Server Anomaly Detection System

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Introduction

- Reliability, Availability, Serviceability (RAS) is a promptly growing area in Server industry.
- Server and its subsystem components may behave unexpectedly or operate in a suboptimal environment, called anomaly conditions.
- This study attempts to raising RAS level by early detection and diagnosis of anomaly conditions that Server may have exposed before major fault.
- **Project Goal**: Create a Server Anomaly Detection System (SADS). SADS detects anomaly conditions of Server subsystem at component level and analyzes Server status, providing diagnosis to improve Server RAS level.

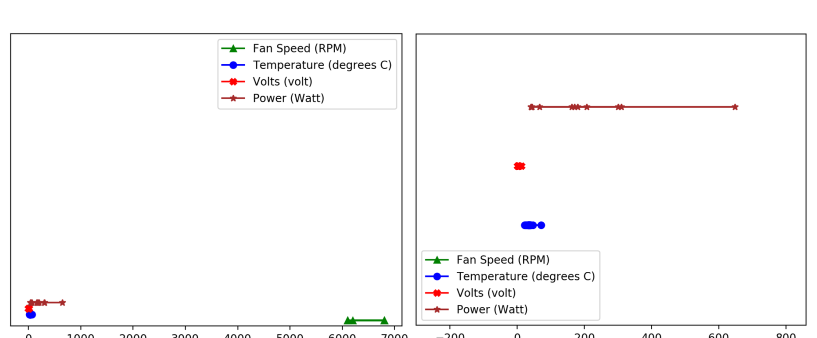
Data Acquisition

- One NVIDIA DGX-1 Server with eight GPUs
- Six datasets of Server telemetry (5 train, 1 test)
  - 10,000 samples per dataset (sampling in 2 second)
  - 72 features per sample

Sample Number Index	Time-stamp	Number of Discrete Sensor	Number of Analog Sensor	Fan	Tempe-rature	Power	Volts	Airflow
integer	seconds	33	72	8	33	16	14	1

Dataset Index and File Name	
DS-0	data-57-00-23_05-11-2019.csv
DS-1	data-04-29-10_06-11-2019.csv
DS-2	data-57-06-17_06-11-2019.csv
DS-3	data-27-18-09_07-11-2019.csv
DS-4	data-15-22-01_08-11-2019.csv
DS-5	data-50-44-15_11-11-2019.csv

