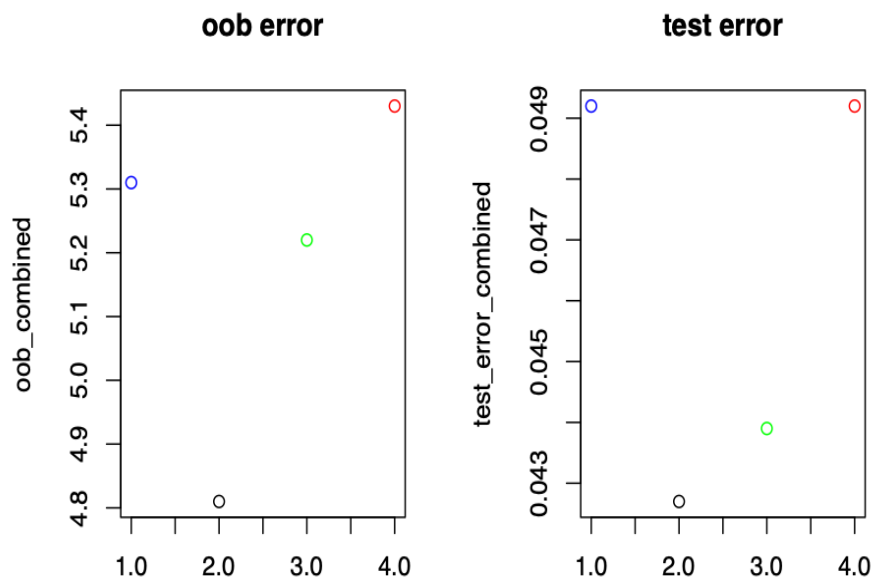


write up for hw5

Hyungkyu Lim

1)

There are plots for oob error and test error in terms of the number of randomly selected inputs for each tree. Total entries that I randomly chosen are 4; entry 3, entry 5, entry 10, entry 20. The maximum of the oob error is 5.43(entry 20) and the minimum of the oob error is 4.81(entry 5). The maximum of the test error is 0.0492(entry 3 and entry 20) and the minimum of the test error is 0.0427(entry 5). Based on two plots, entry 5 has minimum values for both plots.



1:entry 3 , 2:entry 5, 3:entry 10, 4:entry 20 1:entry 3 , 2:entry 5, 3:entry 10, 4:entry 20

2) Based on the test error of neural network method, I think that newural network method is better than the additive model.

```
## [1] 0.0652
```

3)

I selected the 0.01, 1, 5 and 10 for cost. With this, I generated two plots for train error and test error in terms of linear kernel. As the cost incrases, train error decreases however, there is no specific pattren of test error. Optimal cost of linear kernel is 0.01. In radial kernel, there is no specific pattern for two plots. However interesting thing is that most errors for both are about 0. With this, optimal cost of radial kernel is same with linear kernel. For polynomial plots, the train error is about 0.19 and the test error is about 0.11. Three kinds of kernels all have a good performance but I guess radial kernel is just a little bit better than linear and polynomial kernel.

```
##
## Call:
## svm(formula = Purchase ~ ., data = oj.train, kernel = "linear",
##      cost = 0.01)
```

```

##
##
## Parameters:
##   SVM-Type: C-classification
##   SVM-Kernel: linear
##   cost: 0.01
##   gamma: 0.05555555556
##
## Number of Support Vectors: 533
##
## ( 266 267 )
##
##
## Number of Classes: 2
##
## Levels:
## CH MM

##   train.pred
##   CH MM
## CH 539 75
## MM 98 288

## [1] 0.173

##   test.pred
##   CH MM
## CH 36 3
## MM 2 29

## [1] 0.071

##
## Call:
## svm(formula = Purchase ~ ., data = oj.train, kernel = "linear",
##   cost = 1)
##
##
## Parameters:
##   SVM-Type: C-classification
##   SVM-Kernel: linear
##   cost: 1
##   gamma: 0.05555555556
##
## Number of Support Vectors: 425
##
## ( 212 213 )
##
##
## Number of Classes: 2
##
## Levels:
## CH MM

##   train.pred_1
##   CH MM
## CH 537 77

