# Data Frames and dplyr

David Gerard 2019-02-06

# Learning Objectives

- Manipulating data frames.
- Calculating summary statistics.
- $\bullet\,$  Using the basic functions of dplyr
- Chapter 5 of RDS

#### Background

- A data frame consists of variables along the columns and observations along the rows.
- For example, in the msleep data frame, the observations are animals and the the variables are properies of those animals (body weight, total sleep time, etc).
- Data frames are the fundamental data type in most analyses.
- Common operations on a data frame during an analysis:
  - Select specific variables (select()).
  - Select observational units by the values of some variables (filter()).
  - Create new variables from old variables (mutate())
  - Reorder the observational units (arrange())
  - Create summary statistics from many observational units (summarize())
  - Group the observational units by the values of some variables (group\_by()).
- As a taste, let's look at an example from the flights data frame from the nycflights13 package:

```
library(nycflights13)
data("flights")
```

- Suppose we want calculate the average departure delay for the flights from carrier in the second half of the year. The steps would be
  - 1. Select only flights from the second half of the year.
  - 2. Group the flights by the carrier.
  - 3. Calculate the average departure delay time within each carrier.
- In base R, this operation would look like:

```
flights2 <- flights[flights$month >= 7, ]
flights3 <- aggregate(dep_time ~ carrier, FUN = mean, data = flights2)
flights3</pre>
```

• In tidyverse, this looks like

filter(month >= 7) %>%

```
suppressPackageStartupMessages(library(tidyverse))
flights %>%
```

```
group_by(carrier) %>%
summarize(mean_dep = mean(dep_time, na.rm = TRUE))
```

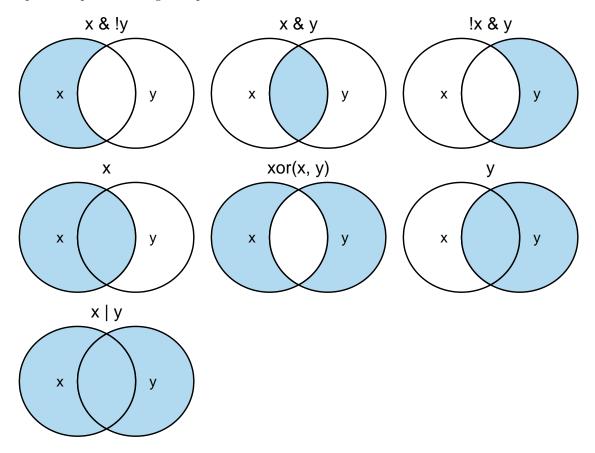
- In the tidyverse:
  - We get to use piping.
  - It's more expressive/clear.

## Filter Rows Based on Variable Values

- In the tidyverse, we use the filter() function to select rows (observations) based on the values of some variables.
- You create logical conditions and the rows that satisfy these logical conditions (return TRUE) are selected.
- Let's extract all flights from new york that occurred in January.

```
flights %>%
filter(month == 1)
```

- You can filter based on more than two variables using logical operators.
- Graphical Depiction of Logical Operations:



• Let's get all flights that were both in January and from JFK.

```
flights %>%
filter(month == 1 & origin == "JFK")
```

- If you don't know what variable values are possible in a categorical variable, then you can try two things:
  - 1. levels() if the variable is a factor.
  - 2. unique() otherwise.

```
unique(flights$origin)
```

```
## [1] "EWR" "LGA" "JFK"
```

• Because the *and* operator is the most used, filter() will also perform the and operation if you separate logical conditions by a comma.

```
flights %>%
  filter(month == 1, origin == "JFK")
```

- You should still know the logical operators in case the filtering gets super complicated.
- Let's extract the January LGA flights and the December JFK flights.

```
flights %>%
filter((month == 1 & origin == "LGA") | (month == 12 & origin == "JFK"))
```

- Exercise: Extract all flights that either occur on odd months, or on odd days of even months.
- Exercise (RDS 5.2.4.1) Find all flights that satisfy the following conditions
  - 1. Had an arrival delay of two or more hours
  - 2. Flew to Houston (IAH or HOU)
  - 3. Were operated by United, American, or Delta
  - 4. Departed in summer (July, August, and September)
  - 5. Arrived more than two hours late, but didn't leave late

#### Missing Values

- filter() will exclude observations with missing values.
- If you want to extract those rows as well, you have to ask for them explicitly using is.na().

• You cannot use NA == NA. If two observations are missing, then you don't know if they are equal, so R will return NA to this:

```
NA == NA
## [1] NA
```

#### near()

- Unless you explicitly tell it, R treats all numerics as floats.
- It's thus dangerous to use == for numerics.
- Instead, use the near() function.

```
sqrt(2) ^ 2
## [1] 2
sqrt(2) ^ 2 == 2
## [1] FALSE
near(sqrt(2) ^ 2, 2)
## [1] TRUE
• If a variable is an integer <int>, then it's OK to use ==
twoint <- as.integer(sqrt(2) ^ 2)
twoint == 2
## [1] TRUE</pre>
```

# Arrange order of rows

• Use arrange() to order the rows by the value of a variable.

