Image Segmentation

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The data for this problem came from two color images from the Berkley Image Segmentation Dataset that were provided to us, 3096 color.jpg (airplane) and 42049 color.jpg (bird). For both images, the same procedure was carried out to use GMM-based clustering to segment the images. The original images are displayed on the left in the figures below.

As preprocessing, a 5-dimensional feature vector was generated for each pixel as described below. First, a raw feature vector was created containing the row index, column index, red, green, and blue value of a pixel. Each feature entry was then normalized individually to the interval of 0 to 1 so that the feature vectors representing all of the pixels in each image could fit into the 5-dimensional unit-hypercube.

With preprocessing complete, maximum likelihood parameter estimation was used to fit a GMM with 2-components to the images. With 2 components, the images were segmented into two parts, the background, and the foreground. Additionally, for all GMM fitting, a regularization value of 0.03 was used to avoid a potential problem of the model always selecting the maximum value of perceptrons.

10-fold cross validation was then used to determine the optimal number of GMM components based on which number of components achieved the lowest average BIC value. Once this optimal number of GMM components was identified, a new GMM with the optimal number of components was fit to all of the image data. For GMM-based clustering, the GMM components were used as class/cluster conditional pdfs and assigned cluster labels using the MAP-classification rule.

The figures below display the original image, the segmented images for 2 component GMMs as per the assignment instructions, and then the segmented images for the optimal number of components. It ended up being that the optimal number of GMM components for both images was 2, which is why that images was displayed twice. I decided to also display the segmented images for 3 component GMMs since, for both images, this was the second most optimal number of components.

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The figures below exhibit the average BIC value vs the corresponding number of GMM components the value was calculated from. From these figures, it can be verified that the lowest BIC value was in fact achieved by 2 GMM components, making it the optimal number of components.

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Chart, scatter chart

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**MATLAB Code in Appendix A**

**Appendix A:**

clear all; close all; clc;

set(0,'DefaultFigureVisible','on');

% Eli MacColl

% 4/14/21

% Machine Learning/Pattern Recognition

images = {'3096\_color.jpg','42049\_color.jpg'};

numCheckGMM = 5;

k = 10;

for i=1:length(images)

switch i

case 1

figure(1);

plane.Data = imread(images{i});

data = plane.Data;

case 2

figure(2);

bird.Data = imread(images{i});

data = bird.Data;

end

subplot(1,3,1);

imshow(data);

title('Original');

[r,c,d] = size(data);

rows = (1:r)'\*ones(1,c);

cols = ones(r,1)\*(1:c);

featureData = [rows(:)';cols(:)'];

data = double(data);

for j=1:d

dataD = data(:,:,j);

featureData = [featureData; dataD(:)'];

end

minF = min(featureData,[],2);

maxF = max(featureData,[],2);

ranges = maxF-minF;

% Normalize and store the data

x = (featureData-minF)./ranges;

switch i

case 1

plane.x = x;

case 2

bird.x = x;

end

% Fitting GMM with 2-components

GMM2Comp=fitgmdist(x',2,'RegularizationValue',0.03);

posteriors2Comp=posterior(GMM2Comp,x')';

lossMatrix2Comp=ones(2,2)-eye(2);

expRisk2Comp =lossMatrix2Comp\*posteriors2Comp;

% 0-1 loss (MAP decision rule)

[~,decisions2Comp] = min(expRisk2Comp,[],1);

% Display segmented image

imLabels2Comp=reshape(decisions2Comp-1,r,c);

dispImLabels2Comp = uint8(imLabels2Comp\*255/2);

subplot(1,3,2);

imshow(dispImLabels2Comp);

title('2 Components');

% k-fold cross-validation to determine optimal number of GMM components

N=length(x);

partSize=floor(N/k);

partInd=[1:partSize:N N];

% Using BIC to identify the best number of Gaussian components

fprintf('Identifying best number of Gaussian components with BIC\n');

for gmm=1:numCheckGMM

fprintf('Image #%d GMM Components: %d\n',i,gmm);

for M=1:k

valIndex=partInd(M):partInd(M+1);

trainIndex=setdiff(1:N,valIndex);

GMMreg = fitgmdist(x(:,trainIndex)',gmm,'RegularizationValue',0.03);

fprintf('Regularized BIC val: %1.4f\n',GMMreg.BIC);

fprintf('===========================\n');

gmmNum(gmm) = {['gmm' num2str(gmm)]}; % BIC

if GMMreg.Converged

regBIC.(gmmNum{gmm}) = GMMreg.BIC; % BIC reg

else

regBIC.(gmmNum{gmm}) = 0; % BIC reg

end

end

%Determine average BIC value for a value of M

avgRegBIC(i,gmm) = mean(regBIC.(gmmNum{gmm})); % BIC reg

info(i).gmm=1:numCheckGMM;

info(i).avgRegBIC=avgRegBIC; % BIC reg

info(i).mRegBIC(:,gmm)=regBIC.(gmmNum{gmm});

end

%Select GMM with lowest average BIC value (closer to true model)

[~,optNumGMM\_BIC\_reg]=min(avgRegBIC(i,:)); % BIC reg

fprintf('optNumGMM\_BIC\_reg: %d\n',optNumGMM\_BIC\_reg); % BIC reg

% Fit a new GMM using all data with the optimal number of perceptrons

fprintf('Fitting Final GMM With Optimal Perceptrons\n');

finalGMM=fitgmdist(x',optNumGMM\_BIC\_reg,'RegularizationValue',0.03);

posteriors=posterior(finalGMM,x')';

lossMatrix=ones(optNumGMM\_BIC\_reg,optNumGMM\_BIC\_reg)-eye(optNumGMM\_BIC\_reg);

expRisk =lossMatrix\*posteriors; % Expected Risk for each label (rows) for each sample (columns)

[~,decisions] = min(expRisk,[],1); % Minimum expected risk decision with 0-1 loss is the same as MAP

%Plot segmented image for Max. Likelihood number of GMMs case

imLabels=reshape(decisions-1,r,c);

dispImLabels = uint8(imLabels\*255/2);

switch i

case 1

plane.OptNumGMM = optNumGMM\_BIC\_reg;

plane.FinalGMM = finalGMM;

plane.ImageLabels = imLabels;

plane.DispImageLabels = dispImLabels;

plane.LossMatrix = lossMatrix;

plane.ExpRisk = expRisk;

plane.Decisions = decisions;

case 2

bird.OptNumGMM = optNumGMM\_BIC\_reg;

bird.FinalGMM = finalGMM;

bird.ImageLabels = imLabels;

bird.DispImageLabels = dispImLabels;

bird.LossMatrix = lossMatrix;

bird.ExpRisk = expRisk;

bird.Decisions = decisions;

end

subplot(1,3,3);

imshow(dispImLabels);

title(sprintf('Optimal: %d',optNumGMM\_BIC\_reg));

end

% Plotting Average BIC Values vs Number of GMM Components for Plane Image

figure(3);

numComponents=[1,2,3,4,5];

stem(numComponents,avgRegBIC(1,:),'Color','b');

xlabel('GMM Components'); ylabel('Average BIC Value');

grid on;

subtitle('Airplane Image');

title('Average BIC Value vs Number of GMM Components');

% Plotting Average BIC Values vs Number of GMM Components for Bird Image

figure(4);

stem(numComponents,avgRegBIC(2,:),'Color','b');

xlabel('GMM Components'); ylabel('Average BIC Value');

grid on;

subtitle('Bird Image');

title('Average BIC Value vs Number of GMM Components');