IIMT2641 Assignment 5

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Q1 Tree Models

Load the Data

```
state <- read.csv("StateData.csv")
head(state) # First 6 rows

##   Population Income Illiteracy LifeExp Murder HighSchoolGrad Frost
Area
## 1       3615   3624        2.1   69.05   15.1           41.3    20
50708
## 2        365   6315        1.5   69.31   11.3           66.7   152
566432
## 3       2212   4530        1.8   70.55    7.8           58.1    15
113417
## 4       2110   3378        1.9   70.66   10.1           39.9    65
51945
## 5      21198   5114        1.1   71.71   10.3           62.6    20
156361
## 6       2541   4884        0.7   72.06    6.8           63.9   166
103766
##   Longitude Latitude Region
## 1  -86.7509  32.5901  South
## 2 -127.2500  49.2500   West
## 3 -111.6250  34.2192   West
## 4  -92.2992  34.7336  South
## 5 -119.7730  36.5341   West
## 6 -105.5130  38.6777   West

dim(state) # Number of observations and variables

## [1] 50 11

names(state) # Names of variables

##  [1] "Population"     "Income"         "Illiteracy"     "LifeExp"
##  [5] "Murder"         "HighSchoolGrad" "Frost"          "Area"
##  [9] "Longitude"      "Latitude"       "Region"
```

Train-test Split

```
library(caTools)
set.seed(12)
```

```r
# Randomly split the dataset with 70% in the training set
spl <- sample.split(state$LifeExp, SplitRatio = 0.7)
train <- state |> subset(spl == TRUE)
test <- state |> subset(spl == FALSE)
```

7-variable Linear Regression Model

```r
lm1 <- lm(LifeExp ~ Population + Murder + Frost + Income + Illiteracy +
Area + HighSchoolGrad, data = train)

lm1_pred <- predict(lm1, newdata = test)
# Out-of-sample R^2
SSE <- sum((test$LifeExp - lm1_pred) ^ 2)
SST <- sum((test$LifeExp - mean(train$LifeExp)) ^ 2)
R2_lm1 <- 1 - SSE/SST
R2_lm1

## [1] 0.05283534
```

4-variable Linear Regression Model

```r
lm2 <- lm(LifeExp ~ Population + Murder + Frost + HighSchoolGrad, data
= train)

lm2_pred <- predict(lm2, newdata = test)
# Out-of-sample R^2
SSE <- sum((test$LifeExp - lm2_pred) ^ 2)
SST <- sum((test$LifeExp - mean(train$LifeExp)) ^ 2)
R2_lm2 <- 1 - SSE/SST
R2_lm2

## [1] 0.6438655
```

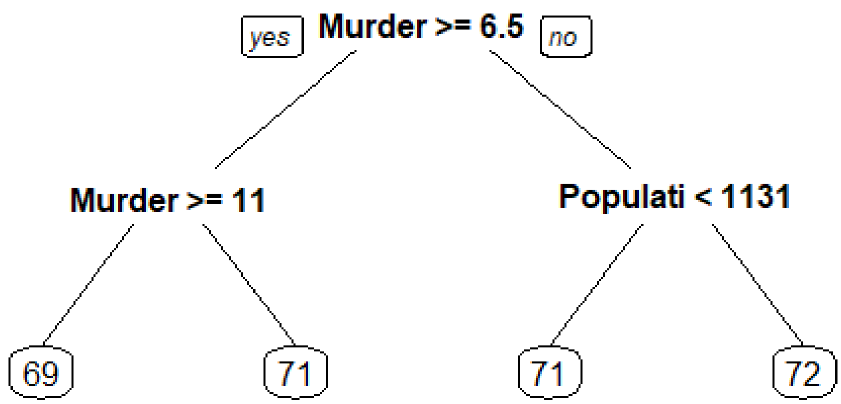
By removing independent variables, the R^2 on the test test is increased, meaning the overfitting problem is alleviated. The equivalent procedure in CART is pruning to have a smaller tree.

CART Model

```r
library(rpart)
library(rpart.plot)

rtree <- rpart(LifeExp ~ Population + Murder + Frost + Income +
Illiteracy + Area + HighSchoolGrad, data = train, method = "anova",
minbucket = 5)

prp(rtree) # Plot the tree
```



Independent variables `Murder` and `Population` appear in the tree. The CART model is easier to interpret.

