

## Class 5 Data Wrangling with R (Part II)

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## Section 1

# Data Wrangling Part II

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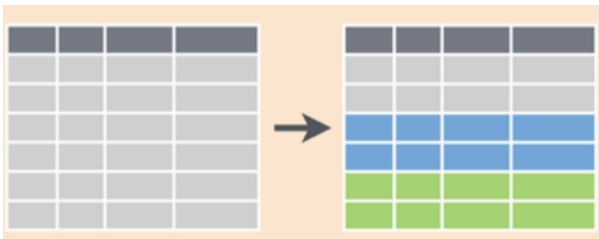
- Select rows (`filter`)
- Sort rows (`arrange`)
- Select columns (`select`)
- Generate new columns (`mutate`)
- **Group aggregation (`group_by`): compute statistics for each group**
- **Merge datasets (`join`): combine datasets from different sources**

## Aggregation by Groups: group\_by

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

```
1 # group by marital status
2 data_demo %>%
3   group_by(Marital_Status)
```

- Internally, the dataset is already grouped based on the specified variable(s).



## Aggregation by Groups: `group_by()` `%>% summarise()`

- After aggregating data, we can use `summarise()` to compute group-specific statistics for us.
  - Similar to `mutate()` in generating new variables
  - Different from `mutate()` in that the new variable is computed based on groups.

```
1 # compute the average income for each marital status group
2 data_demo %>%
3   group_by(Marital_Status) %>%
4   summarise(avg_income = mean(Income, na.rm = T)) %>%
5   ungroup()
```

Marital_Status	avg_income
Alone	43789.00
Divorced	53300.63
Married	51776.36
Single	51091.16
Together	52609.59
Widow	56158.90

- What if you replace `summarise()` with `mutate()`?

## Aggregation by Groups: `group_by()` Multiple Groups

- We can have multiple group variables for `group_by`, such as computing average income for each marital status, education combination

```
1 # compute the average income for each marital, education group
2 data_demo %>%
3   group_by(Marital_Status, Education) %>%
4   summarise(avg_income = mean(Income, na.rm = T)) %>%
5   ungroup() %>%
6   head(5)
```

Marital_Status	Education	avg_income
Alone	Graduation	34176
Alone	Master	61331
Alone	PhD	35860
Divorced	2n Cycle	49345
Divorced	Basic	9548

# Consolidate Multiple Data Frames

- When consolidating multiple data frames, we have 4 types of joining methods.
- `left_join()` handles most data join situations, which we will focus on today.

## Combine Data Sets

a		b	
x1	x2	x1	x3
A	1	A	T
B	2	B	F
C	3	D	T

+

=

### Mutating Joins

x1	x2	x3
A	1	T
B	2	F
C	3	NA

`dplyr::left_join(a, b, by = "x1")`

Join matching rows from b to a.

x1	x3	x2
A	T	1
B	F	2
D	T	NA

`dplyr::right_join(a, b, by = "x1")`

Join matching rows from a to b.

x1	x2	x3
A	1	T
B	2	F

`dplyr::inner_join(a, b, by = "x1")`

Join data. Retain only rows in both sets.

x1	x2	x3
A	1	T
B	2	F
C	3	NA
D	NA	T

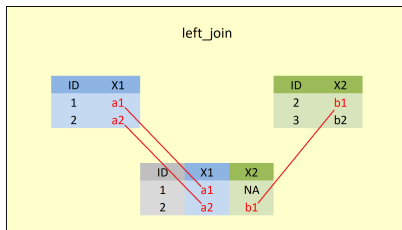
`dplyr::full_join(a, b, by = "x1")`

Join data. Retain all values, all rows.

## left\_join()

- `left_join` keeps everything from the **left data frame** and matches as much as it can from the right data frame based on the chosen IDs.
  - 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 returned

```
1 df_left %>%  
2   left_join(df_right, by = c('ID' = 'ID'))
```





## Caveats for doing left\_join()

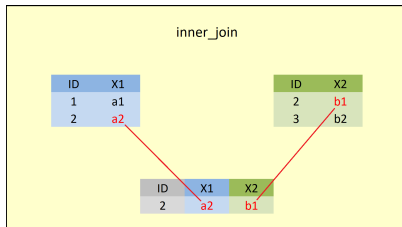
- We can do 1:1, or M:1 left\_joins
- **Never** do 1:M or M:M left\_joins

demographics: 1					Transaction data: M			
ID	age	income			ID	transaction	revenue	
1	15	3000			1	1	12	
2	18	1000			1	2	2	
					2	1	10	
					2	2	5	
					2	3	10	

## inner\_join() (optional)

- 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

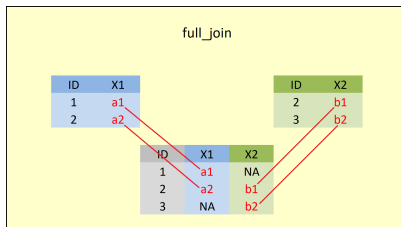
```
1 # Method 1 without pipe operator
2 inner_join(df_left, df_right, by = 'ID')
3 # Method 2 with pipe operator
4 df_left %>%
5   inner_join(df_right, by = 'ID')
6 # Method 3: order of data frames should not matter. Why?
7 df_right %>%
8   inner_join(df_left, by = 'ID')
```



## full\_join() (optional)

- 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

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



## Section 2

# Data Cleaning

# 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

- Sometimes, due to data collection errors, we may have abnormal observations in the data, such as unusually large and small values
- Winsorization is a common way to deal with outliers
  - Remove top 1% and bottom 1% observations

## Section 3

# Descriptive Analytics

# Two Major Tasks of 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.

## 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 spending 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?”



# Summary Statistics

- **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:** mean, the median, 25 percentile, 75 percentile, the mode, etc.
  - **measures of dispersion:** range and standard deviation.
- It's important to include summary statistics table in your dissertation before any statistical analysis!

# 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](#)

```
1  pacman::p_load(modelsummary)
2  ## Summary statistics for numeric variables
3  data_demo %>%
4    datasummary_skim(type = "numeric")
5
6  ## Summary statistics for categorical variables
7  data_demo %>%
8    datasummary_skim(type = "categorical")
```

## Case Study: Preliminary Customer Analysis

- Let's solve the preliminary customer analysis case together in class!