Final Report

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Kaitlyn Lewars and Katie Meehl: The Exposure Experience

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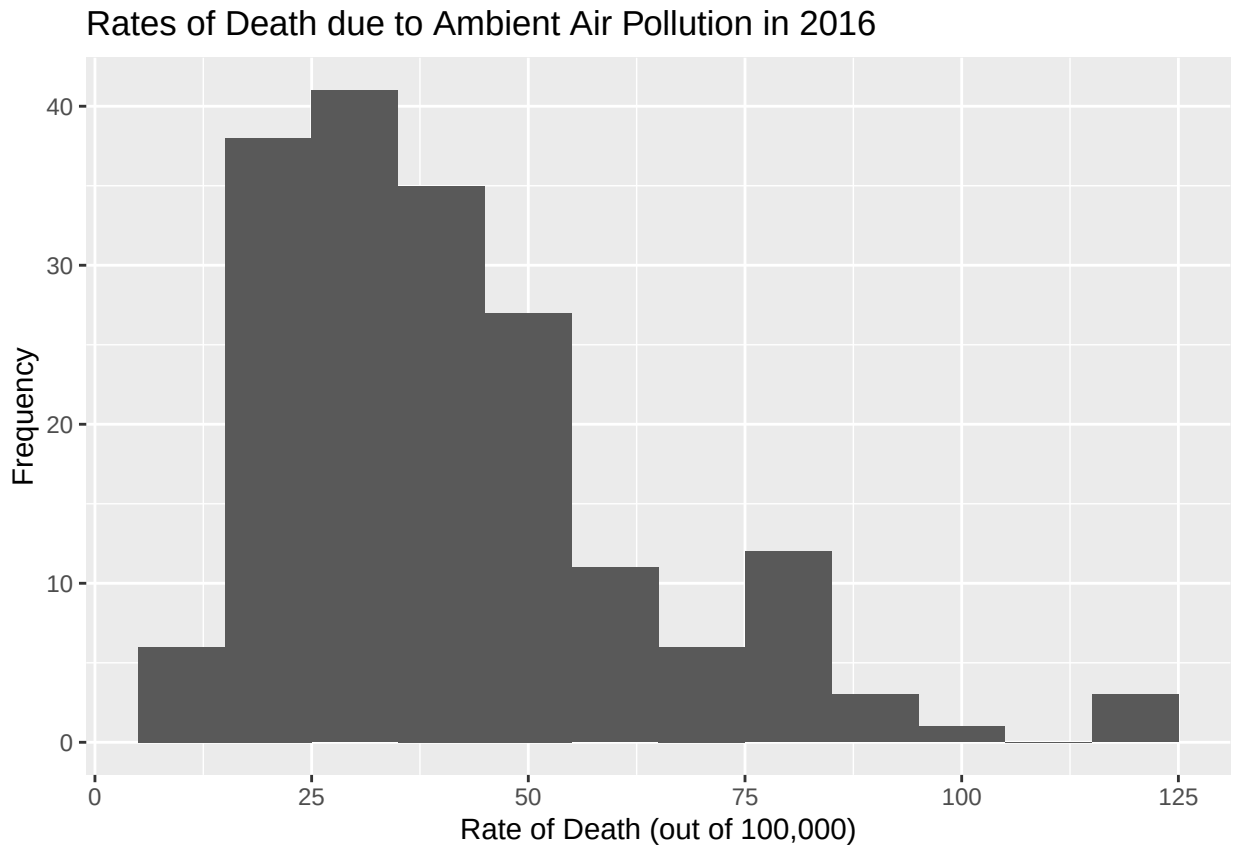
Climate change has been a recurring topic in the news in recent years as it becomes a more pressing problem. One of the important factors of climate change is air pollution. In 2017, air pollution was the 4th leading cause of mortality and the 5th leading cause of morbidity worldwide. As air pollution is a leading cause of morbidity and mortality, we thought it would be important to explore a data set investigating this problem. [Edit, add sources]

