EE583 Pattern Recognition HW3

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1 Question 1

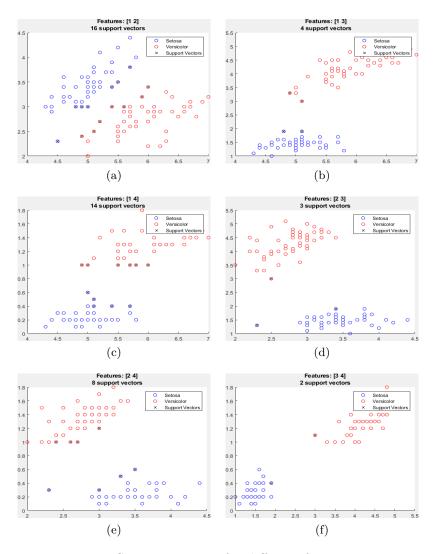


Figure 1: Support Vectors for different feature pairs

The number of support vectors was minimum for the features 3 & 4. One can notice the opposite relationship between the linear separability of the feature space and the number of support vectors. However, it is important to note that one can achieve the same number of minimum vectors for other features by setting the BoxConstraint parameter manually. I observed that setting it to 15 resulted in 2 support vectors for two cases.

2 Question 2

4 Features

 $kfold\ loss = 0$ $LOOCV\ loss = 0$

1 Feature

 $kfold\ loss = 0.1900$ $LOOCV\ loss = 0.1700$

Using four features, having higher dimensions, have resulted in SVM Model linearly separating the feature space. Hence, for both Cross Validation Experiments, the loss rate was 0. On the other hand, when I decreased the number of utilized dimensions to 1, LOOCV loss was slightly less than the 10-Fold CV loss. This may be attributed to the fact that LOOCV utilizes more training data than kfold, resulting in higher more accurate test set predictions, considering that the number of training data is not so large that it causes overfitting.

3 Question 3

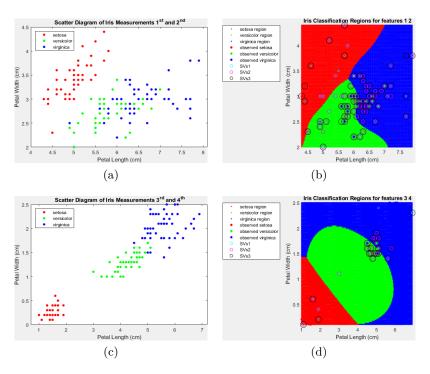


Figure 2: Support Vectors for different feature pairs

Changing feature pairs that are utilized in SVM classification resulted in different distributions. Features 3 and 4 provides a more linearly separable feature space than 1 and 2. The resultant numbers of support vectors 196 and 58 also indicates the same result. In addition, this is also observable in scatter plots.

4 Question 4

The objective function, as a function of BoxConstraint and KernelScale, is optimized using Bayesian optimization. Hence, these parameters determines the cross validation loss and selecting them is a crucial part of optimizing an SVM classifier, keeping in mind that rbf as kernel function is fixed. In addition, I have tried polynomial kernel function, and observed that optimized cross validation loss is different from the one that rbf kernel function is able to achieve. Therefore,

- Box Constraint
- Kernel Scale
- Kernel Function

are the hyperparameters that can be optimized in an SVM to achieve better cross validation success, in terms of loss.

5 APPENDIX

The code given in this section is shared @**o**.

5.1 Q1

```
% HW3 Q1
  load fisheriris
  inds = ~strcmp(species, 'virginica');
  features = 1:4;
  all_feature_pairs = nchoosek(features, 2);
  counter = zeros(size(all_feature_pairs,1),1);
  for i = 1: size (all feature pairs, 1)
       temp_features = all_feature_pairs(i,:);
10
       X = meas(inds, temp_features);
11
       y = species(inds);
12
       setosa_idx = strcmp(y, 'setosa');
13
       versicolor_idx = strcmp(y, 'versicolor');
       SVMModel = fitcsvm(X, y);
15
      % n_support_vectors = sum(SVMModel.IsSupportVector);
16
       n_support_vectors = size (SVMModel. Support Vectors, 1);
17
       idx = SVMModel. IsSupportVector;
18
       figure
19
       scatter (X(setosa_idx,1),X(setosa_idx,2),'bo')
20
       hold on
       scatter (X(versicolor_idx,1),X(versicolor_idx,2),'ro')
22
       hold on
23
       scatter(X(idx,1),X(idx,2),'kx')
24
       title ({['Features: ',mat2str(temp_features)],[num2str(
25
          n_support_vectors), ' support vectors']})
       counter(i) = n_support_vectors;
26
       legend ('Setosa', 'Versicolor', 'Support Vectors')
27
  end
28
29
  min_support_vectors = min(counter);
  min_SV_features = all_feature_pairs(find(counter ==
31
      min_support_vectors),:);
32
33
  % Save all
  chdir('...')
  addpath('export_fig')
  chdir ('HW3')
```

```
38 figHandles = findall(0, 'Type', 'figure');
39
40 for i = 1:numel(figHandles)
41         export_fig(['Q1_', num2str(i)], '-png', figHandles(i), '-append')
42 end
43
44 close all
```

5.2 Q2

```
1 % HW2 Q2
 % All features
3 load fisheriris
  inds = ~strcmp(species, 'virginica');
  features = 1:4;
6 X = meas(inds, features);
  Y = species(inds);
  SVMModel = fitcsvm(X,Y,'Standardize',true,'KernelFunction','RBF'
       'KernelScale', 'auto');
9
10
  CVSVMModel = crossval (SVMModel, 'Kfold', 10, 'Leaveout', 'off');
11
  kfold loss = kfoldLoss(CVSVMModel)
12
  SVMModel = fitcsvm(X,Y, 'Standardize', true, 'KernelFunction', 'RBF'
14
       'KernelScale', 'auto');
15
16
  CVSVMModel_xval = crossval(SVMModel, 'Leaveout', 'on');
17
  leave_one_out_loss = kfoldLoss(CVSVMModel_xval)
19
  % Just 2nd Feature
20
  inds = ~strcmp(species, 'virginica');
  features = 2;
  X = meas(inds, features);
  Y = species(inds);
  SVMModel = fitcsvm(X,Y, 'Standardize', true, 'KernelFunction', 'RBF'
       'KernelScale', 'auto');
26
27
  CVSVMModel = crossval(SVMModel, 'Kfold', 10, 'Leaveout', 'off');
  kfold_loss = kfoldLoss (CVSVMModel)
29
30
  SVMModel = fitcsvm(X,Y, 'Standardize', true, 'KernelFunction', 'RBF'
31
       'KernelScale', 'auto');
32
  CVSVMModel_xval = crossval(SVMModel, 'Leaveout', 'on');
  leave one out loss = kfoldLoss(CVSVMModel xval)
```

5.3 Q3

```
% Same features
2
  load fisheriris
 X = meas(:,1:2);
  Y = species;
  figure ('Position', [250 250 600 400]);
  gscatter(X(:,1),X(:,2),Y);
_{9} h = gca;
  lims = [h.XLim h.YLim]; % Extract the x and y axis limits
  title ('{\bf Scatter Diagram of Iris Measurements 1^{st} and 2^{nd}
      }}');
  xlabel('Petal Length (cm)');
  ylabel('Petal Width (cm)');
  legend('Location', 'Northwest');
14
15
  SVMModels = cell(3,1);
16
  classes = unique(Y);
17
  rng(1); % For reproducibility
18
19
  for j = 1:numel(classes)
20
       indx = strcmp(Y, classes(j)); % Create binary classes for each
21
           classifier
       SVMModels{j} = fitcsvm(X, indx, 'ClassNames', [false true], '
22
          Standardize', true,...
           'KernelFunction', 'rbf', 'BoxConstraint', 1);
23
  end
24
25
  d = 0.02;
26
  [x1Grid, x2Grid] = meshgrid(min(X(:,1)):d:max(X(:,1)),...
27
       \min(X(:,2)):d:\max(X(:,2));
  xGrid = [x1Grid(:), x2Grid(:)];
  N = size(xGrid, 1);
  Scores = zeros(N, numel(classes));
31
32
  for j = 1:numel(classes)
33
       [~, score] = predict(SVMModels{j}, xGrid);
       Scores(:,j) = score(:,2); \% Second column contains positive-
35
          class scores
  end
36
37
  [\sim, \max Score] = \max(Scores, [], 2);
38
39
```

```
figure ('Position', [250 250 600 400]);
  h(1:3) = gscatter(xGrid(:,1),xGrid(:,2),maxScore,...
41
       [1 \ 0 \ 0; \ 0 \ 1 \ 0; \ 0 \ 0 \ 1]);
42
  hold on
  h(4:6) = gscatter(X(:,1),X(:,2),Y);
   title ('{\bf Iris Classification Regions for features 1 2}');
46
   xlabel('Petal Length (cm)');
47
  ylabel ('Petal Width (cm)');
48
49
  hold on
51
  colors = [0 \ 1 \ 1; \ 1 \ 0 \ 1; \ 0 \ 0 \ 0];
  sizes = [15,60,150];
  for i = 1:3
 SVM_SV = X(SVMModels{j}.IsSupportVector,:);
_{56} h(j+6) = scatter(SVM_SV(:,1),SVM_SV(:,2), 'CData', repmat(colors(j
      ,:), size (SVM_SV,1),1), 'SizeData', sizes (j)*ones (size (SVM_SV,1)
      ,1));
  hold on
  sum(SVMModels{j}.IsSupportVector)
58
  end
59
60
  legend(h, { 'setosa region', 'versicolor region', 'virginica region'
61
       'observed setosa', 'observed versicolor', 'observed virginica'
62
       'SVs1', 'SVs2', 'SVs3'},...
63
       'Location', 'NorthwestOutside')
65
  axis tight
66
  hold on
67
68
  % Other features
69
70
  load fisheriris
71
  X = meas(:, 3:4);
  Y = species;
73
  figure ('Position', [250 250 600 400]);
  gscatter(X(:,1),X(:,2),Y);
76
_{77} h = gca;
  lims = [h.XLim h.YLim]; % Extract the x and y axis limits
  title ('{\bf Scatter Diagram of Iris Measurements 3^{rd} and 4^{th
      }}');
```

```
xlabel('Petal Length (cm)');
   ylabel ('Petal Width (cm)');
   legend('Location', 'Northwest');
83
   SVMModels = cell(3,1);
   classes = unique(Y);
   rng(1); % For reproducibility
86
87
   for j = 1:numel(classes)
88
        indx = strcmp(Y, classes(j)); % Create binary classes for each
89
             classifier
        SVMModels{j} = fitcsvm(X, indx, 'ClassNames', [false true], '
90
           Standardize', true,...
             'KernelFunction', 'rbf', 'BoxConstraint',1);
91
        sum(SVMModels{ j }. IsSupportVector)
92
   end
93
   d = 0.02;
   [x1Grid, x2Grid] = meshgrid(min(X(:,1)):d:max(X(:,1)),...
        \min(X(:,2)):d:\max(X(:,2));
97
   xGrid = [x1Grid(:), x2Grid(:)];
98
   N = size(xGrid, 1);
   Scores = zeros(N, numel(classes));
101
   for j = 1:numel(classes)
102
        [~, score] = predict(SVMModels{j}, xGrid);
103
        Scores (:, j) = score (:,2); % Second column contains positive -
104
           class scores
   end
105
106
   [\sim, \max Score] = \max(Scores, [], 2);
107
108
   figure ('Position', [250 250 600 400]);
109
110
   h(1:3) = gscatter(xGrid(:,1),xGrid(:,2),maxScore,...
111
        [1 \ 0 \ 0; \ 0 \ 1 \ 0; \ 0 \ 0 \ 1]);
112
   hold on
113
   h(4:6) = gscatter(X(:,1),X(:,2),Y);
114
115
   title ('{\bf Iris Classification Regions for features 3 4}');
   xlabel('Petal Length (cm)');
117
   ylabel('Petal Width (cm)');
118
119
   colors = [0 \ 1 \ 1; \ 1 \ 0 \ 1; \ 0 \ 0 \ 0];
120
   sizes = [15,60,150];
```

```
for j = 1:3
SVM_SV = X(SVMModels{j}.IsSupportVector,:);
h(j+6) = scatter(SVM\_SV(:,1),SVM\_SV(:,2), CData', repmat(colors(j),SVM\_SV(:,2), CData')
       ,:), size (SVM_SV,1),1), 'SizeData', sizes (j)*ones (size (SVM_SV,1)
       ,1));
   hold on
125
   end
126
127
   legend(h,{ 'setosa region', 'versicolor region', 'virginica region'
128
        'observed setosa', 'observed versicolor', 'observed virginica'
129
        'SVs1', 'SVs2', 'SVs3'},...
130
        'Location', 'NorthwestOutside')
131
132
   axis tight
133
   % Save all
135
   chdir('...')
136
   addpath('export_fig')
137
   chdir ('HW3')
138
   figHandles = findall(0, 'Type', 'figure');
139
140
   for i = 1:numel(figHandles)
141
        export_fig(['Q3_',num2str(i)], '-png', figHandles(i), '-
142
           append')
   end
143
   close all
145
```

5.4 Q4

```
1
  rng default % For reproducibility
  grnpop = mvnrnd([1,0], eye(2),10);
  redpop = mvnrnd([0,1], eye(2),10);
  plot (grnpop (:,1), grnpop (:,2), 'go')
  hold on
  plot (redpop (:,1), redpop (:,2), 'ro')
  hold off
10
  redpts = zeros(100,2); grnpts = redpts;
11
   for i = 1:100
12
       grnpts(i,:) = mvnrnd(grnpop(randi(10),:), eye(2)*0.02);
13
       redpts(i,:) = mvnrnd(redpop(randi(10),:), eye(2)*0.02);
14
  end
15
16
  figure
17
  plot (grnpts (:,1), grnpts (:,2), 'go')
  hold on
  plot (redpts (:,1), redpts (:,2), 'ro')
  hold off
21
22
  cdata = [grnpts; redpts];
23
  grp = ones(200,1);
  \% Green label 1, red label -1
  grp(101:200) = -1;
26
27
  c = cvpartition(200, 'KFold', 10);
28
29
30
  opts = struct('Optimizer', 'bayesopt', 'ShowPlots', true, '
31
      CVPartition', c,...
       'AcquisitionFunctionName', 'expected-improvement-plus');
32
  symmod = fitcsym(cdata,grp,'KernelFunction','rbf',...
33
       'OptimizeHyperparameters', 'auto', '
34
          HyperparameterOptimizationOptions', opts)
35
  lossnew = kfoldLoss(fitcsvm(cdata,grp,'CVPartition',c,'
36
      KernelFunction', 'rbf',...
       'BoxConstraint', symmod. HyperparameterOptimizationResults.
37
          XAtMinObjective.BoxConstraint,...
       'KernelScale', symmod. HyperparameterOptimizationResults.
38
          XAtMinObjective. KernelScale))
```

```
39
  d = 0.02;
40
  [x1Grid, x2Grid] = meshgrid(min(cdata(:,1)):d:max(cdata(:,1)),...
41
       \min(\text{cdata}(:,2)):d:\max(\text{cdata}(:,2));
  xGrid = [x1Grid(:), x2Grid(:)];
  [~, scores] = predict(symmod, xGrid);
  figure;
  h = nan(3,1); \% Preallocation
  h(1:2) = gscatter(cdata(:,1), cdata(:,2), grp, 'rg', '+*');
  hold on
  h(3) = plot(cdata(symmod.IsSupportVector,1),...
       cdata(svmmod.IsSupportVector,2), 'ko');
50
  contour(x1Grid, x2Grid, reshape(scores(:,2), size(x1Grid)),[0 0], 'k'
      );
  legend(h,{'-1','+1','Support Vectors'},'Location','Southeast');
  axis equal
54 hold off
```