Pattern Recognition

Assignment #4

Hidden Markov Model &
Dynamic Time Warping

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1.1 Hidden Markov Model

In Hidden Markov Model the states are hidden and we can only observation the symbols emitted by any state. Further it is Markov as each state depend upon the previous states. As when we talk about the sequential data then GMM does't work so then HMM comes into picture which can handle the data which folds in time. Some examples of HMM applications are speech recognition, handwriting recognition, gesture recognition, biometrics etc. Here we will be working on two applications of HMM as follows:-

1. HMM on Isolated Digits
2. HMM on Connected Digits
3. HMM on Isolated Handwritten Letters
4. HMM on Connected Handwritten Letters

1.1.1 Hidden Markov Model on Isolated Digits

In this we have made the HMM models for each digit individually and trained them using 70% data. Further during validation we have tried to find the best k(clusters) for which the models give best accuracy. And finaly we have tested the rest of the data on all the models and find the best model which give maximum probability. In this we are given '1','o','z' as the digits.

Unnormalized Digits for K = 8 & S = 4 with Accuracy 88%

Predicted	Actual Class		
	Digit 1	Digit o	Digit z
Digit 1	17	2	0
Digit o	0	15	4
Digit z	0	0	13

Normalized Digits for K = 6 & S = 6 with Accuracy 92%

Predicted	Actual Class		
	Digit 1	Digit o	Digit z
Digit 1	15	1	0
Digit o	0	15	0
Digit z	2	1	17

Normalized Digits for K = 8 & S = 4 with Accuracy 98%

Predicted	Actual Class		
	Digit 1	Digit o	Digit z
Digit 1	16	0	0
Digit o	1	17	0
Digit z	0	0	17

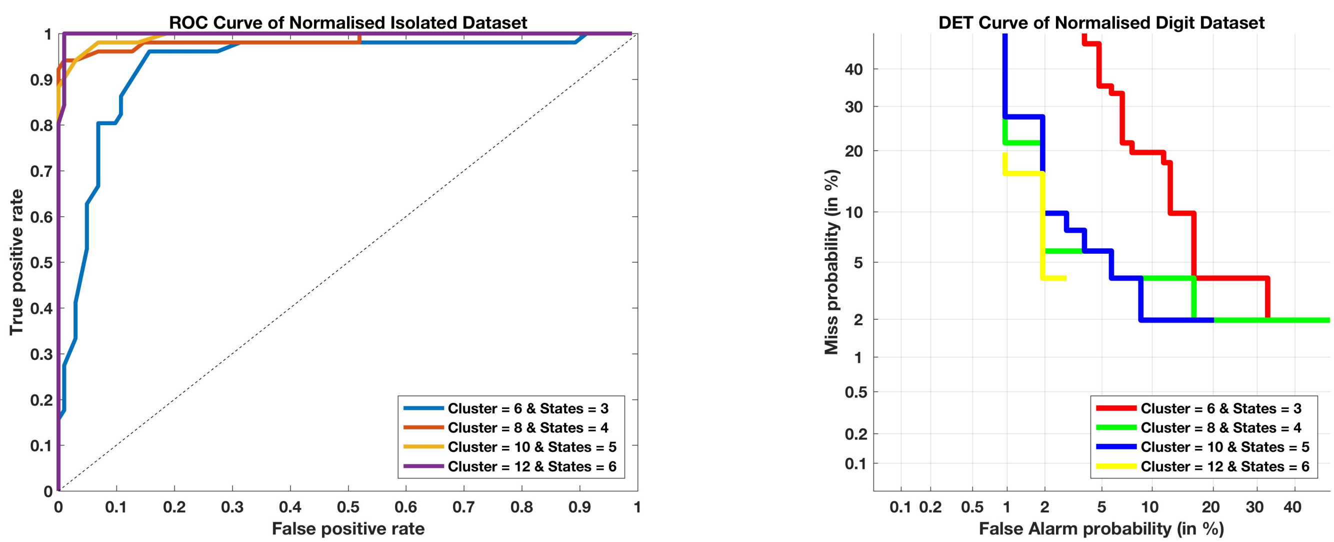

Figure 1.1: ROC & DET of Isolated Digits - Normalised Dataset for different States & Symbols

