# Module 1: Tabular Data

**Working with larger-than-RAM data using duckdbfs**

ESPM 288

2026-02-18

## Introduction

In this module, we will explore high-performance workflows for tabular data. We will use `duckdbfs` to work with datasets that are larger than available RAM by leveraging DuckDB's streaming and remote file access capabilities.

## Case Study: Global Supply Chains

We will be working with EXIOBASE 3.8.1, a global Multi-Regional Input-Output (MRIO) database. This dataset tracks economic transactions between sectors and regions, along with their environmental impacts (emissions, resource use, etc.).

**Data description:** - **Coverage**: 44 countries + 5 rest-of-world regions. - **Timeframe**: 1995–2022. - **Content**: Economic transactions (Z matrix), final demand (Y matrix), and environmental stressors (F matrix). - **Format**: Cloud-optimized Parquet, partitioned by year and matrix type.

## Setup

```
Warning: package 'duckdbfs' was built under R version 4.5.2
```

```
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
```

### Exercise 1: connecting to remote data

We can open the entire dataset without downloading it using `open_dataset()`. The data is hosted on Source Cooperative. The `**` pattern allows recursive scanning of the partitioned parquet files.

```
[1] 1
```

```
Rows: ??
Columns: 8
Database: DuckDB 1.4.3 [madis@Windows 10 x64:R 4.5.1/:memory:]
$ stressor <chr> "Value Added", "Value Added", "Value Added", "Value Added", "~
$ region   <chr> "AT", "AT", "AT", "AT", "AT", "AT", "AT", "AT", "AT", "AT", "~
$ sector   <chr> "Cultivation of wheat", "Cultivation of cereal grains nec", "~
$ value    <dbl> 183.1118891, 402.2305799, 830.2127384, 101.9705426, 31.763189~
$ unit     <chr> "M.EUR", "M.EUR", "M.EUR", "M.EUR", "M.EUR", "M.EUR", "M.EUR"~
$ year     <dbl> 1995, 1995, 1995, 1995, 1995, 1995, 1995, 1995, 1995, 1995, 1~
$ format   <chr> "ixi", "ixi", "ixi", "ixi", "ixi", "ixi", "ixi", "ixi", "ixi"~
$ matrix   <chr> "F_impacts", "F_impacts", "F_impacts", "F_impacts", "F_impact~
```

### Exercise 2: Efficient Filtering

The dataset is large. We should filter *before* collecting any data into R.

```
exio |>
    filter(year == 2022, region == "US") |>
    head() |> # view the first 6 rows
    collect()
```

```
# A tibble: 6 x 8
  stressor    region sector                     value unit   year format matrix
  <chr>       <chr>  <chr>                      <dbl> <chr> <dbl> <chr>  <chr>
1 Value Added US     Cultivation of paddy rice    750. M.EUR  2022 ixi    F_imp~
2 Value Added US     Cultivation of wheat        2019. M.EUR  2022 ixi    F_imp~
3 Value Added US     Cultivation of cereal gra~  7355. M.EUR  2022 ixi    F_imp~
4 Value Added US     Cultivation of vegetables~ 26878. M.EUR  2022 ixi    F_imp~
```

```
5 Value Added US     Cultivation of oil seeds    5003. M.EUR  2022 ixi    F_imp~
6 Value Added US     Cultivation of sugar cane~   290. M.EUR  2022 ixi    F_imp~
```

> **Task**: Construct a query to find the top 5 sectors in the US by CO2 emissions in 2022. Remember to check the column names in `exio` to find the appropriate emissions flow.

```
# Solution: Top 5 sectors in US by CO2 emissions (2022)

# Target the F_satellite matrix directly to access stressor column
exio_f_sat <- open_dataset(
    "s3://us-west-2.opendata.source.coop/youssef-harby/exiobase-3/4588235/parquet/year=2022/
)

exio_f_sat |>
    filter(
        grepl("CO2", stressor)
    ) |>
    group_by(sector) |>
    summarize(total_co2 = sum(value, na.rm = TRUE), .groups = "drop") |>
    arrange(desc(total_co2)) |>
    head(5) |>
    collect()
```

```
# A tibble: 5 x 2
  sector                                                          total_co2
  <chr>                                                               <dbl>
1 Production of electricity by coal                             8.33e12
2 Manufacture of cement, lime and plaster                       2.54e12
3 Production of electricity by gas                              2.30e12
4 Steam and hot water supply                                    2.07e12
5 Manufacture of basic iron and steel and of ferro-alloys and first p~  1.84e12
```

