Natural Language Processing

Sequence labeling

Yulia Tsvetkov

yuliats@cs.washington.edu

PAUL G. ALLEN SCHOOL
OF COMPUTER SCIENCE & ENGINEERING

Your feedback - positives

- Positive feedbacks on course content, lectures, assignments, helpful TAs
  - Thank you!

Moving forward

Lectures

- Too much time on ML basics
- Math too hard, annotate formulas in lectures
- Too many questions

Ed questions

- More coding parts can be added into assignments/projects to help us become machine learning engineers.

Homework assignments

- The spec for Project 1 vague
- I believe updating the code documentation and changing the requirements for some of the problems would allow for a more intuitive coding experience and learning.
- More instructions in Assignment coding will be helpful (currently the instructions is kind of vague)
  - We updated instructions for Assignment 2
  - please publish on Ed if anything is unclear and we'll fix the documentation
- Megathread earlier
  - done

Announcements

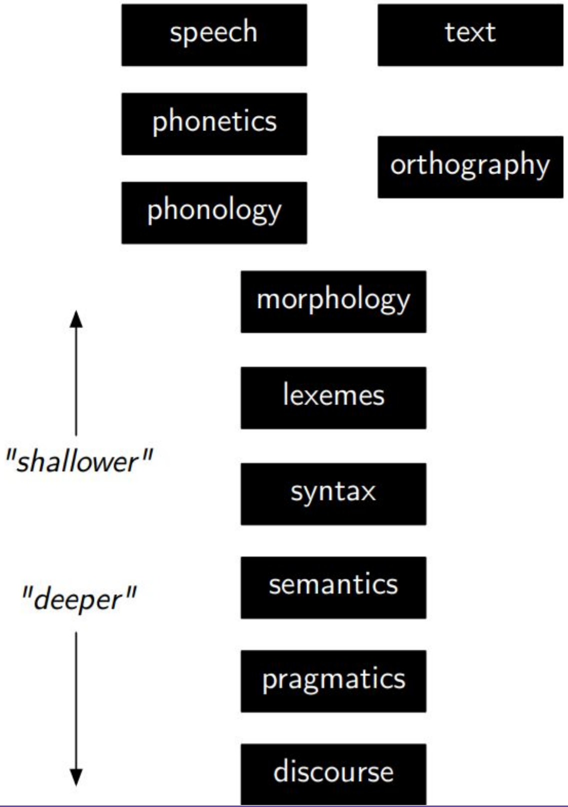
- Quiz 3 regraded
- HW 2 grades will be released today, you have 7 days for regrading requests
- HW 2 released
  - Start early

- HW2 content will be covered in lectures by the end of the next week

Readings

- J&M SLP3 https://web.stanford.edu/~jurafsky/slp3/8.pdf
- Collins (2011) http://www.cs.columbia.edu/~mcollins/hmms-spring2013.pdf
- Eis 7.1-7.4, 8.1

Levels of linguistic knowledge



Phonetics	The study of the sounds of human language
Phonology	The study of sound systems in human language
Morphology	The study of the formation and internal structure of words
Syntax	The study of the formation and internal structure of sentences
Semantics	The study of the meaning of sentences
Pragmatics	The study of the way sentences with their semantic meanings are used for particular communicative goals

Sequence labeling problems

Map a sequence of words to a sequence of labels

- Part-of-speech tagging (Church, 1988; Brants, 2000)
- Named entity recognition (Bikel et al., 1999)
- Text chunking and shallow parsing (Ramshaw and Marcus, 1995)
- Word alignment of parallel text (Vogel et al., 1996)
- Compression (Conroy and O'Leary, 2001)
- Acoustic models, discourse segmentation, etc.

Part of speech tagging

PART OF SPEECH	DT	VBZ	DT	JJ	NN
WORDS	This	is	a	simple	sentence

Parts of speech

- Open classes
  - nouns
  - verbs
  - adjectives
  - adverbs

- Closed classes
  - prepositions
  - determiners
  - pronouns
  - conjunctions
  - auxiliary verbs

Parts of speech, more fine-grained classes

- Open classes
  - nouns
    - proper
    - common
      - count
      - mass
  - verbs
  - adjectives
  - adverbs
    - directional
    - degree
    - manner
    - temporal

Actually, I ran home *extremely quickly yesterday*

Parts of speech, closed classes

prepositions: on, under, over, near, by, at, from, to, with
particles: up, down, on, off, in, out, at, by
determiners: a, an, the
conjunctions: and, but, or, as, if, when
pronouns: she, who, I, others
auxiliary verbs: can, may, should, are
numerals: one, two, three, first, second, third

