## BE 521: Homework 3 Questions

Spring 2025

68 points

Due: Feb 13th, 2025

Objective: Extract features from data and build a simple detector

#### Al Usage Notice

The use of artificial intelligence tools (e.g., large language models, code assistants) is permitted. However, students must explicitly state the specific ways AI was used in completing their work. Failure to disclose AI usage may result in an oral examination to assess understanding, at the discretion of Dr. Litt.

If AI was used in the completion of this assignment, please provide a statement below:

[Enter your statement here]

## 1. Features and Simulations (39 pts)

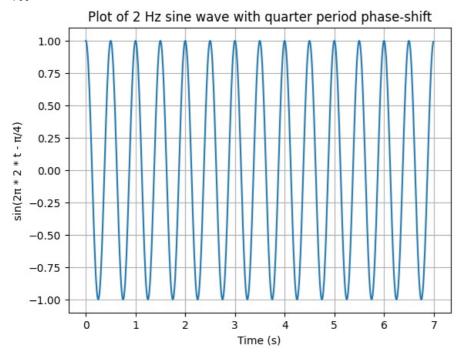
As you learned in class, features are the backbone of almost all detection strategies, from seizures in EEG to faces in images. Features are usually defined in journal articles as an equation or set of equations, and the task for the reader - if she wants to use that feature - is to implement that feature in code. In this section, you will explore and implement some features commonly used in EEG analysis and test them on simulated time-series data.

```
In [ ]: !jupyter nbconvert --to html /Prakriti HW1.ipynb
In [1]: #Set up the notebook environment
        !pip install git+https://github.com/ieeg-portal/ieegpy.git # Install ieegpy toolbox directly from github
        from ieeq.auth import Session
        from IPython.display import Image
        import matplotlib.pyplot as plt
        import numpy as np
        from scipy import signal as sig
        import datetime
        import time
       Collecting git+https://github.com/ieeg-portal/ieegpy.git
         Cloning https://github.com/ieeg-portal/ieegpy.git to /tmp/pip-req-build-5yg4z21i
         Running command git clone --filter=blob:none --quiet https://github.com/ieeg-portal/ieegpy.git /tmp/pip-req-bu
       ild-5yq4z21i
         Resolved https://github.com/ieeg-portal/ieegpy.git to commit 080bfa42a8503380ef164b5e7b116613f75073bb
         Preparing metadata (setup.py) \dots done
       Requirement already satisfied: deprecation in /usr/local/lib/python3.11/dist-packages (from ieeg==1.6) (2.1.0)
       Requirement already satisfied: requests in /usr/local/lib/python3.11/dist-packages (from ieeg==1.6) (2.32.3)
       Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from ieeg==1.6) (1.26.4)
       Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages (from ieeg==1.6) (2.2.2)
       Requirement already satisfied: pennprov==2.2.4 in /usr/local/lib/python3.11/dist-packages (from ieeg==1.6) (2.2.
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       Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-packages (from pennprov==2.2
       .4->ieeg==1.6) (2025.1.31)
       Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.11/dist-packages (from pennprov==2
       .2.4 - ieeq = 1.6) (2.8.2)
       Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.11/dist-packages (from pennprov==2.2.4->ieeg=
       =1.6)(1.17.0)
       Requirement already satisfied: urllib3>=1.23 in /usr/local/lib/python3.11/dist-packages (from pennprov==2.2.4->i
       eeq==1.6) (2.3.0)
       Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-packages (from deprecation->ieeg==1.6
       ) (24.2)
       Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas->ieeg==1.6)
       (2025.1)
       Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas->ieeg==1.6
       ) (2025.1)
       Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from request
       s \rightarrow ieeq = 1.6) (3.4.1)
       Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests->ieeg==1.6
       ) (3.10)
```

Plot the signal (2 pts)

```
In [2]: #your code here
        fs = 100 # sampling frequency
        time = np.arange(0, 7, 1/fs)
        frequency = 2 # freq
        #create sin wave - with quarter period phase-shift, period = 2pi, shift = 2pi * 1/4
        \# y = sin(x - pi/2) right shift
        y = np.sin(2* np.pi* frequency* time + (np.pi/2))
        print(y.size)
        # Create the plot
        plt.plot(time, y)
        # Add labels and title
        plt.xlabel('Time (s)')
        plt.ylabel('sin(2\pi * 2 * t - \pi/4)')
        plt.title('Plot of 2 Hz sine wave with quarter period phase-shift')
        # Add grid for better readability
        plt.grid(True)
        # Display the plot
        plt.show()
```

700



Your answer here

1b

Create a function for the line-length feature  $LL(x) = \sum_{i=1}^{n} |x_i - x_{i-1}|$ . This function can be implemented as a (cheeky) one-liner using Numpy. You may find np.ediffld, np.sum, and np.absolute to be helpful. (4 pts)

#### 55.99211470131448

Your answer here

1c

What is the line length of this signal? (2 pts)

```
In [4]: #your code here
print(line_length(y))
```

55.99211470131448

Your answer here

2

Consider line length of the signal using a sliding window with a certain amount of window overlap (or, to think of it another way, displacement with each "slide"). Now, instead of having just one value for the line length, you will have a number of values.

