Data Analytics Final Project

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1 Abstract and Motivation

According to the World Health Organization, “health equity is a priority in the post-2015 sustainable development agenda and other major health initiatives” (WHO). The goal of health equity is to ensure that across the world, everyone has access to necessary and quality health care. Health financing is an important aspect to health equity and can offer insight into the efficacy and influence of government spending on health care. While there are many communicable and non-communicable diseases impacting countries today, one of the most prominent is Chronic Obstructive Pulmonary Disease (COPD), which is the third leading cause of death worldwide (WHO). Chronic Obstructive Pulmonary Disease (COPD) refers to a group of diseases that cause airflow blockage and breathing-related problems. It is typically caused by long-term exposure to irritating gases or particulate matter. According to the World Health Organization, low- and middle-income countries are disproportionately affected by COPD, with nearly 90% of COPD deaths in those under 70 occurring in these countries. To observe how access to healthcare impacts COPD deaths, I will be utilizing data on the percent of gross domestic product (GDP) spent on health care by country. As mentioned previously, particulate matter is a significant risk factor for COPD. Therefore it is important to consider how this may impact case numbers for certain countries. To analyze how particulate matter contributes to countries with higher COPD cases, I am using data on particulate matter 2.5 (PM2.5) by country. Particulate matter 2.5, and air pollutant, refers to tiny particles or droplets in the air that are two and one half microns or less in width. These particles are able to travel deeply into the respiratory tract, reaching the lungs (NY State Department of Health). The goal of the following analysis is to determine whether government spending on healthcare and pollution levels contribute significantly to COPD deaths.

Hypotheses
i. Countries with a higher percent of GDP spent on health will have lower COPD deaths.
ii. Air pollution, quantified here by PM2.5, is also a contributing factor that accounts for an increased amount of COPD deaths despite a high percentage of GDP spent on health care.

2 The Data and Exploratory Data Analysis

Background of the Data:
To perform my analysis, I am using three World Health Organization data sets:

1. Deaths by sex and age group for a selected country or area and year for chronic obstructive pulmonary disease

2. Domestic general government health expenditure (GGHE-D) as percentage of gross domestic product (GDP) (%)

3. Concentrations of Fine Particulate Matter (PM2.5)

For simplicity, I will be referring to each of these data sets in a summarized manner, COPD, GDP, and PM2.5 respectively. After initial data cleaning, which will be elaborated on further in section 3, there was data available for 104 countries. This includes 21 years for the COPD and GDP data and 10 years for the PM2.5 data. As mentioned in the previous section, each of the data sets were chosen for specific purposes. The COPD data allows us to determine how many individuals died due to COPD based on country and year. The GDP data represents access to health care by determining how much the government spends on health care based on their GDP, this allows a standard measure of comparison. Lastly, the PM2.5 data will be representative of pollution levels in each country.
Exploratory Data Analysis:
COPD data

```
R Code:
copd <- read.csv("/Users/keertisundaram/Dropbox/Data Analytics/
mortality_csv.csv", header=T)
str(copd)
summary(copd)
#find number of NAs
sum(is.na(copd))
#filtering out country labels and grand totals for boxplots
no_labels_copd <- copd[-1]
boxplot(no_labels_copd[-length(no_labels_copd)], main = "COPD
cases of all Countries over 2000-2020")
hist(copd$Grand.Total, main = "Grand Total Deaths due COPD")
```

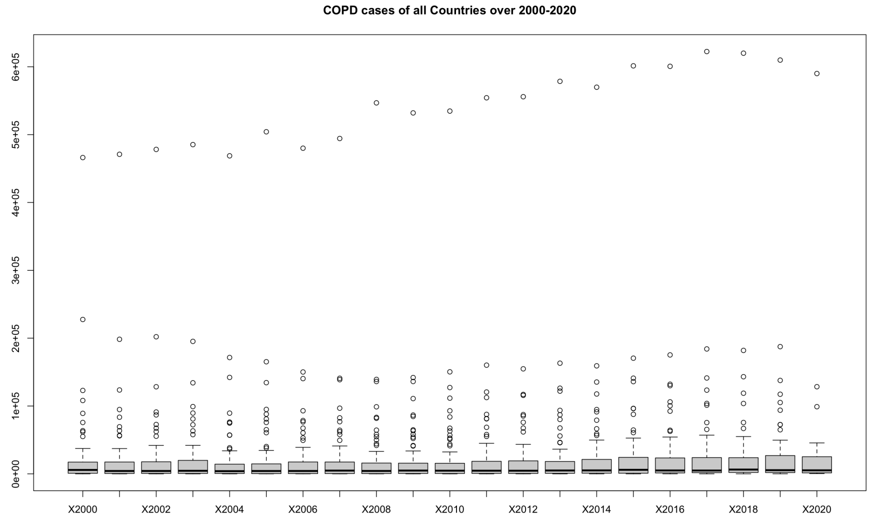


Figure 1: COPD all Countries Boxplot

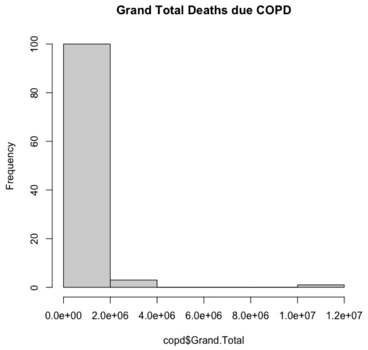


Figure 2: COPD Histogram

GDP data

```
R Code:
gdp <- read.csv("/Users/keertisundaram/Dropbox/Data Analytics/
gdp_csv.csv", header=T)
str(gdp)
summary(gdp)
#find number of NAs
sum(is.na(gdp))
no_labels_gdp <- gdp[-1]
boxplot(no_labels_copd[-length(no_labels_gdp)], main = "Percent
of GDP Spent on Health of all Countries over 2000-2020")
hist(gdp$Grand.Total, main = "Grand Total Percent of GDP Spent
on Health")
```

