# data607\_assignment5A

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#### Overview

##

<chr>

<chr>>

This report uses the charted airline arrival delays in 5 cities. The provided data was used to create a CSV file with that data. I tidied into a long format and analyzed the data by comparing the percentage of delayed flights per city and among all cities. I created a table and plots to visualize these comparisons.

```
library(tidyverse)
```

## Load Libraries and Data

```
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr
              1.1.4
                        v readr
                                    2.1.5
## v forcats
              1.0.0
                                    1.5.1
                        v stringr
## v ggplot2
              3.5.2
                        v tibble
                                    3.2.1
## v lubridate 1.9.4
                                    1.3.1
                        v tidyr
## v purrr
              1.0.4
## -- Conflicts -----
                           ## x dplyr::filter() masks stats::filter()
## x dplyr::lag()
                    masks stats::lag()
## i Use the conflicted package (<a href="http://conflicted.r-lib.org/">http://conflicted.r-lib.org/</a>) to force all conflicts to become error
library(readr)
raw_url <- "https://raw.githubusercontent.com/JDO-MSDS/DATA-607/refs/heads/main/Assignment5A/arrivals%2
wide_data <- readr::read_csv(raw_url, show_col_types = FALSE)</pre>
## New names:
## * '' -> '...1'
## * '' -> '...2'
wide_data
## # A tibble: 5 x 7
                    'Los Angeles' Phoenix 'San Diego' 'San Francisco' Seattle
    . . . 1
           . . . 2
```

<dbl>

<dbl>

<dbl>

<dbl>

<dbl>

```
## 2 <NA>
             delayed
                                        12
                                                     20
                                                                    102
                                                                             305
                                62
## 3 <NA>
             <NA>
                                NA
                                        NA
                                                     NA
                                                                     NA
                                                                             NA
## 4 AM WEST on time
                               694
                                                    383
                                                                    320
                                                                             201
                                       4840
## 5 <NA>
             delayed
                               117
                                        415
                                                     65
                                                                    129
                                                                              61
nm <- names(wide_data)</pre>
stopifnot(length(nm) >= 2)
df <- wide_data %>%
  setNames(replace(nm, 1:2, c("airline", "status"))) %>%
 tidyr::fill(airline, .direction = "down") %>%
  # get rid of the empty row
  filter(!(is.na(status) & if_all(-c(airline, status), is.na))) %>%
  mutate(status = tolower(status),
         status = ifelse(status %in% c("on time","on-time"), "on_time", status)
  )
# Reformat to long format
city_columns <- setdiff(names(df), c("airline", "status"))</pre>
long <- df %>%
 pivot_longer(all_of(city_columns), names_to = "city", values_to = "count") %>%
 mutate(count = as.numeric(count))
# percentage of delayed flights per city
per_city <- long %>%
  group_by(airline, city, status) %>%
  summarise(count = sum(count, na.rm = TRUE), .groups = "drop") %>%
  tidyr::pivot_wider(names_from = status, values_from = count, values_fill = 0) %>%
 mutate(
   total_city = delayed + on_time,
   pct delayed = ifelse(total city > 0, 100 * delayed / total city, NA real )
# percentage of total delayed flights
all_city <- per_city %>%
  group_by(airline) %>%
  summarise(
   delayed = sum(delayed), on_time = sum(on_time),
   total = delayed + on_time,
   pct_delayed = 100 * delayed / total,
    .groups = "drop"
  )
# tables
print(per_city %>% select(city, airline, pct_delayed) %>% arrange(city, airline))
## # A tibble: 10 x 3
##
      city
                    airline pct_delayed
                                  <dbl>
##
      <chr>
                    <chr>
## 1 Los Angeles
                    ALASKA
                                  11.1
## 2 Los Angeles
                    AM WEST
                                  14.4
## 3 Phoenix
                    ALASKA
                                   5.15
## 4 Phoenix
                    AM WEST
                                   7.90
```

## 1 ALASKA on time

497

221

212

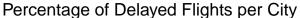
503

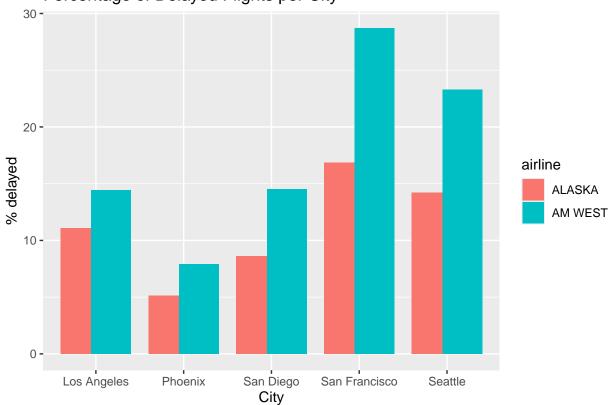
1841

```
8.62
## 5 San Diego
                   ALASKA
                                  14.5
## 6 San Diego
                   AM WEST
                                  16.9
## 7 San Francisco ALASKA
## 8 San Francisco AM WEST
                                  28.7
## 9 Seattle
                   ALASKA
                                  14.2
## 10 Seattle
                   AM WEST
                                  23.3
```

```
print(all_city %>% select(airline, pct_delayed) %>% arrange(airline))
```

```
ggplot(per_city, aes(x = city, y = pct_delayed, fill = airline)) +
  geom_col(position = position_dodge(width = 0.7)) +
  labs(title = "Percentage of Delayed Flights per City", x = "City", y = "% delayed")
```





Plots

```
ggplot(all_city, aes(airline, pct_delayed, fill = airline)) +
  geom_col() +
  labs(title = "Percentage of Delayed Flights", x = "City", y = "% delayed")
```





# Conclusion

By looking at the plot with the percentage of delayed flights per city, we can see that AM WEST has a higher percentage of delayed flights in every single city. However, the plot representing the percentage of delayed flights in all cities combined shows that ALASKA has an overall higher percentage of delayed flights when compared with AM WEST. This discrepancy comes from the fact that the percentage of combined cities might be impacted by a lot of flights in a single airport that usually has more delayed flights.