

# DATA SOCIETY®

Intro to R programming - day 4

*"One should look for what is and not what he thinks should be."  
-Albert Einstein.*

# Module completion checklist

Objective	Complete
Rank data using the arrange function	
Select specific variables, sometimes using specific rules, using the select command	
Derive new variables from the existing variables using the mutate and transmute commands	
Perform multiple functions with the pipe operator (%>%)	
Summarize columns using the summary and group by functions	
Convert wide to long data using tidyr package	
Manipulate columns by using the separate and unite functions	

# Directory settings

- First, let's make sure to set our directories correctly, this way, we will not have to worry about this throughout the course

```
# Set `main_dir` to the location of your `af-werx` folder (for Mac/Linux).  
main_dir = "~/Desktop/af-werx"  
  
# Set `main_dir` to the location of your `af-werx` folder (for Windows).  
main_dir = "C:/Users/[username]/Desktop/af-werx"  
  
# Make `data_dir` from the `main_dir` and  
# remainder of the path to data directory.  
data_dir = paste0(main_dir, "/data")  
  
# Make `plots_dir` from the `main_dir` and  
# remainder of the path to plots directory.  
plot_dir = paste0(main_dir, "/plots")
```

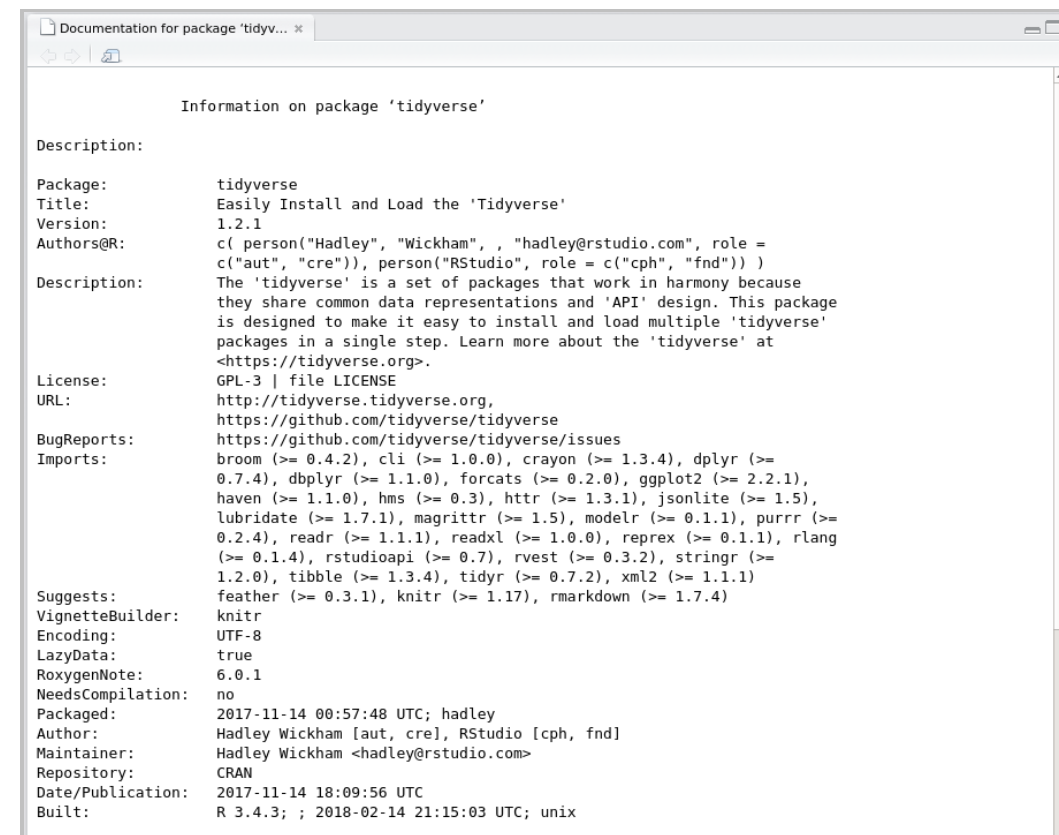
# Set working directory and load data

```
setwd(data_dir)
load("tidyr_tables.RData")

# Load the dataset and save it as 'flights'.
# It is native to R so we can load it like this.
flights = nycflights13::flights
```

# Installing packages

```
# Install package.  
install.packages("tidyverse")  
  
# Load the package into the environment.  
library(tidyverse)  
  
# View package documentation.  
library(help = "tidyverse")
```



# Recap: basics of dplyr

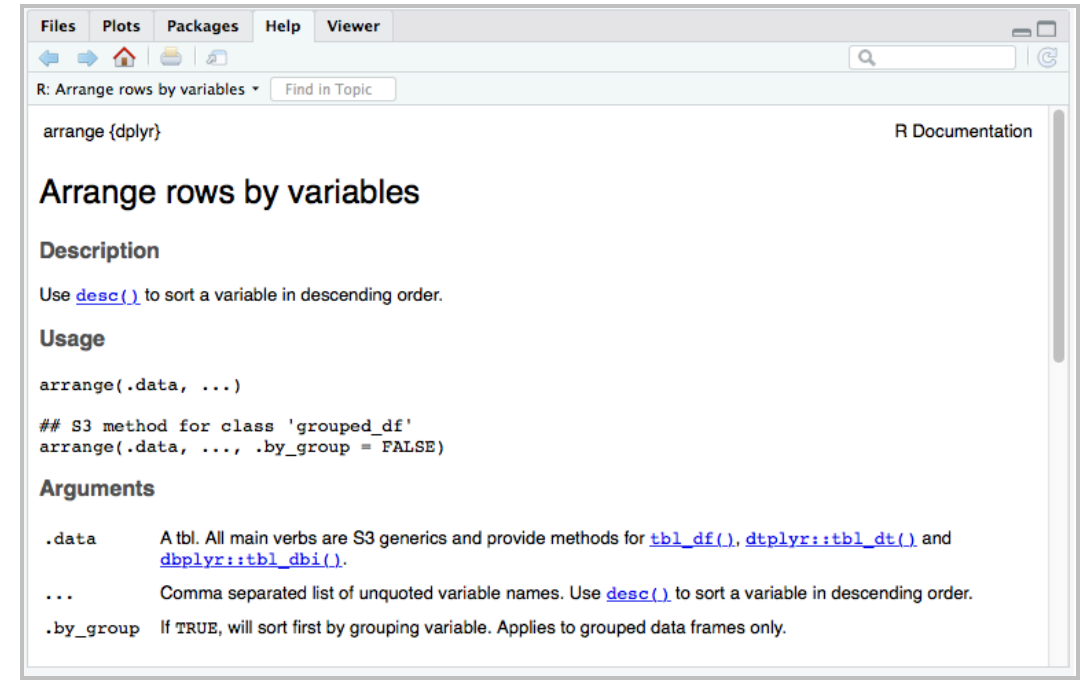
- There are six functions that provide the verbs for the language of data manipulation
- They will most definitely make your life as a data scientist easier
- They are:

Function	Use Case	Data Type
<code>filter</code>	Pick observations by their value	All data types
<code>arrange</code>	Reorder the rows	All data types
<code>select</code>	Pick variables by their names	All data types
<code>mutate</code>	Create new variables with functions of existing variables	All data types
<code>summarise</code>	Collapse many values down to a single summary	All data types
<code>group_by</code>	Allows the first five functions to operate on a dataset group by group	All data types

# Arrange

```
?dplyr::arrange  
  
arrange(df,                #<- dataframe  
        arrange_cond1,    #<- column by which  
        ...,              #   to arrange  
        ...,              #<- other args.)
```

- `arrange` is used to change the order of rows within the specified column(s)
- `arrange` is the equivalent of `sort` in SAS or `order by` in SQL
- When using multiple columns with `arrange`, the additional columns will be used to break ties in the values of preceding columns



# Arrange example

```
# Arrange data by year, then month, and then day.
arrange(flights, #<- dataframe we want to arrange
  year,         #<- 1st: arrange by year
  month,        #<- 2nd: arrange by month
  day)          #<- 3rd: arrange by day
```

```
# A tibble: 336,776 x 19
  year month   day dep_time sched_dep_time dep_delay arr_time
  <int> <int> <int>   <int>         <int>         <dbl>   <int>
1  2013     1     1     517             515           2       830
2  2013     1     1     533             529           4       850
3  2013     1     1     542             540           2       923
4  2013     1     1     544             545          -1      1004
5  2013     1     1     554             600          -6       812
6  2013     1     1     554             558          -4       740
7  2013     1     1     555             600          -5       913
8  2013     1     1     557             600          -3       709
9  2013     1     1     557             600          -3       838
10 2013     1     1     558             600          -2       753
# ... with 336,766 more rows, and 12 more variables: sched_arr_time <int>,
#   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
#   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
#   minute <dbl>, time_hour <dtm>
```



# Arrange options

- arrange by default sorts everything in ascending order; to arrange in descending, use desc

```
# Arrange data by year, descending month and then day.
arrange(flights,      #<- dataframe we want to arrange
        year,        #<- 1st: arrange by year
        desc(month), #<- 2nd: arrange by month in descending order
        day)         #<- 3rd: arrange by day
```

```
# A tibble: 336,776 x 19
   year month   day dep_time sched_dep_time dep_delay arr_time
  <int> <int> <int>   <int>         <int>         <dbl>   <int>
1  2013    12     1      13           2359           14     446
2  2013    12     1      17           2359           18     443
3  2013    12     1     453           500           -7     636
4  2013    12     1     520           515            5     749
5  2013    12     1     536           540           -4     845
6  2013    12     1     540           550          -10    1005
7  2013    12     1     541           545           -4     734
8  2013    12     1     546           545            1     826
9  2013    12     1     549           600          -11     648
10 2013    12     1     550           600          -10     825
# ... with 336,766 more rows, and 12 more variables: sched_arr_time <int>,
#   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
#   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
#   minute <dbl>, time_hour <dtm>
```

- You can now see that the month at the top of the dataset is December (i.e. 12th month)

# Arrange with NA values

- Missing values are **always** sorted at the end


```
# Create a dataframe with 2 columns.  
NA_df = data.frame(x = c(1, NA, 2), #<- column x with 3 entries with 1 NA  
                   y = c(1, 2, 3))   #<- column y with 3 entries  
  
# Arrange data with missing values.  
arrange(NA_df, x)
```

```
  x y  
1  1 1  
2  2 3  
3 NA 2
```

```
# Even when we use `desc`, the `NA` is taken to the last row.  
arrange(NA_df, desc(x))
```

```
  x y  
1  2 3  
2  1 1  
3 NA 2
```

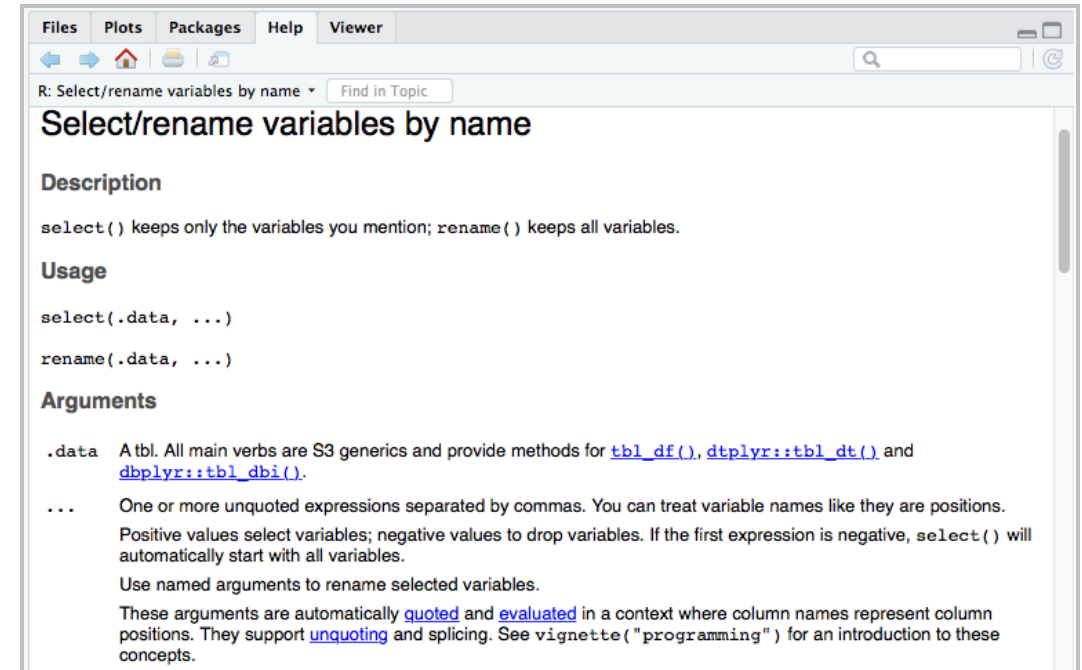
# Module completion checklist

Objective	Complete
Rank data using the arrange function	
Select specific variables, sometimes using specific rules, using the select command	
Derive new variables from the existing variables using the mutate and transmute commands	
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Summarize columns using the summary and group by functions	
Convert wide to long data using tidyr package	
Manipulate columns by using the separate and unite functions	

# Select

```
?dplyr::select  
  
select(df,           #<- dataframe  
       select_cond1, #<- selection rule(s)  
       ...)
```

- `select` helps you select specific columns within your dataframe
- We often use this function with pipes. We will cover pipes (`%>%`) later in this lesson
- The selection criteria can be written in multiple ways, shown in the next couple of slides



The screenshot shows the R help interface for the `select` function. The title is "Select/rename variables by name". The description states: "select() keeps only the variables you mention; rename() keeps all variables." The usage section shows: `select(.data, ...)` and `rename(.data, ...)`. The arguments section defines `.data` as a tibble and `...` as unquoted expressions. It also mentions that arguments are automatically quoted and evaluated.

**R: Select/rename variables by name**

**Select/rename variables by name**

**Description**

`select()` keeps only the variables you mention; `rename()` keeps all variables.

**Usage**

```
select(.data, ...)  
rename(.data, ...)
```

**Arguments**

`.data` A tibble. All main verbs are S3 generics and provide methods for `tbl_df()`, `dtplyr::tbl_dt()` and `dbplyr::tbl_dbi()`.

`...` One or more unquoted expressions separated by commas. You can treat variable names like they are positions. Positive values select variables; negative values to drop variables. If the first expression is negative, `select()` will automatically start with all variables.

Use named arguments to rename selected variables.

These arguments are automatically [quoted](#) and [evaluated](#) in a context where column names represent column positions. They support [unquoting](#) and splicing. See [vignette\("programming"\)](#) for an introduction to these concepts.

# Select a subset

- You can simply specify each column name

```
# Select columns from `flights` dataframe.
select(flights, #<- specify the dataframe
        year,   #<- specify the 1st column
        month,  #<- specify the 2nd column
        day)    #<- specify the 3rd column
```

```
# A tibble: 336,776 x 3
   year month   day
  <int> <int> <int>
1  2013     1     1
2  2013     1     1
3  2013     1     1
4  2013     1     1
5  2013     1     1
6  2013     1     1
7  2013     1     1
8  2013     1     1
9  2013     1     1
10 2013     1     1
# ... with 336,766 more rows
```

- You can also specify a range of columns with the range operator (i.e. :)

```
# Select columns from `flights` dataframe.
select(flights, #<- specify dataframe
        year:day) #<- specify range of cols
```

```
# A tibble: 336,776 x 3
   year month   day
  <int> <int> <int>
1  2013     1     1
2  2013     1     1
3  2013     1     1
4  2013     1     1
5  2013     1     1
6  2013     1     1
7  2013     1     1
8  2013     1     1
9  2013     1     1
10 2013     1     1
# ... with 336,766 more rows
```

# Select by excluding

- Finally, you can select by excluding certain columns using the exclusion operator (i.e. -)

```
# Select multiple columns from `flights` dataframe
# by providing which columns to exclude in selection.
select(flights,          #<- specify the dataframe
       -(year:day))    #<- specify the range of columns to exclude
```

```
# A tibble: 336,776 x 16
  dep_time sched_dep_time dep_delay arr_time sched_arr_time arr_delay
  <int>      <int>      <dbl>    <int>      <int>      <dbl>
1     517         515          2      830         819          11
2     533         529          4      850         830          20
3     542         540          2      923         850          33
4     544         545         -1     1004        1022         -18
5     554         600         -6      812         837         -25
6     554         558         -4      740         728          12
7     555         600         -5      913         854          19
8     557         600         -3      709         723         -14
9     557         600         -3      838         846          -8
10    558         600         -2      753         745           8
# ... with 336,766 more rows, and 10 more variables: carrier <chr>,
# flight <int>, tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>,
# distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dtm>
```

# Helper functions for select

- There are multiple functions you can use with `select` that act like `regex` but in a more simplified manner
- Here are some of the more commonly used helper functions:

Helper Function	Use Case
<code>starts_with("abc")</code>	matches names that begin with "abc"
<code>ends_with("xyz")</code>	matches names that end with "xyz"
<code>contains("ijk")</code>	matches names that contain "ijk"
<code>num_range("x", 1:3)</code>	matches "x1", "x2" and "x3"

# Knowledge check 1





# Exercise 1



# Module completion checklist

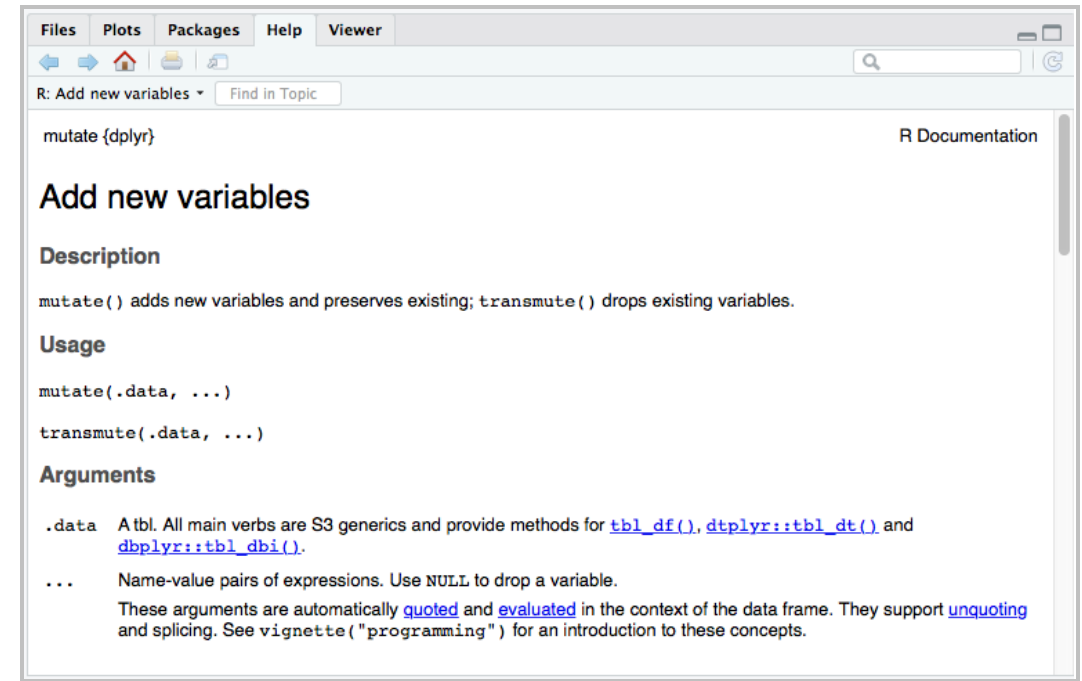
Objective	Complete
Rank data using the arrange function	✓
Select specific variables, sometimes using specific rules, using the select command	✓
Derive new variables from the existing variables using the mutate and transmute commands	
Perform multiple functions with the pipe operator (%>%)	
Summarize columns using the summary and group by functions	
Convert wide to long data using tidyr package	
Manipulate columns by using the separate and unite functions	

# Mutate

```
?dplyr::mutate
```

```
mutate(df,           # <- dataframe  
       new_col1,    # <- rule(s) for new col  
       ...)
```

- `mutate` is an essential function to `dplyr`, it allows us to create new variables using the current data and append these variables to the existing dataframe
- `Mutate` always adds columns to the end of the dataset, so we want to be able to see the last columns



# Mutate

- Create the dataset using select

```
# Let's select columns of `flights` dataframe and save them as `flights_sml`.
flights_sml = select(flights,           #<- specify dataframe
                     year:day,         #<- specify range of columns to include
                     ends_with("delay"), #<- find all columns that end with `delay`
                     distance,         #<- select `distance` column
                     air_time)         #<- select `air_time` column

flights_sml
```

```
# A tibble: 336,776 x 7
   year month   day dep_delay arr_delay distance air_time
  <int> <int> <int>   <dbl>   <dbl>   <dbl>   <dbl>
1  2013     1     1         2        11    1400     227
2  2013     1     1         4        20    1416     227
3  2013     1     1         2        33    1089     160
4  2013     1     1        -1       -18    1576     183
5  2013     1     1        -6       -25     762     116
6  2013     1     1        -4        12     719     150
7  2013     1     1        -5        19    1065     158
8  2013     1     1        -3       -14     229      53
9  2013     1     1        -3        -8     944     140
10 2013     1     1        -2         8     733     138
# ... with 336,766 more rows
```

# Adding to the dataframe

1. The first argument is the dataframe
2. The following arguments are the columns that we would like to add to the dataframe

```
# Add two columns `gain` and `speed` to `flights_sml`.
mutate(flights_sml,                                #<- specify the dataframe
      gain = arr_delay - dep_delay,                 #<- create `gain` column by subtracting departure delay
                                              # from arrival delay
      speed = distance / air_time * 60)             #<- create `speed` from distance and air time columns
```

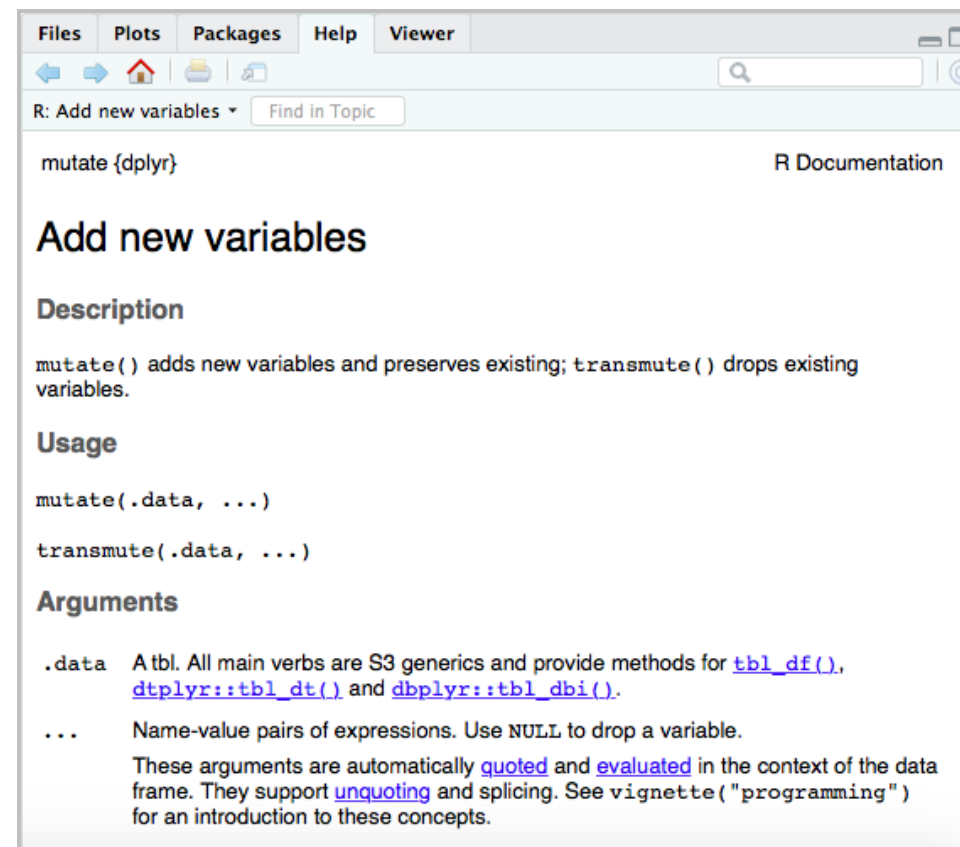
```
# A tibble: 336,776 x 9
   year month   day dep_delay arr_delay distance air_time gain speed
  <int> <int> <int>   <dbl>   <dbl>   <dbl>   <dbl> <dbl> <dbl>
1  2013     1     1         2        11    1400    227     9   370.
2  2013     1     1         4        20    1416    227    16   374.
3  2013     1     1         2        33    1089    160    31   408.
4  2013     1     1        -1       -18    1576    183   -17   517.
5  2013     1     1        -6       -25     762    116   -19   394.
6  2013     1     1        -4        12     719    150    16   288.
7  2013     1     1        -5        19    1065    158    24   404.
8  2013     1     1        -3       -14     229     53   -11   259.
9  2013     1     1        -3        -8     944    140    -5   405.
10 2013     1     1        -2         8     733    138    10   319.
# ... with 336,766 more rows
```

# Transmute

```
transmute(df,      # <- dataframe  
          new_coll, # <- rule(s) for new column  
          ...)
```

- `transmute` is a function that does the same thing as `mutate` except that it will only keep the new columns
- The 1st argument is the dataframe
- The following arguments are the columns that will be created in your new dataframe

**REMEMBER: you are isolating only these new columns**



# Transmute example

- Only returns the new columns

```
# Add two columns `gain` and `speed` to `flights_sml`.
example = transmute(flights_sml,           #<- specify the dataframe
  gain = arr_delay - dep_delay,           #<- create `gain` column by subtracting departure delay
                                           #   from arrival delay
  speed = distance / air_time * 60)       #<- create `speed` from distance and air time columns
example
```

```
# A tibble: 336,776 x 2
   gain speed
  <dbl> <dbl>
1      9  370.
2     16  374.
3     31  408.
4    -17  517.
5    -19  394.
6     16  288.
7     24  404.
8    -11  259.
9      -5  405.
10     10  319.
# ... with 336,766 more rows
```

# Useful functions for mutate and transmute

When creating new variables with `mutate`, there are many helpful functions that can assist in creating interesting features:

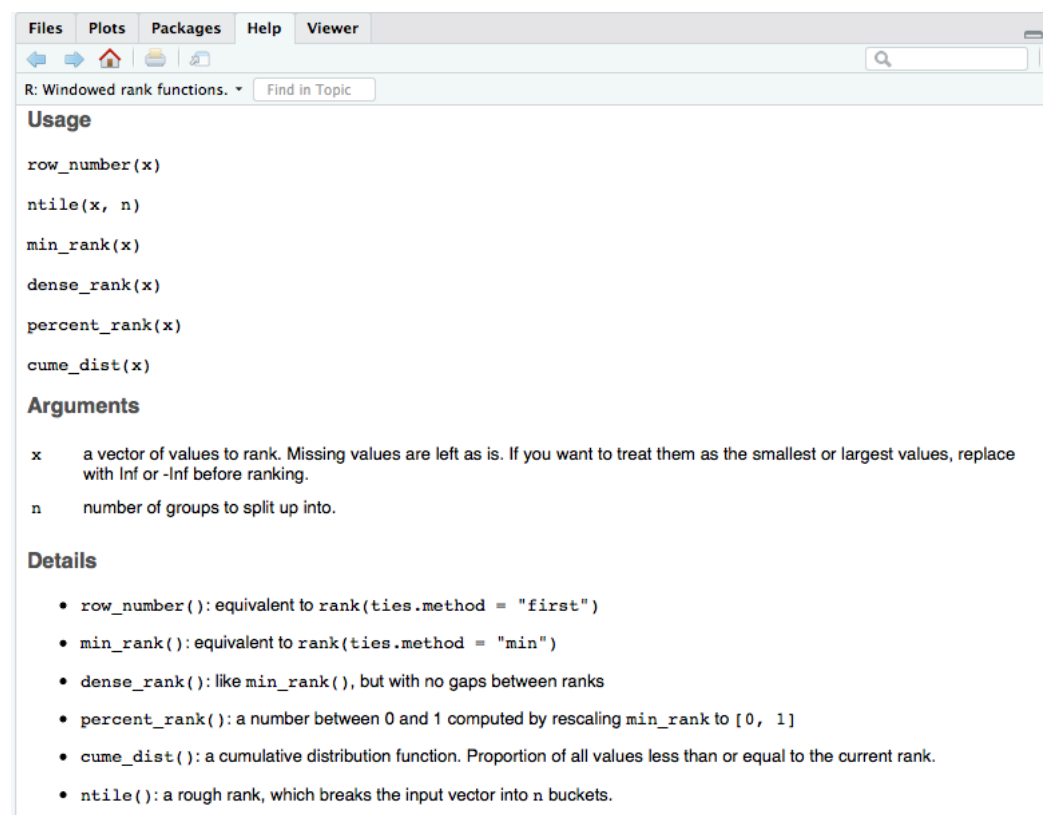
Useful Functions	Explanation
<code>+, -, *, /, ^</code>	all mathematic operators can be used on variables
<code>log, log2, log10</code>	logarithmic functions for variable transformation can be used
<code>%/%</code> and <code>%%</code>	modulus and remainder are useful when converting time
<code>lag(x)</code> and <code>lead(x)</code>	lag and lead allow reference to leading or lagging values - useful for detecting changes in values
<code>cumsum(x)</code> , <code>cummean(x)</code> , <code>cummax(x)</code> , <code>cumprod(x)</code>	cumulative, running functions, mins, max, prod, mean, etc.



# Useful functions for mutate & transmute cont'd

```
?dplyr::ranking  
  
rank_function(x) #<- a rank function with  
                #   vector of values
```

- Ranking functions are very helpful; there are several within the `dplyr` package that you can use



The screenshot shows the R help window for the `dplyr::ranking` package. The title bar includes 'Files', 'Plots', 'Packages', 'Help', and 'Viewer'. The main content area is titled 'R: Windowed rank functions.' and contains the following sections:

- Usage**
  - `row_number(x)`
  - `ntile(x, n)`
  - `min_rank(x)`
  - `dense_rank(x)`
  - `percent_rank(x)`
  - `cume_dist(x)`
- Arguments**
  - `x`: a vector of values to rank. Missing values are left as is. If you want to treat them as the smallest or largest values, replace with `Inf` or `-Inf` before ranking.
  - `n`: number of groups to split up into.
- Details**
  - `row_number()`: equivalent to `rank(ties.method = "first")`
  - `min_rank()`: equivalent to `rank(ties.method = "min")`
  - `dense_rank()`: like `min_rank()`, but with no gaps between ranks
  - `percent_rank()`: a number between 0 and 1 computed by rescaling `min_rank` to `[0, 1]`
  - `cume_dist()`: a cumulative distribution function. Proportion of all values less than or equal to the current rank.
  - `ntile()`: a rough rank, which breaks the input vector into `n` buckets.

# Exercise 2



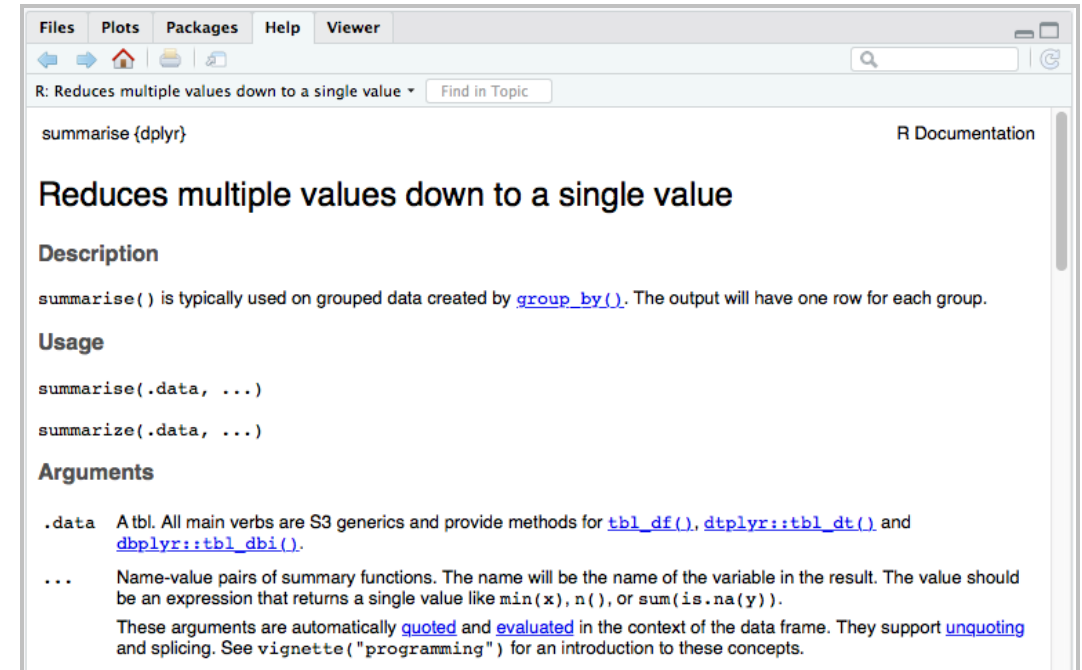
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Objective	Complete
Rank data using the arrange function	✓
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# Summarise and group\_by

```
?dplyr::summarise  
  
summarise(df,                #<- dataframe  
           summary_func1,    #<- summary rule(s)  
           ...               #   for new col  
           )
```

- `summarise` collapses a dataframe to a single row
- By itself, `summarise` is not very helpful. We will usually use it with `group_by`



The screenshot shows the R Documentation page for `summarise` from the `dplyr` package. The page title is "summarise {dplyr}" and it is categorized under "R Documentation". The main heading is "Reduces multiple values down to a single value". The "Description" section states that `summarise()` is typically used on grouped data created by `group_by()`, and the output will have one row for each group. The "Usage" section shows two function signatures: `summarise(.data, ...)` and `summarize(.data, ...)`. The "Arguments" section describes the parameters: `.data` is a `tbl` object, and `...` represents name-value pairs of summary functions. It also mentions that arguments are automatically quoted and evaluated in the context of the data frame.

Files Plots Packages Help Viewer

R: Reduces multiple values down to a single value Find in Topic

summarise {dplyr} R Documentation

## Reduces multiple values down to a single value

### Description

`summarise()` is typically used on grouped data created by `group_by()`. The output will have one row for each group.

### Usage

```
summarise(.data, ...)  
summarize(.data, ...)
```

### Arguments

`.data` A `tbl`. All main verbs are S3 generics and provide methods for `tbl_df()`, `dtplyr::tbl_dt()` and `dbplyr::tbl_dbi()`.

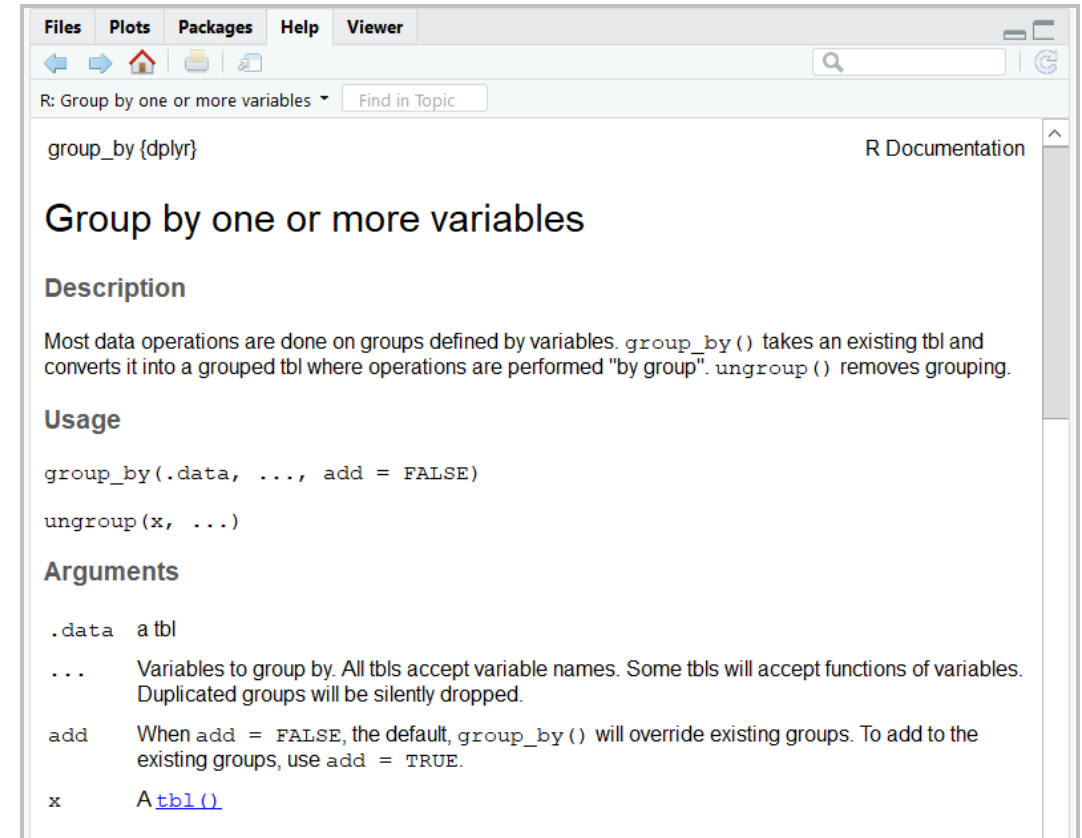
`...` Name-value pairs of summary functions. The name will be the name of the variable in the result. The value should be an expression that returns a single value like `min(x)`, `n()`, or `sum(is.na(y))`. These arguments are automatically `quoted` and `evaluated` in the context of the data frame. They support `unquoting` and `splicing`. See `vignette("programming")` for an introduction to these concepts.

# Understanding grouping

```
?dplyr::group_by

group_by(df,          #<- dataframe
  variable1, #<- 1st var to group by
  variable2, #<- 2nd var to group by
  ...)
```

- Grouping doesn't change how the data looks (apart from listing how it's grouped).
- It changes how it acts with the other dplyr verbs.
- To removing grouping, use `ungroup`.

A screenshot of the R Documentation window for the `group_by` function from the `dplyr` package. The window has a menu bar with 'Files', 'Plots', 'Packages', 'Help', and 'Viewer'. Below the menu bar is a search bar and a dropdown menu showing 'R: Group by one or more variables'. The main content area displays the function signature `group_by {dplyr}` and the title 'Group by one or more variables'. Under the 'Description' section, it states that most data operations are done on groups defined by variables, and `group_by()` takes an existing `tbl` and converts it into a grouped `tbl` where operations are performed "by group". The 'Usage' section shows the functions `group_by(.data, ..., add = FALSE)` and `ungroup(x, ...)`. The 'Arguments' section lists the parameters: `.data` (a `tbl`), `...` (Variables to group by), `add` (When `add = FALSE`, the default, `group_by()` will override existing groups), and `x` (A `tbl()`).

# Summarise and group\_by alone

```
# Produce a summary.  
summarise(flights, delay = mean(dep_delay, na.rm = TRUE))
```

```
# A tibble: 1 x 1  
  delay  
  <dbl>  
1  12.6
```

```
# Create `by_day` by grouping `flights` by year, month, and day.  
by_day = group_by(flights, year, month, day)  
by_day
```

```
# A tibble: 336,776 x 19  
# Groups:   year, month, day [365]  
   year month   day dep_time sched_dep_time dep_delay arr_time  
   <int> <int> <int>   <int>         <int>         <dbl>   <int>  
1  2013     1     1     517           515           2     830  
2  2013     1     1     533           529           4     850  
3  2013     1     1     542           540           2     923  
4  2013     1     1     544           545          -1    1004  
5  2013     1     1     554           600          -6     812  
6  2013     1     1     554           558          -4     740  
7  2013     1     1     555           600          -5     913  
8  2013     1     1     557           600          -3     709  
9  2013     1     1     557           600          -3     838  
10 2013     1     1     558           600          -2     753  
# ... with 336,766 more rows, and 12 more variables: sched_arr_time <int>,  
#   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,  
#   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>
```

# Summarise and group\_by together

```
# Now use grouped `by_day` data and summarise it to  
# see the average delay by year, month and day.  
summarise(by_day, delay = mean(dep_delay, na.rm = TRUE))
```

```
# A tibble: 365 x 4  
# Groups:   year, month [12]  
  year month   day delay  
  <int> <int> <int> <dbl>  
1  2013     1     1  11.5  
2  2013     1     2  13.9  
3  2013     1     3  11.0  
4  2013     1     4   8.95  
5  2013     1     5   5.73  
6  2013     1     6   7.15  
7  2013     1     7   5.42  
8  2013     1     8   2.55  
9  2013     1     9   2.28  
10 2013     1    10   2.84  
# ... with 355 more rows
```

- summarise and group\_by are two of the most used functions within dplyr!

# Dplyr and the pipe: without it

Now we get to the best part, connecting it all. Let's say we want to do these three things:

1. Group flights by destination
2. Summarise to compute distance, average delay, and number of flights
3. Filter to remove noisy points and Honolulu airport, which is almost twice as far away as the next closest airport

We might think we have to write out a `dplyr` function for each, save each as a variable and then perform the next function, which should look something like this:

```
# Step 1: Create a new grouped data
frame `by_dest`.
by_dest = group_by(flights, dest)

# Step 2: Create a summary of `by_dest` and save as `delay`.
delay = summarise(by_dest,
                  count = n(),
                  dist = mean(distance, na.rm = TRUE),
                  delay = mean(arr_delay, na.rm = TRUE))

# Step 3: Filter `delay` by their count and destination.
delay = filter(delay, count > 20, dest != "HNL")
```



# Dplyr and the pipe: a better way

- Sure, that works, but can we do it cleaner? Faster? - **YES!**
- We can use the pipe operator (i.e. %>%) and do it all in a single step without creating extra variables

```
delays = flights %>%  
  group_by(dest) %>%  
  summarise(count = n(),  
            dist = mean(distance, na.rm = TRUE),  
            delay = mean(arr_delay, na.rm = TRUE)) %>%  
  filter(count > 20, dest != "HNL")  
delays
```

#<- take flights data  
#<- group it by destination  
#<- then summarize by creating count variable  
#<- and computing mean distance  
#<- and mean arrival delay  
#<- then filter it

```
# A tibble: 96 x 4  
  dest    count    dist delay  
  <chr> <int> <dbl> <dbl>  
1 ABQ      254  1826   4.38  
2 ACK      265   199   4.85  
3 ALB      439   143  14.4  
4 ATL    17215   757.  11.3  
5 AUS     2439  1514.   6.02  
6 AVL      275   584.   8.00  
7 BDL      443   116   7.05  
8 BGR      375   378   8.03  
9 BHM      297   866.  16.9  
10 BNA     6333   758.  11.8  
# ... with 86 more rows
```

# Module completion checklist

Objective	Complete
Rank data using the arrange function	✓
Select specific variables, sometimes using specific rules, using the select command	✓
Derive new variables from the existing variables using the mutate and transmute commands	✓
Perform multiple functions with the pipe operator (%>%)	✓
Summarize columns using the summary and group by functions	
Convert wide to long data using tidyr package	
Manipulate columns by using the separate and unite functions	

# Summarise and handling NAs

## We do NOT address NAs

```
flights %>%  
  group_by(year, month, day) %>%  
  summarise(mean = mean(dep_delay))
```

```
# A tibble: 365 x 4  
# Groups:   year, month [12]  
  year month   day mean  
  <int> <int> <int> <dbl>  
1  2013     1     1   NA  
2  2013     1     2   NA  
3  2013     1     3   NA  
4  2013     1     4   NA  
5  2013     1     5   NA  
6  2013     1     6   NA  
7  2013     1     7   NA  
8  2013     1     8   NA  
9  2013     1     9   NA  
10 2013     1    10   NA  
# ... with 355 more rows
```

- If we do not address NAs, the aggregation functions will return NAs for each item if there is just one NA in the input

## We address NAs

```
flights %>%  
  group_by(year, month, day) %>%  
  summarise(mean = mean(dep_delay,  
                      na.rm = TRUE))
```

```
# A tibble: 365 x 4  
# Groups:   year, month [12]  
  year month   day mean  
  <int> <int> <int> <dbl>  
1  2013     1     1 11.5  
2  2013     1     2 13.9  
3  2013     1     3 11.0  
4  2013     1     4  8.95  
5  2013     1     5  5.73  
6  2013     1     6  7.15  
7  2013     1     7  5.42  
8  2013     1     8  2.55  
9  2013     1     9  2.28  
10 2013     1    10  2.84  
# ... with 355 more rows
```

- Moral of the story: remember to address NAs when using summarise!

# A few more useful summary functions

Summary Functions	Explanation
<code>n()</code>	Will count the number of entries that come from a summarise
<code>min(x), quantile(x, 0.25), max(x)</code>	Measures of rank and distribution can be used
<code>first(x), nth(x, 2), last(x)</code>	Measures of position and order
<code>n_distinct</code>	Will count the number of distinct values

# Summarise n to count

n will count the number of entries that come from a summarise function

```
flights %>%
  group_by(year, month, day) %>%
  summarise(mean = mean(dep_delay, na.rm = TRUE),
            n = n()) #<- add a column with summary counts
```

```
# A tibble: 365 x 5
# Groups:   year, month [12]
   year month   day mean     n
  <int> <int> <int> <dbl> <int>
1  2013     1     1  11.5   842
2  2013     1     2  13.9   943
3  2013     1     3  11.0   914
4  2013     1     4   8.95   915
5  2013     1     5   5.73   720
6  2013     1     6   7.15   832
7  2013     1     7   5.42   933
8  2013     1     8   2.55   899
9  2013     1     9   2.28   902
10 2013     1    10   2.84   932
# ... with 355 more rows
```

# Actually, we do not need summarise to count

count is a function to just count, even if you have not used a summary function

```
flights %>%  
  count(day) #<- count number of instances of entry in `day` column
```

```
# A tibble: 31 x 2  
  day     n  
  <int> <int>  
1     1 11036  
2     2 10808  
3     3 11211  
4     4 11059  
5     5 10858  
6     6 11059  
7     7 10985  
8     8 11271  
9     9 10857  
10    10 11227  
# ... with 21 more rows
```

# Summarise rank

Measures of rank: `min(x)`, `quantile(x, 0.25)`, `max(x)`

```
flights %>%  
  group_by(year, month) %>%  
  summarise(first = min(dep_time, na.rm = TRUE),  
            last = max(dep_time, na.rm = TRUE))
```

```
# A tibble: 12 x 4  
# Groups:   year [1]  
   year month first last  
   <int> <int> <dbl> <dbl>  
1  2013     1     1 2359  
2  2013     2     1 2400  
3  2013     3     1 2400  
4  2013     4     1 2400  
5  2013     5     1 2400  
6  2013     6     1 2400  
7  2013     7     1 2400  
8  2013     8     1 2400  
9  2013     9     2 2400  
10 2013    10     6 2400  
11 2013    11     1 2400  
12 2013    12     1 2400
```

# Summarise position

```
# 1. Build a subset of all flights that were not cancelled.
not_cancelled = flights %>%
  filter(!is.na(dep_time)) #<- filter flights where `dep_time` was not `NA`

# 2. Group and summarize all flights that were not cancelled to get desired results.
not_cancelled %>%
  group_by(year, month, day) %>% #<- group the not cancelled flights
  summarise(first = min(dep_time), #<- then summarise them by calculating the first
            last = max(dep_time)) #<- and last flights in the `dep_time` in each group
```

```
# A tibble: 365 x 5
# Groups:   year, month [12]
   year month   day first last
  <int> <int> <int> <dbl> <dbl>
1  2013     1     1    517  2356
2  2013     1     2     42  2354
3  2013     1     3     32  2349
4  2013     1     4     25  2358
5  2013     1     5     14  2357
6  2013     1     6     16  2355
7  2013     1     7     49  2359
8  2013     1     8    454  2351
9  2013     1     9      2  2252
10 2013     1    10      3  2320
# ... with 355 more rows
```



# Summarise distinct values

`n_distinct(x)` will count the number of distinct values

```
# Number of flights that take off, by day.  
not_cancelled %>%  
  group_by(year, month, day) %>%  
  summarise(flights_that_take_off = n_distinct(dep_time)) #<- calculate distinct departure times
```

```
# A tibble: 365 x 4  
# Groups:   year, month [12]  
   year month   day flights_that_take_off  
   <int> <int> <int>          <int>  
1  2013     1     1            552  
2  2013     1     2            583  
3  2013     1     3            589  
4  2013     1     4            589  
5  2013     1     5            495  
6  2013     1     6            564  
7  2013     1     7            572  
8  2013     1     8            573  
9  2013     1     9            580  
10 2013     1    10            572  
# ... with 355 more rows
```

# Remember to ungroup before you regroup

```
# Take the same `not_cancelled` data, but now group by month instead of by day.
not_cancelled %>%                                     #<- set dataframe
  ungroup() %>%                                       #<- first ungroup it
  group_by(year, month) %>%                           #<- then group by year and month
  summarise(flights_by_year = n_distinct(dep_time)) #<- then do the rest ...
```

```
# A tibble: 12 x 3
# Groups:   year [1]
   year month flights_by_year
  <int> <int>         <int>
1  2013     1         1165
2  2013     2         1171
3  2013     3         1199
4  2013     4         1216
5  2013     5         1186
6  2013     6         1220
7  2013     7         1242
8  2013     8         1204
9  2013     9         1156
10 2013    10         1139
11 2013    11         1135
12 2013    12         1191
```

# Knowledge check 2



# Exercise 3



# Module completion checklist

Objective	Complete
Rank data using the arrange function	✓
Select specific variables, sometimes using specific rules, using the select command	✓
Derive new variables from the existing variables using the mutate and transmute commands	✓
Perform multiple functions with the pipe operator (%>%)	✓
Summarize columns using the summary and group by functions	✓
Convert wide to long data using tidyr package	
Manipulate columns by using the separate and unite functions	

# Defining data wrangling

- Data transformation prepares the dataset for wrangling
- We want all the variables and values, all the new columns to be created, and all the NAs taken care of before making sure it is in `tidy` form
- `tidyr`, the package within `tidyverse`, allows us to get our data into tidy format!
- We will use the `tidyr_tables.Rdata` file that we loaded at the beginning of the lesson
- For further reading and understanding of tidy data and where it originated, check out this link:  
<http://www.jstatsoft.org/v59/i10/paper>

# Would analysis of these datasets be easy?

key\_value\_country

```
# A tibble: 12 x 4
  country    year key      value
  <fct>    <int> <fct>    <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
```

year\_country

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

rate\_country

```
# A tibble: 6 x 3
  country    year rate
  <fct>    <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
```

# What makes data 'tidy'?

- Three interrelated rules make a dataset tidy:
  - Each variable must have its own column
  - Each observation must have its own row
  - Each value must have its own cell

- `tidy_country` is the only table that follows all 3 rules

`tidy_country`

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



# What are the advantages of tidy data?

- Consistent way of storing data: it's easier to learn the tools that work with it because of the underlying uniformity
- Making use of R's internal vectorization: most built-in R functions work with vectors of values
- Making use of `spread` and `gather`: the functions of `tidyr` that will help you transform `messy` data to `tidy` data

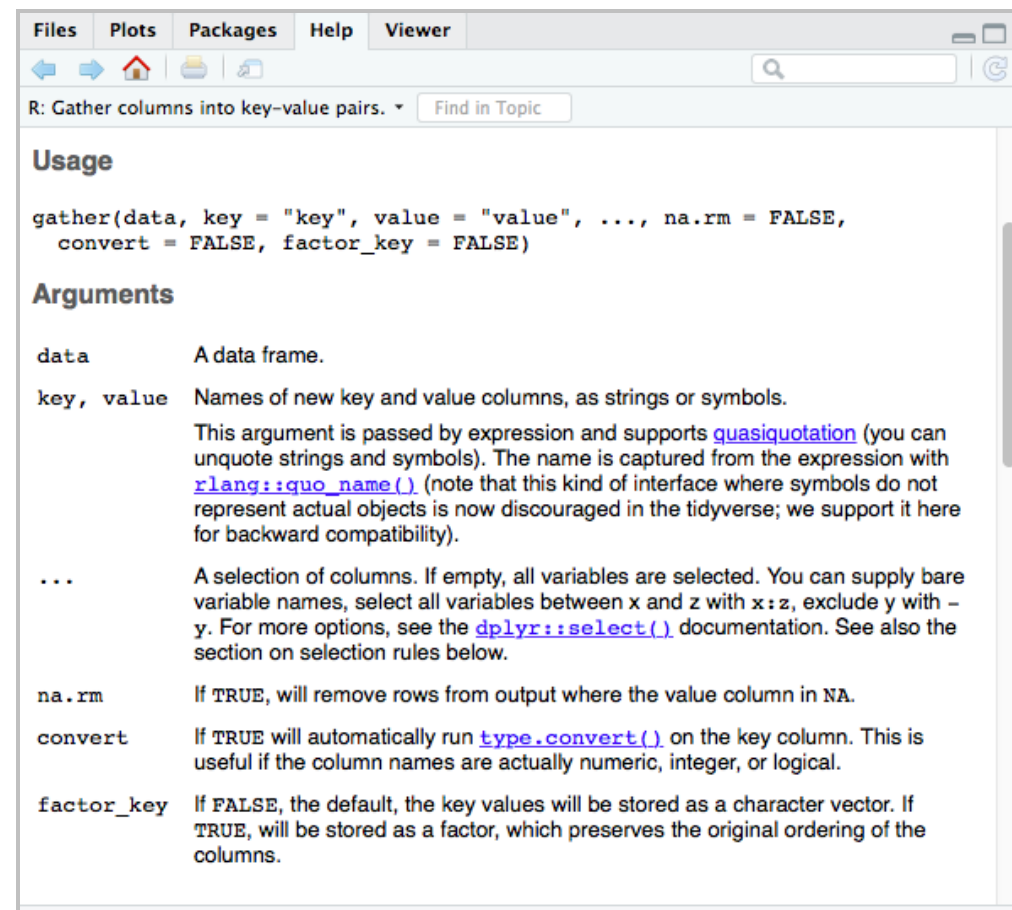
# Gathering

- `gather` pulls multiple columns into one new variable

```
?dplyr::gather
```

```
gather(df,      #<- dataframe  
       key,     #<- name of new key column  
       value ) #<- name of new value column
```

- We need three parameters to describe the operation of `gather`:
  - The columns that represent the values
  - The name of the variable (the `key`) that represents those values
  - The name of the variable (the `value`) that represents the values that are currently within the value columns



The screenshot shows the RStudio interface with the documentation for `dplyr::gather` open in the Viewer pane. The title bar indicates the topic is "R: Gather columns into key-value pairs." The documentation includes a "Usage" section with the function signature: `gather(data, key = "key", value = "value", ..., na.rm = FALSE, convert = FALSE, factor_key = FALSE)`. Below this is an "Arguments" section that defines each parameter: `data` is a data frame; `key, value` are names of new columns; `...` is a selection of columns; `na.rm` is a logical value to remove NA values; `convert` is a logical value to automatically convert the key column; and `factor_key` is a logical value to store key values as a factor.

**Usage**

```
gather(data, key = "key", value = "value", ..., na.rm = FALSE,  
       convert = FALSE, factor_key = FALSE)
```

**Arguments**

<code>data</code>	A data frame.
<code>key, value</code>	Names of new key and value columns, as strings or symbols. This argument is passed by expression and supports <a href="#">quasiquotation</a> (you can unquote strings and symbols). The name is captured from the expression with <a href="#">rlang::quo_name()</a> (note that this kind of interface where symbols do not represent actual objects is now discouraged in the tidyverse; we support it here for backward compatibility).
<code>...</code>	A selection of columns. If empty, all variables are selected. You can supply bare variable names, select all variables between <code>x</code> and <code>z</code> with <code>x:z</code> , exclude <code>y</code> with <code>-y</code> . For more options, see the <a href="#">dplyr::select()</a> documentation. See also the section on selection rules below.
<code>na.rm</code>	If TRUE, will remove rows from output where the value column is NA.
<code>convert</code>	If TRUE will automatically run <a href="#">type.convert()</a> on the key column. This is useful if the column names are actually numeric, integer, or logical.
<code>factor_key</code>	If FALSE, the default, the key values will be stored as a character vector. If TRUE, will be stored as a factor, which preserves the original ordering of the columns.

# Gathering problem - colnames as values

```
# Let's look at `year_country`.  
year_country
```

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

- Notice that the second and third column are both values, these could be in one variable `year`
- Let's use `gather` to bring the two columns, 1999 and 2000 into one column `year`
- Let's make the second column `cases`, which will contain the count that currently appears in each year's column

# Gather function example

```
# Gather the `year_country` dataframe to make it tidy.
year_country %>% #<- set the dataframe and use pipe to use it as input into `gather`
  gather(`1999`, #<- set 1st column to gather
        `2000`, #<- set 2nd column to gather
        key = "year", #<- set `year` column as a key
        value = "cases") #<- set `cases` column as the values from the columns we gather
```

```
# A tibble: 6 x 3
  country    year  cases
  <fct>      <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
```

- Remember, the combination of data, function parameters, and the pipe (%>%) is common not only to `dplyr`, but also to all of the packages within `tidyverse`!

# Gather function: specifying a range

```
# Gather the `year_country` dataframe to make it tidy.
year_country %>% #<- set the dataframe and use pipe to use it as input into `gather`
  gather(2:3,    #<- provide a range of columns to gather
         key = "year", #<- set `year` column as a key
         value = "cases") #<- set `cases` column as the values from the columns we gather
```

```
# A tibble: 6 x 3
  country    year cases
  <fct>     <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
```

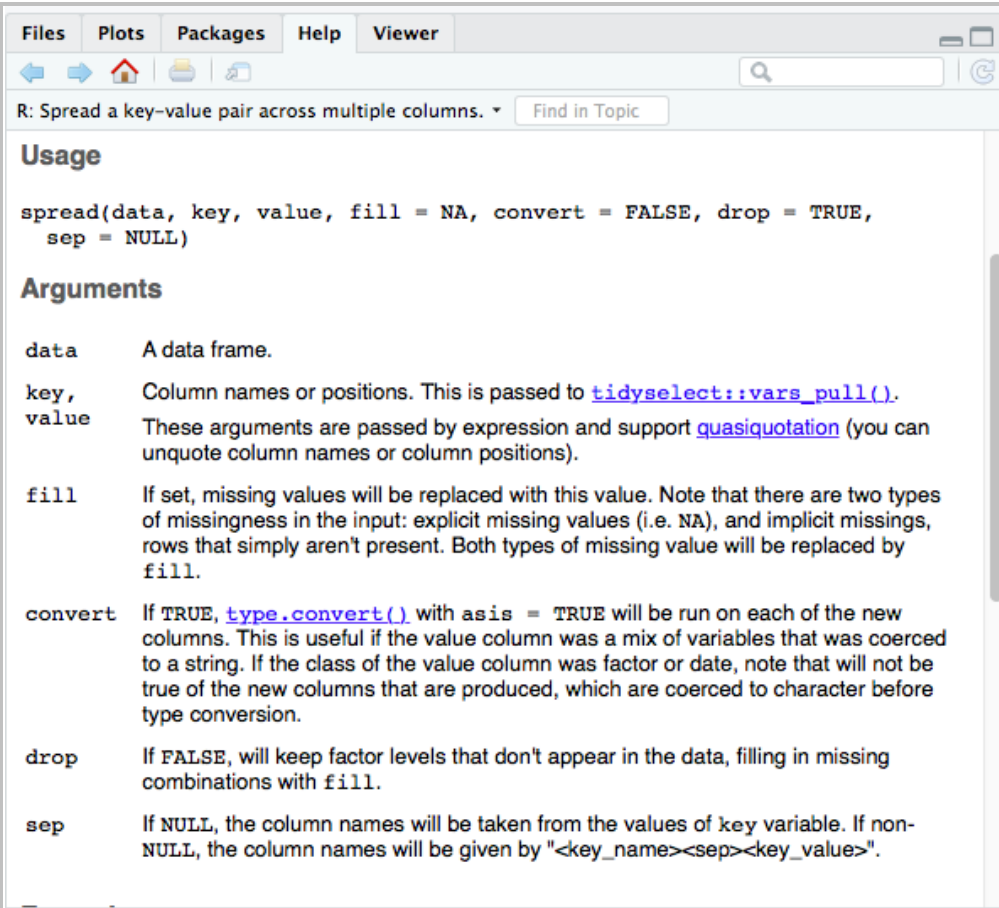
- Note that the code substituted 2 : 3 rather than the named columns

# Spreading

```
?dplyr::spread
```

```
spread(df,      #<- dataframe  
       key,      #<- name of current key column  
       value)    #<- name of current value column
```

- spread spreads one column into multiple variables
- Spreading is the opposite of gathering
- You use it when an observation is scattered across multiple rows
- There are two parameters we need to pay attention to when using spread:
  - The column that contains the variable names, the `key` column
  - The column that contains the values for the multiple variables, the `value` column



The screenshot shows the RStudio Viewer window with the documentation for the `spread` function. The window title is "R: Spread a key-value pair across multiple columns." and it includes a "Find in Topic" search bar. The documentation is organized into sections: "Usage", "Arguments", and "Examples".

**Usage**

```
spread(data, key, value, fill = NA, convert = FALSE, drop = TRUE,  
       sep = NULL)
```

**Arguments**

Argument	Description
<code>data</code>	A data frame.
<code>key</code> , <code>value</code>	Column names or positions. This is passed to <code>tidyselect::vars_pull()</code> . These arguments are passed by expression and support <a href="#">quasiquotation</a> (you can unquote column names or column positions).
<code>fill</code>	If set, missing values will be replaced with this value. Note that there are two types of missingness in the input: explicit missing values (i.e. NA), and implicit missings, rows that simply aren't present. Both types of missing value will be replaced by <code>fill</code> .
<code>convert</code>	If TRUE, <code>type.convert()</code> with <code>asis = TRUE</code> will be run on each of the new columns. This is useful if the value column was a mix of variables that was coerced to a string. If the class of the value column was factor or date, note that will not be true of the new columns that are produced, which are coerced to character before type conversion.
<code>drop</code>	If FALSE, will keep factor levels that don't appear in the data, filling in missing combinations with <code>fill</code> .
<code>sep</code>	If NULL, the column names will be taken from the values of key variable. If non-NULL, the column names will be given by " <code>&lt;key_name&gt;&lt;sep&gt;&lt;key_value&gt;</code> ".

# Spreading

```
# Let's look at `key_value_country`.  
key_value_country
```

```
# A tibble: 12 x 4  
  country    year key      value  
  <fct>    <int> <fct>    <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
```

- How would we use spread?
- Use `key_value_country` as initial dataframe
- Use spread with **2 main parameters**:
  - The `key`, which contains the variables
  - The `value`, which contains the values for each of the rows of the variables in the `key` column

# Spread: two ways

```
# Spread the data
# Pass data to spread with pipe.
key_value_country %>%
  spread(key = key,
         value = value)
```

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

```
# Spread without the pipe.
# Dataframe passed in.
spread(key_value_country,
       key = key,
       value = value)
```

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



# Module completion checklist

Objective	Complete
Rank data using the arrange function	✓
Select specific variables, sometimes using specific rules, using the select command	✓
Derive new variables from the existing variables using the mutate and transmute commands	✓
Perform multiple functions with the pipe operator (%>%)	✓
Summarize columns using the summary and group by functions	✓
Convert wide to long data using tidyr package	✓
Manipulate columns by using the separate and unite functions	

# Defining Separating and uniting

- How would we adjust a single variable?
- What would we use for a dataframe like `rate_country`?

```
rate_country
```

```
# A tibble: 6 x 3
  country    year rate
  <fct>    <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
```

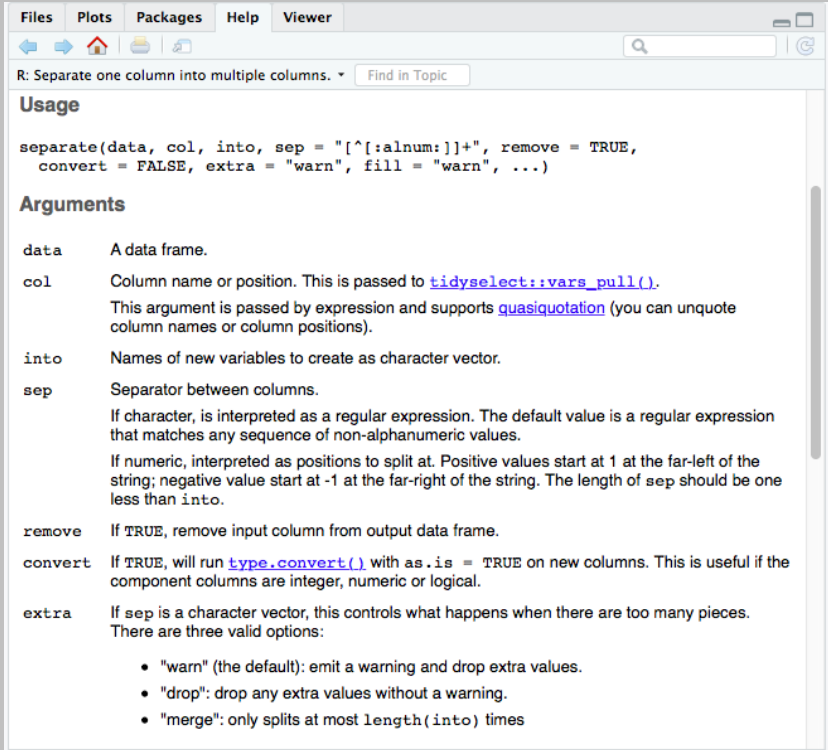
- What do we do with the `rate` column?
- We can use the function `separate`
- The opposite of `separate` is `unite`
- We will learn how to use this as well

# Separate

```
?dplyr::separate
```

```
separate(df,      #<- dataframe  
         col,     #<- name of column to separate  
         into)   #<- name of new variables to  
               #   create as a character vector
```

- `separate` divides a single character column into multiple columns and takes two arguments:
  - The first argument is the dataframe
  - Next we pipe it to `separate`
1. The first parameter is the column to be separated
  2. The second is what we want to separate the variable into, using `into = c("var_1", "var_2")`



The screenshot shows the R help page for the `separate` function. The title bar indicates the window is titled "R: Separate one column into multiple columns." The "Usage" section shows the function signature: `separate(data, col, into, sep = "[^[:alnum:]]+", remove = TRUE, convert = FALSE, extra = "warn", fill = "warn", ...)`. The "Arguments" section lists the parameters: `data` (A data frame), `col` (Column name or position), `into` (Names of new variables), `sep` (Separator between columns), `remove` (If TRUE, remove input column), `convert` (If TRUE, run `type.convert()`), and `extra` (Controls what happens when there are too many pieces). The `extra` argument has three options: "warn" (default), "drop", and "merge".

**Usage**

```
separate(data, col, into, sep = "[^[:alnum:]]+", remove = TRUE,  
         convert = FALSE, extra = "warn", fill = "warn", ...)
```

**Arguments**

**data** A data frame.

**col** Column name or position. This is passed to `tidyselect::vars_pull()`. This argument is passed by expression and supports [quasiquotation](#) (you can unquote column names or column positions).

**into** Names of new variables to create as character vector.

**sep** Separator between columns.  
If character, is interpreted as a regular expression. The default value is a regular expression that matches any sequence of non-alphanumeric values.  
If numeric, interpreted as positions to split at. Positive values start at 1 at the far-left of the string; negative value start at -1 at the far-right of the string. The length of `sep` should be one less than `into`.

**remove** If TRUE, remove input column from output data frame.

**convert** If TRUE, will run `type.convert()` with `as.is = TRUE` on new columns. This is useful if the component columns are integer, numeric or logical.

**extra** If `sep` is a character vector, this controls what happens when there are too many pieces. There are three valid options:

- "warn" (the default): emit a warning and drop extra values.
- "drop": drop any extra values without a warning.
- "merge": only splits at most `length(into)` times

# Separate

```
# Using `rate_country`, separate the `rate` column into two.
rate_country %>%                                     #<- set dataframe and pass it to next function with pipe
  separate(rate,                                     #<- separate `rate`
            into = c("cases",                         #<- into column `cases`, and
                      "population")) #<-          column `population`
```

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

# Separate

- By default, `separate` will separate on any non alpha-numeric character
- However, you can also specify the character to separate on

```
# Using `rate_country`, separate the `rate` column into two.
rate_country %>%
  separate(rate,
            into = c("cases",
                     "population"),
            sep = "/") #<- set the separating character to `/`
```

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

# Separate: sep set to index

- You can use the `sep` parameter to separate the year column on the character index into century and year

```
# Using `rate_country`, separate the `year` column into two.
rate_country %>%
  separate(year,           #<- separate `year`
            into= c("century", #<- into two columns: `century`, and
                    "year"),   #<- `year`
            sep = 2)         #<- set the separator at index = 2
```

```
# A tibble: 6 x 4
  country    century year  rate
  <fct>      <chr>   <chr> <chr>
1 Afghanistan 19      99    745/19987071
2 Afghanistan 20      00    2666/20595360
3 Brazil      19      99    37737/172006362
4 Brazil      20      00    80488/174504898
5 China       19      99    212258/1272915272
6 China       20      00    213766/1280428583
```

# Separate: data type conversion

When we use `separate`, the data type of the original column will be preserved

```
# The new columns are now also
characters.
rate_country %>%
  separate(rate, into = c("cases",
    "population"))
```

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

However, we can tell `separate` to convert to what it thinks the new columns should be

```
rate_country %>%
  separate(rate, into = c("cases", "population"), convert =
    TRUE)
```

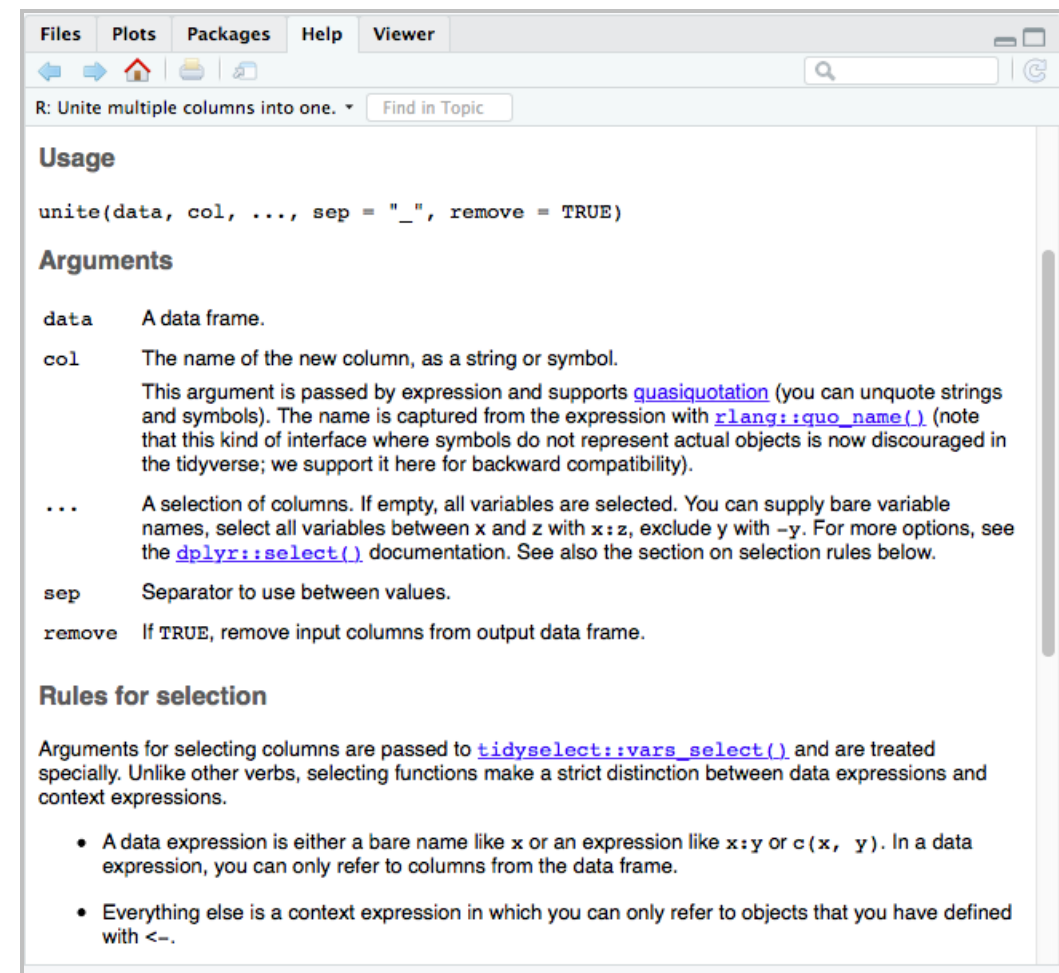
```
# A tibble: 6 x 4
  country    year cases population
  <fct>    <int> <int>    <int>
1 Afghanistan 1999   745    19987071
2 Afghanistan 2000   2666   20595360
3 Brazil      1999  37737   172006362
4 Brazil      2000  80488   174504898
5 China       1999 212258  1272915272
6 China       2000 213766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

# Unite

```
?dplyr::unite
```

```
unite(df, #<- dataframe  
      col, #<- name of column to unite  
      sep) #<- separator to use
```

- `unite` combines multiple character columns into a single one
- `unite` is the inverse of `separate`



The screenshot shows the R help window for the `unite` function. The title bar includes 'Files', 'Plots', 'Packages', 'Help', and 'Viewer'. The search bar at the top shows 'R: Unite multiple columns into one.' with a 'Find in Topic' button. The main content area is titled 'Usage' and shows the function signature: `unite(data, col, ..., sep = "_", remove = TRUE)`. Below this is the 'Arguments' section, which lists the parameters: `data` (A data frame), `col` (The name of the new column, as a string or symbol), `...` (A selection of columns), `sep` (Separator to use between values), and `remove` (If TRUE, remove input columns from output data frame). The 'Rules for selection' section explains that arguments for selecting columns are passed to `tidyselect::vars_select()` and are treated specially. It includes two bullet points: one stating that a data expression is either a bare name like `x` or an expression like `x:y` or `c(x, y)`, and another stating that everything else is a context expression in which you can only refer to objects that you have defined with `<-`.

**Usage**

```
unite(data, col, ..., sep = "_", remove = TRUE)
```

**Arguments**

**data** A data frame.

**col** The name of the new column, as a string or symbol.

This argument is passed by expression and supports [quasiquotation](#) (you can unquote strings and symbols). The name is captured from the expression with `rlang::quo_name()` (note that this kind of interface where symbols do not represent actual objects is now discouraged in the tidyverse; we support it here for backward compatibility).

**...** A selection of columns. If empty, all variables are selected. You can supply bare variable names, select all variables between `x` and `z` with `x:z`, exclude `y` with `-y`. For more options, see the [dplyr::select\(\)](#) documentation. See also the section on selection rules below.

**sep** Separator to use between values.

**remove** If TRUE, remove input columns from output data frame.

**Rules for selection**

Arguments for selecting columns are passed to `tidyselect::vars_select()` and are treated specially. Unlike other verbs, selecting functions make a strict distinction between data expressions and context expressions.

- A data expression is either a bare name like `x` or an expression like `x:y` or `c(x, y)`. In a data expression, you can only refer to columns from the data frame.
- Everything else is a context expression in which you can only refer to objects that you have defined with `<-`.



# Unite example

We will use the separated-on-year example of `rate_country` to show `unite`

```
# Let's separate the `rate_country`'s `year` column into `century` and `year` first.
ex_table = rate_country %>%
  separate(year, into = c("century", "year"), sep = 2, convert = TRUE)

# Now we use `unite` to combine the two new columns back into one.
# By default, unite will combine columns using `_` so we can use `sep` to specify that we
# do not want anything between the two columns when combined into one cell.
ex_table %>%
  unite(time,      #<- specify the dataframe to pipe into `unite`
        century,   #<- set the column `time` for combined values
        year,      #<- 1st column to unite
        sep = "")  #<- 2nd column to unite
                  #<- set the separator to an empty string
```

```
# A tibble: 6 x 3
  country    time    rate
  <fct>      <chr> <chr>
1 Afghanistan 1999  745/19987071
2 Afghanistan 200   2666/20595360
3 Brazil      1999  37737/172006362
4 Brazil      200   80488/174504898
5 China       1999  212258/1272915272
6 China       200   213766/1280428583
```

# Knowledge check 3



# Exercise 4



# Module completion checklist

Objective	Complete
Rank data using the arrange function	✓
Select specific variables, sometimes using specific rules, using the select command	✓
Derive new variables from the existing variables using the mutate and transmute commands	✓
Perform multiple functions with the pipe operator (%>%)	✓
Summarize columns using the summary and group by functions	✓
Convert wide to long data using tidyr package	✓
Manipulate columns by using the separate and unite functions	✓

# Workshop!

- **Today will be your first *after class* workshop**
- Workshops are to be completed outside of class and emailed to the instructor by the beginning of class tomorrow
- Make sure to comment your code so that it is easy for others to understand what you are doing
- This is an exploratory exercise to get you comfortable with the content we discussed today
- Workshop objectives:
  - Practice different `tidyverse` functions on the dataset you have chosen in the last class
  - Clean the dataset
  - Create new variables using mutate functions as you seem fit

# Congratulations on completing the module!