CDC 500 Cities: Healthcare Access, Behaviors, and Health Outcomes

Stat 198 Final Project

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Description of Data

(Include description of how you edited the data)

Research Questions

1) Do cities with a greater lack of healthcare access have poorer mental health and/or physical health outcomes?

2)Does healthcare access, mental health, and/or physical health outcomes vary by state?

Variables of Interest

Explanatory Variables:

1) Healthcare Access for Adults (18+): Percent of City Population that Lacks Insurance, Percent of City Population with visits to doctor for routine checkup within the past year, Percent of City Population who have high blood pressure and are taking medicine for high blood pressure control.
2) Geographic Distribution by State

Response Variables:

1) Behavior for Adults (18+): Percent of city population currently smoking, percent of city population currently reporting binge drinking habits, percent of city population reporting No leisure-time physical activity
2) Health Outcomes for Adults (18+): Percent of city population with coronary heart disease, percent of population diagnosed with diabetes, percent of city population with kidney disease

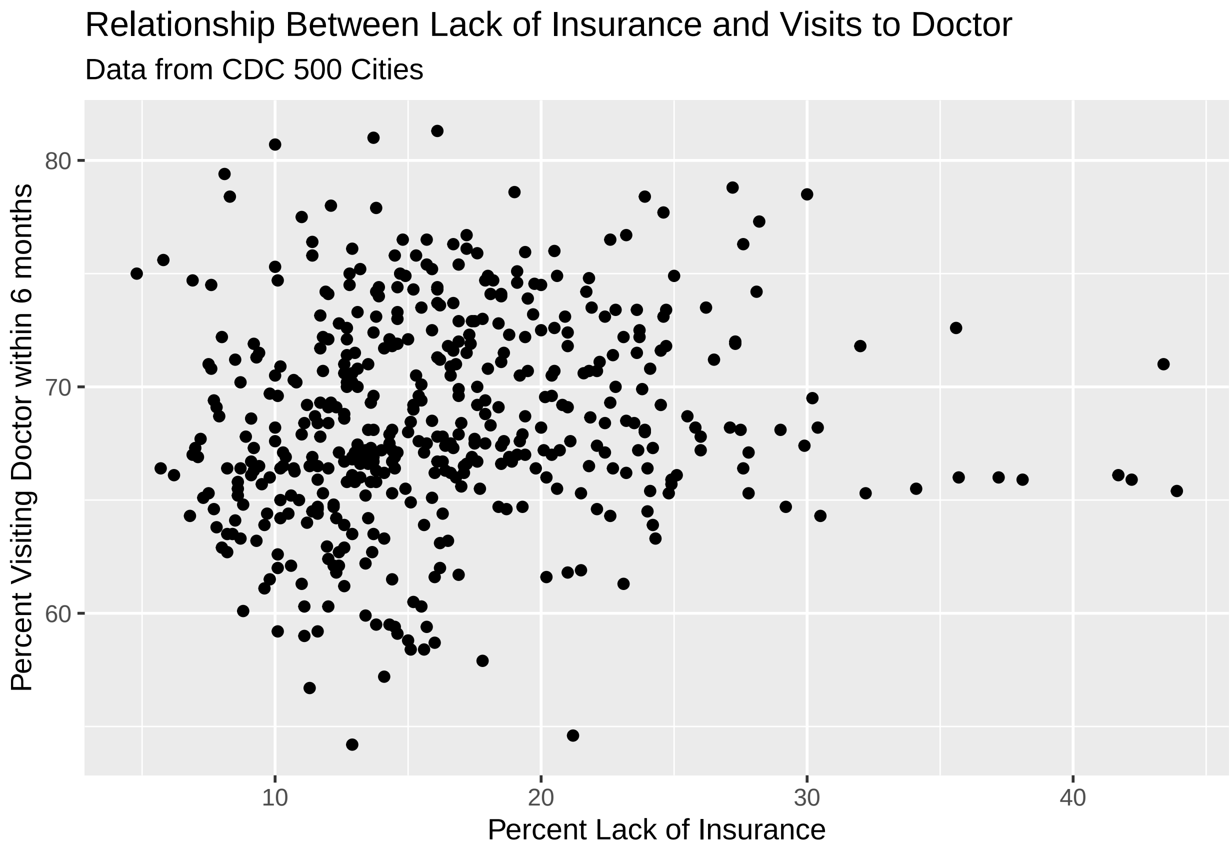
Linear Regressions

New Method:

a) Run correlations between the explanatory variables
b) Run linear regressions and adjusted r squared values
c) Assess which regression is better
d) Run the residual plot and the graph

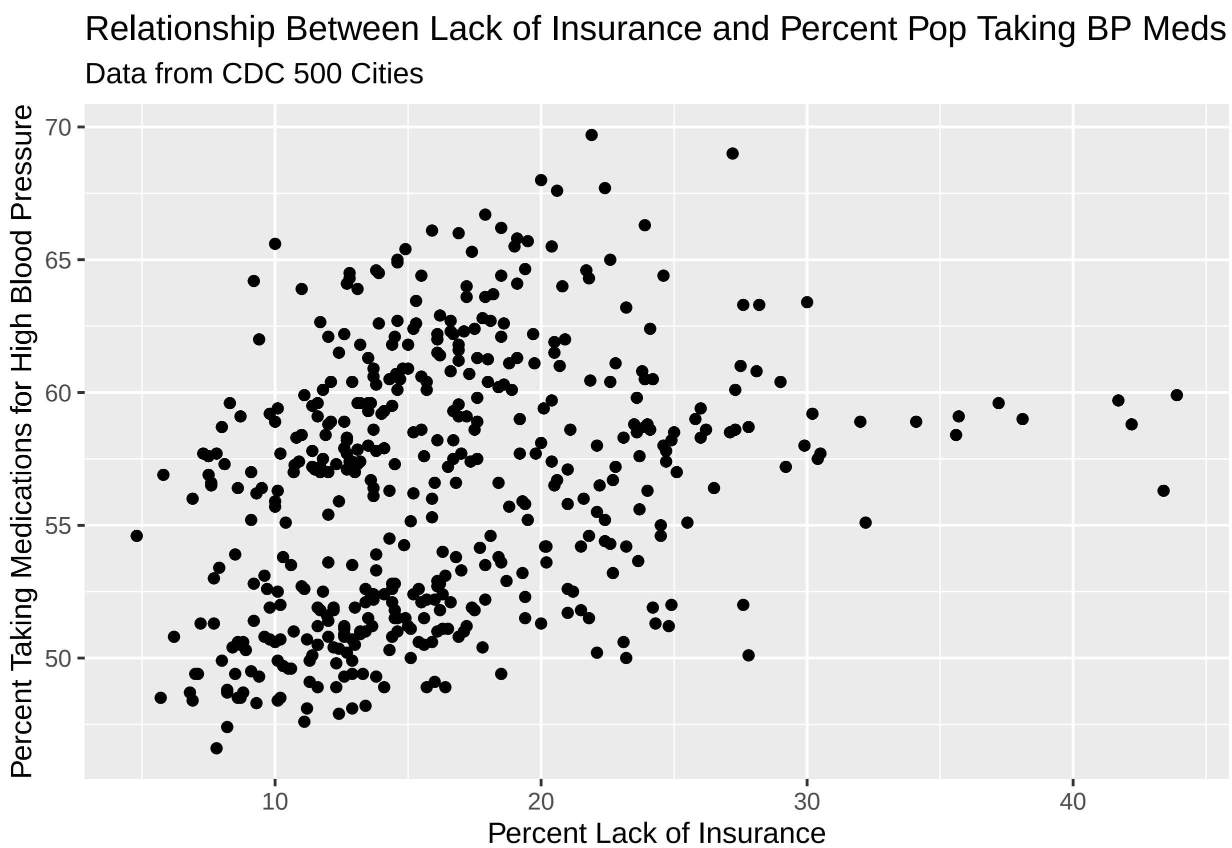
Correlations between Explanatory Variables

```
data_500_cities %>%
  ggplot(mapping = aes(x = insurance, y = visits_to_doctor)) +
  geom_point() +
  labs(
    title = "Relationship Between Lack of Insurance and Visits to Doctor",
    subtitle = "Data from CDC 500 Cities",
    x = "Percent Lack of Insurance",
    y = "Percent Visiting Doctor within 6 months"
  )
```



