"COMPSCIX 415.2 Homework 5/Midterm"

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Github location

My homework assignments can be found at https://github.com/santumagic/compscix-415-2assignments.git

RStudio and R Markdown

Question: 1

As part of this question, I have loaded the required packages and added instructions for table of contents etc in the YAML header.

```
# Load the required packages
library(tidyverse)
library(mdsr)
library(nycflights13)
```

The tidyverse packages

Question: 1

```
Plotting - ggplot2
Data munging/wrangling - dplyr
Reshaping (speading and gathering) data - tidyr
Importing/exporting data - readr
```

Question: 2

```
Plotting - ggplot() and aes()
Data munging/wrangling - select() and filter()
Reshaping (speading and gathering) data - separate() and extract()
Importing/exporting data - read_csv() and read_delim()
```

R Basics

Question: 1

```
My_data.name___is.too00ooLong <- c( 1 , 2 , 3 )
My_data.name___is.too00ooLong</pre>
```

```
## [1] 1 2 3
```

Answer: Just with one change (removal of '!'), the code works.

```
# this is a charactor vector
my_string <- c('has', 'an', 'error', 'in', 'it')
my_string
## [1] "has" "an" "error" "in" "it"</pre>
```

Question: 3

```
my_vector <- c(1, 2, '3', '4', 5)
my_vector
## [1] "1" "2" "3" "4" "5"</pre>
```

Answer: This is a numeric vector and with or without the single or double quotes, vector takes values.

Data import/export

Question: 1

```
# Download and import the file rail_trail.txt
rail_trail.txt <- read.delim("/Users/skanutal/Documents/Santosh/Learning/Berkeley/rail_trail.txt", sep=
#glimpse the data from txt file
glimpse(rail_trail.txt)
## Observations: 90
## Variables: 10
## $ hightemp
                <int> 83, 73, 74, 95, 44, 69, 66, 66, 80, 79, 78, 65, 41,...
## $ lowtemp
                <int> 50, 49, 52, 61, 52, 54, 39, 38, 55, 45, 55, 48, 49,...
                <dbl> 66.5, 61.0, 63.0, 78.0, 48.0, 61.5, 52.5, 52.0, 67....
## $ avgtemp
                <int> 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, ...
## $ spring
## $ summer
                <int> 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, ...
```

<int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, ...

<dbl> 0.00, 0.29, 0.32, 0.00, 0.14, 0.02, 0.00, 0.00, 0.0...

<int> 501, 419, 397, 385, 200, 375, 417, 629, 533, 547, 4...

<int> 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, ...

\$ cloudcover <dbl> 7.6, 6.3, 7.5, 2.6, 10.0, 6.6, 2.4, 0.0, 3.8, 4.1, ...

Question: 2

\$ spring

\$ summer

\$ fall

\$ fall

\$ precip

\$ volume

\$ weekday

```
# Export the .txt file as csv into a different location
rail_trail_csv <- write_delim(</pre>
 rail_trail.txt, delim = '|',path = "/Users/skanutal/Documents/Santosh/Learning/Berkeley/3. Intro to D
  )
# Load the newly created csv file
rail_trail_csv_final <- read.csv(</pre>
  "/Users/skanutal/Documents/Santosh/Learning/Berkeley/3. Intro to DS/Assignments/rail_trail.csv", sep=
  )
# glimpse the data from the final csv file
glimpse(rail_trail_csv_final)
## Observations: 90
## Variables: 10
## $ hightemp
                <int> 83, 73, 74, 95, 44, 69, 66, 66, 80, 79, 78, 65, 41,...
## $ lowtemp
                <int> 50, 49, 52, 61, 52, 54, 39, 38, 55, 45, 55, 48, 49,...
## $ avgtemp
                <dbl> 66.5, 61.0, 63.0, 78.0, 48.0, 61.5, 52.5, 52.0, 67....
```

<int> 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, ...

<int> 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, ...

<int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, ...

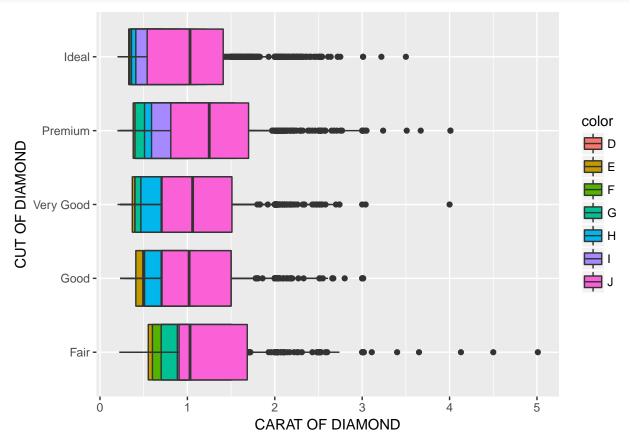
Visualization

Question: 1

Answer:

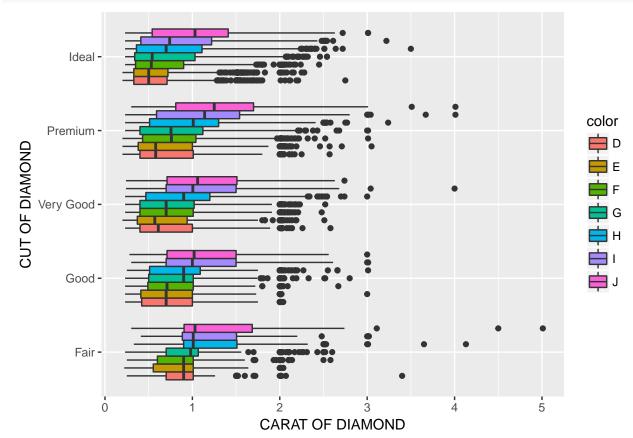
- 1. Both the categories age group and gender are plotted on same axis, which is confusing at a first glanse.
- 2. These are two separate charts, but they look like one. The first chart is a chart with three ranges (<45, 45 to 64, and >64), the second chart is a men vs women chart. This simple difference is not easily visible with how it is layed out currently.
- 3. With the way the data is currently layed out it is not clear that yes/no data points are proportions and the title should visually be represented.

```
# Reproduce the given graph
ggplot(data = diamonds, mapping = aes(x = cut, y = carat, fill = color)) +
geom_boxplot (position = "identity") +
coord_flip() +
labs(x = "CUT OF DIAMOND", y = "CARAT OF DIAMOND")
```



Question: 3

```
# Enhancing the graph by changing the position to "dodge"
ggplot(data = diamonds, mapping = aes(x = cut, y = carat, fill = color)) +
geom_boxplot (position = "dodge") +
coord_flip() +
labs(x = "CUT OF DIAMOND", y = "CARAT OF DIAMOND")
```



Explanation: By using position = "dodge", we can compare the individual values side by side.

Data munging and wrangling

Question: 1

Finding the dataset tidy or not table2

```
## # A tibble: 12 x 4
##
      country
                                        count
                  year type
      <chr>
                  <int> <chr>
##
                                        <int>
   1 Afghanistan 1999 cases
##
                                          745
   2 Afghanistan 1999 population
                                     19987071
   3 Afghanistan 2000 cases
                                         2666
##
   4 Afghanistan 2000 population
                                     20595360
## 5 Brazil
                  1999 cases
                                        37737
                  1999 population 172006362
   6 Brazil
```

```
## 7 Brazil
                   2000 cases
                                         80488
## 8 Brazil
                   2000 population 174504898
## 9 China
                   1999 cases
                                        212258
                   1999 population 1272915272
## 10 China
## 11 China
                   2000 cases
                                        213766
## 12 China
                   2000 population 1280428583
# It is not a tidy data, so below code makes it a tidy dataset
table2_tidy <- spread(table2, type, count)</pre>
# Display table2 in tidy way
table2_tidy
## # A tibble: 6 x 4
     country
                  year
                        cases population
##
     <chr>>
                 <int>
                        <int>
                                    <int>
                                19987071
## 1 Afghanistan 1999
                          745
## 2 Afghanistan
                         2666
                                20595360
                  2000
## 3 Brazil
                  1999
                        37737
                              172006362
## 4 Brazil
                  2000
                        80488 174504898
## 5 China
                  1999 212258 1272915272
## 6 China
                  2000 213766 1280428583
```

Answer: To make this data tidy, there needs to be one observation per row, which we can achieve with a "spread".

Question: 2

```
# modify the diamonds dataset by adding an additional column
enhanced_diamonds <- diamonds %>% mutate(price_per_carat = price / carat)
```

Question: 3

```
# finding the number of diamonds with price > 10000 and carat <1.5
diamond_target <- diamonds %>%
mutate (target_segment = (price > 10000 & carat < 1.5)) %>%
group_by(cut)
# finding the proportion
diamond_target %>%
   summarise(target_propotion = (sum(target_segment)/length(target_segment))*100,
target_count = sum(target_segment))
## # A tibble: 5 x 3
```

```
##
     cut
                target_propotion target_count
##
     <ord>
                            <dbl>
## 1 Fair
                            0.248
                                              4
## 2 Good
                            0.347
                                             17
## 3 Very Good
                            1.28
                                            155
## 4 Premium
                            1.25
                                            173
## 5 Ideal
                            2.25
                                            485
```

Answer:

As seen in the above dataset there are 485 ideal diamonds, and they comprise 2.25% of all ideal diamonds. This makes sense, since as the diamond is more ideal, small diamonds are more expensive. Similarly, most

fair diamonds won't have the same price as any of the others. It is interesting that very-good and premium diamonds are the same. Which implies that we are missing some other parameter, likely clarity, colour or some such variable.

EDA

Question: 1

```
# Select year and month from the dataset with default sorting order
txhousing %>% select(year,month)
## # A tibble: 8,602 x 2
##
      year month
##
      <int> <int>
   1 2000
##
   2 2000
##
  3 2000
##
                3
##
   4 2000
                4
##
   5 2000
                5
   6 2000
##
##
   7 2000
                7
   8 2000
##
                8
   9 2000
                9
##
## 10 2000
               10
## # ... with 8,592 more rows
#Select year and month from the dataset and finding the maximum year and month
txhousing %>% select(year,month) %>% arrange(desc(year), desc(month))
## # A tibble: 8,602 x 2
##
      year month
      <int> <int>
##
##
   1 2015
                7
   2 2015
                7
##
##
   3 2015
                7
   4 2015
                7
##
##
   5 2015
##
   6 2015
                7
   7 2015
                7
##
                7
##
   8 2015
                7
##
   9
      2015
## 10 2015
                7
## # ... with 8,592 more rows
Answer:
The data is from Jan 2000 to July 2015
```

```
# total number of cities in the dataset
total_cities <- txhousing %>% select(city) %>% unique()
count(total_cities)
```

```
## # A tibble: 1 x 1
## n
## <int>
## 1 46
```

Answer:

There are 46 unique cities in the dataset.

Question: 3

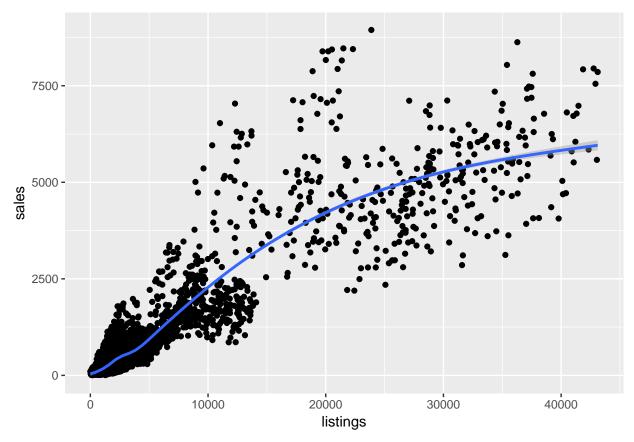
```
# arrange the volumes in descending order and find the top city
txhousing %>% arrange(desc(volume))
```

```
## # A tibble: 8,602 x 9
##
      city
              year month sales
                                   volume median listings inventory date
##
             <int> <int> <dbl>
                                    <dbl> <dbl>
                                                    <dbl>
                                                             <dbl> <dbl>
      <chr>
##
   1 Houston
              2015
                       7 8945 2568156780 217600
                                                    23875
                                                               3.4 2016.
##
  2 Houston 2015
                       6 8449 2490238594 222400
                                                               3.2 2015.
                                                    22311
                       6 8391 2342443127 211200
                                                    19725
                                                               2.9 2014.
## 3 Houston 2014
## 4 Houston
              2014
                       7 8391 2278932511 199700
                                                    20214
                                                                   2014.
                       8 8167 2195184825 202400
                                                               2.9 2015.
## 5 Houston 2014
                                                    20007
## 6 Houston 2013
                       7 8468 2168720825 187800
                                                    21497
                                                               3.3 2014.
                                                               2.8 2014.
## 7 Houston 2014
                       5 7877 2154791886 199300
                                                   18883
                                                               3.3 2013.
## 8 Houston 2013
                       5 8439 2121508529 186100
                                                    20526
                                                               3.1 2015.
## 9 Houston 2015
                       5 7357 2097957518 220100
                                                    21101
                       8 8155 2083377894 186700
                                                    21366
                                                               3.3 2014.
## 10 Houston 2013
## # ... with 8,592 more rows
```

Answer:

From the above dataset, Houston, in July/2015 had sales volume of \$ 2.568 B.

```
# plotting the relation between listings and sales
ggplot(data = txhousing,mapping = aes(x=listings, y = sales)) +
geom_point() +
geom_smooth()
```



Answer:

From the above plot, we can assume that the sales are incresing along with the number of listings.

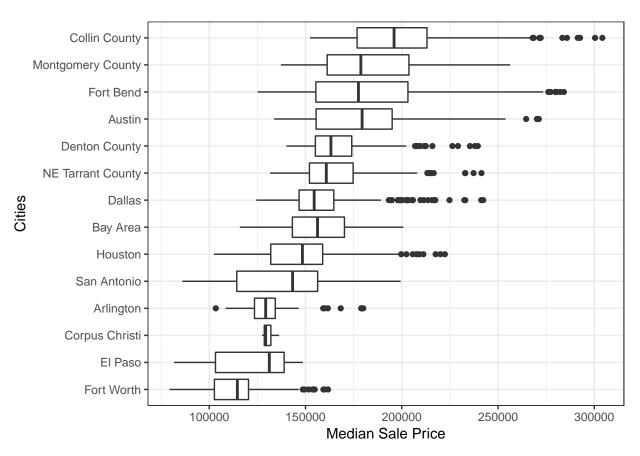
```
# finding the cities with valid sales
valid_cities <- txhousing %>%
mutate(valid_sales = !is.na(sales)) %>%
group_by(city)
valid_cities # show valid cities
## # A tibble: 8,602 x 10
## # Groups:
               city [46]
##
      city
               year month sales
                                   volume median listings inventory
                                                                      date
##
      <chr>
              <int> <int> <dbl>
                                    <dbl>
                                           <dbl>
                                                     <dbl>
                                                               <dbl> <dbl>
                                           71400
               2000
                                  5380000
                                                       701
                                                                 6.3 2000
##
    1 Abilene
                              72
                         1
    2 Abilene
               2000
                         2
                              98
                                  6505000
                                           58700
                                                       746
                                                                 6.6 2000.
##
##
    3 Abilene
               2000
                         3
                             130
                                  9285000
                                           58100
                                                       784
                                                                 6.8 2000.
##
    4 Abilene
               2000
                         4
                              98
                                  9730000
                                           68600
                                                       785
                                                                 6.9 2000.
    5 Abilene
               2000
                             141 10590000
                                           67300
                                                       794
                                                                 6.8 2000.
##
                        5
               2000
##
    6 Abilene
                        6
                             156 13910000
                                           66900
                                                       780
                                                                 6.6 2000.
                             152 12635000
                                                       742
                                                                 6.2 2000.
##
    7 Abilene
               2000
                        7
                                           73500
                                                       765
##
    8 Abilene
               2000
                         8
                             131 10710000
                                           75000
                                                                 6.4 2001.
##
    9 Abilene
               2000
                        9
                             104
                                 7615000
                                           64500
                                                       771
                                                                 6.5 2001.
## 10 Abilene
               2000
                       10
                             101
                                  7040000
                                           59300
                                                       764
                                                                 6.6 2001.
## # ... with 8,592 more rows, and 1 more variable: valid_sales <lgl>
```

```
# finding the proportions
proportions_cities <- valid_cities %>%
summarize(proportion = round(1 - sum(valid_sales)/length(valid_sales),4)) %>%
arrange(desc(proportion))
proportions_cities # city proportions
## # A tibble: 46 x 2
##
      city
                         proportion
##
      <chr>
                              <dbl>
##
                             0.620
  1 South Padre Island
   2 Kerrville
                             0.556
## 3 Midland
                             0.401
## 4 Odessa
                             0.385
## 5 San Marcos
                             0.246
## 6 Laredo
                             0.192
## 7 Harlingen
                             0.134
## 8 Waco
                             0.102
## 9 Texarkana
                             0.0909
## 10 Brazoria County
                             0.0749
## # ... with 36 more rows
```

Question: 6

Are the distributions of the median sales price (column name median), when grouped by city, different? The same? Show your work.

```
# cities above 500 summarise by volume
txhousing %>% group_by(sales > 500)
## # A tibble: 8,602 x 10
## # Groups:
               sales > 500 [3]
##
                                  volume median listings inventory date
      city
               year month sales
                                                              <dbl> <dbl>
      <chr>
              <int> <int> <dbl>
                                   <dbl>
                                          <dbl>
                                                    <dbl>
                                                                6.3 2000
##
  1 Abilene
               2000
                             72
                                 5380000
                                          71400
                                                      701
                        1
##
   2 Abilene
               2000
                        2
                             98
                                 6505000
                                          58700
                                                      746
                                                                6.6 2000.
  3 Abilene
               2000
                                                      784
##
                        3
                            130
                                 9285000
                                          58100
                                                                6.8 2000.
## 4 Abilene
               2000
                             98 9730000
                                          68600
                                                     785
                                                                6.9 2000.
                        4
## 5 Abilene
               2000
                            141 10590000
                                                     794
                                                                6.8 2000.
                        5
                                          67300
## 6 Abilene
               2000
                        6
                            156 13910000
                                          66900
                                                     780
                                                                6.6 2000.
## 7 Abilene 2000
                        7
                            152 12635000
                                          73500
                                                     742
                                                                6.2 2000.
## 8 Abilene
               2000
                        8
                            131 10710000
                                          75000
                                                     765
                                                                6.4 2001.
## 9 Abilene
               2000
                        9
                            104 7615000
                                          64500
                                                      771
                                                                6.5 2001.
                                                                6.6 2001.
## 10 Abilene 2000
                       10
                            101 7040000 59300
                                                      764
## # ... with 8,592 more rows, and 1 more variable: `sales > 500` <lg!>
# cities above 500 distributions
cities_above500 <- txhousing %>% filter(sales > 500)
ggplot(data = cities_above500, mapping = aes(x = reorder(city,median,mean), y = median)) +
  geom_boxplot() +
  labs(x = 'Cities', y = 'Median Sale Price') +
  coord_flip() +
  theme_bw()
```

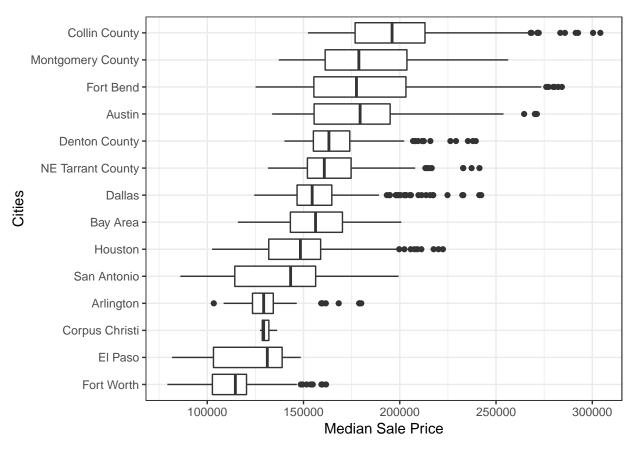


Answer: From the graph above interestingly we can observe that the median price is higher compared to other cities.

- San Antonio
- El Paso
- Austin

Any cities that stand out that you'd want to investigate further?

```
cities_above500_outliers <- txhousing %>% filter(sales > 500)
ggplot(data = cities_above500, mapping = aes(x = reorder(city,median,mean), y = median)) +
geom_boxplot() +
labs(x = 'Cities', y = 'Median Sale Price') +
coord_flip() +
theme_bw()
```

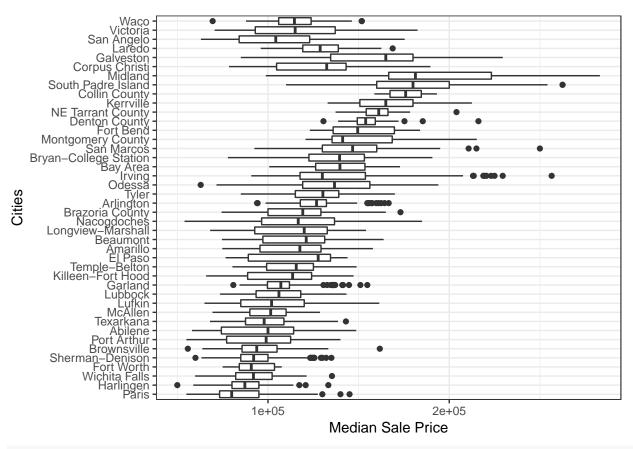


Answer: By the above plaot we can conclude that the following cities with lots of outliers needs to be investigated.

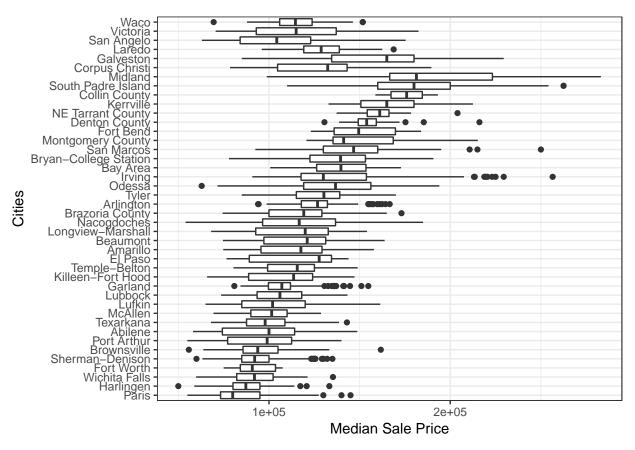
- Denton County
- Dallas
- Houston

Why might we want to filter out all cities and months with sales less than 500?

```
# Let's take a look at cities below 500 sales
small_cities <- txhousing %>% filter (sales < 500)
ggplot(data = small_cities, mapping = aes(x = reorder(city,median,mean), y = median)) +
geom_boxplot() +
labs(x = 'Cities', y = 'Median Sale Price') +
coord_flip() +
theme_bw()</pre>
```



```
# Let's take a look at cities abvove 500 sales
large_cities <- txhousing %>% filter (sales < 500)
ggplot(data = large_cities, mapping = aes(x = reorder(city,median,mean), y = median)) +
   geom_boxplot() +
   labs(x = 'Cities', y = 'Median Sale Price') +
   coord_flip() +
   theme_bw()</pre>
```



Answer: By looking at the above two box plot graph, it is clearly observed that the small cities with sales < 500 are high in number and they are just adding noise to the dataset.

Git and Github

Answer: Git hub location is added in the front page of this document