HW 2

Dutchak Bohdan

Hide Assignment Information Instructions This assignment is worth 100 points, which is 25% of the overall course grade, This assignment is to be completed individually. Please consult the course syllabus for a description of our academic honesty policy.

Pick any 3 of the following Ensemble Techniques below and compare the results with homework-1 * CrossValidation, * Leave One out Cross Validation * Bagging * RandomForest * Boosting * Stacking Lastly, determine Variance and bias and compare, Submit a report and also include what does cross validation do to bias and variance?

```r
library(mltest)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(e1071)
library(caret)
```

```
## Loading required package: ggplot2
```

```
## Loading required package: lattice
```

```r
library(rpart)
library(ipred)
library(tidyverse)
```

```
## ── Attaching packages
## ───────────────────────────────────────
## tidyverse 1.3.2 ──
```

```
## ✓ tibble  3.1.8     ✓ purrr   0.3.4
## ✓ tidyr   1.2.0     ✓ stringr 1.4.0
## ✓ readr   2.1.2     ✓ forcats 0.5.1
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✕ dplyr::filter() masks stats::filter()
## ✕ dplyr::lag()    masks stats::lag()
## ✕ purrr::lift()   masks caret::lift()
```

```
library(randomForest)
```

```
## randomForest 4.7-1.1
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
##
## The following object is masked from 'package:ggplot2':
##
##     margin
##
## The following object is masked from 'package:dplyr':
##
##     combine
```

```
library(Metrics)
```

```
##
## Attaching package: 'Metrics'
##
## The following objects are masked from 'package:caret':
##
##     precision, recall
```

```
library(ggplot2)
library(cvms)
```

```
options(warn = -1)
data <- read.csv("data/all_seasons.csv")
data$Pos <- replace(data$Pos, data$Pos=='C', 5)
data$Pos <- replace(data$Pos, data$Pos=='PF', 4)
data$Pos <- replace(data$Pos, data$Pos=='SF', 3)
data$Pos <- replace(data$Pos, data$Pos=='SG', 2)
data$Pos <- replace(data$Pos, data$Pos=='PG', 1)
data$Pos <- as.factor(data$Pos)

data <- data[,c('Pos','Ht','Wt','AST','X3PA','ORB','BLK')]

head(data)
```

	Pos	Ht	Wt	AST	X3PA	ORB	BLK
	<fct>	<int>	<int>	<dbl>	<dbl>	<dbl>	<dbl>
1	2	198	93	1.7	5.5	1.2	0.2
2	2	193	88	2.4	2.5	0.6	0.1
3	3	198	95	1.1	0.8	0.7	0.1
4	1	185	86	1.2	0.9	0.8	0.1
5	5	216	110	3.0	0.3	2.1	1.3
6	4	206	104	0.4	0.0	1.3	0.3

6 rows

```
set.seed(1)
```

```
sample <- sample(c(TRUE, FALSE), nrow(data), replace=TRUE, prob=c(0.8,0.2))
train <- data[sample, ]
test <- data[!sample, ]

test.X <- test[2:7]
test.Y <- test[1]

train.X<-train[2:7]
train.Y<-train[1]
```

I decided not no choose LOOCV, since in has extremely large computation complexity and time, but I still wanted to run cross-validation, so I chose lighter model - k-fold cross validation. It has smaller complexity and computing time. But unfortunately I didn't get how to compute it's bias and variance. The `train()` method doesn't allow to get predicted values, it only shows the results. Speaking about them, they are not great. For some reasons my Decision Tree from HW1 had accuracy of 74%, but cross-validation returns avg of 72%.

I didn't manage to finish 8th chapter of ISLR, but I learned something, that is why I chose Random Forest and Bagging method.

In theory cross validation fits different combinations of training and testing data samples and looking for the one with the smallest testing error. The smallest error means the best bias/variance trade-off, so the certain random training data sample has the smallest observed bias and the biggest observed variance. So that model is as far as possible from overfitting and underfitting.

Cross validation

```
train.control <- trainControl(method = "cv", number=20, p=0.8)
model <- train(Pos ~., data = data, method = "ctree",trControl = train.control)
print(model)
```

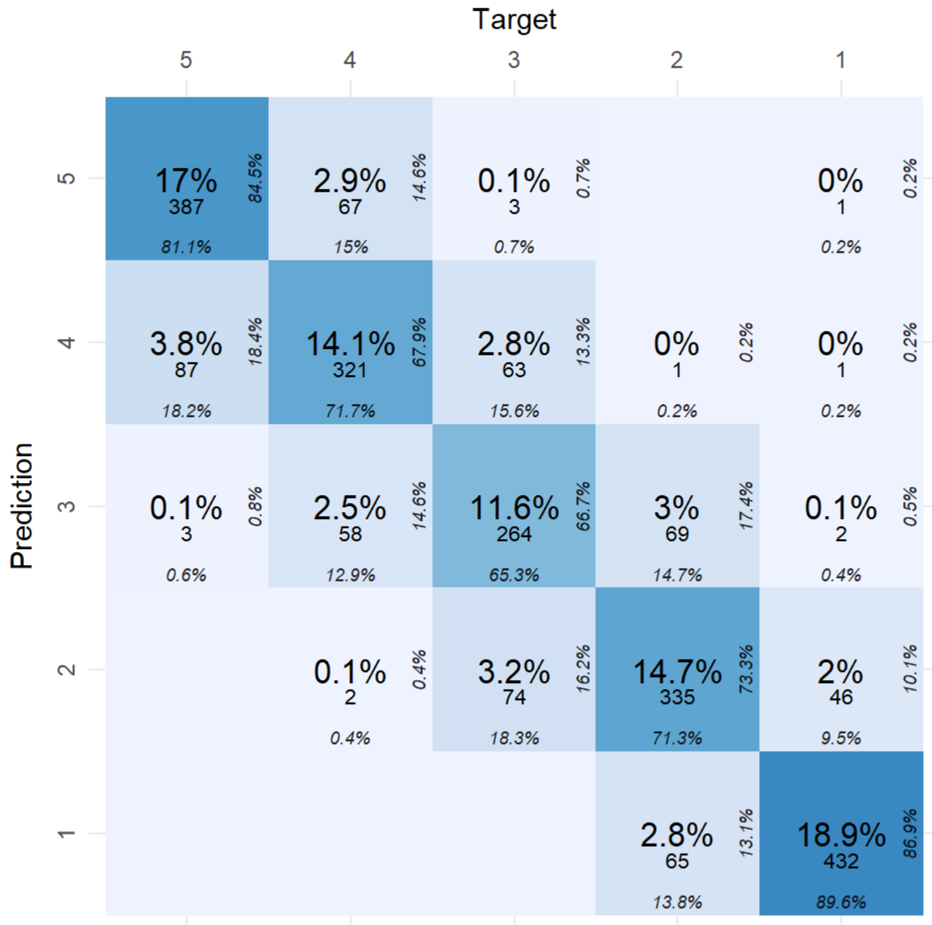
```
## Conditional Inference Tree
##
## 11071 samples
##     6 predictor
##     5 classes: '1', '2', '3', '4', '5'
##
## No pre-processing
## Resampling: Cross-Validated (20 fold)
## Summary of sample sizes: 10517, 10517, 10518, 10517, 10518, 10519, ...
## Resampling results across tuning parameters:
##
##   mincriterion  Accuracy   Kappa
##   0.01          0.7212475  0.6514819
##   0.50          0.7263952  0.6579603
##   0.99          0.7191692  0.6486777
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mincriterion = 0.5.
```

I can’t say anything about bias and variance of this method. I only assume, it has worse trade-off, since it’s accuracy is worse than the Decision Tree from my HW1. Honestly I don’t get why. I set the same parameters of sample etc.

Random Forest

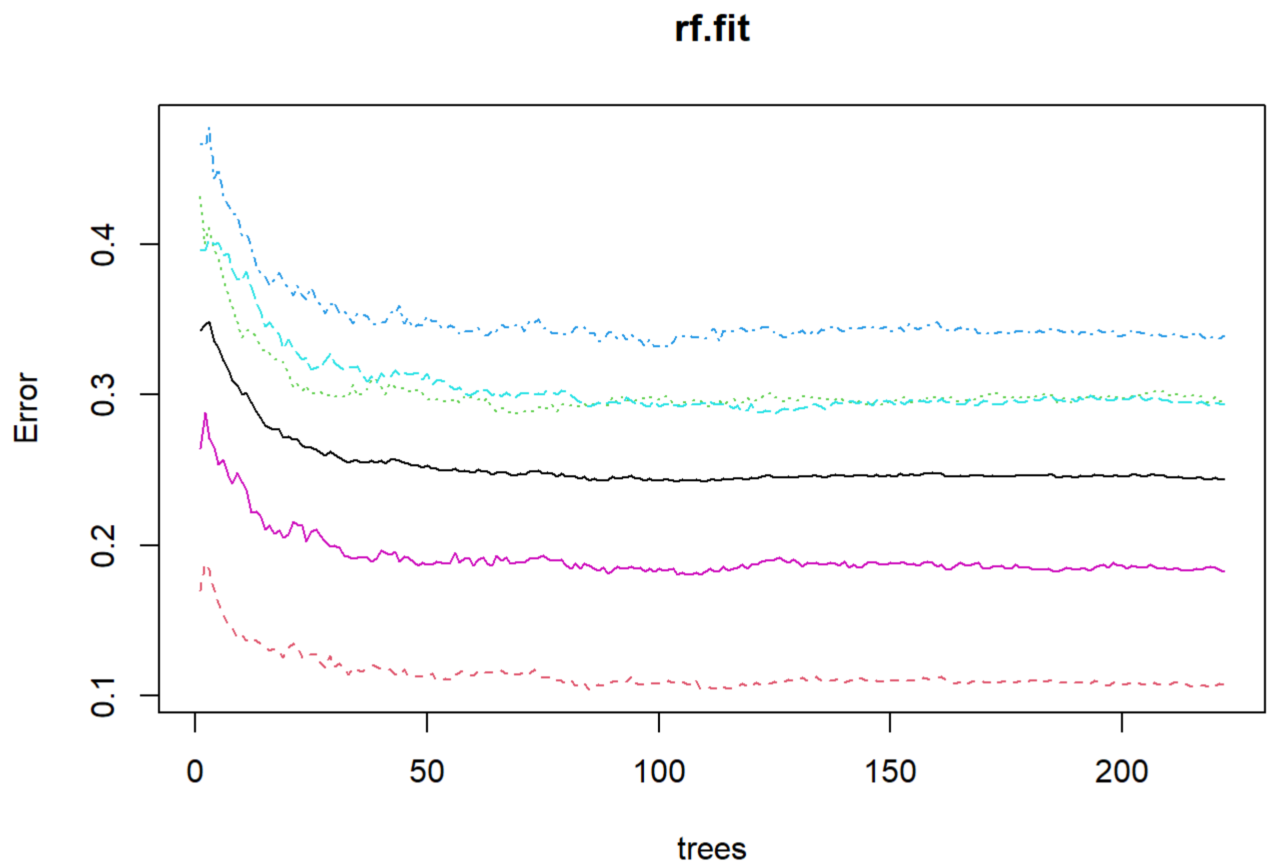
```
rf.fit <- randomForest(x = train.X, y = train$Pos, ntree = 222)
population.rf <- randomForest(x = data[2:7], y = data$Pos, ntree = 222)

rf.pred <- predict(rf.fit, newdata = test.X)
population.pred <- predict(population.rf, newdata = test.X)
```

```
plot_confusion_matrix(confusion_matrix(targets=test.Y$Pos, prediction=rf.pred))
```

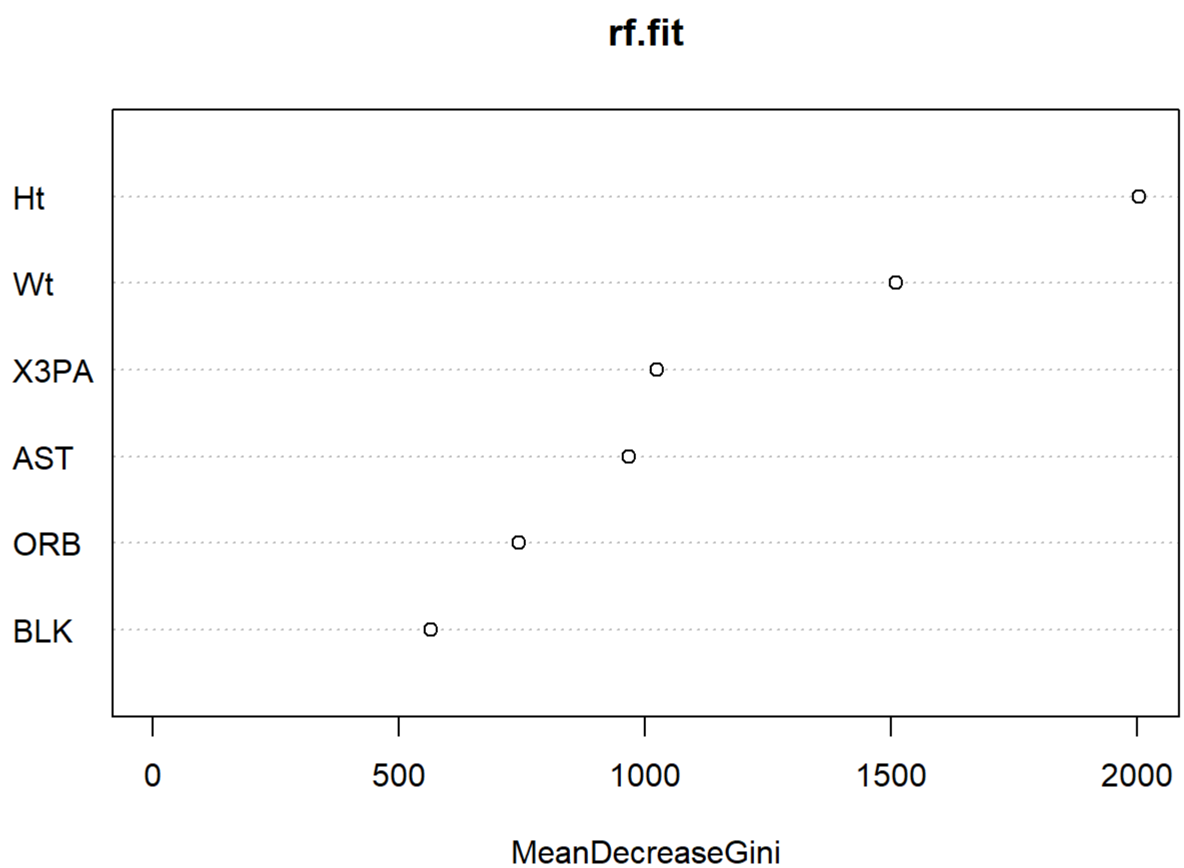


Target
Prediction
5
4
3
2
1
17%
387
84.5%
81.1%
2.9%
67
14.6%
15%
0.1%
3
0.7%
0.7%
0%
1
0.2%
0.2%
3.8%
87
18.4%
18.2%
14.1%
321
67.9%
71.7%
2.8%
63
13.3%
15.6%
0%
1
0.2%
0.2%
0%
1
0.2%
0.2%
0.1%
3
0.8%
0.6%
2.5%
58
14.6%
12.9%
11.6%
264
66.7%
65.3%
3%
69
17.4%
14.7%
0.1%
2
0.5%
0.4%
0.1%
2
0.4%
0.4%
3.2%
74
16.2%
18.3%
14.7%
335
73.3%
71.3%
2%
46
10.1%
9.5%
2.8%
65
13.1%
13.8%
18.9%
432
86.9%
89.6%


```
plot(rf.fit)
```




```
varImpPlot(rf.fit)
```




```
stats <- ml_test(rf.pred, test.Y$Pos, output.as.table=FALSE)
rf.results <- data.frame(
    Accuracy = stats$accuracy,
    Bias = mean(abs(as.integer(population.pred) - as.integer(rf.pred))),
    Variance = var(as.integer(population.pred), as.integer(rf.pred))
)
rf.results
```

Accuracy <dbl>	Bias <dbl>	Variance <dbl>
0.7623849	0.2371767	1.96286

1 row

This model very good results. The highest accuracy, with relatively low computation time. Since Random forest is more flexible version of Decision Tree, it obvious why Variance is high, but I expected smaller bias. Probably the problem is with my data.

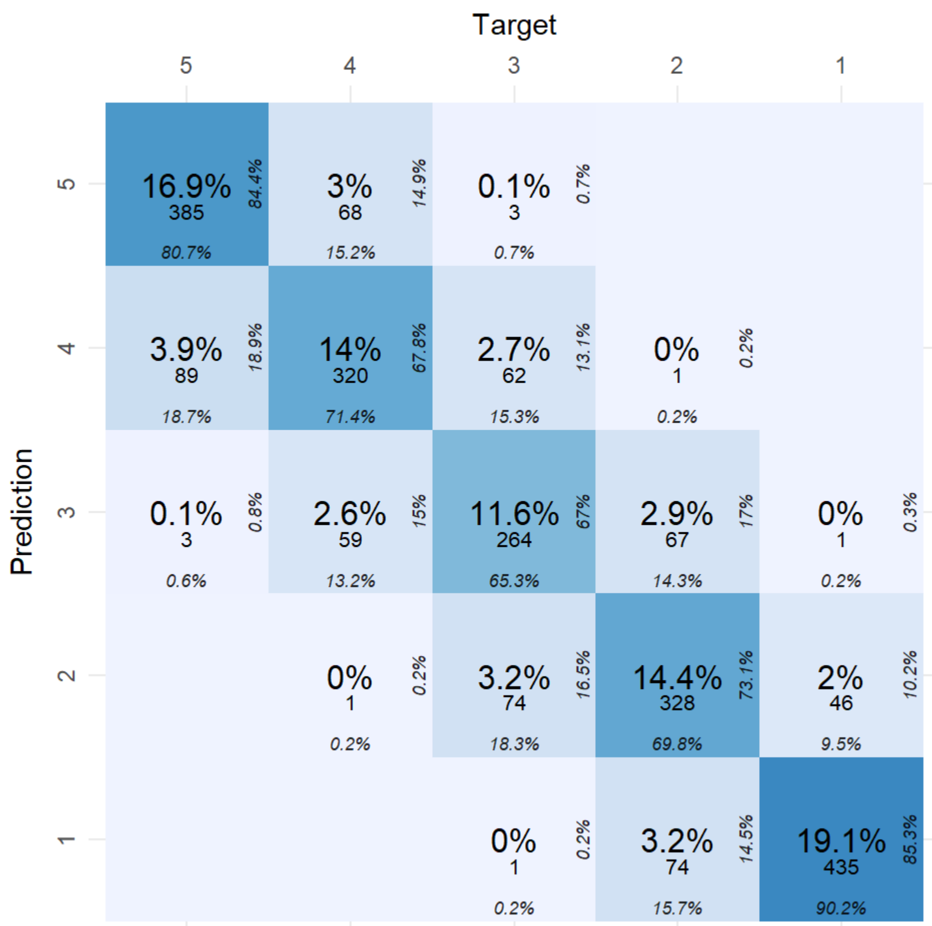
Also I would like to notice, that feature importance for Random forest completely corresponds to the one, ANOVA predicted. Very nice!

Bagging

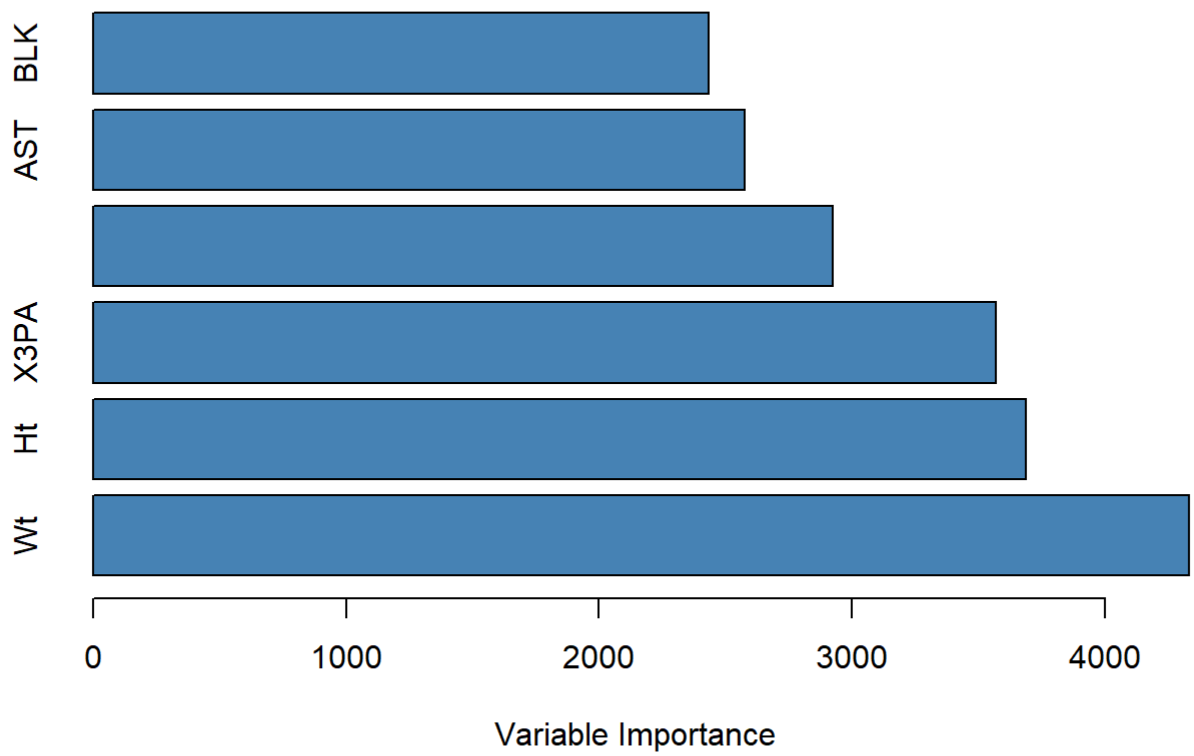
```
bag.fit <- bagging(formula = Pos ~ ., data = train, nbagg = 150, coob = TRUE,
  control = rpart.control(minsplit = 2, cp = 0)
)
population.bag <- bagging(formula = Pos ~ ., data = data, nbagg = 150, coob = TRUE,
  control = rpart.control(minsplit = 2, cp = 0)
)

bag.pred <- predict(bag.fit, newdata = test.X)
population.pred <- predict(population.bag, newdata = test.X)

bag.fit
```

```
##
## Bagging classification trees with 150 bootstrap replications
##
## Call: bagging.data.frame(formula = Pos ~ ., data = train, nbagg = 150,
##     coob = TRUE, control = rpart.control(minsplit = 2, cp = 0))
##
## Out-of-bag estimate of misclassification error:  0.2522
```

```
plot_confusion_matrix(confusion_matrix(targets=test.Y$Pos, prediction=bag.pred))
```



```
VI <- data.frame(var=names(data[,-1]), imp=varImp(bag.fit))
VI_plot <- VI[order(VI$Overall, decreasing=TRUE),]
barplot(VI_plot$Overall,
        names.arg=rownames(VI_plot),
        horiz=TRUE,
        col='steelblue',
        xlab='Variable Importance')
```




```
stats <- ml_test(bag.pred, test.Y$Pos, output.as.table=FALSE)
bag.results <- data.frame(
    Accuracy = stats$accuracy,
    Bias = mean(abs(as.integer(population.pred) - as.integer(bag.pred))),
    Variance = var(as.integer(population.pred), as.integer(bag.pred))
)
bag.results
```

Accuracy <dbl>	Bias <dbl>	Variance <dbl>
0.7593161	0.2428759	1.965283

1 row

Bagging showed good results, but here, as with the RF, I am surprissed with big bias. Also the feature importance is similar to the one's ANOVA predicted.