

Exploratory Data Analysis
Data Wrangling
Winter Institute in Data Science

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EDA

Visualization for EDA

Numeric EDA

EDA Exercise: ANES data

Wrangling

Reading

Writing

Tidy Data, Anonymization, Exercise

EDA

“EDA is a state of mind.”

– Wickham, *R4DS*, p. 81

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- ▶ Visualize
- ▶ Transform
- ▶ Model

...with an eye toward *discovery*

EDA is **not**

- ▶ formal hypothesis testing

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- ▶ formal hypothesis testing
 - ▶ (if you find $x \rightarrow y$ via EDA, “training” data)
- ▶ specification-searching for “effects”
- ▶ p -hacking
- ▶ (even in obs designs: pre-specify analyses, standards, decisions, conclusions, ...)

EDA: Search for Patterns and Models

- ▶ What pattern observed?
- ▶ What relationship does pattern represent?
- ▶ How strong?
- ▶ Holds in subgroups?
- ▶ Due to another factor? chance?

Visualization for EDA

Unidimensional visualizations

- ▶ Discrete variables
 - ▶ `geom_bar()`
 - ▶ `count()` for tibbular
- ▶ Continuous variables
 - ▶ `geom_histogram()`
 - ▶ `geom_boxplot()`
 - ▶ `geom_freqpoly()`
 - ▶ `geom_violin()`
 - ▶ `geom_density()`

Unidimensional visualizations

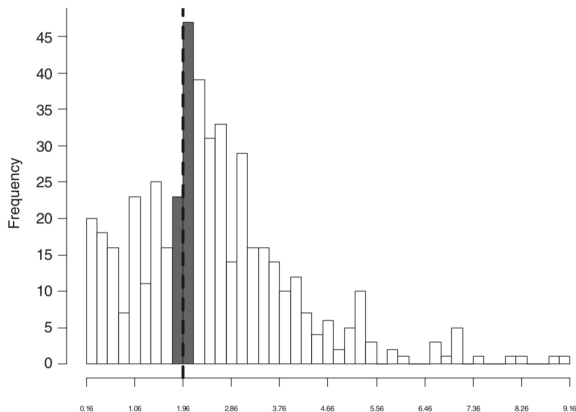
- ▶ Discrete variables
 - ▶ `geom_bar()`
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- ▶ Continuous variables
 - ▶ `geom_histogram()`
 - ▶ `geom_boxplot()`
 - ▶ `geom_freqpoly()`
 - ▶ `geom_violin()`
 - ▶ `geom_density()`

(See the `ggplot2` Cheatsheet for more)

Histograms

Gerber & Malhotra, *SM&R* (2008):

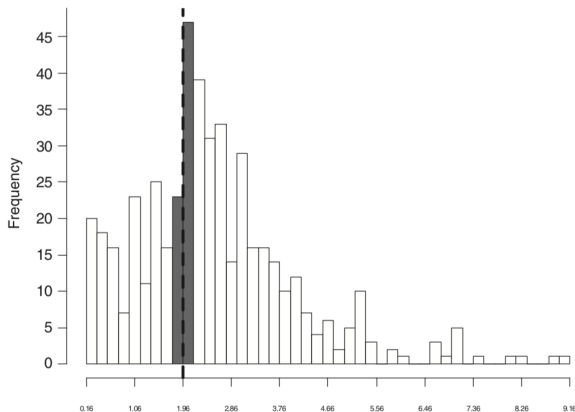
Histogram of z Statistics From the *American Sociological Review*, the *American Journal of Sociology*, and *The Sociological Quarterly* (Two-Tailed)



Histograms

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Histogram of z Statistics From the *American Sociological Review*, the *American Journal of Sociology*, and *The Sociological Quarterly* (Two-Tailed)



“Publication Bias in Empirical Sociological Research: Do Arbitrary Significance Levels Distort Published Results?”

ANES 2016 Pilot Data

```
anes_16 <- read_csv(here("data", "anes_pilot_2016.csv"))  
str(anes_16)
```

```
## Classes 'spec_tbl_df', 'tbl_df', 'tbl' and 'data.frame':  
## $ version           : chr  "ANES 2016 Pilot"  
## $ caseid            : num  1 2 3 4 5 6 7 8  
## $ weight            : num  0.951 2.67 1.43  
## $ weight_spss       : num  0.542 1.522 0.81  
## $ follow            : num  1 2 1 1 1 1 1 1  
## $ turnout12         : num  1 2 1 1 1 1 1 1  
## $ turnout12b        : num  9 9 9 9 9 9 9 9  
## $ vote12            : num  2 9 1 2 1 3 3 1  
## $ percent16         : num  100 50 100 100 1  
## $ meet              : num  1 4 1 5 2 3 1 5  
## $ givefut           : num  3 5 1 4 1 3 1 4  
## $ info              : num  4 4 1 5 3 2 1 5  
## $ march             : num  1 2 1 2 1 2 2 2  
## $ sign              : num  2 2 1 2 2 1 2 1  
## $ sign12m           : num  2 2 1 2 1 1 1 2
```

Some Demographics, Attitudes, Behaviors

```
demog_names <- c("birthyr", "gender", "race", "educ",  
                "marstat", "speakspanish", "faminc",  
                "state", "pid3", "pid7", "ideo5")  
  
behavior_names <- c("turnout12", "vote12", "meet",  
                   "givefut", "info", "march", "sign")  
  
# Feeling thermometers all start with "ft"
```

Recoding with Meaningful Labels

```
anes_16$pid3_chr <- recode(anes_16$pid3,  
                           `1` = "Dem",  
                           `2` = "Rep",  
                           `3` = "Ind",  
                           `4` = "Oth",  
                           `5` = "DK")
```

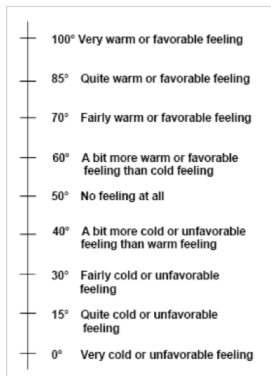
Recoding with Meaningful Labels

```
anes_16$pid3_chr <- recode(anes_16$pid3,  
                           `1` = "Dem",  
                           `2` = "Rep",  
                           `3` = "Ind",  
                           `4` = "Oth",  
                           `5` = "DK")
```

(Be careful with %>% here ...)

Some Demographics, Attitudes, Behaviors

*...Ratings between 50 degrees and 100 degrees
...favorable and warm toward the person. Ratings
between 0 degrees and 50 degrees ...don't feel favorable
toward the person and that you don't care too much for
that person. ...50 degree mark if you don't feel
particularly warm or cold toward the person.*

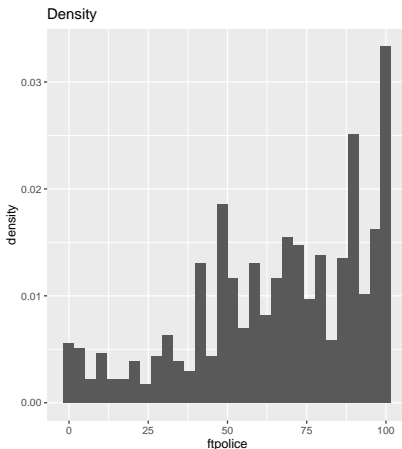
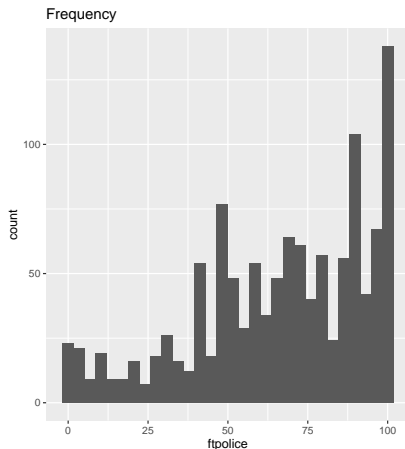


Histograms

```
p1 <- ggplot(anes_16, aes(ftpolice)) +  
  geom_histogram() + ggtitle("Frequency")  
p2 <- ggplot(anes_16, aes(ftpolice, ..density..)) +  
  geom_histogram() + ggtitle("Density")
```

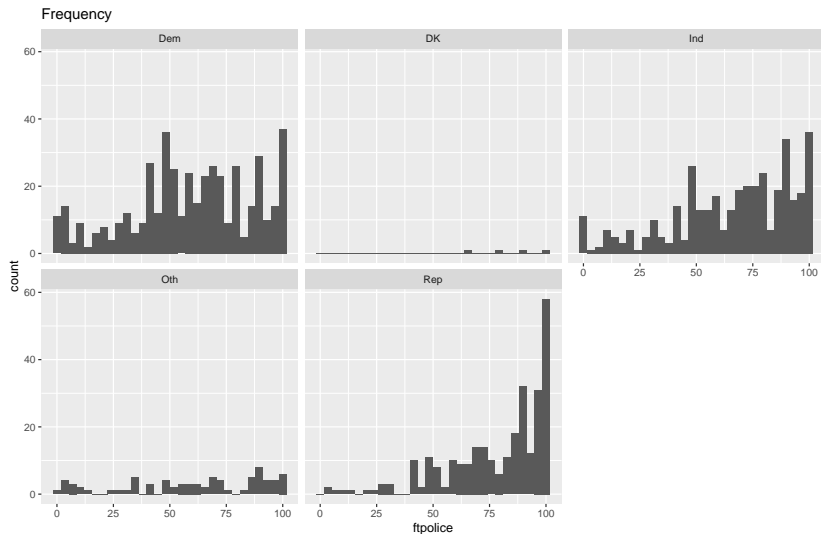
Histograms

```
p1 <- ggplot(anes_16, aes(ftpolice)) +  
  geom_histogram() + ggtitle("Frequency")  
p2 <- ggplot(anes_16, aes(ftpolice, ..density..)) +  
  geom_histogram() + ggtitle("Density")
```



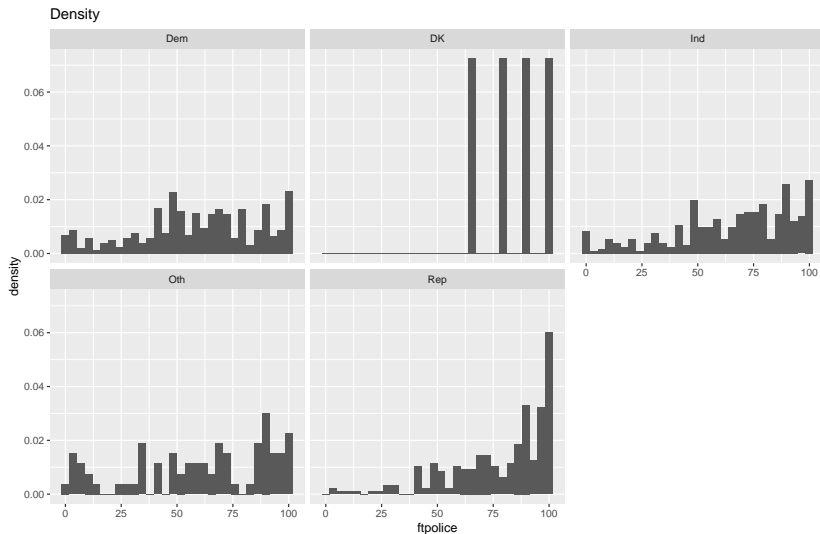
Histograms

```
ggplot(anes_16, aes(ftpolice)) + geom_histogram() +  
  ggtitle("Frequency") + facet_wrap(~ pid3_chr)
```



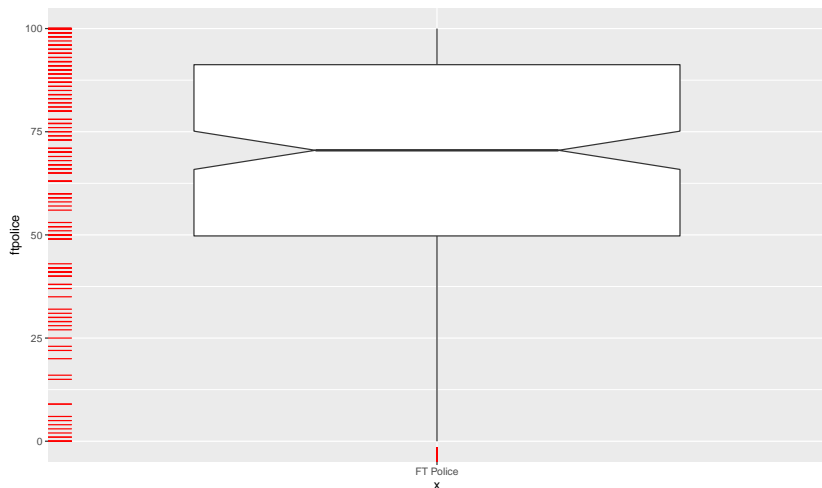
Histograms

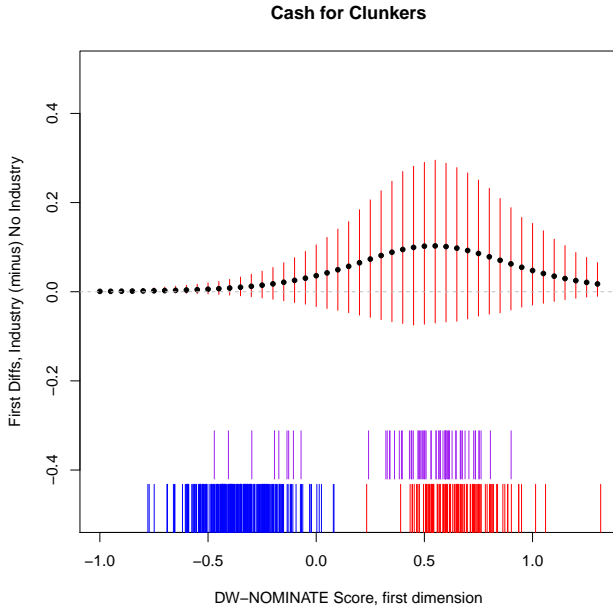
```
ggplot(anes_16, aes(ftpolice, ..density..)) + geom_histogram(  
  ggtitle("Density") + facet_wrap(~ pid3_chr)
```

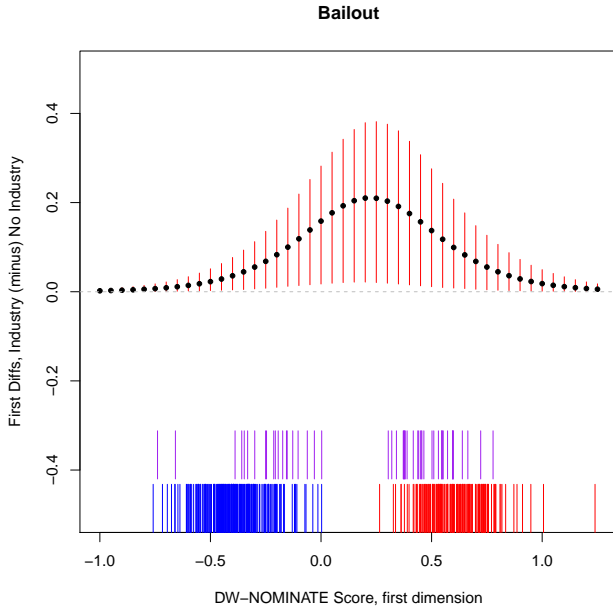


Boxplots

```
ggplot(anes_16 %>% sample_n(200), aes("FT Police", ftpolice)) +  
  geom_boxplot(notch = TRUE) + geom_rug(color = "red")
```

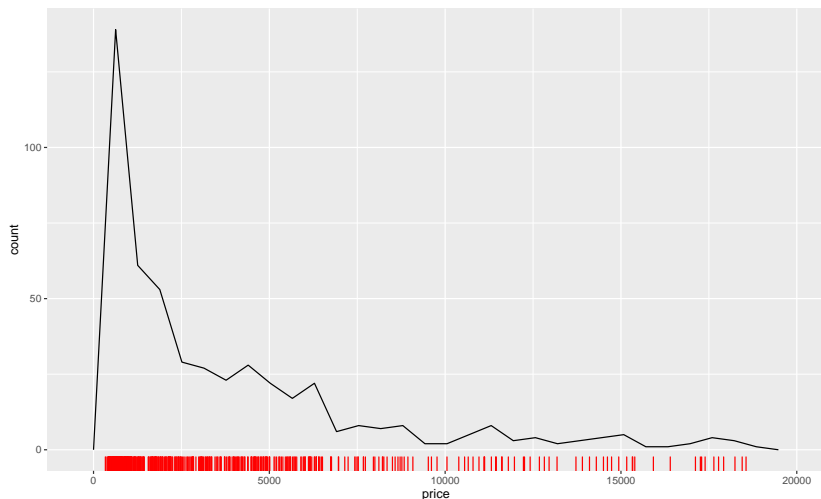






Frequency Polygons

```
ggplot(diamonds %>% sample_n(500), aes(price)) +  
  geom_freqpoly() + geom_rug(color = "red")
```



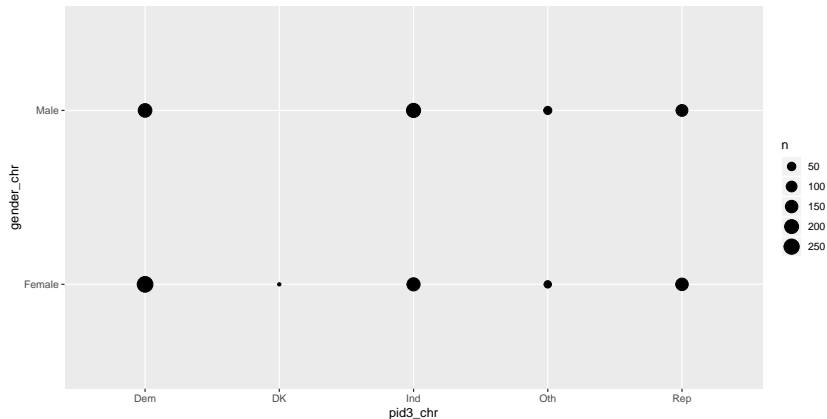
Multidimensional Visualizations

- ▶ Discrete \times Discrete
 - ▶ `geom_count()`
 - ▶ `count()` for tibbular
- ▶ Continuous \times Discrete
 - ▶ set of continuous distributions
 - ▶ `geom_boxplot(varwidth = TRUE)`
 - ▶ `dotplot`
- ▶ Continuous \times Continuous
 - ▶ `scatterplot`
 - ▶ `geom_bin2d()`
 - ▶ `hexbin::geom_hex()`
- ▶ Continuous \times Continuous \times Continuous
 - ▶ `geom_contour()`
 - ▶ `geom_tile()`
 - ▶ heat maps

(See the `ggplot2` Cheatsheet for more)

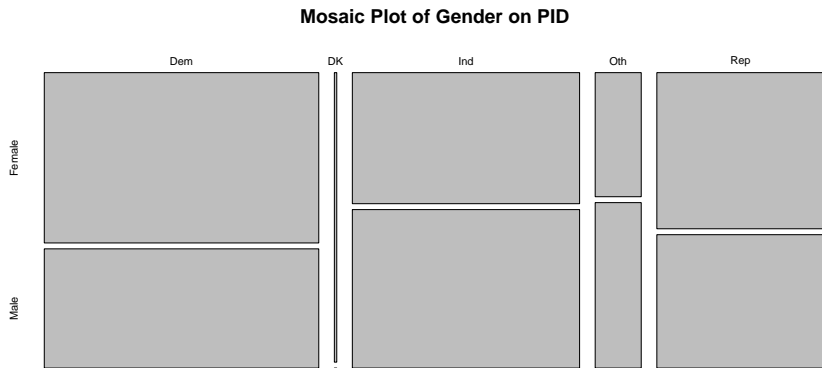
Count Distribution

```
anes_16$gender_chr <- recode(anes_16$gender,  
                             `1` = "Male", `2` = "Female")  
ggplot(anes_16, aes(pid3_chr, gender_chr)) + geom_count()
```

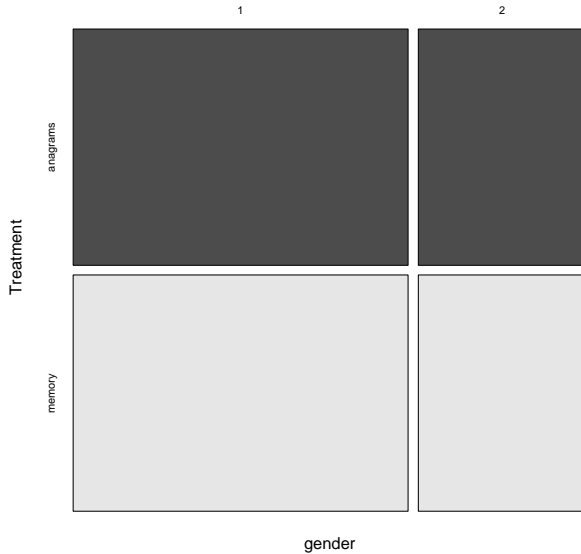


Mosaic Plot

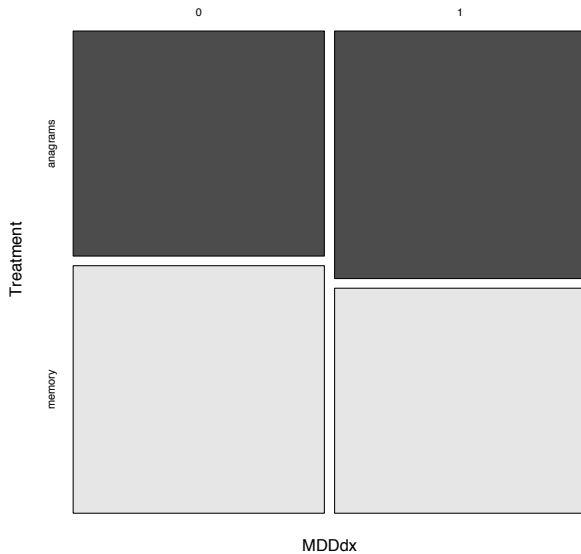
```
mosaicplot(table(anes_16$pid3_chr, anes_16$gender_chr),  
            main = "Mosaic Plot of Gender on PID")
```



Mosaic Plot



Mosaic Plot

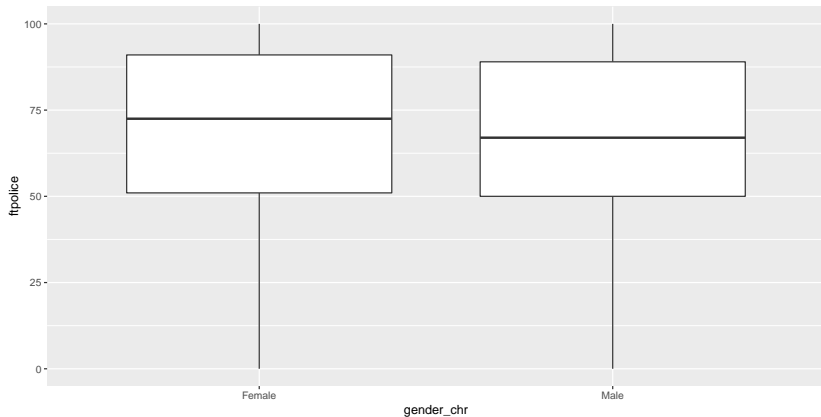


Boxplots

```
ggplot(anes_16, aes(gender_chr, ftpolice)) + geom_boxplot()
```

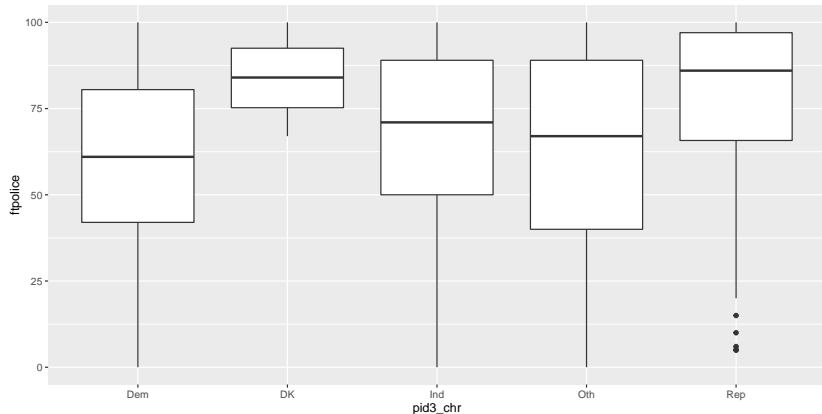
Boxplots

```
ggplot(anes_16, aes(gender_chr, ftpolice)) + geom_boxplot()
```



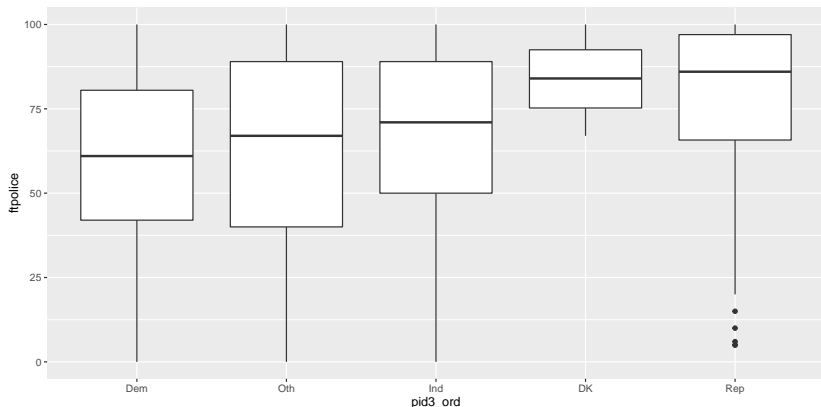
Conditional Boxplots

```
ggplot(anes_16, aes(pid3_chr, ftpolice)) + geom_boxplot()
```



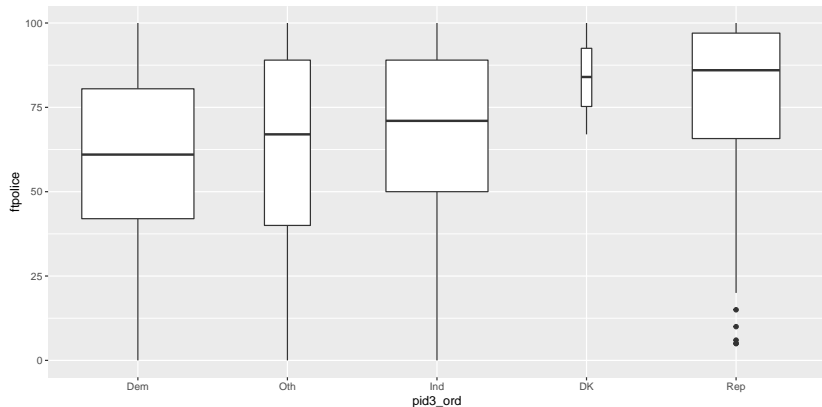
Conditional Boxplots

```
anes_16$pid3_ord <- reorder(anes_16$pid3_chr,  
                             anes_16$ftpolice, median)  
#(NB: if NA's in ftpolice, those PIDs are ordered *last*)  
ggplot(anes_16, aes(pid3_ord, ftpolice)) + geom_boxplot()
```

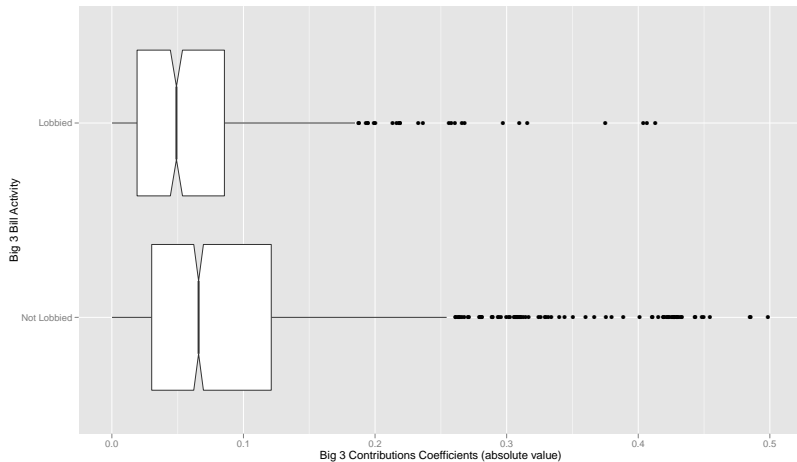


Conditional Boxplots

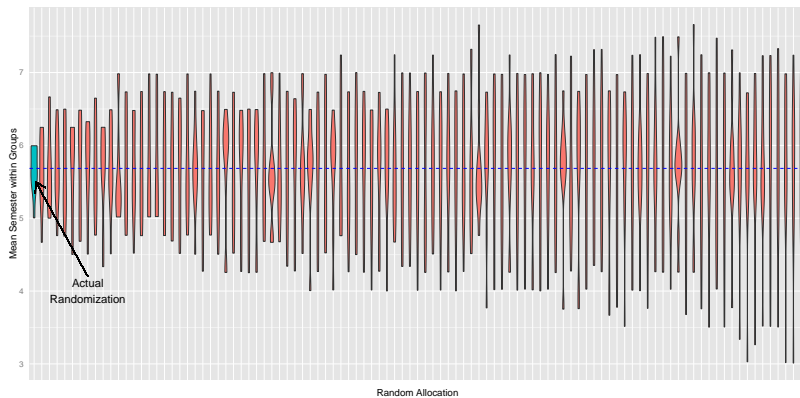
```
ggplot(anes_16, aes(pid3_ord, ftpolice)) +  
  geom_boxplot(varwidth = TRUE)
```



Conditional Boxplots



Violins

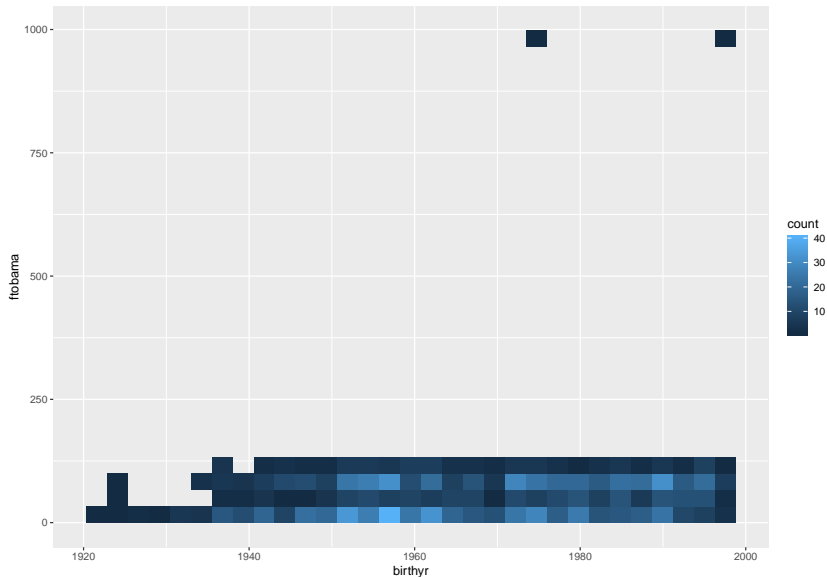


(Rectangular) Heat Maps

```
ggplot(anes_16, aes(birthyr, ftobama)) + geom_bin2d()
```

