CZ4045 Natural Language Processing

Tutorial 4 POS Tagging and HMM

Question 1

- Find one tagging error in each of the following sentences that are tagged with the Penn Treebank tagset:

1. How/WRB do/VBP I/PRP get/VB to/TO Singapore/NN
2. Do/VBP you/PRP have/VB any/DT vacancies/NN
3. This/DT room/NN is/VBZ too/JJ noisy/JJ
4. Can/VB you/PRP give/VB me/PRP another/DT room/NN

Review

Penn TreeBank POS Tagset

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*			

Answer 1

- How/WRB do/VBP I/PRP get/VB to/TO Singapore/NN
  - **Singapore/NNP**
- Do/VBP you/PRP have/VB any/DT vacancies/NN
  - **vacancies/NNS**
- This/DT room/NN is/VBZ too/JJ noisy/JJ
  - **too/RB**
- Can/VB you/PRP give/VB me/PRP another/DT room/NN
  - **Can/MD**

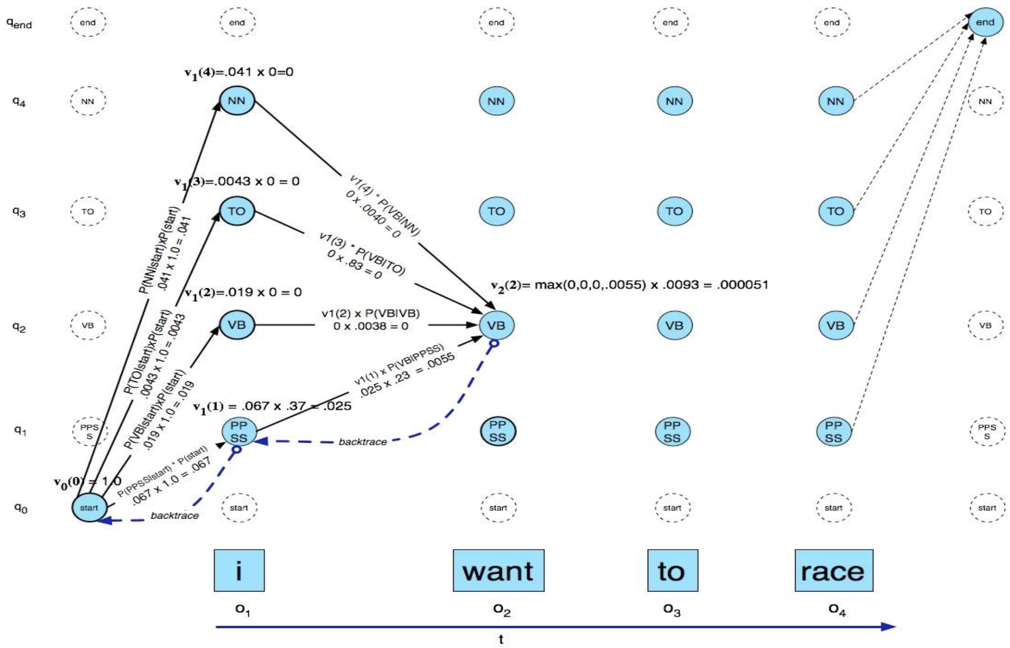
Tag	Description	Example	Tag	Description	Example
CC	coordin. conjunction	*and, but, or*	SYM	symbol	+,%, &
CD	cardinal number	*one, two, three*	TO	“to”	*to*
DT	determiner	*a, the*	UH	interjection	*ah, oops*
EX	existential ‘there’	*there*	VB	verb, base form	*eat*
FW	foreign word	*mea culpa*	VBD	verb, past 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*			

Question 2

- Finish the computation of the Viterbi algorithm in the example used in the lecture for HMM. The transition probability and word likelihood probabilities are in the following tables.

	VB	TO	NN	PPSS
<s>	.019	.0043	.041	.067
VB	.0038	.035	.047	.0070
TO	.83	0	.00047	0
NN	.0040	.016	.087	.0045
PPSS	.23	.00079	.0012	.00014

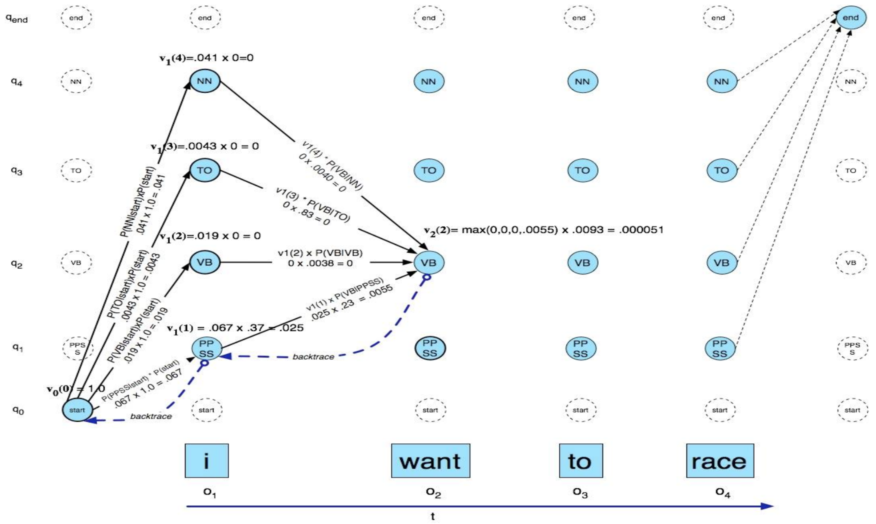
	I	want	to	race
VB	0	.0093	0	.00012
TO	0	0	.99	0
NN	0	.000054	0	.00057
PPSS	.37	0	0	0



Main Idea

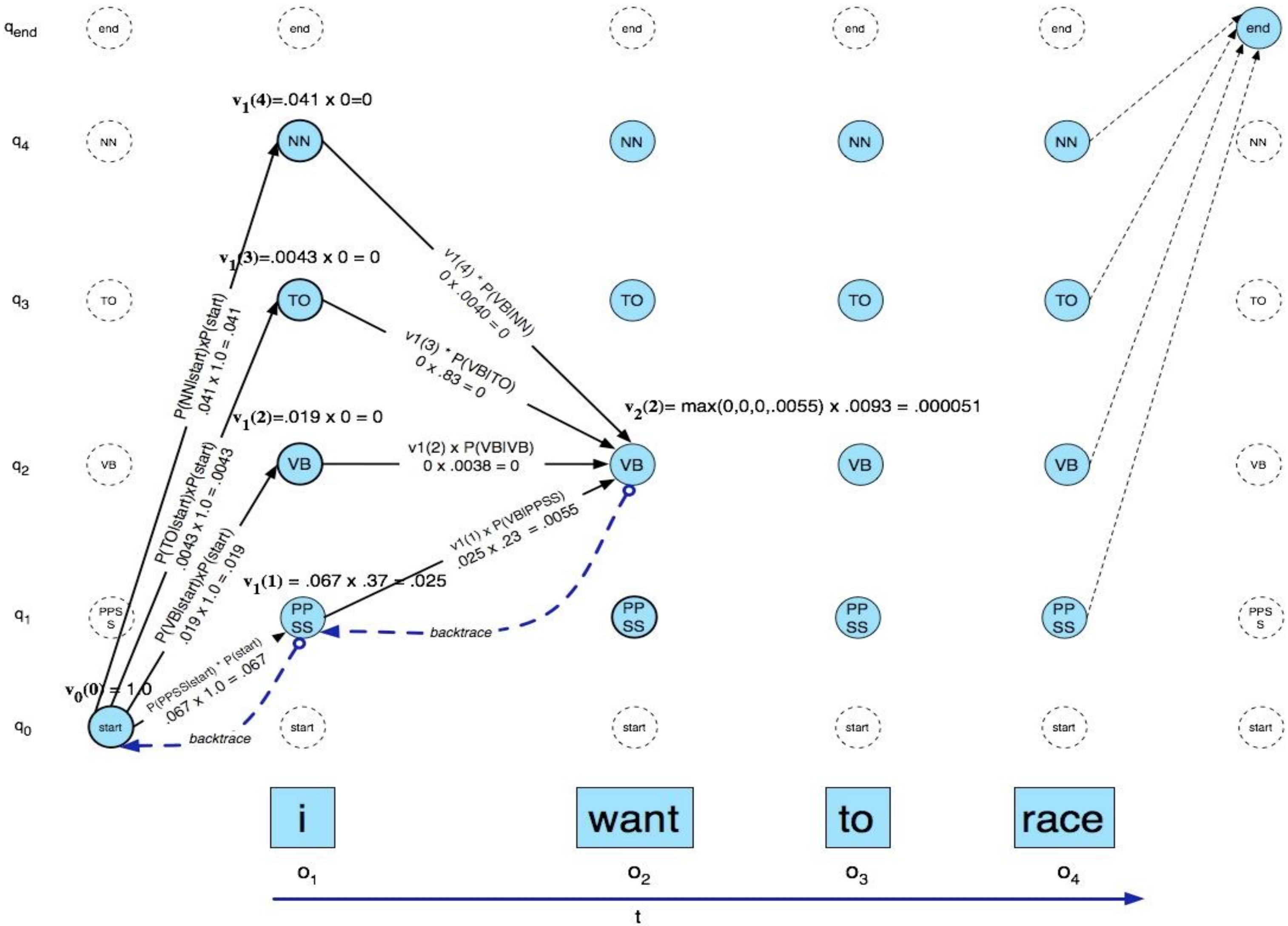
Review

- We also have a matrix.
  - Each column– a time ‘t’ (observation)
  - Each row – a state ‘i’
  - For each cell $v_t[i]$, we compute the probability of the **best path** to the cell
- the **Viterbi path probability** at time t for state i
  - there are $|Q|$ number of paths from $t-1$ to $v_t[i]$
  - if we know **the best path** to each cell in $t-1$, or $v_{t-1}[j]$
  - $\arg\max_j v_{t-1}[j] \times P(i|j) \times P(s_t|i)$

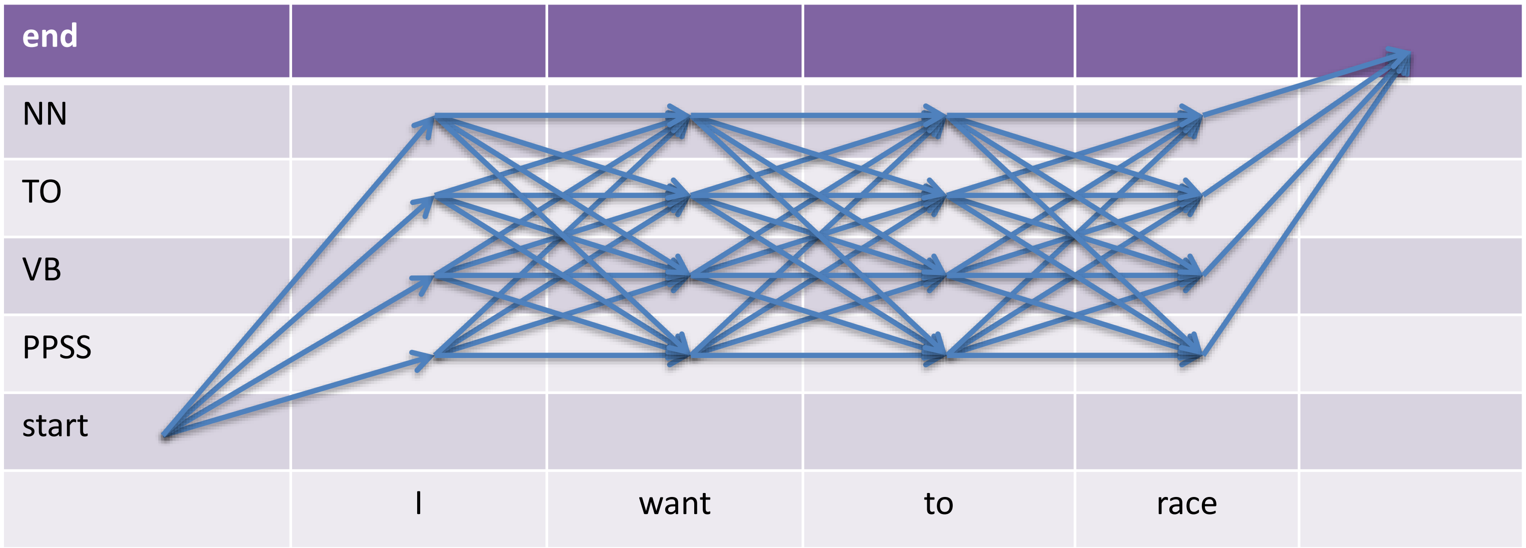


Viterbi Example

Review



Required computations



(This figure does not show the backtrace pointers)

Hint

	VB	TO	NN	PPSS
<s>	.019	.0043	.041	.067
VB	.0038	.035	.047	.0070
TO	.83	0	.00047	0
NN	.0040	.016	.087	.0045
PPSS	.23	.00079	.0012	.00014

	I	want	to	race
VB	0	.0093	0	.00012
TO	0	0	.99	0
NN	0	.000054	0	.00057
PPSS	.37	0	0	0

end					
NN	$p(NN\| < s >) * p(I\|NN) = 0$				
TO	$p(TO\| < s >) * p(I\|TO) = 0$				
VB	$p(VB\| < s >) * p(I\|VB) = 0$				
PPSS	$p(PPSS\| < s >) * p(I\|PPSS) = 0.067 * 0.37 = 0.02479$				
start					
	I	want	to	race	

Answer 2

	VB	TO	NN	PPSS
<s>	.019	.0043	.041	.067
VB	.0038	.035	.047	.0070
TO	.83	0	.00047	0
NN	.0040	.016	.087	.0045
PPSS	.23	.00079	.0012	.00014

	I	want	to	race
VB	0	.0093	0	.00012
TO	0	0	.99	0
NN	0	.000054	0	.00057
PPSS	.37	0	0	0

end					
NN	0	$.02479 * p(NN \mid PPSS) * p(want \mid NN) =$ $.02479 * .0012 * .000054 =$ 0.00000000160639			
TO	0	$.02479 * p(TO \mid PPSS) * p(want \mid TO) = 0$			
VB	0	$.02479 * p(VB \mid PPSS) * p(want \mid VB) =$ $.02479 * .23 * .0093 =$ 0.00005302581			
PPSS	0.02479	$.02479 * p(PPSS \mid PPSS) * p(want \mid PPSS) = 0$			
start					
	I	want	to	race	

Answer 2

	VB	TO	NN	PPSS
<s>	.019	.0043	.041	.067
VB	.0038	.035	.047	.0070
TO	.83	0	.00047	0
NN	.0040	.016	.087	.0045
PPSS	.23	.00079	.0012	.00014

	I	want	to	race
VB	0	.0093	0	.00012
TO	0	0	.99	0
NN	0	.000054	0	.00057
PPSS	.37	0	0	0

end					
NN	0	1.6*10e-9	$\max(1.6 * 10e-9 * p(NN \mid NN), 5.3 * 10e-5 * p(NN \mid VB)) * p(to \mid NN) = 0$		
TO	0	0	$\max\left(1.6 * 10e-9 * p(TO \mid NN), \quad 5.3 * 10e-5 * p(TO \mid VB)\right) * p(to \mid TO) =$ $\max(1.6 * 10e-9 * .016, 5.3 * 10e-5 * .035) * .99$ $= 1.84 * 10e-6$		
VB	0	5.3*10e-5	$\max(1.6 * 10e-9 * p(VB \mid NN), 5.3 * 10e-5 * p(VB \mid VB)) * p(to \mid VB) = 0$		
PPSS	0.02479	0	$\max(1.6 * 10e-9 * p(PPSS \mid NN), 5.3 * 10e-5 * p(PPSS \mid VB)) * p(to \mid PPSS) = 0$		
start					
	I	want	to	race	

Answer 2

	VB	TO	NN	PPSS
<s>	.019	.0043	.041	.067
VB	.0038	.035	.047	.0070
TO	.83	0	.00047	0
NN	.0040	.016	.087	.0045
PPSS	.23	.00079	.0012	.00014

	I	want	to	race
VB	0	.0093	0	.00012
TO	0	0	.99	0
NN	0	.000054	0	.00057
PPSS	.37	0	0	0

end					
NN	0	1.6*10e-9	0	$1.84 * 10e-6 * p(NN\|TO) * p(race\|NN) =$ $1.84 * 10e-6 * .00047 * .00057 = 4.92 * 10e-14$	
TO	0	0	1.84*10e-6	$1.84 * 10e-6 * p(TO\|TO) * p(race\|TO) = 0$	
VB	0	5.3*10e-5	0	$1.84 * 10e-6 * p(VB\|TO) * p(race\|VB) =$ $1.84 * 10e-6 * .83 * .00012 = 1.83 * 10e-10$	
PPSS	0.02479	0	0	$1.84 * 10e-6 * p(PPSS\|TO) * p(race\|PPSS) = 0$	
start					
	I	want	to	race	

Answer 2

	VB	TO	NN	PPSS
<s>	.019	.0043	.041	.067
VB	.0038	.035	.047	.0070
TO	.83	0	.00047	0
NN	.0040	.016	.087	.0045
PPSS	.23	.00079	.0012	.00014

	I	want	to	race
VB	0	.0093	0	.00012
TO	0	0	.99	0
NN	0	.000054	0	.00057
PPSS	.37	0	0	0

end					
NN	0	1.6*10e-9	0	$1.84*10e-6* p(NN\|TO) * p(race\|NN) =$ $1.84*10e-6* .00047 * .00057 = 4.92*10e-14$	
TO	0	0	1.84*10e-6	$1.84*10e-6* p(TO\|TO) * p(race\|TO) = 0$	
VB	0	5.3*10e-5	0	$1.84*10e-6 * p(VB\|TO) * p(race\|VB) =$ $1.84*10e-6* .83 * .00012 = 1.83*10e-10$	
PPSS	0.02479	0	0	$1.84*10e-6* p(PPSS\|TO) * p(race\|PPSS) = 0$	
start					
	I	want	to	race	

Answer 2

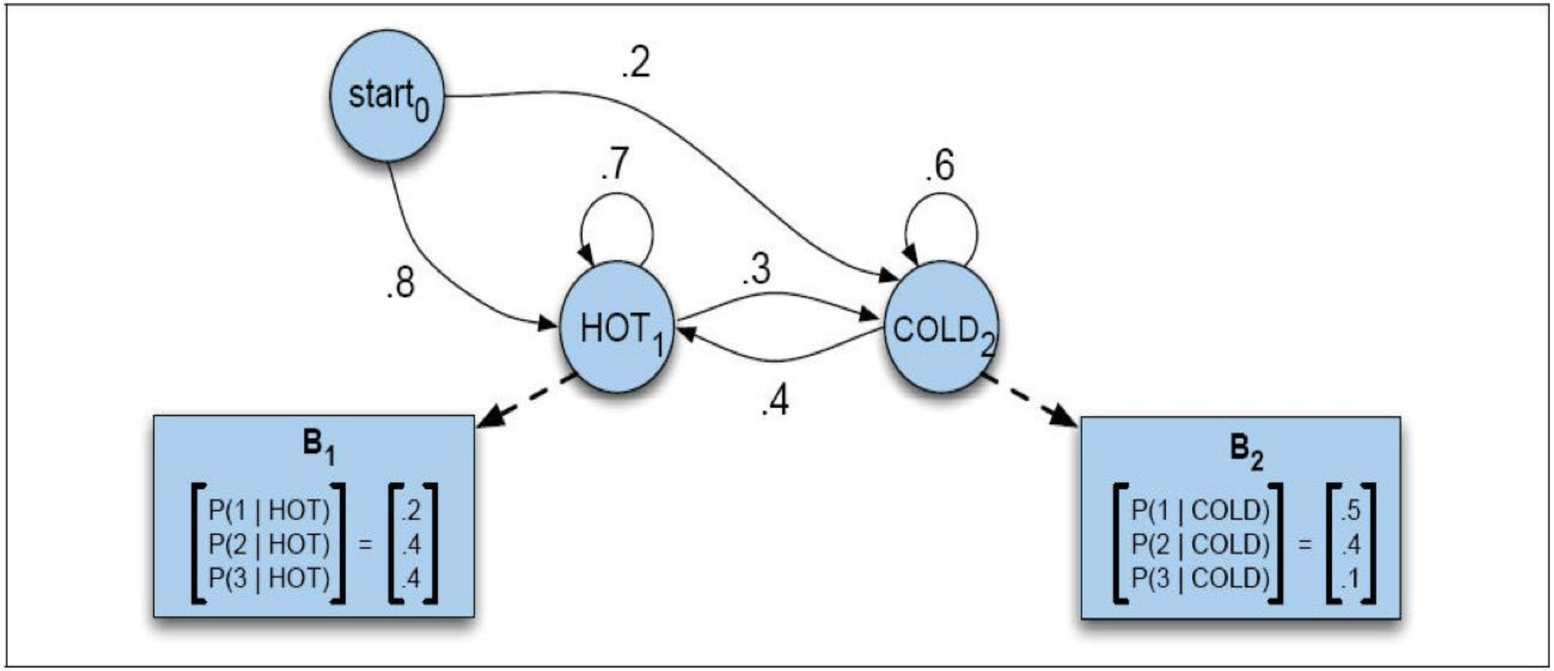
	VB	TO	NN	PPSS
<s>	.019	.0043	.041	.067
VB	.0038	.035	.047	.0070
TO	.83	0	.00047	0
NN	.0040	.016	.087	.0045
PPSS	.23	.00079	.0012	.00014

