Nolan Ryan or Tommy John?

Matt Misterka

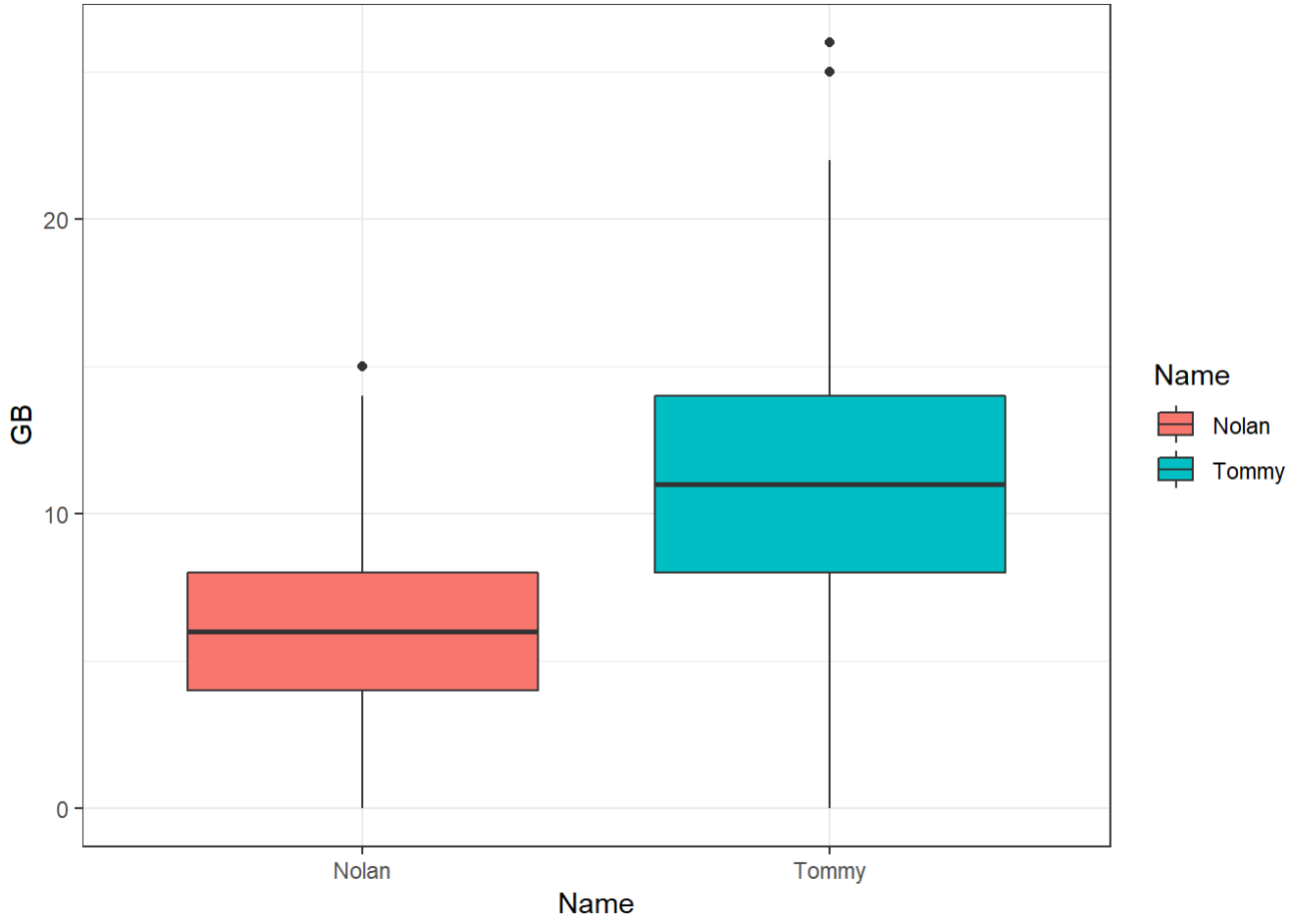
June 3, 2019

```
setwd("C:\\Users\\Matt\\Documents\\Statistics\\Stat_Learning")
load("baseball_test.Rda")
load("baseball_train.Rda")
```

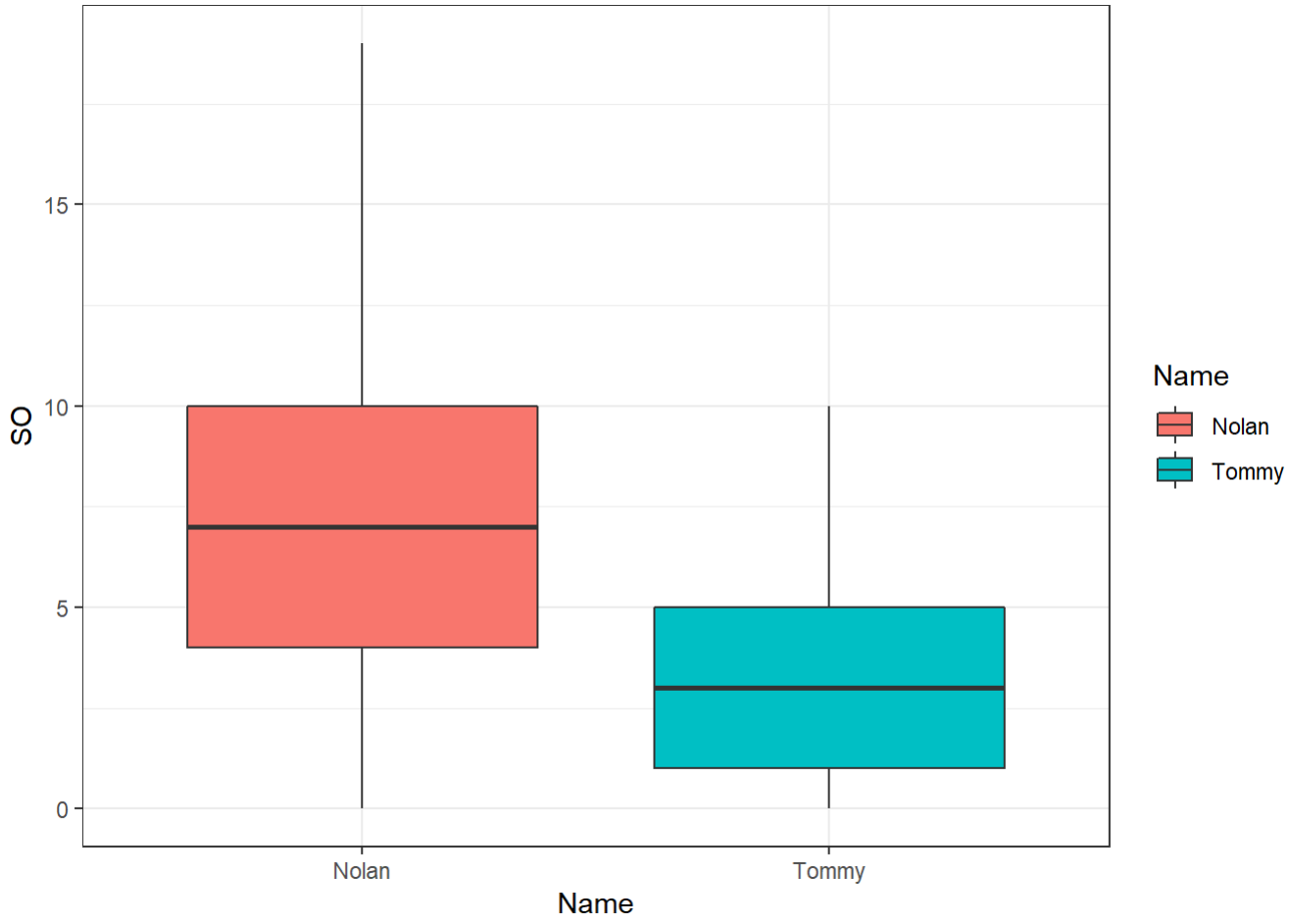
Data Visualization

Let's look at boxplots of strike outs, ground balls, and walks (BB).

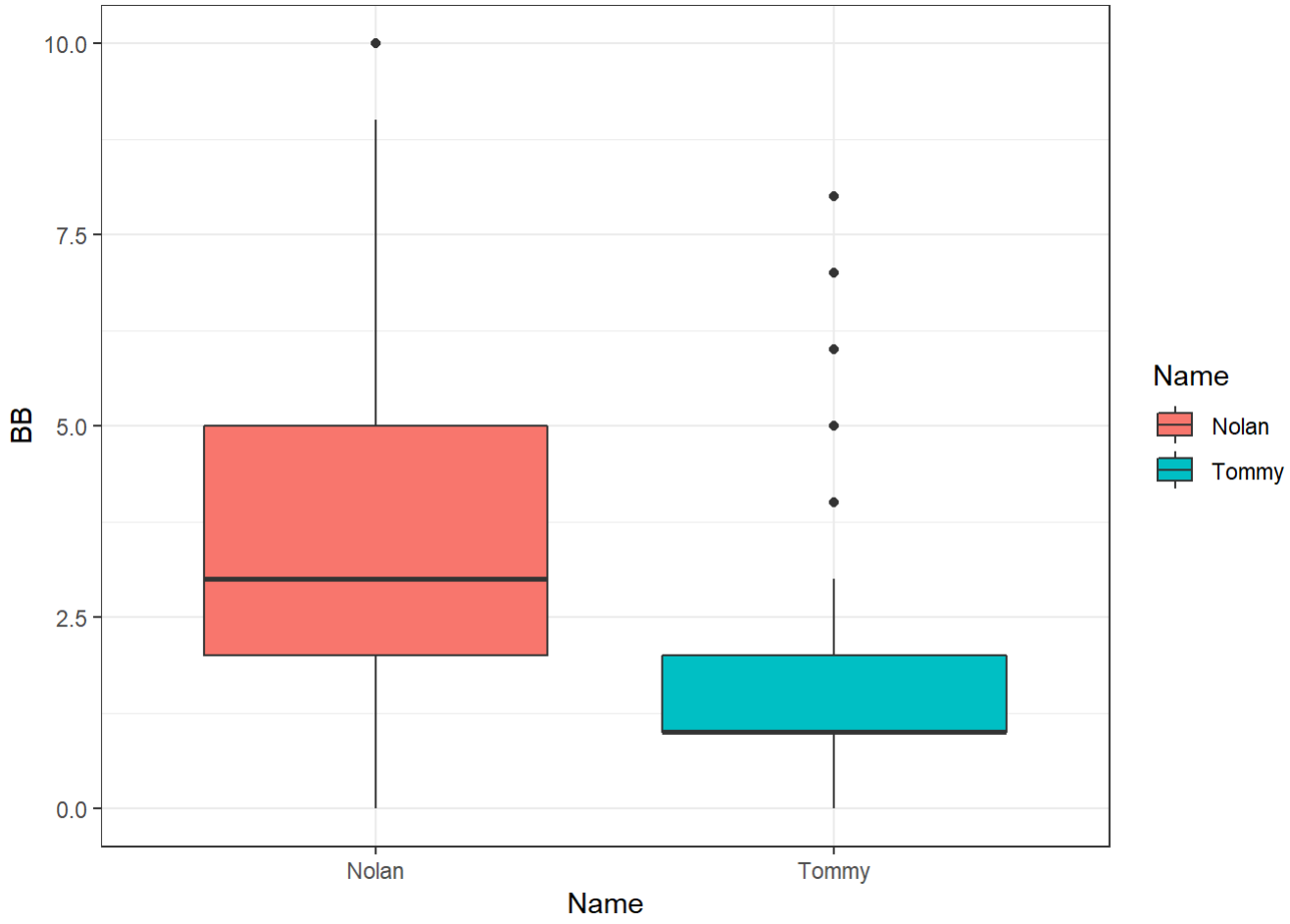
```
ggplot(baseball.train, aes(x=Name, y=GB, fill=Name)) +
  geom_boxplot()+theme_bw()
```




```
ggplot(baseball.train, aes(x=Name, y=SO, fill=Name)) +
  geom_boxplot()+theme_bw()
```




```
ggplot(baseball.train, aes(x=Name, y=BB, fill=Name)) +
  geom_boxplot()+theme_bw()
```



Logistic Model

Start off with a logistic model.

```
ctrl <- trainControl(method="repeatedcv", number=5, repeats=10,
                     classProbs=TRUE, summaryFunction=twoClassSummary)

set.seed(21191)
logit <- train(Name ~.,
                      data=baseball.train,
                      method="glm",
                      metric="ROC",
                      preProcess=c("center", "scale"),
                      family=binomial(link="logit"),
                      trControl=ctrl)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

Forward Logistic Model

I removed the opponent variables in this model to speed up the computation.

```
set.seed(21191)
forward_logit <- train(Name ~.-Opp,
                       data=baseball.train,
                       method="glmStepAIC",
                       direction="forward",
                       preProcess=c("center", "scale"),
                       family=binomial(link="logit"),
                       trace=FALSE,
                       trControl=ctrl)
```

```
## Warning in train.default(x, y, weights = w, ...): The metric "Accuracy" was
## not in the result set. ROC will be used instead.
```

```
forward_logit$finalModel
```

```
##
## Call:  NULL
##
## Coefficients:
## (Intercept)           SO           GB           BB           FB
##     -0.5859      -2.2773       2.0378      -1.0383      -1.3816
##         Unk           SB           LD            R           PU
##      0.7173      -0.5631       0.5051      -0.7279      -0.5429
##           H           PO           DR          ERA          IBB
##      0.7723      -0.1949       0.2043      -0.2158       0.1989
##
## Degrees of Freedom: 1545 Total (i.e. Null);  1531 Residual
## Null Deviance:       2142
## Residual Deviance: 672   AIC: 702
```

Lasso Model

Let's look at the lasso model. This model does implicit variable selection - setting some coefficients to 0.

```
set.seed(21191)
lasso.mod <- train(Name ~.,
                        data=baseball.train,
                        method="glmnet",
                        metric="ROC",
                        preProcess=c("center", "scale"),
                        trControl=ctrl,
                        tuneGrid=expand.grid(alpha=1,
                                             lambda=10^seq(-2,0,0.01)))

kable(data.frame(Variable=c("Intercept",lasso.mod$coefnames),
           Coef=as.numeric(predict(lasso.mod$finalModel, type="coefficients",
                                   s=as.numeric(lasso.mod$bestTune[2])))) %>%
  kable_styling(c("bordered"),full_width = FALSE,position = "left")
```

Variable	Coef
Intercept	-0.3208870
OppBAL	0.1105138
OppBOS	0.0000000
OppCAL	0.1469484
OppCHC	-0.0947144
OppCHW	0.0000000
OppCIN	-0.0614289
OppCLE	0.0713630
OppDET	0.1279084
OppHOU	0.0000000
OppKCA	0.0811649
OppKCR	0.0000000
OppLAA	0.0000000
OppLAD	-0.3519144
OppMIL	0.0000000
OppMIN	0.0362213
OppMON	-0.1458874
OppNYM	0.0000000
OppNYY	0.0000000
OppOAK	0.1060652
OppPHI	-0.0921314
OppPIT	-0.1038198
OppSDP	-0.1364058
OppSEA	0.0000000
OppSEP	0.0000000

Variable	Coef
OppSFG	-0.0408885
OppSTL	-0.0494123
OppTEX	0.0000000
OppTOR	0.0000000
OppWSA	0.2515334
DR	0.0000000
IP	0.0000000
H	0.3922035
R	-0.2209528
ER	0.0000000
BB	-0.8687787
SO	-1.5791283
HR	0.0000000
HBP	0.0000000
ERA	-0.0364412
BF	0.0000000
GB	1.4969367
FB	-0.6865643
LD	0.0070053
PU	-0.3398111
Unk	0.2909305
SB	-0.2894411
CS	0.0000000
PO	-0.0263786
X2B	0.0000000

Variable	Coef
X3B	0.0000000
IBB	0.0284480
GDP	0.0000000
SF	0.0000000
ROE	0.0000000
ResultW	0.0000000

Elastic Model

This model finds a balance between ridge and lasso models. Investigate the coefficients.

```
set.seed(21191)
elastic.mod <- train(Name ~.,
                        data=baseball.train,
                        method="glmnet",
                        metric="ROC",
                        preProcess=c("center", "scale"),
                        trControl=ctrl,
                        tuneGrid=expand.grid(alpha=seq(0,1,0.1),
                                             lambda=10^seq(-2,0,0.01)))

kable(data.frame(Variable=c("Intercept",elastic.mod$coefnames),
           Coef=as.numeric(predict(elastic.mod$finalModel, type="coefficients",
                                   s=as.numeric(elastic.mod$bestTune[2])))) %>%
  kable_styling(c("bordered"),full_width = FALSE,position = "left")
```

Variable	Coef
Intercept	-0.2673120
OppBAL	0.1965888
OppBOS	0.0833879
OppCAL	0.2489383
OppCHC	-0.1280430
OppCHW	-0.0556663
OppCIN	-0.1029527
OppCLE	0.1712717

Variable	Coef
OppDET	0.2360914
OppHOU	0.0555533
OppKCA	0.1926901
OppKCR	0.0437148
OppLAA	0.0790201
OppLAD	-0.4067321
OppMIL	0.0758785
OppMIN	0.1496479
OppMON	-0.1731363
OppNYM	-0.0159089
OppNYY	0.0793489
OppOAK	0.2223586
OppPHI	-0.1318333
OppPIT	-0.1498254
OppSDP	-0.1551157
OppSEA	0.0558354
OppSEP	0.0207793
OppSFG	-0.0878814
OppSTL	-0.1029952
OppTEX	0.0019301
OppTOR	0.0934764
OppWSA	0.3338432
DR	0.0667944
IP	-0.0494596
H	0.4357988

Variable	Coef
R	-0.2261503
ER	-0.1006617
BB	-0.8240784
SO	-1.2875154
HR	-0.0008173
HBP	-0.0920938
ERA	-0.1129718
BF	-0.0841588
GB	1.2654914
FB	-0.6691734
LD	0.2131488
PU	-0.4562659
Unk	0.4404366
SB	-0.3344358
CS	0.0055955
PO	-0.0946002
X2B	0.0000000
X3B	0.0036886
IBB	0.1143809
GDP	0.0877615
SF	-0.0548286
ROE	0.0000000
ResultW	0.0583913

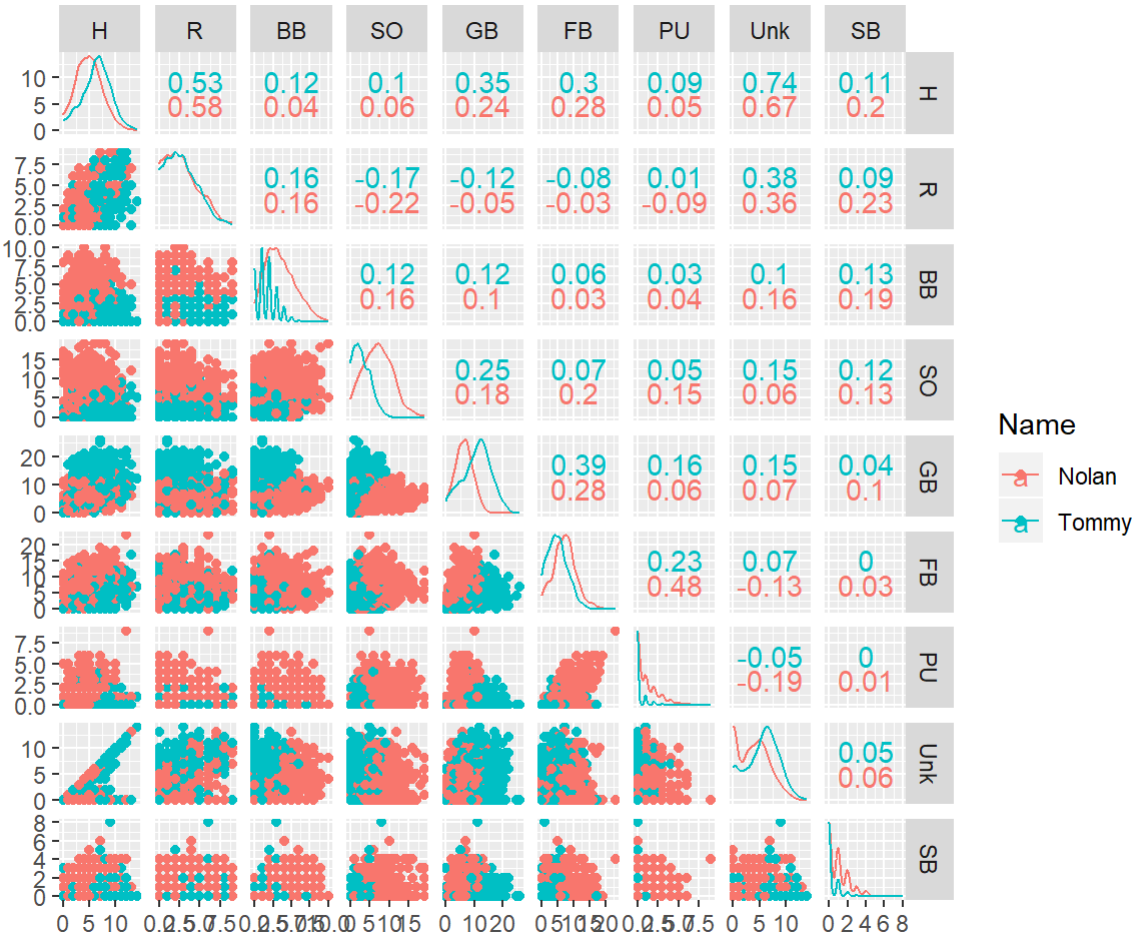
Dummy Variables and LDA

I create five dummy variables for opponents. Variables were chosen by looking at coefficients of the elastic model. I also took into consideration the teams that each player played on as well as divisional opponents. I selected a subset of numeric variables. Train LDA model - assumes a common covariance structure. Examine the coviance structure.

```
baseball.train$MON<-ifelse(baseball.train$Opp=="MON",1,0)
baseball.train$CAL<-ifelse(baseball.train$Opp=="CAL",1,0)
baseball.train$LAD<-ifelse(baseball.train$Opp=="LAD",1,0)
baseball.train$OAK<-ifelse(baseball.train$Opp=="OAK",1,0)
baseball.train$WSA<-ifelse(baseball.train$Opp=="WSA",1,0)

cols <- c("MON","CAL","LAD","OAK","WSA")
baseball.train[cols] <- lapply(baseball.train[cols],as.factor)

ggscatmat(baseball.train, c(4:5,7:8,13:14,16:18), color="Name",alpha = 1)
```



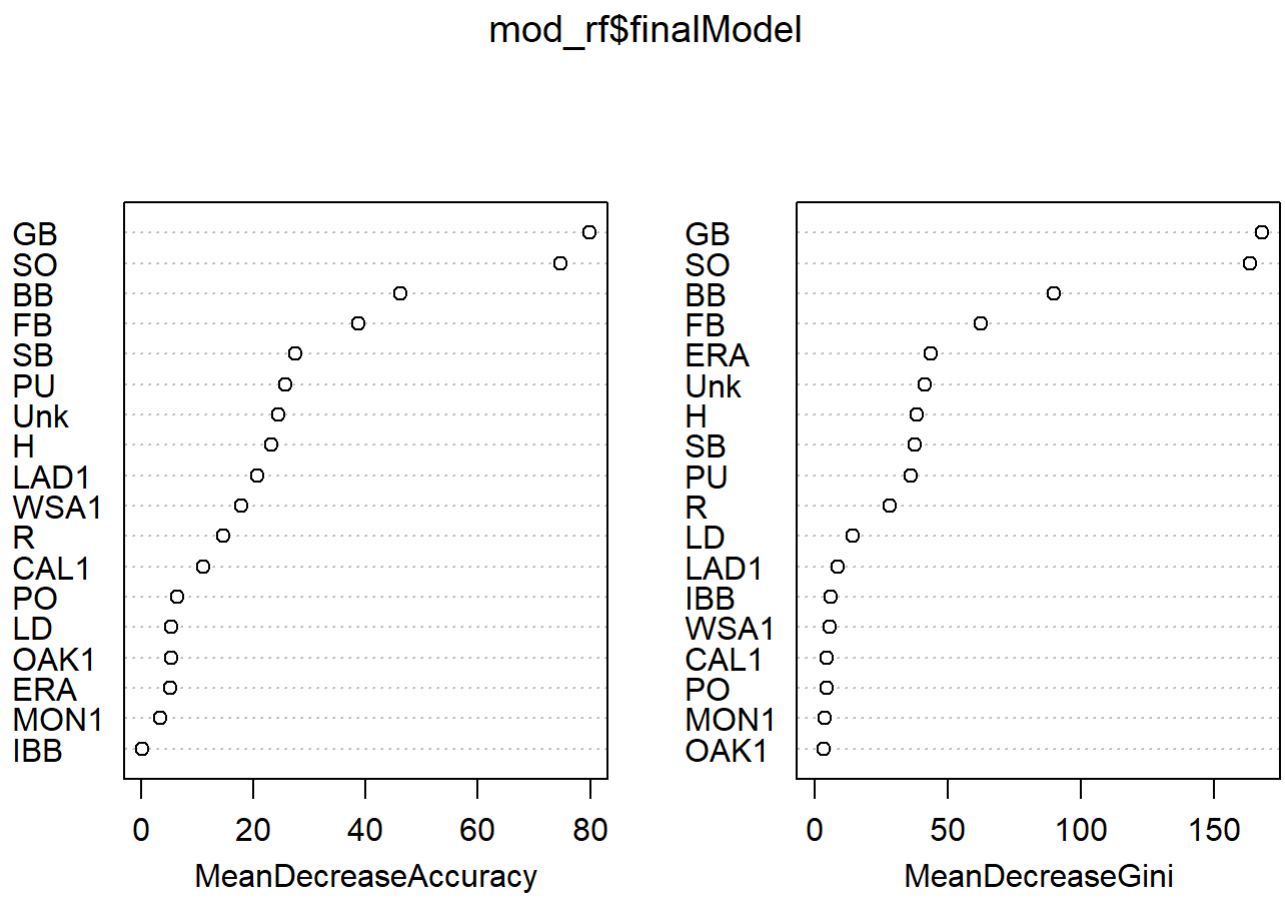

```
set.seed(21191)
mod.lda <- train(Name ~ H+R+BB+SO+GB+FB+PU+Unk+SB+MON+CAL+LAD+OAK+WSA,
                         data=baseball.train,
                       method="lda",
                       metric="ROC",
                       output=FALSE,
                       trControl=ctrl)
```

Random Forest

A random forest with selected oppenents and numeric variables present in forward, lasso, and elastic models simultaneously. Let's look at a variable importance plot.

```
set.seed(21191)
mod_rf <- train(Name ~ H+R+ERA+BB+SO+GB+FB+LD+PO+PU+Unk+SB+IBB+MON+CAL+LAD+OAK+WSA,
                data=baseball.train,
                method="rf",
                metric="ROC",
                preProcess=c("center", "scale"),
                trControl=ctrl,
                tuneGrid=expand.grid(mtry=c(4,5)),
                importance=TRUE)

varImpPlot(mod_rf$finalModel)
```



Boosted Tree

```
set.seed(21191)
mod.boosttree <- train(Name ~ H+R+ERA+BB+SO+GB+FB+LD+PO+PU+Unk+SB+IBB+MON+CAL+LAD+OAK+WSA,
                       data=baseball.train,
                       method="gbm",
                       metric="ROC",
                       preProcess=c("center", "scale"),
                       trControl=ctrl,
                       distribution="bernoulli",
                       verbose=FALSE,
                       tuneGrid=expand.grid(n.trees=c(1000),
                                            interaction.depth=1:2,
                                            shrinkage=c(0.1,0.01,0.001),
                                            n.minobsinnode=c(10,20) ) )
```

KNN Model

```
set.seed(21191)
mod.knn <- train(Name ~ H+R+ERA+BB+SO+GB+FB+LD+PO+PU+Unk+SB+IBB+MON+CAL+LAD+OAK+WSA,
                     data=baseball.train,
                     method="knn",
                     preProcess=c("center", "scale"),
                     metric="ROC",
                     trControl=ctrl,
                     tuneGrid=expand.grid(k=seq(1,49,2)))
```

Partial Least Squares

```
set.seed(21191)
mod.pls <- train(Name ~ H+R+ERA+BB+SO+GB+FB+LD+PO+PU+Unk+SB+IBB+MON+CAL+LAD+OAK+WSA,
                   data=baseball.train,
                   method="pls",
                   preProcess=c("center", "scale"),
                   metric="ROC",
                   trControl=ctrl,
                   tuneGrid=expand.grid(ncomp=1:18))
```

Generalized Additive Model

```
set.seed(21191)
mod.gamCubic <- train(Name ~ H+R+ERA+BB+SO+GB+FB+LD+PO+PU+Unk+SB+IBB+MON+CAL+LAD+OAK+WSA,
                      data=baseball.train,
                      method="gam",
                      preProcess=c("center", "scale"),
                      metric="ROC",
                      trControl=ctrl,
                      tune.length=20)
```

```
## Loading required package: mgcv
```

```
## Loading required package: nlme
```

```
##
## Attaching package: 'nlme'
```

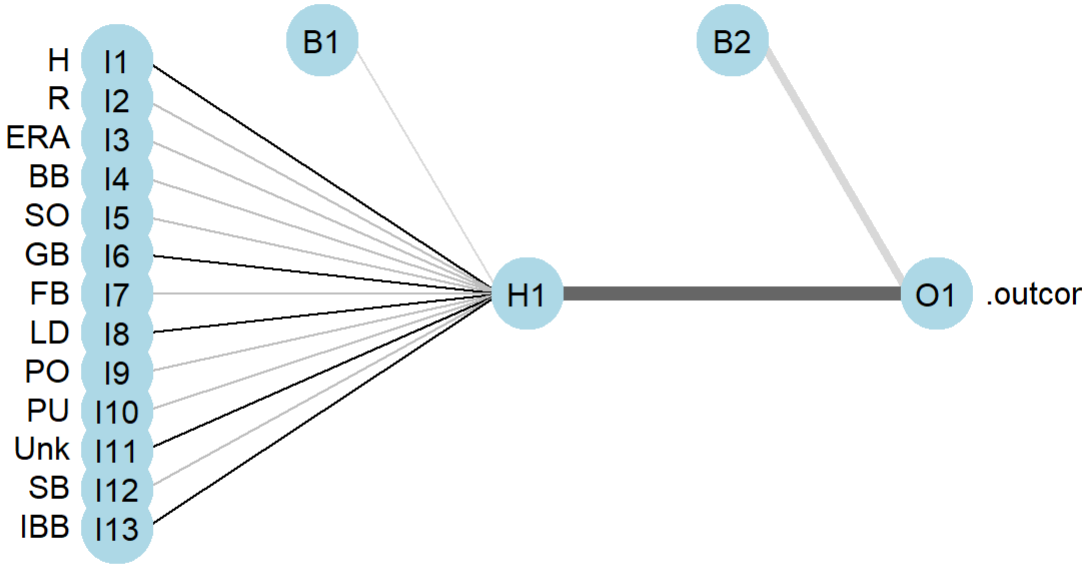
```
## The following object is masked from 'package:dplyr':
##
##     collapse
```

```
## This is mgcv 1.8-26. For overview type 'help("mgcv-package")'.
```

Neural Net

```
set.seed(21191)
mod.nnet <- train(Name ~ H+R+ERA+BB+SO+GB+FB+LD+PO+PU+Unk+SB+IBB,
                  data=baseball.train,
                  method="nnet",
                  preProcess=c("center", "scale"),
                  metric="ROC",
                  trControl=ctrl,
                  tuneGrid=expand.grid(size=seq(1,7,1),
                                       decay=seq(0,0.1,0.005) ),
                  linout=0,
                  trace=FALSE)
```

```
plotnet(mod.nnet$finalModel, alpha=0.6)
```



Support Vector Machine

```
set.seed(21191)
mod.svm.lin <- train(Name ~ H+R+ERA+BB+SO+GB+FB+LD+PO+PU+Unk+SB+IBB+MON+CAL+LAD+OAK+WSA,
                     data=baseball.train,
                     method="svmLinear",
                     metric="ROC",
                     trControl=ctrl,
                     preProcess = c("center", "scale"),
                     tuneGrid=expand.grid(C=c(seq(0.1,1,0.1),1.5,2,3,4)))
```

Comparison of Models

It looks like the elastic model does well in terms of ROC.

```
out <- resamples(list(Logistic=logit, StepLogit=forward_logit,
                      Lasso=lasso.mod, Elastic=elastic.mod,
                      LDA=mod.lda, RandomForest=mod_rf,
                      Boosted=mod.boosttree, KNN=mod.knn,
                      PLS=mod.pls,GAM=mod.gamCubic, NNET=mod.nnet,
                      SVM=mod.svm.lin))
summary(out)$statistics$ROC %>%
kable() %>% kable_styling(full_width=FALSE)
```

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
Logistic	0.9586164	0.9716781	0.9756946	0.9750286	0.9796646	0.9901048	0
StepLogit	0.9419706	0.9632075	0.9675262	0.9673915	0.9727044	0.9825577	0
Lasso	0.9565199	0.9701048	0.9747500	0.9741430	0.9788574	0.9872117	0
Elastic	0.9603354	0.9733229	0.9767505	0.9767082	0.9823166	0.9896855	0
LDA	0.9514885	0.9703197	0.9751153	0.9734875	0.9785010	0.9854927	0
RandomForest	0.9294549	0.9591929	0.9624896	0.9629822	0.9697013	0.9800629	0
Boosted	0.9421384	0.9667505	0.9731656	0.9717552	0.9775472	0.9865409	0
KNN	0.9270650	0.9535744	0.9599790	0.9586416	0.9640503	0.9774843	0
PLS	0.9500210	0.9696541	0.9751153	0.9742318	0.9792453	0.9880922	0
GAM	0.9431447	0.9631447	0.9697484	0.9683535	0.9738050	0.9822642	0
NNET	0.9441929	0.9646570	0.9694047	0.9683315	0.9735325	0.9838574	0
SVM	0.9536268	0.9689937	0.9745667	0.9738032	0.9785430	0.9876310	0

Predict

Looks like the knn model does well. Correctly classifying 17 of 20.

```
baseball.test$MON<-ifelse(baseball.test$Opp=="MON",1,0)
baseball.test$CAL<-ifelse(baseball.test$Opp=="CAL",1,0)
baseball.test$LAD<-ifelse(baseball.test$Opp=="LAD",1,0)
baseball.test$OAK<-ifelse(baseball.test$Opp=="OAK",1,0)
baseball.test$WSA<-ifelse(baseball.test$Opp=="WSA",1,0)

cols <- c("MON","CAL","LAD","OAK","WSA")
baseball.test[cols] <- lapply(baseball.test[cols],as.factor)

our.pred <- data.frame(Logistic=predict(logit, newdata=baseball.test),
                       StepLogistic=predict(forward_logit, newdata=baseball.test),
                       Lasso=predict(lasso.mod, newdata=baseball.test),
                       Elastic=predict(elastic.mod, newdata=baseball.test),
                       LDA=predict(mod.lda, newdata=baseball.test),
                       RF=predict(mod_rf, newdata=baseball.test),
                       Boosted=predict(mod.boosttree, newdata=baseball.test),
                       KNN=predict(mod.knn, newdata=baseball.test),
                       PLS=predict(mod.pls, newdata=baseball.test),
                       GAM=predict(mod.gamCubic, newdata=baseball.test),
                       NeuralNet=predict(mod.nnet, newdata=baseball.test),
                       SVM=predict(mod.svm.lin, newdata=baseball.test))

true<-baseball.test$Name

out <- data.frame(t(apply(our.pred, 2, function(x) { tmp<-confusionMatrix(as.factor(x), referenc
e=true); c(tmp$overall[1], tmp$byClass[1:2])  } ) ) )

names(out) <- c("Accuracy", "Sensitivity", "Specificity")
out %>% kable() %>%
  kable_styling(full_width=FALSE,
                bootstrap_options = "bordered")
```

	Accuracy	Sensitivity	Specificity
Logistic	0.85	1.0000000	0.6666667
StepLogistic	0.75	0.9090909	0.5555556
Lasso	0.80	0.9090909	0.6666667
Elastic	0.80	0.8181818	0.7777778
LDA	0.80	0.9090909	0.6666667
RF	0.75	0.8181818	0.6666667
Boosted	0.80	1.0000000	0.5555556
KNN	0.85	0.8181818	0.8888889
PLS	0.80	0.9090909	0.6666667

	Accuracy	Sensitivity	Specificity
GAM	0.75	0.9090909	0.5555556
NeuralNet	0.75	0.9090909	0.5555556
SVM	0.80	0.9090909	0.6666667

```
preds<-data.frame(true,our.pred[8])
names(preds)<-c("truth","prediction")
kable(preds)%>%
  kable_styling(c("bordered"),full_width = FALSE)
```

truth	prediction
Nolan	Nolan
Tommy	Tommy
Tommy	Tommy
Nolan	Nolan
Nolan	Tommy
Nolan	Nolan
Nolan	Nolan
Tommy	Tommy
Nolan	Nolan
Nolan	Nolan
Nolan	Nolan
Nolan	Tommy
Tommy	Tommy
Tommy	Nolan
Tommy	Tommy
Tommy	Tommy
Tommy	Tommy
Nolan	Nolan

truth	prediction
Tommy	Tommy
Nolan	Nolan