Exercise 5

AUTHOR
Collin Real (yhi267)

8.1 - Recrease simulated data from Exercise 4

```
library(mlbench)
library(tidyverse)
library(base)
library(MASS)
library(earth)
library(AppliedPredictiveModeling)
library(randomForest)
library(caret)
set.seed(200)
simulated <- mlbench.friedman1(200, sd = 1)
simulated <- cbind(simulated$x, simulated$y)
simulated <- as.data.frame(simulated)
colnames(simulated)[ncol(simulated)] <- "y"
```

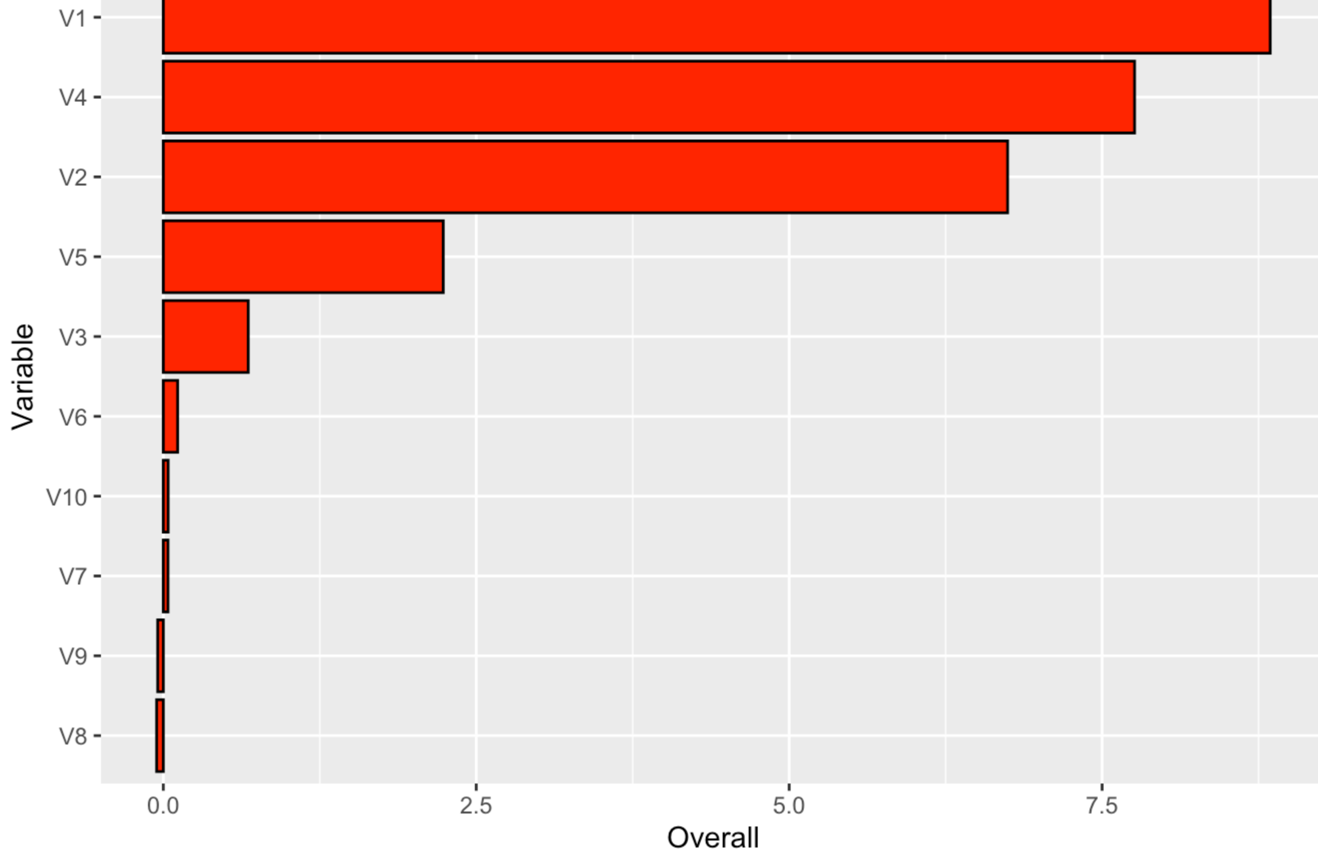
a. Fit a random forest model to all of the predictors, then estimate the variable importance scores:

```
model1 <- randomForest(y ~ ., data = simulated, importance = TRUE, ntree = 1000)
rfImp1 <- varImp(model1, scale = FALSE)
print(rfImp1)
```

```
        Overall
V1   8.84289608
V2   6.74508245
V3   0.67830653
V4   7.75934674
V5   2.23628276
V6   0.11429887
V7   0.03724747
V8  -0.05349642
V9  -0.04495617
V10  0.03863205
```

