CS&SS 321 - Data Science and Statistics for Social Sciences

Module II - Data management and exploratory visual analysis

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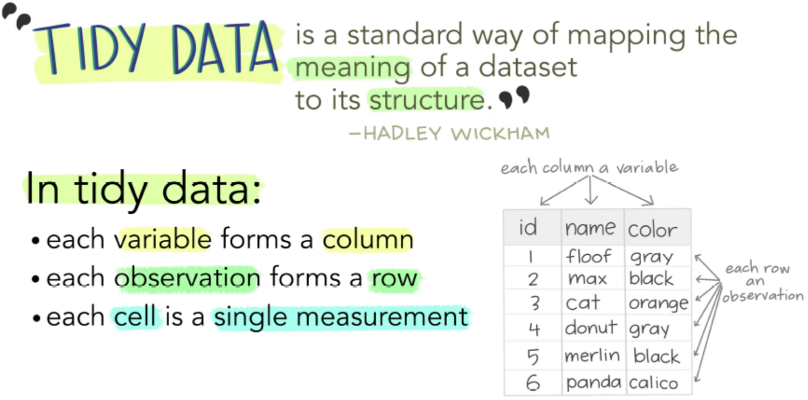
Module II

- This module will equip students with essential data science skills in `R`.
- In the next quiz sections, we will cover the following topics:
  - **Data frames**, **logical** relations, and **subsetting.**
  - **Quantile** and `NA` data.
  - **Pivoting** and **merging** data.
  - Introduction to `ggplot2`.

Creating and manipulating `data frames`.

- Think about *data* in terms of **data** *frame*.



Wickham, H. (2014). Tidy Data. Journal of Statistical Software 59 (10). DOI: 10.18637/jss.v059.i10

Creating and manipulating `data frames`.

- A data frame is a special type of object in R that can store **multiple vectors** of data.
- We can create data frames using the function `data.frame()`.

```
# vectors with student's names and grades
student <- c("Alice", "Bob", "Charlie","Sean","Brandy")
grades_M <- c(76, 82, 94, 45, 75)
grades_F <- c(82, 90, 89, NA, 64)

# create a df with grades
(df_new <- data.frame(student,grades_M,grades_F))
```

```
##   student grades_M grades_F
## 1   Alice       76       82
## 2     Bob       82       90
## 3 Charlie       94       89
## 4    Sean       45       NA
## 5  Brandy       75       64
```

Creating and manipulating `data frames`.

- We can create data frames by directly writing the vectors/columns as separate elements within the `data.frame()` function:

```
df_new <- data.frame(student=c("Alice", "Bob", "Charlie",
                                "Sean","Brandy"),
                     grades_M=c(76, 82, 94, 45, 75),
                     grades_F=c(82, 90, 89, NA, 64))

df_new
```

```
##   student grades_M grades_F
## 1   Alice       76       82
## 2     Bob       82       90
## 3 Charlie       94       89
## 4    Sean       45       NA
## 5  Brandy       75       64
```

Creating and manipulating `data frames`.

- To select a specific column from a data frame, use the `$` operator followed by the *name* of the column.

```
df_new$grades_M
```

```
## [1] 76 82 94 45 75
```

- To select specific rows and/or columns from a data frame, we use brackets `[]`.
- If the object is a single vector, we use a single numeric value in the brackets to select an element within the vector.

```
# select element 2 from vector grade_M:
grades_M[2]
```

```
## [1] 82
```

Creating and manipulating `data frames`.

- If the object is a matrix or data frame, we can select elements by their row and column positions.
  - **Note**: we input two different values separated by a **comma** to select the row and column

```
# select row 2 from object df:
df_new[2,]
```

```
##   student grades_M grades_F
## 2     Bob       82       90
```

```
# select column 2 from object df:
df_new[,2]
```

```
## [1] 76 82 94 45 75
```

```
# select element in row 2 and column 2:
df_new[2,2]
```

Creating and manipulating data frames.

- We can also use **characters** to select columns by their names, for example:

```
# select column name "grade_M" from object df:

df_new[,c("grades_M")]
```

```
## [1] 76 82 94 45 75
```

```
# select columns name "student" and "grade_M":

df_new[,c("student","grades_M")]
```

```
##   student grades_M
## 1   Alice       76
## 2     Bob       82
## 3 Charlie       94
## 4    Sean       45
## 5  Brandy       75
```

tibbles are data frames too!

- Another type of data frame are **tibbles**.
  - `tibble()` is a fancy version of `data.frame()`.
  - All `dplyr` functions provide outputs `as_tibbles`.

```
as_tibble(df_new) ; class(as_tibble(df_new))
```

```
## # A tibble: 5 x 3
##   student grades_M grades_F
##   <chr>      <dbl>    <dbl>
## 1 Alice         76       82
## 2 Bob           82       90
## 3 Charlie       94       89
## 4 Sean          45       NA
## 5 Brandy        75       64

## [1] "tbl_df"     "tbl"        "data.frame"
```

Logical relations

- **Logical Data Class:**
  - Represents binary values: `TRUE` or `FALSE`.
  - Can be transformed into numeric form: `TRUE` becomes 1, and `FALSE` becomes 0.
  - Useful for relational analyses and evaluating proportions of `TRUE` within a vector using the `mean()` function.
  - Used to set **conditional tests**; useful for **subsetting** or create new variables.

```r
3 + 5 < 10 # is 3 + 5 less than 10?
```

```
## [1] TRUE
```

Logical relations

```
# select column name "grade_M" from object df:
df_new$grades_M
```

```
## [1] 76 82 94 45 75
```

```
# Is each value greater or equal to 80?
df_new$grades_M >= 80 # the condition ">= 80" sets a logical tes
```

```
## [1] FALSE  TRUE  TRUE FALSE FALSE
```

```
# What proportion of TRUEs are in this vector?
mean(df_new$grades_M >= 80) # `TRUE` == 1, and `FALSE` == 0
```

```
## [1] 0.4
```

Subsetting: `ifelse()`.

- We can use the `ifelse()` function to create new variables based on *conditions* from other variables.
  1 - We set a *logical test* that evaluates to `TRUE` or `FALSE`.
  2 - We specify what value to assign if the test is `TRUE`, and a different value if the test is `FALSE`.

```
# if test is TRUE, then "pass", otherwise, then "fail"
df_new$midterm <- ifelse(df_new$grades_M > 60, "pass", "fail")

df_new
```

```
##   student grades_M grades_F midterm
## 1   Alice       76       82    pass
## 2     Bob       82       90    pass
## 3 Charlie       94       89    pass
## 4    Sean       45       NA    fail
## 5  Brandy       75       64    pass
```

Subsetting: Base R.

- We can use *logical tests* in **vectors** within the **row element** of an object `x[ test , ]` to subset those cases that are `TRUE`.

```
# In the vector midterm, what values are "pass"?
df_new$midterm=="pass"
```

```
## [1]  TRUE  TRUE  TRUE FALSE  TRUE
```

```
# subset those rows where this test is TRUE
df_new[ df_new$midterm=="pass" , ]
```

```
##   student grades_M grades_F midterm
## 1   Alice       76       82    pass
## 2     Bob       82       90    pass
## 3 Charlie       94       89    pass
## 5  Brandy       75       64    pass
```

Subsetting: `subset()`/`filter()`.

- To subset data, we can use the functions `subset()` or `filter()`.
  - The `subset()` function is part of base R, while `filter()` is a function from the `dplyr` package.
  - If you plan to use `filter()`, you need to load the `tidyverse` or `dplyr` package first.

```
# subset the df into a new one with final exam grades of above 85

subset(df_new, grades_F > 85)
```

```
##   student grades_M grades_F midterm
## 2     Bob       82       90    pass
## 3 Charlie       94       89    pass
```

```
filter(df_new, grades_F > 85) # from dplyr package
```

```
##   student grades_M grades_F midterm
## 1     Bob       82       90    pass
## 2 Charlie       94       89    pass
```

Processing `NA` data.

- An initial step in data science project analysis is to examine the `NA` values.

```
dat
```

```
##      name age gender score
## 1   Alice  20      F    85
## 2     Bob  30      M    62
## 3 Charlie  NA      M    75
## 4    Dave  28      M    80
## 5     Eve  22      F    95
## 6   Marta  21      F    NA
```

Processing NA data.

- The function `is.na()` will return a vector of logical values

```r
is.na(dat)
```

```
##       name   age gender score
## [1,] FALSE FALSE  FALSE FALSE
## [2,] FALSE FALSE  FALSE FALSE
## [3,] FALSE  TRUE  FALSE FALSE
## [4,] FALSE FALSE  FALSE FALSE
## [5,] FALSE FALSE  FALSE FALSE
## [6,] FALSE FALSE  FALSE  TRUE
```

```r
mean(is.na(dat))
```

```
## [1] 0.08333333
```

Processing `NA` data.

- Several packages have functions to assists the analysis of `NA` values.
  - function `freq.na()` from package `questionr` is an example:

```r
library(questionr)
freq.na(dat)
```

```
##        missing  %
## age          1 17
## score        1 17
## name         0  0
## gender       0  0
```

Processing NA data.

- We already know that some functions have the argument `na.rm`, but this is not the norm.

```r
dat$score
```

```
## [1] 85 62 75 80 95 NA
```

```r
mean(dat$score)
```

```
## [1] NA
```

```r
mean(dat$score, na.rm = TRUE)
```

```
## [1] 79.4
```

Processing NA data.

- The `na.omit()` function in base R removes all rows with any NA value.

```
dat
```

```
##      name age gender score
## 1   Alice  20      F    85
## 2     Bob  30      M    62
## 3 Charlie  NA      M    75
## 4    Dave  28      M    80
## 5     Eve  22      F    95
## 6   Marta  21      F    NA
```

```
na.omit(dat)
```

```
##    name age gender score
## 1 Alice  20      F    85
## 2   Bob  30      M    62
```

Processing `NA` data.

- The `drop_na()` function from `dplyr` removes all rows with any NA value of a specific column.

```
drop_na(dat, score)
```

```
##      name age gender score
## 1   Alice  20      F    85
## 2     Bob  30      M    62
## 3 Charlie  NA      M    75
## 4    Dave  28      M    80
## 5     Eve  22      F    95
```

```
drop_na(dat, age)
```

```
##    name age gender score
## 1 Alice  20      F    85
## 2   Bob  30      M    62
## 3  Dave  28      M    80
## 4   Eve  22      F    95
## 5 Marta  21      F    NA
```

Processing NA data.

- We can use ifelse() function to substitute NA values.

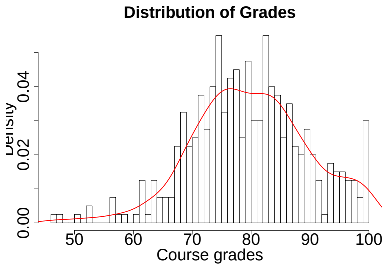
```
dat$score <- ifelse( is.na( dat$score ),
                     0, # if TRUE
                     dat$score) # if FALSE

dat
```

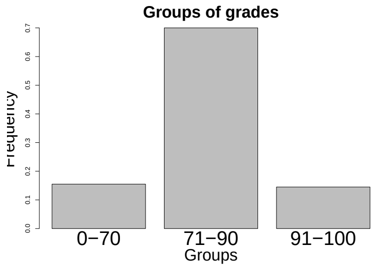
```
##      name age gender score
## 1   Alice  20      F    85
## 2     Bob  30      M    62
## 3 Charlie  NA      M    75
## 4    Dave  28      M    80
## 5     Eve  22      F    95
## 6   Marta  21      F     0
```

Distributions

- A **distribution** describes how variable values are **spread across** possible outcomes.
  - A **probability** distribution represents the **likelihood** of specific outcomes.
  - A **frequency** distribution summarizes counts of **distinct** values or ranges in dataset.
- **Continuous vs. Discrete Distributions:**
  - **Continuous** distributions involve numerical variables that can take any value within a range (e.g., height, weight), while
  - **Discrete** distributions involve variables that take distinct, separate values (e.g., number of cars, number of people).

Continuous vs. Discrete Distributions





Data Generating Process

- A **Data Generating Process** (DGP) refers to the hypothetical or real mechanism that generates a dataset.
  - It is a conceptual model that describes **how** the observed data is generated or produced.
- **Distributions** represent **systematic behavior** (aka, DGP).
- When looking at a distributions:
  - think in terms of a **DGP**, and
  - **how** the data was generated.

Data Generating Process

- Two very useful pieces of information from a DGP are its **mean** and **standard deviation**.

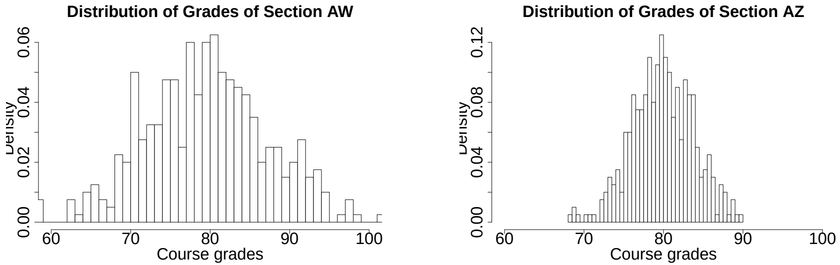
$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \quad ; \quad S = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2}$$

where

- $\bar{X}$ represents the **sample mean**.
- n is the number of **observations** in the sample.
- X_i represents **values** from a variable in the sample.
- S represents the **sample standard deviation**.

Data Generating Process: standard deviation

- The **standard deviation** gives us information about how spread is the data around the mean.



Reporting distributions

- When analyzing data, always report **descriptive statistics**.
  - *Mean.*
  - *Median.*
  - *Standard deviation.*
  - *Minimum.*
  - *Maximum.*
  - *Quartiles.*
- Note:
  - When comparing distributions of the same quantities, use the **median** instead of the **mean** as the reference point. **Why?**

quantile and data distribution.

