Anomaly Detection in Spacecraft telemetry

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AGENDA

- Introduction to anomaly detection
- Dataset Description
- Convolutional Autoencoder
- Temporal Convolutional Network
- Key takeaway

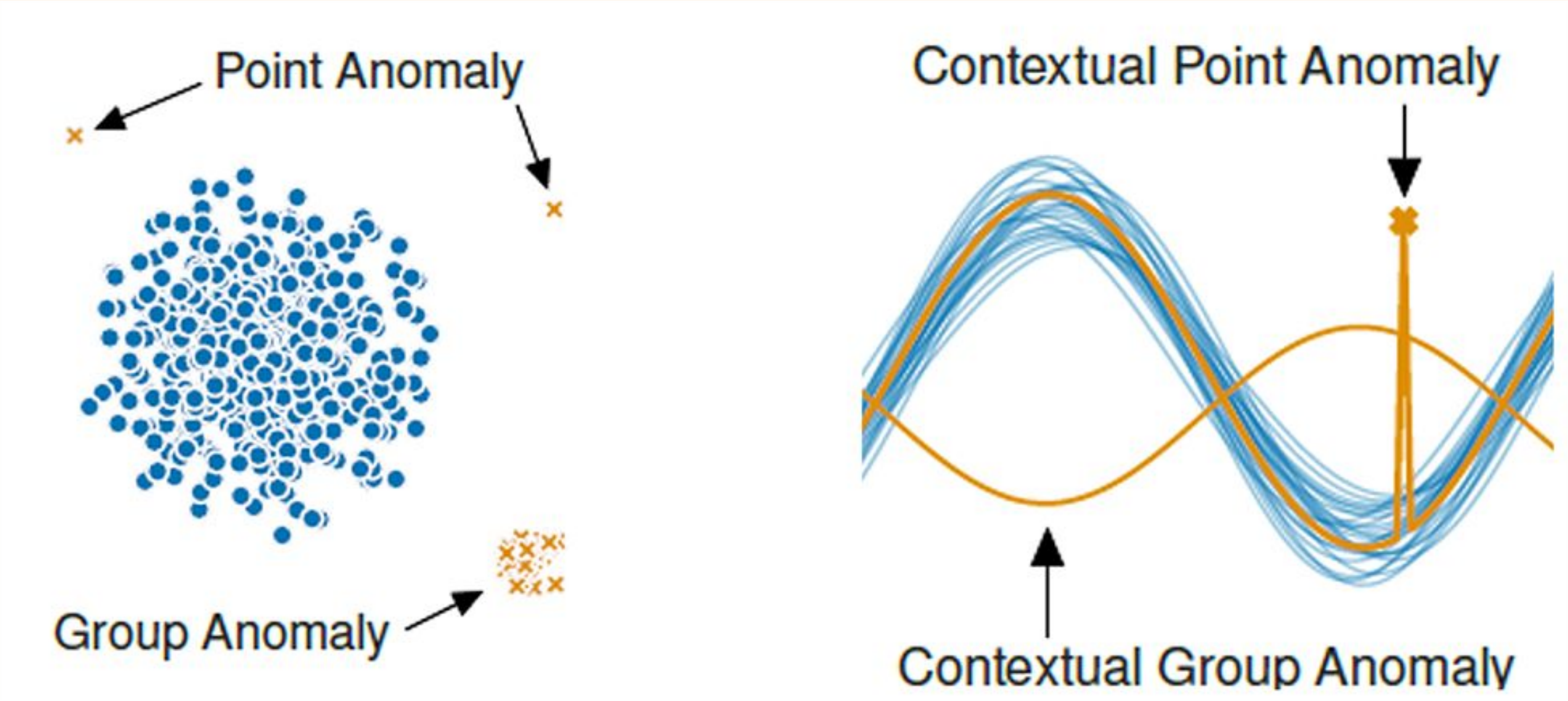
Introduction to Anomaly Detection

What are anomalies?

- Anomalies are unusual or unexpected data points that deviate from normal operational patterns.

- These can indicate potential issues within systems, such as equipment malfunctions or failures.

Anomalies



Point Anomaly
Group Anomaly
Contextual Point Anomaly
Contextual Group Anomaly

Importance of Anomaly Detection

- Early Issue Identification: Detects potential problems early, preventing escalation.
- Health Monitoring: Ensures continuous operational integrity of the systems.
- Preventative Maintenance: Enables timely interventions that save costs and extend component lifespan.
- Safety and Efficiency: Enhances mission safety and optimizes system performance.

Anomaly Detection in Spacecraft telemetry

- Anomalies in spacecraft telemetry are statistical deviations that flag potential system issues. They emerge within datasets tracking critical parameters such as voltage, temperature, and mechanical component speeds.

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Overview of the datasets

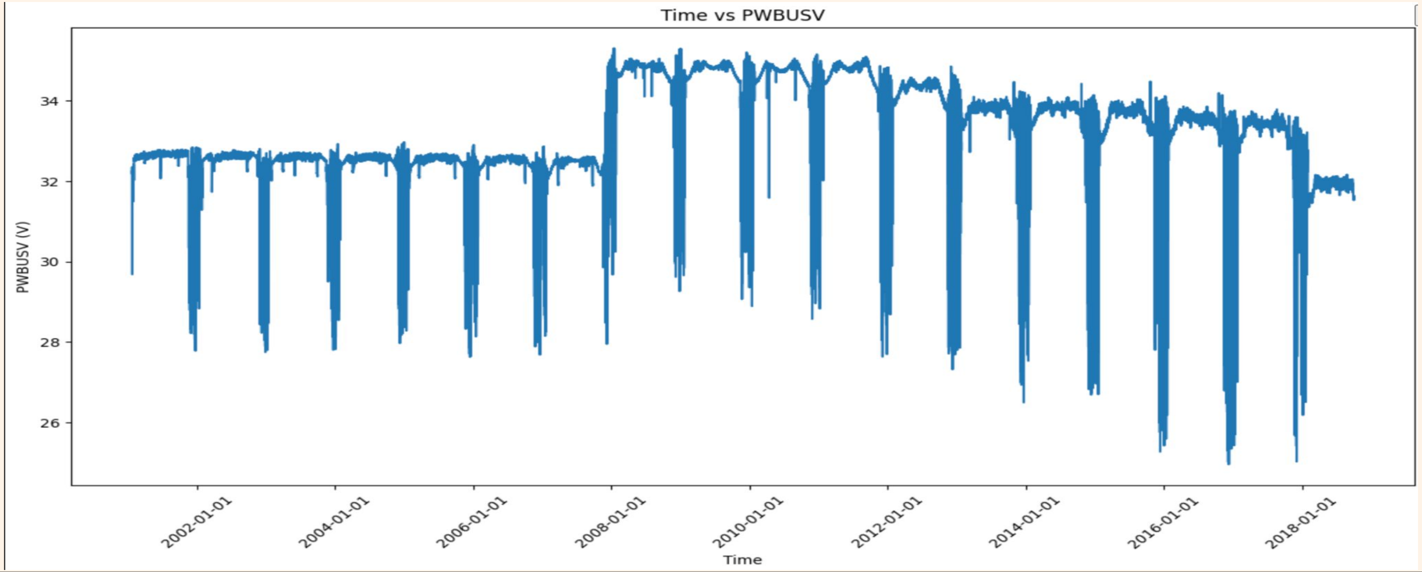
- Our dataset consists of several time-series data collections from different spacecraft systems, such as voltage levels, current readings, battery temperatures, and mechanical component temperatures and speeds. These datasets track the ongoing performance and status of critical spacecraft components over time.

