

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 likelihood of all three HMM-models on this datapoint are obtained. The predicted class is the one having the maximum likelihood.

Experiments : The number of states and the number of symbols are the free variables. Each state-symbol combination corresponds to one experiment. The ROC-DET curves are plotted for all these models.

Performance as a function of symbols

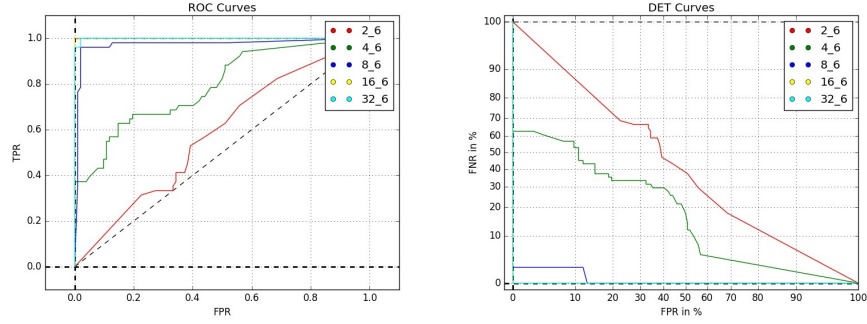


Figure 1: HMM is labelled as < symbols > - < states >

Performance as a function of states

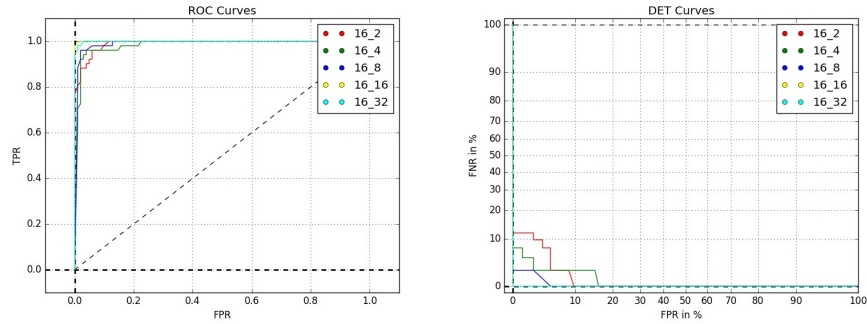


Figure 2: HMM is labelled as < symbols > - < states >

The best model

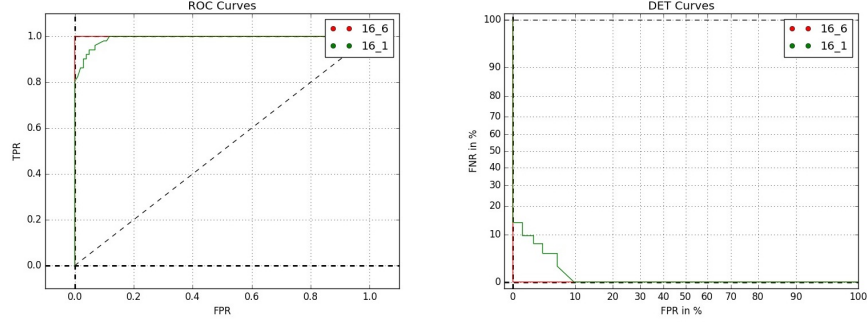


Figure 3: HMM is labelled as < symbols > - < states >

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

1.2 DTW

DTW-kNN classifier

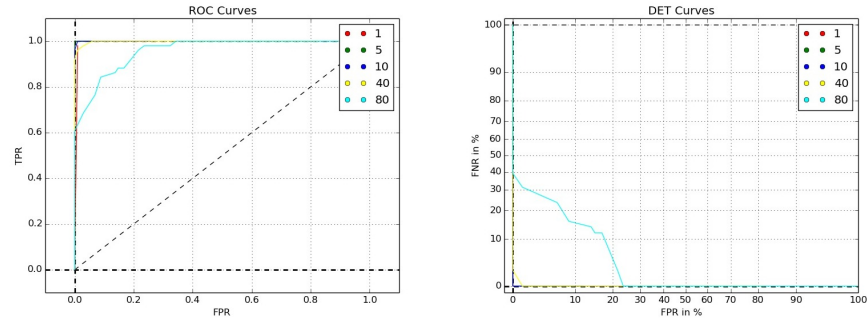


Figure 4: Each model is labelled by the number of nearest neighbours chosen.

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.

1.3 HMMs versus DTW

- No training or hyperparameter tuning required in DTW.
- Unlike HMMs, DTW is memory and compute intensive during test time.

2 Connected Digits

Results on test-1		
Ground truth	Known model length	Unknown model length
11z	11z	11z
15	15	1555
15z	1zz	1zz
1z51	1z51	1z51z
1z	1z	1z5z1
1zz	1zz	1zz
1zzz1	1zzz1	1zzz1
51	51	511z1
51z	51z	51z1z
51zz5	51zz1	51zz1
55	55	55
z1	z1	z1zzz
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	155z1
156.txt	151	15151
157.txt	1zz	1zz15
158.txt	z51	z51z1
159.txt	551	55111
160.txt	1zz	1zz
161.txt	z1z	z1zzz
162.txt	zz5	zz5z1
163.txt	zz5	zz5z1
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.

