

# Lab3 - Assignment 5

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## Parse Rosbag

```
import numpy as np

from pathlib import Path

from rosbags.highlevel import AnyReader
from rosbags.typesys import Stores, get_typestore

bagpath = Path('./door_data_bag')

# Create a type store to use if the bag has no message definitions.
typestore = get_typestore(Stores.ROS2_FOXY)

torque_list = []          # will hold (timestamp, torque)
feature_mean_list = []    # will hold (timestamp, feature_mean)

# Create reader instance and open for reading.
with AnyReader([bagpath], default_typestore=typestore) as reader:
    connections = [x for x in reader.connections]

    for c in connections:
        print(f"Topic: {c.topic}  Type: {c.msgtype}")

    for connection, timestamp, rawdata in reader.messages(connections=connections):
        msg = reader.deserialize(rawdata, connection.msgtype)
        if connection.topic == "/hinged_glass_door/torque" and hasattr(msg, "data"):
            torque_list.append((timestamp, float(msg.data)))
        elif connection.topic == "/feature_mean" and hasattr(msg, "data"):
```

```

        feature_mean_list.append((timestamp, float(msg.data)))

torque_array = np.array(torque_list)
feature_mean_array = np.array(feature_mean_list)

print("Collected:", len(torque_list), "torque samples;",
      len(feature_mean_list), "feature_mean samples")

```

Topic: /hinged\_glass\_door/torque Type: std\_msgs/msg/Float64

Topic: /feature\_mean Type: std\_msgs/msg/Float64

Collected: 67 torque samples; 2442 feature\_mean samples

```

import matplotlib.pyplot as plt

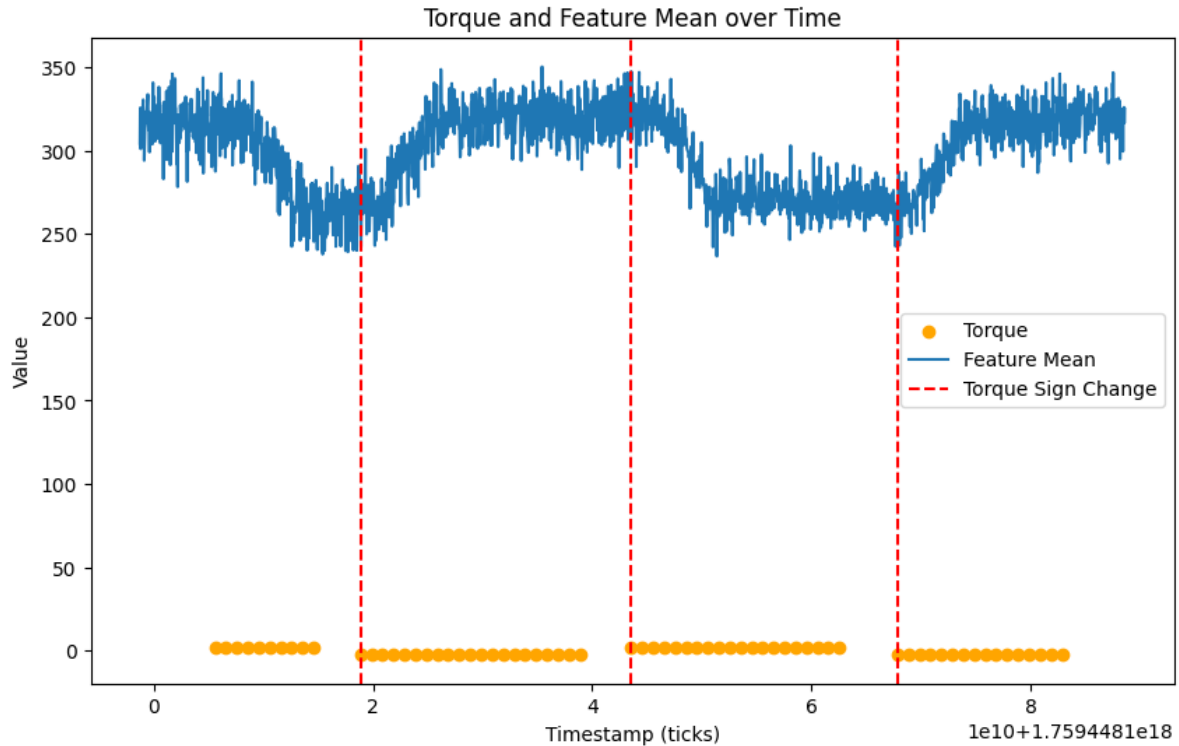
torque_signs = np.sign(torque_array[:, 1])
sign_changes = np.where((torque_signs[:-1] != torque_signs[1:]) &
                        (torque_signs[:-1] != 0) &
                        (torque_signs[1:] != 0))[0] + 1
change_timestamps = torque_array[sign_changes, 0]

plt.figure(figsize=(10, 6))
plt.scatter(torque_array[:, 0], torque_array[:, 1],
            label='Torque', color='orange')
plt.plot(feature_mean_array[:, 0], feature_mean_array[:, 1],
         label='Feature Mean')

# Add vertical lines at sign changes
for ts in change_timestamps:
    plt.axvline(x=ts, color='red', linestyle='--',
                label='Torque Sign Change' if ts == change_timestamps[0] else "")

plt.xlabel('Timestamp (ticks)')
plt.ylabel('Value')
plt.title('Torque and Feature Mean over Time')
plt.legend()
plt.show()

