NYC Flight Delays

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Importing libraries

```
library(knitr)
opts_chunk$set(tidy.opts=list(width.cutoff=40),tidy=TRUE)
library(nycflights13)
library(dplyr)
library(ggplot2)
library(car)
library(knitr)
opts_chunk$set(tidy.opts=list(width.cutoff=60),tidy=TRUE)
```

Introduction

Using the nycflights13 dataset we found data to back up insights that relate to flight delay times at JFK, Newark, and La Guardia airports in New York. To do this, we first inspected the data through analysis of the various factors included to better understand what information we have available to us. After this, we used statistical modeling to find the most important variables in the dataset that relate to the flight delay times in order to back up our findings. Using the results, we developed insights on the most important variables that need to be addressed in order to decrease delay times in the future.

Getting data

```
data(flights)
data(weather)
```

EDA

Checking for na in weather

```
# number of na per column
cbind(lapply(lapply(weather, is.na), sum))
```

```
##            [,1]
## origin     0
## year       0
## month      0
## day        0
## hour       0
## temp       1
## dewp       1
## humid      1
## wind_dir   460
## wind_speed 4
## wind_gust  20778
## precip     0
## pressure   2729
## visib      0
## time_hour  0
```

```
# removing wind gust (too many NA and just a confusing var)
if ("wind_gust" %in% colnames(weather)) {
    # cleaned weather
    w = subset(weather, select = -c(wind_gust))
}
```

We decided to remove the wind gust variable because it had a large amount of NA values. About three quarters of the data do not have values for this predictor. Also, from reading the data dictionary it was hard to understand what the wind gust variable meant.

Cleaning flights data

```
cbind(lapply(lapply(flights, is.na), sum))
```

```
##                [,1]
## year           0
## month          0
## day            0
## dep_time       8255
## sched_dep_time 0
## dep_delay      8255
## arr_time       8713
## sched_arr_time 0
## arr_delay      9430
## carrier        0
## flight         0
## tailnum        2512
## origin         0
## dest           0
## air_time       9430
## distance       0
## hour           0
## minute         0
## time_hour      0
```

```
# cleaned flights
f = flights[!is.na(flights$air_time), ]

f$sigDelay = f$dep_delay > 15
```

Within the flights data set, there is another issue of NA values with the air time variable having the most. We interpreted NA for air time as meaning the flights was cancelled. Since cancellation is different from departure delays, we removed all observations with out an air time. This gets rid of the rest of NA values for the whole flights data set.

We also created a variable named "sigDelay" which is a binary variable that encodes whether of not a flight was delayed according to the FAA's definition of a 15 minute threshold for if a flight is delayed.

Checking for multicollinearity

Weather Correlation

```
# getting only numeric columns and removing na's
w_numeric <- w[, sapply(w, is.numeric)]
w_numeric <- na.omit(w_numeric[, c(5:12)])

cor(w_numeric)
```

```
##                   temp        dewp      humid   wind_dir  wind_speed
## temp        1.00000000  0.90162405  0.1071538 -0.1290057 -0.10894880
## dewp        0.90162405  1.00000000  0.5193125 -0.2460956 -0.18136793
## humid       0.10715384  0.51931252  1.0000000 -0.3249786 -0.20582870
## wind_dir   -0.12900567 -0.24609556 -0.3249786  1.0000000  0.25445501
## wind_speed -0.10894880 -0.18136793 -0.2058287  0.2544550  1.00000000
## precip     -0.02950825  0.04208537  0.1865167 -0.0780323  0.03005549
## pressure   -0.25366597 -0.28858075 -0.1803573 -0.1988064 -0.13249274
## visib       0.04323954 -0.12773124 -0.4523975  0.1873828  0.04883138
##                 precip   pressure       visib
## temp       -0.02950825 -0.2536660  0.04323954
## dewp        0.04208537 -0.2885808 -0.12773124
## humid       0.18651675 -0.1803573 -0.45239754
## wind_dir   -0.07803230 -0.1988064  0.18738277
## wind_speed  0.03005549 -0.1324927  0.04883138
## precip      1.00000000 -0.1079932 -0.34709198
## pressure   -0.10799318  1.0000000  0.12277393
## visib      -0.34709198  0.1227739  1.00000000
```

Before we look for trends with delays, its important to get a feel for the data and understand how variables related to each other. There seems to be some high correlations within the weather data set which could lead to come multicollinearity issues. This means that multiple variables encode similar information. When modeling, this can reduce the model's effectiveness. The variables with the highest correlations are temperature, dew point, and humidity.

Flights Correlation

```r
# getting only numeric columns and removing na's
f_numeric <- f[, sapply(f, is.numeric)]
f_numeric <- na.omit(f_numeric[, c(4:12)])

cor(f_numeric)
```

```
##                   dep_time sched_dep_time   dep_delay   arr_time sched_arr_time
## dep_time        1.00000000     0.95482687  0.25961272 0.66250900     0.78444199
## sched_dep_time  0.95482687     1.00000000  0.19892350 0.64438677     0.78058744
## dep_delay       0.25961272     0.19892350  1.00000000 0.02942101     0.16049724
## arr_time        0.66250900     0.64438677  0.02942101 1.00000000     0.79078877
## sched_arr_time  0.78444199     0.78058744  0.16049724 0.79078877     1.00000000
## arr_delay       0.23230573     0.17389620  0.91480276 0.02448214     0.13326129
## flight          0.04153017     0.02840127  0.05396975 0.02500740     0.01394723
## air_time       -0.01461948    -0.01553213 -0.02240508 0.05429603     0.07891830
## distance       -0.01413373    -0.01293250 -0.02168090 0.04718917     0.07361354
##                  arr_delay      flight    air_time    distance
## dep_time        0.23230573  0.04153017 -0.01461948 -0.01413373
## sched_dep_time  0.17389620  0.02840127 -0.01553213 -0.01293250
## dep_delay       0.91480276  0.05396975 -0.02240508 -0.02168090
## arr_time        0.02448214  0.02500740  0.05429603  0.04718917
## sched_arr_time  0.13326129  0.01394723  0.07891830  0.07361354
## arr_delay       1.00000000  0.07286208 -0.03529709 -0.06186776
## flight          0.07286208  1.00000000 -0.47283836 -0.48146018
## air_time       -0.03529709 -0.47283836  1.00000000  0.99064965
## distance       -0.06186776 -0.48146018  0.99064965  1.00000000
```

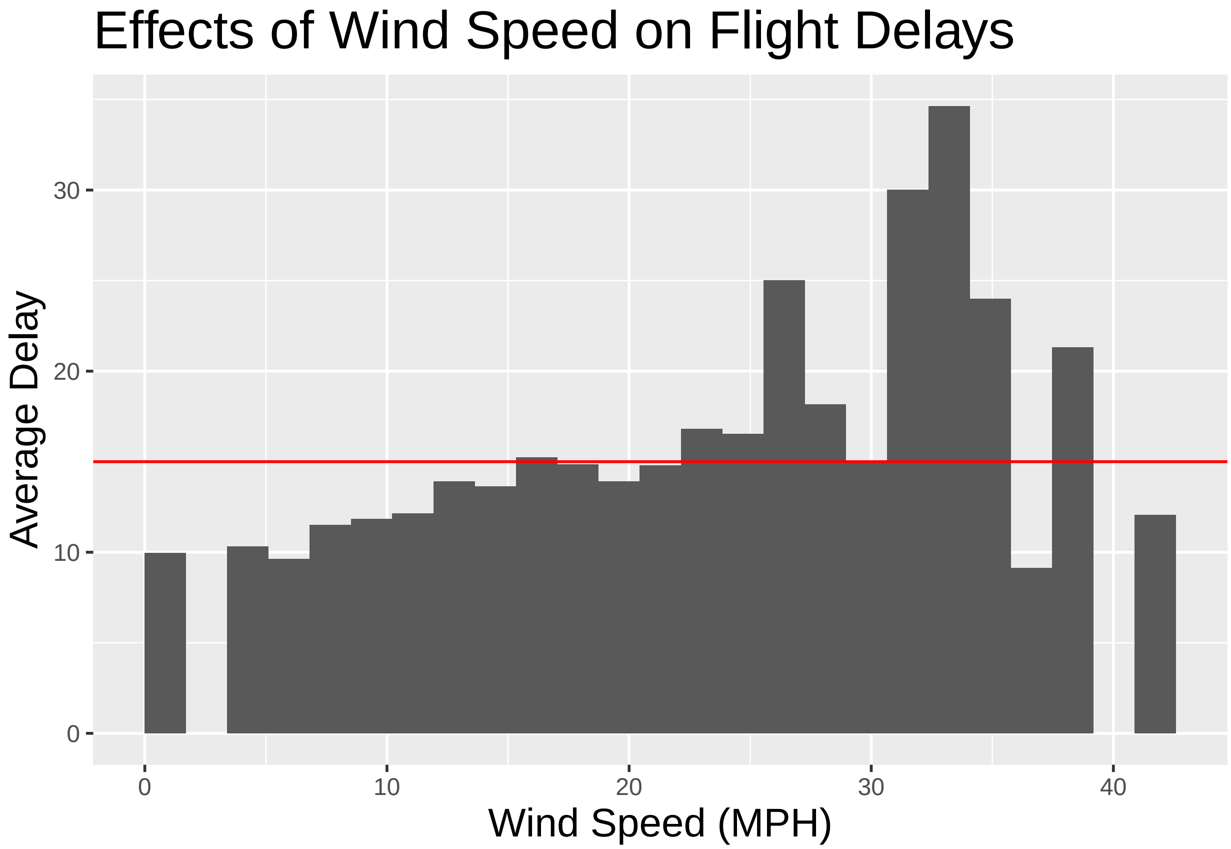
The flights data set looks to have more cases of multicollinearity. This makes sense when looking at the variables and what the represent. Since most of the variables are related to departure and arrival times, the scheduled and actual times for each particular flight are similar. Also, variables like departure delay and arrival delay are derived from the difference between the actual and scheduled times. This means that only a few of these variables will prove to be useful when we begin modeling. Finally, variables like arrival delay or arrival time should not be used because in practice those will not be known before a flight takes off from New York.

# Looking for trends with Departure Delay

```
# merging together cleaned weather and flights data
wf <- merge(f, w, by = c("time_hour", "origin"))
```

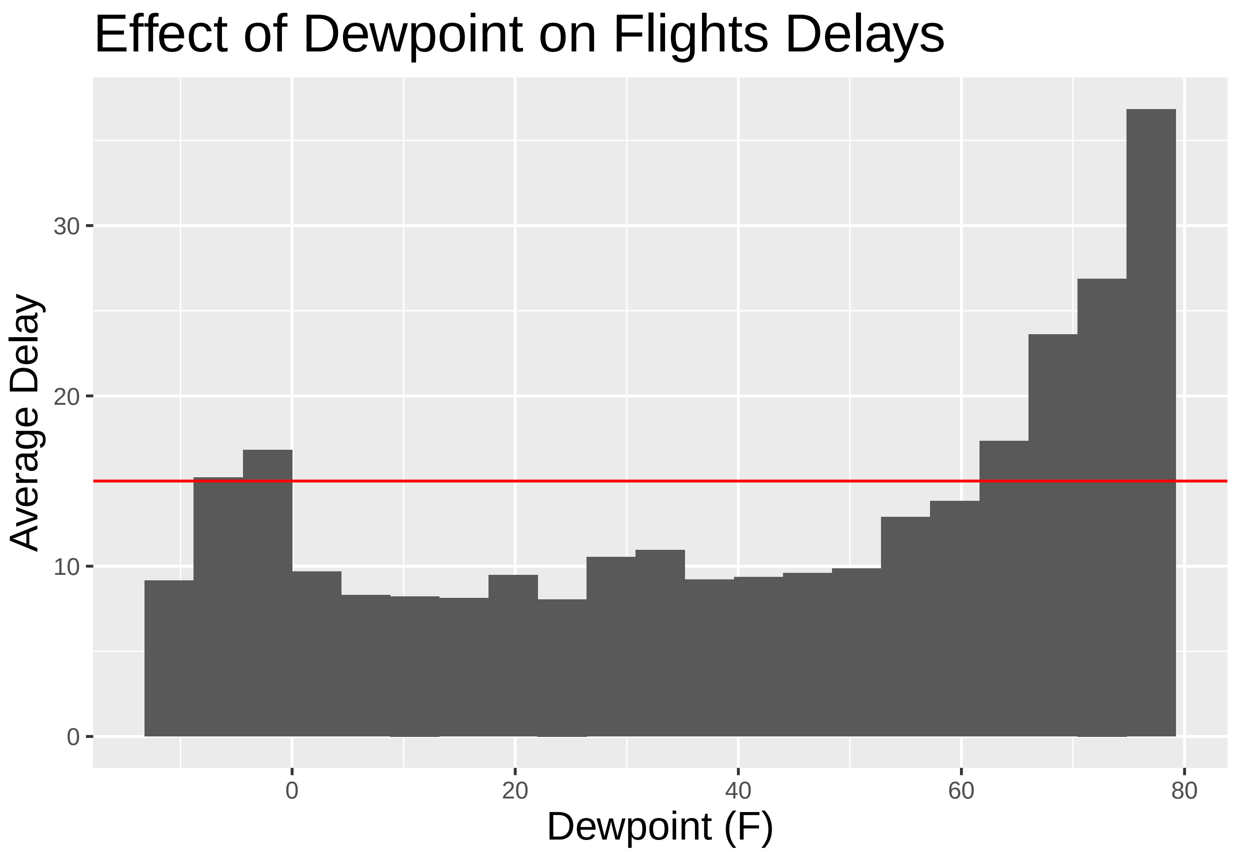
```
ggplot(wf, aes(x = wind_speed, y = dep_delay)) + stat_summary_bin(fun = "mean",
    geom = "bar", bins = 25) + ylab("Average Delay") + xlab("Wind Speed (MPH)") +
    ggtitle("Effects of Wind Speed on Flight Delays ") + geom_hline(yintercept = 15,
    color = "red") + theme(axis.title = element_text(size = 15),
    plot.title = element_text(size = 20))
```

```
## Warning: Removed 78 rows containing non-finite values (‘stat_summary_bin()‘).
```



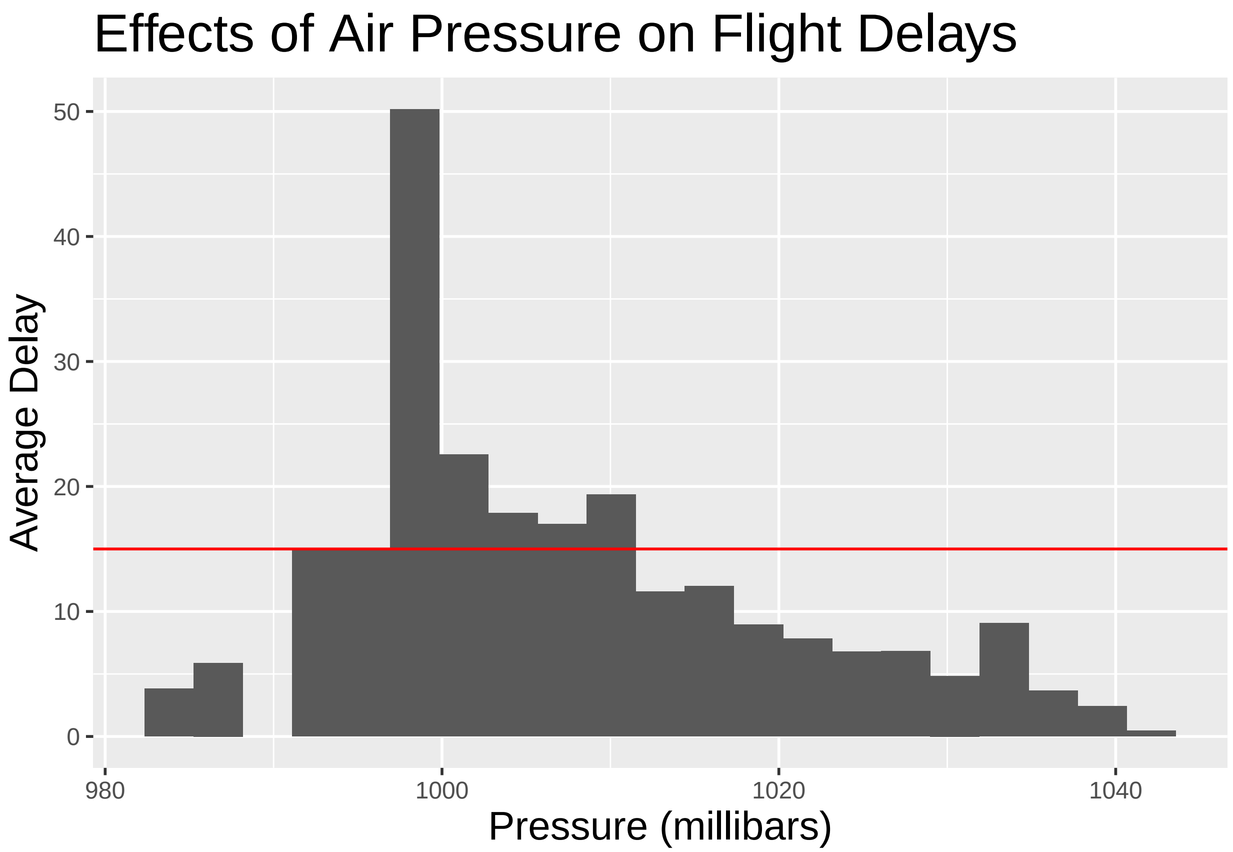
```
ggplot(wf, aes(x = temp, y = dep_delay)) + stat_summary_bin(fun = "mean",
    geom = "bar", bins = 20) + ylab("Average Delay") + xlab("Temperature (F)") +
    ggtitle("Effects of Temperature on Flight Delays ") + geom_hline(yintercept = 15,
    color = "red") + theme(axis.title = element_text(size = 15),
    plot.title = element_text(size = 20))
```

```
## Warning: Removed 17 rows containing non-finite values (‘stat_summary_bin()‘).
```



