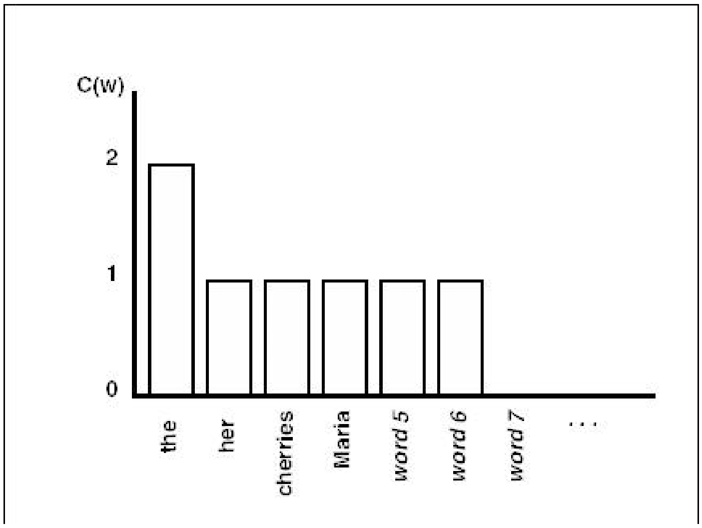
Task: predict the next word of the trigram “inferior to ________”

from test data, *Persuasion*:

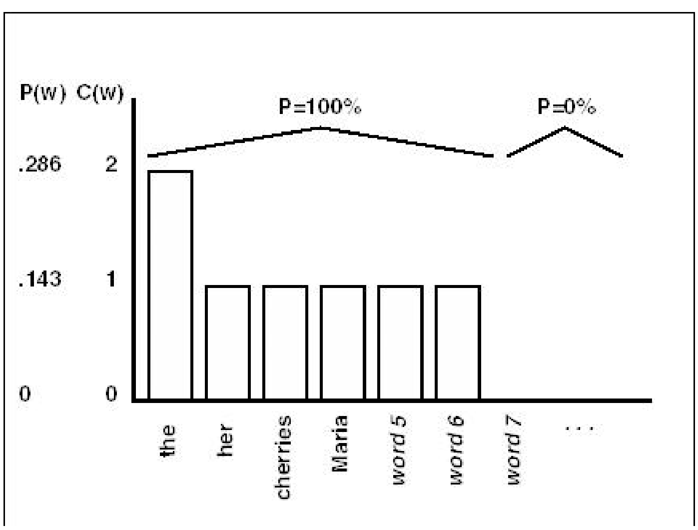
“[In person, she was] inferior to *both* [sisters.]”

Instances in the Training Corpus:

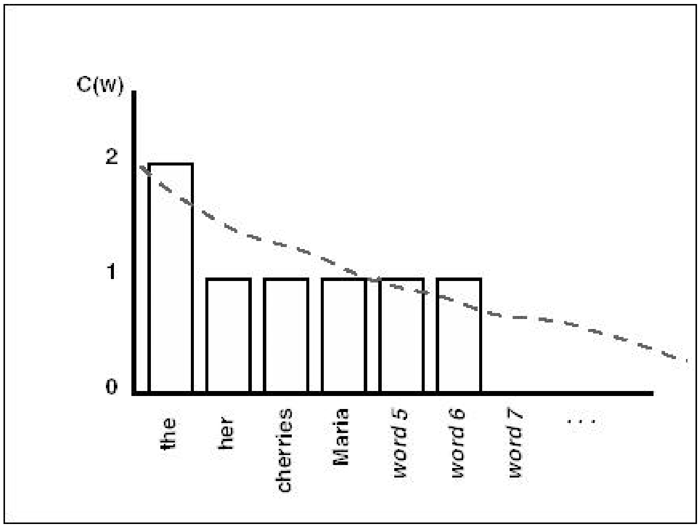
"inferior to ________"



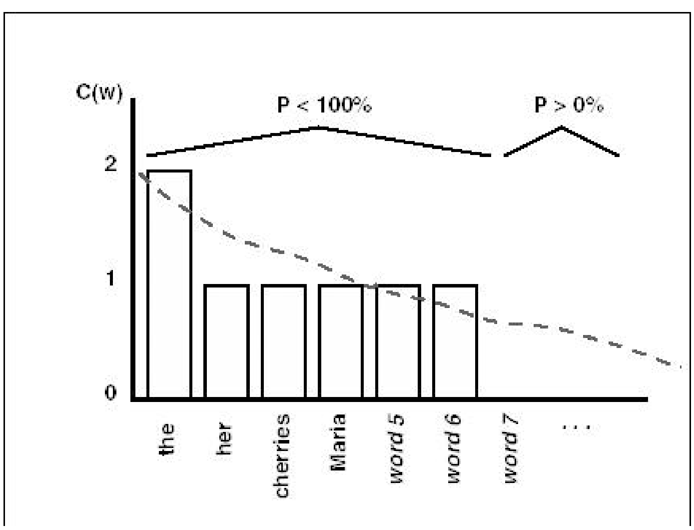
Maximum likelihood estimate



Actual probability distribution



Comparison



Smoothing

- Develop a model which decreases probability of seen events and allows the occurrence of previously unseen n-grams
- a.k.a. “Discounting methods”
- “Cross-Validation” – Smoothing methods which utilize a second batch of data.

How to use *Pr(Label | Data)* ?

- Assume we have a training corpus, i.e. a bunch of *Data* with their *Labels*.
- Then we can compute Maximum Likelihood Estimates (MLEs) of the probabilities as relative frequencies:

$$\Pr(Label \mid Data) = \frac{count(Label, Data)}{count(Data)}$$

- To predict a *Label* for a new bunch of *Data*, we just look up *Pr(Label | Data)* for all possible *Labels* and output the *argmax*.

Practical limitations

- Equivalently,

$$\Pr(Label \mid Data) = \frac{\Pr(Label, Data)}{\Pr(Data)}$$

- Let *Data* = (w_1, w_2, ..., w_d).
- Let *v* = size of vocabulary.
- Then we need v^d probability estimates!

We can use n-grams for tagging

- Replace 'words' with 'tags'
- Find best maximum likelihood estimates
- Estimates calculated this way:
  - P(noun|det) = p(det, noun)/p(det) replace:
  - $\approx \frac{\text{count(det at position i-1 \& noun at i)}}{\text{count(det at position i-1)}}$
  - Correction: include frequency of context word

    $\approx \frac{\text{count(det at position i-1 \& noun at I)}}{\text{count(det at position i-1)*count noun at i)}}$

Find optimal path – highest p, using dynamic programming algorithm, approx. linear in length of tag sequence

Example

The guy still saw her
Det NN NN NN PPO
VB VB VBD PP$
RB

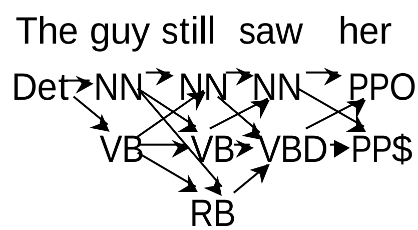
Table 2 from DeRose (1988)
Det=determiner, NN=noun, VB=verb, RB=adverb, VBD=past-tense-verb, PPO=object pronoun and PP$=possessive pronoun

Find the Max likelihood estimate (MLE) path through this 'trellis'

Transitional probability estimates from counts

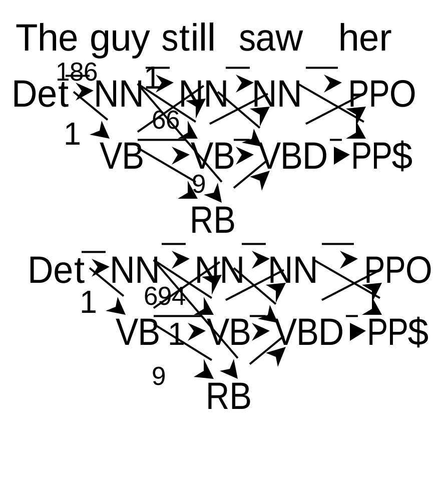
	DT	NN	PPO	PP$	RB	VB	VBD
DT	0	186	0	8	1	8	9
NN	40	1	3	40	9	66	186
PPO	7	3	16	164	109	16	313
PP$	176	0	0	5	1	1	2
RB	5	3	16	164	109	16	313
VB	22	694	146	98	9	1	59
VBD	11	584	143	160	2	1	91

Tagging search tree (trellis)



Step 1. c(DT-NN)= 186
c(DT-VB) = 1
Keep both paths. (Why?)
Step 2. Pick *max* to each of the tags NN, VB, RB
need keep only the *max.* Why?

Trellis search



Smoothing

- We don’t see many of the words in English (uniqram)
- We don’t see the huge majority of bigrams in English
- We see only a tiny sliver of the possible trigrams
- So: most of the time, bigram model assigns p(0) to bigram:

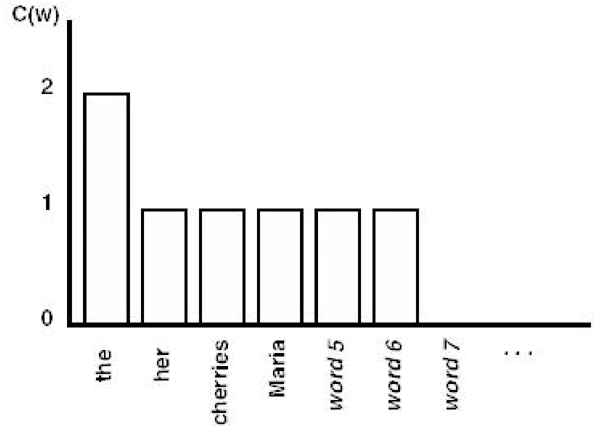
  p(food|want) = |want food| /|want| = 0/whatever

But means event can’t happen – we aren’t warranted to conclude this... therefore, we must adjust...how?

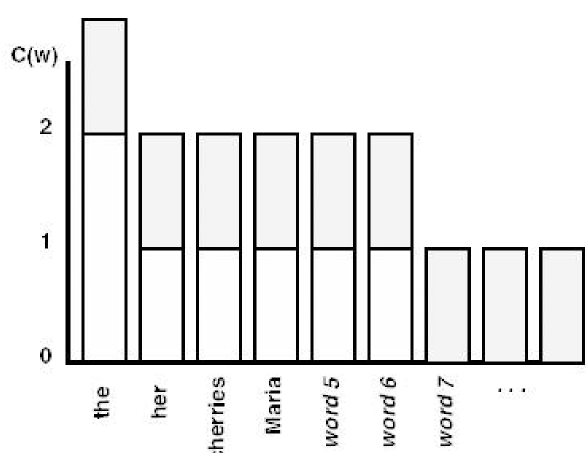
Simplest idea: add-1 smoothing

- Add 1 to every cell of
- P(food | want) = |want to| ÷ |want| = 1 ÷ 2931 = .0003

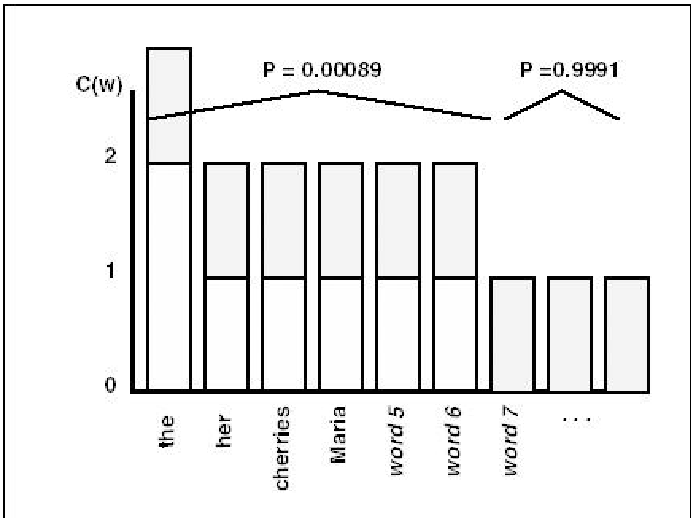
Laplace's law (add 1)



Laplace's Law (add 1)



Laplace's Law



Initial counts – Berkeley restaurant project

	I	want	to	eat	Chinese	food	lunch
I	8	1087	0	13	0	0	0
want	3	0	786	0	6	8	6
to	3	0	10	860	3	0	12
eat	0	0	2	0	19	2	52
Chinese	2	0	0	0	0	120	1
food	19	0	17	0	0	0	0
lunch	4	0	0	0	0	1	0

	I	want	to	eat	Chinese	food	lunch
I	.0023	.32	0	.0038	0	0	0
want	.0025	0	.65	0	.0049	.0066	.0049
to	.00092	0	.0031	.26	.00092	0	.0037
eat	0	0	.0021	0	.020	.0021	.055
Chinese	.0094	0	0	0	0	.56	.0047
food	.013	0	.011	0	0	0	0
lunch	.0087	0	0	0	0	.0022	0

Old vs.New table

	I	want	to	eat	Chinese	food	lunch
I	.0023	.32	0	.0038	0	0	0
want	.0025	0	.65	0	.0049	.0066	.0049
to	.00092	0	.0031	.26	.00092	0	.0037
eat	0	0	.0021	0	.020	.0021	.055
Chinese	.0094	0	0	0	0	.56	.0047
food	.013	0	.011	0	0	0	0
lunch	.0087	0	0	0	0	.0022	0

	I	want	to	eat	Chinese	food	lunch
I	.0018	.22	.00020	.0028	.00020	.00020	.00020
want	.0014	.00035	.28	.00035	.0025	.0032	.0025
to	.00082	.00021	.0023	.18	.00082	.00021	.0027
eat	.00039	.00039	.0012	.00039	.0078	.0012	.021
Chinese	.0016	.00055	.00055	.00055	.00055	.066	.0011
food	.0064	.00032	.0058	.00032	.00032	.00032	.00032
lunch	.0024	.00048	.00048	.00048	.00048	.00096	.00048

Changes

- All non-zero probs went *down*
- Sometimes probs don’t change much
- Some predictable events become less predictable (P(to|want) [0.65 to 0.22])
- Other probs change by large factors (P(lunch|Chinese) [0.0047 to 0.001]
- Conclusion: generally good idea, but effect on nonzeroes not always good – blur original model – too much prob to the zeros, we want less ‘weight’ assigned to them (zero-sum game, ‘cause probs always sum to 0)

So far, then...

- n-gram models are a.k.a. Markov models/chains/processes.
- They are a model of how a sequence of observations comes into existence.
- The model is a probabilistic walk on a FSA.
- $Pr(a|b)$ = probability of entering state *a*, given that we're currently in state *b*.

How well does this work for tagging?

- 90% accuracy (for unigram) pushed up to 96%
- So what?
- How *good* is this? Evaluation!

Evaluation of systems

- The principal measures for information extraction tasks are recall and precision.
- *Recall* is the number of answers the system got right divided by the number of possible right answers
  - It measures how complete or comprehensive the system is in its extraction of relevant information
- *Precision* is the number of answers the system got right divided by the number of answers the system gave
  - It measures the system's correctness or accuracy
  - Example: there are 100 possible answers and the system gives 80 answers and gets 60 of them right, its recall is 60% and its precision is 75%.

A better measure - Kappa

- Takes baseline & complexity of task into account – if 99% of tags are Nouns, getting 99% correct no great shakes
- Suppose no "Gold Standard" to compare against?
- P(A) = proportion of times hypothesis *agrees* with standard (% correct)
- P(E) = proportion of times hypothesis and standard would be *expected* to agree by chance (computed from some other knowledge, or actual data)

Kappa [p. 315 J&M text]

$$k = \frac{P(A) - P(E)}{1 - P(E)}$$

- Note K ranges between 0 (no agreement, except by chance; to complete agreement, 1)
- Can be used even if no ‘Gold standard’ that everyone agrees on
- K> 0.8 is good

Kappa

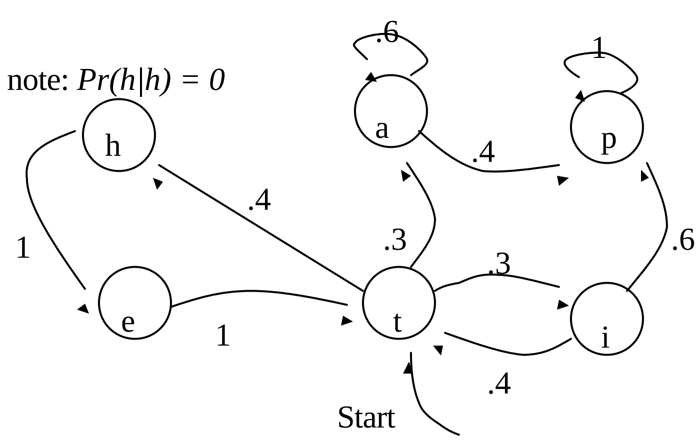
$$k = \frac{P(A) - P(E)}{1 - P(E)}$$

- *A* = actual agreement; *E* = expected agreement
- consistency is more important than “truth”
- methods for raising consistency
  - style guides (often have useful insights into data)
  - group by task, not chronologically, etc.
  - annotator acclimatization