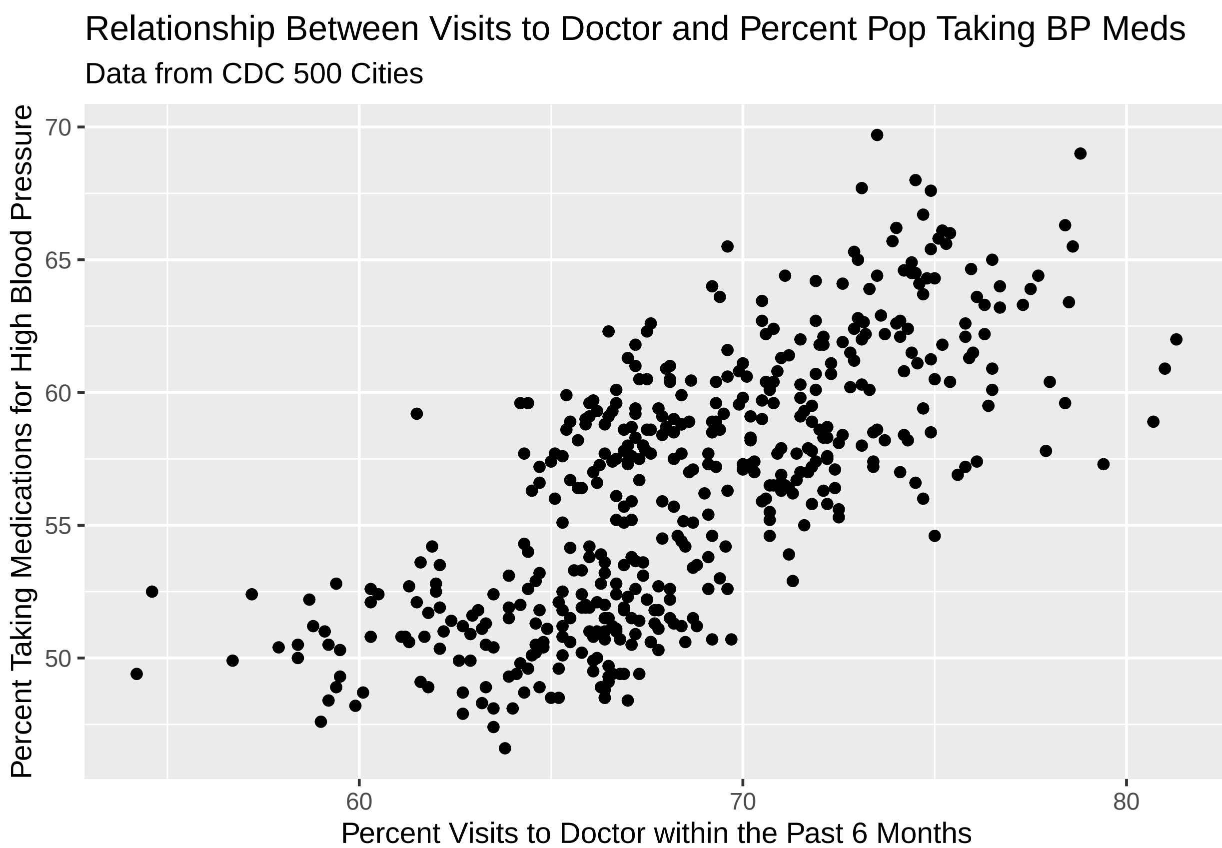
There does not seem to be any significant correlation.

```
data_500_cities %>%
  ggplot(mapping = aes(x = insurance, y = medicine_high_bp)) +
  geom_point() +
  labs(
    title = "Relationship Between Lack of Insurance and Percent Pop Taking BP Meds",
    subtitle = "Data from CDC 500 Cities",
    x = "Percent Lack of Insurance",
    y = "Percent Taking Medications for High Blood Pressure"
  )
```



There does not seem to be any significant correlation.

```
data_500_cities %>%
  ggplot(mapping = aes(x = visits_to_doctor, y = medicine_high_bp)) +
  geom_point() +
  labs(
    title = "Relationship Between Visits to Doctor and Percent Pop Taking BP Meds",
    subtitle = "Data from CDC 500 Cities",
    x = "Percent Visits to Doctor within the Past 6 Months",
    y = "Percent Taking Medications for High Blood Pressure"
  )
```



There seems to be a significant correlation between Visits to Doctor and Taking Medications.

As a result, I will test three models: one with no interaction variables, one with only one interaction variable (Visits_to_Doctor * medicine_high_bp), and one with all three interaction variables.

Access Variables vs. Smoking

Running Linear Regressions

Linear Regression with No Interaction Variables:

```
access_smoking_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(smoking ~ insurance + visits_to_doctor + medicine_high_bp, data = data_500_cities)
access_smoking_fit_aug <- augment(access_smoking_fit$fit)
tidy(access_smoking_fit) %>%
  print()
```

```
## # A tibble: 4 x 5
##   term             estimate std.error statistic  p.value
##   <chr>               <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)      -15.0       2.08       -7.23 1.99e-12
## 2 insurance          0.0523    0.0237      2.21 2.79e- 2
## 3 visits_to_doctor  -0.0966    0.0446     -2.17 3.08e- 2
## 4 medicine_high_bp   0.674     0.0438     15.4  1.59e-43
```

Linear Regression with one interaction variable:

```
one_access_smoking_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(smoking ~ insurance + visits_to_doctor + medicine_high_bp + (visits_to_doctor * medicine_high_bp)
one_access_smoking_fit_aug <- augment(one_access_smoking_fit$fit)
tidy(one_access_smoking_fit) %>%
  print()
```

```
## # A tibble: 5 x 5
##   term                              estimate std.error statistic   p.value
##   <chr>                                <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept)                        84.8     24.7          3.43 0.000657
## 2 insurance                           0.0653   0.0235       2.77 0.00576
## 3 visits_to_doctor                   -1.54     0.360       -4.29 0.0000217
## 4 medicine_high_bp                   -1.12     0.444       -2.52 0.0121
## 5 visits_to_doctor:medicine_high_bp   0.0258   0.00637      4.05 0.0000594
```

Linear Regression with All Interaction Variables

```
int_access_smoking_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(smoking ~ insurance + visits_to_doctor + medicine_high_bp + (insurance * visits_to_doctor) + (insu
int_access_smoking_fit_aug <- augment(int_access_smoking_fit$fit)
tidy(int_access_smoking_fit) %>%
  print()
```

```
## # A tibble: 7 x 5
##   term                              estimate std.error statistic  p.value
##   <chr>                                <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)                        88.9     24.0          3.70 2.41e- 4
## 2 insurance                           0.872    0.417        2.09 3.71e- 2
## 3 visits_to_doctor                   -2.13     0.362       -5.90 6.95e- 9
## 4 medicine_high_bp                   -0.756    0.463       -1.63 1.03e- 1
## 5 insurance:visits_to_doctor          0.0227   0.00634      3.59 3.69e- 4
## 6 insurance:medicine_high_bp         -0.0414   0.00628     -6.58 1.25e-10
## 7 visits_to_doctor:medicine_high_bp   0.0299   0.00667      4.48 9.60e- 6
```

Comparing Adj R-Squared Values

Adj R-Squared Value with No Interactions:

```
glance(access_smoking_fit)$adj.r.squared %>%
  print()
```

```
## [1] 0.5150724
```

Adj R-Squared Value with One Interactions:

```
glance(one_access_smoking_fit)$adj.r.squared %>%
  print()
```

```
## [1] 0.5305757
```

Adj R-Squared Value with All Interactions:

```
glance(int_access_smoking_fit)$adj.r.squared %>%
  print()
```

