ApplianceTelemetryCorrelationAnalysis

October 19, 2024

0.1 Provided as-is (w/o support)

Kubernetes clusters collect various application and infrastrcuture statistics. While this information is useful, it's very difficult to identify which metrics are useful for monitoring and troubleshooting. The Goal here is to collect this information, and use a statistical model to identify which metrics should be included in reports/dashboard such that: * Unnecessary overhead and sensory overload can be reduced. * Time can be saved by prioritising monitoring the correct metrics.

This process needs to assume `zero knowlidge` of the workings of the cluster, workload being run and any other information. This way, `generic` clusters can be monitored without explicitly programming dashboards based on internal knowlidge. This is also a good method to discover/verify application knowlidge/bottlenecks with statistical data analyis.

0.2 Step1: Data Loading

We will load cpu, memory, task_queue information along with stats from strcutured and unstrucutred scans from csv files stored on disk using the `dataframeLoader` helper.

 # The dataframeLoader helper function implements the loadApplianceTimeSeriesData method.
 # This method loads the csv files, and pivots them to generate distinct "metrics" timeseries.
 # see https://github.com/amitgupta7/docker-jupy-ntbk-s3-reporting/blob/main/dataframeLoader.py

[1]:
```python
import sys
sys.path.append('../')

import dataframeLoader as dfl
import pandas as pd
from importlib import reload
reload(dfl)

# Provide csv data location and appliance and timerange information.
root = '../../.dataDir'
fromDt = '2024-08-15'
toDt = '2024-10-15'

# Provide list of prometheus metrics to load.
# metricsArr = ['cpu_used', 'download_workers_count', 'memory_used',␣
 ↪'task_queue_length', 'infra_access_latency', 'pod_cpu_usage',␣
 ↪'pod_memory_usage']
metricsArr = ['cpu_used'
```

```
              ,'task_queue_length'
              , 'memory_used'
              ]

daterange=[fromDt, toDt]
df = dfl.loadApplianceTimeSeriesData(root, metricsArr, daterange)
```

```
loading Unstrctured Data from file: SCANPROC-*.csv

loading Strctured Data from file: STRUCTURED-*.csv

processing securiti_appliance_cpu_used-max*.csv

processing securiti_appliance_cpu_used-avg*.csv

processing securiti_appliance_task_queue_length-max*.csv

processing securiti_appliance_task_queue_length-avg*.csv

processing securiti_appliance_memory_used-max*.csv

processing securiti_appliance_memory_used-avg*.csv

loading Unstrctured Data from file: UNSTRUCTURED-*.csv
```

0.3 Step2: Data Pivoting

We now aggregate the data by `appliance_id` (unique identifier for our cluster) and `ts` timestamp, to get different metrics values as separate columns. Notice there are: * 21 metrics -> 15 metrics * Decide between `max` or `avg` values if both are present. * We chose to display `avg` values metrics in this case after some trial and error.

- Tracked every hour

[2]:
```
dfp = df.pivot_table(index=['appliance_id','ts'], columns=['metrics'],
 ↪values='value', aggfunc='sum').reset_index()
dfp = dfp[dfp.columns.drop(list(dfp.filter(regex='max')))]
dfp.head()
```

[2]:
```
metrics                          appliance_id                  ts  \
0        0036f473-ad7f-4439-8d37-f65fdeb50b2d 2024-10-13 14:00:00
1        0036f473-ad7f-4439-8d37-f65fdeb50b2d 2024-10-13 15:00:00
2        0036f473-ad7f-4439-8d37-f65fdeb50b2d 2024-10-13 16:00:00
3        0036f473-ad7f-4439-8d37-f65fdeb50b2d 2024-10-13 17:00:00
4        0036f473-ad7f-4439-8d37-f65fdeb50b2d 2024-10-13 18:00:00

metrics  IdleTimeInHrs  avgFileSizeInMB  cpu_used_avg  dataScannedinGB  \
0                  NaN              NaN      3.021810              NaN
1                  NaN              NaN      1.569917              NaN
2                  NaN              NaN      1.748750              NaN
3                  NaN              NaN      1.740000              NaN
4                  NaN              NaN      1.740000              NaN
```

```
metrics  fileDownloadTimeInHrs  linkerq_avg  memory_used_avg  numFilesScanned  \
0                          NaN          NaN        66.473448              NaN
1                          NaN          NaN        66.172250              NaN
2                          NaN          NaN        66.286750              NaN
3                          NaN          NaN        66.285000              NaN
4                          NaN          NaN        66.285000              NaN

metrics  numberOfChunksScanned  numberOfColsScanned  scanTime  taskq_avg  \
0                          NaN                  NaN       NaN        NaN
1                          NaN                  NaN       NaN        NaN
2                          NaN                  NaN       NaN        NaN
3                          NaN                  NaN       NaN        NaN
4                          NaN                  NaN       NaN        NaN

metrics  tmp_taskq_avg  uniqPodCount
0                  NaN           NaN
1                  NaN           NaN
2                  NaN           NaN
3                  NaN           NaN
4                  NaN           NaN
```

0.4 Step 3: Data transformation and correlation

We need to acheve two main goals: 1. Isolate data for individual appliance. 2. Remove ghost correlation between unrelated metrics. * We will calculate percentage change between adjacent timeseries values. 3. Calculate absolute correlation between metrics for each single appliance. * Transpose every `metrics` corelation. 4. Generate correlation for every `appliance_id` and `metric` identifier using steps 1, 2 and 3

[3]:
```
# appliance = '01c75278-9c0d-41be-b693-c970b18dbedc'
# for metric in metrics_category_order:
dfc_arr = []
for pod in dfp.appliance_id.unique():
    dfa = dfp[(dfp.appliance_id == pod)]
    dfa = dfa.drop(['appliance_id', 'ts'], axis=1)
    dfa = dfa.pct_change(periods=1, fill_method=None)
    dfca = dfa.corr().abs()
    # print(type(dfca))
    for col in dfca.columns:
        # print(col)
        dfc = dfca[col].to_frame().T
        dfc.insert(0, 'metric', col )
        dfc.insert(0, 'appliance_id', pod )
        dfc_arr.append(dfc)
dfc = pd.concat(dfc_arr, ignore_index=True)
dfc.set_index('appliance_id', inplace=True)
```

```
dfc.head()
```

[3]:
```
metrics                                          metric  IdleTimeInHrs  \
appliance_id
0036f473-ad7f-4439-8d37-f65fdeb50b2d        IdleTimeInHrs            NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d       avgFileSizeInMB            NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d          cpu_used_avg            NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d       dataScannedinGB            NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d  fileDownloadTimeInHrs            NaN

metrics                               avgFileSizeInMB  cpu_used_avg  \
appliance_id
0036f473-ad7f-4439-8d37-f65fdeb50b2d              NaN           NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d              NaN           NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d              NaN           1.0
0036f473-ad7f-4439-8d37-f65fdeb50b2d              NaN           NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d              NaN           NaN

metrics                               dataScannedinGB  fileDownloadTimeInHrs  \
appliance_id
0036f473-ad7f-4439-8d37-f65fdeb50b2d              NaN                    NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d              NaN                    NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d              NaN                    NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d              NaN                    NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d              NaN                    NaN

metrics                               linkerq_avg  memory_used_avg  \
appliance_id
0036f473-ad7f-4439-8d37-f65fdeb50b2d          NaN              NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d          NaN              NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d          NaN         0.323098
0036f473-ad7f-4439-8d37-f65fdeb50b2d          NaN              NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d          NaN              NaN

metrics                               numFilesScanned  numberOfChunksScanned  \
appliance_id
0036f473-ad7f-4439-8d37-f65fdeb50b2d              NaN                    NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d              NaN                    NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d              NaN                    NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d              NaN                    NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d              NaN                    NaN

metrics                               numberOfColsScanned  scanTime  \
appliance_id
0036f473-ad7f-4439-8d37-f65fdeb50b2d                  NaN       NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d                  NaN       NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d                  NaN       NaN
```

```
0036f473-ad7f-4439-8d37-f65fdeb50b2d                    NaN       NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d                    NaN       NaN

metrics                                taskq_avg  tmp_taskq_avg  uniqPodCount
appliance_id
0036f473-ad7f-4439-8d37-f65fdeb50b2d         NaN            NaN           NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d         NaN            NaN           NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d         NaN            NaN           NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d         NaN            NaN           NaN
0036f473-ad7f-4439-8d37-f65fdeb50b2d         NaN            NaN           NaN
```

0.5 Step 4: Isolate related metrics using correlation

We now iterate over each `metric`, to see if there is any significant statistical correlation to be found across `appliance_ids`. This is done with two steps:

1. Removing outliers:
    - Remove any metrics with `mean correlation value below the cut-off`. The cut-off can be varied for depending on use cases:
        - 0.9 for Exec Dashboards
        - 0.7 for Customer Ops
        - 0.5 for L1 - support
        - 0.3 for L2 - suport

Please note that we are filtering metrics with `mean` correlation below the `low cut-off`. This ensures that atleast half of the values are correlated to reduce outliers.

2. Plot box chart to visually represent metrics with any correlation (for cutoff as 0.3).
3. Decide between `max` or `avg` values if both are present. We chose to display `avg` values metrics in this case after some trial and error.

0.6 Final List of metrics

The below table shows the list of `metrics` that are useful with respective correlation `cutoff`. The cut-off values can be interpreted as follows: * below 0.3 negligible correlation * 0.3 to 0.5 Low positive (negative) correlation * 0.5 to 0.7 Moderate positive (negative) correlation * 0.7 to 0.9 High positive (negative) correlation * 0.9 to 0.1 Very High positive (negative) correlation

0.9	0.7	0.5	0.3
numFilesScanned numberOfChunksScanned numberOfColsScanned	numFilesScanned numberOfChunksScanned numberOfColsScanned fileDownloadTimeInHrs scanTime	numFilesScanned numberOfChunksScanned numberOfColsScanned fileDownloadTimeInHrs scanTime taskq_avg cpu_used_avg dataScannedinGB avgFileSizeInMB	numFilesScanned numberOfChunksScanned numberOfColsScanned fileDownloadTimeInHrs scanTime taskq_avg cpu_used_avg dataScannedinGB avgFileSizeInMB

0.9	0.7	0.5	0.3
		linkerq_avg IdleTimeInHrs	linkerq_avg IdleTimeInHrs uniqPodCount memory_used_avg

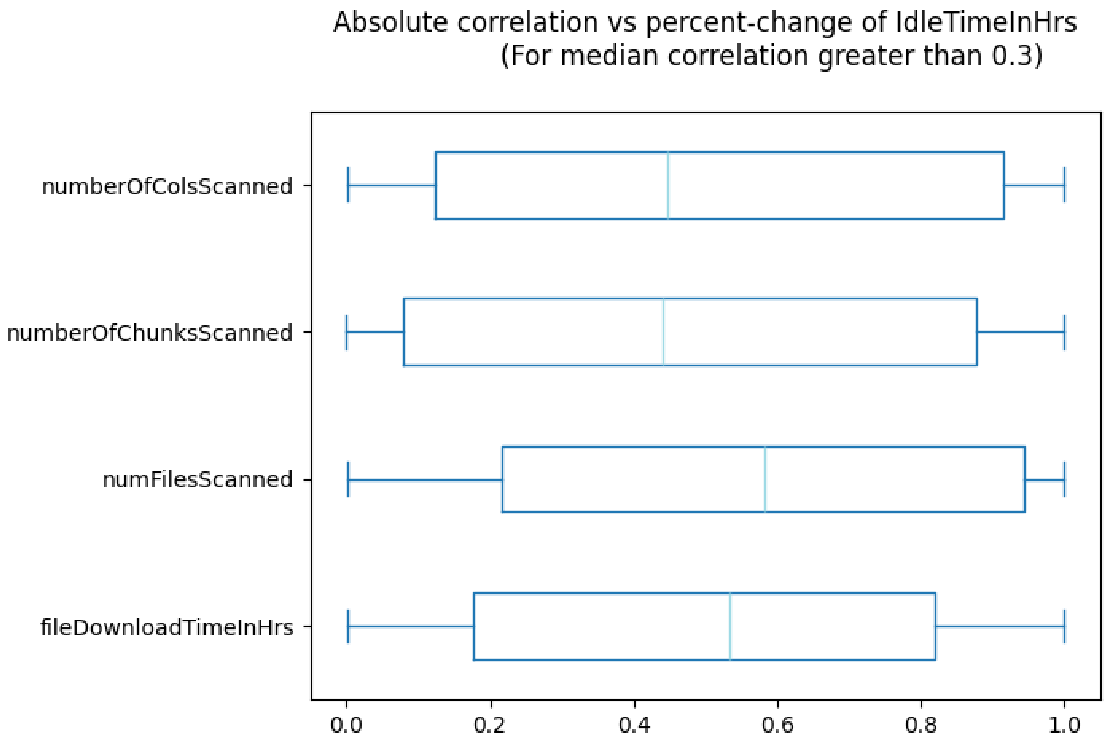
[4]:
```python
import gravis as gv
import networkx as nx
corr_vals = [0.9, 0.7, 0.5, 0.3]
line = set()
graph_arr = []
for cutoff in corr_vals:
    arr = []
    for metr in dfc.metric.unique():
        dfcm = dfc[(dfc.metric == metr)]
        dfcm = dfcm.drop('metric', axis=1)
        dfcm = dfcm.drop(metr, axis=1)
        dfcm = dfcm.dropna(axis = 0, how = 'all')
        dfcm = dfcm.loc[:, dfcm.median() > cutoff]
        for x in dfcm.columns:
            arr.append(x)
            graph_arr.append((metr, x))
        if(cutoff == 0.3):
            if len(dfcm.columns) > 0:
                title=f'''Absolute correlation vs percent-change of {metr}
                (For median correlation greater than {cutoff})
                '''
                dfcm.plot(kind='box'
                        ,vert=False
                        ,title=title
                        ,colormap='tab20'
                        )

    print(cutoff, set(arr))

g = nx.DiGraph()
g.add_edges_from(graph_arr)
gv.vis(g
       , graph_height=500
       , zoom_factor=2
       , layout_algorithm_active=False
       )
```

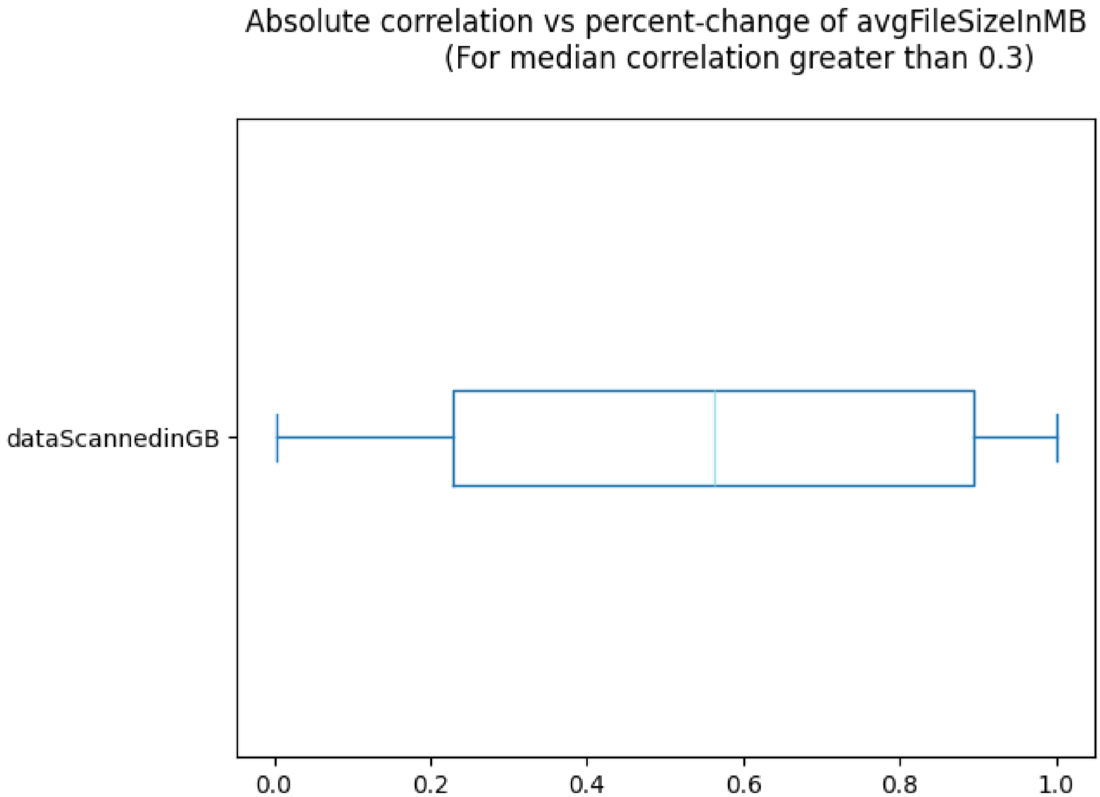
```
0.9 {'numberOfColsScanned', 'numberOfChunksScanned', 'numFilesScanned'}
0.7 {'numberOfColsScanned', 'scanTime', 'fileDownloadTimeInHrs',
'numberOfChunksScanned', 'numFilesScanned'}
0.5 {'linkerq_avg', 'dataScannedinGB', 'scanTime', 'numberOfColsScanned',
```

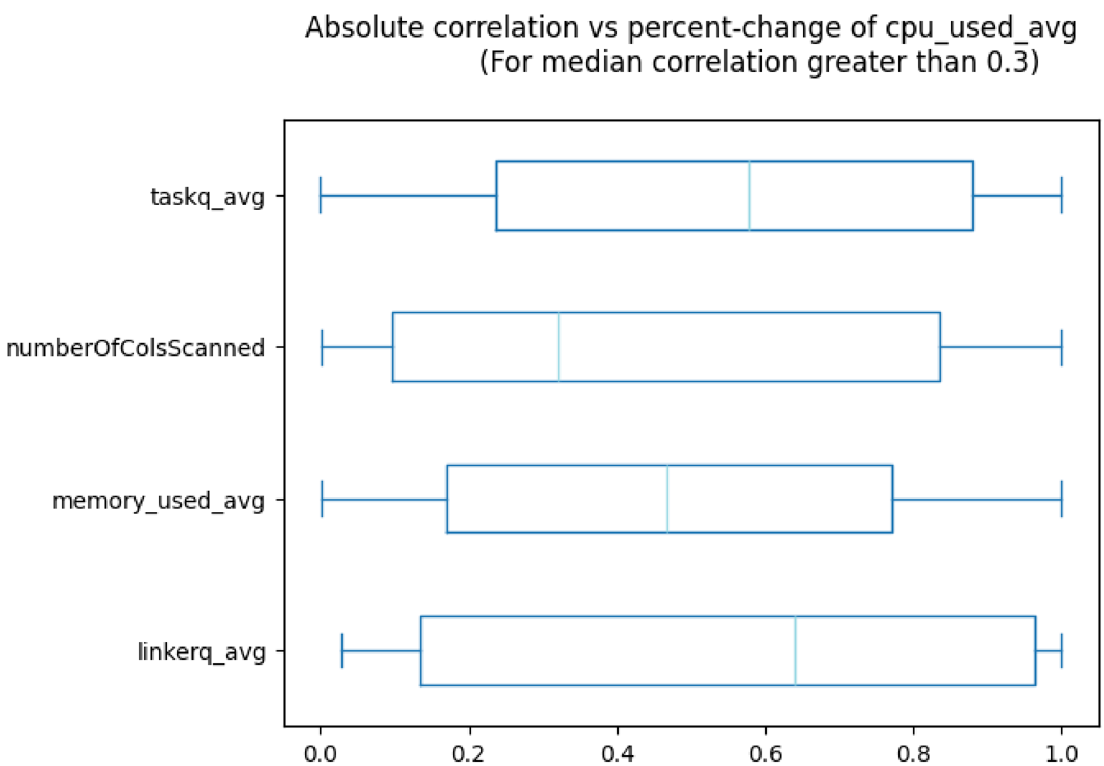
```
'fileDownloadTimeInHrs', 'taskq_avg', 'IdleTimeInHrs', 'numberOfChunksScanned',
'cpu_used_avg', 'avgFileSizeInMB', 'numFilesScanned'}
```

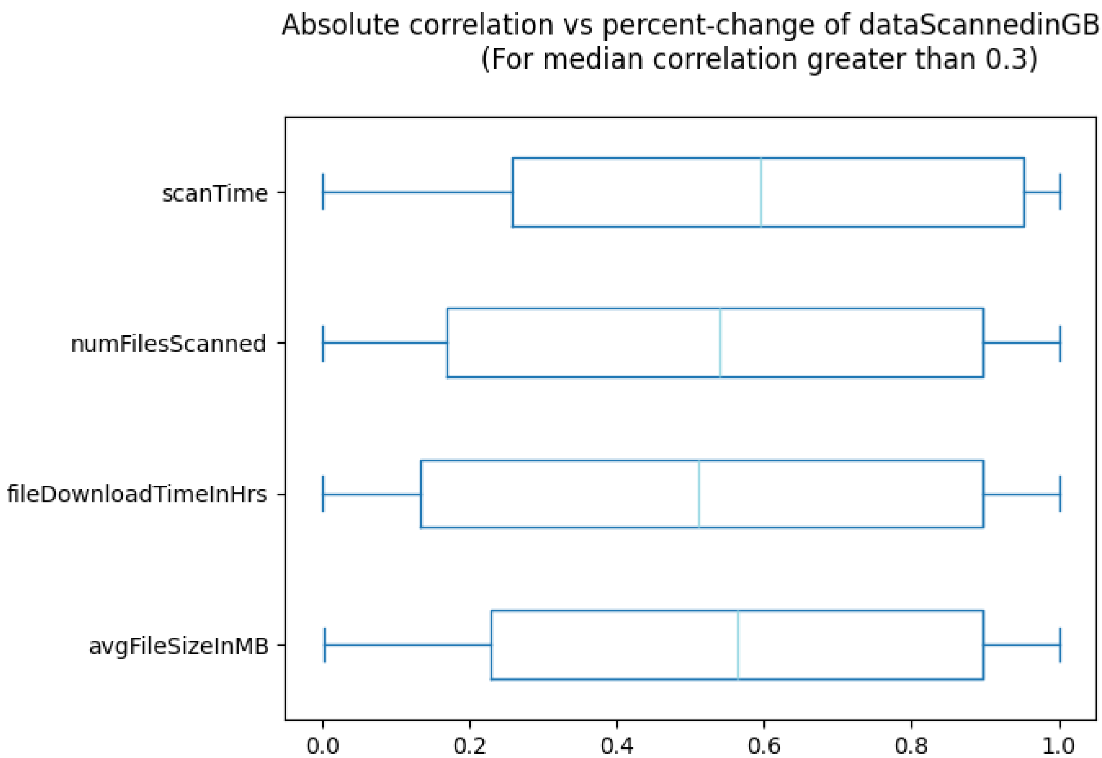
```
0.3 {'linkerq_avg', 'numberOfColsScanned', 'dataScannedinGB', 'scanTime',
'fileDownloadTimeInHrs', 'memory_used_avg', 'numberOfChunksScanned',
'taskq_avg', 'IdleTimeInHrs', 'cpu_used_avg', 'avgFileSizeInMB',
'numFilesScanned', 'uniqPodCount'}
```

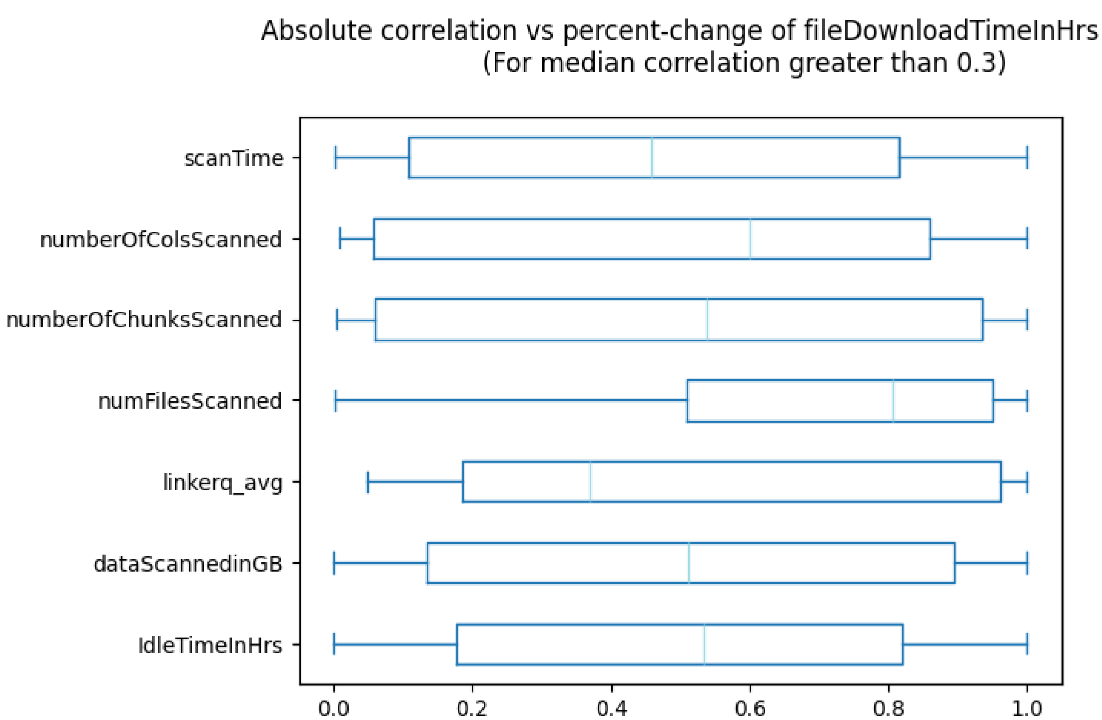
[4]: <gravis._internal.plotting.data_structures.Figure at 0x120a349d0>

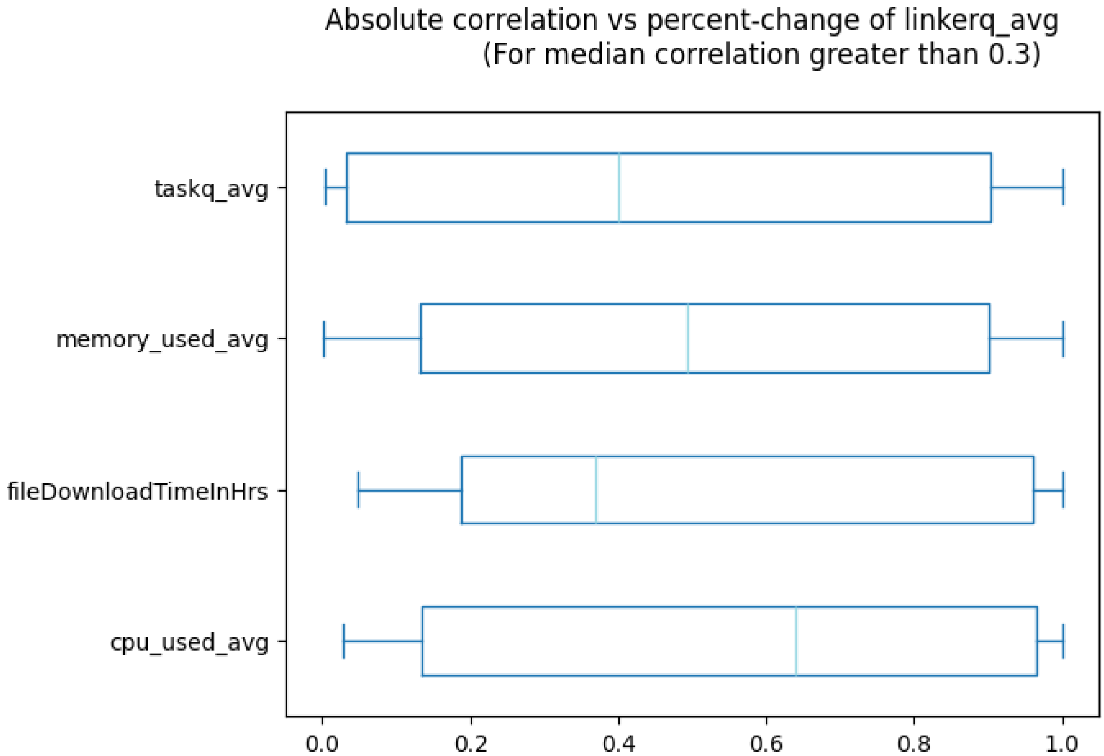


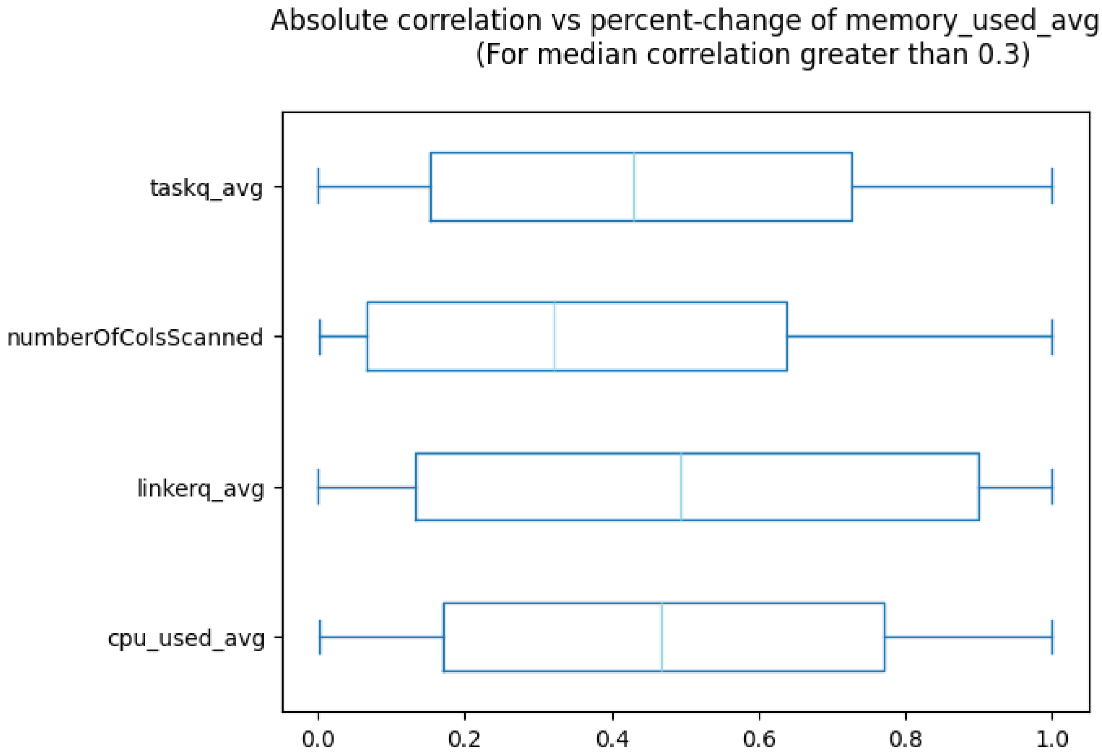

Absolute correlation vs percent-change of avgFileSizeInMB
(For median correlation greater than 0.3)
dataScannedinGB
0.0
0.2
0.4
0.6
0.8
1.0


Absolute correlation vs percent-change of cpu_used_avg
(For median correlation greater than 0.3)
taskq_avg
numberOfColsScanned
memory_used_avg
linkerq_avg
0.0
0.2
0.4
0.6
0.8
1.0

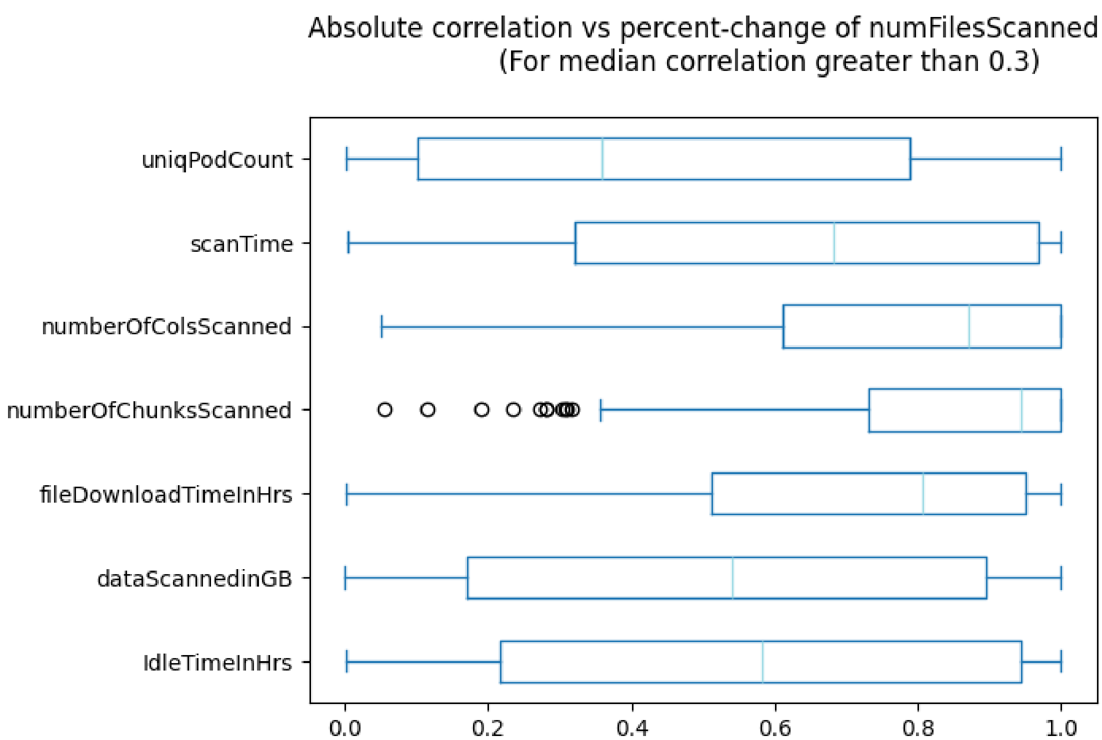

Absolute correlation vs percent-change of dataScannedinGB
(For median correlation greater than 0.3)
scanTime
numFilesScanned
fileDownloadTimeInHrs
avgFileSizeInMB
0.0
0.2
0.4
0.6
0.8
1.0


Absolute correlation vs percent-change of fileDownloadTimeInHrs
(For median correlation greater than 0.3)
scanTime
numberOfColsScanned
numberOfChunksScanned
numFilesScanned
linkerq_avg
dataScannedinGB
IdleTimeInHrs
0.0
0.2
0.4
0.6
0.8
1.0

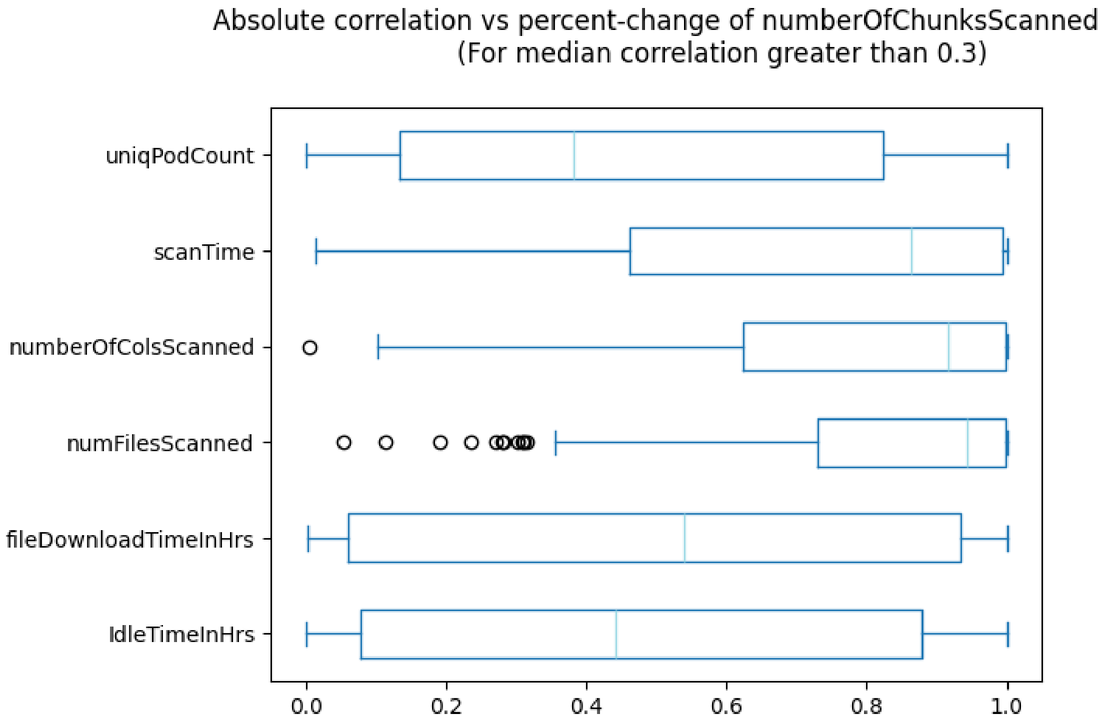

Absolute correlation vs percent-change of linkerq_avg
(For median correlation greater than 0.3)
taskq_avg
memory_used_avg
fileDownloadTimeInHrs
cpu_used_avg
0.0
0.2
0.4
0.6
0.8
1.0

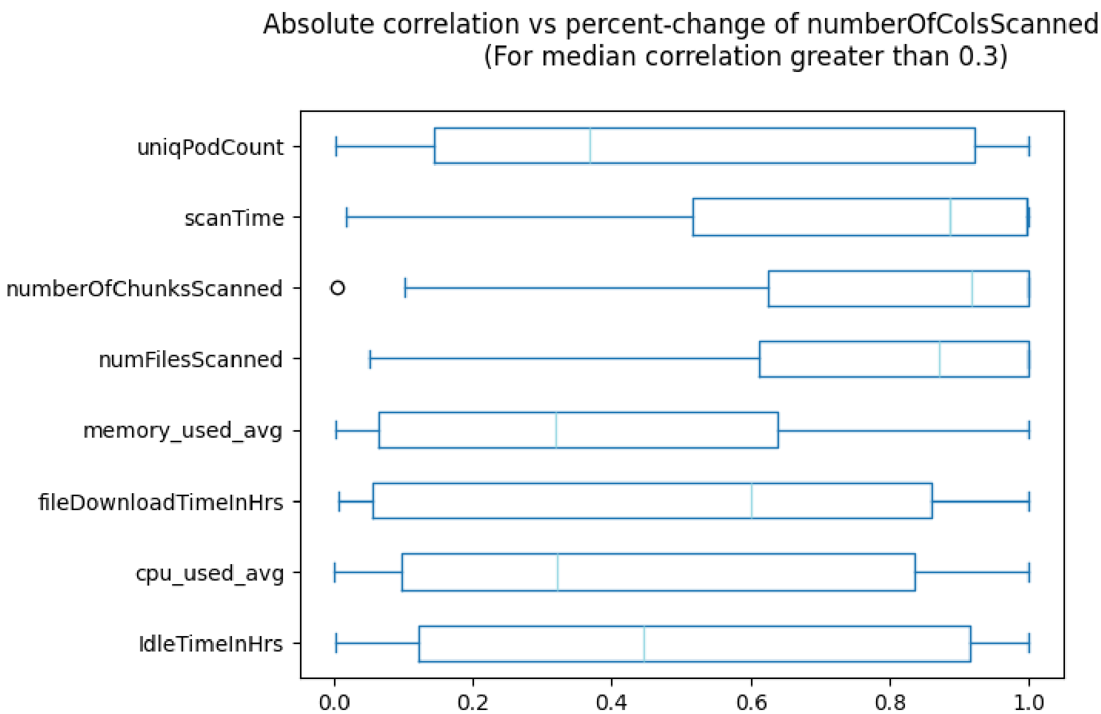


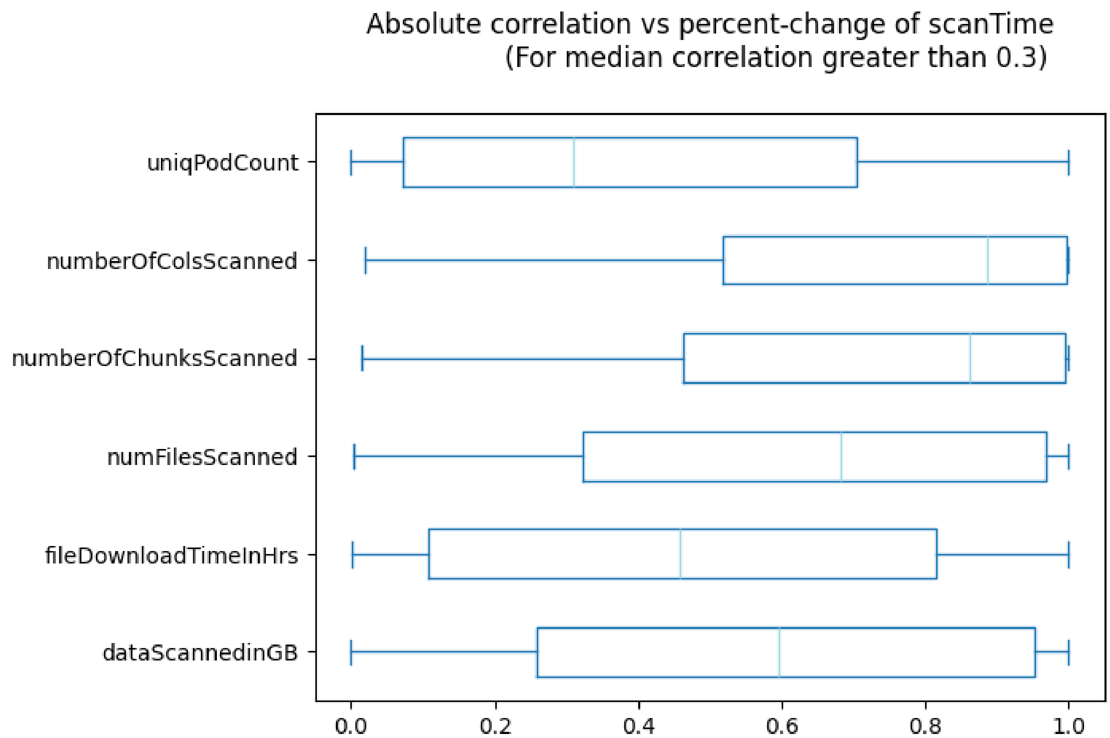
Absolute correlation vs percent-change of memory_used_avg
(For median correlation greater than 0.3)
taskq_avg
numberOfColsScanned
linkerq_avg
cpu_used_avg
0.0
0.2
0.4
0.6
0.8
1.0

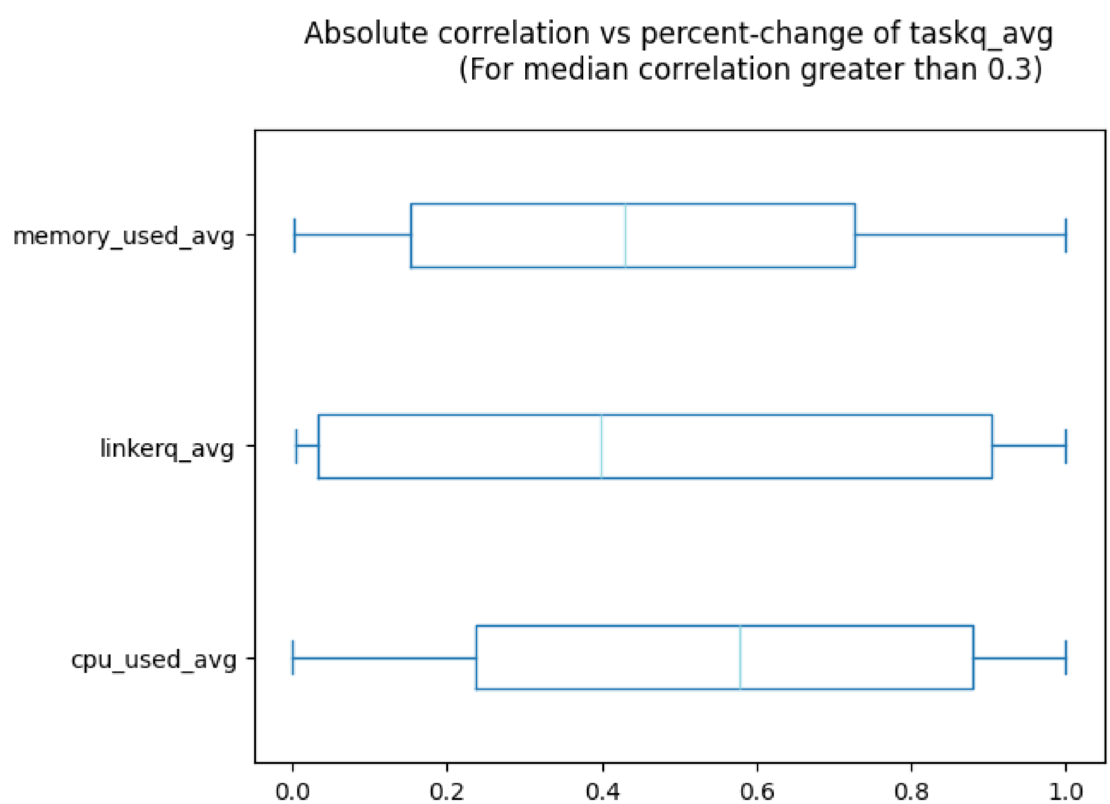


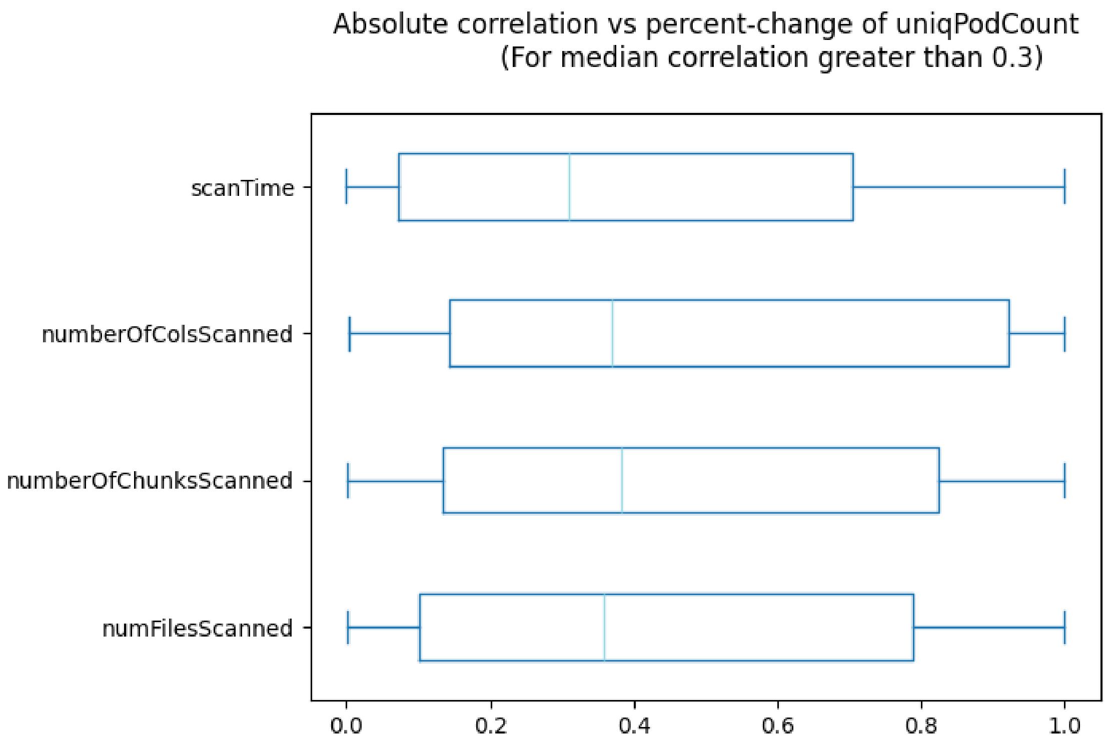
Absolute correlation vs percent-change of numFilesScanned
(For median correlation greater than 0.3)
uniqPodCount
scanTime
numberOfColsScanned
numberOfChunksScanned
fileDownloadTimeInHrs
dataScannedinGB
IdleTimeInHrs
0.0
0.2
0.4
0.6
0.8
1.0


Absolute correlation vs percent-change of numberOfChunksScanned
(For median correlation greater than 0.3)
uniqPodCount
scanTime
numberOfColsScanned
numFilesScanned
fileDownloadTimeInHrs
IdleTimeInHrs
0.0
0.2
0.4
0.6
0.8
1.0


Absolute correlation vs percent-change of numberOfColsScanned
(For median correlation greater than 0.3)
uniqPodCount
scanTime
numberOfChunksScanned
numFilesScanned
memory_used_avg
fileDownloadTimeInHrs
cpu_used_avg
IdleTimeInHrs
0.0
0.2
0.4
0.6
0.8
1.0


Absolute correlation vs percent-change of scanTime
(For median correlation greater than 0.3)
uniqPodCount
numberOfColsScanned
numberOfChunksScanned
numFilesScanned
fileDownloadTimeInHrs
dataScannedinGB
0.0
0.2
0.4
0.6
0.8
1.0


Absolute correlation vs percent-change of taskq_avg
(For median correlation greater than 0.3)
memory_used_avg
linkerq_avg
cpu_used_avg
0.0
0.2
0.4
0.6
0.8
1.0


Absolute correlation vs percent-change of uniqPodCount
(For median correlation greater than 0.3)
scanTime
numberOfColsScanned
numberOfChunksScanned
numFilesScanned
0.0
0.2
0.4
0.6
0.8
1.0