# MT18052\_Assignment 1

#### September 3, 2019

In [4]: import pandas as pd

import numpy as np

import numpy as np

from sklearn.utils import shuffle

```
from wordcloud import WordCloud as wcl
        from wordcloud import STOPWORDS
        import matplotlib.pyplot as plt
        import pandas as pd
        import seaborn as sns
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
   Tweets
1
In [80]: import sys
         print(sys.executable)
/home/ashish/anaconda3/bin/python
In [81]: df = pd.read_csv(r"1377884570_tweet_global_warming.csv", encoding ="latin-1")
In [82]: df.tail()
Out[82]:
                                                             tweet existence confidence \
               @bloodless_coup "The phrase 'global warming' s...
                                                                           Y
         6085
         6086 Virginia to Investigate Global Warming Scienti...
                                                                         NaN
         6087
               Global warming you tube parody you will enjoy ...
                                                                           N
                                                                                  0.6411
         6088
               One-Eyed Golfer: Don't dare tell me about glob...
                                                                                       1
                                                                           N
         6089 man made global warming a hair brained theory ...
                                                                                       1
                                                                           N
              other1 other2 other3
         6085
                 {\tt NaN}
                        {\tt NaN}
                                 NaN
         6086
                        {\tt NaN}
                 NaN
                                 NaN
         6087
                        NaN
                 NaN
                                 NaN
```

```
6088
                        NaN
                                 NaN
                 NaN
         6089
                 NaN
                        NaN
                                 NaN
In [83]: df=df.replace(to_replace ="Y", value ="Yes")
In [84]: df=df.replace(to_replace ="N", value ="No")
In [85]: y1 = df[df.existence == 'Yes']
In [86]: n1 = df[df.existence =='No']
In [87]: n2 = df[df.existence =='NA']
In [88]: y1.tail()
Out[88]:
                                                             tweet existence confidence
         6080 Bats, Birds and Lizards Can Fight Climate Chan...
                                                                         Yes
                                                                                  0.6751
         6081 Bats, Birds and Lizards Can Fight Climate Chan...
                                                                         Yes
                                                                                       1
         6082 Global warming: The fossil fuel dilemma: Ameri...
                                                                         Yes
                                                                                       1
         6084 It's 83ï£i_ï£i and climbing in NYC. August wea...
                                                                         Yes
                                                                                       1
               @bloodless_coup "The phrase 'global warming' s...
         6085
                                                                         Yes
                                                                                       1
              other1 other2
                             other3
         6080
                 NaN
                        NaN
                                 NaN
         6081
                        NaN
                                 NaN
                 NaN
         6082
                 NaN
                        NaN
                                 NaN
         6084
                                 NaN
                 NaN
                        NaN
         6085
                 NaN
                        NaN
                                 NaN
In [89]: d1=pd.concat([y1,n1])
         df=pd.concat([d1,n2])
In [90]: def word_cloud(words):
             stopwords = set(STOPWORDS)
             wordcloud = wcl(max_words=204, width = 603, height = 603, background_color = 'black'
                         min_font_size = 10).generate(words)
             plt.figure(figsize = (9, 9), facecolor = None)
             plt.imshow(wordcloud)
             plt.axis("off")
             plt.tight_layout(pad = 0)
             plt.show()
In [91]: def extract_words(tweets):
             distinct_words = ' '
             for tweet in tweets:
                 tweet = str(tweet)
                 tokens = tweet.split()
                 for i in range(len(tokens)):
```

```
tokens[i] = tokens[i].lower()
for words in tokens:
    distinct_words = distinct_words + words + ' '
return distinct_words
```

In [92]: unique\_wrds = extract\_words(df.tweet)

In [53]: word\_cloud(unique\_wrds)

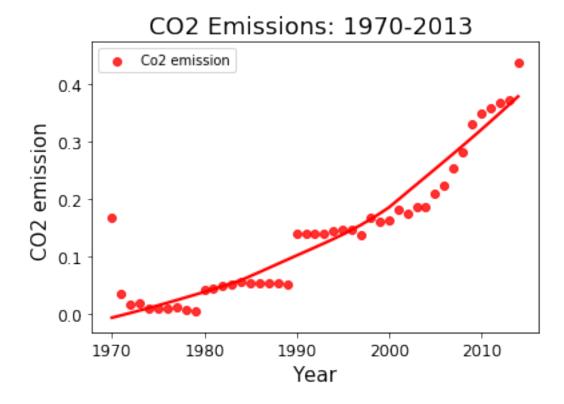
```
carbon
                                                                  change climate
                                               tinyurl
      warming maytackle
                                                tcot p2
        skeptic
problem
                                                 government '
Volcano
  major
                                   great
                       new federal scientist
                                               china
                                          protect wildlife
                        change legislation
                        conference climate dioxideat climate
                                                                              gd
      warming collapse
sign global action change
```

From Tweets we can infer that increase in carbon dioxide leads to increase in temperature which is responsible for awareness among people about global warming.

