Climate Change :

Importing the Necessary Libraries

```
import pandas as pd
from pandas import Series,DataFrame
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import bokeh as bk
sns.set_style('whitegrid')
%matplotlib inline
from sklearn import linear_model
from sklearn import metrics
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
import xgboost
```

Reading the Data using Pandas

```
# get global temp csv file as a DataFrame
df = pd.read_csv("C://Users//user//Downloads//GlobalTemperatures.csv", sep=',')
df.head()
```

	dt	LandAverageTemperature	LandAverageTemperatureUncertainty	LandMaxTemperature	LandMaxTemperatureUncertainty	LandMinTemperature	LandM
0	1750-01-01	3.034	3.574	NaN	NaN	NaN	
1	1750-02-01	3.083	3.702	NaN	NaN	NaN	
2	1750-03-01	5.626	3.076	NaN	NaN	NaN	
3	1750-04-01	8.490	2.451	NaN	NaN	NaN	
4	1750-05-01	11.573	2.072	NaN	NaN	NaN	

Data has Multiple Null values , So we are Dropping Few Columns

```
# Delete all columns except dates, Land Average Temperatures, Land Average Temperature Uncertainty
df=df.drop(df.columns[3:], axis=1)

#Delete all empty lines
df=df.dropna()

```

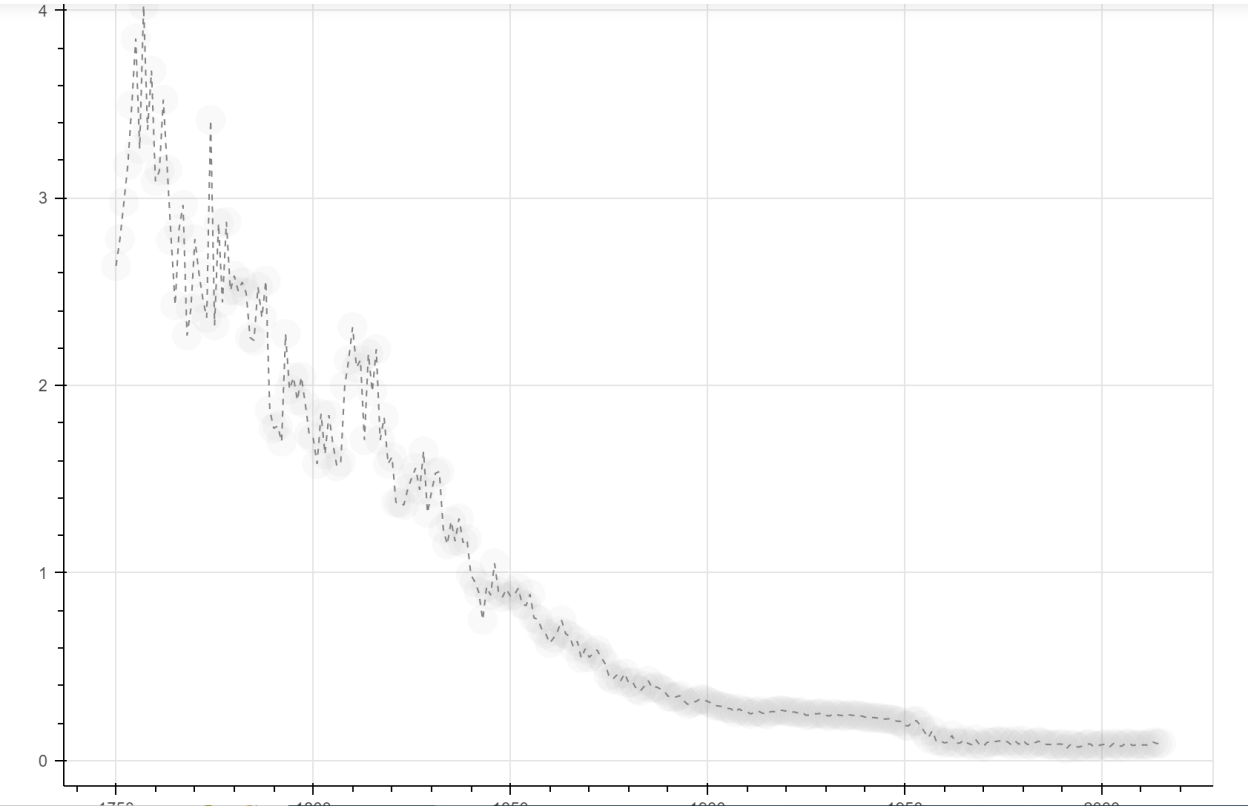
Resizing the Datasets and only keeps Averages

```
#Resizing the datasets, we only keep the year averages

date=df['dt'].apply(lambda x: x[:4])
years = np.unique(date)
mean_temps_global=[]
mean_temps_uncertainty=[]

for y in years:

    mean_temps_global.append(df[y==date]['LandAverageTemperature'].mean())
    mean_temps_uncertainty.append(df[y==date]['LandAverageTemperatureUncertainty'].mean())

#Defining a function that classifies the average temperatures

def heat(x):

    if type(x) is str:
        return x
    elif x<=7:
        return 3
    elif x>7 and x<=8:
        return 2
    else:
        return 1
```

```
#Building of a new, simpler dataframe

years=pd.to_numeric(years)

d1={'Dates': pd.Series(years),'Temperatures':pd.Series(mean_temps_global),'Uncertainty':pd.Series(mean_temps_uncertainty

df_global_mean=pd.DataFrame(d1)

#Adding the heat function

e=df_global_mean.applymap(heat)

d2={'Dates': pd.Series(years),'Temperatures':pd.Series(mean_temps_global),'Uncertainty':pd.Series(mean_temps_uncertainty
    'Heat':e['Temperatures']}

df_global_mean=pd.DataFrame(d2)
```

Plotting the Uncertainty

```
#Now, we plot the 95% Uncertainty regarding the temperature evolution

from bokeh.plotting import figure, show
from bokeh.models import ColumnDataSource, Circle, HoverTool, CustomJS
from bokeh.io import output_notebook

output_notebook()

(x, y) = (df_global_mean['Dates'], df_global_mean['Uncertainty'])

# Basic plot setup
p = figure(width=800, height=600, toolbar_location=None, title='A clear decreasing of uncertainty')

p.line(x, y, line_dash="4 4", line_width=1, color='gray')


# Add a circle, that is visible only when selected
source = ColumnDataSource({'x': x, 'y': y})
invisible_circle = Circle(x='x', y='y', fill_color='gray', fill_alpha=0.05, line_color=None, size=20)
visible_circle = Circle(x='x', y='y', fill_color='firebrick', fill_alpha=0.5, line_color=None, size=20)
cr = p.add_glyph(source, invisible_circle, selection_glyph=visible_circle, nonselection_glyph=invisible_circle)

# Add a hover tool, that selects the circle
code = "source.set('selected', cb_data['index']);"
callback = CustomJS(args={'source': source}, code=code)
p.add_tools(HoverTool(tooltips=None, callback=callback, renderers=[cr], mode='hline'))

show(p)
```



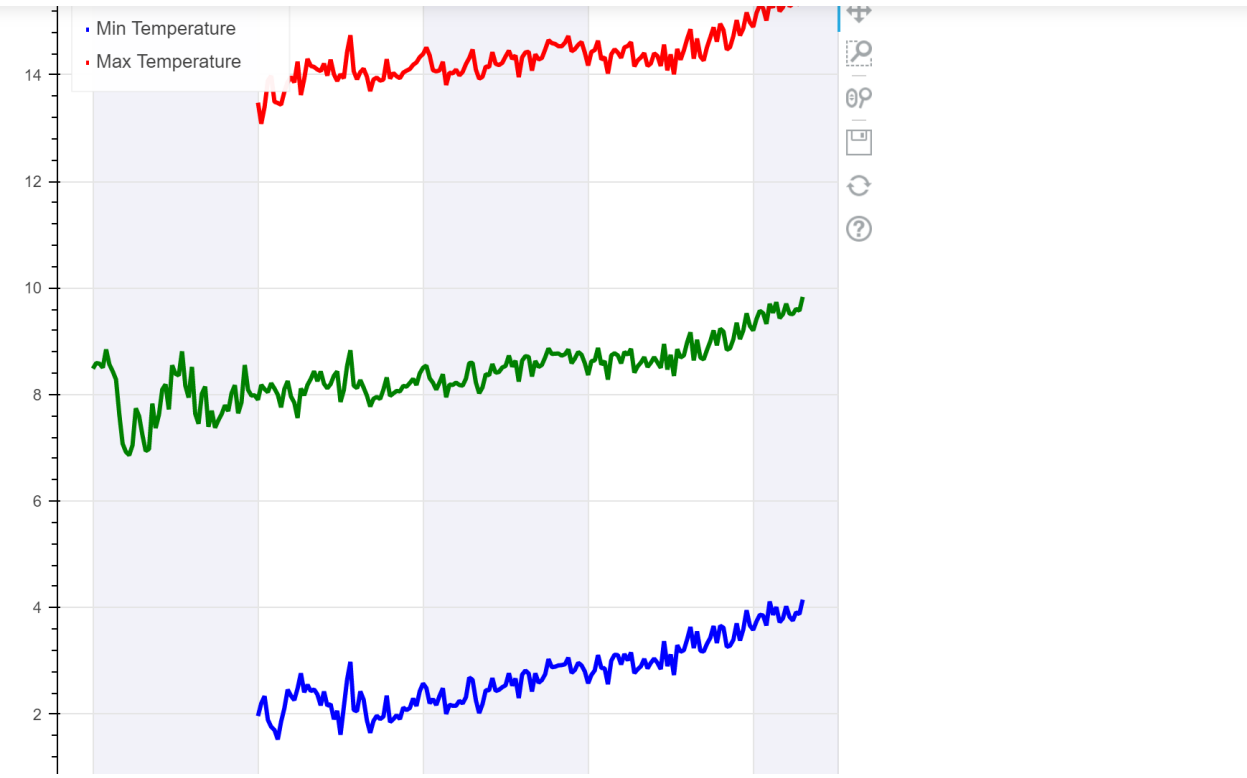
Loading the Min and Max Data

```
2
3  global_temps2 = pd.read_csv("C://Users//user//Downloads//GlobalTemperatures.csv", sep=',')
4
5  # Starting in 1800 when data is more significant (less NaN)
6
7  list_of_years_1800=years[50:]
8
9  # Compute Average, Max, Min Temperature by Year since 1800
10
11 date=global_temps2['dt'].apply(lambda x: x[:4])
12 list_of_years_1800=np.unique(date)
13 list_of_years_1800=list_of_years_1800[50:]
14
15 mean_temps_1800=[]
16 min_temps_1800=[]
17 max_temps_1800=[]
18
19 for y in list_of_years_1800:
20
21     mean_temps_1800.append(global_temps2[y==date]['LandAverageTemperature'].mean())
22     max_temps_1800.append(global_temps2[y==date]['LandMaxTemperature'].mean())
23     min_temps_1800.append(global_temps2[y==date]['LandMinTemperature'].mean())
24
```

```
25 #Building of a new, simpler dataframe
26
27 list_of_years_1800=pd.to_numeric(list_of_years_1800)
28
29 d1={'Average Temperature':pd.Series(mean_temps_1800), 'Dates': pd.Series(list_of_years_1800),
30    'Min Temperature':pd.Series(min_temps_1800),'Max Temperature':pd.Series(max_temps_1800)}
31
32 global_temps_1800=pd.DataFrame(d1)
33
34 global_temps_1800=global_temps_1800[['Dates','Average Temperature','Min Temperature','Max Temperature']]
35
```

Plotting the Tempurature

```
from bokeh.plotting import figure, show
from bokeh.models import ColumnDataSource, Circle, HoverTool, CustomJS
from bokeh.io import output_notebook

output_notebook()

x = global_temps_1800['Dates']
y = global_temps_1800['Average Temperature']
z = global_temps_1800['Min Temperature']
t = global_temps_1800['Max Temperature']

p = figure(plot_width=600, plot_height=600)


p.line(x, y, legend="Average Temperature", line_color="green", line_width=3)

p.line(x,z, legend="Min Temperature", line_color="blue", line_width=3)

p.line(x, t, legend="Max Temperature", line_color="red", line_width=3)

# change just some things about the x-grid
p.xgrid.band_fill_alpha = 0.05
p.xgrid.band_fill_color = "navy"

p.legend.location = "top_left"
p.legend.glyph_width = 2
p.legend.label_width=2


show(p)
```



Linear Regression

```
import matplotlib.pyplot as plt
import numpy as np
from sklearn import linear_model


temp=global_temps_1800['Average Temperature']
time=global_temps_1800['Dates']


# The data sets
dates_X = time.iloc[0:,]

# The targets
temperature_y = temp.iloc[0:,]

# Create linear regression object
reg = linear_model.LinearRegression()

# Train the model using the data sets
reg.fit(dates_X.to_frame(),temperature_y.to_frame())

# The estimation
output_reg=reg.predict(dates_X.to_frame())
output_simple=np.copy(output_reg)
output=pd.DataFrame(index=pd.DataFrame(output_simple).index.values)
```

```
# The coefficients
print('Coefficients: \n', reg.coef_)
# The intercept
print('Intercept: \n', reg.intercept_)


# The mean squared error
print("Mean squared error: %.2f" % np.mean((reg.predict(dates_X.to_frame()) - temperature_y.to_frame()) ** 2))

# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' % reg.score(dates_X.to_frame(), temperature_y.to_frame()))

```

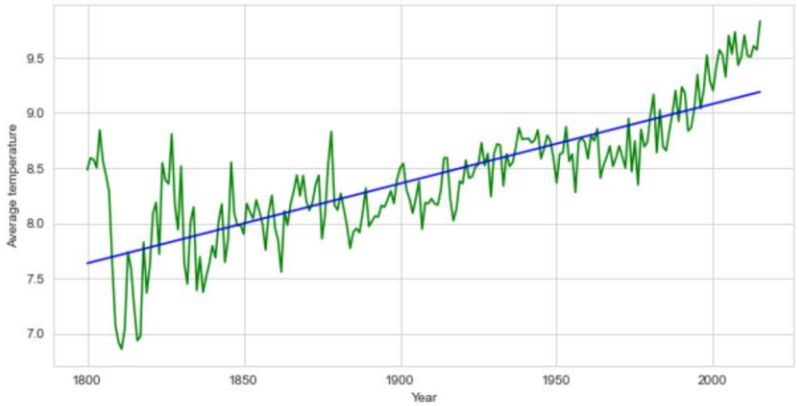
```
Coefficients:
 [[0.00721859]]
Intercept:
 [-5.35578585]
Mean squared error: 0.12
Variance score: 0.64
```

Regression Curve on Predicted Values

```
# Linear regression cuve on the predicted values

# Simple Linear Regression: t : Regression done on the values between 1800 and 1950 and testes between 1950 and 2016
fig, axes = plt.subplots(figsize=(10,5))
axes.set_ylabel('Average temperature')
axes.set_xlabel('Year')
plt.plot(dates_X, temperature_y, label='Annual Mean temperature', color='g')
plt.plot(dates_X,output_simple,label='Forecast Temperature by Regression',color='b')
```

```
# Linear regression cuve on the predicted values

# Simple Linear Regression: t : Regression done on the values between 1800 and 1950 and testes between 1950 and 2016
fig, axes = plt.subplots(figsize=(10,5))
axes.set_ylabel('Average temperature')
axes.set_xlabel('Year')
plt.plot(dates_X, temperature_y, label='Annual Mean temperature', color='g')
plt.plot(dates_X,output_simple,label='Forecast Temperature by Regression',color='b')
```

```
[<matplotlib.lines.Line2D at 0x1ca24f527c0>]
```



LINEAR MODEL

```
from sklearn import linear_model

#Define the input and output
temp=global_temps_1800['Average Temperature']
time=global_temps_1800['Dates']

# Split the data into training/testing sets
dates_X_train = time.iloc[0:150,]
dates_X_test = time.iloc[150:,]

# Split the targets into training/testing sets
temperature_y_train = temp.iloc[0:150,]
temperature_y_test = temp.iloc[150:,]

# Create linear regression object
reg = linear_model.LinearRegression()

# Train the model using the training sets
reg.fit(dates_X_train.to_frame(),temperature_y_train.to_frame())

# The coefficients
print('Coefficients: \n', reg.coef_)
# The intercept
print('Intercept: \n', reg.intercept_)
```

```
# The prediction
output_simple=reg.predict(dates_X_test.to_frame())
# The mean squared error
print("Mean squared error: %.2f"
      % np.mean((reg.predict(dates_X_test.to_frame()) - temperature_y_test.to_frame()) ** 2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' % reg.score(dates_X_test.to_frame(), temperature_y_test.to_frame()))

```

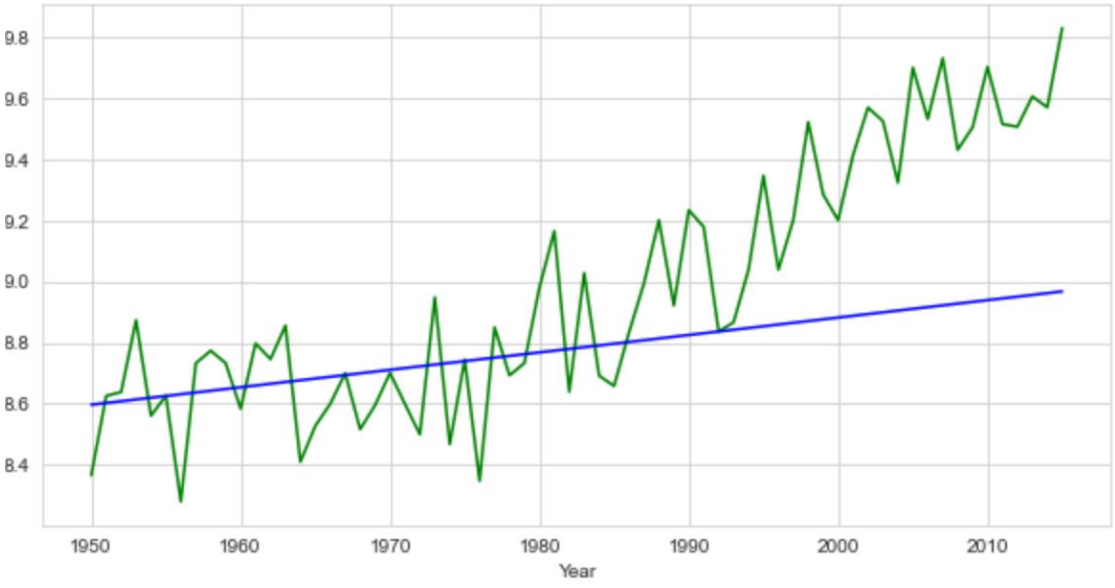
```
Coefficients:
 [[0.00570766]]
Intercept:
 [-2.53305848]
Mean squared error: 0.14
Variance score: 0.16
```

Simple Linear Regression

```
# Simple Linear Regression: t : Regression done on the values between 1800 and 1950 and testes between 1950 and 2016
fig, axes = plt.subplots(figsize=(10,5))
axes.set_ylabel('Average temperature')
axes.set_xlabel('Year')
plt.plot(dates_X_test, temperature_y_test, label='Annual Mean temperature', color='g')
plt.plot(dates_X_test,output_simple,label='Forecast Temperature by Regression',color='b')

```

```
[<matplotlib.lines.Line2D at 0x1ca26013ca0>]
```

[<matplotlib.lines.Line2D at 0x1ca26013ca0>]



Polynomial Regression

Polynomial Regression

```
time=pd.DataFrame()
time["Dates"]=global_temps_1800['Dates']
time["Dates^2"]=global_temps_1800['Dates']*global_temps_1800['Dates']
time["Dates^3"]=global_temps_1800['Dates']*global_temps_1800['Dates']*global_temps_1800['Dates']
temp=global_temps_1800['Average Temperature']


# The data sets
dates_X = time.iloc[0:,0]

# The targets
temperature_y = temp.iloc[0:,]

# Create linear regression object
reg = linear_model.LinearRegression()

# Train the model using the training sets
reg.fit(time.iloc[0:,],temperature_y.to_frame())
```

```
# The prediction
output_reg=reg.predict(time.iloc[0:,])
output_multiple=np.copy(output_reg)
output=pd.DataFrame(index=pd.DataFrame(output_simple).index.values)
# The coefficients
print('Coefficients: \n', reg.coef_)
# The intercept
print('Intercept: \n', reg.intercept_)

# The mean squared error
print("Mean squared error: %.2f" % np.mean((output_reg - temperature_y.to_frame()) ** 2
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' % reg.score(time.iloc[0:,], temperature_y.to_frame()))

# Euclidian Distance
output['Predicted Temperature']=pd.DataFrame(output_multiple)
output["Average Temperature"]=temp
```

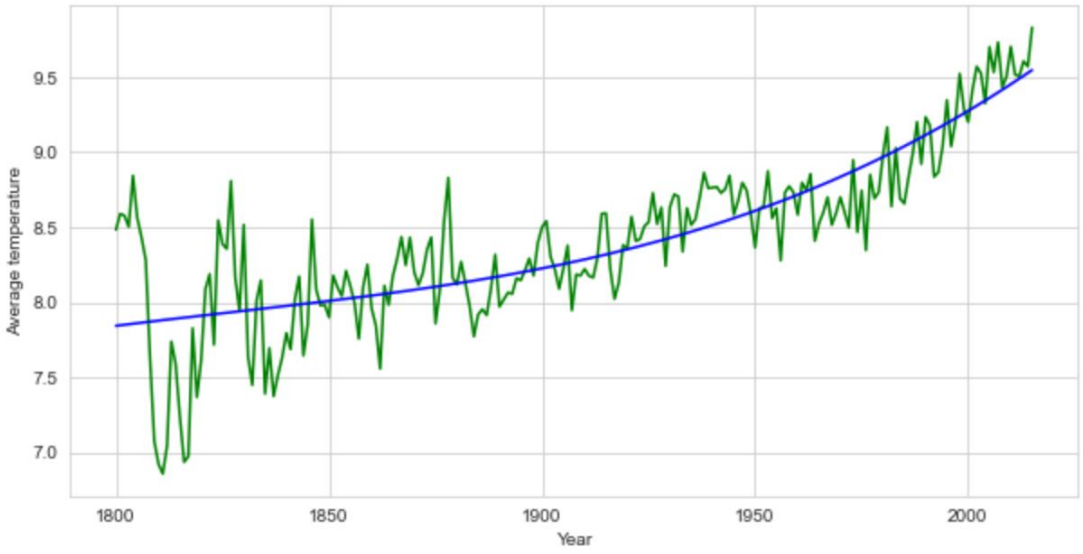
```
Coefficients:
 [[ 1.54583760e+00 -8.43972200e-04  1.53912499e-07]]
Intercept:
 [-937.81103858]
Mean squared error: 0.10
Variance score: 0.69
```

It has High Variance Score

```
#Regression done on the values between 1800 and 1950 and testes between 1950 and 2016
fig, axes = plt.subplots(figsize=(10,5))
axes.set_ylabel('Average temperature')
axes.set_xlabel('Year')
plt.plot(dates_X, temperature_y, label='Annual Mean temperature', color='g')
plt.plot(dates_X,output_multiple,label='Forecast Reg',color='b')
```

```
[<matplotlib.lines.Line2D at 0x1ca260a02b0>]
```

|: [<matplotlib.lines.Line2D at 0x1ca260a02b0>]



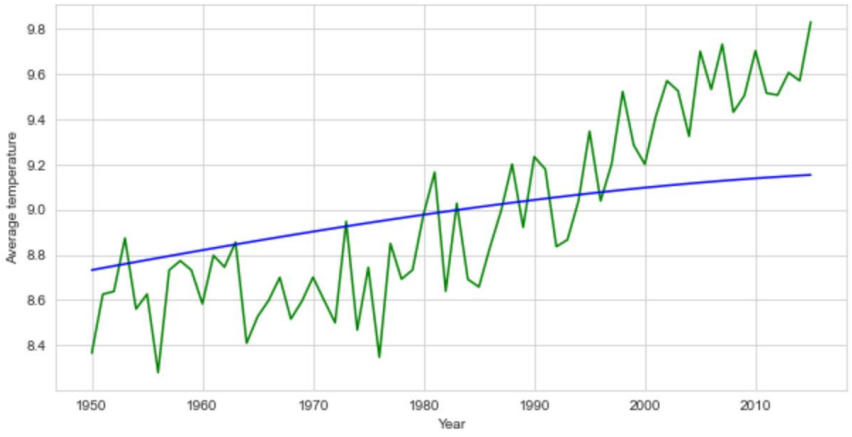

```
temp=global_temps_1800['Average Temperature']
time=pd.DataFrame()
time["Dates"]=global_temps_1800['Dates']
time["Dates^2"]=global_temps_1800['Dates']*global_temps_1800['Dates']
time["Dates^3"]=global_temps_1800['Dates']*global_temps_1800['Dates']*global_temps_1800['Dates']

# Split the data into training/testing sets
dates_X_train = time.iloc[0:150,0]
dates_X_test = time.iloc[150:,0]

# Split the targets into training/testing sets
temperature_y_train = temp.iloc[0:150,]
temperature_y_test = temp.iloc[150:,]

# Create linear regression object
reg = linear_model.LinearRegression()

# Train the model using the training sets
reg.fit(time.iloc[0:150,],temperature_y_train.to_frame())

# The coefficients
print('Coefficients: \n', reg.coef_)
# The intercept
print('Intercept: \n', reg.intercept_)

# The prediction
output_multiple=reg.predict(time.iloc[150:,])
```

```
print("Mean squared error: %.2f"
      % np.mean((reg.predict(time.iloc[150:,]) - temperature_y_test.to_frame()) ** 2))
# Explained variance score: 1 is perfect prediction
print('Variance score: %.2f' % reg.score(time.iloc[150:,], temperature_y_test.to_frame()))
```

```
Coefficients:
 [[-3.37849536e+00  1.75645409e-03 -3.03542634e-07]]
Intercept:
 [2168.61282323]
Mean squared error: 0.10
Variance score: 0.42
```

```
fig, axes = plt.subplots(figsize=(10,5))
axes.set_ylabel('Average temperature')
axes.set_xlabel('Year')
#
plt.plot(dates_X_test, temperature_y_test, label='Annual Mean temperature', color='g')
plt.plot(dates_X_test,output_multiple,label='Forecast Reg',color='b')

```

]: [<matplotlib.lines.Line2D at 0x1ca26102250>]



Plotting the Correlation Matrix

Correlation Matrix

```
#Correlation Matrix for the following features : LandAverageTemperature, LandMaxTemperature, LandMinTemperature,LandAnd
global_temperatures=pd.read_csv("C://Users//user//Downloads//GlobalTemperatures.csv", sep=',')
global_temperatures['dt'] = pd.to_datetime(global_temperatures['dt'])
global_temperatures=global_temperatures.drop(['LandAverageTemperatureUncertainty',"LandMaxTemperatureUncertainty","Land
global_temperatures=global_temperatures.dropna()
corr=global_temperatures.corr()
sns.heatmap(corr,xticklabels=['LandAverage','LandMax','LandMin','LandOcean'], yticklabels=['LandAverage','LandMax','Lan

```

t[26]: <AxesSubplot:>

Random Forest

Train Data

```
# Train
train_df_copy=pd.DataFrame.copy(global_temperatures[global_temperatures['dt'].map(lambda x: x.year)<1980])
train_df=pd.DataFrame.copy(train_df_copy)
train_df.drop(train_df.index[:1], inplace=True)
train_df_copy.drop(train_df.index[-1],inplace=True)

# To predict each average land temperature we use the previous year's temperatures (landandocean, min, max)
for j in (train_df.index):
    for column in train_df.columns[1:-1]:
        train_df.loc[j,column]=train_df_copy.loc[j-1,column]
forest = RandomForestRegressor(n_estimators=10)
train_df=train_df.drop(['dt'],axis=1)
forest = forest.fit(train_df.drop(["LandAverageTemperature"],axis=1),train_df["LandAverageTemperature"])
```

Test Data

```
# Test
test_df_copy=pd.DataFrame.copy(global_temperatures[global_temperatures['dt'].map(lambda x: x.year)>=1980])
test_df=pd.DataFrame.copy(test_df_copy)
test_df.drop(test_df.index[:1], inplace=True)
test_df_copy.drop(test_df.index[-1], inplace=True)

# To predict each average land temperature we use the previous year's temperatures (landandocean, min , max)
for j in (test_df.index):
    for column in test_df.columns[1:-1]:
        test_df.loc[j,column]=test_df_copy.loc[j-1,column]
test_df=test_df.drop(['dt'],axis=1)
output = forest.predict(test_df.drop(["LandAverageTemperature"],axis=1))
```

```
#Adding the predicted temperature to our output DF
test_df['Predicted_temp']=output
```

```
# Distance computing
MED=abs(test_df['LandAverageTemperature']-test_df['Predicted_temp']).mean()
```

```
MED
```

```
0.24371299303944335
```

IT has MED 0.24 score

XGB REGRESSOR And Train

XGBoost

```
# Packages
import xgboost
from xgboost import XGBRegressor
```

```
# Train
train_df_copy_2=pd.DataFrame.copy(global_temperatures[global_temperatures['dt'].map(lambda x: x.year)<1980])
train_df_2=pd.DataFrame.copy(train_df_copy_2)
train_df_2.drop(train_df_2.index[:1], inplace=True)
train_df_copy_2.drop(train_df_2.index[-1], inplace=True)

# To predict each average land temperature we use the previous year's temperatures (Landandocean, min , max)
for j in (train_df_2.index):
    for column in train_df_2.columns[1:-1]:
        train_df_2.loc[j,column]=train_df_copy_2.loc[j-1,column]
forest2 = XGBRegressor()
train_df_2=train_df_2.drop(['dt'],axis=1)
forest2 = forest2.fit(train_df_2.drop(["LandAverageTemperature"],axis=1),train_df_2["LandAverageTemperature"])
```

Test

```
# Test
test_df_copy_2=pd.DataFrame.copy(global_temperatures[global_temperatures['dt'].map(lambda x: x.year)>=1980])
test_df_2=pd.DataFrame.copy(test_df_copy_2)
test_df_2.drop(test_df_2.index[:1], inplace=True)
test_df_copy_2.drop(test_df_2.index[-1], inplace=True)
# To predict each average land temperature we use the previous year's temperatures (Landandocean, min , max)
for j in (test_df_2.index):
    for column in test_df_2.columns[1:-1]:
        test_df_2.loc[j,column]=test_df_copy_2.loc[j-1,column]
test_df_2=test_df_2.drop(['dt'],axis=1)
output = forest2.predict(test_df_2.drop(["LandAverageTemperature"],axis=1))
```

MED on XGB

```
test_df_2['Predicted_temp']=output
```

```
# Distance computing
MED=abs(test_df_2['LandAverageTemperature']-test_df_2['Predicted_temp']).mean()
```

```
MED
```

```
0.24781643837399955
```

KNN and Train Data

Nearest neighbors

```
from sklearn.neighbors import KNeighborsRegressor
```

```
# Train
neigh = KNeighborsRegressor(n_neighbors=2)
train_df_copy_3=pd.DataFrame.copy(global_temperatures[global_temperatures['dt'].map(lambda x: x.year)<1980])
train_df_3=pd.DataFrame.copy(train_df_copy_3)
train_df_3.drop(train_df_3.index[:1], inplace=True)
train_df_copy_3.drop(train_df_3.index[-1], inplace=True)

# To predict each average land temperature we use the previous year's temperatures (landandocean, min , max)
for j in (train_df_3.index):
    for column in train_df_3.columns[1:-1]:
        train_df_3.loc[j,column]=train_df_copy_3.loc[j-1,column]
train_df_3=train_df_3.drop(['dt'],axis=1)
neighbors=neigh.fit(train_df_3.drop(["LandAverageTemperature"],axis=1),train_df_3["LandAverageTemperature"])
```

Test Data

```
# Test
test_df_copy_3=pd.DataFrame.copy(global_temperatures[global_temperatures['dt'].map(lambda x: x.year)>=1980])
test_df_3=pd.DataFrame.copy(test_df_copy_3)
test_df_3.drop(test_df_3.index[:1], inplace=True)
test_df_copy_3.drop(test_df_3.index[-1], inplace=True)

# To predict each average land temperature we use the previous year's temperatures (landandocean, min , max)
for j in (test_df_3.index):
    for column in test_df_3.columns[1:-1]:
        test_df_3.loc[j,column]=test_df_copy_3.loc[j-1,column]
test_df_3=test_df_3.drop(['dt'],axis=1)
neigh_output = neighbors.predict(test_df_3.drop(["LandAverageTemperature"],axis=1))
```

```
# Adding the predicted temperature to our output DF
test_df_3['Predicted_temp']=neigh_output
```

```
MED=abs(test_df_3['LandAverageTemperature']-test_df_3['Predicted_temp']).mean()
```

```
MED
```

```
0.23760904872389793
```

Knn Has low MED

Minimizing the MED

```
#Definition of the function we want to minimize

def MED_XGB(n,maxi,learn,
       X_train, y_train, X_test,y_test,
       MED_limit):



    xgb_model = xgboost.XGBRegressor(n_estimators = n , learning_rate = learn, max_depth = maxi )
    model_fit = xgb_model.fit(X_train , y_train )
    y_predict = model_fit.predict(X_test)
    MED=abs(y_test-y_predict).mean()

    if MED<MED_limit:
        return MED , n, learn, maxi
    else:
        return 0
```

Separating the Train and Test

```
#### Data Sets ####

#Train
train_df_copy=pd.DataFrame.copy(global_temperatures[global_temperatures['dt'].map(lambda x: x.year)<1980])
train_df=pd.DataFrame.copy(train_df_copy)
train_df.drop(train_df.index[:1], inplace=True)
train_df_copy.drop(train_df.index[-1], inplace=True)
for j in (train_df.index):
    for column in train_df.columns[1:-1]:
        train_df.loc[j,column]=train_df_copy.loc[j-1,column]

train_df=train_df.drop(['dt'],axis=1)

#Test
test_df_copy=pd.DataFrame.copy(global_temperatures[global_temperatures['dt'].map(lambda x: x.year)>=1980])
test_df=pd.DataFrame.copy(test_df_copy)
test_df.drop(test_df.index[:1], inplace=True)
test_df_copy.drop(test_df.index[-1], inplace=True)
for j in (test_df.index):
    for column in test_df.columns[1:-1]:
        test_df.loc[j,column]=test_df_copy.loc[j-1,column]

test_df=test_df.drop(['dt'],axis=1)

```

```
24
25
26 X_train = train_df.drop("LandAverageTemperature", axis = 1)
27 y_train = train_df['LandAverageTemperature']
28
29 X_test = test_df.drop("LandAverageTemperature", axis = 1)
30 y_test = test_df['LandAverageTemperature']
```

```
1 #### HyperParameters ####
```

Hyperparameters and their Values

```
1 #### HyperParameters ####
2
3 max_depth = [2+i for i in range(5)]
4 learning_rate = [0.01*(i+1) for i in range(5)]
5 n_estimators = [370+i for i in range(20)]
6 MED_limit =  0.21
7 l=[]
```

```
1 #### Very long loop depending on parameters ####
2
3 for n in n_estimators:
4     for learn in learning_rate:
5         for maxi in max_depth:
6             a = MED_XGB(n,maxi,learn,X_train,y_train,X_test,y_test,MED_limit)
7             if a != 0:
8                 l.append(a)
9                 l.sort()
10
11 l[:5] # 5 Best MED Results
```

Best Results and Their Values

```
[(0.20242728570995633, 385, 0.04, 2),
 (0.2024370215962491, 386, 0.04, 2),
 (0.20244119143209427, 387, 0.04, 2),
 (0.20250209825166132, 384, 0.04, 2),
 (0.20251078753017762, 383, 0.04, 2)]
```

Applying Grid Search

```
#### GridSearch (Take some time to compute) ####

from xgboost import plot_importance,to_graphviz, plot_tree
from sklearn.model_selection  import GridSearchCV

xgb_model = xgboost.XGBRegressor()

clf = GridSearchCV(xgb_model,
                   {'max_depth': max_depth,
                    'n_estimators': n_estimators,
                   'learning_rate': learning_rate}, verbose=1)

clf.fit(X_train,y_train)
clf.best_score_, clf.best_params_
```

```
Fitting 5 folds for each of 500 candidates, totalling 2500 fits
```

9]:
```
(0.9925820953088234,
 {'learning_rate': 0.02, 'max_depth': 2, 'n_estimators': 370})
```

It has got best score of 99.25

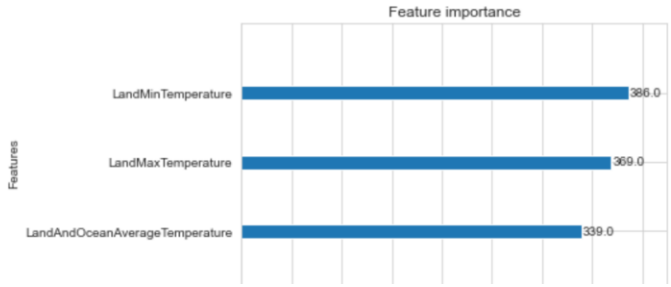
Feature Importances

Features importance

:
```
maxi = 2
learn = 0.04
n = 385

xgb_model = xgboost.XGBRegressor(max_depth = maxi,
                                 learning_rate = learn,
                                 n_estimators = n)

model_fit = xgb_model.fit(X_train,y_train)
```

:
```
#Ranking the features'importance
plot_importance(model_fit)
```

[61]:
```
<AxesSubplot:title={'center':'Feature importance'}, xlabel='F score', ylabel='Features'>
```



Adding C02 as a Feature

```
# Adding the CO2 Level as a a feature

CO2=pd.read_csv("C://Users//user//Downloads//co2-mm-mlo.csv",sep=",")

# We drop the year 2016 since we don't have the temperatures of 2016
CO2 = CO2.drop(CO2.index[-10:])
CO2["Date"]=CO2["Date"]+"-01"
CO2["Date"]=pd.to_datetime(CO2["Date"])
CO2=CO2.drop(["Decimal Date","Interpolated","Trend","Number of Days"],axis=1)

# We merge the temperatures data with the CO2 data and we keep
#only the months where we have the average CO2 levels
temperatures=pd.merge(left=global_temperatures,right=CO2, left_on='dt', right_on='Date', how='outer')
temp=pd.DataFrame.copy(temperatures[temperatures['dt'].map(lambda x: x.year)<1980])
temp=temp.dropna()
```

Random Forest

```
#Sets

# Train
train_df_copy=pd.DataFrame.copy(temp)
train_df=pd.DataFrame.copy(train_df_copy)
train_df.drop(train_df.index[:1], inplace=True)
train_df_copy.drop(train_df.index[-1], inplace=True)

X_train = train_df.drop(["LandAverageTemperature","dt","Date"], axis = 1)
y_train = train_df['LandAverageTemperature']

# Test
test_df_copy=pd.DataFrame.copy(temperatures[temperatures['dt'].map(lambda x: x.year)>=1980])
test_df=pd.DataFrame.copy(test_df_copy)
test_df.drop(test_df.index[:1], inplace=True)
test_df_copy.drop(test_df.index[-1], inplace=True)

X_test = test_df.drop(["LandAverageTemperature","dt","Date"],axis = 1 )
y_test = test_df['LandAverageTemperature']
```

Minimizing the Function

```
#Definition of the Minimization Function

def MED_RF(n,maxi,
       X_train, y_train, X_test,y_test,
       MED_limit):

#Note that there is no learning_rate for the random forest regressor



    forest = RandomForestRegressor(n_estimators=n,max_depth = maxi)
    model_fit = forest.fit(X_train , y_train )
    y_predict = model_fit.predict(X_test)
    MED=abs(y_test-y_predict).mean()

    if MED<MED_limit:
        return MED, n, maxi
    else:
        return 0
```