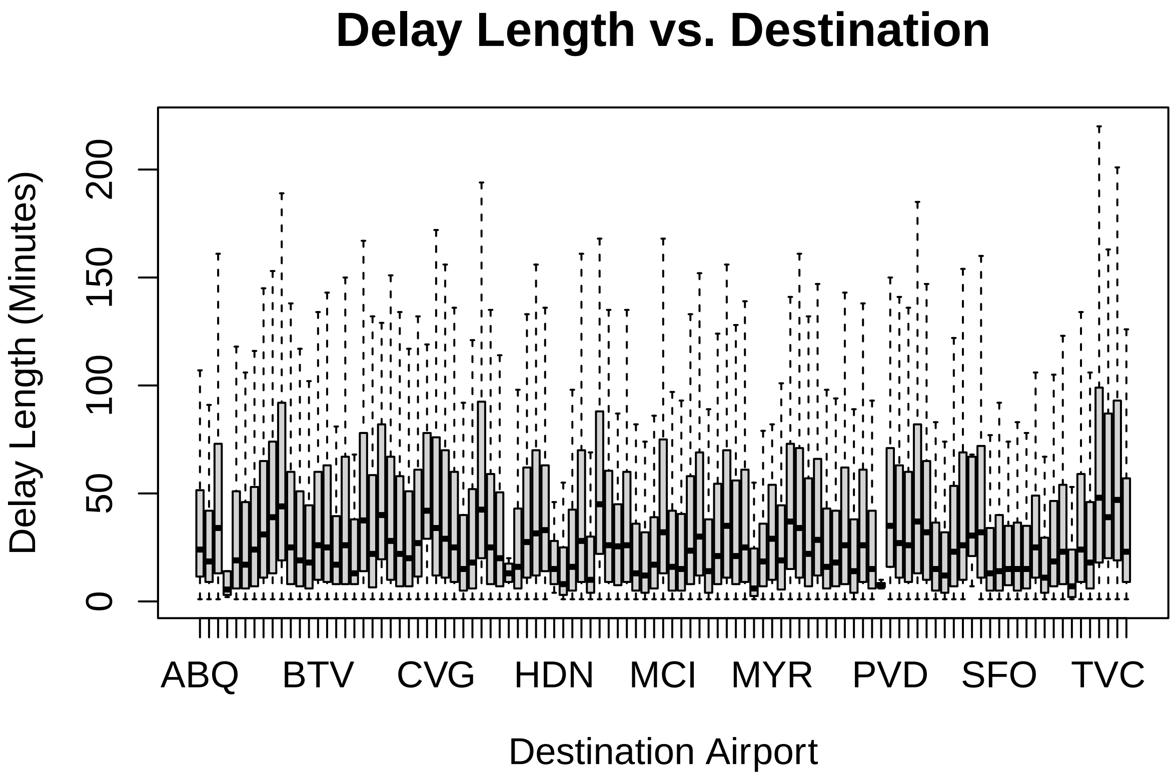
```
ggplot(wf, aes(x = humid, y = dep_delay)) + stat_summary_bin(fun = "mean",
    geom = "bar", bins = 20) + ylab("Average Delay") + xlab("Relative Humidity") +
    ggtitle("Effect of Humidity on Flights Delays") + geom_hline(yintercept = 15,
    color = "red") + theme(axis.title = element_text(size = 15),
    plot.title = element_text(size = 20))
```

```
## Warning: Removed 17 rows containing non-finite values (‘stat_summary_bin()‘).
```



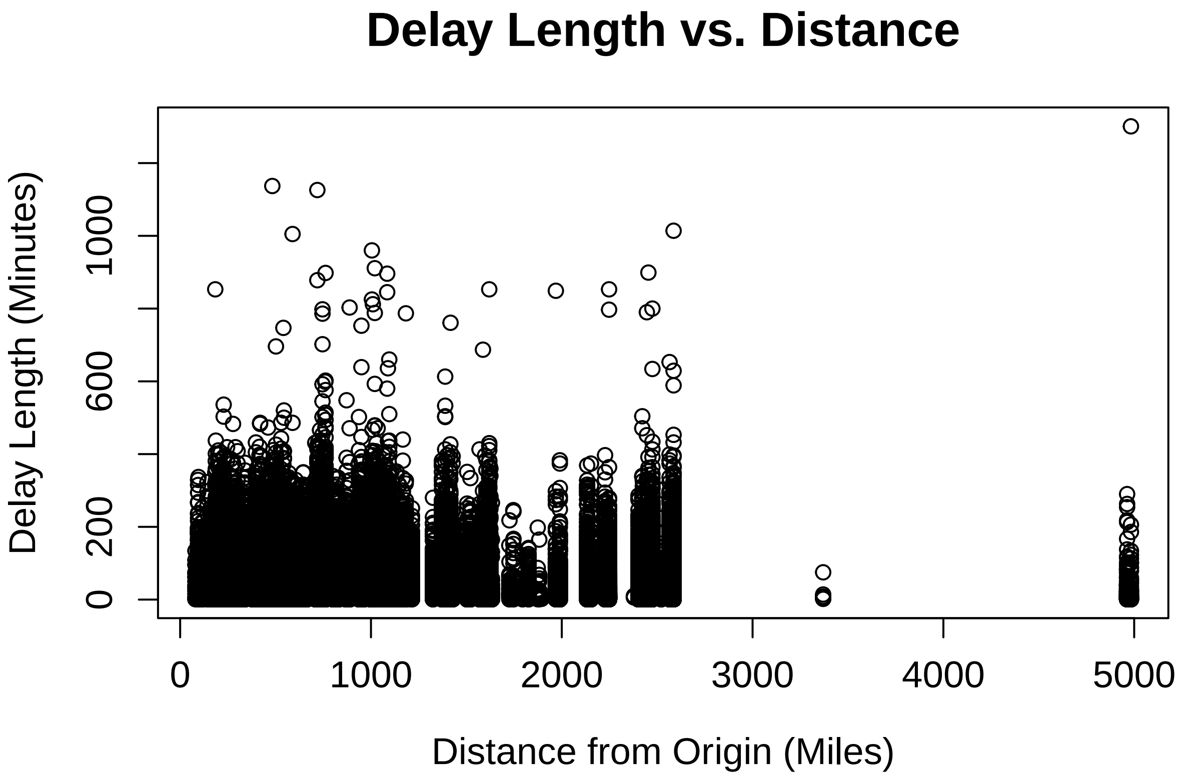
Takeways

It seems like wind speed, temperature, dew point, pressure, and humidity are the variables with strongest relationship with departure delay.



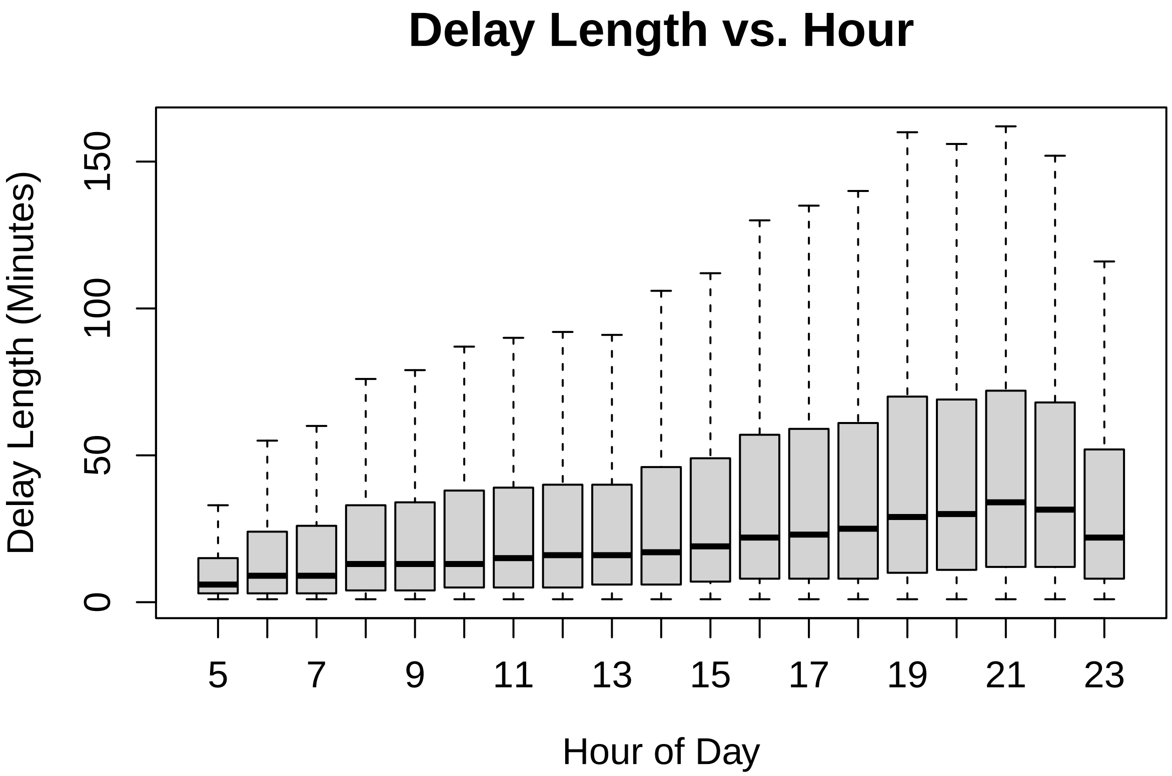
Frankly it's hard to tell which destinations are which, but it's enough to tell that there are clearly some with much better delay times than others, so this is definitely a variable we will want to use, at least during variable selection.

```
plot(flights$dep_delay[which(flights$dep_delay >
    0)] ~ flights$distance[which(flights$dep_delay >
    0)], xlab = "Distance from Origin (Miles)",
    ylab = "Delay Length (Minutes)", main = "Delay Length vs. Distance",
    cex.lab = 1.2, cex.main = 1.5, cex.axis = 1.2)
```



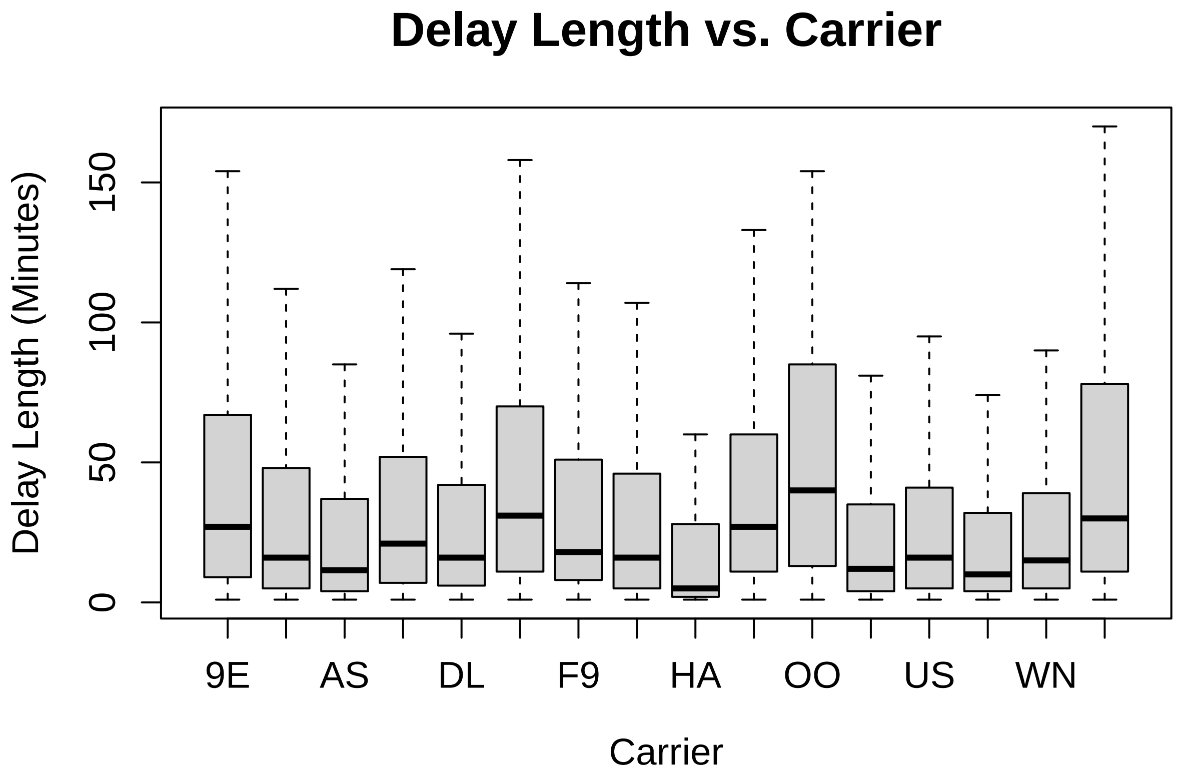
In our opinion, destination does not seem useful. The only real difference visually is at the ~3300 mile mark, but that has very few observations which makes it hard to say anything for sure.

```
boxplot(flights$dep_delay[which(flights$dep_delay >
    0)] ~ flights$hour[which(flights$dep_delay >
    0)], outline = F, xlab = "Hour of Day",
    ylab = "Delay Length (Minutes)", main = "Delay Length vs. Hour",
    cex.lab = 1.2, cex.main = 1.5, cex.axis = 1.2)
```



It seems pretty cut and dry that delay length goes up throughout the day until flights stop being scheduled. This makes perfect sense as delays are going to compound as delayed flights start getting in the way of other flights.

```
boxplot(flights$dep_delay[which(flights$dep_delay >
    0)] ~ flights$carrier[which(flights$dep_delay >
    0)], outline = F, xlab = "Carrier", ylab = "Delay Length (Minutes)",
    main = "Delay Length vs. Carrier", cex.lab = 1.2,
    cex.main = 1.5, cex.axis = 1.2)
```



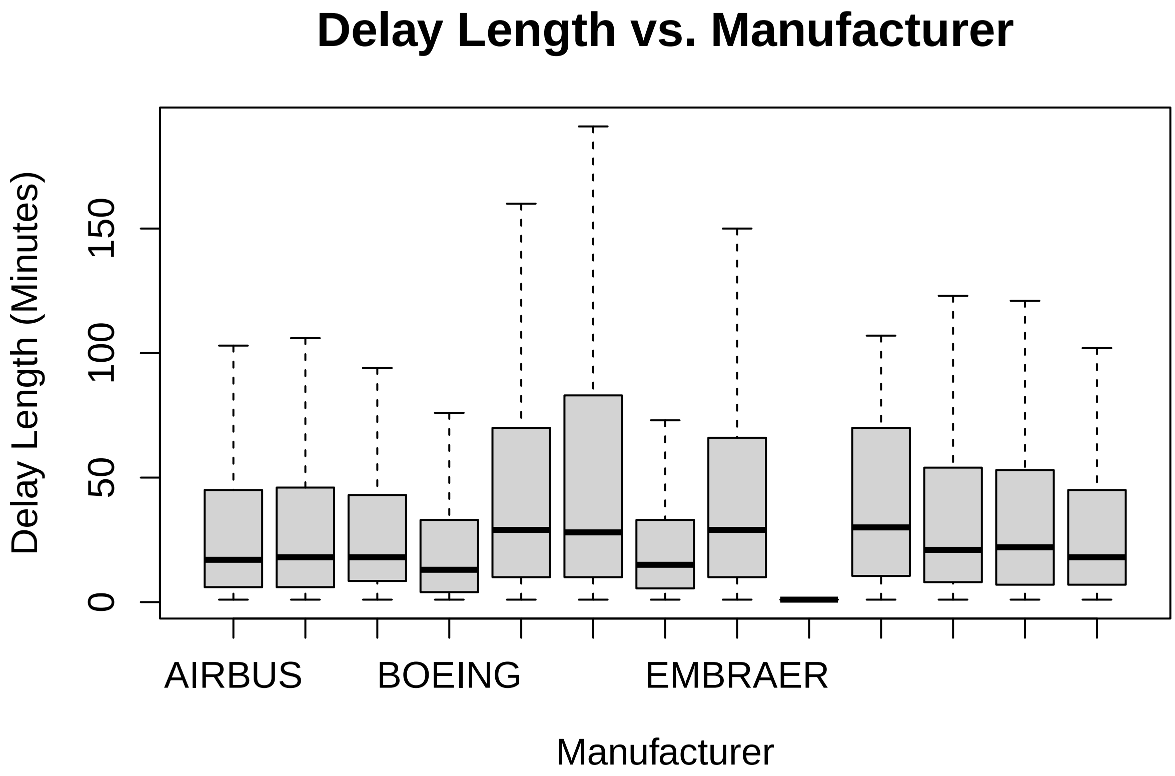
There does appear to be significant differences between carrier; we will continue with carrier into variable selection.