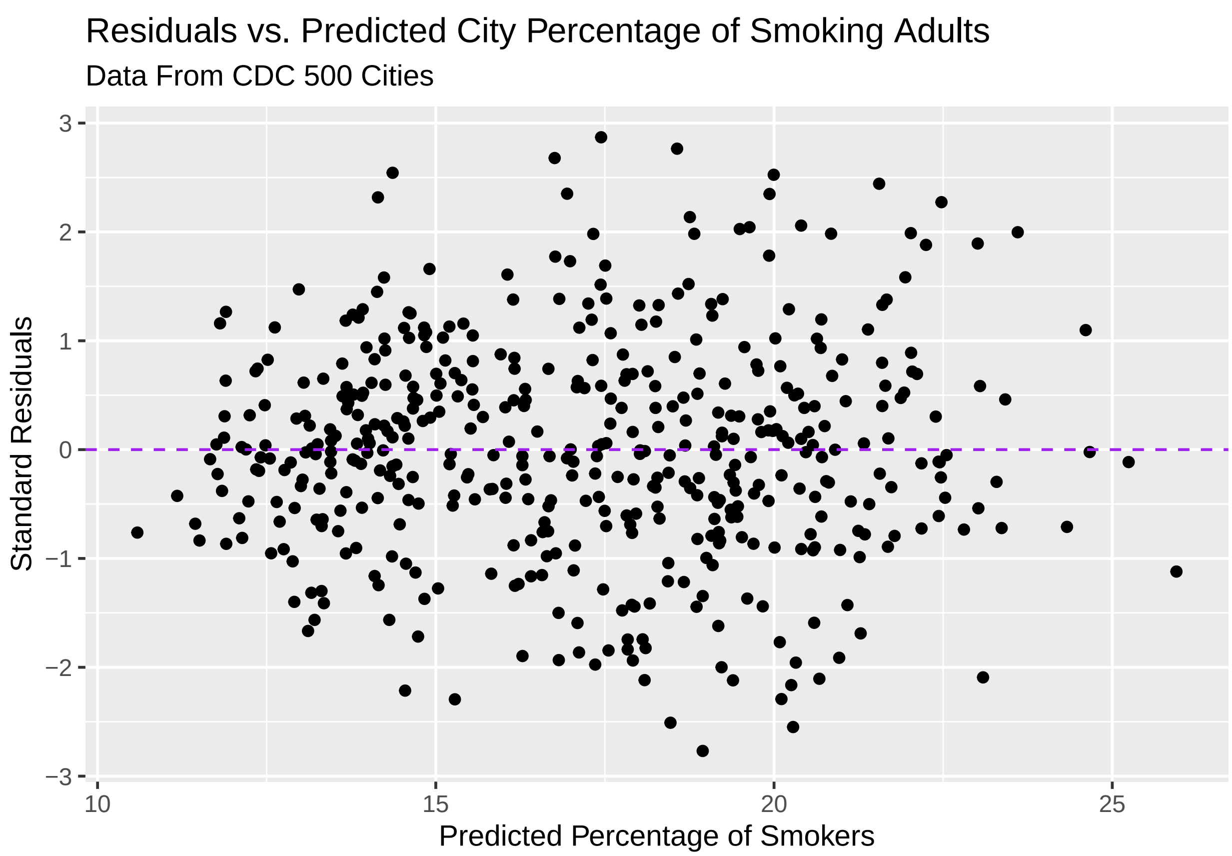
```
## [1] 0.5691301
```

Make some kind of statement here about which regression is most appropriate

Displaying Graphs (Edit Based on Which Interaction is Most Appropriate)

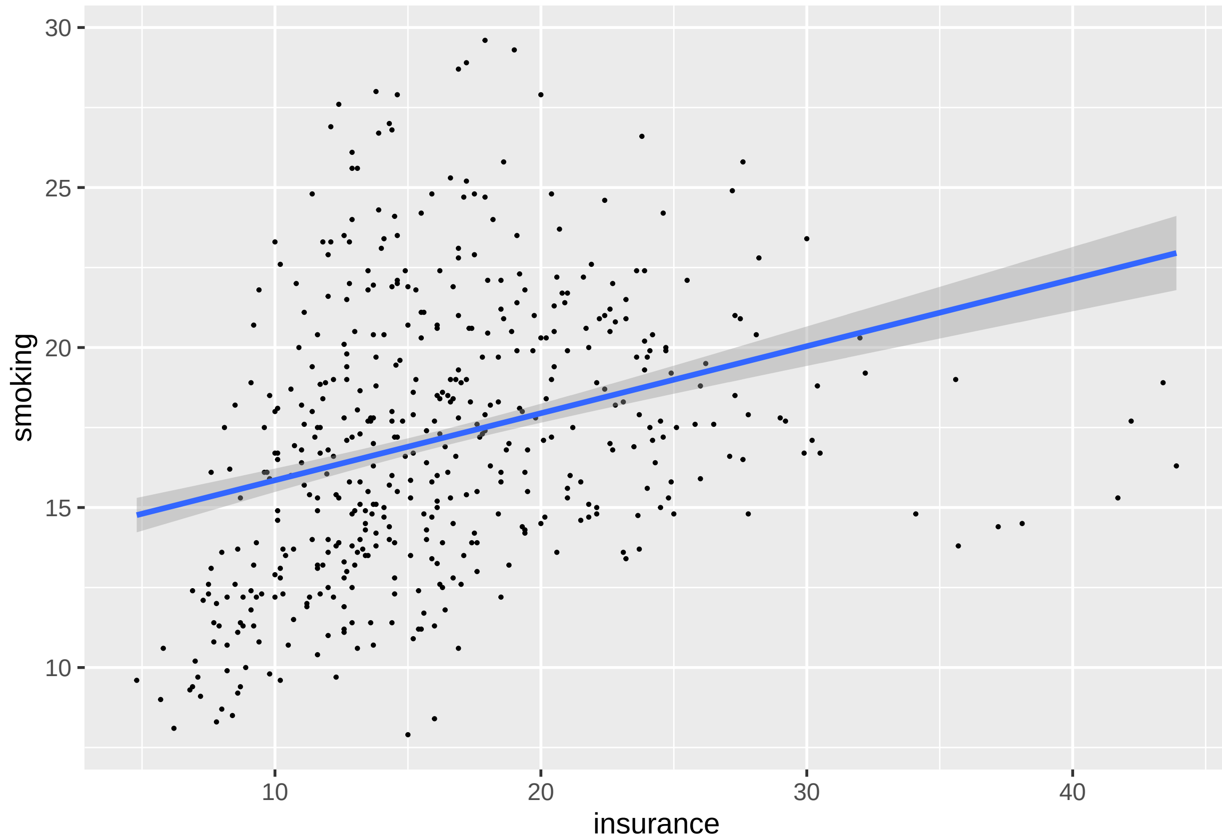
Residual Graph (Note any patterns)

```
access_smoking_fit_aug %>%
  ggplot(mapping = aes(x = .fitted, y = .std.resid)) +
  geom_point() +
  geom_hline(yintercept = 0, color = "purple", lty = "dashed") +
  labs(
    title = "Residuals vs. Predicted City Percentage of Smoking Adults",
    subtitle = "Data From CDC 500 Cities",
    x = "Predicted Percentage of Smokers",
    y = "Standard Residuals"
  )
```



Graph Between Explanatory and Response Variables

```
data_500_cities %>%
ggplot( mapping = aes(x = insurance, y = smoking)) +
geom_point(size = 0.25) +
geom_smooth(method = "lm", data = access_smoking_fit_aug, mapping = aes(x = insurance, y = .fitted))
```



Access Variables vs. Binge Drinking

Running Linear Regressions

Linear Regression for no interactions:

```
access_binge_drinking_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(binge_drinking ~ insurance + visits_to_doctor + medicine_high_bp, data = data_500_cities)
access_binge_drinking_fit_aug <- augment(access_binge_drinking_fit$fit)
tidy(access_binge_drinking_fit) %>%
  print()
```

```
## # A tibble: 4 x 5
##   term             estimate std.error statistic  p.value
##   <chr>               <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)       24.2       1.58       15.3  2.65e-43
## 2 insurance         -0.162     0.0179     -9.02 4.74e-18
## 3 visits_to_doctor   0.0565    0.0337      1.68 9.45e- 2
## 4 medicine_high_bp  -0.137     0.0331     -4.13 4.39e- 5
```

Linear regression with one interaction:

```
one_access_binge_drinking_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(binge_drinking ~ insurance + visits_to_doctor + medicine_high_bp + (visits_to_doctor * medicine_hi
one_access_binge_drinking_fit_aug <- augment(one_access_binge_drinking_fit$fit)
tidy(one_access_binge_drinking_fit) %>%
```

```
  print()
```

```
## # A tibble: 5 x 5
##   term                              estimate std.error statistic  p.value
##   <chr>                                <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)                       -133.      17.6         -7.57 1.97e-13
## 2 insurance                           -0.183    0.0167     -10.9  8.43e-25
## 3 visits_to_doctor                     2.34     0.256        9.13 2.03e-18
## 4 medicine_high_bp                     2.69     0.316        8.50 2.50e-16
## 5 visits_to_doctor:medicine_high_bp   -0.0407   0.00453     -8.98 6.76e-18
```

Linear regression with all interactions:

```
int_access_binge_drinking_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(binge_drinking ~ insurance + visits_to_doctor + medicine_high_bp + (insurance * visits_to_doctor)
int_access_binge_drinking_fit_aug <- augment(int_access_binge_drinking_fit$fit)
tidy(int_access_binge_drinking_fit) %>%
  print()
```

```
## # A tibble: 7 x 5
##   term                               estimate std.error statistic  p.value
##   <chr>                                 <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)                       -132.       17.8        -7.40  6.26e-13
## 2 insurance                           -0.125     0.309      -0.406 6.85e- 1
## 3 visits_to_doctor                     2.41      0.268       8.98  6.70e-18
## 4 medicine_high_bp                     2.54      0.344       7.38  7.12e-13
## 5 insurance:visits_to_doctor          -0.00655   0.00470    -1.39  1.64e- 1
## 6 insurance:medicine_high_bp           0.00686   0.00466     1.47  1.42e- 1
## 7 visits_to_doctor:medicine_high_bp   -0.0401    0.00495    -8.10  4.93e-15
```

Comparing Adj R-Squared Values

Adj R-squared value for regression with no interactions:

```
glance(access_binge_drinking_fit)$adj.r.squared %>%
  print()
```

```
## [1] 0.2367489
```

Adj R-squared value for regression with one interaction:

```
glance(one_access_binge_drinking_fit)$adj.r.squared %>%
  print()
```

```
## [1] 0.347712
```

Adj R-squared value for regression with all interactions:

```
glance(int_access_binge_drinking_fit)$adj.r.squared %>%
  print()
```

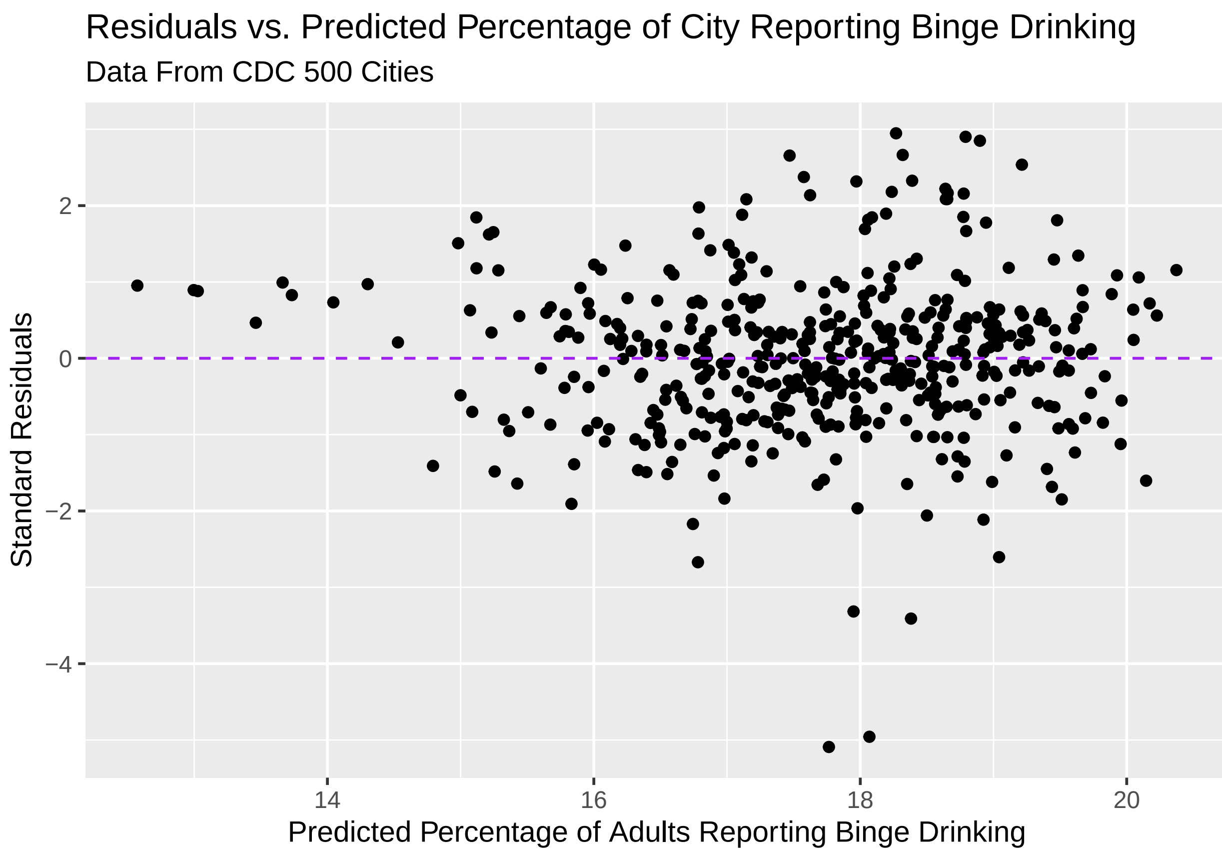
```
## [1] 0.3488416
```

Make some kind of statement about which linear regression is most apporpriate

Displaying Graphs (Edit Based on which regression you choose)

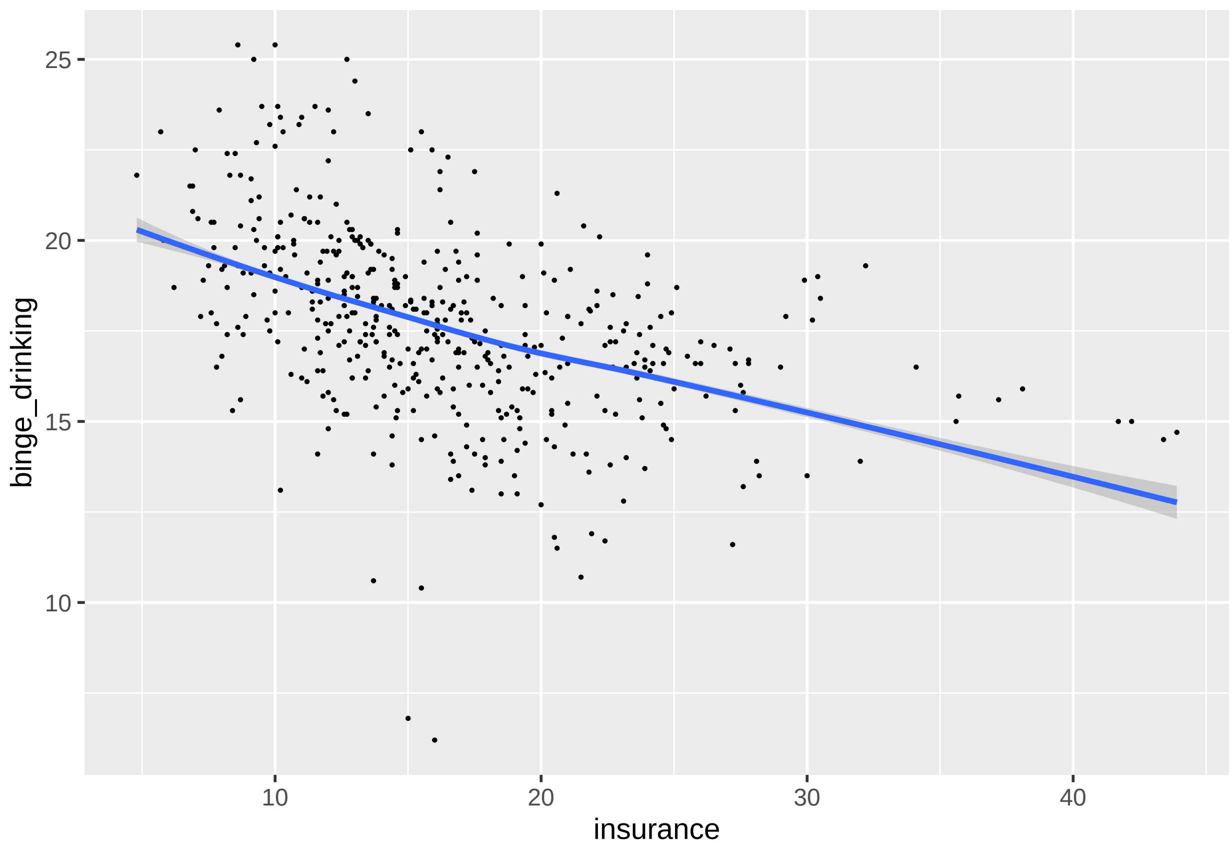
Residual Graph (Note any patterns)

```
access_binge_drinking_fit_aug %>%
  ggplot(mapping = aes(x = .fitted, y = .std.resid)) +
  geom_point() +
  geom_hline(yintercept = 0, color = "purple", lty = "dashed") +
  labs(
    title = "Residuals vs. Predicted Percentage of City Reporting Binge Drinking",
    subtitle = "Data From CDC 500 Cities",
    x = "Predicted Percentage of Adults Reporting Binge Drinking",
    y = "Standard Residuals"
  )
```



Graph Comparing Explanatory and Response Variables

```
data_500_cities %>%
ggplot( mapping = aes(x = insurance, y = binge_drinking)) +
geom_point(size = 0.25) +
geom_smooth(data = access_binge_drinking_fit_aug, mapping = aes(x = insurance, y = .fitted))
```



Access Variables vs. Physical Activity

Running Linear Regressions

Linear regression with no interactions

```
access_physical_activity_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(physical_activity ~ insurance + visits_to_doctor + medicine_high_bp, data = data_500_cities)
access_physical_activity_fit_aug <- augment(access_physical_activity_fit$fit)
tidy(access_physical_activity_fit) %>%
  print()
```

```
## # A tibble: 4 x 5
##   term             estimate std.error statistic  p.value
##   <chr>               <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)      -28.1       1.77      -15.9  5.76e-46
## 2 insurance          0.533     0.0201     26.5  3.31e-95
## 3 visits_to_doctor   0.0625    0.0378      1.65 9.95e- 2
## 4 medicine_high_bp   0.738     0.0371     19.9  3.54e-64
```

Linear regression with one interaction

```
one_access_physical_activity_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(physical_activity ~ insurance + visits_to_doctor + medicine_high_bp + (visits_to_doctor * medicine
one_access_physical_activity_fit_aug <- augment(one_access_physical_activity_fit$fit)
tidy(one_access_physical_activity_fit) %>%
```

```
  print()
```

```
## # A tibble: 5 x 5
##   term                               estimate std.error statistic  p.value
##   <chr>                                 <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)                         43.5     21.1          2.06 3.98e- 2
## 2 insurance                            0.543    0.0201      27.0  1.71e-97
## 3 visits_to_doctor                    -0.976    0.307       -3.18 1.57e- 3
## 4 medicine_high_bp                    -0.548    0.379       -1.44 1.49e- 1
## 5 visits_to_doctor:medicine_high_bp   0.0185   0.00543      3.41 7.11e- 4
```

Linear regression with all interactions

```
int_access_physical_activity_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(physical_activity ~ insurance + visits_to_doctor + medicine_high_bp + (insurance * visits_to_docto
int_access_physical_activity_fit_aug <- augment(int_access_physical_activity_fit$fit)
tidy(int_access_physical_activity_fit) %>%
  print()
```

```
## # A tibble: 7 x 5
##   term                                estimate std.error statistic      p.value
##   <chr>                                  <dbl>     <dbl>     <dbl>        <dbl>
## 1 (Intercept)                         55.1       20.8          2.64  0.00845
## 2 insurance                            1.96       0.361        5.42  0.0000000972
## 3 visits_to_doctor                    -1.47       0.313       -4.69  0.00000361
## 4 medicine_high_bp                    -0.744      0.402       -1.85  0.0646
## 5 insurance:visits_to_doctor           0.000790   0.00549      0.144 0.886
## 6 insurance:medicine_high_bp          -0.0257     0.00545     -4.72  0.00000317
## 7 visits_to_doctor:medicine_high_bp    0.0271     0.00578      4.68  0.00000373
```

Comparing Adj R-Squared Values

Adj R-squared value for regression with no interactions

```
glance(access_physical_activity_fit)$adj.r.squared %>%
  print()
```

```
## [1] 0.8369087
```

Adj R-squared value for regression with one interaction

```
glance(one_access_physical_activity_fit)$adj.r.squared %>%
  print()
```

```
## [1] 0.8405259
```

Adj R-squared value for regression with all interactions

```
glance(int_access_physical_activity_fit)$adj.r.squared %>%
  print()
```

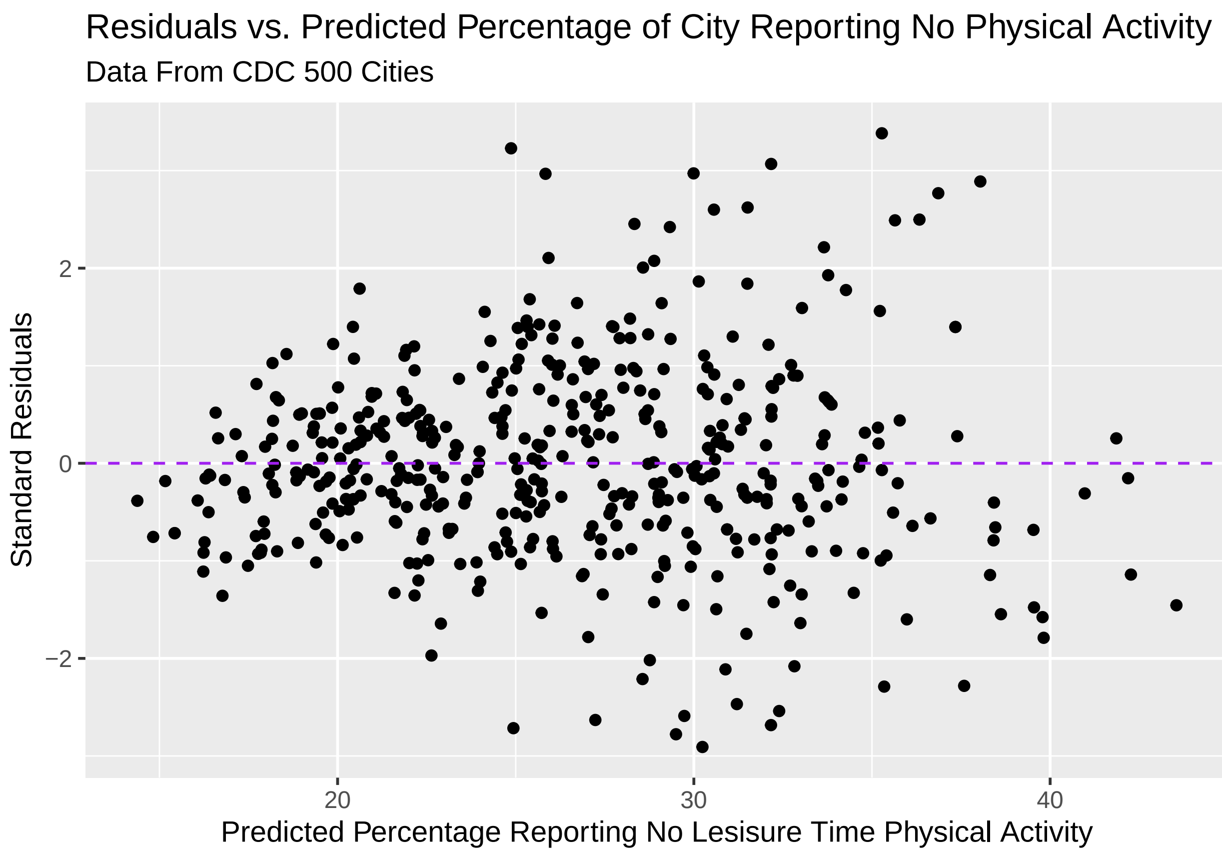
```
## [1] 0.8488063
```

Make some kind of statement about which regression is most appropriate

Displaying Graphs (Edit based on which regression you choose)

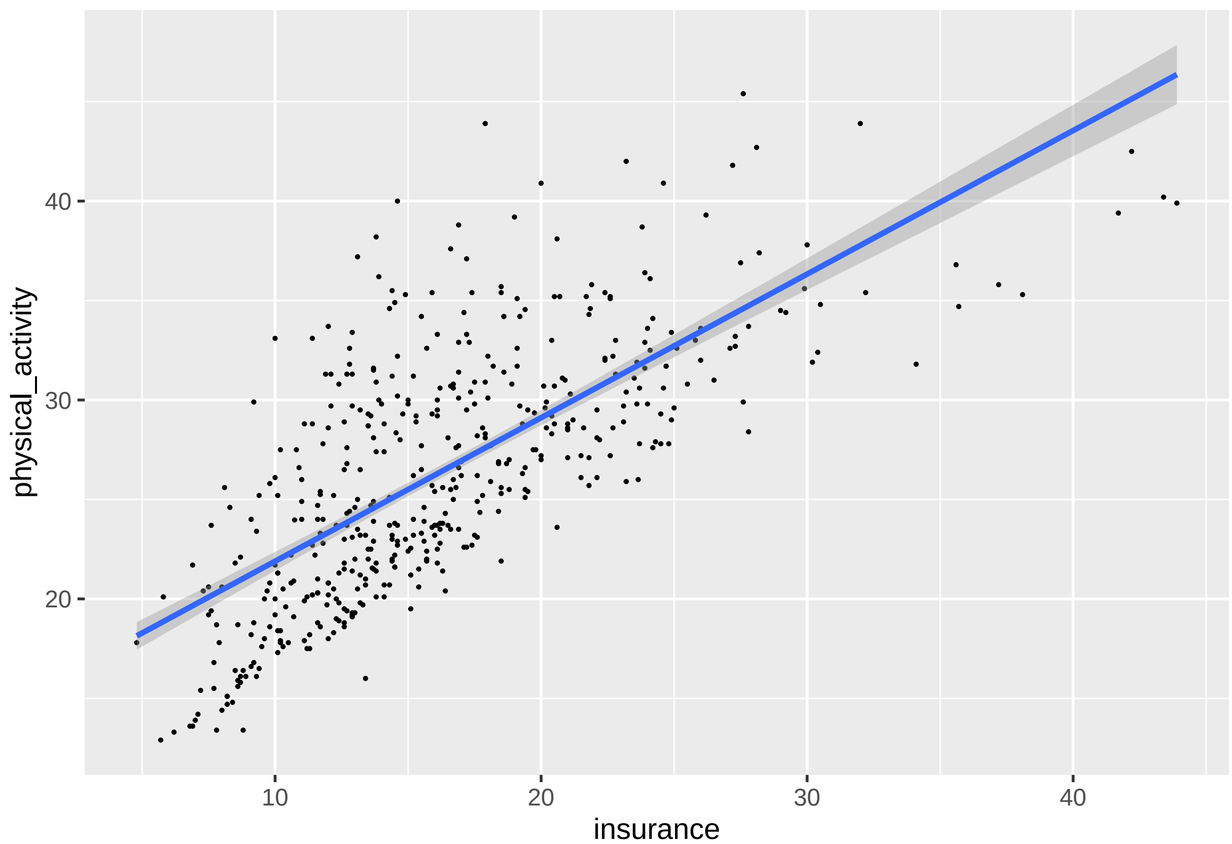
Residual Graph (Note any patterns)

```
access_physical_activity_fit_aug %>%
  ggplot(mapping = aes(x = .fitted, y = .std.resid)) +
  geom_point() +
  geom_hline(yintercept = 0, color = "purple", lty = "dashed") +
  labs(
    title = "Residuals vs. Predicted Percentage of City Reporting No Physical Activity",
    subtitle = "Data From CDC 500 Cities",
    x = "Predicted Percentage Reporting No Lesisure Time Physical Activity",
    y = "Standard Residuals"
  )
```



Graph Comparing Explanatory and Response Variables

```
data_500_cities %>%
ggplot( mapping = aes(x = insurance, y = physical_activity)) +
geom_point(size = 0.25) +
geom_smooth(method = "lm", data = access_physical_activity_fit_aug, mapping = aes(x = insurance, y = .fi
```



Access Variables vs. Coronary Heart Disease

Running Linear Regressions

Linear regression with no interactions:

```
access_heart_disease_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(heart_disease ~ insurance + visits_to_doctor + medicine_high_bp, data = data_500_cities)
access_heart_disease_fit_aug <- augment(access_heart_disease_fit$fit)
tidy(access_heart_disease_fit) %>%
  print()
```

```
## # A tibble: 4 x 5
##   term             estimate std.error statistic  p.value
##   <chr>               <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)       -1.54     0.427       -3.60 3.56e- 4
## 2 insurance          0.0669   0.00487     13.7  2.32e-36
## 3 visits_to_doctor  -0.0113   0.00916     -1.23 2.20e- 1
## 4 medicine_high_bp   0.122    0.00898     13.6  1.16e-35
```

Linear regression with one interaction

```
one_access_heart_disease_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(heart_disease ~ insurance + visits_to_doctor + medicine_high_bp + (visits_to_doctor * medicine_hig
access_heart_disease_fit_aug <- augment(access_heart_disease_fit$fit)
tidy(access_heart_disease_fit) %>%
```

```
  print()
```

```
## # A tibble: 4 x 5
##   term             estimate std.error statistic  p.value
##   <chr>               <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)       -1.54     0.427       -3.60 3.56e- 4
## 2 insurance          0.0669   0.00487     13.7  2.32e-36
## 3 visits_to_doctor  -0.0113   0.00916     -1.23 2.20e- 1
## 4 medicine_high_bp   0.122    0.00898     13.6  1.16e-35
```

Linear regression with all interactions

```
int_access_heart_disease_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(heart_disease ~ insurance + visits_to_doctor + medicine_high_bp + (insurance * visits_to_doctor) +
int_access_heart_disease_fit_aug <- augment(int_access_heart_disease_fit$fit)
tidy(int_access_heart_disease_fit) %>%
  print()
```

```
## # A tibble: 7 x 5
##   term                              estimate std.error statistic  p.value
##   <chr>                                <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)                       23.9       4.94         4.84 1.74e- 6
## 2 insurance                          0.352     0.0857       4.10 4.79e- 5
## 3 visits_to_doctor                  -0.480     0.0743      -6.46 2.70e-10
## 4 medicine_high_bp                  -0.289     0.0952      -3.04 2.52e- 3
## 5 insurance:visits_to_doctor         0.00239   0.00130      1.84 6.67e- 2
## 6 insurance:medicine_high_bp        -0.00780   0.00129     -6.04 3.19e- 9
## 7 visits_to_doctor:medicine_high_bp  0.00767   0.00137      5.59 3.80e- 8
```

Comparing Adj R Squared Values

Adj R-squared values for regression with no interactions

```
glance(access_heart_disease_fit)$adj.r.squared %>%
  print()
```

```
## [1] 0.6254959
```

Adj R-squared values for regression with one interaction

```
glance(one_access_heart_disease_fit)$adj.r.squared %>%
  print()
```

```
## [1] 0.6413167
```

Adj R-squared values for regression with all interactions

```
glance(int_access_heart_disease_fit)$adj.r.squared %>%
  print()
```

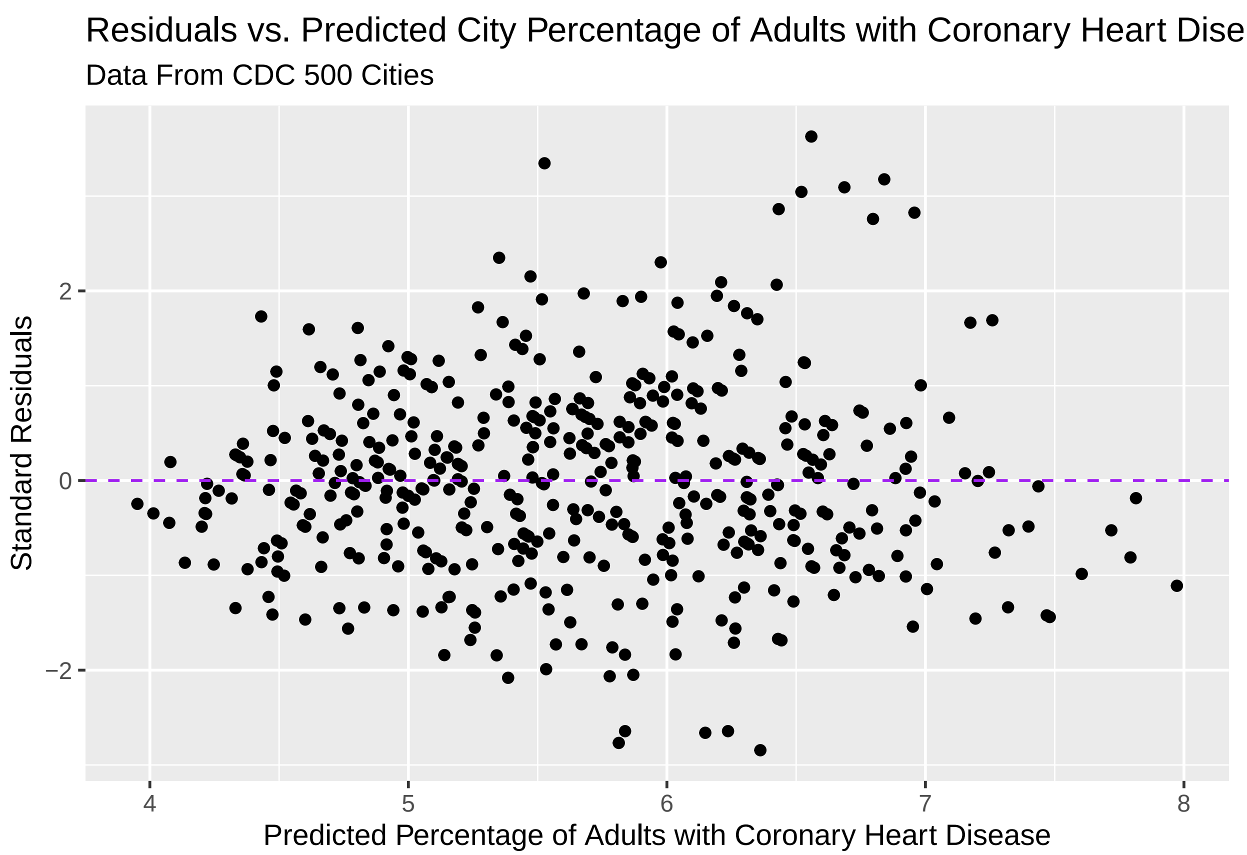
```
## [1] 0.6667498
```

Displaying Graphs (Edit based on which regression you choose)

Residual Graphs (Note any Patterns)

```
access_heart_disease_fit_aug %>%
  ggplot(mapping = aes(x = .fitted, y = .std.resid)) +
```

```
  geom_point() +
  geom_hline(yintercept = 0, color = "purple", lty = "dashed") +
  labs(
    title = "Residuals vs. Predicted City Percentage of Adults with Coronary Heart Disease",
    subtitle = "Data From CDC 500 Cities",
    x = "Predicted Percentage of Adults with Coronary Heart Disease",
    y = "Standard Residuals"
  )
```



Graph Comparing Explanatory and Response Variables

Access Variables vs. Diabetes

Running linear regressions

Linear regression with one interaction

```
access_diabetes_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(diabetes ~ insurance + visits_to_doctor + medicine_high_bp, data = data_500_cities)
access_diabetes_fit_aug <- augment(access_diabetes_fit$fit)
tidy(access_diabetes_fit) %>%
  print()
```

```
## # A tibble: 4 x 5
##   term              estimate std.error statistic  p.value
##   <chr>                <dbl>     <dbl>     <dbl>    <dbl>
```

```
## 1 (Intercept)       -7.57      0.982      -7.71 7.45e-14
## 2 insurance          0.239     0.0112     21.4  2.12e-71
## 3 visits_to_doctor   0.0650    0.0210      3.09 2.13e- 3
## 4 medicine_high_bp   0.171     0.0206      8.29 1.18e-15
```

Linear regression with one interaction

```
one_access_diabetes_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(diabetes ~ insurance + visits_to_doctor + medicine_high_bp + (visits_to_doctor * medicine_high_bp)
access_diabetes_fit_aug <- augment(access_diabetes_fit$fit)
tidy(access_diabetes_fit) %>%
  print()
```

```
## # A tibble: 4 x 5
##   term             estimate std.error statistic  p.value
##   <chr>               <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)       -7.57      0.982      -7.71 7.45e-14
## 2 insurance          0.239     0.0112     21.4  2.12e-71
## 3 visits_to_doctor   0.0650    0.0210      3.09 2.13e- 3
## 4 medicine_high_bp   0.171     0.0206      8.29 1.18e-15
```

Linear regression with all interactions

```
int_access_diabetes_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(diabetes ~ insurance + visits_to_doctor + medicine_high_bp + (insurance * visits_to_doctor) + (ins
int_access_diabetes_fit_aug <- augment(int_access_diabetes_fit$fit)
tidy(int_access_diabetes_fit) %>%
  print()
```

```
## # A tibble: 7 x 5
##   term                              estimate std.error statistic  p.value
##   <chr>                                <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)                       69.9      11.4         6.12  1.97e- 9
## 2 insurance                          0.975     0.198       4.92  1.22e- 6
## 3 visits_to_doctor                  -1.07      0.172      -6.25  9.40e-10
## 4 medicine_high_bp                  -1.40      0.220      -6.36  4.72e-10
## 5 insurance:visits_to_doctor        -0.00935   0.00301    -3.10  2.03e- 3
## 6 insurance:medicine_high_bp        -0.00147   0.00299    -0.493 6.22e- 1
## 7 visits_to_doctor:medicine_high_bp  0.0230    0.00317     7.24  1.87e-12
```

Comparing Adj R-Squared Values

Adj R-squared value for regression with no interactions

```
glance(access_diabetes_fit)$adj.r.squared %>%
  print()
```

```
## [1] 0.6797326
```

Adj R-squared value for regression with one interaction

```
glance(one_access_diabetes_fit)$adj.r.squared %>%
  print()
```

```
## [1] 0.703361
```

Adj R-squared value for regression with all interactions

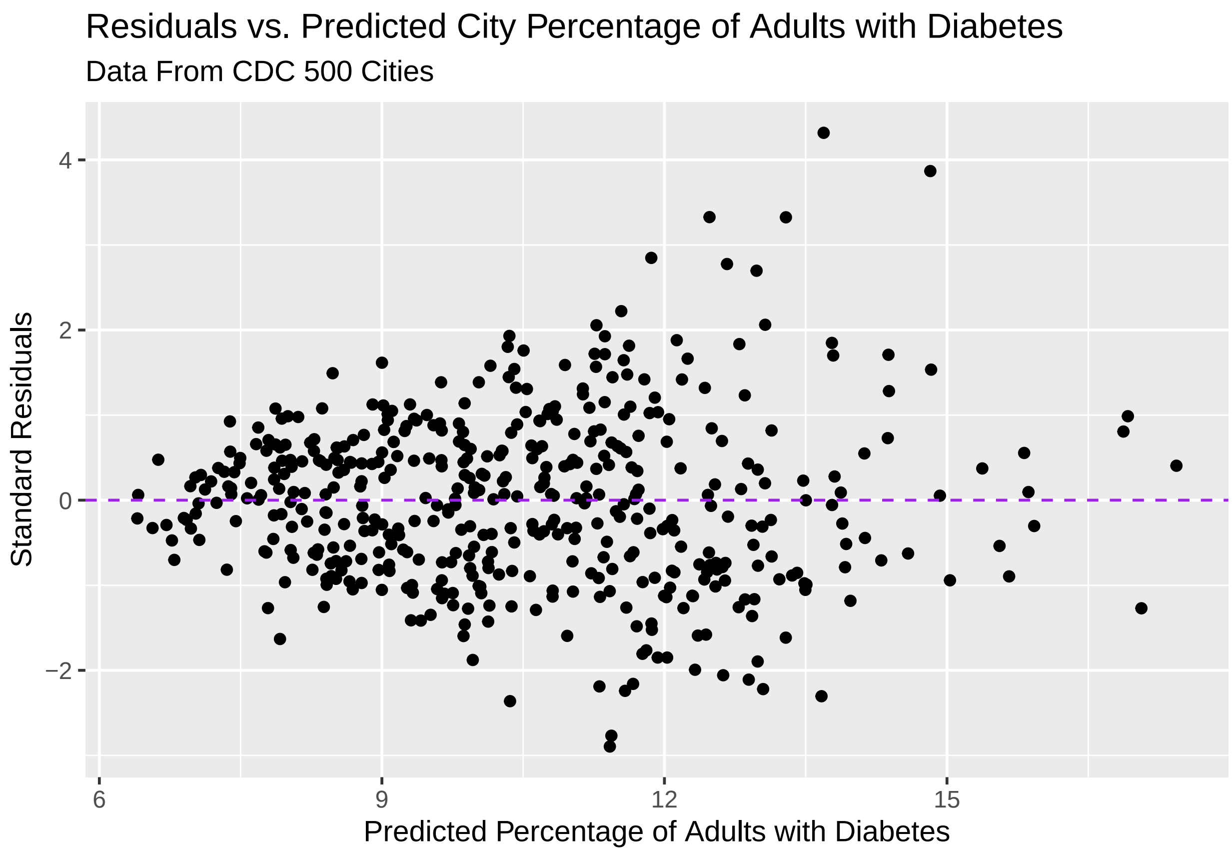
```
glance(int_access_diabetes_fit)$adj.r.squared %>%
  print()
```

```
## [1] 0.7110294
```

Dosplaying Graphs (Edit based on which regression you choose)

Residual Graph (Note any patterns)

```
access_diabetes_fit_aug %>%
  ggplot(mapping = aes(x = .fitted, y = .std.resid)) +
  geom_point() +
  geom_hline(yintercept = 0, color = "purple", lty = "dashed") +
  labs(
    title = "Residuals vs. Predicted City Percentage of Adults with Diabetes",
    subtitle = "Data From CDC 500 Cities",
    x = "Predicted Percentage of Adults with Diabetes",
    y = "Standard Residuals"
  )
```



Graph comparing explanatory and response variables

Access Variables vs. Kidney Disease

Running Linear Regression Models

Linear Regression Model with no interactions

```r
access_kidney_disease_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(kidney_disease ~ insurance + visits_to_doctor + medicine_high_bp, data = data_500_cities)
access_kidney_disease_fit_aug <- augment(access_kidney_disease_fit$fit)
tidy(access_kidney_disease_fit) %>%
  print()
```

```
## # A tibble: 4 x 5
##   term             estimate std.error statistic  p.value
##   <chr>               <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)       0.290     0.225        1.29 1.97e- 1
## 2 insurance         0.0424    0.00256     16.6  7.48e-49
## 3 visits_to_doctor  0.00522   0.00482      1.08 2.79e- 1
## 4 medicine_high_bp  0.0305    0.00472      6.47 2.54e-10
```

Linear regression model with one interaction

```r
one_access_kidney_disease_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(kidney_disease ~ insurance + visits_to_doctor + medicine_high_bp + (visits_to_doctor * medicine_hi
one_access_kidney_disease_fit_aug <- augment(one_access_kidney_disease_fit$fit)
tidy(one_access_kidney_disease_fit) %>%
  print()
```

```
## # A tibble: 5 x 5
##   term                              estimate std.error statistic  p.value
##   <chr>                                <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)                       21.7      2.53          8.59 1.34e-16
## 2 insurance                          0.0452   0.00241      18.8  4.81e-59
## 3 visits_to_doctor                  -0.305    0.0368       -8.30 1.16e-15
## 4 medicine_high_bp                  -0.354    0.0454       -7.79 4.40e-14
## 5 visits_to_doctor:medicine_high_bp  0.00554  0.000651      8.50 2.54e-16
```

Linear regression model with all interactions

```r
int_access_kidney_disease_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(kidney_disease ~ insurance + visits_to_doctor + medicine_high_bp + (insurance * visits_to_doctor)
int_access_kidney_disease_fit_aug <- augment(int_access_kidney_disease_fit$fit)
tidy(int_access_kidney_disease_fit) %>%
  print()
```

```
## # A tibble: 7 x 5
##   term                               estimate std.error statistic  p.value
##   <chr>                                 <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)                       22.9       2.50         9.16  1.63e-18
## 2 insurance                          0.198     0.0435       4.56  6.44e- 6
## 3 visits_to_doctor                  -0.361     0.0377      -9.57  6.10e-20
## 4 medicine_high_bp                  -0.372     0.0483      -7.70  8.53e-14
## 5 insurance:visits_to_doctor         0.000243  0.000661     0.368 7.13e- 1
## 6 insurance:medicine_high_bp        -0.00297   0.000655    -4.53  7.40e- 6
## 7 visits_to_doctor:medicine_high_bp  0.00646   0.000696     9.28  6.23e-19
```

Comparing Adj R-Squared Values

Adj R-squared value for regression with no interactions

```
glance(access_kidney_disease_fit)$adj.r.squared %>%
  print()
```

```
## [1] 0.5403031
```

Adj R-squared value for regression with one interaction

```
glance(one_access_kidney_disease_fit)$adj.r.squared %>%
  print()
```

```
## [1] 0.6010605
```

Adj R-squared value for regression with all interactions

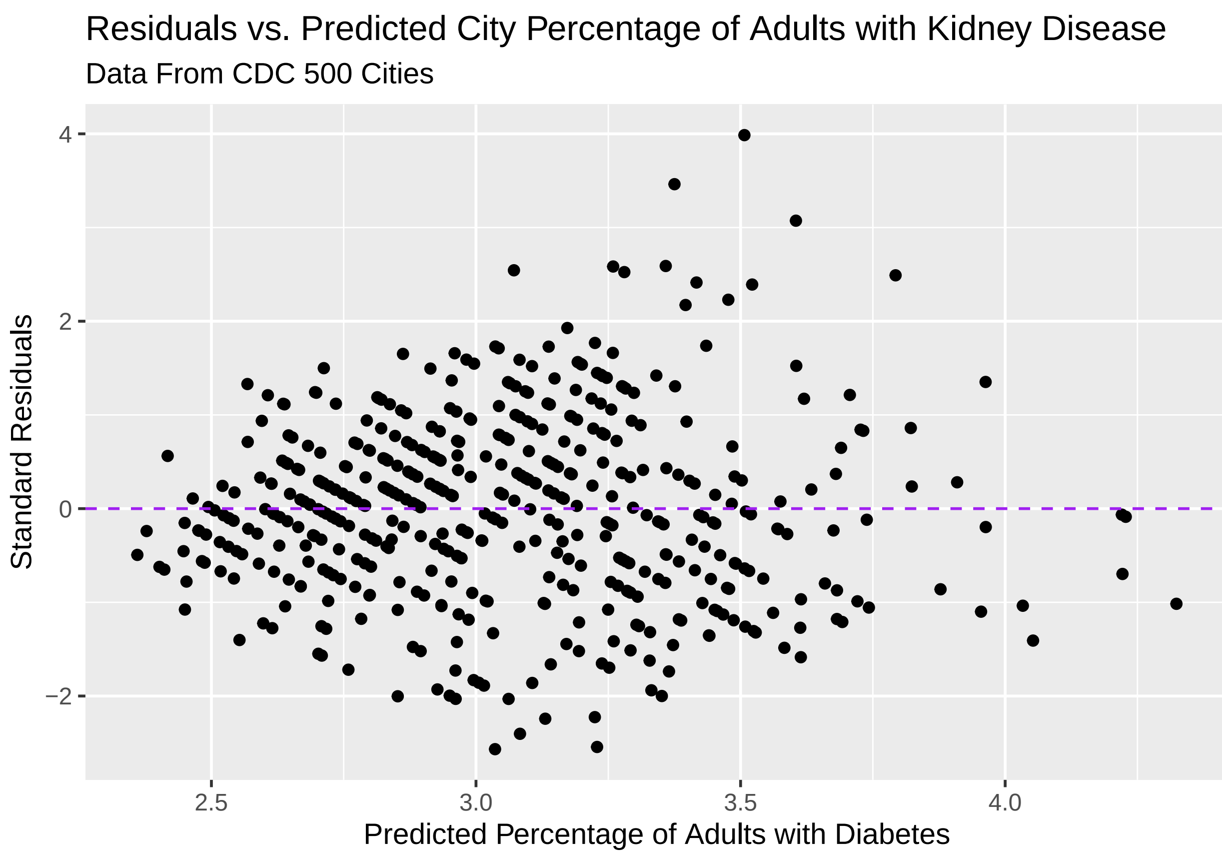
```
glance(int_access_kidney_disease_fit)$adj.r.squared %>%
  print()
```

```
## [1] 0.6193093
```

Displaying Graphs:

Residual Graph (Note any patterns)

```
access_kidney_disease_fit_aug %>%
  ggplot(mapping = aes(x = .fitted, y = .std.resid)) +
  geom_point() +
  geom_hline(yintercept = 0, color = "purple", lty = "dashed") +
  labs(
    title = "Residuals vs. Predicted City Percentage of Adults with Kidney Disease",
    subtitle = "Data From CDC 500 Cities",
    x = "Predicted Percentage of Adults with Diabetes",
    y = "Standard Residuals"
  )
```



Graph Comparing Explanatory and Response Variables

ANOVA Testing

Initial Visualizations

NOTE: Use initial visualizations to check if assumptions of ANOVA are met!

Overall Tests

```
summary(aov(insurance~StateDesc,data=data_500_cities)) %>%
  print()
```

```
##                Df Sum Sq Mean Sq F value Pr(>F)    
## StateDesc      50   9260  185.20   8.487 <2e-16 ***
## Residuals     424   9252   21.82                   
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(aov(visits_to_doctor~StateDesc,data=data_500_cities)) %>%
  print()
```

```
##                Df Sum Sq Mean Sq F value Pr(>F)    
## StateDesc      50   8395  167.90   44.01 <2e-16 ***
## Residuals     421   1606    3.81                   
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
## 3 observations deleted due to missingness
```

```
summary(aov(medicine_high_bp~StateDesc,data=data_500_cities)) %>%
  print()
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## StateDesc    50   9541  190.82   44.25 <2e-16 ***
## Residuals   422   1820    4.31
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 2 observations deleted due to missingness
```

```
summary(aov(smoking~StateDesc,data=data_500_cities)) %>%
  print()
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## StateDesc    50   4752   95.03   9.747 <2e-16 ***
## Residuals   420   4095    9.75
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 4 observations deleted due to missingness
```

```
summary(aov(binge_drinking~StateDesc,data=data_500_cities)) %>%
  print()
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## StateDesc    50   1719   34.37   9.579 <2e-16 ***
## Residuals   421   1511    3.59
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 3 observations deleted due to missingness
```

```
summary(aov(physical_activity~StateDesc,data=data_500_cities)) %>%
  print()
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## StateDesc    50  10657  213.13   10.76 <2e-16 ***
## Residuals   421   8343   19.82
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 3 observations deleted due to missingness
```

```
summary(aov(heart_disease~StateDesc,data=data_500_cities)) %>%
  print()
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## StateDesc    50  201.1   4.021   5.974 <2e-16 ***
## Residuals   421  283.4   0.673
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 3 observations deleted due to missingness
```

```
summary(aov(diabetes~StateDesc,data=data_500_cities)) %>%
  print()
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## StateDesc    50   1061   21.21   4.632 <2e-16 ***
## Residuals   421   1928    4.58
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 3 observations deleted due to missingness
```

```
summary(aov(kidney_disease~StateDesc,data=data_500_cities)) %>%
  print()
```

```
##              Df Sum Sq Mean Sq F value   Pr(>F)
## StateDesc    50  21.77  0.4354   2.102 4.48e-05 ***
## Residuals   422  87.41  0.2071
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 2 observations deleted due to missingness
```

It seems like pretty much all the overall tests indicate significant variance across the groups.

Step Down Tests

```
insurance_state_pair <- pairwise.t.test(data_500_cities$insurance,    data_500_cities$StateDesc, p.adj =
sig_ins_state_pairs <- broom::tidy(insurance_state_pair) %>%
  filter(p.value<0.05) %>%
  arrange(group1,group2)
nrow(sig_ins_state_pairs)
```

```
## [1] 0
```

```
print(sig_ins_state_pairs)
```

```
## # A tibble: 0 x 3
## # ... with 3 variables: group1 <chr>, group2 <chr>, p.value <dbl>
```

The overall ANOVA test says there is a significance but the Step Down stests show no significant pairs?

```
doctor_state_pair <- pairwise.t.test(data_500_cities$visits_to_doctor,    data_500_cities$StateDesc, p.a
sig_doctor_state_pairs <- broom::tidy(doctor_state_pair) %>%
  filter(p.value<0.05) %>%
  arrange(group1,group2)
nrow(sig_doctor_state_pairs)
```

```
## [1] 0
```

```
print(sig_doctor_state_pairs)
```

```
## # A tibble: 0 x 3
## # ... with 3 variables: group1 <chr>, group2 <chr>, p.value <dbl>
```

Ok so there is clearly an issue. I think I am interpreting the F-statistic incorrectly?

```
smoking_state_pair <- pairwise.t.test(data_500_cities$smoking,    data_500_cities$StateDesc, p.adj = "ho
sig_smoking_state_pairs <- broom::tidy(smoking_state_pair) %>%
  filter(p.value<0.05) %>%
  arrange(group1,group2)
nrow(sig_smoking_state_pairs)
```

```
## [1] 0
```

```
print(sig_smoking_state_pairs)
```

```
## # A tibble: 0 x 3
## # ... with 3 variables: group1 <chr>, group2 <chr>, p.value <dbl>
```

Map Visualization