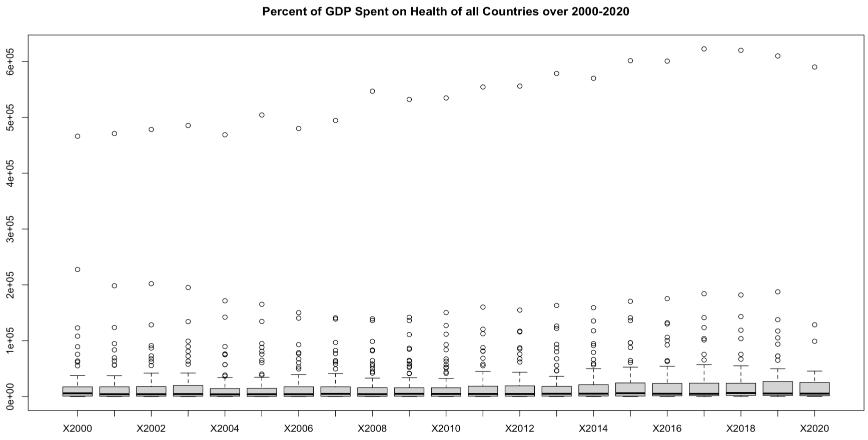


Figure 3: GDP all Countries Boxplot

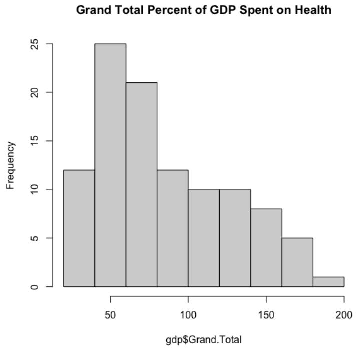


Figure 4: GDP Histogram

PM2.5 Data

```
R code:
pm2.5 <- read.csv("/Users/keertisundaram/Dropbox/Data Analytics
/Final_Project/pm2.5.csv", header=T)
str(pm2.5)
summary(pm2.5)
#adding a grand total column to maintain same structure as copd
#and gdp datasets
grand_total <- rowSums(pm2.5[-1])
pm2.5$Grand.Total <- grand_total
#find number of NAs
sum(is.na(pm2.5))
no_labels_pm2.5 <- pm2.5[-1]
boxplot(no_labels_pm2.5[-length(no_labels_pm2.5)], main = "PM2.5
Concentrations of all Countries over 2010-2019")
hist(pm2.5$Grand.Total, main = "Grand Total PM2.5
Concentrations")
```

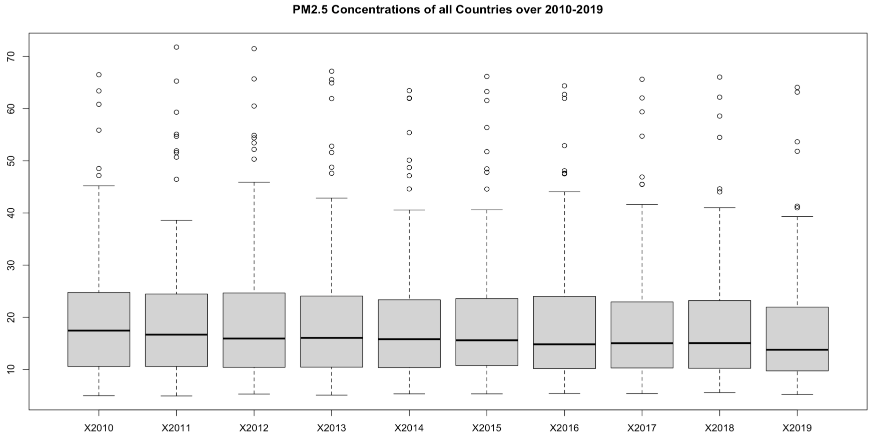


Figure 5: PM2.5 Concentrations of all Countries Boxplot

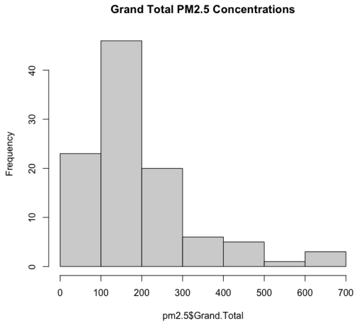


Figure 6: PM2.5 Histogram

For readability I did not include the outputs for the str and summary function calls. However, each of the data frames are set up in the same way, with one country column, the years columns, and the grand total column. Additionally, I found that the COPD data contains 418 NA values, the GDP data contains 22 NA values, and the PM2.5 data contains 0 NA values. For each of the datasets, I created a boxplot for each year, meaning each box is representative of all 104 countries for that year. I also created a histogram for each data set based off the grand totals for each country (i.e. sum of numbers over the years for each country). Based on a visual analysis of the figures, many of the countries have a similar amount of total COPD cases, however on the boxplot, there are outliers (countries with higher cases). The GDP data has more variance than the COPD data yet there are still outliers (countries that spend more on health care) that are revealed by the boxplot. Lastly, the PM2.5 data also has more variance than the COPD data when comparing the histograms. Based on the boxplots, the boxes are bigger than compared to the COPD and GDP boxes. This means that there is more variance (i.e. larger ranges between the 1st and 3rd quartiles) between the PM2.5 data than the COPD and GDP data. [COME BACK AND CHECK]

3 Analysis of Data and Pre processing

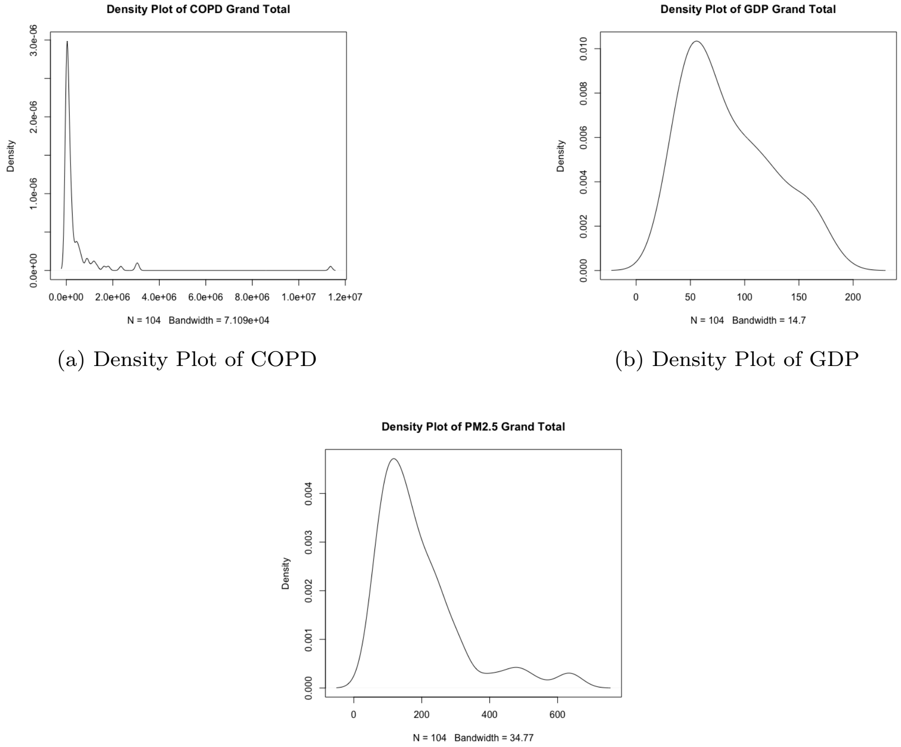
Each of the data sets needed a significant amount of formatting to create uniform rows and columns. I used several Excel pivot tables to format the raw data into the current format. The COPD raw data was formatted by age, sex, country, and year. I formatted the data so it was the sum of all deaths over a year for each country. The GDP data was formatted by country and year but required reformatting of the columns and rows to ensure the format matched the COPD data. The PM2.5 data was organized by country and year as well but required me to aggregate the columns as they were split up by location (i.e. split up into Urban, Rural, and Cities and I combined them into one value). Additionally, I filtered the data to ensure the analysis only focused on countries with available data, I matched this based on country name. It is important to note that I filtered the years for the GDP data so it had the same years as the COPD data (2000-2020), but the PM2.5 data is from years (2010-2019). I did this to ensure the cluster analyses using the GDP and COPD data would have as much data as possible. Whereas for the regression analysis on the COPD and PM2.5 data I limited the years to 2010-2019. This will be elaborated on further in the next section. As revealed in the exploratory data analysis, both the COPD and GDP data had missing values. I decided that data imputation to fill in missing values would be the best option for this application. I utilized the nearest-neighbor algorithm in the VIM package to accomplish this. I also updated the grand total column based on the imputed values.
Credit: https://search.r-project.org/CRAN/refmans/VIM/html/kNN.html

```
R code:
#data imputation, nearest-neighbor imputation
library(VIM)
#copd data
copd_imp <- kNN(copd[-length(copd)], k=5)
summary(copd_imp)
#removing extra imputation columns
copd_imp <- subset(copd_imp, select=Country:X2020)
#updating grand total column
grand_total <- rowSums(copd_imp[-1])
copd_imp$Grand.Total <- grand_total

#gdp data
gdp_imp <- kNN(gdp[-length(gdp)], k=5)
#removing extra imputation columns
```

```
gdp_imp <- subset(gdp_imp, select=Country:X2020)
#updating grand total column
grand_total <- rowSums(gdp_imp[-1])
gdp_imp$Grand.Total <- grand_total
```

While data imputation was decided to best the best route for this application, it is possible it may lead to a possible source of error. The data is not exact and is based on the closest values, therefore it creates limitations on the analysis.
I then created density plots using the data with the imputed values. Density plots may offer better insight into the distribution that histograms with the default bin width could not.

```
R code:
plot(density(copd_imp$Grand.Total), main="Density Plot of COPD Grand Total")
plot(density(gdp_imp$Grand.Total), main= "Density Plot of GDP Grand Total")
plot(density(pm2.5$Grand.Total), main= "Density Plot of PM2.5 Grand Total")
```



(a) Density Plot of COPD

(b) Density Plot of GDP

(c) Density Plot of PM2.5

Figure 7: Density Plots

Based on a visual analysis of the density plots, the COPD data appears to follow an exponential distribution. The GDP data appears to follow a weibull distribution. Lastly, the PM2.5 data appears to follow an F distribution [COME BACK]. It is important to note however that the visual analysis of these plots is limited and may not be accurate in categorizing the actual distribution.

4 Model Development and Application

1. K-Means Clustering K-Means Clustering was performed on both the COPD and GDP datasets. The goal of clustering was to determine which countries are grouped together for both datasets. Clustering was initially done on the entire dataset. To determine the value of k, I created elbow plots. Based on these figures, I set k = 4 for both datasets.

```
R code:
library(factoextra)
fviz_nbclust(copd_imp[-1], kmeans, method="wss") #bend at 4
fviz_nbclust(gdp_imp[-1], kmeans, method="wss") #bend at 4
```

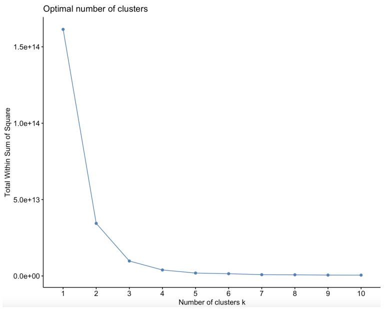


Figure 8: COPD Elbow Plot

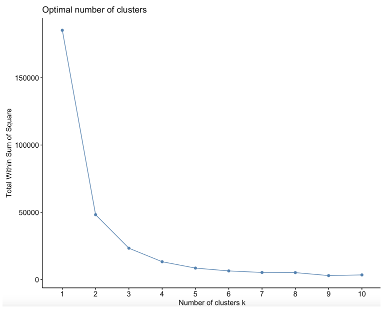
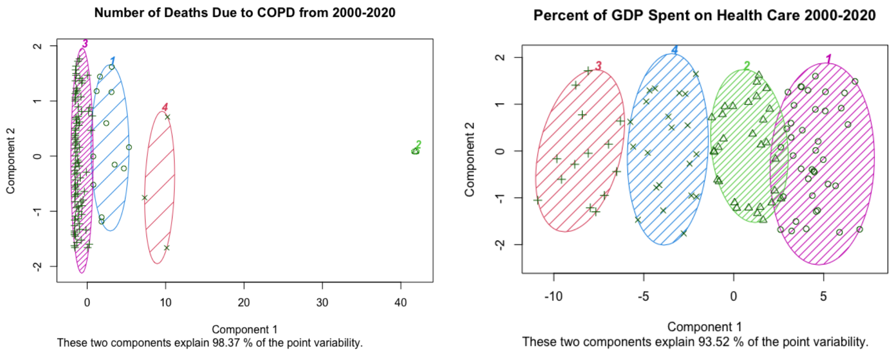


