Class 5 Data Wrangling with R (Part II)

Dr Wei Miao

UCL School of Management

Thu, Oct 20 2022

Section 1

Data Wrangling

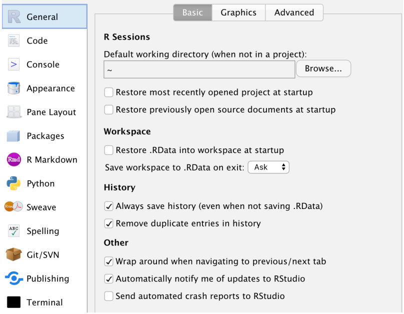
R Tips: More Convenient Package Management Using `pacman`

```
pacman::p_load(dplyr,ggplot2)
```

- Please install `pacman` on your RStudio
- `pacman`'s functionality
  - Load all packages stated in the parantheses, seperated by commas
  - If the package is not downloaded yet, download it, and then load it
- R tip: if you want to use a function without loading the whole package, you can use two colons to call the function: `package::function`

R Tips: Managing Objects in the RStudio Environment

- Best practice is to not save any objects once you close your RStudio session



- `rm(list = ls())` is the command to remove everything in the current environment
  - `ls()` is a function that returns the list of all objects in the current environment
  - `rm(list = )` removes any objects passed to `list` argument

Recap: `filter()`, `arrange()`, and `mutate()`

- `filter(dataset, criteria)`: pick observations by their values

- `arrange(dataset,variable)`: reorder the rows
- `mutate(dataset, newvariable = )`: create new variables with functions of existing variables

Pipe Operator

- Imagine a factory with different machines placed along a belt. Each machine is a **dplyr function** that performs a data cleaning step, like filtering or arranging data.
- The pipe therefore works like a conveyor belt, passing the output of one machine to another for further processing.

input %>% functionName(, ...)

other inputs

functionName(input, ...)

other inputs

Pipe Operator

- The pipe has a huge advantage over any other method of processing data in R or Python: It makes data wrangling processes easy to read. If we read %>% as “then”, the code will be very easy to interpret as a set of instructions in plain English:

```
mtcars %>%
  filter(cyl>=5) %>%
  mutate(sqrt_wt=sqrt(wt)) %>%
  filter(sqrt_wt>1.5) %>%
  arrange(hp)
## can go on and on
```

1. take the mtcars data, THEN
2. find cars cyl >= 5, THEN
3. mutate a new variable sqrt_wt, THEN
4. find cars sqrt_wt > 1.5 THEN
5. reorder all cars based on hp
6. chain more operations …

Without Pipe Operator

- As a comparison, without using pipe operators, the previous data cleaning steps need to be done as follows. Overwriting our output dataframe `new_data` in every line is problematic.
  - First, doing this for a procedure with lots of steps isn't efficient and creates unnecessary repetition in the code.
  - Second, this repetition also makes it harder to identify exactly what is changing on each line in some cases.

```
new_data <- filter(mtcars, cyl >=5)
new_data <- mutate(new_data, sqrt_wt=sqrt(wt))
new_data <- filter(new_data,sqrt_wt>1.5)
new_data <- arrange(new_data,hp)
```

Select Variables: `select`

- `select()` can select variables into a smaller dataset.

```
# Select two columns: hp and cyl
mtcars%>%
  select(hp, cyl) %>%
  head()
```

	hp	cyl
Mazda RX4	110	6
Mazda RX4 Wag	110	6
Datsun 710	93	4
Hornet 4 Drive	110	6
Hornet Sportabout	175	8
Valiant	105	6

Aggregation by Groups: `group_by`

- `group_by()` allows us to aggregate data by group and compute statistics for each group

```r
# group by cyl
mtcars %>%
  group_by(cyl)
```

- Although nothing seemingly happens to the dataset, internally, the dataset is already grouped based on the specified variable(s).

Aggregation by Groups: group_by() + summarise()

- summarise() creates a new data frame after aggregating data. The final dataset
  - has one row for each pair of grouping variables (for each cyl value)
  - contains one column for each grouping variable (cyl)
  - contains one column for each new summarised variable (avg_mp)

```r
# compute the average mpg for each cyl group
mtcars %>%
  group_by(cyl) %>% # group by cyl
  summarise(avg_mp = mean(mpg)) %>% # compute the average mpg
  ungroup()
```

cyl	avg_mp
4	26.66364
6	19.74286
8	15.10000

Aggregation by Groups: `group_by()` + `summarise()`

- We can have multiple group variables for `group_by`

```
# compute the average mpg for each cyl,vs group
mtcars %>%
  group_by(cyl,vs) %>% # group by cyl
  summarise(avg_mp = mean(mpg)) %>% # compute the average mpg
  ungroup()
```

Aggregation by Groups: group_by() + mutate()

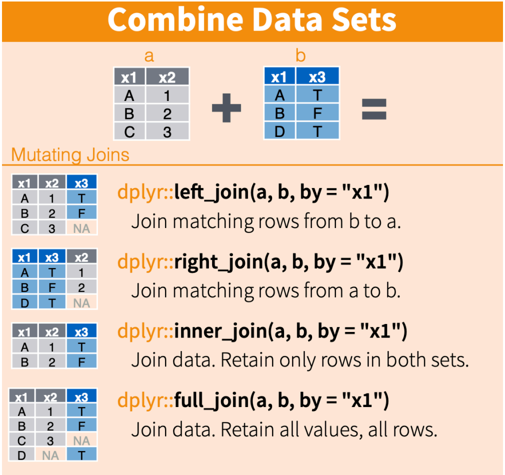
- Try the following code by replacing summarise() with mutate(), what do you get now?

```
# compute the average mpg for each cyl,vs group
mtcars %>%
  group_by(cyl,vs) %>% # group by cyl
  mutate(avg_mp = mean(mpg)) %>% # compute the average mpg
  ungroup()
```

- A new column is added to the original dataset, the value of which is from the group-by aggregation.

Consolidate Multiple Data Frames

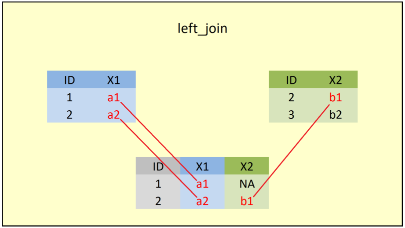
- When consolidating multiple data frames, we usually have 4 types of joining methods



left_join

- `left_join` keeps everything from the left data frame and matches as much as it can from the right data frame.
    - All IDs **in the left data frame** will be retained
    - If a match can be found, value from the right data frame will be filled in
    - If a match cannot be found, a missing value will be filled in

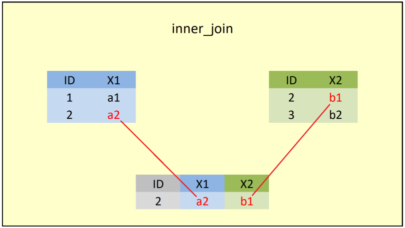
```
# Method 1 without pipe operator
left_join(df_left, df_right, by = 'ID')
# Method 2 with pipe operator
df_left %>%
  left_join(df_right, by = 'ID')
```



inner_join

- inner_join only keeps the observations that appear in both data frames
  - Only common IDs **in both data frames** will be retained
  - If a match can be found, values will be filled in from both data frames

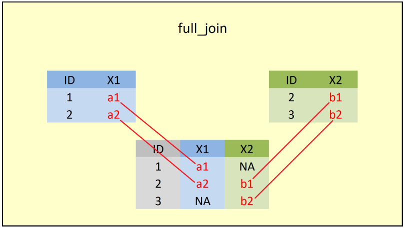
```
# Method 1 without pipe operator
inner_join(df_left, df_right, by = 'ID')
# Method 2 with pipe operator
df_left %>%
  inner_join(df_right, by = 'ID')
# Method 3: order of data frames should not matter. Why?
df_right %>%
  inner_join(df_left, by = 'ID')
```



full_join

- `full_join` keeps all observations from both data frames
  - All IDs **in either data frames** will be retained
  - If a match can be found, values will be filled in from both data frames

```
# Method 1 without pipe operator
full_join(df_left, df_right, by = 'ID')
# Method 2 with pipe operator
df_left %>%
  full_join(df_right, by = 'ID')
# Method 3: order of data frames should not matter. Why?
df_right %>%
  full_join(df_left, by = 'ID')
```



Section 2

Data Cleaning

Variable Types

- Non-metric
  - Categorical (gender, region, brand, religion)
  - Ordinal (Business Week rankings, NCAA rankings)
- Metric
  - Continuous (age, height, sales, rainfall)
- Different types of variables are handled in different ways in statistics
  - Can talk about an average age, but not an average color
  - Some statistical techniques only work with one type of variable
- We need to make sure the variables are of the correct data types. Or we may need to convert them to the correct types.
  - e.g., from character to date time using `lubridate` package

Missing Values

- In R, missing values are represented by the symbol `NA` (i.e., *not available*).
- Most statistical models cannot handle missing values, so we need to deal with them in R.
    - Few missing values: remove them from analysis.
    - Many missing values: need to replace them with appropriate values: mean/median/imputation

Outliers

- In statistics, an outlier is a data point that differs significantly from other observations.
  - Few outliers: remove them from analysis
  - Many outliers: winsorize data
  - **If the distribution of a variable is not normal distribution, we often log transform variables to mitigate outlier issues**

Section 3

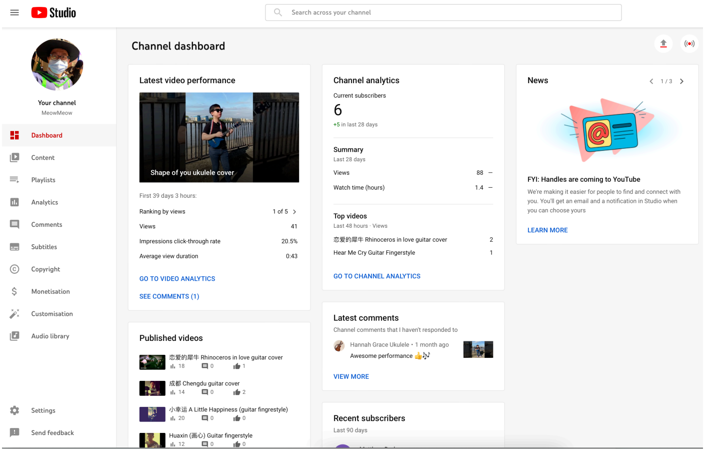
Descriptive Analytics

Two Major Tasks of Descriptive Analytics

1. **Describe data depending on your business purposes**
   - "How much do our customers spend each month on average?"
   - "What percentage of our customers are unprofitable?"
   - "What is the difference between the retention rates of men and women?"
2. **Make statistical inferences from data**
   - "Based on our sample, does the difference between the spendings of men and women indicate that men and women respond differently in the customer base at large?"
   - "Based on our sample, can we conclude that customers who sign up for online banking are more profitable than customers who do not?"
   - "Based on our test mailing, can we conclude that ad-copy A works better than ad-copy B?"

Descriptive Analytics

- You can think of descriptive analytics as **creating a dashboard** to display the key information you would like to know for your business.



Summary Statistics

- In descriptive analytics, **summary statistics** are used to summarize a set of observations, in order to communicate the largest amount of information as simply as possible.
- There are two main types of summary statistics used in evaluation: **measures of central tendency** and **measures of dispersion**.
  - Measures of central tendency provide different versions of the average, including the mean, the median, 25 percentile, 75 percentile, the mode, etc.
  - Measures of dispersion provide information about how much variation there is in the data, including the range and the standard deviation.
- It's good to include summary statistics table in your dissertation before any statistical analysis!
  - Commonly reported summary statistics include *mean*, *standard deviation*, *number of observations*, *min*, *25 percentile*, *median*, *75 percentile*, and *max*.
  - Then describe the distribution of the variable, dispersion of the variable, etc.

Summary Statistics with R

- In R, a nice package to report summary statistics is `modelsummary`. `datasummary_skim()` is a shortcut to conduct basic summary statistics
- For more features, refer to the package tutorial here, especially `datasummary()` function.
    - `datasummary_skim()` is a special case of more general `datasummary()`, which outputs a pre-determined set of summary statistics

```r
pacman::p_load(modelsummary)
mtcars %>%
  datasummary_skim()
```

Correlation Matrix

- Correlation matrix helps us understand the co-movement of any two variables in the data
- `datasummary_correlation()` reports the pairwise correlation coefficient
- In general, in a statistical model, variables of high correlation should not be included together, which leads to instability

```
mtcars %>%
  datasummary_correlation()
```

Section 4

Preliminary Customer Analysis

Preliminary Customer Analysis

- Spend 30 min-ish to work on the case study in a group.
- There are 7 questions in total. At the end of the discussion, each group selects a group leader to answer one question.
- To show your codes, join the Zoom link under "Module Overview" on Moodle.
- The group that did not answer correctly needs to do a performance next week!

After-Class Exercise

- What percent of customers are single? Try alternative ways to do the calculation.
- Is the average total spending by responders and non-responders statistically different? Answer this question using a t-test.
- Is income and total spending correlated?
- Are PhDs more likely to respond to marketing offers than Graduation? Use a statistical test to answer the question. Is the result what you expected?
- What would be the other useful descriptive analytics you would like to know for Tesco?