Exploratory Data Analysis

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Descriptive Statistics

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Examples: t-tests, χ^2 tests of association

The `summary()` function

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It gives different output depending on the class of the object passed to it. For a data frame, it provides the mean, median, min, and max, and quartiles for **continuous** variables:

```
> summary(anes$fthrc)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
   0.00    3.00   44.00   42.99   76.00  100.00       1
```

And it displays frequencies for **factor** variables:

```
> summary(anes$vote12)
 Mitt Romney Barack Obama Someone else         NA's
         371          512           68          249
```

The `dfSummary()` function

The `dfSummary()` from the `summarytools` package provides many descriptive statistics in a neat HTML format.

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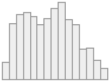
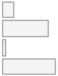
```
dfSummary(gss, plain.ascii = FALSE, style = "grid",
          graph.magnif = 0.75, valid.col = FALSE,
          tmp.img.dir = "/tmp", headings = FALSE)
```

No	Variable	Stats / Values	Freqs (% of Valid)	Graph	Missing
1	sex [factor]	1. female 2. male	1586 (55.5%) 1273 (44.5%)		0 (0%)
2	age [numeric]	Mean (sd) : 49.1 (17.7) min < med < max: 18 < 49 < 89 IQR (CV) : 28 (0.4)	72 distinct values		10 (0.35%)
3	artexbt [factor]	1. no 2. yes	987 (67.2%) 481 (32.8%)		1391 (48.65%)
4	class [factor]	1. lower class 2. middle class 3. upper class 4. working class	286 (10.1%) 1143 (40.3%) 80 (2.8%) 1328 (46.8%)		22 (0.77%)

Quick calculations

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- `mean()` — calculates the mean
- `median()` — calculates the median
- `sd()` — calculates the standard deviation
- `var()` — calculates the variance
- `min()` — calculates the minimum value
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- `min()` — calculates the minimum value
- `max()` — calculates the maximum value

If there are missing values for an object, these functions will return `NA` unless you also specify the argument `na.rm=TRUE`, in which case it ignores the missing values.

Percentiles

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To find percentiles, use the `quantile()` function. Use the `probs` argument to specify the percentiles you want to see.

Here are the 10th, 40th, and 85th percentiles for Hillary Clinton's thermometer scores in the 2016 ANES pilot study:

```
> quantile(anes$fthrc, probs=c(.1, .4, .85), na.rm=TRUE)
10% 40% 85%
  0  20  89
```

Frequency tables

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There are three functions that report frequencies:

- `table()`
- `plyr::count()`
- `xtabs()`

`table()` displays these frequencies side by side:

```
> table(anes$vote12)

 Mitt Romney Barack Obama Someone else
         371          512           68
```

Frequency tables

`plyr::count()` displays these frequencies vertically:

```
> plyr::count(anes$vote12)
             x freq
1  Mitt Romney  371
2 Barack Obama  512
3 Someone else   68
4         <NA>  249
```

Frequency tables

`plyr::count()` displays these frequencies vertically:

```
> plyr::count(anes$vote12)
             x freq
1  Mitt Romney  371
2 Barack Obama  512
3 Someone else   68
4         <NA>  249
```

`xtabs()` also displays these frequencies side by side, but requires a slightly different syntax:

```
> xtabs( ~ vote12, data=anes)
vote12
 Mitt Romney Barack Obama Someone else
         371          512           68
```

Cross tabulations

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Both `table()` and `xtabs()` can create cross tabulations. For `table()`, write the rows variable first, the columns variable second:

```
> table(anes$gender, anes$vote12)

         Mitt Romney Barack Obama Someone else
  Male           191          236           46
  Female         180          276           22
```

Cross tabulations

For `xtabs()`, write a

$$\sim$$

first, then rows variable, then $+$, then the columns variable:

```
> xtabs( ~ gender + vote12, data=anes)
        vote12
gender   Mitt Romney Barack Obama Someone else
  Male           191          236           46
  Female         180          276           22
```

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first, then rows variable, then $+$, then the columns variable:

```
> xtabs( ~ gender + vote12, data=anes)
        vote12
gender    Mitt Romney Barack Obama Someone else
  Male            191          236           46
  Female          180          276           22
```

You get a slightly cleaner display by placing this function within `ftable()` (this creates a "flat table"):

```
ftable(xtabs( ~ gender + vote12, data=anes))
       vote12 Mitt Romney Barack Obama Someone else
gender
Male                  191          236           46
Female                180          276           22
```

Cross tabulations

If you write a third variable in the formula, it displays a different cross-tab for each value of the third variable:

```
> xtabs( ~ gender + vote12 + sign, data=anes)
, , sign = Have done this in the past 12 months

        vote12
gender   Mitt Romney Barack Obama Someone else
  Male            50           69           15
  Female          35           75            1

, , sign = Have not done this in the past 12 months

        vote12
gender   Mitt Romney Barack Obama Someone else
  Male           141          167           31
  Female         145          201           21
```

Cross tabulations

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my.table <- table(anes$gender, anes$vote12)
```

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```
my.table <- table(anes$gender, anes$vote12)
```

Then use the `prop.table()` function. By default it gives cell proportions (percents/100)

```
> prop.table(my.table)

         Mitt Romney Barack Obama Someone else
  Male    0.20084122   0.24815983   0.04837014
  Female  0.18927445   0.29022082   0.02313354
```

Cross tabulations

For row proportions, use the argument `margin=1`:

```
> prop.table(my.table, margin=1)

         Mitt Romney Barack Obama Someone else
  Male    0.40380550   0.49894292   0.09725159
  Female  0.37656904   0.57740586   0.04602510
```

Cross tabulations

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```
> prop.table(my.table, margin=1)

       Mitt Romney Barack Obama Someone else
Male    0.40380550   0.49894292   0.09725159
Female  0.37656904   0.57740586   0.04602510
```

For column proportions, use the argument `margin=2`:

```
> prop.table(my.table, margin=2)

       Mitt Romney Barack Obama Someone else
Male     0.5148248    0.4609375    0.6764706
Female   0.4851752    0.5390625    0.3235294
```

Cross tabulations

For row proportions, use the argument `margin=1`:

```
> prop.table(my.table, margin=1)

       Mitt Romney Barack Obama Someone else
  Male    0.40380550   0.49894292   0.09725159
  Female  0.37656904   0.57740586   0.04602510
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> prop.table(my.table, margin=2)

       Mitt Romney Barack Obama Someone else
  Male     0.5148248    0.4609375    0.6764706
  Female   0.4851752    0.5390625    0.3235294
```

For percents, multiply by 100:

```
> 100*prop.table(my.table, margin=2)

       Mitt Romney Barack Obama Someone else
  Male      51.48248     46.09375     67.64706
  Female    48.51752     53.90625     32.35294
```

Correlation

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Positive correlation means that as one variable changes, the other changes in the same direction. If the correlation is 1, there's a perfect upward-sloping linear formula that describes this relationship.

Negative correlation means that as one variable changes, the other changes in the opposite direction. If the correlation is -1, there's a perfect downward-sloping linear formula that describes this relationship.

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Then use the `cor()` function on the data.

```
> cor.data <- select(anes, fthrc, ftobama, fttrump, ftcruz)
> cor.data <- na.omit(cor.data)
> cor(cor.data)
             fthrc    ftobama    fttrump     ftcruz
fthrc    1.0000000  0.7936290 -0.4505056 -0.4266794
ftobama  0.7936290  1.0000000 -0.5849056 -0.5280243
fttrump -0.4505056 -0.5849056  1.0000000  0.5071978
ftcruz  -0.4266794 -0.5280243  0.5071978  1.0000000
```

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A t-test takes the following steps:

- Calculate the mean of both variables and the difference between these two means
- Suppose the means are equal in the population, and that the sample is random
- Ask: how likely is it that the difference could have been as far from 0 as it is? Calculate a probability called a p-**value**.

Student's *t*-test

A *t*-test is a way to test whether or not two variables **have equal means**.

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A *t*-test takes the following steps:

- Calculate the mean of both variables and the difference between these two means
- Suppose the means are equal in the population, and that the sample is random
- Ask: how likely is it that the difference could have been as far from 0 as it is? Calculate a probability called a *p*-**value**.
- If $p < .05$ (or another standard), then it's not likely the mean could have been this far from 0. In that case conclude that the means weren't equal in the population after all.

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When working with data frames, we usually test whether the means of variables are equal. In this case, the test should be paired, since the observations correspond.

To run a paired *t*-test, use the `t.test()` function with the `paired=TRUE` argument:

```
> t.test(anes$fthrc, anes$fttrump, paired=TRUE)

        Paired t-test

data:  anes$fthrc and anes$fttrump
t = 2.5485, df = 1195, p-value = 0.01094
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 1.055163 8.113733
sample estimates:
mean of the differences
               4.584448
```

χ^2 test of association

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```

Does gender appear to have anything to do with voting?

Are men more likely than women to vote for Romney?

Is there enough evidence here to conclude the relationship is real?

χ^2 test of association

To run a χ^2 test of association in R, save the table as a separate object. Then use the `chisq.test()` function to run the test:

```
> my.table <- table(anes$gender, anes$vote12)
> chisq.test(my.table)

        Pearson's Chi-squared test

data:  my.table
X-squared = 11.896, df = 2, p-value = 0.002611
```

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(3) Maximizing the Data-Ink Ratio – remove superfluous elements that do not report or describe the data.

(4) Aesthetic Elegance – use as simple a design as possible to convey a complex data structure.

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Like anything else in R, there are many ways to do the same thing. The advantage of `ggplot()` is that it is relatively simple, prettier, and more elegant than the other systems are by default.

The disadvantage of `ggplot()` is it's **inflexibility** when you want to customize elements of the graphic.

The `ggplot()` function

There are two ways to run a `ggplot()` function. If you call `ggplot()` directly:

```
ggplot(data, aes(x, y)) + . . .
```

then the graphic will appear immediately in the plot window in R Studio, or in the markdown file output.

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```

then the graphic will appear immediately in the plot window in R Studio, or in the markdown file output.

If you save the `ggplot()` output to an object, then the graphic won't display until you call the object directly.

```
g <- ggplot(data, aes(x, y)) + . . .
```

Nothing will be displayed until I type `g`. That's useful if I want to create the graphic, but I don't want to slow down compilation by displaying it right away.

The `ggplot()` function

The `ggplot()` function has three parts:

1. The data frame that contains the data to be plotted
2. An aesthetics statement: which variable is x? which is y? which is a grouping variable? etc
3. Additional information about the **type of plot**, labels, grids

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1. The data frame that contains the data to be plotted
2. An aesthetics statement: which variable is x? which is y? which is a grouping variable? etc
3. Additional information about the **type of plot**, labels, grids

Just like all the `tidyverse` commands, the first argument is the **data frame**. To make a plot from the ANES data we've been using, begin the command by typing

```
g <- ggplot(anes,
```

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To make a plot (such as a scatterplot, more on this later) with Hillary Clinton's thermometer score on the x axis and Donald Trump's thermometer on the y axis, type

```
g <- ggplot(anes, aes(x=fthrc, y=fttrump))
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```
g <- ggplot(anes, aes(x=fthrc, y=fttrump))
```

It's easy to forget about `aes()`, but it's required. Don't forget!

Different kinds of plots with `geom` functions

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There are currently 44 different functions that all begin `geom_...()`, where the dots are replaced by different words. Each `geom` function works with `ggplot()` to create a different graph.

Here's a few of the `geom_...()` functions

`geom_point()` – creates a scatterplot for two **continuous variables**. Draws a point for every observation, with the two variables providing the x and y coordinates.

`geom_smooth()` – draw best-fit lines or curves

`geom_line()` and `geom_path()` – create line plots

`geom_bar()` – create bar charts

`geom_histogram()` – create histograms

`geom_boxplot()` – create box plots

`geom_density()` and `geom_violin()` – draws the density of a continuous variable (shows the relative frequency of values)

Different kinds of plots with `geom` functions

Different `geom_...()` require different options, and there are too many to memorize right away. You will have to look up examples for a while – that's fine.

Different kinds of plots with geom functions

Different `geom_...()` require different options, and there are too many to memorize right away. You will have to look up examples for a while – that's fine.

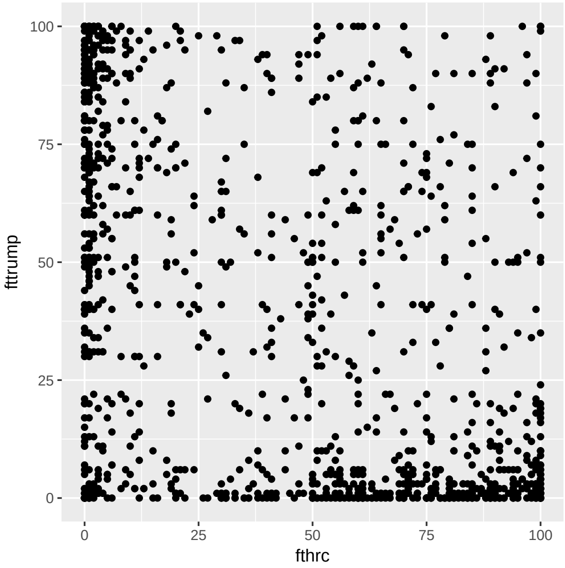
To create a scatterplot of Clinton and Trump's thermometer scores, add `geom_point()` to the code:

```
g <- ggplot(anes, aes(x=fthrc, y=fttrump)) +
        geom_point()
```

Style point: I like to press enter after every + sign to make the code easier to look at.

Then to display the graphic, type `g` in the script, console, or markdown file.

Different kinds of plots with `geom` functions



Different kinds of plots with `geom` functions

You can use more than one `geom_...()` function within one graphic. This overlays one graph over another.

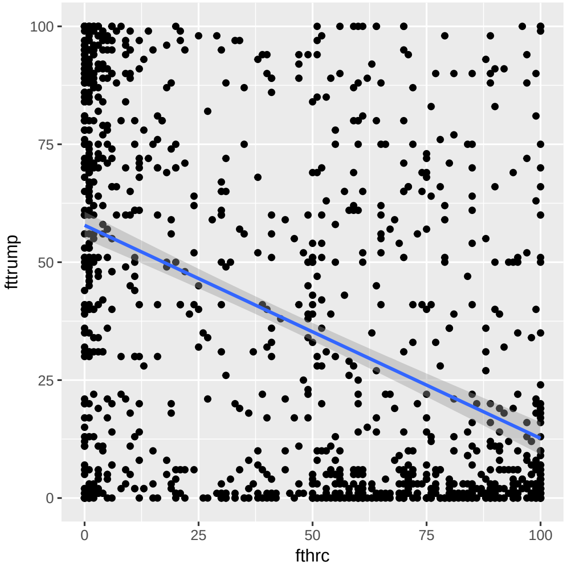
Different kinds of plots with geom functions

You can use more than one `geom_...()` function within one graphic. This overlays one graph over another.

To superimpose a best-fit line over the scatterplot, add `geom_smooth(method="lm")` to the code:

```
g <- ggplot(anes, aes(x=fthrc, y=fttrump)) +
        geom_point() +
        geom_smooth(method="lm")
```

Different kinds of plots with `geom` functions



Axis labels and titles

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To label the x and y axes, add `xlab("x-axis label")` and `ylab("y-axis label")` to the code.

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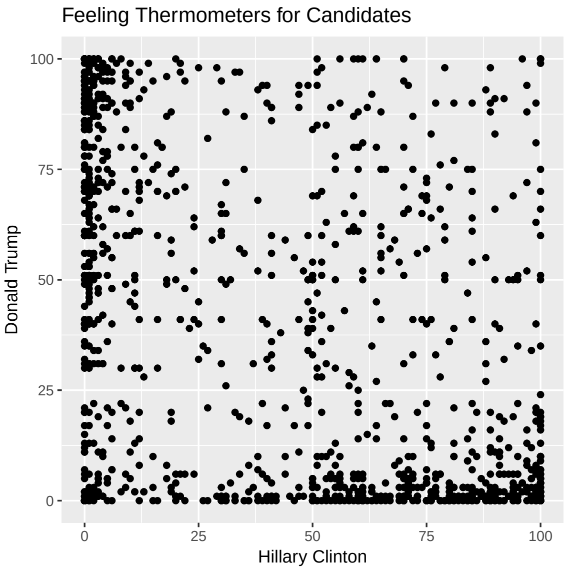
To label the x and y axes, add `xlab("x-axis label")` and `ylab("y-axis label")` to the code.

To give the graph a title, add `ggtitle("title")` to the code.

```
g <- ggplot(anes, aes(x=fthrc, y=fttrump)) +
      geom_point() +
      xlab("Hillary Clinton") +
      ylab("Donald Trump") +
      ggtitle("Feeling Thermometers for Candidates")
```

Axis labels and titles



Using colors, shapes, or line types for groups

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In the scatterplot, we can distinguish men and women, Democrats and Republicans, voters from non-voters, and so on. We can use **colors, shapes, or both** to distinguish these groups.

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In the scatterplot, we can distinguish men and women, Democrats and Republicans, voters from non-voters, and so on. We can use **colors, shapes, or both** to distinguish these groups.

Inside the `aes()` function, after specifying `x` and `y`, type `col=gender` to use different colors for the points that refer to men and the points that refer to women:

```
g <- ggplot(anes, aes(x=fthrc, y=fttrump, col=gender)) +
      geom_point() +
      xlab("Hillary Clinton") +
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```

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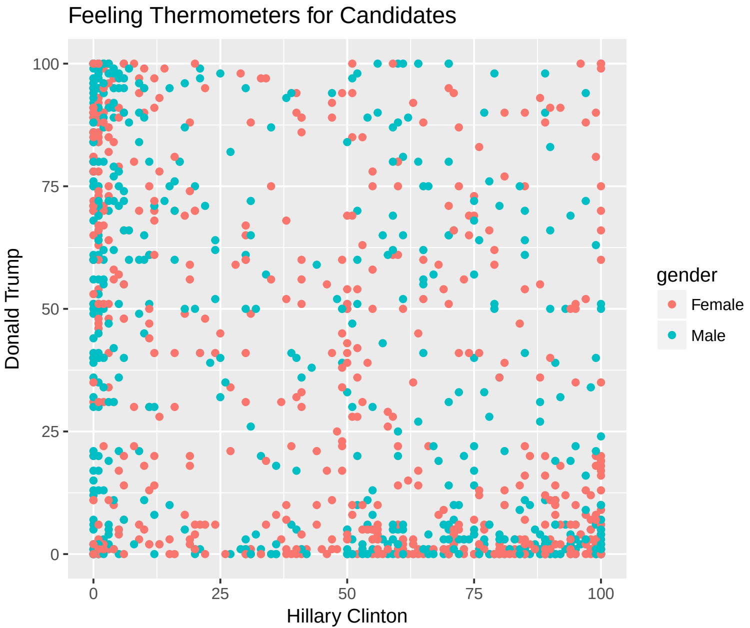

Using colors, shapes, or line types for groups

To use different shapes, type `pch=gender`.

```
g <- ggplot(anes, aes(x=fthrc, y=fttrump, pch=gender)) +
      geom_point() +
      xlab("Hillary Clinton") +
      ylab("Donald Trump") +
      ggtitle("Feeling Thermometers for Candidates")
```

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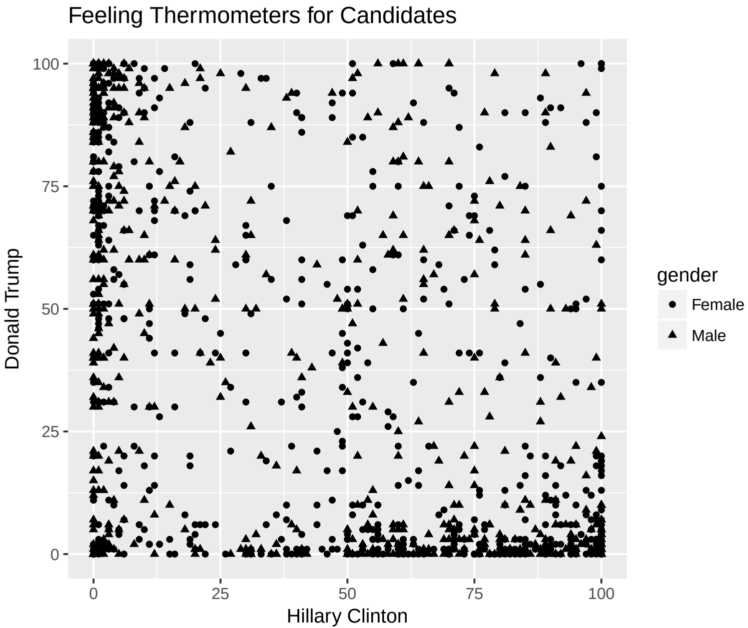
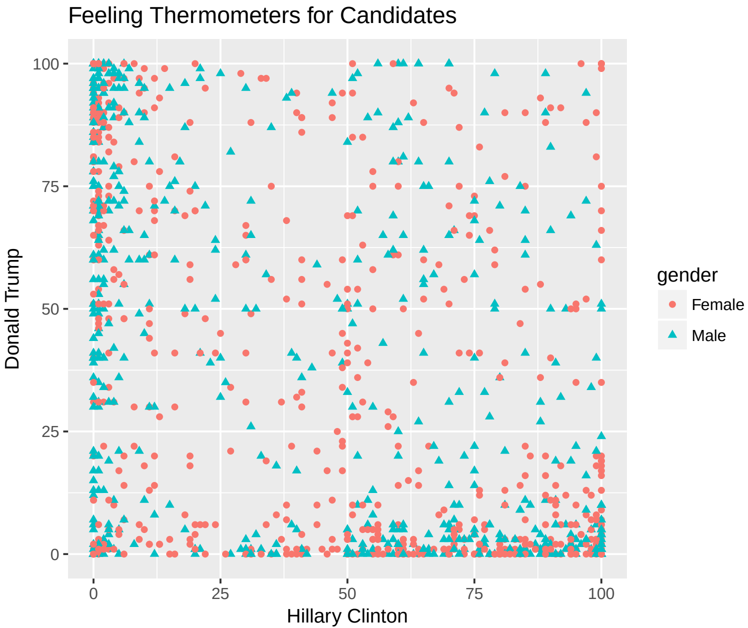


Using colors, shapes, or line types for groups

You can set both colors and shapes to vary based on the same variable:

```
g <- ggplot(anes, aes(x=fthrc, y=fttrump, col=gender, pch=gender)) +
      geom_point() +
      xlab("Hillary Clinton") +
      ylab("Donald Trump") +
      ggtitle("Feeling Thermometers for Candidates")
```

Using colors, shapes, or line types for groups

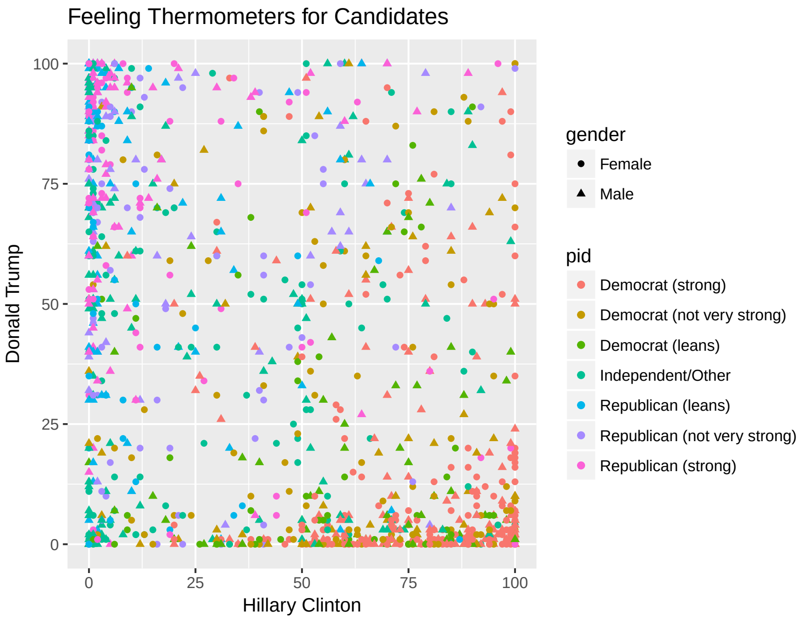


Using colors, shapes, or line types for groups

You can set both colors and shapes to vary based on the two different variables:

```
g <- ggplot(anes, aes(x=fthrc, y=fttrump, col=pid, pch=gender)) +
      geom_point() +
      xlab("Hillary Clinton") +
      ylab("Donald Trump") +
      ggtitle("Feeling Thermometers for Candidates")
```

Using colors, shapes, or line types for groups



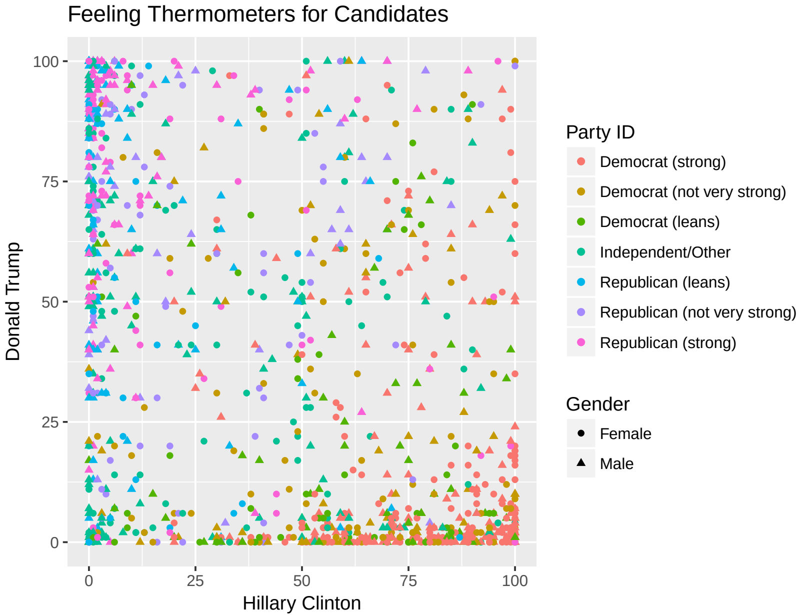
Using colors, shapes, or line types for groups

Notice that when you use colors or shapes to denote groups, `ggplot()` automatically creates a legend. You might want to change the legend title.

To do that, type `labs(color = "Party ID")` to change the legend title for the colors, and type `labs(pch = "Gender")` to change the legend title for the shapes:

```
g <- ggplot(anes, aes(x=fthrc, y=fttrump, col=pid, pch=gender)) +
      geom_point() +
      xlab("Hillary Clinton") +
      ylab("Donald Trump") +
      ggtitle("Feeling Thermometers for Candidates") +
      labs(color = "Party ID") +
      labs(pch = "Gender")
```

Using colors, shapes, or line types for groups



Creating a grid of plots

Colors and shapes are good ways to distinguish groups, but they aren't the only ways to do it. Another option is to create a grid of corresponding graphs, one for each category of a group.

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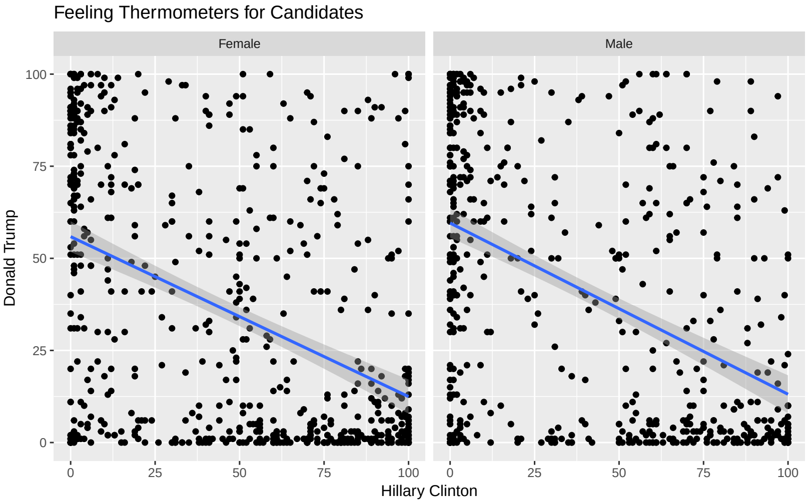
(2) `facet_grid(gender ~ .)` will place the plots for men and women in different rows

Creating a grid of plots

Here's an example breaking up gender into columns:

```
g <- ggplot(anes, aes(x=fthrc, y=fttrump)) +
     geom_point() +
     geom_smooth(method="lm") +
     xlab("Hillary Clinton") +
     ylab("Donald Trump") +
     ggtitle("Feeling Thermometers for Candidates") +
     facet_grid(. ~ gender)
```

Creating a grid of plots

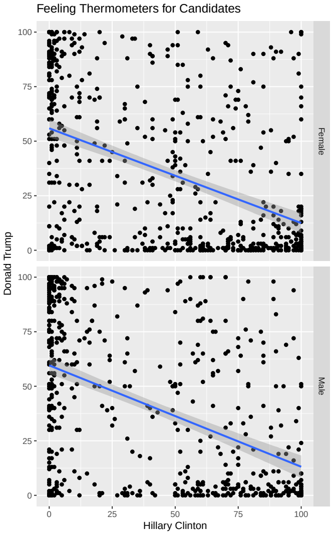


Creating a grid of plots

Here's an example breaking up gender into rows:

```
g <- ggplot(anes, aes(x=fthrc, y=fttrump)) +
     geom_point() +
     geom_smooth(method="lm") +
     xlab("Hillary Clinton") +
     ylab("Donald Trump") +
     ggtitle("Feeling Thermometers for Candidates") +
     facet_grid(gender ~ .)
```

Creating a grid of plots



Creating a grid of plots

(3) `facet_grid(gender ~ pid)` will create a plot for **each combination of party ID and gender**, and will place them in a grid where the rows represent genders and the columns represent party IDs.

