

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

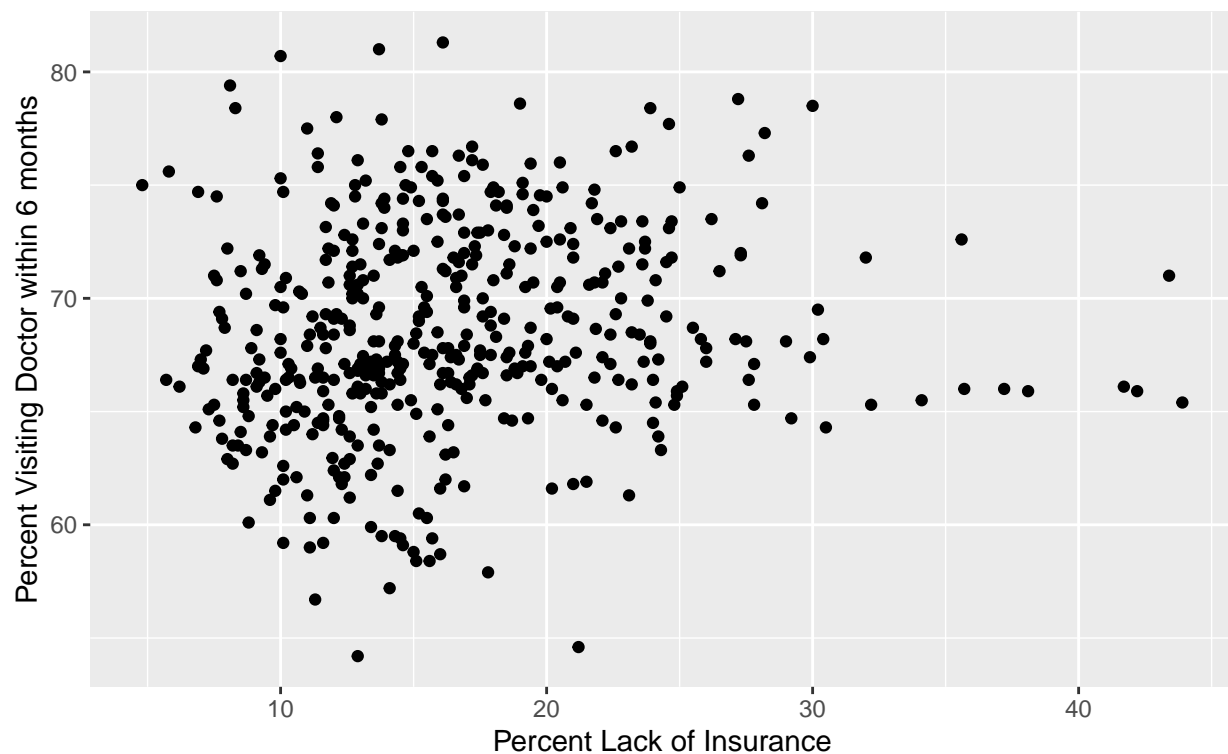
New Method:

- 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"  
  )
```

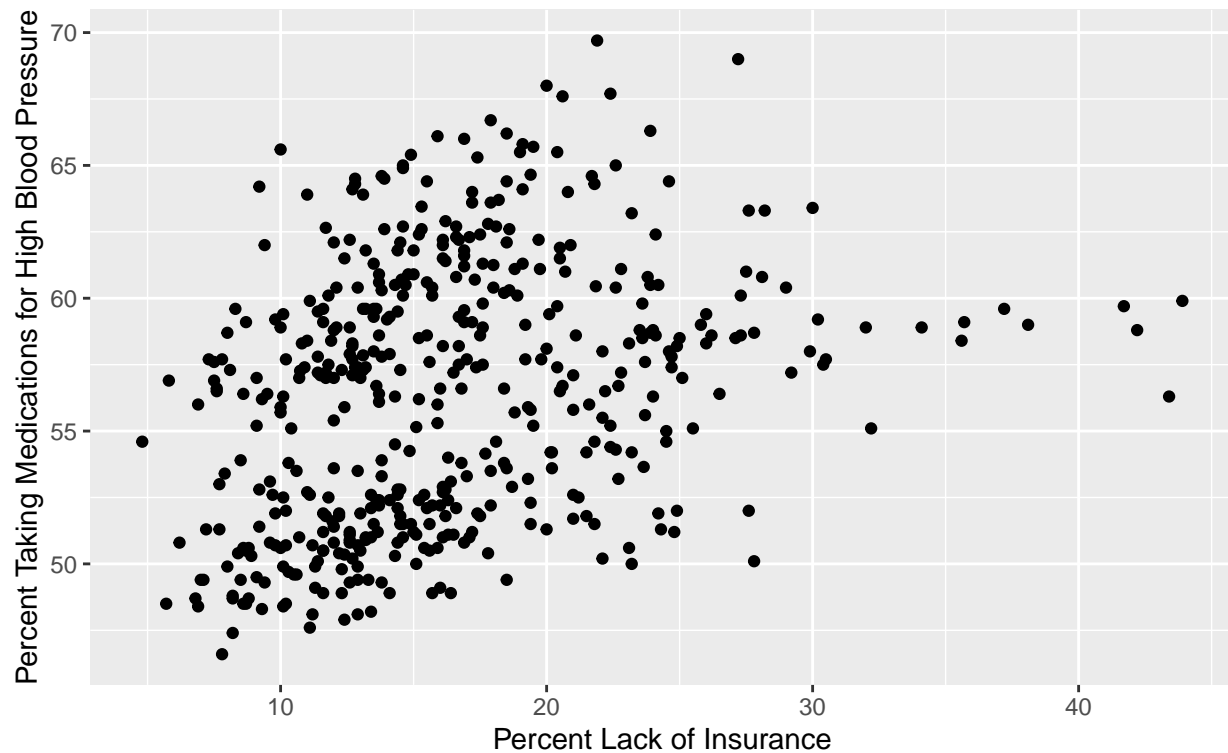
Relationship Between Lack of Insurance and Visits to Doctor
Data from CDC 500 Cities



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"  
  )
```

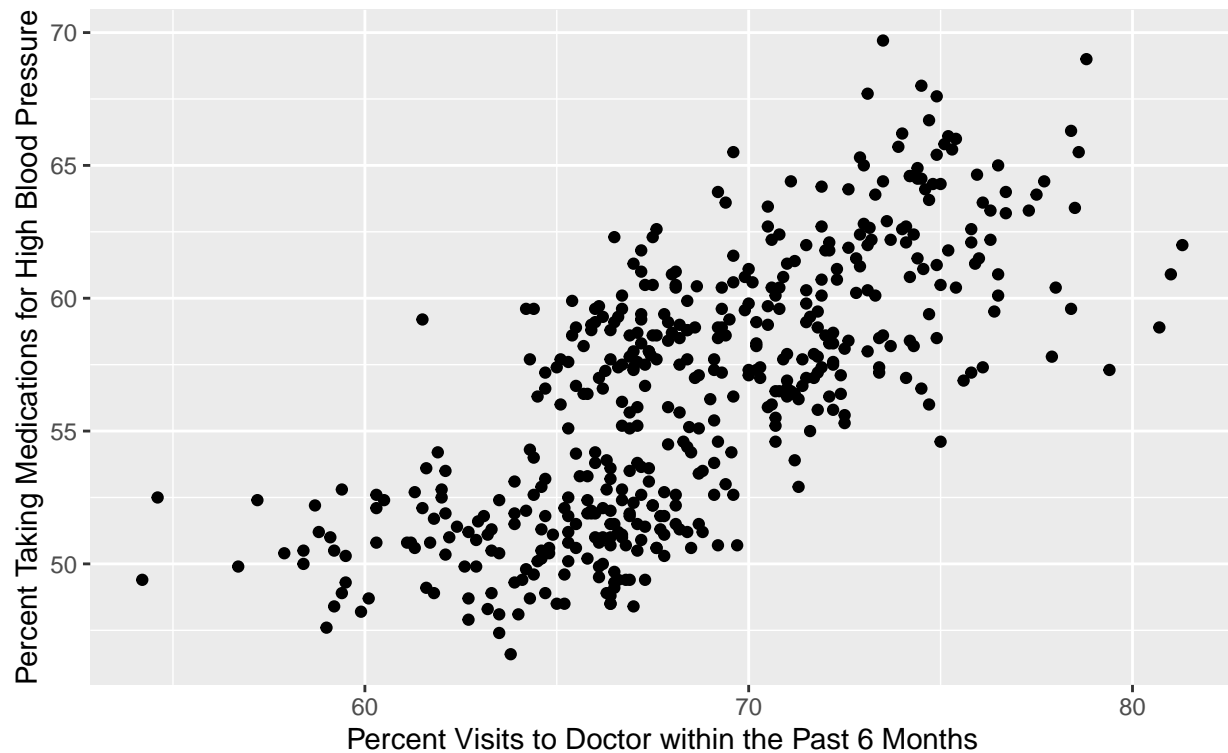
Relationship Between Lack of Insurance and Percent Pop Taking BP Meds
Data from CDC 500 Cities



