Data Wrangling

Kylie Ariel Bemis

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Housekeeping

- Homework 1 is due today on Piazza
- I will be traveling next week (again)
  - Sara Taheri will work through a case study on Tuesday
  - Jesse (Jianchao) Yang will review R and discuss Python on Friday

Introduction to Data Wrangling

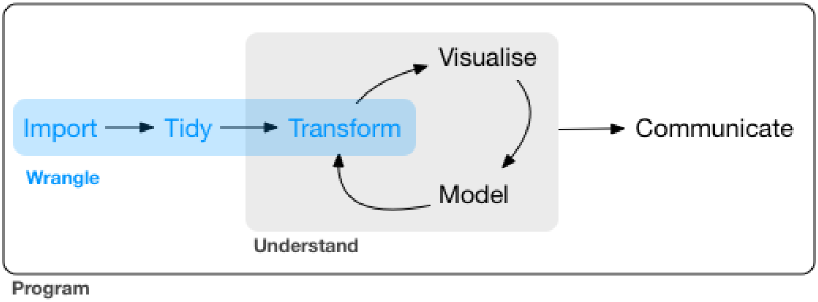


Figure 1: Wickham and Grolemund, *R for Data Science*

Introduction to Data Wrangling

Last week we discussed exploratory data analysis. Today we will discuss the often-frustrating but necessary steps that come before it.

- Importing data (read it into your analysis software)
- Tidying data (put it in a tidy format for data analysis)
- Transforming data (perform any transformations necessary)

Together, these steps are often collectively refered to as data wrangling.

We will focus on importing and tidying today.

Tibbles

Tibbles are a type of lightweight data frame used by the `tidyverse`.

They inherit many behaviors from `data.frame`.

In fact, as an S3 class, they inherit from `data.frame` directly.

```
class(mpg)
```

```
## [1] "tbl_df"     "tbl"        "data.frame"
```

The `tbl_df` part tells us that it's a tibble.

`tbl` is the tidyverse's generic notion of tabular data. They will become important again when we discuss working with databases.

We will also discuss more on S3 classes in general later in the semester.

Differences versus `data.frame`

- Tibbles print only the first 10 rows
- Tibbles print only as many columns as fit on your console
- Tibbles print information about the column data type
- Tibbles don't require `row.names`
- Tibbles don't munge column names
- Tibbles don't coerce inputs (`stringsAsFactors=FALSE`)
- Tibbles always use `drop=FALSE` when subsetting with `data[,j]`
- You can always use `as.data.frame` to get an ordinary `data.frame`

Coercing tibbles with as_tibble

```r
as_tibble(iris)
```

```
## # A tibble: 150 x 5
##    Sepal.Length Sepal.Width Petal.Length Petal.Width Species
##           <dbl>       <dbl>        <dbl>       <dbl>  <fctr>
##  1          5.1         3.5          1.4         0.2  setosa
##  2          4.9         3.0          1.4         0.2  setosa
##  3          4.7         3.2          1.3         0.2  setosa
##  4          4.6         3.1          1.5         0.2  setosa
##  5          5.0         3.6          1.4         0.2  setosa
##  6          5.4         3.9          1.7         0.4  setosa
##  7          4.6         3.4          1.4         0.3  setosa
##  8          5.0         3.4          1.5         0.2  setosa
##  9          4.4         2.9          1.4         0.2  setosa
## 10          4.9         3.1          1.5         0.1  setosa
## # ... with 140 more rows
```

Creating tibbles with tibble

```r
tibble(x=1:10, y=11:20, z=letters[1:10])
```

```
## # A tibble: 10 x 3
##        x     y     z
##    <int> <int> <chr>
##  1     1    11     a
##  2     2    12     b
##  3     3    13     c
##  4     4    14     d
##  5     5    15     e
##  6     6    16     f
##  7     7    17     g
##  8     8    18     h
##  9     9    19     i
## 10    10    20     j
```

Creating tibbles with `tribble`

```
tribble(~x, ~y, ~z,
        1,   2,  'i',
        2,   4,  'j',
        3,   8,  'k')
```

```
## # A tibble: 3 x 3
##         x     y     z
##     <dbl> <dbl> <chr>
## 1       1     2     i
## 2       2     4     j
## 3       3     8     k
```

A note on factors

- Categorical variables are stored in R as the `factor` data type
- Factors are stored as integers with character information about levels
  - This allows them to be smaller than `character` vectors
  - This is also useful for many statistical methods
- Many base R functions automatically coerce `character` to `factor`
  - `data.frame()`
  - `read.csv()`
- `ordered` is an ordered version for categorical variables with order levels
- Can change levels with `levels()<-` or `dplyr::recode()`
- Use `factor` or `character`?

```r
fc <- factor(c("red", "red", "blue"))
fc
```

```
## [1] red  red  blue
## Levels: blue red
```

```r
levels(fc) <- c("blue2", "red1")
fc
```

```
## [1] red1  red1  blue2
## Levels: blue2 red1
```

```r
dplyr::recode(fc, red1="one", blue2="two")
```

```
## [1] one one two
## Levels: two one
```

Importing data

At some point, it is necessary to import outside datasets into your data analysis software (R in our case).

Sometimes this can be easy, but sometimes this can be the most tedious and frustrating step in data science.

Data files can be:

- Messy
- Have errors
- An unknown file format
- Text or binary
- Structured or unstructured

Today, we will focus on ways of importing tabular data in a flat text file.

Later in the semester, we will discuss importing other types of data.

Importing data with `readr`

The `readr` package is the part of the tidyverse responsible for importing data.

It provides multiple functions for the importing of tabular data.

- `read_csv()` and family read delimited files
  - `read_csv()` and `read_csv2()` read in comma or semicolon separated files, respectively
  - `read_tsv()` reads in tab-delimited files
  - `read_delim()` allows the user to specify the delimiter
- `read_fwf()` reads fixed-width files
- `read_file()` and `read_lines()` simply read in lines or full files as `character` data or `raw` (byte) data

We will primarily discuss `read_csv()`.

Differences with `read.csv()` and related functions

`read.csv()` and similar functions are also provided in any default R installation (package `utils`, loaded by automatically in most R sessions).

The `readr` versions such as `read_csv()` have certain advantages:

- They are typically faster (up to 10x)
- They typically use less memory
- They output data as tibbles
  - `character` vectors aren't coerced to `factor`
  - `row.names` are not added
  - Column names are not munged

Reading csv files with read_csv

First argument is the path to the file.

This may be a relative path or the full path.

R understands typicaly *nix shortcuts.

```
output1 <- read_csv("path/to/file.csv")
output1 <- read_csv("/Users/username/data/path/to/file.csv")
output2 <- read_csv("~/path/to/other/file.csv")
output1 <- read_csv("../data/path/to/file.csv")
```

```r
mtcars2 <- read_csv(readr_example("mtcars.csv"))
```

```
## Parsed with column specification:
## cols(
##   mpg = col_double(),
##   cyl = col_integer(),
##   disp = col_double(),
##   hp = col_integer(),
##   drat = col_double(),
##   wt = col_double(),
##   qsec = col_double(),
##   vs = col_integer(),
##   am = col_integer(),
##   gear = col_integer(),
##   carb = col_integer()
## )
```

```r
mtcars2
```

```
## # A tibble: 32 x 11
##      mpg   cyl  disp    hp  drat    wt  qsec    vs    am  gea
##    <dbl> <int> <dbl> <int> <dbl> <dbl> <dbl> <int> <int> <int
##  1  21.0     6 160.0   110  3.90 2.620 16.46     0     1
##  2  21.0     6 160.0   110  3.90 2.875 17.02     0     1
##  3  22.8     4 108.0    93  3.85 2.320 18.61     1     1
##  4  21.4     6 258.0   110  3.08 3.215 19.44     1     0
##  5  18.7     8 360.0   175  3.15 3.440 17.02     0     0
##  6  18.1     6 225.0   105  2.76 3.460 20.22     1     0
##  7  14.3     8 360.0   245  3.21 3.570 15.84     0     0
##  8  24.4     4 146.7    62  3.69 3.190 20.00     1     0
##  9  22.8     4 140.8    95  3.92 3.150 22.90     1     0
## 10  19.2     6 167.6   123  3.92 3.440 18.30     1     0
## # ... with 22 more rows
```

