

Lesson 08 - Data management and aggregation using `dplyr`

Last Updated 01-18-2022

[Introduction (video)]

When working with data you must:

1. Figure out what you want to do.
2. Precisely describe what you want in the form of a computer program.
3. Execute the code.

The `dplyr` package makes each of these steps as fast and easy as possible by:

1. Elucidating the most common data manipulation operations, so that your options are helpfully constrained when thinking about how to tackle a problem.
2. Providing simple functions that correspond to the most common data manipulation verbs, so that you can easily translate your thoughts into code.
3. Using efficient data storage back ends, so that you spend as little time waiting for the computer as possible.

Student Learning Outcomes

After completing this lesson students will be able to

- Explain the difference between a `data.table` and a `tibble`.
- Build and execute a chain of command to accomplish a data management task
- Extract certain rows using `select`.
- Create new variables using `mutate`.
- Rename variables using `rename`
- Subset the data based on a criteria using `filter`.
- Create summary statistics using `group_by` and `summarize`
- Learn how to use code chunk options to disable warning messages.

Preparation

Prior to this lesson students should

- Download the [08_dplyr_notes.Rmd] R markdown file and save into your `Math130/notes` folder.
- Ensure that the `dplyr` and `nyflights13` data sets are installed by running the first code chunk.

```
library(dplyr)
flights <- nycflights13::flights
```

Exploring airline flight data with `dplyr`.

The `nycflights13` package contains several data sets that can be used to help understand what causes delays. We will be using the `flights` data set which contains information about all flights that departed

from NYC (e.g. EWR, JFK and LGA) in 2013.

Tibbles

The `flights` data set, and any data set created with `dplyr`, has a specific data type called a `tibble`. These are not as furry and prolific as their cousins the `tribbles`. `tibbles` behaves for all intents and purposes as a `data.frame`, just gets displayed differently. For example, the `flights` data set contains data on 19 characteristics (variables) from 336,776 flights. There's no way I would want to print out a data set that large. But I'm gonna....

```
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 <dtm>
```

The output has been trimmed to something more reasonable for our viewing pleasure. This may not seem such a big deal because R Studio already provides some level of truncation for our viewing pleasure.

[Basic verbs (video)]

The `dplyr` package contains new data manipulation functions, also called verbs. We will look at the following verbs:

- `filter()`: Returns a subset of the rows.
- `select()`: Returns only the listed columns.
- `rename()`: Renames the variables listed.
- `mutate()`: Adds columns from existing data.
- `summarise()`: Reduces each group to a single row by calculating aggregate measures.
- `group_by()`: Groups a data set on a factor variable, such that all functions performed are then done on each level of the factor.

Filter

`filter()` allows you to select a subset of the rows of a data frame. The first argument is the name of the data frame, and the second and subsequent are filtering expressions evaluated in the context of that data frame. For example, we can select all flights on January 1st with

```
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 <dtm>
```

`filter()` works similarly to `subset()` except that you can give it any number of filtering conditions which are joined together with `&`. You can use other Boolean operators explicitly. Here we select flights in January or February.

```
filter(flights, month == 1 | month == 2)
```

```
## # A tibble: 51,955 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 51,945 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 <dtm>
```

Select

Often you work with large data sets with many columns where only a few are actually of interest to you. `select()` allows you to rapidly zoom in on a useful subset using operations that usually only work on numeric variable positions.

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

```
## # A tibble: 336,776 x 3
##   month   day year
##   <int> <int> <int>
## 1     1     1 2013
## 2     1     1 2013
```

```
## 3 1 1 2013
## 4 1 1 2013
## 5 1 1 2013
## 6 1 1 2013
## 7 1 1 2013
## 8 1 1 2013
## 9 1 1 2013
## 10 1 1 2013
## # ... with 336,766 more rows
```

You can use a colon (:) to select all columns physically located between two variables.

```
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
```

To exclude specific columns you use the minus sign (-)

```
select(flights, -carrier)
```

```
## # A tibble: 336,776 x 18
##   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 10 more variables: arr_delay <dbl>,
## #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>,
## #   distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dtm>
```

This also works to exclude all columns EXCEPT the ones between two variables.

```
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 <dtm>
```

Rename

Sometimes variables come to you in really obscure naming conventions. What the heck is SBA641? New to dplyr 1.0.0 is the `rename()` function. Works like magic to convert old name to a new name. The generic syntax is `rename(new = old)`

So to rename `dep_time` to `departure_time` we would type

```
rename(flights, departure_time = dep_time)
```

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

The variable name on the 3rd column now says `departure_time` instead of `dep_time`.

For the purpose of these lecture notes I am not making this change permanent. There is no assignment operator `<-` used here, so this change is not going to persist into later code.

Mutate

As well as selecting from the set of existing columns, it's often useful to add new columns that are functions of existing columns. This is the job of `mutate()`!

Here we create two variables: `gain` (as arrival delay minus departure delay) and `speed` (as distance divided by time, converted to hours).

```
a <- mutate(flights, gain = arr_delay - dep_delay,
            speed = distance / air_time * 60)
select(a, gain, distance, air_time, speed)
```

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

One key advantage of mutate is that you can refer to the columns you just created. Mutate flights to create two variables, gain = arr_delay - dep_delay and gain_per_hour = gain / (air_time / 60).

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

```
## # A tibble: 336,776 x 21
##   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 13 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 <dtm>,
## #   gain <dbl>, gain_per_hour <dbl>
```

Summarize

The last verb is summarise(), which collapses a data frame to a single row. It's not very useful yet. We can create a new variable called delay that is the average departure delay on the entire flights data set.

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

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

[Grouped Operations (video)]

The above verbs are useful, but they become really powerful when you combine them with the idea of “group by”, repeating the operation individually on groups of observations within the dataset. In `dplyr`, you use the `group_by()` function to describe how to break a dataset down into groups of rows. You can then use the resulting object in exactly the same functions as above; they’ll automatically work “by group” when the input is a grouped.

Let’s demonstrate how some of these functions work after grouping the flights data set by month. First we’ll create a new data set that is grouped by month.

```
by_month <- group_by(flights, month)
```

- The `summarise()` verb allows you to calculate summary statistics for each group. This is probably the most common function that is used in conjunction with `group_by`. For example, the average distance flown per month.

```
summarise(by_month, avg_airtime = mean(distance, na.rm=TRUE))
```

```
## # A tibble: 12 x 2
##   month avg_airtime
##   <int> <dbl>
## 1     1    1007.
## 2     2    1001.
## 3     3    1012.
## 4     4    1039.
## 5     5    1041.
## 6     6    1057.
## 7     7    1059.
## 8     8    1062.
## 9     9    1041.
## 10    10    1039.
## 11    11    1050.
## 12    12    1065.
```

Or simply the total number of flights per month.

```
summarize(by_month, count=n())
```

```
## # A tibble: 12 x 2
##   month count
##   <int> <int>
## 1     1 27004
## 2     2 24951
## 3     3 28834
## 4     4 28330
## 5     5 28796
## 6     6 28243
## 7     7 29425
## 8     8 29327
## 9     9 27574
## 10    10 28889
## 11    11 27268
## 12    12 28135
```

[Chaining Operations (video)]

Consider the following group of operations that take the data set `flights`, and produce a final data set (`a4`) that contains only the flights where the daily average delay is greater than a half hour.

```
a1 <- group_by(flights, year, month, day)
a2 <- select(a1, arr_delay, dep_delay)

## Adding missing grouping variables: `year`, `month`, `day`
a3 <- summarise(a2,
                arr = mean(arr_delay, na.rm = TRUE),
                dep = mean(dep_delay, na.rm = TRUE))

## `summarise()` has grouped output by 'year', 'month'. You can override using the `.groups` argument.
a4 <- filter(a3, arr > 30 | dep > 30)
head(a4)

## # A tibble: 6 x 5
## # Groups:   year, month [3]
##   year month   day   arr   dep
##   <int> <int> <int> <dbl> <dbl>
## 1  2013     1    16  34.2  24.6
## 2  2013     1    31  32.6  28.7
## 3  2013     2    11  36.3  39.1
## 4  2013     2    27  31.3  37.8
## 5  2013     3     8  85.9  83.5
## 6  2013     3    18  41.3  30.1
```

It does the trick, but what if you don't want to save all the intermediate results (`a1 - a3`)? Well these verbs are *function*, so they can be wrapped inside other functions to create a nesting type structure.

```
filter(
  summarise(
    select(
      group_by(flights, year, month, day),
      arr_delay, dep_delay
    ),
    arr = mean(arr_delay, na.rm = TRUE),
    dep = mean(dep_delay, na.rm = TRUE)
  ),
  arr > 30 | dep > 30
)
```

Woah, that is HARD to read! This is difficult to read because the order of the operations is from inside to out, and the arguments are a long way away from the function. To get around this problem, `dplyr` provides the `%>%` operator. `x %>% f(y)` turns into `f(x, y)` so you can use it to rewrite multiple operations so you can read from left-to-right, top-to-bottom:

```
flights %>%
  group_by(year, month, day) %>%
  select(arr_delay, dep_delay) %>%
  summarise(
    arr = mean(arr_delay, na.rm = TRUE),
    dep = mean(dep_delay, na.rm = TRUE)
  ) %>%
  filter(arr > 30 | dep > 30)
```



```
## Adding missing grouping variables: `year`, `month`, `day`
## `summarise()` has grouped output by 'year', 'month'. You can override using the `.groups` argument.
## # A tibble: 49 x 5
## # Groups:   year, month [11]
##   year month   day   arr   dep
##   <int> <int> <int> <dbl> <dbl>
## 1  2013     1    16  34.2  24.6
## 2  2013     1    31  32.6  28.7
## 3  2013     2    11  36.3  39.1
## 4  2013     2    27  31.3  37.8
## 5  2013     3     8  85.9  83.5
## 6  2013     3    18  41.3  30.1
## 7  2013     4    10  38.4  33.0
## 8  2013     4    12  36.0  34.8
## 9  2013     4    18  36.0  34.9
## 10 2013     4    19  47.9  46.1
## # ... with 39 more rows
```

Another way you can read this is by thinking “and then” when you see the %>% operator. So the above code takes the data set flights

```
.. and then groups by day
.. and then selects the delay variables
.. and then calculates the means
.. and then filters on a delay over half hour.
```

The same 4 steps that resulted in the `a4` data set, but without all the intermediate data saved! This can be **very important** when dealing with Big Data. R stores all data in memory, so if your little computer only has 2G of RAM and you’re working with a data set that is 500M in size, your computers memory will be used up fast. `a1` takes 500M, `a2` another 500M, by now your computer is getting slow. Make another copy at `a3` and it gets worse, `a4` now likely won’t even be able to be created because you’ll be out of memory.

Go Back to Week 3