PROJECT 1

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Subject: `Machine Learning`

Problem Statement

Write complete code to train a linear/non-linear model for predicting corona cases in USA and world with regularization.

- In this model, linear regression model with regularization is implemented for predicting corona cases in USA different states.

Multivariate Linear Regression Model for Predicting Corona Cases in USA

Step 1: Importing necesaary libraries for the model.

In [8]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

Useful links from where data was taken and cleaned for this specific model.

For corona cases data

- 1) https://covidtracking.com/data/api (https://covidtracking.com/data/api)

For weather states temperarure avg data

- 2) https://www.weatherbase.com/weather/state.php3?c=US&name=United+States+of+America (https://www.weatherbase.com/weather/state.php3?c=US&name=United+States+of+America)

For humidity data of states

- 3) https://www.currentresults.com/Weather/US/annual-average-humidity-by-state.php-main (https://www.currentresults.com/Weather/US/annual-average-humidity-by-state.php-main)
- https://www.forbes.com/sites/brianbrettschneider/2018/08/23/oh-the-humidity-why-is-alaska-the-most-humid-state/?sh=72a82a2e330c (https://www.forbes.com/sites/brianbrettschneider/2018/08/23/oh-the-humidity-why-is-alaska-the-most-humid-state/?sh=72a82a2e330c)

Population density

- 4)https://worldpopulationreview.com/state-rankings/state-densities (https://worldpopulationreview.com/state-rankings/state-densities)

Simple population

- 5)https://www.worldometers.info/coronavirus/country/us/ (https://www.worldometers.info/coronavirus/country/us/)

Step 2: Importing csv file of USA Data using pandas

`USA Final` is the name of csv file which will be converted to dataframe (df) using pandas.

In [9]:

```
df=pd.read_csv('USA Final.csv')
```

Imported Data named `df`

In [10]:

```
df
```

Out[10]:

	Date	XO	Date_Code	States_Code	Temperatures_(F)	Humidity_(%)	Population_
0	12/6/2020	1	0	1	11.6	77.1	
1	12/6/2020	1	0	2	46.6	71.6	
2	12/6/2020	1	0	3	41.3	70.9	
3	12/6/2020	1	0	4	38.0	80.0	
4	12/6/2020	1	0	5	43.6	38.5	
...	...	...	...	...	...	...	
14835	3/17/2020	1	264	52	28.6	71.7	
14836	3/17/2020	1	264	53	41.4	71.4	
14837	3/17/2020	1	264	54	30.0	71.6	
14838	3/17/2020	1	264	55	41.0	69.7	
14839	3/17/2020	1	264	56	31.6	57.1	

14840 rows × 10 columns

Step 3: Cleaning Data frame

In [11]:

```
df.dtypes
```

Out[11]:

```
Date                    object
XO                       int64
Date_Code                int64
States_Code              int64
Temperatures_(F)       float64
Humidity_(%)           float64
Population_per_state     int64
LandArea_(sq miles)      int64
Population_Density      object
Cases_per_day            int64
dtype: object
```

Population Desnsity column is object type, so it will converted to float.

In [12]:

```
df["Population_Density"]= df["Population_Density"].astype(float)
```

In [13]:

```
df.dtypes
```

Out[13]:

```
Date                        object
XO                           int64
Date_Code                    int64
States_Code                  int64
Temperatures_(F)           float64
Humidity_(%)               float64
Population_per_state         int64
LandArea_(sq miles)          int64
Population_Density         float64
Cases_per_day                int64
dtype: object
```

Here, We have 8 valid features:

```
- *1) XO (Bias Term) = 1
- *2) DATE_CODE = In this model "date" is numerically coded. For example:
    Model date starts from 6th December 2020 and ends at 17th March 2020.
    - *Here: 17th march 2020 is 264 and 6th December is 0.
- *3) States_Code: States codes are also numerically coded. For example:
     *Here: 1 = Alaska, 2= Alabama and 56=Wyoming.
- *4) Temperatures_(F): Tempearures in F of particular state at particular date.
- *5) Humidity_(%): Average humidity in % of particular state at particular dat
e.
- *6) Population_per_state: Average populationin of particular state at particul
ar date.
- *7) LandArea_(sq miles): Land Area in square miles of particular state .
- *8) POPULATION_DENSITY: Population Density of particular state.
```

Here, We have 1 label : Cases_per_day in particulat state at particular date

Step 4: Assigning features of model to x and prediction label to y

Assigning the features columns to x and label column (Cases per day) to y.

