

CSC 522 : Automated Learning and Data Analysis

Homework 5

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1 Question 1 [57 Points (25 + 32)] - Regression

In this problem we will investigate various methods for fitting a linear model for regression. Download the regprob.zip file from the course website.

1. Given a set of n real-valued responses y_i and a set of p predictors, we might try to model y_i as a linear combination of the p predictors. The form of this type of linear model is:

$$y_i = \beta_0 + \sum_{j=1}^p \beta_j \times x_{ij}$$

where y_i is the value of the response for the i^{th} observation, x_{ij} is the value for the j^{th} predictor for observation i , and β_0 is the intercept. To find good values for all of the β s, one approach is to minimize the sum of squared errors (SSE), shown below:

$$SSE = \sum_{i=1}^n (y_i - \beta_0 - \sum_{j=1}^p \beta_j \times x_{ij})^2$$

This approach is known as regression via ordinary least squares (OLS). Representing this model in matrix notation, the model can be written in an equivalent form as $Y = X\beta$. Now Y is an $n \times 1$ column vector containing the response variable, X is an $n \times (p+1)$ matrix that contains the p predictors for all n observations as well as a column of all 1s to represent the intercept, and β is a $p+1$ vector. With some matrix calculus it can be shown the value of β that minimizes the SSE is given by:

$$\hat{\beta}_{OLS} = (X^T X)^{-1} X^T Y$$

where T indicates a matrix transpose. This formula will give a $(p+1)$ vector containing the estimated regression coefficients.

Complete the following tasks:

- Load *train.csv*

```
> train <- read.csv(file.choose())
```
- Compute the OLS estimates using the data in train.csv. Do not use a package to do this, instead compute it directly from the formula given above. There are 10 predictors in the file, so your solution should contain 11 estimated regression coefficients (1 for each predictor plus 1 for the intercept, 11 numbers in total).

```

> library(caret)
Loading required package: cluster
Loading required package: foreach
foreach: simple, scalable parallel programming from Revolution Analytics
Use Revolution R for scalability, fault tolerance and more.
http://www.revolutionanalytics.com
Loading required package: lattice
Loading required package: plyr
Loading required package: reshape2
> x_data <- train[2:11]
> y_data <- train[1]
> X0 <- rep(1,100)
> x_data <- cbind(X0,x_data)
> xt <- t(x_data)
> xtx <- as.matrix(xt) %*% t(xt)
> xty <- as.matrix(xt) %*% as.matrix(y_data)
> beta <- solve(xtx) %*% xty
> beta

```

	Y
X0	2.0011897376
X1	1.4866088726
X2	-1.9616801211
X3	3.0082822263
X4	1.7619676828
X5	-0.4978060382
X6	-0.0319859478
X7	0.0120974698
X8	-0.0006889951
X9	-0.0060084271
X10	0.0112536257

Note: In the above case X0 is the coefficient of β for the intercept

- Estimate the mean squared error on an unseen test set by performing 5-fold crossvalidation. Recall the MSE for a set of y observations and \hat{y} predictions is dened as

$$MSE = \frac{1}{N} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

```

> folds2 <- createFolds(train[,"Y"], k=5, list=FALSE)
> mse <- rep(0,5)
> for(i in 1:5) {
+
+   fold.rows <- which(folds2 == i)
+   cv.train <- train[-fold.rows,]
+
+   cv.test <- train[fold.rows,]
+
+   x_train <- cv.train[2:11]
+   y_train <- cv.train[1]
+   X0 <- rep(1,80)
+   x_train <- cbind(X0,x_train)
+   xt <- t(x_train)
+   xtx <- as.matrix(xt) %*% t(xt)
+   xty <- as.matrix(xt) %*% as.matrix(y_train)
+   beta <- solve(xtx) %*% xty
+
+ }

```

```

+
+   x_test <- cv.test[2:11]
+   y_act <- cv.test[1]
+   xpred <- mapply("*",t(beta)[2:11],x_test)
+   xpred <- cbind(t(beta)[1],xpred)
+   y_pred <- rowSums(xpred)
+   ydiff <- cbind(y_act,y_pred)
+   ydiff$diff <- ydiff$Y - ydiff$y_pred
+   yd_sq <- ydiff$diff^2
+   mse[i] <- sum(yd_sq)/20
+ }
> mse
[1] 0.03354157 0.04317550 0.06382128 0.03696788 0.04751039
> mean(mse)
[1] 0.04500332

```

We get the Mean MSE to be 0.04500332.

2. The term ‘linear model’ indicates that a model is linear with respect to β . However, we can model higher order polynomial terms by explicitly computing them, including them in the X matrix, and then fit a linear model to this matrix. Perform the following tasks:

- Load *polynomial.train.csv*

```
> data <- read.csv(file.choose())
```
- Plot Y as a function of X

```
> plot(data[["X"]],data[["Y"]],xlab="X data",ylab="Y data")
```

