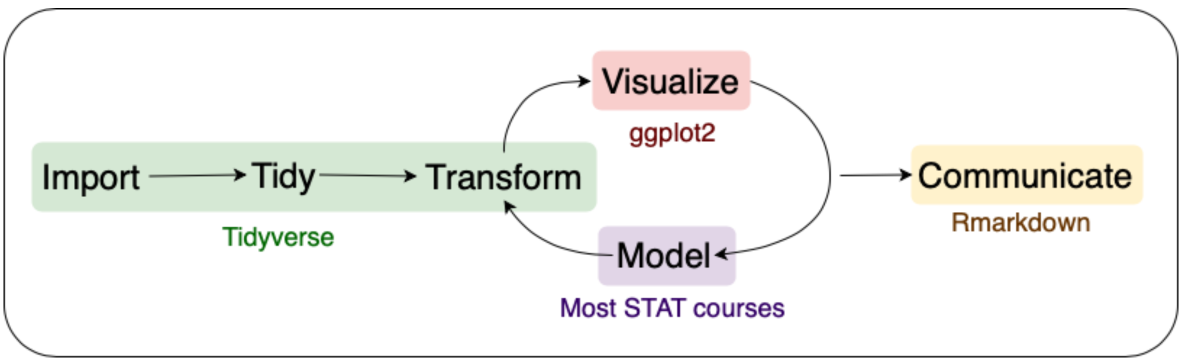
# 3 tidyverse

The tidyverse is a suite of packages released by RStudio that work very well together ("verse") to make data analysis run smoothly ("tidy"). It's also a package in `R` that loads all the packages in the tidyverse at once.

```
library(tidyverse)
```

You actually already know one member of the tidyverse – `ggplot2`! We will highlight three more packages in the tidyverse for data analysis.




Data Analysis Pipeline

Adapted from R for Data Science, Wickham & Grolemund (2017)

## 3.1 readr

The first step in (almost) any data analysis task is reading data into `R`. Data can take many formats, but we will focus on text files.

> But what about `.xlsx`??

File extensions `.xls` and `.xlsx` are proprietary Excel formats/ These are binary files (meaning if you open one outside of Excel it will not be human readable). An alternable for rectangular data is a `.csv`.

`.csv` is an extension for *comma separated value* files. They are text files – directly readable – where each column is separated by a comma and each row a new line.

```
Rank,Major_code,Major,Total,Men,Women,Major_category,ShareWomen
1,2419,PETROLEUM ENGINEERING,2339,2057,282,Engineering,0.120564344
```

```
,2416,MINING AND MINERAL ENGINEERING,756,679,77,Engineering,0.101851852
```

`.tsv` is an extension for *tab separated value* files. These are also text files, but the columns are separated by tabs instead of commas. Sometimes these will be `.txt` extension files.

```
Rank    Major_code    Major    Total    Men    Women    Major_category
ShareWomen
1    2419    PETROLEUM ENGINEERING    2339    2057    282
Engineering    0.120564344
2    2416    MINING AND MINERAL ENGINEERING    756    679    77
Engineering    0.101851852
```

The package `readr` provides a fast and friendly way to ready rectangular text data into `R`.

Here is an example csv file from fivethirtyeight.com on how to choose your college major (https://fivethirtyeight.com/features/the-economic-guide-to-picking-a-college-major/).

```
# load readr
library(readr)

# read a csv
recent_grads <- read_csv(file =
        "https://raw.githubusercontent.com/fivethirtyeight/data/master/college-
        majors/recent-grads.csv")
```

`read_csv()` is just one way to read a file using the `readr` package.

- `read_delim()`: the most generic function. Use the delim argument to read a file with any type of delimiter
- `read_tsv()`: read tab separated files
- `read_lines()`: read a file into a vector that has one element per line of the file
- `read_file()`: read a file into a single character element
- `read_table()`: read a file separated by space

# Your Turn

1. Read the NFL salaries dataset from https://raw.githubusercontent.com/ada-lovecraft/ProcessingSketches/master/Bits%20and%20Pieces/Football_Stuff/data/nfl-salaries.tsv into `R`.

