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Cloud Computing Assignment

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Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

In an increasingly connected world, cloud computing and the Internet of Things (IoT) are revolutionising many fields, including environmental monitoring. This technological development offers unprecedented possibilities for managing and analysing air quality, a major public health issue. This report, drawn up as part of my Master's degree in Cloud and Embedded Systems Science and Technology (CSTE), focuses on the use of these technologies to collect, process and distribute environmental data.

The main aim of this assignment is to store and make accessible the latest air quality data, captured by a network of small environmental IoT sensors. The project aims to provide a reliable platform for real-time consultation of environmental data, a crucial tool for researchers, decision-makers and the general public.

We face a number of technical challenges in achieving this objective. Firstly, managing the large quantities of data generated by IoT sensors requires a robust and adaptable cloud infrastructure. Secondly, calculating the Air Quality Index (AQI) from this data in real time requires considerable processing power and accuracy. Finally, the need to keep the system adaptable and responsive to varying workloads presents an additional challenge.

To address these challenges, our approach is to use a database located in the cloud, specifically designed to manage and process large volumes of IoT data. This database will be regularly updated with new data, while allowing quick and easy access for end users. In addition, we will be implementing advanced algorithms for calculating the AQI, guaranteeing the accuracy and reliability of the information provided.

The importance of this system is not limited to environmental monitoring; it also has a significant impact on public health, urban planning and environmental awareness. By providing accurate and up-to-date data, we contribute to a better understanding and management of air quality.

In conclusion, this report will detail our methodology, the architecture of the system, the challenges encountered and the solutions adopted. We will also discuss the implications of our work, not only in technical terms but also in terms of its practical applications and impact on different stakeholders.

Chapter 2

Methodologies

2.1 Data Collecting, Processing & Storing

2.1.1 Overview of the Pipeline Architecture

The initial pipeline in this project consists of three primary components: **Data Collecting**, **Data Processing**, and **Data Storing**.

During the **Data Collecting** phase, the most recent version of the dataset is acquired from its source. This is followed by the **Data Processing** phase, where the data is formatted, and the Air Quality Index (AQI) is calculated for each particulate matter sensor. Lastly, in the **Data Storing** phase, the data from each sensor is methodically stored in a time-series database.
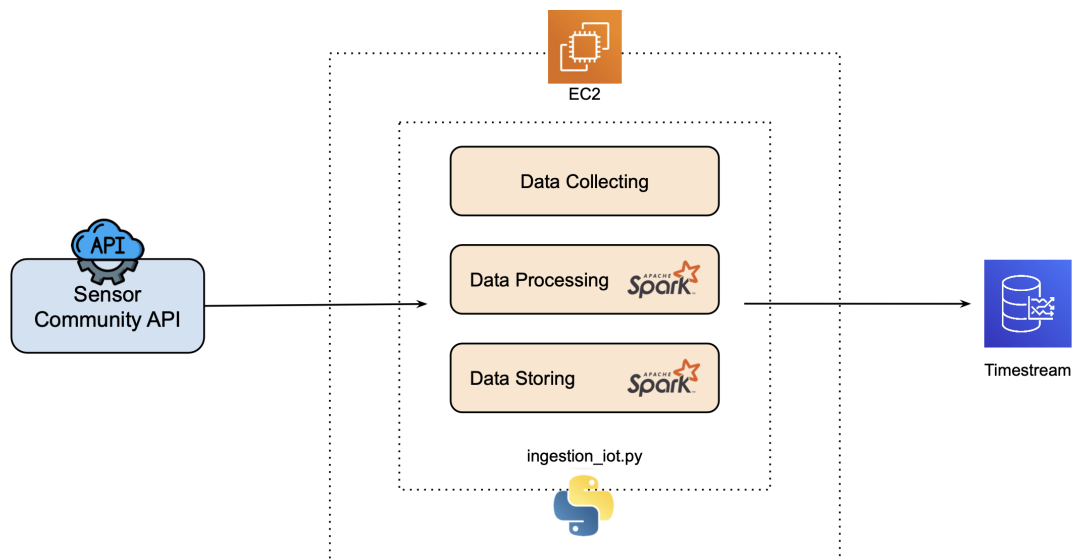

Figure 2.1: Data Collecting, Processing & Storing Pipeline Diagram

2.1.2   Data Collecting

2.1.2.1   Data Source

The Sensor Community network is a global, contributor-driven initiative that collects open environmental data through a vast network of sensors. These sensors, deployed in over 70 countries, collect real-time data on air quality, temperature, humidity and pressure. On average, the sensors send new data every 145 seconds (**?**). The Sensor Community network offers two main API endpoints for accessing their environmental data:

1. **5-Minute Averaged Data API:** This API provides data averaged over the last 5 minutes for each sensor. This is useful for near real-time analysis or immediate air quality assessments, particularly in test or active monitoring contexts.

2. **24 Hour Averaged Data API:** This API provides data averaged over the last 24 hours for each sensor. It is particularly suited to analysing daily trends and understanding environmental changes over a longer period.

2.1.2.2   Python Script

In this project, both APIs were used to collect data from the Sensor Community. The data was collected using the `requests` library in Python and stored in the cache of the local machine in a Spark DataFrame. This step is performed every 10 seconds to ensure that the data is up to date.

2.1.3   Choice of Database

This project uses Amazon Timestream, which is a cloud-native time series database. It is a wise choice because of its superior time series management capabilities, which are particularly well suited to data from IoT sensors. This database is distinguished by its speed of ingestion and efficiency in processing vast volumes of data, facilitating regular updates and in-depth analyses of the Air Quality Index. Its ability to adjust to variations in workload is a major asset, ensuring consistent performance. What's more, Timestream's advanced security features meet strict standards of confidentiality and data sovereignty, an essential criterion for the secure management of sensitive information.

2.1.4   Query 3

2.2 Queries Optimisation

2.3   Pipeline of the Project

2.3.1   Pipeline Overview

The pipeline of this project is composed of four main components: **data ingestion**, **query 1**, **query 2** and **query 3**.

The **ingestion** task retrieves the last version of the data set from the source and stores it in the data lake (CSV file stored in local storage). Then, the **queries 1, 2 & 3** tasks retrieves the data from the data lake and performs the queries on the data.

2.3.2   Pipeline Orchestration

In order to orchestrate and automate the pipeline, a scheduled task must be run every day to retrieve the latest version of the dataset and run the tasks when a new daily row is added at 23:59 UTC to the dataset.

To perform this task, a DAG (Directed Acyclic Graph) was created using Apache Airflow. The DAG is scheduled to run every day at 00:00 UTC and is composed of four tasks: **ingestion**, **query 1**, **query 2** and **query 3**. The screenshot below **??** shows the DAG graph of the pipeline in the web interface of Apache Airflow.

The benefits of using a workflow platform such as Apache Airflow are its ability to schedule and automate the pipeline, as well as its ability to monitor the pipeline and send alerts if a task fails.
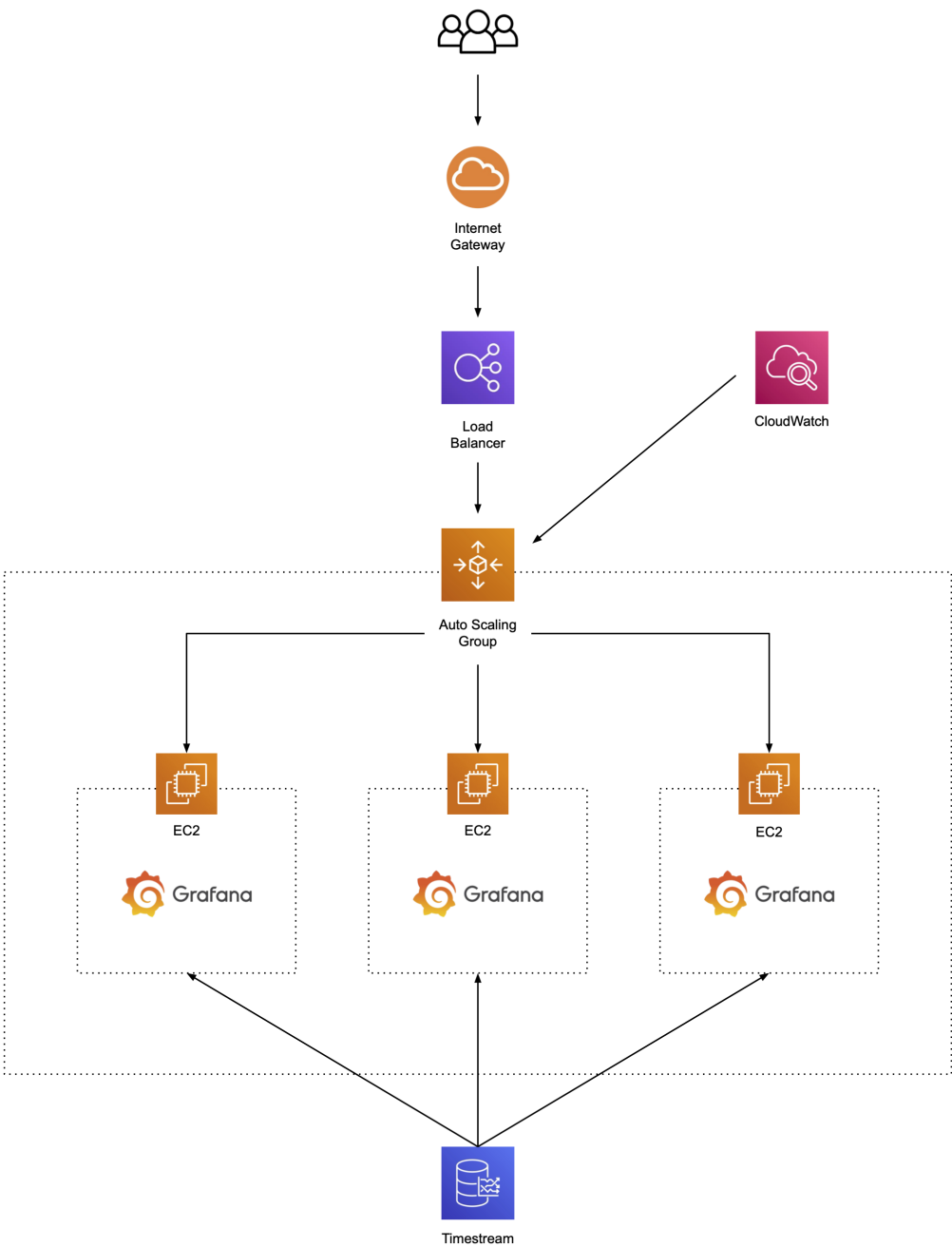
Figure 2.2: Data Distributing Pipeline Diagram

Chapter 3

Results & Discussion

3.1 Queries Results

The programme was last run on 18 November 2023. The appendix **??** shows the output of the program on the terminal.

3.1.1 Grafana Dashboard

The first query takes around 3 seconds, and the table **??** shows a sample of the data calculated during the task. In order to evaluate performance, an equivalent script not using Spark was run. Execution time was 0.5 sec. The **??** section will cover this point. The results are consistent with what was expected (**?**). For example, the figure **??** shows that Brazil was heavily impacted by the pandemic, reaching an average peak in February 2022. The same is true for Korea in figure **??** and the United States in figure **??**, which were heavily impacted.
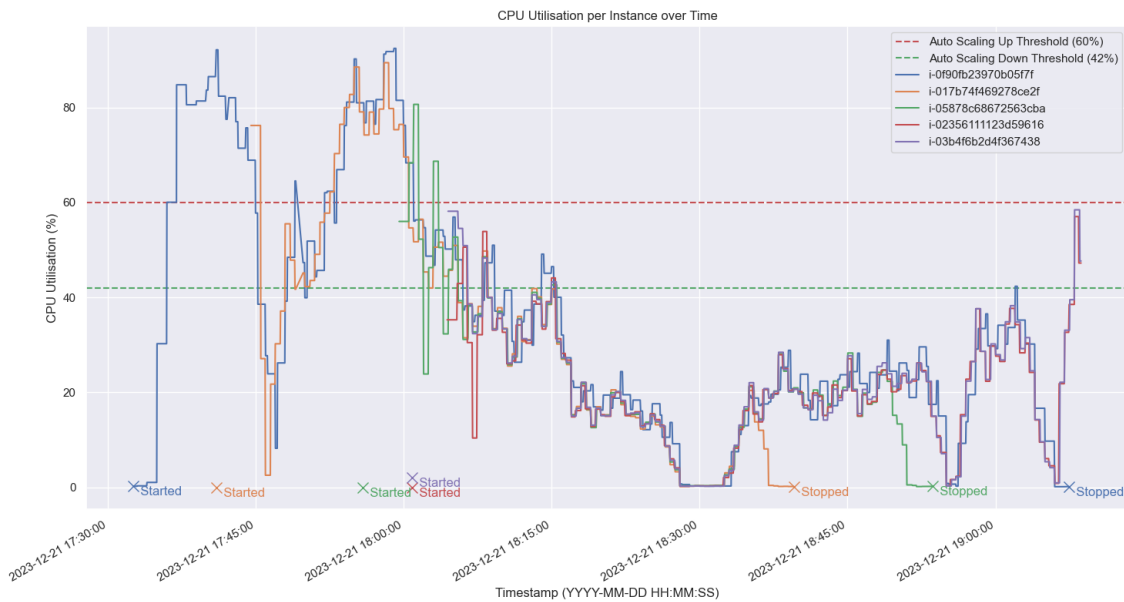

Figure 3.1: Load Test Result

3.1.2   Query 2

The second query takes around 15 seconds, and the table **??** shows a sample of the data calculated during the task. In order to evaluate performance, an equivalent script not using Spark was run. Execution time was 6 sec. The **??** section will cover this point. Locations used to compute the statistics are shown on the map of figure **??**. The area of the circles is proportional to how the location has been affected by the pandemic.

```
images/top-100-locations-most-affected.png
```

Figure 3.2: Top 100 Locations most affected by the pandemic

Table 3.1: Query 2 Results Sample

	Continent	WeekRange	Mean	Std	Min	Max
1	Africa	19/01/2020-25/01/2020	0.0	0.0	0	0
2	Africa	26/01/2020-01/02/2020	0.0	0.0	0	0
3	Africa	02/02/2020-08/02/2020	0.0	0.0	0	0
4	Africa	09/02/2020-15/02/2020	0.0	0.0	0	0
5	Africa	16/02/2020-22/02/2020	0.0	0.0	0	0
6	Africa	23/02/2020-29/02/2020	0.0	0.0	0	0
7	Africa	01/03/2020-07/03/2020	0.02857	0.16903	0	1
8	Africa	08/03/2020-14/03/2020	0.65714	1.73108	0	9
9	Africa	15/03/2020-21/03/2020	2.74285	4.53964	0	17
10	Africa	22/03/2020-28/03/2020	12.62857	15.33754	0	59
11	Africa	29/03/2020-04/04/2020	14.97142	19.31242	0	82

The figures below **??** and **??** show the mean and standard deviation of the number of confirmed cases by week and continent. The results are consistent with expectations: the continents most affected are America and Europe (**?**).
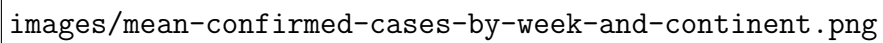
images/mean-confirmed-cases-by-week-and-continent.png

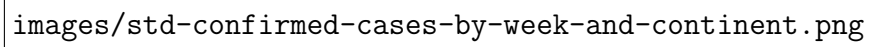Figure 3.3: Mean Confimed Cases By Week and Continent

images/std-confirmed-cases-by-week-and-continent.png

Figure 3.4: Standard Deviation Confimed Cases By Week and Continent

The figures **??** and **??** show the maximum and minimum of the number of confirmed cases by week and continent.
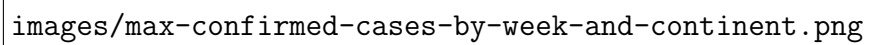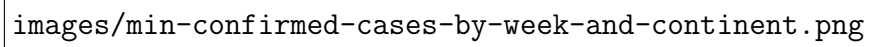
images/max-confirmed-cases-by-week-and-continent.png

Figure 3.5: Maximum Confimed Cases By Week and Continent
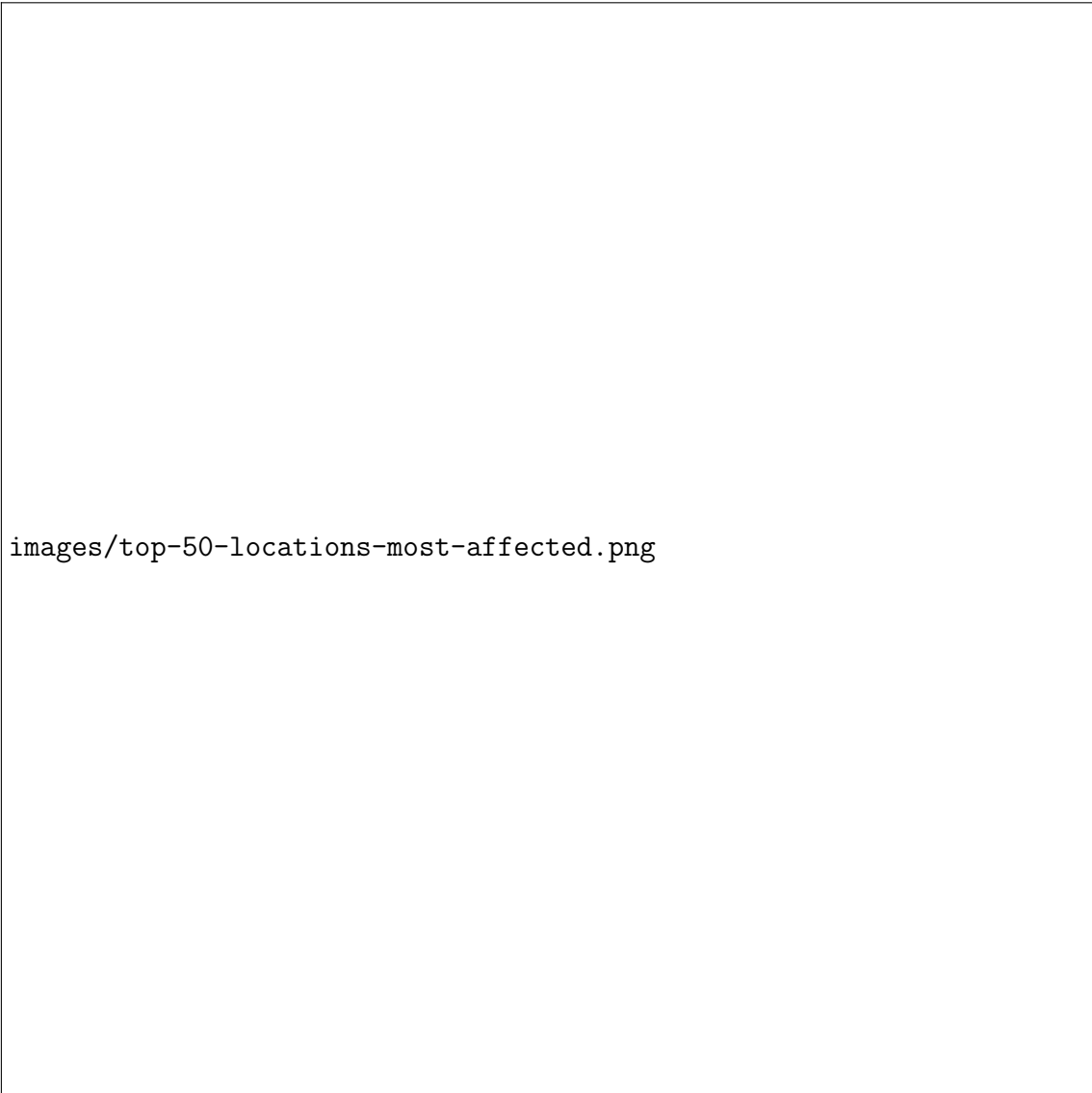
images/min-confirmed-cases-by-week-and-continent.png

Figure 3.6: Minimum Confimed Cases By Week and Continent

3.1.3   Query 3

The third query takes around 3 minutes as clustering with the custom implementation takes 60 seconds and clustering with the Spark MLlib implementation takes 110 seconds. The table **??** shows a sample of the data calculated during the task with the custom implementation and the table **??** with the Spark MLlib implementation. Locations used to compute the statistics are shown on the map of figure **??**. The area of the circles is proportional to how the location has been affected by the pandemic.

images/top-50-locations-most-affected.png

Figure 3.7: Top 50 Locations most affected by the pandemic

Table 3.2: Query 3 Results Sample - Custom KMeans Clustering

	Location	Month	Cluster
1	Argentina	2020-01	2
2	Austria	2020-01	2
3	Brazil	2020-01	2
4	Czechia	2020-01	2
5	France	2020-01	1
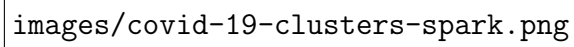
Table 3.3: Query 3 Results Sample - Spark MLlib KMeans Clustering

	Location	Month	Cluster
1	Argentina	2020-01	2
2	Austria	2020-01	0
3	Brazil	2020-01	2
4	Czechia	2020-01	2
5	France	2020-01	1

The figures below **??** and **??** show the clusters of the top 50 locations most affected by the pandemic in March 2020. The clusters are represented by different colours.

images/covid-19-clusters-custom.png

Figure 3.8: Custom KMeans Clustering on 03/2020

images/covid-19-clusters-spark.png

Figure 3.9: Spark MLlib KMeans Clustering on 03/2020

3.2 Discussion of Results

As the previous results show, it seems that scripts not using Spark are faster. While these differences in execution time may seem surprising at first glance, they can in fact be attributed to several factors:

1. **Data size and structure:** The DataFrame, with its 289 entries and 1147 columns occupying 2.5 MB of memory, is relatively modest in size. Pandas is particularly efficient at processing such large amounts of data in memory on a single node. Spark, on the other hand, is designed for distributed processing of large datasets. In this case, the overheads of distributing the data and managing the Spark environment may outweigh the benefits of using it for smaller datasets.

2. **Operational efficiency:** Pandas performs vectorised operations that are optimised for speed, especially with datasets that fit easily into memory on a single computer. Spark, while powerful for processing large volumes of data, introduces an initial overhead for distributing data and configuring the distributed environment, which can slow down processing for smaller datasets.

3. **Complexity of the environment:** Complexity of the environment: Running operations in a Spark environment involves initializing a cluster (even in local mode), distributing tasks, and managing distributed memory, which adds extra processing time compared to running in-memory Pandas directly.

Thus in this project run locally, Pandas is faster than Spark, due to its efficient management of in-memory operations on a single node. Spark's distributed processing overhead makes it less efficient for such tasks.

3.3 Ethical Considerations and Challenges

Chapter 4

Conclusion

References

1. peoter. Are all Sensor Community sensors synchronized?. Sensor Community Forum; 2023. Available at: `https://forum.sensor.community/t/are-all-sensor-community-sensors-synchronized/2479/2`. (Accessed: December 18, 2023).

Appendix A

Documentation

Appendix A.A   Project tree

```
lib/
collecting.py
processing.py
storing.py
scripts/
    get_iam_credentials.sh
    start_spark_job.sh
services/
    get_iam_credentials.service
    spark_python_job.service
    grafana_server.service
test/
    artillery_load_test.yml
    monitoring.py
    metrics.csv
    results.json
    visualisation_load_test.ipynb
ingestion_iot_data_flatten.py
main.py
README.md
requirements.txt
```

Appendix A.B   Getting Started

To run the program, follow these steps:

1. Create a virtual environment using `python3 -m venv venv`.

2. Activate the virtual environment using `source venv/bin/activate`.

3. Install the required dependencies using `pip3 install -r requirements.txt`.

4. Run the program using `python3 main.py`.

5. Visualise the results using `visualisation.ipynb` (Jupyter Notebook).

Appendix A.C   Detailed Features of Functions

`collecting.py`

- `fetch_sensors_data(sparkSession)`: Function to ingest the latest data from the sensors and returns it as a Spark DataFrame.

`processing.py`

- `get_aqi_value_p25(value)`: Function for calculating the AQI value for PM2.5.
- `get_aqi_value_p10(value)`: Function for calculating the AQI value for PM10.
- `computeAQI(df)`: Function for calculating the AQI value for each particulate matter sensor and returning the DataFrame with the AQI column.

`storing.py`

- `keepOnlyUpdatedRows(database_name, table_name, df)`: Function for keeping only the rows that have been updated in the DataFrame.
- `_print_rejected_records_exceptions(err)`: Internal function for printing the rejected records exceptions.
- `write_records(database_name, table_name, client, records)`: Internal function for writing a batch of records to the Timestream database.
- `writeToTimestream(database_name, table_name, partionned_df)`: Function for writing the DataFrame to the Timestream database.

Appendix B

Source Codes

Appendix B.A Ingestion, Processing & Storing Pipeline Source Code

```python
1  import findspark
2
3  findspark.init()  # Initializing Spark
4
5  from pyspark.sql import SparkSession
6
7  import datetime as dt
8  import time
9
10 from lib.collecting import fetch_sensors_data
11 from lib.processing import computeAQI
12 from lib.storing import keepOnlyUpdatedRows, writeToTimestream
13
14 if __name__ == "__main__":
15     # Define the Timestream database and table names
16     DATABASE_NAME = "iot_project"
17     TABLE_NAME = "iot_table"
18
19     # Initializing Spark Session
20     sparkSession = (
21         SparkSession.builder.appName("Cloud Computing Project")
22         .master("local[*]")
23         .config("spark.sql.inMemoryColumnarStorage.compressed", "true")
24         .config("spark.sql.inMemoryColumnarStorage.batchSize", "10000")
25         .config("spark.serializer", "org.apache.spark.serializer.KryoSerializer")
26         .config("spark.ui.enabled", "true")
27         .config("spark.io.compression.codec", "snappy")
28         .config("spark.rdd.compress", "true")
29         .getOrCreate()
30     )
31
32     while True:
33         try:
34             print(
35                 dt.datetime.now().strftime("%Y-%m-%d %H:%M:%S")
36                 + " Starting the pipeline..."
37             )
38             # Fetch the data from the sensors
39             iotDfRaw = fetch_sensors_data(sparkSession)
40
41             # Compute the AQI for each sensor
42             iotDfFormatted = computeAQI(iotDfRaw)
43
44             # Filter the data to keep only the updated rows
```

```
45            dataFiltered = keepOnlyUpdatedRows(
46                DATABASE_NAME, TABLE_NAME, iotDfFormatted
47            )
48
49            # Write the data to Timestream
50            print(
51                dt.datetime.now().strftime("%Y-%m-%d %H:%M:%S")
52                + " 4. Writing the data to Timestream..."
53            )
54            dataFiltered.foreachPartition(
55                lambda partition: writeToTimestream(
56                    DATABASE_NAME, TABLE_NAME, partition
57                )
58            )
59            print(
60                dt.datetime.now().strftime("%Y-%m-%d %H:%M:%S")
61                + " Done writing the data to Timestream.\n"
62            )
63
64            # Sleep for 10 seconds
65            print(
66                dt.datetime.now().strftime("%Y-%m-%d %H:%M:%S")
67                + " Done with the pipeline. Waiting for 2 minutes.\n"
68            )
69            time.sleep(10)
70        except Exception as e:
71            print(f"Exception: {e}")
```

Appendix B.B   Data Collecting Source Code

```python
1  # collecting.py
2  # The first step of the pipeline
3
4  from requests import Session
5  import datetime as dt
6
7
8  def fetch_sensors_data(sparkSession):
9      """
10     Fetches the latest data from the sensors and returns it as a Spark DataFrame
11
12     Args:
13         sparkSession (SparkSession): The SparkSession instance
14
15     Returns:
16         df (DataFrame): The DataFrame containing the last data from the sensors
17     """
18
19     # Fetches the latest data from the data.sensor.community API
20     url = "https://data.sensor.community/static/v2/data.json"
21     # Use a session to avoid creating a new connection for each request
22     session = Session()
23     try:
24         print(
25             dt.datetime.now().strftime("%Y-%m-%d %H:%M:%S")
26             + " 1. Fetching the latest data..."
27         )
28         response = session.get(url)
29         # If the response was successful, no Exception will be raised
30         if response.status_code == 200 and response.content:
31             # Convert the response to a Spark DataFrame
32             df = sparkSession.read.option("multiline", "true").json(
33                 sparkSession.sparkContext.parallelize([response.text])
34             )
35             print(
36                 dt.datetime.now().strftime("%Y-%m-%d %H:%M:%S")
37                 + " Done fetching the latest data.\n"
38             )
39             return df
40     except Exception as e:
41         print(f"Request failed with exception {e}")
42     finally:
43         session.close()
44     return None
```

Appendix B.C   Data Processing Source Code

```python
1  # collecting.py
2  # The second step of the pipeline
3
4  from pyspark.sql.types import FloatType, IntegerType
5  import pyspark.sql.functions as F
6  import datetime as dt
7
8
9  # Defining a UDF to compute the AQI value for PM2.5
10 @F.udf(returnType=IntegerType())
11 def get_aqi_value_p25(value):
12     """
13     Computes the AQI value for PM2.5
14
15     Args:
16         value (float): The value of PM2.5
17     Returns:
18         aqi (int): The AQI value
19     """
20
21     if value is None:
22         return None
23     if 0 <= value <= 11:
24         return 1
25     elif 12 <= value <= 23:
26         return 2
27     elif 24 <= value <= 35:
28         return 3
29     elif 36 <= value <= 41:
30         return 4
31     elif 42 <= value <= 47:
32         return 5
33     elif 48 <= value <= 53:
34         return 6
35     elif 54 <= value <= 58:
36         return 7
37     elif 59 <= value <= 64:
38         return 8
39     elif 65 <= value <= 70:
40         return 9
41     return 10
42
43
44 # Defining a UDF to compute the AQI value for PM10
45 @F.udf(returnType=IntegerType())
46 def get_aqi_value_p10(value):
47     """
48     Computes the AQI value for PM10
49
50     Args:
51         value (float): The value of PM10
52
53     Returns:
54         aqi (int): The AQI value
55     """
56
57     if value is None:
58         return None
59     if 0 <= value <= 16:
60         return 1
61     elif 17 <= value <= 33:
62         return 2
63     elif 34 <= value <= 50:
64         return 3
65     elif 51 <= value <= 58:
66         return 4
67     elif 59 <= value <= 66:
```

```
68          return 5
69      elif 67 <= value <= 75:
70          return 6
71      elif 76 <= value <= 83:
72          return 7
73      elif 84 <= value <= 91:
74          return 8
75      elif 92 <= value <= 99:
76          return 9
77      return 10
78
79
80  def computeAQI(df):
81      """
82      Computes the AQI for each particulate matter sensor
83
84      Args:
85          df (DataFrame): The DataFrame containing the data from the sensors
86
87      Returns:
88          df_grouped (DataFrame): The DataFrame containing the AQI for each sensor
89      """
90
91      print(dt.datetime.now().strftime("%Y-%m-%d %H:%M:%S") + " 2. Computing the AQI
        ...")
92      df_exploded = df.withColumn(
93          "sensordatavalue",
94          F.explode("sensordatavalues"),  # Explode the sensordatavalues column
95      ).withColumn(
96          "aqi",
97          F.when(
98              F.col("sensordatavalue.value_type") == "P1",
99              get_aqi_value_p25(
100                 F.col("sensordatavalue.value").cast(FloatType())
101             ),  # Cast the value to float and compute the AQI of PM2.5
102         ).when(
103             F.col("sensordatavalue.value_type") == "P2",
104             get_aqi_value_p10(
105                 F.col("sensordatavalue.value").cast(FloatType())
106             ),  # Cast the value to float and compute the AQI of PM10
107         ),
108     )
109     df_exploded.cache()  # Cache the DataFrame to avoid recomputing it
110     df_grouped = (
111         df_exploded.groupBy("sensor.id", "timestamp")  # Group by sensor and
        timestamp
112         .agg(
113             F.first("id").alias("id"),
114             F.first("location").alias("location"),
115             F.first("sensor").alias("sensor"),
116             F.max("aqi").alias("aqi"),  # Compute the maximum AQI between PM2.5 and
         PM10
117             F.collect_list("sensordatavalue").alias("sensordatavalues"),
118         )  # Aggregate the AQI and the sensordatavalues
119         .selectExpr(
120             "sensor.id as sensor_id",
121             "sensor.pin as sensor_pin",
122             "sensor.sensor_type.id as sensor_type_id",
123             "sensor.sensor_type.manufacturer as sensor_type_manufacturer",
124             "sensor.sensor_type.name as sensor_type_name",
125             "location.country as country",
126             "location.latitude as latitude",
127             "location.longitude as longitude",
128             "location.altitude as altitude",
129             "location.id as location_id",
130             "aqi",
131             "sensordatavalues",
132             "timestamp",
133         )  # Select the columns to keep
134     )
```

29

```
135    df_exploded.unpersist()  # Unpersist the DataFrame to free memory
136    print(
137        dt.datetime.now().strftime("%Y-%m-%d %H:%M:%S") + " Done computing the AQI
       .\n"
138    )
139    return df_grouped
```

Appendix B.D   Data Storing Source Code

```python
1  # storing.py
2  # The last step of the pipeline
3
4  from pyspark.sql.types import BooleanType
5  import pyspark.sql.functions as F
6  from pyspark.sql import Row
7  from botocore.config import Config
8  import boto3
9  import time
10 import datetime as dt
11
12
13 def keepOnlyUpdatedRows(database_name, table_name, df):
14     """
15     Verifies if the data is already stored in Timestream and keeps only the updated
       values
16
17     Args:
18         database_name (string): The name of the database
19         table_name (string): The name of the table
20         df (DataFrame): The DataFrame containing the data to be stored
21
22     Returns:
23         df_updated (DataFrame): The DataFrame containing only the updated rows
24     """
25
26     print(
27         dt.datetime.now().strftime("%Y-%m-%d %H:%M:%S")
28         + " 3. Filtering the data to keep only the updated rows..."
29     )
30     query = """
31         SELECT sensor_id, MAX(time) as last_timestamp
32         FROM {}.{}
33         GROUP BY sensor_id
34     """.format(
35         database_name, table_name
36     )
37
38     # Initialize the boto3 client
39     session = boto3.Session()  # Create a boto3 session
40     query_client = session.client(
41         "timestream-query", config=Config(region_name="us-east-1")
42     )  # Create a boto3 client
43     paginator = query_client.get_paginator("query")  # Create a paginator
44
45     # Get the last timestamp for each sensor
46     last_timestamps = (
47         {}
48     )  # Initialize a dictionary to store the last timestamp for each sensor
49     response_iterator = paginator.paginate(QueryString=query)  # Paginate the query
50     for response in response_iterator:
51         for row in response["Rows"]:
52             sensor_id = row["Data"][0]["ScalarValue"]
53             last_timestamps[sensor_id] = row["Data"][1]["ScalarValue"]
54
55     # If there is no data in Timestream, return the DataFrame as is
56     if len(last_timestamps) == 0:
57         print("No data in Timestream")
58         return df
59
60     # Define an UDF to check if the row is updated
61     @F.udf(returnType=BooleanType())
62     def isUpdated(sensor_id, timestamp):
63         """
64         Checks if the row is updated
65
66         Args:
```

31

```python
 67              sensor_id (string): The sensor ID
 68              timestamp (string): The timestamp of the row
 69
 70          Returns:
 71              isUpdated (boolean): True if the row is updated, False otherwise
 72          """
 73
 74          if str(sensor_id) not in last_timestamps:
 75              return True
 76          current_timestamp = dt.datetime.strptime(timestamp, "%Y-%m-%d %H:%M:%S")
 77          last_timestamp_micro = last_timestamps[str(sensor_id)][
 78              :26
 79          ]  # Keep only up to microseconds
 80          last_sensor_timestamp = dt.datetime.strptime(
 81              last_timestamp_micro, "%Y-%m-%d %H:%M:%S.%f"
 82          )
 83          return (
 84              current_timestamp > last_sensor_timestamp
 85          )  # Return True if the row is updated
 86
 87      df_updated = df.filter(
 88          isUpdated("sensor_id", "timestamp")
 89      )  # Filter the DataFrame to keep only the updated rows
 90      print(
 91          dt.datetime.now().strftime("%Y-%m-%d %H:%M:%S")
 92          + " Done filtering the data to keep only the updated rows.\n"
 93      )
 94      return df_updated
 95
 96
 97  def _print_rejected_records_exceptions(err):
 98      """
 99      Prints the rejected records exceptions
100
101      Args:
102          err (RejectedRecordsException): The RejectedRecordsException
103      """
104
105      print("RejectedRecords: ", err)
106      for rr in err.response["RejectedRecords"]:
107          print("Rejected Index " + str(rr["RecordIndex"]) + ": " + rr["Reason"])
108          if "ExistingVersion" in rr:
109              print("Rejected record existing version: ", rr["ExistingVersion"])
110
111
112  def write_records(database_name, table_name, client, records):
113      """
114      Helper function to write records to Timestream
115
116      Args:
117          database_name (string): The name of the database
118          table_name (string): The name of the table
119          client (TimestreamWriteClient): The TimestreamWriteClient
120          records (list): The list of records to write
121      """
122      try:
123          result = client.write_records(
124              DatabaseName=database_name,
125              TableName=table_name,
126              CommonAttributes={},
127              Records=records,
128          )
129          print(
130              "WriteRecords Status: [%s]" % result["ResponseMetadata"]["
131      HTTPStatusCode"]
132          )
133      except client.exceptions.RejectedRecordsException as err:
134          _print_rejected_records_exceptions(err)
135      except Exception as err:
136          print("Error:", err)
```

```
136
137
138 def writeToTimestream(database_name, table_name, partionned_df):
139     """
140     Writes the data to Timestream
141
142     Args:
143         database_name (string): The name of the database
144         table_name (string): The name of the table
145         partionned_df (DataFrame): The DataFrame containing the data to be stored
146     """
147
148     # Initialize the boto3 client for each partition
149     session = boto3.Session()
150     write_client = session.client(
151         "timestream-write",
152         config=Config(
153             read_timeout=20, max_pool_connections=5000, retries={"max_attempts":
     10}
154         ),
155     )
156
157     # Create a list of records
158     records = []
159     for row in partionned_df:
160         try:
161             # Skip rows that are not of type Row
162             if not isinstance(row, Row):
163                 continue
164
165             # Convert timestamp to Unix epoch time in milliseconds
166             timestamp_datetime = dt.datetime.strptime(
167                 row.timestamp, "%Y-%m-%d %H:%M:%S"
168             )
169             row_timestamp = str(int(timestamp_datetime.timestamp() * 1000))
170
171             # altitude
172             altitude = row.altitude if row.altitude != "" else 0
173
174             # Create dimensions list
175             dimensions = [
176                 {"Name": "country", "Value": str(row.country)},
177                 {"Name": "latitude", "Value": str(row.latitude)},
178                 {"Name": "longitude", "Value": str(row.longitude)},
179                 {"Name": "altitude", "Value": str(altitude)},
180                 {"Name": "location_id", "Value": str(row.location_id)},
181                 {"Name": "sensor_id", "Value": str(row.sensor_id)},
182                 {"Name": "sensor_pin", "Value": str(row.sensor_pin)},
183                 {
184                     "Name": "sensor_type_manufacturer",
185                     "Value": str(row.sensor_type_manufacturer),
186                 },
187                 {"Name": "sensor_type_name", "Value": str(row.sensor_type_name)},
188                 {"Name": "sensor_type_id", "Value": str(row.sensor_type_id)},
189             ]
190
191             # Create a record for each measurement
192             measuresValues = []
193             for measure in row.sensordatavalues:
194                 measureValue = {
195                     "Name": measure.value_type,
196                     "Value": str(measure.value),
197                     "Type": "DOUBLE",
198                 }
199                 measuresValues.append(measureValue)
200
201                 if measure.value_type == "P2" and row.aqi is not None:
202                     aqi_measureValue = {
203                         "Name": "aqi",
204                         "Value": str(row.aqi),
```

```
205                        "Type": "BIGINT",
206                    }
207                    measuresValues.append(aqi_measureValue)
208
209            # Create a record for each sensor
210            record = {
211                "Dimensions": dimensions,
212                "Time": row_timestamp,
213                "TimeUnit": "MILLISECONDS",
214                "MeasureName": "air_quality",
215                "MeasureValueType": "MULTI",
216                "MeasureValues": measuresValues,
217            }
218            records.append(record)
219
220            # Write records to Timestream if there are 98 records
221            if len(records) >= 98:
222                write_records(
223                    database_name, table_name, write_client, records
224                )  # Write records to Timestream
225                records = []  # Reset the records list
226                time.sleep(1)  # Sleep for 1 second
227
228        except Exception as e:
229            print(f"Error processing row: {row}")
230            print(f"Exception: {e}")
231
232    # Write records to Timestream if there are any remaining records
233    if len(records) > 100:
234        while len(records) > 100:
235            write_records(
236                database_name, table_name, write_client, records[:99]
237            )  # Write records to Timestream
238            records = records[99:]  # Keep the remaining records
239            time.sleep(1)  # Sleep for 1 second
240    elif len(records) > 0:
241        write_records(database_name, table_name, write_client, records)
```

Appendix B.E   Scripts & Services Source Codes

B.E.1   Scripts

Script used by the `get_iam_credentials` service to retrieve the IAM credentials from the metadata server.

```bash
#!/bin/bash

# Get the authentication token from the EC2 metadata service
TOKEN=$(curl -X PUT "http://169.254.169.254/latest/api/token" -H "X-aws-ec2-
    metadata-token-ttl-seconds: 21600" -s)

# Name of the IAM role to assume
ROLE_NAME="LabRole"

# Get temporary credentials using the IAM role
IAM_ROLE_CREDENTIALS=$(curl -H "X-aws-ec2-metadata-token: $TOKEN" -s http
    ://169.254.169.254/latest/meta-data/iam/security-credentials/$ROLE_NAME)

# Extract the credentials and session token
AWS_ACCESS_KEY_ID=$(echo $IAM_ROLE_CREDENTIALS | jq -r .AccessKeyId)
AWS_SECRET_ACCESS_KEY=$(echo $IAM_ROLE_CREDENTIALS | jq -r .SecretAccessKey)
AWS_SESSION_TOKEN=$(echo $IAM_ROLE_CREDENTIALS | jq -r .Token)
AWS_DEFAULT_REGION="us-east-1"

# Export the credentials and session token
export AWS_ACCESS_KEY_ID
export AWS_SECRET_ACCESS_KEY
export AWS_SESSION_TOKEN
export AWS_DEFAULT_REGION
```

Script used by the `spark_python_job` service to run the Python Spark job.

```bash
#!/bin/bash

# Run the spark job in the background and log output to output.log file
nohup python3 /home/ubuntu/iot_project/ingestion_iot.py >/home/ubuntu/iot_project/
    output.log 2>&1 &
```

B.E.2   Services

B.E.2.1   Get IAM Credentials Service

Service used by the Ubuntu EC2 instance to retrieve the IAM credentials from the metadata server.

```
[Unit]
Description=Script to setup AWS cli thanks to the attached IAM Profile

[Service]
ExecStart=/usr/local/bin/get_iam_credentials.sh

[Install]
WantedBy=multi-user.target
```

B.E.2.2   Spark Python Job Service

Service used by the Ubuntu EC2 instance to run the Python Spark job (Data Collecting, Processing and Storing).

```
[Unit]
Description=Script to run the ingestion python script

[Service]
ExecStart=/usr/local/bin/start_spark_job.sh

[Install]
WantedBy=multi-user.target
```

B.E.2.3   Grafana Server Service

Service used by the Linux EC2 instances to run the Grafana server (Data Distributing).

```
[Unit]
Description=Grafana instance
Documentation=http://docs.grafana.org
Wants=network-online.target
After=network-online.target
After=postgresql.service mariadb.service mysqld.service influxdb.service

[Service]
EnvironmentFile=/etc/sysconfig/grafana-server
User=grafana
Group=grafana
Type=notify
Restart=on-failure
WorkingDirectory=/usr/share/grafana
RuntimeDirectory=grafana
RuntimeDirectoryMode=0750
ExecStart=/usr/share/grafana/bin/grafana server
    \
                          --config=${CONF_FILE}
    \
                          --pidfile=${PID_FILE_DIR}/grafana-server.pid
    \
                          --packaging=rpm
    \
                          cfg:default.paths.logs=${LOG_DIR}
    \
                          cfg:default.paths.data=${DATA_DIR}
    \
                          cfg:default.paths.plugins=${PLUGINS_DIR}
    \
                          cfg:default.paths.provisioning=${PROVISIONING_CFG_DIR}
LimitNOFILE=10000
TimeoutStopSec=20
CapabilityBoundingSet=
DeviceAllow=
LockPersonality=true
MemoryDenyWriteExecute=false
NoNewPrivileges=true
PrivateDevices=true
PrivateTmp=true
ProtectClock=true
ProtectControlGroups=true
ProtectHome=true
ProtectHostname=true
ProtectKernelLogs=true
ProtectKernelModules=true
ProtectKernelTunables=true
ProtectProc=invisible
ProtectSystem=full
RemoveIPC=true
RestrictAddressFamilies=AF_INET AF_INET6 AF_UNIX
RestrictNamespaces=true
RestrictRealtime=true
RestrictSUIDSGID=true
SystemCallArchitectures=native
UMask=0027

[Install]
WantedBy=multi-user.target
```

Appendix B.F   Load Test Source Codes

B.F.1   Artillery Load Test Configuration File

```yaml
config:
  # This is a test server run by team Artillery
  # It's designed to be highly scalable
  target: "http://grafana-1777174802.us-east-1.elb.amazonaws.com"
  phases:
    - duration: 50
      arrivalRate: 1
      name: "Stage 1"
    - pause: 30
    - duration: 50
      arrivalRate: 1
      name: "Stage 2"
    - pause: 60
    - duration: 60
      arrivalRate: 1
      name: "Stage 3"
    - pause: 30
    - duration: 60
      arrivalRate: 1
      name: "Stage 4"
    - pause: 60
    - duration: 50
      arrivalRate: 1
      name: "Stage 5"
    - pause: 60
    - duration: 50
      arrivalRate: 1
      name: "Stage 6"

  # Load & configure a couple of useful plugins
  # https://docs.art/reference/extensions
  plugins:
    ensure: {}
    apdex: {}
    metrics-by-endpoint: {}
  apdex:
    threshold: 100
  ensure:
    thresholds:
      - http.response_time.p99: 100
      - http.response_time.p95: 75
scenarios:
  - flow:
      - loop:
          - get:
              url: "/dashboards"
          - get:
              url: "/d/f8742187-f440-4ee8-96cc-bad5af8edef1/air-quality-monitoring?
    orgId=1&var-measure_name=aqi&var-location_id=64294"
        count: 100
```

B.F.2   Instances Monitoring Script

```python
import boto3
import csv
import time
from datetime import datetime, timedelta

# AWS Config
ec2_client = boto3.client("ec2")  # EC2 Client
autoscaling_client = boto3.client("autoscaling")  # Auto Scaling Group Client
cloudwatch_client = boto3.client("cloudwatch")  # CloudWatch Client
asg_name = "grafana-v2"  # Auto Scaling Group Name

# Store the previous states of the instances
previous_states = {}


def get_instance_states(ec2_client, instance_ids):
    """
    Retrives the state of the instances

    Args:
        ec2_client (boto3.client): EC2 Client
        instance_ids (list): List of instances IDs

    Returns:
        states (dict): Dictionary of instances IDs and their states
    """
    states = {}
    response = ec2_client.describe_instances(InstanceIds=instance_ids)
    for reservation in response["Reservations"]:
        for instance in reservation["Instances"]:
            states[instance["InstanceId"]] = instance["State"]["Name"]
    return states


def get_instance_ids(asg_client, asg_name):
    """
    Retrives the instance IDs of the instances in the Auto Scaling Group

    Args:
        asg_client (boto3.client): Auto Scaling Group Client
        asg_name (str): Auto Scaling Group Name

    Returns:
        instance_ids (list): List of instances IDs
    """
    asg = asg_client.describe_auto_scaling_groups(AutoScalingGroupNames=[asg_name])
    return [
        instance["InstanceId"] for instance in asg["AutoScalingGroups"][0]["
    Instances"]
    ]


def get_ram_usage(cloudwatch_client, instance_id):
    """
    Retrives the average RAM usage of the instance

    Args:
        cloudwatch_client (boto3.client): CloudWatch Client
        instance_id (str): Instance ID

    Returns:
        ram_usage (float): Average RAM usage
    """
    end_time = datetime.utcnow()
    start_time = end_time - timedelta(minutes=3)  # Period of 3 minutes
    metric_data = cloudwatch_client.get_metric_statistics(
        Namespace="CWAgent",
```

```
67              MetricName="mem_used_percent",
68              Dimensions=[{"Name": "InstanceId", "Value": instance_id}],
69              StartTime=start_time,
70              EndTime=end_time,
71              Period=180,
72              Statistics=["Average"],
73          )
74          if metric_data["Datapoints"]:
75              return metric_data["Datapoints"][0]["Average"]
76          return None
77
78
79  def get_cpu_usage(cloudwatch_client, instance_id):
80          """
81          Retrives the average CPU usage of the instance
82
83          Args:
84              cloudwatch_client (boto3.client): CloudWatch Client
85              instance_id (str): Instance ID
86
87          Returns:
88              cpu_usage (float): Average CPU usage
89          """
90          end_time = datetime.utcnow()
91          start_time = end_time - timedelta(minutes=3)  # Period of 3 minutes
92          metric_data = cloudwatch_client.get_metric_statistics(
93              Namespace="CWAgent",
94              MetricName="cpu_usage_user",
95              Dimensions=[{"Name": "InstanceId", "Value": instance_id}],
96              StartTime=start_time,
97              EndTime=end_time,
98              Period=180,
99              Statistics=["Average"],
100         )
101         if metric_data["Datapoints"]:
102             return metric_data["Datapoints"][0]["Average"]
103         return None
104
105
106 # Main loop
107 while True:
108     # Gets the instances IDs and their states in the Auto Scaling Group
109     instance_ids = get_instance_ids(
110         autoscaling_client, asg_name
111     )  # Gets the instances IDs
112     current_states = get_instance_states(
113         ec2_client, instance_ids
114     )  # Gets the instances states
115     # Write the metrics to the CSV file
116     with open("test/metrics.csv", "a", newline="") as file:
117         writer = csv.writer(file)
118         for instance_id in instance_ids:
119             print("Instance ID: ", instance_id)
120             ram_usage = get_ram_usage(
121                 cloudwatch_client, instance_id
122             )  # Gets the RAM usage
123             print("RAM usage: ", ram_usage)
124             cpu_usage = get_cpu_usage(
125                 cloudwatch_client, instance_id
126             )  # Gets the CPU usage
127             print("CPU usage: ", cpu_usage)
128             # Check if the state of the instance has changed
129             state_changed = (
130                 instance_id in previous_states
131                 and previous_states[instance_id] != current_states[instance_id]
132             )
133             # Update the previous state
134             previous_states[instance_id] = current_states[instance_id]
135             print("Current state: ", current_states[instance_id])
136             # Handle pending state
```

40

```
137                if instance_id not in previous_states:
138                    current_states[instance_id] = "pending"
139                    ram_usage = None
140                    cpu_usage = None
141                # Write the metrics to the CSV file
142                if (
143                    current_states[instance_id] == "pending"
144                    or state_changed
145                    or (
146                        current_states[instance_id] == "running"
147                        and ram_usage is not None
148                        and cpu_usage is not None
149                    )
150                ):
151                    writer.writerow(
152                        [
153                            datetime.now().strftime("%Y-%m-%d %H:%M:%S"),
154                            instance_id,
155                            current_states[instance_id],
156                            ram_usage,
157                            cpu_usage,
158                        ]
159                    )  # Write the metrics to the CSV file
160                    file.flush()  # Flush the buffer
161        # Wait 1 second
162        time.sleep(1)
```