2a

Given a signal x with sampling frequency fs and windows of length winLen and displacement winDisp (both in seconds), create a function called NumWins that calculates the number of possible (full) windows in your signal of length xLen (in samples). You may assume that winDisp is a factor of both winLen and the length (in seconds) of x . (4 pts)

```
In [5]: # 0 - 4
# 4 -2 = 2, 2 + 4 = 6, 2 - 6
# 6 - 2 = 4 , 4 + 4 = 8, 4 - 8
# 6 - 10

def NumWins( signal, fs, winlen, winDisp):

    xlen = signal.size # duration * fs , but the signals size gives us that as well
# Convert window length and displacement from seconds to samples
winLen_samples = (winlen * fs)
winDisp_samples = (winDisp * fs)

# Calculate the number of full windows
num_windows = (xlen - winLen_samples) // winDisp_samples
num_windows = num_windows + 1

return int(num_windows)
```

Your answer here

2b

Use this function to calculate the number of windows for the signal described in Question 1.1 for a 400ms window with 200ms displacement. (1 pts)

```
In [6]: #your code here
a = NumWins(y, 100, 0.4, 0.2)
print(a)
```

Your answer here

2c

34

Repeat the above calculation for 50 ms window displacement. (1 pt)

```
In [7]: #your code here
# 133

a = NumWins(y, 100, 0.4, 0.05)
print(a)
```

133

Your answer here

Repeat the above calculation for 100 ms window displacement. (1 pts)

```
In [8]: #your code here
# 67

a = NumWins(y, 100, 0.4, 0.1)
print(a)
```

67

Your answer here

3

За

Create a function called MovingWinFeats(x, fs, winLen, winDisp, featFn) that returns a vector of the values of the feature on the signal x in all possible windows, where featFn is a feature function like the one you wrote in Question 1.1.b. You may find it useful to use your NumWins function. You may assume that the product of winDisp and the sampling rate fs is an integer. (6 pts)

```
In [9]: #your code here
        # 0 - 4
        #4 -2 = 2, 2 + 4 = 6, 2 - 6
        #6 - 2 = 4, 4 + 4 = 8, 4 - 8
        # 6 - 10
        def featFn(window):
            return np.sum(np.abs(np.ediffld(window)))
        def MovingWinFeats(x, fs, winLen, winDisp, featFn):
            xlen = x.size # duration * fs , but the signals size gives us that as well
            winLen_samples = int(winLen * fs)
            winDisp_samples = int(winDisp * fs)
            n = NumWins(x, fs, winLen, winDisp)
            # print(n)
            vector = []
            # vector.append(np.sum(np.abs(np.ediff1d(x[0:winLen samples]))))
            for i in range(n):
              start win = i * winDisp samples
              end_win = start_win + winLen_samples
              x in win = x[start win:end win]
              feature value = featFn(x in win)
                # Store the computed feature
              vector.append(feature_value)
              # winLen samples = end win
            return vector
```

Your answer here

3b

Using the signal you defined in Question 1.1 and the function you created in Question 1.1.b, calculate the line-length over windows of length 400 ms and displacement 200 ms. (2 pts)

```
In [10]: b = MovingWinFeats(y, fs , 0.4 , 0.2, featFn)
# print(len(b))
print(b)
```

[3.1873813145857244, 2.7652037140599783, 2.81467632558119, 3.3011316956894254, 3.5379856217963583, 3.18738131458 57257, 2.765203714059981, 2.8146763255811886, 3.301131695689424, 3.537985621796359, 3.187381314585726, 2.7652037 1405998, 2.814676325581189, 3.301131695689425, 3.537985621796359, 3.1873813145857253, 2.7652037140599806, 2.8146 76325581189, 3.3011316956894254, 3.5379856217963646, 3.1873813145857177, 2.76520371405998, 2.8146763255811824, 3.301131695689419, 3.5379856217963592, 3.187381314585711, 2.765203714059971, 2.8146763255811895, 3.30113169568943 25, 3.5379856217963632, 3.187381314585724, 2.7652037140599717, 2.814676325581189, 3.3011316956894334]

Your answer here

Зс

Add a unit-amplitude 10 Hz signal (in the form of a sine wave) to your original signal and again calculate the line length over the same window and displacement. (2 pts)

```
In [11]: #your code here
                            fs = 100 # sampling frequency
                            time = np.arange(0, 7, 1/fs)
                             frequency = 2 # freq
                            #create sin wave - with quarter period phase-shift, period = 2pi, shift = 2pi * 1/4
                            \# y = sin(x - pi/4) right shift
                            x = np.sin(2* np.pi* frequency* time + (np.pi/2)) + np.sin(2* np.pi* 10 * time)
                            b = MovingWinFeats(x, fs , 0.4 , 0.2, featFn)
                            # print(len(b))
                            print(b)
                          [15.213982873452375,\ 15.276263833971537,\ 15.202645443068086,\ 15.259481541227782,\ 15.444331583060304,\ 15.213982873452375,\ 15.276263833971537,\ 15.202645443068086,\ 15.259481541227782,\ 15.444331583060304,\ 15.213982873452375,\ 15.276263833971537,\ 15.202645443068086,\ 15.259481541227782,\ 15.444331583060304,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982873452375,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.213982875,\ 15.
                         3452373, 15.276263833971534, 15.202645443068066, 15.259481541227787, 15.44433158306033, 15.21398287345241, 15.27
                         6263833971544, \ 15.202645443068064, \ 15.259481541227736, \ 15.444331583060237, \ 15.213982873452352, \ 15.27626383397153, \ 15.213982873452352, \ 15.27626383397153, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452352, \ 15.213982873452, \ 15.213982873452352, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.213982873452, \ 15.21398287452, \ 15.21398287452, \ 15.21398287452, \ 15.21398
                         4306809, 15.259481541227792, 15.44433158306036, 15.213982873452364, 15.276263833971512, 15.202645443068052, 15.2
                         59481541227766, 15.44433158306034, 15.21398287345247, 15.276263833971578, 15.202645443068121, 15.259481541227835
                            Your answer here
                            4
                            Code the following 3 additional features. You only need one line for each.
                            4a
                            Area, A(x) = \sum_{i=1}^{n} |x_i| (2 pts)
In [12]: #your code here
                            def Area(x):
                                 area = np.sum(np.abs(x))
                                  # print(area)
                                  return area
                            Your answer here
                            4b
                            Energy, E(x) = \sum_{i=1}^{n} x_i^2 (2 pts)
In [13]: #your code here
                            def Energy(x):
                                 energy = np.sum((np.square(x)))
                                  return energy
                            Your answer here
                            4c
                            Zero-Crossings around mean, ZX(x) = \sum_{i=2}^{n} [\Phi(FromAbove) \text{ OR } \Phi(FromBelow)].
                                             \Phi is the indicator function which returns 0 if its argument is false, and 1 if it is true.
                                              FromAbove denotes (x_{i-1} - \bar{x} > 0)AND(x_i - \bar{x} < 0).
                                             FromBelow denotes (x_{i-1} - \bar{x} < 0)AND(x_i - \bar{x} > 0).
                                           \bar{x} denotes the mean of x. (4 pts)
In [14]: #your code here
                            def zero crossings mean(x):
                                        x_{mean} = np.mean(x) # Mean of the signal
                                        zero crossings = 0  # To store the number of zero-crossings around the mean
                                        # Loop through the signal from the second element to the last element
                                        for i in range(1, len(x)):
                                                     # FromAbove condition
                                                     if (x[i-1] - x_mean) > 0 and (x[i] - x_mean) < 0:
```

```
zero_crossings += 1
# FromBelow condition
elif (x[i-1] - x_mean) < 0 and (x[i] - x_mean) > 0:
    zero_crossings += 1

return zero_crossings
```