Did the random forest model significantly use the uninformative predictors (V6 - V10)?

```
rfImp1 %>%
  mutate (var = rownames(rfImp1)) %>%
  ggplot(aes(Overall, reorder(var, Overall, sum), var)) +
  geom_col(fill = 'red', colour = 'black') +
  labs(title = 'Model 1 Variable Importance' , y = 'Variable')
```



** The cumulative bar graph above shows that V6-10 were not significantly used in our random forest model.**

b. Now add an additional predictor that is highly correlated with one of the informative predictors. For example:

```
simulated$duplicate1 <- simulated$V1 + rnorm(200) * .1
cor(simulated$duplicate1, simulated$V1)
```

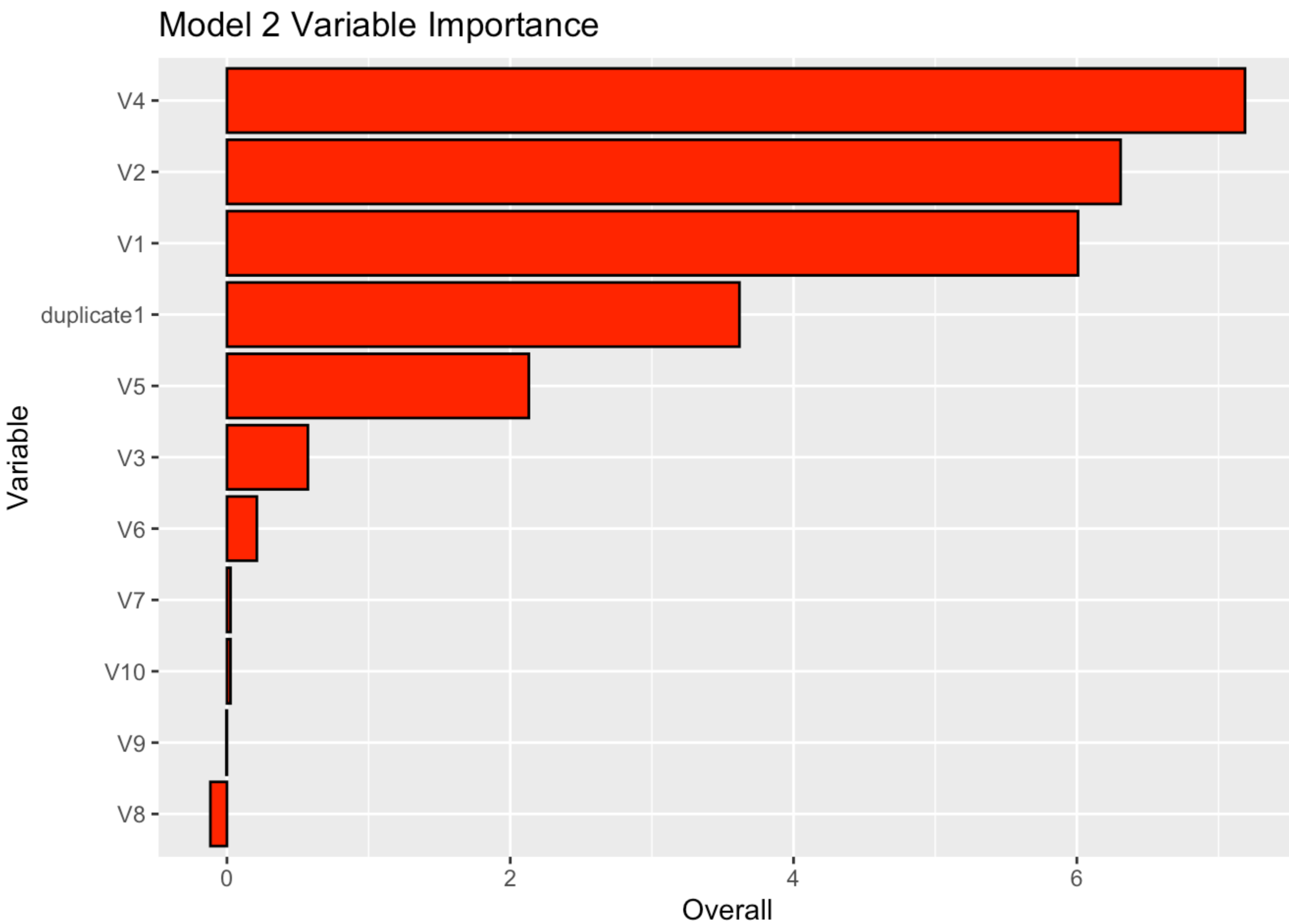
```
[1] 0.9396216
```

Fit another random forest model to these data. Did the importance score for V1 change? What happens when you add another predictor that is also highly correlated with V1?

```
rf_model2 <- randomForest(y ~ ., data = simulated, importance = TRUE, ntree = 1000)
rfImp2 <- varImp(rf_model2, scale = FALSE)
print(rfImp2)
```

```
                Overall
V1          6.008319352
V2          6.308908170
V3          0.571604465
V4          7.187015958
V5          2.131040245
V6          0.211304611
V7          0.025100355
V8         -0.116980037
V9         -0.003679481
V10         0.024878337
duplicate1  3.618101735
```

```
rfImp2 %>%
  mutate (var = rownames(rfImp2)) %>%
  ggplot(aes(Overall, reorder(var, Overall, sum), var)) +
  geom_col(fill = 'red', colour = 'black') +
  labs(title = 'Model 2 Variable Importance' , y = 'Variable')
```



The importance score for V1 decreased, but increased for the other variables when another highly correlated variable with V1 is added.

c. Use the cforest function in the party package to fit a random forest model using conditional inference trees. The party package function varimp can calculate predictor importance. The conditional argument of that function toggles between the traditional importance measure and the modified version. Do these importances show the same pattern as the traditional random forest model?

```
library(partykit)
library(party)

# Fit cforest model
set.seed(123)
cf_model <- cforest(y ~ ., data = simulated, controls = cforest_unbiased(ntree = 1000))

# Calculate variable importance
cf_varimp <- varimp(cf_model, conditional = FALSE)
print(cf_varimp)
```

