Terapixel Dataset: Exploratory Data Analysis

The objective of this report is to evaluate the performance of Terapixel rendering in cloud super computing. The motive is to address the issue of how to deliver the supercomputer scale resources needed to compute a realistic terapixel visualization of the city of Newcastle upon Tyne and its environmental data as captured by the Newcastle Urban Observatory. We're provided with different processes and their time stamps, GPU details, and task details. We'll further analyse these datasets in order to assess speed and accuracy of the super computing, we'll try to know more about the processes involved and their impact on different GPUs. 3 data files: Application checkpoint, GPU and task are loaded

Three datasets are provided here, this data was produced using inputs from system metrics and application checkpoints during the creation of terapixel.

In [138…

```
import pandas as pd
checkpoint = pd.read_csv("C:/Users/arush/Downloads/Terapixel_data/application-checkpoints.csv")
gpu=pd.read_csv("C:/Users/arush/Downloads/Terapixel_data/gpu.csv")
task=pd.read_csv("C:/Users/arush/Downloads/Terapixel_data/task-x-y.csv")
```

In [139…

```
!pip install -U pandasql
```

```
Requirement already satisfied: pandasql in c:\users\arush\anaconda3\lib\site-packages (0.7.3)
Requirement already satisfied: pandas in c:\users\arush\anaconda3\lib\site-packages (from pandasql) (1.2.4)
Requirement already satisfied: numpy in c:\users\arush\anaconda3\lib\site-packages (from pandasql) (1.19.5)
Requirement already satisfied: sqlalchemy in c:\users\arush\anaconda3\lib\site-packages (from pandasql) (1.4.7)
Requirement already satisfied: python-dateutil>=2.7.3 in c:\users\arush\anaconda3\lib\site-packages (from pandas-
>pandasql) (2.8.1)
Requirement already satisfied: pytz>=2017.3 in c:\users\arush\anaconda3\lib\site-packages (from pandas->pandasql)
(2021.1)
Requirement already satisfied: six>=1.5 in c:\users\arush\anaconda3\lib\site-packages (from python-dateutil>=2.7.
3->pandas->pandasql) (1.15.0)
Requirement already satisfied: greenlet!=0.4.17 in c:\users\arush\anaconda3\lib\site-packages (from sqlalchemy->p
andasql) (1.0.0)
```

In [140…

```
#libraries
from sklearn import datasets
import seaborn as sns
from pandasql import sqldf
pysqldf = lambda q: sqldf(q, globals())
```

In [251…

```
checkpoint.head().sort_values(by=['timestamp'])
```

Out[251…

	timestamp	hostname	eventName	eventType	jobId	taskId
0	2018-11-08T07:41:55.921Z	0d56a730076643d585f77e00d2d8521a00000N	Tiling	STOP	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	b47f0263-ba1c-48a7-8d29-4bf021b72043
1	2018-11-08T07:42:29.842Z	0d56a730076643d585f77e00d2d8521a00000N	Saving Config	START	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	20fb9fcf-a927-4a4b-a64c-70258b66b42d
2	2018-11-08T07:42:29.845Z	0d56a730076643d585f77e00d2d8521a00000N	Saving Config	STOP	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	20fb9fcf-a927-4a4b-a64c-70258b66b42d
3	2018-11-08T07:42:29.845Z	0d56a730076643d585f77e00d2d8521a00000N	Render	START	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	20fb9fcf-a927-4a4b-a64c-70258b66b42d
4	2018-11-08T07:43:13.957Z	0d56a730076643d585f77e00d2d8521a00000N	TotalRender	STOP	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	20fb9fcf-a927-4a4b-a64c-70258b66b42d

Application checkpoint

It is saved as checkpoint, q_start_stop is created as a self join to extract rows which contain information about when an event started and stopped,later time taken by each task is calculated and added as a column. The join is based on taskID.

In [143…

```
q_start_stop='select a.hostname,a.taskId, a.jobId, a.eventName,a.eventType as Start,a.timestamp as Start_Time,b.e
q_start_stop=pysqldf(q_start_stop)
q_start_stop.head()
```

Out[143…

	hostname	taskId	jobId	eventName	Start	Start_Time	Stop	Stop_Time
0	0d56a730076643d585f77e00d2d8521a00000N	20fb9fcf-a927-4a4b-a64c-70258b66b42d	1024-lvl12-7e026be3-5fd0-48ee-b7d1-	Render	START	2018-11-08T07:42:29.845Z	STOP	2018-11-08T07:43:10.965Z

			abd61f747705					
1	0d56a730076643d585f77e00d2d8521a00000N	e7776af5-510d-4ec4-b2d3-222b5df3307b	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Render	START	2018-11-08T08:14:53.364Z	STOP	2018-11-08T08:15:32.380Z
2	0d56a730076643d585f77e00d2d8521a00000N	339d3724-dcf6-41f1-b30d-c71107befcee	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Render	START	2018-11-08T08:21:58.845Z	STOP	2018-11-08T08:22:38.257Z
3	0d56a730076643d585f77e00d2d8521a00000N	8d663dcb-7a8c-42e9-93de-21d0e6a508f5	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Render	START	2018-11-08T07:48:06.922Z	STOP	2018-11-08T07:48:47.993Z
4	0d56a730076643d585f77e00d2d8521a00000N	244fd4f0-104e-4512-93b4-d9f83e2d0d9c	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Render	START	2018-11-08T07:59:32.698Z	STOP	2018-11-08T08:00:11.667Z

In [252…

```
#Changing data format
q_start_stop["Start_Time"]=q_start_stop["Start_Time"].astype('datetime64')
q_start_stop["Stop_Time"]=q_start_stop["Stop_Time"].astype('datetime64')
q_start_stop.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 332670 entries, 0 to 332669
Data columns (total 9 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   hostname    332670 non-null  object
 1   taskId      332670 non-null  object
 2   jobId       332670 non-null  object
 3   eventName   332670 non-null  object
 4   Start       332670 non-null  object
 5   Start_Time  332670 non-null  datetime64[ns]
 6   Stop        332670 non-null  object
 7   Stop_Time   332670 non-null  datetime64[ns]
 8   Time_taken  332670 non-null  float64
dtypes: datetime64[ns](2), float64(1), object(6)
memory usage: 22.8+ MB
```

In [255…

```
#Adding the Time taken column
q_start_stop['Time_taken']=(q_start_stop['Stop_Time']-q_start_stop['Start_Time']).dt.total_seconds()
q_start_stop
```

Out[255…

	hostname	taskId	jobId	eventName	Start	Start_Time	Stop	Stop_Time	Time_tak
0	0d56a730076643d585f77e00d2d8521a00000N	20fb9fcf-a927-4a4b-a64c-70258b66b42d	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Render	START	2018-11-08 07:42:29.845	STOP	2018-11-08 07:43:10.965	41.1
1	0d56a730076643d585f77e00d2d8521a00000N	e7776af5-510d-4ec4-b2d3-222b5df3307b	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Render	START	2018-11-08 08:14:53.364	STOP	2018-11-08 08:15:32.380	39.0
2	0d56a730076643d585f77e00d2d8521a00000N	339d3724-dcf6-41f1-b30d-c71107befcee	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Render	START	2018-11-08 08:21:58.845	STOP	2018-11-08 08:22:38.257	39.4
3	0d56a730076643d585f77e00d2d8521a00000N	8d663dcb-7a8c-42e9-93de-21d0e6a508f5	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Render	START	2018-11-08 07:48:06.922	STOP	2018-11-08 07:48:47.993	41.0
4	0d56a730076643d585f77e00d2d8521a00000N	244fd4f0-104e-4512-93b4-d9f83e2d0d9c	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Render	START	2018-11-08 07:59:32.698	STOP	2018-11-08 08:00:11.667	38.9
...	...	...	...	...	...	...	...	...	
332665	265232c5f6814768aeefa66a7bec6ff6000019	8d236089-ade1-4dc8-81c9-5d0a7a84962f	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Uploading	START	2018-11-08 08:30:09.748	STOP	2018-11-08 08:30:10.667	0.9
		46f6a589-a0ff-	1024-lvl12-7e026be3-			2018-11-08		2018-11-08	

