AQ_Walk

Join Data

```
rm(list = ls())   # Clear the Environment

setwd("~/GitHub/ehs200c")
#setwd("G:/Documents/One Drive/OneDrive - UCLA IT Services/UCLA Coursework/Y1 Q3/EHS C200C/Project/Sour
#setwd("C:/Users/arbar/OneDrive - UCLA IT Services/UCLA Coursework/Y1 Q3/EHS C200C/Project/Source Files


activetransport.data <-
  readxl::read_xlsx('Walk-Bike_Tract_Estimates_11.20.14.xlsx')
```

```
## New names:
## * fipsct -> fipsct...1
## * fipsct -> fipsct...56
```

```
particulatematter.data <- read.csv('Geoid_krieg_2010.csv')

medianincome.data <-
  read_csv('ACS_IncomeData.csv') #From 2010 1-Year ACS (not available in the decennial census)
```

```
## New names:
## * id -> id...1
## * id -> id...2
```

```
## Rows: 2347 Columns: 132
```

```
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (123): id...1, id...2, Households!!Estimate!!Less than $10,000, Househol...
## dbl   (9): GEOID, Households!!Estimate!!Total, Households!!Margin of Error!!...
```

```
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Load in Demographic Data from the Census

```
# Load census key - here's a key we made for this project
census_api_key("d36944270723067a4158478e96cd3221c602fdd3")

# Load 2010 deccenial  estimate variables
census_variables <- load_variables (2010,"sf1",cache=T)

# List variables we want
vars <- c (population_race="P003001", #race/ethnic total
           race_white="P005003", #white NH alone
           race_black="P005004", #black/african american NH
           race_amindian="P005005", #american indian/alaska native NH
           race_asian="P005006", #asian NH
           race_pacisl="P005007", #native hawaiian and other pacific islander NH
           race_other="P005008", #some other race alone NH
           race_twoplus="P005009", #two or more races NH
           race_hisp ="P005010", #total Hisp
           totalHH = "H004001", #total households
           renterHH = "H004004" # renterhouseholds
           )
# Define geography
# Geographies and calls here:https://walkerke.github.io/tidycensus/articles/basic-usage.html
# Geometry = T/F for coordinates
census_data <-get_decennial (state = "06", #California
                 geography = "tract",
                 variables = vars,
                 geometry = T,
                 output = "wide",
                 year = 2010)
```

```
##   |                                                                              |
```

```
census_data$race_white_per = census_data$race_white / census_data$population_race #White NH
census_data$race_black_per = census_data$race_black / census_data$population_race #Black NH
census_data$race_amindian_per = census_data$race_amindian / census_data$population_race #American India
census_data$race_asian_per = census_data$race_asian / census_data$population_race #Asian  NH
census_data$race_pacisl_per = census_data$race_pacisl / census_data$population_race #Pacific islander N
census_data$race_other_per = census_data$race_other / census_data$population_race #Other NH
census_data$race_twoplus_per = census_data$race_twoplus / census_data$population_race #Two or more NH
census_data$race_hisp_per = census_data$race_hisp / census_data$population_race #Hispanic/Latino of any


census_data$renter_per = census_data$renterHH / census_data$totalHH #Renters
```

Join the Data Together!

```
census_data$GEOID_Numeric <-
  as.numeric(census_data$GEOID) #Create a numeric join column in the Census Data
```

```r
particulatematter.data$GEOID_Numeric <- #Create a numeric join column in the PM Data
  as.numeric(particulatematter.data$GEOID10)

joinedData <-
  merge(
    census_data,
    activetransport.data,
    by.x = 'GEOID_Numeric',
    by.y = 'fipsct...1',
    all.x = T
  )  #Join the Active Transport and Demographic Variables
joinedData <-
  merge(
    joinedData,
    medianincome.data,
    by.x = 'GEOID_Numeric',
    by.y = 'GEOID',
    all.x = T
  )  #Join Median Income Information
joinedData <-
  merge(
    joinedData,
    particulatematter.data,
    by.x = 'GEOID_Numeric',
    by.y = 'GEOID_Numeric',
    all.x = F
  ) #Join AQ and drop tracts

#Create a smaller database for our use, that only includes the variables we are concerned about.
small.data <- joinedData %>% select(
  GEOID,
  GEOID_Numeric,
  NAME,
  population_race,
  race_white_per,
  race_black_per,
  race_asian_per,
  race_amindian_per,
  race_pacisl_per,
  race_other_per,
  race_hisp_per,
  race_twoplus_per,
  renter_per,
  popdense,
  land_area,
  miles_b_chts,
  miles_w_chts,
  MEAN,
  `Households!!Estimate!!Median income (dollars)`,
  nh_type,
  geometry
)
```

```
small.data <-
  small.data %>% rename(PM_mean = MEAN, income = `Households!!Estimate!!Median income (dollars)`) #rena

small.data$income <-
  small.data$income %>% as.numeric() #Change income to a numeric variable
```

```
## Warning in small.data$income %>% as.numeric(): NAs introduced by coercion
```

```
small.data$nh_type_str <-
  small.data$nh_type %>% as.character() #Change the Neighborhood Type Variable to be a character so we
```

Let's set up some of our columns for calculations.

