Data Analysis Report - GROUP 7

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Contents

1 Abstraction

This project explores what factors influence how often volcanoes rate of eruption. We got our data for The Smithsonian Institute which has one of the world's most comprehensive databases on volcanoes and volcanic eruptions active within the last 100,000 years. We combined two data sets from the database that included eruption records and volcanic characteristics to look for patterns. Our main focus was on variable tectonic settings, primary rock type, volcano type, region and continuous factors such as longitude, latitude, elevation and the year of the last eruption from each volcano. Through EDA we noticed certain trends. Tectonic settings, volcano types and regions had more frequent eruptions. Of the continuous variables, the year of the last eruption had the strongest correlation with eruption count which was followed by elevation. We also found a noticeable exponential relationship between eruption count and the recency of eruptions, volcanoes that have erupted more recently tend

to have more recorded eruptions. Because our response variable was count, we used Poisson regression to model eruption frequency. After fitting the model, in the Diagnostic plots we noticed a funnel-shaped pattern in the residuals plot and some deviation from normality that hinted at some overdispersion in our data. We adjusted this in our final model. We also saw that latitude and longitude effectively captured regional geographical influence. In the end, we found that when and where a volcano erupted, along with what type of volcano it is and the tectonic settings are key predictors of eruption frequency. These insights can support better risk assessments, especially in identifying volcanoes that may be more active and hazardous. Identifying these patterns can help communicate and help policymakers be more prepared for volcanic threats.

2 Introduction

Volcanoes are deadly and destructive natural disasters that occur every year. While it is hard to fully estimate, one study reports that volcanoes cause, on average, a billion dollars of property damage each year . There have been eruptions that have caused one billion in damage and another that has caused seven[Encyclopædia Britannica, 2025]. This does not take into account the lasting effects. Volcanic eruptions are something that is hard to predict. The information surrounding volcanic eruptions is not always accurate and complete because some of these volcanoes predate human life [Institution, 2023]. While they are hard to predict, we are interested in looking at if there are factors that potentially make a volcano have more frequent eruptions compared to others.

3 Data and Methods

3.1 Data

Our data comes from The Smithsonian Institution, which has the world's most comprehensive database on volcanoes and volcanic eruptions active within the last 100,000 years.

In particular, we examined two datasets, the volcano dataset and the eruption dataset. The volcano dataset contains 958 volcanoes, each with 26 variables. The eruption dataset consists of 11,178 eruptions and 15 variables for each eruption.

3.2 Data Cleaning

From these initial 41 variables across two datasets, we eventually cut down to eight variables that we would consider for our model. Among these eight variables, there were four continuous predictors, last_eruption_year, latitude, longitude, and elevation. The other four variables were categorical: tectonic_settings, major_rock_1, primary_volcano_type, and region.

From the volcano dataset, we removed country and subregion as there was already region, longitude, and latitude which took into account the geographical location of the volcano. Further, country and subregion were deemed too specific, with 89 unique countries and 91 unique subregions. The evidence_category variable was removed as it indicated the type of evidence used to determine that the geological structure was indeed a volcano, which does not make sense to include when predicting eruptions. All major and minor rock types were removed except for major_rock_1 as these columns were mostly NAs. Volcanoes with more than one major rock or any minor rocks were uncommon. Finally, we did not consider any of the variables measuring the population surrounding the volcano area. Due to the sheer magnitude of the geological forces at play during a volcanic eruption, it is very unreasonable to believe that humans can influence a volcanic eruption [Layton, 2023].

For the eruptions dataset, no variables were ultimately considered for model selection. It did not make sense to use most of the variables from an individual eruption event to predict the eruption frequency. Columns indicating the starting and end times were removed for this reason, as they did not pertain to the actual characteristics of the volcano. Similar reasoning was applied to area_of_activity, which was also a mostly NA column. Analogous to the evidence_category column in the volcano dataset, it did not make sense to include evidence_method_dating. Latitude and longitude were omitted as they both were a duplicate of volcano data. The one index we considered potentially useful was the Volcano Explosivity Index (VEI) [Wikipedia contributors, 2025]. We considered gathering the average VEI for a given volcano, however there were too many NAs in this column to utilize.

