Library Preparation

```
library(dplyr)
library(ggplot2)
library(tidyr)
library(scales)
library(readr)
library(readxl)
library(ggthemes)
library(forcats)
```

ANALYSIS OF CO2 EMISSION FROM TRANSPORT DATA (my_data3)

my_data3 will be used for this part of analysis. Therefore, here is the general information that's needed:

```
str(my_data3)
```

```
'data.frame':   2232 obs. of  4 variables:
 $ entity                  : chr  "Afghanistan" "Africa" "Albania" "Algeria" ...
 $ code                    : chr  "AFG" "" "ALB" "DZA" ...
 $ year                    : int  2011 2011 2011 2011 2011 2011 2011 2011 2011 2011 ...
 $ transport_co2_emissions: num  6.71e+06 2.68e+08 2.36e+06 3.42e+07 6.28e+06 ...
```

entity: A character column in my_data3 data set which represents the countries, continents, some income levels and the world.

code: A character column in my_data3 data set which represents the codes of the countries. (There are no codes for non-countries)

year: An integer column in my_data3 data set which represents the year.

transport_co2_emissions: A numeric column in my_data3 data set which represents the total carbon emission in tons.

Country Based Mean Transportation CO2 Emission

Let's take a look at the top 20 countries' mean transportation carbondioxide emission from 2011 to 2021. To do this, the **entity** column of my_data3 has tidied to exclude the entities that are non-countries.

```
non_countries <- c(
  "World",
  "Upper-middle-income countries",
  "Lower-middle-income countries",
  "Low-income countries",
  "High-income countries",
  "European Union (27)",
  "Europe",
```

```
  "Asia",
  "Africa",
  "North America",
  "South America",
  "Oceania"
)

mean_co2_emission_by_country <- my_data3 |>
  filter(!entity %in% non_countries) |>
  group_by(entity) |>
  summarize(mean_co2_emission_per_year = mean(transport_co2_emissions,
                                              na.rm = TRUE)) |>
  mutate(entity_lumped = fct_lump_n(entity, n = 20,
                                    w = mean_co2_emission_per_year)) |>
  group_by(entity_lumped) |>
  summarize(mean_co2_emission_per_year = mean(mean_co2_emission_per_year,
                                              na.rm = TRUE), .groups = "drop")

head(mean_co2_emission_by_country)
```

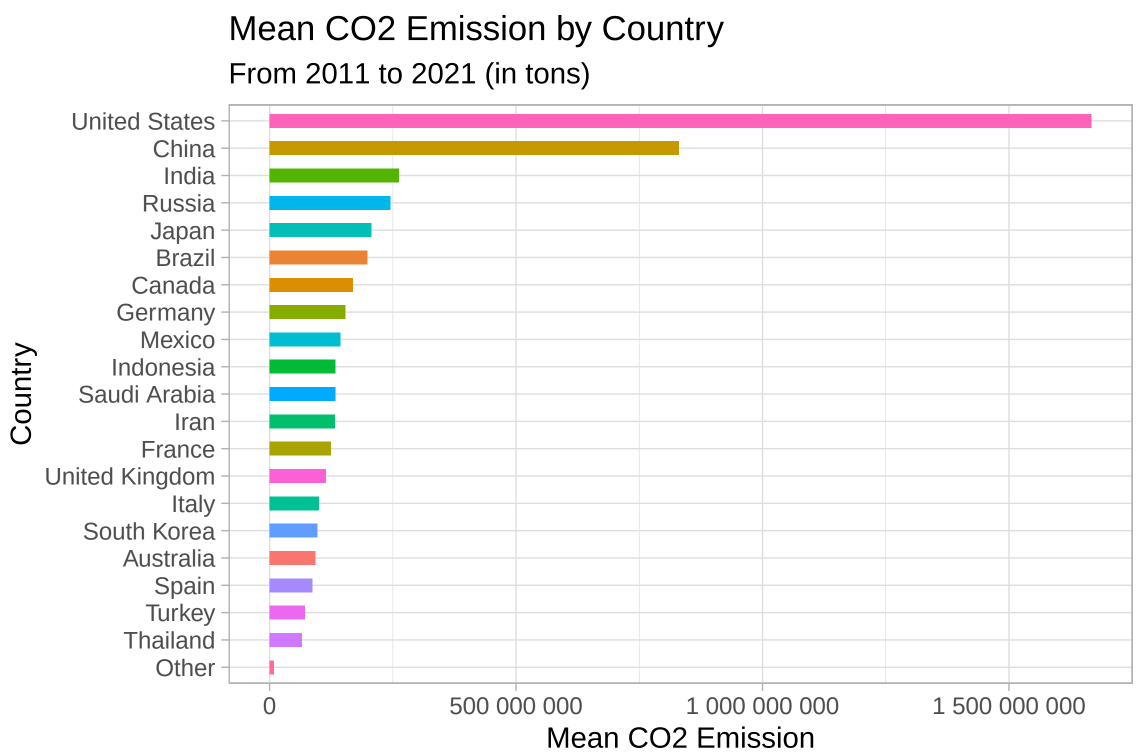
```
# A tibble: 6 x 2
  entity_lumped mean_co2_emission_per_year
  <fct>                              <dbl>
1 Australia                      92412727.
2 Brazil                        198190000
3 Canada                        169276364.
4 China                         830712727.
5 France                        124309090
6 Germany                       154080000
```

Note that to be able to see the mean carbondioxide emission of **the rest of the world**, it is combined into the observation **Other**.

