Analysis and Performance evaluation of Terapixel rendering in (Super)Cloud Computing Data

1.Introduction

The purpose of this study is to analyze the IoT environmental data collected by Newcastle Urban Observatory for the city of Newcastle Upon Tyne. The main objective is to evaluate and explore performance timings of render application and GPU card and in each task, the details of which part of the image was being rendered. Terapixel images are rendered using a scalable cloud-based visualization architecture. The Terapixel image, once created, allows for interactive exploration of the city and its data at a wide range of sensing scales ranging from the entire city to a separate desk in a room, and is accessible via a broad range of thin client devices. CRISP-DM (Cross- Industry Standard Process for Data Mining) model will be used in this data analysis. This project will be entirely dedicated to the EDA (Exploratory Data Analysis) process.

2. Data Exploration Planning and Analysis Requirement:

Tera scope terapixel data is subjected to preliminary analysis to better understand the data and provide information to business stakeholders. Based on the data set, this analysis of GPU cards and XY coordinates will aid in rendering Terapixel images in an efficient and effective manner.

2.1 Data Exploration Planning:

- Assessing the event types that dominate task runtimes.
- Examining the correlation between GPU temperature and performance.
- Analyzing the connection between increased power draw and render time.
- Identifying GPU cards (based on their serial numbers) whose performance differs to other cards.

- Exploring the effectiveness of the task scheduling process.

2.2 Analysis Plan and Requirement:

The analysis strategy for this report is to investigate the three data sets generated while different virtual machines render 3D images on 1024 GPU nodes during a run. This run is divided into three jobs to render the data visualization output, which show performance timing of the render application, performance of the GPU card, and details of which part of the image was rendered in each task. The requisite is to understand the data, then clean and preprocess the data before performing exploratory data analysis. This analysis will aid in the betterment of the rendering process.

```
# Installing pandasql

!pip install pandasql
```

```
Requirement already satisfied: pandasql in
/Users/gowtham/opt/anaconda3/lib/python3.9/site-packages (0.7.3)
Requirement already satisfied: pandas in
/Users/gowtham/opt/anaconda3/lib/python3.9/site-packages (from
pandasql) (1.4.4)
Requirement already satisfied: numpy in
/Users/gowtham/opt/anaconda3/lib/python3.9/site-packages (from
pandasql) (1.21.5)
Requirement already satisfied: sqlalchemy in
/Users/gowtham/opt/anaconda3/lib/python3.9/site-packages (from
pandasql) (1.4.39)
Requirement already satisfied: python-dateutil>=2.8.1 in
/Users/gowtham/opt/anaconda3/lib/python3.9/site-packages (from pandas-
>pandasql) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/Users/gowtham/opt/anaconda3/lib/python3.9/site-packages (from pandas-
>pandasql) (2022.1)
Requirement already satisfied: greenlet!=0.4.17 in
/Users/gowtham/opt/anaconda3/lib/python3.9/site-packages (from
sqlalchemy->pandasql) (1.1.1)
Requirement already satisfied: six>=1.5 in
/Users/gowtham/opt/anaconda3/lib/python3.9/site-packages (from python-
dateutil>=2.8.1->pandas->pandasql) (1.16.0)
```

```
# Importing all the required libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
import datetime
from pandasql import sqldf
from datetime import datetime
from pandas import Series
sqlfn = lambda q: sqldf(q, globals())
```

3. Data Understanding:

This analysis utilizes data from a dataset generated during a run with 1024 nodes. This analysis will be performed using three csv files application-checkpoints.csv, gpu.csv, task-x-y.csv. Below all the three csv files are read:

```
# Reading all the three CSV files

appcheckpoint=pd.read_csv("application-checkpoints.csv")
gpu=pd.read_csv("gpu.csv")
xy=pd.read_csv("task-x-y.csv")
```

Table **application-checkpoints.csv**:

```
# Displaying first three rows of appcheckpoint table

appcheckpoint.head(3)
```

```
                  timestamp                                  hostname  \
0  2018-11-08T07:41:55.921Z  0d56a730076643d585f77e00d2d8521a00000N
1  2018-11-08T07:42:29.842Z  0d56a730076643d585f77e00d2d8521a00000N
2  2018-11-08T07:42:29.845Z  0d56a730076643d585f77e00d2d8521a00000N

       eventName eventType
jobId  \
0         Tiling      STOP  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
1  Saving Config     START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
2  Saving Config      STOP  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705

                                 taskId
0  b47f0263-ba1c-48a7-8d29-4bf021b72043
1  20fb9fcf-a927-4a4b-a64c-70258b66b42d
2  20fb9fcf-a927-4a4b-a64c-70258b66b42d
```

```
# Displaying data types of columns in appcheckpoint table

appcheckpoint.dtypes
```

```
timestamp    object
hostname     object
eventName    object
eventType    object
jobId        object
taskId       object
dtype: object
```

Table **gpu.csv**

```
# Displaying first three rows of GPU table

gpu.head(3)
```

```
                  timestamp                                  hostname  \
0  2018-11-08T08:27:10.314Z  8b6a0eebc87b4cb2b0539e81075191b900001C
1  2018-11-08T08:27:10.192Z  d8241877cd994572b46c861e5d144c85000000
2  2018-11-08T08:27:10.842Z  db871cd77a544e13bc791a64a0c8ed50000006

      gpuSerial                                    gpuUUID
powerDrawWatt  \
0  323217055910  GPU-1d1602dc-f615-a7c7-ab53-fb4a7a479534
```

```
131.55
1  323617020295  GPU-04a2dea7-f4f1-12d0-b94d-996446746e6f
117.03
2  323217056562  GPU-f4597939-a0b4-e78a-2436-12dbab9a350f
121.64
```

```
   gpuTempC  gpuUtilPerc  gpuMemUtilPerc
0        48           92              53
1        40           92              48
2        45           91              44
```

```
# Displaying data types of columns in gpu table

gpu.dtypes
```

```
timestamp          object
hostname           object
gpuSerial           int64
gpuUUID            object
powerDrawWatt     float64
gpuTempC            int64
gpuUtilPerc         int64
gpuMemUtilPerc      int64
dtype: object
```

Table **task-x-y.csv**

```
# Displaying first three rows of task-x-y table

xy.head(3)
```

```
                                  taskId  \
0  00004e77-304c-4fbd-88a1-1346ef947567
1  0002afb5-d05e-4da9-bd53-7b6dc19ea6d4
2  0003c380-4db9-49fb-8e1c-6f8ae466ad85

                                              jobId    x    y  level
0  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  116  178     12
1  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  142  190     12
2  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  142   86     12
```

```
# Displaying data types of columns in xy table

xy.dtypes
```

```
taskId    object
jobId     object
x          int64
y          int64
level      int64
dtype: object
```

```
# Displaying the number of rows and columns in all the three tables
print("Number of rows and columns in appcheckpoint table :
",appcheckpoint.shape)
print("Number of rows and columns in gpu table : ",gpu.shape)
print("Number of rows and columns in xy table : ",xy.shape)
```

```
Number of rows and columns in appcheckpoint table :  (660400, 6)
Number of rows and columns in gpu table :  (1543681, 8)
Number of rows and columns in xy table :  (65793, 5)
```

4. Data Preparation:

After Data Understanding, the data is cleaned and preprocessed in preparation for further data analysis. There are some redundant (duplicate) data values in this data set that must be cleaned before further processing.

Count of all the duplicates rows in all the three tables are displayed

```
# Count of duplicate records in appcheckpoint table

appcheckpoint.duplicated().sum()
```

```
2470
```

```
# Count of duplicate records in gpu table

gpu.duplicated().sum()
```

```
9
```

```
# Count of duplicate records in xy table

xy.duplicated().sum()
```

```
0
```

Duplicate records from appcheckpoint table is dropped

```
# Removing duplicate records from appcheckpoint table

appcheck = appcheckpoint.drop_duplicates()
appcheck
```

```
                        timestamp
hostname  \
0       2018-11-08T07:41:55.921Z
0d56a730076643d585f77e00d2d8521a00000N
1       2018-11-08T07:42:29.842Z
0d56a730076643d585f77e00d2d8521a00000N
2       2018-11-08T07:42:29.845Z
0d56a730076643d585f77e00d2d8521a00000N
3       2018-11-08T07:42:29.845Z
```

```
0d56a730076643d585f77e00d2d8521a00000N
4       2018-11-08T07:43:13.957Z
0d56a730076643d585f77e00d2d8521a00000N
...                          ...                                        .
..
660395  2018-11-08T08:30:10.296Z
0745914f4de046078517041d70b22fe700000I
660396  2018-11-08T08:30:10.325Z
0745914f4de046078517041d70b22fe700000I
660397  2018-11-08T08:30:14.081Z
a77ef58b13ad4c01b769dac8409af3f800000H
660398  2018-11-08T08:30:14.127Z
a77ef58b13ad4c01b769dac8409af3f800000H
660399  2018-11-08T08:30:12.159Z
0d56a730076643d585f77e00d2d8521a000009

            eventName eventType  \
0              Tiling      STOP
1       Saving Config     START
2       Saving Config      STOP
3              Render     START
4         TotalRender      STOP
...                ...       ...
660395         Tiling      STOP
660396       Uploading      STOP
660397         Tiling      STOP
660398    TotalRender      STOP
660399      Uploading      STOP

                                                      jobId  \
0       1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705
1       1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705
2       1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705
3       1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705
4       1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705
...                                                   ...
660395  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705
660396  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705
660397  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705
660398  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705
660399  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705

                                       taskId
0       b47f0263-ba1c-48a7-8d29-4bf021b72043
1       20fb9fcf-a927-4a4b-a64c-70258b66b42d
2       20fb9fcf-a927-4a4b-a64c-70258b66b42d
3       20fb9fcf-a927-4a4b-a64c-70258b66b42d
4       20fb9fcf-a927-4a4b-a64c-70258b66b42d
...                                      ...
660395  8261c0ff-03d6-48b3-a50f-da41cb3291fd
```

```
660396  8261c0ff-03d6-48b3-a50f-da41cb3291fd
660397  ce97e3e9-494a-43a7-aa85-edd2db4cf099
660398  ce97e3e9-494a-43a7-aa85-edd2db4cf099
660399  bbf4ff73-c754-4111-95cd-a339c87a2b17

[657930 rows x 6 columns]
```

Duplicate records from gpu table is dropped

```
# Removing duplicate records from gpu table

gpufinal = gpu.drop_duplicates()
gpufinal
```

```
                        timestamp
hostname  \
0        2018-11-08T08:27:10.314Z
8b6a0eebc87b4cb2b0539e81075191b900001C
1        2018-11-08T08:27:10.192Z
d8241877cd994572b46c861e5d144c85000000
2        2018-11-08T08:27:10.842Z
db871cd77a544e13bc791a64a0c8ed50000006
3        2018-11-08T08:27:10.424Z
b9a1fa7ae2f74eb68f25f607980f97d7000010
4        2018-11-08T08:27:10.937Z
db871cd77a544e13bc791a64a0c8ed50000003
...                           ...
...
1543676  2018-11-08T08:31:18.873Z
0d56a730076643d585f77e00d2d8521a00000N
1543677  2018-11-08T08:31:24.933Z
0d56a730076643d585f77e00d2d8521a00000N
1543678  2018-11-08T08:31:32.998Z
0d56a730076643d585f77e00d2d8521a00000N
1543679  2018-11-08T08:31:39.057Z
0d56a730076643d585f77e00d2d8521a00000N
1543680  2018-11-08T08:31:45.108Z
0d56a730076643d585f77e00d2d8521a00000N

            gpuSerial                                    gpuUUID  \
0        323217055910  GPU-1d1602dc-f615-a7c7-ab53-fb4a7a479534
1        323617020295  GPU-04a2dea7-f4f1-12d0-b94d-996446746e6f
2        323217056562  GPU-f4597939-a0b4-e78a-2436-12dbab9a350f
3        325217085931  GPU-ad773c69-c386-a4be-b214-1ea4fc6045df
4        323217056464  GPU-2d4eed64-4ca8-f12c-24bc-28f036493ea2
...               ...                                       ...
1543676  325217086221  GPU-1265fef9-aea4-4a5e-8a63-cc5af7b19f4f
1543677  325217086221  GPU-1265fef9-aea4-4a5e-8a63-cc5af7b19f4f
1543678  325217086221  GPU-1265fef9-aea4-4a5e-8a63-cc5af7b19f4f
1543679  325217086221  GPU-1265fef9-aea4-4a5e-8a63-cc5af7b19f4f
```

```
1543680  325217086221  GPU-1265fef9-aea4-4a5e-8a63-cc5af7b19f4f

         powerDrawWatt  gpuTempC  gpuUtilPerc  gpuMemUtilPerc
0               131.55        48           92              53
1               117.03        40           92              48
2               121.64        45           91              44
3                50.23        38           90              43
4               141.82        41           90              47
...                ...       ...          ...             ...
1543676          26.99        30            0               0
1543677          26.90        29            0               0
1543678          26.88        29            0               0
1543679          26.89        29            0               0
1543680          26.89        29            0               0

[1543672 rows x 8 columns]
```

Duplicate records from xy table is dropped

```
# Removing duplicate records from xy table

xyfinal = xy.drop_duplicates()
xyfinal
```

```
                                      taskId  \
0      00004e77-304c-4fbd-88a1-1346ef947567
1      0002afb5-d05e-4da9-bd53-7b6dc19ea6d4
2      0003c380-4db9-49fb-8e1c-6f8ae466ad85
3      000993b6-fc88-489d-a4ca-0a44fd800bd3
4      000b158b-0ba3-4dca-bf5b-1b3bd5c28207
...                                     ...
65788  fce56316-25a6-44b8-b0cc-d135bc84deea
65789  feb48593-c70e-49b0-b19c-a4e2a5d2d760
65790  feb580b7-e879-40f2-aa57-28f3872af561
65791  ff1758b0-0a39-4f72-be8e-8ead79d691a6
65792  ff17a467-9962-4f3d-8e5e-5957efc3e8ab

                                                 jobId    x    y
level
0      1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  116  178
12
1      1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  142  190
12
2      1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  142   86
12
3      1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  235   11
12
4      1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  171   53
12
...                                                 ...  ...  ...    ..
```

```
.
65788   1024-lvl8-5ad819e1-fbf2-42e0-8f16-a3baca825a63   15    2
8
65789   1024-lvl8-5ad819e1-fbf2-42e0-8f16-a3baca825a63    5   14
8
65790   1024-lvl8-5ad819e1-fbf2-42e0-8f16-a3baca825a63    3    6
8
65791   1024-lvl8-5ad819e1-fbf2-42e0-8f16-a3baca825a63    1    2
8
65792   1024-lvl8-5ad819e1-fbf2-42e0-8f16-a3baca825a63    7   12
8

[65793 rows x 5 columns]
```

```
# Change the datatype of a column
appcheck["timestamp"] = appcheck["timestamp"].apply(lambda x:
pd.Timestamp(x))

# Display the datatype of each column
appcheck.dtypes
```

```
timestamp    datetime64[ns, UTC]
hostname                  object
eventName                 object
eventType                 object
jobId                     object
taskId                    object
dtype: object
```

```
# Change the datatype
gpufinal["timestamp"] = gpufinal["timestamp"].apply(lambda x:
pd.Timestamp(x))
# Change the datatype
gpufinal["gpuSerial"] = gpufinal["gpuSerial"].apply(lambda x: str(x))

# Display the datatype of each column
gpufinal.dtypes
```

```
timestamp         datetime64[ns, UTC]
hostname                       object
gpuSerial                      object
gpuUUID                        object
powerDrawWatt                 float64
gpuTempC                        int64
gpuUtilPerc                     int64
gpuMemUtilPerc                  int64
dtype: object
```

```
# Create a new dataframe by filtering
appcheck_start = appcheck.loc[appcheck["eventType"] == "START"]
```

```
# Create a new dataframe by filtering
appcheck_stop = appcheck.loc[appcheck["eventType"] == "STOP"]

# Merge(Join) dataframes on multiple columns
appcheck_start_stop = pd.merge(appcheck_start, appcheck_stop,
how='left', on=['hostname','eventName','jobId','taskId'],
                         suffixes=('_Start_Time', '_Stop_Time'))

# # Display the first 3 rows
appcheck_start_stop.tail(4)
```

```
                   timestamp_Start_Time  \
328961 2018-11-08 08:30:11.174000+00:00
328962 2018-11-08 08:30:08.759000+00:00
328963 2018-11-08 08:30:09.642000+00:00
328964 2018-11-08 08:30:09.649000+00:00

                                        hostname  eventName  \
328961  b9a1fa7ae2f74eb68f25f607980f97d7000005  Uploading
328962  6139a35676de44d6b61ec247f0ed865700001D     Tiling
328963  0d56a730076643d585f77e00d2d8521a00000D  Uploading
328964  0d56a730076643d585f77e00d2d8521a00000D     Tiling

       eventType_Start_Time
jobId  \
328961                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
328962                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
328963                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
328964                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705

                                        taskId
timestamp_Stop_Time  \
328961  120e5f6f-67a7-4973-b431-026f1a68400c 2018-11-08
08:30:12.074000+00:00
328962  30caa975-249a-445d-a6c0-61fa38d4c4bf 2018-11-08
08:30:09.730000+00:00
328963  423b8511-cb2e-4aa4-bb5c-85ca4a2b7ac6 2018-11-08
08:30:10.614000+00:00
328964  423b8511-cb2e-4aa4-bb5c-85ca4a2b7ac6 2018-11-08
08:30:10.548000+00:00

       eventType_Stop_Time
328961                STOP
328962                STOP
328963                STOP
328964                STOP
```

```
# Create a new column from other two columns
appcheck_start_stop["Event_RenderTime"] =
(appcheck_start_stop["timestamp_Stop_Time"] -
appcheck_start_stop["timestamp_Start_Time"]).dt.total_seconds()

# Display datatype of each column
appcheck_start_stop.dtypes
```

```
timestamp_Start_Time    datetime64[ns, UTC]
hostname                             object
eventName                            object
eventType_Start_Time                 object
jobId                                object
taskId                               object
timestamp_Stop_Time     datetime64[ns, UTC]
eventType_Stop_Time                  object
Event_RenderTime                    float64
dtype: object
```

```
# Display first 2 rows
appcheck_start_stop.tail(3)
```

```
                   timestamp_Start_Time  \
328962 2018-11-08 08:30:08.759000+00:00
328963 2018-11-08 08:30:09.642000+00:00
328964 2018-11-08 08:30:09.649000+00:00

                                       hostname  eventName  \
328962  6139a35676de44d6b61ec247f0ed865700001D     Tiling
328963  0d56a730076643d585f77e00d2d8521a00000D  Uploading
328964  0d56a730076643d585f77e00d2d8521a00000D     Tiling

       eventType_Start_Time
jobId  \
328962                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
328963                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
328964                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705

                                       taskId
timestamp_Stop_Time  \
328962  30caa975-249a-445d-a6c0-61fa38d4c4bf 2018-11-08
08:30:09.730000+00:00
328963  423b8511-cb2e-4aa4-bb5c-85ca4a2b7ac6 2018-11-08
08:30:10.614000+00:00
328964  423b8511-cb2e-4aa4-bb5c-85ca4a2b7ac6 2018-11-08
08:30:10.548000+00:00
```

```
       eventType_Stop_Time  Event_RenderTime
328962                STOP             0.971
328963                STOP             0.972
328964                STOP             0.899

# Change the datatype
appcheck_start_stop["Event_RenderTime"] =
appcheck_start_stop["Event_RenderTime"].astype(str)

# Change the datatype
appcheck_start_stop["Event_RenderTime"] =
appcheck_start_stop["Event_RenderTime"].astype('float32')

# Display first 2 rows
appcheck_start_stop.tail(3)

                    timestamp_Start_Time  \
328962 2018-11-08 08:30:08.759000+00:00
328963 2018-11-08 08:30:09.642000+00:00
328964 2018-11-08 08:30:09.649000+00:00

                                      hostname  eventName  \
328962  6139a35676de44d6b61ec247f0ed865700001D     Tiling
328963  0d56a730076643d585f77e00d2d8521a00000D  Uploading
328964  0d56a730076643d585f77e00d2d8521a00000D     Tiling

       eventType_Start_Time
jobId  \
328962                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
328963                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
328964                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705

                                      taskId
timestamp_Stop_Time  \
328962  30caa975-249a-445d-a6c0-61fa38d4c4bf 2018-11-08
08:30:09.730000+00:00
328963  423b8511-cb2e-4aa4-bb5c-85ca4a2b7ac6 2018-11-08
08:30:10.614000+00:00
328964  423b8511-cb2e-4aa4-bb5c-85ca4a2b7ac6 2018-11-08
08:30:10.548000+00:00

       eventType_Stop_Time  Event_RenderTime
328962                STOP             0.971
328963                STOP             0.972
328964                STOP             0.899
```

```
# Sort the dataframe based on a column
appcheck_start_stop.sort_values(by=["hostname"], inplace=True)

# Display first 5 rows
appcheck_start_stop.tail(7)
```

```
                   timestamp_Start_Time  \
285814 2018-11-08 07:46:50.935000+00:00
300124 2018-11-08 08:21:20.994000+00:00
218933 2018-11-08 07:43:33.460000+00:00
218938 2018-11-08 07:43:30.381000+00:00
277668 2018-11-08 08:00:45.782000+00:00
194757 2018-11-08 08:19:59.217000+00:00
229631 2018-11-08 08:13:37.033000+00:00

                                       hostname  eventName  \
285814  e7adc42d28814e518e9601ac2329c51300001D  Uploading
300124  e7adc42d28814e518e9601ac2329c51300001D     Render
218933  e7adc42d28814e518e9601ac2329c51300001D     Render
218938  e7adc42d28814e518e9601ac2329c51300001D  Uploading
277668  e7adc42d28814e518e9601ac2329c51300001D  Uploading
194757  e7adc42d28814e518e9601ac2329c51300001D     Render
229631  e7adc42d28814e518e9601ac2329c51300001D  Uploading

       eventType_Start_Time
jobId  \
285814                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
300124                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
218933                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
218938                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
277668                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
194757                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
229631                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705

                                       taskId
timestamp_Stop_Time  \
285814  ad543e64-be07-4294-b562-c0588639d861 2018-11-08
07:46:52.016000+00:00
300124  ea7c0679-ff57-480f-a8b1-507c094b7c65 2018-11-08
08:21:59.023000+00:00
218933  de595141-d9c8-4e35-ac71-f14d1c9ebe80 2018-11-08
07:44:20.792000+00:00
218938  472afcae-6f17-43c1-8f1c-8df4116cfed7 2018-11-08
```

```
07:43:31.506000+00:00
277668  4001ba74-396f-4c68-80cb-165723760b6a 2018-11-08
08:00:46.780000+00:00
194757  4b2777ea-b877-498f-bace-43d867a86046 2018-11-08
08:20:33.780000+00:00
229631  69bfa379-618d-4d74-b9ad-ddb7d7765837 2018-11-08
08:13:38.079000+00:00
```

```
       eventType_Stop_Time  Event_RenderTime
285814                STOP          1.081000
300124                STOP         38.028999
218933                STOP         47.332001
218938                STOP          1.125000
277668                STOP          0.998000
194757                STOP         34.563000
229631                STOP          1.046000
```

```
# Filter the dataframe
host_PT = appcheck_start_stop.loc[appcheck_start_stop["eventName"] ==
"TotalRender"]

# Group the dataframe and average the other numerical columns
host_PT = host_PT.groupby(by=["hostname"], as_index=False).mean()

# Display the last 3 rows
host_PT.head(3)
```

```
                                  hostname  Event_RenderTime
0  04dc4e9647154250beeee51b866b0715000000         44.350327
1  04dc4e9647154250beeee51b866b0715000001         45.698051
2  04dc4e9647154250beeee51b866b0715000002         40.275421
```

```
# Dispaly all column names
gpufinal.columns
```

```
Index(['timestamp', 'hostname', 'gpuSerial', 'gpuUUID',
'powerDrawWatt',
       'gpuTempC', 'gpuUtilPerc', 'gpuMemUtilPerc'],
      dtype='object')
```

```
# Group the dataframe and average the other numerical columns
gpu_PF =
gpufinal[["hostname","gpuUUID","gpuSerial","powerDrawWatt","gpuTempC",
"gpuUtilPerc","gpuMemUtilPerc"]].groupby(by=["hostname","gpuUUID","gpu
Serial"], as_index=False).mean()

# Display the first 3 rows
gpu_PF.tail(5)
```

```
                                     hostname  \
1019  e7adc42d28814e518e9601ac2329c513000019
```

```
1020  e7adc42d28814e518e9601ac2329c51300001A
1021  e7adc42d28814e518e9601ac2329c51300001B
1022  e7adc42d28814e518e9601ac2329c51300001C
1023  e7adc42d28814e518e9601ac2329c51300001D

                                          gpuUUID     gpuSerial
powerDrawWatt  \
1019  GPU-53f2e984-36f3-a70f-0944-752868d6a833  320118119210
89.386562
1020  GPU-05e3f5b6-553b-1a37-bf7a-271c5b999a64  325117063265
82.943504
1021  GPU-8646ce3a-be99-02fa-a138-dafee7ea3cf2  325017048638
88.354997
1022  GPU-b0b09148-0762-390d-08d6-93c1a5ccd768  325117173230
88.411319
1023  GPU-0cee5a9f-749e-7780-791a-ff2b29590a38  320118119027
97.399313

       gpuTempC  gpuUtilPerc  gpuMemUtilPerc
1019  39.095270    64.512325       36.449034
1020  37.712858    61.762825       30.990007
1021  38.569046    63.919947       35.593062
1022  37.205863    64.930047       36.289141
1023  39.816000    64.793333       36.607333
```

```
# Merge (Join) two dataframes
TP = pd.merge(host_PT, gpu_PF, on="hostname")

# Display first 5 rows
TP.head(3)
```

```
                                  hostname  Event_RenderTime  \
0  04dc4e9647154250beeee51b866b0715000000         44.350327
1  04dc4e9647154250beeee51b866b0715000001         45.698051
2  04dc4e9647154250beeee51b866b0715000002         40.275421

                                     gpuUUID     gpuSerial
powerDrawWatt  \
0  GPU-a1119ee9-9cd1-919f-a479-b902142c717d  323217056165
95.868947
1  GPU-3dc1601f-0e52-2e31-6b8d-8537d356b84d  323617042956
91.813693
2  GPU-e2deaca4-3041-9bbd-b6ac-6d36e09ab116  323617021222
82.537798

    gpuTempC  gpuUtilPerc  gpuMemUtilPerc
0  43.525333    63.602667       35.876000
1  40.992000    64.630000       35.510000
2  38.048193    61.548862       30.505355
```

```
appcheck_start_stop.head(3)
```

```
                    timestamp_Start_Time  \
190313 2018-11-08 08:16:43.895000+00:00
283469 2018-11-08 07:47:22.860000+00:00
283468 2018-11-08 07:47:22.863000+00:00

                                        hostname      eventName  \
190313  04dc4e9647154250beeee51b866b0715000000         Tiling
283469  04dc4e9647154250beeee51b866b0715000000  Saving Config
283468  04dc4e9647154250beeee51b866b0715000000         Render

       eventType_Start_Time
jobId  \
190313                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
283469                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705
283468                START  1024-lvl12-7e026be3-5fd0-48ee-b7d1-
abd61f747705

                                        taskId
timestamp_Stop_Time  \
190313  a164499b-4bb8-42b7-9dc0-cf049b62731e 2018-11-08
08:16:44.897000+00:00
283469  ffd69831-0ba4-457b-b8a8-e37c49779d94 2018-11-08
07:47:22.863000+00:00
283468  ffd69831-0ba4-457b-b8a8-e37c49779d94 2018-11-08
07:47:55.554000+00:00

       eventType_Stop_Time  Event_RenderTime
190313                STOP          1.002000
283469                STOP          0.003000
283468                STOP         32.691002
```

```
# Merge two dataframes on multiple columns
xyfinal1 = pd.merge(xyfinal,
appcheck_start_stop.loc[appcheck_start_stop["eventName"]=="TotalRender
"],
                    how="inner", on=["jobId","taskId"],
suffixes=("_task","_ap"))

# Filter and create a new dataframe
xy_level8 =
xyfinal1[["Event_RenderTime","x","y"]].loc[xyfinal1["level"]==8]

# Group and aggregate the dataframe
xy_level8 = xy_level8.groupby(by=["x","y"], as_index=False).mean()
xy_level8.head(5)
```

```
   x  y  Event_RenderTime
0  0  0         43.853001
1  0  1         24.809999
2  0  2         27.111000
3  0  3         35.481998
4  0  4         43.898998
```

```
# Create a new dataframe using specific columns from other dataframe
Level_RT = xyfinal1[["level","Event_RenderTime"]]

# Group and aggregate the dataframe
Level_RT = Level_RT.groupby(by=["level"], as_index=False).mean()

# Display the dataframe
Level_RT
```

```
   level  Event_RenderTime
0      4         52.181999
1      8         48.459820
2     12         42.581760
```

Data Analysis

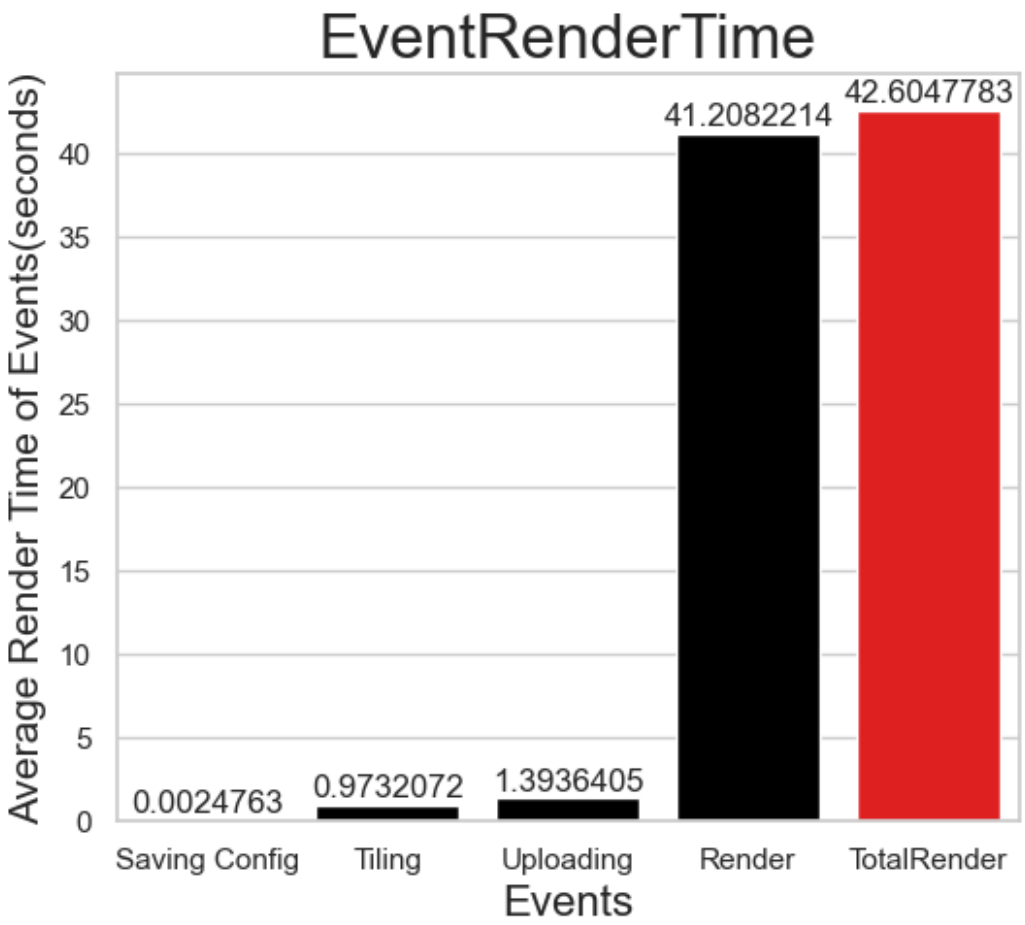
1. Which tasks dominate even run times

```
# Group the dataframe
Event_Tab =
appcheck_start_stop[["eventName","Event_RenderTime"]].groupby(by="even
tName", as_index=False).mean()

# Sort the dataframe
Event_Tab.sort_values(by="Event_RenderTime", ascending=False,
inplace=True)

# Reset dataframe index to default
Event_Tab = Event_Tab.reset_index(drop=True)

# Display the dataframe
Event_Tab
```

```
       eventName  Event_RenderTime
0    TotalRender         42.604778
1         Render         41.208221
2      Uploading          1.393641
3         Tiling          0.973207
4  Saving Config          0.002476
```

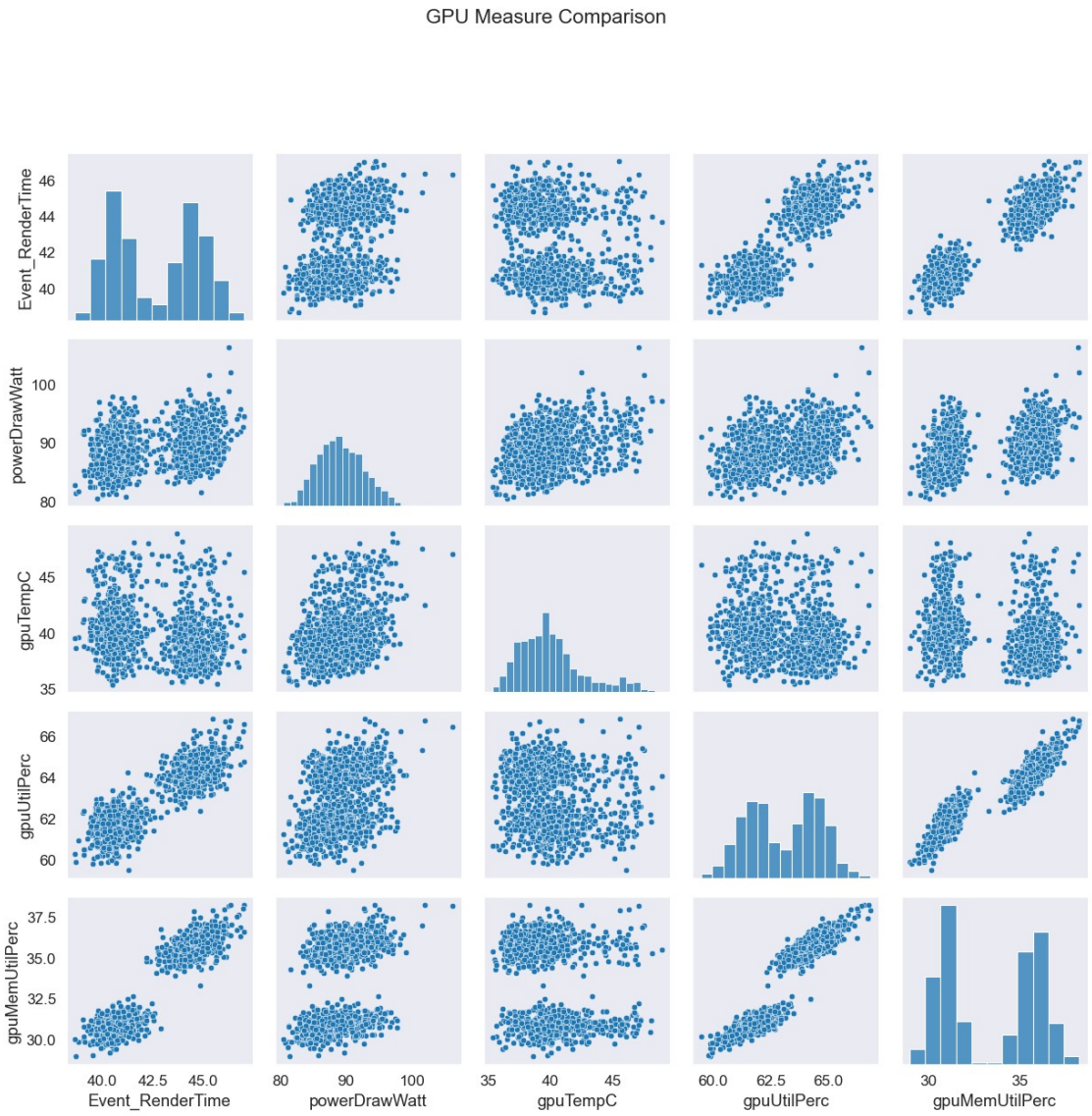
```
Event_Tab = Event_Tab.sort_values(by='Event_RenderTime',
ascending=True)

# Plot a barplot using seaborn library
sns.set_style('whitegrid')
```

```
sns.set_context('notebook', font_scale=1.0)
plt.subplots(figsize=(6,5))
palette = {i: "red" if i == "TotalRender" else 'black' for i in
Event_Tab["eventName"]}
RenderTime_Plot = sns.barplot(data=Event_Tab, x="eventName",
y="Event_RenderTime",palette=palette)

# Add respective value on each bar
for g in RenderTime_Plot.patches:
    RenderTime_Plot.annotate(format(g.get_height(), '.7f'),
                        (g.get_x() + g.get_width() / 2.,
g.get_height()),
                        ha = 'center', va = 'center',
                        xytext = (0, 6),
                        textcoords = 'offset points')

# Change characteristics of the visual
plt.title("EventRenderTime", size=23)
plt.xlabel("Events", size = 16)
plt.ylabel("Average Render Time of Events(seconds)", size = 15)
plt.show()
```



2. Comparisons of GPU metrics

```
# Plot a Joint Plot
sns.set_style('dark')
plt.figure(figsize=(7,6))
sns.set_context('paper', font_scale=1.4)
p = sns.pairplot(data=TP)
p.fig.tight_layout()
p.fig.subplots_adjust(top=0.87)
p.fig.suptitle("GPU Measure Comparison", y=1.0)

Text(0.5, 1.0, 'GPU Measure Comparison')

<Figure size 700x600 with 0 Axes>
```

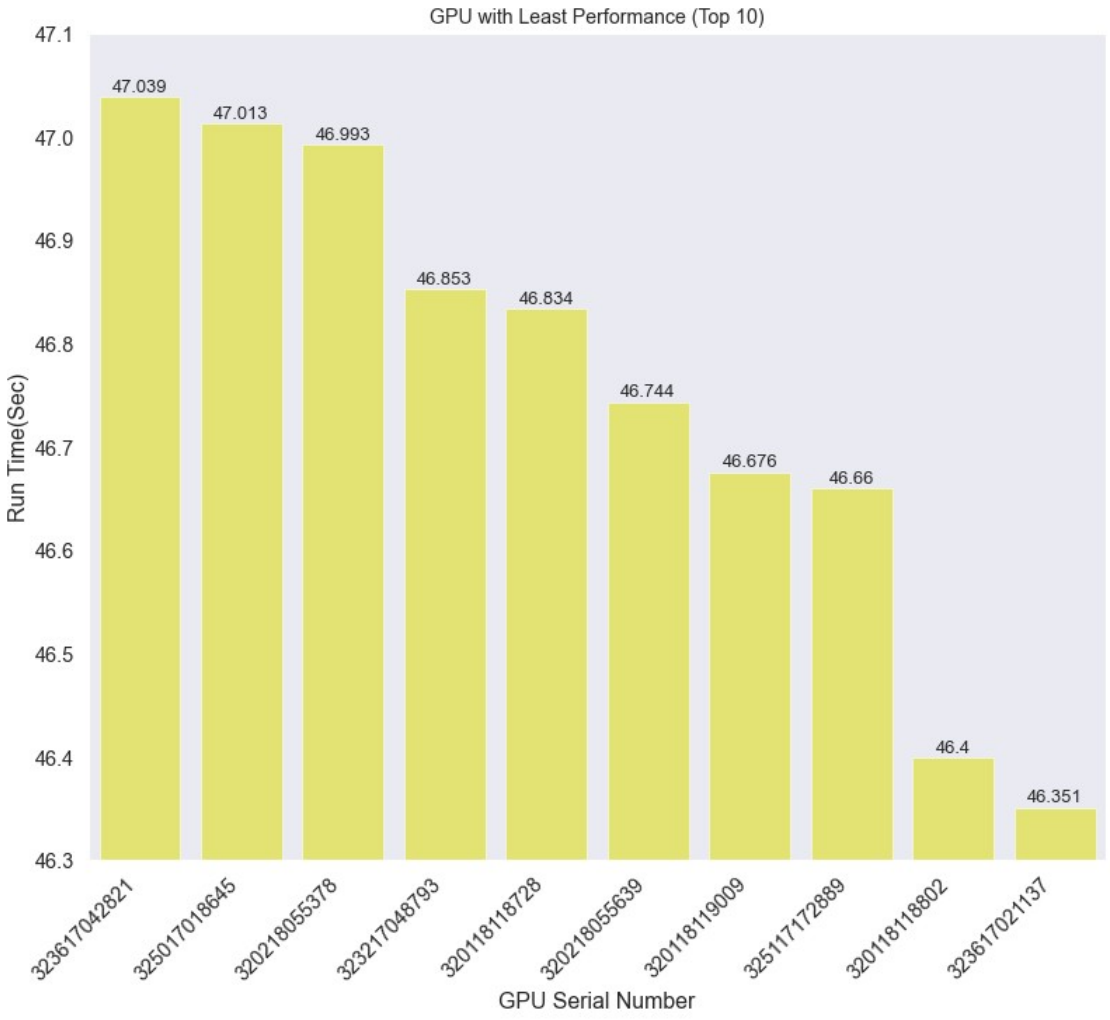


3. Identification of serial numbers of GPU with least performance

```
# Worst performing GPU is calculated
Worst = """ select  gpuSerial, Event_RenderTime As "Time" from TP
 group by gpuSerial order by Time desc limit 10; """
GPU_Worst = pd.DataFrame(sqlfn(Worst))

GPU_Worst.index.name='Order'

GPU_Worst
```

Order	gpuSerial	Time
0	323617042821	47.038776
1	325017018645	47.013439
2	320218055378	46.993168
3	323217048793	46.853237
4	320118118728	46.833710
5	320218055639	46.743965
6	320118119009	46.675816
7	325117172889	46.660000
8	320118118802	46.399696
9	323617021137	46.350880

```
# Create Fig and gridspec
import matplotlib.pyplot as plt
fg = plt.figure(figsize=(11,9), dpi= 85)
pg = plt.GridSpec(5, 4, hspace=0.6, wspace=0.3)
subp = fig.add_subplot(grid[:-2, :-1])

#Plotting Bar chart for displaying the time for each event
import seaborn as sns
g = sns.barplot(data=GPU_Worst, x="gpuSerial",
y="Time",order=GPU_Worst.sort_values('Time',ascending =
False).gpuSerial,color='yellow',alpha=.6)
# Annotate Text
# Annotate Text
for i, cty in enumerate(GPU_Worst.Time):
    g.text(i, cty+0.005, round(cty, 3),size = 11,
horizontalalignment='center')

# Title, Label, Ticks and Ylim
g.set_title('GPU with Least Performance (Top 10)',
fontdict={'size':12})
g.set(ylabel='Run Time(Sec)',xlabel='GPU Serial Number',ylim=(46.3,
47.1),)
g.set_xticklabels(g.get_xticklabels(), rotation=45,
horizontalalignment='right')
# Add patches to color the X axis labels
plt.show()
```



TP

	hostname	Event_RenderTime	\
0	04dc4e9647154250beeee51b866b0715000000	44.350327	
1	04dc4e9647154250beeee51b866b0715000001	45.698051	
2	04dc4e9647154250beeee51b866b0715000002	40.275421	
3	04dc4e9647154250beeee51b866b0715000003	40.822983	
4	04dc4e9647154250beeee51b866b0715000004	45.969166	
...	...	...	
1019	e7adc42d28814e518e9601ac2329c513000019	45.212002	
1020	e7adc42d28814e518e9601ac2329c51300001A	40.272308	
1021	e7adc42d28814e518e9601ac2329c51300001B	45.223820	
1022	e7adc42d28814e518e9601ac2329c51300001C	44.953407	
1023	e7adc42d28814e518e9601ac2329c51300001D	45.705097	

	gpuUUID	gpuSerial	powerDrawWatt	\
0	GPU-a1119ee9-9cd1-919f-a479-b902142c717d	323217056165	95.868947	

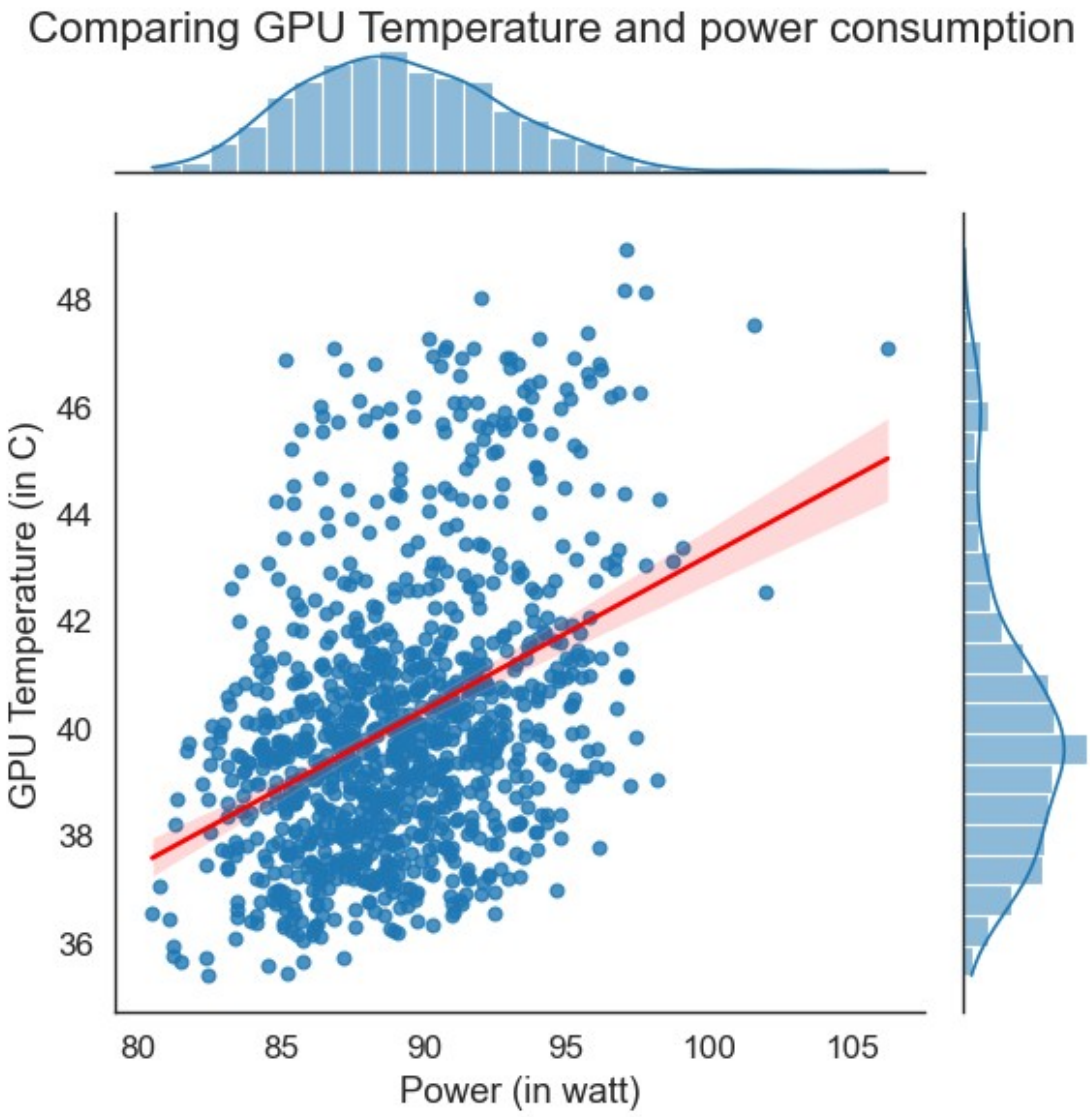
```
1     GPU-3dc1601f-0e52-2e31-6b8d-8537d356b84d  323617042956
91.813693
2     GPU-e2deaca4-3041-9bbd-b6ac-6d36e09ab116  323617021222
82.537798
3     GPU-173a16e7-07e7-3677-b499-9e20353f81a3  323617021168
86.558581
4     GPU-c1bb7aec-1afc-3226-db53-58f077365bea  323217056664
94.292392
...                                        ...           ...
...
1019  GPU-53f2e984-36f3-a70f-0944-752868d6a833  320118119210
89.386562
1020  GPU-05e3f5b6-553b-1a37-bf7a-271c5b999a64  325117063265
82.943504
1021  GPU-8646ce3a-be99-02fa-a138-dafee7ea3cf2  325017048638
88.354997
1022  GPU-b0b09148-0762-390d-08d6-93c1a5ccd768  325117173230
88.411319
1023  GPU-0cee5a9f-749e-7780-791a-ff2b29590a38  320118119027
97.399313

       gpuTempC  gpuUtilPerc  gpuMemUtilPerc
0     43.525333    63.602667       35.876000
1     40.992000    64.630000       35.510000
2     38.048193    61.548862       30.505355
3     41.576282    60.127249       29.832778
4     39.742838    64.545636       35.549634
...         ...          ...             ...
1019  39.095270    64.512325       36.449034
1020  37.712858    61.762825       30.990007
1021  38.569046    63.919947       35.593062
1022  37.205863    64.930047       36.289141
1023  39.816000    64.793333       36.607333

[1024 rows x 8 columns]
```

4. Interplay of temperature and power

```
# Plot a Joint Plot
sns.set_style('white')
plt.figure(figsize=(8,8))
sns.set_context('paper', font_scale=1.4)
p = sns.jointplot(x='powerDrawWatt', y='gpuTempC', data=TP,
kind='reg',joint_kws={'line_kws':{'color':'red'}})
p.fig.suptitle("Comparing GPU Temperature and power consumption")
p.ax_joint.set_xlabel('Power (in watt)')
p.ax_joint.set_ylabel('GPU Temperature (in C)')
p.fig.tight_layout()
p.fig.subplots_adjust(top=0.95)
```

```
print(f'The correlation coeeficient between temperature and power =
{np.round(np.corrcoef(TP.powerDrawWatt, TP.gpuTempC)[0,1], 2)}')
```

```
The correlation coeeficient between temperature and power = 0.4

<Figure size 800x800 with 0 Axes>
```

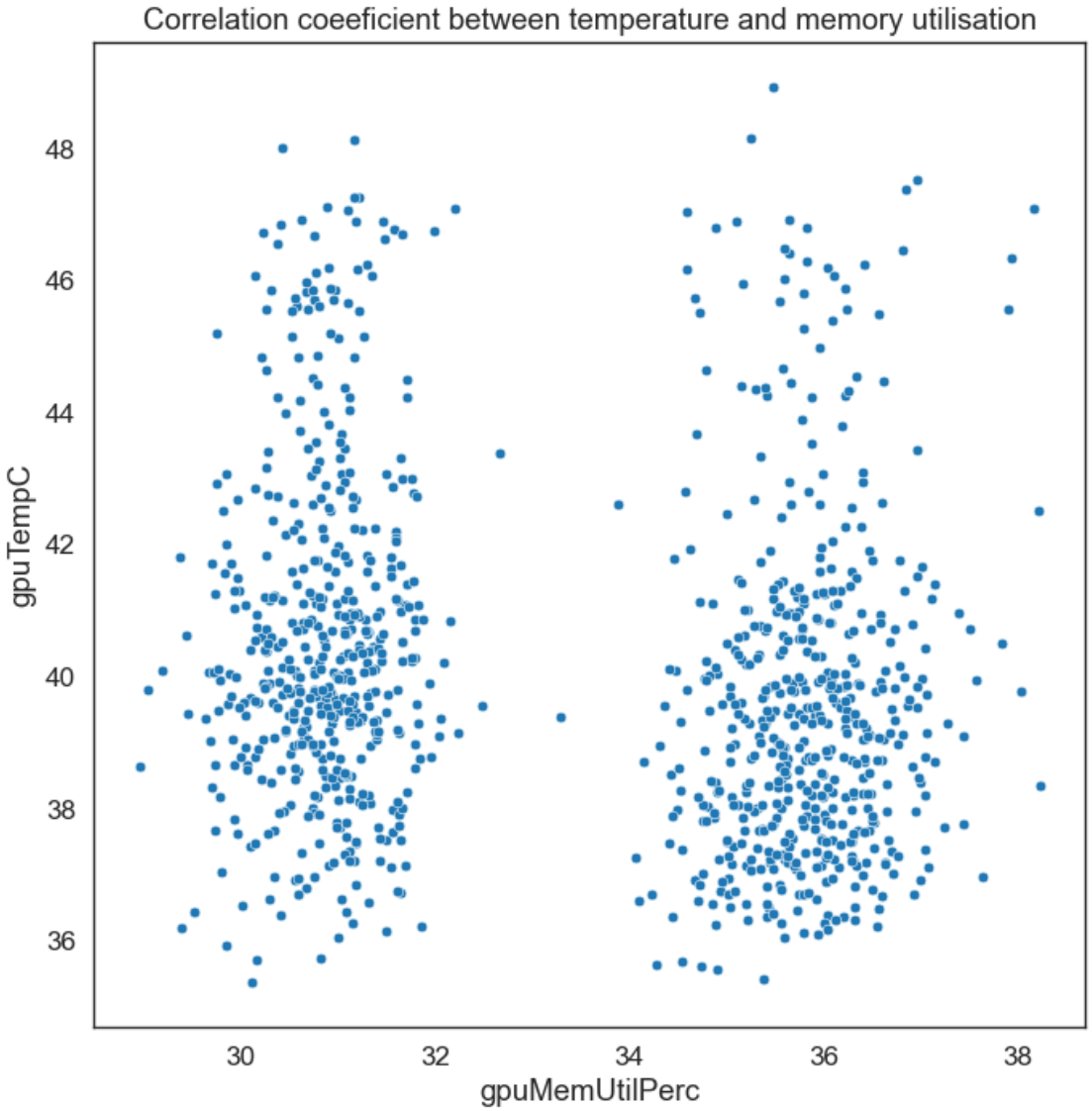


5. variation in memory utlization percentage of the gpu with temperature

```
# Plot a Joint Plot
sns.set_style('white')
plt.figure(figsize=(8,8))
sns.set_context('paper', font_scale=1.4)
sns.scatterplot(x='gpuMemUtilPerc', y='gpuTempC', data=TP)
plt.title('Correlation coeeficient between temperature and memory
utilisation')
```

```
print(f'The correlation coeeficient between temperature and memory
utilisation = {np.round(np.corrcoef(TP.gpuMemUtilPerc, TP.gpuTempC)
[0,1], 2)}')
```

```
The correlation coeeficient between temperature and memory utilisation
= -0.18
```

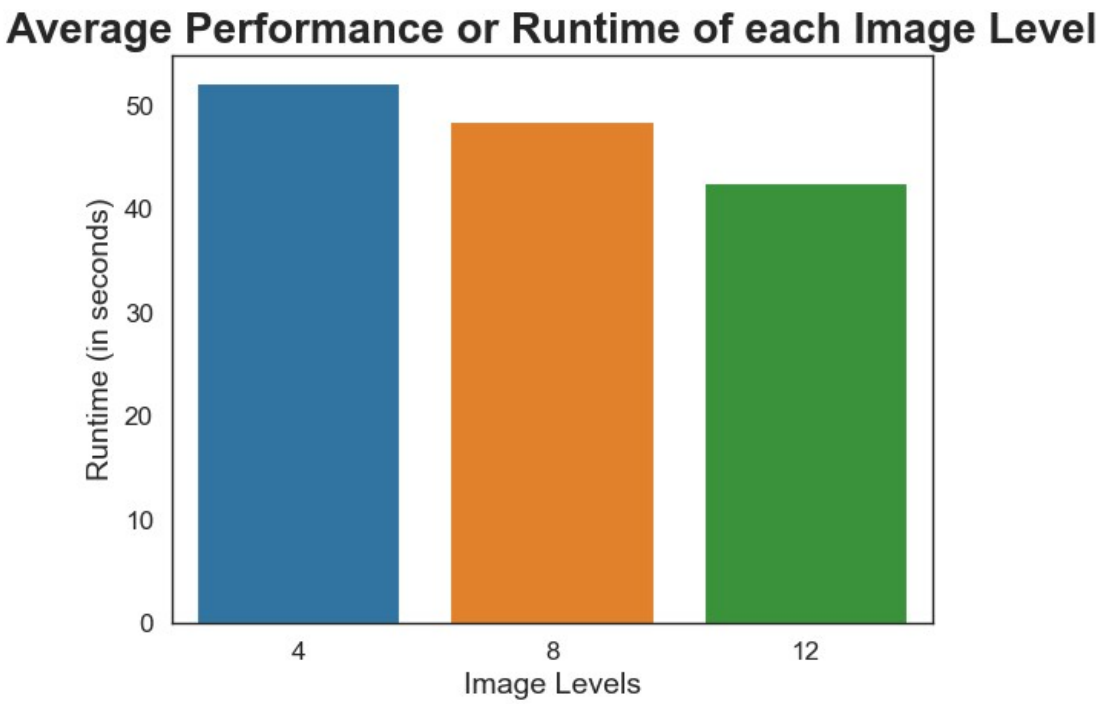



```
Level_RT
```

```
   level  Event_RenderTime
0      4         52.181999
1      8         48.459820
2     12         42.581760
```

```
# Plot barplot
sns.barplot(data=Level_RT, x="level", y="Event_RenderTime")
```

```
plt.title("Average Performance or Runtime of each Image Level",
size=20,fontweight='bold')
plt.xlabel("Image Levels", size = 14)
plt.ylabel("Runtime (in seconds)", size = 14)
plt.show()
```




```
xy_level8
```

	x	y	Event_RenderTime
0	0	0	43.853001
1	0	1	24.809999
2	0	2	27.111000
3	0	3	35.481998
4	0	4	43.898998
..	..	..	...
251	15	11	64.322998
252	15	12	47.679001
253	15	13	47.452000
254	15	14	43.641998
255	15	15	45.969002

```
[256 rows x 3 columns]

# Plot seaborn heatmap
sns.set(font_scale=0.8)
sns.set_context('paper', font_scale=1.4)
fig, ax = plt.subplots(figsize=(15,10))
glue = xy_level8[["x","y","Event_RenderTime"]].pivot("x", "y",
"Event_RenderTime")
```

```
ax = sns.heatmap(glue, cmap='YlGnBu', annot=False, xticklabels=False,
yticklabels=False)
ax.tick_params()

# Change characteristics of the visual
plt.title("Heatmap based on Runtime for each co-ordinate of the
Rendered Tile", size=20,fontweight='bold' )
```

```
Text(0.5, 1.0, 'Heatmap based on Runtime for each co-ordinate of the
Rendered Tile')
```