Figure 9: GDP Elbow Plot

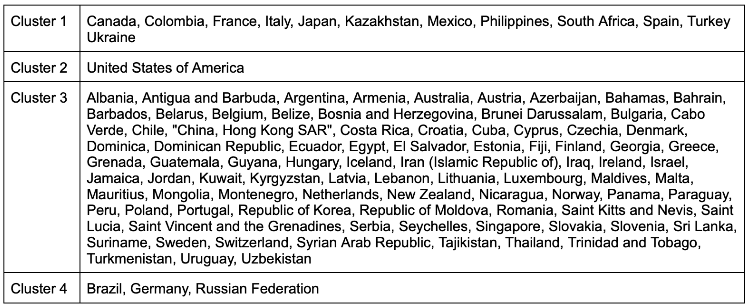
The results from the initial clustering is shown below.

```
library(ISLR)
set.seed(101)
library(cluster)
totalClusters <- kmeans(copd_imp[-1], 4, nstart = 20)
#nstart is the number of random start
print(totalClusters$cluster)
clusplot(copd_imp,totalClusters$cluster, color = TRUE,
shade = TRUE, labels = 4, lines = 0,  main = "Number of Deaths Due
to COPD from 2000-2020")
#gdp
totalClusters <- kmeans(gdp_imp[-1], 4, nstart = 20)
print(totalClusters$cluster)
clusplot(gdp_imp,totalClusters$cluster, color = TRUE,
shade = TRUE, labels = 4, lines = 0, main = "Percent of GDP Spent on
Health Care 2000-2020")
```



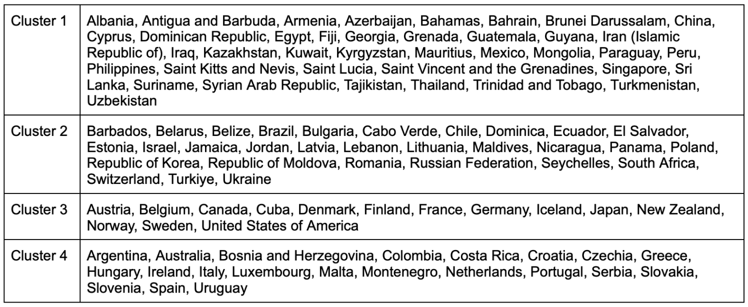
(a) COPD clusters

(b) GDP clusters



Cluster 1	Canada, Colombia, France, Italy, Japan, Kazakhstan, Mexico, Philippines, South Africa, Spain, Turkey Ukraine
Cluster 2	United States of America
Cluster 3	Albania, Antigua and Barbuda, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Barbados, Belarus, Belgium, Belize, Bosnia and Herzegovina, Brunei Darussalam, Bulgaria, Cabo Verde, Chile, "China, Hong Kong SAR", Costa Rica, Croatia, Cuba, Cyprus, Czechia, Denmark, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Fiji, Finland, Georgia, Greece, Grenada, Guatemala, Guyana, Hungary, Iceland, Iran (Islamic Republic of), Iraq, Ireland, Israel, Jamaica, Jordan, Kuwait, Kyrgyzstan, Latvia, Lebanon, Lithuania, Luxembourg, Maldives, Malta, Mauritius, Mongolia, Montenegro, Netherlands, New Zealand, Nicaragua, Norway, Panama, Paraguay, Peru, Poland, Portugal, Republic of Korea, Republic of Moldova, Romania, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Serbia, Seychelles, Singapore, Slovakia, Slovenia, Sri Lanka, Suriname, Sweden, Switzerland, Syrian Arab Republic, Tajikistan, Thailand, Trinidad and Tobago, Turkmenistan, Uruguay, Uzbekistan
Cluster 4	Brazil, Germany, Russian Federation

Figure 10: COPD Clusters

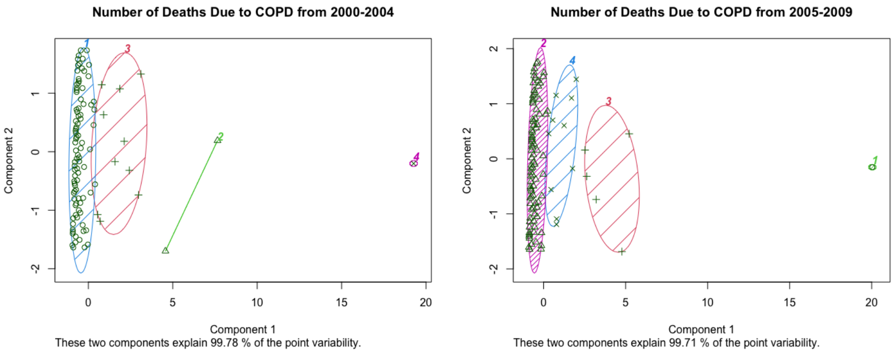


Cluster 1	Albania, Antigua and Barbuda, Armenia, Azerbaijan, Bahamas, Bahrain, Brunei Darussalam, China, Cyprus, Dominican Republic, Egypt, Fiji, Georgia, Grenada, Guatemala, Guyana, Iran (Islamic Republic of), Iraq, Kazakhstan, Kuwait, Kyrgyzstan, Mauritius, Mexico, Mongolia, Paraguay, Peru, Philippines, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Singapore, Sri Lanka, Suriname, Syrian Arab Republic, Tajikistan, Thailand, Trinidad and Tobago, Turkmenistan, Uzbekistan
Cluster 2	Barbados, Belarus, Belize, Brazil, Bulgaria, Cabo Verde, Chile, Dominica, Ecuador, El Salvador, Estonia, Israel, Jamaica, Jordan, Latvia, Lebanon, Lithuania, Maldives, Nicaragua, Panama, Poland, Republic of Korea, Republic of Moldova, Romania, Russian Federation, Seychelles, South Africa, Switzerland, Turkiye, Ukraine
Cluster 3	Austria, Belgium, Canada, Cuba, Denmark, Finland, France, Germany, Iceland, Japan, New Zealand, Norway, Sweden, United States of America
Cluster 4	Argentina, Australia, Bosnia and Herzegovina, Colombia, Costa Rica, Croatia, Czechia, Greece, Hungary, Ireland, Italy, Luxembourg, Malta, Montenegro, Netherlands, Portugal, Serbia, Slovakia, Slovenia, Spain, Uruguay