It's needed to see the transportation carbondioxide emission levels of countries through the years to get more information about them. Below, the amounts of some of those 20 countries' (which are chosen specifically by team NRG) mean transportation carbondioxide emission (in tons) are displayed in the graph with the tidied version of my_data3.

```
ggplot(mean_co2_emission_by_country, aes(x = reorder(entity_lumped, mean_co2_emission_per_year
                                         fill = entity_lumped)) +
# AI generated content based on the prompt: I want to plot a graph showing the
# highest mean carbondioxide emission on the top, lowest on the bottom.
# Can you aprovide a code? I think there is a reorder() function
# that could help.
  geom_col(width = 0.5) +
  scale_y_continuous(labels = label_number(scale = 1, accuracy = 1)) +
# AI generated content based on the prompt: Values are shown as a scientific
# notation, I want to show them with a standard notation.
  coord_flip() +
  labs(x = "Country",
       y = "Mean CO2 Emission",
       title = "Mean CO2 Emission by Country",
       subtitle = "From 2011 to 2021 (in tons)") +
```

```r
theme_light() +
theme(legend.position = "none")
```



Conclusions:

- The histogram above clearly demonstrates that per capita CO emissions in both the United States and China are significantly higher than the global average. This disparity has been one of the primary drivers behind the recent surge in renewable energy investments and efforts to move away from fossil fuels in both countries.
- High emission levels have placed immense pressure on the United States and China to address climate change, accelerating their transition to sustainable energy sources.
- The renewable energy initiatives undertaken by these two nations have created a significant domino effect worldwide, propelling the global shift toward the sustainability era. These efforts are not only aimed at reducing their own high emission levels but also serve as an example for other countries to transition to cleaner energy systems. One of the most tangible examples of this influence is the rapidly growing electric vehicle (EV) sector, driven by the United States as a hub of technological innovation and China as the world's largest manufacturer and market for EVs.
- **The big majority** of mean transportation carbondioxide emissions consisted of top 20 countries.
- **Turkey** is **19th country** with the largest mean transportation carbondioxide emission level.

After this plot, the group has chosen specific countries to explore their behaviour over time. **United States and China** has chosen for being in first two place in the mean carbondioxide emission standings, **Norway and Denmark** for not being in top 20 countries list, and even they have been successful at decreasing their emission, **Turkey and Japan** to investigate the important parameters that carbondioxide emission is dependent.

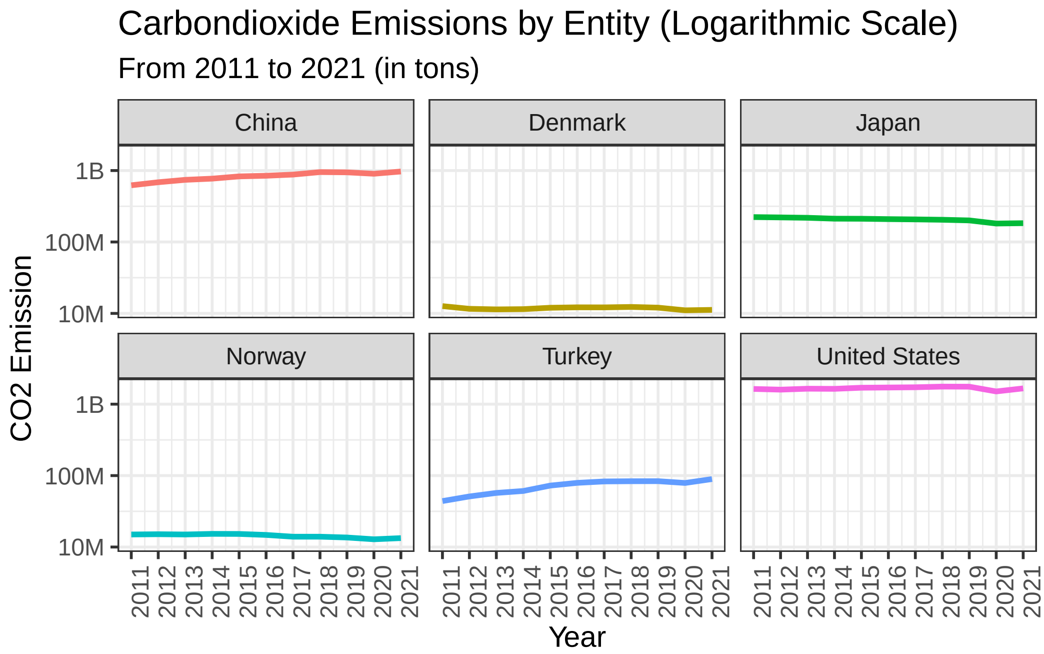
```r
top6_countries <- c("United States", "Norway", "Denmark", "China", "Japan",
                    "Turkey")

emission_by_country <- my_data3 |>
  filter(entity %in% top6_countries)

head(emission_by_country)
```

```
         entity code year transport_co2_emissions
1         China  CHN 2011               621890000
2       Denmark  DNK 2011                12640000
3         Japan  JPN 2011               223030000
4        Norway  NOR 2011                14980000
5        Turkey  TUR 2011                44000000
6 United States  USA 2011              1633590000
```

Here, **emission_by_country** is the more tidied version of my_data3 in which the interested countries' carbondioxide emission is analyzed.

The line plot below visualizes how much tons of carbondioxide did each selected country emit:

```r
ggplot(emission_by_country, aes(x = year, y = transport_co2_emissions, color = entity)) +
  geom_line(size = 1) +
  scale_y_continuous(
    trans = "log10",
    breaks = c(1, 10, 100, 1000, 10000, 100000, 1000000, 10000000, 100000000, 1000000000, 1000
    labels = c("1", "10", "100", "1K", "10K", "100K", "1M", "10M", "100M", "1B", "10B")
  ) +
  scale_x_continuous(breaks = 2011:2021) +
  facet_wrap(~ entity) +
  labs(x = "Year",
       y = "CO2 Emission",
       title = "Carbondioxide Emissions by Entity (Logarithmic Scale)",
       subtitle = "From 2011 to 2021 (in tons)"
       ) +
  theme_bw() +
  theme(legend.position = "none",
        axis.text.x = element_text(angle = 90, hjust = 1))
```