Potential Predictors from Planes Dataset

Looking at the documentation for planes, you can't merge flights with planes simply as American Airways and Envoy Air report their tail numbers in a different way than is reported in flights. As a result, we will remove these two airlines to allow us to look at variables in planes properly.

```
flightsPlanes = left_join(flights, planes,
    by = "tailnum")
flightsPlanes = flightsPlanes[-which(flightsPlanes$carrier %in%
    c("AA", "MQ")), ]
```

```
boxplot(flightsPlanes$dep_delay[which(flightsPlanes$dep_delay >
    0)] ~ flightsPlanes$manufacturer[which(flightsPlanes$dep_delay >
    0)], outline = F, xlab = "Manufacturer",
    ylab = "Delay Length (Minutes)", main = "Delay Length vs. Manufacturer",
    cex.lab = 1.2, cex.main = 1.5, cex.axis = 1.2)
```

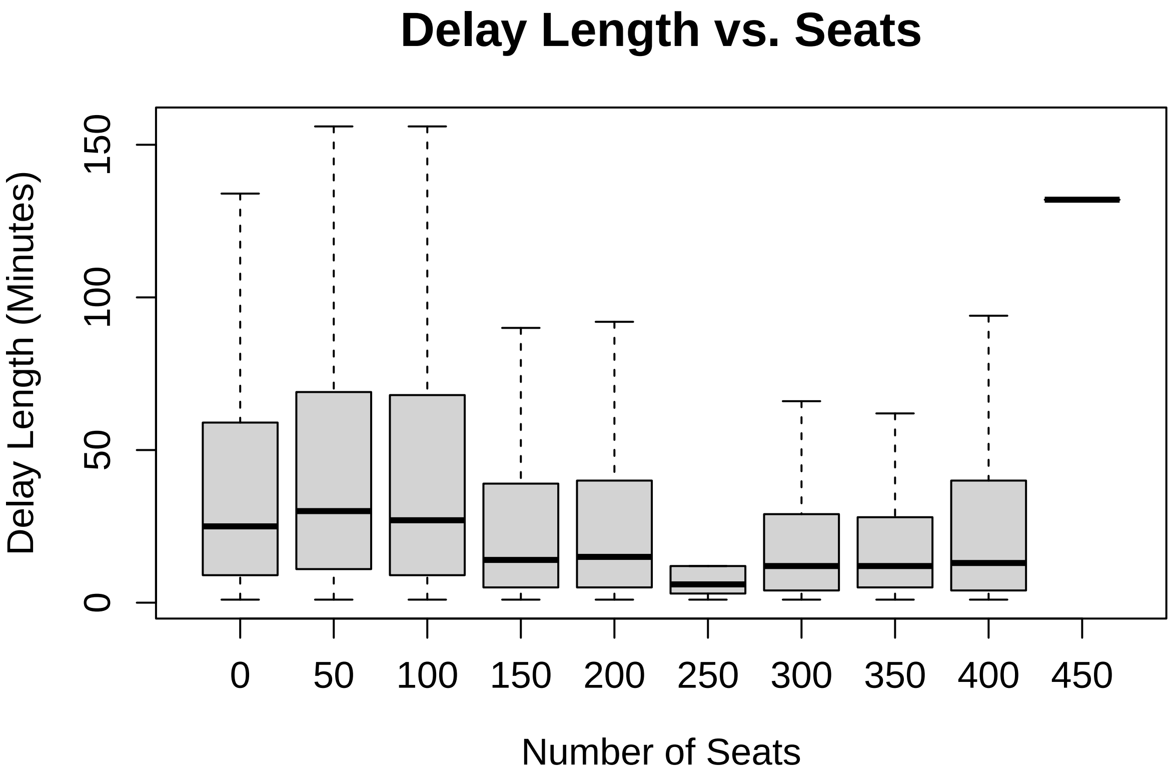


Some differences as usual, but difficult to say how significant. Will look into further.

```
table(round_any(flightsPlanes$seats[which(flightsPlanes$dep_delay >
    20)], 50, f = round))
```

```
##
##     0    50   100   150   200   250   300   350   400   450
##  4406 13290  5743  9265 18530     3   243   243   362     1
```

```
boxplot(flightsPlanes$dep_delay[which(flightsPlanes$dep_delay >
    0)] ~ round_any(flightsPlanes$seats[which(flightsPlanes$dep_delay >
    0)], 50, f = round), outline = F, xlab = "Number of Seats",
    ylab = "Delay Length (Minutes)", main = "Delay Length vs. Seats",
    cex.lab = 1.2, cex.main = 1.5, cex.axis = 1.2)
```



Based on the table and the graph together, while some seat numbers don't have very many observations for them, it does seem like there could be a difference in delay between planes with fewer than 150 seats and between 150-250 seats.

```
table(flightsPlanes$engine)
```

```
##
##      4 Cycle Reciprocating     Turbo-fan     Turbo-jet   Turbo-shaft
##            3           543        231780         40387           286
```

Frankly, nearly every plane has a Turbo-fan engine, so there is not much to look at.

Modeling

- Goal: Create a model to help decide which variables are most useful and maybe get a hierarchy within them.

Checking Assumptions

Logistic regression has less assumptions than Linear regression. It requires a binary response, which we have with our ‘sigDelay’ variable. Also, there cannot be multicollinearity. Earlier from the correlation matrix, we saw that dew point and temperature had high correlation which could be an indication of multicollinearity. So dew point was chosen as the variable to add to the model because it had visually had the strongest relationship with the response. Finally, our sample size is still very large even after eliminating rows for missing data and removing variables.

```
wd = wf[, c(20, 26, 27, 29:32)]
sample <- sample(c(TRUE, FALSE), nrow(wd), replace = TRUE, prob = c(0.7,
    0.3))
test = wd[sample, ]
train = wd[!sample, ]
test_x = test[, -1]
test_y = test$sigDelay

weather.model = glm(sigDelay ~ ., data = train, family = "binomial")

summary(weather.model)
```

```
##
## Call:
## glm(formula = sigDelay ~ ., family = "binomial", data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.5980  -0.7048  -0.6296  -0.5181   2.2629
##
## Coefficients:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept) 25.0239100  1.3047980  19.178  < 2e-16 ***
## dewp         0.0058146  0.0005364  10.841  < 2e-16 ***
## humid        0.0044429  0.0006232   7.129 1.01e-12 ***
## wind_speed   0.0234981  0.0016831  13.961  < 2e-16 ***
## precip       3.4997427  0.6023654   5.810 6.25e-09 ***
## pressure    -0.0263921  0.0012710 -20.765  < 2e-16 ***
## visib       -0.0319282  0.0064229  -4.971 6.66e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 88029  on 87196  degrees of freedom
## Residual deviance: 86454  on 87190  degrees of freedom
##   (10280 observations deleted due to missingness)
## AIC: 86468
```

```
##
## Number of Fisher Scoring iterations: 4
```

```
full_pred = predict(weather.model, newdata = test_x, type = "response")
delay_preds = rep(FALSE, length(full_pred))
delay_preds[full_pred > 0.4] = TRUE
print("TEST RESULTS")
```

```
## [1] "TEST RESULTS"
```

```
table(delay_preds, test_y)
```

```
##             test_y
## delay_preds  FALSE   TRUE
##       FALSE 178974  48449
##       TRUE     553    366
```

```
mean(delay_preds == test_y)
```

```
## [1] 0.7854008
```

