1 Class-Conditional Densities for Binary Data

Question A:

$$p(x|y=c) = p(x_1|y=c)p(x_2|x_1, y=c) \cdots p(x_D|x_1, \cdots, x_{D-1}, y=c) = \prod_{i=1}^{D} \theta_{x_i i}$$

Since all the D features are binary, $x_j \in \{0, 1\}$,

for each class of C we need 2^{j-1} parameters for $p(x_j|x_1,\cdots,x_{j-1},y=c)$. In total $\sum_{j=1}^D 2^{j-1} = O(2^D)$. Therefore, we need $O(C\times 2^D)$ parameters for C classes.

Question B: Without factorization, since all the D features are binary, $x_j \in \{0, 1\}$, and C classes for y, in total we need $O(C \times 2^D)$, which is the same as that with factorization.

Question C: For a small N, Naive Bayes is likely to give lower test set error. This is because full models are more likely to overfit with a small N.

Question D: For a large N, full models are likely to give lower test set error. This is because Naive Bayes is simple and is likely to underfit with a large N, while full models have more parameters and will do better.

Question E: For Naive Bayes,

$$p(y|x) = \frac{p(x,y)}{p(x)} = \frac{p(y)}{p(x)} \prod_{d} p(x^{d}|y) = \frac{p(y)}{\sum_{i=1}^{C} p(x|y=c_i)} \prod_{d} p(x^{d}|y)$$

Since we assumed a uniform class prior p(y), O(p(y)) = O(1), and computation complexity of p(y|x) = O(CD).

For full model,

$$p(y|x) = \frac{p(x,y)}{p(x)} = \frac{p(y)}{p(x)}p(x|y)$$

, and computation complexity of D-dimensional vector is O(D). Different from Naive Bayes, full model doesn't take into account every y = c, but their overall probability. Therefore, computation complexity of p(y|x) = O(D).

2 Sequence Prediction

Question A:

Runnin	######################################		

File #0:			
Emission Sequence	Max Probability State Sequence		

25421	31033		
01232367534	22222100310		
5452674261527433	1031003103222222		
7226213164512267255	1310331000033100310		
0247120602352051010255241	22222222222222222222103		
File #1:			
Emission Sequence	Max Probability State Sequence		
,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,			
77550	22222		
7224523677	2222221000		
505767442426747	222100003310031		
72134131645536112267	10310310000310333100		
4733667771450051060253041	2221000003222223103222223		
File #2:		File #4:	
File #2. Emission Sequence	Max Probability State Sequence	Emission Sequence	Max Probability State Sequence
######################################			
60622	11111	23664	01124
4687981156	2100202111	3630535602	0111201112
815833657775062	02101111111111	350201162150142	011244012441112
21310222515963505015	0202011111111111021	00214005402015146362	11201112412444011112
6503199452571274006320025	1110202111111102021110211	2111266524665143562534450	2012012424124011112411124
		File #5:	
File #3:		Emission Sequence	Max Probability State Sequence
Emission Sequence Max Probability State Sequence		#######################################	
***************************************		68535	10111
13661	00021	4546566636	1111111111
2102213421	3131310213	638436858181213	110111010000011
166066262165133 53164662112162634156	133333133133100	13240338308444514688	00010000000111111100
03104002112102034150	20000021313131002133 1310021333133133133133133	0111664434441382533632626	21111111111111001111110101

${\bf Question}~{\bf B:}$ The results using Forward algorithm are as follows:

The results using Backward algorithm are as follows:

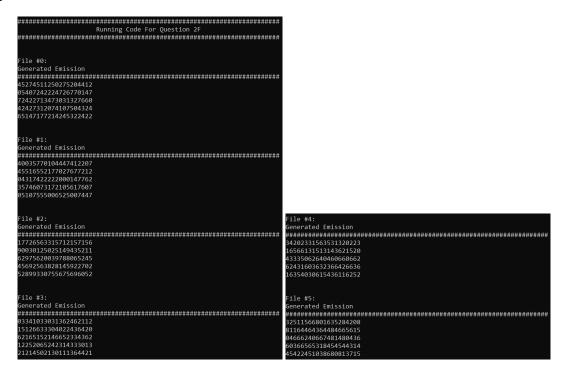
Question C:

Question D:

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Remains Remain
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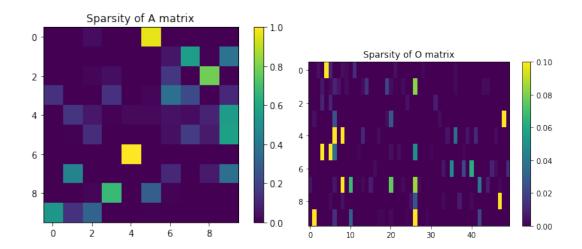
Question E: The transition and emission matrices from 2C and 2D are different, supervised matrices are more uniform, while unsupervised are sparse and nonuniform. 2C (supervised HMM) provides a more accurate representation. This is because for unsupervised 2D, we simply random the initial matrices, which cannot truly reflect Ron's moods. To improve the unsupervised learning data, we might need to initialize the transition and emission matrices A & O more precisely, such as using probability distributions from supervised matrices.

Question F:



Ouestion G:

The trained A and O matrices are both sparse, with most elements near 0. The sparsity of transition matrix A means that for each state, there might be very few states to transit to, and the sparsity of observation matrix O means that for each state, there might be very few observations to belong to.



Question H: As the number of hidden states is increased, sample emission sentences from the HMM becomes more coherent and smooth. When there is only one hidden state, then there is no more transitions, meaning that observation words are just randomly picked from the dataset. Allowing more hidden states will increase the training data likelihood, but when we have too many hidden states for the fixed observation set, this will lead to overfitting and may increase the test error.

Question I: As shown in the figure, I think state 7 is semantically meaningful. This state is filled with



law-related words, such as 'law', 'court', 'representative', 'justice', 'rules'. I think this state represent all law-related words in the dataset, which is distinct from other states.