```
small.data <-
  small.data %>% mutate(miles_biked_walked_total = miles_b_chts + miles_w_chts) %>% #Add Walked + Biked
  mutate(miles_bike_walked_percapita = miles_biked_walked_total / population_race) %>%  # Scale teh Wal
  mutate(nonwhite_per = race_black_per +  race_asian_per+ race_amindian_per + race_pacisl_per +
           race_other_per + race_hisp_per+race_twoplus_per) %>% # Add a percent nonwhite column
  mutate(pop_dens_sqm = population_race/land_area) #Calculate a new density
```

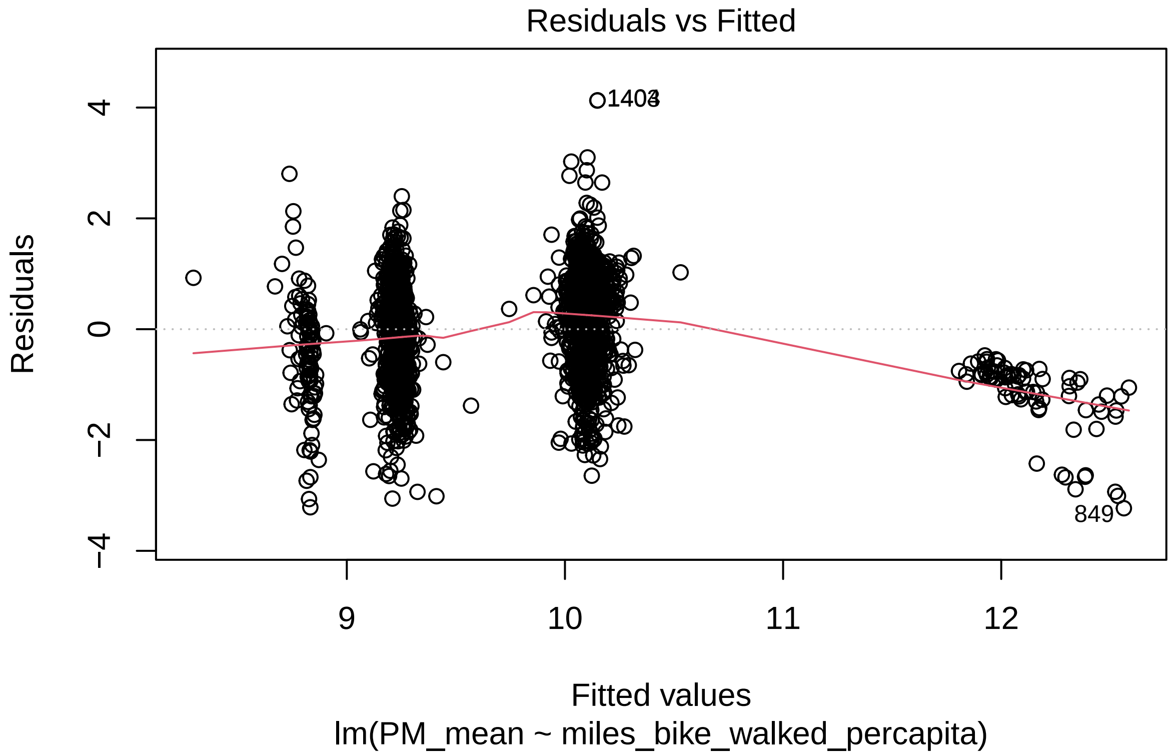
OLS Regression

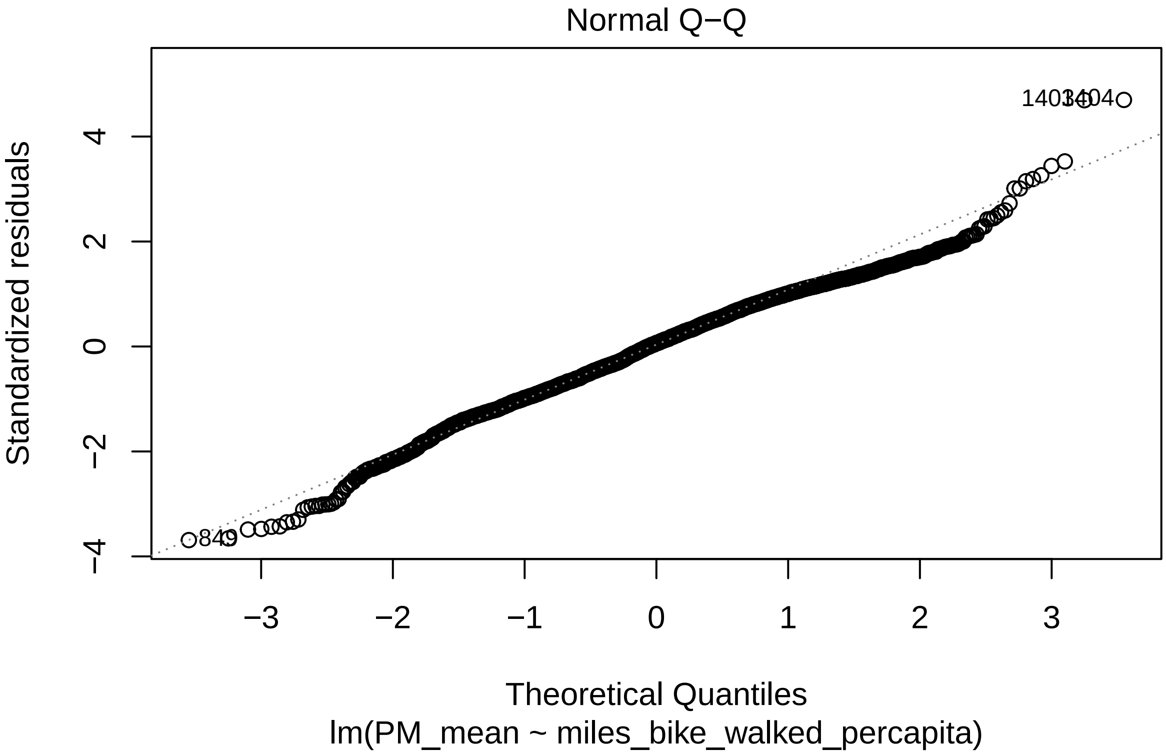
Regression Time

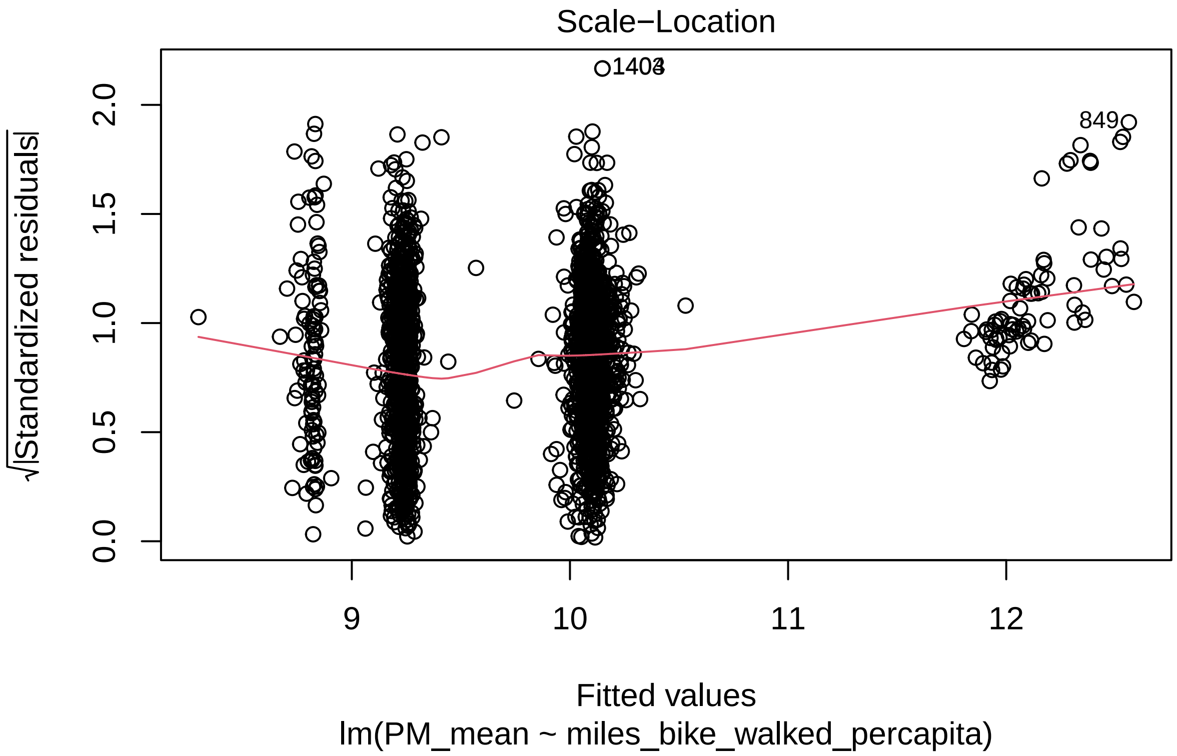
```
#Simple bivariate regression.
pm.active.simplelm <-
  lm(data = small.data, PM_mean ~ miles_bike_walked_percapita)
summary(pm.active.simplelm)
```

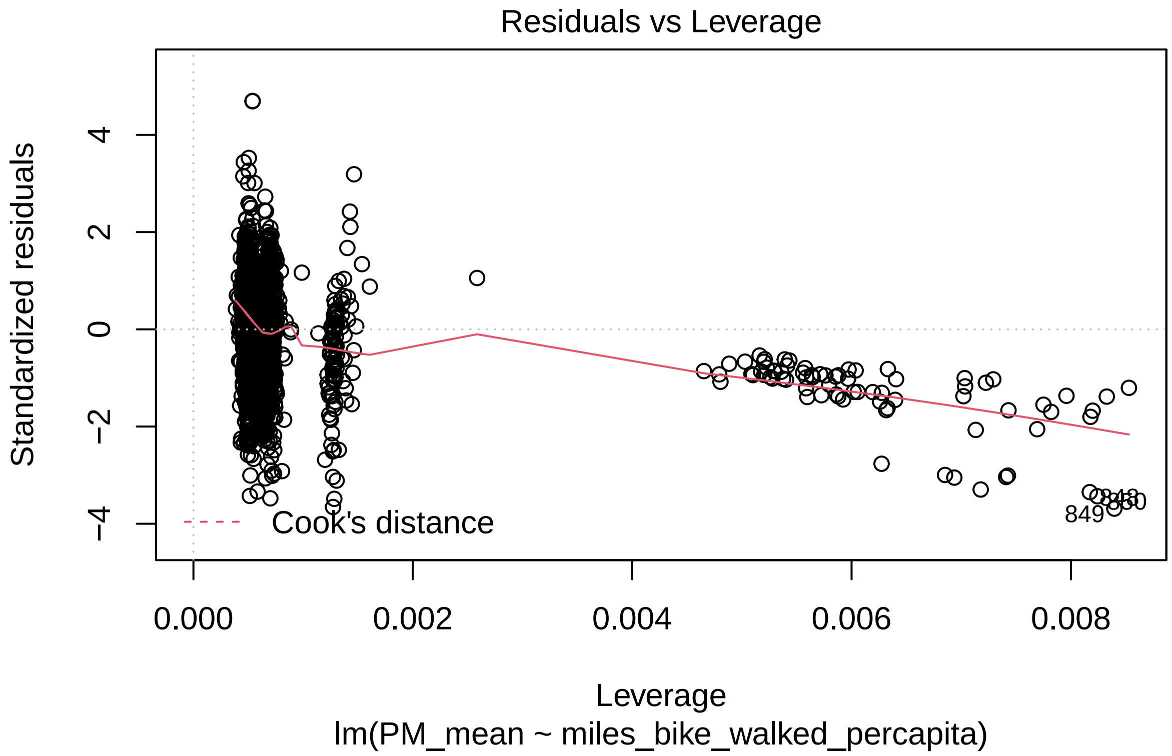
```
##
## Call:
## lm(formula = PM_mean ~ miles_bike_walked_percapita, data = small.data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.2311 -0.5902  0.0552  0.6539  4.1311
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  8.06469    0.05082  158.70   <2e-16 ***
## miles_bike_walked_percapita  3.56684    0.10032   35.56   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8796 on 2581 degrees of freedom
##   (8 observations deleted due to missingness)
## Multiple R-squared:  0.3288, Adjusted R-squared:  0.3285
## F-statistic:  1264 on 1 and 2581 DF,  p-value: < 2.2e-16
```

