PSTAT 131 Final Project

Micheal Alexander, Sriharsha Addepalli

3/23/2018

Background

1) Voting behavior predition is a hard problem because the data is based off of human behavior. The human behavior is complex and there is no easy way to predict what decisions humans are going to make. Additionally, there are many factors that influence a person's voting behavior such as race, gender, political views, location, etc. In addition, there are some factors that are hard to collect information about such as what media they consume, how they are influenced by media, opinions affected by friends, family, and others, etc. People also tend to change their mind about who they are voting for, which adds another factor of unpredictability.

2) Nate Silver was able to make accurate predictions because he made a model that was very adjustable. He took the variables that could be easily affected just by random, and made new predictions based on that so his model adjusts by time. He also made it so that he can predict what the future voting behavior is going to look like by measuring uncertainty as a random factor, making it possible to generate varied predictions for voting behavior in each state with some accuracy. Silver also measured variance and looked at the range of variance to compute probability that a candidate would win each day. Using this, he was able to predict what the results would be at the actual election.

3) Several things went wrong in the 2016 election polling results. First of all, there is polling error such as nonresponse bias and statistical noise. Also, response bias was also prevalent as a lot of Trump supporters did not want to admit to the fact that they are voting for Trump, undermining the polling results, and there were many people who were undecided which led to a large error rate in polling results as well. Future predictions can be made better by improving the bias-variance tradeoff and decreasing nonresponse and response biases. Additionally, predictions have to take into account all voters stances in order to reduce undermining of certaing presidential candidates.

Data

```
election.raw = read.csv("~/final-project/data/election/election.csv") %>% as.tbl
census_meta = read.csv("~/final-project/data/census/metadata.csv", sep = ";") %>% as.tbl
census = read.csv("~/final-project/data/census/census.csv") %>% as.tbl
census$CensusTract = as.factor(census$CensusTract)
```

Data Wrangling

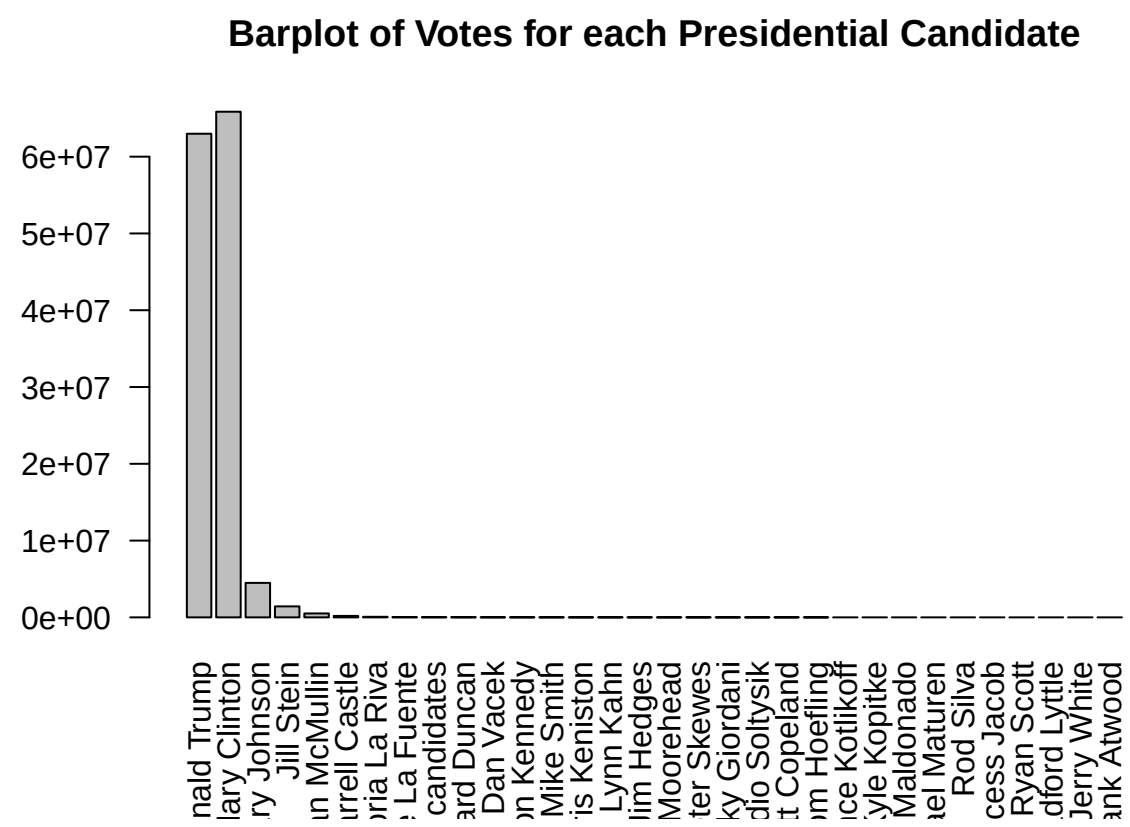
4)

```
election_federal <- filter(election.raw, state == "US")
election_state_no <- filter(election.raw[33:18351,], is.na(county))
election_no <- filter(election.raw, county != 'NA')
election_state <- election_state_no[1:286,] %>% rbind(election_state_no[293:308,])
election <- election_no %>% rbind(election_state_no[287:292,]) %>% rbind(election_state_no[309:312,])
```

There were 31 presidential candidates in the 2016 election.

5)

```
barplot(names.arg = election_federal$candidate, height = election_federal$votes, las = 2,
        main = "Barplot of Votes for each Presidential Candidate")
```



6)

```
county_winner <- election  %>% group_by(fips) %>% mutate(pct = votes/sum(votes)) %>% top_n(n = 1)
```

```
## Selecting by pct
```

```
#creates winner by each county
state_winner <- election_state %>% group_by(fips) %>% mutate(pct = votes/sum(votes)) %>% top_n(n = 1)
```

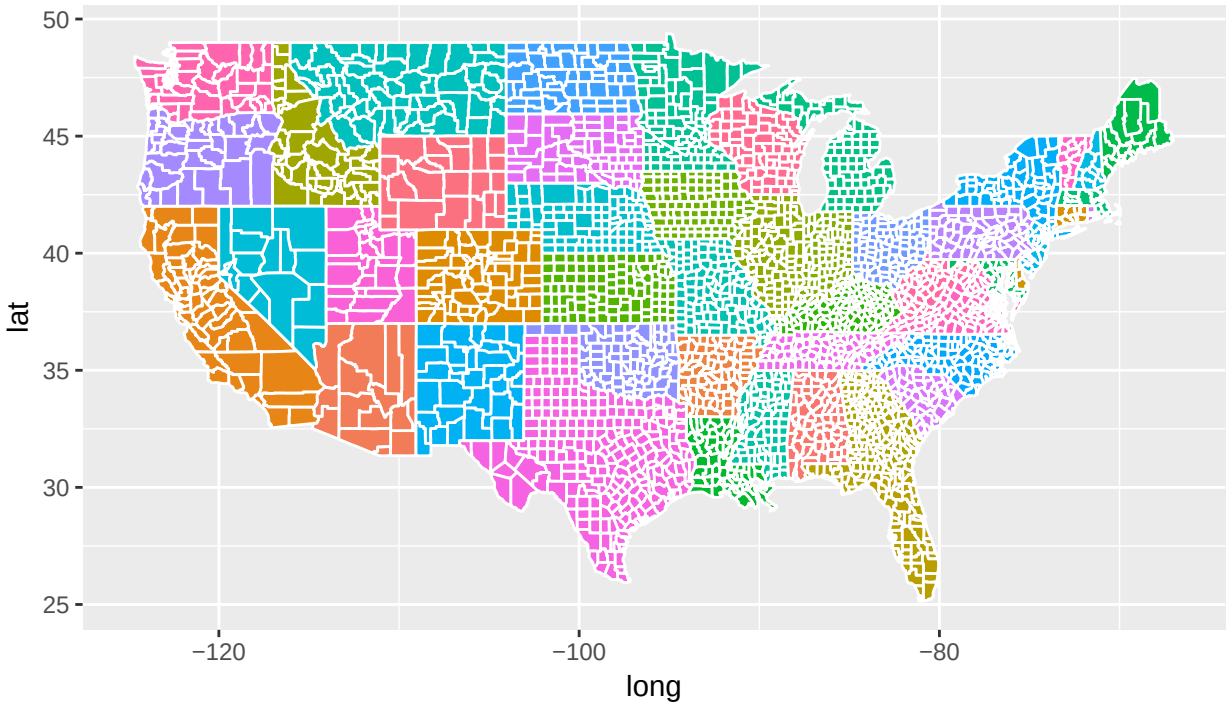
```
## Selecting by pct
```

```
#creates winner by each state
```