I. Data Processing & Clustering

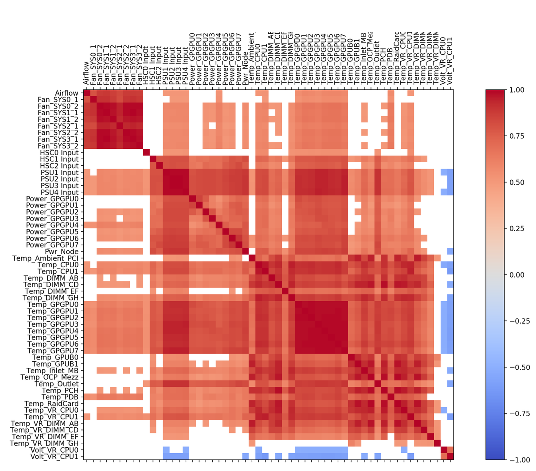


Telemetry Clustering

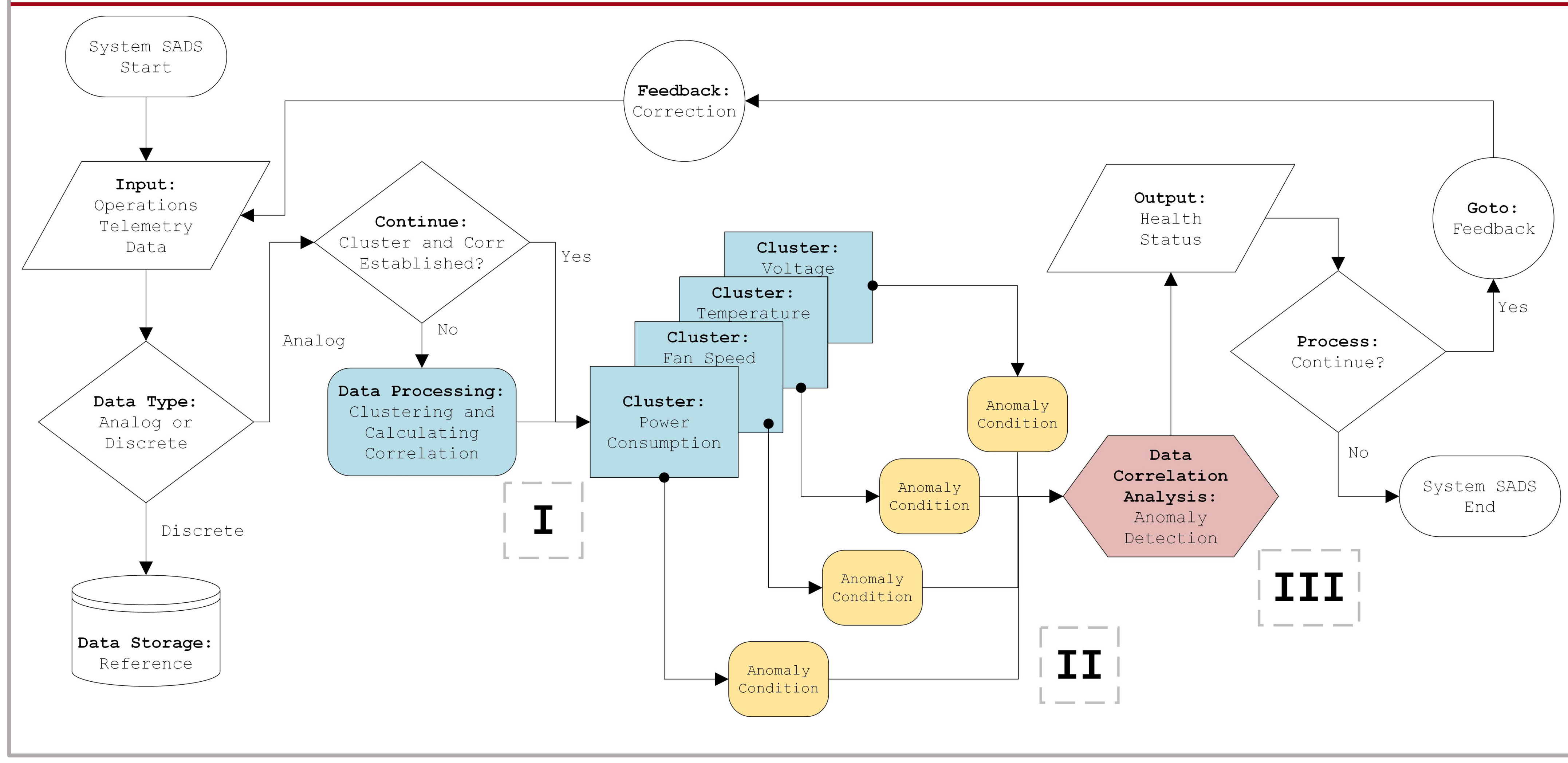
- K-means (K = 4)
- Select init centroids

Telemetry Correlations

- $Corr(Fan_{SYS},\ TempCPU) > 0.6$
- $Corr(Temp_{GPU},\ PowerPSU) > 0.6$
- $Corr(Temp_{GPU},\ VoltCPU) < -0.6$



SADS System Diagram & Implementation Approach



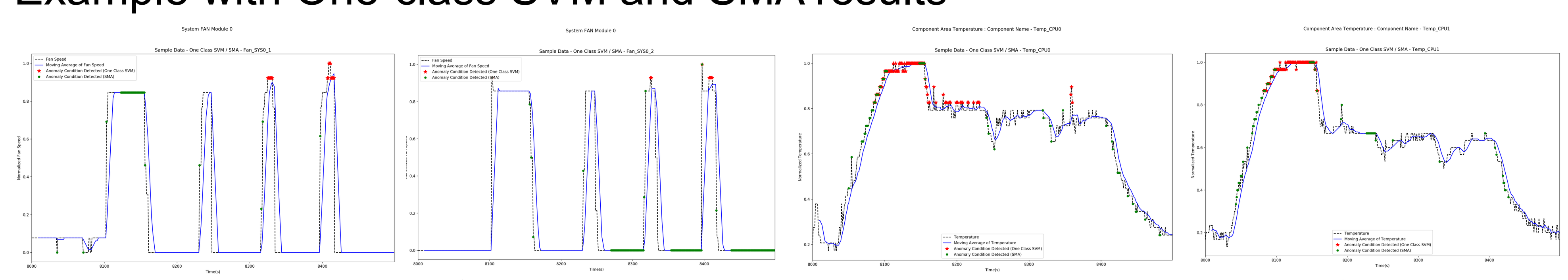
I. Data Processing & Clustering
- Divide telemetry data
  - ✓ K-means
  - ✓ Select initial centroids

II. Detecting Anomaly Conditions
- Two comparable methods
  - ✓ One-class SVM
  - ✓ Simple Moving Average (SMA)

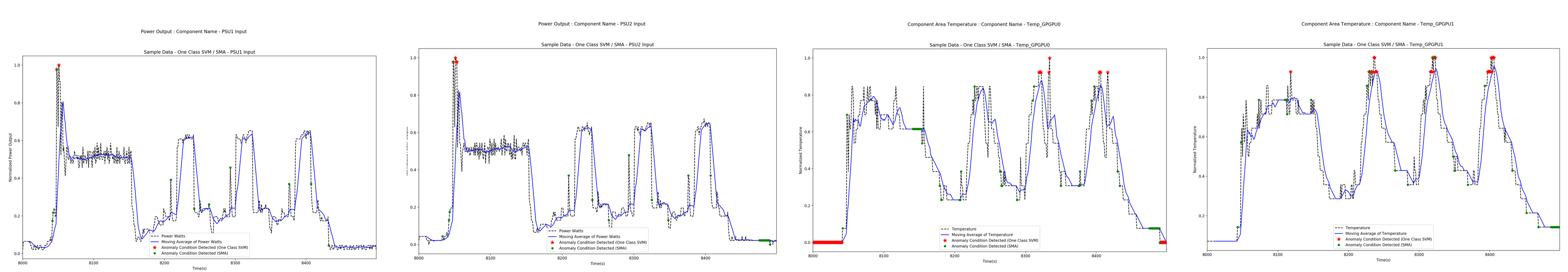
III. System Health Analysis
- Correlation matrix
  - ✓ Cluster-local Anomaly
  - ✓ System-global Anomaly

II. Detecting Anomaly Conditions

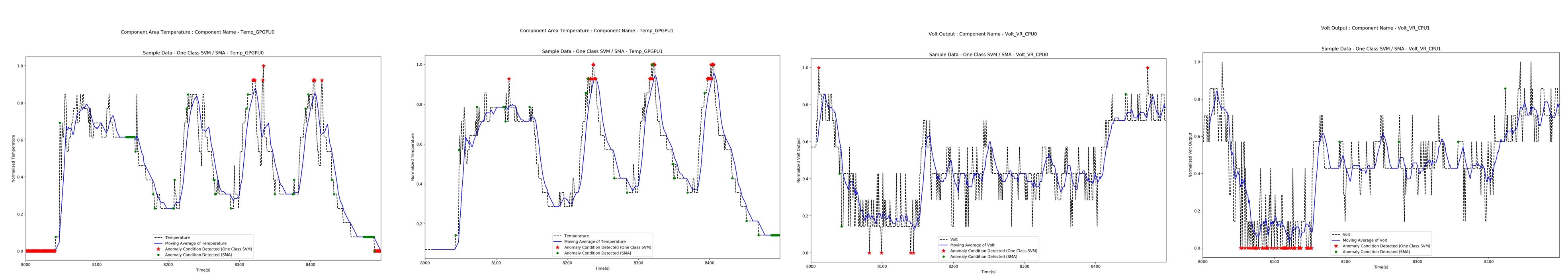
- Example with One-class SVM and SMA results



Example 1. – $(Fan_{SYS01},\ Fan_{SYS02},\ Temperature_{CPU0},\ Temperature_{CPU1})$



Example 2. – $(Power_{PSU1},\ Power_{PSU2},\ Temperature_{GPU0},\ Temperature_{GPU1})$



Example 3. – $(Temperature_{GPU0},\ Temperature_{GPU1},\ Volt_{CPU0},\ Volt_{CPU1})$

- Anomaly Detected with / without corresponding to highly-correlated feature
  - Example 1 - SVM detected Anomaly for $Fan_{SYS01,\ SYS02}$ at [(8320, 8400), (8320, 8400)]
  - Example 1 - SVM and SMA detected Anomaly for $Temp_{CPU0}$ at [(8360)]
  - Example 2 - SVM detected Anomaly for $Power_{PSU1,\ PSU2}$ at [(8035, 8040), (8035, 8040)]
  - Example 2 - SVM and SMA detected anomaly for $Temp_{GPU1}$ at [(8130), (8240)]
  - Example 3 - SVM detected Anomaly for $Volt_{CPU0,\ CPU1}$ at [(8010, [8070, 8150], 8470), ([8050, 8160])]
  - Example 3 - SVM and SMA detected Anomaly for $Temp_{GPU1}$ at [(8130), (8240)]

III. System Health

- Correlation matrix $|Corr| \geq 0.6$

	Fan_{SYS01}	Fan_{SYS02}	Pwr_{PSU1}	Pwr_{PSU2}	$Volt_{CPU0}$	$Volt_{CPU1}$	$Temp_{CPU0}$	$Temp_{CPU1}$	$Temp_{GPU1}$	$Temp_{GPU2}$
Fan_{SYS01}	1	0.9	0.6	0.6			0.6	0.6	0.6	0.6
Fan_{SYS02}	0.9	1	0.6	0.6			0.6	0.6	0.6	0.6
Pwr_{PSU1}	0.6	0.6	1	0.9	-0.85	-0.85	0.7	0.7	0.85	0.85
Pwr_{PSU2}	0.6	0.6	0.9	1	-0.85	-0.85	0.7	0.7	0.85	0.85
$Volt_{CPU0}$			-0.85	-0.85	1	0.9	-0.9	-0.9	-0.8	-0.8
$Volt_{CPU1}$			-0.85	-0.85	0.9	1	-0.9	-0.9	-0.8	-0.8
$Temp_{CPU0}$	0.6	0.6	0.7	0.7	-0.9	-0.9	1	0.9	0.85	0.85
$Temp_{CPU1}$	0.6	0.6	0.7	0.7	-0.9	-0.9	0.9	1	0.85	0.85
$Temp_{GPU1}$	0.6	0.6	0.85	0.85	-0.8	-0.8	0.85	0.85	1	0.9
$Temp_{GPU2}$	0.6	0.6	0.85	0.85	-0.8	-0.8	0.85	0.85	0.9	1

- Inside Cluster with high local correlations
  - Determine Cluster-local Anomaly
    - ✓ $Temp_{CPU0}$ at [(8360)], $Temp_{GPU1}$ at [(8130), (8240)], $Volt_{CPU0}$ at [(8010), (8470)]
- Outside Cluster with level of correlations
  - Determine System-global Anomaly
    - ✓ $Volt_{CPU0}$ at [(8010), (8470)]

Conclusion

- This study presents detection of Anomaly conditions at levels of Server component, Cluster-local, and System-global.
- We achieved unsupervised machine learning by adapting K-means and one-class SVM methodology with selected initializations.
- Delta between one-class SVM and SMA is significant. In some scenarios, SMA is more practical. Though, SVM does learning.
- Hyper-parameters are crucial to precision.