Imports

In [1]:
```
import os
os.environ['R_HOME'] = 'C:/Users/timot/miniforge3/envs/525_2025/lib/R'
import re
import glob
import zipfile
import requests
from urllib.request import urlretrieve
import json
import pandas as pd

%load_ext rpy2.ipython
import pyarrow.dataset as ds
import pyarrow as pa
import pandas as pd
import pyarrow
from pyarrow import csv
import rpy2_arrow.pyarrow_rarrow as pyra
```

```
c:\Users\timot\miniforge3\envs\525_2025\Lib\site-packages\rpy2\robjects\packages.py:
367: UserWarning: The symbol 'quartz' is not in this R namespace/package.
  warnings.warn(
```

1) Downloading the Data

In [2]:
```
# We are downloading to the data/ folder in this repository

%mkdir data
# %cd data/
```

```
A subdirectory or file data already exists.
```

In [3]:
```
# Setting metadata for download
article_id = 14096681  # this is the unique identifier of the article on figshare
url = f"https://api.figshare.com/v2/articles/{article_id}"
headers = {"Content-Type": "application/json"}
output_directory = "data/"
```

In [4]:
```
response = requests.request("GET", url, headers=headers)
data = json.loads(response.text)  # this contains all the articles data, feel free
files = data["files"]             # this is just the data about the files, which is
files
```

Out[4]:
```
[{'id': 26579150,
  'name': 'daily_rainfall_2014.png',
  'size': 58863,
  'is_link_only': False,
  'download_url': 'https://ndownloader.figshare.com/files/26579150',
  'supplied_md5': 'fd32a2ffde300a31f8d63b1825d47e5e',
  'computed_md5': 'fd32a2ffde300a31f8d63b1825d47e5e',
  'mimetype': 'image/png'},
 {'id': 26579171,
  'name': 'environment.yml',
  'size': 192,
  'is_link_only': False,
  'download_url': 'https://ndownloader.figshare.com/files/26579171',
  'supplied_md5': '060b2020017eed93a1ee7dd8c65b2f34',
  'computed_md5': '060b2020017eed93a1ee7dd8c65b2f34',
  'mimetype': 'text/plain'},
 {'id': 26586554,
  'name': 'README.md',
  'size': 5422,
  'is_link_only': False,
  'download_url': 'https://ndownloader.figshare.com/files/26586554',
  'supplied_md5': '61858c6cc0e6a6d6663a7e4c75bbd88c',
  'computed_md5': '61858c6cc0e6a6d6663a7e4c75bbd88c',
  'mimetype': 'text/x-python'},
 {'id': 26766812,
  'name': 'data.zip',
  'size': 814041183,
  'is_link_only': False,
  'download_url': 'https://ndownloader.figshare.com/files/26766812',
  'supplied_md5': 'b517383f76e77bd03755a63a8ff83ee9',
  'computed_md5': 'b517383f76e77bd03755a63a8ff83ee9',
  'mimetype': 'application/zip'},
 {'id': 26766815,
  'name': 'get_data.py',
  'size': 4113,
  'is_link_only': False,
  'download_url': 'https://ndownloader.figshare.com/files/26766815',
  'supplied_md5': '7829028495fd9dec9680ea013474afa6',
  'computed_md5': '7829028495fd9dec9680ea013474afa6',
  'mimetype': 'text/x-python'}]
```

In [5]:
```
%%time

# Download the file "data.zip"
files_to_dl = ["data.zip"]
for file in files:
    if file["name"] in files_to_dl:
        os.makedirs(output_directory, exist_ok=True)
        urlretrieve(file["download_url"], output_directory + file["name"])
```

```
CPU times: total: 2.28 s
Wall time: 1min 19s
```

In [6]:
```
%%time

# Unzip the CSVs from the zip file
```

```python
with zipfile.ZipFile(os.path.join(output_directory, "data.zip"), 'r') as f:
    f.extractall(output_directory)
```

```
CPU times: total: 13.4 s
Wall time: 33.3 s
```

In [7]:

```python
# View files that were extracted
%ls -ltr data
```

```
 Volume in drive C is OS
 Volume Serial Number is 1837-1226

 Directory of c:\Users\timot\OneDrive - UBC\Documents\Semester 2\Block 6\525\rainfal
l-predictor


 Directory of c:\Users\timot\OneDrive - UBC\Documents\Semester 2\Block 6\525\rainfal
l-predictor\data

29/03/2025  11:39 am    <DIR>          .
27/03/2025  12:33 am    <DIR>          ..
25/03/2025  02:34 pm    <DIR>          __MACOSX
29/03/2025  11:39 am       127,613,760 ACCESS-CM2_daily_rainfall_NSW.csv
29/03/2025  11:39 am       114,707,410 ACCESS-ESM1-5_daily_rainfall_NSW.csv
29/03/2025  11:39 am        94,960,113 AWI-ESM-1-1-LR_daily_rainfall_NSW.csv
29/03/2025  11:39 am       294,260,911 BCC-CSM2-MR_daily_rainfall_NSW.csv
29/03/2025  11:39 am        55,224,437 BCC-ESM1_daily_rainfall_NSW.csv
29/03/2025  11:39 am        46,286,371 CanESM5_daily_rainfall_NSW.csv
29/03/2025  11:39 am       330,360,682 CMCC-CM2-HR4_daily_rainfall_NSW.csv
29/03/2025  11:39 am       328,787,320 CMCC-CM2-SR5_daily_rainfall_NSW.csv
29/03/2025  11:39 am       328,852,379 CMCC-ESM2_daily_rainfall_NSW.csv
29/03/2025  03:24 am     9,358,818,363 combined_data.csv
29/03/2025  11:39 am       814,041,183 data.zip
29/03/2025  11:39 am       295,768,615 EC-Earth3-Veg-LR_daily_rainfall_NSW.csv
29/03/2025  11:39 am       232,118,894 FGOALS-f3-L_daily_rainfall_NSW.csv
29/03/2025  11:39 am       116,179,272 FGOALS-g3_daily_rainfall_NSW.csv
29/03/2025  11:39 am       235,661,418 GFDL-CM4_daily_rainfall_NSW.csv
29/03/2025  11:39 am       124,586,961 GFDL-ESM4_daily_rainfall_NSW.csv
29/03/2025  11:39 am       102,517,965 INM-CM4-8_daily_rainfall_NSW.csv
29/03/2025  11:39 am       102,692,289 INM-CM5-0_daily_rainfall_NSW.csv
29/03/2025  11:39 am        93,829,697 KIOST-ESM_daily_rainfall_NSW.csv
29/03/2025  11:39 am       206,822,938 MIROC6_daily_rainfall_NSW.csv
29/03/2025  11:39 am        95,376,895 MPI-ESM-1-2-HAM_daily_rainfall_NSW.csv
29/03/2025  11:39 am       515,458,033 MPI-ESM1-2-HR_daily_rainfall_NSW.csv
29/03/2025  11:39 am        95,640,682 MPI-ESM1-2-LR_daily_rainfall_NSW.csv
29/03/2025  11:39 am       254,009,247 MRI-ESM2-0_daily_rainfall_NSW.csv
29/03/2025  11:39 am        67,784,105 NESM3_daily_rainfall_NSW.csv
29/03/2025  11:39 am        82,474,546 NorESM2-LM_daily_rainfall_NSW.csv
29/03/2025  11:39 am       337,555,851 NorESM2-MM_daily_rainfall_NSW.csv
29/03/2025  11:39 am           952,202 observed_daily_rainfall_SYD.csv
29/03/2025  11:39 am       333,489,879 SAM0-UNICON_daily_rainfall_NSW.csv
29/03/2025  11:39 am       332,813,281 TaiESM1_daily_rainfall_NSW.csv
              30 File(s) 15,519,645,699 bytes
               3 Dir(s)  98,321,985,536 bytes free
```

```
File Not Found
```

2) Combining CSVs

In [8]:

```
%%time
# Remove un-needed file
remove_file = "data//observed_daily_rainfall_SYD.csv"

if os.path.exists(remove_file):
    os.remove(remove_file)
    print(f"{remove_file} deleted successfully.")
else:
    print(f"{remove_file} not found.")

# Combine
use_cols = ["time", "lat_min", "lat_max", "lon_min", "lon_max", "rain (mm/day)"]
files = glob.glob('data/*.csv')
df = pd.concat(pd.read_csv(file, index_col=0, usecols=use_cols)
               .assign(model=re.findall(r"data\\([^_]*)", file)[0])    # Extra dat
               for file in files
              )
df.to_csv("data/combined_data.csv")
```

```
data//observed_daily_rainfall_SYD.csv deleted successfully.
CPU times: total: 13min 23s
Wall time: 14min 20s
```

Time Comparison with Lab Members

preferred lab partner(s)	Operating System	RAM	Processor	Is SSD	Time taken
Timothy Singh	Windows 11 Home	16GB	Intel i7-11800H	Yes	14 minutes
Benjamin Frizzell*	MacOS	8GB	Intel i5 Duo Core	Yes	3 minutes
Stephanie Ta	Windows 10	16GB	Intel i7-1065G7	Yes	4 minutes
Meagan Gardener	MacOS	16GB	Apple M3	Yes	3 minutes

*loaded with a parquet file

From the comparison table it is seen that his task took much longer for me when compared with the members of my group. This was the lowest result of several attempts, which gave times of 17 minutes, 22 minutes, 31 minutes and 14 minutes. Some troubleshooting was attempted, by closing background programs, restarting my device and even varying between VS Code and JupyterLab (in browser). Note that VS Code yielded better times than JupyterLab in the browser. It was also noticed when combining RAM usage increased a bit, but peaked around 85%. The reason for such deviation in time could possibly be explained by the difference in OS, since I was the only member using Windows 11. Additionally, there were updates that were pending install, which could have potentially affected this.

From the comparison, it appeared as though devices running MacOS performed this best in this task. Even though one member loaded with a parquet file, their device had 8GB RAM, and still performed better than the Windows 10 and Windows 11 devices. The member using Windows 10 still had a longer time than the member used MacOS with 8GB RAM. This further demonstrates that the Windows OS possibly takes more resources when compared to MacOS.

3) Load the combined CSV to memory and perform a simple EDA

Here, we will load the data in chunks, getting rid of the `lat_min`, `lat_max`, `lon_min` and `lon_max` columns, and convert values in the `rain (mm/day)` column to `float32`

In [9]:
```
%%time

# Load only "time". "model" and "rain (mm/day) columns, with
# "time" as datetime, "model" as string and "rain (mm/day) as float32
# Also read as chunks, and perform EDA on each chunk

usecols = ["time", "rain (mm/day)", "model"]
dtypes = {"time": "string",
          "rain (mm/day)": "float32",
          "model": "string"}

value_counts = pd.Series(dtype=int)
rainfall_total = pd.Series(dtype=float)

for chunk in pd.read_csv("data/combined_data.csv",
    usecols = usecols,
    dtype = dtypes,
    parse_dates=["time"] ,
    chunksize=500_000
):
    value_counts = value_counts.add(chunk["model"].value_counts(), fill_value=0)
    rainfall_total = rainfall_total.add(chunk.groupby("model")["rain (mm/day)"].sum
```

```
CPU times: total: 5min 50s
Wall time: 6min 3s
```

In [10]:
```
eda_summary = pd.DataFrame({
    "model": rainfall_total.index,
    "rainfall_total": rainfall_total.values,
    "values_count": value_counts.values
    }
)

eda_summary
```