Part of speech tagsets

- Penn treebank tagset (Marcus et al., 1993)

Tag	Description	Example	Tag	Description	Example	Tag	Description	Example
CC	coordinating conjunction	*and, but, or*	PDT	predeterminer	*all, both*	VBP	verb non-3sg present	*eat*
CD	cardinal number	*one, two*	POS	possessive ending	*'s*	VBZ	verb 3sg pres	*eats*
DT	determiner	*a, the*	PRP	personal pronoun	*I, you, he*	WDT	wh-determ.	*which, that*
EX	existential 'there'	*there*	PRP$	possess. pronoun	*your, one's*	WP	wh-pronoun	*what, who*
FW	foreign word	*mea culpa*	RB	adverb	*quickly*	WP$	wh-possess.	*whose*
IN	preposition/ subordin-conj	*of, in, by*	RBR	comparative adverb	*faster*	WRB	wh-adverb	*how, where*
JJ	adjective	*yellow*	RBS	superlatv. adverb	*fastest*	$	dollar sign	$
JJR	comparative adj	*bigger*	RP	particle	*up, off*	#	pound sign	#
JJS	superlative adj	*wildest*	SYM	symbol	+,%, &	“	left quote	‘ or “
LS	list item marker	*1, 2, One*	TO	“to”	*to*	”	right quote	’ or ”
MD	modal	*can, should*	UH	interjection	*ah, oops*	(	left paren	[, (, {, <
NN	sing or mass noun	*llama*	VB	verb base form	*eat*	)	right paren	],), }, >
NNS	noun, plural	*llamas*	VBD	verb past tense	*ate*	,	comma	,
NNP	proper noun, sing.	*IBM*	VBG	verb gerund	*eating*	.	sent-end punc	. ! ?
NNPS	proper noun, plu.	*Carolinas*	VBN	verb past part.	*eaten*	:	sent-mid punc	: ; ... – -

Example of POS tagging

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

There/EX are/VBP 70/CD children/NNS **there/RB**

Preliminary/JJ findings/NNS were/VBD **reported/VBN** in/IN today/NN **'s/POS** New/NNP England/NNP Journal/NNP of/IN Medicine/NNP ./.

The Universal Dependencies

Universal Dependencies

Universal Dependencies (UD) is a framework for consistent annotation of grammar (parts of speech, morphological features, and syntactic dependencies) across different human languages. UD is an open community effort with over 300 contributors producing more than 150 treebanks in 90 languages. If you're new to UD, you should start by reading the first part of the Short Introduction and then browsing the annotation guidelines.

- Short introduction to UD
- UD annotation guidelines
- More information on UD:
  - How to contribute to UD
  - Tools for working with UD
  - Discussion on UD
  - UD-related events
- Query UD treebanks online:
  - SETS treebank search maintained by the University of Turku
  - PML Tree Query maintained by the Charles University in Prague
  - Kontext maintained by the Charles University in Prague
  - Grew-match maintained by Inria in Nancy
  - INESS maintained by the University of Bergen
- Download UD treebanks

Open class words	Closed class words	Other
ADJ	ADP	PUNCT
ADV	AUX	SYM
INTJ	CCONJ	X
NOUN	DET	
PROPN	NUM	
VERB	PART	
	PRON	
	SCONJ	

Why POS tagging

- Goal: resolve ambiguities
- Text-to-speech
  - record, lead, protest
- Lemmatization
  - saw/V → see, saw/N → saw
- Preprocessing for harder disambiguation problems
  - syntactic parsing
  - semantic parsing

Ambiguities in POS tags

Types:		**WSJ**	**Brown**
Unambiguous	(1 tag)	44,432 (**86%**)	45,799 (**85%**)
Ambiguous	(2+ tags)	7,025 (**14%**)	8,050 (**15%**)

Ambiguities in POS tags

Types:		WSJ		Brown	
Unambiguous	(1 tag)	44,432	(**86%**)	45,799	(**85%**)
Ambiguous	(2+ tags)	7,025	(**14%**)	8,050	(**15%**)
Tokens:					
Unambiguous	(1 tag)	577,421	(**45%**)	384,349	(**33%**)
Ambiguous	(2+ tags)	711,780	(**55%**)	786,646	(**67%**)

Most frequent class baseline

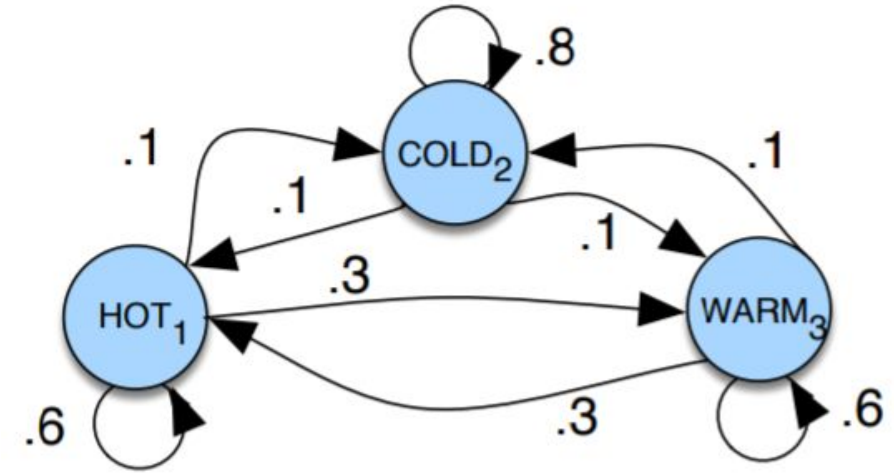
- Assigning each token to **the class it occurred in most often** in the training set
- Always compare a classifier against a baseline at least as good as the most frequent class baseline
- The WSJ training corpus and test on sections 22-24 of the same corpus the most-frequent-tag baseline achieves an accuracy of 92.34%.
- 97% tag accuracy achievable by most algorithms (HMMs, MEMMs, neural networks, rule-based algorithms)

Sequence labeling as text classification

$$\hat{y}_i = \underset{y \in \mathcal{L}}{\operatorname{argmax}}\, s(\boldsymbol{x}, i, y)$$

Generative sequence labeling: Hidden Markov Models

Markov Chain: Weather



Markov Assumption: $P(q_i = a | q_1 \ldots q_{i-1}) = P(q_i = a | q_{i-1})$

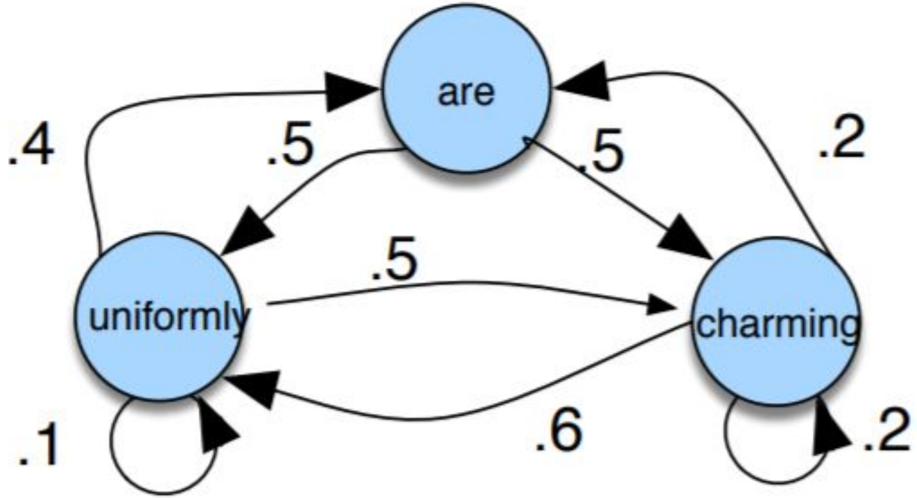
the future is independent of the past given the present

Markov chain

Formally, a Markov chain is specified by the following components:

$Q = q_1 q_2 \ldots q_N$	a set of N **states**
$A = a_{11} a_{12} \ldots a_{n1} \ldots a_{nn}$	a **transition probability matrix** A, each a_{ij} representing the probability of moving from state i to state j, s.t. $\sum_{j=1}^{n} a_{ij} = 1 \quad \forall i$
$\pi = \pi_1, \pi_2, \ldots, \pi_N$	an **initial probability distribution** over states. π_i is the probability that the Markov chain will start in state i. Some states j may have $\pi_j = 0$, meaning that they cannot be initial states. Also, $\sum_{i=1}^{n} \pi_i = 1$

Markov Chain: words

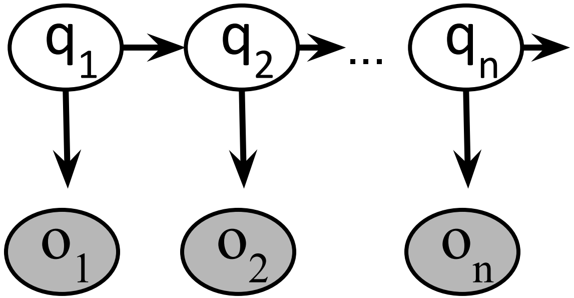


$$\pi = [0.1, 0.7, 0.2]$$

the future is independent of the past given the present

Hidden Markov Models

- In real world many events are not observable
- Speech recognition: we observe acoustic features but not the phones
- POS tagging: we observe words but not the POS tags



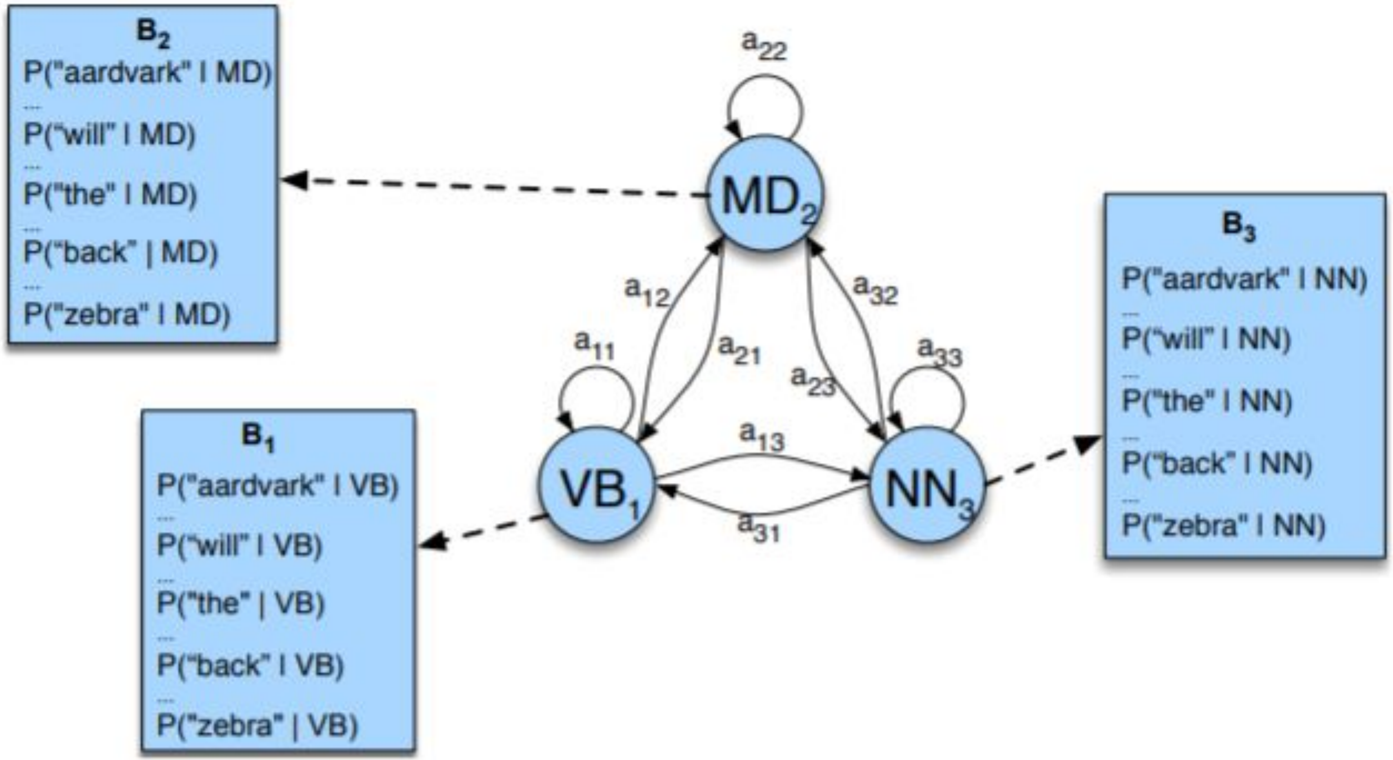
Markov Assumption: $P(q_i|q_1 \dots q_{i-1}) = P(q_i|q_{i-1})$

Output Independence: $P(o_i|q_1 \dots q_i, \dots, q_T, o_1, \dots, o_i, \dots, o_T) = P(o_i|q_i)$

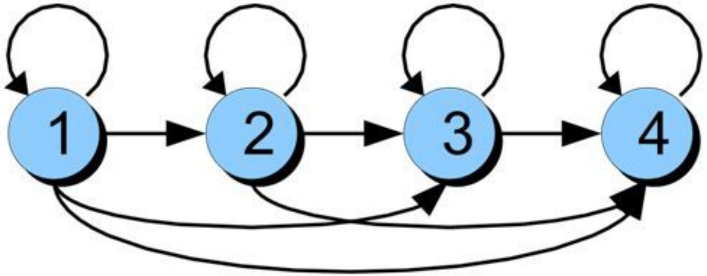
Hidden Markov Models (HMMs)

$Q = q_1 q_2 \ldots q_N$	a set of N **states**
$A = a_{11} \ldots a_{ij} \ldots a_{NN}$	a **transition probability matrix** A, each a_{ij} representing the probability of moving from state i to state j, s.t. $\sum_{j=1}^{N} a_{ij} = 1 \quad \forall i$
$O = o_1 o_2 \ldots o_T$	a sequence of T **observations**, each one drawn from a vocabulary $V = v_1, v_2, \ldots, v_V$
$B = b_i(o_t)$	a sequence of **observation likelihoods**, also called **emission probabilities**, each expressing the probability of an observation o_t being generated from a state q_i
$\pi = \pi_1, \pi_2, \ldots, \pi_N$	an **initial probability distribution** over states. π_i is the probability that the Markov chain will start in state i. Some states j may have $\pi_j = 0$, meaning that they cannot be initial states. Also, $\sum_{i=1}^{n} \pi_i = 1$

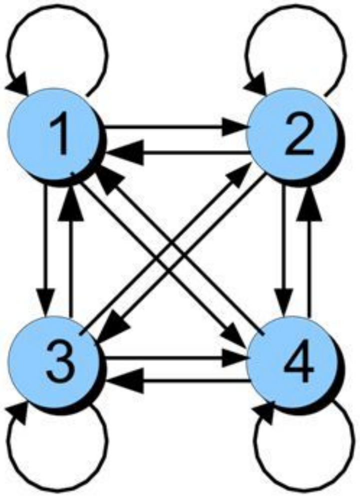
HMM example


B2
P("aardvark" I MD)
P("will" I MD)
P("the" I MD)
P("back" | MD)
P("zebra" I MD)
a22
MD2
a12
a21
a32
a23
a11
a33
a13
a31
VB1
NN3
B1
P("aardvark" I VB)
P("will" I VB)
P("the" | VB)
P("back" I VB)
P("zebra" | VB)
B3
P("aardvark" I NN)
P("will" I NN)
P("the" I NN)
P("back" I NN)
P("zebra" I NN)

Types of HMMs



Bakis = left-to-right



Ergodic =
fully-connected

HMMs in language technologies

- Part-of-speech tagging (Church, 1988; Brants, 2000)
- Named entity recognition (Bikel et al., 1999) and other information extraction tasks
- Text chunking and shallow parsing (Ramshaw and Marcus, 1995)
- Word alignment of parallel text (Vogel et al., 1996)
- Acoustic models in speech recognition (emissions are continuous)
- Discourse segmentation (labeling parts of a document)

HMM parameters

$Q = q_1 q_2 \ldots q_N$	a set of N **states**
$A = a_{11} a_{12} \ldots a_{n1} \ldots a_{nn}$	a **transition probability matrix** A, each a_{ij} representing the probability of moving from state i to state j, s.t. $\sum_{j=1}^{n} a_{ij} = 1 \quad \forall i$
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$B = b_i(o_t)$	a sequence of **observation likelihoods**, also called **emission probabilities**, each expressing the probability of an observation o_t being generated from a state i
q_0, q_F	a special **start state** and **end (final) state** that are not associated with observations, together with transition probabilities $a_{01} a_{02} \ldots a_{0n}$ out of the start state and $a_{1F} a_{2F} \ldots a_{nF}$ into the end state

HMMs: algorithms

Forward	**Problem 1 (Likelihood):**	Given an HMM $\lambda = (A, B)$ and an observation sequence O, determine the likelihood $P(O\|\lambda)$.
Viterbi	**Problem 2 (Decoding):**	Given an observation sequence O and an HMM $\lambda = (A, B)$, discover the best hidden state sequence Q.
Forward–Backward; Baum–Welch	**Problem 3 (Learning):**	Given an observation sequence O and the set of states in the HMM, learn the HMM parameters A and B.

HMM tagging as decoding

Decoding: Given as input an HMM $\lambda = (A, B)$ and a sequence of observations $O = o_1, o_2, \ldots, o_T$, find the most probable sequence of states $Q = q_1 q_2 q_3 \ldots q_T$.

$$\hat{t}_1^n = \underset{t_1^n}{\operatorname{argmax}} P(t_1^n | w_1^n) \approx \underset{t_1^n}{\operatorname{argmax}} \prod_{i=1}^{n} \overbrace{P(w_i | t_i)}^{\text{emission}} \overbrace{P(t_i | t_{i-1})}^{\text{transition}}$$

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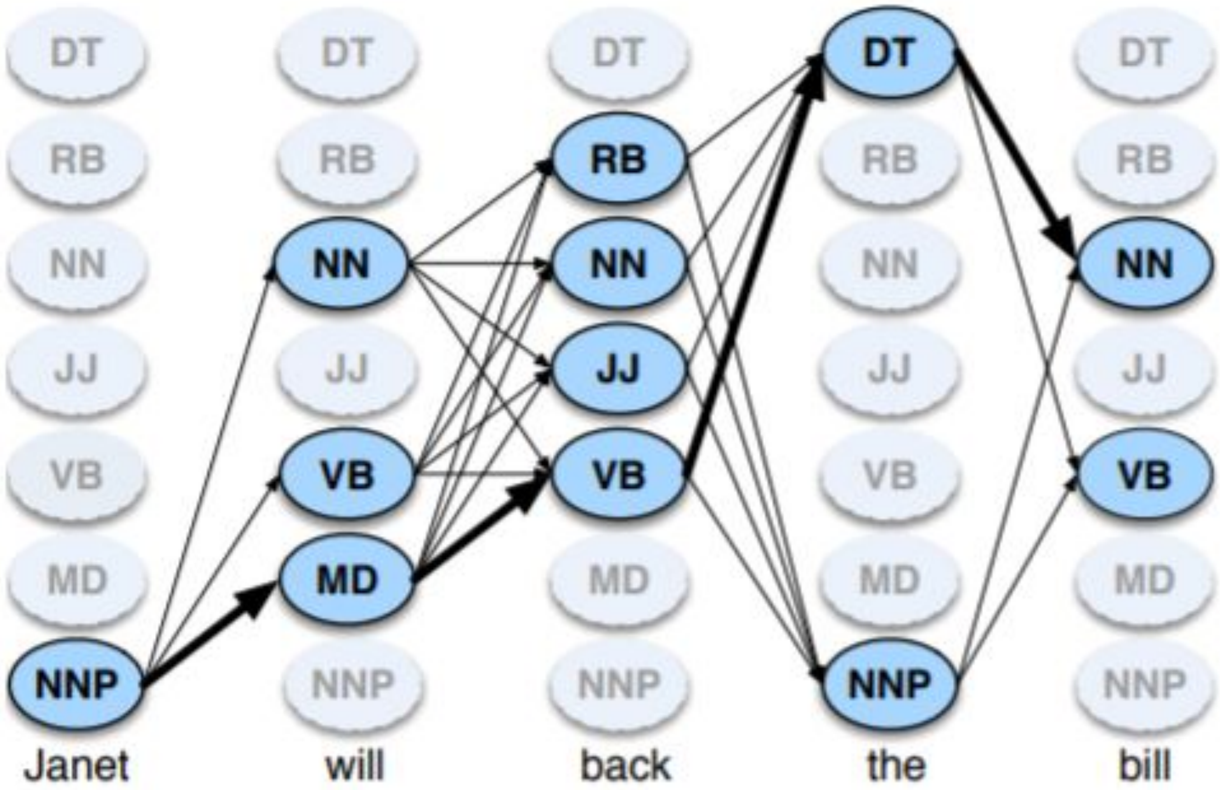
How many possible choices?

Part of speech tagging example

	I	suspect	the	present	forecast	is	pessimistic	.
noun	•	•	•	•	•	•		
adj.		•		•	•		•	
adv.				•				
verb		•		•	•	•		
num.	•							
det.			•					
punc.								•

With this very simple tag set, $7^8 = 5.7$ million labelings.
(Even restricting to the possibilities above, 288 labelings.)

The Viterbi algorithm



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The Viterbi algorithm

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

create a path probability matrix *viterbi[N,T]*

for each state *s* **from** 1 **to** *N* **do** ; initialization step

$viterbi[s,1] \leftarrow \pi_s * b_s(o_1)$

$backpointer[s,1] \leftarrow 0$

for each time step *t* **from** 2 **to** *T* **do** ; recursion step

for each state *s* **from** 1 **to** *N* **do**

$$viterbi[s,t] \leftarrow \max_{s'=1}^{N} viterbi[s',t-1] * a_{s',s} * b_s(o_t)$$

$$backpointer[s,t] \leftarrow \operatorname{argmax}_{s'=1}^{N} viterbi[s',t-1] * a_{s',s} * b_s(o_t)$$

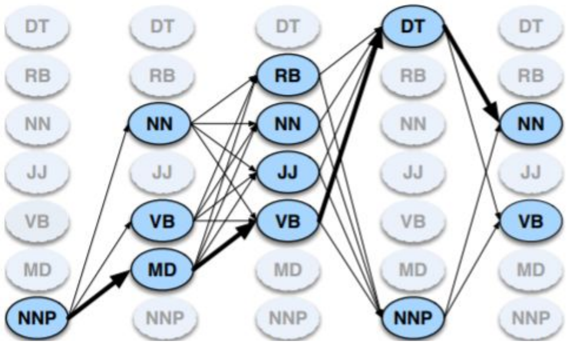
$$bestpathprob \leftarrow \max_{s=1}^{N} viterbi[s,T]$$; termination step

$$bestpathpointer \leftarrow \operatorname{argmax}_{s=1}^{N} viterbi[s,T]$$; termination step

bestpath ← the path starting at state *bestpathpointer*, that follows backpointer[] to states back in time

return *bestpath*, *bestpathprob*

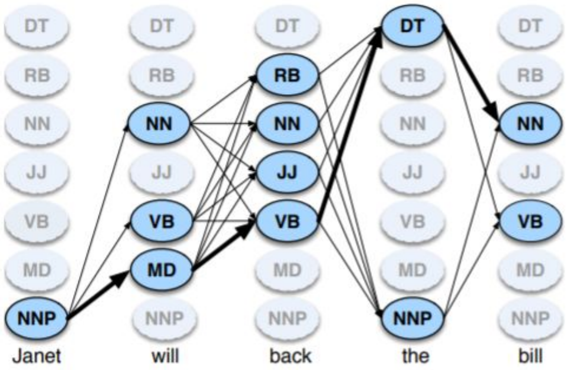
The Viterbi algorithm



$$v_t(j) = \max_{i=1}^{N} v_{t-1}(i)\, a_{ij}\, b_j(o_t)$$

$v_{t-1}(i)$	the **previous Viterbi path probability** from the previous time step
a_{ij}	the **transition probability** from previous state q_i to current state q_j
$b_j(o_t)$	the **state observation likelihood** of the observation symbol o_t given the current state j

The Viterbi algorithm



$$v_t(j) = \max_{i=1}^{N} v_{t-1}(i)\, a_{ij}\, b_j(o_t)$$

	NNP	MD	VB	JJ	NN	RB	DT
<s>	0.2767	0.0006	0.0031	0.0453	0.0449	0.0510	0.2026
NNP	0.3777	0.0110	0.0009	0.0084	0.0584	0.0090	0.0025
MD	0.0008	0.0002	0.7968	0.0005	0.0008	0.1698	0.0041
VB	0.0322	0.0005	0.0050	0.0837	0.0615	0.0514	0.2231
JJ	0.0366	0.0004	0.0001	0.0733	0.4509	0.0036	0.0036
NN	0.0096	0.0176	0.0014	0.0086	0.1216	0.0177	0.0068
RB	0.0068	0.0102	0.1011	0.1012	0.0120	0.0728	0.0479
DT	0.1147	0.0021	0.0002	0.2157	0.4744	0.0102	0.0017

	Janet	will	back	the	bill
NNP	0.000032	0	0	0.000048	0
MD	0	0.308431	0	0	0
VB	0	0.000028	0.000672	0	0.000028
JJ	0	0	0.000340	0	0
NN	0	0.000200	0.000223	0	0.002337
RB	0	0	0.010446	0	0
DT	0	0	0	0.506099	0

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  for each state *s* **from** 1 **to** *N* **do**
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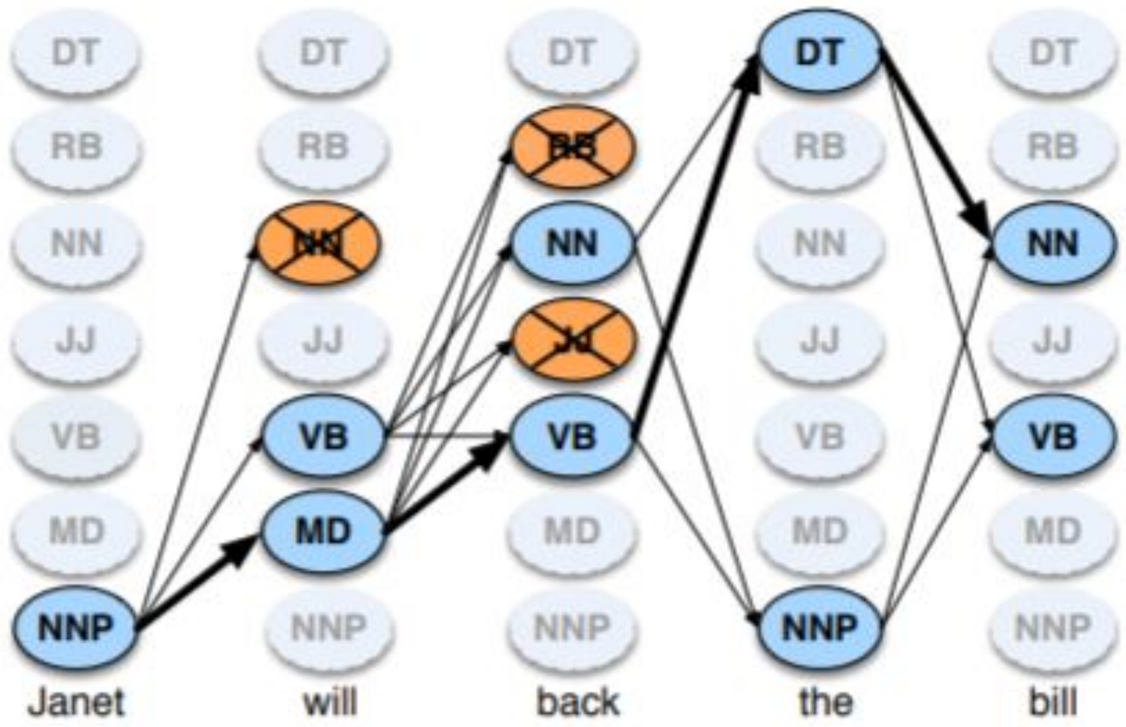
bestpath ← the path starting at state *bestpathpointer*, that follows backpointer[] to states back in time
return *bestpath*, *bestpathprob*