Impact of Anomalies

Data Type	Description	Impacts of anomalies
Bus Voltage (V)	Measures the spacecraft's electrical system voltage	Sudden drops or spikes in voltage
Battery Temperature (°C)	Monitors the temperature of battery units	Extreme temperatures can degrade battery life and performance,
Wheel Temperature (°C)	Records temperature of reaction wheel systems	Overheating could indicate mechanical failures.
Reaction Wheel RPM	Speed readings of reaction wheels	Irregular RPMs can result from mechanical wear or damage, impacting navigation and control.
Bus Current (A)	Current flowing through the spacecraft’s bus	Anomalies could suggest issues like short circuits

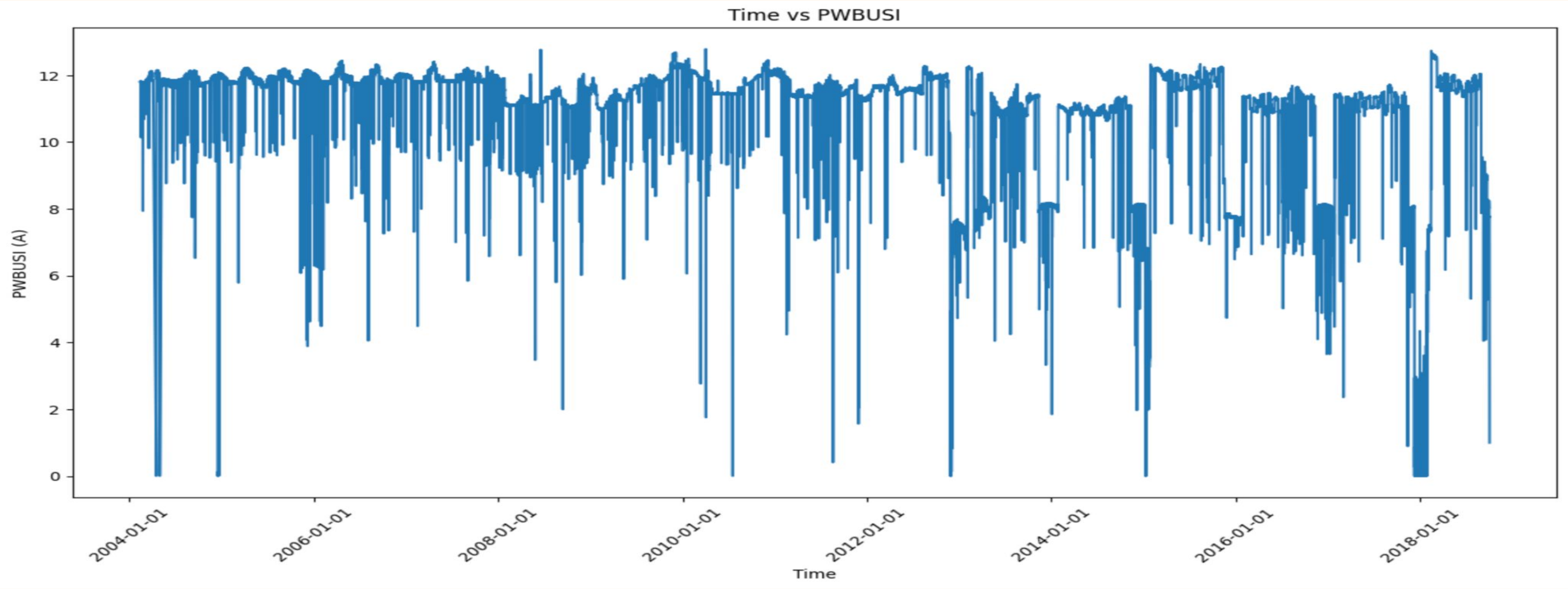
Bus voltage dataset

- Univariate time series with 1.8 million 5-min bus voltage readings, down-sampled to every 8 hours for a total of 18,807 data points, excluding missing values.
- Exhibits annual voltage dips and a significant trend change with a voltage spike in early 2008, followed by a decline.



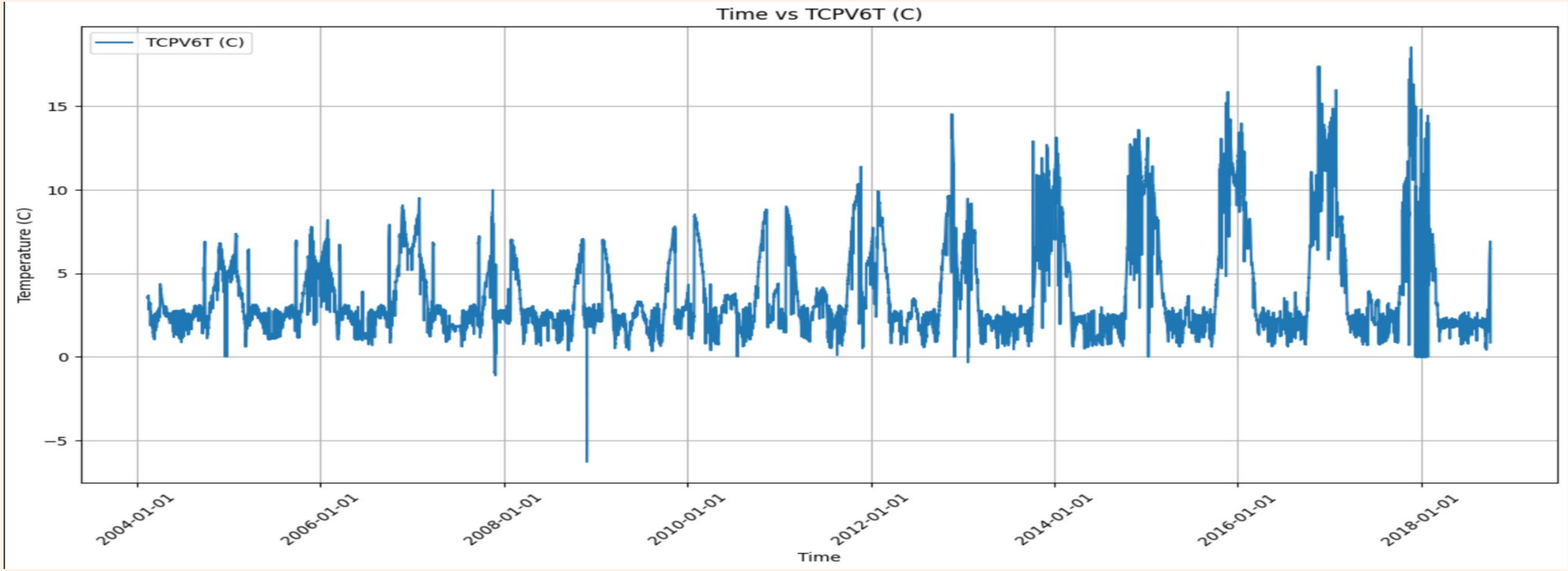
Total Spacecraft Bus Current dataset

- Time series with 1.5 million 5-min interval entries, down-sampled to 8-hour intervals, omitting missing and zero values, showing stable current patterns with notable surges indicating possible operational changes or anomalies.



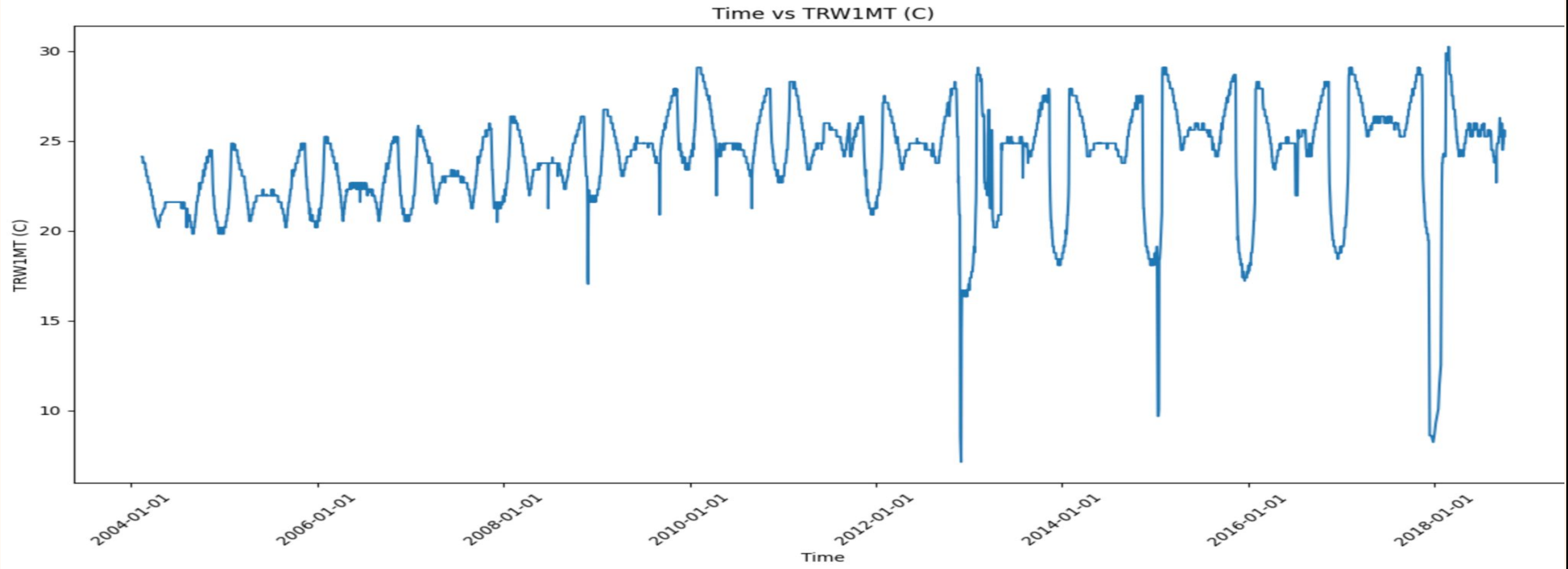
Battery Temperature dataset

- Time series with over 1.5 million readings from Feb 2004 to Oct 2018 at 5-minute intervals; crucial for satellite efficiency and safety, with deviations potentially signaling anomalies needing maintenance or indicating unique, expected behaviors.



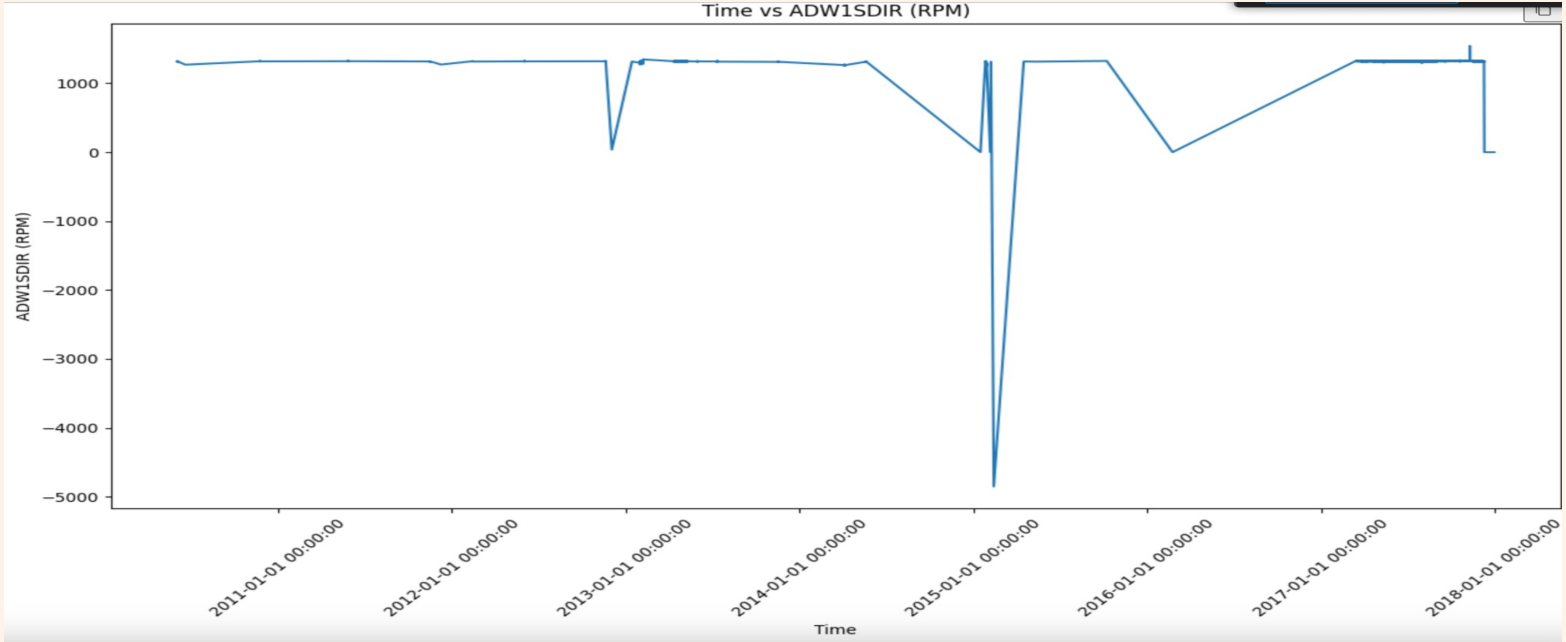
Reaction Wheel Temperature dataset

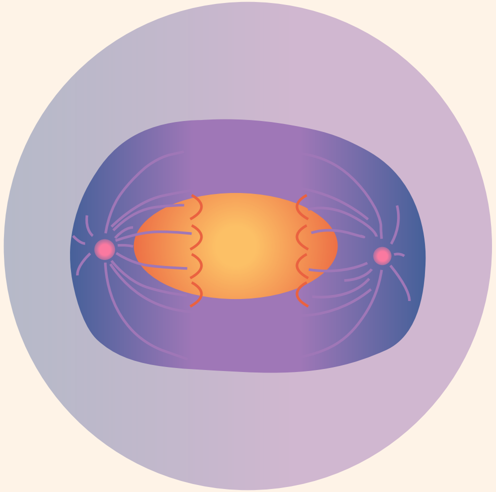
- Time series with approximately 1.5 million data points measured every 5 minutes from original 1-second intervals; data cleaned to exclude missing values and zeros (inactive periods), showcasing high variability without predictable patterns or seasonality.



Reaction Wheel RPM dataset

- Reaction Wheel RPM: Consists of roughly 48.87 million RPM readings over 9 years (Jan 2011 to Jan 2018), tracking the rotations per minute of spacecraft reaction wheels, essential for attitude control; features high-resolution, densely sampled data.





CAE

Convolutional Autoencoder

What is a CAE?

Convolutional Autoencoder (CAE)

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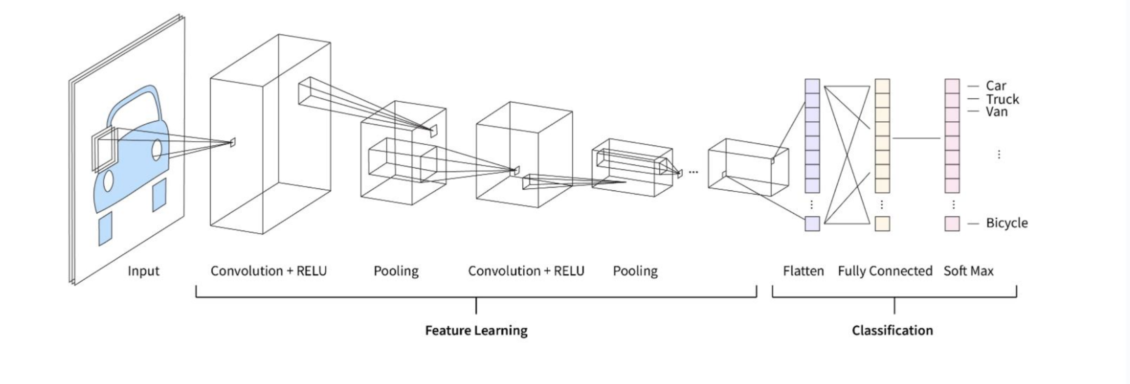
Convolutional Neural Network

+

Autoencoder

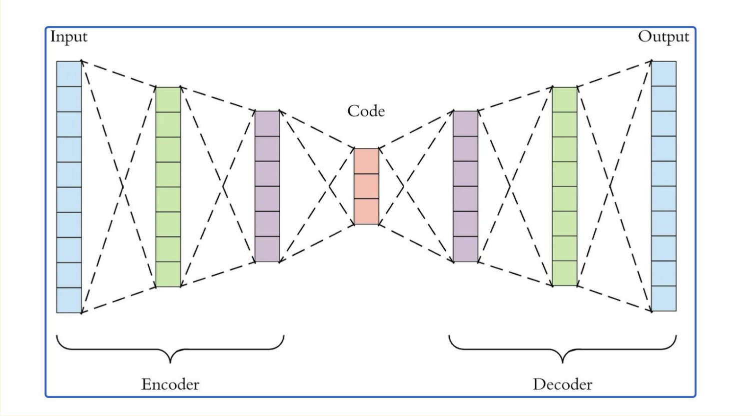
What is a CNN?

- Convolutional Neural Network (CNN)
    - Deep learning that can learn to identify pattern in input data
    - Can understand spatial and temporal dependencies



Back to CAE now…

- Autoencoder
  - A neural network where the input is the same as output
    - Great for unlabelled data
  - Compress input
  - Latent space representation
  - Reconstruct output



Our architecture & configs

Layer (type)	Output Shape	Param #
input_layer_15 (InputLayer)	(None, 5, 1)	0
conv1d_45 (Conv1D)	(None, 5, 16)	64
batch_normalization_30 (BatchNormalization)	(None, 5, 16)	64
dropout_30 (Dropout)	(None, 5, 16)	0
conv1d_46 (Conv1D)	(None, 5, 8)	392
conv1d_47 (Conv1D)	(None, 5, 4)	100
conv1d_transpose_45 (Conv1DTranspose)	(None, 5, 8)	104
batch_normalization_31 (BatchNormalization)	(None, 5, 8)	32
dropout_31 (Dropout)	(None, 5, 8)	0
conv1d_transpose_46 (Conv1DTranspose)	(None, 5, 16)	400
conv1d_transpose_47 (Conv1DTranspose)	(None, 5, 1)	49
global_average_pooling1d_15 (GlobalAveragePooling1D)	(None, 1)	0

Hyperparameters

- Number of hidden layers
- Dropout layer
- Activation function
- Learning rate

What was the input again? Let’s Reconstruct!

- After training the model, reconstruct the test data using the trained model
- Evaluation metric: Mean Squared Error (MSE)

$$\underbrace{\sum_{i=1}^{\overset{\text{number of samples}}{\boxed{n}}} \left(\overset{\text{real value}}{\boxed{Y_i}} - \overset{\text{predicted value}}{\boxed{\hat{Y}_i}}\right)^2}_{\text{sum of the errors of all samples}}$$

Anomaly Detection

- Threshold value:
  - @ each epoch: loss + 2* std. Dev.
  - Average
- Anomalies: instance where (true value - predicted value) > threshold

Result?

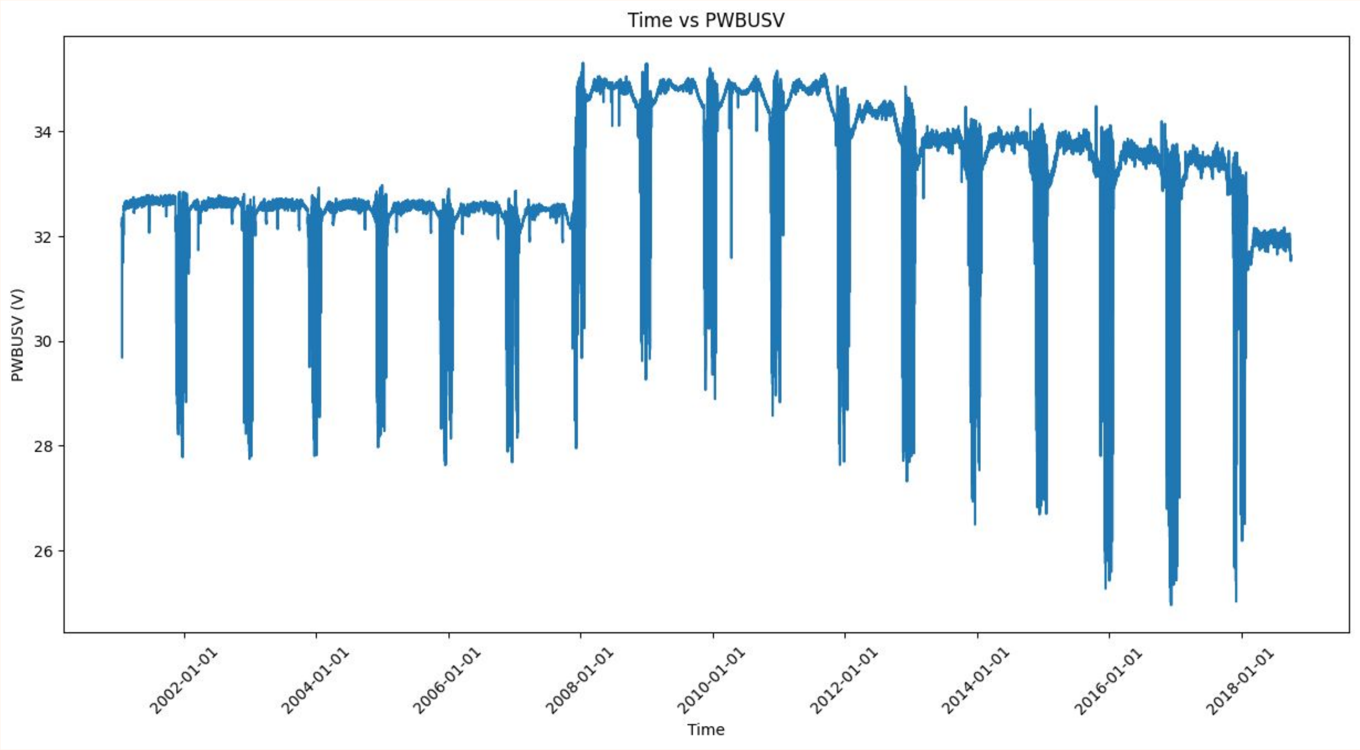
Spoiler alert:

Not so great

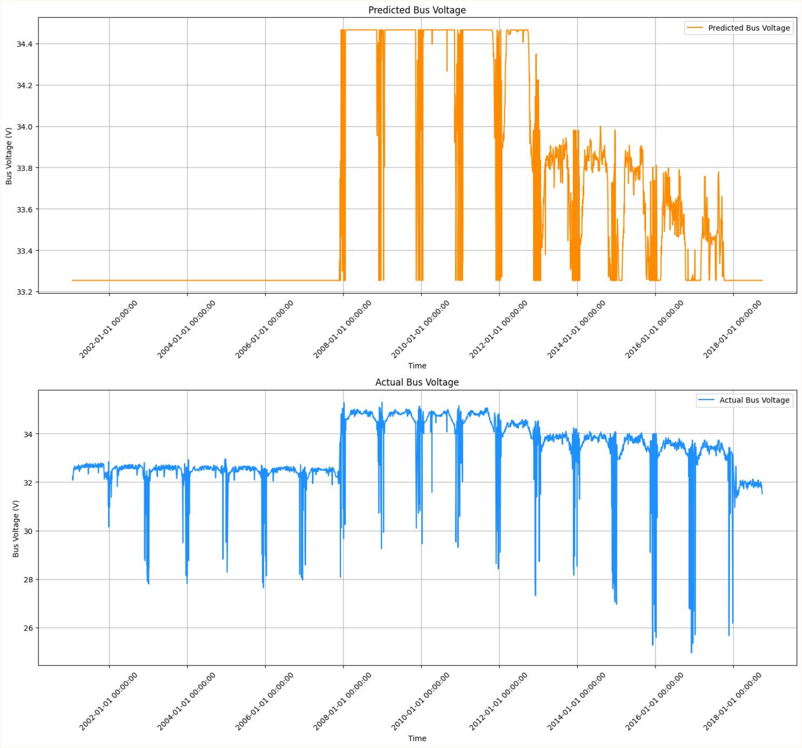
Bus Voltage Result

- Loss on last epoch during training for train set: 0.63
- Test data MSE: 0.68
- ~20% of the dataset were anomalies

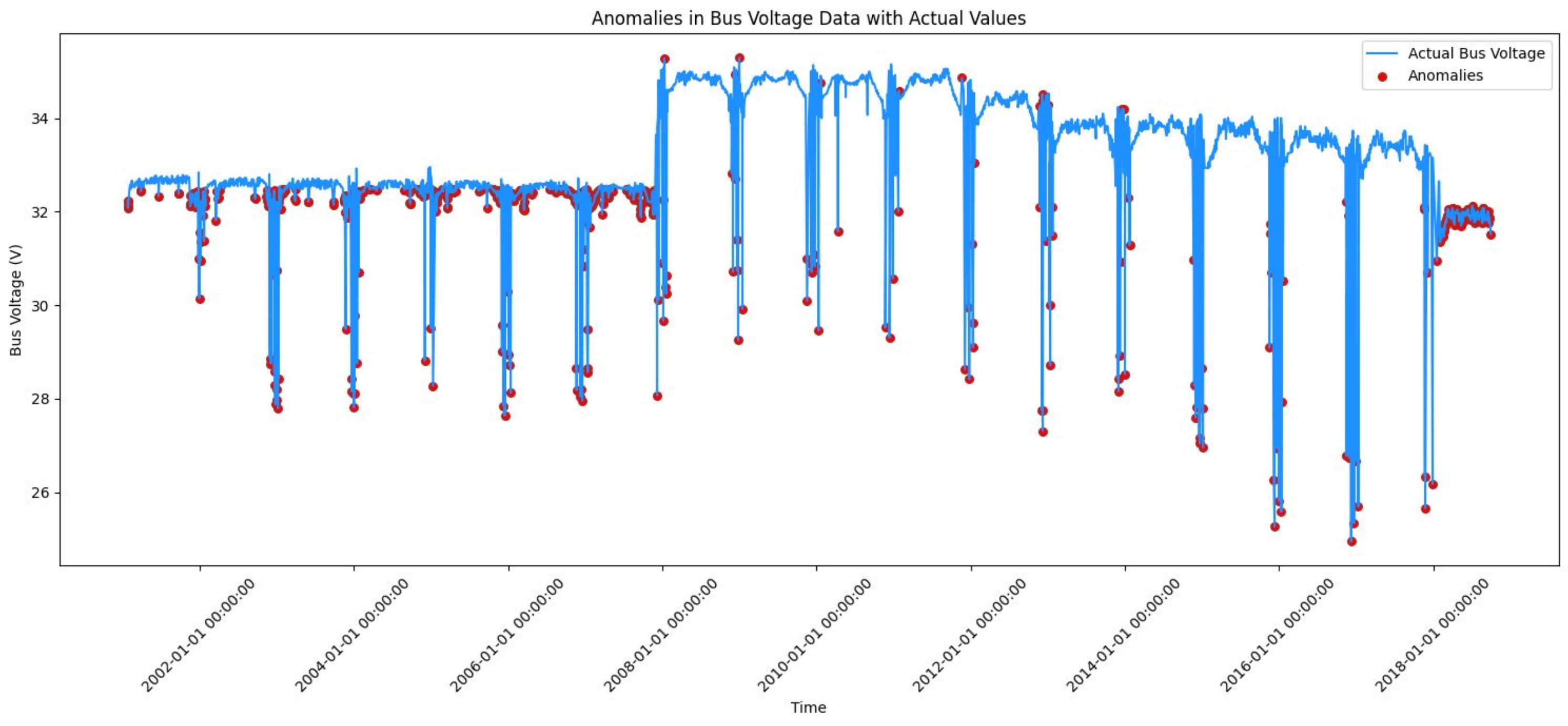
Bus Voltage Result: Original full downsampled data



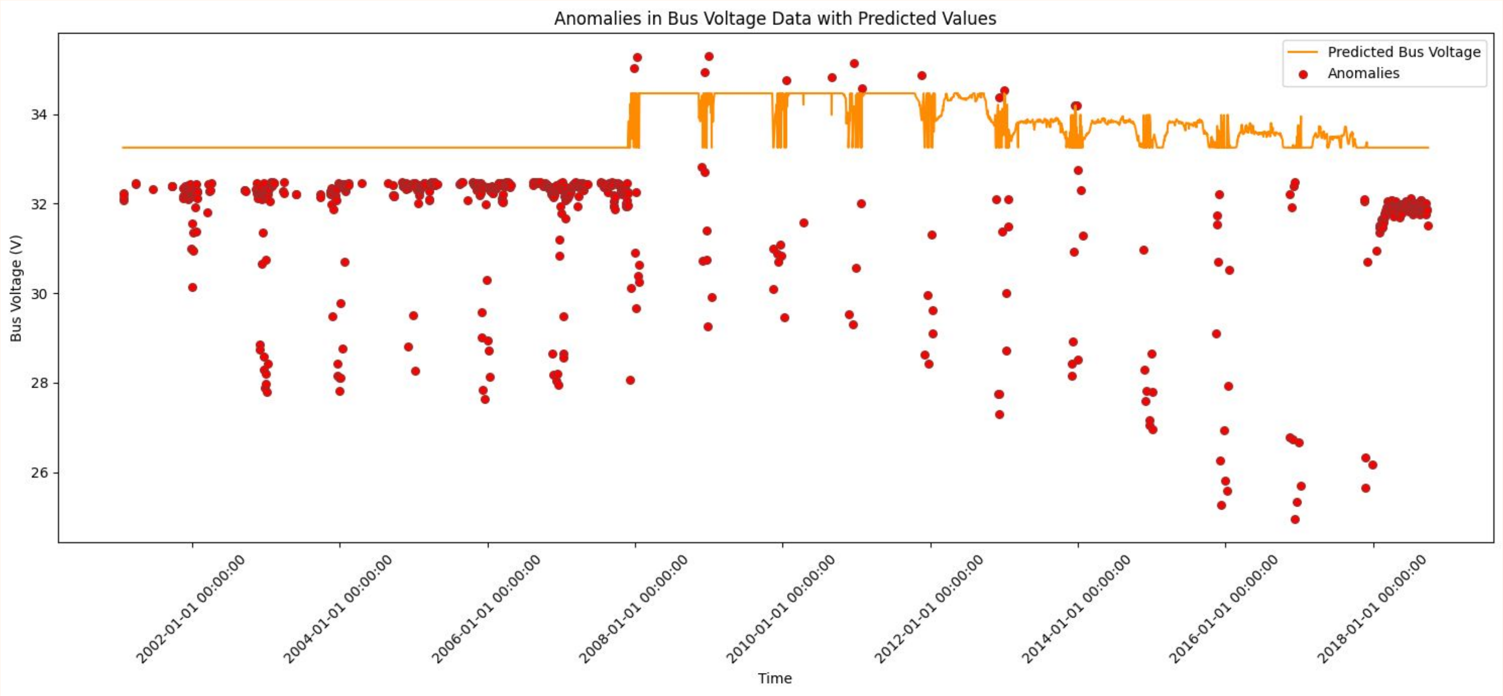
Bus Voltage Result: Predicted vs. Actual on test dataset



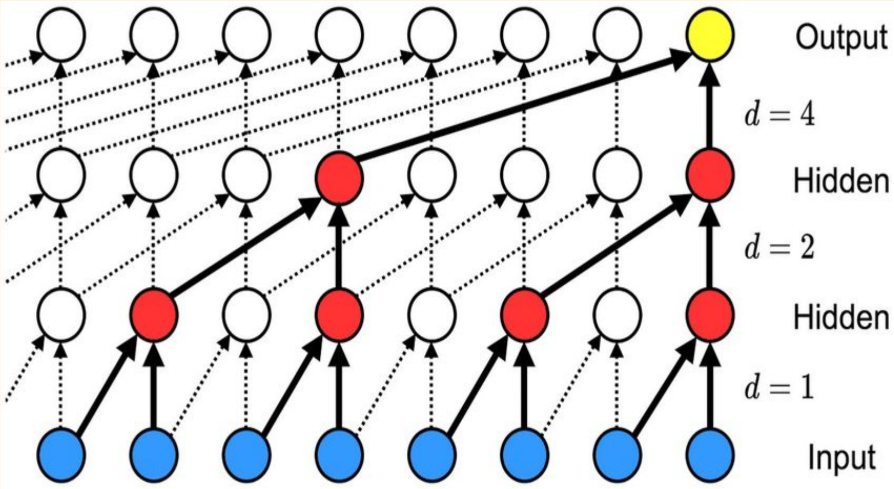
Bus Voltage Result: Actual Bus Voltage with Anomalies on test



Bus Voltage Result: Predicted Bus Voltage with Anomalies on test



Temporal Convolutional Network (TCN)



What is a TCN?

- 1D Convolutional Network - takes in and gives out a 3-dimensional tensor
- Kernel Size (K) - how much consecutive data is covered?
- Dilation Rate (D) - At what gaps to take the data?
- Receptive field (R) - What data are we looking at?

Receptive field size for one layer: $R = (K-1) * D + 1$

Receptive field size across all layers: $R = 1 + \sum(K-1) * D$

Receptive field size if dilation rate doubles each layer: $R = 1 + (K-1) * \sum 2^i$

Structure of our TCN

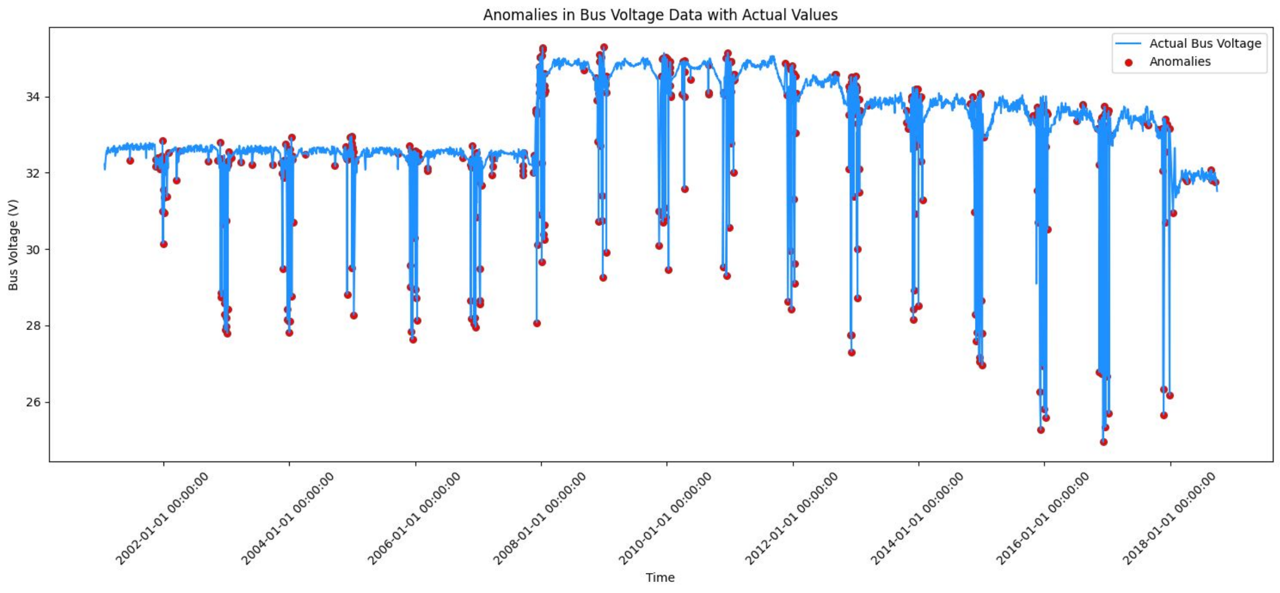
```
inputs = Input(shape=(X_train.shape[1], 1))
x = Conv1D(filters=64, kernel_size=1, dilation_rate=1, activation='relu')(inputs)
x = Dropout(0.2)(x)
x = Conv1D(filters=64, kernel_size=1, dilation_rate=2, padding='causal',
activation='relu')(x)
x = Dropout(0.2)(x)
x = Conv1D(filters=64, kernel_size=1, dilation_rate=4, padding='causal',
activation='relu')(x)
x = Dropout(0.2)(x)
x = Flatten()(x)
outputs = Dense(1, activation='linear')(x)
```

TCN Architecture

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 150, 1)	0
conv1d (Conv1D)	(None, 150, 64)	128
dropout (Dropout)	(None, 150, 64)	0
conv1d_1 (Conv1D)	(None, 150, 64)	4,160
dropout_1 (Dropout)	(None, 150, 64)	0
conv1d_2 (Conv1D)	(None, 150, 64)	4,160
dropout_2 (Dropout)	(None, 150, 64)	0
flatten (Flatten)	(None, 9600)	0
dense (Dense)	(None, 1)	9,601

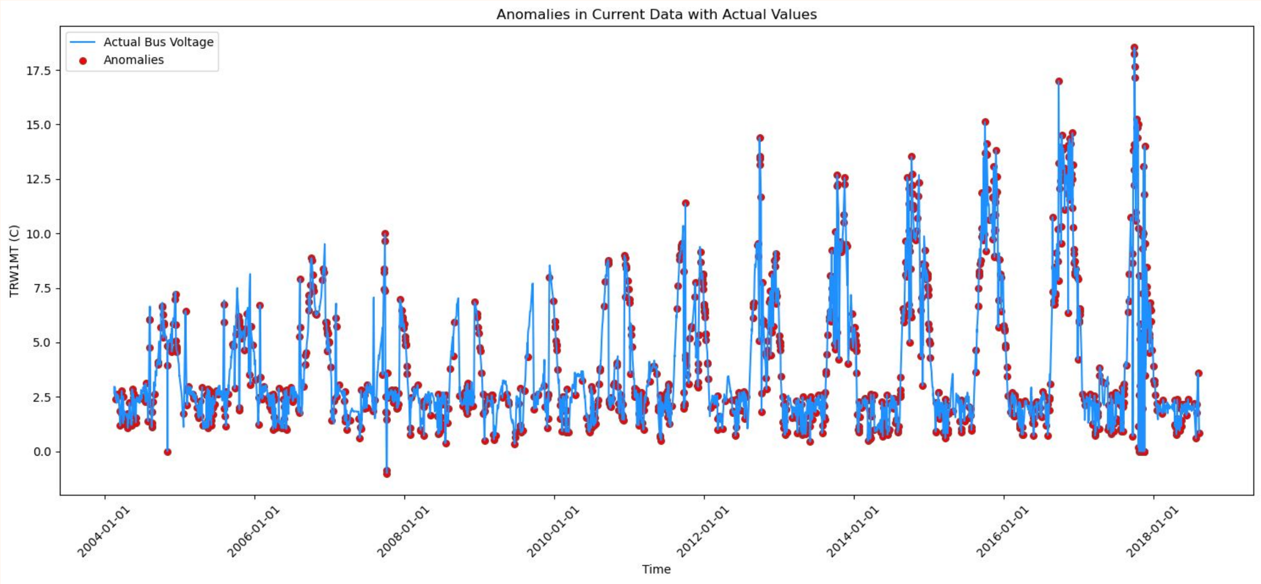
Bus Voltage (V)

- Anomalies Detected: 1221
- MSE: 0.163
- Threshold: 0.188



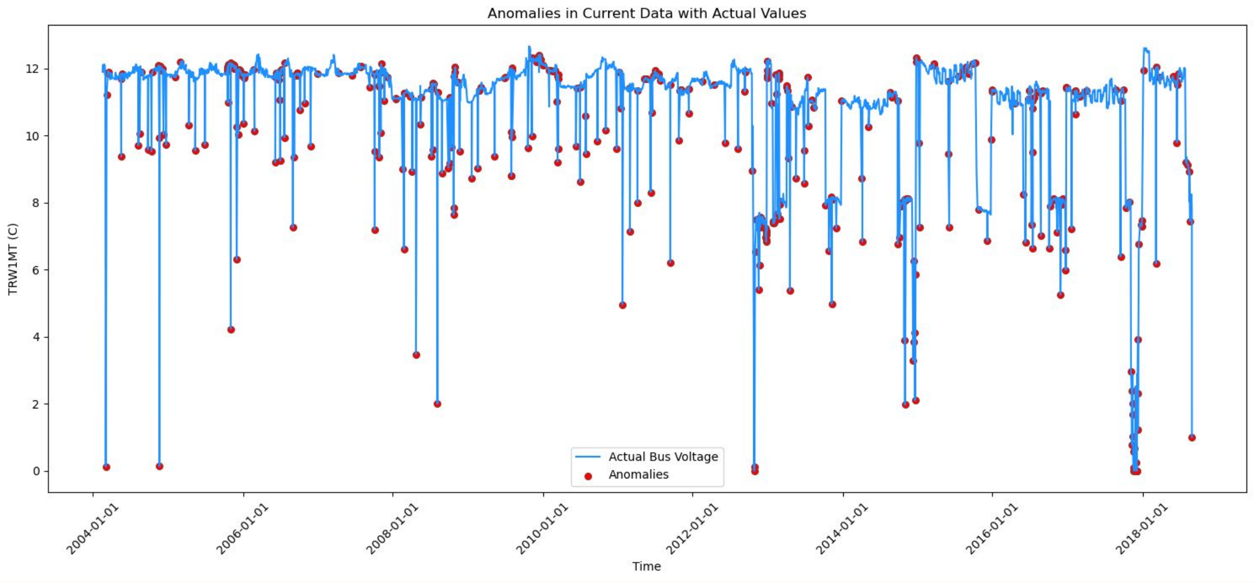
Battery Temperature (C)

- Anomalies Detected: 1253
- MSE: 0.092
- Threshold: 0.111



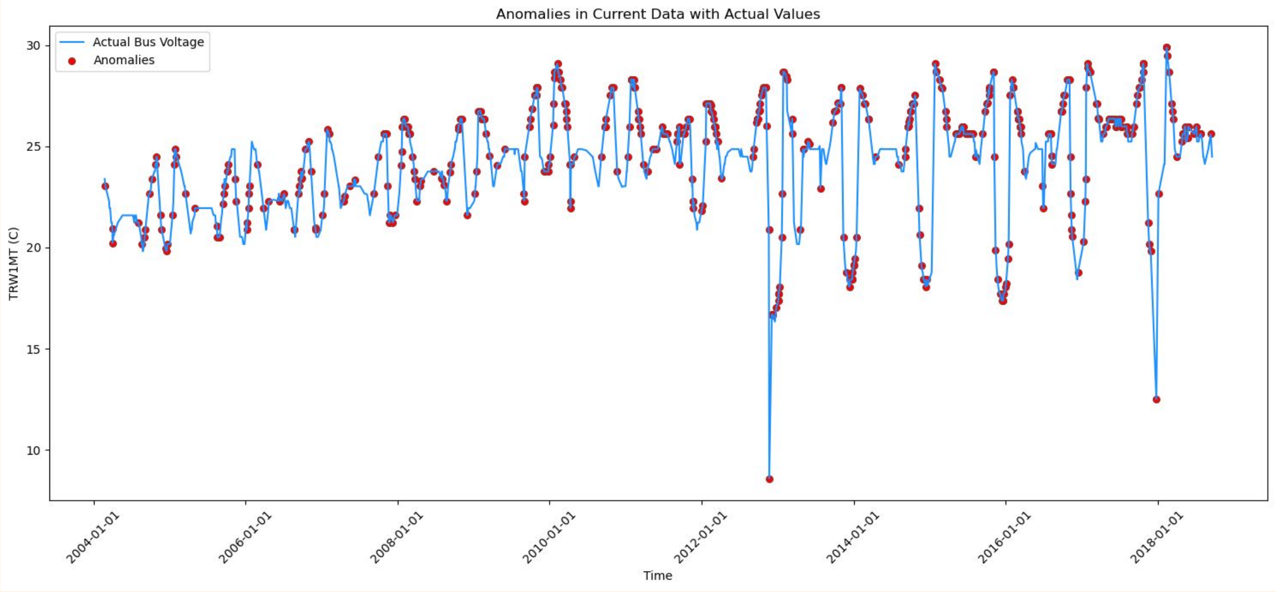
Bus Current (A)

- Anomalies Detected: 398
- MSE: 0.190
- Threshold: 0.267



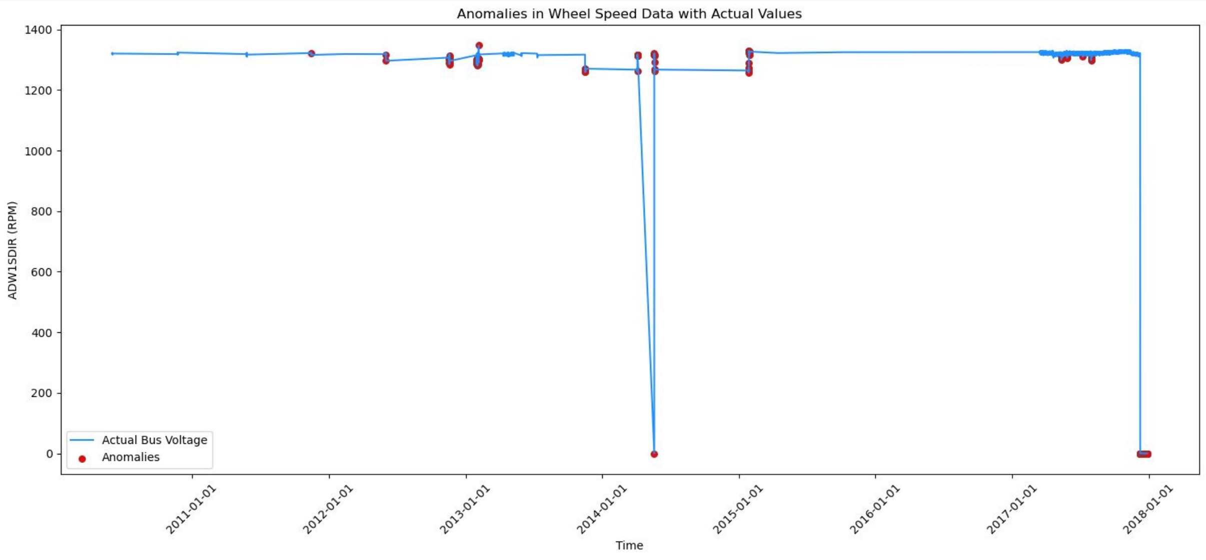
Reaction Wheel Temperature (C)

- Anomalies Detected: 474
- MSE: 0.068
- Threshold: 0.091



Reaction Wheel Speed (RPM)

- Anomalies Detected: 213
- MSE: 0.012
- Threshold: 0.092



Key Takeaways

References

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