Exploratory Data Analysis (EDA) in R

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Learning Objectives

- Strategies for EDA
- Chapter 7 of RDS

General Strategies

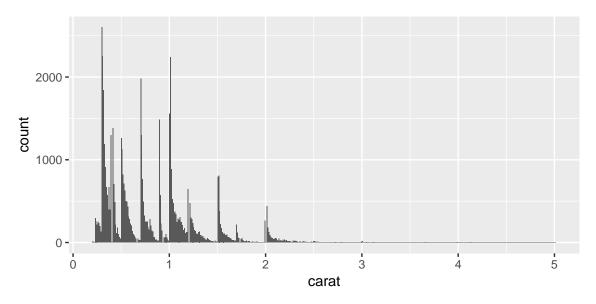
- Plot the distribution of every variable.
- Plot the bivariate distribution of every pair of variables (to find which variables are associated).
- Color code by variables to try and see if relationships can be explained.
- Calculate lots of summary statistics.
- Look at missingness.
- Look at outliers.
- EDA is about **curiosity**. Ask *many* questions, use *many* plots, investigate *many* aspects of your data. This will let you hone in on the few *interesting* questions you want to pursue deeper.

```
library(tidyverse)
data("diamonds")
```

Distribution of Every Variable:

- Quantitative: Use a histogram.
 - Look for modality. Indicates multiple groups of units. What can explain the modes? Can any of the other variables explain the modes?
 - Are certain values more likely than other values?
 - Look for skew.
 - geom_histogram()
 - Mean, median, standard deviation, five number summary.

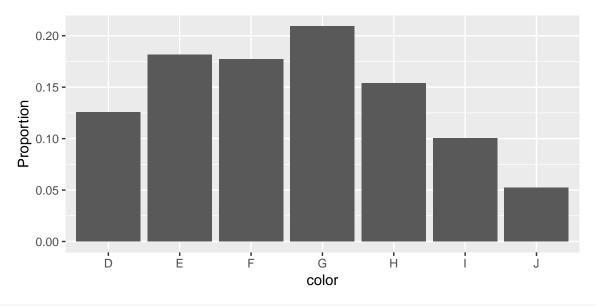
```
ggplot(data = diamonds, mapping = aes(x = carat)) +
  geom_histogram(bins = 500)
```



```
fivenum(diamonds$carat)
## [1] 0.20 0.40 0.70 1.04 5.01
mean(diamonds$carat)
## [1] 0.7979
sd(diamonds$carat)
## [1] 0.474
```

- Categorical: Use a bar chart. Or just a table of *proportions* (table() then prop.table()).
 - Absolute counts are sometimes interesting, but usually you want to look at the proportion of observations in each category.
 - Is there a natural ordering of the categories (bad, medium, good)?
 - Why are some categories more represented than others?
 - geom_bar(), geom_col()
 - Proportion of observations within each group.

```
ggplot(diamonds, aes(x = color, y = ..)) +
  geom_bar(aes(y = ..count.. / sum(..count..))) +
  ylab("Proportion")
```

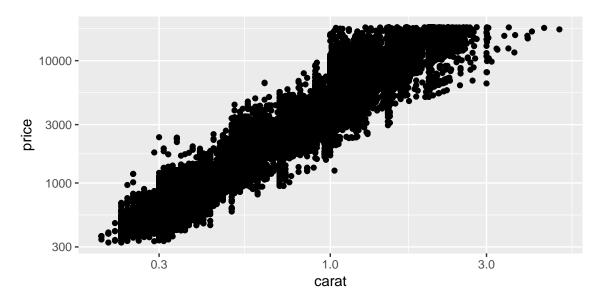


```
table(diamonds$color)
##
##
       D
             Ε
                    F
                          G
                                Н
                                       Ι
                                             J
    6775
          9797
                9542 11292
                             8304
                                          2808
                                    5422
prop.table(table(diamonds$color))
##
##
                  Ε
                                   G
                                           Η
                                                    Ι
                          F
## 0.12560 0.18163 0.17690 0.20934 0.15395 0.10052 0.05206
```

Bivariate Distribution of Every Pair of Variables

- Quantitative vs Quantitative: Use a scatterplot
 - Is the relationship linear? Quadratic? Exponential?
 - Logging is useful tool to make some associations linear. If the relationship is (i) monotonic and (ii) curved, then try logging the x-variable if the x-variable is all positive. If it is also (iii) more variable at larger y-values, then try logging the y-variable instead of the x-variable if the y-variable is all positive. Try logging both if you still see curvature if both variables are all positive.
 - Ask if an observed association can be explained by another variable?
 - Correlation coefficient (only appropriate if association is linear).
 - Kendall's tau (always appropriate).

```
ggplot(diamonds, aes(x = carat, y = price)) +
  geom_point() +
  scale_y_log10() +
  scale_x_log10()
```



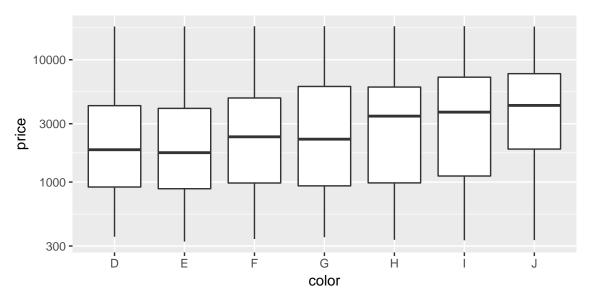
```
cor(diamonds$carat, diamonds$price)
```

```
## [1] 0.9216
```

```
## cor(diamonds$carat, diamonds$price, method = "kendall")
```

- Categorical vs Quantitative: Use a boxplot
 - For which levels of the categorical variable is the quantitative variable higher or lower?
 - For which levels is the quantitative variable more spread out?
 - Aggregated means, medians, standard deviations, quantiles

```
ggplot(diamonds, aes(x = color, y = price)) +
  geom_boxplot() +
  scale_y_log10()
```



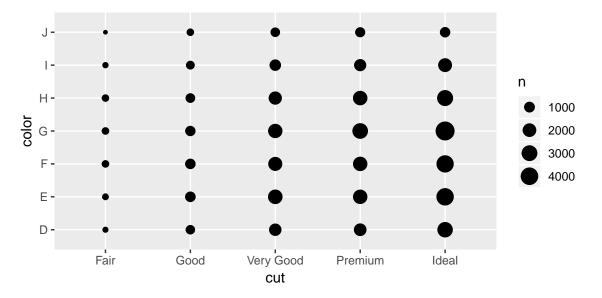
```
diamonds %>%
  mutate(logprice = log(price)) %>%
  group_by(color) %>%
```

```
summarize(mean = mean(logprice),
    sd = sd(logprice),
    median = median(logprice),
    Q1 = quantile(logprice, 0.25),
    Q3 = quantile(logprice, 0.75))
```

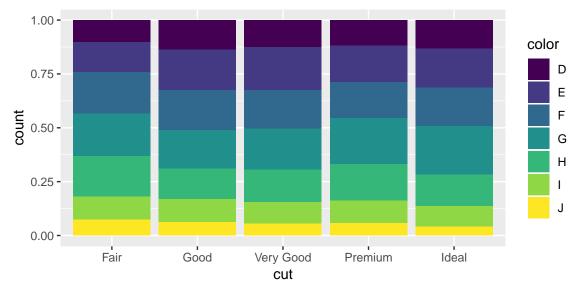
```
## # A tibble: 7 x 6
    color mean
                   sd median
                                Q1
                                      Q3
    <ord> <dbl> <dbl> <dbl> <dbl> <dbl>
##
## 1 D
           7.62 0.926
                        7.52 6.81
                                   8.35
## 2 E
           7.58 0.925
                        7.46 6.78 8.29
## 3 F
           7.76 0.968
                        7.76 6.89 8.49
## 4 G
           7.79 1.03
                        7.72 6.84 8.71
## 5 H
           7.92 1.06
                        8.15 6.89 8.70
## 6 I
           8.02 1.11
                        8.22 7.02 8.88
## 7 J
           8.15 1.04
                        8.35 7.53 8.95
```

- Categorical vs Categorical: Use a mosaic plot or a count plot
 - For which pairs of values of the categorical variables are there the most number of units?
 - Does the conditional distribution of a categorical variable change at different levels of the other categorical variable?
 - prop.table()

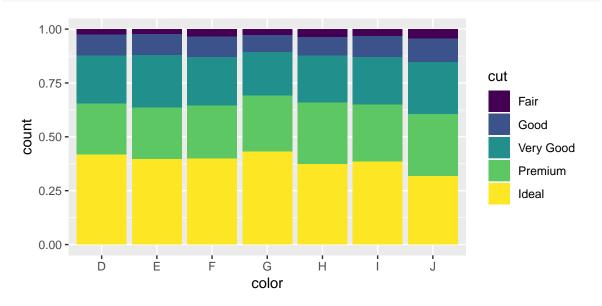
```
## Only gives you the bivariate distribution
ggplot(diamonds, aes(x = cut, y = color)) +
  geom_count()
```



```
## Gives you the conditional distributions of color given cut
ggplot(diamonds, aes(x = cut, fill = color)) +
  geom_bar(position = "fill")
```



Gives you the conditional distributions of cut given color
ggplot(diamonds, aes(x = color, fill = cut)) +
 geom_bar(position = "fill")



Bivariate Distribution
prop.table(table(diamonds\$color, diamonds\$cut))

```
##
##
          Fair
                    Good Very Good Premium
                                               Ideal
##
    D 0.003022 0.012273 0.028050 0.029718 0.052540
    E 0.004153 0.017297 0.044494 0.043326 0.072358
    F 0.005784 0.016852
                         0.040119 0.043215 0.070931
    G 0.005821 0.016148
                         0.042621 0.054208 0.090545
##
##
    H 0.005617 0.013014
                         0.033815 0.043752 0.057749
##
    I 0.003244 0.009677
                          0.022321 0.026474 0.038802
     J 0.002206 0.005692 0.012570 0.014980 0.016611
```

```
## Conditional distributions of column variable conditional on row variable
prop.table(table(diamonds$color, diamonds$cut), margin = 1)
##
##
         Fair
                 Good Very Good Premium
##
   D 0.02406 0.09771
                        0.22332 0.23661 0.41830
    E 0.02286 0.09523
                        0.24497 0.23854 0.39839
##
    F 0.03270 0.09526
                        0.22679 0.24429 0.40096
##
    G 0.02781 0.07713
                        0.20360 0.25894 0.43252
   H 0.03649 0.08454
                        0.21965 0.28420 0.37512
##
    I 0.03228 0.09627
                        0.22206 0.26337 0.38602
    J 0.04238 0.10933
                        0.24145 0.28775 0.31909
## Conditional distributions of row variable conditional on column variable
prop.table(table(diamonds$color, diamonds$cut), margin = 2)
##
##
         Fair
                 Good Very Good Premium
                                          Ideal
    D 0.10124 0.13494
                        0.12523 0.11624 0.13150
##
   E 0.13913 0.19018
                        0.19864 0.16946 0.18111
    F 0.19379 0.18528
##
                        0.17911 0.16902 0.17753
    G 0.19503 0.17754
                        0.19028 0.21202 0.22663
    Н 0.18820 0.14309
##
                        0.15097 0.17113 0.14454
   I 0.10870 0.10640
                        0.09965 0.10355 0.09712
##
   J 0.07391 0.06258 0.05612 0.05859 0.04158
##
```