Report Analysis

What typically leads to this kind of problem?

Earth's temperature is determined by the balance between energy entering and leaving the planet. It warms when incoming solar energy is absorbed and cools when this energy is reflected or released back into space. Factors like variations in solar energy, changes in Earth's reflectivity, and fluctuations in the greenhouse effect can alter this energy balance.

Data Cleaning

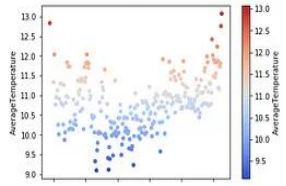
We can move on to what discoveries were made throughout my Exploratory Data Analysis. After importing and analyzing the dataset, I noticed some missing data, with a few rows containing empty values (NaN). Unlike tutorial datasets, real-world data is rarely clean and often has missing values due to errors, omissions, and other causes. These missing values, indicated in various ways by different sources, needed to be removed to prevent inaccurate predictions or classifications in our model.

	Year	Month	Decimal Date	Carbon Dioxide (ppm)	Seasonally Adjusted CO2 (ppm)	Carbon Dioxide Fit (ppm)	Seasonally Adjusted CO2 Fit (ppm)
0	1958	1	1958.0411	NaN	NaN	NaN	NaN
1	1958	2	1958.1260	NaN	NaN	NaN	NaN
2	1958	3	1958.2027	315.69	314.42	316.18	314.89
3	1958	4	1958.2877	317.45	315.15	317.30	314.98
4	1958	5	1958.3699	317.50	314.73	317.83	315.06

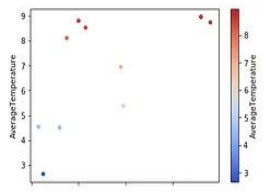
After cleaning data I can move further Analysis

For my initial prediction, I focused on the average temperature of each U.S. state over the selected period. I began by creating a scatter plot to understand the data better. My goal was to visualize the states with average temperatures above and below 9° degrees.

```
In [11]: # Average Temperature above 9 degrees
         df_nine = dfa[dfa['AverageTemperature'] >= 9]
         df_nine.plot.scatter(x='year', y='AverageTemperature', c = 'AverageTemperature', cmap ='coolwarm')
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x116d2b4e0>
```



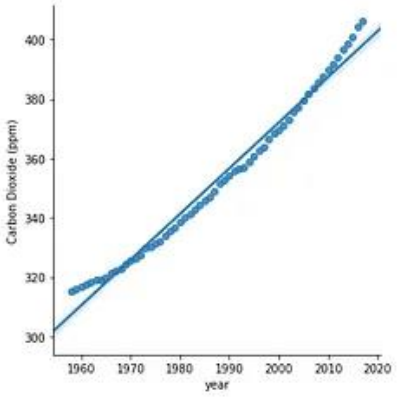

```
In [12]: # Average Temperature below 9 degrees
         df_nine = dfa[dfa['AverageTemperature'] <= 9]
         df_nine.plot.scatter(x='year', y='AverageTemperature', c = 'AverageTemperature', cmap ='coolwarm')
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x1a212722b0>
```



The average temperature over the years. There is a visible trend of increasing average temperatures over time, particularly in the most recent years

Seaborn offers two main functions, regplot() and lmplot(), to visualize linear relationships through regression. These functions are closely related, sharing much of their core functionality. However, understanding their differences is crucial for selecting the right tool for specific tasks. Both functions can draw a scatterplot of two variables, x and y, and fit a regression model y ~ x. They then plot the resulting regression line along with a 95% confidence interval.

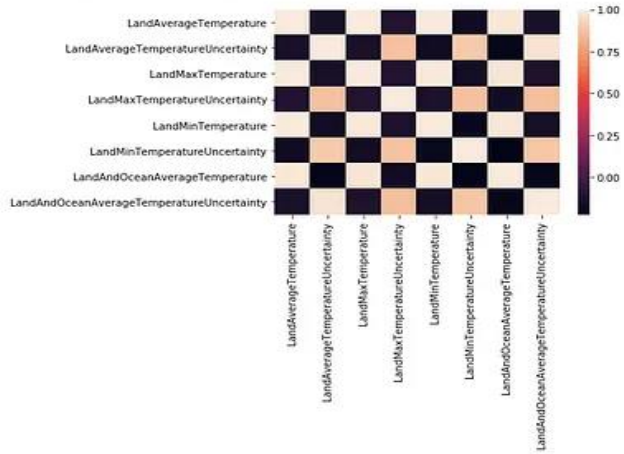
```
In [16]: sns.lmplot(x='year', y='Carbon Dioxide (ppm)', data=dfc)
Out[16]: <seaborn.axisgrid.FacetGrid at 0x1a2111aef0>
```



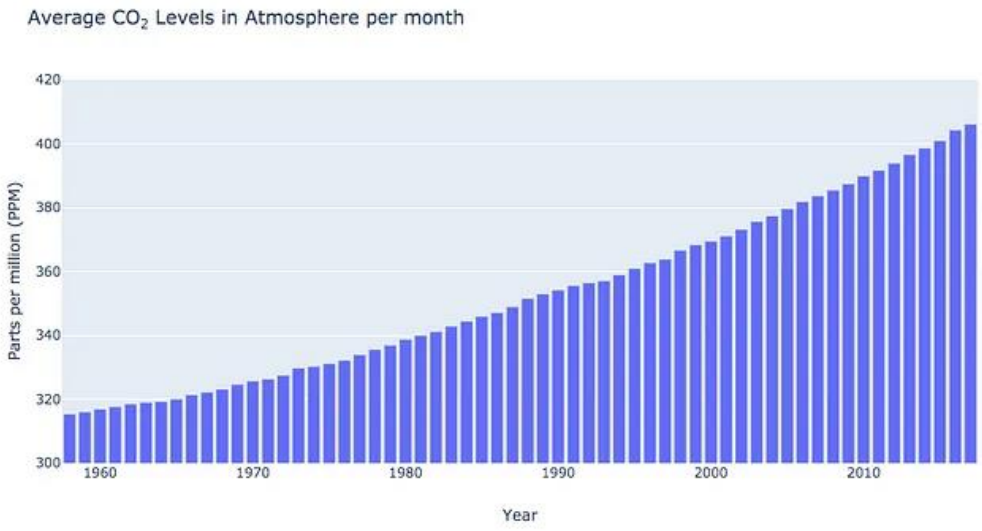
The plot illustrates the rise of carbon dioxide levels in the atmosphere across several years. Unfortunately, during the 1760s, at the onset of the first industrial revolution, our technology was insufficient to monitor atmospheric carbon dioxide. It wasn't until a decade after the third industrial revolution that our technology advanced enough to accurately measure these levels.

As depicted in the plot, by 2010, global carbon dioxide levels approached nearly 400 parts per million (ppm). Upon discovering this finding, I sought to investigate correlations among the variables under study.

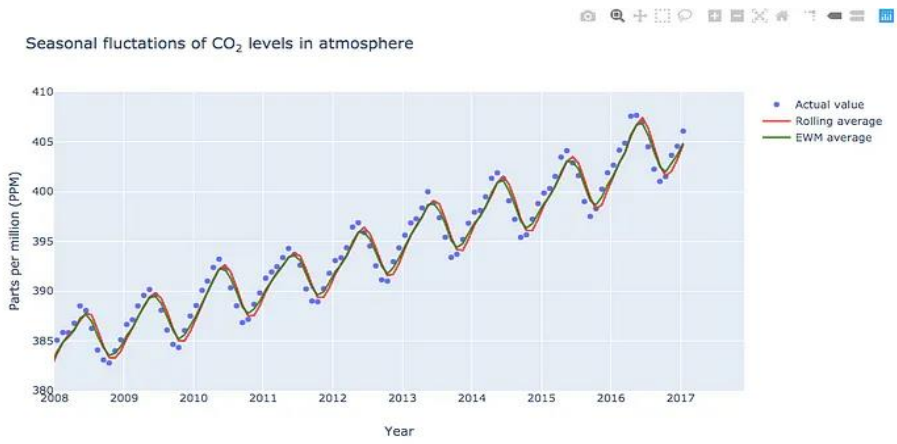
```
In [18]: sns.heatmap(global_temp.corr())
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x1a19a77710>
```



The heat map reveals significant correlations between the different temperature metrics and their uncertainties. Land average temperature and land max temperature show a strong positive correlation. Temperature uncertainties also show a significant correlation, which indicates that uncertainties in measurements are consistent across different types of temperature data. Understanding these correlations helps in comprehending the interdependencies between various climate metrics.

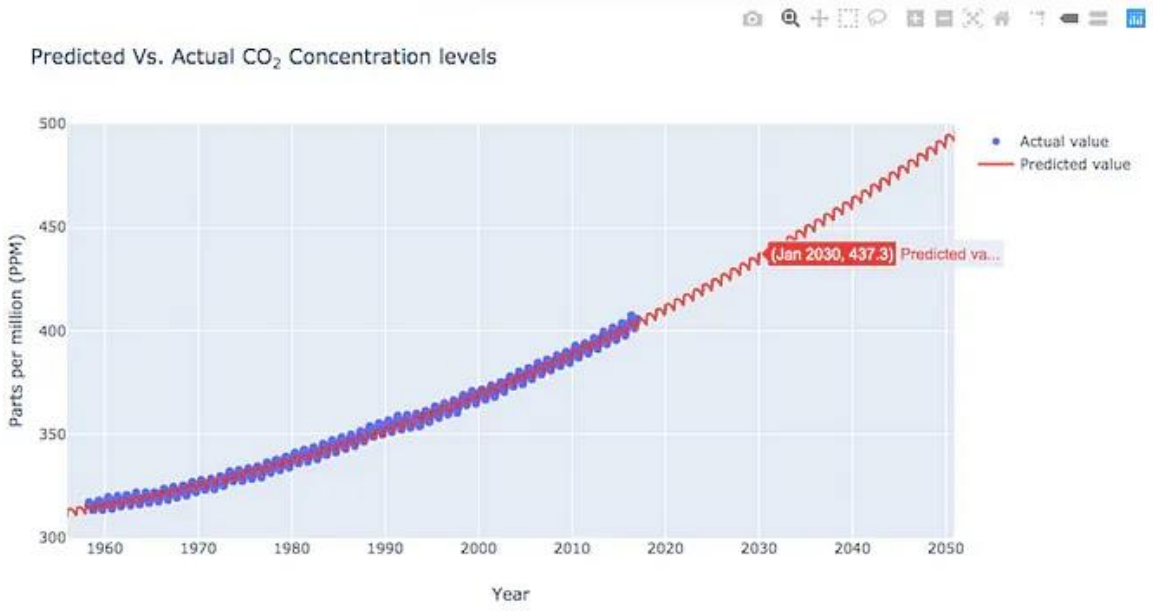


This plot revealed that in 2017 the average level of CO_2 was 406.07 (ppm), which is a major swing compared to the level of CO_2 in 2010. Now, let's check what does the Seasonal fluctuations of CO_2 levels are



The chart reveals a cyclical pattern in CO2 levels, with regular peaks and troughs each year. This seasonality is likely due to natural processes such as plant growth and decay cycles. Despite the seasonal fluctuations, the overall trend shows an increase in CO2 levels over time.

After training the model, I visualized and compared the difference between the actual levels of CO_2 and the predicted levels, and the results were disquieting to say the least.



In the plot above, I highlighted the year 2030, which the IPCC reported to the United Nations as the deadline for altering our behaviors to curb CO_2 levels in the atmosphere before irreversible damage occurs. By January 2030, the projected CO_2 level in the atmosphere is anticipated to reach 437.3 ppm, marking a significant increase.

Next, let's examine the state or country with the highest average temperature level in the dataset and identify the year in which this temperature was recorded.

```
In [30]: # State that had the highest average temperature level
         temp_by_state.loc[temp_by_state['AverageTemperature'].idxmax()]

Out[30]: dt                                2012-06-01
         AverageTemperature                    36.339
         AverageTemperatureUncertainty          0.385
         State                                  Delhi
         Country                                India
         year                                    2012
         Name: 116037, dtype: object

In [32]: # Country that had the highest Average Temperature
         # Kuwait (Western Asia)
         temp_by_country.loc[temp_by_country['AverageTemperature'].idxmax()]

Out[32]: dt                                2012-07-01
         AverageTemperature                    38.842
         AverageTemperatureUncertainty          0.464
         Country                               Kuwait
         Name: 284851, dtype: object
```

The state with the highest average temperature on record is Delhi, India.The recorded average temperature was 36.139°C.This data point is from June 1, 2012.The uncertainty in the average temperature measurement is 0.385°C.Query for the Country with the Highest Average.The country with the highest average temperature on record is Kuwait..The recorded average temperature was

38.942°C.This data point is from July 1, 2012.The uncertainty in the average temperature measurement is 0.464°C.Both queries utilize the idxmax() function to find the index of the maximum average temperature, and then loc[] is used to retrieve the row corresponding to that index. The results show that Delhi, India had the highest average temperature at the state level, while Kuwait had the highest at the country level during the specified times in 2012.

Conclusion

In conclusion, climate change is a pressing global issue, highlighted by the rapid rise in global temperatures and the urgent need for immediate action before irreversible consequences unfold.

Through exploratory data analysis, I navigated complexities such as missing data and data cleaning, essential for accurate insights. Utilizing visualization tools like seaborn and plotly, I examined trends in atmospheric CO_2 levels over time, revealing significant increases, particularly alarming projections for 2030. This underscores the IPCC's warning and the need for collective action to mitigate further climate impacts.

Moreover, I identified the highest recorded average temperatures across states or countries, underscoring the global impact of climate change. The data-driven approach highlighted correlations and seasonal variations in CO_2 levels, providing insights crucial for understanding climate dynamics. These findings reinforce the urgency for policy changes, sustainable practices, and global collaboration to safeguard our planet's future.

Take bold climate action by using energy wisely, which not only benefits the planet but also saves money. Embrace renewables to power up your life sustainably. Make mindful food choices to support a stable climate. Start conversations about climate issues to raise awareness. Opt for green transportation options to reduce your carbon footprint. Practice mindful consumption to minimize waste and maximize enjoyment. Consider investing in renewables and divesting from fossil fuels to support sustainable energy solutions. Join youth-led movements advocating for climate action or get politically active by voting for leaders committed to environmental stewardship.