E1 213 : Pattern Recognition and Neural Networks Assignment 1 Report

Bhartendu Kumar, Jeevithiesh Duggani, Nishanth Shetty, Rahul Raju Pogu

I. Maximum Likelihood Estimation of Class-Conditional densities

Dataset - PneumoniaMNIST with labels $\in \{0,1\}$.

1) Gaussian class conditional density

Accuracy	0.7644
F-1 Score	0.8389

2) GMM class conditional density

Components	2	3	4	5	6
Accuracy	0.9523	0.9484	0.8950	0.8846	0.7462
F-1 Score	0.9675	0.9659	0.9336	0.9152	0.85400

GMMs seem to model the class conditional densities better than multivariate Gaussians. This is as expected from GMMs since they are universal density estimators. Higher accuracy and F1 score is seen with GMMs. However, we also notice that increasing the number of mixture coefficients doesn't improve the accuracy, possibly indicating overfitting of some sort happening. The results seem to indicate that two major clusters approximate the class conditional densities the best.

II. Naive Bayes Classifier for Binary Classification

Dataset - PneumoniaMNIST with labels $\in \{0,1\}$. The assumption of independence of features which enables naive Bayes to work in the first place seems to give reasonable results as seen below.

Accuracy	0.79647
F-1 Score	0.8535

III. Maximum A Posterior with Gaussian class conditional densities

Dataset - PneumoniaMNIST with labels $\in \{0,1\}$. The MAP estimate is worse than the maximum likelihood estimate mainly due the priors being chosen for the means of the Gaussians of the class conditional densities not being truely representative of the actual mean.

Accuracy	0.625
F-1 Score	0.769

IV. Parzen Window Estimation

The main issue faced was the curse of dimensionality considering the exponential increase in memory requirements when we needed to reduce the volume element for density calculation. The overall accuracy is much lower than other methods possibly due to the local approximating nature of the method. Dataset - PneumoniaMNIST with labels $\in \{0,1\}$

Accuracy	0.47
F-1 Score	0.53
AUC	0.33

Dataset - PneumoniaMNIST with labels $\in \{0,1\}$

Accuracy	0.534
F-1 Score	0.59
AUC	0.52

V. KNN for classification

Dataset - PneumoniaMNIST with labels $\in \{0,1\}$. We observed best results with K=3 which also closely matches what we observed with GMMs where only two clusters best approximated the class conditional densities.

Accuracy	0.83
F-1 Score	0.76
AUC	0.87

Dataset - BloodMNIST with labels $\in \{0,1,...,7\}$.

	Colour Image	Grayscale Image
Accuracy	0.71	0.67
F-1 Score	0.75	0.684
AUC	0.77	0.75

VI. Linear Regression with polynomial kernels

Downsampled the input by a factor of 10, which gave $MSE = 60, MAE = 2$. Without downsampling the computations were prohibitively expensive to run, but it came at the cost of worse MSE and MAE.

VII. Logistic Regression for binary classification

Dataset - PneumoniaMNIST with labels $\in \{0,1\}$

Accuracy	0.833
F-1 Score	0.879

Confusion matrix, $C = \begin{bmatrix} 141 & 94 \\ 10 & 380 \end{bmatrix}$

VIII. Bounding Box Regression

Dataset - Vegetable with labels being the coordinates of the bounding box containing the object in the image. We observe that regularization improves the performance by reducing overfitting and improving the model's generalization.

Regularizers	None	L2	L1	Elastic
Test MSE	213	210	153	156
Test MAE	11	11	4.5	4
Test mIoU	0.70	0.71	0.82	0.74

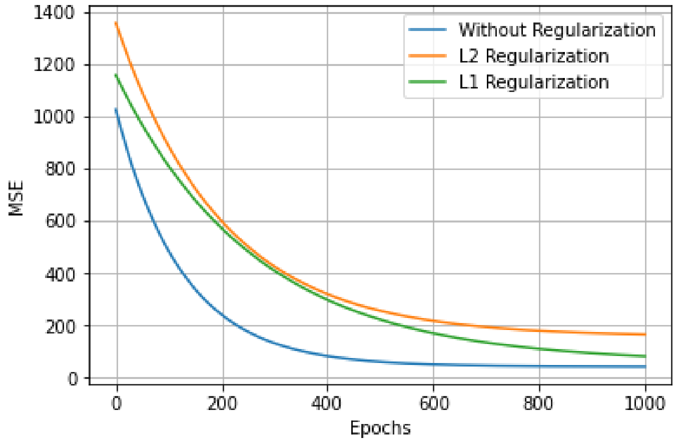

Fig. 1. MSE vs Epochs plot

IX. Linear Models for Classification with Regularizers

The weights W of $h(W, X) = \text{sign}(W^T X + b)$ are learnt via gradient descent and different regularizers - L1, L2 and Elastic are tested to check their effect of performance. L2 regularizatoin

Regularizers	L2	L1	Elastic
Train Accuracy	94.12%	94.39%	94.14%
Test Accuracy	82.53%	82.05%	82.37%
F1 Score	0.875	0.872	0.874
AUC	0.776	0.768	0.774

X. Gaussian Mixture Models as Generative Models

Implementing Expectation Maximization to fit a GMM to given data proved to be extremely challenging considering memory issues and precision issues that arose from using large matrices. We downscaled the (64, 64, 3) image to (16, 16, 3) to alleviate the memory issues but this came at the cost of poor generated image quality. Upsampling the resultant image, also did not seem to help. While there is some similarity to the original data, the resulting sample is blurred. The main challenge was the high dimensionality of the input data. It was very difficult to find a dimensionality reduction technique that worked uniformly across multiple datasets. The generated images yield an average FID score = 200 which seems to suggest that the images generated are of not great perceptual quality.

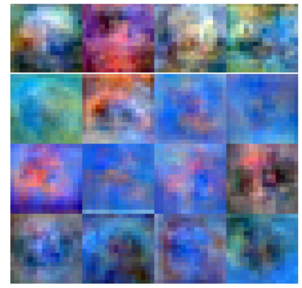

Fig. 2. Generated Images for GMM trained on Jellyfish class of tinyimagenet dataset

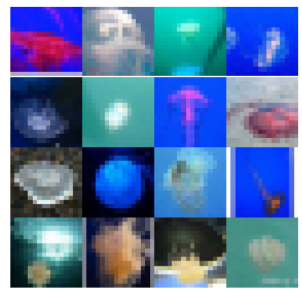

Fig. 3. Real images of Jellyfish class of tinyimagenet dataset

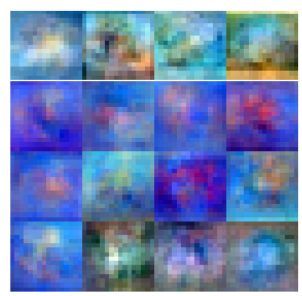

Fig. 4. Generated Images for GMM trained on Jellyfish class of tinyimagenet dataset

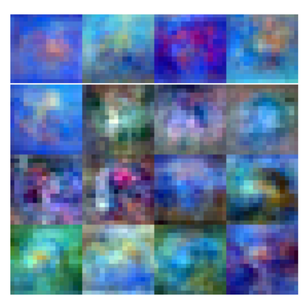

Fig. 5. Generated Images for GMM trained on Jellyfish class of tinyimagenet dataset