	I	want	to	race
VB	0	.0093	0	.00012
TO	0	0	.99	0
NN	0	.000054	0	.00057
PPSS	.37	0	0	0

end					
NN	0	1.6*10e-9	0	$1.84 * 10e-6 * p(NN\|TO) * p(race\|NN) =$ $1.84 * 10e-6 * .00047 * .00057 = 4.92 * 10e-14$	
TO	0	0	1.84*10e-6	$1.84 * 10e-6 * p(TO\|TO) * p(race\|TO) = 0$	
VB	0	5.3*10e-5	0	$1.84 * 10e-6 * p(VB\|TO) * p(race\|VB) =$ $1.84 * 10e-6 * .83 * .00012 = \mathbf{1.83 * 10e-10}$	
PPSS	0.02479	0	0	$1.84 * 10e-6 * p(PPSS\|TO) * p(race\|PPSS) = 0$	
start					
	I	want	to	race	

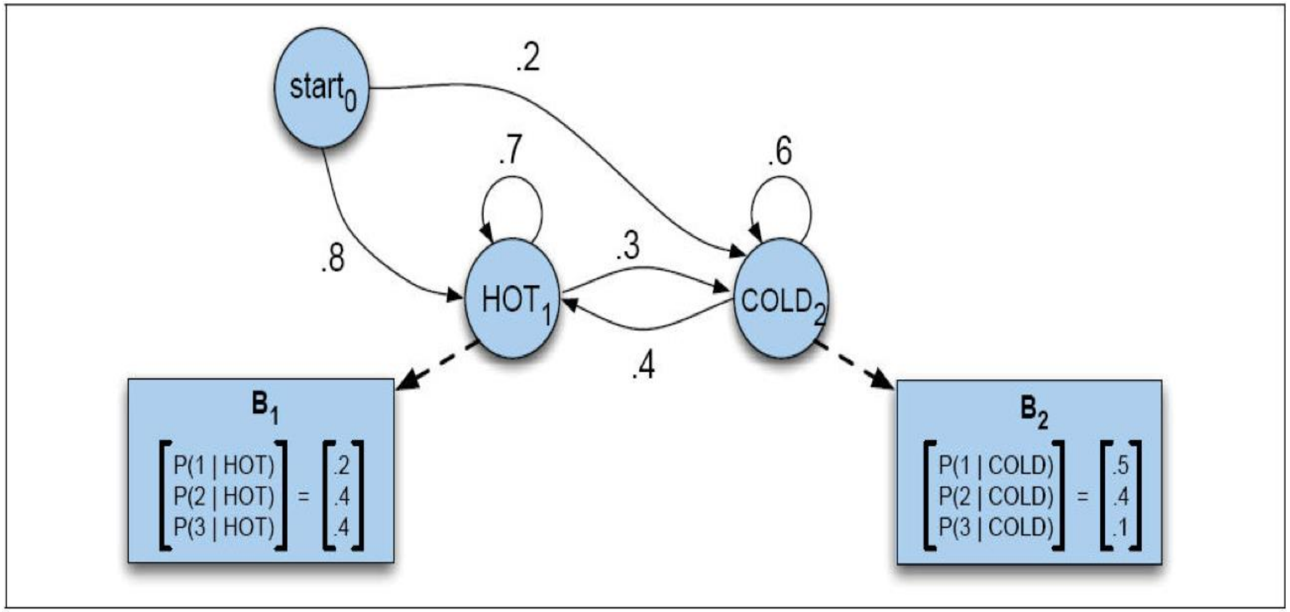
Question 3

- Run the Viterbi algorithm with the HMM below to compute the most likely weather sequences for each of the two observation sequences,
  - 312312312
  - 311233112.