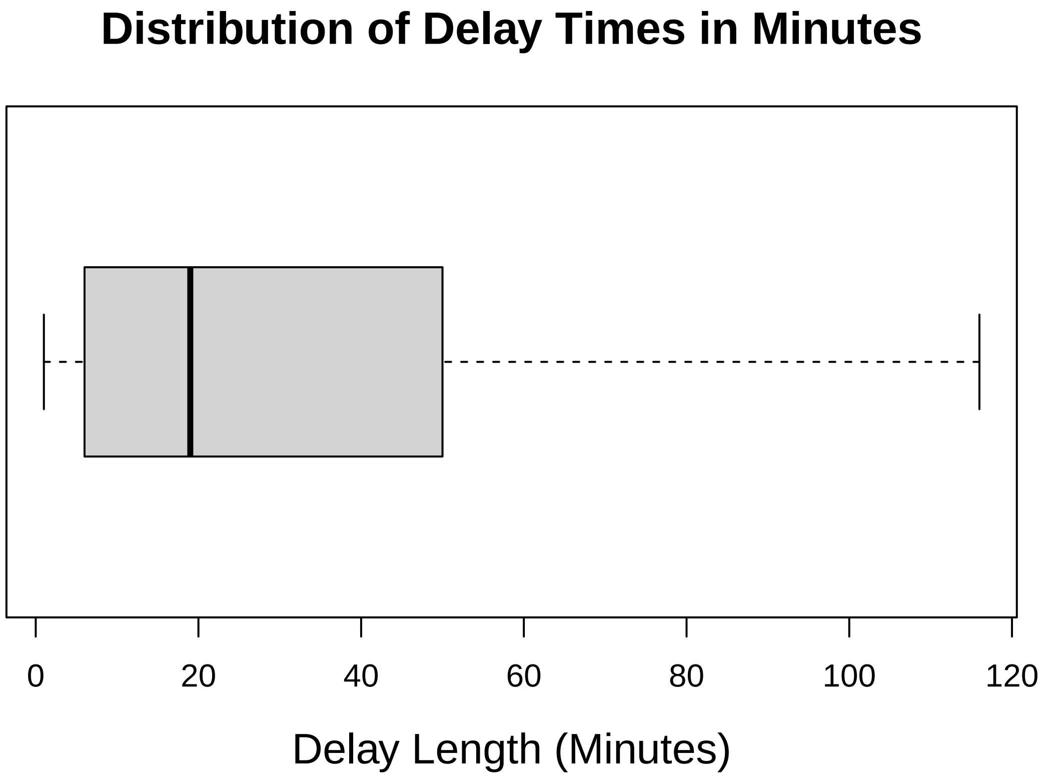
Model Results

Our model shows that dew point, wind speed, and pressure seem to be the most power predictors of a delay occurring. Variables such as precipitation and visibility should be taken with a grain of salt because they have very skewed distributions of data.

Using the model to predict on training data resulted in a 78% accuracy rate. At first glance this seems like a positive, however it overwhelmingly predicts flights to not be delayed. In fact, ~80% of flights were not delayed in this data set so always predicting no delay results in ~ 80% accuracy anyway. Therefore, this model is not ideal for prediction and should just be used to determine useful variables.

The Dependent Variable

```
boxplot(flights$dep_delay[flights$dep_delay >
    0], outline = F, xlab = "Delay Length (Minutes)",
    main = "Distribution of Delay Times in Minutes",
    cex.lab = 1.3, cex.main = 1.4, horizontal = T)
```



```
mean(flights$dep_delay[which(flights$dep_delay >
    0)])
```

```
## [1] 39.37323
```

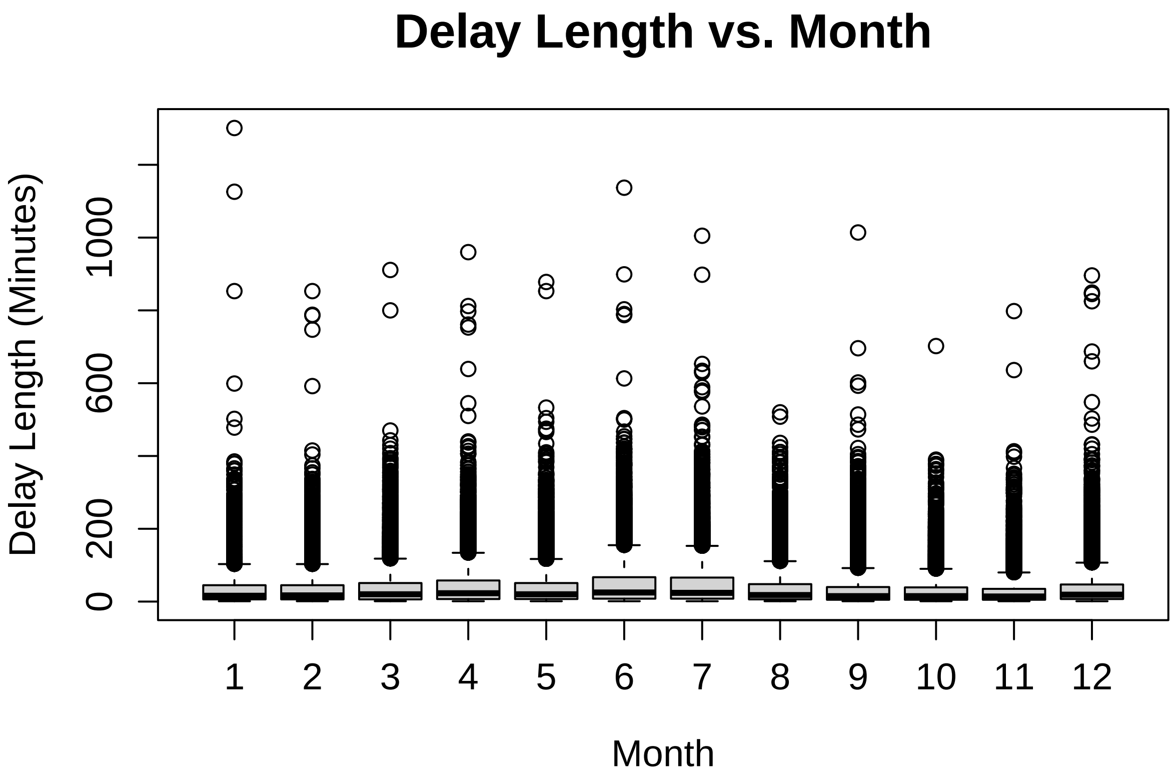
Looking at the distribution of delays by itself (omitting outliers for formatting, though they are still used in calculation), it seems quite skewed. 75% of delays are under 45 minutes, and 25% are just 5 minutes or less. Additionally, despite the median being around 20, the mean is 40, which is closer to the 3rd quartile than the median.

Considering the minor distinction 10 minutes makes in a delay and the relative lack of variance in this distribution, it may be unreasonable to try and model delay in minutes. Perhaps a binary dependent variable would be better.

Potential Predictors From Flights Dataset

By our understanding, each observation is a record of a single flight. This would imply that variables such as arrival delay would be the delay of a plane arriving at the destination after it departed, not the arrival of the same plane but from the previous flight. Thus, we think arr_time, arr_delay, and air_time don't make sense to include at all, since they cannot possibly be used to predict departure delays.

```
boxplot(flights$dep_delay[flights$dep_delay >
    0] ~ flights$month[flights$dep_delay >
    0], xlab = "Month", ylab = "Delay Length (Minutes)",
    main = "Delay Length vs. Month", cex.lab = 1.2,
    cex.main = 1.5, cex.axis = 1.2)
```



At an initial glance, it seems like month will be a helpful variable. There is a fairly clear upward trend from the beginning of year into summer which peaks around July, and then falls again until December. This is intuitive, as one would expect more traffic and thus more delays in the summer and holidays.

```
boxplot(flights$dep_delay[which(flights$dep_delay >
    0)] ~ flights$origin[which(flights$dep_delay >
    0)], outline = F, xlab = "Origin Airport",
    ylab = "Delay Length (Minutes)", main = "Delay Length vs. Origin",
    cex.lab = 1.2, cex.main = 1.5, cex.axis = 1.2)
```

