# 05 - Aggregation

Data and Information Engineering

*SYS 2202 | Fall 2019*

*05-aggregate.pdf*

## Contents



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### Required Packages and Data

```r
library(tidyverse)
library(nycflights13)
data(flights)
```

# 1 Single table verbs

## 1.1 dplyr single table verbs

- `filter()`: select rows
- `arrange()`: reorder rows
  - `desc()` to use descending order
- `select()`: select certain columns
  - helper functions: `starts_with()`, `ends_with()`, `matches()`, `contains()`, `?select`
- `mutate()`: modify or create new variables
  - `transmute()`: only return new variables
- `summarize()`: reduce variables to values
  - Most useful when data is grouped

## 1.2 `summarize()`

The `summarize()` function calculates summary statistics for a column (or multiple columns). It collapses a data frame to a *single row*:

```
summarize(flights, avg.dist = mean(distance))    # mean distance
#> # A tibble: 1 x 1
#>   avg.dist
#>      <dbl>
#> 1    1040.
summarize(flights, avg.dist = mean(distance), med.dist = median(distance))
#> # A tibble: 1 x 2
#>   avg.dist med.dist
#>      <dbl>    <dbl>
#> 1    1040.      872
summarize(flights,
          n.records = n(),                          # number of records
          n.missing = sum(is.na(arr_delay)),        # number of NA's
          num.delay = sum(arr_delay>0, na.rm=TRUE),   # num of delayed flights
          prop.delay = mean(arr_delay>0, na.rm=TRUE) ) # proportion of delayed flights
#> # A tibble: 1 x 4
#>   n.records n.missing num.delay prop.delay
#>       <int>     <int>     <int>      <dbl>
#> 1    336776      9430    133004      0.406
```

Just to check the numbers, $133004/(336776 - 9430) = 0.406$

It works like this `summarize(<data>, name1 = f(<colname>), name2=g(<colname>))` where $f, g$ are some functions (e.g., `mean()`, `median()`, `sd()`).

It can also use functions that take more than one column as input, but most return a single value. E.g.,

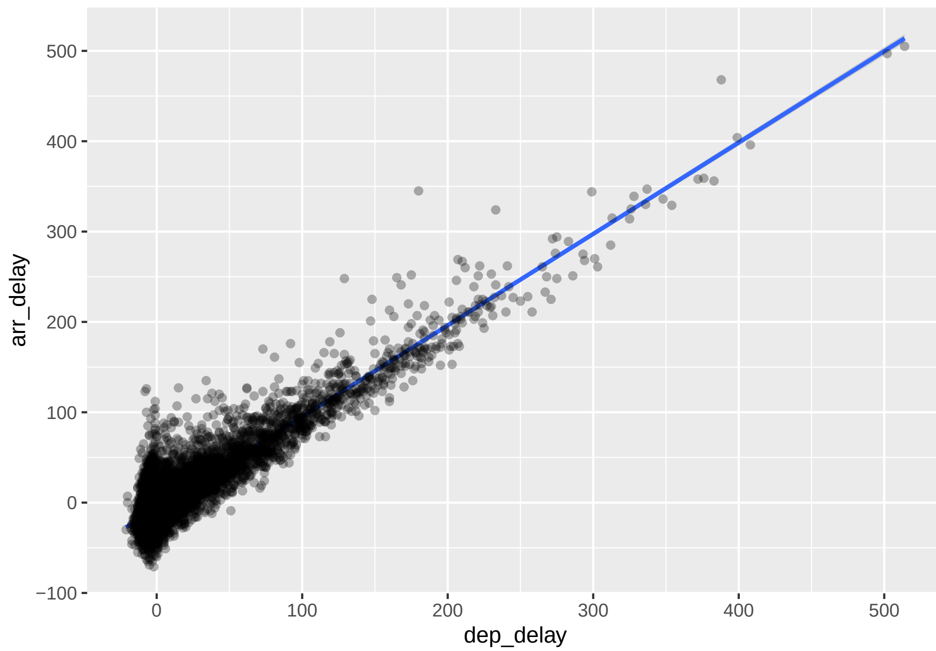
```
#- correlation of dep_delay and arr_delay
summarize(flights, delay_cor = cor(dep_delay, arr_delay, use="complete.obs"))
#> # A tibble: 1 x 1
```

```
#>   delay_cor
#>       <dbl>
#> 1     0.915

# same as:
# cor(flights$dep_delay, flights$arr_delay, use="complete.obs")
```

This is a strong positive correlation (close to 1), which is to be expected. The correlation coefficient is a number that measures how far away the points are from a straight trend line fit to the data. If we plot the scatter plot and add a linear smooth, we should see the points close to the line.

```
ggplot(sample_n(flights,10000), aes(dep_delay, arr_delay)) +
  geom_smooth(method='lm') + geom_point(alpha=.3)
#> Warning: Removed 259 rows containing non-finite values (stat_smooth).
#> Warning: Removed 259 rows containing missing values (geom_point).
```




The warning message indicates that some rows are not plotted. It is also wise to know why rows are being dropped. In this case, it is because some of the `dep_delay` and `arr_delay` values are missing.

Hopefully you were not on any of those flights that were delayed by over 600 mins (10 hrs)!

## 1.3 `summary()` is not `summarize()`

The `summary()` function is a base R function that reports some basic summary stats for all columns.

```
summary(flights)                                # base R function
#>       year           month             day            dep_time
#>  Min.   :2013   Min.   : 1.00   Min.   : 1.0   Min.   :   1
#>  1st Qu.:2013   1st Qu.: 4.00   1st Qu.: 8.0   1st Qu.: 907
#>  Median :2013   Median : 7.00   Median :16.0   Median :1401
#>  Mean   :2013   Mean   : 6.55   Mean   :15.7   Mean   :1349
#>  3rd Qu.:2013   3rd Qu.:10.00   3rd Qu.:23.0   3rd Qu.:1744
```

```
#>  Max.   :2013   Max.   :12.00   Max.   :31.0   Max.   :2400
#>                                                 NA's   :8255
#>  sched_dep_time   dep_delay       arr_time    sched_arr_time
#>  Min.   : 106   Min.   : -43   Min.   :   1   Min.   :   1
#>  1st Qu.: 906   1st Qu.:  -5   1st Qu.:1104   1st Qu.:1124
#>  Median :1359   Median :  -2   Median :1535   Median :1556
#>  Mean   :1344   Mean   :  13   Mean   :1502   Mean   :1536
#>  3rd Qu.:1729   3rd Qu.:  11   3rd Qu.:1940   3rd Qu.:1945
#>  Max.   :2359   Max.   :1301   Max.   :2400   Max.   :2359
#>                 NA's   :8255   NA's   :8713
#>    arr_delay      carrier             flight       tailnum
#>  Min.   : -86   Length:336776      Min.   :   1   Length:336776
#>  1st Qu.: -17   Class :character   1st Qu.: 553   Class :character
#>  Median :  -5   Mode  :character   Median :1496   Mode  :character
#>  Mean   :   7                      Mean   :1972
#>  3rd Qu.:  14                      3rd Qu.:3465
#>  Max.   :1272                      Max.   :8500
#>  NA's   :9430
#>     origin              dest              air_time       distance
#>  Length:336776      Length:336776      Min.   : 20    Min.   :  17
#>  Class :character   Class :character   1st Qu.: 82    1st Qu.: 502
#>  Mode  :character   Mode  :character   Median :129    Median : 872
#>                                        Mean   :151    Mean   :1040
#>                                        3rd Qu.:192    3rd Qu.:1389
#>                                        Max.   :695    Max.   :4983
#>                                        NA's   :9430
#>       hour          minute       time_hour
#>  Min.   : 1.0   Min.   : 0.0   Min.   :2013-01-01 05:00:00
#>  1st Qu.: 9.0   1st Qu.: 8.0   1st Qu.:2013-04-04 13:00:00
#>  Median :13.0   Median :29.0   Median :2013-07-03 10:00:00
#>  Mean   :13.2   Mean   :26.2   Mean   :2013-07-03 05:22:54
#>  3rd Qu.:17.0   3rd Qu.:44.0   3rd Qu.:2013-10-01 07:00:00
#>  Max.   :23.0   Max.   :59.0   Max.   :2013-12-31 23:00:00
#>
```

The `summarize()` function applies a function that summarizes each column down to a single number.

```
summarize(flights,
          min=min(arr_delay, na.rm=TRUE),
          Q1 = quantile(arr_delay, 0.25, na.rm=TRUE),
          median=median(arr_delay, na.rm=TRUE),
          mean = mean(arr_delay, na.rm=TRUE),
          Q3 = quantile(arr_delay, 0.75, na.rm=TRUE),
          max = max(arr_delay, na.rm=TRUE),
          count.NA = sum(is.na(arr_delay)))
#> # A tibble: 1 x 7
#>     min    Q1 median  mean    Q3   max count.NA
#>   <dbl> <dbl>  <dbl> <dbl> <dbl> <dbl>    <int>
#> 1   -86   -17     -5  6.90    14  1272     9430
```

# 2 Group-wise operations

## 2.1 Split-Apply-Combine

The `summarize()` function becomes more powerful when it can be used with grouping variables. Split - Apply - Combine.

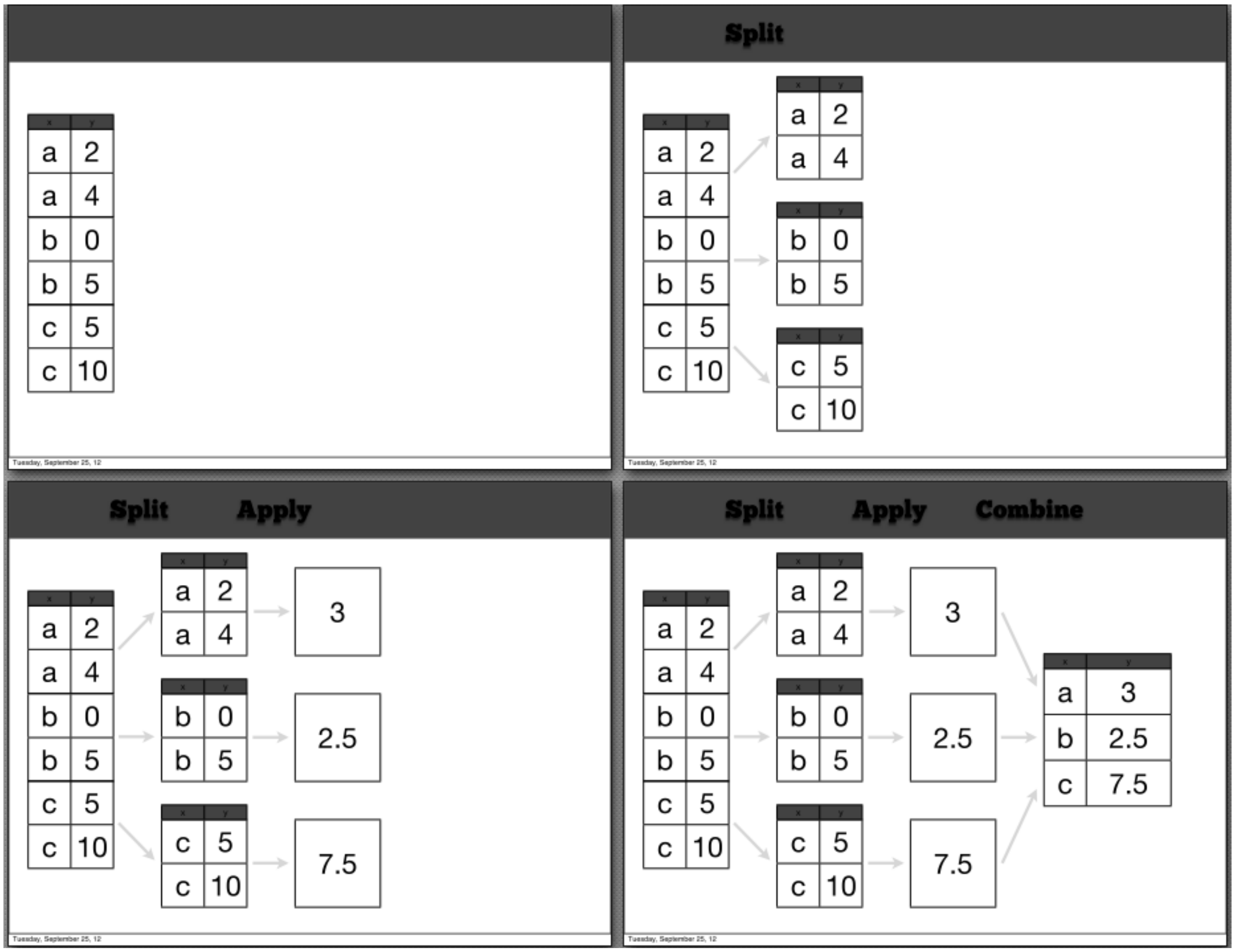



Image from Hadley Wickham UseR tutorial June 2014 http://www.dropbox.com/sh/i8qnluwmuieicxc/AAAgt9tIKoIm7WZKIyK25lh6a

## 2.2 group_by()

First use the `group_by()` function to group the data (determines how to split), then apply function(s) to each group using the `summarise()` function. Note: grouping should to be applied on discrete variables (categorical, factor, or maybe integer valued columns).

```
#- Get maximum delay by origin
by_origin = group_by(flights, origin)
summarize(by_origin, max.delay = max(arr_delay, na.rm=TRUE))
#> # A tibble: 3 x 2
#>   origin max.delay
```

```
#>   <chr>      <dbl>
#> 1 EWR         1109
#> 2 JFK         1272
#> 3 LGA          915


#- Get delay info by origin and destination
by_dest = group_by(flights, origin, dest)
summarize(by_dest,
          max.delay = max(arr_delay, na.rm=TRUE),
          avg.delay = mean(arr_delay, na.rm=TRUE),
          min.delay = min(arr_delay, na.rm=TRUE),
          count = n() )
#> # A tibble: 224 x 6
#> # Groups:   origin [3]
#>   origin dest  max.delay avg.delay min.delay count
#>   <chr>  <chr>     <dbl>     <dbl>     <dbl> <int>
#> 1 EWR    ALB         328    14.4         -34   439
#> 2 EWR    ANC          39    -2.5         -47     8
#> 3 EWR    ATL         796    13.2         -39  5022
#> 4 EWR    AUS         349    -0.474       -59   968
#> 5 EWR    AVL         228     8.80        -26   265
#> 6 EWR    BDL         266     7.05        -43   443
#> # ... with 218 more rows


#- derived columns: partition air_time into 5 categories (check the NA row too)
by_air_time = group_by(flights, air_time2 = cut_number(air_time, n=5)) # added column
#> Warning: Factor `air_time2` contains implicit NA, consider using
#> `forcats::fct_explicit_na`
summarize(by_air_time,
          max.delay = max(arr_delay, na.rm=TRUE),
          avg.delay = mean(arr_delay, na.rm=TRUE),
          min.delay = min(arr_delay, na.rm=TRUE),
          count = n() )
#> # A tibble: 6 x 5
#>   air_time2 max.delay avg.delay min.delay count
#>   <fct>         <dbl>     <dbl>     <dbl> <int>
#> 1 [20,71]         851      8.23       -62 65510
#> 2 (71,112]       1127      8.16       -63 67342
#> 3 (112,146]       931      6.94       -68 64410
#> 4 (146,214]       915      7.35       -68 65115
#> 5 (214,695]      1272      3.74       -86 64969
#> 6 <NA>           -Inf    NaN          Inf  9430
```

The `cut_number()` function *discretized* the numeric `air_time` variable into a factor vector with `n=5` levels (actually 6 levels due to the cases with missing (NA) `air_time` values).
The `cut_width()` and `cut_interval()` are similar, but use different methods to *discretize* the numeric values.

### 2.2.1 Your Turn

**Your Turn #1 : group_by**

Which plane (`tailnum`) has the worst on-time record?

## 2.3 Counting

We often need to count the number of observations in each group. It is so frequently needed, that `dplyr` has included some shortcuts with `n()` and `count()`

1. use `summarize()` with `n()` (must use *grouped* data)

```
#- tally(.) is same as summarize(., n=n())
summarize(by_origin, n=n())
#> # A tibble: 3 x 2
#>   origin      n
#>   <chr>   <int>
#> 1 EWR    120835
#> 2 JFK    111279
#> 3 LGA    104662
```

2. use `count()` (don't use *grouped* data)

```
#- count(., colnames) is same as group_by(., colnames) %>% summarize(n=n())
count(flights, origin)
#> # A tibble: 3 x 2
#>   origin      n
#>   <chr>   <int>
#> 1 EWR    120835
#> 2 JFK    111279
#> 3 LGA    104662
```

### 2.3.1 Counts over multiple variables

```
#- Count for each route (origin and destination)
count(flights, origin, dest)
#> # A tibble: 224 x 3
#>   origin dest      n
#>   <chr>  <chr> <int>
#> 1 EWR    ALB     439
#> 2 EWR    ANC       8
#> 3 EWR    ATL    5022
#> 4 EWR    AUS     968
#> 5 EWR    AVL     265
#> 6 EWR    BDL     443
#> # ... with 218 more rows

#- Count for each route by month
count(flights, origin, dest, month)
#> # A tibble: 2,313 x 4
#>   origin dest  month     n
```

```
#>   <chr>  <chr> <int> <int>
#> 1 EWR    ALB       1    64
#> 2 EWR    ALB       2    58
#> 3 EWR    ALB       3    57
#> 4 EWR    ALB       4    13
#> 5 EWR    ALB       5    59
#> 6 EWR    ALB       6    34
#> # ... with 2,307 more rows
```

Sometimes it is convienient to arrange the data to the rows with the largest counts are displayed first. The `count()` function has the handy `sort=TRUE` argument to give you this shortcut. For example,

```
count(flights, origin, dest, month, sort=TRUE)
#> # A tibble: 2,313 x 4
#>   origin dest  month     n
#>   <chr>  <chr> <int> <int>
#> 1 JFK    LAX       7   985
#> 2 JFK    LAX       8   979
#> 3 JFK    LAX      10   965
#> 4 JFK    LAX       3   960
#> 5 JFK    LAX       5   960
#> 6 JFK    LAX      12   947
#> # ... with 2,307 more rows
```

### 2.3.2 Plotting the counts

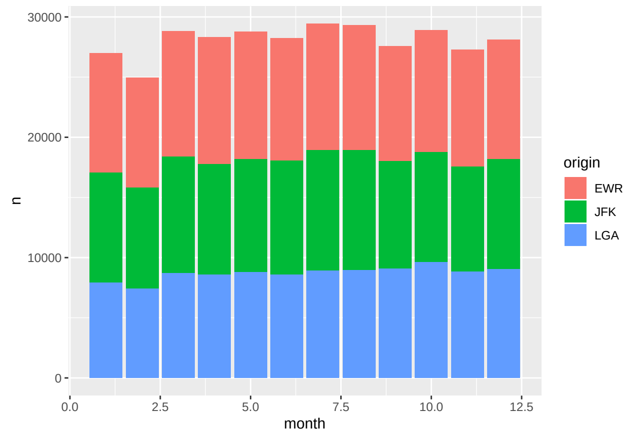
Get the monthly counts

```
(monthly = count(flights, origin, month))
#> # A tibble: 36 x 3
#>   origin month     n
#>   <chr>  <int> <int>
#> 1 EWR        1  9893
#> 2 EWR        2  9107
#> 3 EWR        3 10420
#> 4 EWR        4 10531
#> 5 EWR        5 10592
#> 6 EWR        6 10175
#> # ... with 30 more rows
```

Notice that `count()` creates the column named `n` (integer).

```
#- (left) Bar Plot
ggplot(monthly) + geom_col(aes(x=month, y=n, fill=origin))
# ggplot(flights) + geom_bar(aes(x=month, fill=origin)) # alternative

#- (right) Line Plot
ggplot(monthly) + geom_line(aes(x=month, y=n, col=origin))
```





### 2.3.3 Your Turn

**Your Turn #2 : Thinking about plots**

1. Are the plots better than the table?
2. Which plot do you think is better?
3. How can the plots be improved?

### 2.3.4 Additional arguments

Check out the help for the `count()` function: `?count` There are four additional arguments:

- `wt` gives a weighted sum (instead of plain count)
- `sort=TRUE` arranges the results from largest to smallest (based on `n`)
- `name` get the name of the new count column
- `.drop` controls if empty levels are dropped or reported as zero counts

```
#-- total arrival delay by flight number (set column name to total_delay)
count(flights, flight, wt=arr_delay, sort=TRUE, name = 'total_delay')
#> # A tibble: 3,844 x 2
#>    flight total_delay
#>     <int>       <dbl>
#> 1    4131       12989
#> 2     527       11694
#> 3    4333       11433
#> 4     415       11390
#> 5    4224       10204
#> 6    4543       10148
#> # ... with 3,838 more rows
```

### 2.3.5 Other types of counts

Some useful counts are

- count the number of distinct items with `n_distinct()`

```
summarize(by_origin, n_flights=n(), n_dests=n_distinct(dest))
#> # A tibble: 3 x 3
#>   origin n_flights n_dests
#>   <chr>      <int>   <int>
#> 1 EWR       120835      86
#> 2 JFK       111279      70
#> 3 LGA       104662      68
```

- count the number of missing (`NA`) or non-missing (not-`NA`) values

```
summarize(by_origin, n_flights=n(), n_missing = sum(is.na(dep_time)),
          n_not_missing=sum(!is.na(dep_time)))
#> # A tibble: 3 x 4
#>   origin n_flights n_missing n_not_missing
#>   <chr>      <int>     <int>         <int>
#> 1 EWR       120835      3239        117596
#> 2 JFK       111279      1863        109416
#> 3 LGA       104662      3153        101509
```

### 2.3.6 Your Turn

**Your Turn #3 : counting**

1. How many flights does the plane with the worst on-time record have? You need to determine what is meant by "worst on-time record".
2. Which plane (`tailnum`) has made the most flights?
3. Which plane (`tailnum`) has flown the most overall distance?

## 2.4 Chaining

Multiple operations can be chained together with the `%>%` operator (pronounced as *then*). Technically, it performs `x %>% f(y) -> f(x, y)`. This lets you focus on the verbs, or actions you are performing.

```
#- group then summarize then filter then arrange
by_dest = group_by(flights, dest)
delay = summarize(by_dest,
          count = n(),
          avg.delay = mean(arr_delay, na.rm=TRUE))
delay2 = filter(delay, count > 20)
arrange(delay2, desc(avg.delay))
#> # A tibble: 97 x 3
#>   dest  count avg.delay
#>   <chr> <int>     <dbl>
#> 1 CAE     116      41.8
#> 2 TUL     315      33.7
#> 3 OKC     346      30.6
#> 4 JAC      25      28.1
#> 5 TYS     631      24.1
#> 6 MSN     572      20.2
#> # ... with 91 more rows
```

```
flights %>%
  group_by(dest) %>%
  summarize( count = n(),
             avg.delay = mean(arr_delay, na.rm=TRUE)) %>%
  filter(count > 20) %>%
  arrange(desc(avg.delay))
#> # A tibble: 97 x 3
#>   dest  count avg.delay
#>   <chr> <int>     <dbl>
#> 1 CAE     116      41.8
#> 2 TUL     315      33.7
#> 3 OKC     346      30.6
#> 4 JAC      25      28.1
#> 5 TYS     631      24.1
#> 6 MSN     572      20.2
#> # ... with 91 more rows
```

**Your Turn #4 : Chaining**

Use chaining to redo:

1. How many flights does the plane with the worst on-time record have?
2. Which plane (`tailnum`) has made the most flights?
3. Which plane (`tailnum`) has flown the most overall distance?

## 2.5 Multiple grouping levels

Notice how each operation *strips away* a grouping level.

```
#- grouped by: year, month, day
(daily <- group_by(flights, year, month, 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
#> # ... with 3.368e+05 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>

#- grouped by: year, month
(per_day   <- summarise(daily, flights = n()))
#> # A tibble: 365 x 4
#> # Groups:   year, month [12]
#>    year month   day flights
#>   <int> <int> <int>   <int>
#> 1  2013     1     1     842
#> 2  2013     1     2     943
#> 3  2013     1     3     914
#> 4  2013     1     4     915
```

```
#> 5  2013     1     5     720
#> 6  2013     1     6     832
#> # ... with 359 more rows

#- grouped by: year
(per_month <- summarise(per_day, flights = sum(flights)))
#> # A tibble: 12 x 3
#> # Groups:   year [1]
#>    year month flights
#>   <int> <int>   <int>
#> 1  2013     1   27004
#> 2  2013     2   24951
#> 3  2013     3   28834
#> 4  2013     4   28330
#> 5  2013     5   28796
#> 6  2013     6   28243
#> # ... with 6 more rows

#- grouped by: nothing (i.e., this is not grouped data)
(per_year  <- summarise(per_month, flights = sum(flights)))
#> # A tibble: 1 x 2
#>    year flights
#>   <int>   <int>
#> 1  2013  336776
```

If you want to remove the grouping, use `ungroup()` function.

```
(per_year   <- daily %>% ungroup() %>% summarise(flights = n()))
#> # A tibble: 1 x 1
#>   flights
#>     <int>
#> 1  336776
```

Note that `count()` automatically performs `ungroup()`

### 2.5.1 Your Turn

**Your Turn #5 : Multiple groups**

1. Find the top 5 routes (`origin`, `dest`), in terms of number of flights.
2. Which route (`origin`, `dest`) is most often delayed by more than 10 minutes? Are infrequent routes a concern? If so, what could we do about it?
3. Find the top 3 destinations (`dest`) for each origin (`origin`).

Notice that `arrange()` ignores the grouping unless `.by_group=TRUE`.

## 2.6 Grouped Mutate and Filter

The last exercise (find the top 3 destinations for each origin) requires a *grouped filter*. That is, perform filtering *within* each group separately.

A *grouped mutate* can calculate standardizations per group

```
#- find the proportion of carrier at each dest
flights %>%
  count(dest, carrier) %>%             # ungrouped
  group_by(dest) %>%                   # group by dest
  mutate(total=sum(n), p=n/sum(n)) %>% # grouped mutate sum(n) is by group
  arrange(desc(total), desc(p))        # arrange by most freq dest, then p
#> # A tibble: 314 x 5
#> # Groups:   dest [105]
#>   dest  carrier     n total        p
#>   <chr> <chr>   <int> <int>    <dbl>
#> 1 ORD   UA       6984 17283 0.404
#> 2 ORD   AA       6059 17283 0.351
#> 3 ORD   MQ       2276 17283 0.132
#> 4 ORD   9E       1056 17283 0.0611
#> 5 ORD   B6        905 17283 0.0524
#> 6 ORD   EV          2 17283 0.000116
#> # ... with 308 more rows
```

To do a *grouped* filter or mutate, the data frame must be grouped with `group_by()`. Functions that work most naturally in grouped mutates and filters are known as *window functions*.

## 2.7 Window Functions

A *window function* is a variation on an aggregation function. Where an aggregation function, like `sum()` and `mean()`, takes `n` inputs and return a single value, a window function returns `n` values. The output of a window function depends on all its input values, so window functions don't include functions that work element-wise, like + or `round()`. Window functions include variations on aggregate functions, like `cumsum()` and `cummean()`, functions for ranking and ordering, like `rank()`, and functions for taking offsets, like `lead()` and `lag()`. The Z-score can be considered a window function.

More description of some window functions and their use can be found:
- data transform cheatsheet
- [Window function vignette](https://dplyr.tidyverse.org/articles/window-functions.html