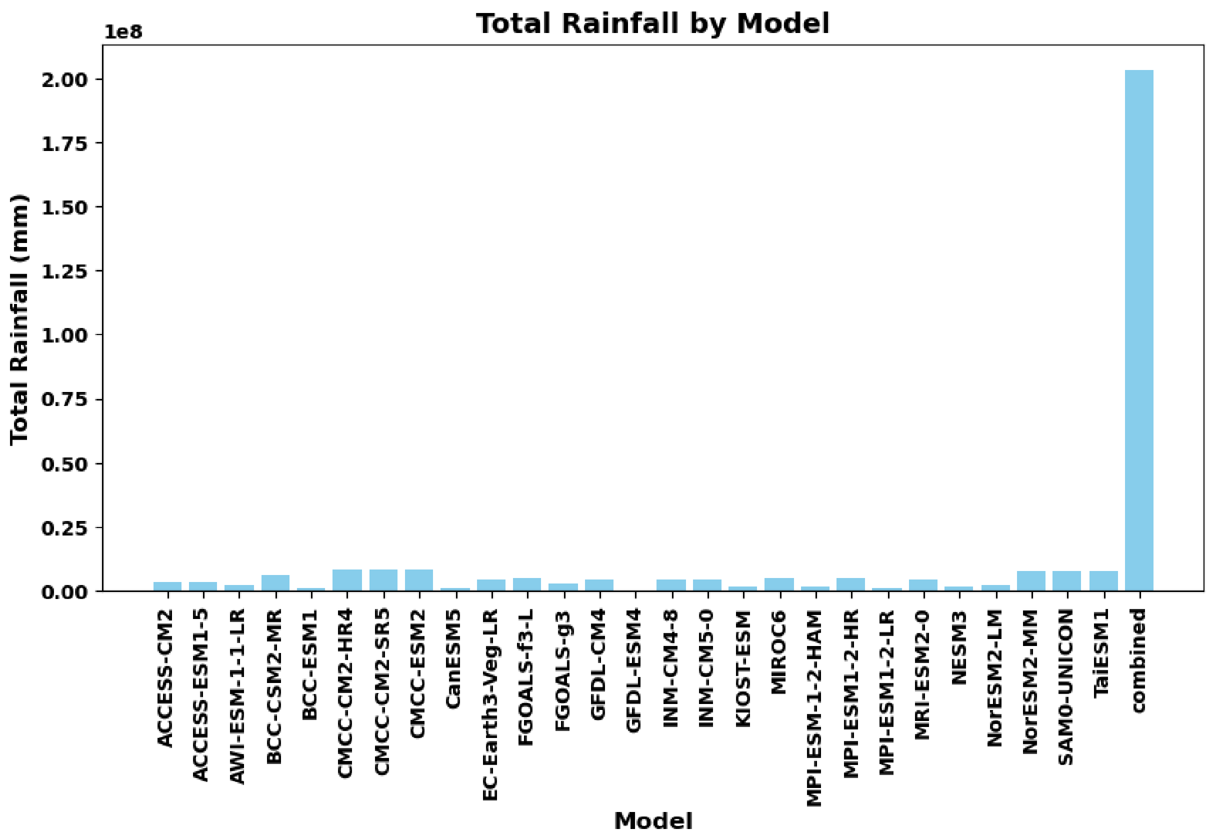
Out[10]:

	model	rainfall_total	values_count
0	ACCESS-CM2	3.454034e+06	1932840.0
1	ACCESS-ESM1-5	3.571729e+06	1610700.0
2	AWI-ESM-1-1-LR	1.958036e+06	966420.0
3	BCC-CSM2-MR	5.924474e+06	3035340.0
4	BCC-ESM1	9.994724e+05	551880.0
5	CMCC-CM2-HR4	8.071704e+06	3541230.0
6	CMCC-CM2-SR5	8.440127e+06	3541230.0
7	CMCC-ESM2	8.024869e+06	3541230.0
8	CanESM5	1.045442e+06	551880.0
9	EC-Earth3-Veg-LR	4.605362e+06	3037320.0
10	FGOALS-f3-L	5.239002e+06	3219300.0
11	FGOALS-g3	2.776864e+06	1287720.0
12	GFDL-CM4	4.553653e+06	3219300.0
13	GFDL-ESM4	0.000000e+00	3219300.0
14	INM-CM4-8	4.525471e+06	1609650.0
15	INM-CM5-0	4.296175e+06	1609650.0
16	KIOST-ESM	1.419522e+06	1287720.0
17	MIROC6	4.766511e+06	2070900.0
18	MPI-ESM-1-2-HAM	1.556632e+06	966420.0
19	MPI-ESM1-2-HR	5.131401e+06	5154240.0
20	MPI-ESM1-2-LR	1.038233e+06	966420.0
21	MRI-ESM2-0	4.155145e+06	3037320.0
22	NESM3	1.567471e+06	966420.0
23	NorESM2-LM	2.051889e+06	919800.0
24	NorESM2-MM	7.907445e+06	3541230.0
25	SAM0-UNICON	7.683156e+06	3541153.0
26	TaiESM1	7.877735e+06	3541230.0
27	combined	2.030462e+08	94388832.0

In [11]:

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 5))
```

```
plt.bar(eda_summary["model"], eda_summary["rainfall_total"], color="skyblue")

# Titles and labels
plt.title("Total Rainfall by Model", fontsize=14)
plt.xlabel("Model", fontsize=12)
plt.ylabel("Total Rainfall (mm)", fontsize=12)
plt.xticks(rotation=90)

plt.show();
```



Time Comparison with Lab Members

preferred lab partner(s)	Operating System	RAM	Processor	Is SSD	Time taken	Methods used for Loading
Timothy Singh	Windows 11 Home	16GB	Intel i7-11800H	Yes	6 minutes	Only relevant columns, data type conversion, chunk loading
Benjamin Frizzell	MacOS	8GB	Intel i5 Duo Core	Yes	1 minute	Only relevant columns, data type conversion, parquet file saving
Stephanie Ta	Windows 10	16GB	Intel i7-1065G7	Yes	1 minute	Only relevant columns, data type conversion
Meagan Gardener	MacOS	16GB	Apple M3	Yes	20 seconds	Only relevant columns, data type conversion

Similar to the results in Question 2, my device yielded the longest time for this operation when compared to my group members. Other than myself, no other member performmed "chunk loading", but the times are not an accurate comparison due to the unusually long times on my device. This was attempted with a chunk size of 1_000_000, then 500_000, of which the latter gave slightly better performance (~25 seconds faster). Other than OS, a possible cause of this could be that multiple cores of the CPU not being utilized for this task, resulting in slower times. Overall, the comparison shows that the Apple M3 CPU yields the best performances among the difference CPUs, along with the MacOS operating systems also performing the best among operating systems.

4) Perform a simple EDA in R

In [18]:

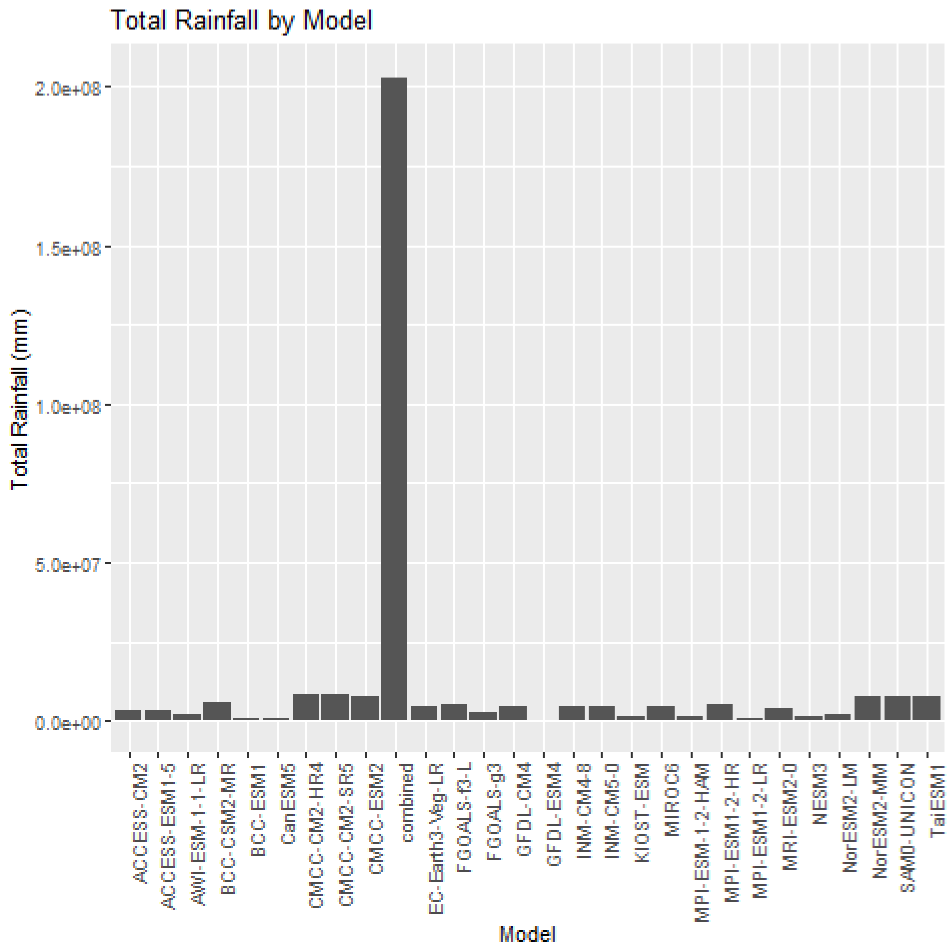
```
# Since we already have the entire dataset loaded in memory from
# as a dataframe (df), we can use pyarrow to convert it into a
# table and subsequently pyra.

filepathcsv = "data/combined_data.csv"
dataset = ds.dataset(filepathcsv, format="csv")
table = dataset.to_table()
%time r_table = pyra.converter.py2rpy(table)
```

```
CPU times: total: 188 ms
Wall time: 530 ms
```

In [19]:

```
%%R -i r_table

# Load libraries
suppressMessages(library(tidyverse))
suppressMessages(library(ggplot2))

# Perform data wrangling to do EDA. Just as before, we are getting
# the total rainfall and value counts per model
result <- r_table |>
    select(time, model, `rain (mm/day)`) |>
    group_by(model) |>
    summarize(rainfall_total = sum(`rain (mm/day)`, na.rm = TRUE),
              values_count = n())
print(as.data.frame(result))

# Make a similar plot as in Python
plot <- as.data.frame(result) |>
    ggplot(aes(x = model, y = rainfall_total)) +
    geom_bar(stat = "identity") +
    ggtitle("Total Rainfall by Model") +
    xlab("Model") +
    ylab("Total Rainfall (mm)") +
    theme(axis.text.x = element_text(angle = 90, hjust = 1))

plot
```

	model	rainfall_total	values_count
1	ACCESS-CM2	3454033.5	1932840
2	ACCESS-ESM1-5	3571729.0	1610700
3	AWI-ESM-1-1-LR	1958035.9	966420
4	BCC-CSM2-MR	5924474.2	3035340
5	BCC-ESM1	999472.4	551880
6	CanESM5	1045441.6	551880
7	CMCC-CM2-HR4	8071704.2	3541230
8	CMCC-CM2-SR5	8440126.9	3541230
9	CMCC-ESM2	8024868.6	3541230
10	combined	203046194.9	94388832
11	EC-Earth3-Veg-LR	4605362.0	3037320
12	FGOALS-f3-L	5239002.4	3219300
13	FGOALS-g3	2776864.5	1287720
14	GFDL-CM4	4553652.5	3219300
15	GFDL-ESM4	0.0	3219300
16	INM-CM4-8	4525471.1	1609650
17	INM-CM5-0	4296175.4	1609650
18	KIOST-ESM	1419521.5	1287720
19	MIROC6	4766511.2	2070900
20	MPI-ESM-1-2-HAM	1556631.6	966420
21	MPI-ESM1-2-HR	5131400.6	5154240
22	MPI-ESM1-2-LR	1038233.2	966420
23	MRI-ESM2-0	4155145.1	3037320
24	NESM3	1567471.4	966420
25	NorESM2-LM	2051889.0	919800
26	NorESM2-MM	7907445.0	3541230
27	SAM0-UNICON	7683156.1	3541153
28	TaiESM1	7877735.4	3541230



Arrow exchange (using pyarrow) was selected as the method for transferring the entire dataframe from Python to R. Serialization refers to the process of saving an object state as a sequence of bytes so it can be saved as a file (typically a CSV). Deserialization is the opposite of serialization where these bytes are reconstructed into an object that can be used in a programming language. This method of arrow exchange simplifies the serialization/deserialization process allowing the data to be transferred directly from Python to R, without any extra overhead of reading another file into memory. Also this method supports and even abstracts chunking and parallelism, improving the efficiency of loading and transferring the data.

Another viable option could have been to use parquet file, which decreases the reading time in R, but this comes with the disadvantage of having to save an additional file to disk. This would increase the overall time, since a new file would have to be created and read into memory. To preserve the limited disk space, the arrow exchange method was used in this case. The pandas exchange method requires loading the data, and converting which is slow and less efficient.