Tables manipulation II

M1 MIDS/MFA/LOGOS
Université Paris Cité
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Course Homepage
Moodle

> **Objectives**

Setup

We will use the following packages. If needed, we install them.

```
old_theme <- theme_set(theme_minimal())
```

Check nycflights13 for any explanation concerning the tables and their columns.

Data loading

```
flights <- nycflights13::flights
weather <- nycflights13::weather
airports <- nycflights13::airports
airlines <- nycflights13::airlines
planes <- nycflights13::planes
```

```
con <- DBI::dbConnect(RSQLite::SQLite(), ":memory:")
flights_lite <- copy_to(con, nycflights13::flights)
airports_lite <- copy_to(con, nycflights13::airports)
planes_lite <-  copy_to(con, nycflights13::planes)
weather_lite <- copy_to(con, nycflights13::weather)
airlines_lite <- copy_to(con, nycflights13::airlines)
```

```
flights_lite |>
  select(contains("delay")) |>
  show_query()
```

```
<SQL>
SELECT `dep_delay`, `arr_delay`
FROM `nycflights13::flights`
```

View data in spreadsheet style.

```
View(flights)
```

Ask for help about table `flights`

Solution

```
?flights
```

```
flights |>
  glimpse()
```

```
Rows: 336,776
Columns: 19
$ year           <int> 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2~
$ month          <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
$ day            <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
$ dep_time       <int> 517, 533, 542, 544, 554, 554, 555, 557, 557, 558, 558, ~
$ sched_dep_time <int> 515, 529, 540, 545, 600, 558, 600, 600, 600, 600, 600, ~
$ dep_delay      <dbl> 2, 4, 2, -1, -6, -4, -5, -3, -3, -2, -2, -2, -2, -2, -1~
$ arr_time       <int> 830, 850, 923, 1004, 812, 740, 913, 709, 838, 753, 849,~
$ sched_arr_time <int> 819, 830, 850, 1022, 837, 728, 854, 723, 846, 745, 851,~
$ arr_delay      <dbl> 11, 20, 33, -18, -25, 12, 19, -14, -8, 8, -2, -3, 7, -1~
$ carrier        <chr> "UA", "UA", "AA", "B6", "DL", "UA", "B6", "EV", "B6", "~
$ flight         <int> 1545, 1714, 1141, 725, 461, 1696, 507, 5708, 79, 301, 4~
$ tailnum        <chr> "N14228", "N24211", "N619AA", "N804JB", "N668DN", "N394~
$ origin         <chr> "EWR", "LGA", "JFK", "JFK", "LGA", "EWR", "EWR", "LGA",~
$ dest           <chr> "IAH", "IAH", "MIA", "BQN", "ATL", "ORD", "FLL", "IAD",~
$ air_time       <dbl> 227, 227, 160, 183, 116, 150, 158, 53, 140, 138, 149, 1~
$ distance       <dbl> 1400, 1416, 1089, 1576, 762, 719, 1065, 229, 944, 733, ~
$ hour           <dbl> 5, 5, 5, 5, 6, 5, 6, 6, 6, 6, 6, 6, 6, 6, 6, 5, 6, 6, 6~
$ minute         <dbl> 15, 29, 40, 45, 0, 58, 0, 0, 0, 0, 0, 0, 0, 0, 0, 59, 0~
$ time_hour      <dttm> 2013-01-01 05:00:00, 2013-01-01 05:00:00, 2013-01-01 0~
```

```
airports |>
  glimpse()
```

```
Rows: 1,458
Columns: 8
$ faa   <chr> "04G", "06A", "06C", "06N", "09J", "0A9", "0G6", "0G7", "0P2", "~
$ name  <chr> "Lansdowne Airport", "Moton Field Municipal Airport", "Schaumbur~
$ lat   <dbl> 41.13047, 32.46057, 41.98934, 41.43191, 31.07447, 36.37122, 41.4~
$ lon   <dbl> -80.61958, -85.68003, -88.10124, -74.39156, -81.42778, -82.17342~
$ alt   <dbl> 1044, 264, 801, 523, 11, 1593, 730, 492, 1000, 108, 409, 875, 10~
$ tz    <dbl> -5, -6, -6, -5, -5, -5, -5, -5, -5, -8, -5, -6, -5, -5, -5, -5, ~
$ dst   <chr> "A", "A", "A", "A", "A", "A", "A", "A", "U", "A", "A", "U", "A",~
$ tzone <chr> "America/New_York", "America/Chicago", "America/Chicago", "Ameri~
```

First Queries (the `dplyr` way)

Find all flights that

- Had an arrival delay of two or more hours

Solution

```
flights |>
  filter(arr_delay >= 120) |>
  nrow()
```

```
[1] 10200
```

```
flights_lite |>
  filter(arr_delay >= 120) |>
  count()  |>
  show_query()
```

```
<SQL>
SELECT COUNT(*) AS `n`
FROM (
  SELECT `nycflights13::flights`.*
  FROM `nycflights13::flights`
  WHERE (`arr_delay` >= 120.0)
) AS `q01`
```

Solution

We can translate the `dplyr` pipeline into an `SQL` query.

```
flights_lite |>
  filter(arr_delay >= 120) |>
  show_query()
```

```
<SQL>
SELECT `nycflights13::flights`.*
FROM `nycflights13::flights`
WHERE (`arr_delay` >= 120.0)
```

We can even get some explanations

```
flights_lite |>
  filter(arr_delay >= 120) |>
  explain()
```

- Flew to Houston (`IAH` or `HOU`)

Solution

```
flights |>
  filter(dest %in% c("HOU", "IAH")) |>
  nrow()
```

```
[1] 9313
```

```
flights |>
  filter(dest == "HOU" | dest == "IAH") |>
  count()
```

```
# A tibble: 1 x 1
      n
  <int>
1  9313
```

Solution

```
flights_lite |>
  filter(dest %in% c("HOU", "IAH")) |>
  show_query()
```

```
<SQL>
SELECT `nycflights13::flights`.*
FROM `nycflights13::flights`
WHERE (`dest` IN ('HOU', 'IAH'))
```

Solution

```
flights_lite |>
  filter(dest == "HOU" | dest == "IAH") |>
  show_query()
```

```
<SQL>
SELECT `nycflights13::flights`.*
FROM `nycflights13::flights`
WHERE (`dest` = 'HOU' OR `dest` = 'IAH')
```

- Were operated by United, American, or Delta

Package **stringr** could be useful.

```
airlines |>
  filter(stringr::str_starts(name, "United") |
         stringr::str_starts(name, "American") |
         stringr::str_starts(name, "Delta"))
```

```
# A tibble: 3 x 2
  carrier name
  <chr>   <chr>
1 AA      American Airlines Inc.
2 DL      Delta Air Lines Inc.
3 UA      United Air Lines Inc.
```

```
airlines |>
  filter(stringr::str_detect(name, ("United|American|Delta"))) |>
  pull(carrier)
```

```
[1] "AA" "DL" "UA"
```

```
#| eval: false
airlines_lite |>
  filter(stringr::str_starts(name, "United") |
         stringr::str_starts(name, "American") |
         stringr::str_starts(name, "Delta")) |>
  show_query()
```

```
SELECT *
FROM `nycflights13::airlines`
WHERE "name" LIKE 'United%' OR
      "name" LIKE 'American%' OR
      "name" LIKE 'Delta%' ;
```

stringr is part of tidyverse

Solution

We build on the tip above to extract the matching airlines codes.
We may proceed using a *subquery*

```
flights |>
  filter(carrier %in% (
        airlines |>
        filter(stringr::str_detect(name, ("United|American|Delta"))) |>
        pluck("carrier")
      )
) |>
head(6)
```

```
# A tibble: 6 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      554            600        -6      812            837
5  2013     1     1      554            558        -4      740            728
6  2013     1     1      558            600        -2      753            745
# i 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>
```

```
flights_lite |>
  filter(carrier %in% c("AA", "DL", "UA")) |>
  show_query()
```

```
<SQL>
SELECT `nycflights13::flights`.*
FROM `nycflights13::flights`
WHERE (`carrier` IN ('AA', 'DL', 'UA'))
```

```
SELECT *
FROM `nycflights13::flights`
WHERE carrier IN (SELECT carrier
  FROM `nycflights13::airlines`
  WHERE "name" LIKE 'United%' OR
        "name" LIKE 'American%' OR
        "name" LIKE 'Delta%')
) ;
```


We may also rely on a NATURAL JOIN

- Departed in summer (July, August, and September)

Solution

```
flights |>
  filter(month %in% c(7,8,9)) |>
  count()
```

```
# A tibble: 1 x 1
      n
  <int>
1 86326
```

A more ambitious (and sustainable) approach relies on the date/time manipulation function from `lubridate`

```
flights |>
  filter(lubridate::month(time_hour) %in% 7:9) |>
  head()
```

```
# A tibble: 6 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     7     1        1           2029       212      236           2359
2  2013     7     1        2           2359         3      344            344
3  2013     7     1       29           2245       104      151              1
4  2013     7     1       43           2130       193      322             14
5  2013     7     1       44           2150       174      300            100
6  2013     7     1       46           2051       235      304           2358
# i 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>
```

or even

```
my_locale <- 'en_US.UTF-8'

flights |>
  filter(lubridate::month(time_hour, label=T, abbr=F,
                          locale=my_locale) %in%
                     c('juillet', 'August', 'September')) |>
  head()
```

```
# A tibble: 6 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     8     1       12           2130       162      257             14
2  2013     8     1       12           2359        13      349            350
3  2013     8     1       22           2146       156      255             30
4  2013     8     1       26           2051       215      333           2358
5  2013     8     1       32           2359        33      420            344
6  2013     8     1       33           2231       122      412            226
# i 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>
```

! When manipulating temporal information (date, time, duration), keep an eye on what `lubridate` offers. The API closely parallels what RDMS and Python offer.

- Arrived more than two hours late, but didn't leave late

Solution

```
flights |>
  filter(arr_delay >= 120, dep_delay <= 0) |>
  count()
```

```
# A tibble: 1 x 1
      n
  <int>
1    29
```

- Were delayed by at least an hour, but made up over 30 minutes in flight

Solution

```
flights |>
  filter(dep_delay > 60,
         arr_delay < dep_delay -30) |>
  count()
```

```
# A tibble: 1 x 1
      n
  <int>
1  1819
```

- Departed between midnight and 6am (inclusive)

Solution

```
flights |>
  filter(dep_time<=600, dep_time>0) |>
  head()
```

```
# A tibble: 6 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
# i 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>
```

```
flights |>
  filter(lubridate::hour(time_hour)<=5  | (
         lubridate::hour(time_hour)==6 & minute(time_hour)==0)) |>
  head()
```

```
# A tibble: 6 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
# i 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>
```

Read `filter()` in R for Data Science 1st Ed
Read Chapter Transform in R for Data Science 2nd Ed

Missing data

- How many flights per `origin` have a missing `dep_time`?

Solution

```
flights |>
  filter(is.na(dep_time)) |>
  count(by=origin)
```

```
# A tibble: 3 x 2
  by        n
  <chr> <int>
1 EWR    3239
2 JFK    1863
3 LGA    3153
```

```
flights_lite |>
  filter(is.na(dep_time)) |>
  count(by=origin) |>
  show_query()
```

```
<SQL>
SELECT `by`, COUNT(*) AS `n`
FROM (
  SELECT `nycflights13::flights`.*, `origin` AS `by`
  FROM `nycflights13::flights`
  WHERE ((`dep_time` IS NULL))
) AS `q01`
GROUP BY `by`
```

Not far from a spontaneous answer! We could obtain the latter anyway.

```
flights_lite |>
  filter(is.na(dep_time)) |>
  group_by(origin) |>
  summarise(n=n()) |>
  show_query()
```

```
<SQL>
SELECT `origin`, COUNT(*) AS `n`
FROM (
  SELECT `nycflights13::flights`.*
  FROM `nycflights13::flights`
  WHERE ((`dep_time` IS NULL))
) AS `q01`
GROUP BY `origin`
```

Note that combining `dplyr` verbs and pipes (`|>` or `|>`) provides a much more readable and modular approach than vanilla `SQL`.

- Using `dplyr` and pipe, the order in which operation are executed is clear and obvious. In SQL, it is counterintuitive.
-

In table `flights`, 8255 (`nrow(filter(flights, is.na(dep_time)))`) rows have a missing `dep_time` field.

- What other variables are missing?

The introduction to `tidyselect` is a must read.

Solution

```
flights |>
  filter(is.na(dep_time)) |>
  summarize(across(everything(), ~ all(is.na(.)))) |>
  pivot_longer(cols = everything()) |>
  filter(value) |>
  select(name)
```

```
# A tibble: 5 x 1
  name
  <chr>
1 dep_time
2 dep_delay
3 arr_time
4 arr_delay
5 air_time
```

```
flights_lite |>
  filter(is.na(dep_time)) |>
  show_query()
```

```
<SQL>
SELECT `nycflights13::flights`.*
FROM `nycflights13::flights`
WHERE ((`dep_time` IS NULL))
```

- What might these rows with missing data represent?

All the information you can only get if the flight did take off.

```
not_cancelled <-  flights |>
  filter(!is.na(dep_time))
```

- More questions: for each column in `flight` report the number of missing values.

Solution

```
flights |>
  summarise(across(everything(), ~  sum(is.na(.)))) |>
  pivot_longer(cols = everything()) |>
  filter(value > 0) |>
  arrange(desc(value))
```

```
# A tibble: 6 x 2
  name      value
  <chr>     <int>
1 arr_delay  9430
2 air_time   9430
3 arr_time   8713
4 dep_time   8255
5 dep_delay  8255
6 tailnum    2512
```

Solution

```
flights |>
  skimr::skim()
```

Table 2: Data summary

Name	flights
Number of rows	336776
Number of columns	19
_____	
Column type frequency:	
character	4
numeric	14
POSIXct	1
_____	
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
carrier	0	1.00	2	2	0	16	0
tailnum	2512	0.99	5	6	0	4043	0
origin	0	1.00	3	3	0	3	0
dest	0	1.00	3	3	0	105	0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
year	0	1.00	2013.00	0.00	2013	2013	2013	2013	2013	
month	0	1.00	6.55	3.41	1	4	7	10	12	
day	0	1.00	15.71	8.77	1	8	16	23	31	
dep_time	8255	0.98	1349.11	488.28	1	907	1401	1744	2400	
sched_dep_time	0	1.00	1344.25	467.34	106	906	1359	1729	2359	
dep_delay	8255	0.98	12.64	40.21	-43	-5	-2	11	1301	
arr_time	8713	0.97	1502.05	533.26	1	1104	1535	1940	2400	
sched_arr_time	0	1.00	1536.38	497.46	1	1124	1556	1945	2359	
arr_delay	9430	0.97	6.90	44.63	-86	-17	-5	14	1272	
flight	0	1.00	1971.92	1632.47	1	553	1496	3465	8500	
air_time	9430	0.97	150.69	93.69	20	82	129	192	695	
distance	0	1.00	1039.91	733.23	17	502	872	1389	4983	
hour	0	1.00	13.18	4.66	1	9	13	17	23	
minute	0	1.00	26.23	19.30	0	8	29	44	59	

Variable type: POSIXct

skim_variable	n_missing	complete_rate	min	max	median	n_unique
time_hour	0	1	2013-01-01 05:00:00	2013-12-31 23:00:00	2013-07-03 10:00:00	6936

Arrange

- How could you use `arrange()` to sort all missing values to the start? (Hint: use `is.na()`).

Solution

- Sort flights to find the most delayed flights.

Solution

```
flights |>
  arrange(desc(dep_delay)) |>
  select(dep_delay, arr_delay, everything())
```

```
# A tibble: 336,776 x 19
   dep_delay arr_delay  year month   day dep_time sched_dep_time arr_time
       <dbl>     <dbl> <int> <int> <int>    <int>          <int>    <int>
 1      1301      1272  2013     1     9      641            900     1242
 2      1137      1127  2013     6    15     1432           1935     1607
 3      1126      1109  2013     1    10     1121           1635     1239
 4      1014      1007  2013     9    20     1139           1845     1457
 5      1005       989  2013     7    22      845           1600     1044
 6       960       931  2013     4    10     1100           1900     1342
 7       911       915  2013     3    17     2321            810      135
 8       899       850  2013     6    27      959           1900     1236
 9       898       895  2013     7    22     2257            759      121
10       896       878  2013    12     5      756           1700     1058
# i 336,766 more rows
# i 11 more variables: sched_arr_time <int>, carrier <chr>, flight <int>,
#   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
#   hour <dbl>, minute <dbl>, time_hour <dttm>
```

- Pick the ten most delayed flights (with finite `dep_delay`)

Solution

```
flights |>
  slice_max(order_by=dep_delay, n = 10, na_rm = T)
```

```
# A tibble: 10 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
# i 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>
```

- Find the flights that left earliest.

Solution

```
flights |>
  arrange(dep_time) |>
  select(dest, origin, dep_time)
```

```
# A tibble: 336,776 x 3
   dest  origin dep_time
   <chr> <chr>     <int>
 1 SYR   JFK           1
 2 MDW   LGA           1
 3 SJU   JFK           1
 4 BQN   JFK           1
 5 SJU   JFK           1
 6 SJU   JFK           1
 7 BQN   JFK           1
 8 MDW   LGA           1
 9 PWM   JFK           1
10 PSE   JFK           1
# i 336,766 more rows
```

- Sort flights to find the fastest (highest speed) flights.

Solution

```
flights |>
  filter(!is.na(air_time)) |>
  mutate(speed = distance/air_time) |>
  arrange(desc(speed)) |>
  select(speed, distance, air_time, origin, dest, everything())
```

```
# A tibble: 327,346 x 20
   speed distance air_time origin dest   year month   day dep_time
   <dbl>    <dbl>    <dbl> <chr>  <chr> <int> <int> <int>    <int>
 1 11.7       762       65 LGA    ATL    2013     5    25     1709
 2 10.8      1008       93 EWR    MSP    2013     7     2     1558
 3 10.8       594       55 EWR    GSP    2013     5    13     2040
 4 10.7       748       70 EWR    BNA    2013     3    23     1914
 5  9.86     1035      105 LGA    PBI    2013     1    12     1559
 6  9.4      1598      170 JFK    SJU    2013    11    17      650
 7  9.29     1598      172 JFK    SJU    2013     2    21     2355
 8  9.27     1623      175 JFK    STT    2013    11    17      759
 9  9.24     1598      173 JFK    SJU    2013    11    16     2003
10  9.24     1598      173 JFK    SJU    2013    11    16     2349
# i 327,336 more rows
# i 11 more variables: sched_dep_time <int>, dep_delay <dbl>, arr_time <int>,
#   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>, flight <int>,
#   tailnum <chr>, hour <dbl>, minute <dbl>, time_hour <dttm>
```

This is an overkill. We are sorting in order to perform maximum selection. Recall that sorting requires more comparisons than selection. The comparison between sorting and selecting with respect to data shuffling is even less favourable.

```
flights |>
  filter(!is.na(air_time)) |>
  mutate(speed = distance/air_time) |>
  slice_max(n=10, speed) |>
  select(speed, distance, air_time, origin, dest, everything())
```

```
# A tibble: 15 x 20
   speed distance air_time origin dest   year month   day dep_time
   <dbl>    <dbl>    <dbl> <chr>  <chr> <int> <int> <int>    <int>
 1 11.7       762       65 LGA    ATL    2013     5    25     1709
 2 10.8      1008       93 EWR    MSP    2013     7     2     1558
 3 10.8       594       55 EWR    GSP    2013     5    13     2040
 4 10.7       748       70 EWR    BNA    2013     3    23     1914
 5  9.86     1035      105 LGA    PBI    2013     1    12     1559
 6  9.4      1598      170 JFK    SJU    2013    11    17      650
 7  9.29     1598      172 JFK    SJU    2013     2    21     2355
 8  9.27     1623      175 JFK    STT    2013    11    17      759
 9  9.24     1598      173 JFK    SJU    2013    11    16     2003
10  9.24     1598      173 JFK    SJU    2013    11    16     2349
11  9.24     1598      173 JFK    SJU    2013    11    17      851
12  9.24     1598      173 JFK    SJU    2013    11    17     1926
13  9.24     1598      173 JFK    SJU    2013    12     5     1858
14  9.24     1598      173 JFK    SJU    2013     2    10     1658
15  9.24     1598      173 JFK    SJU    2013     2    10     1958
# i 11 more variables: sched_dep_time <int>, dep_delay <dbl>, arr_time <int>,
#   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>, flight <int>,
#   tailnum <chr>, hour <dbl>, minute <dbl>, time_hour <dttm>
```

- Which flights travelled the farthest?

> The database provides all we need with columns `distance` and `air_time`. Otherwise, with the positions of airports from table `airports`, we should be able to compute distances using :
> 'Haversine' formula.
> https://en.wikipedia.org/wiki/Haversine_formula

> **Solution**

```
flights |>
  arrange(desc(distance)) |>
  distinct(distance, dest, origin)
```

```
# A tibble: 226 x 3
   distance dest  origin
      <dbl> <chr> <chr>
 1     4983 HNL   JFK
 2     4963 HNL   EWR
 3     3370 ANC   EWR
 4     2586 SFO   JFK
 5     2576 OAK   JFK
 6     2569 SJC   JFK
 7     2565 SFO   EWR
 8     2521 SMF   JFK
 9     2475 LAX   JFK
10     2465 LGB   JFK
# i 216 more rows
```

- Which travelled the shortest?

Solution

```
flights |>
  arrange(distance) |>
  select(distance, dest, origin, everything())
```

```
# A tibble: 336,776 x 19
   distance dest  origin  year month   day dep_time sched_dep_time dep_delay
      <dbl> <chr> <chr>  <int> <int> <int>    <int>          <int>     <dbl>
 1       17 LGA   EWR     2013     7    27       NA            106        NA
 2       80 PHL   EWR     2013     1     3     2127           2129        -2
 3       80 PHL   EWR     2013     1     4     1240           1200        40
 4       80 PHL   EWR     2013     1     4     1829           1615       134
 5       80 PHL   EWR     2013     1     4     2128           2129        -1
 6       80 PHL   EWR     2013     1     5     1155           1200        -5
 7       80 PHL   EWR     2013     1     6     2125           2129        -4
 8       80 PHL   EWR     2013     1     7     2124           2129        -5
 9       80 PHL   EWR     2013     1     8     2127           2130        -3
10       80 PHL   EWR     2013     1     9     2126           2129        -3
# i 336,766 more rows
# i 10 more variables: arr_time <int>, sched_arr_time <int>, arr_delay <dbl>,
#   carrier <chr>, flight <int>, tailnum <chr>, air_time <dbl>, hour <dbl>,
#   minute <dbl>, time_hour <dttm>
```

Avoid an overkill …

```
flights |>
  distinct(distance, origin, dest) |>
  slice_min(distance, n=10)
```

```
# A tibble: 11 x 3
   distance origin dest
      <dbl> <chr>  <chr>
 1       17 EWR    LGA
 2       80 EWR    PHL
 3       94 JFK    PHL
 4       96 LGA    PHL
 5      116 EWR    BDL
 6      143 EWR    ALB
 7      160 EWR    PVD
 8      169 EWR    BWI
 9      173 JFK    MVY
10      184 JFK    BWI
11      184 LGA    BOS
```

Projection

- Brainstorm as many ways as possible to select `dep_time`, `dep_delay`, `arr_time`, and `arr_delay` from `flights`.

Solution

```
flights |>
  select(dep_time, dep_delay, arr_time, arr_delay) |>
  head()
```

```
# A tibble: 6 x 4
  dep_time dep_delay arr_time arr_delay
     <int>     <dbl>    <int>     <dbl>
1      517         2      830        11
2      533         4      850        20
3      542         2      923        33
4      544        -1     1004       -18
5      554        -6      812       -25
6      554        -4      740        12
```

Solution

```
flights |>
  select(starts_with("dep"), starts_with("arr")) |>
  head()
```

```
# A tibble: 6 x 4
  dep_time dep_delay arr_time arr_delay
     <int>     <dbl>    <int>     <dbl>
1      517         2      830        11
2      533         4      850        20
3      542         2      923        33
4      544        -1     1004       -18
5      554        -6      812       -25
6      554        -4      740        12
```

Solution

```
flights |>
  select(starts_with("dep_") | starts_with("arr")) |>
  head()
```

```
# A tibble: 6 x 4
  dep_time dep_delay arr_time arr_delay
     <int>     <dbl>    <int>     <dbl>
1      517         2      830        11
2      533         4      850        20
3      542         2      923        33
4      544        -1     1004       -18
5      554        -6      812       -25
6      554        -4      740        12
```

- What happens if you include the name of a variable multiple times in a `select()` call?

Solution

It is included once in the result.

```
flights |>
  select(arr_time, starts_with("dep_") | starts_with("arr"), arr_time) |>
  head()
```

```
# A tibble: 6 x 4
  arr_time dep_time dep_delay arr_delay
     <int>    <int>     <dbl>     <dbl>
1      830      517         2        11
2      850      533         4        20
3      923      542         2        33
4     1004      544        -1       -18
5      812      554        -6       -25
6      740      554        -4        12
```

- What does the `any_of()` function do? Why might it be helpful in conjunction with this vector?

```
vars <- c("year", "month", "day", "dep_delay", "arr_delay")
```

Solution

```
vars <- c("year", "month", "day", "dep_delay", "arr_delay")

flights |>
  filter(across(any_of(vars), is.numeric))
```

```
Warning: Using `across()` in `filter()` was deprecated in dplyr 1.0.8.
i Please use `if_any()` or `if_all()` instead.
# 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
# i 336,766 more rows
# i 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>
```

```
flights |>
  filter(if_any(vars, \(x) x<0)) |>
  relocate(ends_with('delay')) |>
  head()
```

```
Warning: Using an external vector in selections was deprecated in tidyselect 1.1.0.
i Please use `all_of()` or `any_of()` instead.
  # Was:
  data %>% select(vars)

  # Now:
  data %>% select(all_of(vars))

See <https://tidyselect.r-lib.org/reference/faq-external-vector.html>.
# A tibble: 6 x 19
  dep_delay arr_delay  year month   day dep_time sched_dep_time arr_time
      <dbl>     <dbl> <int> <int> <int>    <int>          <int>    <int>
1        -1       -18  2013     1     1      544            545     1004
2        -6       -25  2013     1     1      554            600      812
3        -4        12  2013     1     1      554            558      740
4        -5        19  2013     1     1      555            600      913
5        -3       -14  2013     1     1      557            600      709
6        -3        -8  2013     1     1      557            600      838
# i 11 more variables: sched_arr_time <int>, carrier <chr>, flight <int>,
#   tailnum <chr>, origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
#   hour <dbl>, minute <dbl>, time_hour <dttm>
```

- Does the result of running the following code surprise you?

```
select(
  flights,
  contains("TIME", ignore.case =TRUE))  |>
  head()
```

```
# A tibble: 6 x 6
  dep_time sched_dep_time arr_time sched_arr_time air_time time_hour
     <int>          <int>    <int>          <int>    <dbl> <dttm>
1      517            515      830            819      227 2013-01-01 05:00:00
2      533            529      850            830      227 2013-01-01 05:00:00
3      542            540      923            850      160 2013-01-01 05:00:00
4      544            545     1004           1022      183 2013-01-01 05:00:00
5      554            600      812            837      116 2013-01-01 06:00:00
6      554            558      740            728      150 2013-01-01 05:00:00
```

- How do the select helpers deal with case by default?

Solution

By default, `select` helpers ignore case. This complies with a similar behavior in RDBMS

- How can you change that default?

Solution

```
select(flights,
  contains("TIME", ignore.case=FALSE))  |>
  head()
```

```
# A tibble: 6 x 0
```

Mutations

- 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.

Solution

```
flights |>
  mutate(across(ends_with('dep_time') | ends_with('arr_time'),
                (\(x) 60L * (x %/% 100L) + (x %% 100L)),
                .names="cor_{.col}")) |>
  select(ends_with('dep_time'), ends_with('arr_time'), everything())
```

```
# A tibble: 336,776 x 23
   dep_time sched_dep_time cor_dep_time cor_sched_dep_time arr_time
      <int>          <int>        <int>               <int>    <int>
 1      517            515          317                 315      830
 2      533            529          333                 329      850
 3      542            540          342                 340      923
 4      544            545          344                 345     1004
 5      554            600          354                 360      812
 6      554            558          354                 358      740
 7      555            600          355                 360      913
 8      557            600          357                 360      709
 9      557            600          357                 360      838
10      558            600          358                 360      753
# i 336,766 more rows
# i 18 more variables: sched_arr_time <int>, cor_arr_time <int>,
#   cor_sched_arr_time <int>, year <int>, month <int>, day <int>,
#   dep_delay <dbl>, 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>
```

```
df <- flights |>
  mutate(across(ends_with('dep_time') | ends_with('arr_time'),
                (\(x) 60L * (x %/% 100L) + (x %% 100L)),
                .names="{.col}"))
```

- Compare `air_time` with `arr_time - dep_time`. What do you expect to see? What do you see? What do you need to do to fix it?

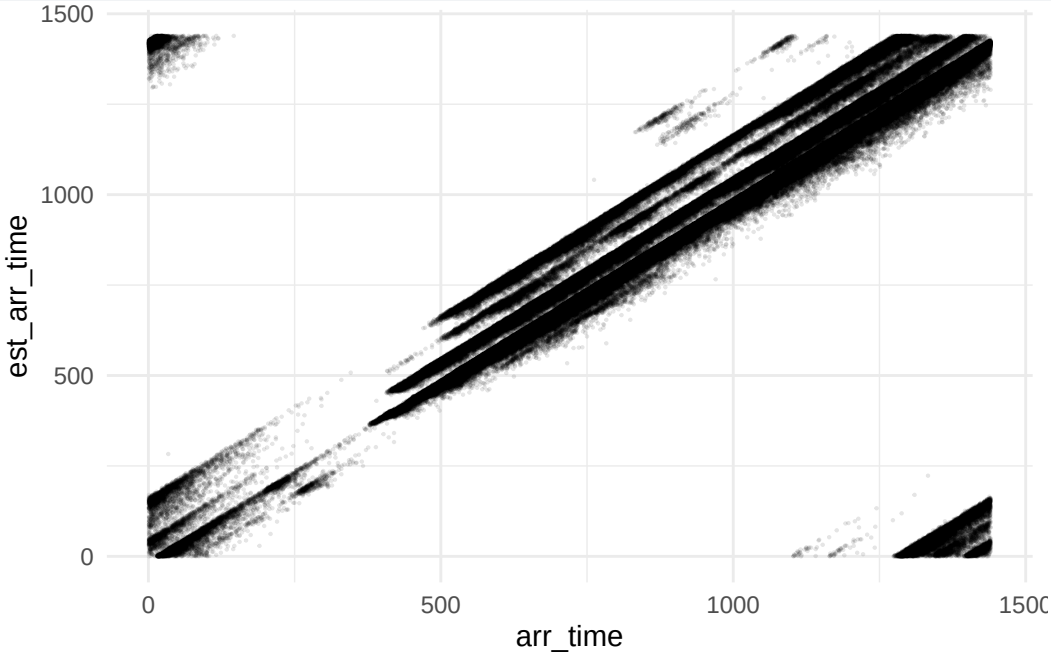
Solution

```
df |>
  mutate(est_arr_time = (dep_time + air_time) %% 1440) |>
  filter(abs(est_arr_time - arr_time)<1000) |>
  arrange(desc(abs(est_arr_time - arr_time))) |>
  select(dest, arr_time, est_arr_time, ends_with("time"), everything())
```

```
# A tibble: 314,414 x 20
   dest  arr_time est_arr_time dep_time sched_dep_time sched_arr_time air_time
   <chr>    <int>        <dbl>    <int>          <int>          <int>    <dbl>
 1 HNL        881         1226      594            600            890      632
 2 HNL        858         1203      594            600            910      609
 3 HNL        865         1210      594            600            900      616
 4 HNL       1084         1429      810            815           1097      619
 5 HNL        855         1199      598            600            890      601
 6 HNL       1090         1434      815            809           1093      619
 7 HNL        842         1186      585            600            885      601
 8 HNL       1062         1405      809            809           1093      596
 9 HNL        889         1232      597            600            890      635
10 HNL        900         1243      597            600            930      646
# i 314,404 more rows
# i 13 more variables: year <int>, month <int>, day <int>, dep_delay <dbl>,
#   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>, origin <chr>,
#   distance <dbl>, hour <dbl>, minute <dbl>, time_hour <dttm>
```

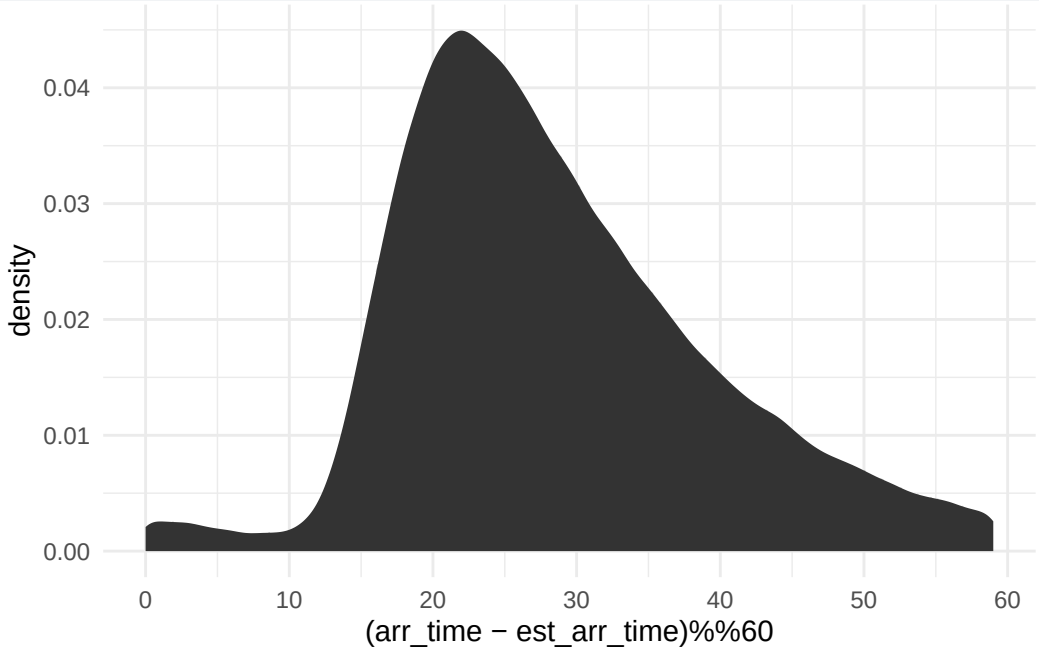
Solution

```
df |>
  mutate(est_arr_time = (dep_time + air_time) %% 1440) |>
  filter(!is.na(arr_time), !is.na(est_arr_time)) |>
  ggplot() +
  aes(x = arr_time, y = est_arr_time) +
  geom_point(alpha=.1, size=.1)
```



Solution

```
df |>
  mutate(est_arr_time = (dep_time + air_time) %% 1440) |>
  filter(!is.na(arr_time), !is.na(est_arr_time)) |>
  filter(abs(arr_time -est_arr_time) <600) |>
  ggplot() +
  aes(x = (arr_time -est_arr_time)%%60) +
  stat_density() +
  scale_x_continuous(breaks=seq(0, 60, 10))
```



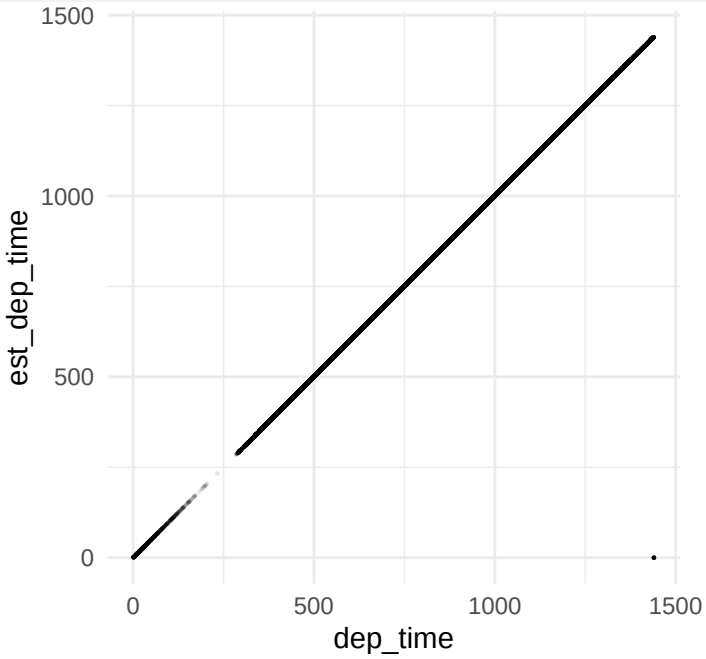
Solution

- Compare `dep_time`, `sched_dep_time`, and `dep_delay`. How would you expect those three numbers to be related?

  We expect `dep_time == sched_dep_time + dep_delay %% 1440`

Solution

```
df |>
  filter(!is.na(dep_time)) |>
  mutate(est_dep_time = (sched_dep_time + dep_delay) %% 1440L) |>
  ggplot() +
  aes(x=dep_time, y=est_dep_time) +
  geom_point(alpha=.1, size=.1) +
  coord_fixed()
```



For most of the flights, the discrepancy between `dep_time` and the computed value is `0`.

For `29` flights it is positive. The discrepancy is then exactly equal to `24` hours.

Solution

```
df |>
  filter(!is.na(dep_time)) |>
  mutate(discr = dep_time - (sched_dep_time + dep_delay) %% 1440L) |>
  filter(discr > 0) |>
  select(dest, origin, carrier, distance, discr) |>
  left_join(airports, by=c("dest"="faa")) |>
  arrange(carrier, desc(distance), dest) |>
  select(dest, origin, carrier, name, discr)
```

```
# A tibble: 29 x 5
   dest  origin carrier name                discr
   <chr> <chr>  <chr>   <chr>               <dbl>
 1 MIA   LGA    AA      Miami Intl           1440
 2 ORD   LGA    AA      Chicago Ohare Intl   1440
 3 PSE   JFK    B6      <NA>                 1440
 4 PSE   JFK    B6      <NA>                 1440
 5 PSE   JFK    B6      <NA>                 1440
 6 PSE   JFK    B6      <NA>                 1440
 7 PSE   JFK    B6      <NA>                 1440
 8 PSE   JFK    B6      <NA>                 1440
 9 SJU   JFK    B6      <NA>                 1440
10 SJU   JFK    B6      <NA>                 1440
# i 19 more rows
```

- Find the 10 most delayed flights using a ranking function. How do you want to handle ties?

Carefully read the documentation for `min_rank()`.

Windowed rank functions.

Solution

```
flights |>
  filter(dense_rank(-arr_delay) <=10) |>
  arrange(desc(arr_delay)) |>
  sample_n(10)
```

```
# A tibble: 10 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     6    15     1432           1935      1137     1607           2120
 2  2013     5     3     1133           2055       878     1250           2215
 3  2013     9    20     1139           1845      1014     1457           2210
 4  2013     4    10     1100           1900       960     1342           2211
 5  2013     3    17     2321            810       911      135           1020
 6  2013    12     5      756           1700       896     1058           2020
 7  2013     1     9      641            900      1301     1242           1530
 8  2013     1    10     1121           1635      1126     1239           1810
 9  2013     7    22     2257            759       898      121           1026
10  2013     7    22      845           1600      1005     1044           1815
# i 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>
```

Aggregations

- Brainstorm at least 5 different ways to assess the typical delay characteristics of a group of flights. Consider the following scenarios:
  - A flight is 15 minutes early 50% of the time, and 15 minutes late 10% of the time.
  - A flight is always 10 minutes late.
  - A flight is 30 minutes early 50% of the time, and 30 minutes late 50% of the time.
  - 99% of the time a flight is on time. 1% of the time it's 2 hours late.

Solution

```
flights_gp <- flights |>
  group_by(flight, carrier, dest, origin)
```

```
flights_gp |>
  summarize(q50 = quantile(arr_delay,.5, , na.rm=T),
            q90 = quantile(arr_delay,.9, , na.rm=T),
            .groups="drop") |>
  filter(q50<=-15, q90>=15) |>
  head()
```

```
# A tibble: 6 x 6
  flight carrier dest  origin   q50   q90
   <int> <chr>   <chr> <chr>  <dbl> <dbl>
1      5 AS      SEA   EWR      -21  26.4
2      6 DL      SLC   JFK      -18  20
3     10 UA      IAH   LGA      -19  28.5
4     11 AS      SEA   EWR      -15  26.4
5     31 DL      SFO   JFK      -22  17.2
6     59 AA      SFO   JFK      -16  20.2
```

Another approach builds on experimental `reframe()`

```
quantile_df <- function(x, probs = c(0.5, 0.9)) {
  tibble(
    val = quantile(x, probs, na.rm = TRUE),
    quant = probs
  )
}
```

```
tmp <- flights_gp |>
  reframe(q= quantile_df(arr_delay)) |>
  unnest(cols=q)
```

`reframe()` generates a list-column (a column is tibble-valued). The result has to be *unnested*.

```
tmp |>
  pivot_wider(
    id_cols=c(flight, carrier, dest, origin),
    names_from= quant,
    values_from= val,
    names_prefix="q"
  ) |>
  head()
```

```
# A tibble: 6 x 6
  flight carrier dest  origin  q0.5   q0.9
   <int> <chr>   <chr> <chr>  <dbl>  <dbl>
1      1 AA      LAX   JFK    -13    19
2      1 B6      FLL   JFK      2    47.8
3      1 DL      SJU   JFK    -21    -6.40
4      1 UA      ORD   EWR    -26   -26
5      1 UA      PBI   EWR    -19   -14.2
6      1 WN      MDW   LGA      2.5  33.6
```

```
flights |>
  group_by(dest) |>
  summarise(n_cancelled = sum(is.na(dep_time)))
```

```
# A tibble: 105 x 2
   dest  n_cancelled
   <chr>       <int>
 1 ABQ             0
 2 ACK             0
 3 ALB            20
 4 ANC             0
 5 ATL           317
 6 AUS            21
 7 AVL            12
 8 BDL            31
 9 BGR            15
10 BHM            25
# i 95 more rows
```

```
flights_lite |>
  group_by(dest) |>
  summarise(n_cancelled = sum(is.na(dep_time))) |>
  show_query()
```

```
Warning: Missing values are always removed in SQL aggregation functions.
Use `na.rm = TRUE` to silence this warning
This warning is displayed once every 8 hours.
```

```
<SQL>
SELECT `dest`, SUM((`dep_time` IS NULL)) AS `n_cancelled`
FROM `nycflights13::flights`
GROUP BY `dest`
```

Solution

```
flights |>
  group_by(flight, carrier, dest, origin) |>
  summarize(q = quantile(arr_delay,.5, na.rm=T), m=mean(arr_delay, na.rm=TRUE)) |>
  filter((q < -15) | (q > 15)) |>
  arrange(desc(m))
```

```
`summarise()` has grouped output by 'flight', 'carrier', 'dest'. You can
override using the `.groups` argument.
# A tibble: 4,161 x 6
# Groups:   flight, carrier, dest [4,106]
   flight carrier dest  origin     q     m
    <int> <chr>   <chr> <chr>  <dbl> <dbl>
 1    372 UA      CLE   LGA      455   455
 2    488 UA      DEN   LGA      359   359
 3    521 WN      BNA   EWR      335   335
 4   5017 EV      DTW   LGA      334   334
 5    468 UA      MCO   EWR      323   323
 6    390 DL      DEN   LGA      318   318
 7    809 DL      SLC   EWR      299   299
 8   3261 EV      CLE   EWR      292   292
 9   3760 9E      RIC   JFK      288   288
10   1510 UA      IAH   EWR      283   283
# i 4,151 more rows
```

Solution

```
flights |>
  group_by(jour=lubridate::wday(time_hour, label=T, abbr = F)) |>
  summarise(n_cancelled=sum(is.na(dep_time)), n_tot=n())  |>
  mutate(prop_cancelled = n_cancelled/n_tot)
```

```
# A tibble: 7 x 4
  jour     n_cancelled n_tot prop_cancelled
  <ord>          <int> <int>          <dbl>
1 dimanche         714 46357         0.0154
2 lundi           1220 50690         0.0241
3 mardi           1152 50422         0.0228
4 mercredi        1202 50060         0.0240
5 jeudi           1562 50219         0.0311
6 vendredi        1608 50308         0.0320
7 samedi           797 38720         0.0206
```

```
?lubridate::wday
```

- Which is more important: arrival delay or departure delay?

Solution

- Come up with another approach that will give you the same output as `not_cancelled |> count(dest)` and `(without using`count()‘).

Solution

```
not_cancelled |>
  summarise(n_distinct(dest), n_distinct(tailnum))
```

```
# A tibble: 1 x 2
  `n_distinct(dest)` `n_distinct(tailnum)`
               <int>                 <int>
1                104                  4037
```

- Our definition of cancelled flights `(is.na(dep_delay) | is.na(arr_delay) )` is slightly suboptimal. Why? Which is the most important column?

Solution

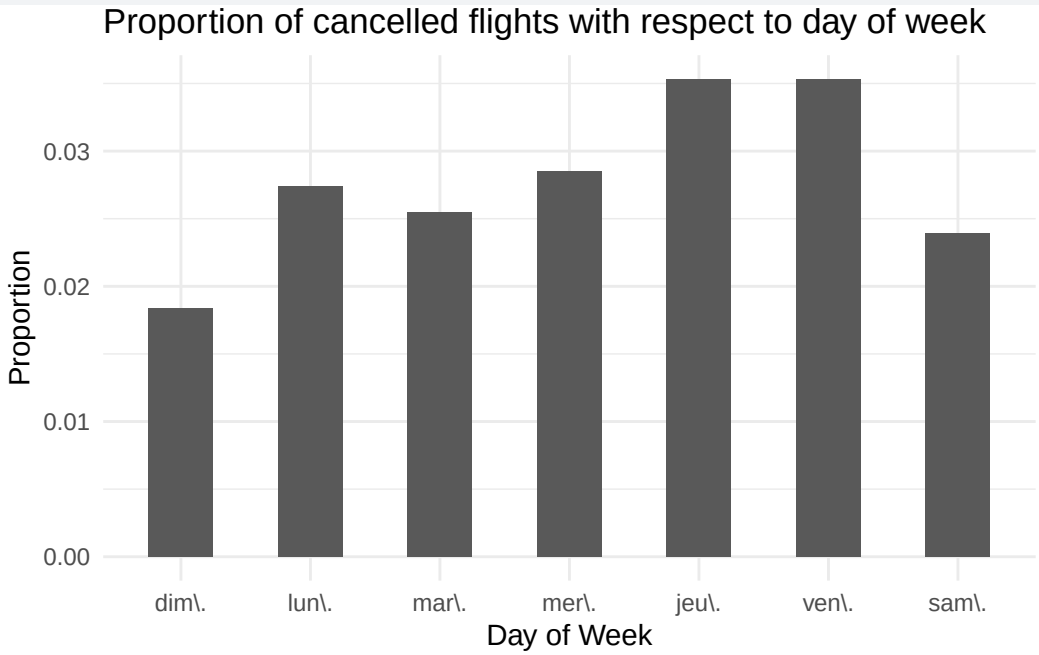
```
flights |>
  filter(xor(is.na(arr_delay), is.na(dep_delay))) |>
  group_by(is.na(arr_delay), is.na(dep_delay)) |>
  summarise(n())
```

```
`summarise()` has grouped output by 'is.na(arr_delay)'. You can override using
the `.groups` argument.
# A tibble: 1 x 3
# Groups:   is.na(arr_delay) [1]
  `is.na(arr_delay)` `is.na(dep_delay)` `n()`
  <lgl>              <lgl>              <int>
1 TRUE               FALSE               1175
```

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

Solution

```
flights |>
  mutate(day_of_week=wday(time_hour, label=TRUE)) |>
  group_by(day_of_week) |>
  summarise(n_cancelled= sum(is.na(arr_delay)), n(), prop= n_cancelled/n()) |>
  ggplot() +
  aes(x=day_of_week, y=prop) +
  geom_col(width=.5) +
  labs(title="Proportion of cancelled flights with respect to day of week") +
  xlab("Day of Week") +
  ylab("Proportion")
```



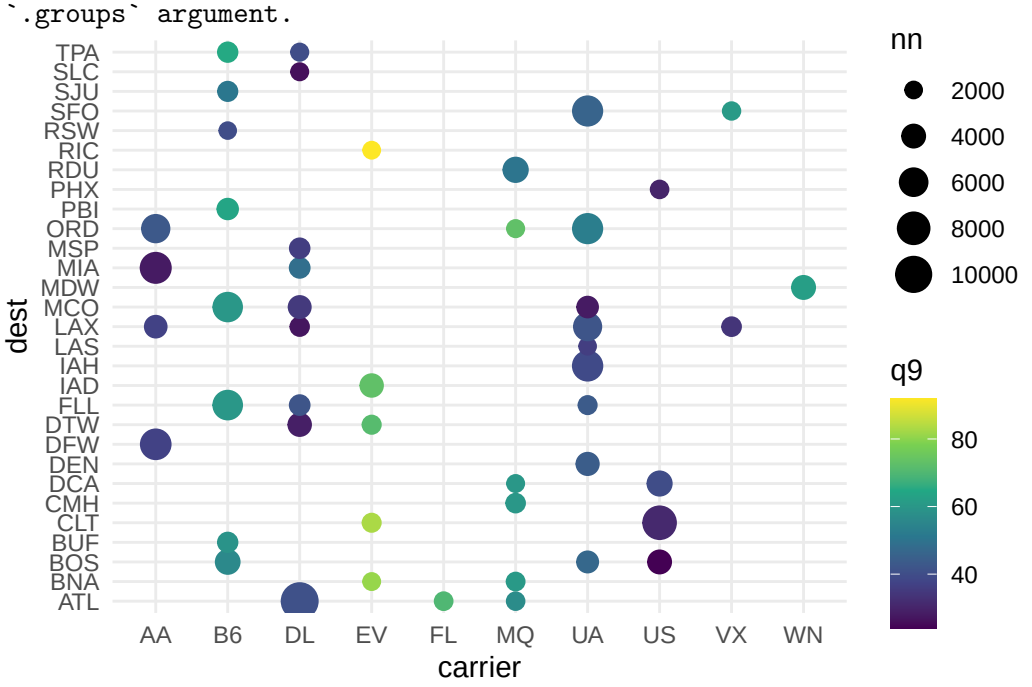
- Which carrier has the worst delays?

Challenge: can you disentangle the effects of bad airports vs. bad carriers? Why/why not? (Hint: think about `flights |> group_by(carrier, dest) |> summarise(n())`)

Solution

```
flights |>
  filter(!is.na(arr_delay)) |>
  group_by(carrier, dest) |>
  summarise(m=mean(arr_delay), q9=quantile(arr_delay, (c(9)/10)), nn=n()) |>
  ungroup() |>
  filter(min_rank(-nn) <50) |>
  ggplot() +
  aes(x=carrier, y=dest) +
  geom_point(aes(color=q9, size=nn)) +
  scale_color_viridis_c() +
  scale_size_area()
```

```
`summarise()` has grouped output by 'carrier'. You can override using the
`.groups` argument.
```



- What does the `sort` argument to `count()` do. When might you use it?

Solution

Miscellanea

- Which `carriers` serve all destination airports (in the table) ?

Solution

```
flights |>
  distinct(origin, dest) |>
  mutate(tot_dest = n_distinct(dest)) |>
  group_by(tot_dest, origin) |>
  summarise(n_dest=n(), .groups="drop") |>
  filter(n_dest==tot_dest)
```

```
# A tibble: 0 x 3
# i 3 variables: tot_dest <int>, origin <chr>, n_dest <int>
```

☛ Verb `mutate()` handles function `n_distinct()` as a window function with trivial window.

There is no need to perform grouping and aggregation to answer this question. Basic relational algebra is enough. This operation is called *division* in SQL language

```
R <- flights |>
    distinct(carrier, dest)

C <- R |> distinct(carrier)
D <- R |> distinct(dest)

setdiff(C, crossing(C, D) |>
           setdiff(R) |>
           distinct(carrier))
```

```
# A tibble: 0 x 1
# i 1 variable: carrier <chr>
```

Let $\mathcal{R}(A, B$ be the schema of some table R, then

$$R \div \pi_B(R) = \pi_A(R) \setminus (\pi_A(\pi_A(R) \times \pi_B(R) \setminus R))$$

More generally if S has schema $\mathcal{S}(B)$

$$R \div S = \pi_A(R) \setminus (\pi_A(\pi_A(R) \times \pi_B(S) \setminus R))$$

- Refer back to the lists of useful mutate and filtering functions.
- Describe how each operation changes when you combine it with grouping.

Solution

- Which plane (`tailnum`) has the worst on-time record amongst planes with at least ten flights?

Solution

```
flights |>
  filter(!is.na(arr_delay)) |>
  group_by(tailnum) |>
  summarise(m = mean(arr_delay), n_flights=n() ) |>
  filter(n_flights > 10 ) |>
  filter(min_rank(-m) == 1) |>
  inner_join(distinct(flights, tailnum, carrier))
```

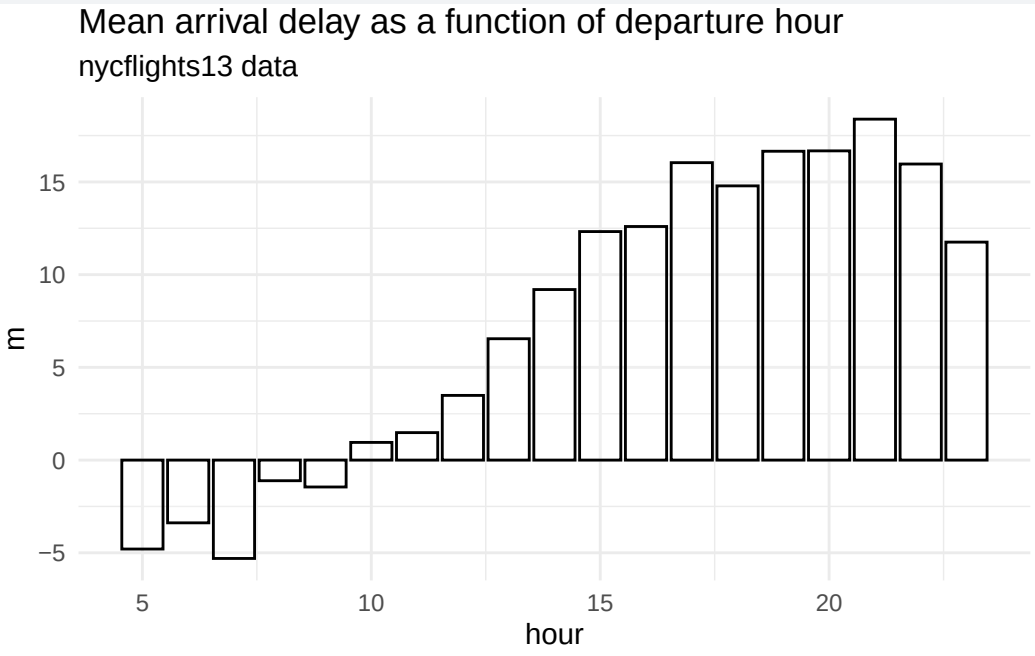
```
Joining with `by = join_by(tailnum)`
# A tibble: 1 x 4
  tailnum     m n_flights carrier
  <chr>   <dbl>     <int> <chr>
1 N337AT   66.5        13 FL
```

- What time of day should you fly if you want to avoid delays as much as possible?

Solution

Definitely before 9a.m.

```
flights |>
  filter(!is.na(arr_delay)) |>
  group_by(hour) |>
  summarise(m = mean(arr_delay, na.rm=T)) |>
  arrange(m) |>
  ggplot() +
  aes(x=hour, y=m) +
  geom_col(color="black", fill="white", alpha=.2) +
  labs(title="Mean arrival delay as a function of departure hour",
       subtitle= "nycflights13 data")
```



- For each destination, compute the total minutes of delay.

Solution

```
flights |>
    filter(!is.na(arr_delay)) |>
    group_by(dest) |>
    summarise(m = sum(arr_delay, na.rm = T)) |>
    arrange(desc(m)) |>
    rename(faa=dest) |>
    dplyr::inner_join(airports)
```

```
Joining with `by = join_by(faa)`
# A tibble: 100 x 9
   faa        m name                           lat    lon   alt    tz dst   tzone
   <chr>  <dbl> <chr>                        <dbl>  <dbl> <dbl> <dbl> <chr> <chr>
 1 ATL   190260 Hartsfield Jackson Atlanta~  33.6  -84.4  1026    -5 A     Amer~
 2 CLT   100645 Charlotte Douglas Intl       35.2  -80.9   748    -5 A     Amer~
 3 ORD    97352 Chicago Ohare Intl           42.0  -87.9   668    -6 A     Amer~
 4 FLL    96153 Fort Lauderdale Hollywood ~  26.1  -80.2     9    -5 A     Amer~
 5 DCA    82609 Ronald Reagan Washington N~  38.9  -77.0    15    -5 A     Amer~
 6 RDU    78107 Raleigh Durham Intl          35.9  -78.8   435    -5 A     Amer~
 7 MCO    76185 Orlando Intl                 28.4  -81.3    96    -5 A     Amer~
 8 IAD    74631 Washington Dulles Intl       38.9  -77.5   313    -5 A     Amer~
 9 BNA    71867 Nashville Intl               36.1  -86.7   599    -6 A     Amer~
10 DEN    61700 Denver Intl                  39.9 -105.   5431    -7 A     Amer~
# i 90 more rows
```

- For each flight, compute the proportion of the total positive arrival delays for its destination.

Solution

Would be easy with `ROLLUP (dest, flight)`

```
WITH R AS (
  SELECT dest, flight, sum(arr_delay)
  FROM flights
  WHERE arr_delay >0
  GROUP BY ROLLUP(dest, flight)
)
SELECT r1.dest, r2.flight, r2.sum/r1.sum AS rap
FROM (SELECT dest, sum
      FROM R WHERE flight IS NULL) r1
      JOIN R r2
      ON (r1.dest=r2.dest)
WHERE r2.flight IS NOT NULL AND r2.sum/r1.sum >.1
ORDER BY r1.dest, r2.flight ;
```

With `WINDOW` it is even easier

Using `dplyr`, it is easy. See A second look at `group_by`

Solution

```
flights |>
   dplyr::filter(arr_delay >0 ) |>
   group_by(dest, flight) |>
   summarise(total_delay_flight=sum(arr_delay)) |> # result is a grouped tibble
   mutate(total_delay_dest=sum(total_delay_flight),
          delay_ratio= total_delay_flight/total_delay_dest)  |>
  filter(dest %in% c('LAX', 'ATL'), delay_ratio > .02)
```

```
`summarise()` has grouped output by 'dest'. You can override using the
`.groups` argument.
# A tibble: 20 x 5
# Groups:   dest [2]
   dest  flight total_delay_flight total_delay_dest delay_ratio
   <chr>  <int>              <dbl>            <dbl>       <dbl>
 1 ATL      348               7000           300299      0.0233
 2 ATL      926               9908           300299      0.0330
 3 ATL      947               8670           300299      0.0289
 4 ATL     1147               6968           300299      0.0232
 5 ATL     1499               6155           300299      0.0205
 6 ATL     1942               6224           300299      0.0207
 7 ATL     2042              11583           300299      0.0386
 8 ATL     4705               6458           300299      0.0215
 9 LAX       21               8378           203226      0.0412
10 LAX      119               4685           203226      0.0231
11 LAX      133               5644           203226      0.0278
12 LAX      169               6560           203226      0.0323
13 LAX      181               8228           203226      0.0405
14 LAX      185               5925           203226      0.0292
15 LAX      413               6271           203226      0.0309
16 LAX      415              10102           203226      0.0497
17 LAX      523               5055           203226      0.0249
18 LAX      535               6030           203226      0.0297
19 LAX      771               6963           203226      0.0343
20 LAX     2363               4273           203226      0.0210
```

Solution

We have used the fact that the output of `summarise(., total_delay_flight=sum(arr_delay))` is still a grouped dataframe/tibble (with grouping variable `dest`). At the following line, `mutate` performs aggregation with `sum()` in a groupwise manner, that is per group, and the result of the aggregation is appended to each row of the group, because we use `mutate` instead of `summarize`.

```
WITH R AS (
  SELECT dest,
         flight,
         SUM(arr_delay)  AS  total_delay_per_flight
  FROM flights
WHERE arr_delay > 0
GROUP BY dest, flight
)
SELECT dest, flight,
       total_delay_per_flight,
       SUM(total_delay_per_flight) OVER w_per_dest AS     total_delay_per_dest
FROM R
WINDOW w_per_dest AS (PARTITION BY dest) ;
```

- Delays are typically temporally correlated: even once the problem that caused the initial delay has been resolved, later flights are delayed to allow earlier flights to leave. Using `lag()`, explore how the delay of a flight is related to the delay of the immediately preceding flight.

Solution

```
flights |>
    group_by(origin)  |>
    arrange(year,month, day, sched_dep_time, .by_group=T) |>   # .by_group -> see docu
    mutate(prev_delay=lag(dep_delay, n=1L), prev_origin=lag(origin, n=1L)) |>
    slice_head(n=6L) |>    # inspect the result
    select(origin, prev_origin, dep_delay, prev_delay, everything())
```

```
# A tibble: 18 x 21
# Groups:   origin [3]
   origin prev_origin dep_delay prev_delay  year month   day dep_time
   <chr>  <chr>           <dbl>      <dbl> <int> <int> <int>    <int>
 1 EWR    <NA>                2         NA  2013     1     1      517
 2 EWR    EWR                -4          2  2013     1     1      554
 3 EWR    EWR                -5         -4  2013     1     1      555
 4 EWR    EWR                -2         -5  2013     1     1      558
 5 EWR    EWR                -1         -2  2013     1     1      559
 6 EWR    EWR                 1         -1  2013     1     1      601
 7 JFK    <NA>                2         NA  2013     1     1      542
 8 JFK    JFK                -1          2  2013     1     1      544
 9 JFK    JFK                 0         -1  2013     1     1      559
10 JFK    JFK                -3          0  2013     1     1      557
11 JFK    JFK                -2         -3  2013     1     1      558
12 JFK    JFK                -2         -2  2013     1     1      558
13 LGA    <NA>                4         NA  2013     1     1      533
14 LGA    LGA                -6          4  2013     1     1      554
15 LGA    LGA                -3         -6  2013     1     1      557
16 LGA    LGA                -2         -3  2013     1     1      558
17 LGA    LGA                -1         -2  2013     1     1      559
18 LGA    LGA                 0         -1  2013     1     1      600
# i 13 more variables: sched_dep_time <int>, arr_time <int>,
#   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>, flight <int>,
#   tailnum <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hour <dbl>,
#   minute <dbl>, time_hour <dttm>
```

`lag()` is an example of *window* function. If we were using `SQL`, we would define a `WINDOW` using an expression like

```
WINDOW w As (PARTITION BY origin ORDER BY year, month, day, sched_dep_time)
```

Something still needs fixing here: some flights never took off (`is.na(dep_time)`). Should they be sided out? assigned an infinite departure delay?

- Look at each destination. Can you find flights that are suspiciously fast? (i.e. flights that represent a potential data entry error). Compute the air time of a flight relative to the shortest flight to that destination. Which flights were most delayed in the air?

Solution

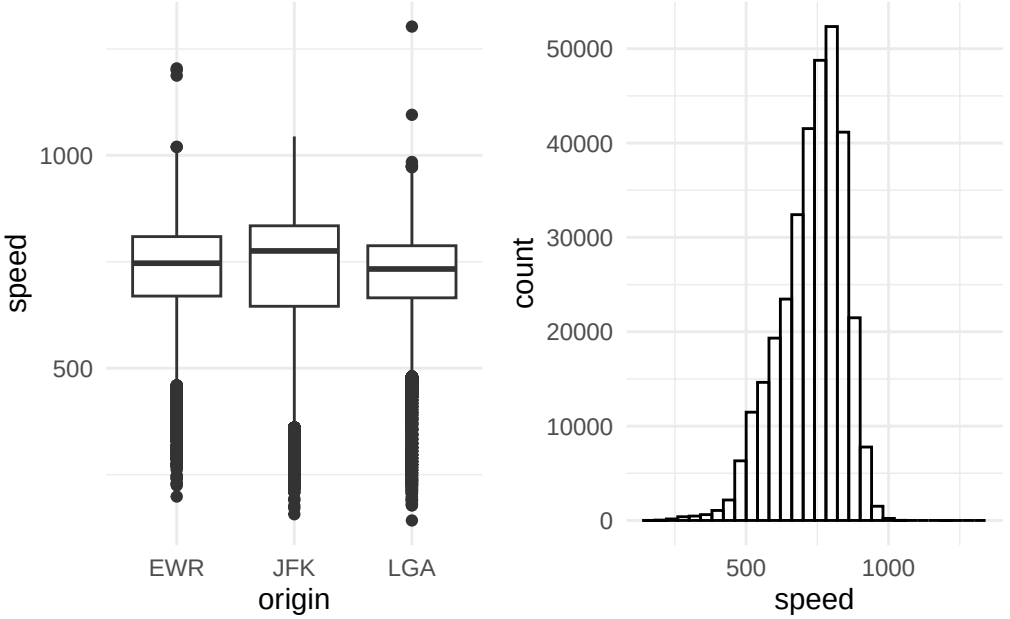
```
df <- flights |>
    filter(!is.na(air_time), air_time > 0) |>
    mutate(speed= (distance * 1.852)/ (air_time/60))

p1 <- df |>
    ggplot() +
        aes(x=origin, y=speed) +
        geom_boxplot()

p2 <- df |>
    ggplot() +
        aes(x=speed) +
        geom_histogram(color="black", fill="white", alpha=.2)


patchwork::wrap_plots(p1 + p2 )
```

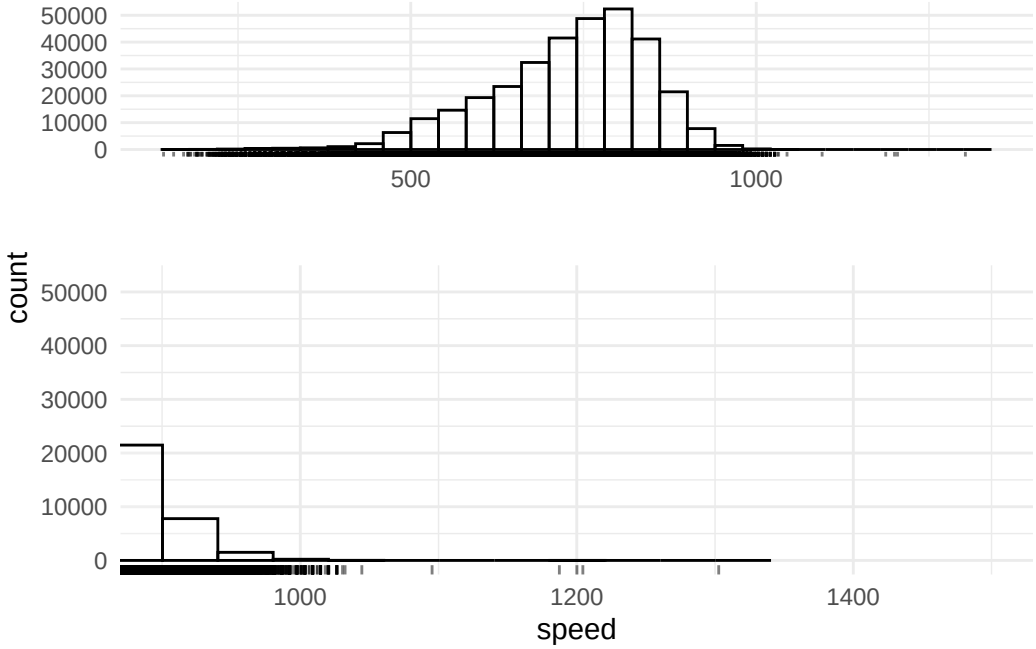
```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Solution

```
p2 + geom_rug(alpha=.5) +
    facet_zoom(xlim=c(900,1500))
```

```
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

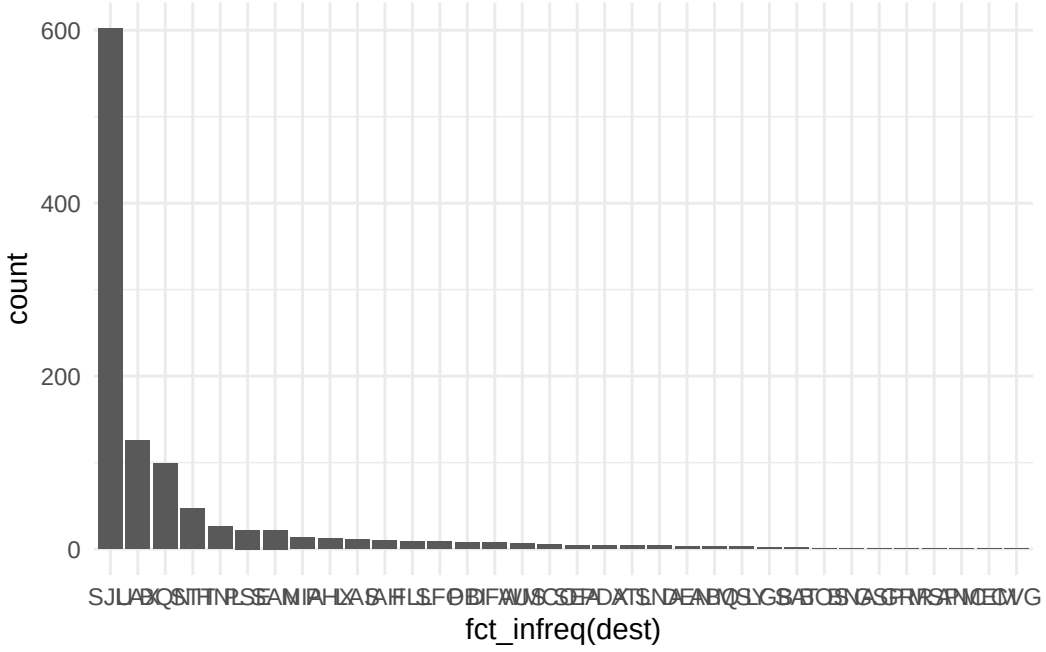


Consider all flights with average speed above 950km/h as suspicious.

Let us visualize destinations and origins of the speedy flights.

Solution

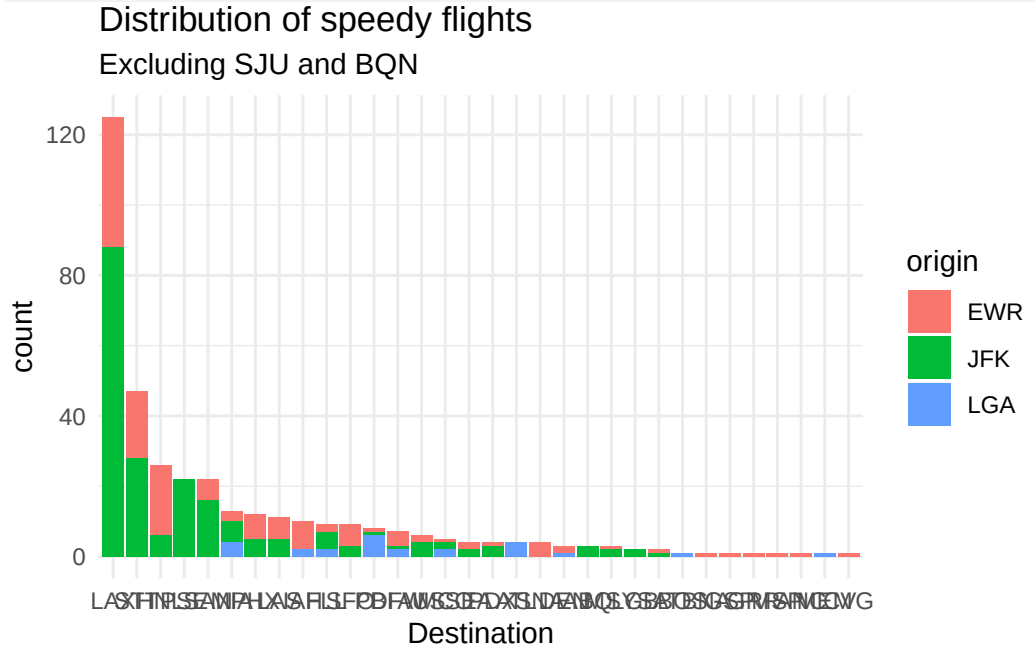
```
df |>
    filter(speed>950) |>
    mutate(dest=as_factor(dest)) |>
    ggplot() +
        aes(x=fct_infreq(dest)) +
        geom_bar()
```



`SJU`, `BQN` are located in Puerto Rico. `LAX` is Los Angeles airport. `STT` is located in Virgin Islands.

Solution

```
df |>
    filter(speed>950, ! dest %in% c('SJU', 'BQN')) |>
    mutate(dest=as_factor(dest)) |>
    ggplot() +
        aes(x=fct_infreq(dest), fill=origin) +
        geom_bar() +
        labs(x="Destination",
        title="Distribution of speedy flights",
        subtitle="Excluding SJU and BQN")
```



- Find all destinations that are flown by at least two carriers. Use that information to rank the carriers.

Solution

- For each plane, count the number of flights before the first delay greater than 1 hour.

Assume a plane is characterized by `tailnum`. Some flights have no `tailnum`. We ignore them.

Solution

```
flights |>
  filter(!is.na(tailnum)) |>
  group_by(tailnum) |>
  arrange(year, month, day, sched_dep_time, .bygroup=T) |>
  mutate(rnk=row_number(), tot=n()) |>
  filter(is.na(arr_time) | arr_delay >=60) |>
  slice_head(n=1)  |>
  mutate(rel_rnk = rnk/tot) |>
  select(tailnum, rnk, tot,  rel_rnk, carrier) |>
  arrange(desc(tot), desc(rel_rnk)) |>
  ungroup()
```

```
# A tibble: 3,454 x 5
   tailnum   rnk   tot rel_rnk carrier
   <chr>   <int> <int>   <dbl> <chr>
 1 N725MQ     17   575 0.0296  MQ
 2 N722MQ     31   513 0.0604  MQ
 3 N723MQ     24   507 0.0473  MQ
 4 N711MQ     24   486 0.0494  MQ
 5 N713MQ      4   483 0.00828 MQ
 6 N258JB      8   427 0.0187  B6
 7 N298JB     17   407 0.0418  B6
 8 N353JB     34   404 0.0842  B6
 9 N351JB     10   402 0.0249  B6
10 N735MQ      3   396 0.00758 MQ
# i 3,444 more rows
```

References

- Data transformation cheatsheet
- R4Data Science Tidy
- Benchmarking
- `dplyr` and `vctrs`
- Posts on `dplyr`
- Window functions on `dplyr`

https://www.youtube.com/watch?v=Ue08LVuk790