3 Handwriting

The characters

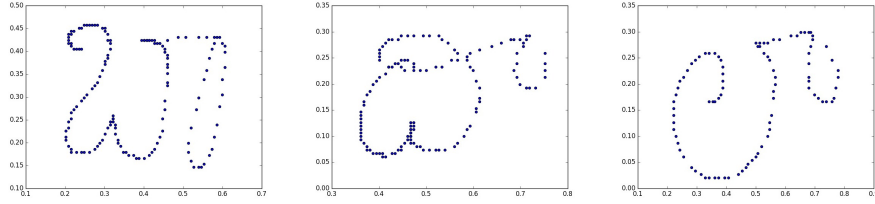


Figure 5: bA, dA, lA

3.1 HMM

3.1.1 Isolated

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

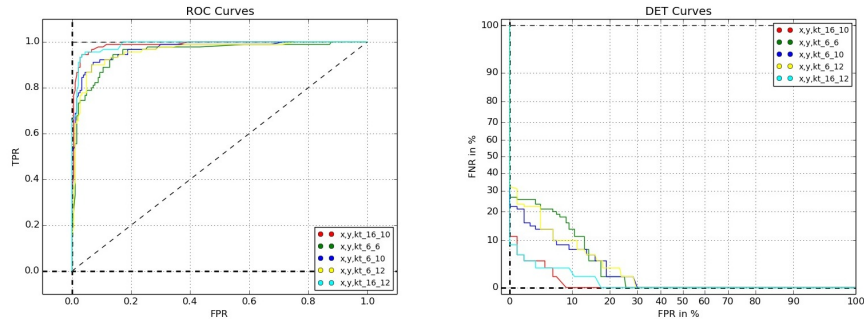


Figure 6: HMM is labelled as < features > _ < symbols > _ < states >

The effect of features on performance

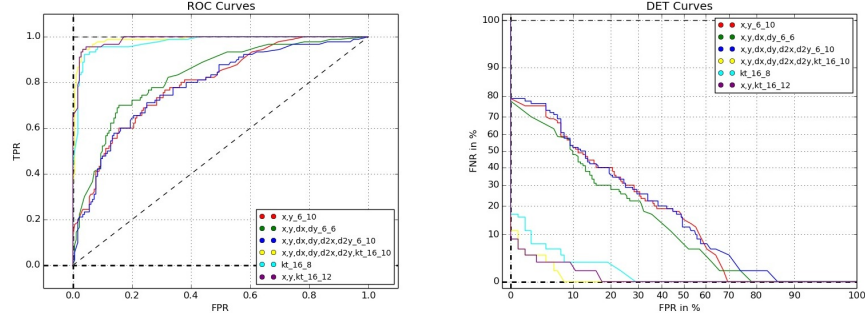


Figure 7: HMM is labelled as < features > _ < symbols > _ < states >

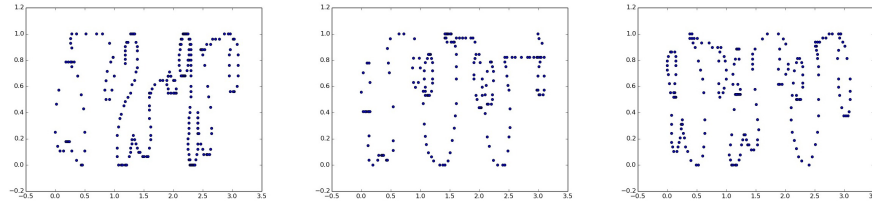
Confusion Matrix on Test Data			
	bA	dA	lA
bA	29	1	0
dA	0	30	0
lA	0	5	25

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. Though “bA” and “dA” have very similar curvatures for the second half of the stroke, the first halves have inverse curvature. This is a discriminating aspect.

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

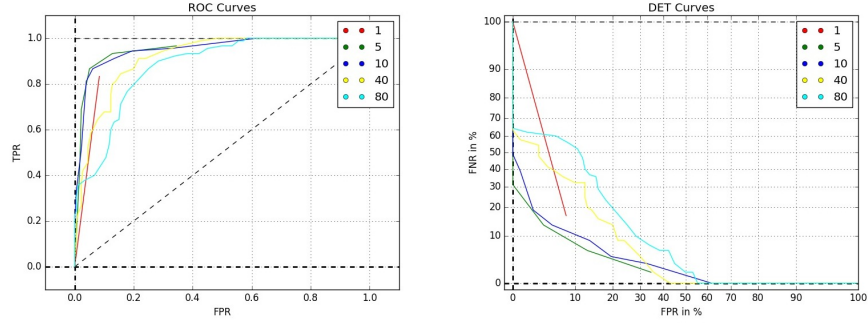


Figure 8: Each model is labelled by the number of nearest neighbours chosen

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