Final Project Proposal STAT167

Group Name: Statistically Speaking

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2025-04-27

Installation & Packages

```r
library(nycflights13)
library(tidyverse)
```

```
-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v dplyr     1.1.4     v readr     2.1.5
v forcats   1.0.0     v stringr   1.5.1
v ggplot2   3.5.1     v tibble    3.2.1
v lubridate 1.9.3     v tidyr     1.3.1
v purrr     1.0.2
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

Introduction

The primary goal of this research is to explore factors influencing flight delays from New City airports in 2013.

Problem Statement and Motivation

Understanding factors that contribute to flight delays is critical for informing Federal Aviation Administration (FAA) policies and guiding airlines and airports in improving operational efficiency, enhancing weather preparedness, and reducing delays through controllable factors. By analyzing weather conditions, airline differences, holiday effects, fleet age, and airport specific challenges, this research can provide data-driven insights to optimize air travel and ensure compliance with aviation regulations in heavily congested areas like New York City.

Main Research Question

What are the key correlations between flight delays from NYC airports?

Sub-questions:

The following questions will guide the analysis:

1. How do weather conditions affect flight delays?
    a. Are specific weather variables (e.g., precipitation, wind speed, humidity) correlated with departure and arrival delays?
2. How do differences between airlines influence flight delays?
    a. Do certain airlines experience more delays than other, if so, what operational or fleet-related factors contribute to these differences?
    b. How do metrics like cancelation rates and plane speed vary across airlines, and what impact do these metrics have on delays?
3. Are delays more frequent during major holidays?
    a. Are there differences during peak travel periods (e.g., Thanksgiving, Christmas, New Year's Day)
4. Does the age of the plane affect flight delays?
    a. Do older planes experience more delays compared to newer ones?
    b. Are there specific plane models or manufactures associated with better on-time performance?
5. How do environmental factors like humidity, visibility, and wind affect flight delays?
    a. Are these effects observed across all airports?
6. What impact does precipitation have on specific airports and weather-related delays?
    a. Do airports in regions with higher average precipitation experience more delays?

Datasets

1. Flights dataset: All flights that departed from NYC in 2013

```r
head(flights)
```

```
# 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>
```

```r
dim(flights)
```

```
[1] 336776     19
```

```r
names(flights)
```

```
 [1] "year"           "month"          "day"            "dep_time"
 [5] "sched_dep_time" "dep_delay"      "arr_time"       "sched_arr_time"
 [9] "arr_delay"      "carrier"        "flight"         "tailnum"
[13] "origin"         "dest"           "air_time"       "distance"
[17] "hour"           "minute"         "time_hour"
```

```r
str(flights)
```

```
tibble [336,776 x 19] (S3: tbl_df/tbl/data.frame)
 $ year          : int [1:336776] 2013 2013 2013 2013 2013 2013 2013 2013 2013 2013 ...
 $ month         : int [1:336776] 1 1 1 1 1 1 1 1 1 1 ...
 $ day           : int [1:336776] 1 1 1 1 1 1 1 1 1 1 ...
 $ dep_time      : int [1:336776] 517 533 542 544 554 554 555 557 557 558 ...
 $ sched_dep_time: int [1:336776] 515 529 540 545 600 558 600 600 600 600 ...
 $ dep_delay     : num [1:336776] 2 4 2 -1 -6 -4 -5 -3 -3 -2 ...
 $ arr_time      : int [1:336776] 830 850 923 1004 812 740 913 709 838 753 ...
 $ sched_arr_time: int [1:336776] 819 830 850 1022 837 728 854 723 846 745 ...
 $ arr_delay     : num [1:336776] 11 20 33 -18 -25 12 19 -14 -8 8 ...
 $ carrier       : chr [1:336776] "UA" "UA" "AA" "B6" ...
 $ flight        : int [1:336776] 1545 1714 1141 725 461 1696 507 5708 79 301 ...
 $ tailnum       : chr [1:336776] "N14228" "N24211" "N619AA" "N804JB" ...
 $ origin        : chr [1:336776] "EWR" "LGA" "JFK" "JFK" ...
 $ dest          : chr [1:336776] "IAH" "IAH" "MIA" "BQN" ...
 $ air_time      : num [1:336776] 227 227 160 183 116 150 158 53 140 138 ...
 $ distance      : num [1:336776] 1400 1416 1089 1576 762 ...
 $ hour          : num [1:336776] 5 5 5 5 6 5 6 6 6 6 ...
 $ minute        : num [1:336776] 15 29 40 45 0 58 0 0 0 0 ...
 $ time_hour     : POSIXct[1:336776], format: "2013-01-01 05:00:00" "2013-01-01 05:00:00" ...
```

```r
glimpse(flights)
```

```
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~
```

Variables:

- flights (year, month, day, dep_time, arr_time, sched_dep_time, sched_arr_time, dep_delay, arr_delay, carrier, origin, dest, air_time, distance, time_hour)
  - year, month, day : date of departure
  - dep_time, arr_time : actual departure and arrival times in HHMM
  - sched_dep_time, sched_arr_time : scheduled departure and arrival times in HHMM
  - dep_delay, arr_delay : departure and arrival delays in minutes
  - carrier : two letter carrier abbreviation of the carrier
  - origin, dest : origin and destination
  - air_time : amount of time spent in air in minutes
  - distance : distance between airport in miles
  - time_hour : scheduled date and hour of the flight as POSIXct date

2. Airlines dataset: Translation between two letter carrier codes and names

```r
head(airlines)
```

```
# A tibble: 6 x 2
  carrier name
  <chr>   <chr>
1 9E      Endeavor Air Inc.
2 AA      American Airlines Inc.
```

```
3 AS      Alaska Airlines Inc.
4 B6      JetBlue Airways
5 DL      Delta Air Lines Inc.
6 EV      ExpressJet Airlines Inc.
```

```r
dim(airlines)
```

```
[1] 16  2
```

```r
names(airlines)
```

```
[1] "carrier" "name"
```

```r
str(airlines)
```

```
tibble [16 x 2] (S3: tbl_df/tbl/data.frame)
 $ carrier: chr [1:16] "9E" "AA" "AS" "B6" ...
 $ name   : chr [1:16] "Endeavor Air Inc." "American Airlines Inc." "Alaska Airlines Inc." "JetBlue A
```

```r
glimpse(airlines)
```

```
Rows: 16
Columns: 2
$ carrier <chr> "9E", "AA", "AS", "B6", "DL", "EV", "F9", "FL", "HA", "MQ", "O~
$ name    <chr> "Endeavor Air Inc.", "American Airlines Inc.", "Alaska Airline~
```

Variables:

- airlines (carrier, name)
  - carrier : two-letter abbreviation of the airlines
  - name : full name of the airlines

3. Airports dataset: Airport names and locations

```r
head(airports)
```

```
# A tibble: 6 x 8
  faa   name                             lat   lon   alt    tz dst   tzone
  <chr> <chr>                          <dbl> <dbl> <dbl> <dbl> <chr> <chr>
1 04G   Lansdowne Airport               41.1 -80.6  1044    -5 A     America/Ne~
2 06A   Moton Field Municipal Airport   32.5 -85.7   264    -6 A     America/Ch~
3 06C   Schaumburg Regional             42.0 -88.1   801    -6 A     America/Ch~
4 06N   Randall Airport                 41.4 -74.4   523    -5 A     America/Ne~
5 09J   Jekyll Island Airport           31.1 -81.4    11    -5 A     America/Ne~
6 0A9   Elizabethton Municipal Airport  36.4 -82.2  1593    -5 A     America/Ne~
```

```r
dim(airports)
```

```
[1] 1458    8
```

```r
names(airports)
```

```
[1] "faa"   "name"  "lat"   "lon"   "alt"   "tz"    "dst"   "tzone"
```

```r
str(airports)
```

```
tibble [1,458 x 8] (S3: tbl_df/tbl/data.frame)
 $ faa  : chr [1:1458] "04G" "06A" "06C" "06N" ...
 $ name : chr [1:1458] "Lansdowne Airport" "Moton Field Municipal Airport" "Schaumburg Regional" "Ran
 $ lat  : num [1:1458] 41.1 32.5 42 41.4 31.1 ...
 $ lon  : num [1:1458] -80.6 -85.7 -88.1 -74.4 -81.4 ...
 $ alt  : num [1:1458] 1044 264 801 523 11 ...
 $ tz   : num [1:1458] -5 -6 -6 -5 -5 -5 -5 -5 -5 -8 ...
 $ dst  : chr [1:1458] "A" "A" "A" "A" ...
 $ tzone: chr [1:1458] "America/New_York" "America/Chicago" "America/Chicago" "America/New_York" ...
 - attr(*, "spec")=
  .. cols(
  ..   id = col_double(),
  ..   name = col_character(),
  ..   city = col_character(),
  ..   country = col_character(),
  ..   faa = col_character(),
  ..   icao = col_character(),
  ..   lat = col_double(),
  ..   lon = col_double(),
  ..   alt = col_double(),
  ..   tz = col_double(),
  ..   dst = col_character(),
  ..   tzone = col_character()
  .. )
```

```r
glimpse(airports)
```

```
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~
```

Variables:

- airports (faa, name, lat, lon)
  - faa : FAA airport code
  - name : usual name of the airport
  - lat, lon : location of airport

4. Planes dataset: Construction information about each plane

```r
head(planes)
```

```
# A tibble: 6 x 9
  tailnum  year type                manufacturer model engines seats speed engine
  <chr>   <int> <chr>               <chr>        <chr>   <int> <int> <int> <chr> 
1 N10156   2004 Fixed wing multi ~ EMBRAER      EMB-~       2    55    NA Turbo~
2 N102UW   1998 Fixed wing multi ~ AIRBUS INDU~ A320~       2   182    NA Turbo~
3 N103US   1999 Fixed wing multi ~ AIRBUS INDU~ A320~       2   182    NA Turbo~
4 N104UW   1999 Fixed wing multi ~ AIRBUS INDU~ A320~       2   182    NA Turbo~
5 N10575   2002 Fixed wing multi ~ EMBRAER      EMB-~       2    55    NA Turbo~
6 N105UW   1999 Fixed wing multi ~ AIRBUS INDU~ A320~       2   182    NA Turbo~
```

```r
dim(planes)
```

```
[1] 3322    9
```

```r
names(planes)
```

```
[1] "tailnum"      "year"         "type"         "manufacturer" "model"       
[6] "engines"      "seats"        "speed"        "engine"      
```

```r
str(planes)
```

```
tibble [3,322 x 9] (S3: tbl_df/tbl/data.frame)
 $ tailnum     : chr [1:3322] "N10156" "N102UW" "N103US" "N104UW" ...
 $ year        : int [1:3322] 2004 1998 1999 1999 2002 1999 1999 1999 1999 1999 ...
 $ type        : chr [1:3322] "Fixed wing multi engine" "Fixed wing multi engine" "Fixed wing multi e
 $ manufacturer: chr [1:3322] "EMBRAER" "AIRBUS INDUSTRIE" "AIRBUS INDUSTRIE" "AIRBUS INDUSTRIE" ...
 $ model       : chr [1:3322] "EMB-145XR" "A320-214" "A320-214" "A320-214" ...
 $ engines     : int [1:3322] 2 2 2 2 2 2 2 2 2 2 ...
 $ seats       : int [1:3322] 55 182 182 182 55 182 182 182 182 182 ...
 $ speed       : int [1:3322] NA NA NA NA NA NA NA NA NA NA ...
 $ engine      : chr [1:3322] "Turbo-fan" "Turbo-fan" "Turbo-fan" "Turbo-fan" ...
```

```r
glimpse(planes)
```

```
Rows: 3,322
Columns: 9
$ tailnum      <chr> "N10156", "N102UW", "N103US", "N104UW", "N10575", "N105UW~
$ year         <int> 2004, 1998, 1999, 1999, 2002, 1999, 1999, 1999, 1999, 199~
$ type         <chr> "Fixed wing multi engine", "Fixed wing multi engine", "Fi~
$ manufacturer <chr> "EMBRAER", "AIRBUS INDUSTRIE", "AIRBUS INDUSTRIE", "AIRBU~
$ model        <chr> "EMB-145XR", "A320-214", "A320-214", "A320-214", "EMB-145~
$ engines      <int> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, ~
$ seats        <int> 55, 182, 182, 182, 55, 182, 182, 182, 182, 182, 55, 55, 5~
$ speed        <int> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N~
$ engine       <chr> "Turbo-fan", "Turbo-fan", "Turbo-fan", "Turbo-fan", "Turb~
```

Variables:

- planes (year, type, manufacturer, model, engines, seats, speed, engine)
  - year : year manufactured
  - type : type of plane
  - manufacturer, model : manufacturer and model
  - engines, seats : number of engines and seats
  - speed : average cruising speed in mph
  - engine : type in engine

5. Weather dataset: Hourly meterological data for each airport

```r
head(weather)
```

```
# A tibble: 6 x 15
  origin  year month   day  hour  temp  dewp humid wind_dir wind_speed wind_gust
  <chr>  <int> <int> <int> <int> <dbl> <dbl> <dbl>    <dbl>      <dbl>     <dbl>
1 EWR     2013     1     1     1  39.0  26.1  59.4      270      10.4         NA
2 EWR     2013     1     1     2  39.0  27.0  61.6      250       8.06        NA
3 EWR     2013     1     1     3  39.0  28.0  64.4      240      11.5         NA
4 EWR     2013     1     1     4  39.9  28.0  62.2      250      12.7         NA
5 EWR     2013     1     1     5  39.0  28.0  64.4      260      12.7         NA
6 EWR     2013     1     1     6  37.9  28.0  67.2      240      11.5         NA
# i 4 more variables: precip <dbl>, pressure <dbl>, visib <dbl>,
#   time_hour <dttm>
```

```r
dim(weather)
```

```
[1] 26115    15
```

```r
names(weather)
```

```
 [1] "origin"     "year"       "month"      "day"        "hour"      
 [6] "temp"       "dewp"       "humid"      "wind_dir"   "wind_speed"
[11] "wind_gust"  "precip"     "pressure"   "visib"      "time_hour" 
```

```r
str(weather)
```

```
tibble [26,115 x 15] (S3: tbl_df/tbl/data.frame)
 $ origin    : chr [1:26115] "EWR" "EWR" "EWR" "EWR" ...
 $ year      : int [1:26115] 2013 2013 2013 2013 2013 2013 2013 2013 2013 2013 ...
 $ month     : int [1:26115] 1 1 1 1 1 1 1 1 1 1 ...
 $ day       : int [1:26115] 1 1 1 1 1 1 1 1 1 1 ...
 $ hour      : int [1:26115] 1 2 3 4 5 6 7 8 9 10 ...
 $ temp      : num [1:26115] 39 39 39 39.9 39 ...
 $ dewp      : num [1:26115] 26.1 27 28 28 28 ...
 $ humid     : num [1:26115] 59.4 61.6 64.4 62.2 64.4 ...
 $ wind_dir  : num [1:26115] 270 250 240 250 260 240 240 250 260 260 ...
 $ wind_speed: num [1:26115] 10.36 8.06 11.51 12.66 12.66 ...
 $ wind_gust : num [1:26115] NA NA NA NA NA NA NA NA NA NA ...
 $ precip    : num [1:26115] 0 0 0 0 0 0 0 0 0 0 ...
 $ pressure  : num [1:26115] 1012 1012 1012 1012 1012 ...
 $ visib     : num [1:26115] 10 10 10 10 10 10 10 10 10 10 ...
 $ time_hour : POSIXct[1:26115], format: "2013-01-01 01:00:00" "2013-01-01 02:00:00" ...
```

```r
glimpse(weather)
```

```
Rows: 26,115
Columns: 15
$ origin     <chr> "EWR", "EWR", "EWR", "EWR", "EWR", "EWR", "EWR", "EWR", "EW~
$ year       <int> 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013, 2013,~
$ month      <int> 1, 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, 1,~
$ hour       <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 14, 15, 16, 17, 18, ~
$ temp       <dbl> 39.02, 39.02, 39.02, 39.92, 39.02, 37.94, 39.02, 39.92, 39.~
$ dewp       <dbl> 26.06, 26.96, 28.04, 28.04, 28.04, 28.04, 28.04, 28.04, 28.~
$ humid      <dbl> 59.37, 61.63, 64.43, 62.21, 64.43, 67.21, 64.43, 62.21, 62.~
$ wind_dir   <dbl> 270, 250, 240, 250, 260, 240, 240, 250, 260, 260, 260, 330,~
$ wind_speed <dbl> 10.35702, 8.05546, 11.50780, 12.65858, 12.65858, 11.50780, ~
$ wind_gust  <dbl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, 20.~
$ precip     <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,~
$ pressure   <dbl> 1012.0, 1012.3, 1012.5, 1012.2, 1011.9, 1012.4, 1012.2, 101~
$ visib      <dbl> 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10,~
$ time_hour  <dttm> 2013-01-01 01:00:00, 2013-01-01 02:00:00, 2013-01-01 03:00~
```

Variables:

- weather (origin, year, month, day, hour, temp, dewp, humid, wind_dir, wind_speed, wind_gust, precip, pressure, visib, time_hour)
  - origin : weather station
  - year, month, day, hour : time of recording
  - temp, dewp : temperature and dew point in Fahrenheit
  - humid : relative humidity
  - wind_dir, wind_speed, wind_gust : wind direction in degrees, wind speed and gust in mph
  - precip : precipitation in inches
  - pressure : sea level pressure in millibars
  - visib : visibility in miles
  - time_hour : date and hour of the recording as POSIXct date

We can join the data tables by combining them through similar attributes, such as combining flights : time_hour with weather : time_hour.

EDA:

Summary Statistics & Check for Missing Values:

```r
summary(flights)
```

```
      year          month             day           dep_time    sched_dep_time
 Min.   :2013   Min.   : 1.000   Min.   : 1.00   Min.   :   1   Min.   : 106
 1st Qu.:2013   1st Qu.: 4.000   1st Qu.: 8.00   1st Qu.: 907   1st Qu.: 906
 Median :2013   Median : 7.000   Median :16.00   Median :1401   Median :1359
 Mean   :2013   Mean   : 6.549   Mean   :15.71   Mean   :1349   Mean   :1344
 3rd Qu.:2013   3rd Qu.:10.000   3rd Qu.:23.00   3rd Qu.:1744   3rd Qu.:1729
 Max.   :2013   Max.   :12.000   Max.   :31.00   Max.   :2400   Max.   :2359
                                                 NA's   :8255
   dep_delay          arr_time    sched_arr_time   arr_delay
 Min.   : -43.00   Min.   :   1   Min.   :   1   Min.   : -86.000
 1st Qu.:  -5.00   1st Qu.:1104   1st Qu.:1124   1st Qu.: -17.000
 Median :  -2.00   Median :1535   Median :1556   Median :  -5.000
 Mean   :  12.64   Mean   :1502   Mean   :1536   Mean   :   6.895
 3rd Qu.:  11.00   3rd Qu.:1940   3rd Qu.:1945   3rd Qu.:  14.000
 Max.   :1301.00   Max.   :2400   Max.   :2359   Max.   :1272.000
 NA's   :8255      NA's   :8713                  NA's   :9430
   carrier              flight       tailnum             origin
 Length:336776      Min.   :   1   Length:336776      Length:336776
 Class :character   1st Qu.: 553   Class :character   Class :character
 Mode  :character   Median :1496   Mode  :character   Mode  :character
                    Mean   :1972
                    3rd Qu.:3465
                    Max.   :8500
```

```
     dest              air_time        distance          hour
 Length:336776      Min.   : 20.0   Min.   :  17   Min.   : 1.00
 Class :character   1st Qu.: 82.0   1st Qu.: 502   1st Qu.: 9.00
 Mode  :character   Median :129.0   Median : 872   Median :13.00
                    Mean   :150.7   Mean   :1040   Mean   :13.18
                    3rd Qu.:192.0   3rd Qu.:1389   3rd Qu.:17.00
                    Max.   :695.0   Max.   :4983   Max.   :23.00
                    NA's   :9430
     minute         time_hour
 Min.   : 0.00   Min.   :2013-01-01 05:00:00.00
 1st Qu.: 8.00   1st Qu.:2013-04-04 13:00:00.00
 Median :29.00   Median :2013-07-03 10:00:00.00
 Mean   :26.23   Mean   :2013-07-03 05:22:54.64
 3rd Qu.:44.00   3rd Qu.:2013-10-01 07:00:00.00
 Max.   :59.00   Max.   :2013-12-31 23:00:00.00
```

```r
colSums(is.na(flights))
```

```
          year          month            day       dep_time sched_dep_time
             0              0              0           8255              0
     dep_delay       arr_time sched_arr_time      arr_delay        carrier
          8255           8713              0           9430              0
        flight        tailnum         origin           dest       air_time
             0           2512              0              0           9430
      distance           hour         minute      time_hour
             0              0              0              0
```

```r
summary(airlines)
```

```
   carrier              name
 Length:16          Length:16
 Class :character   Class :character
 Mode  :character   Mode  :character
```

```r
colSums(is.na(airlines))
```

```
carrier    name
      0       0
```

```r
summary(airports)
```

```
     faa                name                lat             lon
 Length:1458        Length:1458        Min.   :19.72   Min.   :-176.65
```

```
 Class :character   Class :character   1st Qu.:34.26   1st Qu.:-119.19
 Mode  :character   Mode  :character   Median :40.09   Median : -94.66
                                       Mean   :41.65   Mean   :-103.39
                                       3rd Qu.:45.07   3rd Qu.: -82.52
                                       Max.   :72.27   Max.   : 174.11
      alt                tz               dst                tzone
 Min.   : -54.00   Min.   :-10.000   Length:1458        Length:1458
 1st Qu.:  70.25   1st Qu.: -8.000   Class :character   Class :character
 Median : 473.00   Median : -6.000   Mode  :character   Mode  :character
 Mean   :1001.42   Mean   : -6.519
 3rd Qu.:1062.50   3rd Qu.: -5.000
 Max.   :9078.00   Max.   :  8.000
```

```r
colSums(is.na(airports))
```

```
  faa  name   lat   lon   alt    tz   dst tzone
    0     0     0     0     0     0     0     3
```

```r
summary(planes)
```

```
   tailnum               year          type            manufacturer
 Length:3322        Min.   :1956   Length:3322        Length:3322
 Class :character   1st Qu.:1997   Class :character   Class :character
 Mode  :character   Median :2001   Mode  :character   Mode  :character
                    Mean   :2000
                    3rd Qu.:2005
                    Max.   :2013
                    NA's   :70
    model              engines          seats           speed
 Length:3322        Min.   :1.000   Min.   :  2.0   Min.   : 90.0
 Class :character   1st Qu.:2.000   1st Qu.:140.0   1st Qu.:107.5
 Mode  :character   Median :2.000   Median :149.0   Median :162.0
                    Mean   :1.995   Mean   :154.3   Mean   :236.8
                    3rd Qu.:2.000   3rd Qu.:182.0   3rd Qu.:432.0
                    Max.   :4.000   Max.   :450.0   Max.   :432.0
                                                    NA's   :3299
    engine
 Length:3322
 Class :character
 Mode  :character
```

```r
colSums(is.na(planes))
```

```
     tailnum         year         type manufacturer        model      engines 
           0           70            0            0            0            0 
       seats        speed       engine 
           0         3299            0 
```

```r
summary(weather)
```

```
    origin               year          month             day       
 Length:26115       Min.   :2013   Min.   : 1.000   Min.   : 1.00  
 Class :character   1st Qu.:2013   1st Qu.: 4.000   1st Qu.: 8.00  
 Mode  :character   Median :2013   Median : 7.000   Median :16.00  
                    Mean   :2013   Mean   : 6.504   Mean   :15.68  
                    3rd Qu.:2013   3rd Qu.: 9.000   3rd Qu.:23.00  
                    Max.   :2013   Max.   :12.000   Max.   :31.00  
                                                                   
      hour            temp             dewp           humid       
 Min.   : 0.00   Min.   : 10.94   Min.   :-9.94   Min.   : 12.74  
 1st Qu.: 6.00   1st Qu.: 39.92   1st Qu.:26.06   1st Qu.: 47.05  
 Median :11.00   Median : 55.40   Median :42.08   Median : 61.79  
 Mean   :11.49   Mean   : 55.26   Mean   :41.44   Mean   : 62.53  
 3rd Qu.:17.00   3rd Qu.: 69.98   3rd Qu.:57.92   3rd Qu.: 78.79  
 Max.   :23.00   Max.   :100.04   Max.   :78.08   Max.   :100.00  
                 NA's   :1        NA's   :1       NA's   :1       
    wind_dir       wind_speed         wind_gust         precip        
 Min.   :  0.0   Min.   :   0.000   Min.   :16.11   Min.   :0.000000  
 1st Qu.:120.0   1st Qu.:   6.905   1st Qu.:20.71   1st Qu.:0.000000  
 Median :220.0   Median :  10.357   Median :24.17   Median :0.000000  
 Mean   :199.8   Mean   :  10.518   Mean   :25.49   Mean   :0.004469  
 3rd Qu.:290.0   3rd Qu.:  13.809   3rd Qu.:28.77   3rd Qu.:0.000000  
 Max.   :360.0   Max.   :1048.361   Max.   :66.75   Max.   :1.210000  
 NA's   :460     NA's   :4          NA's   :20778                     
    pressure          visib          time_hour                     
 Min.   : 983.8   Min.   : 0.000   Min.   :2013-01-01 01:00:00.0  
 1st Qu.:1012.9   1st Qu.:10.000   1st Qu.:2013-04-01 21:30:00.0  
 Median :1017.6   Median :10.000   Median :2013-07-01 14:00:00.0  
 Mean   :1017.9   Mean   : 9.255   Mean   :2013-07-01 18:26:37.7  
 3rd Qu.:1023.0   3rd Qu.:10.000   3rd Qu.:2013-09-30 13:00:00.0  
 Max.   :1042.1   Max.   :10.000   Max.   :2013-12-30 18:00:00.0  
 NA's   :2729                                                     
```

```r
colSums(is.na(weather))
```

```
    origin       year      month        day       hour       temp       dewp 
         0          0          0          0          0          1          1 
```

```
    humid   wind_dir wind_speed  wind_gust     precip   pressure      visib 
        1        460          4      20778          0       2729          0 
time_hour 
        0 
```

Planes Dataset EDA

```r
dim(planes)
```

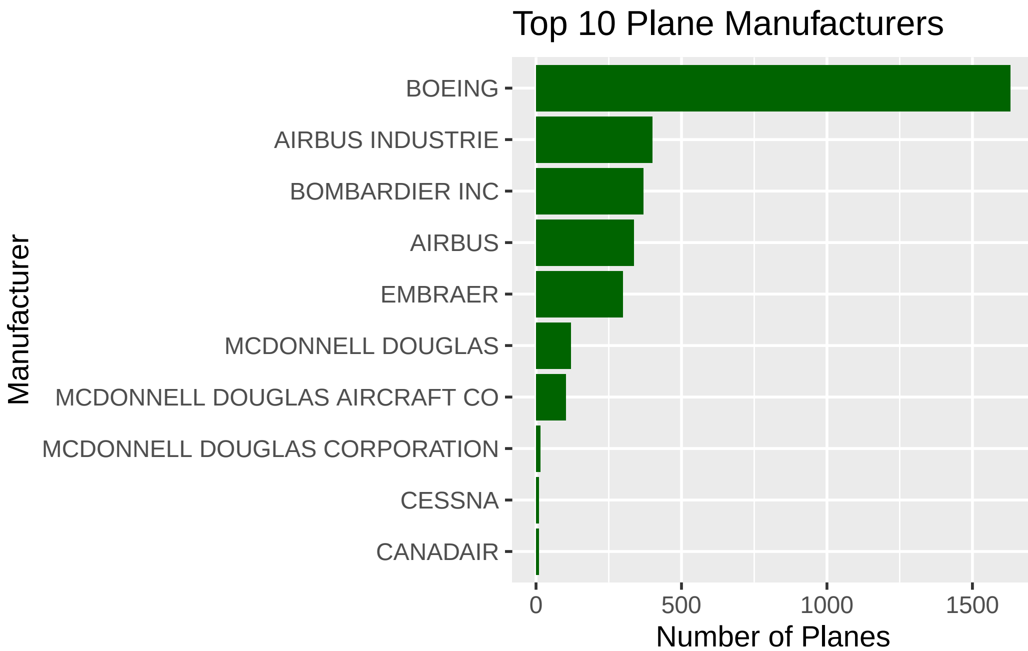
```
[1] 3322    9
```

```r
colnames(planes)
```

```
[1] "tailnum"      "year"         "type"         "manufacturer" "model"       
[6] "engines"      "seats"        "speed"        "engine"      
```

```r
planes %>%
  count(manufacturer, sort = TRUE) %>%
  top_n(10) %>%
  ggplot(aes(x = reorder(manufacturer, n), y = n)) +
  geom_col(fill = "darkgreen") +
  coord_flip() +
  labs(title = "Top 10 Plane Manufacturers", x = "Manufacturer", y = "Number of Planes")
```

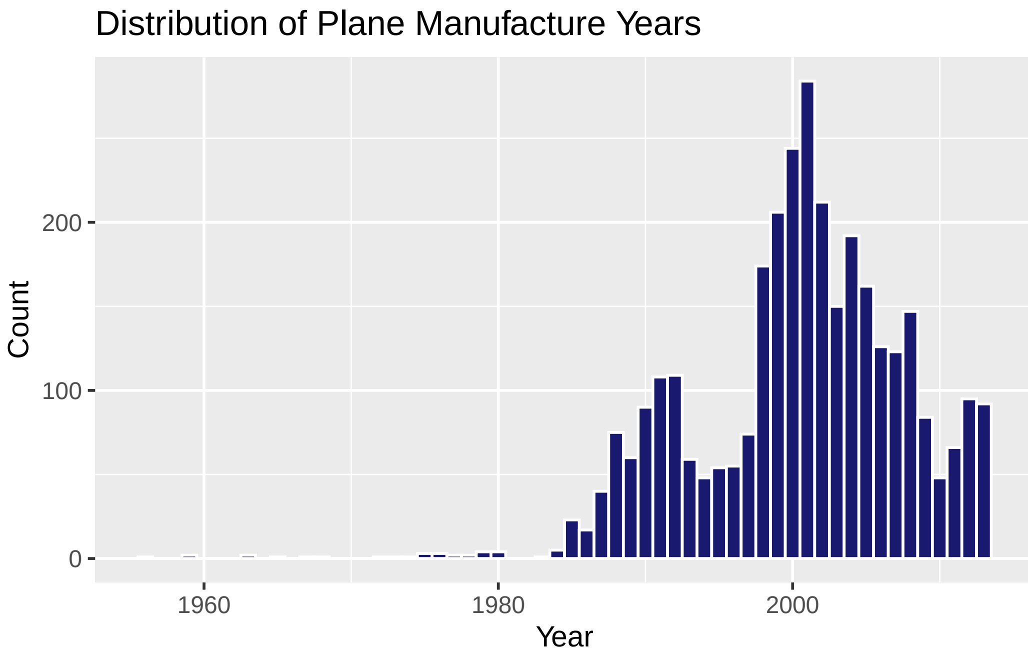
```
Selecting by n
```



The visualization above shows the top 10 plane manufacturers present in the data-set. Boeing has the largest amount of planes with approximately 1750 planes, and Airbus has the second most with approximately 400 planes.

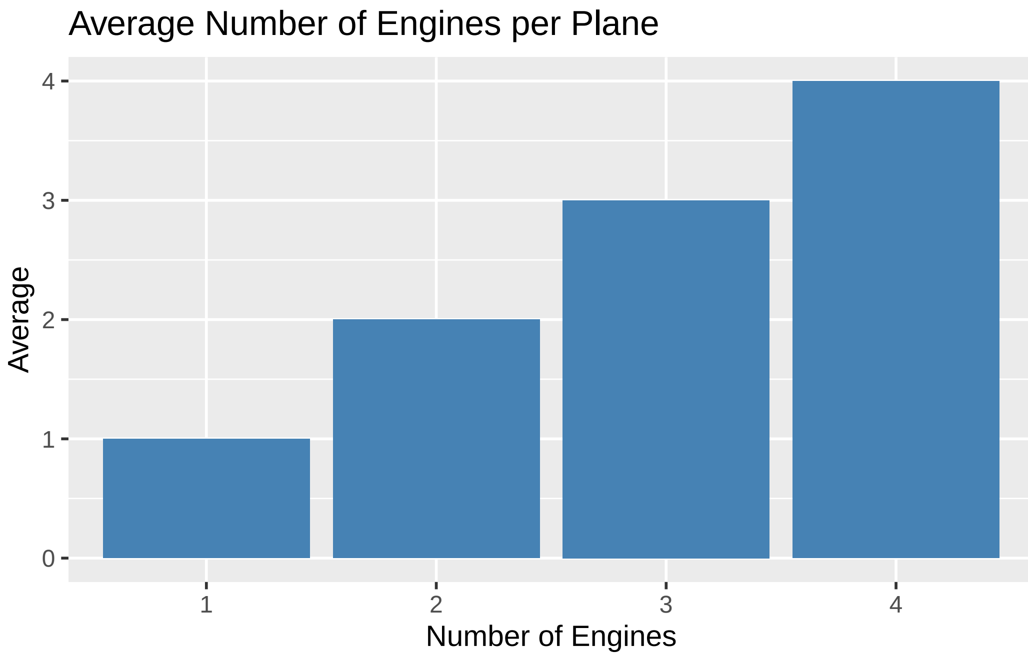
```
ggplot(planes, aes(x = year)) +
  geom_histogram(binwidth = 1, fill = "midnightblue", color = "white") +
  labs(title = "Distribution of Plane Manufacture Years", x = "Year", y = "Count")
```

```
Warning: Removed 70 rows containing non-finite outside the scale range
(`stat_bin()`).
```



This histogram shows the distribution of plane manufacture years, with the majority of planes built between the mid-1990s and early 2000s. There is a notable peak around the year 2000, indicating a surge in plane production during that period.

```
avg_engines <- planes %>%
  group_by(engines) %>%
  summarise(avg = mean(engines, na.rm = TRUE))

# Create the bar plot
ggplot(avg_engines, aes(x = factor(engines), y = avg)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  labs(title = "Average Number of Engines per Plane", x = "Number of Engines", y = "Average")
```



Airlines Dataset EDA

Dimensions and column names of the airlines dataset

```
dim(airlines)
```

```
[1] 16  2
```

```
colnames(airlines)
```

```
[1] "carrier" "name"
```

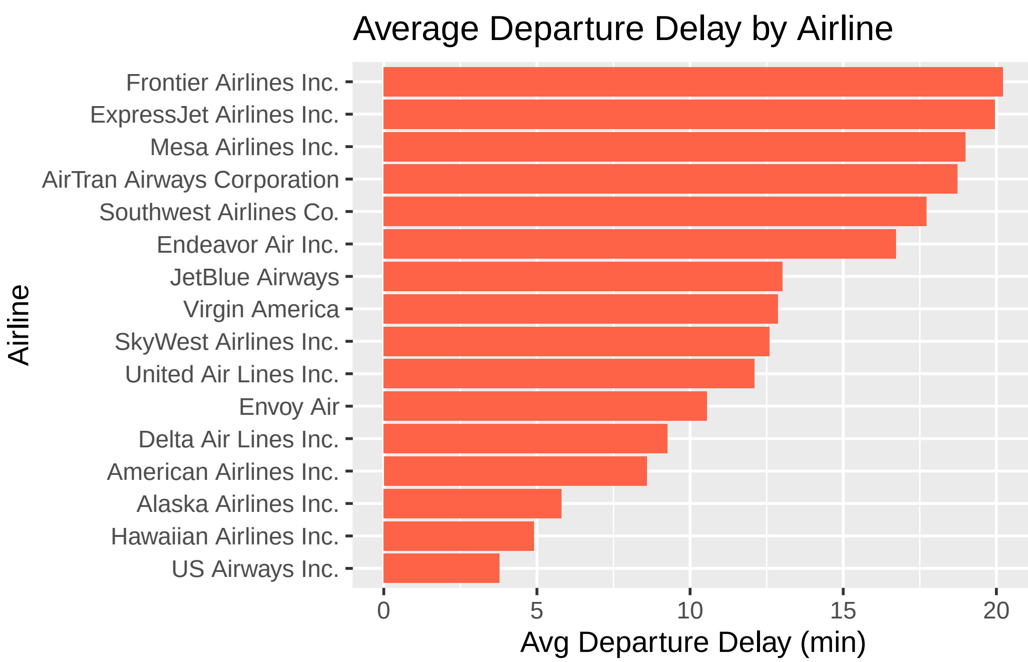
Viewing all the Unique Airlines:

```
airlines %>%
  arrange(name)
```

```
# A tibble: 16 x 2
   carrier name
   <chr>   <chr>
 1 FL      AirTran Airways Corporation
 2 AS      Alaska Airlines Inc.
 3 AA      American Airlines Inc.
```

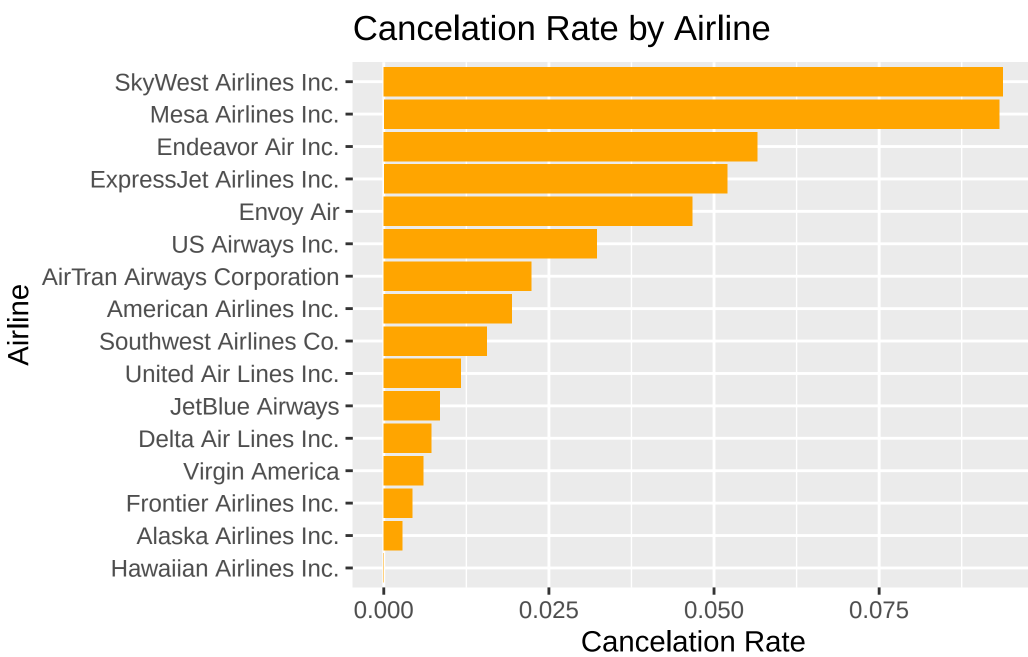
```
 4 DL      Delta Air Lines Inc.
 5 9E      Endeavor Air Inc.
 6 MQ      Envoy Air
 7 EV      ExpressJet Airlines Inc.
 8 F9      Frontier Airlines Inc.
 9 HA      Hawaiian Airlines Inc.
10 B6      JetBlue Airways
11 YV      Mesa Airlines Inc.
12 OO      SkyWest Airlines Inc.
13 WN      Southwest Airlines Co.
14 US      US Airways Inc.
15 UA      United Air Lines Inc.
16 VX      Virgin America
```

```r
# Join flights and airline names
flights_airlines <- flights %>%
  left_join(airlines, by = "carrier")

# Average delay metrics
avg_delays <- flights_airlines %>%
  group_by(name) %>%
  summarise(
    avg_dep_delay = mean(dep_delay, na.rm = TRUE),
    avg_arr_delay = mean(arr_delay, na.rm = TRUE),
    flights = n()
  )

# Plot: Departure Delay
ggplot(avg_delays, aes(x = reorder(name, avg_dep_delay), y = avg_dep_delay)) +
  geom_col(fill = "tomato") +
  coord_flip() +
  labs(
    title = "Average Departure Delay by Airline",
    x = "Airline",
    y = "Avg Departure Delay (min)"
  )
```



We can see that on average, Frontier Airlines has the most departure delay at around 20 min, with ExpressJet roughly around the same 20 minutes. Less than half the Airlines seem to be past the 13 minute delay mark.

```
cancel_rate <- flights_airlines %>%
  mutate(cancelled = is.na(dep_delay)) %>%
  group_by(name) %>%
  summarise(cancel_rate = mean(cancelled), total_flights = n())

ggplot(cancel_rate, aes(x = reorder(name, cancel_rate), y = cancel_rate)) +
  geom_col(fill = "orange") +
  coord_flip() +
  labs(
    title = "Cancelation Rate by Airline",
    x = "Airline",
    y = "Cancelation Rate"
  )
```



As we can see from above, Skywest Airlines Inc has the highest cancellation rate, with Mesa Airlines very closely behind, and a huge drop off at Endeavor Air Inc. ## Planes Dataset EDA

```
dim(planes)
```

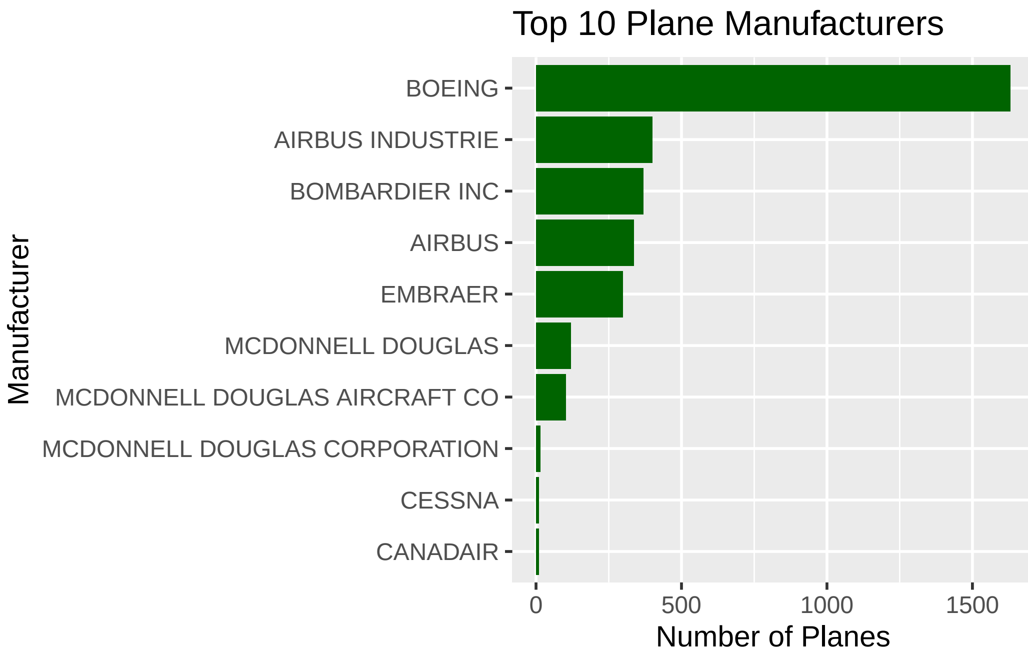
```
[1] 3322    9
```

```
colnames(planes)
```

```
[1] "tailnum"      "year"         "type"         "manufacturer" "model"
[6] "engines"      "seats"        "speed"        "engine"
```

```
planes %>%
  count(manufacturer, sort = TRUE) %>%
  top_n(10) %>%
  ggplot(aes(x = reorder(manufacturer, n), y = n)) +
  geom_col(fill = "darkgreen") +
  coord_flip() +
  labs(title = "Top 10 Plane Manufacturers", x = "Manufacturer", y = "Number of Planes")
```

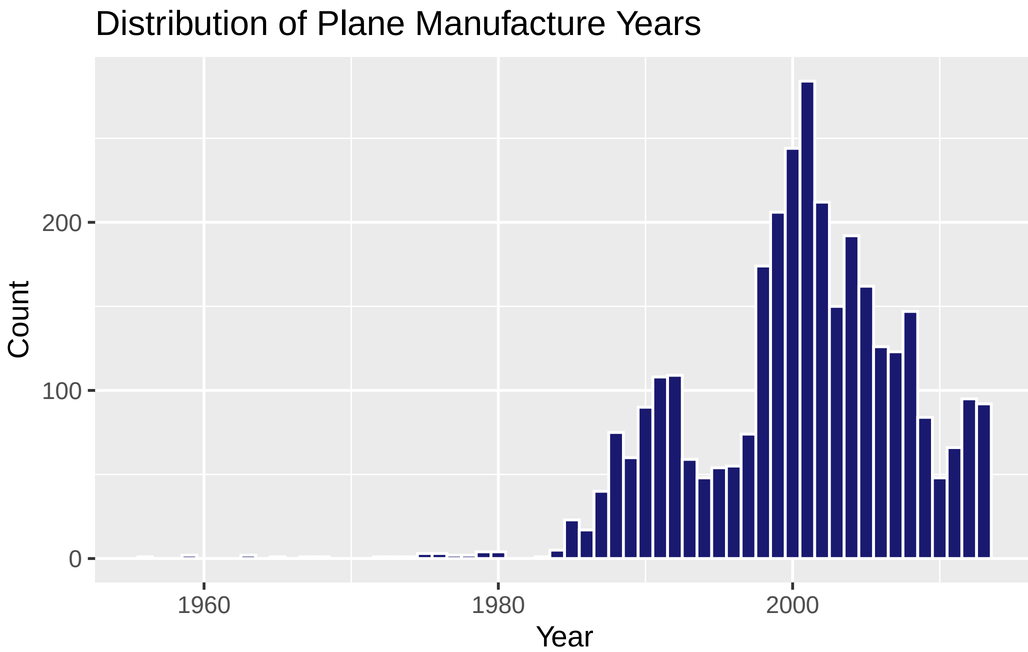
```
Selecting by n
```



The visualization above shows the top 10 plane manufacturers present in the data-set. Boeing has the largest amount of planes with approximately 1750 planes, and Airbus has the second most with approximately 400 planes.

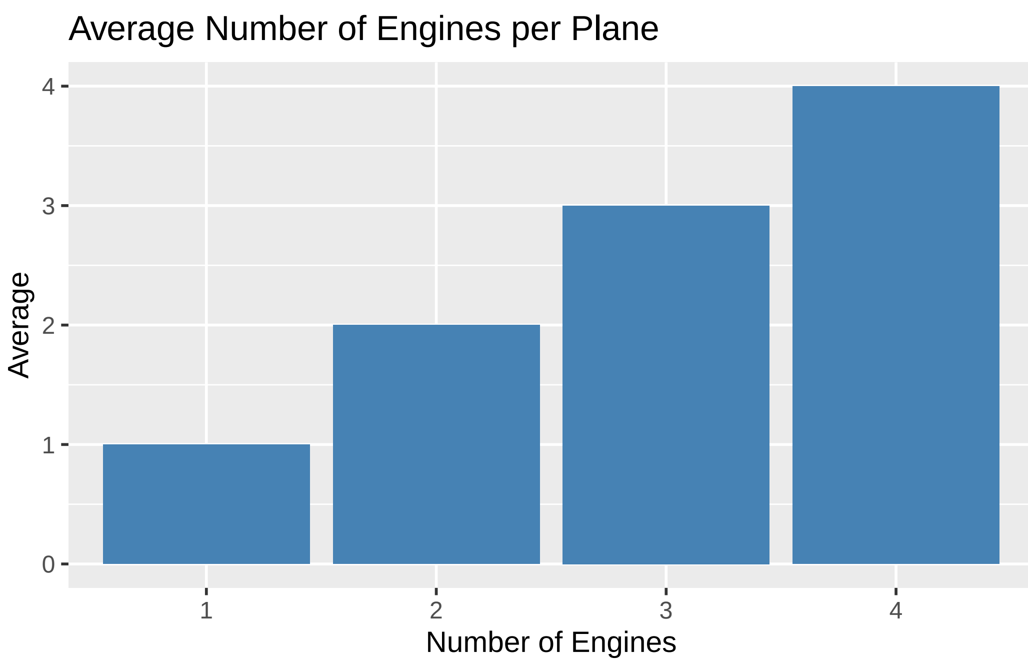
```r
ggplot(planes, aes(x = year)) +
  geom_histogram(binwidth = 1, fill = "midnightblue", color = "white") +
  labs(title = "Distribution of Plane Manufacture Years", x = "Year", y = "Count")
```

```
Warning: Removed 70 rows containing non-finite outside the scale range
(`stat_bin()`).
```



This histogram shows the distribution of plane manufacture years, with the majority of planes built between the mid-1990s and early 2000s. There is a notable peak around the year 2000, indicating a surge in plane production during that period.

```
avg_engines <- planes %>%
  group_by(engines) %>%
  summarise(avg = mean(engines, na.rm = TRUE))

# Create the bar plot
ggplot(avg_engines, aes(x = factor(engines), y = avg)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  labs(title = "Average Number of Engines per Plane", x = "Number of Engines", y = "Average")
```



FLIGHTS EDA:

```r
head(flights)
```

```
# 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>
```

Most of our analysis is based on how other variables and datasets affect and compare to the flights dataset. We are seeing how the arrival time, departure delay time, departure time, arrival delay time, and other variables are affected.

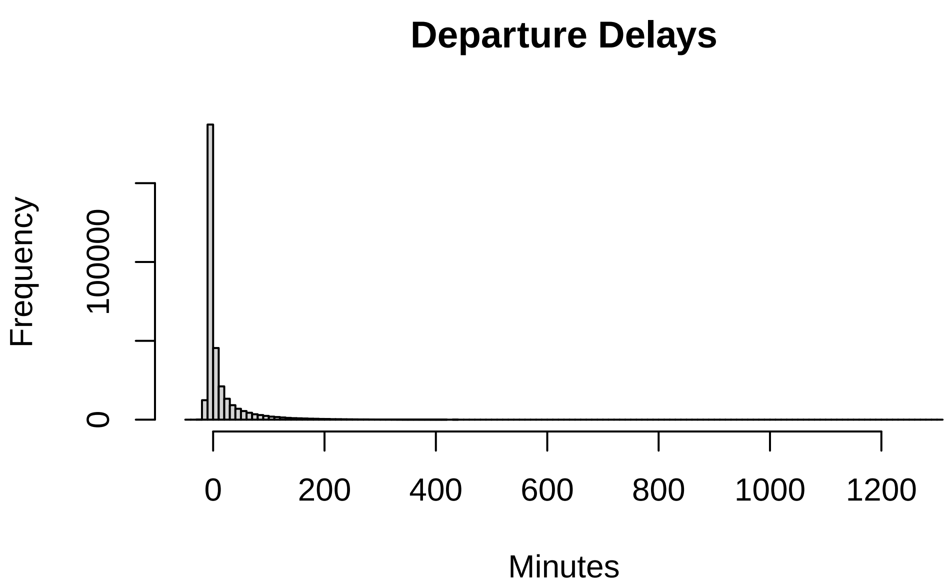
#flights that were not canceled ## We will be using these the not_canceled data for the rest of the EDA

```r
not_canceled <- filter(flights, !is.na(dep_delay), !is.na(arr_delay))
not_canceled
```

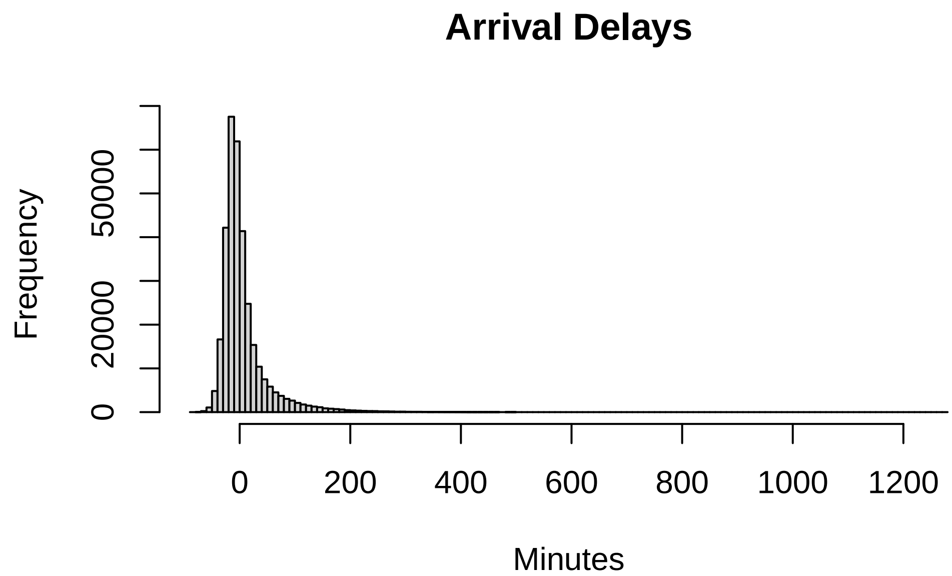
```
# A tibble: 327,346 x 19
    year month   day dep_time sched_dep_time dep_delay arr_time sched_arr_time
   <int> <int> <int>    <int>          <int>     <dbl>    <int>          <int>
 1  2013     1     1      517            515         2      830            819
 2  2013     1     1      533            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 327,336 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>
```

#Basic delay analysis ## Distribution and Proportion of delayed flights that were not canceled

```r
#histograms
hist(not_canceled$dep_delay, breaks=100, main = "Departure Delays",xlab = "Minutes")
```



```
hist(not_canceled$arr_delay, breaks=100, main ="Arrival Delays", xlab = "Minutes")
```




```
#proportions
mean(not_canceled$dep_delay>0, na.rm=TRUE)
```

```
[1] 0.3902446
```

```
mean(not_canceled$arr_delay>0, na.rm=TRUE)
```

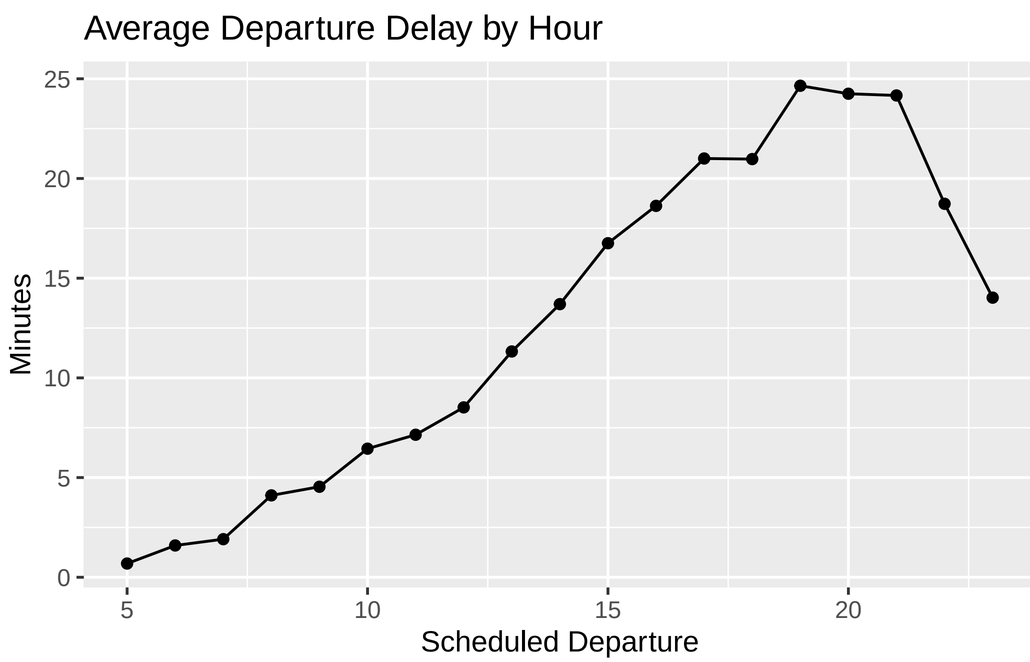
```
[1] 0.4063101
```

#most of the departure delays do not go over 200 minutes and the arrival delays have very few delays past 200 minutes.

#Delay patterns

```
#convert time to hours
not_canceled$dep_hour <-floor(not_canceled$sched_dep_time/100)
not_canceled$arr_hour <-floor(not_canceled$sched_arr_time/100)

#plot
not_canceled |>
  group_by(dep_hour) |>
  summarize(mean_dep_delay = mean(dep_delay, na.rm=TRUE))|>
```

```
  ggplot(aes(x=dep_hour, y =mean_dep_delay))+
  geom_line()+
  geom_point()+
  labs(title = "Average Departure Delay by Hour", x="Scheduled Departure", y="Minutes")
```



#We can see that many of the delays happen further in the day and peak at about 18 hours and then it descends from there.

#Delays by Airport

```
not_canceled |>
  group_by(origin)|>
  summarize(avg_dep_delay= mean(dep_delay, na.rm=TRUE), avg_arr_delay= mean(arr_delay, na.rm=TRUE))
```

```
# A tibble: 3 x 3
  origin avg_dep_delay avg_arr_delay
  <chr>          <dbl>         <dbl>
1 EWR             15.0          9.11
2 JFK             12.0          5.55
3 LGA             10.3          5.78
```

#EWR has the highest average departure and arrival delay followed by JFK and then LGA

#Ranking airlines by delay

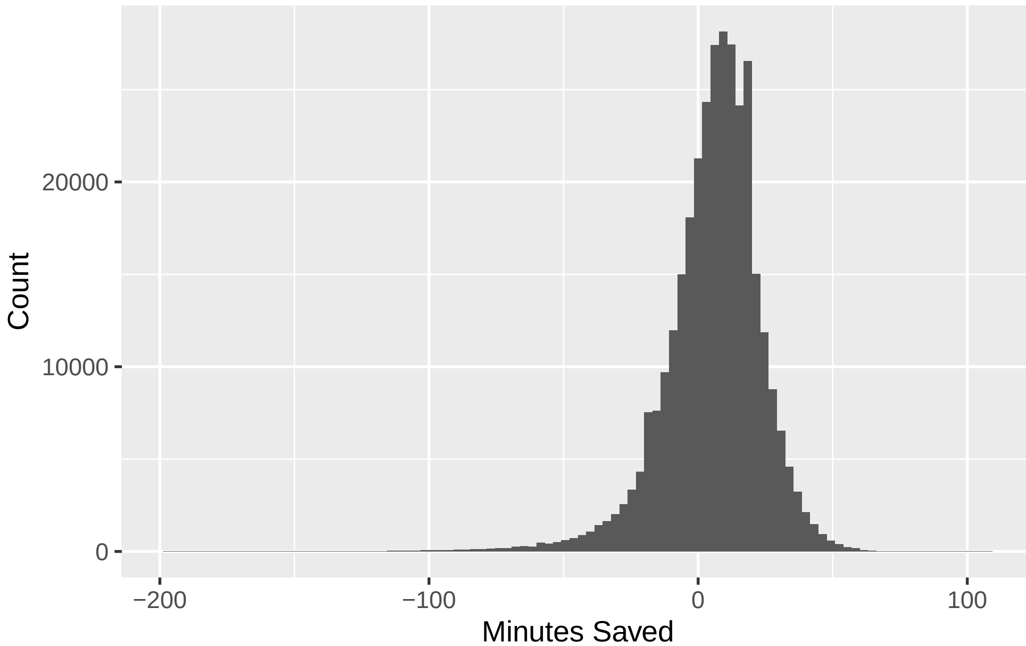
```r
not_canceled|>
  group_by(carrier)|>
  summarize(avg_dep_delay = mean(dep_delay, na.rn=TRUE))|>
  arrange(desc(avg_dep_delay))
```

```
# A tibble: 16 x 2
   carrier avg_dep_delay
   <chr>           <dbl>
 1 F9              20.2
 2 EV              19.8
 3 YV              18.9
 4 FL              18.6
 5 WN              17.7
 6 9E              16.4
 7 B6              13.0
 8 VX              12.8
 9 OO              12.6
10 UA              12.0
11 MQ              10.4
12 DL               9.22
13 AA               8.57
14 AS               5.83
15 HA               4.90
16 US               3.74
```

#F9 has the highest average departure delay at 20 hours.

#Check to see if the flights that were delayed made up the time in the air

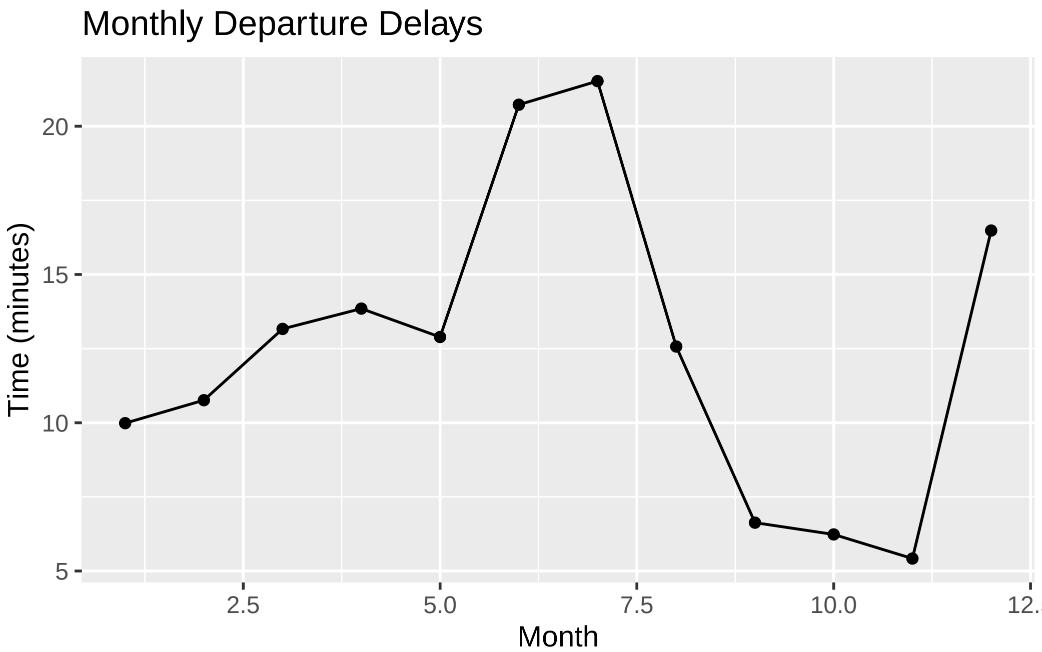
```r
not_canceled|>
  mutate(made_up_time = dep_delay- arr_delay)|>
  ggplot(aes(x=made_up_time))+
  geom_histogram(bins=100)+
  labs(titel="Made up Time in Air", x= "Minutes Saved", y="Count")
```



#We can see that the majority of the flights did not save any minutes on the arrival delay and actually ended up being delayed more. Some flights did in fact save minutes but it was less than 50% of all flights.

#Delays by Month

```
not_canceled|>
  group_by(month)|>
  summarize(mean_dep_delay=mean(dep_delay, na.rm=TRUE))|>
  ggplot(aes(x=month, y=mean_dep_delay))+
  geom_line()+
  geom_point()+
  labs(title = "Monthly Departure Delays", x="Month", y="Time (minutes)")
```

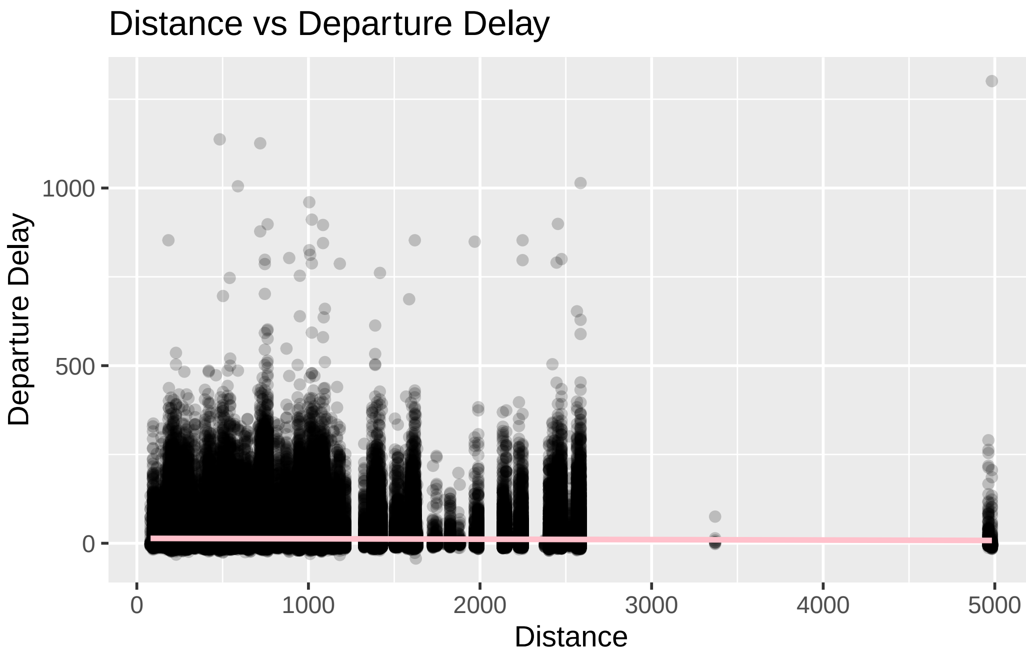


#we see that the majority of flights are delayed from May to mid July, and there is another peak at December. The months with the shortest delays are September and October.

#Does distance affect the amount of delays?

```
ggplot(not_canceled, aes(x=distance, y=dep_delay))+
  geom_point(alpha=0.2)+
  geom_smooth(method = "lm", se=TRUE,color= "Pink")+
  labs(title = "Distance vs Departure Delay", x="Distance", y="Departure Delay")
```

```
`geom_smooth()` using formula = 'y ~ x'
```



#We can see that there is not much of an effect of Distance on Departure delay.

#Flights traveled the longest by distance

```
longest_Distance <- not_canceled|>
arrange(desc(distance))|>
select(carrier, origin, dest)
longest_Distance
```

```
# A tibble: 327,346 x 3
   carrier origin dest
   <chr>   <chr>  <chr>
 1 HA      JFK    HNL
 2 HA      JFK    HNL
 3 HA      JFK    HNL
 4 HA      JFK    HNL
 5 HA      JFK    HNL
 6 HA      JFK    HNL
 7 HA      JFK    HNL
 8 HA      JFK    HNL
 9 HA      JFK    HNL
10 HA      JFK    HNL
# i 327,336 more rows
```

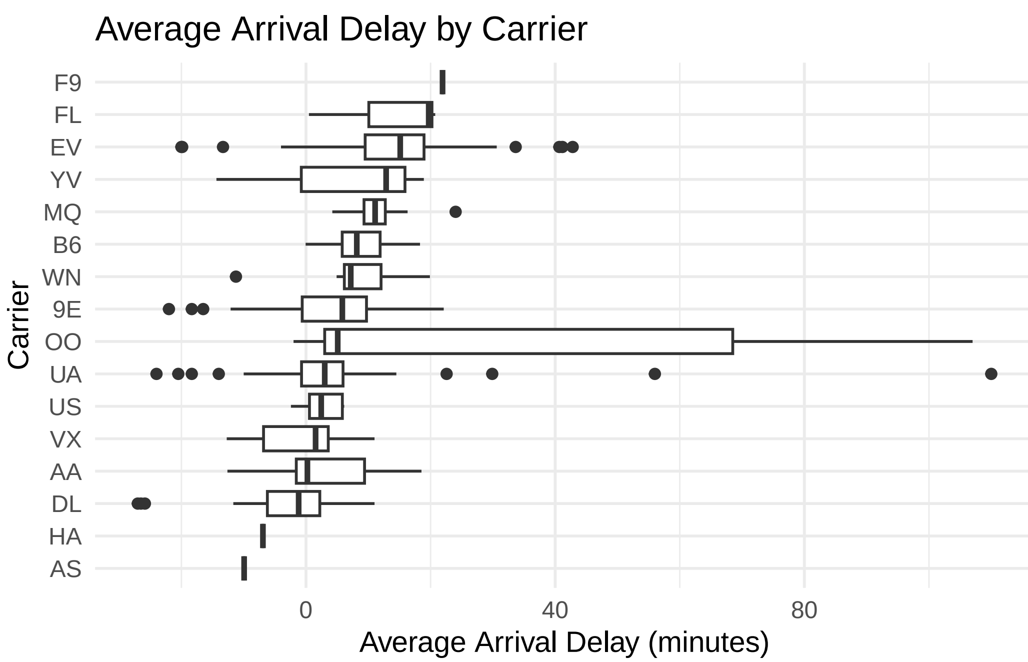
#We see that HA is the carrier with the longest flights and they all start at JFK airport and land at HNL.

#arrival delays per carrier

```r
carrier_Dest<-not_canceled |>
  group_by(carrier, dest) |>
  summarize(avg_arr_Delay = mean(arr_delay, na.rm= TRUE), .group= "drop")
```

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

```r
  ggplot(carrier_Dest, aes(x = reorder(carrier, avg_arr_Delay, median), y= avg_arr_Delay))+
  geom_boxplot()+
  coord_flip()+
  labs(title = "Average Arrival Delay by Carrier",x = "Carrier", y= "Average Arrival Delay (minutes)"
  theme_minimal()
```



Analysis Approach Plan:

Assumptions: All variables are independent

The process of analysis will involve data cleaning after forming our question, basic exploration of the data, comparison of certain datasets with other datasets, visualization of the data, and an interpretation of the data/results. Cleaning of the data will deal with tasks like handling empty cells/columns and NA values. When it comes to exploratory data analysis, we plan on using tools such as histograms and boxplots to gain an understanding of the data and identify patterns and relationships. The statistical analysis that we plan on performing with the data will most likely involve making comparisons between groups to compare airlines, times, and other metrics to make our overall claim. For example, we might be comparing trends in time performance by weeks or month between different airlines to gain a better understanding of how differences in airlines affect delays. In terms of data visualization, we will most likely be using line graphs for trends over time when it comes to comparing flight time under different variables and heatmaps/scatterplots for flight delays to help communicate our findings. Finally, interpretation of the data will involve us answering the proposed question by summarizing our statistics/findings as well as through the presentation of graphical evidence.

Analysis:

Question 4: Does the age of the plane affect flight delays?

Within this main question we will perform hypothesis tests to answer the two following sub-questions:

1. Do older planes experience more delays compared to newer ones?

```r
# Join flights with planes to get plane manufacture year
planes_fixed <- planes %>%
  rename(plane_year = year)

flights_planes <- flights %>%
  inner_join(planes %>% rename(plane_year = year), by = "tailnum") %>%
  filter(!is.na(plane_year), !is.na(arr_delay)) %>%
  mutate(
    plane_age = 2013 - plane_year,
    age_group = case_when(
      plane_age < 10 ~ "0-9 yrs",
      plane_age < 20 ~ "10-19 yrs",
      plane_age < 30 ~ "20-29 yrs",
      TRUE ~ "30+ yrs"
    )
  )

head(flights_planes)
```

```
# A tibble: 6 x 29
   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 21 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>, plane_year <int>, type <chr>,
#   manufacturer <chr>, model <chr>, engines <int>, seats <int>, speed <int>,
#   engine <chr>, plane_age <dbl>, age_group <chr>
```

```r
flights_planes %>%
  group_by(age_group) %>%
  summarise(
    mean_delay = mean(arr_delay, na.rm = TRUE),
    count = n()
  )
```

```
# A tibble: 4 x 3
  age_group mean_delay  count
  <chr>          <dbl>  <int>
1 0-9 yrs         7.36 103366
2 10-19 yrs       7.61 133479
3 20-29 yrs       4.00  35412
4 30+ yrs         5.54   1596
```

```r
anova_age <- aov(arr_delay ~ age_group, data = flights_planes)
summary(anova_age)
```

```
                Df    Sum Sq Mean Sq F value Pr(>F)
age_group        3    383976  127992   63.45 <2e-16 ***
Residuals   273849 552434545    2017
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
TukeyHSD(anova_age)
```

```
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = arr_delay ~ age_group, data = flights_planes)

$age_group
                          diff        lwr        upr     p adj
10-19 yrs-0-9 yrs    0.2442194 -0.2338502  0.7222889 0.5549760
20-29 yrs-0-9 yrs   -3.3601540 -4.0706318 -2.6496761 0.0000000
30+ yrs-0-9 yrs     -1.8245367 -4.7350197  1.0859463 0.3726088
20-29 yrs-10-19 yrs -3.6043733 -4.2940982 -2.9146485 0.0000000
30+ yrs-10-19 yrs   -2.0687561 -4.9742427  0.8367306 0.2595147
30+ yrs-20-29 yrs    1.5356173 -1.4170224  4.4882569 0.5398143
```

2. Are there specific plane models or manufactures associated with better on-time performance?

```r
delay_by_manufacturer <- flights_planes %>%
  group_by(manufacturer) %>%
  summarise(
    mean_delay = mean(arr_delay, na.rm = TRUE),
    count = n()
  ) %>%
  filter(count > 50) %>%  # Filter to manufacturers with enough data for reliable stats
  arrange(mean_delay)

print(delay_by_manufacturer)
```

```
# A tibble: 19 x 3
   manufacturer                  mean_delay count
   <chr>                              <dbl> <int>
 1 KILDALL GARY                      -5.96     51
 2 DEHAVILLAND                       -4.30     61
 3 PIPER                             -2.44    154
 4 MCDONNELL DOUGLAS                 -0.512  3831
 5 BOEING                             3.57  80925
 6 AIRBUS INDUSTRIE                   4.24  40182
 7 MCDONNELL DOUGLAS AIRCRAFT CO      5.66   8840
 8 AIRBUS                             6.32  46147
 9 MCDONNELL DOUGLAS CORPORATION      6.66   1247
10 GULFSTREAM AEROSPACE               7.17    474
11 BELL                               8.05     63
12 BOMBARDIER INC                     8.05  26822
13 CANADAIR LTD                       8.14     93
14 CIRRUS DESIGN CORP                 8.17    289
15 ROBINSON HELICOPTER CO             8.19    281
16 CESSNA                             8.62    623
17 FRIEDEMANN JON                    12.9      56
18 EMBRAER                           13.9   61980
19 CANADAIR                          16.7    1492
```

```r
# Run ANOVA on filtered data
anova_manufacturer <- aov(arr_delay ~ manufacturer, data = flights_planes %>% filter(manufacturer %in

# Summary of ANOVA
summary(anova_manufacturer)
```

```
                 Df    Sum Sq Mean Sq F value Pr(>F)    
manufacturer     18   4687399  260411   130.1 <2e-16 ***
Residuals    273592 547563608    2001                   
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# Run TukeyHSD on the ANOVA model
tukey_manufacturer <- TukeyHSD(anova_manufacturer)

# Convert TukeyHSD result for 'manufacturer' to a data.frame for easier filtering
res_df <- as.data.frame(tukey_manufacturer$manufacturer)
res_df %>%
  # Add comparison names as a column (rownames to column)
  tibble::rownames_to_column(var = "comparison") %>%
  # Select relevant columns
  select(comparison, diff, lwr) %>%
  # Show top 5 rows
  head(5) %>%
  print()
```

```
                 comparison      diff         lwr
1 AIRBUS INDUSTRIE-AIRBUS -2.087228  -3.1608163
2             BELL-AIRBUS  1.722723 -18.1141384
3           BOEING-AIRBUS -2.757445  -3.6752679
4   BOMBARDIER INC-AIRBUS  1.729648   0.5215595
5         CANADAIR-AIRBUS 10.342664   6.2038857
```

```r
# Show only significant comparisons (adjusted p-value < 0.05)
signif_res <- res_df[res_df$`p adj` < 0.05, ]
print(signif_res)
```

```
                                                   diff         lwr
AIRBUS INDUSTRIE-AIRBUS                       -2.087228  -3.1608163
BOEING-AIRBUS                                 -2.757445  -3.6752679
BOMBARDIER INC-AIRBUS                          1.729648   0.5215595
CANADAIR-AIRBUS                               10.342664   6.2038857
EMBRAER-AIRBUS                                 7.598030   6.6306070
MCDONNELL DOUGLAS-AIRBUS                      -6.836773  -9.4822784
BOMBARDIER INC-AIRBUS INDUSTRIE                3.816876   2.5762641
CANADAIR-AIRBUS INDUSTRIE                     12.429892   8.2815036
EMBRAER-AIRBUS INDUSTRIE                       9.685258   8.6775144
MCDONNELL DOUGLAS-AIRBUS INDUSTRIE            -4.749545  -7.4100598
BOMBARDIER INC-BOEING                          4.487093   3.3785247
CANADAIR-BOEING                               13.100109   8.9892781
EMBRAER-BOEING                                10.355475   9.5156219
MCDONNELL DOUGLAS-BOEING                      -4.079328  -6.6808937
MCDONNELL DOUGLAS AIRCRAFT CO-BOEING           2.093069   0.3305533
CANADAIR-BOMBARDIER INC                        8.613016   4.4278022
EMBRAER-BOMBARDIER INC                         5.868382   4.7184107
MCDONNELL DOUGLAS-BOMBARDIER INC              -8.566422 -11.2839983
MCDONNELL DOUGLAS AIRCRAFT CO-BOMBARDIER INC  -2.394024  -4.3236725
CESSNA-CANADAIR                               -8.044767 -15.5501654
DEHAVILLAND-CANADAIR                         -20.962642 -41.5160281
```

GULFSTREAM AEROSPACE-CANADAIR	-9.494565	-17.7904959
KILDALL GARY-CANADAIR	-22.628345	-45.0341438
MCDONNELL DOUGLAS-CANADAIR	-17.179437	-21.9810232
MCDONNELL DOUGLAS AIRCRAFT CO-CANADAIR	-11.007040	-15.4108505
MCDONNELL DOUGLAS CORPORATION-CANADAIR	-10.009180	-16.0462383
PIPER-CANADAIR	-19.109119	-32.4264474
MCDONNELL DOUGLAS-CESSNA	-9.134670	-15.9317435
MCDONNELL DOUGLAS-EMBRAER	-14.434804	-17.0542791
MCDONNELL DOUGLAS AIRCRAFT CO-EMBRAER	-8.262406	-10.0512527
MCDONNELL DOUGLAS CORPORATION-EMBRAER	-7.264547	-11.7648237
PIPER-EMBRAER	-16.364485	-29.0592741
MCDONNELL DOUGLAS-GULFSTREAM AEROSPACE	-7.684873	-15.3459227
MCDONNELL DOUGLAS AIRCRAFT CO-MCDONNELL DOUGLAS	6.172397	3.1289188
MCDONNELL DOUGLAS CORPORATION-MCDONNELL DOUGLAS	7.170257	2.0404145

	upr	p adj
AIRBUS INDUSTRIE-AIRBUS	-1.01363950	1.374346e-09
BOEING-AIRBUS	-1.83962244	1.868505e-13
BOMBARDIER INC-AIRBUS	2.93773705	7.828090e-05
CANADAIR-AIRBUS	14.48144192	1.468825e-13
EMBRAER-AIRBUS	8.56545349	0.000000e+00
MCDONNELL DOUGLAS-AIRBUS	-4.19126825	2.431388e-13
BOMBARDIER INC-AIRBUS INDUSTRIE	5.05748819	1.927347e-13
CANADAIR-AIRBUS INDUSTRIE	16.57827984	1.785239e-13
EMBRAER-AIRBUS INDUSTRIE	10.69300188	0.000000e+00
MCDONNELL DOUGLAS-AIRBUS INDUSTRIE	-2.08903103	5.818840e-08
BOMBARDIER INC-BOEING	5.59566219	0.000000e+00
CANADAIR-BOEING	17.21093986	4.218847e-14
EMBRAER-BOEING	11.19532893	0.000000e+00
MCDONNELL DOUGLAS-BOEING	-1.47776260	5.869151e-06
MCDONNELL DOUGLAS AIRCRAFT CO-BOEING	3.85558477	4.307302e-03
CANADAIR-BOMBARDIER INC	12.79822886	7.794665e-11
EMBRAER-BOMBARDIER INC	7.01835323	0.000000e+00
MCDONNELL DOUGLAS-BOMBARDIER INC	-5.84884486	8.437695e-14
MCDONNELL DOUGLAS AIRCRAFT CO-BOMBARDIER INC	-0.46437634	1.938850e-03
CESSNA-CANADAIR	-0.53936941	2.098917e-02
DEHAVILLAND-CANADAIR	-0.40925652	3.968428e-02
GULFSTREAM AEROSPACE-CANADAIR	-1.19863320	7.967645e-03
KILDALL GARY-CANADAIR	-0.22254550	4.459793e-02
MCDONNELL DOUGLAS-CANADAIR	-12.37785102	0.000000e+00
MCDONNELL DOUGLAS AIRCRAFT CO-CANADAIR	-6.60322939	1.481038e-13
MCDONNELL DOUGLAS CORPORATION-CANADAIR	-3.97212215	9.328420e-07
PIPER-CANADAIR	-5.79179009	7.388958e-05
MCDONNELL DOUGLAS-CESSNA	-2.33759599	3.645865e-04
MCDONNELL DOUGLAS-EMBRAER	-11.81532794	0.000000e+00
MCDONNELL DOUGLAS AIRCRAFT CO-EMBRAER	-6.47356013	0.000000e+00
MCDONNELL DOUGLAS CORPORATION-EMBRAER	-2.76426960	2.309896e-06
PIPER-EMBRAER	-3.66969624	9.027062e-04
MCDONNELL DOUGLAS-GULFSTREAM AEROSPACE	-0.02382241	4.825154e-02
MCDONNELL DOUGLAS AIRCRAFT CO-MCDONNELL DOUGLAS	9.21587547	1.681061e-10

```
MCDONNELL DOUGLAS CORPORATION-MCDONNELL DOUGLAS  12.30009928 1.437203e-04
```

```r
# Sort by absolute difference
res_df_sorted <- res_df[order(-abs(res_df$diff)), ]

# Show top 10 largest differences
head(res_df_sorted, 10)
```

```
                                diff        lwr         upr        p adj
KILDALL GARY-CANADAIR      -22.62834 -45.034144  -0.2225455 4.459793e-02
DEHAVILLAND-CANADAIR       -20.96264 -41.516028  -0.4092565 3.968428e-02
KILDALL GARY-EMBRAER       -19.88371 -41.925178   2.1577557 1.391256e-01
PIPER-CANADAIR             -19.10912 -32.426447  -5.7917901 7.388958e-05
KILDALL GARY-FRIEDEMANN JON -18.90721 -49.362294  11.5478683 7.891113e-01
EMBRAER-DEHAVILLAND         18.21801  -1.937588  38.3736057 1.368215e-01
FRIEDEMANN JON-DEHAVILLAND  17.24151 -11.877792  46.3608135 8.477272e-01
MCDONNELL DOUGLAS-CANADAIR -17.17944 -21.981023 -12.3778510 0.000000e+00
PIPER-EMBRAER              -16.36449 -29.059274  -3.6696962 9.027062e-04
PIPER-FRIEDEMANN JON       -15.38799 -39.940856   9.1648821 7.758514e-01
```

Alternative Strategies & Back Up Plan:

As a backup idea, we are planning on seeing if there is any correlation between the amount of delays present in the different airports. Our data deals with the airports EWR, JFK, and LGA which are all different airports within New York City. Our first question is to figure out if the JFK airport has a different amount of delays compared to LGA or EWR if there is a higher amount of precipitation in the JFK area. Although all the airports are in New York, within the different areas of the city, there can be different amounts of precipitation and rainfall that occur. Our second question is to decide whether the different airports have different models of planes and if the difference affects the amounts of delays. For example if a plane is older or a different configuration, does that lead to more delays due to cleaning or maintenance? And lastly, our third question is whether the three different airports have different airlines coming in and out and if these differing airlines affect the amount of delays present on a given day. For example, if Delta services one airport and not another, does that increase or decrease the amount of total delays for an airport. These questions can be further investigated if our first set of questions are not approved or if we need more content to explore within our project. These sets of backup questions will further explore the flight data we have.