battery

July 14, 2025

0.1 Load and Download Dataset from KaggleHub

We use `kagglehub` to fetch the real-world EV battery telemetry dataset.

[1]:
```
# Install kagglehub if not already installed
%pip install kagglehub

import kagglehub

# Download latest version
path = kagglehub.dataset_download("atechnohazard/
↪battery-and-heating-data-in-real-driving-cycles")

print("Path to dataset files:", path)
```

```
DEPRECATION: Configuring installation scheme with distutils config files is
deprecated and will no longer work in the near future. If you are using a
Homebrew or Linuxbrew Python, please see discussion at
https://github.com/Homebrew/homebrew-core/issues/76621
```

```
Collecting kagglehub
  Using cached kagglehub-0.3.12-py3-none-any.whl.metadata (38 kB)
Requirement already satisfied: packaging in /opt/homebrew/lib/python3.9/site-
packages (from kagglehub) (23.2)
Requirement already satisfied: pyyaml in
/Users/yashkathiriya/Library/Python/3.9/lib/python/site-packages (from
kagglehub) (6.0.2)
Requirement already satisfied: requests in /opt/homebrew/lib/python3.9/site-
packages (from kagglehub) (2.32.3)
Requirement already satisfied: tqdm in /opt/homebrew/lib/python3.9/site-packages
(from kagglehub) (4.67.1)
Requirement already satisfied: charset-normalizer<4,>=2 in
/opt/homebrew/lib/python3.9/site-packages (from requests->kagglehub) (3.4.1)
Requirement already satisfied: idna<4,>=2.5 in /opt/homebrew/lib/python3.9/site-
packages (from requests->kagglehub) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/opt/homebrew/lib/python3.9/site-packages (from requests->kagglehub) (2.3.0)
Requirement already satisfied: certifi>=2017.4.17 in
```

```
/opt/homebrew/lib/python3.9/site-packages (from requests->kagglehub)
(2024.12.14)
Using cached kagglehub-0.3.12-py3-none-any.whl (67 kB)
Installing collected packages: kagglehub
  DEPRECATION: Configuring installation scheme with distutils config files
is deprecated and will no longer work in the near future. If you are using a
Homebrew or Linuxbrew Python, please see discussion at
https://github.com/Homebrew/homebrew-core/issues/76621
DEPRECATION: Configuring installation scheme with distutils config
files is deprecated and will no longer work in the near future. If you are using
a Homebrew or Linuxbrew Python, please see discussion at
https://github.com/Homebrew/homebrew-core/issues/76621
Successfully installed kagglehub-0.3.12
Note: you may need to restart the kernel to use updated packages.
```

```
/opt/homebrew/lib/python3.9/site-packages/tqdm/auto.py:21: TqdmWarning:
IProgress not found. Please update jupyter and ipywidgets. See
https://ipywidgets.readthedocs.io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

```
Path to dataset files:
/Users/yashkathiriya/.cache/kagglehub/datasets/atechnohazard/battery-and-
heating-data-in-real-driving-cycles/versions/1
```

[2]:
```python
import os
import pandas as pd
import matplotlib
import seaborn as sns
```

[3]:
```python
data_path = path
all_data = []
file_list = []
skipped_cycles = []
valid_cycles = []
csv_files = [f for f in os.listdir(data_path) if f.endswith('.csv') and not f.
  ↪startswith('.')]
print(f"  Total CSV files found: {len(csv_files)}")
```

```
 Total CSV files found: 70
```

0.2 Preprocessing Files

We iterate through all CSVs, clean the column names, handle encoding issues, and skip malformed files.

[4]:
```python
for filename in sorted(os.listdir(data_path)):
    if filename.endswith(".csv"):
        full_path = os.path.join(data_path, filename)
        file_status = f"  {filename}: "

        # Try loading the file with fallback encoding
        try:
            df = pd.read_csv(full_path, encoding='utf-8', sep=';')
        except UnicodeDecodeError:
            try:
                df = pd.read_csv(full_path, encoding='ISO-8859-1', sep=';')
            except Exception as e:
                print(file_status + f"  Failed to load (encoding error): {e}")
                bad_files.append(filename)
                continue

        # Clean column names
        df.columns = df.columns.str.strip().str.lower().str.replace(' ', '_').
 ↪str.replace('[^a-z0-9_]', '', regex=True)

        # Check for duplicate columns
        if df.columns.duplicated().any():
            print(file_status + "  Skipped (duplicate columns)")
            skipped_cycles.append(filename)
            continue

        # Check for required structure
        if df.shape[1] < 5 or 'time_s' not in df.columns:
            print(file_status + "  Skipped (missing expected columns or␣
 ↪structure)")
            skipped_cycles.append(filename)
            continue

        # Passed all checks
        df['cycle_id'] = filename.replace('.csv', '')
        all_data.append(df)
        valid_cycles.append(filename)
        print(file_status + "  Loaded successfully")

print(f"\n  Summary:")
print(f"  Loaded: {len(valid_cycles)}")
print(f"  Skipped: {len(skipped_cycles)}")
```

```
TripA01.csv:   Loaded successfully
TripA02.csv:   Loaded successfully
TripA03.csv:   Loaded successfully
TripA04.csv:   Loaded successfully
TripA05.csv:   Loaded successfully
```

```
TripA06.csv:  Loaded successfully
TripA07.csv:  Loaded successfully
TripA08.csv:  Loaded successfully
TripA09.csv:  Loaded successfully
TripA10.csv:  Loaded successfully
TripA11.csv:  Loaded successfully
TripA12.csv:  Loaded successfully
TripA13.csv:  Loaded successfully
TripA14.csv:  Loaded successfully
TripA15.csv:  Loaded successfully
TripA16.csv:  Loaded successfully
TripA17.csv:  Loaded successfully
TripA18.csv:  Loaded successfully
TripA19.csv:  Loaded successfully
TripA20.csv:  Loaded successfully
TripA21.csv:  Loaded successfully
TripA22.csv:  Loaded successfully
TripA23.csv:  Loaded successfully
TripA24.csv:  Loaded successfully
TripA25.csv:  Loaded successfully
TripA26.csv:  Loaded successfully
TripA27.csv:  Loaded successfully
TripA28.csv:  Loaded successfully
TripA29.csv:  Loaded successfully
TripA30.csv:  Loaded successfully
TripA31.csv:  Loaded successfully
TripA32.csv:  Loaded successfully
TripB01.csv:  Skipped (duplicate columns)
TripB02.csv:  Skipped (duplicate columns)
TripB03.csv:  Skipped (duplicate columns)
TripB04.csv:  Skipped (duplicate columns)
TripB05.csv:  Skipped (duplicate columns)
TripB06.csv:  Skipped (duplicate columns)
TripB07.csv:  Skipped (duplicate columns)
TripB08.csv:  Skipped (duplicate columns)
TripB09.csv:  Skipped (duplicate columns)
TripB10.csv:  Skipped (duplicate columns)
TripB11.csv:  Skipped (duplicate columns)
TripB12.csv:  Skipped (duplicate columns)
TripB13.csv:  Skipped (duplicate columns)
TripB14.csv:  Skipped (duplicate columns)
TripB15.csv:  Skipped (duplicate columns)
TripB16.csv:  Skipped (duplicate columns)
TripB17.csv:  Skipped (duplicate columns)
TripB18.csv:  Skipped (duplicate columns)
TripB19.csv:  Skipped (duplicate columns)
TripB20.csv:  Skipped (duplicate columns)
TripB21.csv:  Skipped (duplicate columns)
```

```
TripB22.csv:  Skipped (duplicate columns)
TripB23.csv:  Skipped (duplicate columns)
TripB24.csv:  Skipped (duplicate columns)
TripB25.csv:  Skipped (duplicate columns)
TripB26.csv:  Skipped (duplicate columns)
TripB27.csv:  Skipped (duplicate columns)
TripB28.csv:  Skipped (duplicate columns)
TripB29.csv:  Skipped (duplicate columns)
TripB30.csv:  Skipped (duplicate columns)
TripB31.csv:  Skipped (duplicate columns)
TripB32.csv:  Skipped (duplicate columns)
TripB33.csv:  Skipped (duplicate columns)
TripB34.csv:  Skipped (duplicate columns)
TripB35.csv:  Skipped (duplicate columns)
TripB36.csv:  Skipped (duplicate columns)
TripB37.csv:  Skipped (duplicate columns)
TripB38.csv:  Skipped (duplicate columns)