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"  
  )
```

Relationship Between Visits to Doctor and Percent Pop Taking BP Meds
Data from CDC 500 Cities



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.

Running Linear Regressions

Linear Regression with No Interaction Variables:

Fit without 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()
```

1) Access Variables vs. Smoking

```
## # 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) + (insurance * medicine_high_bp) + (visits_to_doctor * medicine_high_bp))
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()
```

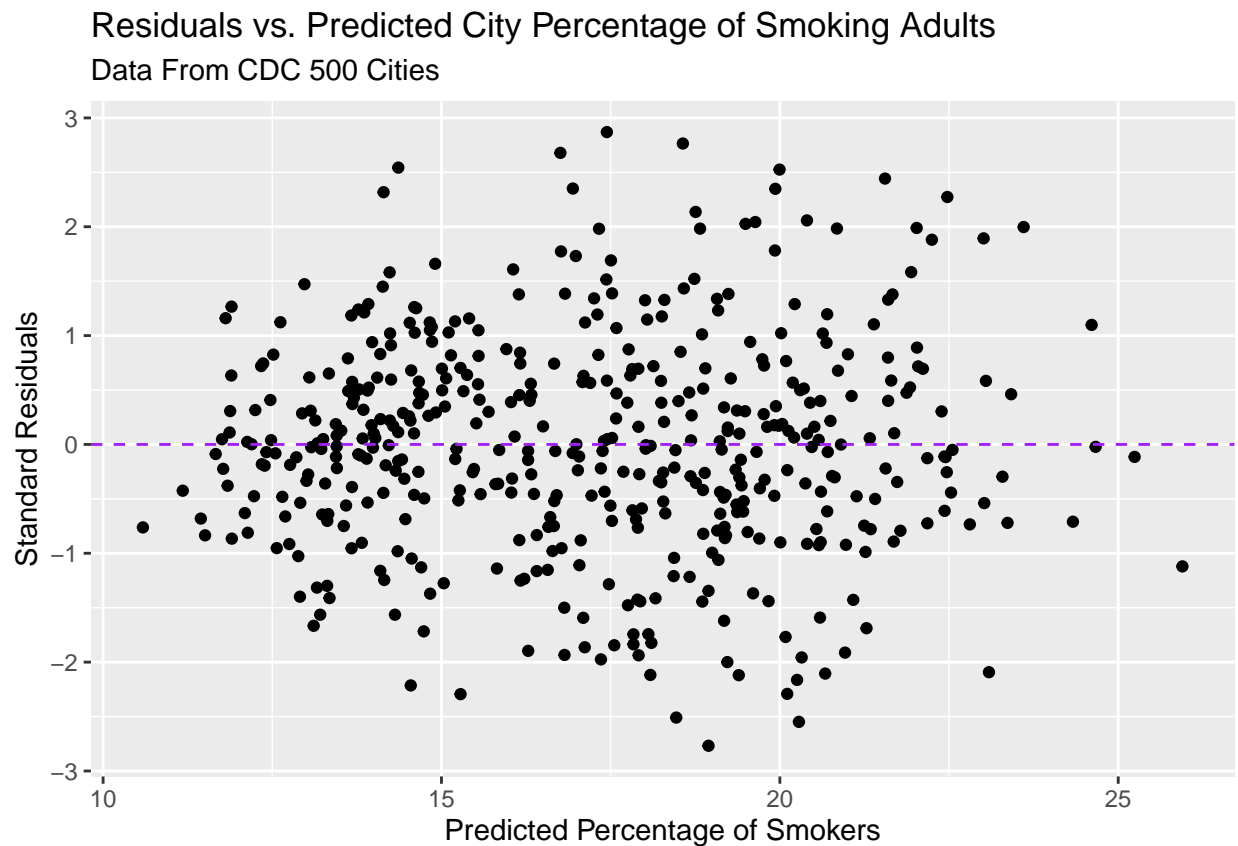
```
## [1] 0.5691301
```

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

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

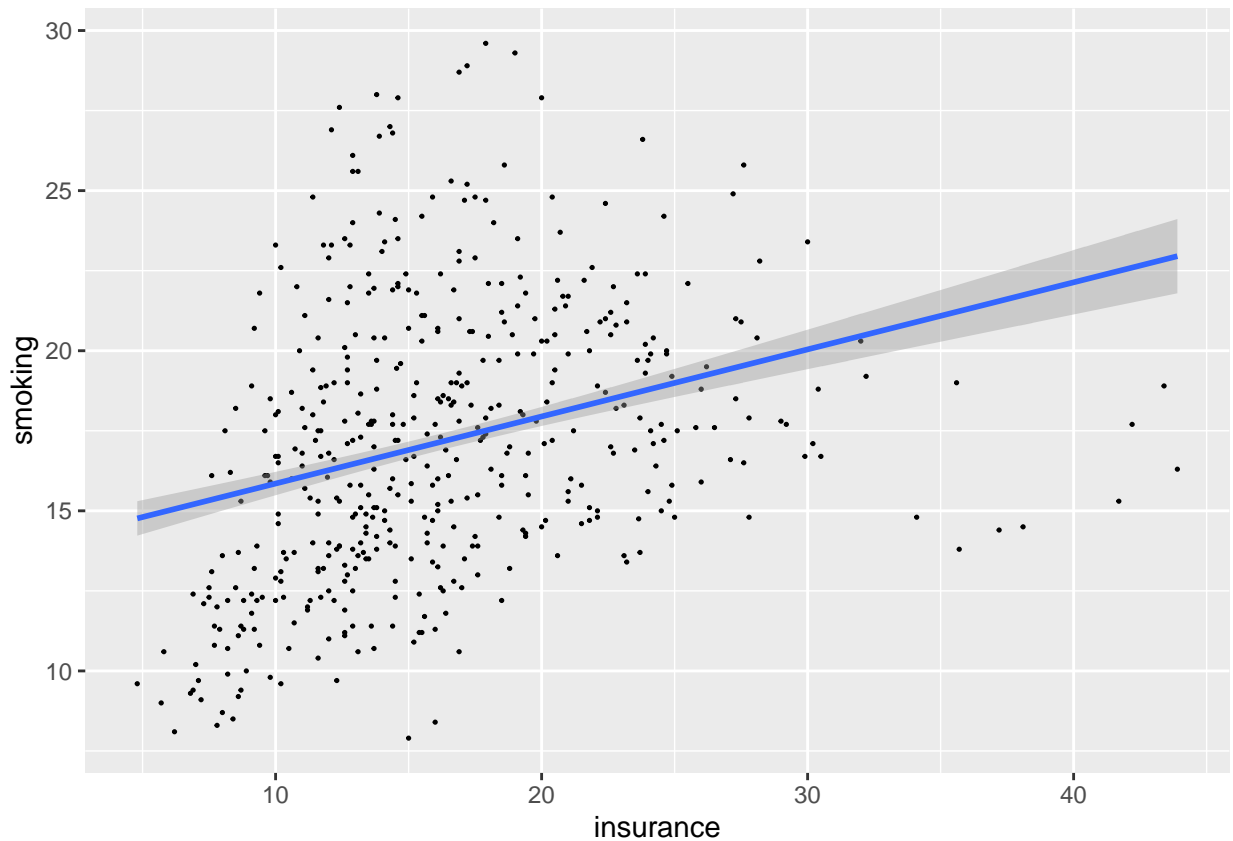
Residual Graph (Note any patterns)

```
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_h
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()
```

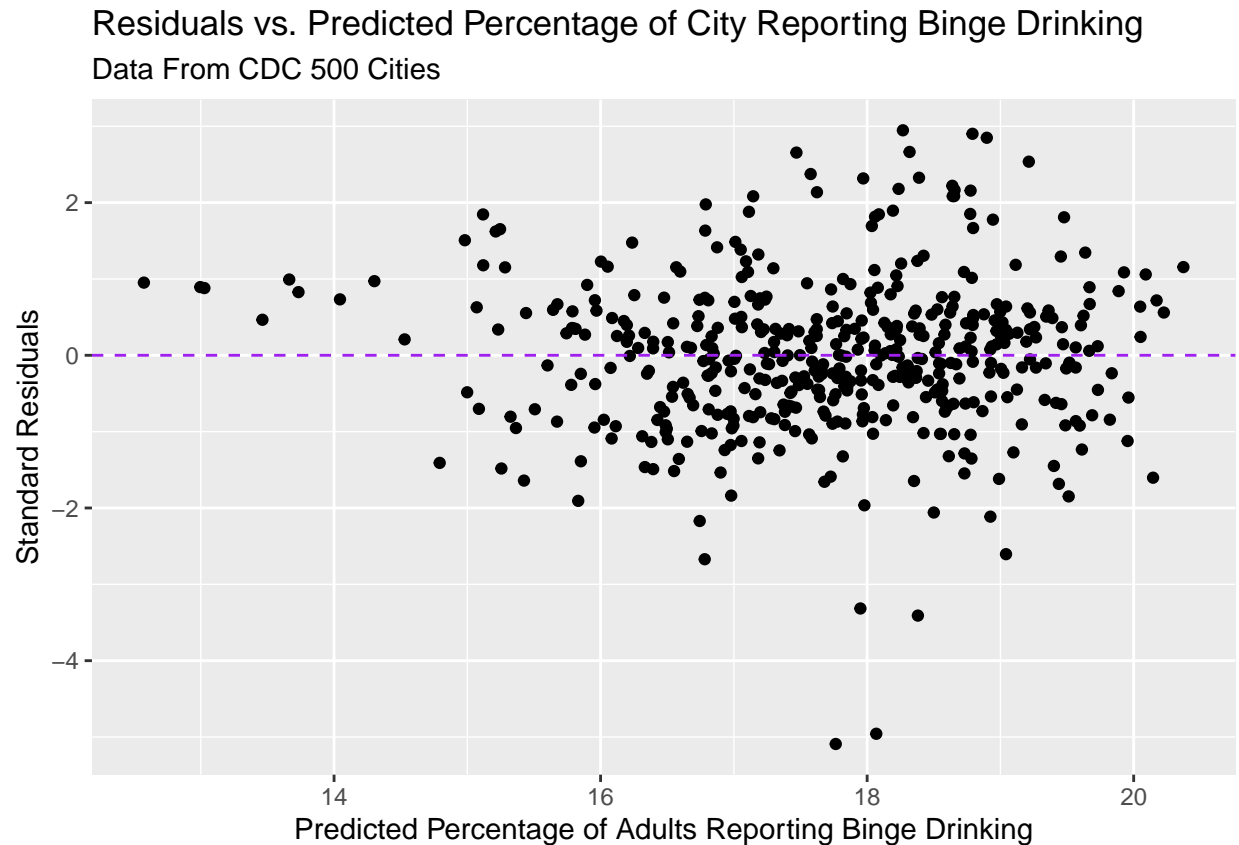
```
## [1] 0.3488416
```

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

Displaying Graphs (Edit Based on which regression you choose)

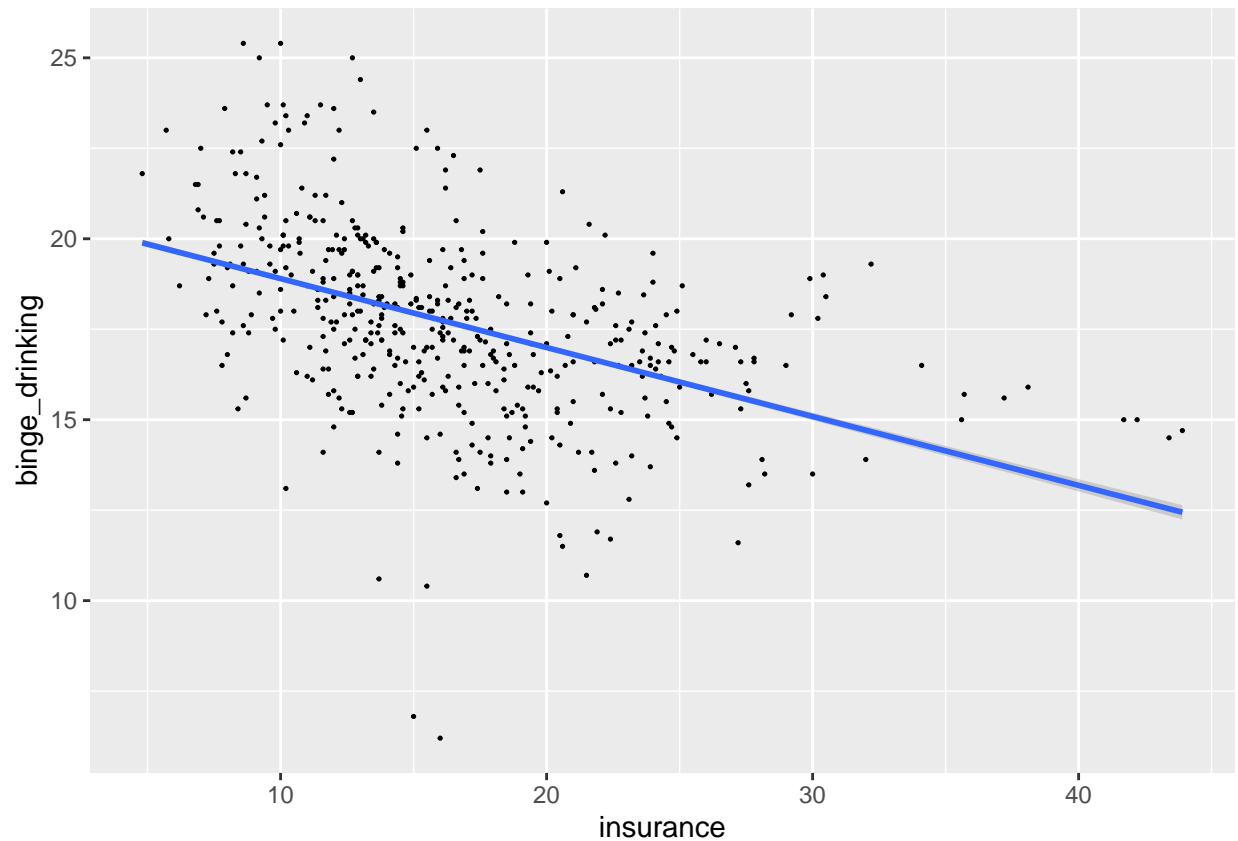
Residual Graph (Note any patterns)


```
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(method = "lm", 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_high_bp))
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_doctor))
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
```

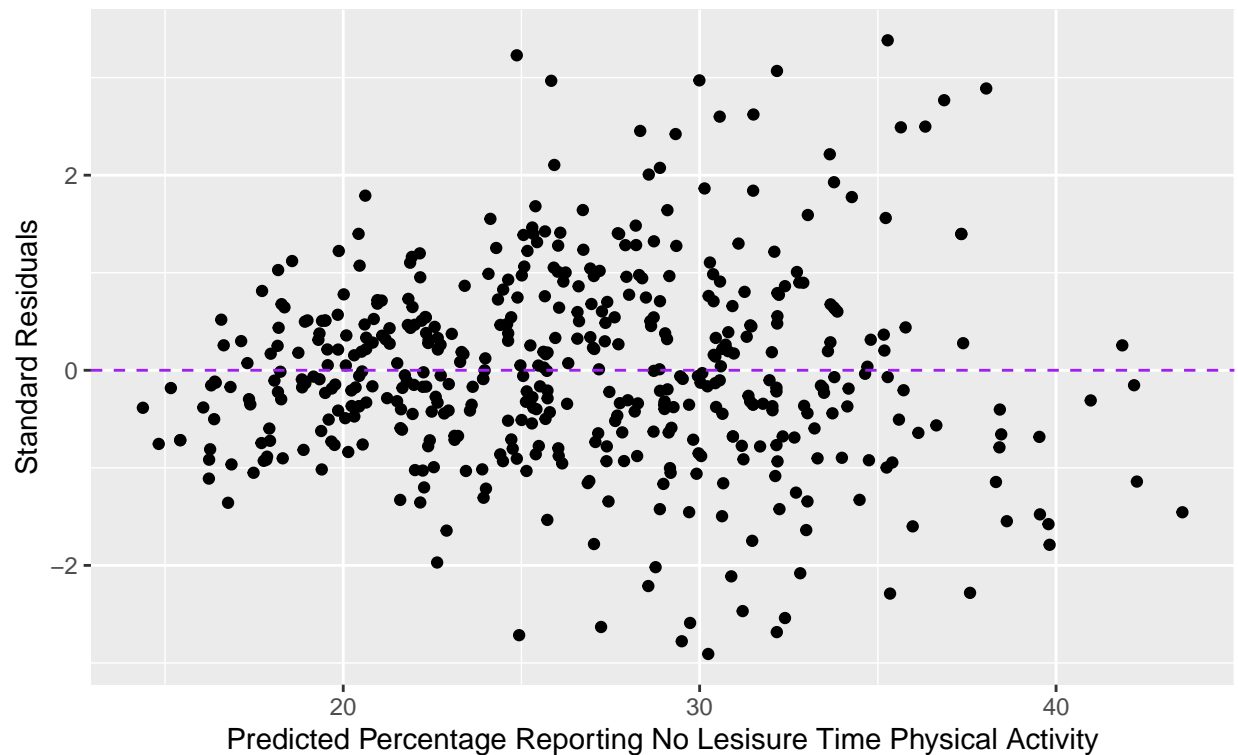
Make some kind of statement about which regression is most appropriate

Displaying Graphs (Edit based on which regression you choose)

Residual Graph (Note any patterns)

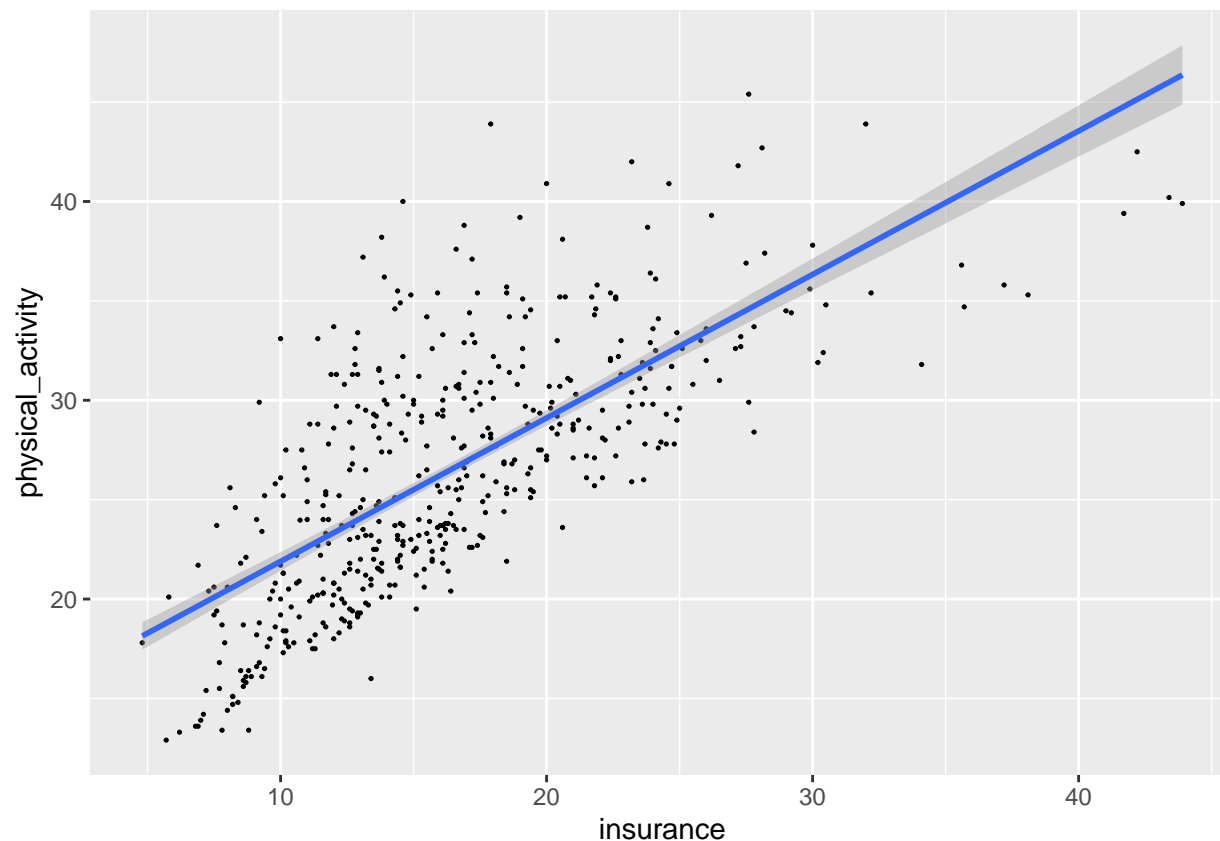
```
access_physical_activity_fit_aug %>%
  ggplot(mapping = aes(x = .fitted, y = .std.resid)) +
  geom_point() +
  geom_hline(yintercept = 0, color = "purple", lty = "dashed") +
  labs(
    title = "Residuals vs. Predicted Percentage of City Reporting No Physical Activity",
    subtitle = "Data From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

Residuals vs. Predicted Percentage of City Reporting No Physical Activity
Data From CDC 500 Cities



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 = .fitted))
```



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_high_bp))
one_access_heart_disease_fit_aug <- augment(one_access_heart_disease_fit$fit)
tidy(one_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) +
    insurance * medicine_high_bp + visits_to_doctor * medicine_high_bp)
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
```

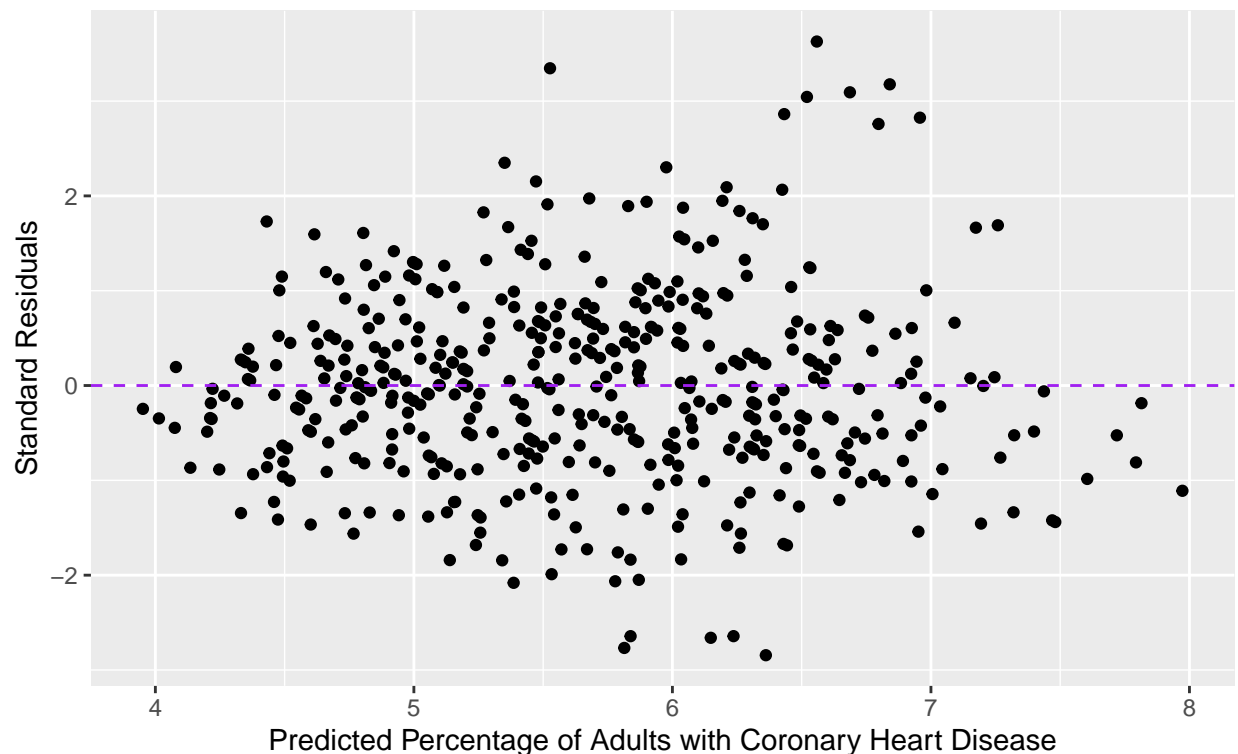
Displaying Graphs (Edit based on which regression you choose)

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"
)
```

Residuals vs. Predicted City Percentage of Adults with Coronary Heart Disease
Data From CDC 500 Cities



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) + (insurance * medicine_high_bp) + (visits_to_doctor * medicine_high_bp)
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

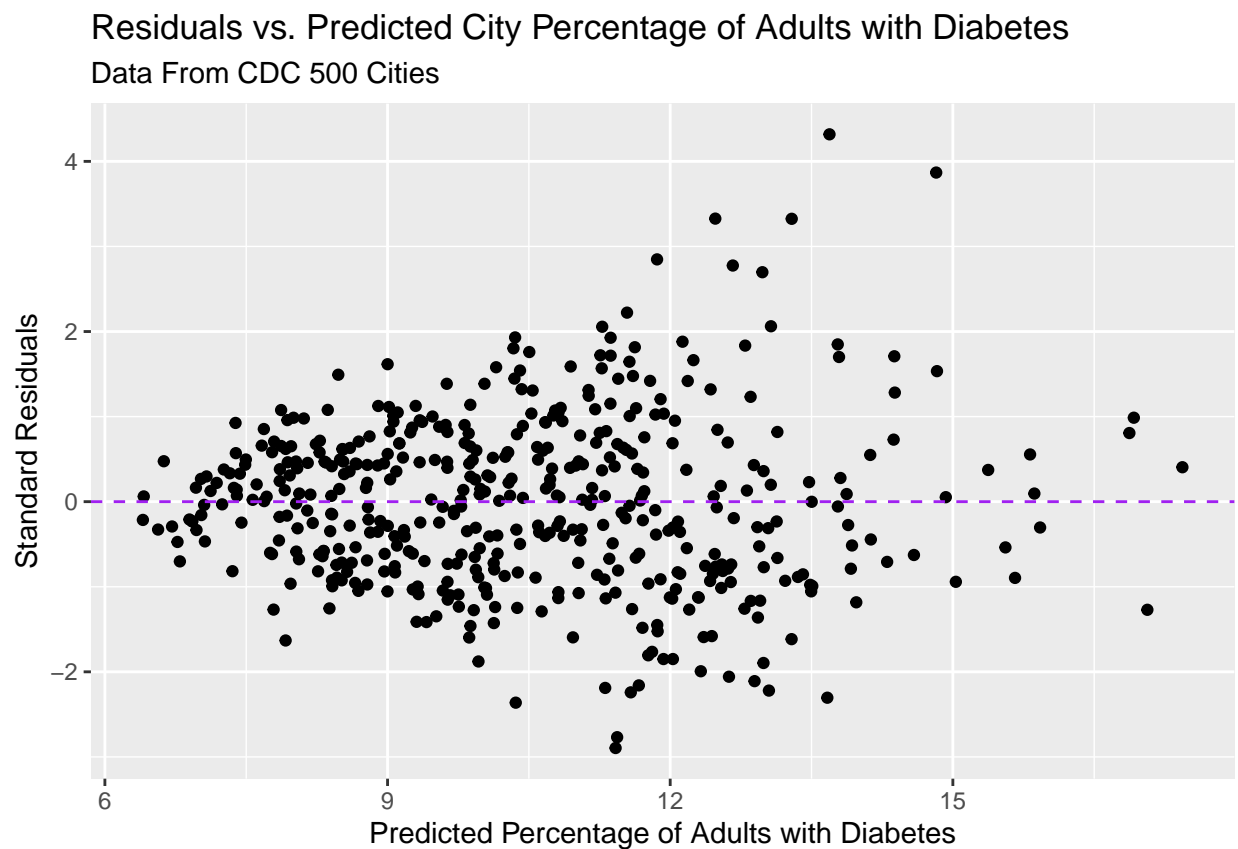

```
glance(int_access_diabetes_fit)$adj.r.squared %>%
  print()
```

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

Displaying 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

```
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

```
one_access_kidney_disease_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(kidney_disease ~ insurance + visits_to_doctor + medicine_high_bp + (visits_to_doctor * medicine_high_bp))
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

```
int_access_kidney_disease_fit <- linear_reg() %>%
  set_engine("lm") %>%
  fit(kidney_disease ~ insurance + visits_to_doctor + medicine_high_bp + (insurance * visits_to_doctor) + (insurance * medicine_high_bp) + (visits_to_doctor * medicine_high_bp))
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()
```

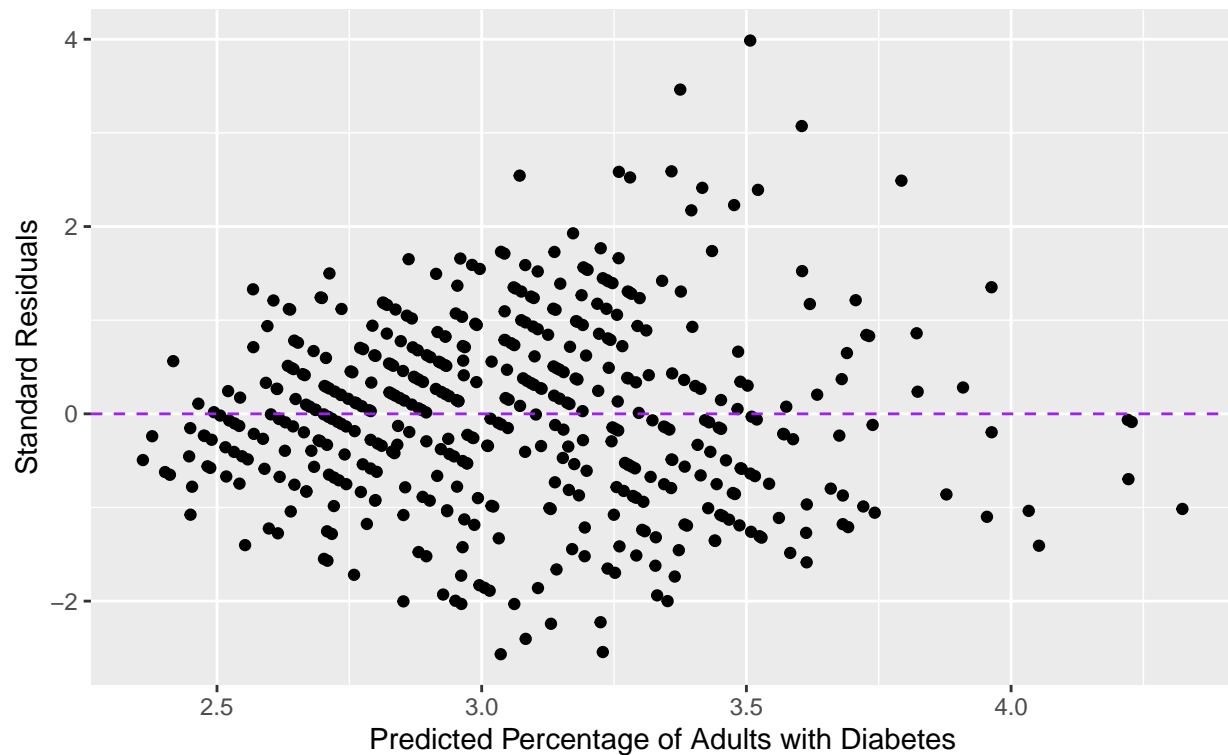
```
## [1] 0.6193093
```

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"  
  )
```

Residuals vs. Predicted City Percentage of Adults with Kidney Disease Data From CDC 500 Cities



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 = "none")
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 tests show no significant pairs?

```
doctor_state_pair <- pairwise.t.test(data_500_cities$visits_to_doctor,    data_500_cities$StateDesc, p.adj = "none")
sig_doctor_state_pairs <- broom::tidy(doctor_state_pair) %>%
  filter(p.value<0.05)
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)
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

```

theme_set(theme_bw())
world <- ne_countries(scale = "medium", returnclass = "sf")
names(world)

## [1] "scalerank" "featurecla" "labelrank" "sovereight" "sov_a3"
## [6] "adm0_dif" "level" "type" "admin" "adm0_a3"
## [11] "geou_dif" "geounit" "gu_a3" "su_dif" "subunit"
## [16] "su_a3" "brk_diff" "name" "name_long" "brk_a3"
## [21] "brk_name" "brk_group" "abbrev" "postal" "formal_en"
## [26] "formal_fr" "note_adm0" "note_brk" "name_sort" "name_alt"
## [31] "mapcolor7" "mapcolor8" "mapcolor9" "mapcolor13" "pop_est"
## [36] "gdp_md_est" "pop_year" "lastcensus" "gdp_year" "economy"
## [41] "income_grp" "wikipedia" "fips_10" "iso_a2" "iso_a3"
## [46] "iso_n3" "un_a3" "wb_a2" "wb_a3" "woe_id"
## [51] "adm0_a3_is" "adm0_a3_us" "adm0_a3_un" "adm0_a3_wb" "continent"
## [56] "region_un" "subregion" "region_wb" "name_len" "long_len"
## [61] "abbrev_len" "tiny" "homepart" "geometry"

state.name

## [1] "Alabama" "Alaska" "Arizona" "Arkansas"
## [5] "California" "Colorado" "Connecticut" "Delaware"
## [9] "Florida" "Georgia" "Hawaii" "Idaho"
## [13] "Illinois" "Indiana" "Iowa" "Kansas"
## [17] "Kentucky" "Louisiana" "Maine" "Maryland"
## [21] "Massachusetts" "Michigan" "Minnesota" "Mississippi"
## [25] "Missouri" "Montana" "Nebraska" "Nevada"
## [29] "New Hampshire" "New Jersey" "New Mexico" "New York"
## [33] "North Carolina" "North Dakota" "Ohio" "Oklahoma"
## [37] "Oregon" "Pennsylvania" "Rhode Island" "South Carolina"
## [41] "South Dakota" "Tennessee" "Texas" "Utah"
## [45] "Vermont" "Virginia" "Washington" "West Virginia"
## [49] "Wisconsin" "Wyoming"

head(world)

## Simple feature collection with 6 features and 63 fields
## Geometry type: MULTIPOLYGON
## Dimension: XY
## Bounding box: xmin: -70.06611 ymin: -18.01973 xmax: 74.89131 ymax: 60.40581
## CRS: +proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0
## scalerank featurecla labelrank sovereign sov_a3 adm0_dif level
## 0 3 Admin-0 country 5 Netherlands NL1 1 2
## 1 1 Admin-0 country 3 Afghanistan AFG 0 2
## 2 1 Admin-0 country 3 Angola AGO 0 2
## 3 1 Admin-0 country 6 United Kingdom GB1 1 2
## 4 1 Admin-0 country 6 Albania ALB 0 2
## 5 3 Admin-0 country 6 Finland FI1 1 2
## type admin adm0_a3 geou_dif geounit gu_a3 su_dif
## 0 Country Aruba ABW 0 Aruba ABW 0
## 1 Sovereign country Afghanistan AFG 0 Afghanistan AFG 0
## 2 Sovereign country Angola AGO 0 Angola AGO 0
## 3 Dependency Anguilla AIA 0 Anguilla AIA 0
## 4 Sovereign country Albania ALB 0 Albania ALB 0

```

## 5	Country	Aland	ALD	0	Aland	ALD	0		
##	subunit	su_a3	brk_diff	name	name_long	brk_a3	brk_name		
## 0	Aruba	ABW	0	Aruba	Aruba	ABW	Aruba		
## 1	Afghanistan	AFG	0	Afghanistan	Afghanistan	AFG	Afghanistan		
## 2	Angola	AGO	0	Angola	Angola	AGO	Angola		
## 3	Anguilla	AIA	0	Anguilla	Anguilla	AIA	Anguilla		
## 4	Albania	ALB	0	Albania	Albania	ALB	Albania		
## 5	Aland	ALD	0	Aland	Aland Islands	ALD	Aland		
##	brk_group	abbrev	postal		formal_en	formal_fr	note_adm0		
## 0	<NA>	Aruba	AW		Aruba	<NA>	Neth.		
## 1	<NA>	Afg.	AF	Islamic State of Afghanistan		<NA>	<NA>		
## 2	<NA>	Ang.	AO	People's Republic of Angola		<NA>	<NA>		
## 3	<NA>	Ang.	AI		<NA>	<NA>	U.K.		
## 4	<NA>	Alb.	AL	Republic of Albania		<NA>	<NA>		
## 5	<NA>	Aland	AI	Åland Islands		<NA>	Fin.		
##	note_brk	name_sort	name_alt	mapcolor7	mapcolor8	mapcolor9	mapcolor13		
## 0	<NA>	Aruba	<NA>	4	2	2	9		
## 1	<NA>	Afghanistan	<NA>	5	6	8	7		
## 2	<NA>	Angola	<NA>	3	2	6	1		
## 3	<NA>	Anguilla	<NA>	6	6	6	3		
## 4	<NA>	Albania	<NA>	1	4	1	6		
## 5	<NA>	Aland	<NA>	4	1	4	6		
##	pop_est	gdp_md_est	pop_year	lastcensus	gdp_year		economy		
## 0	103065	2258.0	NA	2010	NA		6. Developing region		
## 1	28400000	22270.0	NA	1979	NA		7. Least developed region		
## 2	12799293	110300.0	NA	1970	NA		7. Least developed region		
## 3	14436	108.9	NA	NA	NA		6. Developing region		
## 4	3639453	21810.0	NA	2001	NA		6. Developing region		
## 5	27153	1563.0	NA	NA	NA		2. Developed region: nonG7		
##	income_grp	wikipedia	fips_10	iso_a2	iso_a3	iso_n3	un_a3	wb_a2	
## 0	2. High income: nonOECD		NA	<NA>	AW	ABW	533	533	AW
## 1	5. Low income		NA	<NA>	AF	AFG	004	004	AF
## 2	3. Upper middle income		NA	<NA>	AO	AGO	024	024	AO
## 3	3. Upper middle income		NA	<NA>	AI	AIA	660	660	<NA>
## 4	4. Lower middle income		NA	<NA>	AL	ALB	008	008	AL
## 5	1. High income: OECD		NA	<NA>	AX	ALA	248	248	<NA>
##	wb_a3	woe_id	adm0_a3_is	adm0_a3_us	adm0_a3_un	adm0_a3_wb		continent	
## 0	ABW	NA	ABW	ABW	NA	NA		North America	
## 1	AFG	NA	AFG	AFG	NA	NA		Asia	
## 2	AGO	NA	AGO	AGO	NA	NA		Africa	
## 3	<NA>	NA	AIA	AIA	NA	NA		North America	
## 4	ALB	NA	ALB	ALB	NA	NA		Europe	
## 5	<NA>	NA	ALA	ALD	NA	NA		Europe	
##	region_un		subregion		region_wb	name_len	long_len		
## 0	Americas		Caribbean	Latin America & Caribbean		5	5		
## 1	Asia		Southern Asia	South Asia		11	11		
## 2	Africa		Middle Africa	Sub-Saharan Africa		6	6		
## 3	Americas		Caribbean	Latin America & Caribbean		8	8		
## 4	Europe		Southern Europe	Europe & Central Asia		7	7		
## 5	Europe		Northern Europe	Europe & Central Asia		5	13		
##	abbrev_len	tiny	homepart		geometry				
## 0	5	4	NA	MULTIPOLYGON	(((-69.89912 1...				
## 1	4	NA	1	MULTIPOLYGON	(((74.89131 37...				
## 2	4	NA	1	MULTIPOLYGON	(((14.19082 -5...				

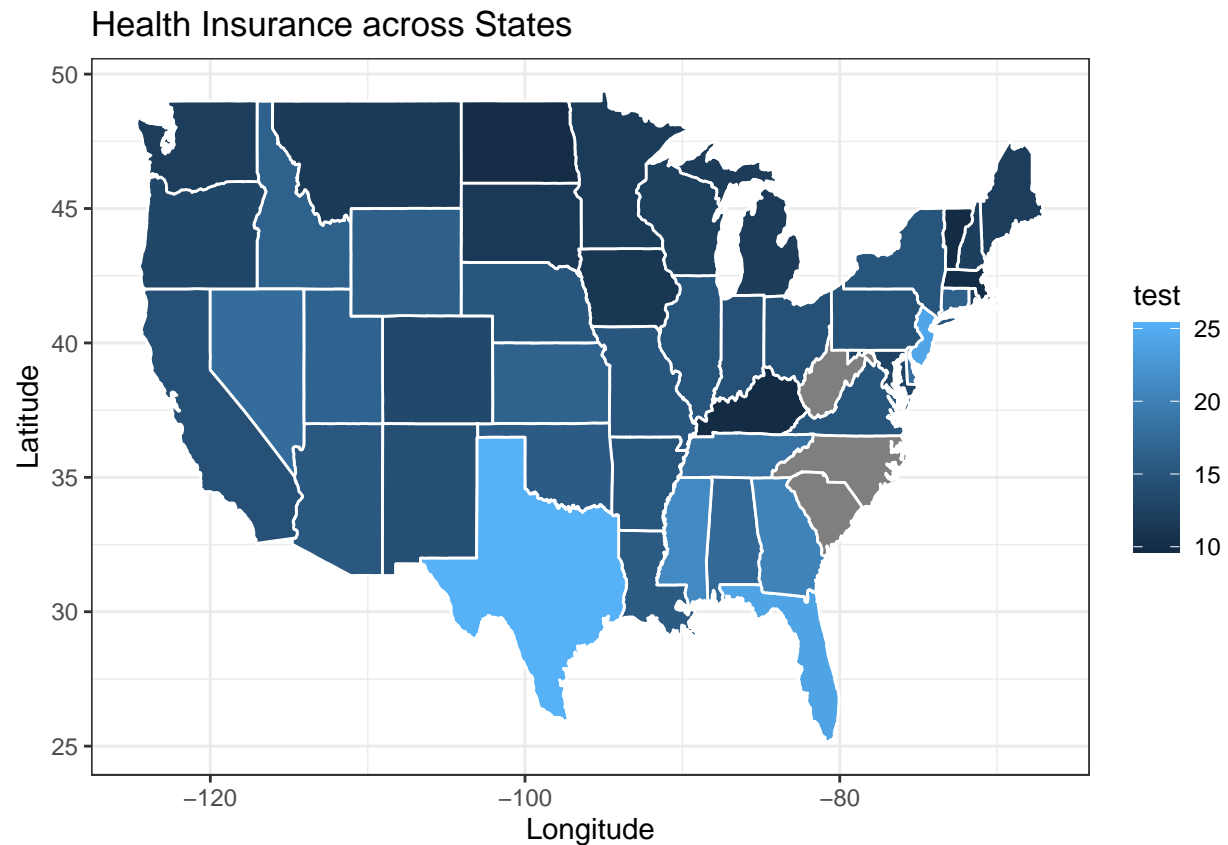

```
## 3      4  NA      NA MULTIPOLYGON (((-63.00122 1...
## 4      4  NA      1 MULTIPOLYGON (((20.06396 42...
## 5      5   5      NA MULTIPOLYGON (((20.61133 60...
```

```
states <- map_data("state")
states %>%
  mutate(StateDesc = str_to_title(region)) -> states
```

