Untitled

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4/4/2022

```
data <- hospitalData
head(hospitalData)
```

```
##       County County.Value State.Rate Year Content.Area       Date
## 1     mohave           46      37.22 2019       Asthma 2019-04-10
## 2       gila           46      37.22 2019       Asthma 2019-04-10
## 3 santa cruz           45      37.22 2019       Asthma 2019-04-10
## 4   maricopa           39      37.22 2019       Asthma 2019-04-10
## 5    cochise           39      37.22 2019       Asthma 2019-04-10
## 6       yuma           34      37.22 2019       Asthma 2019-04-10
##      County.Year
## 1     mohave2019
## 2       gila2019
## 3 santa cruz2019
## 4   maricopa2019
## 5    cochise2019
## 6       yuma2019
```

```
str(hospitalData)
```

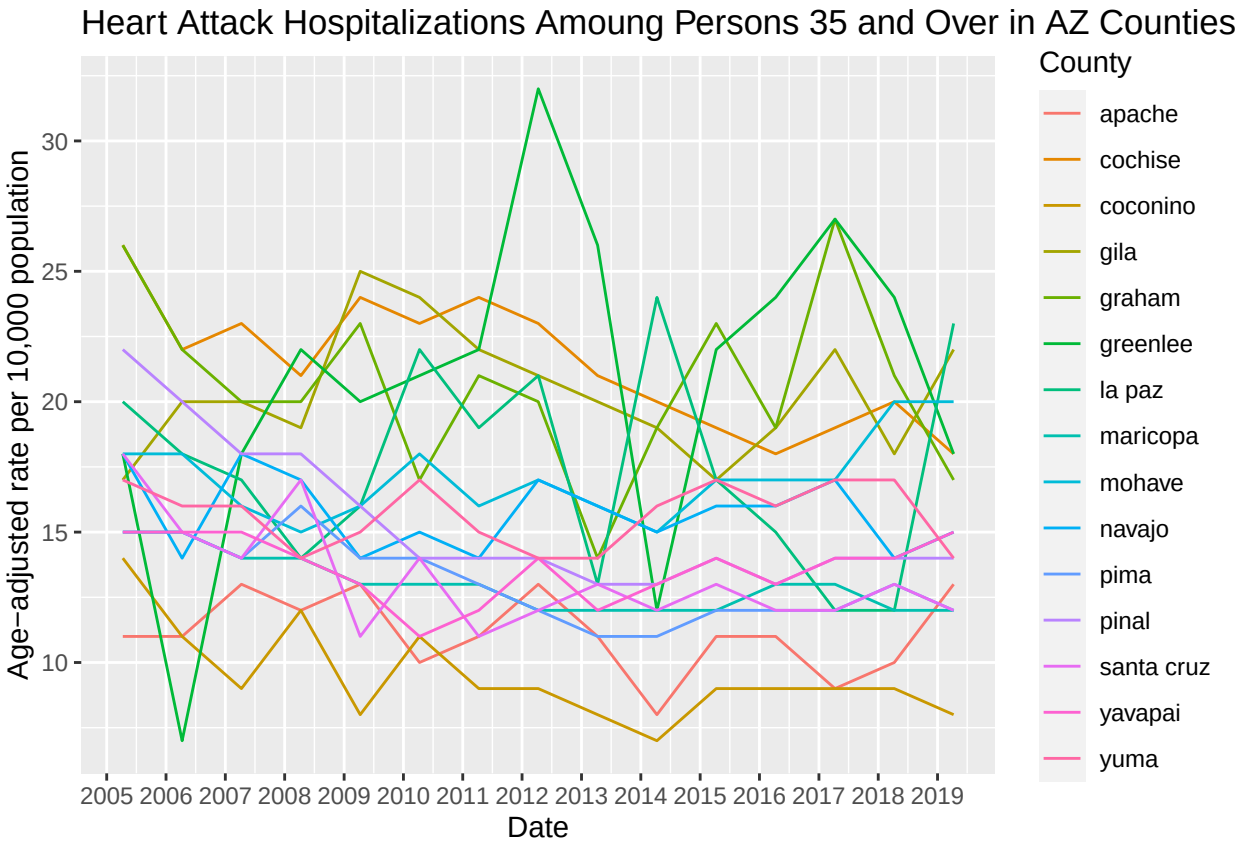
```
## 'data.frame':    1535 obs. of  7 variables:
##  $ County      : Factor w/ 15 levels "apache","cochise",..: 9 4 13 8 2 15 7 11 12 5 ...
##  $ County.Value: int  46 46 45 39 39 34 32 32 32 31 ...
##  $ State.Rate  : num  37.2 37.2 37.2 37.2 37.2 ...
##  $ Year        : chr  "2019" "2019" "2019" "2019" ...
##  $ Content.Area: Factor w/ 9 levels "Asthma","Carbon Monoxide Poisoning",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ Date        : Date, format: "2019-04-10" "2019-04-10" ...
##  $ County.Year : chr  "mohave2019" "gila2019" "santa cruz2019" "maricopa2019" ...
```

```
data.frame(variable = names(hospitalData),
           class = sapply(hospitalData, typeof),
           first.values = sapply(hospitalData, function(x) paste0(head(x),
                                                                  collapse = ",")),
           row.names = NULL) %>%
  kable(caption = "1535 obs. of 7 variables")
```

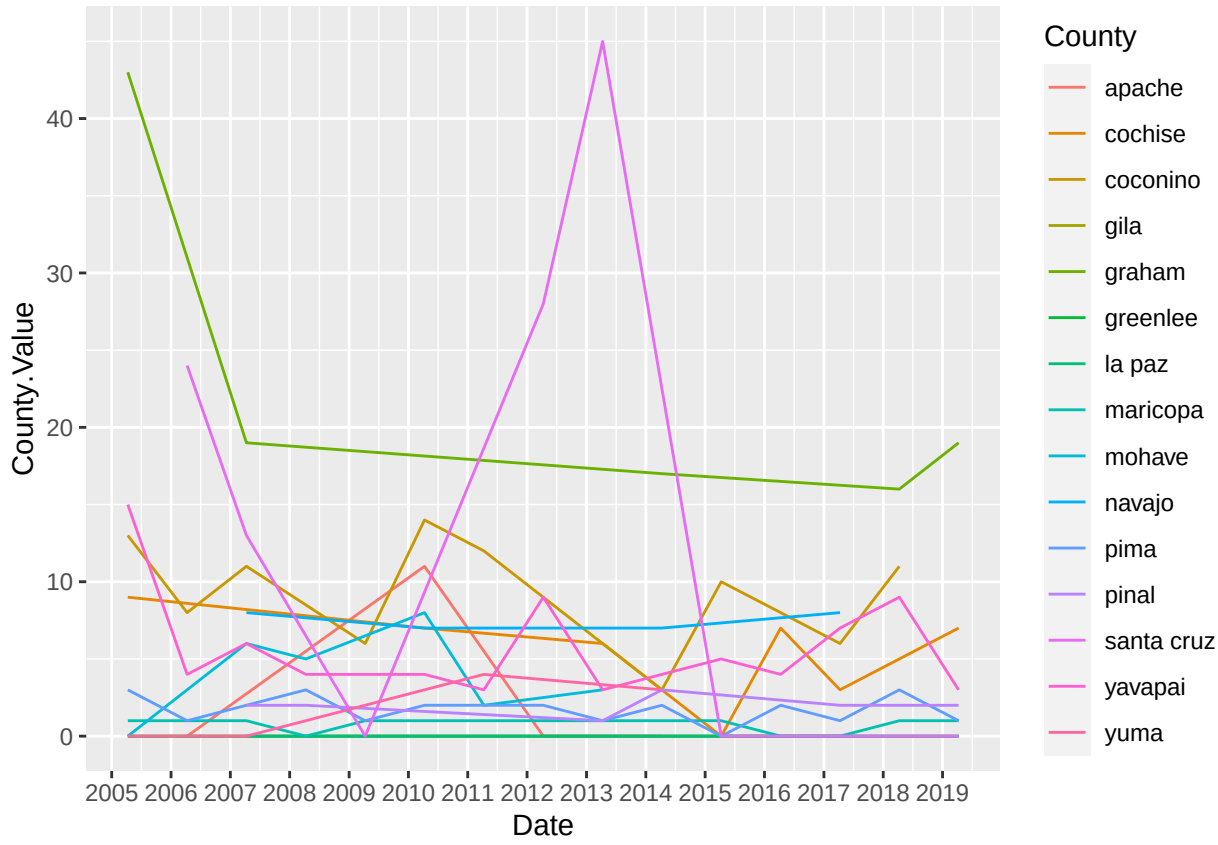
```
asthma <- hospitalData[hospitalData$Content.Area == "Heart Disease",]
ggplot(asthma, aes(x=Date, y=County.Value, color=County)) + geom_line() +
  scale_x_date(date_labels = "%Y", date_breaks = "1 year") +
  ggtitle("Heart Attack Hospitalizations Amoung Persons 35 and Over in AZ Counties") +
  ylab("Age-adjusted rate per 10,000 population")
```

Table 1: 1535 obs. of 7 variables

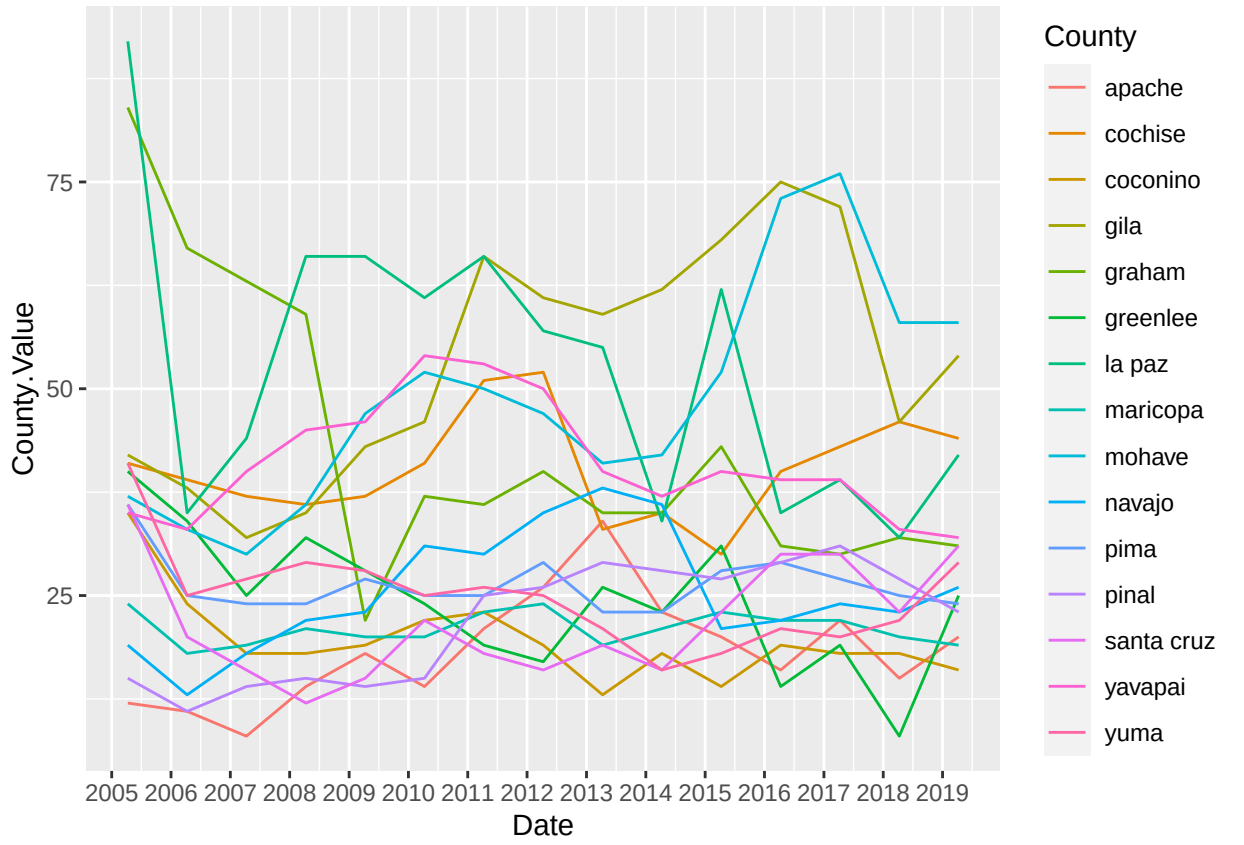
variable	class	first.values
County	integer	mohave,gila,santa cruz,maricopa,cochise,yuma
County.Value	integer	46,46,45,39,39,34
State.Rate	double	37.22,37.22,37.22,37.22,37.22,37.22
Year	character	2019,2019,2019,2019,2019,2019
Content.Area	integer	Asthma,Asthma,Asthma,Asthma,Asthma,Asthma
Date	double	2019-04-10,2019-04-10,2019-04-10,2019-04-10,2019-04-10,2019-04-10
County.Year	character	mohave2019,gila2019,santa cruz2019,maricopa2019,cochise2019,yuma2019



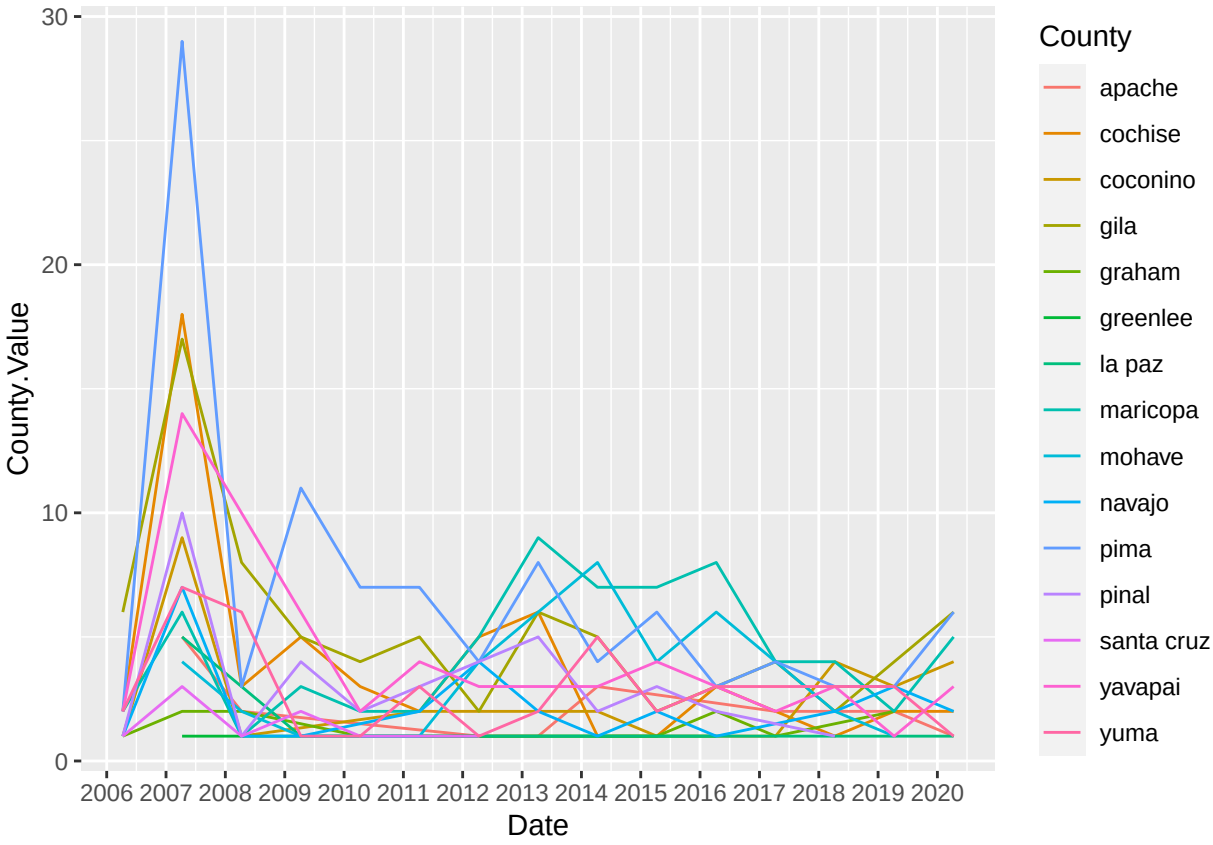

```
cmp <- hospitalData[hospitalData$Content.Area == "Carbon Monoxide Poisoning",]
ggplot(cmp, aes(x=Date, y=County.Value, color=County)) + geom_line() +
  scale_x_date(date_labels = "%Y", date_breaks = "1 year")
```




```
copd <- hospitalData[hospitalData$Content.Area == "Chronic Obstructive Pulmonary Disease (COPD)",]
ggplot(copd, aes(x=Date, y=County.Value, color=County)) + geom_line() +
  scale_x_date(date_labels = "%Y", date_breaks = "1 year")
```

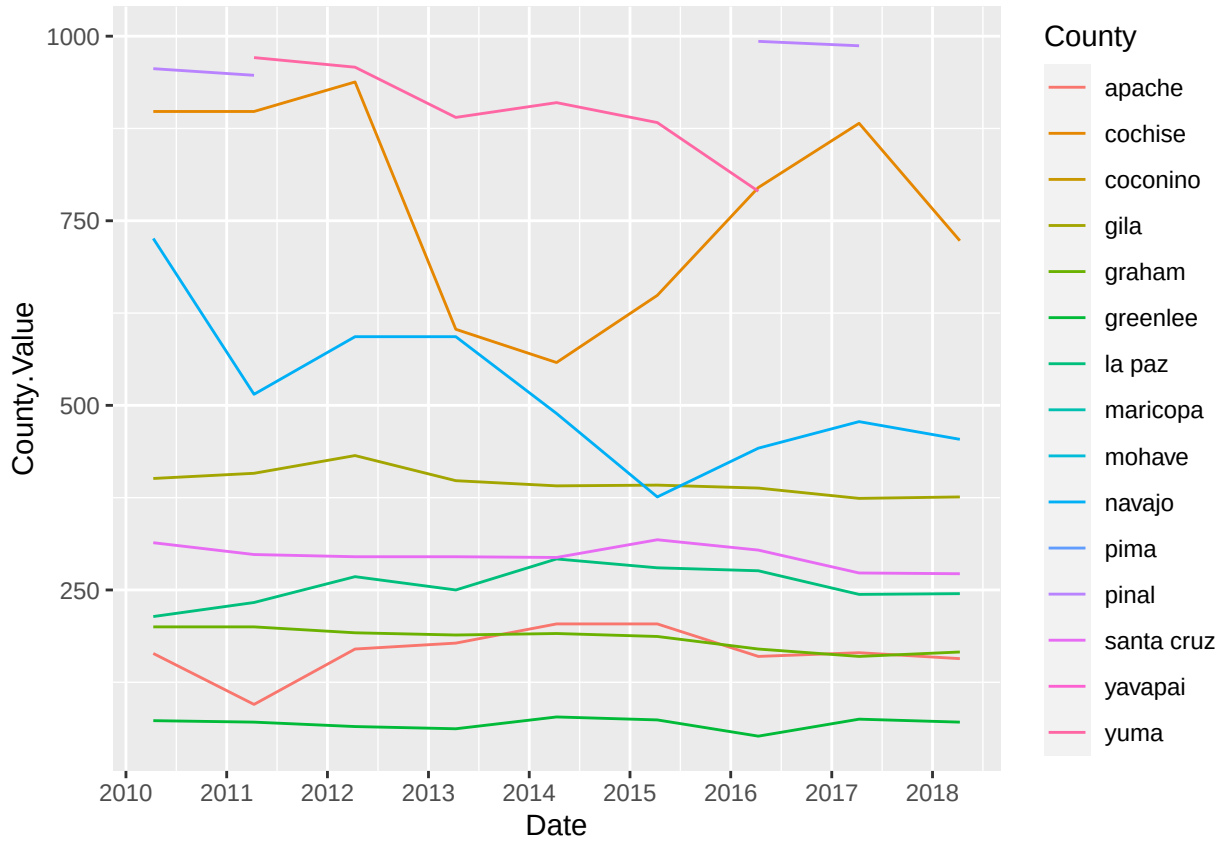



```
dwq <- hospitalData[hospitalData$Content.Area == "Drinking Water Quality",]
ggplot(dwq, aes(x=Date, y=County.Value, color=County)) + geom_line() +
  scale_x_date(date_labels = "%Y", date_breaks = "1 year")
```

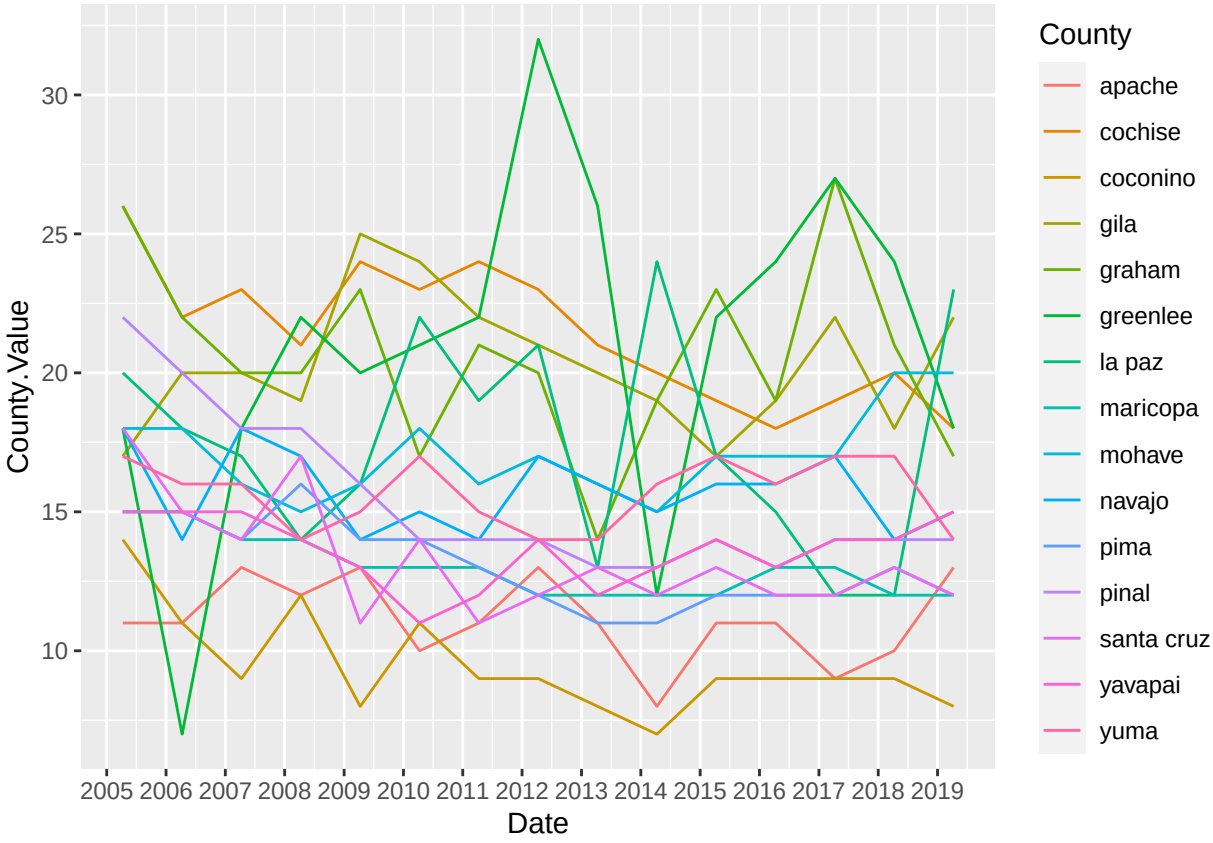



```
fs <- hospitalData[hospitalData$Content.Area == "Food Safety",]
ggplot(fs, aes(x=Date, y=County.Value, color=County)) + geom_line() +
  scale_x_date(date_labels = "%Y", date_breaks = "1 year")
```

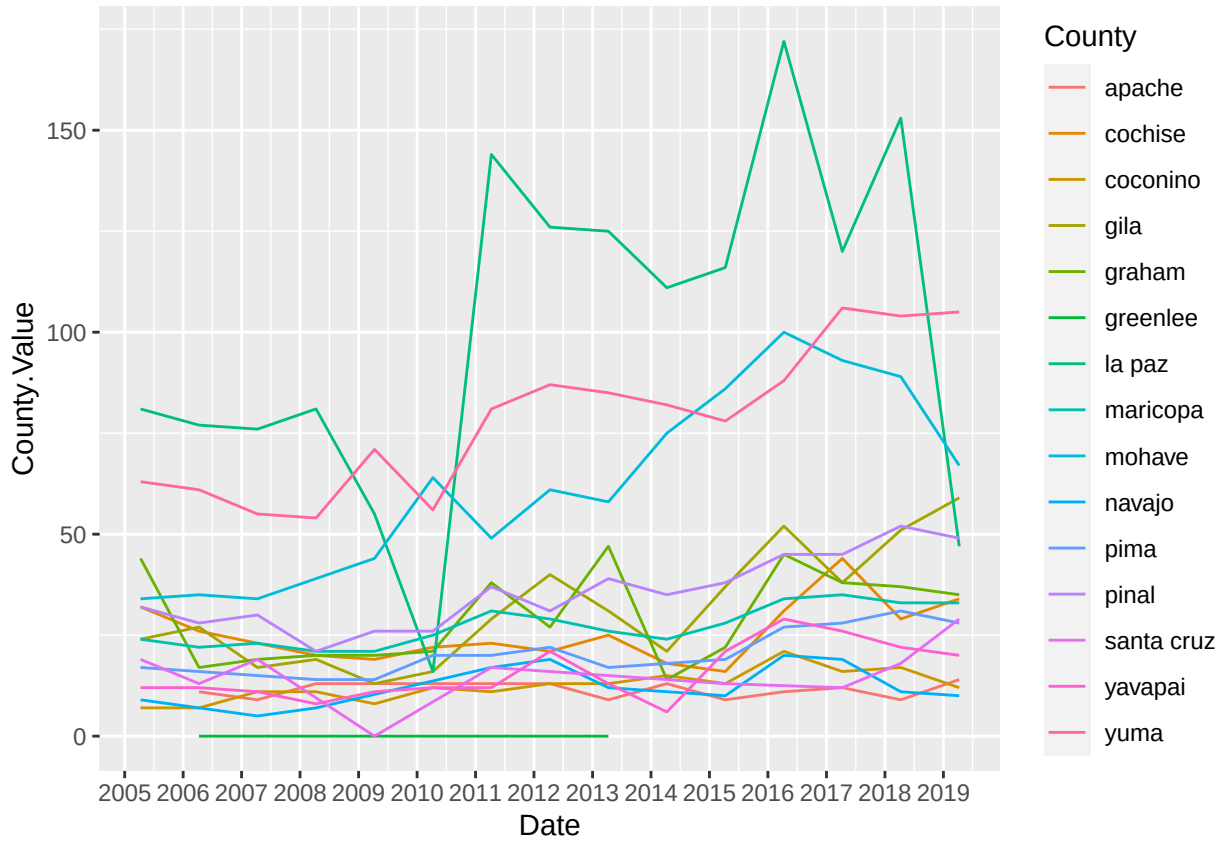
```
## Warning: Removed 47 row(s) containing missing values (geom_path).
```



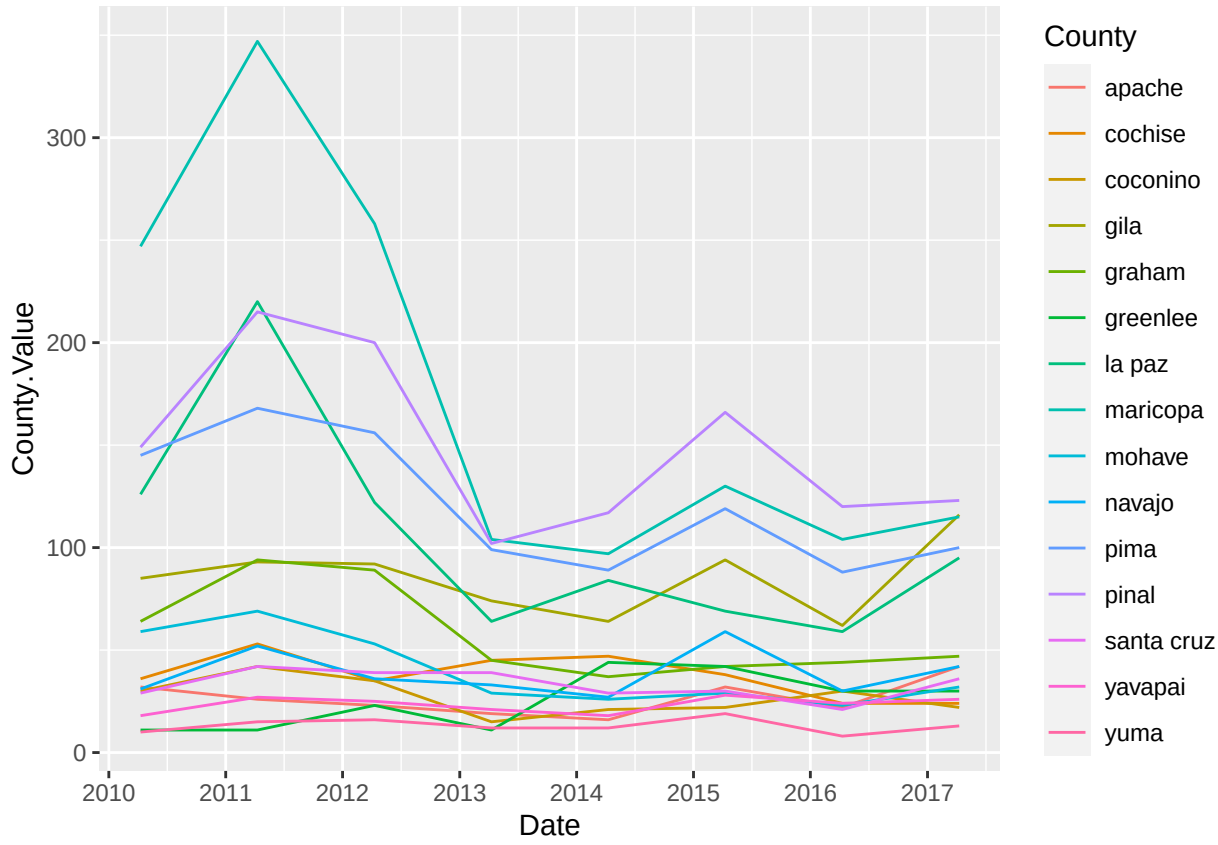

```
hd <- hospitalData[hospitalData$Content.Area == "Heart Disease",]
ggplot(hd, aes(x=Date, y=County.Value, color=County)) + geom_line() +
  scale_x_date(date_labels = "%Y", date_breaks = "1 year")
```



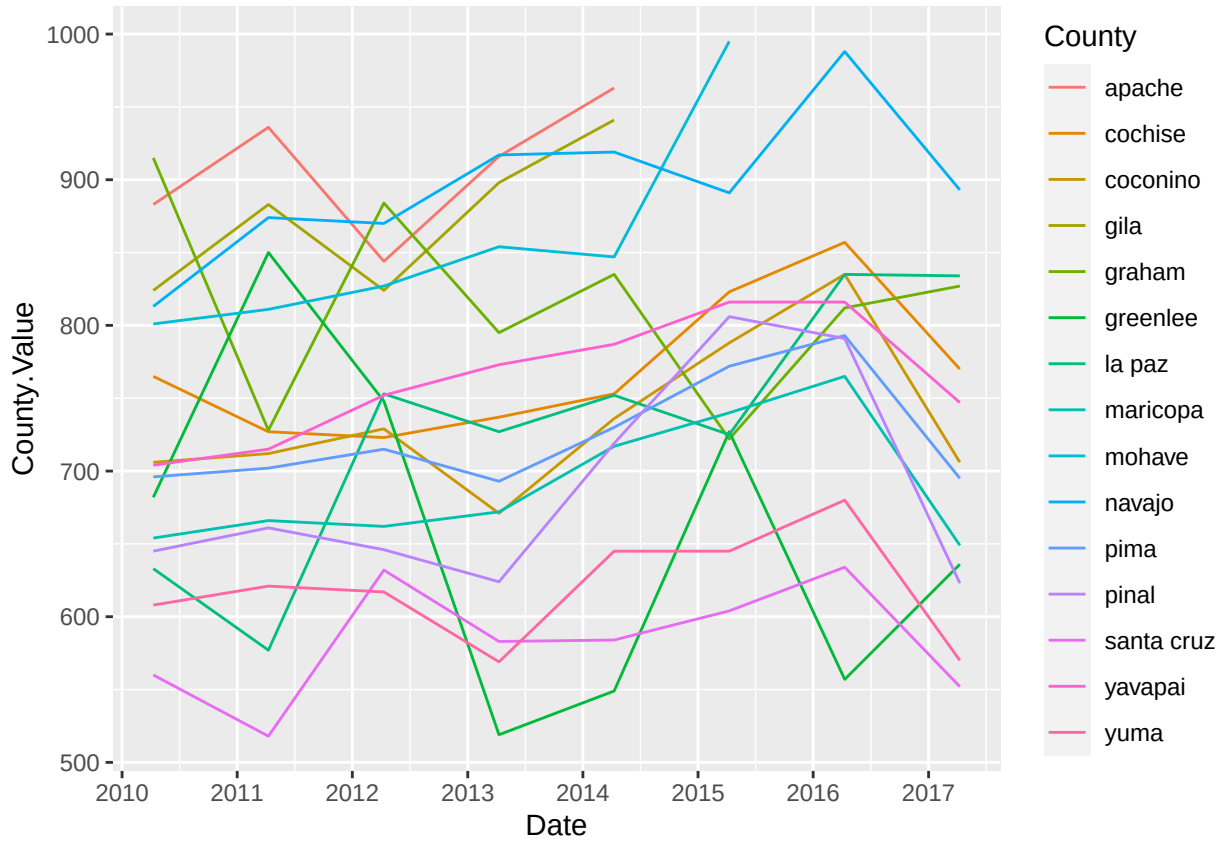

```
hsi <- hospitalData[hospitalData$Content.Area == "Heat Stress Illness",]
ggplot(hsi, aes(x=Date, y=County.Value, color=County)) + geom_line() +
  scale_x_date(date_labels = "%Y", date_breaks = "1 year")
```




```
id <- hospitalData[hospitalData$Content.Area == "Infectious Diseases",]
ggplot(id, aes(x=Date, y=County.Value, color=County)) + geom_line() +
  scale_x_date(date_labels = "%Y", date_breaks = "1 year")
```




```
m <- hospitalData[hospitalData$Content.Area == "Mortality",]
ggplot(m, aes(x=Date, y=County.Value, color=County)) + geom_line() +
  scale_x_date(date_labels = "%Y", date_breaks = "1 year")
```




```
asthma <- hospitalData[hospitalData$Content.Area == "Asthma" &
                         hospitalData$County == "COCONINO",]
asthma <- asthma %>% arrange(Date) %>% pull(County.Value)
plot(asthma)
acf(asthma)
pacf(asthma)
obj <- arima(asthma, order=c(1,0,0))
acf(obj$residuals)
predict(obj, n.ahead = 1)
```

```
hospitalNew <- hospitalData[!(hospitalData$County == "gila" |
                         hospitalData$County == "graham" |
                         hospitalData$County == "greenlee" |
                         hospitalData$County == "la paz" |
                           hospitalData$County == "santa cruz"),]
hospitalNew <- hospitalNew[!(hospitalNew$Date == "2005-04-10" |
                                hospitalNew$Date == "2006-04-10" |
                                hospitalNew$Date == "2007-04-10" |
                                hospitalNew$Date == "2008-04-10" |
                                hospitalNew$Date == "2009-04-10" |
                              hospitalNew$Date == "2020-04-10"),]
asthma <- hospitalNew[hospitalData$Content.Area == "Asthma",]
```

```
hospital.wider <- hospitalNew %>% select(-State.Rate)
hospital.wider <- pivot_wider(hospital.wider, names_from = Content.Area,
```

```
                                values_from = County.Value)
```

```
all.data <- full_join(hospital.wider, censusData, by="County.Year") %>%
  relocate(County.x, Year.x, County.y, Year.y, Date.x, Date.y)
```

```
asthma.wider <- hospital.wider %>% select(c(County.Year, Asthma))
asthma.data <- merge(asthma.wider, censusData)
cmp.wider <- hospital.wider %>% select(c(County.Year, `Carbon Monoxide Poisoning`))
cmp.data <- merge(cmp.wider, censusData)
copd.wider <- hospital.wider %>%
  select(c(County.Year, `Chronic Obstructive Pulmonary Disease (COPD)`))
copd.data <- merge(copd.wider, censusData)
dwq.wider <- hospital.wider %>%
  select(c(County.Year, `Drinking Water Quality`))
dwq.data <- merge(dwq.wider, censusData)
fs.wider <- hospital.wider %>%
  select(c(County.Year, `Food Safety`))
fs.data <- merge(fs.wider, censusData)
hd.wider <- hospital.wider %>%
  select(c(County.Year, `Heart Disease`))
hd.data <- merge(hd.wider, censusData)
hsi.wider <- hospital.wider %>%
  select(c(County.Year, `Heat Stress Illness`))
hsi.data <- merge(hsi.wider, censusData)
id.wider <- hospital.wider %>%
  select(c(County.Year, `Infectious Diseases`))
id.data <- merge(id.wider, censusData)
m.wider <- hospital.wider %>%
  select(c(County.Year, `Mortality`))
m.data <- merge(m.wider, censusData)
```

```
# colnames(cor.data) <- c('x1', 'x2', 'x3', 'x4', 'x5', 'x6', 'x7', 'x8', 'x9',
#                         'x10', 'x11', 'x12', 'x13', 'x14', 'x15', 'x16', 'x17',
#                         'x18', 'x19', 'x20', 'x21', 'x22', 'x23', 'x24',
#                         'x25', 'x26', 'x27', 'x28', 'x29', 'x30', 'x31', 'x32',
#                         'x33', 'x34', 'x35',
#                         'x36', 'x37', 'x38', 'x39', 'x40', 'x41', 'x42', 'x43',
#                         'x44', 'x45', 'x46',
#                         'x47', 'x48', 'x49', 'x50', 'x51', 'x52', 'x53', 'x54',
#                         'x55', 'x56', 'x57',
#                         'x58', 'x59', 'x60', 'x61', 'x62', 'x63', 'x64', 'x65',
#                         'x66', 'x67', 'x68',
#                         'x69', 'x70', 'x71', 'x72', 'x73', 'x74', 'x75', 'x76',
#                         'x77', 'x78', 'x79',
#                         'x80', 'x81', 'x82', 'x83', 'x84', 'x85', 'x86', 'x87',
#                         'x88', 'x89', 'x90',
#                         'x91', 'x92')
```

```
cor.data <- all.data %>% select(-c(County.Year, Year, County))
cor.asthma <- asthma.data %>% select(-c(County.Year, Year, County))
cor.cmp <- cmp.data %>% select(-c(County.Year, Year, County))
cor.copd <- copd.data %>% select(-c(County.Year, Year, County))
```

```
cor.dwq <- dwq.data %>% select(-c(County.Year, Year, County))
cor.fs <- fs.data %>% select(-c(County.Year, Year, County))
cor.hd <- hd.data %>% select(-c(County.Year, Year, County))
cor.hsi <- hsi.data %>% select(-c(County.Year, Year, County))
cor.id <- id.data %>% select(-c(County.Year, Year, County))
cor.m <- m.data %>% select(-c(County.Year, Year, County))
corrplot::corrplot(cor(cor.asthma, use = 'pairwise.complete.obs'), tl.cex = 0.8)
corrplot::corrplot(cor(cor.cmp, use = 'pairwise.complete.obs'), tl.cex = 0.8)
corrplot::corrplot(cor(cor.copd, use = 'pairwise.complete.obs'), tl.cex = 0.8)
corrplot::corrplot(cor(cor.dwq, use = 'pairwise.complete.obs'), tl.cex = 0.8)
corrplot::corrplot(cor(cor.fs, use = 'pairwise.complete.obs'), tl.cex = 0.8)
corrplot::corrplot(cor(cor.hd, use = 'pairwise.complete.obs'), tl.cex = 0.8)
corrplot::corrplot(cor(cor.hsi, use = 'pairwise.complete.obs'), tl.cex = 0.8)
corrplot::corrplot(cor(cor.id, use = 'pairwise.complete.obs'), tl.cex = 0.8)
corrplot::corrplot(cor(cor.m, use = 'pairwise.complete.obs'), tl.cex = 0.8)
corrplot::corrplot(cor(cor.data, use = 'pairwise.complete.obs'), tl.cex = 0.8)
cor.v <- cor(cor.data)
pos.cor <- cor.v[cor.v > 0.5]
```

```
test <- cor.test(hospital.wider$Asthma, censusData$Total.Population)
test$p.value
test$estimate
cor.test(hospital.wider[,4], censusData$Total.Population)
```

```
all.data$Asthma <- as.numeric(all.data$Asthma)
all.data <- all.data %>% select(-c(County.x, Year.x, Date.x, `Food Safety`))
colnames(all.data)[1] <- "County"
colnames(all.data)[2] <- "Year"
colnames(all.data)[3] <- "Date"
all.data$Year <- as.factor(all.data$Year)
names(all.data) <- gsub(" ", ".", names(all.data))
colnames(all.data)[7] <- "COPD"
```

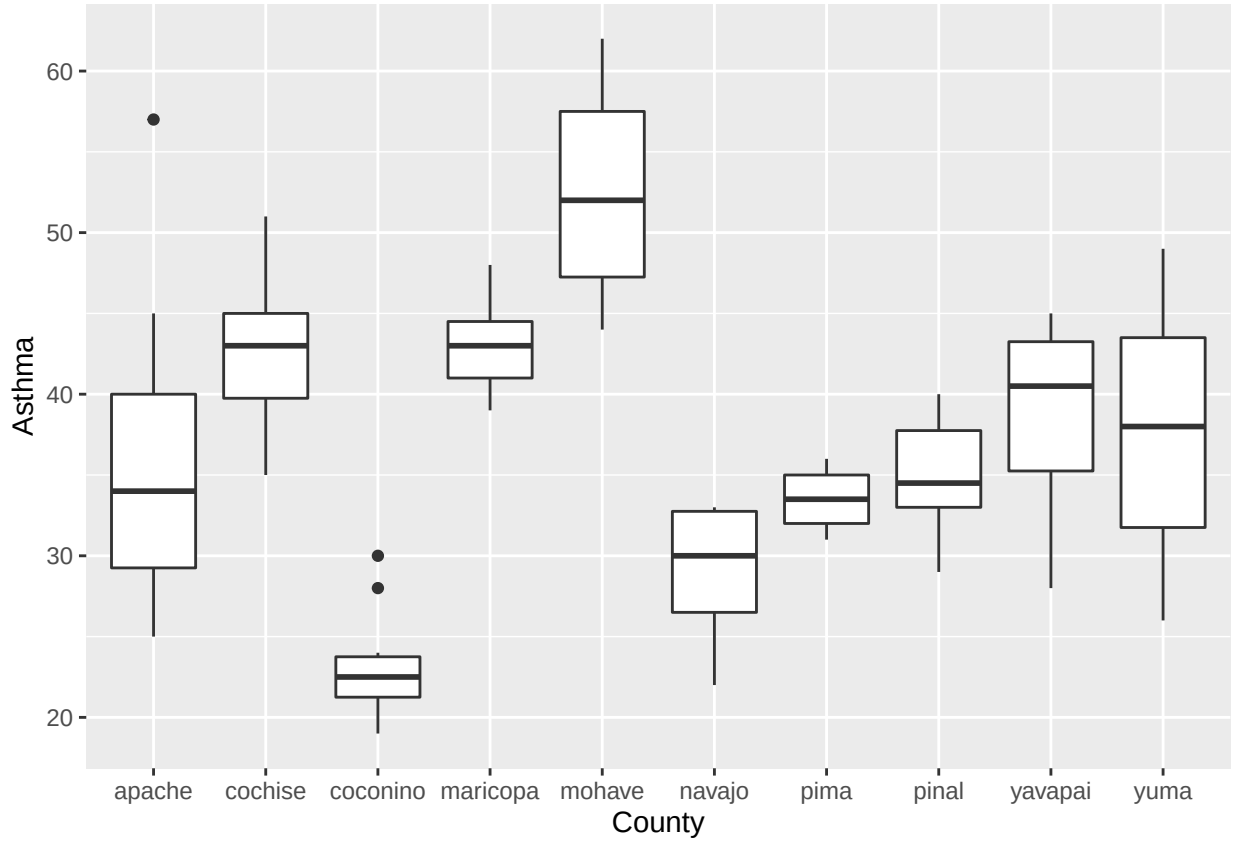
```
correlation <- data.frame(Content.Area = character(),
                          Demographic = character(),
                          p.value = integer(),
                          corr = integer())
for(cont in 5:12){
  for(demo in 13:95){
    #print(paste(cont, demo))
    hold <- cor.test(pull(all.data[,cont]), pull(all.data[,demo]))
    corr.df <- data.frame(Content.Area = c(colnames(all.data)[cont]),
                          Demographic = c(colnames(all.data)[demo]),
                          p.value = c(hold$p.value),
                          corr = c(hold$estimate))
    if(is.na(correlation[1,1])){
      correlation <- corr.df
    }
    else {
      correlation <- rbind(correlation, corr.df)
    }

  }
```

```
}
```

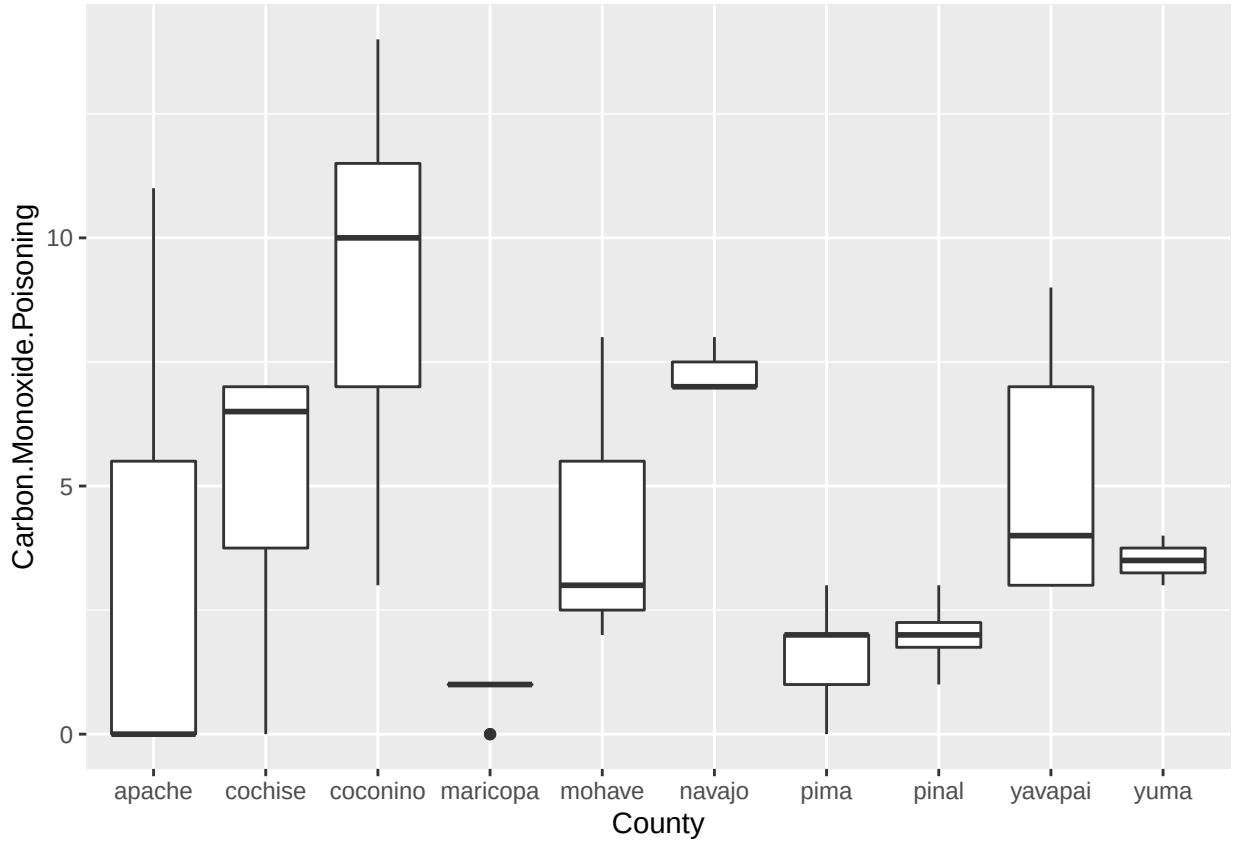
```
correlation$adj.p.value <- p.adjust(correlation$p.value, method="bonferroni")
```

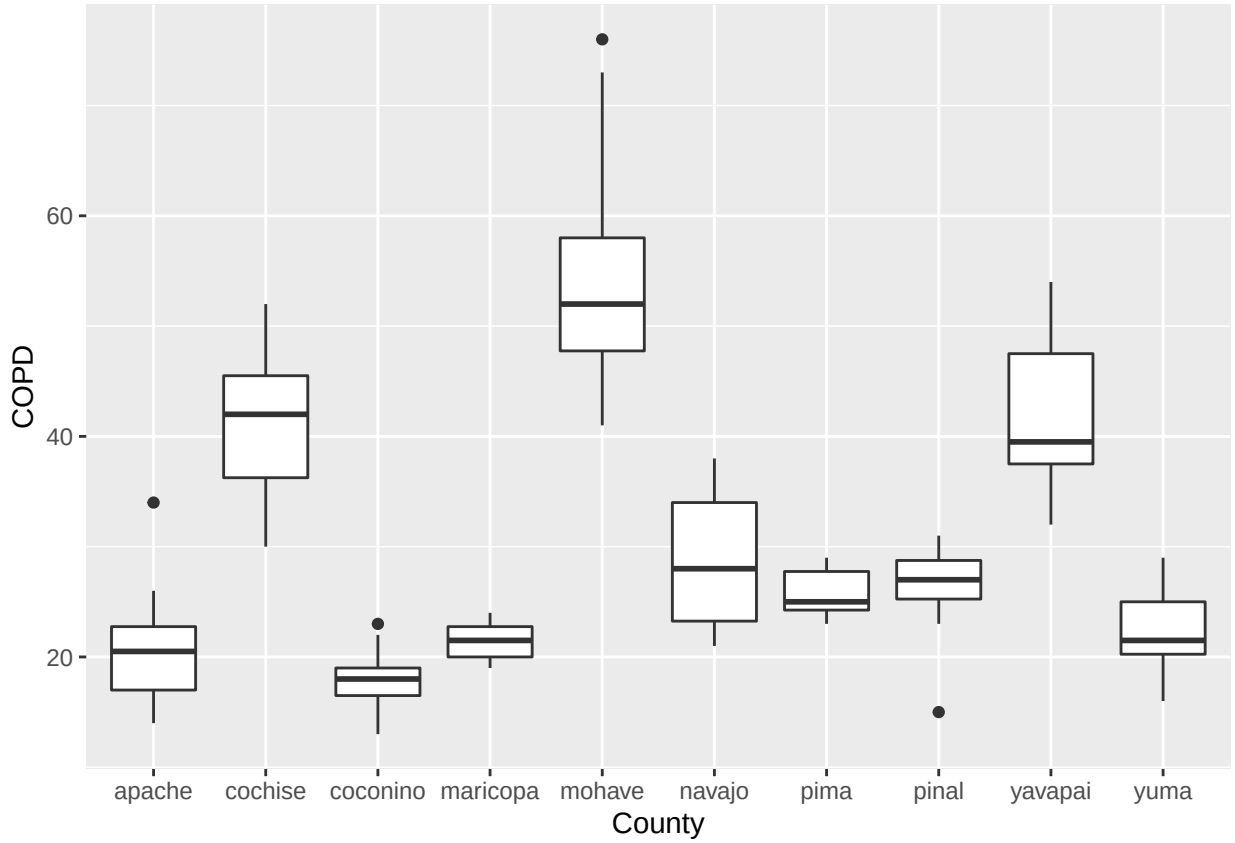
```
adj.cor <- correlation %>% filter(adj.p.value < 0.05) %>% arrange(corr)
```

```
#ggplot(all.data, aes(x=County, y=Asthma)) + geom_boxplot()
for (index in 5:12) {
  print(ggplot(all.data, aes_string(x="County", y=colnames(all.data)[index])) +
    geom_boxplot())
}
```

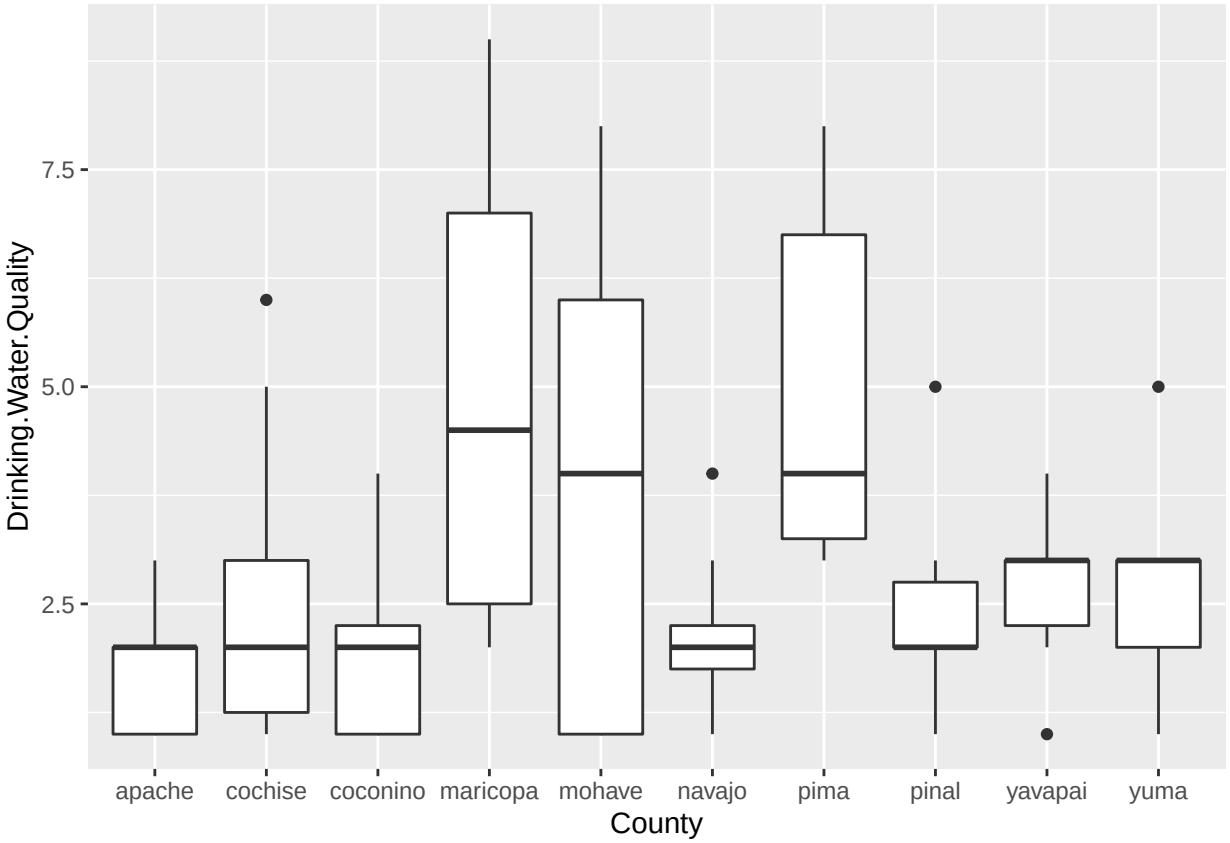


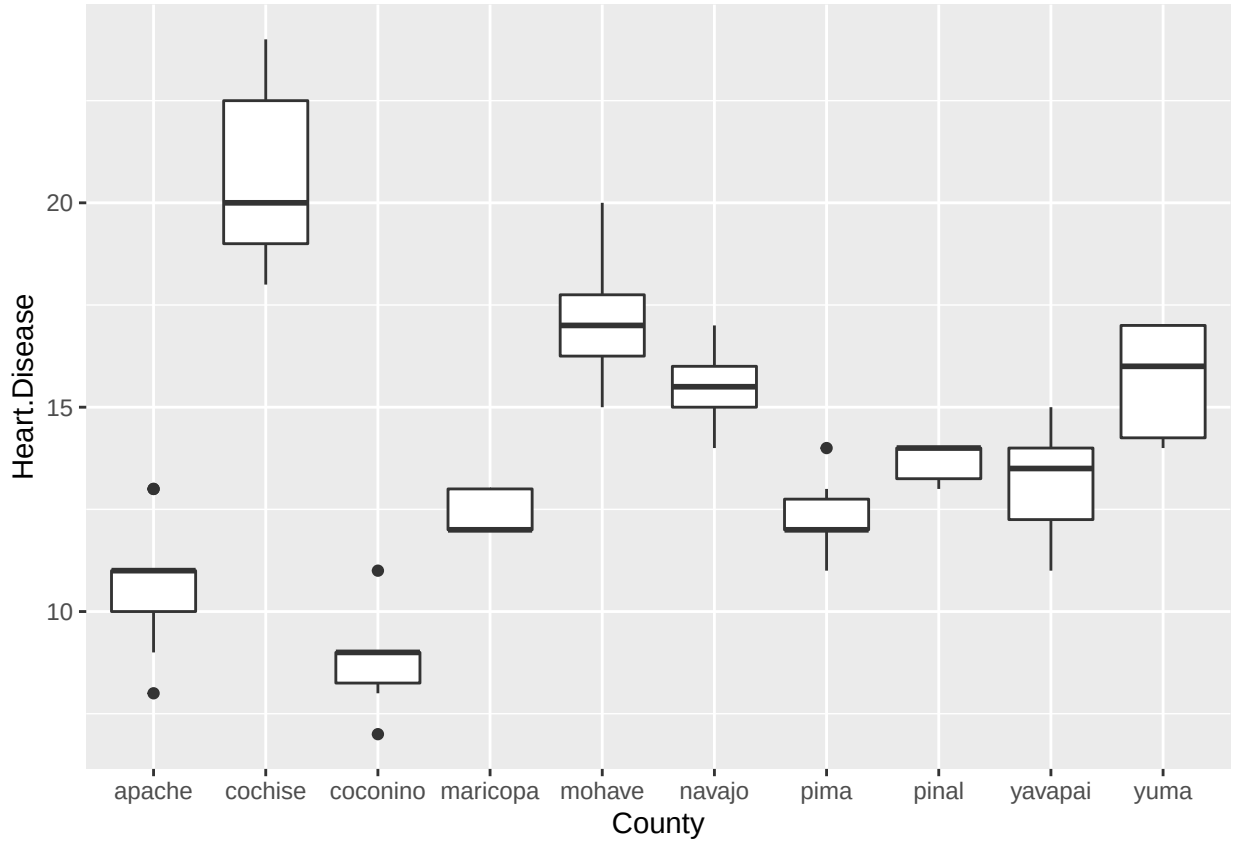

```
## Warning: Removed 43 rows containing non-finite values (stat_boxplot).
```


Carbon.Monoxide.Poisoning
10
5
0
apache
cochise
coconino
maricopa
mohave
navajo
pima
pinal
yavapai
yuma
County

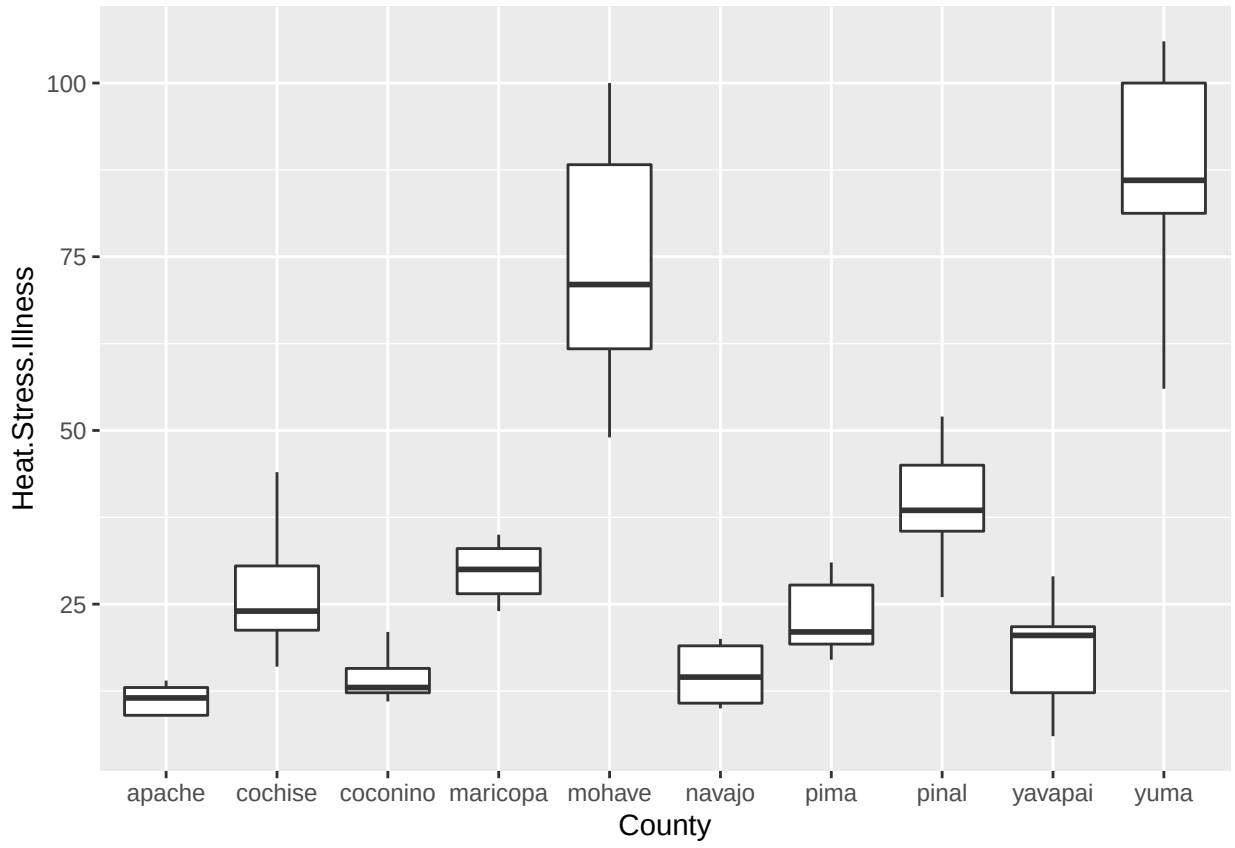



```
## Warning: Removed 14 rows containing non-finite values (stat_boxplot).
```

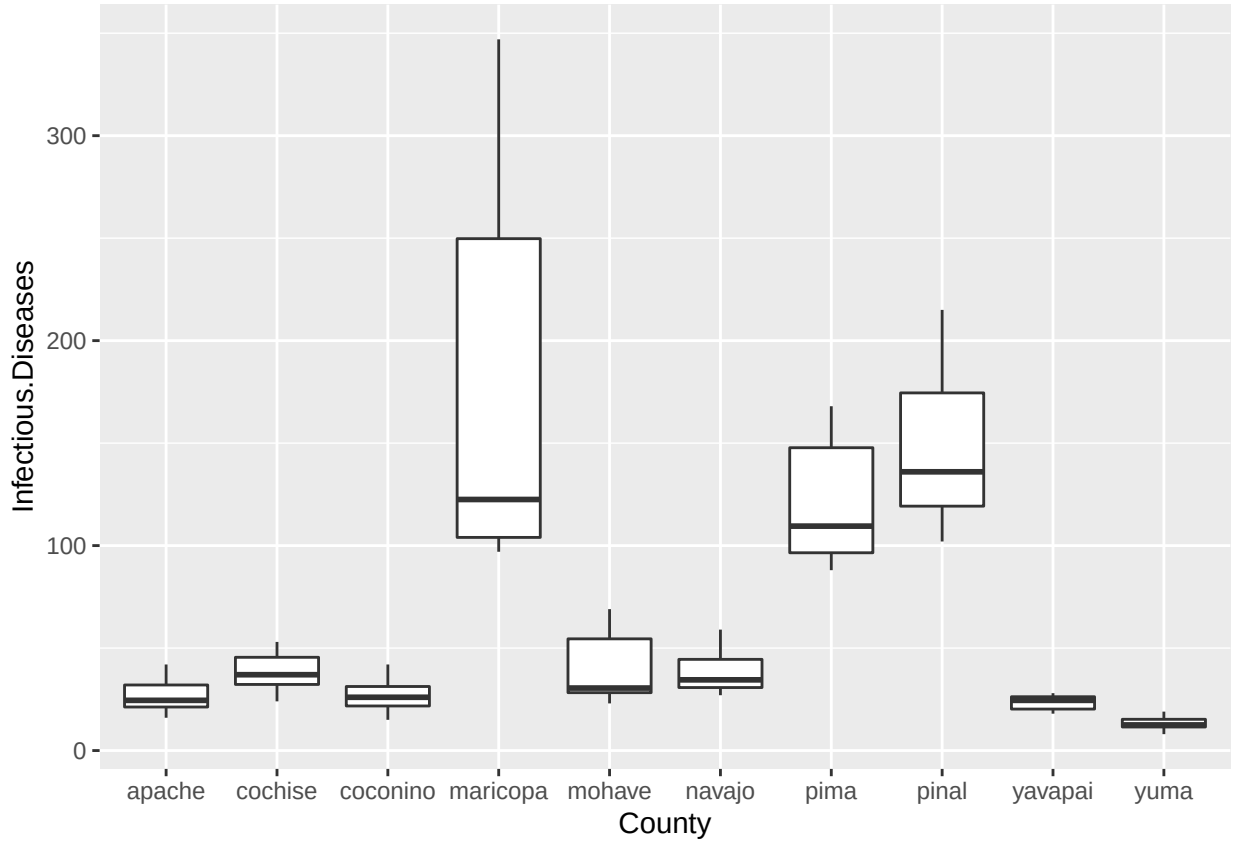

Drinking.Water.Quality
7.5
5.0
2.5
apache
cochise
coconino
maricopa
mohave
navajo
pima
pinal
yavapai
yuma
County



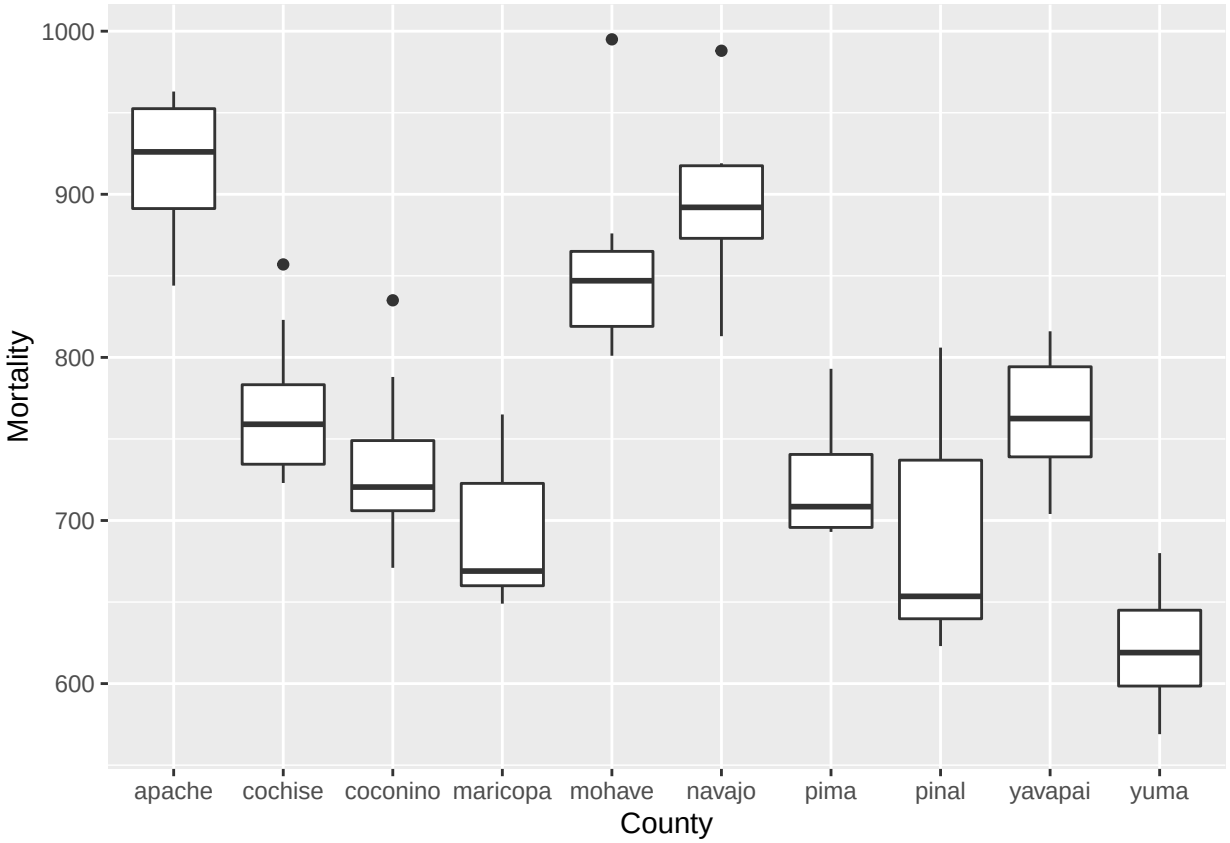

```
## Warning: Removed 4 rows containing non-finite values (stat_boxplot).
```




```
## Warning: Removed 20 rows containing non-finite values (stat_boxplot).
```




```
## Warning: Removed 23 rows containing non-finite values (stat_boxplot).
```

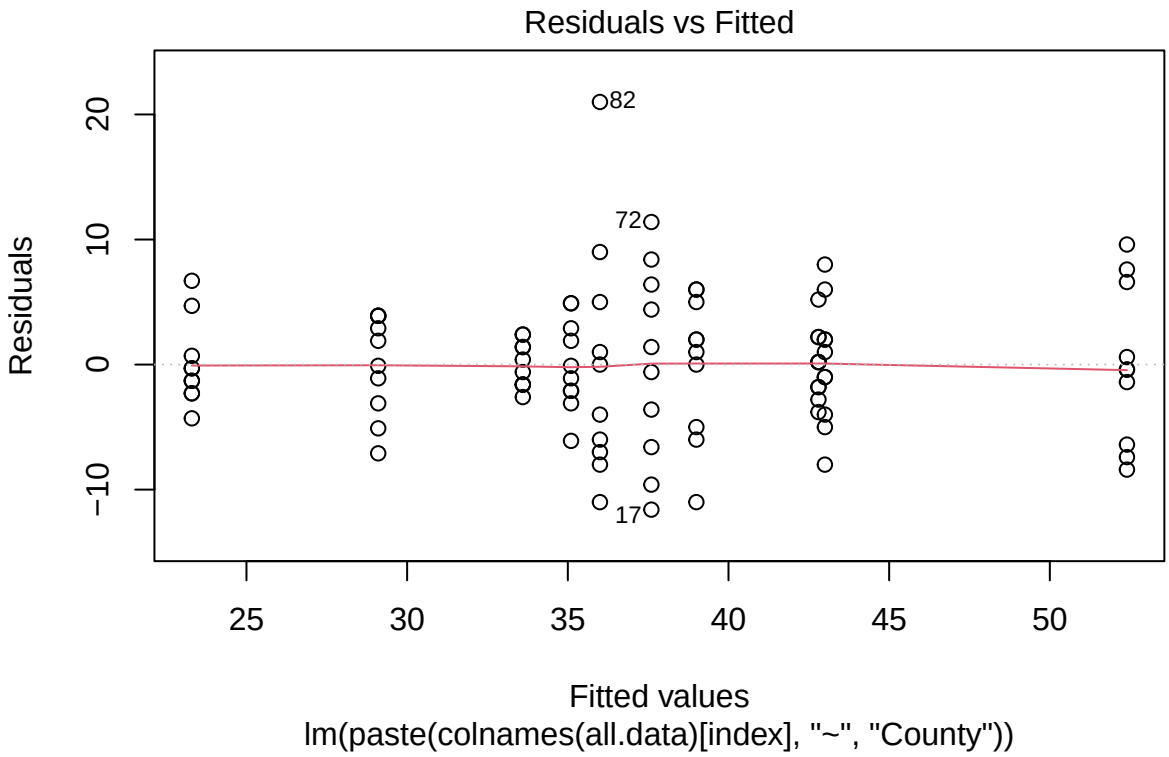


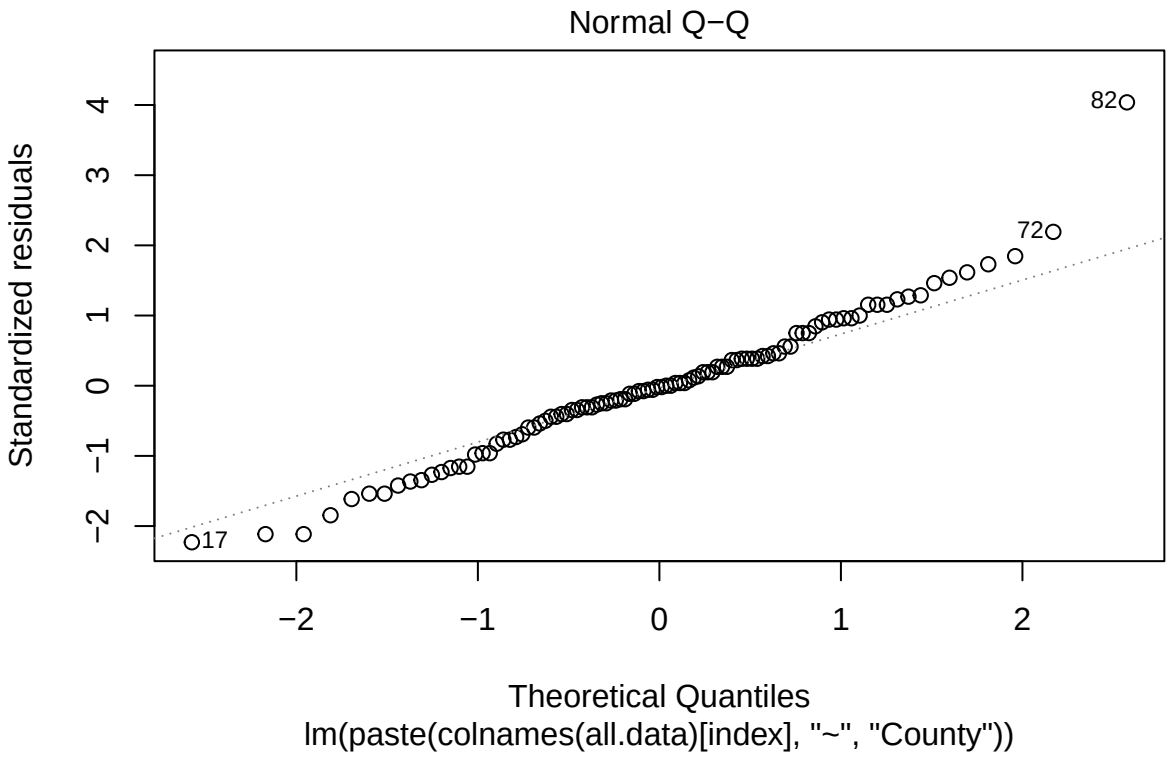

```
obj <- lm(Asthma ~ County, data=all.data)
summary(obj)
plot(obj)
anova(obj)
emmeans(obj, pairwise ~ County)
```