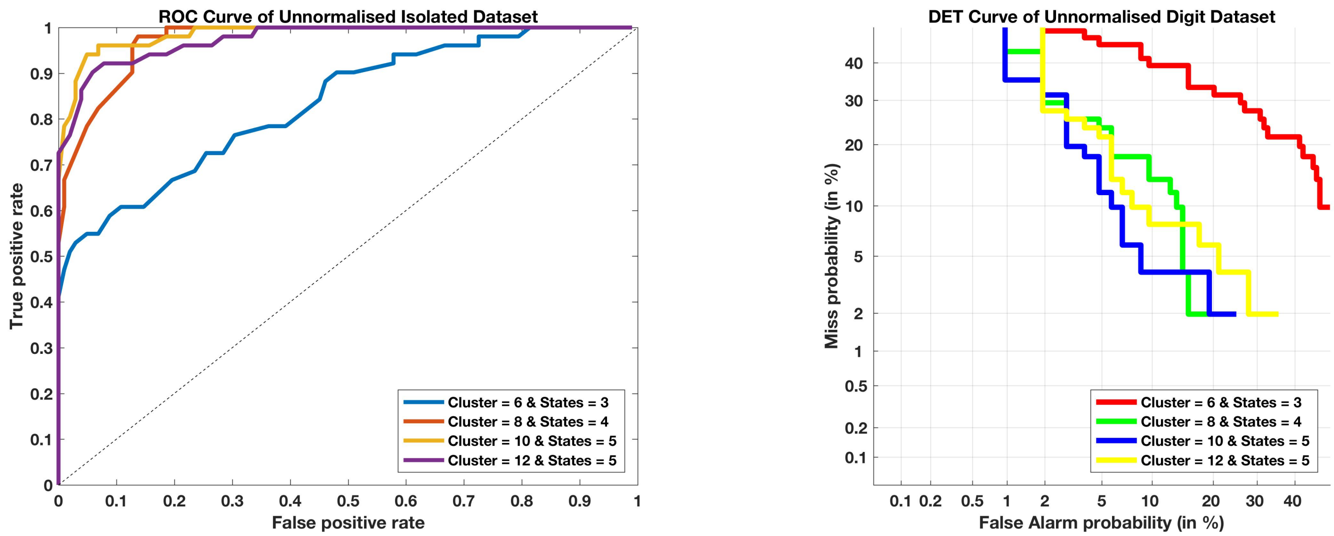

Figure 1.2: ROC & DET of Isolated Digits - Unnormalised Dataset for different States & Symbols

1.1.2 Hidden Markov Model on Connected Digits

For the connected digits we have used the HMMs which are build from the isolated digit HMMs. According to the number of digits in the string we have made the combinations of models. For e.g. in the case of string of 3 we have made 27 combinaltions of models which will try to identify the sequence. After that we have tested the file containing the connected digit sequence on each of the model and which so ever is giving the maximum probability we are assigning that file sequence to that models sequence.

Test1 Data	**Predicted Utterace**
1o	11
1z	1z
o1	1z
oo	oo
z1	zz
zz	zz
1o1	11o
1zz	1zz
11z	1zo
ooo	ooo
z1z	zzz
zz1	zzz
1zzz1	1zzzz
11zz	1zzz

Test2 Data	**Predicted Utterace**
120.txt	1o1
121.txt	11z
122.txt	1zz
123.txt	1zo
124.txt	111
125.txt	ooz
126.txt	ooo
127.txt	zoo
128.txt	zoz
129.txt	zzo
130.txt	zzz

Table 1.1: Predicted Utteraces for Connected Digits for Test1 & Test2 Data

In this we are given the known sequences and we tried on our model and observed the output sequence of that file according to our models. Further we are given the unknown sequences of digits and we have find the sequence according to our model in abpve tables.

1.1.3 Hidden Markov Model on Isolated Handwritten Letters

In this we have made the HMM models for each letters individually and trained them separately using 70% of data. Further during validation we have tried to find the best k(clusters) for which the models give best accuracy.And finaly we have tested the rest of the data on all the models and find the best model which give maximum probability. In this we are given 'ai','bA','lA' as the letters.

Handwritten for K = 4 & S = 2 with Accuracy 80%

Predicted \ Actual Class	Letter ai	Letter bA	Letter lA
Letter ai	12	5	0
Letter bA	3	9	0
Letter lA	0	1	15

Handwritten for K = 8 & S = 4 with Accuracy 97.77%

Predicted \ Actual Class	Letter ai	Letter bA	Letter lA
Letter ai	14	0	0
Letter bA	1	15	0
Letter lA	0	0	15

Handwritten for K = 12 & S = 6 with Accuracy 100%

Predicted \ Actual Class	Letter ai	Letter bA	Letter lA
Letter ai	15	0	0
Letter bA	0	15	0
Letter lA	0	0	15

Figure 1.3: Confusion Matrix of Isolated Handwritten Letters for different States & Symbols

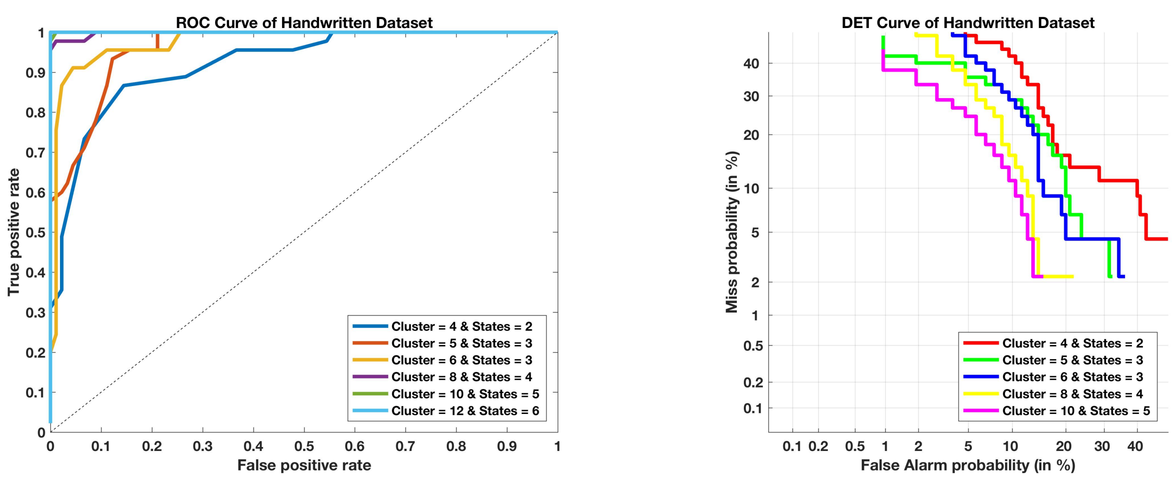

Figure 1.4: ROC & DET of Isolated Handwritten Letters

1.1.4 Hidden Markov Model on Connected Handwritten Letters

For the connected letters we have made the HMMs which are build from the isolated digit HMMs. According to the number of letters in the string we have made the combinations of models. For e.g. in the case of string of 3 we have made 27 combinaltions of models which will try to identify the sequence. After that we have tested the file containing the connected letter sequence on each of the model and which so ever is giving the maximum probability we are assigning that file sequence to that models sequence. Further we are given the unknown sequences of letters and we have find the sequence predicted by our model which is given in below table.

Data	Predicted Sequence
1.mat	bA-ai-ai
2.mat	bA-bA-lA
3.mat	lA-ai-ai

Table 1.2: Predicted Sequence for Connected Handwritten Letters for 12 Symbols & 6 States

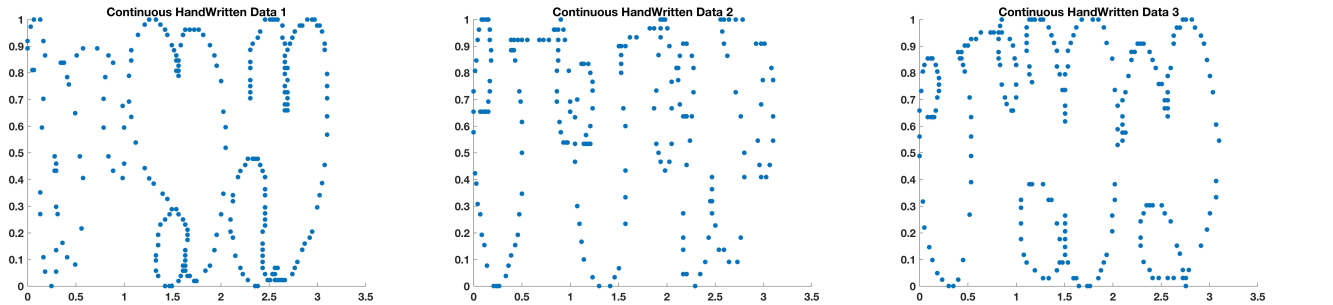

Figure 1.5: Plots of Connected Handwritten Letters

1.2 Dynamic Time Warping on Isolated Digits

As DTW is the technique which is used to find the matching between two patterns which are sequenced in time and are of different lengths. It is a very effective technique for finding match and it uses the Dynamic LCS Algorithms to find the match with minor modification, that as in LCS the vertical moves are not allowed but in DTW the vertical moves are allowed.

We have made the confusion matrix which tells the accuracy of the identification done for every isolated digit. The ROC plot tells the accuracy of the digit identification for different values of clusters(k) done by plotting the graph between TPR(True Positive Rate) and FPR(False Positive Rate). Another graph which tell the accuracy of the model with by making a graph by the Miss Probability and the False Alarm Probability which is the DET.

DTW for Templates = 1 with Accuracy 83.33%

Predicted \ Actual Class	Digit 1	Digit o	Digit z
Digit 1	8	4	0
Digit o	0	4	0
Digit z	0	0	8

DTW for Templates = 2 with Accuracy 95.83%

Predicted \ Actual Class	Digit 1	Digit o	Digit z
Digit 1	8	1	0
Digit o	0	7	0
Digit z	0	0	8

DTW for Templates = 3 with Accuracy 100%

Predicted \ Actual Class	Digit 1	Digit o	Digit z
Digit 1	8	0	0
Digit o	0	8	0
Digit z	0	0	8

Figure 1.6: Confusion Matrix of DTW - Isolated Digits for different templates

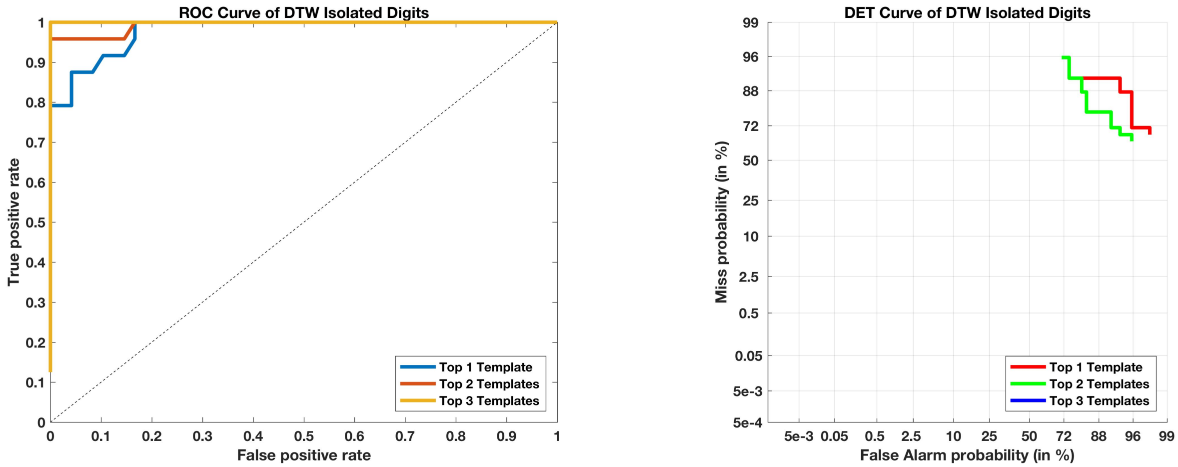

Figure 1.7: ROC & DET of DTW - Isolated Digits

Observations :-

- We learned that to do speech recoginition where each utterence of digits can have different lengths, we can use HMM or DTW.

- DTW is a simple dynamic programming alogrith to measure similarity between two temporal sequences, which may vary in speed. By selecting few templates of each utterences we can then find distance between test utterance to every class template and assign it class which gives minimum distance.We observed that by chossing top 3 templates of every class, we were able to get 100% accuracy for test digits.

- To use HMM we first have to discretize our data and then give it as input to HMM. Then by building Models for indivudual digits, we can then concat thoses models to recognize for connected digits. For modeling HHM, we have to decide about number of states in HMM which would be number of phenoms of each digits.

- From ROC plot we observed that for different values of the clusters and states the accuracy comes out to be different for different cases. For Handwritten Dataset for 6 states and 12 symbols we were able to get 100% accuracy. For Isolated Digits for 4 states and 8 symbols we were able to get 98% accuracy.