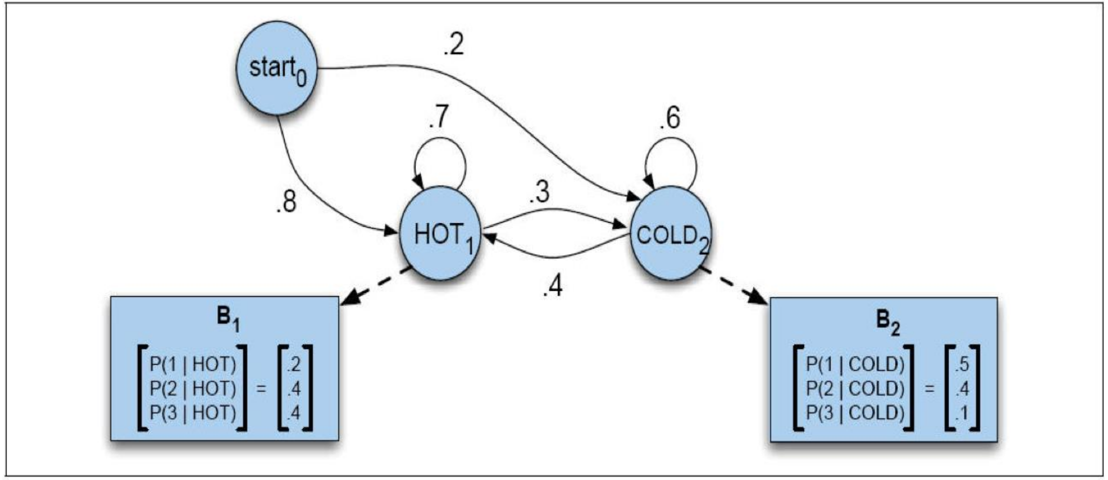


Hint 3

end					
H					
C					
start					
	3	1	2	3	…



Answer 3



- 3
  - H 0.8 *0.4 (P(3|H)) = 0.32
  - C 0.2 *0.1 (P (3|C)) = 0.02
- 1
  - H max (0.32*0.7*0.2, 0.02*0.4*0.2)
  - C max (0.32*0.3*0.5, 0.02*0.6*0.5)
- 2
- 3

Sequence 1: 3 1 2 3 1 2 3 1 2
Decoded states: -Hot--Hot--Hot--Hot--Hot--Hot--Hot--Hot--Hot-

Sequence 2: 3 1 1 2 3 3 1 1 2.
Decoded states: -Hot--Cold--Cold--Hot--Hot--Hot--Cold--Cold--Cold-

Question 4

- The Church tagger (1988) is different from the HMM tagger since it incorporates the probability of the tag given the word.

  - HMM: $p(word|tag) * p(tag|previous\ n\ tags)$
  - Church: $p(tag|word) * p(tag|previous\ n\ tags)$

- Interestingly, this use of a kind of "reverse likelihood" has proven to be useful in the modern log-linear approach to machine translation.

Question 4

- As a gedanken-experiment, construct a sentence, a set of tag transition probabilities, and a set of lexical tag probabilities that demonstrate a way in which the HMM tagger can produce a better answer than the Church tagger, and create another example in which the Church tagger is better.
  - Hint: The Church and HMM taggers will perform differently when, given two tags, tag_1 and tag_2:
    - $p(tag_1|word) > p(tag_2|word)$
    - $p(word|tag_1) < p(word|tag_2)$

Answer 4

- A word "manufacturing" is associated with the following probabilities (from a sample of text from Wall Street Journal).
  - $P(VBG|manufacturing) = 0.231$
  - $P(NN|manufacturing) = 0.769$
  - $P(manufacturing|VBG) = 0.004$
  - $P(manufacturing|NN) = 0.001$

  - So if we are looking at the words, we will expect this word to receive tag NN
  - If we are looking at the tags, we expect this word to be produced more often from VBG state than NN state

Answer 4

- Let's assume $P(NN| < s >) = P(VBG| < s >) = 0.5$
- Then HMM model will select VBG label
  - $P(manufacturing|NN) * P(NN| < s >) \ = \ 0.0005$
  - $P(manufacturing|VBG) * P(VBG| < s >) = 0.002$

- Church(1988) Tagger will select NN label
  - $P(NN|manufacturing) * P(NN| < s >) = 0.3845$
  - $P(VGB|manufacturing) * P(VBG| < s >) = 0.1155$