Data wrangling

Tidyverse

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Preliminaries

```
install.packages(c("tidyverse",
                   "nycflights13"))
```

I assume you are familiar with:

- R
- RStudio
- RMarkdown

Introduction

- Data science is an exciting discipline that allows you to turn raw data into understanding, insight, and knowledge.
- R can help you learn the most important tools that will allow you to do data science.
- Data science is a huge field, and this lectures aim to introduce you on it

Tidyverse

Introduction

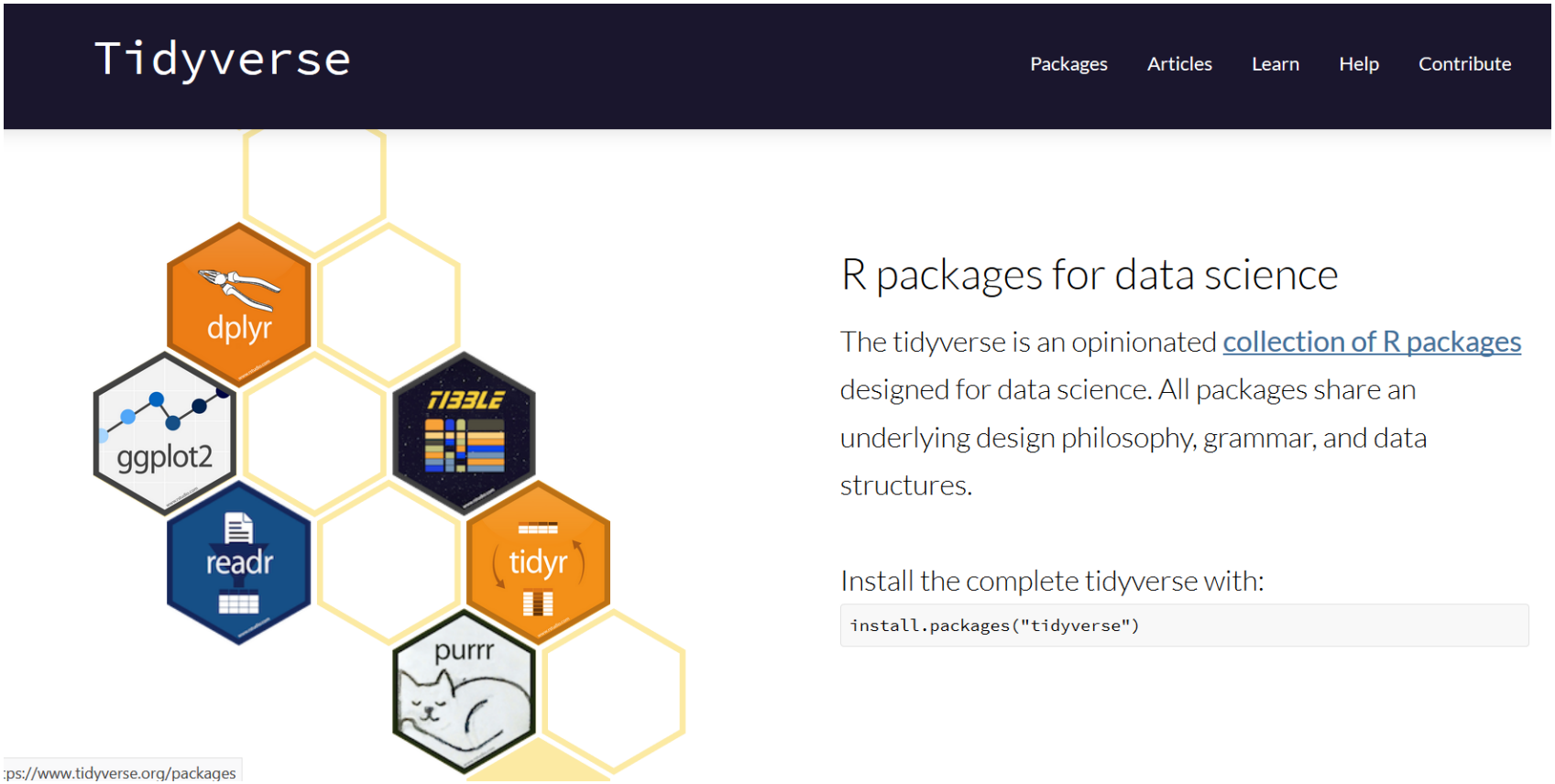


Figure 1: Tidyverse

```
install.packages("tidyverse")
```

What you will learn

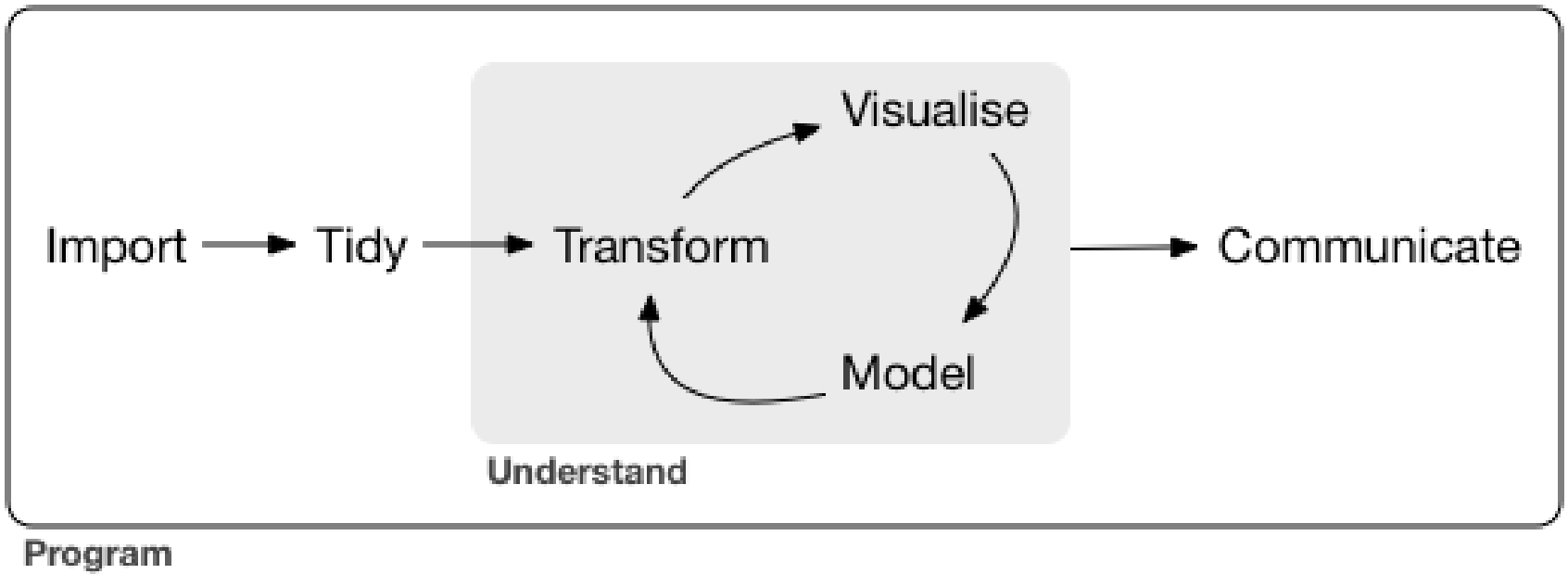


Figure 2: Data science

Tidying data means storing it in a consistent form that matches the semantics of the dataset with the way it is stored

