# Association and Correlation

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## Getting Started

Today we will be using data from Chetty et al's 2014 paper "Where Is The Land Of Opportunity?". The `commuting_zones.csv` dataset comes from the Opportunity Insights Project's website which can be accessed here. (Note how to include links in Markdown: the link title should be in brackets followed by the link destination in parentheses. Only the link title will appear in the knitted file, but it will be clickable.)

Load the data as a data frame called `cz` and load tidyverse.

## Finding Correlation Coefficients

Let's start with the correlation between income segregation and the proportion of workers who commute 15 minutes or less. What is a hypothesis for how these two variables could be related? Would you expect a positive or negative correlation?

The correlation coefficient is calculated as the covariance of x and y divided by the product of the standard deviations of x and y. In mathematical notation, we write:

$cor_{x,y} = \frac{cov_{x,y}}{s_x s_y}$

(If you hover over the equation above, you should see it converted to a more readable format. We won't learn how to write Tex equations in this class, but it could be good to know that R Markdown can handle them.)

We already know how to find the standard deviation using the `sd()` function. To find the covariance we use the `cov()` function and separate the two variables by a comma (just like a cross-tabulation). Let's plug all these values into the equation using `commute15min` as our X variable and `income_seg` as our Y variable.

```
cov(cz$commute15min, cz$income_seg) /
     (sd(cz$commute15min) * sd(cz$income_seg))
```

```
## [1] -0.6083312
```

How would you interpret this correlation?

Fortunately, R can calculate the correlation for us using the `cor()` function. Just like `cov()` or cross-tabulations, we separate both variables with a comma.

```
cor(cz$commute15min, cz$income_seg)
```

