Final project

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1 Introduction

In this project, we will conduct an analysis of global carbon dioxide (CO2) emissions from 1960 to 2019. The main objective is to examine these data, graph them and then predict future trends in CO2 emissions. The aim is to determine whether, in the current situation, the commitments made under the Paris agreements and the targets set for 2030 and 2050 will be reached.

To accomplish this task, we made use of three databases, one containing carbon dioxide emissions by country from 1960 to 2019, another of these databases also included the population of each country in 2019, as well as their respective surface areas. And the last one is containing the total population for each year from 1960 to 2019. We subsequently merged these databases into a single entity, making it easier to exploit the data and produce the necessary estimates.

You can find the databases by clicking here (first database, second database, third)

2 Data cleaning

As a first step, we're going to clean up the database by removing rows containing missing values and ensuring that there are only rows containing country names.

```
# Reading data from CSV files
Data_WorldCO2 <- read_csv("co2_emissions_kt_by_country.csv")

Data_CO2 <- read_csv2("CO2_emission2.csv")
Data_CO2 <- Data_CO2 %>% filter(Year >= 1960)

glob_pop <- read.csv("Global_annual_population.csv")
```

```
# List of words to remove to keep only countries, not regions or others
words_to_remove <- c('Asia', 'Euro', 'Caribbean', 'Africa', 'South Africa', 'demo',
                     'IDA', 'IBRD', 'income', 'World', 'Europe', 'North America',
                     'South Asia', 'OECD members', 'Euro area', 'Arab World',
                     'Heavily indebted poor countries (HIPC)', 'Small states',
                     'Other small states', 'Fragile and conflict-affected situations',
                     'Least developed countries: UN classification',
                     'Pacific island small states', "HIPC", "poor countries")

# Filter data to exclude rows containing specific words
Data_WorldCO2 <- Data_WorldCO2[!grepl(paste(words_to_remove, collapse = '|'),
                                      Data_WorldCO2$country_name), ]
```

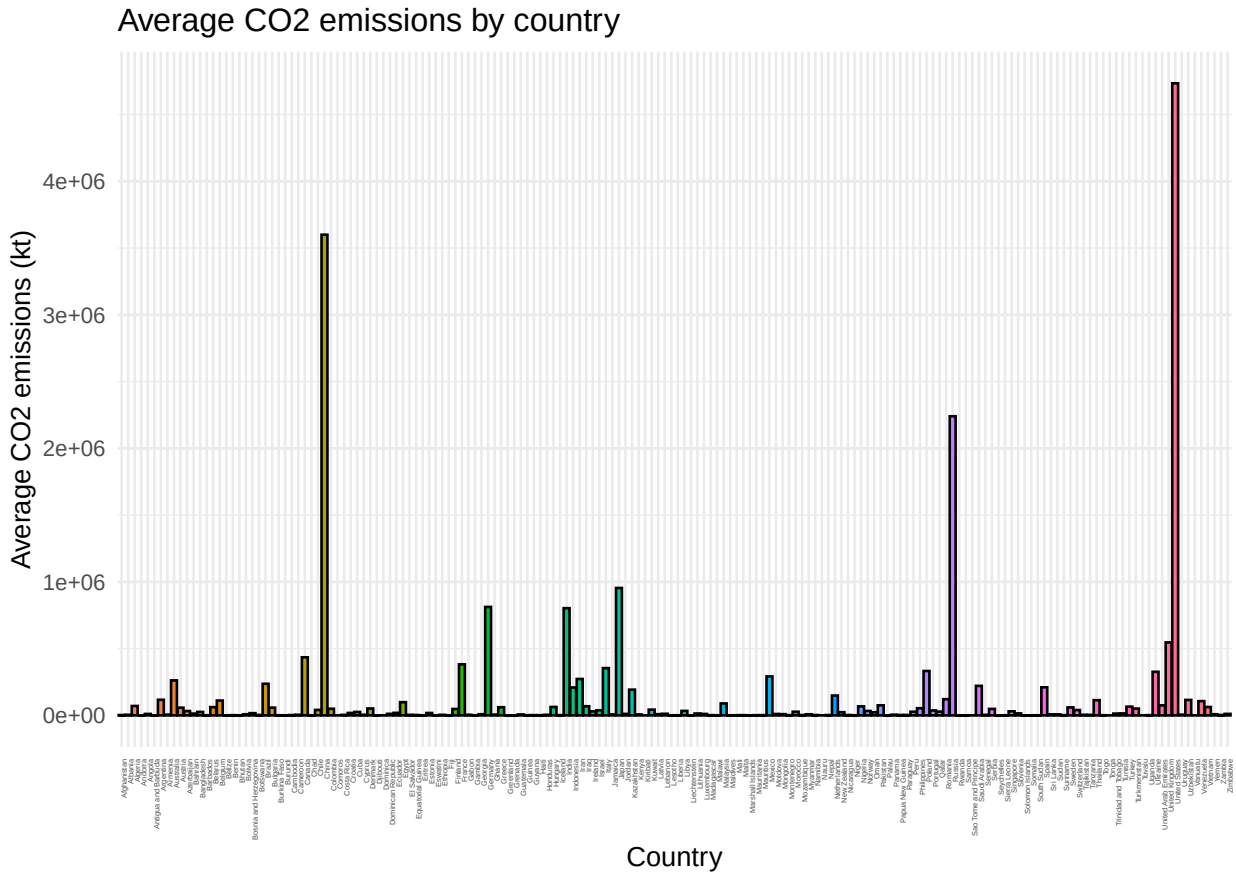
```r
# Modify country names to match the two datasets
Data_WorldCO2 <- Data_WorldCO2 %>%
  mutate(country_name = case_when(
    country_name == "Gambia, The" ~ "Gambia",
    country_name == "Hong Kong SAR, China" ~ "Hong Kong",
    TRUE ~ country_name
  ))

# Replace "Iran, Islamic Rep." with "Iran" in the "country_name" column
Data_WorldCO2 <- Data_WorldCO2 %>%
  mutate(country_name = ifelse(country_name == "Iran, Islamic Rep.", "Iran",
                               country_name))

# Replace "Venezuela, RB" with "Venezuela" in the "country_name" column
Data_WorldCO2 <- Data_WorldCO2 %>%
  mutate(country_name = ifelse(country_name == "Venezuela, RB", "Venezuela",
                               country_name))

# Replace "Egypt, Arab Rep." with "Egypt" in the "country_name" column
Data_WorldCO2 <- Data_WorldCO2 %>%
  mutate(country_name = ifelse(country_name == "Egypt, Arab Rep.", "Egypt",
                               country_name))

# Replace "Yemen, Rep." with "Yemen" in the "country_name" column
Data_WorldCO2 <- Data_WorldCO2 %>%
  mutate(country_name = ifelse(country_name == "Yemen, Rep.", "Yemen",
                               country_name))

Data_WorldCO2 <- select(Data_WorldCO2, -country_code)
Data_WorldCO2 <- Data_WorldCO2 %>%
  mutate(country_name = ifelse(country_name == "Russian Federation", "Russia",
                               country_name))

Data_CO2 <- select(Data_CO2, -Code)

# Rename columns of the Data_CO2 table to match those of Data_WorldCO2
Data_CO2 <- Data_CO2 %>%
  rename(country_name = Country, value = CO2, year = Year)

# Merge the two tables using the "country_name" and "year" columns
result <- left_join(Data_WorldCO2, Data_CO2, by = c("country_name", "year"))
result <- select(result, -value.y)
result <- result %>%
  rename(value = value.x)

# Filter countries with at least one missing value in a column other than "country_name"
countries_with_missing_values <- result %>%
  filter(rowSums(across(everything(), is.na)) > 0) %>%
  select(country_name)


result_cleaned <- anti_join(result, countries_with_missing_values, by = "country_name")
```

```r
# Delete column "X" and rename column "Year".
glob_pop <- glob_pop %>%
  select(-X) %>%
  rename(year = Year) %>%
  mutate(Population = Population * 1e9)
```

3 Visualization

3.1 Average Emissions of all countries

```r
average_emissions <- aggregate(. ~ country_name, data = result_cleaned, mean)

# Create the plot with a condition for the fill color
ggplot(average_emissions, aes(x = country_name, y = value, fill = country_name)) +
  geom_bar(stat = "identity", color = "black") +
  labs(title = "Average CO2 emissions by country",
       x = "Country", y = "Average CO2 emissions (kt)") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, size = 2.5)) +
  guides(fill = "none")
```

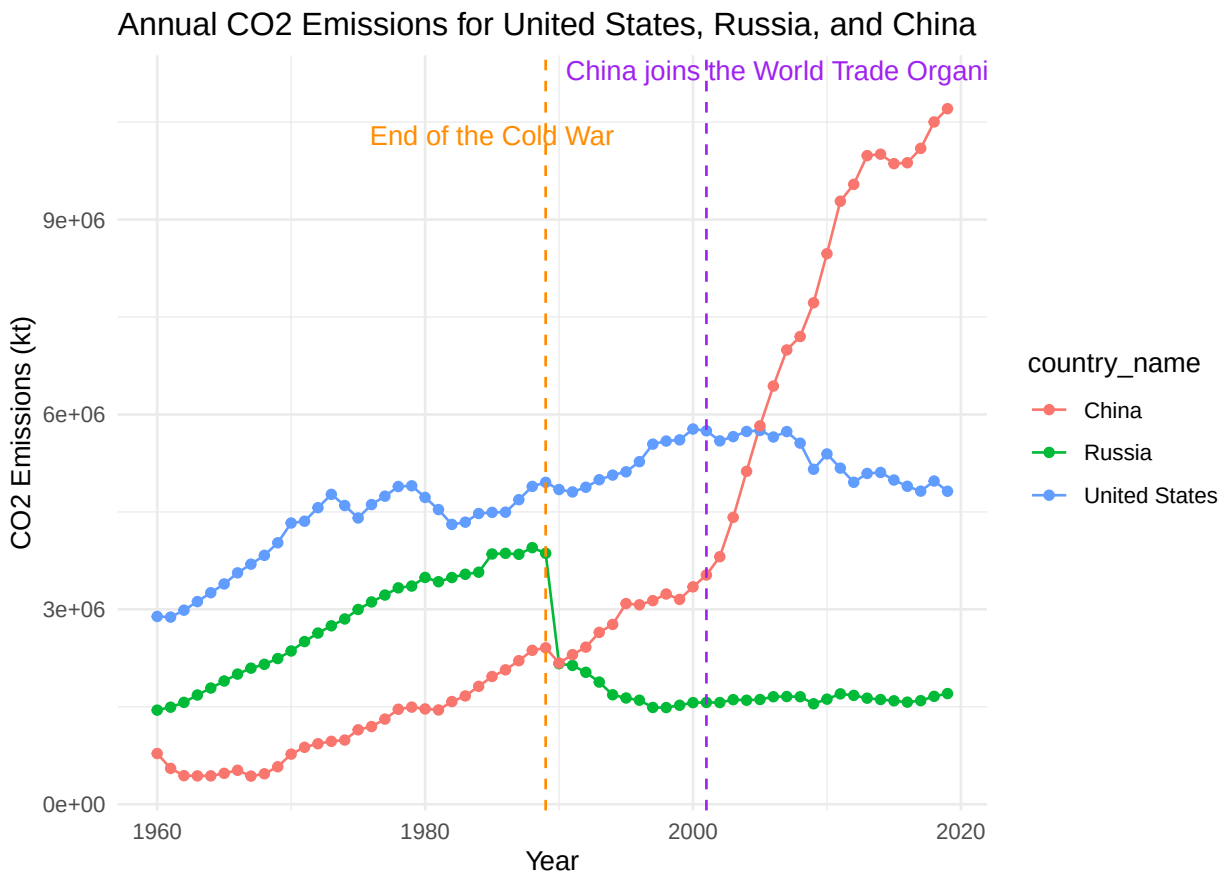


Based on this graph representing the average emissions of each country in the world from 1960 to 2019, we

can see that three countries stand out in terms of CO2 emissions: China, Russia, and the United States. Let's take a closer look at the CO2 emissions of the three biggest polluters.

3.2 Top 3 CO2 Emitting Countries

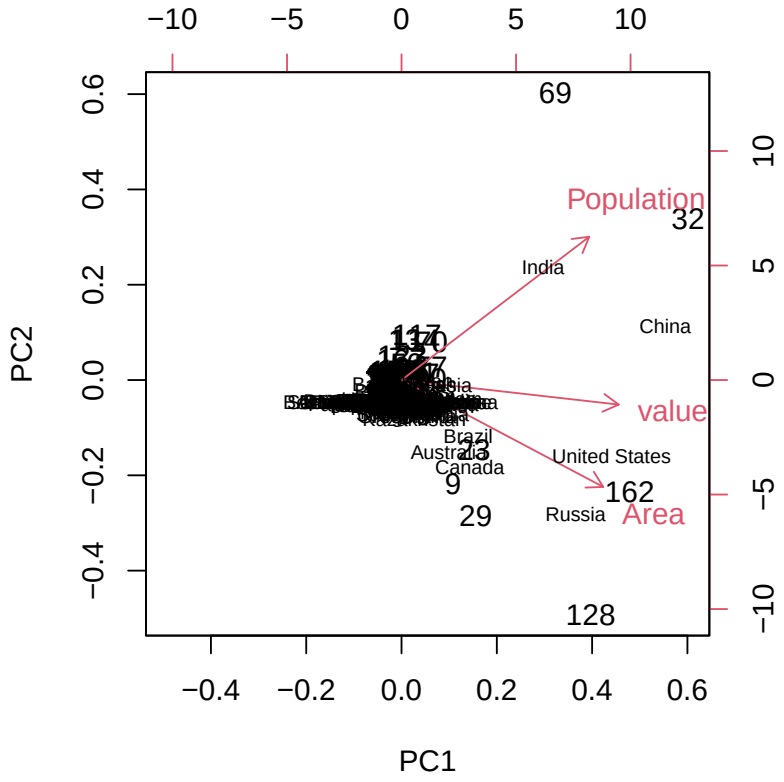
```
top_3_polluters <- c('United States', 'Russia', 'China')
# Subset data for the top 3 polluters
df_subset <- result_cleaned[result_cleaned$country_name %in% top_3_polluters, ]
df_us <- df_subset[df_subset$country_name == 'United States', ]
df_russia <- df_subset[df_subset$country_name == 'Russia', ]
df_china <- df_subset[df_subset$country_name == 'China', ]

# Convert 'year' to factor for categorical x-axis
df_subset$year <- as.factor(df_subset$year)

# Combine the data frames
df_combined <- rbind(df_us, df_russia, df_china)

# Create the ggplot object
ggplot(df_combined, aes(x = year, y = value, color = country_name, group= country_name))+

  # Add lines for each country
  geom_line() +

  # Add points for better visibility of years
  geom_point() +

  # Add annotations
  annotate("text", x = 1985, y = 1e+7, label = 'End of the Cold War', vjust = -0.5,
           color = 'darkorange') +
  annotate("text",x = 2009, y = 1.1e+7, label='China joins the World Trade Organization'
           , vjust = -0.5, color = 'purple') +

  # Add dashed lines
  geom_vline(xintercept = 1989, linetype = "dashed", color = "darkorange") +
  geom_vline(xintercept = 2001, linetype = "dashed", color = "purple") +

  # Customize the plot
  labs(title = "Annual CO2 Emissions for United States, Russia, and China",
       x = "Year",
       y = "CO2 Emissions (kt)") +
  theme_minimal()
```



This graph shows the evolution of CO2 emissions in China, the USA and Russia over the years. We can see that at the end of the Cold War (i.e. the collapse of the USSR), Russia's CO2 emissions dropped drastically. Moreover, when China joined the World Trade Organism", its CO2 emissions increased dramatically.

3.3 PCA Application to Explore Country Differences

```
# Selection of numeric columns for PCA
pca_variables <- average_emissions[, c("value", "Population", "Area")]

# Removal of rows with missing values if necessary
pca_variables <- na.omit(pca_variables)

# Standardization of data if necessary (z-standardization)
pca_variables_standardized <- scale(pca_variables)

# Execution of PCA
pca_results <- prcomp(pca_variables_standardized, scale. = TRUE)

# Principal Components Plot
biplot(pca_results)
# Adding country names next to each point
text(pca_results$x[, 1], pca_results$x[, 2], labels = average_emissions$country_name,
     pos = 1, cex = 0.7, col = "black")
```



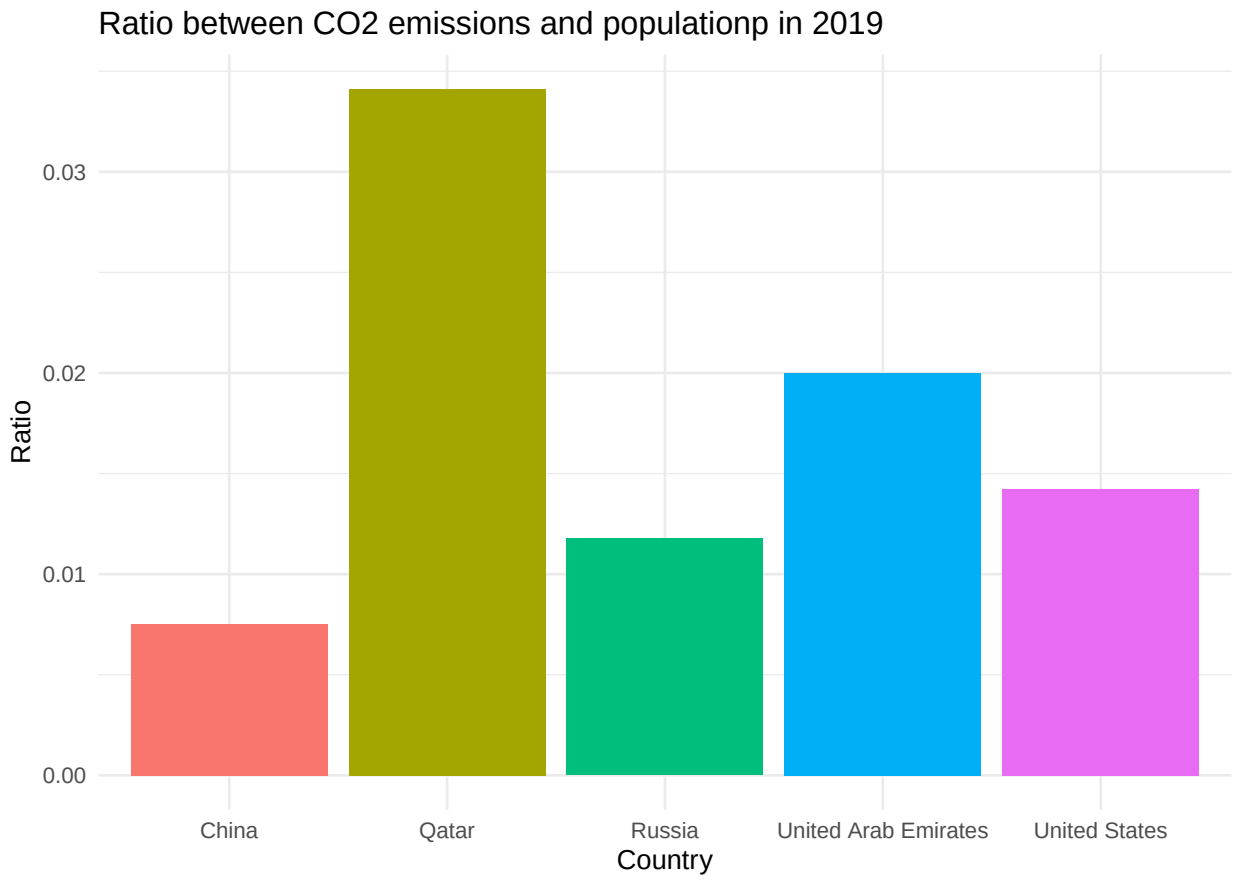
After analyzing this graph, we can see that certain countries stand out. Indeed, China and India differentiate themselves due to their high population compared to other countries, the United States stands out for its high CO2 emissions, and Russia differs due to its large land area.

We've seen that China is the country that currently emits the most CO2, but is also one of the most populous, so it would be interesting to compare emissions with the population of certain countries. To do this, we're going to plot the ratio between CO2 emissions and the number of inhabitants of various countries in a histogram.

3.4 Paralleling CO2 emissions and population for different countries in 2019

```
# Filter data for specific countries and the year 2019
filtered_data <- result %>%
  filter(country_name %in% c("China", "Russia", "United States", "United Arab Emirates",
                             "Qatar") & year == 2019)

# Calculate the ratio between "CO2 emissions" and "Population"
filtered_data <- mutate(filtered_data, ratio = value / Population)

# Create the histogram
histogram <- ggplot(filtered_data, aes(x = country_name, y = ratio, fill =country_name))+
  geom_bar(stat = "identity") +
  labs(title = "Ratio between CO2 emissions and populationp in 2019",
       x = "Country", y = "Ratio") +
  theme_minimal() +
```

```
  theme(legend.position = "none")

# Display the histogram
print(histogram)
```



This graph illustrates the ratio of carbon dioxide emissions per inhabitant in various countries. It becomes apparent that the countries with the highest per inhabitant emissions are not necessarily the world's biggest polluters. For example, China, which stands out as the world's first biggest polluter, is also densely populated, as demonstrated earlier in the principal component analysis. However, when we consider the number of inhabitants, China is not among the countries where the population contributes most to pollution. We could therefore ask about the CO2 emissions of the United Arab Emirates and Qatar, because they pollute a lot compared to their population.

It will therefore be interesting to adapt CO2 emission reduction strategies to each country according to its polluter profile.

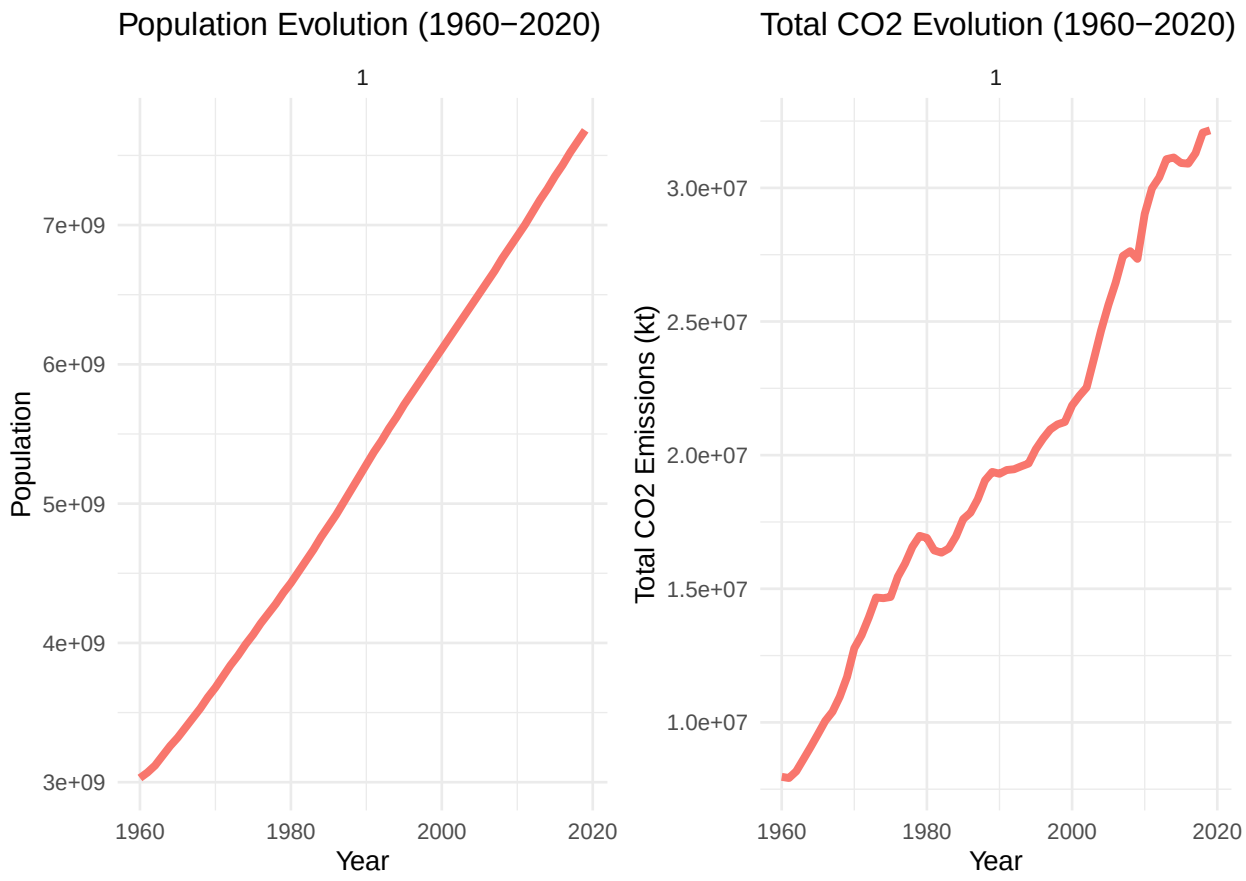
We will now focus on total CO2 emissions worldwide and try to predict the trend up to 2050.

4 Trends and forecastingt total CO2 emissions until 2050

First, let's look at how total co2 emissions have evolved since 1960.

```
#We create a dataset containing CO2 emissions and total population for each year since 1960
TOTAL_data <- result_cleaned %>%
  group_by(year) %>%
```

```r
  summarise(total_value = sum(value))%>%
  left_join(glob_pop %>% select(year, Population), by = "year")


#Visualization

plot1 <- ggplot(TOTAL_data, aes(x = year)) +
  geom_line(aes(y = Population, color = "Population"), size = 1.5) +
  labs(title = "Population Evolution (1960-2020)",
       x = "Year",
       y = "Population") +
  theme_minimal() +
  facet_grid(. ~ 1) +
  theme(legend.position="none")

plot2 <- ggplot(TOTAL_data, aes(x = year)) +
  geom_line(aes(y = total_value, color = "Total CO2 Emissions (kt)"), size = 1.5) +
  labs(title = "Total CO2 Evolution (1960-2020)",
       x = "Year",
       y = "Total CO2 Emissions (kt)") +
  theme_minimal() +
  facet_grid(. ~ 1) +
  theme(legend.position="none")

grid.arrange(plot1, plot2, ncol = 2)
```



As you can see from the two graphs, population and emissions have increased dramatically since 1960. Now we're going to train several regression models on these data to predict total CO2 emssions in 2030 and 2050. We'll then evaluate and compare them to determine which one best fits our data.

4.1 Training several regression model

We aim to compare three distinct models:

- Linear regression
- Lasso regression
- Ridge regression

in order to determine the most suitable approach for predicting global CO2 levels based on the variables of "Year" and "Population".

We will utilize cross-validation as a pivotal criterion to assess the models, with the test Mean Squared Error (MSE) serving as the principal metric for our evaluation of model performance.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

where y_i represents the actual observed values from the test set, and $\hat{y}_i$ represents the predicted values from the model.

To begin, we'll standardize the data and split it into a training set and a test set. Standardization ensures consistent scaling, while the division enables a robust evaluation of Linear regression, Lasso regression, and Ridge regression models.

```
#First of all we standadize the data because we manipulate large numbers (of the order of 10^9)
TOTAL_data$standardized_total_value <- scale(TOTAL_data$total_value)
TOTAL_data$standardized_pop <- scale(TOTAL_data$Population)

#Now we divide the database into two randomly sampled subsets (traning_set and test_set).
set.seed(123)
indices_train <- sample(1:nrow(TOTAL_data), 0.8 * nrow(TOTAL_data))
train_data <- TOTAL_data[indices_train, ]
test_data <- TOTAL_data[-indices_train, ]
```

4.1.1 Linear regression

The Linear regression model is chosen for its simplicity and interpretability. This model allows us to directly understand the impact of each explanatory variable on the global CO2 levels

```
# Create the linear regression model on the training set
model <- lm(standardized_total_value ~ year + standardized_pop, data = train_data)

# Predict on the test set
predictions <- predict(model, newdata = test_data)

# Calculate the MSE
mse <- mean((test_data$standardized_total_value - predictions)^2)

# Display the MSE
cat("Test MSE:", mse)
```

```
## Test MSE: 0.04102
```

The mean square error on the test set is 0.04102. This error is quite small, showing that the model fits the data well.

4.1.2 Lasso Regression Model

Lasso regression is included in our comparison to explore its capability for variable selection. If there is a suspicion that certain variables are less influential, Lasso's tendency to drive some coefficients to zero makes it a valuable tool for feature selection.

```
dat_train <- model.matrix(standardized_total_value ~ year + standardized_pop,
                          data = train_data)
x.train <- dat_train
y.train <- train_data$standardized_total_value

dat_test <- model.matrix(standardized_total_value ~ year + standardized_pop,
                         data = test_data)
x.test <- dat_test
y.test_lasso <- test_data$standardized_total_value
```

```r
lambda.list.lasso <- 2 * exp(seq(0, log(1e-4), length = 100))

# Model for the training set
lasso_model_train <- cv.glmnet(x.train, y.train, alpha = 1,
                               lambda = lambda.list.lasso, nfolds = 10)
# Optimal lambda value
optimal_lambda_lasso_train <- lasso_model_train$lambda.min

# Coefficient estimates
lasso_coefficients_train <- coef(lasso_model_train, s = optimal_lambda_lasso_train)
lasso_coefficients_train
```

```
## 4 x 1 sparse Matrix of class "dgCMatrix"
##                            s1
## (Intercept)      -110.55977
## (Intercept)         .
## year                0.05556
## standardized_pop    .
```

There are some coefficients set to zero in the model selected by cross-validation. In fact, coefficients with a dot (.) as value have been set to zero. This means that variables with a dot have been excluded from the model because they had no impact on the model's predictions. Indeed, the lasso model has the particularity of selecting the variables that are useful for prediction, and setting the unnecessary ones to zero.

```r
# Predictions on the training set
lasso_train_pred <- predict(lasso_model_train, newx = x.train,
                            s = optimal_lambda_lasso_train)

# Training MSE
train_mse <- mean((lasso_train_pred - y.train)^2)
cat("Training MSE for Lasso Regression:", train_mse, "\n")
```

```
## Training MSE for Lasso Regression: 0.02272
```

```r
# Model for the test set
lasso_model_test <- cv.glmnet(x.test, y.test_lasso, alpha = 1,
                              lambda = lambda.list.lasso, nfolds = 10)
# Optimal lambda value
optimal_lambda_lasso_test <- lasso_model_test$lambda.min

# Coefficient estimates
lasso_coefficients_test <- coef(lasso_model_test, s = optimal_lambda_lasso_test)

# Predictions on the test set
lasso_test_pred <- predict(lasso_model_test, newx = x.test, s = optimal_lambda_lasso_test)

# Test MSE
test_mse <- mean((lasso_test_pred - y.test_lasso)^2)
cat("Test MSE for Lasso Regression:", test_mse, "\n")
```

```
## Test MSE for Lasso Regression: 0.02994
```

We can see here that the MSE test of the Lasso regression model is inferior to that of the MSE test of simple linear regression. We will therefore set aside the simple linear regression model.

4.1.3 Ridge

Ridge regression is considered due to its stability in handling multicollinearity. The previous simulation indicated a linear correlation between "Year" and "World Population." Ridge regression, by introducing a regularization term, can be beneficial in managing this correlation and providing stable predictions.

```
dat_train <- model.matrix(standardized_total_value ~ year + standardized_pop,
                          data = train_data)
x.train <- dat_train
y.train <- train_data$standardized_total_value

dat_test <- model.matrix(standardized_total_value ~ year + standardized_pop,
                         data = test_data)
x.test <- dat_test
y.test_ridge <- test_data$standardized_total_value

lambda.list.ridge <- 1000 * exp(seq(0, log(1e-5), length = 100))

# Model for the training set
ridge_model_train <- cv.glmnet(x.train, y.train, alpha = 0,
                               lambda = lambda.list.ridge, nfolds = 10)
# Optimal lambda value
optimal_lambda_ridge_train <- ridge_model_train$lambda.min

# Coefficient estimates
ridge_coefficients_train <- coef(ridge_model_train, s = optimal_lambda_ridge_train)
ridge_coefficients_train
```

```
## 4 x 1 sparse Matrix of class "dgCMatrix"
##                          s1
## (Intercept)      -57.92528
## (Intercept)        .
## year               0.02911
## standardized_pop   0.45786
```

We can see here that the weight of the population is stronger than the weight of the year. Indeed, ridge regression tends to reduce the coefficients towards zero.

```
# Predictions on the training set
ridge_train_pred <- predict(ridge_model_train, newx = x.train,
                            s = optimal_lambda_ridge_train)

# Training MSE
train_mse_ridge <- mean((ridge_train_pred - y.train)^2)
cat("Training MSE for ridge Regression:", train_mse_ridge, "\n")
```

```
## Training MSE for ridge Regression: 0.02328
```

```r
# Model for the test set
ridge_model_test <- cv.glmnet(x.test, y.test_ridge, alpha = 0,
                              lambda = lambda.list.ridge, nfolds = 10)
# Optimal lambda value
optimal_lambda_ridge_test <- ridge_model_test$lambda.min

# Coefficient estimates
ridge_coefficients_test <- coef(ridge_model_test, s = optimal_lambda_ridge_test)
ridge_coefficients_test
```

```
## 4 x 1 sparse Matrix of class "dgCMatrix"
##                          s1
## (Intercept)      -60.2253
## (Intercept)        .
## year               0.0303
## standardized_pop   0.4907
```

As with the training set, with the test set we see that the weight of the population is stronger than the weight of the year.

```r
# Predictions on the test set
ridge_test_pred <- predict(ridge_model_test, newx = x.test,
                           s = optimal_lambda_ridge_test)

# Test MSE
test_mse_ridge <- mean((ridge_test_pred - y.test_ridge)^2)
cat("Test MSE for ridge Regression:", test_mse_ridge, "\n")
```

```
## Test MSE for ridge Regression: 0.03035
```

Here we can see that the ridge regression model has a slightly higher train MSE (0.02328) than the lasso regression model (0.02272). This means that the ridge regression model fits the training data slightly less well than the lasso model. Moreover, the ridge regression model has a higher test MSE (0.03035) than the lasso regression model(0.02994). This means that the ridge model is less well adapted to the test data than the lasso model. We can therefore conclude that the lasso model works better on test data than the ridge model. This could be explained by the fact that the lasso model excludes predictors that could have an impact on prediction. We will therefore use the lasso regression method to make our predictions.

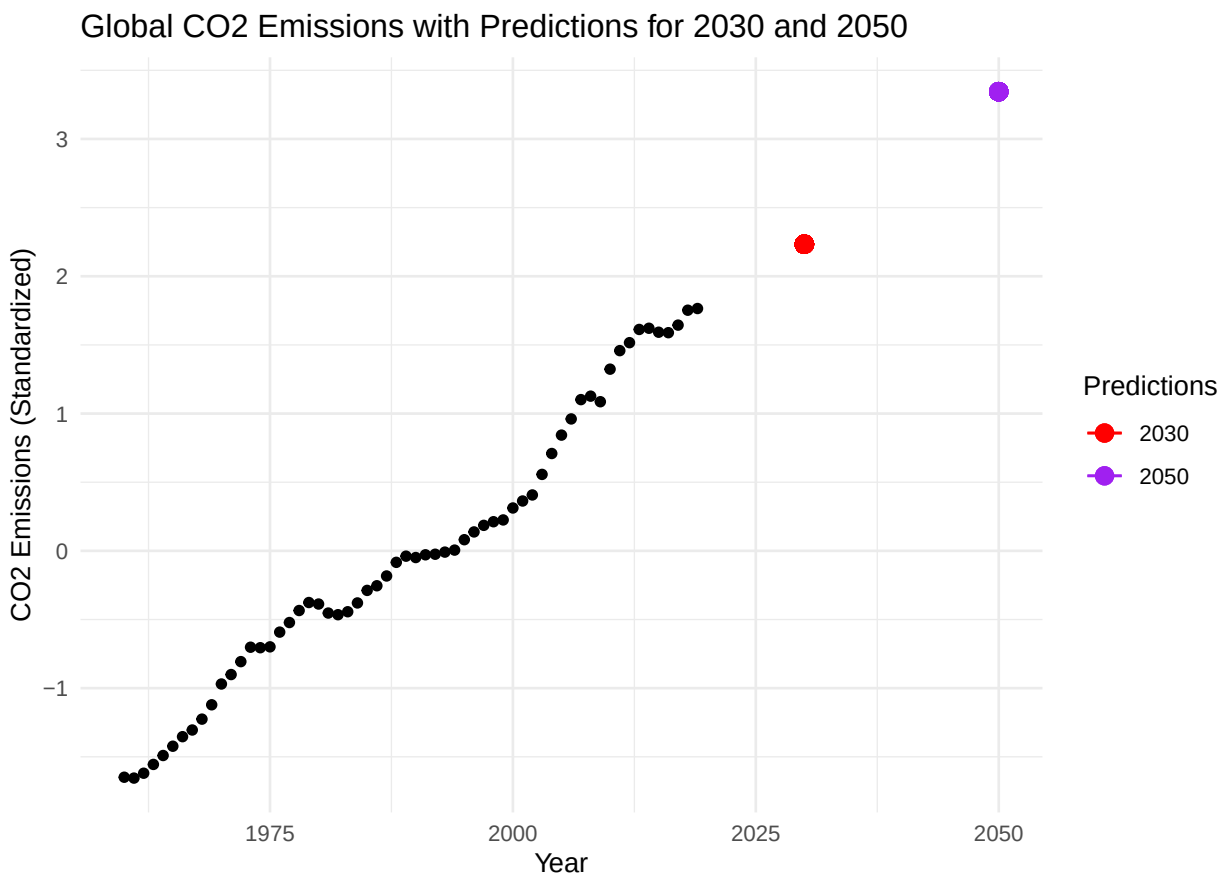
4.2 Forcasting and future visualization

We now want to predict global CO2 emissions. To do this, however, we need estimates of world population between 2030 and 2050. We found these estimates on this website. We then integrated these estimates into a new database to predict worldwide CO2 emissions.

```r
# Create a data frame with new data
new_data <- data.frame(
  year = 2030:2050,
  Population = c(
    8546141327, 8614532745, 8682091984, 8748798542, 8814575171, 8879397401, 8943206702,
    9006026370, 9067889026, 9128661215, 9188250492, 9246673300, 9303896851, 9359836420,
    9414408423, 9467543575, 9519190804, 9569297886, 9617774470, 9664516146, 9709491761
```

```
  )
)

# Remove commas in the population and standardize
new_data$Population <- as.numeric(gsub(",", "", new_data$Population))
new_data$standardized_pop <- scale(new_data$Population,
                                   center = mean(TOTAL_data$Population),
                                   scale = sd(TOTAL_data$Population))
```

```
# Prediction for the year 2050
new_observation_2050 <- data.frame(year = 2050,
                                   standardized_pop = new_data$standardized_pop
                                   [new_data$year == 2030])

# Create the model matrix for the new observation
dat_2050 <- model.matrix( ~ year + standardized_pop,
                          data = new_observation_2050)

# Make the prediction using the LASSO model
prediction_2050 <- predict(lasso_model_train, newx = dat_2050,
                           s = optimal_lambda_lasso_train)

# Prediction for the year 2030
new_observation_2030 <- data.frame(year = 2030,
                                   standardized_pop =new_data$standardized_pop
                                   [new_data$year == 2030])

# Create the model matrix for the new observation
dat_2030 <- model.matrix( ~ year + standardized_pop,
                          data = new_observation_2030)

# Make the prediction using the LASSO model
prediction_2030 <- predict(lasso_model_train, newx = dat_2030,
                           s = optimal_lambda_lasso_train)

# Plotting predictions
ggplot(TOTAL_data, aes(x = year, y = standardized_total_value)) +
  geom_point() +
  geom_line(aes(x = 2030, y = prediction_2030, color = "Prediction 2030")) +
  geom_point(aes(x = 2030, y = prediction_2030, color = "Prediction 2030"), size = 3) +
  geom_line(aes(x = 2050, y = prediction_2050, color = "Prediction 2050")) +
  geom_point(aes(x = 2050, y = prediction_2050, color = "Prediction 2050"), size = 3) +
  labs(
    title = "Global CO2 Emissions with Predictions for 2030 and 2050",
    x = "Year",
    y = "CO2 Emissions (Standardized)"
  ) +
  theme_minimal() +
  scale_color_manual(name = "Predictions",
                     values = c("Prediction 2030" = "red", "Prediction 2050" = "purple"),
                     labels = c("2030", "2050"),
                     breaks = c("Prediction 2030", "Prediction 2050"))
```

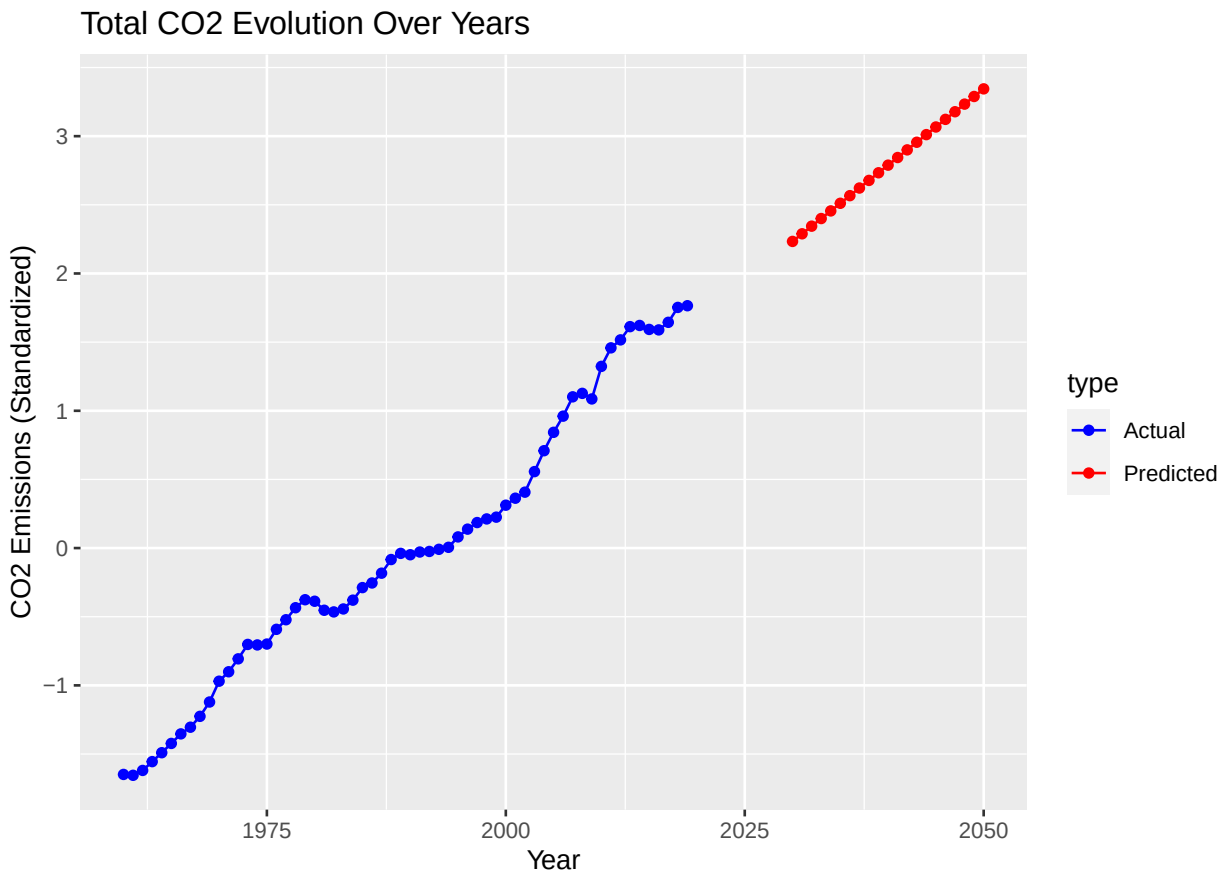


This graph shows that total CO2 emissions on the planet will continue to rise considerably between now and 2030 and 2050.

We are now going to predict total CO2 emissions from 2030 to 2050 to continue the curve and clearly visualize the predictions.

```
# Create the model matrix for the new data
dat_new <- model.matrix(~ year + standardized_pop, data = new_data)

# Select the necessary columns for the LASSO model
x.new <- dat_new

# Predict values with the LASSO model
predicted_values_lasso <- predict(lasso_model_train, newx = x.new,
                                  s = optimal_lambda_lasso_train)

# Create a table with years and predicted values
predicted_table_lasso <- data.frame(year = new_data$year,
                                    predicted_total_value_lasso = predicted_values_lasso)

# Create a data frame with actual values
actual_data <- data.frame(year = TOTAL_data$year,
                          standardized_total_value = TOTAL_data$standardized_total_value,
                          type = "Actual")

predicted_table_lasso$type <- "Predicted"
```

```r
predicted_table_lasso <- predicted_table_lasso %>% rename("standardized_total_value" = s1)

# Combine the data frames actual_data and predicted_table_lasso
combined_data <- rbind(actual_data, predicted_table_lasso)

# Plot the graph
ggplot(combined_data, aes(x = year, y = standardized_total_value, color = type)) +
  geom_line() +
  geom_point() +
  labs(x = "Year", y = "CO2 Emissions (Standardized)",
       title = "Total CO2 Evolution Over Years") +
  scale_color_manual(values = c("Actual" = "blue", "Predicted" = "red"))
```



As previously predicted, CO2 emissions will continue to rise between 2030 and 2050. It is therefore essential to act to reduce these CO2 emissions on a global scale to protect the planet from climate change.

5 Conclusion

In conclusion, this project has enabled us to study global carbon dioxide emissions. We have highlighted the dramatic increase in CO2 emissions since 1960, correlated with population growth. Analysis of the three biggest polluters - the USA, Russia and China - has highlighted significant trends, such as the drastic fall in Russia's CO2 emissions at the end of the Cold War, and the dramatic increase in China's CO2 emissions following its accession to the World Trade Organization.

In addition, the application of Principal Component Analysis (PCA) enabled us to explore the differences between countries in terms of CO2 emissions, population and surface area. This analysis revealed marked disparities between countries, highlighting the importance of taking these differences into account when developing emission reduction strategies.

Finally, the analysis and predictions highlighted the importance of predicting future trends in CO2 emissions to assess whether the commitments made under the Paris agreements and the targets set for 2030 and 2050 will be met. To this end, we have trained and evaluated several regression models, with the aim of determining which one best fits the data.

Thanks to this project, we have highlighted the urgency of taking action to reduce CO2 emissions on a global scale, while underlining the importance of taking into account the specificities of each country when developing strategies to combat climate change.