Transforming and analyzing data

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Contents

This is from the third chapter of learn.r-journalism.com.

Why use **dplyr**?

- Designed to work with data frames, which is what journalists are used to
- Great for data exploration and transformation
- Intuitive to write and easy to read, especially when using the "chaining" syntax of pipes

Five basic verbs

- `filter()`
- `select()`
- `arrange()`
- `mutate()`
- `summarize()` plus `group_by()`

Our data

We're going to be wrangling some pretty big data– murders over decades across the country.

This case-level data was acquired by the Murder Accountability Project from the Justice Department.

We're going to use the basics of **dplyr** verb functions to analyze the data and see if there are any stories there might be worth pursuing.

Remember that huge SPSS data set we imported in the previous chapter?

I saved all that code we wrote to import it, renaming columns, and joining values and labels into an R script: *import_murders.R*. This is reproducibility in action.

Check out what it looks like– it's about 100 lines of code long but only one line is required to run the script below.

Warning: Before running the command, make sure the script is in the working directory folder and that the **SHR76_16.sav.zip** file is in the *data* sub folder. For example, on my computer, the *import_murders.R* script is in the *dplyr* folder and **SHR76_16.sav.zip** file is in the *dplyr/data* folder.

This is going to take a few minutes to run.

```
source("import_murders.R")
```

Alright, the **import_murders.R** script unzipped data, imported it, and transformed it into a workable dataframe and saved it to our environment as the object **murders** for us to analyze. You probably got some warnings in the console but that's okay.

```
View(murders)
```

	ID	CNTYFIPS	Ori	State	Agency	AGENCY_A	Agentype_label	Agentype_value	S
1	197601001AKASP00	02110	AKASP00	Alaska	State Troopers		Primary state LE	5	F
2	197601001AL00102	01073	AL00102	Alabama	Birmingham		Municipal police	3	F
3	197601001AL00104	01073	AL00104	Alabama	Fairfield		Municipal police	3	F
4	197601001AL00106	01073	AL00106	Alabama	Leeds		Municipal police	3	F
5	197601001AL00201	01097	AL00201	Alabama	Mobile		Municipal police	3	F
6	197601001AL00202	01097	AL00202	Alabama	Prichard		Municipal police	3	F
7	197601001AL00300	01101	AL00300	Alabama	Montgomery County		Sheriff	1	F
8	197601001AL00301	01101	AL00301	Alabama	Montgomery		Municipal police	3	F
9	197601001AL00500	01003	AL00500	Alabama	Baldwin County		Sheriff	1	F
10	197601001AL01101	01015	AL01101	Alabama	Anniston		Municipal police	3	F

Here's the data dictionary.

What are we dealing with here?

Number of rows (cases)?

```
nrow(murders)
```

```
## [1] 752313
```

How many municipalities?

We'll use a couple base R functions: `unique()` and `length()`.

```
# Make a list of cities based on the unique() function
how_many <- unique(murders$MSA_label)

# Count up how many are in the list
length(how_many)
```

```
## [1] 409
```

Whew, let's not overwhelm ourselves with all this data as we're getting started out.

When I get a new data set I like to see what it's made of. So I can begin to get a sense of how to summarize it or take it apart.

Start with the `glimpse()` function from **dplyr**– it will give a brief look at the variables in the data set and the data type.

```r
glimpse(murders)
```

```
## Observations: 752,313
## Variables: 47
## $ ID                 <fct> 197601001AKASP00, 197601001AL00102, 1976010...
## $ CNTYFIPS           <fct> 02110          , 01073          , 01073    ...
## $ Ori                <fct> AKASP00, AL00102, AL00104, AL00106, AL00201...
## $ State              <fct> Alaska, Alabama, Alabama, Alabama, Alabama,...
## $ Agency             <fct> State Troopers                             ...
## $ AGENCY_A           <fct>                                            ...
## $ Agentype_label     <fct> Primary state LE, Municipal police, Municip...
## $ Agentype_value     <dbl> 5, 3, 3, 3, 3, 3, 1, 3, 1, 3, 3, 3, 3, 3, 3...
## $ Source_label       <fct> FBI, FBI, FBI, FBI, FBI, FBI, FBI, FBI, FBI...
## $ Source_value       <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1...
## $ Solved_label       <fct> Yes, Yes, Yes, Yes, Yes, Yes, Yes, Yes, Yes...
## $ Solved_value       <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1...
## $ Year               <dbl> 1976, 1976, 1976, 1976, 1976, 1976, 1976, 1...
## $ Month_label        <fct> January, January, January, January, January...
## $ Month_value        <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1...
## $ Incident           <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1...
## $ ActionType         <fct> Normal update, Normal update, Normal update...
## $ Homicide_label     <fct> Murder and non-negligent manslaughter, Murd...
## $ Homicide_value     <fct> A, A, A, A, A, A, A, A, A, A, A, A, A, A, A...
## $ Situation_label    <fct> Single victim/single offender, Single victi...
## $ Situation_value    <fct> A, A, A, A, A, C, A, A, A, A, A, A, A, A, A...
## $ VicAge             <dbl> 48, 65, 45, 43, 35, 25, 27, 42, 41, 50, 51,...
## $ VicSex_label       <fct> Male, Male, Female, Male, Male, Male, Femal...
## $ VicSex_value       <fct> M, M, F, M, M, M, F, F, M, M, M, M, M, M, M...
## $ VicRace_label      <fct> American Indian or Alaskan Native, Black, B...
## $ VicRace_value      <fct> I, B, B, B, W, B, B, B, W, W, W, B, W, W, B...
## $ VicEthnic          <fct> Unknown or not reported, Unknown or not rep...
## $ OffAge             <dbl> 55, 67, 53, 35, 25, 26, 29, 19, 30, 42, 43,...
## $ OffSex_label       <fct> Female, Male, Male, Female, Female, Male, M...
## $ OffSex_value       <fct> F, M, M, F, F, M, M, M, F, M, M, M, M, M, M...
## $ OffRace_label      <fct> American Indian or Alaskan Native, Black, B...
## $ OffRace_value      <fct> I, B, B, B, W, B, B, B, W, W, W, B, W, W, B...
## $ OffEthnic          <fct> Unknown or not reported, Unknown or not rep...
## $ Weapon_label       <fct> Knife or cutting instrument, Shotgun, Shotg...
## $ Weapon_value       <dbl> 20, 14, 14, 20, 80, 13, 12, 20, 14, 12, 13,...
## $ Relationship_label <fct> Husband, Acquaintance, Wife, Brother, Acqua...
## $ Relationship_value <fct> HU, AQ, WI, BR, AQ, FR, WI, UN, HU, BR, ST,...
## $ Circumstance_label <fct> Other arguments, Felon killed by private ci...
## $ Circumstance_value <dbl> 45, 80, 60, 45, 99, 45, 45, 99, 45, 45, 45,...
## $ Subcircum          <fct> NA, Felon killed in commission of a crime, ...
## $ VicCount           <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ OffCount           <dbl> 0, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0...
## $ FileDate           <fct> 030180, 030180, 030180, 030180, 030180, 030...
## $ fstate_label       <fct> Alaska, Alabama, Alabama, Alabama, Alabama,...
## $ fstate_value       <fct> 02    , 01    , 01    , 01    , 01    , 01 ...
## $ MSA_label          <fct> Rural Alaska, Birmingham-Hoover, AL, Birmin...
## $ MSA_value          <dbl> 99902, 13820, 13820, 13820, 33660, 33660, 3...
```

Then, I'll go through the variables that interest me to see how many types there are. The more variables (columns) you have in a data set that are categorical, the deeper you can dive in analyzing it.

For example, if you had a data set with a list of salaries (1 variable) you could:

- Figure out the median salary
- Calculate the difference between the highest and the lowest salaries

If you had a data set with salaries and gender of worker (2 variables) you could additionally:

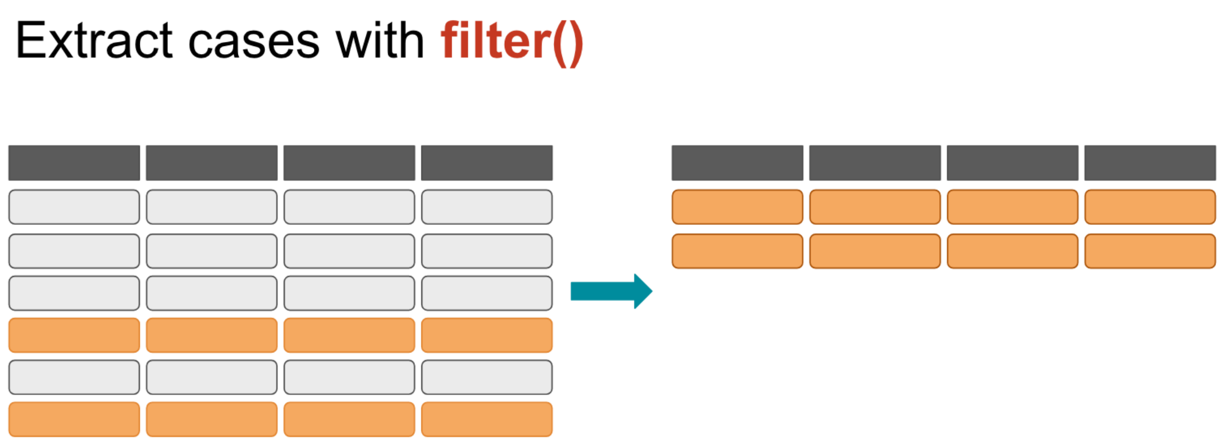
- Figure out median salary for men and women
- Calculate the differences in those medians

If you had a data set with salaries and gender of worker and state where they live (3 variables) you could additionally:

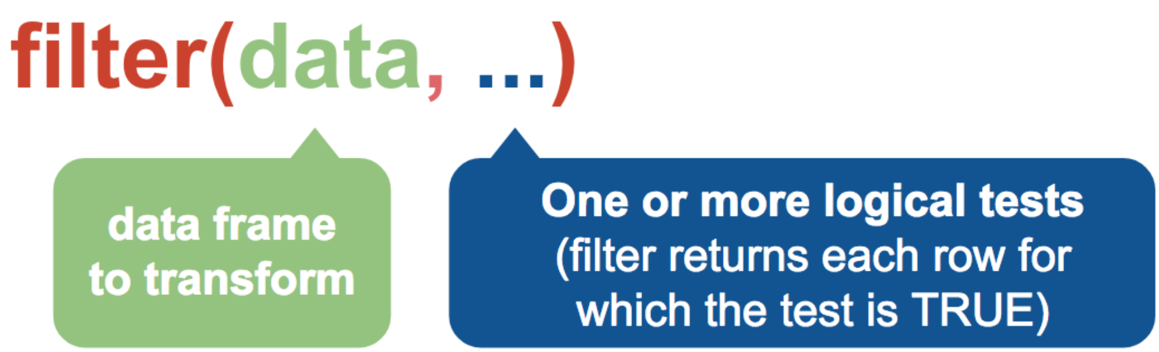
- Find out median salary per state
- Figure out median salary for men and women per state
- Determine which state had the biggest disparity
- See which state women get paid more than men

This is what we'll do with this particular data set:

Let's narrow down our scope by using the `filter()` function.



Filter works by extracting rows that meet a criteria you set.

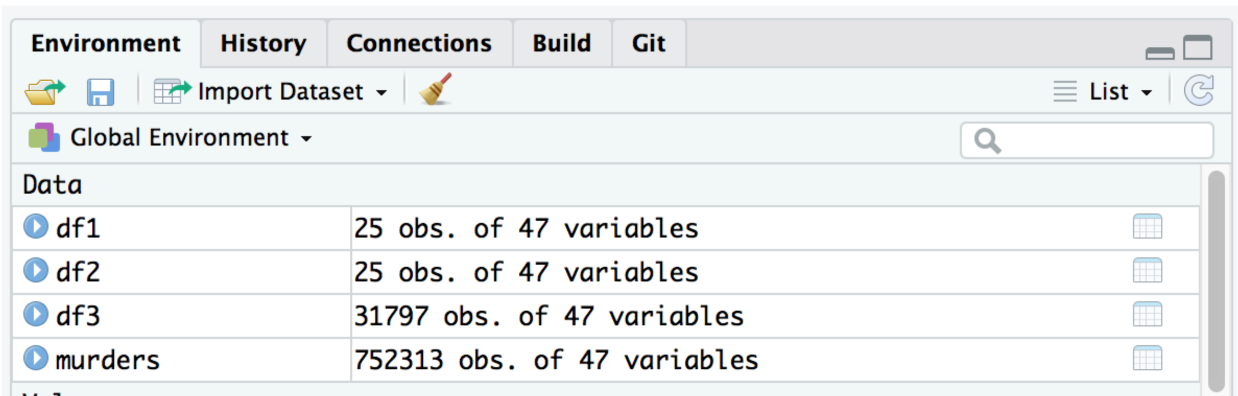


You pass the dataframe as a variable to `filter()` first and then you add any logical tests.

Warning: One `=` in R is the same as `<-` in that it assigns a value. Logical tests requires two, so `==` which tests for equal.

```
df1 <- filter(murders, Relationship_label=="Husband", VicAge > 60, Year==2016)

# same as the line above
df2 <- filter(murders, Relationship_label=="Husband" & VicAge > 60 & Year==2016)

df3 <- filter(murders, Relationship_label %in% c("Husband", "Boyfriend") |
                Circumstance_label=="Lovers triangle")
```

Check out the new objects in the Environment window of RStudio.



Data frames df1 and df2 are exactly the same (Looking for cases in which Husbands were involved, the victim was older than 60, and occurred in 2016)– only 25 were found. Meanwhile d3 has nearly 32,000 cases in which a Husband or Boyfriend were involved or it was labeled by investigators as a lover's triangle.

Logical Operators

Operator	Description
`<`	Less than
`<=`	Less than or equal to
`>`	Greater than
`>=`	Greater than or equal to
`==`	Exactly equal to
`!=`	Not equal to
`!x`	Not x
`x | y`	x or y
`x & y`	x and y
`%in%`	Group membership
`isTRUE(x)`	Test if x is TRUE
`is.na(x)`	Test if x is NA
`!is.na(x)`	Test if x is not NA

Test yourself

Can you use the logical operators and `filter()` to create **df4** which has all the data for murders:

1. in the District of Columbia

2. That were solved in 2015 that involved Black victims
3. in which Handgun - pistol, revolver, etc was victims between the ages of 18 and 21

Common mistakes

1. Using `=` instead of `==`

```
# WRONG
filter(murders, fstate_label="District of Columbia")

# RIGHT
filter(murders, fstate_label=="District of Columbia")
```

2. Forgetting quotes

```
# WRONG
filter(murders, fstate_label=District of Columbia)

# RIGHT
filter(murders, fstate_label="District of Columbia"")
```

3. Collapsing multiple tests into one

```
# WRONG
filter(murders, 1980 < year < 1990)

# RIGHT
filter(murders, 1980 < year, year < 1990)
```

4. Stringing together many tests instead of using %in%

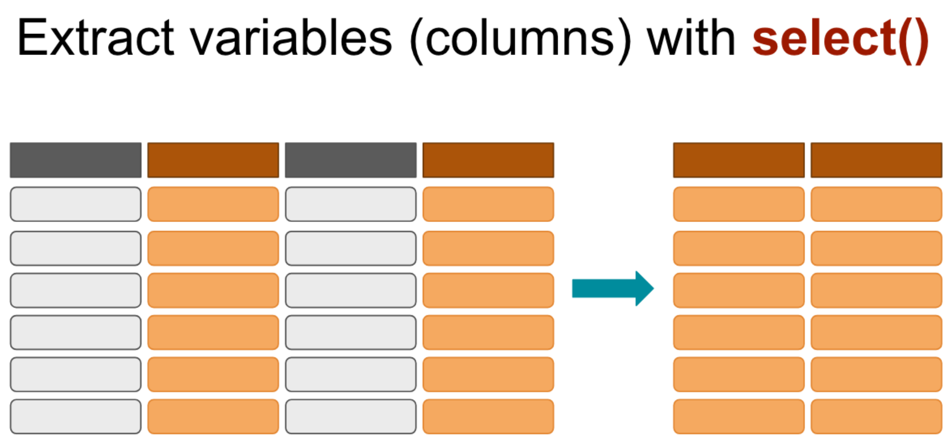
```
# Not WRONG but INEFFICIENT to type out
filter(murders, VicRace_label=="Black" | VicRace_label="Unknown" |
  VicRace_label=="Asian or Pacific Islander")

# RIGHT
filter(murders, VicRace_label %in% c("Black", "Unknown", "Asian or Pacific Islander"))
```

Alright, we've got new data frames narrowed down from 750,000 total to about 25 specific incidents of husbands murdering their partners who were older than 60 in 2016 and about 32,000 cases where either the husband or boyfriend was involved or the victim was involved in a love triangle.

We have 47 variables (aka columns) and we don't need all of them for this basic analysis. Let's narrow that down.

---

select()



You simply list the column names after the data frame you want to extract from.

```
df1_narrow <- select(df1, State, Agency, Solved_label, Year)
```

```
View(df1_narrow)
```

	State	Agency	Solved_label	Year
1	Alabama	Citronelle	Yes	2016
2	Florida	Daytona Beach	Yes	2016
3	Florida	Putnam County	Yes	2016
4	Arizona	Mesa	Yes	2016
5	Arizona	Scottsdale	Yes	2016
6	Arizona	Surprise	Yes	2016
7	Arizona	Yuma County	Yes	2016
8	California	Hayward	Yes	2016
9	California	Fresno	Yes	2016
10	California	San Jose	Yes	2016
11	California	Simi Valley	Yes	2016
12	Georgia	Waycross	Yes	2016

You can use a colon between column names if you want all the columns between.

```
df2_narrow <- select(df1, State, OffAge:OffRace_value, Weapon_label)
```

```
View(df2_narrow)
```

	State	OffAge	OffSex_label	OffSex_value	OffRace_label	OffRace_value	Weapon_label
1	Alabama	999	Unknown	U	Unknown	U	Handgun – pi
2	Florida	61	Female	F	White	W	Personal weap
3	Florida	79	Female	F	White	W	Rifle
4	Arizona	55	Female	F	White	W	Handgun – pi
5	Arizona	57	Female	F	White	W	Handgun – pi
6	Arizona	46	Female	F	White	W	Handgun – pi
7	Arizona	72	Female	F	White	W	Other or type
8	California	61	Female	F	White	W	Firearm, type
9	California	76	Female	F	White	W	Blunt object –
10	California	57	Female	F	Asian or Pacific Islander	A	Blunt object –
11	California	75	Female	F	White	W	Handgun – pi

Use a - next to a column name to drop it (You can drop more than one column at a time, too).

```
# modifying the data frame created above
df3_narrow <- select(df2_narrow, -Weapon_label)
```

```
View(df3_narrow)
```

	State	OffAge	OffSex_label	OffSex_value	OffRace_label	OffRace_value
1	Alabama	999	Unknown	U	Unknown	U
2	Florida	61	Female	F	White	W
3	Florida	79	Female	F	White	W
4	Arizona	55	Female	F	White	W
5	Arizona	57	Female	F	White	W
6	Arizona	46	Female	F	White	W
7	Arizona	72	Female	F	White	W
8	California	61	Female	F	White	W
9	California	76	Female	F	White	W
10	California	57	Female	F	Asian or Pacific Islander	A
11	California	75	Female	F	White	W
12	Georgia	58	Female	F	Black	B

There are so many other functions you can use with `select()` to help make your life easier.