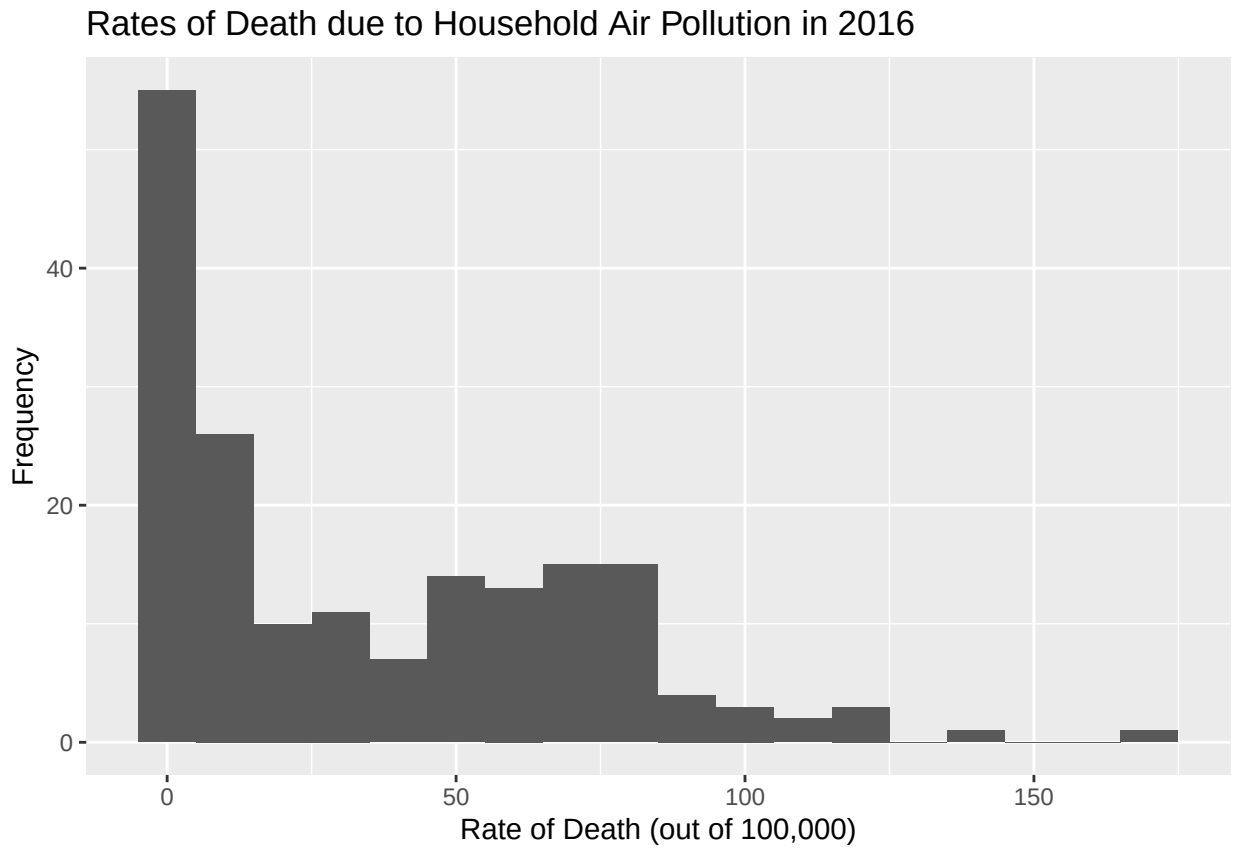
In general we would like to investigate air pollution as a cause of mortality globally. There are several different types of air pollution, but we will look at household pollution and ambient matter pollution. With these two variables we will compare them to see which air pollution is the most fatal. We would also like to look into the trend of air pollution over the last 27 years. Lastly we would like to compare air pollution as a risk factor to other common risk factors. We downloaded this data from the World Health Organization Data Collections. There are several variables in this data including year, country, deaths by each type of air pollution, and deaths by other risk factors.

The data collection is a bit complicated. In order to estimate deaths caused by pollution they use "mathematical functions, derived from epidemiological studies from countries around the world, that relate different levels of exposure to the increased risk of death or disability from each cause, by age and sex, where applicable, estimates of population exposure to PM2.5, ozone, and household air pollution, country-specific data on underlying rates of disease and death for each pollution-linked disease, and a comprehensive set of population data, adjusted to match the UN2015 Population Prospectus and obtained from the Gridded Population of the World (GPW) database for each country" (https://www.stateofglobalair.org/data/estimate-burden).

