SDS 323: Exercises 1 Report

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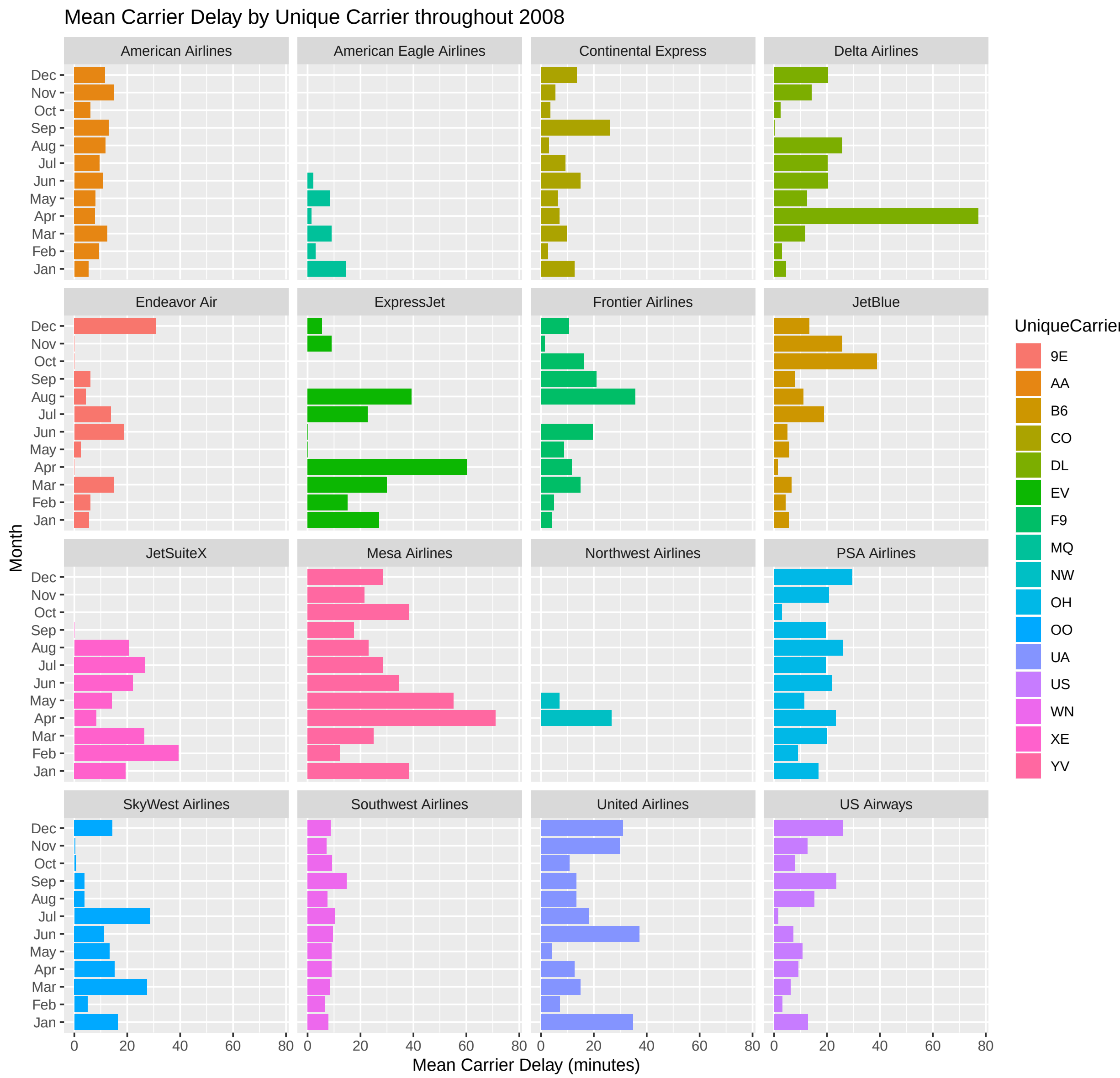
Data visualization: flights at ABIA

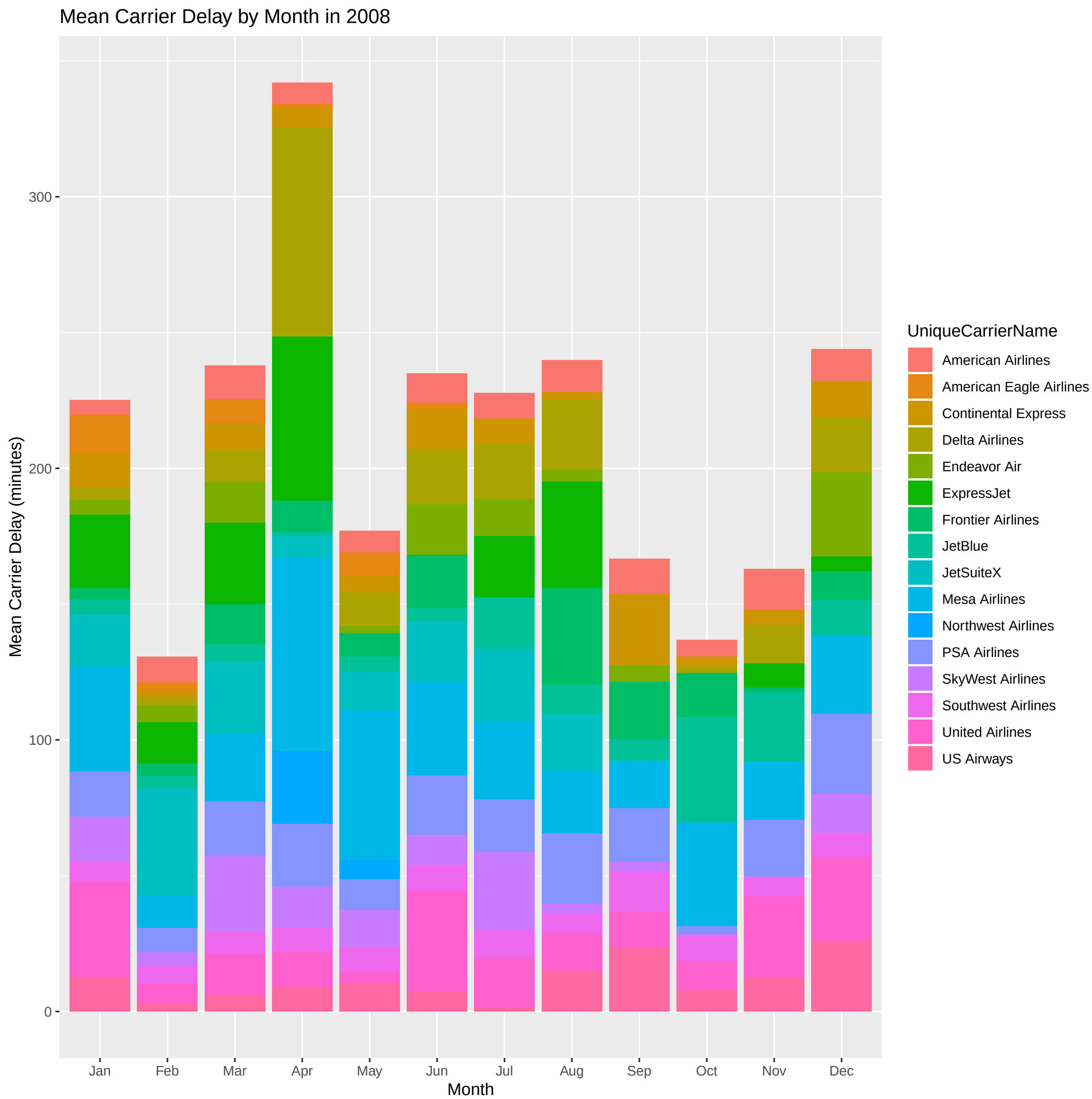
From the `ABIA.csv` data set, we could observe several interesting patterns in the airline data at ABIA in 2008. Some of the questions that we explored with the data included:

- During which times of the year, if any, does each carrier have significantly increased carrier delay?
- How does each carrier's delay compare to other carriers for the same month(s)?
- Is there varied flight activity over time throughout the year?
- How does flight activity compare at various destinations throughout the year?
  - Is there monthly variation in flight activity to JFK throughout the year? If so, what could be a potential reason?
  - Is there monthly variation in flight activity to CLE throughout the year? If so, what could be a potential reason?



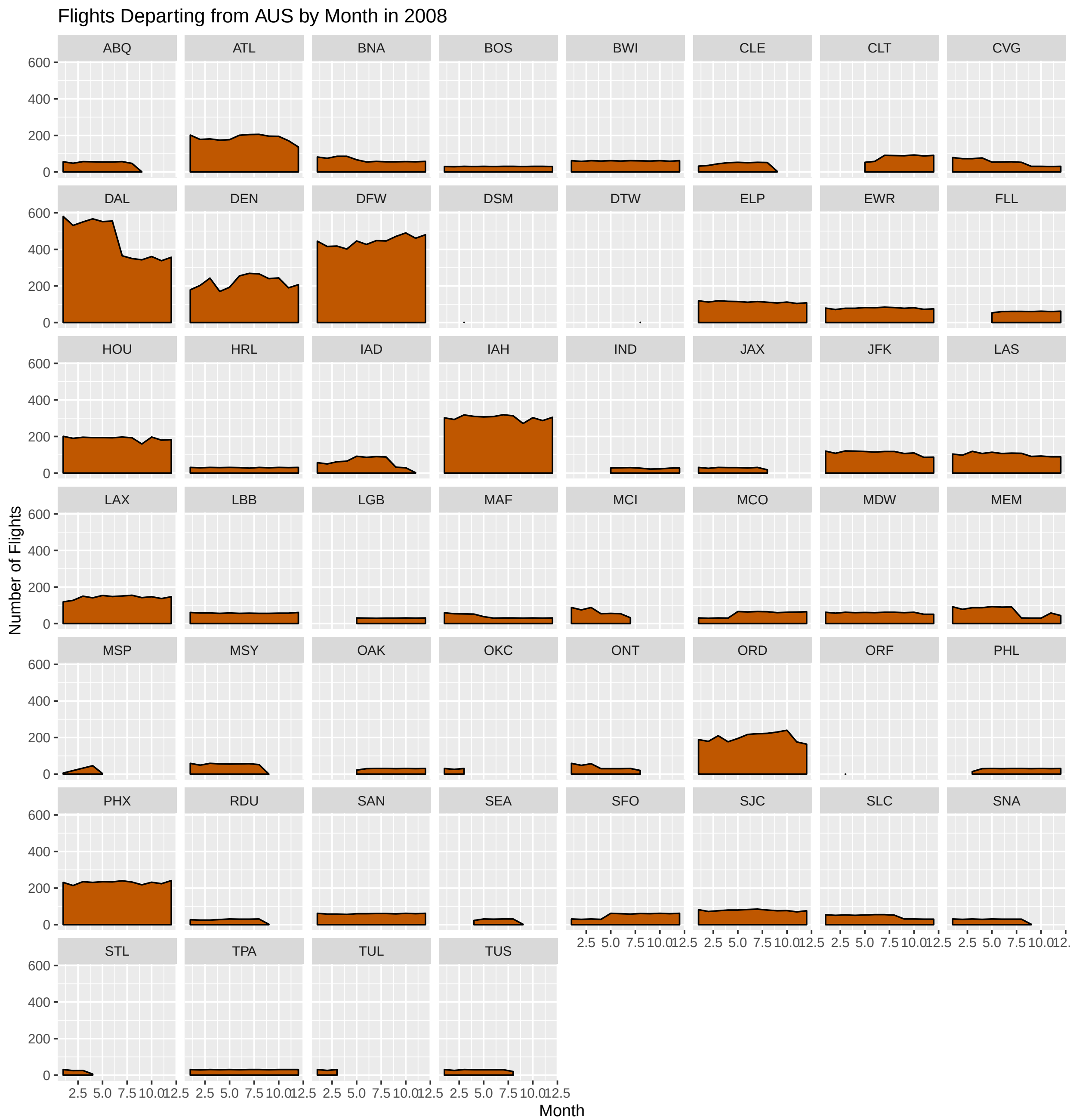
During which months, if any, does each carrier have significantly increased carrier delay?

This figure displays the mean carrier delay by month in 2008 faceted by unique carrier. We can see that prominent airlines such as American Airlines and Southwest Airlines have a relatively constant and low mean carrier delay throughout the year. This is reasonable because they are some of the most dominant carriers at ABIA, so they likely have sufficient staffing and resources to ensure that any flight delays are minimized. By contrast, Mes Airlines has relatively high mean carrier delays throughout the year, with April being the longest mean delay. Since this carrier is less prominent at ABIA, it is logical that they would have a limited number of flight staff and resources, which means they would not be capable of minimizing flight delays. Another interesting point that we notice here is that Delta Airlines had a significant jump in mean carrier delay in the month of April. Upon further research, I learned that there was a major breakdown at ATL (Hartsfield-Jackson Atlanta International Airport), which is the airline hub for Delta Airlines. According to CNN (http://www.cnn.com/2008/TRAVEL/08/26/faa.computer.failure/index.html), Delta Airlines and other ATL-based airlines experienced hours of flight delays after a communications breakdown at a Federal Aviation Administration (FAA) facility in April 2008. This communications breakdown likely caused the significant spike mean delay in April for Delta Airlines, especially since communications issues mean that flights cannot depart until all safety procedures have been completed.



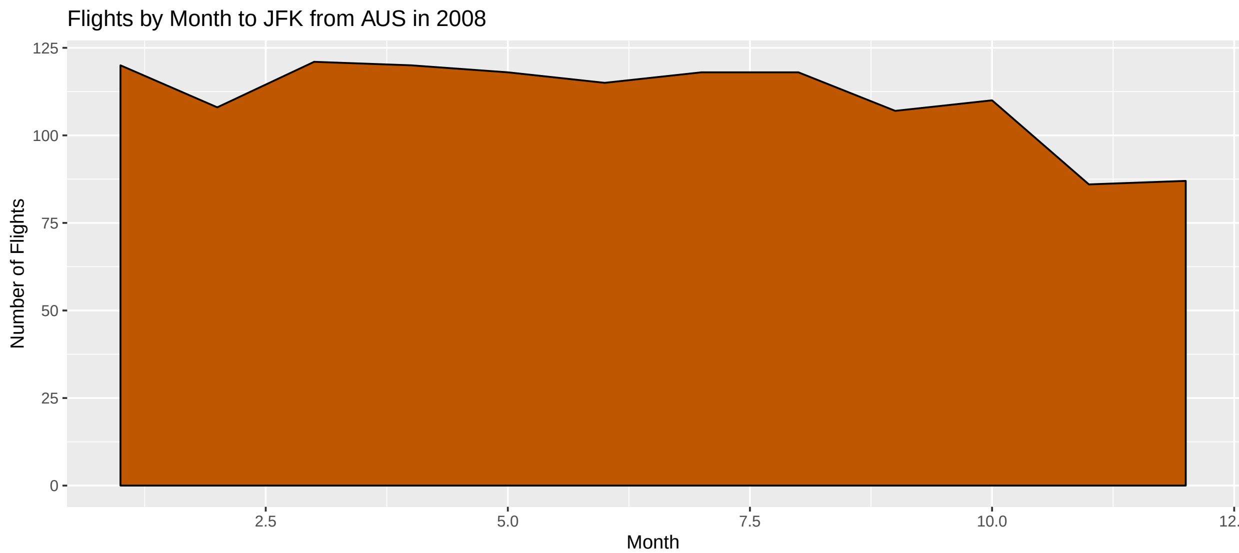
How does each carrier's delay compare to other carriers for the same month(s)?

Similar to the previous figure, the above figure displays the total mean carrier delays by month at ABIA in 2008. This figure provides useful information because it shows that April 2008 saw an increase in mean carrier delays for several airlines. Due to the FAA communications breakdown mentioned earlier, it makes sense that flights arriving from and departing to ATL were delayed, which may have propagated the delay to other flights as well. We also notice that the summer holiday months of June, July, and August as well as the winter holiday months of December and January have relatively the same amount of total mean carrier delay. This is reasonable because these months show heavy travel numbers as families will go on vacation, indicating that each of these months deals with approximately the same throughput. Accordingly, the offseason months of roughly February, May, September, October, and November all show lower total mean carrier delay because the have comparatively less throughput during these months since there would be less external variables that could delay flights.



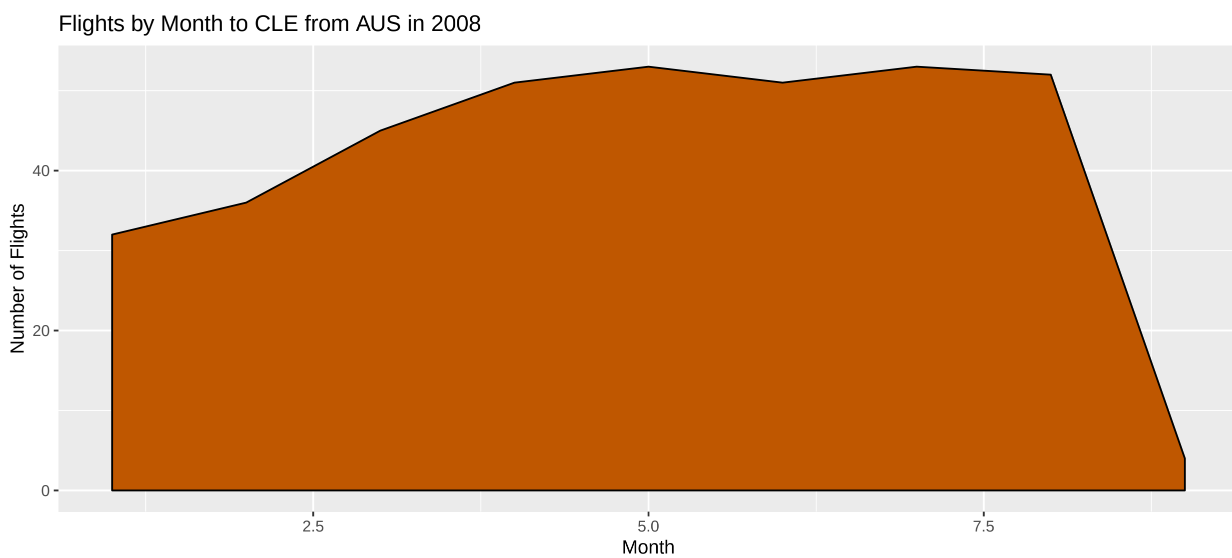
How does flight activity compare at various destinations throughout the year?

Another intriguing figure that we came across (shown above) was showing the number of flights departing from AUS each month in 2008 faceted by destination airport. For airports with close geographic distance (less than 300 miles), we can see that there were a signifiant amount of flights consistently throughout the year. These locations include DFW, DAL, IAH, and HOU. Additionally, the destinations that are hubs for major airlines also had significant numbers of flights throughout the year. For example, American Airlines has hubs in DFW and ORD, Delta Airlines has its hub in ATL, Southwest Airlines has its hub in PHX, and United Airlines has its hub in ORD, all of which show noticeable amounts of flights over 2008. We also acknowledged that other destinations that were more niche locations had seasonal variations in the number of flights. For example, OKC only had a noticeable amount of flights in the early portion of the year, while CLT was more popular in the later months of the year.



Is there monthly variation in flight activity to JFK throughout the year? If so, what could be a potential reason?

Continuing from the previous figure, we can see that flights to JFK dropped significantly in the months of November and December. While this could be because those are holiday months (i.e Thanksgiving, Christmas, etc.) and less people are traveling to New York for business-related matters, I believe that this phenomenon was due to the financial crisis in 2008. Due to the severe recession and economic downturn in 2008, it is plausible that many people who worked in New York in the business industry (like Wall Street) were laid off from their jobs.

