Analyzing UFO Sightings

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Introduction

The data we were working with came from a data set called "UFO sightings scrubbed" that was found on Kaggle.com from a user named Akhil Goyal. The data was last updated three months ago but only contains data from 1906 till 2014. The data could have some bias if UFO sightings from certain regions of the world were not recorded or included in this data set, additionally it is observational data collected by different people around the globe which can create large amounts of variation.
This data is of interest because UFOs have been a topic of public interest for years. With increasing amounts of interest in space travel and extraterrestrials in more recent years, the fascinations with UFOs has only grown stronger. For this project we want to explore what influences sightings as this can be valuable knowledge for those trying to investigate UFOs.
In order to work with our data we had to clean it. This included converting the datetime column into year, month, day, seconds, minutes, hours format. Then we created a new data set where we added columns for years, seconds, and months and kept the updated datetime, city, state, country, longitude, and latitude columns. We then had to convert both longitude and latitude into numeric values in order to work with them. Additionally we had to remove some columns with improper formatting and we dropped any columns with NA's. The variables we used and code for this data cleaning follows:

datetime: the date and time of sighting in year, month, day, hours, minutes, seconds format.
city: city where sighitng occurred
state: state where sighting occurred
country: country where sighting occurred
seconds: duration of sightings in seconds
latitude: latitude of sighting
longitude: longitude of sighing
year: year when sighing occurred
month: month when sighting occurred

```
ufo_raw <- read.csv("ufo_sightings_scrubbed.csv")

#convert date time to ymd_hms format
ufo_raw$datetime <- ymd_hms(ufo_raw$datetime)

#cleaning data
ufo_raw|>
  # keep duration in seconds form only
   mutate(seconds = duration..seconds.,
          # split datetime data into a year and a month column
          year = year(datetime),
          month = month.name[month(datetime)])|>
```

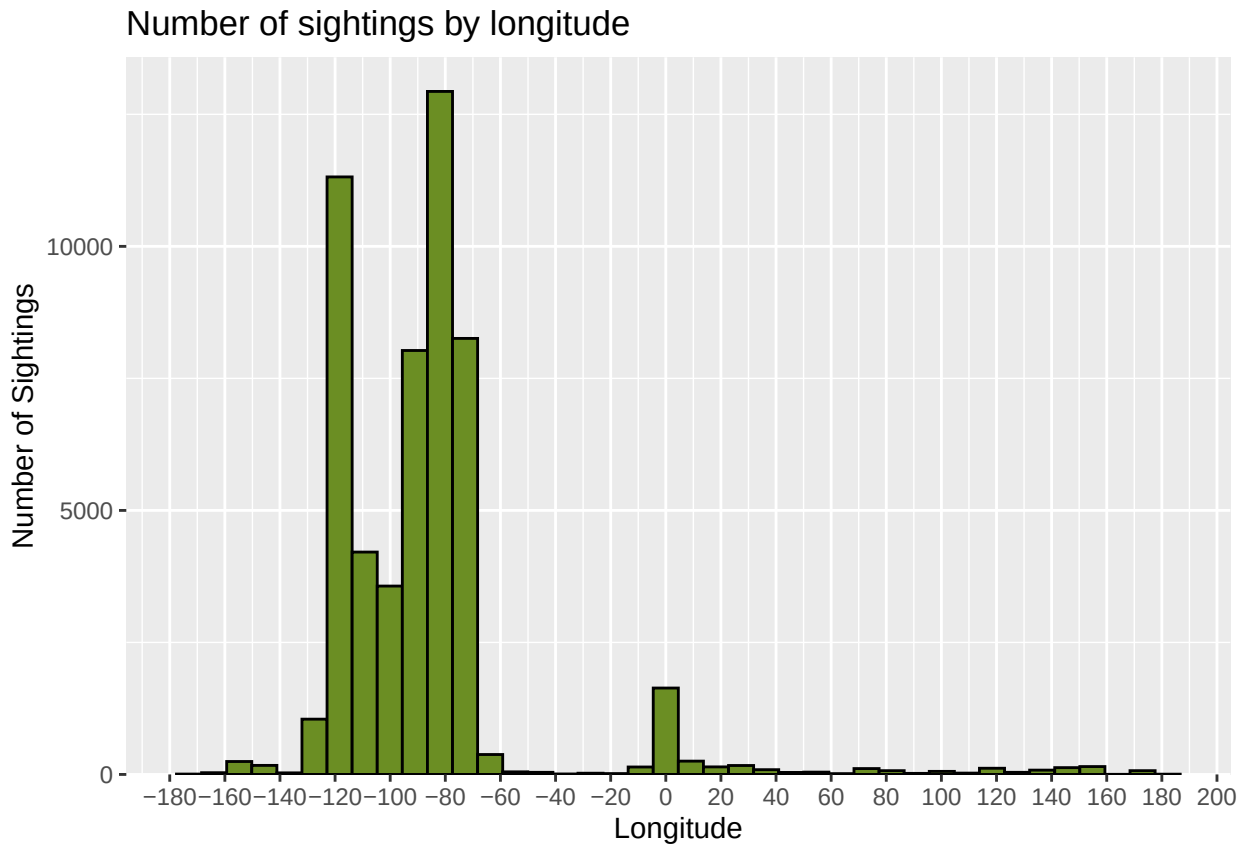
```r
  # select relevant columns
  select(datetime, city, state, country, seconds,latitude,longitude, year, month)|>
    filter(seconds <= 40000) |>
    # filter out badly formatted entries that could cause NA's during the following conversion
    filter(grepl("^[-]?[0-9.]+$", latitude),
           grepl("^[-]?[0-9.]+$", seconds)) -> ufo


ufo$latitude <- as.numeric(ufo$latitude) #changing lat to numeric
ufo$seconds <- as.numeric(ufo$seconds) #changing seconds to numeric

# drop any remaining NA entries
ufo <- ufo |> drop_na(longitude, latitude, seconds)
```