### Exercise 3: CO2 Emissions Over Time by Region (Top 5 Emitters)

First, let's identify the top 5 CO2 emitting regions in 2022:

```
# Find the top 5 emitting regions in 2022
top_emitters_2022 <- exio |>
    filter(year == 2022,
           matrix == "F_satellite",
```

```
            stressor %like% "%CO2%") |>
    group_by(region) |>
    summarise(total_co2 = sum(value, na.rm = TRUE)) |>
    arrange(desc(total_co2)) |>
    head(5) |>
    collect()

top_emitters_2022
```

```
# A tibble: 5 x 2
  region total_co2
  <chr>      <dbl>
1 CN       2.24e13
2 US       7.43e12
3 IN       5.31e12
4 WA       4.12e12
5 WM       4.11e12
```

Now, let's get the time series data for these top 5 regions across all years:

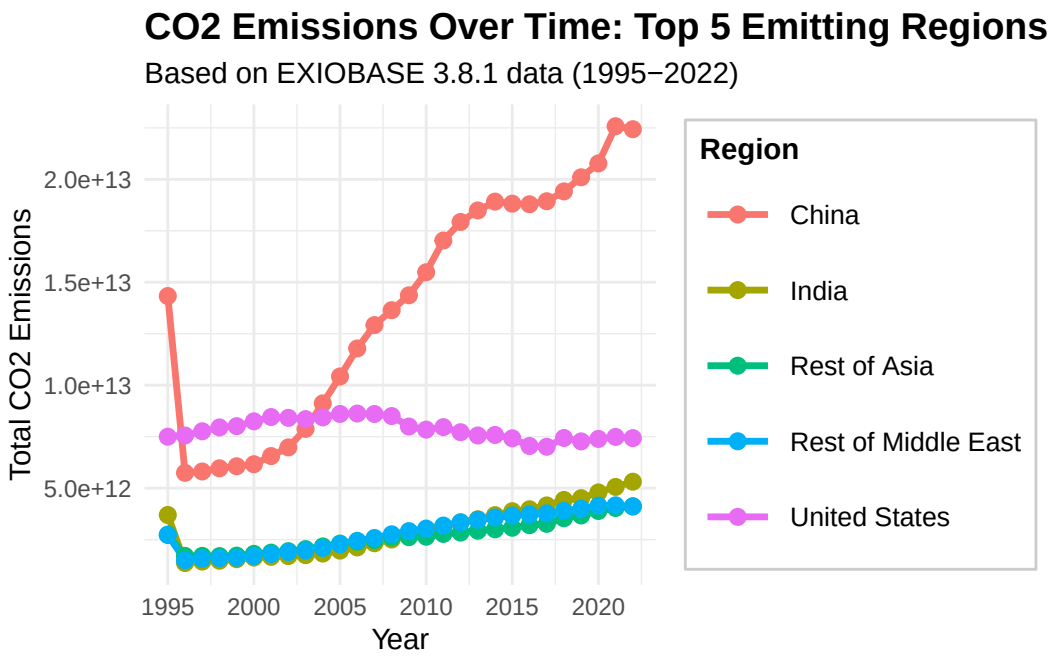
```
`summarise()` has grouped output by "year". You can override using the
`.groups` argument.
```

```
# A tibble: 20 x 3
# Groups:   year [4]
    year region total_co2
   <dbl> <chr>      <dbl>
 1  1995 CN       1.43e13
 2  1995 IN       3.70e12
 3  1995 US       7.50e12
 4  1995 WA       2.74e12
 5  1995 WM       2.73e12
 6  1996 CN       5.74e12
 7  1996 IN       1.36e12
 8  1996 US       7.56e12
 9  1996 WA       1.71e12
10  1996 WM       1.50e12
11  1997 CN       5.81e12
12  1997 IN       1.43e12
13  1997 US       7.76e12
14  1997 WA       1.71e12
```

```
15  1997 WM       1.57e12
16  1998 CN       5.96e12
17  1998 IN       1.47e12
18  1998 US       7.95e12
19  1998 WA       1.70e12
20  1998 WM       1.60e12
```

Create a line plot showing CO2 emissions over time for the top 5 regions:

```r
# Create the time series plot
co2_plot <- ggplot(co2_timeseries, aes(x = year, y = total_co2, color = region_name)) +
    geom_line(linewidth = 1.2) +
    geom_point(size = 2.5) +
    labs(
        title = "CO2 Emissions Over Time: Top 5 Emitting Regions",
        subtitle = "Based on EXIOBASE 3.8.1 data (1995-2022)",
        x = "Year",
        y = "Total CO2 Emissions",
        color = "Region"
    ) +
    theme_minimal() +
    theme(
        plot.title = element_text(face = "bold", size = 14),
        legend.position = "right",
        legend.title = element_text(face = "bold", size = 11),
        legend.text = element_text(size = 10),
        legend.background = element_rect(fill = "white", color = "gray80"),
        legend.key.size = unit(1, "cm")
    ) +
    scale_x_continuous(breaks = seq(1995, 2022, by = 5))

co2_plot
```




### Exercise 4: Regions with Largest CO2 Emission Reductions

Let's identify which regions have reduced their CO2 emissions the most between 1995 and 2022:

```
# Get CO2 emissions for all regions in 1995 and 2022
co2_1995 <- exio |>
    filter(year == 1995,
           matrix == "F_satellite",
           stressor %like% "%CO2%") |>
    group_by(region) |>
    summarise(co2_1995 = sum(value, na.rm = TRUE)) |>
    collect()

co2_2022 <- exio |>
    filter(year == 2022,
           matrix == "F_satellite",
           stressor %like% "%CO2%") |>
    group_by(region) |>
    summarise(co2_2022 = sum(value, na.rm = TRUE)) |>
    collect()
```

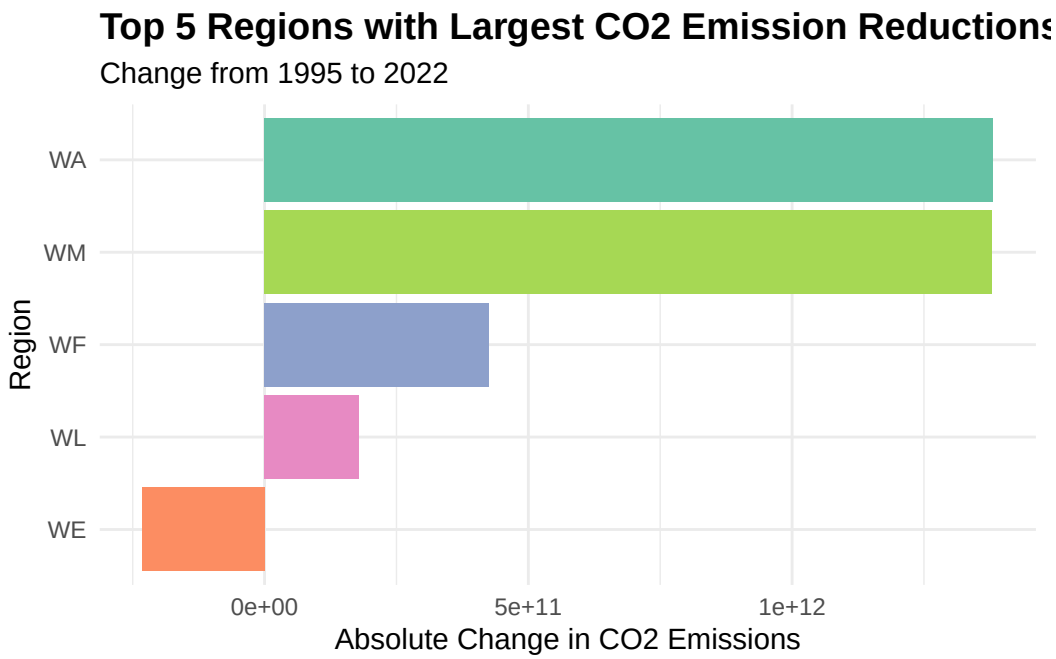
```r
# Join the two datasets and calculate change
co2_change <- co2_1995 |>
    inner_join(co2_2022, by = "region") |>
    mutate(
        absolute_change = co2_2022 - co2_1995,
        percent_change = ((co2_2022 - co2_1995) / co2_1995) * 100
    ) |>
    filter(grepl("^W", region)) |>  # Include only rest-of-world regions (WA, WE, WF, WL, WM)
    arrange(absolute_change)

# View regions with the largest absolute decreases
head(co2_change, 5)
```

```
# A tibble: 5 x 5
  region co2_1995 co2_2022 absolute_change percent_change
  <chr>     <dbl>    <dbl>           <dbl>          <dbl>
1 WE      9.03e11  6.71e11        -2.32e11          -25.7
2 WL      1.03e12  1.21e12         1.78e11           17.3
3 WF      6.19e11  1.05e12         4.26e11           68.7
4 WM      2.73e12  4.11e12         1.38e12           50.6
5 WA      2.74e12  4.12e12         1.38e12           50.4
```

Now let's visualize the top 5 regions with the largest absolute reductions:

```r
# Get top 5 reducers
top_reducers <- co2_change |>
    head(5)

# Create a bar plot
reduction_plot <- ggplot(top_reducers, aes(x = reorder(region, absolute_change), y = absolute
    geom_col() +
    coord_flip() +
    scale_fill_brewer(palette = "Set2") +
    labs(
        title = "Top 5 Regions with Largest CO2 Emission Reductions",
        subtitle = "Change from 1995 to 2022",
        x = "Region",
        y = "Absolute Change in CO2 Emissions"
    ) +
    theme_minimal() +
    theme(
```

```
        plot.title = element_text(face = "bold", size = 14),
        legend.position = "none"
    )

reduction_plot
```



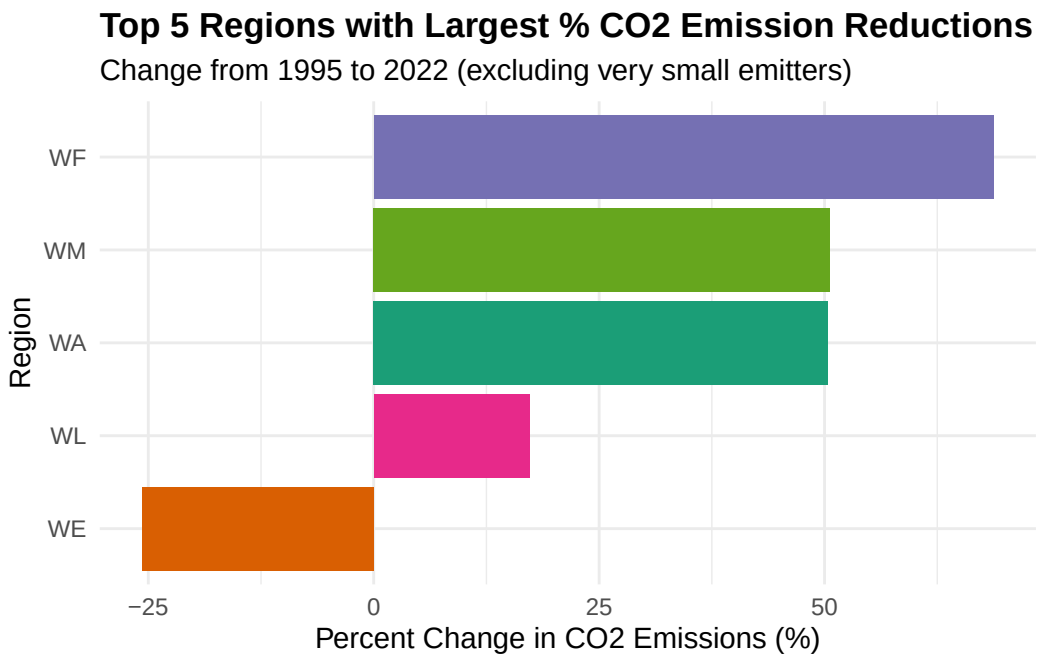

Let's also look at percentage reductions (excluding countries with very low baseline emissions):

```
# Filter to countries with substantial 1995 emissions (>1000 units) to avoid outliers
substantial_emitters <- co2_change |>
    filter(co2_1995 > 1000) |>
    arrange(percent_change) |>
    head(5)

substantial_emitters
```

```
# A tibble: 5 x 5
  region co2_1995 co2_2022 absolute_change percent_change
  <chr>     <dbl>    <dbl>           <dbl>          <dbl>
1 WE      9.03e11  6.71e11        -2.32e11          -25.7
2 WL      1.03e12  1.21e12         1.78e11           17.3
3 WA      2.74e12  4.12e12         1.38e12           50.4
```

```
4 WM      2.73e12  4.11e12          1.38e12           50.6
5 WF      6.19e11  1.05e12          4.26e11           68.7
```

```r
# Visualize percentage reductions
percent_plot <- ggplot(substantial_emitters, aes(x = reorder(region, percent_change), y = per
    geom_col() +
    coord_flip() +
    scale_fill_brewer(palette = "Dark2") +
    labs(
        title = "Top 5 Regions with Largest % CO2 Emission Reductions",
        subtitle = "Change from 1995 to 2022 (excluding very small emitters)",
        x = "Region",
        y = "Percent Change in CO2 Emissions (%)"
    ) +
    theme_minimal() +
    theme(
        plot.title = element_text(face = "bold", size = 13),
        legend.position = "none"
    )

percent_plot
```



### Exercise 5: CO2 Emissions Over Time for Top 5 Emitting Countries

Now let's look at individual countries (excluding rest-of-world aggregates) to see the top 5 emitting countries:

```
# Find the top 5 emitting countries in 2022 (excluding W regions)
top_countries_2022 <- exio |>
    filter(year == 2022,
           matrix == "F_satellite",
           stressor %like% "%CO2%") |>
    group_by(region) |>
    summarise(total_co2 = sum(value, na.rm = TRUE)) |>
    filter(!grepl("^W", region)) |>  # Exclude rest-of-world regions
    arrange(desc(total_co2)) |>
    head(5) |>
    collect()

top_countries_2022
```

```
# A tibble: 5 x 2
  region total_co2
  <chr>      <dbl>
1 CN       2.24e13
2 US       7.43e12
3 IN       5.31e12
4 RU       3.12e12
5 JP       2.01e12
```

Get time series data for these top 5 countries across all years:

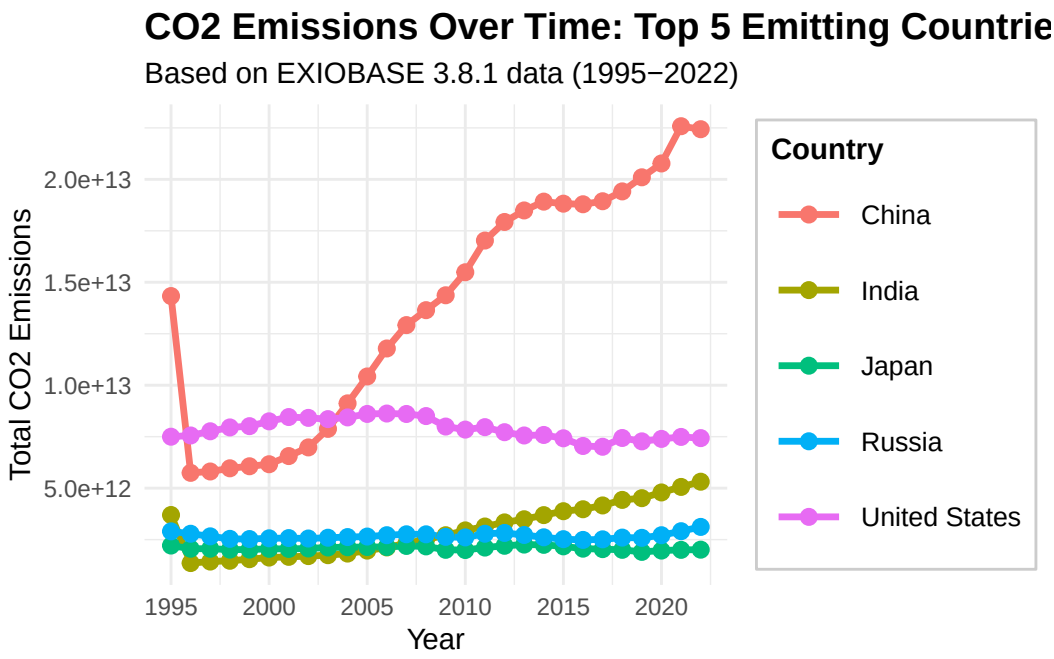
```
`summarise()` has grouped output by "year". You can override using the
`.groups` argument.
```

```
# A tibble: 20 x 3
# Groups:   year [4]
    year region total_co2
   <dbl> <chr>      <dbl>
 1  1995 CN       1.43e13
 2  1995 IN       3.70e12
 3  1995 JP       2.21e12
 4  1995 RU       2.90e12
```

```
 5  1995 US       7.50e12
 6  1996 CN       5.74e12
 7  1996 IN       1.36e12
 8  1996 JP       2.06e12
 9  1996 RU       2.79e12
10  1996 US       7.56e12
11  1997 CN       5.81e12
12  1997 IN       1.43e12
13  1997 JP       2.06e12
14  1997 RU       2.66e12
15  1997 US       7.76e12
16  1998 CN       5.96e12
17  1998 IN       1.47e12
18  1998 JP       2.02e12
19  1998 RU       2.54e12
20  1998 US       7.95e12
```

Create a line plot showing CO2 emissions over time for the top 5 countries:

```r
# Create the time series plot
countries_plot <- ggplot(co2_countries_timeseries, aes(x = year, y = total_co2, color = coun
    geom_line(linewidth = 1.2) +
    geom_point(size = 2.5) +
    labs(
        title = "CO2 Emissions Over Time: Top 5 Emitting Countries",
        subtitle = "Based on EXIOBASE 3.8.1 data (1995-2022)",
        x = "Year",
        y = "Total CO2 Emissions",
        color = "Country"
    ) +
    theme_minimal() +
    theme(
        plot.title = element_text(face = "bold", size = 14),
        legend.position = "right",
        legend.title = element_text(face = "bold", size = 11),
        legend.text = element_text(size = 10),
        legend.background = element_rect(fill = "white", color = "gray80"),
        legend.key.size = unit(1, "cm")
    ) +
    scale_x_continuous(breaks = seq(1995, 2022, by = 5))

countries_plot
```


CO2 Emissions Over Time: Top 5 Emitting Countrie
Based on EXIOBASE 3.8.1 data (1995−2022)
Total CO2 Emissions
2.0e+13
1.5e+13
1.0e+13
5.0e+12
1995
2000
2005
2010
2015
2020
Year
Country
China
India
Japan
Russia
United States