Coding Lab: Manipulating data with `dplyr`

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Data manipulation with `dplyr`

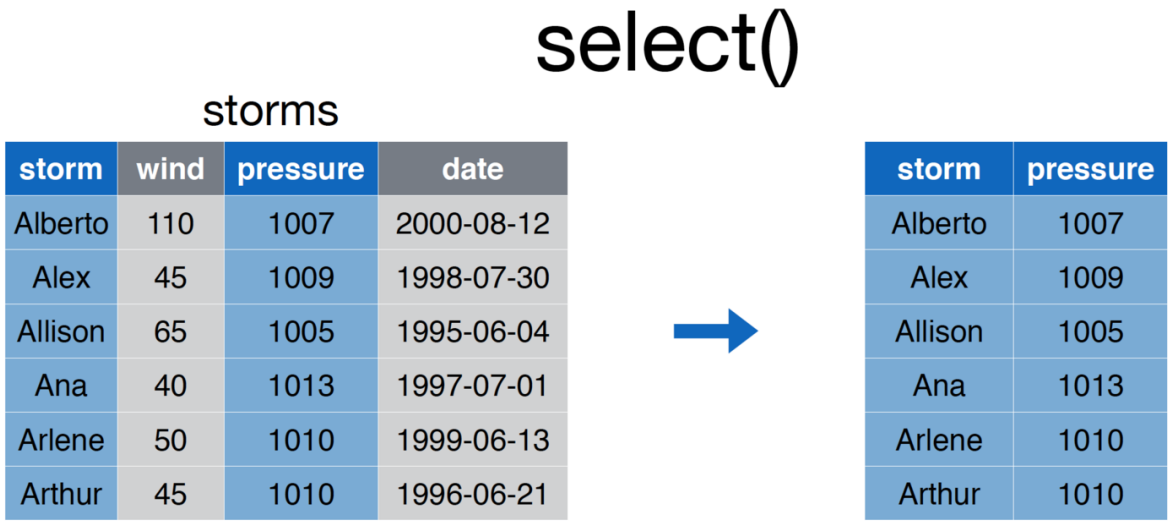
Once you have data in R, you'll want to explore it.

The `tidyverse` package `dplyr` provides a toolkit for data manipulation.

We will cover:

- `select()` to pick columns
- `arrange()` to order the data
- `mutate()` to create new columns
- `filter()` to get rows that meet a criteria
- `summarize()` to summarize data

selecting columns with `select()`



selecting columns with `select()`

Use case: You want to present a subset of your columns

```
select(texas_housing_data, city, date, sales, listings)
```

```
## # A tibble: 8,602 x 4
##    city     date sales listings
##    <chr>   <dbl> <dbl>    <dbl>
##  1 Abilene 2000     72      701
##  2 Abilene 2000.    98      746
##  3 Abilene 2000.   130      784
##  4 Abilene 2000.    98      785
##  5 Abilene 2000.   141      794
##  6 Abilene 2000.   156      780
##  7 Abilene 2000.   152      742
##  8 Abilene 2001.   131      765
##  9 Abilene 2001.   104      771
## 10 Abilene 2001.   101      764
## # ... with 8,592 more rows
```

selecting columns with `select()`

Use case: You want to present a subset of your columns

```
select(texas_housing_data, -c(city, date, sales, listings))
```

The - says to exclude the columns listed in the vector.

selecting columns with `select()`, helpers

Use case: You want to reorder your columns

```
select(texas_housing_data, city, date,
       sales, listings, everything())
```

```
## # A tibble: 8,602 x 9
##    city     date sales listings  year month   volume mea
##    <chr>   <dbl> <dbl>    <dbl> <int> <int>    <dbl>  <d
##  1 Abilene 2000    72      701  2000     1  5380000  71
##  2 Abilene 2000.   98      746  2000     2  6505000  58
##  3 Abilene 2000.  130      784  2000     3  9285000  58
##  4 Abilene 2000.   98      785  2000     4  9730000  68
##  5 Abilene 2000.  141      794  2000     5 10590000  67
##  6 Abilene 2000.  156      780  2000     6 13910000  66
##  7 Abilene 2000.  152      742  2000     7 12635000  73
##  8 Abilene 2001.  131      765  2000     8 10710000  75
##  9 Abilene 2001.  104      771  2000     9  7615000  64
## 10 Abilene 2001.  101      764  2000    10  7040000  59
## # ... with 8,592 more rows
```

sort rows with `arrange()`

arrange()

storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

storm	wind	pressure	date
Ana	40	1013	1997-07-01
Alex	45	1009	1998-07-30
Arthur	45	1010	1996-06-21
Arlene	50	1010	1999-06-13
Allison	65	1005	1995-06-04
Alberto	110	1007	2000-08-12

sort rows with arrange()

```
arrange(texas_housing_data, year)
```

```
## # A tibble: 8,602 x 9
##    city     year month sales   volume median listings in
##    <chr>   <int> <int> <dbl>    <dbl>  <dbl>    <dbl>
##  1 Abilene  2000     1    72  5380000  71400      701
##  2 Abilene  2000     2    98  6505000  58700      746
##  3 Abilene  2000     3   130  9285000  58100      784
##  4 Abilene  2000     4    98  9730000  68600      785
##  5 Abilene  2000     5   141 10590000  67300      794
##  6 Abilene  2000     6   156 13910000  66900      780
##  7 Abilene  2000     7   152 12635000  73500      742
##  8 Abilene  2000     8   131 10710000  75000      765
##  9 Abilene  2000     9   104  7615000  64500      771
## 10 Abilene  2000    10   101  7040000  59300      764
## # ... with 8,592 more rows
```

sort rows with arrange()

To change the order of use desc()

```
arrange(texas_housing_data, desc(year))
```

```
## # A tibble: 8,602 x 9
##    city       year month sales   volume median listings
##    <chr>     <int> <int> <dbl>    <dbl>  <dbl>    <dbl>
##  1 Abilene    2015     1   158 23486998 134100      801
##  2 Abilene    2015     2   151 19834263 126500      767
##  3 Abilene    2015     3   198 31869437 136800      821
##  4 Abilene    2015     4   201 28301159 129600      891
##  5 Abilene    2015     5   199 31385757 144700      919
##  6 Abilene    2015     6   260 41396230 141500      965
##  7 Abilene    2015     7   268 45845730 148700      986
##  8 Amarillo   2015     1   204 33188726 138500     1120
##  9 Amarillo   2015     2   188 34355428 149400     1084
## 10 Amarillo   2015     3   317 53603130 140900     1051
## # ... with 8,592 more rows
```

Introducing the pipe operator

Interlude: Ceci est une %>%

The pipe %>% operator takes the left-hand side and makes it *input* in the right-hand side.

- by default, the left-hand side is the *first argument* of the right-hand side function.

```
# a tibble is the first argument
select(texas_housing_data, city, year, sales, volume)

texas_housing_data %>%
  select(city, year, sales, volume)
```

Ceci est une %>%

We can chain together tidyverse functions to avoid making so many intermediate data frames!

```
texas_housing_data %>%
  select(city, year, month, median) %>%
  arrange(desc(median))
```

```
## # A tibble: 8,602 x 4
##    city           year month median
##    <chr>         <int> <int>  <dbl>
##  1 Collin County  2015     5 304200
##  2 Collin County  2015     6 300400
##  3 Collin County  2015     7 292600
##  4 Collin County  2015     4 291400
##  5 Collin County  2015     3 285800
##  6 Fort Bend      2015     6 284200
##  7 Collin County  2015     2 283400
##  8 Midland        2014     6 283100
##  9 Fort Bend      2014     6 282300
```

creating columns with `mutate()`

mutate()

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

storm	wind	pressure	date	ratio	inverse
Alberto	110	1007	2000-08-12	9.15	0.11
Alex	45	1009	1998-07-30	22.42	0.04
Allison	65	1005	1995-06-04	15.46	0.06
Ana	40	1013	1997-07-01	25.32	0.04
Arlene	50	1010	1999-06-13	20.20	0.05
Arthur	45	1010	1996-06-21	22.44	0.04

creating columns with mutate()

```
texas_housing_data %>%
  mutate(mean_price = volume / sales) %>%
  select(city, year, month,  mean_price, sales, volume)
```

```
## # A tibble: 8,602 x 6
##    city     year month mean_price sales   volume
##    <chr>   <int> <int>      <dbl> <dbl>    <dbl>
##  1 Abilene  2000     1     74722.    72  5380000
##  2 Abilene  2000     2     66378.    98  6505000
##  3 Abilene  2000     3     71423.   130  9285000
##  4 Abilene  2000     4     99286.    98  9730000
##  5 Abilene  2000     5     75106.   141 10590000
##  6 Abilene  2000     6     89167.   156 13910000
##  7 Abilene  2000     7     83125    152 12635000
##  8 Abilene  2000     8     81756.   131 10710000
##  9 Abilene  2000     9     73221.   104  7615000
## 10 Abilene  2000    10     69703.   101  7040000
## # ... with 8,592 more rows
```

Binary operators: Math in R

R is a calculator! We can do math with numbers, using the following symbols:

```
4 + 4
4 - 4
4 * 4
4 / 4
4 ^ 4
5 %% 4  # gives the remainder after dividing
```

creating columns with `mutate()`

When we mutate, you can create new columns.

- On the right side of the equal sign, you have the name of a new column.
- On the left side, you have code that creates a new column (using vector operations)[1]

```
texas_housing_data %>%
  mutate(mean_price = volume / sales) %>%
  select(city, year, month,  mean_price, sales, volume)
```

```
## # A tibble: 8,602 x 6
##    city     year month mean_price sales   volume
##    <chr>   <int> <int>      <dbl> <dbl>    <dbl>
##  1 Abilene  2000     1     74722.    72  5380000
##  2 Abilene  2000     2     66378.    98  6505000
##  3 Abilene  2000     3     71423.   130  9285000
##  4 Abilene  2000     4     99286.    98  9730000
##  5 Abilene  2000     5     75106.   141 10590000
##  6 Abilene  2000     6     80167.   156 12510000
```

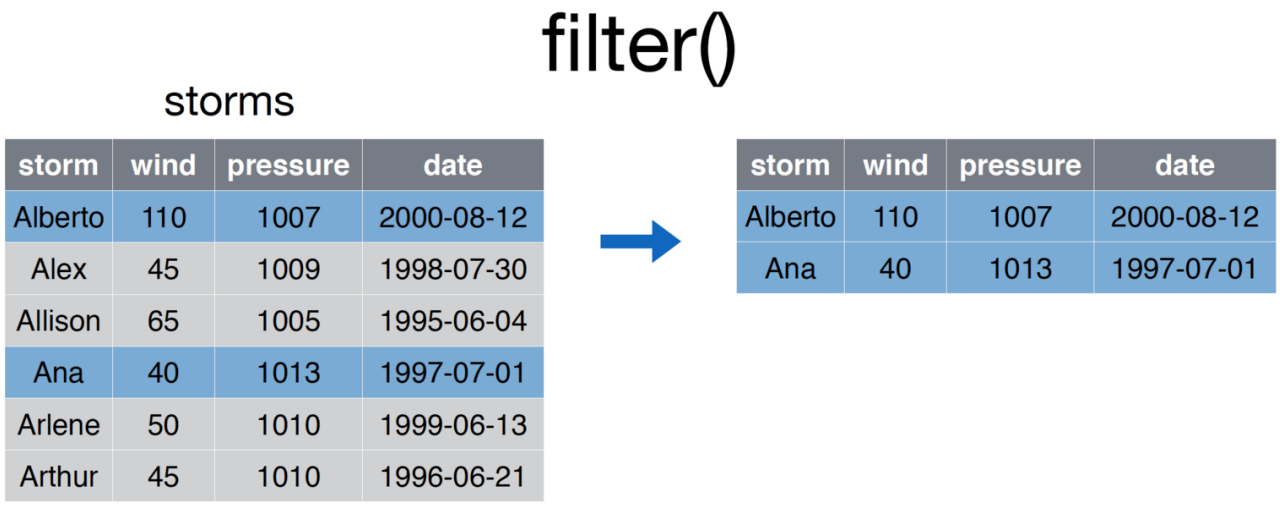
creating columns with `mutate()`

You can create multiple columns at a single time and even use information from a newly created column as input.

```
texas_housing_data %>%
  mutate(mean_price = volume / sales,
         sqrt_mean_price = sqrt(mean_price)) %>%
  select(city, year, month,  mean_price, sales, volume)
```

```
## # A tibble: 8,602 x 6
##    city     year month mean_price sales   volume
##    <chr>   <int> <int>      <dbl> <dbl>    <dbl>
##  1 Abilene  2000     1     74722.    72  5380000
##  2 Abilene  2000     2     66378.    98  6505000
##  3 Abilene  2000     3     71423.   130  9285000
##  4 Abilene  2000     4     99286.    98  9730000
##  5 Abilene  2000     5     75106.   141 10590000
##  6 Abilene  2000     6     89167.   156 13910000
##  7 Abilene  2000     7     83125    152 12635000
##  8 Abilene  2000     8     81756.   131 10710000
```

choose rows that match a condition with `filter()`



choose rows that match a condition with `filter()`

Get all the data from 2013

```
filter(texas_housing_data, year == 2013)
```

```
## # A tibble: 552 x 9
##    city     year month sales   volume median listings in
##    <chr>   <int> <int> <dbl>    <dbl>  <dbl>    <dbl>
##  1 Abilene  2013     1   114 15794494 125300      966
##  2 Abilene  2013     2   140 16552641  94400      943
##  3 Abilene  2013     3   164 19609711 102500      958
##  4 Abilene  2013     4   213 27261796 113700      948
##  5 Abilene  2013     5   225 31901380 130000      923
##  6 Abilene  2013     6   209 29454125 127300      960
##  7 Abilene  2013     7   218 32547446 140000      969
##  8 Abilene  2013     8   236 30777727 120000      976
##  9 Abilene  2013     9   195 26237106 127500      985
## 10 Abilene  2013    10   167 21781187 119000      993
## # ... with 542 more rows
```

Relational operators return TRUE or FALSE

Before moving forward with `filter()`, we need to know about relational operators and logical operators

Operator	Name
<	less than
>	greater than
<=	less than or equal to
>=	greater than or equal to
==	equal to
!=	not equal to
%in%	matches something in

Relational operators in practice

```
4 < 4
```

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

```
4 >= 4
```

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

```
4 == 4
```

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

```
4 != 4
```

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

```
4 %in% c(1, 2, 3)
```

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

logical operators combine TRUEs and FALSEs logically

Operator	Name
!	not
&	and
|	or

```
# not true
! TRUE
```

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

```
# are both x & y TRUE?
TRUE  &  FALSE
```

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

```
# is either x | y TRUE?
TRUE | FALSE
```

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

What do the following return?

Logical operators team up with relational operators.

- First, evaluate the relational operator
- Then, care out the logic.

```
! (4 > 3) # ! TRUE
(5 > 1) & (5 > 2) # TRUE & TRUE
(4 > 10) | (20 > 3) # FALSE | TRUE
```

This is hard to wrap your head around. We'll have plenty of practice!

choose rows that match a condition with `filter()`

Get all the data from 2013 for Houston.

- in `filter()` additional match criteria are treated like `and`

```
texas_housing_data %>%
  filter(year == 2013,
         city == "Houston")
```

```
## # A tibble: 12 x 9
##    city     year month sales     volume median listings
##    <chr>   <int> <int> <dbl>      <dbl>  <dbl>    <dbl>
##  1 Houston  2013     1  4273  852045057 149500    21364
##  2 Houston  2013     2  4886 1060985674 161900    21293
##  3 Houston  2013     3  6382 1479273481 172300    20909
##  4 Houston  2013     4  7116 1770746764 182400    20607
##  5 Houston  2013     5  8439 2121508529 186100    20526
##  6 Houston  2013     6  7935 2073909387 191600    21008
##  7 Houston  2013     7  8468 2168720825 187800    21497
##  8 Houston  2013     8  8155 2083377894 186700    21366
```

choose rows that match a condition with `filter()`

Get all the data from 2013 for Houston or Austin

- in `filter()` additional match criteria are treated like `and`
- we get nothing returned here, because no observation is in Houston AND in Austin.

```
texas_housing_data %>%
  filter(year == 2013,
         city == "Houston", city == "Austin")
```

```
## # A tibble: 0 x 9
## # ... with 9 variables: city <chr>, year <int>, month <i
## #   volume <dbl>, median <dbl>, listings <dbl>, inventor
```

choose rows that match a condition with `filter()`

Get all the data from after than 2013 for Houston OR Austin

```
texas_housing_data %>%
  filter(year > 2013,
         city == "Houston" | city == "Austin")
```

```
## # A tibble: 38 x 9
##    city    year month sales     volume median listings
##    <chr>  <int> <int> <dbl>      <dbl>  <dbl>    <dbl>
##  1 Austin  2014     1  1582  426127544 213700     5118
##  2 Austin  2014     2  1903  550882376 229400     5255
##  3 Austin  2014     3  2434  717821612 235600     5512
##  4 Austin  2014     4  2691  813253968 237000     5838
##  5 Austin  2014     5  3178 1012123948 243900     6539
##  6 Austin  2014     6  3195 1023051880 248900     7040
##  7 Austin  2014     7  3151  982086356 246900     7475
##  8 Austin  2014     8  3023  927019222 243800     7326
##  9 Austin  2014     9  2664  813797562 238900     7072
## 10 Austin  2014    10  2588  796863816 239600     6791
```

choose rows that match a condition with `filter()`

Get all the data from after than 2013 for Houston Galveston

```
texas_housing_data %>%
  filter(year > 2013,
         city %in% c("Houston", "Dallas", "Austin"))
```

```
## # A tibble: 57 x 9
##    city    year month sales     volume median listings
##    <chr>  <int> <int> <dbl>      <dbl>  <dbl>    <dbl>
##  1 Austin  2014     1  1582  426127544 213700     5118
##  2 Austin  2014     2  1903  550882376 229400     5255
##  3 Austin  2014     3  2434  717821612 235600     5512
##  4 Austin  2014     4  2691  813253968 237000     5838
##  5 Austin  2014     5  3178 1012123948 243900     6539
##  6 Austin  2014     6  3195 1023051880 248900     7040
##  7 Austin  2014     7  3151  982086356 246900     7475
##  8 Austin  2014     8  3023  927019222 243800     7326
##  9 Austin  2014     9  2664  813797562 238900     7072
## 10 Austin  2014    10  2588  796863816 239600     6791
```

summarize data with `summarize()`

city	particle size	amount ($\mu g/m^3$)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

median
22.5

summarize data with `summarize()`

Calculate total volume of sales in Texas from 2014.

```
texas_housing_data %>%
  filter(year == 2014) %>%
  summarize(total_volume = sum(volume))
```

```
## # A tibble: 1 x 1
##   total_volume
##          <dbl>
## 1  84760948831
```

summarize data with `summarize()`

Calculate the mean and median number of sales in Texas's three largest cities.

```
texas_housing_data %>%
  filter(city %in%
           c("Houston", "Dallas", "San Antonio")) %>%
  summarize(median_n_sales = median(sales),
            mean_n_sales = mean(sales))
```

```
## # A tibble: 1 x 2
##   median_n_sales mean_n_sales
##            <dbl>        <dbl>
## 1           3996        3890.
```

summarize data with `summarize()`

There are many useful functions that go with summarize. Try `?summarize` for more.

```
texas_housing_data %>%
  filter(city %in%
           c("Houston", "Dallas", "San Antonio")) %>%
  summarize(n_obs = n(),
            n_cities = n_distinct(city))
```

```
## # A tibble: 1 x 2
##   n_obs n_cities
##   <int>    <int>
## 1   561        3
```

summarize data with `summarize()`

If you try to make a summarize statistic that does not collapse the data to a single value (per group), you'll get an error like so:

```
texas_housing_data %>%
  filter(city %in%
           c("Houston", "Dallas", "San Antonio")) %>%
  summarize(mean_price = volume / sales)

Error: Column `mean_price` must be length 1 (a summary valu
```

Get number of observations

Recap: manipulating data with `dplyr`

We learned

- how to employ the 5 `dplyr` verbs of highest importance including
  - `select()` to pick columns
  - `arrange()` to order the data
  - `mutate()` to create new columns
  - `filter()` to get rows that meet a criteria
  - `summarize()` to summarize data
- how to use relation operators, binary operators for math and logical operators in `dplyr` contexts