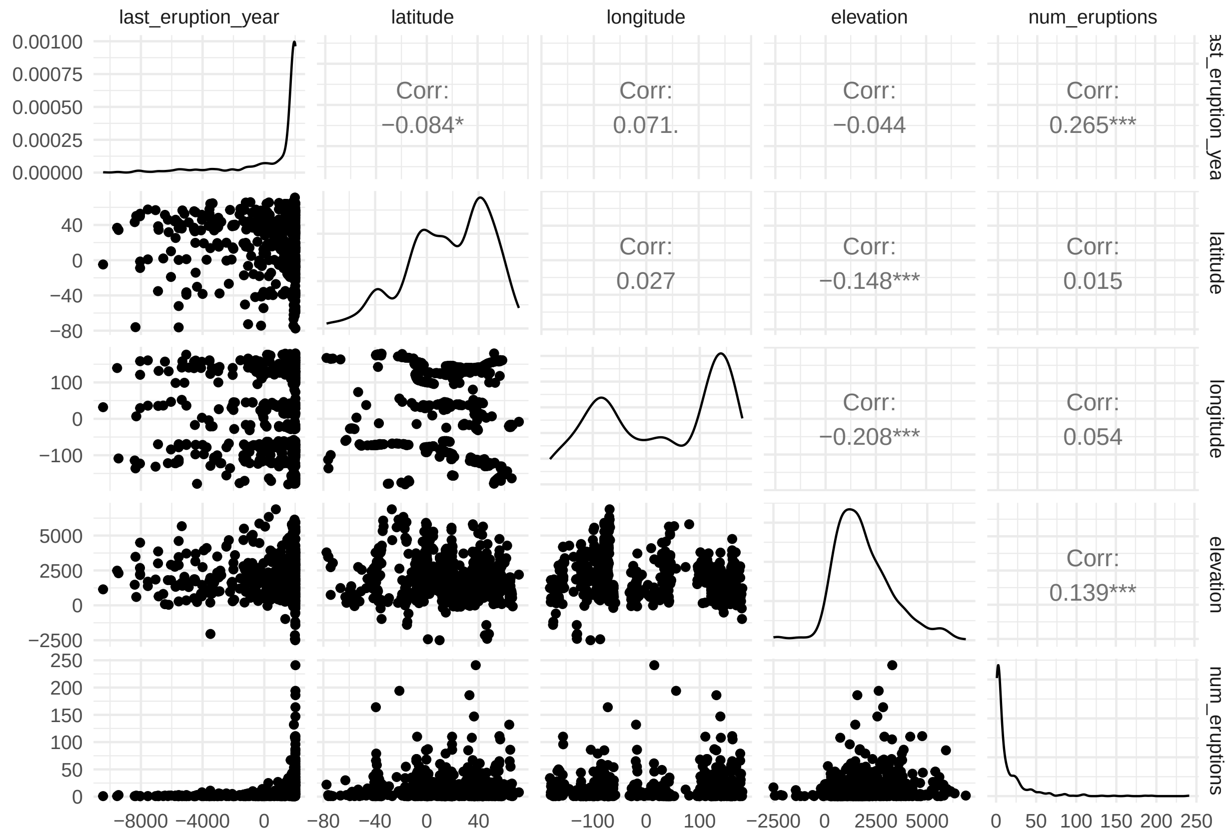
So, the eruption dataset was used solely to gather our response variable for our model, num_eruptions (the number of eruptions for each volcano). Each eruption in the eruption dataset had a volcano_number attached to it which identified which volcano that eruption was associated with. By counting the number of appearances of each unique volcano_number found in the eruptions data, we could count the number of eruptions for a given volcano, and merge that data into our volcano dataset as our response variable.

Now that we had narrowed down our columns, the data underwent some final cleaning. Some volcanoes had NA in their last eruption year as it was unknown when they last erupted. These volcanoes were removed from our dataset. We also needed to clean up the primary volcano type column, which had duplicate types such as “Stratovolcano”, “Stratovolcano(es)” and “Stratovolcano?”. We considered these as one singular volcano type.

Our final cleaned data contained 657 volcanoes and 11 columns. 8 columns were for our predictors, 1 column for our response, and 2 columns provided identifying information for the volcano (volcano_number and volcano_name). There are 10 tectonic settings, 10 major rock types, 16 primary volcano types, and 19 regions.