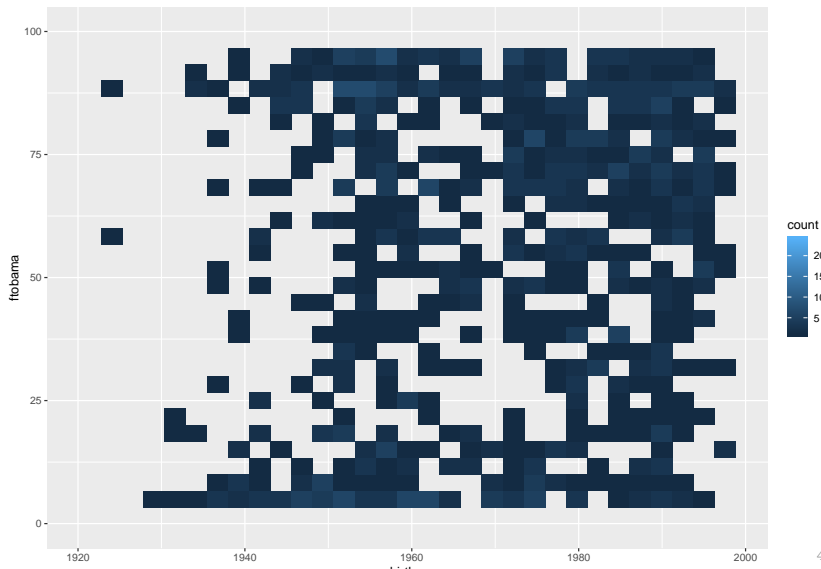
(Rectangular) Heat Maps

```
ggplot(anes_16, aes(birthyr, ftobama)) + geom_bin2d()
```



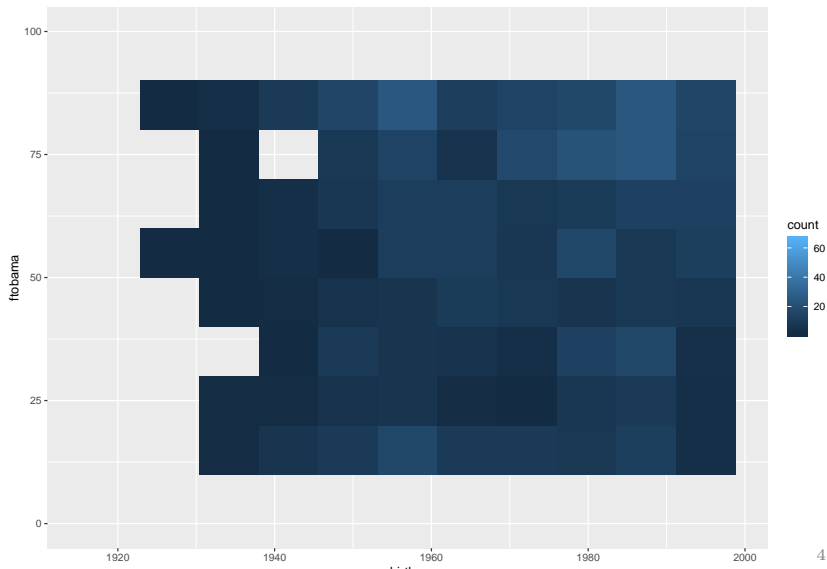
(Rectangular) Heat Maps

```
ggplot(anes_16, aes(birthyr, ftobama)) + geom_bin2d() +  
  ylim(0, 100)
```

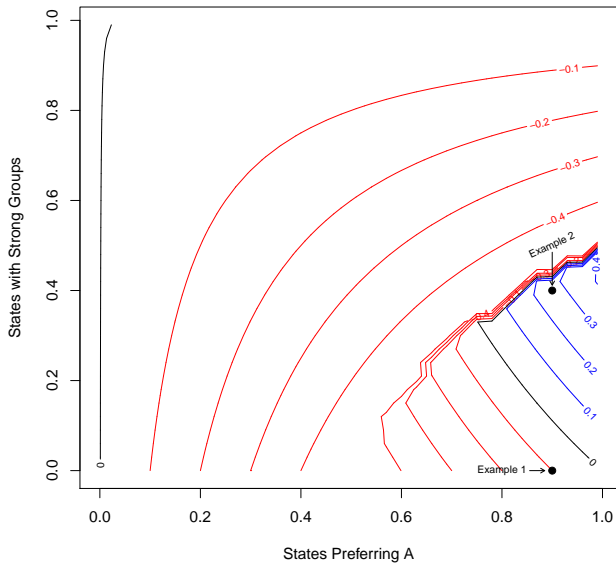


(Rectangular) Heat Maps

```
ggplot(anes_16, aes(birthyr, ftobama)) +  
  geom_bin2d(bins = 10) + ylim(0, 100)
```



Contours



Numeric EDA

Numeric EDA

- ▶ *R4DS* focuses on **graphical** EDA for cleaning, discovery
- ▶ Do **numeric** EDA, too (esp. for cleaning)


```
summary(anes_16)
```

```
##      version                caseid                weight                v
## Length:1200             Min.      :  1.0             Min.      :0.1693             M
## Class :character        1st Qu.: 300.8             1st Qu.:0.3948             1s
## Mode  :character        Median : 600.5             Median :0.8105             Me
##                               Mean   : 600.5             Mean   :1.0000             Me
##                               3rd Qu.: 900.2             3rd Qu.:1.2210             3r
##                               Max.    :1200.0            Max.    :7.0104             Ma
##
##      follow                turnout12                turnout12b                vot
## Min.      :1.000             Min.      :1.000             Min.      :1.000             Min.
## 1st Qu.:1.000             1st Qu.:1.000             1st Qu.:9.000             1st Qu.
## Median :1.000             Median :1.000             Median :9.000             Median
## Mean   :1.732             Mean   :1.275             Mean   :8.668             Mean
## 3rd Qu.:2.000             3rd Qu.:1.000             3rd Qu.:9.000             3rd Qu.
## Max.    :4.000             Max.    :3.000             Max.    :9.000             Max.
##
##      percent16                meet                givefut                in
## Min.      :  0.0             Min.      :1.000             Min.      :1.000             Min.168
```

```
str(anes_16)
```

```
## Classes 'spec_tbl_df', 'tbl_df', 'tbl' and 'data.frame':  
## $ version           : chr  "ANES 2016 Pilot"  
## $ caseid            : num  1 2 3 4 5 6 7 8  
## $ weight            : num  0.951 2.67 1.43  
## $ weight_spss       : num  0.542 1.522 0.8  
## $ follow           : num  1 2 1 1 1 1 1 1  
## $ turnout12        : num  1 2 1 1 1 1 1 1  
## $ turnout12b       : num  9 9 9 9 9 9 9 9  
## $ vote12           : num  2 9 1 2 1 3 3 1  
## $ percent16        : num  100 50 100 100 1  
## $ meet             : num  1 4 1 5 2 3 1 5  
## $ givefut          : num  3 5 1 4 1 3 1 4  
## $ info             : num  4 4 1 5 3 2 1 5  
## $ march            : num  1 2 1 2 1 2 2 2  
## $ sign             : num  2 2 1 2 2 1 2 1  
## $ give12mo         : num  2 2 1 2 1 1 1 2  
## $ compromise       : num  1 1 2 1 2 2 1 1  
## $ ftobama          : num  100 39 1 89 1 0
```

Count Distributions

```
anes_16$gender_chr <- recode(anes_16$gender,  
                             `1` = "Male", `2` = "Female")  
anes_16 %>% count(pid3_chr, gender_chr) %>%  
  arrange(desc(n))
```

```
## # A tibble: 9 x 3  
##   pid3_chr gender_chr      n  
##   <chr>      <chr>      <int>  
## 1 Dem      Female      270  
## 2 Ind      Male       208  
## 3 Dem      Male       189  
## 4 Ind      Female     172  
## 5 Rep      Female     151  
## 6 Rep      Male      129  
## 7 Oth      Male       44  
## 8 Oth      Female     33  
## 9 DK      Female      4
```

EDA Exercise: ANES data

Find a Friend

One	Two
Cameron	JessicaG
Bryce	Lauren
Xiaofeng	Robin
Olan	Zeinabou
Marc	Tanesia
Hubbert	Ethan
JessicaK	Carine
Milika	Kathleen
Hannah	Mark
AndrewZ	Jocelyn
AndrewE	Edward
Katherine	Kelly
Lucas	Erin

The Exercise

1. Create a new R project: `ex_anes`
2. Download `.csv` from GitHub; store in `ex_anes/data/`
3. Start a new `.R` file; read data with `read_csv()`
4. Create small `df` with only vars above (incl. feeling therms)
5. Create informative histogram/freqpoly/etc. of feeling therm scores toward Obama (Note *how*.)
6. Write down at least 3 questions/expectations you have about variation or covariation in the data
7. Recode the variables you're interested in
8. Do EDA. Answer your questions by visualizing, transforming, summarizing, iterating over the data

The Exercise

1. Create a new R project: `ex_anes`
 2. Download `.csv` from GitHub; store in `ex_anes/data/`
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 5. Create informative histogram/freqpoly/etc. of feeling therm scores toward Obama (Note *how*.)
 6. Write down at least 3 questions/expectations you have about variation or covariation in the data
 7. Recode the variables you're interested in
 8. Do EDA. Answer your questions by visualizing, transforming, summarizing, iterating over the data
- ▶ Codebook and survey at <http://j.mp/2E3RzR4>
 - ▶ `recode(x, `1` = "Male", `2` = "Female")`

Wrangling

Tibbles v. Data Frames

Creating a `df` with `tibble()`:

- ▶ Preserves input types
- ▶ Preserves variable names
- ▶ Allows sequential variable creation
- ▶ Avoids row names (\leadsto make them a variable!)
- ▶ Only recycles if `length(variable) == 1`

Tibbles v. Data Frames

Tibbles

- ▶ Print more reasonably
- ▶ Subset more strictly
 - ▶ `[` always \rightarrow `tbl`
 - ▶ `df$x` won't get `df$xyz`

Data frames

- ▶ Print less reasonably
- ▶ Subset more liberally

Tibbles v. Data Frames

Consider

```
df <- data.frame(abc = 1, xyz = "a")  
tbl <- tibble(abc = 1, xyz = "a")
```

Tibbles v. Data Frames

Consider

```
df <- data.frame(abc = 1, xyz = "a")  
tbl <- tibble(abc = 1, xyz = "a")
```

What does R return?

```
df$x  
tbl$x
```

Tibbles v. Data Frames

Consider

```
df <- data.frame(abc = 1, xyz = "a")  
tbl <- tibble(abc = 1, xyz = "a")
```

What does R return?

```
df$x  
tbl$x
```

```
df$x # scalar factor, length 1  
tbl$x # NULL
```

Tibbles v. Data Frames

Consider

```
df <- data.frame(abc = 1, xyz = "a")  
tbl <- tibble(abc = 1, xyz = "a")
```

What does R return?

```
df$x
```

```
tbl$x
```

```
df$x # scalar factor, length 1
```

```
tbl$x # NULL
```

```
tbl$xyz # vector, length 1
```

Tibbles v. Data Frames

Consider

```
df <- data.frame(abc = 1, xyz = "a")  
tbl <- tibble(abc = 1, xyz = "a")
```

What does R return?

```
df[, "xyz"]  
tbl[, "xyz"]
```

Tibbles v. Data Frames

Consider

```
df <- data.frame(abc = 1, xyz = "a")  
tbl <- tibble(abc = 1, xyz = "a")
```

What does R return?

```
df[, "xyz"]  
tbl[, "xyz"]
```

```
df[, "xyz"] # scalar factor, length 1  
tbl[, "xyz"] # tibble, 1x1
```


Tibbles v. Data Frames

Consider

```
df <- data.frame(abc = 1, xyz = "a")  
tbl <- tibble(abc = 1, xyz = "a")
```

What does R return?

```
df[, c("abc", "xyz")]  
tbl[, c("abc", "xyz")]
```

Tibbles v. Data Frames

Consider

```
df <- data.frame(abc = 1, xyz = "a")  
tbl <- tibble(abc = 1, xyz = "a")
```

What does R return?

```
df[, c("abc", "xyz")]  
tbl[, c("abc", "xyz")]
```

```
df[, c("abc", "xyz")] # df, 1x2  
tbl[, c("abc", "xyz")] # tibble, 1x2
```

Type depends on how many cols you select!

Reading Data

`read_csv()` is the tidyverse workhorse. Creates a `tbl`:

```
# 'vignettes' data from Imai, Ch 3:
```

```
vign <- read_csv("https://raw.githubusercontent.com/kosukeimai/q  
vign
```

```
## # A tibble: 781 x 6
```

```
##       self alison  jane moses china  age
```

```
##       <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
```

```
##  1         1         5         5         2         0        31
```

```
##  2         1         1         5         5         0        54
```

```
##  3         2         3         1         1         0        50
```

```
##  4         2         4         2         1         0        22
```

```
##  5         2         3         3         3         0        52
```

```
##  6         1         3         1         5         0        50
```

```
##  7         1         1         1         1         0        35
```

```
##  8         4         4         4         5         0        56
```

```
##  9         3         2         1         2         0        53
```

```
## 10         1         3         1         1         0        22
```

```
## # ... with 771 more rows
```

Reading Data

`read.csv()` is the base R workhorse. Creates a `data.frame`:

```
vign2 <- read.csv("https://raw.githubusercontent.com/kosukeimai/  
vign2")
```

##	self	alison	jane	moses	china	age
## 1	1	5	5	2	0	31
## 2	1	1	5	5	0	54
## 3	2	3	1	1	0	50
## 4	2	4	2	1	0	22
## 5	2	3	3	3	0	52
## 6	1	3	1	5	0	50
## 7	1	1	1	1	0	35
## 8	4	4	4	5	0	56
## 9	3	2	1	2	0	53
## 10	1	3	1	1	0	22
## 11	1	1	1	1	0	32
## 12	3	3	5	1	0	27
## 13	1	1	1	1	0	18
## 14	2	3	3	3	0	82
## 15	2	3	4	4	0	22

Arguments to `read_csv()`, etc.

- ▶ `col_names = TRUE`
- ▶ `locale = ...`
- ▶ `na = c("", "NA")`
- ▶ `quote = "\""`
- ▶ `comment = ""`
- ▶ `trim_ws = TRUE`
- ▶ `skip = 0`
- ▶ `n_max = Inf`

Create data with `tibble()`

```
self <- c(1, 1, 3)
alison <- c(5, 1, 3)
jane <- c(5, 5, 1)
tibble(self, alison, jane)
```

Create data with `tibble()`

```
self <- c(1, 1, 3)
alison <- c(5, 1, 3)
jane <- c(5, 5, 1)
tibble(self, alison, jane)
```

```
## # A tibble: 3 x 3
##   self alison jane
##   <dbl> <dbl> <dbl>
## 1     1     5     5
## 2     1     1     5
## 3     3     3     1
```

Create data with `tibble()`

```
tibble(self = c(1, 1, 3), alison = c(5, 1, 3),  
       jane = c(5, 5, 1))
```

```
## # A tibble: 3 x 3  
##   self alison jane  
##   <dbl> <dbl> <dbl>  
## 1     1     5     5  
## 2     1     1     5  
## 3     3     3     1
```


Create data with `tibble()`

```
tibble(self = c(1, 1, 3), alison = c(5, 1, 3),  
       jane = c(5, 5, 1))
```

```
## # A tibble: 3 x 3  
##   self alison jane  
##   <dbl> <dbl> <dbl>  
## 1     1     5     5  
## 2     1     1     5  
## 3     3     3     1
```

Fine, unless thinking across rows. Create example where a low sees both high, a low sees polar opposites, a med sees peer-low.

Using tribble()

A low sees both high, a low sees polar opposites, a med sees peer-low:

```
tribble(  
  ~ self, ~ alison, ~ jane,  
  #  
  1, 5, 5,  
  1, 1, 5,  
  3, 3, 1  
)
```

```
## # A tibble: 3 x 3  
##   self alison  jane  
##   <dbl> <dbl> <dbl>  
## 1     1     5     5  
## 2     1     1     5  
## 3     3     3     1
```

Viewing, Extracting options

Viewing a `tbl`:

- ▶ `print(tbl, n = 5, width = Inf)` (temporary)

Viewing, Extracting options

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Viewing, Extracting options

Viewing a tbl:

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 - ▶ `options(tibble.width = Inf)`

Viewing, Extracting options

Viewing a tbl:

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- ▶ `options()` (“permanent” for session)
 - ▶ `options(tibble.print_max = Inf)`
 - ▶ `options(tibble.width = Inf)`
- ▶ `as.data.frame(tbl)`

Viewing, Extracting options

Viewing a tbl:

- ▶ `print(tbl, n = 5, width = Inf)` (temporary)
- ▶ `options()` (“permanent” for session)
 - ▶ `options(tibble.print_max = Inf)`
 - ▶ `options(tibble.width = Inf)`
- ▶ `as.data.frame(tbl)`
- ▶ `View(tbl)`

Quick review of Viewing, Extracting

Extracting from df df:

```
##    var1  x  
## 1     a 29  
## 2     b 30
```

```
df$x
```

```
## [1] 29 30
```

```
df[["x"]]
```

```
## [1] 29 30
```

```
df[[2]]
```

```
## [1] 29 30
```

Quick review of Viewing, Extracting

Extracting from tibble `tbl`:

```
##   var1  x  
## 1     a 29  
## 2     b 30
```

```
tbl$x
```

```
## [1] 29 30
```

```
tbl[["x"]]
```

```
## [1] 29 30
```

```
tbl[[2]]
```

```
## [1] 29 30
```

Reading

Locales

A *locale* is a set of language, region, etc. parameters.

Locales

A *locale* is a set of language, region, etc. parameters.

The locale defines the parsing defaults.

Locales

You can define a locale locally:

```
parse_double("1,23",  
             locale = locale(decimal_mark = ","))
```

```
## [1] 1.23
```

Locales

Or use a pre-defined locale:

```
parse_date("15 enero 2000", format = "%d %B %Y")
```

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

Locales

Or use a pre-defined locale:

```
parse_date("15 enero 2000", format = "%d %B %Y")
```

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

```
parse_date("15 enero 2000", locale = locale("es"),  
           format = "%d %B %Y")
```

```
## [1] "2000-01-15"
```


Encodings

An *encoding* is part of a locale.

Encodings map from raw hexadecimal to characters.

E.g.,

```
parse_character("\x52\x54\x4d",  
                locale = locale(encoding = "Latin1"))
```

```
## [1] "RTM"
```

Encodings

An *encoding* is part of a locale.

Encodings map from raw hexadecimal to characters.

E.g.,

```
parse_character("\x52\x54\x4d",  
               locale = locale(encoding = "Latin1"))
```

```
## [1] "RTM"
```

```
parse_character("\x52\x54\x4d",  
               locale = locale(encoding = "Latin2"))
```

```
## [1] "RTM"
```

Encodings

But,

```
parse_character("\xa1\x45\x73\x70\x61\x61\x21",  
               locale = locale(encoding = "Latin2"))
```

```
## [1] "¡España!"
```

Encodings

But,

```
parse_character("\xa1\x45\x73\x70\x61\xfa\x61\x21",  
               locale = locale(encoding = "Latin2"))
```

```
## [1] "¡España!"
```

```
parse_character("\xa1\x45\x73\x70\x61\xfa\x61\x21",  
               locale = locale(encoding = "Latin1"))
```

```
## [1] "ïEspaña!"
```

Encodings

When you get bad characters copy-pasting from Excel ...

Encodings

When you get bad characters copy-pasting from Excel ...
or even opening/closing file in Excel ...

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Excel doesn't use UTF-8.

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For writing a `.csv` that Excel will read:

```
write_excel_csv()
```


Encodings

When you get bad characters copy-pasting from Excel ...
or even opening/closing file in Excel ...

Excel doesn't use UTF-8.

For writing a `.csv` that Excel will read:

```
write_excel_csv()
```

(But, why?)

Some reading functions

- ▶ `read_csv()`: the workhorse
- ▶ `read_csv2()`: the , -not- . workhorse
- ▶ `read_fwf()`: conquer old-school survey files

Some reading functions

- ▶ `read_csv()`: the workhorse
- ▶ `read_csv2()`: the , -not- . workhorse
- ▶ `read_fwf()`: conquer old-school survey files

For `.xlsx/.xls`:

- ▶ `library(readxl)`
- ▶ `read_excel()`

Fixed-width Files

The bad old days:

lat530.dat > No Selection																																				
.64	1.001	5	611	2	1	&	&	1	2	2	3	4	&	3	2	1	2	1	1	2	2	1	1	3	2	2	5	1	2	5	2	6	1	960	1	
.00	2.001	2	292	&	&	1	2	3	2	1	2	2	7	6	2	1	&	&	&	1	&	1	1	3	4	2	4	1	2	1	3	5	2	0	251	
.62	3.001	1	9	1	2	2	&	&	1	2	1	3	2	4	2	6	2	2	1	2	2	2	2	3	3	1	8	1	4	4	7	6	1	990	2	
2.13	4.001	4	552	&	&	2	1	3	2	1	1	6	&	4	4	2	2	2	2	&	1	2	2	3	4	3	7	1	4	4	2	3	2	0	152	
.54	5.001	2	291	2	1	&	&	1	3	1	1	2	7	4	4	2	1	1	1	2	&	2	2	2	4	1	6	1	4	4	7	6	1	750	2	
1.86	6.001	1	9	1	1	1	&	&	1	2	1	1	4	5	4	2	2	1	2	1	2	2	1	2	3	1	2	9	1	&	2	1	5	1	300	2
4.69	7.001	5	612	&	&	1	1	3	1	2	3	0	2	3	0	1	&	&	&	&	1	1	1	2	4	3	9	5	4	&	1	1	2	0	272	
1.55	8.001	4	552	&	&	1	1	3	1	1	2	2	8	6	6	1	2	1	2	2	1	1	1	3	4	3	5	1	&	6	3	6	2	0	881	
.34	9.001	1	1	1	2	2	&	&	1	1	2	2	3	&	1	0	&	&	&	&	1	&	1	1	1	1	2	4	1	3	4	2	1	1	440	1
1.26	10.001	1	9	1	2	1	&	&	1	2	1	1	2	&	4	4	1	&	&	&	&	&	2	1	2	3	&	&	1	2	2	2	1	1	200	1
1.15	11.001	2	292	&	&	1	1	3	2	1	3	10	&	8	1	2	1	2	2	2	1	1	2	4	2	7	1	2	6	1	6	2	0	781		
.68	12.001	4	551	1	1	&	&	1	2	2	3	5	&	2	1	2	1	1	1	&	&	2	2	&	4	2	6	1	&	2	2	6	1	100	&	
2.65	13.001	3	331	1	1	&	&	1	2	2	2	5	5	1	2	2	&	1	1	1	2	2	3	3	2	9	1	4	3	1	3	1	330	2		
.34	14.001	1	1	1	2	1	&	&	1	1	1	1	2	&	6	6	2	1	1	1	2	2	2	2	2	2	1	7	1	3	5	2	4	1	450	2
.75	15.001	5	571	2	2	&	&	1	2	1	3	6	&	2	&	&	&	&	&	&	&	&	&	&	&	&	&	&	&	&	&	&	&	1	110	&
2.25	16.001	5	611	1	2	&	&	1	1	2	2	3	4	2	8	2	1	1	&	1	&	2	2	3	4	2	9	5	4	3	1	1	1	280	2	
.48	17.001	4	551	2	1	&	&	1	2	2	2	9	&	2	2	1	2	1	1	&	&	2	2	3	4	1	4	1	4	6	7	6	1	710	1	

(Free half-day preschool, 2006)

Fixed-width Files

```
wid530 <- c(7,8,2,2,2,2,2,2,2,2,2,2,2,2,2,2,2,2,  
            2,2,2,2,2,2,2,2,2,2,2,2,2,2,2,2)  
lat530 <- read.fwf("../data/lat530.dat", widths = wid530)
```


Fixed-width Files

```
n530 <- c("region", "party", "prop82", "gender", "ideology", "age",  
which530 <- c("V4", "V11", "V12", "V13", "V29", "V30", "V33", "V35",  
lat530s <- lat530[, which530]  
names(lat530s) <- n530  
head(lat530s)
```

##	region	party	prop82	gender	ideology	age	educ	income
## 1	5	1	2	2	2	5	5	6
## 2	2	3	2	1	2	4	1	5
## 3	1	1	2	1	1	8	4	6
## 4	4	3	2	1	3	7	4	3
## 5	2	1	3	1	1	6	4	6
## 6	1	1	2	1	2	9	2	5

Fixed-width Files

```
lat530_guess <- read_fwf("../data/lat530.dat",  
                          fwf_empty("../data/lat530.dat"))
```

```
lat530_guess
```

```
## # A tibble: 2,838 x 33
```

```
##           X1 X2           X3 X4      X5      X6      X7      X8      X9  
##      <dbl> <chr>    <dbl> <chr> <chr> <chr> <chr> <chr> <chr>  
## 1  0.64 1.001        5 611    2      1      &      &      1  
## 2  0      2.001        2 292    &      &      1      2      3  
## 3  0.62 3.001        1 9 1    2      2      &      &      1  
## 4  2.13 4.001        4 552    &      &      2      1      3  
## 5  0.54 5.001        2 291    2      1      &      &      1  
## 6  1.86 6.001        1 9 1    1      1      &      &      1  
## 7  4.69 7.001        5 612    &      &      1      1      3  
## 8  1.55 8.001        4 552    &      &      1      1      3  
## 9  0.34 9.001        1 1 1    2      2      &      &      1  
## 10 1.26 10.001       1 9 1    2      1      &      &      1
```

```
## # ... with 2,828 more rows, and 21 more variables: X13 <chr>, X14 <chr>, X15 <chr>, X16 <chr>, X17 <chr>, X18 <chr>, X19 <chr>, X20 <chr>, X21 <chr>, X22 <chr>, X23 <chr>, X24 <chr>, X25 <chr>, X26 <chr>, X27 <chr>, X28 <chr>, X29 <chr>, X30 <chr>, X31 <chr>, X32 <chr>
```


Tidyverse v. Base R

Translation:

<http://www.science.smith.edu/~amcnamara/Syntax-cheatsheet.pdf>

Why read data with `tidyverse`?

- ▶ Speed
- ▶ Better defaults
 - ▶ `stringsAsFactors = FALSE`
 - ▶ ~~`row.names`~~
 - ▶ `col.names` preserved
- ▶ Reproducible
 - ▶ Indep of OS, environment

Parsing

Reading data is a composition of *parsings*.

`parse_<type>():`

- ▶ `logical`
- ▶ `integer`
- ▶ `double`
- ▶ `number`

Parsing

```
tmp <- "Hi $1.000,00"  
parse_number(tmp)
```

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

Parsing

```
tmp <- "Hi $1.000,00"  
parse_number(tmp)
```

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

```
parse_number(tmp, locale = locale(decimal_mark = ","))
```

```
## [1] 1000
```

Parsing

```
tmp <- "Hi $1.000,00"  
parse_number(tmp)
```

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

```
parse_number(tmp, locale = locale(decimal_mark = ","))
```

```
## [1] 1000
```

```
parse_number(tmp, locale = locale(decimal_mark = ",",  
                                   grouping_mark = "."))
```

```
## [1] 1000
```

Parsing

You will be tempted ...



Parsing

But use the parsers.



Parsing

Reading data is a composition of *parsings*.

`parse_<type>()`:

- ▶ `time`
- ▶ `date`
- ▶ `datetime`
- ▶ `factor`
- ▶ `character`

Parsing Dates and Times

Page 137, 7

```
d1 <- "January 1, 2010"  
parse_date(d1, "%B %d, %Y")
```

```
## [1] "2010-01-01"
```

Parsing Dates and Times

Page 137, 7

```
d1 <- "January 1, 2010"  
parse_date(d1, "%B %d, %Y")
```

```
## [1] "2010-01-01"
```

```
parse_date(d1, "%B%.%d,%.%Y")
```

```
## [1] "2010-01-01"
```

Parsing Dates and Times

Page 137, 7

```
d1 <- "January 1, 2010"  
parse_date(d1, "%B %d, %Y")
```

```
## [1] "2010-01-01"
```

```
parse_date(d1, "%B%.%d,%.%Y")
```

```
## [1] "2010-01-01"
```

```
parse_date(d1, "%B%.%d%.%.%Y")
```

```
## [1] "2010-01-01"
```

Parsing Dates and Times

Page 137, 7

```
d2 <- "2015-Mar-07"  
parse_date(d2, "%Y-%b-%d")
```

```
## [1] "2015-03-07"
```

```
d3 <- "06-Jun-2017"  
parse_date(d3, "%d-%b-%Y")
```

```
## [1] "2017-06-06"
```

```
d4 <- c("August 19 (2015)", "July 1 (2015)")  
parse_date(d4, "%B %d (%Y)")
```

```
## [1] "2015-08-19" "2015-07-01"
```

Parsing Dates and Times

Page 137, 7

```
d5 <- "12/30/14" # Dec 30, 2014  
parse_date(d5, "%m/%d/%y")
```

```
t1 <- "1705"  
parse_time(t1, "%H%M")
```

```
t2 <- "11:15:10.12 PM"  
parse_time(t2, "%H:%M:%OS %p")
```

Writing

Write to more-universal standards

- ▶ Write strings with UTF-8
- ▶ Write dates/times in ISO-8601
- ▶ Write rectangular files to **.csv**

Write to more-universal standards

- ▶ Write strings with UTF-8
- ▶ Write dates/times in ISO-8601
- ▶ Write rectangular files to **.csv**

Be nice.

Tidy Data, Anonymization, Exercise

Structuring Data: tidy Definitions

- ▶ Variable: measured quantity
- ▶ Value: state of variable as measured
- ▶ Observation/Unit/Case: set of values under similar conditions
- ▶ Tidy data
 - ▶ each value is its own cell
 - ▶ each variable is its own column

Tidy Data

1. Each variable is a column.

Tidy Data

1. Each variable is a column.
2. Each observation is a row.

Tidy Data

1. Each variable is a column.
2. Each observation is a row.
3. Each table is a type of observational unit.

The Most Common Messes

1. Column headers are values, not variable names.

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2. Multiple variables are stored in one column.

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1. Column headers are values, not variable names.
2. Multiple variables are stored in one column.
3. Variables are stored in both rows and columns.

The Most Common Messes

1. Column headers are values, not variable names.
2. Multiple variables are stored in one column.
3. Variables are stored in both rows and columns.
4. Multiple types of obs units are stored in the same table.

The Most Common Messes

1. Column headers are values, not variable names.
2. Multiple variables are stored in one column.
3. Variables are stored in both rows and columns.
4. Multiple types of obs units are stored in the same table.
5. A single observational unit is stored in multiple tables.

Mess 1: Column headers are values, not variable names

```
table4a
```

```
## # A tibble: 3 x 3
##   country      `1999` `2000`
## * <chr>      <int>  <int>
## 1 Afghanistan    745    2666
## 2 Brazil         37737  80488
## 3 China          212258 213766
```

Mess 2: Multiple variables stored in one column

```
table3
```

```
## # A tibble: 6 x 3
##   country      year rate
## * <chr>      <int> <chr>
## 1 Afghanistan  1999 745/19987071
## 2 Afghanistan  2000 2666/20595360
## 3 Brazil       1999 37737/172006362
## 4 Brazil       2000 80488/174504898
## 5 China        1999 212258/1272915272
## 6 China        2000 213766/1280428583
```

Mess 3: Variables stored in both rows and columns

```
table2
```

```
## # A tibble: 12 x 4
```

##	country	year	type	count
##	<chr>	<int>	<chr>	<int>
## 1	Afghanistan	1999	cases	745
## 2	Afghanistan	1999	population	19987071
## 3	Afghanistan	2000	cases	2666
## 4	Afghanistan	2000	population	20595360
## 5	Brazil	1999	cases	37737
## 6	Brazil	1999	population	172006362
## 7	Brazil	2000	cases	80488
## 8	Brazil	2000	population	174504898
## 9	China	1999	cases	212258
## 10	China	1999	population	1272915272
## 11	China	2000	cases	213766
## 12	China	2000	population	1280428583

Mess 4. Multiple types of obs units stored in same table

year	artist	time	track	date	week	rank
2000	2 Pac	4:22	Baby Don't Cry	2000-02-26	1	87
2000	2 Pac	4:22	Baby Don't Cry	2000-03-04	2	82
2000	2 Pac	4:22	Baby Don't Cry	2000-03-11	3	72
2000	2 Pac	4:22	Baby Don't Cry	2000-03-18	4	77
2000	2 Pac	4:22	Baby Don't Cry	2000-03-25	5	87
2000	2 Pac	4:22	Baby Don't Cry	2000-04-01	6	94
2000	2 Pac	4:22	Baby Don't Cry	2000-04-08	7	99
2000	2Ge+her	3:15	The Hardest Part Of ...	2000-09-02	1	91
2000	2Ge+her	3:15	The Hardest Part Of ...	2000-09-09	2	87
2000	2Ge+her	3:15	The Hardest Part Of ...	2000-09-16	3	92
2000	3 Doors Down	3:53	Kryptonite	2000-04-08	1	81
2000	3 Doors Down	3:53	Kryptonite	2000-04-15	2	70
2000	3 Doors Down	3:53	Kryptonite	2000-04-22	3	68
2000	3 Doors Down	3:53	Kryptonite	2000-04-29	4	67
2000	3 Doors Down	3:53	Kryptonite	2000-05-06	5	66

Mess 4. Multiple types of obs units stored in same table

id	artist	track	time	id	date	rank
1	2 Pac	Baby Don't Cry	4:22	1	2000-02-26	87
2	2Ge+her	The Hardest Part Of ...	3:15	1	2000-03-04	82
3	3 Doors Down	Kryptonite	3:53	1	2000-03-11	72
4	3 Doors Down	Loser	4:24	1	2000-03-18	77
5	504 Boyz	Wobble Wobble	3:35	1	2000-03-25	87
6	98~0	Give Me Just One Nig...	3:24	1	2000-04-01	94
7	A*Teens	Dancing Queen	3:44	1	2000-04-08	99
8	Aaliyah	I Don't Wanna	4:15	2	2000-09-02	91
9	Aaliyah	Try Again	4:03	2	2000-09-09	87
10	Adams, Yolanda	Open My Heart	5:30	2	2000-09-16	92
11	Adkins, Trace	More	3:05	3	2000-04-08	81
12	Aguilera, Christina	Come On Over Baby	3:38	3	2000-04-15	70
13	Aguilera, Christina	I Turn To You	4:00	3	2000-04-22	68
14	Aguilera, Christina	What A Girl Wants	3:18	3	2000-04-29	67
15	Alice DeeJay	Better Off Alone	6:50	3	2000-05-06	66

Mess 5: A single obs unit stored in multiple tables

What is the observational unit?

```
table4a
```

```
## # A tibble: 3 x 3
##   country    `1999` `2000`
## * <chr>      <int>  <int>
## 1 Afghanistan    745    2666
## 2 Brazil        37737   80488
## 3 China         212258  213766
```

```
table4b
```

```
## # A tibble: 3 x 3
##   country    `1999`    `2000`
## * <chr>      <int>      <int>
## 1 Afghanistan 19987071  20595360
## 2 Brazil      172006362  174504898
## 3 China       1272915272 1280428583
```


The Vignettes data

What's the unit of observation?

```
vign
```

```
## # A tibble: 781 x 6
##       self alison  jane moses china  age
##   <dbl>  <dbl> <dbl> <dbl> <dbl> <dbl>
## 1      1      5      5      2      0    31
## 2      1      1      5      5      0    54
## 3      2      3      1      1      0    50
## 4      2      4      2      1      0    22
## 5      2      3      3      3      0    52
## 6      1      3      1      5      0    50
## 7      1      1      1      1      0    35
## 8      4      4      4      5      0    56
## 9      3      2      1      2      0    53
## 10     1      3      1      1      0    22
## # ... with 771 more rows
```

The Vignettes data

What change? What's lost? What's gained?

```
vign %>% gather(alison, jane, moses, key = "person",  
                value = "score") %>% arrange(age, person, s
```

The Vignettes data

What change? What's lost? What's gained?

```
vign %>% gather(alison, jane, moses, key = "person",  
                value = "score") %>% arrange(age, person, s
```

```
## # A tibble: 2,343 x 5  
##       self china    age person score  
##   <dbl> <dbl> <dbl> <chr>  <dbl>  
## 1      1      0    18 alison     1  
## 2      1      0    18 alison     3  
## 3      1      0    18 alison     3  
## 4      1      0    18 alison     2  
## 5      1      0    18 alison     3  
## 6      1      0    18 alison     1  
## 7      1      0    18 alison     1  
## 8      2      0    18 alison     3  
## 9      2      0    18 alison     3  
## 10     2      1    18 alison     3  
## # ... with 2,333 more rows
```

The Vignettes data

```
vign %>% gather(self, alison, jane, moses, key = "person",  
               value = "score") %>% arrange(age, person)
```

The Vignettes data

```
vign %>% gather(self, alison, jane, moses, key = "person",  
                value = "score") %>% arrange(age, person)
```

```
## # A tibble: 3,124 x 4  
##   china    age person  score  
##   <dbl> <dbl> <chr>   <dbl>  
## 1      0    18 alison     1  
## 2      0    18 alison     3  
## 3      0    18 alison     3  
## 4      0    18 alison     3  
## 5      0    18 alison     3  
## 6      0    18 alison     3  
## 7      0    18 alison     4  
## 8      0    18 alison     2  
## 9      0    18 alison     3  
## 10     0    18 alison     3  
## # ... with 3,114 more rows
```

The Vignettes data

```
# A tbl of respondent data:  
df_respondents <- vign %>% transmute(id = 1:nrow(vign),  
                                       self = self,  
                                       china = china,  
                                       age = age)
```

The Vignettes data

```
# A tbl of respondent data:
```

```
df_respondents <- vign %>% transmute(id = 1:nrow(vign),  
                                       self = self,  
                                       china = china,  
                                       age = age)
```

```
# A tbl of scores:
```

```
df_scores <- vign %>% add_column(id = 1:nrow(vign)) %>%  
  select(-age, -china) %>%  
  gather(self, alison, jane, moses,  
         key = "person", value = "score")
```

The Vignettes data

```
df_respondents
```

```
## # A tibble: 781 x 4
##       id self china  age
##   <int> <dbl> <dbl> <dbl>
## 1     1     1     1     0    31
## 2     2     2     1     0    54
## 3     3     3     2     0    50
## 4     4     4     2     0    22
## 5     5     5     2     0    52
## 6     6     6     1     0    50
## 7     7     7     1     0    35
## 8     8     8     4     0    56
## 9     9     9     3     0    53
## 10    10    10     1     0    22
## # ... with 771 more rows
```

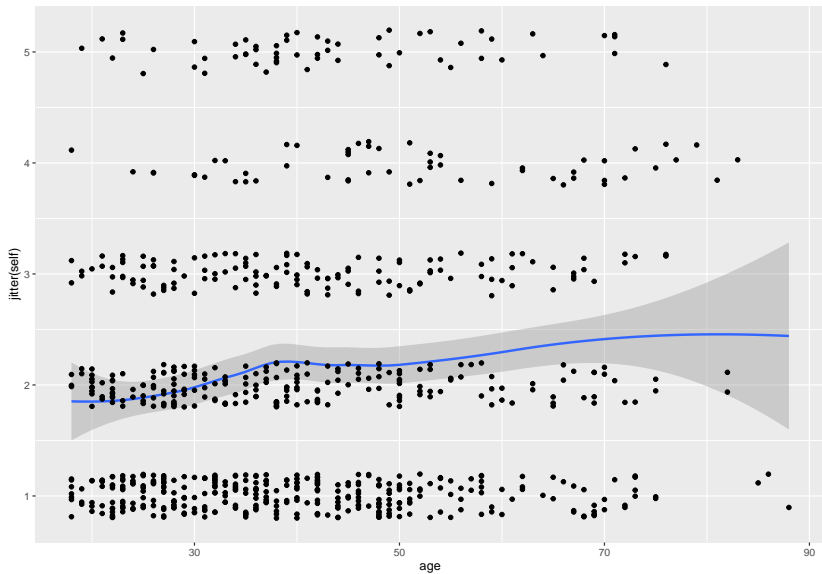

The Vignettes data

```
df_scores
```

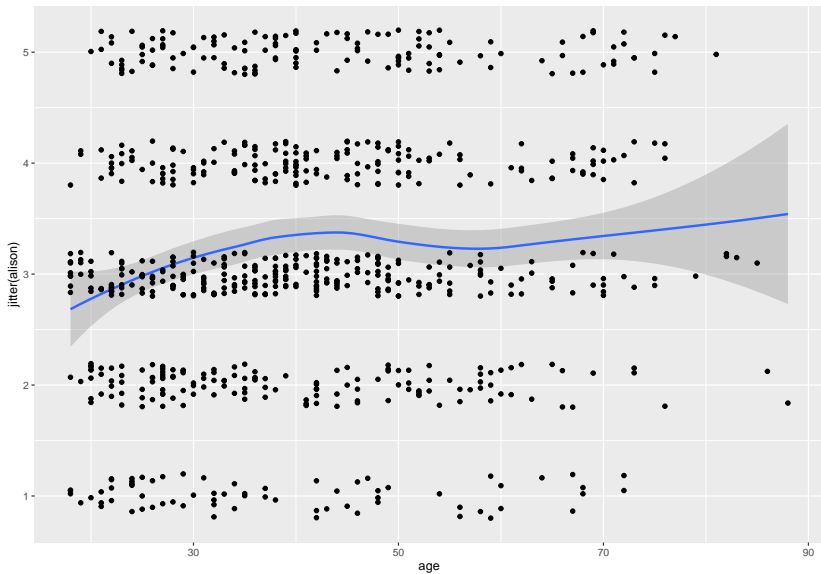
```
## # A tibble: 3,124 x 3
##       id person score
##   <int> <chr>  <dbl>
## 1     1    1 self      1
## 2     2    2 self      1
## 3     3    3 self      2
## 4     4    4 self      2
## 5     5    5 self      2
## 6     6    6 self      1
## 7     7    7 self      1
## 8     8    8 self      4
## 9     9    9 self      3
## 10    10   10 self      1
## # ... with 3,114 more rows
```

```
ggplot(vign, aes(age, jitter(self))) + geom_smooth() +  
  geom_point()
```

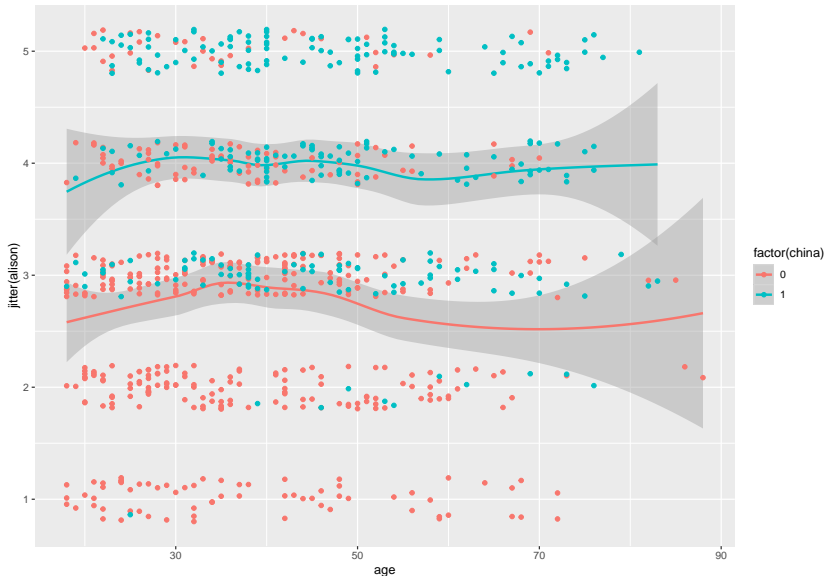
```
ggplot(vign, aes(age, jitter(self))) + geom_smooth() +  
  geom_point()
```



```
ggplot(vign, aes(age, jitter(alison))) + geom_smooth() +  
  geom_point()
```



```
ggplot(vign, aes(age, jitter(alison), group = china, color  
  geom_smooth() + geom_point())
```



The Vignettes data

Better: decide nature of **self**, how to relate it to others, transform, ...

Tidying functions

- ▶ `spread()` and `gather()`
 - ▶ \rightsquigarrow wider and narrower as f(data combinations)
- ▶ `pivot_wider()` and `pivot_longer()`
- ▶ `separate()` and `unite()`
 - ▶ \rightsquigarrow wider and narrower as f(each cell characteristics)

Tidying functions: spread()

```
df_scores
```

```
## # A tibble: 3,124 x 3
##       id person score
##   <int> <chr>  <dbl>
## 1     1    self     1
## 2     2    self     1
## 3     3    self     2
## 4     4    self     2
## 5     5    self     2
## 6     6    self     1
## 7     7    self     1
## 8     8    self     4
## 9     9    self     3
## 10    10    self     1
## # ... with 3,114 more rows
```


Tidying functions: spread()

```
df_scores %>% spread(key = person, value = score)
```

```
## # A tibble: 781 x 5
##       id alison  jane moses  self
##   <int>  <dbl> <dbl> <dbl> <dbl>
## 1     1      5      5      2      1
## 2     2      1      5      5      1
## 3     3      3      1      1      2
## 4     4      4      2      1      2
## 5     5      3      3      3      2
## 6     6      3      1      5      1
## 7     7      1      1      1      1
## 8     8      4      4      5      4
## 9     9      2      1      2      3
## 10    10      3      1      1      1
## # ... with 771 more rows
```

Anonymizing sensitive data

```
sens
```

```
## # A tibble: 3 x 4
##   Donor Address      Phone Score
##   <chr> <chr>      <dbl> <dbl>
## 1 Ryan   10 Downing St    123     90
## 2 Esme   667 Dark Ave     456     50
## 3 Simon  10 Downing St    789     70
```

Anonymizing sensitive data

```
sens
```

```
## # A tibble: 3 x 4
##   Donor Address      Phone Score
##   <chr> <chr>      <dbl> <dbl>
## 1 Ryan   10 Downing St    123    90
## 2 Esme   667 Dark Ave     456    50
## 3 Simon  10 Downing St    789    70
```

```
library(digest)
```

Anonymizing sensitive data

```
cols_to_mask <- c("Address", "Phone")
for(i in cols_to_mask){
  anon <- sapply(unlist(sens[, i]), digest, algo = "sha1")
  short_anon <- substr(anon, 1, 10)
  sens[, i] <- short_anon
}
```

Anonymizing sensitive data

```
cols_to_mask <- c("Address", "Phone")
for(i in cols_to_mask){
  anon <- sapply(unlist(sens[, i]), digest, algo = "sha1")
  short_anon <- substr(anon, 1, 10)
  sens[, i] <- short_anon
}
```

```
sens
```

```
## # A tibble: 3 x 4
##   Donor Address      Phone      Score
##   <chr> <chr>      <chr>    <dbl>
## 1 Ryan  c209e019b6 dac97294d4    90
## 2 Esme  7ccc94e690 0f2c3261a0    50
## 3 Simon c209e019b6 b13ceddf81    70
```

Anonymizing sensitive data

```
cols_to_mask <- c("Address", "Phone")
for(i in cols_to_mask){
  anon <- sapply(unlist(sens[, i]), digest, algo = "sha1")
  short_anon <- substr(anon, 1, 10)
  sens[, i] <- short_anon
}
```

```
sens
```

```
## # A tibble: 3 x 4
##   Donor Address      Phone      Score
##   <chr> <chr>      <chr>    <dbl>
## 1 Ryan  c209e019b6 dac97294d4    90
## 2 Esme  7ccc94e690 0f2c3261a0    50
## 3 Simon c209e019b6 b13ceddf81    70
```

(Warning: don't shorten!)

Wrangling Exercise

Find a Friend

One	Two
Tanesia	Olan
Edward	JessieG
Lauren	AndrewZ
LucasA	Erin
Carine	Jocelyn
Zeinabou	Ethan
Marc	Kathleen
Cameron	JessicaK
Kelly	Milika
LucasG	Mark
AndrewE	Hannah
Hubbert	Kate
Sophie	Bryce

Exercise: Laws Passed data

3-row sample:

```
laws
```

```
## # A tibble: 3 x 6
##   section statyear statmonth statday authorA authorB
##   <chr>      <dbl> <chr>      <dbl> <chr>    <chr>
## 1 1.2        2016 Jan         1 yes     no
## 2 3.8        2017 Feb         2 yes     no
## 3 4.1        2018 Mar         3 no      yes
```

Exercise: Laws Passed data

1. Combine year, month, day into one variable, `stat_date` (use `-` between components).
2. Split section into `section`, `subsection` (numeric).
3. Create a single variable for `author`.
4. Parse the date variable.

Exercise: Laws Passed data

```
laws2 <- laws %>% unite(date, starts_with("stat"),  
                        sep = "-")
```

```
laws2
```

```
## # A tibble: 3 x 4
```

```
##   section date      authorA authorB
```

```
##   <chr>    <chr>      <chr>   <chr>
```

```
## 1 1.2      2016-Jan-1 yes     no
```

```
## 2 3.8      2017-Feb-2 yes     no
```

```
## 3 4.1      2018-Mar-3 no      yes
```

Exercise: Laws Passed data

```
laws3 <- laws2 %>% separate(section,  
                             into = c("section", "subsection",  
                             convert = TRUE)
```

```
laws3
```

```
## # A tibble: 3 x 5
```

##	section	subsection	date	authorA	authorB
##	<int>	<int>	<chr>	<chr>	<chr>
## 1	1	2	2016-Jan-1	yes	no
## 2	3	8	2017-Feb-2	yes	no
## 3	4	1	2018-Mar-3	no	yes

Exercise: Laws Passed data

```
laws4 <- laws3 %>% gather(starts_with("author"),  
                           key = author,  
                           value = wrote_bill)
```

```
laws4
```

```
## # A tibble: 6 x 5
```

```
##   section subsection date      author wrote_bill  
##   <int>      <int> <chr>      <chr>    <chr>  
## 1         1        2 2016-Jan-1 authorA  yes  
## 2         3        8 2017-Feb-2 authorA  yes  
## 3         4        1 2018-Mar-3 authorA  no  
## 4         1        2 2016-Jan-1 authorB  no  
## 5         3        8 2017-Feb-2 authorB  no  
## 6         4        1 2018-Mar-3 authorB  yes
```

Exercise: Laws Passed data

```
laws5 <- laws4 %>% filter(wrote_bill == "yes")  
laws5
```

```
## # A tibble: 3 x 5
```

##	section	subsection	date	author	wrote_bill
##	<int>	<int>	<chr>	<chr>	<chr>
## 1	1	2	2016-Jan-1	authorA	yes
## 2	3	8	2017-Feb-2	authorA	yes
## 3	4	1	2018-Mar-3	authorB	yes

Exercise: Laws Passed data

```
laws5 <- laws4 %>% filter(wrote_bill == "yes")
laws5
```

```
## # A tibble: 3 x 5
##   section subsection date          author wrote_bill
##   <int>         <int> <chr>         <chr>    <chr>
## 1         1           2 2016-Jan-1 authorA yes
## 2         3           8 2017-Feb-2 authorA yes
## 3         4           1 2018-Mar-3 authorB yes
```

```
(laws5 <- laws5 %>% select(- wrote_bill))
```

```
## # A tibble: 3 x 4
##   section subsection date          author
##   <int>         <int> <chr>         <chr>
## 1         1           2 2016-Jan-1 authorA
## 2         3           8 2017-Feb-2 authorA
## 3         4           1 2018-Mar-3 authorB
```

Exercise: Laws Passed data

```
laws5$date <- parse_date(laws5$date, "%Y-%b-%d")  
laws5
```

```
## # A tibble: 3 x 4
```

```
##   section subsection date      author  
##   <int>      <int> <date>    <chr>  
## 1         1         2 2016-01-01 authorA  
## 2         3         8 2017-02-02 authorA  
## 3         4         1 2018-03-03 authorB
```