STATS 506 Problem Set #4

Haiming Li

Tidyverse

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

a. First table

```
flights %>%
  group_by(origin) %>%
  summarise(mean_delay=mean(arr_delay, na.rm=TRUE),
            median_delay=median(arr_delay, na.rm=TRUE),
            n_flights=n()) %>%
  ungroup() %>%
  filter(n_flights >= 10) %>%
  left_join(airports, by=join_by(origin == faa)) %>%
  select(name, mean_delay, median_delay) %>%
  arrange(desc(mean_delay))
```

```
# A tibble: 3 x 3
  name                mean_delay median_delay
  <chr>                    <dbl>        <dbl>
1 Newark Liberty Intl       9.11           -4
2 La Guardia                5.78           -5
3 John F Kennedy Intl       5.55           -6
```

Second table

```r
flights %>%
  group_by(dest) %>%
  summarise(mean_delay=mean(arr_delay, na.rm=TRUE),
            median_delay=median(arr_delay, na.rm=TRUE),
            n_flights=n()) %>%
  ungroup() %>%
  filter(n_flights >= 10) %>%
  left_join(airports, by=join_by(dest == faa)) %>%
  mutate(name = coalesce(name, dest)) %>%
  select(name, mean_delay, median_delay) %>%
  arrange(desc(mean_delay)) %>%
  print(n=102)
```

```
# A tibble: 102 x 3
    name                                  mean_delay median_delay
    <chr>                                      <dbl>        <dbl>
  1 "Columbia Metropolitan"                     41.8           28
  2 "Tulsa Intl"                                33.7           14
  3 "Will Rogers World"                         30.6           16
  4 "Jackson Hole Airport"                      28.1           15
  5 "Mc Ghee Tyson"                             24.1            2
  6 "Dane Co Rgnl Truax Fld"                    20.2            1
  7 "Richmond Intl"                             20.1            1
  8 "Akron Canton Regional Airport"             19.7            3
  9 "Des Moines Intl"                           19.0            0
 10 "Gerald R Ford Intl"                        18.2            1
 11 "Birmingham Intl"                           16.9           -2
 12 "Theodore Francis Green State"              16.2            1
 13 "Greenville-Spartanburg International"      15.9           -0.5
 14 "Cincinnati Northern Kentucky Intl"         15.4           -3
 15 "Savannah Hilton Head Intl"                 15.1           -1
 16 "Manchester Regional Airport"               14.8           -3
 17 "Eppley Afld"                               14.7           -2
 18 "Yeager"                                    14.7           -1.5
 19 "Kansas City Intl"                          14.5            0
 20 "Albany Intl"                               14.4           -4
 21 "General Mitchell Intl"                     14.2            0
 22 "Piedmont Triad"                            14.1           -2
 23 "Washington Dulles Intl"                    13.9           -3
 24 "Cherry Capital Airport"                    13.0          -10
 25 "James M Cox Dayton Intl"                   12.7           -3
 26 "Louisville International Airport"          12.7           -2
```

27	"Chicago Midway Intl"	12.4	-1
28	"Sacramento Intl"	12.1	4
29	"Jacksonville Intl"	11.8	-2
30	"Nashville Intl"	11.8	-2
31	"Portland Intl Jetport"	11.7	-4
32	"Greater Rochester Intl"	11.6	-5
33	"Hartsfield Jackson Atlanta Intl"	11.3	-1
34	"Lambert St Louis Intl"	11.1	-3
35	"Norfolk Intl"	10.9	-4
36	"Baltimore Washington Intl"	10.7	-5
37	"Memphis Intl"	10.6	-2.5
38	"Port Columbus Intl"	10.6	-3
39	"Charleston Afb Intl"	10.6	-4
40	"Philadelphia Intl"	10.1	-3
41	"Raleigh Durham Intl"	10.1	-3
42	"Indianapolis Intl"	9.94	-3
43	"Charlottesville-Albemarle"	9.5	-5
44	"Cleveland Hopkins Intl"	9.18	-5
45	"Ronald Reagan Washington Natl"	9.07	-2
46	"Burlington Intl"	8.95	-4
47	"Buffalo Niagara Intl"	8.95	-5
48	"Syracuse Hancock Intl"	8.90	-5
49	"Denver Intl"	8.61	-2
50	"Palm Beach Intl"	8.56	-3
51	"BQN"	8.25	-1
52	"Bob Hope"	8.18	-3
53	"Fort Lauderdale Hollywood Intl"	8.08	-3
54	"Bangor Intl"	8.03	-9
55	"Asheville Regional Airport"	8.00	-1
56	"PSE"	7.87	0
57	"Pittsburgh Intl"	7.68	-5
58	"Gallatin Field"	7.6	-2
59	"NW Arkansas Regional"	7.47	-2
60	"Tampa Intl"	7.41	-4
61	"Charlotte Douglas Intl"	7.36	-3
62	"Minneapolis St Paul Intl"	7.27	-5
63	"William P Hobby"	7.18	-4
64	"Bradley Intl"	7.05	-10
65	"San Antonio Intl"	6.95	-9
66	"South Bend Rgnl"	6.5	-3.5
67	"Louis Armstrong New Orleans Intl"	6.49	-6
68	"Key West Intl"	6.35	7
69	"Eagle Co Rgnl"	6.30	-4

```
 70 "Austin Bergstrom Intl"                    6.02          -5
 71 "Chicago Ohare Intl"                       5.88          -8
 72 "Orlando Intl"                             5.45          -5
 73 "Detroit Metro Wayne Co"                   5.43          -7
 74 "Portland Intl"                            5.14          -5
 75 "Nantucket Mem"                            4.85          -3
 76 "Wilmington Intl"                          4.64          -7
 77 "Myrtle Beach Intl"                        4.60         -13
 78 "Albuquerque International Sunport"        4.38          -5.5
 79 "George Bush Intercontinental"             4.24          -5
 80 "Norman Y Mineta San Jose Intl"            3.45          -7
 81 "Southwest Florida Intl"                   3.24          -5
 82 "San Diego Intl"                           3.14          -5
 83 "Sarasota Bradenton Intl"                  3.08          -5
 84 "Metropolitan Oakland Intl"                3.08          -9
 85 "General Edward Lawrence Logan Intl"       2.91          -9
 86 "San Francisco Intl"                       2.67          -8
 87 "SJU"                                      2.52          -6
 88 "Yampa Valley"                             2.14           2
 89 "Phoenix Sky Harbor Intl"                  2.10          -6
 90 "Montrose Regional Airport"                1.79         -10.5
 91 "Los Angeles Intl"                         0.547         -7
 92 "Dallas Fort Worth Intl"                   0.322         -9
 93 "Miami Intl"                               0.299         -9
 94 "Mc Carran Intl"                           0.258         -8
 95 "Salt Lake City Intl"                      0.176         -8
 96 "Long Beach"                              -0.0620       -10
 97 "Martha\\\\'s Vineyard"                   -0.286        -11
 98 "Seattle Tacoma Intl"                     -1.10         -11
 99 "Honolulu Intl"                           -1.37          -7
100 "STT"                                     -3.84          -9
101 "John Wayne Arpt Orange Co"               -7.87         -11
102 "Palm Springs Intl"                      -12.7          -13.5
```

b. Here's the table

```
flights %>%
  left_join(planes, by = "tailnum") %>%
  mutate(mph=60*distance/air_time) %>%
  group_by(model) %>%
  summarize(avg_mph = mean(mph, na.rm = TRUE),
            n_flights = n()) %>%
```

```
  arrange(desc(avg_mph)) %>%
  slice_head(n=1)
```

```
# A tibble: 1 x 3
  model   avg_mph n_flights
  <chr>     <dbl>     <int>
1 777-222    483.         4
```

get_temp()

a. Here's the function definition

```
#' Request the average temperature for a given month
#' @param month Numeric or string value represent 1-12
#' @param year A numeric year
#' @param data The dataset
#' @param celsius Logically indicating whether the results should be in Celsius
#' @param average_fn Function to compute average
#' @return Average temperature as an atomic numeric vector
get_temp <- function(month, year, data, celsius=FALSE, average_fn=mean) {
  # input checking
  if (is.numeric(month)) {
    if (month < 1 | month > 12) {
      stop('Invalid month: must between 1 ~ 12')
    }
  }
  else if (is.character(month)) {
    # convert string month to numeric scale of 1 to 12
    months <- c("January", "February", "March", "April",
                "May", "June", "July", "August", "September",
                "October", "November", "December")
    month <- which(match.arg(month, months) == months)
  }
  else {
    stop('Invalid month: must be numeric or string')
  }

  if(!is.numeric(year)) {
    stop('Invalid year: must be numeric')
  }
  if(year < 1997 | year > 2000) {
```

```
    stop('Invalid year: must between 1997 ~ 2000')
  }

  if(!is.function(average_fn)) {
    stop('average_fn must be a function')
  }

  data %>%
    filter((month_numeric == !!month) & (year == !!year)) %>%
    select(temp) %>%
    summarize(avg_tmp = average_fn(temp)) %>%
    mutate(avg_tmp = ifelse(celsius, 5/9*(avg_tmp - 32), avg_tmp)) %>%
    as.numeric -> res
  return(res)
}
```

Here's the demonstration

```
nnmaps <- read_csv('./chicago-nmmaps.csv', show_col_types=FALSE)
get_temp("Apr", 1999, data = nnmaps)
```

```
[1] 49.8
```

```
get_temp("Apr", 1999, data = nnmaps, celsius = TRUE)
```

```
[1] 9.888889
```

```
get_temp(10, 1998, data = nnmaps, average_fn = median)
```

```
[1] 55
```

```
get_temp(13, 1998, data = nnmaps)
```

```
Error in get_temp(13, 1998, data = nnmaps): Invalid month: must between 1 ~ 12
```

```
get_temp(2, 2005, data = nnmaps)
```

```
Error in get_temp(2, 2005, data = nnmaps): Invalid year: must between 1997 ~ 2000
```

```r
get_temp("November", 1999, data =nnmaps, celsius = TRUE,
         average_fn = function(x) {
           x %>% sort -> x
           x[2:(length(x) - 1)] %>% mean %>% return
         })
```

```
[1] 7.301587
```

Visualization

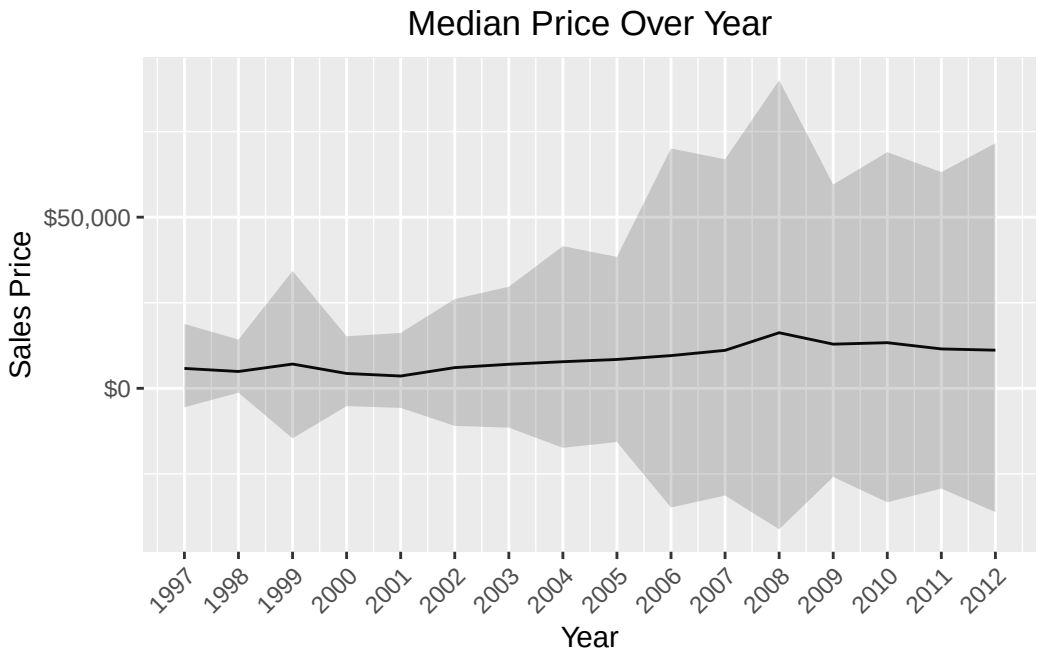
a. Here I plot the median sales price over time, with ribbon of minimum and maximum value based on the IQR method. As shown, there is a slight increasing trend in median price, and the spread of price also has a increasing trend. Thus, there is a change in price over time.

```r
library(ggplot2)
library(tibble)
library(dplyr)

df <- as_tibble(read.csv('./df_for_ml_improved_new_market.csv'))
price_stats <- df %>%
  group_by(year) %>%
  summarize(
    median_price = median(price_usd, na.rm = TRUE),
    Q1 = quantile(price_usd, 0.25, na.rm = TRUE),
    Q3 = quantile(price_usd, 0.75, na.rm = TRUE)) %>%
  ungroup() %>%
  mutate(
    IQR = Q3 - Q1,
    lwr = Q1 - 1.5 * IQR,
    upr = Q3 + 1.5 * IQR
  ) %>%
  select(year, median_price, lwr, upr)

ggplot(price_stats, aes(x=year, y=median_price)) +
  geom_line() +
  geom_ribbon(aes(ymin = lwr, ymax = upr), alpha = .2) +
  labs(title = "Median Price Over Year",
       x = "Year",
       y = "Sales Price") +
  scale_x_continuous(breaks = unique(price_stats$year)) +
```

```
  scale_y_continuous(labels = scales::dollar_format()) +
  theme(plot.title = element_text(hjust = 0.5),
        axis.text.x = element_text(angle = 45, hjust = 1))
```



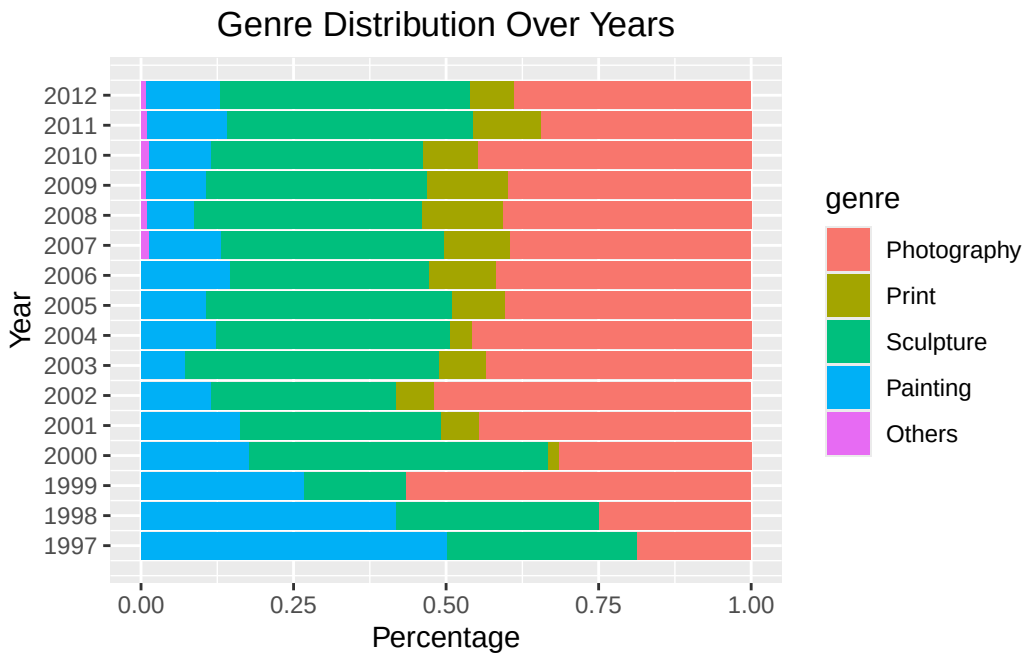
b. As shown, the distribution of genre does change over time. The amount of paintings decreases until 2002 and then maintains at a relatively stable level. Also, the amount of Photography increases until 2002 and then maintains at a relatively stable level. For Sculpture, it has the lowest point in 1999, but is relatively stable since then. Print first appears in 2000, and has a slight increase after that, then remains at a relatively stable level after 2005. Other genre started to appear in 2007, but are taking very little percentages of sales, and is almost negligible.

```
library(reshape2)
genre_columns <- grep('Genre___', colnames(df), value = TRUE)
genre_data <- df[, c('id', 'year', 'price_usd', genre_columns)] %>%
  melt(id.vars = c('id', 'year', 'price_usd')) %>%
  filter(value == 1) %>%
  mutate(genre=sub('Genre___', '', variable)) %>%
  select(id, year, price_usd, genre)

# Ex: If the genre is both 'Other' and 'Painting', the final genre should be
#     'Painting'
```

```r
genre_priority <- c("Photography", "Print", "Sculpture", "Painting", "Others")
genre_data$genre <- factor(genre_data$genre, levels = genre_priority)
genre_data <- genre_data[!duplicated(genre_data$id), 2:4]

ggplot(genre_data, aes(x = year, fill = genre)) +
  geom_bar(position = "fill") +
  labs(title = "Genre Distribution Over Years",
       x = "Year",
       y = "Percentage") +
  scale_x_continuous(breaks = unique(genre_data$year)) +
  coord_flip() +
  theme(plot.title = element_text(hjust = 0.5))
```

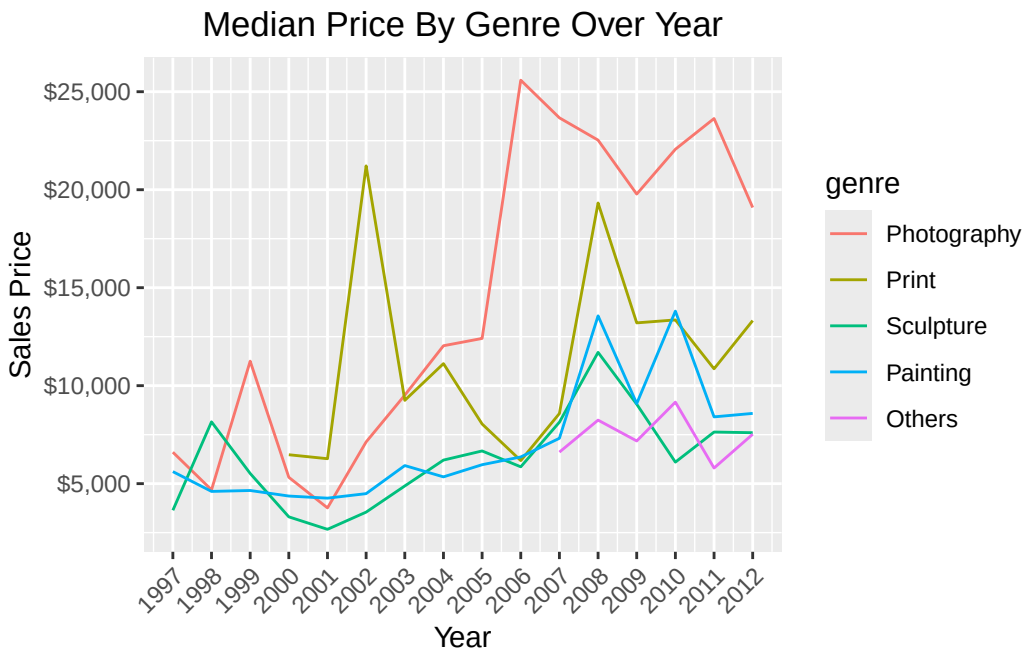


c. As shown, different genre seems to have similar trends over the years. Although there is a unusually high spike in price of Prints genre, other years different genre seems to have similar trend in terms of price fluctuation. Also, on average, Photography tend to have the highest sale price, Print have the second highest, Painting the third, Sculpture the fourth, and Other the cheapest.

```r
genre_data <- genre_data %>%
  group_by(year, genre) %>%
  summarise(median_price=median(price_usd)) %>%
```

```r
  ungroup()

ggplot(genre_data, aes(x=year, y=median_price, colour=genre)) +
  geom_line() +
  labs(title = "Median Price By Genre Over Year",
       x = "Year",
       y = "Sales Price") +
  scale_x_continuous(breaks = unique(genre_data$year)) +
  scale_y_continuous(labels = scales::dollar_format()) +
  theme(plot.title = element_text(hjust = 0.5),
        axis.text.x = element_text(angle = 45, hjust = 1))
```



Attribution of Source

- Github Repo
- Use of aggregate function
- Label manipulation in ggplot