### 2 Co2 Emmision

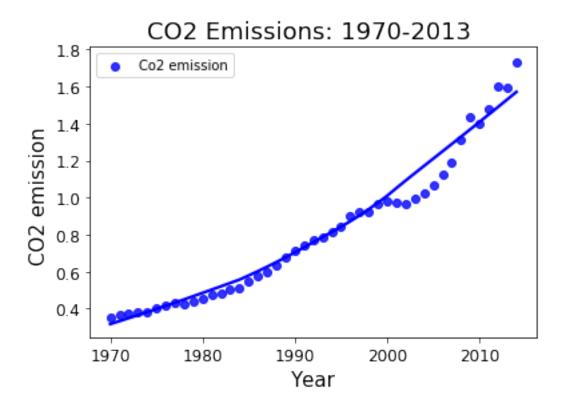
```
In [5]: co2 = pd.read_csv("./data/CO2 emissions per capita per country.csv")
   Unit metric
In [6]: co2.head()
Out [6]:
          Country Name Country Code
                                                      1961
                                                                 1962
                                                                           1963
                                                                                      1964
                                           1960
                  Aruba
                                  ABW
                                                                                       NaN
        0
                                            NaN
                                                       NaN
                                                                  {\tt NaN}
                                                                            NaN
           Afghanistan
        1
                                  AFG
                                       0.046060
                                                  0.053604
                                                            0.073765
                                                                       0.074233
                                                                                  0.086292
                 Angola
                                  AGO
                                       0.097472
                                                  0.079038
                                                            0.201289
                                                                       0.192535
                                                                                  0.201003
        3
               Albania
                                  ALB
                                       1.258195
                                                  1.374186
                                                            1.439956
                                                                       1.181681
                                                                                  1.111742
        4
               Andorra
                                  AND
                                            NaN
                                                       NaN
                                                                  NaN
                                                                            NaN
                                                                                       NaN
                1965
                          1966
                                     1967
                                                      2009
                                                                  2010
                                                                              2011
        0
                                                 25.915833
                                                                        24.505835
                 NaN
                                                            24.670529
                           NaN
                                      NaN
                                            . . .
           0.101467
                                 0.123734
                                                  0.241723
                                                             0.293837
                                                                         0.412017
                      0.107637
           0.191528
                     0.246413
                                0.154912
                                           . . .
                                                  1.232495
                                                             1.243406
                                                                         1.252789
           1.166099
                     1.333055
                                 1.363746
                                                  1.495600
                                                             1.578574
                                                                         1.803715
                                            . . .
        4
                 NaN
                           NaN
                                      NaN
                                           . . .
                                                  6.121652
                                                             6.122595
                                                                         5.867130
                 2012
                           2013
                                      2014 2015
                                                   2016
                                                         2017
                                                                2018
                      8.351294 8.408363
        0
           13.155542
                                             NaN
                                                    NaN
                                                          NaN
                                                                NaN
            0.350371
                       0.315602
                                  0.299445
                                             NaN
                                                    NaN
                                                          NaN
                                                                 NaN
            1.330843
                                                          NaN
                      1.254617 1.291328
                                             NaN
                                                    NaN
                                                                 NaN
            1.692908
                      1.749211 1.978763
                                             NaN
                                                    NaN
                                                          {\tt NaN}
                                                                 NaN
            5.916597 5.900753 5.832170
                                             NaN
                                                    NaN
                                                          {\tt NaN}
                                                                 NaN
        [5 rows x 61 columns]
In [64]: co2 = co2.drop(['2015','2016','2017','2018'],axis=1)
In [65]: y = co2.columns[12:]
In [66]: y = y.to_list()
In [190]: b = []
          for i in y:
              b.append(int(i))
In [191]: values = []
          for key in y:
              val = np.sum(co2[key])
              values.append(val)
In [192]: print (len(values))
45
```

```
In [193]: import pandas as pd
          import seaborn as sns
          import matplotlib.pyplot as plt
In [194]: def plot_CO2_emission(feature, years, col = 'orange'):
              sns.regplot(x=years, y=feature,color=col, lowess=True,label="Co2 emission")
              plt.title("CO2 Emissions: 1970-2013 ", size=18)
              plt.ylabel("CO2 emission ", size=15)
              plt.xlabel("Year", size=15)
              plt.xticks(size=12)
              plt.yticks(size=12)
              plt.legend()
            # plt.show()
In [195]: India = co2.iloc[107,]
          india_values = []
          for key in y:
              india_values.append(India[key])
In [218]: ireland = co2.iloc[109,]
          ireland_values = []
          for key in y:
              ireland_values.append(ireland[key])
In [228]: cambodia = co2.iloc[121,]
          cambodia_values = []
          for key in y:
              cambodia_values.append(cambodia[key])
In [214]: len(india_values)
Out[214]: 45
In [215]: india_values = list(india_values)
In [230]: # india values
          plot_CO2_emission(feature=np.array(cambodia_values), years=np.array(b), col = 'red')
```



Emmision increases and then gets stable for few years and then again on rise

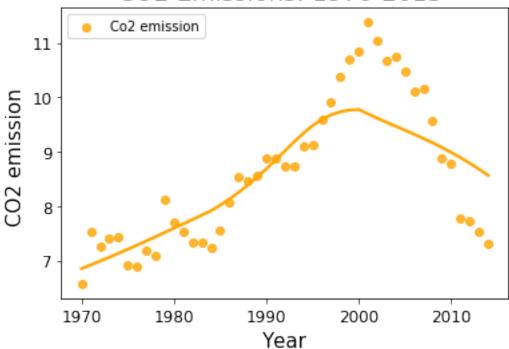
In [226]: plot\_CO2\_emission(feature=np.array(india\_values), years=np.array(b), col = 'blue')



Trend in Increase in Emission level in India

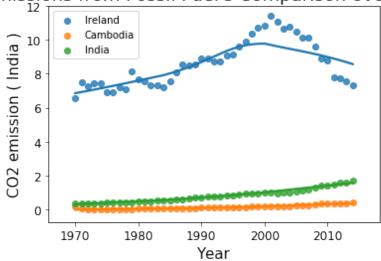
In [227]: plot\_CO2\_emission(feature=np.array(ireland\_values),years=np.array(b),col = 'orange')





There has been decrease in Co2 emmision level in Ireland

CO2 Emissions from Fossil Fuel's Comparison over the years



Emmision of Co2 by different countries in years india emission is low as comparison to ireland but it is increasing whereas in ireland it is decreasing

```
In [167]: countries = np.array(co2.iloc[:,1])
In [168]: len(countries)
Out[168]: 264
In [169]: countries_emmision = []
          for i in range(len(countries)):
              tmp = np.array(co2.iloc[i,2:])
              countries_emmision.append(tmp.mean())
In [170]: def plot_CO2_emission_2(feature,countries_,col='blue'):
              plt.figure(num=None, figsize=(40,6),dpi = 100, facecolor='w', edgecolor='k')
                sns.regplot(x=countries_, y=feature,color='orange', lowess=True,label="Co2 emi
              plt.plot(countries_,feature,color = col)
               plt.annotate(feature)
              plt.title("CO2 Emissions: 1970-2013 ", size=18)
              plt.ylabel("CO2 emission ", size=15)
              plt.xlabel("Countries", size=15)
              plt.xticks(size=12, rotation='vertical')
              plt.yticks(size=12)
              plt.legend(['Co2 Emission'])
In [171]: countries_clear_2 = []
          countries_emmision_clear_2 = []
          for i in range(len(countries_emmision)):
              if(np.isnan(countries_emmision[i]) == False):
                  countries_clear_2.append(countries[i])
                  countries_emmision_clear_2.append(countries_emmision[i])
In [172]: plot_CO2_emission_2(feature=np.array(countries_emmision_clear_2),countries_=np.array
                                      CO2 Emissions: 1970-2013
```

Co2 Emmision sum of QATAR(QAT) is maximum among all others this can be inferred by the graph plotted above

#### 3 Fossil Fuels

Unit million metric tons of carbon

```
In [115]: df = pd.read_csv('Fossil-fuel co2 Global Estimates (1751-2013).csv')
In [116]: df.tail()
Out[116]:
              Year Total
                           Gas Liquids Solids Production Flaring Capita
         258 2009
                     8641 1580
                                   3065
                                           3517
                                                        415
                                                                 64
                                                                       1.26
         259 2010
                    9137 1700
                                   3129
                                           3795
                                                        448
                                                                 66
                                                                       1.32
         260 2011
                     9508 1762
                                   3158
                                           4027
                                                        496
                                                                       1.36
                                                                 64
                                                                       1.36
         261 2012
                     9671 1787
                                 3214
                                           4086
                                                        520
                                                                 65
         262 2013
                     9776 1806
                                   3216
                                           4131
                                                        554
                                                                 68
                                                                       1.36
```

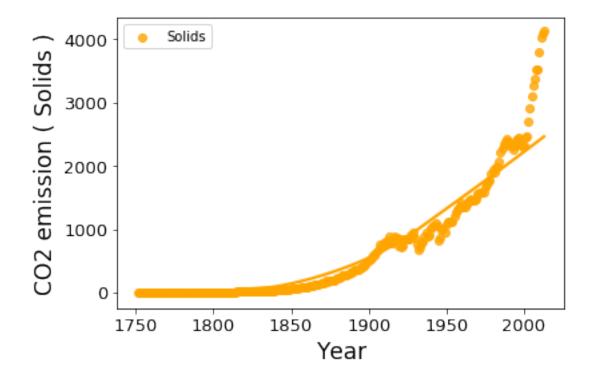
Data snapshot of dataset used

```
In [159]: def plot_CO2_emission(feature1,feature2,name,col='blue'):
              sns.regplot(x=feature1, y=feature2,color=col ,lowess=True,label=name)
                plt.title("CO2 Emissions from Fossil Fuel's via Cement Manufacture, and Gas Fl
              plt.ylabel("CO2 emission ( "+name+" )", size=17)
              plt.xlabel("Year", size=17)
              plt.xticks(size=13)
              plt.yticks(size=13)
              print ("Mean of CO2 " + str(feature2.mean()))
              print ("Variance of CO2 " + str(feature2.var()))
              print ("Standard Deviation of CO2 " + str(feature2.std()))
              plt.legend()
              plt.show()
In [160]: def plot_CO2_emission_all(feature1,feature2,name):
              sns.regplot(x=feature1, y=feature2,lowess=True,label=name)
              plt.title("CO2 Emissions from Fossil Fuel's Comparison over the years ", size=18
              plt.ylabel("CO2 emission ( "+name+" )", size=15)
              plt.xlabel("Year", size=15)
              plt.xticks(size=12)
```

plt.yticks(size=12)
plt.legend()

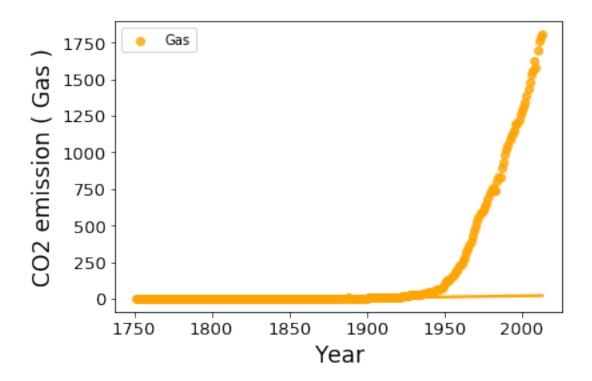
In [161]: plot\_CO2\_emission(df.Year,df.Solids,'Solids','orange')

Mean of CO2 708.4600760456274 Variance of CO2 856818.7302702229 Standard Deviation of CO2 925.6450347029486



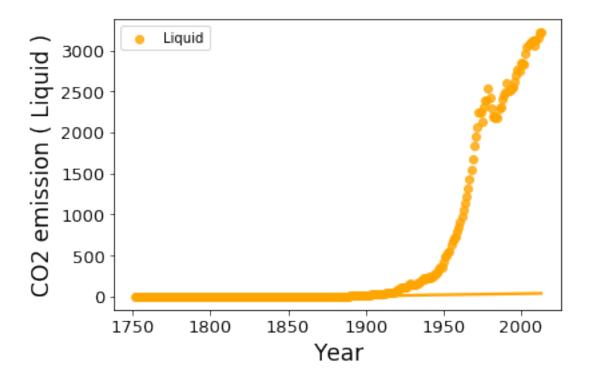
In [162]: plot\_CO2\_emission(df.Year,df.Gas,'Gas','orange')

Mean of CO2 202.92015209125475 Variance of CO2 183397.89818012947 Standard Deviation of CO2 428.2498081495536



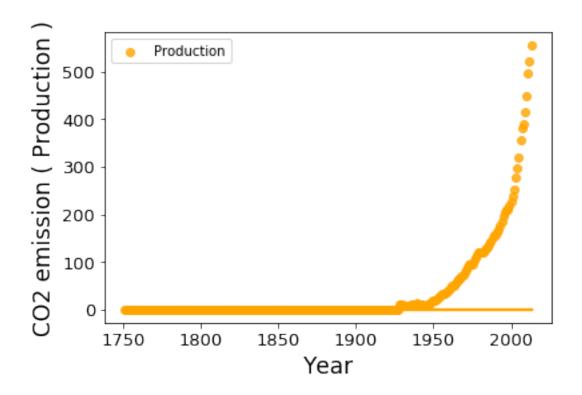
In [163]: plot\_CO2\_emission(df.Year,df.Liquids,'Liquid','orange')

Mean of CO2 526.6045627376426 Variance of CO2 945568.5300554379 Standard Deviation of CO2 972.4034811000205



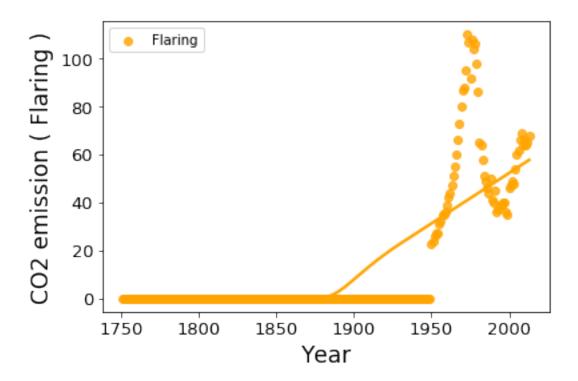
In [164]: plot\_CO2\_emission(df.Year,df.Production,'Production','orange')

Mean of CO2 39.741444866920155 Variance of CO2 8868.513046759357 Standard Deviation of CO2 94.1727829405044



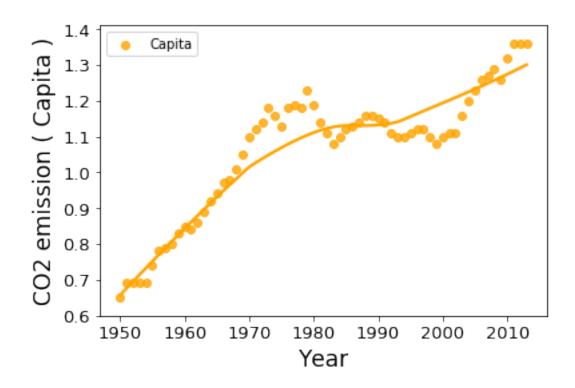
In [165]: plot\_CO2\_emission(df.Year,df.Flaring,'Flaring','orange')

Mean of CO2 13.752851711026617 Variance of CO2 721.0341044321245 Standard Deviation of CO2 26.85207821439757

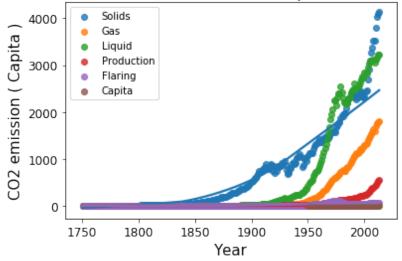


In [166]: plot\_CO2\_emission(df.Year,df.Capita,'Capita','orange')

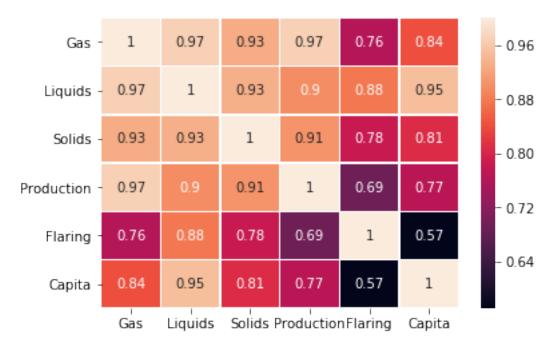
Mean of CO2 1.0643749999999998 Variance of CO2 0.03319007936507937 Standard Deviation of CO2 0.18218144627013852



### CO2 Emissions from Fossil Fuel's Comparison over the years



As per the comparison the rate of emission of Solids is more than any other followed by Liquid.



Increase in levels of emmision of Gas and Liquids are highly coorelated with each other in comparison to others, Production and Flaring are least coorelated to each other

As we can see from multiple plots the trends in climate change and increase in level's of carbon dioxide in our surrounding over the years span.

## 4 Story

As per the plots created above we can see that the level of carbon dioxide gases is increasing day by day leading to increase in temperature. This increase in emission is made from multiple sources including solid, fossil fuels, liquids and gases. As per the deforestation have affected the control of carbondioxide leading to its increase in atmosphere among different countries as we can see from the plots. These increase leads to increase in global temperature and people are spreading awareness about these issues on twitter as we can see from the plot made on frequency of most common words plotted.

In []: