實驗4

實驗 4.1

實驗代碼重要部分解釋:

```
sampleSize = size( Data.samples, DOWN );
maxNorm = realmin;
for iObservation = 1:sampleSize
    observationNorm = norm( Data.samples(iObservation,:) );
    if observationNorm > maxNorm
        maxNorm = observationNorm;
    end
end
end
enclosingBallRadius = maxNorm;
enclosingBallRadiusSquared = enclosingBallRadius .^ 2;
```

●這部分是爲了求出離原點最遠的點,用來給出bias的修正值,以防梯度下降法無法收斂

```
maxNumSteps = 1000;
for iStep = 1:maxNumSteps
    isAnyObsMisclassified = false;
    for iObservation = 1:sampleSize;
        inputObservation = Data.samples( iObservation, : );
                       = Data.labels( iObservation ); % +1 or -1
       desiredLabel
       perceptronOutput = sum( Model.weights .* inputObservation, ACROSS ) + Model.bi
                        = desiredLabel * perceptronOutput;
       margin
       isCorrectLabel = margin > 0;
        % If the model misclassifies the observation, update the
        % weights and the bias.
       if ~isCorrectLabel
            isAnyObsMisclassified = true;
            weightCorrection = desiredLabel * inputObservation;
            Model.weights
                            = Model.weights + weightCorrection;
            biasCorrection = desiredLabel .* enclosingBallRadiusSquared;
                            = Model.bias + biasCorrection;
            Model.bias
            displayPerceptronState( Data, Model );
       end % if this observation misclassified.
    end % loop over observations
    if ~isAnyObsMisclassified
       disp( 'Done!' );
       break;
end % outer loop
```

- •以上代碼爲感知器算法的核心
- •其中perceptronOutput = sum(Model.weights .* inputObservation, ACROSS) + Model.bias;計算了g(x) = w'*x+w0
- ●其中desiredLabel * inputObservation;是g(x)中w矩陣的修正值
- •其中desiredLabel .* enclosingBallRadiusSquared;是g(x)中w0的修正值
- ●多次迭代直至最後沒有分錯的點爲止(或者到1000次)

實驗 4.2

LS.m代碼分析:

●此段爲設置題目要求的Gauss Distribution的mean和covariance

```
% Generate X1 and the required class labels
N1=200;
randn('seed',0)
X1=[mvnrnd(m(:,1),S,fix(N1/2)); mvnrnd(m(:,2),S,N1-fix(N1/2))]';
z1=[ones(1,fix(N1/2)) 2*ones(1,N1-fix(N1/2))];
% Generate X2 and the required class labels
N2=200;
randn('seed',100)
X2=[mvnrnd(m(:,1),S,fix(N2/2)); mvnrnd(m(:,2),S,N2-fix(N2/2))]';
z2=[ones(1,fix(N2/2)) 2*ones(1,N2-fix(N2/2))];
```

- ●這一段爲生成X1,X2
- •爲了數據的可再現,代碼中還使用了固定的隨機數種子

```
% Compute the Bayesian classification error based on X2 S_true(:,:,1)=S; S_true(:,:,2)=S; [z]=bayes_classifier(m,S_true,P,X2); err_Bayes_true=sum(z\sim=z2)/sum(N2)
```

●這一段使用了bayes算法進行分類,並計算了它的正確率

```
% 2. Augment the data vectors of X1
X1=[X1; ones(1,sum(N1))];
y1=2*z1-3;
% Augment the data vectors of X2
X2=[X2; ones(1,sum(N2))];
y2=2*z2-3;
```

● 這一段將 X1, X2 增廣化

```
% Compute the classification error of the LS classifier based on X2 [w]=SSErr(X1,y1,0); SSE\_out=2*(w'*X2>0)-1; err SSE=sum(SSE out.*y2<0)/sum(N2)
```

●這一段使用X1對SSE算法進行訓練,使用它對X2進行分類,並計算了正確率

SSErr.m代碼分析:

```
[1,N]=size(X);
w=inv(X*X'+C*eye(1))*(X*y');
```

●SSE本質上就只做了a = inv(Y'*Y)*Y'*b這個公式的事情,求得的解,即爲分類

實驗 4.3

代碼分析:

```
% This example deals with 2 classes
c1=[1 2;2 3;3 3;4 5;5 5] % the first class 5 observations
c2=[1 0;2 1;3 1;3 2;5 3;6 5] % the second class 6 observations
scatter(c1(:,1),c1(:,2),6,'r'),hold on;
scatter(c2(:,1),c2(:,2),6,'b');
% Number of observations of each class
n1=size(c1,1)
n2=size(c2,1)
%Mean of each class
mu1=mean(c1)
mu2=mean(c2)
```

●生成數據,計算各自的mean

```
% Center the data (data-mean)
d1=c1-repmat(mu1, size(c1,1),1)
d2=c2-repmat(mu2, size(c2,1),1)
% Calculate the within class variance (SW)
s1=d1'*d1
s2=d2'*d2
sw=s1+s2
invsw=inv(sw)
% in case of two classes only use v
v=invsw*(mu1-mu2)'
```

- ●d1的計算即,x(j)-m1的公式,d2同理
- ●s1就是原公式中的前半部分, sum((x(j)-m1)(x(j)-m1)'), s2也同理
- ●sw爲類內散度矩陣
- ●invsw爲sw的逆矩陣
- ●由w正比於inv(sw) * (m2-m1)得到代碼中的v

```
% project the data of the first and second class respectively y2=c2*v y1=c1*v
```

●完成對c1,c2的投影