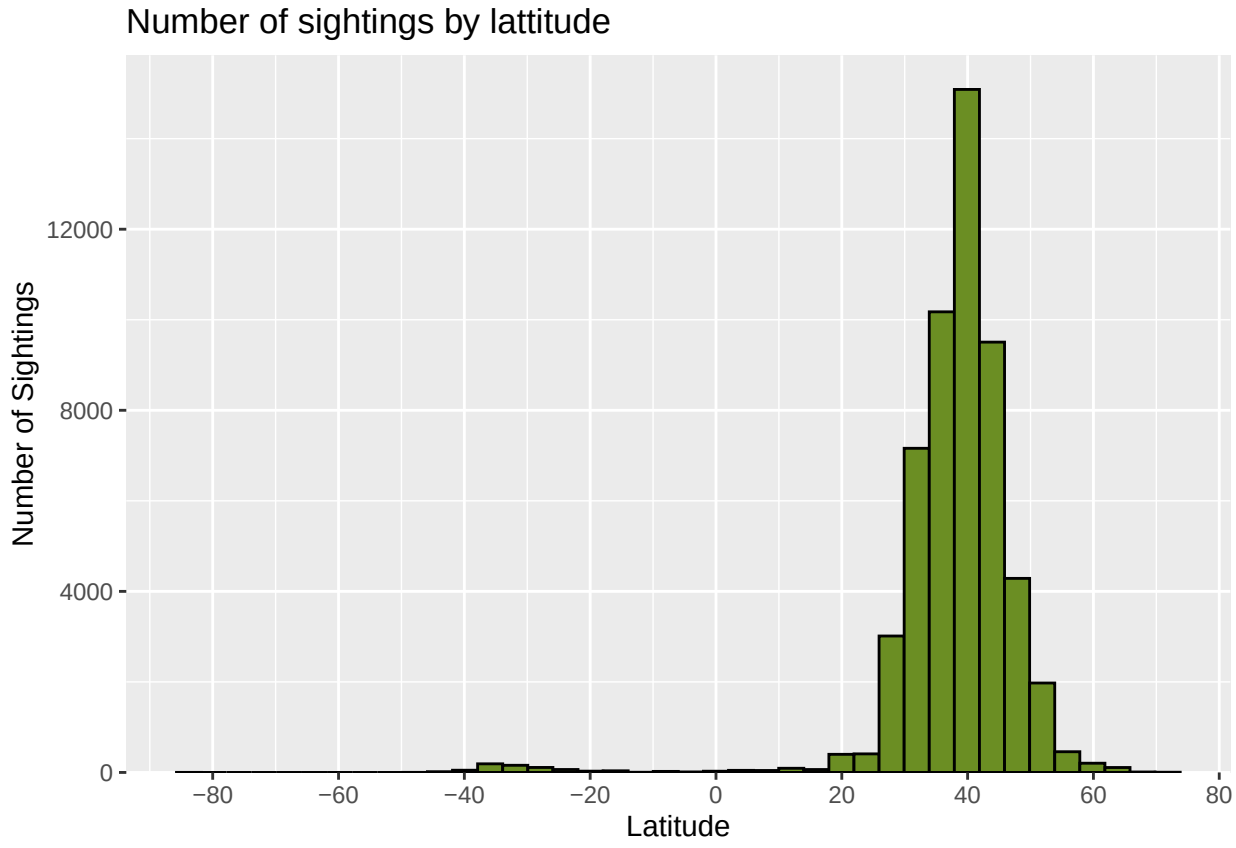
Data Analysis

The first question we had about UFO sightings is how the location around the world influenced the number that occurred. We began by creating histograms for longitude and latitude. From there we created a scatter plot to compare latitude and longitude to see if there was a relationship between the two of them.

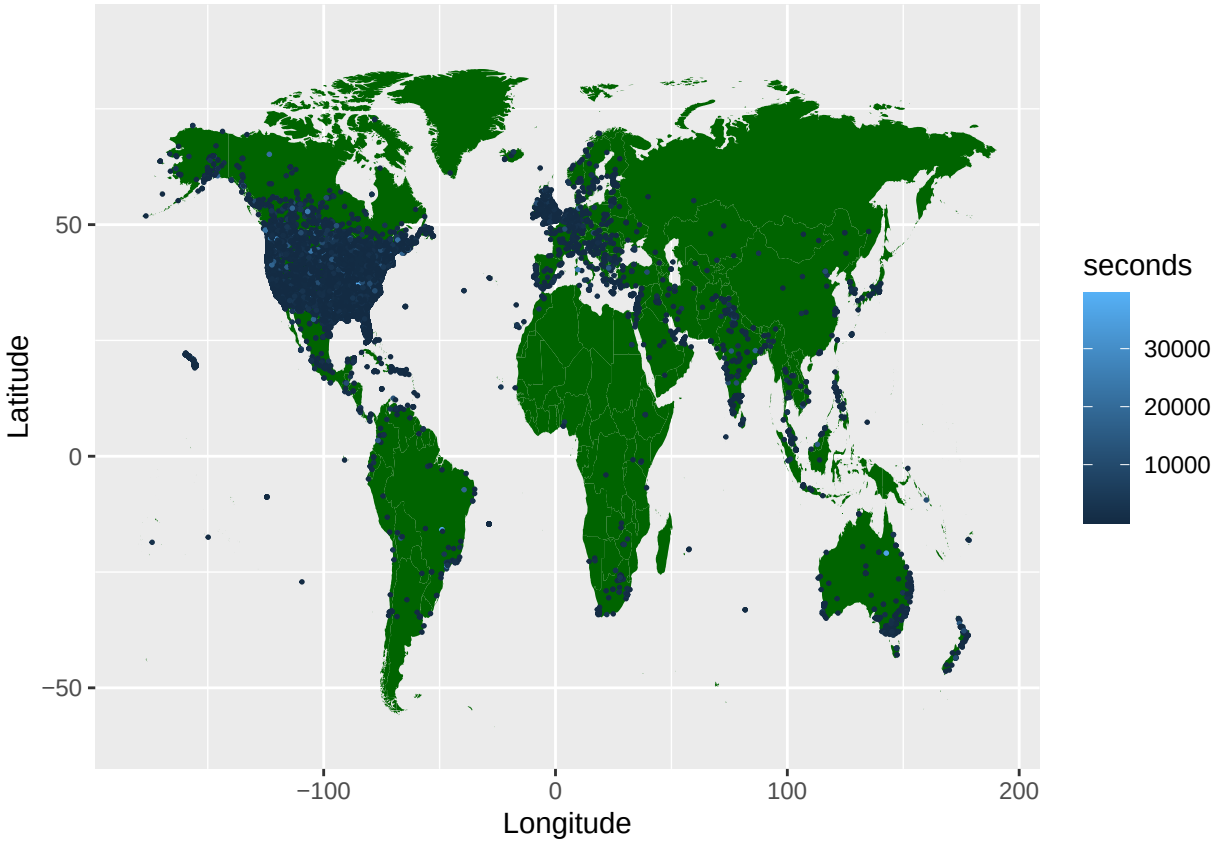


When looking at the histogram of longitude, we notice there are two main peaks within the spread. One peak is around -120 and the seconds is around -80. This make sense because these are the longitudes that correspond with highly populated areas of the US. The relative height of these peaks implies that there are considerably more sightings in the US than anywhere else in the world. This observation can be interpreted

in multiple ways, either that UFO's are more commonly reported in the US than anywhere else (either accurately or inaccurately), or that there really are more UFO visits in the US than anywhere else. We can't make a solid determination between these two based on the data, but we can clearly see that there have been more reports around the US.

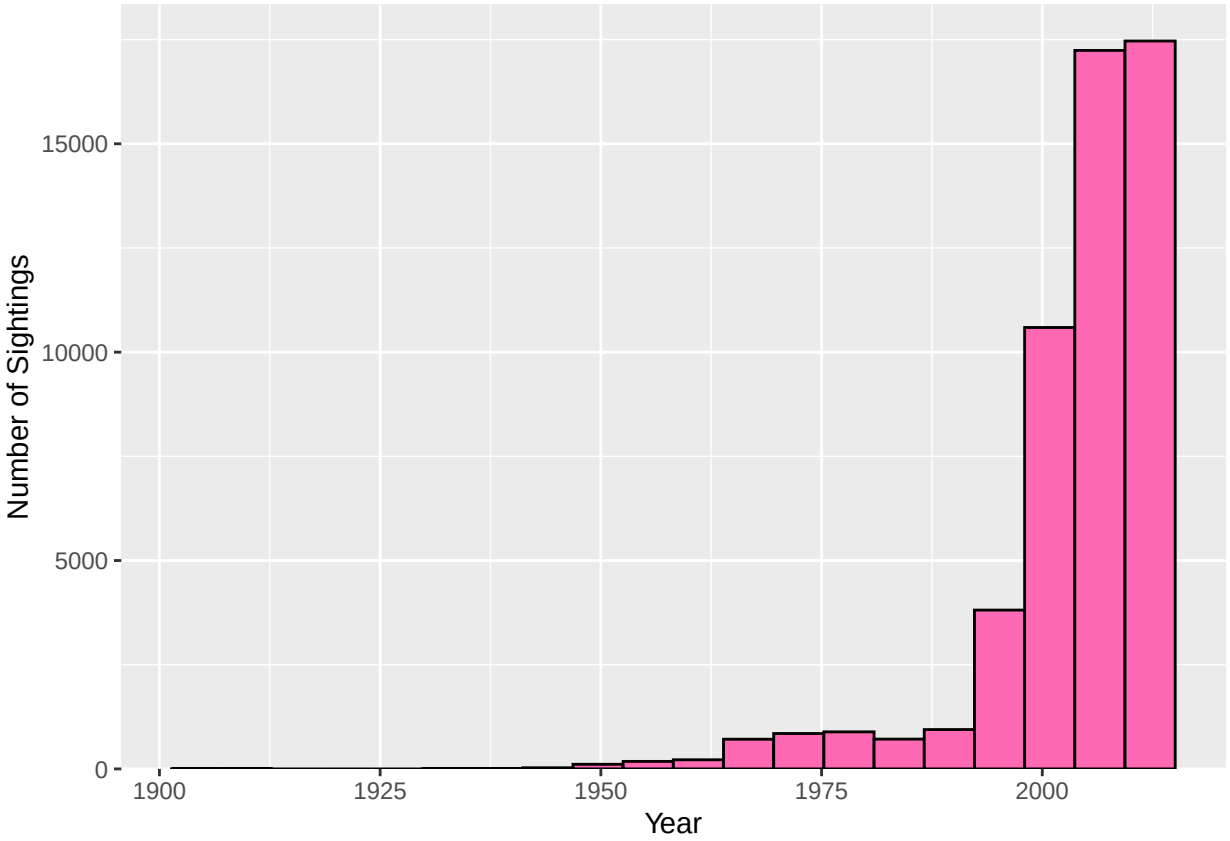


In the latitude histogram, we see than sightings are most prevalent around 40. Again, this corresponds to the coordinates of the US and also Europe, which is the second most frequently reported area of UFO sightings. This data supports the same conclusions we see from the longitude histogram.

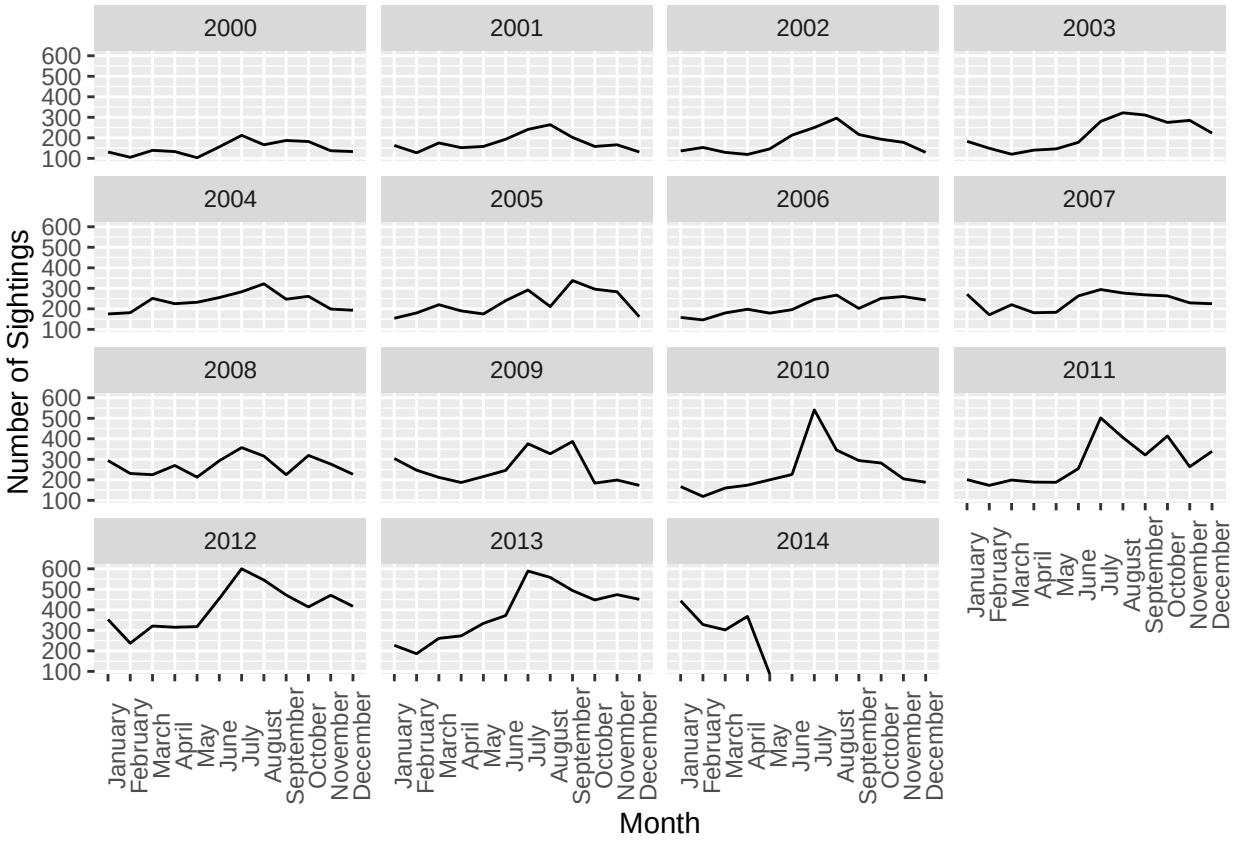


Here, we can see in greater detail the geographical dispersion of the sightings. The graph supports the same claims as the previous two graphs that there is a high volume of sightings in the United States. This graph also indicates other potential hot spots of sightings, specifically Europe and the eastern coast of Australia. The color coding makes it evident that most of the sightings are relatively short.

The next question we had was how the number of sightings had increase or decreased over the full epoch of time that the data set spans. We created a histogram of sightings per group of 5 years to answer this question.



The histogram shows that UFO sightings were relatively infrequent in the early 1900's. Sightings gradually started to increase during the 1950's and then there was a sharp increase at the end of the 1990's and into the 2000's. The number of sightings seems to start to plateau past 2005 also, so it would interesting to see whether the data plateaus in the long term after this point or if it would continue to increase beyond a certain point. This pattern might indicate developments in human history that could be of interest to extraterrestrial beings or have sparked human interest in the existence of extraterrestrials.



Here we have a small multiples graph which shows the seasonal trends in UFO data since the year 2000. Like the previous graph, these graphs also show that total UFO sightings have increased since 2000. Before 2009 sightings are generally consistent over the years. In 2009 we can see the first real peak during June and July. This trend seems to be reflected in the following years since then. It's possible that this is simply because most sightings occur in the northern hemisphere and during these months it is summer. This means more people are outdoors at this time of year, so more UFO visits are reported as sightings. Because of this highly plausible explanation, we can't necessarily determine from the data whether there was an actual increase in UFO visits in the summers.

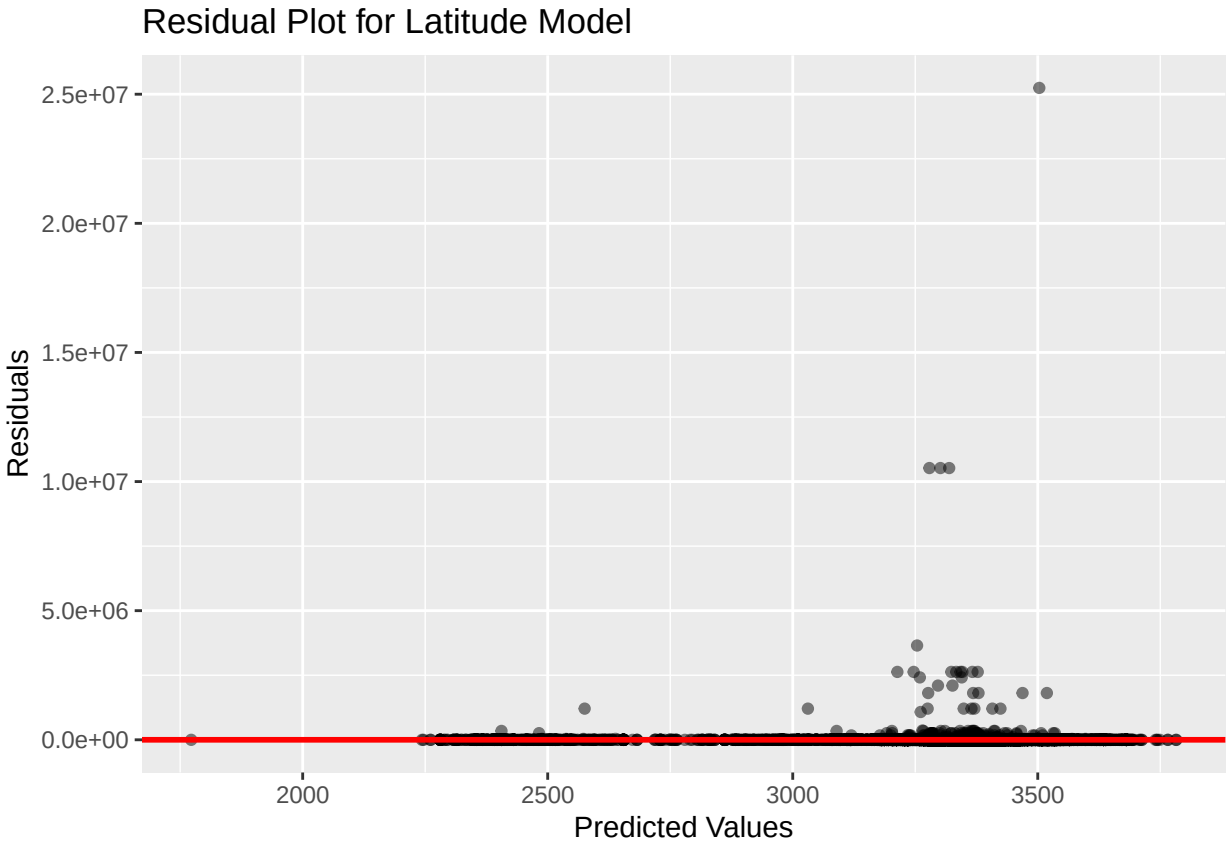
Machine learning

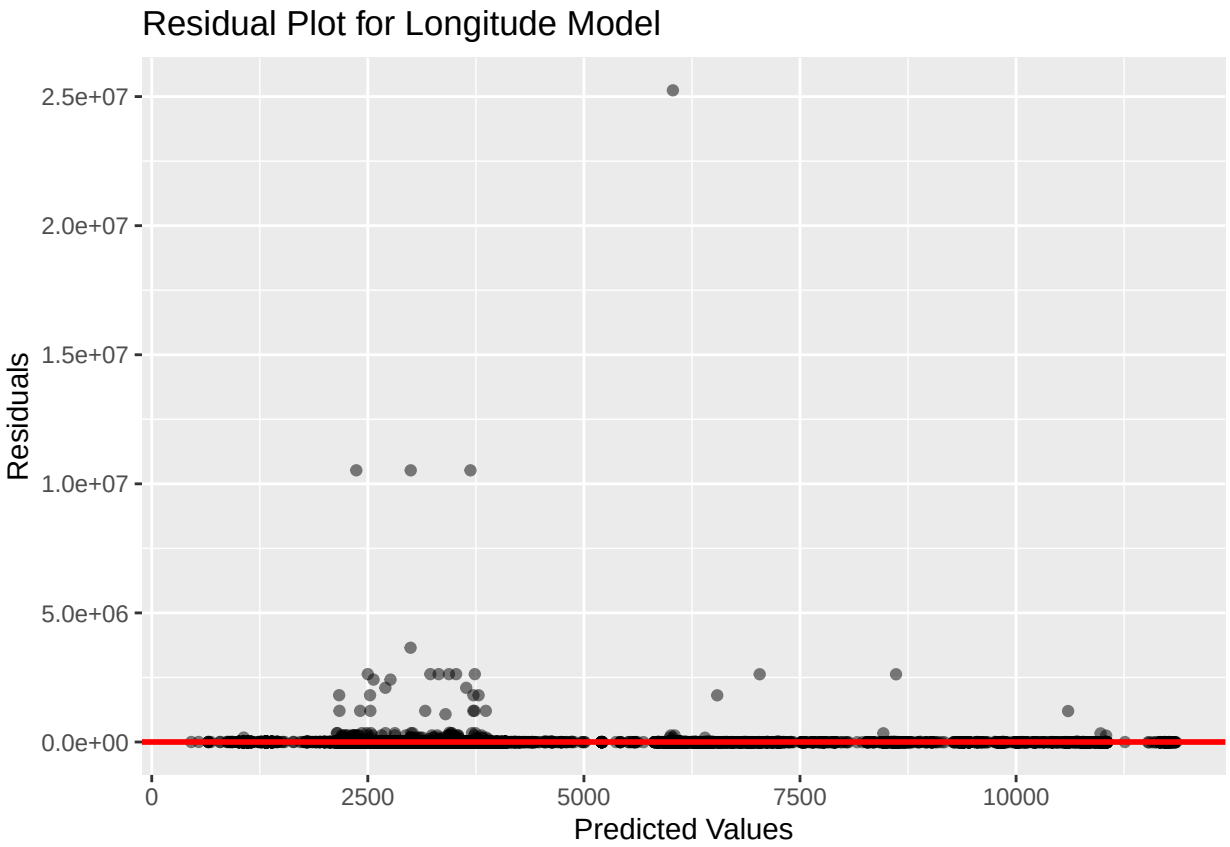
Linear Regression

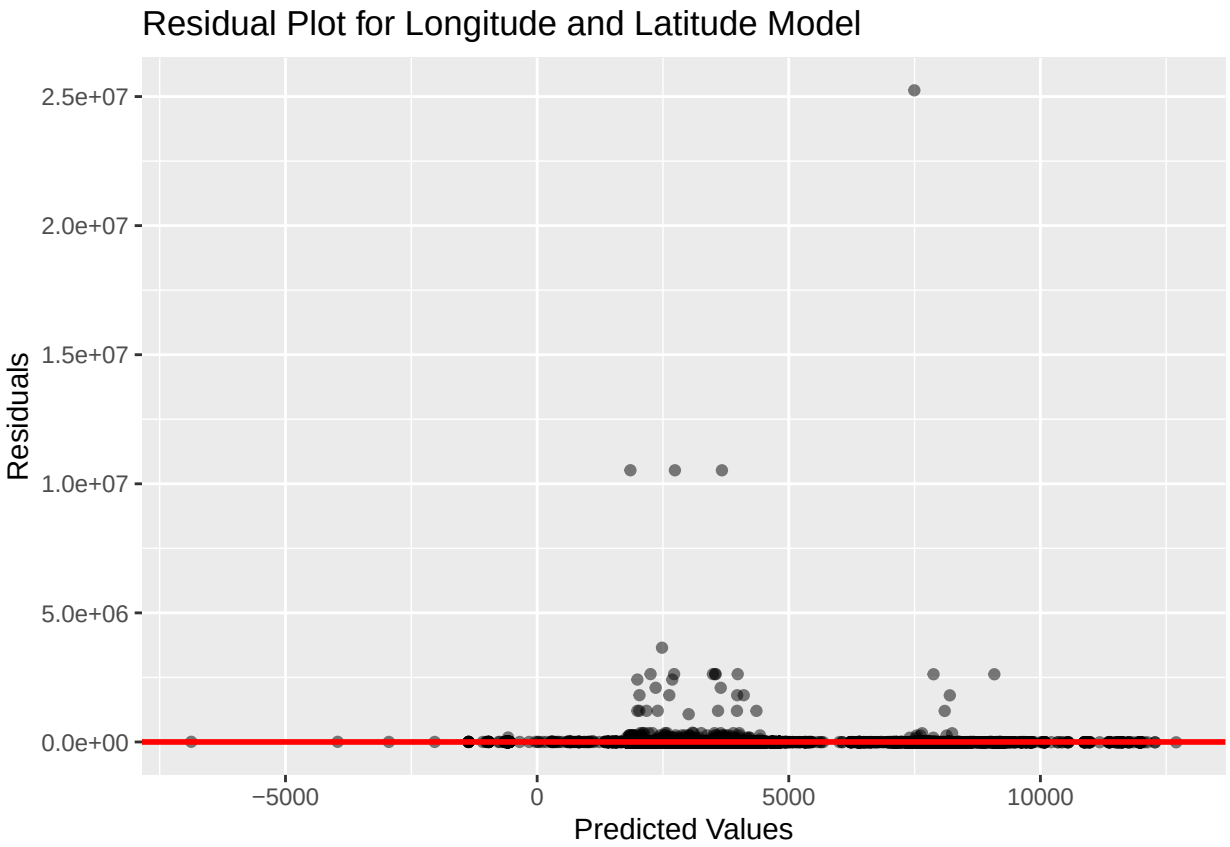
We wanted to use machine learning techniques to predict the duration of sightings and the longitude/latitude they took place at. We first chose to try to create a linear regression model. We thought this would be appropriate as we wanted to explore how our explanatory variables could explain the duration of sightings which is a numerical response variable. We also thought this would be a good technique to use as it is an eager learner and we wanted to create a model.

```
## # A tibble: 3 x 4
##   explanatories          r.squared adj.r.squared   sigma
##   <chr>                      <dbl>         <dbl>   <dbl>
## 1 latitude             0.000000881    -0.0000177 142621.
## 2 longitude            0.0000784       0.0000598 142615.
## 3 latitude + longitude 0.0000999       0.0000627 142615.
```

Residual Plots for Duration of Sightings vs Longitude and Lattitude




Residual Plot for Longitude Model
Residuals
2.5e+07
2.0e+07
1.5e+07
1.0e+07
5.0e+06
0.0e+00
0
2500
5000
7500
10000
Predicted Values

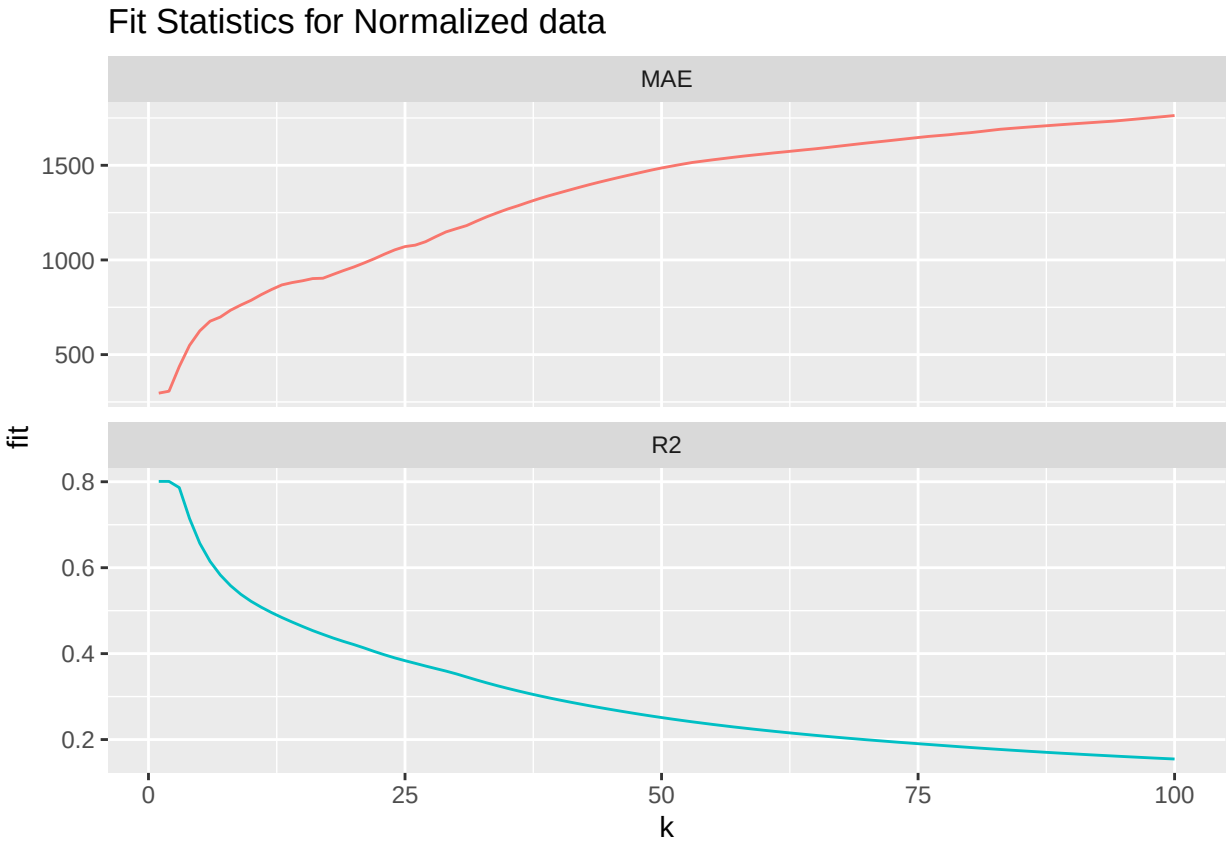


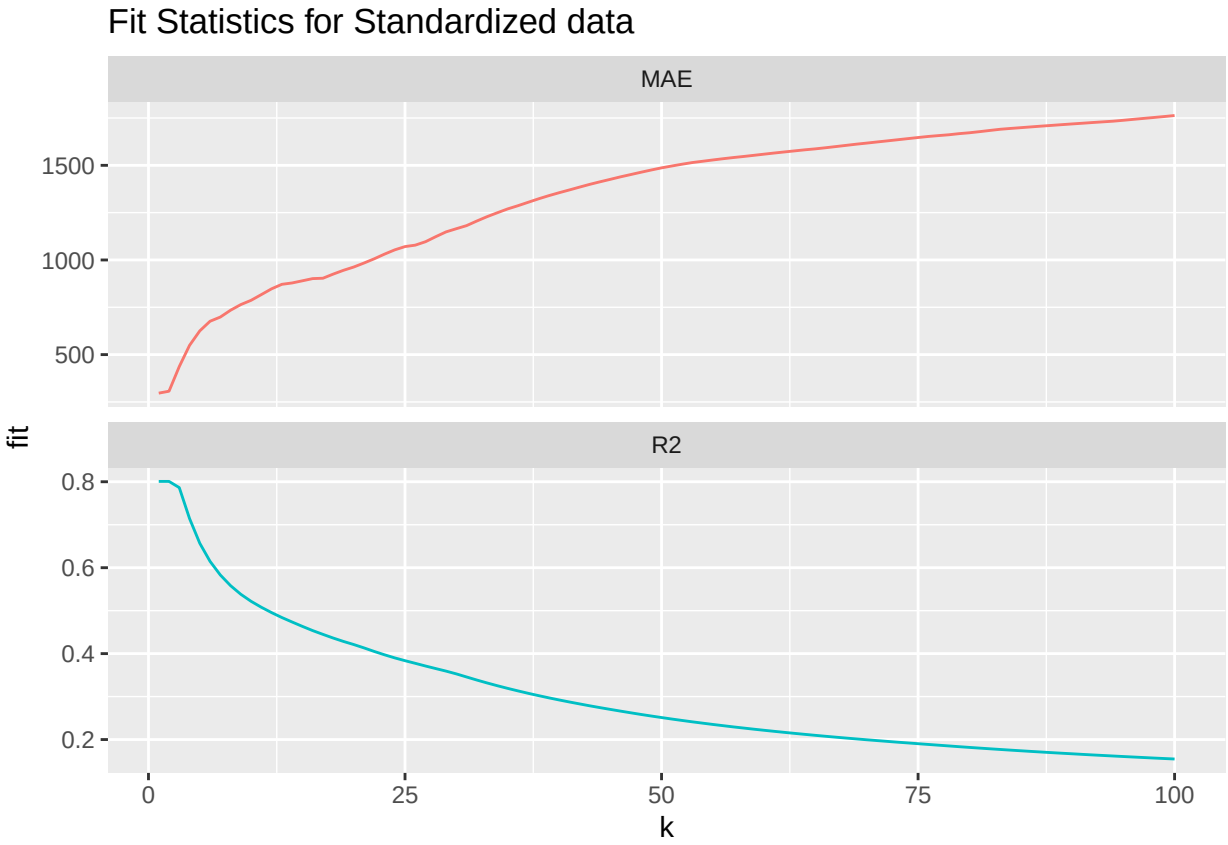
We created three different linear regression models, one with longitude as the explanatory variable, one with latitude as the explanatory variable, and the third with both. We wanted to compare which model would be the most accurate. From the table above we can see that all three models had R-squared values that were very close to zero. This indicates that our models were not a good predictor of duration of UFO sightings.

We then made residual graphs to see what else we could notice about our models and the data. These plots also indicate that the linear model is not a good predictor of duration based on longitude or latitude. In each plot there are clusters of outliers that are significantly higher than the majority of the data so the residuals dont have an even spread.

kNN regression

Since our linear regression proved to not be effective in predicting duration of sightings based on longitude or latitude we decided to try a k Nearest Neighbors regression. We noticed that a large portion of the data was acting differently than the rest, and thought kNN regression could account for this.


Fit Statistics for Normalized data
MAE
R2
fit
1500
1000
500
0.8
0.6
0.4
0.2
0
25
50
75
100
k



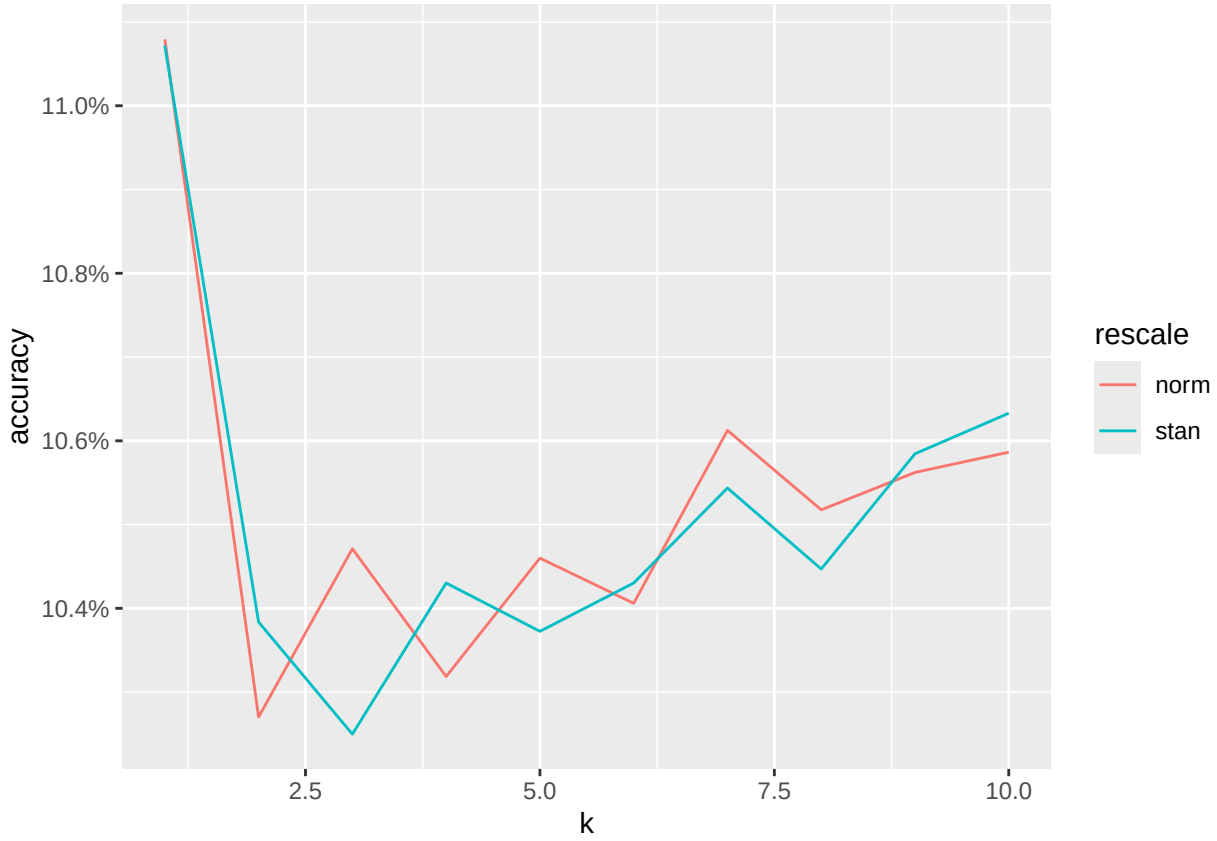

```
##   rescale k       R2     MAE
## 1    norm 1 0.800855 296.486
```

When looking at the fit statistic plots for both the normalized and standardized data we can see the R-squared values are at their max and the MAE is minimized at values close to one. We then searched the data to find the best k value, which ended up being a k value of one when using the normalized data. This k value is unusual and leads up to believe that this model is likely overfit to the data that we used to train it.

Both the linear regression and kNN regression failed to be good techniques for the effect of longitude and latitude on duration. This could be due to a lack of relationship between these variables. There is a large portion of the data where the sightings have a very short duration. There is also a second portion of the data that has much longer duration. Additionally, many sightings are concentrated in the United States and Europe. These nuances of the data could have influenced their behaviors with regression.

kNN Classifications

We were also interested in using machine learning to see if we could use latitude and longitude to predict which month a sighting happened in. We started by using kNN classification because our response variable is categorical and we thought it would be an effective method of predicting month based on longitude and latitude.




```
## # A tibble: 1 x 3
##       k rescale_method accuracy
##   <int> <chr>             <dbl>
## 1     1 norm_acc          0.111
```

```
## Confusion Matrix and Statistics
##
##            predicted
## actual      April August December February January July June March  May
##   April       214    444      207      165     227  596  386   210  182
##   August      281    828      282      208     294 1028  626   296  293
##   December    191    449      297      151     270  586  430   228  184
##   February    189    387      223      117     221  475  356   181  131
##   January     224    446      279      156     272  589  421   248  204
##   July        318    906      342      220     351 1324  674   333  306
##   June        311    682      308      184     320  855  678   335  278
##   March       195    434      241      156     257  548  427   229  209
##   May         199    462      217      111     230  589  382   195  187
##   November    257    492      278      189     269  682  480   296  209
##   October     274    608      277      191     261  790  526   255  239
##   September   282    696      260      188     331  832  569   286  270
##            predicted
## actual      November October September
##   April          303     351       380
##   August         479     553       615
```

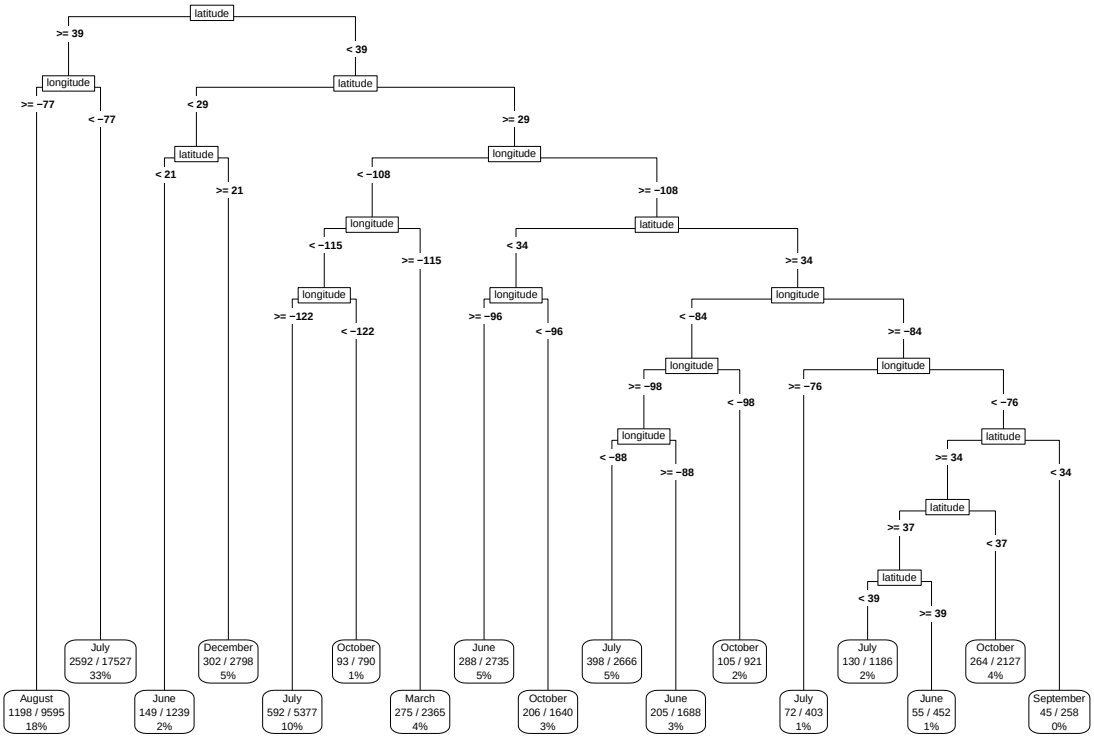
```
##   December       324     348       349
##   February       278     288       302
##   January        306     324       341
##   July           475     556       635
##   June           436     509       548
##   March          327     341       333
##   May            279     316       360
##   November       444     478       411
##   October        390     598       468
##   September      380     461       529
##
## Overall Statistics
##
##                Accuracy : 0.1063
##                  95% CI : (0.1037, 0.109)
##     No Information Rate : 0.1654
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.0166
##
##  Mcnemar's Test P-Value : <2e-16
##
## Statistics by Class:
##
##                      Class: April Class: August Class: December Class: February
## Sensitivity               0.07291        0.1212        0.092495        0.057466
## Specificity               0.93211        0.8944        0.930572        0.941408
## Pos Pred Value            0.05839        0.1432        0.078014        0.037166
## Neg Pred Value            0.94569        0.8748        0.941673        0.962089
## Prevalence                0.05459        0.1271        0.059721        0.037867
## Detection Rate            0.00398        0.0154        0.005524        0.002176
## Detection Prevalence      0.06816        0.1076        0.070806        0.058549
## Balanced Accuracy         0.50251        0.5078        0.511533        0.499437
##                      Class: January Class: July Class: June Class: March
## Sensitivity                0.082349     0.14886     0.11385     0.074062
## Specificity                0.929891     0.88599     0.90032     0.931564
## Pos Pred Value             0.071391     0.20559     0.12454     0.061942
## Neg Pred Value             0.939328     0.84005     0.89080     0.942820
## Prevalence                 0.061432     0.16542     0.11076     0.057507
## Detection Rate             0.005059     0.02462     0.01261     0.004259
## Detection Prevalence       0.070861     0.11978     0.10125     0.068760
## Balanced Accuracy          0.506120     0.51743     0.50709     0.502813
##                      Class: May Class: November Class: October Class: September
## Sensitivity            0.069465        0.100430        0.11673         0.100360
## Specificity            0.934606        0.918109        0.91203         0.906075
## Pos Pred Value         0.053020        0.098997        0.12262         0.104052
## Neg Pred Value         0.950139        0.919301        0.90745         0.902594
## Prevalence             0.050068        0.082225        0.09528         0.098034
## Detection Rate         0.003478        0.008258        0.01112         0.009839
## Detection Prevalence   0.065598        0.083415        0.09071         0.094556
## Balanced Accuracy      0.502036        0.509269        0.51438         0.503218
```

From the confusion matrix displayed above we see that the accuracy of this model is 42.78%. This is about 25% more accurate than predictions made based on no information. The matrix also shows that this

difference is statistically significant, with a p value of 2.2e-16. One odd thing about the model is that a k value of 1 was chosen to be the best. This might indicate that the model is overfit to the data because its only relying on the most close neightbor.

Classification Tree

The accuracy of our kNN classification was relatively low so we decided to make a classification tree to make a model of longitude, latitude, and the month of a sighting. We thought this may work better as it is a very large data set and classification trees are able to run quicker. Additonally it would provide a visualization and steps to take when determining the month of a sighting.




```
##            Overall
## latitude  668.5097
## longitude 397.5401
```

The pruned classification tree is displayed above. This tree has a total of 24 leaves. The leaf that contains the most data is latitude greater than 39 and longitude less than -77. This node contains 33% of the data and classifies the month as July. The fractions on each leaf correspond to how many that were classified into that leaf were classified correctly. Most of them have low rates of correct classification which is likely due to there being a low accuracy of the model as a whole. From the results of the variable importance test we can determine that latitude is a more important predictor of month than longitude is.

Conclusion

Through our data analysis and machine learning we came to a few conclusions. The first is that the vast majority of UFO sightings occur in the United States with additional hot spots of sightings in places like Europe and the eastern coast of Australia. We also found that the increase in UFO sightings began around the 1950s followed by a drastic increase in the early 2000s. Another conclusion we came to was that since 2000, a peak in sightings during the months of June and July has developed. From our regression machine learning techniques we conclude that longitude and latitude were not good predictors for sighting duration and could not produce a good regression model. Finally, we learned that classification techniques result in low accuracy for predicting the month of sightings based on longitude and latitude, but they are better than no information.

Implications and Future Research

A major limitation of this project was the observational aspect of the data. This means our results are more varied and potentially less accurate than if there was a consistent method of recording sightings that could make this data more accurate. In the future other models could be made for the effect between longitude and latitude that had the ability to deal with the apparent gap between long and short duration sightings. Additionally, future research into the topic could collect more accurate data for how sightings change over the seasons or years by focusing in on a smaller range of the globe. Now that we have identified the US and parts of Europe as hot spots, UFO data collection could be concentrated to these locations for the highest probability of collecting a lot of data.