Step-by-Step Walkthrough for CS 643 Programming Assignment 2

Cloud Computing Energy Consumption Prediction with Apache Spark and Docker

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1 Introduction

This document provides a comprehensive guide for completing Programming Assignment 2 in CS 643, Cloud Computing. It details the setup of an AWS cloud environment, parallel training of an energy consumption prediction model using Apache Spark on an EMR cluster, development of a prediction application on a single EC2 instance, and deployment using Docker.

Disclaimer: Although most folders or filenames read as regress or regression, the model used for this assignment is gradient-boost and not regression, the term is just a placeholder that I overlooked.

2 Setting Up the AWS Cloud Environment for Parallel Training

2.1 Creating an EMR Cluster

Step: Launch an Amazon EMR cluster with four EC2 instances for parallel model training.

- Log in to the AWS Management Console and navigate to EMR > Create Cluster.
- Configure the cluster:
 - Release: emr-7.8.0 (compatible with Spark 3.5.5)
 - Applications: Select Spark Initiative bundle
 - Cluster Name: Energy Consumption Prediction Parallel Training
 - Cluster Configuration: Uniform Instance
 - bootstrap actions: load the bootstrap.sh code

sudo pip3 install numpy pandas

Explanation: Ensures NumPy and Pandas are available for data processing.

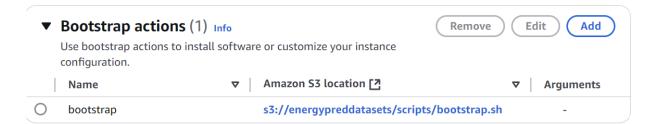


Figure 1: Python Dependency Bootstrap

- · Hardware configuration:
 - Instance Type(both primary and core: m5.xlarge
 - Number of Instances: 4 (1 primary, 3 Core instances)
- Security: Select an EC2 key pair (vokey.ppk).
- IAM: Choose EMRDefault (add a rule to enable ssh).
- Click Create Cluster.

Explanation: This sets up a managed Spark cluster for distributed training on AWS EMR.

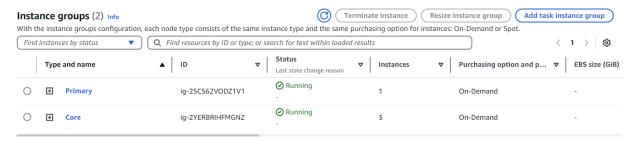


Figure 2: Screenshot of EMR Cluster Running

2.2 Uploading Files to EMR Master Node

Step: Transfer datasets and training script to the EMR master node using SFTP.

- Wait for the EMR cluster to reach the Waiting state.
- Copy the master node's public DNS (hadoop@ec2-3-83-174-73.compute-1.amazonaws.com).
- Open a terminal and start an SFTP session:

```
sftp -i labuser.pem hadoop@ec2-3-83-174-73.compute-1.amazonaws.com
```

Upload files:

```
put TrainingDataset.csv
put train_model.py
```

Explanation: Transfers necessary files to the master node for storage in HDFS. Alternatively you can use winscp as shown below in the figure

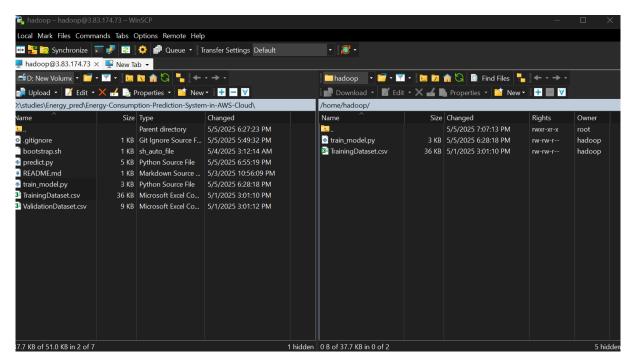


Figure 3: SFTP File Upload to EMR Master Node

2.3 Copying Files to HDFS

Step: Access the master node via SSH and move files to HDFS.

SSH into the master node(Alternatively can use putty):

```
ssh -i labuser.pem hadoop@ec2-3-83-174-73.compute-1.amazonaws.com
```

Copy files to HDFS:

```
hadoop fs -put TrainingDataset.csv /user/hadoop/TrainingDataset.csv hadoop fs -put train_model.py /user/hadoop/train_model.py
```

· Verify files:

```
hdfs dfs -ls -t -R
```

Explanation: Stores datasets and script in HDFS for distributed access by Spark.

```
Authenticating with public key "imported-openssh-key"
       ####
                   Amazon Linux 2023
                   https://aws.amazon.com/linux/amazon-linux-2023
EEEEEEEEEEEEEEEEE MMMMMMM
                                     M:::::::M R::::::::::::::::::::::::::R
                                   M::::::M R:::::RRRRRR::::R
EE:::::EEEEEEEEE:::E M:::::::M
             EEEEE M:::::::M
                                  M::::::: M RR::::R
                   M:::::M M:::M M::::M
                   M:::::M M:::M:::M
 E::::::E
 E::::EEEEEEEEE
                                      M:::::M
                                               R:::RRRRRR::::R
                             M:::M
                                               R:::R
             EEEEE M:::::M
                              MMM
EE:::::EEEEEEEEE::::E M:::::M
M:::::M RR::::R
EEEEEEEEEEEEEEEEEE MMMMMMM
                                      MMMMMM RRRRRRR
                                                          RRRRRR
[hadoop@ip-172-31-81-133 ~]$ ls
.
TrainingDataset.csv train model.py
[hadoop@ip-172-31-81-133 ~]$ hadoop fs -put TrainingDataset.csv /user/hadoop/Tra
[hadoop@ip-172-31-81-133 ~]$ hadoop fs -put train_model.py /user/hadoop/train_mo
[hadoop@ip-172-31-81-133 ~]$ hdfs dfs -ls -t -R
           1 hadoop hdfsadmingroup
                                       35873 2025-05-05 23:17 TrainingDataset
.csv
                                        2825 2025-05-05 23:17 train_model.py
            1 hadoop hdfsadmingroup
[hadoop@ip-172-31-81-133 ~]$
```

Figure 4: HDFS File Listing

3 Parallel Model Training on EMR Cluster

3.1 Launching Model Training

Step: Submit the training job to Spark.

```
spark-submit train_model.py
```

Explanation: Executes the train_model.py script, training an ML model (e.g., linear regression) using MLlib across four EC2 instances. The model is saved to HDFS in a folder (e.g., regression).

Figure 5: Spark-Submit Training Output

3.2 Monitoring Training Job

Step: Verify job execution via the Spark Web UI.

- Access the Spark Web UI through the EMR console's Monitor tab or at http://<master-node-dns>:808
- Confirm job completion.
- Alternatively we can use the below command to list the HDFS to verify if the trained model is saved.

```
hdfs dfs -ls -t -R
```

Figure 6: HDFS listing Trained Model

3.3 Saving and Downloading the Trained Model

Step: Copy and compress the trained model from HDFS.

```
hdfs dfs -copyToLocal regression /home/hadoop/regressionmod
tar -czf model.tar.gz regressionmod/
```

Explanation: Retrieves and compresses the model for transfer.

Step: Download the model to your local machine via SFTP or winscp.

```
get regressionmod/model.tar.gz
```

Explanation: Transfers the model for use in prediction.

```
[hadoop@ip-172-31-81-133 ~]$ hdfs dfs -copyToLocal regression /home/hadoop/regressionmod
[hadoop@ip-172-31-81-133 ~]$ ls
TrainingDataset.csv regressionmod train_model.py
[hadoop@ip-172-31-81-133 ~]$ cd regressionmod/
[hadoop@ip-172-31-81-133 regressionmod]$ ls
data metadata
[hadoop@ip-172-31-81-133 regressionmod]$ cd ..
[hadoop@ip-172-31-81-133 ~]$ tar -czf reg.tar.gz regressionmod/
[hadoop@ip-172-31-81-133 ~]$ ls
TrainingDataset.csv reg.tar.gz regressionmod train_model.py
[hadoop@ip-172-31-81-133 ~]$
```

Figure 7: Model Copy and Compression

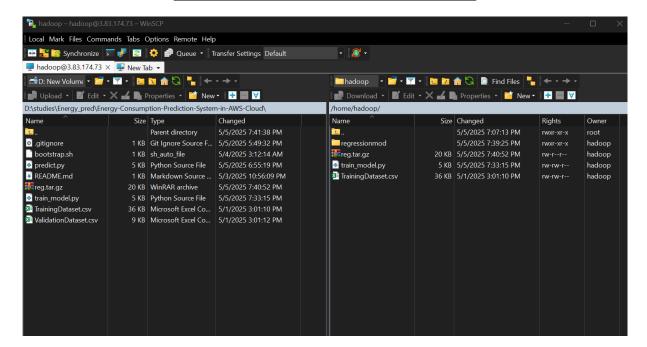


Figure 8: SFTP Model Download

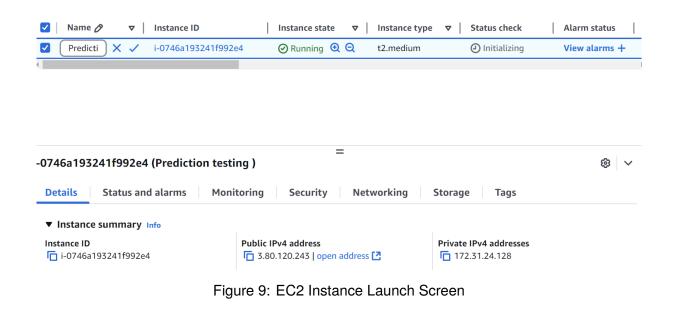
4 Prediction Application on a Single EC2 Instance

4.1 Launching a Single EC2 Instance

Step: Create an EC2 instance for prediction.

- Navigate to **EC2** > **Launch Instance**.
- Select AMI: Ubuntu Server 24.04 LTS.
- Instance Type: t2.medium.
- Select a key pair (e.g., vockey.pem).
- Configure security group: Allow SSH (port 22).
- Launch the instance.

Explanation: Sets up a standalone EC2 instance for prediction.



4.2 Pre-Configuring the EC2 Instance

Step: Install dependencies via SSH(can use putty).

```
ssh -i labuser.pem ubuntu@3.80.120.243
sudo apt-get update
sudo apt-get install -y python3-pip
sudo apt-get install -y python3-numpy
sudo apt-get install -y python3-pandas
sudo apt-get install -y openjdk-11-jdk
```

Explanation: Installs prerequisites for Spark.

Step: Install Apache Spark.

```
wget https://archive.apache.org/dist/spark/spark-3.5.5/spark-3.5.5-bin-
hadoop3.tgz
sudo tar xvf spark-3.5.5-bin-hadoop3.tgz -C /opt
sudo chown -R ubuntu:ubuntu /opt/spark-3.5.5-bin-hadoop3
sudo ln -fs spark-3.5.5-bin-hadoop3 /opt/spark
```

Explanation: Configures Spark 3.5.5.

Step: Configure environment variables.

```
nano ~/.bash_profile
```

Add:

```
export SPARK_HOME=/opt/spark
PATH=$PATH:$SPARK_HOME/bin
export PATH
export JAVA_HOME=/usr/lib/jvm/java-1.11.0-openjdk-amd64
export PATH=$JAVA_HOME/bin:$PATH
```

Apply:

```
source ~/.bash_profile
```

Explanation: Sets up Spark and Java paths.

Step: Configure Spark logging.

```
cp $SPARK_HOME/conf/log4j2.properties.template $SPARK_HOME/conf/log4j2.
properties
nano $SPARK_HOME/conf/log4j2.properties
```

Change rootLogger.level = info to rootLogger.level = ERROR.

Explanation: Reduces logging verbosity.

4.3 Uploading Files to EC2 Instance

Step: Upload files via SFTP.

```
sftp -i labuser.pem ubuntu@3.80.120.243
put predict.py
put ValidationDataset.csv
put model.tar.gz
```

Explanation: Transfers files for prediction. Alternatively can use winscp like the figure below.

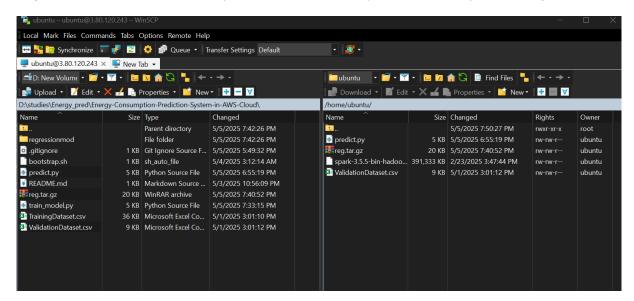


Figure 10: SFTP Upload to EC2

4.4 Extracting the Model

Step: Extract the model archive.

```
tar -xzvf model.tar.gz
```

Explanation: Uncompresses the model for prediction.

4.5 Running Prediction Without Docker

Step: Execute the prediction script.

```
spark-submit predict.py ValidationDataset.csv
```

```
ubuntu@ip-172-31-24-128:~$ 1s

ValidationDataset.csv reg.tar.gz spark-3.5.5-bin-hadoop3.tgz

predict.py regressionmod
ubuntu@ip-172-31-24-128:~$ spark-submit predict.py

Usage: python predict.py <test_dataset_path>
ubuntu@ip-172-31-24-128:~$
```

Figure 11: Model Extraction and Usecase

Explanation: Runs predict.py, which loads the model, predicts, and outputs RMSE.

Instructions for Running Without Docker:

- 1. Set up the EC2 instance (Sections 4.1–4.2).
- Upload predict.py, ValidationDataset.csv, and model.tar.gz.
- 3. Extract the model: tar -xzvf model.tar.gz.
- 4. Run the command, replacing ValidationDataset.csv with the test file path if needed.

Figure 12: Prediction Output Without Docker

5 Building and Deploying the Docker Container

5.1 Installing Docker

Step: Install Docker on the EC2 instance.

```
sudo apt-get install docker.io
```

Explanation: Enables Docker container operations.

5.2 Building the Docker Image

Step: Build the Docker image.

```
sudo docker build -t energypred .
```

Explanation: Creates an image named energypred using the Dockerfile.

5.3 Running the Docker Container

Step: Run the prediction application in a container.

```
sudo docker run -v /home/ubuntu/ValidationDataset.csv:/app/
ValidationDataset.csv energypred /app/ValidationDataset.csv
```

Explanation: Maps the dataset to the container and runs the prediction.

Instructions for Running With Docker:

- 1. Install Docker (Section 5.1).
- 2. Pull the image: docker pull kdshetty/energypred.
- 3. Run the command, replacing paths as needed.

Figure 13: Docker Container Output

```
PS D:\studies\Energy_pred\Energy-Consumption-Prediction-System-in-AWS-Cloud> docker run -v /d/studies/Energy_pred/Energy-Co
nsumption-Prediction-System-in-AWS-Cloud/ValidationDataset.csv:/app/ValidationDataset.csv energypred /app/ValidationDataset
.csv
\lceil \checkmark 
ceil Initializing SparkSession
   Loading test CSV
   Renaming columns
   Encoding categorical columns
[\checkmark] Dropping categorical columns
   Casting columns to float
   Preparing features and labels
   Converting to RDD
   Loading trained model
[√] Making predictions
   Pairing predictions with labels
Evaluating model
      Evaluation Metrics
-----
Metric
                             Value
Root Mean Squared Error (RMSE) | 77.5037
R2 (Coefficient of Determination) | 0.9926
[√] Stopping SparkSession
```

Figure 14: Docker Container Output on VSCode(Alternative)

5.4 Pushing to Docker Hub

Step: Tag and upload the image.

```
docker tag energypred kdshetty/energypred docker push kdshetty/energypred
```

Explanation: Makes the image publicly accessible.

```
PS D:\studies\Energy_pred\Energy-Consumption-Prediction-System-in-AWS-Cloud> docker tag energypred kdshetty/energypred
PS D:\studies\Energy_pred\Energy-Consumption-Prediction-System-in-AWS-Cloud> docker push kdshetty/energypred
Using default tag: latest
The push refers to repository [docker.io/kdshetty/energypred]
718044896e2d: Pushed
76b7c20ae9ff: Pushed
3c8fce41d033: Pushed
13b7e930469f: Pushed
dd4917407f72: Pushed
4636dc9f2a9e: Pushed
4636dc9f2a9e: Pushed
f04934e7711f: Pushed
83084b053cce: Pushed
latest: digest: sha256:da45263f1480560ab96968f14450a4c594eeaacac51e245538e16110ecb2f16f size: 856
PS D:\studies\Energy_pred\Energy-Consumption-Prediction-System-in-AWS-Cloud>
```

Figure 15: Docker Push to Docker Hub(Alternative on VScode)

5.5 Verifying Docker Image

Step: Pull the image to confirm availability.

```
docker pull kdshetty/energypred
```

Explanation: Ensures the image is deployable.

```
Last login: Tue May 6 03:25:34 2025 from 108.53.25.28
ubuntu@ip-172-31-24-128:~$ docker pull kdshetty/energypred
Using default tag: latest
latest: Pulling from kdshetty/energypred
13b7e930469f: Already exists
83084b053cce: Pull complete
718044896e2d: Pull complete
d04917407f72: Pull complete
4636dc9f2a9e: Pull complete
f04934e7711f: Pull complete
5c8fce41d033: Pull complete
Digest: sha256:da45263f1480560ab96968f14450a4c594eeaacac51e245538e16110ecb2f16f
Status: Downloaded newer image for kdshetty/energypred:latest
docker.io/kdshetty/energypred:latest
ubuntu@ip-172-31-24-128:~$
```

Figure 16: Docker Image Pull

6 Repository Links

- GitHub Repository: https://github.com/KDShetty11/Energy-Consumption-Prediction-Sys
- Docker Hub Repository: https://hub.docker.com/repository/docker/kdshetty/energypred

7 Use of ChatGPT/AI Copilots

Code Generated by ChatGPT:

- Initial train model.py structure (Spark DataFrame and MLlib Gradient Boot).
- Partial Dockerfile (base image and dependencies).

Code Written from Scratch:

- Parameter tuning in train_model.py for RMSE optimization.
- predict.py for model loading and prediction.

Code Adapted from ChatGPT:

- Modified MLlib code for dataset-specific columns and RMSE calculation.
- Adjusted Dockerfile for Spark and model inclusion.

Experience with ChatGPT:

- *Usefulness*: Accelerated setup with Spark and Docker templates. MLlib examples were mostly accurate.
- *Limitations*: Generated code used outdated APIs or incorrect paths, requiring debugging. Parameter tuning advice was generic.
- Overall: Effective for boilerplate but required expertise to adapt.

8 Notes

- Ensure sufficient storage and permissions for EMR and EC2. Advisable to use t2.medium or better for the EC2 Instance.
- Test prediction with ValidationDataset.csv to verify RMSE.
- Validate Docker container on a fresh EC2 instance.