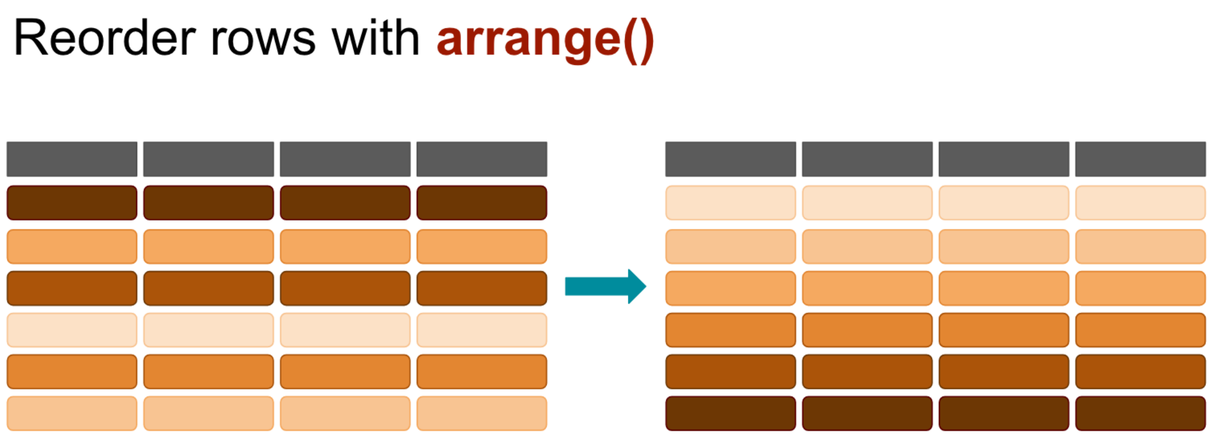
```
# This extracts all variables with names that contain "_label"

labels_only_columns <- select(murders(contains("_label"))
str(labels_only_columns)
```

Check out all the neat `select()` options here.

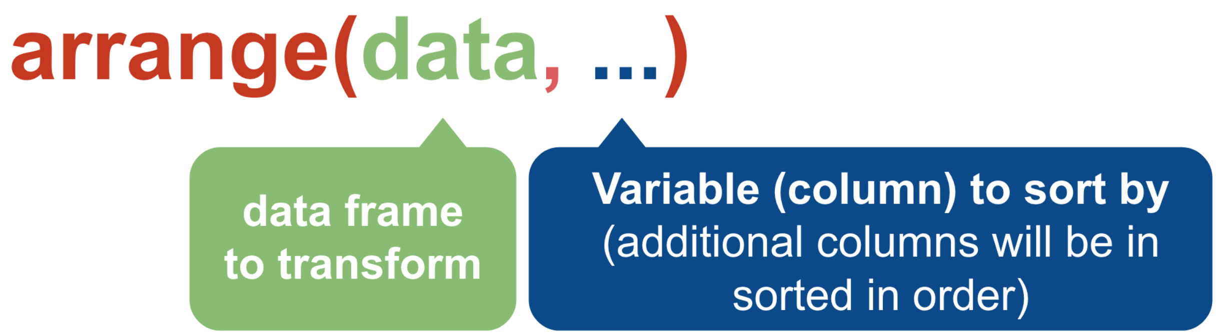
Great, let's move on to the next verb.

---

arrange()



You can include more than one variable (column)– the first one will take priority but subsequent variables will serve as tie breakers.

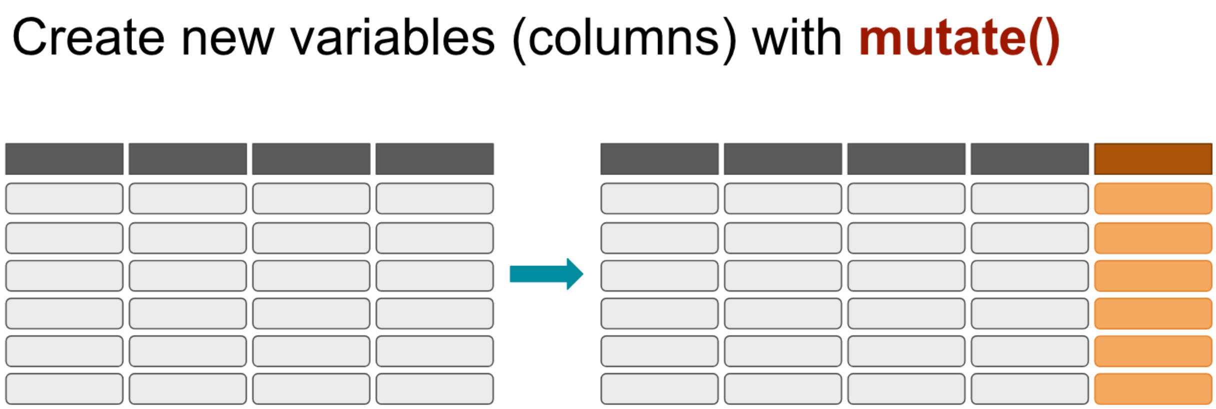



```r
age_df1 <- arrange(murders, VicAge)

age_df2 <- arrange(murders, VicAge, OffAge)

age_df3 <- arrange(murders, VicAge, desc(OffAge))

# Same result as above
age_df3b <- arrange(murders, VicAge, -OffAge)
```

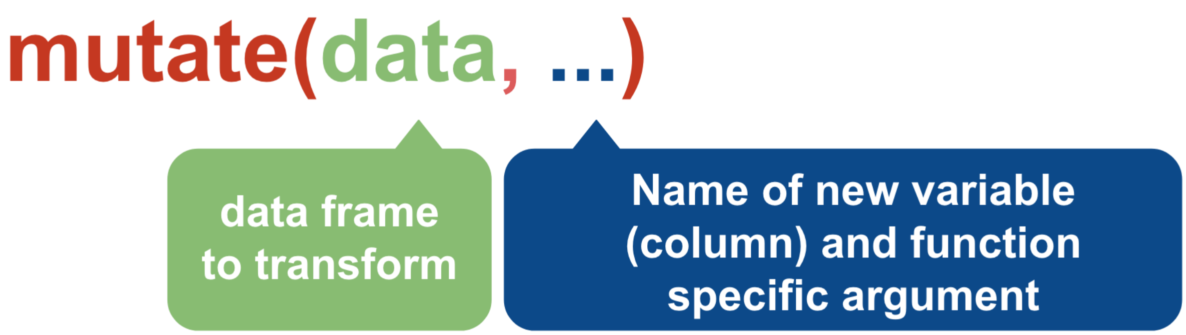
This will be very useful. Let's move on to the next verb.