```

```

## MM 93 293

## [1] 0.17

## test.pred_1
## CH MM
## CH 35 4
## MM 2 29

## [1] 0.08571428571

## [1] 0.09

##
## Call:
## svm(formula = Purchase ~ ., data = oj.train, kernel = "linear",
## cost = 5)
##
##
## Parameters:
## SVM-Type: C-classification
## SVM-Kernel: linear
## cost: 5
## gamma: 0.05555555556
##
## Number of Support Vectors: 423
##
## ( 211 212 )
##
##
## Number of Classes: 2
##
## Levels:
## CH MM

## train.pred_2
## CH MM
## CH 541 73
## MM 94 292

## [1] 0.167

## test.pred_2
## CH MM
## CH 37 2
## MM 3 28

## [1] 0.07142857143

## [1] 0.071

##
## Call:
## svm(formula = Purchase ~ ., data = oj.train, kernel = "linear",
## cost = 10)
##
##
## Parameters:
## SVM-Type: C-classification

```

```

## SVM-Kernel: linear
## cost: 10
## gamma: 0.05555555556
##
## Number of Support Vectors: 423
##
## ( 211 212 )
##
##
## Number of Classes: 2
##
## Levels:
## CH MM

## train.pred_3
## CH MM
## CH 538 76
## MM 90 296

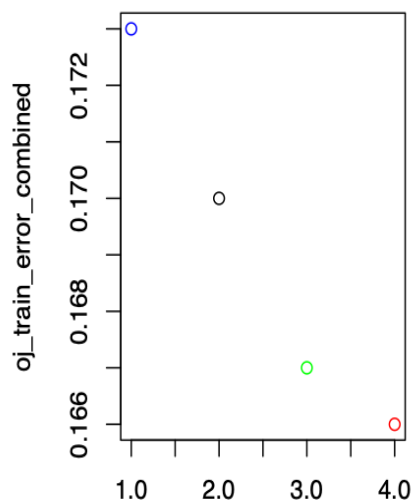
## [1] 0.166

## test.pred_3
## CH MM
## CH 37 2
## MM 4 27

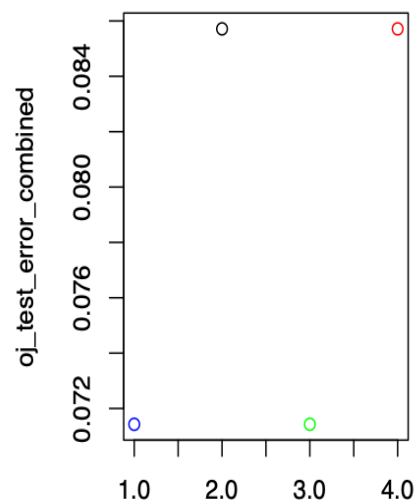
## [1] 0.08571428571
## [1] 0.086

```

oj_train_error



oj_test_error



1:cost 0.01 , 2:cost 1, 3:cost 5, 4:cost 10 1:cost 0.01 , 2:cost 1, 3:cost 5, 4:cost 10

```

##
## Parameter tuning of 'svm':

```

```

##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##   cost
##     10
##
## - best performance: 0.171
##
## - Detailed performance results:
##           cost error   dispersion
## 1  0.01000000000 0.178 0.05050852513
## 2  0.01778279410 0.178 0.05493430420
## 3  0.03162277660 0.173 0.05056349144
## 4  0.05623413252 0.176 0.05037636130
## 5  0.10000000000 0.177 0.04854551129
## 6  0.17782794100 0.173 0.05121848625
## 7  0.31622776602 0.174 0.05232377832
## 8  0.56234132519 0.173 0.05229191567
## 9  1.00000000000 0.174 0.04812021982
## 10 1.77827941004 0.174 0.05015531433
## 11 3.16227766017 0.173 0.04967673276
## 12 5.62341325190 0.172 0.04802776974
## 13 10.00000000000 0.171 0.05087020521
##
## Call:
## svm(formula = Purchase ~ ., data = oj.train, kernel = "radial")
##
##
## Parameters:
##   SVM-Type: C-classification
## SVM-Kernel: radial
##       cost: 1
##       gamma: 0.05555555556
##
## Number of Support Vectors: 465
##
## ( 231 234 )
##
##
## Number of Classes: 2
##
## Levels:
## CH MM
##
##   train.pred
##   CH  MM
## CH 539 75
## MM  98 288
##
## [1] 0.158
##
##   test.pred_radial
##   CH  MM
## CH 36  3

```

```

## MM 4 27

## [1] 0.1

##
## Call:
## svm(formula = Purchase ~ ., data = oj.train, kernel = "radial",
##      cost = 1)
##
##
## Parameters:
##   SVM-Type: C-classification
## SVM-Kernel: radial
##      cost: 1
##   gamma: 0.05555555556
##
## Number of Support Vectors: 465
##
## ( 231 234 )
##
##
## Number of Classes: 2
##
## Levels:
## CH MM

##      train.pred_1_radial
##      CH MM
## CH 558 56
## MM 102 284

## [1] 0.158

##      test.pred_1_radial
##      CH MM
## CH 36 3
## MM 4 27

## [1] 0.1

##
## Call:
## svm(formula = Purchase ~ ., data = oj.train, kernel = "radial",
##      cost = 5)
##
##
## Parameters:
##   SVM-Type: C-classification
## SVM-Kernel: radial
##      cost: 5
##   gamma: 0.05555555556
##
## Number of Support Vectors: 427
##
## ( 208 219 )
##
##

```

```

## Number of Classes: 2
##
## Levels:
## CH MM

##      train.pred_2_radial
##      CH MM
## CH 563 51
## MM 102 284

## [1] 0.153

##      test.pred_2_radial
##      CH MM
## CH 36 3
## MM 4 27

## [1] 0.1

##
## Call:
## svm(formula = Purchase ~ ., data = oj.train, kernel = "radial",
##      cost = 10)
##
##
## Parameters:
## SVM-Type: C-classification
## SVM-Kernel: radial
##      cost: 10
##      gamma: 0.055555555556
##
## Number of Support Vectors: 415
##
## ( 203 212 )
##
##
## Number of Classes: 2
##
## Levels:
## CH MM

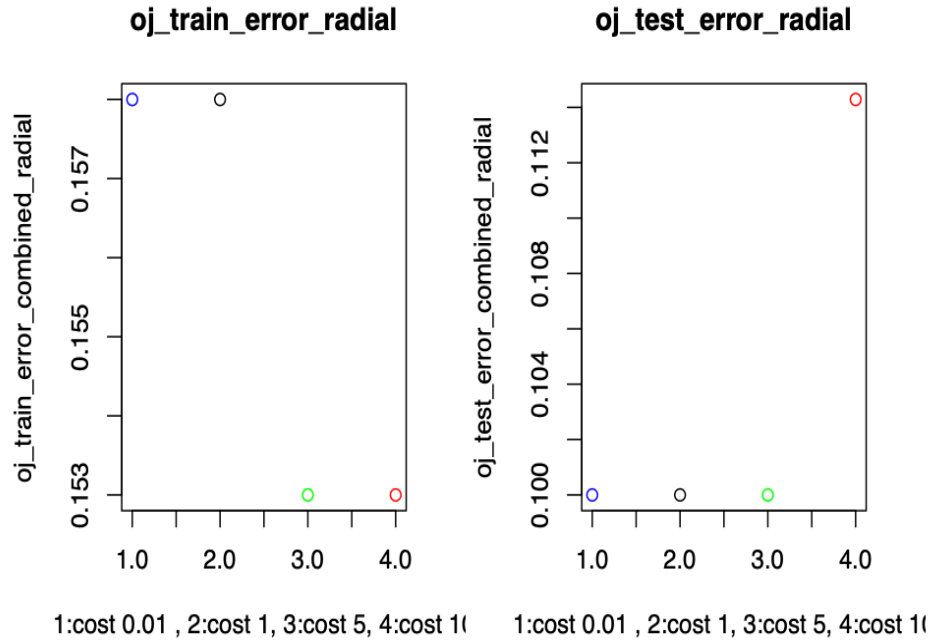
##      train.pred_3_radial
##      CH MM
## CH 561 53
## MM 100 286

## [1] 0.153

##      test.pred_3_radial
##      CH MM
## CH 35 4
## MM 4 27

## [1] 0.1142857143
## [1] 0.114

```



```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##      cost
## 0.316227766
##
## - best performance: 0.179
##
## - Detailed performance results:
##      cost error dispersion
## 1  0.01000000000 0.386 0.03238655414
## 2  0.01778279410 0.386 0.03238655414
## 3  0.03162277660 0.273 0.03917198545
## 4  0.05623413252 0.198 0.04589843861
## 5  0.10000000000 0.189 0.04254409477
## 6  0.17782794100 0.186 0.03777124126
## 7  0.31622776602 0.179 0.04254409477
## 8  0.56234132519 0.179 0.04383048153
## 9  1.00000000000 0.188 0.03392802840
## 10 1.77827941004 0.180 0.03887301263
## 11 3.16227766017 0.183 0.03772709018
## 12 5.62341325190 0.182 0.04049691346
## 13 10.00000000000 0.188 0.03823901440
##
## Call:
## svm(formula = Purchase ~ ., data = oj.train, kernel = "polynomial",
```



```

##      degree = 2)
##
##
## Parameters:
##   SVM-Type: C-classification
##   SVM-Kernel: polynomial
##       cost: 1
##       degree: 2
##       gamma: 0.05555555556
##       coef.0: 0
##
## Number of Support Vectors: 546
##
## ( 268 278 )
##
##
## Number of Classes: 2
##
## Levels:
## CH MM

##      train.pred_poly
##      CH MM
## CH 569 45
## MM 140 246

## [1] 0.185

##      test.pred_poly
##      CH MM
## CH 37 2
## MM 6 25

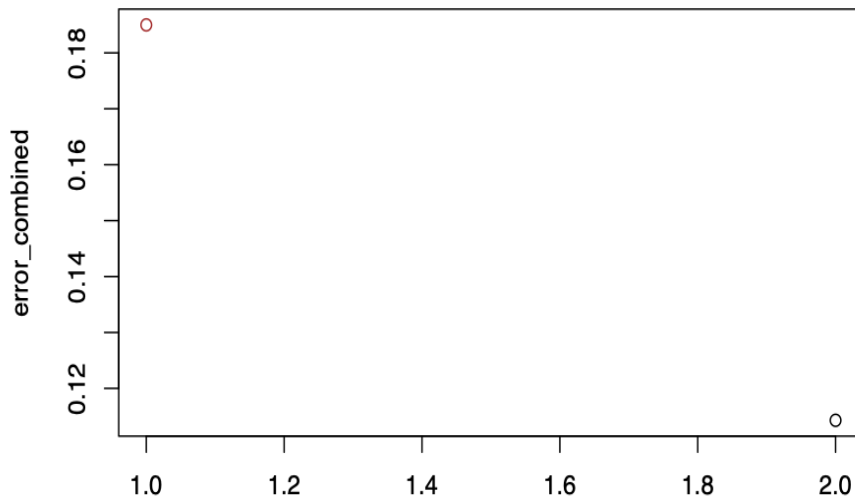
## [1] 0.114

##
## Call:
## svm(formula = Purchase ~ ., data = oj.train, kernel = "polynomial",
##      degree = 2)
##
##
## Parameters:
##   SVM-Type: C-classification
##   SVM-Kernel: polynomial
##       cost: 1
##       degree: 2
##       gamma: 0.05555555556
##       coef.0: 0
##
## Number of Support Vectors: 546
##
## ( 268 278 )
##
##
## Number of Classes: 2
##

```

```
## Levels:
## CH MM
```

train & test error of polynomial (degree =2)

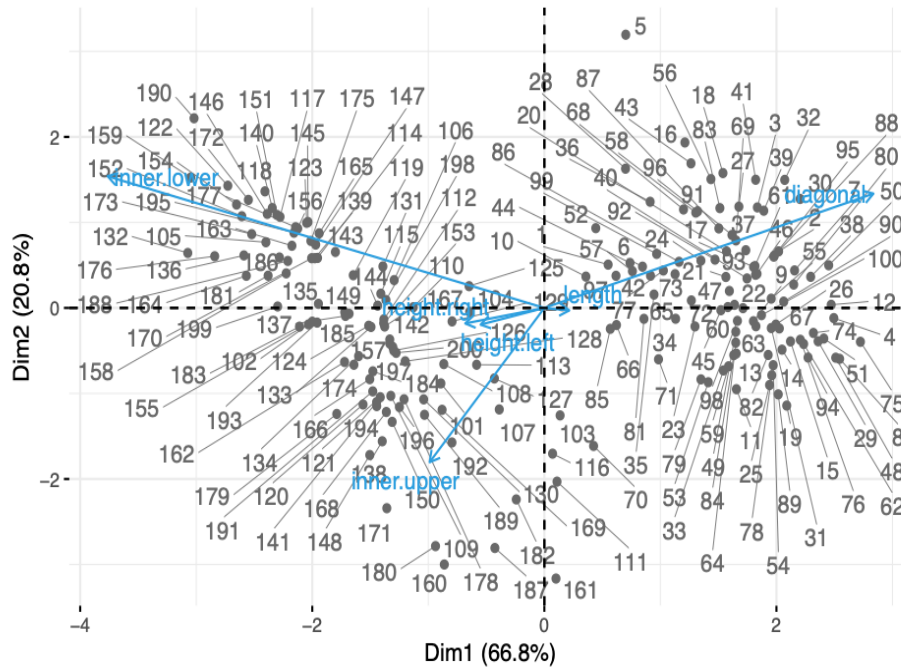


1: train error, 2: test error

5) Based on biplot in terms of 200 bank notes combined, inner.lower, height.right, height.left and inner upper variables are highly correlated. With this diagonal and length are highly variables correlated. If we divide into two groups; group 1: inner.lower,height.right,height.left and inner upper variables and group 2: diagonal and length, they are negatively correlated against group1. In biplot of genuine, it looks all variables are correlated each other except diagonal and all observations are evenly distributed. In biplot of counterfeit, inner.lower, diagonal and height.left are highly correlated and observations are scattered around inner.lower and inner.upper variables. As a result, there is a little bit difference between PCA of the 100 genuine bank notes and PCA of the 100 counterfeit bank notes.

```
## Importance of components:
##
##          PC1      PC2      PC3      PC4      PC5
## Standard deviation  1.732139 0.9672748 0.4933697 0.4412015 0.2919107
## Proportion of Variance 0.667520 0.2081600 0.0541600 0.0433100 0.0189600
## Cumulative Proportion 0.667520 0.8756800 0.9298300 0.9731400 0.9921000
##
##          PC6
## Standard deviation  0.1884534
## Proportion of Variance 0.0079000
## Cumulative Proportion 1.0000000
```

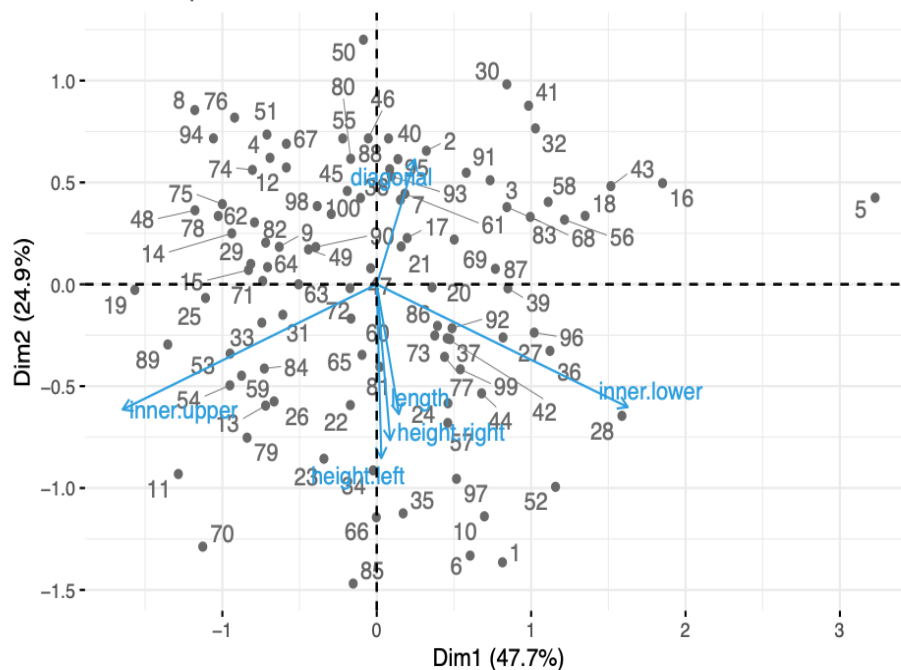
PCA – Biplot



Importance of components:

	PC1	PC2	PC3	PC4	PC5
## Standard deviation	0.8300896	0.5993959	0.4308224	0.295356	0.2831667
## Proportion of Variance	0.4774200	0.2489300	0.1286000	0.060440	0.0555600
## Cumulative Proportion	0.4774200	0.7263500	0.8549500	0.915390	0.9709500
##	PC6				
## Standard deviation	0.2047786				
## Proportion of Variance	0.0290500				
## Cumulative Proportion	1.0000000				

PCA – Biplot



```
## Importance of components:
##
##          PC1      PC2      PC3      PC4      PC5
## Standard deviation  1.244718 0.5649727 0.4401211 0.3222669 0.2904762
## Proportion of Variance 0.681030 0.1403100 0.0851500 0.0456500 0.0370900
## Cumulative Proportion 0.681030 0.8213300 0.9064800 0.9521300 0.9892200
##
##          PC6
## Standard deviation  0.1566098
## Proportion of Variance 0.0107800
## Cumulative Proportion 1.0000000
```

PCA – Biplot