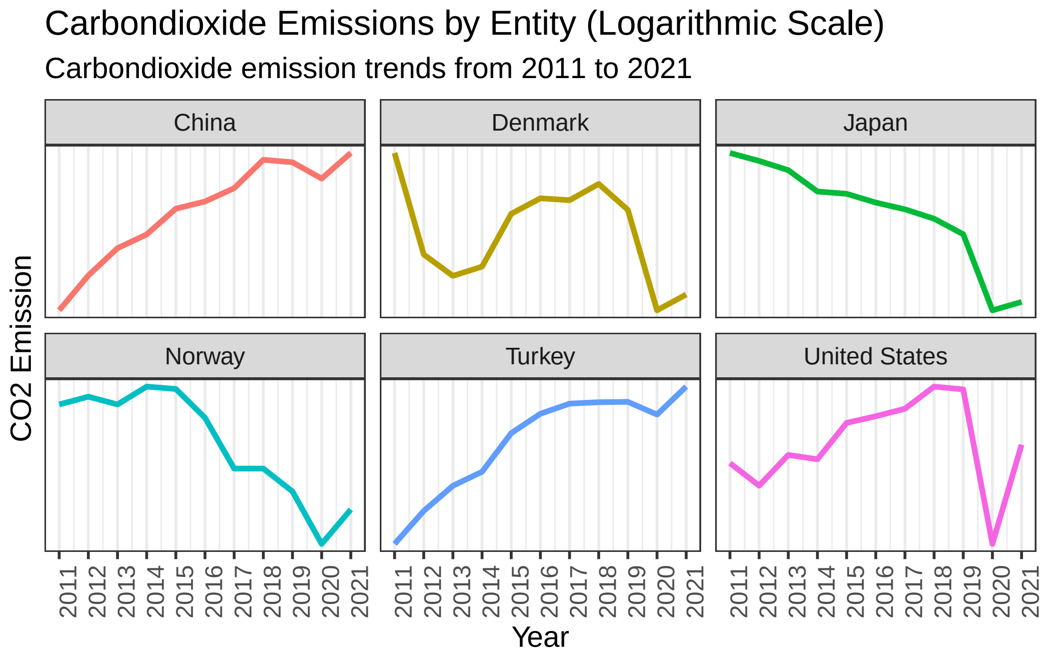


Here are some observations from this graph:

1. It can be observed that there is a persistent increase in the carbondioxide emission levels in **Turkey and China**. China is very close to emit one billion tons of carbondioxide.
2. **Denmark** has decreased its carbondioxide emission level after a 10-year horizon. **Japan and Norway** has a considerable decreasing trend in its carbondioxide emission level.
3. **USA** has the highest carbondioxide emission compared to others, exceeding one billion tons of carbondioxide.

This graph compares those 6 countries very well, but it's not possible to see the trends for each of them. Therefore, the line plot below has been made to display the **trend** in the transportation carbondioxide emission levels of those exactly same countries to make a comparison.

```
ggplot(emission_by_country, aes(x = year, y = transport_co2_emissions, color = entity)) +
  geom_line(size = 1) +
  scale_y_continuous(
    trans = "log10",
    breaks = c(1, 10, 100, 1000, 10000, 100000, 1000000, 10000000, 100000000, 1000000000, 1000
    labels = c("1", "10", "100", "1K", "10K", "100K", "1M", "10M", "100M", "1B", "10B")
  ) +
  scale_x_continuous(breaks = 2011:2021) +
  facet_wrap(~ entity, scale = "free_y") +
  labs(x = "Year",
      y = "CO2 Emission",
      title = "Carbondioxide Emissions by Entity (Logarithmic Scale)",
      subtitle = "Carbondioxide emission trends from 2011 to 2021"
      ) +
  theme_bw() +
  theme(legend.position = "none",
       axis.text.x = element_text(angle = 90, hjust = 1))
```



Here are some observations from this graph:

1. It can be observed that China's, USA's and Turkey's total transportation carbondioxide emission level have an increasing trend over years while Denmark's, Norway's and Japan's have a decreasing trend.

2. All of the countries have a clear reduction of total transportation carbondioxide emission level **in 2020**. This is the effect of **COVID-19 pandemic** which causes a **V-shaped pattern** for all countries listed.

This graphs gives a lot of information about transportation carbondioxide emission levels of those countries. But is it correct to make a decision just by looking at these graphs only? May population be the reason of some countries' low/high total transportation carbondioxide emission levels? Let's analyze it.

ANALYSIS OF THE POPULATION DATA ALONG WITH CO2 EMISSIONS (my_data3 & my_data8)

The Effect of Population on Transport CO2 Emissions

```r
str(my_data8)
```

```
'data.frame':   2816 obs. of  3 variables:
 $ entity    : chr  "Afghanistan" "Afghanistan" "Afghanistan" "Afghanistan" ...
 $ year      : int  2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 ...
 $ population: num  29347709 30560036 31622708 32792527 33831765 ...
```

entity: A character column in my_data3 data set which represents the countries.

year: An integer column in my_data3 data set which represents the year.

population: A numeric column in my_data8 data set which represents the population of each country.

```r
countries_selected <- c("United States", "Norway", "Denmark", "China", "Japan", "Turkey")

pop_n_co2 <- my_data3 |>
  full_join(my_data8, by = c("entity" = "entity", "year" = "year")) |>
  replace_na(list(transport_co2_emissions = 0, population = 0))
head(pop_n_co2)
```

```
                entity code year transport_co2_emissions population
1          Afghanistan  AFG 2011                 6710000   29347709
2               Africa      2011               267989980          0
3              Albania  ALB 2011                 2360000    2911500
4              Algeria  DZA 2011                34220000   36903375
5               Angola  AGO 2011                 6280000   24218358
6  Antigua and Barbuda  ATG 2011                  190000      86349
```

Here, two data frames has been joined to include carbondioxide emissions and population columns in one data frame and replace the NA values to zero.

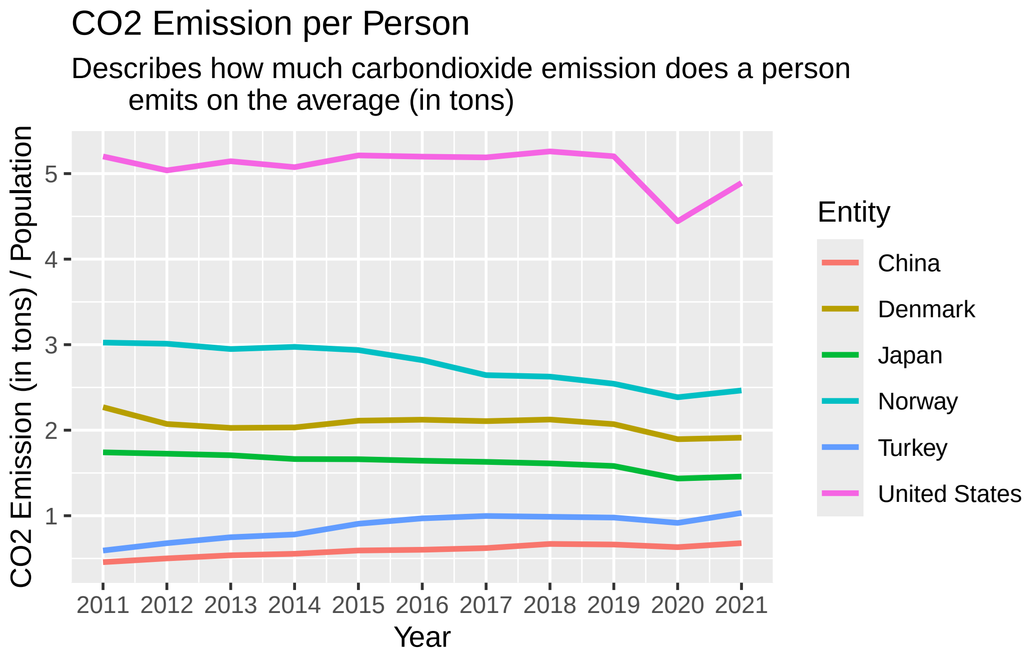
```r
pop_n_co2 <- pop_n_co2 |>
  mutate(prop = transport_co2_emissions / population) |>
  filter(entity %in% countries_selected)
head(pop_n_co2)
```

```
         entity code year transport_co2_emissions population      prop
1         China  CHN 2011               621890000 1360250657 0.4571878
2       Denmark  DNK 2011                12640000    5570846 2.2689552
3         Japan  JPN 2011               223030000  128096431 1.7411102
4        Norway  NOR 2011                14980000    4952968 3.0244492
5        Turkey  TUR 2011                44000000   74215200 0.5928705
6 United States  USA 2011              1633590000  314105078 5.2007755
```

After that, the data has filtered by selected countries.

The line plot below visualizes the selected countries' carbondioxide emission per person on the average over time:

```r
ggplot(pop_n_co2, aes(x = year, y = prop, color = entity)) +
  geom_line(size = 1) +
  scale_x_continuous(breaks = 2011:2021) +
  labs(x = "Year",
       y = "CO2 Emission (in tons) / Population",
       title = "CO2 Emission per Person",
       subtitle = "Describes how much carbondioxide emission does a person
       emits on the average (in tons)",
       color = "Entity")
```



Here are some observations from this graph:

1. When we analyze the transportation carbon emission per person, even China has the one of the highest total transportation carbondioxide emission, it can be seen that **China** has the lowest transportation carbondioxide emission per person among all other countries. While **USA** on the other hand, still has the highest level.
2. **Denmark's, Norway's and Japan's** transportation carbon emission per person have a **decreasing** trend.
3. **Turkey's** transportation carbon emission per person is **not high** but it has an **increasing** trend.
4. The decrease **in 2020** can be seen again.

GLOBAL EV SALES (my_data2)

```r
str(my_data2)
```

```
spc_tbl_ [8,019 x 8] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
 $ region    : chr [1:8019] "Australia" "Australia" "Australia" "Australia" ...
 $ category  : chr [1:8019] "Historical" "Historical" "Historical" "Historical" ...
 $ parameter : chr [1:8019] "EV stock share" "EV sales share" "EV sales" "EV stock" ...
 $ mode      : chr [1:8019] "Cars" "Cars" "Cars" "Cars" ...
 $ powertrain: chr [1:8019] "EV" "EV" "BEV" "BEV" ...
 $ year      : num [1:8019] 2011 2011 2011 2011 2011 ...
 $ unit      : chr [1:8019] "percent" "percent" "Vehicles" "Vehicles" ...
 $ value     : num [1:8019] 3.9e-04 6.5e-03 4.9e+01 4.9e+01 2.2e-02 ...
 - attr(*, "spec")=
  .. cols(
  ..   region = col_character(),
  ..   category = col_character(),
  ..   parameter = col_character(),
```

```
  ..   mode = col_character(),
  ..   powertrain = col_character(),
  ..   year = col_double(),
  ..   unit = col_character(),
  ..   value = col_double()
  .. )
 - attr(*, "problems")=<externalptr>
```

region: A character column in my_data2 data set which represents the countries and the world.

category: A character column in my_data2 data set which represents how the data has collected.

parameter: A character column in my_data2 data set which represents the parameter of the data collected.

mode: A character column in my_data2 data set which represents the vehicle types.

powertrain: A character column in my_data2 data set which represents how the vehicle gets its power from, a.k.a. type of the powertrain that the vehicle uses which are EV, BEV, PHEV etc.

year: A numeric column in my_data2 data set which represents the year.

unit: A character column in my_data2 data set which represents the unit that is used.

value: A numeric column in my_data2 data set which represents the amount of the vehicles in unit.

Sales of No Carbon Vehicles

What about the countries' adoption on EV's? To be able to understand the relationship between EV sales and transportation, my_data2 is used. The same countries are filtered from it.

The types of EV's are summarized below.