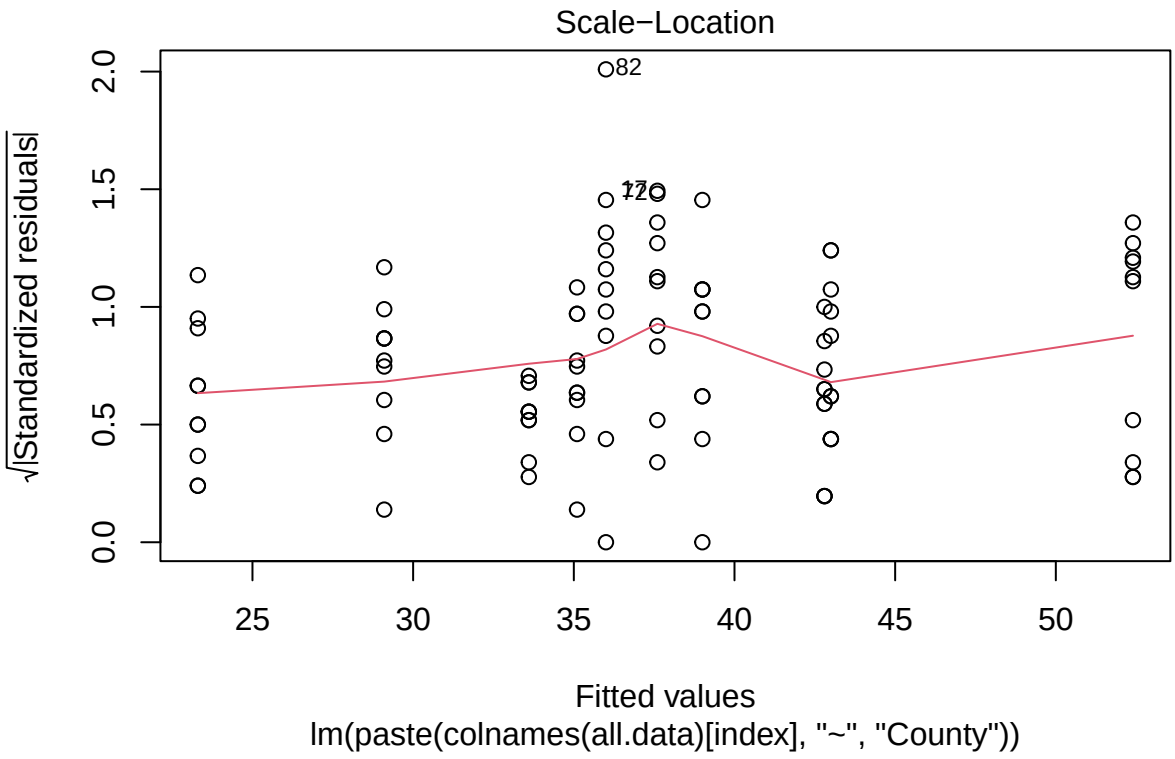
```
content.area.p <- data.frame(
  County = factor(),
  p.value = integer()
)
for (index in 5:12) {
  obj <- lm(paste(colnames(all.data)[index], "~", 'County'), data=all.data)
  sum.obj <- summary(obj)
  f <- sum.obj$fstatistic
  p <- pf(f[1], f[2], f[3], lower.tail=F)
  p.df <- data.frame(County = colnames(all.data)[index],
                     p.value = p)
  if(index == 5)
  {
    content.area.p <- p.df
  }
  else
  {
    content.area.p <- rbind(content.area.p, p.df)
  }
```

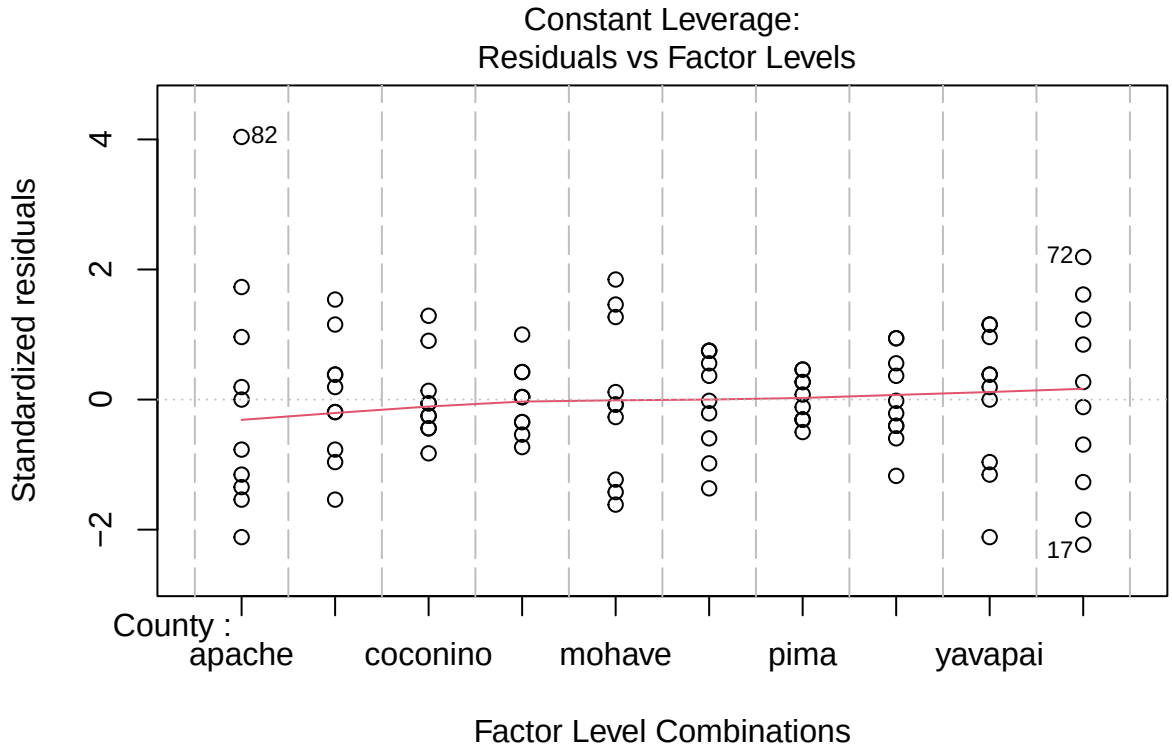
```
  print(sum.obj)
  print(anova(obj))
  print(plot(obj))
  #print(emmeans(obj, pairwise ~ County))
}
```

```
##
## Call:
## lm(formula = paste(colnames(all.data)[index], "~", "County"),
##     data = all.data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -11.600  -2.875  -0.100   2.525  21.000
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)      36.000      1.734  20.767  < 2e-16 ***
## Countycochise     7.000      2.452   2.855  0.00534 **
## Countycoconino  -12.700      2.452  -5.180 1.34e-06 ***
## Countymaricopa    6.800      2.452   2.774  0.00674 **
## Countymohave     16.400      2.452   6.689 1.85e-09 ***
## Countynavajo     -6.900      2.452  -2.814  0.00600 **
## Countypima       -2.400      2.452  -0.979  0.33023
## Countypinal      -0.900      2.452  -0.367  0.71440
## Countyyavapai     3.000      2.452   1.224  0.22427
## Countyyuma        1.600      2.452   0.653  0.51566
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.482 on 90 degrees of freedom
## Multiple R-squared:  0.6809, Adjusted R-squared:  0.649
## F-statistic: 21.34 on 9 and 90 DF,  p-value: < 2.2e-16
##
## Analysis of Variance Table
##
## Response: Asthma
##           Df Sum Sq Mean Sq F value    Pr(>F)
## County     9 5770.7  641.19  21.336 < 2.2e-16 ***
## Residuals 90 2704.7   30.05
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```


Residuals vs Fitted
Residuals
Fitted values
lm(paste(colnames(all.data)[index], "~", "County"))
82
72
17
20
10
0
−10
25
30
35
40
45
50

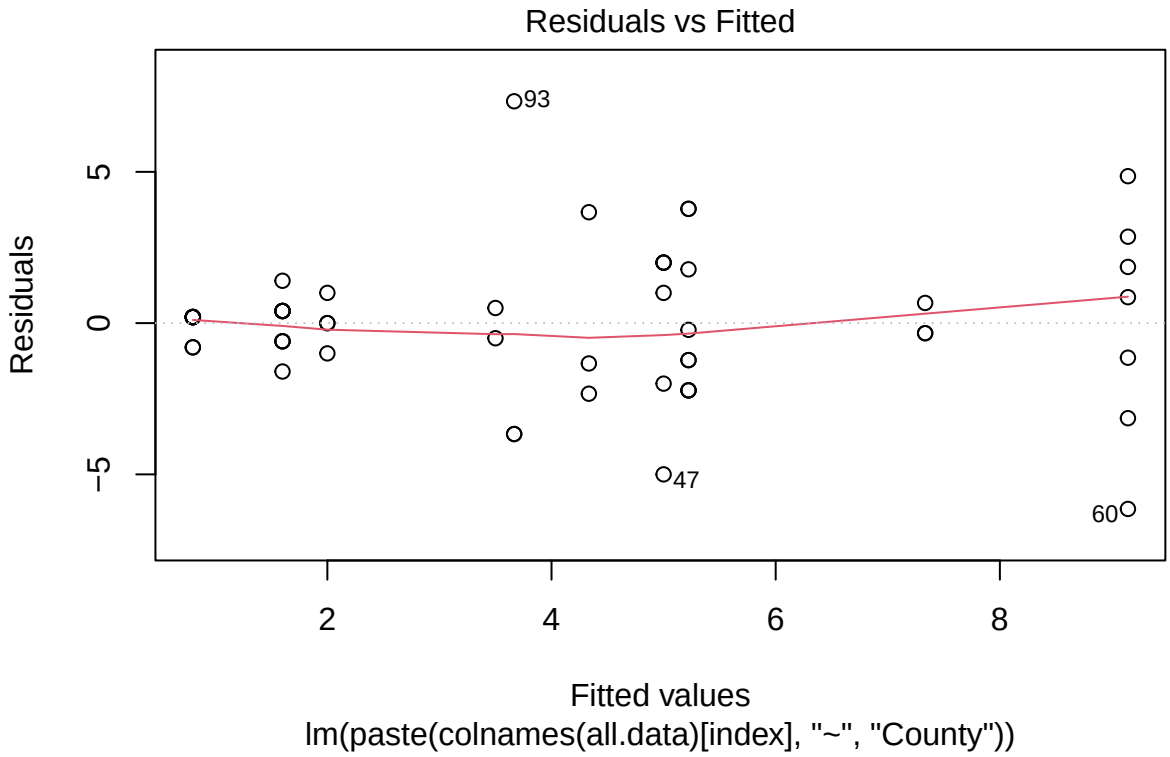

Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(paste(colnames(all.data)[index], "~", "County"))
82
72
17
−2
−1
0
1
2
3
4

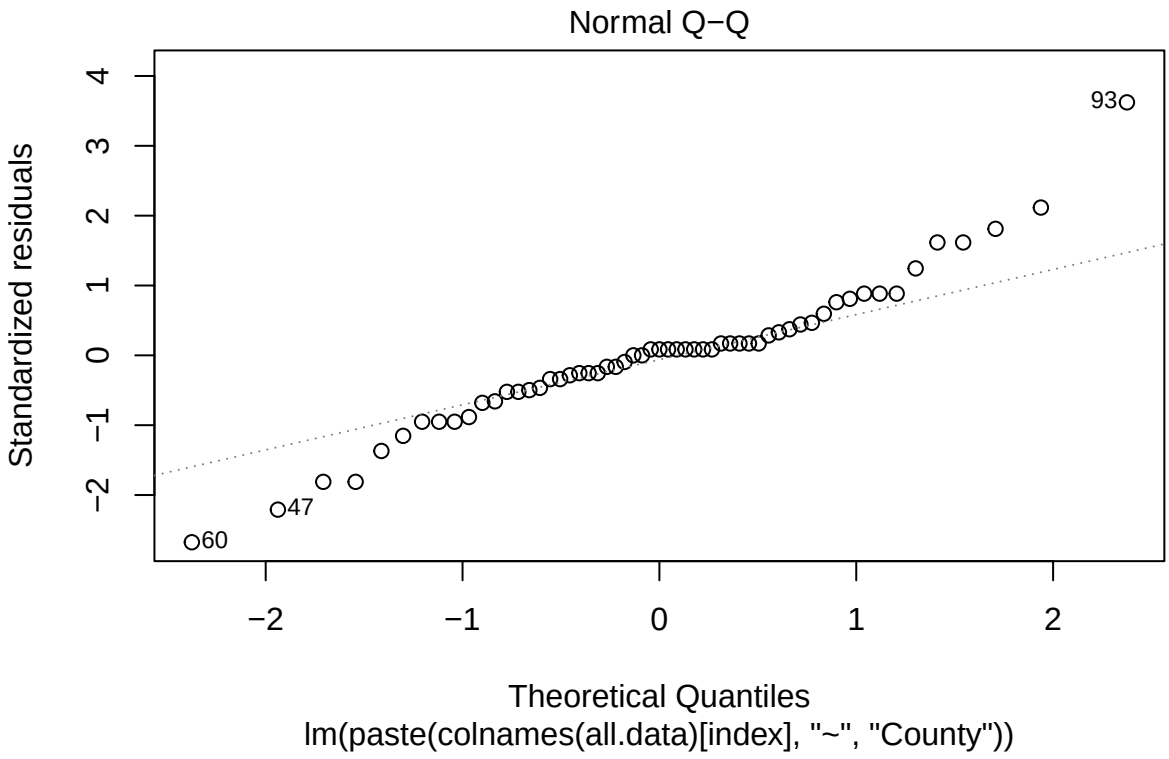

Scale−Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
82
120
25
30
35
40
45
50
Fitted values
lm(paste(colnames(all.data)[index], "~", "County"))

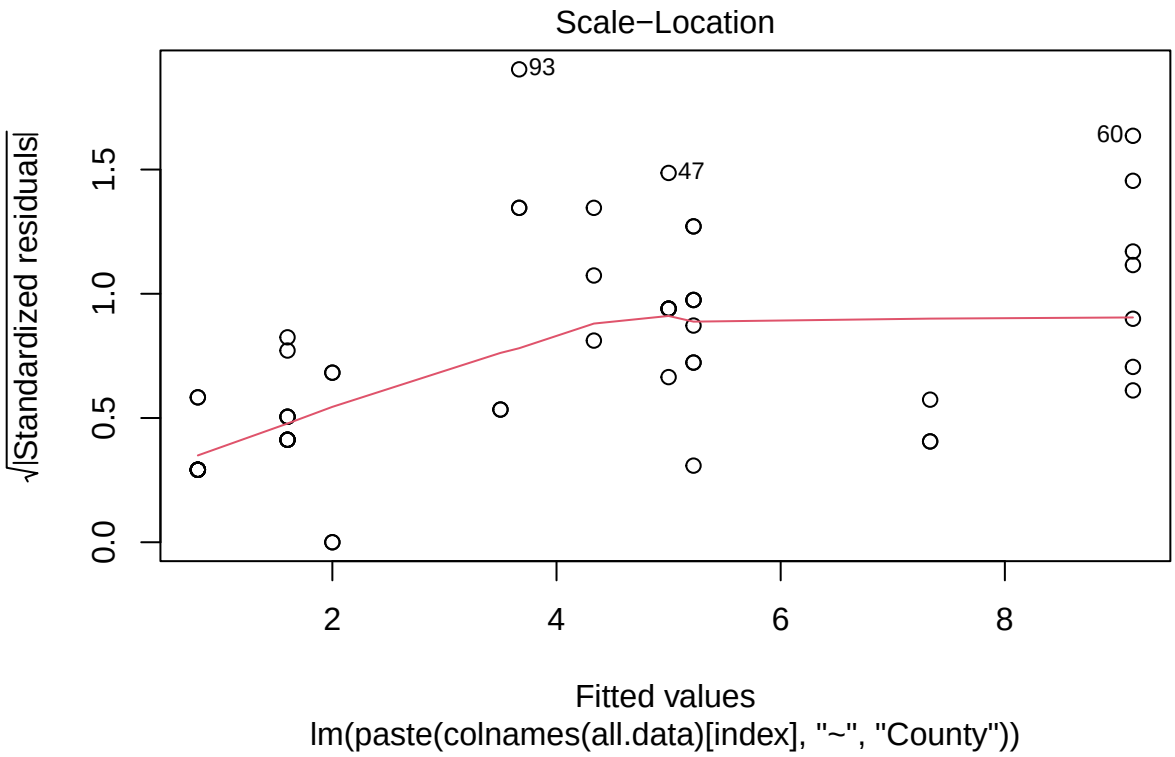


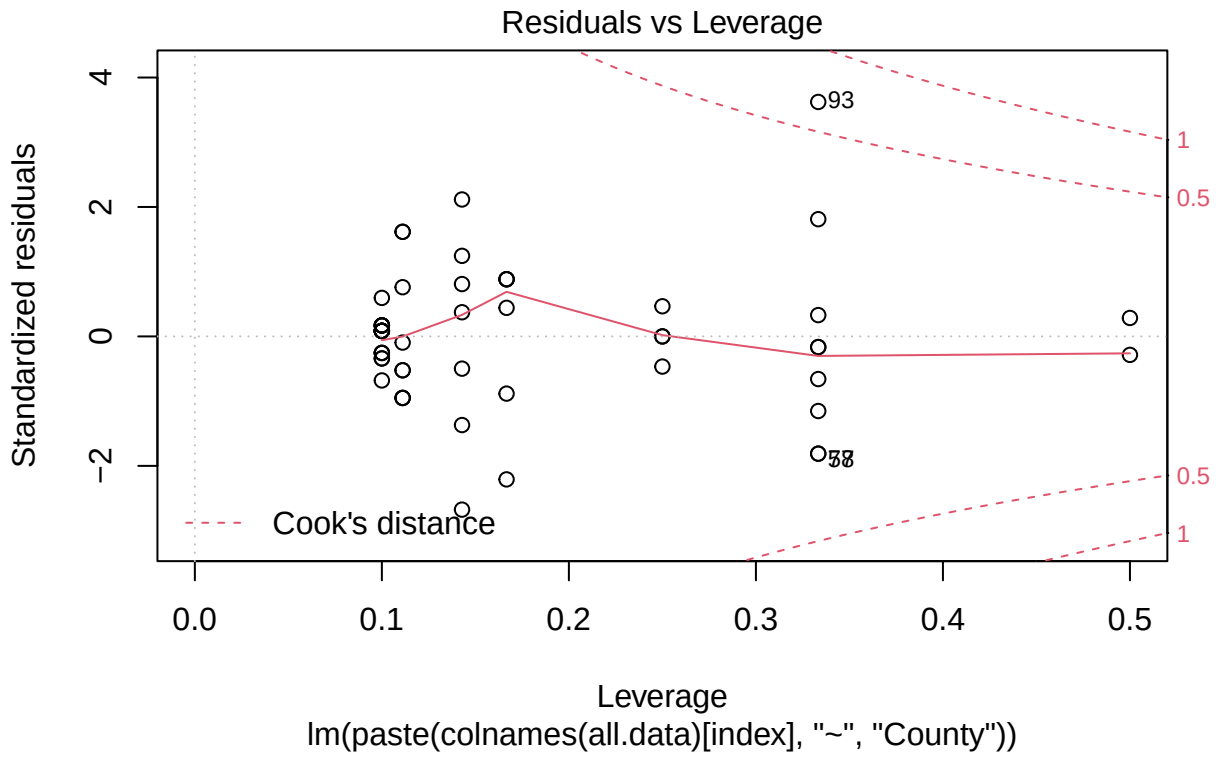

```
## NULL
##
## Call:
## lm(formula = paste(colnames(all.data)[index], "~", "County"),
##     data = all.data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.1429 -1.1429  0.2000  0.8571  7.3333
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)      3.6667     1.4314   2.562  0.01369 *
## Countycochise    1.3333     1.7532   0.761  0.45073
## Countycoconino   5.4762     1.7109   3.201  0.00246 **
## Countymaricopa  -2.8667     1.6321  -1.756  0.08553 .
## Countymohave     0.6667     2.0244   0.329  0.74338
## Countynavajo     3.6667     2.0244   1.811  0.07649 .
## Countypima      -2.0667     1.6321  -1.266  0.21166
## Countypinal     -1.6667     1.8936  -0.880  0.38326
## Countyyavapai    1.5556     1.6529   0.941  0.35146
## Countyyuma      -0.1667     2.2633  -0.074  0.94161
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## Residual standard error: 2.479 on 47 degrees of freedom
```

```
##   (43 observations deleted due to missingness)
## Multiple R-squared:  0.5896, Adjusted R-squared:  0.511
## F-statistic: 7.502 on 9 and 47 DF,  p-value: 1.054e-06
##
## Analysis of Variance Table
##
## Response: Carbon.Monoxide.Poisoning
##           Df Sum Sq Mean Sq F value    Pr(>F)
## County     9 415.02  46.113  7.5016 1.054e-06 ***
## Residuals 47 288.91   6.147
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
```



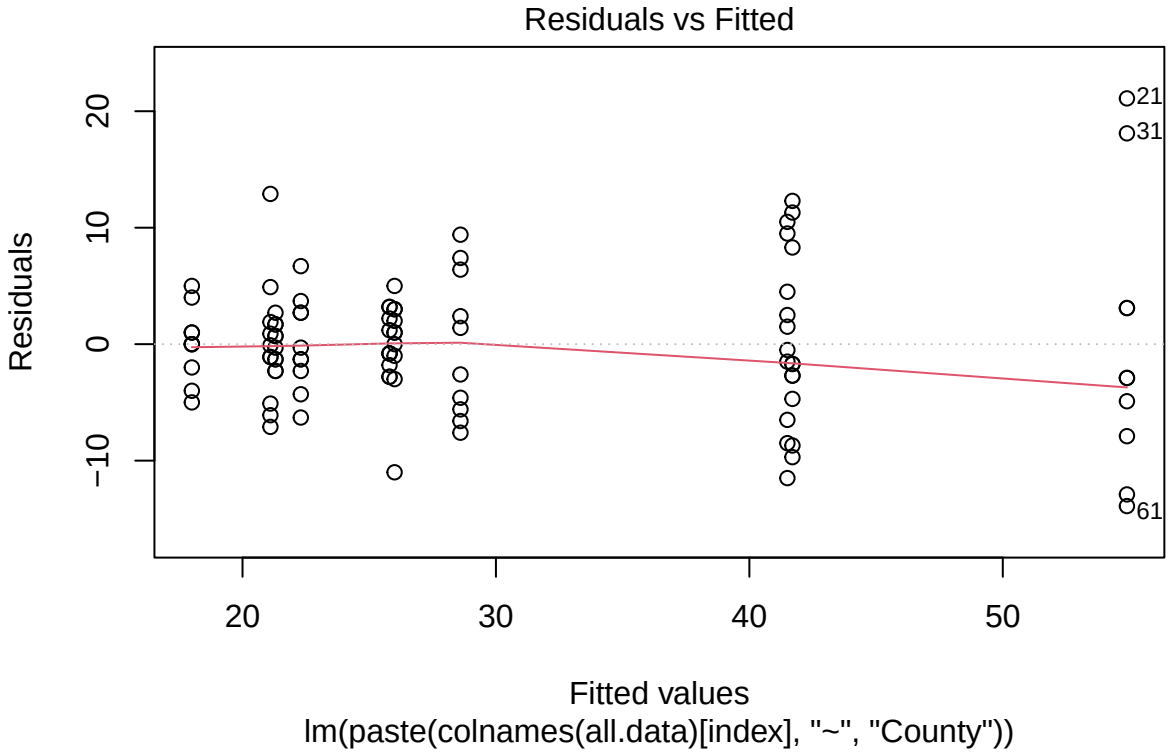

Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(paste(colnames(all.data)[index], "~", "County"))
93
47
60

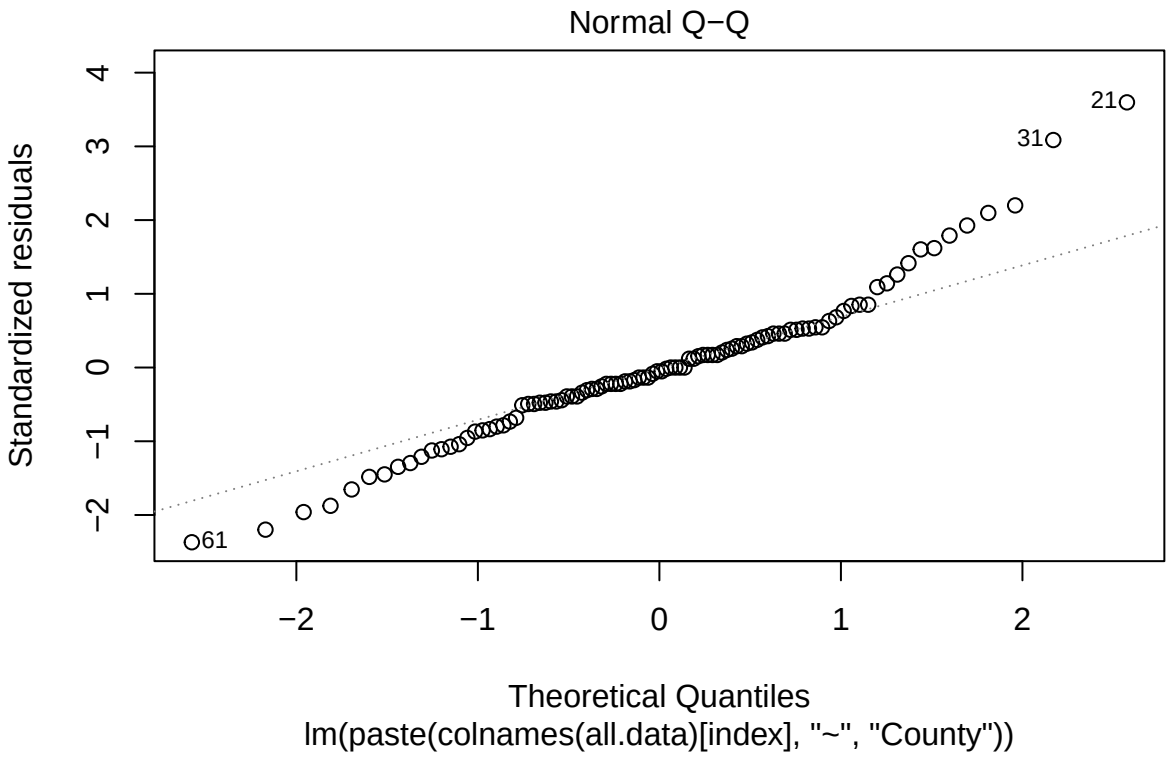

Scale−Location
93
47
60
√|Standardized residuals|
0.0
0.5
1.0
1.5
2
4
6
8
Fitted values
lm(paste(colnames(all.data)[index], "~", "County"))

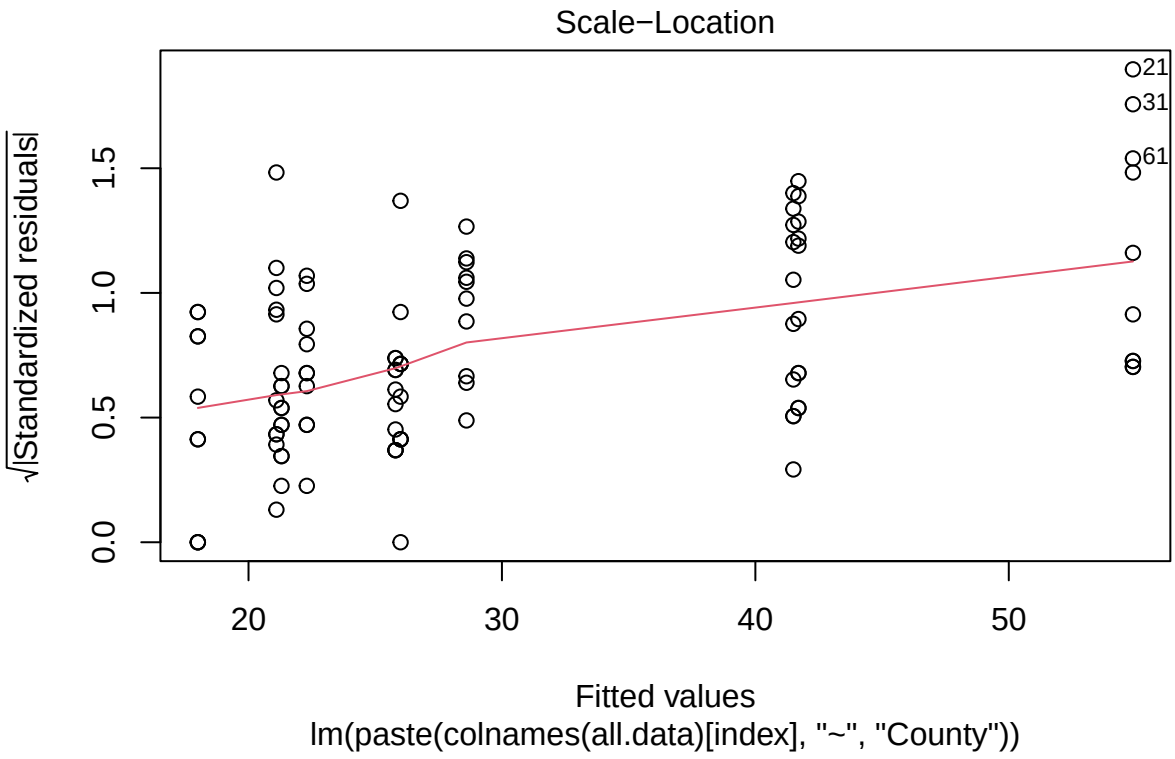


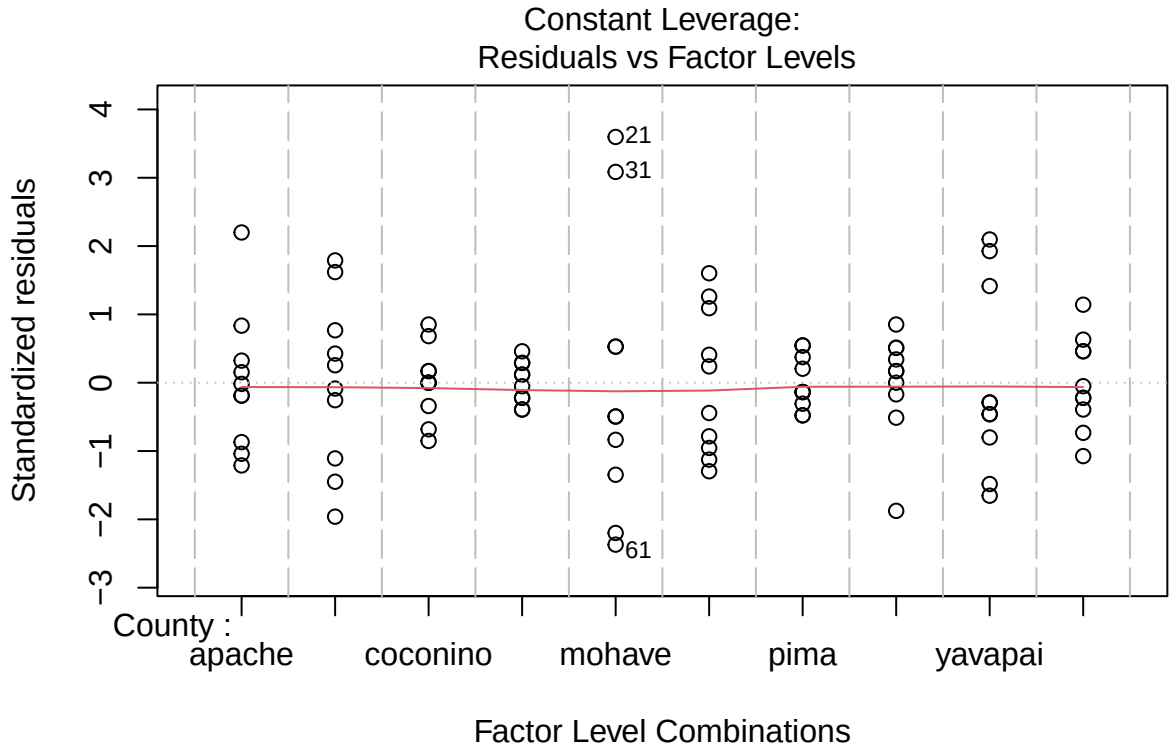

```
## NULL
##
## Call:
## lm(formula = paste(colnames(all.data)[index], "~", "County"),
##     data = all.data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -13.900  -2.825  -0.300   2.700  21.100
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)      21.100      1.955  10.792  < 2e-16 ***
## Countycochise    20.400      2.765   7.378 7.66e-11 ***
## Countycoconino   -3.100      2.765  -1.121   0.2652
## Countymaricopa    0.200      2.765   0.072   0.9425
## Countymohave     33.800      2.765  12.224  < 2e-16 ***
## Countynavajo      7.500      2.765   2.712   0.0080 **
## Countypima        4.700      2.765   1.700   0.0926 .
## Countypinal       4.900      2.765   1.772   0.0798 .
## Countyyavapai    20.600      2.765   7.450 5.46e-11 ***
## Countyyuma        1.200      2.765   0.434   0.6653
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.183 on 90 degrees of freedom
```

```
## Multiple R-squared:  0.7885, Adjusted R-squared:  0.7674
## F-statistic: 37.28 on 9 and 90 DF,  p-value: < 2.2e-16
##
## Analysis of Variance Table
##
## Response: COPD
##           Df  Sum Sq Mean Sq F value    Pr(>F)
## County     9 12828.0 1425.33  37.284 < 2.2e-16 ***
## Residuals 90  3440.6   38.23
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



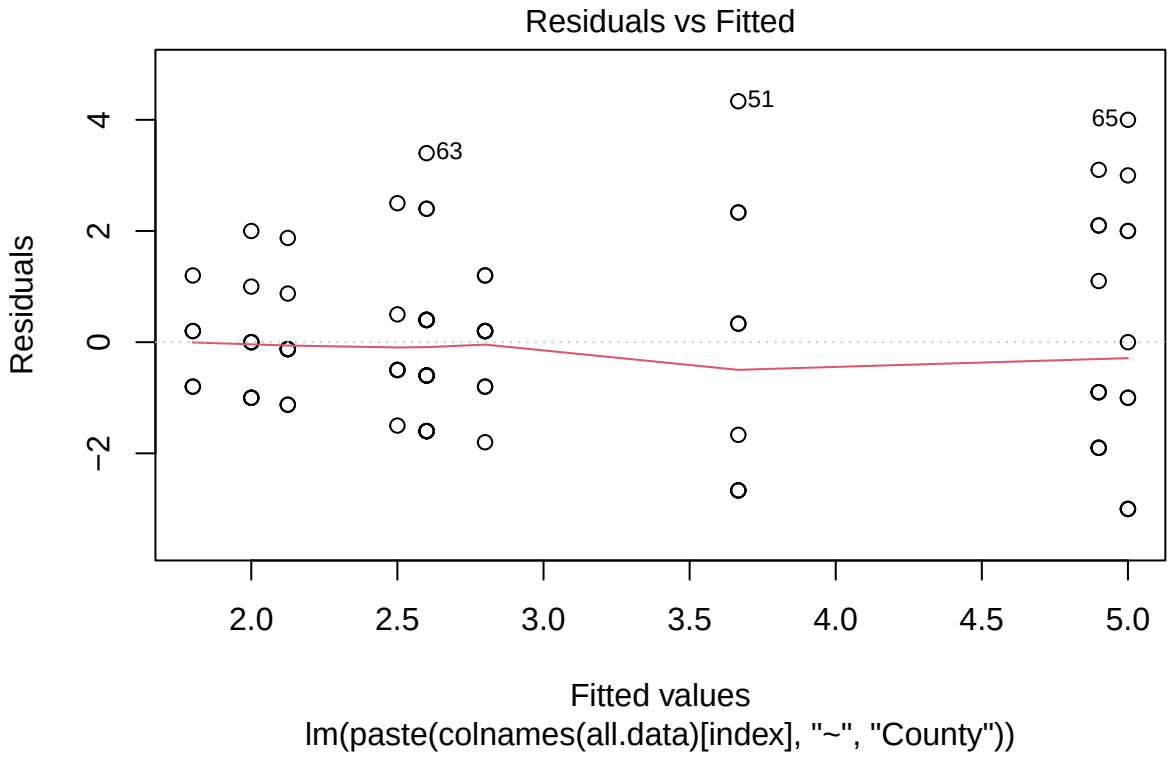

Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(paste(colnames(all.data)[index], "~", "County"))
21
31
61

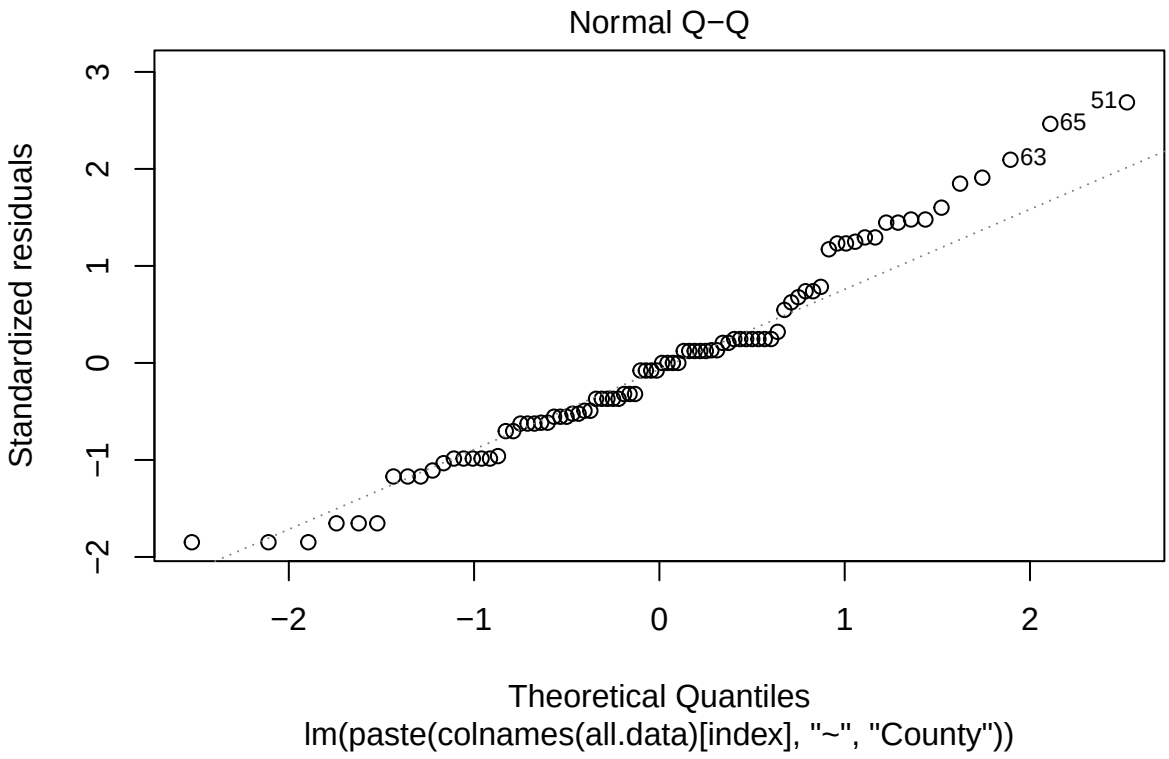

Scale−Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
20
30
40
50
21
31
61
Fitted values
lm(paste(colnames(all.data)[index], "~", "County"))

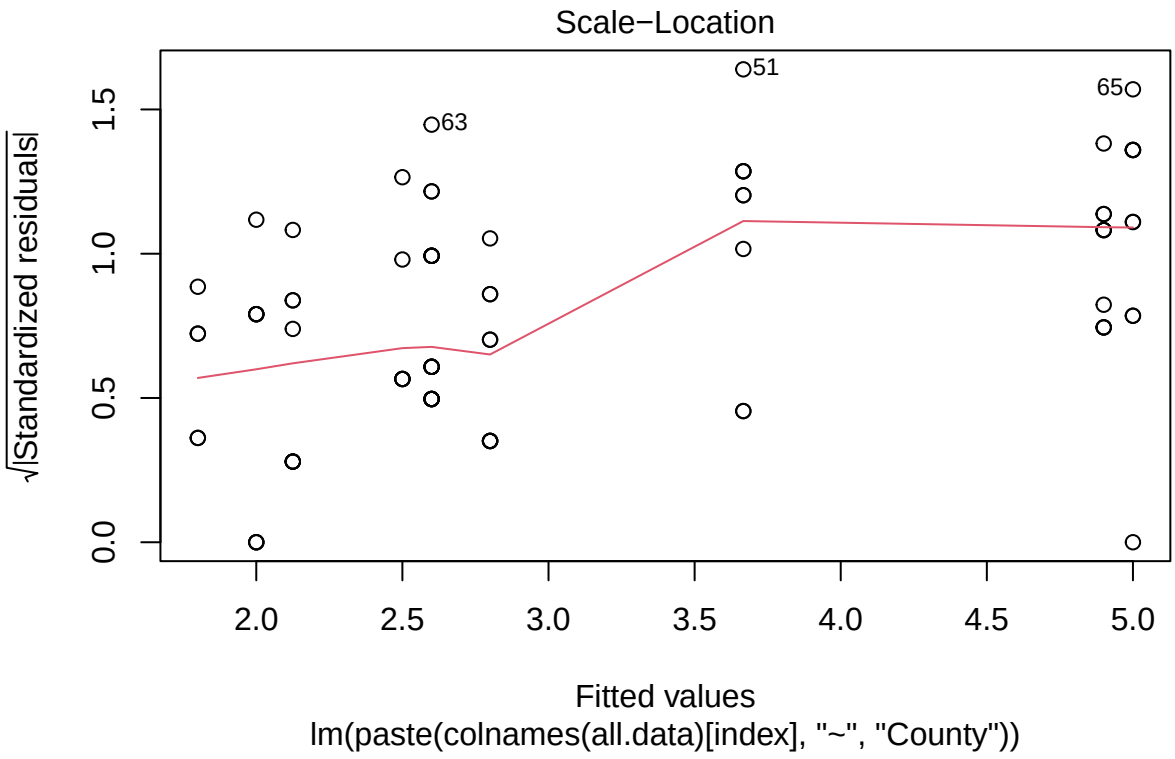


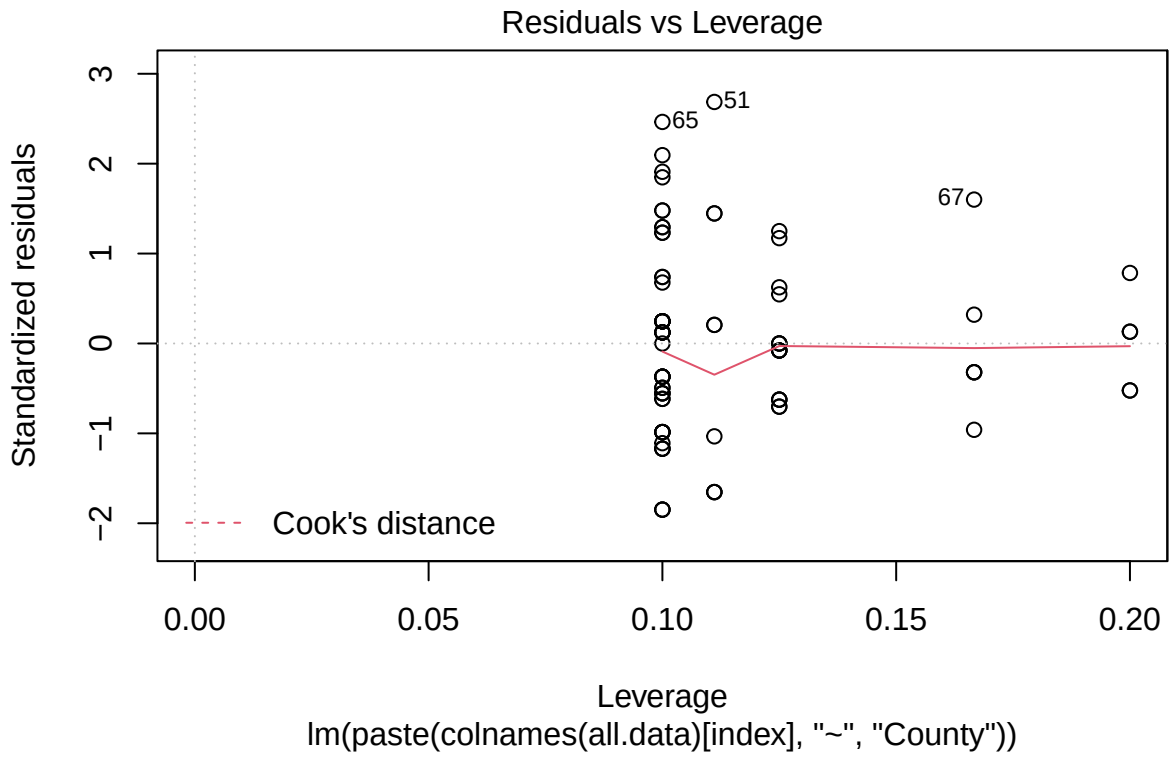

```
## NULL
##
## Call:
## lm(formula = paste(colnames(all.data)[index], "~", "County"),
##     data = all.data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.0000 -1.0000 -0.0625  0.7812  4.3333
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)      1.8000     0.7652   2.352  0.02124 *
## Countycochise    0.8000     0.9371   0.854  0.39596
## Countycoconino   0.2000     0.9754   0.205  0.83808
## Countymaricopa   3.2000     0.9371   3.415  0.00103 **
## Countymohave     1.8667     0.9543   1.956  0.05414 .
## Countynavajo     0.3250     0.9754   0.333  0.73990
## Countypima       3.1000     0.9371   3.308  0.00144 **
## Countypinal      0.7000     1.0360   0.676  0.50131
## Countyyavapai    1.0000     0.9371   1.067  0.28930
## Countyyuma       0.8000     0.9371   0.854  0.39596
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.711 on 76 degrees of freedom
```

```
##   (14 observations deleted due to missingness)
## Multiple R-squared:  0.3209, Adjusted R-squared:  0.2405
## F-statistic:  3.99 on 9 and 76 DF,  p-value: 0.0003327
##
## Analysis of Variance Table
##
## Response: Drinking.Water.Quality
##           Df Sum Sq Mean Sq F value    Pr(>F)
## County     9 105.12 11.6798  3.9899 0.0003327 ***
## Residuals 76 222.47  2.9273
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
```



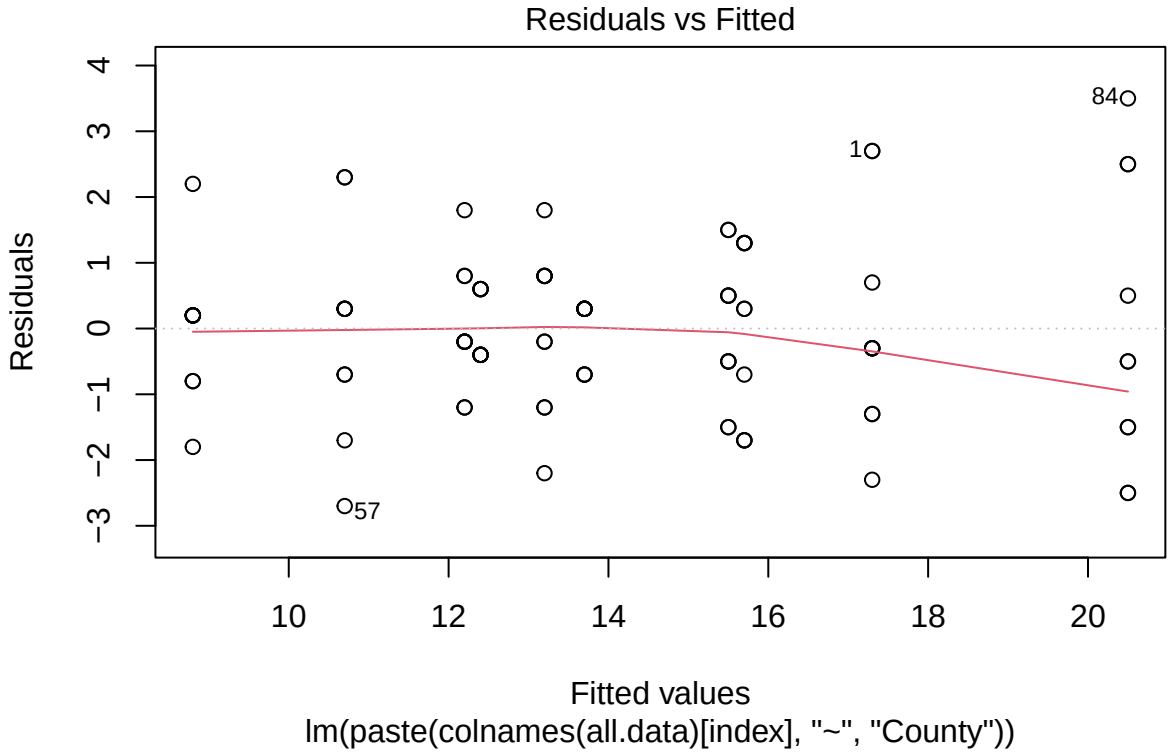

Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(paste(colnames(all.data)[index], "~", "County"))
51
65
63
−2
−1
0
1
2
3

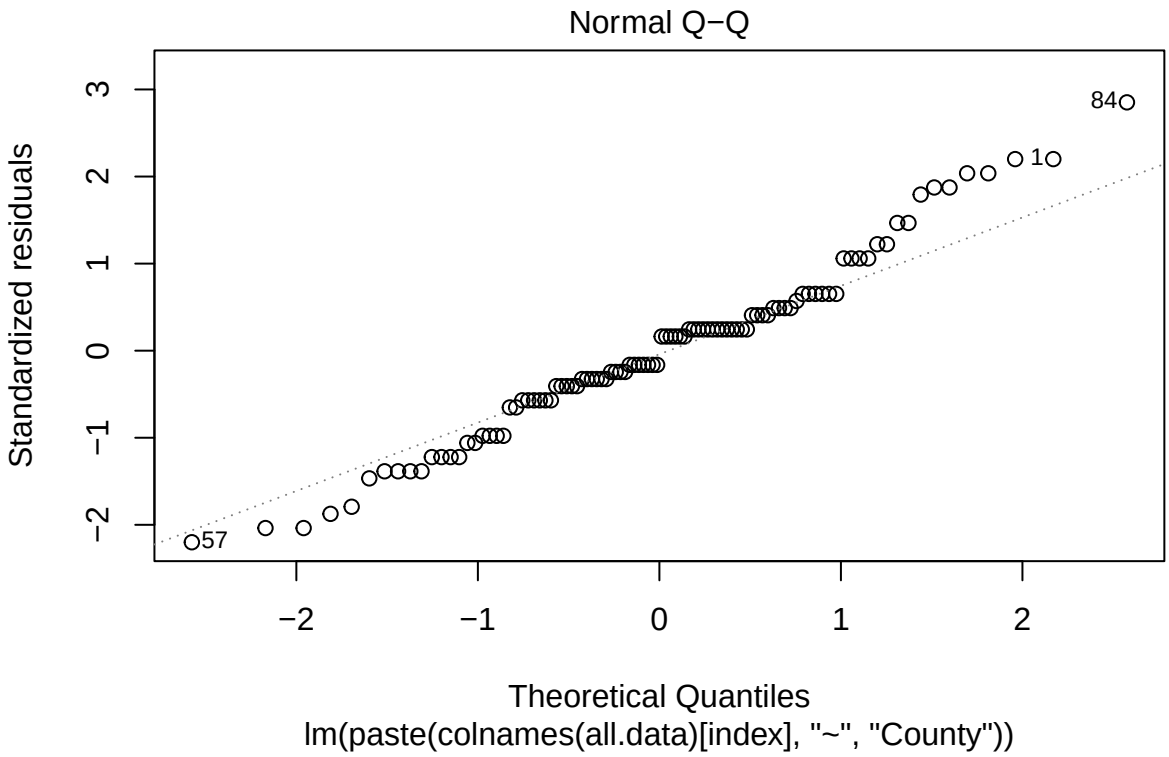

Scale−Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
63
51
65
Fitted values
lm(paste(colnames(all.data)[index], "~", "County"))

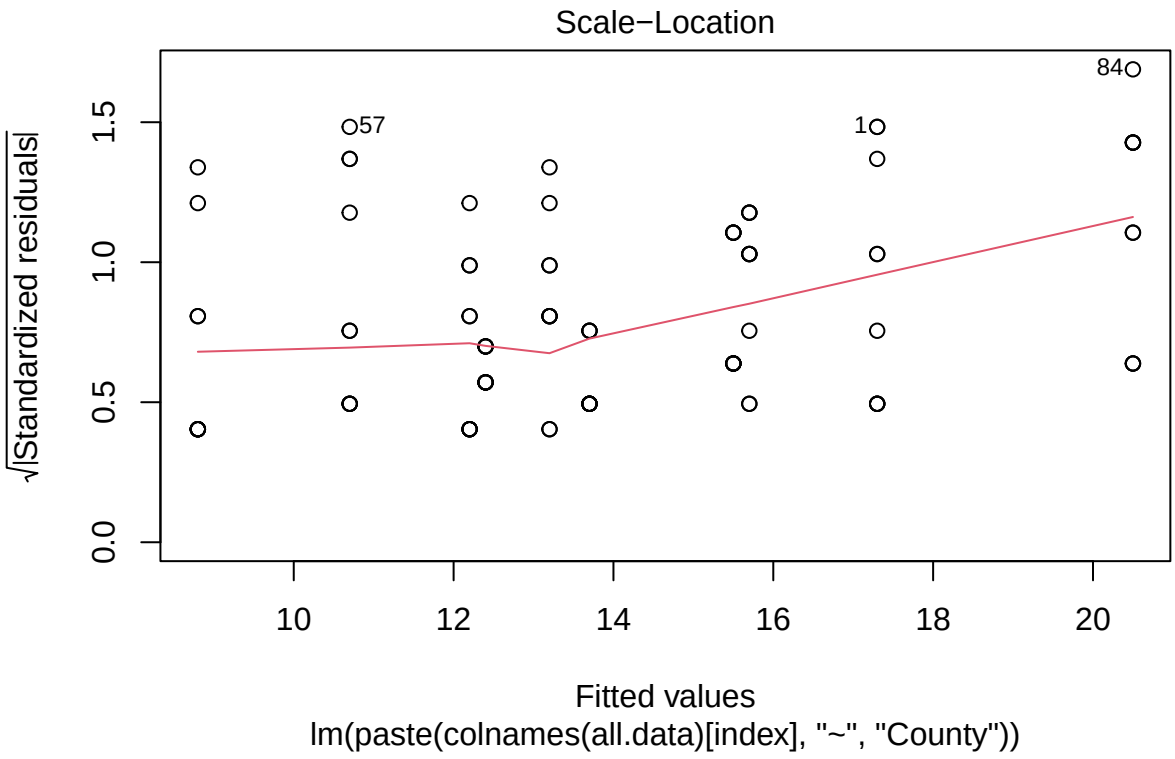


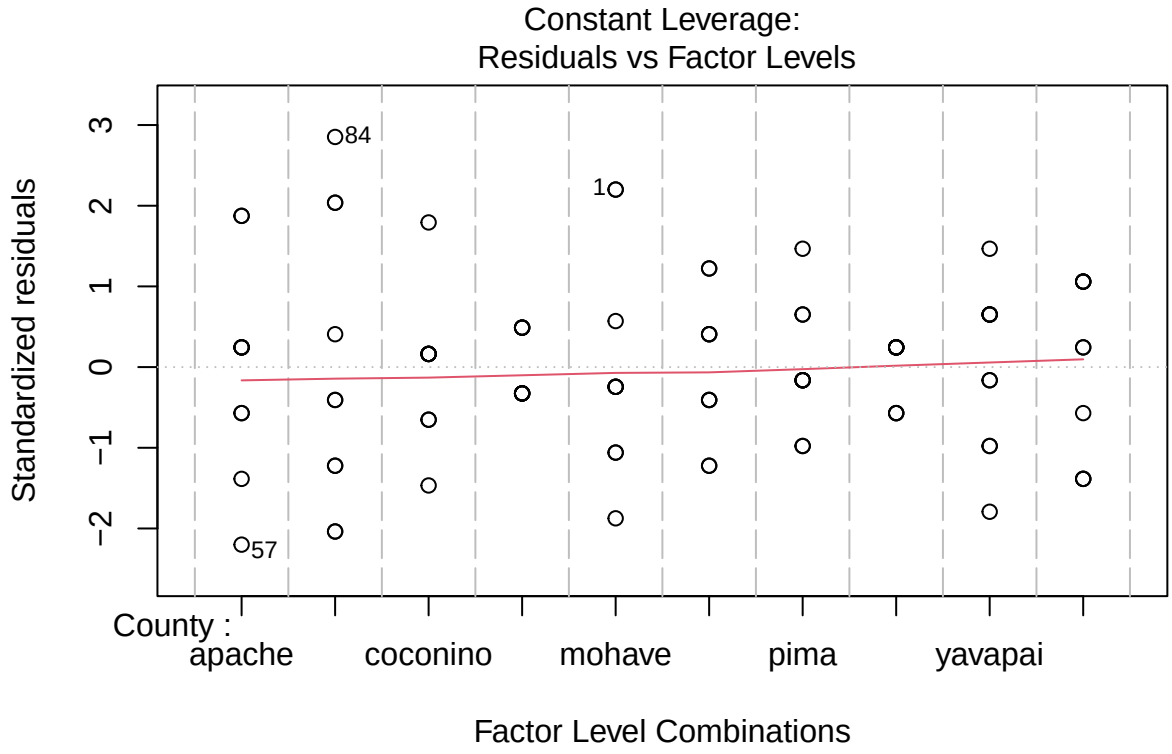

```
## NULL
##
## Call:
## lm(formula = paste(colnames(all.data)[index], "~", "County"),
##     data = all.data)
##
## Residuals:
##    Min     1Q Median     3Q    Max
##   -2.7   -0.7    0.0    0.6    3.5
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)     10.7000     0.4091  26.157  < 2e-16 ***
## Countycochise    9.8000     0.5785  16.940  < 2e-16 ***
## Countycoconino  -1.9000     0.5785  -3.284  0.00146 **
## Countymaricopa   1.7000     0.5785   2.939  0.00419 **
## Countymohave     6.6000     0.5785  11.409  < 2e-16 ***
## Countynavajo     4.8000     0.5785   8.297 9.92e-13 ***
## Countypima       1.5000     0.5785   2.593  0.01111 *
## Countypinal      3.0000     0.5785   5.186 1.31e-06 ***
## Countyyavapai    2.5000     0.5785   4.321 3.99e-05 ***
## Countyyuma       5.0000     0.5785   8.643 1.90e-13 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.294 on 90 degrees of freedom
```

```
## Multiple R-squared:  0.8722, Adjusted R-squared:  0.8594
## F-statistic: 68.22 on 9 and 90 DF,  p-value: < 2.2e-16
##
## Analysis of Variance Table
##
## Response: Heart.Disease
##           Df Sum Sq Mean Sq F value    Pr(>F)
## County     9 1027.4 114.156  68.221 < 2.2e-16 ***
## Residuals 90  150.6   1.673
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



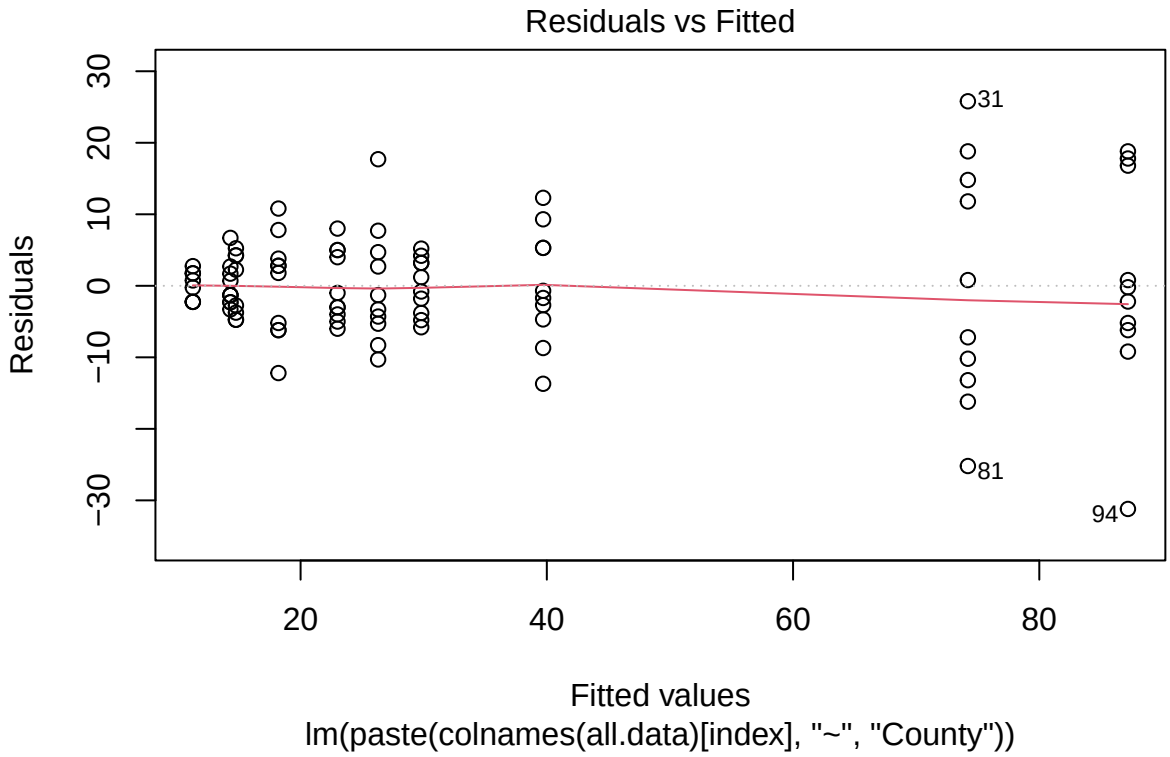

Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(paste(colnames(all.data)[index], "~", "County"))
84
1
57
−2
−1
0
1
2
3

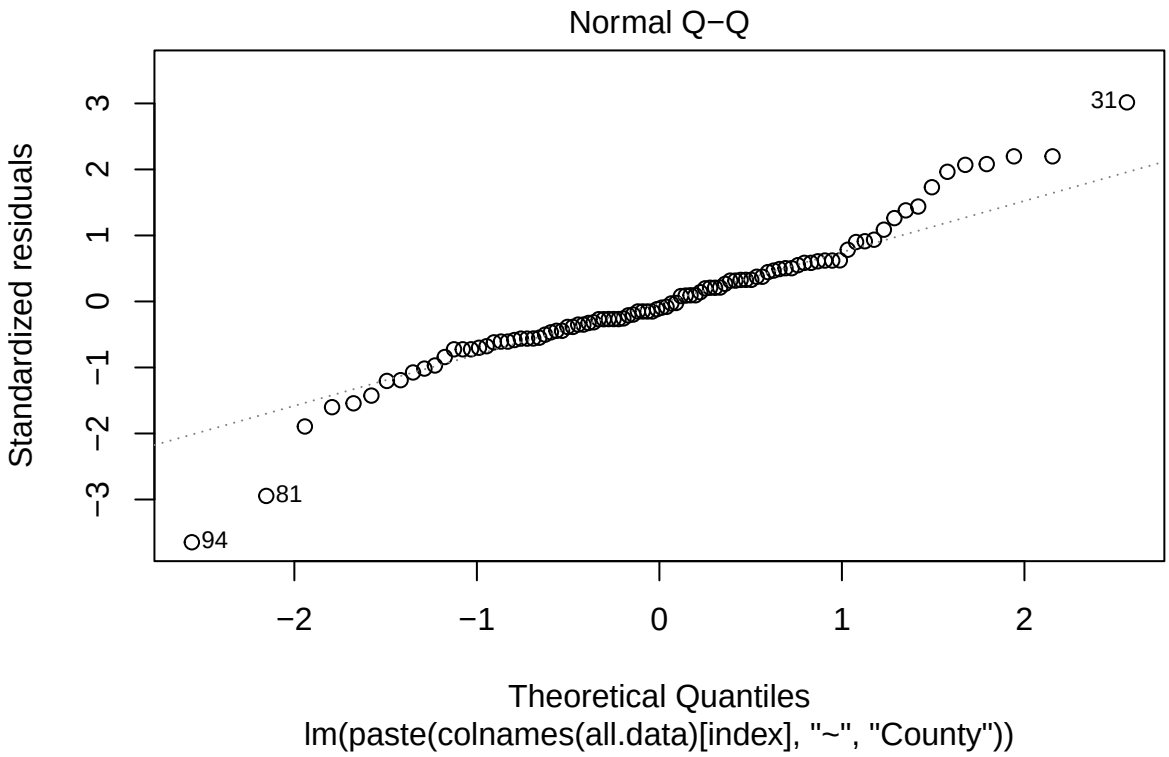

Scale−Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
57
1
84
10
12
14
16
18
20
Fitted values
lm(paste(colnames(all.data)[index], "~", "County"))

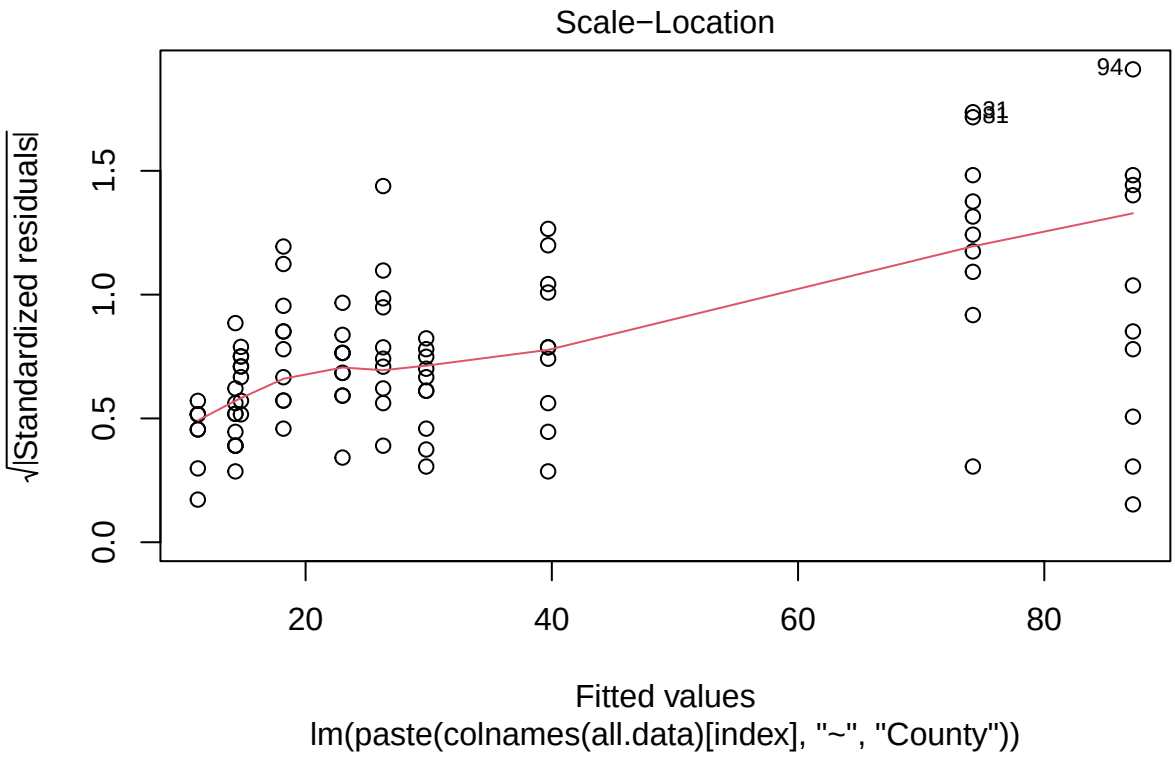


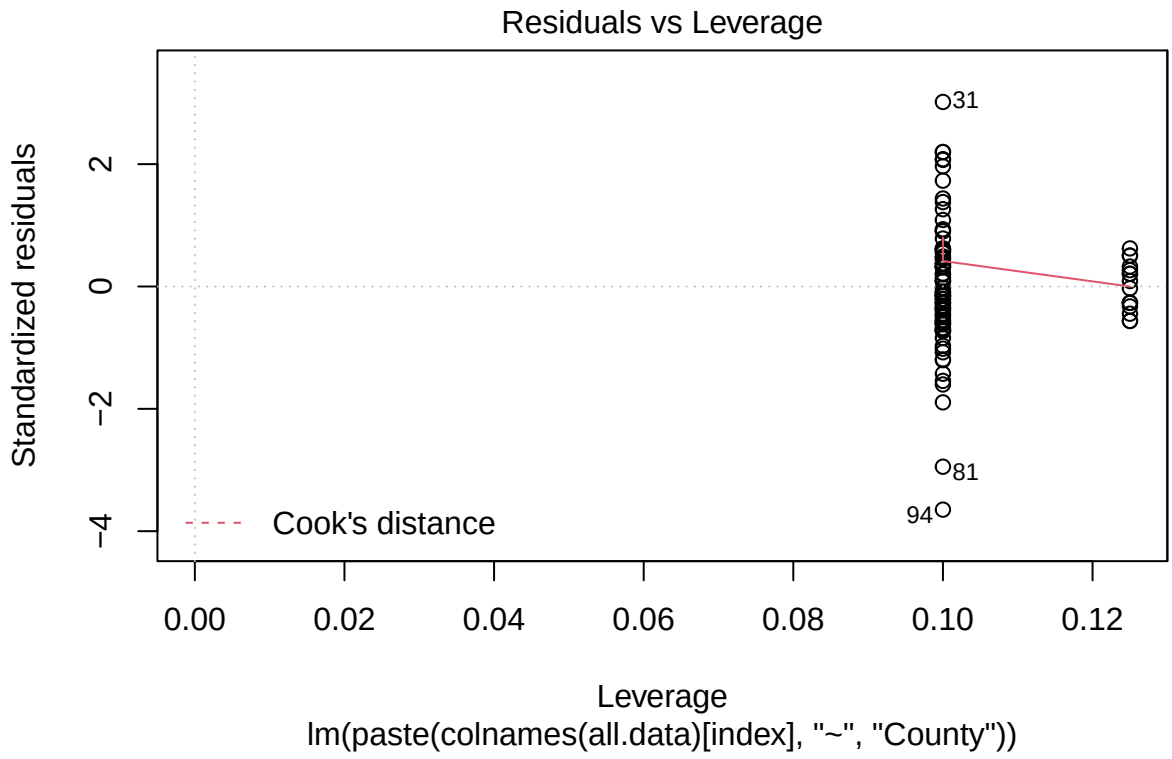

```
## NULL
##
## Call:
## lm(formula = paste(colnames(all.data)[index], "~", "County"),
##     data = all.data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -31.200  -4.713  -0.900   4.213  25.800
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)      11.250      3.188   3.529 0.000672 ***
## Countycochise    15.050      4.277   3.519 0.000695 ***
## Countycoconino    3.050      4.277   0.713 0.477698
## Countymaricopa   18.550      4.277   4.337 3.91e-05 ***
## Countymohave     62.950      4.277  14.718  < 2e-16 ***
## Countynavajo      3.500      4.508   0.776 0.439674
## Countypima       11.750      4.277   2.747 0.007319 **
## Countypinal      28.450      4.277   6.652 2.55e-09 ***
## Countyyavapai     6.950      4.277   1.625 0.107824
## Countyyuma       75.950      4.277  17.758  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.017 on 86 degrees of freedom
```