```
plot(pm.active.simplelm)
```




Normal Q−Q
Standardized residuals
4
2
0
−2
−4
−3
−2
−1
0
1
2
3
Theoretical Quantiles
lm(PM_mean ~ miles_bike_walked_percapita)
1403
1404
849


Scale−Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
1404
849
9
10
11
12
Fitted values
lm(PM_mean ~ miles_bike_walked_percapita)



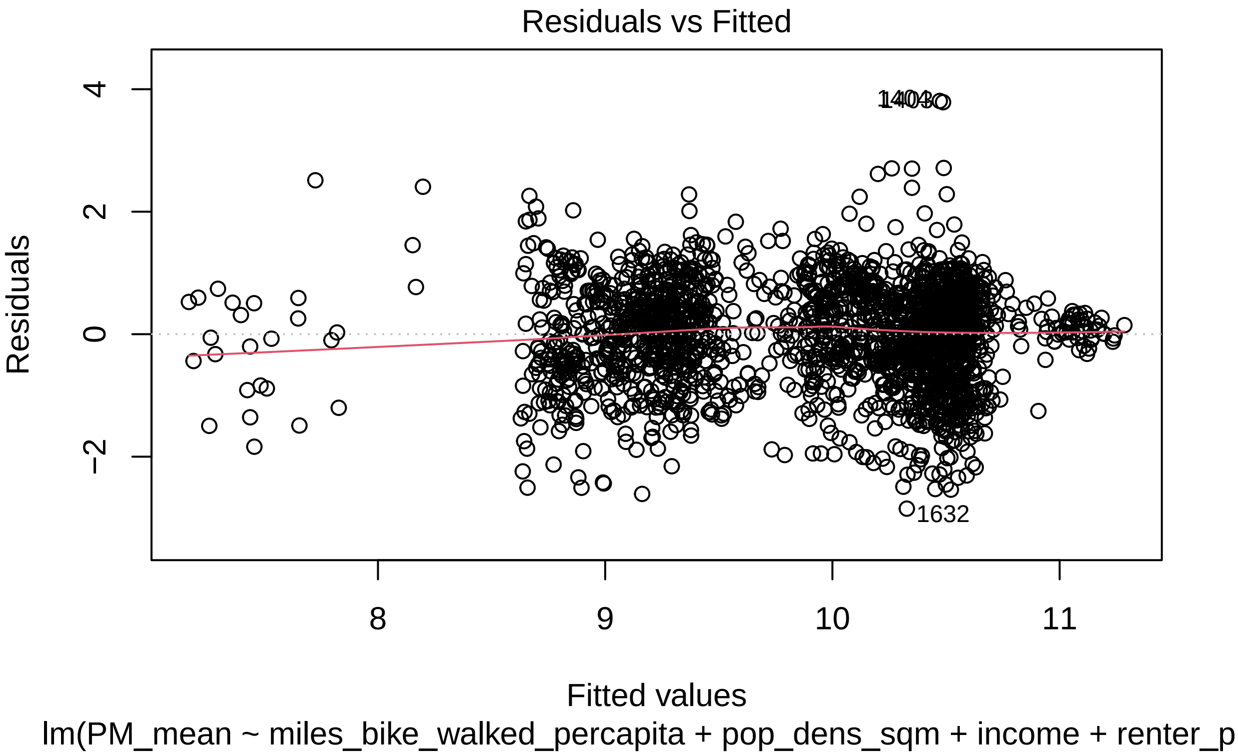
```
# Without including NH_Type
pm.active.adjustedlm <-
  lm(
    data = small.data,
    PM_mean ~ miles_bike_walked_percapita + pop_dens_sqm + income + renter_per +
      nonwhite_per
  )
summary(pm.active.adjustedlm)
```

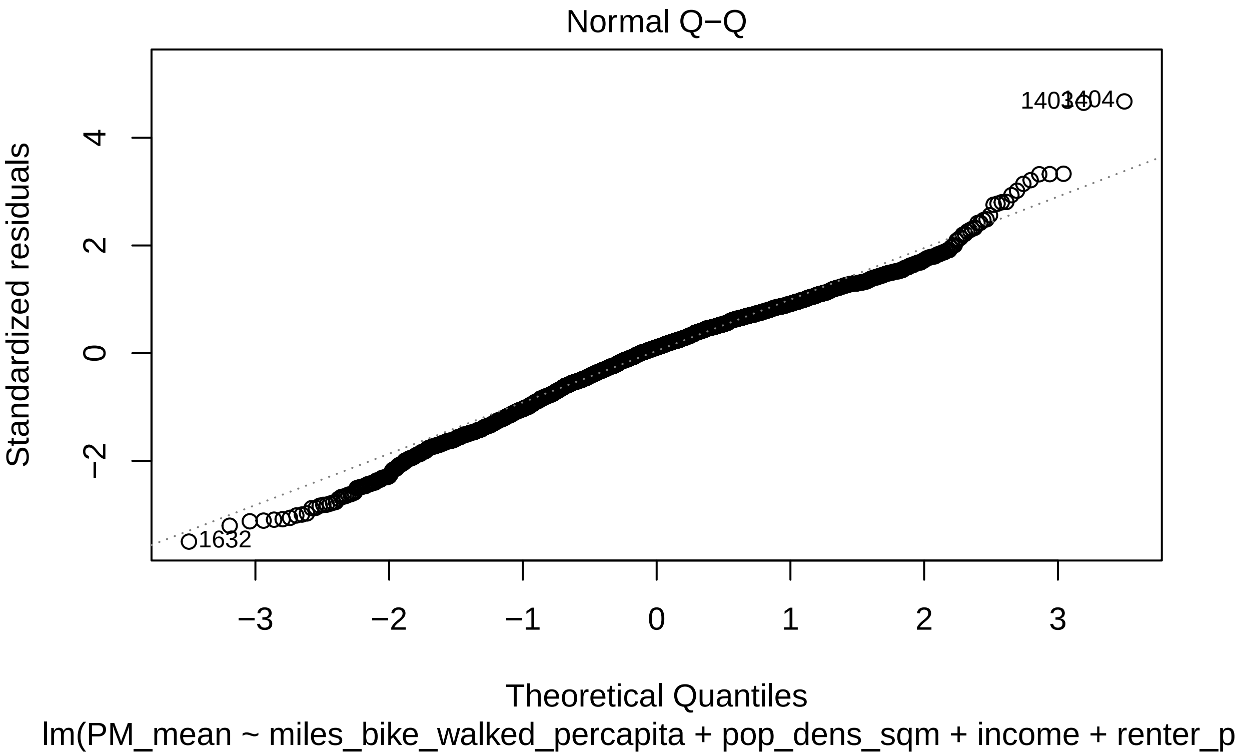
```
##
## Call:
## lm(formula = PM_mean ~ miles_bike_walked_percapita + pop_dens_sqm +
##     income + renter_per + nonwhite_per, data = small.data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.1155 -0.5519  0.0721  0.6177  3.8661
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  7.549e+00  1.812e-01  41.669  < 2e-16 ***
## miles_bike_walked_percapita  2.532e+00  1.528e-01  16.565  < 2e-16 ***
## pop_dens_sqm                -1.061e-05  2.530e-06  -4.195 2.84e-05 ***
## income                       5.341e-07  1.209e-06   0.442    0.659
## renter_per                   9.847e-01  1.307e-01   7.532 7.37e-14 ***
## nonwhite_per                 9.684e-01  1.015e-01   9.543  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8567 on 2122 degrees of freedom
##   (463 observations deleted due to missingness)
## Multiple R-squared:  0.3568, Adjusted R-squared:  0.3553
## F-statistic: 235.5 on 5 and 2122 DF,  p-value: < 2.2e-16
```

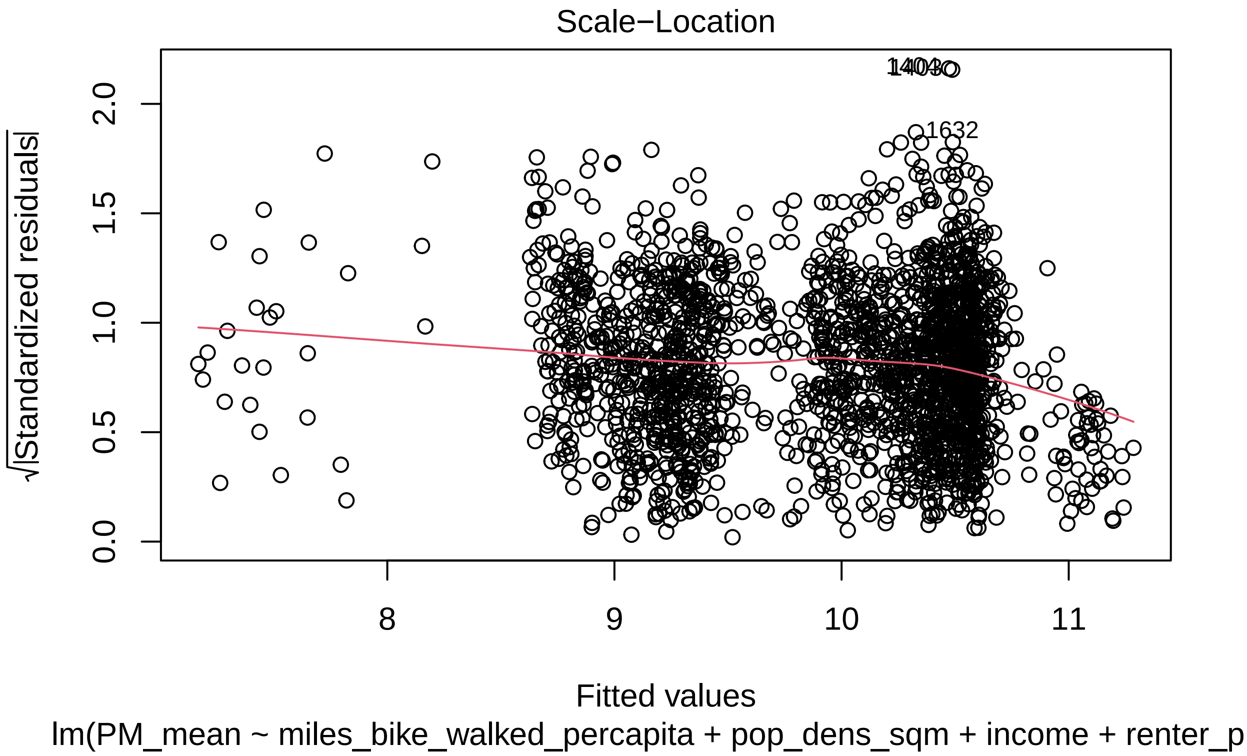
```
# Adjusted regression, accounting for population density and income and nh_type(categorical variable).
pm.active.adjustednhlm <-
  lm(
    data = small.data,
    PM_mean ~ miles_bike_walked_percapita + pop_dens_sqm + income + renter_per +
      nonwhite_per + nh_type_str
  )
summary(pm.active.adjustednhlm)
```

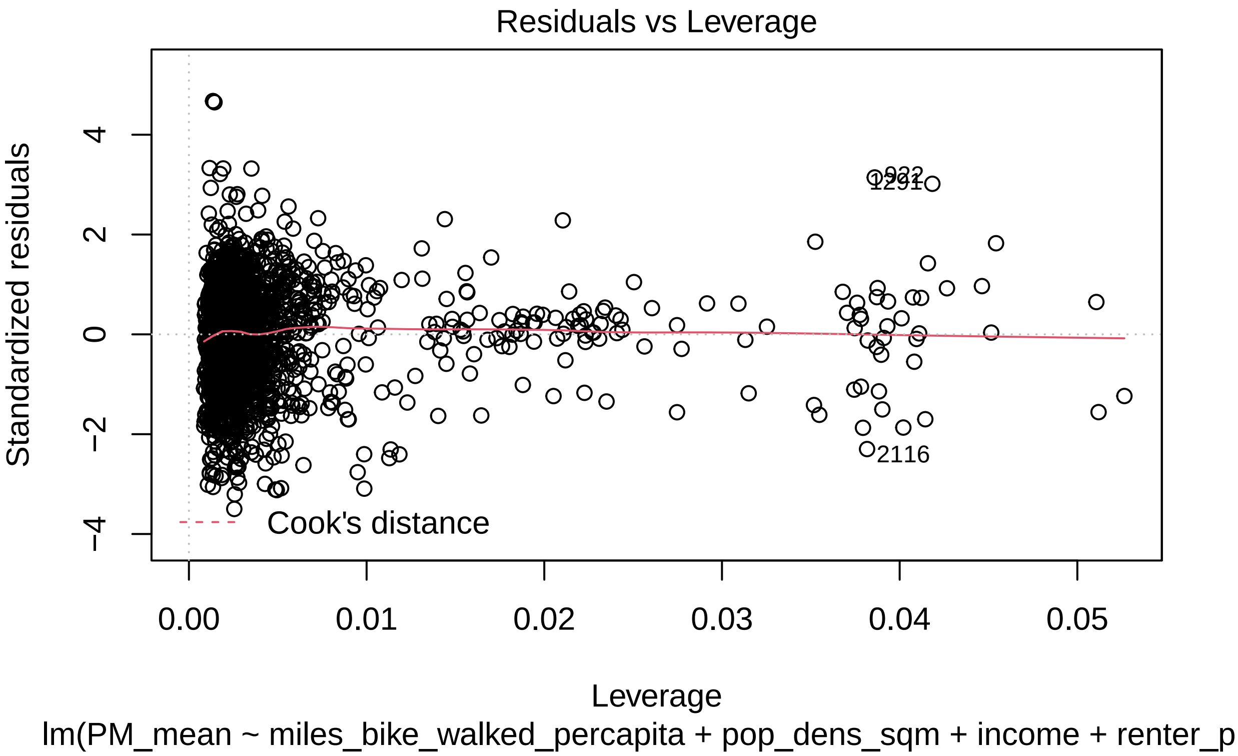
```
##
## Call:
## lm(formula = PM_mean ~ miles_bike_walked_percapita + pop_dens_sqm +
##     income + renter_per + nonwhite_per + nh_type_str, data = small.data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.8482 -0.4891  0.0853  0.5592  3.8082
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 8.850e+00  4.113e-01  21.519  < 2e-16 ***
## miles_bike_walked_percapita -1.020e+00  1.112e+00  -0.917   0.3591
## pop_dens_sqm               -4.160e-06  2.568e-06  -1.620   0.1054
## income                     -1.658e-07  1.155e-06  -0.144   0.8859
## renter_per                  5.639e-01  1.331e-01   4.237 2.36e-05 ***
## nonwhite_per                7.697e-01  9.798e-02   7.855 6.30e-15 ***
## nh_type_str2                1.216e+00  2.737e-01   4.445 9.25e-06 ***
## nh_type_str3               -1.606e+00  2.086e-01  -7.698 2.11e-14 ***
## nh_type_str4                2.321e+00  9.190e-01   2.526   0.0116 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8152 on 2118 degrees of freedom
##   (464 observations deleted due to missingness)
## Multiple R-squared:  0.4186, Adjusted R-squared:  0.4164
## F-statistic: 190.6 on 8 and 2118 DF,  p-value: < 2.2e-16
```

