

Home Work Assignment 4

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My Github repository for my assignments can be found at this URL: [My Github](#)

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

```
not_cancelled <- flights %>%
  filter(!is.na(dep_delay), !is.na(arr_delay))
```

2. Come up with another approach that will give you the same output as

```
not_cancelled %>%
  count(dest)
```

```
## # A tibble: 104 x 2
##   dest      n
##   <chr> <int>
## 1 ABQ    254
## 2 ACK    264
## 3 ALB    418
## 4 ANC      8
## 5 ATL  16837
## 6 AUS   2411
## 7 AVL    261
## 8 BDL    412
## 9 BGR    358
## 10 BHM    269
## # ... with 94 more rows
```

count function counts the data set by a the specified variable. The same result can be achieved if we group by the data set by the same variable. Then using length() function counts the observation in each group

```
not_cancelled %>%
  group_by(dest) %>%
  summarise(n = length(dest))
```

```
## # A tibble: 104 x 2
##   dest      n
##   <chr> <int>
## 1 ABQ    254
## 2 ACK    264
## 3 ALB    418
## 4 ANC      8
## 5 ATL  16837
## 6 AUS   2411
## 7 AVL    261
## 8 BDL    412
## 9 BGR    358
## 10 BHM    269
## # ... with 94 more rows
```

```
not_cancelled %>%
  count(tailnum, wt = distance)
```

```
## # A tibble: 4,037 x 2
##   tailnum      n
##   <chr>    <dbl>
## 1 D942DN    3418
## 2 NOEGMQ  239143
## 3 N10156  109664
## 4 N102UW   25722
## 5 N103US   24619
## 6 N104UW   24616
## 7 N10575  139903
## 8 N105UW   23618
## 9 N107US   21677
## 10 N108UW  32070
## # ... with 4,027 more rows
```

```
not_cancelled %>%
  group_by(tailnum) %>%
  summarise(n = sum(distance))
```

```
## # A tibble: 4,037 x 2
##   tailnum      n
##   <chr>    <dbl>
## 1 D942DN    3418
## 2 NOEGMQ  239143
## 3 N10156  109664
## 4 N102UW   25722
## 5 N103US   24619
## 6 N104UW   24616
## 7 N10575  139903
## 8 N105UW   23618
## 9 N107US   21677
## 10 N108UW  32070
## # ... with 4,027 more rows
```

3. Our definition of cancelled flights ({ Snip } is.na(dep_delay) | is.na(arr_delay)) is slightly suboptimal. Why? Which is the most important column?

I think arr_delay is important. Because if the flight may go land in a different airport other than the Destination Airport. In that case the arr_delay would be NULL. So to know the about the Cancelled Flight both Dep_delay and Arr_delay has to be NULL

4. Look at the number of cancelled flights per day. Is there a pattern? Is the proportion of cancelled flights related to the average delay?

Need to check with robert

```
#canceled_delayed <-
# flights%>%
# group_by(flights, year, month, day)
```

```
flights%>%
  group_by(carrier)%>%
  summarise(arr_delay = mean(arr_delay, na.rm = TRUE)) %>%
  arrange(desc(arr_delay))
```

```
## # A tibble: 16 x 2
##   carrier arr_delay
##   <chr>      <dbl>
## 1 F9         21.9
## 2 FL         20.1
## 3 EV         15.8
## 4 YV         15.6
## 5 OO         11.9
## 6 MQ         10.8
## 7 WN          9.65
## 8 B6          9.46
## 9 9E          7.38
## 10 UA         3.56
## 11 US         2.13
## 12 VX         1.76
## 13 DL         1.64
## 14 AA         0.364
## 15 HA        -6.92
## 16 AS        -9.93
```

```
flights%>%
  count(carrier)%>%
  arrange((carrier))
```

```
## # A tibble: 16 x 2
##   carrier      n
##   <chr>   <int>
## 1 9E     18460
## 2 AA     32729
## 3 AS       714
## 4 B6     54635
## 5 DL     48110
## 6 EV     54173
## 7 F9       685
## 8 FL     3260
## 9 HA       342
## 10 MQ    26397
## 11 OO        32
## 12 UA    58665
## 13 US    20536
## 14 VX     5162
## 15 WN    12275
## 16 YV       601
```

```
as_tibble(flights)
```

```
## # 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 <dtm>
```

```
mtcars
```

```
##      mpg cyl  disp  hp drat   wt  qsec vs am gear carb
## Mazda RX4      21.0   6 160.0 110 3.90 2.620 16.46 0 1   4   4
## Mazda RX4 Wag  21.0   6 160.0 110 3.90 2.875 17.02 0 1   4   4
## Datsun 710      22.8   4 108.0  93 3.85 2.320 18.61 1 1   4   1
## Hornet 4 Drive  21.4   6 258.0 110 3.08 3.215 19.44 1 0   3   1
## Hornet Sportabout 18.7   8 360.0 175 3.15 3.440 17.02 0 0   3   2
## Valiant         18.1   6 225.0 105 2.76 3.460 20.22 1 0   3   1
## Duster 360      14.3   8 360.0 245 3.21 3.570 15.84 0 0   3   4
## Merc 240D       24.4   4 146.7  62 3.69 3.190 20.00 1 0   4   2
## Merc 230        22.8   4 140.8  95 3.92 3.150 22.90 1 0   4   2
## Merc 280        19.2   6 167.6 123 3.92 3.440 18.30 1 0   4   4
## Merc 280C       17.8   6 167.6 123 3.92 3.440 18.90 1 0   4   4
## Merc 450SE      16.4   8 275.8 180 3.07 4.070 17.40 0 0   3   3
## Merc 450SL      17.3   8 275.8 180 3.07 3.730 17.60 0 0   3   3
## Merc 450SLC     15.2   8 275.8 180 3.07 3.780 18.00 0 0   3   3
## Cadillac Fleetwood 10.4   8 472.0 205 2.93 5.250 17.98 0 0   3   4
## Lincoln Continental 10.4   8 460.0 215 3.00 5.424 17.82 0 0   3   4
## Chrysler Imperial 14.7   8 440.0 230 3.23 5.345 17.42 0 0   3   4
## Fiat 128        32.4   4  78.7  66 4.08 2.200 19.47 1 1   4   1
## Honda Civic     30.4   4  75.7  52 4.93 1.615 18.52 1 1   4   2
## Toyota Corolla  33.9   4  71.1  65 4.22 1.835 19.90 1 1   4   1
## Toyota Corona   21.5   4 120.1  97 3.70 2.465 20.01 1 0   3   1
## Dodge Challenger 15.5   8 318.0 150 2.76 3.520 16.87 0 0   3   2
## AMC Javelin     15.2   8 304.0 150 3.15 3.435 17.30 0 0   3   2
## Camaro Z28      13.3   8 350.0 245 3.73 3.840 15.41 0 0   3   4
## Pontiac Firebird 19.2   8 400.0 175 3.08 3.845 17.05 0 0   3   2
## Fiat X1-9       27.3   4  79.0  66 4.08 1.935 18.90 1 1   4   1
## Porsche 914-2   26.0   4 120.3  91 4.43 2.140 16.70 0 1   5   2
## Lotus Europa    30.4   4  95.1 113 3.77 1.513 16.90 1 1   5   2
## Ford Pantera L  15.8   8 351.0 264 4.22 3.170 14.50 0 1   5   4
## Ferrari Dino    19.7   6 145.0 175 3.62 2.770 15.50 0 1   5   6
## Maserati Bora   15.0   8 301.0 335 3.54 3.570 14.60 0 1   5   8
## Volvo 142E     21.4   4 121.0 109 4.11 2.780 18.60 1 1   4   2
```

```
class(mtcars)
```

```
## [1] "data.frame"
```

```
df <- data.frame(abc = 1, xyz = "a")
df$abc
```

```
## [1] 1
```

```
df$xyz
```

```
## [1] a
```

```
## Levels: a
```

```
df[, "xyz"]
```

```
## [1] a
```

```
## Levels: a
```

```
df[, c("abc", "xyz")]
```

```
##   abc xyz
```

```
## 1   1   a
```

If you have the name of a variable stored in an object, e.g. `var <- "mpg"`, how can you extract the reference variable from a tibble?

```
my_data<-read.delim("/Users/pradeepsahoo/Downloads/baby_names.txt")
```

```
glimpse(my_data)
```

```
## Observations: 30,000
```

```
## Variables: 1
```

```
## $ year.sex.name.n.prop <fct> 1880|F|Mary|7065|0.0723843285111266, 1880...
```

```
write.csv(my_data, file = "/Users/pradeepsahoo/Downloads/baby_names.csv")
```

```
my_csv <- read_csv("/Users/pradeepsahoo/Downloads/baby_names.csv")
```

```
## Warning: Missing column names filled in: 'X1' [1]
```

```
## Parsed with column specification:
```

```
## cols(
```

```
##   X1 = col_integer(),
```

```
##   year.sex.name.n.prop = col_character()
```

```
## )
```

```
glimpse(my_csv)
```

```
## Observations: 30,000
```

```
## Variables: 2
```

```
## $ X1                                <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13...
```

```
## $ year.sex.name.n.prop <chr> "1880|F|Mary|7065|0.0723843285111266", "1...
```