Printing the top 5 results

```
#Hyperparameters

max_depth = [8+i for i in range(7)]
n_estimators = [i+1 for i in range(100)]
MED_limit = 0.2
l=[]
```

```
#### Minimization (Very Long Loop depending on parameters) ####

for n in n_estimators:
    for maxi in max_depth:
        a = MED_RF(n,maxi,X_train,y_train,X_test,y_test,MED_limit)
        if a != 0:
            l.append(a)
            l.sort()

l[:5] # 5 Best MED Results
```

```
]: [(0.13500554266563564, 9, 12),
 (0.13506879608146466, 30, 10),
 (0.13692821121428825, 23, 9),
 (0.13729237068377267, 17, 12),
 (0.13780974477958347, 63, 14)]
```

Grid Search on Random Forest with added Features

```
# GridSearch (very long)

clf = GridSearchCV(forest,
                   {'max_depth': max_depth,
                    'n_estimators': n_estimators}, verbose=1)

clf.fit(X_train,y_train)
clf.best_score_, clf.best_params_
```

```
Fitting 5 folds for each of 700 candidates, totalling 3500 fits
```

```
]: (0.9995378623714621, {'max_depth': 14, 'n_estimators': 60})
```

```
#Random Forest (GridSearch MED Test)

# To predict each average land temperature we use the previous year's temperatures (landandocean, min
for j in (train_df.index):
    for column in train_df.columns[1:-2]:
        train_df.loc[j,column]=train_df_copy.loc[j-1,column]
forest = RandomForestRegressor(max_depth=10,n_estimators=462)
train_df=train_df.drop(['dt',"Date"],axis=1)
forest = forest.fit(train_df.drop(["LandAverageTemperature"],axis=1),train_df["LandAverageTemperature"

for j in (test_df.index):
    for column in test_df.columns[1:-2]:
        test_df.loc[j,column]=test_df_copy.loc[j-1,column]
test_df=test_df.drop(['dt',"Date"],axis=1)
output = forest.predict(test_df.drop(["LandAverageTemperature"],axis=1))

# Distance computing
test_df['Predicted_temp']=output
MED=abs(test_df['LandAverageTemperature']-test_df['Predicted_temp']).mean()
MED
```

```
73]: 0.15355030831921537
```

Clustering

Clustering

Preparing the DataFrame

```
country_temps = pd.read_csv("C://Users//user//Downloads//GlobalLandTemperaturesByCountry.csv", sep=',')

#Drop Uncertainty for the clustering
country_temps = country_temps.drop("AverageTemperatureUncertainty", axis = 1)

# Delete all empty lines, change time, and put time as Index
country_temps['dt'] = pd.to_datetime(country_temps['dt'])
country_temps.tail()

#Setting the Countries as Index, time as Columns and Average Temperature as the main Data
pivot = country_temps.pivot("Country","dt","AverageTemperature")
pivot = pivot.drop(pivot.columns[[i for i in range(1274)]+[3238]], axis = 1)
pivot.head()

#Getting rid of all countries with no data

pivot = pivot.dropna(how='all') #aucune donnée pour le pays

#Only one country eliminated
```

Clustering on Country Wise

```
from sklearn.impute import SimpleImputer
```

```

imp = SimpleImputer(strategy="median")
# Beware: here axis = 1 means rows -> http://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.Imputer

#Imputer changes type of DataFrame.

trans_pivot = imp.fit_transform(pivot)
nonan_pivot = pd.DataFrame(trans_pivot)

nonan_pivot.columns = pivot.columns
nonan_pivot.index = pivot.index

nonan_pivot.tail()

print(np.count_nonzero(~np.isnan(nonan_pivot)))

#No missing data, and let's now call the DataFrame : clusterdf

clusterdf = nonan_pivot
```

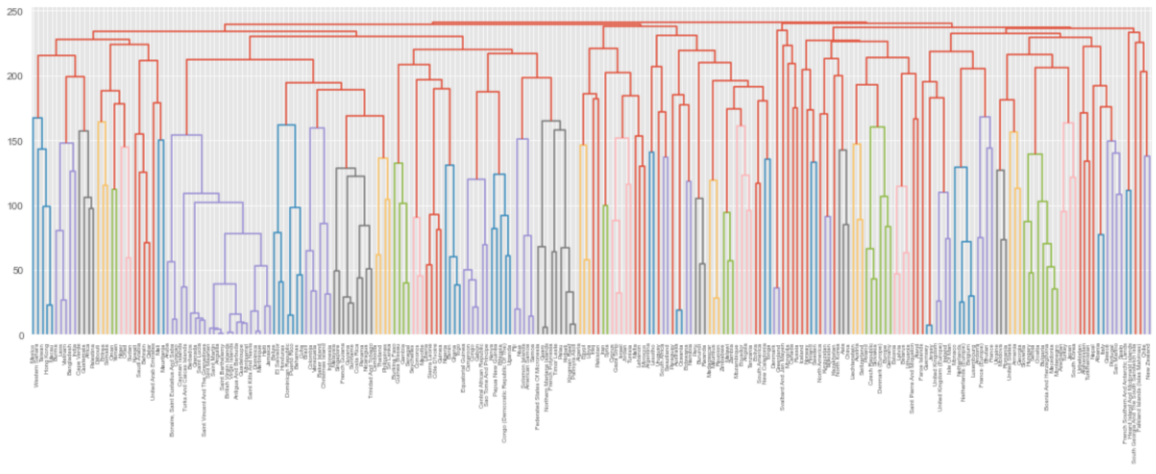
Clustering Code

```
def Clustering(df,x,y,orientation,size):

    from sklearn.cluster import AgglomerativeClustering
    from scipy.cluster.hierarchy import dendrogram
    import matplotlib.pyplot as plt
    plt.style.use('ggplot')

    ward = AgglomerativeClustering(linkage='ward', compute_full_tree=True).fi
    dendro = [ ]
    for a,b in ward.children_:
        dendro.append([a,b,float(len(dendro)+1),len(dendro)+1])

    fig = plt.figure( figsize=(x,y) )
    ax = fig.add_subplot(1,1,1)
    r = dendrogram(
        dendro,
        color_threshold=None,
        labels=df.index,
        distance_sort = True,
        show_leaf_counts=False,
        leaf_font_size = size,
        ax=ax,
        orientation = str(orientation)
    )
```

```python
def Clustering_truncated(df,x,y,orientation,p,size):


    from sklearn.cluster import AgglomerativeClustering
    from scipy.cluster.hierarchy import dendrogram
    import matplotlib.pyplot as plt
    plt.style.use('ggplot')

    ward = AgglomerativeClustering(linkage='ward', compute_full_tree=True).fit(df)
    dendro = [ ]
    for a,b in ward.children_:
        dendro.append([a,b,float(len(dendro)+1),len(dendro)+1])

    fig = plt.figure( figsize=(x,y) )
    ax = fig.add_subplot(1,1,1)
    r = dendrogram(
        dendro,
        color_threshold=None,
        labels=df.index,
        show_leaf_counts=False,
        truncate_mode = 'lastp',  # show only the last p merged clusters
        p = p,  # show only the last p merged clusters
        leaf_font_size = size,
        show_contracted = True,  # to get a distribution impression in truncated branches
        ax=ax,
        orientation = str(orientation)

    )
    return r["ivl"]
```

```python
Clustering(clusterdf,20,6,"top",6)

#The horizontal graph is useful here to see the colors and therefore the links between countries
```

```
C:\Users\user\anaconda3\anaconda_install\lib\site-packages\sklearn\utils\validation.py:1688: FutureWarning: Feature names on
ly support names that are all strings. Got feature names with dtypes: ['Timestamp']. An error will be raised in 1.2.
  warnings.warn(
```

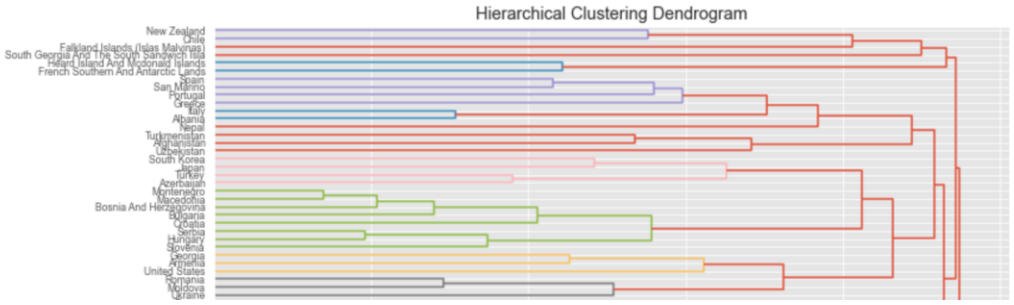


Hierarchical Clustering

```
Clustering(clusterdf,12,30,"right",8.5)
plt.title('Hierarchical Clustering Dendrogram')
plt.ylabel('Countries')
plt.xlabel('Distance')

#Now, even though scrolling is necessary, this vertical dendogram is much clearer
```

```
C:\Users\user\anaconda3\anaconda_install\lib\site-packages\sklearn\utils\validation.py:1688: FutureWarning: Feature names on
ly support names that are all strings. Got feature names with dtypes: ['Timestamp']. An error will be raised in 1.2.
  warnings.warn(
```

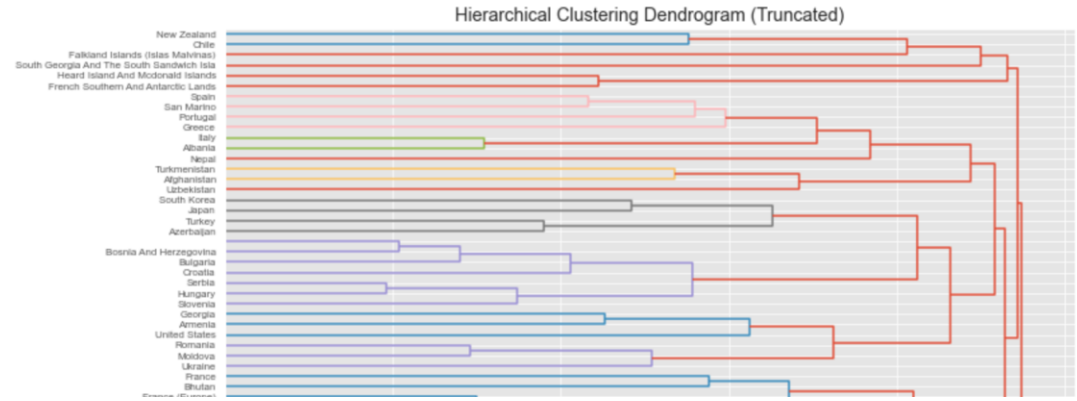
```
4]: Text(0.5, 0, 'Distance')
```




```
Cluster_70 = Clustering_truncated(clusterdf,12,30,"right",200,8)
plt.title('Hierarchical Clustering Dendrogram (Truncated)')
plt.xlabel('Distance')
plt.ylabel('Countries')

```

```
C:\Users\user\anaconda3\anaconda_install\lib\site-packages\sklearn\utils\validation.py:1688: FutureWarning: Feature names
ly support names that are all strings. Got feature names with dtypes: ['Timestamp']. An error will be raised in 1.2.
  warnings.warn(
```

```
85]: Text(0, 0.5, 'Countries')
```



In [86]:

```
def delete_symbol(l,sym):
    for i in range(l.count(sym)):
        l.remove(sym)
    return l, len(l)
```

In [87]:

```
cntry_to_del = delete_symbol(Cluster_70,'')
cntry_to_del
```

```
'Kuwait',
'Saudi Arabia',
'Bahrain',
'Qatar',
'United Arab Emirates',
'Mali',
'Mauritania',
'Aruba',
'Belize',
'Bahamas',
'Cuba',
'Brazil',
'Baker Island',
'Malaysia',
'Singapore',
'Costa Rica',
'Panama',
```

Country wise and Date wise Dataframe

]:

```
clusterdf_new = clusterdf.drop(cntry_to_del[0], axis = 0)
clusterdf_new.head()
```

t[88]:

dt	1850-01-01	1850-02-01	1850-03-01	1850-04-01	1850-05-01	1850-06-01	1850-07-01	1850-08-01	1850-09-01	1850-10-01	...	2012-11-01	2012-12-01	2013-01-01	2013-02-01	2013-03-01	2013-04-01	2013-05-01	2013-06-01
Country																			
American Samoa	13.960	15.370	18.443	20.359	21.059	23.902	24.512	24.570	23.448	22.030	...	27.963	27.316	27.241	27.793	27.683	27.824	28.045	27.650
Anguilla	24.075	24.985	25.064	24.859	25.734	27.073	27.922	27.949	27.696	26.701	...	28.203	26.476	25.919	25.899	26.187	26.679	27.667	28.414
Antigua And Barbuda	23.930	24.845	24.984	24.879	25.711	26.988	27.714	27.672	27.346	26.351	...	27.890	26.329	25.787	25.802	26.089	26.601	27.706	28.322
Australia	13.960	15.370	18.443	20.359	21.059	23.902	24.512	24.570	23.448	22.030	...	26.935	28.417	29.861	28.311	26.590	23.305	19.377	16.018
Barbados	24.249	25.140	25.271	25.304	25.918	27.006	27.312	27.109	26.968	26.298	...	27.922	26.744	26.088	26.182	26.504	26.806	27.849	28.020

5 rows × 1964 columns

```
Clustering(clusterdf_new,12,30,"right",10)
plt.title('Hierarchical Clustering Dendrogram - 70 Countries')
plt.xlabel('Distance')
plt.ylabel('Countries')

```

```
C:\Users\user\anaconda3\anaconda_install\lib\site-packages\sklearn\utils\validation.py:1688: FutureWarning: Feature names on
ly support names that are all strings. Got feature names with dtypes: ['Timestamp']. An error will be raised in 1.2.
  warnings.warn(
```

9]: Text(0, 0.5, 'Countries')