```
plot(pm.active.adjustednhlm)
```


Residuals vs Fitted
Residuals
4
2
0
−2
1404
1403
1632
8
9
10
11
Fitted values
lm(PM_mean ~ miles_bike_walked_percapita + pop_dens_sqm + income + renter_p

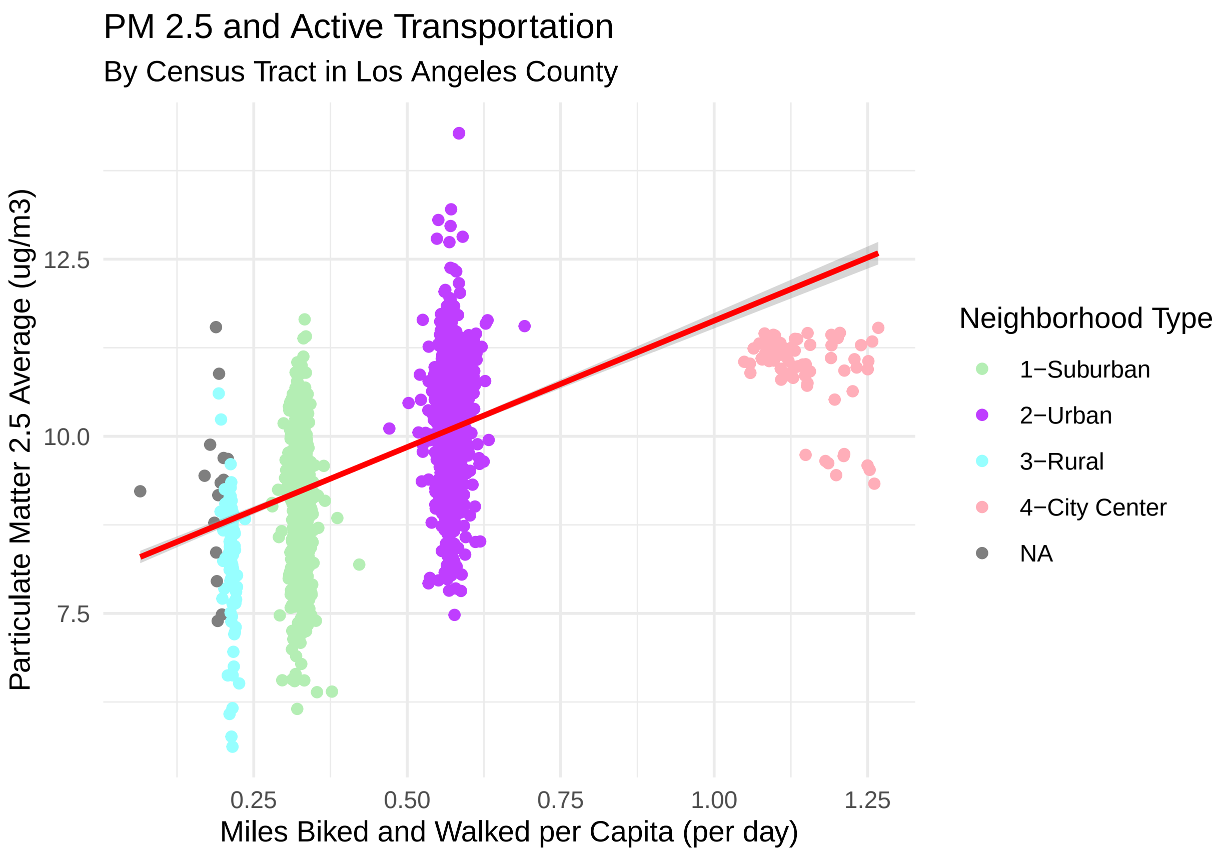

Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(PM_mean ~ miles_bike_walked_percapita + pop_dens_sqm + income + renter_p
4
2
0
−2
−3
−2
−1
0
1
2
3
1403
1404
1632


Scale−Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
1404
1632
8
9
10
11
Fitted values
lm(PM_mean ~ miles_bike_walked_percapita + pop_dens_sqm + income + renter_p

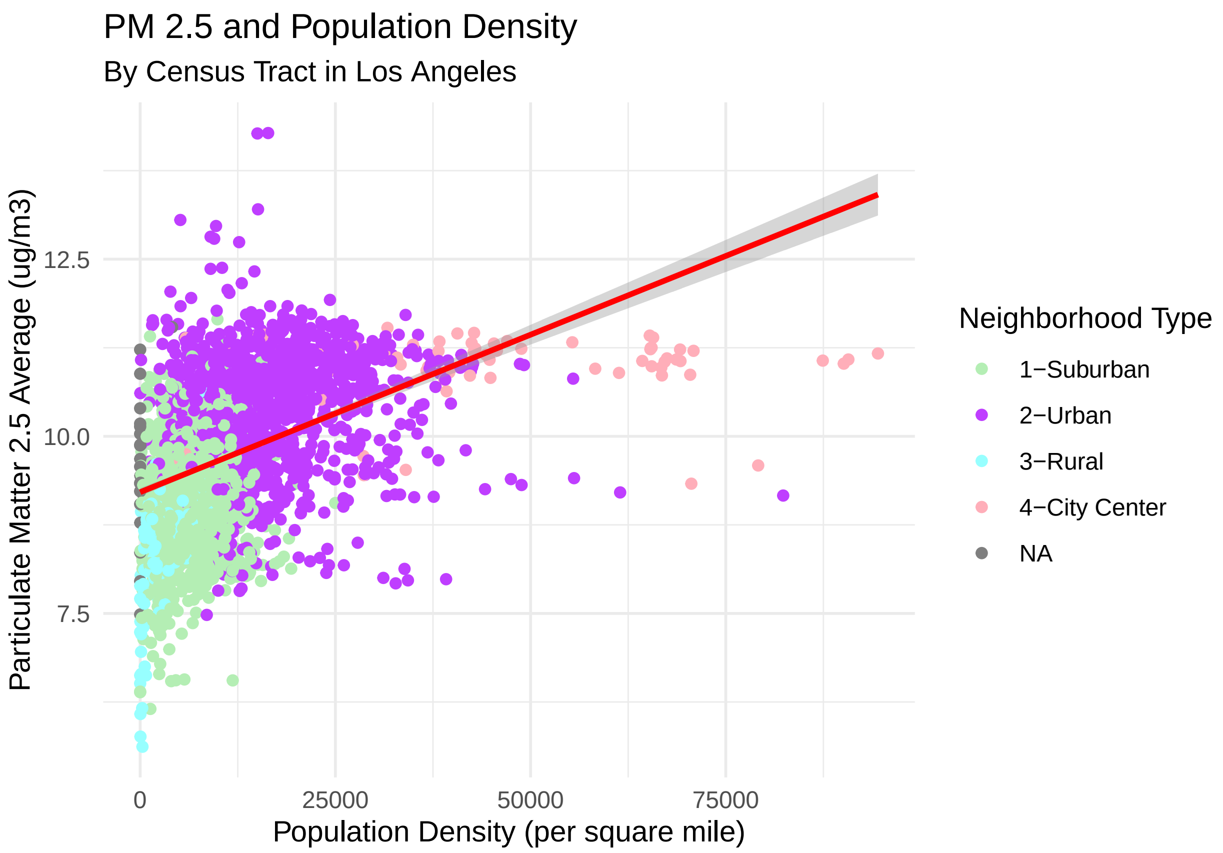


## Plots

```
## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 8 rows containing non-finite values (stat_smooth).

## Warning: Removed 8 rows containing missing values (geom_point).
```

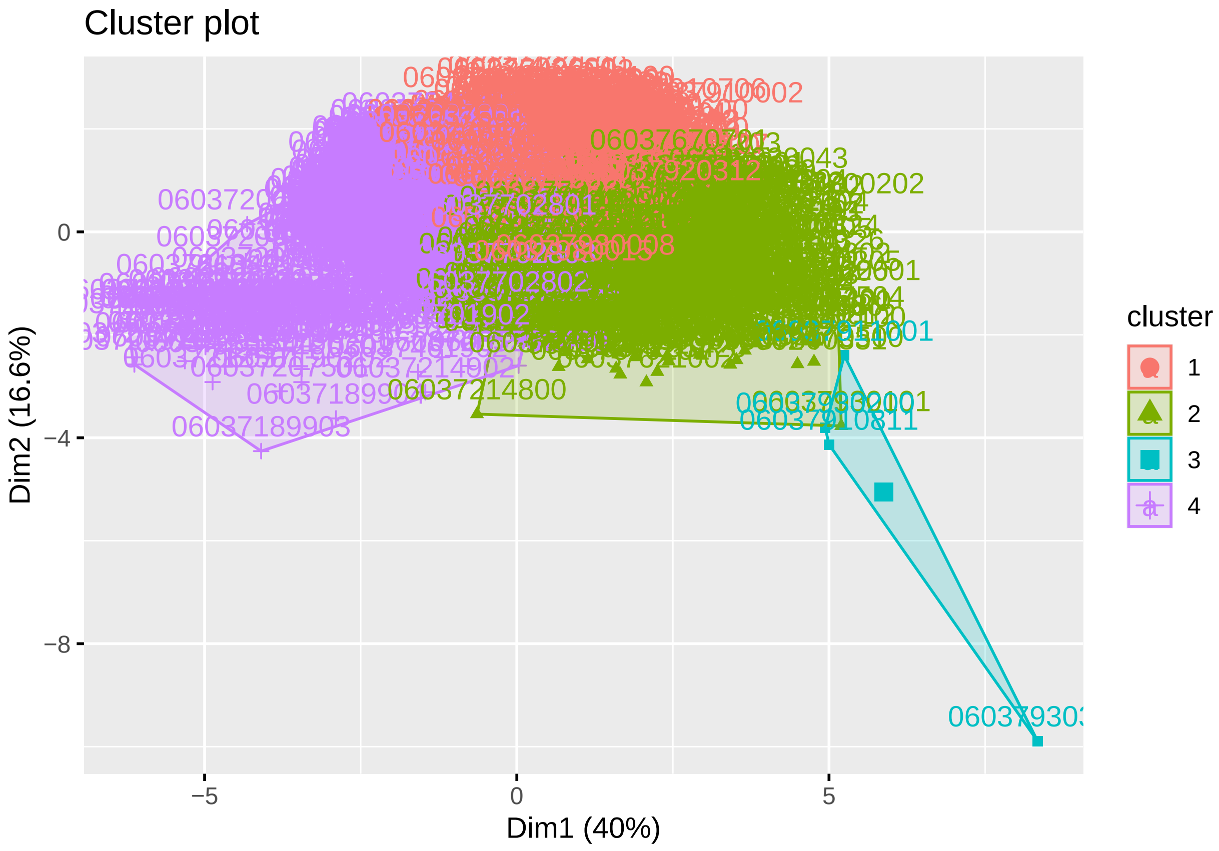


```
## ‘geom_smooth()‘ using formula ’y ~ x’
```



K Means Clustering

```
set.seed(1234)
small.data.k <- small.data %>% select(  #Select the variables we would like to cluster off of.
  GEOID,
  population_race,
  pop_dens_sqm,
  land_area,
  PM_mean,
  income,
  miles_bike_walked_percapita,
  nonwhite_per
)

rownames(small.data.k) <- small.data.k$GEOID #Set the rownames to the Census GEOID

small.data.k <-
  small.data.k[-c(small.data.k$GEOID == '06037911001'),]  # Drop single outlier which is very different

small.data.k <- select(small.data.k,-GEOID) #Remove the GEOID Column (it won't work with K Means)

small.data.k <-
  small.data.k %>% st_drop_geometry() #drop geometry column
small.data.k <- na.omit(small.data.k) #remove all NA values

small.data.k.scaled <-
  scale(small.data.k) #scale data to be between 0 and 1


km <- kmeans(small.data.k.scaled, centers = 4, nstart = 50) #Use four clusters (due to NH_Type)

fviz_cluster(km, data = small.data.k.scaled)
```



```
km.cluster <- km$cluster

km.cluster <- as.data.frame(km.cluster)

small.data.k$GEOID <- small.data.k %>% rownames()
km.cluster$GEOID <- km.cluster %>% rownames()

small.data.joined <-
  merge(km.cluster, small.data, by.x = 'GEOID', by.y = 'GEOID')

small.data.joined <-
  small.data.joined %>% rename(clusterID = km.cluster)

small.data.joined$clusterName
```

```
## NULL
```

```
#small.data.joined[small.data.joined$clusterID ==1,'clusterName']


aggregatedCluster <- aggregate(small.data.joined,
          by = list(cluster = small.data.joined$clusterID),
          mean) #Summary Statistics for the different clusters.

aggregatedCluster
```

```
##   cluster GEOID clusterID GEOID_Numeric NAME population_race race_white_per
## 1       1    NA         1    6037403564   NA        4942.991      0.1913213
## 2       2    NA         2    6037386244   NA        3806.953      0.6492085
## 3       3    NA         3    6037920578   NA        1484.500      0.6001661
## 4       4    NA         4    6037335476   NA        3929.571      0.1304222
##   race_black_per race_asian_per race_amindian_per race_pacisl_per
## 1     0.06902545     0.17762337       0.002059579     0.003054129
## 2     0.03164937     0.12506342       0.001638460     0.001317981
## 3     0.06163207     0.02861895       0.011724098     0.001174812
## 4     0.11349577     0.12319382       0.001657354     0.002038486
##   race_other_per race_hisp_per race_twoplus_per renter_per    popdense
## 1    0.002129019     0.5373674       0.01741983  0.3999344 3.551488456
## 2    0.002810342     0.1553111       0.03300089  0.3459832 2.676725224
## 3    0.000654606     0.2775931       0.01843620  0.2366316 0.003713325
## 4    0.002812801     0.6128464       0.01353317  0.7122770 7.863475165
##     land_area miles_b_chts miles_w_chts   PM_mean   income  nh_type geometry
## 1   0.7805436     741.9928    1250.6922  9.365485 61001.69 1.303030       NA
## 2   1.6451918     604.8033    1093.7303  9.356664 96707.32       NA       NA
## 3 195.9436875     130.9776     184.3911  6.613564 70820.50 3.000000       NA
## 4   0.2601303     725.1070    1672.0048 10.654923 39597.19 2.153767       NA
##   nh_type_str miles_biked_walked_total miles_bike_walked_percapita nonwhite_per
## 1          NA                1992.6850                   0.3955789    0.8086787
## 2          NA                1698.5335                   0.4439610    0.3507915
## 3          NA                 315.3687                   0.2159973    0.3998339
## 4          NA                2397.1118                   0.6150813    0.8695778
##   pop_dens_sqm
## 1  9198.312495
## 2  6932.686205
## 3     9.617439
## 4 20366.306233
```

```
aggregatedCluster <- aggregatedCluster %>%
  arrange(desc(PM_mean))


aggregatedCluster$clusterName
```

```
## NULL
```

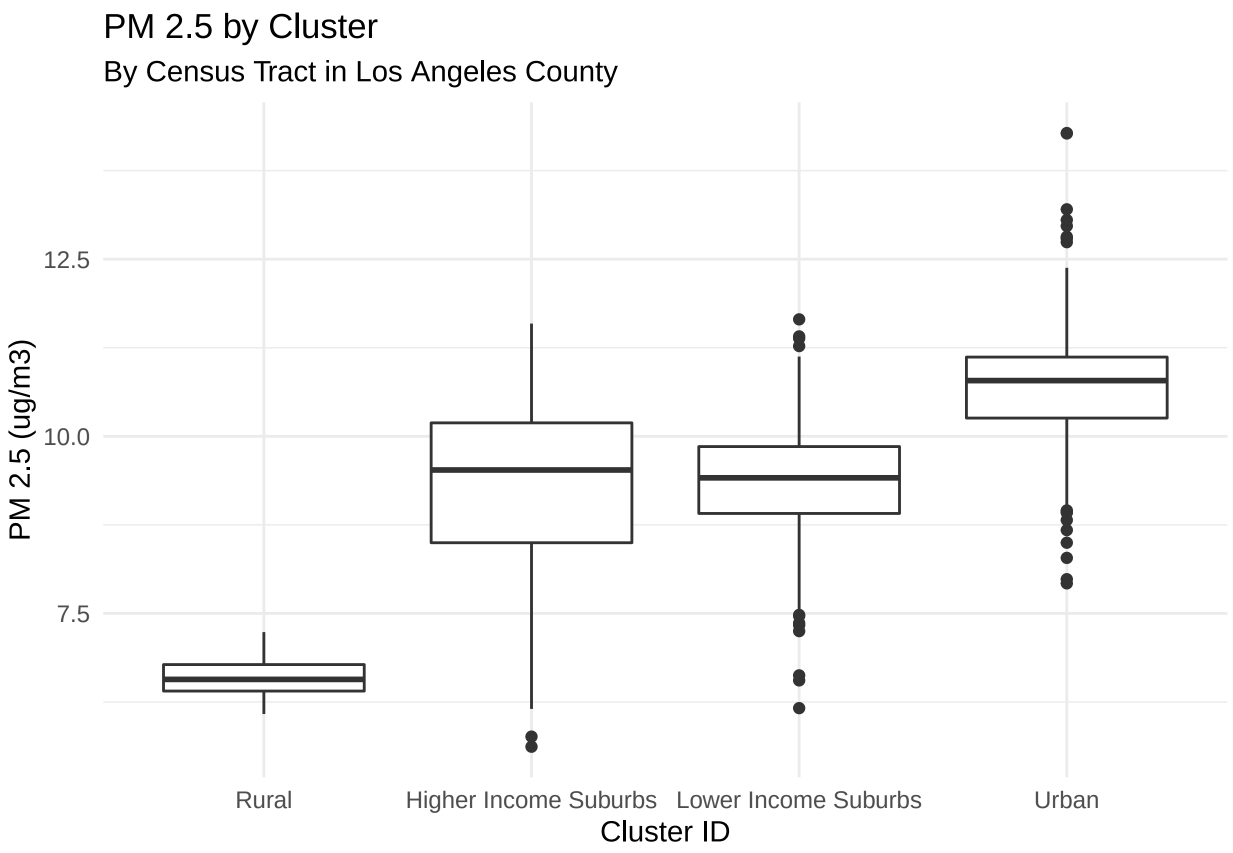
```
aggregatedCluster[1,'clusterName'] = 'Urban'
aggregatedCluster[2,'clusterName'] = 'Lower Income Suburbs'
```

```
aggregatedCluster[3,'clusterName'] = 'Higher Income Suburbs'
aggregatedCluster[4,'clusterName'] = 'Rural'

aggregatedCluster <- aggregatedCluster %>% select('clusterID','clusterName')

# join this back to the small data.

small.data.joined <- merge(small.data.joined,aggregatedCluster,by='clusterID')
table(small.data.joined$clusterName)
```

```
## 
## Higher Income Suburbs  Lower Income Suburbs                 Rural 
##                   494                   660                     4 
##                 Urban 
##                   969
```

```
small.data.joined <-
  sf::st_as_sf(small.data.joined, sf_column_name = 'geometry') #Convert back to a simple feature class.

write_csv(small.data.joined, 'dataExport.csv')
```

```
ggplot(data=small.data.joined,aes(y=PM_mean,x=reorder(clusterName,PM_mean)))+
  geom_boxplot()+
  labs(
  title = 'PM 2.5 by Cluster',
  subtitle = 'By Census Tract in Los Angeles County',
  x = 'Cluster ID',
  y = 'PM 2.5 (ug/m3)',
  ) +
  theme_minimal()
```

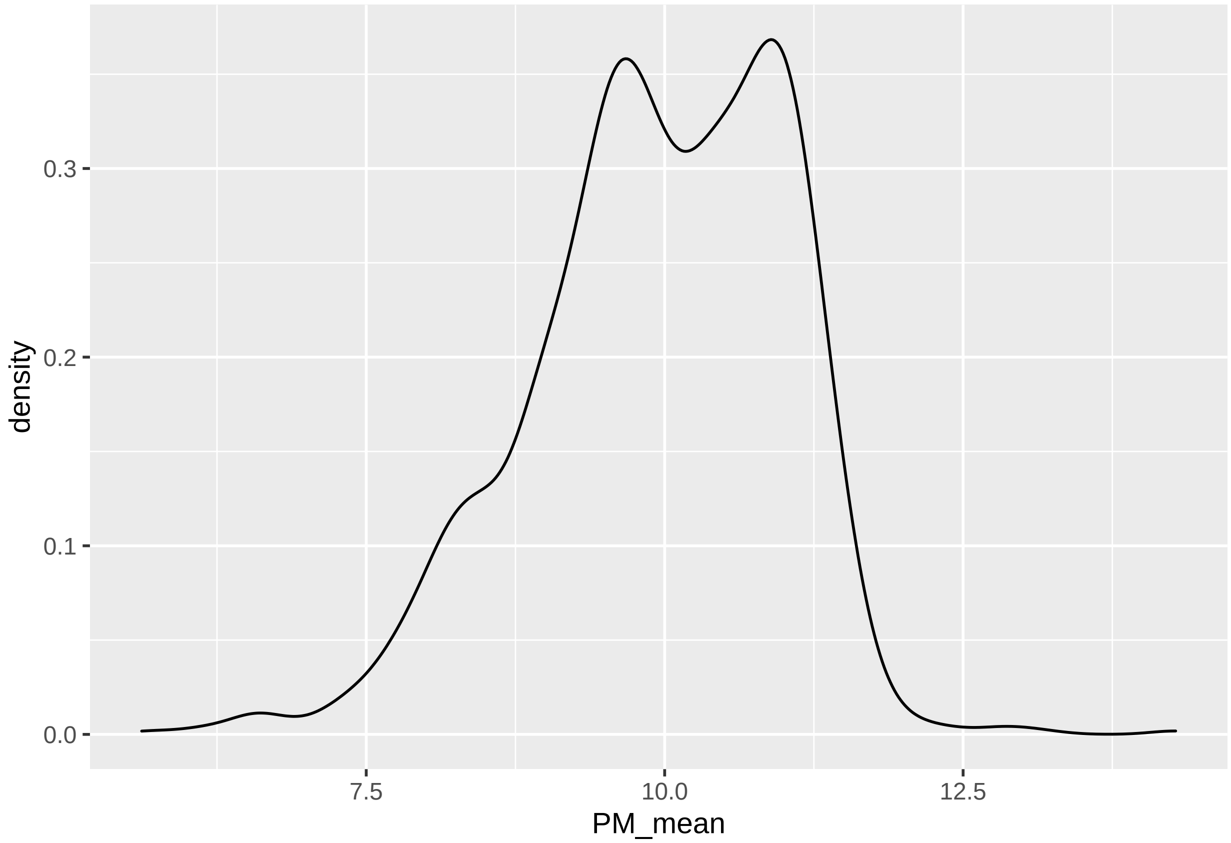


Spatial Autoregression

