Analyse how Fossil fuel impact for global climate change

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Introduction

Companies that produce fossil fuels spend millions on flashy marketing campaigns promoting renewable energy while continuing to grow production of oil and gas, which emit pollutants that have a terrible impact on our world. The evidence is clear: we are in a climate emergency, which fossil fuels are contributing to.
When fossil fuels are burnt, enormous volumes of carbon dioxide, a greenhouse gas, are released into the atmosphere. Greenhouse gases trap heat in our atmosphere, which contributes to global warming. Already, the average global temperature has risen by 1 degree Celsius. Warming exceeding 1.5°C threatens more sea-level rise, severe weather, biodiversity loss, and species extinction, as well as food scarcity, poor health, and poverty for millions of people across the world.
As a result, the goal of this research is to examine how fossil fuels affect climate change using data science techniques.

Data

Three datasets are used in this research:

- Global fossil fuel consumption dataset
- Global Temperature Time Series dataset - There are two categories of data in this dataset. GISS Surface Temperature and the global component of Climate at a Glance are the two.
- Global Average Absolute Sea Level Change, 1880-2014 dataset

Pre-processing

I first imported "global-fossil-fuel-consumption.csv" and then used describe() to see some basic statistical characteristics of a data frame or a series of numeric values such as percentile, mean, standard deviation, and so on.

```
[6]  fosil_en.describe()
```

	Year	Coal (TWh; direct energy)	Oil (TWh; direct energy)	Gas (TWh; direct energy)
count	72.000000	72.000000	72.000000	72.000000
mean	1965.555556	22588.555556	30025.527778	16049.444444
std	55.355163	13253.929402	17895.744924	11796.334029
min	1800.000000	97.000000	0.000000	0.000000
25%	1965.750000	16120.250000	19149.250000	6727.500000
50%	1983.500000	22522.500000	35357.000000	15303.000000
75%	2001.250000	28126.000000	43368.250000	24511.500000
max	2019.000000	44993.000000	53620.000000	39292.000000

Following that, I generated a new dataframe including data from 1970 to 2019. And removed unnecessary columns such as Entity, Code.

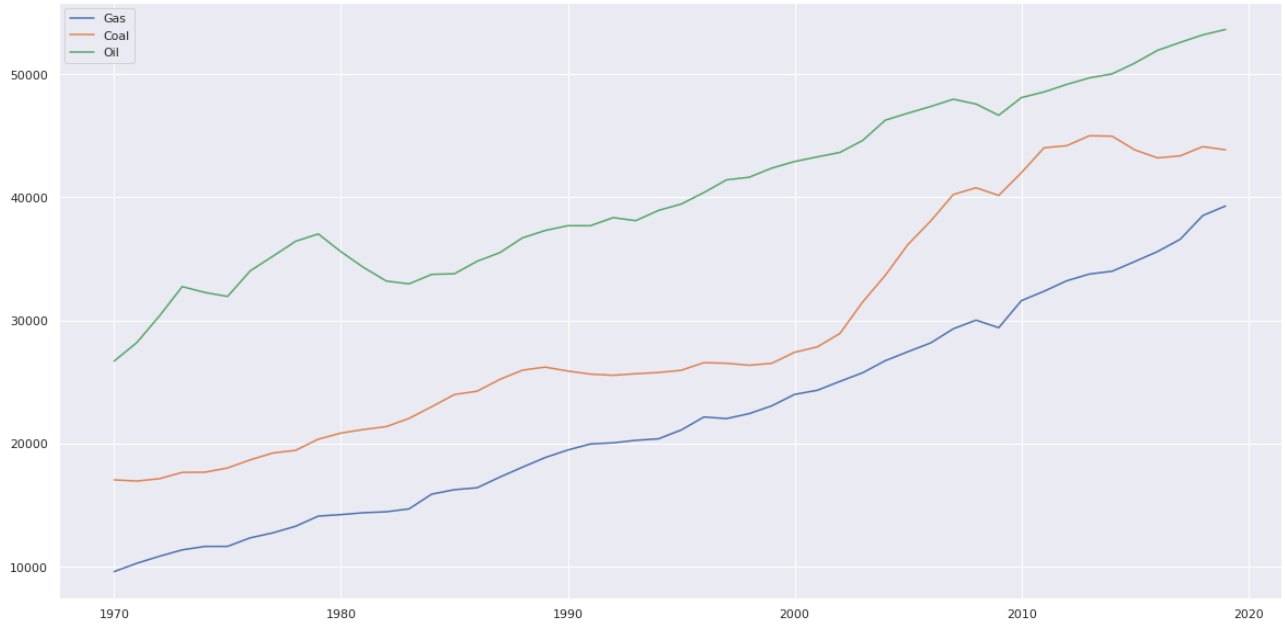
```
fosil_en2 = fosil_en[fosil_en["Year"] > 1969]
```

```
fosil_en2.head()
```

	Entity	Code	Year	Coal (TWh; direct energy)	Oil (TWh; direct energy)	Gas (TWh; direct energy)
22	World	OWID_WRL	1970	17059	26708	9614
23	World	OWID_WRL	1971	16966	28205	10292
24	World	OWID_WRL	1972	17154	30378	10861
25	World	OWID_WRL	1973	17668	32746	11378
26	World	OWID_WRL	1974	17682	32272	11656

Run cell (⌘/Ctrl+Enter)
cell executed since last change

And here is the our fossil fuel dataset look like.



As we can see, the "Gas" data shows a linear regression relationship, but the other two appear to be non-linear regression.

Normalisation

Normalisation is a method that is frequently used in the processing of data for machine learning. The objective of normalisation is to convert the values of numeric columns in a dataset to a common scale while preserving variations in value ranges. Every dataset does not need to be normalised for machine learning. We just need to normalise the fossil fuel dataset in our scenario. We may utilise the z-score technique to do this. Based on the mean and standard deviation, it will produce a normalised value (z-score). A z-score, also known as a standard score, is used to standardise scores on the same scale by dividing the variance of a score by the standard deviation of the data set. As a result, you get a regular score.

```
# apply the z-score method in Pandas using the .mean() and .std() methods
def z_score(df):
    # copy the dataframe
    df_std = df.copy()
    # apply the z-score method

    df_std['Gas'] = (df_std['Gas'] - df_std['Gas'].mean()) / df_std['Gas'].std()
    df_std['coal'] = (df_std['coal'] - df_std['coal'].mean()) / df_std['coal'].std()
    df_std['Oil'] = (df_std['Oil'] - df_std['Oil'].mean()) / df_std['Oil'].std()

    return df_std

# call the z_score function
fosil_norm = z_score(fosil_en2)

fosil_norm
```

	Year	coal	Oil	Gas
22	1970	-1.285211	-1.948589	-1.490184
23	1971	-1.295054	-1.739676	-1.409860
24	1972	-1.275157	-1.436423	-1.342450
25	1973	-1.220756	-1.105958	-1.281201
26	1974	-1.219274	-1.172107	-1.248266
27	1975	-1.182972	-1.217322	-1.247673
28	1976	-1.112801	-0.926769	-1.165336
29	1977	-1.054273	-0.761397	-1.117355

Temperature dataset

We'll choose data from 1970 for the temperature dataset.

```
temp2 = temp[temp["Year"] > 1969]
temp3 = temp2[temp2["Source"] == 'GISTEMP']
temp3.sort_values(by=['Year'], inplace=True)
temp3.head()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: SettingWithCopyWarni
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
  This is separate from the ipykernel package so we can avoid doing imports until
```

	Source	Year	Mean
93	GISTEMP	1970	0.02
91	GISTEMP	1971	-0.09
89	GISTEMP	1972	0.01
87	GISTEMP	1973	0.15
85	GISTEMP	1974	-0.07

We're ready to start now that we've sorted this dataset by year.

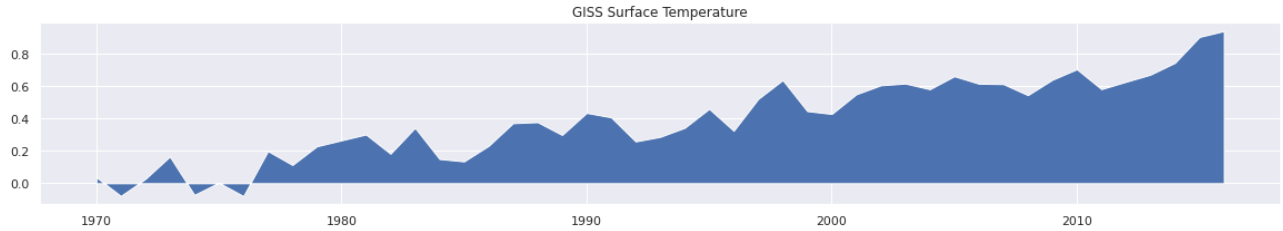
```
temp4 = temp2[temp2["Source"] == 'GCAG']
temp4.sort_values(by=['Year'], inplace=True)
temp4.tail()
```

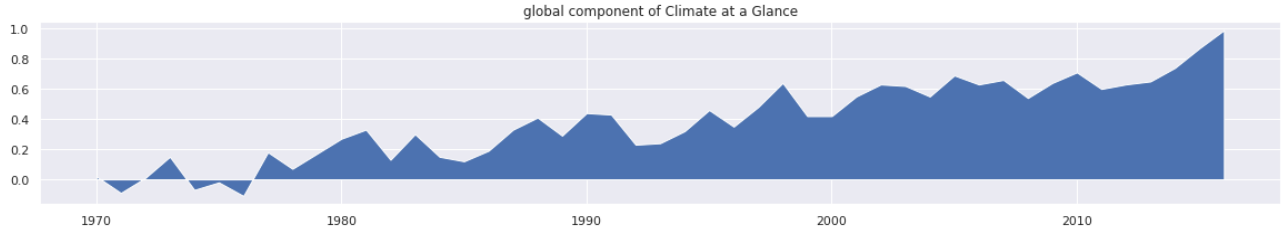
```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.
A value is trying to be set on a copy of a slice from a Da

See the caveats in the documentation: https://pandas.pydat
```

	Source	Year	Mean
8	GCAG	2012	0.6240
6	GCAG	2013	0.6679
4	GCAG	2014	0.7408
2	GCAG	2015	0.8998
0	GCAG	2016	0.9363

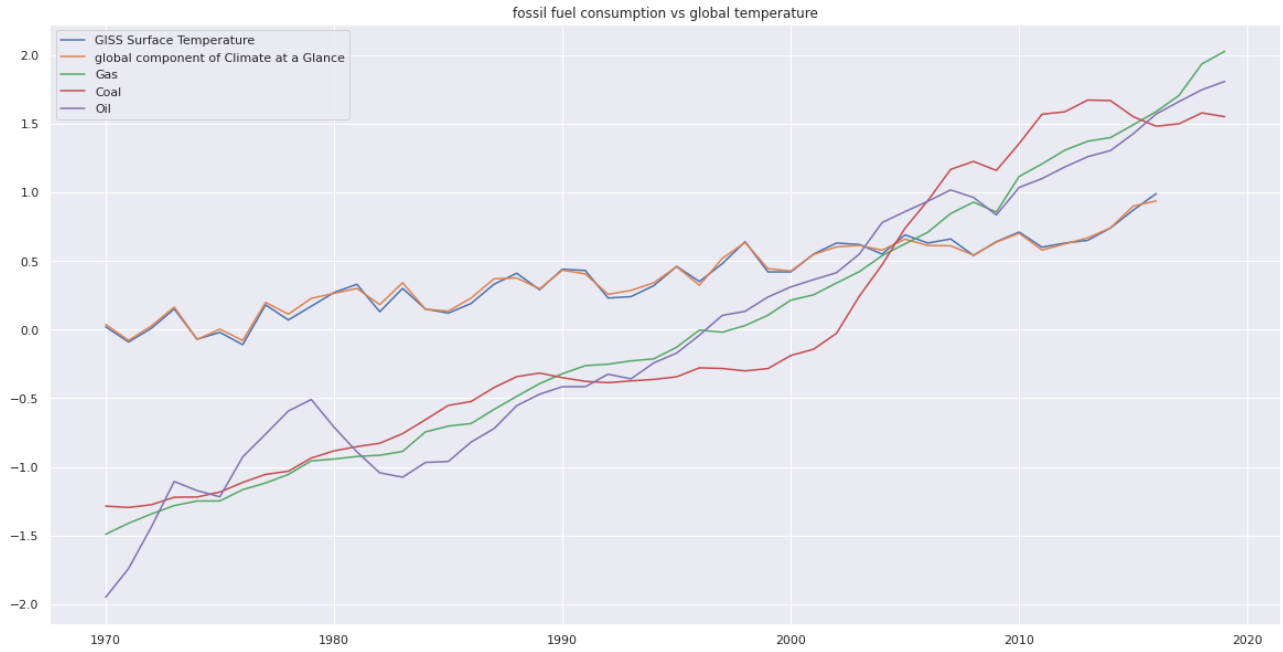
Visualisation

Okay, now we have two datasets to plot and draw conclusions. Matplotlib will be used to plot these data. The graphical depiction of information and data is known as data visualisation. Data visualisation tools, which include visual components like as charts, graphs, and maps, give an easy method to examine and analyze trends, outliers, and patterns in data.





As we can see, both temperatures increased in a linear pattern.



In this graph, I showed the three primary forms of fossil fuels as well as our temperature parameters. As we can see, the usage of oil began to rise in 1970 and then began to fall in 1977. However, total consumption is rising. Coal consumption increased significantly between 2003 and 2007. Also, as we can see, the global temperature began to rise in 2012. The key point about this is that it is longer than the other peaks in the illustration.

Conclusion

The IPCC cautions that if global warming is to be restricted to 1.5°C over pre-industrial levels, fossil fuel emissions must be cut in half within 11 years. The world's nations signed the Paris Agreement in 2015, pledging to cut carbon emissions. However, according to a new UN Environment Programme assessment, we are on course to generate more than twice the amount of coal, oil, and gas by 2030 than we can burn if we are to limit global warming to 1.5 degrees Celsius. As a result, more has to be done.
While experts warn we need a mass transition to renewable energy and efficiency, fossil fuel firms continue to be major polluters, manufacturing and marketing fossil fuel goods. BP spent millions of dollars in 2019 on an advertising campaign touting its low-carbon energy and cleaner natural gas. While its advertising emphasised sustainable energy, more than 96 percent of BP's yearly spending is still on oil and gas. And it's not just BP; it's a problem that affects the whole industry.