In [20]:

```
x=df.drop(["Date",'Cases_per_day'], axis=1)
x.head()
```

Out[20]:

	XO	Date_Code	States_Code	Temperatures_(F)	Humidity_(%)	Population_per_state	Land
0	1	0	1	11.6	77.1	731545	
1	1	0	2	46.6	71.6	4903185	
2	1	0	3	41.3	70.9	3017804	
3	1	0	4	38.0	80.0	55138	
4	1	0	5	43.6	38.5	7278717	

Assigning prediction label "Cases_per_day" to y

In [21]:

```
y=df["Cases_per_day"]
y.head()
```

Out[21]:

```
0     757
1    2288
2    1542
3       0
4    5376
Name: Cases_per_day, dtype: int64
```

In [22]:

```
x.max(), x.min()
```

Out[22]:

```
(XO                           1.0
 Date_Code                  264.0
 States_Code                 56.0
 Temperatures_(F)            82.8
 Humidity_(%)                80.0
 Population_per_state   39512223.0
 LandArea_(sq miles)      570641.0
 Population_Density        11535.0
 dtype: float64,
 XO                        1.00
 Date_Code                 0.00
 States_Code               1.00
 Temperatures_(F)          0.00
 Humidity_(%)             38.30
 Population_per_state   55138.00
 LandArea_(sq miles)       68.00
 Population_Density        1.29
 dtype: float64)
```

Step 5: Normalization/ Scaling of features between 0 and 1

In [23]:

```
for j in range(0, len(x.columns)):
    x=(x-x.min())/(x.max()-x.min())
```

In [24]:

```
x.head()
```

Out[24]:

	XO	Date_Code	States_Code	Temperatures_(F)	Humidity_(%)	Population_per_state	Lan
0	NaN	0.0	0.000000	0.140097	0.930456	0.017143	
1	NaN	0.0	0.018182	0.562802	0.798561	0.122869	
2	NaN	0.0	0.036364	0.498792	0.781775	0.075086	
3	NaN	0.0	0.054545	0.458937	1.000000	0.000000	
4	NaN	0.0	0.072727	0.526570	0.004796	0.183074	

In [25]:

```
x["XO"]=x["XO"].fillna(1)
```

In [26]:

```
len(x.columns)
```

Out[26]:

8

Scaled Features between 0 and 1

In [27]:

```
x.head()
```

Out[27]:

	XO	Date_Code	States_Code	Temperatures_(F)	Humidity_(%)	Population_per_state	Land
0	1.0	0.0	0.000000	0.140097	0.930456	0.017143	
1	1.0	0.0	0.018182	0.562802	0.798561	0.122869	
2	1.0	0.0	0.036364	0.498792	0.781775	0.075086	
3	1.0	0.0	0.054545	0.458937	1.000000	0.000000	
4	1.0	0.0	0.072727	0.526570	0.004796	0.183074	

Step 6: Splitting dataframe into training(60%) validation(20%) and testing data (20%)

Now splitting the data into training, validation and testing data.

In [28]:

```
train_split=round(0.6*len(df))
valid_split=round(train_split+0.20*len(df))

x_train,y_train=x[:train_split],y[:train_split]
x_valid, y_valid=x[train_split:valid_split],y[train_split:valid_split]
x_test, y_test=x[valid_split:],y[valid_split:]
```

- x_train, y_train are features and label of training set.
- x_valid, y_valid are features and label of validation set.
- x_test, y_test are features and label of test set.

Now checking the x_train and y_train length to verify data split.

In [29]:

```
len(x_train), len(y_train) , len(x_valid)
```

Out[29]:

(8904, 8904, 2968)

Training Code

Step 7: Initiating Thetas(Model Parameters) and defining Hypothesis for Linear Regression

As in this model Linear regression is applied, so Hypothesis is Thetas*x_train. Here:

```
* Thetas= Model Parameters or weights for each feature.
* x_train= Features of model
```

In this model, there are total 8 feaures including the bias term Xo. So initiating 8 thetas of value = 0.