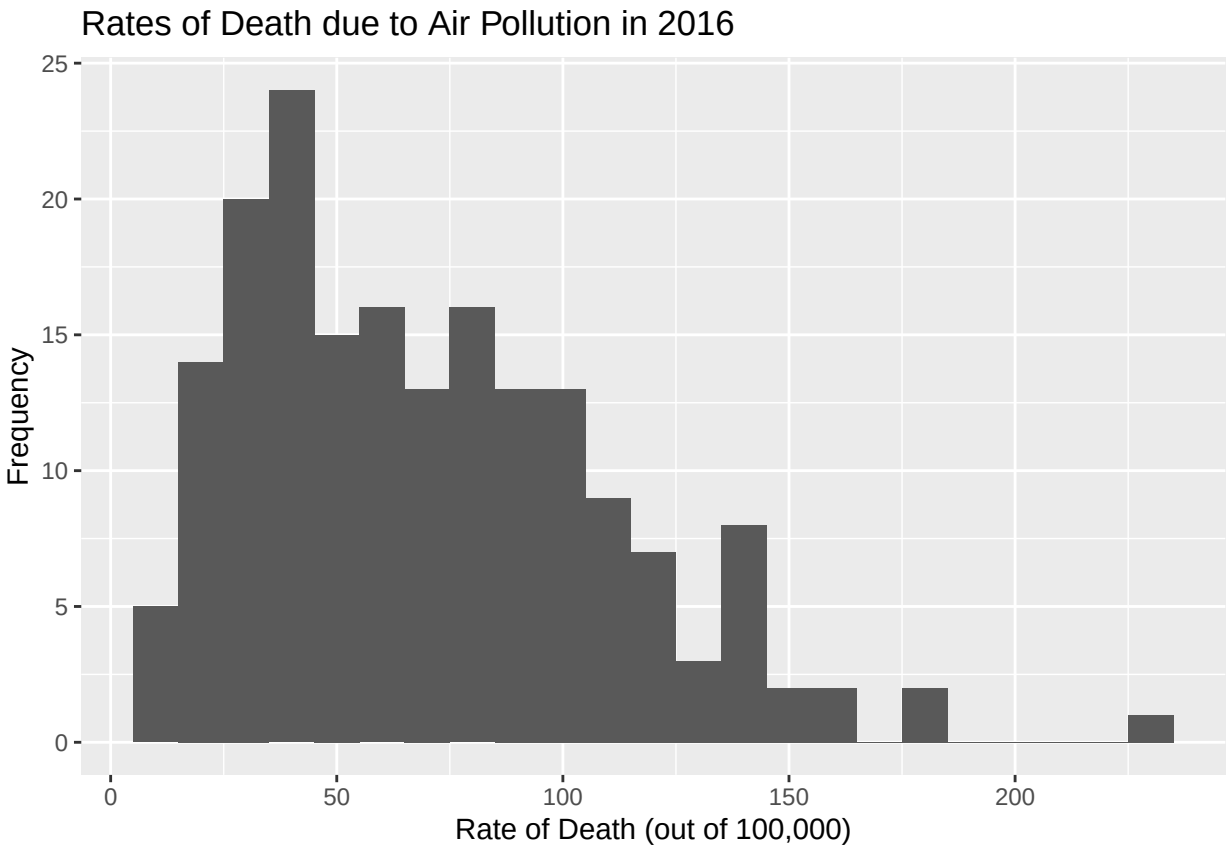
```
Ambient_Air_Pollution_Rate %>%
  filter(Dim2 == "Total", Dim1 == "Both sexes") %>%
  ggplot(aes(x = FactValueNumeric)) +
  geom_histogram(binwidth = 10) +
  scale_x_continuous(labels = label_comma()) +
  labs(x = "Rate of Death (out of 100,000)",
       y = "Frequency",
       title = "Rates of Death due to Ambient Air Pollution in 2016")
```




```
Household_Air_Pollution_Rate %>%
  filter(Dim2 == "Total", Dim1 == "Both sexes") %>%
  ggplot(aes(x = FactValueNumeric)) +
  geom_histogram(binwidth = 10) +
  scale_x_continuous(labels = label_comma()) +
  labs(x = "Rate of Death (out of 100,000)",
       y = "Frequency",
       title = "Rates of Death due to Household Air Pollution in 2016")
```




```
Total_Air_Pollution_Death_Rate %>%
  filter(Dim2 == "Total", Dim1 == "Both sexes") %>%
  ggplot(aes(x = FactValueNumeric)) +
  geom_histogram(binwidth = 10) +
  scale_x_continuous(labels = label_comma()) +
  labs(x = "Rate of Death (out of 100,000)",
       y = "Frequency",
       title = "Rates of Death due to Air Pollution in 2016")
```



The first thing we wanted to look at was the frequency of higher death rates due to the ambient and household air pollution. As seen in the first visualization showing the rates of death due to Ambient Air Pollution, there tends to be a greater amount of countries that have death rates of around 25-30 out of every 100,000 in their population, with very few countries have less than 15 or greater than 75 deaths out of every 100,000.

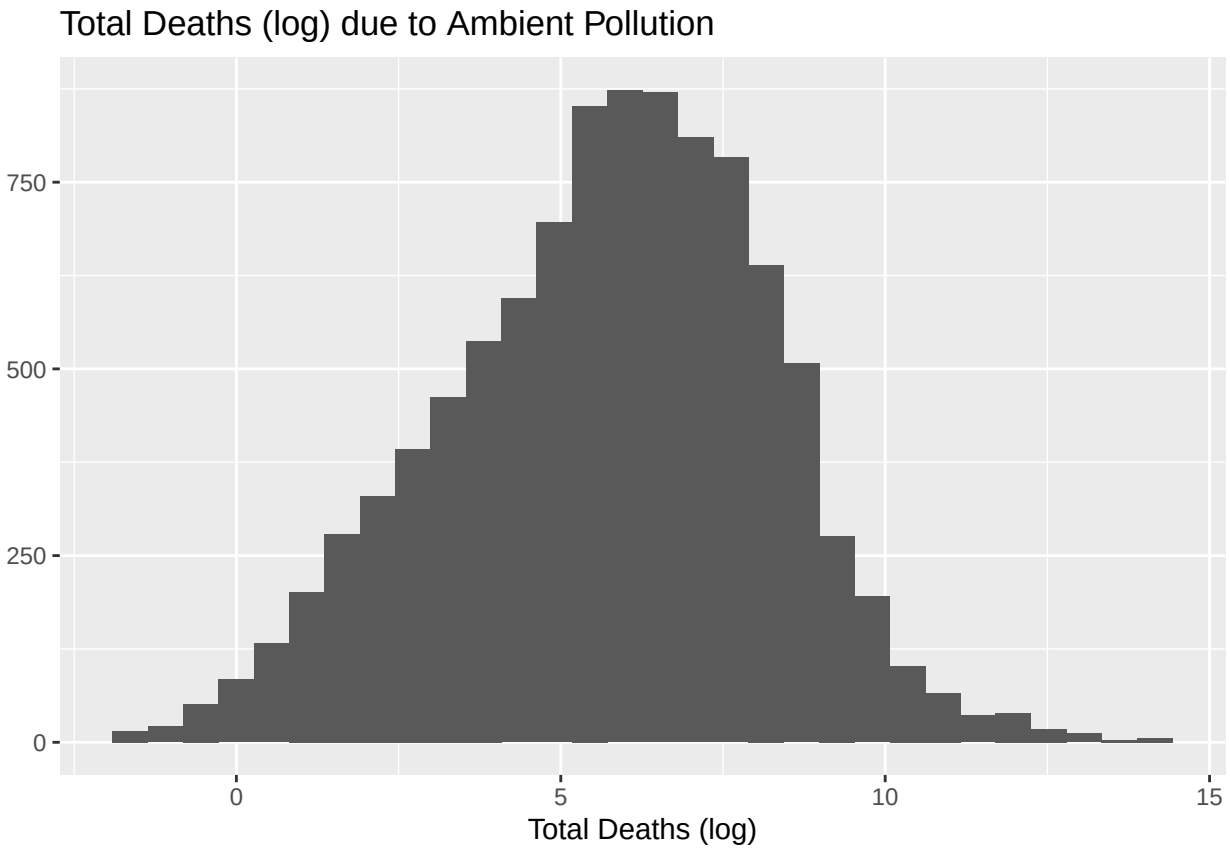
This is much more alarming than the household air pollution death rates, which tend to center around 0 for most countries. However, this visualization also shows quite a few countries that have death rates between 50 and 100 deaths out of every 100,000. Our third visualization shows the total deaths due to air pollution in selected countries around the globe in 2016. Here, we are able to see the sheer amount of countries that have had rates of roughly 50 up to roughly 150 deaths out of 100,000, indicating a serious global issue.

Out of these three plots, there are four countries that should be noted: Democratic People's Republic of Korea, Georgia, Chad, and Bosnia and Herzegovina. These countries are outliers and show much higher death rates due to air pollution than other countries.

Here, we have created a new dataset to explore our discovery that ambient air pollution had a higher average death rate globally than household air pollution. This includes the total deaths due to to ambient pollution, the rates at which countries have had deaths due to ambient air pollution, ambient air concentration, and other factors which will help understand how ambient air pollution affect countries around the world.

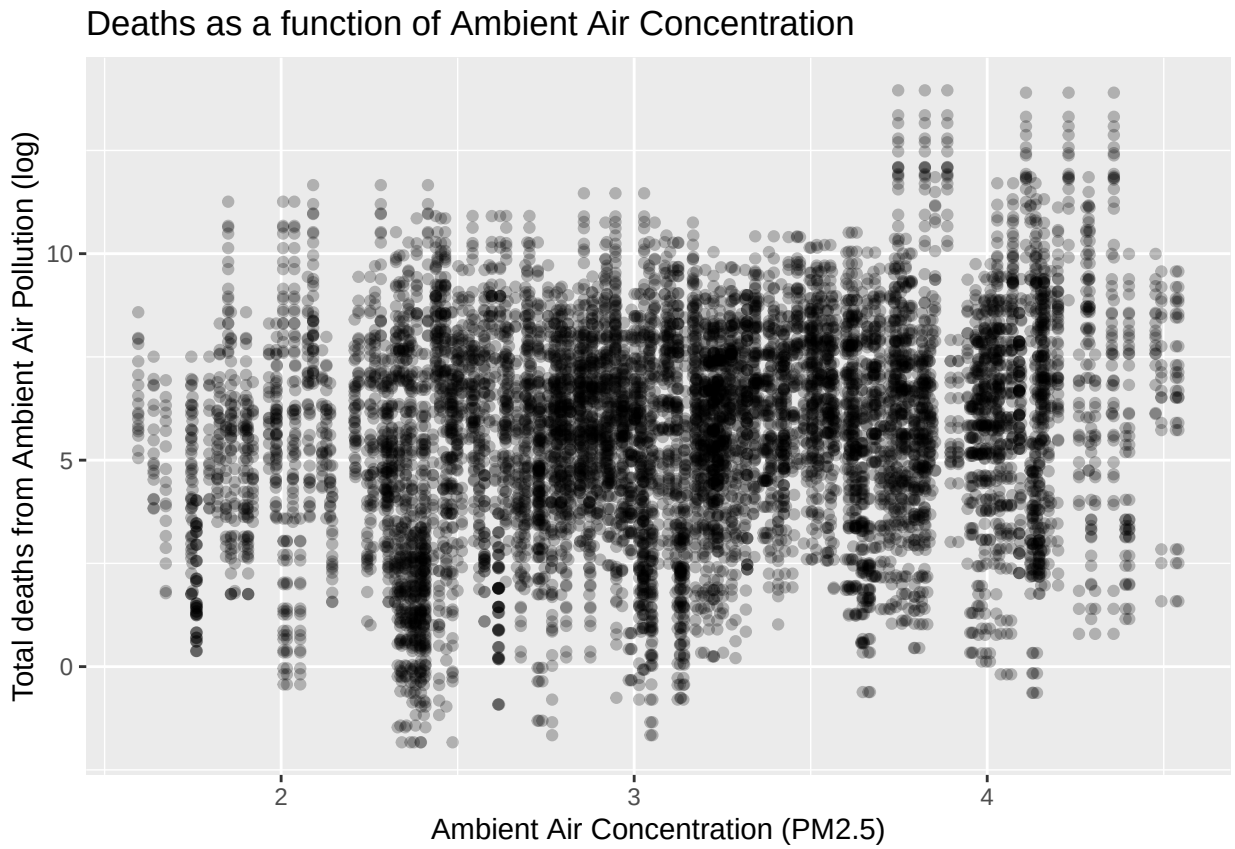
```
ggplot(data = ambient, aes(x = log(Totaldeathsambient))) +
  geom_histogram() +
  labs(x = "Total Deaths (log)", y = NULL, title="Total Deaths (log) due to Ambient Pollution")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



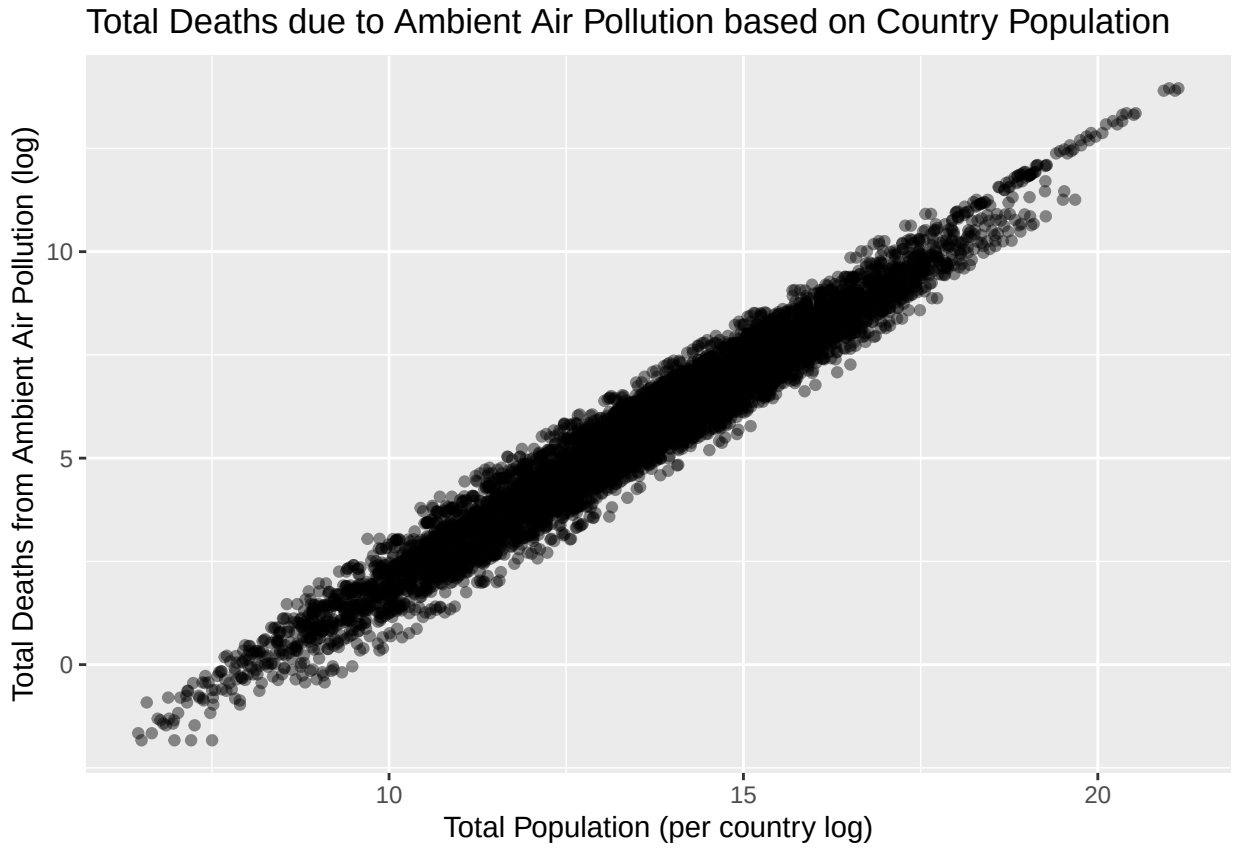
In order to perform a linear regression we evaluated our current variables. First we wanted to see if the total deaths due to ambient air pollution were normal, which they were not. The deaths were left skewed so we calculated the log of deaths which created an approximately normal data set.