332666	0745914f4de046078517041d70b22fe7000017	4e6a-a783-48fac52394ff	5fd0-48ee-b7d1-abd61f747705	Uploading	START	08:30:06.966	STOP	08:30:08.110	1.1
332667	04dc4e9647154250beeee51b866b0715000018	d9e30dd2-b0a5-461c-8bc4-f33030825a2f	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Uploading	START	2018-11-08 08:30:07.303	STOP	2018-11-08 08:30:08.300	0.9
332668	b9a1fa7ae2f74eb68f25f607980f97d7000005	120e5f6f-67a7-4973-b431-026f1a68400c	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Uploading	START	2018-11-08 08:30:11.174	STOP	2018-11-08 08:30:12.074	0.9
332669	0d56a730076643d585f77e00d2d8521a00000D	423b8511-cb2e-4aa4-bb5c-85ca4a2b7ac6	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Uploading	START	2018-11-08 08:30:09.642	STOP	2018-11-08 08:30:10.614	0.9

332670 rows × 9 columns

In [254…

```
q_start_stop[q_start_stop['eventName']=='Saving Config']
#Saving_config takes insignificant time to complete
```

Out[254…

	hostname	taskId	jobId	eventName	Start	Start_Time	Stop	Stop_Time	Time_tak
66534	0d56a730076643d585f77e00d2d8521a00000N	20fb9fcf-a927-4a4b-a64c-70258b66b42d	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Saving Config	START	2018-11-08 07:42:29.842	STOP	2018-11-08 07:42:29.845	0.0
66535	0d56a730076643d585f77e00d2d8521a00000N	c9e249d8-52ed-40c6-8713-b5cbf02ea87e	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Saving Config	START	2018-11-08 07:44:47.555	STOP	2018-11-08 07:44:47.557	0.0
66536	0d56a730076643d585f77e00d2d8521a00000N	fb8b9faa-be63-426c-9742-be30e5298f5b	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Saving Config	START	2018-11-08 08:03:09.698	STOP	2018-11-08 08:03:09.701	0.0
66537	0d56a730076643d585f77e00d2d8521a00000N	674ef19f-b3cb-4aa5-8980-f37cbbca324d	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Saving Config	START	2018-11-08 08:03:46.513	STOP	2018-11-08 08:03:46.515	0.0
66538	0d56a730076643d585f77e00d2d8521a00000N	a3f07861-f633-4c6d-9c12-7fa9a2610524	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Saving Config	START	2018-11-08 08:17:45.406	STOP	2018-11-08 08:17:45.408	0.0
...	...	...	...	...	...	...	...	...	
133063	b9a1fa7ae2f74eb68f25f607980f97d700000V	b8f12d97-bfcd-4724-b617-b15db8192e42	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Saving Config	START	2018-11-08 08:29:23.079	STOP	2018-11-08 08:29:23.082	0.0
133064	04dc4e9647154250beeee51b866b071500000G	a86081e9-57a0-44f6-8694-5a5a8b9fedc1	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Saving Config	START	2018-11-08 08:29:21.018	STOP	2018-11-08 08:29:21.020	0.0
133065	0d56a730076643d585f77e00d2d8521a00000X	4b87d4d9-16a2-4331-b73c-b444eb5415d4	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Saving Config	START	2018-11-08 08:29:23.052	STOP	2018-11-08 08:29:23.055	0.0
133066	0745914f4de046078517041d70b22fe700000I	8261c0ff-03d6-48b3-a50f-da41cb3291fd	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Saving Config	START	2018-11-08 08:29:23.079	STOP	2018-11-08 08:29:23.081	0.0
133067	0d56a730076643d585f77e00d2d8521a00001B	8cd9ae78-e712-4313-81a6-6e509514109b	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Saving Config	START	2018-11-08 08:29:23.079	STOP	2018-11-08 08:29:23.081	0.0

66534 rows × 9 columns

Exploratory Data analysis

Exploratory Data analysis

- We'll try to answer few questions using the given dataset, like
- What is the time taken by different event?
- Which events take more time and which takes the least?
- If there any relationship among different GPU metrics?
- Which GPUs draw most power on average?
- Which GPUs take more time in completing the events?

Now that each event is separated along with its time taken, average time taken by each event is calculated and plotted:

In [147…

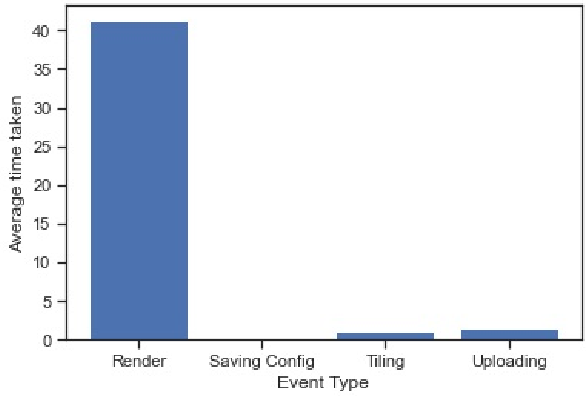
```
q_avg_time_taken="select eventName,AVG(Time_Taken) from q_start_stop where eventName not like '%TotalRender%' gro
q_avg_time_taken=pysqldf(q_avg_time_taken)
q_avg_time_taken
```

Out[147…

	eventName	AVG(Time_Taken)
0	Render	41.227902
1	Saving Config	0.002476
2	Tiling	0.973204
3	Uploading	1.393523

In [148…

```
#Average time V/s Events
import matplotlib.pyplot as plt
plt.bar(q_avg_time_taken['eventName'],q_avg_time_taken['AVG(Time_Taken)'])
plt.xlabel("Event Type")
plt.ylabel("Average time taken")
plt.show()
```



From above plot, it is clearly that Render takes significantly high time as compared to other events.

GPU: Finding relationship between temperature and GPU performance metrics

In [257…

```
gpu.sort_values(by=['hostname'])
```

Out[257…

	timestamp	hostname	gpuSerial	gpuUUID	powerDrawWatt	gpuTempC	gpuUtilPerc	gpuMe
706276	2018-11-08 08:14:40.694	04dc4e9647154250beeee51b866b0715000000	323217056165	GPU-a1119ee9-9cd1-919f-a479-b902142c717d	77.56	45	94	
417017	2018-11-08 07:45:11.221	04dc4e9647154250beeee51b866b0715000000	323217056165	GPU-a1119ee9-9cd1-919f-a479-b902142c717d	89.90	44	89	
1215332	2018-11-08 08:11:59.273	04dc4e9647154250beeee51b866b0715000000	323217056165	GPU-a1119ee9-9cd1-919f-a479-b902142c717d	110.85	46	91	
406575	2018-11-08 07:43:30.338	04dc4e9647154250beeee51b866b0715000000	323217056165	GPU-a1119ee9-9cd1-919f-a479-b902142c717d	144.42	45	89	

1016041	2018-11-08 08:00:59.520	04dc4e9647154250beeee51b866b0715000000	323217056165	GPU-a1119ee9-9cd1-919f-a479-b902142c717d	131.93	44	92
...	...	...	...	...	...	...	...
1295145	2018-11-08 07:47:10.580	e7adc42d28814e518e9601ac2329c51300001D	320118119027	GPU-0cee5a9f-749e-7780-791a-ff2b29590a38	111.33	41	88
195314	2018-11-08 08:00:55.686	e7adc42d28814e518e9601ac2329c51300001D	320118119027	GPU-0cee5a9f-749e-7780-791a-ff2b29590a38	43.39	36	7
491935	2018-11-08 08:00:01.225	e7adc42d28814e518e9601ac2329c51300001D	320118119027	GPU-0cee5a9f-749e-7780-791a-ff2b29590a38	155.29	43	94
1000896	2018-11-08 07:42:30.193	e7adc42d28814e518e9601ac2329c51300001D	320118119027	GPU-0cee5a9f-749e-7780-791a-ff2b29590a38	26.51	33	0
118048	2018-11-08 08:26:16.718	e7adc42d28814e518e9601ac2329c51300001D	320118119027	GPU-0cee5a9f-749e-7780-791a-ff2b29590a38	135.27	40	93

1543681 rows × 8 columns

In [150…

```
gpu['hostname'].value_counts()
```

Out[150…

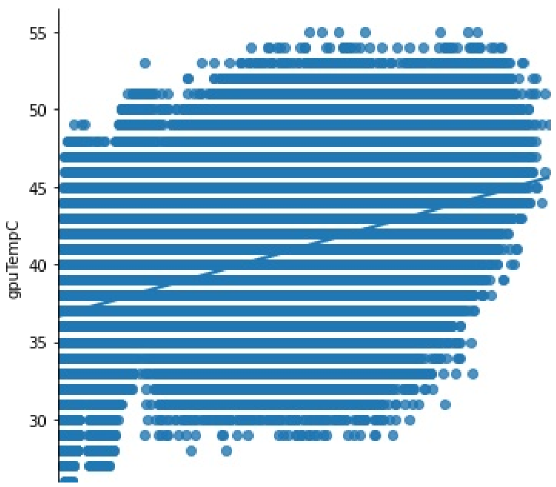
```
4a79b6d2616049edbf06c6aa58ab426a00000Y    3002
4ad946d4435c42dabb5073531ea4f315000001    3002
35bd84d72aca403b8129a7d652cc2750000005    3002
0745914f4de046078517041d70b22fe7000005    3002
95b4ae6d890e4c46986d91d7ac4bf082000010    2992
                                          ...
0d56a730076643d585f77e00d2d8521a00000I    1492
0d56a730076643d585f77e00d2d8521a00000F    1492
0d56a730076643d585f77e00d2d8521a00000N    1492
0d56a730076643d585f77e00d2d8521a00000S    1491
0d56a730076643d585f77e00d2d8521a000012    1489
Name: hostname, Length: 1024, dtype: int64
```

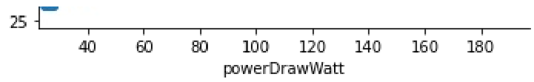
From above, we can conclude the GPU has 15,43,681 records, and for each hostname, there are multiple entries about their temperature, power drawn, GPU utilization percentage, memory utilization percentage at different time intervals.