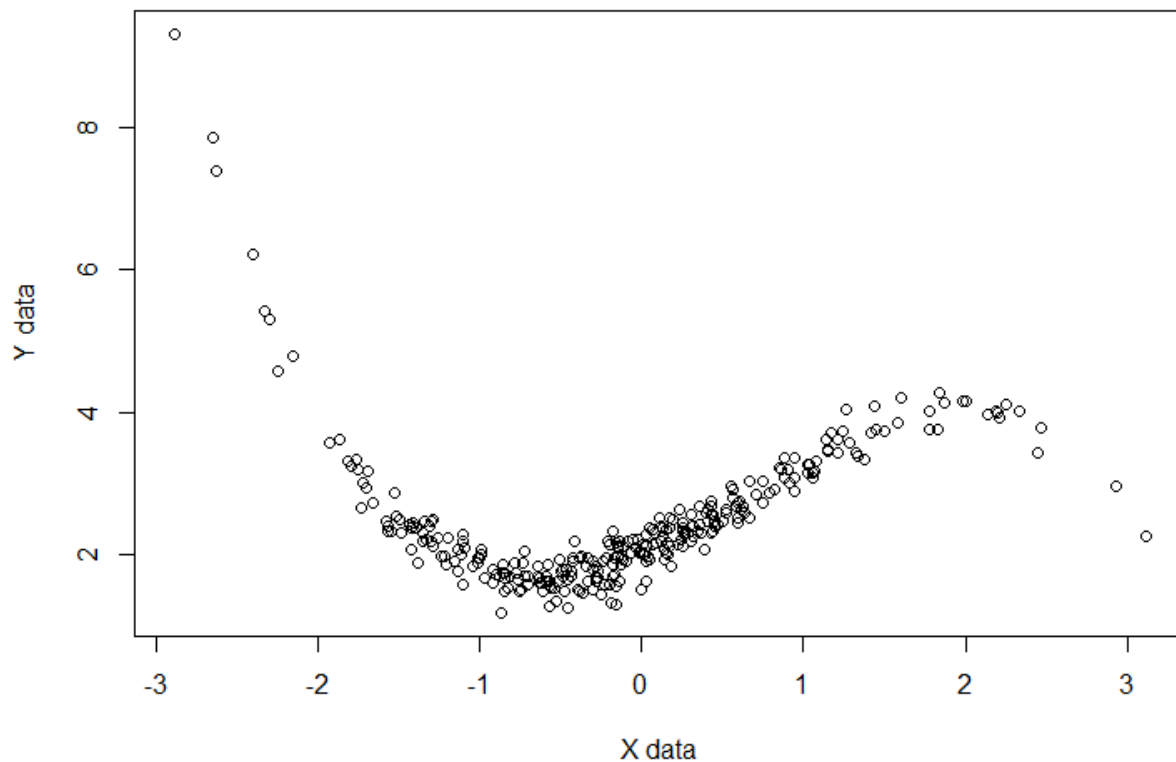


Figure 1: Plot with points

- Create a new X matrix that includes a column of 1s for an intercept, a column for the original X values, and a column of polynomials for each X^i for $i \in 2, 3, 4, 5$. This will create a matrix with dimensions 300×6 .

```
> x_data <- cbind(rep(1,300),data["X"],data["X"]^2,data["X"]^3,data["X"]^4,data["X"]^5)
> names(x_data) <- c("X0","X1","X2","X3","X4","X5")
```
- Find the OLS solution to this using $(X^T X)^{-1} X^T Y$.

```
> xt <- t(x_data)
> xtx <- as.matrix(xt) %*% t(xt)
> xty <- as.matrix(xt) %*% as.matrix(data["Y" ])
> beta <- solve(xtx) %*% xty
> beta
```

	Y
X0	2.0142724145
X1	0.9522479087
X2	0.5014464975
X3	-0.2219555459
X4	0.0001422326
X5	-0.0031247916

Note: Here X_0 is the intercept while X_1, X_2, X_3, X_4, X_5 denote powers of X etc.

- Overlay the fitted values (i.e. $X\hat{\beta}_{OLS}$) as a line on the plot of Y vs. X .

```
> xpred <- mapply("*", t(beta), x_data)
> y_pred <- rowSums(xpred)
> pred <- cbind(y_pred, x_data[2])
> pred_out <- arrange(pred, X1)
> plot(data[["X"]], data[["Y"]], xlab="X_data", ylab="Y_data")
> lines(pred_out$X1, pred_out$y_pred, col="red")
```

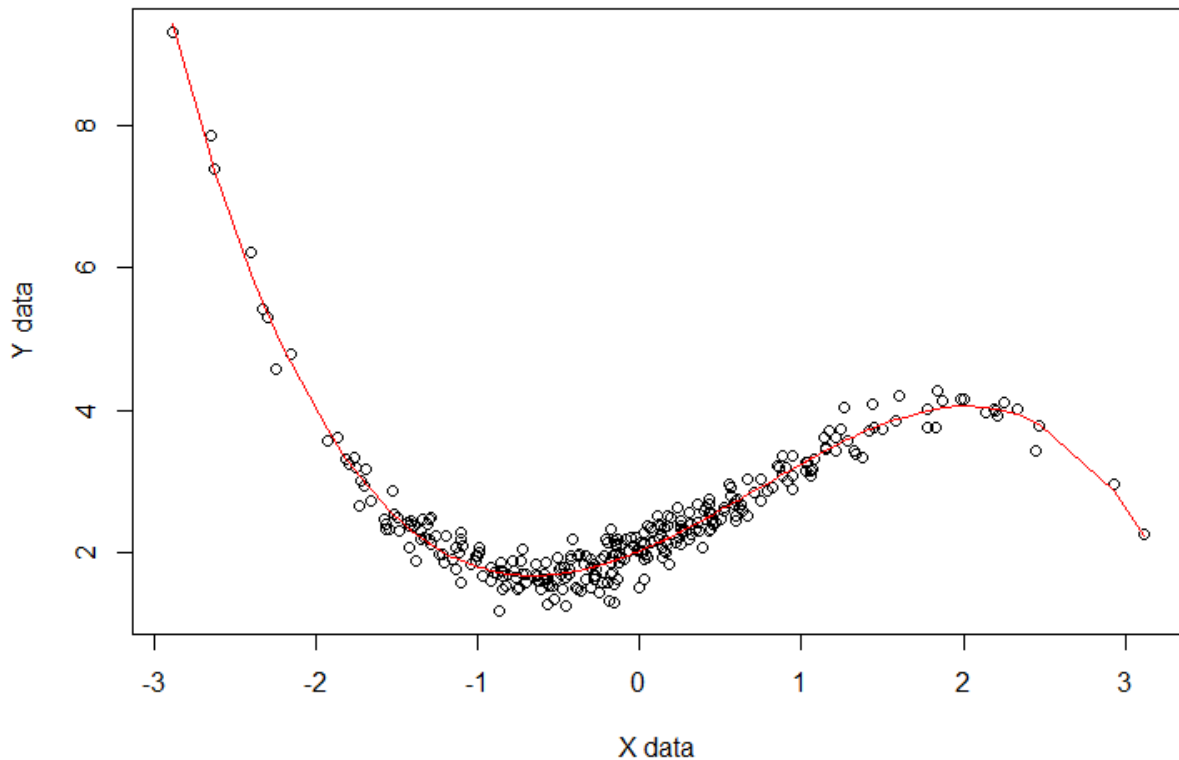


Figure 2: Plot with points and overlaid line

2 Question 2 [30 Points] - Artificial Neural Network

Consider the dataset Image Segmentation Data Set from the UCI repository <http://archive.ics.uci.edu/ml/datasets/Image+Segmentation>. The dataset consists of 19 precomputed attributes of 7 outdoor images, or 7 classes. You are provided with a training set and a test set.

Unlike the problems you are seen in the past, which have all been binary classification, this problem has seven classes. With Artificial Neural Network, there are at least 2 ways to construct a multi-class classifier:

1. Direct approach, where there are 7 output nodes to a neural network
2. One-vs-All classification, where you build one binary classifier per class for each of the 7 classes. When predicting the correct class for a given instance in the test data, we choose the classifier that has the highest confidence.

I did this using MultiClassClassifier and Multilayer Perceptron. By looking up on the internet I was able to find that setting certain values for momentum and learning rate was the best way to go. I wrote a piece of Javacode that loops through various values for hidden layers, training time, learning rate and momentum. It picks up the best value for each and tries to pick the best value for the next attribute. The code and its output are listed below. The accuracy on the test set using this approach is 92.4286%

Accuracy : 92.4286%

Your task is to build the best possible 7-output ANN and the best possible One-vs-All classier. You must submit the following:

- A description of how you built the classiers including the parameters you chose and the reason behind such a choice. The parameters include epoch, momentum, learning rate, number of hidden nodes and any other parameter you think might help.

I used the multiLayer Perceptron in Weka for the Direct Approach. When trying to find values for the number of hidden nodes, I did a bit of searching to see what would be the optimum number of nodes to choose and came across this article at ftp://ftp.sas.com/pub/neural/FAQ3.html#A_hu. After reading it I tried their suggestion of choosing the number of nodes as $(inputs + outputs) * \frac{2}{3}$. Thus the number of hidden nodes was chosen to be 17. Similarly I found values suggested for momentum, training time etc. I set up an array with all these values.

I wrote Java code to use WEKA to loop through and find the best values for hidden layers, training time, learning rate and momentum when using the training set and using Cross Validation. I tried both a chained input and non chained. (Here chained refers to using the best value of hidden layers to find the best value for training time and so on). Once I was able to come up with the lowest possible error using CV on the training set, I used the WEKA GUI to run the parameters on the test set to see the accuracy on the test set.

The reason for choice of the parameters was primarily to improve accuracy on CV and therefore hope to improve accuracy on test set. Some parameters like momentum etc have values which various websites mention as values that could be tried for various reasons.

For one vs all the same technique was used except that a multilayerPerceptron was used with a MultiClassClassifier. Here however I ran the loops using the Weka Java API. After which I decided to try what would happen with 2 hidden layers. So keeping the best values of all values I changed Hidden layers to "10,2". This however seemed to make the accuracy go down. I after tinkering a bit noticed that the momentum had to be changed as the model was probably settling on a local saddle point

Note that program sometimes has many same accuracies on CV for any of the attributes. In this case all of them are tested to see which one is best.

Direct Parameters

Chose Learning Rate as -i0.1
 Chose Hidden Layers as -i30
 Chose Momentum as -i0.15
 Chose training as -i1000
 Accuracy on Test Set : 92.19%

One Vs All Parameters Chose Learning Rate as -i0.35

Chose Hidden Layers as -i "10,2"
 Chose Momentum as -i0.2
 Chose training as -i1000
 Accuracy on Test Set : 92.19%

The output in 2 different cases is given below. Program in code section below.

CV Direct Non chained

run:

FOR Learning ->0.05

```

-----
Correctly Classified Instances      183      87.1429 %
Incorrectly Classified Instances    27      12.8571 %
Kappa statistic                    0.85
Mean absolute error                0.057
Root mean squared error            0.1517
Relative absolute error            23.2803 %
Root relative squared error        43.3575 %
Total Number of Instances          210

```

FOR Learning ->0.1

```

-----
Correctly Classified Instances      189      90      %
Incorrectly Classified Instances    21      10      %
Kappa statistic                    0.8833
Mean absolute error                0.0489
Root mean squared error            0.1479
Relative absolute error            19.9645 %
Root relative squared error        42.2619 %
Total Number of Instances          210

```

FOR Learning ->0.15

```

-----
Correctly Classified Instances      189      90      %
Incorrectly Classified Instances    21      10      %
Kappa statistic                    0.8833
Mean absolute error                0.0424
Root mean squared error            0.1499
Relative absolute error            17.2991 %
Root relative squared error        42.8333 %
Total Number of Instances          210

```

FOR Learning ->0.2

```

-----
Correctly Classified Instances      187      89.0476 %
Incorrectly Classified Instances    23      10.9524 %
Kappa statistic                    0.8722
Mean absolute error                0.043
Root mean squared error            0.1454
Relative absolute error            17.5665 %
Root relative squared error        41.5579 %
Total Number of Instances          210

```

FOR Learning ->0.25

```

-----
Correctly Classified Instances      185      88.0952 %
Incorrectly Classified Instances    25      11.9048 %
Kappa statistic                    0.8611
Mean absolute error                0.0419
Root mean squared error            0.1587
Relative absolute error            17.101  %
Root relative squared error        45.3524 %
Total Number of Instances          210

```

FOR Learning ->0.3

```

-----
Correctly Classified Instances      183      87.1429 %
Incorrectly Classified Instances    27      12.8571 %
Kappa statistic                     0.85
Mean absolute error                 0.044
Root mean squared error             0.1613
Relative absolute error             17.9846 %
Root relative squared error         46.104 %
Total Number of Instances          210

```

FOR Learning ->0.35

```

-----
Correctly Classified Instances      187      89.0476 %
Incorrectly Classified Instances    23      10.9524 %
Kappa statistic                     0.8722
Mean absolute error                 0.0432
Root mean squared error             0.162
Relative absolute error             17.6571 %
Root relative squared error         46.2961 %
Total Number of Instances          210

```

FOR Learning ->0.4

```

-----
Correctly Classified Instances      183      87.1429 %
Incorrectly Classified Instances    27      12.8571 %
Kappa statistic                     0.85
Mean absolute error                 0.0442
Root mean squared error             0.1681
Relative absolute error             18.0383 %
Root relative squared error         48.0418 %
Total Number of Instances          210

```

FOR Learning ->0.9

```

-----
Correctly Classified Instances      185      88.0952 %
Incorrectly Classified Instances    25      11.9048 %
Kappa statistic                     0.8611
Mean absolute error                 0.0423
Root mean squared error             0.1717
Relative absolute error             17.2658 %
Root relative squared error         49.0555 %
Total Number of Instances          210

```

Choosing Learning Rate as ->0.1

For Hidden ->5

```

-----
Correctly Classified Instances      183      87.1429 %
Incorrectly Classified Instances    27      12.8571 %
Kappa statistic                     0.85
Mean absolute error                 0.0523
Root mean squared error             0.1765
Relative absolute error             21.3532 %
Root relative squared error         50.4403 %
Total Number of Instances          210

```

For Hidden ->10


```

-----
Correctly Classified Instances      184      87.619  %
Incorrectly Classified Instances    26      12.381  %
Kappa statistic                    0.8556
Mean absolute error                0.0463
Root mean squared error            0.1626
Relative absolute error            18.924  %
Root relative squared error        46.464  %
Total Number of Instances          210

```

For Hidden ->12

```

-----
Correctly Classified Instances      184      87.619  %
Incorrectly Classified Instances    26      12.381  %
Kappa statistic                    0.8556
Mean absolute error                0.0436
Root mean squared error            0.1604
Relative absolute error            17.7989 %
Root relative squared error        45.8419 %
Total Number of Instances          210

```

For Hidden ->17

```

-----
Correctly Classified Instances      186      88.5714 %
Incorrectly Classified Instances    24      11.4286 %
Kappa statistic                    0.8667
Mean absolute error                0.0423
Root mean squared error            0.1597
Relative absolute error            17.2884 %
Root relative squared error        45.6387 %
Total Number of Instances          210

```

For Hidden ->20

```

-----
Correctly Classified Instances      187      89.0476 %
Incorrectly Classified Instances    23      10.9524 %
Kappa statistic                    0.8722
Mean absolute error                0.0425
Root mean squared error            0.1617
Relative absolute error            17.346  %
Root relative squared error        46.2216 %
Total Number of Instances          210

```

For Hidden ->30

```

-----
Correctly Classified Instances      191      90.9524 %
Incorrectly Classified Instances    19       9.0476 %
Kappa statistic                    0.8944
Mean absolute error                0.0378
Root mean squared error            0.151
Relative absolute error            15.4241 %
Root relative squared error        43.1599 %
Total Number of Instances          210

```

For Hidden ->a

```

-----

```

Correctly Classified Instances	184	87.619 %
Incorrectly Classified Instances	26	12.381 %
Kappa statistic	0.8556	
Mean absolute error	0.0452	
Root mean squared error	0.1674	
Relative absolute error	18.4435 %	
Root relative squared error	47.8406 %	
Total Number of Instances	210	

Choosing Hidden Layers as ->30
For Momentum ->0.05

Correctly Classified Instances	184	87.619 %
Incorrectly Classified Instances	26	12.381 %
Kappa statistic	0.8556	
Mean absolute error	0.0415	
Root mean squared error	0.1532	
Relative absolute error	16.9534 %	
Root relative squared error	43.7935 %	
Total Number of Instances	210	

For Momentum ->0.1

Correctly Classified Instances	186	88.5714 %
Incorrectly Classified Instances	24	11.4286 %
Kappa statistic	0.8667	
Mean absolute error	0.043	
Root mean squared error	0.1628	
Relative absolute error	17.5506 %	
Root relative squared error	46.5356 %	
Total Number of Instances	210	

For Momentum ->0.15

Correctly Classified Instances	190	90.4762 %
Incorrectly Classified Instances	20	9.5238 %
Kappa statistic	0.8889	
Mean absolute error	0.0388	
Root mean squared error	0.1495	
Relative absolute error	15.8378 %	
Root relative squared error	42.7351 %	
Total Number of Instances	210	

For Momentum ->0.2

Correctly Classified Instances	188	89.5238 %
Incorrectly Classified Instances	22	10.4762 %
Kappa statistic	0.8778	
Mean absolute error	0.0388	
Root mean squared error	0.1566	
Relative absolute error	15.8384 %	
Root relative squared error	44.7443 %	
Total Number of Instances	210	

For Momentum ->0.25

Correctly Classified Instances	189	90	%
Incorrectly Classified Instances	21	10	%
Kappa statistic	0.8833		
Mean absolute error	0.0392		
Root mean squared error	0.153		
Relative absolute error	15.9983 %		
Root relative squared error	43.7092 %		
Total Number of Instances	210		

For Momentum ->0.3

Correctly Classified Instances	184	87.619	%
Incorrectly Classified Instances	26	12.381	%
Kappa statistic	0.8556		
Mean absolute error	0.0439		
Root mean squared error	0.1639		
Relative absolute error	17.9291 %		
Root relative squared error	46.8501 %		
Total Number of Instances	210		

For Momentum ->0.9

Correctly Classified Instances	187	89.0476	%
Incorrectly Classified Instances	23	10.9524	%
Kappa statistic	0.8722		
Mean absolute error	0.037		
Root mean squared error	0.1631		
Relative absolute error	15.1114 %		
Root relative squared error	46.6227 %		
Total Number of Instances	210		

Choosing Momentum as ->0.15

For Training ->50

Correctly Classified Instances	187	89.0476	%
Incorrectly Classified Instances	23	10.9524	%
Kappa statistic	0.8722		
Mean absolute error	0.0705		
Root mean squared error	0.1601		
Relative absolute error	28.7859 %		
Root relative squared error	45.7629 %		
Total Number of Instances	210		

For Training ->100

Correctly Classified Instances	184	87.619	%
Incorrectly Classified Instances	26	12.381	%
Kappa statistic	0.8556		
Mean absolute error	0.0544		
Root mean squared error	0.1601		
Relative absolute error	22.2004 %		
Root relative squared error	45.7576 %		
Total Number of Instances	210		

For Training ->250

Correctly Classified Instances	185	88.0952 %
Incorrectly Classified Instances	25	11.9048 %
Kappa statistic	0.8611	
Mean absolute error	0.0478	
Root mean squared error	0.1637	
Relative absolute error	19.5089 %	
Root relative squared error	46.7937 %	
Total Number of Instances	210	

For Training ->500

Correctly Classified Instances	186	88.5714 %
Incorrectly Classified Instances	24	11.4286 %
Kappa statistic	0.8667	
Mean absolute error	0.0408	
Root mean squared error	0.1609	
Relative absolute error	16.6718 %	
Root relative squared error	45.9951 %	
Total Number of Instances	210	

For Training ->750

Correctly Classified Instances	188	89.5238 %
Incorrectly Classified Instances	22	10.4762 %
Kappa statistic	0.8778	
Mean absolute error	0.04	
Root mean squared error	0.1623	
Relative absolute error	16.328 %	
Root relative squared error	46.3705 %	
Total Number of Instances	210	

For Training ->1000

Correctly Classified Instances	191	90.9524 %
Incorrectly Classified Instances	19	9.0476 %
Kappa statistic	0.8944	
Mean absolute error	0.0367	
Root mean squared error	0.1517	
Relative absolute error	14.9992 %	
Root relative squared error	43.3591 %	
Total Number of Instances	210	

For Training ->5000

Correctly Classified Instances	186	88.5714 %
Incorrectly Classified Instances	24	11.4286 %
Kappa statistic	0.8667	
Mean absolute error	0.0384	
Root mean squared error	0.1707	
Relative absolute error	15.6778 %	
Root relative squared error	48.7884 %	
Total Number of Instances	210	

Final Choices of Values

Chose Learning Rate as ->0.1
Chose Hidden Layers as ->30
Chose Momentum as ->0.15
Chose training as ->1000
BUILD SUCCESSFUL (total time: 4 minutes 50 seconds)

CV One Vs ALL Non Chained

run:

FOR Learning ->0.05

```
-----
Correctly Classified Instances      190      90.4762 %
Incorrectly Classified Instances    20      9.5238 %
Kappa statistic                    0.8889
Mean absolute error                0.2342
Root mean squared error            0.3347
Relative absolute error            95.6208 %
Root relative squared error        95.6426 %
Total Number of Instances          210
```

FOR Learning ->0.1

```
-----
Correctly Classified Instances      185      88.0952 %
Incorrectly Classified Instances    25      11.9048 %
Kappa statistic                    0.8611
Mean absolute error                0.234
Root mean squared error            0.3344
Relative absolute error            95.5317 %
Root relative squared error        95.5569 %
Total Number of Instances          210
```

FOR Learning ->0.15

```
-----
Correctly Classified Instances      187      89.0476 %
Incorrectly Classified Instances    23      10.9524 %
Kappa statistic                    0.8722
Mean absolute error                0.2339
Root mean squared error            0.3344
Relative absolute error            95.5219 %
Root relative squared error        95.5503 %
Total Number of Instances          210
```

FOR Learning ->0.2

```
-----
Correctly Classified Instances      190      90.4762 %
Incorrectly Classified Instances    20      9.5238 %
Kappa statistic                    0.8889
Mean absolute error                0.2338
Root mean squared error            0.3341
Relative absolute error            95.4544 %
Root relative squared error        95.4813 %
Total Number of Instances          210
```

FOR Learning ->0.25

```
-----
Correctly Classified Instances      188      89.5238 %
```

Incorrectly Classified Instances	22	10.4762 %
Kappa statistic	0.8778	
Mean absolute error	0.2336	
Root mean squared error	0.3339	
Relative absolute error	95.3806 %	
Root relative squared error	95.4062 %	
Total Number of Instances	210	

FOR Learning ->0.3

Correctly Classified Instances	192	91.4286 %
Incorrectly Classified Instances	18	8.5714 %
Kappa statistic	0.9	
Mean absolute error	0.2337	
Root mean squared error	0.334	
Relative absolute error	95.4189 %	
Root relative squared error	95.4453 %	
Total Number of Instances	210	

FOR Learning ->0.35

Correctly Classified Instances	193	91.9048 %
Incorrectly Classified Instances	17	8.0952 %
Kappa statistic	0.9056	
Mean absolute error	0.2335	
Root mean squared error	0.3337	
Relative absolute error	95.3354 %	
Root relative squared error	95.3626 %	
Total Number of Instances	210	

FOR Learning ->0.4

Correctly Classified Instances	189	90 %
Incorrectly Classified Instances	21	10 %
Kappa statistic	0.8833	
Mean absolute error	0.2335	
Root mean squared error	0.3337	
Relative absolute error	95.3273 %	
Root relative squared error	95.3548 %	
Total Number of Instances	210	

FOR Learning ->0.9

Correctly Classified Instances	185	88.0952 %
Incorrectly Classified Instances	25	11.9048 %
Kappa statistic	0.8611	
Mean absolute error	0.2336	
Root mean squared error	0.3339	
Relative absolute error	95.3949 %	
Root relative squared error	95.4251 %	
Total Number of Instances	210	

Choosing Learning Rate as ->0.35
For Hidden ->5

Correctly Classified Instances	189	90 %
--------------------------------	-----	------

Incorrectly Classified Instances	21	10	%
Kappa statistic	0.8833		
Mean absolute error	0.2335		
Root mean squared error	0.3338		
Relative absolute error	95.3608 %		
Root relative squared error	95.3902 %		
Total Number of Instances	210		

For Hidden ->10

Correctly Classified Instances	188	89.5238 %
Incorrectly Classified Instances	22	10.4762 %
Kappa statistic	0.8778	
Mean absolute error	0.2336	
Root mean squared error	0.3339	
Relative absolute error	95.3942 %	
Root relative squared error	95.4206 %	
Total Number of Instances	210	

For Hidden ->12

Correctly Classified Instances	188	89.5238 %
Incorrectly Classified Instances	22	10.4762 %
Kappa statistic	0.8778	
Mean absolute error	0.2336	
Root mean squared error	0.3339	
Relative absolute error	95.3867 %	
Root relative squared error	95.417 %	
Total Number of Instances	210	

For Hidden ->17

Correctly Classified Instances	189	90	%
Incorrectly Classified Instances	21	10	%
Kappa statistic	0.8833		
Mean absolute error	0.2335		
Root mean squared error	0.3337		
Relative absolute error	95.353 %		
Root relative squared error	95.3754 %		
Total Number of Instances	210		

For Hidden ->20

Correctly Classified Instances	187	89.0476 %
Incorrectly Classified Instances	23	10.9524 %
Kappa statistic	0.8722	
Mean absolute error	0.2337	
Root mean squared error	0.334	
Relative absolute error	95.4289 %	
Root relative squared error	95.4534 %	
Total Number of Instances	210	

For Hidden ->30

Correctly Classified Instances	189	90	%
Incorrectly Classified Instances	21	10	%

Kappa statistic	0.8833
Mean absolute error	0.2337
Root mean squared error	0.3341
Relative absolute error	95.44 %
Root relative squared error	95.4679 %
Total Number of Instances	210

For Hidden ->a

Correctly Classified Instances	190	90.4762 %
Incorrectly Classified Instances	20	9.5238 %
Kappa statistic	0.8889	
Mean absolute error	0.2336	
Root mean squared error	0.3339	
Relative absolute error	95.3858 %	
Root relative squared error	95.4185 %	
Total Number of Instances	210	

Choosing Hidden Layers as ->a
For Momentum ->0.05

Correctly Classified Instances	187	89.0476 %
Incorrectly Classified Instances	23	10.9524 %
Kappa statistic	0.8722	
Mean absolute error	0.2337	
Root mean squared error	0.334	
Relative absolute error	95.4318 %	
Root relative squared error	95.4588 %	
Total Number of Instances	210	

For Momentum ->0.1

Correctly Classified Instances	190	90.4762 %
Incorrectly Classified Instances	20	9.5238 %
Kappa statistic	0.8889	
Mean absolute error	0.2336	
Root mean squared error	0.3338	
Relative absolute error	95.3795 %	
Root relative squared error	95.4052 %	
Total Number of Instances	210	

For Momentum ->0.15

Correctly Classified Instances	188	89.5238 %
Incorrectly Classified Instances	22	10.4762 %
Kappa statistic	0.8778	
Mean absolute error	0.2338	
Root mean squared error	0.3341	
Relative absolute error	95.4552 %	
Root relative squared error	95.4824 %	
Total Number of Instances	210	

For Momentum ->0.2

Correctly Classified Instances	186	88.5714 %
Incorrectly Classified Instances	24	11.4286 %

Kappa statistic	0.8667
Mean absolute error	0.2338
Root mean squared error	0.3342
Relative absolute error	95.4723 %
Root relative squared error	95.501 %
Total Number of Instances	210

For Momentum ->0.25

Correctly Classified Instances	188	89.5238 %
Incorrectly Classified Instances	22	10.4762 %
Kappa statistic	0.8778	
Mean absolute error	0.2338	
Root mean squared error	0.3342	
Relative absolute error	95.466 %	
Root relative squared error	95.4967 %	
Total Number of Instances	210	

For Momentum ->0.3

Correctly Classified Instances	191	90.9524 %
Incorrectly Classified Instances	19	9.0476 %
Kappa statistic	0.8944	
Mean absolute error	0.2337	
Root mean squared error	0.3341	
Relative absolute error	95.4363 %	
Root relative squared error	95.463 %	
Total Number of Instances	210	

For Momentum ->0.9

Correctly Classified Instances	183	87.1429 %
Incorrectly Classified Instances	27	12.8571 %
Kappa statistic	0.85	
Mean absolute error	0.2341	
Root mean squared error	0.3346	
Relative absolute error	95.5844 %	
Root relative squared error	95.6219 %	
Total Number of Instances	210	

Choosing Momentum as ->0.3

For Training ->50

Correctly Classified Instances	189	90 %
Incorrectly Classified Instances	21	10 %
Kappa statistic	0.8833	
Mean absolute error	0.2347	
Root mean squared error	0.3354	
Relative absolute error	95.8259 %	
Root relative squared error	95.8485 %	
Total Number of Instances	210	

For Training ->100

Correctly Classified Instances	187	89.0476 %
Incorrectly Classified Instances	23	10.9524 %

Kappa statistic	0.8722
Mean absolute error	0.2342
Root mean squared error	0.3348
Relative absolute error	95.6388 %
Root relative squared error	95.663 %
Total Number of Instances	210

For Training ->250

Correctly Classified Instances	190	90.4762 %
Incorrectly Classified Instances	20	9.5238 %
Kappa statistic	0.8889	
Mean absolute error	0.2338	
Root mean squared error	0.3341	
Relative absolute error	95.453 %	
Root relative squared error	95.4775 %	
Total Number of Instances	210	

For Training ->500

Correctly Classified Instances	190	90.4762 %
Incorrectly Classified Instances	20	9.5238 %
Kappa statistic	0.8889	
Mean absolute error	0.2337	
Root mean squared error	0.334	
Relative absolute error	95.4337 %	
Root relative squared error	95.4609 %	
Total Number of Instances	210	

For Training ->750

Correctly Classified Instances	191	90.9524 %
Incorrectly Classified Instances	19	9.0476 %
Kappa statistic	0.8944	
Mean absolute error	0.2336	
Root mean squared error	0.3339	
Relative absolute error	95.3783 %	
Root relative squared error	95.4063 %	
Total Number of Instances	210	

For Training ->1000

Correctly Classified Instances	193	91.9048 %
Incorrectly Classified Instances	17	8.0952 %
Kappa statistic	0.9056	
Mean absolute error	0.2335	
Root mean squared error	0.3337	
Relative absolute error	95.3391 %	
Root relative squared error	95.365 %	
Total Number of Instances	210	

For Training ->5000

Correctly Classified Instances	187	89.0476 %
Incorrectly Classified Instances	23	10.9524 %
Kappa statistic	0.8722	

Mean absolute error	0.2337
Root mean squared error	0.3341
Relative absolute error	95.4463 %
Root relative squared error	95.4827 %
Total Number of Instances	210

Final Choices of Values

```
-----
Chose Learning Rate as ->0.35
Chose Hidden Layers as ->a
Chose training as ->1000
Chose Momentum as ->0.3
BUILD SUCCESSFUL (total time: 19 minutes 40 seconds)
```

- A descriptive comparison in performance between the 7-output ANN and the One-vs-All ANN - compare the 2 models based on their predictive performance on the given test data, training time, and your judgment of which approach is better for this problem.

Considerign the fact that I was able to achieve the same accruacy on the training set with both models, commenting on the predictive performance is harder. However it can be noted that with a varied se of attributes the overall accuracy by the One Vs All seems to be better.

In terms of training time it easily noted by the run time taken in Java that the th time taken by the One Vs All method is almost 5 times that of the direct approach.

I think that if it is ok to slightly compromise a very small amount on accuracy the direct approach should be used because it is MUCH faster than the other.

- Any code you have written (using Matlab, R, Wekas Java API)

```
/*
 * To change this template, choose Tools | Templates
 * and open the template in the editor.
 */
package wekacode;
import java.util.Random;
import weka.classifiers.Classifier;
import weka.classifiers.Evaluation;
import weka.classifiers.functions.MultilayerPerceptron;
import weka.core.Instances;
import weka.core.converters.ConverterUtils.DataSource;
import weka.classifiers.meta.MultiClassClassifier;
import weka.core.Attribute;
import weka.core.SelectedTag;
import weka.core.Tag;
/**
 *
 * @author Roopak
 */
public class WekaCode {

    /**
     * @param args the command line arguments
     */
    int direct=0;
    int vary_learning=0;
    double vlearning[] = {0.05,0.1,0.15,0.2,0.25,0.3,0.35,0.4,0.9};
```

```

int vary_hidden_layers=0;
String vhidden [] = {"5","10","12","17","20","30","a"};

int vary_momentum=0;
double vmomentum [] = {0.05,0.1,0.15,0.2,0.25,0.3,0.9};

int vary_training_time=0;
int vtraining [] = {50,100,250,500,750,1000,5000};

Instances train,test;
DataSource source,source2;
public WekaCode() throws Exception
{
    source = new DataSource("D:\\Courses\\data-mining-\\
        + "CSC522\\homework\\hw5\\segmentation.arff");
    train = source.getDataSet();
    //Attribute a = new Attribute("CLASS");
    train.setClassIndex(0);

    source2 = new DataSource("D:\\Courses\\data-mining-\\
        + "CSC522\\homework\\hw5\\segmentation.test.arff");
    test = source2.getDataSet();
    test.setClassIndex(0);
}
public void q2_p1() throws Exception
{

}

public void q2_p2() throws Exception
{

    MultilayerPerceptron mlp = new MultilayerPerceptron();
    mlp.setValidationSetSize(0);
    mlp.setValidationThreshold(20);
    mlp.setNominalToBinaryFilter(true);
    mlp.setNormalizeAttributes(true);
    mlp.setNormalizeNumericClass(true);
    mlp.setReset(true);

    mlp.setDebug(false);
    mlp.setGUI(false);
    mlp.setDecay(false);
    mlp.setAutoBuild(true);

    double temp;
    double maxlrn=0;
    double bestlrn=0.3;
    if(vary_learning==1)
    {
        for(int counter=0; counter < vlearning.length;counter++)
        {
            mlp.setMomentum(0.2);
            mlp.setTrainingTime(500);
            mlp.setHiddenLayers("a");

```

```

        mlp.setLearningRate(vlearning[counter]);
        temp=train_and_predict(mlp, "FOR_Learning_>"
                                + vlearning[counter] + "\n-----");
        if(temp>maxlrn)
        {
            maxlrn = temp;
            bestlrn = vlearning[counter];
        }
    }

System.out.println("Choosing_Learning_Rate_as_>" + bestlrn);
double maxhidden=0;
String besthidden="a";
if(vary_hidden_layers==1)
{
    for(int counter=0; counter < vhidden.length;counter++)
    {
        mlp.setMomentum(0.2);
        mlp.setTrainingTime(500);
        mlp.setLearningRate(0.3);

        mlp.setHiddenLayers(vhidden[counter]);
        temp = train_and_predict(mlp, "For_Hidden_>"
                                + vhidden[counter] + "\n-----");
        if(temp>maxhidden)
        {
            maxhidden = temp;
            besthidden = vhidden[counter];
        }
    }
}

System.out.println("Choosing_Hidden_Layers_as_>" + besthidden);
double maxmom=0;
double bestmom=0.2;
if(vary_momentum==1)
{
    for(int counter=0; counter < vmomentum.length;counter++)
    {
        mlp.setTrainingTime(500);
        mlp.setLearningRate(0.3);
        mlp.setHiddenLayers("a");

        mlp.setMomentum(vmomentum[counter]);
        temp = train_and_predict(mlp, "For_Momentum_>"
                                + vmomentum[counter] + "\n-----");
        if(temp>maxmom)
        {
            maxmom=temp;
            bestmom=vmomentum[counter];
        }
    }
}

```

```

System.out.println("Choosing Momentum as ->" + bestmom);
double maxtt=0;
int besttt=500;
if(vary_training_time==1)
{
    for(int counter=0; counter < vtraining.length; counter++)
    {
        mlp.setLearningRate(0.3);
        mlp.setHiddenLayers("a");
        mlp.setMomentum(0.2);

        mlp.setTrainingTime(vtraining[counter]);
        temp = train_and_predict(mlp, "For Training ->"
                                + vtraining[counter] + "\n-----");
        if(temp>maxtt)
        {
            maxtt=temp;
            besttt=vtraining[counter];
        }
    }
}

System.out.println("Final Choices of Values\n");
System.out.println("-----");
System.out.println("Chose Learning Rate as ->" + bestlrn);
System.out.println("Chose Hidden Layers as ->" + besthidden);
System.out.println("Chose Momentum as ->" + bestmom);
System.out.println("Chose training as ->" + besttt);

}
public double train_and_predict(MultilayerPerceptron mlp, String title)
    throws Exception
{
    if(direct==1)
    {
        return train_and_predict_single(mlp, title);
    }
    MultiClassClassifier c1;
    c1 = new MultiClassClassifier();
    c1.setClassifier(mlp);

    Random rand = new Random();
    Instances randData = new Instances(train);
    randData.randomize(rand);
    if (randData.classAttribute().isNominal())
        randData.stratify(10);

    Evaluation eval = new Evaluation(randData);
    for (int n = 0; n < 10; n++)
    {
        Instances mytrain = randData.trainCV(10, n);
        Instances mytest = randData.testCV(10, n);

        MultiClassClassifier clsCopy = new MultiClassClassifier();
        clsCopy.setClassifier(mlp);

```

```

        clsCopy.buildClassifier(mytrain);
        eval.evaluateModel(clsCopy, mytest);
    }

    //c1.buildClassifier(train);
    //Evaluation eval = new Evaluation(train);
    //eval.evaluateModel(c1, test) ;

    //eval.
    //eval.
    System.out.println(eval.toSummaryString(title, false));
    return eval.pctCorrect();
}

public double train_and_predict_single(MultilayerPerceptron mlp, String title)
    throws Exception
{
    Classifier c1;
    c1 = mlp;

    Random rand = new Random();
    Instances randData = new Instances(train);
    randData.randomize(rand);
    if (randData.classAttribute().isNominal())
        randData.stratify(10);

    Evaluation eval = new Evaluation(randData);
    for (int n = 0; n < 10; n++)
    {
        Instances mytrain = randData.trainCV(10, n);
        Instances mytest = randData.testCV(10, n);

        Classifier clsCopy = Classifier.makeCopy(c1);
        clsCopy.buildClassifier(mytrain);
        eval.evaluateModel(clsCopy, mytest);
    }

    //c1.setClassifier(mlp);
    //Tag t[] = new Tag[1];
    //SelectedTag tg = new SelectedTag("1-against-all", new Tag[1]);
    //c1.setMethod(tg);

    //c1.buildClassifier(train);
    //Evaluation eval = new Evaluation(train);
    //eval.evaluateModel(c1, test) ;

    //eval.
    //eval.
    System.out.println(eval.toSummaryString(title, false));
    return eval.pctCorrect();
}

public static void main(String[] args) {
    // TODO code application logic here

    try
    {

```

```

        WekaCode a = new WekaCode();
        a.vary_hidden_layers=1;
        a.vary_learning=1;
        a.vary_momentum=1;
        a.vary_training_time=1;
        a.direct=1;
        a.q2_p2();
    }
    catch(Exception e)
    {
        e.printStackTrace();
    }
}
}

```

3 Question 3 [10 Points (6 + 4)] - Multi-Class Classification

An electronic nose is a device that can “sniff” gases at various locations. One way to construct the device is using an array of N semiconductors, each of which will have a different voltage response when in contact with certain gases. Each semiconductor responds to at least one gas (i.e., more than one gas). Let us assume that there are 3 gases A, B and C. Some locations can have either one of the gases or a mixture of gases. Thus, possible class labels are: A, B, C, AB, AC, BC, ABC.

1. If you are allowed to use only an Artificial Neural Network, which of the following configurations are possible? State why or why not.

- 1 network with 7 output nodes.

This would be the simple choice. The output nodes would be A, B, C, AB, AC, BC, ABC . Thus this configuration is possible.

- One-vs-All

This is again possible if we are trying to find presence of one vs others etc. So it could be A present vs A not present or maybe AC present vs AC not present

- 1 network with only 3 output nodes

Let us say we construct the neural network in such a way that we output the presence of any gas which the neural network says is present with a confidence of 70% or more. Then we can use this neural network to give the output of gases in the various possibilities. Thus if say the network gives us that A is present with a confidence of 89% and say C is present with 71%. Then we can say that the gases present in the region are AC. Thus with three output nodes we can detect the presence of any of the possible combinations. Thus we can say that this network would be possible with 3 output nodes.

2. Irrespective of your answer for the previous part, for each of the above configurations, comment on the complexity of the network. Comment on how you would choose the number of hidden nodes, training time and number of epochs for each of the networks.

The complexity of the network will vary. With a simple guess it is easy to say that the 1 network with 7 outputs could probably be the simplest while One vs All might be more complex as this would involve the construction of 7 networks and combining them to get the required output.

Epoch represents when training will stop. Usually we can say that if high enough this shouldn't be a problem. But in most cases having too high a value will just increase training time and not really have a positive benefit.

hidden nodes - The article at ftp://ftp.sas.com/pub/neural/FAQ3.html#A_hu says we should try and have $(inputs + outputs) * \frac{2}{3}$ as the number of hidden nodes. Not however that many sources cite that it is best to not have more than 2 levels.

4 Question 4 [8 Points] - Hyperplanes for Classification

Consider N points in a D -dimensional space, some of which are positive and some of which are negative. We all know that for $N = 2$ points in $d = 1$ dimensions, a line can separate positive and negative examples. Based on this, state whether a similar linear separator is possible for each of the following cases. If a linear separator is not possible, give an example and state conditions that must be satisfied for the existence of a linear classifier. The correct answer to this question considers all possible arrangements of the N points in the D -dimensional space. If a linear separator is not possible for even one such arrangement, your answer should state that case as an example for failure and state the conditions when a linear separator is possible.

Note that a trivial case if I chose all points to lie at the same location or to lie on a line it is not possible to separate them.

- $N=3, D=2$

Usually as long as the points don't lie on the same line it should be possible to separate them in this case.

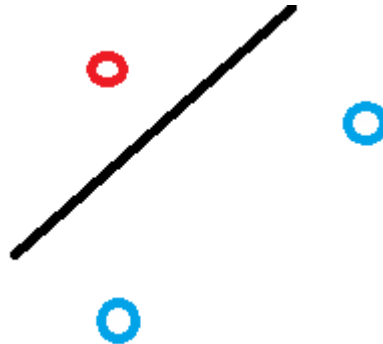


Figure 3: $N=3, D=2$

- $N=4, D=2$

Simple put any variation of XOR where the points are kept in roughly the same configuration but move away or closer but the overall is a skew of XOR CANNOT be separated by a line. However if 2 or more points come together on one side and the other point(s) remain on the other side they can be separated.

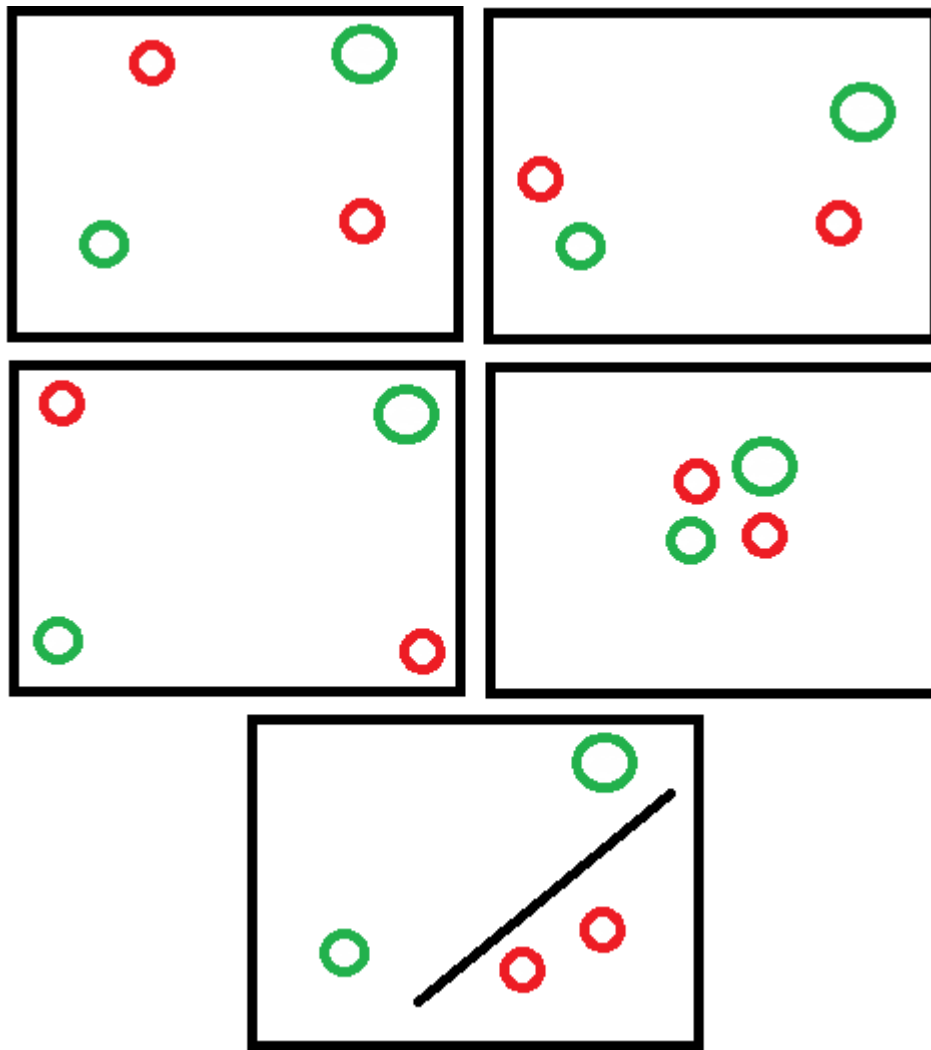


Figure 4: $N=3$, $D=2$

- $N=4$, $D=3$

As long all points dont lie on the same plane it should be able to separate them in this case.

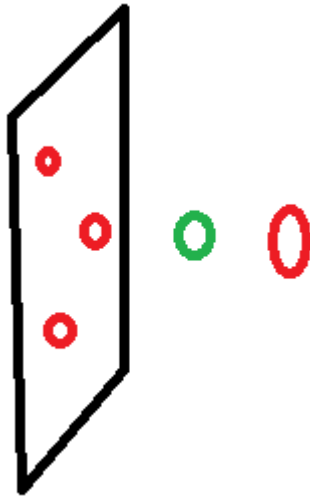


Figure 5: $N=3$, $D=2$

- $N=5$, $D=3$

3 points define a plane. if there are 4 positive and 1 negative. 3 of the positive form a plane. if the negative is between the plane and the other positive its not possible to separate them. If there are 3 of one type and 2 of the other. The only case where it is not possible to separate them would be when the 3 of one type form a plane and the other type are on either side of the plane.

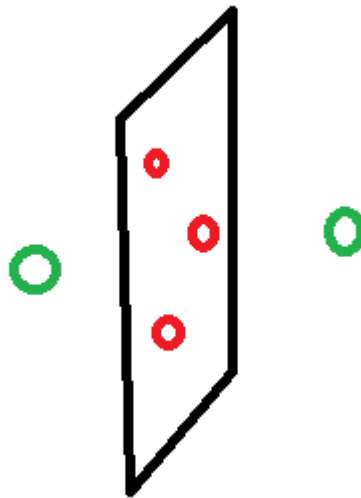


Figure 6: $N=3$, $D=2$