Model for Variable Selection

Cleaning data

```
# Keep only carriers, models, and
# destinations that have over 1% of
# flights
carrierNames = names(table(flightsPlanes$carrier)[(table(flightsPlanes$carrier)/nrow(flightsPlanes)) >
    0.01]/nrow(flightsPlanes))

flightsPlanes = flightsPlanes[flightsPlanes$carrier %in%
    carrierNames, ]

modelNames = names(table(flightsPlanes$model)[(table(flightsPlanes$model)/nrow(flightsPlanes)) >
    0.01]/nrow(flightsPlanes))

flightsPlanes = flightsPlanes[flightsPlanes$model %in%
    modelNames, ]

destNames = names(table(flightsPlanes$dest)[(table(flightsPlanes$dest)/nrow(flightsPlanes)) >
    0.01]/nrow(flightsPlanes))

flightsPlanes = flightsPlanes[flightsPlanes$dest %in%
    destNames, ]

# Creating binary variable
flightsPlanes$sigDelay = ifelse(flightsPlanes$dep_delay >=
    15, 1, 0)

# For modeling purposes, month should
# not be continuous
flightsPlanes$month <- as.factor(flightsPlanes$month)


# Check for NAs and remove
sum(is.na(flightsPlanes))  # 219496, that's a lot
```

```
## [1] 219496
```

```
# Many have multiple columns with all
# NAs, we can try to remove those rows
sum(is.na(flightsPlanes[26]))  # Almost all entries in speed
```

```
## [1] 200699
```

```
# Speed column basically all NA, remove
# it
flightsPlanes = flightsPlanes %>%
    select(-"speed")

sum(is.na(flightsPlanes[6]))
```

```
## [1] 2373
```

```
# Some have no dependent variable, so
# might as well remove these
# observations
flightsPlanes = flightsPlanes[which(!is.na(flightsPlanes[6])),
    ]
# Many are in year
flightsPlanes = flightsPlanes[which(!is.na(flightsPlanes[20])),
    ]
# The rest I'll just remove ad hoc
flightsPlanes = flightsPlanes[which(!is.na(flightsPlanes[7])),
    ]
flightsPlanes = flightsPlanes[which(!is.na(flightsPlanes[9])),
    ]
```

Now we can remove variables that we considered unusable, unhelpful or too big (in the case of tailnum – it has too many levels to run anything in reasonable time).

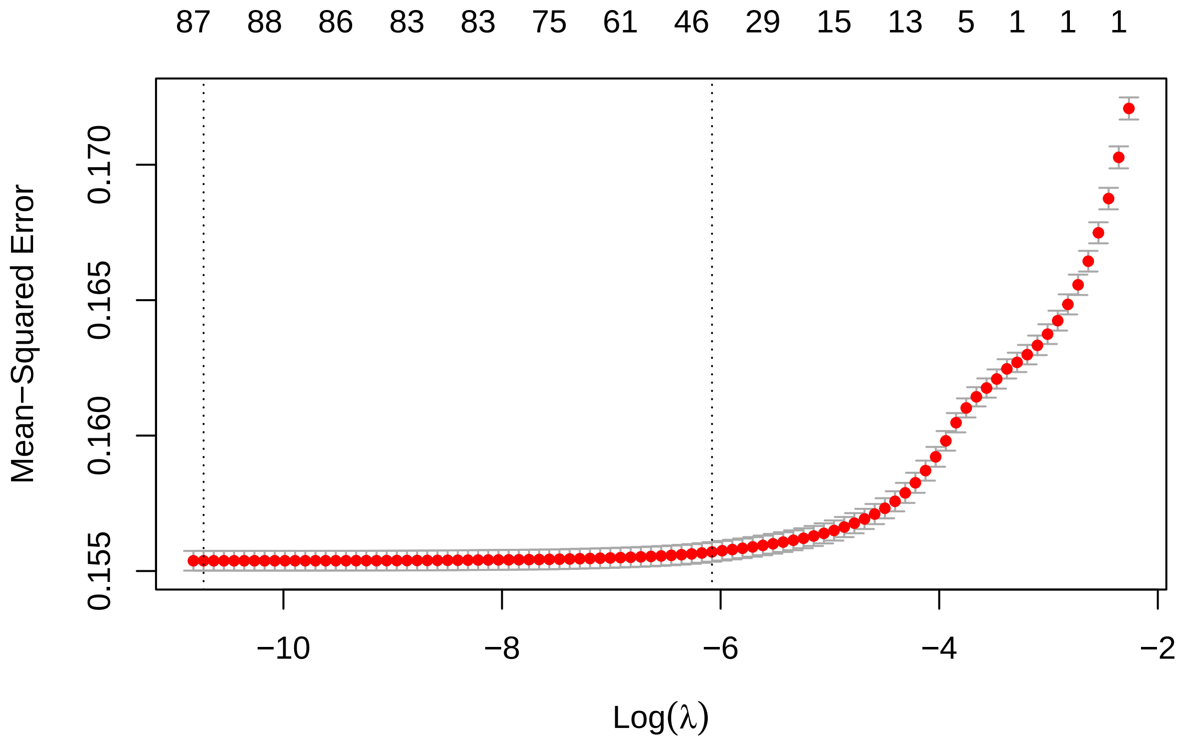
```
flightsPlanes = flightsPlanes %>%
    select(-c(4, 6, 7, 9, 12, 13, 15, 16,
        18, 21, 24, 26))
```

Variable Selection With Flights and Planes

I will run an initial LASSO model to select which variables from the combination of the flights and planes datasets are important. Since many of these variables are factors, we would expect many to have coefficients of zero, making LASSO and reasonable option. We don't plan on doing inference, so the lack of a closed form solution for LASSO is not an issue for us.

```
xInit = model.matrix(sigDelay ~ ., flightsPlanes)[,
    -1]
yInit = flightsPlanes$sigDelay

lasso.cvInit = cv.glmnet(xInit, yInit, alpha = 1)
plot(lasso.cvInit)
```



```
lambda.cvInit = lasso.cvInit$lambda.min
lambda.cvInit

fit.lassoInit = glmnet(xInit, yInit, alpha = 1,
    lambda = lambda.cvInit)

# Let's check which variables seem
# important
CFInit = as.matrix(coef(fit.lassoInit, fit.lassoInit$lambda.cv))
CFInit[CFInit != 0, ][order(CFInit[CFInit !=
    0])]

# Month, carrier, model, destination,
# manufacturer, and hour Some variables
# have coefficients that aren't zero,
# but are below 0.001.  In the interest
# of creating a very interpretable
# model, we will leave these out for
# the full model.
```

Final Model

Now that we have selected variables from flights, planes, and weather, we can create a final model to get the best interpretability.

```
# Pressure, wind speed, dew point

wf <- merge(flights, weather, by = c("time_hour",
    "origin"))

# Removing the unnecessary variables
# except for those needed to combine,
# just because combining everything
# took too much memory

wf = wf[c(4, 8, 12, 14, 15, 18, 25, 28, 31)]

wfp = left_join(wf, planes, by = "tailnum")

wfp = wfp[c(1, 2, 3, 5, 6, 7, 8, 9, 12, 13)]


# Remove AA and MQ because they don't
# join correctly
wfp = wfp[-which(wfp$carrier %in% c("AA",
    "MQ")), ]

# Keep only carriers, models, and
# destinations that have over 1% of
# flights
carrierNames = names(table(wfp$carrier)[(table(wfp$carrier)/nrow(wfp)) >
    0.01]/nrow(wfp))
wfp = wfp[wfp$carrier %in% carrierNames,
    ]

modelNames = names(table(wfp$model)[(table(wfp$model)/nrow(wfp)) >
    0.01]/nrow(wfp))
wfp = wfp[wfp$model %in% modelNames, ]

destNames = names(table(wfp$dest)[(table(wfp$dest)/nrow(wfp)) >
    0.01]/nrow(wfp))
wfp = wfp[wfp$dest %in% destNames, ]

wfp$sigDelay = ifelse(wfp$dep_delay >= 15,
    1, 0)
wfp$month.x <- as.factor(wfp$month.x)

# Remove NAs
colSums(is.na(wfp))
```