Inline csv input is also accepted.

```
read_csv("a,b,c
          1,2,3
          4,5,6")
```

```
## # A tibble: 2 x 3
##       a     b     c
##   <int> <int> <int>
## 1     1     2     3
## 2     4     5     6
```

```r
read_csv("a,b,c\n1,2,3\n4,5,6")
```

```
## # A tibble: 2 x 3
##       a     b     c
##   <int> <int> <int>
## 1     1     2     3
## 2     4     5     6
```

Skip lines with `skip`.

```
read_csv("The first line of metadata
          The second line of metadata
          x,y,z
          1,2,3", skip = 2)
```

```
## # A tibble: 1 x 3
##       x     y     z
##   <int> <int> <int>
## 1     1     2     3
```

Specify comments with `comment`.

```
read_csv("# A comment I want to skip
          x,y,z
          1,2,3", comment = "#")
```

```
## # A tibble: 1 x 3
##       x     y     z
##   <int> <int> <int>
## 1     1     2     3
```

`read_csv()` assumes the first line gives column names.

Set `col_names` to `FALSE` if this is not the case.

```
read_csv("1,2,3\n4,5,6", col_names = FALSE)
```

```
## # A tibble: 2 x 3
##      X1    X2    X3
##   <int> <int> <int>
## 1     1     2     3
## 2     4     5     6
```

Or use `col_names` to set your own column names.

```r
read_csv("1,2,3\n4,5,6", col_names = c("x", "y", "z"))
```

```
## # A tibble: 2 x 3
##       x     y     z
##   <int> <int> <int>
## 1     1     2     3
## 2     4     5     6
```

Use `na` to tell `read_csv()` how missing values are specified

```
read_csv("a,b,c
         1,2,.", na = ".")
```

```
## # A tibble: 1 x 3
##       a     b     c
##   <int> <int> <chr>
## 1     1     2  <NA>
```

read_csv() attempts to guess the correct data type for each column.

Use col_types and cols() to manually specify column data types.

```
read_csv("a,b,c\n1,2,3\n4,5,6",
         col_types = cols(b=col_character(),
                          c=col_character()))
```

```
## # A tibble: 2 x 3
##       a     b     c
##   <int> <chr> <chr>
## 1     1     2     3
## 2     4     5     6
```

You can also set a default column data type.

```
read_csv("a,b,c\n1,2,3\n4,5,6",
         col_types = cols(.default=col_character()))
```

```
## # A tibble: 2 x 3
##       a     b     c
##   <chr> <chr> <chr>
## 1     1     2     3
## 2     4     5     6
```

Sometimes `read_csv()` guesses wrong.

```
challenge <- read_csv(readr_example("challenge.csv"))
```

```
## Parsed with column specification:
## cols(
##   x = col_integer(),
##   y = col_character()
## )
```

```
## Warning in rbind(names(probs), probs_f): number of columns of
## a multiple of vector length (arg 1)
```

```
## Warning: 1000 parsing failures.
## row # A tibble: 5 x 5 col     row   col               expecte
## ... ................. ... ..................................
## See problems(...) for more details.
```

```r
problems(challenge)
```

```
## # A tibble: 1,000 x 5
##      row   col               expected             actual
##    <int> <chr>                  <chr>              <chr>
##  1  1001     x no trailing characters .23837975086644292
##  2  1002     x no trailing characters .41167997173033655
##  3  1003     x no trailing characters  .7460716762579978
##  4  1004     x no trailing characters   .723450553836301
##  5  1005     x no trailing characters   .614524137461558
##  6  1006     x no trailing characters   .473980569280684
##  7  1007     x no trailing characters  .5784610391128808
##  8  1008     x no trailing characters  .2415937229525298
##  9  1009     x no trailing characters .11437866208143532
## 10  1010     x no trailing characters  .2983446326106787
## # ... with 990 more rows, and 1 more variables: file <chr>
```

`x` should be an integer.

```
challenge <- read_csv(readr_example("challenge.csv"),
                      col_types=cols(x=col_double()))
```

```r
challenge
```

```
## # A tibble: 2,000 x 2
##          x     y
##      <dbl> <chr>
##  1     404  <NA>
##  2    4172  <NA>
##  3    3004  <NA>
##  4     787  <NA>
##  5      37  <NA>
##  6    2332  <NA>
##  7    2489  <NA>
##  8    1449  <NA>
##  9    3665  <NA>
## 10    3863  <NA>
## # ... with 1,990 more rows
```

Did `read_csv()` guess correctly for `y`?

```r
challenge[which(!is.na(challenge$y)),]
```

```
## # A tibble: 1,000 x 2
##            x          y
##        <dbl>      <chr>
##  1 0.2383798 2015-01-16
##  2 0.4116800 2018-05-18
##  3 0.7460717 2015-09-05
##  4 0.7234506 2012-11-28
##  5 0.6145241 2020-01-13
##  6 0.4739806 2016-04-17
##  7 0.5784610 2011-05-14
##  8 0.2415937 2020-07-18
##  9 0.1143787 2011-04-30
## 10 0.2983446 2010-05-11
## # ... with 990 more rows
```

y should be a date.

```
challenge <- read_csv(readr_example("challenge.csv"),
                      col_types=cols(x=col_double(),
                                     y=col_date()))
```

By default, `read_csv()` guesses based on the first 1000 rows.

We can tell `read_csv()` to look at more rows before guessing.

```
challenge2 <- read_csv(readr_example("challenge.csv"),
                       guess_max = 1001)
```

```
## Parsed with column specification:
## cols(
##   x = col_double(),
##   y = col_date(format = "")
## )
```

This also fixes the problem in this case.

Writing csv files with `write_csv`

We can also write out files.

The first argument is the data and the second argument is the path.

```
write_csv(mtcars2, "mtcars2.csv")
```

Because the data is written as text, all type information is lost.

Reading tabular and non-tabular data

There are many other packages for reading other types of data formats.

Some packages for reading other formats of tabular data include:

- `haven` for reading SPSS, Stata, and SAS files
- `readxl` for reading Excel files
- `DBI` and a database backend allow working with databases

We will also discuss more on non-tabular data later in the semester.

Tidy data

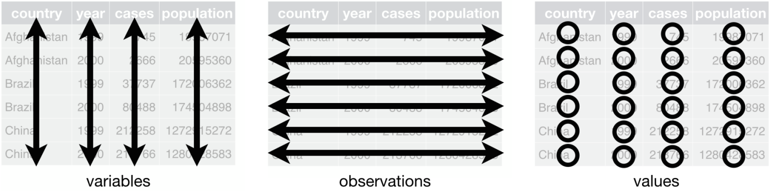


Figure 2: Wickham and Grolemund, *R for Data Science*

Review of tidy data rules

- Each variable must have its own column.
- Each observation must have its own row.
- Each value must have its own cell.

Is it tidy?

```
## # 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
```

Is it tidy?

```
## # 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
```

Is it tidy?

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

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

Is it tidy?

```
## # A tibble: 6 x 4
##       country  year  cases population
##         <chr> <int>  <int>      <int>
## 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
```

Why tidy data?

- Consistent format allows us to work with many datasets with a single set of tools
- Vectorized operations on variables are intuitive and computationally efficient

Tidying data with `tidyr`

The `tidyr` package is the part of the tidyverse responsible for helping you make data tidy.

It is primarily designed around solving two common problems:

- One variable is spread across multiple columns.
- One observation is scattered across multiple rows.

The `spread()` and `gather()` functions are designed to fix these problems.

Gathering

Column names are values rather than variables.