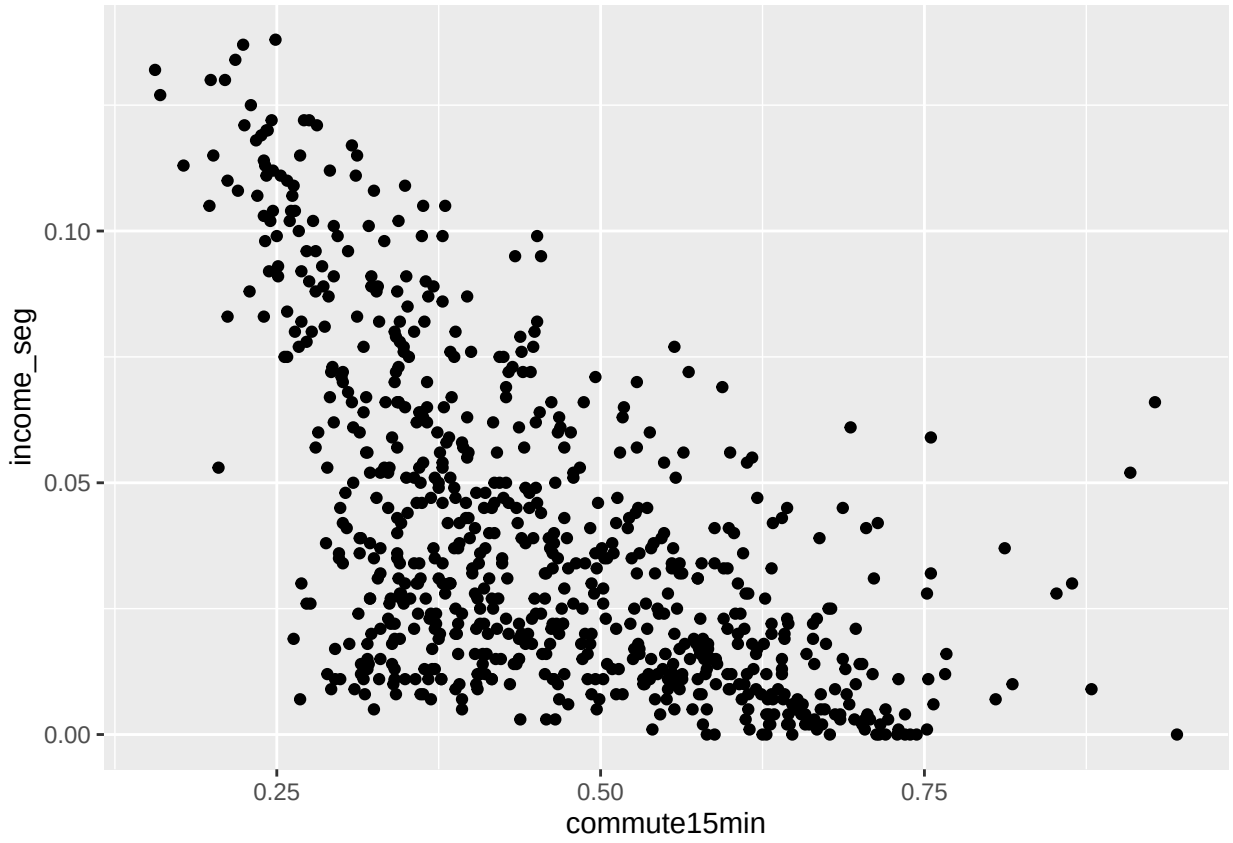
```
## [1] -0.6083312
```

You should get the same value as we calculated earlier.

## Visualizing Correlations With Scatterplots

We can also create a scatterplot showing how the distributions of both variables tend to move together. Set up everything in ggplot using the regular x and y aesthetics. For a scatterplot, the plot type is `geom_point()`.

```
commute_incomeseg_scatter <- ggplot(cz,
                            aes(x = commute15min, y = income_seg))

commute_incomeseg_scatter + geom_point()
```



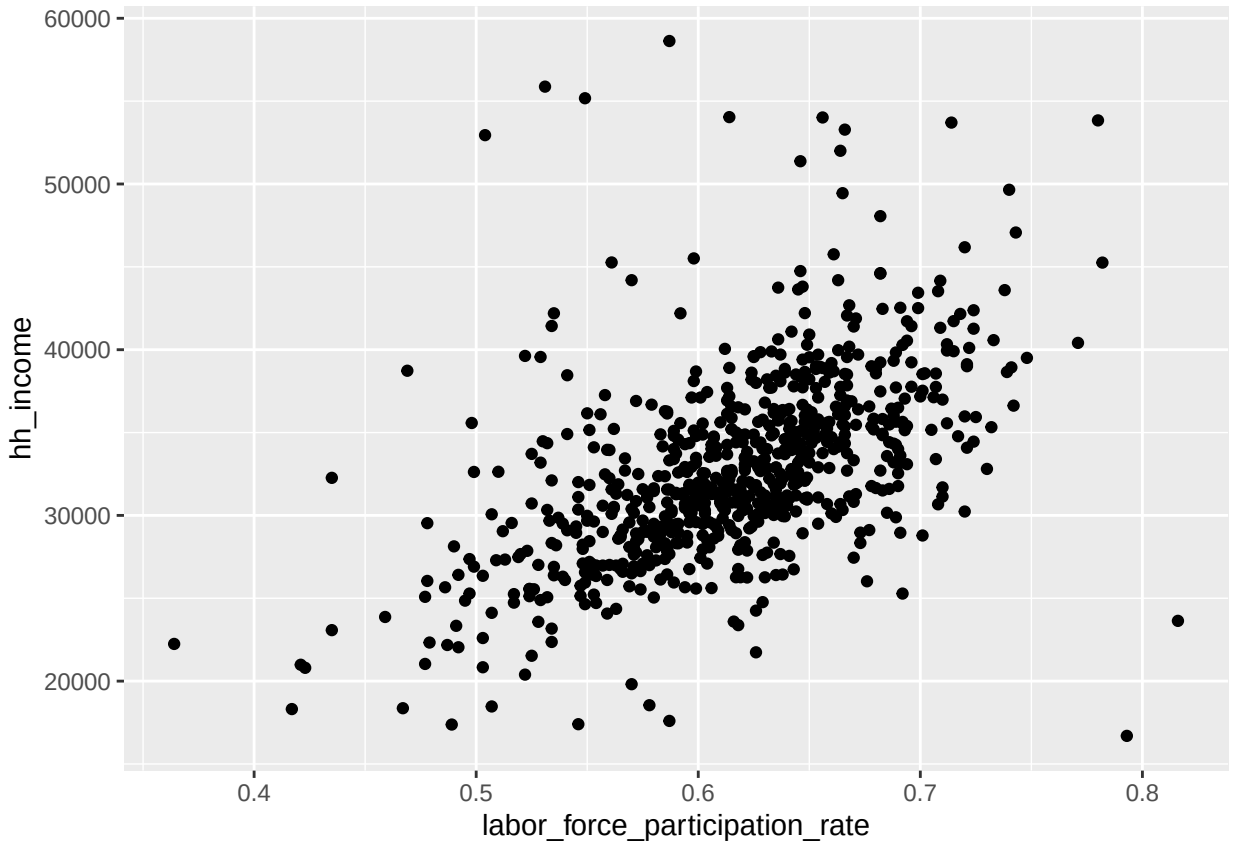

What would your hypothesis be for how commuting zones' median incomes and employment rates are associated? Find the correlation for median household income (`hh_income`) and `labor_force_participation_rate` using the `cor()` function, and create a scatterplot showing how the two variables are associated.

**REPLACE THIS LINE WITH YOUR CODE**

```
cor(cz$hh_income, cz$labor_force_participation_rate)
```

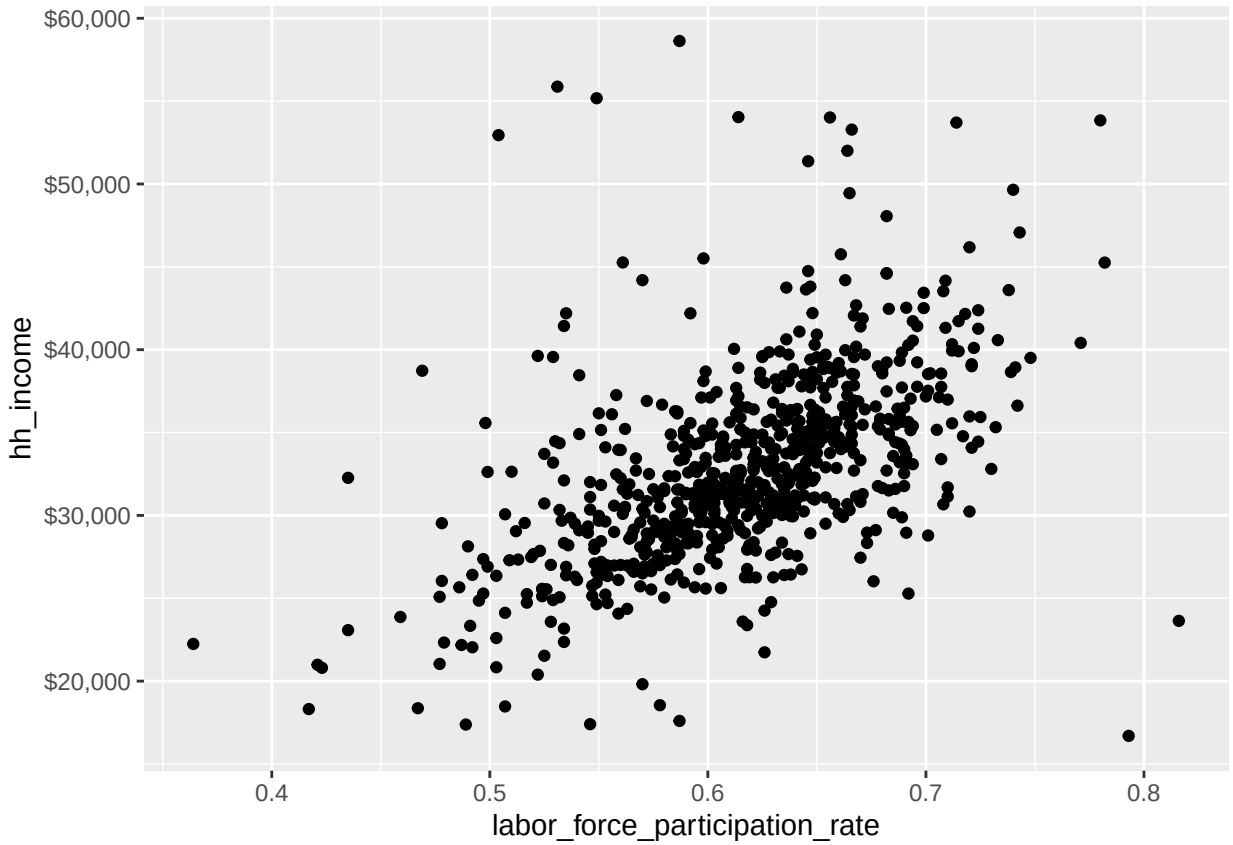
```
## [1] 0.5226587
```

```
income_laborforce_scatter <- ggplot(cz, aes(
     x = labor_force_participation_rate,
     y = hh_income))

income_laborforce_scatter + geom_point()
```