Data wragling

Data wrangling

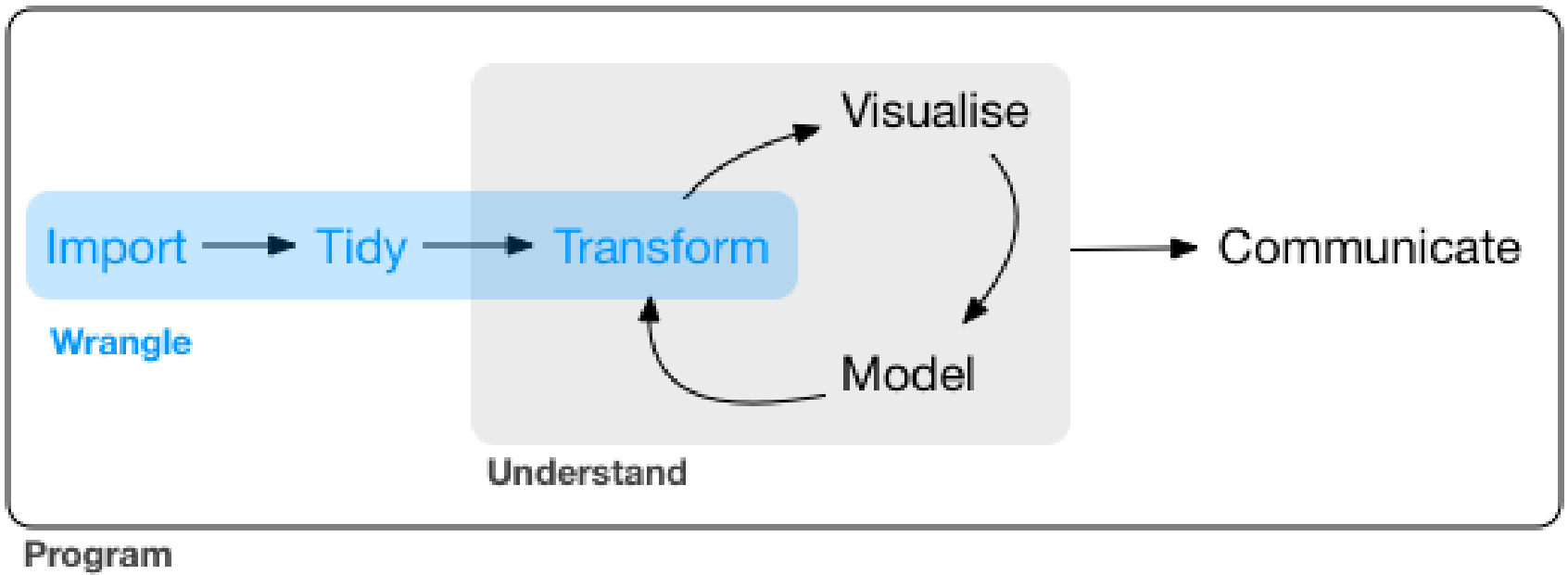


Figure 3: Data wrangling

Data wrangling

- In **tibbles**, the counterpart of data.frames in tidyverse.
- In **data import** you get data from disk into R focusing on plain-text rectangular formats (other types are possible)
- In **tidy** data, a consistent way of storing your data that makes transformation, visualisation, and modelling easier.

Data Wrangling

Also encompasses data transformation (not covered here) that facilitates:

- Relational data will give you tools for working with multiple interrelated datasets.
- Strings will introduce regular expressions, a powerful tool for manipulating strings.
- Factors are how R stores categorical data. They are used when a variable has a fixed set of possible values, or when you want to use a non-alphabetical ordering of a string.
- Dates and times will give you the key tools for working with dates and date-times.

Tibbles

You can learn more by executing vignette("tibble")

```
library(tidyverse)
```

- Creating tibles

```
head(iris)
```

```
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species
1          5.1         3.5          1.4         0.2  setosa
2          4.9         3.0          1.4         0.2  setosa
3          4.7         3.2          1.3         0.2  setosa
4          4.6         3.1          1.5         0.2  setosa
5          5.0         3.6          1.4         0.2  setosa
6          5.4         3.9          1.7         0.4  setosa
```

```
iris.tib <- as_tibble(iris)
iris.tib
```

```
# A tibble: 150 x 5
   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
          <dbl>       <dbl>        <dbl>       <dbl> <fct>
 1          5.1         3.5          1.4         0.2 setosa
 2          4.9         3            1.4         0.2 setosa
 3          4.7         3.2          1.3         0.2 setosa
 4          4.6         3.1          1.5         0.2 setosa
 5          5           3.6          1.4         0.2 setosa
 6          5.4         3.9          1.7         0.4 setosa
 7          4.6         3.4          1.4         0.3 setosa
```

A new tibble can be created by (data is recycled):

```
tibble(
  x = 1:5,
  y = 1,
  z = x ^ 2 + y
)
```

```
# A tibble: 5 x 3
      x     y     z
  <int> <dbl> <dbl>
1     1     1     2
2     2     1     5
3     3     1    10
4     4     1    17
5     5     1    26
```

NOTE: It never changes the type of data (i.e. character to factor)

Tibbles have a refined print method that shows only the first 10 rows, and all the columns that fit on screen. This can be changed

```
print(iris.tib, n = 10, width = Inf)
```

```
# A tibble: 150 x 5
   Sepal.Length Sepal.Width Petal.Length Petal.Width Species
          <dbl>       <dbl>        <dbl>       <dbl> <fct>
 1          5.1         3.5          1.4         0.2 setosa
 2          4.9         3            1.4         0.2 setosa
 3          4.7         3.2          1.3         0.2 setosa
 4          4.6         3.1          1.5         0.2 setosa
 5          5           3.6          1.4         0.2 setosa
 6          5.4         3.9          1.7         0.4 setosa
 7          4.6         3.4          1.4         0.3 setosa
 8          5           3.4          1.5         0.2 setosa
 9          4.4         2.9          1.4         0.2 setosa
10          4.9         3.1          1.5         0.1 setosa
# ... with 140 more rows
```

```r
print(iris.tib, n = 10, width = 25)
```

```
# A tibble: 150 x 5
   Sepal.Length
          <dbl>
 1          5.1
 2          4.9
 3          4.7
 4          4.6
 5          5
 6          5.4
 7          4.6
 8          5
 9          4.4
10          4.9
# ... with 140 more
#   rows, and 4 more
#   variables:
#   Sepal.Width <dbl>,
#   Petal.Length <dbl>,
#   Petal.Width <dbl>,
#   Species <fct>
```

- Subsetting

```
df <- tibble(
  x = runif(5),
  y = rnorm(5)
)

# Extract by name
df$x
```

```
[1] 0.8368846 0.3551210 0.2747260 0.4885011 0.8293500
```

```
df[["x"]]
```

```
[1] 0.8368846 0.3551210 0.2747260 0.4885011 0.8293500
```

```
# Extract by position
df[[1]]
```

```
[1] 0.8368846 0.3551210 0.2747260 0.4885011 0.8293500
```