#### 4d

Plot the values of the four features on the combined signal in the first four cells of a 3x2 subplot. Use a 400ms window with 100ms displacement. Using the right-aligned convention (where the official time of the feature is that of the last data point in the window), give the appropriate time axis for each window point. In addition, plot the original signal with the 2Hz and 10Hz components in the last two cells of the 3x2 subplot (to make comparing down the column easy). Ensure that the time axis in all of your plots is the same. (6 pts)

```
In [34]: import numpy as np
         import matplotlib.pyplot as plt
         # Generate the time axis
         fs = 100 # Sampling frequency in Hz
         t end = 7 # Duration in seconds
         time = np.linspace(0,t end, int(t end * fs),endpoint=False)
         # Define the original 2 Hz signal
         original_signal = np.sin((2 * np.pi * 2 * time) + (np.pi/2))
         # Define the 10 Hz component
         high freq component = np.sin(2 * np.pi * 10 * time)
         # Create the combined signal
         combined_signal = original_signal + high_freq_component
         # Feature extraction functions
         def area(x):
             return np.sum(np.abs(x))
         def energy(x):
             return np.sum(x**2)
         # def zero crossings mean(x):
              x mean = np.mean(x)
               return np.sum((x[:-1] - x mean) * (x[1:] - x mean) < 0)
         def line length(x):
             return np.sum(np.abs(np.diff(x)))
         # # Define window parameters
         win len = 0.4 # 400 ms
         win disp = 0.1 \# 100 \text{ ms}
         # Compute features
         energy values = MovingWinFeats(combined signal, fs, win len, win disp, energy)
         area_values = MovingWinFeats(combined_signal, fs, win_len, win_disp, area)
         zero_crossings = MovingWinFeats(combined_signal, fs, win_len, win_disp, zero_crossings_mean)
         line_length = MovingWinFeats(combined_signal, fs, win_len, win_disp, line_length)
         # Time axis
         num windows = len(line length)
         time axis features = time[int(win len * fs) - 1 : len(time) : int(win disp* fs)]
         # Plot the features and signals in a 3x2 grid
         fig, axes = plt.subplots(3, 2, figsize=(12, 10), sharex=True)
         axes[0, 0].plot(time axis features, energy values, label="Energy", color='orange')
         axes[0, 0].set_title("Energy Feature")
         axes[0, 0].legend()
         axes[0, 1].plot(time axis features, area values, label="Area", color='green')
         axes[0, 1].set_title("Area Feature")
         axes[0, 1].legend()
         axes[1, 0].plot(time axis features, zero crossings, label="Zero Crossings", color='blue')
         axes[1, 0].set_title("Zero Crossings Feature")
         axes[1, 0].legend()
```

```
axes[1, 1].plot(time_axis_features, line_length, label="Line Length", color='red')
 axes[1, 1].set_title("Line Length Feature")
 axes[1, 1].legend()
 axes[2, 0].plot(time[:len(combined_signal)], combined_signal, label="Combined Signal", color='black')
 axes[2, 0].set title("Original Combined Signal")
 axes[2, 0].legend()
 axes[2, 1].plot(time[:len(original_signal)], original_signal, label="2 Hz Component", color='purple')
 axes[2, 1].plot(time[:len(high_freq_component)], high_freq_component, label="10 Hz Component", linestyle='solid
 axes[2, 1].set_title("2 Hz and 10 Hz Components")
 axes[2, 1].legend()
 plt.xlabel("Time (s)")
 plt.tight_layout()
 plt.show()
                          Energy Feature
                                                                                          Area Feature
         Energy
                                                                35
 44
 42
                                                                33
 40
                                                                32
 38
                                                                31
 36
                      Zero Crossings Feature
                                                                                       Line Length Feature
 8.0
                                                              15.40
 7.0
                                                              15.35
 6.5
                                                              15.30
 6.0
                                                              15.25
 5.5
 5.0
                                                              15.20
                                                                                   2 Hz and 10 Hz Components
                     Original Combined Signal
 2.0
                                                               1.00
                                                               0.75
 1.0
                                                               0.50
 0.5
                                                               0.25
                                                                                                             2 Hz Component
 0.0
                                                               0.00
                                                                                                             10 Hz Component
                                                              -0.25
-0.5
                                                              -0.50
-1.0
```

-1.5

# 2. Feature Overlays (17 pts)

In this section, you will use a line-length feature overlay on a segment of EEG containing a seizure. This data is stored in I521\_A0003\_D001.

