# COMPSCIX 415.2 Homework 5/Midterm

*Rajat Jain*

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## Contents



## Exercises (Total Points - 30)

### My Git Repository

My git repository is located at this Github location: https://github.com/rajatmnnit/compscix-415-2-assignments

All the assignments are organized under their individual directories containing .Rmd file and the knitted pdf version and all the required and generated data files.

Midterm assignment can be found under midterm directory.

### RStudio and R Markdown (3 points)

1. **Use markdown headers in your document to clearly separate each midterm question and add a table of contents to your document.**

Done.

## The tidyverse packages (3 points)

**By now you've used at least five different packages from the tidyverse for plotting, data munging, reshaping data, importing/exporting data, and using tibbles (the `tibble` package is used for this without you even realizing it's there).**

1. **Can you name which package is associated with each task below?**

Here is the list of `tidyverse` packages:

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

2. **Now can you name two functions that you've used from each package that you listed above for these tasks?**

Some of the functions we have used from each of these packages are:

- Plotting - `ggplot()`, `geom_point()`
- Data munging/wrangling - `filter()`, `summarise()`
- Reshaping data - `spread()`, `gather()`
- Importing/exporting data - `read_csv()`, `read_delim()`

## R Basics (1.5 points)

1. **Fix this code *with the fewest number of changes* possible so it works:**

```
My_data.name___is.too0OooLong! <- c( 1 , 2   , 3 )
```

While the variable name is too long and doesn't follow any conventions, it is not invalid to use it. The only problem is the ! mark in the variable name. Just removing it is the smallest change which makes this code work.

```
My_data.name___is.too0OooLong <- c( 1 , 2   , 3 )
```

2. **Fix this code so it works:**

```
my_string <- C('has', 'an', 'error', 'in', 'it)
```

Lower case the concat function `c()` and complete quote on the last value to fix this code.

```
my_string <- c('has', 'an', 'error', 'in', 'it')
```

3. **Look at the code below and comment on what happened to the values in the vector.**

```
my_vector <- c(1, 2, '3', '4', 5)
my_vector
```

```
## [1] "1" "2" "3" "4" "5"
```

In R the vectors can contain values of only a single data type. Since we are trying to construct a vector with mixed values of numbers and characters (quoted numbers), R automatically converts everything to character. Hence all values are returned as characters on printing `my_vector`.

## Data import/export (3 points)

1. **Download the rail_trail.txt file from Canvas (in the Midterm Exam section) and successfully import it into R. Prove that it was imported successfully by including your import code and taking a `glimpse` of the result.**

```
# File has been downloaded from Canvas to the midterm directory.
rail_trail <- read_delim("rail_trail.txt", delim = "|")
```

```
## Parsed with column specification:
## cols(
##   hightemp = col_integer(),
##   lowtemp = col_integer(),
##   avgtemp = col_double(),
##   spring = col_integer(),
##   summer = col_integer(),
##   fall = col_integer(),
##   cloudcover = col_double(),
##   precip = col_double(),
##   volume = col_integer(),
##   weekday = col_integer()
## )
```

```
glimpse(rail_trail)
```

```
## 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....
## $ spring     <int> 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, ...
## $ summer     <int> 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, ...
## $ fall       <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, ...
## $ cloudcover <dbl> 7.6, 6.3, 7.5, 2.6, 10.0, 6.6, 2.4, 0.0, 3.8, 4.1, ...
## $ precip     <dbl> 0.00, 0.29, 0.32, 0.00, 0.14, 0.02, 0.00, 0.00, 0.0...
## $ volume     <int> 501, 419, 397, 385, 200, 375, 417, 629, 533, 547, 4...
## $ weekday    <int> 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, ...
```

2. **Export the file into a comma-separated file and name it "rail_trail.csv". Make sure you define the `path` correctly so that you know where it gets saved. Then reload the file. Include your export and import code and take another `glimpse`.**

```
# Write the new CSV file locally to the midterm directory.
write_csv(rail_trail, path = "rail_trail.csv")

# Read back from midterm directory.
rail_trail_csv <- read_csv("rail_trail.csv")
```

```
## Parsed with column specification:
## cols(
##   hightemp = col_integer(),
##   lowtemp = col_integer(),
##   avgtemp = col_double(),
##   spring = col_integer(),
##   summer = col_integer(),
##   fall = col_integer(),
##   cloudcover = col_double(),
##   precip = col_double(),
##   volume = col_integer(),
##   weekday = col_integer()
## )
```

```
glimpse(rail_trail_csv)
```

```
## 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....
## $ spring     <int> 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, ...
## $ summer     <int> 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, ...
## $ fall       <int> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, ...
## $ cloudcover <dbl> 7.6, 6.3, 7.5, 2.6, 10.0, 6.6, 2.4, 0.0, 3.8, 4.1, ...
## $ precip     <dbl> 0.00, 0.29, 0.32, 0.00, 0.14, 0.02, 0.00, 0.00, 0.0...
## $ volume     <int> 501, 419, 397, 385, 200, 375, 417, 629, 533, 547, 4...
## $ weekday    <int> 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, ...
```

## Visualization (6 points)

1. **Critique this graphic: give only three examples of what is wrong with this graphic. Be concise.**

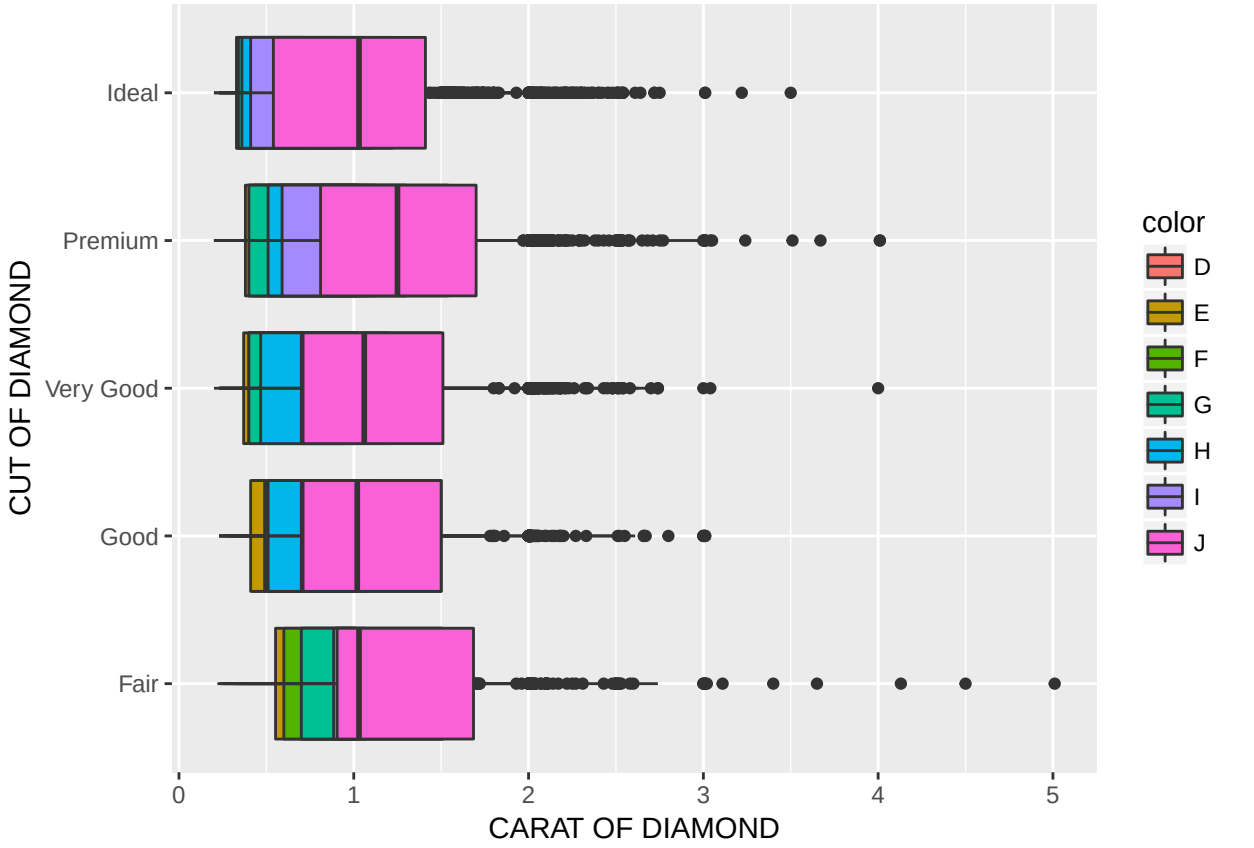
There are a few features of this visualization which I disagree with.

a. **Area** - I do not generally agree with bubble charts because they are area based representations and difficult to compare and interpret.
b. **Dimensions** - It seems like the author used multiple dimensions - Age Group and Sex to represent data in the same graphic. It seems like a bad idea.
c. **Totals** - The totals of percentages between "Yes" and "No" responses do not add up to 100%. In fact they are substantially lower than 100%. I believe there was another category in the survey form "Don't Know" or equivalent `NA`. If this response is not important, I would probably remove NAs before computing percentages.

2. **Reproduce this graphic using the `diamonds` data set.**

Here is the code which reproduces the plot from the question:

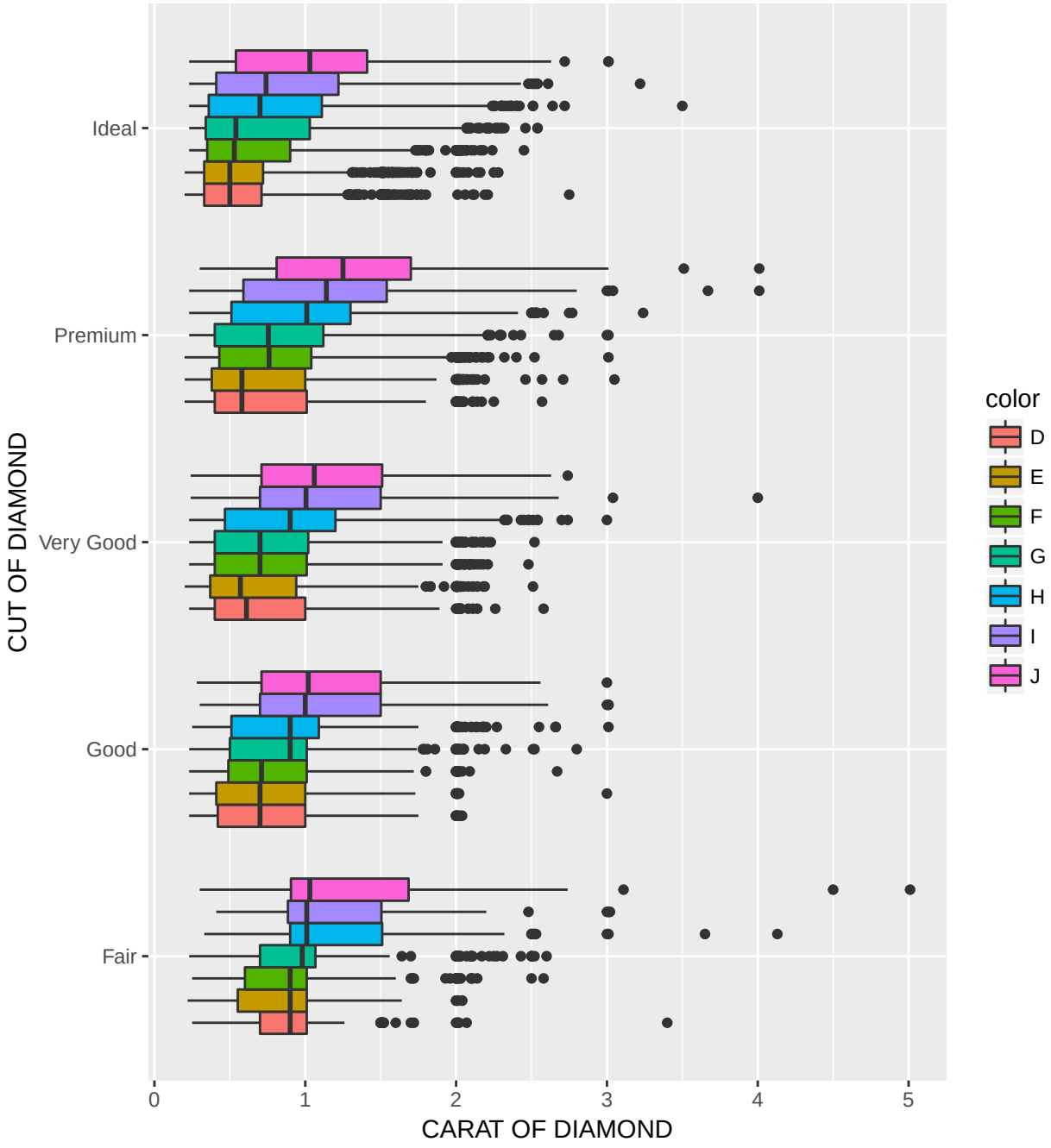
```
ggplot(data = diamonds, aes(x = cut, y = carat, fill = color)) +
  geom_boxplot(position = "identity") +
  xlab("CUT OF DIAMOND") +
  ylab("CARAT OF DIAMOND") +
  coord_flip()
```



3. **The previous graphic is not very useful. We can make it much more useful by changing one thing about it. Make the change and plot it again.**

The previous graphic is not very useful because individual color boxplots overlap each other which makes is unreadable. One simple way to fix this is by using the `dodge` position adjustment. Here is the code which generates the fixed plot:

```
ggplot(data = diamonds, aes(x = cut, y = carat, fill = color)) +
  geom_boxplot(position = "dodge") +
  xlab("CUT OF DIAMOND") +
  ylab("CARAT OF DIAMOND") +
  coord_flip()
```



## Data munging and wrangling (6 points)

1. **Is this data "tidy"? If yes, leave it alone and go to the next problem. If no, make it tidy.** ***Note: this data set is called table2 and is available in the tidyverse package. It should be ready for you to use after you've loaded the tidyverse package.***

```
table2
```

```
## # A tibble: 12 x 4
##    country      year type            count
##    <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
##  6 Brazil       1999 population  172006362
##  7 Brazil       2000 cases           80488
##  8 Brazil       2000 population  174504898
##  9 China        1999 cases          212258
## 10 China        1999 population 1272915272
## 11 China        2000 cases          213766
## 12 China        2000 population 1280428583
```

No, this data is not tidy because observations for `country` and `year` variables are split over multiple rows for different values of `type` variable. A tidy data set should have one column per variable and one row for each observation. Here is the code to make it tidy:

```
table2 %>%
  spread(key = type, value = count)
```

```
## # A tibble: 6 x 4
##   country      year  cases population
##   <chr>       <int>  <int>      <int>
## 1 Afghanistan  1999    745   19987071
## 2 Afghanistan  2000   2666   20595360
## 3 Brazil       1999  37737  172006362
## 4 Brazil       2000  80488  174504898
## 5 China        1999 212258 1272915272
## 6 China        2000 213766 1280428583
```

2. **Create a new column in the `diamonds` data set called `price_per_carat` that shows the price of each diamond per carat (hint: divide). Only show me the code, not the output.**

```
diamonds %>%
  mutate(price_per_carat = price / carat)
```

3. **For each `cut` of diamond in the `diamonds` data set, how many diamonds, and what proportion, have a price $>$ 10000 and a carat $<$ 1.5? There are several ways to get to an answer, but your solution must use the data wrangling verbs from the tidyverse in order to get credit.**

```
diamonds %>%
  group_by(cut) %>%
  summarise(
    count = sum(price > 10000 & carat < 1.5, na.rm = TRUE),
    proportion = mean(price > 10000 & carat < 1.5, na.rm = TRUE)
  )
```

```
## # A tibble: 5 x 3
##   cut       count proportion
##   <ord>     <int>      <dbl>
## 1 Fair          4    0.00248
## 2 Good         17    0.00347
## 3 Very Good   155    0.0128
## 4 Premium     173    0.0125
## 5 Ideal       485    0.0225
```

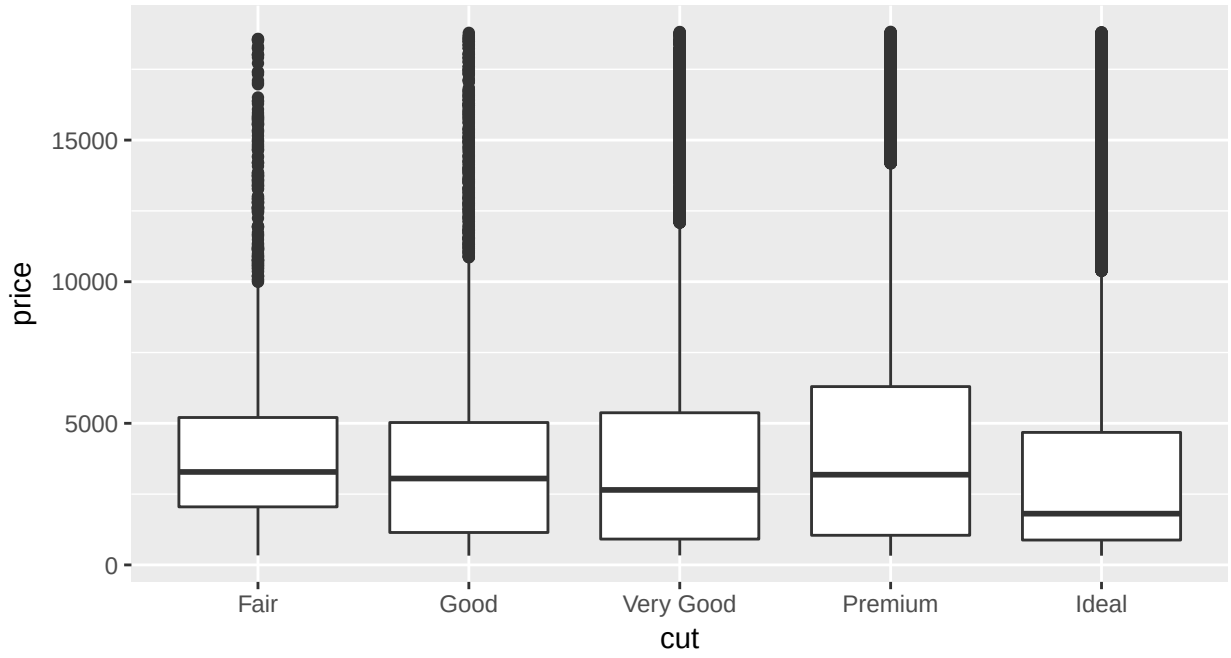
- **Do the results make sense? Why?**

Yes the results make sense to some extent. As the `cut` gets better from Fair to Ideal, the proportion of expensive diamonds, even though with lesser weight, increases. This shows that the price of diamonds also depend on the cut in addition to its weight in carats.

- **Do we need to be wary of any of these numbers? Why?**

Yes, we should be careful while making any inferences based on these numbers. Look at the box plot below of `cut` v/s `price`, we can clearly see that the points we are using lie in the area normally considered as outliers.

```
ggplot(data = diamonds, aes(x = cut, y = price)) +
  geom_boxplot()
```



## EDA (6 points)

**Take a look at the `txhousing` data set that is included with the `ggplot2` package and answer these questions:**

```
glimpse(txhousing)
```

```
## Observations: 8,602
## Variables: 9
## $ city      <chr> "Abilene", "Abilene", "Abilene", "Abilene", "Abilene...
## $ year      <int> 2000, 2000, 2000, 2000, 2000, 2000, 2000, 2000, 2000...
## $ month     <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 1, 2, 3, 4, 5...
## $ sales     <dbl> 72, 98, 130, 98, 141, 156, 152, 131, 104, 101, 100, ...
## $ volume    <dbl> 5380000, 6505000, 9285000, 9730000, 10590000, 139100...
## $ median    <dbl> 71400, 58700, 58100, 68600, 67300, 66900, 73500, 750...
## $ listings  <dbl> 701, 746, 784, 785, 794, 780, 742, 765, 771, 764, 72...
## $ inventory <dbl> 6.3, 6.6, 6.8, 6.9, 6.8, 6.6, 6.2, 6.4, 6.5, 6.6, 6....
## $ date      <dbl> 2000.000, 2000.083, 2000.167, 2000.250, 2000.333, 20...
```

1. **During what time period is this data from?**

```
# TODO: Be careful with the mutate below.
# It is working fine for this data set, but
# min/max may break due to variable lengths of months.
txhousing %>%
  mutate(yr_mon = paste0(year, "-", month)) %>%
  summarize(
    from = min(yr_mon),
    to = max(yr_mon)
  )
```

```
## # A tibble: 1 x 2
##   from   to
##   <chr>  <chr>
## 1 2000-1 2015-7
```

The data in `txhousing` data set is from January 2000 to July 2015.

2. **How many cities are represented?**

```
txhousing %>%
  select(city) %>%
  unique() %>%
  count()
```

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

There are 46 cities represented in `txhousing` data set.

3. **Which city, month and year had the highest number of sales?**

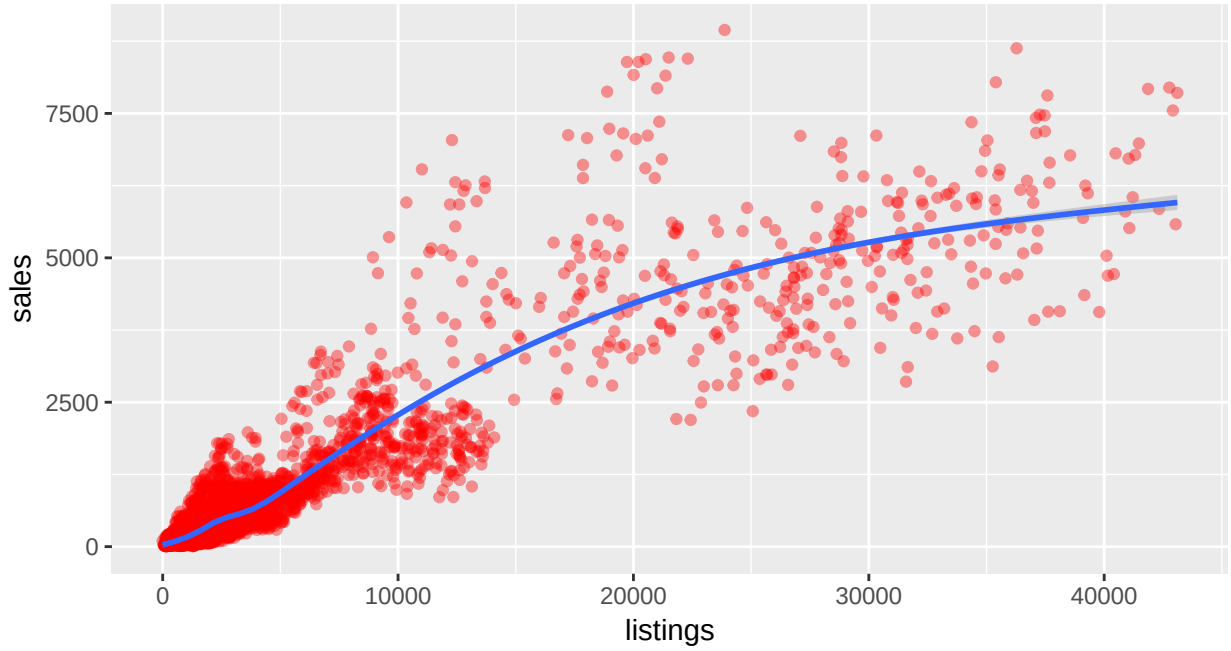
```
txhousing %>%
  arrange(desc(sales))
```

```
## # A tibble: 8,602 x 9
##    city     year month sales      volume  median listings inventory  date
##    <chr>   <int> <int> <dbl>       <dbl>   <dbl>    <dbl>     <dbl> <dbl>
##  1 Houston  2015     7 8945. 2568156780. 217600.   23875.      3.40 2016.
##  2 Houston  2006     6 8628. 1795898108. 155200.   36281.      5.60 2006.
##  3 Houston  2013     7 8468. 2168720825. 187800.   21497.      3.30 2014.
##  4 Houston  2015     6 8449. 2490238594. 222400.   22311.      3.20 2015.
##  5 Houston  2013     5 8439. 2121508529. 186100.   20526.      3.30 2013.
##  6 Houston  2014     6 8391. 2342443127. 211200.   19725.      2.90 2014.
##  7 Houston  2014     7 8391. 2278932511. 199700.   20214.      3.00 2014.
##  8 Houston  2014     8 8167. 2195184825. 202400.   20007.      2.90 2015.
##  9 Houston  2013     8 8155. 2083377894. 186700.   21366.      3.30 2014.
## 10 Houston  2006     5 8040. 1602621368. 151200.   35398.      5.50 2006.
## # ... with 8,592 more rows
```

Houston in the month of July of 2015 had the highest number of sales.

4. **What kind of relationship do you think exists between the number of listings and the number of sales? Check your assumption and show your work.**

```
ggplot(data = txhousing, aes(x = listings, y = sales)) +
  geom_point(alpha = 0.4, color = "red") +
  geom_smooth()
```




As shown in the scatter plot above, number of listings show a positive correlation with number of sales.

5. **What proportion of `sales` is missing for each city?**

Here is a list of proporting of `sales` missing by each `city` sorted in descending order of missing proportion.

```
txhousing %>%
  group_by(city) %>%
  summarize(prop_missing = mean(is.na(sales))) %>%
```

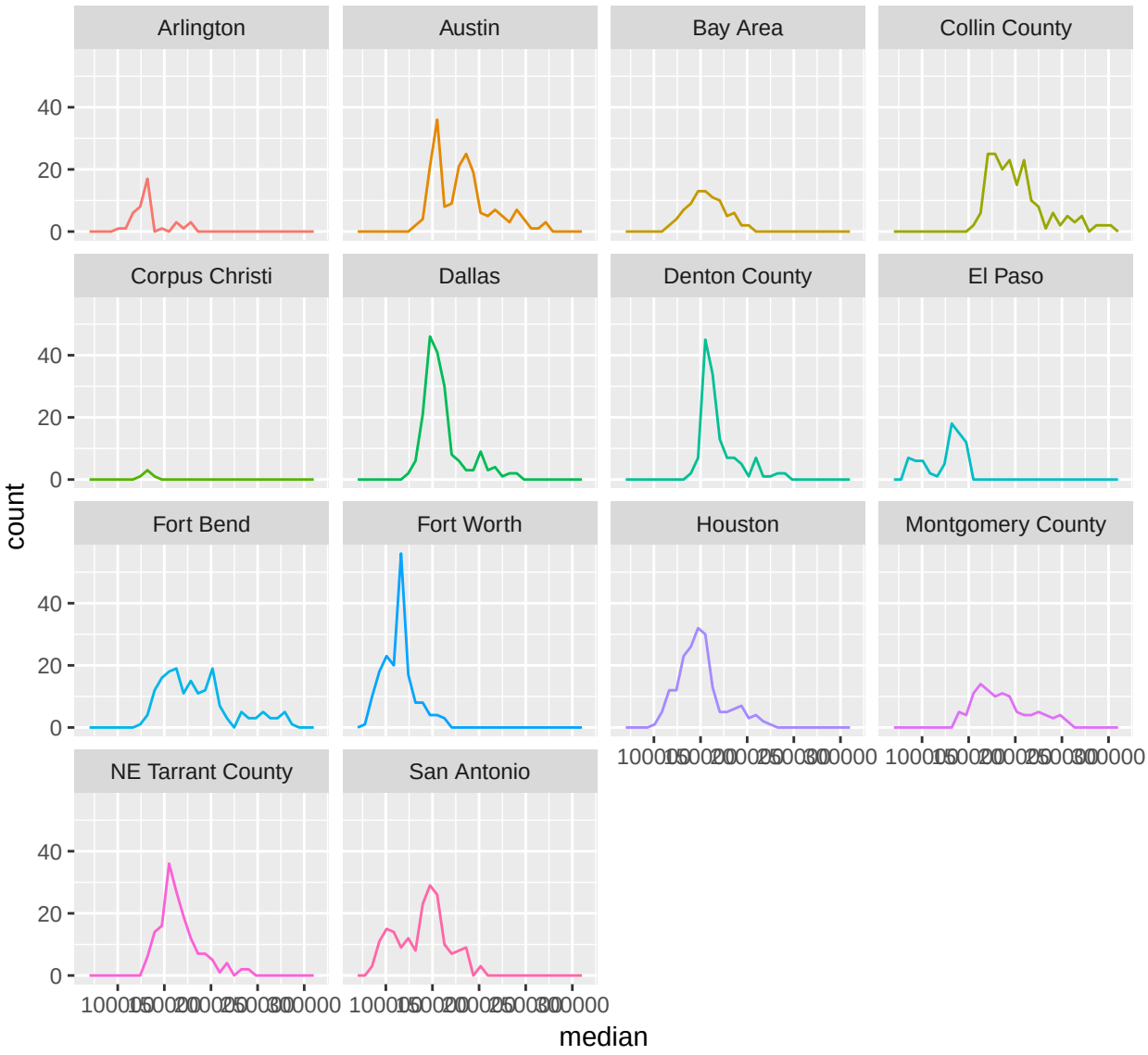
```
  arrange(desc(prop_missing))
```

```
## # A tibble: 46 x 2
##    city               prop_missing
##    <chr>                     <dbl>
##  1 South Padre Island       0.620
##  2 Kerrville                0.556
##  3 Midland                  0.401
##  4 Odessa                   0.385
##  5 San Marcos               0.246
##  6 Laredo                   0.193
##  7 Harlingen                0.134
##  8 Waco                     0.102
##  9 Texarkana                0.0909
## 10 Brazoria County          0.0749
## # ... with 36 more rows
```

6. **Looking at only the cities and months with greater than 500 sales:**

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

```
txhousing %>%
  filter(sales > 500) %>%
  ggplot(aes(x = median, color = city)) +
    geom_freqpoly(show.legend = FALSE) +
    facet_wrap(~city, nrow = 4)
```




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

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

## Git and Github (1.5 points)

**To demonstrate your use of git and Github, at the top of your document put a hyperlink to your Github repository.**

**Once you are finished with your midterm, commit your final changes with the comment "finished the midterm - woohoo" and push your R Markdown file and your html or pdf file to Github.**

See the Section My Git Repository above.