Pattern Recognition

CS6690

IIT Madras

Assignment 4

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Parametric Methods:

Parametric methods is an approach for statistics which assumes that the data have come from a pre-defined probability distribution and makes inferences about the parameters of the distribution.

Gaussian Mixture Models

In this assignment we built a gaussian mixture model to classify speaker identification dataset. A gaussian mixture model is a weighted sum of gaussian density functions. Unlike the K-means which gives a hard clustering, GMM gives us a soft clustering. The initial values for the gaussian mixture model is obtained from k-means clustering.

Speaker Identification

In this dataset we have 149 classes utilizing MFCC features each. We used NIST Male 2003 dataset. We used UBM - GMM for this experiments.

Accuracy=71.89 % (256 mixtures)

Inference

- As the number of mixture increases the accuracy of classification increases till a certain number.
- After certain limit the number of Gaussian don't impact much on the accuracy of results.
- The number of mixtures of different classes affect the accuracy of classification. Different number of Gaussian per class gives better results in some cases.

Hidden Markov Models

In this assignment we built a discrete hidden Markov model to to classify data such as TDIGITS. A hidden Markov model is a Markov process where there exists some hidden states.

TDIGITS

For this dataset we have built 12 models corresponding to the digits and the silence. The training and test data were provided. We performed embedded re-estimation eight times.

Accuracy (Word)=83.76 % (5 states and 2 mixtures)

Accuracy (Sentences)=49.62 % (5 states and 2 mixtures)

Inference

- 10 states, 2 mixtures gives better results than 5 states and 2 mixtures.

Dynamic Time Warping

Dynamic time warping is an algorithm for measuring the similarity between two sequences which may vary in time.

Mandi Dataset

In this dataset we built for 6 classes among 32 with 39 features each. We have kept five templates per class and the remaining for testing.

Accuracy=38.46 %

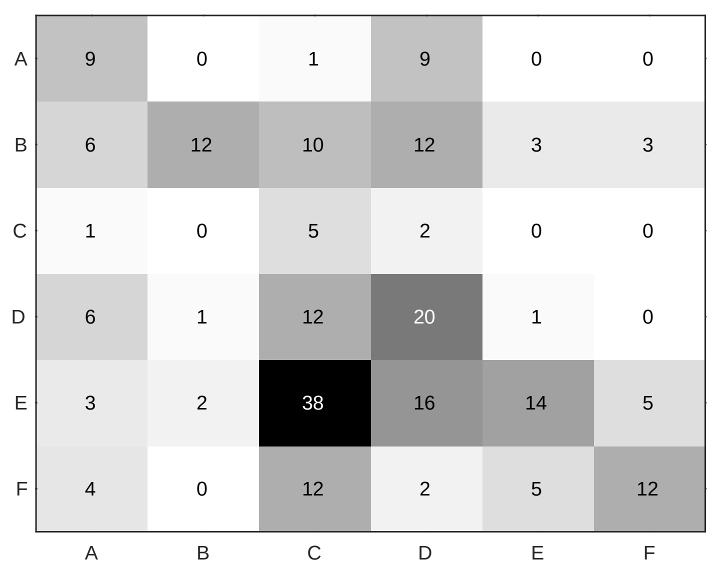


Figure 1: Confusion matrix for DTW for the Mandi Dataset

Inference

- The number of files(templates) representing the classes determines the accuracy.
- C implementation shows significant improvment in time as compared to a MATLAB implementation.
- We chose 5 random templates and best 5 templates for each class for comparison.

Non Parametric Methods:

Non-parametric methods is an approach where statistics are not based on pre-defined probability distributions. The difference between parametric models and non-parametric models is that the parametric approach has a fixed number of parameters, while the non-parametric grows the number of parameters with the amount of training data.

Image dataset:

In this dataset we have 8 classes with 23 features each. We have taken the data into 70 % for training and 30% for testing.

Parzen's Window

In this method, we fix the value of V. A kernel function is used to find the number of corresponding data points (K) within the given volume. Decision boundary depends on the kernel function. We used two kernel functions. The absolute distance and a guassian distribution.

For hyperspehere:
accuracy= 13.8 % (h=1)

accuracy = 17.3% (h=0.2)

accuracy=32.9 % (h=0.15)

For gaussian:
accuracy= 33.5 % (h=1)

accuracy = 38.7% (h=0.2)

accuracy=40.2 % (h=0.15)

Inference:

- For a fixed volume, the accuracy depends on the number of datapoints present in the defined region.
- Using a gaussian distribution provided better accuracy as compared to a absolute difference.

K-Nearest neighbour

In this method, we fix the value of K. By fixing K, we fix V. A kernel function is used. Here we used absolute distance. Decision boundary depends on the kernel function.

Accuracy = 24.9 % (K=1)

Accuracy = 52.7 % (K=15)

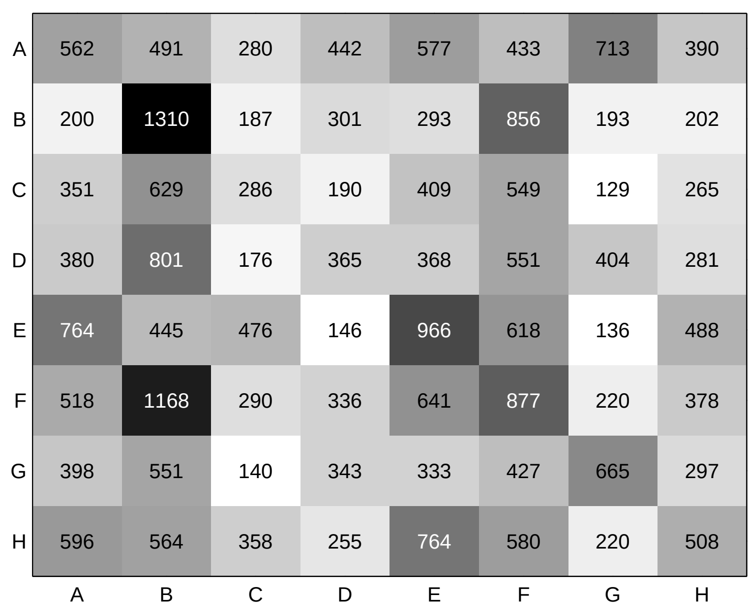


Figure 2: Confusion matrix for KNN for image dataset

Inference:

- For a fixed K, the accuracy depends on the volume required. Smaller volume leads to better accuracy due to greater density of data points.

- Using a gaussian distribution provided better accuracy as compared to a absolute difference.

Perceptron:

It is a supervised learning technique for classification of datasets. The weights are learned based on the learning rate we assign. The error due the inaccurate weights decrease iteratively.

Accuracy=32.76 % (One against all)

Inference:

- One to one classification gives better results than one to all classification.
- This approach is suitable for linearly seperable data.
- As the given data is not linearly seperable, the algorithm did not converge.

Fisher Discriminant Analysis:

In this approach, the data is projected onto a space where the ratio of between class scatter (Sb) to within class scatter (Sw) is maximised.

We find an accuracy of 35% for while classifying multiple classes and an accuracy of 83% while classifying one class with another.

Inference:

- One to one classification gives better results than one to all classification.
- Gave best accuracy among the tried non-parametric results.

Support Vector machine:

Support vectors are training data points that are closest to the hyperplane. These points are the most difficult to classify. The optimal hyperplane is one where the margin of separation is maximised. Once the support vectors are determined, the training data is not needed.

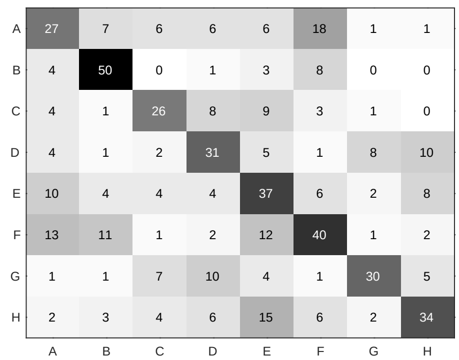
Accuracy=56% (linear)

	A	B	C	D	E	F	G	H
A	800	519	606	302	143	1013	178	327
B	25	2351	96	66	204	325	176	299
C	215	392	900	307	140	276	418	160
D	124	259	435	1062	82	153	680	531
E	247	601	550	173	680	757	414	617
F	427	1643	446	173	280	920	202	337
G	66	283	573	503	125	48	1200	356
H	277	275	405	603	256	210	509	1310

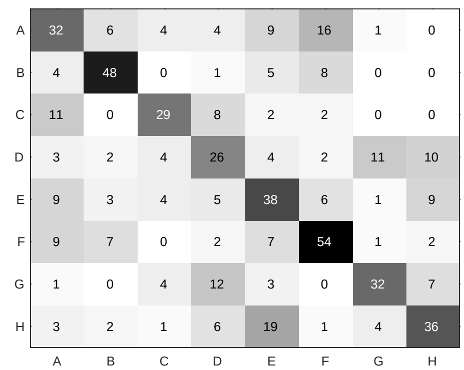
Figure 3: Confusion matrix for FDA for image dataset

Inference:

- By optimizing the parameters we can achieve good accuracy.
- Gaussian gives better results than polynomial and linear.
- Not all the data needs to be stored. We require only the support vector model.



(a) Confusion matrix for SVM (linear) for image dataset



(b) Confusion matrix for SVM (polynomial) for image dataset

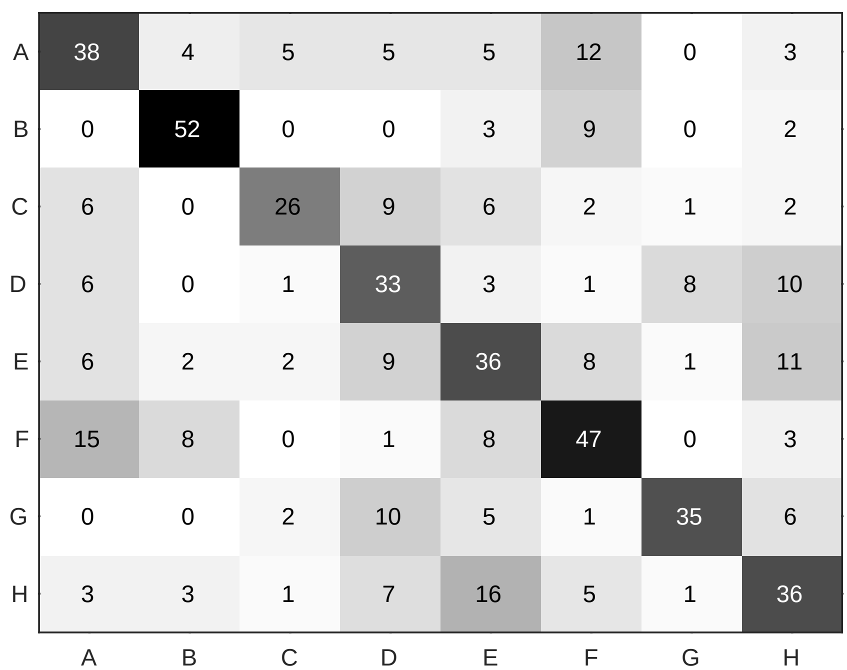


Figure 4: Confusion matrix for SVM (gaussian) for image dataset