```
ggplot(data = ambient, aes(x = log(AmbientAirConcentration), y = log(Totaldeathsambient))) +
geom_point(alpha = 0.25) +
labs(title = "Deaths as a function of Ambient Air Concentration",
x = "Ambient Air Concentration (PM2.5)",
y = "Total deaths from Ambient Air Pollution (log)")
```



We want to explore the different factors affecting deaths due to ambient air pollution. A potential factor in the rise in environmental air pollution could be the concentration of air pollution. In the plot above, we examine the connection between total deaths from ambient air pollution vs. ambient air concentration in fine particulate matter, both of which are on a log scale for normalization of the data. Although slightly centered around the middle, the plot clearly shows a lack of strong relationship between these two variables, indicating that there are likely other factors influencing the data.

```
ggplot(data = ambient2, aes(x = log(totalpopulation), y = log(Totaldeathsambient))) +
geom_point(alpha = 0.25) +
  labs(title = "Total Deaths due to Ambient Air Pollution based on Country Population",
       x = "Total Population (per country log)",
       y = "Total Deaths from Ambient Air Pollution (log)")
```



In continuing our exploration of which factors influence deaths and death rates from ambient air pollution, we compared the total deaths from ambient air pollution to the total population of the countries we selected to examine. Per the linear arrangement of points in the plot, there seems to be a strong relationship between the ambient air pollution deaths and the country population. This is likely because an increased population will naturally lead to a greater chance of citizens facing global health crisis. This also could be related to an increased amount and spread of ambient air pollution in larger countries which rely on greater usage of fossil fuels.

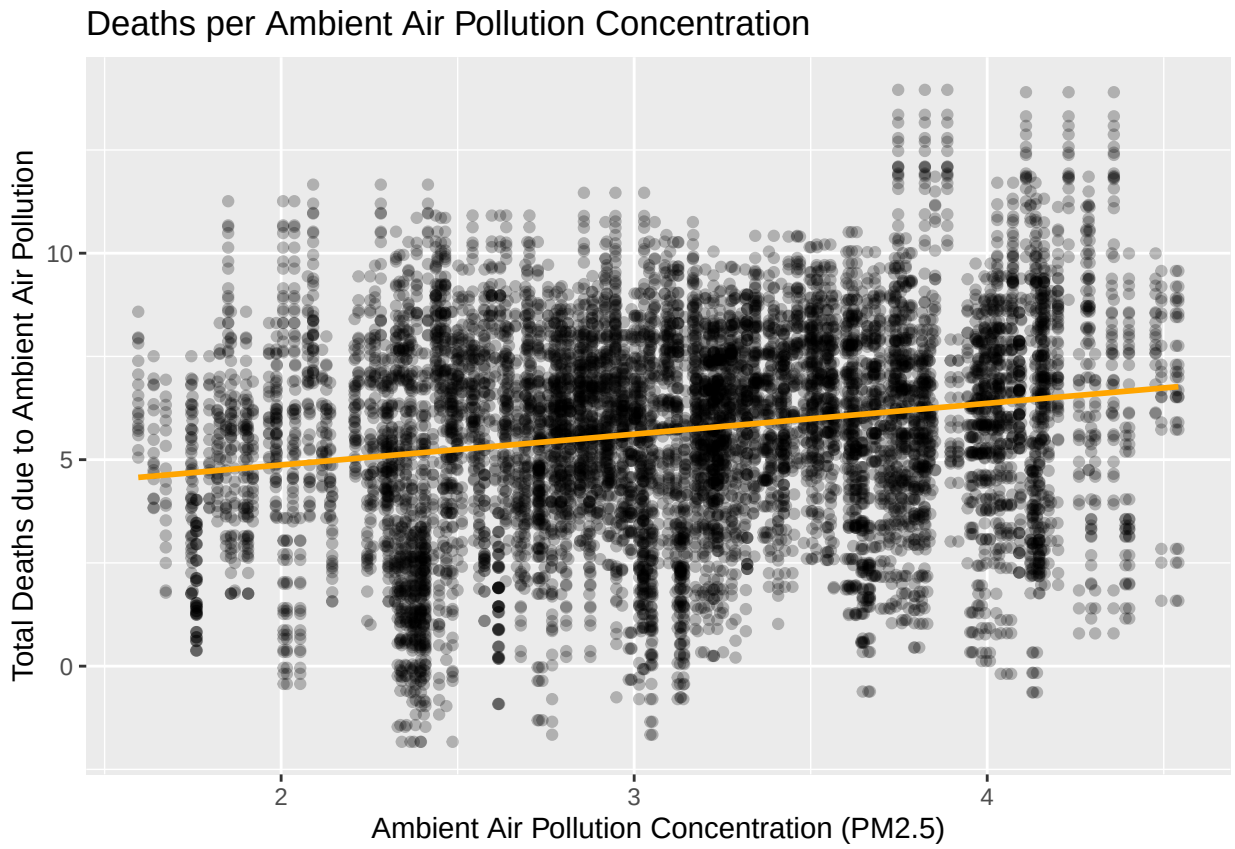
For the next 4 sections we created two different models for a linear regression. The first one we did just based off the outdoor air concentration. The equation we got was deaths = -2601.0 + 274.1(AirConcentration). The air concentration is in PM2.5, which is fine particulate matter.