Data import

Data import

The key package is *readr*

- *read_csv()* reads comma delimited files, *read_csv2()* reads semicolon separated files (common in countries where , is used as the decimal place), *read_tsv()* reads tab delimited files, and *read_delim()* reads in files with any delimiter.
- *read_fwf()* reads fixed width files. You can specify fields either by their widths with *fwf_widths()* or their position with *fwf_positions()*. *read_table()* reads a common variation of fixed width files where columns are separated by white space.
- *read_log()* reads Apache style log files. (But also check out webreadr which is built on top of *read_log()* and provides many more helpful tools.)

Comparison with base R

- They are typically much faster (~10x) than their base equivalents. Long running jobs have a progress bar, so you can see what's happening. If you're looking for raw speed, try data.table::fread(). It doesn't fit quite so well into the tidyverse, but it can be quite a bit faster.
- They produce tibbles, they don't convert character vectors to factors, use row names, or munge the column names. These are common sources of frustration with the base R functions [Hadley statement!].
- They are more reproducible. Base R functions inherit some behaviour from your operating system and environment variables, so import code that works on your computer might not work on someone else's.

```r
library(readr)
system.time(dd1 <- read.delim("../../data/genome.txt"))
```

```
   user  system elapsed
   6.37    0.10    6.47
```

```r
system.time(dd2 <- read_delim("../../data/genome.txt",
                              delim="\t"))
```

```
   user  system elapsed
   0.46    0.05    0.50
```

```r
dim(dd2)
```

```
[1] 733202      5
```

```
head(dd1)
```

```
        Name Chr  Position  Log.R.Ratio B.Allele.Freq
1  rs1000000  12 125456933 -0.002501764   1.000000000
2  rs1000002   3 185118461 -0.029741180   0.000336171
3 rs10000023   4  95952928  0.004015533   0.460671800
4  rs1000003   3  99825597 -0.142527700   0.541123600
5 rs10000030   4 103593179  0.365104000   1.000000000
6 rs10000037   4  38600725 -0.005177616   0.504625300
```

```
dd2
```

```
# A tibble: 733,202 x 5
   Name       Chr    Position Log.R.Ratio B.Allele.Freq
   <chr>      <chr>     <dbl>       <dbl>         <dbl>
 1 rs1000000  12    125456933    -0.00250      1
 2 rs1000002  3     185118461    -0.0297       0.000336
 3 rs10000023 4      95952928     0.00402      0.461
 4 rs1000003  3      99825597    -0.143        0.541
 5 rs10000030 4     103593179     0.365        1
 6 rs10000037 4      38600725    -0.00518      0.505
 7 rs10000041 4     165841405    -0.179        0
 8 rs10000042 4       5288053     0.168        0.998
 9 rs10000049 4     119167668    -0.00238      0
10 rs1000007  2     237416793    -0.00411      0
# ... with 733,192 more rows
```

Data transformation

Data transformation

- It is rare that you get the data in exactly the right form you need.
- Often you'll need to create some new variables or summaries.
- Or maybe you just want to rename the variables or reorder the observations in order to make the data a little easier to work with.

Let us illustrate how to manage available data using NYC fligths database. `nycflights13::flights` data frame contains all 336,776 flights that departed from New York City in 2013. The data comes from the US Bureau of Transportation Statistics, and is documented in `?flights`.

```
library(nycflights13)
library(tidyverse)
```

```
flights
```

```
# A tibble: 336,776 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1  2013     1     1      517            515         2      830            819
 2  2013     1     1      533            529         4      850            830
 3  2013     1     1      542            540         2      923            850
 4  2013     1     1      544            545        -1     1004           1022
 5  2013     1     1      554            600        -6      812            837
 6  2013     1     1      554            558        -4      740            728
 7  2013     1     1      555            600        -5      913            854
 8  2013     1     1      557            600        -3      709            723
 9  2013     1     1      557            600        -3      838            846
10  2013     1     1      558            600        -2      753            745
# ... with 336,766 more rows, and 11 more variables: 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>
```

dlpyr basics

- Pick observations by their values: `filter()`.
- Reorder the rows: `arrange()`.
- Pick variables by their names: `select()`.
- Create new variables with functions of existing variables: `mutate()`.
- Collapse many values down to a single summary: `summarise()`.

All verbs work similarly:

- The first argument is a data frame.
- The subsequent arguments describe what to do with the data frame, using the variable names (without quotes).
- The result is a new data frame.

Filter rows

```
jan1 <- filter(flights, month == 1, day == 1)
```

R either prints out the results, or saves them to a variable. If you want to do both, you can wrap the assignment in parentheses:

```
(jan1 <- filter(flights, month == 1, day == 1))
```

```
# A tibble: 842 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1  2013     1     1      517            515         2      830            819
 2  2013     1     1      533            529         4      850            830
 3  2013     1     1      542            540         2      923            850
 4  2013     1     1      544            545        -1     1004           1022
 5  2013     1     1      554            600        -6      812            837
 6  2013     1     1      554            558        -4      740            728
 7  2013     1     1      555            600        -5      913            854
 8  2013     1     1      557            600        -3      709            723
 9  2013     1     1      557            600        -3      838            846
10  2013     1     1      558            600        -2      753            745
# ... with 832 more rows, and 11 more variables: 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>
```

Logical filtering

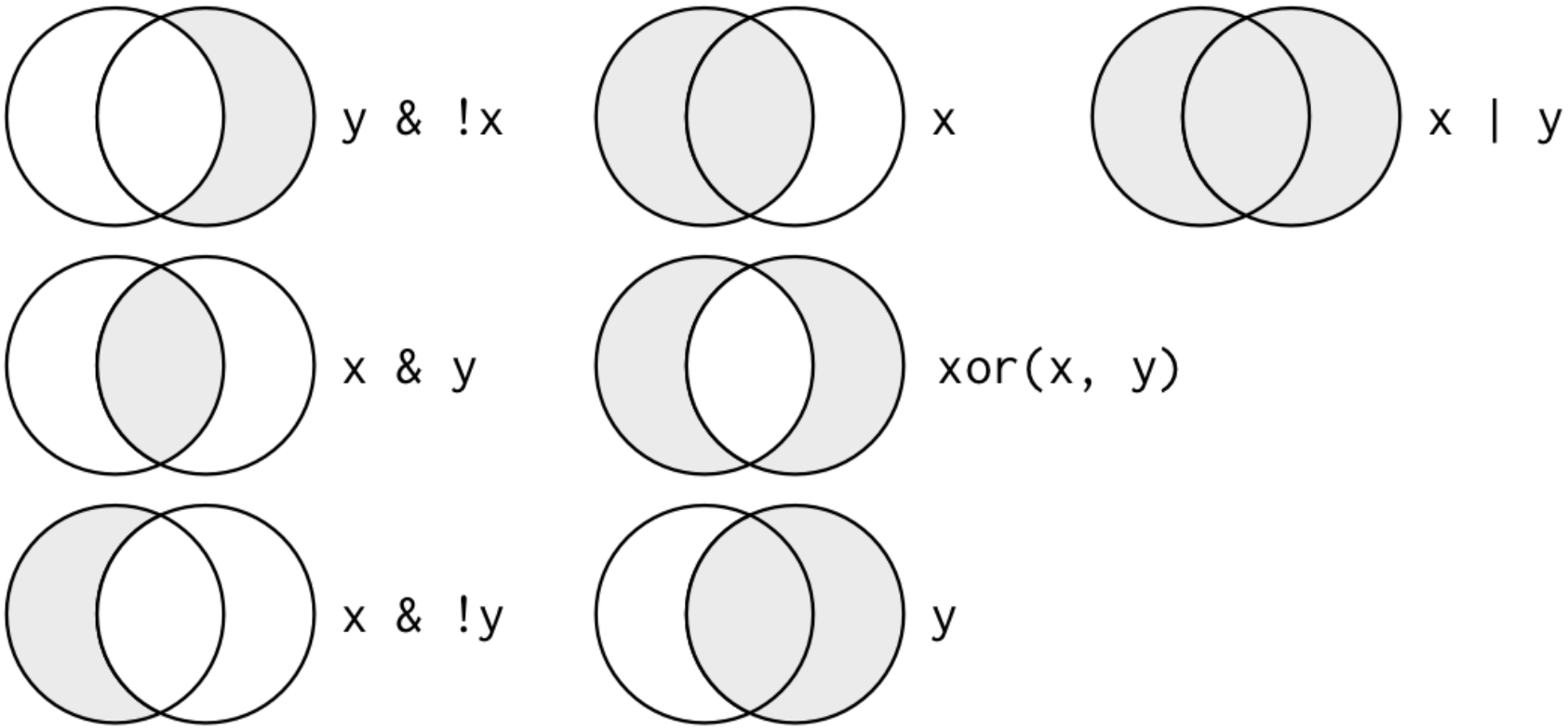


Figure 4: boolean operations

```r
filter(flights, month == 11 | month == 12)
```

```
# A tibble: 55,403 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1  2013    11     1        5           2359         6      352            345
 2  2013    11     1       35           2250       105      123           2356
 3  2013    11     1      455            500        -5      641            651
 4  2013    11     1      539            545        -6      856            827
 5  2013    11     1      542            545        -3      831            855
 6  2013    11     1      549            600       -11      912            923
 7  2013    11     1      550            600       -10      705            659
 8  2013    11     1      554            600        -6      659            701
 9  2013    11     1      554            600        -6      826            827
10  2013    11     1      554            600        -6      749            751
# ... with 55,393 more rows, and 11 more variables: 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>
```

```r
filter(flights, !(arr_delay > 120 | dep_delay > 120))
```

```
# A tibble: 316,050 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1  2013     1     1      517            515         2      830            819
 2  2013     1     1      533            529         4      850            830
 3  2013     1     1      542            540         2      923            850
 4  2013     1     1      544            545        -1     1004           1022
 5  2013     1     1      554            600        -6      812            837
 6  2013     1     1      554            558        -4      740            728
 7  2013     1     1      555            600        -5      913            854
 8  2013     1     1      557            600        -3      709            723
 9  2013     1     1      557            600        -3      838            846
10  2013     1     1      558            600        -2      753            745
# ... with 316,040 more rows, and 11 more variables: 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 rows

```
arrange(flights, year, month, day)
```

```
# A tibble: 336,776 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1  2013     1     1      517            515         2      830            819
 2  2013     1     1      533            529         4      850            830
 3  2013     1     1      542            540         2      923            850
 4  2013     1     1      544            545        -1     1004           1022
 5  2013     1     1      554            600        -6      812            837
 6  2013     1     1      554            558        -4      740            728
 7  2013     1     1      555            600        -5      913            854
 8  2013     1     1      557            600        -3      709            723
 9  2013     1     1      557            600        -3      838            846