---

mutate()



We can create new variables (new columns) with the `mutate()` function.




```
murders_ver2 <- mutate(murders,
                       age_difference=OffAge-VicAge)
```

```
View(murders_ver2)
```

nt	FileDate	fstate_label	fstate_value	MSA_label	MSA_value	age_difference
0	030180	Alaska	02	Rural Alaska	99902	7
0	030180	Alabama	01	Birmingham-Hoover, AL	13820	2
0	030180	Alabama	01	Birmingham-Hoover, AL	13820	8
0	030180	Alabama	01	Birmingham-Hoover, AL	13820	-8
0	030180	Alabama	01	Mobile, AL	33660	-10
2	030180	Alabama	01	Mobile, AL	33660	1
0	030180	Alabama	01	Montgomery, AL	33860	2
0	030180	Alabama	01	Montgomery, AL	33860	-23
0	030180	Alabama	01	Rural Alabama	99901	-11

Arithmetic Operators

Operator	Description
+	Addition
-	Subtraction
*	Multiplication
/	Division
^	Exponentiation

You can do more than just math in the context of `mutate()`.

You can use `case_when()` in `mutate()` to create new values based on other values, kind of like an if_else statement.

```
# creates an age_difference column
# and creates a vic_category column that is populated with values
# depending on the VicRace_label column

murders_ver3 <- mutate(murders,
                       age_difference=OffAge-VicAge,
                       vic_category=case_when(
                         VicRace_label == "White" ~ "White",
                         VicRace_label != "White" ~ "Non-White"
                       ))
```

Tip: This is the first of a few times you'll see the `~` (tilde) operator. It means it's a one-sided formula, usually in statistical model formulas. It can be described as "depends on" You don't need to really to understand why a tilde is necessary– only that this is how this particular function needs to be set up to work successfully.

There are two variables being created in the `mutate()` function separated by commas.

- one is **age_difference** which just subtracts the values in **OffAge** and **VicAge**.
- the other is **vic_category** that is either assigned "White" or "Non-White" depending on if the value of the column **VicRace_label** is "White" or *not* "White".

```
View(murders_ver3)
```

_label	VicSex_value	VicRace_label	age_difference	vic_category
	M	American Indian or Alaskan Native	7	Non-White
	M	Black	2	Non-White
	F	Black	8	Non-White
	M	Black	-8	Non-White
	M	White	-10	White
	M	Black	1	Non-White
	F	Black	2	Non-White
	F	Black	-23	Non-White
	M	White	-11	White
	M	White	-8	White
	M	White	-8	White

This is an example of a vectorized function in action. There are some really great ones like `lag()` and `lead()` and `rank()` and we might get into them later. In the meantime, here's a neat list.

Rename

You can rename variables (columns) easily with the function `rename()`

```
colnames(df3_narrow)
```

```
## [1] "State"          "OffAge"         "OffSex_label"   "OffSex_value"
## [5] "OffRace_label" "OffRace_value"
```

```
# OK, you see the column names above-- let's change a couple of them

df3_renamed <- rename(df3_narrow,
                      offender_gender=OffSex_label,
                      offender_age=OffAge)
colnames(df3_renamed)
```

```
## [1] "State"             "offender_age"     "offender_gender" "OffSex_value"
## [5] "OffRace_label"    "OffRace_value"
```

You can also rename variables (columns) with the `select()` function. This is just a way to cut down on extra lines of code

```
colnames(df3_narrow)
```

```
## [1] "State"          "OffAge"         "OffSex_label"   "OffSex_value"
## [5] "OffRace_label" "OffRace_value"
```

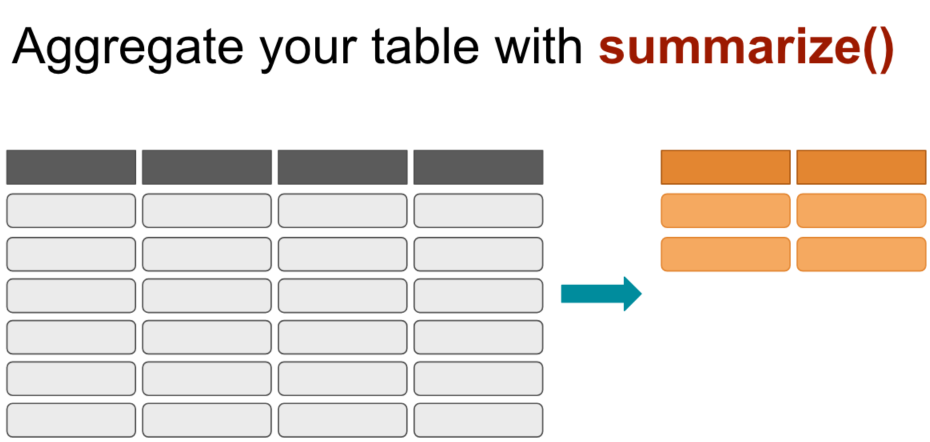
```
# Keeping only the State and offender gender and age columns but renaming the
# OffSex_label and OffAge columns

df4_renamed <- select(df3_narrow,
                      State,
```

```
                      offender_gender=OffSex_label,
                      offender_age=OffAge)

df4_renamed
```

```
##             State offender_gender offender_age
## 1         Alabama         Unknown          999
## 2         Florida          Female           61
## 3         Florida          Female           79
## 4         Arizona          Female           55
## 5         Arizona          Female           57
## 6         Arizona          Female           46
## 7         Arizona          Female           72
## 8      California          Female           61
## 9      California          Female           76
## 10     California          Female           57
## 11     California          Female           75
## 12        Georgia          Female           58
## 13       Kentucky          Female           77
## 14       Kentucky          Female           67
## 15       Michigan          Female           72
## 16       Michigan          Female           72
## 17    Mississippi          Female           46
## 18     New Mexico            Male           83
## 19       Oklahoma          Female           58
## 20   Pennsylvania          Female           57
## 21  Rhodes Island          Female           57
## 22 South Carolina          Female           72
## 23 South Carolina          Female           76
## 24      Tennessee          Female           63
## 25          Texas          Female           71
```

---

summarize()



This is the equivalent of creating a pivot table in Excel.