Note that IEEG can only send so much data at once (about 600,000 datapoints per channel at a time). To help you import the longer datasets we'll be using in this homework (and in some of the future ones), we've included the following loading function. Feel free to use it.

-0.75

-1.00

Time (s)

```
Returns:
    [n, m] ndarry of the channels' values.
"""

#stores the segments of the channel's data
chn_segments = []

#how many segments do we expect?
num_segments = int(np.ceil(duration_secs * sampling_rate / 6e5))

#segment start times and the step
seg_start, step = np.linspace(1, duration_secs*le6, num_segments, endpoint=False, retstep=True)

#get the segments
for start in seg_start:
    chn_segments.append(dataset.get_data(start, step, chn_idx))

#concatenate the segments vertically
return np.vstack(chn_segments)
```

1

What is the length using hrs:min:sec.ms of the recording? You may find divmod to be helpful. Also, the time and datetime packages are imported and can also be used. (2 pts)

```
In [46]: #your code here
         # get channel label and detials of time series
         with open('/content/pra_ieeglogin(9).bin', 'r') as f:
           session = Session('prasadpr', f.read())
         dataset= session.open dataset('I521 A0003 D001')
         dataset.get_channel_labels()
         key = list(dataset.ts_details.keys())[0]
         time = dataset.get_time_series_details(key)
         print(time)
         print("Sampling rate of this data: ", time.sample_rate)
         key = list(dataset.ts details.keys())[0]
         channels = dataset.get channel indices([key])[0]
         duration_secs = 4880.39
         hours, remainder = divmod(duration secs, 3600)
         minutes, seconds = divmod(remainder, 60)
         milliseconds = (seconds - int(seconds)) * 1000 # Fractional seconds to milliseconds
         print(f"Duration: {int(hours)}:{int(minutes)}:{int(seconds)}.{int(milliseconds)}")
```

None(szChirps) spans 4880390000.0 usec, range [-204300-204700] in 976079 samples. Starts @1 uUTC, ends @48803900 01 uUTC with sample rate 200.0 Hz and voltage conv factor 0.01 Sampling rate of this data: 200.0 Duration: 1:21:20.390

Your answer here

2

How many data points should we discard at the end if we want to clip the recording to the last full second? Do this clipping. (1 pt)

```
In [47]: # compute the number of data points per second:
         # samples per second=sampling rate
         # Compute how many extra samples are in the 0.39 seconds:
         # samples to remove=0.39×sampling rate
         # Convert this to an integer (since we deal with whole samples).
         # Remove these samples from the data.
         # Get the sampling rate from the dataset
         sampling rate = time.sample rate # Hz (samples per second)
         # Compute how many samples to remove
         extra_time = 0.395 # Fractional seconds
         samples to remove = (extra time * sampling rate)
         # Get total number of samples in the dataset
         # number of samples = (duration secs * sampling rate) # Convert duration to total samples
         number of samples = 976079
         # Clip the recording using dataset.get data()
         I_clipped = dataset.get_data(0, number_of_samples - samples_to_remove, [channels])
         remaining_samples = number_of_samples - samples_to_remove
```

```
# Print results
print(f"Number of samples removed: {samples_to_remove}")
print(f"New number of samples: {len(I_clipped)}")
print(f"Number of samples remaining: {(remaining_samples)}")
print(f"New dataset shape: {I_clipped.shape}")

Number of samples removed: 79.0
New number of samples: 196
Number of samples remaining: 976000.0
New dataset shape: (196, 1)
```

3

Your answer here

If we want to overlay a feature trace on the original signal, we have to interpolate that feature (which has been calculated over windows) for each data point of the original signal. One of the simplest methods of doing this is called zero-order interpolation, where we just hold the value constant until we get to the next calculated value. For example, if we had a moving window of 1 second with 1 second displacement, the zero-order interpolated feature vector would have the same value the entire 1s5 second, then the same for the entire 2nd second, etc, where each second contains the same number of points as the sampling frequency of the original signal.

3a

Using the <code>np.tile</code> and <code>np.reshape</code> functions, create an external function <code>zoInterp(x, numInterp)</code> that copies each value of <code>x numInterp</code> times. For <code>np.reshape</code>, setting <code>order='F'</code> may be necessary. You can implement this function in one line. (2 pts)

```
In [48]: # overlay a feature trace, interpolate the feature
import numpy as np

def zoInterp(x, numInterp):
    return np.tile(x, (numInterp, 1)).reshape(-1, order='F')
```

Your answer here

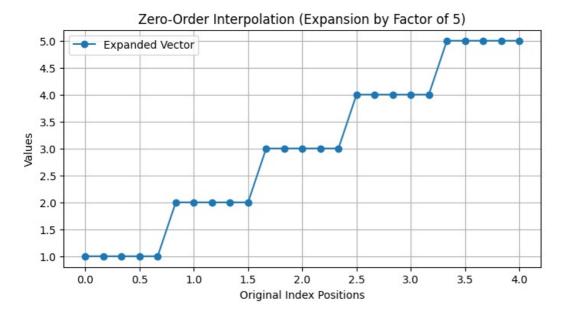
3b

Confirm that this function works correctly by expanding the length of the vector [1, 2, 3, 4, 5] by a factor of 5. Plot your results using the -o plotting option to let us see the individual points and the line that connects them. (2 pts)

Hint: your resulting vector should be a column vector of [1,1,1,1,2,2,2,...]

```
In [51]: #your code here
         a = [1, 2, 3, 4, 5]
         b = zoInterp(a, 5)
         print(b)
         # Generate x-axis indices for plotting
         original_indices = np.arange(len(a))
         expanded_indices = np.linspace(0, len(a) - 1, len(b))
         # Plot results
         plt.figure(figsize=(8, 4))
         plt.plot(expanded_indices, b, '-o', label="Expanded Vector")
         # plt.xticks(original indices, labels=x) # Label original indices
         plt.xlabel("Original Index Positions")
         plt.ylabel("Values")
         plt.title("Zero-Order Interpolation (Expansion by Factor of 5)")
         plt.legend()
         plt.grid()
         plt.show()
         # Print the expanded vector for verification
         # print("Expanded Vector:", b.reshape(-1, 1)) # Column format
```

 $[1\ 1\ 1\ 1\ 1\ 2\ 2\ 2\ 2\ 2\ 3\ 3\ 3\ 3\ 4\ 4\ 4\ 4\ 4\ 5\ 5\ 5\ 5\ 5]$ 



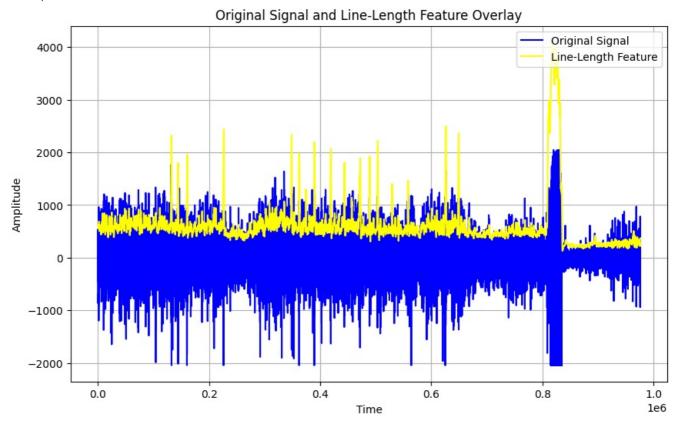
### 4

Using a 5-second sliding window with 1-second displacement, calculate the line-length feature over the entire signal. Normalize the line-length feature values to have a maximum twice that of the original EEG signal maximum. Plot the signal in blue and overlay the right-aligned line-length feature in yellow. Note: you will need to pad your signal in order to get them to line up correctly and be the same length. Be sure to add a legend in a location in the plot that does not cover up any signal or feature. (6 pts)

```
In [52]:
         import numpy as np
         import matplotlib.pyplot as plt
         # Load the EEG signal
         duration = 4880
         I = load full channels(dataset, duration, 200, [channels])
         # Compute the line-length feature
         ll = MovingWinFeats(I, 200, 5, 1, featFn)
         # Normalize the feature
         ll normalized = (ll / np.max(ll)) * (2 * np.max(I))
         # Check interpolation factor
         interp factor = len(I) // len(ll)
         print(f"Interpolation factor: {interp_factor}")
         # Correct zero-order interpolation
         def zoInterp(x, numInterp, target_length):
             return np.repeat(x, numInterp)[:target length]
         ll interpolated = zoInterp(ll_normalized, interp_factor, len(I))
         if len(ll interpolated) < len(I):</pre>
             padding needed = len(I) - len(ll interpolated)
             ll_padded = np.pad(ll_interpolated, (padding_needed, 0), mode='edge')
         else:
             ll padded = ll interpolated[:len(I)] # Trim excess if necessary
         # Pad correctly using window length
         \# padding = int(5 * 200) \# 5-second window * sampling rate (200Hz)
         # ll_padded = np.pad(ll_interpolated, (padding, 0), mode='edge')
         # Plot signal + feature overlay
         plt.figure(figsize=(10, 6))
         plt.plot(I, label='Original Signal', color='blue')
         plt.plot(ll_padded, label='Line-Length Feature', color='yellow')
```

```
plt.xlabel('Time')
plt.ylabel('Amplitude')
plt.title('Original Signal and Line-Length Feature Overlay')
plt.legend(loc='upper right')
plt.grid(True)
plt.show()
```

Interpolation factor: 200



Your answer here

5

What threshold might you use on the raw line-length feature vector (not the normalized one used for plotting) in order to capture the 17 largest pre-seizure chirps that occur? (1 pt)

```
In [55]: #your code here

# print(ll)
print(np.sort(ll))
a = np.sort(ll)
print(a[-17])
# I would use the threshold to be the index of this number 129347.

[ 4399. 4413. 4453. ... 134558. 135295. 136537.]
129347.0
```

I would use the threshold to be the index of this number 129347 or this number depending on how I compute my it

6

Using this threshold value, in another plot draw red vertical dashed lines at the leading point in time where the threshold is crossed. Add these vertical lines on top of the plot you made in Question 2.4. These events should capture the pre-seizure chirps, the seizure onset, and some flickering during the end of the seizure. (3 pts)

```
import numpy as np
import matplotlib.pyplot as plt

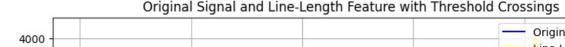
threshold = 1000 # Apply threshold on raw line-length feature
time_axis = np.linspace(0, duration, len(I))

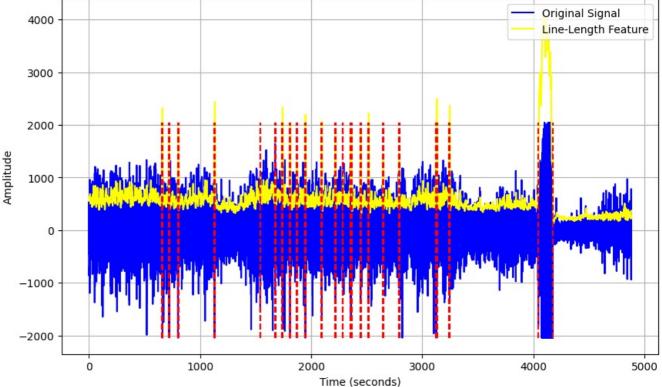
# Detect where line-length crosses the threshold
crossing_indices = np.where(np.diff(np.sign(ll_padded - threshold)))[0] + 1
crossing_times = time_axis[crossing_indices] # Convert to time

# print(f"Crossing times: {crossing_times}")

# Plot signal + feature overlay
```

```
plt.figure(figsize=(10, 6))
plt.plot(time_axis, I, label='Original Signal', color='blue')
plt.plot(time_axis, ll_padded, label='Line-Length Feature', color='yellow')
for time in crossing times:
    plt.vlines(time, ymin=np.min(I), ymax=np.max(I), color='red', linestyle='--')
plt.xlabel('Time (seconds)')
plt.ylabel('Amplitude')
plt.title('Original Signal and Line-Length Feature with Threshold Crossings')
plt.legend(loc='upper right')
plt.grid(True)
plt.show()
```





# 3. Building a Detector (12 pts)

In this section, you will use the features you defined previously to build a seizure detector. Use the EEG data in the file I521 A0003 D002 with channels multiSz 1, and multiSz 2.

1

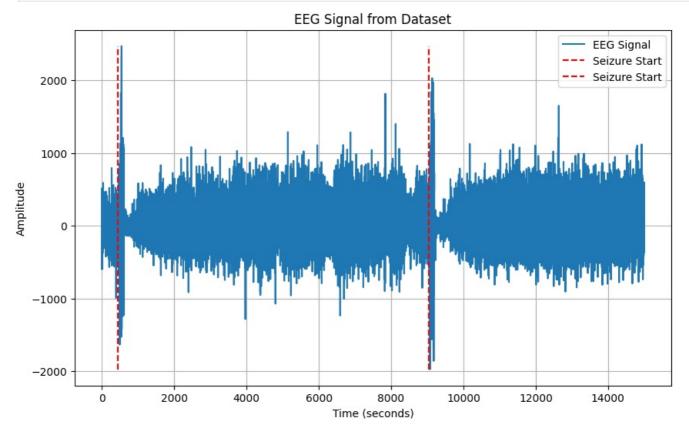
Plot the signal in multiSz\_1 and draw vertical dashed red lines at the times when you think the two seizures begin. You should be able to do this without the need of any features. (2 pts)

```
In [57]: with open('/content/pra ieeglogin(9).bin', 'r') as f:
           session = Session('prasadpr', f.read())
         dataset= session.open_dataset('I521_A0003_D002')
         key = list(dataset.ts_details.keys())[0]
         # channel = dataset.get channel indices([key])[0]
         # time = dataset.get time series details(key)
         # print(time)
         # multiSz_1 = dataset.get_data(0, 14999995000/1000000, [0])
         multiSz 1 = load full channels(dataset, 14999995000/1000000, 200,[0])
         # print(multiSz_1)
         key1 = list(dataset.ts details.keys())[1]
         channel2 = dataset.get_channel_indices([key1])[0]
         multiSz 2 = dataset.get data(0, 488039, [channel2])
         time axis = np.linspace(0, 14999995000/1000000, multiSz 1.shape[0])
         # Plot the data
         plt.figure(figsize=(10, 6))
```

```
plt.plot(time_axis, multiSz_1, label="EEG Signal")
plt.xlabel('Time (seconds)')
plt.ylabel('Amplitude')
plt.title('EEG Signal from Dataset')

seizure_start_times = [450, 9050]
for seizure_time in seizure_start_times:
    plt.vlines(seizure_time, ymin=np.min(multiSz_1), ymax=np.max(multiSz_1), color='red', linestyle='--', label-
plt.legend()
plt.grid(True)
plt.show()

# print(dataset.get_channel_labels())
# a = dataset.get_channel_indices(['multiSz_1'])
# b = dataset.get_channel_indices(['multiSz_2'])
# print(a)
# print(b)
```



