Fahad Fiaz -(303141) - G2

System Info:

Processor	i7-5500U , 2.40GHz
Cores	4
Operating system	Windows 64 Bit
Ram	8GB
Programming Language	Python 3.7.7

Exercise 1: Parallel Linear Regression?

Steps:

- 1. Consider 1st process as master node and other as slave node.
- 2. Master process will first read data from files. Since there are multiple files in dataset so we use glob library to read names of multiple files at once. Then the dataset is randomly shuffled and preprocessed to get X as Feature matrix and Y as Prediction Vector. Then we split data into 70% train and 30% test data. Then master process divides the training data into equal chunks according to number of workers and scatters it to child Nodes.

```
# Pre_processing function to convert data to specific format

def pre_processing(feature_example):
    total_features = np.zeros(482)
    y = 0.0
    processed_features = feature_example.split(" ")
    if (processed_features[0].strip() != ''):
        y = float(processed_features[0])
    for i in range(len(processed_features)):
        split_features = processed_features[i].split(":")
        if (len(split_features) == 2):
            total_features[int(split_features[0])] = int(split_features[1])
    return total_features, y
```

```
Total_data = []
    path = "dataset"
    All_Files = glob.glob(path + "/*.txt")
    for name in All Files:
        File = open(name)
        File_data = File.read().split("\n")
        Total data.append(File data)
    np.random.shuffle(Total_data) # shuffle complete dataset randomly
    for i in range(len(Total_data)):
        for j in range(len(Total_data[i])):
            x, y = pre_processing(Total_data/i]/j])
            X.append(x)
            Y.append(y)
    X = np.array(X) # feature matrix
    Y = np.array(Y) # prediction vector
    FullDataset = X.shape[0]
    X Train = X[:(FullDataset * 70) // 100, :]
      Test = X[(FullDataset * 70) // 100:, :]
    Y_Train = Y[:(FullDataset * 70) // 100]
    Y_Test = Y[(FullDataset * 70) // 100:]
    data_size = len(X_Train)
    partition = data_size // size
    for process in range(0, size): # partition data in equal portions
        start = process * partition
        end = (process + 1) * partition
if process == size - 1 and end != data_size:
            end = data size
        X_Chunk.append(X_Train[start:end])
        Y_Chunk.append(Y_Train[start:end])
```

3. Slave processes received chunk of Feature Matrix and Prediction Vector. Then they use SGD algorithm to find parameters (**Beta**) of model.

```
# scattering data to child processes
Feature_chunk = np.array(comm.scatter(X_Chunk))
Prediction_chunk = np.array(comm.scatter(Y_Chunk))
Parameters = SGD(Feature_chunk, Prediction_chunk, alpha)
```

```
def SGD(X_Train, Y_Train, alpha): # function to apply Stochastic Gradient Descent
algorithm
   if flag == False: # checking if you are running sgd for 1st epoch else
Parameters will get value from broadcasting
        Parameters = np.zeros(len(X_Train[0]))
   for i in range(len(X_Train)):
        my_prediction = np.dot(Parameters.T, X_Train[i])
        error = Y_Train[i] - my_prediction
        Parameters = Parameters + (2 * (alpha * error))
        return Parameters
```

4. Master process then gathers the local parameters (**Beta**) of model from slave workers and averages them and broadcast the new global model parameters (**Beta**) to each worker for the next epoch. We also calculate RMSE loss on Test data using averaged model parameters.

```
All Local Parameters = comm.gather(Parameters, root=Master)
if (rank == Master):
   if (size > 1): # checking if there were multiple child processes
       Global Parameters Mean = np.mean(All Local Parameters,
fo parameters
        Loss.append(RMSE(X_Test, Y_Test, Global_Parameters_Mean)) # calculating Loss
        Global Parameters Mean = All Local Parameters # If there was single process
   Global_Parameters Mean = None
Global_Parameters_Mean = comm.bcast(Global_Parameters_Mean, root=Master) # sending
average of parameters to child proceses for next epoch
if len(Global Parameters Mean) > 0:
   flag = True
   Parameters = Global_Parameters_Mean
Epoch = Epoch + 1
def RMSE(X, Y, Global_Parameters_Mean): # function to calculate RMSE
   Predictions = []
```

```
for i in range(len(X)):
    Predictions.append(np.dot(X[i], Global_Parameters_Mean.T))
Final_Predictions = np.reshape(np.array(Predictions), -1)
Error = sum((Y - Final_Predictions) ** 2)
return Error
```

Code working for arbitrary number of clusters and doing parallel processing:

```
In [2]: Impiexec -n 1 python exercise4.py

Train/Test Loss: 11693.26126902823
Total working time: 31.00262250006199

In [3]: !mpiexec -n 2 python exercise4.py

Train/Test Loss: 12091.201923924275
Total working time: 25.588684600079432

In [4]: !mpiexec -n 3 python exercise4.py

Train/Test Loss: 12488.4175282204
Total working time: 18.973370800027624

In [5]: !mpiexec -n 4 python exercise4.py

Train/Test Loss: 12762.193729963828
Total working time: 20.494305700063705
```

In [6]: !mpiexec -n 5 python exercise4.py

Train/Test Loss: 12914.32067656716 Total working time: 20.691015099873766

In [7]: !mpiexec -n 6 python exercise4.py

Train/Test Loss: 12984.266807230139 Total working time: 19.21289510000497

In [8]: !mpiexec -n 7 python exercise4.py

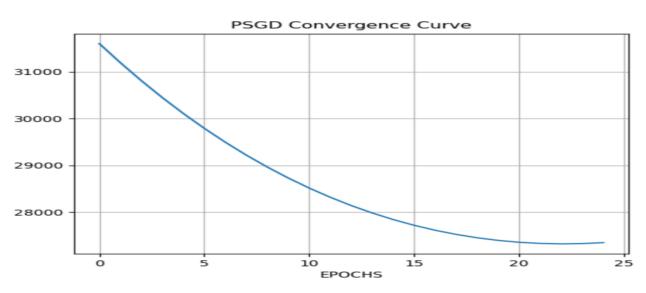
Train/Test Loss: 13143.402004668993 Total working time: 18.94527080003172

In [9]: !mpiexec -n 8 python exercise4.py

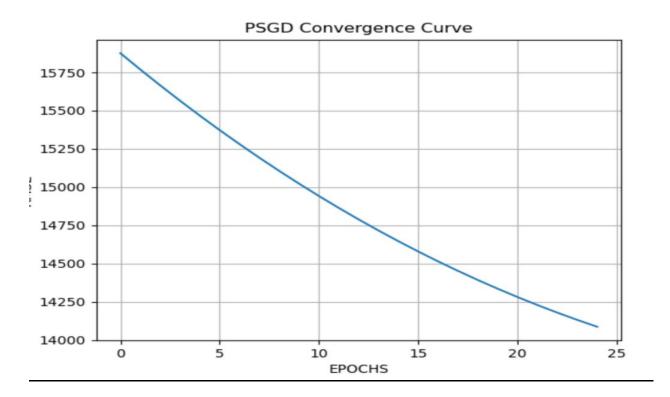
Train/Test Loss: 13147.863157772854 Total working time: 19.287448999937624

Convergence Graphs:

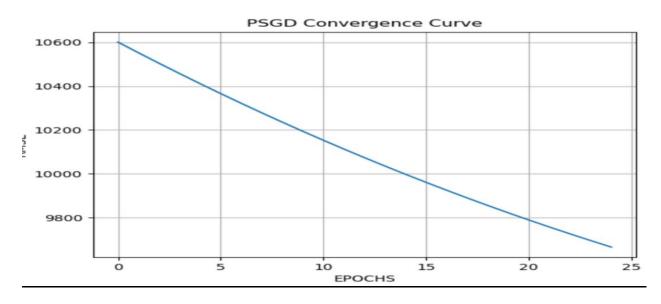
P=1



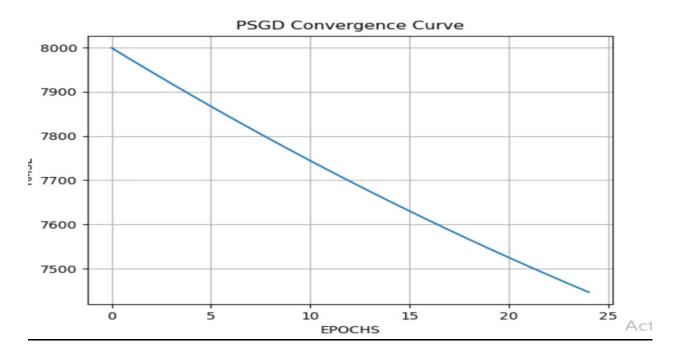
<u>P=2</u>



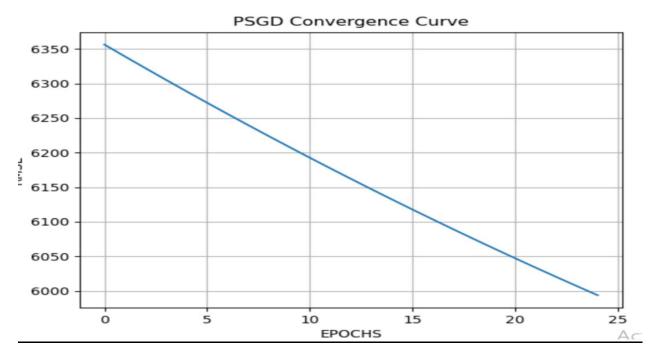
<u>P=3</u>



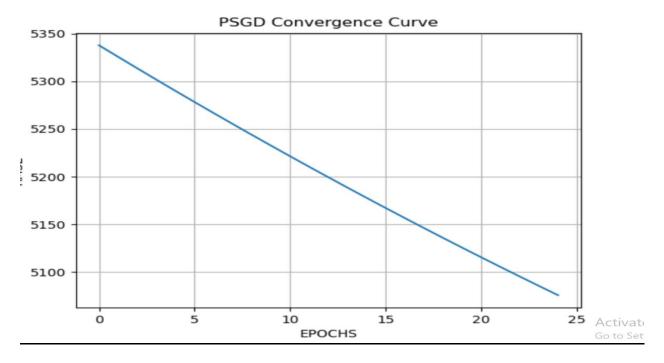
<u>P=4</u>



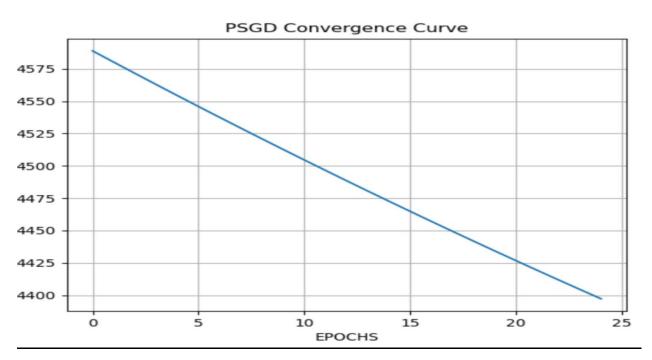
<u>P=5</u>



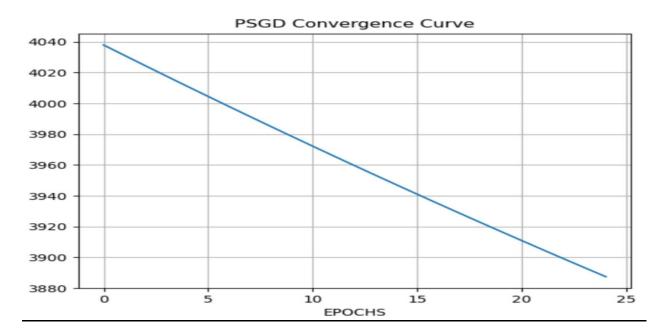
<u>P=6</u>



<u>P=7</u>



<u>P=8</u>



Performance analysis by epochs vs time graph:

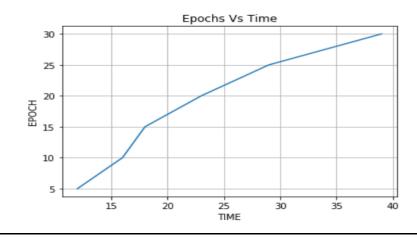
P=1:

```
In [18]: !mpiexec -n 1 python exercise4.py

Total working time: 29.152129899943247
Epochs: 25
```

```
In [19]: !mpiexec -n 1 python exercise4.py

Total working time: 39.83932360005565
Epochs: 30
```



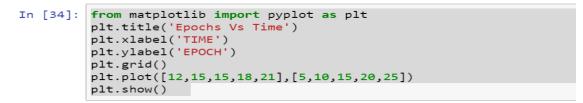
P=2:

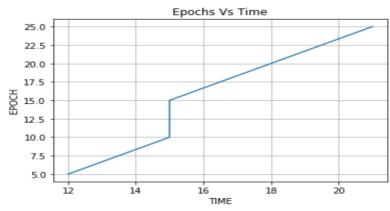
```
In [32]: !mpiexec -n 2 python exercise4.py

Total working time: 21.139919500099495
Epochs: 25

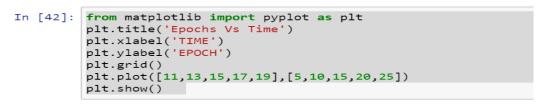
In [19]: !mpiexec -n 2 python exercise4.py

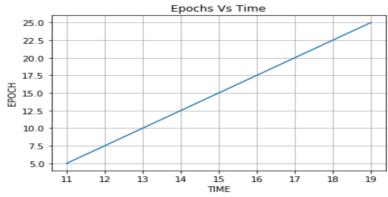
Total working time: 39.83932360005565
Epochs: 30
```



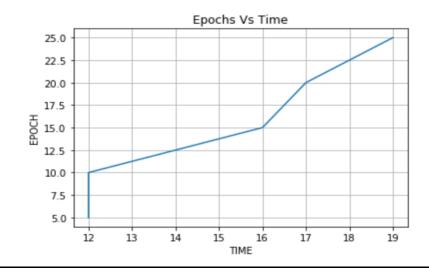


P=3:





<u>P=4:</u>



<u>P=6:</u>

[53]: !mpiexec -n 6 python exercise4.py

Total working time: 13.263573499862105

Epochs: 10

[50]: !mpiexec -n 6 python exercise4.py

Total working time: 15.36391680012457

Epochs: 15

[45]: !mpiexec -n 6 python exercise4.py

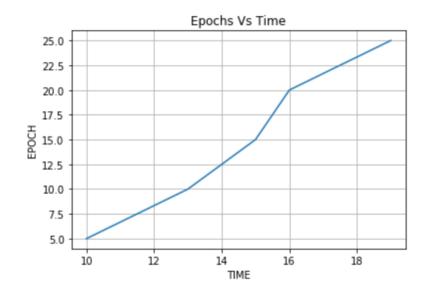
Total working time: 16.589137600036338

Epochs: 20

[47]: !mpiexec -n 6 python exercise4.py

Total working time: 19.090309400111437

Epochs: 25

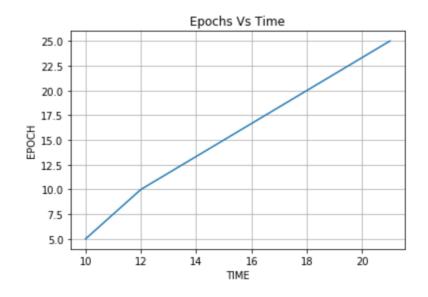


P=8:

In [48]: !mpiexec -n 8 python exercise4.py

Total working time: 21.63312439993024

Epochs: 25



All these above graphs shows that more epochs per unit time can be achieved using a parallel parallel processing.