In [30]:

```
Thetas=np.array([0]*len(x_train.columns))
Thetas
```

Out[30]:

```
array([0, 0, 0, 0, 0, 0, 0, 0])
```

Hypothesis is given by following function:

In [31]:

```
def Hypothesis(Thetas,x_train):
    return Thetas*x_train
```

`m` is the length is our training set

In [33]:

```
m = len(x_train)
m
```

Out[33]:

```
8904
```

Step 8: Cost function

Cost function is basically the difference between prediction by the model and the prediction label.Here, Regularization is also applied with Cost Function.

```
*lambda_ is the regulzarization parameter.
```

Cost function is given by:

In [34]:

```
def Cost_Function(x_train,y_train,Thetas,lambda_):
    H=Hypothesis(Thetas,x_train)
    H=np.sum(H,axis=1)
    Cost=(np.sum(np.power((H-y_train),2))+lambda_*np.sum(np.power(Thetas[1:],2)))/(2*m)
    return Cost
```

In [35]:

```
n=len(x_valid)
```

In [36]:

```
def Cost_Function_valid(x_valid,y_valid,Thetas,lambda_):
    H=Hypothesis_v(Thetas,x_valid)
    H=np.sum(H,axis=1)
    Cost=(np.sum(np.power((H-y_valid),2))+lambda_*np.sum(np.power(Thetas[1:],2)))/(2*n)
    return Cost
```

Step 9: Gradient Descent

Gradient Descenet is used to find the minimum values of thetas, so that our cost will be minimum. Mimimum cost indicates that the difference between our prediction and actual label is very low. Here, Regularization is also applied with Gradient Descnet to prevent overfitting

Gradient Descent is given by:

In [37]:

```
def Gradient_Descent(x_train, y_train, Thetas,lambda_, alpha, iterations):
    J_train = []  #cost of training set in each iterations is saved in this list
    J_valid = []  #cost of valid set in each iterations is saved in this list
    J_test =  []  #cost of test set in each iterations is saved in this list
    temp_var = 0
    while temp_var < iterations:
        H = Hypothesis(Thetas, x_train)
        H = np.sum(H, axis=1)
        for  i in range(0, len(x_train.columns)):
            if i==0:
                Thetas[0]=Thetas[0]-alpha*(sum((H-y_train)*x_train.iloc[:,0])/(m))
            else:
                Thetas[i] = Thetas[i]*(1-alpha*(lambda_/m)) - alpha*(sum((H-y_train)*x_
train.iloc[:,i])/(m))

                #thethas[i] = thethas[i] - alpha*(sum((H-y_train)*x_train.iloc[:,i])/
(m))
        j_t = Cost_Function(x_train,y_train, Thetas,lambda_)
        J_train.append(j_t)
        j_v = Cost_Function_valid(x_valid,y_valid, Thetas,lambda_)
        J_valid.append(j_v)
        j_te = Cost_Function_valid(x_test,y_test, Thetas,lambda_)
        J_test.append(j_te)
        temp_var += 1
    return J_train,J_valid,J_test, j_t,j_v,j_te, Thetas
```

Calculating cost using gradient descent with the following parameters:

- alpha is learning rate =0.01
- Iterations is our loop running factor =2000
- lambda_ is regularization = 10

Here, when we put

```
*lambda_ = 0, there will no regularizarion
```

In [38]:

```
J_train,J_valid,J_test, j_t,j_v,j_te,Thetas = Gradient_Descent(x_train,y_train,Thetas,1
0,0.01,2000)
```

Thetas (paramters) of our model on training data are as follows:

In [39]:

```
Thetas
```

Out[39]:

```
array([ 598,    0,    2,   24,  350, 2864,   56,    0])
```

In [40]:

```
 J_train[:5],J_valid[:5], J_test[:5]
```

Out[40]:

```
([3126345.44681938,
  3088199.718780892,
  3053022.768976592,
  3019180.9576043244,
  2986070.103949517],
 [404530.01570733025,
  391788.7212958417,
  380573.43672683585,
  370321.0583992374,
  360865.09726979514],
 [604193.3338288635,
  592266.143645967,
  581804.488504365,
  572276.7593128103,
  563492.9124969577])
```

Prediction Function Code

Step 10: Calculating Predictions using Hypothesis function and model parameters

`py_train` is our prediction and we are applying our model parameters on training set to check the predictions and accuracy of our model.

In [41]:

```
py_train= Hypothesis(Thetas,x_train)
py_train= np.sum(py_train,axis=1)
```

In [42]:

```
py_train.head()
```

Out[42]:

```
0    1032.118922
1    1247.900402
2    1103.810921
3     959.124467
4    1147.928876
dtype: float64
```

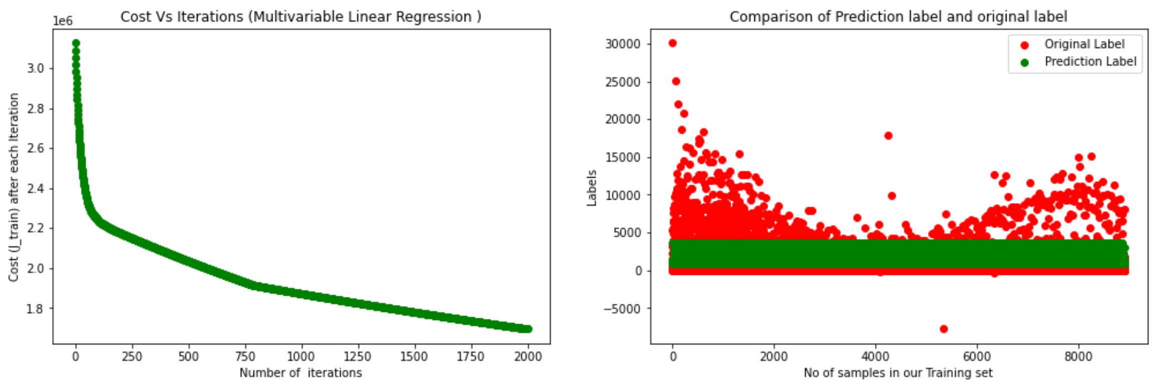
Step 10.1 Result Visualization

A) Graph of Cost vs Iterations to check the working of our model.

B) Scattter plot for our predictions and y_train.

In [43]:

```
fig,(ax1,ax2)=plt.subplots(figsize=(17,5),
                          nrows=1,
                          ncols=2)
ax1.scatter(x=list(range(0,2000)),y=J_train,color='green')
ax1.set(xlabel='Number of  iterations',
      ylabel='Cost (J_train) after each Iteration',
      title='Cost Vs Iterations (Multivariable Linear Regression )')
ax2.scatter(x=list(range(0,len(x_train))),y=y_train,color='red',label='Original Label')
ax2.scatter(x=list(range(0,len(x_train))),y=py_train,color='green',label='Prediction La
bel')
ax2.set(xlabel='No of samples in our Training set',
       ylabel='Labels',
       title='Comparison of Prediction label and original label')
ax2.legend();
```



Step 10.2 Calculating Mean Absolute Error on training set

In [44]:

```
MAE_train=np.sum(np.absolute(y_train-py_train))/len(x_train)

MAE_train
```

Out[44]:

```
1087.1478347699021
```

Mean absolute Error is `1087` for training set. It means that model is predicting `1087` values different from actual cases

Step 11: Applying model paramters on validation data set

`py_validation` is our prediction on validation set and we are applying our model parameters on validation set to check the predictions and accuracy of our model.

In [45]:

```
py_validation= Hypothesis(Thetas,x_valid)
py_validation= np.sum(py_validation,axis=1)
```

In [46]:

```
py_validation.head()
```

Out[46]:

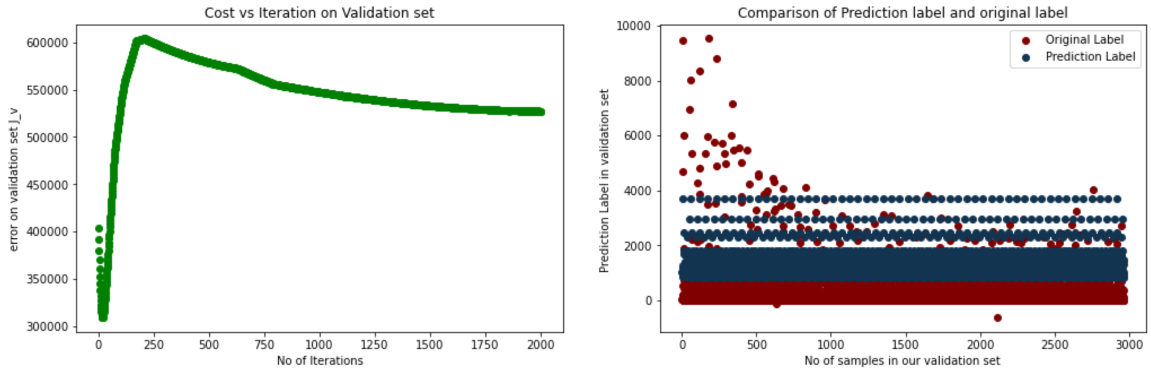
```
8904    1043.771096
8905    1256.393156
8906    1114.071791
8907     948.109974
8908    1157.320180
dtype: float64
```

Step 11.1 Result Visualization for validation data

Creating scattter plots for our predictions on validation data and y_valid label.

In [47]:

```
fig,(ax1,ax2)=plt.subplots(figsize=(17,5),
                          nrows=1,
                          ncols=2)
ax1.scatter(x=list(range(0,2000)),y=J_valid,color="green")
ax1.set(xlabel="No of Iterations", ylabel = "error on validation set J_v", title ="Cost
vs Iteration on Validation set")
ax2.scatter(x=list(range(0,len(x_valid))),y=y_valid,color='maroon',label='Original Labe
l')
ax2.scatter(x=list(range(0,len(x_valid))),y=py_validation,color='#123450',label='Predic
tion Label')
ax2.set(xlabel='No of samples in our validation set',
       ylabel='Prediction Label in validation set ',
       title='Comparison of Prediction label and original label')
ax2.legend();
```



Step 11.2 Mean Absolute Error for validation set

In [48]:

```
MAE_validation=np.sum(np.absolute(y_valid-py_validation))/len(x_valid)
MAE_validation
```

Out[48]:

```
932.9972011398406
```

Mean absolute Error is `932` for validation set. It means that model is predicting `932` values wrong from actual cases

Step 12: Applying model paramters on test data set

`py_test` is our prediction on test set and we are applying our model parameters on test set to check the predictions and accuracy of our model.

In [49]:

```
py_test= Hypothesis(Thetas,x_test)
py_test= np.sum(py_test,axis=1)
```

In [50]:

```
py_test.head()
```

Out[50]:

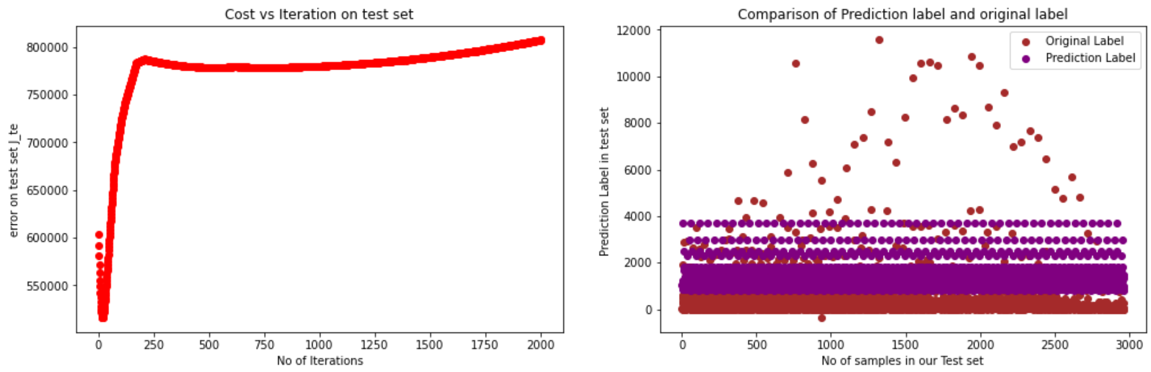
```
11872    1040.843559
11873    1254.596055
11874    1111.810921
11875     948.109974
11876    1154.682499
dtype: float64
```

Step 12.1 Result Visualization for test data

Creating scattter plots for our predictions on test data and y_test label.

In [51]:

```
fig,(ax1,ax2)=plt.subplots(figsize=(17,5),
                          nrows=1,
                          ncols=2)
ax1.scatter(x=list(range(0,2000)),y=J_test,color="red")
ax1.set(xlabel="No of Iterations", ylabel = "error on test set J_te", title ="Cost vs I
teration on test set")
ax2.scatter(x=list(range(0,len(x_test))),y=y_test,color='brown',label='Original Label')
ax2.scatter(x=list(range(0,len(x_test))),y=py_test,color='purple',label='Prediction Lab
el')
ax2.set(xlabel='No of samples in our Test set',
       ylabel='Prediction Label in test set ',
       title='Comparison of Prediction label and original label')
ax2.legend();
```



Step 12.2 Mean Absolute Error for test set

In [52]:

```
MAE_test=np.sum(np.absolute(y_test-py_test))/len(x_test)
MAE_test
```

Out[52]:

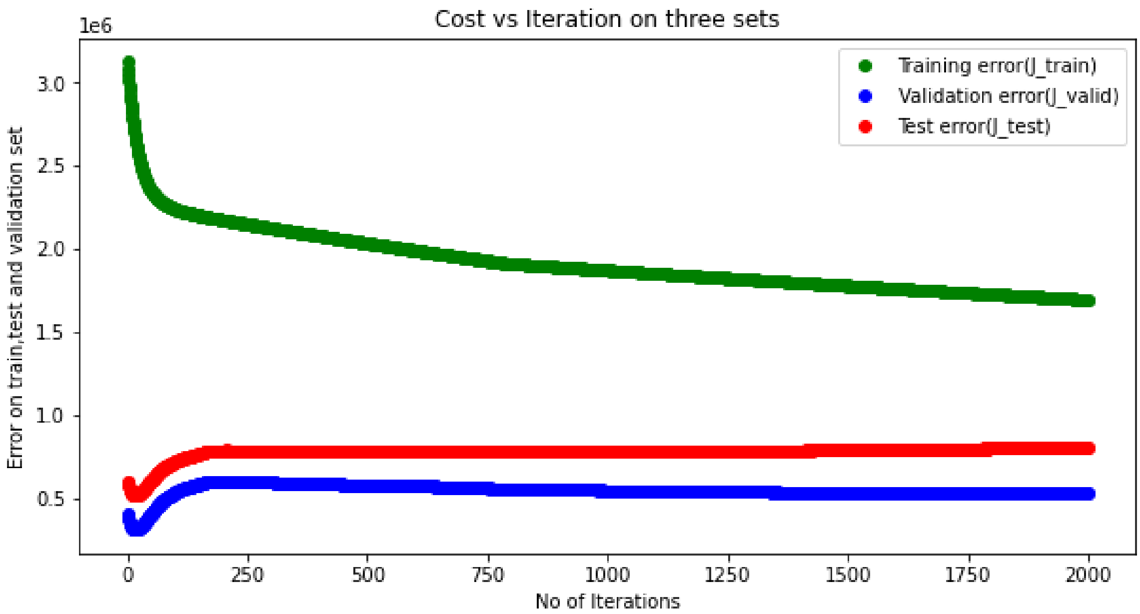
```
1068.2771819330865
```

Mean absolute Error is `1068.34` for test set. It means that model is predicting `1068` values wrong from actual cases in test set.

Plot FOR ALL THREE ERRORS

In [53]:

```
fig,(ax1)=plt.subplots(figsize=(10,5),
                          nrows=1,
                          ncols=1)
ax1.scatter(x=list(range(0,2000)),y=J_train,color='green',label='Training error(J_trai
n)')
ax1.scatter(x=list(range(0,2000)),y=J_valid,color='blue',label='Validation error(J_vali
d)')
ax1.scatter(x=list(range(0,2000)),y=J_test,color="red",label='Test error(J_test)')
ax1.set(xlabel="No of Iterations", ylabel = "Error on train,test and validation set", t
itle ="Cost vs Iteration on three sets")
ax1.legend();
```



In [ ]: