Telemetry Anomaly Detection System using Machine Learning to Streamline Mission Operations

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Abstract— Spacecraft housekeeping telemetry is monitored at flight control centers by the operations engineers using tools that can perform limit checking or simple trend analysis. Recent developments in machine learning techniques for anomaly detection enables the implementation of more sophisticated systems that aim to augment current state-of-the-art mission tools to provide valuable decision support for the spacecraft operators, assisting in anomaly detection and potentially saving console time for the engineers. We will show some results of the implementation of an anomaly detection tool for the NASA Mars Science Laboratory mission.

Keywords—anomaly detection, machine learning

I. INTRODUCTION

Evaluating the health state of current flight and ground systems using traditional parameter limit checking, model-based, or rule-based methods is becoming more difficult as the systems complexity grows. Data-driven monitoring techniques are complementary to the current methods and have been developed to analyze system operations data to automatically characterize normal system behavior. System health can be monitored by comparing real time operating data with these nominal characterizations, providing detection of anomalous data signatures indicative of system faults, failures, or precursors of significant failures. While rule based methods can only flag known anomalies, these data driven methods go a step further in the direction of detecting never seen before anomalies.

The deployment of machine learning tools to the mission operations environment can assist spacecraft operators by detecting anomalies (known or never seen before) in the telemetry received from the spacecraft. While the techniques are applicable to any space mission, as a proof of concept, we have applied the methods to MSL mission data.

II. MARS SCIENCE LABORATORY USE CASE

Part of NASA's Mars Science Laboratory mission (MSL), Curiosity [1] is the largest and most capable rover ever sent to Mars. It launched November 26, 2011 and landed on Mars at 10:32 p.m. PDT on Aug. 5, 2012 (1:32 a.m. EDT on Aug. 6, 2012).

Curiosity set out to answer the question: Did Mars ever have the right environmental conditions to support small life forms called microbes? Early in its mission, Curiosity's scientific tools found chemical and mineral evidence of past habitable environments on Mars. It continues to explore the rock record from a time when Mars could have been home to microbial life.

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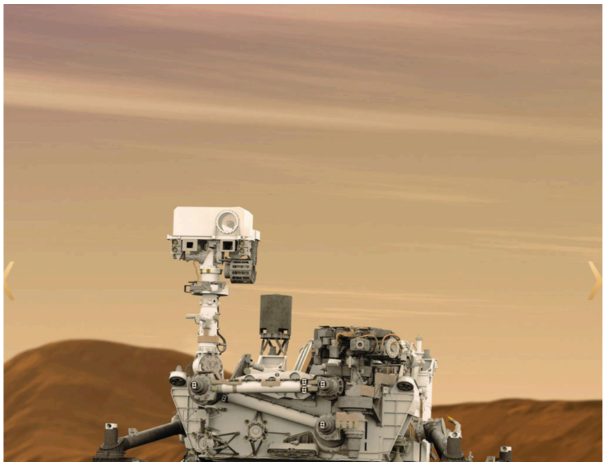


Fig. 1. Curiosity rover on the surface of Mars

It is critical to keep Curiosity running flawlessly to maximize science return.

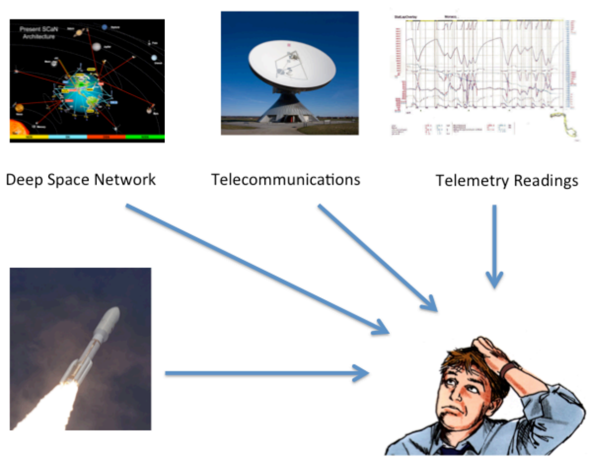


Fig. 2. Anomaly detection by the spacecraft operator- systems involved.

The current methods to monitor telemetry are mainly based on parameter limit checking. We propose to complement the current systems by developing an anomaly detector based on known machine learning techniques.