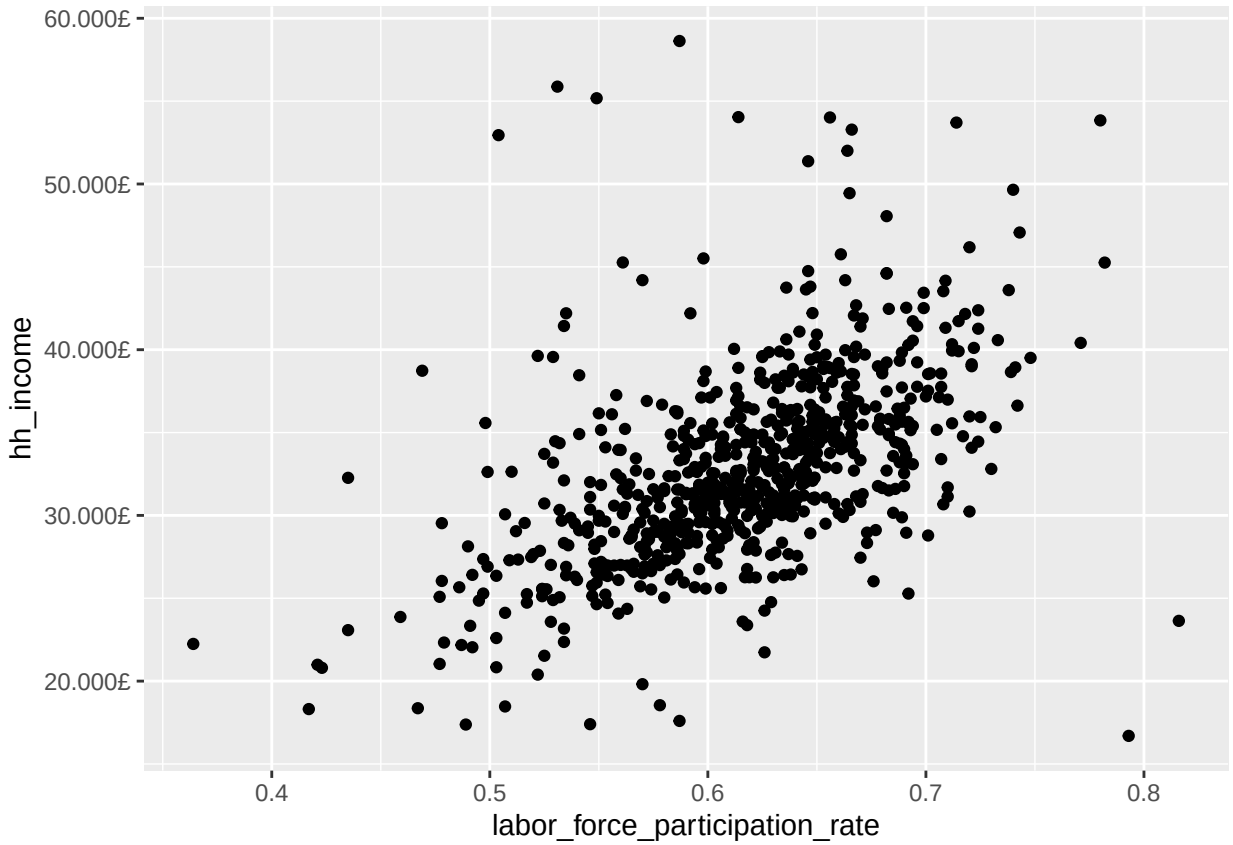

Here's a nice little trick using the `scales` package to change all the median income values on the y axis to dollar amounts:

```
#install.packages("scales") # install the scales package

income_laborforce_scatter <- ggplot(cz, aes(
     x = labor_force_participation_rate,
     y = hh_income))

income_laborforce_scatter + geom_point() +
  scale_y_continuous(labels = scales::label_dollar()) # To set y axis values to dollars
```




Need to define other currencies before using them

```
pound <- scales::label_dollar(
  prefix = "",
  suffix = "\u00a3", # use "\u20ac" for euro
  big.mark = ".",
  decimal.mark = ","
)

income_laborforce_scatter + geom_point() +
  scale_y_continuous(labels = pound) # To set y axis values to pounds
```




Let's look at one more association. What is your hypothesis for how `commute15min` and `mobility` would be related? Find the correlation coefficient for these two variables using the `cor()` function.

**REPLACE THIS LINE WITH YOUR CODE**

```
cor(cz$commute15min, cz$mobility)
```

```
## [1] NA
```

Uh oh. It looks like there is an error somewhere. To investigate, get a summary of all the variables in the dataframe using `summary()` and the data frame name:

```
summary(cz)
```

```
##      cz_id          cz_name             state           population_2000
##  Min.   :  100   Length:741         Length:741         Min.   :    1193
##  1st Qu.:12701   Class :character   Class :character   1st Qu.:   38384
##  Median :26106   Mode  :character   Mode  :character   Median :  103842
##  Mean   :22444                                         Mean   :  379787
##  3rd Qu.:31301                                         3rd Qu.:  289849
##  Max.   :39400                                         Max.   :16393360
##
##     mobility         urban          frac_black        racial_seg
##  Min.   :26.70   Min.   :0.0000   Min.   :0.00000   Min.   :0.0000
```

```
##  1st Qu.:39.90   1st Qu.:0.0000   1st Qu.:0.00400   1st Qu.:0.0560
##  Median :43.30   Median :0.0000   Median :0.02200   Median :0.1070
##  Mean   :43.94   Mean   :0.4386   Mean   :0.07781   Mean   :0.1298
##  3rd Qu.:47.10   3rd Qu.:1.0000   3rd Qu.:0.08200   3rd Qu.:0.1810
##  Max.   :64.00   Max.   :1.0000   Max.   :0.65800   Max.   :0.5540
##  NA's   :32
##    income_seg       poverty_seg      affluence_seg      commute15min
##  Min.   :0.00000   Min.   :0.00000   Min.   :0.00000   Min.   :0.1560
##  1st Qu.:0.01400   1st Qu.:0.01300   1st Qu.:0.01300   1st Qu.:0.3450
##  Median :0.03100   Median :0.02800   Median :0.03200   Median :0.4360
##  Mean   :0.03952   Mean   :0.03626   Mean   :0.04162   Mean   :0.4572
##  3rd Qu.:0.05700   3rd Qu.:0.05400   3rd Qu.:0.06000   3rd Qu.:0.5630
##  Max.   :0.13800   Max.   :0.12900   Max.   :0.15400   Max.   :0.9450
##
##    hh_income          gini         top1pc_share    local_tax_rate
##  Min.   :16696   Min.   :0.2020   Min.   : 2.673   Min.   :0.00800
##  1st Qu.:29327   1st Qu.:0.3480   1st Qu.: 8.005   1st Qu.:0.01700
##  Median :32372   Median :0.3980   Median :10.119   Median :0.02200
##  Mean   :32870   Mean   :0.4055   Mean   :10.842   Mean   :0.02359
##  3rd Qu.:35816   3rd Qu.:0.4570   3rd Qu.:12.545   3rd Qu.:0.02700
##  Max.   :58628   Max.   :0.8470   Max.   :64.788   Max.   :0.08200
##                                   NA's   :32       NA's   :1
##  local_govt_expenditures school_expenditures_per_student
##  Min.   :  952           Min.   : 3.920
##  1st Qu.: 1722           1st Qu.: 5.168
##  Median : 2112           Median : 5.897
##  Mean   : 2309           Mean   : 6.037
##  3rd Qu.: 2638           3rd Qu.: 6.627
##  Max.   :13621           Max.   :11.906
##  NA's   :2               NA's   :10
##  test_score_percentile_adj hs_dropout_rate_adj number_of_colleges
##  Min.   :-32.78500         Min.   :-0.04300    Min.   :0.00100
##  1st Qu.: -4.29300         1st Qu.:-0.01500    1st Qu.:0.01200
##  Median :  0.74100         Median :-0.00400    Median :0.01700
##  Mean   :  0.00001         Mean   :-0.00001    Mean   :0.02311
##  3rd Qu.:  5.55400         3rd Qu.: 0.01100    3rd Qu.:0.02600
##  Max.   : 20.07100         Max.   : 0.10900    Max.   :0.24300
##  NA's   :36                NA's   :148         NA's   :157
##  college_grad_rate_adj labor_force_participation_rate
##  Min.   :-0.35000      Min.   :0.364
##  1st Qu.:-0.09700      1st Qu.:0.581
##  Median :-0.01600      Median :0.619
##  Mean   :-0.00001      Mean   :0.616
##  3rd Qu.: 0.08300      3rd Qu.:0.653
##  Max.   : 0.52800      Max.   :0.816
##  NA's   :160
##  manufacturing_employment_share migration_inflow  migration_outflow
##  Min.   :0.0020                 Min.   :0.00000   Min.   :0.00000
##  1st Qu.:0.0760                 1st Qu.:0.01000   1st Qu.:0.01200
##  Median :0.1330                 Median :0.01400   Median :0.01600
##  Mean   :0.1404                 Mean   :0.01653   Mean   :0.01683
##  3rd Qu.:0.1990                 3rd Qu.:0.02100   3rd Qu.:0.02100
##  Max.   :0.4490                 Max.   :0.07700   Max.   :0.05200
##                                 NA's   :17        NA's   :17
```

```
##  frac_foreign_born social_capital_index frac_religion    violent_crime_rate
##  Min.   :0.00000   Min.   :-3.1990      Min.   :0.1100   Min.   :0.000000
##  1st Qu.:0.01200   1st Qu.:-0.7655      1st Qu.:0.4250   1st Qu.:0.001000
##  Median :0.02400   Median : 0.0640      Median :0.5250   Median :0.001000
##  Mean   :0.04117   Mean   : 0.1717      Mean   :0.5456   Mean   :0.001594
##  3rd Qu.:0.04600   3rd Qu.: 0.9653      3rd Qu.:0.6430   3rd Qu.:0.002000
##  Max.   :0.39700   Max.   : 7.3050      Max.   :1.3080   Max.   :0.028000
##                    NA's   :19                            NA's   :27
##  frac_children_single_mothers frac_adults_divorced frac_adults_married
##  Min.   :0.0820               Min.   :0.04000      Min.   :0.3730
##  1st Qu.:0.1710               1st Qu.:0.08500      1st Qu.:0.5450
##  Median :0.1960               Median :0.09800      Median :0.5800
##  Mean   :0.2017               Mean   :0.09666      Mean   :0.5745
##  3rd Qu.:0.2260               3rd Qu.:0.10900      3rd Qu.:0.6070
##  Max.   :0.4340               Max.   :0.19000      Max.   :0.6950
##
##  income_growth_06_10 drop_this_column   cz_state
##  Min.   :-0.118000   Mode:logical     Length:741
##  1st Qu.:-0.008000   NA's:741         Class :character
##  Median :-0.002000                    Mode  :character
##  Mean   :-0.001669
##  3rd Qu.: 0.004000
##  Max.   : 0.046000
##
```

## Dealing With Missing Values

There are 32 observations where the value for `mobility` is "NA". That is R's way of telling us the values are missing, or "not available". Most datasets will have some missing values, so we need ways to deal with them. For correlations, the way to tell R we only want to use cases without any missing values is to add the `use=complete` option:

```
cor(cz$commute15min, cz$mobility, use="complete")
```

```
## [1] 0.6048691
```

For many other functions, use `na.rm = TRUE` to remove all values with an NA. For example:

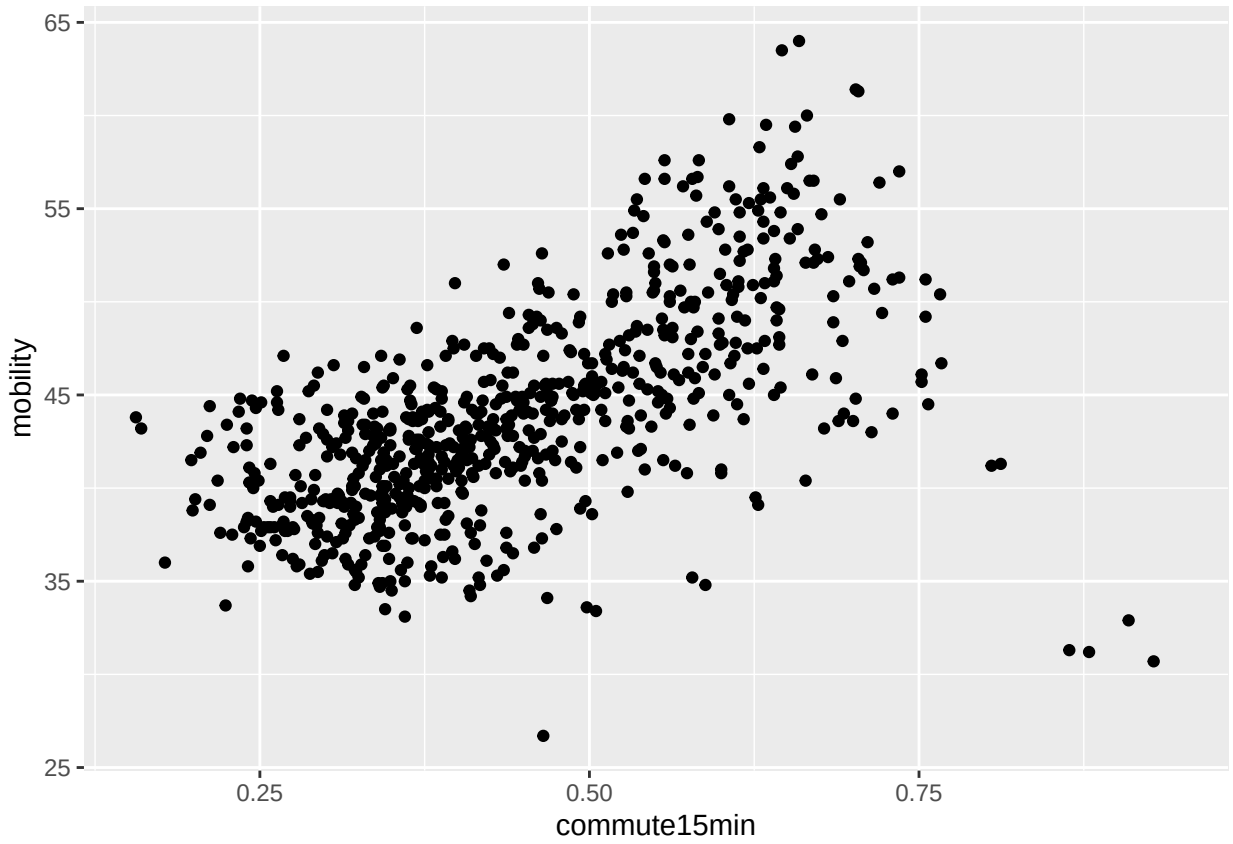
```
mean(cz$mobility, na.rm = TRUE)
```

```
## [1] 43.94344
```

Fortunately, ggplot2 knows to only use complete cases so we do not have to adjust our code to get a scatterplot:

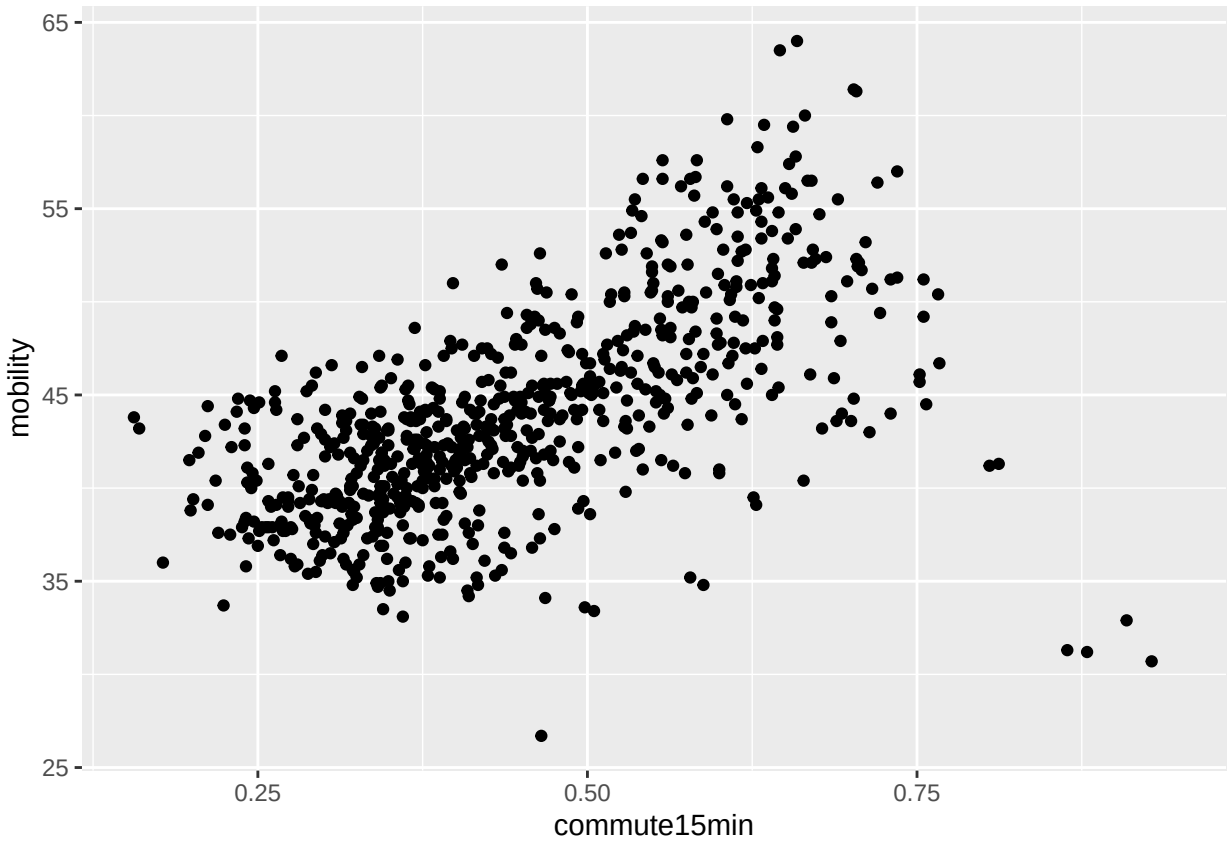
```
mobility_commute_scatter <- ggplot(cz,
                                   aes(x = commute15min, y = mobility))

mobility_commute_scatter + geom_point()
```

```
## Warning: Removed 32 rows containing missing values (geom_point).
```




You can see that there is a warning message alerting us to the fact that there are 32 missing values. To get rid of that, add `warning=FALSE` to the code chunk header:

```
mobility_commute_scatter <- ggplot(cz,
                                   aes(x = commute15min, y = mobility))

mobility_commute_scatter + geom_point()
```




If for some reason you have a column with only NA values, you can drop the column:

```
cz <- cz |>
  select(-drop_this_column) # Use - with select to drop
```

## Plots With Labeled Points

The plots we have been making so far show points for every commuting zone (for which data are available). It is often helpful to identify specific points that are important for the analysis. Let's start by making our figure interactive using the `plotly()` package.

```
#install.packages("plotly")
library(plotly)
```

```
##
## Attaching package: 'plotly'
```

```
## The following object is masked from 'package:ggplot2':
##
##     last_plot
```

```
## The following object is masked from 'package:stats':
##
##     filter
```

```
## The following object is masked from 'package:graphics':
##
##     layout
```

This package makes it very easy to get some info about each point when you hover over it. All you have to do is save the plot as an object and then wrap that object in `ggplotly()`.

```
plotly_test <- ggplot(cz, aes(x = commute15min, y = mobility)) + geom_point()

ggplotly(plotly_test)
```

```
## PhantomJS not found. You can install it with webshot::install_phantomjs(). If it is installed, pleas
```

For exploring your own data, the above chunk is probably sufficient. For sharing the data, you might prefer to customize the text in the hover tooltips using the text option in the aesthetics map.

```
plotly_test <- ggplot(cz, aes(x = commute15min, y = mobility,
                              text = paste("CZ:", cz_state, "<br>",
                                           "Commute < 15 Mins:", commute15min, "<br>",
                                           "Mobilty rate:", mobility))) +
  geom_point()

ggplotly(plotly_test, tooltip = "text") # Add tooltip option for custom hover
```

## Exercise With Other Variables

Take a few minutes to explore how other variables in this dataset are associated with mobility. What is a relationship where you would expect a negative association? What is a relationship where you would expect a positive association? What is a relationship where you would expect no association?

Here are the other four of the "big five" variables correlated with mobility:

- `gini` = Gini coefficient of income inequality; higher gini values indicate more inequality
- `social_capital` = Social capital index
- `frac_children_single_mothers` = Proportion of children living in single-parent households
- `hs_dropout_rate_adj` = High school dropout rate adjusted for family income; positive values indicate that the hs dropout rate is larger than expected given a commuting zone's median family income, and negative values indicate that the hs dropout rate is smaller than expected given a commuting zone's median family income