Summary:
Loaded: 32
Skipped: 38
```

[5]:

```python
import json

def save_cycle_file_status(valid_cycles, skipped_cycles,␣
↪base_name="cycle_file_status"):
    # Save as TXT
    with open(f"{base_name}_valid_cycles.txt", "w") as f:
        for file in valid_cycles:
            f.write(f"{file}\n")

    with open(f"{base_name}_skipped_cycles.txt", "w") as f:
        for file in skipped_cycles:
            f.write(f"{file}\n")

    with open(f"{base_name}_summary.txt", "w") as f:
        f.write(f" Valid cycles ({len(valid_cycles)}):\n")
        f.writelines([f"  - {name}\n" for name in valid_cycles])
        f.write(f"\n Skipped cycles ({len(skipped_cycles)}):\n")
        f.writelines([f"  - {name}\n" for name in skipped_cycles])

    # Save as JSON
    with open(f"{base_name}.json", "w") as f:
        json.dump({
            "valid_cycles": valid_cycles,
            "skipped_cycles": skipped_cycles
        }, f, indent=2)
```

```
    print(f"  Saved: {base_name}_valid_cycles.txt, {base_name}_skipped_cycles.
↪txt, {base_name}.json, and summary.")
```

[6]:
```
save_cycle_file_status(valid_cycles, skipped_cycles)
```

```
 Saved: cycle_file_status_valid_cycles.txt,
cycle_file_status_skipped_cycles.txt, cycle_file_status.json, and summary.
```

[7]:
```
df_all = pd.concat(all_data, ignore_index=True)
print(df_all.shape)
```

```
(467701, 30)
```

[8]:
```
df_all.head()
```

[8]:
```
   time_s  velocity_kmh  elevation_m  throttle_  motor_torque_nm  \
0     0.0           0.0        574.0        0.0              0.0
1     0.1           0.0        574.0        0.0              0.0
2     0.2           0.0        574.0        0.0              0.0
3     0.3           0.0        574.0        0.0              0.0
4     0.4           0.0        574.0        0.0              0.0

   longitudinal_acceleration_ms2  regenerative_braking_signal  \
0                          -0.03                          0.0
1                           0.00                          0.0
2                          -0.01                          0.0
3                          -0.03                          0.0
4                          -0.03                          0.0

   battery_voltage_v  battery_current_a  battery_temperature_c  …  \
0              391.4              -2.20                   21.0  …
1              391.4              -2.21                   21.0  …
2              391.4              -2.26                   21.0  …
3              391.4              -2.30                   21.0  …
4              391.4              -2.30                   21.0  …

   heater_voltage_v  heater_current_a  ambient_temperature_c  \
0               0.0               0.0                   25.5
1               0.0               0.0                   25.5
2               0.0               0.0                   25.5
3               0.0               0.0                   25.5
4               0.0               0.0                   25.5

   coolant_temperature_heatercore_c  requested_coolant_temperature_c  \
0                               0.0                              0.0
1                               0.0                              0.0
2                               0.0                              0.0
```

```
3                            0.0                            0.0
4                            0.0                            0.0

   coolant_temperature_inlet_c  heat_exchanger_temperature_c  \
0                          0.0                          30.5
1                          0.0                          30.5
2                          0.0                          30.5
3                          0.0                          30.5
4                          0.0                          30.5

   cabin_temperature_sensor_c  cycle_id  unnamed_23
0                        24.5   TripA01         NaN
1                        24.5   TripA01         NaN
2                        24.5   TripA01         NaN
3                        24.5   TripA01         NaN
4                        24.5   TripA01         NaN

[5 rows x 30 columns]
```

[9]:
```
df_all.columns.tolist()
```

[9]:
```
['time_s',
 'velocity_kmh',
 'elevation_m',
 'throttle_',
 'motor_torque_nm',
 'longitudinal_acceleration_ms2',
 'regenerative_braking_signal',
 'battery_voltage_v',
 'battery_current_a',
 'battery_temperature_c',
 'max_battery_temperature_c',
 'soc_',
 'displayed_soc_',
 'min_soc_',
 'max_soc_',
 'heating_power_can_kw',
 'heating_power_lin_w',
 'requested_heating_power_w',
 'aircon_power_kw',
 'heater_signal',
 'heater_voltage_v',
 'heater_current_a',
 'ambient_temperature_c',
 'coolant_temperature_heatercore_c',
 'requested_coolant_temperature_c',
 'coolant_temperature_inlet_c',
```

```
 'heat_exchanger_temperature_c',
 'cabin_temperature_sensor_c',
 'cycle_id',
 'unnamed_23']
```

0.3 Aggregating Trip-Level Summary

We group by each driving cycle (`cycle_id`) and extract statistics like max temperature, average current, voltage, and heating power.

[10]:
```
# columns for focused analysis
selected_columns = [
    'cycle_id',
    'time_s',
    'battery_temperature_c',
    'max_battery_temperature_c',
    'battery_current_a',
    'battery_voltage_v',
    'soc_',
    'ambient_temperature_c',
    'requested_heating_power_w',
    'coolant_temperature_inlet_c',
    'heat_exchanger_temperature_c',
    'cabin_temperature_sensor_c'
]


df_selected = df_all[selected_columns].dropna()
print(df_selected.shape)
df_selected.head()
```

```
(157114, 12)
```

[10]:
```
  cycle_id  time_s  battery_temperature_c  max_battery_temperature_c  \
0  TripA01     0.0                   21.0                       22.0
1  TripA01     0.1                   21.0                       22.0
2  TripA01     0.2                   21.0                       22.0
3  TripA01     0.3                   21.0                       22.0
4  TripA01     0.4                   21.0                       22.0

   battery_current_a  battery_voltage_v  soc_  ambient_temperature_c  \
0              -2.20              391.4  86.9                   25.5
1              -2.21              391.4  86.9                   25.5
2              -2.26              391.4  86.9                   25.5
3              -2.30              391.4  86.9                   25.5
4              -2.30              391.4  86.9                   25.5

   requested_heating_power_w  coolant_temperature_inlet_c  \
```

```
0                       85.0                        0.0
1                       85.0                        0.0
2                       85.0                        0.0
3                       85.0                        0.0
4                       85.0                        0.0

   heat_exchanger_temperature_c  cabin_temperature_sensor_c
0                          30.5                        24.5
1                          30.5                        24.5
2                          30.5                        24.5
3                          30.5                        24.5
4                          30.5                        24.5
```

[11]:
```
#one row per driving cycle
summary_df = df_selected.groupby('cycle_id').agg({
    'battery_temperature_c': ['max', 'mean'],
    'max_battery_temperature_c': 'max',
    'battery_current_a': 'mean',
    'battery_voltage_v': 'mean',
    'soc_': ['min', 'max'],
    'ambient_temperature_c': 'mean',
    'requested_heating_power_w': 'mean',
    'time_s': lambda x: x.max() - x.min()  #seconds
}).reset_index()
```

[12]:
```
# flattening multiindex
summary_df.columns = [
    'cycle_id',
    'temp_max', 'temp_mean',
    'temp_max_reported',
    'current_mean', 'voltage_mean',
    'soc_min', 'soc_max',
    'ambient_temp_mean',
    'heating_power_mean',
    'trip_duration_s'
]
```

[13]:
```
print(summary_df.shape)
summary_df.head()
```

```
(12, 11)
```

[13]:
```
  cycle_id  temp_max  temp_mean  temp_max_reported  current_mean  \
0  TripA01      22.0  21.940141               23.0    -11.953476
1  TripA02      26.0  24.972960               27.0    -20.384738
2  TripA23      17.0  16.886255               17.0    -11.885933
3  TripA24      19.0  18.103831               19.0    -31.208109
4  TripA25      20.0  19.543322               21.0    -26.908419
```

```
   voltage_mean  soc_min  soc_max  ambient_temp_mean  heating_power_mean  \
0    388.483996     81.5     86.9          30.769972           85.000000
1    381.553837     66.9     80.3          31.127573           85.000000
2    388.445060     81.8     87.4          19.242787          977.274806
3    380.906925     74.2     81.9          18.713403         1065.378183
4    377.404315     65.1     74.4          17.960967         1414.107541

   trip_duration_s
0           1008.9
1           1412.9
2           1042.5
3            532.1
4            762.6
```

0.4 Step 4: Detect Anomalies Using Z-Scores

We calculate Z-scores for key metrics and flag cycles that significantly deviate from the norm.

[14]:
```python
summary_df.to_csv("cycle_summary.csv", index=False)
```

Z-score anomaly detection when battery temperature is significantly high/low than usual

[15]:
```python
from scipy.stats import zscore
summary_df['z_temp_max'] = zscore(summary_df['temp_max']) #calculate z
summary_df['is_anomaly'] = summary_df['z_temp_max'].abs() > 1.5 # flagging␣
↪outliers
temperature_anomalies = summary_df[summary_df['is_anomaly']]
print(f" Found {len(temperature_anomalies)} anomalous cycles:")
temperature_anomalies[['cycle_id', 'temp_max', 'z_temp_max']]
```

```
 Found 3 anomalous cycles:
```

[15]:

	cycle_id	temp_max	z_temp_max
1	TripA02	26.0	1.875854
2	TripA23	17.0	-1.617116
11	TripA32	26.0	1.875854

[16]:
```python
summary_df['z_current'] = zscore(summary_df['current_mean'])
summary_df['is_current_anomaly'] = summary_df['z_current'].abs() > 1.5
current_anomalies = summary_df[summary_df['is_current_anomaly']]
print(f" Found {len(current_anomalies)} anomalous cycles:")
current_anomalies[['cycle_id', 'current_mean', 'z_current']]
```

```
 Found 2 anomalous cycles:
```

[16]:

	cycle_id	current_mean	z_current
3	TripA24	-31.208109	-1.562939
11	TripA32	-35.867802	-2.098234

0.5 Scoring and Ranking Cycles with Anomaly Score

We define an overall anomaly score by summing absolute Z-scores of key metrics.

[17]:
```
summary_df['z_voltage'] = zscore(summary_df['voltage_mean'])
summary_df['is_voltage_anomaly'] = summary_df['z_voltage'].abs() > 1.5
voltage_anomalies = summary_df[summary_df['is_voltage_anomaly']]
print(f" Found {len(voltage_anomalies)} anomalous cycles:")
voltage_anomalies[['cycle_id', 'voltage_mean', 'z_voltage']]
```

```
Found 1 anomalous cycles:
```

[17]:

	cycle_id	voltage_mean	z_voltage
4	TripA25	377.404315	-1.617079

[18]:
```
#anomaly score for singular metric, ranking trips, and for continuous health␣
↪assessment
summary_df['anomaly_score'] = (
    summary_df['z_temp_max'].abs() +
    summary_df['z_current'].abs() +
    summary_df['z_voltage'].abs()
)
```

[19]:
```
#top anomalies
summary_df.sort_values('anomaly_score', ascending=False).head(5)[
    ['cycle_id', 'anomaly_score', 'z_temp_max', 'z_current', 'z_voltage']
]
```

[19]:

	cycle_id	anomaly_score	z_temp_max	z_current	z_voltage
11	TripA32	5.314756	1.875854	-2.098234	-1.340667
2	TripA23	3.453017	-1.617116	0.656751	1.179151
4	TripA25	3.138871	-0.452792	-1.069000	-1.617079
3	TripA24	3.133831	-0.840900	-1.562939	-0.729992
9	TripA30	2.994015	-0.452792	1.198493	1.342730

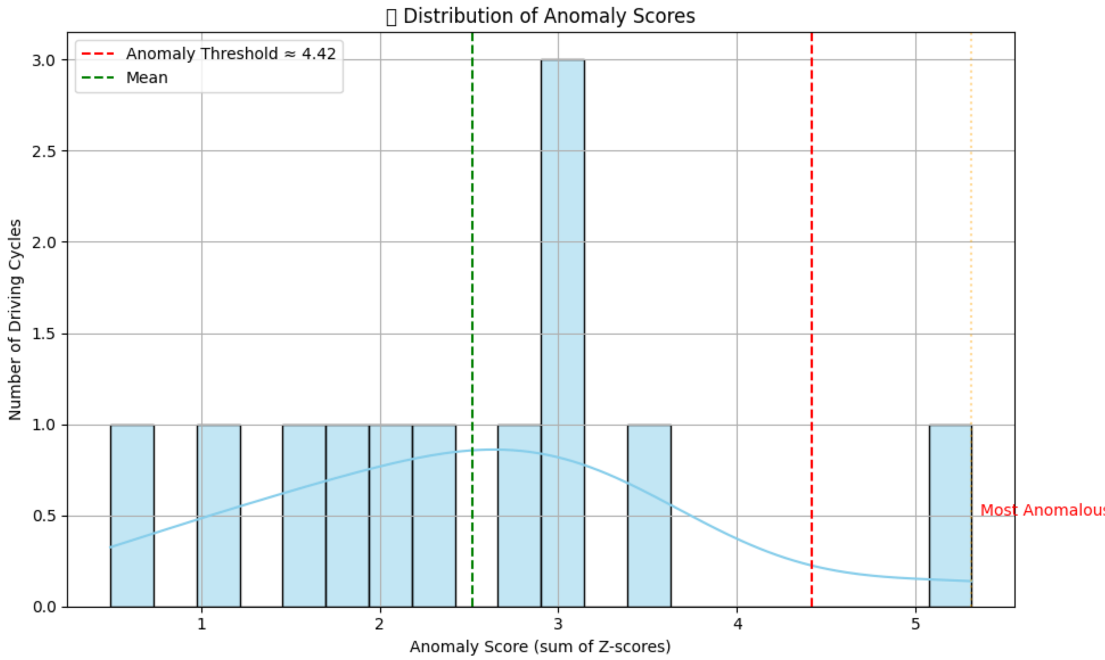
0.6 Visualization of Anomaly Score Distribution

We plot a histogram of anomaly scores and highlight the threshold for what counts as an outlier.

[20]:
```
import matplotlib.pyplot as plt

# Set up threshold
threshold = summary_df['anomaly_score'].mean() + 1.5 *␣
↪summary_df['anomaly_score'].std()

# Plot
plt.figure(figsize=(10, 6))
sns.histplot(summary_df['anomaly_score'], bins=20, kde=True, color='skyblue')
```

```
# Add threshold line
plt.axvline(threshold, color='red', linestyle='--', label=f'Anomaly Threshold ␣
↪{threshold:.2f}')
plt.axvline(summary_df['anomaly_score'].mean(), color='green', linestyle='--',␣
↪label='Mean')

for score in summary_df[summary_df['anomaly_score'] >␣
↪threshold]['anomaly_score']:
    plt.axvline(score, color='orange', linestyle=':', alpha=0.4)

max_score = summary_df['anomaly_score'].max()
plt.text(max_score + 0.05, 0.5, 'Most Anomalous', color='red')


# Titles and labels
plt.title("  Distribution of Anomaly Scores")
plt.xlabel("Anomaly Score (sum of Z-scores)")
plt.ylabel("Number of Driving Cycles")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
/var/folders/c_/jkdnc4n94cs06lzjk51cbzfm0000gn/T/ipykernel_23347/2240525402.py:2
7: UserWarning: Glyph 128202 (\N{BAR CHART}) missing from font(s) DejaVu Sans.
  plt.tight_layout()
/Users/yashkathiriya/Library/Python/3.9/lib/python/site-
packages/IPython/core/pylabtools.py:152: UserWarning: Glyph 128202 (\N{BAR
CHART}) missing from font(s) DejaVu Sans.
  fig.canvas.print_figure(bytes_io, **kw)
```



This chart visualizes the distribution of anomaly scores across 70 real-world electric vehicle driving cycles. Each anomaly score is computed as the sum of absolute Z-scores for three key battery health indicators: 1. Maximum battery temperature 2. Mean current draw 3. Mean battery voltage

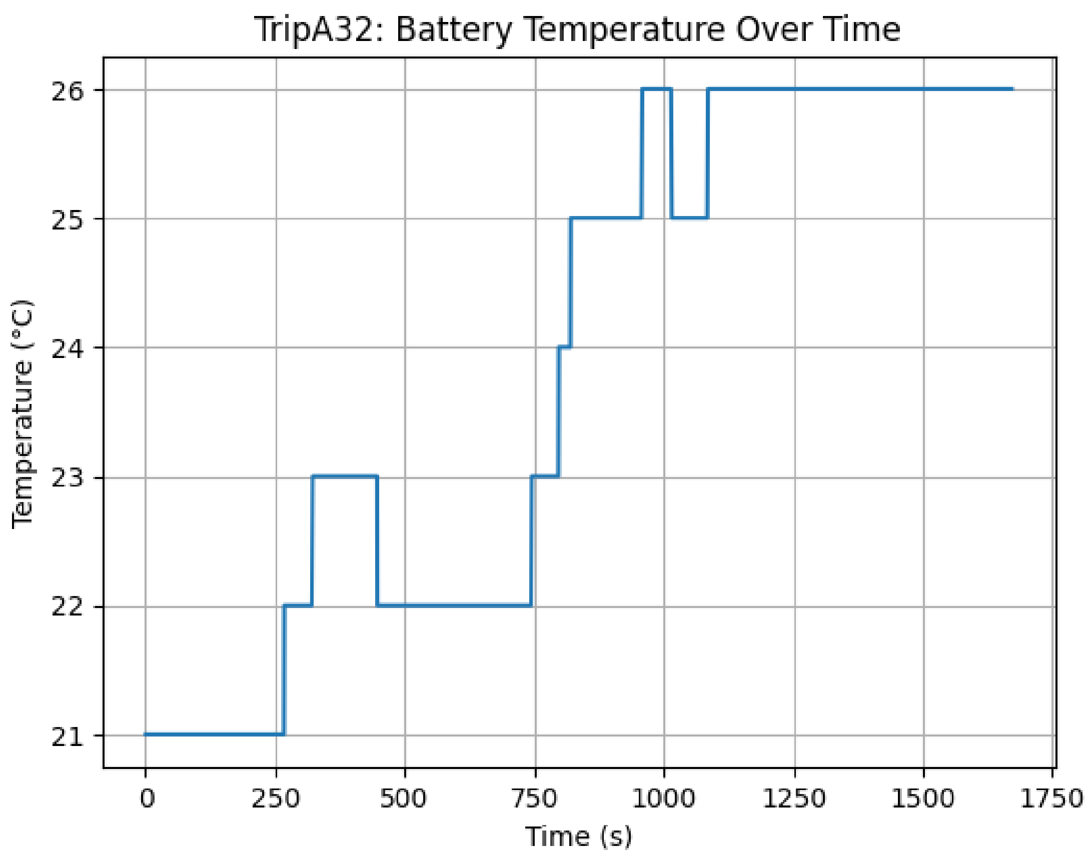
The green dashed line represents the mean anomaly score, while the red dashed line marks the anomaly threshold. Trips to the right of the red line are statistically unusual and may warrant diagnostic attention. The faint orange marker highlights the most anomalous trip — TripA32 — which exhibited significantly abnormal behavior across all three metrics.

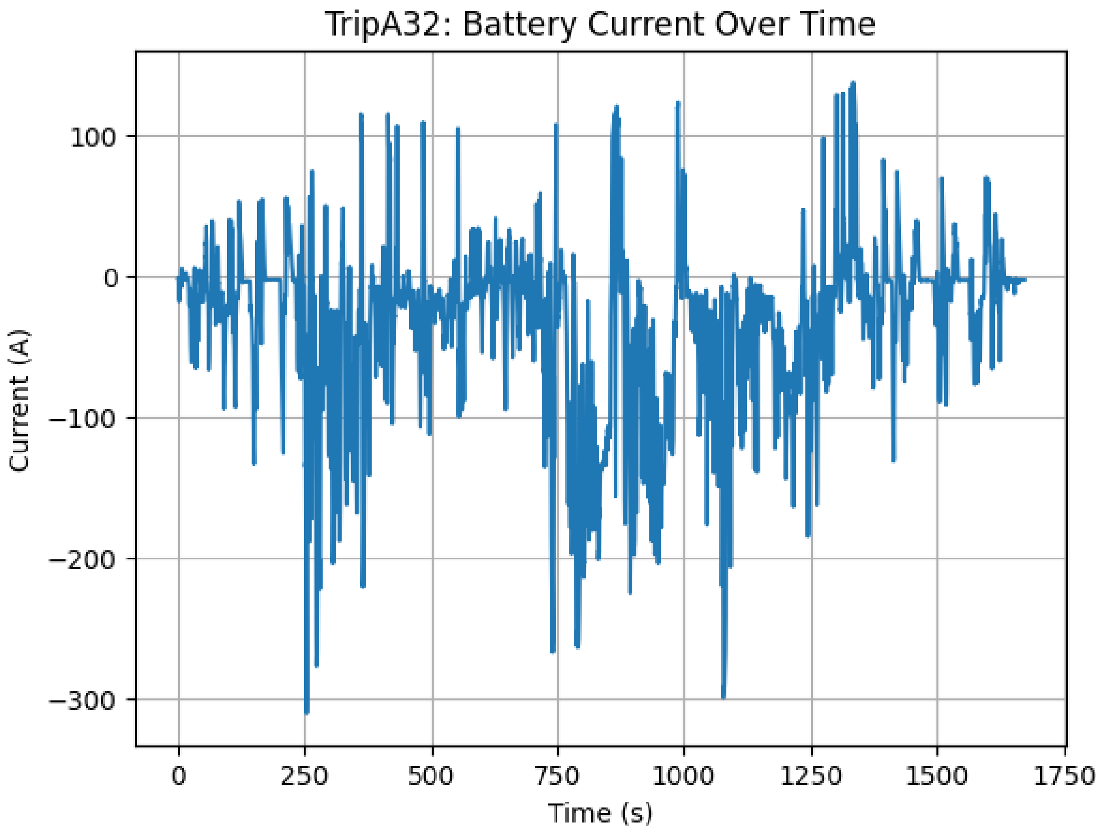
Let's focus on Trip 32 and look at what might have caused the anomalous results

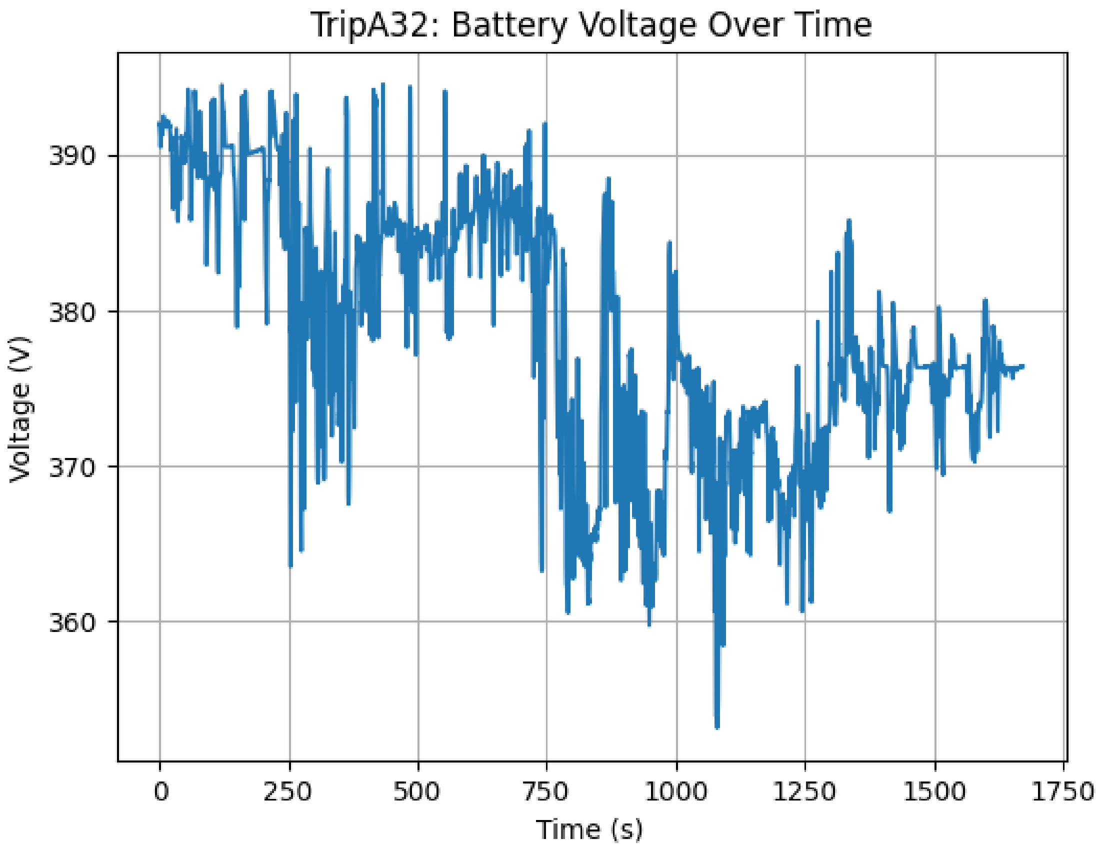
[21]:
```
df_trip32 = df_selected[df_selected['cycle_id'] == 'TripA32']

import matplotlib.pyplot as plt

# 1) Battery Temperature
plt.figure()
plt.plot(df_trip32['time_s'], df_trip32['battery_temperature_c'])
plt.title('TripA32: Battery Temperature Over Time')
plt.xlabel('Time (s)')
plt.ylabel('Temperature (°C)')
plt.grid(True)
plt.show()

# 2) Battery Current
plt.figure()
plt.plot(df_trip32['time_s'], df_trip32['battery_current_a'])
```

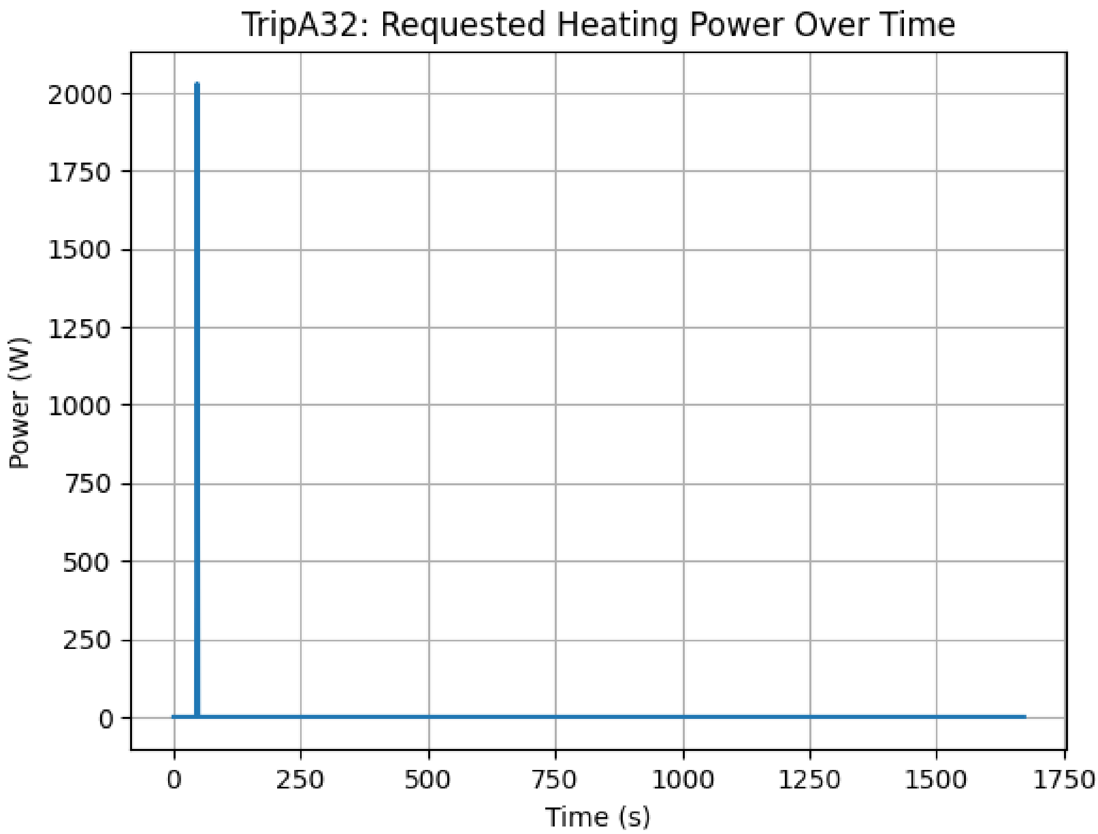
```
plt.title('TripA32: Battery Current Over Time')
plt.xlabel('Time (s)')
plt.ylabel('Current (A)')
plt.grid(True)
plt.show()

# 3) Battery Voltage
plt.figure()
plt.plot(df_trip32['time_s'], df_trip32['battery_voltage_v'])
plt.title('TripA32: Battery Voltage Over Time')
plt.xlabel('Time (s)')
plt.ylabel('Voltage (V)')
plt.grid(True)
plt.show()

# 4) Requested Heating Power
plt.figure()
plt.plot(df_trip32['time_s'], df_trip32['requested_heating_power_w'])
plt.title('TripA32: Requested Heating Power Over Time')
plt.xlabel('Time (s)')
plt.ylabel('Power (W)')
plt.grid(True)
plt.show()

# Define thresholds
thresholds = {
    'high_current': -60,        # A
    'low_voltage': 375,         # V
    'high_heating_power': 1000  # W
}

# flags for segments
df_trip32['flag_high_current'] = df_trip32['battery_current_a'] < thresholds['high_current']
df_trip32['flag_low_voltage'] = df_trip32['battery_voltage_v'] < thresholds['low_voltage']
df_trip32['flag_heater_on'] = df_trip32['requested_heating_power_w'] > thresholds['high_heating_power']

# Segment time ranges
high_current_range = df_trip32[df_trip32['flag_high_current']]['time_s']
low_voltage_range = df_trip32[df_trip32['flag_low_voltage']]['time_s']
heater_on_range = df_trip32[df_trip32['flag_heater_on']]['time_s']

print("High Current Period (A < -60):", high_current_range.min(), "-", high_current_range.max())
```

```
print("Low Voltage Period (V < 375):", low_voltage_range.min(), "-",
    low_voltage_range.max())
print("Heater On Period (Power > 1000W):", heater_on_range.min(), "-",
    heater_on_range.max())
```




TripA32: Battery Current Over Time
100
0
−100
−200
−300
Current (A)
0
250
500
750
1000
1250
1500
1750
Time (s)


TripA32: Battery Voltage Over Time
Voltage (V)
390
380
370
360
0
250
500
750
1000
1250
1500
1750
Time (s)



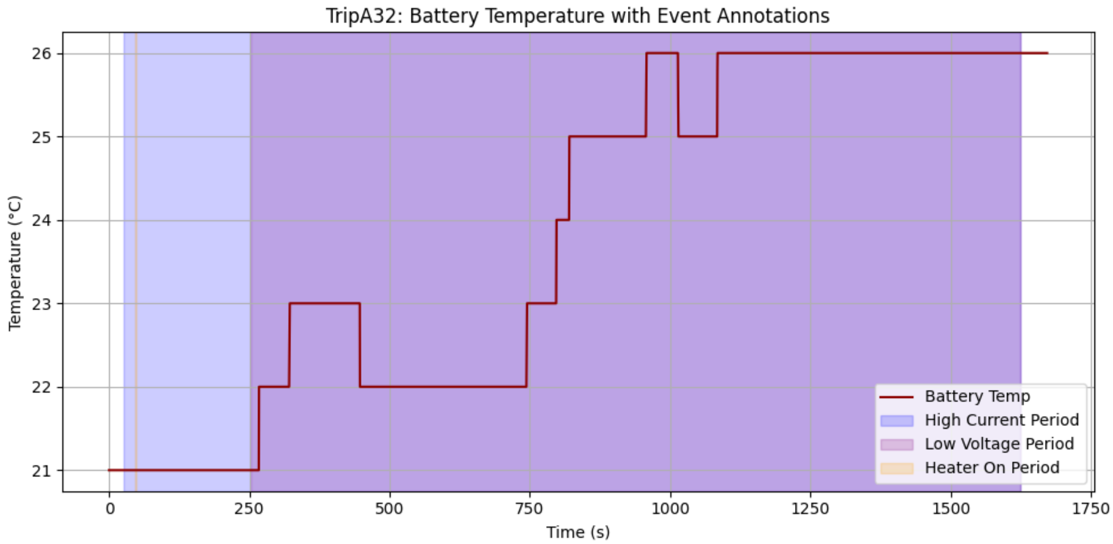

```
High Current Period (A < -60): 26.4 - 1623.4
Low Voltage Period (V < 375): 253.0 - 1625.0
Heater On Period (Power > 1000W): 45.8 - 47.7
```

```
/var/folders/c_/jkdnc4n94cs06lzjk51cbzfm0000gn/T/ipykernel_23347/3528339944.py:4
9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_trip32['flag_high_current'] = df_trip32['battery_current_a'] <
thresholds['high_current']
/var/folders/c_/jkdnc4n94cs06lzjk51cbzfm0000gn/T/ipykernel_23347/3528339944.py:5
0: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_trip32['flag_low_voltage'] = df_trip32['battery_voltage_v'] <
```

```
thresholds['low_voltage']
/var/folders/c_/jkdnc4n94cs06lzjk51cbzfm0000gn/T/ipykernel_23347/3528339944.py:5
1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_trip32['flag_heater_on'] = df_trip32['requested_heating_power_w'] >
thresholds['high_heating_power']
```

[22]:

```python
plt.figure(figsize=(10, 5))
plt.plot(df_trip32['time_s'], df_trip32['battery_temperature_c'],␣
 ↪label='Battery Temp', color='darkred')

# Overlays
if not high_current_range.empty:
    plt.axvspan(high_current_range.min(), high_current_range.max(),␣
 ↪color='blue', alpha=0.2, label='High Current Period')
if not low_voltage_range.empty:
    plt.axvspan(low_voltage_range.min(), low_voltage_range.max(),␣
 ↪color='purple', alpha=0.2, label='Low Voltage Period')
if not heater_on_range.empty:
    plt.axvspan(heater_on_range.min(), heater_on_range.max(), color='orange',␣
 ↪alpha=0.2, label='Heater On Period')

plt.title('TripA32: Battery Temperature with Event Annotations')
plt.xlabel('Time (s)')
plt.ylabel('Temperature (°C)')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

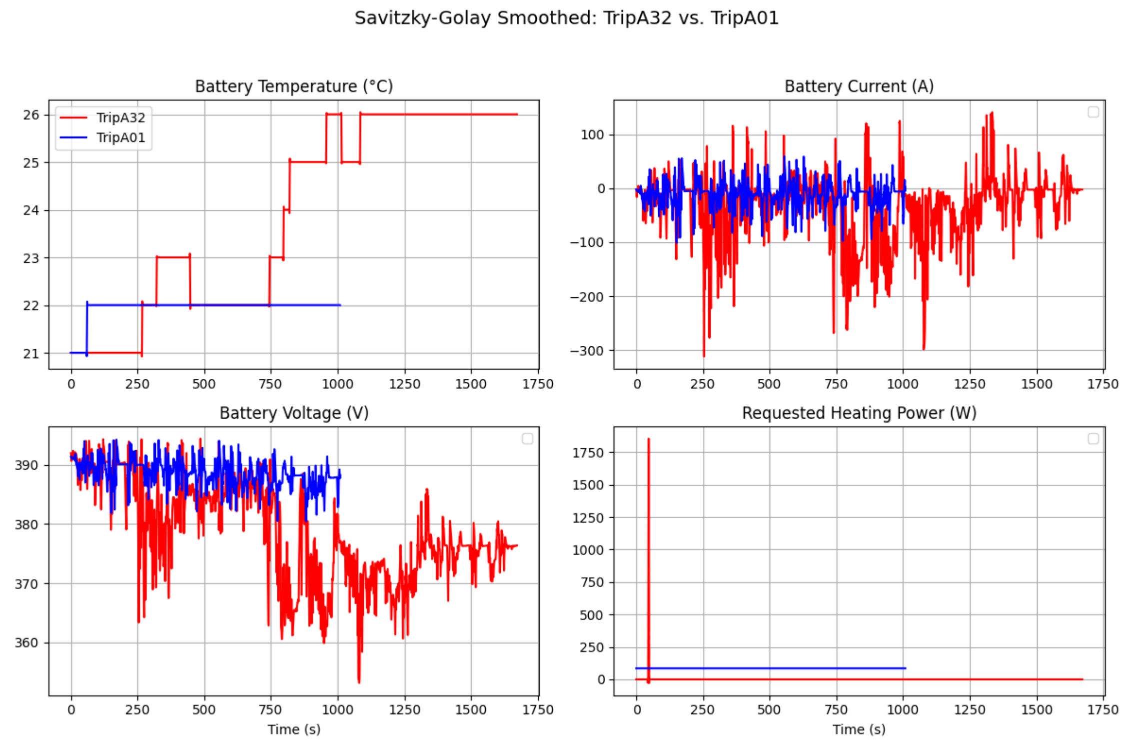


TripA32 exhibits a distinct thermal anomaly characterized by a combination of compounding stressors. The drive begins with an early heater activation event (0–~30s), causing an immediate thermal load. Shortly after, a sustained period of high current draw ($_{30–}$900s) coincides with a steady increase in battery temperature. This suggests elevated energy demand and potential strain on the battery's cooling system. Midway through the trip ($_{250–}$1670s), a prolonged voltage drop below 375V indicates possible power delivery inefficiencies or stress under load, even as heating power subsides. By this stage, battery temperature has plateaued at its maximum (26°C), failing to dissipate effectively. The compounding effects of thermal load, electrical draw, and voltage instability likely explain the high anomaly score of TripA32 — the highest among all recorded cycles.

[23]:
```
from scipy.signal import savgol_filter
import matplotlib.pyplot as plt

# Filter the two trips from your full dataset
df_trip32 = df_selected[df_selected['cycle_id'] == 'TripA32'].copy()
df_typical = df_selected[df_selected['cycle_id'] == 'TripA01'].copy()

# Apply Savitzky-Golay smoothing
window = 21  # must be odd
poly = 2     # quadratic fit

for col in ['battery_temperature_c', 'battery_current_a', 'battery_voltage_v',␣
↪'requested_heating_power_w']:
    df_trip32[f'smooth_{col}'] = savgol_filter(df_trip32[col], window, poly)
    df_typical[f'smooth_{col}'] = savgol_filter(df_typical[col], window, poly)

# Plot 2x2 subplot grid
fig, axs = plt.subplots(2, 2, figsize=(12, 8))
fig.suptitle("Savitzky-Golay Smoothed: TripA32 vs. TripA01", fontsize=14)
```

```
# Battery Temperature
axs[0, 0].plot(df_trip32['time_s'], df_trip32['smooth_battery_temperature_c'],␣
↪color='red', label='TripA32')
axs[0, 0].plot(df_typical['time_s'],␣
↪df_typical['smooth_battery_temperature_c'], color='blue', label='TripA01')
axs[0, 0].set_title('Battery Temperature (°C)')
axs[0, 0].grid(True)

# Battery Current
axs[0, 1].plot(df_trip32['time_s'], df_trip32['smooth_battery_current_a'],␣
↪color='red')
axs[0, 1].plot(df_typical['time_s'], df_typical['smooth_battery_current_a'],␣
↪color='blue')
axs[0, 1].set_title('Battery Current (A)')
axs[0, 1].grid(True)

# Battery Voltage
axs[1, 0].plot(df_trip32['time_s'], df_trip32['smooth_battery_voltage_v'],␣
↪color='red')
axs[1, 0].plot(df_typical['time_s'], df_typical['smooth_battery_voltage_v'],␣
↪color='blue')
axs[1, 0].set_title('Battery Voltage (V)')
axs[1, 0].set_xlabel('Time (s)')
axs[1, 0].grid(True)

# Requested Heating Power
axs[1, 1].plot(df_trip32['time_s'],␣
↪df_trip32['smooth_requested_heating_power_w'], color='red')
axs[1, 1].plot(df_typical['time_s'],␣
↪df_typical['smooth_requested_heating_power_w'], color='blue')
axs[1, 1].set_title('Requested Heating Power (W)')
axs[1, 1].set_xlabel('Time (s)')
axs[1, 1].grid(True)

# Add legends
for ax in axs.flat:
    ax.legend()

plt.tight_layout(rect=[0, 0, 1, 0.95])
plt.show()
```

```
/var/folders/c_/jkdnc4n94cs06lzjk51cbzfm0000gn/T/ipykernel_23347/4130124178.py:4
8: UserWarning: No artists with labels found to put in legend.  Note that
artists whose label start with an underscore are ignored when legend() is called
with no argument.
  ax.legend()
```



0.7 Deep Dive into TripA32

We examine TripA32, which was flagged as highly anomalous, and visualize its temperature, current, and voltage over time.

TripA32 experiences thermal buildup, aggressive current draw, voltage degradation, and a heater spike, all contributing to its highest anomaly score. These deviations, not seen in TripA01, reinforce the validity of TripA32 as a high-risk or high-load scenario for battery performance monitoring.

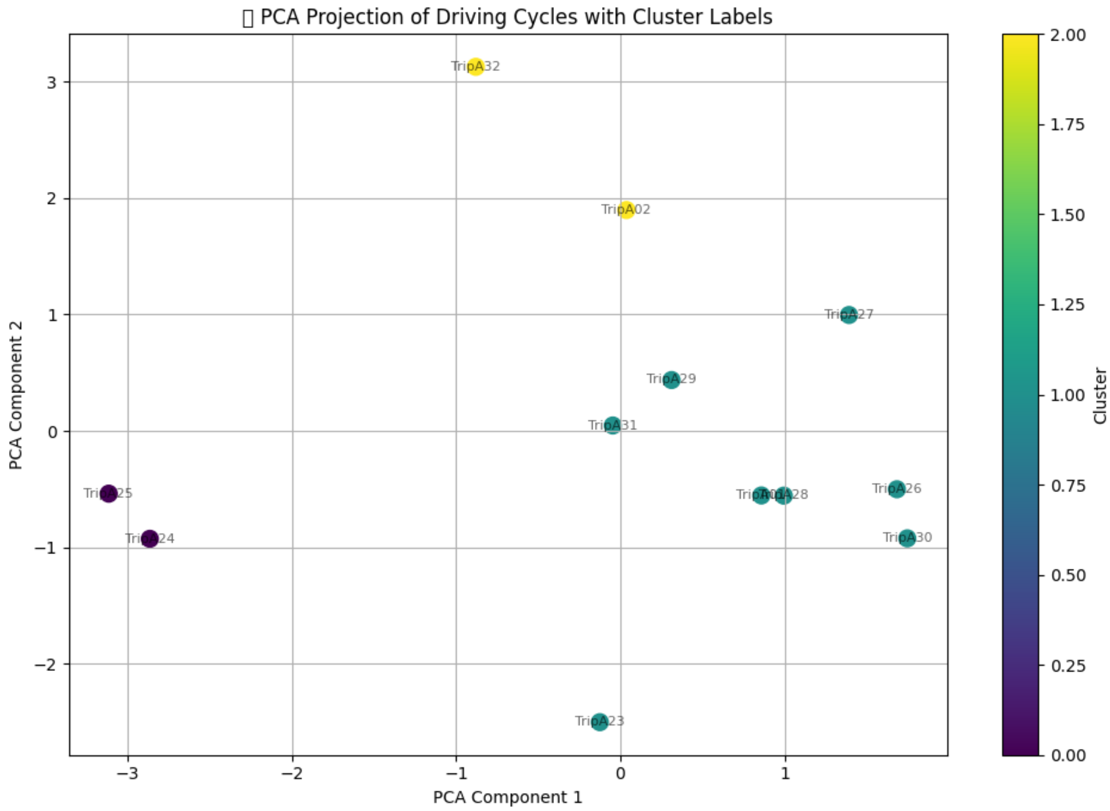
Clustering driving patterns

[24]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

# Features to cluster on
features = summary_df[[
    'trip_duration_s',
    'temp_max',
    'current_mean',
    'voltage_mean',
    'heating_power_mean'
]]
```

```python
# Normalize
scaler = StandardScaler()
X_scaled = scaler.fit_transform(features)
```

[25]:
```python
# Apply PCA for visualization (after scaling)
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

# Run KMeans clustering
kmeans = KMeans(n_clusters=3, random_state=42)
clusters = kmeans.fit_predict(X_scaled)

# Add results to summary_df
summary_df['cluster'] = clusters
summary_df['pca1'] = X_pca[:, 0]
summary_df['pca2'] = X_pca[:, 1]

# Plot with cycle IDs
plt.figure(figsize=(10, 7))
scatter = plt.scatter(summary_df['pca1'], summary_df['pca2'],␣
↪c=summary_df['cluster'], cmap='viridis', s=100)

# Annotate each point with its cycle ID
for _, row in summary_df.iterrows():
    plt.text(row['pca1'], row['pca2'], row['cycle_id'], fontsize=8,␣
↪ha='center', va='center', alpha=0.6)

plt.title("  PCA Projection of Driving Cycles with Cluster Labels")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.colorbar(scatter, label="Cluster")
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
/var/folders/c_/jkdnc4n94cs06lzjk51cbzfm0000gn/T/ipykernel_23347/1586034699.py:2
7: UserWarning: Glyph 128269 (\N{LEFT-POINTING MAGNIFYING GLASS}) missing from
font(s) DejaVu Sans.
  plt.tight_layout()
/Users/yashkathiriya/Library/Python/3.9/lib/python/site-
packages/IPython/core/pylabtools.py:152: UserWarning: Glyph 128269 (\N{LEFT-
POINTING MAGNIFYING GLASS}) missing from font(s) DejaVu Sans.
  fig.canvas.print_figure(bytes_io, **kw)
```

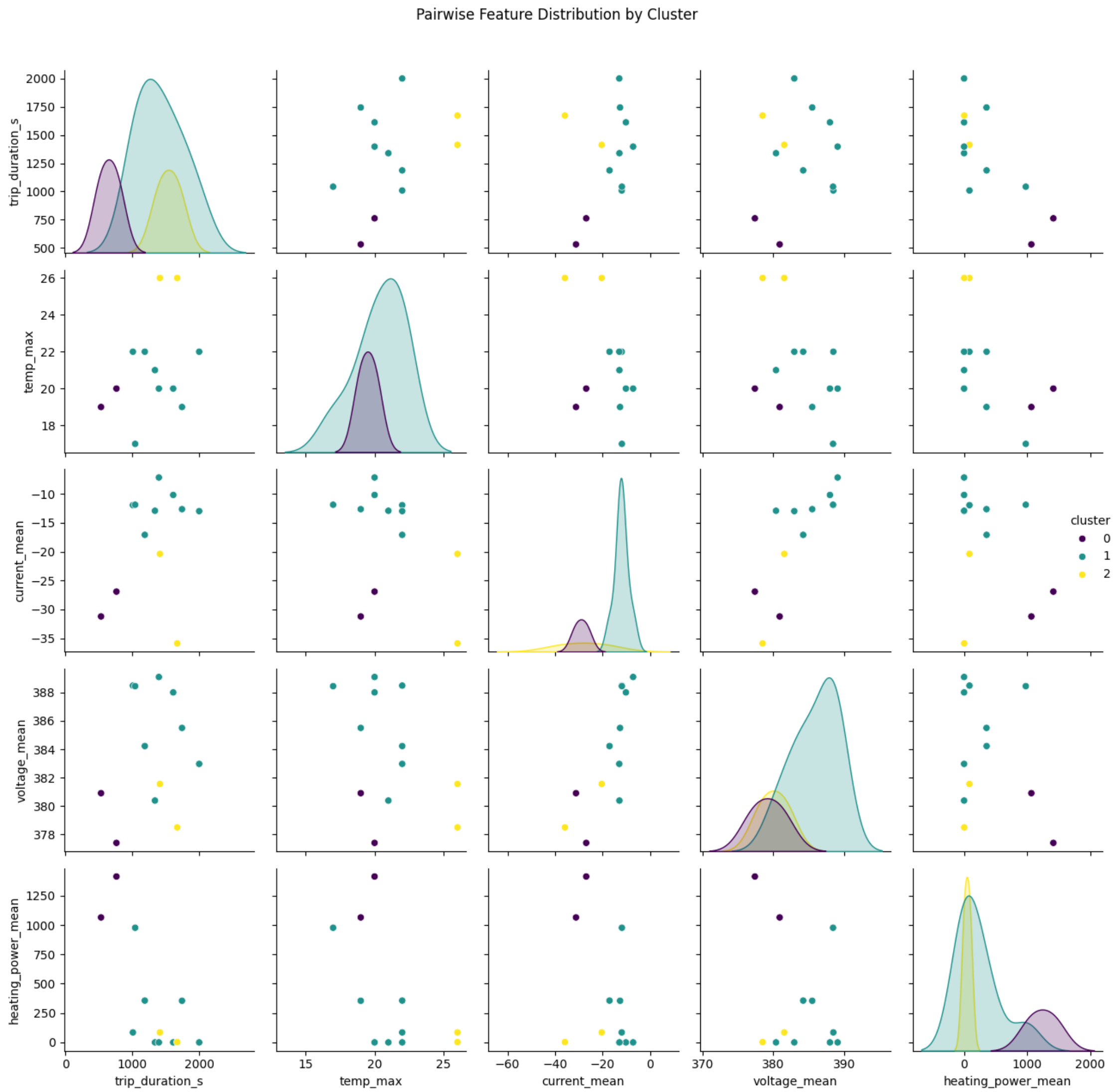


[26]:
```
summary_df.groupby('cluster')[[
    'trip_duration_s', 'temp_max', 'current_mean', 'voltage_mean',␣
 ↪'heating_power_mean'
]].mean()
```

[26]:
```
         trip_duration_s  temp_max  current_mean  voltage_mean  \
cluster
0               647.3500    19.500    -29.058264    379.155620
1              1416.3125    20.375    -12.108190    385.888782
2              1542.5000    26.000    -28.126270    380.024774

         heating_power_mean
cluster
0               1239.742862
1                221.690352
2                 43.715226
```

[27]:
```
sns.pairplot(summary_df, vars=[
    'trip_duration_s', 'temp_max', 'current_mean', 'voltage_mean',␣
 ↪'heating_power_mean'
], hue='cluster', palette='viridis')
```

```
plt.suptitle("Pairwise Feature Distribution by Cluster", y=1.02)
plt.tight_layout()
plt.show()
```



0.8 PCA and Cluster Driving Cycles

We reduce dimensionality with PCA and apply KMeans to identify similar usage patterns.

[28]:
```
# Mean values per cluster

cluster_means = summary_df.groupby('cluster')[
    ['trip_duration_s', 'temp_max', 'current_mean', 'voltage_mean',␣
 ↪'heating_power_mean']
```

```
].mean()
print(cluster_means)
```

```
         trip_duration_s  temp_max  current_mean  voltage_mean  \
cluster
0               647.3500    19.500    -29.058264    379.155620
1              1416.3125    20.375    -12.108190    385.888782
2              1542.5000    26.000    -28.126270    380.024774

         heating_power_mean
cluster
0               1239.742862
1                221.690352
2                 43.715226
```

[29]:

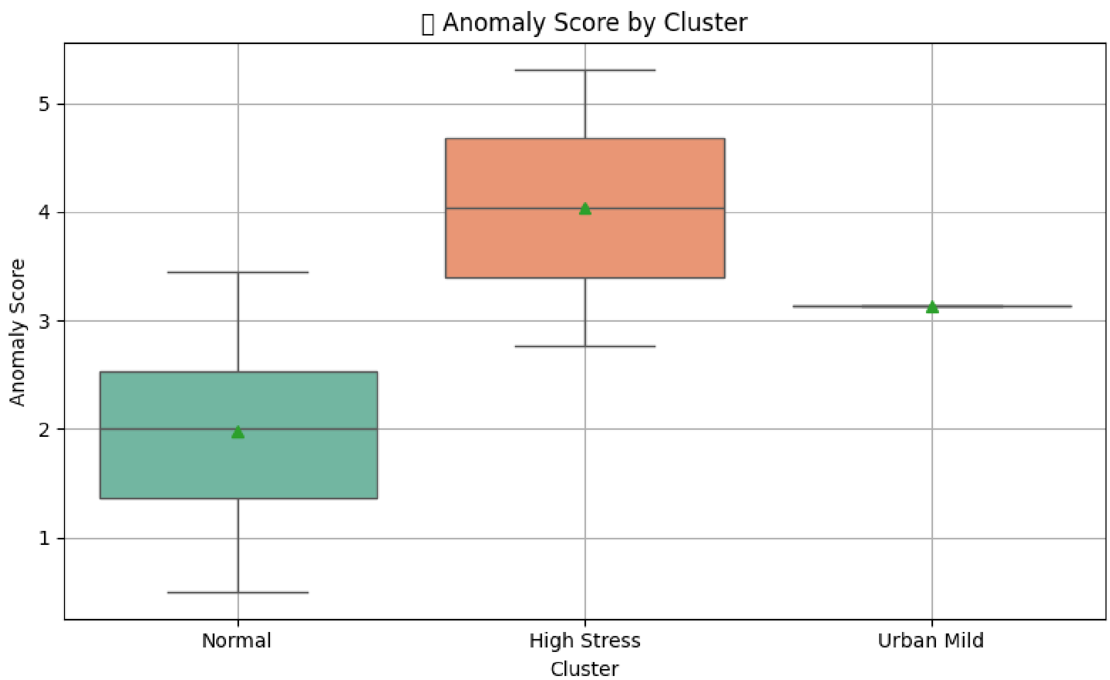
```
cluster_labels = {
    0: 'Urban Mild',
    1: 'Normal',
    2: 'High Stress'
}
summary_df['cluster_label'] = summary_df['cluster'].map(cluster_labels)
```

[30]:

```
plt.figure(figsize=(8, 5))
sns.boxplot(
    x='cluster_label',
    y='anomaly_score',
    data=summary_df,
    palette='Set2',
    showmeans=True  # will add a dot for single point
)
plt.title("  Anomaly Score by Cluster")
plt.xlabel("Cluster")
plt.ylabel("Anomaly Score")
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
/var/folders/c_/jkdnc4n94cs06lzjk51cbzfm0000gn/T/ipykernel_23347/566446037.py:2:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(
/var/folders/c_/jkdnc4n94cs06lzjk51cbzfm0000gn/T/ipykernel_23347/566446037.py:13
: UserWarning: Glyph 128202 (\N{BAR CHART}) missing from font(s) DejaVu Sans.
  plt.tight_layout()
```

```
/Users/yashkathiriya/Library/Python/3.9/lib/python/site-
packages/IPython/core/pylabtools.py:152: UserWarning: Glyph 128202 (\N{BAR
CHART}) missing from font(s) DejaVu Sans.
  fig.canvas.print_figure(bytes_io, **kw)
```



While most cycles grouped into 'Normal' or 'High Stress', the algorithm isolated one cycle into a distinct Urban Mild cluster — characterized by short duration and low power demands. Though limited in sample size, this reflects a low-stress urban usage profile.

0.9 Interactive Anomaly Dashboard

To make this project interactive, I built a Streamlit dashboard that allows users to: - Upload a driving cycle summary (e.g., `cycle_summary.csv`) - Select any trip by ID - View anomaly scores calculated using Z-score aggregation - Get an instant flag for potentially anomalous behavior

How to run: 1. Install Streamlit: `pip install streamlit` 2. Run the app: `streamlit run battery_dashboard.py` 3. Upload your CSV file and explore each trip!

This dashboard demonstrates how the analysis could be integrated into a diagnostic tool or telemetry dashboard for engineers or fleet managers.

0.10 Takeaway

This project provided a comprehensive framework for identifying anomalous electric vehicle battery behavior across real-world driving cycles. By combining statistical outlier detection with unsupervised clustering, I was able to surface usage patterns linked to elevated thermal load, voltage instability, and high current draw — all of which may contribute to long-term battery stress. The system flags early behavioral indicators (e.g., temperature spikes, excessive heating power, sharp voltage drops) that are known precursors to degradation and potential failure modes.