

# Lab 3

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## Lab 3

### Exercise 1

Create a new dataset that only contains flights that do not have a missing departure time. Include the columns year, month, day, dep\_time, dep\_delay, and dep\_delay\_hours

```
# A tibble: 328,521 x 6
  year month   day dep_time dep_delay dep_delay_hours
  <int> <int> <int>    <int>     <dbl>            <dbl>
1  2013     1     9      641     1301           21.7
2  2013     6    15     1432     1137           19.0
3  2013     1    10     1121     1126           18.8
4  2013     9    20     1139     1014           16.9
5  2013     7    22      845     1005           16.8
6  2013     4    10     1100      960            16
7  2013     3    17     2321      911           15.2
8  2013     6    27      959      899           15.0
9  2013     7    22     2257      898           15.0
10 2013    12     5      756      896           14.9
# i 328,511 more rows
```

### Exerxise 2

For each airplane (uniquely identified by tailnum), use a group\_by() paired with summarize() to find the sample size, mean, and standard deviation of flight distances. Then include only the top 5 and bottom 5 airplanes in terms of mean distance traveled per flight in the final data frame.

### Top 5 Rows

```
# A tibble: 5 x 4
  tailnum Distance_Mean Distance_Standard_Deviation Distance_Sample_Size
  <chr>      <dbl>                  <dbl>                  <int>
1 D942DN     854.                  107.                   4
2 NOEGMQ     676.                  200.                  371
3 N10156     758.                  332.                  153
4 N102UW     536.                  6.75                  48
5 N103US     535.                  6.62                  46
```

### Bottom 5 rows

```
# A tibble: 5 x 4
  tailnum Distance_Mean Distance_Standard_Deviation Distance_Sample_Size
  <chr>      <dbl>                  <dbl>                  <int>
1 N103US     535.                  6.62                  46
2 N102UW     536.                  6.75                  48
3 N10156     758.                  332.                  153
4 NOEGMQ     676.                  200.                  371
5 D942DN     854.                  107.                   4
```

### Exercise 3

**Exercise:** Find the maximum arrival delay

```
# A tibble: 1 x 3
  flight arr_delay    n
  <int>     <dbl> <int>
1      51      1272     1
```

### Exercise 4

#### 4A

Flights that flew to Portland (PWM)

```
# A tibble: 2,352 x 2
  dest   tailnum
  <chr>  <chr>
1 PWM    N306JB
2 PWM    N11544
3 PWM    N216JB
4 PWM    N11544
5 PWM    N13988
6 PWM    N16561
7 PWM    N279JB
8 PWM    N14993
9 PWM    N353JB
10 PWM   N13903
# i 2,342 more rows
```

#### 4B

Flights with arrival delay exceeding 2 hrs.

```
# A tibble: 123,096 x 2
  tailnum arr_delay
  <chr>     <dbl>
1 N14228      11
2 N24211      20
3 N619AA      33
4 N39463      12
5 N516JB      19
6 N3ALAA       8
7 N29129       7
8 N3DUAA      31
9 N542MQ      12
10 N730MQ     16
# i 123,086 more rows
```

#### 4C

Had arrival delay more than 2 hrs, but did not depart late.

```
# A tibble: 34,583 x 3
  tailnum arr_delay dep_delay
  <chr>     <dbl>     <dbl>
```

```

1 N39463      12      -4
2 N516JB      19      -5
3 N3ALAA       8      -2
4 N29129       7      -2
5 N3DUAA      31      -1
6 N542MQ      12       0
7 N730MQ      16      -3
8 N807AW       3      -8
9 N11107      29      -6
10 N518MQ     10      -6
# i 34,573 more rows

```

## 4D

How many flights have missing arrival time? What other variables are missing?

### Missing Arrival Time

```

# A tibble: 1 x 1
  n
  <int>
1 8713

```

### Variables With NA values.

```

# A tibble: 8,713 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    2016        1930       46     NA        2220
2 2013     1     1      NA        1630       NA     NA        1815
3 2013     1     1      NA        1935       NA     NA        2240
4 2013     1     1      NA        1500       NA     NA        1825
5 2013     1     1      NA        600        NA     NA        901
6 2013     1     2    2041        2045      -4     NA        2359
7 2013     1     2    2145        2129      16     NA         33
8 2013     1     2      NA        1540       NA     NA        1747
9 2013     1     2      NA        1620       NA     NA        1746
10 2013    1     2      NA        1355       NA     NA        1459
# i 8,703 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>
```

**dep\_time, dep\_delay, arr\_delay, arr\_time, air\_time, & dep\_time.** are the variables with NA values. This bit of code: `filter(flights, !is.na(arr_time))` returns all values of arr\_time that aren't NA. Here is an example:

```
# A tibble: 328,063 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 328,053 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>
```

## Exercise 5

Suppose we want to see how much time was gained in the air. We would want to subtract arr\_delay-dep\_delay. Create a data frame that represents the difference between arrival and departure delays. What is the average gain for all flights?

```
# A tibble: 1 x 1
  mean_delay
  <dbl>
1     -5.66
```

The average gain for all flights is roughly **-5.66**.

## 5A

Are some airlines better than others regarding delays?

```
# A tibble: 16 x 7
  carrier avg_arrival_delay avg_dep_delay avg_dist flown avg_arr_time
  <chr>          <dbl>        <dbl>        <dbl>      <dbl>
1 9E            7.38         16.7        530.     1639.
2 AA            0.364        8.59       1340.     1521.
3 AS           -9.93        5.80       2402.     1565.
4 B6            9.46         13.0       1069.     1406.
5 DL            1.64         9.26       1237.     1573.
6 EV            15.8          20.0       563.     1488.
7 F9            21.9          20.2       1620.     1672.
8 FL            20.1          18.7       665.     1574.
9 HA            -6.92        4.90       4983.    1474.
10 MQ            10.8          10.6       570.     1551.
11 OO            11.9          12.6       501.     1913.
12 UA            3.56          12.1       1529.    1509.
13 US            2.13          3.78       553.     1402.
14 VX            1.76          12.9       2499.    1523.
15 WN            9.65          17.7       996.     1443.
16 YV            15.6          19.0       375.     1761.
# i 2 more variables: avg_dep_time <dbl>, avg_air_time <dbl>
```

We may also want to study whether delay times have anything to do with things like distance flown, destination, etc.

Yes, there are some airlines that have better times. While for some variables like *avg\_arr\_time* or *avg\_dep\_time* where there is little difference between times, this difference is seen more in the delays.

## Exercise 6

### 6A

Which airlines have the greatest mean departure and arrival delays?

```
# A tibble: 16 x 3
  carrier mean_dep_delay mean_arr_delay
  <chr>          <dbl>        <dbl>
```

1 F9	20.2	21.9
2 EV	20.0	15.8
3 YV	19.0	15.6
4 FL	18.7	20.1
5 WN	17.7	9.65
6 9E	16.7	7.38
7 B6	13.0	9.46
8 VX	12.9	1.76
9 OO	12.6	11.9
10 UA	12.1	3.56
11 MQ	10.6	10.8
12 DL	9.26	1.64
13 AA	8.59	0.364
14 AS	5.80	-9.93
15 HA	4.90	-6.92
16 US	3.78	2.13

The top 3 airlines with greatest mean delays are *F9*, *EV*, and *YV*.

## 6B

Which airlines have the most flights?

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

The top 3 airlines with the most flights are *UA*, *B6*, and *EV*.

## 6C

**How many planes are there? Find the total miles flown by each plane.**

These are the # of miles flown for each plain, with the total # of planes adding up to exactly **336,776**

```
# A tibble: 1 x 1
  True_Plane_Sum
  <int>
1     336776
```

## 6D

**Find which airlines fly to which destinations and give count of number of flights**

I cannot create a graph that represents this clearly, nor do I know how to attempt this question. I tried creating a graph and it turns out to be rubbish, and I've tried creating a table but I can't use it to explain myself.

## 6E

**Find which airlines fly to Honolulu (HNL)? Honalulu and Ankorage?**

```
# A tibble: 2 x 3
# Groups:   carrier [2]
  carrier dest  flights_num
  <chr>    <chr>      <int>
1 HA       HNL        342
2 UA       HNL        365
```

The airlines flying to *Honolulu* are *UA* and *HA*.

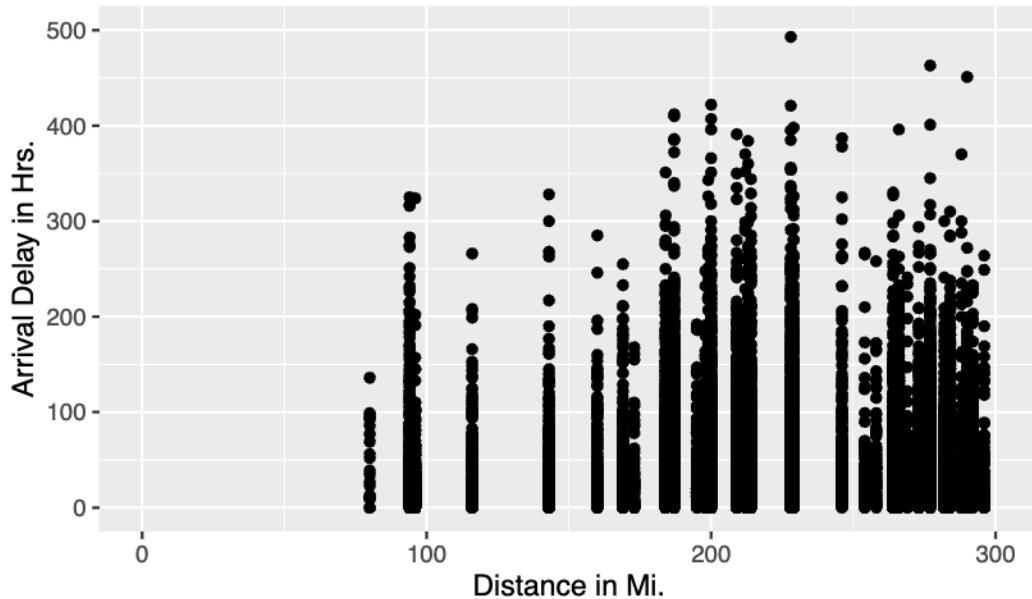
```
# A tibble: 1 x 3
# Groups:   carrier [1]
  carrier dest  flights_num
  <chr>    <chr>      <int>
1 UA       ANC        8
```

the airline flying to *Ankorage* is *UA*.

## 6F

Study the relationship between distance and arrival delay with a suitable plot.  
We might want to filter out outliers.

Distance VS. Arrival Delay



The relationship between Distance and Arrival delay is directly positive. As *distance* increases, *arrival delay* increases as well. While this may not seem to be the case at first glance, there are an upwards of 300,000 flights, compared to the handful of outliers present within the plot. This means that the mean and/or median will be widely different when compared to the uneducated first guess.