Visualization

7)

```
counties = map_data("county")

ggplot(data = counties) +
  geom_polygon(aes(x = long, y = lat, fill = region, group = group), color = "white") +
  coord_fixed(1.3) +
  guides(fill=FALSE)
```



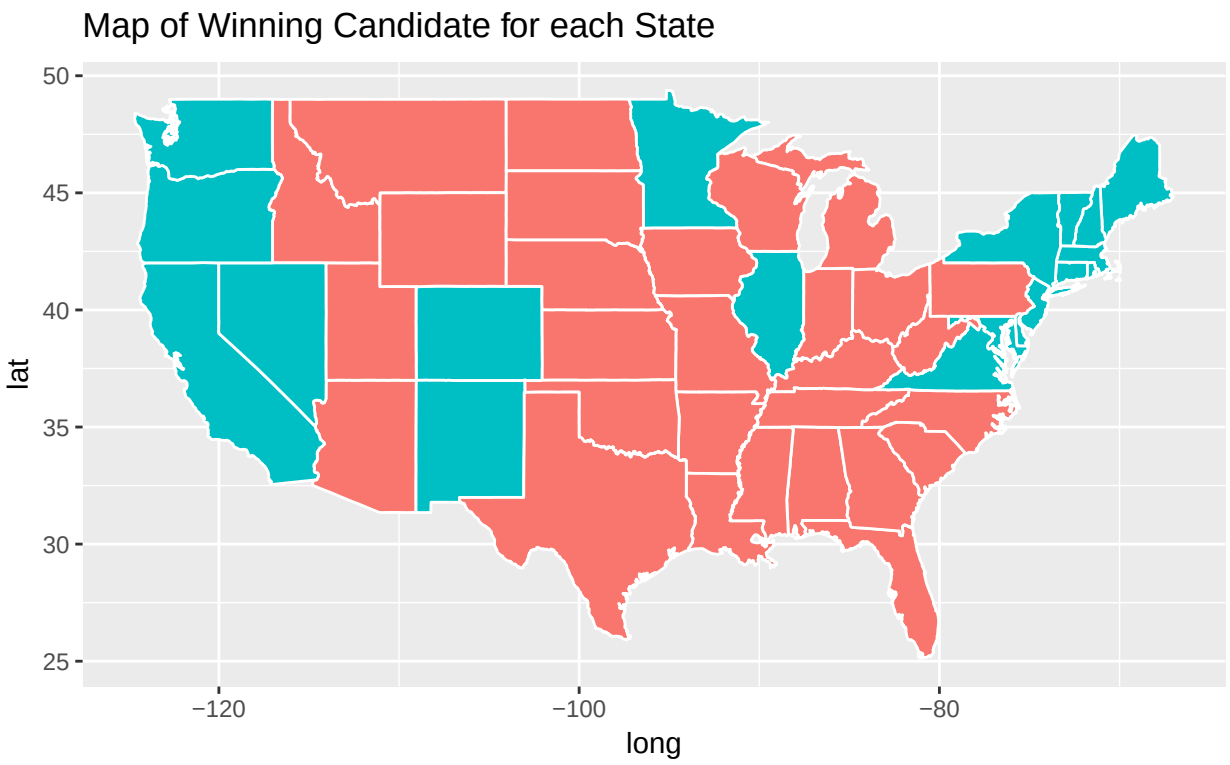
8)

```
states = map_data("state")
states <- states %>% mutate(fips = state.abb[match(region, tolower(state.name))])
statesplot <- left_join(states,state_winner)
```

```
## Joining, by = "fips"
```

```
## Warning: Column `fips` joining character vector and factor, coercing into
## character vector
```

```
ggplot(data = statesplot) +
  geom_polygon(aes(x = long, y = lat, fill = candidate, group = group), color = "white") +
  coord_fixed(1.3) +
  guides(fill=FALSE) +
  ggtitle("Map of Winning Candidate for each State")
```



9)

```
region <- c()
for (i in 1:3085){
  region = c(region,strsplit(maps::county.fips$polyname, ',')[[i]][1])
}
subregion <- c()
for (i in 1:3085){
  subregion = c(subregion,strsplit(maps::county.fips$polyname, ',')[[i]][2])
}
countyregion <- maps::county.fips
countyregion <- countyregion %>% cbind(region) %>% cbind(subregion)
countyleft <- left_join(countyregion,counties)
```

```
## Joining, by = c("region", "subregion")
```

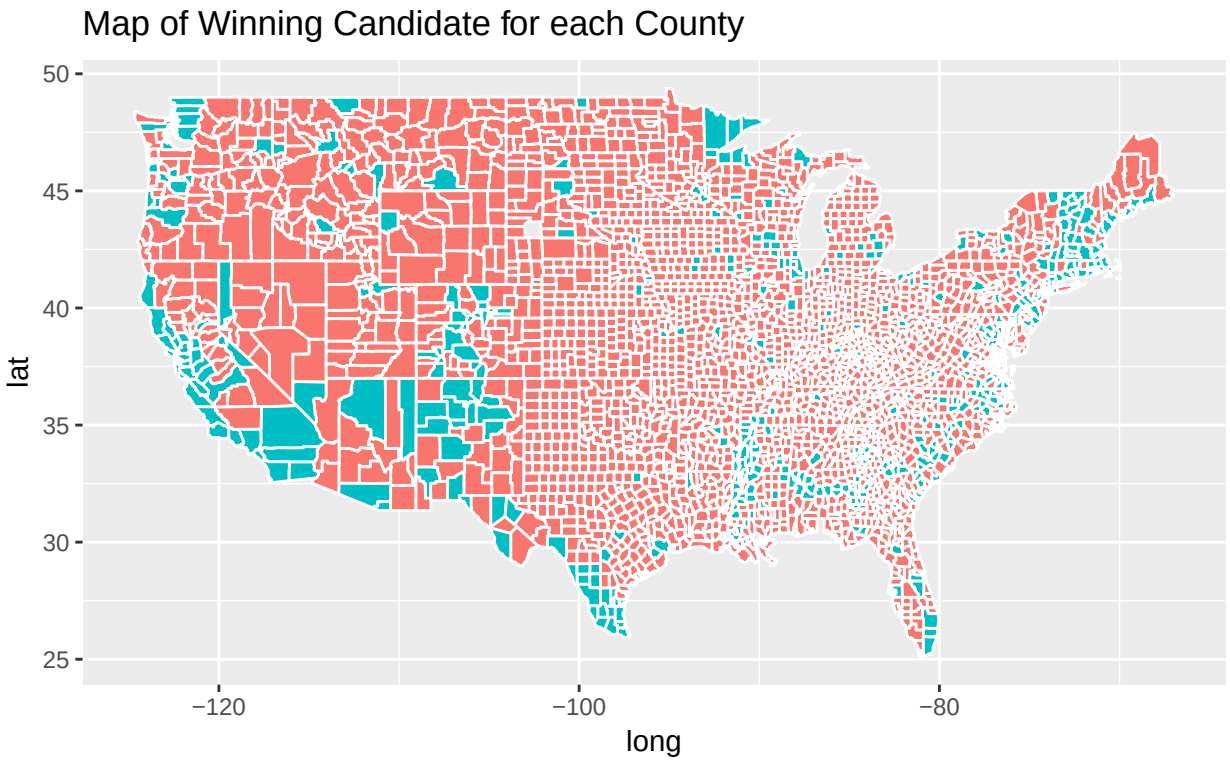
```
## Warning: Column `region` joining factor and character vector, coercing into
## character vector
```

```
## Warning: Column `subregion` joining factor and character vector, coercing
## into character vector
```

```
countywinnerstrings <- county_winner
countyleftstrings <- countyleft
countywinnerstrings$fips <- as.character(countywinnerstrings$fips)
countyleftstrings$fips <- as.character(countyleftstrings$fips)
countyleft2 <- left_join(countywinnerstrings,countyleftstrings)
```

```
## Joining, by = "fips"
```

```
ggplot(data = countyleft2) +
  geom_polygon(aes(x = long, y = lat, fill = candidate, group = group), color = "white") +
  coord_fixed(1.3) +
  guides(fill=FALSE) +
  ggtitle("Map of Winning Candidate for each County")
```



10 and 11)

```
census.del <- na.omit(census)
census.del$Men <- census.del$Men/sum(census.del$Men)
census.del$Citizen <- census.del$Citizen/sum(census.del$Citizen)
census.del$Employed <- census.del$Employed/sum(census.del$Employed)
census.del <- mutate(census.del, Minority = Hispanic + Black + Native + Asian + Pacific)
census.del <- select(census.del, -c(Walk, PublicWork, Construction))

census.subct <- census.del %>% group_by(State,County) %>% add_tally() %>% mutate(weight = TotalPop/n)

census.ct <- census.subct %>% summarize_at(vars(TotalPop:weight), sum)

head(census.ct)
```

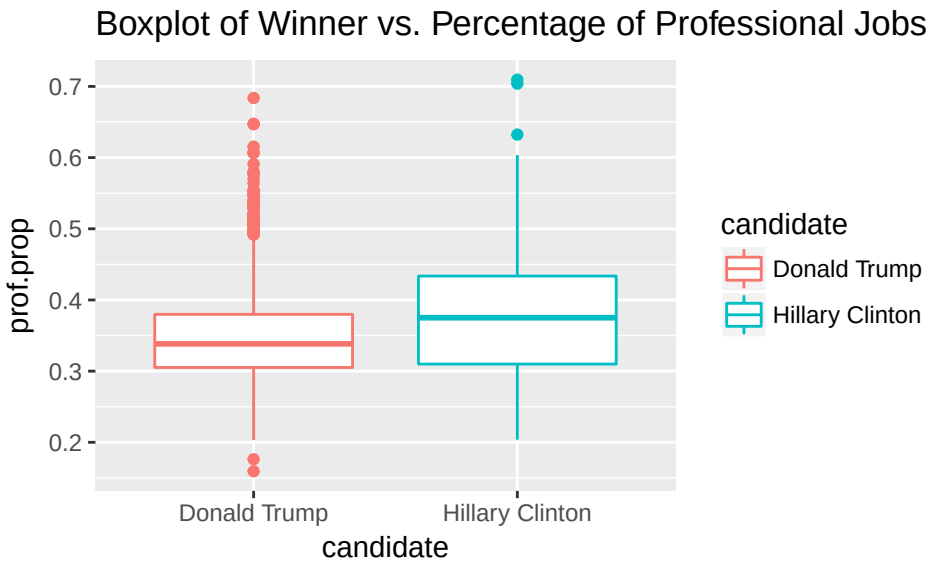
```
## # A tibble: 6 x 36
## # Groups:   State [1]
##     State  County TotalPop          Men Women Hispanic  White Black Native
##    <fctr>  <fctr>    <int>        <dbl> <int>    <dbl>  <dbl> <dbl>  <dbl>
## 1 Alabama Autauga    55221 1.707379e-04 28476     34.2  877.8 249.9    6.8
## 2 Alabama Baldwin   195121 6.084768e-04 99807    126.0 2587.1 298.4   18.6
```

```
## 3 Alabama Barbour    26932 9.254767e-05 12435     43.2  419.5 418.4    1.3
## 4 Alabama    Bibb    22604 7.707305e-05 10531      9.9  310.0  70.9    1.8
## 5 Alabama  Blount    57710 1.820183e-04 29198     80.0  790.2  12.2    2.5
## 6 Alabama Bullock    10678 3.613298e-05  5018      8.3   66.0 217.4    4.1
## # ... with 27 more variables: Asian <dbl>, Pacific <dbl>, Citizen <dbl>,
## #   Income <dbl>, IncomeErr <int>, IncomePerCap <int>,
## #   IncomePerCapErr <int>, Poverty <dbl>, ChildPoverty <dbl>,
## #   Professional <dbl>, Service <dbl>, Office <dbl>, Production <dbl>,
## #   Drive <dbl>, Carpool <dbl>, Transit <dbl>, OtherTransp <dbl>,
## #   WorkAtHome <dbl>, MeanCommute <dbl>, Employed <dbl>,
## #   PrivateWork <dbl>, SelfEmployed <dbl>, FamilyWork <dbl>,
## #   Unemployment <dbl>, Minority <dbl>, n <int>, weight <dbl>
```

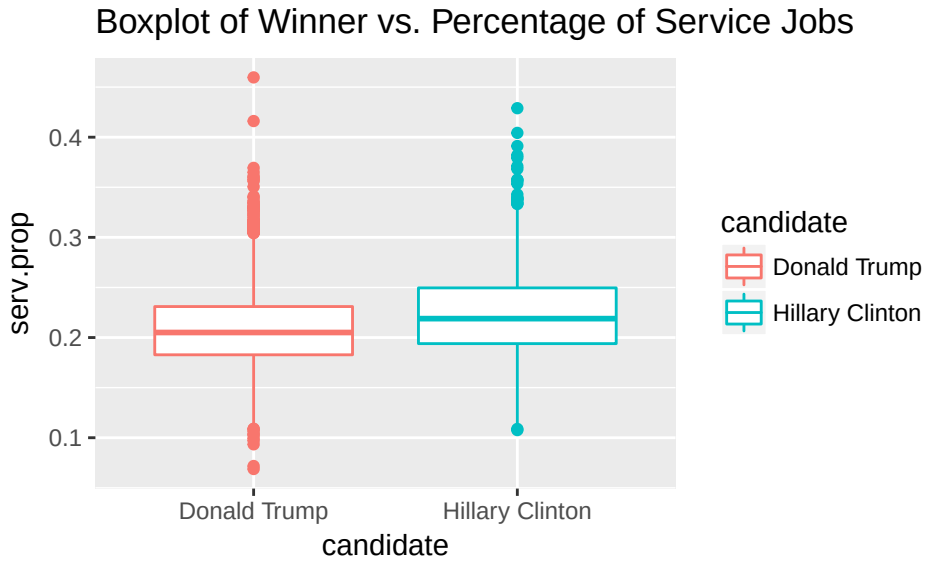
```
tmpwinner = county_winner %>% ungroup %>%
  mutate(state = state.name[match(state, state.abb)]) %>%               ## state abbreviations
  mutate_at(vars(state, county), tolower) %>%                           ## to all lowercase
  mutate(county = gsub(" county| columbia| city| parish", "", county))  ## remove suffixes
tmpcensus = census.ct %>% ungroup %>% mutate_at(vars(State, County), tolower)

election.cl = tmpwinner %>%
  left_join(tmpcensus, by = c("state"="State", "county"="County")) %>%
  na.omit

## saves meta information to attributes
attr(election.cl, "location") = election.cl %>% select(c(county, fips, state, votes, pct))
election.cl = election.cl %>% select(-c(county, fips, state, votes, pct))
```

```
election.cl.jobs <- election.cl %>%
  mutate(prof.prop = Professional/(Professional+Service+Office+Production)) %>%
  mutate(serv.prop = Service/(Professional+Service+Office+Production)) %>%
  mutate(office.prop = Office/(Professional+Service+Office+Production)) %>%
  mutate(prod.prop = Production/(Professional+Service+Office+Production))

p <- (ggplot(election.cl.jobs,aes(candidate,prof.prop,color=candidate)) + geom_boxplot() +
        ggtitle("Boxplot of Winner vs. Percentage of Professional Jobs"))
s <- (ggplot(election.cl.jobs,aes(candidate,serv.prop,color=candidate)) + geom_boxplot() +
        ggtitle("Boxplot of Winner vs. Percentage of Service Jobs"))
o <- (ggplot(election.cl.jobs,aes(candidate,office.prop,color=candidate)) + geom_boxplot() +
        ggtitle("Boxplot of Winner vs. Percentage of Office Jobs"))
pro <- (ggplot(election.cl.jobs,aes(candidate,prod.prop,color=candidate)) + geom_boxplot() +
        ggtitle("Boxplot of Winner vs. Percentage of Production Jobs"))
```

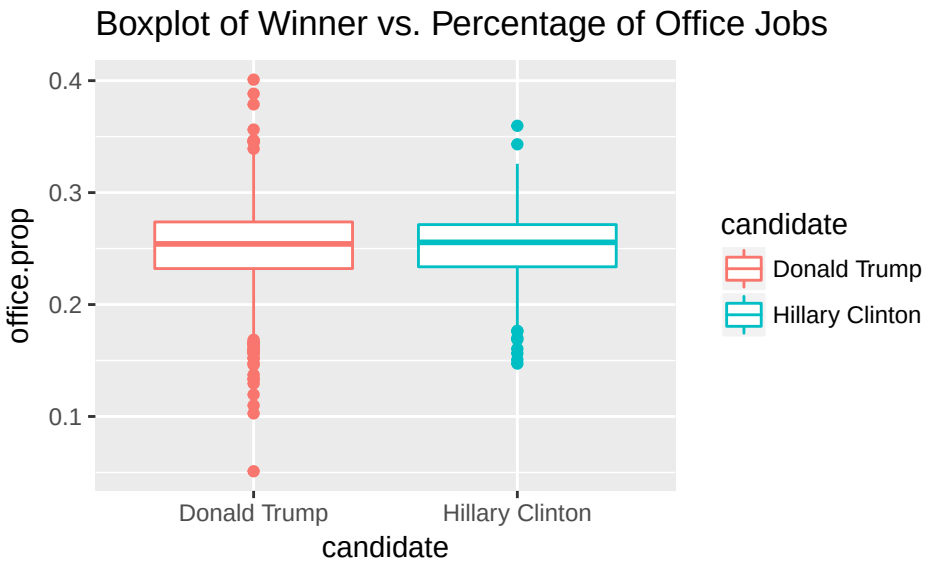
```
p
```


Boxplot of Winner vs. Percentage of Professional Jobs
prof.prop
0.7
0.6
0.5
0.4
0.3
0.2
Donald Trump
Hillary Clinton
candidate
candidate
Donald Trump
Hillary Clinton

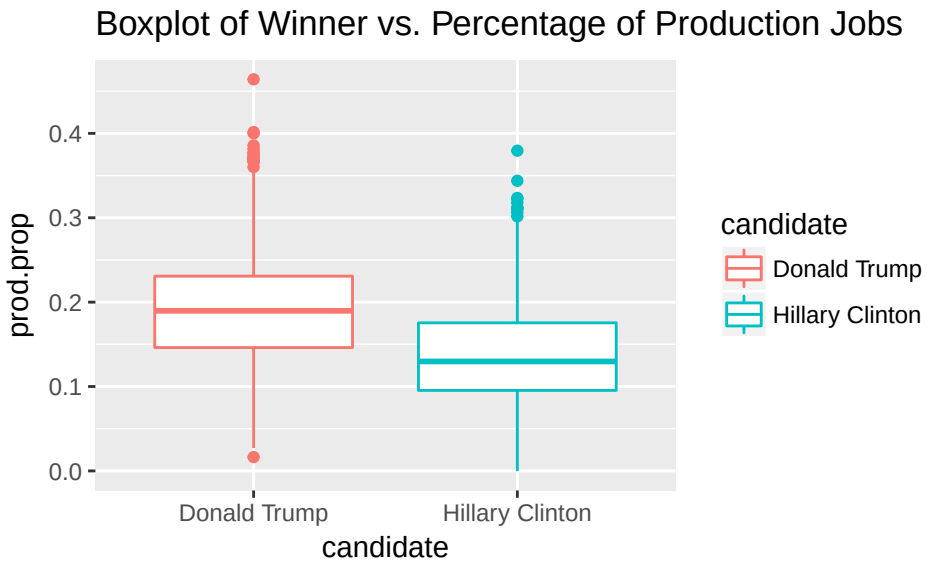
s


Boxplot of Winner vs. Percentage of Service Jobs
serv.prop
0.4
0.3
0.2
0.1
Donald Trump
Hillary Clinton
candidate
candidate
Donald Trump
Hillary Clinton

o




```
pro
```



These boxplots show the winning candidate for each county based on the profession (professional, service, office, and production). For the boxplot of candidate versus professional jobs and candidate versus service jobs, we observed that the quantiles are slightly higher for Clinton than Trump. In the boxplot of candidate versus office jobs, we observed that the quantiles are similar but Clinton seems to have a smaller variance than Trump. In the boxplot of candidate versus production jobs, the quantiles are slightly higher for Trump than Clinton.

Dimensionality Reduction

12)

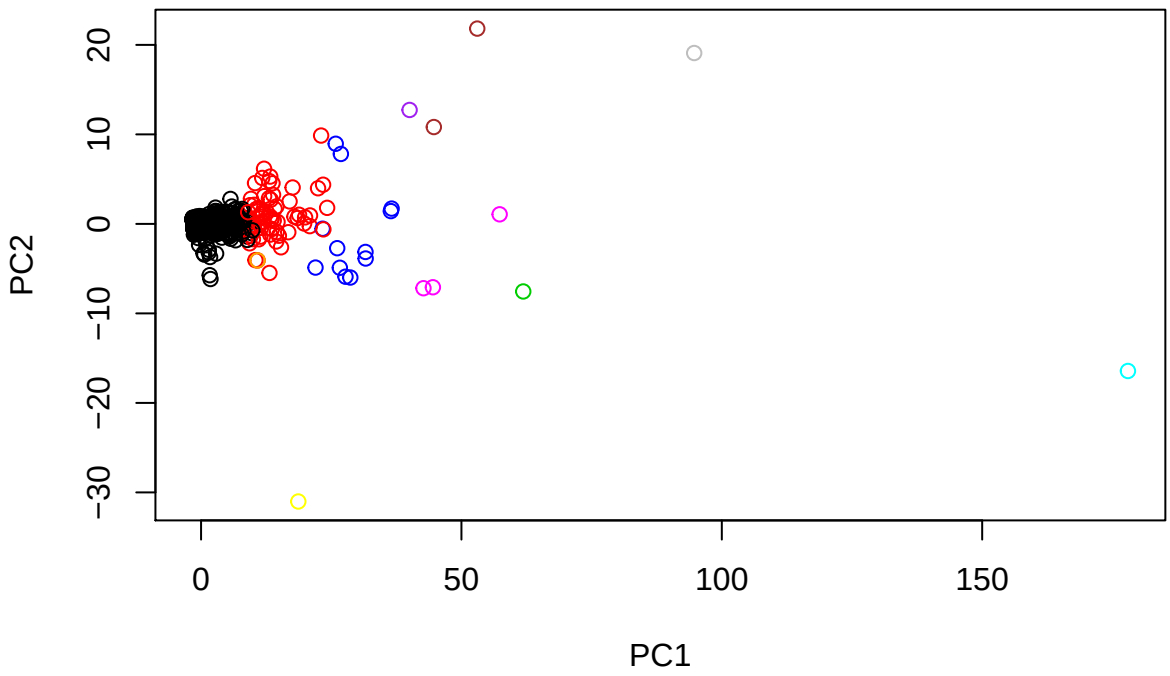
```
censuscounty.pca <- prcomp(census.ct[,3:36], scale = T)
censussubcounty.pca <- prcomp(census.subct[,4:37], scale = T)
ct.pc <- data.frame(censuscounty.pca$x)
subct.pc <- data.frame(censussubcounty.pca$x)
```

The most prominent loadings are from PC1. This is because PC1 explains the most variance, thus has the more prominent loadings.

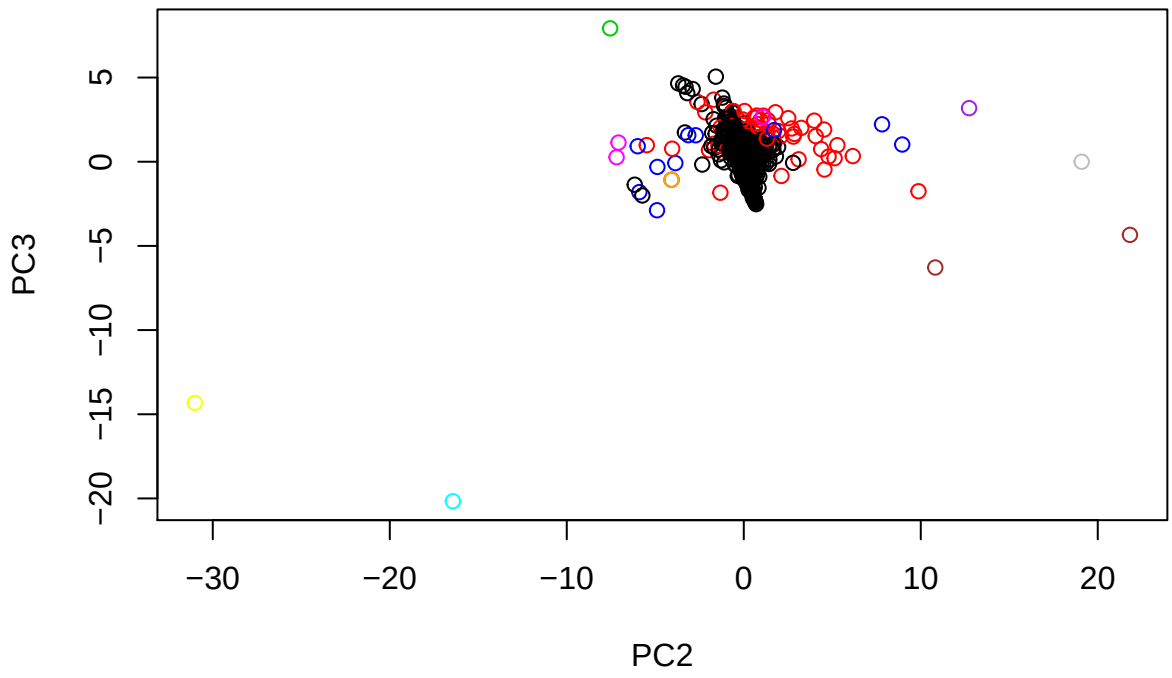
Clustering

13)

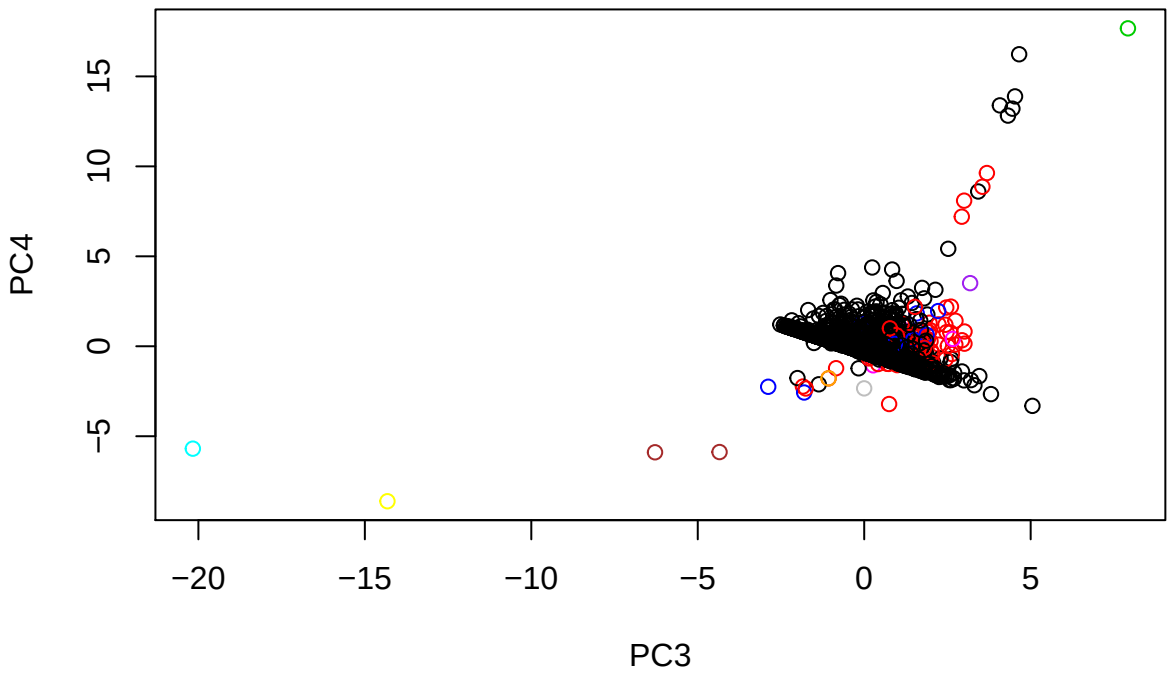
```
scaled_census <- scale(census.ct[,-c(1,2)],center = T,scale = T)
dist.ct <- dist(scaled_census)
hc.ct <- hclust(dist.ct, method = "complete")

ct.pc2 <- data.frame(censuscounty.pca$x[,1:5])
cc <- palette()
palette(c(cc,"purple","brown"))
plot(ct.pc2[,1:2], col = cutree(hc.ct, k = 10))
points(ct.pc[227,1],ct.pc[227,2], col = "orange")
```



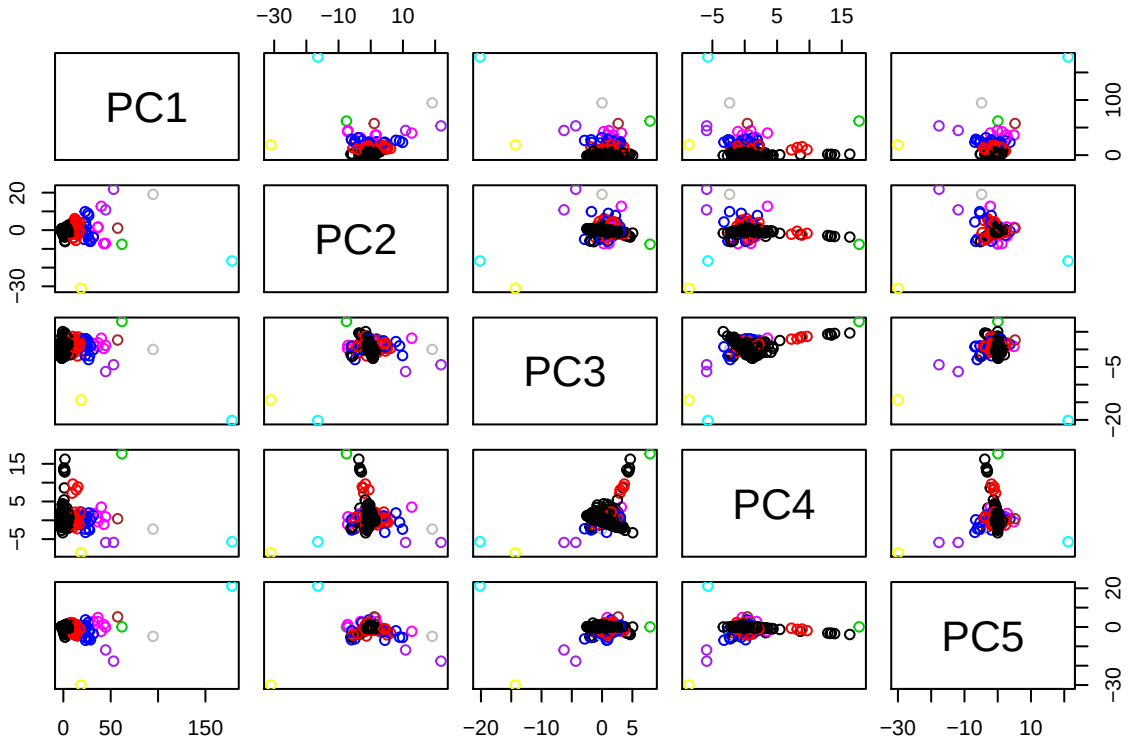

```
plot(ct.pc2[,2:3], col = cutree(hc.ct, k = 10))
points(ct.pc2[227,2],ct.pc2[227,3], col = "orange")
```




```
plot(ct.pc2[,3:4], col = cutree(hc.ct, k = 10))
points(ct.pc2[227,3],ct.pc2[227,4], col = "orange")
```




```
dist.pc <- dist(ct.pc2)
hc.pc <- hclust(dist.pc, method = "complete")
plot(ct.pc2, col = cutree(hc.pc, k=10))
```



The San Mateo county point is indicated on the plots by the orange point. Above are three plots of clusters with different PC loadings, and the overall scatterplot matrix of all the principal componenet with one another. San Mateo county is part of one of the big clusters but deviates from the rest of the points in that cluster. This may be because Income seems to be much higher than other counties along with many more professionals compared to service and office.

Classification

```
set.seed(10)
n = nrow(election.cl)
in.trn= sample.int(n, 0.8*n)
trn.cl = election.cl[ in.trn,]
tst.cl = election.cl[-in.trn,]

set.seed(20)
nfold = 10
folds = sample(cut(1:nrow(trn.cl), breaks=nfold, labels=FALSE))

calc_error_rate = function(predicted.value, true.value){
  return(mean(true.value!=predicted.value))
}
records1 = matrix(NA, nrow=3, ncol=2)
colnames(records1) = c("train.error","test.error")
rownames(records1) = c("tree","knn","logistic regression")
```

Classification native-attributes

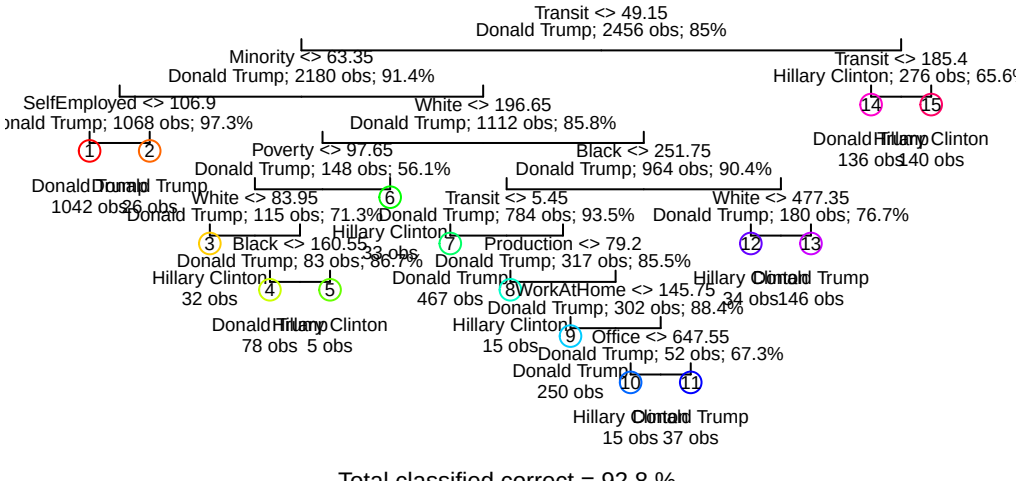
13)

```
set.seed(20)
electiontree <- tree(candidate ~ ., data = trn.cl, control = tree.control(nobs = nrow(trn.cl)))
cv <- cv.tree(electiontree, FUN = prune.misclass, K = nfold, rand = folds)
cv
```

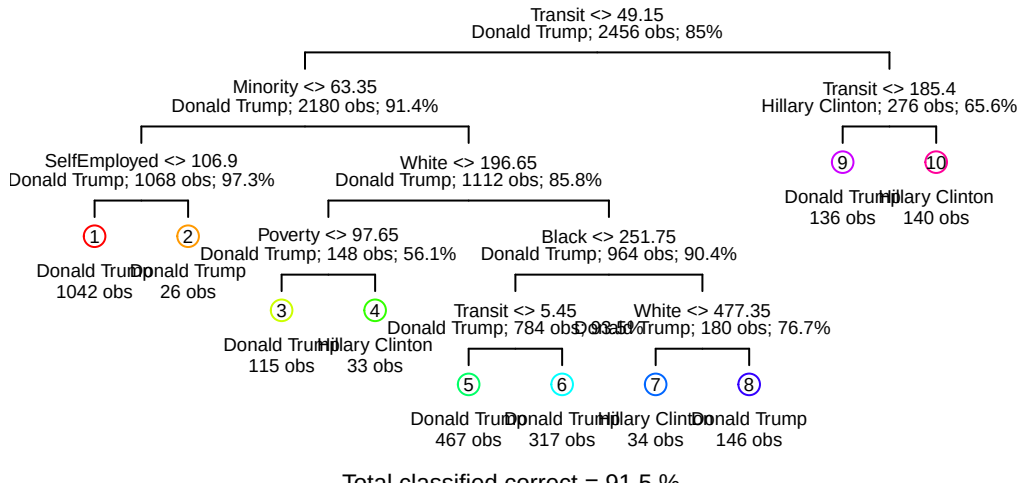
```
## $size
## [1] 15 14 10  9  7  3  2  1
##
## $dev
## [1] 246 246 242 247 252 262 281 363
##
## $k
## [1]  -Inf  0.00  4.00  5.00  9.00 10.75 24.00 86.00
##
## $method
## [1] "misclass"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"
```

We can see that the best size of the cv is going to be the one with the least deviation, and if multiple sizes have the same deviation, we prefer the one with the smallest size. In our case, the size with the smallest deviation would be 10.

```
best.size.cv <- 10
draw.tree(electiontree, cex=0.6, nodeinfo=TRUE)
```




```
electiontree.pruned <- prune.tree(electiontree, best = best.size.cv)
draw.tree(electiontree.pruned, cex = 0.6, nodeinfo = TRUE)
```




```
set.seed(20)
electiontree.pruned.predvl <- predict(electiontree.pruned, tst.cl, type = 'class')
electiontree.pruned.predtr <- predict(electiontree.pruned, trn.cl, type = 'class')
records1[1,1] = calc_error_rate(electiontree.pruned.predtr, trn.cl$candidate)
records1[1,2] = calc_error_rate(electiontree.pruned.predvl, tst.cl$candidate)
records1
```

```
##                     train.error test.error
## tree                 0.08509772 0.08794788
## knn                          NA         NA
## logistic regression          NA         NA
```

14)

```
kvec = 29:32 # we evaluated 1:50 but we reduced it to this to speed up knitting time
do.chunk <- function(chunkid, folddef, Xdat, Ydat, k){
train = (folddef!=chunkid)
Xtr = Xdat[train,]
Ytr = Ydat[train]
Xvl = Xdat[!train,]
Yvl = Ydat[!train]
## get classifications for current training chunks
predYtr = knn(train = Xtr, test = Xtr, cl = Ytr, k = k)
## get classifications for current test chunk
predYvl = knn(train = Xtr, test = Xvl, cl = Ytr, k = k)
data.frame(train.error = calc_error_rate(predYtr, Ytr),
val.error = calc_error_rate(predYvl, Yvl))
}
```

```
error.folds = NULL
for (j in kvec){
  tmp = lapply(1:9, do.chunk, folds, election.cl %>% select(-candidate), election.cl$candidate, j)
  tmp$neighbors = j
  error.folds = rbind(error.folds, tmp)
}


#errors = melt(error.folds, id.vars='neighbors', value.name='error')
#val.error.means = errors %>%
#filter(variable=='val.error') %>%
#group_by(neighbors, variable) %>%
#summarise_each(funs(mean), error) %>%
#ungroup() %>%
#filter(error==min(error))
```

```
#val.error.means <-- this says 31 neighbors with error 0.1209213
```

The best number of neighbors is 31.

```
best.kfold <- 31
set.seed(20)
Ytrain <- trn.cl$candidate
Xtrain <- trn.cl %>% select(-candidate)
Xtest <- tst.cl %>% select(-candidate)
Ytest <- tst.cl$candidate

pred.YTrain = knn(train=Xtrain, test=Xtrain, cl=Ytrain, k=31)
pred.YTest = knn(train=Xtrain, test=Xtest, cl=Ytrain, k=31)
records1[2,1] = calc_error_rate(pred.YTrain, trn.cl$candidate)
records1[2,2] = calc_error_rate(pred.YTest, tst.cl$candidate)
records1
```

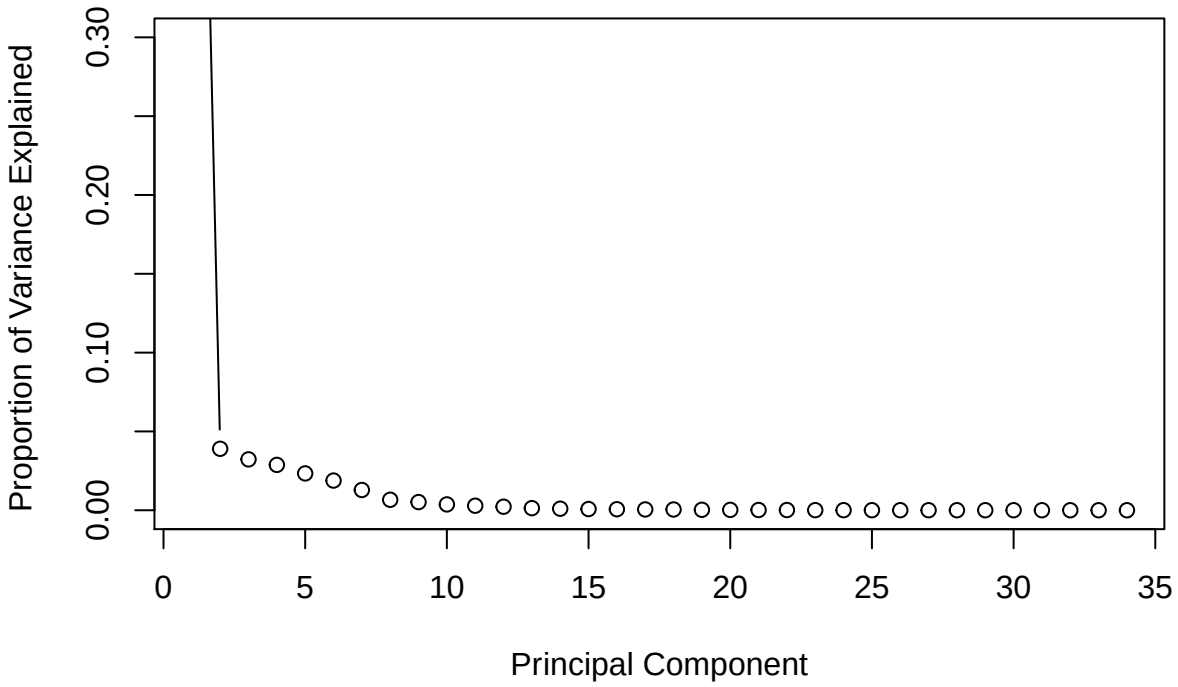
```
##                     train.error test.error
## tree                 0.08509772 0.08794788
## knn                  0.11970684 0.12703583
## logistic regression          NA         NA
```

Classification: principal components

```
pca.records = matrix(NA, nrow=2, ncol=2)
colnames(pca.records) = c("train.error","test.error")
rownames(pca.records) = c("tree","knn")
```

15)

```
trn.cl.indp <- trn.cl %>% select(-candidate)
trn.cl.indp.pc <- prcomp(trn.cl.indp, scale = T)

pr.var = trn.cl.indp.pc$sdev ^2
pve = pr.var/sum(pr.var)
plot(pve, xlab="Principal Component",ylab="Proportion of Variance Explained ", ylim=c(0,0.3),type='b')
```



The minimum number of PC's required to capture 90% of the variance is 4.

16)

```
tr.pca <- data.frame(trn.cl.indp.pc$x[,1:4])
tr.pca <- cbind(trn.cl$candidate, tr.pca)

tst.cl.indp <- tst.cl %>% select(-candidate)
tst.cl.indp.pc <- prcomp(tst.cl.indp, scale = T)

test.pca <- data.frame(tst.cl.indp.pc$x[,1:4])
test.pca <- cbind(tst.cl$candidate, test.pca)
colnames(tr.pca)[1] <- "candidate"
colnames(test.pca)[1] <- "candidate"
```

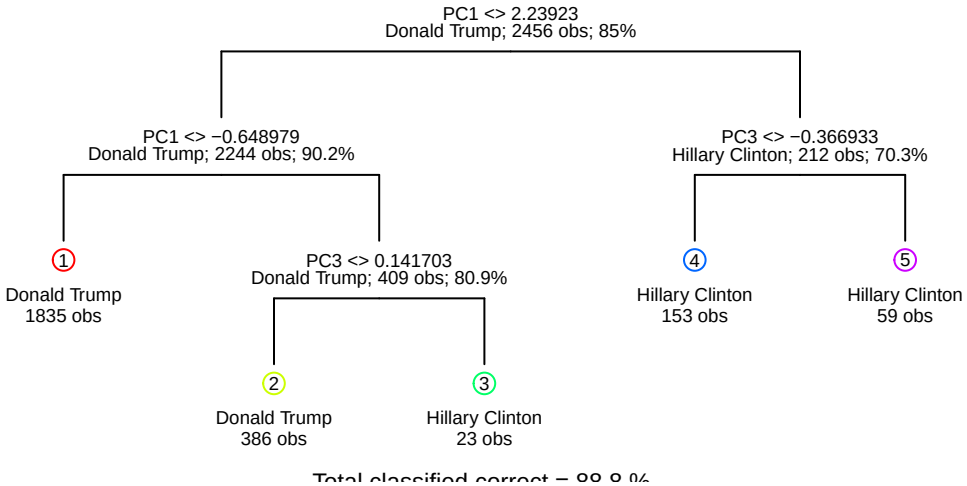
17)

```
set.seed(20)
pcatree <- tree(candidate ~ ., data = tr.pca, control = tree.control(nobs = nrow(tr.pca)))
cvtree <- cv.tree(pcatree, FUN = prune.misclass, K = nfold, rand = folds)
cvtree #best size is 2
```

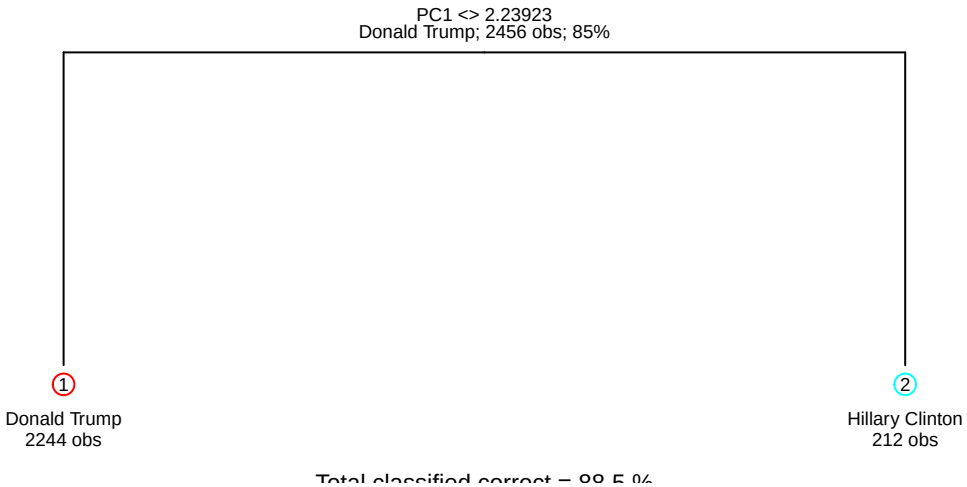
```
## $size
## [1] 5 4 2 1
##
## $dev
## [1] 293 293 286 368
##
## $k
```

```
## [1] -Inf  0.0  3.5 86.0
##
## $method
## [1] "misclass"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"
```

```
best.size.cvtree <- 2
draw.tree(pcatree, cex=0.6, nodeinfo=TRUE)
```




```
pcatree.pruned <- prune.tree(pcatree, best = best.size.cvtree)
draw.tree(pcatree.pruned, cex = 0.6, nodeinfo = TRUE)
```




```
set.seed(20)
pcatree.pruned.predvl <- predict(pcatree.pruned, test.pca, type = 'class')
pcatree.pruned.predtr <- predict(pcatree.pruned, tr.pca, type = 'class')
pca.records[1,1] = calc_error_rate(pcatree.pruned.predtr, tr.pca$candidate)
pca.records[1,2] = calc_error_rate(pcatree.pruned.predvl, test.pca$candidate)
pca.records
```

```
##      train.error test.error
## tree   0.1148208  0.1563518
## knn           NA         NA
## lda           NA         NA
```

18)

```
kvec1 <- 17:19 # we evaluated 1:50 but we reduced it to this to speed up knitting time
election.cl.indp <- election.cl %>% select(-candidate)
election.cl.indp.pc <- prcomp(election.cl.indp, scale = T)

election.pca <- data.frame(election.cl.indp.pc$x[,1:4])
election.pca <- cbind(election.cl$candidate, election.pca)
colnames(election.pca)[1] <- "candidate"

error.folds = NULL
for (j in kvec1){
  tmp = lapply(1:9, do.chunk, folds, election.pca %>% select(-candidate), election.pca$candidate, j)
  tmp$neighbors = j
  error.folds = rbind(error.folds, tmp)
```

```
}

#errors = melt(error.folds, id.vars='neighbors', value.name='error')
#val.error.means.pca = errors %>%
#filter(variable=='val.error') %>%
#summarise_each(funs(mean), error) %>%
#ungroup() %>%
#filter(error==min(error))
```

```
#val.error.means.pca <-- give neighbors of 18 and error 0.117608
```

The best choice of neighbors is 18.

```
best.kfold <- 18
set.seed(20)
Ytrainpca <- tr.pca$candidate
Xtrainpca <- tr.pca %>% select(-candidate)
Xtestpca <- test.pca %>% select(-candidate)
Ytestpca <- test.pca$candidate

pred.YTrainpca = knn(train=Xtrainpca, test=Xtrainpca, cl=Ytrainpca, k=18)
pred.YTestpca = knn(train=Xtrainpca, test=Xtestpca, cl=Ytrainpca, k=18)
pca.records[2,1] = calc_error_rate(pred.YTrainpca, tr.pca$candidate)
pca.records[2,2] = calc_error_rate(pred.YTestpca, test.pca$candidate)
pca.records
```

```
##      train.error test.error
## tree   0.1148208  0.1563518
## knn    0.1123779  0.1677524
## lda           NA         NA
```

Interpretation and Discussion

19) Our classification methods using decision tress and KNN show how the polls did not predict the outcome of the election. We noticed that in the classification of native attributes, our error rate for decision trees was 8.8% while error for KNN was 12.7%. In the article, it said that polling errors are usually around 3%, but our error rates show that this is not true. These error rates show that 8.8% (decision trees) and 12.7% (KNN) of predictions for winner of the county was classified incorrectly.

Our classification methods with pca yielded higher test error rates. This may be because of some relationship between the variables that PCA is not accounting for properly.

If there is additional data collection, one thing that may be asked is whether a person is a democrat, republican, or affiliated to any other political party. This may reduce the bias and undermining of polls as people may be more comfortable to answer what their political affiliation in addition to who they are going to vote for.

Taking it Further

20) We also wanted to perform logistic regression to see if it will produce less test error:

```
set.seed(20)
trn.cl.fact <- as.factor(trn.cl$candidate)
trn.cl.fact <- cbind(trn.cl.fact,trn.cl[,2:35])
```

```
colnames(trn.cl.fact)[1] <- "candidate"


glm.fit <- glm(candidate ~ .,data = trn.cl, family = binomial)
```

```
## Warning: glm.fit: algorithm did not converge
```

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

```
probtraining <- round(predict(glm.fit,type='response'))

prob.cl.training3 = trn.cl %>%
mutate(predy = as.factor(ifelse(probtraining<=0.5, "Donald Trump", "Hillary Clinton")))

prob.cl.training3$candidate <- factor(prob.cl.training3$candidate)

pred_prob_training <- calc_error_rate(prob.cl.training3$predy,prob.cl.training3$candidate)
pred_prob_training
```

```
## [1] 0.1001629
```

```
probtest <-round(predict(glm.fit,tst.cl,type='response'))
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading
```

```
prob.cl.test = tst.cl %>%
mutate(predy = as.factor(ifelse(probtest<=0.5, "Donald Trump", "Hillary Clinton")))

prob.cl.test$candidate <- factor(prob.cl.test$candidate)

pred_prob_test <- calc_error_rate(prob.cl.test$predy,prob.cl.test$candidate)
pred_prob_test
```

```
## [1] 0.1156352
```

```
records1[3,1] <- pred_prob_training
records1[3,2] <- pred_prob_test
records1
```

```
##                      train.error test.error
## tree                  0.08509772 0.08794788
## knn                   0.11970684 0.12703583
## logistic regression   0.10016287 0.11563518
```

With logistic regression, we got a smaller test error than KNN gave, but a higher test error than decision trees. If the decision boundary is linear, than logistic regression outperforms KNN, which was the case for this data. Decision tress most likely had the least test error because decision trees are not sensitive to scale invariants and transformations of the predictors. In our case, the predictors did have many different scales, so this follows the intuition.