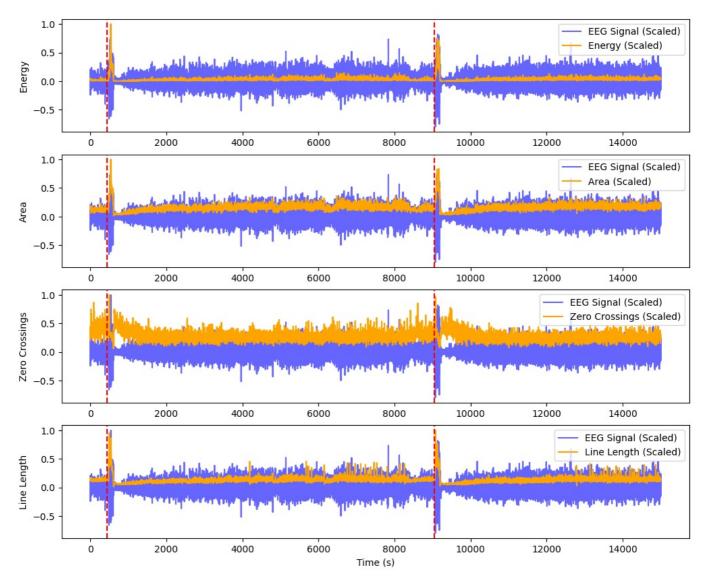
2

Produce feature overlay plots similar to that of Question 2.4 for each of the four features you have implemented along with the red vertical dashed lines at each seizure. Use a 4-second sliding window with 1 second displacement. (4 pts)

```
In [25]: import numpy as np
         import matplotlib.pyplot as plt
         # Feature Functions
         def Area(x):
             return np.sum(np.abs(x))
         def Energy(x):
             return np.sum(np.square(x))
         def zero_crossings_mean(x):
             x mean = np.mean(x)
             zero crossings = 0
             for i in range(1, len(x)):
                 if (x[i-1] - x_mean) > 0 and (x[i] - x_mean) < 0:
                     zero crossings += 1
                 elif (x[i-1] - x_mean) < 0 and (x[i] - x_mean) > 0:
                     zero crossings += 1
             return zero_crossings
```

```
def line length(x):
    return np.sum(np.abs(np.ediff1d(x))) # Line Length (Mean Abs Diff)
# Compute number of windows
def NumWins(x, fs, winLen, winDisp):
    return int((len(x) - winLen * fs) / (winDisp * fs)) + 1
# Moving Window Feature Extraction
def MovingWinFeats(x, fs, winLen, winDisp, featFn):
   winLen_samples = int(winLen * fs)
   winDisp_samples = int(winDisp * fs)
   n = NumWins(x, fs, winLen, winDisp)
   features = []
    for i in range(n):
        start win = i * winDisp samples
        end win = start win + winLen samples
        x in win = x[start win:end win]
        features.append(featFn(x_in_win))
    return np.array(features)
# Load EEG Data
fs = 200 # Assuming a sampling rate of 200 Hz
winLen = 4 # 4-second window
winDisp = 1 # 1-second displacement
# Use EEG data from `multiSz_1`
signal = multiSz_1[:, 0] # Assuming single-channel EEG data
# Compute Features
energy feat = MovingWinFeats(signal, fs, winLen, winDisp, Energy)
area_feat = MovingWinFeats(signal, fs, winLen, winDisp, Area)
zc_feat = MovingWinFeats(signal, fs, winLen, winDisp, zero_crossings_mean)
ll_feat = MovingWinFeats(signal, fs, winLen, winDisp, line_length)
# Generate Time Axis
time_axis = np.linspace(0, len(signal) / fs, len(signal))
feature_time_axis = np.linspace(winLen / 2, (len(signal) / fs) - (winLen / 2), len(energy_feat))
# Seizure timestamps (example values, replace with actual seizure times)
seizure times = [450, 9050] # In seconds
# Plot Features with Original EEG Overlay
plt.figure(figsize=(12, 10))
plt.subplot(4, 1, 1)
plt.plot(time_axis, signal / np.max(np.abs(signal)), color='blue', alpha=0.6, label="EEG Signal (Scaled)")
plt.plot(feature_time_axis, energy_feat / np.max(energy_feat), color='orange', label="Energy (Scaled)")
for seizure in seizure times:
   plt.axvline(x=seizure, color='r', linestyle='dashed')
plt.ylabel("Energy")
plt.legend()
plt.subplot(4, 1, 2)
plt.plot(time_axis, signal / np.max(np.abs(signal)), color='blue', alpha=0.6, label="EEG Signal (Scaled)")
plt.plot(feature_time_axis, area_feat / np.max(area_feat), color='orange', label="Area (Scaled)")
for seizure in seizure_times:
   plt.axvline(x=seizure, color='r', linestyle='dashed')
plt.ylabel("Area")
plt.legend()
plt.subplot(4, 1, 3)
plt.plot(time axis, signal / np.max(np.abs(signal)), color='blue', alpha=0.6, label="EEG Signal (Scaled)")
plt.plot(feature_time_axis, zc_feat / np.max(zc_feat), color='orange', label="Zero Crossings (Scaled)")
for seizure in seizure_times:
   plt.axvline(x=seizure, color='r', linestyle='dashed')
plt.ylabel("Zero Crossings")
plt.legend()
plt.subplot(4, 1, 4)
plt.plot(time\_axis, signal / np.max(np.abs(signal)), color='blue', alpha=0.6, label="EEG Signal (Scaled)")
plt.plot(feature time axis, ll feat / np.max(ll feat), color='orange', label="Line Length (Scaled)")
for seizure in seizure times:
   plt.axvline(x=seizure, color='r', linestyle='dashed')
plt.ylabel("Line Length")
plt.legend()
plt.xlabel("Time (s)")
plt.suptitle("EEG Signal & Feature Overlays with Seizure Markers")
plt.show()
```

EEG Signal & Feature Overlays with Seizure Markers



Your answer here

3

За

Based on your plots in the previous question, which of the four features seems to give the largest signal (relative to the background) for when a seizure occurs? Explain why you think this feature is the best. (3 pts)

Based on the corrected plots, Energy appears to give the largest signal relative to the background during a seizure. We could also use Area and line lengths.

Largest Contrast Between Seizure and Baseline

The energy feature shows a significant increase during seizure periods compared to the non-seizure background

Energy Captures High-Amplitude Changes

Seizures are often characterized by high-amplitude and high-frequency activity, both of which contribute to a large energy value.

Low Baseline During Non-Seizure Periods

Unlike Zero Crossings, which may remain noisy even in non-seizure states, the Energy feature stays relatively low in normal EEG activity.

3h

What threshold would you use to determine if a seizure is occurring? (1 pt)

- I would use 1000 if I need to capture pre-seizure chirps, the seizure onset, and some flickering during the end of the seizure.
- But if I want to detect only seizure then I would use 4000 or above

### 4

The signal in multiSz\_2 contains another seizure (whose location should again be fairly obvious). Plot the data along with the feature and threshold (horizontal black line, with correct normalization for the signal in data2) you determined in the previous question. (2 pts)

\*\*Considering only the energy graph based on my above answer, I think energy works pretty well. I set the threshold to 4500. The threshold 4000 worked for the above graphs. \*\*

```
In [66]: import numpy as np
         import matplotlib.pyplot as plt
         # Load EEG Data (restricting to 100,000 samples for performance)
         multiSz_2 = load_full_channels(dataset, 14999995000 / 1000000, 200, [1])
         multiSz 2 = multiSz 2[:1000000] # Limit dataset for efficiency
         # Feature Functions
         def Area(x):
             return np.sum(np.abs(x))
         def Energy(x):
             return np.sum(np.square(x))
         def zero_crossings_mean(x):
             x mean = np.mean(x)
             return np.sum((x[:-1] - x_mean) * (x[1:] - x_mean) < 0)
         def line length(x):
             return np.sum(np.abs(np.ediffld(x))) # Line Length (Mean Abs Diff)
         # Compute number of windows
         def NumWins(x, fs, winLen, winDisp):
             return int((len(x) - winLen * fs) / (winDisp * fs)) + 1
         # Moving Window Feature Extraction
         def MovingWinFeats(x, fs, winLen, winDisp, featFn):
             winLen_samples = int(winLen * fs)
             winDisp_samples = int(winDisp * fs)
             n = NumWins(x, fs, winLen, winDisp)
             features = np.zeros(n)
             for i in range(n):
                 start win = i * winDisp samples
                 end_win = start_win + winLen_samples
                 features[i] = featFn(x[start_win:end_win])
             return features
         # Sampling rate and window parameters
         fs = 200 # 200Hz sampling rate
         winLen = 4 # 4-second window
         winDisp = 1 # 1-second displacement
         # Compute Features
         energy feat = MovingWinFeats(multiSz 2, fs, winLen, winDisp, Energy)
         area_feat = MovingWinFeats(multiSz_2, fs, winLen, winDisp, Area)
         zc_feat = MovingWinFeats(multiSz_2, fs, winLen, winDisp, zero_crossings_mean)
         ll_feat = MovingWinFeats(multiSz_2, fs, winLen, winDisp, line_length)
         # Define time axes (right-aligned convention)
         time axis = np.linspace(0, len(multiSz 2) / fs, len(multiSz 2))
         feature time axis = np.linspace(winLen, (len(multiSz 2) / fs), len(energy feat)) # Adjusted to right-align
         # Example seizure timestamps (modify accordingly)
         seizure times = [4500] # Adjust based on actual seizure locations in seconds
         # Plot Features with Original EEG Overlay
         plt.figure(figsize=(12, 10))
```

```
plt.subplot(4, 1, 1)
plt.plot(time_axis, multiSz_2 / np.max(np.abs(multiSz_2)), color='blue', alpha=0.6, label="EEG Signal (Scaled)"
plt.plot(feature_time_axis, energy_feat / np.max(energy_feat), color='orange', label="Energy (Scaled)")
for seizure in seizure times:
   plt.axvline(x=seizure, color='r', linestyle='dashed')
plt.ylabel("Energy")
plt.legend()
plt.subplot(4, 1, 2)
plt.plot(time_axis, multiSz_2 / np.max(np.abs(multiSz_2)), color='blue', alpha=0.6, label="EEG Signal (Scaled)"
plt.plot(feature_time_axis, area_feat / np.max(area_feat), color='orange', label="Area (Scaled)")
for seizure in seizure times:
    plt.axvline(x=seizure, color='r', linestyle='dashed')
plt.ylabel("Area")
plt.legend()
plt.subplot(4, 1, 3)
plt.plot(time axis, multiSz 2 / np.max(np.abs(multiSz 2)), color='blue', alpha=0.6, label="EEG Signal (Scaled)"
plt.plot(feature_time_axis, zc_feat / np.max(zc_feat), color='orange', label="Zero Crossings (Scaled)")
for seizure in seizure times:
    plt.axvline(x=seizure, color='r', linestyle='dashed')
plt.ylabel("Zero Crossings")
plt.legend()
plt.subplot(4, 1, 4)
plt.plot(time axis, multiSz 2 / np.max(np.abs(multiSz 2)), color='blue', alpha=0.6, label="EEG Signal (Scaled)"
plt.plot(feature_time_axis, ll_feat / np.max(ll_feat), color='orange', label="Line Length (Scaled)")
for seizure in seizure times:
    plt.axvline(x=seizure, color='r', linestyle='dashed')
plt.ylabel("Line Length")
plt.legend()
plt.xlabel("Time (s)")
plt.suptitle("EEG Signal & Feature Overlays with Seizure Markers")
plt.show()
```