Figure 11: GDP Clusters

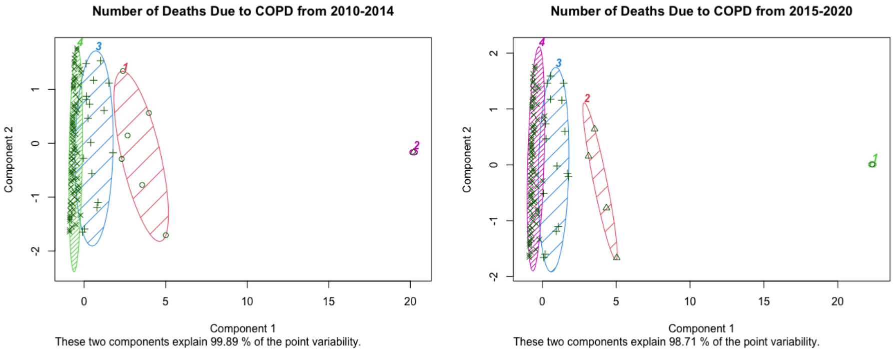
Based on the results of the initial clustering, I wanted to investigate the COPD clusters further. Interestingly, most of the countries are contained in one cluster. Since this clustering was done for all of the years (2000-2020), I decided to split up the years into groups and perform additional clustering. My goal was to determine if there were countries that had a different clustering pattern throughout the years. In other words, I was looking to find countries that ”changed” clusters at some point throughout the years. I split up the years into 4 groups, below are the results from the clustering done on these groups.

```
R code:
group1<- data.frame(copd_imp$Country, copd_imp[,c(2:6)])
group2<- data.frame(copd_imp$Country, copd_imp[,c(7:11)])
group3<- data.frame(copd_imp$Country, copd_imp[,c(12:16)])
group4<- data.frame(copd_imp$Country, copd_imp[,c(17:22)])

group1Clusters <- kmeans(group1[-1], 4, nstart = 20)
clusplot(group1,group1Clusters$cluster, color = TRUE, shade = TRUE,
labels = 4, lines = 0, main = "Number of Deaths Due to COPD from 2000-2004")

group2Clusters <- kmeans(group2[-1], 4, nstart = 20)
clusplot(group2,group2Clusters$cluster, color = TRUE, shade = TRUE,
labels = 4, lines = 0, main = "Number of Deaths Due to COPD from 2005-2009")

group3Clusters <- kmeans(group3[-1], 4, nstart = 20)
clusplot(group3,group3Clusters$cluster, color = TRUE, shade = TRUE,
labels = 4, lines = 0, main = "Number of Deaths Due to COPD from 2010-2014")

group4Clusters <- kmeans(group4[-1], 4, nstart = 20)
clusplot(group4,group4Clusters$cluster, color = TRUE, shade = TRUE,
labels = 4, lines = 0, main = "Number of Deaths Due to COPD from 2015-2020")
```



(a) COPD 2000-2004

(b) COPD 2005-2009



(a) COPD 2010-2014

(b) COPD 2015-2020

While many of the countries remained in similar clusters (i.e. grouped with the same countries throughout the years), I found several that switched their groupings at some point throughout the years. Countries that switched: Argentina, Australia, France, Germany, Hungary, Italy, Kazakhstan, Mexico, Netherlands, Poland, Republic of Korea, Romania, Thailand, Turkey. Since there was not a large difference between splitting the countries into groups compared to using all of the data, I decided to move forward with my analysis using the clustering that utilized the entire data set.

As mentioned, my first hypothesis was that countries with a higher percent of GDP spent on health will have lower COPD deaths. To analyze the clustering in relation to the hypothesis, I looked at how the countries were grouped together. Based on my hypothesis the groupings of both clusterings (i.e. COPD and GDP clustering) would be similar if not the same. In other words, countries that spent a higher percent of their GDP on health care would be clustered together in the GDP clustering. These same countries would be grouped together in the COPD clustering, more specifically would be grouped as countries with low COPD deaths. When comparing the clusters, many of the countries are grouped similarly (i.e. grouped with the same countries). The countries that are not: Brazil, Canada, Colombia, France, Germany, Italy, Japan, Kazakhstan, Mexico, Philippines, Russian Federation, South Africa, Spain, Turkey, Ukraine, United States of America. These are the countries that I will be utilizing in the next analysis on the impact of PM2.5 concentrations.

2. Regression Analysis Regression analysis was done using the COPD and PM2.5 data. The goal of the regression analysis was to determine whether PM2.5 concentration levels have a signficant relationship to COPD deaths. The analysis was performed using the 16 countries listed in the previous section. Initially, I created 10 linear models for each year that there was available data (2010-2019) and performed the analysis for all 16 countries. In other words I had each model representing all 16 countries in a given year. The predictor variable is PM2.5 concentration level and the response variable is number of COPD deaths.

```
R code:
df_2010 <- data.frame(copd$Country, pm2.5$X2010, copd$X2010)
colnames(df_2010) <- c(’Country’, ’pm2.5’, ’copd’)
lm_2010 <- lm(copd ˜ pm2.5, data = df_2010)
summary(lm_2010)
```

For simplicity I only included one model, similar code was written for years 2011-2019.
Output:

```
> summary(lm_2010)

Call:
lm(formula = copd ˜ pm2.5, data = df_2010)

Residuals:
    Min      1Q  Median      3Q     Max
-138067  -52316   -9984   25707  368613

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   247622      90450   2.738    0.016 *
pm2.5          -8777       5007  -1.753    0.101
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 114700 on 14 degrees of freedom
Multiple R-squared:   0.18,Adjusted R-squared:  0.1214
F-statistic: 3.072 on 1 and 14 DF,  p-value: 0.1015
```

```
> summary(lm_2011)

Call:
lm(formula = copd ~ pm2.5, data = df_2011)

Residuals:
    Min      1Q  Median      3Q     Max
-126806  -57560  -19342   27344  395518

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   228018      87382   2.609   0.0206 *
pm2.5          -7396       4733  -1.562   0.1405
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 121000 on 14 degrees of freedom
Multiple R-squared:  0.1485,Adjusted R-squared:  0.08766
F-statistic: 2.441 on 1 and 14 DF,  p-value: 0.1405

> summary(lm_2012)

Call:
lm(formula = copd ~ pm2.5, data = df_2012)

Residuals:
    Min      1Q  Median      3Q     Max
-116927  -61826  -17677   21208  405380

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   212628      82721   2.570   0.0222 *
pm2.5          -6849       4630  -1.479   0.1612
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 122400 on 14 degrees of freedom
Multiple R-squared:  0.1352,Adjusted R-squared:  0.07339
F-statistic: 2.188 on 1 and 14 DF,  p-value: 0.1612

> summary(lm_2013)

Call:
lm(formula = copd ~ pm2.5, data = df_2013)

Residuals:
    Min      1Q  Median      3Q     Max
-123329  -59762  -20241   30285  418637

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   222089      87398   2.541   0.0235 *
pm2.5          -7106       4923  -1.444   0.1709
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 127300 on 14 degrees of freedom
Multiple R-squared:  0.1296,Adjusted R-squared:  0.06739
F-statistic: 2.084 on 1 and 14 DF,  p-value: 0.1709

> summary(lm_2014)

Call:
lm(formula = copd ~ pm2.5, data = df_2014)

Residuals:
    Min      1Q  Median      3Q     Max
-121723  -58712  -15730   30066  412259

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   220541      89171   2.473   0.0268 *
pm2.5          -7298       5248  -1.391   0.1860
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 125900 on 14 degrees of freedom
Multiple R-squared:  0.1214,Adjusted R-squared:  0.05862
F-statistic: 1.934 on 1 and 14 DF,  p-value: 0.186

> summary(lm_2015)

Call:
lm(formula = copd ~ pm2.5, data = df_2015)

Residuals:
    Min      1Q  Median      3Q     Max
-129008  -73070  -15202   32016  433151

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   233264      90824   2.568   0.0223 *
```

```
pm2.5          -7824       5374  -1.456   0.1675
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 132500 on 14 degrees of freedom
Multiple R-squared:  0.1315,Adjusted R-squared:  0.06944
F-statistic: 2.119 on 1 and 14 DF,  p-value: 0.1675

> summary(lm_2016)

Call:
lm(formula = copd ~ pm2.5, data = df_2016)

Residuals:
    Min      1Q  Median      3Q     Max
-125745  -67890  -20395   35213  435807

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   216227      84269   2.566   0.0224 *
pm2.5          -6814       5092  -1.338   0.2022
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 132600 on 14 degrees of freedom
Multiple R-squared:  0.1134,Adjusted R-squared:  0.05008
F-statistic: 1.791 on 1 and 14 DF,  p-value: 0.2022

> summary(lm_2017)

Call:
lm(formula = copd ~ pm2.5, data = df_2017)

Residuals:
    Min      1Q  Median      3Q     Max
-137038  -65281  -33761   21070  457394

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   231248      96071   2.407   0.0305 *
pm2.5          -8311       5923  -1.403   0.1823
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 141800 on 14 degrees of freedom
Multiple R-squared:  0.1233,Adjusted R-squared:  0.06068
```

```
F-statistic: 1.969 on 1 and 14 DF,  p-value: 0.1823

> summary(lm_2018)

Call:
lm(formula = copd ˜ pm2.5, data = df_2018)

Residuals:
    Min      1Q  Median      3Q     Max
-120124  -78056  -26569   28722  459085

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   233677      94967   2.461   0.0275 *
pm2.5          -8944       5983  -1.495   0.1571
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 140500 on 14 degrees of freedom
Multiple R-squared:  0.1376,Adjusted R-squared:  0.07605
F-statistic: 2.235 on 1 and 14 DF,  p-value: 0.1571

> summary(lm_2019)

Call:
lm(formula = copd ˜ pm2.5, data = df_2019)

Residuals:
    Min      1Q  Median      3Q     Max
-120389  -69940  -36537   30261  446397

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   220110      89232   2.467   0.0272 *
pm2.5          -7886       5823  -1.354   0.1971
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 137300 on 14 degrees of freedom
Multiple R-squared:  0.1158,Adjusted R-squared:  0.05266
F-statistic: 1.834 on 1 and 14 DF,  p-value: 0.1971
```

All of the p-values for the pm2.5 variable are above 0.05, this means we can not say that pm2.5 concentrations attribute to the variance in COPD deaths. Additionally, each of the models have large residual standard errors which means they do not fit the data well. Each model also has a low multiple R-squared

value which tells us the model may explain some of the variance in the data but not as much as I would have expected. Lastly, the p-value for all of the models is above 0.05 which means we can not use them to declare a significant relationship between the variables.
Based on prior research, I was expecting to find a significant relationship between these two variables. Since I found that these models were not the best fit for the data, I decided to reformat the data and perform additional linear regressions. For the following models I performed the regression using data over the years 2010-2019 from only a specific country.

```
R code:
df <- data.frame(t(pm2.5[pm2.5$Country == ’Brazil’, ]),
t(copd[copd$Country == ’Brazil’, ]))
colnames(df) <- c(’pm2.5’, ’copd’)
df <- df[-1,]
df$pm2.5 <- as.numeric(df$pm2.5)
df$copd <- as.numeric(df$copd)
brazil_lm <- lm(copd ~ pm2.5, data = df)
summary(brazil_lm)
```

For simplicity I only included one model, similar code was written for the following countries: Canada, Colombia, France, Germany, Italy, Japan, Kazakhstan, Mexico, Philippines, Russian Federation, South Africa, Spain, Turkey, Ukraine, and United States of America.
Output:

```
> summary(brazil_lm)

Call:
lm(formula = copd ~ pm2.5, data = df)

Residuals:
   Min     1Q Median     3Q    Max
-37832 -19824  -6458  17774  46324

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)    697.7    10766.4   0.065     0.95
pm2.5        12842.6      259.6  49.468 2.83e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 29220 on 9 degrees of freedom
Multiple R-squared:  0.9963,Adjusted R-squared:  0.9959
F-statistic:  2447 on 1 and 9 DF,  p-value: 2.828e-12

> summary(canada_lm)
```

```
Call:
lm(formula = copd ~ pm2.5, data = df)

Residuals:
    Min      1Q  Median      3Q     Max
-8676.2 -4336.9   443.7  4667.4  8039.6

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)     98.6     2290.4   0.043    0.967
pm2.5         6446.6      100.7  63.993  2.8e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6216 on 9 degrees of freedom
Multiple R-squared:  0.9978,Adjusted R-squared:  0.9976
F-statistic:  4095 on 1 and 9 DF,  p-value: 2.804e-13

> summary(Colombia_lm)

Call:
lm(formula = copd ~ pm2.5, data = df)

Residuals:
     Min       1Q   Median       3Q      Max
-11415.7  -9069.9   -371.9   4943.9  21930.3

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   182.11    3975.67   0.046    0.964
pm2.5        3053.53      75.43  40.482 1.71e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 10790 on 9 degrees of freedom
Multiple R-squared:  0.9945,Adjusted R-squared:  0.9939
F-statistic:  1639 on 1 and 9 DF,  p-value: 1.705e-11

> summary(France_lm)

Call:
lm(formula = copd ~ pm2.5, data = df)

Residuals:
     Min       1Q   Median       3Q      Max
```

```
-25965.8  -2079.5   -181.9   6211.3  13167.0

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   -40.43    4315.81  -0.009    0.993
pm2.5        2336.78     110.25  21.195 5.44e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 11710 on 9 degrees of freedom
Multiple R-squared:  0.9804,Adjusted R-squared:  0.9782
F-statistic: 449.2 on 1 and 9 DF,  p-value: 5.439e-09

> summary(Germany_lm)

Call:
lm(formula = copd ~ pm2.5, data = df)

Residuals:
   Min     1Q Median     3Q    Max
-40379 -13411   3011  19307  31103

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)    669.2     9641.8   0.069    0.946
pm2.5         9871.0      237.2  41.622 1.33e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 26170 on 9 degrees of freedom
Multiple R-squared:  0.9948,Adjusted R-squared:  0.9943
F-statistic:  1732 on 1 and 9 DF,  p-value: 1.33e-11

> summary(Italy_lm)

Call:
lm(formula = copd ~ pm2.5, data = df)

Residuals:
   Min     1Q Median     3Q    Max
-56473  -2774   1550   7664  31068

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)    91.58    8622.86   0.011    0.992
pm2.5        4454.44     157.55  28.274 4.21e-10 ***
```