2. What is the highest NFL salary in this dataset? Who is the highest paid player?

3. Make a histogram and describe the distribution of NFL salaries.

## 3.2 dplyr

We almost never will read in data and have it in exactly the right form for visualizing and modeling. Often we need to create variable or summaries.

To facilitate easy transformation of data, we're going to learn how to use the `dplyr` package. `dplyr` uses 6 main verbs, which correspond to some main tasks we may want to perform in an analysis.

We will do this with the `recent_grads` data from fivethiryeight.com we just read into `R` using `readr`.

### 3.2.1 |>

Before we get into the verbs in `dplyr`, I want to introduce a new paradigm. All of the functions in the tidyverse are structured such that the first argument is a data frame and they also return a data frame. This allows for efficient use of the pipe operator `|>` (pronounce this as "then").

```
a |> b()
```

Taked the result on the left and passes it to the first argument on the right. This is equivalent to

```
b(a)
```

This is useful when we want to chain together many operations in an analysis.

### 3.2.2 filter()

`filter()` lets us subset observations based on their values. This is similar to using `[]` to subset a data frame, but simpler.

The first argument is the name of the data frame. The second and subsequent arguments are the expressions that filter the data frame.

Let's subset the `recent_grad` data set to focus on Statistics majors.

```
recent_grads |> filter(Major == "STATISTICS AND DECISION SCIENCE")
```

```
## # A tibble: 1 × 21
##    Rank Major_…¹ Major Total   Men Women Major…² Share…³ Sampl…⁴
Emplo…⁵ Full_…⁶
##   <dbl>    <dbl> <chr> <dbl> <dbl> <dbl> <chr>     <dbl>   <dbl>
<dbl>   <dbl>
## 1    47     3702 STAT…  6251  2960  3291 Comput…   0.526      37
4247    3190
## # … with 10 more variables: Part_time <dbl>, Full_time_year_round
<dbl>,
## #   Unemployed <dbl>, Unemployment_rate <dbl>, Median <dbl>, P25th
<dbl>,
## #   P75th <dbl>, College_jobs <dbl>, Non_college_jobs <dbl>,
## #   Low_wage_jobs <dbl>, and abbreviated variable names ¹Major_code,
## #   ²Major_category, ³ShareWomen, ⁴Sample_size, ⁵Employed, ⁶
Full_time
## # ℹ Use `colnames()` to see all variable names
```

Alternatively, we could look at all Majors in the same category, "Computers & Mathematics", for comparison.

```
recent_grads |> filter(Major_category == "Computers & Mathematics")
```

```
## # A tibble: 11 × 21
##     Rank Major_code Major      Total   Men Women Major…¹ Share…²
Sampl…³ Emplo…⁴
##    <dbl>      <dbl> <chr>      <dbl> <dbl> <dbl> <chr>     <dbl>
<dbl>   <dbl>
##  1    21       2102 COMPUTER… 128319 99743 28576 Comput…   0.223
1196  102087
##  2    42       3700 MATHEMAT…  72397 39956 32441 Comput…   0.448
541   58118
##  3    43       2100 COMPUTER…  36698 27392  9306 Comput…   0.254
425   28459
##  4    46       2105 INFORMAT…  11913  9005  2908 Comput…   0.244
158    9881
##  5    47       3702 STATISTI…   6251  2960  3291 Comput…   0.526
37    4247
##  6    48       3701 APPLIED …   4939  2794  2145 Comput…   0.434
45    3854
##  7    53       4005 MATHEMAT…    609   500   109 Comput…   0.179
7      559
##  8    54       2101 COMPUTER…   4168  3046  1122 Comput…   0.269
43
```

```
3257
## 9     82        2106 COMPUTER…   8066  6607  1459 Comput…   0.181
103    6509
## 10    85        2107 COMPUTER…   7613  5291  2322 Comput…   0.305
97    6144
## 11   106        2001 COMMUNIC…  18035 11431  6604 Comput…   0.366
208   14779
## # … with 11 more variables: Full_time <dbl>, Part_time <dbl>,
## #   Full_time_year_round <dbl>, Unemployed <dbl>, Unemployment_rate
<dbl>,
## #   Median <dbl>, P25th <dbl>, P75th <dbl>, College_jobs <dbl>,
## #   Non_college_jobs <dbl>, Low_wage_jobs <dbl>, and abbreviated
variable names
## #   ¹Major_category, ²ShareWomen, ³Sample_size, ⁴Employed
## # ℹ Use `colnames()` to see all variable names
```

Notice we are using |> to pass the data frame to the first argument in `filter()` and we do not need to use `recent_grads$Colum Name` to subset our data.

`dplyr` functions never modify their inputs, so if we need to save the result, we have to do it using `<-`.

```
math_grads <- recent_grads |> filter(Major_category == "Computers &
        Mathematics")
```

Everything we've already learned about logicals and comparisons comes in handy here, since the second argument of `filter()` is a comparitor expression telling `dplyr` what rows we care about.

### 3.2.3 `arrange()`

`arrange()` works similarly to `filter()` except that it changes the order of rows rather than subsetting. Again, the first parameter is a data frame and the additional parameters are a set of column names to order by.

```
math_grads |> arrange(ShareWomen)
```

```
## # A tibble: 11 × 21
##       Rank Major_code Major       Total   Men Women Major…¹ Share…²
Sampl…³ Emplo…⁴
##     <dbl>      <dbl> <chr>       <dbl> <dbl> <dbl> <chr>     <dbl>
<dbl>   <dbl>
##   1    53        4005 MATHEMAT…    609   500   109 Comput…   0.179
```

```
7     559
## 2    82       2106 COMPUTER…   8066  6607  1459 Comput…   0.181
103    6509
## 3    21       2102 COMPUTER… 128319 99743 28576 Comput…   0.223
1196  102087
## 4    46       2105 INFORMAT…  11913  9005  2908 Comput…   0.244
158    9881
## 5    43       2100 COMPUTER…  36698 27392  9306 Comput…   0.254
425   28459
## 6    54       2101 COMPUTER…   4168  3046  1122 Comput…   0.269
43    3257
## 7    85       2107 COMPUTER…   7613  5291  2322 Comput…   0.305
97    6144
## 8   106       2001 COMMUNIC…  18035 11431  6604 Comput…   0.366
208   14779
## 9    48       3701 APPLIED …   4939  2794  2145 Comput…   0.434
45    3854
## 10    42       3700 MATHEMAT…  72397 39956 32441 Comput…   0.448
541   58118
## 11    47       3702 STATISTI…   6251  2960  3291 Comput…   0.526
37    4247
## # … with 11 more variables: Full_time <dbl>, Part_time <dbl>,
## #   Full_time_year_round <dbl>, Unemployed <dbl>, Unemployment_rate
<dbl>,
## #   Median <dbl>, P25th <dbl>, P75th <dbl>, College_jobs <dbl>,
## #   Non_college_jobs <dbl>, Low_wage_jobs <dbl>, and abbreviated
variable names
## #   ¹Major_category, ²ShareWomen, ³Sample_size, ⁴Employed
## # ℹ Use `colnames()` to see all variable names
```

If we provide more than one column name, each additional column will be used to break ties in the values of preceding columns.