Statistical Tagging Methods

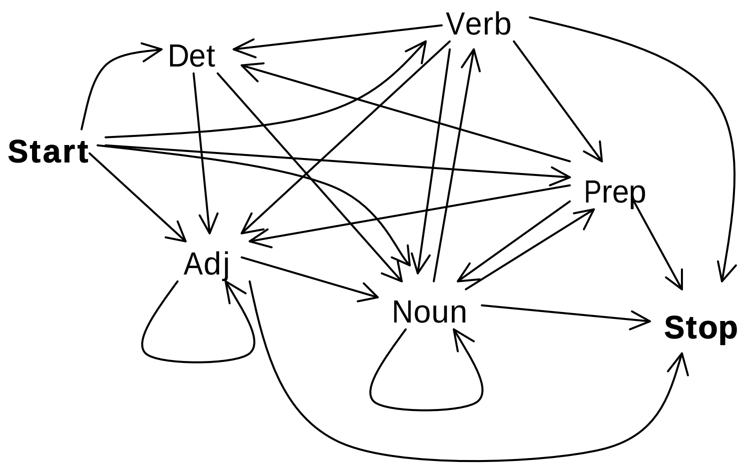
- Simple bigram – ok, done
- Combine bigram and unigram

Markov chain...



$$\forall y \sum_{x} \Pr(x \mid y) = 1$$

First-order Markov (bigram) model as fsa



Markov inferences

1. Given a Markov model M, we can compute the (MLE) probability of a given observation sequence.
2. Given the states of a Markov model, and an observation sequence, we can estimate the state transition probabilities.
3. Given a pair of Markov models and an observation sequence, we can choose the more likely model.

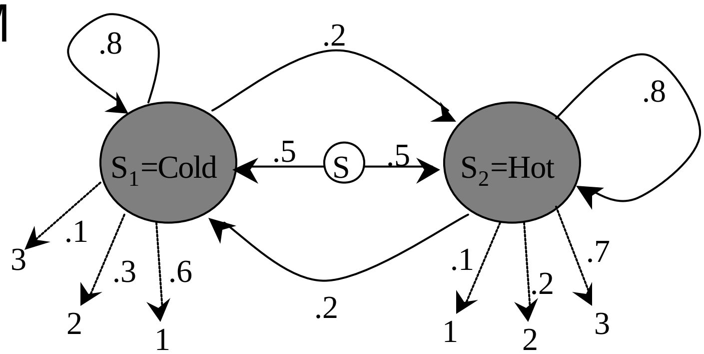
From Markov models to Hidden Markov models (HMMs)

- The HMM of how an observation sequence comes into existence adds one step to a (simple/visible) Markov model.
- Instead of <u>being</u> observations, the states now probabilistically <u>emit</u> observations.
- The relationship between states and observations is, in general, many-to-many.
- We can't be sure what sequence of states emitted a given sequence of observations

HMM for ice-cream consumption

- Predict Boston weather given my consumption (observable) of ice-creams, 1, 2, 3.
- Underlying state is either H(ot) or C(old)
- Prob of moving between states, and also prob of eating 1, 2, 3, *given* in state H or C. Formally:

HMM

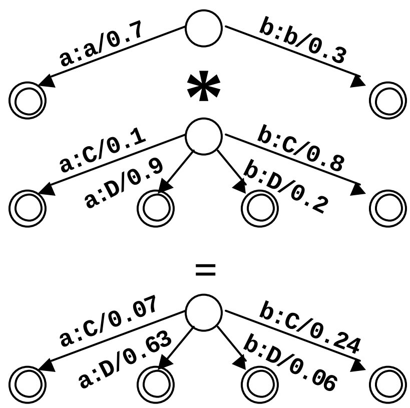


- Start in state S_i with probability p_i.
- While (t++) do:
  - Move from S_i to S_j with probability a_{ij} (i.e. $X_{t+1}=j$)
  - Emit observation $o_t=k$ with probability b_{ik}.

Noisy channel maps well to our fsa/fst notions

- What's p(X)?
- Ans: p(tag sequence) – i.e., some finite state automaton
- What's p(Y|X)?
- Ans: transducer that takes tags$\rightarrow$words
- What's P(X,Y)?
- The joint probability of the tag sequence, given the words (well, gulp, almost… we will need one more twist – why? What is Y?)

The plan modeled as composition (x-product) of finite-state machines



p(X)

*****

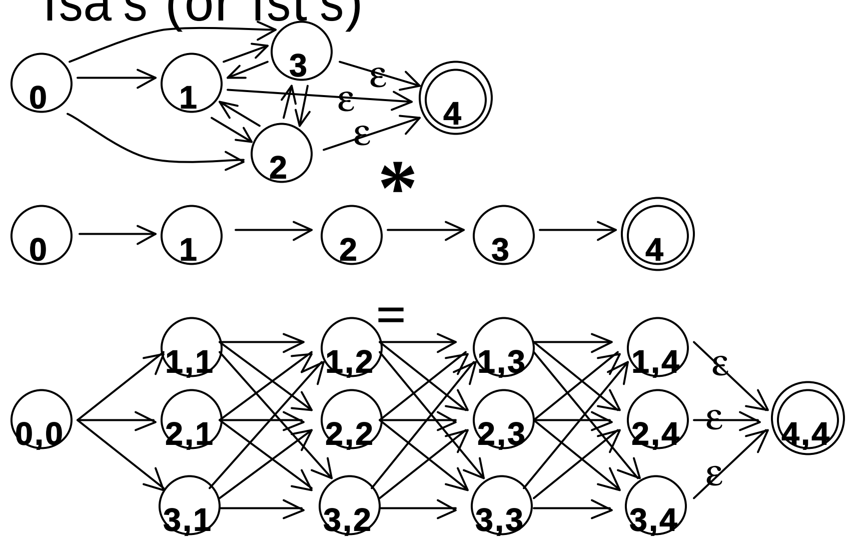
p(Y | X)

=

p(X,Y)

Note p(x,y) sums to 1.

Cross-product construction for fsa's (or fst's)



Pulled a bit of a fast one here...

- So far, we have a plan to compute P(X,Y) – but is this correct?
- Y= all the words in the world
- X= all the tags in the world (well, for English)
- What we get to see as input is **y Î Y** *not* Y!
- What we want to compute is REALLY this:

want to recover xÎ X from yÎ Y
choose x that <u>maximizes</u> p(X | y) so...

The real plan...

$$\mathbf{p(X)}$$

$$\mathbf{*}$$

$$\mathbf{p(Y \mid X)}$$

$$\mathbf{*}$$

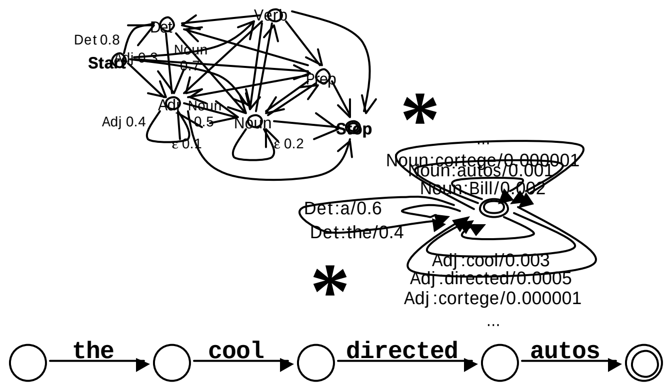
$$\mathbf{p(y \mid Y)}$$

Find x that maximizes
this quantity

$$=$$

$$\mathbf{p(X, y)}$$

Cartoon version



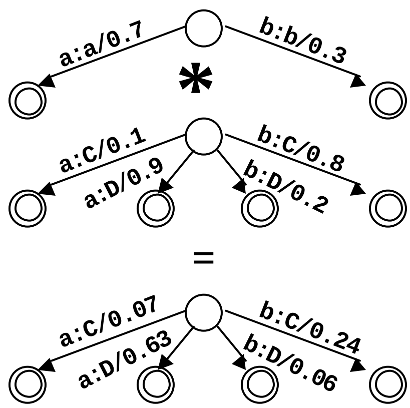
transducer: scores candidate tag seqs on their joint probability with obs words; we should pick best path

$$p(X)$$
$$*$$
$$p(Y \mid X)$$
$$*$$
$$p(y \mid Y)$$
$$=$$
$$p(X, y)$$

This is an HMM for tagging

- Each hidden tag state produces a word in the sentence
- Each word is
  - Uncorrelated with all the other words and their tags
  - Probabilistic depending on the N previous tags only

The plan modeled as composition (product) of finite-state machines



p(X)

*****

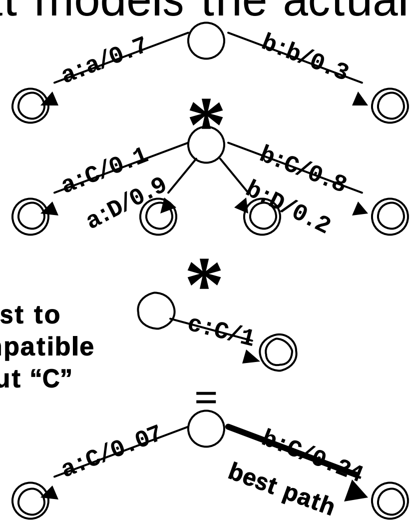
p(Y | X)

=

p(X,Y)

Note p(x,y) sums to 1.
Suppose y="C"; what is best "x"?

We need to factor in one more machine that models the actual word sequence, y



restrict just to paths compatible with output "C"

p(X)

*****

p(Y | X)

*****

p(y | Y)

find x to =
maximize p(X, y)

The statistical view, in short:

- We are modeling p(word seq, tag seq)
- The tags are *hidden*, but we see the words
- What is the most likely tag sequence?
- Use a finite-state automaton, that can emit the observed words
- FSA has limited memory
- AKA this Noisy channel model is a "Hidden Markov Model" -

Put the punchline before the joke

Bill directed a cortege of autos through the dunes

Recover tags

Punchline – recovering (words, tags)

tags X→

Start PN Verb Det Noun Prep Noun Prep Det Noun **Stop**

Bill directed a cortege of autos through the dunes

words Y→

Find tag sequence X that maximizes probability product

Punchline – ok, where do the pr numbers come from?

tags X→

0.4 0.6

Start PN Verb Det Noun Prep Noun Prep Det Noun **Stop**

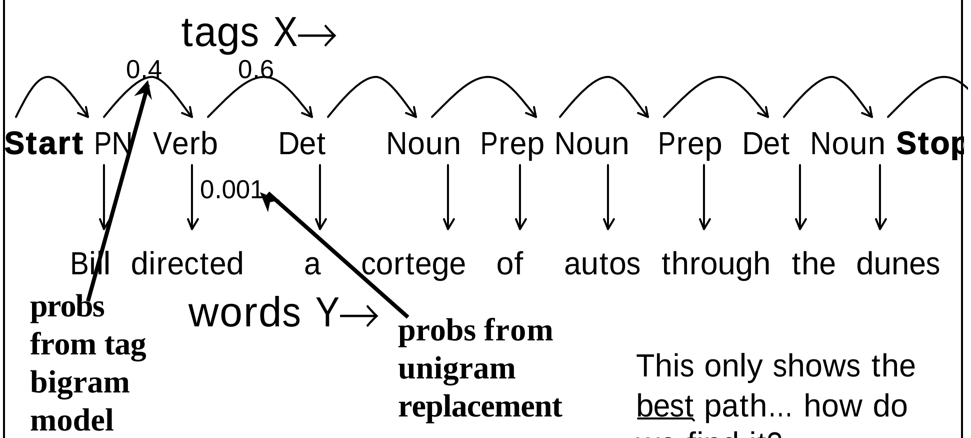
0.001

Bill directed a cortege of autos through the dunes

words Y→

the tags are not observable & they are states of some fsa
We estimate transition probabilities between states
We also have 'emission' pr's from states
En tout: a <u>Hidden Markov Model</u> (HMM)

Our model uses <u>both</u> *bigrams* & *unigrams*:



This only shows the <u>best</u> path... how do we find it?

Submenu for probability theory – redo n-grams a bit more formally

- Define all this p(X), p(Y|X), P(X,Y) notation
- p, event space, conditional probability & chain rule;
- Bayes' Law
- (Eventually) how do we estimate all these probabilities from (limited) text? (Backoff & Smoothing)

Rush intro to probability

p(Paul Revere wins | weather's clear) = 0.9

What's this mean?

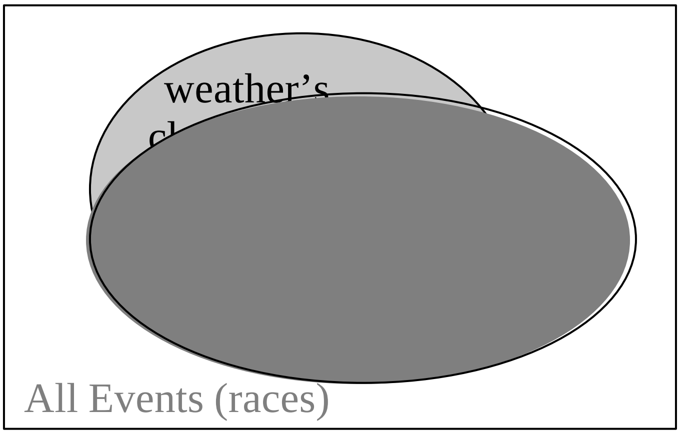
p(Paul Revere wins | weather's clear) = 0.9

- Past performance?
  - Revere's won 90% of races with clear weather
- Hypothetical performance?
  - If he ran the race in many parallel universes ...
- Subjective strength of belief?
  - Would pay up to 90 cents for chance to win $1
- Output of some computable formula?
  - But then which formulas should we trust?

    p(X | Y) versus q(X | Y)

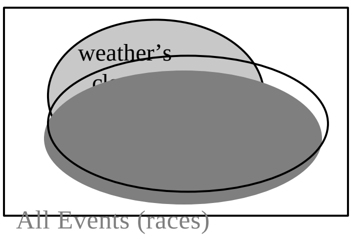
p is a function on event sets

p(win | clear) ≡ p(win, clear) / p(clear)



p is a function on event sets

$$\underbrace{p(win \mid clear)}_{\text{syntactic sugar}} \equiv p(\underbrace{win, clear}_{\text{logical conjunction of predicates}}) / p(\underbrace{clear}_{\text{predicate selecting races where weather's clear}})$$



p measures total probability of a set of events.

Commas in p(x,y) mean conjunction – on the left…

p(Paul Revere wins, Valentine places, Epitaph shows | weather's clear)

what happens as we add conjuncts to <u>left</u> of bar ?

- probability can only decrease
- numerator of historical estimate likely to go to zero:

$$\frac{\text{\# times Revere wins AND Val places… AND weather's clear}}{\text{\# times weather's clear}}$$

Commas in p(x,y)…on the right

p(Paul Revere wins | weather's clear, ground is dry, jockey getting over sprain, Epitaph also in race, Epitaph was recently bought by Gonzalez, race is on May 17, …)

what happens as we add conjuncts to <u>right</u> of bar ?

- probability could increase or decrease
- probability gets more relevant to our case (less ***bias***)
- probability *estimate* gets less reliable (more ***variance*****)**

$$\frac{\text{\# times Revere wins AND weather clear AND … it's May 17}}{\text{\# times weather clear AND … it's May 17}}$$

Backing off: simplifying the right-hand side...

p(Paul Revere wins | weather's clear, ~~ground is dry, jockey getting over sprain, Epitaph also in race, Epitaph was recently bought by Gonzale~~z, ~~race is on May 17,~~ ...)

- not exactly what we want but at least we can get a reasonable estimate of it!
- try to *keep* the conditions that we suspect will have the most influence on whether Paul Revere wins
- Recall 'backing off' in using just p(rabbit|white) instead of p(rabbit|Just then a white) – so this is a general method

What about simplifying the left-hand side?

p(Paul Revere wins~~, Valentine places, Epitaph shows~~ | weather's clear)

NOT ALLOWED!

but we can do something similar to help …

We can FACTOR this information – the so-called "Chain Rule"

Chain rule: factoring lhs

p(Revere, Valentine, Epitaph | weather's clear) RVEW/W

= p(Revere | ~~Valentine, Epitaph~~, weather's clear) = RVEW/VEW

* p(Valentine | ~~Epitaph~~, weather's clear) * VEW/EW

* p(Epitaph | weather's clear) * EW/W

True because numerators cancel against denominators

Makes perfect sense when read from bottom to top

Moves material to right of bar so it can be ignored

If this prob is unchanged by backoff, we say Revere was CONDITIONALLY INDEPENDENT of Valentine and Epitaph (conditioned on the weather's being clear). Often we just ASSUME conditional independence to get the nice product above.

The plan: summary so far

automaton: p(tag sequence) p(X)

"Markov Model"

* *

transducer: tags → words p(Y | X)

"Unigram Replacement"

* *

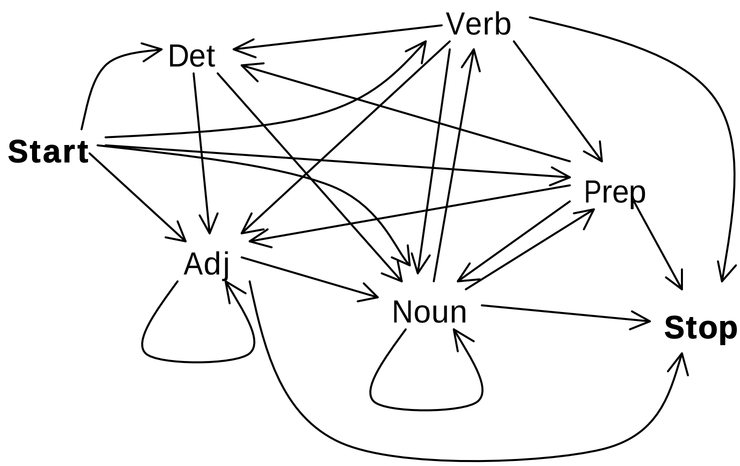
automaton: the observed words p(y | Y)

"straight line"

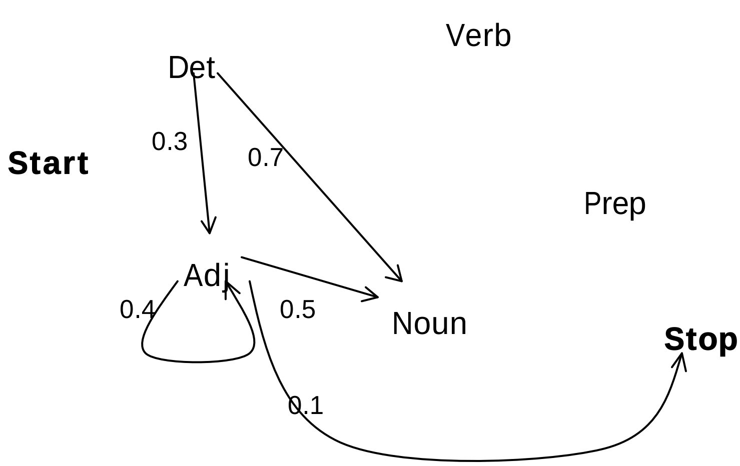
= =

transducer: scores candidate tag seqs on their joint probability with obs words; pick best path p(X, y)

First-order Markov (bigram) model as fsa

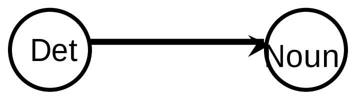


Add in transition probs - sum to 1

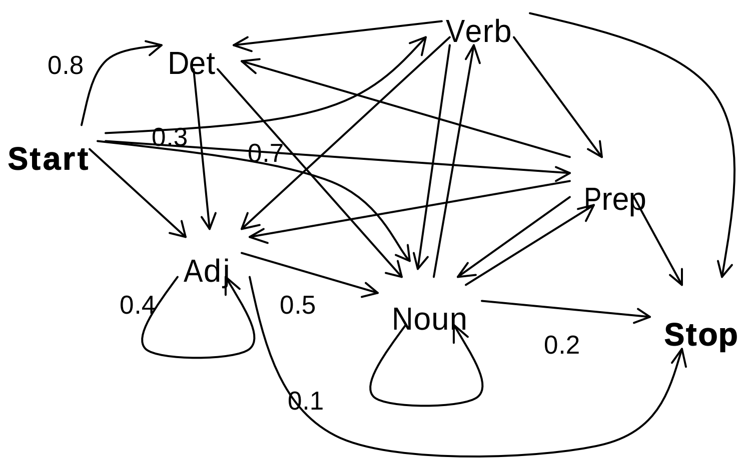


Same as bigram

P(Noun|Det)=0.7 ≡

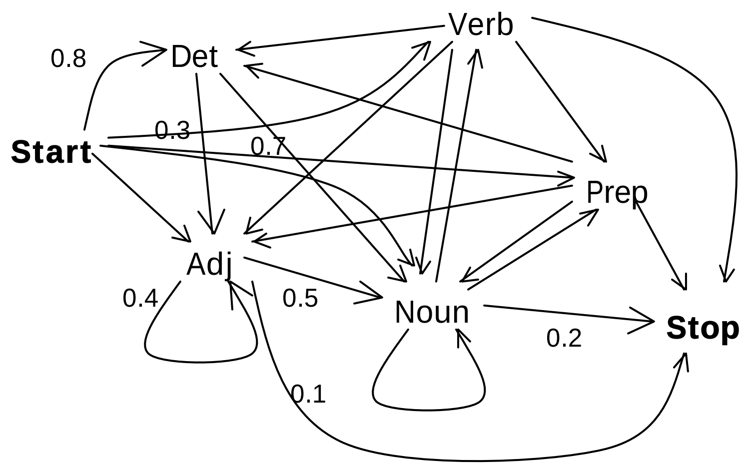


Add in start & etc.



Markov Model

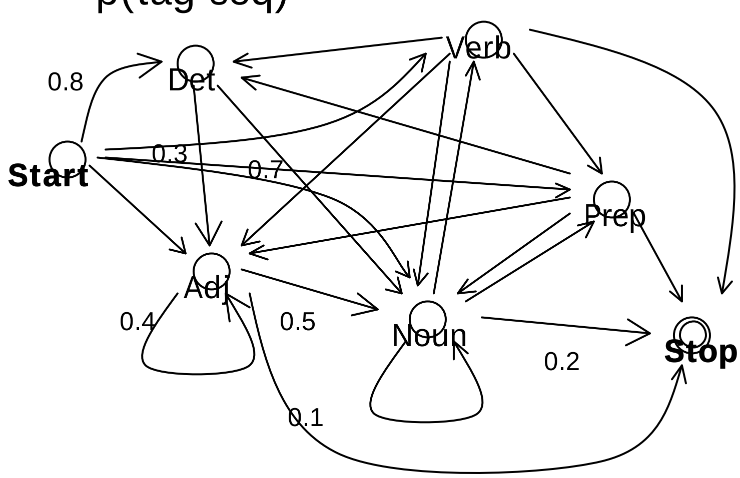
p(tag seq)



Start Det Adj Adj Noun **Stop** = 0.8 * 0.3 * 0.4 * 0.5 * 0.2

Markov model as fsa

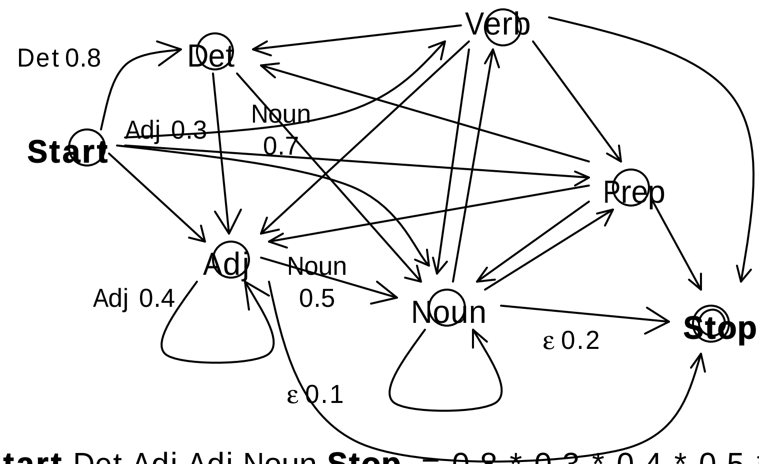
p(tag seq)



Start Det Adj Adj Noun **Stop** = 0.8 * 0.3 * 0.4 * 0.5 * 0.2

Add ‘output tags’ (transducer)

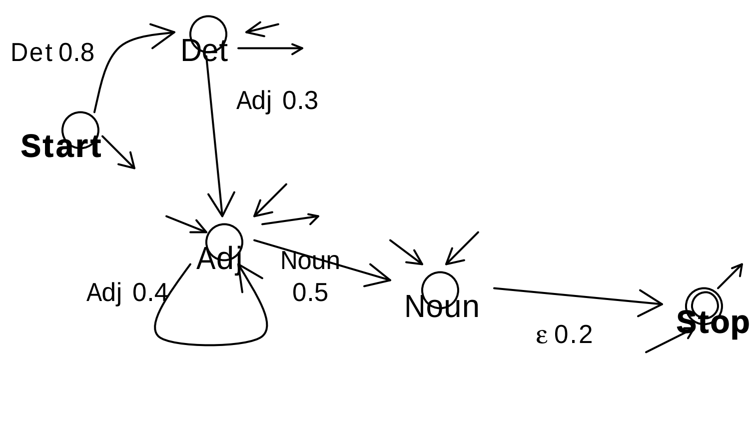
p(tag seq)



Start Det Adj Adj Noun **Stop** = 0.8 * 0.3 * 0.4 * 0.5 * 0.2

Tag bigram picture

p(tag seq)



Start Det Adj Adj Noun **Stop** = 0.8 * 0.3 * 0.4 * 0.5 * 0.2

Our plan

automaton: p(tag sequence) — p(X)

"Markov Model"

* — *

transducer: tags → words — p(Y | X)

"Unigram Replacement"

* — *

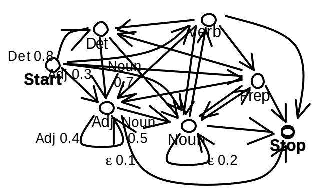
automaton: the observed words — p(y | Y)

"straight line"

= — =

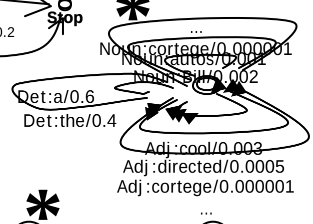
transducer: scores candidate tag seqs on their joint probability with obs words; pick best path — p(X, y)

Cartoon form again



p(X)

*



p(Y | X)

*

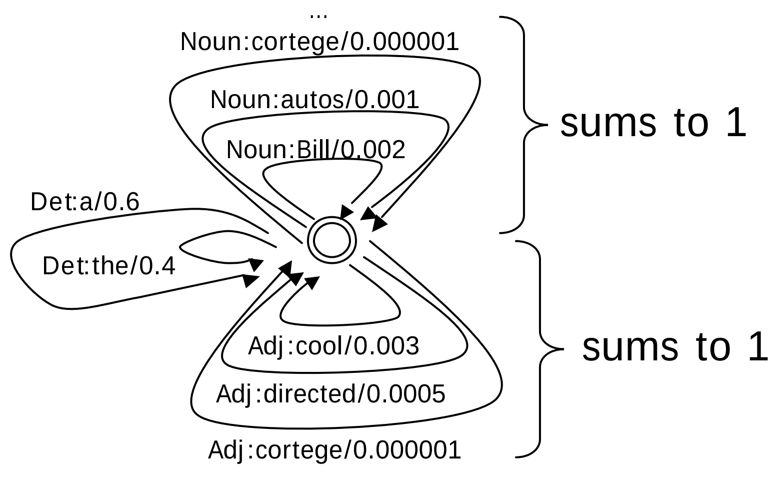
p(y | Y)

= — =

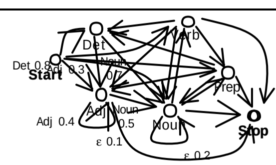
transducer: scores candidate tag seqs on their joint probability with obs words; we should pick best path — p(X, y)

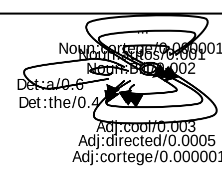
Next up: unigram replacement model

p(word seq | tag seq)

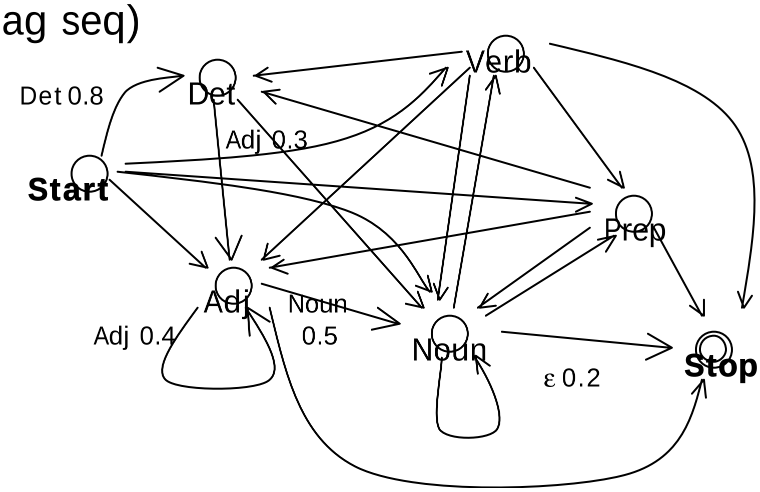


Compose

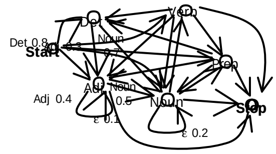


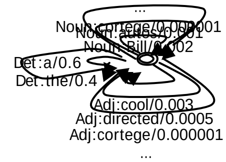


p(tag seq)

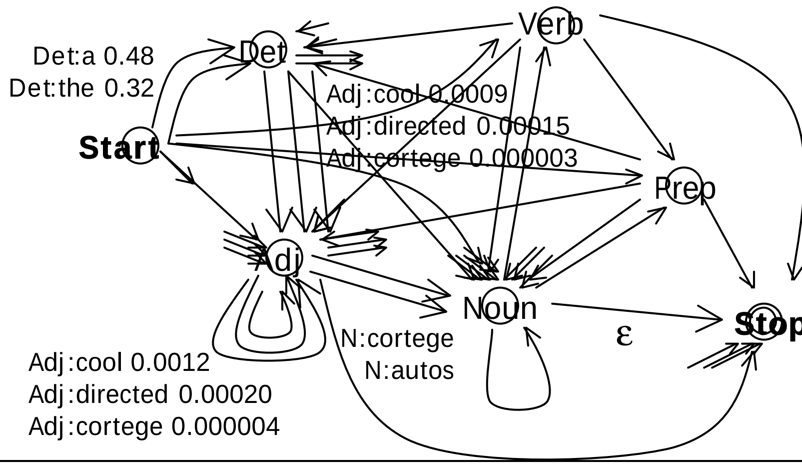


Compose



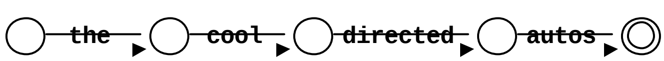


p(word seq, tag seq) = p(tag seq) * p(word seq | tag seq)

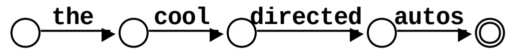


Observed words as straight-line fsa

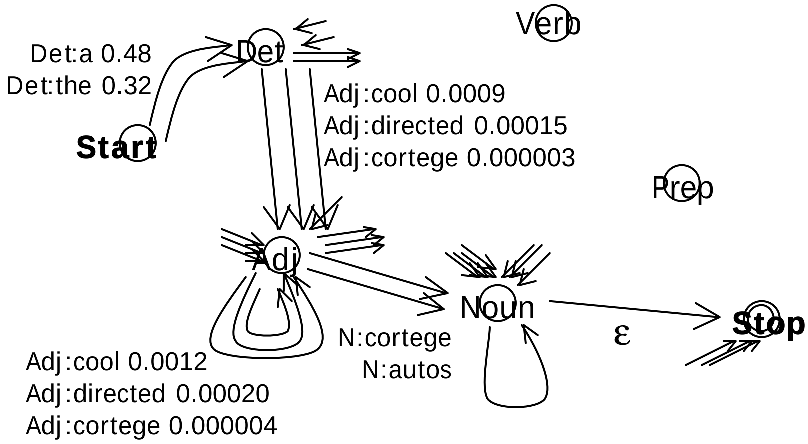
word seq



Compose with

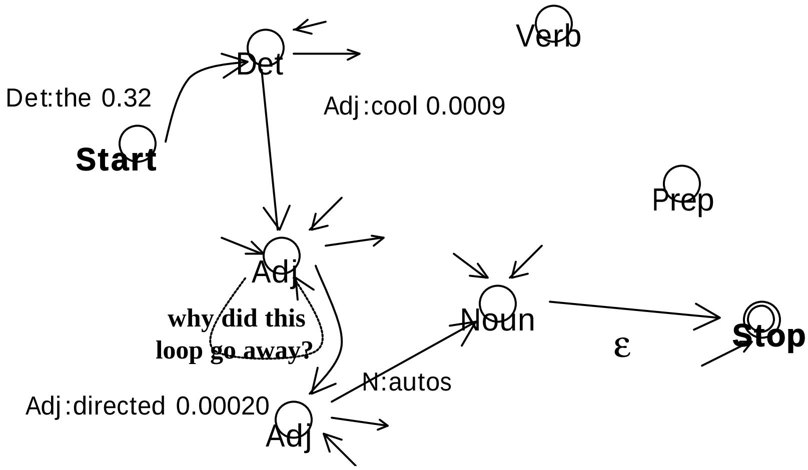


p(word seq, tag seq) = p(tag seq) * p(word seq | tag seq)



Compose with

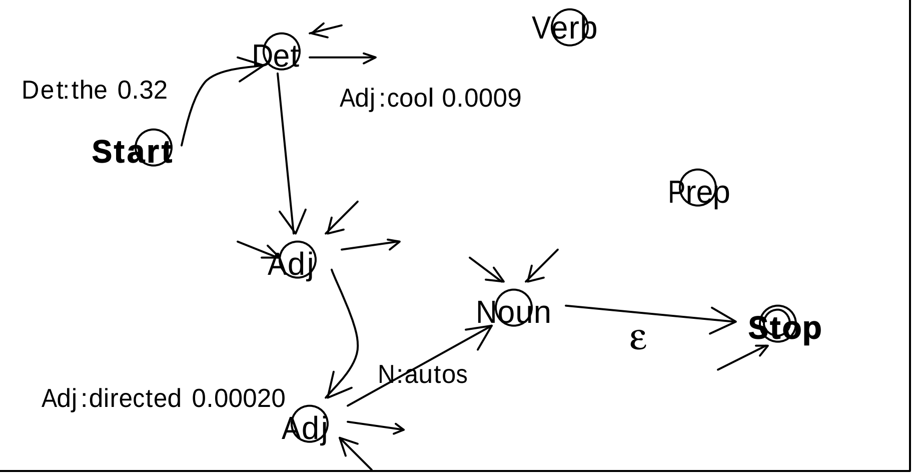
p(word seq, tag seq) = p(tag seq) * p(word seq | tag seq)



The best path:

Start Det Adj Adj Noun **Stop** = 0.32 * 0.0009*0.00020...
the cool directed autos

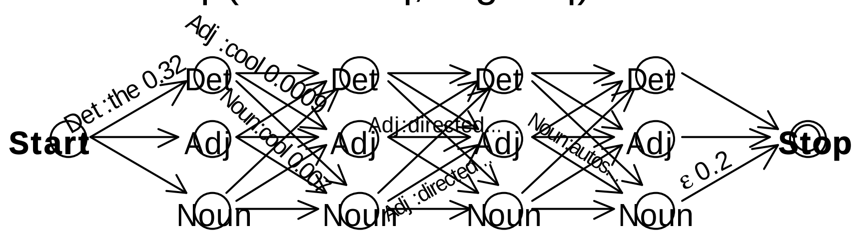
p(word seq, tag seq) = p(tag seq) * p(word seq | tag seq)



But...how do we find this ‘best’ path???

All paths together form ‘trellis’

p(word seq, tag seq)



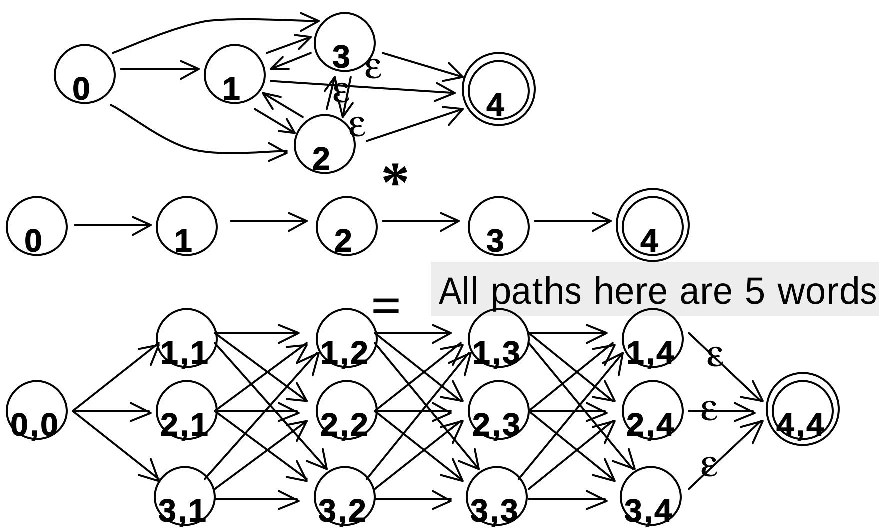
WHY?

The best path:

Start Det Adj Adj Noun **Stop** = 0.32 * 0.0009 ...

the cool directed autos

Cross-product construction forms trellis

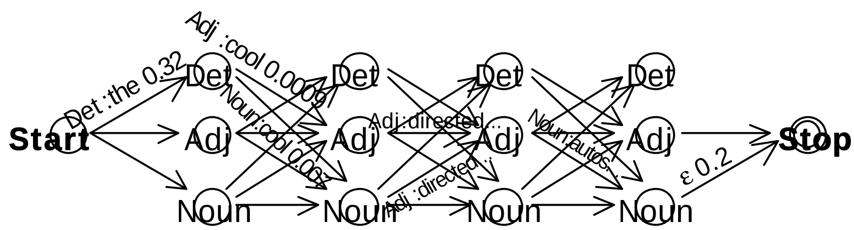


So all paths here must have 5 words on output side

Trellis isn't complete

p(word seq, tag seq)

Lattice has no Det → Det or Det →Stop arcs; why?



The best path:

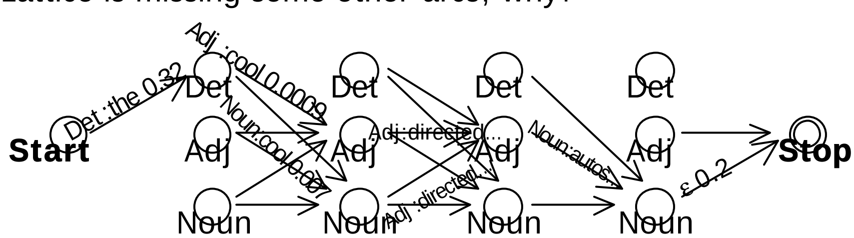
Start Det Adj Adj Noun **Stop** = 0.32 * 0.0009 ...

the cool directed autos

Trellis incomplete

p(word seq, tag seq)

Lattice is missing some other arcs; why?



The best path:

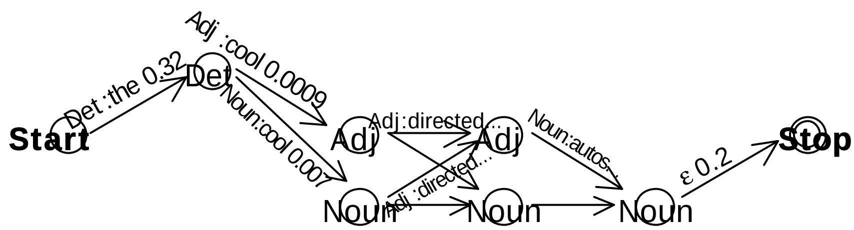
Start Det Adj Adj Noun **Stop** = 0.32 * 0.0009 ...

the cool directed autos

And missing some states...

p(word seq, tag seq)

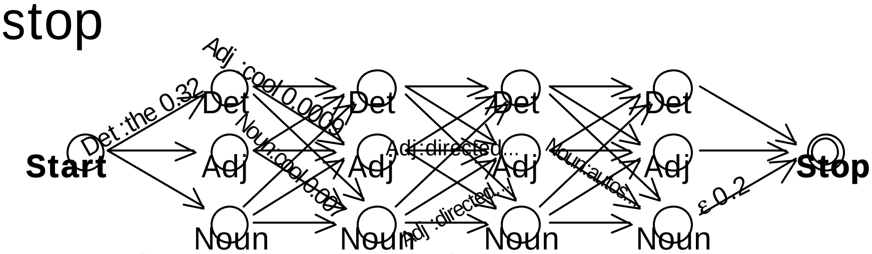
Lattice is missing some states; why?



The best path:

Start Det Adj Adj Noun **Stop** = 0.32 * 0.0009 ...
the cool directed autos

Finding the best path from start to stop



- Use dynamic programming
- What is best path from Start to *each* node?
  - Work from left to right
  - Each node stores its best path from Start (as probability plus one backpointer)
- Special acyclic case of Dijkstra’s shortest-path algorithm
- Faster if some arcs/states are absent

Method: Viterbi algorithm

- For each path reaching state s at step (word) t, we compute a path probability. We call the max of these viterbi(s,t)
- [Base step] Compute viterbi(0,0)=1
- [Induction step] Compute viterbi(s',t+1), assuming we know viterbi(s,t) for all s

Viterbi recursion

path-prob(s'|s,t) =	viterbi(s,t)	*	a[s,s']
probability of path to s' through s	max path score for state s at time t	*	transition p $s \to s'$

viterbi(s',t+1) = max$_{\text{s in STATES}}$ path-prob(s' | s,t)

Method...

- This is *almost* correct...but again, we need to factor in the *unigram* prob of a state s' given an observed surface word *w*
- So the correct formula for the path prob is:

  path-prob(s'|s,t) = viterbi(s,t) * a[s,s'] * $b_{s'}(o_t)$

  bigram unigram

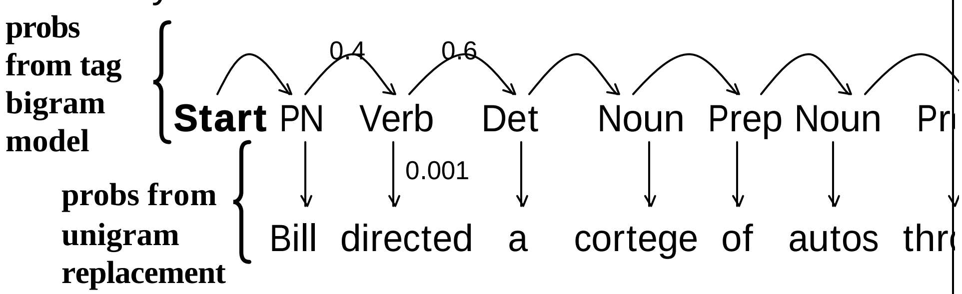
Or as in your text...p. 179

function VITERBI(*observations* of len *T*,*state-graph*) **returns** *best-path*

num-states ← NUM-OF-STATES(*state-graph*)
Create a path probability matrix *viterbi[num-states+2,T+2]*
viterbi[0,0] ← 1.0
for each time step *t* **from** 0 **to** *T* **do**
  for each state *s* **from** 0 **to** *num-states* **do**
    for each transition *s'* from *s* specified by *state-graph*
      ~~*new-score* ← *viterbi*[*s*, *t*] * *a*[*s*,*s'*] * $b_{s'}(o_t)$~~
      if ((*viterbi*[*s'*,*t+1*] = 0) || (*new-score* > *viterbi*[*s'*, *t+1*]))
        then
          viterbi[*s'*, *t+1*] ← *new-score*
          back-pointer[*s'*, *t+1*] ← *s*
Backtrace from highest probability state in the final column of *viterbi[]* and return path

Summary

- We are modeling p(word seq, tag seq)
- The tags are hidden, but we see the words
- Is tag sequence X likely with these words?
- Noisy channel model is a “Hidden Markov Model”:



- Find X that maximizes probability product

Evaluation of systems...redux

- The principal measures for information extraction tasks are recall and precision.
- *Recall* is the number of answers the system got right divided by the number of possible right answers
  - It measures how complete or comprehensive the system is in its extraction of relevant information
- *Precision* is the number of answers the system got right divided by the number of answers the system gave
  - It measures the system's correctness or accuracy
  - Example: there are 100 possible answers and the system gives 80 answers and gets 60 of them right, its recall is 60% and its precision is 75%.

A better measure - Kappa

- Takes baseline & complexity of task into account – if 99% of tags are Nouns, getting 99% correct no great shakes
- Suppose no “Gold Standard” to compare against?
- P(A) = proportion of times hypothesis *agrees* with standard (% correct)
- P(E) = proportion of times hypothesis and standard would be *expected* to agree by chance (computed from some other knowledge, or actual data)

Kappa [p. 315 J&M text]

$$k = \frac{P(A) - P(E)}{1 - P(E)}$$

- Note K ranges between 0 (no agreement, except by chance; to complete agreement, 1)
- Can be used even if no ‘Gold standard’ that everyone agrees on
- K> 0.8 is good

Two approaches

1. Noisy Channel Model (statistical) – what's that?? (we will have to learn some statistics)

2. Deterministic baseline tagger composed with a cascade of fixup transducers

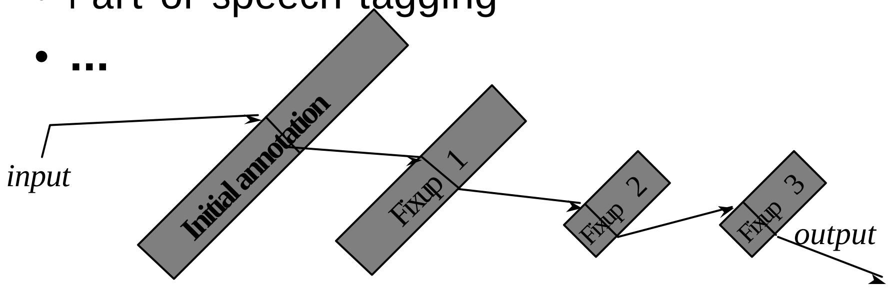
These two approaches will the guts of Lab 2

(lots of others: decision trees, ...)

Fixup approach: Brill tagging

Another FST Paradigm: Successive Fixups

- Like successive markups but *alter*
- Morphology
- Phonology
- Part-of-speech tagging
- …



Transformation-Based Tagging (Brill 1995)

figure from Brill's thesis

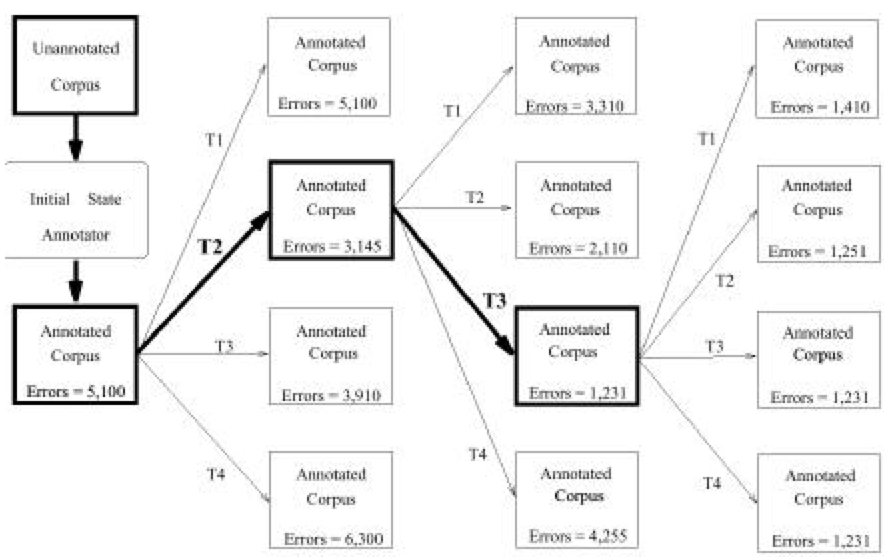


figure from Brill's thesis

Transformations Learned

#	Change Tag From	To	Condition
1	NN	VB	Previous tag is *TO*
2	VBP	VB	One of the previous three tags is *MD*
3	NN	VB	One of the previous two tags is *MD*
4	VB	NN	One of the previous two tags is *DT*
5	VBD	VBN	One of the previous three tags is *VBZ*
6	VBN	VBD	Previous tag is *PRP*
7	VBN	VBD	Previous tag is *NNP*
8	VBD	VBN	Previous tag is *VBD*
9	VBP	VB	Previous tag is *TO*
10	POS	VBZ	Previous tag is *PRP*
11	VB	VBP	Previous tag is *NNS*
12	VBD	VBN	One of previous three tags is *VBP*
13	IN	WDT	One of next two tags is *VB*
14	VBD	VBN	One of previous two tags is *VB*
15	VB	VBP	Previous tag is *PRP*
16	IN	WDT	Next tag is *VBZ*
17	IN	DT	Next tag is *NN*
18	JJ	NNP	Next tag is *NNP*
19	IN	WDT	Next tag is *VBD*
20	JJR	RBR	Next tag is *JJ*

BaselineTag*
NN @→ VB / / TO _
VBP @→ VB / / ... _
etc.

Compose this cascade of FSTs.

Get a big FST that does the initial tagging and the sequence of fixups "all at once."

figure from Brill's thesis

Initial Tagging of OOV Words

#	Change Tag From	To	Condition
1	NN	NNS	Has suffix **-s**
2	NN	CD	Has character **.**
3	NN	JJ	Has character **-**
4	NN	VBN	Has suffix **-ed**
5	NN	VBG	Has suffix **-ing**
6	??	RB	Has suffix **-ly**
7	??	JJ	Adding suffix **-ly** results in a word.
8	NN	CD	The word **$** can appear to the left.
9	NN	JJ	Has suffix **-al**
10	NN	VB	The word **would** can appear to the left.
11	NN	CD	Has character **0**
12	NN	JJ	The word **be** can appear to the left.
13	NNS	JJ	Has suffix **-us**
14	NNS	VBZ	The word **it** can appear to the left.
15	NN	JJ	Has suffix **-ble**
16	NN	JJ	Has suffix **-ic**
17	NN	CD	Has character **1**
18	NNS	NN	Has suffix **-ss**
19	??	JJ	Deleting the prefix **un-** results in a word
20	NN	JJ	Has suffix **-ive**

Laboratory 2

- Goals:

1. Use both HMM and Brill taggers
2. Find errors that both make
3. Compare performance – use of kappa & ‘confusion matrix’
4. All the slings & arrows of corpora – use Wall Street Journal excerpts