

Basic Data Wrangling & Exploration, ft. Tidyverse

Kursus R: Pengenalan dan Praktikal

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Packages

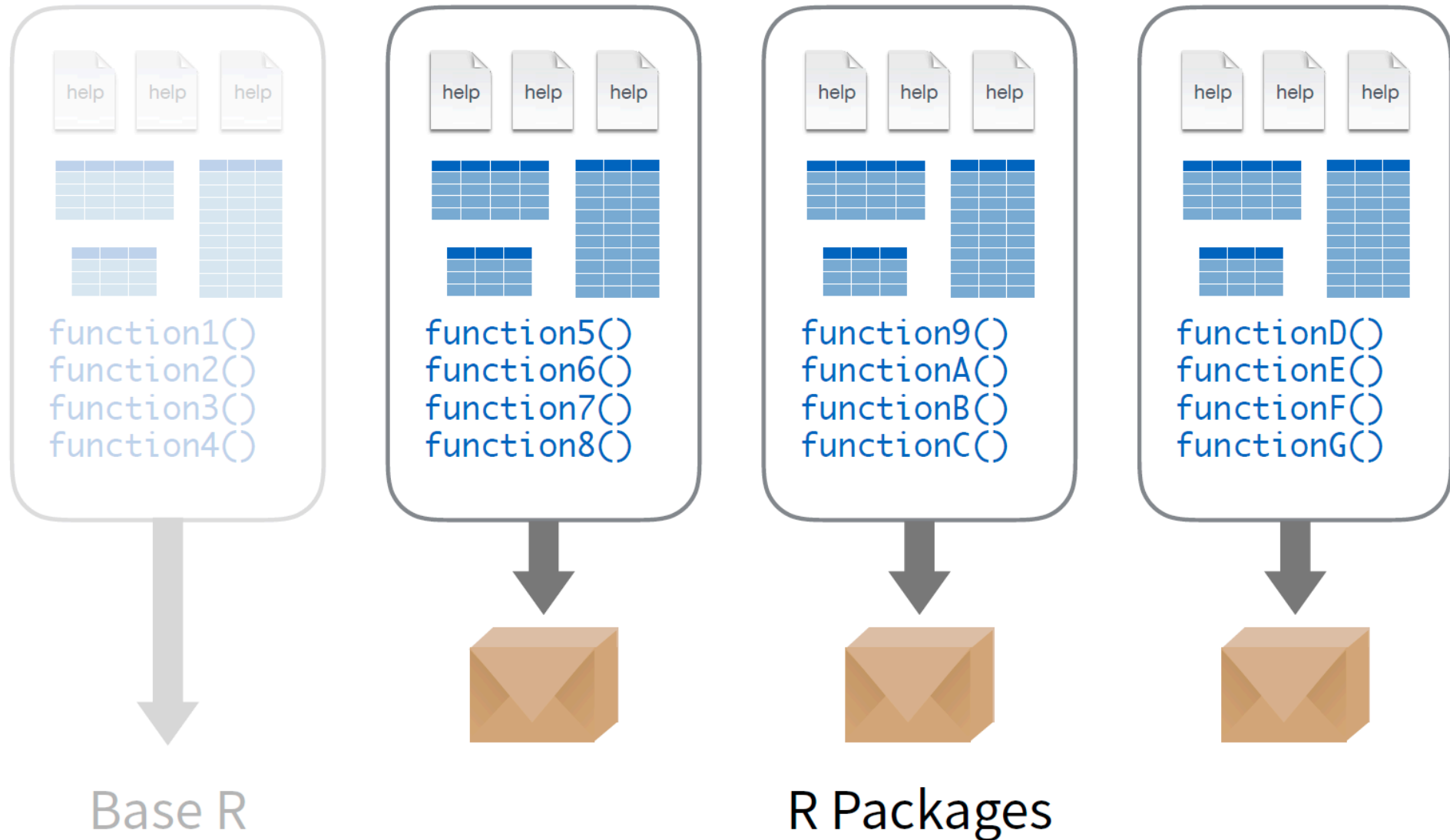
Packages in R

- The strength of R is its open-source philosophy
- When installing R, you get a basic set of packages
- Package in R is a collection of functions, data, and compiled code
- R allow for custom function, and even custom package
- The custom package can be shared with others, e.g., via CRAN
- These custom packages enriched the R ecosystem

Packages in R



Packages in R



Packages in R

- Among common packages in R

Package	Description
tidyverse	collection of packages designed for data science
haven	import/export SPSS, Stata and SAS files
readxl	import/export excel files
lubridate	work with date and time
ggplot2	data visualisation
dplyr	data manipulation
stringr	string manipulation
forcats	factor manipulation

Packages in R

- Install once
 - using `install.packages("package_name")`
 - can also click on `install` button at **Packages** pane
- Load every time you use R
 - using `library(package_name)`
 - can also tick at respective library at **Packages** pane

Packages in R

- Lets try install **tibble** package using code

```
1 install.packages("tibble")
```

- Then load the package using code

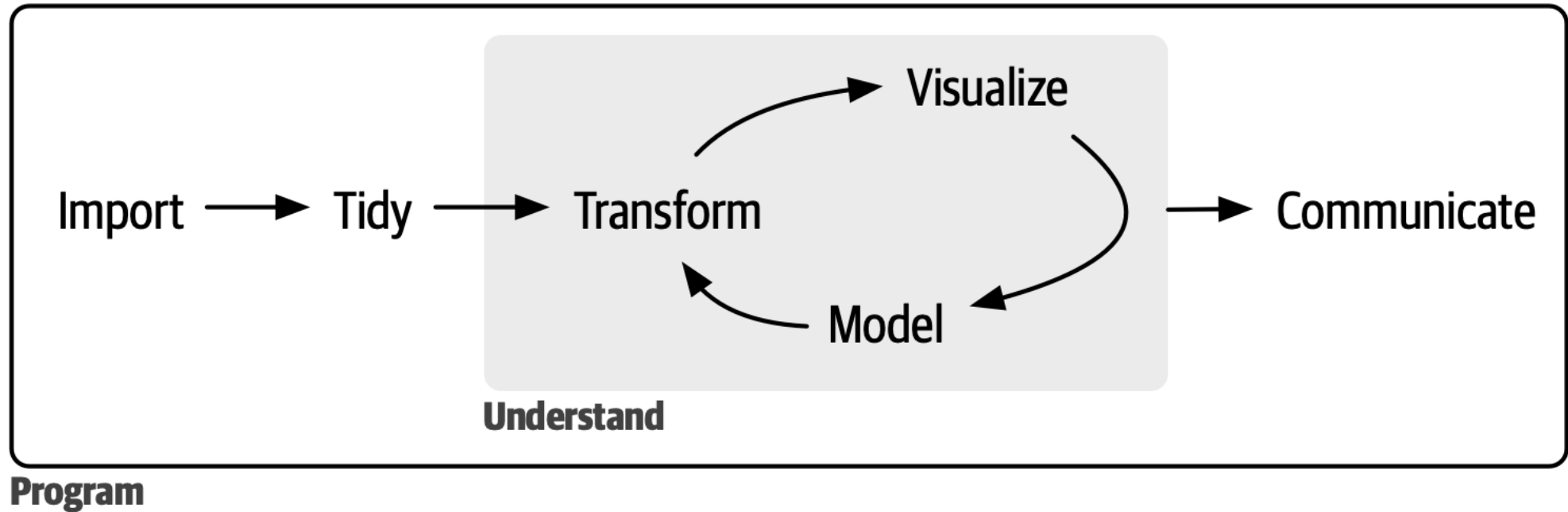
```
1 library(tibble)
```


Can you try install **tidyverse** package?

Data Wrangling

What is data wrangling?

- Common data analysis look like this



source: r4ds.hadley.nz

What is data wrangling?

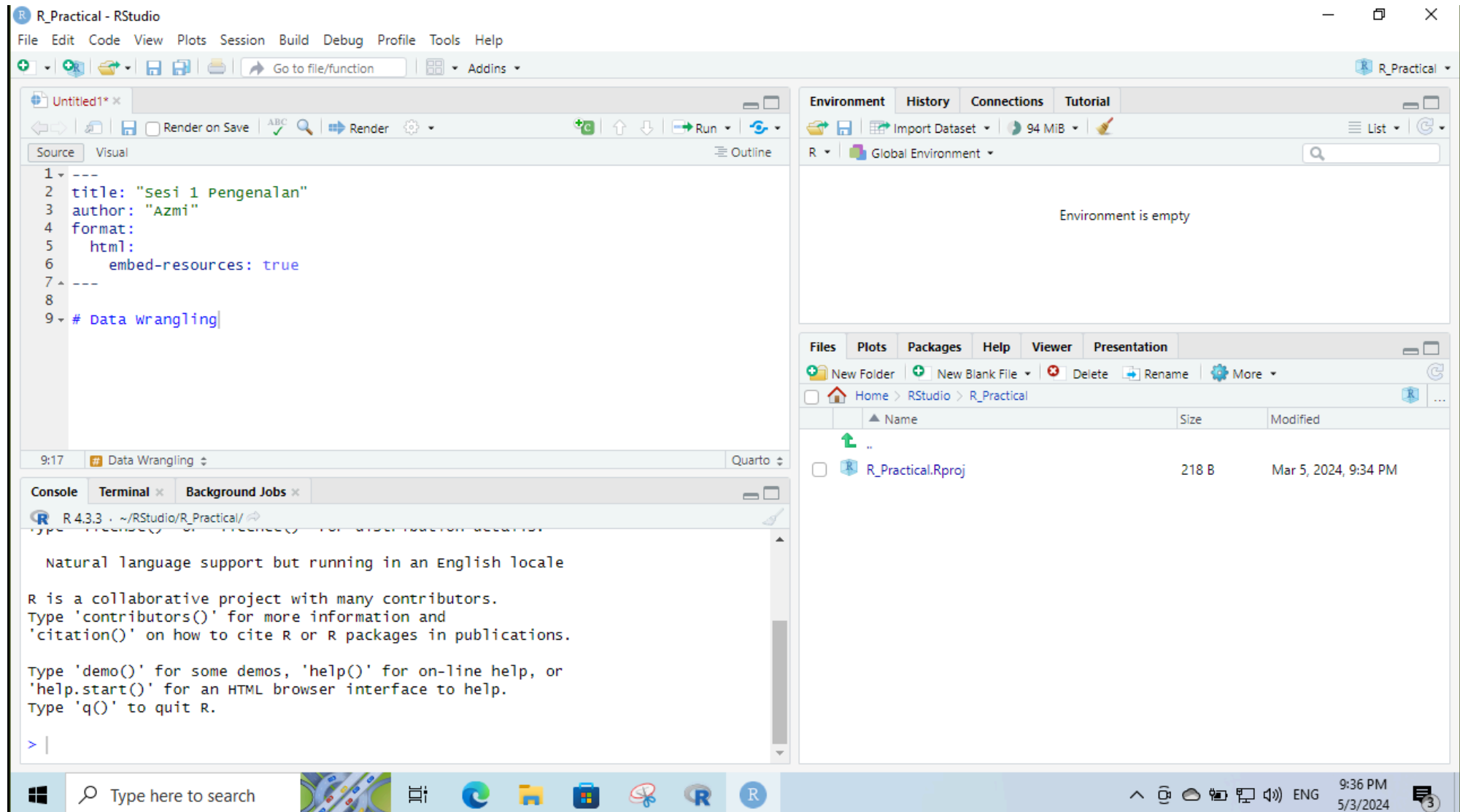
- real world data commonly messy!
- 80% of time taken spend on data cleaning
- improving data quality > improving the accuracy & efficiency
- data wrangling involving **tidying** and **transforming** data, from raw form to analysis-ready data.
- common data wrangling action
 - label data
 - recategorise categorical variable - usually collapsing groups
 - binning continuous variable

Lets try some data wrangling

Setup your project

- We will use
 - current project **R_Practical**
 - current Quarto document **Sesi 1 Pengenalan**
- Add new level 1 header
 - Single # symbol
 - Followed by the title **Data Wrangling**

Setup your project

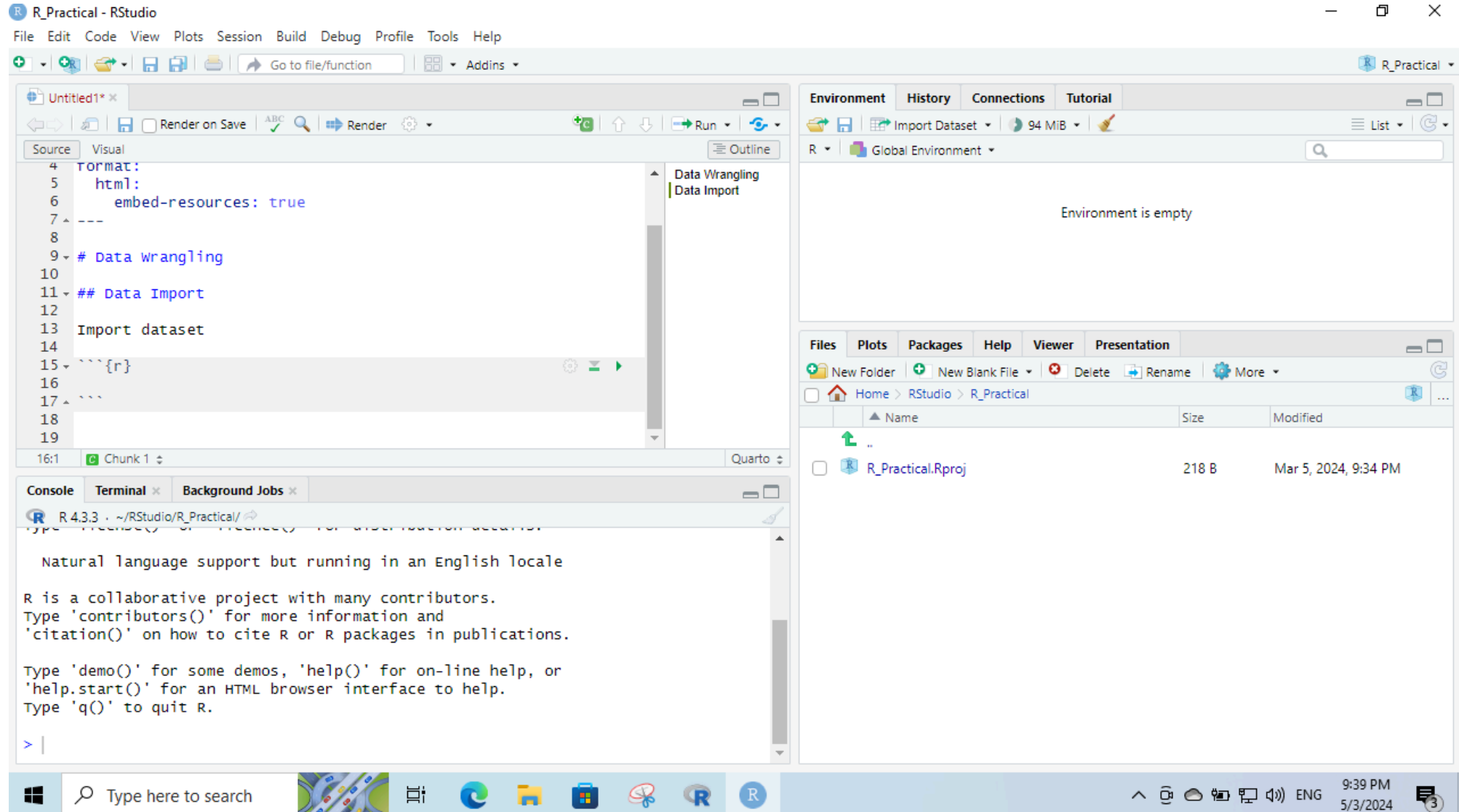


Import Dataset

Import Dataset

- We will use the `asthma_ds.sav` dataset (SPSS file)
- Copy the dataset to the `R_Practical` project folder (working directory)
- Add new level 2 header
 - Double `##` symbol
 - Followed by the title `Import Dataset`
- Insert new R code chunk

Import Dataset



The screenshot displays the RStudio interface with a Quarto document open. The document is titled "Untitled1" and contains the following code:

```
format:
  html:
    embed-resources: true
---
# Data Wrangling
## Data Import
Import dataset
```{r}```
```

The Environment pane on the right shows "Global Environment" and "Environment is empty". The Files pane on the right shows the project structure:

Name	Size	Modified
..		
R_Practical.Rproj	218 B	Mar 5, 2024, 9:34 PM

The Console pane at the bottom shows the R startup message:

```
R 4.3.3 ~ /RStudio/R_Practical/
Natural language support but running in an English locale
R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.
Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.
> |
```

# Import Dataset

- We will use the `read_sav` `haven` package to import the dataset
- The dataset is stored in R object `asthma_ds0`

```
1 library(tidyverse)
2 library(haven)
3
4 asthma_ds0 <- read_sav("Dataset/asthma_ds.sav")
```

# Import Dataset

- We can view the dataset by writing the object name

```
1 asthma_ds0
```

```
A tibble: 150 × 16
```

	id	idR	Gender	Age	WorkStatus	Height	Weight_Pre	PA_HW	Weight_Post
	<dbl>	<chr>	<dbl+lbl>	<dbl>	<dbl+lbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	1	nXSw	2 [Female]	34	2 [Unemploy...	179	84.2	5	76.7
2	2	yg2t	1 [Male]	31	2 [Unemploy...	169	81.8	1	75.7
3	3	QBW4	1 [Male]	25	1 [Employed]	164	88.5	1	84.1
4	4	2x2S	2 [Female]	33	2 [Unemploy...	136	53.2	4	46.9
5	5	mOnn	1 [Male]	28	2 [Unemploy...	172	71.3	2	63.3
6	6	D3sl	1 [Male]	33	2 [Unemploy...	178	87.3	0	82.6
7	7	le6j	2 [Female]	31	2 [Unemploy...	140	48.8	5	41.9
8	8	r3gC	2 [Female]	34	1 [Employed]	140	49.1	2	43.6
9	9	3Tyt	1 [Male]	31	1 [Employed]	171	60.1	1	54.7
10	10	cmKF	1 [Male]	28	1 [Employed]	163	93.1	1	86.2

```
i 140 more rows
```

```
i 7 more variables: Tx2 <dbl+lbl>, PEFr_Pre <dbl>, PEFr_Post <dbl>,
SxWheeze_Pre <dbl+lbl>, SxWheeze_Post <dbl+lbl>, PS_Pre <dbl>,
PS_Post <dbl>
```

# Import Dataset

- We can also use **View** function (capital V)

```
1 View(asthma_ds0)
```

# Import Dataset

- In this dataset, we can notice that the **Gender** variable is coded as **1** and **2**, with label **Male** and **Female** respectively.
- Similar to other factor (categorical) variables in this dataset.
- This is common in SPSS dataset, where the label is stored separately from the data.
- We can use **as\_factor** function to convert the variable to factor, and apply the label to the factor.

```
1 asthma_ds <- as_factor(asthma_ds0)
```

# Import Dataset

```
1 head(asthma_ds)
```

```
A tibble: 6 × 16
 id idR Gender Age WorkStatus Height Weight_Pre PA_HW Weight_Post Tx2
 <dbl> <chr> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <fct>
1 1 nXSw Female 34 Unemployed 179 84.2 5 76.7 Drug B
2 2 yg2t Male 31 Unemployed 169 81.8 1 75.7 Place...
3 3 QBW4 Male 25 Employed 164 88.5 1 84.1 Drug B
4 4 2x2S Female 33 Unemployed 136 53.2 4 46.9 Drug A
5 5 mOnn Male 28 Unemployed 172 71.3 2 63.3 Place...
6 6 D3sl Male 33 Unemployed 178 87.3 0 82.6 Drug A
i 6 more variables: PEFr_Pre <dbl>, PEFr_Post <dbl>, SxWheeze_Pre <fct>,
SxWheeze_Post <fct>, PS_Pre <dbl>, PS_Post <dbl>
```

# Simple Data Wrangling



# Select Variable/Column

- We can select variable/column using **select** function
- We can use **:** to select range of variable

```
1 asthma_ds1 <- select(asthma_ds, idR:Weight_Post)
2
3 head(asthma_ds1)
```

```
A tibble: 6 × 8
```

	idR	Gender	Age	WorkStatus	Height	Weight_Pre	PA_HW	Weight_Post
	<chr>	<fct>	<dbl>	<fct>	<dbl>	<dbl>	<dbl>	<dbl>
1	nXSw	Female	34	Unemployed	179	84.2	5	76.7
2	yg2t	Male	31	Unemployed	169	81.8	1	75.7
3	QBW4	Male	25	Employed	164	88.5	1	84.1
4	2x2S	Female	33	Unemployed	136	53.2	4	46.9
5	mOnn	Male	28	Unemployed	172	71.3	2	63.3
6	D3sl	Male	33	Unemployed	178	87.3	0	82.6

# Arithmetic Transformation

- We can perform arithmetic transformation using `mutate` function
  - For example, we can calculate BMI using `Weight_Pre` and `Height` variable

```
1 asthma_ds2 <- asthma_ds1
2 asthma_ds2$Ht_m <- asthma_ds2$Height/100
3 asthma_ds2$BMI_Pre <- asthma_ds2$Weight_Pre/(asthma_ds2$Ht_m^2)
4
5 head(asthma_ds2)
```

```
A tibble: 6 × 10
 idR Gender Age WorkStatus Height Weight_Pre PA_HW Weight_Post Ht_m
<chr> <fct> <dbl> <fct> <dbl> <dbl> <dbl> <dbl> <dbl>
1 nXSw Female 34 Unemployed 179 84.2 5 76.7 1.79
2 yg2t Male 31 Unemployed 169 81.8 1 75.7 1.69
3 QBW4 Male 25 Employed 164 88.5 1 84.1 1.64
4 2x2S Female 33 Unemployed 136 53.2 4 46.9 1.36
5 mOnn Male 28 Unemployed 172 71.3 2 63.3 1.72
6 D3sl Male 33 Unemployed 178 87.3 0 82.6 1.78
1 more variable: BMI_Pre <dbl>
```

# Binning Continuous Variable

- We can bin continuous variable using `cut` function
  - For example, we can bin `BMI_Pre` variable into 4 categories

BMI Category	BMI Range
Underweight	$\leq 18.49$
Normal	18.50 - 22.99
Overweight	23.00 - 24.99
Obese	$\geq 25.00$

# Binning Continuous Variable

- For example, we can bin **BMI\_Pre** variable into 4 categories

```
1 asthma_ds3 <- asthma_ds2
2 asthma_ds3$BMI_PreCat <- cut(asthma_ds3$BMI_Pre,
3 breaks = c(0, 18.49, 22.99, 24.99, 100),
4 labels = c("Underweight", "Normal",
5 "Overweight", "Obese"))
6
7 head(asthma_ds3)
```

```
A tibble: 6 × 11
```

	idR	Gender	Age	WorkStatus	Height	Weight_Pre	PA_HW	Weight_Post	Ht_m
	<chr>	<fct>	<dbl>	<fct>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	nXSw	Female	34	Unemployed	179	84.2	5	76.7	1.79
2	yg2t	Male	31	Unemployed	169	81.8	1	75.7	1.69
3	QBW4	Male	25	Employed	164	88.5	1	84.1	1.64
4	2x2S	Female	33	Unemployed	136	53.2	4	46.9	1.36
5	mOnn	Male	28	Unemployed	172	71.3	2	63.3	1.72
6	D3sl	Male	33	Unemployed	178	87.3	0	82.6	1.78

```
i 2 more variables: BMI_Pre <dbl>, BMI_PreCat <fct>
```

# Tidyverse

# What is Tidyverse?

- Tidyverse is a collection of packages designed for data science
- The strength of Tidyverse is the **tidy** data philosophy
- Pipe operator `%>%` is the main feature of Tidyverse
- The packages are:

Package	Description
ggplot2	data visualisation
dplyr	data manipulation
tidyr	data tidying
readr	data import
purrr	functional programming

Package	Description
tibble	data structure
stringr	string manipulation
forcats	factor manipulation
broom	tidy statistical output
modelr	modelling functions

# How does tidyverse make code more readable?

- Tidyverse is designed to work together
- `mutate` function is used to create new variable
- While pipe operator `%>%` is used to chain multiple function
- These two were commonly used in Tidyverse

# mutate function

- **mutate** function is used to
  - create new variable
  - modify existing variable

```
1 asthma_ds4 <- asthma_ds1
2 asthma_ds4 <- mutate(asthma_ds4, Ht_m = Height/100)
3 head(asthma_ds4)
```

# A tibble: 6 × 9

	idR	Gender	Age	WorkStatus	Height	Weight_Pre	PA_HW	Weight_Post	Ht_m
	<chr>	<fct>	<dbl>	<fct>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	nXSw	Female	34	Unemployed	179	84.2	5	76.7	1.79
2	yg2t	Male	31	Unemployed	169	81.8	1	75.7	1.69
3	QBW4	Male	25	Employed	164	88.5	1	84.1	1.64
4	2x2S	Female	33	Unemployed	136	53.2	4	46.9	1.36
5	mOnn	Male	28	Unemployed	172	71.3	2	63.3	1.72
6	D3sl	Male	33	Unemployed	178	87.3	0	82.6	1.78



# mutate function + Pipe Operator

- We can use pipe operator `%>%` to chain multiple function

# Example of Data Wrangling **without** Pipe Operator

```
1 asthma_ds0 <- read_sav("Dataset/asthma_ds.sav")
2 asthma_ds1 <- as_factor(asthma_ds0)
3 asthma_ds2 <- select(asthma_ds1, idR:Weight_Post)
4 asthma_ds3 <- asthma_ds2
5 asthma_ds3$Ht_m <- asthma_ds3$Height/100
6 asthma_ds3$BMI_Pre <- asthma_ds3$Weight_Pre/(asthma_ds3$Ht_m^2)
7 asthma_ds3$BMI_PreCat <- cut(asthma_ds3$BMI_Pre,
8 breaks = c(0, 18.49, 22.99, 24.99, 100),
9 labels = c("Underweight", "Normal",
10 "Overweight", "Obese"))
11 head(asthma_ds3)
```

```
A tibble: 6 × 11
```

	idR	Gender	Age	WorkStatus	Height	Weight_Pre	PA_HW	Weight_Post	Ht_m
	<chr>	<fct>	<dbl>	<fct>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	nXSw	Female	34	Unemployed	179	84.2	5	76.7	1.79
2	yg2t	Male	31	Unemployed	169	81.8	1	75.7	1.69
3	QBW4	Male	25	Employed	164	88.5	1	84.1	1.64
4	2x2S	Female	33	Unemployed	136	53.2	4	46.9	1.36
5	mOnn	Male	28	Unemployed	172	71.3	2	63.3	1.72
6	D3sl	Male	33	Unemployed	178	87.3	0	82.6	1.78

```
i 2 more variables: BMI_Pre <dbl>, BMI_PreCat <fct>
```

# Example of Data Wrangling **with** Pipe Operator

```
1 asthma_ds5 <- read_sav("Dataset/asthma_ds.sav") %>%
2 as_factor() %>%
3 select(idR:Weight_Post) %>%
4 mutate(Ht_m = Height/100,
5 BMI_Pre = Weight_Pre/(Ht_m^2),
6 BMI_PreCat = cut(BMI_Pre, breaks = c(0, 18.49, 22.99, 24.99, 100),
7 labels = c("Underweight", "Normal",
8 "Overweight", "Obese")))
9
10 head(asthma_ds5)
```

# A tibble: 6 × 11

	idR	Gender	Age	WorkStatus	Height	Weight_Pre	PA_HW	Weight_Post	Ht_m
	<chr>	<fct>	<dbl>	<fct>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	nXSw	Female	34	Unemployed	179	84.2	5	76.7	1.79
2	yg2t	Male	31	Unemployed	169	81.8	1	75.7	1.69
3	QBW4	Male	25	Employed	164	88.5	1	84.1	1.64
4	2x2S	Female	33	Unemployed	136	53.2	4	46.9	1.36
5	mOnn	Male	28	Unemployed	172	71.3	2	63.3	1.72
6	D3sl	Male	33	Unemployed	178	87.3	0	82.6	1.78

# i 2 more variables: BMI\_Pre <dbl>, BMI\_PreCat <fct>

# Data Exploration with Tidyverse

# Data Exploration

- Data exploration is the first step in data analysis
- But data exploration also commonly use at various stage of data analysis

# Summary Statistics with `summarise` function

- Tidyverse provide various function to get summary statistics  
→ `summarise` function

```
1 asthma_ds5 %>%
2 summarise(Mean_Height = mean(Height),
3 SD_Height = sd(Height),
4 Min_Height = min(Height),
5 Max_Height = max(Height))
```

# A tibble: 1 × 4

	Mean_Height	SD_Height	Min_Height	Max_Height
	<dbl>	<dbl>	<dbl>	<dbl>
1	164.	15.3	129	195

# Summary Statistics with `count` function

- `count` function is used to count the frequency of each level of a factor variable

```
1 asthma_ds5 %>%
2 count(Gender)
```

```
A tibble: 2 × 2
 Gender n
 <fct> <int>
1 Male 86
2 Female 64
```

# Summary Statistics with `group_by` function

- `group_by` function is used to group the data by a factor variable

```
1 asthma_ds5 %>%
2 group_by(Gender) %>%
3 summarise(Mean_Height = mean(Height),
4 SD_Height = sd(Height),
5 Min_Height = min(Height),
6 Max_Height = max(Height))
```

# A tibble: 2 × 5

	Gender	Mean_Height	SD_Height	Min_Height	Max_Height
	<fct>	<dbl>	<dbl>	<dbl>	<dbl>
1	Male	174.	8.98	151	195
2	Female	150.	11.0	129	179



# Cross Tabulation with `table` function

- `table` function is used for crosstabulation

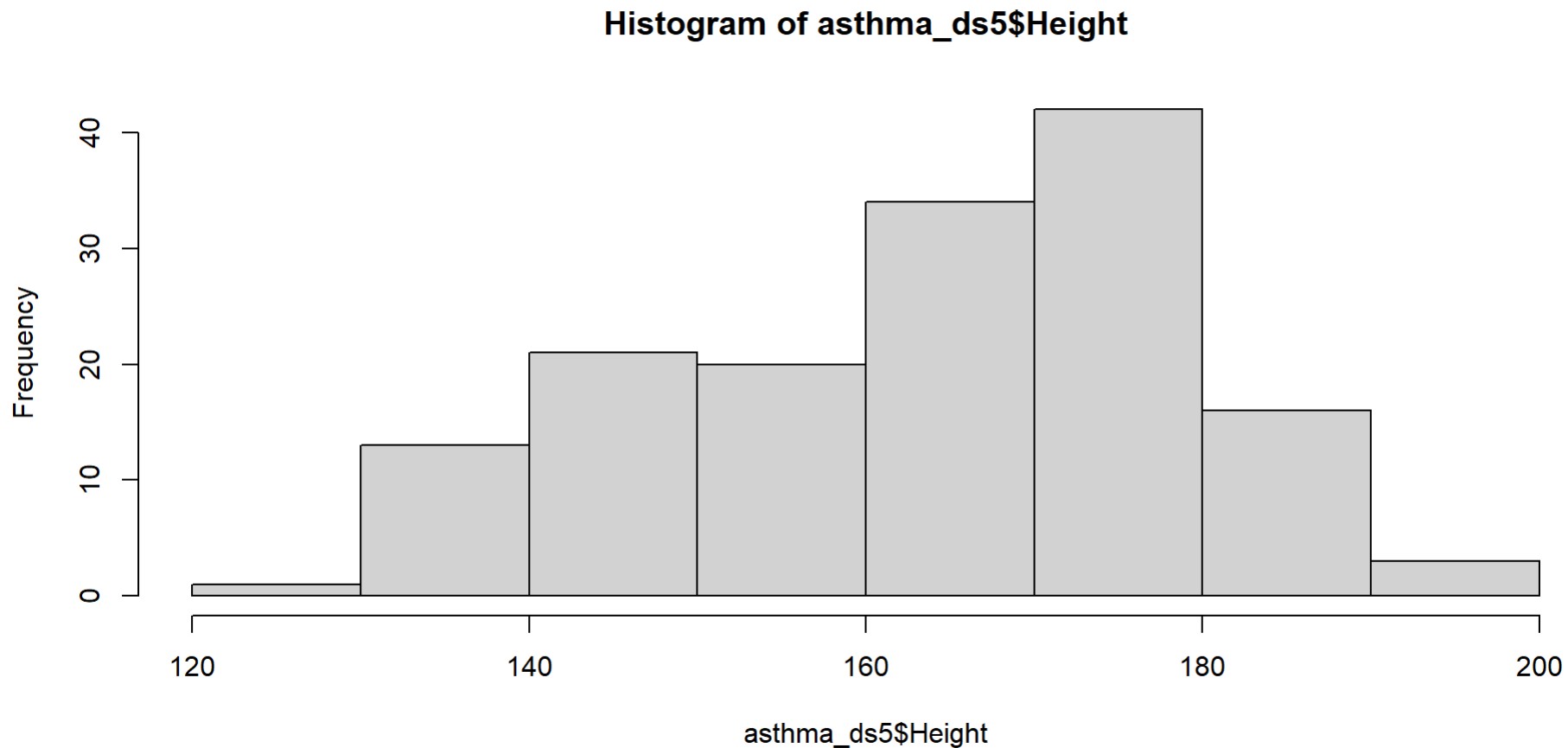
```
1 with(asthma_ds5, table(WorkStatus, Gender))
```

	Gender	
WorkStatus	Male	Female
Employed	53	17
Unemployed	33	47

# Plot: Histogram

- We can quickly plot histogram using base R function `hist`

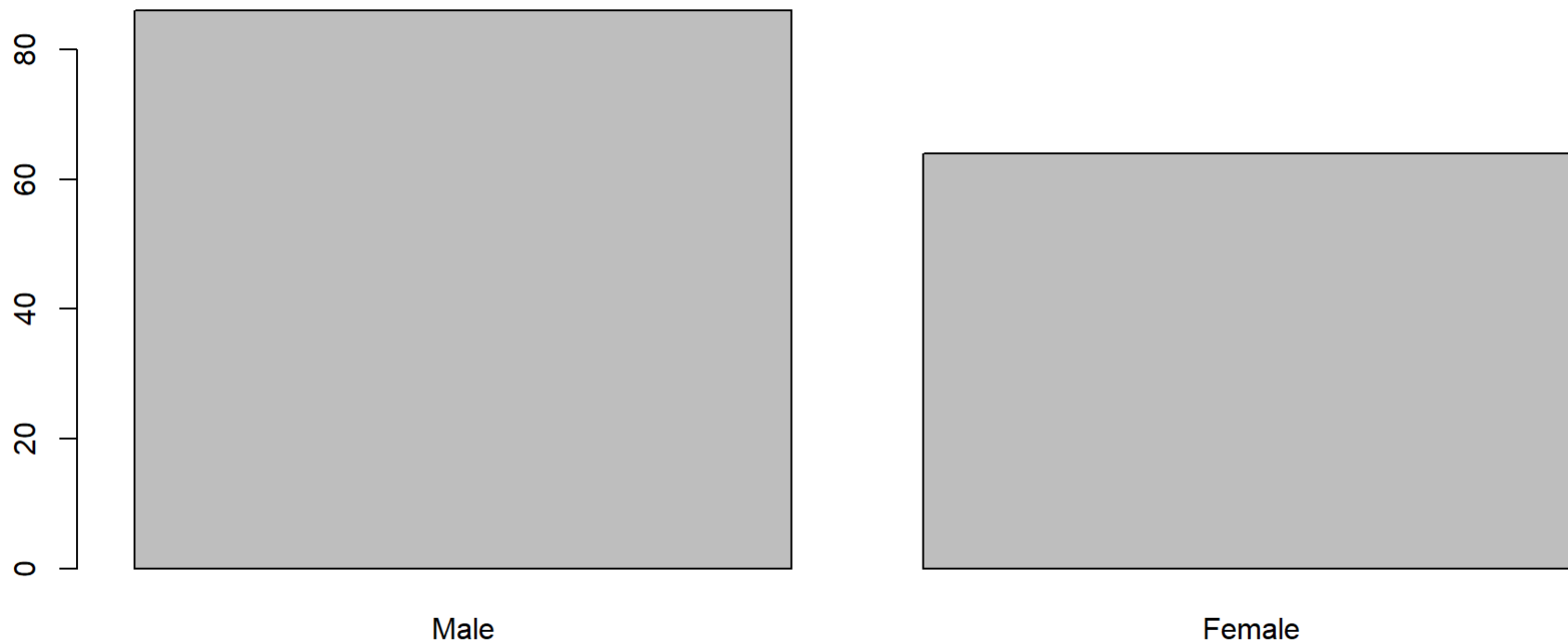
```
1 hist(asthma_ds5$Height)
```



# Plot: Bar Chart

- We can quickly plot bar chart using base R function `barplot`

```
1 barplot(table(asthma_ds5$Gender))
```



Finish! See you tomorrow~