Figure 3: Wickham and Grolemund, *R for Data Science*

1999 and 2000 are values of an omitted variable `year`.

```
table4a
```

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

```r
gather(table4a, `1999`, `2000`, key = "year", value = "cases")
```

```
## # A tibble: 6 x 3
##        country  year  cases
##          <chr> <chr>  <int>
## 1 Afghanistan  1999    745
## 2      Brazil  1999  37737
## 3       China  1999 212258
## 4 Afghanistan  2000   2666
## 5      Brazil  2000  80488
## 6       China  2000 213766
```

Spreading

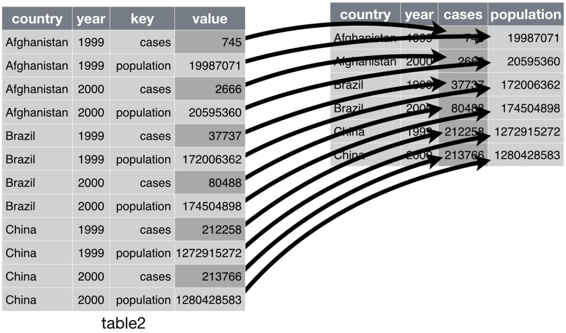


Figure 4: Wickham and Grolemund, *R for Data Science*

Observation is scattered in multiple rows.

The values of `type` should be their own variables.

```
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
```

```r
spread(table2, key = type, value = count)
```

```
## # A tibble: 6 x 4
##       country  year  cases population
## *       <chr> <int>  <int>      <int>
## 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
```

Separating

Sometimes character strings are used to encode values for more than one variable.

country	year	rate
Afghanistan	1999	**745** / 19987071
Afghanistan	2000	**2666** / 20595360
Brazil	1999	**37737** / 172006362
Brazil	2000	**80488** / 174504898
China	1999	**212258** / 1272915272
China	2000	**213766** / 1280428583

table3

country	year	cases	population
Afghanistan	1999	**745**	19987071
Afghanistan	2000	**2666**	20595360
Brazil	1999	**37737**	172006362
Brazil	2000	**80488**	174504898
China	1999	**212258**	1272915272
China	2000	**213766**	1280428583

Figure 5: Wickham and Grolemund, *R for Data Science*

`rate` encodes both `cases` and `population` as a single string.

```
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
```

```r
separate(table3, rate, into = c("cases", "population"))
```

```
## # A tibble: 6 x 4
##       country  year  cases population
## *       <chr> <int>  <chr>      <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
```

```r
pets <- tribble(~name, ~description,
                "Daisy", "CAT_F",
                "Johnny", "CAT_M",
                "Patsy", "CAT_F",
                "Yuma", "DOG_F")
```

Sometimes you want to separate at a specific character.

```
separate(pets, description, into=c("species", "sex"), sep="_")
```

```
## # A tibble: 4 x 3
##      name species   sex
## *   <chr>   <chr> <chr>
## 1   Daisy     CAT     F
## 2  Johnny     CAT     M
## 3   Patsy     CAT     F
## 4    Yuma     DOG     F
```

```
separate(pets, description, into=c("species", "sex"), sep=4)
```

```
## # A tibble: 4 x 3
##      name species   sex
## *   <chr>   <chr> <chr>
## 1   Daisy    CAT_     F
## 2  Johnny    CAT_     M
## 3   Patsy    CAT_     F
## 4    Yuma    DOG_     F
```

Uniting

Sometimes you want to create a variable that combines character encodings from multiple rows.