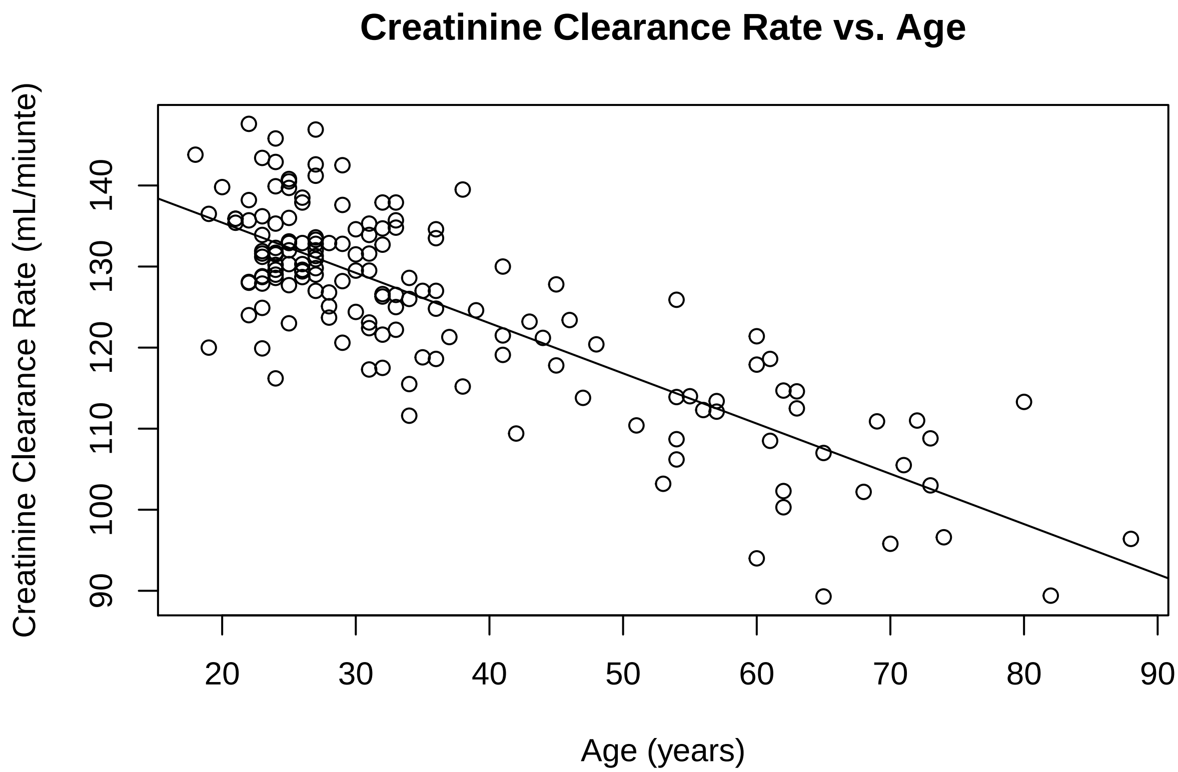


Is there monthly variation in flight activity to CLE throughout the year? If so, what could be a potential reason?

Another extension of the 3rd figure, we noticed that there were significantly fewer flights to CLE in the months of January, February, and March. Upon further research (https://www.weather.gov/cle/event_2008_notable), we identified that February and March gathered most of the monthly precipitation records for 2008 for Cleveland, Ohio. Accordingly, this density plot shows that there were noticeably fewer flights to CLE in the months of February and March compared to the following months. Due to the inclement weather during these early months, it is logical that fewer flights were scheduled for Cleveland.

Regression practice

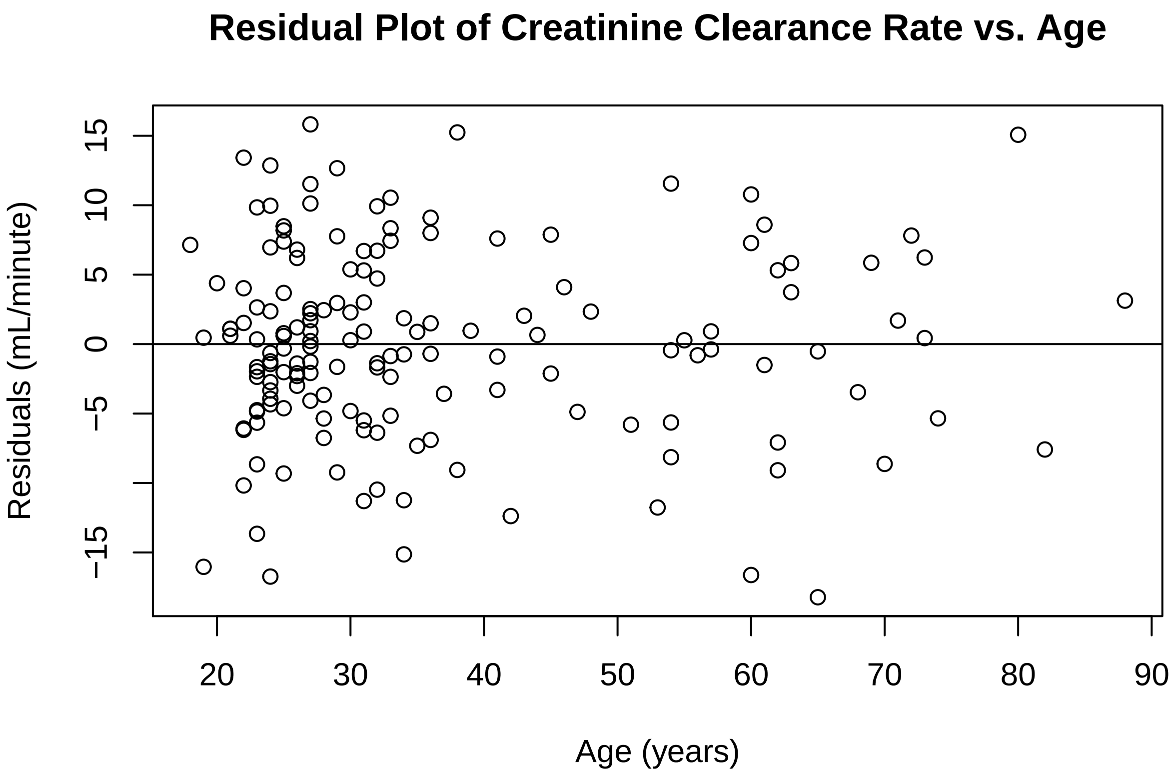
Using the data given in `creatinine.csv`, we can plot the values in a scatterplot that shows creatinine clearance rate against age. On this scatterplot, we can fit a linear model as the line of best fit. This linear regression model will allow us to predict creatinine clearance rate given age and vice versa. The scatterplot and the coefficients of the linear model are given below.




```
## (Intercept)         age
## 147.8129158  -0.6198159
```

The slope coefficient (shown as `age` above) of the linear model indicates that the creatinine clearance rate decreases by 0.6198 mL/minute per year. This is a reasonable rate of change because we know that a higher creatinine clearance rate is better and that it should generally decrease as age increases.

From the linear regression model, we can also compute the residuals for each of the data points and plot them on a residual plot as shown below.



We can also interpolate new data points to predict their values:

```
# make prediction on new data
new_data = data.frame(age = c(55))
predict(lm1, new_data)
```

```
##       1
## 113.723
```

Accordingly, we can see that, for an average 55-year-old, we should expect a creatinine clearance rate of 113.723 mL/minute.

To identify whether a 40-year-old with a rate of 135 or a 60-year-old with a rate of 112 is healthier for their respective age, we can predict creatinine clearance rates for average people of their age and compute the residuals.

```
# make predictions on new data to compare patients
patient_data = data.frame(age = c(40, 60))
predict(lm1, patient_data)
```

```
##        1        2
## 123.0203 110.6240
```

```
# compute residuals for each patient
135 - 123.0203
```

```
## [1] 11.9797
```

```r
112 - 110.6240
```

```
## [1] 1.376
```