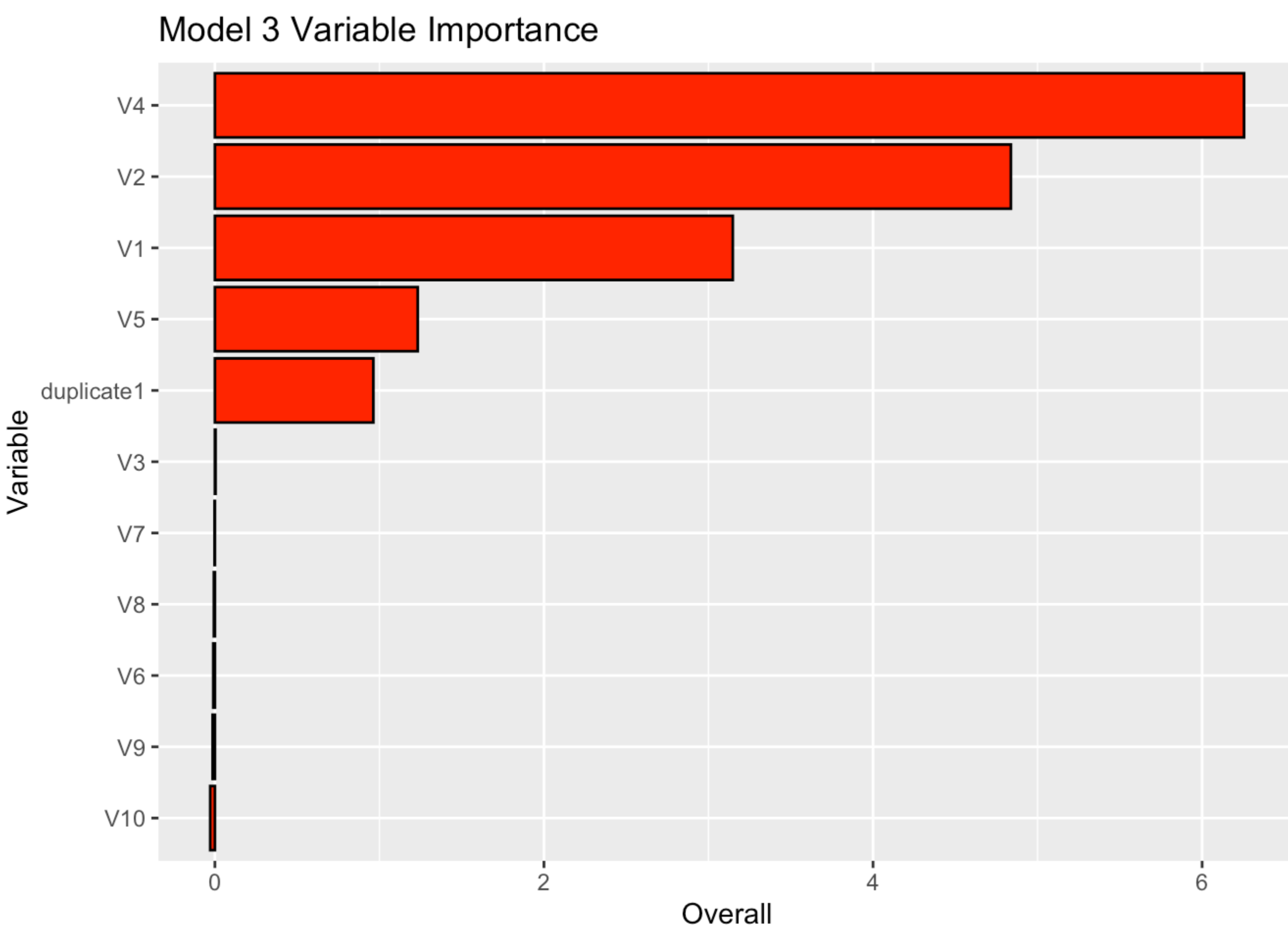
```
          V1          V2          V3          V4          V5          V6
```

```
6.762175680  6.011214623 -0.002809259  7.857594235  2.053362995  0.007422406
         V7           V8           V9          V10   duplicate1
0.033006890 -0.025242264  0.008089810 -0.057880930  2.773897304
```

```r
# Calculate conditional variable importance
cf_cond_varimp <- varimp(cf_model, conditional = TRUE)
print(cf_cond_varimp)
```

```
         V1           V2           V3           V4           V5           V6
3.186416009  4.786623908  0.004089477  6.277869376  1.186573199  0.009167534
         V7           V8           V9          V10   duplicate1
0.007945494 -0.019904985 -0.002481725 -0.021467387  1.006965608
```

```r
rf_model3 <- cforest(y ~ ., data = simulated)
rfImp3 <- varimp(rf_model3, conditional = TRUE) %>% as.data.frame()
rfImp3 %>%
  rename(Overall = '.') %>%
  mutate (var = rownames(rfImp3)) %>%
  ggplot(aes(Overall, reorder(var, Overall, sum), var)) +
  geom_col(fill = 'red', colour = 'black') +
  labs(title = 'Model 3 Variable Importance' , y = 'Variable')
```



** The pattern of importance remains the same and V6-V10 remain unimportant.**

d. Repeat this process with different tree models, such as boosted trees and Cubist. Does the same pattern occur?

```r
library(gbm)

# Fit gbm model
set.seed(123)
gbm_model <- train(y ~ ., data = simulated, method = "gbm", trControl = trainControl(method =

# Calculate variable importance
gbm_varimp <- varImp(gbm_model, scale = FALSE)
print(gbm_varimp)
```

```
gbm variable importance

           Overall
V4         4896.32
V2         3865.06
V1         3516.32
V5         1781.39
V3         1276.47
duplicate1  609.03
V7          170.98
V9          124.41
V6          101.75
V10         100.11
V8           76.49
```

```r
library(Cubist)

# Fit Cubist model
set.seed(123)
cubist_model <- train(y ~ ., data = simulated, method = "cubist", trControl = trainControl(me

# Calculate variable importance
cubist_varimp <- varImp(cubist_model, scale = FALSE)
print(cubist_varimp)
```

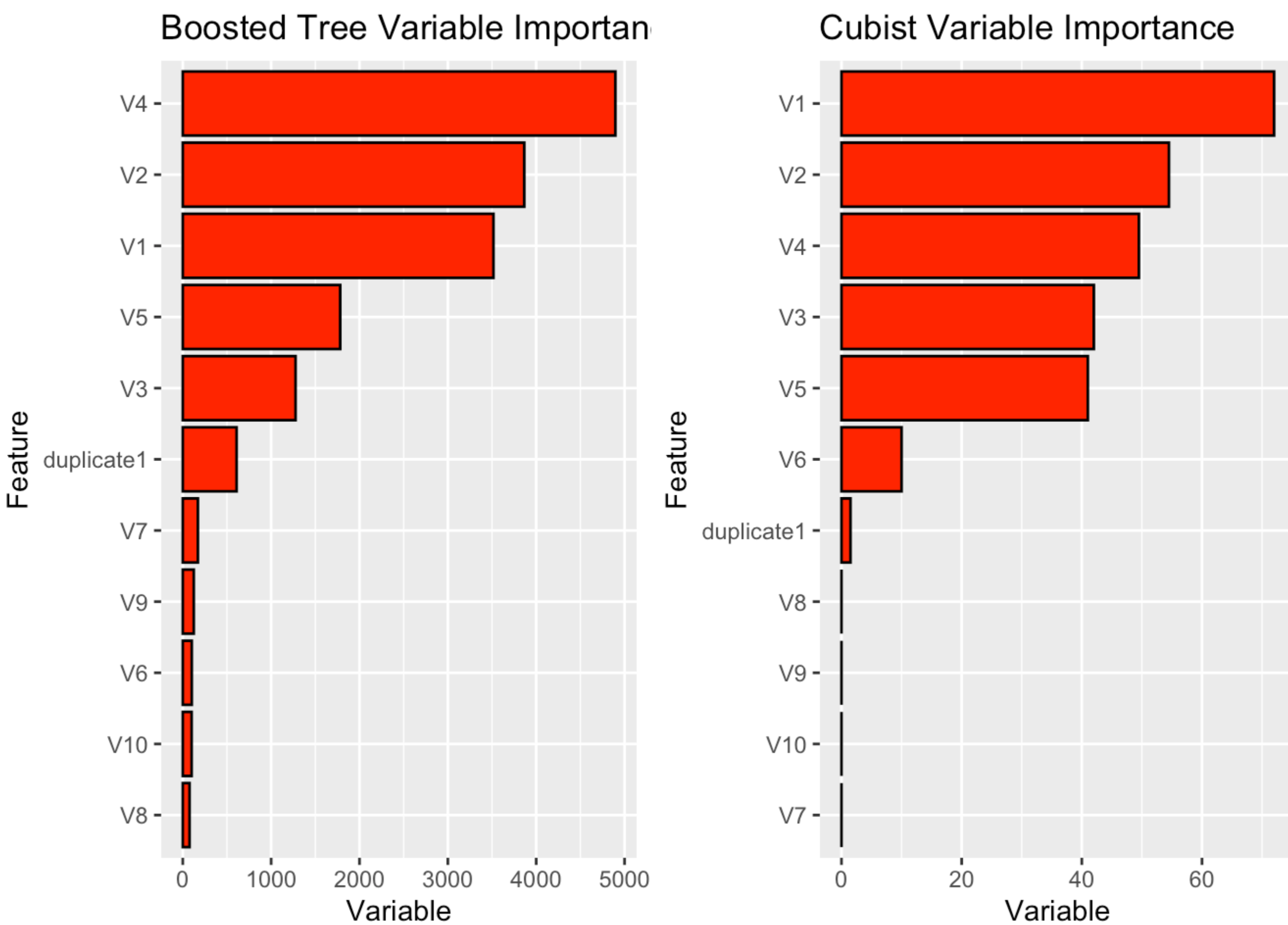
```
cubist variable importance

           Overall
V1            72.0
V2            54.5
V4            49.5
V3            42.0
V5            41.0
V6            10.0
duplicate1     1.5
V9             0.0
V7             0.0
V8             0.0
V10            0.0
```

```r
gbm_plot <- gbm_varimp %>%
  ggplot(aes(Overall, reorder(var, Overall, sum), var)) +
  geom_col(fill = 'red', colour = 'black') +
  labs(title = 'Boosted Tree Variable Importance' , y = 'Variable')
```

```
cubist_plot <- cubist_varimp %>%
  ggplot(aes(Overall, reorder(var, Overall, sum), var)) +
  geom_col(fill = 'red', colour = 'black') +
  labs(title = 'Cubist Variable Importance' , y = 'Variable')
```

```
library(ggpubr)
ggarrange(gbm_plot, cubist_plot)
```



V1-V5 are both significant predictors in the boosted tree and cubist models, but their patterns of importance differ. The ranked order (most -> least important) for the boosted tree model is V4, V2, V1, V5, and V3. The ranked order for the Cubist model is V1, V2, V4, V3, and V5.