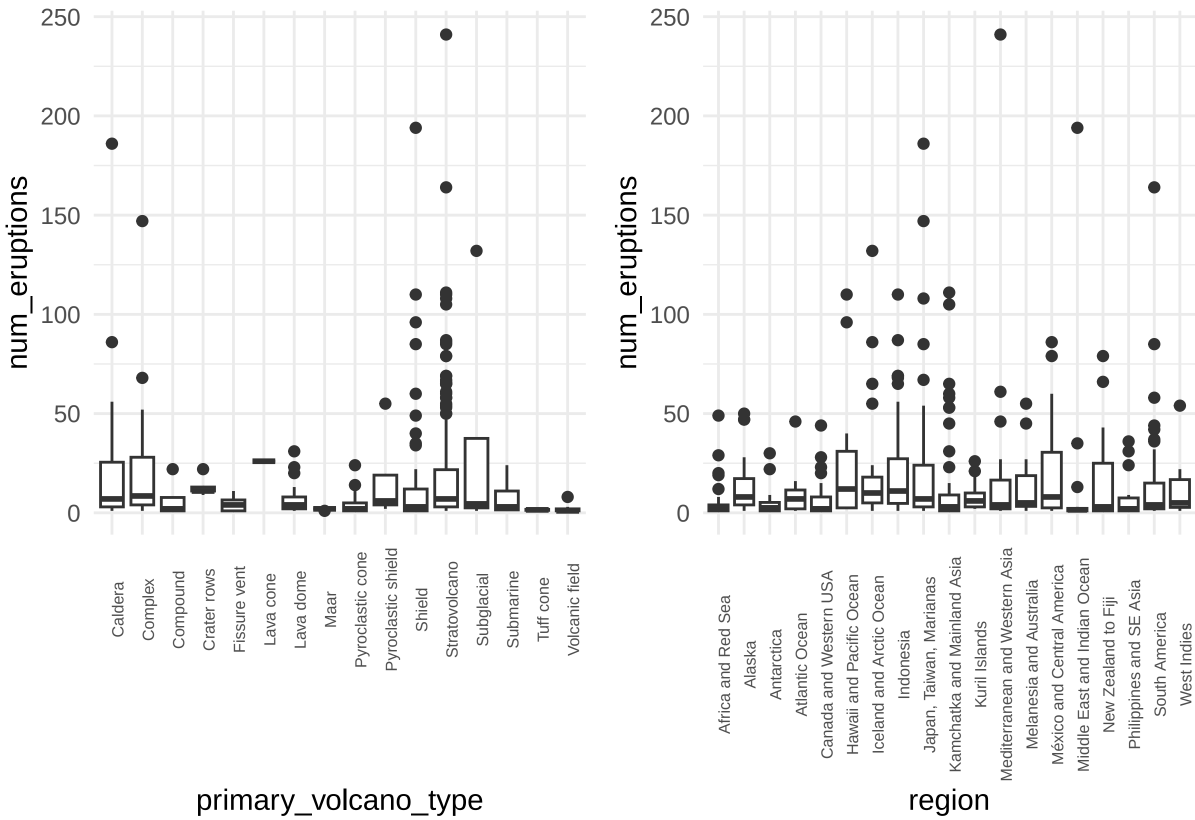
4 EDA

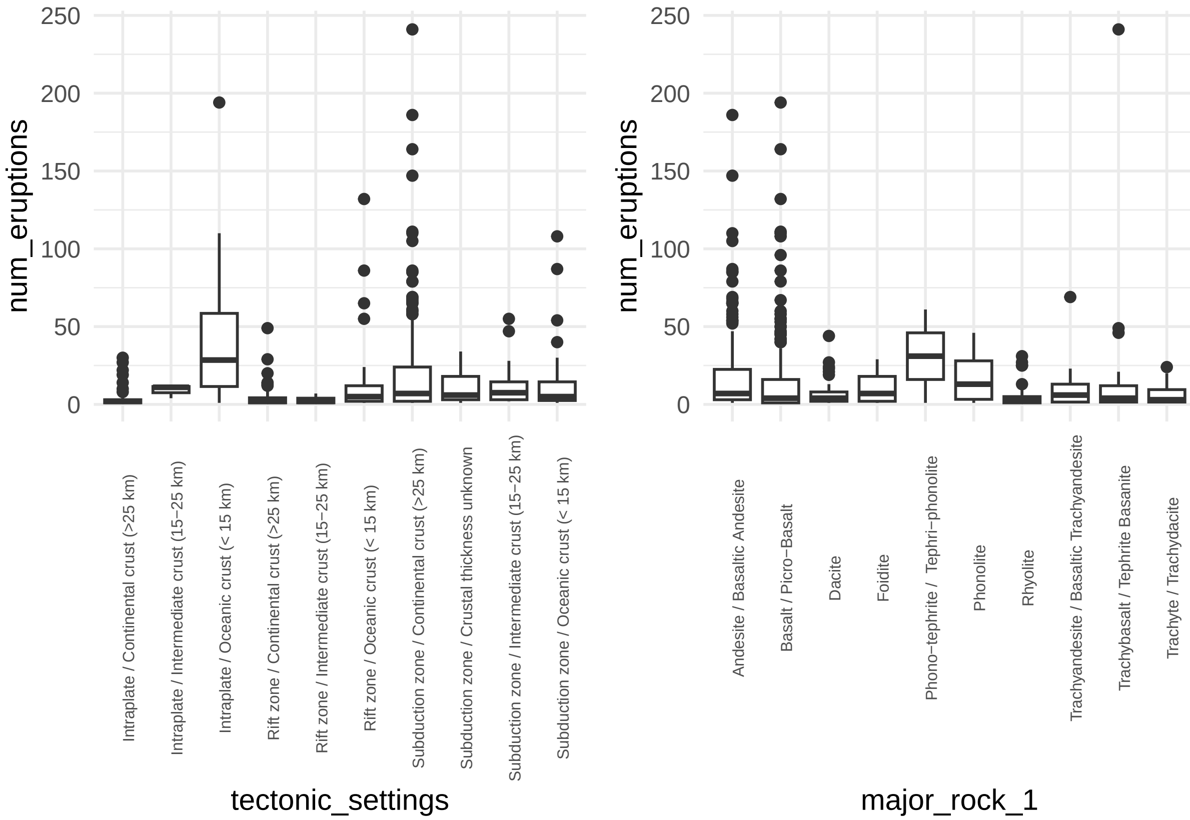
Once our data was cleaned, and we narrowed down the variables we wanted to consider, we started by creating a correlation matrix that was produced for our four continuous variables, and the response (Figure below).



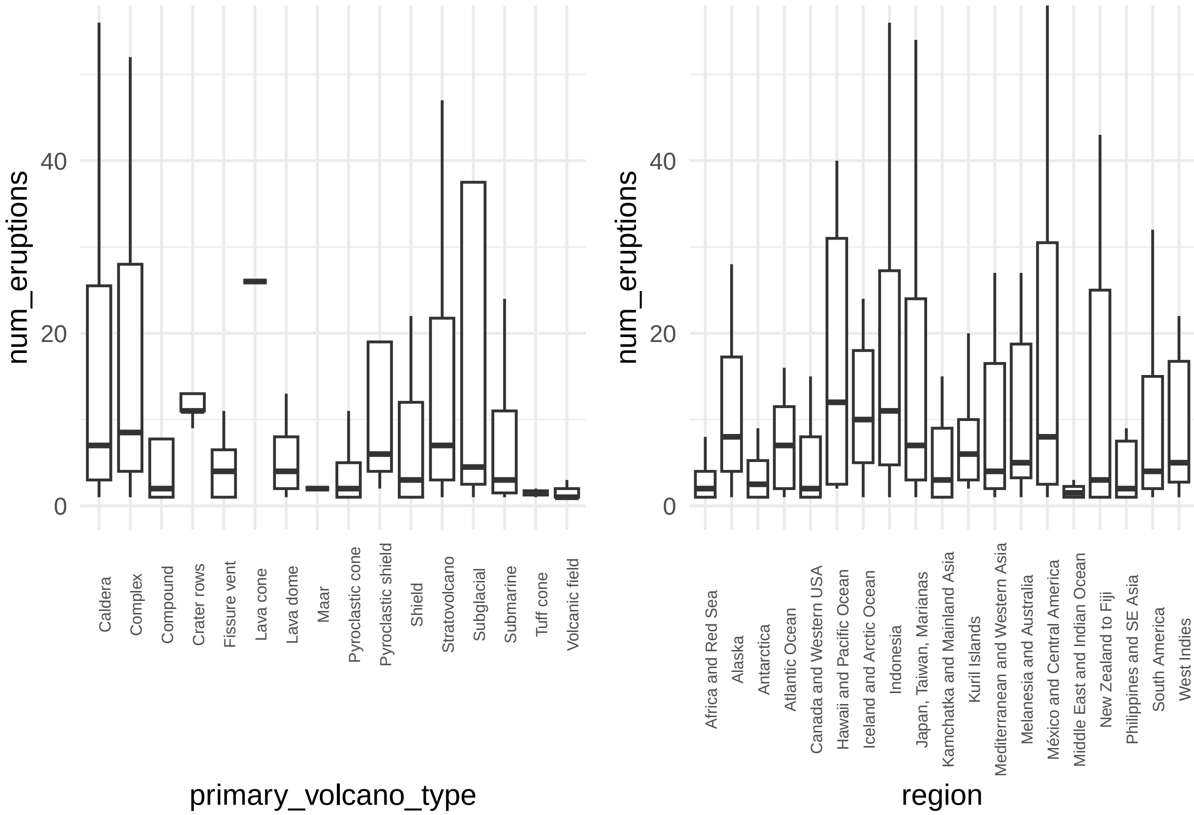
Based on the plots, it appears that most of the variables were not very correlated with each other or with the response. There were a couple plots that stood out though. First, elevation appeared to be at least slightly positively correlated with our response (num_eruptions). A volcano's last eruption year appeared to have a very strong exponential relationship with the response. This seems reasonable, as volcanoes that erupt more frequently probably also have erupted more recently. Finally, across the plots that include either latitude or longitude, there appears to be some sort of clustering across the plots. This can be observed most strongly with longitudes. This may be due to the fact the volcanoes most commonly form along the edges of tectonic plates, leading to the grouping in the data [Service, 2022].

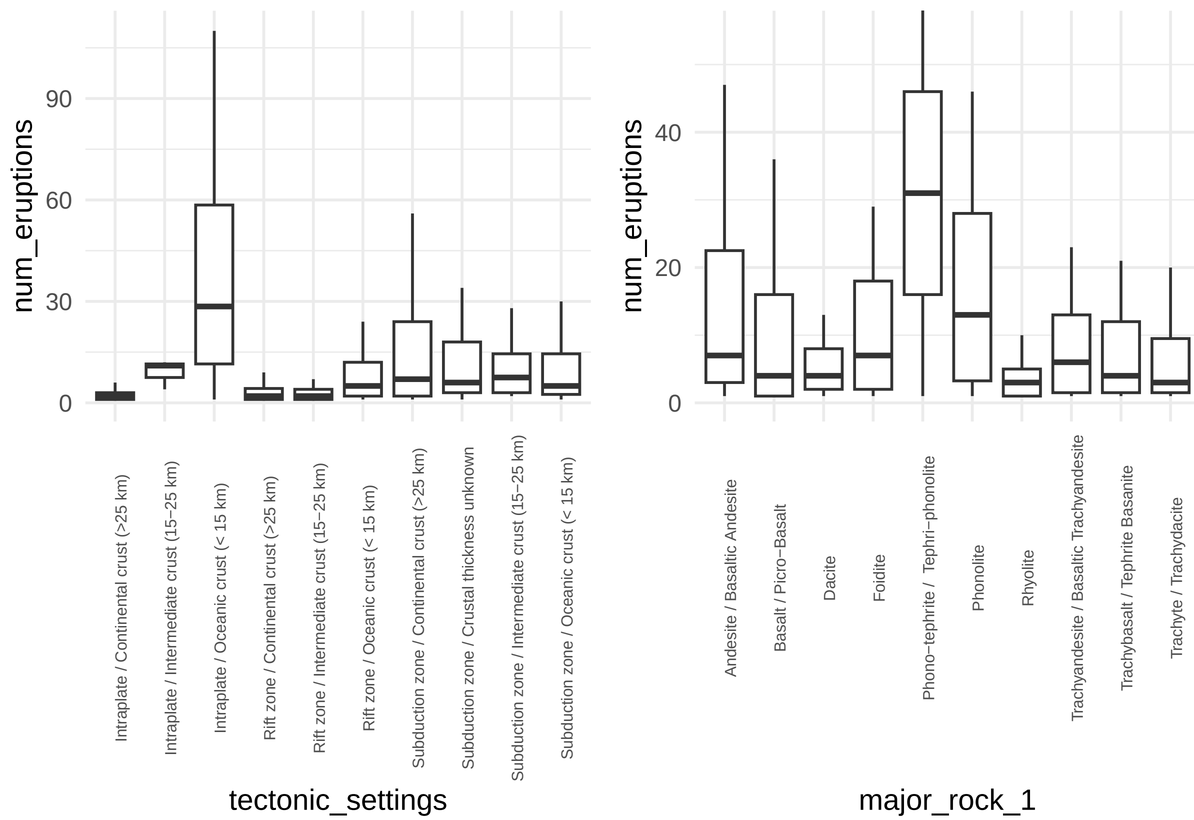
Next, we created boxplots for the four categorical variables plotted against the number of eruptions (the response), to investigate the effects of different categories on. We made two iterations of these plots. The first of these included the outliers, and is shown here.


num_eruptions
250
200
150
100
50
0
Caldera
Complex
Compound
Crater rows
Fissure vent
Lava cone
Lava dome
Maar
Pyroclastic cone
Pyroclastic shield
Shield
Stratovolcano
Subglacial
Submarine
Tuff cone
Volcanic field
primary_volcano_type
num_eruptions
250
200
150
100
50
0
Africa and Red Sea
Alaska
Antarctica
Atlantic Ocean
Canada and Western USA
Hawaii and Pacific Ocean
Iceland and Arctic Ocean
Indonesia
Japan, Taiwan, Marianas
Kamchatka and Mainland Asia
Kuril Islands
Mediterranean and Western Asia
Melanesia and Australia
México and Central America
Middle East and Indian Ocean
New Zealand to Fiji
Philippines and SE Asia
South America
West Indies
region



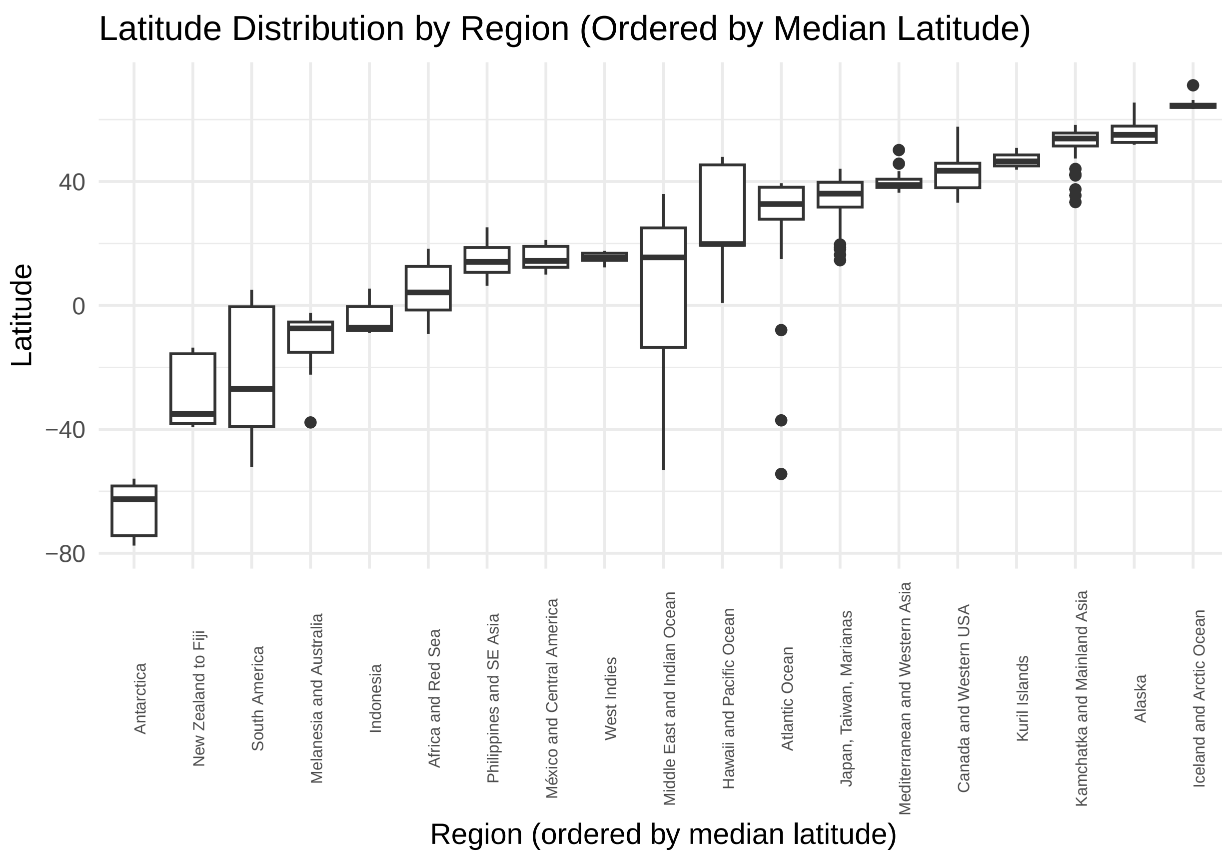
From these plots, it seems that there are quite a few outliers across the dataset in general, and some categories have greater variance than other categories. It also appears that the median values are mostly the same for across a given category barring a few exceptions. Due to the magnitude of the variance across the data, however, it was difficult to distinguish the differences in median across categories. So, we also plotted these categories while hiding the outliers in order to better visualize the difference.

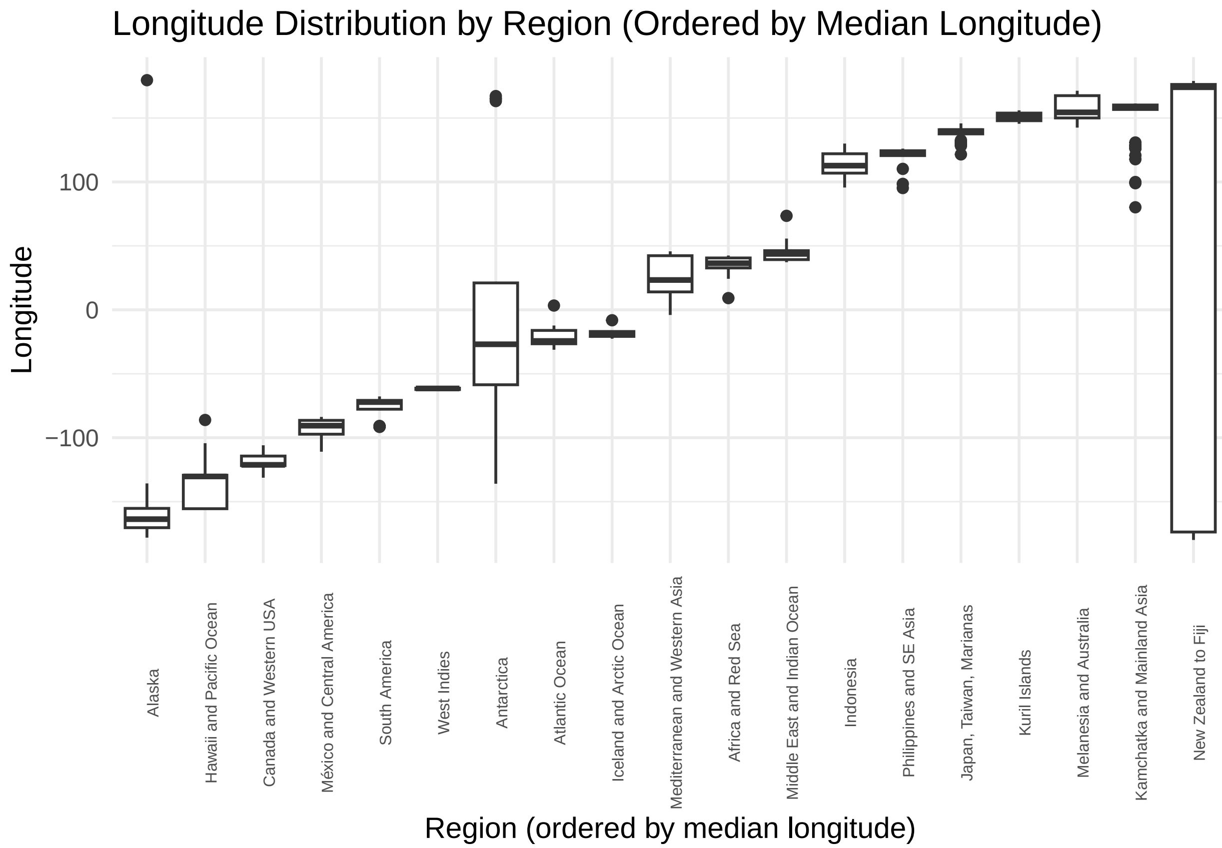

num_eruptions
0
20
40
Caldera
Complex
Compound
Crater rows
Fissure vent
Lava cone
Lava dome
Maar
Pyroclastic cone
Pyroclastic shield
Shield
Stratovolcano
Subglacial
Submarine
Tuff cone
Volcanic field
primary_volcano_type
num_eruptions
0
20
40
Africa and Red Sea
Alaska
Antarctica
Atlantic Ocean
Canada and Western USA
Hawaii and Pacific Ocean
Iceland and Arctic Ocean
Indonesia
Japan, Taiwan, Marianas
Kamchatka and Mainland Asia
Kuril Islands
Mediterranean and Western Asia
Melanesia and Australia
México and Central America
Middle East and Indian Ocean
New Zealand to Fiji
Philippines and SE Asia
South America
West Indies
region



