Assignment-4 : Pattern Recognition

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1 Isolated Digits

1.1 HMM

Data : Classes given to us are “1”, “5” and “z”.
Algorithm : The data is divided into train (70%) and test (30%). The data is quantized using K-means with the number of symbols being equal to the number of means. A left-right HMM is trained on each class. Given a test datapoint, the likelihoods of the three models on this data-point are obtained, with the predicted class being the one having the maximum likelihood.
Experiments : The number of states and symbols are the free variables. Each state-symbol combination is one run.

Performance as a function of symbols

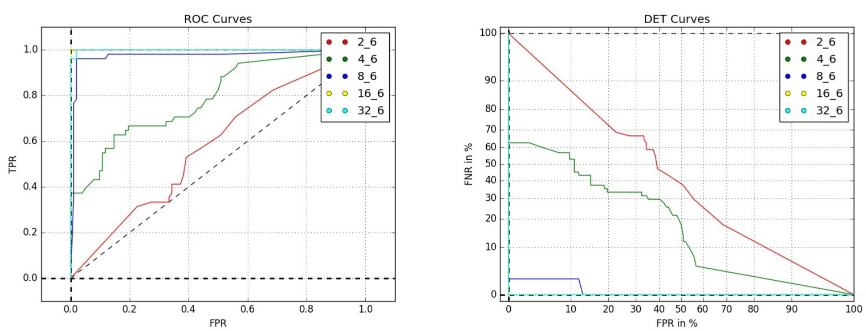


Figure 1: HMM is labelled as $<$ symbols $>$ _ $<$ states $>$

Performance as a function of states

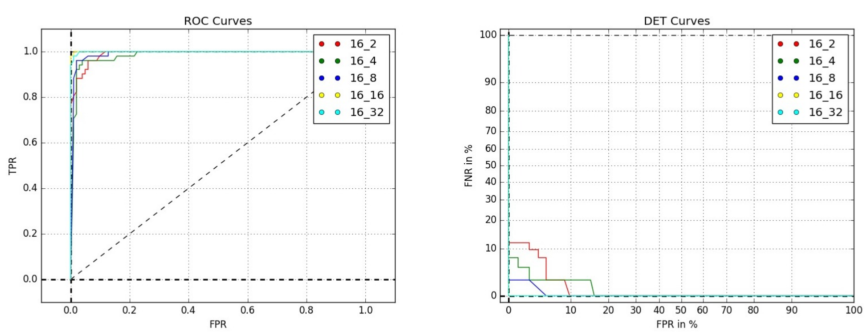


Figure 2: HMM is labelled as $<$ symbols $>$ _ $<$ states $>$

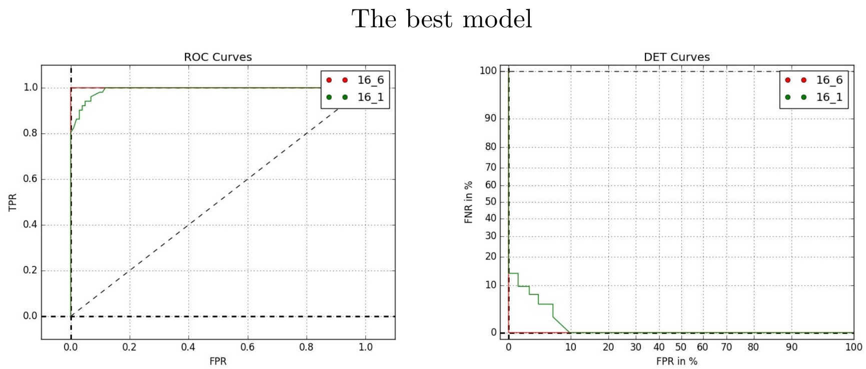


Figure 3: HMM is labelled as < symbols > _ < states >

Observations : The design of the codebook has a much greater impact on the performance than the states. 16 is observed to be the optimal codebook size. Even a single state HMM with 16-symbols performs better than HMMs with a smaller codebook.

1.2 DTW

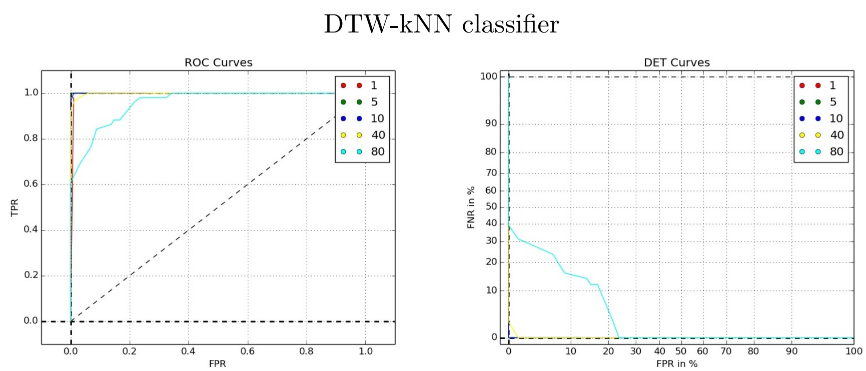


Figure 4: Each model is labelled by the number of nearest neighbours chosen.

Observations : Near perfect classification is obtained using just a single neighbour. This suggests that DTW is a very good distance measure for time series data.

2 Connected Digits

Results on test-1		
Ground truth	Known model length	Unknown model length
11z	11z	11z
15	15	155
15z	1zz	1zz
1z51	1z51	1z51z
1z	1z	1z5
1zz	1zz	1zz
1zzz1	1zzz1	1zzz1
51	51	511
51z	51z	51z1
51zz5	51zz1	51zz1
55	55	55
z1	z1	z1z
z1z	zzz	zzz
z51z	z1z5	z1z5
z5	z5	z51
z5z	z5z	z5z1
z5zzz	z5zzz	z5zzz
zz	zz	zz

Results on test-2		
Ground truth	Fixed model length = 3	Unknown model length
154.txt	111	11
155.txt	155	155z
156.txt	151	151
157.txt	1zz	1zz1
158.txt	z51	z51z
159.txt	551	551
160.txt	1zz	1zz
161.txt	z1z	z1z
162.txt	zz5	zz5
163.txt	zz5	zz5z
164.txt	zzz	zz
165.txt	zzz	zzz5z
166.txt	zzz	zzz

16-symbol, 10-state HMM models trained on each class are used for this task. The HMMs are then concatenated to form different continuous models. During concatenation the final state's self-transition probability is set to 0.5, and its next state transition probability is also set to 0.5. Sequence lengths upto 5 are considered. So there are a total of $3^1 + 3^2 + 3^3 + 3^4 + 3^5 = 363$ HMM models against which each datapoint is tested. In the case of a tie, the smallest length model is chosen.

3 Handwriting

The characters

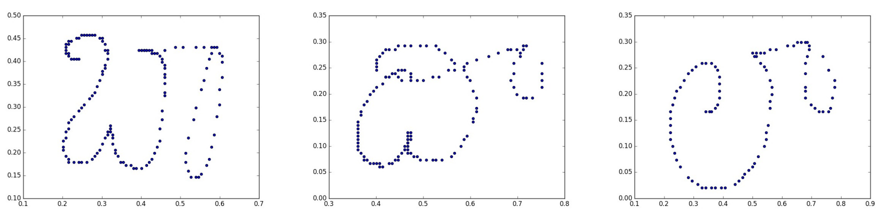


Figure 5: bA, dA, lA

3.1 HMM

3.1.1 Isolated

Four types of features are used : coordinates, first derivatives, second derivatives, curvature. Different combination of these features are used to prepare different datasets.

The effect of curvature

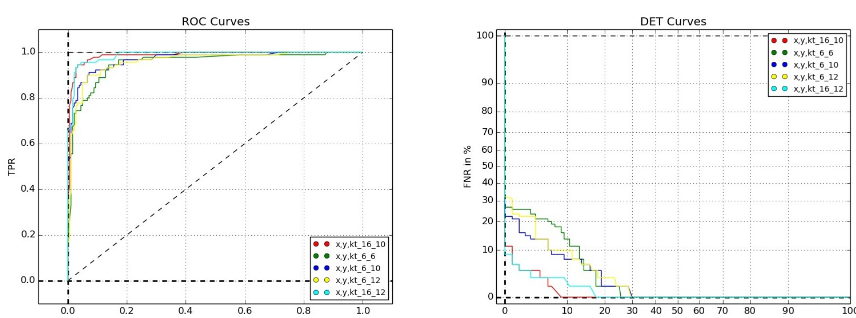


Figure 6: HMM is labelled as < features > _ < symbols > _ < states >

The effect of features on performance

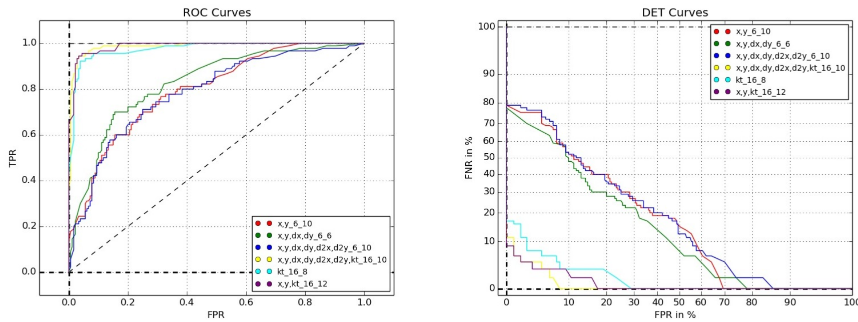


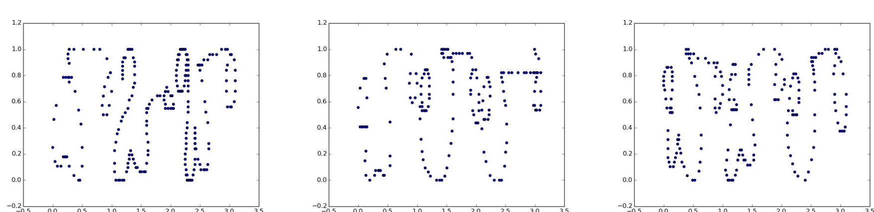
Figure 7: HMM is labelled as < features > _ < symbols > _ < states >

Confusion Matrix on Test Data			
	bA	dA	lA
bA	29	1	0
dA	0	30	0
lA	0	5	25

Observations : The curvature is the most important feature. The first and second derivatives capture the speed and acceleration of the stroke. Though the dataset has been generated in an online fashion by sampling points as they are written, the prediction happens offline, after the entire stroke has been recorded. Hence the speed and acceleration do not have any impact on the classification. In fact the second derivatives make the performance worse.
There is a confusion between the characters “dA” and “lA”. Since the curvature is the main feature, we need to study the variation in curvature across a stroke for each of these characters. The kind of curves that are traced on the paper while writing a letter, and the order in which these curves are traced carries the signature of a letter. In this respect, it appears that “dA” and “lA” have a lot of common curves that are traced in a similar manner.

3.1.2 Continuous

1, 2 and 3



Results for 1, 2 and 3		
Ground truth	Fixed model length = 3	Unknown model length
dA–bA–bA (1)	bA–dA–dA, bA–dA–bA, bA–dA–lA	bA–dA–bA
bA–lA–lA (2)	**bA–lA–lA**, bA–lA–dA, bA–lA–bA	bA–lA–lA–bA–dA
bA–bA–lA (3)	dA–bA–bA	dA–bA–bA–dA

3.2 DTW

DTW-kNN classifier

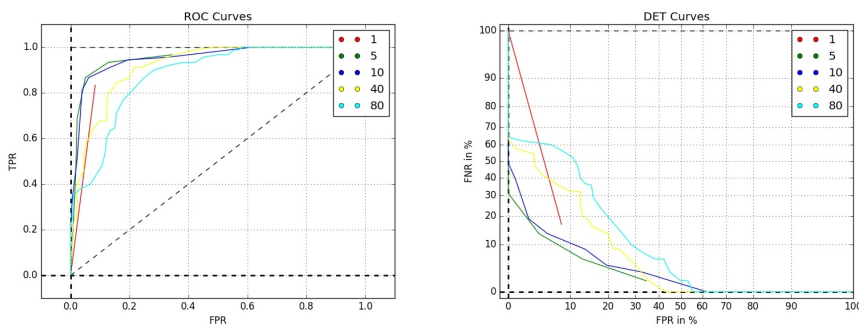


Figure 8: Each model is labelled by the number of nearest neighbours chosen

Confusion Matrix on Test Data			
	bA	dA	lA
bA	28	2	0
dA	0	22	8
lA	1	0	29