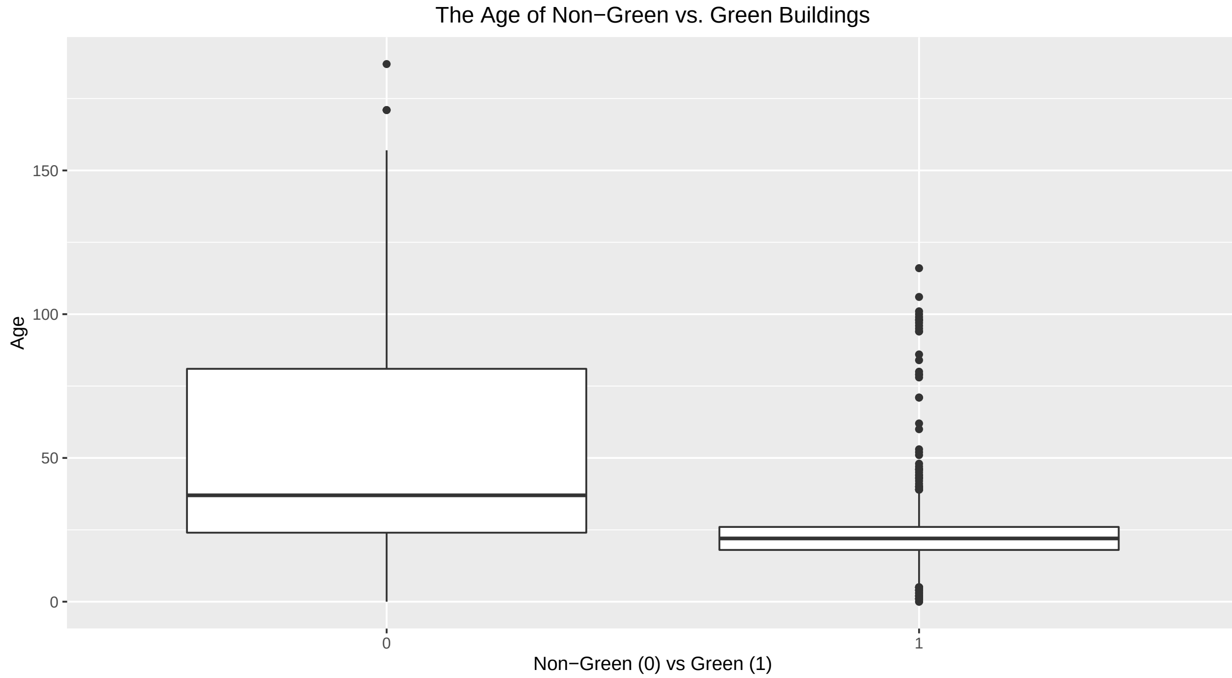
Since the 40-year-old with a rate of 135 mL/minute has a residual of 11.9797 mL/minute and the 60-year-old with a rate of 112 mL/minute has a residual of 1.376 mL/minute, the 40-year-old has a healthier creatinine clearance rate. This is because a higher positive residual value is considered to indicate better health since it means that the actual rate of the 40-year-old subject is much greater than the predicted rate for 40-year-olds while the actual rate of the 60-year-old subject is only slightly greater than the predicted rates for 60-year-olds.

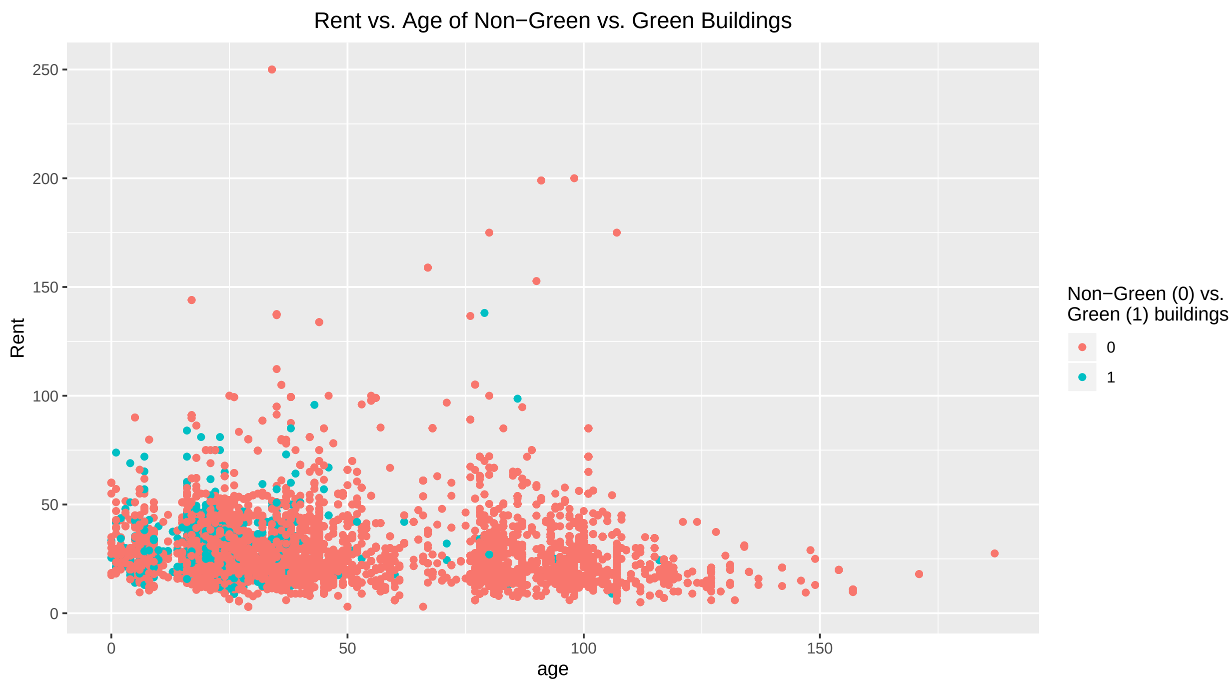
Green buildings

In order to aid the Austin real-estate developer in determining the possible economic impact of "going green" and investing in a green building, we can analyze `greenbuildings.csv` to identify whether green building status indeed affects the rent costs of a building. If not, we can also examine the data set to identify other potential factors that could contribute to the rent costs of a building.

After understanding the on-staff data guru's analysis, we conclude that their analysis is not entirely accurate, and that they fail to take into account various confounding variables that may be better indicators of whether a building will be profitable or not. To begin, we also filtered out the buildings with less than 10% occupancy, but we also filtered out the buildings that had the `net` feature equal to 0. This meant we were removing buildings where the tenant paid for their own utilities because this could skew the rent that they were paying. Next, we looked at various correlation coefficients between different features of the data set to see if anything was more correlated to the `Rent` feature than the `green rating`. We found that `cluster_rent` and `electricity_costs` were each very strongly correlated with `Rent`, with r-values of 0.75 and 0.41, respectively. We also found that the r-value between `green_rating` and `Rent` was only 0.03, indicating a poor correlation between the two values. In addition, we created a few plots to identify the effect of confounding variables:

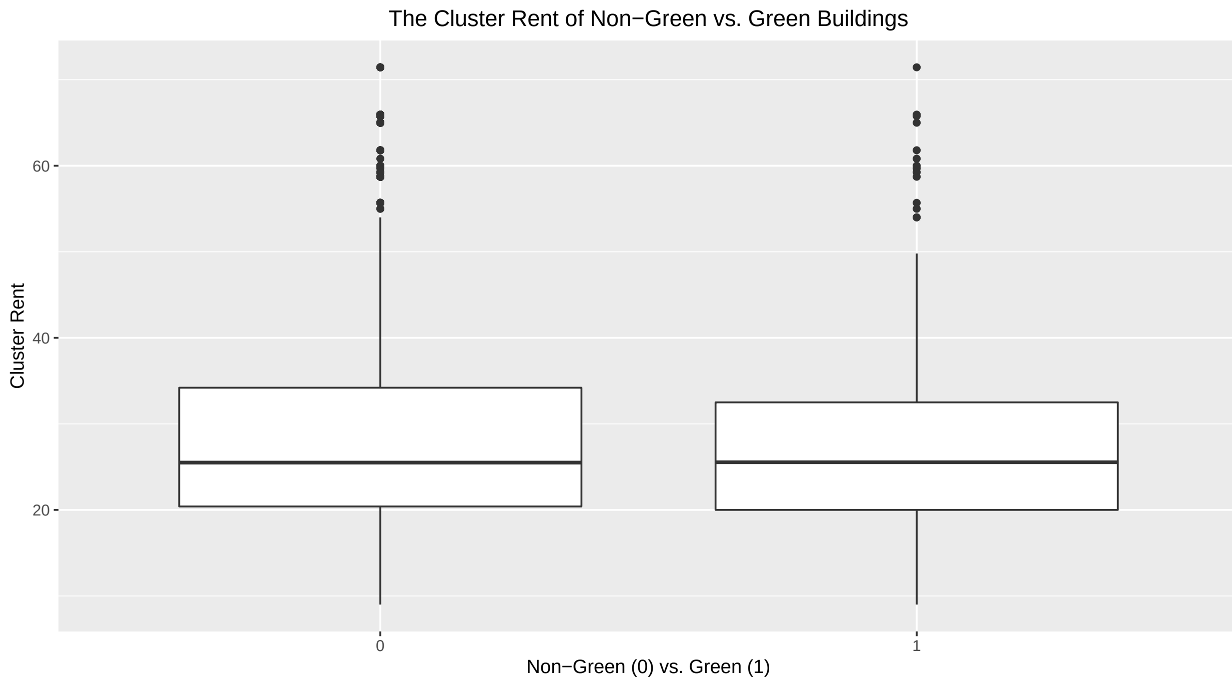
Age

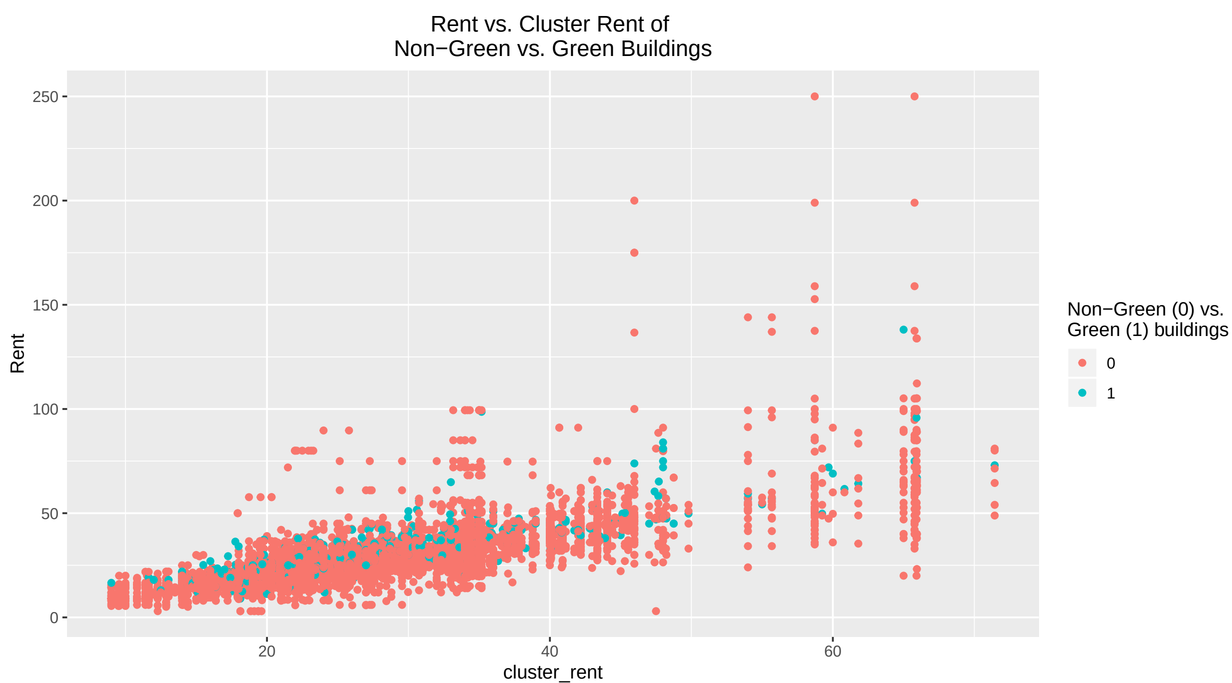




The first plot shows that green buildings on average tend to be newer (younger age) than non-green buildings. This shows that green buildings could be more expensive and require higher rent costs because they are more premium real estate. The second plot is a scatterplot of all the data points plotted by rent and age, where it is apparent that the green buildings are concentrated towards the left side of the graph, indicating that they are generally younger than non-green buildings.

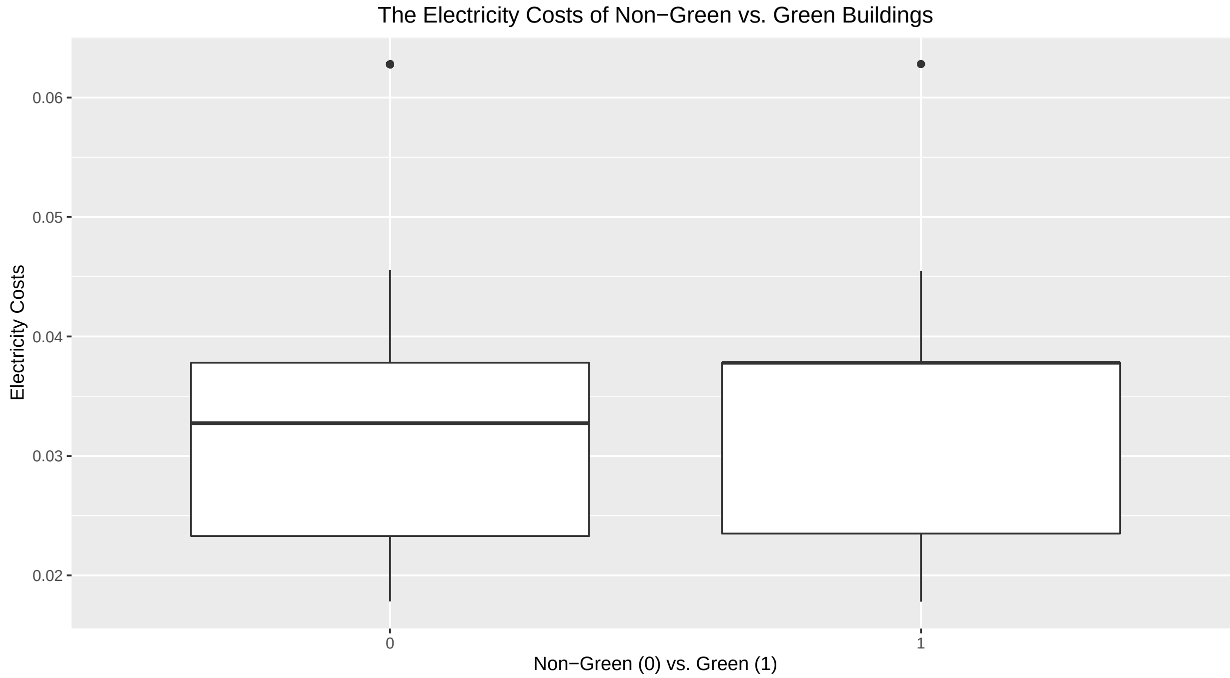
Cluster Rent

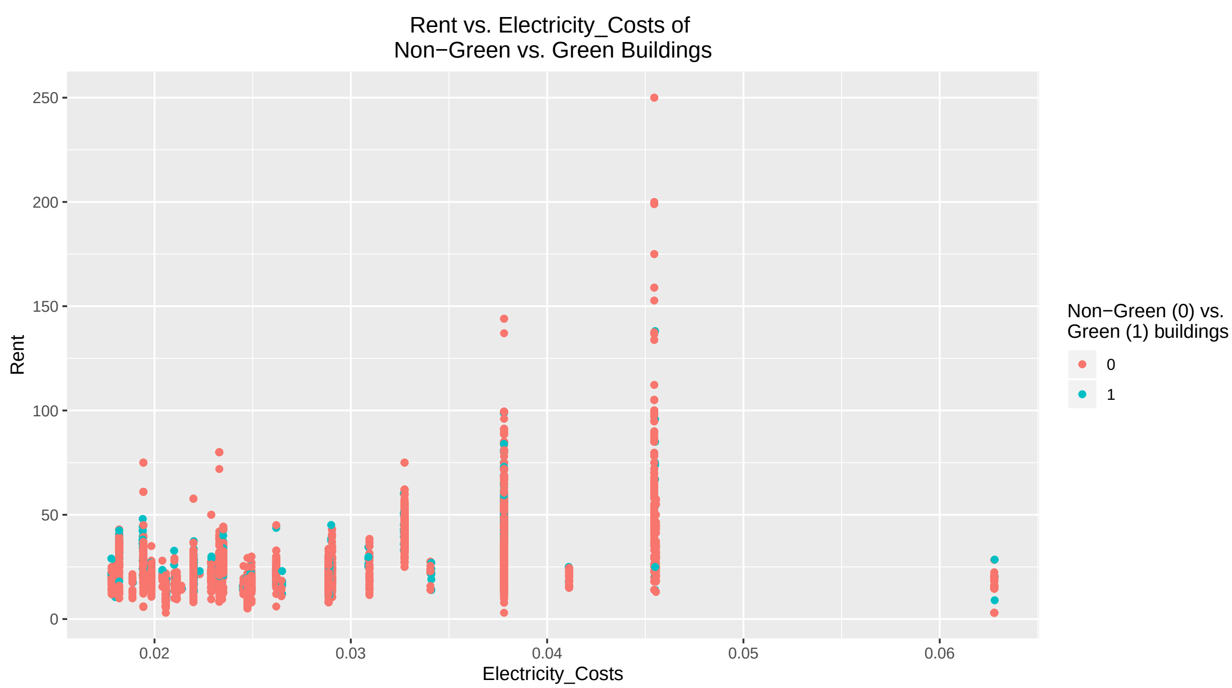




The plot above shows that when controlled for cluster rent, it seems that green and non-green buildings could potentially be equally profitable. Cluster rent, as mentioned above, has the strongest correlation to rent (evidenced by the scatterplot above), which simply means that the rent of all the buildings in a similar geographic region has the strongest effect on the rent of a building. If we take this variable into account, the rents seem to be equalized. This is reasonable because the rent costs in a metro area will generally be higher overall than the rent costs in suburban or rural areas.

Electricity Costs





Another potential confounding variable is the electricity costs of the area that the building is in, which was mentioned above as having the 2nd highest correlation with rent. The box plot clearly indicates that the median electricity cost in the areas green buildings are built is higher, which could explain the higher rent. The scatter plot also supports this idea, with most of the blue dots (green buildings) above the red dots (non-green buildings). The plots combined indicate that electricity costs in the area might be a better indicator of rent, especially as electricity costs are intrinsically tied to the concept of green/non-green buildings.

All in all, we can see through the various different plots that variables such as the age of the building, the mean rent of the cluster the building is part of, and the cost of electricity in the geographic region of the building all played an important role in determining the rent of the building itself. We conclude that due to the sheer number of other variables at work here that explain some of the causality and correlation between green vs non-green buildings and higher rent, the analysis in the case study isn't entirely accurate and is worth revisiting. Solely building a green building for higher profits may not result in the desired outcome, so the investor should take into account other factors in order to make their decision.

Milk prices

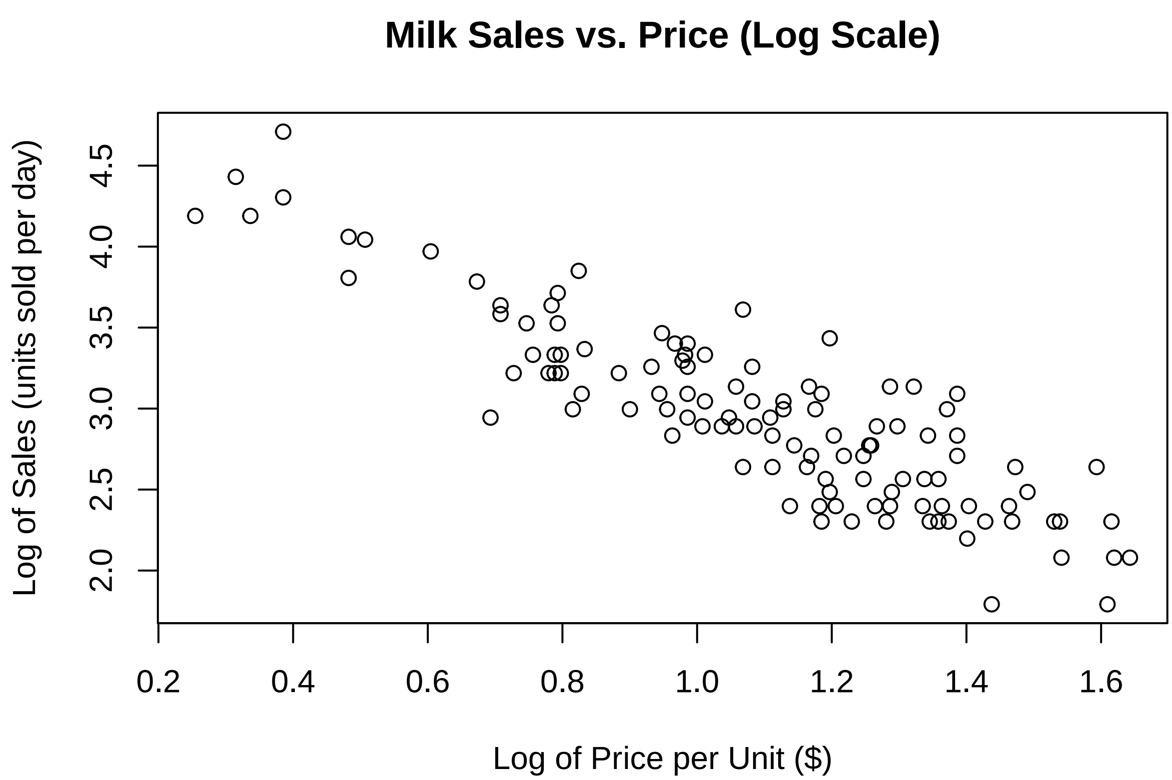
The `milk.csv` data set includes certain days' quantity in units of milk sold and the price it was sold for at a specific small neighborhood grocery store. From the perspective of the merchant, we would like to maximize the profit. To do so, we need to identify the optimal price to sell the milk. Our profit equation for this scenario is $N = (P - c) \cdot Q$ where P is the selling price, Q is the quantity sold, N is the profit, and c is the cost to buy from wholesaler.

```
# scatterplot of sales vs price
plot(sales ~ price, data = milk, main = "Milk Sales vs. Price",
     xlab = "Price per Unit ($)",
     ylab = "Sales (units sold per day)")
```

From basic economic laws of supply and demand, we know that P and Q are inversely related because the demand for the milk will increase as the price decreases. Therefore, we can set $Q = f(P)$ and our profit equation becomes $N = (P - c) \cdot f(P)$.

Using the Power law, we can show this as $Q = \alpha \cdot P^{\beta}$ where β is the price elasticity of demand and α is a constant. Taking the logarithm of both sides of the equation, we reach $\log(Q) = \log(\alpha) + \beta \cdot \log(P)$.

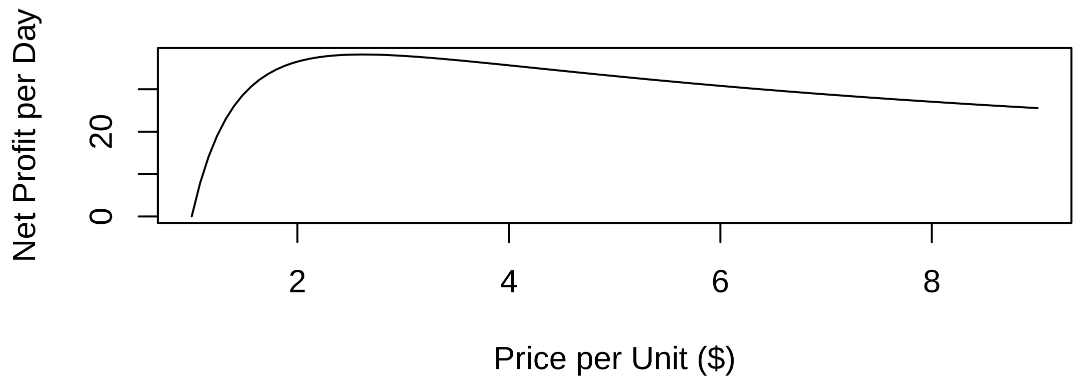
```r
# scatterplot of log(sales) vs log(price)
plot(log(sales) ~ log(price), data = milk, main = "Milk Sales vs. Price (Log Scale)",
     xlab = "Log of Price per Unit ($)",
     ylab = "Log of Sales (units sold per day)")
```

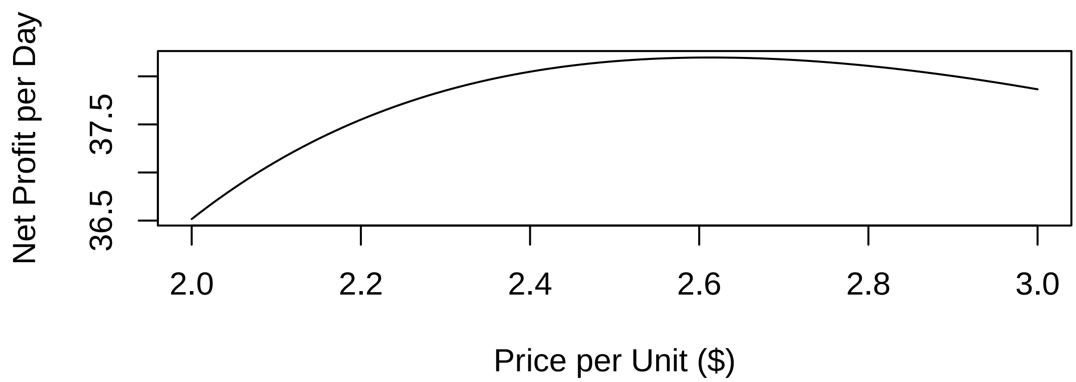


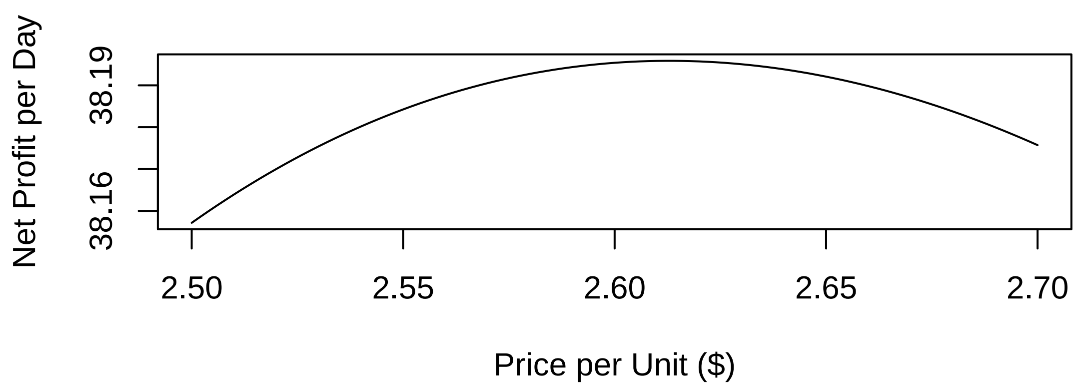

```r
# linear model for line of best fit for log scatterplot
lm_ped = lm(log(sales) ~ log(price), data = milk)
coef(lm_ped)
```

```
## (Intercept)  log(price)
##    4.720604   -1.618578
```

We can now see that the coefficients of the linear regression model are 4.720604 and -1.618578. Plugging these values in for $\log(\alpha)$ and β, respectively, we get $\log(Q) = 4.72 - 1.62 \cdot \log(P)$. By raising both sides to the exponent, we can remove the logarithm on the LHS and solve for Q as $Q = e^{4.72} \cdot P^{-1.62}$. Now that we have solved for Q as a function of P, we can plug Q back into our profit equation as $N = (P - c) \cdot e^{4.72} \cdot P^{-1.62}$. Computing the exponent value gives us $N = (P - c) \cdot 112.24 \cdot P^{-1.62}$. Since we know that the per-unit cost c is \$1, we can plot the curve with the equation $N = (P - 1) \cdot 112.24 \cdot P^{-1.62}$.







Plotting these curves and zooming into the region where the global maximum lies, we can observe that the function peaks at approximately $P = 2.61$. Thus, we should charge a price of \$2.61 per unit in order obtain a maximum profit of approximately \$38.20 per day.