DATA SOCIETY®

Week 2 Day 1 - Fundamentals of R Part 2

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

Module completion checklist

Topic	Complete
Demonstrate installing a package and loading a library	
Define the six functions that provide verbs for the language of data manipulation, from the package dplyr	
Apply the filter function to subset data	
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	
Summarize columns using the summary and group by functions	
Convert wide to long data using tidyr package	
Discuss 3 reasons of why it is important to transform and wrangle data before moving forward with analyses	
Manipulate columns by using the separate and unite functions	

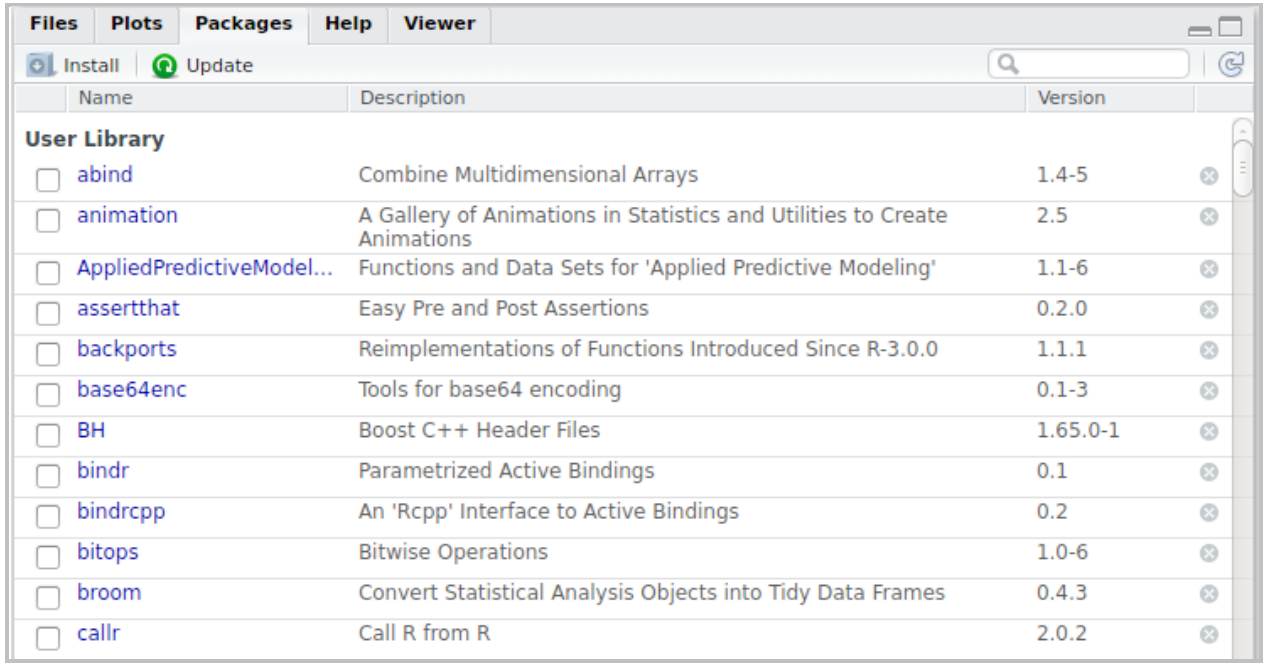
Installing packages: package explorer

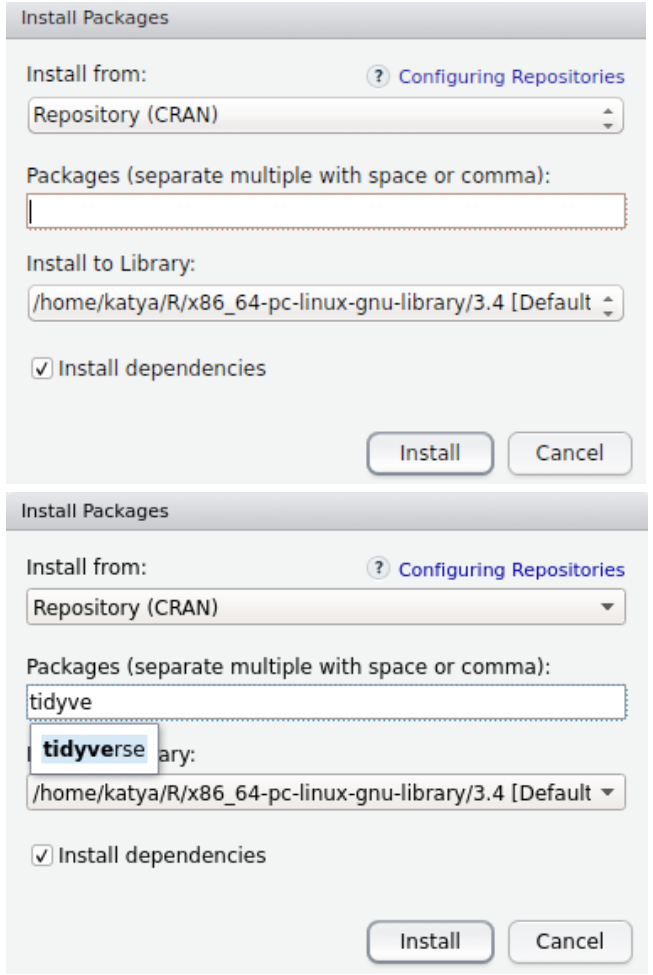
RStudio has a built-in package manager in the bottom right pane to help us install packages

Click on **`Packages`** tab in the **bottom-right** pane

Click **`Install`** button next to `Update`

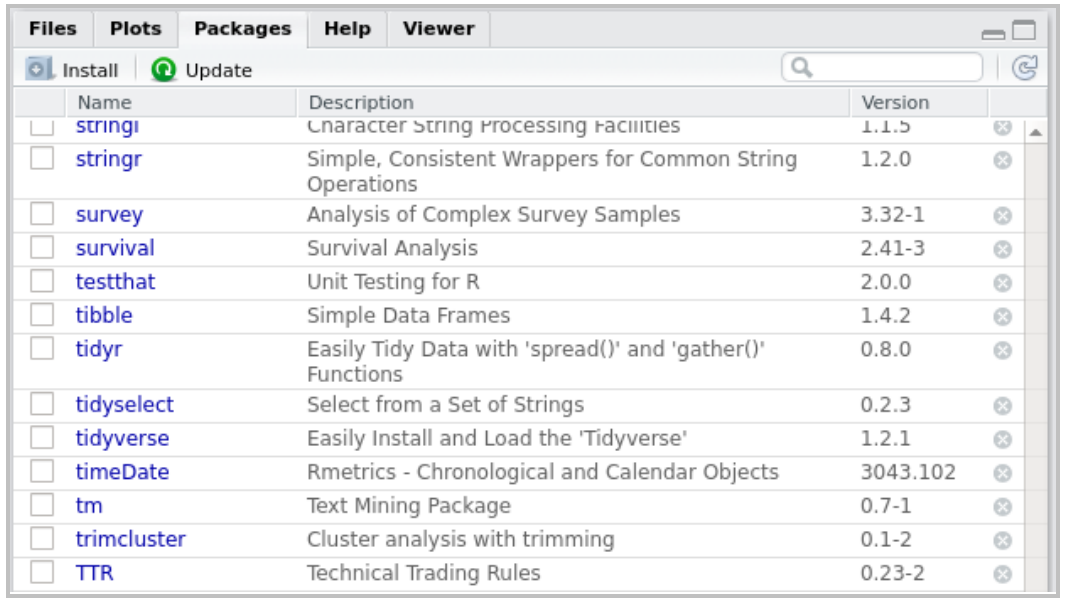
Type package name in the box and install



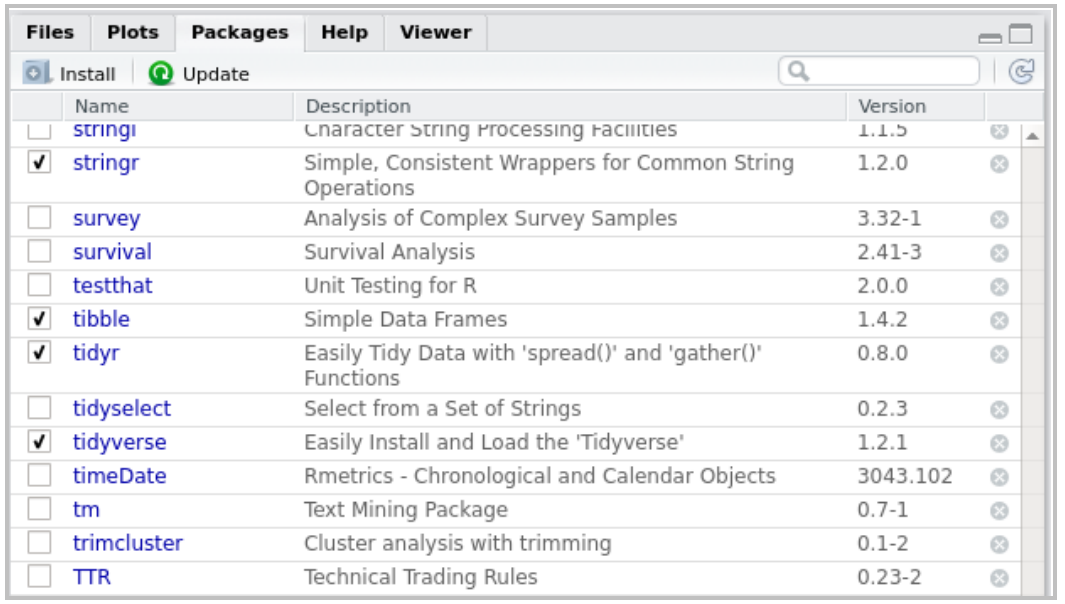


Installing packages: package explorer

The installed package should appear in the list of packages in the package explorer



