National Aeronautics and
Space Administration

Jet Propulsion Laboratory
California Institute of Technology
Pasadena, California

Automated Data Accountability for Mars Science Lab

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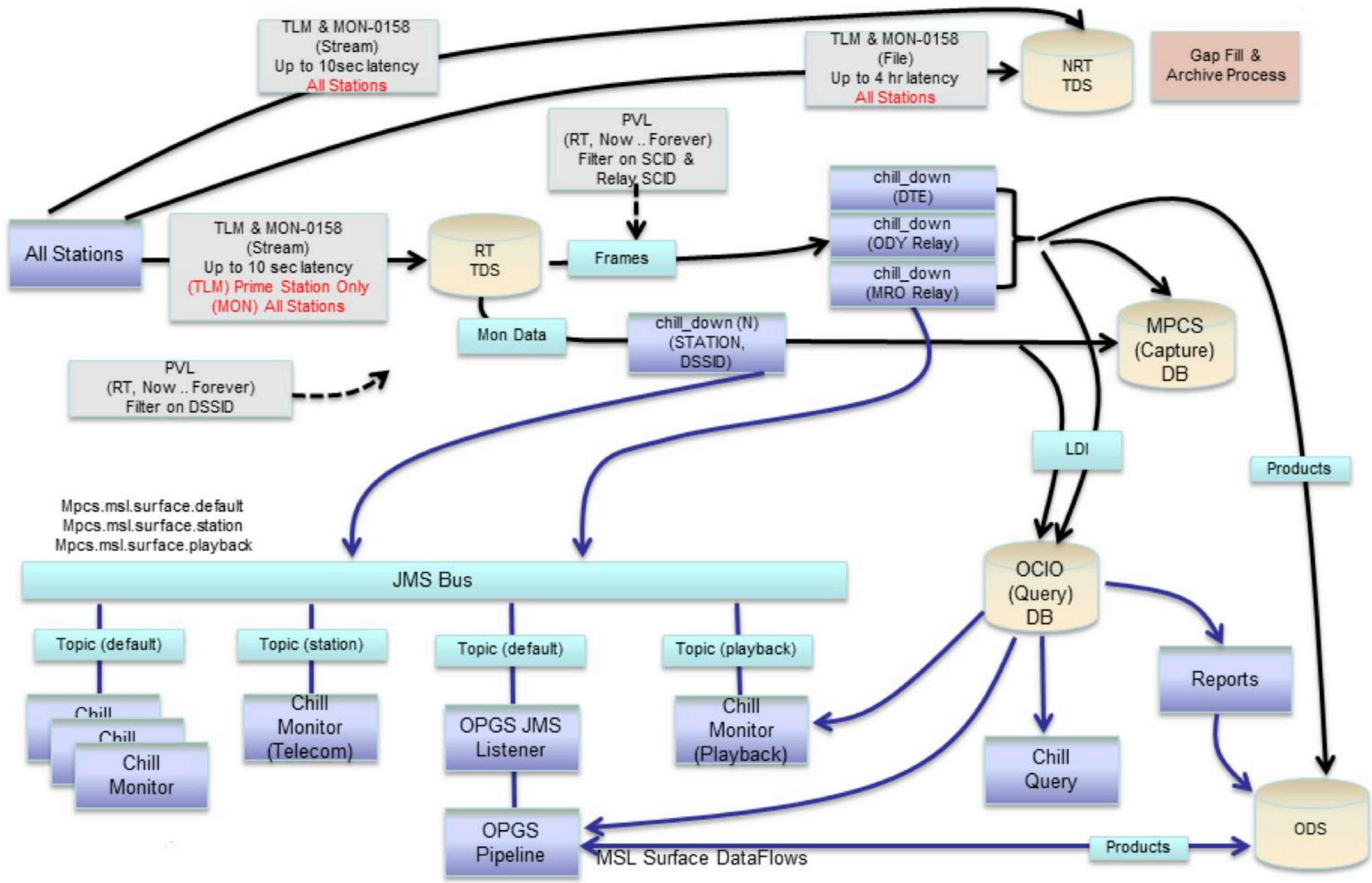
Overview of the MSL Ground Data System

- The MSL Ground Data System is complex



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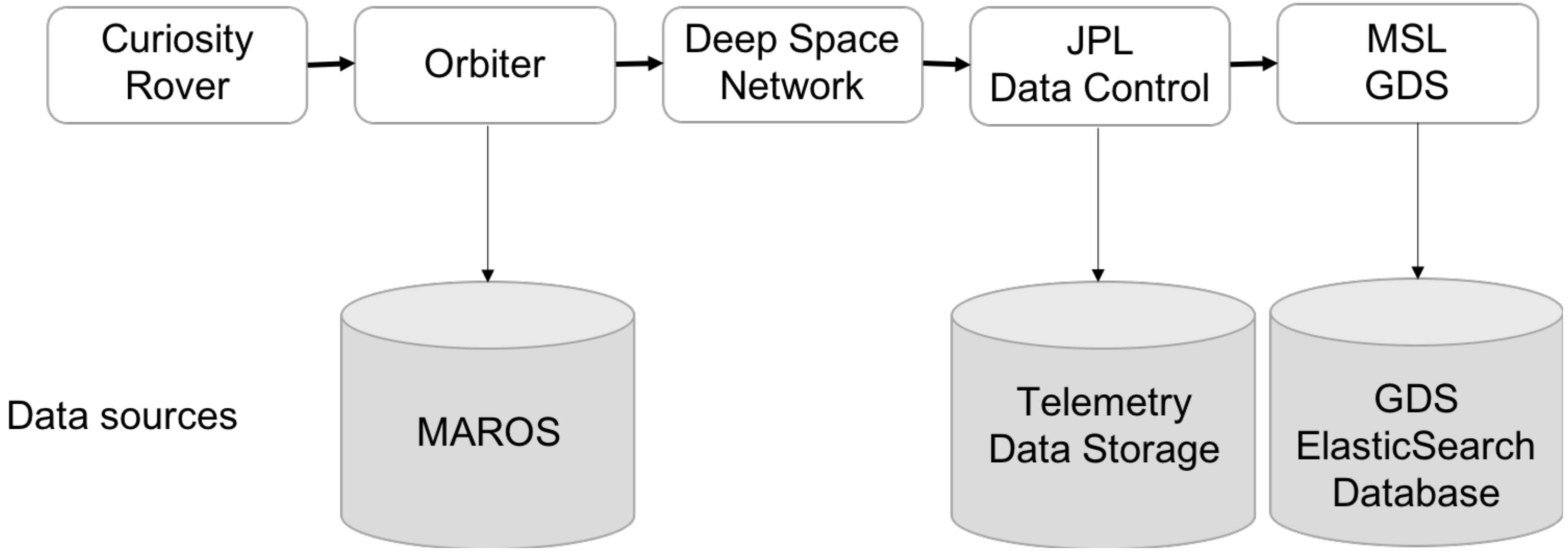
Overview of the MSL Downlink Process

- We simplified the problem and identified where data is available



Approach

- Data Collector gathers data from various APIs
- Signal Processor formats the data and computes features
- Machine Learning Algorithms train on historical data
  - Classify each downlink as complete or incomplete
  - Detect anomalies in real-time data

Dataset Description

- Examples of types of data available
  - Predicted Data Volume of the Downlink
  - Actual Data Volume at each step in Downlink Process
  - Predicted start and end time of the Downlink
  - Timestamp received at each step in Downlink Process
  - The orbiter used to transmit the data
  - Elevation of the orbiter
  - The DSN station that received the data
  - Number of in-sync frames
  - Number of out-of-sync frames

Automated Feature Analysis

- Three Different Methods
  - P-score
  - Variance
  - Random Forest
- Important Features
  - Differences in Data Volume
  - Difference between Actual and Predicted Start Time
  - Out-of-sync frames
- Non-important Features
  - Orbiter ID
  - Deep Space Station ID

Current Techniques

- GDSA Dashboard labels passes as complete or incomplete
  - No longer reliable in operations

Sol 2433					
34330	MRO_MSL_2019_161_04	Complete		401.112	344.419
34331	MRO_MSL_2019_162_01	Complete		357.719	403.643
34331	MRO_MSL_2019_162_01	Incomplete	Wrong ERT Times	357.809	403.643
44330	TGO_MSL_2019_162_01	Complete		236.015	58.931

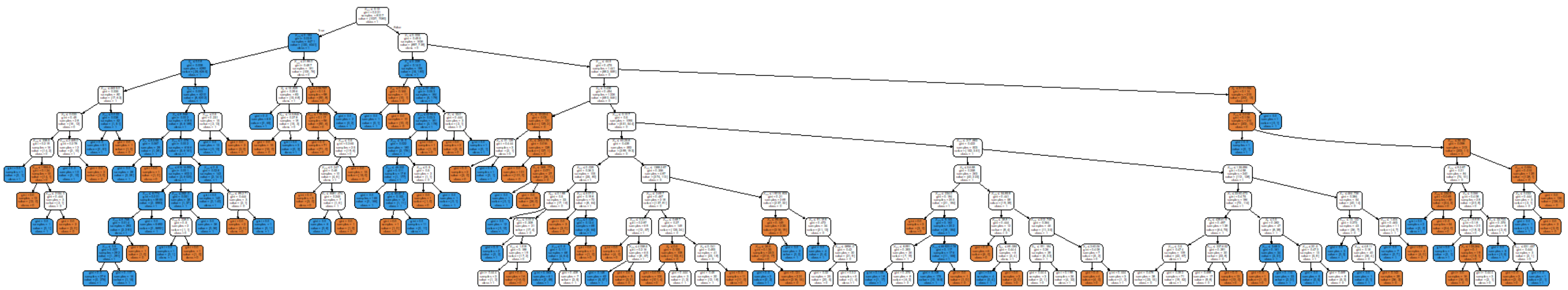
  - Overall Accuracy: 91.9%

	Precision	Recall	f1-score	Support
0	0.74	0.55	0.63	1141
1	0.94	0.97	0.95	7867
Avg / Total	0.91	0.92	0.91	9008

		Dashboard	
		0	1
Actual	0	625	516
Actual	1	218	7649

Results

- Random Forest Classifier
  - Image of one Decision Tree



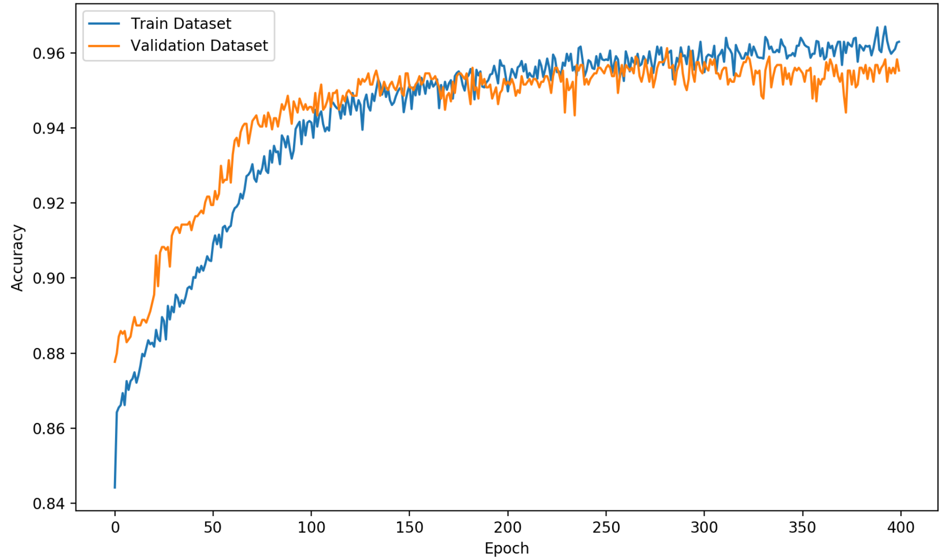
  - Overall Accuracy: 98.3%

	Precision	Recall	f1-score	Support
0	0.94	0.93	0.93	114
1	0.99	0.99	0.99	787
Avg / Total	0.98	0.98	0.98	901

		Decision Tree	
		0	1
Actual	0	106	8
	1	7	780

Results

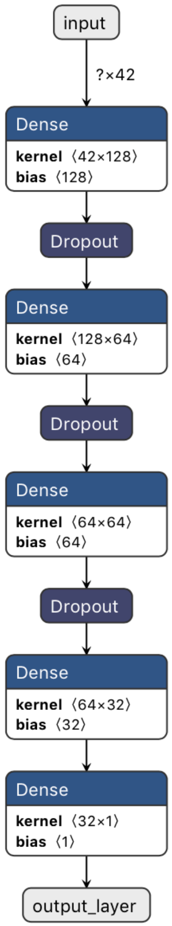
- Deep Neural Network
  - 97% training accuracy, 95.5% validation accuracy



  - Overall Accuracy: 95.1%

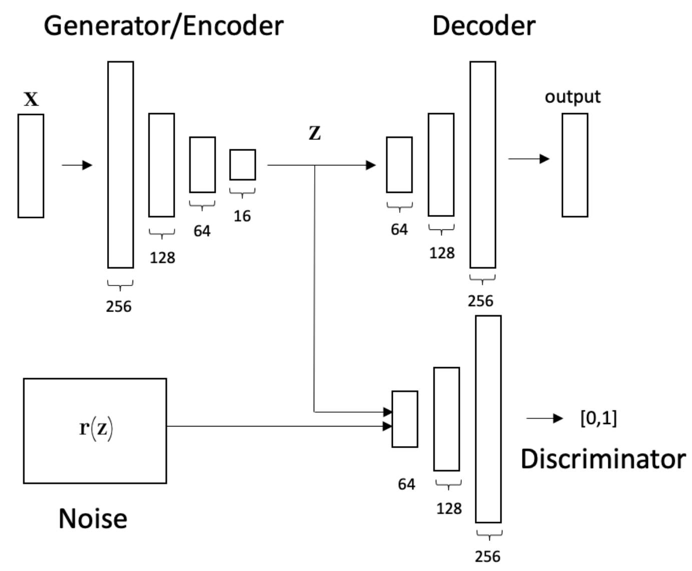
	Precision	Recall	f1-score	Support
0	0.84	0.77	0.80	176
1	0.97	0.98	0.97	1175
Avg / Total	0.98	0.98	0.98	1351

		Decision Tree	
		0	1
Actual	0	135	41
	1	25	1150



Results

- Anomaly Detection
  - Adversarial Autoencoder
    - Imposed Gaussian Distribution on the latent space



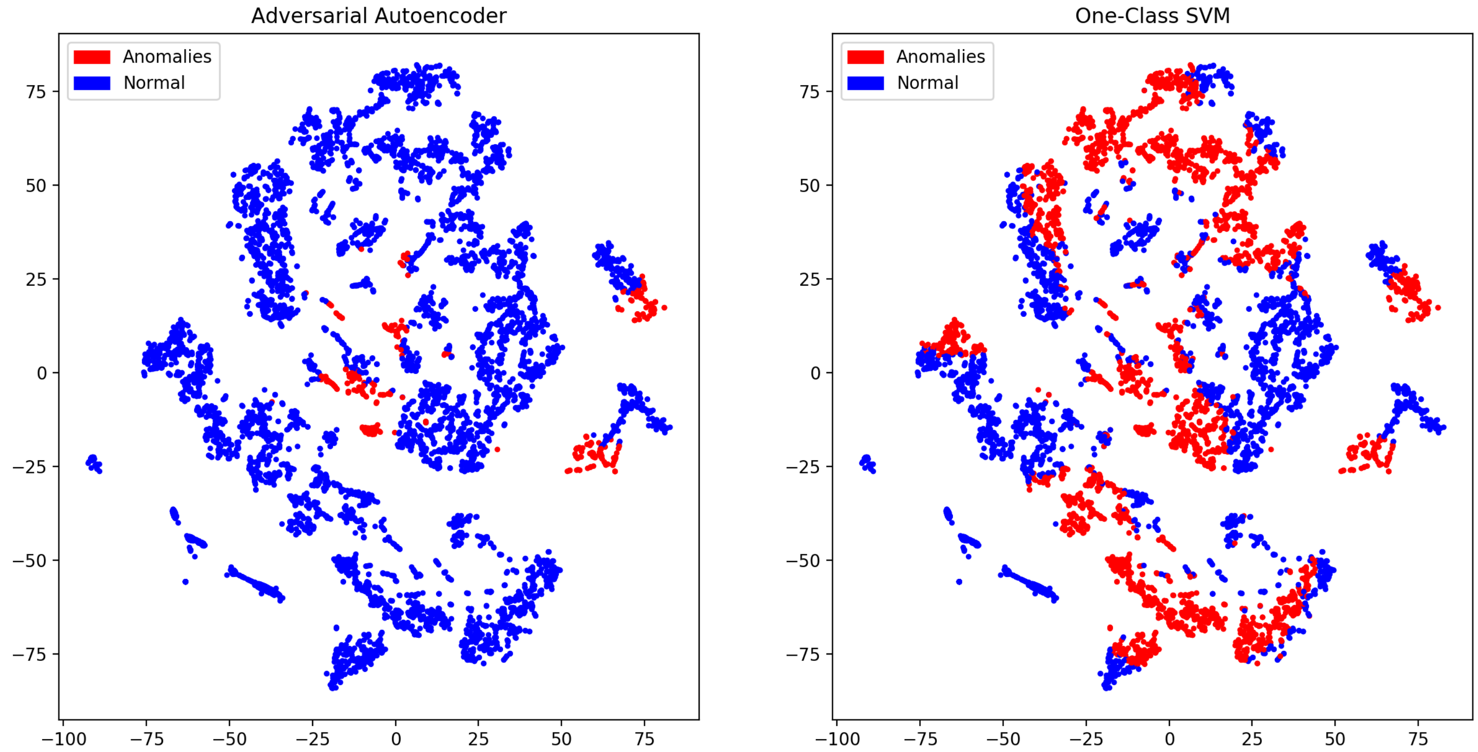
  - One-Class Support Vector Machine (SVM)
    - Sigmoid Kernel yielded the best results

$$k(x, y) = \tanh(\alpha x^T y + c)$$

  - Autoencoders and reconstruction thresholds are not well-suited for our classification problem. Our other methods (NN, Decision Tree) produced more accurate results.

Results

- Anomalies found in the Training Dataset



Results

- Anomalies found in the Testing Dataset