country	year	rate
Afghanistan	1999	745 / 19987071
Afghanistan	2000	2666 / 20595360
Brazil	1999	37737 / 172006362
Brazil	2000	80488 / 174504898
China	1999	212258 / 1272915272
China	2000	213766 / 1280428583

country	century	year	rate
Afghanistan	19	99	745 / 19987071
Afghanistan	20	0	2666 / 20595360
Brazil	19	99	37737 / 172006362
Brazil	20	0	80488 / 174504898
China	19	99	212258 / 1272915272
China	20	0	213766 / 1280428583

table6

Figure 6: Wickham and Grolemund, *R for Data Science*

```r
unite(pets, id, name, description)
```

```
## # A tibble: 4 x 1
##             id
## *        <chr>
## 1  Daisy_CAT_F
## 2 Johnny_CAT_M
## 3  Patsy_CAT_F
## 4   Yuma_DOG_F
```

```r
addressbook <- tribble(~name,   ~city,           ~state,
                        "Kylie", "Jamaica Plain", "MA",
                        "Olga",  "Brookline",     "MA")
```

```r
unite(addressbook, address, city, state, sep=", ")
```

```
## # A tibble: 2 x 2
##    name             address
## * <chr>               <chr>
## 1 Kylie Jamaica Plain, MA
## 2  Olga     Brookline, MA
```

When to make data 'untidy'?

Sometimes it can be helpful to transform a dataset into an 'untidy' format for a particular purpose.

For example, consider a survey that allows you to select more than one option for a particular question.

The following tibble contains information on students and the classes in which they are enrolled.

```
classes <- tibble(student = c(0, 1, 2, 3, 4, 5, 6, 7, 8, 9),
                  year =    c(1, 2, 1, 1, 2, 3, 3, 4, 4, 3),
                  algrthm = c(1, 1, 1, 0, 0, 0, 1, 1, 1, 1),
                  datastr = c(1, 0, 0, 1, 0, 1, 0, 0, 0, 0),
                  opersys = c(0, 0, 0, 0, 1, 1, 1, 0, 0, 1),
                  prglang = c(0, 1, 0, 0, 1, 1, 1, 0, 0, 0))
```

What if we want to calculate summaries based on each class?

We would like to `group_by(class)` using `dplyr`.

To do that, we need to create a `class` variable.

```
classes2 <- classes %>%
  gather(key="class", value="is_enrolled",
         algrthm, datastr, opersys, prglang) %>%
  filter(is_enrolled == 1) %>%
  select(-is_enrolled)
```

A student may now appear in more than one row.

```
classes2
```

```
## # A tibble: 18 x 3
##    student  year   class
##      <dbl> <dbl>   <chr>
##  1       0     1 algrthm
##  2       1     2 algrthm
##  3       2     1 algrthm
##  4       6     3 algrthm
##  5       7     4 algrthm
##  6       8     4 algrthm
##  7       9     3 algrthm
##  8       0     1 datastr
##  9       3     1 datastr
## 10       5     3 datastr
## 11       4     2 opersys
## 12       5     3 opersys
## 13       6     3 opersys
## 14       9     3 opersys
## 15       1     2 prglang
## 16       4     2 prglang
```

Get the number of students in each class.

```
classes2 %>% group_by(class) %>% count()
```

```
## # A tibble: 4 x 2
## # Groups:   class [4]
##     class     n
##     <chr> <int>
## 1 algrthm     7
## 2 datastr     3
## 3 opersys     4
## 4 prglang     4
```

We can use a similar technique for when a categorical variable is spread across multiple rows.

```r
pets2 <- tribble(~name, ~is_cat, ~is_dog,
                 "Daisy", "yes", "no",
                 "Johnny", "yes", "no",
                 "Patsy", "yes", "no",
                 "Yuma", "no", "yes")
```

```r
pets2 %>%
  gather(key="species", value="is_it", is_cat, is_dog) %>%
  filter(is_it == "yes") %>%
  select(-is_it) %>%
  mutate(species=recode(species,
                        is_cat="cat",
                        is_dog="dog"))
```

```
## # A tibble: 4 x 2
##     name species
##    <chr>   <chr>
## 1  Daisy     cat
## 2 Johnny     cat
## 3  Patsy     cat
## 4   Yuma     dog
```

R and databases

Oftentimes, we will need to work with data that lives in a database.

A database can also be a good solution for data which you do not want to load all into memory at once.

R and `dplyr` can interface with databases through the `DBI` package and a suitable backend:

- `RSQLite` works with SQLite databases
- `RMySQL` works with MySQL databases
- `RPostgreSQL` works with PostgreSQL databases

etc.

We can work with these with `dplyr` using the `dbplyr` package.

R and databases with dbplyr

Suppose we wish to work with an SQLite database.

First we need to install the necessary packages.

```
install.packages(c("DBI", "RSQLite", "dbplyr"))
```

```
library(dbplyr)
```

```
##
## Attaching package: 'dbplyr'

## The following objects are masked from 'package:dplyr':
##
##     ident, sql
```

```
library(RSQLite)
```

Connecting to a database in R

The DBLP is a database containing bibliographic data on major computer science journals and proceedings. A subset of it has been loaded into the SQLite database file "dblp.db".

First, we need to open a *connection* to the database using `dbConnect()`.

The first argument of `dbConnect()` is the backend to use (provided by the `RSQLite` package in this case), and the second is the filepath to the database.

```
dbpath <- paste0("~/Documents/Northeastern/",
                 "Courses/DS5110-Fall2017/data/",
                 "DBLP-CSR-sqlite/dblp.db")
con <- dbConnect(SQLite(), dbname=dbpath)
```

Creating a `tbl` of the connected database

A `tbl` is the tidyverse's generalized notion of tabular data.

A tibble is a type of `tbl`. We can also create a `tbl` from a database.

```
dblp <- tbl(con, "general")
```

The first argument is the data source (our database connection).

The second argument is the name of the table within the database.

Our SQLite database contains the table "general", which has information about papers published in computer science journals and proceedings.

```
dblp
```

```
## # Source:   table<general> [?? x 10]
## # Database: sqlite 3.19.3
## #   [/Users/kuwisdelu/Dropbox/Northeastern/Courses/DS5110-Fal
##                           k  year  conf        crossref    cs
##                       <chr> <int> <chr>           <chr> <int> <in
##  1     conf/aaai/0001M13  2013  AAAI conf/aaai/2013     1
##  2     conf/aaai/0001T15  2015  AAAI conf/aaai/2015     1
##  3  conf/aaai/0001TZLL14  2014  AAAI conf/aaai/2014     1
##  4    conf/aaai/0001VD15  2015  AAAI conf/aaai/2015     1
##  5    conf/aaai/0001YT15  2015  AAAI conf/aaai/2015     1
##  6 conf/aaai/0002GYSZL14  2014  AAAI conf/aaai/2014     1
##  7     conf/aaai/0002Z15  2015  AAAI conf/aaai/2015     1
##  8    conf/aaai/0002ZL15  2015  AAAI conf/aaai/2015     1
##  9   conf/aaai/0003MGF14  2014  AAAI conf/aaai/2014     1
## 10   conf/aaai/0005YJZ15  2015  AAAI conf/aaai/2015     1
## # ... with more rows, and 3 more variables: th <int>, publish
## #   link <chr>
```

We can perform dplyr operations on the database using dplyr verbs.

```
dblp %>% summarise(cs_papers=sum(cs))
```

```
## # Source:   lazy query [?? x 1]
## # Database: sqlite 3.19.3
## #   [/Users/kuwisdelu/Dropbox/Northeastern/Courses/DS5110-Fal
##   cs_papers
##       <int>
## 1     96823
```

```r
dblp %>%
  filter(year > 2010) %>%
  group_by(year) %>%
  summarise(cs_papers=sum(cs))
```

```
## # Source:   lazy query [?? x 2]
## # Database: sqlite 3.19.3
## #   [/Users/kuwisdelu/Dropbox/Northeastern/Courses/DS5110-Fal
##    year cs_papers
##   <int>     <int>
## 1  2011      6060
## 2  2012      5772
## 3  2013      7391
## 4  2014      6538
## 5  2015      5910
```

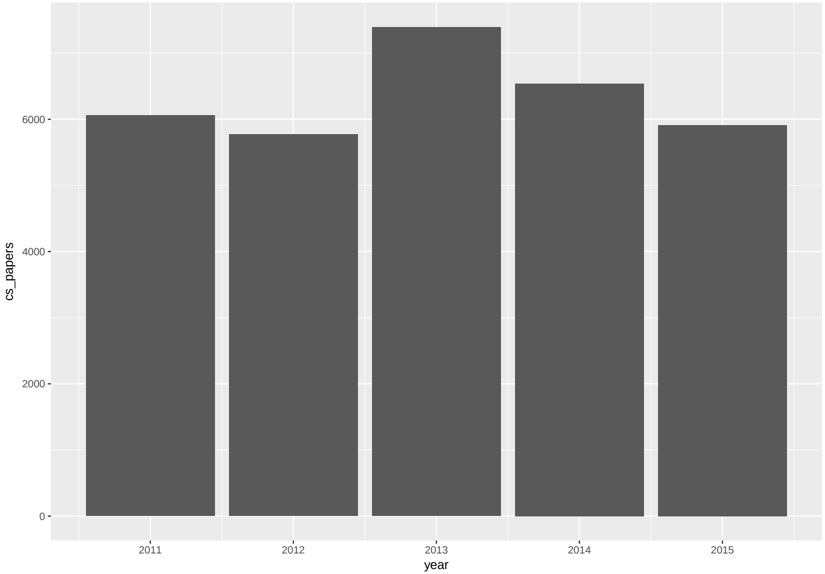
Note that the result isn't actually pulled into memory automatically.

```
dblp %>%
  filter(year > 2010) %>%
  group_by(year) %>%
  summarise(cs_papers=sum(cs)) %>%
  ggplot() +
  geom_col(aes(x=year, y=cs_papers))
```

```
## Error: ggplot2 doesn't know how to deal with data of class tb
```

To force `dplyr` to execute the operations and pull the result into memory, we need to use `collect()`.

```
dblp %>%
  filter(year > 2010) %>%
  group_by(year) %>%
  summarise(cs_papers=sum(cs)) %>%
  collect() %>%
  ggplot() +
  geom_col(aes(x=year, y=cs_papers))
```


6000
4000
2000
0
cs_papers
2011
2012
2013
2014
2015
year

When working with databases, dbplyr tries to offload as much work as possible to the database itself, and delay execution until we need the result.

We can see the actual SQL commands generated using show_query()

```
query <- dblp %>%
  filter(year > 2010) %>%
  group_by(year) %>%
  summarise(cs_papers=sum(cs))
show_query(query)
```

```
## <SQL>
## SELECT `year`, SUM(`cs`) AS `cs_papers`
## FROM `general`
## WHERE (`year` > 2010.0)
## GROUP BY `year`
```

Pulling database data into R

Not all databases support all dplyr data manipulation verbs, so if necessary (and the data is small enough), we can always pull the data into R as a tibble and work that way.

```
dblp %>% collect()
```

```
## # A tibble: 148,521 x 10
##                            k  year  conf        crossref    cs
##                        <chr> <int> <chr>           <chr> <int> <in
##  1      conf/aaai/0001M13  2013  AAAI conf/aaai/2013     1
##  2      conf/aaai/0001T15  2015  AAAI conf/aaai/2015     1
##  3   conf/aaai/0001TZLL14  2014  AAAI conf/aaai/2014     1
##  4     conf/aaai/0001VD15  2015  AAAI conf/aaai/2015     1
##  5     conf/aaai/0001YT15  2015  AAAI conf/aaai/2015     1
##  6 conf/aaai/0002GYSZL14  2014  AAAI conf/aaai/2014     1
##  7      conf/aaai/0002Z15  2015  AAAI conf/aaai/2015     1
##  8     conf/aaai/0002ZL15  2015  AAAI conf/aaai/2015     1
##  9    conf/aaai/0003MGF14  2014  AAAI conf/aaai/2014     1
## 10    conf/aaai/0005YJZ15  2015  AAAI conf/aaai/2015     1
## # ... with 148,511 more rows, and 3 more variables: th <int>,
## #   publisher <chr>, link <chr>
```