Finding relationship between GPU temperature & other GPU performance metrics

In [25]:

```
# Power drawn v/s Temperature
plt.rcParams['figure.figsize'] = [10, 6]
sns.lmplot(x="powerDrawWatt",y="gpuTempC", data=gpu)
plt.show()
```

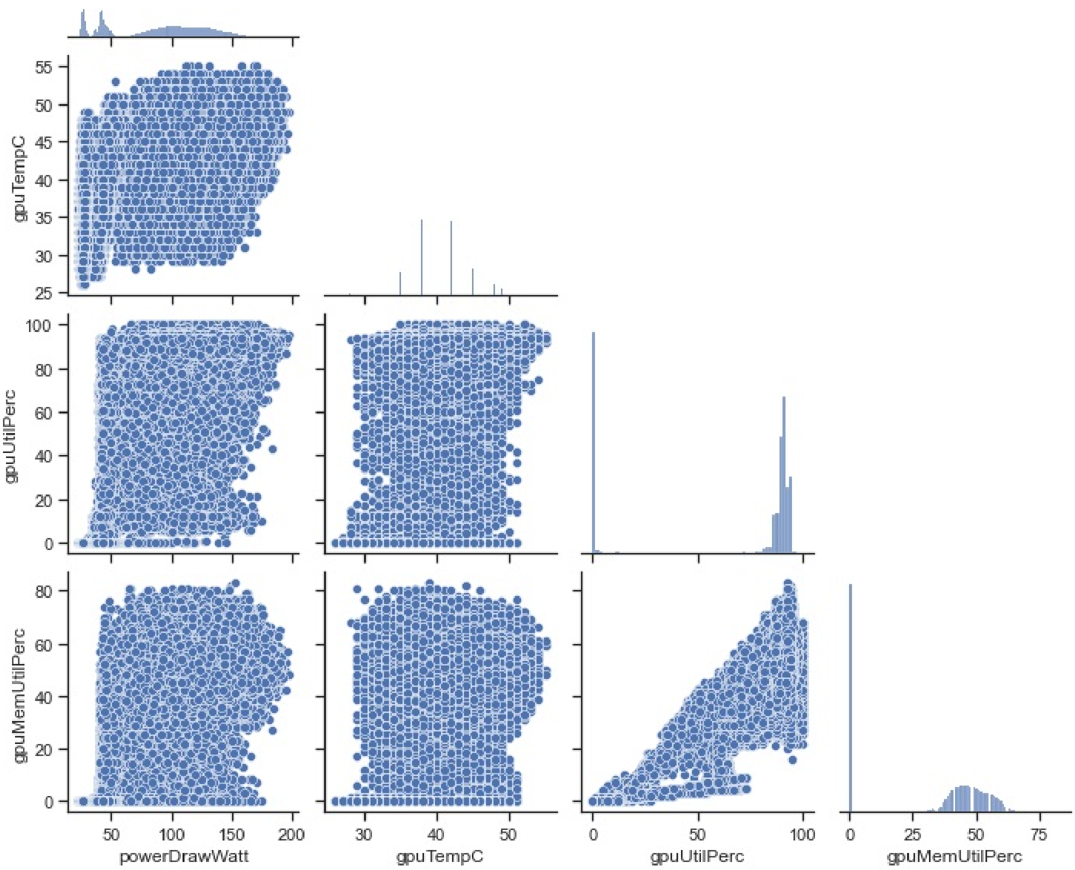




The above plot do not clearly forms a relation but gives a vague linear proportional relation between power drawn and temperature

Pairplot for Performance metrics and Temperature

In [62]:
```
sns.pairplot(
    gpu,
    x_vars=["powerDrawWatt","gpuTempC","gpuUtilPerc","gpuMemUtilPerc"],
    y_vars=["powerDrawWatt","gpuTempC","gpuUtilPerc","gpuMemUtilPerc"],corner=True
)
plt.show()
```



This graph clearly highlight an approx. direct relationship between GPU memory utilization percentage and GPU utilization percentage.

Analyzing GPU and q_start_stop(refined application checkpoint data)

In [60]:
```
gpu['hostname'].shape# 1,024 hostnames; 15,43,681 records
```

Out[60]: (1543681,)

In [27]:
```
q_start_stop.head()
```

Out[27]:

	hostname	taskId	jobId	eventName	Start	Start_Time	Stop	Stop_Time	Time_taken
0	0d56a730076643d585f77e00d2d8521a00000N	20fb9fcf-a927-4a4b-a64c-70258b66b42d	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Render	START	2018-11-08 07:42:29.845	STOP	2018-11-08 07:43:10.965	41.120

1	0d56a730076643d585f77e00d2d8521a00000N	e7776af5-510d-4ec4-b2d3-222b5df3307b	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Render	START	2018-11-08 08:14:53.364	STOP	2018-11-08 08:15:32.380	39.016
2	0d56a730076643d585f77e00d2d8521a00000N	339d3724-dcf6-41f1-b30d-c71107befcee	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Render	START	2018-11-08 08:21:58.845	STOP	2018-11-08 08:22:38.257	39.412
3	0d56a730076643d585f77e00d2d8521a00000N	8d663dcb-7a8c-42e9-93de-21d0e6a508f5	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Render	START	2018-11-08 07:48:06.922	STOP	2018-11-08 07:48:47.993	41.071
4	0d56a730076643d585f77e00d2d8521a00000N	244fd4f0-104e-4512-93b4-d9f83e2d0d9c	1024-lvl12-7e026be3-5fd0-48ee-b7d1-abd61f747705	Render	START	2018-11-08 07:59:32.698	STOP	2018-11-08 08:00:11.667	38.969

In [151…

```
gpu["timestamp"]=gpu["timestamp"].astype('datetime64')
```

In [66]:

```
gpu.head()
```

Out[66]:

	timestamp	hostname	gpuSerial	gpuUUID	powerDrawWatt	gpuTempC	gpuUtilPerc	gpuMemUtilPe
0	2018-11-08 08:27:10.314	8b6a0eebc87b4cb2b0539e81075191b900001C	323217055910	GPU-1d1602dc-f615-a7c7-ab53-fb4a7a479534	131.55	48	92	
1	2018-11-08 08:27:10.192	d8241877cd994572b46c861e5d144c85000000	323617020295	GPU-04a2dea7-f4f1-12d0-b94d-996446746e6f	117.03	40	92	
2	2018-11-08 08:27:10.842	db871cd77a544e13bc791a64a0c8ed50000006	323217056562	GPU-f4597939-a0b4-e78a-2436-12dbab9a350f	121.64	45	91	
3	2018-11-08 08:27:10.424	b9a1fa7ae2f74eb68f25f607980f97d7000010	325217085931	GPU-ad773c69-c386-a4be-b214-1ea4fc6045df	50.23	38	90	
4	2018-11-08 08:27:10.937	db871cd77a544e13bc791a64a0c8ed50000003	323217056464	GPU-2d4eed64-4ca8-f12c-24bc-28f036493ea2	141.82	41	90	

In [84]:

```
q_start_stop['hostname'].value_counts().head(20) #1024 hostnames
```

Out[84]:

```
0d56a730076643d585f77e00d2d8521a000000    1240
b9a1fa7ae2f74eb68f25f607980f97d7000009    1240
0d56a730076643d585f77e00d2d8521a00000P    1240
b9a1fa7ae2f74eb68f25f607980f97d700000Y    1220
8b6a0eebc87b4cb2b0539e81075191b900000D     355
35bd84d72aca403b8129a7d652cc275000000N     350
d8241877cd994572b46c861e5d144c8500001C     350
265232c5f6814768aeefa66a7bec6ff600000W     350
dcc19f48bb3445a28338db3a8f002e9c000000     350
a77ef58b13ad4c01b769dac8409af3f8000015     350
a77ef58b13ad4c01b769dac8409af3f8000018     345
b9a1fa7ae2f74eb68f25f607980f97d7000008     345
a77ef58b13ad4c01b769dac8409af3f8000014     345
0d56a730076643d585f77e00d2d8521a00001C     345
0745914f4de046078517041d70b22fe700000H     345
d8241877cd994572b46c861e5d144c85000004     345
0d56a730076643d585f77e00d2d8521a00000Z     345
0745914f4de046078517041d70b22fe7000014     345
35bd84d72aca403b8129a7d652cc2750000000     345
cd44f5819eba427a816e7ce648adceb200000Z     345
Name: hostname, dtype: int64
```

In [79]:

```
(gpu['hostname'].value_counts()).head(20) # 1024 hostnames
```

Out[79]:

```
4ad946d4435c42dabb5073531ea4f315000001    3002
0745914f4de046078517041d70b22fe7000005    3002
35bd84d72aca403b8129a7d652cc2750000005    3002
4a79b6d2616049edbf06c6aa58ab426a00000Y    3002
95b4ae6d890e4c46986d91d7ac4bf082000010    2992
04dc4e9647154250beeee51b866b071500000G    1502
a77ef58b13ad4c01b769dac8409af3f800000G    1502
db871cd77a544e13bc791a64a0c8ed5000000A    1502
a77ef58b13ad4c01b769dac8409af3f800000I    1502
a77ef58b13ad4c01b769dac8409af3f8000018    1502
4a79b6d2616049edbf06c6aa58ab426a000007    1501
e7adc42d28814e518e9601ac2329c51300000X    1501
a77ef58b13ad4c01b769dac8409af3f800000Q    1501
83ea61ac1ef54f27a3bf7bd0f41ecaa700000X    1501
a77ef58b13ad4c01b769dac8409af3f800000A    1501
b9a1fa7ae2f74eb68f25f607980f97d7000006    1501
b9a1fa7ae2f74eb68f25f607980f97d700000M    1501
5903af3699134795af7eafc605ae5fc700000C    1501
265232c5f6814768aeefa66a7bec6ff6000009    1501
0d56a730076643d585f77e00d2d8521a000002    1501
Name: hostname, dtype: int64
```

In [85]:

```
q_start_stop[q_start_stop['hostname']=="4ad946d4435c42dabb5073531ea4f315000001"]
```

Out[85]:

	hostname	taskId	eventName	Start	Start_Time	Stop	Stop_Time	Time_taken
55	4ad946d4435c42dabb5073531ea4f315000001	ef4839e2-ebde-4834-ae7c-c8908e2600d7	Render	START	2018-11-08 07:41:31.206	STOP	2018-11-08 07:42:16.958	45.752
1089	4ad946d4435c42dabb5073531ea4f315000001	b73094ce-822a-4ad2-8eec-80d98d95882c	Render	START	2018-11-08 07:53:47.398	STOP	2018-11-08 07:54:36.071	48.673
2460	4ad946d4435c42dabb5073531ea4f315000001	1f6e40dd-d2d0-40d0-bb29-2f9b336f0806	Render	START	2018-11-08 07:58:47.872	STOP	2018-11-08 07:59:34.617	46.745
3260	4ad946d4435c42dabb5073531ea4f315000001	2d5d501f-4534-4e55-b958-d0f02c689a56	Render	START	2018-11-08 08:01:44.106	STOP	2018-11-08 08:02:27.117	43.011
5354	4ad946d4435c42dabb5073531ea4f315000001	20f6cd42-1fb6-47fe-990c-2c842d066ad8	Render	START	2018-11-08 07:50:19.442	STOP	2018-11-08 07:51:04.290	44.848
...	...	...	...	...	...	...	...	...
324032	4ad946d4435c42dabb5073531ea4f315000001	170b25ba-7288-431d-b835-8cf242989d7f	Uploading	START	2018-11-08 07:48:03.775	STOP	2018-11-08 07:48:04.792	1.017
324184	4ad946d4435c42dabb5073531ea4f315000001	b63749b4-4462-4c64-b456-ed7123411334	Uploading	START	2018-11-08 07:48:45.125	STOP	2018-11-08 07:48:46.048	0.923
324378	4ad946d4435c42dabb5073531ea4f315000001	0ead2431-3ee5-4bbd-9c16-ba9e89ab779f	Uploading	START	2018-11-08 07:49:24.201	STOP	2018-11-08 07:49:25.327	1.126
324837	4ad946d4435c42dabb5073531ea4f315000001	20f6cd42-1fb6-47fe-990c-2c842d066ad8	Uploading	START	2018-11-08 07:51:04.290	STOP	2018-11-08 07:51:05.233	0.943
325518	4ad946d4435c42dabb5073531ea4f315000001	f9f306b9-97ac-40c2-b0ce-1578b8f7f43c	Uploading	START	2018-11-08 08:03:57.930	STOP	2018-11-08 08:03:58.949	1.019

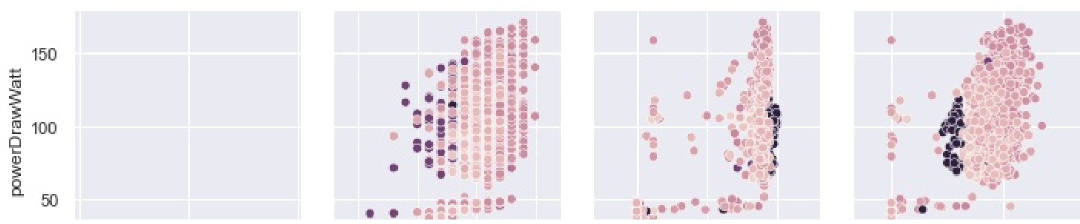
315 rows × 8 columns

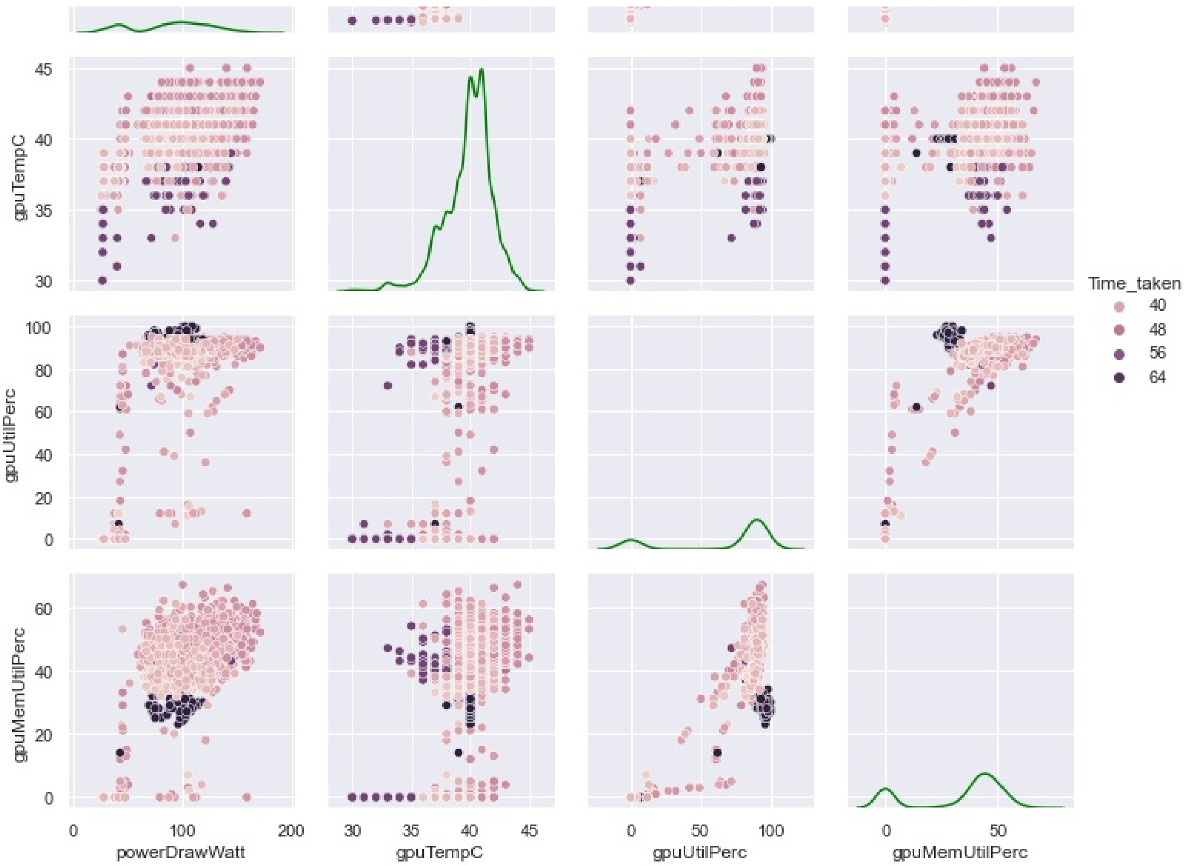
GPU and q_start_stop, both files have 1024 hostname entries and both have multiple entries for each hostname. Merging these 2 datafiles would create a very large datafile which can be difficult to handle. Hence, first we can take one hostname at a time and find a relation:

In [261…

```
ss_gpu_totalrender2="select gpu.*,ss.eventName,ss.Time_taken from q_start_stop ss INNER JOIN gpu on ss.hostname=
ss_gpu_totalrender2=pysqldf(ss_gpu_totalrender2)

g = sns.PairGrid(ss_gpu_totalrender2,vars=["powerDrawWatt","gpuTempC","gpuUtilPerc","gpuMemUtilPerc"], hue="Time_
g.map_diag(sns.kdeplot, hue=None, color="green")
g.map_offdiag(sns.scatterplot)
g.add_legend()
plt.show()
```





Above pairplot shows similar relation for total render event for one hostname. It is interesting to note that high time taking total render event clustered around the same place. This pattern is seen in Power drawn Vs. GPU utilisation percentage, power drawn Vs. GPU memory utilisation percentage, and GPU utilisation percentage Vs. GPU memory utilisation percentage.

Finding GPUs with top average Power drawn

In [153…

```
query="select hostname,AVG(powerDrawWatt) as avg_power from gpu group by hostname;"
query=pysqldf(query)
query
```

Out[153…

	hostname	avg_power
0	04dc4e9647154250beeee51b866b0715000000	95.868947
1	04dc4e9647154250beeee51b866b0715000001	91.813693
2	04dc4e9647154250beeee51b866b0715000002	82.537798
3	04dc4e9647154250beeee51b866b0715000003	86.558581
4	04dc4e9647154250beeee51b866b0715000004	94.292392
...	...	...
1019	e7adc42d28814e518e9601ac2329c513000019	89.386562
1020	e7adc42d28814e518e9601ac2329c51300001A	82.943504
1021	e7adc42d28814e518e9601ac2329c51300001B	88.354997
1022	e7adc42d28814e518e9601ac2329c51300001C	88.411319
1023	e7adc42d28814e518e9601ac2329c51300001D	97.399313

1024 rows × 2 columns

In [154…

```
query=query.sort_values(by=['avg_power'],ascending=False).head(10)
query
```

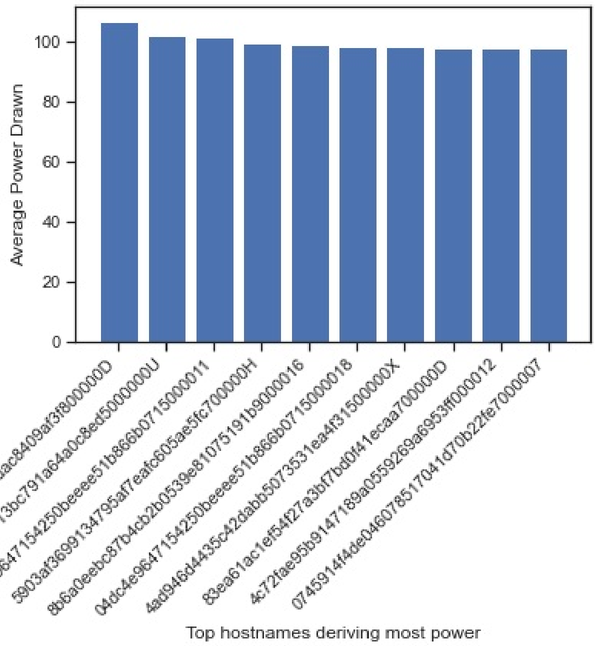
Out[154…

	hostname	avg_power
687	a77ef58b13ad4c01b769dac8409af3f800000D	106.247462
904	db871cd77a544e13bc791a64a0c8ed5000000U	101.974324
37	04dc4e9647154250beeee51b866b0715000011	101.549633
441	5903af3699134795af7eafc605ae5fc700000H	99.057575

616	8b6a0eebc87b4cb2b0539e81075191b9000016	98.698678
44	04dc4e9647154250beeee51b866b0715000018	98.250353
357	4ad946d4435c42dabb5073531ea4f31500000X	98.150566
537	83ea61ac1ef54f27a3bf7bd0f41ecaa700000D	97.795836
412	4c72fae95b9147189a0559269a6953ff000012	97.771817
57	0745914f4de046078517041d70b22fe7000007	97.535805

In [155…

```
plt.bar(query['hostname'],query['avg_power'])
plt.xlabel("Top hostnames deriving most power")
plt.ylabel("Average Power Drawn")
plt.xticks(rotation=45, ha='right')
plt.show()
```



These are the top 10 average power drawing CPUs.

Merging checkpoint data with GPU data considering the top 10 average power drawing GPUs.

GPU dataset and application checkpoint dataset are merged based on top 10 power drawing hostname and timestamp to find out average power drawn by each event. Top 10 hostnames are selected since GPU data is itself a very large dataset, and merging it with checkpoint data would create a dataset which is manyfold in size, hence considering any 10 hostnames with a special characteristics (here, most power drawn) seems like a good evaluation and would create a window to the larger picture.

Assumption : Since saving config takes less than a milli second to complete, it can be neglected from the analysis. This is specially because GPU data is recorded for different timestamps, and since saving config completes in fraction of seconds, no GPU data is recorded for saving config. Hence, from now on, we’re considering Render, tiling and uploading, and total render as the total event.

In [228…

```
eventVSgpu="select g.*,ss.eventName,ss.Time_taken from q_start_stop ss INNER JOIN gpu g on ss.hostname=g.hostname
eventVSgpu=pysqldf(eventVSgpu)
eventVSgpu
```

Out[228…

	timestamp	hostname	gpuSerial	gpuUUID	powerDrawWatt	gpuTempC	gpuUtilPerc	gpuM
0	2018-11-08 07:41:32.960000	4ad946d4435c42dabb5073531ea4f31500000X	320118119710	GPU-bf2d15ed-ed8b-dd41-71d7-11f73b27719b	28.64	28	0	
1	2018-11-08 07:41:34.978000	4ad946d4435c42dabb5073531ea4f31500000X	320118119710	GPU-bf2d15ed-ed8b-dd41-71d7-11f73b27719b	28.63	28	0	
2	2018-11-08 07:41:36.995000	4ad946d4435c42dabb5073531ea4f31500000X	320118119710	GPU-bf2d15ed-ed8b-dd41-71d7-11f73b27719b	42.67	29	0	

3	2018-11-08 07:41:39.011000	4ad946d4435c42dabb5073531ea4f31500000X	320118119710	GPU-bf2d15ed-ed8b-dd41-71d7-11f73b27719b	131.96	31	67
4	2018-11-08 07:41:41.028000	4ad946d4435c42dabb5073531ea4f31500000X	320118119710	GPU-bf2d15ed-ed8b-dd41-71d7-11f73b27719b	120.09	33	91
...	...	...	...	...	...	...	...
27495	2018-11-08 08:16:31.340000	83ea61ac1ef54f27a3bf7bd0f41ecaa700000D	323617042624	GPU-3c70c815-37f7-30cd-5aae-028b84687738	54.42	43	0
27496	2018-11-08 08:17:23.416000	4c72fae95b9147189a0559269a6953ff000012	325217084671	GPU-5bb7cd24-69b4-199a-2b0f-2d36b39a37c2	47.24	46	0
27497	2018-11-08 08:27:52.110000	db871cd77a544e13bc791a64a0c8ed5000000U	323617021202	GPU-a69f6567-f08c-9c67-06a3-eab81fe834d2	44.38	40	0
27498	2018-11-08 08:28:19.013000	4c72fae95b9147189a0559269a6953ff000012	325217084671	GPU-5bb7cd24-69b4-199a-2b0f-2d36b39a37c2	53.25	48	0
27499	2018-11-08 08:29:49.812000	4ad946d4435c42dabb5073531ea4f31500000X	320118119710	GPU-bf2d15ed-ed8b-dd41-71d7-11f73b27719b	52.89	39	0

27500 rows × 10 columns

It is worth noting that this dataset eventVSgpu has no data about Saveconfig. This could be specially because saveconfig took insignificant amount of time in completing and no entry for any timestamp between that short duration (in mili seconds) was recorded.

In [229…

```
eventVSgpu['eventName'].value_counts()
```

Out[229…

```
TotalRender    13603
Render         13184
Uploading        419
Tiling           294
Name: eventName, dtype: int64
```

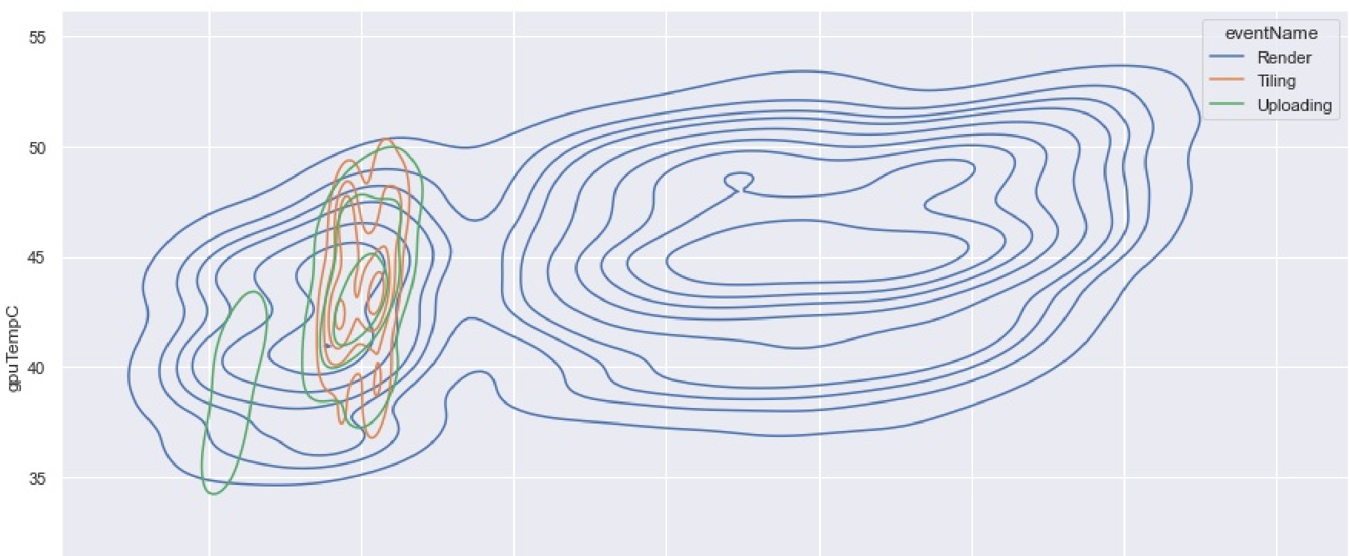
Different events showing relationship between power drawn and GPU temperature

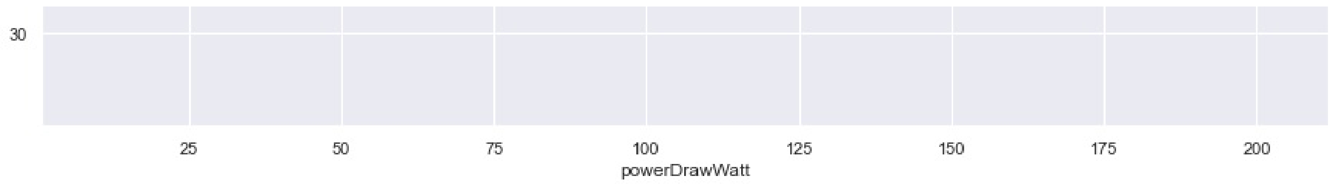
In [234…

```
sns.kdeplot(data=eventVSgpu[eventVSgpu['eventName']!="TotalRender"], x="powerDrawWatt", y="gpuTempC",hue="eventNa
```

Out[234…

```
<AxesSubplot:xlabel='powerDrawWatt', ylabel='gpuTempC'>
```





This graph depicts that render shows an elaborate and slightly linear relation between power drawn and GPU temperature and these values are higher for only render. Tiling and uploading are confined to smaller space, depicting low power drawn but comparatively higher temperatures.

Average Power drawn by each Event

In [235…

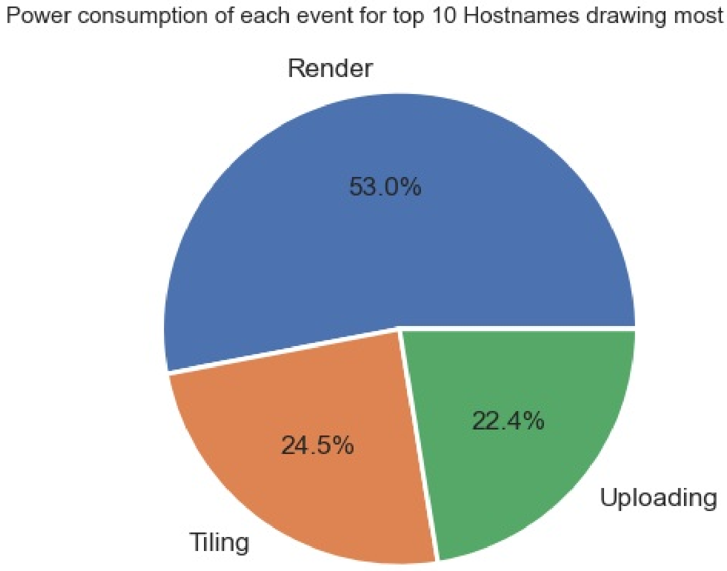
```
avgpower_eventtime="select AVG(powerDrawWatt),eventName from eventVSgpu where eventName not like '%TotalRender%'
avgpower_eventtime=pysqldf(avgpower_eventtime)
avgpower_eventtime
```

Out[235…

	AVG(powerDrawWatt)	eventName
0	108.204798	Render
1	50.078061	Tiling
2	45.704105	Uploading

In [236…

```
fig, ax = plt.subplots(figsize=(6, 6))
ax.pie(avgpower_eventtime['AVG(powerDrawWatt)'], labels=avgpower_rendertime['eventName'], autopct='%.1f%%',
       wedgeprops={'linewidth': 3.0, 'edgecolor': 'w'},
       textprops={'size': 'x-large'})
ax.set_title('Power consumption of each event for top 10 Hostnames drawing most power', fontsize=15)
plt.tight_layout()
```



From above pie chart, it is clear that Render takes more than half of the power drawn.

Different Events and GPU temperature

In [186…

```
eventVSgpu.sort_values(by=['gpuTempC'],ascending=False).head(20)
```

Out[186…

	timestamp	hostname	gpuSerial	gpuUUID	powerDrawWatt	gpuTempC	gpuUtilPerc	gpuMe
6467	2018-11-08 07:58:30.632000	04dc4e9647154250beeee51b866b0715000011	323217056368	GPU-a906c711-24a4-24b5-0261-3babb6dec5e9	124.27	54	94	
				GPU-a906c711-				

6465	2018-11-08 07:58:26.598000	04dc4e9647154250beeee51b866b0715000011	323217056368	24a4-24b5-0261-3babb6dec5e9	164.41	54	97
6468	2018-11-08 07:58:32.648000	04dc4e9647154250beeee51b866b0715000011	323217056368	GPU-a906c711-24a4-24b5-0261-3babb6dec5e9	129.90	54	96
6469	2018-11-08 07:58:34.666000	04dc4e9647154250beeee51b866b0715000011	323217056368	GPU-a906c711-24a4-24b5-0261-3babb6dec5e9	157.60	54	91
6837	2018-11-08 08:11:26.080000	04dc4e9647154250beeee51b866b0715000011	323217056368	GPU-a906c711-24a4-24b5-0261-3babb6dec5e9	124.06	54	94
6466	2018-11-08 07:58:28.614000	04dc4e9647154250beeee51b866b0715000011	323217056368	GPU-a906c711-24a4-24b5-0261-3babb6dec5e9	147.26	54	94
6836	2018-11-08 08:11:24.063000	04dc4e9647154250beeee51b866b0715000011	323217056368	GPU-a906c711-24a4-24b5-0261-3babb6dec5e9	173.57	53	96
4407	2018-11-08 08:19:24.446000	4c72fae95b9147189a0559269a6953ff000012	325217084671	GPU-5bb7cd24-69b4-199a-2b0f-2d36b39a37c2	169.94	53	90
4406	2018-11-08 08:19:22.430000	4c72fae95b9147189a0559269a6953ff000012	325217084671	GPU-5bb7cd24-69b4-199a-2b0f-2d36b39a37c2	175.02	53	92
4258	2018-11-08 08:11:22.309000	4c72fae95b9147189a0559269a6953ff000012	325217084671	GPU-5bb7cd24-69b4-199a-2b0f-2d36b39a37c2	133.97	53	89
4257	2018-11-08 08:11:20.290000	4c72fae95b9147189a0559269a6953ff000012	325217084671	GPU-5bb7cd24-69b4-199a-2b0f-2d36b39a37c2	110.90	53	92
4256	2018-11-08 08:11:18.273000	4c72fae95b9147189a0559269a6953ff000012	325217084671	GPU-5bb7cd24-69b4-199a-2b0f-2d36b39a37c2	176.24	53	91
4255	2018-11-08 08:11:16.256000	4c72fae95b9147189a0559269a6953ff000012	325217084671	GPU-5bb7cd24-69b4-199a-2b0f-2d36b39a37c2	98.31	53	89
4635	2018-11-08 08:12:51.074000	4c72fae95b9147189a0559269a6953ff000012	325217084671	GPU-5bb7cd24-69b4-199a-2b0f-2d36b39a37c2	168.62	53	93
4254	2018-11-08 08:11:14.240000	4c72fae95b9147189a0559269a6953ff000012	325217084671	GPU-5bb7cd24-69b4-199a-2b0f-2d36b39a37c2	133.54	53	92
4253	2018-11-08 08:11:12.220000	4c72fae95b9147189a0559269a6953ff000012	325217084671	GPU-5bb7cd24-69b4-199a-2b0f-2d36b39a37c2	121.69	53	94
4252	2018-11-08 08:11:10.203000	4c72fae95b9147189a0559269a6953ff000012	325217084671	GPU-5bb7cd24-69b4-199a-2b0f-2d36b39a37c2	179.13	53	92
6456	2018-11-08 07:58:08.438000	04dc4e9647154250beeee51b866b0715000011	323217056368	GPU-a906c711-24a4-24b5-0261-3babb6dec5e9	116.18	53	97
6457	2018-11-08 07:58:10.456000	04dc4e9647154250beeee51b866b0715000011	323217056368	GPU-a906c711-24a4-24b5-	168.04	53	94

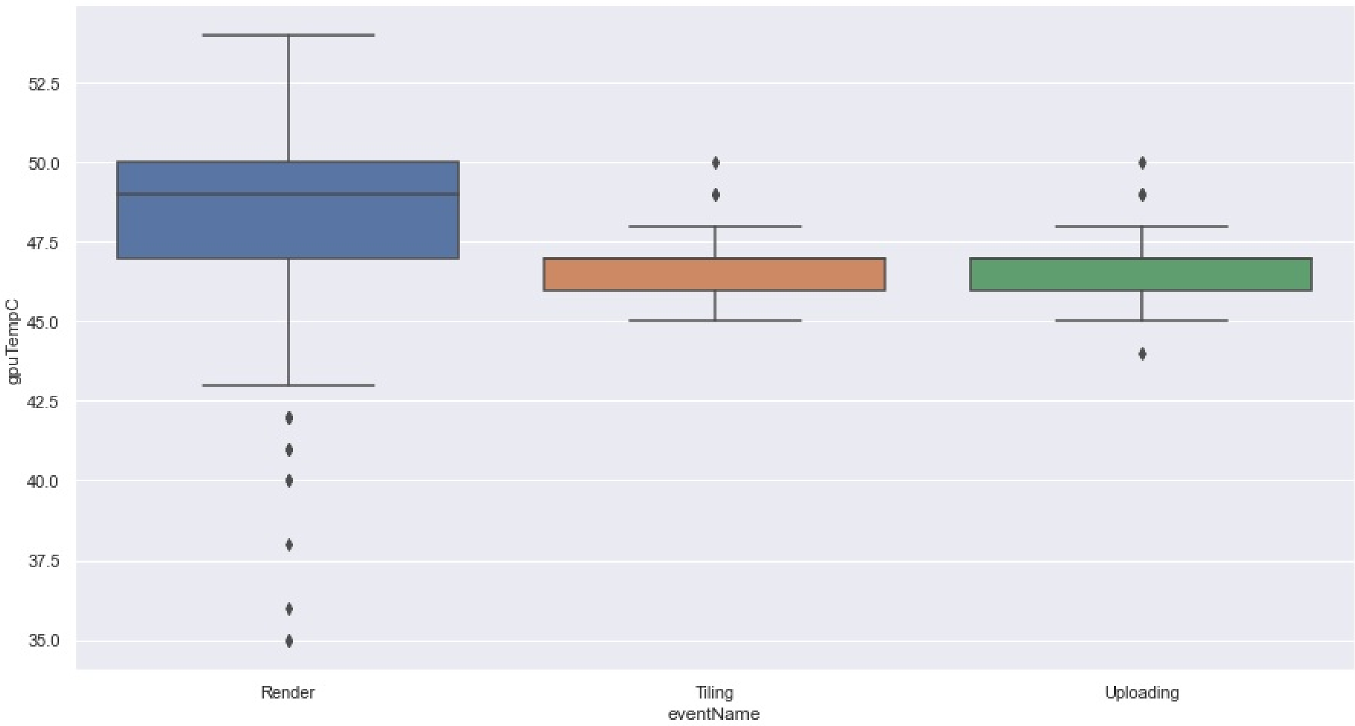
				0261-3babb6dec5e9			
6458	2018-11-08 07:58:12.473000	04dc4e9647154250beeee51b866b0715000011	323217056368	GPU-a906c711-24a4-24b5-0261-3babb6dec5e9	160.15	53	94

In [238…

```
difrnt_event=eventVSgpu[eventVSgpu['eventName']!="TotalRender"]
sns.boxplot(data=difrnt_event[difrnt_event['gpuSerial']==323217056368], x="eventName", y="gpuTempC")
```

Out[238…

```
<AxesSubplot:xlabel='eventName', ylabel='gpuTempC'>
```



This box plot depicts that higher range of temperature is noted during Render process with higher mean temperature as well. Other 2 events although had lower temperature than render, but both had almost similar temperature distribution.

GPU and average time taken for Total Render

In [271…

```
toptemp_gpu="select gpuSerial,hostname, eventName,Avg(gpuTempC) as avg_temp from eventVSgpu where eventName not l
toptemp_gpu=pysqldf(toptemp_gpu)
toptemp_gpu
```

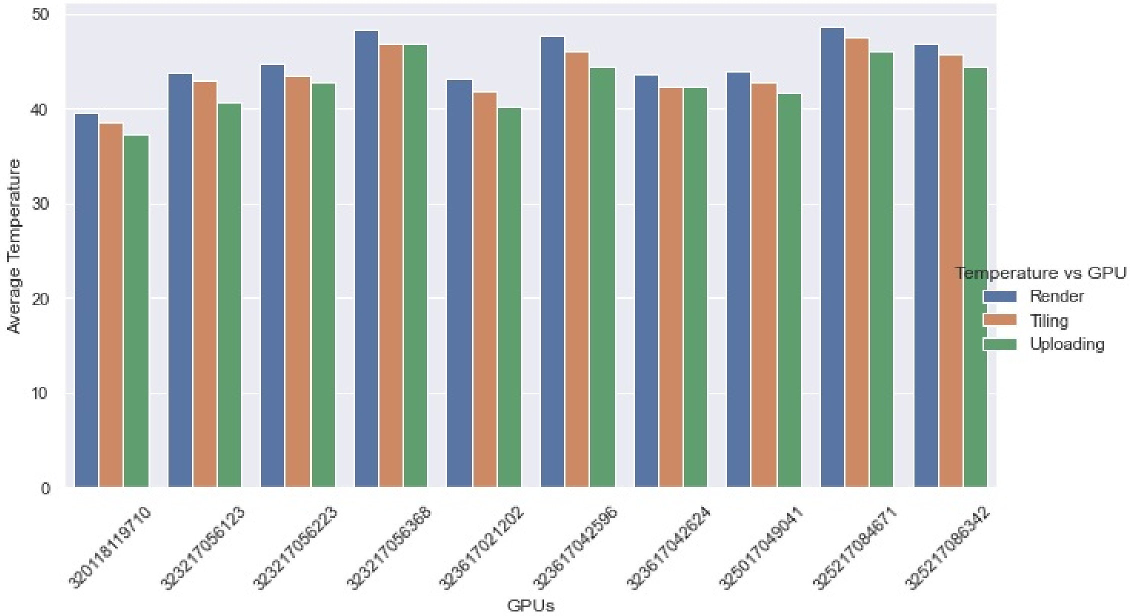
Out[271…

	gpuSerial	hostname	eventName	avg_temp
0	320118119710	4ad946d4435c42dabb5073531ea4f31500000X	Uploading	37.317073
1	320118119710	4ad946d4435c42dabb5073531ea4f31500000X	Tiling	38.482759
2	320118119710	4ad946d4435c42dabb5073531ea4f31500000X	Render	39.552691
3	323617021202	db871cd77a544e13bc791a64a0c8ed5000000U	Uploading	40.256410
4	323217056123	8b6a0eebc87b4cb2b0539e81075191b9000016	Uploading	40.740741
5	325017049041	5903af3699134795af7eafc605ae5fc700000H	Uploading	41.673913
6	323617021202	db871cd77a544e13bc791a64a0c8ed5000000U	Tiling	41.880000
7	323617042624	83ea61ac1ef54f27a3bf7bd0f41ecaa700000D	Uploading	42.256410
8	323617042624	83ea61ac1ef54f27a3bf7bd0f41ecaa700000D	Tiling	42.361111
9	323217056223	04dc4e9647154250beeee51b866b0715000018	Uploading	42.718750
10	325017049041	5903af3699134795af7eafc605ae5fc700000H	Tiling	42.750000
11	323217056123	8b6a0eebc87b4cb2b0539e81075191b9000016	Tiling	42.968750
12	323617021202	db871cd77a544e13bc791a64a0c8ed5000000U	Render	43.117603
13	323217056223	04dc4e9647154250beeee51b866b0715000018	Tiling	43.500000
14	323617042624	83ea61ac1ef54f27a3bf7bd0f41ecaa700000D	Render	43.656489
15	323217056123	8b6a0eebc87b4cb2b0539e81075191b9000016	Render	43.810185

16	325017049041	5903af3699134795af7eafc605ae5fc700000H	Render	43.938683
17	323617042596	a77ef58b13ad4c01b769dac8409af3f800000D	Uploading	44.447368
18	325217086342	0745914f4de046078517041d70b22fe7000007	Uploading	44.452830
19	323217056223	04dc4e9647154250beeee51b866b0715000018	Render	44.810629
20	325217086342	0745914f4de046078517041d70b22fe7000007	Tiling	45.777778
21	323617042596	a77ef58b13ad4c01b769dac8409af3f800000D	Tiling	46.000000
22	325217084671	4c72fae95b9147189a0559269a6953ff000012	Uploading	46.088889
23	323217056368	04dc4e9647154250beeee51b866b0715000011	Uploading	46.781250
24	325217086342	0745914f4de046078517041d70b22fe7000007	Render	46.803982
25	323217056368	04dc4e9647154250beeee51b866b0715000011	Tiling	46.866667
26	325217084671	4c72fae95b9147189a0559269a6953ff000012	Tiling	47.437500
27	323617042596	a77ef58b13ad4c01b769dac8409af3f800000D	Render	47.673897
28	323217056368	04dc4e9647154250beeee51b866b0715000011	Render	48.253618
29	325217084671	4c72fae95b9147189a0559269a6953ff000012	Render	48.685736

In [269…

```
g = sns.catplot(
    data=toptemp_gpu, kind="bar",
    x="gpuSerial", y="avg_temp", hue="eventName",aspect=15/8.27
)
g.set_xticklabels(rotation=45)
g.set_axis_labels("GPUs", "Average Temperature")
g.legend.set_title("Temperature vs GPU ")
```



From above plot, we can see that highest temperatures were noted during render,then tiling and then uploading. On average, fourth GPU takes most time in completing the tasks, followed by 9th GPU and 6th GPU.

average time vs Total Render

In [240…

```
gpu_speed_totalrender="select gpuSerial,eventName,AVG(Time_taken) as avg_time  from eventVSgpu where eventName li
gpu_speed_totalrender=pysqldf(gpu_speed_totalrender)
gpu_speed_totalrender
```

Out[240…

	gpuSerial	eventName	avg_time
0	323617021202	TotalRender	47.394788
1	323617042596	TotalRender	46.955827
2	323217056123	TotalRender	46.829567
3	323217056368	TotalRender	46.134329
4	323217056223	TotalRender	45.997412
5	325017049041	TotalRender	45.489765
6	320118119710	TotalRender	45.183658

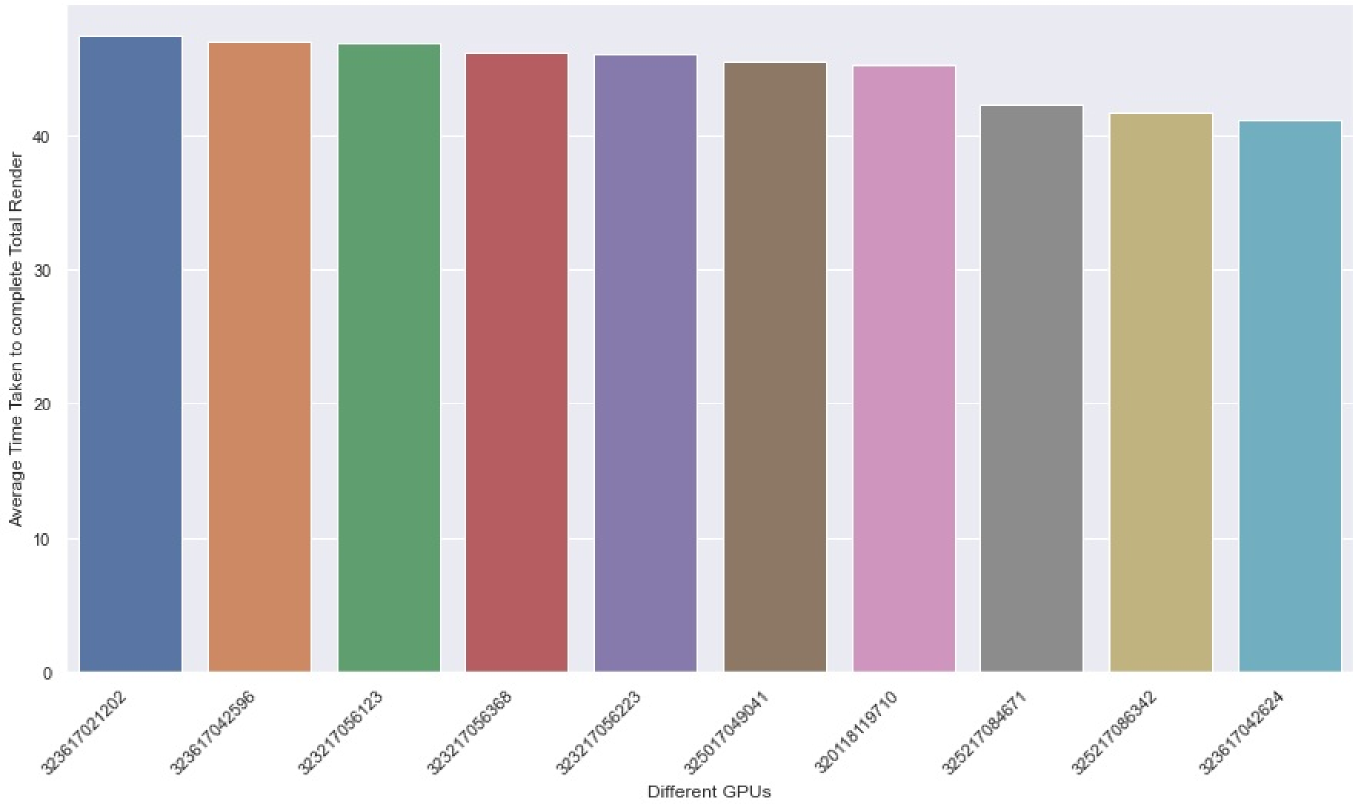
7	325217084671	TotalRender	42.307426
8	325217086342	TotalRender	41.675820
9	323617042624	TotalRender	41.160521

In [248…

```
gpu_speed_totalrender['gpuSerial']=gpu_speed_totalrender['gpuSerial'].astype(str)
```

In [249…

```
#plt.bar(gpu_speed_totalrender[''],gpu_speed_totalrender['avg_time'],color='hotpink')
sns.barplot(data=gpu_speed_totalrender, x="gpuSerial", y="avg_time")
plt.xlabel("Different GPUs")
plt.ylabel("Average Time Taken to complete Total Render")
plt.xticks(rotation=45, ha='right')
plt.show()
```



It is interesting to see the order of GPUs taking most time to complete total render. It is quite different from previous bar plot where 3 events were considered. This could be due to the absence of Saving Config time duration which could bridge this gap between the 2 graphs.

In [ ]: