# ECE271A HW3 Report

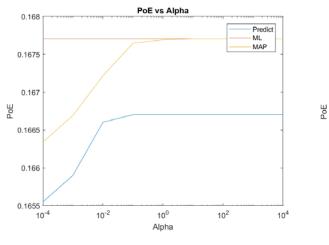
# Yan Sun

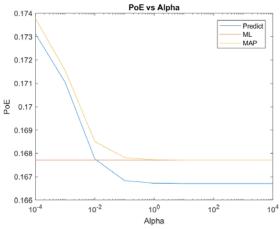
# A53240727

# **Computer Problem**

(The results are shown in the following pictures. I will show the plots firstly and then answer each question.)

### Dataset1

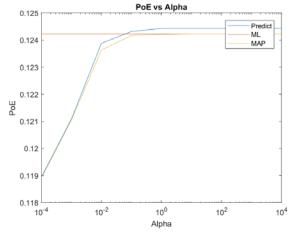


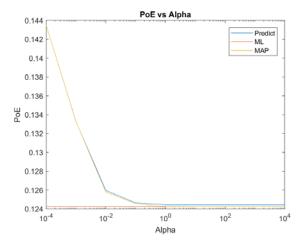


Strategy1

Strategy2

### Dataset2

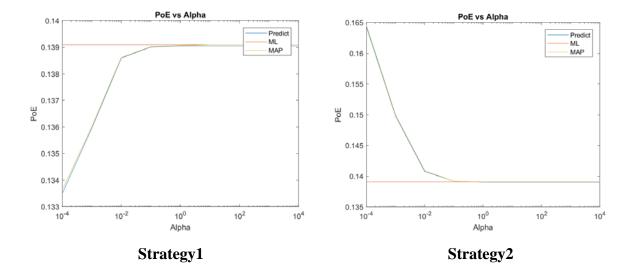




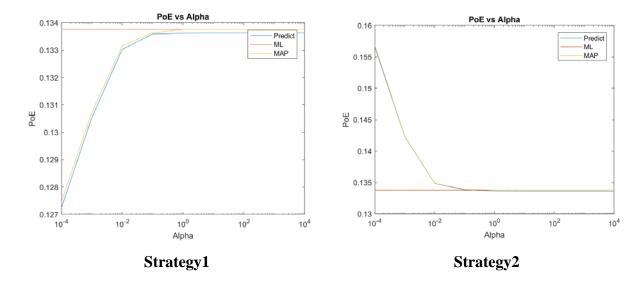
Strategy1

Strategy2

#### Dataset3



### Dataset4



#### (1) The relative behavior of these three curves:

### Observation:

In this problem, I use dataset one and strategy one to plot the curve of probability of error (PoE) versus alpha. The PoE of dataset one for both strategies is around 16%~17%. In this curve, PoE increases as alpha increases obviously when alpha is small. When alpha is large, however, the PoE tend to be fixed at a constant value.

$$(\Sigma_0)_{ii} = \alpha w_i.$$

$$egin{align} oldsymbol{\mu}_n &= oldsymbol{\Sigma}_0 \Big(oldsymbol{\Sigma}_0 + rac{1}{n}oldsymbol{\Sigma}\Big)^{-1} \hat{oldsymbol{\mu}}_n + rac{1}{n}oldsymbol{\Sigma}\Big(oldsymbol{\Sigma}_0 + rac{1}{n}oldsymbol{\Sigma}\Big)^{-1} \hat{oldsymbol{\mu}}_0 \ &oldsymbol{\Sigma}_n &= oldsymbol{\Sigma}_0 \Big(oldsymbol{\Sigma}_0 + rac{1}{n}oldsymbol{\Sigma}\Big)^{-1} rac{1}{n}oldsymbol{\Sigma}. \end{split}$$

### Explain:

When alpha is small, based on the intuitive combination of mean value, it could be found that the prior information has more weights within the total  $\mu$  value considered. At this time, MAP and Prediction model share the same mu value and they tend to have similar PoE value. The  $\Sigma n$  term will be small so that the contribution of prior covariance is small in  $\Sigma + \Sigma n$ , which also sontributed to the phenomenon that MAP and Bayes predictive model's PoE tends to be close. The difference of PoE between ML and Bayes is large, which is mainly caused by the large difference of  $\mu$  used in different methods.

When alpha becomes large enough, in the equation of  $\mu n$ , the term with primitive  $\mu$  ( $\mu$  hat) will have more weights. At this time, the PoE of MAP tends to be close to ML since they already share the same covariance. In the end, when alpha is very large, the ML part in Bayes predictive model has enough weights so that the PoE of Bayes is comparably close to ML compared to the time when alpha is small. Although the PoE seems fixed at this time, the prior information is also considered to be part of Bayes predictive model so that their performance will be different based on the dataset who provided the prior information.

#### (2) How that behavior changes from dataset to dataset:

#### Observation:

It could be observed that in dataset one, Bayes predictive model is obviously performed better than ML and MAP. In dataset two, Bayes predictive model is obviously performed worse than ML and MAP. In dataset three and four, Bayes predictive model just performs slightly better than ML and MAP.

#### Explain:

The difference of dataset has influence on prior information, which is showed in the equation when we try to get the prior  $\mu$  or  $\Sigma$ . To be specific, the size of dataset is the primary reason since the value of N in those equations will make a difference. Dataset three and four has more data than dataset one and dataset two so the prior information provided by them will not count much (in the expression of  $\mu$ n and  $\Sigma$ n, the 1/n term will make the prior information less importance so that the big size of data will make the ML part more weighted instead). In this way, when alpha is large enough, Bayes predictive models' performance will be closer to ML and Map compared to dataset one and dataset two. Dataset one and dataset two has comparably smaller size of data than dataset three and dataset four. In this way, their Bayes predictive model performance will

tend to depend on the prior information provided by specific dataset so that the ultimate performance when alpha is large enough will be either better or worse than ML and MAP obviously.

### (3) How all of the above change when strategy 1 is replaced by strategy 2:

#### Observation:

In both strategies, the PoE of ML is fixed. In strategy one, the PoE of MAP and Bayes increases as alpha increases while in strategy two the PoE of MAP and Bayes decreases as alpha increases. When alpha is large enough, all the PoE values tend to be fixed and the relative performance stays the same for same dataset on these two strategies.

### Explain:

The different trend is caused by the different definition of prior information defined in two strategies. As aforementioned explanation mentioned in (1), when alpha is small, prior information has more weights for the Classifier. However, strategy one gives two classes different mean while strategy two gives two classes same mean. It is obviously that these two classes should be weighted differently so that strategy two's prior information is worse that strategy one. In this way, when alpha is small, strategy one's prior information makes Bayes and MAP better than ML while strategy two's prior information makes Bayes and MAP worse than ML. When alpha is large enough, all the models' performance under strategy two tend to be close to what it is under strategy one since the ML part in Bayes and MAP ted to be more weighted. The relative performance among three methods are also similar to what it is under strategy one.

#### Code:

The total running time could be around 15 minutes. It may be varied depends on the device and MATLAB version.

```
train_set = load('TrainingSamplesDCT_subsets_8.mat');
alpha = load('Alpha.mat');
alpha = alpha.alpha;
for strategy idx = 1:2
  if strategy_idx == 1
    strategy = load('Prior 1.mat');
  elseif strategy_idx == 2
    strategy = load('Prior_2.mat');
  end
  for dataset idx = 1:4
    if dataset idx == 1
      d1 BG = train set.D1 BG;
      d1 FG = train set.D1 FG;
    elseif dataset_idx == 2
      d1 BG = train set.D2 BG;
      d1_FG = train_set.D2_FG;
    elseif dataset idx == 3
      d1 BG = train set.D3 BG;
      d1_FG = train_set.D3_FG;
    elseif dataset idx == 4
      d1_BG = train_set.D4_BG;
      d1 FG = train set.D4 FG;
    end
    bayes error = [];
    mle_error = [];
    map error = [];
    n_FG = size(d1_FG,1);
    n BG = size(d1 BG,1);
    % Loop for different alpha
    for alpha_idx = 1:size(alpha,2)
```

```
cov 0 = zeros(64,64);
                 for idx = 1:64
                      cov 0(idx,idx) = alpha(alpha idx)*strategy.W0(idx);
                  end
                  % FG
                 d1 FG cov = cov(d1 FG) * (n FG-1)/ n FG;
                 tmp2 = inv(cov 0 + (1/n FG)*d1 FG cov);
                 mu_1FG = cov_0 * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * transpose(mean(d1_FG)) + (1/n FG) * d1 FG cov * tmp2 * tmp2
transpose(strategy.mu0_FG);
                  cov 1 FG = cov 0 * tmp2 * (1/ n FG) * d1 FG cov;
                 % predictive distribution (normal distribution)
                 mu pred FG = mu 1 FG;
                  cov_pred_FG = d1_FG_cov + cov_1_FG;
                 % BG
                 d1 BG cov = cov(d1 BG) * (n BG-1)/ n BG;
                 tmp3 = inv(cov 0 + (1/ n BG)*d1 BG cov);
                 mu_1BG = cov_0 * tmp3 * transpose(mean(d1_BG)) + (1/n_BG) * d1_BG_cov * tmp3 *
transpose(strategy.mu0_BG);
                 cov 1 BG = cov 0 * tmp3 * (1/ n BG) * d1 BG cov;
                 % predictive distribution (normal distribution)
                 mu pred BG = mu 1 BG;
                 cov pred BG = d1 BG cov + cov 1 BG;
                 % Prior
                 num FG = size(d1 FG,1);
                 num BG = size(d1 BG,1);
                  prior FG = num FG / (num FG + num BG);
                  prior_BG = num_BG / (num_FG + num_BG);
                  %%%%
                  % Bayes-BDR
                 % BDR
                 img = imread('cheetah.bmp');
                 img = im2double(img);
                 % Add paddle
                 img = [zeros(size(img,1),2) img];
                 img = [zeros(2, size(img,2)); img];
```

```
img = [img; zeros(5, size(img,2))];
       %%% DCT
       [m,n] = size(img);
       Blocks = ones(m-7,n-7);
       det_cov_FG = det(cov_pred_FG);
       det cov BG = det(cov pred BG);
       ave tmp FG = transpose(mu pred FG);
       ave_tmp_BG = transpose(mu_pred_BG);
      inv tmp FG = inv(cov pred FG);
       inv_tmp_BG = inv(cov_pred_BG);
       % predict
       const_FG = ave_tmp_FG*inv_tmp_FG*transpose(ave_tmp_FG) + log(det_cov_FG) - 2*log(prior_FG);
       const_BG = ave_tmp_BG*inv_tmp_BG*transpose(ave_tmp_BG) + log(det_cov_BG) - 2*log(prior_BG);
       for i=1:m-7
         for j=1:n-7
           DCT = dct2(img(i:i+7,j:j+7));
           zigzag order = zigzag(DCT);
           feature = zigzag_order;
           g_{cheetah} = 0;
           g_grass = 0;
           % cheetah
           g_cheetah = g_cheetah + feature*inv_tmp_FG*transpose(feature);
           g_cheetah = g_cheetah - 2*feature*inv_tmp_FG*transpose(ave_tmp_FG);
           g cheetah = g cheetah + const FG;
           % grass
           g_grass = g_grass + feature*inv_tmp_BG*transpose(feature);
           g_grass = g_grass - 2*feature*inv_tmp_BG*transpose(ave_tmp_BG);
           g_grass = g_grass + const_BG;
           if g cheetah >= g grass
              Blocks(i,j) = 0;
           end
         end
       end
      % save prediction
      imwrite(Blocks, ['bayes prediction alpha 'int2str(alpha idx) 'dataset 'int2str(dataset idx)
'_strategy_' int2str(strategy_idx) '.jpg']);
```

img = [img zeros(size(img,1),5)];

```
ground truth = imread('cheetah mask.bmp')/255;
      x = size(ground truth, 1);
      y = size(ground_truth, 2);
      count1 = 0;
      count2 = 0;
      count cheetah truth = 0;
      count grass truth = 0;
      for i=1:x
        for j=1:y
           if prediction(i,j) > ground truth(i,j)
             count2 = count2 + 1;
             count_grass_truth = count_grass_truth + 1;
           elseif prediction(i,j) < ground_truth(i,j)</pre>
             count1 = count1 + 1;
             count_cheetah_truth = count_cheetah_truth + 1;
           elseif ground truth(i,j) >0
             count_cheetah_truth = count_cheetah_truth + 1;
           else
             count_grass_truth = count_grass_truth + 1;
           end
        end
      end
      error1 64 = (count1/count cheetah truth) * prior FG;
      error2 64 = (count2/count grass truth) * prior BG;
      total error 64 = error1 64 + error2 64;
      bayes error = [bayes error total error 64];
      %%%%
      % ML-BDR
      % ML prediction
      img = imread('cheetah.bmp');
      img = im2double(img);
      % Add paddle
      img = [zeros(size(img,1),2) img];
      img = [zeros(2, size(img,2)); img];
      img = [img zeros(size(img,1),5)];
      img = [img; zeros(5, size(img,2))];
```

prediction = mat2gray(Blocks);

```
%%% DCT
       [m,n] = size(img);
       Blocks = ones(m-7,n-7);
       mean_FG = mean(d1_FG);
       mean BG = mean(d1 BG);
       ave_tmp_FG = mean_FG;
       ave tmp BG = mean BG;
       inv covFG = inv(d1 FG cov);
       inv_covBG = inv(d1_BG_cov);
       DcovFG = det(d1 FG cov);
       DcovBG = det(d1_BG_cov);
       %%% predict
       const_FG = ave_tmp_FG*inv_covFG*transpose(ave_tmp_FG) + log(DcovFG) - 2*log(prior_FG);
       const_BG = ave_tmp_BG*inv_covBG*transpose(ave_tmp_BG) + log(DcovBG) - 2*log(prior_BG);
       for i=1:m-7
         for j=1:n-7
           DCT = dct2(img(i:i+7,j:j+7));
           zigzag_order = zigzag(DCT);
           feature = zigzag_order;
           g_{cheetah} = 0;
           g_grass = 0;
           % cheetah
           g_cheetah = g_cheetah + feature*inv_covFG*transpose(feature);
           g_cheetah = g_cheetah - 2*feature*inv_covFG*transpose(ave_tmp_FG);
           g cheetah = g cheetah + const FG;
           % grass
           g_grass = g_grass + feature*inv_covBG*transpose(feature);
           g_grass = g_grass - 2*feature*inv_covBG*transpose(ave_tmp BG);
           g_grass = g_grass + const_BG;
           if g cheetah >= g grass
              Blocks(i,j) = 0;
           end
         end
       end
       %%% save prediction
       imwrite(Blocks, ['mle prediction alpha 'int2str(alpha idx) ' dataset 'int2str(dataset idx) ' strategy '
int2str(strategy_idx) '.jpg']);
```

```
ground truth = imread('cheetah mask.bmp')/255;
      x = size(ground truth, 1);
      y = size(ground_truth, 2);
      count1 = 0;
      count2 = 0;
      count cheetah truth = 0;
      count grass truth = 0;
      for i=1:x
        for j=1:y
           if prediction(i,j) > ground_truth(i,j)
             count2 = count2 + 1;
             count_grass_truth = count_grass_truth + 1;
           elseif prediction(i,j) < ground_truth(i,j)</pre>
             count1 = count1 + 1;
             count_cheetah_truth = count_cheetah_truth + 1;
           elseif ground truth(i,j) >0
             count_cheetah_truth = count_cheetah_truth + 1;
           else
             count_grass_truth = count_grass_truth + 1;
           end
        end
      end
      error1 64 = (count1/count cheetah truth) * prior FG;
      error2 64 = (count2/count grass truth) * prior BG;
      total error 64 = error1 64 + error2 64;
      mle error = [mle error total error 64];
      %%%%
      % MAP-BDR
      % BDR
      img = imread('cheetah.bmp');
      img = im2double(img);
      % Add paddle
      img = [zeros(size(img,1),2) img];
      img = [zeros(2, size(img,2)); img];
      img = [img zeros(size(img,1),5)];
      img = [img; zeros(5, size(img,2))];
```

prediction = mat2gray(Blocks);

```
%%% DCT
       [m,n] = size(img);
       Blocks = ones(m-7,n-7);
       det_cov_FG = det(d1_FG_cov);
       det cov BG = det(d1 BG cov);
       ave_tmp_FG = transpose(mu_pred_FG);
       ave tmp BG = transpose(mu pred BG);
       % predict
       const_FG = ave_tmp_FG*inv_covFG*transpose(ave_tmp_FG) + log(det_cov_FG) - 2*log(prior_FG);
       const_BG = ave_tmp_BG*inv_covBG*transpose(ave_tmp_BG) + log(det_cov_BG) - 2*log(prior_BG);
       for i=1:m-7
         for j=1:n-7
            DCT = dct2(img(i:i+7,j:j+7));
            zigzag_order = zigzag(DCT);
            feature = zigzag order;
            g_cheetah = 0;
            g_grass = 0;
            % cheetah
            g_cheetah = g_cheetah + feature*inv_covFG*transpose(feature);
            g cheetah = g cheetah - 2*feature*inv covFG*transpose(ave tmp FG);
            g_cheetah = g_cheetah + const FG;
            % grass
            g_grass = g_grass + feature*inv_covBG*transpose(feature);
            g_grass = g_grass - 2*feature*inv_covBG*transpose(ave_tmp_BG);
            g_grass = g_grass + const_BG;
           if g_cheetah >= g_grass
              Blocks(i,j) = 0;
           end
         end
       end
       % save prediction
       imwrite(Blocks, ['map_prediction_alpha_' int2str(alpha_idx) '_dataset_' int2str(dataset_idx) '_strategy_'
int2str(strategy_idx) '.jpg']);
       prediction = mat2gray(Blocks);
       ground truth = imread('cheetah mask.bmp')/255;
       x = size(ground_truth, 1);
```

```
y = size(ground truth, 2);
      count1 = 0;
      count2 = 0;
      count cheetah truth = 0;
      count grass truth = 0;
      for i=1:x
        for j=1:y
          if prediction(i,j) > ground truth(i,j)
            count2 = count2 + 1;
            count_grass_truth = count_grass_truth + 1;
          elseif prediction(i,j) < ground truth(i,j)</pre>
            count1 = count1 + 1;
            count cheetah truth = count cheetah truth + 1;
          elseif ground_truth(i,j) >0
            count_cheetah_truth = count_cheetah_truth + 1;
          else
            count grass truth = count grass truth + 1;
          end
        end
      end
      error1 64 = (count1/count cheetah truth) * prior FG;
      error2_64 = (count2/count_grass_truth) * prior BG;
      total error 64 = error1 64 + error2 64;
      map error = [map error total error 64];
    end
   %%%%%
   % plot
    plot(alpha,bayes error,alpha,mle error,alpha,map error);
   legend('Predict','ML','MAP');
    set(gca, 'XScale', 'log');
   title('PoE vs Alpha');
   xlabel('Alpha');
   ylabel('PoE');
   saveas(gcf,['Strategy_' int2str(strategy_idx) '_dataset_' int2str(dataset_idx) '_PoEvsAlpha.png']);
  end
end
function output = zigzag(in)
% initializing the variables
```

```
%-----
h = 1;
v = 1;
vmin = 1;
hmin = 1;
vmax = size(in, 1);
hmax = size(in, 2);
i = 1;
output = zeros(1, vmax * hmax);
%-----
while ((v <= vmax) && (h <= hmax))
  if (mod(h + v, 2) == 0)
                                 % going up
    if (v == vmin)
       output(i) = in(v, h);
                           % if we got to the first line
      if (h == hmax)
         v = v + 1;
       else
         h = h + 1;
       end
      i = i + 1;
    elseif ((h == hmax) && (v < vmax)) % if we got to the last column
      output(i) = in(v, h);
      v = v + 1;
      i = i + 1;
    elseif ((v > vmin) && (h < hmax)) % all other cases
       output(i) = in(v, h);
      v = v - 1;
      h = h + 1;
      i = i + 1;
  end
  else
                           % going down
    if ((v == vmax) && (h <= hmax))
                                     % if we got to the last line
       output(i) = in(v, h);
      h = h + 1;
      i = i + 1;
    elseif (h == hmin)
                                % if we got to the first column
       output(i) = in(v, h);
      if (v == vmax)
```

```
h = h + 1;
    else
        v = v + 1;
      end
      i = i + 1;
    elseif ((v < vmax) && (h > hmin)) % all other cases
      output(i) = in(v, h);
      v = v + 1;
      h = h - 1;
      i = i + 1;
    end
  end
  if ((v == vmax) && (h == hmax))
                                       % bottom right element
    output(i) = in(v, h);
    break
  end
end
```