```
##   (4 observations deleted due to missingness)
## Multiple R-squared:  0.8959, Adjusted R-squared:  0.885
## F-statistic: 82.27 on 9 and 86 DF,  p-value: < 2.2e-16
##
## Analysis of Variance Table
##
## Response: Heat.Stress.Illness
##           Df Sum Sq Mean Sq F value    Pr(>F)
## County     9  60197  6688.5  82.271 < 2.2e-16 ***
## Residuals 86   6992    81.3
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
```



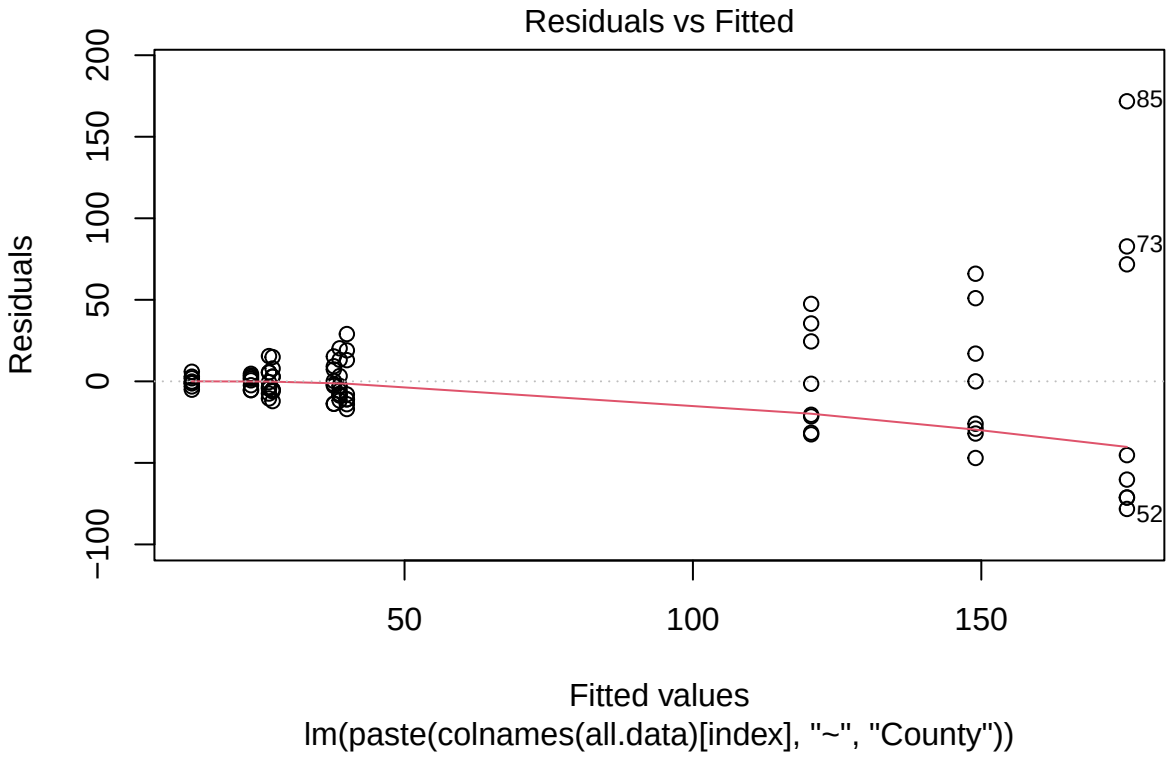

Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(paste(colnames(all.data)[index], "~", "County"))
31
81
94
−3
−2
−1
0
1
2
3

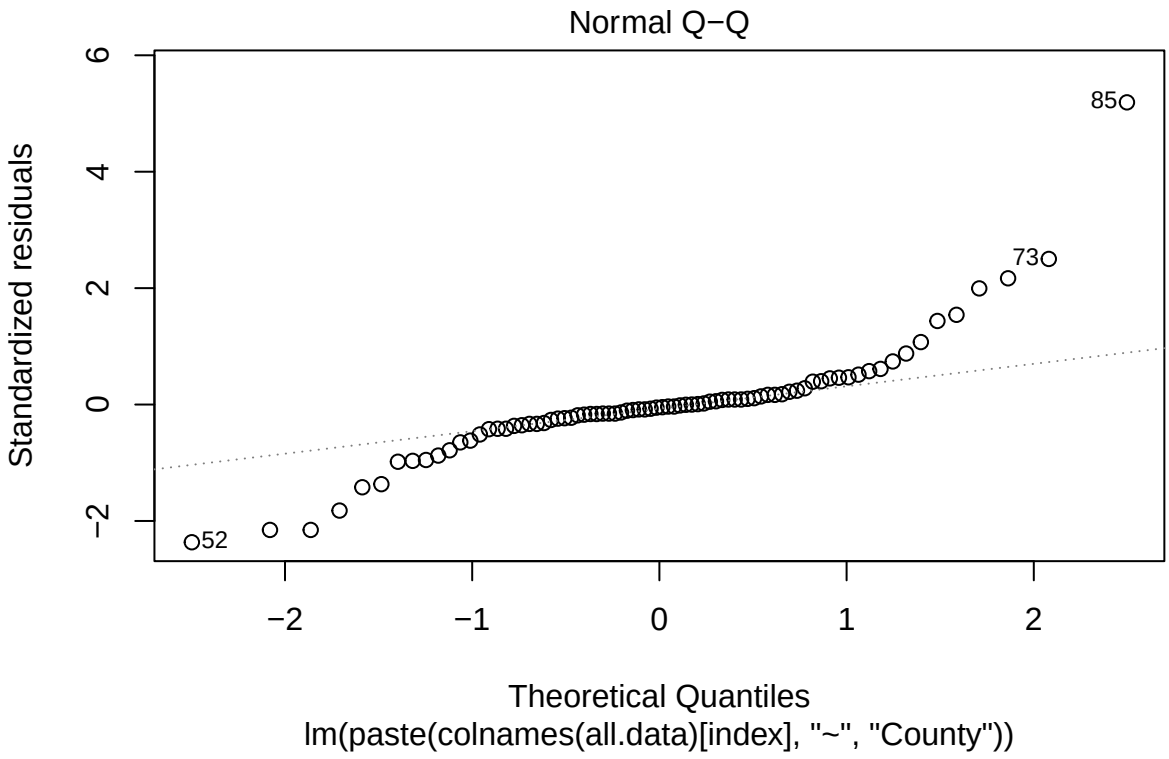

Scale−Location
94
√|Standardized residuals|
0.0
0.5
1.0
1.5
20
40
60
80
Fitted values
lm(paste(colnames(all.data)[index], "~", "County"))

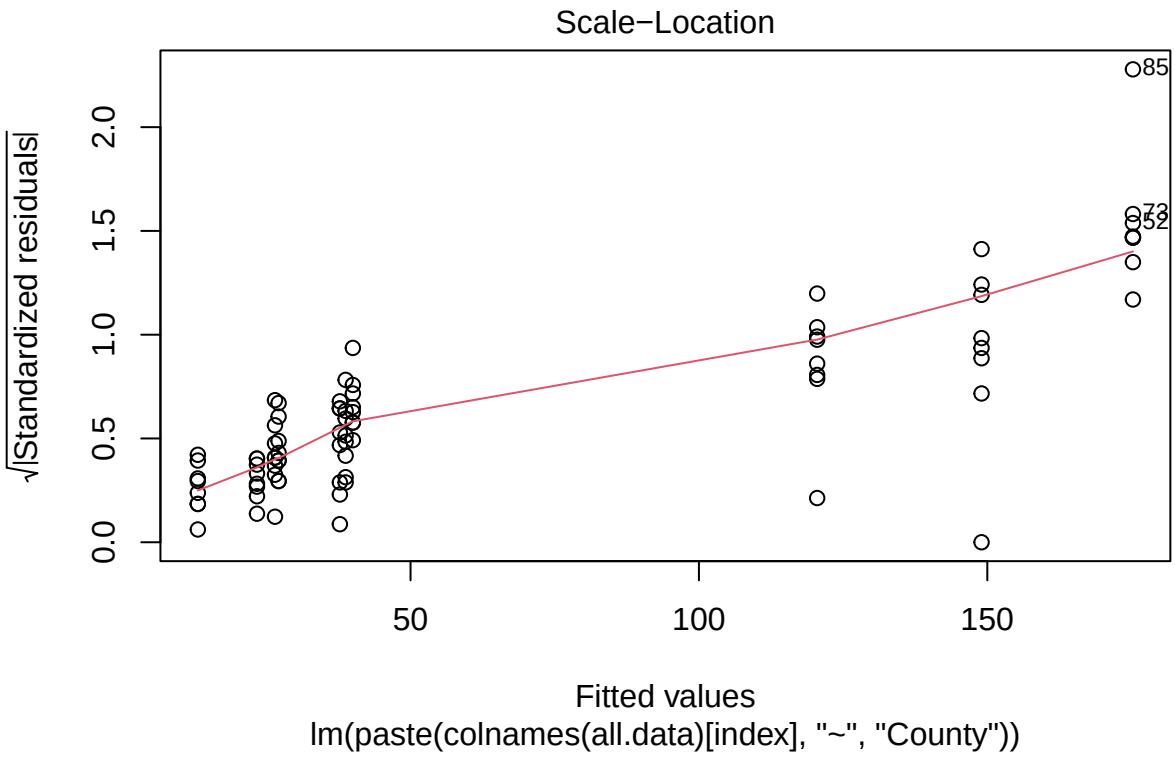


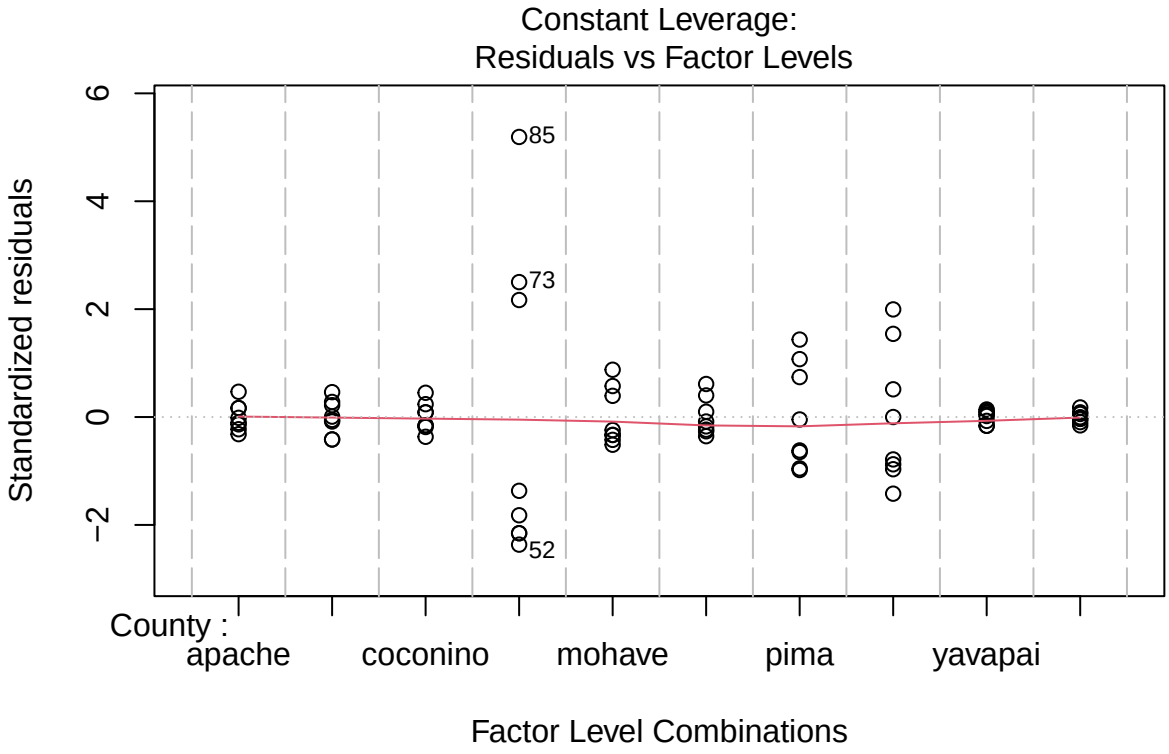

```
## NULL
##
## Call:
## lm(formula = paste(colnames(all.data)[index], "~", "County"),
##     data = all.data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -78.250 -11.000  -1.625   6.219 171.750
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)      26.500     12.504   2.119   0.0376 *
## Countycochise    11.250     17.683   0.636   0.5267
## Countycoconino    0.625     17.683   0.035   0.9719
## Countymaricopa  148.750     17.683   8.412 3.18e-12 ***
## Countymohave     13.500     17.683   0.763   0.4478
## Countynavajo     12.250     17.683   0.693   0.4908
## Countypima       94.000     17.683   5.316 1.20e-06 ***
## Countypinal     122.500     17.683   6.927 1.69e-09 ***
## Countyyavapai    -3.125     17.683  -0.177   0.8602
## Countyyuma      -13.375     17.683  -0.756   0.4520
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 35.37 on 70 degrees of freedom
```

```
##   (20 observations deleted due to missingness)
## Multiple R-squared:  0.7433, Adjusted R-squared:  0.7103
## F-statistic: 22.52 on 9 and 70 DF,  p-value: < 2.2e-16
##
## Analysis of Variance Table
##
## Response: Infectious.Diseases
##           Df Sum Sq Mean Sq F value    Pr(>F)
## County     9 253505 28167.3  22.519 < 2.2e-16 ***
## Residuals 70  87556  1250.8
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



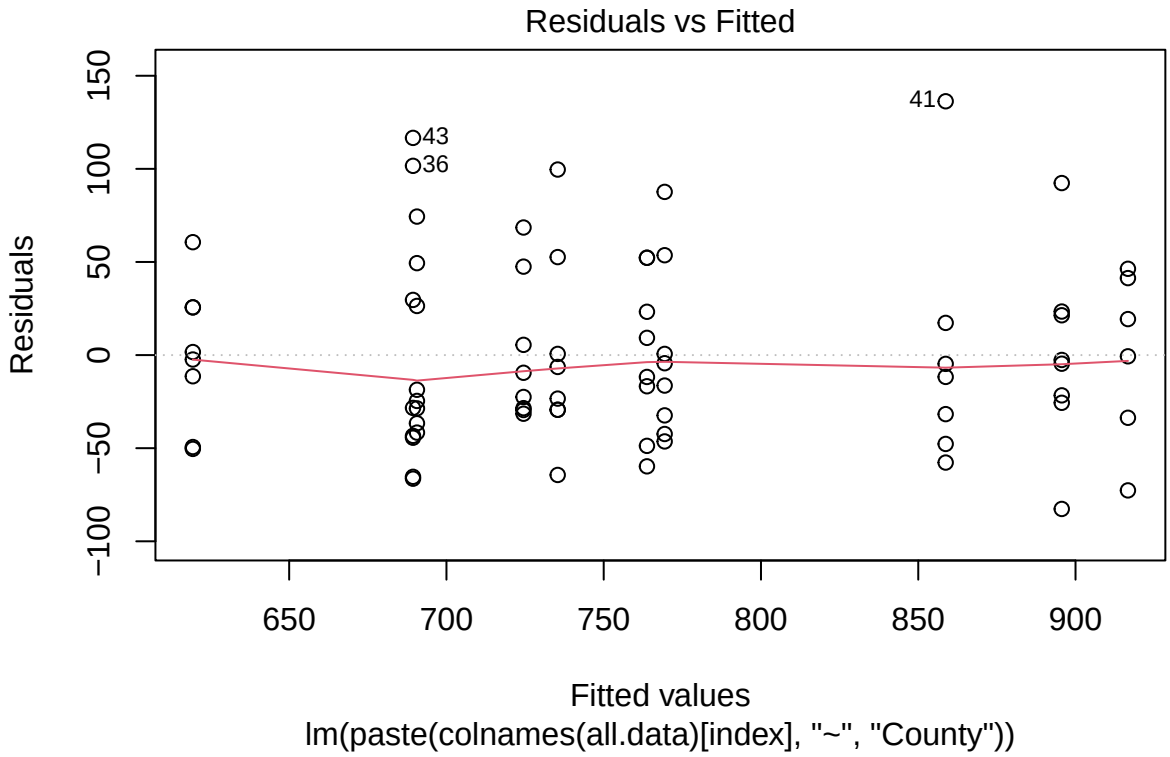

Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(paste(colnames(all.data)[index], "~", "County"))
85
73
52
−2
0
2
4
6
−2
−1
0
1
2

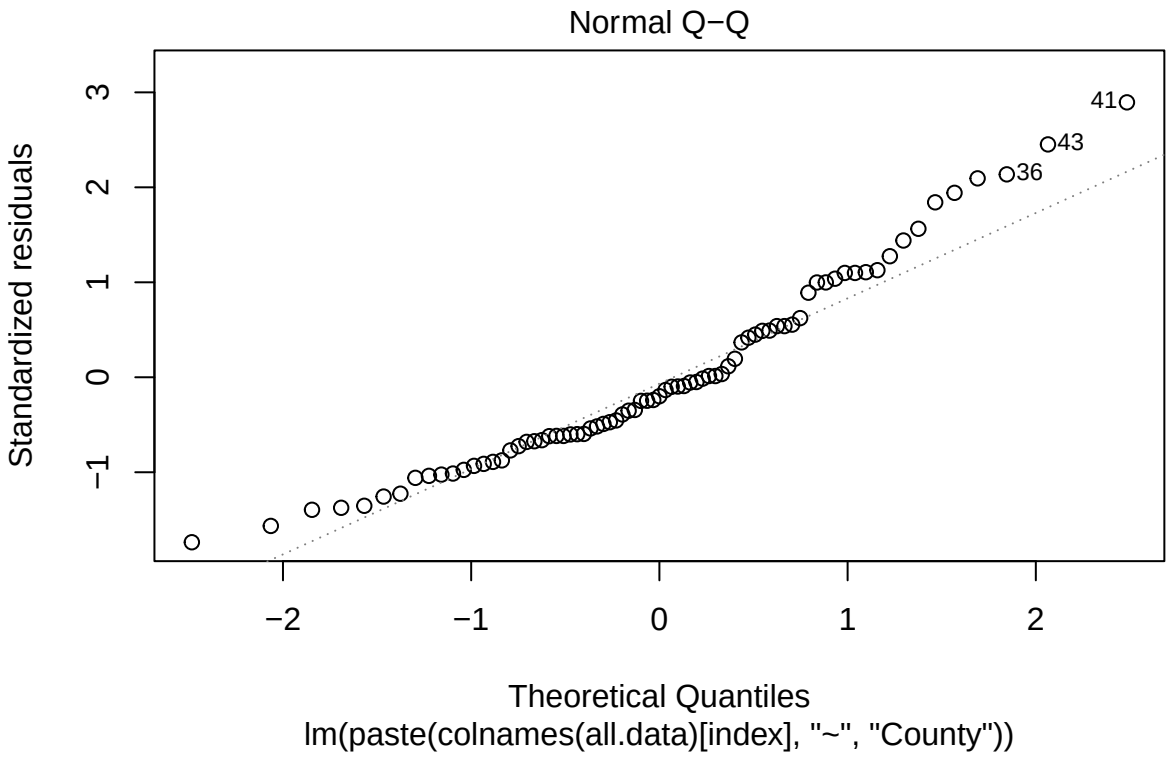

Scale−Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
50
100
150
85
73
52
Fitted values
lm(paste(colnames(all.data)[index], "~", "County"))

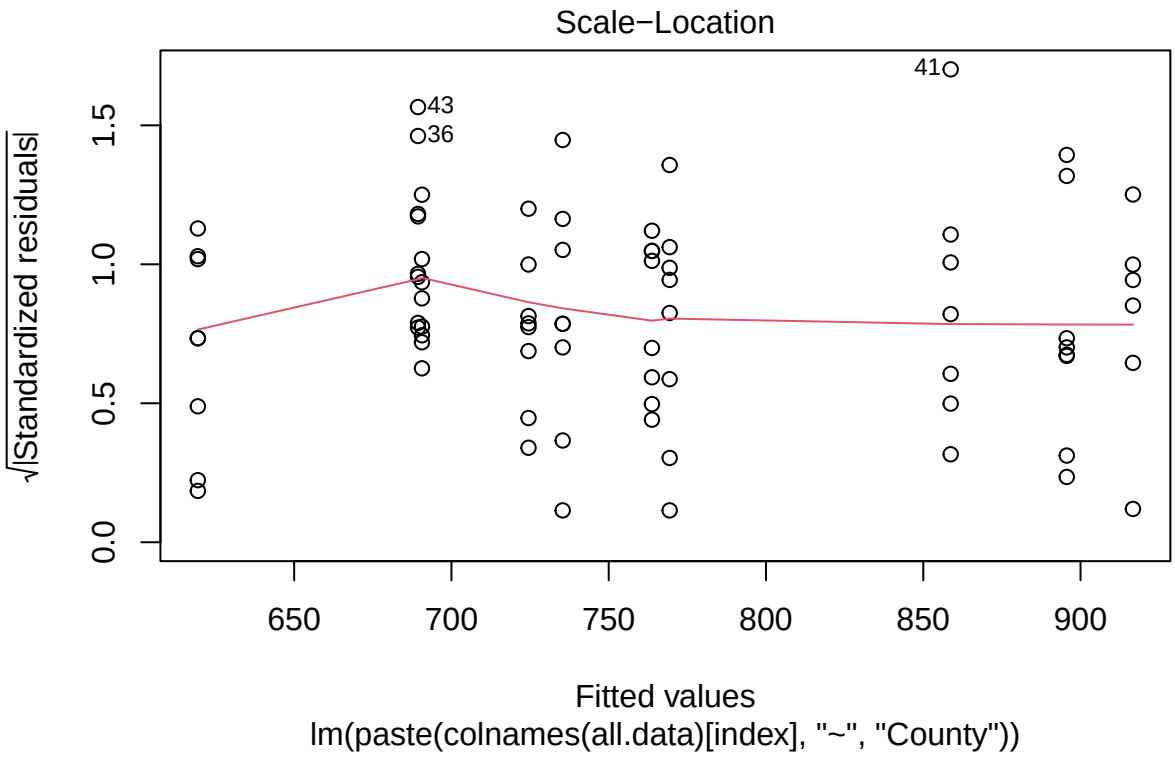


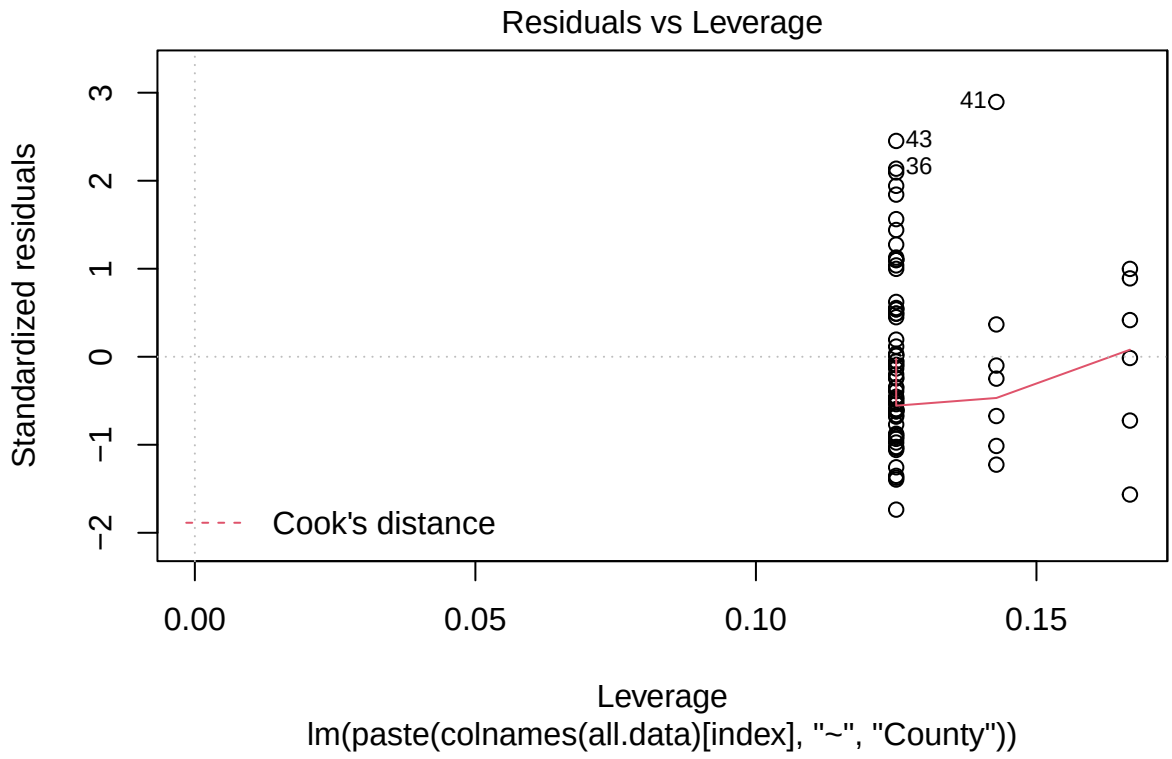

```
## NULL
##
## Call:
## lm(formula = paste(colnames(all.data)[index], "~", "County"),
##     data = all.data)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -82.62 -31.71  -9.50  25.62 136.29
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)      916.67      20.76  44.156  < 2e-16 ***
## Countycochise   -147.29      27.46  -5.363 1.09e-06 ***
## Countycoconino  -181.29      27.46  -6.601 7.78e-09 ***
## Countymaricopa  -226.04      27.46  -8.231 9.23e-12 ***
## Countymohave     -57.95      28.29  -2.048   0.0444 *
## Countynavajo     -21.04      27.46  -0.766   0.4463
## Countypima      -192.17      27.46  -6.997 1.53e-09 ***
## Countypinal     -227.29      27.46  -8.276 7.64e-12 ***
## Countyyavapai   -152.92      27.46  -5.568 4.91e-07 ***
## Countyyuma      -297.29      27.46 -10.825 2.34e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 50.85 on 67 degrees of freedom
```

```
##   (23 observations deleted due to missingness)
## Multiple R-squared:  0.7802, Adjusted R-squared:  0.7506
## F-statistic: 26.42 on 9 and 67 DF,  p-value: < 2.2e-16
##
## Analysis of Variance Table
##
## Response: Mortality
##           Df Sum Sq Mean Sq F value    Pr(>F)
## County     9 614872   68319  26.421 < 2.2e-16 ***
## Residuals 67 173250    2586
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```




Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(paste(colnames(all.data)[index], "~", "County"))
41
43
36
−2
−1
0
1
2
−1
0
1
2
3


Scale−Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
650
700
750
800
850
900
43
36
41
Fitted values
lm(paste(colnames(all.data)[index], "~", "County"))

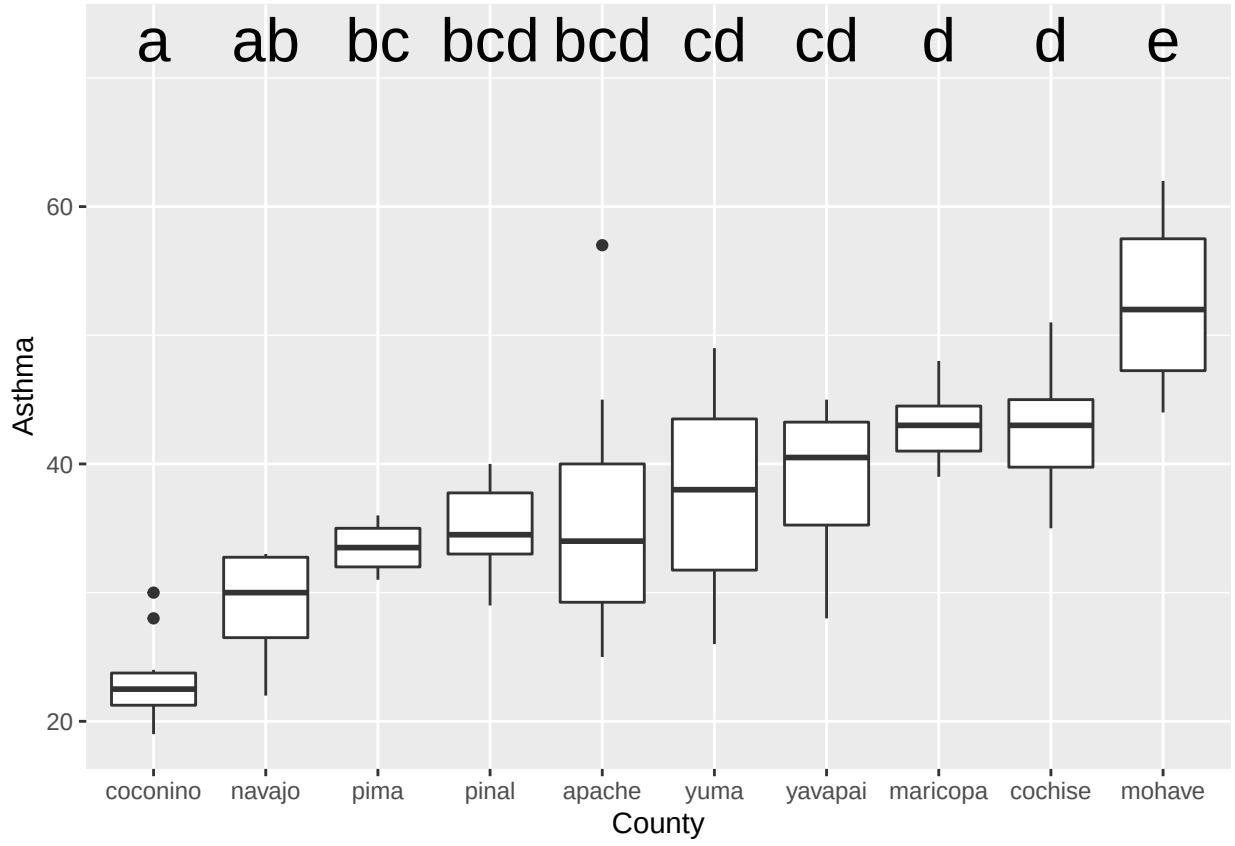



```
## NULL
```

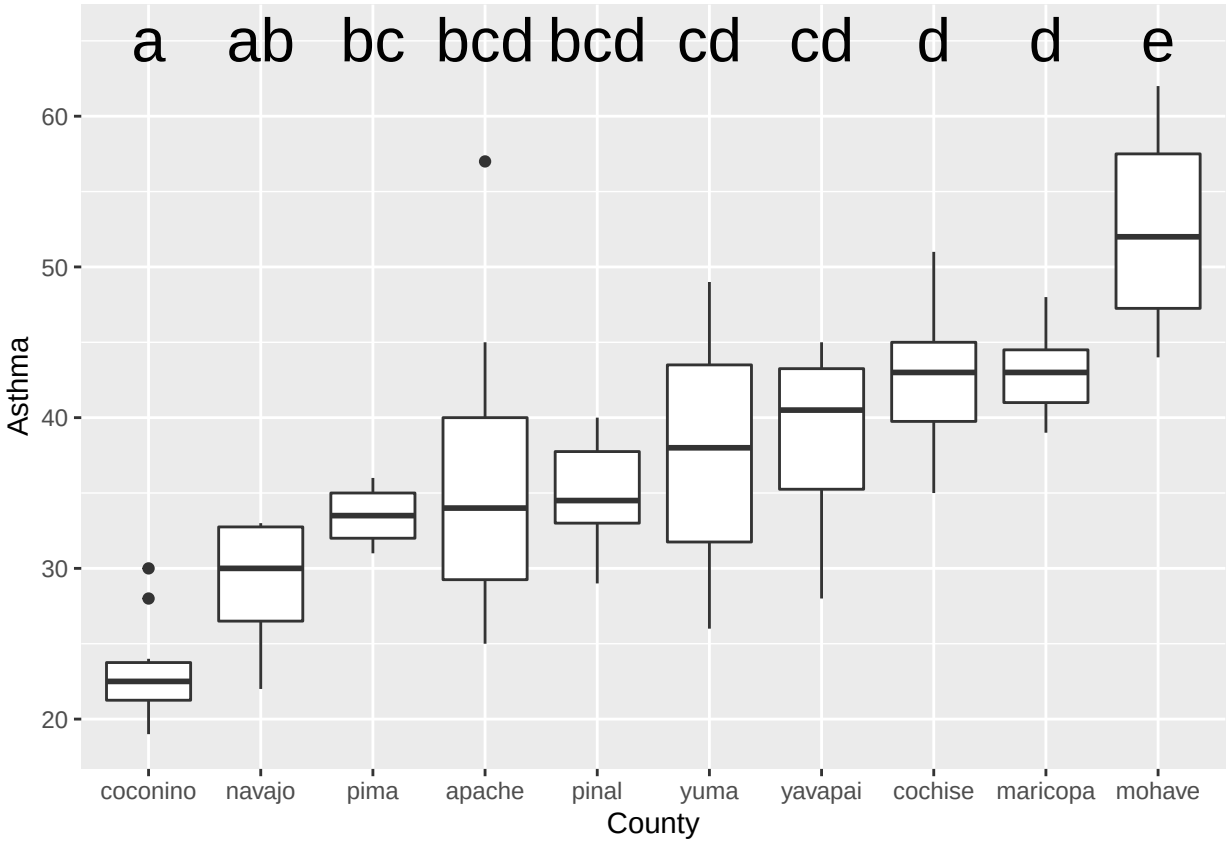
```
content.area.p <- content.area.p %>% arrange(p.value)
```

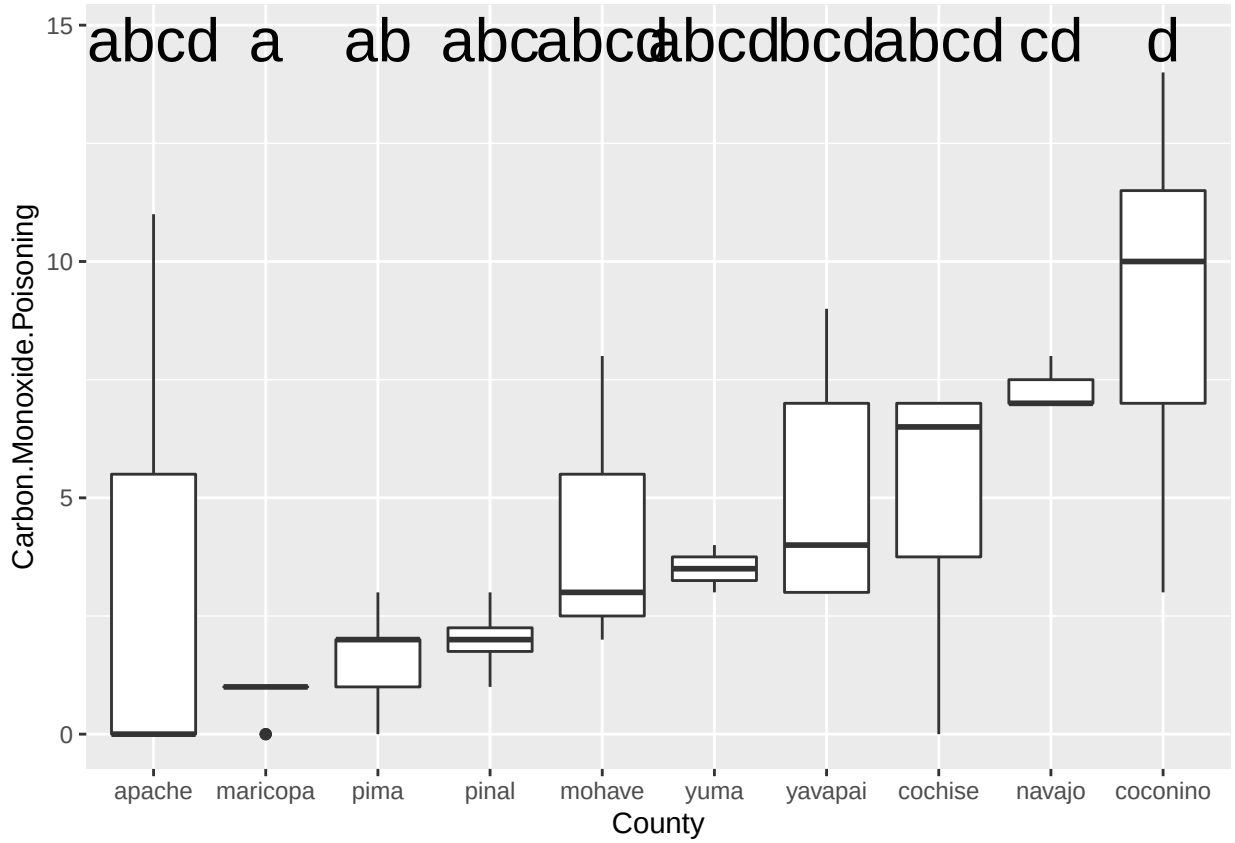
```
obj <- lm(Asthma ~ County, data=all.data)
letter.data.asthma <- emmeans(obj, specs = ~ County) %>%
  multcomp::cld(Letters = letters, level = 0.95) %>%
  mutate(.group = str_remove_all(.group, '\\s')) %>%
  mutate(y=73)
```

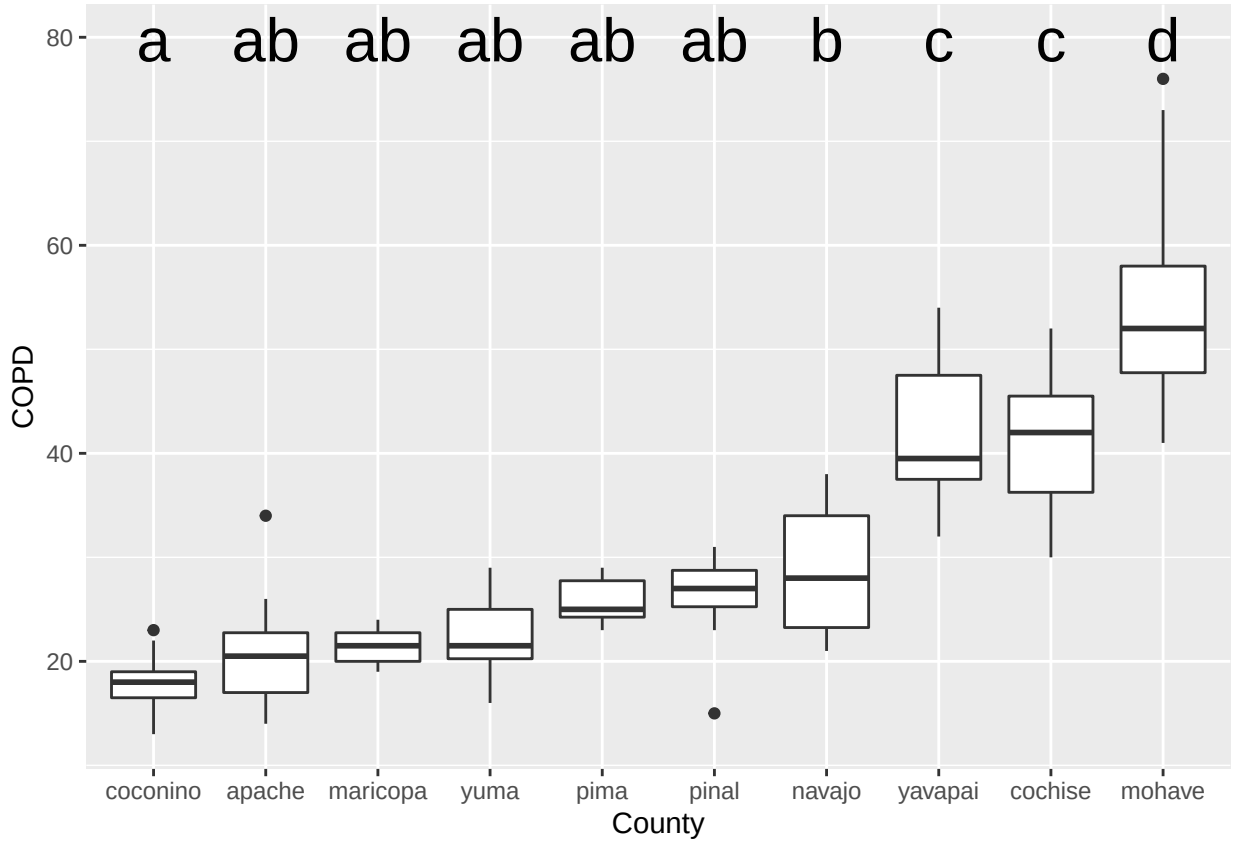
```
ggplot(all.data, aes(x=reorder(County, Asthma), y=Asthma)) +
  geom_boxplot() +
  labs(x = 'County', y = 'Asthma') +
  geom_text(data=letter.data.asthma, aes(x=County, y=y, label=.group), size=8)
```

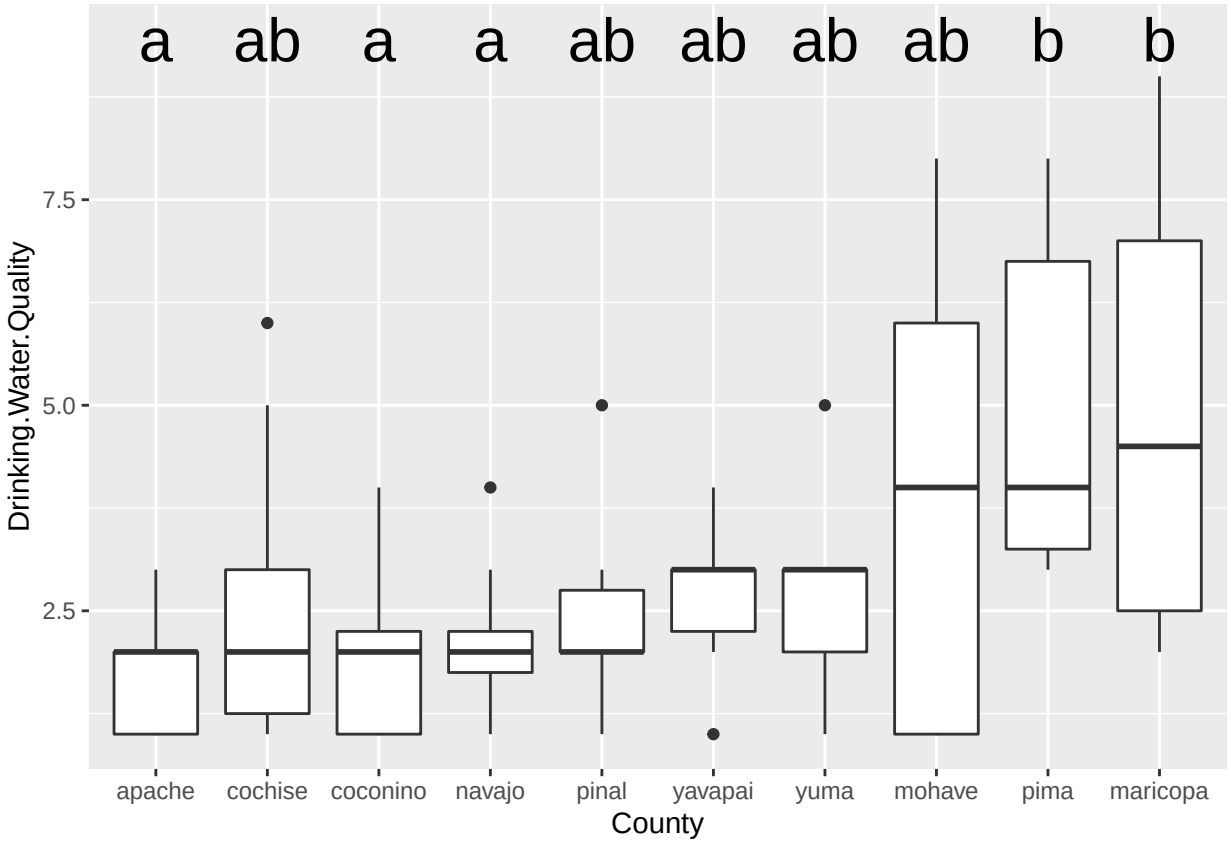


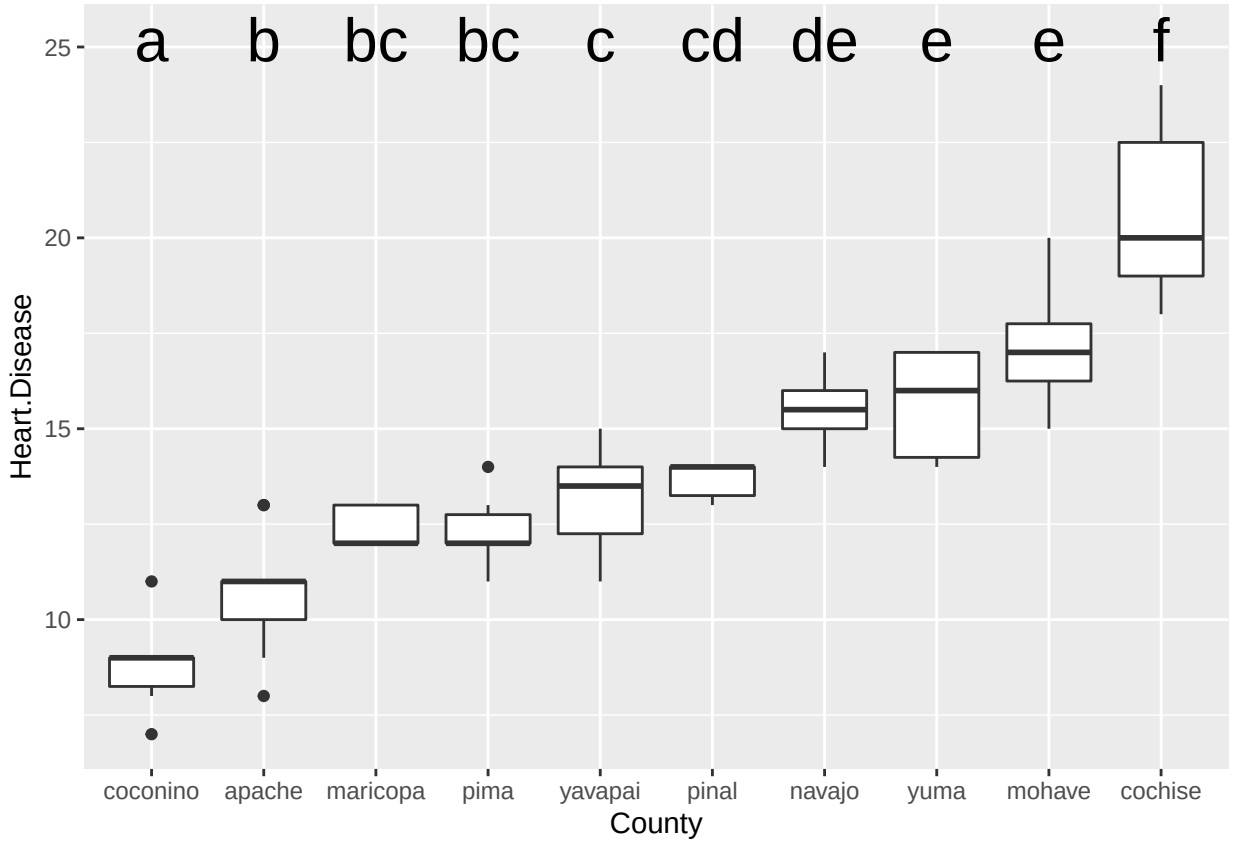

```
for(iter in 5:12)
{
  obj <- lm(paste(colnames(all.data)[iter], "~", 'County'), data=all.data)
  letter.data <- emmeans(obj, specs = ~ County) %>%
    multcomp::cld(Letters = letters, level = 0.95) %>%
    mutate(.group = str_remove_all(.group, '\\s')) %>%
    mutate(y = max(all.data[,iter], na.rm=T) + (max(all.data[,iter], na.rm=T) * .05))
  hold.data <- data.frame(
    County = all.data$County,
    Value = all.data[,iter]
  )
  hold.data <- hold.data %>% na.omit()
  print(ggplot(hold.data,
               aes(x=reorder(County, !!sym(colnames(hold.data)[2]), FUN = median),
                   y=!!sym(colnames(hold.data)[2]))) +
          geom_boxplot() +
          labs(x = "County") +
          geom_text(data = letter.data, aes(x=County, y=y, label=.group),
                    size = 8))
}
```

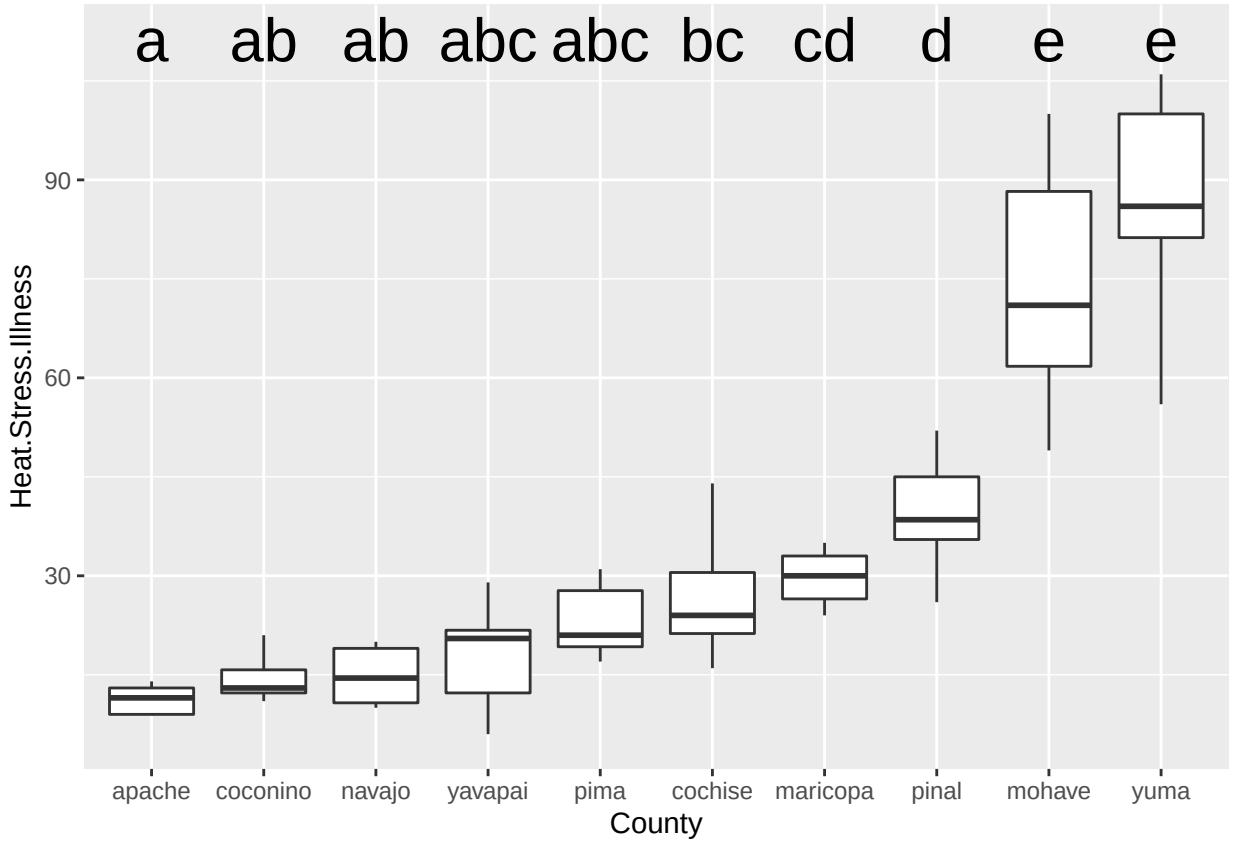

a
ab
bc
bcd
bcd
cd
cd
d
d
e
60
50
40
30
20
Asthma
coconino
navajo
pima
apache
pinal
yuma
yavapai
cochise
maricopa
mohave
County

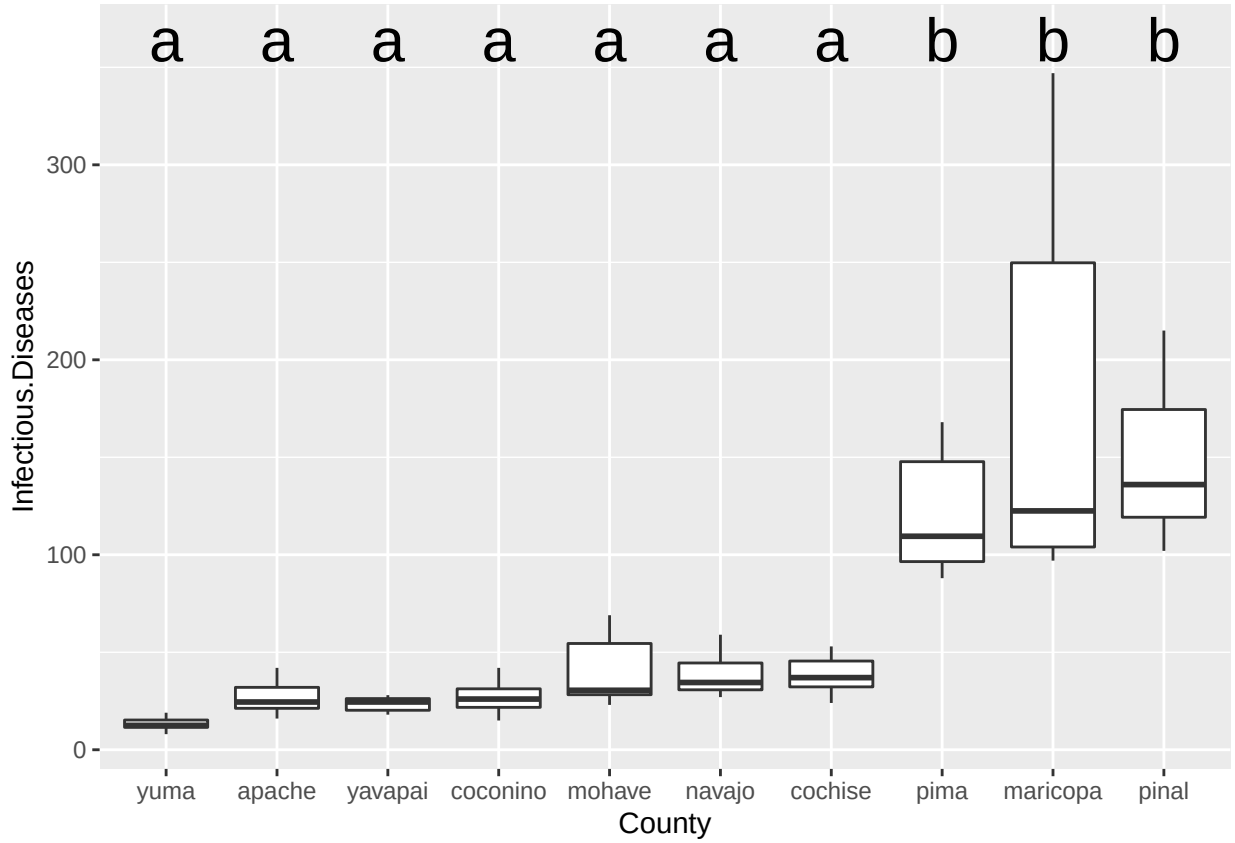

abcd
a
ab
abc
abcd
abcd
bcd
abcd
cd
d
15
10
5
0
Carbon.Monoxide.Poisoning
apache
maricopa
pima
pinal
mohave
yuma
yavapai
cochise
navajo
coconino
County

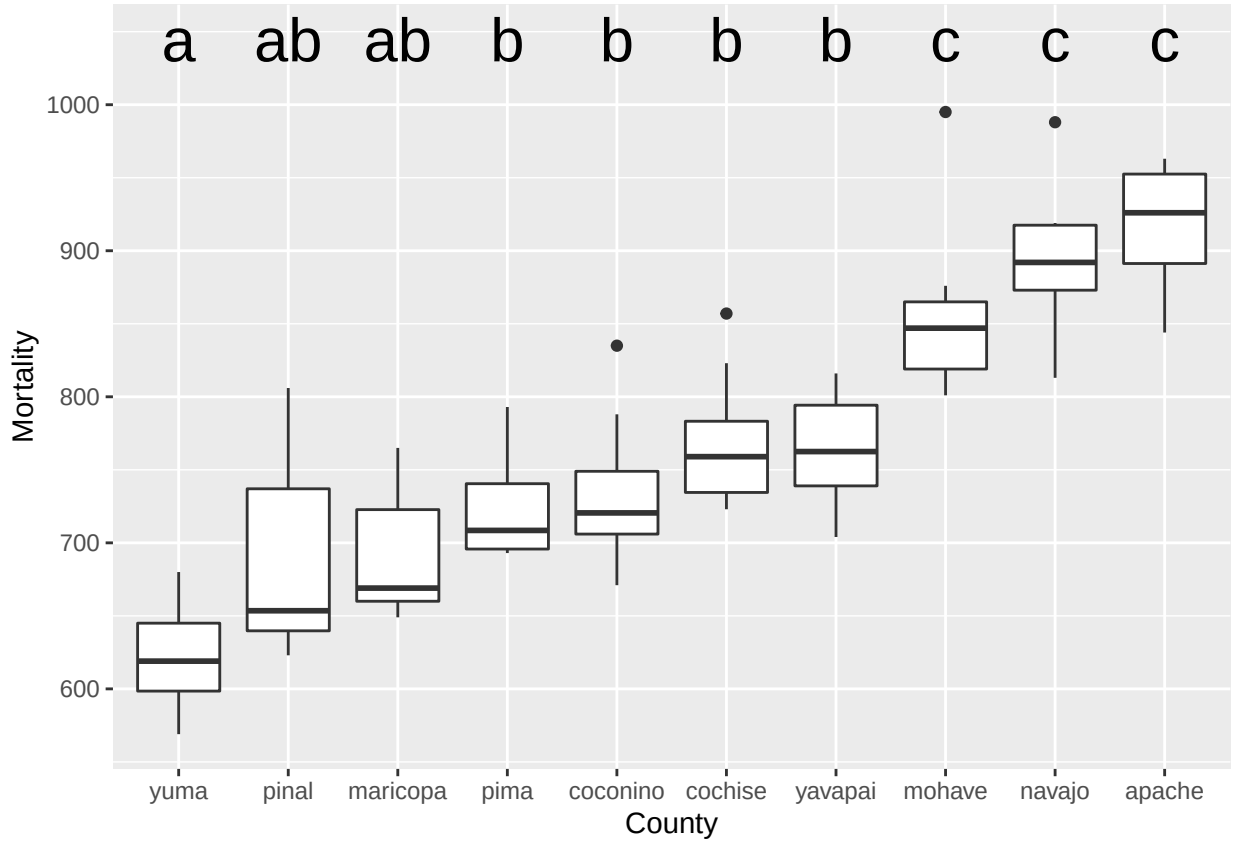

a
ab
ab
ab
ab
ab
b
c
c
d
80
60
40
20
COPD
coconino
apache
maricopa
yuma
pima
pinal
navajo
yavapai
cochise
mohave
County


a
ab
a
a
ab
ab
ab
ab
b
b
7.5
5.0
2.5
Drinking.Water.Quality
apache
cochise
coconino
navajo
pinal
yavapai
yuma
mohave
pima
maricopa
County


a
b
bc
bc
c
cd
de
e
e
f
25
20
15
10
Heart.Disease
coconino
apache
maricopa
pima
yavapai
pinal
navajo
yuma
mohave
cochise
County

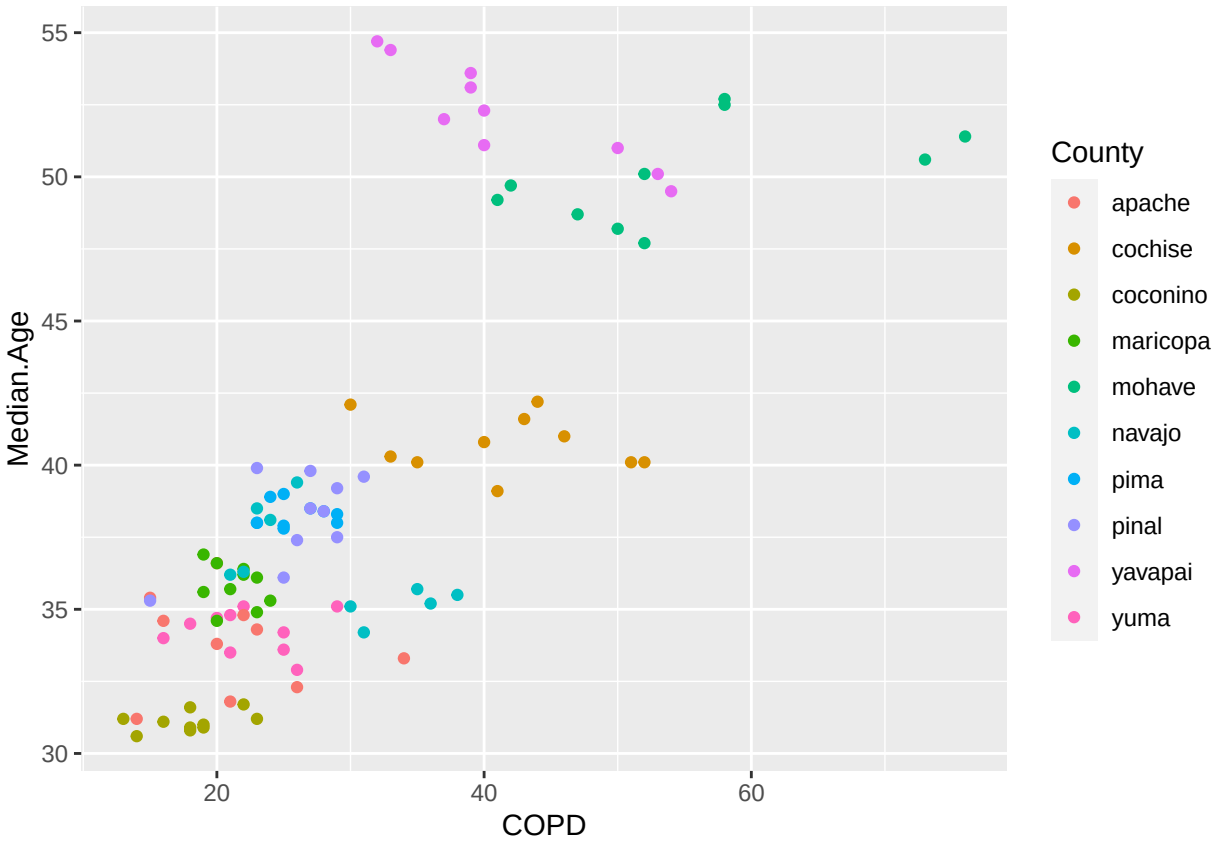

a
ab
ab
abc
abc
bc
cd
d
e
e
90
60
30
Heat.Stress.Illness
apache
coconino
navajo
yavapai
pima
cochise
maricopa
pinal
mohave
yuma
County


a a a a a a a b b b
300
200
100
0
Infectious.Diseases
yuma
apache
yavapai
coconino
mohave
navajo
cochise
pima
maricopa
pinal
County



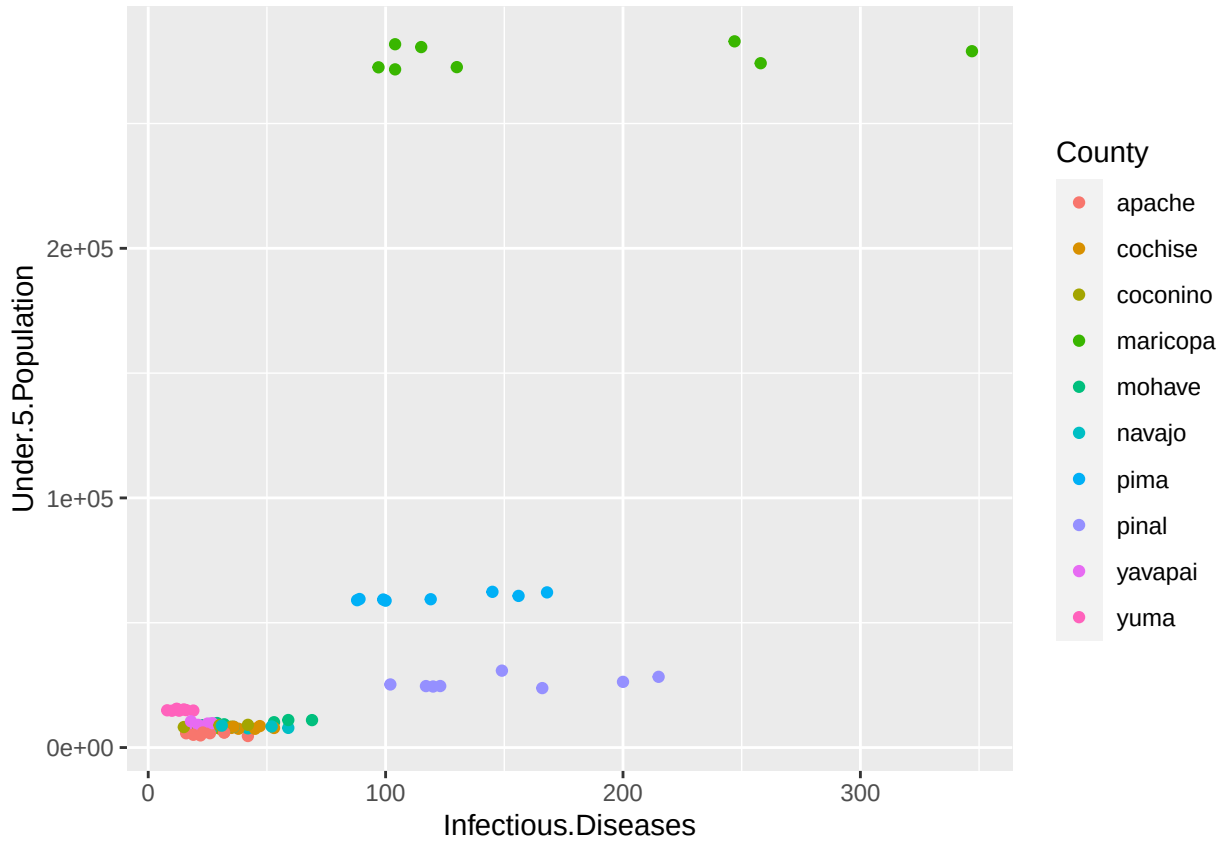

```
final.p.value <- adj.cor %>%
  group_by(Content.Area) %>% slice(which.min(adj.p.value)) %>%
  arrange(adj.p.value)
```

```
ggplot(all.data, aes(x=COPD, y=Median.Age, color=County)) + geom_point()
```

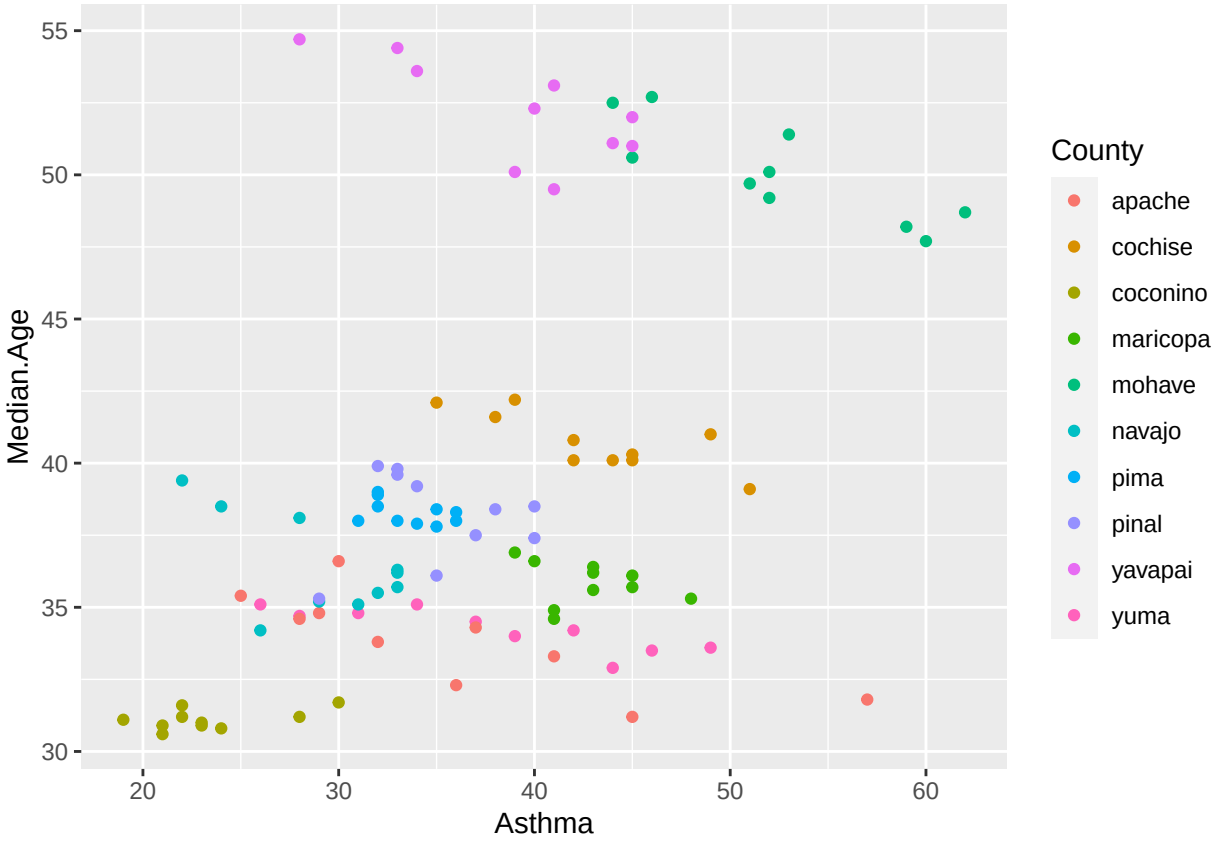



```
ggplot(all.data, aes(x=Infectious.Diseases, y=Under.5.Population, color=County)) +
  geom_point()
```

```
## Warning: Removed 20 rows containing missing values (geom_point).
```




```
ggplot(all.data, aes(x=Asthma, y=Median.Age, color=County)) + geom_point()
```

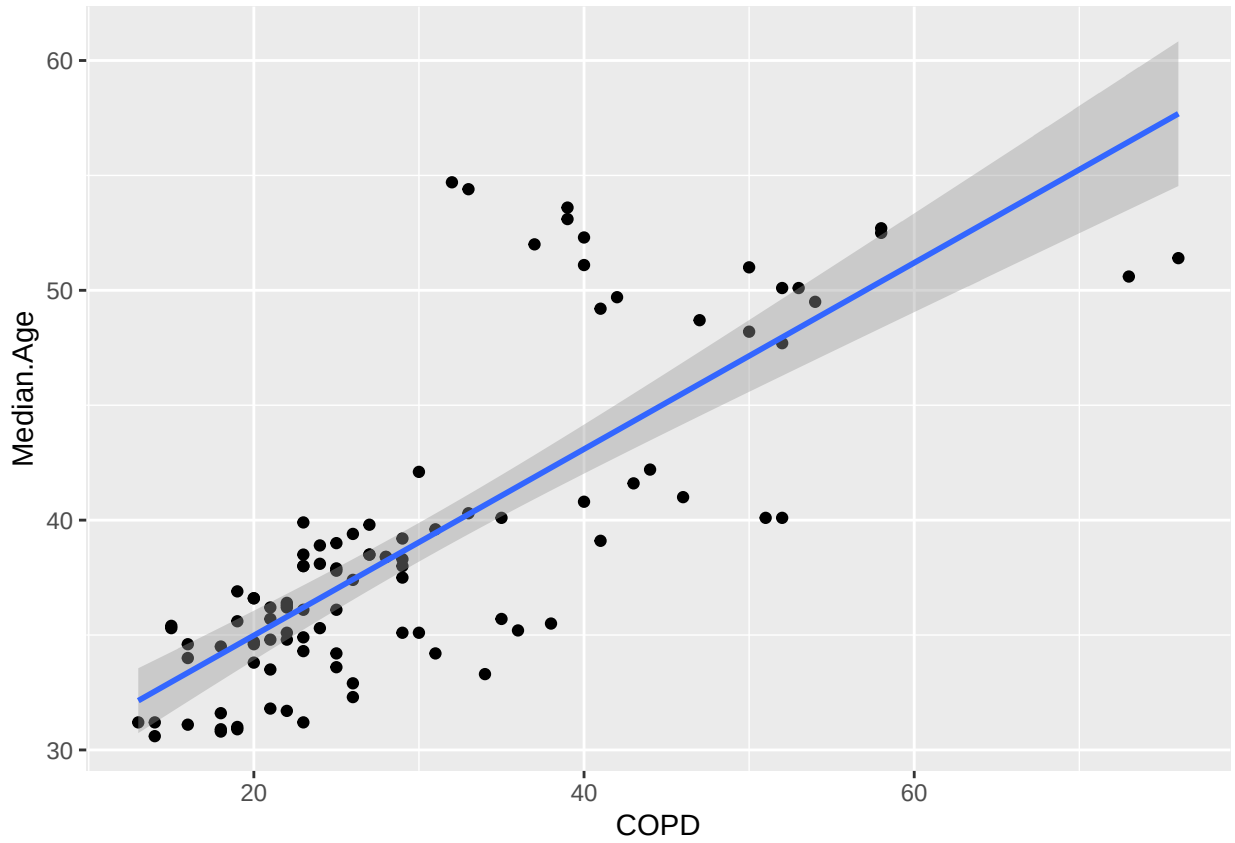