- The quantile function in R can be used to calculate the values that separate a distribution into different quantiles.

```r
quantile(df$grades)
```

```
##     0%    25%    50%    75%   100%
##  46.00  74.00  80.00  86.25 100.00
```

```r
quantile(df$grades, probs = c(0.25, 0.5, 0.75))
```

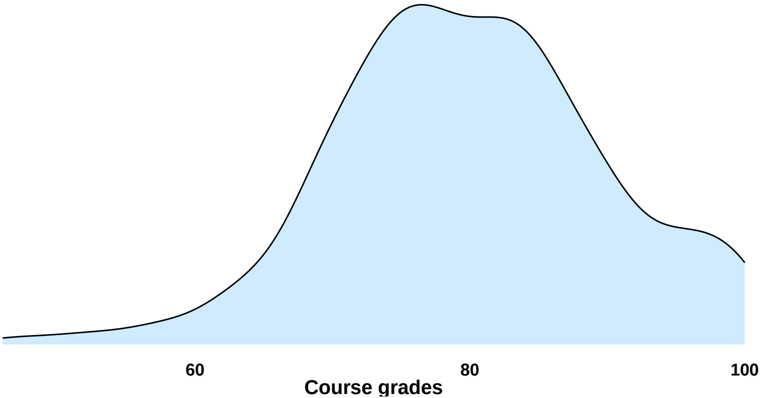
```
##   25%   50%   75%
## 74.00 80.00 86.25
```

```r
summary(df$grades)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   46.00   74.00   80.00   79.98   86.25  100.00
```

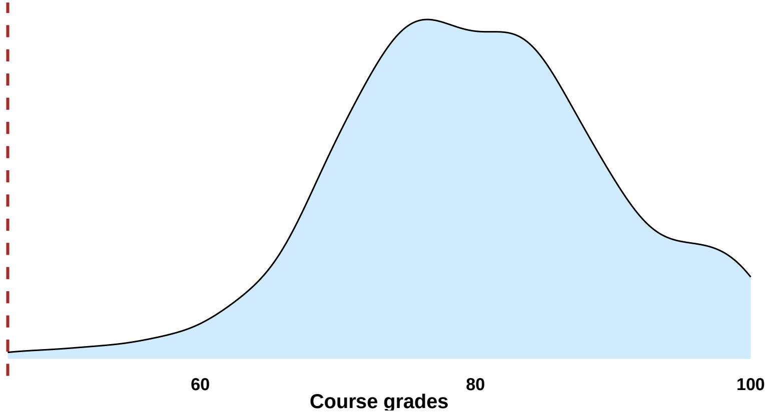
`quantile` and data distribution.

- Visualizing quantiles.
- Use the argument `probs` to specify segments of the data.



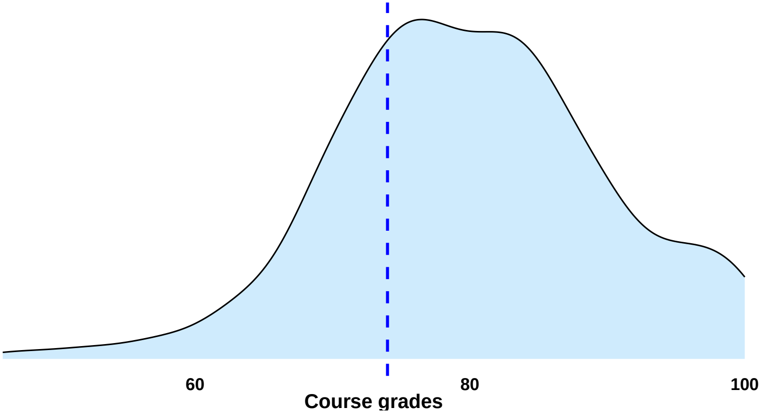
`quantile` and data distribution.

- Visualizing quantiles: **minimum**.
- `quantile(df$x, probs = 0)`



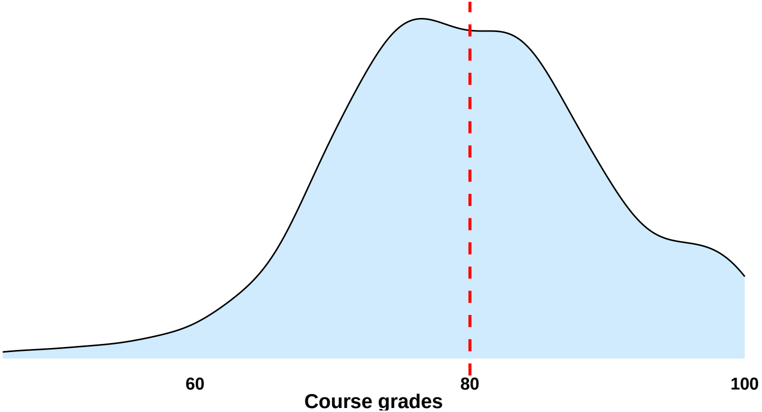
`quantile` and data distribution.

- Visualizing quantiles: **1st Quartile (Q1)** or **25th Percentile**.
- `quantile(df$x, probs = 0.25)`



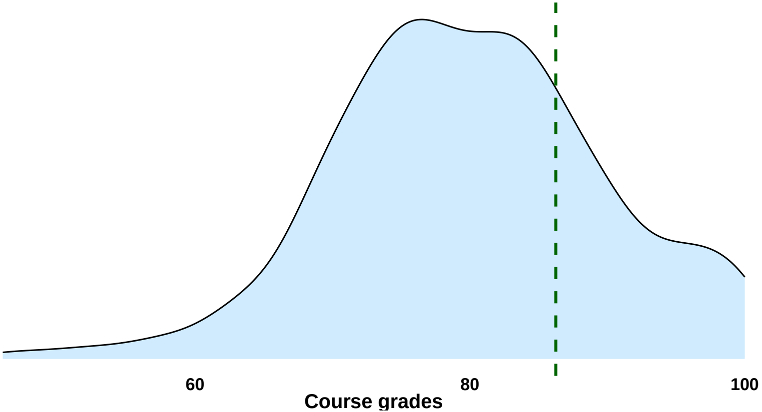
`quantile` and data distribution.

- Visualizing quantiles: **2st Quartile (Q2)** or **50th Percentile** or **median** or **5th Decile**.
- `quantile(df$x, probs = 0.5)`



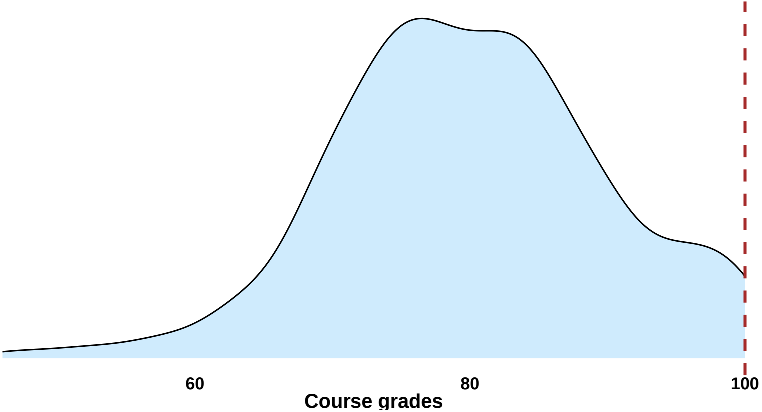
`quantile` and data distribution.

- Visualizing quantiles: **3st Quartile (Q3)** or **75th Percentile**.
- `quantile(df$x, probs = 0.75)`



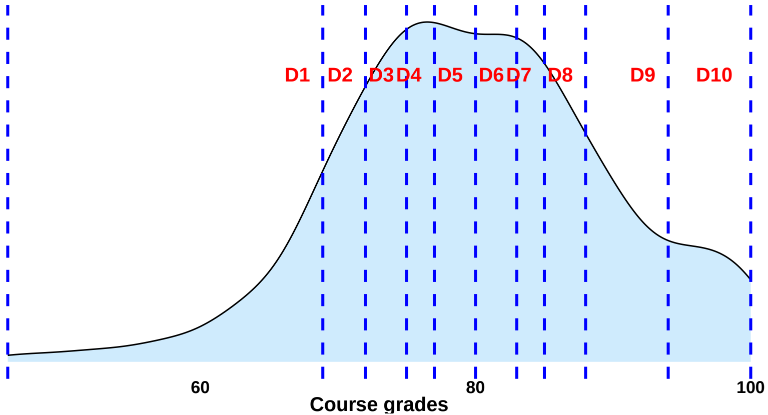
`quantile` and data distribution.

- Visualizaing quantiles: **maximum** or **100th percentile** or **10th decile**.
- `quantile(df$x, probs = 1)`



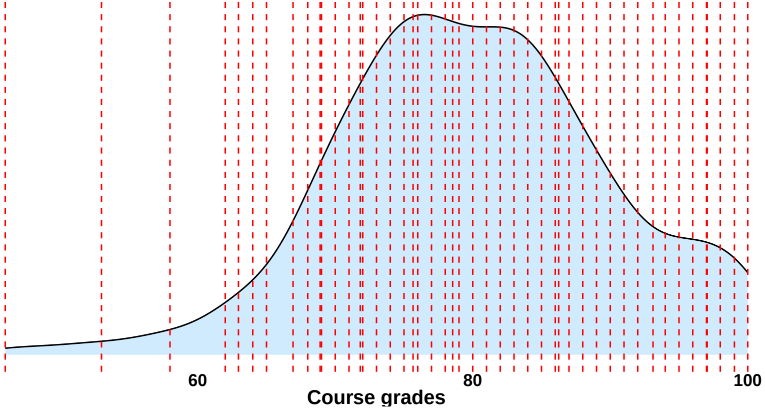
`quantile` and data distribution.

- Visualizing quantiles: **deciles** (1-10).
- `quantile(df$x, probs = seq(from=0,to=1,by=0.1))`



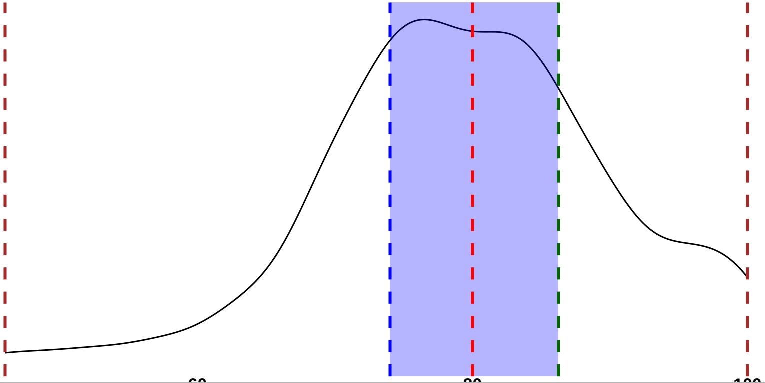
`quantile` and data distribution.

- Visualizing quantiles: **percentiles** (1-100).
- `quantile(df$x, probs = seq(from=0,to=1,by=0.01))`



`quantile` and data distribution.

- The **interquartile range** (IQR) is a measure of variability that represents the difference between the **first** and the **third** quartiles.
- It provides information about the spread of the middle 50% of the data.



More functions: nested `ifelse`.

- To create a new discrete variable, *letter*, with three levels (C, B, and A) based on exam scores, consider using `ifelse`.

```
dat$letter <- ifelse(dat$score < 70,
                     "C", # if TRUE
                     "Otherwise") # if FALSE
dat
```

```
##      name age gender score    letter
## 1   Alice  20      F    85 Otherwise
## 2     Bob  30      M    62         C
## 3 Charlie  NA      M    75 Otherwise
## 4    Dave  28      M    80 Otherwise
## 5     Eve  22      F    95 Otherwise
## 6   Marta  21      F     0         C
```

More functions: nested `ifelse`.

- However, note that `ifelse` yields binary results determined by the conditional test's `TRUE` or `FALSE`.

```
dat$letter <- ifelse(dat$score >= 70 & dat$score < 85,
                     "B", # if TRUE
                     "Otherwise") # if FALSE
dat
```

```
##      name age gender score    letter
## 1   Alice  20      F    85 Otherwise
## 2     Bob  30      M    62 Otherwise
## 3 Charlie  NA      M    75         B
## 4    Dave  28      M    80         B
## 5     Eve  22      F    95 Otherwise
## 6   Marta  21      F     0 Otherwise
```

More functions: nested `ifelse`.

- Can we do better and use `ifelse` to map several characters into a vector using conditional tests?

```
dat$letter <- ifelse(dat$score >= 85,
                     "A", # if TRUE
                     "Otherwise") # if FALSE
dat
```

```
##      name age gender score    letter
## 1   Alice  20      F    85         A
## 2     Bob  30      M    62 Otherwise
## 3 Charlie  NA      M    75 Otherwise
## 4    Dave  28      M    80 Otherwise
## 5     Eve  22      F    95         A
## 6   Marta  21      F     0 Otherwise
```

More functions: nested `ifelse`.

- Yes! `ifelse` function can be nested on itself for multiple tests.

```
dat$letter <- ifelse(dat$score < 70,
                     "C", # if TRUE
                     ifelse(dat$score >= 70 & dat$score < 85, # if FALSE
                            "B", # if TRUE
                        ifelse(dat$score >= 85, # if FALSE
                               "A",  # if TRUE
                           NA))) # if FALSE
dat
```

```
##      name age gender score letter
## 1   Alice  20      F    85      A
## 2     Bob  30      M    62      C
## 3 Charlie  NA      M    75      B
## 4    Dave  28      M    80      B
## 5     Eve  22      F    95      A
## 6   Marta  21      F     0      C
```

More functions: nested `case_when`.

- You can use the `case_when` function from the `dplyr` package to produce the same output.

```
dat$letter <- case_when(dat$score < 70 ~ "C",
                        dat$score >= 70 & dat$score < 85 ~ "B",
                        dat$score >= 85 ~ "A")
dat
```

```
##      name age gender score letter
## 1   Alice  20      F    85      A
## 2     Bob  30      M    62      C
## 3 Charlie  NA      M    75      B
## 4    Dave  28      M    80      B
## 5     Eve  22      F    95      A
## 6   Marta  21      F     0      C
```

Data class: factors

- **Categorical variables** can take on a limited, and usually fixed, number of different values or levels.
  - Voted:
    - Yes/No
  - Political parties:
    - Social democrat, Liberals, Conservatives, Green party, etc
  - *Likert scales* in survey opinions:
    - Strongly Agree, Agree, Disagree, Strongly Disagree
- However, `character` data type in R is used to store sequences of characters (text).

Factors

- A factor is a data structure used to represent categorical variables.

```
gender <- c("Male", "Female", "Male", "Female")

class(gender)
```

```
## [1] "character"
```

```
gender_factor <- as.factor(gender)

class(gender_factor)
```

```
## [1] "factor"
```

Factors: levels

- Factors have levels, which are the distinct values that the categorical variable can take.
- The levels are determined by the unique values in the original vector.

```r
# Checking levels of a factor
levels(gender_factor)
```

```
## [1] "Female" "Male"
```

Factors: Ordering Levels

By default, levels are ordered alphabetically. You can customize the order using the levels argument.

```
# Example: Specifying custom order
(ordered_gender <- factor(gender,
                          levels = c("Male", "Female")))
```

```
## [1] Male   Female Male   Female
## Levels: Male Female
```

```
# Checking the levels of a facto variable
levels(ordered_gender)
```

```
## [1] "Male"   "Female"
```

Good practice: create factor variables

- Some functions, especially in ggplot2 for visualization, require factors to function properly.
- It is a good practice to create new variables as **factors** when initiating an analysis.

```
(female <- c(0,1,0,1,0,0))
```