```



We will discard all data samples before the first torque sign change, since the scene was not ready

```
first_ts = change_timestamps[0]

torque_filtered = torque_array[torque_array[:, 0] >= first_ts]
feature_mean_filtered = feature_mean_array[feature_mean_array[:, 0] >= first_ts]

torque_signs_filtered = np.sign(torque_filtered[:, 1])
sign_changes_filtered = (np.where((torque_signs_filtered[:-1] != torque_signs_filtered[1:]) &
                                   (torque_signs_filtered[:-1] != 0) &
                                   (torque_signs_filtered[1:] != 0))[0] + 1)
change_timestamps_filtered = torque_filtered[sign_changes_filtered, 0]

plt.figure(figsize=(10, 6))
plt.scatter(torque_filtered[:, 0], torque_filtered[:, 1], label='Torque', color='orange')
plt.plot(feature_mean_filtered[:, 0], feature_mean_filtered[:, 1], label='Feature Mean')
```

```

for ts in change_timestamps_filtered:
    plt.axvline(x=ts, color='red', linestyle='--',
                label='Torque Sign Change' if ts == change_timestamps_filtered[0] else "")

plt.xlabel('Timestamp (ticks)')
plt.ylabel('Value')
plt.title('Torque and Feature Mean over Time (After First Sign Change)')
plt.legend()
plt.show()

```



We also need to discard all data samples 8 seconds after a torque switch to allow the door to fully change state

```

import numpy as np

seg1_end_idx = sign_changes_filtered[0] - 1
seg2_start_idx = sign_changes_filtered[0]
seg2_end_idx = sign_changes_filtered[1] - 1

```

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seg3_start_idx = sign_changes_filtered[1]

discard_count = 8

start_ts_neg1 = (torque_filtered[discard_count, 0]
                 if seg1_end_idx - 0 + 1 > discard_count
                 else float('inf'))
start_ts_neg3 = (torque_filtered[seg3_start_idx + discard_count, 0]
                 if len(torque_filtered) - seg3_start_idx > discard_count
                 else float('inf'))

mask_neg = (((feature_mean_filtered[:, 0] >= start_ts_neg1) &
              (feature_mean_filtered[:, 0] <= torque_filtered[seg1_end_idx, 0])) |
            ((feature_mean_filtered[:, 0] >= start_ts_neg3) &
              (feature_mean_filtered[:, 0] <= torque_filtered[-1, 0])))
feature_mean_negative = feature_mean_filtered[mask_neg]

mask_torque_neg = (((torque_filtered[:, 0] >= start_ts_neg1) &
                    (torque_filtered[:, 0] <= torque_filtered[seg1_end_idx, 0])) |
                  ((torque_filtered[:, 0] >= start_ts_neg3) &
                    (torque_filtered[:, 0] <= torque_filtered[-1, 0])))
torque_negative = torque_filtered[mask_torque_neg]

start_ts_pos = (torque_filtered[seg2_start_idx + discard_count, 0]
                if seg2_end_idx - seg2_start_idx + 1 > discard_count
                else float('inf'))

mask_pos = ((feature_mean_filtered[:, 0] >= start_ts_pos) &
            (feature_mean_filtered[:, 0] <= torque_filtered[seg2_end_idx, 0]))
feature_mean_positive = feature_mean_filtered[mask_pos]

mask_torque_pos = ((torque_filtered[:, 0] >= start_ts_pos) &
                  (torque_filtered[:, 0] <= torque_filtered[seg2_end_idx, 0]))
torque_positive = torque_filtered[mask_torque_pos]

plt.figure(figsize=(15, 6))