We can use `desc()` to re-order by a column in descending order.

```
math_grads |> arrange(desc(ShareWomen))
```

```
## # A tibble: 11 × 21
##      Rank Major_code Major      Total   Men Women Major…¹ Share…²
Sampl…³ Emplo…⁴
##     <dbl>      <dbl> <chr>      <dbl> <dbl> <dbl> <chr>     <dbl>
<dbl>   <dbl>
## 1    47       3702 STATISTI…   6251  2960  3291 Comput…   0.526
37    4247
## 2    42       3700 MATHEMAT…  72397 39956 32441 Comput…   0.448
```

```
     541   58118
## 3    48       3701 APPLIED …   4939  2794  2145 Comput…   0.434
45    3854
## 4   106       2001 COMMUNIC…  18035 11431  6604 Comput…   0.366
208   14779
## 5    85       2107 COMPUTER…   7613  5291  2322 Comput…   0.305
97    6144
## 6    54       2101 COMPUTER…   4168  3046  1122 Comput…   0.269
43    3257
## 7    43       2100 COMPUTER…  36698 27392  9306 Comput…   0.254
425   28459
## 8    46       2105 INFORMAT…  11913  9005  2908 Comput…   0.244
158    9881
## 9    21       2102 COMPUTER… 128319 99743 28576 Comput…   0.223
1196  102087
## 10    82       2106 COMPUTER…   8066  6607  1459 Comput…   0.181
103    6509
## 11    53       4005 MATHEMAT…    609   500   109 Comput…   0.179
7     559
## # … with 11 more variables: Full_time <dbl>, Part_time <dbl>,
## #   Full_time_year_round <dbl>, Unemployed <dbl>, Unemployment_rate
<dbl>,
## #   Median <dbl>, P25th <dbl>, P75th <dbl>, College_jobs <dbl>,
## #   Non_college_jobs <dbl>, Low_wage_jobs <dbl>, and abbreviated
variable names
## #   ¹Major_category, ²ShareWomen, ³Sample_size, ⁴Employed
## # ℹ Use `colnames()` to see all variable names
```

### 3.2.4 select()

Sometimes we have data sets with a ton of variables and often we want to narrow down the ones that we actually care about. `select()` allows us to do this based on the names of the variables.

```
math_grads |> select(Major, ShareWomen, Total, Full_time, P75th)
```

```
## # A tibble: 11 × 5
##    Major                                                    ShareW…¹  Total
Full_…² P75th
##    <chr>                                                       <dbl>  <dbl>
<dbl> <dbl>
##  1 COMPUTER SCIENCE                                            0.223 128319
91485 70000
##  2 MATHEMATICS                                                 0.448  72397
```

```
6399 60000
##   3 COMPUTER AND INFORMATION SYSTEMS                    0.254  36698
26348 60000
##   4 INFORMATION SCIENCES                                0.244  11913
9105 58000
##   5 STATISTICS AND DECISION SCIENCE                     0.526   6251
3190 60000
##   6 APPLIED MATHEMATICS                                 0.434   4939
3465 63000
##   7 MATHEMATICS AND COMPUTER SCIENCE                    0.179    609
584 78000
##   8 COMPUTER PROGRAMMING AND DATA PROCESSING            0.269   4168
3204 46000
##   9 COMPUTER ADMINISTRATION MANAGEMENT AND SECURITY     0.181   8066
6289 50000
## 10 COMPUTER NETWORKING AND TELECOMMUNICATIONS          0.305   7613
5495 49000
## 11 COMMUNICATION TECHNOLOGIES                          0.366  18035
11981 45000
## # … with abbreviated variable names ¹ShareWomen, ²Full_time
```

We can also use

- `:` to select all columns between two columns
- `-` to select all columns except those specified
- `starts_with("abc")` matches names that begin with "abc"
- `ends_with("xyz")` matches names that end with "xyz"
- `contains("ijk")` matches names that contain "ijk"
- `everything()` mathes all columns

```
math_grads |> select(Major, College_jobs:Low_wage_jobs)
```

```
## # A tibble: 11 × 4
##    Major                                              College_jobs
Non_co…¹ Low_w…²
##    <chr>                                                     <dbl>
<dbl>   <dbl>
##  1 COMPUTER SCIENCE                                          68622
25667    5144
##  2 MATHEMATICS                                               34800
14829    4569
##  3 COMPUTER AND INFORMATION SYSTEMS                          13344
11783    1672
##  4 INFORMATION SCIENCES                                       4390
```

```
     4102     608
## 5 STATISTICS AND DECISION SCIENCE                         2298
1200     343
## 6 APPLIED MATHEMATICS                                     2437
803     357
## 7 MATHEMATICS AND COMPUTER SCIENCE                         452
67      25
## 8 COMPUTER PROGRAMMING AND DATA PROCESSING                2024
1033     263
## 9 COMPUTER ADMINISTRATION MANAGEMENT AND SECURITY         2354
3244     308
## 10 COMPUTER NETWORKING AND TELECOMMUNICATIONS             2593
2941     352
## 11 COMMUNICATION TECHNOLOGIES                             4545
8794    2495
## # … with abbreviated variable names ¹Non_college_jobs, ²
Low_wage_jobs
```

`rename()` is a function that will rename an existing column and select all columns.

```
math_grads |> rename(Code_major = Major_code)
```

```
## # A tibble: 11 × 21
##     Rank Code_major Major      Total   Men Women Major…¹ Share…²
Sampl…³ Emplo…⁴
##    <dbl>      <dbl> <chr>      <dbl> <dbl> <dbl> <chr>     <dbl>
<dbl>   <dbl>
## 1    21       2102 COMPUTER… 128319 99743 28576 Comput…   0.223
1196  102087
## 2    42       3700 MATHEMAT…  72397 39956 32441 Comput…   0.448
541   58118
## 3    43       2100 COMPUTER…  36698 27392  9306 Comput…   0.254
425   28459
## 4    46       2105 INFORMAT…  11913  9005  2908 Comput…   0.244
158    9881
## 5    47       3702 STATISTI…   6251  2960  3291 Comput…   0.526
37    4247
## 6    48       3701 APPLIED …   4939  2794  2145 Comput…   0.434
45    3854
## 7    53       4005 MATHEMAT…    609   500   109 Comput…   0.179
7     559
## 8    54       2101 COMPUTER…   4168  3046  1122 Comput…   0.269
43    3257
## 9    82       2106 COMPUTER…   8066  6607  1459 Comput…   0.181
103
```

```
6509
## 10    85       2107 COMPUTER…   7613  5291  2322 Comput…   0.305
97    6144
## 11   106       2001 COMMUNIC…  18035 11431  6604 Comput…   0.366
208   14779
## # … with 11 more variables: Full_time <dbl>, Part_time <dbl>,
## #   Full_time_year_round <dbl>, Unemployed <dbl>, Unemployment_rate
<dbl>,
## #   Median <dbl>, P25th <dbl>, P75th <dbl>, College_jobs <dbl>,
## #   Non_college_jobs <dbl>, Low_wage_jobs <dbl>, and abbreviated
variable names
## #   ¹Major_category, ²ShareWomen, ³Sample_size, ⁴Employed
## # ℹ Use `colnames()` to see all variable names
```

### 3.2.5 mutate()

Besides selecting sets of existing columns, we can also add new columns that are functions of existing columns with `mutate()`. `mutate()` always adds new columns at the end of the data frame.

```
math_grads |> mutate(Full_time_rate = Full_time_year_round/Total)
```

```
## # A tibble: 11 × 22
##     Rank Major_code Major      Total   Men Women Major…¹ Share…²
Sampl…³ Emplo…⁴
##    <dbl>      <dbl> <chr>      <dbl> <dbl> <dbl> <chr>     <dbl>
<dbl>   <dbl>
##  1    21       2102 COMPUTER… 128319 99743 28576 Comput…   0.223
1196  102087
##  2    42       3700 MATHEMAT…  72397 39956 32441 Comput…   0.448
541   58118
##  3    43       2100 COMPUTER…  36698 27392  9306 Comput…   0.254
425   28459
##  4    46       2105 INFORMAT…  11913  9005  2908 Comput…   0.244
158    9881
##  5    47       3702 STATISTI…   6251  2960  3291 Comput…   0.526
37    4247
##  6    48       3701 APPLIED …   4939  2794  2145 Comput…   0.434
45    3854
##  7    53       4005 MATHEMAT…    609   500   109 Comput…   0.179
```

```
 7     559
## 8     54        2101 COMPUTER…   4168  3046  1122 Comput…   0.269
43    3257
## 9     82        2106 COMPUTER…   8066  6607  1459 Comput…   0.181
103    6509
## 10    85        2107 COMPUTER…   7613  5291  2322 Comput…   0.305
97    6144
## 11   106        2001 COMMUNIC…  18035 11431  6604 Comput…   0.366
208   14779
## # … with 12 more variables: Full_time <dbl>, Part_time <dbl>,
## #   Full_time_year_round <dbl>, Unemployed <dbl>, Unemployment_rate
<dbl>,
## #   Median <dbl>, P25th <dbl>, P75th <dbl>, College_jobs <dbl>,
## #   Non_college_jobs <dbl>, Low_wage_jobs <dbl>, Full_time_rate
<dbl>, and
## #   abbreviated variable names ¹Major_category, ²ShareWomen, ³
Sample_size,
## #   ⁴Employed
## # ℹ Use `colnames()` to see all variable names
```

```
# we can't see everything
math_grads |>
  mutate(Full_time_rate = Full_time_year_round/Total) |>
  select(Major, ShareWomen, Full_time_rate)
```

```
## # A tibble: 11 × 3
##    Major                                                ShareWomen
Full_time_rate
##    <chr>                                                     <dbl>
<dbl>
##  1 COMPUTER SCIENCE                                          0.223
0.553
##  2 MATHEMATICS                                               0.448
0.466
##  3 COMPUTER AND INFORMATION SYSTEMS                          0.254
0.576
##  4 INFORMATION SCIENCES                                      0.244
0.619
##  5 STATISTICS AND DECISION SCIENCE                           0.526
0.344
##  6 APPLIED MATHEMATICS                                       0.434
0.525
##  7 MATHEMATICS AND COMPUTER SCIENCE                          0.179
0.642
##  8 COMPUTER PROGRAMMING AND DATA PROCESSING                  0.269
```

```
0.589
##  9 COMPUTER ADMINISTRATION MANAGEMENT AND SECURITY      0.181
0.612
## 10 COMPUTER NETWORKING AND TELECOMMUNICATIONS            0.305
0.574
## 11 COMMUNICATION TECHNOLOGIES                            0.366
0.504
```

### 3.2.6 summarise()

The last major verb is summarise(). It collapses a data frame to a single row based on a summary function.

```
math_grads |> summarise(mean_major_size = mean(Total))
```

```
## # A tibble: 1 × 1
##   mean_major_size
##             <dbl>
## 1          27183.
```

A useful summary function is a count (`n()`), or a count of non-missing values (`sum(!is.na())`).

```
math_grads |> summarise(mean_major_size = mean(Total), num_majors =
        n())
```

```
## # A tibble: 1 × 2
##   mean_major_size num_majors
##             <dbl>      <int>
## 1          27183.         11
```

### 3.2.7 group_by()

`summarise()` is not super useful unless we pair it with `group_by()`. This changes the unit of analysis from the complete dataset to individual groups. Then, when we use the `dplyr` verbs on a grouped data frame they'll be automatically applied "by group".

```
recent_grads |>
  group_by(Major_category) |>
  summarise(mean_major_size = mean(Total, na.rm = TRUE)) |>
```

```
  arrange(desc(mean_major_size))
```

```
## # A tibble: 16 × 2
##    Major_category                      mean_major_size
##    <chr>                                         <dbl>
##  1 Business                                    100183.
##  2 Communications & Journalism                  98150.
##  3 Social Science                               58885.
##  4 Psychology & Social Work                     53445.
##  5 Humanities & Liberal Arts                    47565.
##  6 Arts                                         44641.
##  7 Health                                       38602.
##  8 Law & Public Policy                          35821.
##  9 Education                                    34946.
## 10 Industrial Arts & Consumer Services          32827.
## 11 Biology & Life Science                       32419.
## 12 Computers & Mathematics                      27183.
## 13 Physical Sciences                            18548.
## 14 Engineering                                  18537.
## 15 Interdisciplinary                            12296 
## 16 Agriculture & Natural Resources               8402.
```

We can group by multiple variables and if we need to remove grouping, and return to operations on ungrouped data, we use `ungroup()`.

Grouping is also useful for `arrange()` and `mutate()` within groups.

# Your Turn

Using the NFL salaries from https://raw.githubusercontent.com/ada-lovecraft/ProcessingSketches/master/Bits%20and%20Pieces/Football_Stuff/data/nfl-salaries.tsv that you loaded into `R` in the previous your turn, perform the following.

1. What is the team with the highest paid roster?
2. What are the top 5 paid players?
3. What is the highest paid position on average? the lowest? the most variable?

## 3.3 `tidyr`

> "Happy families are all alike; every unhappy family is unhappy in its own way." –– Leo Tolstoy

> "Tidy datasets are all alike, but every messy dataset is messy in its own way." –– Hadley Wickham

*Tidy data* is an organization strategy for data that makes it easier to work with, analyze, and visualize. `tidyr` is a package that can help us tidy our data in a less painful way.

The following all contain the same data, but show different levels of "tidiness".

```
table1
```

```
## # A tibble: 6 × 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
```

```
table2
```

```
## # A tibble: 12 × 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
```

```
table3
```

```
## # A tibble: 6 × 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
```

```
# spread across two data frames
table4a
```

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

```
table4b
```

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

While these are all representations of the same underlying data, they are not equally easy to use.

There are three interrelated rules which make a dataset tidy:

1. Each variable must have its own column.

2. Each observation must have its own row.
3. Each value must have its own cell.

In the above example,

`table2` isn't tidy because each variable doesn't have its own column.

`table3` isn't tidy because each value doesn't have its own cell.

`table4a` and `table4b` aren't tidy because each observation doesn't have its own row.

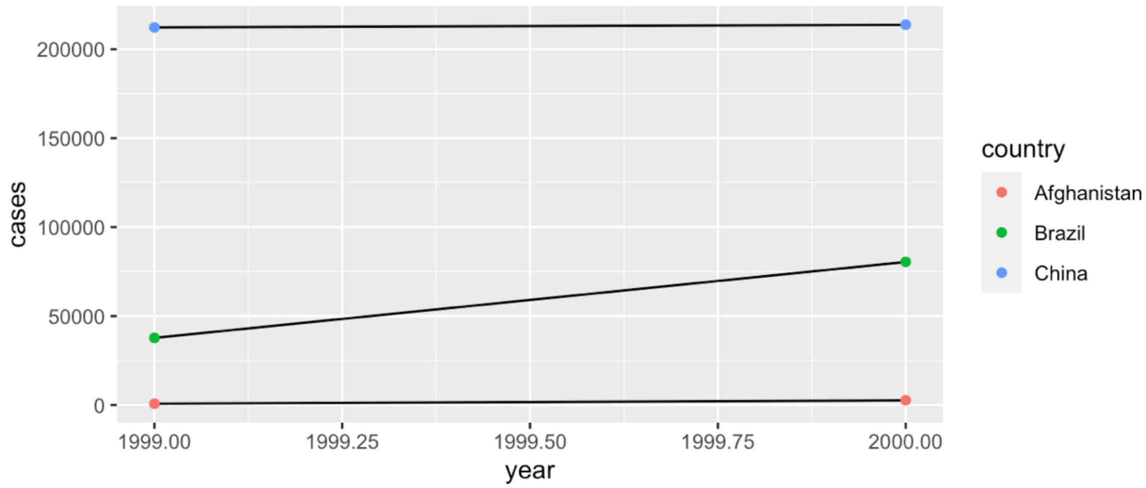
`table1` is tidy!

Being tidy with our data is useful because it's a consistent set of rules to follow for working with data and because it allows `R` to be efficient.

```
# Compute rate per 10,000
table1 |>
  mutate(rate = cases / population * 10000)
```

```
## # A tibble: 6 × 5
##   country      year  cases population  rate
##   <chr>       <int>  <int>      <int> <dbl>
## 1 Afghanistan  1999    745   19987071 0.373
## 2 Afghanistan  2000   2666   20595360 1.29
## 3 Brazil       1999  37737  172006362 2.19
## 4 Brazil       2000  80488  174504898 4.61
## 5 China        1999 212258 1272915272 1.67
## 6 China        2000 213766 1280428583 1.67
```

```
# Visualize cases over time
library(ggplot2)
ggplot(table1, aes(year, cases)) +
  geom_line(aes(group = country)) +
  geom_point(aes(colour = country))
```




### 3.3.1 Pivoting

Unfortunately, most of the data you will find in the "wild" is not tidy. So, we need tools to help us tidy unruly data.

The main tools in `tidyr` are the ideas of `pivot_longer()` and `pivot_wider()`. As the names imply, `pivot_longer()` "lengthens" our data, increasing the number of rows and decreasing the number of columns. `pivot_wider` does the opposite, increasing the number of columns and decreasing the number of rows.

These two functions resolve one of two common problems:

1. One variable might be spread across multiple columns. (`pivot_longer()`)
2. One observation might be scattered across multiple rows. (`pivot_wider()`)

A common issue with data is when values are used as column names.

```
table4a
```

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

We can fix this using `pivot_longer()`.

```
table4a |>
  pivot_longer(-country, names_to = "year", values_to = "cases")
```

Notice we specified with columns we wanted to consolidate by telling the function the column we *didn't* want to change (`-country`). We can use the `dplyr::select()` syntax here for specifying the columns to pivot.

We can do the same thing with `table4b` and then **join** the databases together by specifying unique identifying attributes.

```
table4a |>
  pivot_longer(-country, names_to = "year", values_to = "cases") |>
  left_join(table4b |> pivot_longer(-country, names_to = "year",
         values_to = "population"))
```

If, instead, variables don't have their own column, we can `pivot_wider()`.

```
table2

table2 |>
  pivot_wider(names_from = type, values_from = count)
```

### 3.3.2 Separating and Uniting

So far we have tidied `table2` and `table4a` and `table4b`, but what about `table3`?

```
table3
```

```
## # A tibble: 6 × 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
```

We need to split the `rate` column into the cases and population columns so that each value has its own cell. The function we will use is `separate()`. We need to specify the column, the value to split on ("/"), and the names of the new coumns.

```
table3 |>
  separate(rate, into = c("cases", "population"), sep = "/")
```

```
## # A tibble: 6 × 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
```

By default, `separate()` will split values wherever it sees a character that isn't a number or letter.

`unite()` is the opposite of `separate()` – it combines multiple columns into a single column.

# Your Turn

1. Is the NFL salaries from https://raw.githubusercontent.com/ada-lovecraft/ProcessingSketches/master/Bits%20and%20Pieces/Football_Stuff/data/nfl-salaries.tsv that you loaded into `R` in a previous your turn tidy? Why or why not?

2. There is a data set in `tidyr` called `world_bank_pop` that contains information about population from the World Bank (https://data.worldbank.org/). Why is this data not tidy? You may want to read more about the data to answer (`?world_bank_pop`).

3. Use functions in `tidyr` to turn this into a tidy form.

## 3.4 Additional resources

`readr` (https://readr.tidyverse.org)

`dplyr` (https://dplyr.tidyverse.org)

`tidyr` (https://tidyr.tidyverse.org)