 $dfdat \leftarrow data.frame(x = c(1, 2, 1, 2),$ 

```
flights %>%
arrange(dep_delay)
```

• The default is the arrange in ascending order. To arrange in descending order, use the desc() function.

```
flights %>%
arrange(desc(dep_delay))
```

• If there are ties, then you can break the ties by arranging by another variable.

```
y = c(2, 2, 1, 1))
dfdat

## x y
## 1 1 2
## 2 2 2
## 3 1 1
## 4 2 1
dfdat %>%
    arrange(x)

## x y
```

```
## 1 1 2
## 2 1 1
## 3 2 2
## 4 2 1
```

• Observations with missing values are always placed at the end (even when using the desc() function)

### Select Specific Columns

- The select() function will extract variables and place them in a smaller data frame.
- Select specific variables

```
flights %>%
  select(dep_delay, arr_delay)
```

• Select a range of variables with:

```
flights %>%
select(year:day)
```

• Select all variables except certain ones with -

```
flights %>%
select(-dep_delay, -arr_delay)
```

• Select all variables except within a range of columns.

```
flights %>%
select(-(year:day))
```

- Useful helper functions for 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.

```
flights %>%
  select(ends_with("delay"))

flights %>%
  select(starts_with("dep"), year, month, day)
```

• Exercise: Select all variables that have anything to do with the arrival. Also keep the year, month, and day. Use as few characters as possible in your select() call.

#### Rename Variables

• Use rename() to rename a variable.

```
flights %>%
  rename(departureTime = dep_time)
```

#### Create New Variables

- The variables we have are usually not enough for an analysis.
  - Take a log-transformation of positive data to make associations more linear.
  - Create new features based on existing features.
- We can use mutate() to create new variables from old.

• If you only want to keep new variables, use transmute()

```
## # 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
##
        -31 2.67
                         -11.6
##
        17 3.05
                           5.57
##
   5
        19 1.93
                           9.83
##
   6
       -162.5
                          -6.4
        -24 2.63
##
   7
                          -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
```

• Exercise: (RDS 3.5.2.1) Currently dep\_time and sched\_dep\_time are convenient to look at, but hard to compute with because they're not really continuous numbers. Convert them to a more convenient representation of number of minutes since midnight. Hint: %/% is integer division and %% is remainder.

#### **Summaries**

- We can create summary statistics using the summarize() function.
- The following will calculate the mean departure delay time.

```
flights %>%
  summarize(mean_del = mean(dep_delay, na.rm = TRUE))
```

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

• Exercise: What is the standard deviation of the departure delay time?

## **Grouped Summaries**

- You can create a grouped data frame using the group\_by() function.
- You define what variables to group the observational units by.
- Each unique combination of the values of the grouping variables will create a new group.
- Consider the data set:

```
## # A tibble: 7 x 3
##
     Х
           У
##
     <chr> <chr> <dbl>
## 1 a
           С
                      1
## 2 a
           d
                      2
## 3 a
                      3
           С
## 4 a
           С
                      4
## 5 b
                      5
           С
## 6 b
                      6
                      7
## 7 b
```

- If we group by the variable x, then there are two groups:
  - i. Rows 1, 2, 3, 4 (corresponding to "a")
  - ii. Rows 5, 6, 7 (corresponding to "b")
- If we group by the variable y then there are also two groups:
  - i. Rows 1, 3, 4, 7, 5 (corresponding to "c")
  - ii. Rows 2, 6 (corresponding to "d")
- If we group by both x and y then we have four groups:
  - i. Rows 1, 3, 4 (corresponding to "a" and "c")
  - ii. Row 1 (corresponding to "a" and "d")
  - iii. Rows 5, 7 (corresponding to "b" and "c")
  - iv. Row 6 (corresponding to "b" and "d")

```
dfdat %>%
  group_by(x) ->
  grouped_dfdat
attributes(grouped_dfdat)
```

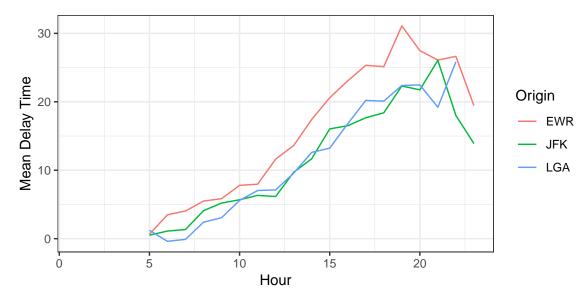
```
## $names
## [1] "x" "y" "z"
##
## $row.names
## [1] 1 2 3 4 5 6 7
##
## $class
## [1] "grouped_df" "tbl_df"
                                  "tbl"
                                                "data.frame"
##
## $vars
## [1] "x"
##
## $drop
## [1] TRUE
##
## $indices
## $indices[[1]]
## [1] 0 1 2 3
## $indices[[2]]
## [1] 4 5 6
##
##
## $group_sizes
## [1] 4 3
## $biggest_group_size
## [1] 4
##
## $labels
##
## 1 a
## 2 b
```

- The grouping function is most useful to calculate summaries within each group.
- The summarize(), filter(), arrange(), mutate() functions will now all operate in a group-specific manner.
- Suppose we want to calculate the mean and standard deviation of the delays within each airport?

- Or at a particular time of day within each airport:
- Suppose we want to calculate the mean and standard deviation of the delays within each airport?

• We can save this output and feed into ggplot2

## Warning: Removed 1 rows containing missing values (geom\_path).



• The n() function will count the number of observational units in a group. \*\*It is a good idea to always include this function in a summarize() call.

• Exercise: Look at the number and proportion of cancelled flights per day. Is there a pattern? Is the proportion of cancelled flights related to the average delay? We'll define a flight to be canceled by is.na(dep\_delay) | is.na(arr\_delay).

# Select Specific Rows

• You can select sertain rows of a data frame using the slice() function.

```
flights %>%
slice(c(1, 4, 6))
```

flights %>%
 slice(10:n())