Internet of Things - CSC8112 Coursework 2023-24 Project Report

Ronil Rodrigues
MSc Cloud Computing
230112209

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AIM:

The aim of this coursework is to process sensor data in the edge and cloud environment and able to implement machine learning model to create IOT data processing pipeline. The pipeline will be able to do operations like data collection, data pre-processing, data visualization and data prediction in edge cloud setting, and be able to use a lightweight virtualization technology stack, such as Docker, to implement IOT data processing pipeline in the edge cloud setting.

Introduction:

The coursework focuses on creating an IoT pipeline by sourcing input from the Urban Observatory and subsequently channeling the data through various layers, including Azure Edge and the cloud, to generate the desired results. Figure 1 below illustrates the flow of the IoT pipeline.

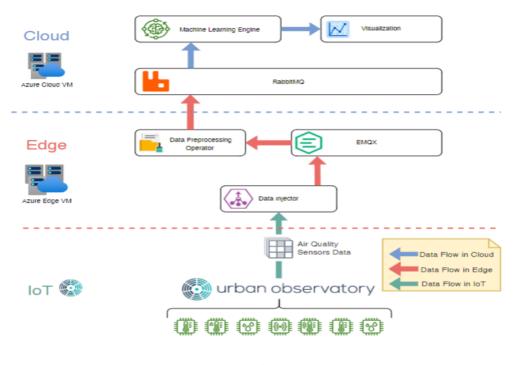


Figure 1: Overview

IoT tier:

• Newcastle Urban Observatory (NCL UO) [https://urbanobservatory.ac.uk/]: The largest set of publicly available real-time urban data in the UK. NCL UO sensors are gathering data across Newcastle city. With over 50 data types and counting, there are lots of live data for you to access.

Edge tier:

• Data Injector: This will be a software component that you will design and implement in

Task 1, focusing on (i) reading data from Urban Observatory API and (ii) transmitting data to the machine learning pipeline.

- EMQX: A broker of MQTT protocol, a message queuing system given to you as a Docker image, which forms the basis for enabling asynchronous service-to-service communication in a complex Machine Learning (ML)-based IoT data processing pipeline.
- Data Pre-processing Operator: A software component that you will develop in Task 2, Responsible for preparing training data of Machine Learning model.

Cloud tier:

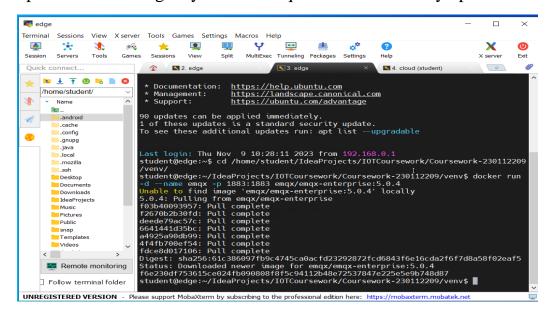
- RabbitMQ: A cloud-based message queuing system.
- Machine Learning Model/Classifier/Engine: A software component that can be trained to predict particular types of future events.
- Visualization: A component that will visualize the trend of raw time-series data and the prediction results (input from the Machine Learning Model/Classifier/Engine)

IMPLEMENTATION:

Task 1: Design a data injector component by leveraging Newcastle Urban Observatory IoT data streams

1) Pull and run the Docker image "emqx/emqx" from Docker Hub in the virtual machine running on Azure lab (Edge). Perform this task first using the command line interface (CLI).

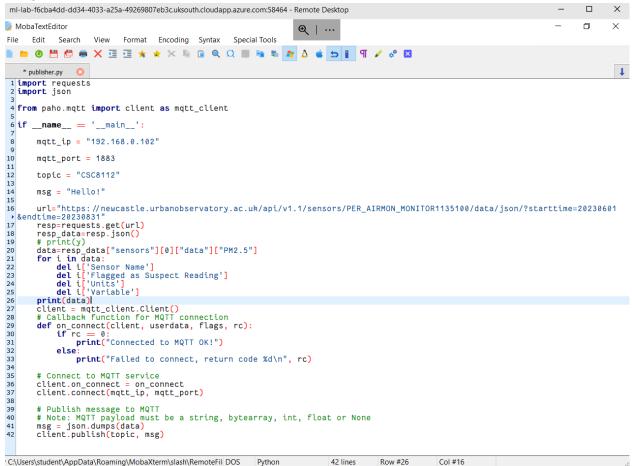
We execute the Docker image emqx/emqx with the command "docker run -d --name emqx -p 1883:1883 emqx/emqx-enterprise:5.0.4". The image is fetched from Docker Hub and operates on the Edge layer. The Emqx broker is currently operational on the edge layer.



2) Develop a data injector component with the following functions (Code) in Azure Lab (Edge) or the Azure Lab Localhost:

The Following code is developed for MQTT Publisher. In this code we receive data from Urban Observatory using the provided URL, which is then filtered out to get 2.5PM data. This 2.5PM data is then send to MQTT Subscriber using the Emqx broker operating in the edge layer.

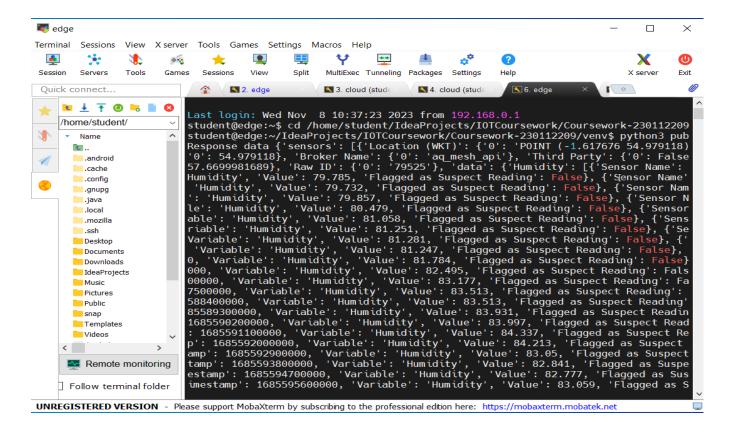
MQTT PUBLISHER CODE:



A) Collect data from Urban Observatory platform by sending HTTP request to the following url

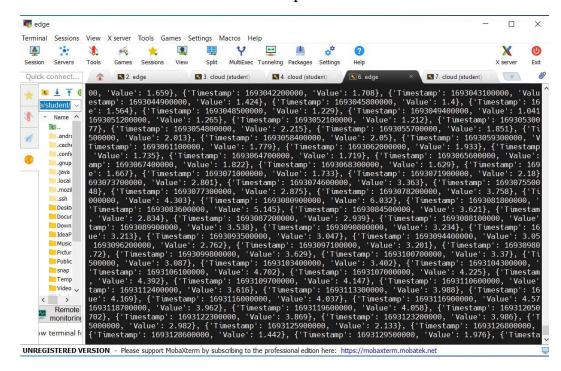
([http://uoweb3.ncl.ac.uk/api/v1.1/sensors/PER_AIRMON_MONITOR1135100/data/json/?starttime=20230601&endtime=20230831]). Following that, please print out the raw data streams that you collected on the console.

The below figure shows output after running publisher.py, we are able to get raw data from Newcastle urban observatory.



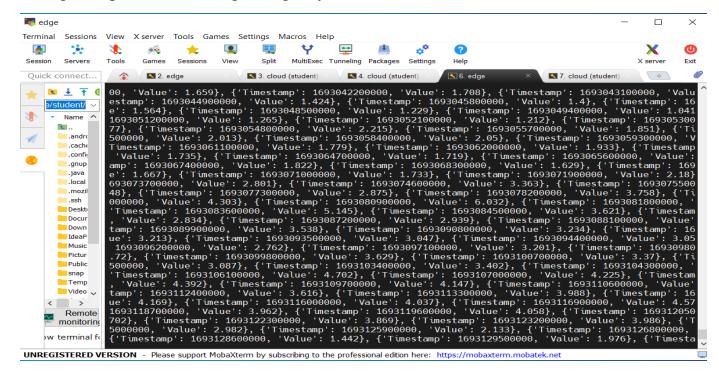
(b) Although the raw air quality data you collected from the Urban Observatory API contains many metrics including NO2, NO, CO2, PM2.5, and PM10, among others, for the purpose of this coursework you only need to store and analyze PM2.5 data. While many meta-data are available for PM2.5 data, such as sensor name, timestamp, value, and location, you only need to store the metrics related to the Timestamp and Value meta-data fields.

We filter out the data obtained from Urban Observatory API to include only the Time stamp and Value meta-data fields and then print out the same on console.



(c) Send all PM2.5 data to be used by Task 2.2 (a) to EMQX service of Azure lab (Edge).

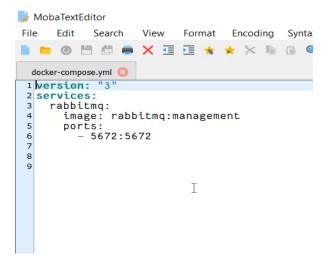
In the following code we filtered out data obtained from urban observatory and store metrics related to Timestamp and Value fields. The same 2.5PM data is shared to mqtt subscriber through emqx broker running in edge layer.



TASK 2: DATA PRE PROCESSING OPERATOR DESIGN:

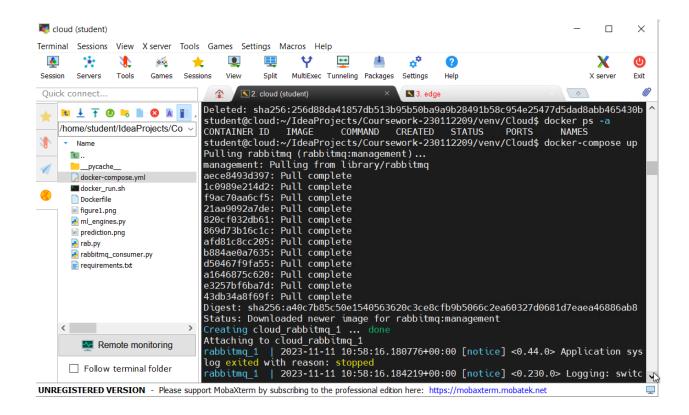
1) Define a Docker compose file which contains the following necessary configurations and instructions for deploying and instantiating the following set of Docker images on Azure lab (Cloud):

The below figure shows the Docker file created to run the docker image rabbitmq on the specified ports.



(a) Download and run RabbitMQ image (rabbitmq:management);

The below image shows RabbitMQ image running on Azure Lab (Cloud) after running docker-compose up command on cloud.



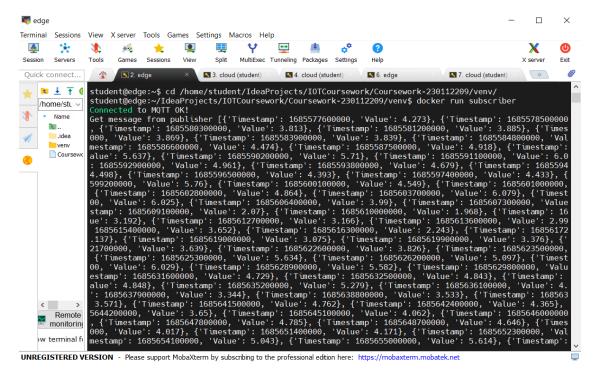
- 2. DESIGN A DATA PREPROCESSING OPERATOR WITH THE FOLLOWING FUNCTIONS (CODE) IN AZURE LAB (EDGE):
- (a) Collect all PM2.5 data published by Task 1.2 (c) from EMQX service, and please print out the PM2.5 data to the console (this operator will run as a Docker container, so the logs can be seen in the Docker logs console automatically

The following code is written for MQTT Subscriber to collect PM2.5 data published in Task1 from EMQX service. The output obtained after running MQTT Subscriber is displayed below the code.

MQTT_SUBSCRIBER CODE:

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 1 import json
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from paho.mqtt import client as mqtt_client
from preprocess import process_data
         __name__ = '__main__':
mqtt_ip = "192.168.0.102"
mqtt_port = 1883
topic = "CSC8112"
         # Create a mqtt client object
client = mqtt_client.Client()
# Callback function for MQTT connection
def on_connect(client, userdata, flags, rc):
    if rc = 0:
                if rc = 0:
    print("Connected to MQTT OK!")
else:
                      print("Failed to connect, return code %d\n", rc)
         # Connect to MQTT service
client.on_connect = on_connect
client.connect(mqtt_ip, mqtt_port)
            Callback function will be triggered
               on_message(client, userdata, msg):
    print(f"Get message from publisher {json.loads(msg.payload)}")
    process_data(json.loads(msg.payload))
         # Subscribe MQTT topic
client.subscribe(topic)
client.on_message = on_message
         # Start a thread to monitor message from publisher
client.loop_forever()
```

Below is the PM2.5 data received in the edge layer by running the command "docker-compose up".



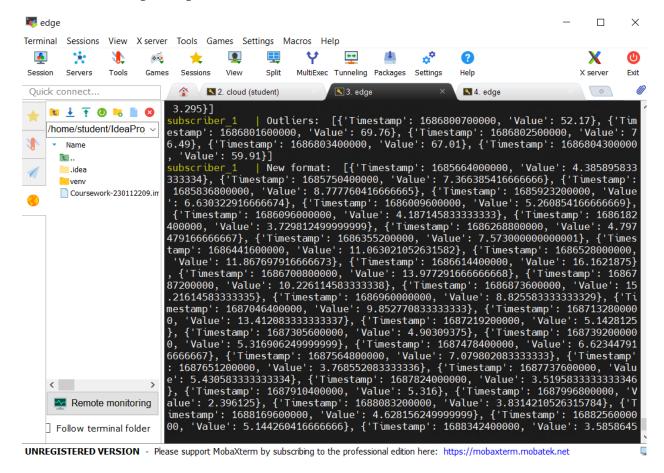
(b) Filter out outliers (the value greater than 50), and please print out outliers to the console (docker logs console).

We filter out outliers (the value greater than 50) value from the PM2.5 data obtained and print them to docker logs console.

```
subscriber_1 | Outliers: [{'Timestamp': 1686800700000, 'Value': 52.17}, {'Timestamp': 1686801600000, 'Value': 69.76}, {'Timestamp': 1686802500000, 'Value': 76.49}, {'Timestamp': 1686803400000, 'Value': 67.01}, {'Timestamp': 1686804300000, 'Value': 59.91}]
```

(c) Since the original PM2.5 data readings are collected every 15 mins, so please implement a python code to calculate the averaging value of PM2.5 data on daily basis (every 24 hours), please pick the first start date of a day or a 24 hours interval as the new timestamp of averaged PM2.5 data, and please print out the result to the console (docker logs console).

The Obtained data is then averaged over a 24 hour interval as the new timestamp of PM2.5 data and the output is printed on docker console.



The below shows pre-processor code written to find outliers and calculate average PM2.5 data which contains process_data function, where data obtained in the previous step is passed to filter out the outliers and then the filtered data is processed to get average daily PM2.5 data. The final averaged Pm2.5 data is passed to rabbitMQ_publisher function to send it over to cloud layer using rabbitmq.

PREPROCESSOR CODE:

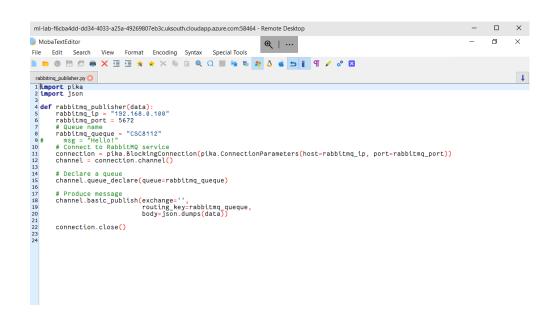
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1 import json
2 import datetime
  from paho.mqtt import client as mqtt_client
from rabbitmq_publisher import rabbitmq_publisher
 7 def process_data(data):
8 outliers = []
9 daily_average = []
10 daily_total = 0
11 daily_count = 0
12 current_date = None
            for d in data:
    if d['Value'] ≥ 50:
        outliers.append(d)
        del d
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            print("Outliers: ", outliers,flush=True)
           for entry in data:
    timestamp = entry['Timestamp']
    value = entry['Value']
    date_time = datetime.datetime.fromtimestamp(timestamp / 1000)
    date = date_time.strftime('%d %b %Y')
                                                                                                                                                                                       Ι
                   if date_time.date() #= current_date:
    if current_date is not None:
        daily_average.append({'Timestamp':timestamp, 'Value': daily_total / daily_count})
                           daily_average.append({'Time
current_date = date_time.date()
daily_total = value
daily_count = 1
                   else:

daily_total += value
daily_count += 1
            # Add the last day's data
if current_date is not None:
    daily_average.append({'Timestamp':timestamp, 'Value': daily_total / daily_count})
              rint("New format: ", daily_average, flush<mark>=True)</mark>
abbitmq_publisher(daily_average)
```

(d) Transfer all results (averaged PM2.5 data) to be used by Task 3.2 (a) into RabbitMQ service on Azure lab (Cloud).

The output obtained from pre-processor code is then sent over to Azure lab (Cloud) through RabbitMQ publisher. The following displays the code crafted to transmit the data from the Azure Edge layer to the cloud.

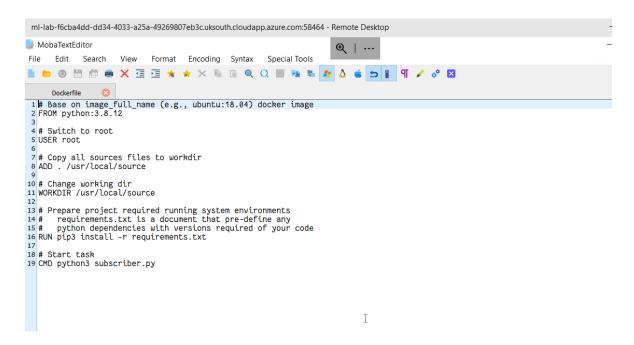
RABBITMQ_PUBLISHER CODE:



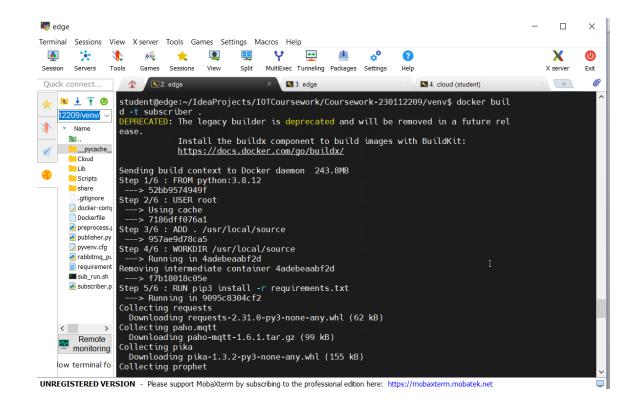
3. Define a Dockerfile to migrate your "data preprocessing operator" source code into a Docker image and then define a docker-compose file to run it as a container locally on the Azure lab (Edge).

We created a Docker file to install all of our dependencies required to build our Docker image which are specified in "requirements.txt". We build the image using the command "docker build –t subscriber ." . Where subscriber refers to the image name and "." refers to the current directory.

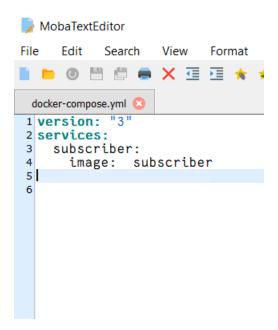
DOCKERFILE:



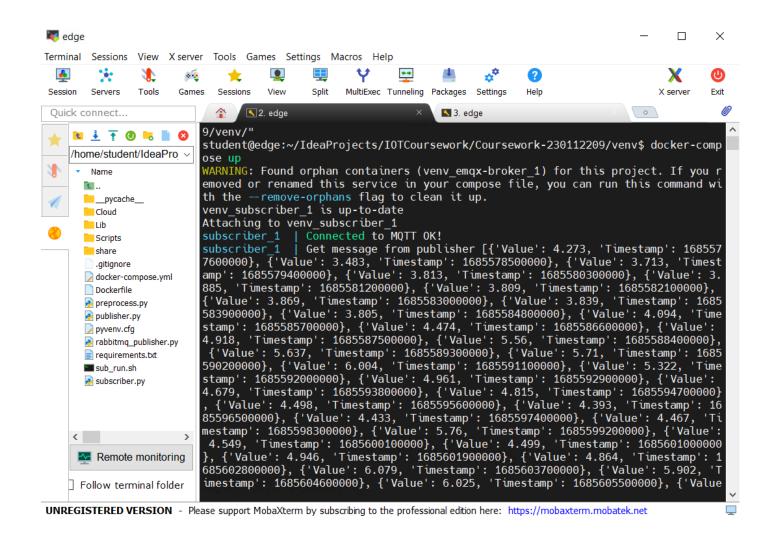
We use the "docker build –t subscriber." command to build subscriber image.



We created a Docker compose file to run the subscriber image.



We use the "docker-compose up" command to run the Docker container locally on the Azure lab (Edge).



Task 3: Time-series data prediction and visualization\

1. Download a pre-defined Machine Learning (ML) engine code from [https://github.com/ ncl-iot-team/CSC8112_MLEngine].

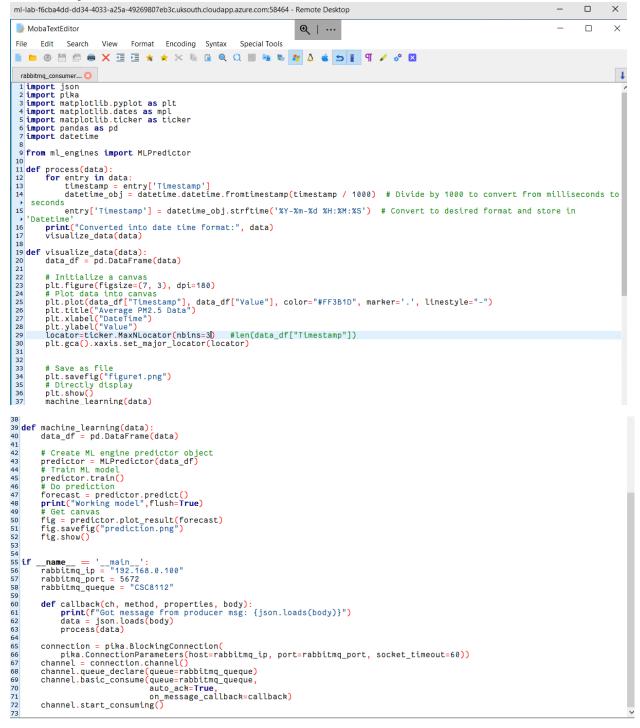
We download and use a pre-defined machine learning code to predict data.

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5 Official guide book of Prophet: https://facebook.github.io/prophet/docs/quick_start.html#python-api
 7 from prophet import Prophet
 9 class MLPredictor(object):
         Example usage method:
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               mple usage method:|
from ml_engine import MLPredictor
predictor = MLPredictor(pm25_df)
predictor.train()
forecast = predictor.predict()
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               fig = predictor.plot_result(forecast)
fig.savefig(os.path.join("Your target dir path", "Your target file name))
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         def __init__(self, data_df):
               :param data_df: Dataframe type dataset
               self.__train_data = self.__convert_col_name(data_df)
self.__trainer = Prophet(changepoint_prior_scale=12)
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         def train(self):
               self.__trainer.fit(self.__train_data)
               __convert_col_name(self, data_df):
data_df.rename(columns={"Timestamp": "ds", "Value": "y"}, inplace=True)
print(f"After rename columns \n{data_df.columns}")
return data_df
                  _make_future(self, periods=15):
               __make_ruture(self, periods=15):
future = self.__trainer.make_future_dataframe(periods=periods)
return future
         def predict(self):
    future = self.__make_future()
    forecast = self.__trainer.predict(future)
               return forecast
         def plot_result(self, forecast):
    fig = self.__trainer.plot(forecast, figsize=(15, 6))
               return fig
```

2. Design a PM2.5 prediction operator with the following functions (code) in Azure Lab (Cloud)

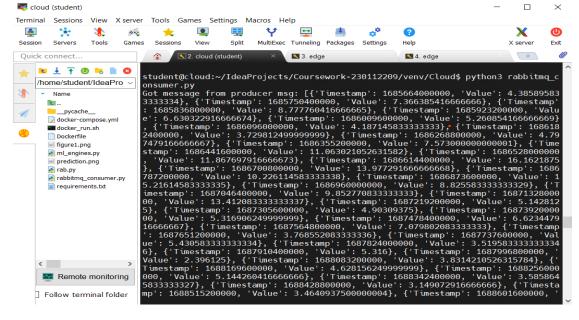
We have implemented a function to receive the code sent through RabbitMQ. This function then channels the data to the processing function, where it undergoes conversion into a date-time format. Subsequently, the processed data is transferred to the visualize data function for a graphical representation of the given dataset. In the final step, the data is forwarded to a machine learning model to generate predictions and facilitate visualizations.

RABBITMQ_CONSUMER:



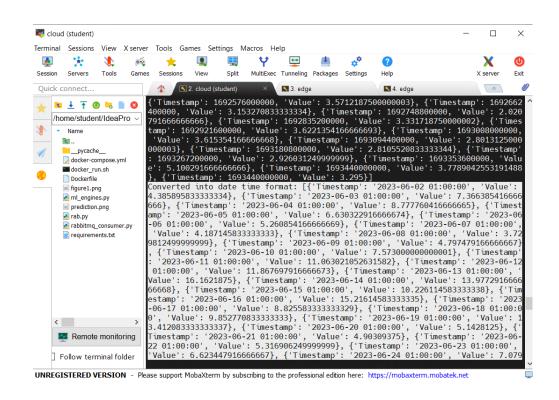
(a) Collect all averaged daily PM2.5 data computed by Task 2.2 (d) from RabbitMQ service, and please print out them to the console.

We run rabbitmq_consumer.py code which collects all the data published by RabbitMQ service and then prints out the result to console.



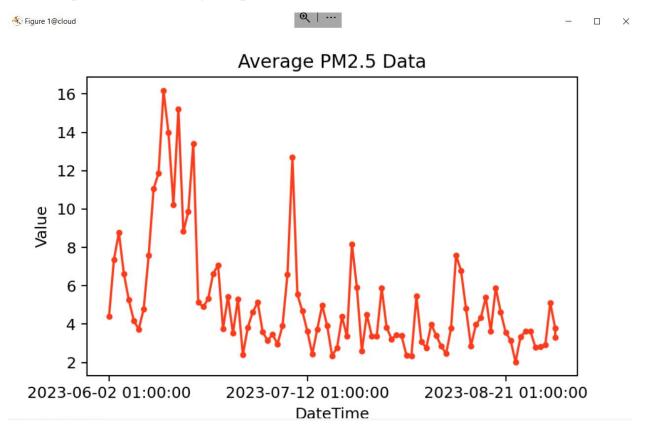
(b) Convert timestamp to date time format (year-month-day hour: minute: second), and please print out the PM2.5 data with the reformatted timestamp to the console.

We convert the obtained into date time format by passing it to the process function as specified in the above code.



(c) Use the line chart component of matplotlib to visualize averaged PM2.5 daily data, directly display the figure or save it as a file.

We pass the obtained averaged PM2.5 daily data into visualize_data function to create a visual representation using matplotlib.

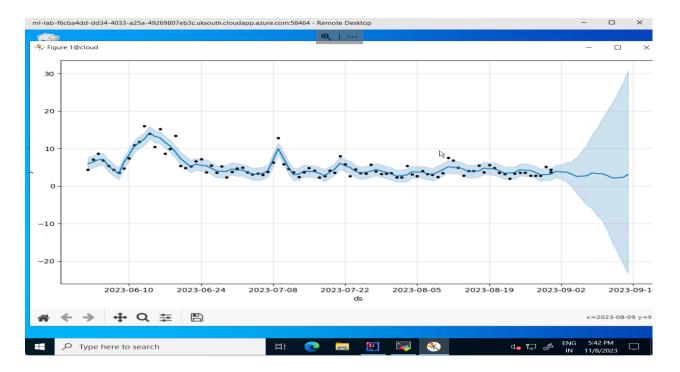


(d) Feed averaged PM2.5 data to machine learning model to predict the trend of PM2.5 for the next 15 days (this predicted time period is a default setting of provided machine learning predictor/classifier model).

We feed the average daily PM2.5 data into the provided machine learning model (provided above in task3 part 1) which helps us predict the PM2.5 data for the next 15 days.

(e) Visualize predicted results from Machine Learning predictor/classifier model, directly display the figure or save as it a file (pre-defined in the provided Machine Learning code)

After implementing the machine learning model we are able to visualize the predicted PM2.5data for the next 15 days.



Analytical Discussion:

In the given project we have obtained some insight about the PM2.5 data obtained over a period of time and also have got a predicted value of the same data which shows the decrease in its value over the period of next 15 days. The PM2.5 data graph shows that the value of PM2.5 was maximum in the month of June and had a decline over time from June till November.

Conclusion:

In this project we were able to implement an IOT pipeline using two different message (EMQX and RABBITMQ) queuing systems operating in two different layers i.e. Azure Edge and Azure Cloud layer. This project helped me to understand the use of IOT principles using various tools such as Docker to containerize the code into lightweight Docker file and run the same on the edge layer to reduce computing. The project has equipped with knowledge pertaining to various modules and techniques to implement a basic IOT pipeline.

REFERENCES:

- 1) https://stackoverflow.com/: For various doubts related to implementation.
- 2) https://docker-curriculum.com/: Docker documentation.