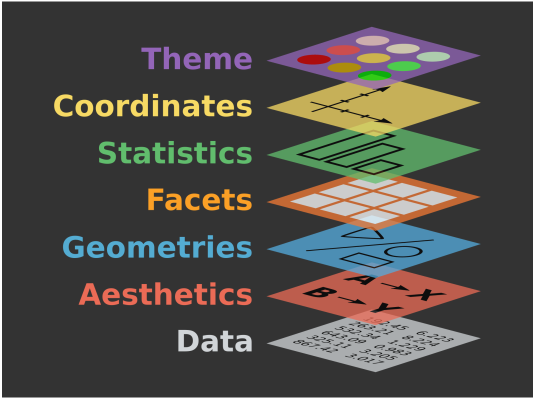
```
## [1] 0 1 0 1 0 0
```

```
(female_f <- factor(female,
                    levels = c(0,1), # map the levels order
                    labels = c("male","female")))
```

```
## [1] male   female male   female male   male
## Levels: male female
```

Grammar of graphics

- A statistical graphic is a `mapping` of `data` variables to `aes`thetic attributes of `geo`metric objects. (Wilkinson 2005)



Grammar of graphics in `ggplot2`

- `ggplot2`: A *layered* grammer of graphics (Wickham 2009).
  - Build a graphic from multiple layers; each consists of some geometric objects or transformation
  - Use + to stack up layers
- *What* data do you want to visualize?
  - **`ggplot(data = ...)`**
- *How* are variables mapped to specific aesthetic attributes?
  - **`aes(... = ...)`**
    - positions (`x`, `y`), `shape`, `colour`, `size`, `fill`, `alpha`, `linetype`, `label`...
    - If the value of an attribute do not vary w.r.t. some variable, don't wrap it within `aes(...)`
- *Which* geometric shapes do you use to represent the data?
  - **`geom_{}`**:
    - `geom_point`, `geom_line`, `geom_ribbon`, `geom_polygon`, `geom_label`...

Tidy data

- `ggplot2` works well only with tidy data
  - *Tidy data*:
    - Each **variable** must have its own **column**
    - Each **observation** must have its own **row**
    - Each value must have its own cell

Intro to ggplot

- How to create a **scatter plot**: *continuous* vs. *continuous* variables
- How to create a **boxplot**: *continuous* vs **categorical** variables

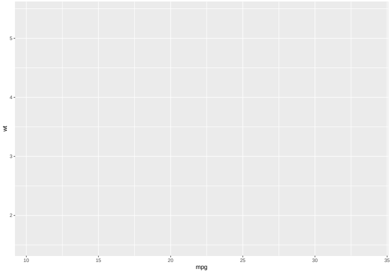
```
summary(mtcars[,c("mpg","wt","cyl")])
```

```
##       mpg              wt             cyl       
##  Min.   :10.40   Min.   :1.513   Min.   :4.000  
##  1st Qu.:15.43   1st Qu.:2.581   1st Qu.:4.000  
##  Median :19.20   Median :3.325   Median :6.000  
##  Mean   :20.09   Mean   :3.217   Mean   :6.188  
##  3rd Qu.:22.80   3rd Qu.:3.610   3rd Qu.:8.000  
##  Max.   :33.90   Max.   :5.424   Max.   :8.000  
```

Building a plot from scratch

Step 1: Define a basic ggplot object with x and y aesthetics

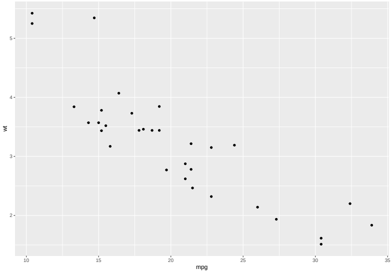
```
library(ggplot2)

ggplot(data=mtcars,
       aes(x=mpg,
           y=wt))
```



Building a plot from scratch: scatter plot

Step 2: Define a geometric shape

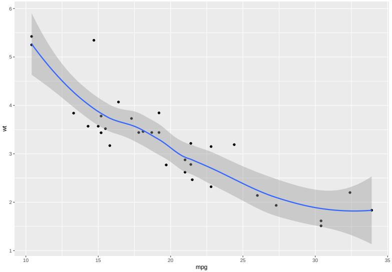
```
ggplot(data=mtcars,
       aes(x=mpg,
           y=wt)) +
  geom_point()
```



Building a plot from scratch: scatter plot

Note: we are not limited to have a single geometric form,

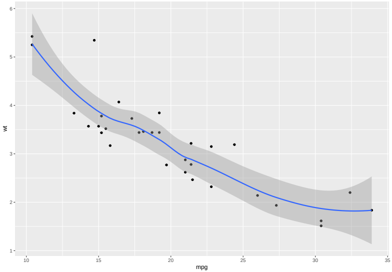
```
ggplot(data=mtcars,
       aes(x=mpg,
           y=wt)) +
  geom_point() +
  geom_smooth()
```



Building a plot from scratch: scatter plot

Note: we are not limited to have a single geometric form,

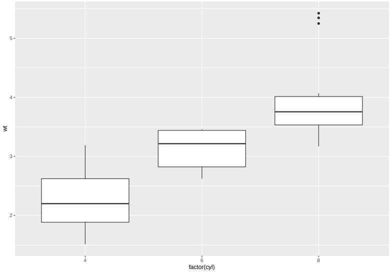
```
ggplot(data=mtcars,
       aes(x=mpg,
           y=wt)) +
  geom_point() +
  geom_smooth()
```



Building a plot from scratch: boxplot

Note: we are not limited to have a single geometric form,

```
ggplot(data=mtcars,
       aes(x=factor(cyl),
           y=wt)) +
  geom_boxplot()
```



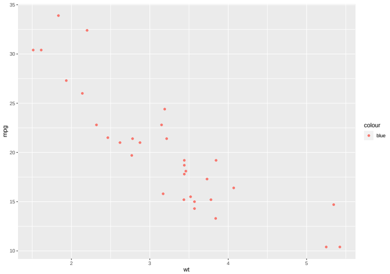
More on `ggplot`: colors

- In `ggplot`, the **color** `aesthetic` is used to group data by a categorical or numerical variable, with each group automatically assigned a unique color.
- Customize the color aesthetic using the argument in a `geom` shape, you cannot manually fit **colors** in the `aes()` function because ggplot will assume that you are fiting a **factor variable**.
- Use the `scale_color_manual()` function to set specific colors for values in a plot by passing a named vector of colors to the values argument.
- You can create your own custom color palette with the `scale_color_manual()` function by specifying a named vector of colors.

More on ggplot: colors

- Why the following plot is not blue?

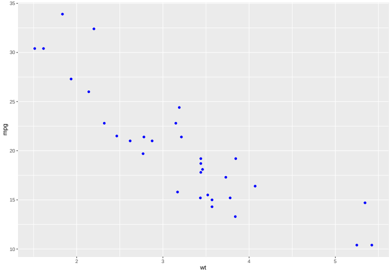
```
ggplot(mtcars, aes(x = wt,
                   y = mpg,
                   color="blue")) +
  geom_point()
```



More on `ggplot`: colors

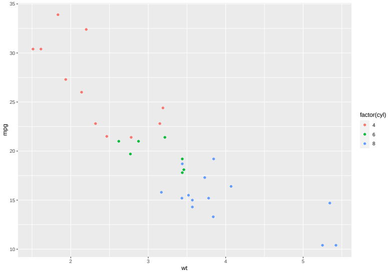
- Customize the color aesthetic using the argument in a `geom` shape, you cannot manually fit **colors** in the `aes()` function because ggplot will assume that you are fiting a **factor variable**.

```r
ggplot(mtcars, aes(x = wt,
                   y = mpg)) +
  geom_point(color = "blue")
```



More on ggplot: colors

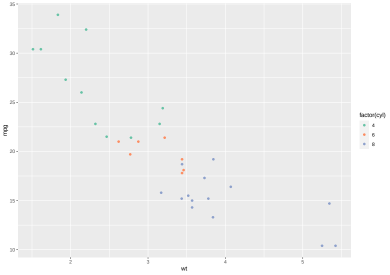
```
ggplot(mtcars, aes(x = wt,
                   y = mpg,
                   color = factor(cyl)))
  geom_point()
```



More on ggplot: colors

- Built-in ggplot color **palettes** can be used by passing the name of the palette to the palette argument of the `scale_color_()` function. For instance, `scale_color_brewer()` can be used to apply a palette from the **ColorBrewer library**.

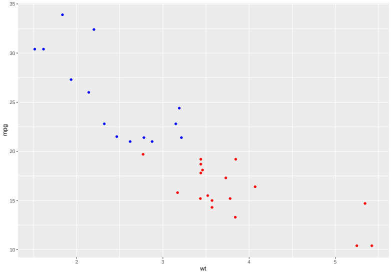
```
library(RColorBrewer)

ggplot(mtcars, aes(x = wt,
                   y = mpg,
                   color = factor(cyl))) +
  geom_point() +
  scale_color_brewer(palette = "Set2")
```



More on `ggplot`: colors

- You can customize which elements shall be colored using `filter`

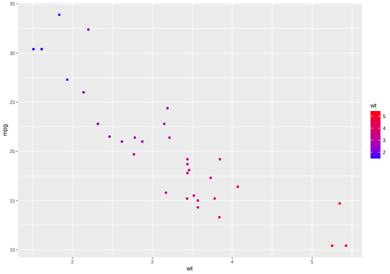
```
ggplot(mtcars, aes(x = wt,
                   y = mpg)) +
  geom_point(color =
               ifelse(mtcars$mpg > 20,
                      "blue", "red"))
```



More on `ggplot`: colors

- You can also fit numerical variables or manually sacle the gradient between several colors.

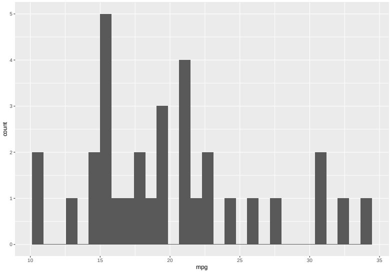
```
ggplot(mtcars, aes(x = wt,
                   y = mpg,
                   color = wt)) +
  geom_point() +
  scale_color_gradient(low = "blue",
                       high = "red")
```



More on `ggplot`: histograms

- When defining histograms or barplots, you only need to define the x aesthetics as y becomes the relative or absolute frequencies

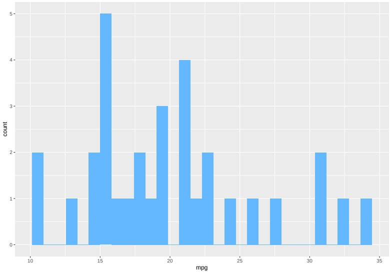
```r
ggplot(mtcars,
       aes(x = mpg)) +
  geom_histogram()
```



More on `ggplot`: histograms

- To color geometries with large areas, you will need to use the `fill=` argument.

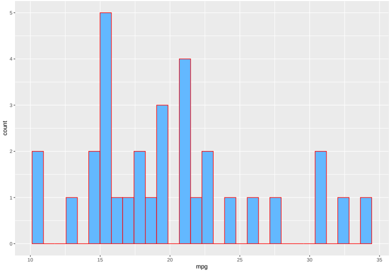
```
ggplot(mtcars,
       aes(x = mpg)) +
  geom_histogram(fill="steelblue1")
```



More on `ggplot`: histograms

- The argument color will provide color in the surface of the geometry.

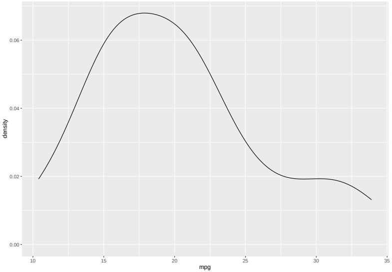
```r
ggplot(mtcars,
       aes(x = mpg)) +
  geom_histogram(fill="steelblue1",
                 color="red")
```



More on ggplot: density plots

- For a density plots, use geom_density.

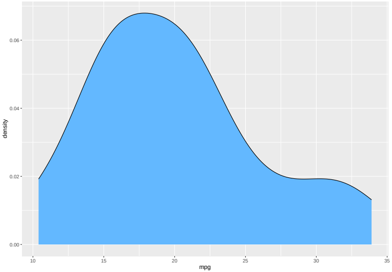
```
ggplot(mtcars,
       aes(x = mpg)) +
  geom_density()
```



More on ggplot: density plots

- For a density plots, use geom_density.

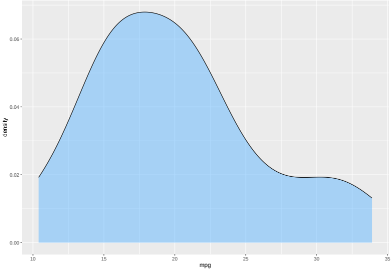
```
ggplot(mtcars,
       aes(x = mpg)) +
  geom_density(fill="steelblue1")
```



More on `ggplot`: density plots

- Geometric shapes have `alpha=` which controls the transparency of the geometry.
  - `alpha` values range from 0 (transparent) to 1 (opaque).

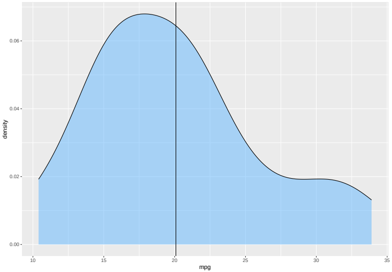
```
ggplot(mtcars,
       aes(x = mpg)) +
  geom_density(fill="steelblue1",
               alpha=0.5)
```



More on `ggplot`: density plots

- You can use the geometry `geom_vline` to include vertical lines and highlight points or thresholds of interest, like the `mean`

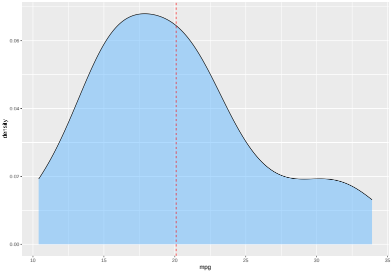
```
ggplot(mtcars,
       aes(x = mpg)) +
  geom_density(fill="steelblue1",
               alpha=0.5) +
  geom_vline(xintercept = mean(mtcars$mpg
```



More on ggplot: density plots

- The geometry geom_vline can be customized with colors and linetype arguments.

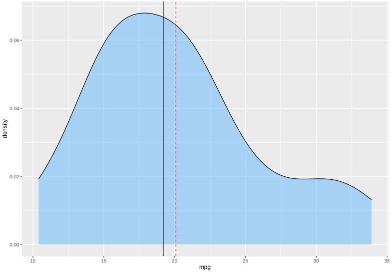
```
ggplot(mtcars,
       aes(x = mpg)) +
  geom_density(fill="steelblue1",
               alpha=0.5) +
  geom_vline(xintercept = mean(mtcars$mpg
             color="red",
             linetype="dashed")
```



More on `ggplot`: density plots

- You can have multiple geometries at once.

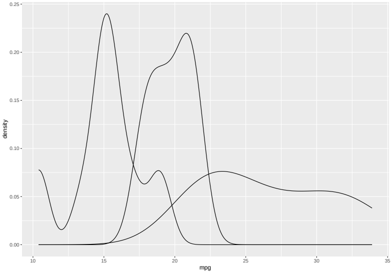
```
ggplot(mtcars,
       aes(x = mpg)) +
  geom_density(fill="steelblue1",
               alpha=0.5) +
  geom_vline(xintercept = mean(mtcars$mpg
             color="red",
             linetype="dashed") +
  geom_vline(xintercept = median(mtcars$m
```



More on `ggplot`: density plots

- In the aesthetics, you can include an index factor to the `group=` argument to subset a geometry in different levels

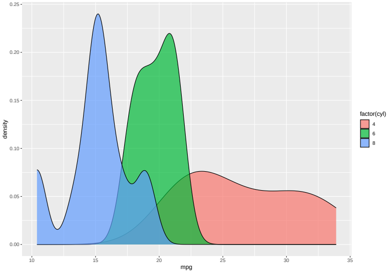
```
ggplot(mtcars,
       aes(x = mpg,
           group=factor(cyl))) +
  geom_density()
```



More on `ggplot`: density plots

- When doing so, make sure to provide `color` to all the factor levels by setting fill or color arguments in the general aesthetics `aes()` argument.

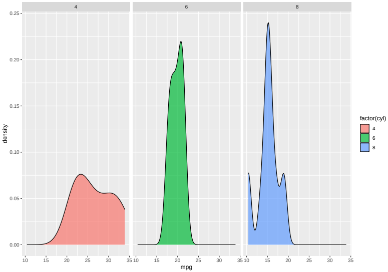
```
ggplot(mtcars,
       aes(x = mpg,
           group=factor(cyl),
           fill=factor(cyl))) +
  geom_density(alpha=0.7)
```



More on ggplot: facets

- When a group factor has many levels, is sometimes useful to split the plot in multiple facets using the geometries of `facet_wrap` or `facet_grid`.
  - Notice the syntax, requires a ~ before the factor.

```
ggplot(mtcars,
       aes(x = mpg,
           group=factor(cyl),
           fill=factor(cyl))) +
  geom_density(alpha=0.7) +
  facet_wrap( ~  factor(cyl))
```

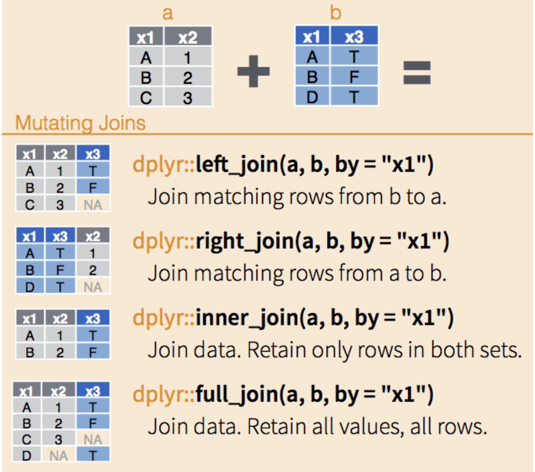


Grammar of graphics in `ggplot2`

- Browse the most common named colors in R.
- `ggplot2` is a powerful tool for creating professional visualizations.
- Search on the internet or ask ChatGPT for help with specific plot types using keywords based on geometries, such as **line plots**, **histograms**, **boxplots**, **coefficient plots**, etc.

Merging datasets

- Merging two datasets is actually more complicated than you might think



Merging datasets: key variables

```
polity <- read_csv("data/polity2.csv")
gapminder <- read_csv("data/gapminder2.csv")
names(gapminder)
```

```
## [1] "cntry"     "continent" "year"      "lifeExp"   "pop"       "gdpPercap"
```

```
names(polity)
```

```
## [1] "country" "year"    "polity"
```

```
# with dplyr, rename()
gapminder <- gapminder %>% rename(country=cntry)

# with base R, either colnames() or names()
colnames(gapminder)[1] <- "country"

names(gapminder)
```

```
## [1] "country"   "continent" "year"      "lifeExp"   "pop"       "gdpPercap"
```

Merging datasets: base R

```
dim(gapminder)
```

```
## [1] 1704    6
```

```
dim(polity)
```

```
## [1] 17228     3
```

```
merged_df <- merge(gapminder, polity,
                      by = c("country", "year"))

nrow(merged_df)
```

```
## [1] 1324
```

Merging datasets: dplyr

```
merged_data1 <- inner_join(gapminder, polity)
merged_data2 <- full_join(gapminder, polity)
merged_data3 <- left_join(gapminder, polity)
merged_data4 <- right_join(gapminder, polity)


nrow(merged_data1)
```

```
## [1] 1324
```

```
nrow(merged_data2)
```

```
## [1] 17608
```

```
nrow(merged_data3)
```

```
## [1] 1704
```

```
nrow(merged_data4)
```

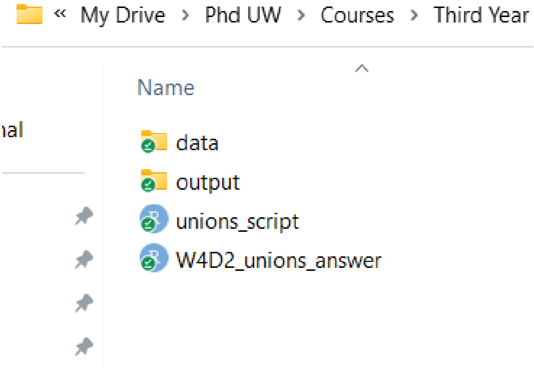
```
## [1] 17228
```

More functions

- The remaining slides feature useful functions for data management and exploratory analyses, provided for your personal reference.
- While not essential for completing the remaining problem sets in CS&SS 321, these functions can prove valuable for your final projects.

Save your output with `ggsave`

- From now on, you will include a new sub-folder in your project folder that we will call **output**.



Save your output with ggsave

- The ggsave function is used to save a ggplot object as a file. For example, if you save a plot as "myplot.pdf", the file format will be PDF.
- By default, ggsave will save the last plot created, but you can also specify a specific plot object to save.
- You can use the width and height arguments to adjust the size of the output file.

```
ggsave("output/gincdif_dis.pdf", width = 6, height = width/1.618)
```

`aggregate()` for summarizing data.

- So far we have been using `tapply()` from base R to *apply* a functions over variables and categories.

```
df <- read.csv("data/gapminder.csv")

head(df)
```

```
##       country continent year lifeExp      pop gdpPercap
## 1 Afghanistan      Asia 1952  28.801  8425333  779.4453
## 2 Afghanistan      Asia 1957  30.332  9240934  820.8530
## 3 Afghanistan      Asia 1962  31.997 10267083  853.1007
## 4 Afghanistan      Asia 1967  34.020 11537966  836.1971
## 5 Afghanistan      Asia 1972  36.088 13079460  739.9811
## 6 Afghanistan      Asia 1977  38.438 14880372  786.1134
```

aggregate() for summarizing data.

- So far we have been using tapply() from base R to *apply* a functions over variables and categories.

```
df <- read.csv("data/gapminder.csv")

head(df)
```

```
##       country continent year lifeExp      pop gdpPercap
## 1 Afghanistan      Asia 1952  28.801  8425333  779.4453
## 2 Afghanistan      Asia 1957  30.332  9240934  820.8530
## 3 Afghanistan      Asia 1962  31.997 10267083  853.1007
## 4 Afghanistan      Asia 1967  34.020 11537966  836.1971
## 5 Afghanistan      Asia 1972  36.088 13079460  739.9811
## 6 Afghanistan      Asia 1977  38.438 14880372  786.1134
```

```
# what is the average income (gdpPercap) per continent?

tapply(df$gdpPercap,df$continent,FUN=mean)
```

```
##    Africa  Americas      Asia    Europe   Oceania
##  2193.755  7136.110  7902.150 14469.476 18621.609
```

`aggregate()` for summarizing data.

- However, `tapply()` have some short comings:
  - `tapply()` returns output in a **tabular format**, but it is not in a `data.frame` or a tidy format, which can be inconvenient for further processing and analysis.
  - `tapply()` can only be used with **one variable** at a time, making it difficult to work with multiple variables or to create summaries of more than one variable.

`aggregate()` for summarizing data.

- `aggregate()` is used for performing grouped operations on data.
- It allows you to split the data into groups based on one or more variables and apply a function to each group.
- The basic syntax of `aggregate()` is `aggregate(formula, data, FUN)`, where:
  - `formula`: A formula indicating the variables to be aggregated and the grouping variables.
  - `data`: The data frame containing the variables.
  - `FUN`: The function to be applied to each group.

`aggregate()` for summarizing data.

- In the this example, the formula `gdpPercap ~ year` returns the `mean` of **gdpPercap** for each unique **year**.

```r
aggregate(gdpPercap ~ year,
          data = gapminder,
          FUN = mean)
```

```
##    year gdpPercap
## 1  1952  3829.259
## 2  1957  4347.034
## 3  1962  4727.467
## 4  1967  5644.276
## 5  1972  6772.800
## 6  1977  6929.658
## 7  1982  7393.556
## 8  1987  8267.596
## 9  1992  8271.349
## 10 1997  9174.090
## 11 2002  9534.104
## 12 2007 11729.335
```

aggregate() for summarizing data.

- You can use the function cbind() to combine several variables and compute their mean by year.

```r
aggregate(cbind(gdpPercap,lifeExp) ~ year
          data = gapminder,
          FUN = mean)
```

```
##    year gdpPercap  lifeExp
## 1  1952  4083.527 49.03691
## 2  1957  4779.593 52.17170
## 3  1962  4899.751 54.21721
## 4  1967  5288.622 56.65886
## 5  1972  6717.851 57.77570
## 6  1977  6625.197 59.08070
## 7  1982  7272.690 61.18568
## 8  1987  7885.416 63.49598
## 9  1992  7444.501 62.54807
## 10 1997  9308.846 65.17629
## 11 2002  8676.260 64.46458
## 12 2007 11337.348 66.90237
```

aggregate() for summarizing data.

- You can also include more than one index variable.
- In this case, we estimate means for each unique combination of **continent** and **year**.

```
aggregate(cbind(gdpPercap,lifeExp) ~ cont
          data = gapminder,
          FUN = mean)
```

```
##    continent year gdpPercap  lifeExp
## 1     Africa 1952  1070.733 39.02677
## 2   Americas 1952  3873.925 52.00900
## 3       Asia 1952  6998.046 45.50209
## 4     Europe 1952  5568.622 64.22723
## 5    Oceania 1952 10298.086 69.25500
## 6     Africa 1957  1427.367 41.39056
## 7   Americas 1957  5106.036 57.49638
## 8       Asia 1957  7003.774 50.02065
## 9     Europe 1957  6872.857 66.19986
## 10   Oceania 1957 11598.522 70.29500
## 11    Africa 1962  1644.498 43.79219
## 12  Americas 1962  4088.299 57.83894
## 13      Asia 1962  6749.832 52.91864
## 14    Europe 1962  8082.578 68.09822
## 15   Oceania 1962 12696.452 71.08500
## 16    Africa 1967  1928.330 45.03909
```

`aggregate()` for summarizing data.

- `aggregate()` is a part of base R, making it available without additional package dependencies.
- The result of `aggregate()` is often used for further analysis, visualization, or reporting summary statistics.
  - It combines very well with **ggplot**!

reshaping data with `dplyr`

- **Reshaping** a data frame is a crucial skill in data science that enables you to perform various necessary tasks efficiently.
- There are two main types of data structures: **long** and **wide** formats.
- **Long format** is the preferred structure for most R functions and packages, including ggplot2. It is **tidy data** that is easy to manipulate and analyze.
- Although not tidy, **wide format** can be useful for presenting tables to audiences as it conveys more information in a smaller space. However, it is not ideal for data analysis.

long vs wide

country	year	metric
x	1960	10
x	1970	13
x	2010	15
y	1960	20
y	1970	23
y	2010	25
z	1960	30
z	1970	33
z	2010	35

```
pivot_wider(names_from = "year",
            names_prefix = "yr",
            values_from = "metric")
```

country	yr1960	yr1970	yr2010
x	10	13	15
y	20	23	25
z	30	33	35

```
pivot_longer(cols = yr1960:yr2010,
             names_to = "year",
             names_prefix = "yr"
             values_to = "metric")
```

reshaping data with `dplyr`

- The `pivot_` functions allow you to **reshape** data frames from long to wide or vice versa, which can be useful for data wrangling and visualization purposes.

```r
# Create example data
(df <- data.frame(
  id = c(1, 2, 3),
  treatment = c("A", "B", "C"),
  day1 = c(10, 15, 12),
  day2 = c(12, 16, 18),
  day3 = c(8, 14, 10)
))
```

```
##   id treatment day1 day2 day3
## 1  1         A   10   12    8
## 2  2         B   15   16   14
## 3  3         C   12   18   10
```

reshaping data with `dplyr`

- `pivot_longer()` is used to convert a wide data frame to a **long format** by stacking columns into rows.
- You must specify which **columns** to pivot, the **names** for the new columns, and the name of the column to store the **values**.

```r
# Use pivot_longer() to reshape
# the data from wide to long

df_long <-
  pivot_longer(df,
               cols = starts_with("day"),
               names_to = "day",
               values_to = "result")
df_long
```

```
## # A tibble: 9 x 4
##      id treatment day   result
##   <dbl> <chr>     <chr>  <dbl>
## 1     1 A         day1      10
## 2     1 A         day2      12
## 3     1 A         day3       8
## 4     2 B         day1      15
## 5     2 B         day2      16
## 6     2 B         day3      14
## 7     3 C         day1      12
## 8     3 C         day2      18
## 9     3 C         day3      10
```

reshaping data with dplyr

- while pivot_wider() does the opposite by spreading rows into columns.

pivot_wider() takes similar arguments, but also requires specifying which column to use for the column names and which column to use for the values in the new columns.

```r
# Use pivot_wider() to reshape
# the data from long to wide

df_wide <-
  pivot_wider(df_long,
              names_from = "day",
              values_from = "result")
df_wide
```

```
## # A tibble: 3 x 5
##      id treatment  day1  day2  day3
##   <dbl> <chr>     <dbl> <dbl> <dbl>
## 1     1 A            10    12     8
## 2     2 B            15    16    14
## 3     3 C            12    18    10
```

Function: stargazer()

- To present results from several linear models in a output table, use the function `stargazer()`.
  - In the `RMarkdown`, you will need to set the code chunk option `results='asis'`

```
library(stargazer)
m1 <- lm(mpg ~ hp, data=mtcars)
m2 <- lm(mpg ~ hp + cyl, data=mtcars)
```

Function: `stargazer()`

```r
stargazer(m1,m2,header = FALSE,type="latex") # type="text" for R console
```

Table 1:

	Dependent variable:	
	mpg	
	(1)	(2)
hp	-0.068^{***}	-0.019
	(0.010)	(0.015)
cyl		-2.265^{***}
		(0.576)
Constant	30.099^{***}	36.908^{***}
	(1.634)	(2.191)
Observations	32	32
R^2	0.602	0.741
Adjusted R^2	0.589	0.723