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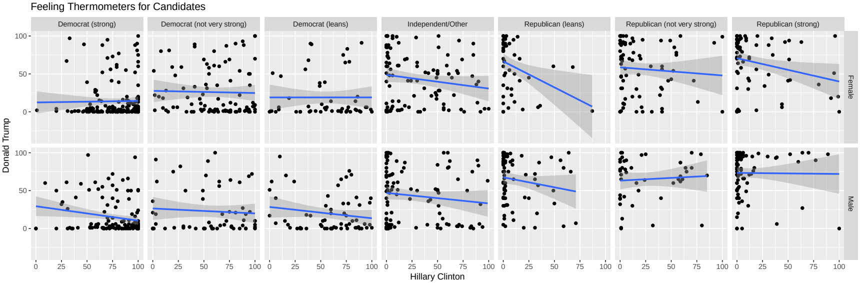
     facet_grid(gender ~ pid)
```

Creating a grid of plots



Creating a grid of plots

(4) `facet_wrap( ~ pid)` will make a graph for every party ID, but will automatically fill several rows to make it look good.

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     ggtitle("Feeling Thermometers for Candidates") +
     facet_wrap(~ pid)
```
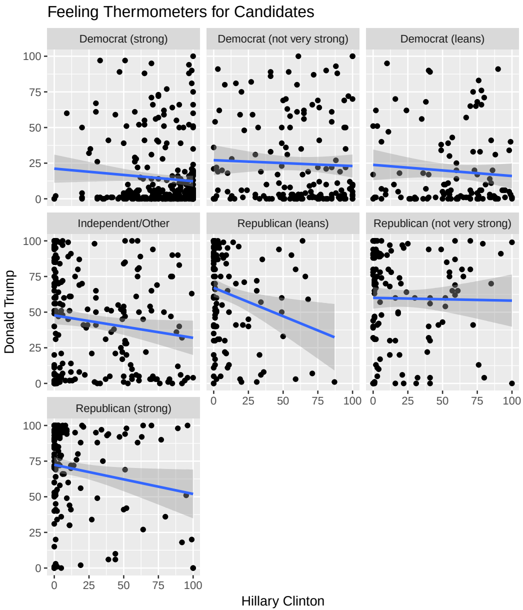

Creating a grid of plots



Saving graphics as PDF, JPEG, BMP, or PNG files

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For a PDF, the code is

```
pdf("filename.pdf", width=5, height=5)
g
dev.off()
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The `pdf()` function has three arguments. First, write the name of the file you want to create. Then specify the width and height you want this image to be, in inches.

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g is just the name of your ggplot graphic object.

`dev.off()` turns off the PDF recording device that R uses. If you don't write this function, R will continue to print all visual output to the same PDF as new pages.

Saving graphics as PDF, JPEG, BMP, or PNG files

To save as a JPEG, use this code:

```
jpeg("filename.jpg", width=5, height=5, units="in")
g
dev.off()
```

Saving graphics as PDF, JPEG, BMP, or PNG files

To save as a JPEG, use this code:

```
jpeg("filename.jpg", width=5, height=5, units="in")
g
dev.off()
```

This command works similarly to `pdf()`, but you have to specify `units="in"` for R to understand that the width and heights are in inches.

Saving graphics as PDF, JPEG, BMP, or PNG files

To save as a JPEG, use this code:

```
jpeg("filename.jpg", width=5, height=5, units="in")
g
dev.off()
```

This command works similarly to `pdf()`, but you have to specify `units="in"` for R to understand that the width and heights are in inches.

To save a BMP or PNG file, use the same code as above, but replace `jpeg` with `bmp` or `png`.

Using `ggplot()` within an R markdown document

`ggplot()` works really well within code chunks in an R markdown file.

Using ggplot() within an R markdown document

ggplot() works really well within code chunks in an R markdown file.

You can control the width, height, and position of the graphic directly in the **code chunk options**. For example, to set a figure to be 4 inches wide, 6 inches tall, and centered, type this code chunk:

````
```{r chunkname, fig.width=4, fig.height=6, fig.align="center"}
g <- ggplot(anes, aes(x=fthrc, y=fttrump)) +
      geom_point() +
      xlab("Hillary Clinton") +
      ylab("Donald Trump") +
      ggtitle("Feeling Thermometers for Candidates")
g
```
````