Session 2 - Data wrangling

R training

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Government Analytics and R Training:

Strengthening Public Sector Reporting and Data Analysis

January 13 – January 17, 2025



Introduction

Access to Training Materials

All the materials for this training are available at the following link: https://osf.io/r3fn5/

Here's what you will find there:

- **Data**: All datasets we'll use throughout the training sessions.
- **Slides**: The presentation slides for each session.
- **Solutions**: Will be added to the folder after each session.

Introduction

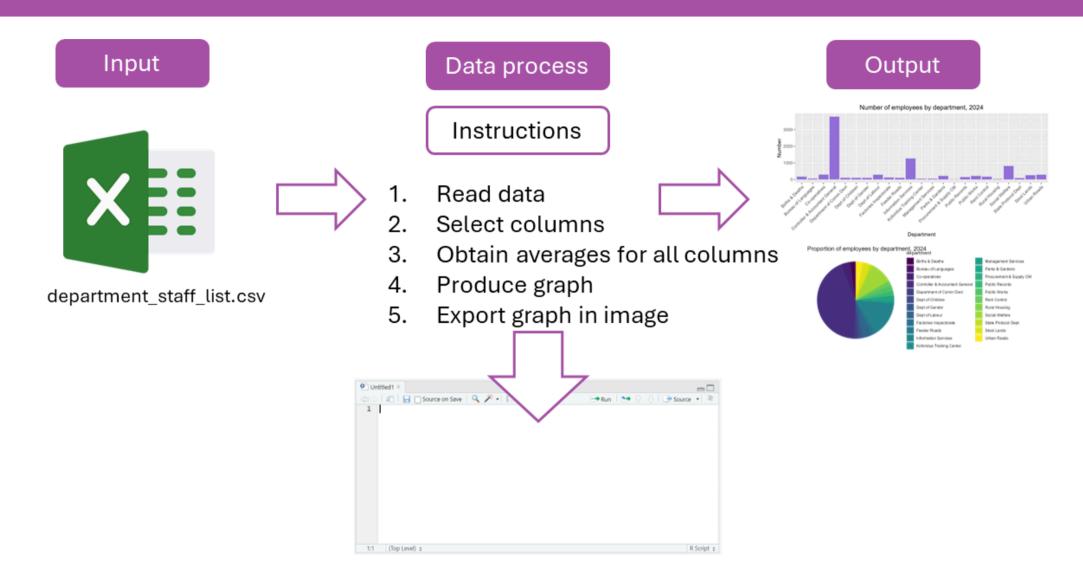
Course Structure

This training will cover the basics of coding in R. Below is the structure of the course:

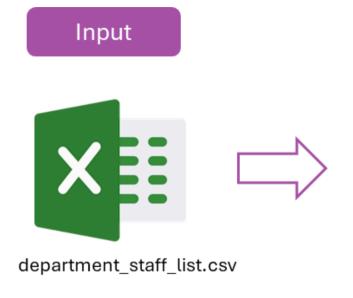
- **Day 1**: Introduction to R Get familiar with the R environment and basic syntax.
- ★ Day 2: Data Wrangling Learn to clean and transform data effectively.
- **Day 3**: Descriptive Statistics Explore methods to summarize and analyze data.
- **Day 4**: Data Visualization Create meaningful and impactful data visualizations.

About this session

About this session



About this session

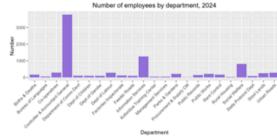


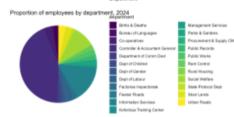
Data process

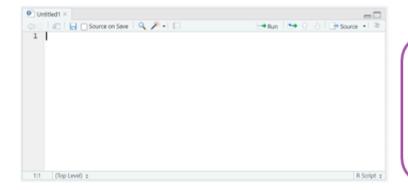
Instructions

- 1. Read data
- 2. Select columns
- 3. Obtain averages for all columns
- 4. Produce graph
- 5. Export graph in image

Output



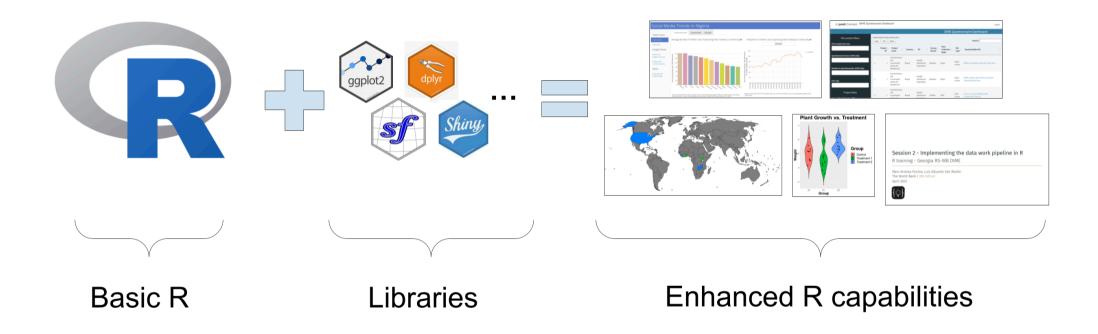




This session: getting data ready to be used to create our outputs

- Installing R in your computer gives you access to its basic functions
- Additionally, you can also install packages. Packages are a collection of R functions that allow you to do:
 - Operations that basic R functions don't do (example: work with geographic data)
 - Operations that basic R functions do, but easier (example: data wrangling)
- They contain code that other R users have prepared for the community.

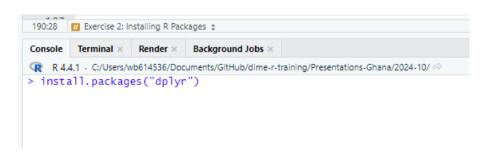
In a nutshell:



We'll use one package in today's session: dplyr and tidyr (really useful library for data cleaning and wrangling).

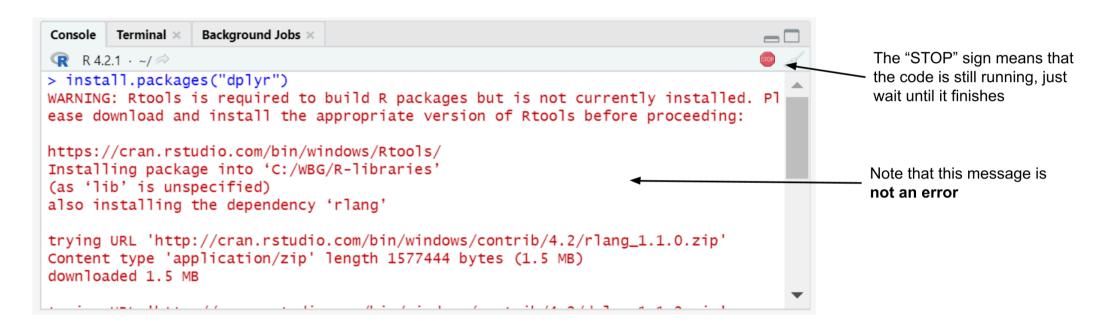
Exercise 1: Installing R Packages

- 1. Install the R Packages by using install.packages()
 - o install.packages("dplyr")
 - Note the quotes (" ") in the packages names
 - Introduce this code in the console, not the script panel



R packages

Installing packages



R packages

Now that dplyr is installed, we only need to load them to start using the functions they have.

Exercise 2: Loading packages

- 1. Open a new script with File >> New File >> R
 Script
- 2. Load the packages with:

```
library(dplyr)
```

- Run this code from the new script you just opened
- Notice that we don't use quotes in the package names this time

```
Console Terminal × Render × Background Jobs ×

R R 4.2.1 · C:/WBG/Repos/dime-r-training/Presentations-GeorgiaRS/ ◇

> library(dplyr)

Attaching package: 'dplyr'

The following objects are masked from 'package:stats':
    filter, lag

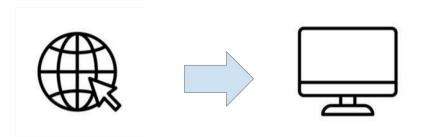
The following objects are masked from 'package:base':
    intersect, setdiff, setequal, union

Warning message:
    package 'dplyr' was built under R version 4.2.3

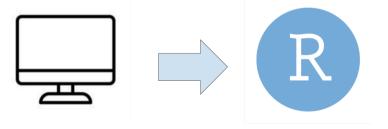
> |
```

R packages

• Library installation:



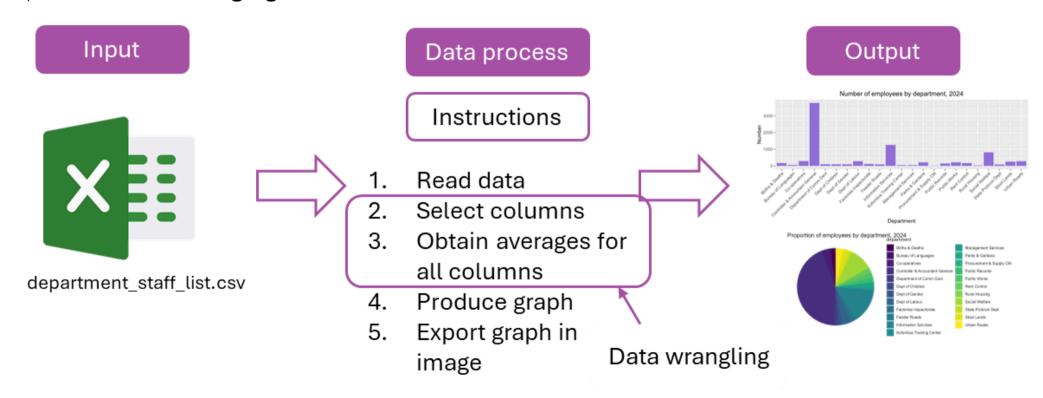
• Library loading:



- You install R packages only once in your computer
- You load packages every time you open a new RStudio window (only load the packages you will use)

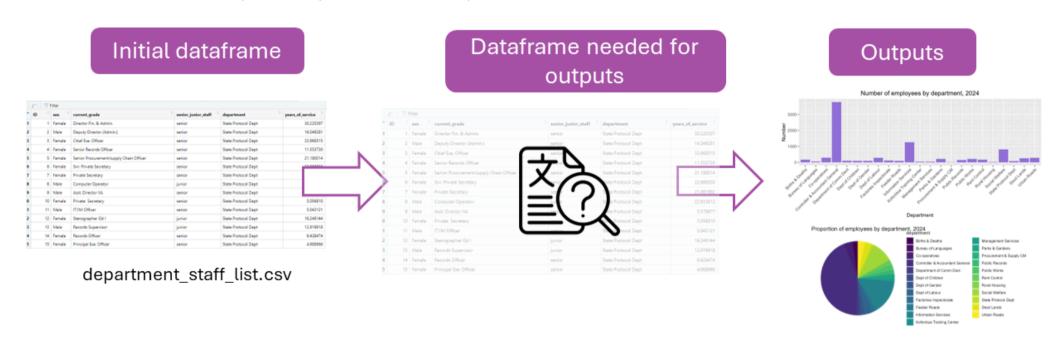
Getting your data ready

- Data is rarely in a format where it can be converted in an output right away
- In statistical programming, the process of transforming data into a condition where it's ready to be converted into an output is called **data wrangling**



Getting your data ready

- Data wrangling is one of the most crucial and time-consuming aspects of analytics
- It involves not only coding, but also the mental exercise of thinking what is the shape and condition that your dataframe needs to have in order to produce your desired output



Getting your data ready

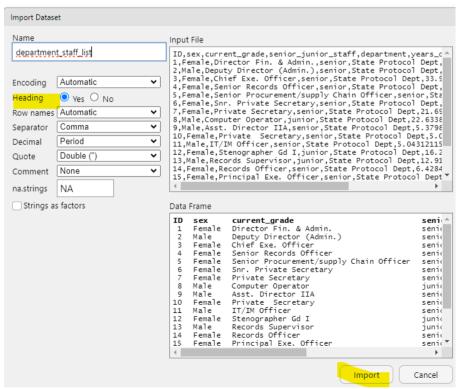
- As we said before we'll use **dplyr** for data wrangling in this training
- You can also use basic R, but we recommend these packages because its functions are easier to use

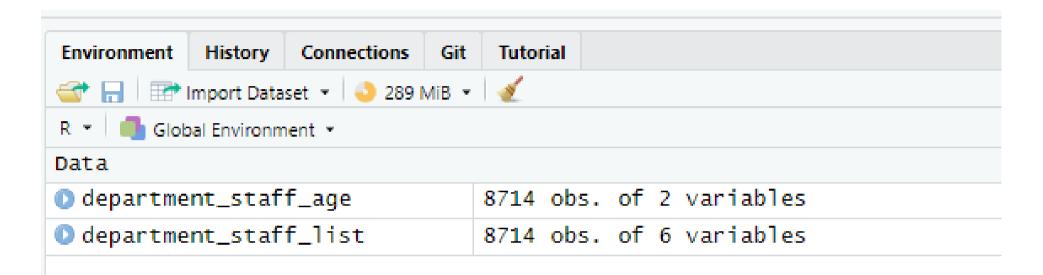


Exercise 3: Loading data

Note that this part of this is the same exercise we did in session 1, but it's okay to repeat it in order to start using a new RStudio session. If you have RStudio open, start by closing the window and opening RStudio again.

- 1. Inyou new RStudio window, go to File > Import
 Dataset > From Text(base) and select again the file
 department_staff_list.csv
 - if you don't know where the file is, check in the
 Downloads folder
 - if you need to download it again, it's here: https://osf.io/chdgj
- 2. Make sure to select **Heading** > **Yes** in the next window
- 3. Select Import
- 4. Download this new file department_staff_age.csv:
 https://osf.io/qsmke and repeat steps 1-3 with it





Note: loading data with a function

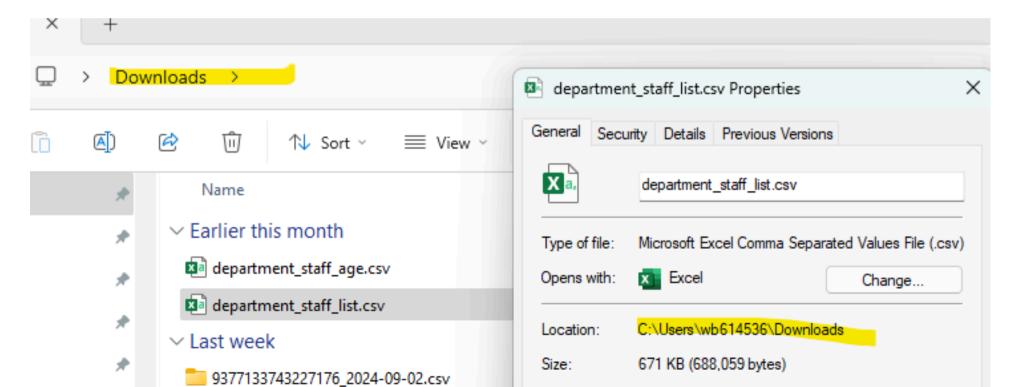
- You can also load csv files with the function read.csv() instead of using this point-and-click approach
- The **argument** of read.csv() is the path in your computer where your data is. For example

```
department_staff_list <-read.csv("C:/Users/wb614536/Downloads/department_staff_list.csv")</pre>
```

• As usual, you need to save the result of read.csv() into a dataframe object with the arrow operator (<-) for it to be stored in the environment

Note on file paths

- A file path tells R where to find your file on your computer. It is like giving R the directions to your file.
- If you downloaded the data and haven't moved it, the data path for the department_list dataset will be probably something like: "C:/Users/wb614536/Downloads/department_staff_list.csv"
- You can find the path of a file by right-clicking>properties>and seeing the location, or by clicking on the top bar (see below)



Recap: knowing your data

• Dataframe department_staff_list is the same dataframe we used last session that contains the data from your department.

Recap: knowing your data

• Now we are introducing a second dataset that only has the ID number (one that I invented), and the age of that person.

```
glimpse(department_staff_age)

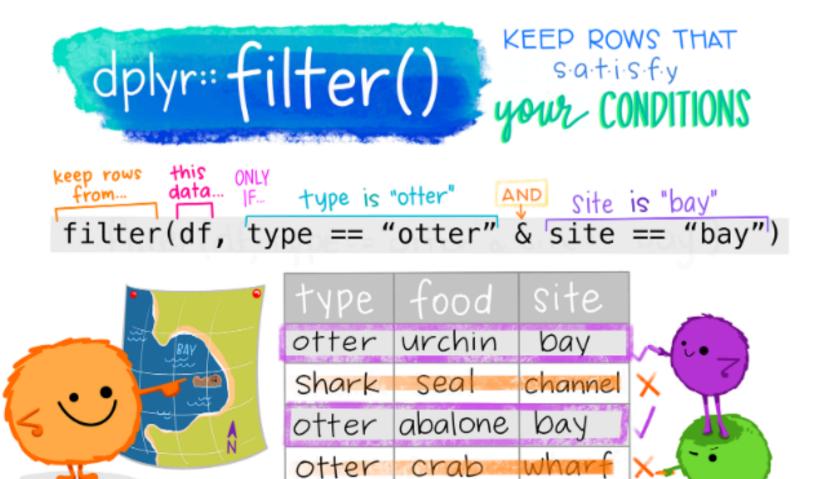
## Rows: 8,714

## Columns: 2

## $ ID <int> 8603, 3695, 5563, 3529, 5032, 4391, 3069, 6048, 4680, 8551, 5107, ...
```

\$ age <dbl> 18.00442, 18.00657, 18.00669, 18.00874, 18.01030, 18.01677, 18.018...

- We will only use this second dataframe in one of the next exercises, but we load it now because it's in general a good practice to have data loaded into the memory so it's ready to be used.
- For the next exercises, we will propose scenarios that could show up while doing your annual reports or in day-to-day operations.
- We will do everything using **functions** from the dplyr package, that is already in our environment.



Government analytics request

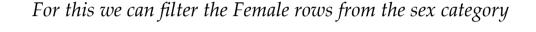
We will use the data from our dataframe department_staff_list

exercises-session2.R* × department_staff_list × ID current grade sex Director Fin. & Admin. Female 2 2 Male Deputy Director (Admin.) Chief Exe. Officer 3 Female Senior Records Officer Female 5 Female Senior Procurement/supply Snr. Private Secretary 6 Female 7 Female Private Secretary 8 Male Computer Operator 9 Male Asst. Director IIA 10 10 Female Private Secretary IT/IM Officer 11 11 Male

Female

Stenographer Gd I

12





Government analytics request

Now let's say that we are also interested at a first glance of the females that recently joined the department. We would have to do the following

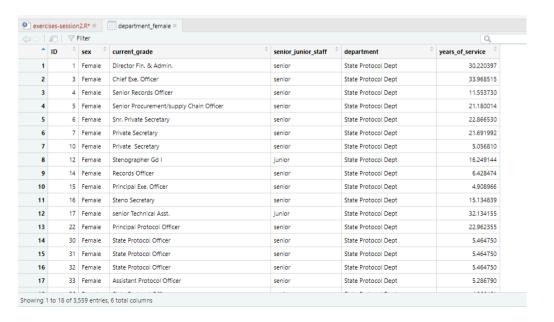
- 1. Keeping only the female employees
- 2. Sorting by years of service
- In Excel: We would filter and then use arrange by years of service.

1. Keeping only the female employees

```
Use filter() for this:
```

Remember how we use functions in this case 1st argument is **data**, second argument is **filter** (sex takes the value female in this case)

```
temp1 <- filter(department_staff_list, sex == "Female")</pre>
```



2. Sorting by years of service

Use the function <code>arrange()</code> to sort. Sortings are ascending by default in R (this will get us from less years of service to more years of service).

department_female <- arrange(temp1, years_of_service) # arrange by years of service</pre>

exerc	ises-session	12.R* ×	department_female ×			
	@ TI	Filter				
^	ID [‡]	sex ÷	current_grade	senior_junior_staff	department	years_of_service
1	5003	Female	Records Supervisor	junior	Public Records	0.9171800
2	6497	Female	Asst. Prog Officer	senior	Dept of Gender	0.9527721
3	4969	Female	Assistant Internal Auditor	senior	Public Records	0.9993155
4	201	Female	PRINCIPAL.ACCOUNTS TECHNICIANCAGD	senior	Controller & Accountant General	1.1334702
5	232	Female	ASSISTANT.ACCOUNTANTCAGD	senior	Controller & Accountant General	1.1498973
6	7555	Female	Assistant Information Officer	senior	Information Services	1.1608487
7	8568	Female	Assistant Information Officer	senior	Information Services	1.1854894
8	4890	Female	Procurement & Supply Chain Manager	senior	Procurement & Supply CM	1.1882272
9	8566	Female	Assistant Information Officer	senior	Information Services	1.1882272
10	8569	Female	Assistant Information Officer	senior	Information Services	1.1882272
11	8570	Female	Assistant Information Officer	senior	Information Services	1.1882272
12	8572	Female	Assistant Information Officer	senior	Information Services	1.1909651
13	8565	Female	Assistant Information Officer	senior	Information Services	1.2019165
14	7549	Female	Senior Information Assistant	junior	Information Services	1.2238193
15	3020	Female	ASSISTANT.ACCOUNTANTCAGD	senior	Controller & Accountant General	1,2429843

Exercise 4: Now let's do it.. filter and sort your data

We can write the whole code for this in our exercise script. (You can copy and paste the code below)

```
1.- Filter by Female:
```

2.- Sort by years_of_service:

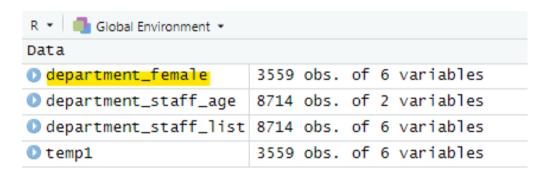
```
temp1 <- filter(department_staff_list, sex == "Female") # filter by female
department_female <- arrange(temp1, years_of_service) # order by years of service</pre>
```

Some notes:

- filter() and arrange() are all functions from dplyr.

 Remember you have to always load dplyr first with

 library(dplyr) to be able to use them
- The resulting dataframe is **department_female** (and we also have **temp1**)



- Filtering and sorting are two very common data wrangling operations in statistical programming
- Now we'll review a new data wrangling operation that is also quite common and useful: **mutate**, which basically means creating new variables

Mutate

Mutate

• mutate will take a statement like this:

```
mutate(variable_name = some_calculation)
```

• And attach variable_name at the end of the dataset.



Mutate

Example

Using our data frame let's say that we want to include a variable that instead of years of service we want days of service. We would do this by doing the following:

```
example_mutate <- mutate(department_staff_list, days_of_service = years_of_service*365)</pre>
```

We will not use that variable for our government analytics examples, but this is a really useful data wrangling function.

Questions?

Merging data is a common task in data analysis, especially when working with data from multiple departments.

Let's see how it would apply to our dataframes.

Government analytics request

Scenario 2:

Let's imagine that for our annual report we are also interested in the age distribution from the employees but these are in different datasets

Government analytics request

Use the data <code>department_staff_list</code> that you already know with the department_staff_age

We want to include the age variable to our dataframe

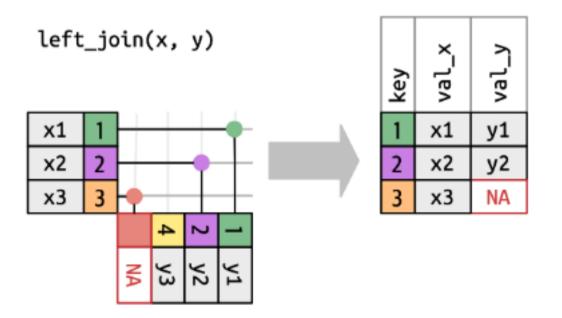
9	÷ ÷	surrent arada	conies iunies stres	donortment ÷	ware of consist
,	sex	current_grade	senior_junior_staff	department	years_of_service
	Female	Director Fin. & Admin.	senior	State Protocol Dept	30.220397
2	Male	Deputy Director (Admin.)	senior	State Protocol Dept	16.049281
	Female	Chief Exe. Officer	senior	State Protocol Dept	33.968515
4	Female	Senior Records Officer	senior	State Protocol Dept	11.553730
	Female	Senior Procurement/supply Chain Officer	senior	State Protocol Dept	21.180014
(Female	Snr. Private Secretary	senior	State Protocol Dept	22.866530
7	7 Female	Private Secretary	senior	State Protocol Dept	21.691992
8	Male	Computer Operator	junior	State Protocol Dept	22.633812
9	Male	Asst. Director IIA	senior	State Protocol Dept	5.37987
10	Female	Private Secretary	senior	State Protocol Dept	5.05681
11	Male	IT/IM Officer	senior	State Protocol Dept	5.043121
12	Female	Stenographer Gd I	junior	State Protocol Dept	16.24914
13	Male	Records Supervisor	junior	State Protocol Dept	12.91991
14	Female	Records Officer	senior	State Protocol Dept	6.428474
15	Female	Principal Exe. Officer	senior	State Protocol Dept	4,90896
16	Female	Steno Secretary	senior	State Protocol Dept	15.13483



To do this we will use left_join() to merge the dataframes:

• The arguments of the function are 1. the "principal" dataset and 2. the dataframe we want to merge (paste) into that one

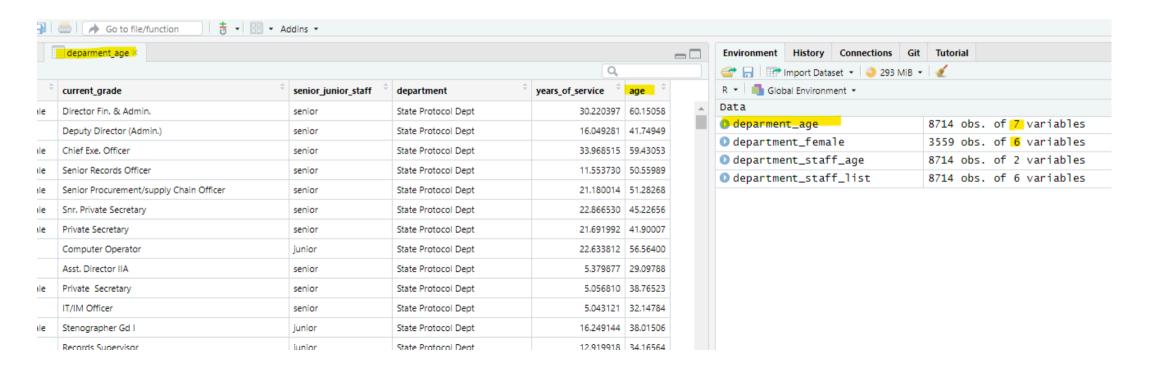
department_age <- left_join(department_staff_list, department_staff_age) # Our original data frame</pre>



Exercise 5: Now let's do it.

• You can copy and paste the code to your exercise script.

deparment_age <- left_join(deparment_staff_list, department_staff_age) # Our original data frame</pre>

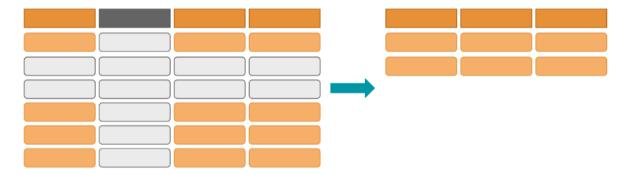


group_by() and summarize()

We use this when we want to aggregate your data (by groups).

This is one of the most commons operations. Sometimes we want to calculate statistics by groups





Grouping and summarizing

Government analytics request

Let's say that we are interested again in the number of employees by department

We will use our department_staff_list dataset to do this.

1. The first step is to define the group, in this case **department**

```
employees_by_department <- group_by(department_staff_list, department)</pre>
```

If we **only** do this, this won't do anything, to complete the function we need to use this with summarise()

Grouping and summarizing

Exercise 6: Government analytics request

summarize works in a similar way to mutate:

```
variable_name = some_calculation
```

In this case the some_calculation will be to count the number of employees

```
temp1 <- group_by(department_staff_list, department)
employees_by_department <- summarise(temp1, number = n())</pre>
```

Grouping and summarizing

Government analytics request

This will create the following dataframe/table:

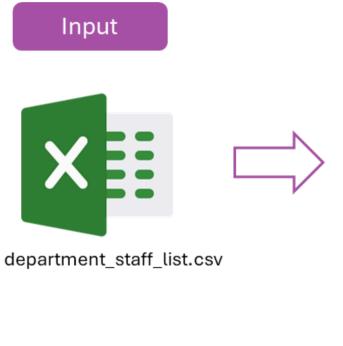
```
## # A tibble: 23 × 2
##
      department
                                       numher
##
      <chr>
                                        <int>
   1 Births & Deaths
                                          172
                                           58
   2 Bureau of Languages
    3 Co-operatives
                                          293
    4 Controller & Accountant General
                                         3776
    5 Department of Comm Devt
                                          109
##
   6 Dept of Children
                                          101
    7 Dept of Gender
                                          100
   8 Dept of Labour
                                          290
    9 Factories Inspectorate
                                          121
## 10 Feeder Roads
                                          102
## # i 13 more rows
```

More wrangling operations

These were two examples we chose to show different possible data wrangling operations. A summary of these and other common operations are:

Operation	Function in dplyr	
Subset columns	select()	
Subset rows (based on condition)	filter()	
Create new columns	<pre>mutate()</pre>	
Create new columns based on condition	<pre>mutate() and case_when()</pre>	
Create new rows	add_row()	
Merge dataframes	<pre>inner_join(), left_join(), right_join(), full_join()</pre>	
Append dataframes	bind_rows()	
Deduplicate	<pre>distinct()</pre>	
Collapse and create summary indicators	<pre>group_by(), summarize()</pre>	
Pass a result as the first argument for the next function	%>% (operator, not function (tomorrow))	

- Until now, we've seen full examples of part 1 and 2 of the Government analytics pipeline
- What about exporting outputs?





Data process

Instructions

- 1. Read data
- 2. Select columns
- 3. Sort
- 4. Filter rows
- 5. Create averages
- 6. Produce dataframe

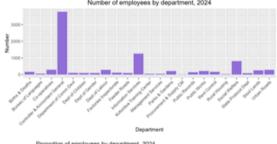


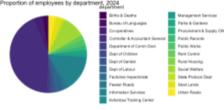




employees_ by_departme nt.csv

Output







Exporting dataframes

- We can export it as a csv file with the function write.csv()
- write.csv() creates a csv file with the dataframe
- It takes two basic arguments:
 - 1. The name of the object you want to export
 - 2. A file path to export the object to

Exercise 7 (if time allows): Export employees_by_deparment and

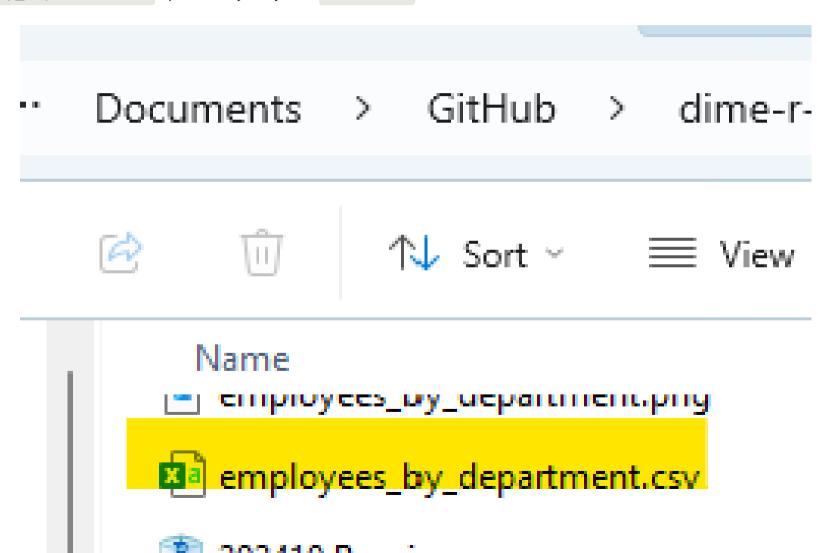
```
department_staff_final
```

1. Use this code to export the results of the last two exercises:

```
write.csv(employees_by_department, "employees_by_department", row.names = FALSE)
write.csv(department_age, "department_staff_final", row.names = FALSE)
```

Note: This files are already in our data folder online, so if you don't have time to do it don't worry.

Now employees_by_deparment.csv (probably in your Documents folder).



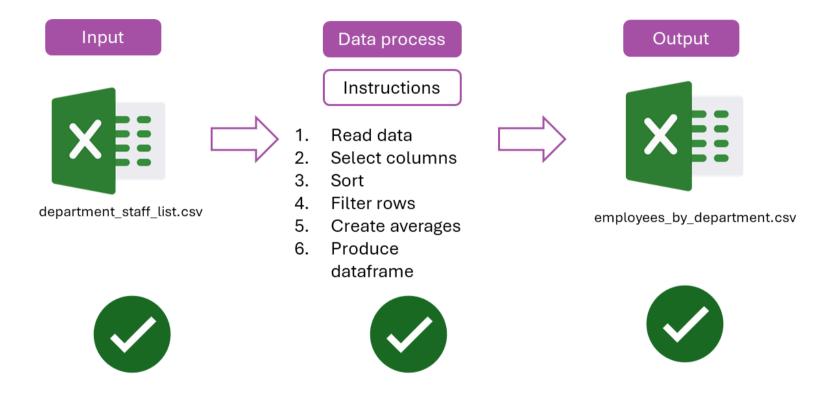
Some notes on file paths

• The second argument of write.csv() specifies the file path we export the dataframe to

```
write.csv(employees_by_department, "employees_by_department", row.names = FALSE)
```

- You can include any path in your computer and R will write the file in that location
 - For example: "C:/Users/wb614536/OneDrive WBG/Desktop" exports the file to the desktop of my computer (this will not work in other computers)
 - Note that file paths in R use forward slashes (/). Back slashes (\) do not work in R

Our data pipeline has been fully implemented at this point. Great!

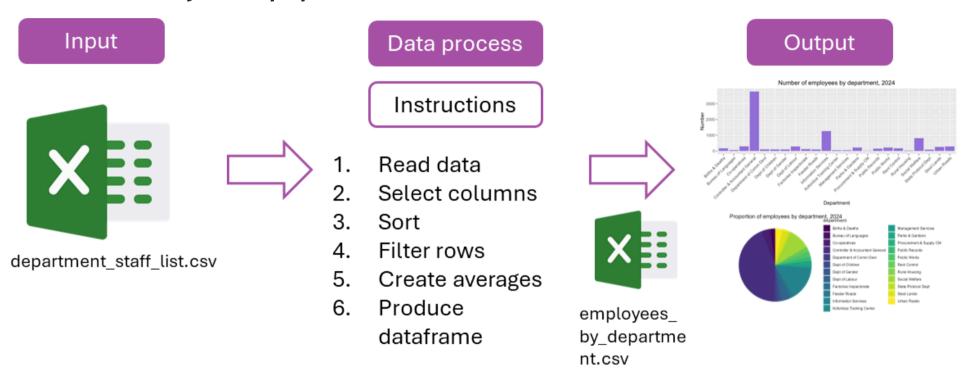


Don't forget to save your work!

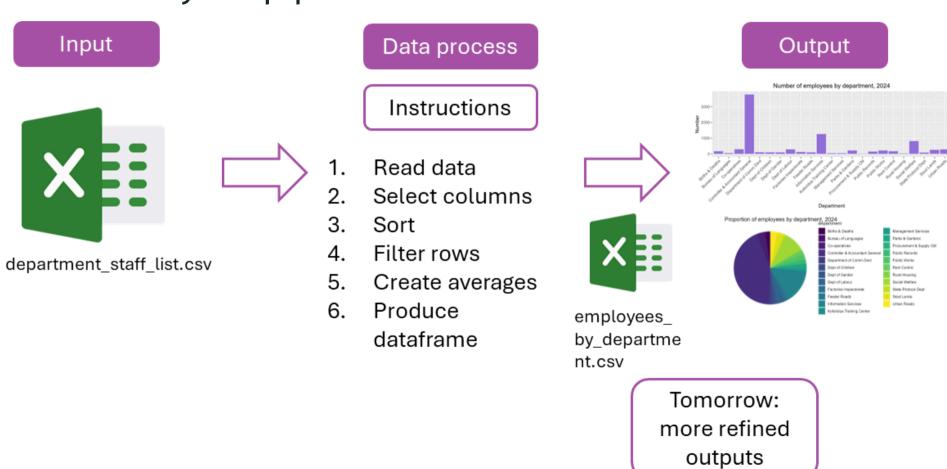
- If you haven't, add code comments with # to differentiate your solutions for each exercise
- Click the floppy disk to save your work
- Make sure to remember where you're saving your file

```
2024-10 - prancn_review_gnana - KStudio Source Editor
exercises-session2.R* ×
          ☐ Source on Save Q ※ • [
     # Exercise 2: Install needed packages (for this session only dplyr and tidyr
     # Exercise 3: load libraries
     library(dplyr)
     library(tidyr)
     # Exercise 4: load data
     department_staff_list <- read.csv("data/department_staff_list.csv")</pre>
     department_staff_age <- read.csv("data/department_staff_age.csv")</pre>
 13
     # you can also to it using our point and click method.
 15
     # Exercise 5: filter and sorting
 17
     # step 1 filter
     temp1 <- filter(department_staff_list, sex == "Female")</pre>
 20
     # step 2 sort (arrange)
    department_female <- arrange(temp1, years_of_service)</pre>
     # order by years of service
 25 # Evercice 6: join datacete
```

Government analytics pipeline



Government analytics pipeline



Thanks! // ¡Gracias! // Obrigado!



Appendix

Appendix

Keeping only relevant columns

Imaging I only want a list with ID and department.

Use select() for this:

```
temp1 <- select(department_staff_list, ID, department)</pre>
```

Appendix

Calculating aggregated columns: total and average income

```
Use summarize() combined with sum() and mean():
```

For our current data this does not apply, but this will be really useful for budget dataframes.

This would look something like this

Useful links

- R for Data Science by Hadley Wickham and Garrett Grolemund
 - Comprehensive introduction to data wrangling and visualization.
 - Read it online for free.

• Tidyverse Cookbook

- Practical solutions for common data wrangling tasks.
- Tidyverse Cookbook GitHub.

• Tidyverse Cheat Sheets

- Official cheat sheets for dplyr, tidyr, and other Tidyverse packages.
- Tidyverse Resources.