test

Levi Lee

11/21/2020

Setup

First, we set working directories, install required libraries and import the data.

```r
setwd("~/Documents/GitHub/Fall2020-Project4-group-4/doc")
```

```r
packages.used <- c("dplyr", "ggplot2", "WeightedROC", "rpart", "rpart.plot")

# check packages that need to be installed.
packages.needed <- setdiff(packages.used, intersect(installed.packages()[,1], packages.used))

# install additional packages
if(length(packages.needed) > 0){
  install.packages(packages.needed, dependencies = TRUE)
}

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(ggplot2)
library(WeightedROC)
library(rpart)
library(rpart.plot)
```

```r
df_high <- read.csv("../data/highDim_dataset.csv")
df_low <- read.csv("../data/lowDim_dataset.csv")
```

Introduction

Description

About the Data

Description

Background: Trees

Description

Cross-Validation

Description

Step 1: Set Controls and Establish Hyperparameters

Description

```
K <- 5  # number of CV folds
sample.reweight <- TRUE # run sample reweighting in model training

# setting the following to false loads data generated from a previous run
# this data is the same in each run due to a set seed

run.cv.trees_high <- FALSE # run cross-validation on the training set for trees on high dim data

run.cv.trees_low <- FALSE # run cross-validation on the training set for trees on low dim data
```

Description

```
# hyperparameters for trees
hyper_grid_trees <- expand.grid(
  cp = c(2^(0), 2^(-1), 2^(-2), 2^(-3), 2^(-4),
         2^(-5), 2^(-6), 2^(-7), 2^(-8), 2^(-9),
         2^(-10), 2^(-11), 2^(-12), 2^(-13), 2^(-14),
         2^(-15), 2^(-16), 2^(-17), 0, -2^(0))
)
```

Step 2: Cross-Validate the Hyperparameters

Description

Description

```
# features are the predictors: V1 - Vp
# column 1 is the response Y
# column 2 is the treatment A

feature_train_high = df_high[, -1:-2]
label_train_high = df_high[, 2]

feature_train_low = df_low[, -1:-2]
label_train_low = df_low[, 2]
```

High Dimensional Data

Description

```
set.seed(5243)

if(run.cv.trees_high){
  res_cv_trees_high <- matrix(0, nrow = nrow(hyper_grid_trees), ncol = 4)
  for(i in 1:nrow(hyper_grid_trees)){
    cat("complexity = ", hyper_grid_trees$cp[i], "\n", sep = "")
```

```r
    res_cv_trees_high[i,] <- cv.function(features = feature_train_high, labels = label_train_high,
                                         cp = hyper_grid_trees$cp[i],
                                         K, reweight = sample.reweight)
  save(res_cv_trees_high, file = "../output/res_cv_trees_high.RData")
  }
}else{
  load("../output/res_cv_trees_high.RData")
}
```

Low Dimensional Data

Description

```r
set.seed(5243)

if(run.cv.trees_low){
  res_cv_trees_low <- matrix(0, nrow = nrow(hyper_grid_trees), ncol = 4)
  for(i in 1:nrow(hyper_grid_trees)){
    cat("complexity = ", hyper_grid_trees$cp[i], "\n", sep = "")
    res_cv_trees_low[i,] <- cv.function(features = feature_train_low, labels = label_train_low,
                                        cp = hyper_grid_trees$cp[i],
                                        K, reweight = sample.reweight)
  save(res_cv_trees_low, file="../output/res_cv_trees_low.RData")
  }
}else{
  load("../output/res_cv_trees_low.RData")
}
```

Step 3: Visualize CV Error and AUC

Description

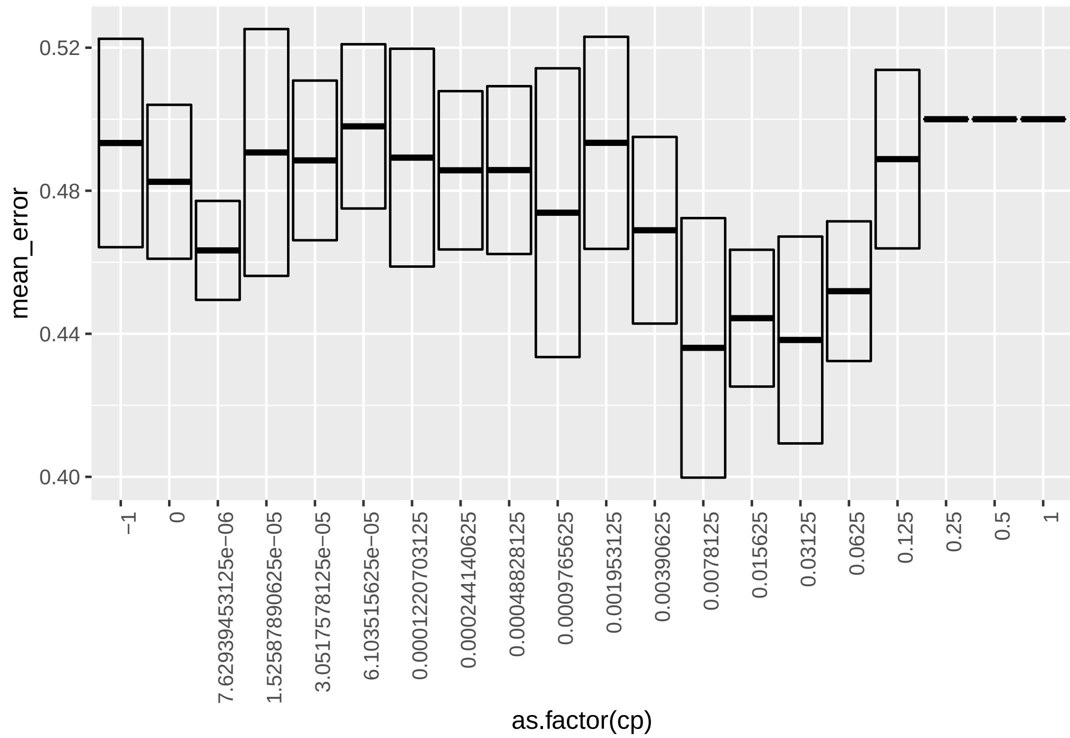
High Dimensional Data

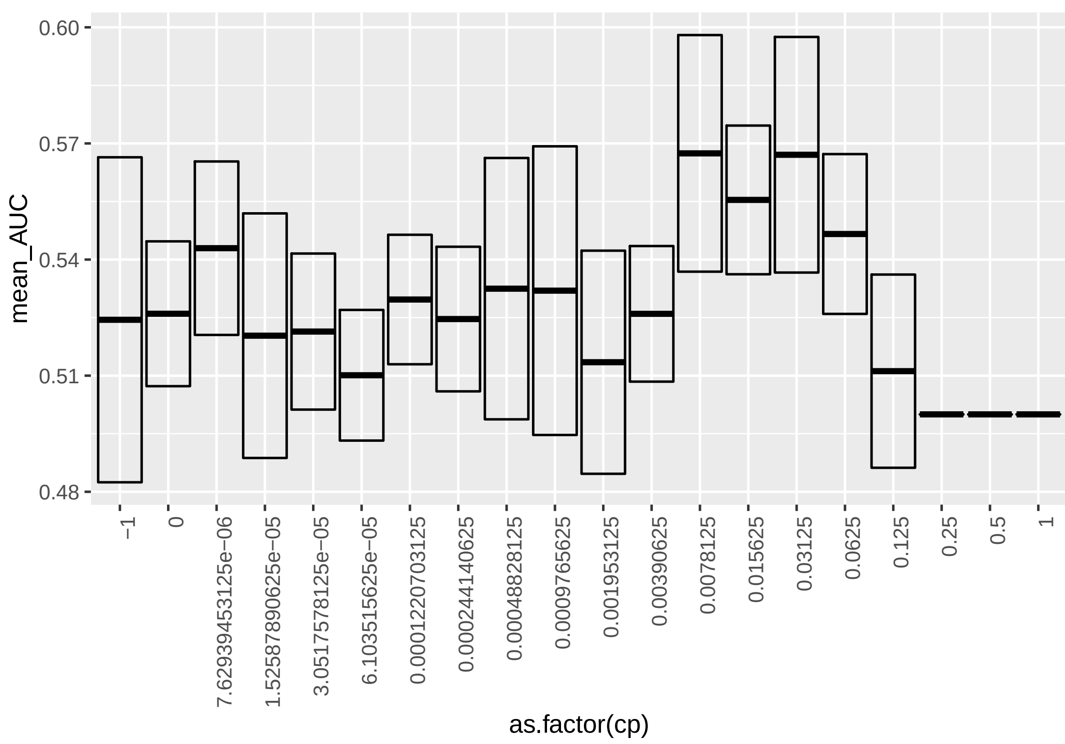
Description

```r
# create data frame to organize results
res_cv_trees_high <- as.data.frame(res_cv_trees_high)
colnames(res_cv_trees_high) <- c("mean_error", "sd_error", "mean_AUC", "sd_AUC")
cv_results_trees_high = data.frame(hyper_grid_trees, res_cv_trees_high)

# look at top 5 models with highest AUC
cv_results_trees_high[order(cv_results_trees_high$mean_AUC, decreasing = TRUE), ][1:5, ]
```

```
##                cp mean_error   sd_error  mean_AUC     sd_AUC
## 8  7.812500e-03  0.4360668 0.03628091 0.5674343 0.03056252
## 6  3.125000e-02  0.4382665 0.02892494 0.5670732 0.03043522
## 7  1.562500e-02  0.4443627 0.01912652 0.5554088 0.01920727
## 5  6.250000e-02  0.4519064 0.01953579 0.5466031 0.02064263
## 18 7.629395e-06  0.4633120 0.01383644 0.5429351 0.02240466
```






```r
best_cp_high <- cv_results_trees_high$cp[cv_results_trees_high$mean_AUC ==
                                          max(cv_results_trees_high$mean_AUC)]

best_cp_high
```

```
## [1] 0.0078125
```

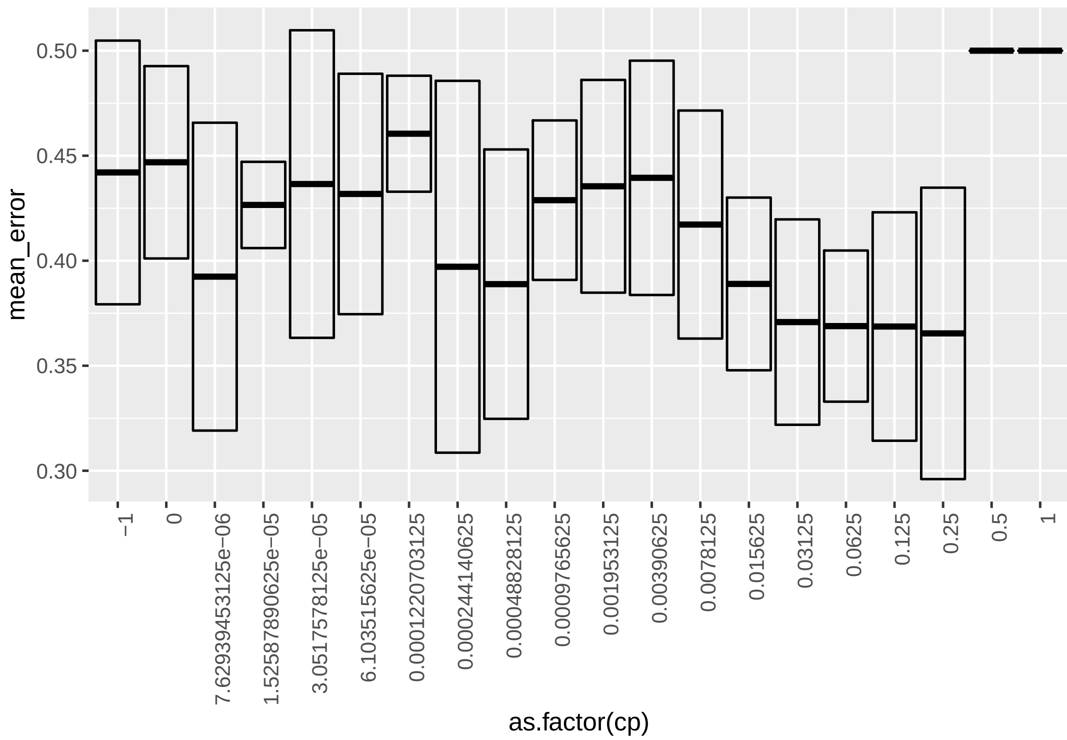
Low Dimensional Data

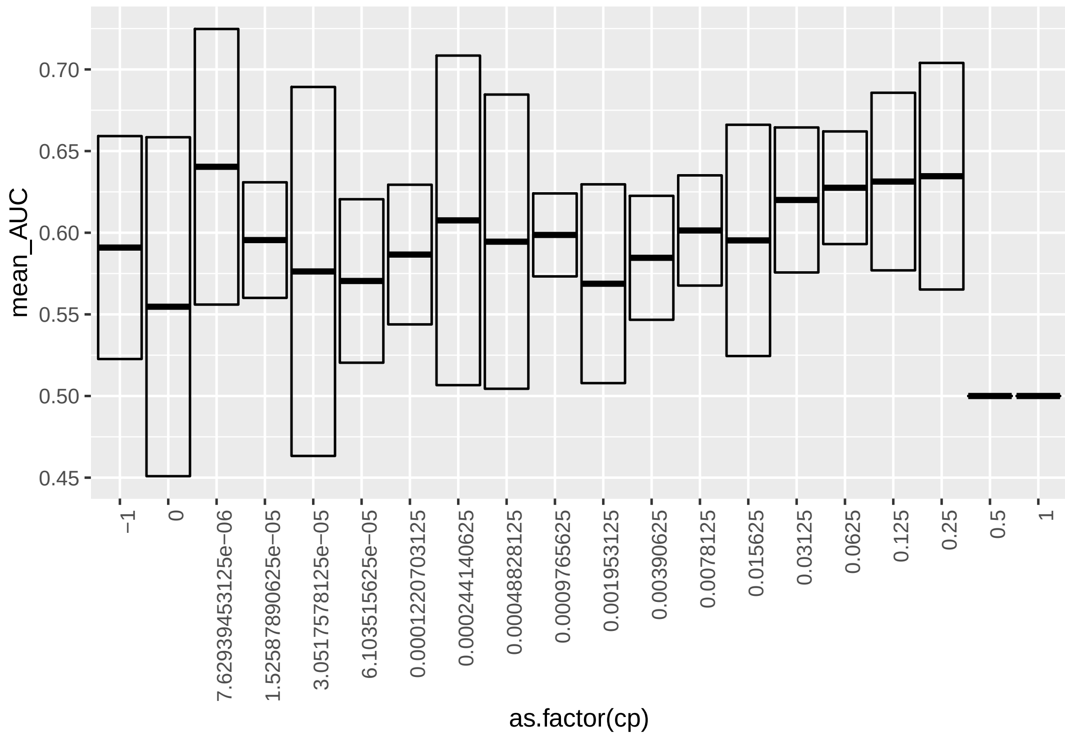
Description

```r
# create data frame to organize results
res_cv_trees_low <- as.data.frame(res_cv_trees_low)
colnames(res_cv_trees_low) <- c("mean_error", "sd_error", "mean_AUC", "sd_AUC")
cv_results_trees_low = data.frame(hyper_grid_trees, res_cv_trees_low)

# look at top 5 models with lowest AUC
cv_results_trees_low[order(cv_results_trees_low$mean_AUC, decreasing = TRUE), ][1:5, ]
```

```
##              cp mean_error   sd_error  mean_AUC     sd_AUC
## 18 7.629395e-06  0.3924126 0.07329778 0.6403787 0.08438962
## 3  2.500000e-01  0.3653965 0.06938198 0.6346035 0.06938198
## 4  1.250000e-01  0.3686625 0.05437925 0.6313375 0.05437925
## 5  6.250000e-02  0.3688654 0.03598451 0.6275346 0.03449488
## 6  3.125000e-02  0.3707763 0.04889355 0.6200507 0.04439815
```






```
best_cp_low <- cv_results_trees_low$cp[cv_results_trees_low$mean_AUC ==
                                         max(cv_results_trees_low$mean_AUC)]

best_cp_low
```

```
## [1] 7.629395e-06
```

Propensity Score Estimation

Description

```
# imbalanced dataset requires weights
# to be used in the trained model

weights_high <- rep(NA, length(df_high$A))
for (v in unique(df_high$A)){
  weights_high[df_high$A == v] = 0.5 * length(df_high$A) / length(df_high$A[df_high$A == v])
}


weights_low <- rep(NA, length(df_low$A))
for (v in unique(df_low$A)){
  weights_low[df_low$A == v] = 0.5 * length(df_low$A) / length(df_low$A[df_low$A == v])
}
```

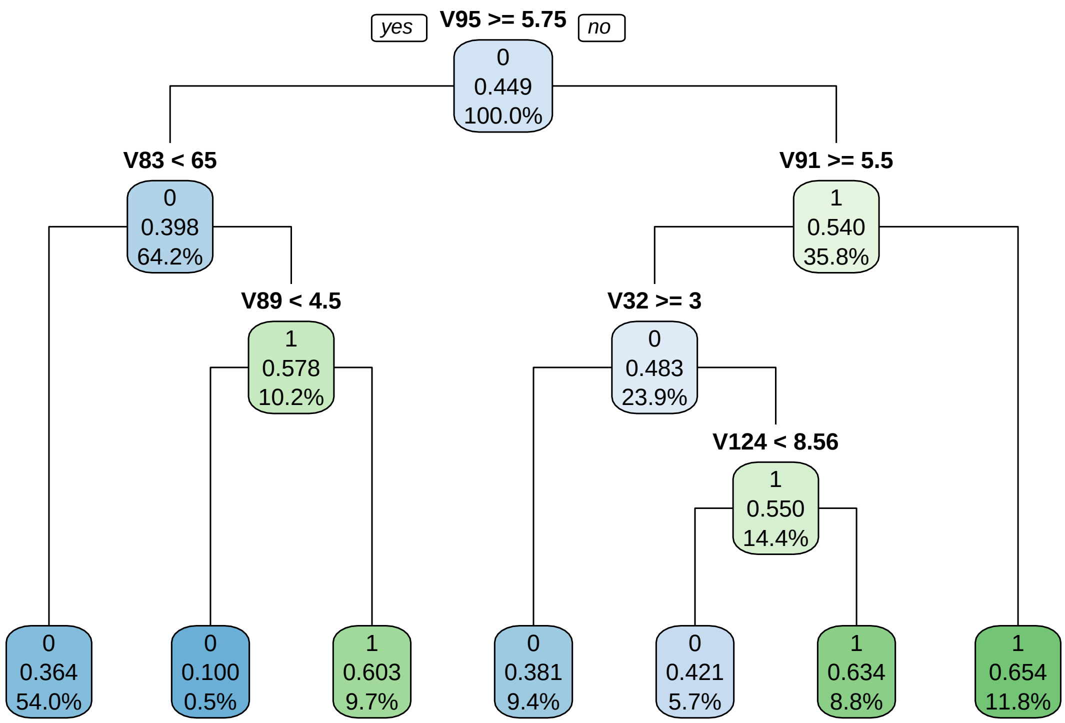
High Dimensional Data

```
############### SET START TIME HERE

# create tree model for high dimensional data with best cp parameter
tree_high <- rpart(A ~ . - Y, method = "class", data = df_high, cp = best_cp_high)
```

```r
# calculate propensity scores
prop_score_high <- predict(tree_high, newdata = df_high[, -2], type = "prob")[, 2]

############### SET END TIME HERE
```



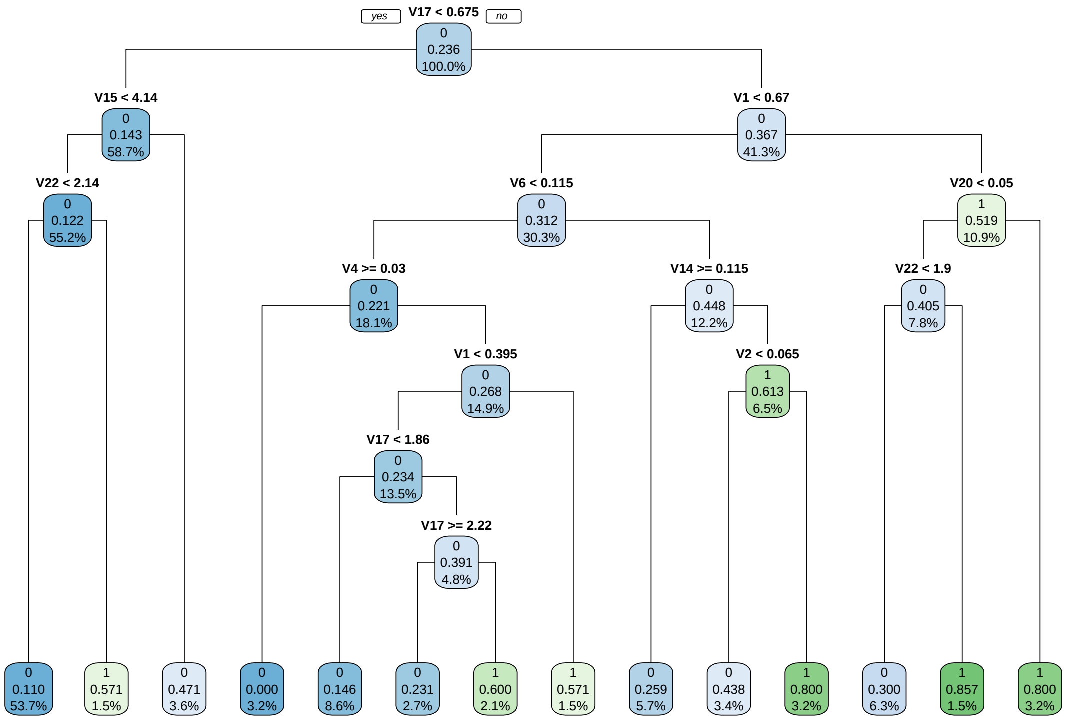
Low Dimensional Data

```r
############### SET START TIME HERE

# create tree model for low dimensional data with best cp parameter
tree_low <- rpart(A ~ . - Y, method = "class", data = df_low, cp = best_cp_low)

# calculate propensity scores
prop_score_low <- predict(tree_low, newdata = df_low[, -2], type = "prob")[, 2]

############### SET END TIME HERE
```



ATE Estimation

Description

Stratification

Description

```
K = 5
quintiles <- seq(0, 1, by = 1/K)
```

High Dimensional Data

Description Also need run times here

Low Dimensional Data

Description Also need run times here

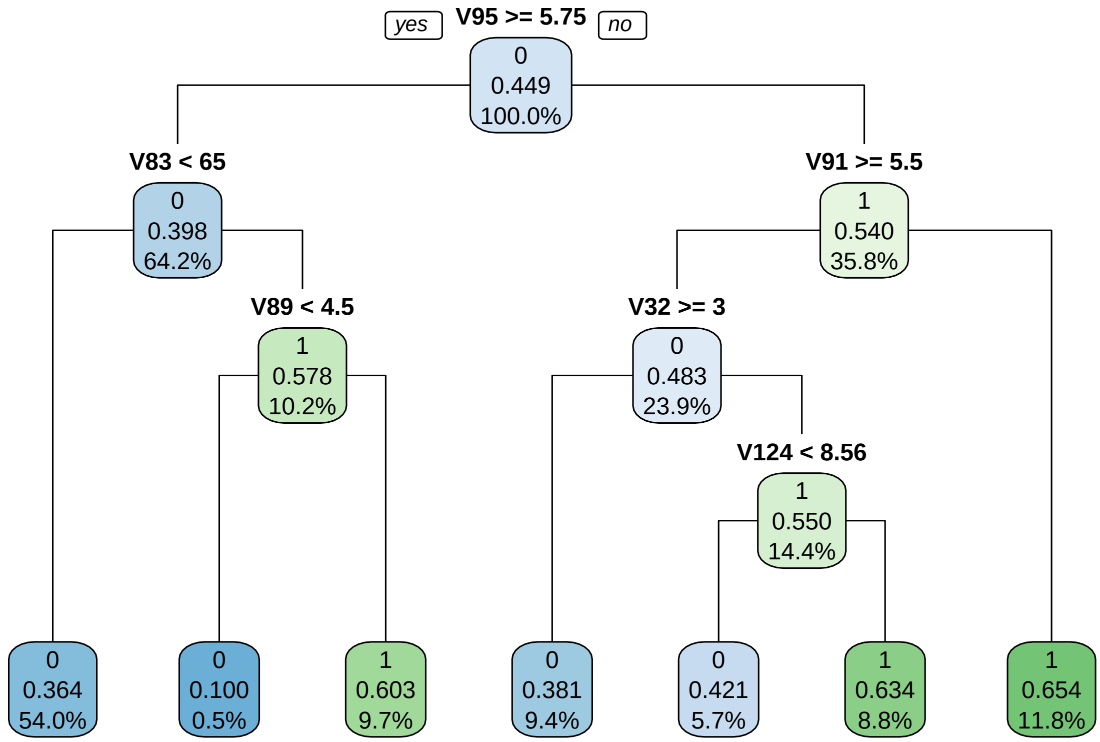
Regression Adjustment

Description

High Dimensional Data

Description Also need run times here

```
regression_adjustment_high <- rpart(A ~ . - Y, data = df_high, method = "class", cp = 7.812500e-03)
rpart.plot(regression_adjustment_high, type = 1, digits = 3, fallen.leaves = TRUE)
```




```r
ps_RA_high <- predict(regression_adjustment_high, df_high, type = "prob")
high_data_ps <- cbind(ps_RA_high, df_high)
pred_high <- lm(Y ~ A + ps_RA_high, data = high_data_ps)
summary(pred_high)
```

```
##
## Call:
## lm(formula = Y ~ A + ps_RA_high, data = high_data_ps)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -17.4713  -3.4878  -0.6694   2.7522  30.0897
##
## Coefficients: (1 not defined because of singularities)
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    5.9564     0.6207   9.596   <2e-16 ***
## A             -2.5271     0.2569  -9.836   <2e-16 ***
## ps_RA_high0  -30.5718     1.0322 -29.617   <2e-16 ***
## ps_RA_high1        NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.535 on 1997 degrees of freedom
## Multiple R-squared:  0.3068, Adjusted R-squared:  0.3061
## F-statistic: 441.8 on 2 and 1997 DF,  p-value: < 2.2e-16
```

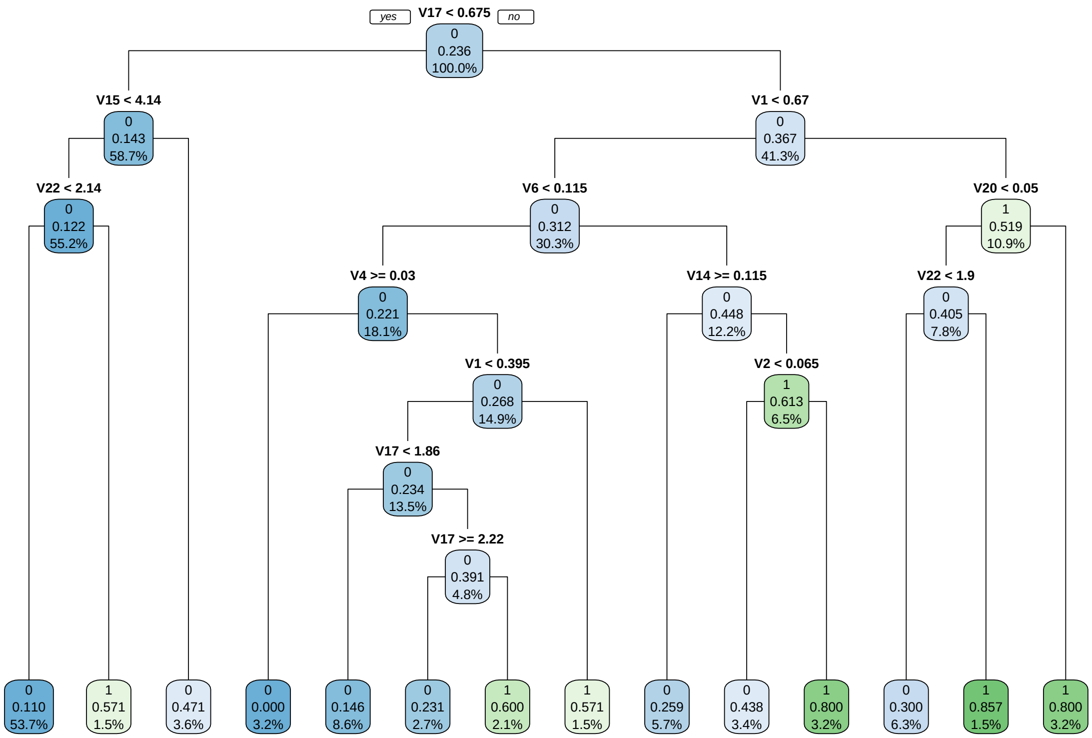
```r
ATE_RA_high = pred_high$coefficients[2]
ATE_RA_high
```

```
##         A
## -2.527116
```

Low Dimensional Data

Description Also need run times here

```r
regression_adjustment_low <- rpart(A ~ . - Y, data = df_low, method = "class", cp = 7.629395e-06)
rpart.plot(regression_adjustment_low, type = 1, digits = 3, fallen.leaves = TRUE)
```




```r
ps_RA_low <- predict(regression_adjustment_low, df_low, type = "prob")
low_data_ps <- cbind(ps_RA_low, df_low)
pred_low <- lm(Y ~ A + ps_RA_low, data = low_data_ps)
summary(pred_low)
```

```
##
## Call:
## lm(formula = Y ~ A + ps_RA_low, data = low_data_ps)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.5153  -2.6807  -0.5655   1.8184  26.9282
##
## Coefficients: (1 not defined because of singularities)
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  22.5693     0.8535  26.445  < 2e-16 ***
## A             3.0532     0.5089   5.999 3.95e-09 ***
## ps_RA_low0   -7.5200     1.0017  -7.507 3.04e-13 ***
## ps_RA_low1        NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.055 on 472 degrees of freedom
## Multiple R-squared:  0.2829, Adjusted R-squared:  0.2798
## F-statistic: 93.08 on 2 and 472 DF,  p-value: < 2.2e-16
```

```r
ATE_RA_low = pred_low$coefficients[2]
ATE_RA_low
```

```
##       A
## 3.05324
```

Stratification and Regression Adjustment

Description

High Dimensional Data

Description Also need run times here

Low Dimensional Data

Description Also need run times here

Results

Insert Comparison of ATE and all Runtimes Here

Conclusion

Description

References

Description