Access Variable: Health Insurance

```
states %>%
  left_join(data_500_cities, by = "StateDesc") -> test
data_500_cities %>%
  group_by(StateDesc) %>%
  summarise(test = mean(insurance)) %>%
  right_join(states, by = "StateDesc") -> test2

ggplot(test2, aes(x = long, y = lat, group = group, fill = test)) +
  geom_polygon(color = "white")+
  labs(x = "Longitude",
       y = "Latitude",
       title = "Health Insurance across States")
```

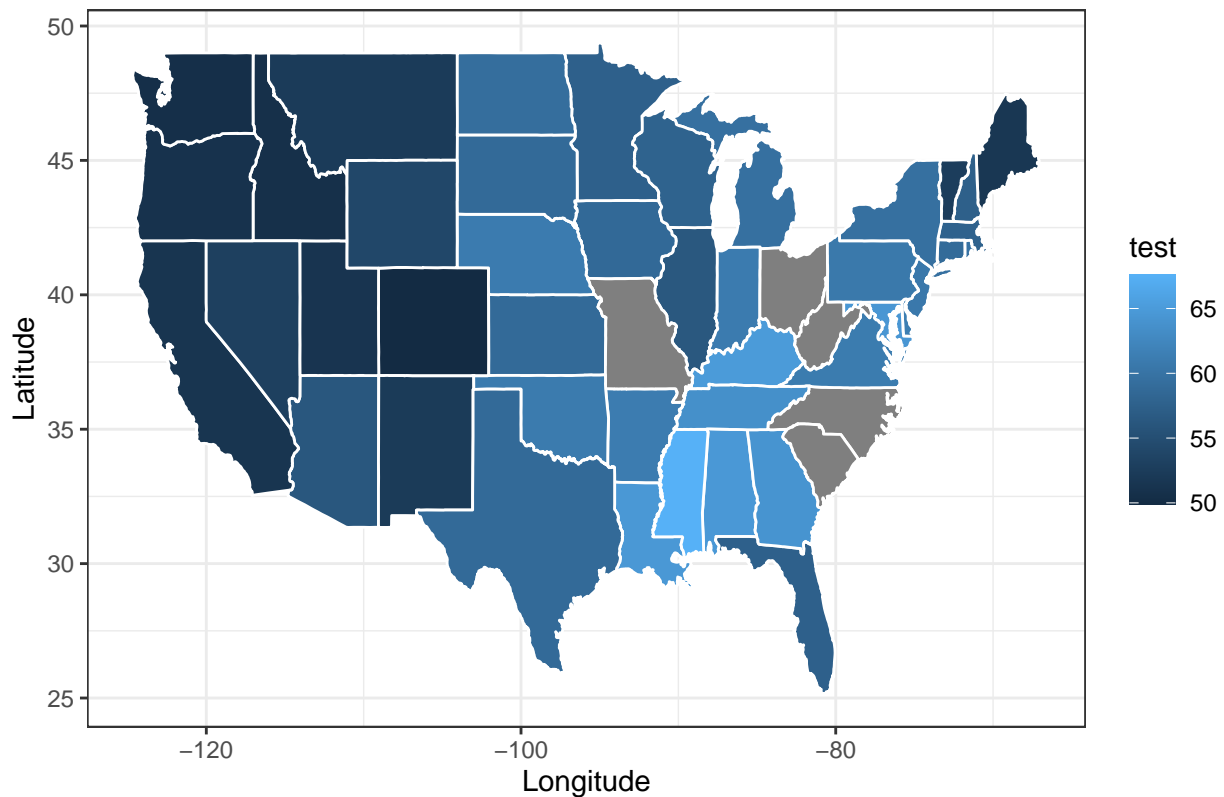


Access Variables: High Blood Pressure Medicine

```
states %>%
  left_join(data_500_cities, by = "StateDesc") -> test
data_500_cities %>%
  group_by(StateDesc) %>%
  summarise(test = mean(medicine_high_bp)) %>%
  right_join(states, by = "StateDesc") -> test2

ggplot(test2, aes(x = long, y = lat, group = group, fill = test)) +
  geom_polygon(color = "white")+
  labs(x = "Longitude",
       y = "Latitude",
       title = "High Blood Pressure Medicine across States")
```

High Blood Pressure Medicine across States



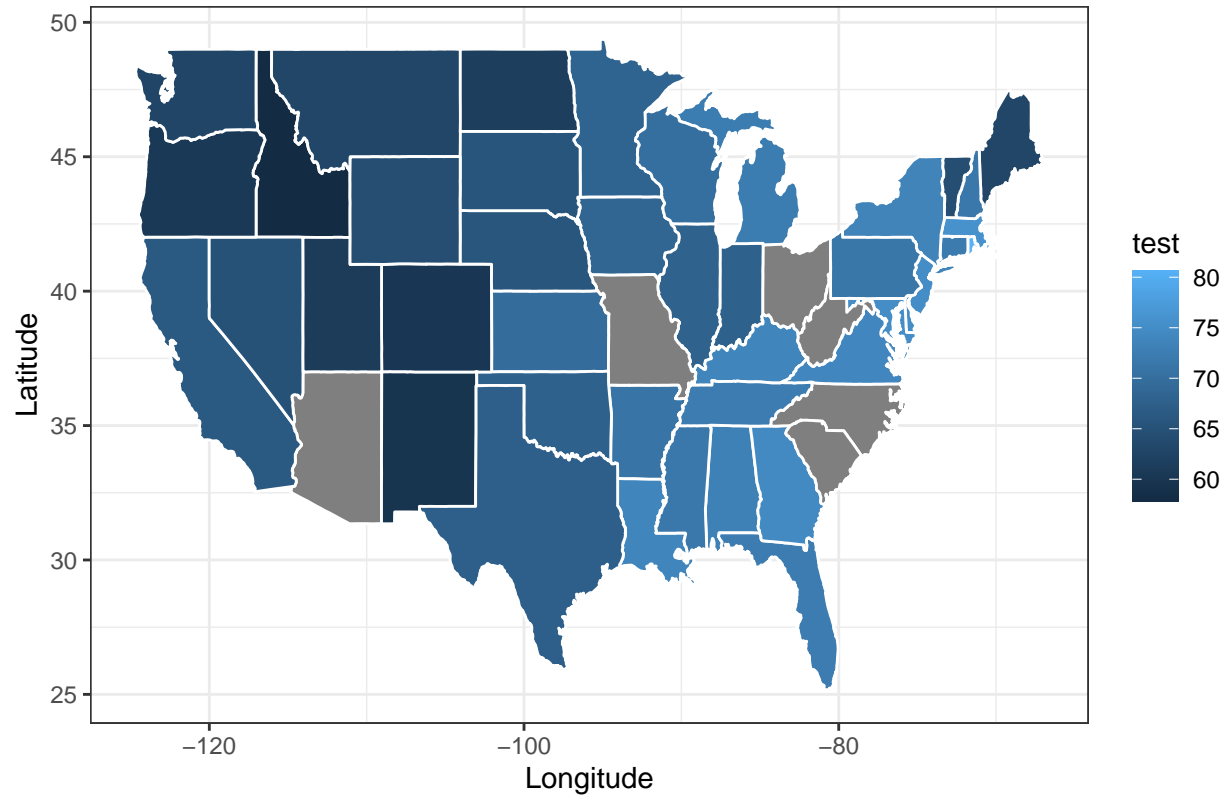
Access Variable: Visits to Doctor

```
states %>%
  left_join(data_500_cities, by = "StateDesc") -> test
data_500_cities %>%
  group_by(StateDesc) %>%
  summarise(test = mean(visits_to_doctor)) %>%
  right_join(states, by = "StateDesc") -> test2

ggplot(test2, aes(x = long, y = lat, group = group, fill = test)) +
  geom_polygon(color = "white")+
  labs(x = "Longitude",
       y = "Latitude",
       title = "Visits to Doctor across States")
```

```
labs(x = "Longitude",
     y = "Latitude",
     title = "Visits to Doctor across States")
```

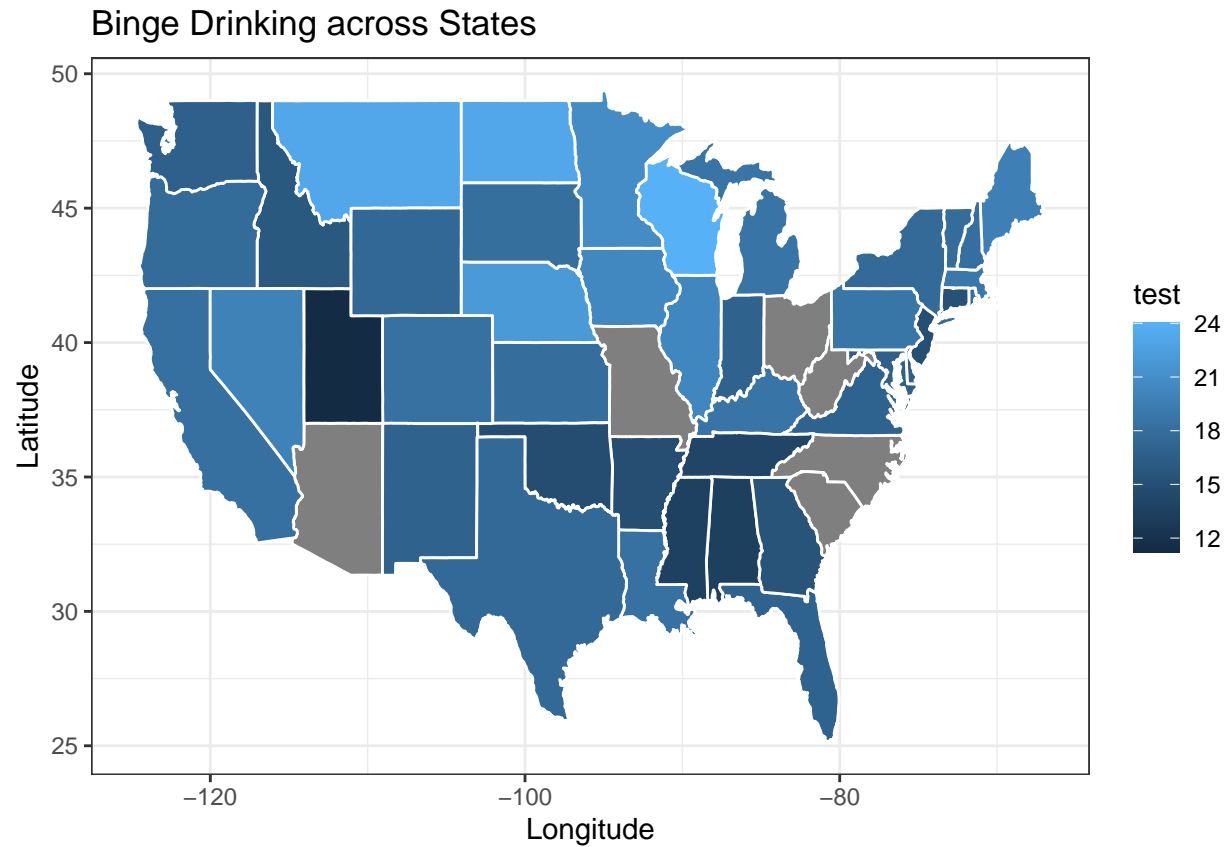
Visits to Doctor across States



Behaviour: Binge Drinking

```
states %>%
  left_join(data_500_cities, by = "StateDesc") -> test
data_500_cities %>%
  group_by(StateDesc) %>%
  summarise(test = mean(binge_drinking)) %>%
  right_join(states, by = "StateDesc") -> test2

ggplot(test2, aes(x = long, y = lat, group = group, fill = test)) +
  geom_polygon(color = "white")+
  labs(x = "Longitude",
       y = "Latitude",
       title = "Binge Drinking across States")
```

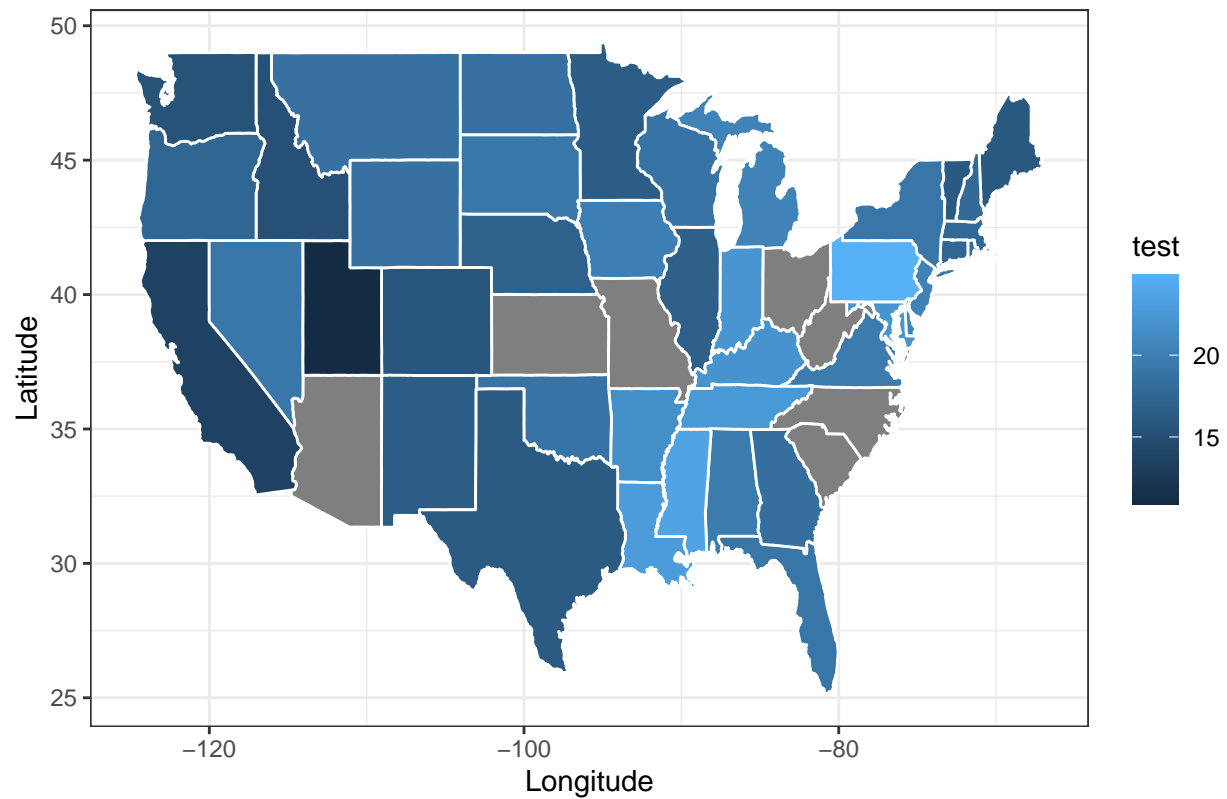


Behaviour: Smoking

```
states %>%
  left_join(data_500_cities, by = "StateDesc") -> test
data_500_cities %>%
  group_by(StateDesc) %>%
  summarise(test = mean(smoking)) %>%
  right_join(states, by = "StateDesc") -> test2

ggplot(test2, aes(x = long, y = lat, group = group, fill = test)) +
  geom_polygon(color = "white")+
  labs(x = "Longitude",
       y = "Latitude",
       title = "Smoking across States")
```

Smoking across States



Behaviour: Physical Activity

```
states %>%
  left_join(data_500_cities, by = "StateDesc") -> test
data_500_cities %>%
  group_by(StateDesc) %>%
  summarise(test = mean(physical_activity)) %>%
  right_join(states, by = "StateDesc") -> test2

ggplot(test2, aes(x = long, y = lat, group = group, fill = test)) +
  geom_polygon(color = "white")+
  labs(x = "Longitude",
       y = "Latitude",
       title = "Physical Activity across States")
```