- Battery Electric Vehicle (BEV)
- Plug-in Hybrid Electric Vehicle (PHEV)
- Fuel Cell Electric Vehicle (FCEV)
- Hybrid Electric Vehicle (HEV)
- Mild Hybrid Vehicle (MHEV)

BEV and FCEV sales are analysed since they're the no carbon ones.

```r
my_data2$region[my_data2$region == "Turkiye"] <- "Turkey"
# AI generated content based on the prompt: In my R data frame, I have a region
# column and I have seen that Turkey in one data set is written as Turkiye in
# another data set so that I want to make Turkiye as Turkey. How can I change
# it?
top6_countries = c("USA", "Norway", "Denmark", "China", "Japan", "Turkey")
no_carbon = c("BEV", "FCEV")

top6_ev_sales <- my_data2 |>
  filter(region %in% top6_countries, parameter == "EV sales", powertrain %in% no_carbon)

top6_ev_sales |> mutate(value = as.numeric(format(value, scientific = FALSE)))
```

```
# A tibble: 276 x 8
   region  category   parameter mode  powertrain  year unit      value
   <chr>   <chr>      <chr>     <chr> <chr>      <dbl> <chr>     <dbl>
 1 China   Historical EV sales  Buses BEV         2011 Vehicles    440
 2 China   Historical EV sales  Vans  BEV         2011 Vehicles    150
 3 China   Historical EV sales  Cars  BEV         2011 Vehicles   4800
 4 Denmark Historical EV sales  Vans  BEV         2011 Vehicles     23
 5 Denmark Historical EV sales  Cars  BEV         2011 Vehicles    420
 6 Denmark Historical EV sales  Buses BEV         2011 Vehicles      1
 7 Japan   Historical EV sales  Cars  BEV         2011 Vehicles 13000
 8 Japan   Historical EV sales  Buses BEV         2011 Vehicles      2
 9 Japan   Historical EV sales  Vans  BEV         2011 Vehicles    850
10 Norway  Historical EV sales  Vans  BEV         2011 Vehicles     42
# i 266 more rows
```

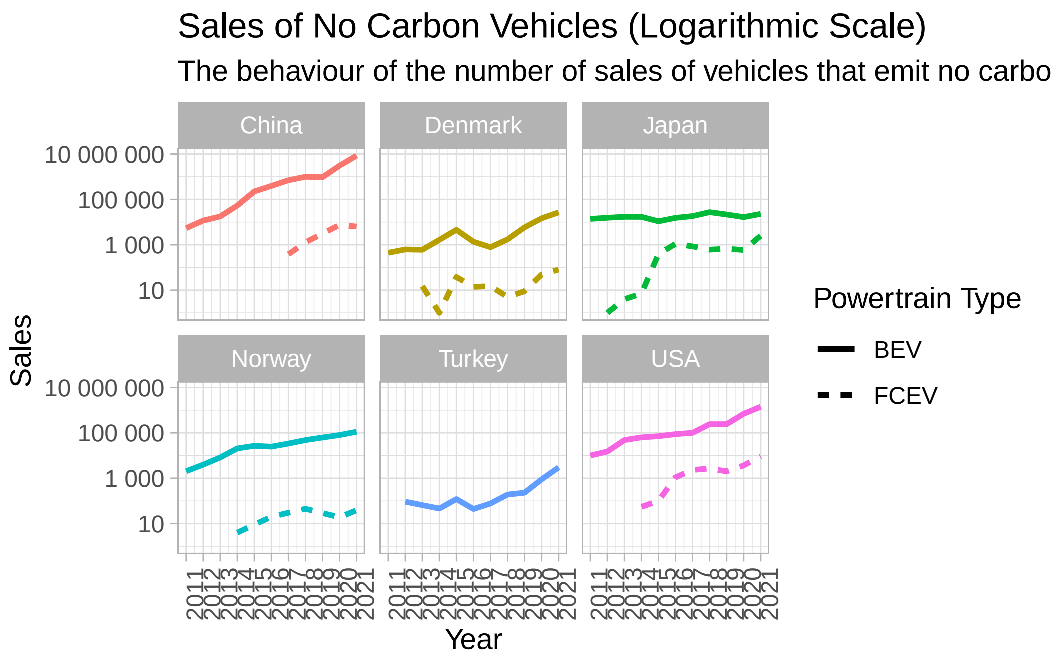
```r
# AI generated content based on the prompt: In my R data set, there are values
# something like 1.0e+01 that makes me harder to interpret, I don't want
# scientific notations, how can I fix this?
# AI generated content based on the prompt: How can I mutate them in a data
# frame?
head(top6_ev_sales)
```

```
# A tibble: 6 x 8
  region  category   parameter mode  powertrain  year unit      value
  <chr>   <chr>      <chr>     <chr> <chr>      <dbl> <chr>     <dbl>
1 China   Historical EV sales  Buses BEV         2011 Vehicles    440
2 China   Historical EV sales  Vans  BEV         2011 Vehicles    150
3 China   Historical EV sales  Cars  BEV         2011 Vehicles   4800
4 Denmark Historical EV sales  Vans  BEV         2011 Vehicles     23
5 Denmark Historical EV sales  Cars  BEV         2011 Vehicles    420
6 Denmark Historical EV sales  Buses BEV         2011 Vehicles      1
```

The line plot below visualizes how the EV Sales of Non-Carbon Vehicles has evolved over the 10-year horizon:

```r
top6_ev_sales |> group_by(year, region, powertrain) |>
  summarize(total_sales = sum(value, na.rm = TRUE), .groups = "drop") |>
  ggplot(aes(x = year, y = total_sales, color = region,
             linetype = powertrain)) +
  geom_line(size = 1) +
  scale_x_continuous(breaks = 2011:2021) +
  scale_y_continuous(trans = "log10",
                     labels = label_number(scale = 1, accuracy = 1)
                     ) +
  labs(x = "Year",
       y = "Sales",
       title = "Sales of No Carbon Vehicles (Logarithmic Scale)",
       subtitle = "The behaviour of the number of sales of vehicles that emit no carbon over t
       color = "Region",
       linetype = "Powertrain Type"
  ) +
  facet_wrap(~ region) +
```

```
  theme_light() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
  guides(color = "none") # AI generated content based on the prompt: I have two legends in the
```



Here are some observations from this graph:

1. All countries in the plot increased their non-carbon emitting vehicle sales after 10-year horizon. However, **Turkey** has not been adopted **FCEV's through 2021** yet, while the other countries are using **FCEV's** more year by year. **China** has started using **FCEV's** (in 2016) **later** than the others (in 2011-2014). It can be also observed that **BEV** sales has started **2012 in Turkey**.
2. **China** has increased its **BEV** and **FCEV** sales more than any other country, however from the last analyses we know that it couldn't make any big difference in total transportation carbondioxide emission since it's population is too high. On the other hand, **in Norway and Denmark**, **BEV's** and **FCEV's** has a **positive** effect on total transportation carbondioxide emission since their populations are much lower than **China**.
3. It can be seen that **Japan** didn't increase the sales of **BEV's**. Yet, they managed to decrease the total transportation carbondioxide emission by increasing the **FCEV** sales considerably, which means they have done some other applications.

The Relationship Between CO2 Emission & Total EV Sales (my_data2 & my_data3)

So, how carbondioxide emission has been affected by total EV sales?

For this part of analysis, **my_data2** and **my_data3** will be used. The selected countries will be analyzed again.

```
countries_selected <- c("United States", "Norway", "Denmark", "China", "Japan", "Turkey")

my_data2$region[my_data2$region == "USA"] <- "United States"

my_data2_selected <- my_data2 |>
  filter(region %in% countries_selected, parameter == "EV sales") |>
```

```
  group_by(region, year) |>
  summarize(total_ev_sales = sum(value), .groups = "keep")

my_data3_selected <- my_data3 |>
  filter(entity %in% countries_selected) |>
  select(-code)

my_data2_3_selected <- my_data2_selected |>
  full_join(my_data3_selected, by = c("region" = "entity", "year" = "year")) |>
  replace_na(list(total_ev_sales = 0, transport_co2_emissions = 0))
head(my_data2_3_selected)
```

```
# A tibble: 6 x 4
# Groups:   region, year [6]
  region  year total_ev_sales transport_co2_emissions
  <chr>  <dbl>          <dbl>                   <dbl>
1 China   2011           5870               621890000
2 China   2012          12440               686130000
3 China   2013          20280               741090050
4 China   2014          83480               770349950
5 China   2015         299000               828460000
6 China   2016         479600               845360000
```

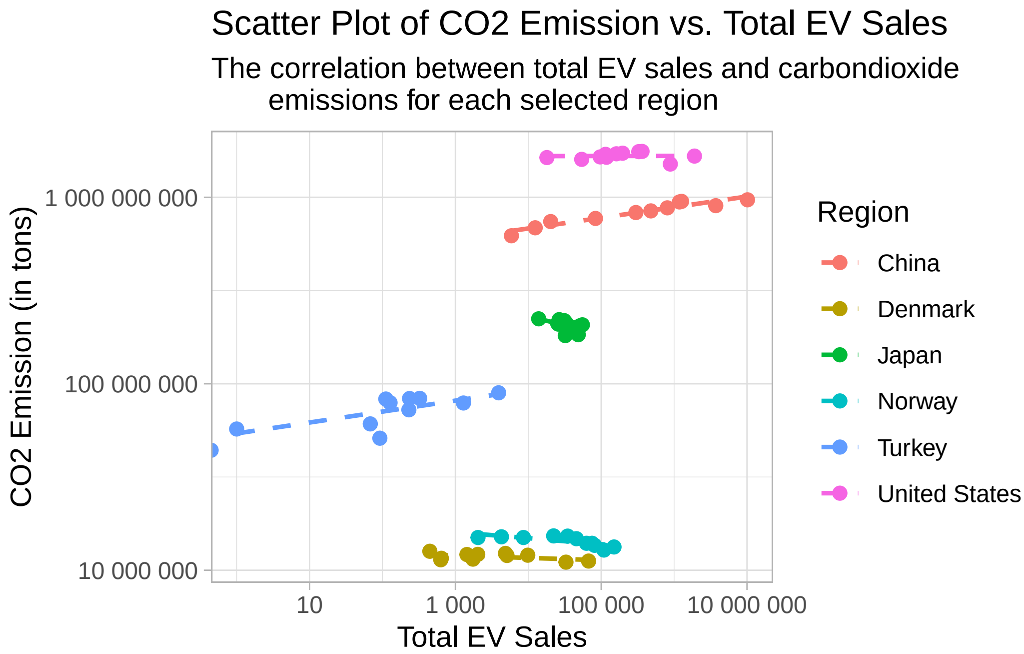
Join operation is used again. NA values stems from joining operation has been set to zero.

However, one of the selected countries has named differently, which is USA. To avoid this, **USA** in my_data2 has been changed to **United States**.

Now, the total EV sales and transport CO2 emissions can be seen in one tibble.

The scatter plot below visualizes the behaviour including trend lines connecting these points in each selected country.

```
ggplot(my_data2_3_selected, aes(x = total_ev_sales, y = transport_co2_emissions,
                                color = region)) +
  geom_point(size = 2) +
  geom_smooth(method = "lm", se = FALSE, linetype = "dashed", size = 0.8,
              alpha = 0.5) +
  scale_x_continuous(trans = "log10",
                     labels = label_number(scale = 1, accuracy = 1)) +
  scale_y_continuous(trans = "log10",
                     labels = label_number(scale = 1, accuracy = 1)) +
  labs(x = "Total EV Sales",
       y = "CO2 Emission (in tons)",
       title = "Scatter Plot of CO2 Emission vs. Total EV Sales",
       subtitle = "The correlation between total EV sales and carbondioxide
       emissions for each selected region",
       color = "Region") +
  theme_light()
```



The correlation between total sales and carbondioxide emission is **not always** positive. **Half of the countries** has succeeded to decrease their carbondioxide emissions despite their increase in the **total EV sales**.