```
death_ambientairpol <- linear_reg() %>%
  set_engine("lm") %>%
  fit(log(Totaldeathsambient) ~ log(AmbientAirConcentration), data = ambient)
  tidy(death_ambientairpol, conf.int=TRUE, exponentiate=TRUE)
```

```
## # A tibble: 2 x 7
##   term                 estimate std.error statistic   p.value conf.low conf.high
##   <chr>                   <dbl>     <dbl>     <dbl>     <dbl>    <dbl>     <dbl>
## 1 (Intercept)             3.38     0.120       28.2 7.31e-169    3.15      3.62
## 2 log(AmbientAirConce~    0.746    0.0374      20.0 6.29e- 87    0.673     0.819
```

```
ggplot(data = ambient, aes(x = log(AmbientAirConcentration), y = log(Totaldeathsambient))) +
  geom_point(alpha = 0.25) +
  geom_smooth(method = "lm", se = FALSE, color = "orange") +
  labs(title = "Deaths per Ambient Air Pollution Concentration",
       x = "Ambient Air Pollution Concentration (PM2.5)",
```

```
       y = "Total Deaths due to Ambient Air Pollution")
```




```
glance(death_ambientairpol)$r.squared
```

```
## [1] 0.03876003
```

To further express that the simple linear model of ambient air pollution concentration in PM2.5 as a function of total deaths does not fit the data very well, we displayed the linear regression against the scatter plot data and determined the R-squared value. The linear regression, the orange line, clearly does not fit the data. Furthermore, the R-squared value is 0.039, meaning the model only explains 3.9% variance in the model.

We continue exploring related factors by creating a linear regression comparing total ambient air pollution deaths and ambient air concentration alongside other factors like sex, being female or male, and residence type, being urban or rural.

```
death_ambientairpol_totalpopulation <- linear_reg() %>%
    set_engine("lm") %>%
    fit(log(Totaldeathsambient) ~ log(AmbientAirConcentration) + Sex + Residencetype, data = ambient2)

tidy(death_ambientairpol_totalpopulation, conf.int=TRUE, exponentiate=TRUE)
```

```
## # A tibble: 4 x 7
##   term                 estimate std.error statistic   p.value conf.low conf.high
##   <chr>                   <dbl>     <dbl>     <dbl>     <dbl>    <dbl>     <dbl>
## 1 (Intercept)          3.45e+ 0    0.106   3.26e+ 1 7.91e-224   3.24      3.66
## 2 log(AmbientAirConc~  7.35e- 1    0.0322  2.28e+ 1 3.09e-113   0.672     0.798
## 3 SexMale             -1.30e-17    0.0426 -3.05e-16 1    e+  0  -0.0835    0.0835
## 4 ResidencetypeUrban  -6.70e- 2    0.0427 -1.57e+ 0 1.17e-  1  -0.151     0.0167
```

```
glance(death_ambientairpol_totalpopulation)$r.squared
```

```
## [1] 0.03808491
```

Once again, this linear regression model fails to accurately predict the total ambient air pollution deaths. In fact, it was a R-squared value of 0.038, or explains only 3.8% of the data variance, which is worse. The variables here are not significant [show -values and confidence intervals].

Instead of continuing with linear regression models, we chose to create a binomial regression model to predict the likelihood of a person dying based on the level of ambient air concentration. This was because we saw that the linear model was not a good model due to the r squared value and the additional predictors did not create a better fit for our model.

Here we created a binomial regression model to predict the likelihood of a person dying based on the level of ambient air concentration. The resulting equation is likelihood of dying = 0.0003+ 1.0124(Ambient Air Concentration). Because the p-value is less than alpha = 0.05 and thus statistically significant and the odds ratio is within the confidence interval, we reject the null hypothesis and have enough evidence to say that ambient air concentration is related to dying. The odds ratio confirms that it is 1.0124 times more likely for individuals that experience ambient air concentration, specifically 1 PM2.5 to die than those who do not.

```
Alive <- ambient2$totalpopulation - ambient2$Totaldeathsambient

modelagg1<-glm(cbind(round(Totaldeathsambient), round(Alive)) ~ AmbientAirConcentration, data=ambient2,

summary(modelagg1)
```

```
##
## Call:
## glm(formula = cbind(round(Totaldeathsambient), round(Alive)) ~
##     AmbientAirConcentration, family = binomial, data = ambient2)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -161.24   -12.68    -3.56     0.39   430.08
##
## Coefficients:
##                            Estimate Std. Error z value Pr(>|z|)
## (Intercept)              -8.005e+00  2.763e-04  -28975   <2e-16 ***
## AmbientAirConcentration  1.237e-02  5.419e-06    2282   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 14254994  on 13175  degrees of freedom
## Residual deviance:  9023120  on 13174  degrees of freedom
## AIC: 9122756
##
## Number of Fisher Scoring iterations: 4
```

```
tidy(modelagg1, conf.int=TRUE, exponentiate=TRUE)
```

```
## # A tibble: 2 x 7
##   term                    estimate  std.error statistic p.value conf.low conf.high
##   <chr>                      <dbl>      <dbl>     <dbl>   <dbl>    <dbl>     <dbl>
## 1 (Intercept)             0.000334 0.000276     -28975.       0 0.000333  0.000334
## 2 AmbientAirConcentration 1.01     0.00000542     2282.       0 1.01      1.01
```

Here we created a binomial regression model to predict the likelihood of a person dying based on the level of ambient air concentration, gender, and where they live. The resulting equation is likelihood of dying = 0.0003 + 1.0124(Ambient Air Concentration) + 1.1822(Sex) + 0.9270(Residence Type). Because the p-values for all 3 of these variables are less than alpha = 0.05 and thus statistically significant and the odds ratio is within the confidence interval, we reject the null hypothesis and have enough evidence to say that ambient air concentration, sex and residential type are all related to dying. The odds ratio confirms that it is 1.1822 times more likely for males to die than females when the ambient air pollution concentration is 0 and they live in a rural community. The odds ratio confirms that it is 0.9270 times more likely for someone living in a rural community to die than someone living in an urban community when the ambient air pollution concentration is 0 and they are a female.

```
Alive <- ambient2$totalpopulation - ambient2$Totaldeathsambient

modelagg2<-glm(cbind(round(Totaldeathsambient), round(Alive)) ~ AmbientAirConcentration + Sex + Residen

summary(modelagg2)
```

```
##
## Call:
## glm(formula = cbind(round(Totaldeathsambient), round(Alive)) ~
##     AmbientAirConcentration + Sex + Residencetype, family = binomial,
##     data = ambient2)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -143.52   -12.84    -3.78     0.17   347.88
##
## Coefficients:
##                            Estimate Std. Error  z value Pr(>|z|)
## (Intercept)              -8.058e+00  3.130e-04 -25742.6   <2e-16 ***
## AmbientAirConcentration  1.261e-02  5.509e-06   2288.9   <2e-16 ***
## SexMale                  1.674e-01  2.427e-04    689.6   <2e-16 ***
## ResidencetypeUrban      -7.582e-02  2.458e-04   -308.4   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 14254994  on 13175  degrees of freedom
## Residual deviance:  8452356  on 13172  degrees of freedom
## AIC: 8551996
##
## Number of Fisher Scoring iterations: 4
```

```
tidy(modelagg2, conf.int=TRUE, exponentiate=TRUE)
```

```
## # A tibble: 4 x 7
##   term                    estimate  std.error statistic p.value conf.low conf.high
##   <chr>                      <dbl>      <dbl>     <dbl>   <dbl>    <dbl>     <dbl>
## 1 (Intercept)             0.000317 0.000313     -25743.       0 0.000316  0.000317
## 2 AmbientAirConcentration 1.01     0.00000551     2289.       0 1.01      1.01
## 3 SexMale                 1.18     0.000243        690.       0 1.18      1.18
## 4 ResidencetypeUrban      0.927    0.000246       -308.       0 0.927     0.927
```

While we cannot directly compare the models we are concluding that the last model we made is the best one given the data we have. We are concluding this because the the two additional predictors we added are

significant which likely means they are needed in addition to the air concentration graph. Also the AIC value in the second graph is smaller than the one in the first binomial regression, which indicates it is a better fit than the first model.

Lastly we wanted to explore the difference in effects between the two different types of air pollution within our datasets, household and ambient air pollution. So we conducted a paired t-test because the two types of pollution are coming from the same country and measuring the same outcome (deaths). We wanted to see if the two different types of air pollution had the same impact on mortality. We saw that they did not through the two sided paired t-test, but wanted to do a one sided t-test to see which type of air pollution had a greater effect on mortality. When we conducted the one sided t-test we saw that household air pollution had less of an effect on mortality than ambient air pollution. This was significant because the p-value was less than 0.05 and the mean was within the confidence interval for both t-tests.This goes along with our earlier exploratory graphs where we noticed the alarming amount of deaths due to household air pollution. It is important to note that it is likely that these two predictors are highly correlated as it is impossible to ethically separate and test the effects of different air pollutants.

```
t.test(household$Totaldeathshoushold, household$Totaldeathsambient, paired = TRUE, alternative = "two.s
```

```
##
##  Paired t-test
##
## data:  household$Totaldeathshoushold and household$Totaldeathsambient
## t = -5.8255, df = 174959, p-value = 5.704e-09
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -734.9047 -364.8837
## sample estimates:
## mean of the differences
##               -549.8942
```

```
t.test(household$Totaldeathshoushold, household$Totaldeathsambient, paired = TRUE, alternative = "less"
```

```
##
##  Paired t-test
##
## data:  household$Totaldeathshoushold and household$Totaldeathsambient
## t = -5.8255, df = 174959, p-value = 2.852e-09
## alternative hypothesis: true difference in means is less than 0
## 95 percent confidence interval:
##       -Inf -394.6288
## sample estimates:
## mean of the differences
##               -549.8942
```