```
for (index in 1:6) {
  print(ggplot(all.data,
               aes_string(x=pull(final.p.value[index,1]),
                          y=pull(final.p.value[index,2]))) +
          geom_point() + geom_smooth(method="lm", model='y~x'))
}
```

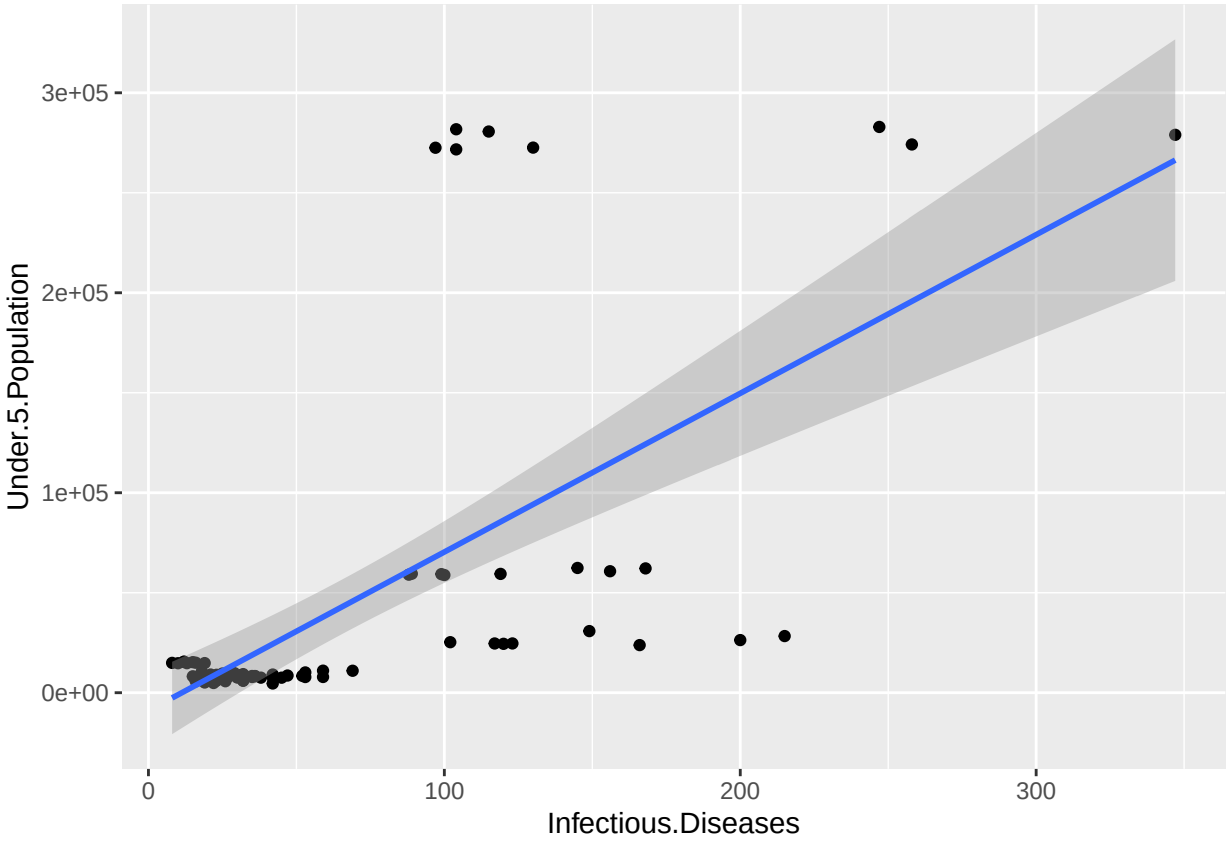
```
## Warning: Ignoring unknown parameters: model
```

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

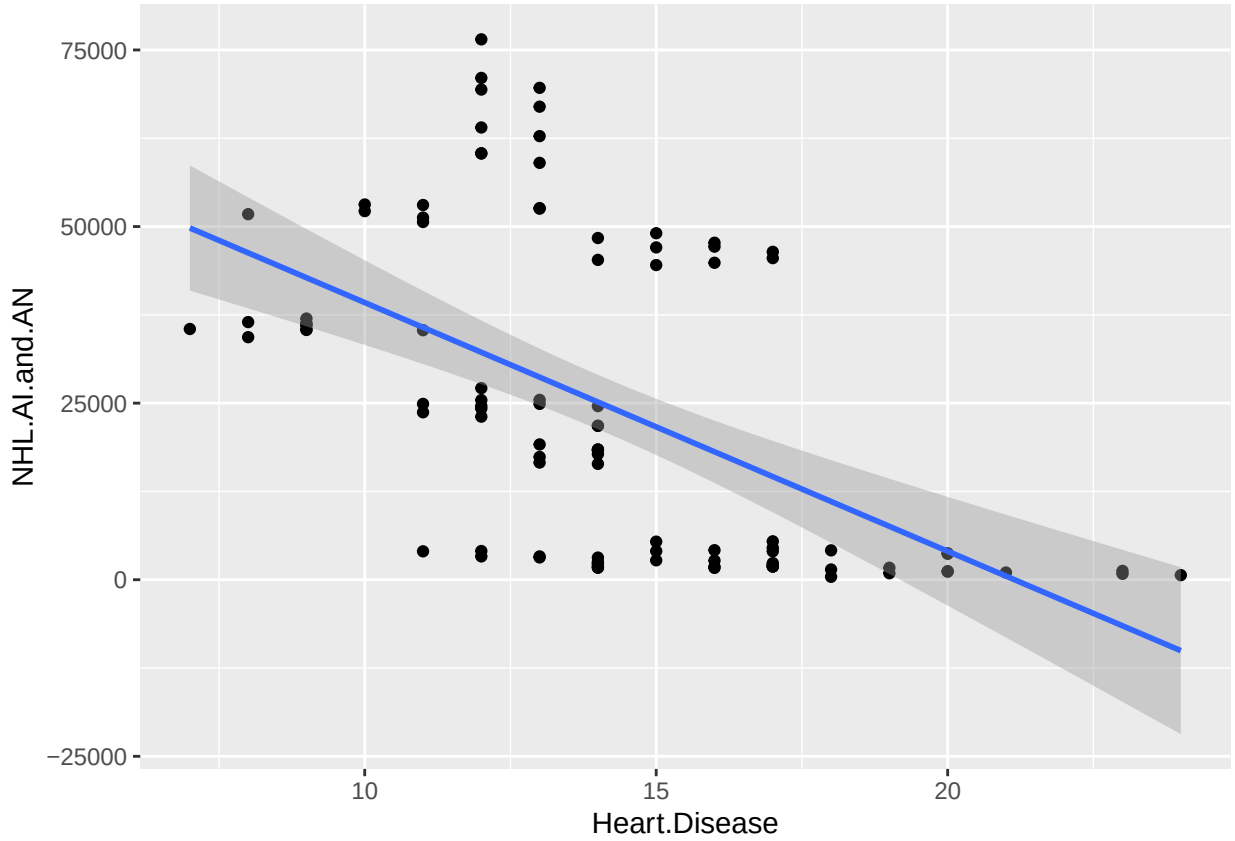
```
## Warning: Ignoring unknown parameters: model
```



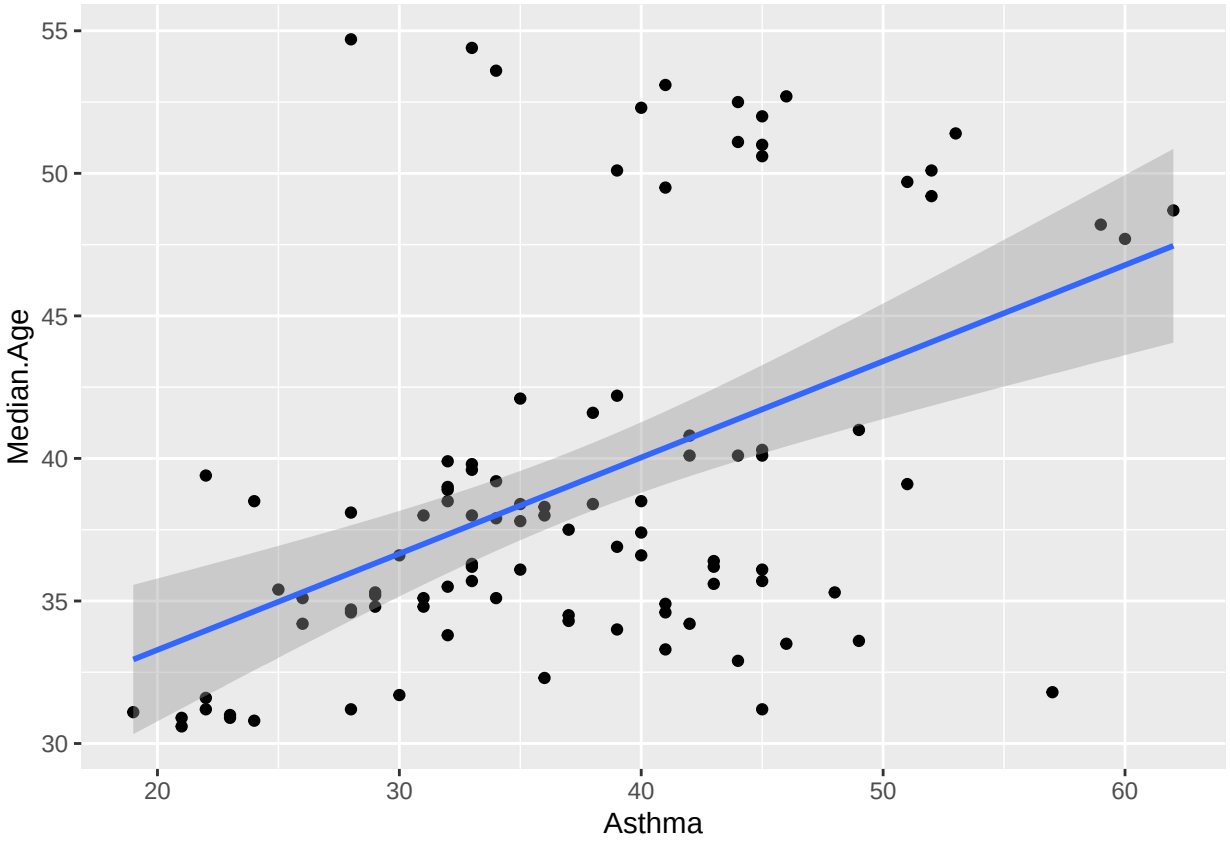

```
## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 20 rows containing non-finite values (stat_smooth).

## Warning: Removed 20 rows containing missing values (geom_point).

## Warning: Ignoring unknown parameters: model
```



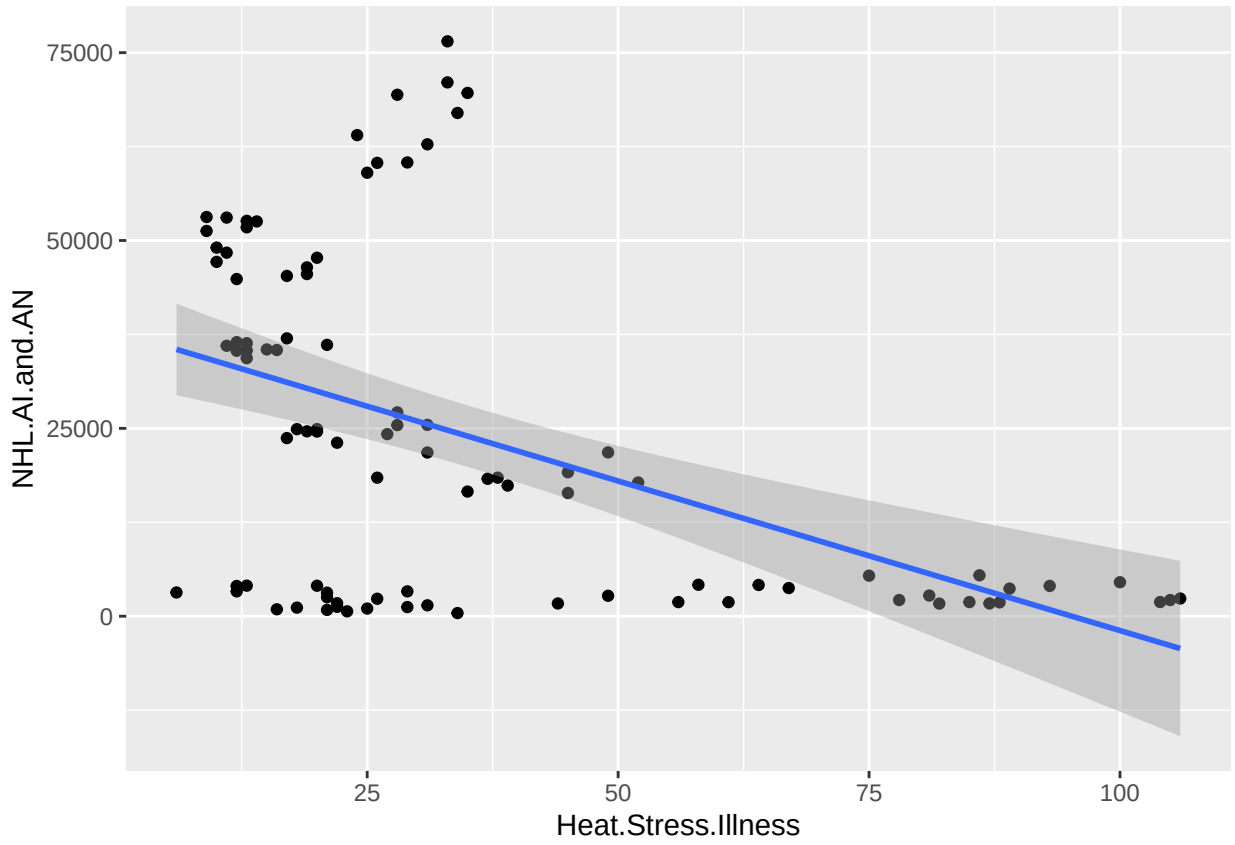

```
## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 2 rows containing non-finite values (stat_smooth).

## Warning: Removed 2 rows containing missing values (geom_point).

## Warning: Ignoring unknown parameters: model
```



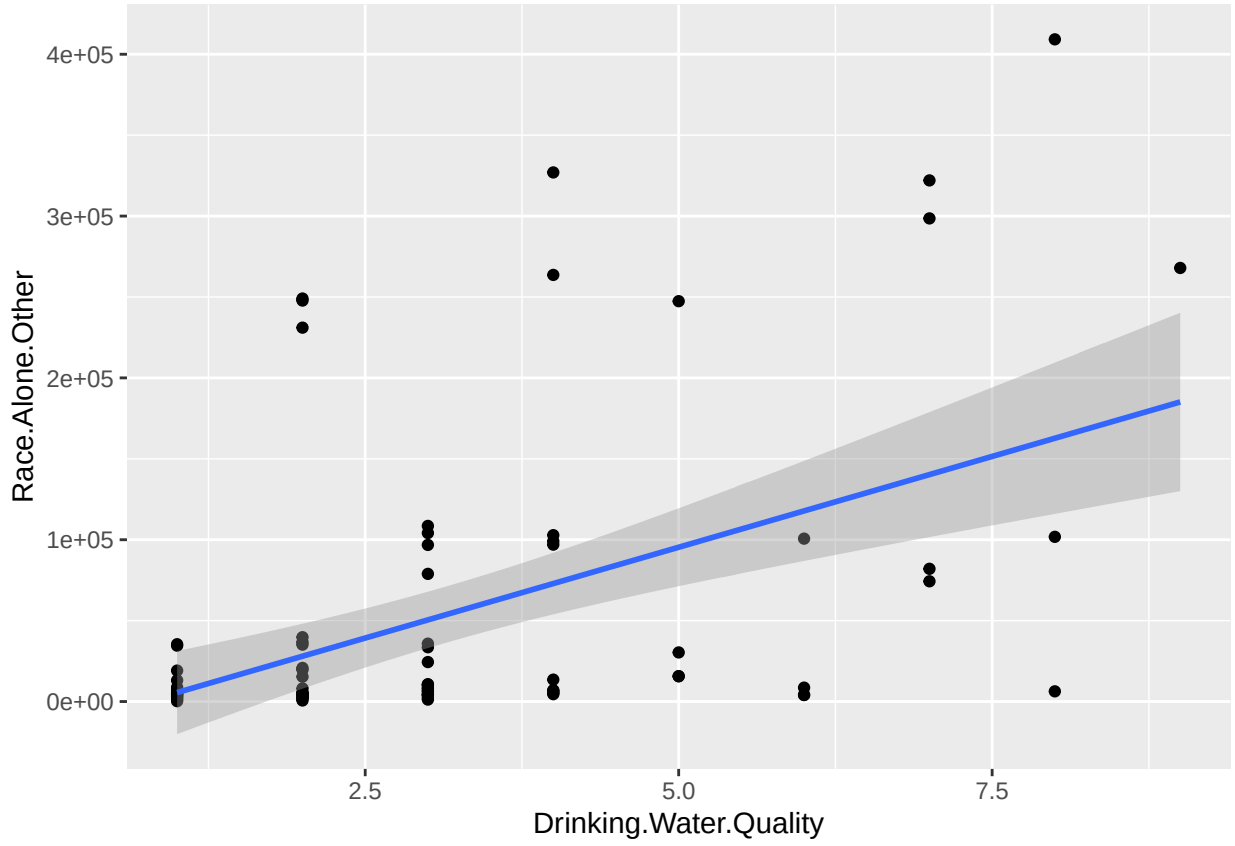

```
## `geom_smooth()` using formula 'y ~ x'

## Warning: Ignoring unknown parameters: model
```




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

## Warning: Removed 6 rows containing non-finite values (stat_smooth).

## Warning: Removed 6 rows containing missing values (geom_point).

## Warning: Ignoring unknown parameters: model
```




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

## Warning: Removed 14 rows containing non-finite values (stat_smooth).

## Warning: Removed 14 rows containing missing values (geom_point).
```



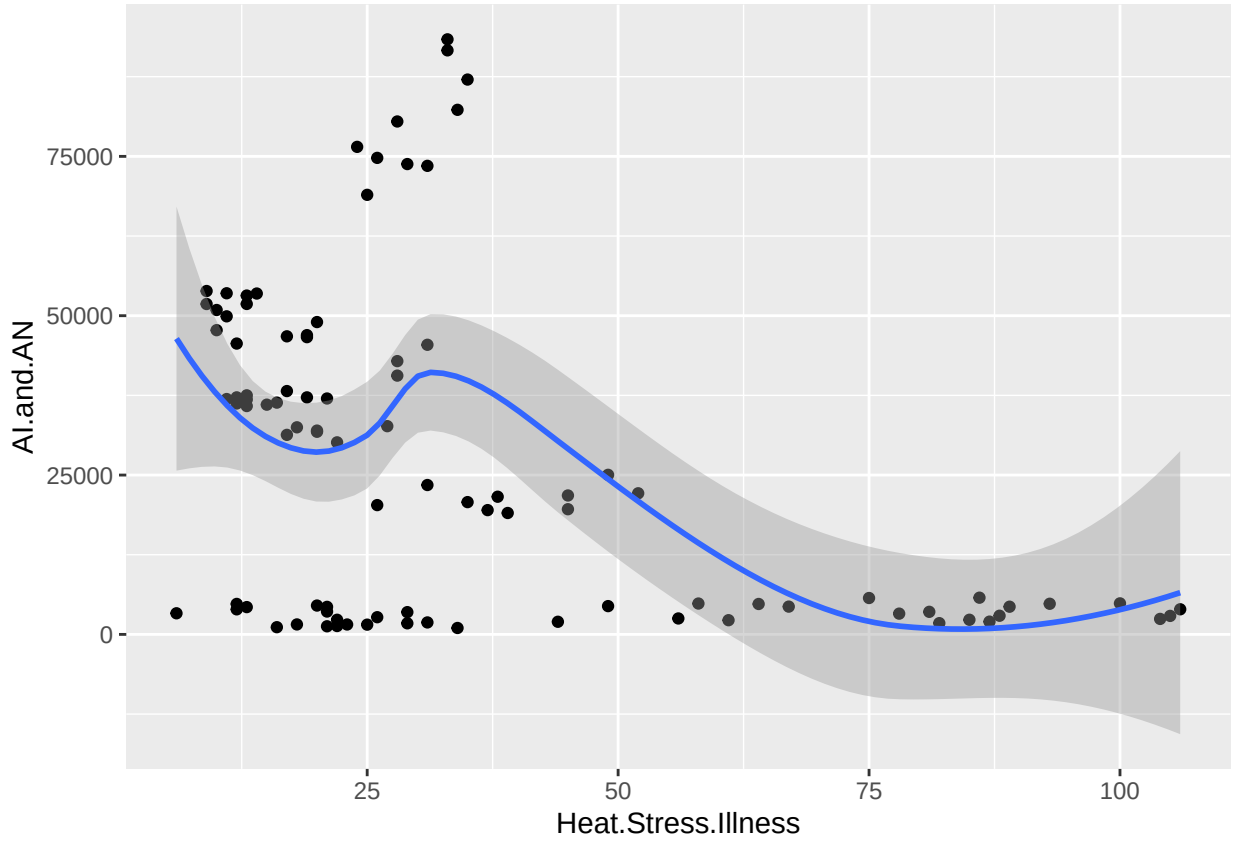

```
ggplot(all.data,
       aes(x=Heat.Stress.Illness, y=AI.and.AN)) +
  geom_point() + geom_smooth(method="loess", model='y~x')
```

```
## Warning: Ignoring unknown parameters: model
```

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

```
## Warning: Removed 6 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 6 rows containing missing values (geom_point).
```




```
hospital.info <- str(hospital.wider)
write.table(hospital.info, file = "hospital.txt", sep = ",", quote = FALSE, row.names = T)
```

```
data.frame(variable = names(hospital.wider),
           class = sapply(hospital.wider, typeof),
           first.values = sapply(hospital.wider, function(x) paste0(head(x),
                                                                    collapse = ",")),
           row.names = NULL) %>%
  kable(caption = "100 obs. of 13 variables")
```

```
data.frame(variable = names(censusData),
           class = sapply(censusData, typeof),
           first.values = sapply(censusData, function(x) paste0(head(x),
                                                                collapse = ",")),
           row.names = NULL) %>%
  kable()
```

Table 2: 100 obs. of 13 variables

variable	class	first.values
County	integer	mohave,maricopa,cochise,yuma,pima,pinal
Year	character	2019,2019,2019,2019,2019,2019
Date	double	2019-04-10,2019-04-10,2019-04-10,2019-04-10,2019-04-10,20
County.Year	character	mohave2019,maricopa2019,cochise2019,yuma2019,pima201
Asthma	integer	46,39,39,34,32,32
Carbon Monoxide Poisoning	integer	NA,1,7,NA,1,2
Chronic Obstructive Pulmonary Disease (COPD)	integer	58,19,44,29,24,23
Drinking Water Quality	integer	1,2,2,3,3,NA
Food Safety	integer	NA,NA,NA,NA,NA,NA
Heart Disease	integer	20,12,18,14,12,14
Heat Stress Illness	integer	67,33,34,105,28,49
Infectious Diseases	integer	NA,NA,NA,NA,NA,NA
Mortality	integer	NA,NA,NA,NA,NA,NA

variable	class	first.values
Year	character	2019,2019,2019,2019,2019,2019
County	integer	apache,cochise,coconino,maricopa,mohave,navajo
Date	double	2019-04-10,2019-04-10,2019-04-10,2019-04-10,2019-04-10,2019-04-10
County.Year	character	apache2019,cochise2019,coconino2019,maricopa2019,mohave2019,navajo2019
Total.Population	double	71887,125922,143476,4485414,212181,110924
Male.Total.Population	double	36435,64204,71036,2217116,106919,54994
Female.Total.Population	double	35452,61718,72440,2268298,105262,55930
Sex.Ratio	double	102.8,104,98.1,97.7,101.6,98.3
Under.5.Population	double	4558,6855,6900,276119,8997,7448
5.to.9.Population	double	5138,7951,7749,283710,9216,8115
10.to.14.Population	double	6089,7437,8629,312364,11202,9016
15.to.19.Population	double	5631,7424,17156,299470,10381,7021
20.to.24.Population	double	4216,7822,18360,296675,9174,5838
25.to.34.Population	double	9316,15467,19997,658682,20109,12793
35.to.44.Population	double	7153,14188,15283,583814,19281,13028
45.to.54.Population	double	8286,13124,14245,555903,22856,12009
55.to.59.Population	double	4905,7725,9092,271428,13249,7727
60.to.64.Population	double	4992,8990,7479,250782,21889,7369
65.to.74.Population	double	7110,16326,11890,402314,37168,12703
75.to.84.Population	double	3551,9222,5699,221756,23634,6473
Over.85.Population	double	942,3391,997,72397,5025,1384
Median.Age	double	36.6,42.2,31.1,36.9,52.7,39.4
Under.18.Population	double	19100,27003,28005,1052439,35605,29122
Over.16.Population	double	54969,101567,118789,3553180,181081,84586
Over.18.Population	double	52787,98919,115471,3432975,176576,81802
Over.21.Population	double	49300,95081,97207,3254644,170466,78557
Over.62.Population	double	14961,34619,23241,842012,78366,24828
Over.65.Population	double	11603,28939,18586,696467,65827,20560
Over.18	double	52787,98919,115471,3432975,176576,81802
Over.18.Male	double	26304,50636,56074,1680405,89165,40681
Over.18.Female	double	26483,48283,59397,1752570,87411,41121
Over.18.Sex.Ratio	double	99.3,104.9,94.4,95.9,102,98.9
Over.65.Male	double	5433,14060,8595,313899,32587,9748
Over.65.Female	double	6170,14879,9991,382568,33240,10812
Over.65.Sex.Ration	double	88.1,94.5,86,82.1,98,90.2
One.Race.Total.Population	double	70612,120411,137246,4322940,204279,107609
Two.Or.More.Races.Population	double	1275,5511,6230,162474,7902,3315
White	double	15109,108177,91649,3547155,188756,51262
Black.Or.African.American	double	721,6163,1364,266128,1496,1309
AI.and.AN	double	53480,1006,37187,93358,4358,50892

```
data.frame(variable = names(all.data),
           class = sapply(all.data, typeof),
           first.values = sapply(all.data, function(x) paste0(head(x),
                                                              collapse = ",")),
           row.names = NULL) %>%
  kable()
```

variable	class	first.values
County	integer	mohave,maricopa,cochise,yuma,pima,pinal
Year	integer	2019,2019,2019,2019,2019,2019
Date	double	2019-04-10,2019-04-10,2019-04-10,2019-04-10,2019-04-10,2019-04-10
County.Year	character	mohave2019,maricopa2019,cochise2019,yuma2019,pima2019,pinal2019
Asthma	double	46,39,39,34,32,32
Carbon.Monoxide.Poisoning	integer	NA,1,7,NA,1,2
COPD	integer	58,19,44,29,24,23
Drinking.Water.Quality	integer	1,2,2,3,3,NA
Heart.Disease	integer	20,12,18,14,12,14
Heat.Stress.Illness	integer	67,33,34,105,28,49
Infectious.Diseases	integer	NA,NA,NA,NA,NA,NA
Mortality	integer	NA,NA,NA,NA,NA,NA
Total.Population	double	212181,4485414,125922,213787,1047279,462789
Male.Total.Population	double	106919,2217116,64204,110189,516110,241369
Female.Total.Population	double	105262,2268298,61718,103598,531169,221420
Sex.Ratio	double	101.6,97.7,104,106.4,97.2,109
Under.5.Population	double	8997,276119,6855,15099,57113,25490
5.to.9.Population	double	9216,283710,7951,14298,60599,28129
10.to.14.Population	double	11202,312364,7437,15550,61314,31894
15.to.19.Population	double	10381,299470,7424,14941,69026,28912
20.to.24.Population	double	9174,296675,7822,16812,88778,24346
25.to.34.Population	double	20109,658682,15467,30027,135885,60718
35.to.44.Population	double	19281,583814,14188,22967,120304,60986
45.to.54.Population	double	22856,555903,13124,21689,112541,50925
55.to.59.Population	double	13249,271428,7725,10460,63631,29151
60.to.64.Population	double	21889,250782,8990,11136,65492,26572
65.to.74.Population	double	37168,402314,16326,19820,119874,56517
75.to.84.Population	double	23634,221756,9222,16790,69655,30749
Over.85.Population	double	5025,72397,3391,4198,23067,8400
Median.Age	double	52.7,36.9,42.2,35.1,38.9,39.9
Under.18.Population	double	35605,1052439,27003,53571,215606,102573
Over.16.Population	double	181081,3553180,101567,164744,853555,370055
Over.18.Population	double	176576,3432975,98919,160216,831673,360216
Over.21.Population	double	170466,3254644,95081,150446,778821,343421
Over.62.Population	double	78366,842012,34619,47136,252031,111333
Over.65.Population	double	65827,696467,28939,40808,212596,95666
Over.18	double	176576,3432975,98919,160216,831673,360216
Over.18.Male	double	89165,1680405,50636,83103,405576,188926
Over.18.Female	double	87411,1752570,48283,77113,426097,171290
Over.18.Sex.Ratio	double	102,95.9,104.9,107.8,95.2,110.3
Over.65.Male	double	32587,313899,14060,19321,96614,45770
Over.65.Female	double	33240,382568,14879,21487,115982,49896
Over.65.Sex.Ration	double	98,82.1,94.5,89.9,83.3,91.7
One.Race.Total.Population	double	204279,4322940,120411,207267,987957,442591
Two.Or.More.Races.Population	double	7902,162474,5511,6520,59322,20198
White	double	188756,3547155,108177,189117,795391,366928
Black.Or.African.American	double	1496,266128,6163,3244,38343,21264
AI.and.AN	double	4358,93358,1006,2900,40603,25035
Cherokee.TG	double	NA,1294,NA,NA,0,NA
Chippewa.TG	double	NA,518,NA,NA,606,NA
Navajo.TG	double	NA,39306,NA,NA,2814,NA
Sioux.TG	double	NA,1130,NA,NA,504,NA
Asian	double	1923,192301,2795,2388,29276,6642
Asian.Indian	double	NA,63846,NA,173,4411,1482
Chinese	double	NA,33121,NA,61,7446,661
Filipino	double	NA,34749,NA,928,6429,2228
Japanese	double	NA,6943,NA,405,1293,321

```
content.area.p %>%
  mutate_if(is.numeric, funs(as.character(signif(., 3)))) %>%
  kable(.)
```

```
## Warning: `funs()` was deprecated in dplyr 0.8.0.
## Please use a list of either functions or lambdas:
##
##   # Simple named list:
##   list(mean = mean, median = median)
##
##   # Auto named with `tibble::lst()`:
##   tibble::lst(mean, median)
##
##   # Using lambdas
##   list(~ mean(., trim = .2), ~ median(., na.rm = TRUE))
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was generated.
```

	County	p.value
value5	Heat.Stress.Illness	2.04e-38
value4	Heart.Disease	2.47e-36
value2	COPD	1.2e-26
value	Asthma	8.02e-19
value7	Mortality	9.23e-19
value6	Infectious.Diseases	2.13e-17
value1	Carbon.Monoxide.Poisoning	1.05e-06
value3	Drinking.Water.Quality	0.000333

```
adj.cor[adj.cor$Content.Area == "Heat.Stress.Illness",] %>% kable()
```

	Content.Area	Demographic	p.value	corr	adj.p.value
cor487	Heat.Stress.Illness	NHL.AI.and.AN	1.7e-06	-0.4709142	0.0011076
cor450	Heat.Stress.Illness	AI.and.AN	1.0e-05	-0.4382536	0.0066211

```
adj.cor[adj.cor$Content.Area == "Heart.Disease",] %>%
  mutate_if(is.numeric, funs(as.character(signif(., 3)))) %>% kable()
```

	Content.Area	Demographic	p.value	corr	adj.p.value
cor404	Heart.Disease	NHL.AI.and.AN	1.4e-08	-0.535	9.33e-06
cor367	Heart.Disease	AI.and.AN	3.05e-08	-0.524	2.03e-05
cor392	Heart.Disease	Race.Alone.AI.and.AN	5.46e-07	-0.476	0.000362
cor349	Heart.Disease	Median.Age	3.17e-05	0.403	0.0211
cor362	Heart.Disease	Over.65.Sex.Ration	7.85e-06	0.718	0.00521

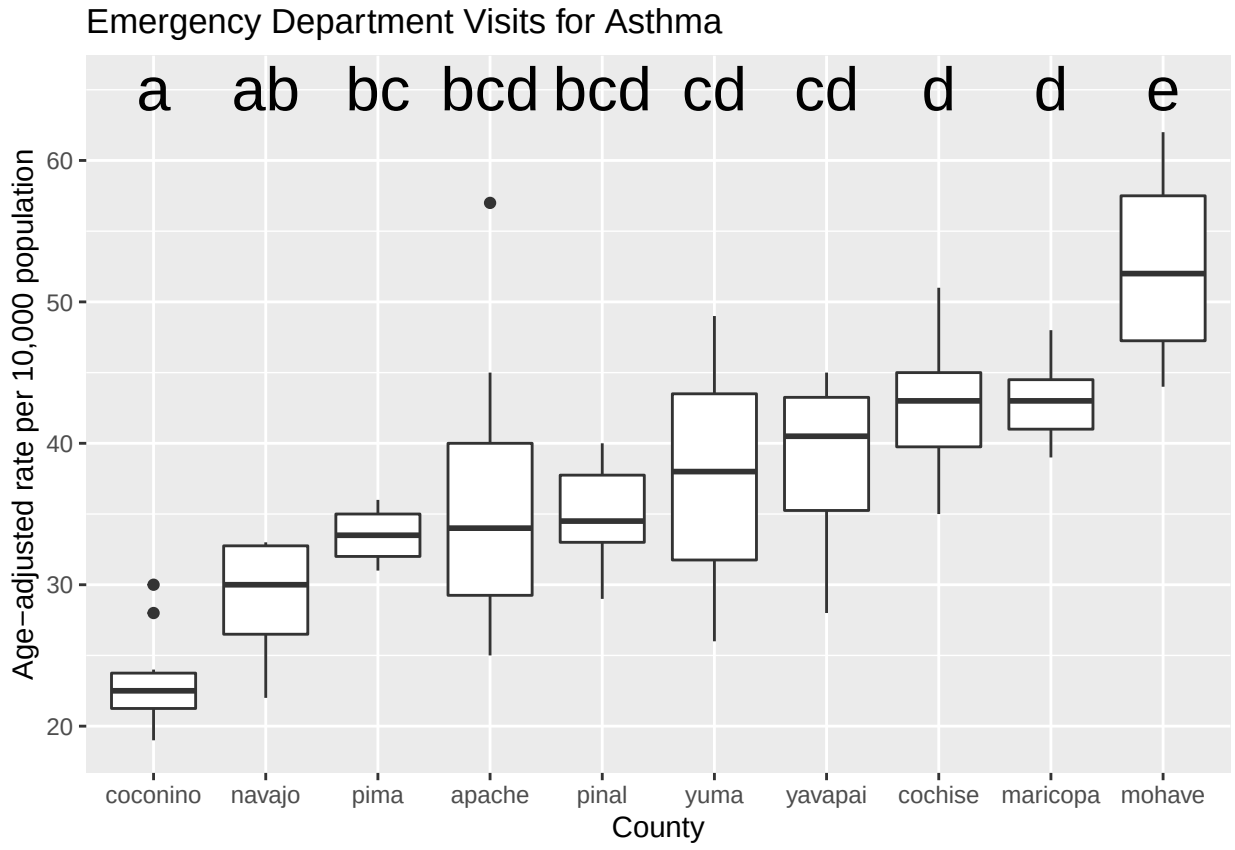
```
adj.cor[adj.cor$Content.Area == "COPD",] %>%
  mutate_if(is.numeric, funs(as.character(signif(., 3)))) %>% kable()
```

	Content.Area	Demographic	p.value	corr	adj.p.value
cor238	COPD	NHL.AI.and.AN	2.88e-09	-0.556	1.91e-06
cor201	COPD	AI.and.AN	5.1e-09	-0.548	3.39e-06
cor226	COPD	Race.Alone.AI.and.AN	1.04e-07	-0.502	6.93e-05
cor196	COPD	Over.65.Sex.Ration	1e-05	0.712	0.00667
cor183	COPD	Median.Age	2.63e-21	0.776	1.75e-18

```
adj.cor[adj.cor$Content.Area == "Asthma",] %>%
  mutate_if(is.numeric, funs(as.character(signif(., 3)))) %>% kable()
```

	Content.Area	Demographic	p.value	corr	adj.p.value
cor17	Asthma	Median.Age	1.02e-06	0.466	0.00068
cor46	Asthma	Vietnamese	7.41e-05	0.585	0.0492

```
obj <- lm(Asthma ~ County, data=all.data)
letter.data <- emmeans(obj, specs = ~ County) %>%
  multcomp::cld(Letters = letters, level = 0.95) %>%
  mutate(.group = str_remove_all(.group, '\\s')) %>%
  mutate(y = max(all.data$Asthma, na.rm=T) +
           (max(all.data$Asthma, na.rm=T) * .05))
hold.data <- data.frame(
  County = all.data$County,
  Value = all.data$Asthma
)
hold.data <- hold.data %>% na.omit()
ggplot(hold.data,
               aes(x=reorder(County, Value, FUN = median),
                   y=Value)) +
          geom_boxplot() +
          labs(x = "County",
               y = "Age-adjusted rate per 10,000 population",
               title = "Emergency Department Visits for Asthma") +
          geom_text(data = letter.data, aes(x=County, y=y, label=.group),
                    size = 8)
```



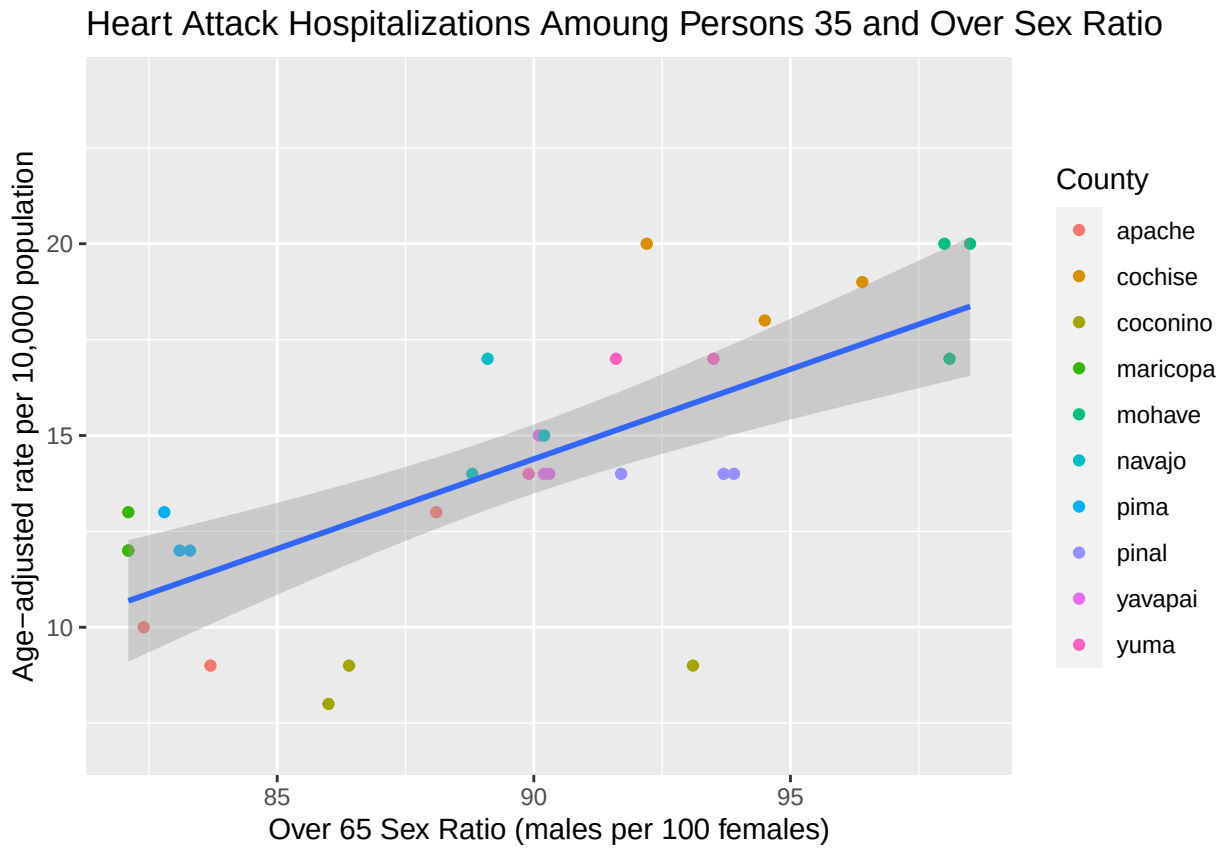

```
ggplot(all.data,
               aes(x=Over.65.Sex.Ration,
                           y=Heart.Disease)) +
          geom_point(aes(color=County)) + geom_smooth(method="lm", model='y~x') +
  labs(x="Over 65 Sex Ratio (males per 100 females)",
       y="Age-adjusted rate per 10,000 population",
       title="Heart Attack Hospitalizations Amoung Persons 35 and Over Sex Ratio")
```

```
## Warning: Ignoring unknown parameters: model
```

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

```
## Warning: Removed 70 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 70 rows containing missing values (geom_point).
```

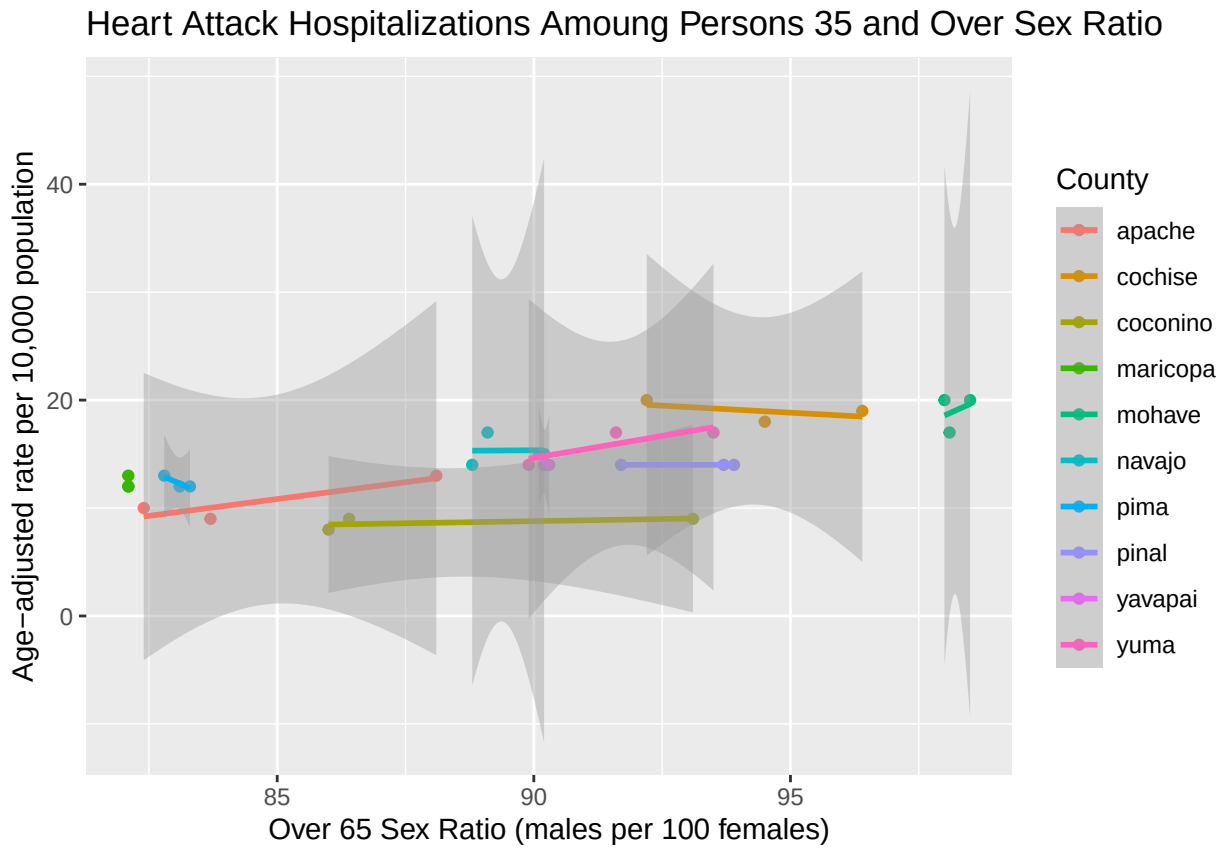



```
ggplot(all.data,
               aes(x=Over.65.Sex.Ration,
                           y=Heart.Disease, color=County)) +
          geom_point() + geom_smooth(method="lm", model='y~x') +
  labs(x="Over 65 Sex Ratio (males per 100 females)",
       y="Age-adjusted rate per 10,000 population",
       title="Heart Attack Hospitalizations Amoung Persons 35 and Over Sex Ratio")
```

```
## Warning: Ignoring unknown parameters: model
```

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

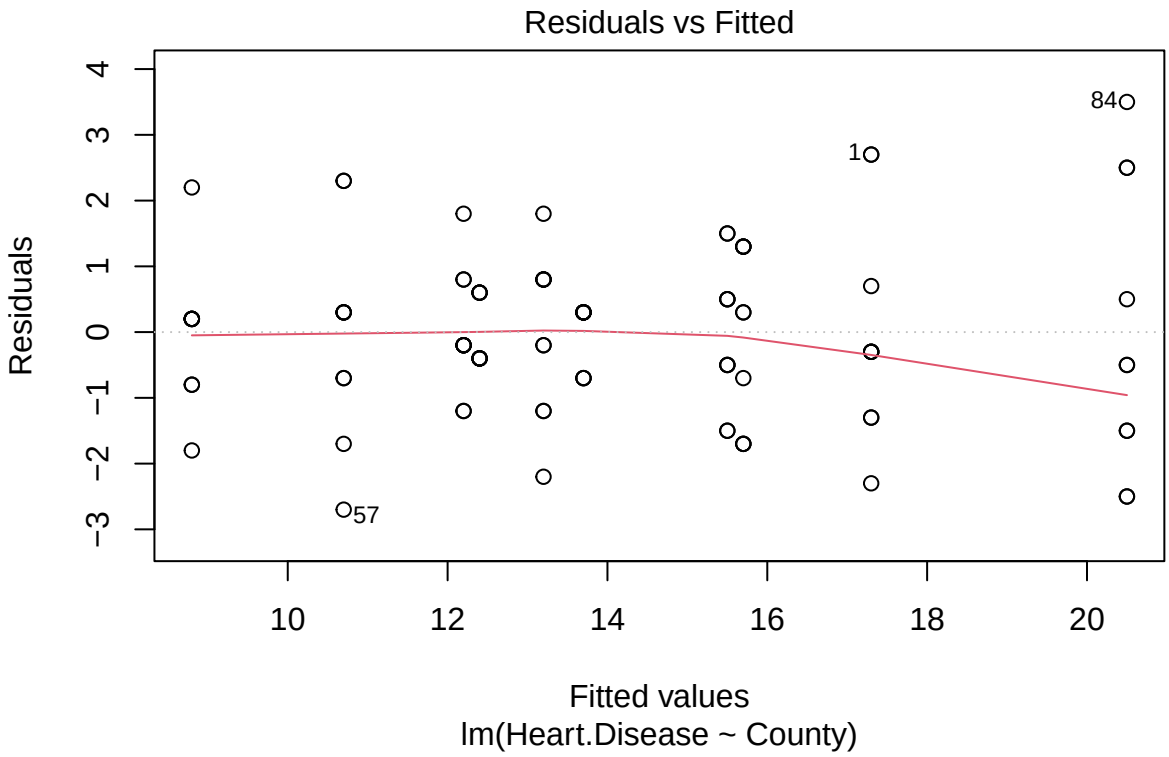
```
## Warning: Removed 70 rows containing non-finite values (stat_smooth).
## Removed 70 rows containing missing values (geom_point).
```

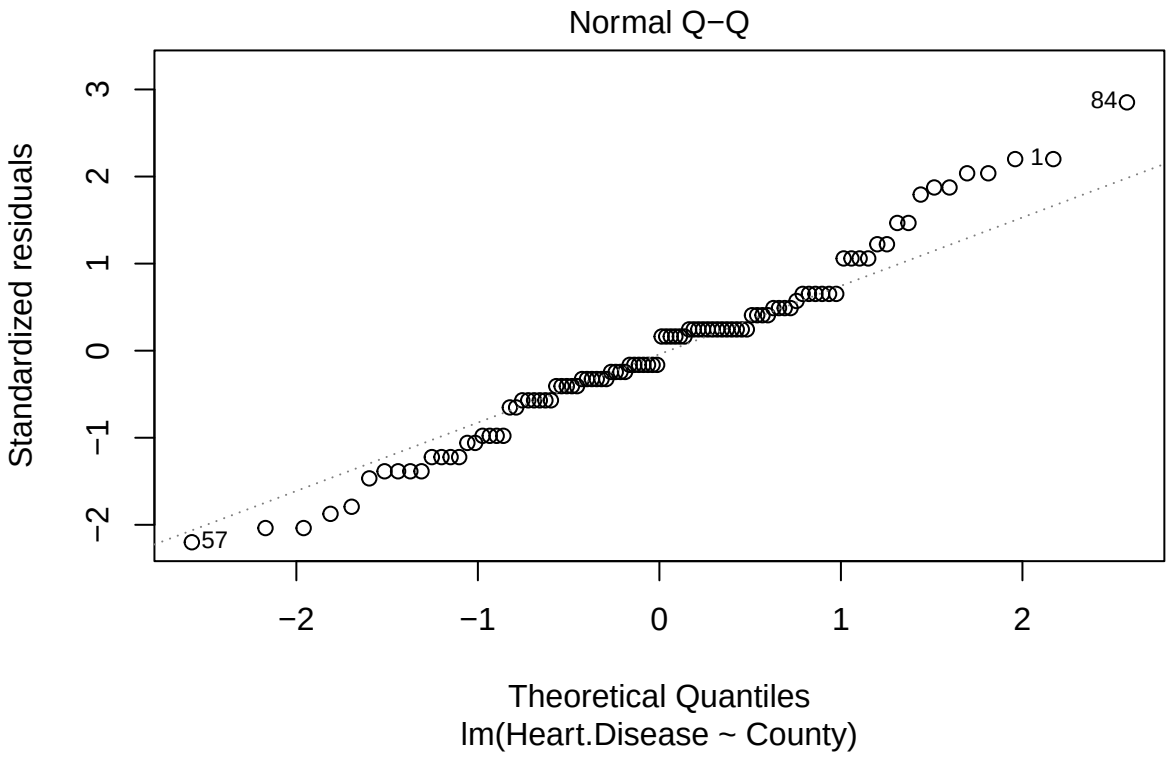


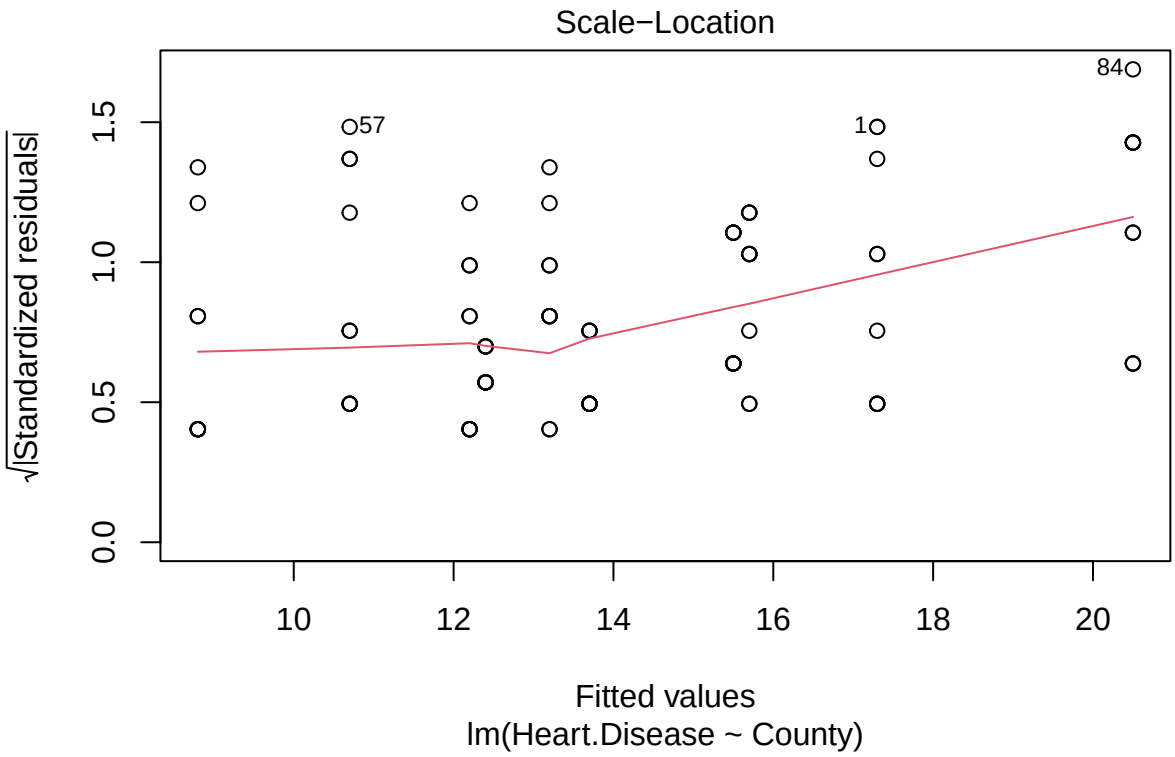

```
obj <- lm(Heart.Disease ~ County, data = all.data)
anova(obj)
```

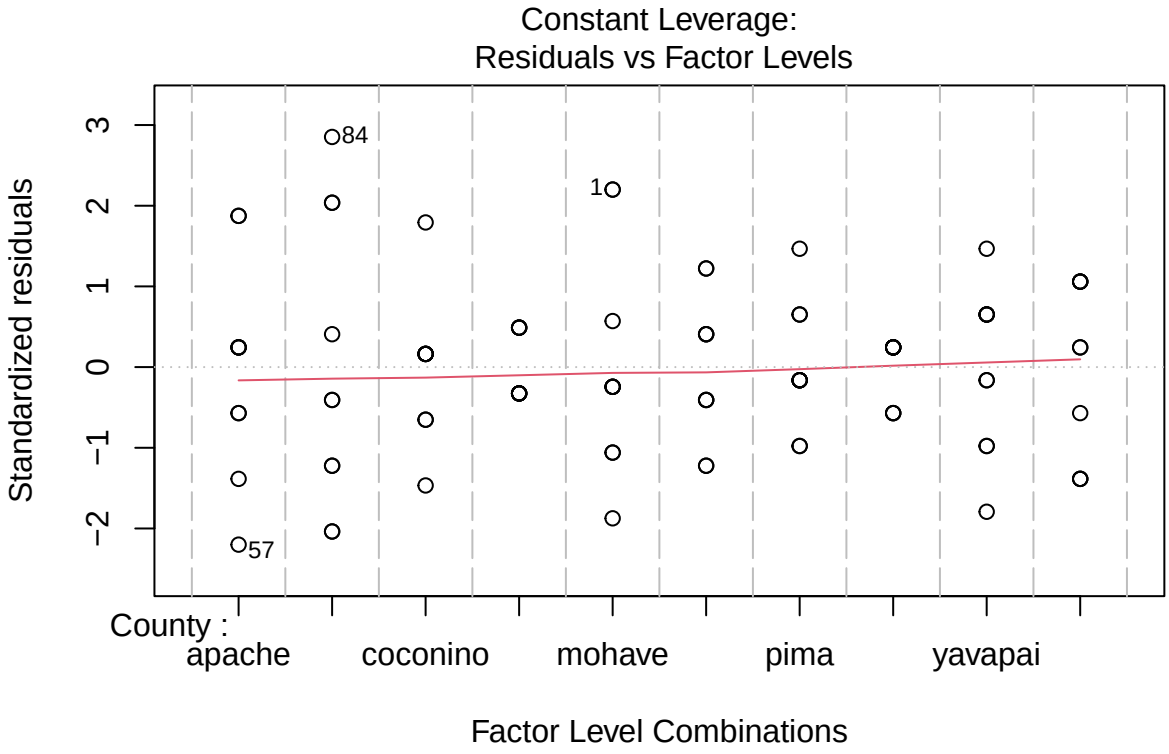
```
## Analysis of Variance Table
##
## Response: Heart.Disease
##            Df Sum Sq Mean Sq F value    Pr(>F)
## County      9 1027.4 114.156  68.221 < 2.2e-16 ***
## Residuals 90  150.6   1.673
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
plot(obj)
```


Residuals vs Fitted
Residuals
Fitted values
lm(Heart.Disease ~ County)
84
1
57
10
12
14
16
18
20
−3
−2
−1
0
1
2
3
4


Normal Q−Q
Standardized residuals
Theoretical Quantiles
lm(Heart.Disease ~ County)
84
1
57
−2
−1
0
1
2
3


Scale−Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
57
1
84
10
12
14
16
18
20
Fitted values
lm(Heart.Disease ~ County)


Constant Leverage:
Residuals vs Factor Levels
Standardized residuals
3
2
1
0
−1
−2
84
1
57
County :
apache
coconino
mohave
pima
yavapai
Factor Level Combinations

```
str(hospitalData)
```

```
## 'data.frame':    1535 obs. of  7 variables:
##  $ County      : Factor w/ 15 levels "apache","cochise",..: 9 4 13 8 2 15 7 11 12 5 ...
##  $ County.Value: int  46 46 45 39 39 34 32 32 32 31 ...
##  $ State.Rate  : num  37.2 37.2 37.2 37.2 37.2 ...
##  $ Year        : chr  "2019" "2019" "2019" "2019" ...
##  $ Content.Area: Factor w/ 9 levels "Asthma","Carbon Monoxide Poisoning",..: 1 1 1 1 1 1 1 1 1 ...
##  $ Date        : Date, format: "2019-04-10" "2019-04-10" ...
##  $ County.Year : chr  "mohave2019" "gila2019" "santa cruz2019" "maricopa2019" ...
```

```
str(hospital.wider)
```

```
## tibble [100 x 13] (S3: tbl_df/tbl/data.frame)
##  $ County                                       : Factor w/ 15 levels "apache","cochise",..: 9 8 2 15
##  $ Year                                         : chr [1:100] "2019" "2019" "2019" "2019" ...
##  $ Date                                         : Date[1:100], format: "2019-04-10" "2019-04-10" ...
##  $ County.Year                                  : chr [1:100] "mohave2019" "maricopa2019" "cochise201
##  $ Asthma                                       : int [1:100] 46 39 39 34 32 32 30 28 22 19 ...
##  $ Carbon Monoxide Poisoning                    : int [1:100] NA 1 7 NA 1 2 NA 3 NA NA ...
##  $ Chronic Obstructive Pulmonary Disease (COPD): int [1:100] 58 19 44 29 24 23 20 32 26 16 ...
##  $ Drinking Water Quality                       : int [1:100] 1 2 2 3 3 NA 2 1 3 3 ...
##  $ Food Safety                                  : int [1:100] NA NA NA NA NA NA NA NA NA NA ...
##  $ Heart Disease                                : int [1:100] 20 12 18 14 12 14 13 15 15 8 ...
##  $ Heat Stress Illness                          : int [1:100] 67 33 34 105 28 49 14 20 10 12 ...
##  $ Infectious Diseases                          : int [1:100] NA NA NA NA NA NA NA NA NA NA ...
##  $ Mortality                                    : int [1:100] NA NA NA NA NA NA NA NA NA NA ...
```

```
str(censusData)
```

```
## tibble [100 x 87] (S3: tbl_df/tbl/data.frame)
##  $ Year                         : chr [1:100] "2019" "2019" "2019" "2019" ...
##  $ County                       : Factor w/ 10 levels "apache","cochise",..: 1 2 3 4 5 6 7 8 9 10 ...
##  $ Date                         : Date[1:100], format: "2019-04-10" "2019-04-10" ...
##  $ County.Year                  : chr [1:100] "apache2019" "cochise2019" "coconino2019" "maricopa2019
##  $ Total.Population             : num [1:100] 71887 125922 143476 4485414 212181 ...
##  $ Male.Total.Population        : num [1:100] 36435 64204 71036 2217116 106919 ...
##  $ Female.Total.Population      : num [1:100] 35452 61718 72440 2268298 105262 ...
##  $ Sex.Ratio                    : num [1:100] 102.8 104 98.1 97.7 101.6 ...
##  $ Under.5.Population           : num [1:100] 4558 6855 6900 276119 8997 ...
##  $ 5.to.9.Population            : num [1:100] 5138 7951 7749 283710 9216 ...
##  $ 10.to.14.Population          : num [1:100] 6089 7437 8629 312364 11202 ...
##  $ 15.to.19.Population          : num [1:100] 5631 7424 17156 299470 10381 ...
##  $ 20.to.24.Population          : num [1:100] 4216 7822 18360 296675 9174 ...
##  $ 25.to.34.Population          : num [1:100] 9316 15467 19997 658682 20109 ...
##  $ 35.to.44.Population          : num [1:100] 7153 14188 15283 583814 19281 ...
##  $ 45.to.54.Population          : num [1:100] 8286 13124 14245 555903 22856 ...
##  $ 55.to.59.Population          : num [1:100] 4905 7725 9092 271428 13249 ...
##  $ 60.to.64.Population          : num [1:100] 4992 8990 7479 250782 21889 ...
##  $ 65.to.74.Population          : num [1:100] 7110 16326 11890 402314 37168 ...
##  $ 75.to.84.Population          : num [1:100] 3551 9222 5699 221756 23634 ...
##  $ Over.85.Population           : num [1:100] 942 3391 997 72397 5025 ...
```

```
##  $ Median.Age                  : num [1:100] 36.6 42.2 31.1 36.9 52.7 39.4 38.9 39.9 54.7 35.1 ...
##  $ Under.18.Population         : num [1:100] 19100 27003 28005 1052439 35605 ...
##  $ Over.16.Population          : num [1:100] 54969 101567 118789 3553180 181081 ...
##  $ Over.18.Population          : num [1:100] 52787 98919 115471 3432975 176576 ...
##  $ Over.21.Population          : num [1:100] 49300 95081 97207 3254644 170466 ...
##  $ Over.62.Population          : num [1:100] 14961 34619 23241 842012 78366 ...
##  $ Over.65.Population          : num [1:100] 11603 28939 18586 696467 65827 ...
##  $ Over.18                     : num [1:100] 52787 98919 115471 3432975 176576 ...
##  $ Over.18.Male                : num [1:100] 26304 50636 56074 1680405 89165 ...
##  $ Over.18.Female              : num [1:100] 26483 48283 59397 1752570 87411 ...
##  $ Over.18.Sex.Ratio           : num [1:100] 99.3 104.9 94.4 95.9 102 ...
##  $ Over.65.Male                : num [1:100] 5433 14060 8595 313899 32587 ...
##  $ Over.65.Female              : num [1:100] 6170 14879 9991 382568 33240 ...
##  $ Over.65.Sex.Ration          : num [1:100] 88.1 94.5 86 82.1 98 90.2 83.3 91.7 90.1 89.9 ...
##  $ One.Race.Total.Population   : num [1:100] 70612 120411 137246 4322940 204279 ...
##  $ Two.Or.More.Races.Population: num [1:100] 1275 5511 6230 162474 7902 ...
##  $ White                       : num [1:100] 15109 108177 91649 3547155 188756 ...
##  $ Black.Or.African.American   : num [1:100] 721 6163 1364 266128 1496 ...
##  $ AI.and.AN                   : num [1:100] 53480 1006 37187 93358 4358 ...
##  $ Cherokee.TG                 : num [1:100] NA NA NA 1294 NA ...
##  $ Chippewa.TG                 : num [1:100] NA NA NA 518 NA NA 606 NA NA NA ...
##  $ Navajo.TG                   : num [1:100] NA NA NA 39306 NA ...
##  $ Sioux.TG                    : num [1:100] NA NA NA 1130 NA NA 504 NA NA NA ...
##  $ Asian                       : num [1:100] 160 2795 2730 192301 1923 ...
##  $ Asian.Indian                : num [1:100] NA NA 201 63846 NA ...
##  $ Chinese                     : num [1:100] NA NA 773 33121 NA ...
##  $ Filipino                    : num [1:100] NA NA 664 34749 NA ...
##  $ Japanese                    : num [1:100] NA NA 28 6943 NA ...
##  $ Korean                      : num [1:100] NA NA 222 10546 NA ...
##  $ Vietnamese                  : num [1:100] NA NA 37 18613 NA ...
##  $ Other.Asian                 : num [1:100] NA NA 805 24483 NA ...
##  $ NH.and.OPI                  : num [1:100] 15 129 419 10045 138 ...
##  $ NH                          : num [1:100] NA NA NA 1479 NA ...
##  $ Guamanian.or.Chamorro       : num [1:100] NA NA NA 2203 NA ...
##  $ Samoan                      : num [1:100] NA NA NA 2862 NA ...
##  $ OPI                         : num [1:100] NA NA NA 3501 NA ...
##  $ Some.Other.Race             : num [1:100] 1127 2141 3897 213953 7608 ...
##  $ White.and.Black.or.AA       : num [1:100] NA 1404 1322 40575 2200 ...
##  $ White.and.AI.and.AN         : num [1:100] NA 1711 2458 20001 2563 ...
##  $ White.and.Asian             : num [1:100] NA 1181 1376 41246 1031 ...
##  $ Black.or.AA.and.AI.and.AN   : num [1:100] NA 49 250 4796 113 ...
##  $ Race.Alone.White            : num [1:100] 15889 113474 97323 3686959 196065 ...
##  $ Race.Alone.Black.or.AA      : num [1:100] 946 7966 3033 324706 3809 ...
##  $ Race.Alone.AI.and.AN        : num [1:100] 54253 2938 40104 128196 7034 ...
##  $ Race.Alone.Asian            : num [1:100] 381 4516 4677 251318 3671 ...
##  $ Race.Alone.NH.and.OPI       : num [1:100] NA 309 684 20342 964 ...
##  $ Race.Alone.Other            : num [1:100] 1764 2715 4150 249043 8777 ...
##  $ HL                          : num [1:100] 4736 44988 20542 1408855 35919 ...
##  $ Mexican                     : num [1:100] NA 40400 NA 1214522 29081 ...
##  $ Puerto.Rico                 : num [1:100] NA 1238 NA 32610 748 ...
##  $ Cuban                       : num [1:100] NA 59 NA 11749 1432 ...
##  $ OH.or.LP                    : num [1:100] NA 3291 NA 149974 4658 ...
##  $ Not.Hispanic.or.Latino      : num [1:100] 67151 80934 122934 3076559 176262 ...
##  $ NHL.White                   : num [1:100] 12935 68968 77608 2437462 162524 ...
```

```
##  $ NHL.Black.or.AA             : num [1:100] 721 4713 1287 248228 1441 ...
##  $ NHL.AI.and.AN               : num [1:100] 52536 415 36474 76504 3745 ...
##  $ NHL.Asian.Alone             : num [1:100] 160 2614 2730 187233 1923 ...
##  $ NHL.NH.and.OPI              : num [1:100] 15 129 419 9438 138 ...
##  $ NHL.Other                   : num [1:100] 218 0 0 8045 0 ...
##  $ NHL.Two.or.More.Races       : num [1:100] 566 4095 4416 109649 6491 ...
##  $ NHL.Two.Races.Including     : num [1:100] 0 0 0 3919 311 ...
##  $ NHL.Two.Races.Excluding     : num [1:100] 566 4095 4416 105730 6180 ...
##  $ HL.Total.Housing.Units      : num [1:100] 33021 61588 67491 1789265 116201 ...
##  $ Citizens.Over.18            : num [1:100] 52650 93194 112926 3082468 171003 ...
##  $ Male.Citizen.Over.18        : num [1:100] 26167 48203 55075 1503528 86451 ...
##  $ Female.Citizen.Over.18      : num [1:100] 26483 44991 57851 1578940 84552 ...
```

```
str(all.data)
```

```
## tibble [100 x 95] (S3: tbl_df/tbl/data.frame)
##  $ County                      : Factor w/ 10 levels "apache","cochise",..: 5 4 2 10 7 8 1 9 6 3 ...
##  $ Year                        : Factor w/ 10 levels "2010","2011",..: 10 10 10 10 10 10 10 10 10 10
##  $ Date                        : Date[1:100], format: "2019-04-10" "2019-04-10" ...
##  $ County.Year                 : chr [1:100] "mohave2019" "maricopa2019" "cochise2019" "yuma2019" ..
##  $ Asthma                      : num [1:100] 46 39 39 34 32 32 30 28 22 19 ...
##  $ Carbon.Monoxide.Poisoning   : int [1:100] NA 1 7 NA 1 2 NA 3 NA NA ...
##  $ COPD                        : int [1:100] 58 19 44 29 24 23 20 32 26 16 ...
##  $ Drinking.Water.Quality      : int [1:100] 1 2 2 3 3 NA 2 1 3 3 ...
##  $ Heart.Disease               : int [1:100] 20 12 18 14 12 14 13 15 15 8 ...
##  $ Heat.Stress.Illness         : int [1:100] 67 33 34 105 28 49 14 20 10 12 ...
##  $ Infectious.Diseases         : int [1:100] NA NA NA NA NA NA NA NA NA NA ...
##  $ Mortality                   : int [1:100] NA NA NA NA NA NA NA NA NA NA ...
##  $ Total.Population            : num [1:100] 212181 4485414 125922 213787 1047279 ...
##  $ Male.Total.Population       : num [1:100] 106919 2217116 64204 110189 516110 ...
##  $ Female.Total.Population     : num [1:100] 105262 2268298 61718 103598 531169 ...
##  $ Sex.Ratio                   : num [1:100] 101.6 97.7 104 106.4 97.2 ...
##  $ Under.5.Population          : num [1:100] 8997 276119 6855 15099 57113 ...
##  $ 5.to.9.Population           : num [1:100] 9216 283710 7951 14298 60599 ...
##  $ 10.to.14.Population         : num [1:100] 11202 312364 7437 15550 61314 ...
##  $ 15.to.19.Population         : num [1:100] 10381 299470 7424 14941 69026 ...
##  $ 20.to.24.Population         : num [1:100] 9174 296675 7822 16812 88778 ...
##  $ 25.to.34.Population         : num [1:100] 20109 658682 15467 30027 135885 ...
##  $ 35.to.44.Population         : num [1:100] 19281 583814 14188 22967 120304 ...
##  $ 45.to.54.Population         : num [1:100] 22856 555903 13124 21689 112541 ...
##  $ 55.to.59.Population         : num [1:100] 13249 271428 7725 10460 63631 ...
##  $ 60.to.64.Population         : num [1:100] 21889 250782 8990 11136 65492 ...
##  $ 65.to.74.Population         : num [1:100] 37168 402314 16326 19820 119874 ...
##  $ 75.to.84.Population         : num [1:100] 23634 221756 9222 16790 69655 ...
##  $ Over.85.Population          : num [1:100] 5025 72397 3391 4198 23067 ...
##  $ Median.Age                  : num [1:100] 52.7 36.9 42.2 35.1 38.9 39.9 36.6 54.7 39.4 31.1 ...
##  $ Under.18.Population         : num [1:100] 35605 1052439 27003 53571 215606 ...
##  $ Over.16.Population          : num [1:100] 181081 3553180 101567 164744 853555 ...
##  $ Over.18.Population          : num [1:100] 176576 3432975 98919 160216 831673 ...
##  $ Over.21.Population          : num [1:100] 170466 3254644 95081 150446 778821 ...
##  $ Over.62.Population          : num [1:100] 78366 842012 34619 47136 252031 ...
##  $ Over.65.Population          : num [1:100] 65827 696467 28939 40808 212596 ...
##  $ Over.18                     : num [1:100] 176576 3432975 98919 160216 831673 ...
##  $ Over.18.Male                : num [1:100] 89165 1680405 50636 83103 405576 ...
```

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##  $ Over.18.Female              : num [1:100] 87411 1752570 48283 77113 426097 ...
##  $ Over.18.Sex.Ratio           : num [1:100] 102 95.9 104.9 107.8 95.2 ...
##  $ Over.65.Male                : num [1:100] 32587 313899 14060 19321 96614 ...
##  $ Over.65.Female              : num [1:100] 33240 382568 14879 21487 115982 ...
##  $ Over.65.Sex.Ration          : num [1:100] 98 82.1 94.5 89.9 83.3 91.7 88.1 90.1 90.2 86 ...
##  $ One.Race.Total.Population   : num [1:100] 204279 4322940 120411 207267 987957 ...
##  $ Two.Or.More.Races.Population: num [1:100] 7902 162474 5511 6520 59322 ...
##  $ White                       : num [1:100] 188756 3547155 108177 189117 795391 ...
##  $ Black.Or.African.American   : num [1:100] 1496 266128 6163 3244 38343 ...
##  $ AI.and.AN                   : num [1:100] 4358 93358 1006 2900 40603 ...
##  $ Cherokee.TG                 : num [1:100] NA 1294 NA NA 0 ...
##  $ Chippewa.TG                 : num [1:100] NA 518 NA NA 606 NA NA NA NA NA ...
##  $ Navajo.TG                   : num [1:100] NA 39306 NA NA 2814 ...
##  $ Sioux.TG                    : num [1:100] NA 1130 NA NA 504 NA NA NA NA NA ...
##  $ Asian                       : num [1:100] 1923 192301 2795 2388 29276 ...
##  $ Asian.Indian                : num [1:100] NA 63846 NA 173 4411 ...
##  $ Chinese                     : num [1:100] NA 33121 NA 61 7446 ...
##  $ Filipino                    : num [1:100] NA 34749 NA 928 6429 ...
##  $ Japanese                    : num [1:100] NA 6943 NA 405 1293 ...
##  $ Korean                      : num [1:100] NA 10546 NA 210 2985 ...
##  $ Vietnamese                  : num [1:100] NA 18613 NA 400 3552 ...
##  $ Other.Asian                 : num [1:100] NA 24483 NA 211 3160 ...
##  $ NH.and.OPI                  : num [1:100] 138 10045 129 242 1733 ...
##  $ NH                          : num [1:100] NA 1479 NA NA NA ...
##  $ Guamanian.or.Chamorro       : num [1:100] NA 2203 NA NA NA ...
##  $ Samoan                      : num [1:100] NA 2862 NA NA NA ...
##  $ OPI                         : num [1:100] NA 3501 NA NA NA ...
##  $ Some.Other.Race             : num [1:100] 7608 213953 2141 9376 82611 ...
##  $ White.and.Black.or.AA       : num [1:100] 2200 40575 1404 1411 8272 ...
##  $ White.and.AI.and.AN         : num [1:100] 2563 20001 1711 1323 19188 ...
##  $ White.and.Asian             : num [1:100] 1031 41246 1181 1213 11524 ...
##  $ Black.or.AA.and.AI.and.AN   : num [1:100] 113 4796 49 204 2064 ...
##  $ Race.Alone.White            : num [1:100] 196065 3686959 113474 195251 848158 ...
##  $ Race.Alone.Black.or.AA      : num [1:100] 3809 324706 7966 5910 53700 ...
##  $ Race.Alone.AI.and.AN        : num [1:100] 7034 128196 2938 5464 64289 ...
##  $ Race.Alone.Asian            : num [1:100] 3671 251318 4516 4158 44817 ...
##  $ Race.Alone.NH.and.OPI       : num [1:100] 964 20342 309 574 3438 ...
##  $ Race.Alone.Other            : num [1:100] 8777 249043 2715 10509 96795 ...
##  $ HL                          : num [1:100] 35919 1408855 44988 138130 395446 ...
##  $ Mexican                     : num [1:100] 29081 1214522 40400 132427 355285 ...
##  $ Puerto.Rico                 : num [1:100] 748 32610 1238 777 8939 ...
##  $ Cuban                       : num [1:100] 1432 11749 59 652 2340 ...
##  $ OH.or.LP                    : num [1:100] 4658 149974 3291 4274 28882 ...
##  $ Not.Hispanic.or.Latino      : num [1:100] 176262 3076559 80934 75657 651833 ...
##  $ NHL.White                   : num [1:100] 162524 2437462 68968 64294 535435 ...
##  $ NHL.Black.or.AA             : num [1:100] 1441 248228 4713 2825 35055 ...
##  $ NHL.AI.and.AN               : num [1:100] 3745 76504 415 2147 25427 ...
##  $ NHL.Asian.Alone             : num [1:100] 1923 187233 2614 2388 28844 ...
##  $ NHL.NH.and.OPI              : num [1:100] 138 9438 129 176 1599 ...
##  $ NHL.Other                   : num [1:100] 0 8045 0 71 751 ...
##  $ NHL.Two.or.More.Races       : num [1:100] 6491 109649 4095 3756 24722 ...
##  $ NHL.Two.Races.Including     : num [1:100] 311 3919 0 88 687 ...
##  $ NHL.Two.Races.Excluding     : num [1:100] 6180 105730 4095 3668 24035 ...
##  $ HL.Total.Housing.Units      : num [1:100] 116201 1789265 61588 94648 466337 ...
```

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##  $ Citizens.Over.18           : num [1:100] 171003 3082468 93194 131800 761110 ...
##  $ Male.Citizen.Over.18       : num [1:100] 86451 1503528 48203 69067 371071 ...
##  $ Female.Citizen.Over.18     : num [1:100] 84552 1578940 44991 62733 390039 ...
```