# Predict Network, Application Performance Using Machine Learning and Predictive Analytics

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# Predict Network, Application Performance Using Machine Learning and Predictive Analytics

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# 1. Abstract

In this thesis, a study is performed to find the effect of applications on resource consumption in computer networks and how to make use of available technologies such as predictive analytics, machine learning and business intelligence to predict if an application can degrade the network performance or consume computer system resources. In recent years, having a healthy computer system and the network is essential for continuity of business. The study focusses on analyzing the performance metrics collected from real networks using scripts and available programs created specifically for monitoring applications and network in real-time.

This work has significant importance because monitoring real-time performance doesn't give accurate or concise information about the reasons behind any degradation in network or application performance. On the other hand, analyzing those performance metrics over a certain period and find a correlation between metrics and applications gives much more relevant information about the root cause of problems.

The findings proved that there is a correlation between certain performance metrics, besides correlation found between metrics and applications which conclude the study objectives. The benefits of this study could be seen in analyzing complex networks where there is uncertainty in determining the root cause of a problem in applications or networks.

# 2. Introduction

Nowadays, Computer Networks are more complex than before, the number of applications that runs on Clients/Servers increasing leading to a resources management problem. The IT professionals tasked with maintaining the computer network facing serious challenges in determining which applications consume computer resources or degrade network performance. Analyze the performance metrics collected from Clients/Servers using traditional methods is not enough anymore to make a correct decision whether an application consumes computer and network resources. The improvement of the network performance is not an easy task, even with network bandwidth upgrade might not be an optimal solution to solve the problem of high network utilization.

In this thesis will make use of machine learning and business intelligence and data analytics to compare and show the benefits of using those techniques in analyzing network performance metrics. Through collecting performance metrics from a real computer network. A constructed database combine performance metrics will be further analyzed to find pattern and correlation to give a better understanding of the application and network performance. The database will be used to applying machine learning algorithms to predict future performance under certain conditions. The implementation of those techniques in the future will cut the cost of running a network and reduce investigation time whenever a problem occurs and make IT professional life much easier.

## 2.1 Literature Review

The predictive data analytics and machine learning evolution changed the world. The applications are endless to apply those techniques to various aspects of life. Computer networking can utilize predictive analytics and machine learning to monitor network performance and further predict its performance [1]. The predictive analysis utilizes the data-mining tools to make a prediction and provide a recommendation based on historical data [2].

The predictive analytics models can perform the statistical and analytics analysis on diverse types of data. The data collected require preprocessing before applying predictive analysis methods such as machine learning algorithms. The raw data is processed and transformed into a format which is suitable for the future operation machine learning analysis or business intelligence techniques.

The processed data used as input to the machine learning models to produce the required prediction. The raw data is obtained by using data mining techniques. Data Mining is the extraction of obscure or hidden predictive information next searching for a pattern using techniques of statistical and pattern recognition such as decision trees and neural networks [2]. The data is divided into predictors and variables that are used to create a predictive model. The study performed by using data mining to extract and find a hidden pattern from data collected in a real computer network.

Machine learning algorithms such as decision trees are used to perform analysis on network performance metrics after being divided into predictors and response variables [2]. Moreover, the data are analyzed using statistical techniques on the same network performance metrics to compare the results of both techniques. The predictive analytics combines several statistical techniques includes machine learning algorithms.

By using this approach, we combine several techniques stretched from statistics to machine learning and data mining [3]. The data forecasting carried out by knowing the entire elements of the decisions and using the decision models to find the relationship between those elements [2]. The development of machine learning algorithms makes it easy to be used in networking domain [1].

Machine learning algorithms can tackle problems in networking domains, create unlimited potentials and unforeseen benefits in the next few decades. Classification and prediction in machine learning can solve networking problems in network performance and security. Those problems were very hard to deal with because of the complexity of networks.

The application of a machine learning in a typical network problem go through steps. The first step identifying the problem type that requires attention (prediction, regression or decision making). The second step collects unbiased data from network and applications that comprise application performance logs, network metrics, etc. The third step is performed analysis on the data being collected from preprocessing to feature extraction [1]. The fourth step is model construction that's basically a learning model or algorithm require training using data [1]. Step five is model validation which involves accuracy testing and verifies if the model is overfitting. The last step called deployment and inference because the implementation phase requires adjustment and consideration not applied in the testing phase.

Learning depends on data availability and accuracy. The real-time responses from a learning model require having a huge amount of historical data and a very complex learning model. In the study, the learning model doesn’t provide real-time responses, but it can analyze historical data when it is presented [1]. The learning model able to predict the applications which consume computer resources such as CPU utilization. The goal is to improve the network and application behavior and help in end-end network design.

# 3. Architecture

The Architecture shows an overview of the entire experiment and the testbed environment created to prove the thesis statement.

## 3.1 Diagram

The following diagram represents the network topology and name of tools used to collect the data from client/server as well as communication links. The diagram illustrates the flow of data between client/server and PowerShell scripts created to retrieve application metrics and CPU utilization from client/server. In addition, it shows the commands run on client/server that is used to test communication links between them. Every monitoring tool, PowerShell script, and command runs on the client/server produce an output file (raw data). Those files require preprocessing to transform data into a suitable format to apply data analytics techniques and machine learning algorithm.

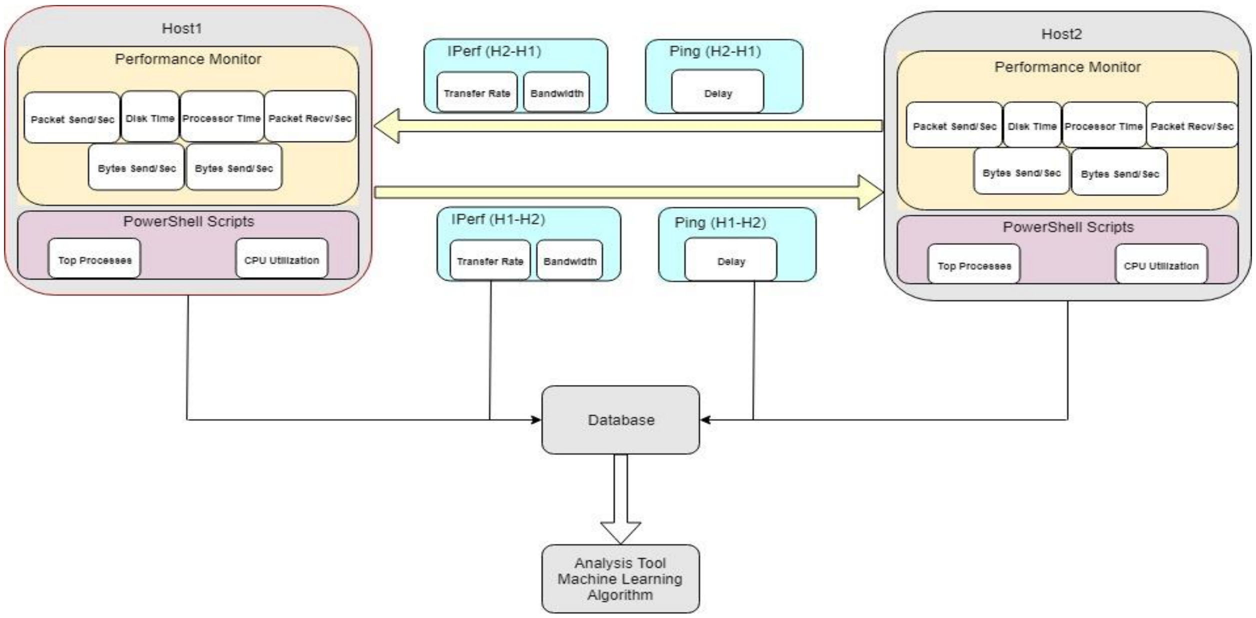


*Figure 1: Architecture Diagram*

## 3.2 The Network Topology

The below figure represents the network topology and shows how the two hosts are connected and can reach each other.

- The network topology is a hub and spoke
- Host1 located in the main office
- Host2 located in one of the remote branches
- Remote offices are connected through a VPN Tunnels or Leased Line connection.

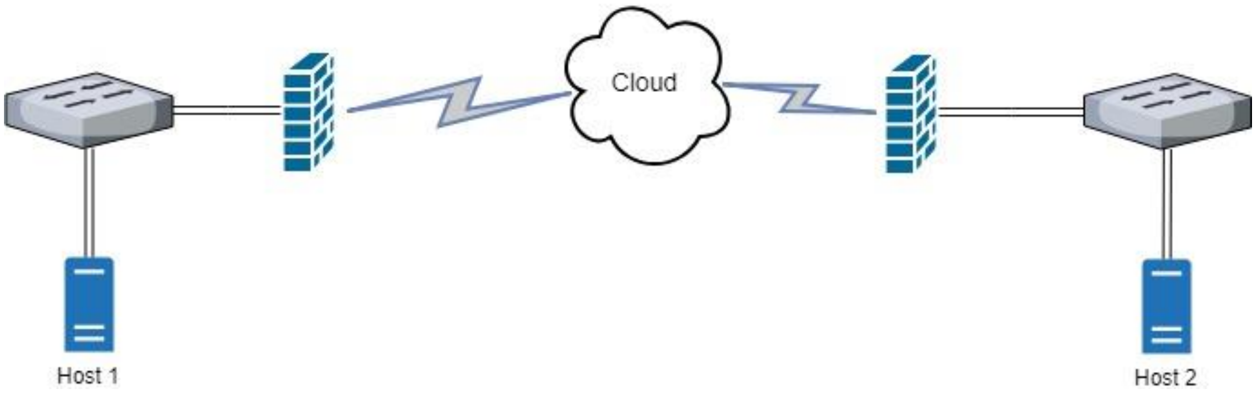
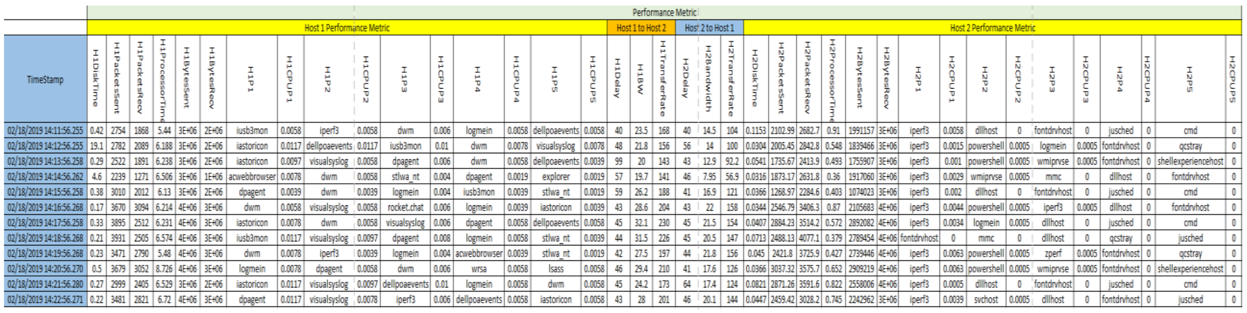


*Figure 2: Network Topology*

The following table represents the database that was created from processing the output files from PowerShell scripts, Performance monitor, IPerf network testing tool and commands run on Client/Server.

*Table 1: Database Table*



| | Performance Metric | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Host 1 Performance Metric | | | | | | | | | | | | | | | |
| TimeStamp | H1DiskTime | H1PacketsSent | H1PacketsRecv | H1ProcessorTim | H1BytesSent | H1BytesRecv | H1P1 | H1CPUP1 | H1P2 | H1CPUP2 | H1P3 | H1CPUP3 | H1P4 | H1CPUP4 | H1P5 | H1CPUP5 |
| 02/18/2019 14:11:56.255 | 0.42 | 2754 | 1868 | 5.44 | 3E+06 | 2E+06 | iusb3mon | 0.0058 | iperf3 | 0.0058 | dwm | 0.006 | logmein | 0.0058 | dellpoaevents | 0.0058 |
| 02/18/2019 14:12:56.255 | 19.1 | 2782 | 2089 | 6.188 | 3E+06 | 2E+06 | iastoricon | 0.0117 | dellpoaevents | 0.0117 | iusb3mon | 0.01 | dwm | 0.0078 | visualsyslog | 0.0078 |
| 02/18/2019 14:13:56.258 | 0.29 | 2522 | 1891 | 6.238 | 3E+06 | 2E+06 | iastoricon | 0.0097 | visualsyslog | 0.0058 | dpagent | 0.006 | dwm | 0.0058 | dellpoaevents | 0.0039 |
| 02/18/2019 14:14:56.262 | 4.6 | 2239 | 1271 | 6.506 | 3E+06 | 1E+06 | acwebbrowser | 0.0078 | dwm | 0.0058 | stlwa_nt | 0.004 | dpagent | 0.0019 | explorer | 0.0019 |
| 02/18/2019 14:15:56.258 | 0.38 | 3010 | 2012 | 6.13 | 3E+06 | 2E+06 | dpagent | 0.0039 | dwm | 0.0039 | logmein | 0.004 | iusb3mon | 0.0039 | stlwa_nt | 0.0019 |
| 02/18/2019 14:16:56.268 | 0.17 | 3670 | 3094 | 6.214 | 4E+06 | 3E+06 | dwm | 0.0058 | visualsyslog | 0.0058 | rocket.chat | 0.006 | logmein | 0.0039 | iastoricon | 0.0039 |
| 02/18/2019 14:17:56.258 | 0.33 | 3895 | 2512 | 6.231 | 4E+06 | 3E+06 | iastoricon | 0.0078 | dwm | 0.0058 | visualsyslog | 0.006 | dpagent | 0.0058 | dellpoaevents | 0.0058 |
| 02/18/2019 14:18:56.268 | 0.21 | 3931 | 2505 | 6.574 | 4E+06 | 3E+06 | iusb3mon | 0.0117 | visualsyslog | 0.0097 | dpagent | 0.008 | logmein | 0.0058 | stlwa_nt | 0.0039 |
| 02/18/2019 14:19:56.268 | 0.23 | 3471 | 2790 | 5.48 | 4E+06 | 3E+06 | dwm | 0.0078 | iperf3 | 0.0039 | logmein | 0.004 | acwebbrowser | 0.0039 | stlwa_nt | 0.0019 |
| 02/18/2019 14:20:56.270 | 0.5 | 3679 | 3052 | 8.726 | 4E+06 | 3E+06 | logmein | 0.0078 | dpagent | 0.0058 | dwm | 0.006 | wrsa | 0.0058 | lsass | 0.0058 |
| 02/18/2019 14:21:56.280 | 0.27 | 2999 | 2405 | 6.529 | 3E+06 | 2E+06 | iastoricon | 0.0117 | visualsyslog | 0.0097 | dellpoaevents | 0.01 | logmein | 0.0058 | dwm | 0.0058 |
| 02/18/2019 14:22:56.271 | 0.22 | 3481 | 2821 | 6.72 | 4E+06 | 3E+06 | dpagent | 0.0117 | visualsyslog | 0.0078 | iperf3 | 0.006 | dellpoaevents | 0.0058 | iastoricon | 0.0058 |

| | Performance Metric | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Host 1 to Host 2 | | | Host 2 to Host 1 | | | Host 2 Performance Metric | | | | | |
| TimeStamp | H1Delay | H1BW | H1TransferRate | H2Delay | H2Bandwidth | H2TransferRate | H2DiskTime | H2PacketsSent | H2PacketsRecv | H2ProcessorTim | H2BytesSent | H2BytesRecv |
| 02/18/2019 14:11:56.255 | 40 | 23.5 | 168 | 40 | 14.5 | 104 | 0.1153 | 2102.99 | 2682.7 | 0.91 | 1991157 | 3E+06 |
| 02/18/2019 14:12:56.255 | 48 | 21.8 | 156 | 56 | 14 | 100 | 0.0304 | 2005.45 | 2842.8 | 0.548 | 1839466 | 3E+06 |
| 02/18/2019 14:13:56.258 | 99 | 20 | 143 | 43 | 12.9 | 92.2 | 0.0541 | 1735.67 | 2413.9 | 0.493 | 1755907 | 3E+06 |
| 02/18/2019 14:14:56.262 | 57 | 19.7 | 141 | 46 | 7.95 | 56.9 | 0.0316 | 1873.17 | 2631.8 | 0.36 | 1917060 | 3E+06 |
| 02/18/2019 14:15:56.258 | 59 | 26.2 | 188 | 41 | 16.9 | 121 | 0.0366 | 1268.97 | 2284.6 | 0.403 | 1074023 | 3E+06 |
| 02/18/2019 14:16:56.268 | 43 | 28.6 | 204 | 43 | 22 | 158 | 0.0344 | 2546.79 | 3406.3 | 0.87 | 2105683 | 4E+06 |
| 02/18/2019 14:17:56.258 | 45 | 32.1 | 230 | 45 | 21.5 | 154 | 0.0407 | 2884.23 | 3514.2 | 0.572 | 2892082 | 4E+06 |
| 02/18/2019 14:18:56.268 | 44 | 31.5 | 226 | 45 | 20.5 | 147 | 0.0713 | 2488.13 | 4077.1 | 0.379 | 2789454 | 4E+06 |
| 02/18/2019 14:19:56.268 | 42 | 27.5 | 197 | 44 | 21.8 | 156 | 0.045 | 2421.8 | 3725.9 | 0.427 | 2739446 | 4E+06 |
| 02/18/2019 14:20:56.270 | 46 | 29.4 | 210 | 41 | 17.6 | 126 | 0.0366 | 3037.32 | 3575.7 | 0.652 | 2909219 | 4E+06 |
| 02/18/2019 14:21:56.280 | 45 | 24.2 | 173 | 64 | 17.4 | 124 | 0.0821 | 2871.26 | 3591.6 | 0.822 | 2558006 | 4E+06 |
| 02/18/2019 14:22:56.271 | 43 | 28 | 201 | 46 | 20.1 | 144 | 0.0447 | 2459.42 | 3028.2 | 0.745 | 2242962 | 3E+06 |

| | Performance Metric | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Host 2 Performance Metric | | | | | | | | | |
| TimeStamp | H2P1 | H2CPUP1 | H2P2 | H2CPUP2 | H2P3 | H2CPUP3 | H2P4 | H2CPUP4 | H2P5 | H2CPUP5 |
| 02/18/2019 14:11:56.255 | iperf3 | 0.0058 | dllhost | 0 | fontdrvhost | 0 | jusched | 0 | cmd | 0 |
| 02/18/2019 14:12:56.255 | iperf3 | 0.0015 | powershell | 0.0005 | logmein | 0.0005 | fontdrvhost | 0 | qcstray | 0 |
| 02/18/2019 14:13:56.258 | iperf3 | 0.001 | powershell | 0.0005 | wmiprvse | 0.0005 | fontdrvhost | 0 | shellexperiencehost | 0 |
| 02/18/2019 14:14:56.262 | iperf3 | 0.0029 | wmiprvse | 0.0005 | mmc | 0 | dllhost | 0 | fontdrvhost | 0 |
| 02/18/2019 14:15:56.258 | iperf3 | 0.002 | dllhost | 0 | fontdrvhost | 0 | jusched | 0 | cmd | 0 |
| 02/18/2019 14:16:56.268 | iperf3 | 0.0044 | powershell | 0.0005 | iperf3 | 0.0005 | dllhost | 0 | fontdrvhost | 0 |
| 02/18/2019 14:17:56.258 | iperf3 | 0.0034 | logmein | 0.0005 | dllhost | 0 | jusched | 0 | cmd | 0 |
| 02/18/2019 14:18:56.268 | fontdrvhost | 0 | mmc | 0 | dllhost | 0 | qcstray | 0 | jusched | 0 |
| 02/18/2019 14:19:56.268 | iperf3 | 0.0063 | powershell | 0.0005 | zperf | 0.0005 | fontdrvhost | 0 | qcstray | 0 |
| 02/18/2019 14:20:56.270 | iperf3 | 0.0063 | powershell | 0.0005 | wmiprvse | 0.0005 | fontdrvhost | 0 | shellexperiencehost | 0 |
| 02/18/2019 14:21:56.280 | iperf3 | 0.0005 | dllhost | 0 | fontdrvhost | 0 | jusched | 0 | cmd | 0 |
| 02/18/2019 14:22:56.271 | iperf3 | 0.0039 | svchost | 0.0005 | dllhost | 0 | fontdrvhost | 0 | jusched | 0 |

## 3.3 Performance Metric Tools

The network and application performance is measured through several performance metrics such as Bandwidth, Throughput, Disk time, CPU Utilization, number of packets send/Recv per sec, and number of bytes send/Recv per send.

The testbed used in the implementation has several tools to collect network and application metrics. The metrics collected on both hosts and the communication links between two hosts.

The below tables show the performance metrics categorized by the tool used:

*Table 2: Network and Application Performance Metrics Per Tool*

| Performance Monitor | PowerShell Script | IPerf |
|---|---|---|
| • Packets Sent/Sec | • Top Processes | • Bandwidth |
| • Packets Recv/Sec | • CPU Utilization | • Transfer Rate |
| • Processor Time | • Ping(Delay) | |
| • Disk Time | | |
| • Bytes Sent/Sec | | |
| • Bytes Recv/Sec | | |

The below figure shows performance metrics categorized by the metric extraction point:

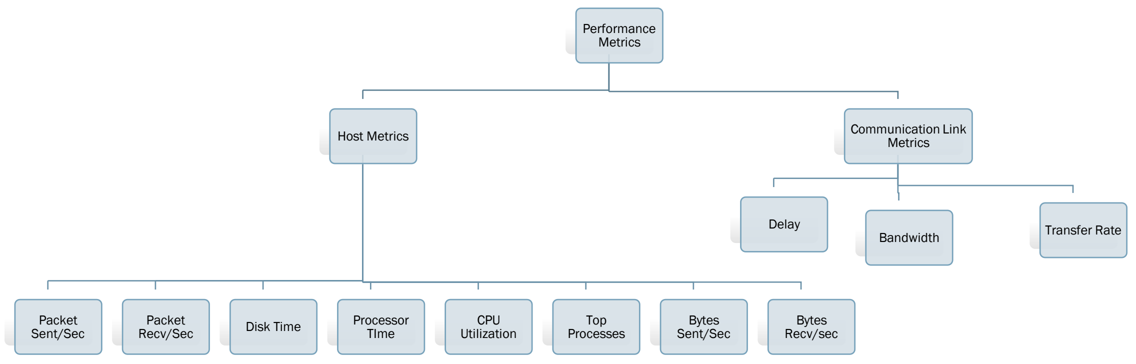


*Figure 3: Performance metric per extraction point*

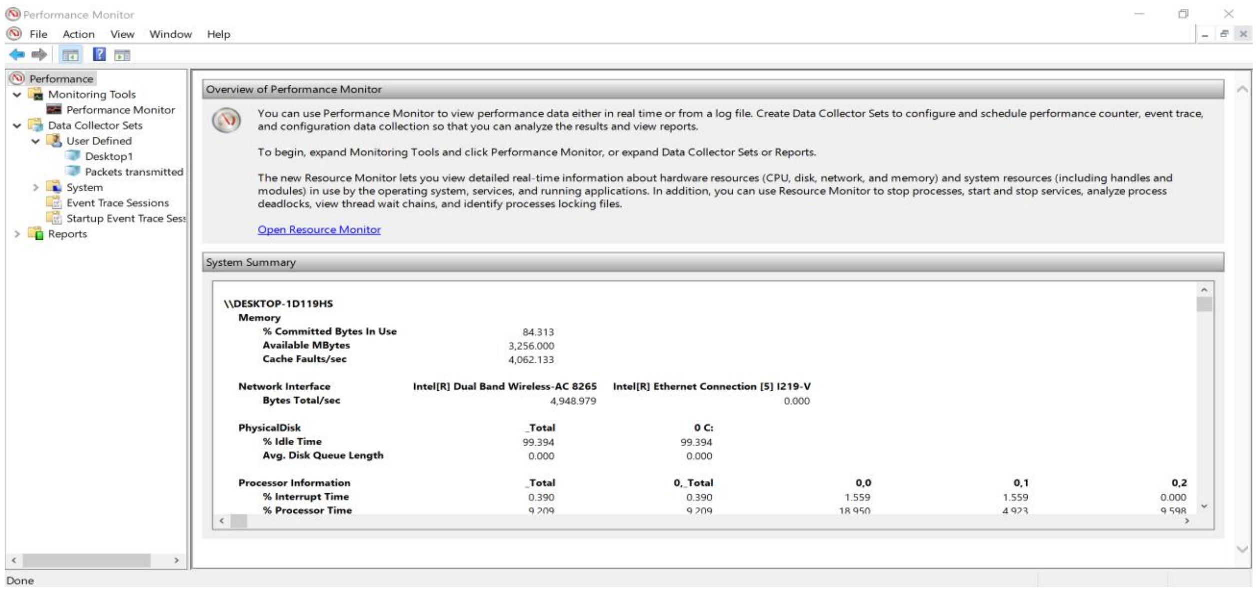
The table below shows network and application performance metrics definitions:

*Table 3: Metrics Definition Table*

| Metric Name | Definition |
|---|---|
| %Disk Time | The percentage of elapsed time that the selected disk drive was busy servicing read or write requests. |
| Packets Recv/sec | The rate at which packets are received on the network interface. |
| Packets Sent/Sec | The rate at which packets are sent on the network interface. |
| %Processor Time | The percentage of elapsed time that the processor spends to execute a non-Idle thread. It is calculated by measuring the percentage of time that the processor spends executing the idle thread and then subtracting that value from 100%. |
| Top Processes | Provide the names of the top five processes which consume more CPU Utilization. |
| CPU Utilization | Provide the CPU Utilization for the processor per process. |
| Delay | The time elapsed for a packet to travel from source to destination and back. |
| Bandwidth | The number of bits per second sends on the link. |
| Transfer Rate | The number of bytes transferred per second on the link. |
| Bytes Recv/Sec | The rate at which bytes are received over each network adapter, including framing characters. Network Interface\Bytes Received/sec is a subset of Network Interface\Bytes Total/sec. |
| Bytes Sent/Sec | The rate at which bytes are sent over each network adapter, including framing characters. Network Interface\Bytes Sent/sec is a subset of Network Interface\Bytes Total/sec |

### 3.3.1 Performance Monitor Tool

Performance Monitor Tool used to view performance data in real-time or produce logs files. Performance monitor tool is a built-in tool within Windows and doesn't require any installation. The requirement to obtain performance metric data is to configure a data collector set. The output of the data collector is configured to produce a Comma Separated file that will be used in further analysis. Creating a data collector set and configure it through adding specific metrics require collecting. The study focuses on collecting metrics related to applications and network performance.



Overview of Performance Monitor

You can use Performance Monitor to view performance data either in real time or from a log file. Create Data Collector Sets to configure and schedule performance counter, event trace, and configuration data collection so that you can analyze the results and view reports.

To begin, expand Monitoring Tools and click Performance Monitor, or expand Data Collector Sets or Reports.

The new Resource Monitor lets you view detailed real-time information about hardware resources (CPU, disk, network, and memory) and system resources (including handles and modules) in use by the operating system, services, and running applications. In addition, you can use Resource Monitor to stop processes, start and stop services, analyze process deadlocks, view thread wait chains, and identify processes locking files.

Open Resource Monitor

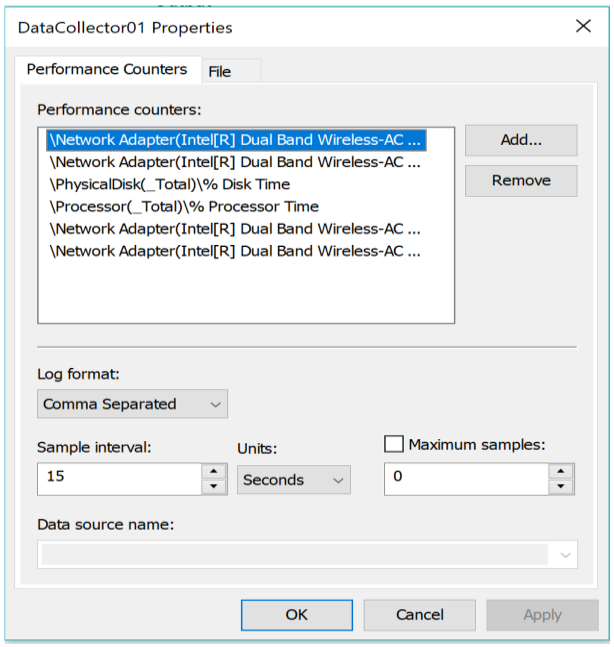
System Summary

```
\\DESKTOP-1D119HS
  Memory
      % Committed Bytes In Use                  84.313
      Available MBytes                       3,256.000
      Cache Faults/sec                       4,062.133

  Network Interface            Intel[R] Dual Band Wireless-AC 8265   Intel[R] Ethernet Connection [5] I219-V
      Bytes Total/sec                                    4,948.979                                   0.000

  PhysicalDisk                            _Total        0 C:
      % Idle Time                         99.394      99.394
      Avg. Disk Queue Length               0.000       0.000

  Processor Information                   _Total    0,_Total        0,0        0,1        0,2
      % Interrupt Time                     0.390       0.390      1.559      1.559      0.000
      % Processor Time                     9.209       9.209     18.950      4.923      9.598
```

*Figure 4: Performance Monitor Tool*

Metrics added on data collector set

- Packets Recv/sec
- Packets sent/sec
- Bytes Recv/sec
- Bytes Sent/sec
- Processor Time
- Disk Time



Performance counters:

```
\Network Adapter(Intel[R] Dual Band Wireless-AC ...
\Network Adapter(Intel[R] Dual Band Wireless-AC ...
\PhysicalDisk(_Total)\% Disk Time
\Processor(_Total)\% Processor Time
\Network Adapter(Intel[R] Dual Band Wireless-AC ...
\Network Adapter(Intel[R] Dual Band Wireless-AC ...
```

Log format: Comma Separated

Sample interval: 15

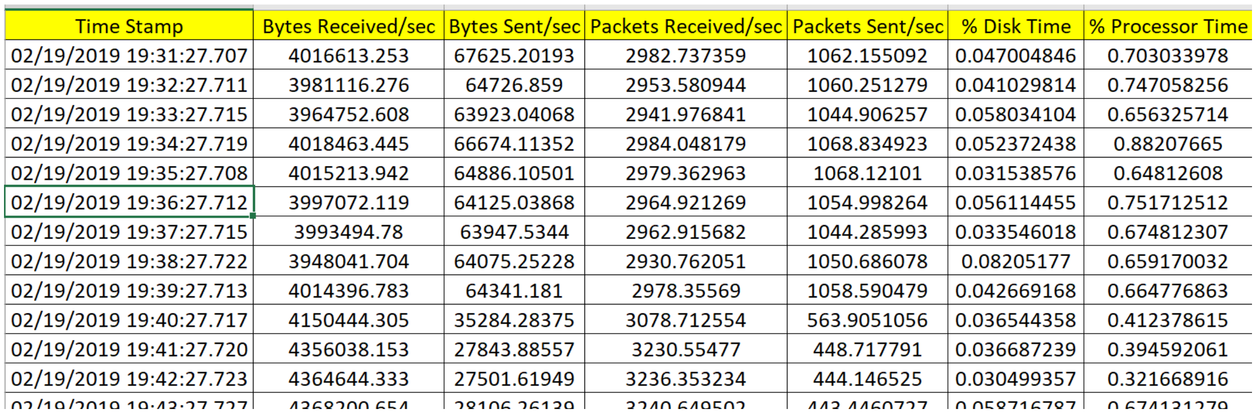
Units: Seconds

Maximum samples: 0

Data source name:

*Figure 5: Data Collector Set*

The below Figure show the output log file from Performance Monitor Tool:



| Time Stamp | Bytes Received/sec | Bytes Sent/sec | Packets Received/sec | Packets Sent/sec | % Disk Time | % Processor Time |
|---|---|---|---|---|---|---|
| 02/19/2019 19:31:27.707 | 4016613.253 | 67625.20193 | 2982.737359 | 1062.155092 | 0.047004846 | 0.703033978 |
| 02/19/2019 19:32:27.711 | 3981116.276 | 64726.859 | 2953.580944 | 1060.251279 | 0.041029814 | 0.747058256 |
| 02/19/2019 19:33:27.715 | 3964752.608 | 63923.04068 | 2941.976841 | 1044.906257 | 0.058034104 | 0.656325714 |
| 02/19/2019 19:34:27.719 | 4018463.445 | 66674.11352 | 2984.048179 | 1068.834923 | 0.052372438 | 0.88207665 |
| 02/19/2019 19:35:27.708 | 4015213.942 | 64886.10501 | 2979.362963 | 1068.12101 | 0.031538576 | 0.64812608 |
| 02/19/2019 19:36:27.712 | 3997072.119 | 64125.03868 | 2964.921269 | 1054.998264 | 0.056114455 | 0.751712512 |
| 02/19/2019 19:37:27.715 | 3993494.78 | 63947.5344 | 2962.915682 | 1044.285993 | 0.033546018 | 0.674812307 |
| 02/19/2019 19:38:27.722 | 3948041.704 | 64075.25228 | 2930.762051 | 1050.686078 | 0.08205177 | 0.659170032 |
| 02/19/2019 19:39:27.713 | 4014396.783 | 64341.181 | 2978.35569 | 1058.590479 | 0.042669168 | 0.664776863 |
| 02/19/2019 19:40:27.717 | 4150444.305 | 35284.28375 | 3078.712554 | 563.9051056 | 0.036544358 | 0.412378615 |
| 02/19/2019 19:41:27.720 | 4356038.153 | 27843.88557 | 3230.55477 | 448.717791 | 0.036687239 | 0.394592061 |
| 02/19/2019 19:42:27.723 | 4364644.333 | 27501.61949 | 3236.353234 | 444.146525 | 0.030499357 | 0.321668916 |
| 02/19/2019 19:43:27.727 | 4368200.654 | 28106.26139 | 3240.649502 | 443.4460727 | 0.058716787 | 0.674131279 |

*Figure 6: Performance Monitor Output File*

## 3.3.2 IPerf

It is a tool used to test network bandwidth and provide measurement [4], IPerf can generate TCP/UDP traffic. IPerf uses a client/server model. It's compatible with several platforms from Windows/Linux. IPerf has built-in features to customize the testing process and dump the output into CSV files for further analysis. The IPerf support different protocols (TCP, UDP, SCTP with IPv4 or IPV6). IPerf reports two important network performances metrics (Transfer Rate, Bandwidth). IPerf version used on the testbed and the real environment is version iperf-3.1.3. IPerf command can make use of any of the following programs to run its commands (Command Prompt or PowerShell).

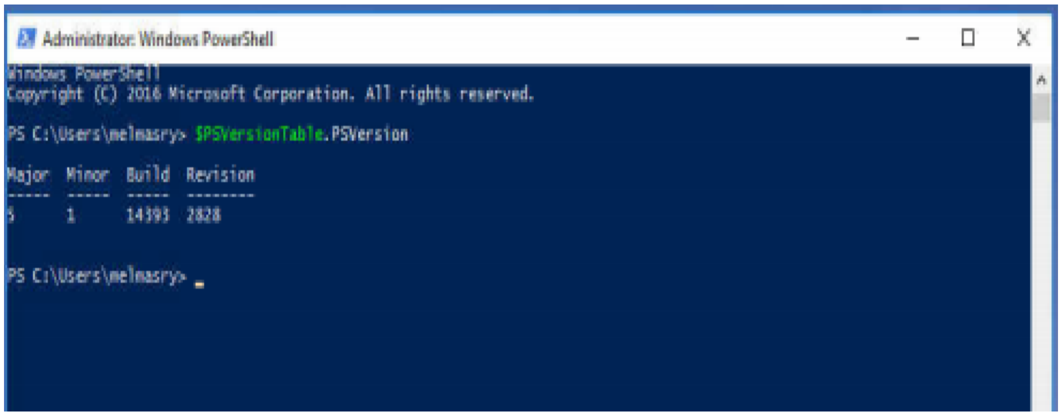
The below table explains option features which can be used to customize the testing command:

*Table 4: IPerf Command Line Option*

| Command Line Option | Description |
|---|---|
| **-p, --port n** | The server port for the server to listen on and the client to connect to. This should be the same in both client and server. The default is 5201. |
| **-i, --interval n** | Sets the interval time in seconds between periodic bandwidth, jitter, and loss reports. |
| **-V, --verbose** | Give a more detailed output. |
| **--logfile** | Send output to a log file. |
| **-s, --server** | Run IPerf in server mode (This will only allow one IPerf connection at a time). |
| **-c, --client host** | Run IPerf in client mode, connecting to an IPerf server running on the host. |
| **-t, --time n** | The time in seconds to transmit for. |

### 3.3.3 PowerShell Scripts

The PowerShell is a command-line task-based framework and scripting language from Microsoft. For any System Administrator, it is a powerful tool that can be used to perform different kinds of operation on any supported Windows platform, macOS and Linux. It used to automate processes and tasks, schedule operations to run on specific times. Latest PowerShell version 6 is independent of Windows, free and open source [5]. The PowerShell version utilized in this research is version 5.1



```
Administrator: Windows PowerShell
Windows PowerShell
Copyright (C) 2016 Microsoft Corporation. All rights reserved.

PS C:\Users\melmasry> $PSVersionTable.PSVersion

Major  Minor  Build  Revision
-----  -----  -----  --------
5      1      14393  2828

PS C:\Users\melmasry> _
```

*Figure 7: PowerShell Version*

The PowerShell is used in this research to develop scripts that automate the extraction of network and application performance metrics from clients and servers running Windows Platform. The developed script used to automate the running of IPerf network testing tool, collect top processes which are utilizing CPU and ping command to test the delay on the network between server and client.

The below figure shows the Ping script:

```
Test-Connection 10.5.1.229 -delay 60 -count 720 | Format-list @{n='TimeStamp';e={Get-
Date}},__SERVER, Address,IPV4Address,ResponseTime | out-file
C:\Users\melmasry\Desktop\ThesisWork\Server-ping.txt -Append
```

*Figure 8: Ping Script*

The below figure shows Top-Processes script:

```
function TopProcess {
  Param (
    [Parameter(Position=1)] [Alias("l")]
    [int]$TotalList=5,
    [Parameter(Position=2)] [Alias("r")]
    [int]$Invertal=60
  )
  Begin {}
  Process {
    While ($true) {
      $CounterSamples = Get-Counter '\Process(*)\ID Process','\Process(*)\% Processor Time','\Process(*)\Working
Set' | Select-Object -Expand CounterSamples
      Clear-Host
      $CounterSamples | Group-Object { Split-Path $_.Path } | Where-Object {$_.Group[1].InstanceName -notmatch
"^Idle|_Total|System$"} | Sort-Object -Property {$_.Group[1].CookedValue} -Descending | Select-Object -First
$TotalList | Format-Table @{n='TimeStamp';e={Get-
Date}},@{Name="ProcessId";Expression={$_.Group[0].CookedValue}},@{Name="ProcessorUsage";Expression
={[System.Math]::Round($_.Group[1].CookedValue/100/$env:NUMBER_OF_PROCESSORS,4)}},@{Name="Pr
ocessName";Expression={$_.Group[1].InstanceName}},@{Name="WorkingSet";Expression={[System.Math]::Ro
und($_.Group[2].CookedValue/1MB,4)}}
      Sleep -Seconds $Invertal
    }
  }
  End {}
}

 TopProcess | Out-File C:\Users\melmasry\Desktop\ThesisWork\Server-Task.txt -Append
```

*Figure 9: Top Process*

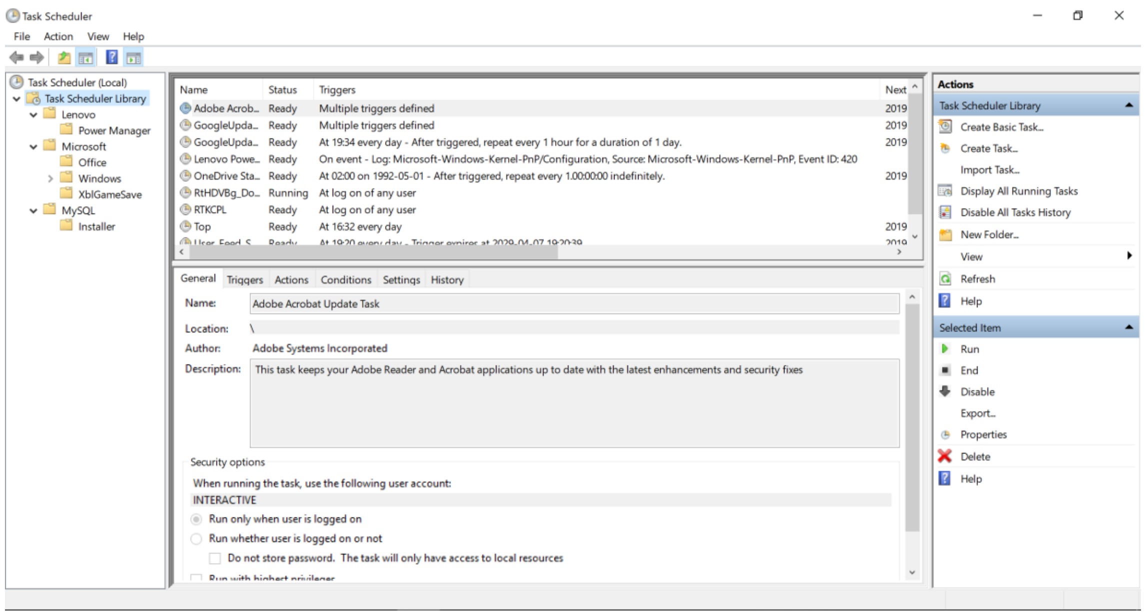
The below figure shows the IPerf script:

```
cd c:/
cd iperf-3.1.3-win64
./iperf3.exe -c 10.5.1.229 -i 60 -t 900 -p 5021 -u  -V  --logfile Server.csv
```

*Figure 10: IPerf Script*

### 3.3.4 Task Scheduler

The task scheduler enables the Windows users to automate tasks and run scripts on specific times and run programs or even sending emails. There are several features to utilize and allow more control parameters to be adjusted in any scheduled running task. The task scheduler is built in several Windows platforms by default.



| Name | Status | Triggers | Next |
|---|---|---|---|
| Adobe Acrob... | Ready | Multiple triggers defined | 2019 |
| GoogleUpda... | Ready | Multiple triggers defined | 2019 |
| GoogleUpda... | Ready | At 19:34 every day - After triggered, repeat every 1 hour for a duration of 1 day. | 2019 |
| Lenovo Powe... | Ready | On event - Log: Microsoft-Windows-Kernel-PnP/Configuration, Source: Microsoft-Windows-Kernel-PnP, Event ID: 420 | |
| OneDrive Sta... | Ready | At 02:00 on 1992-05-01 - After triggered, repeat every 1.00:00:00 indefinitely. | 2019 |
| RtHDVBg_Do... | Running | At log on of any user | |
| RTKCPL | Ready | At log on of any user | |
| Top | Ready | At 16:32 every day | 2019 |
| User_Feed_S... | Ready | At 19:20 every day - Trigger expires at 2029-04-07 19:20:39 | 2019 |

General | Triggers | Actions | Conditions | Settings | History

Name: Adobe Acrobat Update Task

Location: \

Author: Adobe Systems Incorporated

Description: This task keeps your Adobe Reader and Acrobat applications up to date with the latest enhancements and security fixes

Security options

When running the task, use the following user account:

INTERACTIVE

[✓ Run only when user is logged on]

Run whether user is logged on or not

Do not store password. The task will only have access to local resources

Run with highest privileges

*Figure 11: Task Scheduler*

The main components of task scheduler that were utilized in this research are:

- Task Action
- Task Trigger
- Repeating A Task

### 3.3.5 Ku-Tools

It is an add-on used with excel Microsoft, allow advanced functions and operations to be implemented on excel, CSV files. The function that is used in this research called Transform Range.

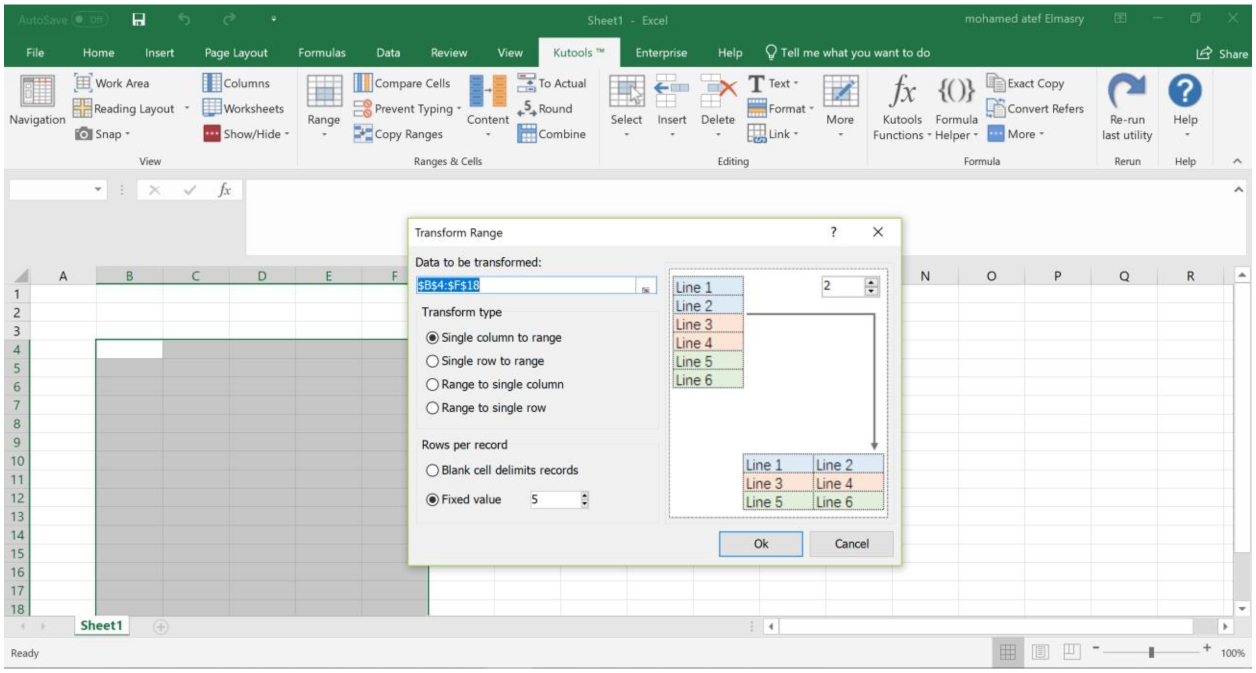


*Figure 12: KU-Tools*

# 4. Methodology

The experiment is carried out to find the effects of applications on resource consumption in computer networks through extracting performance metrics. The data is analyzed using machine learning and data analytics techniques, also finding any correlation exists between those metrics. The performance metrics are extracted from the client as well as the server. The client is accessing files on the server or using installed network applications.

The synchronization between tasks running in this experiment is the most important factor to have accurate performance metrics which converted into a database. The performance metrics are measured and extracted using installed independent software, built-in programs within the Windows Operating Systems.

## 4.1 Collecting Data

The software used are Performance Monitor, Task Scheduler, PowerShell Scripts, and IPerf network testing tool. IPerf is introduced into the experiment to test network bandwidth and transfer rate. This aims at increasing the amount of the data exchanged between the client and the server. The IPerf tool generates UDP or TCP traffic protocols. In this experiment, only a TCP traffic is generated by IPerf tool. Windows PowerShell is used to run IPerf commands. A PowerShell script is created and imported into Task Scheduler and configured to run at a specific time. The performance metrics are collected every one-minute interval.

- Command used to initiate traffic from client to server (run on the client):

```
iperf.exe -c 10.5.1.229 -i 60 -t 900 -p 5021 -V  --logfile client-iperf.csv
```

- Command used to initiate traffic from the server to the client (run on the server):

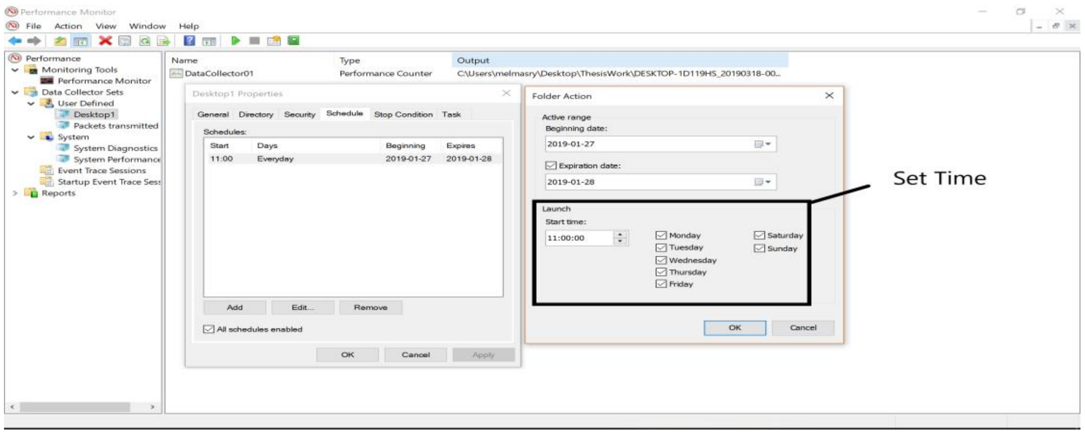
```
iperf.exe -c 10.3.1.8 -i 60 -t 900 -p 5021 -V  --logfile server-iperf.csv
```

- Command used to allow the client and server to listen to port 5021(run on server and client):

```
iperf.exe -s -p 5021
```

The data collection tasks are required to run exactly at the same time across the client or servers. The main reason behind this is to take a snapshot from performance metrics on both the client and server at the same second in time.

The Performance Monitor has a component called schedule. This component is used after data collector set created and performance metrics were added.



| Name | Type | Output |
|---|---|---|
| DataCollector01 | Performance Counter | C:\Users\melmasry\Desktop\ThesisWork\DESKTOP-1D119HS_20190318-00... |

Schedules:

| Start | Days | Beginning | Expires |
|---|---|---|---|
| 11:00 | Everyday | 2019-01-27 | 2019-01-28 |

☑ All schedules enabled

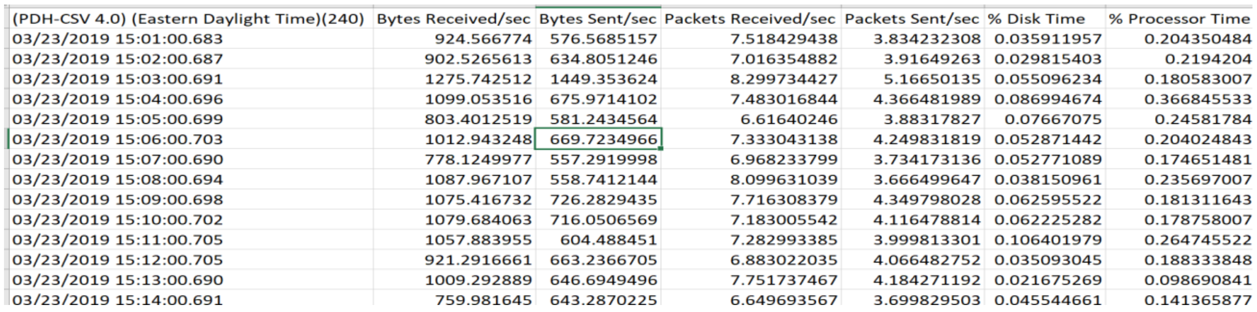
Active range
Beginning date: 2019-01-27
☑ Expiration date: 2019-01-28

Launch
Start time: 11:00:00
☑ Monday ☑ Tuesday ☑ Wednesday ☑ Thursday ☑ Friday ☑ Saturday ☑ Sunday

*Figure 13: Performance Monitor Scheduled Task*

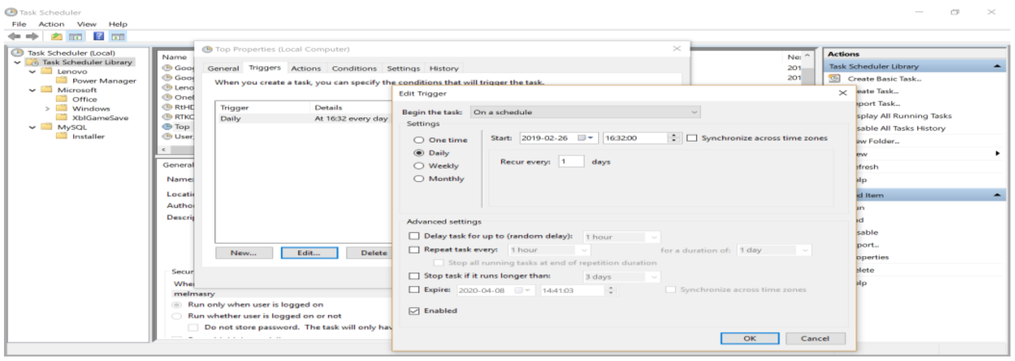
Data collector set is configured to generate a CSV file that is preprocessed and later analyzed. The below table shows the CSV output file from Performance Monitor.

*Table 5: Performance Monitor Output*



| (PDH-CSV 4.0) (Eastern Daylight Time)(240) | Bytes Received/sec | Bytes Sent/sec | Packets Received/sec | Packets Sent/sec | % Disk Time | % Processor Time |
|---|---|---|---|---|---|---|
| 03/23/2019 15:01:00.683 | 924.566774 | 576.5685157 | 7.518429438 | 3.834232308 | 0.035911957 | 0.204350484 |
| 03/23/2019 15:02:00.687 | 902.5265613 | 634.8051246 | 7.016354882 | 3.91649263 | 0.029815403 | 0.2194204 |
| 03/23/2019 15:03:00.691 | 1275.742512 | 1449.353624 | 8.299734427 | 5.16650135 | 0.055096234 | 0.180583007 |
| 03/23/2019 15:04:00.696 | 1099.053516 | 675.9714102 | 7.483016844 | 4.366481989 | 0.086994674 | 0.366845533 |
| 03/23/2019 15:05:00.699 | 803.4012519 | 581.2434564 | 6.61640246 | 3.88317827 | 0.07667075 | 0.24581784 |
| 03/23/2019 15:06:00.703 | 1012.943248 | 669.7234966 | 7.333043138 | 4.249831819 | 0.052871442 | 0.204024843 |
| 03/23/2019 15:07:00.690 | 778.1249977 | 557.2919998 | 6.968233799 | 3.734173136 | 0.052771089 | 0.174651481 |
| 03/23/2019 15:08:00.694 | 1087.967107 | 558.7412144 | 8.099631039 | 3.666499647 | 0.038150961 | 0.235697007 |
| 03/23/2019 15:09:00.698 | 1075.416732 | 726.2829435 | 7.716308379 | 4.349798028 | 0.062595522 | 0.181311643 |
| 03/23/2019 15:10:00.702 | 1079.684063 | 716.0506569 | 7.183005542 | 4.116478814 | 0.062225282 | 0.178758007 |
| 03/23/2019 15:11:00.705 | 1057.883955 | 604.488451 | 7.282993385 | 3.999813301 | 0.106401979 | 0.264745522 |
| 03/23/2019 15:12:00.705 | 921.2916661 | 663.2366705 | 6.883022035 | 4.066482752 | 0.035093045 | 0.188333848 |
| 03/23/2019 15:13:00.690 | 1009.292889 | 646.6949496 | 7.751737467 | 4.184271192 | 0.021675269 | 0.098690841 |
| 03/23/2019 15:14:00.691 | 759.981645 | 643.2870225 | 6.649693567 | 3.699829503 | 0.045544661 | 0.141365877 |

Task Scheduler is used to schedule PowerShell Scripts to start at the exact time. Task Trigger component is used to perform this operation.



When you create a task, you can specify the conditions that will trigger the task.

| Trigger | Details |
|---|---|
| Daily | At 16:32 every day |

Edit Trigger

Begin the task: On a schedule

Settings

( ) One time [✓ Daily] ( ) Weekly ( ) Monthly

Start: 2019-02-26 16:32:00 ☐ Synchronize across time zones

Recur every: 1 days

Advanced settings

☐ Delay task for up to (random delay): 1 hour

☐ Repeat task every: 1 hour for a duration of: 1 day

☐ Stop all running tasks at end of repetition duration

☐ Stop task if it runs longer than: 3 days

☐ Expire: 2020-04-08 14:41:03 ☐ Synchronize across time zones

☑ Enabled

melmasry

Run only when user is logged on

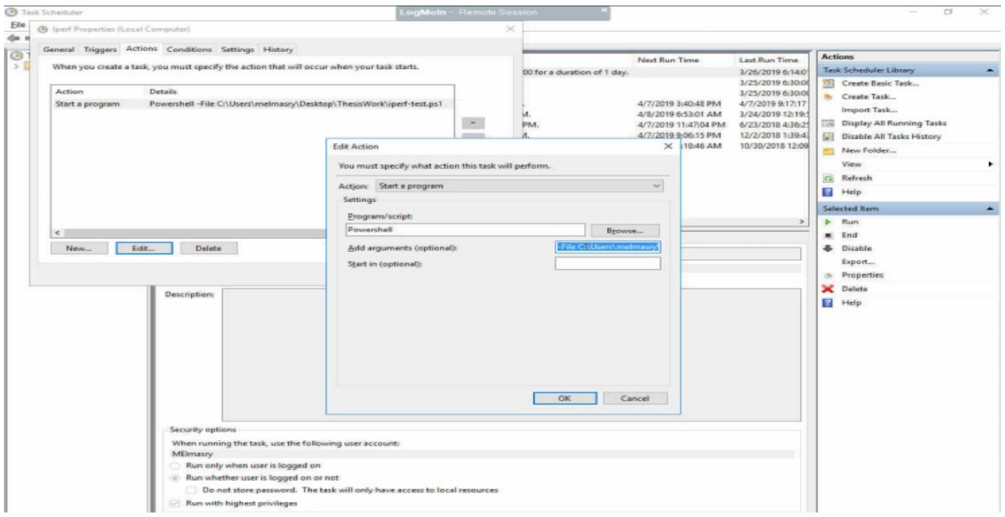
Run whether user is logged on or not

Do not store password. The task will only hav

*Figure 14: Task Trigger*

Task Scheduler component is used Task Action to import PowerShell script to run. Argument Option is used to locate PowerShell Script

"-File C:\Users\melmasry\Desktop\ThesisWork\iperf-test.ps1"



When you create a task, you must specify the action that will occur when your task starts.

| Action | Details |
|---|---|
| Start a program | Powershell -File C:\Users\melmasry\Desktop\ThesisWork\iperf-test.ps1 |

You must specify what action this task will perform.

Action: Start a program

Settings

Program/script: Powershell

Add arguments (optional): -File C:\Users\melmasry\

Start in (optional):

Description:

Security options

When running the task, use the following user account:
MElmasry

Run only when user is logged on

[✓ Run whether user is logged on or not]

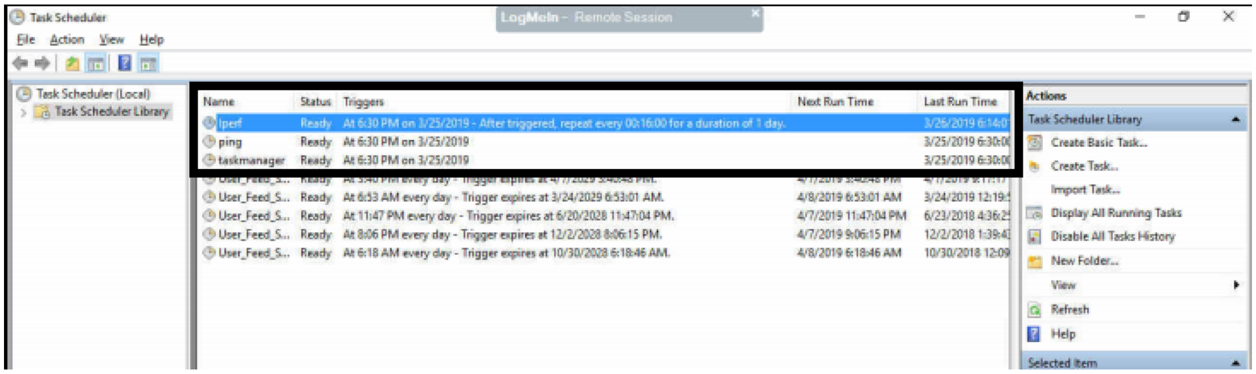
Do not store password. The task will only have access to local resources

[✓ Run with highest privileges]

Figure 15: Task Scheduler Action

Task Scheduler is used to run three different PowerShell scripts scheduled to run at the same time on both the client and server:

- Task 1: IPerf script
- Task 2: Ping command script
- Task 3: Top Processes script

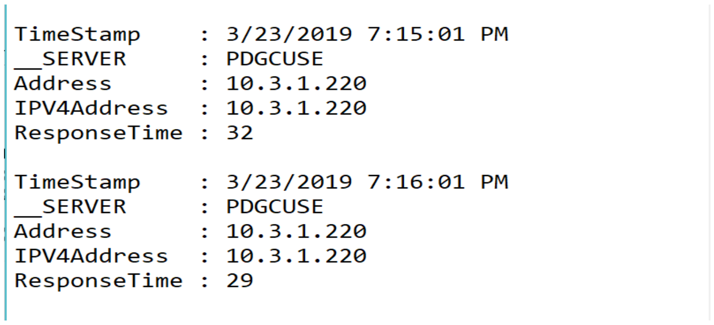


| Name | Status | Triggers | Next Run Time | Last Run Time |
|---|---|---|---|---|
| Iperf | Ready | At 6:30 PM on 3/25/2019 - After triggered, repeat every 00:16:00 for a duration of 1 day. | | 3/26/2019 6:14:0 |
| ping | Ready | At 6:30 PM on 3/25/2019 | | 3/25/2019 6:30:0 |
| taskmanager | Ready | At 6:30 PM on 3/25/2019 | | 3/25/2019 6:30:0 |
| User_Feed_S... | Ready | At 3:40 PM every day - Trigger expires at 4/7/2029 3:40:48 PM. | 4/7/2019 3:40:48 PM | 4/7/2019 9:17:17 |
| User_Feed_S... | Ready | At 6:53 AM every day - Trigger expires at 3/24/2029 6:53:01 AM. | 4/8/2019 6:53:01 AM | 3/24/2019 12:19: |
| User_Feed_S... | Ready | At 11:47 PM every day - Trigger expires at 6/20/2028 11:47:04 PM. | 4/7/2019 11:47:04 PM | 6/23/2018 4:36:2 |
| User_Feed_S... | Ready | At 8:06 PM every day - Trigger expires at 12/2/2028 8:06:15 PM. | 4/7/2019 9:06:15 PM | 12/2/2018 1:39:4 |
| User_Feed_S... | Ready | At 6:18 AM every day - Trigger expires at 10/30/2028 6:18:46 AM. | 4/8/2019 6:18:46 AM | 10/30/2018 12:09 |

Figure 16: Scheduled Task

Each of the script used in task scheduler provides an output file. The output file is text-based that requires preprocessing before converted into a database. The PowerShell scripts are designed to provide output accompanied by a time stamp. This time stamp is used to align the output of all PowerShell scripts, Performance Monitor and IPerf Script.

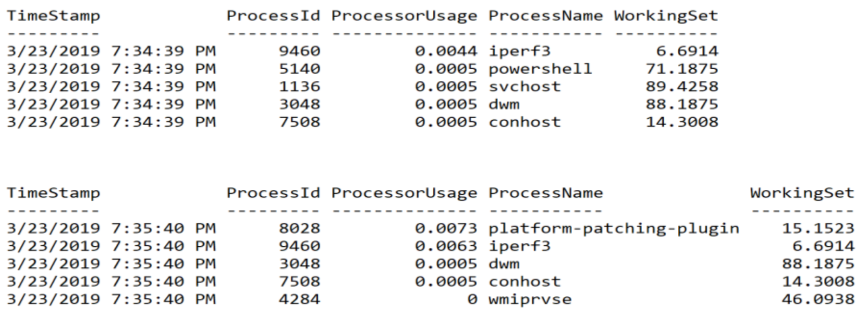
The below figures show the output of Ping Command PowerShell script, the PowerShell script used in this experiment implemented another command is used as a replacement and provide the same output called Test-Connection:



```
TimeStamp    : 3/23/2019 7:15:01 PM
__SERVER     : PDGCUSE
Address      : 10.3.1.220
IPV4Address  : 10.3.1.220
ResponseTime : 32

TimeStamp    : 3/23/2019 7:16:01 PM
__SERVER     : PDGCUSE
Address      : 10.3.1.220
IPV4Address  : 10.3.1.220
ResponseTime : 29
```

Figure 17: Ping Script Output

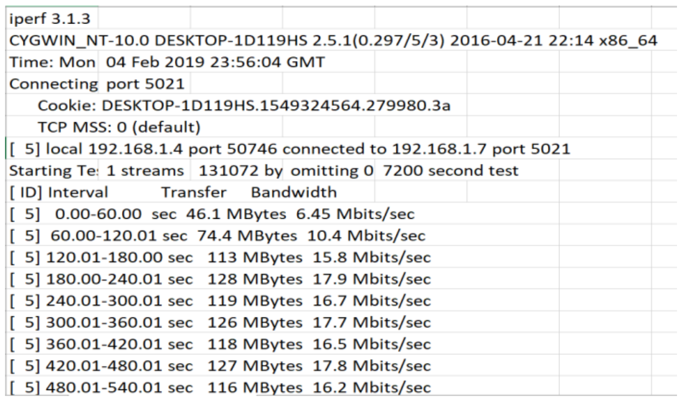
The below figure shows the output of Top Processes PowerShell script:



```
TimeStamp            ProcessId ProcessorUsage ProcessName WorkingSet
---------            --------- -------------- ----------- ----------
3/23/2019 7:34:39 PM      9460         0.0044 iperf3          6.6914
3/23/2019 7:34:39 PM      5140         0.0005 powershell     71.1875
3/23/2019 7:34:39 PM      1136         0.0005 svchost        89.4258
3/23/2019 7:34:39 PM      3048         0.0005 dwm            88.1875
3/23/2019 7:34:39 PM      7508         0.0005 conhost        14.3008


TimeStamp            ProcessId ProcessorUsage ProcessName                WorkingSet
---------            --------- -------------- -----------                ----------
3/23/2019 7:35:40 PM      8028         0.0073 platform-patching-plugin      15.1523
3/23/2019 7:35:40 PM      9460         0.0063 iperf3                         6.6914
3/23/2019 7:35:40 PM      3048         0.0005 dwm                           88.1875
3/23/2019 7:35:40 PM      7508         0.0005 conhost                       14.3008
3/23/2019 7:35:40 PM      4284              0 wmiprvse                      46.0938
```

*Figure 18: Top Processes Output*

The below figure shows the output of the IPerf PowerShell script:



```
iperf 3.1.3
CYGWIN_NT-10.0 DESKTOP-1D119HS 2.5.1(0.297/5/3) 2016-04-21 22:14 x86_64
Time: Mon  04 Feb 2019 23:56:04 GMT
Connecting  port 5021
    Cookie: DESKTOP-1D119HS.1549324564.279980.3a
    TCP MSS: 0 (default)
[  5] local 192.168.1.4 port 50746 connected to 192.168.1.7 port 5021
Starting Te: 1 streams  131072 by  omitting 0  7200 second test
[ ID] Interval          Transfer     Bandwidth
[  5]   0.00-60.00  sec  46.1 MBytes  6.45 Mbits/sec
[  5]  60.00-120.01 sec  74.4 MBytes  10.4 Mbits/sec
[  5] 120.01-180.00 sec   113 MBytes  15.8 Mbits/sec
[  5] 180.00-240.01 sec   128 MBytes  17.9 Mbits/sec
[  5] 240.01-300.01 sec   119 MBytes  16.7 Mbits/sec
[  5] 300.01-360.01 sec   126 MBytes  17.7 Mbits/sec
[  5] 360.01-420.01 sec   118 MBytes  16.5 Mbits/sec
[  5] 420.01-480.01 sec   127 MBytes  17.8 Mbits/sec
[  5] 480.01-540.01 sec   116 MBytes  16.2 Mbits/sec
```

*Figure 19: IPerf Script Output*

## 4.2 Parsing the Data

The output from the PowerShell scripts is pure text files. Those files require processing to extract the required data. Each text file is imported into Microsoft Excel and using KuTools an add-in. The transform function among other advanced operations used to extract the required performance metrics.

A database is constructed from the data extracted from PowerShell script output. The database columns consist of two sides, one side represents the performance metrics of the client and the other side the server. Each row in the database represents performance metrics collected in the one-minute interval. Once the database is created, the analysis phase using machine learning and data analytics techniques begin.

Python is a powerful programming language that can be used in many different fields to solve real-world problems. Python has rich libraries that allow the programmers to perform many actions without having to write long code. In the thesis work, Python programming language along with a couple of libraries are utilized to analyze the data using machine learning and data analytics. The Pandas library provides data manipulation and analysis tools. The Numpy library provides high-level mathematical functions that can work on multi-dimensional arrays. The scikit-learn library is a free machine learning library provides classification, regression and clustering algorithms. It's used in this research work for regression and decision trees. The matplotlib library is a powerful plotting library for Python that can be incorporated with other libraries such as Pandas and Numpy.

The statistical analysis used to understand the nature of the data being analyzed. It's a component of data analytics and related to business intelligent [6]. It is applied to the database using Python powerful libraries and mathematical functions to identify the trends and find patterns in structured and semi-structured data. The database is analyzed to find the correlation coefficient between application and network performance metric. The correlation coefficient provides us with insights into the cause-effect relationship between performance metrics. There are three correlation coefficient methods (Pearson, Kendall, Spearman). Below figure shows an example python code used to calculate the Spearman correlation coefficient:

```
import pandas as pd
import numpy as np
import math as m
import statistics
FileServer = pd.read_csv('FileServerMetrics.csv')
Correlation_Coefficient=FileServer.corr(method='spearman')
```

*Figure 20: Python Correlation Coefficient Code*

The statistical analysis is continued to analyze the database by calculating standard deviation, mean, count, percentile, minimum and maximum values for performance metrics.

The below figure shows the Python code as well as output obtained from using a Python method called describe()

```
import pandas as pd
import numpy as np
import math as m
import statistics
Client = pd.read_csv('Client Data.csv')
Client.describe()
```

Figure 21: Statistical Analysis describe method

## 4.3 Generating Graphs

The database collected is analyzed further to find the trend in applications consumed the resources in computer networks. One performance metric column “H1CPUP1” represent a top process that used the CPU for the longest time per minute. Each value represents a process name of an application installed on the client or server. The frequency of the process name in “H1CPUP1” is investigated to determine the top applications that utilize the CPU.

The below figure shows the Python code used to find the most occurred top processes:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
Server = pd.read_csv('Server-2.csv')
pd.set_option('display.float_format', lambda x: '%.4f' % x)
plt.rcParams["figure.figsize"] = (20,20)
plt.xlabel('occurance')
plt.ylabel('process names')
Server.H2P1.value_counts().plot(kind='Barh')
```

*Figure 22: Top Processes Python Code*

A graph generated as the output from the above Python code displays the most frequent processes occurred as Top Process:

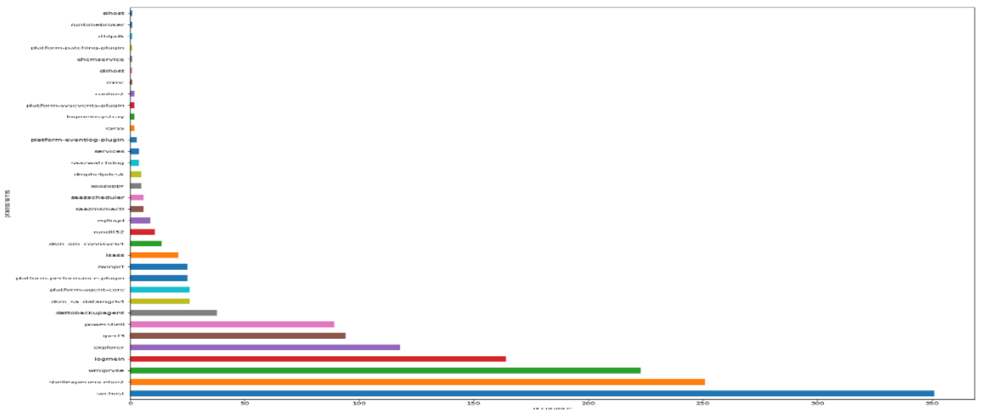


*Figure 23: Most Frequent Processes*

The seaborn library provides a toolset to draw graphs, the below graph represents pair plot for performance metrics to show data analysis visualization of database and how much the data are scattered.

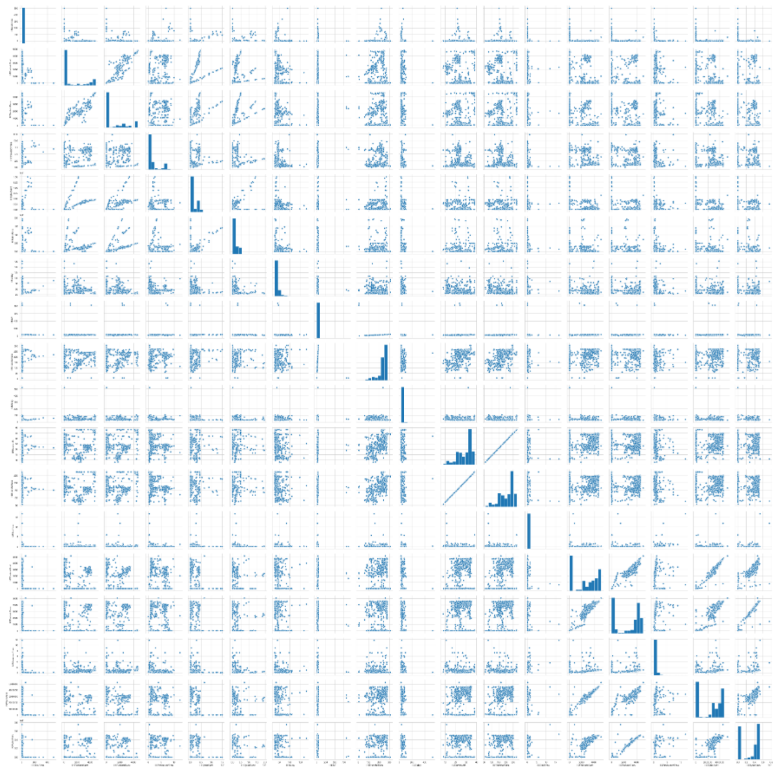


*Figure 24: Data Analysis Visualization*

The decision tree algorithm covers both regression and classification in machine learning, this provides a wealth of information about performance metric database. The decision tree provides a visual representation of the decisions and decision making through classification and decision tree models. It is considered a data mining tool to enable finding a hidden pattern as well as a prediction for future values. It revolves around asking the right questions to make better decisions about which features are more important than others. In this research, the decision trees illustrate which performance metrics have higher effects on the resource consumption and performance prediction in the computer network. The performance metrics are divided into groups predictor and target. The database is also divided into test and train sets into 20-80 or 10-90 split to increase precision.

The below figure shows the part of the code developed to create a decision tree and visualized:

```
X = df1.drop(columns=['H1P1'])
Y = df1['H1P1']
x_train, x_test, y_train, y_test = train_test_split(X,Y,test_size=0.1)
model = DecisionTreeClassifier(max_depth=4)
model.fit(x_train,y_train)
predications = model.predict(x_test)
score = accuracy_score(y_test, predications)
import graphviz
feature_names = list(df1.drop(['H1P1'], axis=1))
dot_data = tree.export_graphviz(model, out_file=None, filled=True, rounded=True,
feature_names=feature_names,class_names=Y)
graph = graphviz.Source(dot_data)
graph
```

*Figure 25: Decision Tree Python Code*

Below decision tree figure shows prediction accuracy and classification for determining future top processes that utilizing computer network resources.

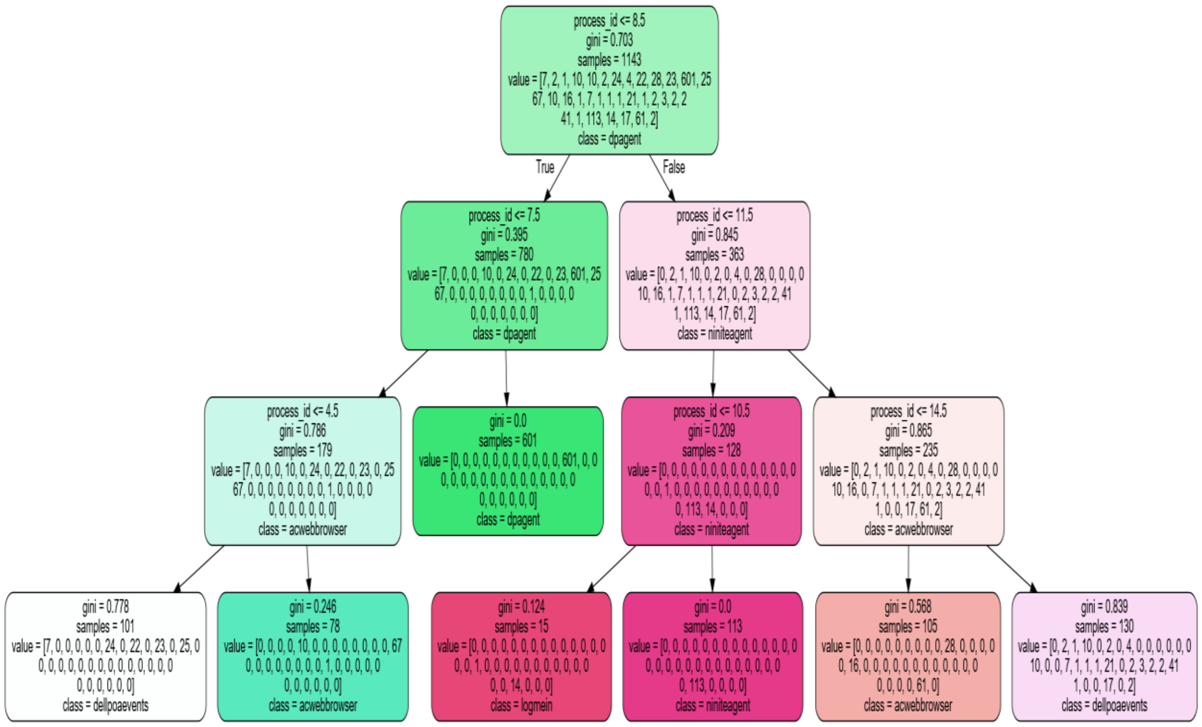


*Figure 26: Decision Tree Graph*

The learning model and the decision tree has been created then the training database is used to train the model and test database used to verify the prediction of target top processes. The process is done by verifying the predicted output with the actual values of the test database.

# 5. Results

The experiments started by setup a testing environment and scenarios to collect reliable real-time data from a working network. The testing environment was carried out on a standalone server. The built-in programs in windows operating system and developed PowerShell scripts were tested to check their output if it matches what is required to run the experiment and obtain accurate performance metrics values.

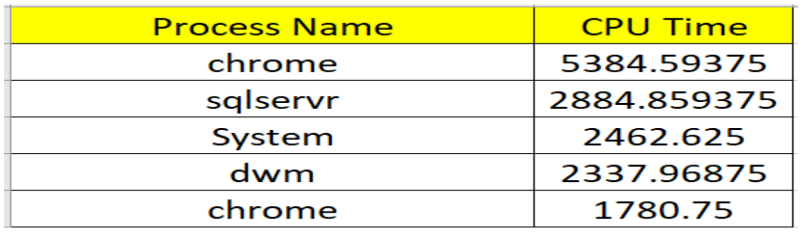
## 5.1 Top Processes

The first mission was choosing the significant performance metrics that have a high effect on the application and network performance. The next step was finding a method to obtain values of those performance metrics. A number of the performance metrics data were obtained using the built-in programs while others were obtained through developing PowerShell scripts. The main goal also is to automate this task.

The results obtained were not as expected in the beginning. For example, the CPU Time used by a single application in one minute was required to determine which applications consume the computer network resources. The challenge facing this task, the Windows Operating System gives by default the accumulated time since the process started. A PowerShell script was developed to perform this task calculates CPU Time used by the application in one minute. The output was obtained as expected and required for the experiment success.

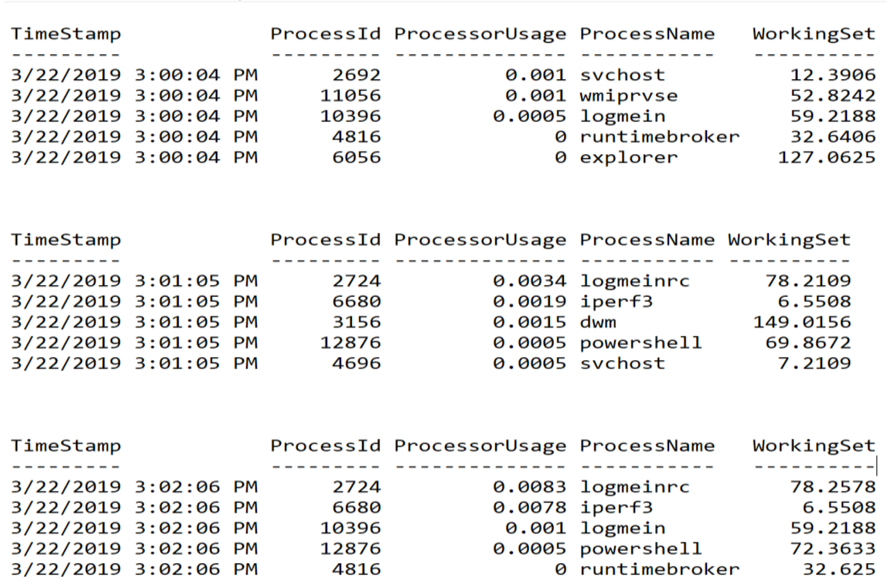
The two tables below show the difference in the result while trying to extract CPU Time used by a single application in one minute:

*Table 6: incorrect calculation for CPU Time Usage*



| Process Name | CPU Time |
|---|---|
| chrome | 5384.59375 |
| sqlservr | 2884.859375 |
| System | 2462.625 |
| dwm | 2337.96875 |
| chrome | 1780.75 |

*Table 7: Correction calculation for CPU Time usage*



```
TimeStamp              ProcessId ProcessorUsage ProcessName   WorkingSet
---------              --------- -------------- -----------   ----------
3/22/2019 3:00:04 PM        2692          0.001 svchost          12.3906
3/22/2019 3:00:04 PM       11056          0.001 wmiprvse         52.8242
3/22/2019 3:00:04 PM       10396         0.0005 logmein          59.2188
3/22/2019 3:00:04 PM        4816              0 runtimebroker    32.6406
3/22/2019 3:00:04 PM        6056              0 explorer        127.0625


TimeStamp              ProcessId ProcessorUsage ProcessName WorkingSet
---------              --------- -------------- ----------- ----------
3/22/2019 3:01:05 PM        2724         0.0034 logmeinrc      78.2109
3/22/2019 3:01:05 PM        6680         0.0019 iperf3          6.5508
3/22/2019 3:01:05 PM        3156         0.0015 dwm           149.0156
3/22/2019 3:01:05 PM       12876         0.0005 powershell     69.8672
3/22/2019 3:01:05 PM        4696         0.0005 svchost         7.2109


TimeStamp              ProcessId ProcessorUsage ProcessName   WorkingSet
---------              --------- -------------- -----------   ----------
3/22/2019 3:02:06 PM        2724         0.0083 logmeinrc        78.2578
3/22/2019 3:02:06 PM        6680         0.0078 iperf3            6.5508
3/22/2019 3:02:06 PM       10396          0.001 logmein          59.2188
3/22/2019 3:02:06 PM       12876         0.0005 powershell       72.3633
3/22/2019 3:02:06 PM        4816              0 runtimebroker    32.625
```

The delay is an essential metric to characterize the network performance, it provides an indication on the congestion of the network due to traffic utilized by application communicating between client and server. The usual command used in most of operating systems is ping command. The goal is to schedule sending a single ICMP ping packet every minute for a specific period of time and the result of the delay should be accompanied by a time stamp of ping initiation.

The first approach is to use the ping command, but it was ineffective in this experiment due to lack of customization in output. Another approach was using a PowerShell script with a command called test-connection, this command was appropriate and satisfy the need of this experiment from the output and repetition. The Task Scheduler is used to run this script.

## 5.2 Statistics Analysis

The data collection phase resulted in creating a performance database using the output from multiple programs and scripts. The Analysis of this database resulted in an interesting finding. The analysis included using data analytics techniques as well as applying machine learning algorithms.

The database included five top processes who utilized the CPU Time in one minute. The first column represents the number one in the list of top processes. The column was analyzed to determine which applications are more frequent to appear in this column than others as well as compare against the total time each process utilized the CPU Time. Using the matplotlib library and describe a method to analyze the top process column.

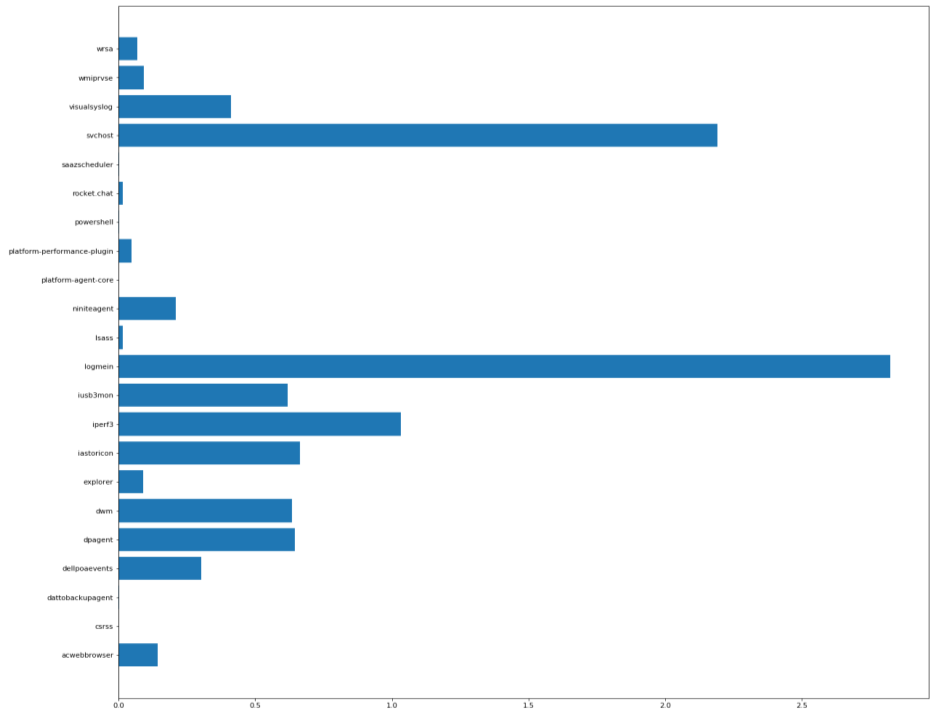


*Figure 27: Total CPU Time per Process*

Several applications appeared more than others but other applications who appeared less in the Top Process column consumed more CPU Time. The result is logical and proves that it is not about how frequent application usage CPU but for how long each application takes to complete a certain task. An example, referring to the graph in figure 23 above, the most frequent Top Processes is “logmein” while the second most frequent Top Processes is “IPerf3”. Examining the graph in figure 27, we found that the second Top Processes used the CPU Time is svhost process which contradicts that the second most frequent application appeared as the top process was “IPerf3”.

Filtering the database to include only the values belong to the most frequent application appeared as top process and analyze this part of the database. Using statistical methods to calculate the min, max, mean, standard deviation and quartile provides insights about the data distribution in each column. describe() method is used to provide this output.

*Table 8: describe method output*

| | mean | std | min | 25% | 50% | 75% | max | SD/mean |
|---|---|---|---|---|---|---|---|---|
| **H1DiskTime** | 0.6968 | 1.6632 | 0.0045 | 0.0323 | 0.0634 | 0.5982 | 15.4442 | 2.386911596 |
| **H1PacketsSent** | 1209.8453 | 1907.2108 | 1.2332 | 2.3332 | 36.9648 | 2296.6207 | 4817.5659 | 1.576408819 |
| **H1PacketsRecv** | 1163.8365 | 1834.906 | 1.8493 | 2.9665 | 49.6131 | 1822.2873 | 4619.0421 | 1.576601181 |
| **H1ProcessorTime** | 1.1159 | 0.7487 | 0.1303 | 0.9023 | 1.0226 | 1.1804 | 8.9249 | 0.670938256 |
| **H1BytesSent** | 1294659.1 | 1829841 | 122.32 | 5039.789 | 138766.58 | 2880897.7 | 6042295.7 | 1.413376683 |
| **H1BytesRecv** | 1406656.8 | 2336037.8 | 167.4 | 282.9439 | 57981.627 | 1856004.9 | 19384944 | 1.660702015 |
| **H1CPUP1** | 0.0038 | 0.0021 | 0.0005 | 0.002 | 0.0034 | 0.0049 | 0.0107 | 0.552631579 |
| **H1CPUP2** | 0.0008 | 0.0008 | 0 | 0.0005 | 0.0005 | 0.001 | 0.0078 | 1 |
| **H1CPUP3** | 0.0004 | 0.0006 | 0 | 0 | 0.0005 | 0.0005 | 0.0068 | 1.5 |
| **H1CPUP4** | 0.0003 | 0.0005 | 0 | 0 | 0 | 0.0005 | 0.0058 | 1.666666667 |
| **H1CPUP5** | 0.0001 | 0.0004 | 0 | 0 | 0 | 0 | 0.0058 | 4 |
| **H1Delay** | 34.0239 | 10.7934 | 28 | 30 | 31 | 33 | 166 | 0.317229947 |
| **H1BW** | 33.3257 | 6.4725 | 8.9 | 33 | 35.5 | 37.9 | 38.4 | 0.194219476 |

The coefficient of variation (CV) is calculated by dividing the standard deviation over the mean value. If the value is higher than 1 this means high standard deviation and data points are tend not to be too close to each other. This is a measure for the spreading in the data points of performance metrics. The performance metrics with a coefficient of variation larger than 1 refer to having substantial changes through the data collection period. This allows the understanding of the nature of the performance metrics and in the future improve the network and application performance.

Each process consumes a certain amount of resources from CPU Time to how much delay the network experience due to data exchanged between client and server. The following code developed to combine the resource's consumption by each process.

```
Client.groupby('H1P1')['H1CPUP1','H1Delay','H1BW'].sum()
```

The table shows the output for each process accompanied by the total CPU time, Bandwidth and delays the network experienced:

*Table 9: Resource Consumption summation*

| H1P1 | H1CPUP1 | H1Delay | H1BW |
|---|---|---|---|
| **acwebbrowser** | 0.144 | 798 | 534 |
| **csrss** | 0.0005 | 39 | 12.9 |
| **dattobackupagent** | 0.0029 | 68 | 10.5 |
| **dellpoaevents** | 0.3036 | 1156 | 746.24 |
| **dpagent** | 0.6462 | 2739 | 1789.33 |
| **dwm** | 0.6356 | 3279 | 5142.13 |
| **explorer** | 0.09 | 633 | 395.6 |
| **iastoricon** | 0.6639 | 2454 | 1567.4 |
| **iperf3** | 1.0323 | 7867 | 6377.7 |
| **iusb3mon** | 0.6186 | 2444 | 1657.17 |
| **logmein** | 2.8228 | 11482 | 8493.31 |
| **lsass** | 0.0159 | 209 | 156.9 |
| **niniteagent** | 0.2102 | 90 | 61.4 |
| **platform-agent-core** | 0.001 | 60 | 58.3 |

| H1P1 | H1CPUP1 | H1Delay | H1BW |
|---|---|---|---|
| **platform-performance-plugin** | 0.0468 | 86 | 62.2 |
| **powershell** | 0.002 | 243 | 90.9 |
| **rocket.chat** | 0.0156 | 86 | 60.8 |
| **saazscheduler** | 0.0034 | 78 | 15.1 |
| **svchost** | 2.1914 | 1840 | 1048.26 |
| **visualsyslog** | 0.4127 | 1438 | 978 |
| **wmiprvse** | 0.093 | 455 | 242.3 |
| **wrsa** | 0.0699 | 305 | 213.8 |

The correlation coefficient provides insights if there is a mutual relationship or association between quantities. In this research work, it is used to find if there are a cause and effect relationship between performance metrics and measure the strength as well. The relationship can be either positive or negative correlation and ranging between +1 and -1. It used to predict one value from another present value.

Utilizing Python libraries and methods to calculate the correlation coefficient between the performance metrics. There are several types of correlation coefficient that can be calculated for the performance metrics. The below table shows the Pearson correlation coefficient between several performance metrics:

*Table 10: Pearson Correlation Coefficient*

| | BytesRecv | BytesSent | PacketsRecv | PacketsSent | DiskTime | ProcessorTime |
|---|---|---|---|---|---|---|
| BytesRecv | 1 | 0.490388 | 0.665255 | 0.550588 | 0.225197 | 0.290407 |
| BytesSent | 0.490388 | 1 | 0.926307 | 0.941955 | -0.096438 | 0.073245 |
| PacketsRecv | 0.665255 | 0.926307 | 1 | 0.986419 | -0.056017 | 0.116562 |
| PacketsSent | 0.550588 | 0.941955 | 0.986419 | 1 | -0.097931 | 0.077764 |
| DiskTime | 0.225197 | -0.096438 | -0.056017 | -0.097931 | 1 | 0.637152 |
| ProcessorTime | 0.290407 | 0.073245 | 0.116562 | 0.077764 | 0.637152 | 1 |

The Pearson correlation coefficient was used to calculate the correlation, but the results showed it was not the best suitable coefficient type. Because it calculates a linear association between continuous variables. The second correlation coefficient used is the Spearman correlation coefficient, it is more appropriate for continuous and discrete data. The table below shows the Spearman correlation coefficient for performance metrics:

*Table 11: Spearman Correlation Coefficient*

| | H1DiskTime | H1PacketsSent | H1PacketsRecv | H1ProcessorTime | H1BytesSent | H1BytesRecv | H1CPUP1 | H1Delay | H1BW | H1TransferRate |
|---|---|---|---|---|---|---|---|---|---|---|
| **H1DiskTime** | 1 | -0.0945 | -0.1498 | 0.2201 | -0.0925 | -0.1264 | -0.0613 | 0.1219 | -0.1159 | -0.1152 |
| **H1PacketsSent** | -0.0945 | 1 | 0.9039 | 0.5941 | 0.991 | 0.9061 | 0.4324 | -0.4963 | 0.4989 | 0.4971 |
| **H1PacketsRecv** | -0.1498 | 0.9039 | 1 | 0.6045 | 0.8852 | 0.8792 | 0.453 | -0.4905 | 0.4738 | 0.4689 |
| **H1ProcessorTime** | 0.2201 | 0.5941 | 0.6045 | 1 | 0.5868 | 0.5373 | 0.5459 | -0.282 | 0.331 | 0.3333 |
| **H1BytesSent** | -0.0925 | 0.991 | 0.8852 | 0.5868 | 1 | 0.8705 | 0.4355 | -0.4772 | 0.5023 | 0.501 |
| **H1BytesRecv** | -0.1264 | 0.9061 | 0.8792 | 0.5373 | 0.8705 | 1 | 0.4028 | -0.5273 | 0.4975 | 0.4974 |
| **H1CPUP1** | -0.0613 | 0.4324 | 0.453 | 0.5459 | 0.4355 | 0.4028 | 1 | -0.3558 | 0.4084 | 0.4039 |
| **H1Delay** | 0.1219 | -0.4963 | -0.4905 | -0.282 | -0.4772 | -0.5273 | -0.3558 | 1 | -0.4179 | -0.4137 |
| **H1BW** | -0.1159 | 0.4989 | 0.4738 | 0.331 | 0.5023 | 0.4975 | 0.4084 | -0.4179 | 1 | 0.9978 |
| **H1TransferRate** | -0.1152 | 0.4971 | 0.4689 | 0.3333 | 0.501 | 0.4974 | 0.4039 | -0.4137 | 0.9978 | 1 |

The Spearman correlation coefficient shows stronger association and relationship between performance metrics because it looks at the monotonic relationship which is the variables changes together but not with the constant rate. The third correlation coefficient utilized in this research is the Kendall correlation coefficient. It is more suitable for a discrete variable.

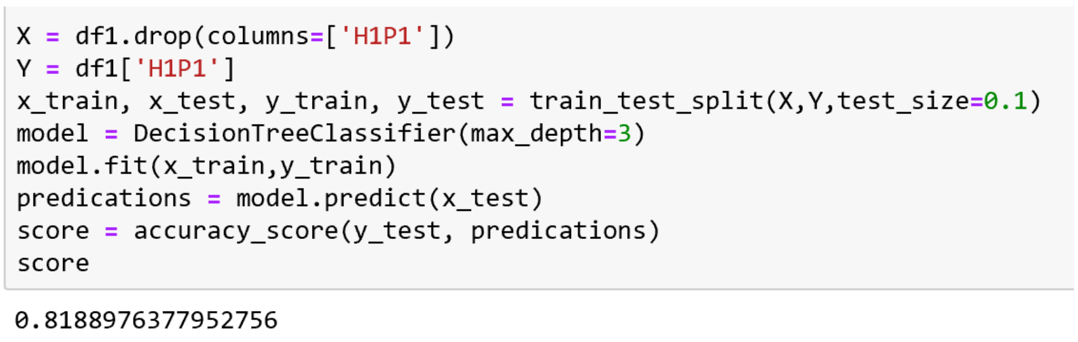
*Table 12:Kendall correlation coefficient*

| | H1DiskTime | H1PacketsSent | H1PacketsRecv | H1ProcessorTime | H1BytesSent | H1BytesRecv | H1CPUP1 | H1Delay | H1BW | H1TransferRate |
|---|---|---|---|---|---|---|---|---|---|---|
| **H1DiskTime** | 1.0000 | -0.2402 | -0.2076 | 0.4187 | -0.1915 | -0.2041 | 0.3613 | 0.2623 | -0.1292 | -0.1179 |
| **H1PacketsSent** | -0.2402 | 1.0000 | 0.6667 | -0.2406 | 0.8688 | 0.5422 | -0.1742 | -0.3472 | 0.2858 | 0.2931 |
| **H1PacketsRecv** | -0.2076 | 0.6667 | 1.0000 | -0.2278 | 0.5411 | 0.7769 | -0.1735 | -0.4033 | 0.2833 | 0.2870 |
| **H1ProcessorTime** | 0.4187 | -0.2406 | -0.2278 | 1.0000 | -0.1840 | -0.1829 | 0.5124 | 0.2377 | -0.0608 | -0.0763 |
| **H1BytesSent** | -0.1915 | 0.8688 | 0.5411 | -0.1840 | 1.0000 | 0.4142 | -0.1284 | -0.2793 | 0.2759 | 0.2828 |
| **H1BytesRecv** | -0.2041 | 0.5422 | 0.7769 | -0.1829 | 0.4142 | 1.0000 | -0.1685 | -0.3929 | 0.3220 | 0.3128 |
| **H1CPUP1** | 0.3613 | -0.1742 | -0.1735 | 0.5124 | -0.1284 | -0.1685 | 1.0000 | 0.2335 | -0.0586 | -0.0530 |
| **H1Delay** | 0.2623 | -0.3472 | -0.4033 | 0.2377 | -0.2793 | -0.3929 | 0.2335 | 1.0000 | -0.2706 | -0.2816 |
| **H1BW** | -0.1292 | 0.2858 | 0.2833 | -0.0608 | 0.2759 | 0.3220 | -0.0586 | -0.2706 | 1.0000 | 0.9628 |
| **H1TransferRate** | -0.1179 | 0.2931 | 0.2870 | -0.0763 | 0.2828 | 0.3128 | -0.0530 | -0.2816 | 0.9628 | |

The Kendall correlation coefficient showed less association than the Spearman coefficient. This provides information about the nature of the performance metrics used in this research.

## 5.3 Decision Trees and Regression

The decision tree is basically a binary tree flowchart used to split the data into groups, extremely helpful in classification and regression. The split is made according to certain conditions or question aiming at categorizes the data with similar attributes to highlight hidden information exist in data. In this research, decision trees are utilized to map and classify the performance metrics to predictors and target. The decision tree algorithm used is a classification and regression decision tree. Gini index value ranges from 0 (all target values belong to one label) to a maximum value of 1(all target values are distributed equally). From Navigating the decision tree, the applications that properly consume the resources in computer networks can be predicted. The learning model accuracy was measured and provided accuracy between 70-80 percent. The below code shows the code and output for measuring the accuracy of the learning model.



```
X = df1.drop(columns=['H1P1'])
Y = df1['H1P1']
x_train, x_test, y_train, y_test = train_test_split(X,Y,test_size=0.1)
model = DecisionTreeClassifier(max_depth=3)
model.fit(x_train,y_train)
predications = model.predict(x_test)
score = accuracy_score(y_test, predications)
score
```

```
0.8188976377952756
```

*Figure 28: Measuring Decision Learning Model Accuracy*

Dataset split into train and test, the highest accuracy achieved in splitting the dataset to 90% train and 10% test. The results could be improved more with a larger dataset. Also, the maximum depth used in the decision tree is three, to avoid creating a more complex tree.

The decision tree is taking the decision of splitting data based on rules, the figure 29 shows a decision tree included the following performance metrics (H1BytesSent, H1BytesRecv, H1DiskTime, H1ProcessorTime, H1PacketsSent, H1PacketsRecv, H1P1).

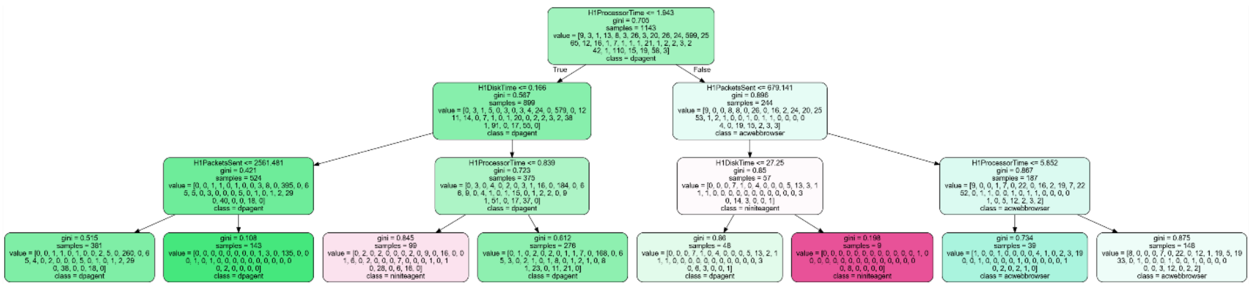
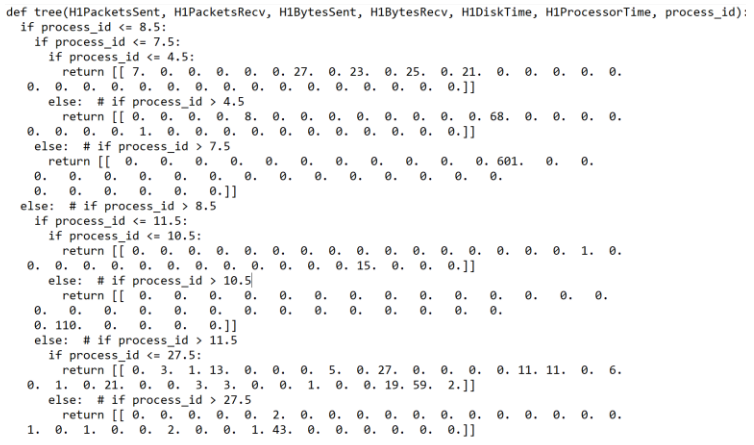

H1ProcessorTime <= 1.943 gini = 0.705 samples = 1143 value = [9, 3, 1, 13, 8, 3, 26, 3, 20, 26, 24, 599, 25 65, 12, 16, 1, 7, 1, 1, 1, 21, 1, 2, 2, 3, 2 42, 1, 110, 15, 19, 58, 3] class = dpagent
True
False
H1DiskTime <= 0.166 gini = 0.587 samples = 899 value = [0, 3, 1, 5, 0, 3, 0, 3, 4, 24, 0, 579, 0, 12 11, 14, 0, 7, 1, 0, 1, 20, 0, 2, 2, 3, 2, 38 1, 91, 0, 17, 55, 0] class = dpagent
H1PacketsSent <= 679.141 gini = 0.896 samples = 244 value = [9, 0, 0, 8, 8, 0, 26, 0, 16, 2, 24, 20, 25 53, 1, 2, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0 4, 0, 19, 15, 2, 3, 3] class = acwebbrowser
H1PacketsSent <= 2561.481 gini = 0.421 samples = 524 value = [0, 0, 1, 1, 0, 1, 0, 0, 3, 8, 0, 395, 0, 6 5, 5, 0, 3, 0, 0, 0, 5, 0, 1, 0, 1, 2, 29 0, 40, 0, 0, 18, 0] class = dpagent
H1ProcessorTime <= 0.839 gini = 0.723 samples = 375 value = [0, 3, 0, 4, 0, 2, 0, 3, 1, 16, 0, 184, 0, 6 6, 9, 0, 4, 1, 0, 1, 15, 0, 1, 2, 2, 0, 9 1, 51, 0, 17, 37, 0] class = dpagent
H1DiskTime <= 27.25 gini = 0.85 samples = 57 value = [0, 0, 0, 7, 1, 0, 4, 0, 0, 0, 5, 13, 3, 1 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3 0, 14, 3, 0, 0, 1] class = niniteagent
H1ProcessorTime <= 5.852 gini = 0.867 samples = 187 value = [9, 0, 0, 1, 7, 0, 22, 0, 16, 2, 19, 7, 22 52, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0 1, 0, 5, 12, 2, 3, 2] class = acwebbrowser
gini = 0.515 samples = 381 value = [0, 0, 1, 1, 0, 1, 0, 0, 2, 5, 0, 260, 0, 6 5, 4, 0, 2, 0, 0, 0, 5, 0, 1, 0, 1, 2, 29 0, 38, 0, 0, 18, 0] class = dpagent
gini = 0.108 samples = 143 value = [0, 0, 0, 0, 0, 0, 0, 0, 1, 3, 0, 135, 0, 0 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0 0, 2, 0, 0, 0, 0] class = dpagent
gini = 0.845 samples = 99 value = [0, 2, 0, 2, 0, 0, 0, 2, 0, 9, 0, 16, 0, 0 1, 6, 0, 2, 0, 0, 0, 7, 0, 0, 0, 1, 0, 1 0, 28, 0, 6, 16, 0] class = niniteagent
gini = 0.612 samples = 276 value = [0, 1, 0, 2, 0, 2, 0, 1, 1, 7, 0, 168, 0, 6 5, 3, 0, 2, 1, 0, 1, 8, 0, 1, 2, 1, 0, 8 1, 23, 0, 11, 21, 0] class = dpagent
gini = 0.86 samples = 48 value = [0, 0, 0, 7, 1, 0, 4, 0, 0, 0, 5, 13, 2, 1 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3 0, 6, 3, 0, 0, 1] class = dpagent
gini = 0.198 samples = 9 value = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0 0, 8, 0, 0, 0, 0] class = niniteagent
gini = 0.734 samples = 39 value = [1, 0, 0, 1, 0, 0, 0, 0, 4, 1, 0, 2, 3, 19 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1 0, 2, 0, 2, 1, 0] class = acwebbrowser
gini = 0.875 samples = 148 value = [8, 0, 0, 0, 7, 0, 22, 0, 12, 1, 19, 5, 19 33, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0 0, 0, 3, 12, 0, 2, 2] class = acwebbrowser

*Figure 29: Decision Tree with seven Performance metrics*

The below figure shows the rules created to generate the decision tree above:



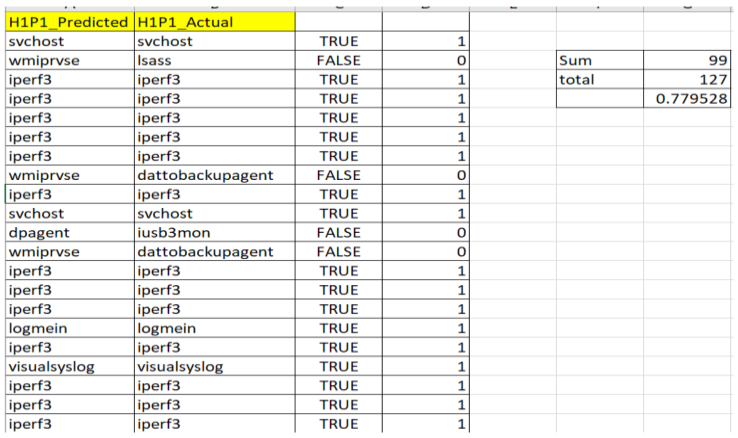
```
def tree(H1PacketsSent, H1PacketsRecv, H1BytesSent, H1BytesRecv, H1DiskTime, H1ProcessorTime, process_id):
  if process_id <= 8.5:
    if process_id <= 7.5:
      if process_id <= 4.5:
        return [[ 7.   0.   0.   0.   0.   0. 27.   0. 23.   0. 25.   0. 21.   0.   0.   0.   0.   0.
   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]]
      else:  # if process_id > 4.5
        return [[ 0.   0.   0.   0.   8.   0.   0.   0.   0.   0.   0.   0.   0. 68.   0.   0.   0.   0.
   0.   0.   0.   0.   1.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.]]
    else:  # if process_id > 7.5
      return [[   0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0. 601.    0.    0.
    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
    0.    0.    0.    0.    0.    0.]]
  else:  # if process_id > 8.5
    if process_id <= 11.5:
      if process_id <= 10.5:
        return [[ 0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   1.   0.
   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0. 15.   0.   0.   0.]]
      else:  # if process_id > 10.5
        return [[   0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.    0.
    0. 110.    0.    0.    0.    0.]]
    else:  # if process_id > 11.5
      if process_id <= 27.5:
        return [[ 0.   3.   1. 13.   0.   0.   0.   5.   0. 27.   0.   0.   0.   0. 11. 11.   0.   6.
   0.   1.   0. 21.   0.   0.   3.   3.   0.   0.   1.   0.   0. 19. 59.   2.]]
      else:  # if process_id > 27.5
        return [[ 0.   0.   0.   0.   0.   2.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
   1.   0.   1.   0.   0.   2.   0.   0.   1. 43.   0.   0.   0.   0.   0.   0.]]
```

*Figure 30: Decision Tree Rules*

Previously, the decision tree learning model was measured and it was expected to provide accuracy from 70-80 %. The test dataset used as input to the learning model after using the train dataset. A code was developed to compare between predicted output and the actual output of test data and dump it into CSV file.

```
from pandas import DataFrame
predict = model.predict(x_test)
output = DataFrame({'H1P1_Predicted': predict,'H1P1_Actual': y_test})
output.to_csv('Network_Output.csv', index = False)
```

The output can be seen below, using a simple calculation to calculate the accuracy of the output in percentage:



| H1P1_Predicted | H1P1_Actual | | | | | |
|---|---|---|---|---|---|---|
| svchost | svchost | TRUE | 1 | | | |
| wmiprvse | lsass | FALSE | 0 | | Sum | 99 |
| iperf3 | iperf3 | TRUE | 1 | | total | 127 |
| iperf3 | iperf3 | TRUE | 1 | | | 0.779528 |
| iperf3 | iperf3 | TRUE | 1 | | | |
| iperf3 | iperf3 | TRUE | 1 | | | |
| iperf3 | iperf3 | TRUE | 1 | | | |
| wmiprvse | dattobackupagent | FALSE | 0 | | | |
| iperf3 | iperf3 | TRUE | 1 | | | |
| svchost | svchost | TRUE | 1 | | | |
| dpagent | iusb3mon | FALSE | 0 | | | |
| wmiprvse | dattobackupagent | FALSE | 0 | | | |
| iperf3 | iperf3 | TRUE | 1 | | | |
| iperf3 | iperf3 | TRUE | 1 | | | |
| iperf3 | iperf3 | TRUE | 1 | | | |
| logmein | logmein | TRUE | 1 | | | |
| iperf3 | iperf3 | TRUE | 1 | | | |
| visualsyslog | visualsyslog | TRUE | 1 | | | |
| iperf3 | iperf3 | TRUE | 1 | | | |
| iperf3 | iperf3 | TRUE | 1 | | | |
| iperf3 | iperf3 | TRUE | 1 | | | |

*Figure 31: Decision Tree Accuracy Calculation*

The calculation shows the accuracy is 77.95% that falls within the range of predicted value.

# 6. Discussion

The usage of machine learning and data analytics in computer networking has huge potentials. In the thesis work, specific machine learning algorithm and data analytics techniques were explored to find the benefits of applying those techniques and algorithm on a real-life problem. In this case, the goal was to predict the application and network performance.

The work started by navigating and analyze a database constructed from collecting performance metrics. The performance metrics were extracted from a real computer network. The work started by using data analytics techniques. The statistical analysis put some lights on hidden information unseen to the ordinary person. The nature of performance metrics become easier to understand through the statistics and numbers.

Calculating the correlation coefficient has shown the cause and effect relationship between performance metrics which is shown in high correlation discovered between processor time and disk time among other correlation and association were discovered. As a result, the interpretation of applications behavior is not impossible even in the complex computer networks. The complexity of the network is not a concern or a factor anymore because the important is to collect accurate metrics and data then analyze it.

The regression and classification of decision tree helped in predicting the future values of resource consumption in the computer network. The CPU time consumed by application as well as the amount of traffic send or received by edge nodes can be predicted with enough accuracy. The measured accuracy was between 70-80 percent for the decision tree. The accuracy of the results depends on how big the database is.

In this study, a private company network was used to collect the performance metrics from its clients and servers, in addition to, the communication links between branches. The data analytics results were interesting. We were able to find the applications that consume most of the resources at the company network. For example, two processes named logmein and svchost consumed most of the CPU time.

We were able to calculate the proper correlation coefficient to discover the association between performance metrics. The performance is affected by the amount of data exchanged between client/server. A positive correlation was discovered between the number of packets sent/recv per second and processor time. Consequently, the processor time increase as a response to the increment number of packets exchanged between the clients/server.

The calculation of the standard deviation, mean and quartile explained the data point samples taken from each performance metrics. The processor time had a coefficient of variation less than one (0.67) indicating that the difference between processor time data point is minimal. On the other hand, the coefficient of variation disk time was bigger than one (2.386) informing us that the data point collected have a long margin.

We were able to create a decision tree using the metrics collected from the company network and the target was predicting the application that consumes CPU time most of the time. The model was trained using dataset then, using a test sample compromised from 127 samples. The success rate reached 77.9% for this experiment.

The findings can help any IT professionals to analyze the application and network performance and obtain information with acceptable accuracy on the application consumes the resources and predict the future values of performance metrics.

## 6.1 Limitation

The experiment was performed on a standalone server. The goal was to isolate any failure which can result in interrupting the business in case of using a real-life computer network. This extended the time frame of establishing a working environment. The multiple simultaneous actions and the synchronization between the task are essential factors in the success of the experiment. The experiment requires having a huge database to obtain a good result. Consequently, the data collection phase took a long time to prepare a dataset big to provide reliable results.

## 6.2 Recommendation

The thesis work proved that there is a potential to take this work further and recommendation to apply other data analytics techniques and machine learning algorithms. The work requires more care when creating the database from performance metrics because of the sensitivity of alignment values.

# 7. Summary and Conclusion

The application and network performance are a major concern for the network professional. The thesis addressed several concerns related to determining the applications that may misuse the resources in the computer networks. The suggested techniques to address and solve this problem relied on using high trended technologies machine learning and data analytics.

Both techniques have the reputation of solving many problems in a variety of field. The work resulted in understanding more about the network and application performance metrics. In addition, the nature of the metrics if they are categorical or continuous or discrete. Moreover, the cause and effect relationship between performance metrics by calculating the correlation coefficient. Furthermore, the decision trees helped in the prediction of application performance through analyzing and classifying the performance metrics.

The performance metrics that are responsible for affecting or consuming the resources in the computer network can be predicted with satisfactory accuracy ranging between 70-80%. The decision tree graphs were able to show the classification of performance metrics and the changes in values would affect the target performance metric.

The application of this work will cut cost and provide substantial benefits to IT professionals and mid-large companies to optimize the network and application performance. Nowadays, as the networks become more complex and applications requires much more resources. The traditional approaches to deal with network and application performance is not enough. The thesis work could be extended to provide more benefits through using other algorithms that provide better results.

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