TURKEY's STATUS (my_data4)

```
str(my_data4)
```

```
tibble [11 x 15] (S3: tbl_df/tbl/data.frame)
 $ year                 : chr [1:11] "2011" "2012" "2013" "2014" ...
 $ total                : chr [1:11] "8113111" "8648875" "9283923" "9857915" ...
 $ percentage_total     : chr [1:11] "100" "100" "100.000000000001" "100.000000000001" ...
 $ gas                  : chr [1:11] "3036129" "2929216" "2888610" "2855078" ...
 $ percentage_gas       : chr [1:11] "37.422500444034348" "33.868173606393896" "31.1141098434357
 $ diesel               : chr [1:11] "1756034" "2101206" "2497209" "2882885" ...
 $ percentage_diesel    : chr [1:11] "21.644397568331065" "24.294558540850687" "26.8982088714005
 $ lpg                  : chr [1:11] "3259288" "3569143" "3852336" "4076730" ...
 $ percentage_lpg       : chr [1:11] "40.173097594745101" "41.267135899177639" "41.4947000314414
 $ hybrid               : chr [1:11] "23" "53" "83" "113" ...
 $ percentage_hybrid    : chr [1:11] "0.00028349174564479642" "0.00061279646196759697" "0.000894
 $ electric             : chr [1:11] "24" "175" "353" "412" ...
 $ percentage_electric: chr [1:11] "0.00029581747371630932" "0.0020233845442326312" "0.0038022
 $ unknown              : chr [1:11] "61613" "49082" "45332" "42697" ...
 $ percentage_unknown : chr [1:11] "0.75942508367012351" "0.56749577257157724" "0.488284963156
```

year: A character column in my_data4 data set which represents the year.

total: A character column in my_data4 data set which represents the total number of vehicles that are on traffic.

percentage_total: A character column which represents the total number of vehicles over total number of vehicles.

gas: A column in my_data4 data set which represents the vehicles which operates with gas.

percentage_gas: A character column which represents the number of vehicles that uses gas over total number of vehicles.

diesel: A column in my_data4 data set which represents the vehicles which operates with diesel.

percentage_diesel: A character column which represents the number of vehicles that are diesel over total number of vehicles.

lpg: A column in my_data4 data set which represents the vehicles which operates with LPG.

percentage_lpg: A character column which represents the number of vehicles that uses lpg over total number of vehicles.

hybrid: A column in my_data4 data set which represents the vehicles which operates with hybrid.

percentage_hybrid: A character column which represents the number of vehicles that are hybrid over total number of vehicles.

electric: A column in my_data4 data set which represents the vehicles which operates with electric.

percentage_electric: A character column which represents the number of vehicles that uses electric over total number of vehicles.

unknown: A column in my_data4 data set which represents the vehicles which operates with unknown power.

percentage_unknown: A character column which represents the number of vehicles that are unknown over total number of vehicles.

Vehicle Trends in Turkey

How about the adoption of **EV's** and **the others in Turkey?**

my_data4 will be used for this part of analysis.

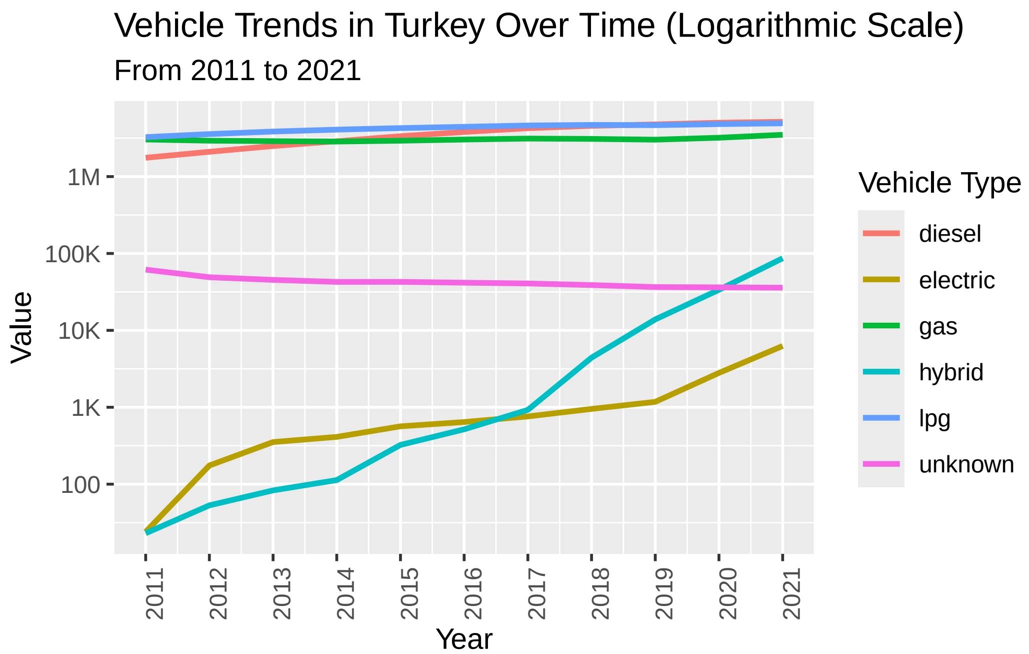
```
tr_vehicle_num <- my_data4 |>
  mutate(across(everything(), as.numeric)) |>
# AI generated content based on the prompt: I want to make all the variables
# numeric so how can I do that in dplyr?
  select(-starts_with("percentage"))

tr_vehicle_num_long <- tr_vehicle_num |>
  pivot_longer(
    cols = c(gas, diesel, lpg, hybrid, electric, unknown),
    names_to = "vehicle_type",
    values_to = "value"
  )

head(tr_vehicle_num_long)
```

```
# A tibble: 6 x 4
   year   total vehicle_type   value
  <dbl>   <dbl> <chr>          <dbl>
1  2011 8113111 gas          3036129
2  2011 8113111 diesel       1756034
3  2011 8113111 lpg          3259288
```

```
4  2011 8113111 hybrid           23
5  2011 8113111 electric         24
6  2011 8113111 unknown       61613
```

Here, the percentage column is deleted, and all other columns of vehicle types and their values have been brought into columns named **vehicle_type** and **value** by using **pivot_longer()** function.

In order to visualize the vehicles trend in Turkey, the following code is used:



Although there was an **increase** in **EV's** and **hybrid** vehicles, **Turkey's** total transportation carbon-dioxide emission has increased **consistently** (information from Country Based Mean Transportation CO2 Emission section) and the effect of COVID-19 pandemic was quite **temporary** on it.

The behaviour of the number of vehicles is known now. However, an important question is, have these increases in the number of **EV** and **hybrid** vehicles been considerable on a proportional view?

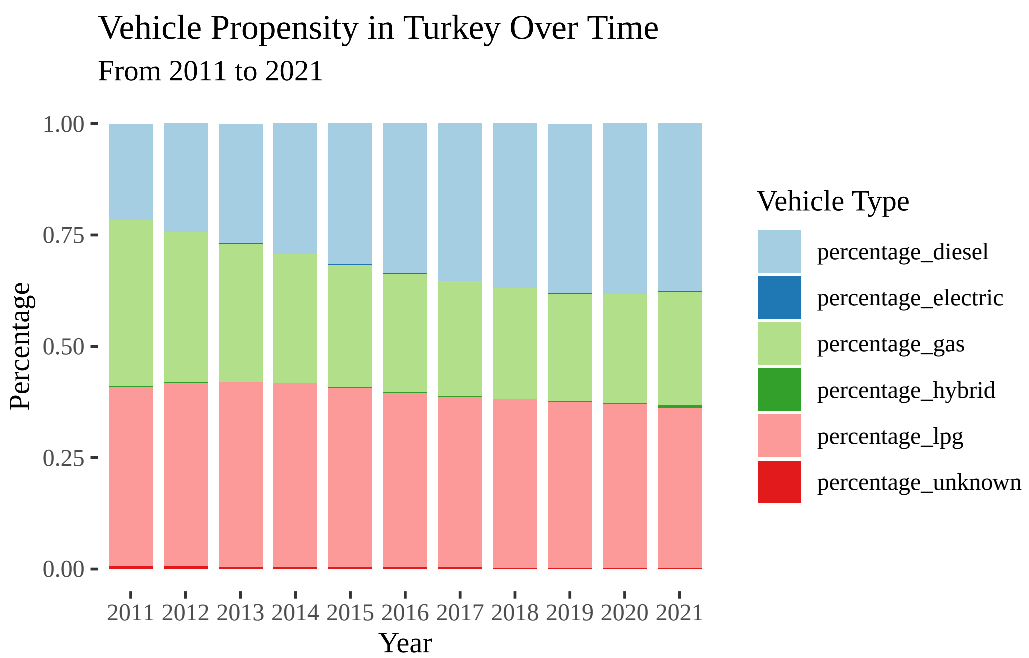
```
vehicle_prop <- c("percentage_gas", "percentage_diesel", "percentage_lpg", "percentage_hybrid"

tr_vehicle_perc_long <- my_data4 |>
  pivot_longer(cols = vehicle_prop, names_to = "vehicle_type", values_to = "percentage") |>
  select(year, vehicle_type, starts_with("percentage"))

tr_vehicle_perc_long$percentage <- as.numeric(tr_vehicle_perc_long$percentage)

head(tr_vehicle_perc_long)
```

```
# A tibble: 6 x 4
  year  vehicle_type        percentage_total percentage
  <chr> <chr>               <chr>                 <dbl>
1 2011  percentage_gas      100                37.4
2 2011  percentage_diesel   100                21.6
3 2011  percentage_lpg      100                40.2
4 2011  percentage_hybrid   100                 0.000283
5 2011  percentage_electric 100                 0.000296
6 2011  percentage_unknown  100                 0.759
```

This time, columns including percentages and their values have been selected brought into columns named **vehicle_type** and **percentage**, respectively, by using **pivot_longer()** function.

The cumulative bar plot below displays the proportion of vehicle types over time.

```
ggplot(tr_vehicle_perc_long, aes(x = year, y = percentage,
                                 fill = vehicle_type)) +
  geom_bar(stat = "identity", position = "fill", width = 0.8) +
  scale_fill_brewer(palette = "Paired") +
  labs(x = "Year",
       y = "Percentage",
       title = "Vehicle Propensity in Turkey Over Time",
       subtitle = "From 2011 to 2021",
       fill = "Vehicle Type"
  ) +
  theme_tufte()
```



In fact, **non-EV's** were still used widely **in Turkey**, leading to be the one of the reason of increase in carbondioxide emission levels.

KEY TAKEAWAYS

- **Electric Vehicles (EV's) and CO2 Emissions:** This study examines the impact of EV adoption on CO2 emissions in the transportation sector. The analysis covers global EV sales trends and CO2 emission levels in various countries over the past decade. • Data sources and scope: The analysis uses data from my_data3, my_data2, and my_data4, which include information on transportation-related CO2 emissions, population statistics, and EV sales. The study focuses on both global and Turkey-specific trends.
- **Key Findings:** While countries like China and the United States have seen an increase in CO2 emissions, Norway and Denmark have demonstrated a decrease in emissions due to strong adoption of non-carbon emitting vehicles.

Although Turkey has increased the number of electric and hybrid vehicles, overall CO_2 emissions have not significantly decreased, highlighting the need for infrastructure improvements and greater use of renewable energy sources.

- **Factors Influencing Success:** The adoption of electric vehicles is most effective when influenced by factors such as population density and energy infrastructure.
- **Main Outcome:** The study concludes that while EV adoption has the potential to significantly reduce transportation-related emissions, its effectiveness depends on factors such as population density and the transition to renewable energy sources.