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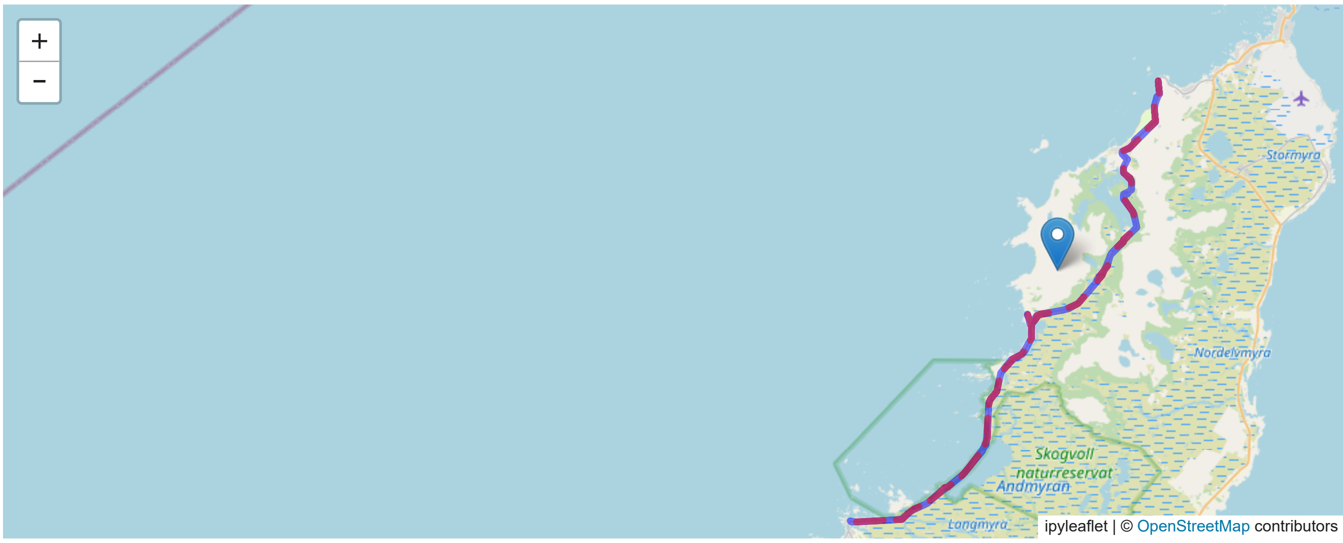
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import pandas as pd
from ipyleaflet import Map, Marker, AntPath

# Load the NMEA data
nmea_data = pd.read_csv('/content/drive/MyDrive/nmea.csv')

# Display the first few rows to check the structure
print(nmea_data.head())

# Clean column names to remove leading/trailing spaces
nmea_data.columns = nmea_data.columns.str.strip()

# Extract coordinates and plot
latitudes = nmea_data['lat']
longitudes = nmea_data['lon']
coordinates = list(zip(latitudes, longitudes))

# Initialize the map centered at the experiment area
from ipyleaflet import Map, Marker, AntPath
experiment_center = (latitudes.mean(), longitudes.mean())  # Centering on the average position
m = Map(center=experiment_center, zoom=10)

# Add the path
ant_path = AntPath(locations=coordinates, delay=1000, color='blue', pulse_color='red')
m.add_layer(ant_path)

# Add a marker at the experiment center
marker = Marker(location=experiment_center, draggable=False)
m.add_layer(marker)

# Display the map
m
```




```
           timestamp        lat        lon  height
0  2024-09-10T090057  69.212358  15.858596     4.2
1  2024-09-10T090058  69.212358  15.858596     4.3
2  2024-09-10T090059  69.212360  15.858596     4.4
3  2024-09-10T090100  69.212360  15.858595     4.5
4  2024-09-10T090101  69.212361  15.858596     4.7
```

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```
print("Missing values in each column:")
print(nmea_data.isnull().sum())
```

```
# Check for duplicate rows
print("\nNumber of duplicate rows:")
print(nmea_data.duplicated().sum())

# Display the data types of each column
print("\nData types in the dataset:")
print(nmea_data.dtypes)

# Check for anomalies in latitude and longitude ranges
print("\nLatitude range: ", nmea_data['lat'].min(), "-", nmea_data['lat'].max())
print("Longitude range: ", nmea_data['lon'].min(), "-", nmea_data['lon'].max())
```

```
Missing values in each column:
timestamp    0
lat          0
lon          0
height       0
dtype: int64

Number of duplicate rows:
0

Data types in the dataset:
timestamp     object
lat          float64
lon          float64
height       float64
dtype: object

Latitude range:  69.136349 - 69.297479
Longitude range:  15.676663 - 15.995005
```

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```
import pandas as pd

# Load the AGC data
agc_data = pd.read_csv('/content/drive/MyDrive/agc.csv')

# Clean column names
agc_data.columns = agc_data.columns.str.strip()

# Drop columns with 100% missing values
agc_data_cleaned = agc_data.dropna(axis=1, how='all')

# Select relevant columns for jamming detection
relevant_columns = ['DriftNanosPerSecond', 'DriftUncertaintyNanosPerSecond']
agc_data_cleaned = agc_data_cleaned[relevant_columns]

# Convert relevant columns to numeric
for col in relevant_columns:
    agc_data_cleaned[col] = pd.to_numeric(agc_data_cleaned[col], errors='coerce')

# Handle missing values
for col in relevant_columns:
    agc_data_cleaned[col].fillna(agc_data_cleaned[col].median(), inplace=True)

# Save the cleaned data
agc_data_cleaned.to_csv('agc_cleaned.csv', index=False)

print("Cleaned AGC data:")
print(agc_data_cleaned.info())
```

```
<ipython-input-3-19c6929f8fb6>:4: DtypeWarning: Columns (1,2,3,4,5,6,7,8,9,10,11,12,13) have mixed types. Specify dtype option on ir
  agc_data = pd.read_csv('/content/drive/MyDrive/agc.csv')
<ipython-input-3-19c6929f8fb6>:22: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained ass
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col


  agc_data_cleaned[col].fillna(agc_data_cleaned[col].median(), inplace=True)
Cleaned AGC data:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 84273 entries, 0 to 84272
Data columns (total 2 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   DriftNanosPerSecond             84273 non-null  float64
 1   DriftUncertaintyNanosPerSecond  84273 non-null  float64
dtypes: float64(2)
memory usage: 1.3 MB
None
```

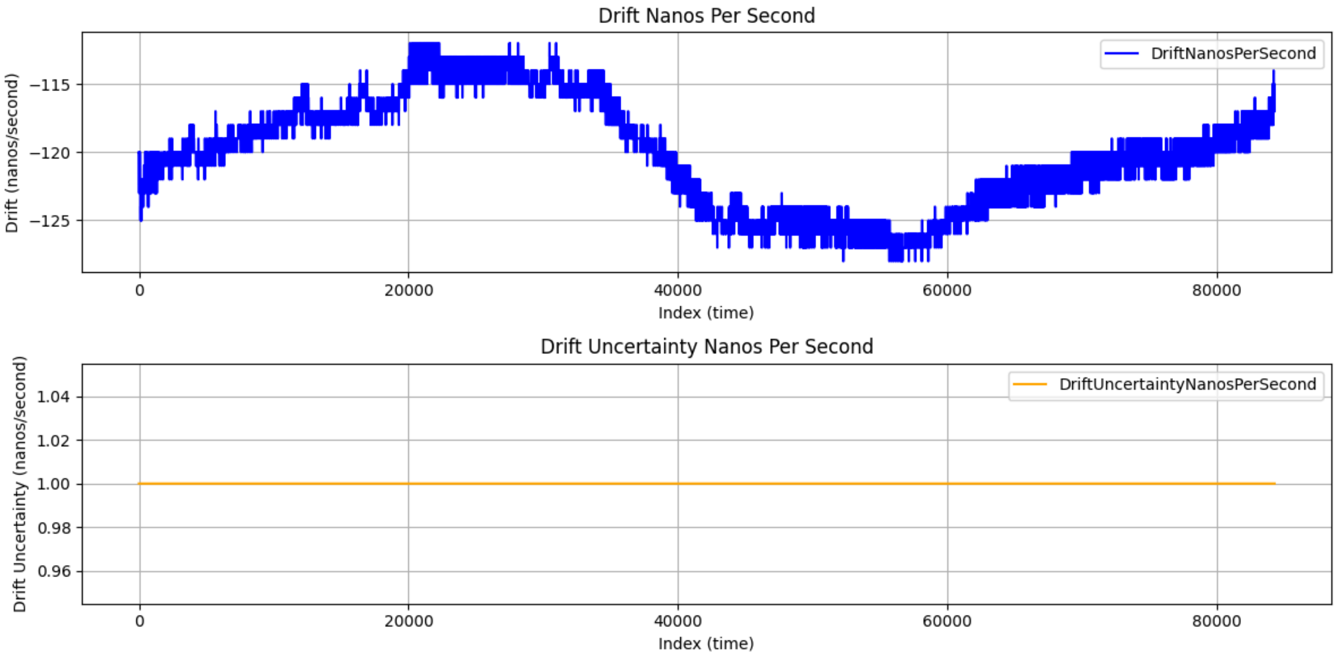
```
import matplotlib.pyplot as plt

# Plot trends for DriftNanosPerSecond and DriftUncertaintyNanosPerSecond
plt.figure(figsize=(12, 6))

# Plot DriftNanosPerSecond
plt.subplot(2, 1, 1)
plt.plot(agc_data_cleaned['DriftNanosPerSecond'], label='DriftNanosPerSecond', color='blue')
plt.title('Drift Nanos Per Second')
plt.xlabel('Index (time)')
plt.ylabel('Drift (nanos/second)')
plt.grid()
plt.legend()

# Plot DriftUncertaintyNanosPerSecond
plt.subplot(2, 1, 2)
plt.plot(agc_data_cleaned['DriftUncertaintyNanosPerSecond'], label='DriftUncertaintyNanosPerSecond', color='orange')
plt.title('Drift Uncertainty Nanos Per Second')
plt.xlabel('Index (time)')
plt.ylabel('Drift Uncertainty (nanos/second)')
plt.grid()
plt.legend()

plt.tight_layout()
plt.show()
```



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```
# Calculate rate of change (difference between successive values)
agc_data_cleaned['Drift_RateOfChange'] = agc_data_cleaned['DriftNanosPerSecond'].diff()
agc_data_cleaned['Uncertainty_RateOfChange'] = agc_data_cleaned['DriftUncertaintyNanosPerSecond'].diff()

# Calculate rolling averages (window size: 10)
agc_data_cleaned['Drift_RollingMean'] = agc_data_cleaned['DriftNanosPerSecond'].rolling(window=10).mean()
agc_data_cleaned['Uncertainty_RollingMean'] = agc_data_cleaned['DriftUncertaintyNanosPerSecond'].rolling(window=10).mean()

# Calculate Z-scores for anomaly detection
agc_data_cleaned['Drift_ZScore'] = (agc_data_cleaned['DriftNanosPerSecond'] - agc_data_cleaned['DriftNanosPerSecond'].mean()) / agc_data
agc_data_cleaned['Uncertainty_ZScore'] = (agc_data_cleaned['DriftUncertaintyNanosPerSecond'] - agc_data_cleaned['DriftUncertaintyNanosPe

# Preview engineered features
print(agc_data_cleaned.head())
```

```
   DriftNanosPerSecond  DriftUncertaintyNanosPerSecond  Drift_RateOfChange  \
0               -120.0                             1.0                 NaN
1               -120.0                             1.0                 0.0
2               -120.0                             1.0                 0.0
3               -120.0                             1.0                 0.0
4               -120.0                             1.0                 0.0

   Uncertainty_RateOfChange  Drift_RollingMean  Uncertainty_RollingMean  \
0                       NaN                NaN                      NaN
1                       0.0                NaN                      NaN
2                       0.0                NaN                      NaN
3                       0.0                NaN                      NaN
4                       0.0                NaN                      NaN

   Drift_ZScore  Uncertainty_ZScore
0     -0.006434                 NaN
1     -0.006434                 NaN
2     -0.006434                 NaN
3     -0.006434                 NaN
4     -0.006434                 NaN
```

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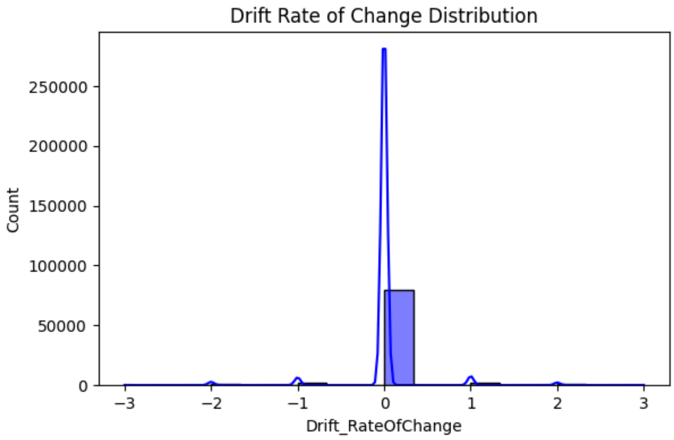
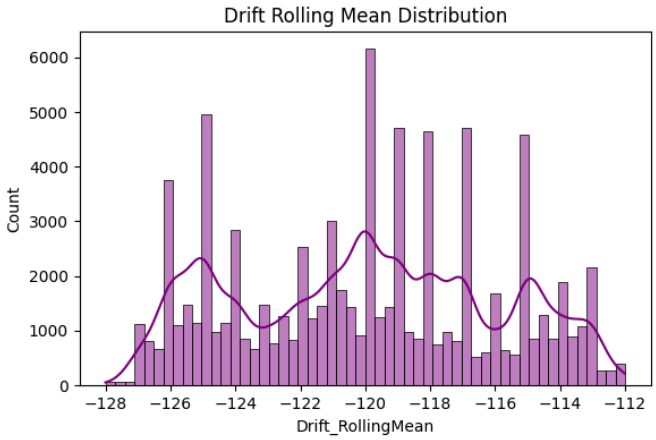
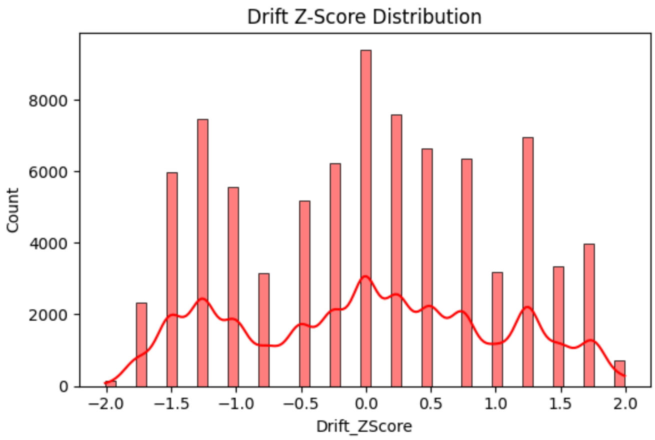
```
# Forward-fill or drop rows with incomplete rolling mean calculations
agc_data_cleaned['Drift_RollingMean'] = agc_data_cleaned['Drift_RollingMean'].fillna(agc_data_cleaned['DriftNanosPerSecond'])
agc_data_cleaned['Uncertainty_RollingMean'] = agc_data_cleaned['Uncertainty_RollingMean'].fillna(agc_data_cleaned['DriftUncertaintyNanos

# Replace NaN Z-scores with 0
agc_data_cleaned['Drift_ZScore'] = agc_data_cleaned['Drift_ZScore'].fillna(0)
agc_data_cleaned['Uncertainty_ZScore'] = agc_data_cleaned['Uncertainty_ZScore'].fillna(0)
```

```
import seaborn as sns
import matplotlib.pyplot as plt

# Plot histograms for new features
plt.figure(figsize=(12, 8))

plt.subplot(2, 2, 1)
sns.histplot(agc_data_cleaned['Drift_RateOfChange'], kde=True, color='blue')
plt.title('Drift Rate of Change Distribution')

plt.subplot(2, 2, 2)
sns.histplot(agc_data_cleaned['Drift_RollingMean'], kde=True, color='purple')
plt.title('Drift Rolling Mean Distribution')

plt.subplot(2, 2, 3)
sns.histplot(agc_data_cleaned['Drift_ZScore'], kde=True, color='red')
plt.title('Drift Z-Score Distribution')


plt.tight_layout()
plt.show()
```







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```
import pandas as pd

# Load the odometer files (update the file paths as needed)
file1 = pd.read_csv('/content/drive/MyDrive/odometer_2024-09-10T1407.log', sep='\t', header=None)
file2 = pd.read_csv('/content/drive/MyDrive/odometer_2024-09-10T1429.log', sep='\t', header=None)

# Concatenate the files into a single DataFrame
odometer_data = pd.concat([file1, file2], ignore_index=True)

# Step 1: Extract and clean the Timestamp and Speed columns

# Extract timestamp from the first column by splitting the text at the first comma
odometer_data['Timestamp'] = odometer_data[0].str.split(',', expand=True)[0]

# Extract the correct speed field (third segment after splitting by comma)
odometer_data['Speed'] = odometer_data[0].str.split(',', expand=True)[2].str.strip()

# Remove irrelevant text like "kilometer_per_hour" and convert to numeric
odometer_data['Speed'] = odometer_data['Speed'].str.extract('([0-9.]+)').astype(float)

# Step 2: Convert the cleaned Timestamp to datetime format
odometer_data['Timestamp'] = pd.to_datetime(odometer_data['Timestamp'], unit='s', errors='coerce')

# Drop rows with invalid timestamps or speeds
odometer_data = odometer_data.dropna(subset=['Timestamp', 'Speed'])

# Preview the cleaned data
print("\nCleaned Odometer Data:")
print(odometer_data.head())
```

```
Cleaned Odometer Data:
                                                    0  \
1  1725970102.516497 , 30878.6 , 0.0 kilometer_pe...
2  1725970102.699386 , 30878.6 , 0.0 kilometer_pe...
```

```
3  1725970102.847159 , 30878.6 , 0.0 kilometer_pe...
4  1725970102.99026 , 30878.6 , 0.0 kilometer_per...
5  1725970103.136788 , 30878.6 , 0.0 kilometer_pe...

                      Timestamp  Speed
1 2024-09-10 12:08:22.516496897    0.0
2 2024-09-10 12:08:22.699385881    0.0
3 2024-09-10 12:08:22.847158909    0.0
4 2024-09-10 12:08:22.990259886    0.0
5 2024-09-10 12:08:23.136787891    0.0
<ipython-input-8-653f65cfc32a>:22: FutureWarning: The behavior of 'to_datetime' with 'unit' when parsing strings is deprecated. In a
  odometer_data['Timestamp'] = pd.to_datetime(odometer_data['Timestamp'], unit='s', errors='coerce')
```

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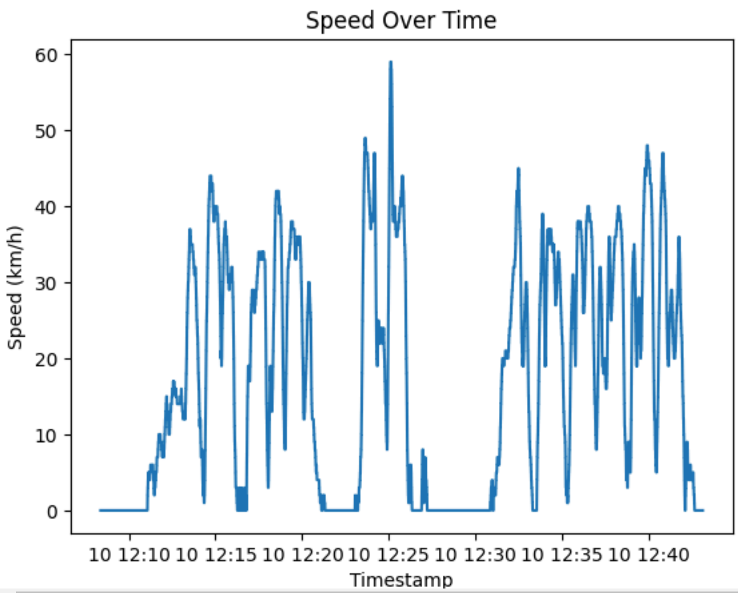
```
import matplotlib.pyplot as plt

plt.plot(odometer_data['Timestamp'], odometer_data['Speed'])
plt.xlabel('Timestamp')
plt.ylabel('Speed (km/h)')
plt.title('Speed Over Time')
plt.show()
```




```
import pandas as pd


# Preview the column
print("\nPreview of `utcTimeMillis` Column:")
print(agc_data['utcTimeMillis'].head())

# Convert to numeric directly, handling invalid rows
agc_data['utcTimeMillis'] = pd.to_numeric(agc_data['utcTimeMillis'], errors='coerce')

# Drop rows with invalid utcTimeMillis
invalid_rows = agc_data[agc_data['utcTimeMillis'].isna()]
print(f"Number of invalid rows removed: {len(invalid_rows)}")
agc_data = agc_data.dropna(subset=['utcTimeMillis']).copy()

# Convert to datetime
agc_data['Timestamp'] = pd.to_datetime(agc_data['utcTimeMillis'], unit='ms')

# Preview the cleaned and converted data
print("\nCleaned AGC Data with Timestamps:")
print(agc_data[['utcTimeMillis', 'Timestamp']].head())
```

```
Preview of `utcTimeMillis` Column:
0    utcTimeMillis
1    1725958857000
2    1725958857000
3    1725958857000
4    1725958857000
Name: utcTimeMillis, dtype: object
```

```
Number of invalid rows removed: 1

Cleaned AGC Data with Timestamps:
   utcTimeMillis           Timestamp
1   1.725959e+12 2024-09-10 09:00:57
2   1.725959e+12 2024-09-10 09:00:57
3   1.725959e+12 2024-09-10 09:00:57
4   1.725959e+12 2024-09-10 09:00:57
5   1.725959e+12 2024-09-10 09:00:57
```

```
# Shift odometer timestamps earlier by 3 hours
odometer_data['Timestamp'] = odometer_data['Timestamp'] - pd.Timedelta(hours=3)

# Check the new timestamp range
print("Adjusted Odometer Timestamp Range:", odometer_data['Timestamp'].min(), odometer_data['Timestamp'].max())
```

```
Adjusted Odometer Timestamp Range: 2024-09-10 09:08:22.516496897 2024-09-10 09:43:05.841784
```

Resample and Interpolate odometer_data Resample the odometer_data at 1-second intervals and fill gaps using interpolation.

```
# Ensure odometer_data_interpolated is defined before extending the range
odometer_data_interpolated = (
    odometer_data
    .set_index('Timestamp')  # Set Timestamp as the index
    .sort_index()
    .interpolate(method='time')
    .reset_index()
)

# Extend odometer timestamps to match the full AGC range
full_range = pd.date_range(
    start=agc_data['Timestamp'].min(),
    end=agc_data['Timestamp'].max(),
    freq='1s'
)

# Reindex odometer data to match the full range
odometer_data_extended = (
    odometer_data_interpolated
    .set_index('Timestamp')
    .reindex(full_range)
    .infer_objects()
    .interpolate()
    .reset_index()
)

# Rename the new index back to Timestamp
odometer_data_extended.rename(columns={'index': 'Timestamp'}, inplace=True)

# Check the new extended range
print("Corrected Extended Odometer Timestamp Range:",
      odometer_data_extended['Timestamp'].min(),
      odometer_data_extended['Timestamp'].max())
```

```
Corrected Extended Odometer Timestamp Range: 2024-09-10 09:00:57 2024-09-10 11:56:40
<ipython-input-11-a1c0bb111ee0>:3: FutureWarning: DataFrame.interpolate with object dtype is deprecated and will raise in a future v
  odometer_data
```

```
# Perform an exact merge to match rows with the same Timestamp
merged_data = pd.merge(
    agc_data,
    odometer_data_extended,
    on='Timestamp',
    how='inner'
)

# Check the number of matched rows
print(f"Number of rows matched with direct merge: {len(merged_data)}")

# Preview the merged dataset
print("\nExact Merged Data Preview:")
print(merged_data.head())
```

```
Number of rows matched with direct merge: 49440

Exact Merged Data Preview:
  # Raw  utcTimeMillis    TimeNanos LeapSecond TimeUncertaintyNanos  \
```

```
0   Agc   1.725959e+12  14118000000        NaN                 NaN
1   Agc   1.725959e+12  14118000000        NaN                 NaN
2   Agc   1.725959e+12  14118000000        NaN                 NaN
3   Agc   1.725959e+12  14118000000        NaN                 NaN
4   Agc   1.725959e+12  14118000000        NaN                 NaN

          FullBiasNanos BiasNanos BiasUncertaintyNanos DriftNanosPerSecond  \
0  -1409994060882236537       0.0     5.16689718106489                 NaN
1  -1409994060882236537       0.0     5.16689718106489                 NaN
2  -1409994060882236537       0.0     5.16689718106489                 NaN
3  -1409994060882236537       0.0     5.16689718106489                 NaN
4  -1409994060882236537       0.0     5.16689718106489                 NaN

  DriftUncertaintyNanosPerSecond  ... BasebandCn0DbHz  \
0                            NaN  ...             NaN
1                            NaN  ...             NaN
2                            NaN  ...             NaN
3                            NaN  ...             NaN
4                            NaN  ...             NaN

  FullInterSignalBiasNanos FullInterSignalBiasUncertaintyNanos  \
0                      NaN                                 NaN
1                      NaN                                 NaN
2                      NaN                                 NaN
3                      NaN                                 NaN
4                      NaN                                 NaN

  SatelliteInterSignalBiasNanos  SatelliteInterSignalBiasUncertaintyNanos  \
0                           NaN                                       NaN
1                           NaN                                       NaN
2                           NaN                                       NaN
3                           NaN                                       NaN
4                           NaN                                       NaN

   CodeType  ChipsetElapsedRealtimeNanos           Timestamp   0  Speed
0       NaN                          NaN 2024-09-10 09:00:57 NaN    NaN
1       NaN                          NaN 2024-09-10 09:00:57 NaN    NaN
2       NaN                          NaN 2024-09-10 09:00:57 NaN    NaN
3       NaN                          NaN 2024-09-10 09:00:57 NaN    NaN
4       NaN                          NaN 2024-09-10 09:00:57 NaN    NaN

[5 rows x 40 columns]
```

```
# Replace NaN Speed values with 0.0
merged_data['Speed'] = merged_data['Speed'].fillna(0.0)

# Preview the updated merged dataset
print("\nUpdated Merged Data Preview with Speed Values:")
print(merged_data.head())
```

```
Updated Merged Data Preview with Speed Values:
  # Raw  utcTimeMillis    TimeNanos LeapSecond TimeUncertaintyNanos  \
0   Agc   1.725959e+12  14118000000        NaN                 NaN
1   Agc   1.725959e+12  14118000000        NaN                 NaN
2   Agc   1.725959e+12  14118000000        NaN                 NaN
3   Agc   1.725959e+12  14118000000        NaN                 NaN
4   Agc   1.725959e+12  14118000000        NaN                 NaN

          FullBiasNanos BiasNanos BiasUncertaintyNanos DriftNanosPerSecond  \
0  -1409994060882236537       0.0     5.16689718106489                 NaN
1  -1409994060882236537       0.0     5.16689718106489                 NaN
2  -1409994060882236537       0.0     5.16689718106489                 NaN
3  -1409994060882236537       0.0     5.16689718106489                 NaN
4  -1409994060882236537       0.0     5.16689718106489                 NaN

  DriftUncertaintyNanosPerSecond  ... BasebandCn0DbHz  \
0                            NaN  ...             NaN
1                            NaN  ...             NaN
2                            NaN  ...             NaN
3                            NaN  ...             NaN
4                            NaN  ...             NaN

  FullInterSignalBiasNanos FullInterSignalBiasUncertaintyNanos  \
0                      NaN                                 NaN
1                      NaN                                 NaN
2                      NaN                                 NaN
3                      NaN                                 NaN
4                      NaN                                 NaN

  SatelliteInterSignalBiasNanos  SatelliteInterSignalBiasUncertaintyNanos  \
0                           NaN                                       NaN
1                           NaN                                       NaN
2                           NaN                                       NaN
3                           NaN                                       NaN
4                           NaN                                       NaN
```

```
   CodeType  ChipsetElapsedRealtimeNanos           Timestamp   0  Speed
0       NaN                          NaN 2024-09-10 09:00:57 NaN    0.0
1       NaN                          NaN 2024-09-10 09:00:57 NaN    0.0
2       NaN                          NaN 2024-09-10 09:00:57 NaN    0.0
3       NaN                          NaN 2024-09-10 09:00:57 NaN    0.0
4       NaN                          NaN 2024-09-10 09:00:57 NaN    0.0

[5 rows x 40 columns]
```

```
# Save the merged dataset to a CSV file
merged_data.to_csv('merged_data.csv', index=False)
```

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```
# Convert 'DriftNanosPerSecond' to numeric and handle missing values
merged_data['DriftNanosPerSecond'] = pd.to_numeric(merged_data['DriftNanosPerSecond'], errors='coerce')
merged_data['DriftNanosPerSecond'] = merged_data['DriftNanosPerSecond'].fillna(merged_data['DriftNanosPerSecond'].median())

# Derive features for analysis
merged_data['Speed_Deviation'] = abs(merged_data['Speed'] - merged_data['Speed'].mean())  # Deviation from mean speed
merged_data['Speed_RollingMean'] = merged_data['Speed'].rolling(window=10).mean()  # Rolling mean for speed
merged_data['Drift_RollingMean'] = merged_data['DriftNanosPerSecond'].rolling(window=10).mean()  # Rolling mean for drift
merged_data['Speed_RateOfChange'] = merged_data['Speed'].diff()  # Rate of change for speed
merged_data['Drift_RateOfChange'] = merged_data['DriftNanosPerSecond'].diff()  # Rate of change for drift

# Display the first few rows of the engineered dataset
feature_columns = ['Speed', 'Speed_Deviation', 'Speed_RollingMean',
                   'Speed_RateOfChange', 'Drift_RollingMean',
                   'Drift_RateOfChange']
print("\nPreview of Feature-Engineered Data:")
print(merged_data[feature_columns].head())
```

```
Preview of Feature-Engineered Data:
   Speed  Speed_Deviation  Speed_RollingMean  Speed_RateOfChange  \
0    0.0              0.0                NaN                 NaN
1    0.0              0.0                NaN                 0.0
2    0.0              0.0                NaN                 0.0
3    0.0              0.0                NaN                 0.0
4    0.0              0.0                NaN                 0.0

   Drift_RollingMean  Drift_RateOfChange
0                NaN                 NaN
1                NaN                 0.0
2                NaN                 0.0
3                NaN                 0.0
4                NaN                 0.0
```

Drop speed-based feature computations since Speed is constant

```
# Drop speed-based feature computations since Speed is constant
print("Skipping Speed-based features: Speed is constant.")

# Validate Drift-based features
print("DriftNanosPerSecond Summary:")
print(merged_data['DriftNanosPerSecond'].describe())
print("\nNon-NaN Drift Values:")
print(merged_data[merged_data['DriftNanosPerSecond'].notna()].head())
```

```
Skipping Speed-based features: Speed is constant.
DriftNanosPerSecond Summary:
count    49440.000000
mean      -121.139644
std          3.076050
min       -128.000000
25%       -124.000000
50%       -121.000000
75%       -119.000000
max       -114.000000
Name: DriftNanosPerSecond, dtype: float64
```

```
Non-NaN Drift Values:
  # Raw  utcTimeMillis    TimeNanos LeapSecond TimeUncertaintyNanos  \
0   Agc   1.725959e+12  14118000000        NaN                  NaN
1   Agc   1.725959e+12  14118000000        NaN                  NaN
2   Agc   1.725959e+12  14118000000        NaN                  NaN
3   Agc   1.725959e+12  14118000000        NaN                  NaN
4   Agc   1.725959e+12  14118000000        NaN                  NaN

          FullBiasNanos BiasNanos BiasUncertaintyNanos  DriftNanosPerSecond  \
0  -1409994060882236537       0.0     5.16689718106489               -121.0
1  -1409994060882236537       0.0     5.16689718106489               -121.0
2  -1409994060882236537       0.0     5.16689718106489               -121.0
3  -1409994060882236537       0.0     5.16689718106489               -121.0
4  -1409994060882236537       0.0     5.16689718106489               -121.0

  DriftUncertaintyNanosPerSecond  ... CodeType ChipsetElapsedRealtimeNanos  \
0                            NaN  ...      NaN                         NaN
1                            NaN  ...      NaN                         NaN
2                            NaN  ...      NaN                         NaN
3                            NaN  ...      NaN                         NaN
4                            NaN  ...      NaN                         NaN

            Timestamp   0  Speed  Speed_Deviation  Speed_RollingMean  \
0 2024-09-10 09:00:57 NaN    0.0              0.0                NaN
1 2024-09-10 09:00:57 NaN    0.0              0.0                NaN
2 2024-09-10 09:00:57 NaN    0.0              0.0                NaN
3 2024-09-10 09:00:57 NaN    0.0              0.0                NaN
4 2024-09-10 09:00:57 NaN    0.0              0.0                NaN

   Drift_RollingMean  Speed_RateOfChange  Drift_RateOfChange
0                NaN                 NaN                 NaN
1                NaN                 0.0                 0.0
2                NaN                 0.0                 0.0
3                NaN                 0.0                 0.0
4                NaN                 0.0                 0.0

[5 rows x 45 columns]
```

```python
# Drop speed-related features
merged_data = merged_data.drop(columns=['Speed_Deviation', 'Speed_RollingMean', 'Speed_RateOfChange'], errors='ignore')

# Retain and preview drift-related features
feature_columns = ['DriftNanosPerSecond', 'Drift_RollingMean', 'Drift_RateOfChange']
print("\nPreview of Drift Features:")
print(merged_data[feature_columns].head(15))  # Show more rows to visualize rolling features
```

```
Preview of Drift Features:
    DriftNanosPerSecond  Drift_RollingMean  Drift_RateOfChange
0                -121.0                NaN                 NaN
1                -121.0                NaN                 0.0
2                -121.0                NaN                 0.0
3                -121.0                NaN                 0.0
4                -121.0                NaN                 0.0
5                -121.0                NaN                 0.0
6                -121.0                NaN                 0.0
7                -121.0                NaN                 0.0
8                -123.0                NaN                -2.0
9                -123.0             -121.4                 0.0
10               -123.0             -121.6                 0.0
11               -123.0             -121.8                 0.0
12               -123.0             -122.0                 0.0
13               -123.0             -122.2                 0.0
14               -123.0             -122.4                 0.0
```

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```python
# Handle NaN values in rolling mean and rate of change features
merged_data['Drift_RollingMean'] = merged_data['Drift_RollingMean'].fillna(merged_data['DriftNanosPerSecond'].mean())
merged_data['Drift_RateOfChange'] = merged_data['Drift_RateOfChange'].fillna(0)  # Replace NaN with 0 for initial rows

# Display refined feature-engineered dataset
print("\nRefined Feature-Engineered Data:")
print(merged_data[feature_columns].head())
```

```
Refined Feature-Engineered Data:
   DriftNanosPerSecond  Drift_RollingMean  Drift_RateOfChange
0               -121.0        -121.139644                 0.0
1               -121.0        -121.139644                 0.0
2               -121.0        -121.139644                 0.0
3               -121.0        -121.139644                 0.0
4               -121.0        -121.139644                 0.0
```

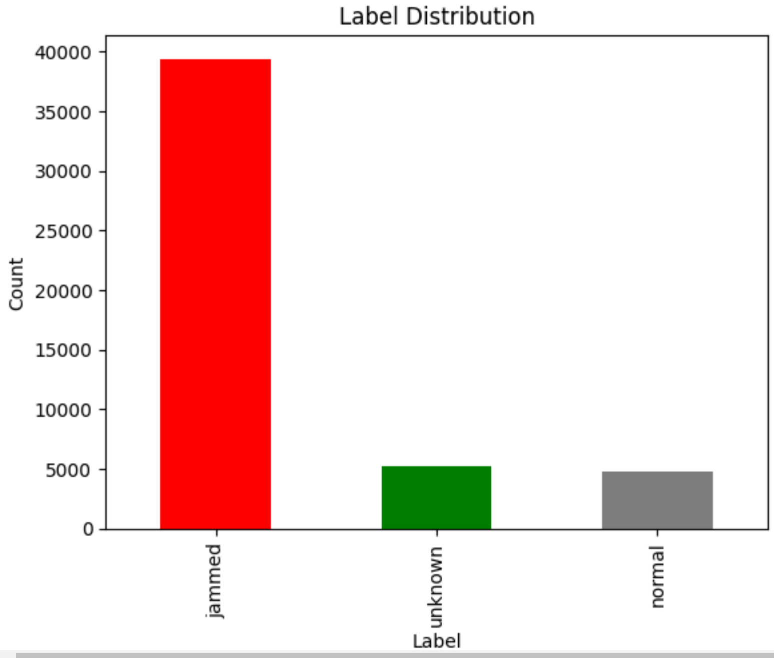
Label data The refactored method ensures consistency by prioritizing "jammed" over "normal" intervals, which avoids conflicts caused by overlapping intervals in the dataset. It provides scalability and efficiency, using structured interval prioritization and vectorized operations, making it more suitable for large datasets. The high-quality labels generated by the refactored method improve data reliability, which is crucial for training accurate and robust classification models.

```
import pandas as pd

# Paths to plan files
plan_files = [
    r"/content/drive/MyDrive/plan-monday-2024-09-09.json",
    r"/content/drive/MyDrive/plan-friday-2024-09-13.json",
    r"/content/drive/MyDrive/plan-wednesday-2024-09-11.json",
    r"/content/drive/MyDrive/plan-thursday-2024-09-12.json",
    r"/content/drive/MyDrive/plan-tuesday-2024-09-10.json"
]

# Load and combine plan files
plan_data_list = [pd.read_json(file) for file in plan_files]
combined_plan_data = pd.concat(plan_data_list, ignore_index=True)

# Extract intervals for "jammed" and "normal"
jammed_intervals = pd.DataFrame([
    (pd.to_datetime(test['start_time']), pd.to_datetime(test['end_time']), 'jammed')
    for location in combined_plan_data['locations']
    for test in location['tests']
    if test['power_w'] > 0
], columns=['start', 'end', 'Label'])

normal_intervals = pd.DataFrame([
    (pd.to_datetime(test['start_time']), pd.to_datetime(test['end_time']), 'normal')
    for location in combined_plan_data['locations']
    for test in location['tests']
    if test['power_w'] == 0
], columns=['start', 'end', 'Label'])

# Combine intervals with priorities
jammed_intervals['Priority'] = 1  # Higher priority for jammed
normal_intervals['Priority'] = 2  # Lower priority for normal
all_intervals = pd.concat([jammed_intervals, normal_intervals]).sort_values(by=['start', 'Priority'])

# Initialize default label
merged_data['Label'] = 'unknown'

# Apply labels based on combined intervals
for _, row in all_intervals.iterrows():
    mask = (merged_data['Timestamp'] >= row['start']) & (merged_data['Timestamp'] <= row['end'])
    merged_data.loc[mask, 'Label'] = row['Label']

# Display final label distribution
print("\nFinal Label Distribution:")
print(merged_data['Label'].value_counts())

# Preview labeled data
print("\nSample of Labeled Data:")
print(merged_data[['Timestamp', 'Label']].head())

# Debug: Check overlap for normal intervals
overlap_with_normal = []
for _, row in normal_intervals.iterrows():
    overlap = merged_data[(merged_data['Timestamp'] >= row['start']) &
                          (merged_data['Timestamp'] <= row['end'])]
    overlap_with_normal.append(len(overlap))

print(f"\nNumber of timestamps overlapping with normal intervals: {sum(overlap_with_normal)}")

# Validate rows labeled as normal
print("\nSample of Rows Labeled as Normal:")
print(merged_data[merged_data['Label'] == 'normal'].head())
```

```
unknown     5256
normal      4800
Name: count, dtype: int64

Sample of Labeled Data:
```

```
3 2024-09-10 09:00:57  jammed
4 2024-09-10 09:00:57  jammed

Number of timestamps overlapping with normal intervals: 9608

Sample of Rows Labeled as Normal:
      # Raw  utcTimeMillis      TimeNanos LeapSecond TimeUncertaintyNanos  \
20128   Agc   1.725966e+12  6677117000000        NaN                  NaN
20129   Agc   1.725966e+12  6677117000000        NaN                  NaN
20130   Agc   1.725966e+12  6677117000000        NaN                  NaN
20131   Agc   1.725966e+12  6677117000000        NaN                  NaN
20132   Agc   1.725966e+12  6677117000000        NaN                  NaN

              FullBiasNanos BiasNanos BiasUncertaintyNanos  \
20128  -1409994060883043116       0.0             1.899304
20129  -1409994060883043116       0.0             1.899304
20130  -1409994060883043116       0.0             1.899304
20131  -1409994060883043116       0.0             1.899304
20132  -1409994060883043116       0.0             1.899304

       DriftNanosPerSecond DriftUncertaintyNanosPerSecond  ...  \
20128               -127.0                             1.0  ...
20129               -127.0                             1.0  ...
20130               -127.0                             1.0  ...
20131               -127.0                             1.0  ...
20132               -127.0                             1.0  ...

      SatelliteInterSignalBiasNanos SatelliteInterSignalBiasUncertaintyNanos  \
20128                           NaN                                      NaN
20129                           NaN                                      NaN
20130                           NaN                                      NaN
20131                           NaN                                      NaN
20132                           NaN                                      NaN

      CodeType ChipsetElapsedRealtimeNanos           Timestamp   0  Speed  \
20128      NaN                         NaN 2024-09-10 10:52:00 NaN    0.0
20129      NaN                         NaN 2024-09-10 10:52:00 NaN    0.0
20130      NaN                         NaN 2024-09-10 10:52:00 NaN    0.0
20131      NaN                         NaN 2024-09-10 10:52:00 NaN    0.0
20132      NaN                         NaN 2024-09-10 10:52:00 NaN    0.0

       Drift_RollingMean  Drift_RateOfChange   Label
20128             -126.0                -1.0  normal
20129             -126.2                 0.0  normal
20130             -126.3                 0.0  normal
20131             -126.4                 0.0  normal
20132             -126.5                 0.0  normal

[5 rows x 43 columns]
```

```
import matplotlib.pyplot as plt

# Plot label distribution
label_counts = merged_data['Label'].value_counts()
label_counts.plot(kind='bar', color=['red', 'green', 'gray'])
plt.title("Label Distribution")
plt.xlabel("Label")
plt.ylabel("Count")
plt.show()
```




```
merged_data.to_csv("merged_data_refactored.csv", index=False)
```

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```
# Select features for training
features = ['Drift_RollingMean', 'Drift_RateOfChange']  # Focus on drift-based features
X = merged_data[features]
y = merged_data['Label']  # 'jammed', 'normal', or 'unknown'

# Remove rows with 'unknown' labels, as they cannot be used for binary classification
valid_data = merged_data[merged_data['Label'].isin(['jammed', 'normal'])]

# Update features (X) and labels (y) with valid data
X = valid_data[features]
y = valid_data['Label']

# Convert labels to binary format (0 = normal, 1 = jammed)
y_binary = y.map({'normal': 0, 'jammed': 1})

# Verify the prepared data
print("Selected Features (X) Preview:")
print(X.head())

print("\nBinary Labels (y_binary) Distribution:")
print(y_binary.value_counts())
```

```
Selected Features (X) Preview:
   Drift_RollingMean  Drift_RateOfChange
0        -121.139644                 0.0
1        -121.139644                 0.0
2        -121.139644                 0.0
3        -121.139644                 0.0
4        -121.139644                 0.0

Binary Labels (y_binary) Distribution:
Label
1    39384
0     4800
Name: count, dtype: int64
```

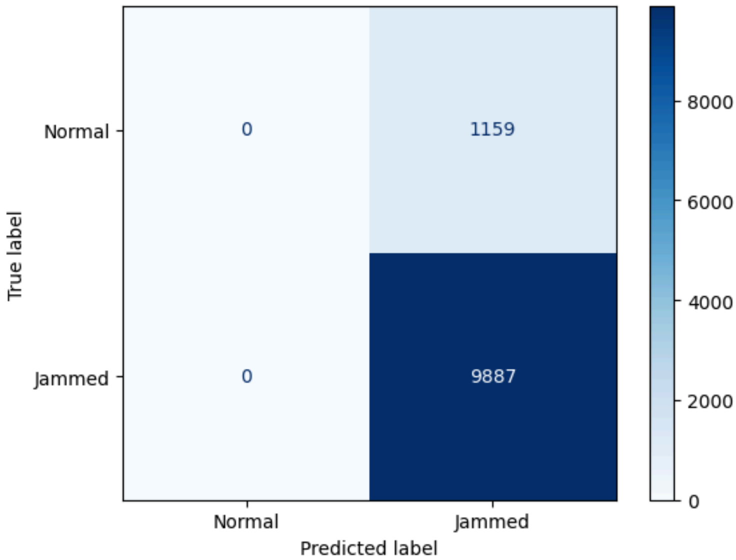
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y_binary, test_size=0.25, random_state=0)

print(f"Training set size: {len(X_train)}, Testing set size: {len(X_test)}")
```

```
Training set size: 33138, Testing set size: 11046
```

Apply LogisticRegression

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay


# Train Logistic Regression
model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Evaluate the model
print("\nClassification Report:")
print(classification_report(y_test, y_pred))


# Display confusion matrix
cm = confusion_matrix(y_test, y_pred, labels=model.classes_)
ConfusionMatrixDisplay(cm, display_labels=["Normal", "Jammed"]).plot(cmap="Blues")
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00      1159
           1       0.90      1.00      0.94      9887

    accuracy                           0.90     11046
   macro avg       0.45      0.50      0.47     11046
weighted avg       0.80      0.90      0.85     11046

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined ar
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7a2659d48460>
```



Double-click (or enter) to edit

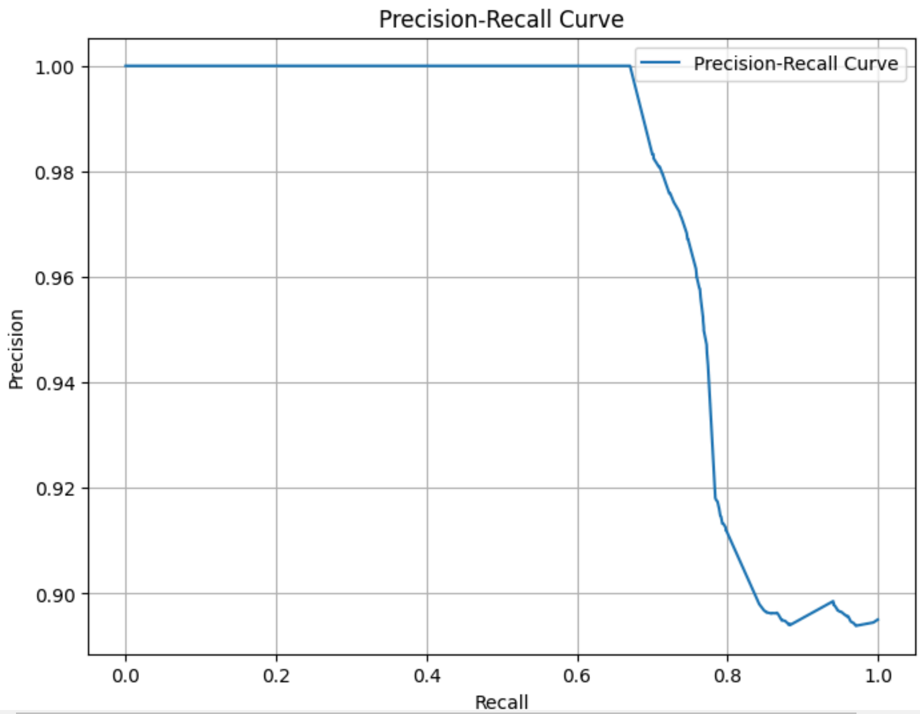
Apply XGB Classifier

```
from xgboost import XGBClassifier

# Train XGBoost with scale_pos_weight
imbalance_ratio = len(y_train[y_train == 0]) / len(y_train[y_train == 1])
xgb_model = XGBClassifier(eval_metric='logloss', use_label_encoder=False, scale_pos_weight=imbalance_ratio)
xgb_model.fit(X_train, y_train)

# Evaluate the model
y_pred_xgb = xgb_model.predict(X_test)
print("\nXGBoost Classification Report:")
```

```
print(classification_report(y_test, y_pred_xgb))
```

```
/usr/local/lib/python3.10/dist-packages/xgboost/core.py:158: UserWarning: [12:51:09] WARNING: /workspace/src/learner.cc:740: 
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)

XGBoost Classification Report:
              precision    recall  f1-score   support

           0       0.33      0.97      0.49      1159
           1       1.00      0.77      0.87      9887

    accuracy                           0.79     11046
   macro avg       0.66      0.87      0.68     11046
weighted avg       0.93      0.79      0.83     11046
```

```
from sklearn.metrics import precision_recall_curve, auc
import matplotlib.pyplot as plt

# Compute Precision-Recall curve
precision, recall, thresholds = precision_recall_curve(y_test, model.predict_proba(X_test)[:, 1])

# Plot the curve
plt.figure(figsize=(8, 6))
plt.plot(recall, precision, label="Precision-Recall Curve")
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
plt.legend()
plt.grid()
plt.show()
```



Gradient Boosting Optimization using Bayesian Optimization (via Optuna) to fine-tune the hyperparameters of a Gradient Boosting model like XGBoost. This model builds an ensemble of decision trees, where each tree tries to correct the errors of the previous ones.

Key Steps: Hyperparameters Tuned: max_depth: Controls the complexity of each tree. learning_rate: Determines how much each tree contributes to the overall model. n_estimators: Number of trees in the ensemble. scale_pos_weight: Balances the model for imbalanced datasets (e.g., "jammed" vs. "normal"). The optimization objective is the F1-score, which balances precision and recall. Equations Involved: Logarithmic Loss (Objective Function):

LogLoss = − 1 N ∑ i = 1 N [y i log (p i) + (1 − y i) log (1 − p i)] LogLoss=− N 1

i=1 ∑ N[y ilog(p i)+(1−y i)log(1−p i)] Where:

y i y iis the true label (0 or 1). p i p iis the predicted probability for the positive class. N N is the number of samples. F1-Score (Optimization Target):

F 1 = 2 · Precision · Recall Precision + Recall F1=2· Precision+Recall Precision·Recall

Where:

Precision = True Positives True Positives + False Positives True Positives + False Positives True Positives

Recall = True Positives True Positives + False Negatives True Positives + False Negatives True Positives

```
!pip install optuna
```

```
Collecting optuna
  Downloading optuna-4.1.0-py3-none-any.whl.metadata (16 kB)
Collecting alembic>=1.5.0 (from optuna)
  Downloading alembic-1.14.0-py3-none-any.whl.metadata (7.4 kB)
Collecting colorlog (from optuna)
  Downloading colorlog-6.9.0-py3-none-any.whl.metadata (10 kB)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from optuna) (1.26.4)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from optuna) (24.2)
Requirement already satisfied: sqlalchemy>=1.4.2 in /usr/local/lib/python3.10/dist-packages (from optuna) (2.0.36)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from optuna) (4.66.6)
Requirement already satisfied: PyYAML in /usr/local/lib/python3.10/dist-packages (from optuna) (6.0.2)
Collecting Mako (from alembic>=1.5.0->optuna)
  Downloading Mako-1.3.6-py3-none-any.whl.metadata (2.9 kB)
Requirement already satisfied: typing-extensions>=4 in /usr/local/lib/python3.10/dist-packages (from alembic>=1.5.0->optuna) (4.12.
Requirement already satisfied: greenlet!=0.4.17 in /usr/local/lib/python3.10/dist-packages (from sqlalchemy>=1.4.2->optuna) (3.1.1)
Requirement already satisfied: MarkupSafe>=0.9.2 in /usr/local/lib/python3.10/dist-packages (from Mako->alembic>=1.5.0->optuna) (3.
Downloading optuna-4.1.0-py3-none-any.whl (364 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 364.4/364.4 kB 18.8 MB/s eta 0:00:00
Downloading alembic-1.14.0-py3-none-any.whl (233 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 233.5/233.5 kB 13.7 MB/s eta 0:00:00
Downloading colorlog-6.9.0-py3-none-any.whl (11 kB)
Downloading Mako-1.3.6-py3-none-any.whl (78 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 78.6/78.6 kB 6.5 MB/s eta 0:00:00
Installing collected packages: Mako, colorlog, alembic, optuna
Successfully installed Mako-1.3.6 alembic-1.14.0 colorlog-6.9.0 optuna-4.1.0
```

```
import optuna
from xgboost import XGBClassifier
from sklearn.metrics import f1_score, classification_report

# Define the objective function for Optuna
def objective(trial):
    # Define hyperparameter search space
    param = {
        'max_depth': trial.suggest_int('max_depth', 3, 10),
        'learning_rate': trial.suggest_float('learning_rate', 0.01, 0.3, log=True),
        'n_estimators': trial.suggest_int('n_estimators', 100, 500),
        'scale_pos_weight': trial.suggest_int('scale_pos_weight', 1, 20),
        'colsample_bytree': trial.suggest_float('colsample_bytree', 0.5, 1.0),
        'subsample': trial.suggest_float('subsample', 0.5, 1.0),
        'reg_alpha': trial.suggest_float('reg_alpha', 1e-3, 10, log=True),
        'reg_lambda': trial.suggest_float('reg_lambda', 1e-3, 10, log=True),
    }

    # Train XGBoost model with parameters
    model = XGBClassifier(**param, eval_metric='logloss')
    model.fit(X_train, y_train)

    # Make predictions
    X_test_cleaned = X_test[features]
    y_pred = model.predict(X_test_cleaned)

    # Return F1-score for evaluation
    return f1_score(y_test, y_pred, average='macro')


features = ['Drift_RollingMean', 'Drift_RateOfChange']  # Feature columns used for training

# Start the study with Optuna
study = optuna.create_study(direction='maximize')
study.optimize(objective, n_trials=50)

# Best hyperparameters found
print("\nBest Hyperparameters Found:")
print(study.best_params)

# Train a final model with the best hyperparameters
best_model = XGBClassifier(**study.best_params, eval_metric='logloss')
best_model.fit(X_train, y_train)

# Make predictions with the optimized model
X_test_cleaned = X_test[features]
```

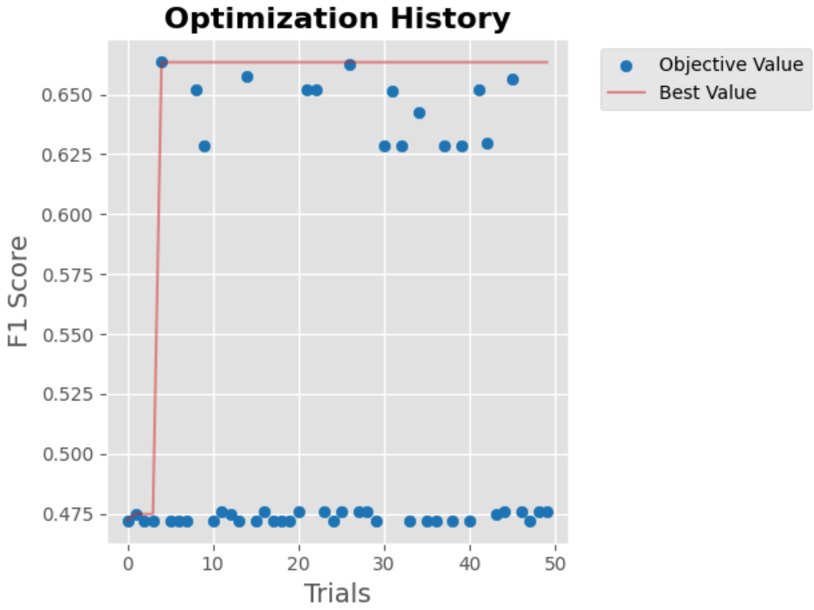
```
y_pred_xgb = best_model.predict(X_test_cleaned)

# Evaluate the final model
print("\nXGBoost Classification Report (Optimized Model):")
print(classification_report(y_test, y_pred_xgb))
```

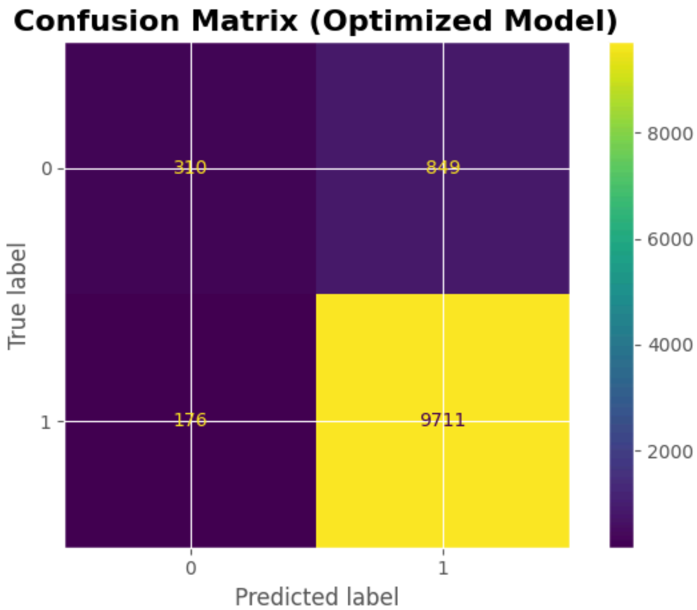
```
[I 2024-11-25 12:53:21,475] Trial 7 finished with value: 0.4723164381598433 and parameters: {'max_depth': 4, 'learning_rate': 0.0
[I 2024-11-25 12:53:21,682] Trial 8 finished with value: 0.6516862983110792 and parameters: {'max_depth': 8, 'learning_rate': 0.0
[I 2024-11-25 12:53:22,223] Trial 9 finished with value: 0.6283609333772887 and parameters: {'max_depth': 8, 'learning_rate': 0.0
[I 2024-11-25 12:53:22,909] Trial 10 finished with value: 0.4723164381598433 and parameters: {'max_depth': 10, 'learning_rate': 0
[I 2024-11-25 12:53:23,124] Trial 11 finished with value: 0.47584608930648586 and parameters: {'max_depth': 10, 'learning_rate':
[I 2024-11-25 12:53:23,490] Trial 12 finished with value: 0.4749658931953327 and parameters: {'max_depth': 7, 'learning_rate': 0.
[I 2024-11-25 12:53:24,055] Trial 13 finished with value: 0.4723164381598433 and parameters: {'max_depth': 6, 'learning_rate': 0.
[I 2024-11-25 12:53:24,438] Trial 14 finished with value: 0.6574442789282774 and parameters: {'max_depth': 9, 'learning_rate': 0.
[I 2024-11-25 12:53:24,893] Trial 15 finished with value: 0.4723164381598433 and parameters: {'max_depth': 9, 'learning_rate': 0.
[I 2024-11-25 12:53:25,577] Trial 16 finished with value: 0.47584608930648586 and parameters: {'max_depth': 6, 'learning_rate': 0
[I 2024-11-25 12:53:26,687] Trial 17 finished with value: 0.4723164381598433 and parameters: {'max_depth': 9, 'learning_rate': 0.
[I 2024-11-25 12:53:27,904] Trial 18 finished with value: 0.4723164381598433 and parameters: {'max_depth': 9, 'learning_rate': 0.
[I 2024-11-25 12:53:28,756] Trial 19 finished with value: 0.4723164381598433 and parameters: {'max_depth': 7, 'learning_rate': 0.
[I 2024-11-25 12:53:29,812] Trial 20 finished with value: 0.47584608930648586 and parameters: {'max_depth': 5, 'learning_rate': 0
[I 2024-11-25 12:53:30,049] Trial 21 finished with value: 0.6516862983110792 and parameters: {'max_depth': 8, 'learning_rate': 0.
[I 2024-11-25 12:53:30,320] Trial 22 finished with value: 0.6516862983110792 and parameters: {'max_depth': 8, 'learning_rate': 0.
[I 2024-11-25 12:53:30,906] Trial 23 finished with value: 0.47584608930648586 and parameters: {'max_depth': 9, 'learning_rate': 0
[I 2024-11-25 12:53:31,524] Trial 24 finished with value: 0.4723164381598433 and parameters: {'max_depth': 6, 'learning_rate': 0.
[I 2024-11-25 12:53:31,918] Trial 25 finished with value: 0.47584608930648586 and parameters: {'max_depth': 10, 'learning_rate':
[I 2024-11-25 12:53:32,169] Trial 26 finished with value: 0.662406713323825 and parameters: {'max_depth': 7, 'learning_rate': 0.0
[I 2024-11-25 12:53:32,501] Trial 27 finished with value: 0.47584608930648586 and parameters: {'max_depth': 7, 'learning_rate': 0
[I 2024-11-25 12:53:32,930] Trial 28 finished with value: 0.47584608930648586 and parameters: {'max_depth': 6, 'learning_rate': 0
[I 2024-11-25 12:53:33,171] Trial 29 finished with value: 0.4723164381598433 and parameters: {'max_depth': 4, 'learning_rate': 0.
[I 2024-11-25 12:53:33,733] Trial 30 finished with value: 0.6283609333772887 and parameters: {'max_depth': 5, 'learning_rate': 0.
[I 2024-11-25 12:53:33,985] Trial 31 finished with value: 0.6515478179884602 and parameters: {'max_depth': 8, 'learning_rate': 0.
[I 2024-11-25 12:53:34,303] Trial 32 finished with value: 0.6283609333772887 and parameters: {'max_depth': 7, 'learning_rate': 0.
[I 2024-11-25 12:53:34,566] Trial 33 finished with value: 0.4723164381598433 and parameters: {'max_depth': 9, 'learning_rate': 0.
[I 2024-11-25 12:53:34,922] Trial 34 finished with value: 0.64256586011508 and parameters: {'max_depth': 8, 'learning_rate': 0.02
[I 2024-11-25 12:53:35,182] Trial 35 finished with value: 0.4723164381598433 and parameters: {'max_depth': 7, 'learning_rate': 0.
[I 2024-11-25 12:53:35,617] Trial 36 finished with value: 0.4723164381598433 and parameters: {'max_depth': 6, 'learning_rate': 0.
[I 2024-11-25 12:53:35,830] Trial 37 finished with value: 0.6283609333772887 and parameters: {'max_depth': 8, 'learning_rate': 0.
[I 2024-11-25 12:53:36,381] Trial 38 finished with value: 0.4723164381598433 and parameters: {'max_depth': 9, 'learning_rate': 0.
[I 2024-11-25 12:53:36,755] Trial 39 finished with value: 0.6283609333772887 and parameters: {'max_depth': 3, 'learning_rate': 0.
[I 2024-11-25 12:53:37,149] Trial 40 finished with value: 0.4723164381598433 and parameters: {'max_depth': 7, 'learning_rate': 0.
[I 2024-11-25 12:53:37,362] Trial 41 finished with value: 0.6516862983110792 and parameters: {'max_depth': 8, 'learning_rate': 0.
[I 2024-11-25 12:53:37,593] Trial 42 finished with value: 0.6295489466447941 and parameters: {'max_depth': 8, 'learning_rate': 0.
[I 2024-11-25 12:53:37,881] Trial 43 finished with value: 0.4749658931953327 and parameters: {'max_depth': 7, 'learning_rate': 0.
[I 2024-11-25 12:53:38,173] Trial 44 finished with value: 0.47584608930648586 and parameters: {'max_depth': 10, 'learning_rate':
[I 2024-11-25 12:53:38,467] Trial 45 finished with value: 0.6563446164832676 and parameters: {'max_depth': 8, 'learning_rate': 0.
[I 2024-11-25 12:53:38,783] Trial 46 finished with value: 0.47584608930648586 and parameters: {'max_depth': 6, 'learning_rate': 0
[I 2024-11-25 12:53:39,172] Trial 47 finished with value: 0.4723164381598433 and parameters: {'max_depth': 9, 'learning_rate': 0.
[I 2024-11-25 12:53:40,850] Trial 48 finished with value: 0.47584608930648586 and parameters: {'max_depth': 8, 'learning_rate': 0
[I 2024-11-25 12:53:42,514] Trial 49 finished with value: 0.47584608930648586 and parameters: {'max_depth': 6, 'learning_rate': 0

Best Hyperparameters Found:
{'max_depth': 6, 'learning_rate': 0.02149573290393232, 'n_estimators': 426, 'scale_pos_weight': 1, 'colsample_bytree': 0.90078709

XGBoost Classification Report (Optimized Model):
              precision    recall  f1-score   support

           0       0.64      0.27      0.38      1159
           1       0.92      0.98      0.95      9887

    accuracy                           0.91     11046
   macro avg       0.78      0.62      0.66     11046
weighted avg       0.89      0.91      0.89     11046
```

```
import matplotlib.pyplot as plt
from optuna.visualization import plot_optimization_history, plot_param_importances
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import seaborn as sns

# --- 1. Plot Optimization History ---
optuna.visualization.matplotlib.plot_optimization_history(study)
plt.title("Optimization History", fontsize=16, weight="bold")
plt.xlabel("Trials", fontsize=14)
plt.ylabel("F1 Score", fontsize=14)
plt.tight_layout()
plt.show()


# Confusion Matrix for Final Model ---
# Generate a confusion matrix for the optimized model's predictions
cm = confusion_matrix(y_test, y_pred_xgb)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=best_model.classes_)
disp.plot(cmap='viridis', values_format='d', colorbar=True)
plt.title("Confusion Matrix (Optimized Model)", fontsize=16, weight="bold")
plt.tight_layout()
```

```
plt.show()
```

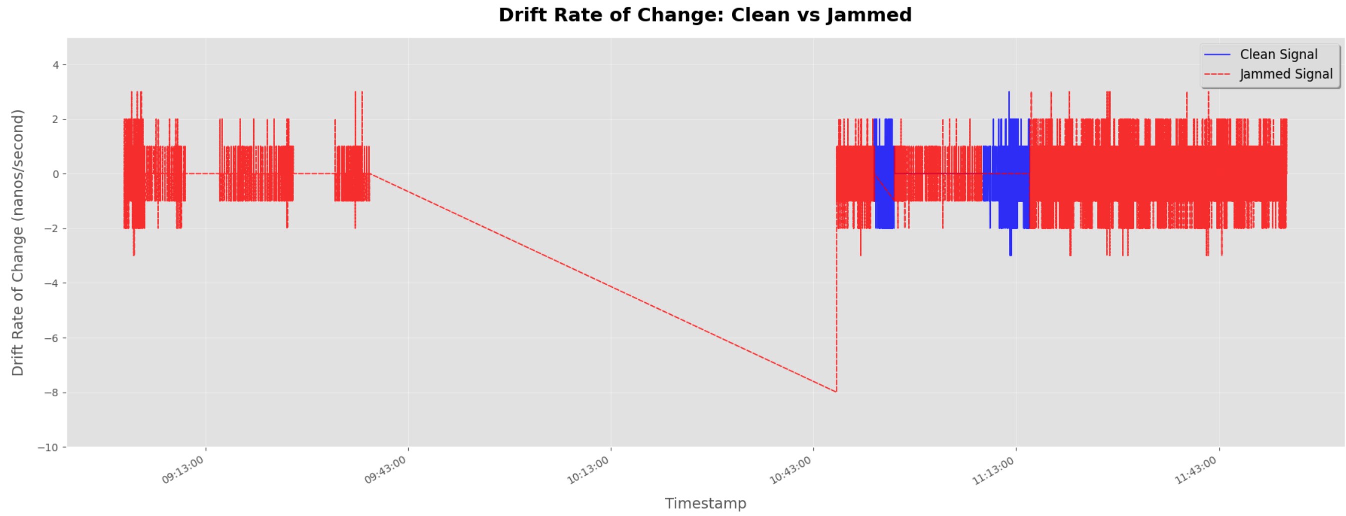
```
<ipython-input-50-2c3c2380e935>:7: ExperimentalWarning: plot_optimization_history is experimental (supported from v2.2.0). The inter
  optuna.visualization.matplotlib.plot_optimization_history(study)
```





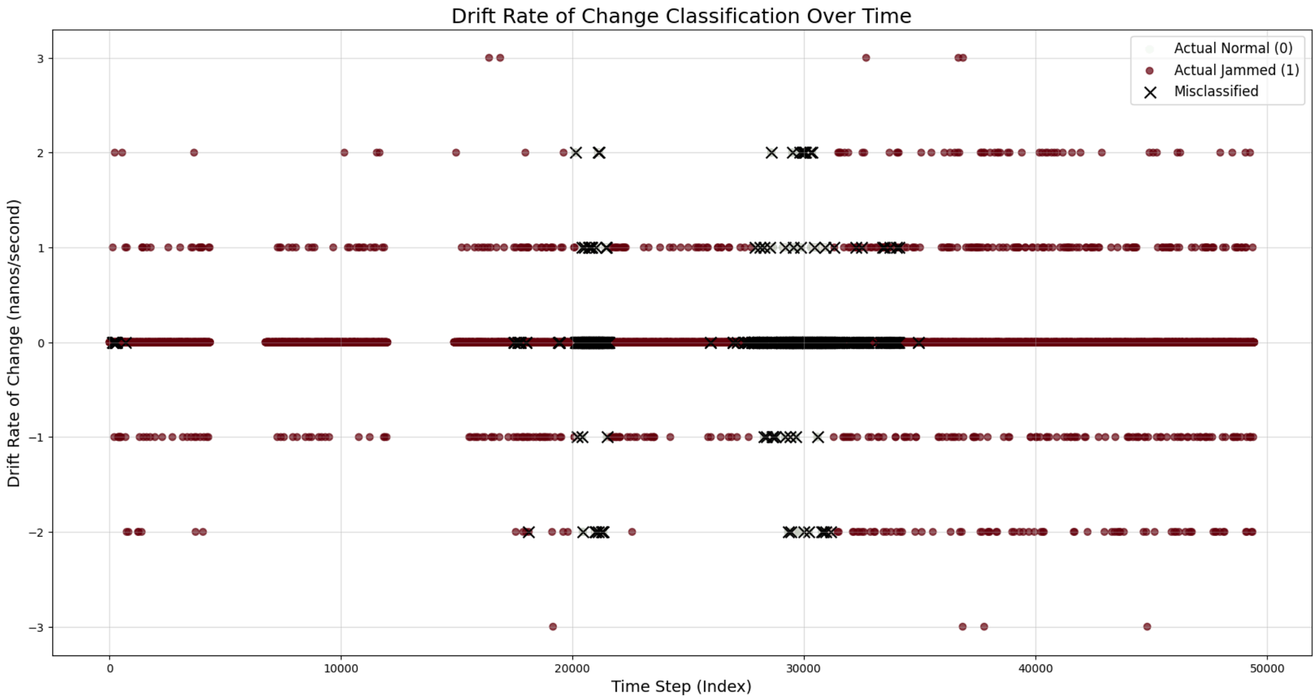

```
import matplotlib.pyplot as plt
import matplotlib.dates as mdates

# Separate clean and jammed signals
clean_signal = merged_data[merged_data['Label'] == 'normal']
jammed_signal = merged_data[merged_data['Label'] == 'jammed']

# --- Optimized Visualization: Clean vs Jammed Signals ---
plt.figure(figsize=(18, 7))
# Format x-axis for timestamps
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%H:%M:%S'))
plt.gca().xaxis.set_major_locator(mdates.MinuteLocator(interval=30))
plt.gcf().autofmt_xdate()

# Plot clean signal
plt.plot(
    clean_signal['Timestamp'],
    clean_signal['Drift_RateOfChange'],
    label='Clean Signal',
    color='blue',
    alpha=0.8,
    linewidth=1.2
)

# Plot jammed signal with clearer dashes and line separation
plt.plot(
```

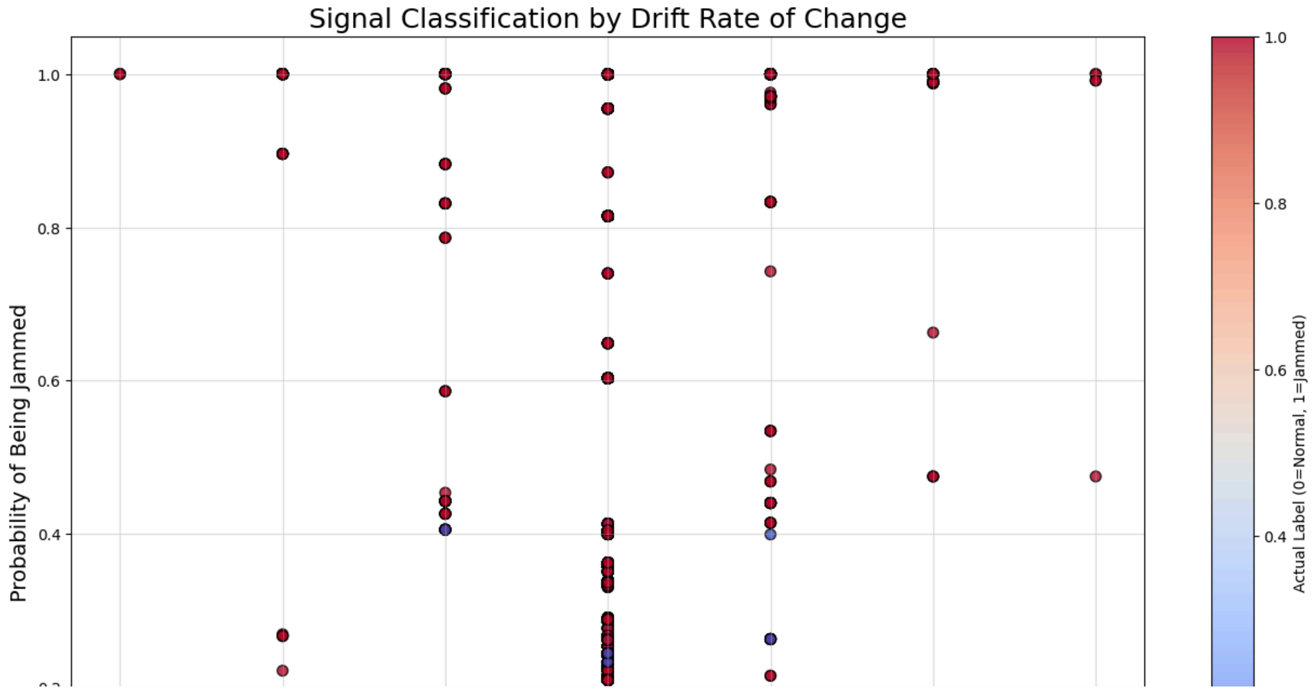
```
plt.plot(
    jammed_signal['Timestamp'],
    jammed_signal['Drift_RateOfChange'],
    label='Jammed Signal',
    color='red',
    alpha=0.8,
    linewidth=1.2,
    linestyle='--',  # Maintain dashed lines for jammed signals
    dash_capstyle='round'
)

# Add labels, title, and legend
plt.title('Drift Rate of Change: Clean vs Jammed', fontsize=18, weight='bold', pad=15)
plt.xlabel('Timestamp', fontsize=14, labelpad=10)
plt.ylabel('Drift Rate of Change (nanos/second)', fontsize=14, labelpad=10)
plt.legend(fontsize=12, loc='upper right', frameon=True, framealpha=0.9, shadow=True)
plt.grid(alpha=0.4)

#
plt.ylim(-10, 5)

# Adjust layout for clarity
plt.tight_layout()
plt.show()
```




```
# Add Actual labels to X_test
X_test = X_test.copy()
X_test['Actual'] = y_test.values

# Add Predictions to X_test
X_test['Prediction'] = y_pred_xgb

# Add Probabilities (if available)
y_prob = xgb_model.predict_proba(X_test[features])[:, 1]
X_test['Probability'] = y_prob

# --- Visualization 1: Signal Behavior Over Time ---
plt.figure(figsize=(20, 10))

# Plot Drift_RateOfChange for Normal Signals
plt.scatter(
    X_test.index,
    X_test['Drift_RateOfChange'],
    c=(X_test['Actual'] == 0).astype(int),
    cmap='Greens',
    label='Actual Normal (0)',
    alpha=0.7
)
```

```
# Plot Drift_RateOfChange for Jammed Signals
plt.scatter(
    X_test.index,
    X_test['Drift_RateOfChange'],
    c=(X_test['Actual'] == 1).astype(int),
    cmap='Reds',
    label='Actual Jammed (1)',
    alpha=0.7
)

# Highlight Misclassifications
misclassified = X_test[X_test['Actual'] != X_test['Prediction']]
plt.scatter(
    misclassified.index,
    misclassified['Drift_RateOfChange'],
    c='black',
    label='Misclassified',
    marker='x',
    s=100
)

# Titles and Labels
plt.title('Drift Rate of Change Classification Over Time', fontsize=18)
plt.xlabel('Time Step (Index)', fontsize=14)
plt.ylabel('Drift Rate of Change (nanos/second)', fontsize=14)
plt.legend(loc='upper right', fontsize=12)
plt.grid(alpha=0.4)
plt.show()

# --- Visualization 2: Signal Distribution in Drift_RateOfChange ---
plt.figure(figsize=(16, 10))

# Plot all signals, coloring by Actual Labels
plt.scatter(
    X_test['Drift_RateOfChange'],
    X_test['Probability'],
    c=X_test['Actual'],
    cmap='coolwarm',
    alpha=0.8,
    s=50,
    edgecolor='k',
    label='Signal Points'
)

# Titles and Labels
plt.title('Signal Classification by Drift Rate of Change', fontsize=18)
plt.xlabel('Drift Rate of Change (nanos/second)', fontsize=14)
plt.ylabel('Probability of Being Jammed', fontsize=14)
plt.grid(alpha=0.4)
plt.colorbar(label="Actual Label (0=Normal, 1=Jammed)")
plt.show()
```


Drift Rate of Change Classification Over Time
Actual Normal (0)
Actual Jammed (1)
Misclassified
Drift Rate of Change (nanos/second)
Time Step (Index)
3
2
1
0
−1
−2
−3
0
10000
20000
30000
40000
50000


Signal Classification by Drift Rate of Change
Probability of Being Jammed
Actual Label (0=Normal, 1=Jammed)
1.0
0.8
0.6
0.4