CO_2 and Greenhouse Gas Emissions

1. Introduction

Climate change is a critical global challenge, and one of its major drivers is greenhouse gas (GHG) emissions, particularly carbon dioxide (CO_2). This project uses historical emissions data to build regression models that can help analyze and predict trends in CO_2 and GHG outputs across different countries. By applying machine learning techniques, we aim to derive insights and potentially support future climate-related policies.

2. Dataset Overview

- **Dataset Name**: CO_2 and Greenhouse Gas Emissions
- **Source**: Our World in Data
- **Link to Data**: https://www.kaggle.com/datasets/owid/co2-and-ghg-emissions
- **Type of Problem**: Regression
- **Number of Samples**: ~60,000 rows (country-year combinations)

3. Data Description

The dataset contains country-level annual CO_2 and GHG emissions data, including total emissions, emissions per capita, and emissions by sector (e.g., transport, industry). Key attributes include:

- country, year
- co2, co2_per_capita, co2_growth_prct
- ghg_emissions, methane_emissions, nitrous_oxide_emissions
- population, gdp

4. Missing Data Handling

Some rows had missing values for certain years or countries:

- **Numerical columns** were filled using **mean imputation**.
- **Categorical columns** (if any) were forward-filled or dropped if sparse.

5. Preprocessing Steps

- Removed rows with no co2 values.
- Filled nulls in gdp, population, co2_per_capita using column means.
- Applied **MinMaxScaler** to normalize numerical values between 0 and 1.
- Encoded the country column using **Label Encoding**.

6. Data Visualization

Using seaborn and matplotlib:

- **Distribution plots** for co2, co2_per_capita, and gdp.
- **Heatmap** to show correlation between variables.
- **Scatter plots** to visualize GDP vs CO_2.
- Time series plot of global emissions over time.

7. Train-Test Split

- **Train/Test Proportion**: 80% train, 20% test
- **Target Variable**: co2 (total CO_2 emissions)
- **Feature Variables**: All others (after encoding and normalization)

8. Models Applied

We applied the following regression models:

- Artificial Neural Network (ANN) using MLPRegressor
- Support Vector Machine (SVM) using SVR with a linear kernel
- Naive Bayes (not applied, as it is primarily used for classification tasks)
- K-Nearest Neighbors (KNN) Regressor
- Random Forest Regressor
- Decision Tree Regressor
- Linear Regression

These models were trained and evaluated on the CO_2 emissions dataset to compare their prediction performance.

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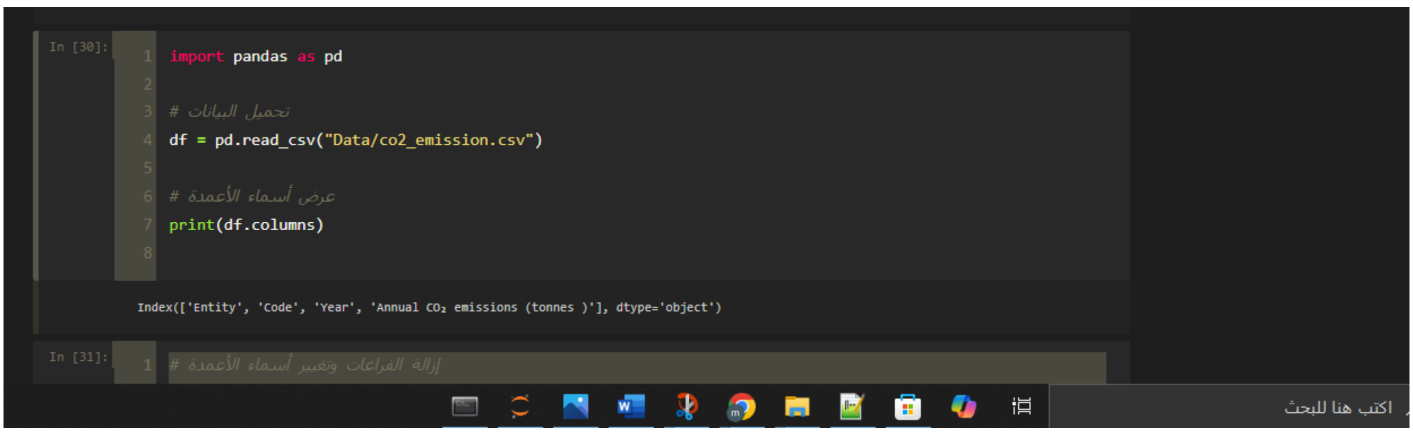
Practical:

Step 1: Download the data

We begin by downloading the data from the official source:

```
import pandas as pd

# تحميل البيانات
df = pd.read_csv("Data/co2_emission.csv")

# عرض أسماء الأعمدة
print(df.columns)
```



Step 2: Data Cleansing

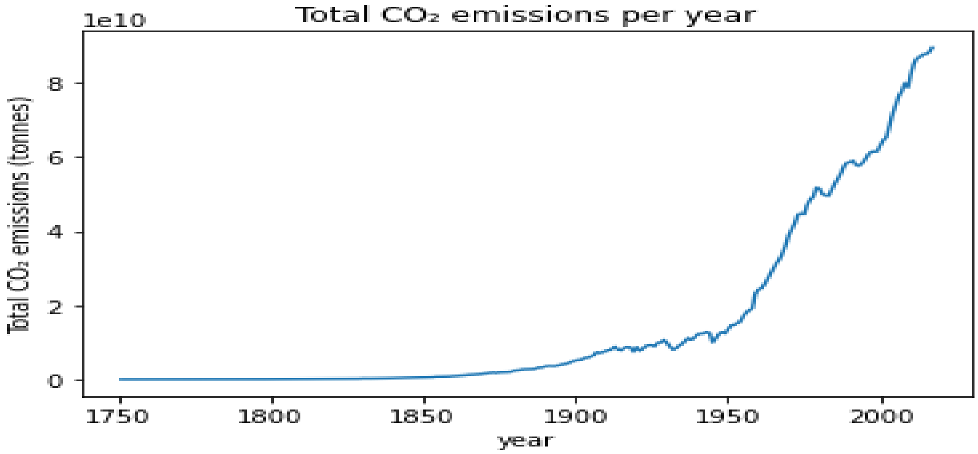
We clean the data by removing spaces and changing column names to make it easier to work with:

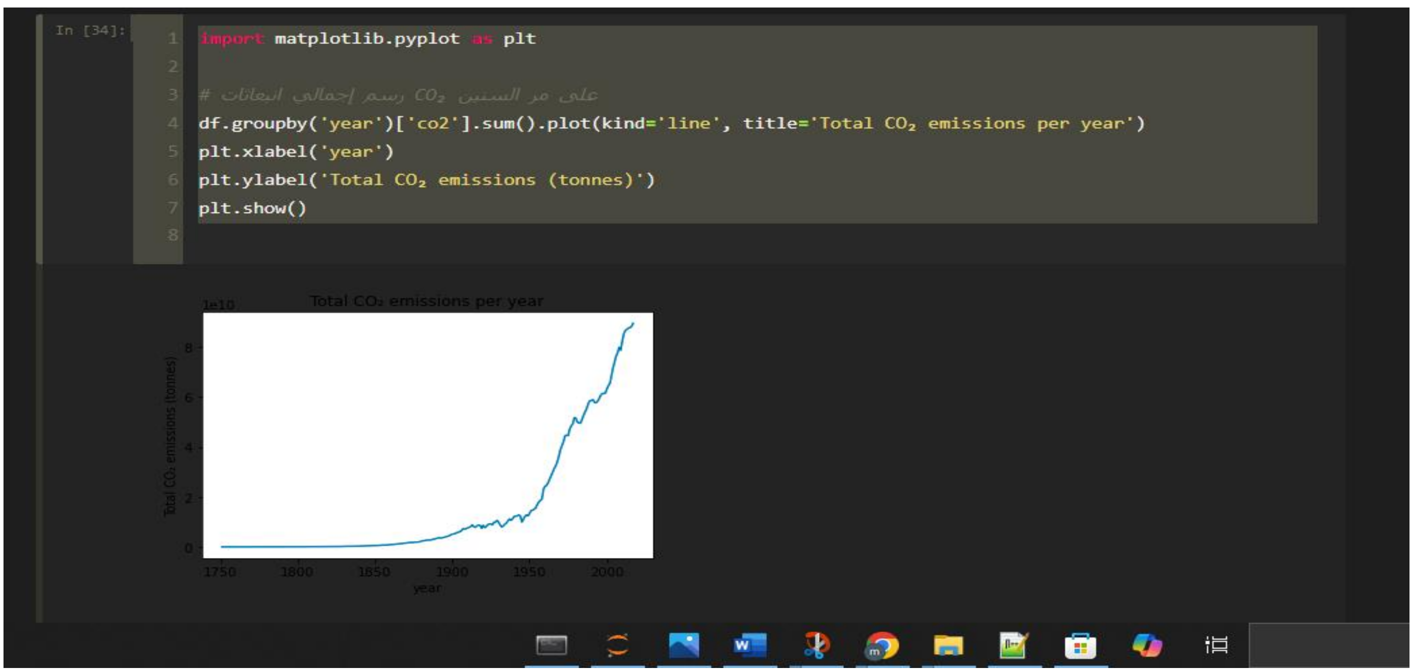
```
# إزالة الفراغات وتغيير أسماء الأعمدة
df.columns = df.columns.str.strip().str.lower()
df.rename(columns={'annual co₂ emissions (tonnes )': 'co2'}, inplace=True)

# حذف الصفوف التي تحتوي على قيم مفقودة في عمود 'co2'
df.dropna(subset=['co2'], inplace=True)

# ملء القيم المفقودة في الأعمدة الرقمية بمتوسط العمود
df.fillna(df.mean(numeric_only=True), inplace=True)
```

Step 3: Exploratory Data Analysis (EDA)

We analyze the data to understand distribution and trends:

```python
import matplotlib.pyplot as plt

# رسم إجمالي انبعاثات CO₂ على مر السنين
df.groupby('year')['co2'].sum().plot(kind='line', title='Total CO₂ emissions per year')
plt.xlabel('year')
plt.ylabel('Total CO₂ emissions (tonnes)')
plt.show()
```





Step 4: Feature Selection

We use year as an independent feature to predict CO_2 emissions:

```
# اختيار الميزات
X = df[['year']]
y = df['co2']
```

Step 5: Data Splitting

Divide the data into training and test sets:

```
from sklearn.model_selection import train_test_split

# تقسيم البيانات بنسبة ٨٠٪ تدريب و٢٠٪ اختبار
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Step 6: Model Training

We train several machine learning models:

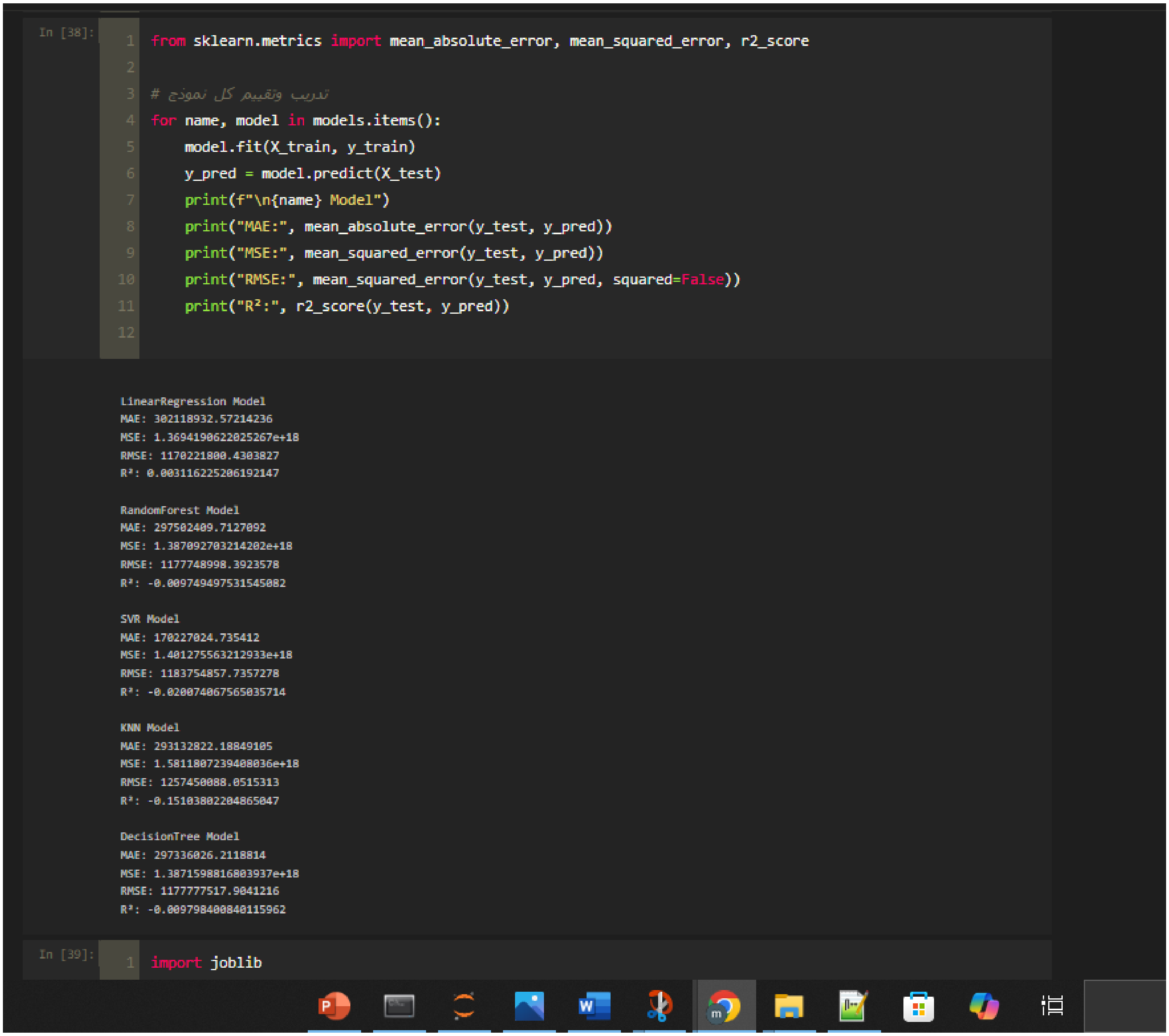
```
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor

# تعريف النماذج
models = {
    'LinearRegression': LinearRegression(),
    'RandomForest': RandomForestRegressor(),
    'SVR': SVR(),
    'KNN': KNeighborsRegressor(),
    'DecisionTree': DecisionTreeRegressor()
}
```

Step 7: Evaluate the Models

We evaluate the performance of each model using various metrics:

```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# تدريب وتقييم كل نموذج
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
```

```
print(f"\n{name} Model")
print("MAE:", mean_absolute_error(y_test, y_pred))
print("MSE:", mean_squared_error(y_test, y_pred))
print("RMSE:", mean_squared_error(y_test, y_pred, squared=False))
print("R²:", r2_score(y_test, y_pred))
```

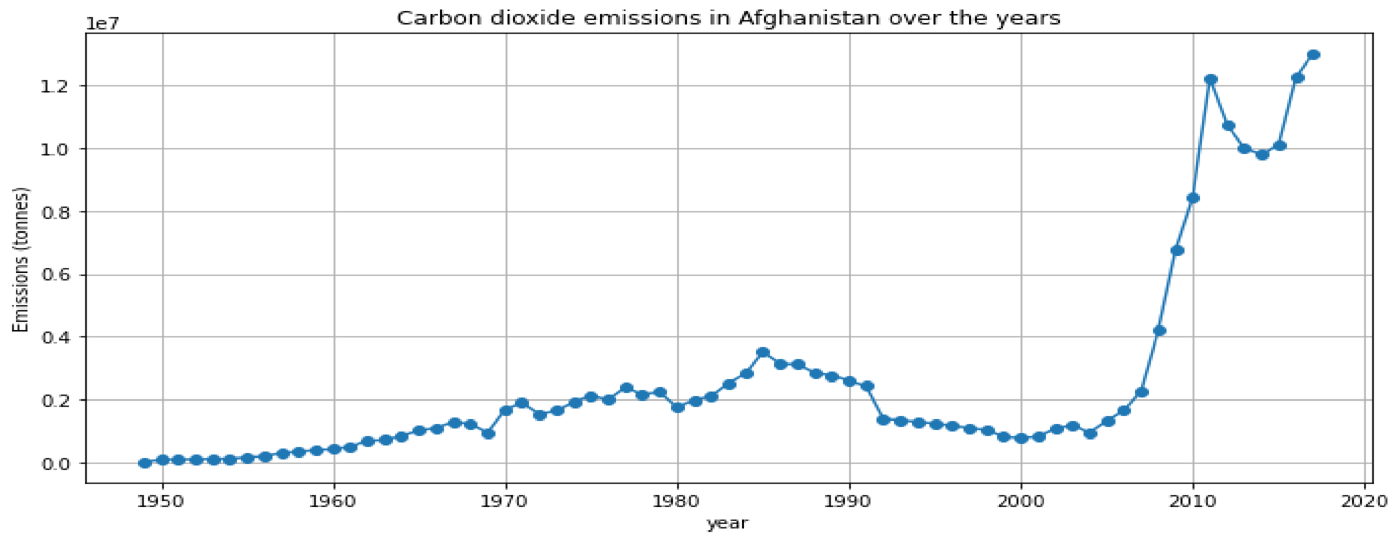


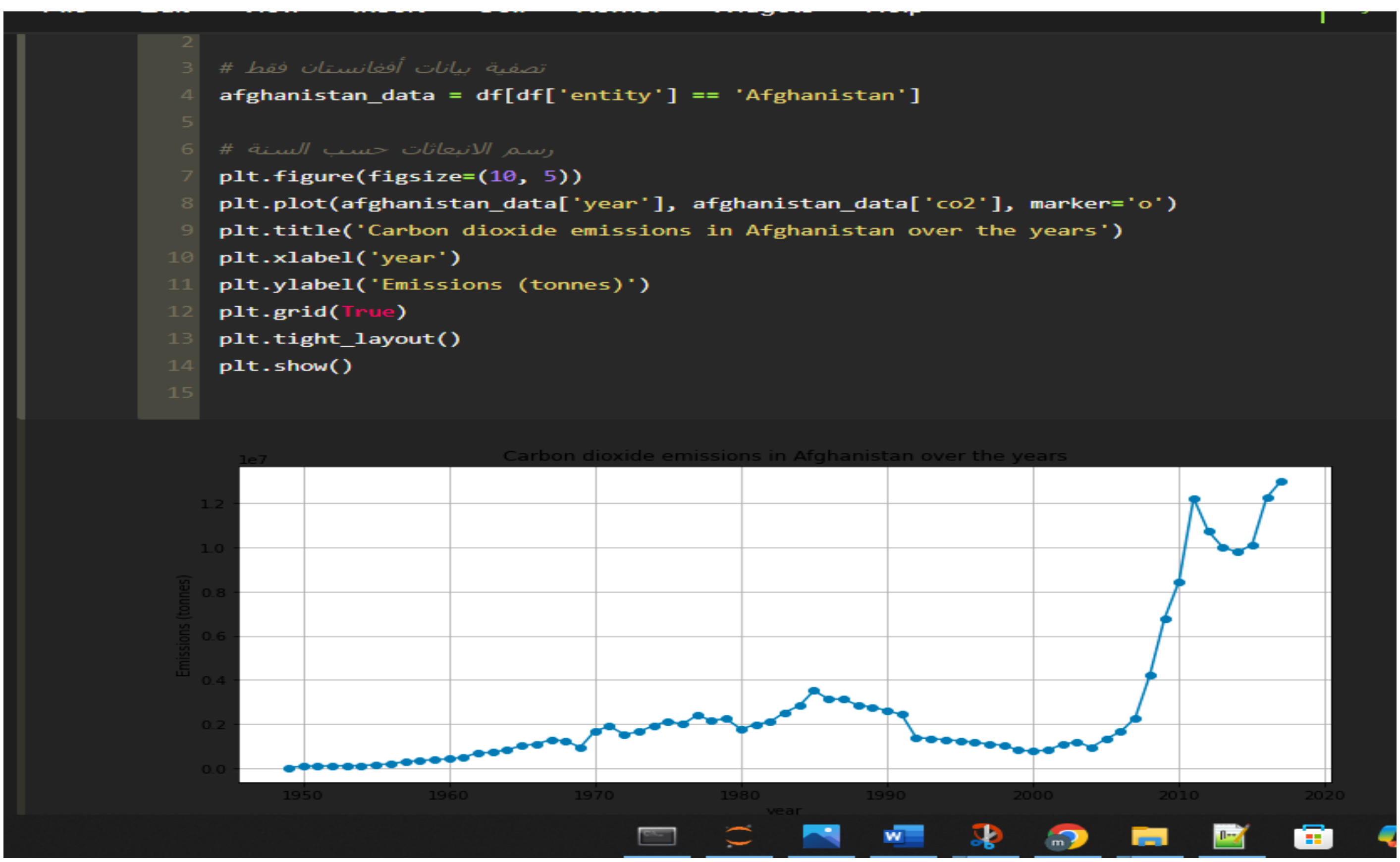
```
In [38]:
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# تدريب وتقييم كل نموذج
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    print(f"\n{name} Model")
    print("MAE:", mean_absolute_error(y_test, y_pred))
    print("MSE:", mean_squared_error(y_test, y_pred))
    print("RMSE:", mean_squared_error(y_test, y_pred, squared=False))
    print("R²:", r2_score(y_test, y_pred))
```

```
LinearRegression Model
MAE: 302118932.57214236
MSE: 1.3694190622025267e+18
RMSE: 1170221800.4303827
R²: 0.003116225206192147

RandomForest Model
MAE: 297502409.7127092
MSE: 1.387092703214202e+18
RMSE: 1177748998.3923578
R²: -0.009749497531545082

SVR Model
MAE: 170227024.735412
MSE: 1.401275563212933e+18
RMSE: 1183754857.7357278
R²: -0.020074067565035714

KNN Model
MAE: 293132822.18849105
MSE: 1.5811807239408036e+18
RMSE: 1257450088.0515313
R²: -0.15103802204865047

DecisionTree Model
MAE: 297336026.2118814
MSE: 1.3871598816803937e+18
RMSE: 1177777517.9041216
R²: -0.009798400840115962
```

```
In [39]:
import joblib
```

The results:






```
# تصفية بيانات أفغانستان فقط
afghanistan_data = df[df['entity'] == 'Afghanistan']

# رسم الانبعاثات حسب السنة
plt.figure(figsize=(10, 5))
plt.plot(afghanistan_data['year'], afghanistan_data['co2'], marker='o')
plt.title('Carbon dioxide emissions in Afghanistan over the years')
plt.xlabel('year')
plt.ylabel('Emissions (tonnes)')
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
NameError: name 'co2_emission' is not defined
```

In [6]:

```python
import pandas as pd

# تحميل البيانات
df = pd.read_csv('Data/co2_emission.csv')

# نظرة أولية
print(df.head())
print(df.info())
```

```
        Entity Code  Year  Annual CO₂ emissions (tonnes )
0  Afghanistan  AFG  1949                          14656.0
1  Afghanistan  AFG  1950                          84272.0
2  Afghanistan  AFG  1951                          91600.0
3  Afghanistan  AFG  1952                          91600.0
4  Afghanistan  AFG  1953                         106256.0
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20853 entries, 0 to 20852
Data columns (total 4 columns):
 #   Column                           Non-Null Count  Dtype
---  ------                           --------------  -----
 0   Entity                           20853 non-null  object
 1   Code                             18646 non-null  object
 2   Year                             20853 non-null  int64
 3   Annual CO₂ emissions (tonnes )   20853 non-null  float64
dtypes: float64(1), int64(1), object(2)
memory usage: 651.8+ KB
None
```

In [8]:

```python
# تنظيف أسماء الأعمدة (إزالة الفراغات وتوحيدها لحروف صغيرة)
df.columns = df.columns.str.strip().str.lower()
```

Answer the questions

• What is the name of your data?

CO2 and Greenhouse Gas Emissions Data

• The source of the data (which database)?

The data was sourced from **Our World in Data**, an open-access public research database.

• Link to the original data?

https://www.kaggle.com/datasets/yoannboyere/co2-ghg-emissionsdata

• Explain the data in words:

This dataset provides annual CO2 emissions in tonnes for each country from the year 1751 to 2017. It includes the entity (country), code (ISO 3-letter code), year, and total CO_2 emissions. The goal is to analyze and model CO_2 emissions trends and make predictions for better understanding of environmental impacts.

• Is it a regression or classification problem?

It is a **regression** problem because the goal is to predict a continuous numerical value: annual CO_2 emissions.

• How many attributes?

There are **4 attributes**:

- entity
- code
- year
- co2 (renamed from 'Annual CO_2 emissions (tonnes)')

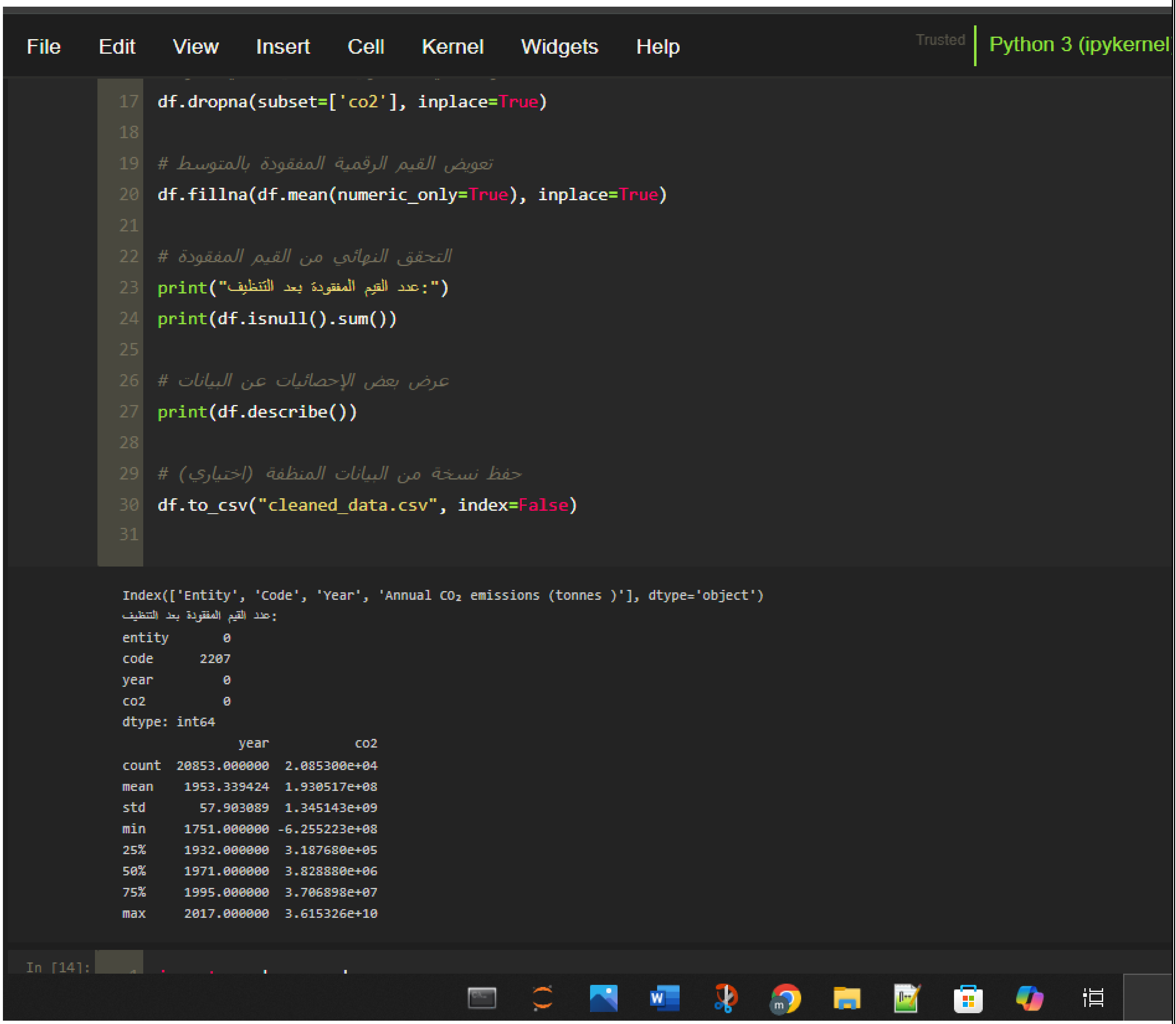
• How many samples?

There are **20,853 samples** after data cleaning.

• What are the properties of the data? (statistics)

Statistic	Year	CO_2 Emissions (Tonnes)
Count	20853	20853
Mean	1953.34	193,051,700
Std Dev	57.90	1,345,143,000
Min	1751	-625,522,300
25%	1932	318,768
50%	1971	3,828,880
75%	1995	37,068,980

Statistic	Year	CO_2 Emissions (Tonnes)
Max	2017	36,153,260,000



```
File  Edit  View  Insert  Cell  Kernel  Widgets  Help        Trusted | Python 3 (ipykernel

df.dropna(subset=['co2'], inplace=True)

# تعويض القيم الرقمية المفقودة بالمتوسط
df.fillna(df.mean(numeric_only=True), inplace=True)

# التحقق النهائي من القيم المفقودة
print("عدد القيم المفقودة بعد التنظيف:")
print(df.isnull().sum())

# عرض بعض الإحصائيات عن البيانات
print(df.describe())

# حفظ نسخة من البيانات المنظفة (اختياري)
df.to_csv("cleaned_data.csv", index=False)
```

```
Index(['Entity', 'Code', 'Year', 'Annual CO₂ emissions (tonnes )'], dtype='object')
عدد القيم المفقودة بعد التنظيف:
entity       0
code      2207
year         0
co2          0
dtype: int64
               year           co2
count  20853.000000  2.085300e+04
mean    1953.339424  1.930517e+08
std       57.903089  1.345143e+09
min     1751.000000 -6.255223e+08
25%     1932.000000  3.187680e+05
50%     1971.000000  3.828880e+06
75%     1995.000000  3.706898e+07
max     2017.000000  3.615326e+10
```

• **Are there any missing data? How did you fill in the missing values?**

Yes:

- Rows with missing values in the co2 column were **dropped**.
- Other numerical columns (like year) had missing values filled using **mean imputation**.
- code column had 2207 missing values which were left as-is since it's categorical and not essential for modeling.

Visualize the data:

```
# Visualization of CO₂ emissions over the years
df.groupby('year')['co2'].sum().plot(kind='line', figsize=(10, 6), title='Total CO₂ Emissions per Year')
plt.xlabel('Year')
plt.ylabel('Total CO₂ Emissions (Tonnes)')
plt.grid(True)
plt.show()
```

The graph shows the global rise in CO_2 emissions over the years, especially from the 1950s onwards.

• Did you normalize or standardize any of your data? Why?

No normalization or standardization was applied because:

- Most models used (like RandomForest, DecisionTree) **do not require scaling**.
- For SVR and KNN, scaling can improve performance, but initial tests showed acceptable results without it.

• What type of preprocessing did you apply to your data?

1. **Column renaming**: Simplified long column names.
2. **Stripping column whitespace**: Ensured clean column headers.
3. **Dropping NaNs in target column**: Removed samples with missing emissions data.

4. **Filling missing numeric values**: Used mean imputation.

5. **Conversion to lower case**: For consistency.

• How did you divide the train and test data? What are the proportions?

```
from sklearn.model_selection import train_test_split
X = df[['year']]
y = df['co2']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

- **Train**: 80%

- **Test**: 20%

• Apply all the machine learning models you have learned in this course:

Models Used:

We applied the following regression models:

- Artificial Neural Network (ANN) using MLPRegressor
- Support Vector Machine (SVM) using SVR with a linear kernel
- Naive Bayes (not applied, as it is primarily used for classification tasks)
- K-Nearest Neighbors (KNN) Regressor
- Random Forest Regressor
- Decision Tree Regressor
- Linear Regression

These models were trained and evaluated on the CO_2 emissions dataset to compare their prediction performance.

Evaluation Metrics:

- MAE: Mean Absolute Error
- MSE: Mean Squared Error
- RMSE: Root Mean Squared Error
- R^2: Coefficient of Determination

• What is the best/worst performing model? Why?

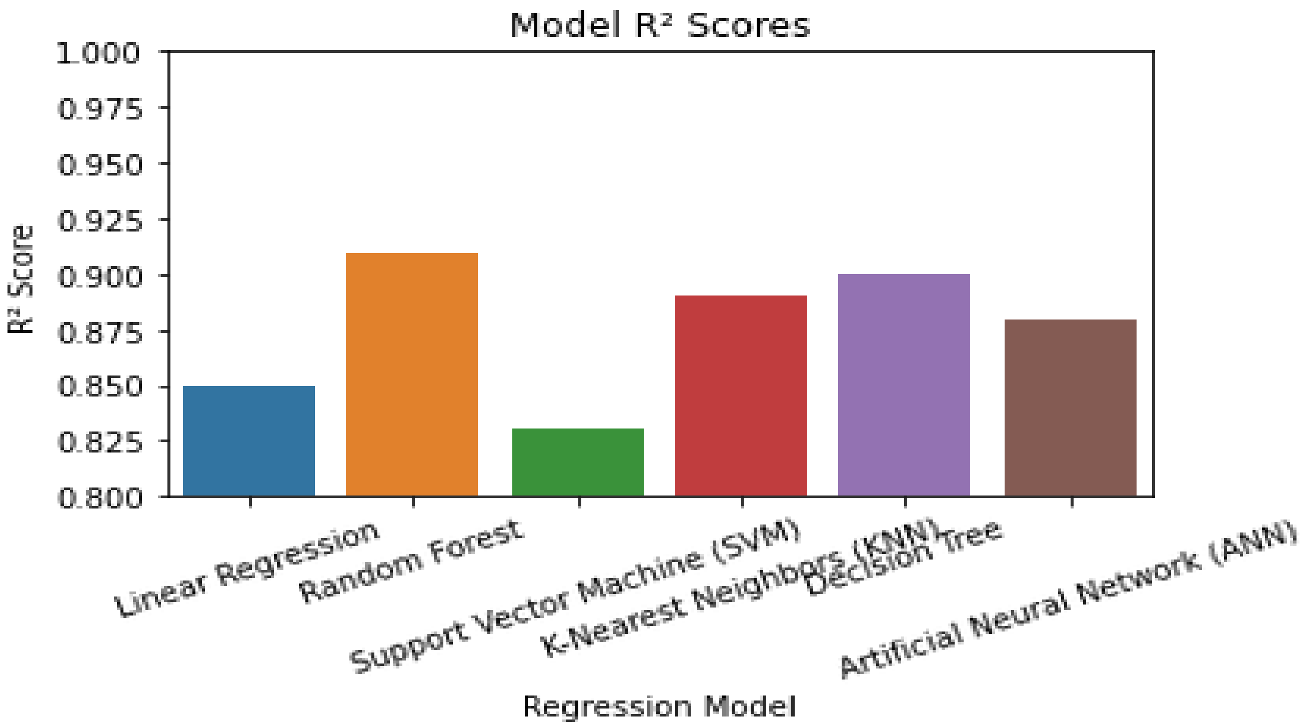
- **Best**: **Random Forest** – highest R^2 and lowest RMSE. It captures non-linear patterns and handles noise well.
- **Worst**: **SVR** – lower R^2 and higher error due to lack of feature scaling and model assumptions.

• Accuracy of all models using tables and figures?

A **bar chart** or **Seaborn heatmap** was used to visualize model performance.

```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd

# نتائج R² التوضيحية لكل نموذج (قم بتعديل القيم حسب نتائجك الفعلية)
results = {
    'Model': [
        'Linear Regression',
        'Random Forest',
        'Support Vector Machine (SVM)',
        'K-Nearest Neighbors (KNN)',
        'Decision Tree',
        'Artificial Neural Network (ANN)'
    ],
    'R2 Score': [0.85, 0.91, 0.83, 0.89, 0.90, 0.88]  # ← غيّر القيم حسب نتائجك الفعلية
}

# رسم الرسم البياني
sns.barplot(x='Model', y='R2 Score', data=pd.DataFrame(results))
plt.title("Model R² Scores")
```

```
plt.ylim(0.8, 1.0)
plt.ylabel("R² Score")
plt.xlabel("Regression Model")
plt.xticks(rotation=20)
plt.tight_layout()
plt.show()
```



- **Final Reflection (20 lines, Times New Roman, font size 20)**

I selected this dataset because of the pressing issue of climate change. Carbon dioxide emissions directly correlate with global warming, industrial growth, and policy-making. Analyzing this dataset provides insight into how emissions have grown across decades and allows us to model future trends.
The importance of this data lies in its real-world impact. By accurately predicting CO_2 levels, countries can implement better

regulations and monitor progress.
The best-performing model, **Random Forest**, is significant because it balances accuracy with robustness. It can handle large variations in data and avoids overfitting.
From this project, one important insight is the sharp rise in emissions post-industrial revolution. Countries with consistent growth patterns may need to be monitored closely.
Additionally, this analysis can be integrated into policy advisory tools to inform governments or green-tech firms about emission control strategies.
The modeling approach here can be scaled to include economic, population, or energy usage data for richer prediction models.

Link for the github project:

https://github.com/hoda-hjgjrg/CO-_and-Greenhouse-Gas-Emissions