To load the package into R's environment, check the box next to the name of your desired package



Installing packages

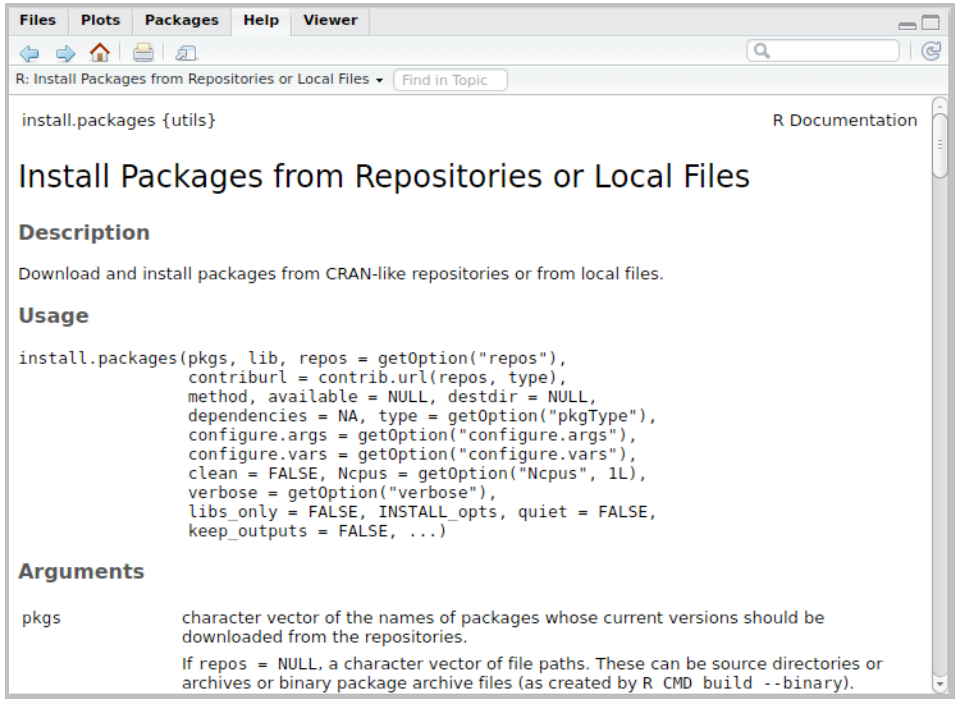
If the function we would like to use comes from a `package`, we need to **install** the `package` first

In addition to installing `packages` with package explorer as we introduced earlier, a more frequent way is to use function

`install.packages()`

For this function, we need to provide a single required argument: a character string corresponding to the `package name`

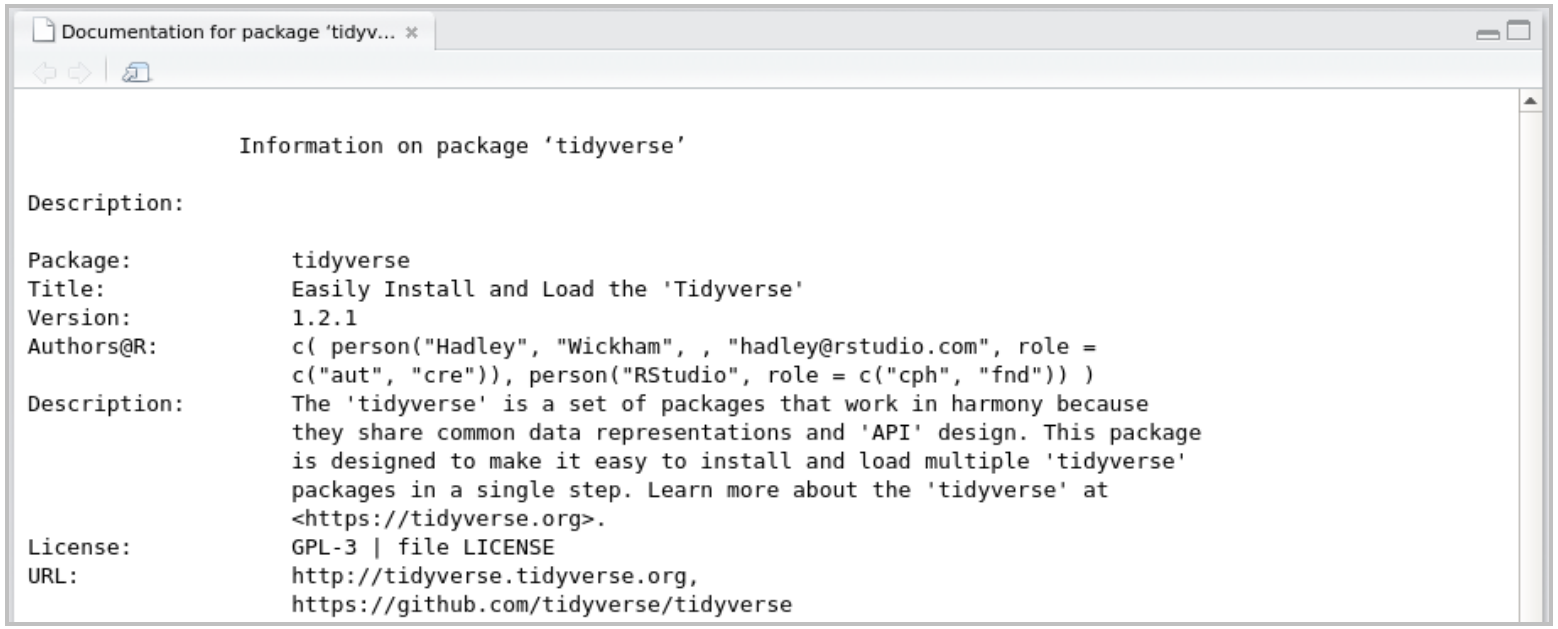
```
# Install package
?install.packages
```



Installing packages

Here is an example of how we install and load packages with function **`install.packages()`**
You can always check the detailed documention of one package with `help = "package name"`

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



Directory settings

In order to maximize the efficiency of your workflow, you may want to encode your directory structure into `variables`

Let the `main_dir` be the variable corresponding to your `hhs-r-2020` folder

```
# Set `main_dir` to the location of your `hhs-r-2020` folder (for Mac/Linux).
main_dir = "~/Desktop/hhs-r-2020"
# Set `main_dir` to the location of your `hhs-r-2020` folder (for Windows).
main_dir = "C:/Users/[username]/Desktop/hhs-r-2020"

# 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 directory to data_dir.
setwd(data_dir)
```

Installing packages and loading data

To review the functions within various R packages, we will need to import our dataset
R comes with several **built-in** data packages. The following is a list of some of the most common datasets:

- **Titanic**: Survival of passengers on the Titanic
- **iris**: Edgar Anderson's Iris Data
- **mtcars**: Motor Trend Car Road Tests

Today we'll be using one built-in dataset from R called **`nycflights13`** which describes **airline on-time information for all flights departing NYC in 2013**

Installing packages and loading data

Let's now install and load the `nycflights13` package

```
#install.packages("nycflights13")
library(nycflights13)
```

The `nycflights13` package contains the following five datasets:

- `flights`: all flights that departed from NYC in 2013
- `weather`: hourly meterological data for each airport
- `planes`: construction information about each plane
- `airports`: airport names and locations
- `airlines`: translation between two letter carrier codes and names

Installing packages and loading data

`.RData` is a specific format designed for storing a complete R workspace, or selected objects from a workspace, in a form that can be easily loaded back into R

RData files are organized as a sequence of objects while each object has a type

We will get back to it with a more detailed introduction later in this module

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

Introduction to data transformation with tidyverse

When you are given messy data, your goal is to transform it into a usable format
To do this, you may need the help from multiple **packages** that can be found within the universe of ***tidyverse***

Some core packages in `tidyverse` are: ggplot2, dplyr, tidyr

In this module, we will go over how to:

- manipulate data with : `dplyr`
- transform data with: `tidyr`

A little more about tidyverse

Packages in the tidyverse change fairly frequently

You can see if updates are available, and optionally install them, by running the following code

```
tidyverse_update()
```

Like we noted previously, there are many libraries within the `tidyverse` package

The packages we will focus on help you wrangle and manipulate data quickly and efficiently

Data transformation

`dplyr` is an essential library within the tidyverse universe

It will be the tool we use for transforming our data by filtering, aggregating, and summarizing

Before starting this lesson, understand that dplyr does **overwrite** some `base R` packages such as `filter` and `lag`

Even functions with exactly the same name can be of different usage and syntax when belonging to different packages

If you have loaded dplyr and want to use the base version of the package, you will have to type in the full name: `stats::filter` and `stats::lag`

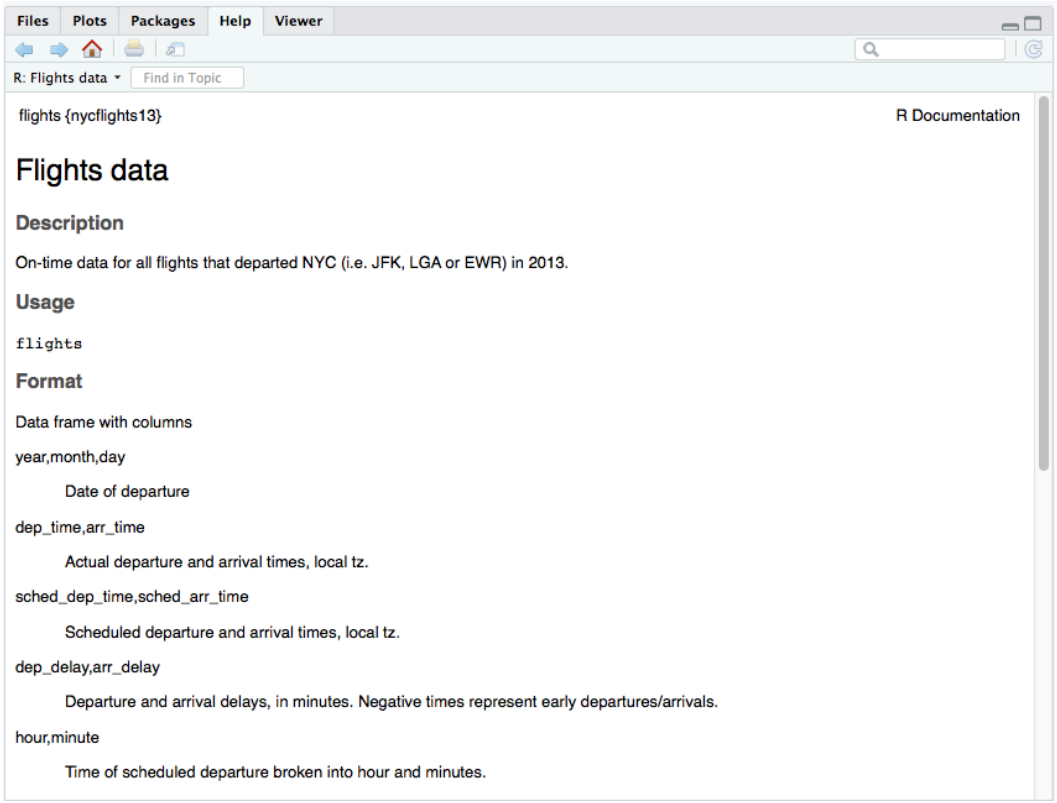
Data transformation

Let's look at the dataset we will be working with from `nycflights13` - **`flights`**

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

You can find the documentation for this dataset like this:

```
?flights
```



Basics of dplyr

After getting familiar with our dataset, let's get back to the package we use - `dplyr`
There are six functions that provide verbs for the language of data manipulation - these functions will make your life as a data scientist much easier
Uses cases for these six key `dplyr` functions are listed in the table below:

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

Framework of dplyr

The framework of `dplyr` is as follows:

- 1. The first argument is a dataframe
- 2. The next arguments describe what to do with the dataframe, using the six key `dplyr` functions
- 3. The final result is a new, transformed dataframe

We will now discuss how each of these six verbs work

Knowledge Check 1

Exercise 1

Module completion checklist

Topic	Complete
Demonstrate installing a package and loading a library	✔
Define the six functions that provide verbs for the language of data manipulation, from the package dplyr	✔
Apply the filter function to subset data	
Rank data using the arrange function	
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Filter

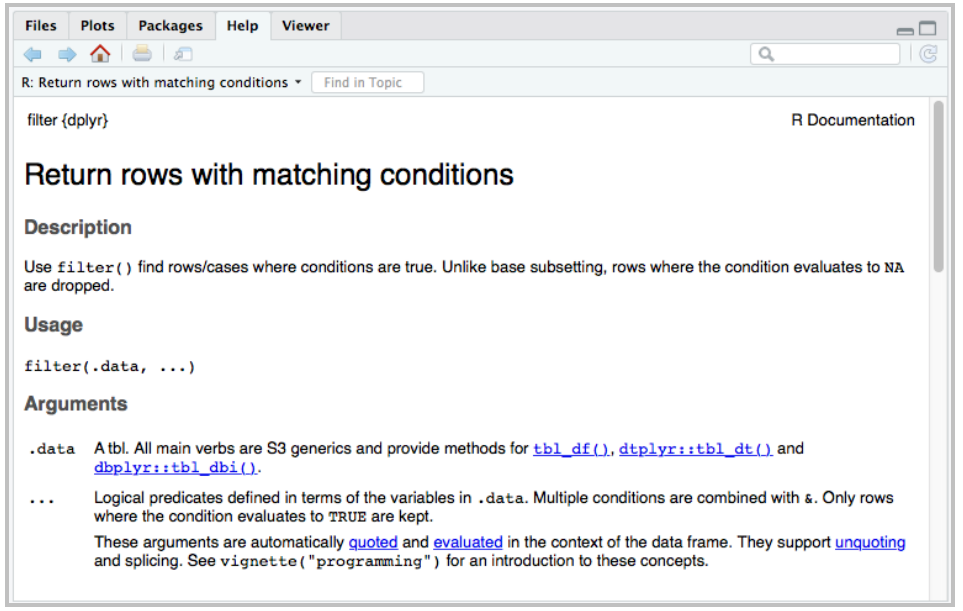
`filter` allows you to subset observations based on their values

Basic use cases for `filter` function include:

```
# Check for detailed documentation
?dplyr::filter

# Use cases for `filter` function
filter(df,           #<- dataframe
       filter_cond1, #<- subsetting rule(s)
       ...)          #<- other arguments
```

Next, we will apply `filter` on our `flights` dataset



Filter

Let's say you would like to see all flights from January 2013

```
# Load the flights dataset into the environment.
data(flights)

# Filter `flights` data frame to display all records from January (month == 1) of 2013 (year == 2013).
filter(flights,      #<- set data
       month == 1,   #<- filter by month
       year == 2013) #<- filter by year
```

```
# A tibble: 27,004 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 26,994 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 <dttm>
```

Filter

If you want to build on top of the filtered dataset, you will need to save your new subset to a new variable and perform further operations on this new subset

```
# You will have to make sure to save the subset. To do this, use `=`.
filter_flights = filter(flights, month == 1, day == 25)

# View your output.
filter_flights
```

```
# A tibble: 922 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>
 1  2013     1    25       15           1815       360      208
 2  2013     1    25       17           2249        88      119
 3  2013     1    25       26           1850       336      225
 4  2013     1    25      123           2000       323      229
 5  2013     1    25      123           2029       294      215
 6  2013     1    25      456            500        -4      632
 7  2013     1    25      519            525        -6      804
 8  2013     1    25      527            530        -3      820
 9  2013     1    25      535            540        -5      826
10  2013     1    25      539            540        -1     1006
# … with 912 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 <dttm>
```

Filter options

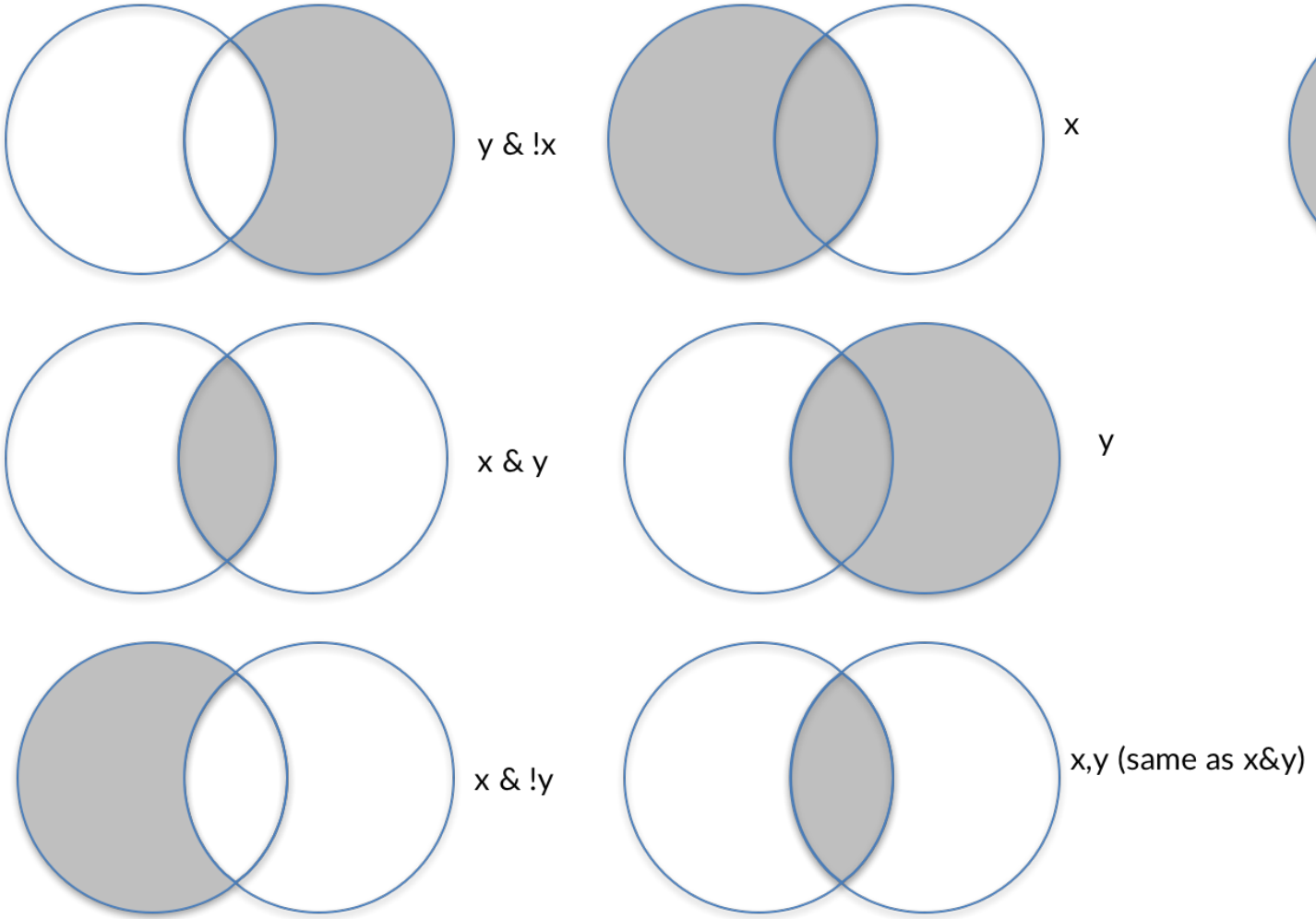
You can use the standard filtering operations when working with integer data types:

Operation	Use Case	Example
>	Greater than	6 > 4
>=	Greater than or equal to	4 >= 4
<	Less than	4 < 6
<=	Less than or equal to	4 <= 4
!=	Not equal to	4 != 6
==	Equal to	4 == 4

And more general operators:

Operation	Use Case	Example
OR or |	either can be true to satisfy	x == 4 OR x == 12, x==2 | x==13
and, &	and, both need to be true	x == 4 & y == 2
!	Not true, inverse selection	x != 4
%in%	value in the following list of values	x %in% c(4,16,32)

Filter - logical operators



Filter - examples of logical operators

What if we want to see all flights from January **and** on the 25th?

```
# Filter with just `&`.
filter(flights, month == 1 & day == 25)
```

```
# A tibble: 922 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>
 1  2013     1    25       15           1815       360      208
 2  2013     1    25       17           2249        88      119
 3  2013     1    25       26           1850       336      225
 4  2013     1    25      123           2000       323      229
 5  2013     1    25      123           2029       294      215
 6  2013     1    25      456            500        -4      632
 7  2013     1    25      519            525        -6      804
 8  2013     1    25      527            530        -3      820
 9  2013     1    25      535            540        -5      826
10  2013     1    25      539            540        -1     1006
# … with 912 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 <dttm>
```

Note: After running each example, we will record the number of rows. This will help illustrate each operator and how different a simple change of one boolean operator can have on the dataset.

Filter - examples of logical operators (cont...)

What if we want to see all flights, but **exclude** those from January and those on the 25th?

```
# Filter with `!`.
filter(flights, month != 1 & day != 25)
```

```
# A tibble: 299,597 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>
 1  2013    10     1      447            500       -13      614
 2  2013    10     1      522            517         5      735
 3  2013    10     1      536            545        -9      809
 4  2013    10     1      539            545        -6      801
 5  2013    10     1      539            545        -6      917
 6  2013    10     1      544            550        -6      912
 7  2013    10     1      549            600       -11      653
 8  2013    10     1      550            600       -10      648
 9  2013    10     1      550            600       -10      649
10  2013    10     1      551            600        -9      727
# … with 299,587 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 <dttm>
```

Here we are looking for all flights that are **not in January** and **not on the 25th**; total number of rows should be **299,587**

Filter - examples of logical operators (cont...)

```
# Filter with `%in%`.
filter(flights, month %in% c(1, 2) & day == 25)
```

```
# A tibble: 1,883 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>
 1  2013     1    25       15           1815       360      208
 2  2013     1    25       17           2249        88      119
 3  2013     1    25       26           1850       336      225
 4  2013     1    25      123           2000       323      229
 5  2013     1    25      123           2029       294      215
 6  2013     1    25      456            500        -4      632
 7  2013     1    25      519            525        -6      804
 8  2013     1    25      527            530        -3      820
 9  2013     1    25      535            540        -5      826
10  2013     1    25      539            540        -1     1006
# … with 1,873 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 <dttm>
```

This is a combination of `&` and `%in%` subsetting **all flights from January and February** that are **on the 25th**; number of rows should be **1,873**

Using filter with NA values

`filter` only includes rows where the condition is TRUE; it **excludes** both FALSE and NA values

If you want to preserve missing values, ask for them explicitly

```
# Create a data frame 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

# Filter without specifying anything regarding NAs.
filter(NA_df, x >= 1)
```

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

```
# Filter with specifying to keep rows if there is an NA.
filter(NA_df, is.na(x) | x >= 1)
```

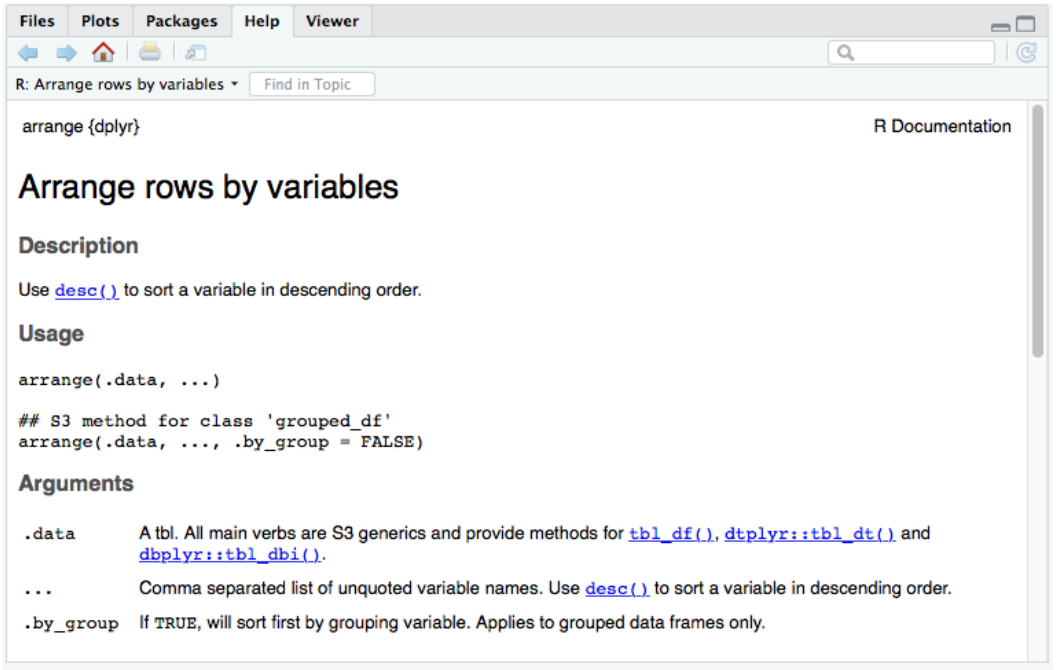
```
   x y
1  1 1
2 NA 2
3  2 3
```

Arrange

`arrange` is used to change the order of rows within the specified column(s)
It is the equivalent of `sort` in SAS or `order by` in SQL

```
# Check for detailed documentation
?dplyr::arrange

# Use cases for `arrange` function
arrange(df,             #<- data frame
        arrange_cond1,  #<- column by which
                        #   to arrange
        ...)            #<- other args.
```



Arrange example

When using multiple columns with `arrange`, the additional columns will be used to break ties in the values of preceding columns

```
# Arrange data by year, then month, and then day.
arrange(flights, #<- data frame 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 <dttm>
```

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,      #<- data frame 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 <dttm>
```

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

```
# 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
```

Knowledge Check 2

Exercise 2

Module completion checklist

Topic	Complete
Demonstrate installing a package and loading a library	✔
Define the six functions that provide verbs for the language of data manipulation, from the package dplyr	✔
Apply the filter function to subset data	✔
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	
Summarize columns using the summary and group by functions	
Convert wide to long data using tidyr package	
Discuss 3 reasons of why it is important to transform and wrangle data before moving forward with analyses	
Manipulate columns by using the separate and unite functions	

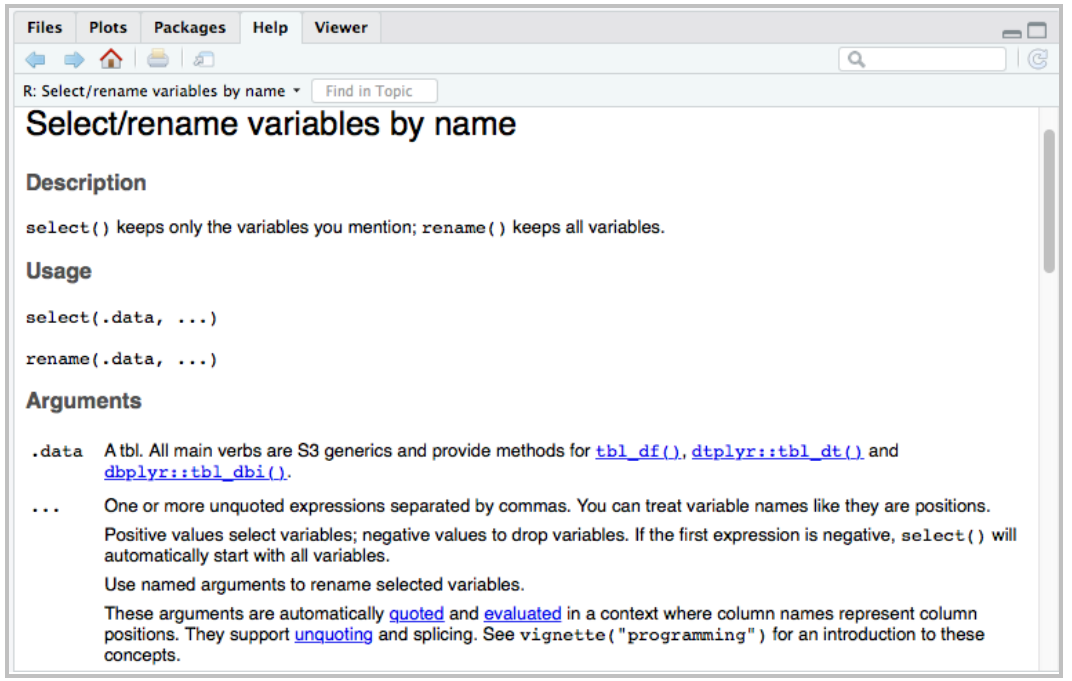
Select

`select` helps you select specific columns within your dataframe

```
# Check for detailed documentation
?dplyr::select

# Use cases for `select` function
select(df,            #<- dataframe
       select_cond1, #<- selection rule(s)
       ...)
```

We often use this function with pipes(%>%) which we will cover it later in this lesson
The selection criteria can be written in multiple ways, shown in the next couple of slides



Select a subset

Simply specify the column name(s)

```
# Select columns from `flights` data frame.
select(flights, #<- specify the data frame
       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` data frame
select(flights,  #<- specify the data frame
       year:day) #<- specify the range of
columns
```

```
# 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 exclusion operator (i.e. –)

```
# Select multiple columns from `flights` data frame by providing which columns to exclude in selection
select(flights,     #<- specify the data frame
       -(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 <dttm>
```

Select - helper functions

Helpers are multiple functions you can use to select variables based on their names

They act like regular expressions but in a more simplified manner

Here are some of the more commonly used helper functions:

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

To select columns whose names start with 'arr':

```
select(flights, starts_with("arr"))
```

Mutate

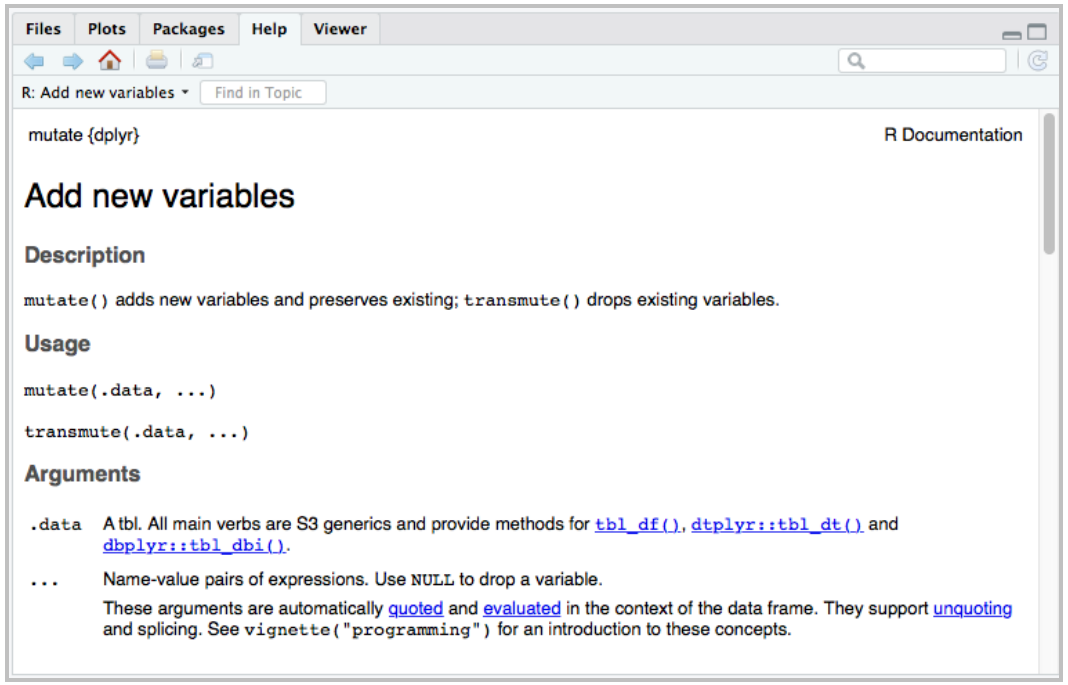
`mutate` is an essential function of dplyr

It allows us to **create** new variables using the current data and **append** these variables to the existing dataframe

```
?dplyr::mutate

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

Mutate always adds columns to the end of the dataset, so make sure you are able to see the last columns



Mutate

Create the dataset using `select`

```
# Let's select columns of `flights` data frame and save them as `flights_sml`.
flights_sml = select(flights,             #<- specify data fra,e
                     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
```

Mutate

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

```
# Add two columns `gain` and `speed` to `flights_sml`.
mutate(flights_sml,                          #<- specify the data frame
       gain = arr_delay - dep_delay,         #<- create `gain` column by subracting depature 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
```

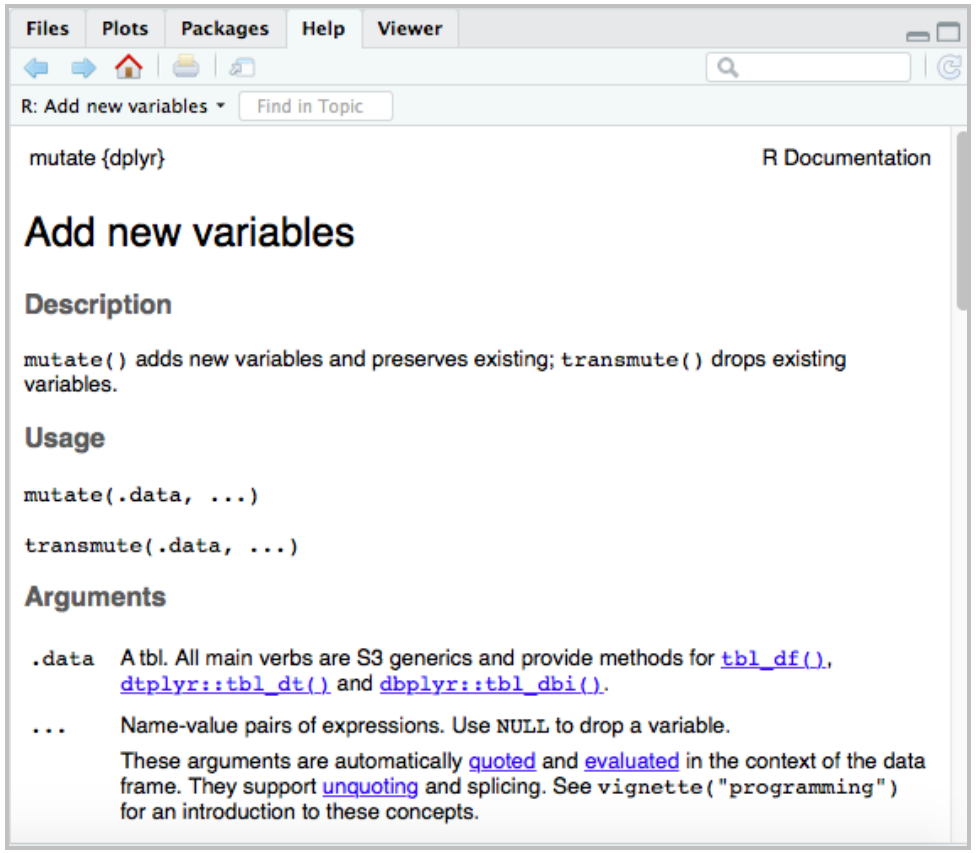
Transmute

`transmute` is a function that does the same thing as `mutate` **except it will only keep the new columns**

```
transmute(df,        # <- dataframe
          new_col1, # <- rule(s) for new column
          ...)
```

The 1st argument is the dataframe
The following arguments are the columns that will be included in your new data frame

Note: you are isolating only these new columns



Transmute Example

With the same arguments as in the `mutate` example, we can see `transmute` function only returns new columns

```
# Add two columns `gain` and `speed` to `flights_sml`.
example = transmute(flights_sml,                          #<- specify the data frame
       gain = arr_delay - dep_delay,      #<- create `gain` column by subracting depature 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
```

Mutate and transmute- useful functions

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

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

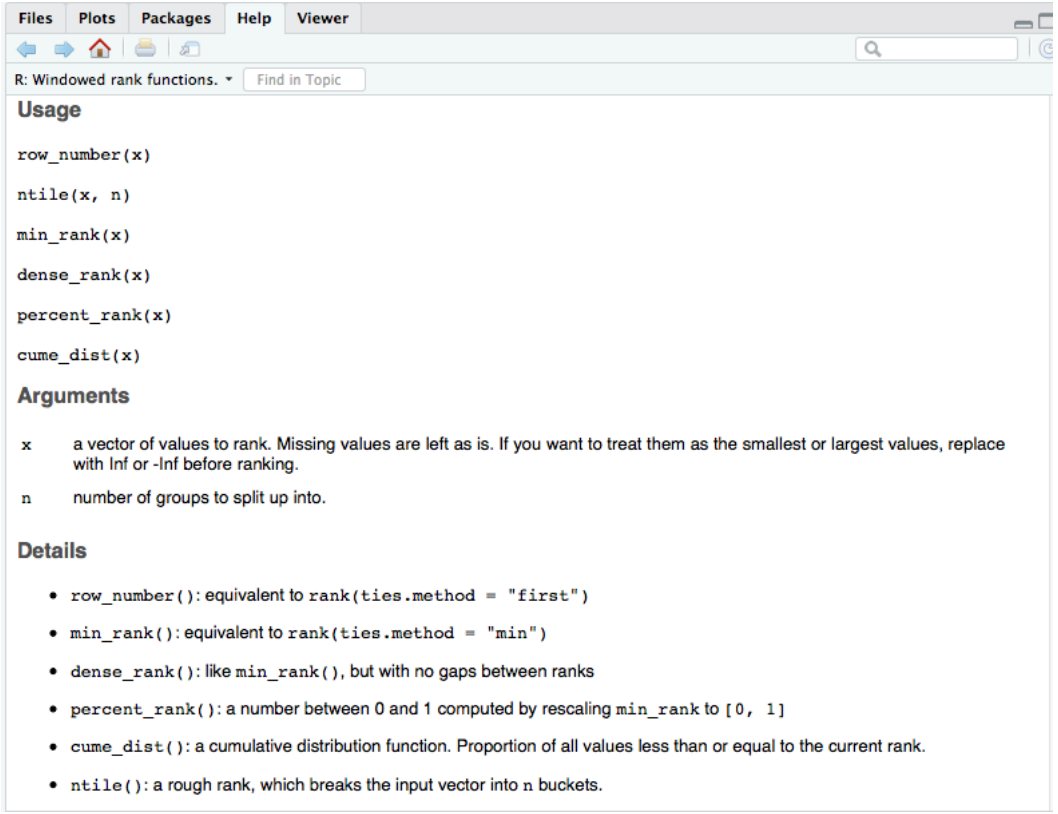
Mutate and transmute - useful functions (cont...)

Ranking functions are very helpful in data manipulation

There are several within the `dplyr` package such as `row_number()`, `ntile()` and `dense_rank()`

```
# Check for detailed documentation
?dplyr::ranking

rank_function(x) # <- one of rank functions with
                 #    a vector of values to rank
```



Knowledge Check 3

Exercise 3

Module completion checklist

Topic	Complete
Demonstrate installing a package and loading a library	✔
Define the six functions that provide verbs for the language of data manipulation, from the package dplyr	✔
Apply the filter function to subset data	✔
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	✔
Summarize columns using the summary and group by functions	
Convert wide to long data using tidyr package	
Discuss 3 reasons of why it is important to transform and wrangle data before moving forward with analyses	
Manipulate columns by using the separate and unite functions	

Summarise and group_by

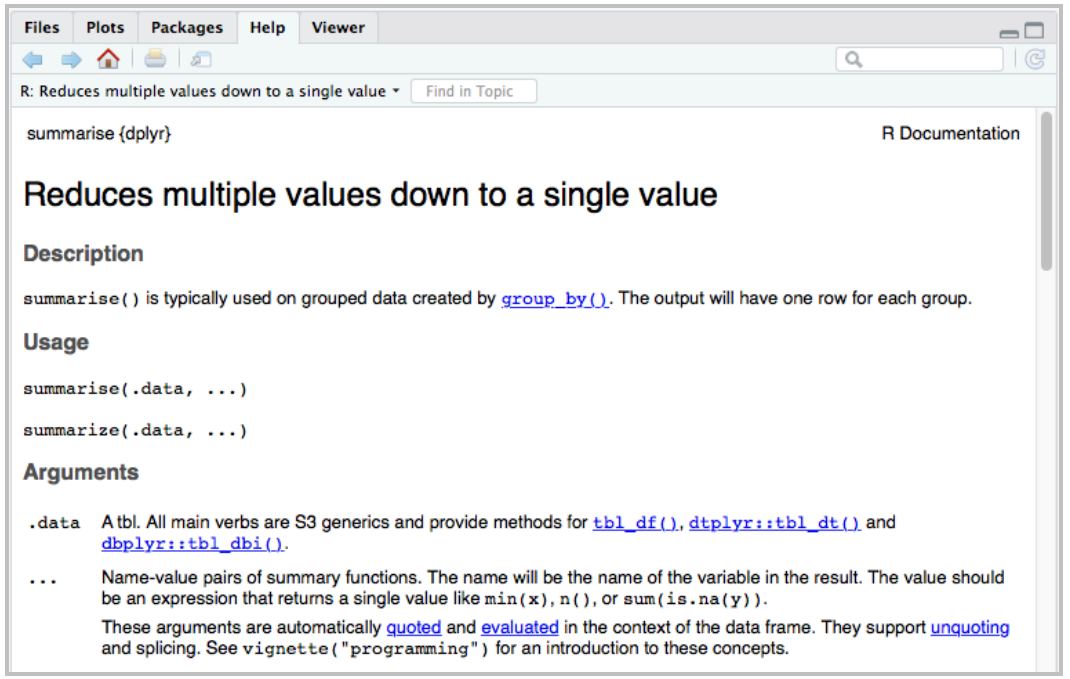
`summarise` collapses a data frame down to a single row

By itself, `summarise` is not very helpful

We will often use it with `group_by`

```
# Check for detailed documentation
?dplyr::summarise

# Use cases for `summarise` function
summarise(df,                  #<- data frame
          summary_function1,   #<- summary rule(s)
                               #   for new column
          ...)
```

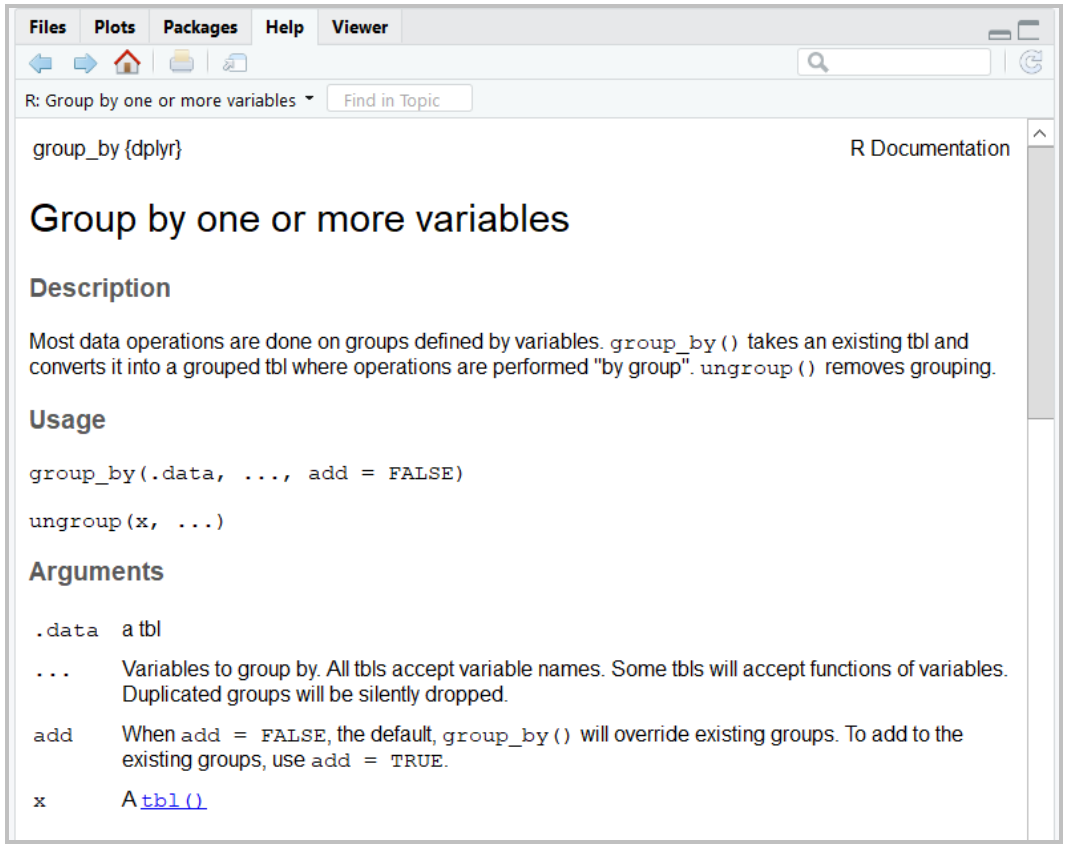


Summarise and group_by

Grouping doesn't change how data looks apart from listing how it's grouped
It will change how it acts with the other dplyr verbs
To remove grouping, use `ungroup`

```
# Check for detailed documentation
?dplyr::group_by

# Use cases for `group_by` function
group_by(df,          #<- data frame
         variable1, #<- 1st variable to group by
         variable2, #<- 2nd variable to group by
         ...)
```



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>,
#   minute <dbl>, time_hour <dttm>
```

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 continue to 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 %>%                                          #<- take flights data
  group_by(dest) %>%                                          #<- group it by destination
  summarise(count = n(),                                      #<- then summarize by creating count variable
            dist = mean(distance, na.rm = TRUE),              #<- and computing mean distance
            delay = mean(arr_delay, na.rm = TRUE)) %>%        #<- and mean arrival delay
  filter(count > 20, dest != "HNL")                           #<- then filter it
delays
```

```
# 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
```

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

Apart from `mean()`, there are many other summary functions describing data from various aspects:

Summary Functions	Explaination
`n()`	will count the number of entries that come from a summarise
`min(x),quantile(x, 0.25),max(x)`	measures of rank and distribution can be used
`first(x),nth(x, 2),last(x)`	measures of position and order
`n_distinct`	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
```

Summarise not needed to count

`count` is a simple count function that does not require the 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> <int> <int>
 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 calcelled 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> <int> <int>
 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 data frame
  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
```

Data wrangling

Data transformation is where you get the dataset ready for wrangling
We want all the variables and values, all the new columns to be created, and all the NAs taken care of before ensuring it is in `tidy` form

`tidyr`, the package within `tidyverse`, allows us to get our data into a tidy format

We will use the `.Rdata` file loaded at the beginning of this lesson to demonstrate

For further reading and understanding of tidy data and where it originated, check out this ***paper***

Would analysis be easy with these datasets?

Here is a list of objects from our RData file

```
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'?

These three interrelated rules make a dataset tidy:

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

`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

Storing data in a **consistent** way:

- 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`**:

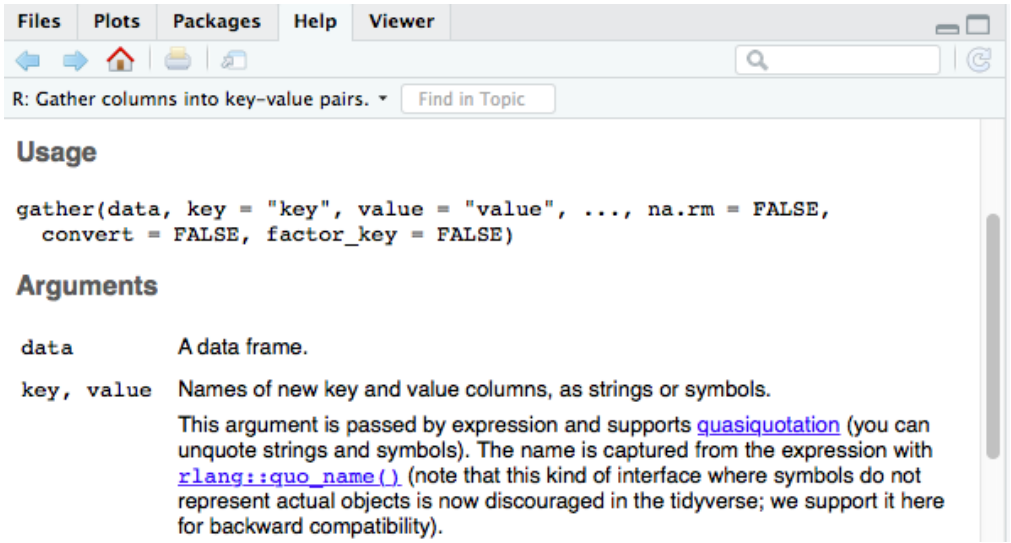
- The functions of `tidyr` that will help you transform `messy` data to `tidy` data

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`:

- 1. The set of columns that represent the values
- 2. The name of the variable (which we decide upon) that represents those values, or the `key`
- 3. The name of the variable (which we decide upon) that represents the values that are currently within the value columns, or the `value`

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 combined into one variable, `year`

Let's use `gather` to combine 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` data frame to make it tidy.
year_country %>%          #<- set the data frame 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 the packages within `tidyverse`!

Gather function: specifying a range

```
# Gather the `year_country` data frame to make it tidy.
year_country %>%          #<- set the data frame 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` with the named columns

Spreading

`spread` spreads one column into multiple variables

Spreading is the opposite of gathering

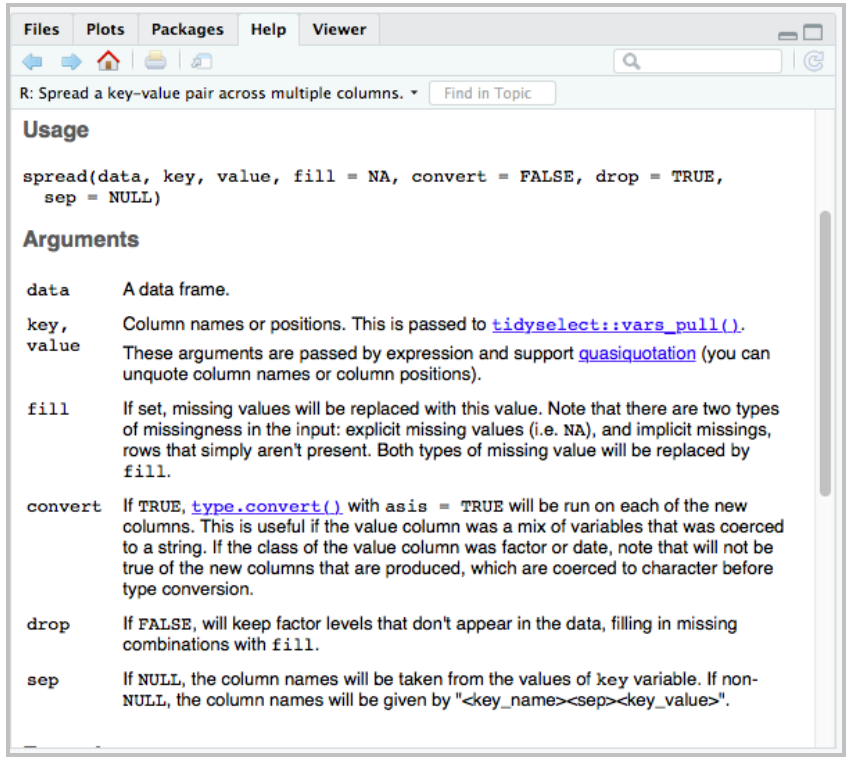
You use `spread` when an observation is scattered across multiple rows

```
?dplyr::spread

summarise(df,    #<- data frame
          key,   #<- name of current key column
          value) #<- name of current value column
```

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



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 data frame

Use `spread` with **2 main parameters:**

- 1. The `key`, which contains the variables
- 2. 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.
# Data frame 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
```

Separating and uniting

But how would we adjust a single variable? What would we use for a data frame 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 complement of `separate` is `unite`

We will learn how to use this as well

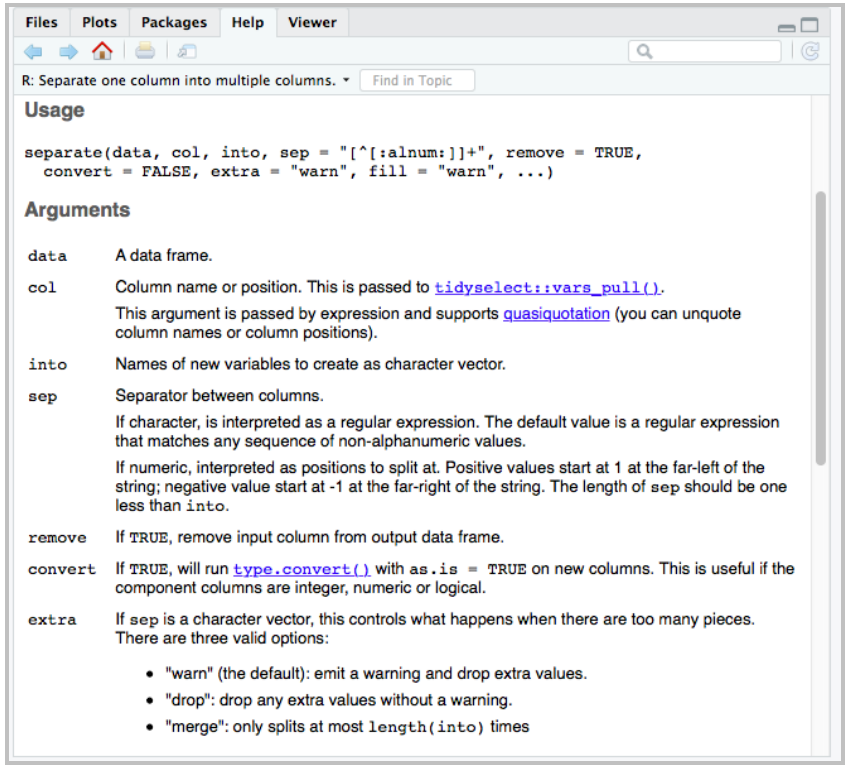
Separate

`separate` separates a single character column into multiple columns and takes two arguments:

- The first argument is the dataframe
- Next we pipe it to `separate`
- The first parameter is the column to be separated
- The second parameter defines how we want to separate the variable, using `into = c("var_1", "var_2")`

```
?dplyr::separate

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



Separate

```
# Using `rate_country` separate its `rate` column into two.
rate_country %>%                    #<- set data frame 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 by which to separate

```
# Using `rate_country` separate its `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 its `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
```

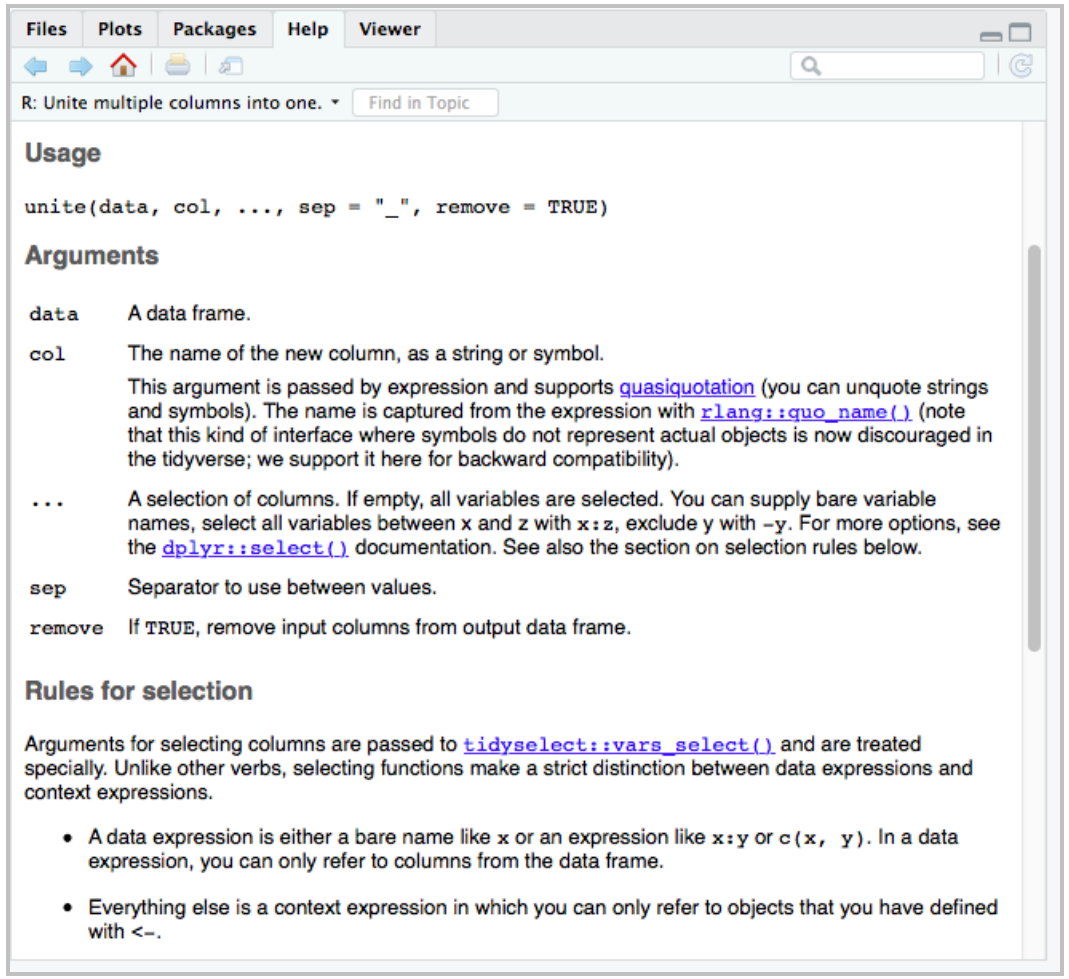
Unite

```
?dplyr::separate

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

`unite` combines multiple character columns into a single column

`unite` is the inverse of separate



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 %>%      #<- specify the data frame to pipe into `unite`
  unite(time,     #<- set the column `time` for combined values
        century,  #<- 1st column to unite
        year,     #<- 2nd column to unite
        sep = "") #<- 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 4

Exercise 4

Module completion checklist

Topic	Complete
Demonstrate installing a package and loading a library	✔
Define the six functions that provide verbs for the language of data manipulation, from the package dplyr	✔
Apply the filter function to subset data	✔
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	✔
Summarize columns using the summary and group by functions	✔
Convert wide to long data using tidyr package	✔
Discuss 3 reasons of why it is important to transform and wrangle data before moving forward with analyses	✔
Manipulate columns by using the separate and unite functions	✔

Review!

Summary

Topics		
Week 1-2	Intro to R programming	
Week 3-5	Machine Learning - Regression and Unsupervised Learning	
Week 6-8	Machine Learning - Classification	

In today's module, we learn two powerful packages in `tidyverse`: **`dplyr`** and **`tidyr`**

With these two packages, we can manipulate data and tidy up datasets in a more elegant way

After class, you can perform your own transformation with other built-in R datasets

In the next module, we will **visualize** our data and make our analysis results more accessible.

Stay excited!

This completes our module

Congratulations!