CODE FOR TERAPIXEL ANALYSIS

January 20, 2023

1 INTRODUCTION

Tera pixel images provide stakeholders with a convenient method of presenting information sets, enabling users to interactively navigate big data at various scales. The main challenge is how to achieve the supercomputer scale resources needed to create a genuine terapixel visualisation of Newcastle upon Tyne and its environmental data as collected by the Newcastle urban observatory. The main objective of the report is to conduct a performance analysis of Terapixel rendering on a cloud-based supercomputer which process intensive visualisation application using TeraScope data set. It is feasible to produce a high-quality terapixel visualisation by the path tracing renderer using public IaaS cloud GPU nodes. The Tera pixel image support interactive browsing of the city and data can be accessed across a wide range of team client devices. TeraScope data set is generated from application checkpoints and system metric output from the production of terraced pixel images. With the help of these data, performance evaluation can be carried out using exploratory Data analysis by focusing on the below main areas. 1. Time consumed for each event type. 2. Anlysis based on hostname,taskId regarding the GPU resources and the properties. 3. study showing how the GPU properties and time taken for rendering related to each tiles or task id. In this report, these areas will be analysed critically, and the information obtained is interpreted to generate useful insights from the data. CRISP-DM methodology is followed for exploratory analysis and answering the main questions.

2 METHODOLOGY (CRISP-DM)

2.1 BUSINESS UNDERSTANDING

The purpose of analyzing the data is to help stakeholders make the appropriate judgment for smooth and effective visualisation of Newcastle city by optimizing computational resources. The information derived from this raw data will help the technical teams (cloud engineers,architect etc) to design the system there by satisfying the requirement of business. The following questions will help to genarate sensible conclusion from the data through exploratory analysis.
1. Which task Id took the highest time as well as lowest time for Total rendering, Rendering, tiling, uploading and saving config processes and their corresponding rendered image coordinates?
2. Which Event Name consumes more run time?
3. Is there any relationship between the variables in the GPU table? If so, how are they related? 4. Can any particular statistical model be fitted to any variables related to GPU performance matrix? If so, describe the model. 5. What are the host names which consumed maximum and minimum time for the rendering process? 6. What are the maximum and minimum values of computational resource used, temperature and power consumption of the GPU and identify the corresponding virtual machines (hostname)?

7. Which virtual machine processed most image rendering tasks? explain this with the help of a histogram.
8. How many image coordinates are associated with each level? 9. How are the tiles of the image and total rendering times related? 10. Explain the GPU properties using suitable graphs on the basis of hostnames and Task Id? 11. How are the GPU properties related to the tile properties of the rendered image?

2.2 DATA UNDERSTANDING

The provided data shows the performance timing of the render applications as well the performance of the GPU card, conveying the details of which part of the image rendering in each task while performing a run using 1024 GPU nodes. 1. Application-checkpoints

Field Names	Data Types(changed)	Description	Example
Timestamp	Timestamp	Shows the time for a particular event	2018-11-08T07:42:29.845ZZ
hostname	String	Host name of the virtual machine	0d56a730076643d585f77e00d2d8521
eventName	String	Name of the event occurring within the rendering application	Render
eventType	String	indicate whether the process starts or stops	START
jobId	String	ID of the Azure Batch job	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705
taskId	String	ID of the Azure Batch task	0002afb5-d05e-4da9-bd53-7b6dc19ea6d4

- Under each taskId there are five processes namely saving config, Render, Tiling and uploading. Total render denotes the sum total of all this process. In conclusion, the data set shows the start time and stop time of each process for a particular taskId , hostName and Job id.
- Primary keys for this table are taskId, eventname and eventType
- Foreign keys are taskId and Hostname.

2. GPU

Field Names	Data Types(changed)	Description	Example
Timestamp	Timestamp	Recoded Time	2018-11-08T08:27:10.424Z
hostname	String	Host name of the virtual machine	db871cd77a544e13bc791a64a0c8ed5

Field Names	Data Types(changed)	Description	Example
gpuSerial	String	The serial number of the physical GPU card	323217056464
gpuUUID	String	The unique system Id assigned by the Azure system to the GPU unit	GPU-2d4eed64-4ca8-f12c-24bc-28f036493ea2
powerDrawWatt	Number	Power draw of the GPU in watts	24.5
gpuTempC	Number	Temparature of the GPU in celcius	44
gpuUtilPerc	Number (%)	Percentage utilization of the GPU memory	88
gpuMemUtilPerc	Number (%)	Percentage utilization of the GPU cores	43

- The table mainly shows the quantity of system resources used by each hostname for a particular time. In addition, it also indicates the temperature and power utilization of the core for each time.
- Primary key is gpuSrial/gpuUUID and the foreign key is the hostname.
- `For each hostName, gpuSrial and gpuUUID are unique.`

3. Task-x-y

Field Names	Data Types(changed)	Description	Example
taskId	String	Id of the Azure Batch task	00004e77-304c-4fbd-88a1-1346ef947567
jobId	String	Id of the Azure Batch job	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705
x	Number	Rendered image Y axis	116
y	Number	Rendered image X axis	118
level	Number	It represent the zooming level	12

- `This table shows the x,y coordinate of the part of rendered image under each tasked`
- `Primary Keys is taskId and foreign keys are taskId and jobId`
- `There are three levels of image rendering based on the zoom feature they are 4,8 and 12.`

Job Id	Level
1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	12
1024-lvl4-90b0c947-dcfc-4eea-a1ee-efe843b698df	4
1024-lvl8-5ad819e1-fbf2-42e0-8f16-a3baca825a63	8

Overall, there are 3 distinct job Id, 1024 unique Host Name and 65793 distinct task Id.

[ ]:
```
#importing necessary libraries and connecting to google cloud
from google.colab import drive
import numpy as np
import pandas as pd
drive.mount('/content/gdrive')
```

```
Mounted at /content/gdrive
```

Before loading data make sure that the 3 Excel files are saved in google cloud. save the files under /content/gdrive/MyDrive/cloud_project/. Then load the data as following below.

[ ]:
```
#locations of the csv files
application_checkpoint_location="/content/gdrive/MyDrive/cloud_project/
 ↪application-checkpoints.csv"
gpu_location='/content/gdrive/MyDrive/cloud_project/gpu.csv'
task_x_y_location='/content/gdrive/MyDrive/cloud_project/task-x-y.csv'
#Loading data
application_checkpoint=pd.read_csv(application_checkpoint_location) #
gpu=pd.read_csv(gpu_location)
task_x_y=pd.read_csv(task_x_y_location)
# This data set is generated from this above two dataset using the query given␣
 ↪in the subsequent section. since the query takes long time to execute ,␣
 ↪pulling the saved csv file reduce time
#a_c_g_join=pd.read_csv('/content/gdrive/MyDrive/cloud_project/all_3_data.csv')
```

The sumary of the GPU table is given below

[ ]:
```
#sumary of GPU table
gpu.describe()#running this code after duplicate removal yield better results
```

[ ]:

	gpuSerial	powerDrawWatt	gpuTempC	gpuUtilPerc	gpuMemUtilPerc
count	1.543681e+06	1.543681e+06	1.543681e+06	1.543681e+06	1.543681e+06
mean	3.239836e+11	8.919838e+01	4.007560e+01	6.305820e+01	3.341359e+01
std	1.228841e+09	3.975742e+01	3.800243e+00	4.144816e+01	2.300107e+01
min	3.201181e+11	2.255000e+01	2.600000e+01	0.000000e+00	0.000000e+00
25%	3.236170e+11	4.499000e+01	3.800000e+01	0.000000e+00	0.000000e+00
50%	3.236170e+11	9.659000e+01	4.000000e+01	8.900000e+01	4.300000e+01
75%	3.250170e+11	1.213400e+02	4.200000e+01	9.200000e+01	5.100000e+01
max	3.252171e+11	1.970100e+02	5.500000e+01	1.000000e+02	8.300000e+01

2.3 DATA PREPARATION

1. New column is added to the Application-checkpoints table to indicate the time taken for each eventName. It is named "delta_dttm".
2. The original field name Timestamp is renamed to dttm to avoid confusion with the data type
3. The field delta_dttm is converted to timestamp/float (seconds) depending on the requirement.
4. There are 2470 duplicates in the Application-checkpoints table. They were removed before processing the data.
5. There are also 9 duplicates in the GPU table. Here, the duplicates are eliminated using suitable queries.
6. The same pre-processing steps for the Application-checkpoint table are used in GPU as well like renaming the column 'Timestamp' to 'dttm', and changing the data type to timestamp/float (seconds) based on the requirements.
7. For the Task-x-y table there are no duplicates. So, renaming of the column was done.

[ ]:
```
#installing dependencies and necessary libraries
!pip install -U pandasql
from pandasql import sqldf
import matplotlib.pyplot as plt
pysqldf = lambda q: sqldf(q, globals())
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: pandasql in /usr/local/lib/python3.8/dist-
packages (0.7.3)
Requirement already satisfied: pandas in /usr/local/lib/python3.8/dist-packages
(from pandasql) (1.3.5)
Requirement already satisfied: numpy in /usr/local/lib/python3.8/dist-packages
(from pandasql) (1.21.6)
Requirement already satisfied: sqlalchemy in /usr/local/lib/python3.8/dist-
packages (from pandasql) (1.4.46)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.8/dist-
packages (from pandas->pandasql) (2022.7)
Requirement already satisfied: python-dateutil>=2.7.3 in
/usr/local/lib/python3.8/dist-packages (from pandas->pandasql) (2.8.2)
Requirement already satisfied: greenlet!=0.4.17 in
/usr/local/lib/python3.8/dist-packages (from sqlalchemy->pandasql) (2.0.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.8/dist-
packages (from python-dateutil>=2.7.3->pandas->pandasql) (1.15.0)
```

[ ]:
```
#dup check found 2470 duplicates for application-checkpoint
q ="""select taskId,jobId,eventName,eventType,hostname from␣
↪application_checkpoint group by 1,2,3,4,5 having count(*)>1;"""
dupe=pysqldf(q)
len(dupe)
```

[ ]: 2470

[ ]:
```python
# colunm name 'timestamp' changes to 'dttm'
application_checkpoint=application_checkpoint.rename(columns={"timestamp":␣
↪"dttm"})
```

[ ]:
```python
#code for removing duplicates
q ="""select dttm,hostname,eventName,eventType,jobId,taskId,count(*) from␣
↪application_checkpoint group by 1,2,3,4,5,6 having count(*)>1;"""
i=pysqldf(q)
q ="""select dttm,hostname,eventName,eventType,jobId,taskId,count(*) from␣
↪application_checkpoint group by 1,2,3,4,5,6 having count(*)=1;"""
application_checkpoint=pd.concat([i.iloc[:,:6],pysqldf(q).iloc[:,:6]])
```

[ ]:
```python
#post dupe check
q ="""select dttm,hostname,eventName,eventType,jobId,taskId,count(*) from␣
↪application_checkpoint group by 1,2,3,4,5,6 having count(*)>1;"""
dupe=pysqldf(q)
len(dupe)
```

[ ]: 0

[ ]:
```python
# data type changing
application_checkpoint["dttm"]=application_checkpoint["dttm"].
↪astype('datetime64[ns]')
print(application_checkpoint.dtypes)
```

```
dttm         datetime64[ns]
hostname             object
eventName            object
eventType            object
jobId                object
taskId               object
dtype: object
```

[ ]:
```python
#renaming colunm-gpu table
gpu=gpu.rename(columns={"timestamp": "dttm"})
```

[ ]:
```python
#dup check and dupe removal starting
q ="""select␣
↪dttm,hostname,gpuSerial,gpuUUID,powerDrawWatt,gpuTempC,gpuUtilPerc,gpuMemUtilPerc,count(*)␣
↪from gpu group by 1,2,3,4,5,6,7,8 having count(*)>1;"""
dupe=pysqldf(q)
len(dupe)
```

[ ]: 9

[ ]:
```python
#dupe  removal
```

```
q ="""select␣
↪dttm,hostname,gpuSerial,gpuUUID,powerDrawWatt,gpuTempC,gpuUtilPerc,gpuMemUtilPerc,count(*)␣
↪from gpu group by 1,2,3,4,5,6,7,8 having count(*)=1;"""
gpu=pd.concat([dupe.iloc[:,:8],pysqldf(q).iloc[:,:8]])
```

[ ]:
```
#post dupe check
q ="""select␣
↪dttm,hostname,gpuSerial,gpuUUID,powerDrawWatt,gpuTempC,gpuUtilPerc,gpuMemUtilPerc,count(*)␣
↪from gpu group by 1,2,3,4,5,6,7,8 having count(*)>1;"""
dupe=pysqldf(q)
len(dupe)
```

[ ]:
```
0
```

[ ]:
```
#data type changing
gpu["dttm"]=gpu["dttm"].astype('datetime64')
gpu.dtypes
```

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

2.4 MODELLING

Exploratory analysis is implemented on these data sets to generate useful information which could represent the performance evaluation of the process and system. In this report, as per the objectives, significant questions will be framed and they are answered with corresponding tables or figures. For carrying out the analysis, Python programming language is used and since it is difficult to analyse the data using python framework, panda SQL module is installed for easy analysis using MySQL query language. The script for the analysis is generated through google colab which offers a markdown feature to create a pdf containing the script as well as the text for efficient communication and for reproducibility.

2.4.1 ASSUMPTIONS

1. Each event starts and stops consecutively which means there is no time gap between succeeding events. (In actual case there is a minute time gap)

2. Only one task Id is executed at a single point in time of a virtual machine. In some hostname multiple events is executed in the same timeframe). So, it is difficult to find the GPU properties for a particular task Id.

2.4.2 METHOD FOR REPRESENTING PERFORMANCE PARAMETER

To evaluate the performance of the virtual machine or GPU, the time taken for a particular activity by each unit is calculated. Then, the assumption is the performance is higher for the machines which take less time to complete the task. The table _ can be used for finding the time taken for each evetime under each task id we can use the following method.

dttm	eventName	eventType	taskId	dttm_delta
07:45:14	Render	START	000993b6-fc88-489d-a4ca-0a44fd800bd3	00:00:39
07:45:53	Render	STOP	000993b6-fc88-489d-a4ca-0a44fd800bd3	
07:45:14	Saving Config	START	000993b6-fc88-489d-a4ca-0a44fd800bd3	00:00:00
07:45:14	Saving Config	STOP	000993b6-fc88-489d-a4ca-0a44fd800bd3	
07:45:53	Tiling	START	000993b6-fc88-489d-a4ca-0a44fd800bd3	00:00:01
07:45:54	Tiling	STOP	000993b6-fc88-489d-a4ca-0a44fd800bd3	
07:45:14	TotalRender	START	000993b6-fc88-489d-a4ca-0a44fd800bd3	00:00:41
07:45:55	TotalRender	STOP	000993b6-fc88-489d-a4ca-0a44fd800bd3	
07:45:53	Uploading	START	000993b6-fc88-489d-a4ca-0a44fd800bd3	00:00:01
07:45:54	Uploading	STOP	000993b6-fc88-489d-a4ca-0a44fd800bd3	

For example, in the above table, the time taken for the Render process is calculated by subtracting the time corresponding to the start event type from the stop event type that is: 07:45:53-07:45:14 = 00:00:39 From the table, we can understand that the eventType saving config took less time compared to the other process and if we extend this method across different hostnames and compare the time taken for a particular task with similar complexities, the performance of the virtual machine can be analysed.

2.4.3 TABLES JOINING

1. The tables Application-checkpoints and GPU can be joined using the Hostname as a foreign key to analysing machine performance, GPU temperature, GPU power and system resources.
2. The tables Application-checkpoints and Task-x-y can be joined using jobId and taskId which will help to explore the coordinate analysis and level-wise analysis.
3. Application-checkpoint (a) and GPU (b) can be joined by hostname, and the timestamp of the GPU table should be in between the start timestamp and end timestamp of the Application-checkpoint table where
   start timestamp column is obtained using even type as **START** for a particular taskId and event name as **Total Render**. similarly, **end timestamp** column is obtained using even type as **STOP** for a particular taskId and event name as **Total Render** The query condition is: (a.start timestamp b.timestamp a.end timestamp and a.hostname=b.hostname) . The result can be joined with the last table using taskId column.

The Questions we are going to answer through Data exploration, and the methods of finding the answer are explained in this session through suitable data visualisation.
1. *Which task Id took the highest time as well as lowest time for Total rendering, Rendering, tiling, uploading and saving config processes and their corresponding rendered image coordinates? Note the minimum time taken denote improved performance*

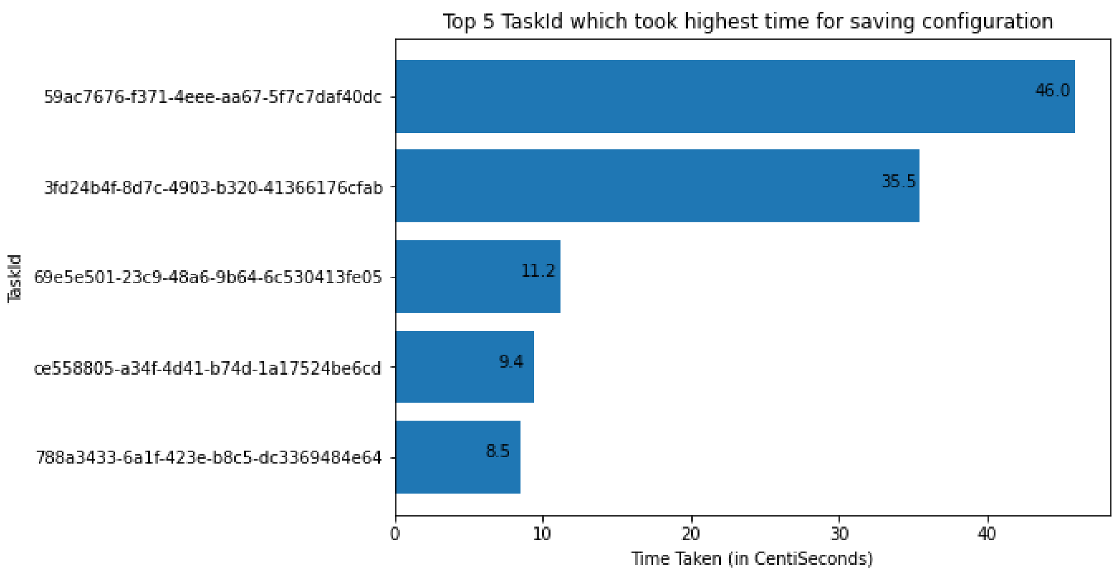
Top 5 TaskId which took most Time for 'saving configuration'

[ ]:
```
q ="""select a.dttm as start_dttm,b.dttm as end_dttm,a.taskId taskId,a.jobId␣
↪jobId,"Saving config" eventname from (select distinct dttm,taskId,jobId from␣
↪application_checkpoint where eventName='Saving Config' and␣
↪eventType='START') a join
(select distinct dttm,taskId,jobId from application_checkpoint where␣
↪eventName='Saving Config' and eventType='STOP') b on a.jobId=b.jobId and a.
↪taskId=b.taskId ;"""
q_1_1=pysqldf(q)
q_1_1["start_dttm"]=q_1_1["start_dttm"].astype('datetime64')
q_1_1["end_dttm"]=q_1_1["end_dttm"].astype('datetime64')
q_1_1['delta_dttm']=q_1_1['end_dttm']-q_1_1['start_dttm']
# arranging in descending order
q_1_1=q_1_1.sort_values(by='delta_dttm', ascending=False)
q_1_1.head()
```

[ ]:
```
                   start_dttm                end_dttm  \
46417 2018-11-08 08:15:09.191 2018-11-08 08:15:09.651
58351 2018-11-08 08:23:54.599 2018-11-08 08:23:54.954
4761  2018-11-08 07:44:45.666 2018-11-08 07:44:45.778
62064 2018-11-08 08:26:39.221 2018-11-08 08:26:39.315
37065 2018-11-08 08:08:18.892 2018-11-08 08:08:18.977

                                     taskId  \
46417  59ac7676-f371-4eee-aa67-5f7c7daf40dc
58351  3fd24b4f-8d7c-4903-b320-41366176cfab
4761   69e5e501-23c9-48a6-9b64-6c530413fe05
62064  ce558805-a34f-4d41-b74d-1a17524be6cd
37065  788a3433-6a1f-423e-b8c5-dc3369484e64

                                                jobId      eventname  \
46417  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  Saving config
58351  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  Saving config
4761   1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  Saving config
62064  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  Saving config
37065  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  Saving config

                  delta_dttm
46417 0 days 00:00:00.460000
58351 0 days 00:00:00.355000
4761  0 days 00:00:00.112000
62064 0 days 00:00:00.094000
37065 0 days 00:00:00.085000
```

[ ]:
```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
langs =q_1_1.head()["taskId"]
students =q_1_1.head()["delta_dttm"].dt.microseconds/10000
```

```
ax.barh(langs,students)
plt.xlabel("Time Taken (in CentiSeconds)")
plt.ylabel("TaskId")
plt.title("Top 5 TaskId which took highest time for saving configuration ")
ax.invert_yaxis()
for i in range(1,6):
   plt.text(-1.5+q_1_1.head()["delta_dttm"].dt.microseconds.iloc[i-1]/
 ↪10000,i-1,q_1_1.head()["delta_dttm"].dt.microseconds.iloc[i-1]/10000,␣
 ↪ha="center",rotation="horizontal")
plt.show()
```

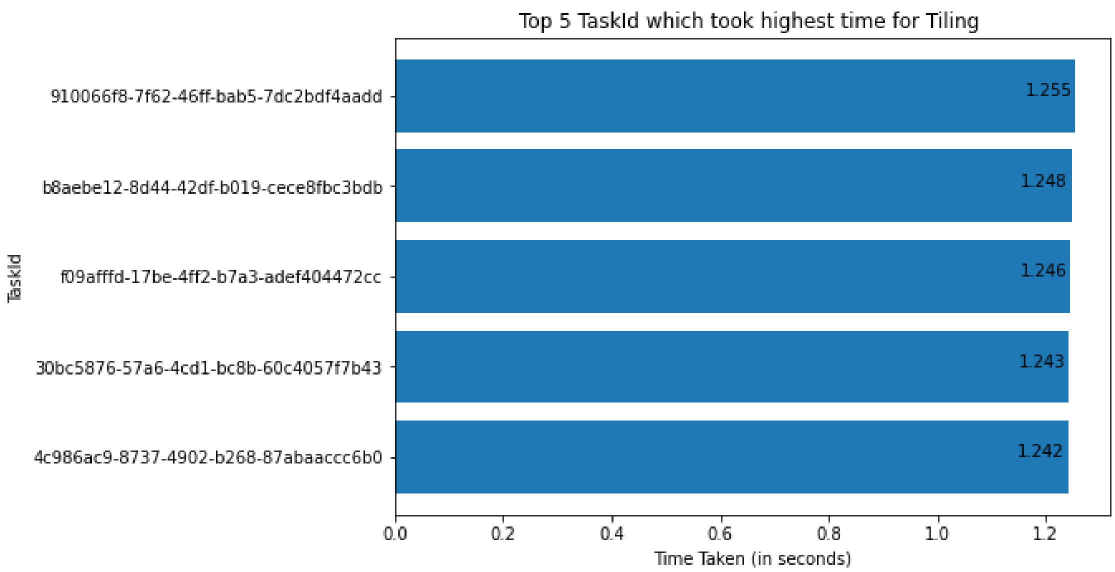


Top 5 TaskId which took most Time for 'Tiling'

```
[ ]: q ="""select a.dttm as start_dttm,b.dttm as end_dttm,a.taskId taskId,a.jobId␣
 ↪jobId,"Tiling" eventname from (select distinct dttm,taskId,jobId from␣
 ↪application_checkpoint where eventName='Tiling' and eventType='START') a␣
 ↪join
(select distinct dttm,taskId,jobId from application_checkpoint where␣
 ↪eventName='Tiling' and eventType='STOP') b on a.jobId=b.jobId and a.taskId=b.
 ↪taskId ;"""
q_1_2=pysqldf(q)
q_1_2["start_dttm"]=q_1_2["start_dttm"].astype('datetime64')
q_1_2["end_dttm"]=q_1_2["end_dttm"].astype('datetime64')
q_1_2['delta_dttm']=q_1_2['end_dttm']-q_1_2['start_dttm']
# arranging in descending order
q_1_2=q_1_2.sort_values(by='delta_dttm', ascending=False)
q_1_2.head()
```

[ ]:
```
                      start_dttm                end_dttm  \
39393 2018-11-08 08:10:42.124 2018-11-08 08:10:43.379
51242 2018-11-08 08:19:22.694 2018-11-08 08:19:23.942
1507  2018-11-08 07:42:57.692 2018-11-08 07:42:58.938
51041 2018-11-08 08:19:15.045 2018-11-08 08:19:16.288
8985  2018-11-08 07:48:30.090 2018-11-08 07:48:31.332

                                     taskId  \
39393  910066f8-7f62-46ff-bab5-7dc2bdf4aadd
51242  b8aebe12-8d44-42df-b019-cece8fbc3bdb
1507   f09afffd-17be-4ff2-b7a3-adef404472cc
51041  30bc5876-57a6-4cd1-bc8b-60c4057f7b43
8985   4c986ac9-8737-4902-b268-87abaaccc6b0

                                                jobId eventname  \
39393  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705    Tiling
51242  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705    Tiling
1507    1024-lvl4-90b0c947-dcfc-4eea-a1ee-efe843b698df    Tiling
51041  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705    Tiling
8985   1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705    Tiling

                   delta_dttm
39393 0 days 00:00:01.255000
51242 0 days 00:00:01.248000
1507  0 days 00:00:01.246000
51041 0 days 00:00:01.243000
8985  0 days 00:00:01.242000
```

[ ]:
```python
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
langs =q_1_2.head()["taskId"]
students =q_1_2.head()["delta_dttm"].dt.total_seconds()
ax.barh(langs,students)
plt.xlabel("Time Taken (in seconds)")
plt.ylabel("TaskId")
plt.title("Top 5 TaskId which took highest time for Tiling ")
ax.invert_yaxis()
for i in range(1,6):
   plt.text(-0.05+q_1_2.head()["delta_dttm"].dt.total_seconds().
 ↪iloc[i-1],i-1,round(q_1_2.head()["delta_dttm"].dt.total_seconds().
 ↪iloc[i-1],3), ha="center",rotation="horizontal")
plt.show()
```



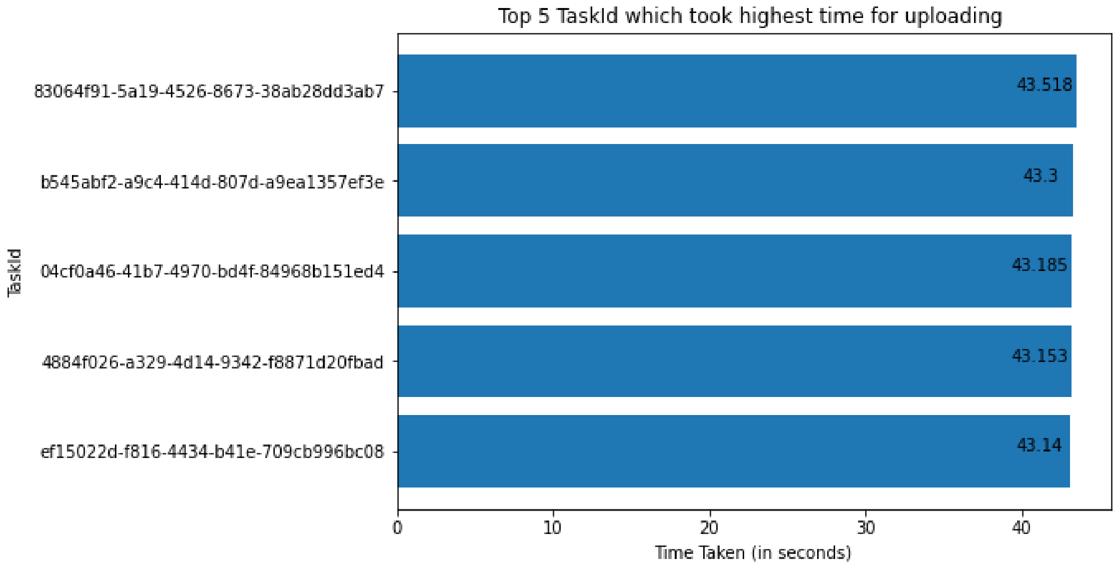
Top 5 TaskId which took most Time for 'Uploading'

[ ]:
```
q ="""select a.dttm as start_dttm,b.dttm as end_dttm,a.taskId taskId,a.jobId␣
↪jobId,"Uploading" eventname from (select distinct dttm,taskId,jobId from␣
↪application_checkpoint where eventName='Uploading' and eventType='START') a␣
↪join
(select distinct dttm,taskId,jobId from application_checkpoint where␣
↪eventName='Uploading' and eventType='STOP') b on a.jobId=b.jobId and a.
↪taskId=b.taskId ;"""
q_1_3=pysqldf(q)
q_1_3["start_dttm"]=q_1_3["start_dttm"].astype('datetime64')
q_1_3["end_dttm"]=q_1_3["end_dttm"].astype('datetime64')
q_1_3['delta_dttm']=q_1_3['end_dttm']-q_1_3['start_dttm']
# arranging in descending order
q_1_3=q_1_3.sort_values(by='delta_dttm', ascending=False)
q_1_3.head()
```

[ ]:
```
                  start_dttm                end_dttm  \
1566 2018-11-08 07:43:00.730 2018-11-08 07:43:44.248
1622 2018-11-08 07:43:01.377 2018-11-08 07:43:44.677
1598 2018-11-08 07:43:01.162 2018-11-08 07:43:44.347
1636 2018-11-08 07:43:01.451 2018-11-08 07:43:44.604
1593 2018-11-08 07:43:01.150 2018-11-08 07:43:44.290

                                    taskId  \
1566  83064f91-5a19-4526-8673-38ab28dd3ab7
1622  b545abf2-a9c4-414d-807d-a9ea1357ef3e
1598  04cf0a46-41b7-4970-bd4f-84968b151ed4
```

```
1636  4884f026-a329-4d14-9342-f8871d20fbad
1593  ef15022d-f816-4434-b41e-709cb996bc08

                                                      jobId  eventname  \
1566   1024-lvl8-5ad819e1-fbf2-42e0-8f16-a3baca825a63  Uploading
1622  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  Uploading
1598   1024-lvl8-5ad819e1-fbf2-42e0-8f16-a3baca825a63  Uploading
1636  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  Uploading
1593   1024-lvl8-5ad819e1-fbf2-42e0-8f16-a3baca825a63  Uploading

                 delta_dttm
1566 0 days 00:00:43.518000
1622 0 days 00:00:43.300000
1598 0 days 00:00:43.185000
1636 0 days 00:00:43.153000
1593 0 days 00:00:43.140000
```

[ ]:
```python
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
langs =q_1_3.head()["taskId"]
students =q_1_3.head()["delta_dttm"].dt.total_seconds()
ax.barh(langs,students)
plt.xlabel("Time Taken (in seconds)")
plt.ylabel("TaskId")
plt.title("Top 5 TaskId which took highest time for uploading ")
ax.invert_yaxis()
for i in range(1,6):
   plt.text(-2+q_1_3.head()["delta_dttm"].dt.total_seconds().
 ↪iloc[i-1],i-1,round(q_1_3.head()["delta_dttm"].dt.total_seconds().
 ↪iloc[i-1],3), ha="center",rotation="horizontal")
plt.show()
```



Top 5 TaskId which took most Time for ‘Rendering’

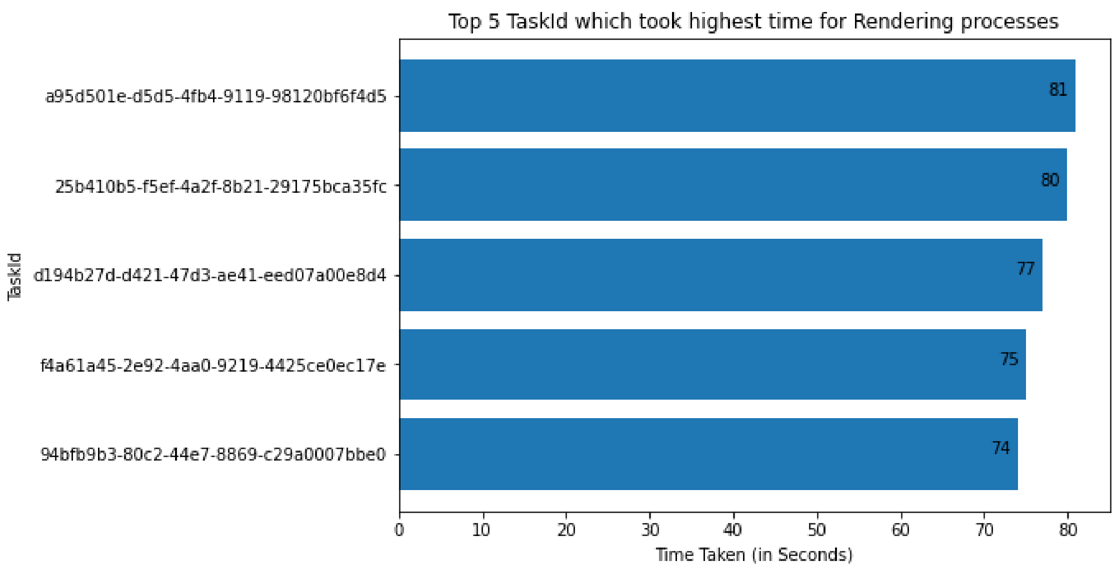
[ ]:
```
q ="""select a.dttm as start_dttm,b.dttm as end_dttm,a.taskId taskId,a.jobId␣
↪jobId,"Render" as eventname from (select distinct dttm,taskId,jobId from␣
↪application_checkpoint where eventName='Render' and eventType='START') a␣
↪join
(select distinct dttm,taskId,jobId from application_checkpoint where␣
↪eventName='Render' and eventType='STOP') b on a.jobId=b.jobId and a.taskId=b.
↪taskId ;"""
q_1=pysqldf(q)
q_1["start_dttm"]=q_1["start_dttm"].astype('datetime64')
q_1["end_dttm"]=q_1["end_dttm"].astype('datetime64')
q_1['delta_dttm']=q_1['end_dttm']-q_1['start_dttm']
# arranging in descending order
q_1=q_1.sort_values(by='delta_dttm', ascending=False)
q_1.head()
```

[ ]:
```
                   start_dttm                end_dttm  \
34739 2018-11-08 08:06:34.098 2018-11-08 08:07:55.606
13324 2018-11-08 07:50:57.638 2018-11-08 07:52:17.799
47084 2018-11-08 08:15:39.327 2018-11-08 08:16:56.916
52068 2018-11-08 08:19:18.949 2018-11-08 08:20:34.065
6062  2018-11-08 07:45:41.852 2018-11-08 07:46:55.870

                                     taskId  \
34739  a95d501e-d5d5-4fb4-9119-98120bf6f4d5
13324  25b410b5-f5ef-4a2f-8b21-29175bca35fc
47084  d194b27d-d421-47d3-ae41-eed07a00e8d4
```

```
52068  f4a61a45-2e92-4aa0-9219-4425ce0ec17e
6062   94bfb9b3-80c2-44e7-8869-c29a0007bbe0

                                                 jobId eventname  \
34739  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705    Render
13324  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705    Render
47084  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705    Render
52068  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705    Render
6062   1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705    Render

                  delta_dttm
34739 0 days 00:01:21.508000
13324 0 days 00:01:20.161000
47084 0 days 00:01:17.589000
52068 0 days 00:01:15.116000
6062  0 days 00:01:14.018000
```

[ ]:

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
langs =q_1.head()["taskId"]
students = q_1.head()["delta_dttm"].dt.total_seconds().astype(int)
ax.barh(langs,students)
plt.xlabel("Time Taken (in Seconds)")
plt.ylabel("TaskId")
ax.invert_yaxis()
plt.title("Top 5 TaskId which took highest time for Rendering processes")
for i in range(1,6):
   plt.text(-2+q_1.head()["delta_dttm"].dt.total_seconds().astype(int).
 ↪iloc[i-1],i-1 ,q_1.head()["delta_dttm"].dt.total_seconds().astype(int).
 ↪iloc[i-1], ha="center",rotation="horizontal")
plt.show()
```



Top 5 TaskId which took most Time for 'Total Rendering'

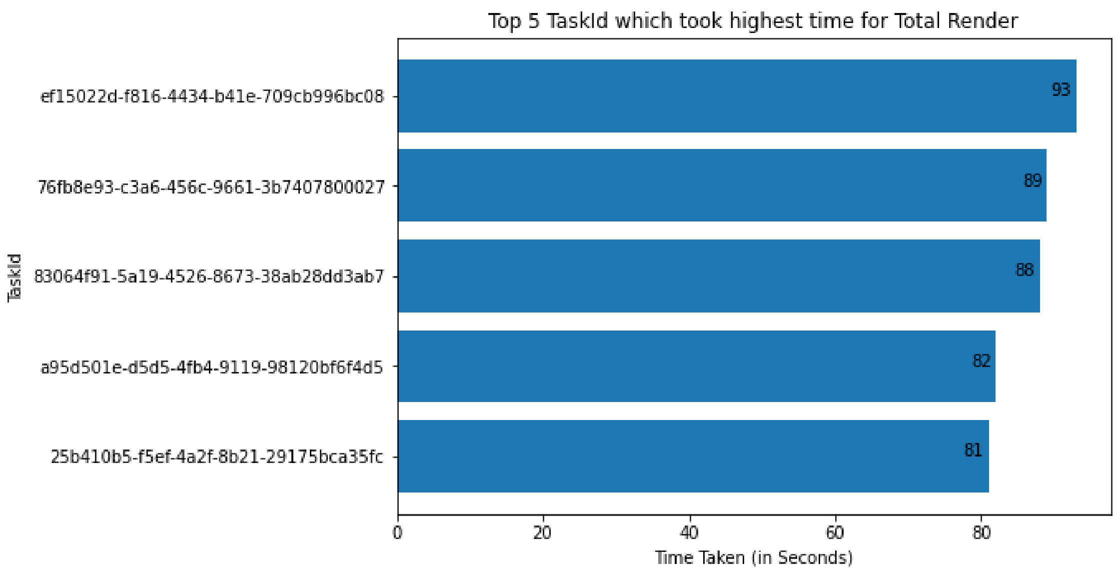
[ ]:
```
q ="""select a.dttm as start_dttm,b.dttm as end_dttm,a.taskId taskId,a.jobId␣
↪jobId,"Total Render" eventname,a.hostname hostname from (select distinct␣
↪dttm,taskId,jobId,hostname from application_checkpoint where␣
↪eventName='TotalRender' and eventType='START') a join
(select distinct dttm,taskId,jobId from application_checkpoint where␣
↪eventName='TotalRender' and eventType='STOP') b on a.jobId=b.jobId and a.
↪taskId=b.taskId ;"""
q_1_4=pysqldf(q)
q_1_4["start_dttm"]=q_1_4["start_dttm"].astype('datetime64')
q_1_4["end_dttm"]=q_1_4["end_dttm"].astype('datetime64')
q_1_4['delta_dttm']=q_1_4['end_dttm']-q_1_4['start_dttm']
# arranging in descending order
q_1_4=q_1_4.sort_values(by='delta_dttm', ascending=False)
q_1_4.head()
```

[ ]:
```
                   start_dttm                end_dttm  \
1372  2018-11-08 07:42:10.593 2018-11-08 07:43:44.290
1462  2018-11-08 07:42:14.867 2018-11-08 07:43:44.392
1475  2018-11-08 07:42:16.024 2018-11-08 07:43:44.248
34739 2018-11-08 08:06:34.096 2018-11-08 08:07:56.607
13324 2018-11-08 07:50:57.636 2018-11-08 07:52:18.946

                                    taskId  \
1372   ef15022d-f816-4434-b41e-709cb996bc08
1462   76fb8e93-c3a6-456c-9661-3b7407800027
1475   83064f91-5a19-4526-8673-38ab28dd3ab7
```

```
34739  a95d501e-d5d5-4fb4-9119-98120bf6f4d5
13324  25b410b5-f5ef-4a2f-8b21-29175bca35fc

                                                       jobId     eventname  \
1372    1024-lvl8-5ad819e1-fbf2-42e0-8f16-a3baca825a63  Total Render
1462   1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  Total Render
1475    1024-lvl8-5ad819e1-fbf2-42e0-8f16-a3baca825a63  Total Render
34739  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  Total Render
13324  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  Total Render

                                   hostname             delta_dttm
1372   0745914f4de046078517041d70b22fe7000015 0 days 00:01:33.697000
1462   b9a1fa7ae2f74eb68f25f607980f97d7000000 0 days 00:01:29.525000
1475   265232c5f6814768aeefa66a7bec6ff6000000 0 days 00:01:28.224000
34739  0d56a730076643d585f77e00d2d8521a00000I 0 days 00:01:22.511000
13324  4a79b6d2616049edbf06c6aa58ab426a000003 0 days 00:01:21.310000
```

[ ]:

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
langs =q_1_4.head()["taskId"]
students = q_1_4.head()["delta_dttm"].dt.total_seconds().astype(int)
ax.barh(langs,students)
plt.xlabel("Time Taken (in Seconds)")
plt.ylabel("TaskId")
ax.invert_yaxis()
plt.title("Top 5 TaskId which took highest time for Total Render")
for i in range(1,6):
   plt.text(-2+q_1_4.head()["delta_dttm"].dt.total_seconds().astype(int).
 ↪iloc[i-1],i-1 ,q_1_4.head()["delta_dttm"].dt.total_seconds().astype(int).
 ↪iloc[i-1], ha="center",rotation="horizontal")
plt.show()
```



[ ]:
```
m=pd.DataFrame()

m=m.append(q_1.tail(1))
m=m.append(q_1.head(1))

m=m.append(q_1_1.tail(1))
m=m.append(q_1_1.head(1))

m=m.append(q_1_2.tail(1))
m=m.append(q_1_2.head(1))

m=m.append(q_1_3.tail(1))
m=m.append(q_1_3.head(1))

m=m.append(q_1_4.iloc[:,[0,1,2,3,4,6]].tail(1))
m=m.append(q_1_4.iloc[:,[0,1,2,3,4,6]].head(1))
m["delta_dttm"]=m["delta_dttm"].dt.total_seconds().astype(float)
m
```

[ ]:
```
                    start_dttm                  end_dttm  \
63401 2018-11-08 08:27:36.636 2018-11-08 08:27:59.215
34739 2018-11-08 08:06:34.098 2018-11-08 08:07:55.606
65792 2018-11-08 08:29:23.158 2018-11-08 08:29:23.160
46417 2018-11-08 08:15:09.191 2018-11-08 08:15:09.651
1656  2018-11-08 07:43:01.595 2018-11-08 07:43:02.280
39393 2018-11-08 08:10:42.124 2018-11-08 08:10:43.379
14843 2018-11-08 07:52:42.790 2018-11-08 07:52:43.512
1566  2018-11-08 07:43:00.730 2018-11-08 07:43:44.248
```

```
5322  2018-11-08 07:45:08.580 2018-11-08 07:45:31.951
1372  2018-11-08 07:42:10.593 2018-11-08 07:43:44.290

                                     taskId  \
63401  0849dfbf-51a2-43d3-b0e4-bfa11f830010
34739  a95d501e-d5d5-4fb4-9119-98120bf6f4d5
65792  5140e07a-71fb-4b6c-ad80-c0695b5a626e
46417  59ac7676-f371-4eee-aa67-5f7c7daf40dc
1656   02029980-be9c-401f-b7ff-2313fa2a495b
39393  910066f8-7f62-46ff-bab5-7dc2bdf4aadd
14843  37ebe851-9042-49e3-9e81-6443603a98ab
1566   83064f91-5a19-4526-8673-38ab28dd3ab7
5322   bb205a5e-251e-4349-b8b0-3402a57e357e
1372   ef15022d-f816-4434-b41e-709cb996bc08

                                              jobId      eventname  \
63401  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705         Render
34739  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705         Render
65792  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  Saving config
46417  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705  Saving config
1656   1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705         Tiling
39393  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705         Tiling
14843  1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705      Uploading
1566    1024-lvl8-5ad819e1-fbf2-42e0-8f16-a3baca825a63      Uploading
5322   1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705   Total Render
1372    1024-lvl8-5ad819e1-fbf2-42e0-8f16-a3baca825a63   Total Render

       delta_dttm
63401      22.579
34739      81.508
65792       0.002
46417       0.460
1656        0.685
39393       1.255
14843       0.722
1566       43.518
5322       23.371
1372       93.697
```

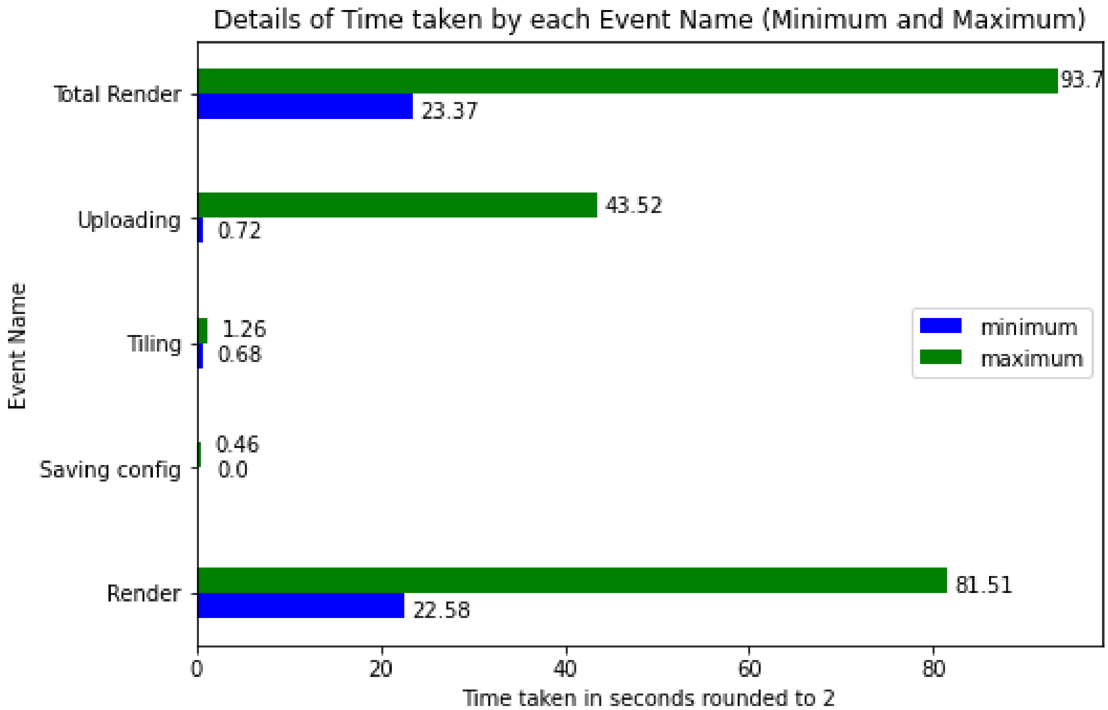
[ ]:
```
q="""select a.taskId taskId,eventname,x,y,level,delta_dttm from m a join␣
 ↪task_x_y b on a.taskId=b.taskId;"""
m_join_taskxy=pysqldf(q)
m_join_taskxy
```

[ ]:
```
                                 taskId      eventname   x    y  level  \
0  0849dfbf-51a2-43d3-b0e4-bfa11f830010         Render  30   21     12
1  a95d501e-d5d5-4fb4-9119-98120bf6f4d5         Render  91  105     12
```

```
2  5140e07a-71fb-4b6c-ad80-c0695b5a626e  Saving config   13   14      12
3  59ac7676-f371-4eee-aa67-5f7c7daf40dc  Saving config  174   41      12
4  02029980-be9c-401f-b7ff-2313fa2a495b         Tiling   41    0      12
5  910066f8-7f62-46ff-bab5-7dc2bdf4aadd         Tiling  166   89      12
6  37ebe851-9042-49e3-9e81-6443603a98ab      Uploading   20   31      12
7  83064f91-5a19-4526-8673-38ab28dd3ab7      Uploading   14    1       8
8  bb205a5e-251e-4349-b8b0-3402a57e357e   Total Render    2   32      12
9  ef15022d-f816-4434-b41e-709cb996bc08   Total Render    3    7       8

   delta_dttm
0      22.579
1      81.508
2       0.002
3       0.460
4       0.685
5       1.255
6       0.722
7      43.518
8      23.371
9      93.697
```

[ ]:
```python
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
la=["Render","Saving config","Tiling","Uploading","Total Render"]
m_m=["minimum","maximum"]
co=["blue","green"]
al=["center","edge"]
n=[]
f=[0.4,0.2]
t=1
j=0
for i in range(0,len(m)):
  if(i%2==0):
    t=0
    j+=1
  n.append(ax.barh(la[j-1],m.
 ↪iloc[i,5],f[t],align=al[t],label=m_m[t],color=co[t]))
  i+=1
  t=1
plt.ylabel("Event Name")
plt.xlabel("Time taken in seconds rounded to 2")
plt.title("Details of Time taken by each Event Name (Minimum and Maximum)")
ax.legend(handles=[n[0],n[1]])
m["delta_dttm"]=round(m.delta_dttm,2)
plt.text(4+m.iloc[0,5],-0.2,m.iloc[0,5], ha="center",rotation="horizontal")
plt.text(4+m.iloc[1,5],-0.2+0.2,m.iloc[1,5], ha="center",rotation="horizontal")
plt.text(4+m.iloc[2,5],0.925,m.iloc[2,5], ha="center",rotation="horizontal")
```

```
plt.text(4+m.iloc[3,5],0.925+0.2,m.iloc[3,5], ha="center",rotation="horizontal")
plt.text(4+m.iloc[4,5],1.85,m.iloc[4,5], ha="center",rotation="horizontal")
plt.text(4+m.iloc[5,5],1.85+0.2,m.iloc[5,5], ha="center",rotation="horizontal")
plt.text(4+m.iloc[6,5],2.85,m.iloc[6,5], ha="center",rotation="horizontal")
plt.text(4+m.iloc[7,5],2.85+0.2,m.iloc[7,5], ha="center",rotation="horizontal")
plt.text(4+m.iloc[8,5],3.8,m.iloc[8,5], ha="center",rotation="horizontal")
plt.text(2.5+m.iloc[9,5],3.85+0.2,m.iloc[9,5],␣
↪ha="center",rotation="horizontal")
plt.show()
```



[ ]:
```
q_1_4["end_dttm"].max()-q_1_4["start_dttm"].min()
```

[ ]:
```
Timedelta('0 days 00:48:45.388000')
```

Comments: The task Id ef15022d-f816-4434-b41e-709cb996bc08 took the highest time (93.7 seconds) for Total Rendering of the image coordinates (x, y) = (3,7) under level 8 and the task Id bb205a5e-251e-4349-b8b0-3402a57e357e took the lowest time (23.57 seconds) for Total Rendering the image coordinates (x, y) = (2,32) under level 12. Task d 83064f91-5a19-4526-8673-38ab28dd3ab7 took the highest time (43.52 seconds) for Uploading the image coordinates (x, y) = (14,1) under level 8 and the task Id 37ebe851-9042-49e3-9e81-6443603a98ab took the lowest time (0.72 seconds) for Uploading the image coordinates (x, y) = (20,31) under level 12.
The task Id 910066f8-7f62-46ff-bab5-7dc2bdf4aadd took the highest time (1.26 seconds) for Tiling the image coordinates (x, y) = (166,89) under level 12 and task Id 02029980-be9c-401f-b7ff-2313fa2a495b took the lowest time (0.68 seconds) for Tiling the image coordinates (x, y) =(41,0)

under level 12.
The task Id 59ac7676-f371-4eee-aa67-5f7c7daf40dc took the highest time (0.46 seconds) for Saving configuration of the image coordinates (x, y) = (174, 41) under level 12 and task Id 5140e07a-71fb-4b6c-ad80-c0695b5a626e took the lowest time (0.002 seconds) for Saving configuration the image coordinates (x, y) = (13,14) under level 12.

The task Id a95d501e-d5d5-4fb4-9119-98120bf6f4d5 took the highest time (81.51 seconds) for Rendering the image coordinates (x, y) = (91,105) under level 12 and task Id 0849dfbf-51a2-43d3-b0e4-bfa11f830010 took the lowest time (22.58 seconds) for Rendering the image coordinates (x, y) = (30,21) under level 12.
Most importantly the total time taken for Total rendering the image is 48 Minutes and 45 Seconds.

2. *Which Event Name consumes more run time?*

[ ]:
```
q ="""select a.dttm as start_dttm,b.dttm as end_dttm,a.taskId taskId,a.jobId␣
↪jobId,a.eventName eventName,a.hostname hostname from (select distinct␣
↪dttm,taskId,jobId,eventName,hostname from application_checkpoint where␣
↪eventType='START') a join
(select distinct dttm,taskId,jobId,eventName,hostname from␣
↪application_checkpoint where eventType='STOP') b on a.jobId=b.jobId and a.
↪taskId=b.taskId and a.eventName=b.eventName and a.hostname=b.hostname;"""
p_1=pysqldf(q)
p_1["start_dttm"]=p_1["start_dttm"].astype('datetime64')
p_1["end_dttm"]=p_1["end_dttm"].astype('datetime64')
p_1['delta_dttm']=p_1['end_dttm']-p_1['start_dttm']
p_1=p_1.sort_values(by='delta_dttm', ascending=False)
p_1_1=p_1
p_1_1["delta_dttm"]=p_1_1["delta_dttm"].astype("string")
p_1_1["delta_dttm"] = pd.to_timedelta(p_1_1["delta_dttm"])
p_1_1['delta_dttm'] = p_1_1['delta_dttm'].dt.total_seconds().astype(int)
```

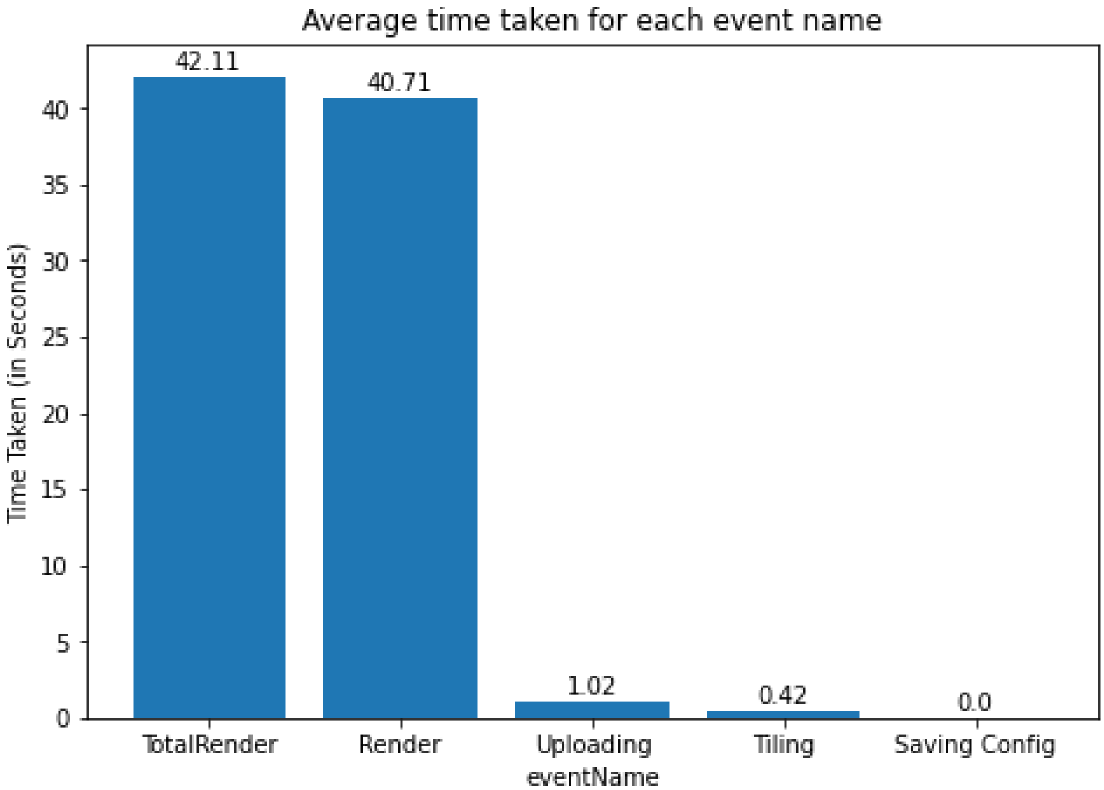
[ ]:
```
q ="""select eventName,avg(delta_dttm) avg_timedelta from p_1_1 group by 1 ;"""
h_1=pysqldf(q)
h_1=h_1.sort_values(by='avg_timedelta', ascending=False)
h_1
```

[ ]:

	eventName	avg_timedelta
3	TotalRender	42.107002
0	Render	40.710987
4	Uploading	1.024364
2	Tiling	0.415090
1	Saving Config	0.000000

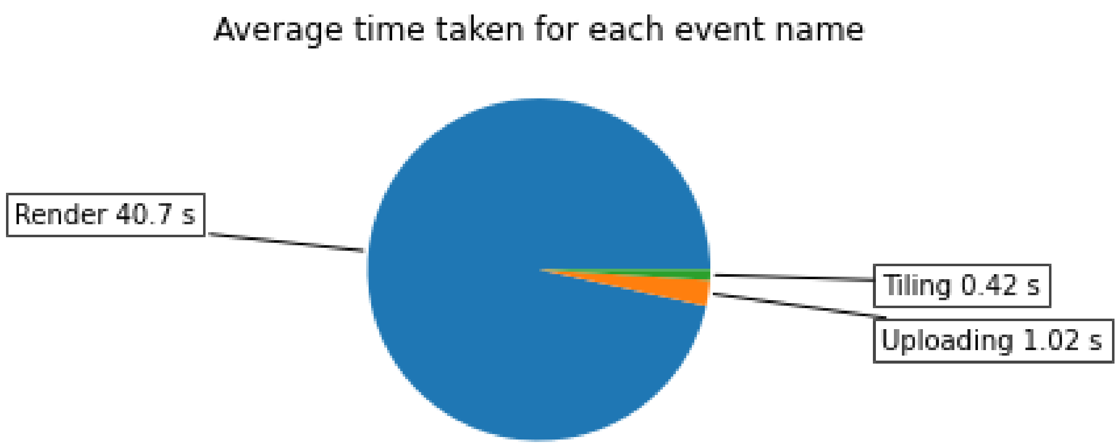
[ ]:
```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
label =h_1["eventName"]
val = h_1["avg_timedelta"]
ax.bar(label,val)
```

```python
plt.ylabel("Time Taken (in Seconds)")
plt.xlabel("eventName")
#ax.invert_yaxis()
plt.title("Average time taken for each event name")
for i in range(1,6):
   plt.text(i-1,0.5+h_1["avg_timedelta"].iloc[i-1] ,round(h_1["avg_timedelta"].
 ↪iloc[i-1],2), ha="center",rotation="horizontal")
plt.show()
```



[ ]:
```python
fig, ax = plt.subplots(figsize=(6, 3), subplot_kw=dict(aspect="equal"))

labels = ["Render 40.7 s","Uploading 1.02 s","Tiling 0.42 s"]

data = [40.71,1.02,0.42]

wedges, texts = ax.pie(data)

bbox_props = dict(boxstyle="square,pad=0.3", fc="w", ec="k", lw=0.72)
kw = dict(arrowprops=dict(arrowstyle="-"),
          bbox=bbox_props, zorder=0, va="center")
```

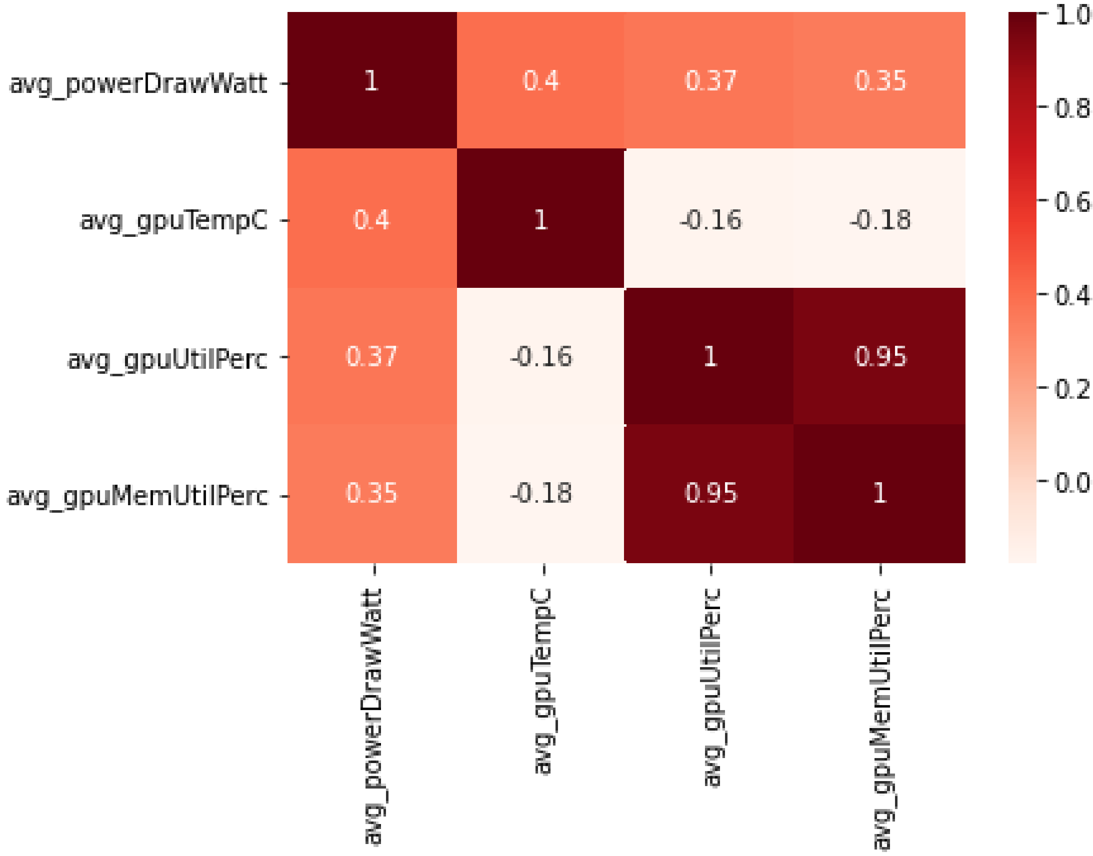
```python
for i, p in enumerate(wedges):
    ang = (p.theta2 - p.theta1)/2. + p.theta1
    y = np.sin(np.deg2rad(ang))
    x = np.cos(np.deg2rad(ang))
    horizontalalignment = {-1: "right", 1: "left"}[int(np.sign(x))]
    connectionstyle = "angle,angleA=0,angleB={}".format(ang)
    kw["arrowprops"].update({"connectionstyle": connectionstyle})
    ax.annotate(labels[i], xy=(x, y), xytext=(2*np.sign(x), 3*y),
                horizontalalignment=horizontalalignment, **kw)

ax.set_title("Average time taken for each event name")

plt.show()
```



Comments: The above bar plot shows that Rendering consumes more run time whereas saving config process consumed the least run time. Total Render will always consume more time as it is the sum that includes all four processes.

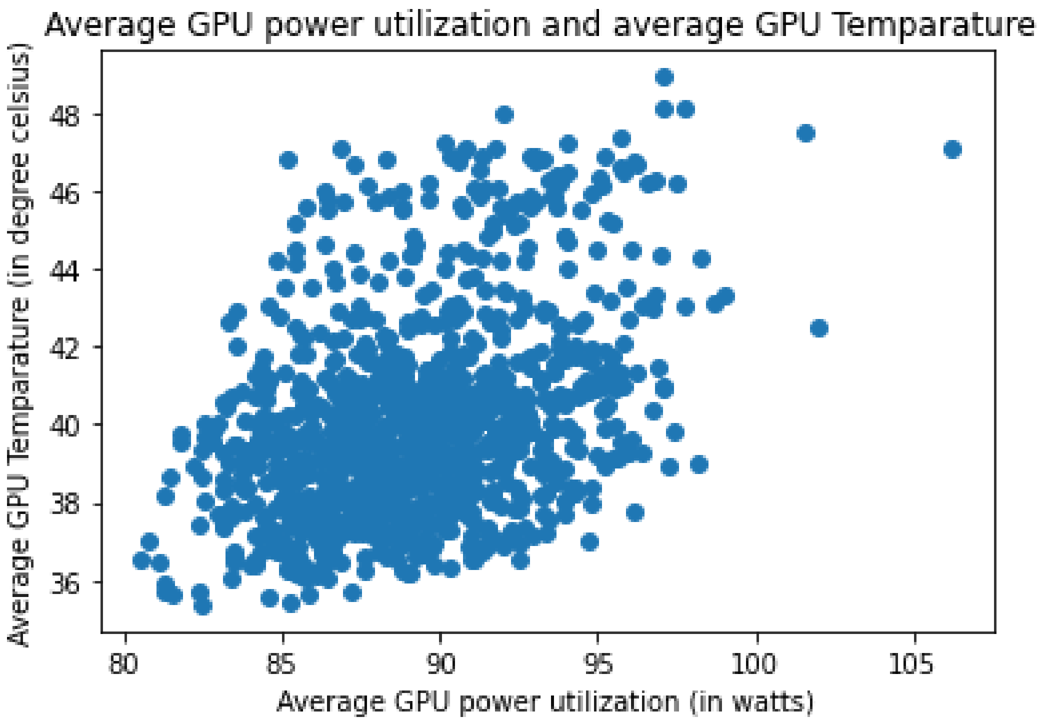
3. *Is there any relationship between the variables in the GPU table? If so, how are they related?* For answering this question, the averages of the numerical variables are used after grouping based on hostName.

[ ]:
```python
import seaborn as sns
q ="""select hostname,avg(powerDrawWatt) avg_powerDrawWatt,avg(gpuTempC)␣
 ↪avg_gpuTempC,avg(gpuUtilPerc) avg_gpuUtilPerc,avg(gpuMemUtilPerc)␣
 ↪avg_gpuMemUtilPerc from gpu group by 1;"""
mean_gpu=pysqldf(q)
sns.heatmap(mean_gpu.iloc[:,1:].corr(), cmap = 'Reds',annot=True)
plt.show()
```



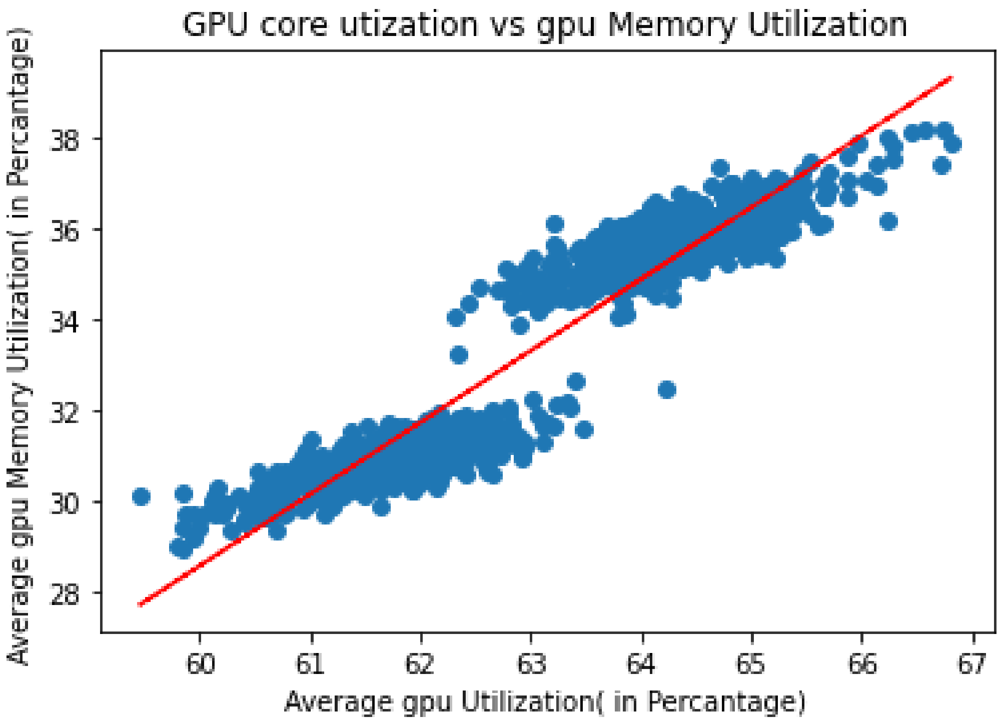
Comments: The heat plot shows there is a strong relationship between the average GPU utilization percentage and average memory utilization percentage. There are no other significant relationships that can be identified from the heat plot.

[ ]:
```
plt.scatter(mean_gpu.iloc[:,1], mean_gpu.iloc[:,2])
plt.title("Average GPU power utilization and average GPU Temparature ")
plt.xlabel('Average GPU power utilization (in watts)')
plt.ylabel('Average GPU Temparature (in degree celsius)')
plt.show()
```



Comments: The above figure shows that there is a slight increase in temperature as the power consumption increases.

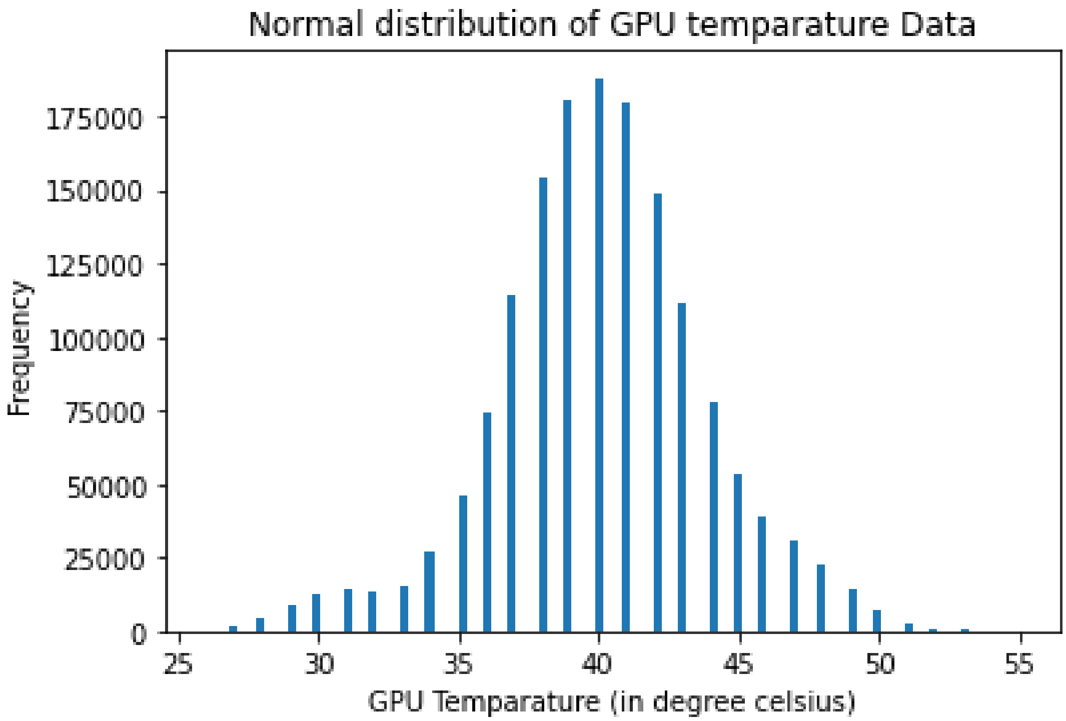
[ ]:
```
plt.scatter(mean_gpu.iloc[:,3], mean_gpu.iloc[:,4])
plt.title('GPU core utization vs gpu Memory Utilization')
plt.xlabel('Average gpu Utilization( in Percantage)')
plt.ylabel('Average gpu Memory Utilization( in Percantage)')
z = np.polyfit(mean_gpu.avg_gpuUtilPerc, mean_gpu.avg_gpuMemUtilPerc, 1)

p = np.poly1d(z)

plt.plot(mean_gpu.avg_gpuUtilPerc,p(mean_gpu.avg_gpuUtilPerc),"r--")
plt.show()
```



Comments: The scatter plot shows that as the core utilization increases memory utilization also increases.

4. *Can any particular statistical model be fitted to any variables related to GPU performance matrix? If so, describe the model.*

[ ]:
```
plt.hist(gpu['gpuTempC'], bins=100)
plt.title('Normal distribution of GPU temparature Data')
plt.xlabel('GPU Temparature (in degree celsius)')
plt.ylabel('Frequency')
plt.show()
```



Comments: The Histogram reveals that the temperature is distributed normally in the data. The mean temperature is 40 degrees Celsius and Standard Deviation is 3.8.

5. ***What are the host names which consumed maximum and minimum time for the rendering process?***

[ ]:
```
q_1_4["delta_dttm"]=q_1_4["delta_dttm"].dt.total_seconds().astype(float)
q="""select hostname,avg(delta_dttm) Time from q_1_4 group by 1;"""
host_5_time=pysqldf(q)
host_5_time_mx=host_5_time.copy().sort_values(by="Time",ascending=0).head(3)
host_5_time_mn=host_5_time.copy().sort_values(by="Time",ascending=0).tail(3)
```

Top 3 hostname which took least time for rendering process

[ ]:
```
host_5_time_mn
```

[ ]:

	hostname	Time
273	35bd84d72aca403b8129a7d652cc275000000N	38.824471
182	265232c5f6814768aeefa66a7bec6ff600000W	38.667857
587	8b6a0eebc87b4cb2b0539e81075191b900000D	38.627915

Top 3 hostname which took maximum time for rendering process

[ ]:
```
host_5_time_mx
```

[ ]:

```
                                  hostname       Time
952  dcc19f48bb3445a28338db3a8f002e9c00000S  47.038776
147  0d56a730076643d585f77e00d2d8521a00001B  47.013441
987  e7adc42d28814e518e9601ac2329c51300000D  46.993169
```

Comments: The hostname 8b6a0eebc87b4cb2b0539e81075191b900000D took minimum time to render the image whereas the hostname dcc19f48bb3445a28338db3a8f002e9c00000S took maximum rendering time. Based on the assumption, it can be seen that the hostnames which took lowest time for rendering is the one which performed well.

6. *What are the maximum and minimum values of computational resource used, temperature and power consumption of the GPU and identify the corresponding virtual machines (hostname)?*

[ ]:

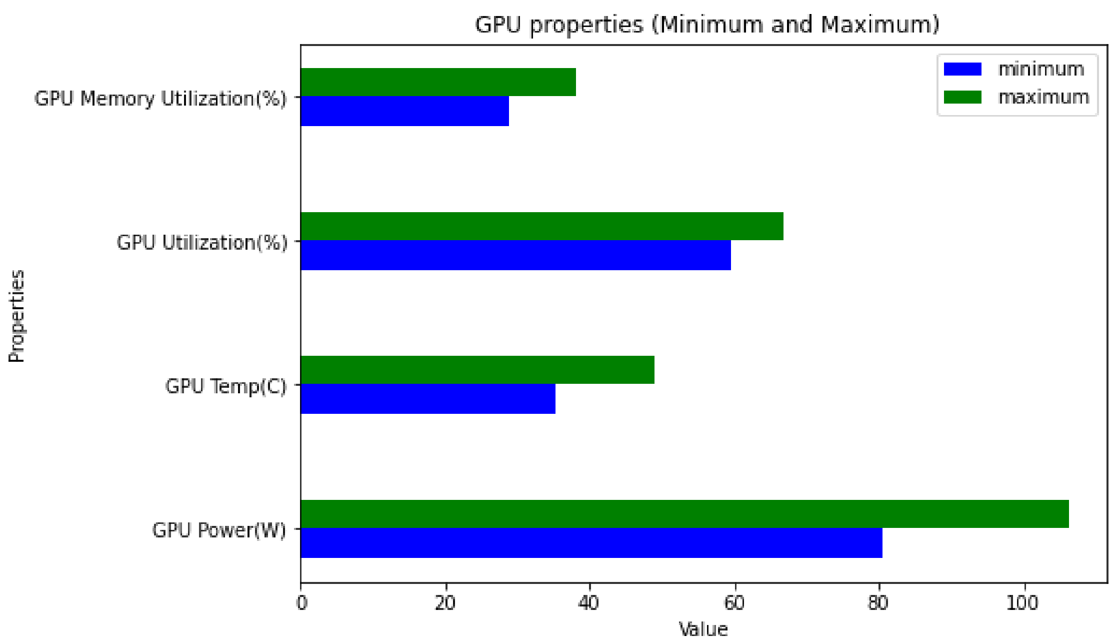
```python
q ="""select hostname,avg(powerDrawWatt) avg_powerDrawWatt,avg(gpuTempC)␣
↪avg_gpuTempC,avg(gpuUtilPerc) avg_gpuUtilPerc,avg(gpuMemUtilPerc)␣
↪avg_gpuMemUtilPerc from gpu group by 1;"""
h=pysqldf(q)
h_p=pd.concat([h.sort_values(by="avg_powerDrawWatt").head(1),h.
↪sort_values(by="avg_powerDrawWatt").tail(1)]) # 1st 2 rows shows max and min␣
↪data by power use
h_p=h_p.append(pd.concat([h.sort_values(by="avg_gpuTempC").head(1),h.
↪sort_values(by="avg_gpuTempC").tail(1)]))#
h_p=h_p.append(pd.concat([h.sort_values(by="avg_gpuUtilPerc").head(1),h.
↪sort_values(by="avg_gpuUtilPerc").tail(1)]))
h_p=h_p.append(pd.concat([h.sort_values(by="avg_gpuMemUtilPerc").head(1),h.
↪sort_values(by="avg_gpuMemUtilPerc").tail(1)]))
h_p
```

[ ]:

```
                                  hostname  avg_powerDrawWatt  avg_gpuTempC  \
126  0d56a730076643d585f77e00d2d8521a00000Q          80.510313     36.533644
687  a77ef58b13ad4c01b769dac8409af3f800000D         106.247462     47.088608
772  b9a1fa7ae2f74eb68f25f607980f97d700001C          82.447675     35.371752
791  cd44f5819eba427a816e7ce648adceb200000H          97.116562     48.926716
855  d8241877cd994572b46c861e5d144c8500000V          91.070781     46.062750
729  b9a1fa7ae2f74eb68f25f607980f97d7000005          92.832931     45.551632
182  265232c5f6814768aeefa66a7bec6ff600000W          81.400200     38.646862
147  0d56a730076643d585f77e00d2d8521a00001B          94.302272     38.357761

     avg_gpuUtilPerc  avg_gpuMemUtilPerc
126        61.221852           30.011992
687        66.451033           38.159227
772        60.662891           30.119254
791        64.073951           35.473684
855        59.464619           30.147530
729        66.825450           37.894071
182        59.859813           28.954606
```

```
147          66.564290          38.231179
```

[ ]:
```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
la=["GPU Power(W)","GPU Temp(C)","GPU Utilization(%)","GPU Memory␣
↪Utilization(%)"]
m_m=["minimum","maximum"]
co=["blue","green"]
al=["center","edge"]
n=[]
f=[0.4,0.2]
j=0
t=1
for i in range(0,8):
  if(i%2==0):
    j+=1
    t=0
  n.append(ax.barh(la[j-1],h_p.
↪iloc[i,j],f[t],align=al[t],label=m_m[t],color=co[t]))
  i+=1
  t=1
plt.ylabel("Properties")
plt.xlabel("Value")
plt.title(" GPU properties (Minimum and Maximum)")
ax.legend(handles=[n[0],n[1]])
plt.show()
```

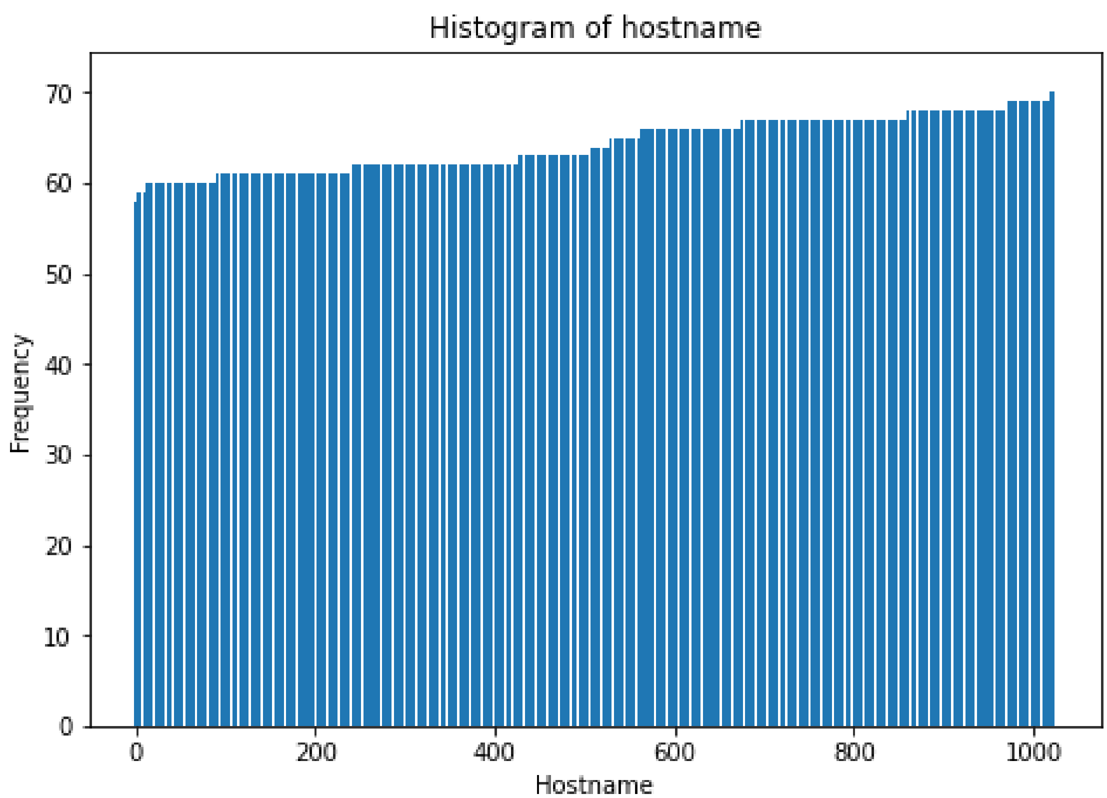


Comments: The above-shown table as well as the figure together shows the details of virtual machines which use maximum as well as minimum computational resources and physical properties of GPU.

7. Which virtual machine processed most image rendering tasks? explain this with the help of a histogram.

```
[ ]: # histogram of hostname

q="""select hostname,count(*) cnt from p_1 where eventname="TotalRender" group␣
 ↪by 1;"""
f=pysqldf(q)
f=f.sort_values(by ="cnt")
```

```
[ ]: fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
langs = list(range(0, 1024))
students = f.cnt
ax.bar(langs,students)
plt.ylabel("Frequency")
plt.xlabel("Hostname")
plt.title("Histogram of hostname")
plt.show()
```



[ ]:
```
print("max= ",f.max(),"min= ",f.min(),"mean=",f.mean(),"standard)deviation=",f.
 ↪std())
```

```
max=  hostname    e7adc42d28814e518e9601ac2329c51300001D
cnt                                                   71
dtype: object min=  hostname    04dc4e9647154250beeee51b866b0715000000
cnt                                                   58
dtype: object mean= cnt    64.250977
dtype: float64 standard)deviation= cnt    2.972421
dtype: float64
```

```
<ipython-input-75-689eb9b01d5f>:1: FutureWarning: Dropping of nuisance columns
in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future
version this will raise TypeError.  Select only valid columns before calling the
reduction.
  print("max= ",f.max(),"min=
",f.min(),"mean=",f.mean(),"standard)deviation=",f.std())
```

[ ]:
```
f[f["cnt"]==f.cnt.min()] # hostname having min count
```

[ ]:

	hostname	cnt
952	dcc19f48bb3445a28338db3a8f002e9c00000S	58

[ ]:
```
f[f["cnt"]==f.cnt.max()] # hostname having max count
```

[ ]:

	hostname	cnt
587	8b6a0eebc87b4cb2b0539e81075191b900000D	71

[ ]:
```
f.cnt.mean() # average of  count
```

[ ]: 64.2509765625

Comments: The histogram shows that a minimum of 58 image coordinates were processed by each virtual machine and the maximum image processing was done by the hostname with Id 8b6a0eebc87b4cb2b0539e81075191b900000D which is 71 image coordinates. The average number of task Id is 64.25 for one hostname with a standard deviation of 2.97.

8. *How many image coordinates are associated with each level?*

[ ]:
```
q="""select level,count(*) cnt from task_x_y group by 1 ;"""
lvl=pysqldf(q)
lvl
```

[ ]:

	level	cnt
0	4	1
1	8	256
2	12	65536

Comments: The highest count is for level 12 which is 65536 and the level with the lowest count is 1 for level 4.

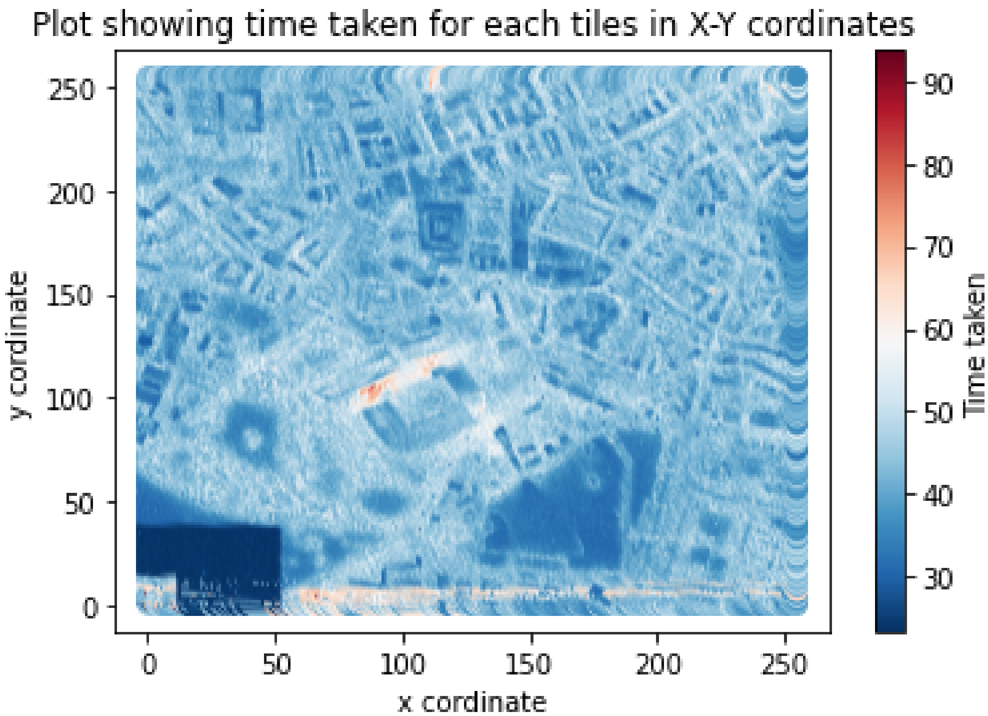
9. *How are the tiles of the image and total rendering times related?*

[ ]:
```
q_1_4["delta_dttm"]=q_1_4["delta_dttm"].dt.total_seconds().astype(float)
```

[ ]:
```
q="""select x,y,max(delta_dttm) delta_dttm from task_x_y a join q_1_4 b on a.
↪taskId =b.taskId group by 1,2;"""
d_plot=pysqldf(q)
d_plot.sort_values(by="delta_dttm")
```

[ ]:
```
         x    y  delta_dttm
544      2   32      23.371
6921    27    9      23.380
8971    35   11      23.418
2838    11   22      23.429
7701    30   21      23.434
…       ..  …          …
23658   92  106      81.310
23401   91  105      82.511
3585    14    1      88.224
17926   70    6      89.525
775      3    7      93.697

[65536 rows x 3 columns]
```

[ ]:
```
d_plot=d_plot.rename(columns={"delta_dttm":"Time taken"})
ax=d_plot.plot.scatter(x="x", y="y", c="Time taken",␣
↪s=50,sharex=False,cmap="RdBu_r")
ax.set_xlabel("x cordinate")
ax.set_ylabel("y cordinate")
ax.set_title("Plot showing time taken for each tiles in X-Y cordinates")
plt.show()
```



Comments: Figure 10 shows the plot generated using the data from the data set Application-check points and Task-x-y. Here, x and y coordinates are the corresponding x and y coordinates from the dataset and colour represent the time taken for the total rendering process of each tile. Subsequently, the scatter plot shows some similarities with the original image which concludes that the tile time taken for processing depends on the tile/pixel values of the original image. The dark-shaded region indicates that the process took a long time to execute for the particular tiles.

10. *Explain the GPU properties using suitable graphs on the basis of hostnames and Task Id?*

[ ]:
```
#converting timestamp to seconds for the tables application checkpoints and GPU
new_tf_1=application_checkpoint.copy()
new_tf_2=gpu.copy()
new_tf_1=new_tf_1.sort_values(by="dttm")
new_tf_2=new_tf_2.sort_values(by="dttm")
q ="""select a.dttm as start_dttm,b.dttm as end_dttm,a.taskId taskId,a.jobId␣
 ↪jobId,"Total Render" eventname,a.hostname hostname from (select distinct␣
 ↪dttm,taskId,jobId,hostname from new_tf_1 where eventName='TotalRender' and␣
 ↪eventType='START') a join
(select distinct dttm,taskId,jobId,hostname from new_tf_1 where␣
 ↪eventName='TotalRender' and eventType='STOP') b on a.jobId=b.jobId and a.
 ↪taskId=b.taskId ;"""
```

```
new_tf_1=pysqldf(q)
new_tf_1["start_dttm"]=new_tf_1["start_dttm"].astype('datetime64')
new_tf_1["end_dttm"]=new_tf_1["end_dttm"].astype('datetime64')
```

Joining all thes 3 tables

[ ]:
```
q =""" select a.start_dttm start_dttm,a.end_dttm end_dttm,b.dttm dttm,a.taskId␣
↪taskId,a.jobId jobId,a.eventname eventname,a.hostname hostname,c.x x,c.y y,c.
↪level level,gpuSerial,gpuUUID,powerDrawWatt,
gpuTempC,gpuUtilPerc,gpuMemUtilPerc from new_tf_1 a join new_tf_2 b on a.
↪hostname=b.hostname and b.dttm<=a.end_dttm and b.dttm>=a.start_dttm join␣
↪task_x_y c on a.taskId=c.taskId;"""
a_c_g_join=pysqldf(q)
```

[ ]:
```
q =""" select hostname,taskId,avg(powerDrawWatt) powerDrawWatt,avg(gpuTempC)␣
↪gpuTempC,avg(gpuUtilPerc) gpuUtilPerc,avg(gpuMemUtilPerc) gpuMemUtilPerc from
a_c_g_join group by 1,2;"""
m_m_m=pysqldf(q)
```

[ ]:
```
#the table showing maximum and minimum of GPU properties by hostname and task Id
u=[]
u=pd.concat([m_m_m.sort_values(by="powerDrawWatt").head(1),m_m_m.
↪sort_values(by="powerDrawWatt").tail(1)])
u=u.append(pd.concat([m_m_m.sort_values(by="gpuTempC").head(1),m_m_m.
↪sort_values(by="gpuTempC").tail(1)]))
u=u.append(pd.concat([m_m_m.sort_values(by="gpuUtilPerc").head(1),m_m_m.
↪sort_values(by="gpuUtilPerc").tail(1)]))
u=u.append(pd.concat([m_m_m.sort_values(by="gpuMemUtilPerc").head(1),m_m_m.
↪sort_values(by="gpuMemUtilPerc").tail(1)]))
u
```

[ ]:
```
                                       hostname  \
2043   04dc4e9647154250beeee51b866b071500000V
13277  2ecb9d8d51bc457aac88073f6da05461000005
31305  6139a35676de44d6b61ec247f0ed865700000F
50799  cd44f5819eba427a816e7ce648adceb200000H
56994  db871cd77a544e13bc791a64a0c8ed5000000C
17954  4a79b6d2616049edbf06c6aa58ab426a000003
14574  2ecb9d8d51bc457aac88073f6da0546100000P
25920  4c72fae95b9147189a0559269a6953ff00000T

                                     taskId  powerDrawWatt   gpuTempC  \
2043   e4c83dfd-c1c2-4805-a8cb-6cf64b01904c      36.941250  31.781250
13277  26c9de8f-d54d-4bda-b02e-f17d38dbbda3     144.278571  46.107143
31305  2744c60b-abea-47fe-a0eb-0be3d1fd4b5b      47.684286  29.571429
50799  f32bc56e-118e-4f9a-8fd9-49b0ecca2525     118.071154  52.423077
56994  54f9f5e7-b737-49f3-8221-787a2b8145ad      41.655152  34.757576
```

```
17954  25b410b5-f5ef-4a2f-8b21-29175bca35fc      96.211750  39.375000
14574  14ed2dea-1470-4455-9267-592e06e58a23      39.501875  36.750000
25920  4f13081c-5c45-43d0-b744-05caaf5377e2     125.296538  39.192308

       gpuUtilPerc  gpuMemUtilPerc
2043     20.312500        8.031250
13277    77.000000       38.285714
31305    27.714286       11.333333
50799    75.692308       47.500000
56994    17.121212        6.878788
17954    87.025000       34.825000
14574    19.375000        6.718750
25920    78.730769       53.076923
```

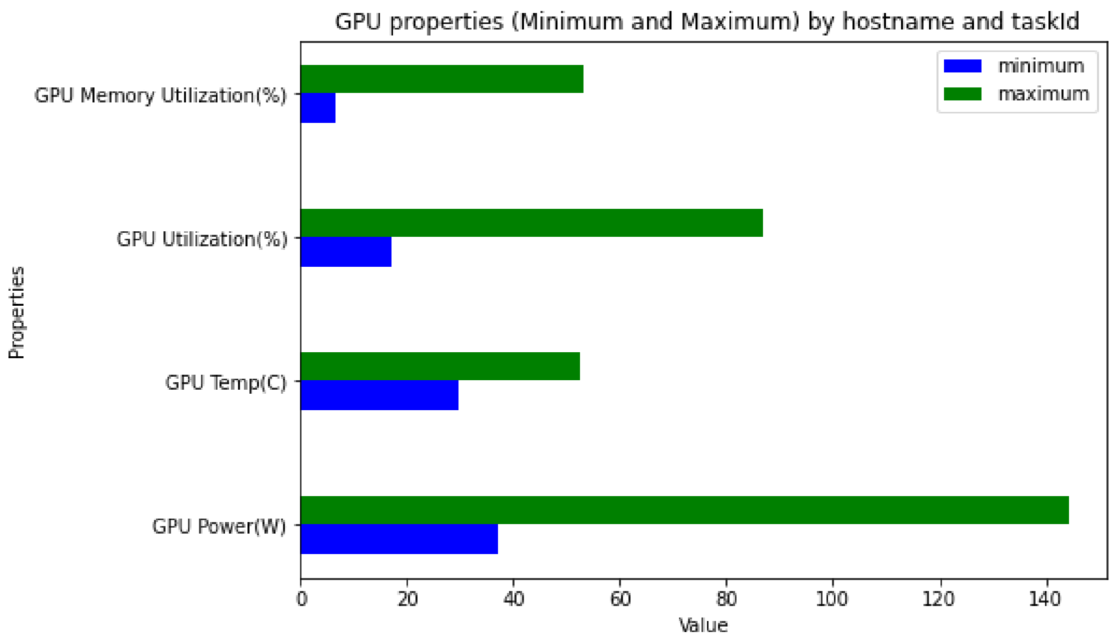
corresponding x-y cordinates of the task Ids of the records in last table

[ ]:
```
q="""select x,y,a.taskid taskid from u a join task_x_y b on a.taskid=b.taskid;
 ↪"""
xy=pysqldf(q)
xy
```

[ ]:
```
     x    y                                taskid
0   51    3  e4c83dfd-c1c2-4805-a8cb-6cf64b01904c
1  113  111  26c9de8f-d54d-4bda-b02e-f17d38dbbda3
2   26    7  2744c60b-abea-47fe-a0eb-0be3d1fd4b5b
3  207  152  f32bc56e-118e-4f9a-8fd9-49b0ecca2525
4   51    0  54f9f5e7-b737-49f3-8221-787a2b8145ad
5   92  106  25b410b5-f5ef-4a2f-8b21-29175bca35fc
6   22    6  14ed2dea-1470-4455-9267-592e06e58a23
7  238  208  4f13081c-5c45-43d0-b744-05caaf5377e2
```

[ ]:
```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
la=["GPU Power(W)","GPU Temp(C)","GPU Utilization(%)","GPU Memory␣
 ↪Utilization(%)"]
m_m=["minimum","maximum"]
co=["blue","green"]
al=["center","edge"]
n=[]
f=[0.4,0.2]
j=0
t=1
for i in range(0,8):
  if(i%2==0):
    j+=1
    t=0
```

```
    n.append(ax.barh(la[j-1],u.
    ↪iloc[i,j+1],f[t],align=al[t],label=m_m[t],color=co[t]))
    i+=1
    t=1
plt.ylabel("Properties")
plt.xlabel("Value")
plt.title(" GPU properties (Minimum and Maximum) by hostname and taskId")
ax.legend(handles=[n[0],n[1]])
plt.show()
```

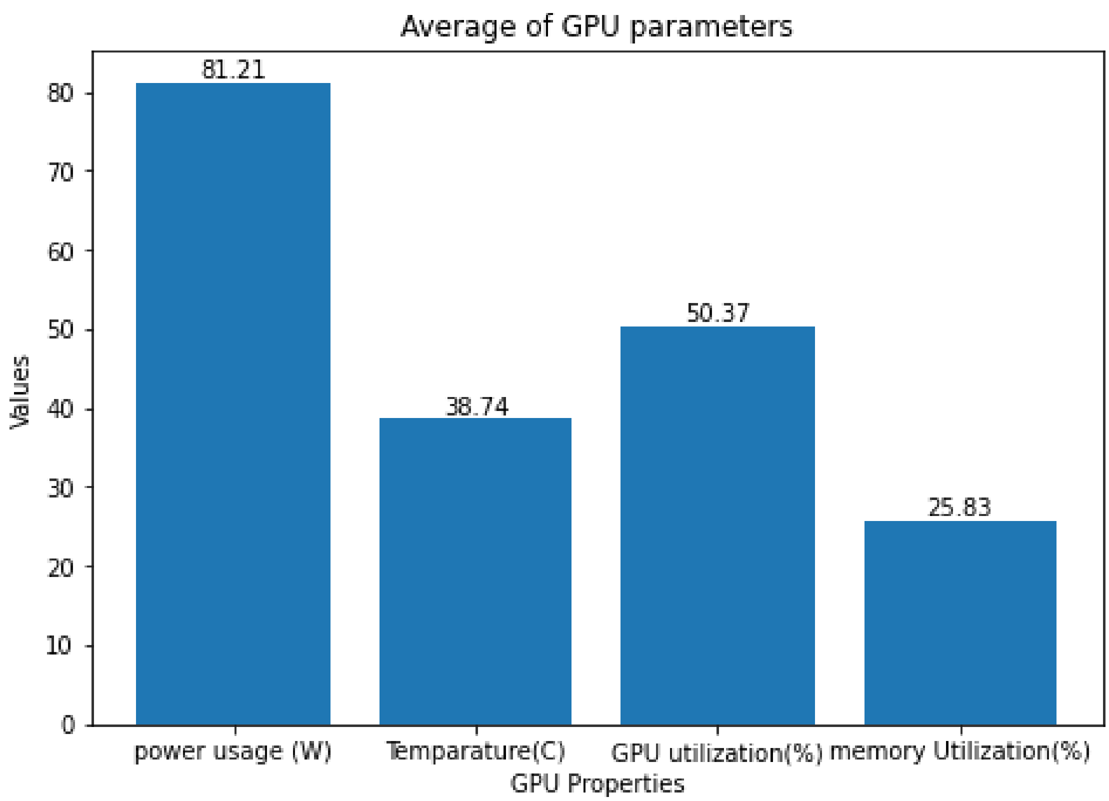


Comments:

- The above Figure and the two tables show that the task Id 26c9de8f-d54d-4bda-b02e-f17d38dbbda3 (113,11) while running in the hostname 2ecb9d8d51bc457aac88073f6da05461000005 and the taskId e4c83dfd-c1c2-4805-a8cb-6cf64b01904c (51,3) executed under 04dc4e9647154250beeee51b866b071500000V consumed maximum and minimum power of 114.28 and 36.94 respectively.
- 52.42 and 29.57 were the extreme temperatures that were recorded for the host Names cd44f5819eba427a816e7ce648adceb200000H and 6139a35676de44d6b61ec247f0ed865700000F while processing the ask Ids f32bc56e-118e-4f9a-8fd9-49b0ecca2525 and 2744c60b-abea-47fe-a0eb-0be3d1fd4b5b respectively.
- TaskIds 54f9f5e7-b737-49f3-8221-787a2b8145ad(51,0) and 25b410b5-f5ef-4a2f-8b21-29175bca35fc (92,106) which executed under 4a79b6d2616049edbf06c6aa58ab426a000003 and db871cd77a544e13bc791a64a0c8ed5000000C respectively showed the GPU utilization percentage of 87.03 and 17.12 which is also the maximum and minimum utilization percentage

- The maximum and minimum GPU memory were utilized by the task ids 4f13081c-5c45-43d0-b744-05caaf5377e2(238,208) and 14ed2dea-1470-4455-9267-592e06e58a23(22,6) while running in the host Names 4c72fae95b9147189a0559269a6953ff00000T and 2ecb9d8d51bc457aac88073f6da0546100000P respectively. They are 53.08 and 6.78.
  The below figure indicates the average of these four GPU parameters

[ ]:
```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
labels =["power usage (W)","Temparature(C)","GPU utilization(%)","memory␣
 ↪Utilization(%)"]
values = [u.powerDrawWatt.mean(),u.gpuTempC.mean(),u.gpuUtilPerc.mean(),u.
 ↪gpuMemUtilPerc.mean()]
ax.bar(labels,values)
plt.ylabel("Values")
plt.xlabel("GPU Properties")
#ax.invert_yaxis()
plt.title("Average of GPU parameters")
for i in range(0,4):
   plt.text(i,0.5+ values[i],round(values[i],2),␣
 ↪ha="center",rotation="horizontal")
plt.show()
```

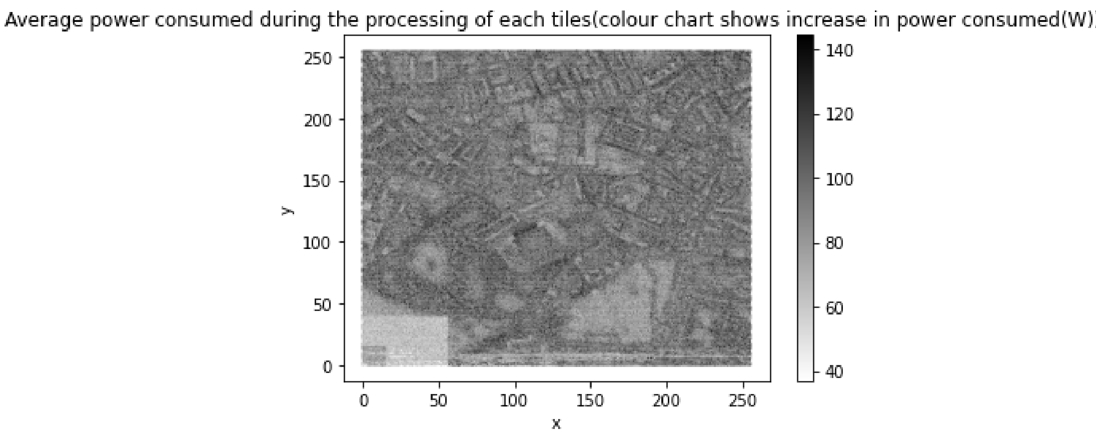


11. ***How are the GPU properties related to the tile properties of the rendered image?***

[ ]:
```
q =""" select taskId,x,y,avg(powerDrawWatt) powerDrawWatt,avg(gpuTempC)␣
↪gpuTempC,avg(gpuUtilPerc) gpuUtilPerc,avg(gpuMemUtilPerc) gpuMemUtilPerc from
a_c_g_join group by 1,2,3;"""
x_y_gpu=pysqldf(q)
```

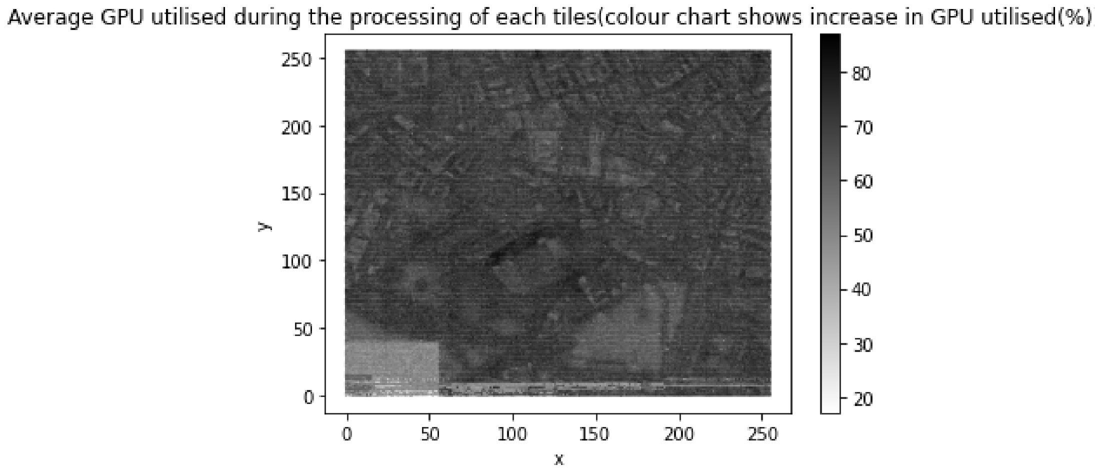
[ ]:
```
x_y_gpu.plot.hexbin(x="x", y="y", C="powerDrawWatt", reduce_C_function=np.
↪average,
                    title='Average power consumed during the processing of each␣
↪tiles(colour chart shows increase in power consumed(W)) ',
                    gridsize=500,cmap='gist_yarg',sharex=False)
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fea1cde1c10>



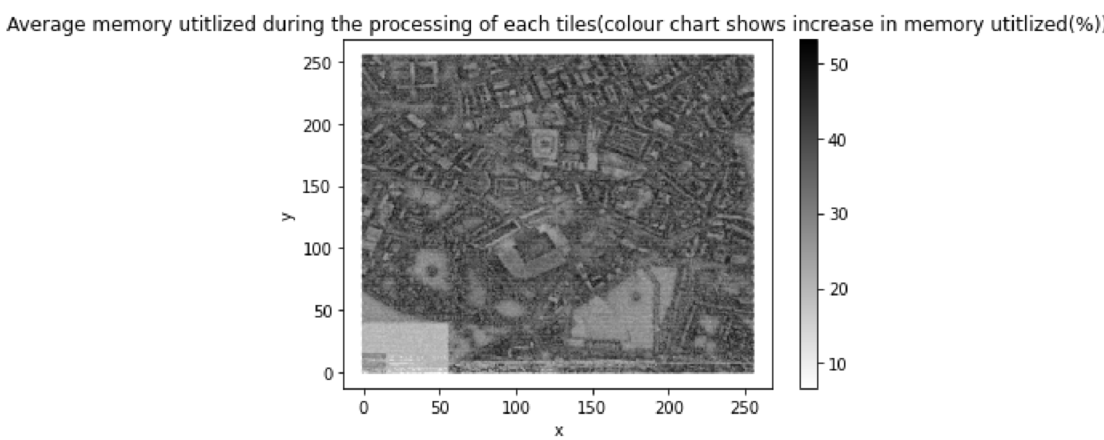
[ ]:
```
x_y_gpu.plot.hexbin(x="x", y="y", C="gpuUtilPerc", reduce_C_function=np.average,
                    title='Average GPU utilised during the processing of each␣
↪tiles(colour chart shows increase in GPU utilised(%)) ',
                    gridsize=500,cmap='gist_yarg',sharex=False)
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fea078e4820>




```
[ ]: x_y_gpu.plot.hexbin(x="x", y="y", C="gpuMemUtilPerc", reduce_C_function=np.
      ↪average, gridsize=500,
                          title='Average memory utitlized during the processing of␣
      ↪each tiles(colour chart shows increase in memory utitlized(%))',
                          xlabel='x',cmap='gist_yarg',sharex=False)
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fea08c91670>
```



comments The colour maps show that the tiles associated with the building and other structure took less power, GPU utilization and memory Utilization. This indicates that colur depth affect these properties. That is as colour depth increases, power, GPU utilization and memory Utilization also increases.

3 EVALUATION

The demand for scaling supercomputer resources can be assessed and confirmed by this EDA analysis. Furthermore, the thorough study offers some suggestions for further research and optimization of the cloud architecture.

According to the analysis's findings, the rendering process took significantly longer than the other 3 stages. Additionally, there is a minimal correlation between the GPU's power consumption and temperature whereas the GPU utilisation and memory utilisation both exhibit a strong linear relationship.

It's interesting to note that the measured temperature is normally distributed, with a mean and expected value of 40 degrees Celsius. In addition, the statistical analysis shows that the host names process an average of 62.41 task IDs. Additionally, the average GPU performance is 25.83% (GPU memory utilisation), 50.37% (GPU utilisation), 81.21 W (power consumption), and 38.74 C (temperature) (GPU temperature). Besides that, the scatter plot created by plotting GPU memory utilisation, Total Render time, GPU utilisation, and power consumption produced a similar representation of the image, indicating a strong correlation between the image's pixel/tile values and these properties in the XY plane, where x denotes the tile's x coordinate and y denotes the tile's y coordinate. In other words, the colour depth affects the rendering parameters. Lastly, It took around 48 minutes and 45 seconds to render the image completely.

The outcome can be used to improve rendering performance and it guides our decision-making over whether to adopt a different cloud architecture or add more virtual machines. The exploratory data analysis aids in determining whether or not additional system resources are required. In summary, by examining the data produced during the rendering process, this exploratory analysis offers helpful information that aids in the assessment of the supercomputer.

4 CONCLUSION

The main objective of the report is to analyse the performance of a cloud-based supercomputer which render a realistic tera-pixel image of the city of Newcastle upon Tyne. In addition, it provides interactive support for the city visualization to various stakeholders. Through this EDA analysis, the need for scaling supercomputer resources can be evaluated and verified. Moreover, the rigorous analysis provides some ideas about the areas of development and to perform optimization in the cloud architecture.

The dataset for the analysis is generated while processing the image shown in figure 9. There are total 65793 tiles in which each tile is linked to a particular task Id. Each tile is associated with x coordinates and y coordinates values. There are mainly 4 tasks namely saving the configuration, Tiling, Rendering and uploading. The time at which these tasks start and stop are given in the application checkpoints table. The hostname is the virtual machine which processes these tasks. There is a total of 1024 virtual machines which render the full-size image. One hostname can execute many task Ids and the GPU properties of these hostnames while executing a particular task Id can be obtained from the GPU table.

The results of the analysis show that the Rendering process took a significant amount of time compared to the other 3 processes. Also, there is slight relation between the GPU temperature and the power it consumed. At the same time, a strong linear relationship can be found between the GPU utilization and memory utilization. Interestingly, the temperature recorded is distributed normally with the mean and expected value of 40 degrees Celsius. Besides that, the statistical analysis indicates an average number of 62.41 task IDs is processed by the host names. Also, The

mean GPU parameters are 25.83 % (GPU memory Utilization), 50.37 % GPU utilization, 81.21 W Power consumption, and 38.74 degree Celsius (GPU temperature). Moreover, the scatter plot obtained by plotting GPU memory utilization, Total Render time, GPU utilization and power consumption generated a similar representation of the image which implies that there is a strong relation between the pixel/ tile values of the image and these properties in the XY plane, where x denote tile x coordinate and y denote tile y coordinate. Lastly, It took around 48 minutes and 45 seconds to render the image completely.
The result obtained can be used to optimize the rendering performance and it helps us to decide whether to choose different cloud architecture or to increase the number of virtual machines. The exploratory data analysis also helps to decide if more system resource is needed or not. In conclusion, this exploratory analysis provides useful information which helps in the evaluation of the supercomputer by analysing the data generated during the rendering process.