Models trained on historical data learn to recognize both nominal and off-nominal behaviors, including never-before-seen anomalies reaching the goal of reducing the time required to evaluate system health and identify and resolve the root cause of anomalies.

Efficient real-time diagnosis allows problems to be solved quickly, especially in time-critical situations where delays in evaluation increase the risk of losing the spacecraft.
Accelerating anomaly identification saves operator time avoiding the need to process specific data channels unless the system flags data anomalies. This system is the first step towards reducing operator console time.

III. TELEMETRY ANOMALY DETECTOR SYSTEM

We have studied historical data and past anomalies and it is not uncommon that a whole week of planning could be severely disrupted due to anomaly investigations, which impacted science activities, and ultimately science data return. A tool that could provide early warning of the anomalies would benefit MSL and future Mars missions.

We started the process by architecting a prototype set of building blocks shown in the following figure:

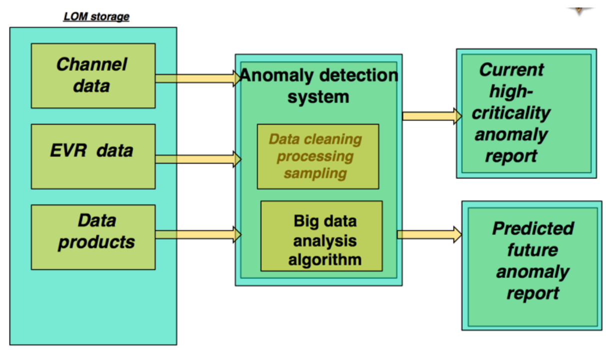


Fig. 3. Prototype set of building blocks.

Channel data, Event Record (EVR) and data products could be analyzed and run through the anomaly detection system to generate a daily high-criticality anomaly report as a first step and eventually update the system to be able to generate a predicted future anomaly report. The work covered in this paper describes the first part of performing anomaly detection of individual telemetry channels (only channel data) providing the operator with the current high-criticality anomaly report. Future work would include augmenting the system to also provide a predicted anomaly report.

We queried data from the NASA Advanced Multi-Mission Operations System (AMMOS) Mission Data Processing and Control System (AMPCS):

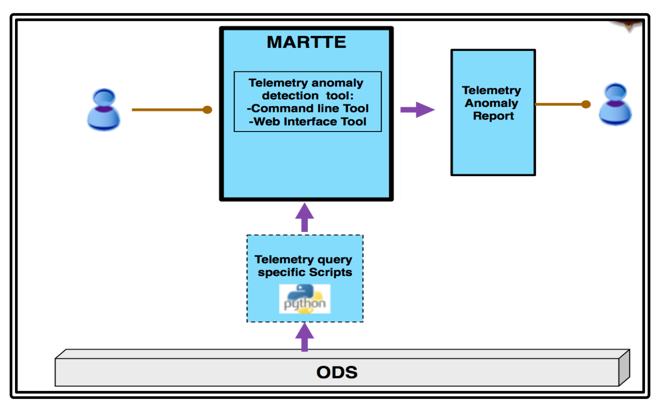


Fig. 4. MARTTE High Level Architecture Diagram.

The first step was to use the prototype to ingest only channel data. We had to become familiar with the MSL telemetry in order to perform data exploration and preparation to develop an anomaly detector that would meet the requirements needed by the MSL project. The first subsystem to analyze was telecommunications which provides communications functions to the spacecraft for uplink (Earth to spacecraft link for commands and load data) and downlink (spacecraft to Earth for science and/or engineering telemetry data). There are two separate subsystems:

1. X-Band for direct to/from earth (DTE/DFE)
2. UHF subsystem for data relay to/from Mars orbiting assets

The anomaly detector ingests the housekeeping telecom telemetry from MSL that covers X-Band, UHF-Band and Monitor Deep Space Network (DSN) channels. Data are queried and read in raw format. For each Martian sol, the channels under study are analyzed to detect anomalies.

Each channel is a time series that includes the channel value in Engineering Units (EU) or Data Number (DN), and the time associated with the channel value.

Finding the periodic patterns contained in time series data, requires some analyses. A time series *Xt* usually has three components:

1. Trend component *Tt*
2. Seasonal component *St*
3. Residual component *et*

A method to perform a seasonal decomposition of *Xt* is by determining *Tt* using a Loess regression (linear regression plus k-nearest-neighbors), and then calculating the seasonal component *St* and residuals *et* from the differences *Xt – Tt* [2]. The residual component of the time series is extracted from the input time series and then statistical learning techniques are applied [3].