10  2013     1     1      558            600        -2      753            745
# ... with 336,766 more rows, and 11 more variables: 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(flights, desc(dep_delay))
```

```
# A tibble: 336,776 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1  2013     1     9      641            900      1301     1242           1530
 2  2013     6    15     1432           1935      1137     1607           2120
 3  2013     1    10     1121           1635      1126     1239           1810
 4  2013     9    20     1139           1845      1014     1457           2210
 5  2013     7    22      845           1600      1005     1044           1815
 6  2013     4    10     1100           1900       960     1342           2211
 7  2013     3    17     2321            810       911      135           1020
 8  2013     6    27      959           1900       899     1236           2226
 9  2013     7    22     2257            759       898      121           1026
10  2013    12     5      756           1700       896     1058           2020
# ... with 336,766 more rows, and 11 more variables: 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: missing values are located at the end

Select columns

```
select(flights, year, month, day)
```

```
# 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
```

```r
select(flights, year:day)
```

```
# 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(flights, -(year:day))
```

```
# A tibble: 336,776 x 16
   dep_time sched_dep_time dep_delay arr_time sched_arr_time arr_delay carrier
      <int>          <int>     <dbl>    <int>          <int>     <dbl> <chr>
 1      517            515         2      830            819        11 UA
 2      533            529         4      850            830        20 UA
 3      542            540         2      923            850        33 AA
 4      544            545        -1     1004           1022       -18 B6
 5      554            600        -6      812            837       -25 DL
 6      554            558        -4      740            728        12 UA
 7      555            600        -5      913            854        19 B6
 8      557            600        -3      709            723       -14 EV
 9      557            600        -3      838            846        -8 B6
10      558            600        -2      753            745         8 AA
# ... with 336,766 more rows, and 9 more variables: flight <int>,
#   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
#   hour <dbl>, minute <dbl>, time_hour <dttm>
```

There are a number of helper functions you can use within select():

- `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”.
- `matches("(.)\\1")`: selects variables that match a regular expression. This one matches any variables that contain repeated characters. You’ll learn more about regular expressions in `strings`.
- `num_range("x", 1:3)`: matches x1, x2 and x3.

Add new variables

```
flights_sml <- select(flights,
  year:day,
  ends_with("delay"),
  distance,
  air_time
)
mutate(flights_sml,
  gain = dep_delay - arr_delay,
  speed = distance / air_time * 60
)
```

```
# 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
```

If you only want to keep the new variables, use `transmute()`:

```
transmute(flights,
  gain = dep_delay - arr_delay,
  hours = air_time / 60,
  gain_per_hour = gain / hours
)
```

```
# A tibble: 336,776 x 3
    gain hours gain_per_hour
   <dbl> <dbl>         <dbl>
 1    -9 3.78          -2.38
 2   -16 3.78          -4.23
 3   -31 2.67         -11.6
 4    17 3.05           5.57
 5    19 1.93           9.83
 6   -16 2.5           -6.4
 7   -24 2.63          -9.11
 8    11 0.883         12.5
 9     5 2.33           2.14
10   -10 2.3           -4.35
# ... with 336,766 more rows
```

Grouped summaries

```
summarise(flights, delay = mean(dep_delay, na.rm = TRUE))
```

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

```r
by_day <- group_by(flights, year, month, 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
```

The pipe %>%

Imagine that we want to explore the relationship between the distance and average delay for each location. The steps are:

There are three steps to prepare this data:

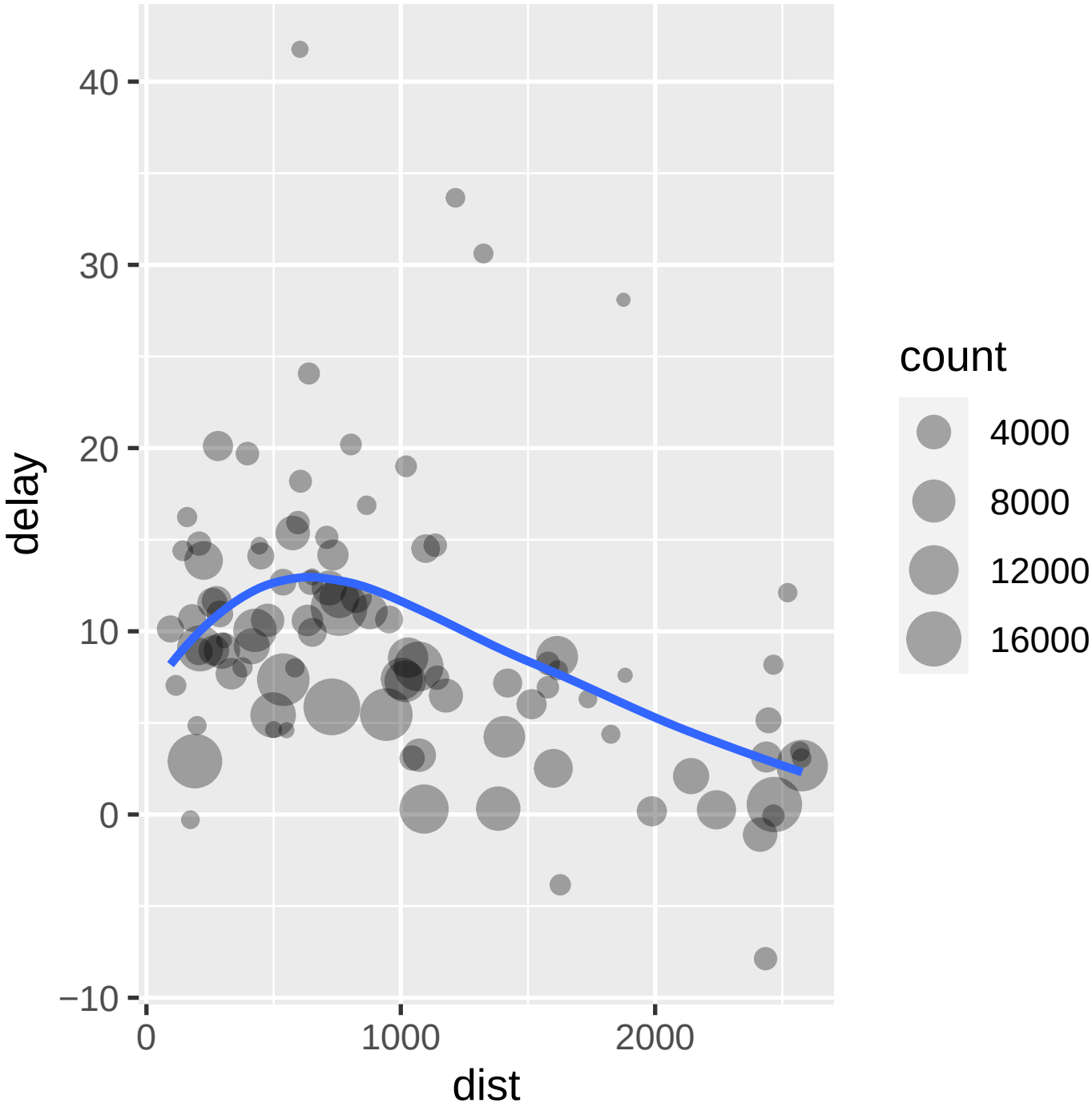
- Group flights by destination.
- Summarise to compute distance, average delay, and number of flights.
- Filter to remove noisy points and Honolulu airport, which is almost twice as far away as the next closest airport.

Using what you know about dplyr, you might write code like this:

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

```
# 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
```

```r
ggplot(data = delay, mapping = aes(x = dist, y = delay)) +
  geom_point(aes(size = count), alpha = 1/3) +
  geom_smooth(se = FALSE)
```


40
30
20
10
0
−10
delay
0
1000
2000
dist
count
4000
8000
12000
16000

```r
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
```

```
# 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
```

Group by different variables

```
flights %>%
  group_by(year, month, day) %>%
  summarise(
    avg_delay1 = mean(arr_delay, na.rm=TRUE),
    avg_delay2 = mean(arr_delay[arr_delay > 0], na.rm=TRUE)
  )
```

```
# A tibble: 365 x 5
# Groups:   year, month [12]
    year month   day avg_delay1 avg_delay2
   <int> <int> <int>      <dbl>      <dbl>
 1  2013     1     1     12.7         32.5
 2  2013     1     2     12.7         32.0
 3  2013     1     3      5.73        27.7
 4  2013     1     4     -1.93        28.3
 5  2013     1     5     -1.53        22.6
 6  2013     1     6      4.24        24.4
 7  2013     1     7     -4.95        27.8
 8  2013     1     8     -3.23        20.8
 9  2013     1     9     -0.264       25.6
10  2013     1    10     -5.90        27.3
# ... with 355 more rows
```

Useful summary functions

- `count()`
- `mean()`
- `median()`
- `min()`
- `max()`
- `quantile(x, 0.25)`
- `IQR()`
- `mad()`

Ejercicios (manejo de datos)

Los siguientes ejercicios os ayudarán a trabajar con las tareas más básicas de `dplyr`. **Debéis realizarlos usando las funciones que hemos visto en esta presentación - no vale usar código R básico**. Usaremos los datos `mtcars` vistos en clase. Recordad que podemos obtener más información sobre las variables con `?mtcars`. También podemos usar `glimpse()` para ver qué tipo de variables tenemos, y en caso de ser variables categóricas, qué categorías hay (Siempre es muy recomendable hacer este tipo de visualización de datos para ver que no hayan valores raros ni categorías no definidas o errores en la definición de categorías - por ejemplo tener la variable sexo como: H, M, h, m, hombre).

1. Visualiza la variable 'hp' usando la función `select()`. Intenta usar la función `pull()` para hacer lo mismo y ver cuál es la diferencia.

2. Visualiza todos los datos excepto la columna 'hp'.

3. Visualiza las columnas mpg, hp, vs, am y gear escribiendo el código más corto posible.

4. Crea un objeto que se llame 'mycars' que contenga las columnas mpg y hp pero que el nombre de la variable sea 'miles_per_gallon' y 'horse_power' respectivamente. Pon los rownames del data.frame en una variable que se llame 'model' [PISTA: debes buscar qué función hay para poner los rownames en una columna].

5. Crea una nueva variable en 'mycars' que sea 'km_per_litre' que describa el consumo del coche (variable 'mpg'). NOTA: 1 mpg es 0.425 km / l.

6. Selecciona al azar (y visualiza) la mitad de las observaciones de 'mycars' [PISTA: busca una función de `dplyr` que haga esto de forma sencilla (similar a `sample` en R tradicional).

7. Crea un objeto 'mycars_s' que contenga de la 10ª a la 35ª fila de mycars [PISTA: considera usar la función `slice()`].

8. Visualiza el objeto 'mycars_s' sin duplicados [PISTA_ encia: considera usar la función `distinct()`].
9. Visualiza del objeto 'mycars_s' todas las observaciones que tengan mpg$>$ 20 y hp$>$ 100.
10. Visualiza la la fila correspondiente al coche Lotus Europa.

Session info

```
sessionInfo()
```

```
R version 4.0.2 (2020-06-22)
Platform: x86_64-w64-mingw32/x64 (64-bit)
Running under: Windows 10 x64 (build 18362)

Matrix products: default

locale:
[1] LC_COLLATE=Spanish_Spain.1252  LC_CTYPE=Spanish_Spain.1252
[3] LC_MONETARY=Spanish_Spain.1252 LC_NUMERIC=C
[5] LC_TIME=Spanish_Spain.1252

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base

other attached packages:
 [1] nycflights13_1.0.1 forcats_0.5.0      stringr_1.4.0      dplyr_1.0.2
 [5] purrr_0.3.4        readr_1.3.1        tidyr_1.1.2        tibble_3.0.3
 [9] ggplot2_3.3.2      tidyverse_1.3.0

loaded via a namespace (and not attached):
 [1] tidyselect_1.1.0 xfun_0.16        lattice_0.20-41  splines_4.0.2
 [5] haven_2.3.1      colorspace_1.4-1 vctrs_0.3.3      generics_0.0.2
 [9] htmltools_0.5.0  mgcv_1.8-33      yaml_2.2.1       utf8_1.1.4
[13] blob_1.2.1       rlang_0.4.7      pillar_1.4.6     glue_1.4.2
[17] withr_2.2.0      DBI_1.1.0        dbplyr_1.4.4     modelr_0.1.8
[21] readxl_1.3.1     lifecycle_0.2.0  munsell_0.5.0    gtable_0.3.0
[25] cellranger_1.1.0 rvest_0.3.6      codetools_0.2-16 evaluate_0.14
[29] labeling_0.3     knitr_1.29       fansi_0.4.1      broom_0.7.0
[33] Rcpp_1.0.5       scales_1.1.1     backports_1.1.9  jsonlite_1.7.0
[37] farver_2.0.3     fs_1.5.0         hms_0.5.3        digest_0.6.25
```