You're aggregating the whole table into something simplified.

```
summarize(murders, average_victim_age=mean(VicAge))
```

```
##   average_victim_age
## 1           47.96203
```

You can create a table of summaries.

```
summarize(murders,
          average_victim_age=mean(VicAge),
          average_offender_age=mean(OffAge))
```

```
##   average_victim_age average_offender_age
## 1           47.96203             352.7295
```

Warning: There's something wrong with the average_offender_age value. Can you figure out what happened?

Summarize the data frame **murders**

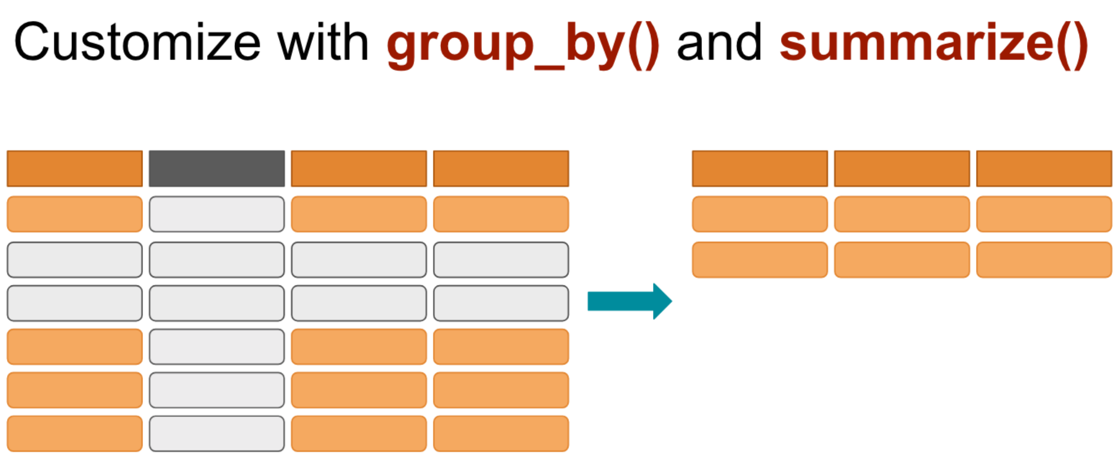
```
summarize(murders,
          first=min(Year),
          last=max(Year),
          metro_areas=n_distinct(MSA_label),
          cases=n())
```

```
##   first last metro_areas  cases
## 1  1976 2016         409 752313
```

---

group_by()

You can aggregate data by groups before summarizing.



```r
# This is the same process as before but we're telling R to group up
# the metro areas before summarizing the data

murders <- group_by(murders, MSA_label)

summarize(murders,
          first=min(Year),
          last=max(Year),
          cases=n())
```

```
## # A tibble: 409 x 4
##    MSA_label                          first  last cases
##    <fct>                              <dbl> <dbl> <int>
##  1 Abilene, TX                         1976  2016   366
##  2 Akron, OH                           1976  2016  1080
##  3 Albany, GA                          1976  2016   633
##  4 Albany-Schenectady-Troy, NY         1976  2016   829
##  5 Albuquerque, NM                     1976  2016  2374
##  6 Alexandria, LA                      1976  2016   576
##  7 Allentown-Bethlehem-Easton, PA-NJ   1976  2016   882
##  8 Altoona, PA                         1976  2016   120
##  9 Amarillo, TX                        1976  2016   724
## 10 Ames, IA                            1978  2016    26
## # ... with 399 more rows
```

This might be a tough concept to fully understand at first, but we'll go over a few more examples soon so it will hopefully make more sense.

Also, I want to point out that the opposite of `group_by()` is `ungroup()` which you might need later on as you progress.

But let's get over some very useful functionality that comes with the **dplyr** package.

---

pipe %>%

Data analyses will most often involve more than one step.

We're going to over some **options** on how to approach multi-step processes with this data set and then we'll go over the *best* way to deal with them.

Description of theoretical process to run on the **murders** data frame:

1. **Extract rows** for cases that happened in Washington DC, then
2. **Group** case by year and then
3. **Count** the number of cases
4. **Arrange** the by decreasing cases

Option 1

Build out a new dataframe for each step.

```r
dc_annual_murders1 <- filter(murders, State=="District of Columbia")
dc_annual_murders2 <- group_by(dc_annual_murders1, Year)
dc_annual_murders3 <- summarize(dc_annual_murders2, total=n())
dc_annual_murders4 <- arrange(dc_annual_murders3, desc(total))
```

```r
# looking at the first 6 rows of data

head(dc_annual_murders4)
```

```
## # A tibble: 6 x 2
##    Year total
##   <dbl> <int>
## 1  1991   489
## 2  1990   481
## 3  1992   450
## 4  1989   439
## 5  1993   423
## 6  1994   417
```

Option 2

Do it all in one line by nesting functions.

```r
dc_annual_murders <- arrange(
  summarize(
    group_by(
      filter(murders, State=="District of Columbia"),
      Year),
    total=n()),
  desc(total))

# looking at the first 6 rows of data

head(dc_annual_murders)
```

```
## # A tibble: 6 x 2
##    Year total
##   <dbl> <int>
## 1  1991   489
## 2  1990   481
## 3  1992   450
## 4  1989   439
## 5  1993   423
## 6  1994   417
```

These options aren't great because the first one involves just way too much typing, even if it's pretty clear to an outside reader what's happening to the data frame. The second one is no good because, while it's efficient with coding, it's way too difficult to follow what's happening to the data.

Let's talk about the pipe operator `%>%`

You might have noticed that all the functions from **dplyr** all structured similarly: *The first argument is always the data frame.*

It takes in a data frame and spits out a data frame.

This function structure is what allows for something like the `%>%` to work.

dataframe %>% filter(_____, variable=="some string")

These commands do the same thing. Give it a try.

```r
filter(murders, OffAge==2)
```

```
## # A tibble: 3 x 47
## # Groups:   MSA_label [3]
##   ID    CNTYFIPS Ori   State Agency AGENCY_A Agentype_label Agentype_value
##   <fct> <fct>    <fct> <fct> <fct>  <fct>    <fct>                   <dbl>
## 1 1977~ "13121 ~ GA06~ Geor~ "East~ "      ~ Municipal pol~              3
## 2 1979~ "36061 ~ NY03~ New ~ "New ~ "      ~ Municipal pol~              3
## 3 2015~ "18089 ~ IN04~ Indi~ "Gary~ "      ~ Municipal pol~              3
## # ... with 39 more variables: Source_label <fct>, Source_value <dbl>,
## #   Solved_label <fct>, Solved_value <dbl>, Year <dbl>, Month_label <fct>,
## #   Month_value <dbl>, Incident <dbl>, ActionType <fct>,
## #   Homicide_label <fct>, Homicide_value <fct>, Situation_label <fct>,
## #   Situation_value <fct>, VicAge <dbl>, VicSex_label <fct>,
## #   VicSex_value <fct>, VicRace_label <fct>, VicRace_value <fct>,
## #   VicEthnic <fct>, OffAge <dbl>, OffSex_label <fct>, OffSex_value <fct>,
## #   OffRace_label <fct>, OffRace_value <fct>, OffEthnic <fct>,
## #   Weapon_label <fct>, Weapon_value <dbl>, Relationship_label <fct>,
## #   Relationship_value <fct>, Circumstance_label <fct>,
## #   Circumstance_value <dbl>, Subcircum <fct>, VicCount <dbl>,
## #   OffCount <dbl>, FileDate <fct>, fstate_label <fct>,
## #   fstate_value <fct>, MSA_label <fct>, MSA_value <dbl>
```

```r
murders %>% filter(OffAge==2)
```

```
## # A tibble: 3 x 47
## # Groups:   MSA_label [3]
##   ID    CNTYFIPS Ori   State Agency AGENCY_A Agentype_label Agentype_value
##   <fct> <fct>    <fct> <fct> <fct>  <fct>    <fct>                   <dbl>
## 1 1977~ "13121 ~ GA06~ Geor~ "East~ "      ~ Municipal pol~              3
## 2 1979~ "36061 ~ NY03~ New ~ "New ~ "      ~ Municipal pol~              3
## 3 2015~ "18089 ~ IN04~ Indi~ "Gary~ "      ~ Municipal pol~              3
## # ... with 39 more variables: Source_label <fct>, Source_value <dbl>,
## #   Solved_label <fct>, Solved_value <dbl>, Year <dbl>, Month_label <fct>,
## #   Month_value <dbl>, Incident <dbl>, ActionType <fct>,
## #   Homicide_label <fct>, Homicide_value <fct>, Situation_label <fct>,
## #   Situation_value <fct>, VicAge <dbl>, VicSex_label <fct>,
## #   VicSex_value <fct>, VicRace_label <fct>, VicRace_value <fct>,
## #   VicEthnic <fct>, OffAge <dbl>, OffSex_label <fct>, OffSex_value <fct>,
## #   OffRace_label <fct>, OffRace_value <fct>, OffEthnic <fct>,
## #   Weapon_label <fct>, Weapon_value <dbl>, Relationship_label <fct>,
## #   Relationship_value <fct>, Circumstance_label <fct>,
## #   Circumstance_value <dbl>, Subcircum <fct>, VicCount <dbl>,
## #   OffCount <dbl>, FileDate <fct>, fstate_label <fct>,
## #   fstate_value <fct>, MSA_label <fct>, MSA_value <dbl>
```

In essence, a `%>%` is the grammatical equivalent of *and then...*.

Again, a description of the theoretical process:

- **Extract rows** for cases that happened in Washington DC, then
- **Group** case by year and then
- **Count** the number of cases
- **Arrange** the by decreasing cases

Option 3

Use the `%>%` pipe

```
filter(murders, State=="District of Columbia") %>%
  group_by(Year) %>%
  summarize(total=n()) %>%
  arrange(desc(total)) %>%
  head()
```

```
## # A tibble: 6 x 2
##    Year total
##   <dbl> <int>
## 1  1991   489
## 2  1990   481
## 3  1992   450
## 4  1989   439
## 5  1993   423
## 6  1994   417
```

So readable and simple, right?

Here's the shortcut to type `%>%` in RStudio:

- Mac: Cmd + Shift + M
- Windows: Ctrl + Shift + M

Why "M"? I think it's because the pipe was first introduced in the **magrittr** package by Stefan Milton Bache.

Mutate again

There are a lot of interesting things you can do with `mutate()`.

Let's try out `lag()` within `mutate()` – it lets you do math based on the previous row of a vector.

For example, in the data frame above we've got the number of murders in DC. With `lag()` and some math, we can calculate the difference in the number of murders year over year.

```
# We can keep the code from before but now we add a new mutate line
filter(murders, State=="District of Columbia") %>%
  group_by(Year) %>%
  summarize(total=n()) %>%
  mutate(previous_year=lag(total)) %>%
  mutate(change=total-previous_year)
```

```
## # A tibble: 35 x 4
##     Year total previous_year change
##    <dbl> <int>         <int>  <int>
##  1  1976   203            NA     NA
##  2  1977   202           203     -1
##  3  1978   196           202     -6
```

```
## 4  1979   171            196    -25
## 5  1980   180            171      9
## 6  1981   232            180     52
## 7  1982   204            232    -28
## 8  1983   188            204    -16
## 9  1984   175            188    -13
## 10 1985   149            175    -26
## # ... with 25 more rows
```

So `mutate()` returns a vector the same length as the input.

We summarized the code and then we mutated a new column based on `lag()` and then we mutated a second column based on the new column and the old column.

You can use mutate more than once

```
# Here's an example of the same code above but with mutate called just once
# previous_year was able to be referenced a second time because it was created in first
years <- filter(murders, State=="District of Columbia") %>%
  group_by(Year) %>%
  summarize(total=n()) %>%
  mutate(previous_year=lag(total), change=previous_year-total)

years
```

```
## # A tibble: 35 x 4
##     Year total previous_year change
##    <dbl> <int>         <int>  <int>
## 1  1976   203            NA     NA
## 2  1977   202           203      1
## 3  1978   196           202      6
## 4  1979   171           196     25
## 5  1980   180           171     -9
## 6  1981   232           180    -52
## 7  1982   204           232     28
## 8  1983   188           204     16
## 9  1984   175           188     13
## 10 1985   149           175     26
## # ... with 25 more rows
```

So `mutate()` works when the formula you pass it returns a vectorized output. For example, if a vector has 10 instances in it, then the formula needs to output 10 instances, too.

Passing it a formula like `sum()` would confuse it.

```
years %>% mutate(all_murders=sum(total))
```

```
## # A tibble: 35 x 5
##     Year total previous_year change all_murders
##    <dbl> <int>         <int>  <int>       <int>
## 1  1976   203            NA     NA        8209
## 2  1977   202           203      1        8209
## 3  1978   196           202      6        8209
## 4  1979   171           196     25        8209
## 5  1980   180           171     -9        8209
## 6  1981   232           180    -52        8209
## 7  1982   204           232     28        8209
## 8  1983   188           204     16        8209
```

```
## 9  1984  175          188    13       8209
## 10 1985  149          175    26       8209
## # ... with 25 more rows
```

This is what differentiates `mutate()` from `summarize()`.

Summary functions

What `summarize()` does is it takes a vector as an input, and returns a single value as output. Like `sum()` did in the previous example.

Here are some examples of summary functions:

Function	Description
`mean(x)`	Mean (average). `mean(c(1,10,100,1000))` returns 277.75
`median(x)`	Median. `median(c(1,10,100,1000))` returns 55
`sd(x)`	Standard deviation. `sd(c(1,10,100,1000))` returns 483.57
`quantile(x, probs)`	Where x is the numeric vector whose quantiles are desired and probs is a numeric vector with probabilities
`range(x)`	Range. `range(c(1,10,100,1000))` returns c(1, 1000) and `diff(range(c(1,10,100,1000)))` returns 999
`sum(x)`	Sum. `sum(c(1,10,100,1000))` returns 1111
`min(x)`	Minimum. `min(c(1,10,100,1000))` returns 1
`max(x)`	Maximum. `max(c(1,10,100,1000))` returns 1000
`abs(x)`	Absolute value. `abs(-8)` returns 8

Here are some examples of summary functions specific to **dplyr** and `summarize()` – Learn about the others.

Function	Description
`n()`	returns the number of values/rows
`n_distinct()`	returns number of uniques
`first()`	Only returns the first value within an arranged group
`last()`	Only returns the last value within an arranged group
`nth()`	Only returns the nth location of a vector

group_by() again

Let's put together everything we've learned by calculating percentages.

You can use `group_by()` on more than one variable (column).

Let's go over the difference, really quick.

We can summarize the data by how many men were murdered versus women by

```
murders %>%
  group_by(VicSex_label) %>%
  summarize(total=n())
```

```
## # A tibble: 3 x 2
##   VicSex_label  total
##   <fct>         <int>
## 1 Female       169028
## 2 Male         582092
## 3 Unknown        1193
```

By grouping *VicSex_label* we got the counts (`n()`) for all the instances available in that variable.

We can add another variable (column) name into the `group_by()` to drill deeper. Watch what happens when we add *State*.

```
murders %>%
  group_by(State, VicSex_label) %>%
  summarize(total=n())
```

```
## # A tibble: 147 x 3
## # Groups:   State [?]
##    State    VicSex_label total
##    <fct>    <fct>        <int>
##  1 Alaska   Female         565
##  2 Alaska   Male          1385
##  3 Alaska   Unknown          2
##  4 Alabama  Female        3586
##  5 Alabama  Male         11955
##  6 Alabama  Unknown        146
##  7 Arkansas Female        2019
##  8 Arkansas Male          6049
##  9 Arkansas Unknown         28
## 10 Arizona  Female        3252
## # ... with 137 more rows
```

Interesting, right? The structure for the data here might be foreign to you. As it stands, this data is considered tidy. Each variable is a column and each observation (or case) is a row. This makes it easier to analyze the data in R and create charts.

But you're probably used to data that looks like

```
## # A tibble: 51 x 4
## # Groups:   State [51]
##    State                 Female  Male Unknown
##    <fct>                  <int> <int>   <int>
##  1 Alaska                   565  1385       2
##  2 Alabama                 3586 11955     146
##  3 Arkansas                2019  6049      28
##  4 Arizona                 3252 11203      29
```

```
##   5 California            21826 92756      38
##   6 Colorado               2233  5476       5
##   7 Connecticut            1394  4139       5
##   8 District of Columbia   1041  7155      13
##   9 Delaware                399  1048      NA
##  10 Florida               10699 32632     128
## # ... with 41 more rows
```

And that's fine, too, for presentation. We'll get into how to do this later in the next chapter or so.

The prior tidy structure makes it easier to run calculations such as percentages, however.

Percents

Now we get a chance to chain together all the verbs we've used

```
percent_murders <- murders %>%
  group_by(State, VicSex_label) %>%
  summarize(total=n()) %>%
  # okay, we've got the total, now we can do some math with mutate
  mutate(percent=total/sum(total, na.rm=T)*100)
  # did you notice the na.rm=T added to the sum function? This removes NAs
  # That's necessary because if you have a single NA then it will not sum correctly
  # (thanks, statisticians!)

percent_murders
```

```
## # A tibble: 147 x 4
## # Groups:   State [51]
##    State    VicSex_label total percent
##    <fct>    <fct>        <int>   <dbl>
##  1 Alaska   Female         565  28.9
##  2 Alaska   Male          1385  71.0
##  3 Alaska   Unknown          2   0.102
##  4 Alabama  Female        3586  22.9
##  5 Alabama  Male         11955  76.2
##  6 Alabama  Unknown        146   0.931
##  7 Arkansas Female        2019  24.9
##  8 Arkansas Male          6049  74.7
##  9 Arkansas Unknown         28   0.346
## 10 Arizona  Female        3252  22.5
## # ... with 137 more rows
```

Interesting. We can use more `dplyr()` verbs to find something of interest. Like, which states have a higher percent of women murdered?

```
percent_murders_women <- murders %>%
  group_by(State, VicSex_label) %>%
  summarize(total=n()) %>%
  mutate(percent=total/sum(total, na.rm=T)*100) %>%
  filter(VicSex_label=="Female") %>%
  arrange(-percent)

# Using the DT (DataTables) library that lets us create searchable tables with the
# plug-in for jQuery
# If you don't have DT installed yet, uncomment the line below and run it
```

```r
#install.packages("DT")

library(DT)
```

Congratulations, we've gone through a bunch of ways to analyze data.

Now that we've got the tools, let's interrogate the data further using a couple other methods involving tidying and joining data.

Your turn

Challenge yourself with these exercises so you'll retain the knowledge of this section.

Instructions on how to run the exercise app are on the intro page to this section.