```
completeSpatial <- sf::st_as_sf(small.data, sf_column_name = 'geometry')

spatial.dropEmpty <-
  completeSpatial[!st_is_empty(completeSpatial), ] #drop columns with empty geometries
spatial.dropEmpty <- spatial.dropEmpty %>% drop_na() #Drop NAs

nb <- poly2nb(spatial.dropEmpty)

lw <- nb2listw(nb, style = "W", zero.policy = TRUE)

#Do General Test for Normality.
shapiro.test(spatial.dropEmpty$PM_mean)  #Data is not normal
```

```
##
##  Shapiro-Wilk normality test
##
## data:  spatial.dropEmpty$PM_mean
## W = 0.97659, p-value < 2.2e-16
```

```
ggplot(data = spatial.dropEmpty, aes(x = PM_mean)) +
  geom_density()
```



```
spatial.dropEmpty$nh_type_str <- as.factor(spatial.dropEmpty$nh_type_str)



#Spatial Lag Adjusted Model

#Simple, Bivariate Model
m1.spatial <- lagsarlm(PM_mean~miles_bike_walked_percapita,data=spatial.dropEmpty,lw,zero.policy = TRUE
  summary(m1.spatial)
```

```
##
## Call:
## lagsarlm(formula = PM_mean ~ miles_bike_walked_percapita, data = spatial.dropEmpty,
##     listw = lw, zero.policy = TRUE)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -1.5201090 -0.1105556 -0.0039104  0.1140388  1.3652946
##
## Type: lag
## Coefficients: (asymptotic standard errors)
##                              Estimate Std. Error z value  Pr(>|z|)
## (Intercept)                 0.202010   0.042637  4.7379 2.159e-06
## miles_bike_walked_percapita 0.128527   0.030331  4.2375 2.261e-05
##
## Rho: 0.97298, LR test value: 5284.9, p-value: < 2.22e-16
## Asymptotic standard error: 0.0045056
##     z-value: 215.95, p-value: < 2.22e-16
## Wald statistic: 46635, p-value: < 2.22e-16
##
## Log likelihood: -178.4739 for lag model
## ML residual variance (sigma squared): 0.051564, (sigma: 0.22708)
## Number of observations: 2127
## Number of parameters estimated: 4
## AIC: 364.95, (AIC for lm: 5647.8)
## LM test for residual autocorrelation
## test value: 4.1057, p-value: 0.04274
```

```
#Adjusted for other variables
m2.spatial <-
  lagsarlm(
    PM_mean ~ miles_bike_walked_percapita + pop_dens_sqm + income + renter_per +
      nonwhite_per,
    data = spatial.dropEmpty,
    lw,
    zero.policy = TRUE
  )
summary(m2.spatial)
```

```
##
## Call:lagsarlm(formula = PM_mean ~ miles_bike_walked_percapita + pop_dens_sqm +
##     income + renter_per + nonwhite_per, data = spatial.dropEmpty,
##     listw = lw, zero.policy = TRUE)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -1.5017196 -0.1132457 -0.0032577  0.1152654  1.4206186
##
## Type: lag
## Coefficients: (asymptotic standard errors)
##                                Estimate  Std. Error z value  Pr(>|z|)
## (Intercept)                  2.2876e-01  6.2363e-02  3.6681 0.0002443
## miles_bike_walked_percapita  1.4134e-01  4.1326e-02  3.4202 0.0006256
## pop_dens_sqm                -1.9164e-06  6.7069e-07 -2.8573 0.0042729
## income                      -2.9990e-07  3.2070e-07 -0.9351 0.3497156
## renter_per                   4.9190e-02  3.4810e-02  1.4131 0.1576204
## nonwhite_per                 3.2772e-02  2.7157e-02  1.2068 0.2275278
##
## Rho: 0.96906, LR test value: 5028.1, p-value: < 2.22e-16
## Asymptotic standard error: 0.0048023
##     z-value: 201.79, p-value: < 2.22e-16
## Wald statistic: 40720, p-value: < 2.22e-16
##
## Log likelihood: -170.4095 for lag model
## ML residual variance (sigma squared): 0.051467, (sigma: 0.22686)
## Number of observations: 2127
## Number of parameters estimated: 8
## AIC: 356.82, (AIC for lm: 5382.9)
## LM test for residual autocorrelation
## test value: 4.0331, p-value: 0.044617
```

```
#Adjusted + includes neighborhood type./
m3.spatial <-
   lagsarlm(
    PM_mean ~ miles_bike_walked_percapita + pop_dens_sqm + income + renter_per +
      nonwhite_per+nh_type_str,
    data = spatial.dropEmpty,
    lw,
    zero.policy = TRUE
  )
summary(m3.spatial)
```

```
##
## Call:lagsarlm(formula = PM_mean ~ miles_bike_walked_percapita + pop_dens_sqm +
##     income + renter_per + nonwhite_per + nh_type_str, data = spatial.dropEmpty,
##     listw = lw, zero.policy = TRUE)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -1.4770086 -0.1152467 -0.0030365  0.1121873  1.4157357
##
## Type: lag
## Coefficients: (asymptotic standard errors)
##                               Estimate  Std. Error z value Pr(>|z|)
## (Intercept)                  4.8488e-01  1.2404e-01  3.9092 9.26e-05
## miles_bike_walked_percapita -4.7145e-01  3.0926e-01 -1.5245  0.12740
## pop_dens_sqm                -1.5320e-06  7.1411e-07 -2.1454  0.03192
## income                      -3.6708e-07  3.2099e-07 -1.1436  0.25279
## renter_per                   1.9609e-02  3.7014e-02  0.5298  0.59627
## nonwhite_per                 1.7947e-02  2.7431e-02  0.6542  0.51295
## nh_type_str2                 1.8576e-01  7.6444e-02  2.4301  0.01510
## nh_type_str3                -1.4938e-01  5.8199e-02 -2.5667  0.01027
## nh_type_str4                 4.6654e-01  2.5587e-01  1.8234  0.06825
##
## Rho: 0.96397, LR test value: 4838.5, p-value: < 2.22e-16
## Asymptotic standard error: 0.0050424
##     z-value: 191.17, p-value: < 2.22e-16
## Wald statistic: 36547, p-value: < 2.22e-16
##
## Log likelihood: -159.6666 for lag model
## ML residual variance (sigma squared): 0.051308, (sigma: 0.22651)
## Number of observations: 2127
## Number of parameters estimated: 11
## AIC: 341.33, (AIC for lm: 5177.8)
## LM test for residual autocorrelation
## test value: 5.8364, p-value: 0.015698
```

```
## Corellation (Spearman and Pearson)
```

```
#pearson
cor(x=small.data.joined$PM_mean,y=small.data.joined$miles_bike_walked_percapita,method = 'pearson')
```

```
## [1] 0.5192146
```

```
#Spearman
cor(x=small.data.joined$PM_mean,y=small.data.joined$miles_bike_walked_percapita,method = 'spearman')
```

```
## [1] 0.4908499
```

```
?cor
```

```
## starting httpd help server ... done
```