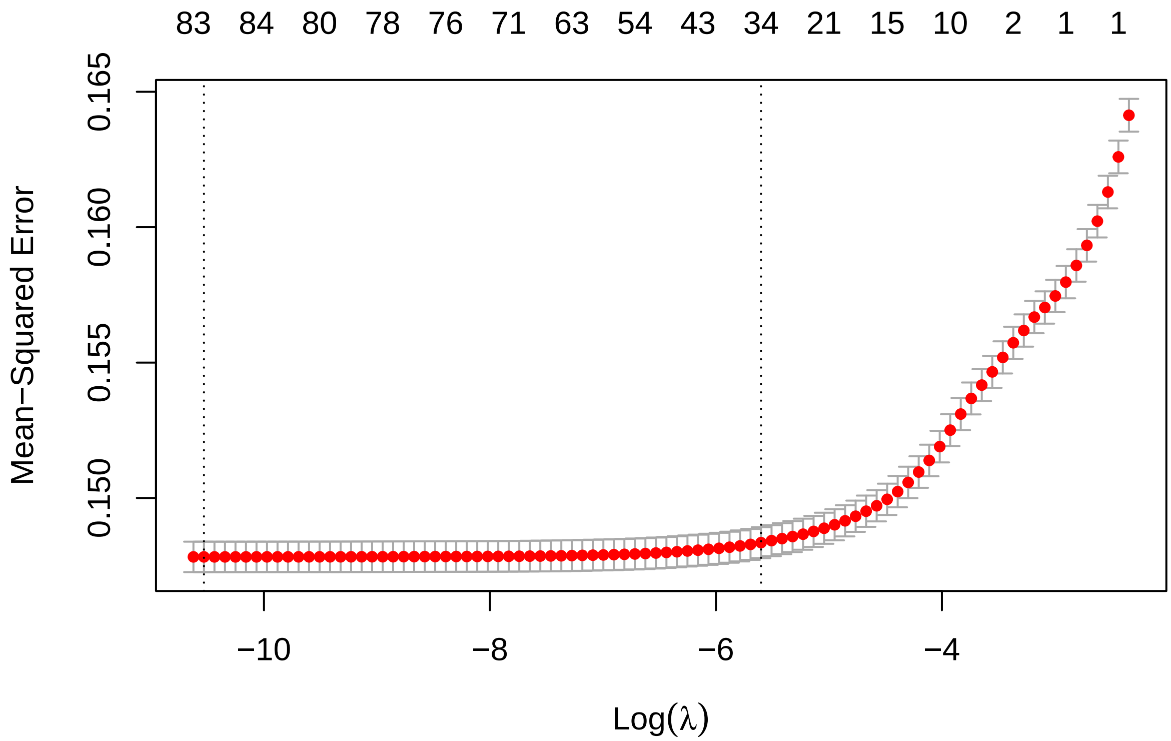
```
##      month.x    dep_delay      carrier         dest       hour.x         dewp
##            0         2370            0            0            0           13
##   wind_speed     pressure manufacturer        model     sigDelay
##           60        22040            0            0         2370
```

```
wfp = wfp[which(!is.na(wfp$dep_delay)), ]
wfp = wfp[which(!is.na(wfp$pressure)), ]
wfp = wfp[which(!is.na(wfp$wind_speed)),
    ]
```

Final Model

```
x = model.matrix(sigDelay ~ ., wfp[-2])[,
    -1]
y = wfp$sigDelay

# LASSO
lasso.cv = cv.glmnet(x, y, alpha = 1)
plot(lasso.cv)
```

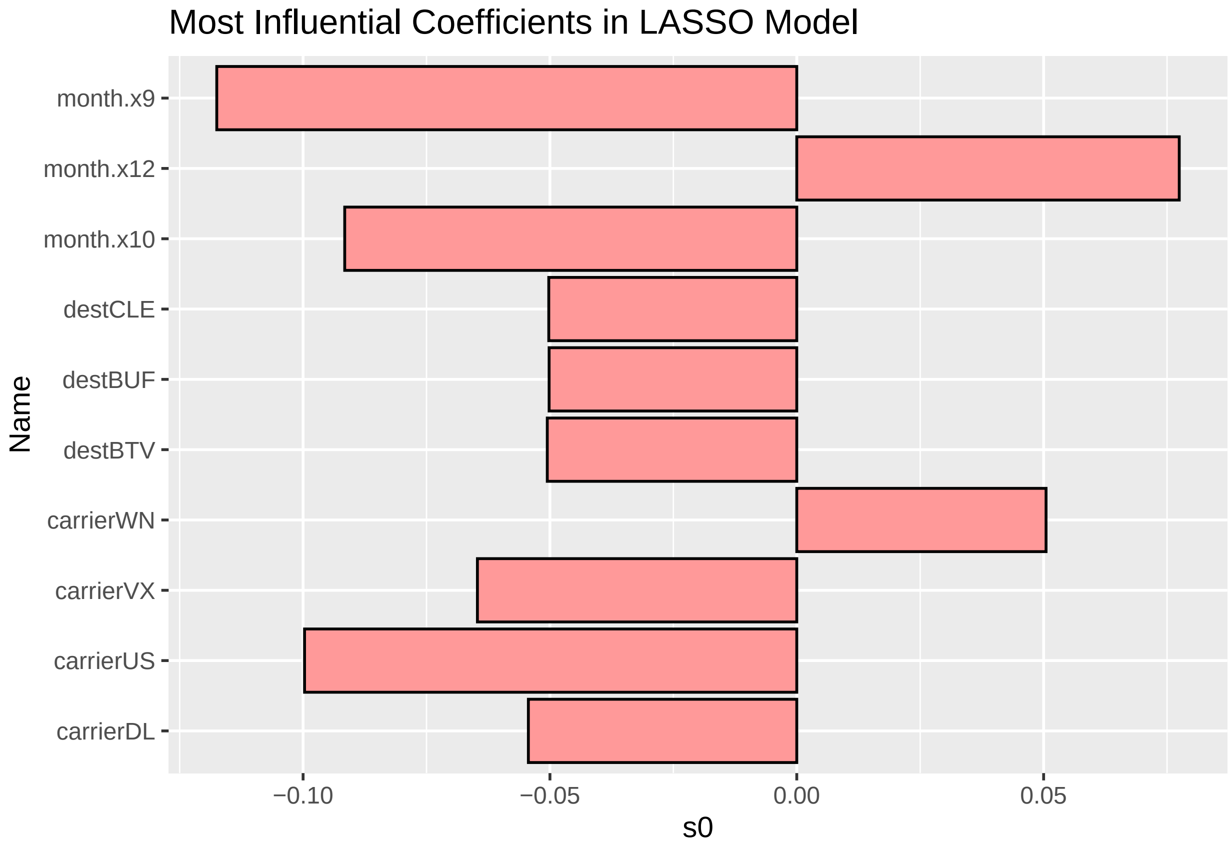


```
lambda.cv = lasso.cv$lambda.min
lambda.cv

fit.lasso = glmnet(x, y, alpha = 1, lambda = lambda.cv)

CF = as.matrix(coef(fit.lasso, fit.lasso$lambda.cv))
CF[CF != 0, ][order(CF[CF != 0])]

# Plotting most influential predictors
lasso_coef <- as.data.frame(as.matrix(coef(fit.lasso)))
lasso_coef <- cbind(Name = rownames(lasso_coef),
    lasso_coef)
lasso_coef <- lasso_coef[-1, ]
o <- order(abs(lasso_coef$s0), decreasing = TRUE)
lasso_coef <- lasso_coef[o, ]
lasso_coef <- lasso_coef[c(1:10), ]
rownames(lasso_coef) <- 1:nrow(lasso_coef)
p <- ggplot(data = lasso_coef, aes(x = Name,
    y = s0)) + geom_bar(stat = "identity",
    fill = "#FF9999", colour = "black")
p + coord_flip() + ggtitle("Most Influential Coefficients in LASSO Model")
```



The Lasso model results show that the most influential positive variables to be Month 12 and carrierWN (Southwest Airlines) The most influential negative variables are Month 9, Month 10, and carrierUS

Key Insights

Increase in Delay Variables:

Months: April - August, and December
Carriers: Southwest, AirTran, JetBlue, ExpressJet
Manufacturers: Embracer, Bombardier, Airbus

Decrease in Delay Variables:

Months: March, September
Carriers: United, US Airways, Delta, Virgin America

Along with these we found many other variables that also have trends associated with delay times such as:
Destination —
Increased Delay: Miami, Palm Beach
Decreased Delay: George Bush International, Nashville

Model —
Increased Delay: EMB-145LR, 737-924ER, and EMB-145XR
Decreased Delay: 757-232, 757-224, and ERJ 190-100 IGW

Dew Point —
Increased Delay when over 65 F

Wind Speed —
Increasing Delay with higher wind speed. Significant after 25 mph

Pressure —
Increasing Delay with lower pressures values

These results show that the Port Authority should focus on specific Months, Carriers, and Manufacturers to ensure delay is decreased as they have the highest influence on the departure delay of airplanes. This might include optimizing the number of flights being scheduled during high traffic months and placing stricter guidelines for certain carriers who have a high tendency to delay their flights so that customers are able to get to their destinations on time more often.