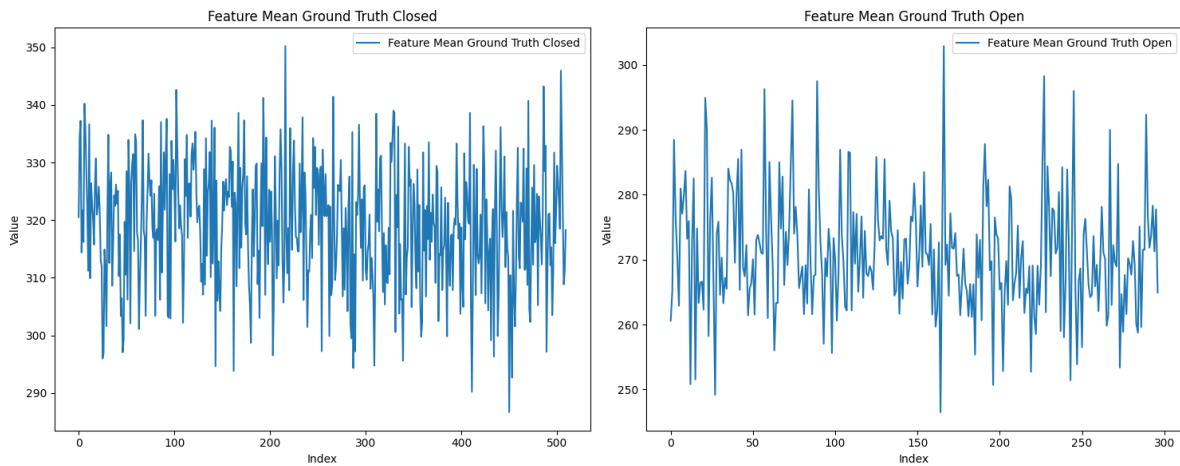
plt.subplot(1, 2, 1)
plt.plot(np.arange(len(feature_mean_negative)), feature_mean_negative[:, 1], label='Feature Mean')
plt.xlabel('Index')
plt.ylabel('Value')
plt.title('Feature Mean Ground Truth Closed')

```

```
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(np.arange(len(feature_mean_positive)), feature_mean_positive[:, 1], label='Feature Mean Positive')
plt.xlabel('Index')
plt.ylabel('Value')
plt.title('Feature Mean Ground Truth Open')
plt.legend()

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



## Computing Probabilities with Threshold 290

We will compute four probabilities using a decision threshold of 290 for the feature mean values. This threshold helps classify the door state based on the feature mean signal.

- **For ground truth closed (feature\_mean\_negative):**
  - Count the number of samples where `feature_mean < 290`. This gives the count for  $P(z=open|x=closed)$ .
  - $P(z=open|x=closed) = (\text{count of feature\_mean} < 290) / \text{len}(\text{feature\_mean\_negative})$
  - $P(z=closed|x=closed) = 1 - P(z=open|x=closed)$
- **For ground truth open (feature\_mean\_positive):**
  - Count the number of samples where `feature_mean > 290`. This gives the count for  $P(z=closed|x=open)$ .
  - $P(z=closed|x=open) = (\text{count of feature\_mean} > 290) / \text{len}(\text{feature\_mean\_positive})$

$$- P(z=\text{open}|x=\text{open}) = 1 - P(z=\text{closed}|x=\text{open})$$

```
threshold = 295

# For ground truth closed (feature_mean_negative)
count_open_given_closed = np.sum(feature_mean_negative[:, 1] < threshold)
p_open_given_closed = count_open_given_closed / len(feature_mean_negative)
p_closed_given_closed = 1 - p_open_given_closed
indices_open_given_closed = np.where(feature_mean_negative[:, 1] < threshold)[0]

print(f"P(z=open|x=closed): {p_open_given_closed}")
print(f"P(z=closed|x=closed): {p_closed_given_closed}")

# For ground truth open (feature_mean_positive)
count_closed_given_open = np.sum(feature_mean_positive[:, 1] > threshold)
p_closed_given_open = count_closed_given_open / len(feature_mean_positive)
p_open_given_open = 1 - p_closed_given_open
indices_closed_given_open = np.where(feature_mean_positive[:, 1] > threshold)[0]

print(f"P(z=closed|x=open): {p_closed_given_open}")
print(f"P(z=open|x=open): {p_open_given_open}")
```

```
P(z=open|x=closed): 0.013725490196078431
P(z=closed|x=closed): 0.9862745098039216
P(z=closed|x=open): 0.016835016835016835
P(z=open|x=open): 0.9831649831649831
```

```
plt.figure(figsize=(15, 6))

plt.subplot(1, 2, 1)
plt.plot(np.arange(len(feature_mean_negative)), feature_mean_negative[:, 1], label='Feature Mean Ground Truth Closed')
plt.scatter(indices_open_given_closed, feature_mean_negative[indices_open_given_closed, 1],
            color='red', label='Misclassified (Predicted Open)', zorder=5)
plt.axhline(y=threshold, color='green', linestyle='--', label=f'Threshold = {threshold}')
plt.xlabel('Index')
plt.ylabel('Value')
plt.title('Feature Mean Ground Truth Closed')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(np.arange(len(feature_mean_positive)), feature_mean_positive[:, 1], label='Feature Mean Ground Truth Open')
plt.scatter(indices_closed_given_open, feature_mean_positive[indices_closed_given_open, 1],
            color='red', label='Misclassified (Predicted Closed)', zorder=5)
plt.axhline(y=threshold, color='green', linestyle='--', label=f'Threshold = {threshold}')
plt.xlabel('Index')
plt.ylabel('Value')
plt.title('Feature Mean Ground Truth Open')
plt.legend()
```

```

        color='red', label='Misclassified (Predicted Closed)', zorder=5)
plt.axhline(y=threshold, color='green', linestyle='--', label=f'Threshold = {threshold}')
plt.xlabel('Index')
plt.ylabel('Value')
plt.title('Feature Mean Ground Truth Open')
plt.legend()

plt.tight_layout()
plt.show()

```