CART Prediction

```
rtree_pred <- predict(rtree, newdata = test, type = "vector")
# Out-of-sample R^2
SSE <- sum((test$LifeExp - rtree_pred) ^ 2)
SST <- sum((test$LifeExp - mean(train$LifeExp)) ^ 2)
R2_rtree <- 1 - SSE/SST
R2_rtree

## [1] 0.1813543
```

Random Forest

```
library(randomForest)

## randomForest 4.7-1.1

## Type rfNews() to see new features/changes/bug fixes.

set.seed(1234)
rf <- randomForest(LifeExp ~ Population + Murder + Frost + Income +
Illiteracy + Area + HighSchoolGrad, data = train, ntree = 100, nodesize
= 5)

rf_pred <- predict(rf, newdata = test)
# Out-of-sample R^2
```

```r
SSE <- sum((test$LifeExp - rf_pred) ^ 2)
SST <- sum((test$LifeExp - mean(train$LifeExp)) ^ 2)
R2_rf <- 1 - SSE/SST
R2_rf

## [1] 0.6121284
```

Best Model

```r
# Out-of-sample R^2
c("7-variable lm" = R2_lm1, "4-variable lm" = R2_lm2,
  "Tree" = R2_rtree, "Random Forest" = R2_rf)

## 7-variable lm 4-variable lm          Tree Random Forest
##    0.05283534    0.64386555    0.18135431    0.61212838
```

The 4-variable linear regression model has the highest out-of-sample R^2. The tree model is the easiest to interpret.

Q2 Clustering

```r
bow <- read.csv("DailyKos.csv")
```

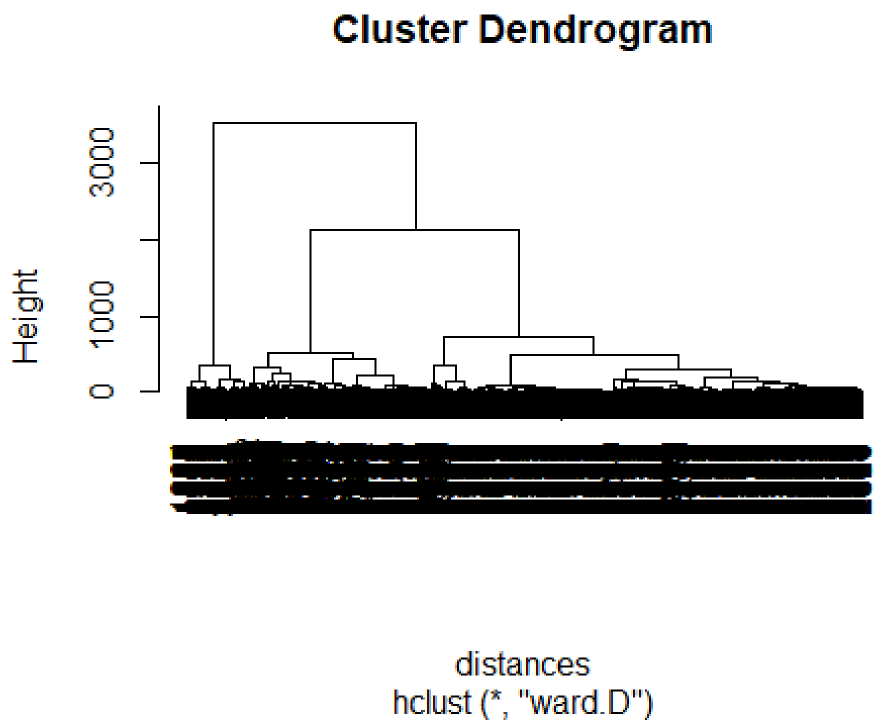
Hierarchical Clustering

```r
# Compute distances between points
distances <- dist(bow, method = "euclidean")
# Hierarchical clustering
hbow <- hclust(distances, method = "ward.D")
```

Euclidean distance metrics is used to calculate distances.
Hierarchical clustering takes lot of time because in each recursion, it calculates the distance of all combinations between every two data points.

Plot the dendrogram

```r
plot(hbow)
```



Choose the Number of Clusters

10 clusters are recommended for different categories of articles.

```
no_clusters <- 10
# Cut the tree into 10 clusters
h_10clust <- cutree(hbow, no_clusters)
# No. of observations in each cluster
table(h_10clust)

## h_10clust
##    1    2    3    4    5    6    7    8    9   10
## 1266  179  279  139  407  714   63   95  146  142
```

Split the Clusters and Analyze Each Cluster

```
# Split the dataset into a dataset for each cluster
# Find the six most frequent words in each cluster
no_clusters <- 10
for (i in 1:no_clusters){
  bow |>
    subset(h_10clust == i) |>  # Filter
    colMeans() |>  # Take the average of each column
    sort(decreasing = TRUE) |>
    head() |>
    print.data.frame()
  cat("\n")  # Add a line for easier reading
}
```

```
## [1] bush       kerry      democrat   poll       republican state
## <0 rows> (or 0-length row.names)
##
## [1] november   vote       poll       challenge  bush
republican
## <0 rows> (or 0-length row.names)
##
## [1] democrat   republican state      bush       parties    senate
## <0 rows> (or 0-length row.names)
##
## [1] kerry    bush     poll     presided voter    campaign
## <0 rows> (or 0-length row.names)
##
## [1] bush           iraq           war            administration
presided
## [6] american
## <0 rows> (or 0-length row.names)
##
## [1] poll     democrat elect    kerry    bush     race
## <0 rows> (or 0-length row.names)
##
## [1] dean     kerry    democrat campaign edward   gephardt
## <0 rows> (or 0-length row.names)
##
## [1] bush           administration presided       war            iraq
## [6] house
## <0 rows> (or 0-length row.names)
##
## [1] kerry     dean      poll      edward    clark     primaries
## <0 rows> (or 0-length row.names)
##
## [1] november  poll      challenge democrat  vote      house
## <0 rows> (or 0-length row.names)
```

There is a cluster that is mostly about the Iraq war. There are several clusters that are mostly about the democratic party.

K-means Clustering

```
no_clusters <- 10
set.seed(23)
kbow <- kmeans(bow, no_clusters)
k_10clust <- kbow$cluster
# No. of observations in each cluster
table(k_10clust)

## k_10clust
##    1    2    3    4    5    6    7    8    9   10
##   46  280   43  142  293  195 1750  356  160  165
```

The number of observations in each cluster is different from hierarchical clustering, because the clustering algorithms are different.

Split the Clusters and Analyze Each Cluster

```
# Split the dataset into a dataset for each cluster
# Find the six most frequent words in each cluster
no_clusters <- 10
for (i in 1:no_clusters){
  bow |>
    subset(k_10clust == i) |>
    colMeans() |>
    sort(decreasing = TRUE) |>
    head() |>
    print.data.frame()
  cat("\n")
}

## [1] democrat   parties    republican state      seat       senate
## <0 rows> (or 0-length row.names)
##
## [1] bush           administration presided       time           year
## [6] house
## <0 rows> (or 0-length row.names)
##
## [1] bush     kerry    presided iraq     vote     democrat
## <0 rows> (or 0-length row.names)
##
## [1] dean      kerry     clark     edward    democrat  primaries
## <0 rows> (or 0-length row.names)
##
## [1] kerry    bush     poll     campaign presided democrat
## <0 rows> (or 0-length row.names)
##
## [1] iraq     war      bush     iraqi    american official
## <0 rows> (or 0-length row.names)
##
## [1] bush     poll     kerry    democrat general  elect
## <0 rows> (or 0-length row.names)
##
## [1] democrat   republican state      elect      senate     parties
## <0 rows> (or 0-length row.names)
##
## [1] november  poll      challenge democrat  vote      house
## <0 rows> (or 0-length row.names)
##
## [1] november   vote       poll       challenge  bush
republican
## <0 rows> (or 0-length row.names)
```

Overall, these two groups of clusters have very similar keywords, like “bush”, “kerry”, “republican”, “november”, “iraq”, etc.
2 clusters starting with “november” among 10 clusters are identical with hierarchical clustering.