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 23410 on 9 degrees of freedom
Multiple R-squared:  0.9889,Adjusted R-squared:  0.9876
F-statistic: 799.4 on 1 and 9 DF,  p-value: 4.212e-10

> summary(Japan_lm)

Call:
lm(formula = copd ~ pm2.5, data = df)

Residuals:
   Min     1Q Median     3Q    Max
-10490  -6472  -4355   5678  16165

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   189.11    3567.42   0.053    0.959
pm2.5        5458.85      89.32  61.113 4.24e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 9682 on 9 degrees of freedom
Multiple R-squared:  0.9976,Adjusted R-squared:  0.9973
F-statistic:  3735 on 1 and 9 DF,  p-value: 4.24e-13

> summary(Kazakhstan_lm)

Call:
lm(formula = copd ~ pm2.5, data = df)

Residuals:
   Min     1Q Median     3Q    Max
-23271  -9155   7395   9939  13032

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   179.44    5618.37   0.032    0.975
pm2.5        1272.44      57.51  22.126 3.72e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 15250 on 9 degrees of freedom
Multiple R-squared:  0.9819,Adjusted R-squared:  0.9799
F-statistic: 489.6 on 1 and 9 DF,  p-value: 3.719e-09
```

```
> summary(Mexico_lm)

Call:
lm(formula = copd ~ pm2.5, data = df)

Residuals:
   Min     1Q Median     3Q    Max 
-19545  -9974  -3096  10057  23845 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)   265.56    5420.29   0.049    0.962    
pm2.5        4544.31      80.57  56.403 8.71e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 14710 on 9 degrees of freedom
Multiple R-squared:  0.9972,Adjusted R-squared:  0.9969 
F-statistic:  3181 on 1 and 9 DF,  p-value: 8.712e-13

> summary(Philippines_lm)

Call:
lm(formula = copd ~ pm2.5, data = df)

Residuals:
     Min       1Q   Median       3Q      Max 
-16083.5  -7440.7    341.2   7781.2  15930.7 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)    75.81    4172.21   0.018    0.986    
pm2.5        2522.47      58.22  43.325 9.28e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 11320 on 9 degrees of freedom
Multiple R-squared:  0.9952,Adjusted R-squared:  0.9947 
F-statistic:  1877 on 1 and 9 DF,  p-value: 9.284e-12

> summary(RF_lm)

Call:
lm(formula = copd ~ pm2.5, data = df)
```

```
Residuals:
   Min     1Q Median     3Q    Max
-24150 -12287   1308  10339  21068

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)    332.3     5783.7   0.057    0.955
pm2.5        12713.6      185.5  68.553 1.51e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 15700 on 9 degrees of freedom
Multiple R-squared:  0.9981,Adjusted R-squared:  0.9979
F-statistic:  4700 on 1 and 9 DF,  p-value: 1.511e-13

> summary(S_Afr_lm)

Call:
lm(formula = copd ~ pm2.5, data = df)

Residuals:
     Min       1Q   Median       3Q      Max
-10791.2   -856.5     21.4   2291.8   4597.0

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)     4.75    1599.85   0.003    0.998
pm2.5        1762.76      26.53  66.446    2e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4341 on 9 degrees of freedom
Multiple R-squared:  0.998,Adjusted R-squared:  0.9977
F-statistic:  4415 on 1 and 9 DF,  p-value: 2e-13

> summary(Spain_lm)

Call:
lm(formula = copd ~ pm2.5, data = df)

Residuals:
    Min      1Q  Median      3Q     Max
-8975.5  -547.5  1318.1  3211.8  3970.4

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept)    97.83    1764.63   0.055    0.957
pm2.5        5106.01      50.73 100.658 4.78e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4790 on 9 degrees of freedom
Multiple R-squared:  0.9991,Adjusted R-squared:  0.999
F-statistic: 1.013e+04 on 1 and 9 DF,  p-value: 4.783e-15

> summary(Turkey_lm)

Call:
lm(formula = copd ˜ pm2.5, data = df)

Residuals:
   Min     1Q Median     3Q    Max
-67038  -5617   7933  21844  29545

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)    26.93   11961.33   0.002    0.998
pm2.5        3141.24     164.01  19.153 1.33e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 32460 on 9 degrees of freedom
Multiple R-squared:  0.9761,Adjusted R-squared:  0.9734
F-statistic: 366.8 on 1 and 9 DF,  p-value: 1.329e-08

> summary(Ukraine_lm)

Call:
lm(formula = copd ˜ pm2.5, data = df)

Residuals:
     Min       1Q   Median       3Q      Max
-12636.1  -6954.1   -275.6   6262.6  21143.4

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   -61.25    3921.89  -0.016    0.988
pm2.5        2419.34      81.97  29.513 2.87e-10 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 10640 on 9 degrees of freedom
```

```
Multiple R-squared:  0.9898,Adjusted R-squared:  0.9886
F-statistic:   871 on 1 and 9 DF,  p-value: 2.874e-10

> summary(US_lm)

Call:
lm(formula = copd ~ pm2.5, data = df)

Residuals:
    Min      1Q  Median      3Q     Max
-111011  -52143    6671   61892  110498

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)     1482      28880   0.051     0.96
pm2.5          69346       1084  63.962 2.82e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 78380 on 9 degrees of freedom
Multiple R-squared:  0.9978,Adjusted R-squared:  0.9976
F-statistic:  4091 on 1 and 9 DF,  p-value: 2.816e-13
```

Based on the above results, these models are better fit for the data. All of the p-values for the pm2.5 attribute are less than 0.05 which means the variable is significant to the model and attributes to variance in the COPD data. There is also a small residual standard error for each model as compared to the previous yearly models. Therefore these models fit the data better compared to the other models. Each model also has a high multiple R-squared value which would indicate that pm2.5 concentrations explain a high amount of variation within the COPD data. Lastly, the p-value of all the models is less than 0.05 which means they can be used to declare a significant relationship between the variables.

Therefore, utilizing these models allows us to come to the conclusion that there is a significant relationship between PM2.5 concentrations and deaths due to COPD when examining the data by country.

To continue the analysis, I will refer back to hypothesis 2: Air pollution, quantified here by PM2.5, is also a contributing factor that accounts for an increased amount of COPD deaths despite a high percentage of GDP spent on health care.

The linear regression models have proved part of this hypothesis, that PM2.5 is a contributing factor to COPD deaths. In order to prove or disprove the rest of this hypothesis, we need to look specifically at the countries used for the regression models. In the next section, I will rephrase the conclusions of hypothesis 1 and continue looking at hypothesis 2.

5 Conclusions and Discussions

i. In terms of hypothesis 1, we can not say for certain that countries that spend more on healthcare have lower COPD cases. As I mentioned previously, I compared the clusters of the COPD and GDP data sets. If hypothesis 1 was true we would expect to see similar groupings of the countries between both clusters. Although many countries are grouped similarly (except for the 16 used for the regression analysis), all four of the gdp clusters are split among the four copd clusters (i.e. no GDP cluster is entirely contained in a COPD cluster). Additionally, the countries that are grouped similarly may be attributed to the fact that most countries are contained in one COPD cluster. Based on these results, we can not prove or disprove my first hypothesis.

ii. Moving to hypothesis 2, the regression analysis proved that there is a significant relationship between COPD deaths and PM2.5 concentrations. Additionally, for the 16 countries I looked at, all of the models had a positive estimate coefficient for pm2.5, this means copd has a positive increase when pm2.5 increases. The 16 countries used for the regression analysis were also the countries with the 16 highest COPD deaths (when using the total number of deaths over 2000-2020). However, only 7 of these countries were in the top 20 for total amount spent on healthcare (i.e. sum of percent of GDP spent on healthcare over 2000-2020). Therefore, it is not necessarily true for these 16 countries that an increase in COPD deaths is due to lower spending on healthcare. However, PM2.5 concentrations have a significant relationship to COPD deaths. Although I have proved part of hypothesis 2 (PM2.5 as a contributing factor to COPD deaths), we can not say that it is the only factor that accounts for differences between the clusters of the data sets. As of now I can only draw conclusions for these 16 countries. In the future, it would be worthwhile to perform the regression analysis utilizing all of the countries in the data set.

Other Considered Approaches:
In a previous section, I mentioned how I utilized year groupings to see if the COPD clusters would change. I also discussed how these clusterings did not offer new insight and so I decided to move forward with the total clustering.
Another path I pursued was using COPD death ratio instead of number of deaths. I had suspected that the COPD clustering may have been impacted by the fact that I was using the number of deaths as opposed to the ratio of deaths to total population. Assuming that countries with a higher population would experience more COPD deaths I wanted to see if the clustering would change when using the ratio instead. To investigate this I used population data from the world bank. I matched the datasets using country name and created a new data frame with the ratios.

```
R code:
population <- read.csv("/Users/keertisundaram/Dropbox/Data
Analytics/Final_Project/population.csv", header=T)
```

```
View(population)
copd <- copd[order(copd$Country),]
population <- population[order(population$Country),]
copd_no_labels <- copd_imp[-1]
ratios <- cbind(population[1], round(copd_no_labels[
-length(copd_no_labels)]/population[-1],5))
View(ratios)

library(ISLR)
library(cluster)
totalClusters <- kmeans(ratios[-1], 4, nstart = 20)
print(totalClusters$cluster)
clusplot(ratios,totalClusters$cluster, color = TRUE, shade = TRUE,
labels = 4, lines = 0,  main = "Number of Deaths Due to COPD
from 2000-2020")
```

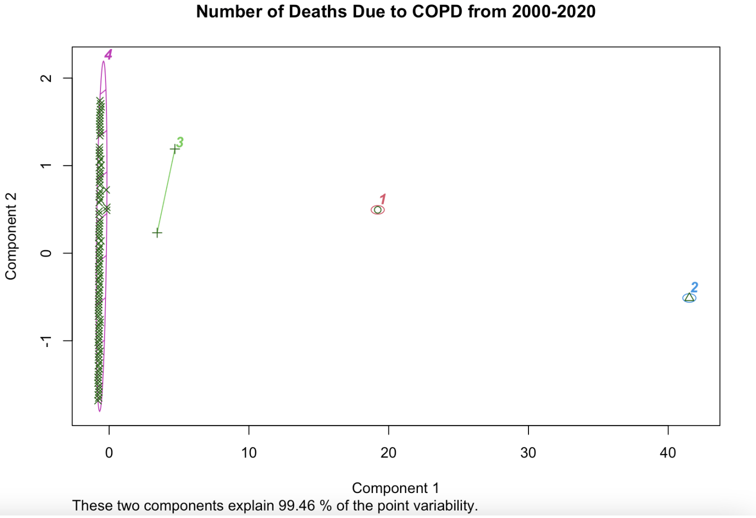


Figure 12: COPD Clusters Using Ratios

Based on the output from this clustering, I decided not to pursue the ratio approach. I found that most of the countries still remained in one cluster with the exception of South Africa (cluster 2) , Spain (cluster 1), Sri Lanka (cluster 3), and Mexico (cluster 3). It may be interesting to look specifically at these countries to determine why they are outliers within the data.

Further studies:
In addition to further regression analysis using all of the countries in the data set, subsequent analysis would involve looking into other contributing factors to COPD such as smoking.

The code utilized for this analysis can be accessed at: [LINK]

6 References