For Primary volcano type and Region, it is more difficult to tell which categories are significant, or if any categories display some sort of relationship with the response. However, the Intraplate / Oceanic Crust (<15 km) category in tectonic settings and the Phono-tephrite / Tephri-phonolite rock type in major_rock_1 seem to stand out as having an effect on the response. This exploration will help us in our attempt to simplify our categorical variables in our model.

Finally, though most geographical variables were removed during cleaning, region as well as latitude in longitude were kept. We did take note that these two variables were likely correlated. We investigated this by plotting the boxplots showing the distribution of latitude and longitude for a given region, ordered by increasing median, shown below.


Latitude Distribution by Region (Ordered by Median Latitude)
Latitude
40
0
−40
−80
Antarctica
New Zealand to Fiji
South America
Melanesia and Australia
Indonesia
Africa and Red Sea
Philippines and SE Asia
México and Central America
West Indies
Middle East and Indian Ocean
Hawaii and Pacific Ocean
Atlantic Ocean
Japan, Taiwan, Marianas
Mediterranean and Western Asia
Canada and Western USA
Kuril Islands
Kamchatka and Mainland Asia
Alaska
Iceland and Arctic Ocean
Region (ordered by median latitude)



From these plots, it is quite clear that Region is a proxy for both latitude and longitude. Generally, each region has a very small spread of latitudes and longitudes, which makes sense, as they both refer to the geographical location of a volcano. There is an interesting region in the Longitude plot that is worth noting, in particular the far right boxplot for New Zealand and Fiji has a giant spread that covers the entire range of the data. This is actually due to the fact that New Zealand and Fiji sit on the longitude line that transitions between -180 to +180. Beyond being an interesting result in our plot, this may be a red flag for using longitude. 0 longitude is defined somewhat arbitrarily, and if you go east far enough, you will end up west eventually. So, how far east or west a volcano is might not be all that meaningful. We keep all of this in mind during our model selection process.

5 Model

It was quickly identified that the Poisson model is the better suited model for the data as it is looking at counts and rate of volcano eruptions. In order to find the best model using the identified variables, stepAIC was used. This allowed for it to be run both forwards and backwards in order to find the best model. Eventually, it was found that the best model for the data was the full model, consisting of all 8 of our predictors. We determined after investigating this model, that our data was very overdispersed, however, it was decided that a simpler model was desired, if possible. So, model selection continued based on the poisson model, before converting our final model into a Quasi Poisson model to account for the overdispersion.

Following the stepwise model selection, we wanted to look for ways to simplify our model. As noted from our EDA, a region is a proxy to latitude and longitude. As a result, we decided that our model should contain both regions and either longitude or latitude. To determine which one to keep, a series of ANOVA tests were performed to determine which variables to keep. Specifically, we started with a model with all the variables except region, longitude, and latitude. We found that, no matter the order that we added region and longitude/latitude, the addition of the variables all significantly improved the deviance of the model. Unfortunately, not much was gained from this analysis. From here, we compared the AIC and BIC of the models containing everything but longitude and latitude against the model with everything but region. We determined that both the AIC and BIC of the model with region instead of longitude and latitude was better, so we elected to keep region over latitude and longitude.

Building off of our EDA on our categorical variables, we attempted to simplify our categories in the hopes that we could create a simpler model by only examining factors that appeared impactful in our boxplots. We tried selecting certain factors and creating an "Other" category for the remaining categories that didn't exhibit a strong relationship in our EDA, but such a model actually resulted in an increase in deviance, fitting worse than the model with all the categories.

This leaves us with our final model:

$$
\begin{aligned}
\log(Y_i) = \beta_0 & \\
& + \beta_1 \cdot \mathbb{I}(\text{PrimaryVolcanoType} = \text{Complex}) \\
& + \beta_2 \cdot \mathbb{I}(\text{PrimaryVolcanoType} = \text{Compound}) \\
& + \beta_3 \cdot \mathbb{I}(\text{PrimaryVolcanoType} = \text{Crater rows}) \\
& + \beta_4 \cdot \mathbb{I}(\text{PrimaryVolcanoType} = \text{Fissure vent}) \\
& + \beta_5 \cdot \mathbb{I}(\text{PrimaryVolcanoType} = \text{Lava cone}) \\
& + \beta_6 \cdot \mathbb{I}(\text{PrimaryVolcanoType} = \text{Lava dome}) \\
& + \beta_7 \cdot \mathbb{I}(\text{PrimaryVolcanoType} = \text{Maar}) \\
& + \beta_8 \cdot \mathbb{I}(\text{PrimaryVolcanoType} = \text{Pyroclastic cone}) \\
& + \beta_9 \cdot \mathbb{I}(\text{PrimaryVolcanoType} = \text{Pyroclastic shield}) \\
& + \beta_{10} \cdot \mathbb{I}(\text{PrimaryVolcanoType} = \text{Shield}) \\
& + \beta_{11} \cdot \mathbb{I}(\text{PrimaryVolcanoType} = \text{Stratovolcano}) \\
& + \beta_{12} \cdot \mathbb{I}(\text{PrimaryVolcanoType} = \text{Subglacial}) \\
& + \beta_{13} \cdot \mathbb{I}(\text{PrimaryVolcanoType} = \text{Submarine}) \\
& + \beta_{14} \cdot \mathbb{I}(\text{PrimaryVolcanoType} = \text{Tuff cone}) \\
& + \beta_{15} \cdot \mathbb{I}(\text{PrimaryVolcanoType} = \text{Volcanic field}) \\
& + \beta_{16} \cdot \text{last\_eruption\_year} \\
& + \beta_{17} \cdot \mathbb{I}(\text{Region} = \text{Alaska}) \\
& + \beta_{18} \cdot \mathbb{I}(\text{Region} = \text{Antarctica}) \\
& + \beta_{19} \cdot \mathbb{I}(\text{Region} = \text{Atlantic Ocean}) \\
& + \cdots \\
& + \beta_{53} \cdot \mathbb{I}(\text{MajorRock1} = \text{Trachyte / Trachydacite})
\end{aligned}
$$

The final model uses reference levels of Africa and Red Sea, Caldera, Intraplate Continental, and Basalt/Picro-Basalalt. Y_i is a realization from $Y_i \sim \text{Poisson}(\lambda_i)$, for i=1,. . . ..,n, where n=number of volcanos.

The final model still has noticeable limitations. One limitation is that despite using a quasi-poisson model, the overdispersion for the data is still quite high. This means that mean and variance are not quite equal in this situation. However, to remain in the scope of this course, this model was still our best option. To continue exploring this data set, it could be worthwhile to investigate using a negative binomial model. Another limitation is that AIC is not a viable option when using a quasi-poisson model. While this was worked around to an extent by doing Poisson and then fitting a quasi poisson, it could potentially lead to a limitation. A more accurate option could have been to create all different types of the model with different combinations of the variable but using our method still creates a usable model. The final noticeable limitation is that the model was formed as a retrospective study. Data that has been collected over the years was used so there is not necessarily a way to draw any causations from the model. However, it is still beneficial to use as information and a way to plan for the future.

6 Results

The results of the model show that there are several factors that contribute to the number of potential eruptions. For example, the volcano type Volcanic field has a significant decrease in your number of eruptions while being a stratovolcanno increases the number of eruptions. We also see a significant exponential relationship between last eruption and eruption frequency. Volcanoes with more recent activity demonstrate a lot higher eruption counts which make sense because these volcanoes are early on in their "active" stage of their volcanic life. We also found through our analysis that there is substantial variability in our categorical variables. Tectonic Settings, major rock types, primary volcano types and geographical regions exhibited high eruption counts, specifically Subduction Zone, Andesite/ Basaltic Andesite, Stratovolcano and Japan, Alaska and Iceland for their respective categorical variables that they are associated with. They all specifically showed higher eruption counts than different categories in their variable category.

According to our model, if everything is kept at its reference level but years since last eruption is increased by 100, the confidence interval at 95% of the percentage increase in number of eruptions is 4.23% and 7.645%. If everything remains constant but elevation is increased by 1000 feet, the percentage increase in the number of eruptions, with a 95% confidence interval, between 12.8% and 38.3%. So increasing the elevation can have a large impact on the number of eruptions. Finally, if everything remains constant but the region goes from Africa and Red Sea to Alaska, the 95% confidence interval is quite wide from a 34.941% increase to a 325% increase.

Since the model is the full model, it is no surprise that the residual plots look pretty good. For the fitted versus residual, the points are fairly randomly distributed. There is some clumping at the beginning but that is a result of this data set being zero-bounded, as it is not possible to have less than zero eruptions. The Q-Q plot of residuals shows some tailing off towards the higher quantities of the plot which is suggesting that our count data does show some overdispersion which is a common challenge when modeling something like volcanic eruptions because they are on the rare side. Overall, the diagnostic plots performed well, which to us, was no surprise because our model was the full model.

7 Conclusion

The overall conclusion is that there are a wide variety of factors that go into the number of eruptions. It is important to look at its region, rock type, last year's eruption, and other factors. Governments who have volcanoes in their country that have factors that could potentially lead to more eruptions should take necessary action to help their country recover. They should look into potentially setting up a perimeter so that people are not allowed to live inside. They should make sure to have adequate funding to support their communities should a disaster strike. The model can give governments a rough idea of their potential risk factor so that they can plan accordingly.

For next steps with this data, as mentioned above, it is worthwhile potentially exploring other models that may better address the overdispersion that was noticed. It is also possible that looking at some of the variables removed, such as minor rock types, could help make the model more precise. As time goes on, tracking of this information may get better allowing for the model to continue to improve.

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