Beam search



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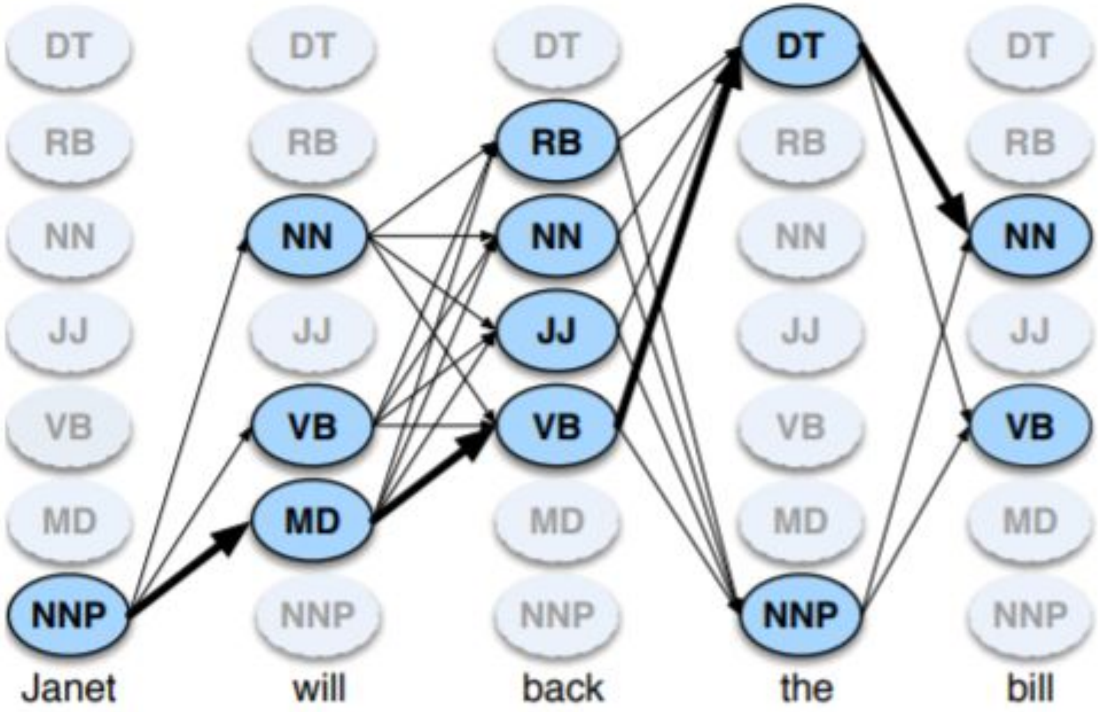
Forward–Backward; Baum–Welch	**Problem 3 (Learning):**	Given an observation sequence O and the set of states in the HMM, learn the HMM parameters A and B.

From J&M

The Forward algorithm

sum instead of m



Viterbi

- n-best decoding
- relationship to sequence alignment

Citation	Field
Viterbi (1967)	information theory
Vintsyuk (1968)	speech processing
Needleman and Wunsch (1970)	molecular biology
Sakoe and Chiba (1971)	speech processing
Sankoff (1972)	molecular biology
Reichert et al. (1973)	molecular biology
Wagner and Fischer (1974)	computer science