We developed an operational tool named **MARTTE**: **M**SL **A**nomaly Detecto**R** **T**elemetry **T**ool Suit**E** that is capable of ingesting the MSL telemetry files as inputs and display to mission operations staff a list of high interest anomalous telemetry readings. The tool suite delivered to MSL OPS includes a command line tool and a web interface tool. MARTTE ingests the MSL telemetry (time series data) and is capable of generating the following ouputs for the operations engineer:

-A histogram mapping Engineering Units (EU) to frequency over the specified sol (598) for a specified channel (TEL-5211)

-A histogram mapping EU to frequency over the specified sol (598) AND over the course of all previous sols (over the past 100 sols) for channel (TEL-5211)

-Summary statistics (mean, median, standard deviation) for channel (TEL-5211) for specified sols (498-598)

-A plot of time vs. EU, with a blue circle highlighting the points the algorithm found to be anomalous.

-A black and white point plot of time vs. unit (EU)

-A table listing all of the timestamps and channel values that the algorithm predicted to be anomalous

A. *Command Line Tool*

We will walk through an example of how the command line tool works to generate image files (histogram of many sols, expected anomalies) and to generate a CSV with the expected anomalies.

First, we run the script to find anomalies regarding a specific sol number on the selected channels of interest. We will have our anomaly detection system look at the telemetry data pertaining to that specific channel over the last 99 sols to give it a better, more reliable sense of normal behavior. For this run, we will look at EU data, but there is the option to use DN (Data Number).

```
-rw-r--r-- 1 mmmsltel msltel  36563 Dec 20 19:07 histogram_many_sols-501_to_600_TEL-5211_eu.png
-rw-r--r-- 1 mmmsltel msltel 140336 Dec 20 19:08 anomalies-identified-501_to_600_TEL-5211_eu.png
-rw-r--r-- 1 mmmsltel msltel   2240 Dec 20 19:08 anoms_table-501_to_600-TEL-5211_0.001_0.05.csv
```

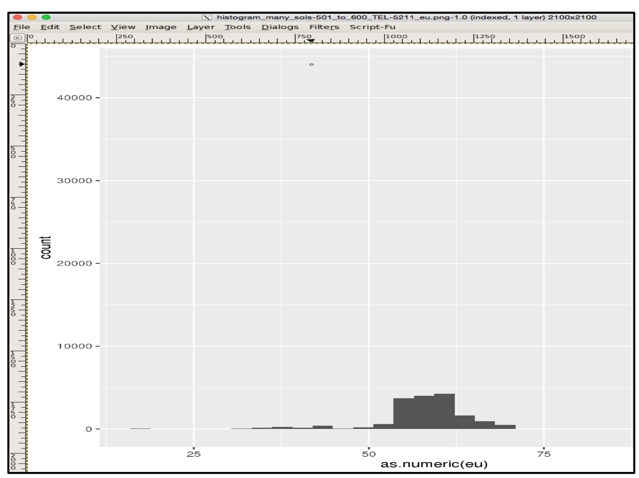
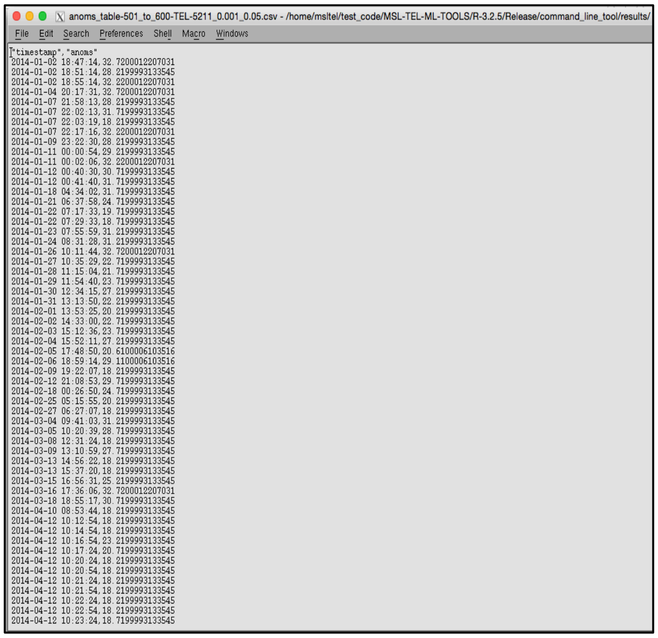


Fig. 5. Histogram generated with MARTTE




```
"timestamp","anoms"
2014-01-02 18:47:14,32.7200012207031
2014-01-02 18:51:14,28.2199993133545
2014-01-02 18:55:14,32.2200012207031
2014-01-04 20:17:31,32.7200012207031
2014-01-07 21:58:13,28.2199993133545
2014-01-07 22:02:13,31.7199993133545
2014-01-07 22:03:19,18.2199993133545
2014-01-07 22:17:16,32.2200012207031
2014-01-09 23:22:30,28.2199993133545
2014-01-11 00:00:54,29.2199993133545
2014-01-11 00:02:06,32.2200012207031
2014-01-12 00:40:30,30.7199993133545
2014-01-12 00:41:40,31.7199993133545
2014-01-18 04:34:02,31.7199993133545
2014-01-21 06:37:58,24.7199993133545
2014-01-22 07:17:33,19.7199993133545
2014-01-22 07:29:33,18.7199993133545
2014-01-23 07:55:59,31.2199993133545
2014-01-24 08:31:28,31.2199993133545
2014-01-26 10:11:44,32.7200012207031
2014-01-27 10:35:29,22.7199993133545
2014-01-28 11:15:04,21.7199993133545
2014-01-29 11:54:40,23.7199993133545
2014-01-30 12:34:15,27.2199993133545
2014-01-31 13:13:50,22.2199993133545
2014-02-01 13:53:25,20.2199993133545
2014-02-02 14:33:00,22.7199993133545
2014-02-03 15:12:36,23.7199993133545
2014-02-04 15:52:11,27.2199993133545
2014-02-05 17:48:50,20.6100006103516
2014-02-06 18:59:14,29.1100006103516
2014-02-09 19:22:07,18.2199993133545
2014-02-12 21:08:53,29.7199993133545
2014-02-18 00:26:50,24.7199993133545
2014-02-25 05:15:55,20.2199993133545
2014-02-27 06:27:07,18.2199993133545
2014-03-04 09:41:03,31.2199993133545
2014-03-05 10:20:39,28.7199993133545
2014-03-08 12:31:24,18.2199993133545
2014-03-09 13:10:59,27.7199993133545
2014-03-13 14:56:22,18.2199993133545
2014-03-13 15:37:20,18.2199993133545
2014-03-15 16:56:31,25.2199993133545
2014-03-16 17:36:06,32.7200012207031
2014-03-18 18:55:17,30.7199993133545
2014-04-10 08:53:44,18.2199993133545
2014-04-12 10:12:54,18.2199993133545
2014-04-12 10:14:54,18.2199993133545
2014-04-12 10:16:54,23.2199993133545
2014-04-12 10:17:24,20.7199993133545
2014-04-12 10:20:24,18.2199993133545
2014-04-12 10:20:54,18.2199993133545
2014-04-12 10:21:24,18.2199993133545
2014-04-12 10:21:54,18.2199993133545
2014-04-12 10:22:24,18.2199993133545
2014-04-12 10:22:54,18.2199993133545
2014-04-12 10:23:24,18.7199993133545
```

Fig. 6. Telemetry anomalies flagged by MARTTE

If the user wants to generate plots and csv files for multiple channels, it is also possible:

```
-rw-r--r-- 1 rmmsltel msltel  36563 Dec 20 19:44 histogram_many_sols-501_to_600_TEL-5211_eu.png
-rw-r--r-- 1 rmmsltel msltel 140336 Dec 20 19:45 anomalies-identified-501_to_600_TEL-5211_eu.png
-rw-r--r-- 1 rmmsltel msltel   2240 Dec 20 19:45 anoms_table-501_to_600-TEL-5211_0.001_0.05.csv
-rw-r--r-- 1 rmmsltel msltel  49331 Dec 20 19:46 histogram_many_sols-501_to_600_TEL-5210_eu.png
-rw-r--r-- 1 rmmsltel msltel 135623 Dec 20 19:47 anomalies-identified-501_to_600_TEL-5210_eu.png
-rw-r--r-- 1 rmmsltel msltel   1568 Dec 20 19:47 anoms_table-501_to_600-TEL-5210_0.001_0.05.csv
```

B. *Web Interface Tool*

The web interface tool provides the same functionality as the command line tool. The reason we also developed the command line tool was to be easily integrated with the rest of the MSL team tools.

When running the tool, we obtain the following GUI to interact with the user in order to provide the required inputs such as a the channel of interest, sol to analyze or data units as it is shown in Fig. 7. The flagged anomalies by the tool are shown in Fig. 8. They correspond with real anomalies reported by the MSL team. The tool generates a histogram and provides a list of the anomalies detected as shown in Fig. 9. Both anomalous Sols (596/598) were detected with MARTTE.

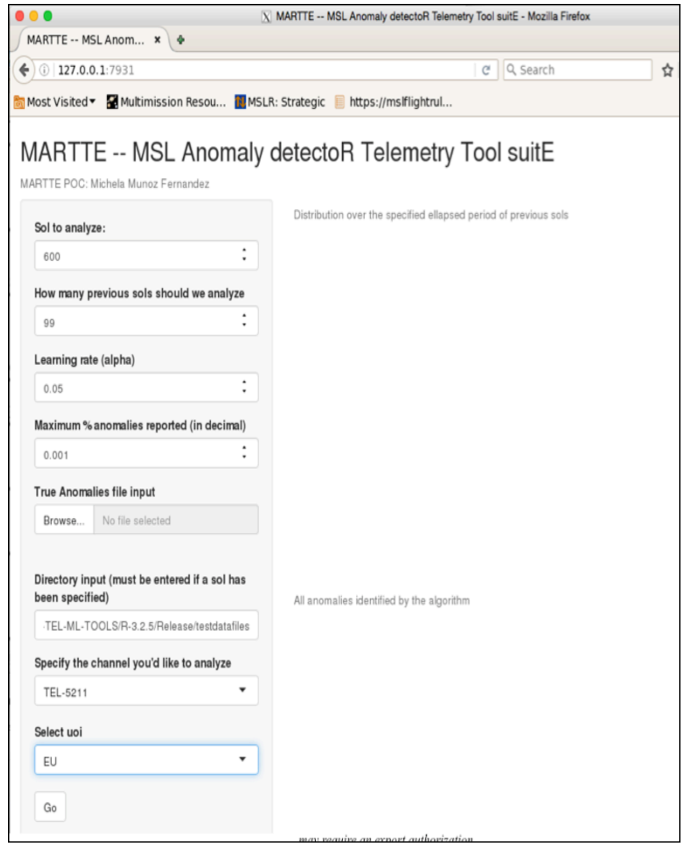


Fig. 7. MARTTE web interface tool display

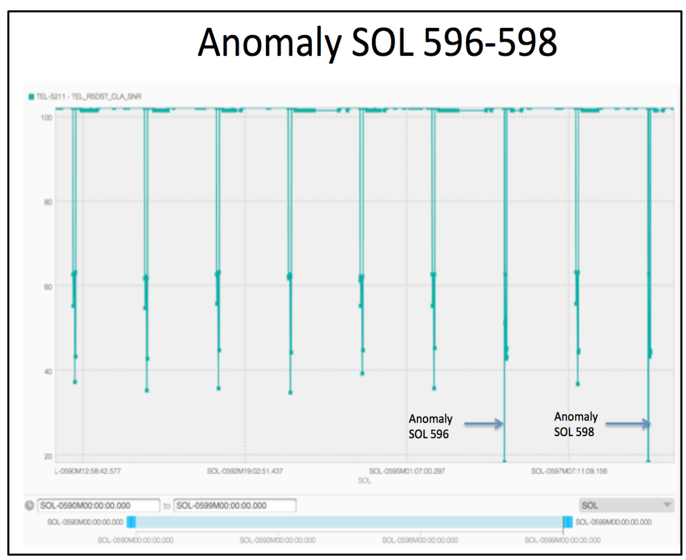
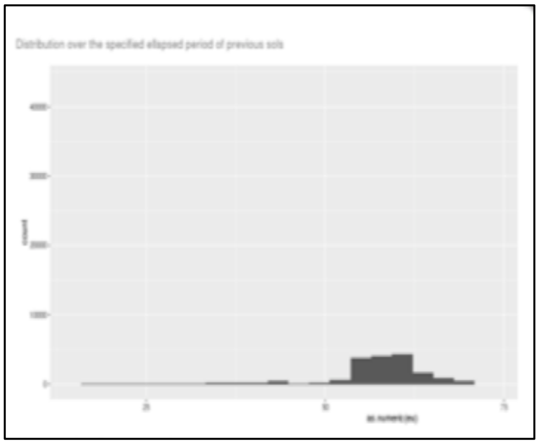


Fig. 8. Data sample of MSL telemetry to be analyzed where two anomalies were detected.



timestamp	anoms
2014-04-12 10:20:24	18.22
2014-04-12 10:20:54	18.22
2014-04-12 10:21:24	18.22
2014-04-12 10:21:54	18.22
2014-04-12 10:22:24	18.22
2014-04-12 10:22:54	18.22
2014-04-12 10:23:24	18.72
2014-04-12 10:23:54	18.22
2014-04-12 10:24:24	18.22
2014-04-13 10:53:58	18.22

Fig. 9. Anomalies flagged for a specific run of MARTTE

We worked very closely with the MSL ground data systems team to make our tools operational in the red ops venue. It was the first time they tested this type of tools so there was some learning involved at the beginning to make sure that we were covering all cases to make MARTTE fully operational. Tools have been run in real time during the telecom shifts and they operate nominally. It only takes about 10-20 minutes to run it helping save time for the telecom operator. It warns of any possible unexpected value. The operator could work remotely monitoring the tool output. It used to take approximately. After each downlink, it used to take the telecom operator almost 4 hours to analyze all the data and evaluate system health. With the new automated system where MARTTE is integrated in, each sol can be analyzed in barely an hour.

The MARTTE tool was tested in real ops for MSL and was run through historical data to see if it was able to detect known anomalies. Preliminary results indicate that for the initial channels tested, where we optimized the learning parameter of the algorithm (for that specific channel), MARTTE scores a false alarm rate of only 4%. MARTTE also detected unexpected system behavior that may have not been noticeable with the traditional tools.

Fig. 8 shows a sample of the telemetry data analyzed with MARTTE:

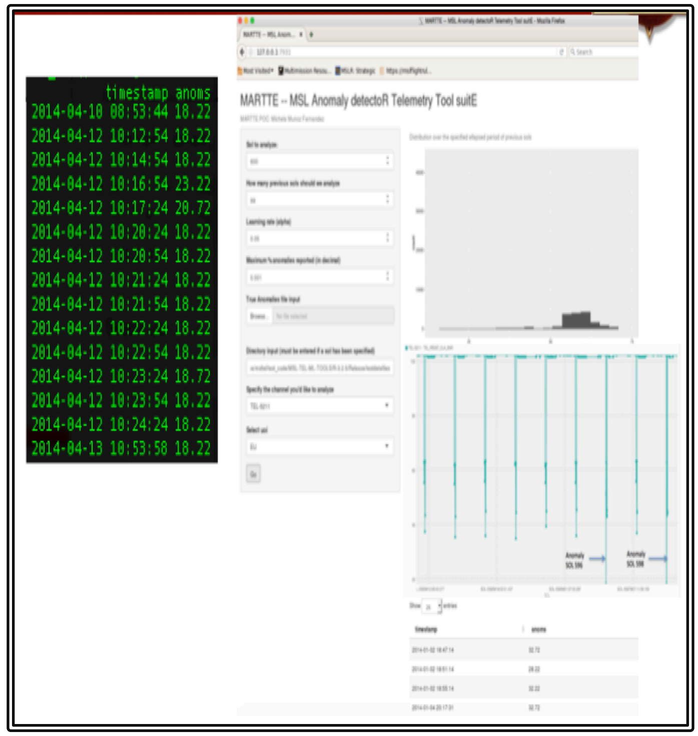


Fig. 10. MARTTE output including detected anomalies.

CONCLUSIONS

The MARTTE: MSL Anomaly DetectoR Telemetry Tool SuitE was prototyped, developed, tested and delivered fully operational to the MSL red OPS team with the capability of detecting the unexpected values in the MSL telemetry to reach the goal to assist the operations engineers monitoring the health status of the spacecraft. A major advantage over conventional anomaly detection methods is that this approach requires little *a priori* knowledge of the system.

Future plans would include developing the second step which would provide a predicted future anomaly report.

This work showcases the benefits of complementing the traditional systems with new tools incorporating recently developed machine learning techniques developed in recent years to assist operators in early detection of spacecraft anomalies.

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