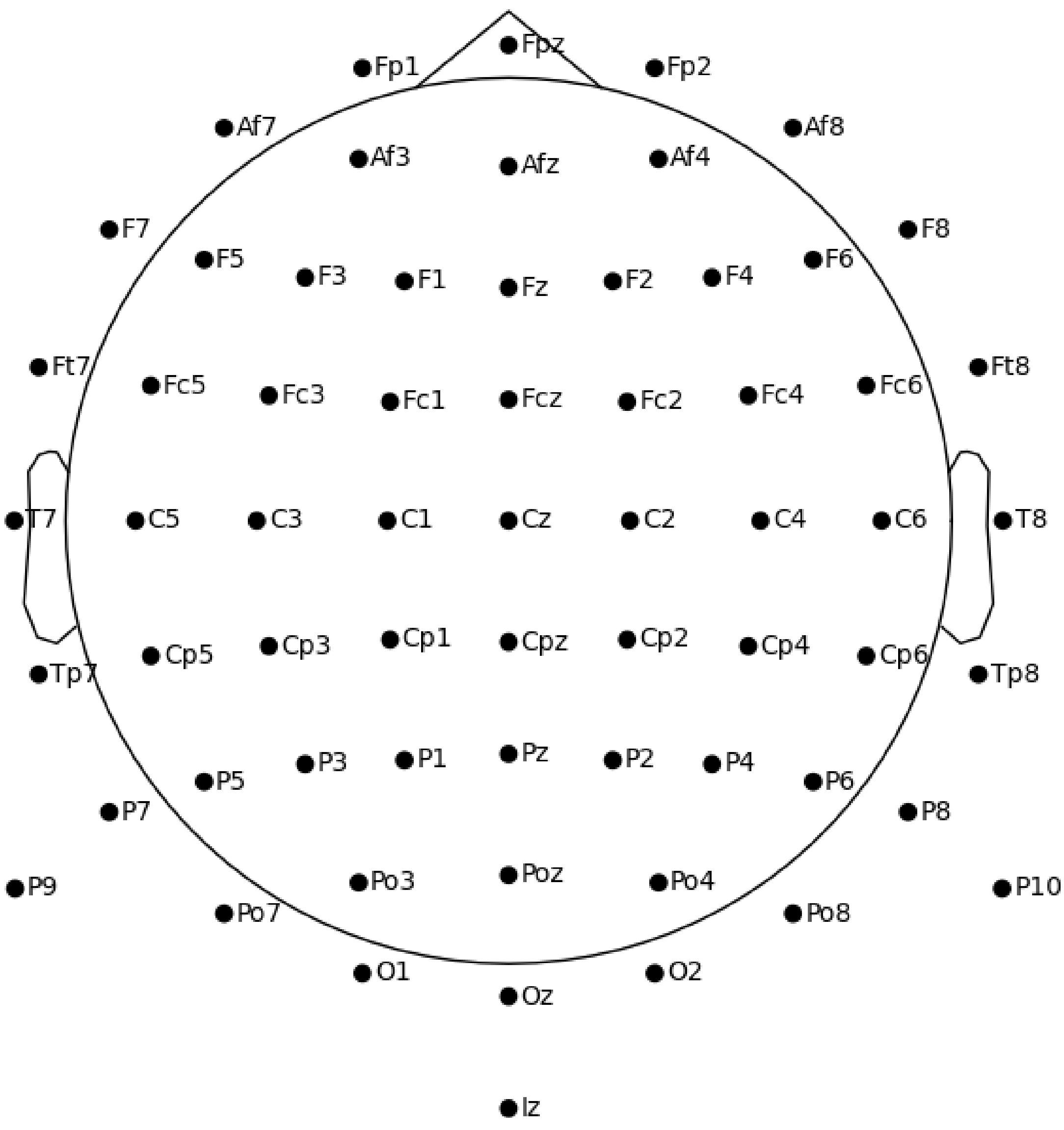
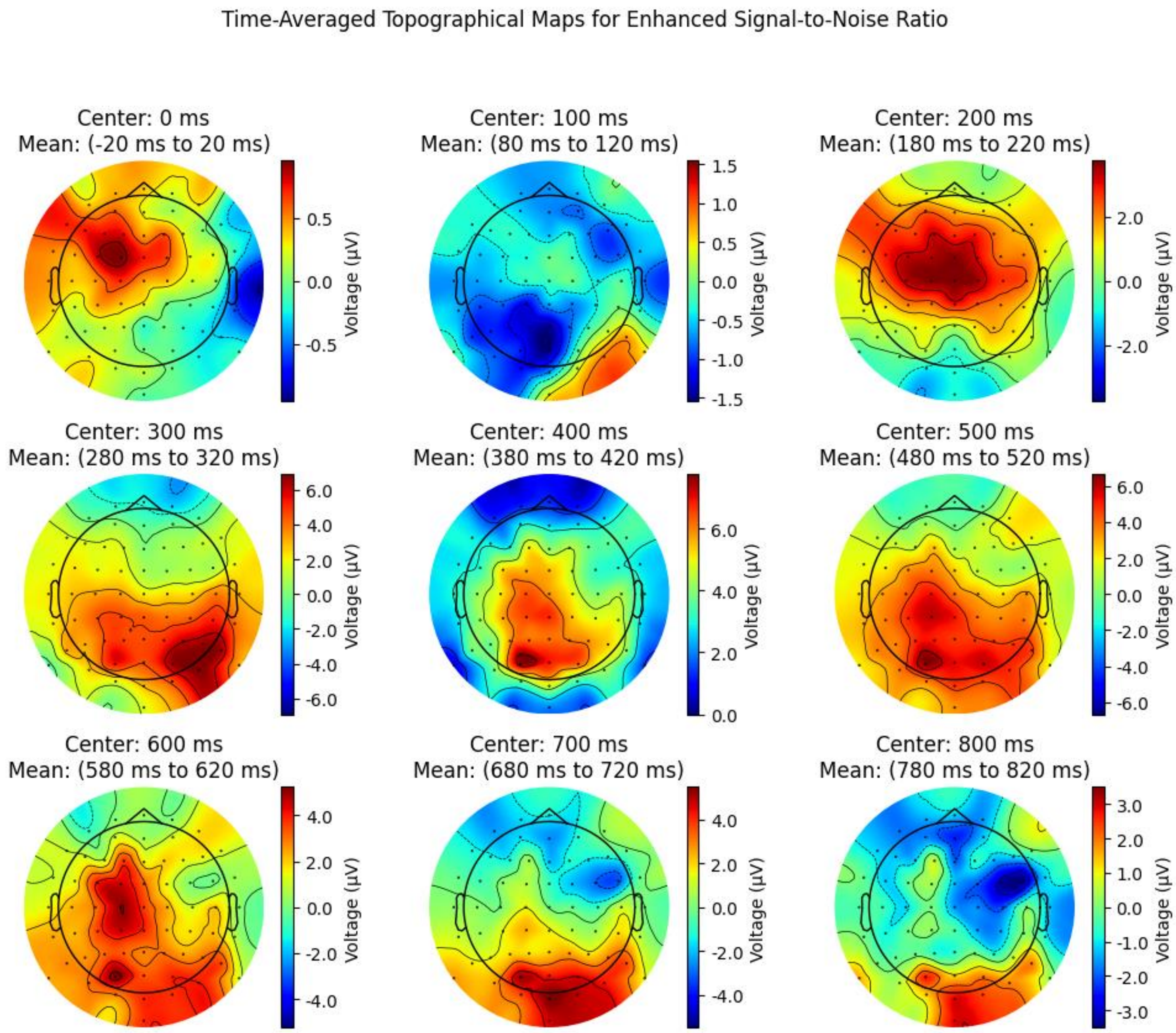
a.

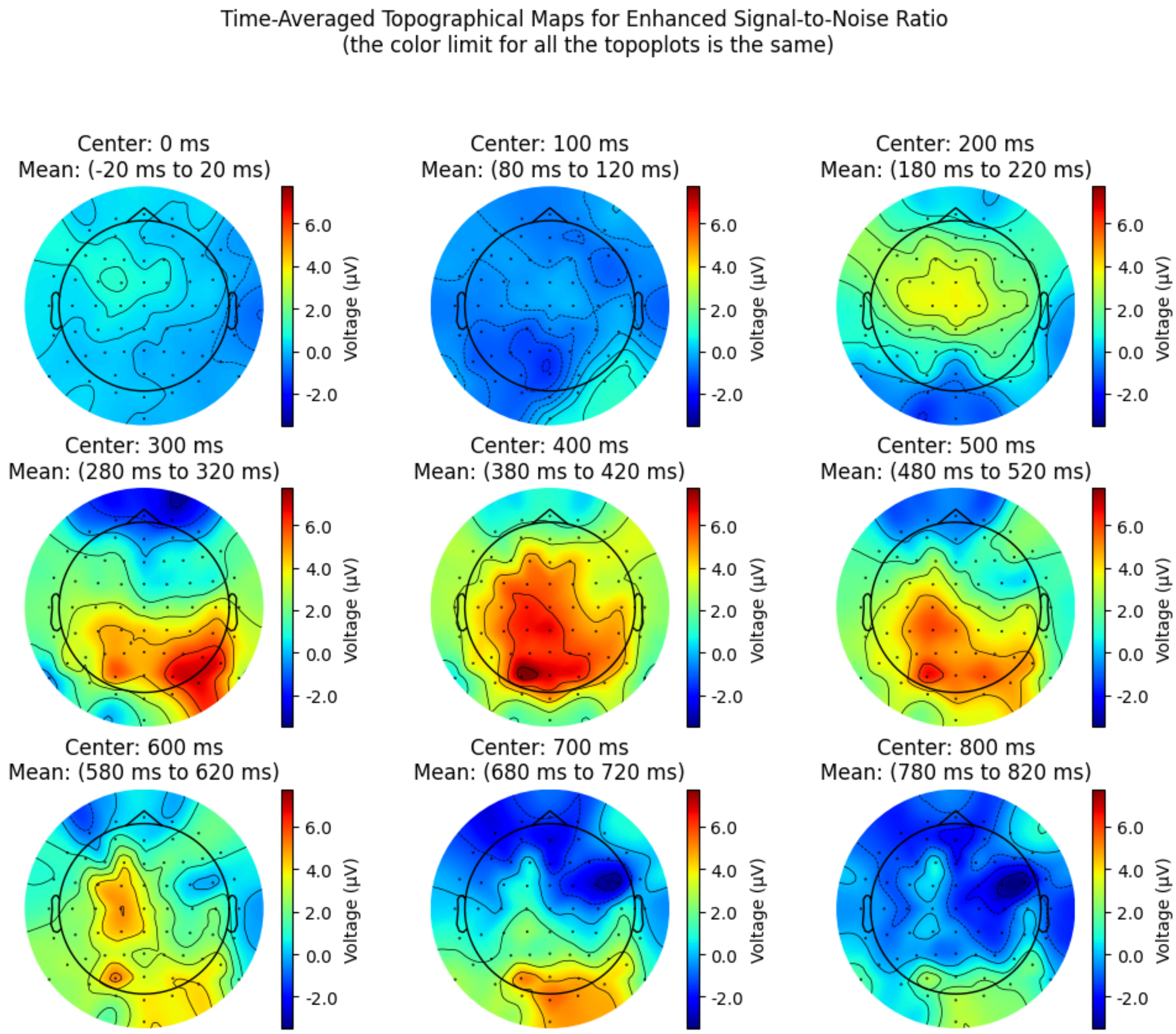
a.1. Loading the data and plotting the sensor locations



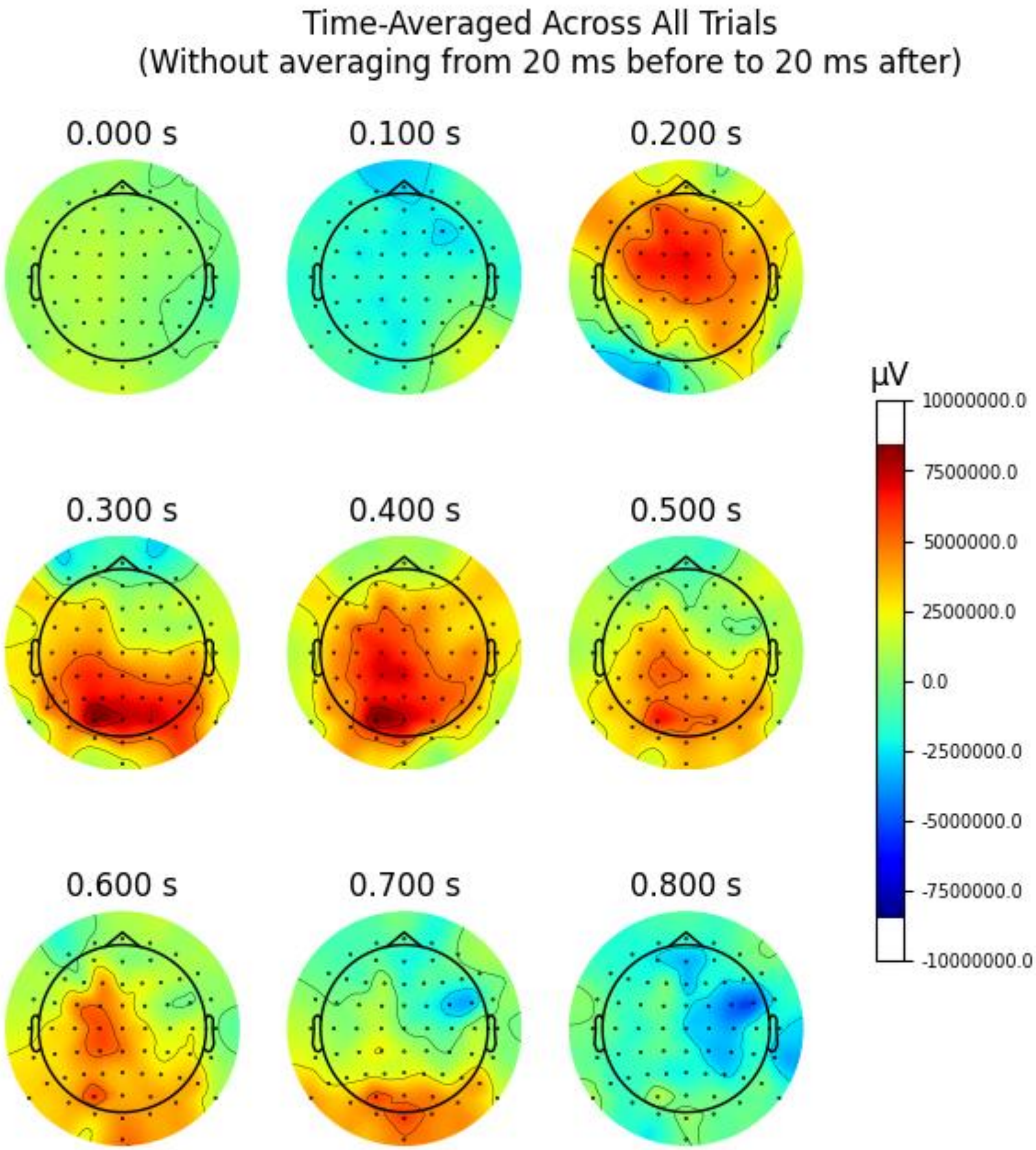
a.2. `Time points: [0, 100, ..., 800] Ms.`



a.3. Making the color limit for all the topo plots the same.

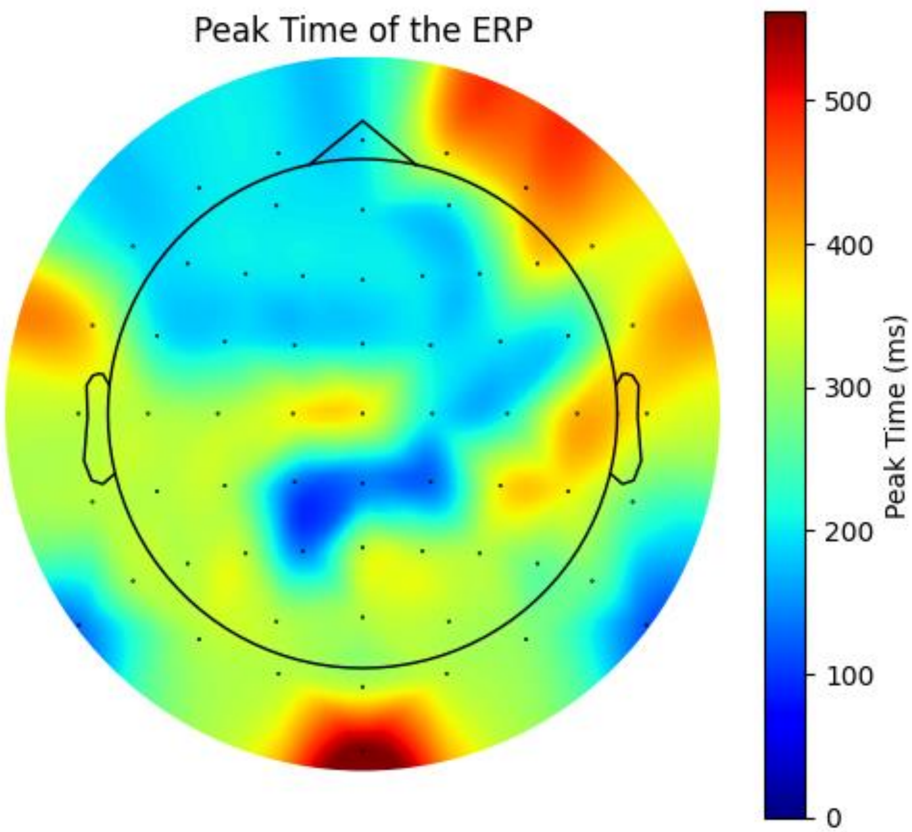


a.4. I also made a series of topographical plots at the same time points without getting the average of data 20 millisecond before and after the time point.



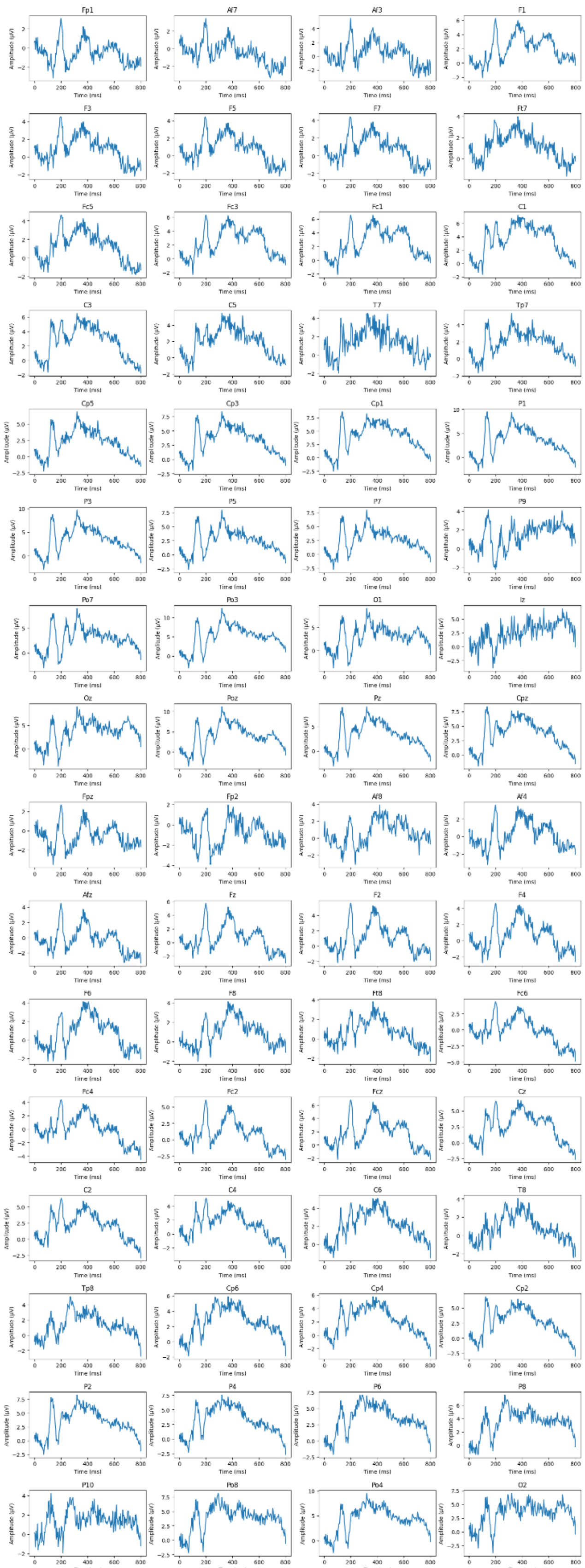
b.1. Finding the peak time of the ERP between 100 and 800 MS and making a topographical plot of the peak.

*In the displayed figure, the color scheme indicates the timing of responses, where blue represents the earliest response and red represents the latest. Shades in between denote relative response timings based on their color intensity. Upon examination, electrodes **Cpz, Cp2, Cp1, P1, P10, P9** exhibit the **earliest** response. This trend is also evident in the **upper left section of the scalp**. Conversely, electrodes like **Iz, Fp2, Af8,** and **F8** show the **latest response.***



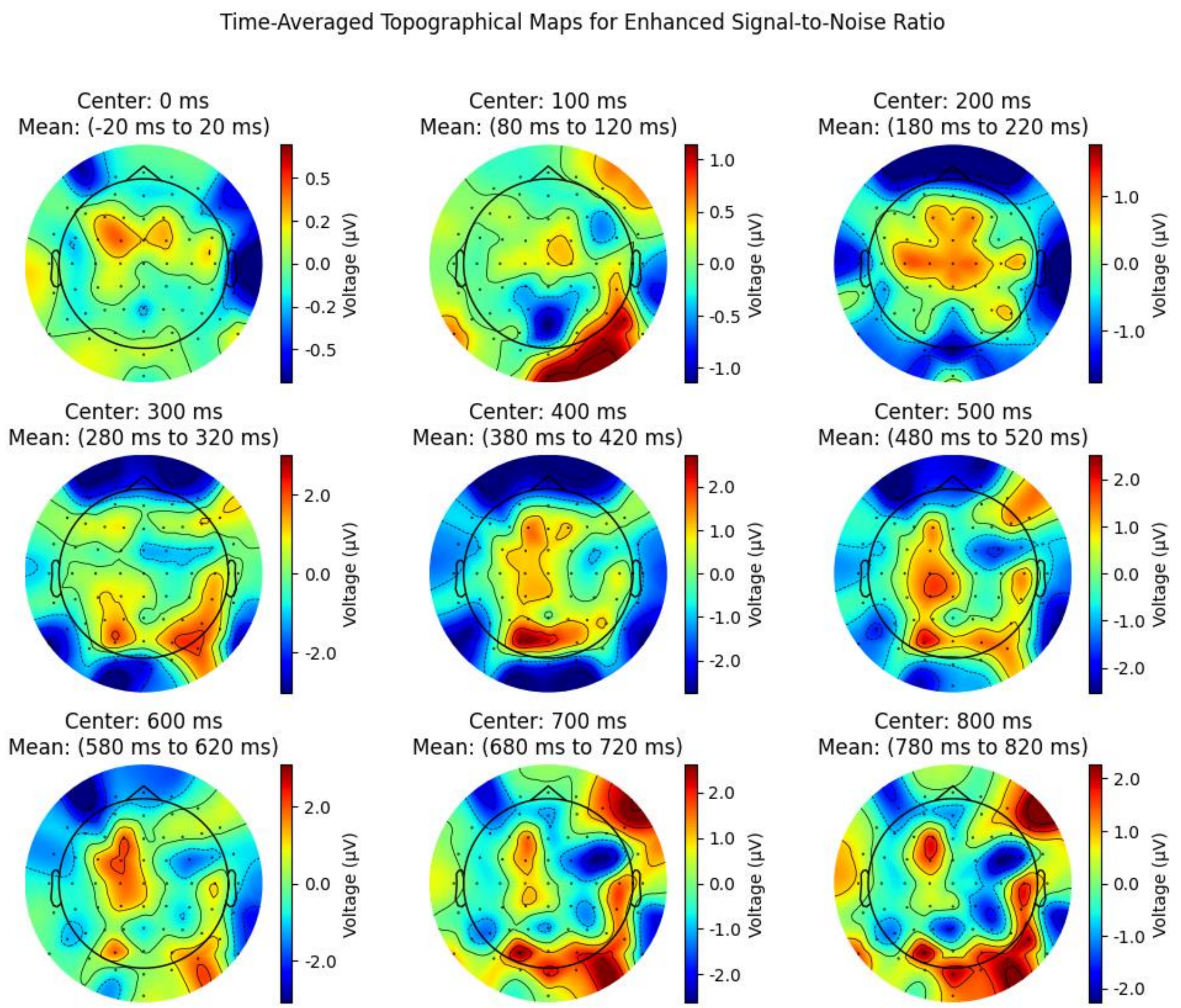
b.2. *Below you can find the temporal average visualization for each electrode, presented separately.*

Temporal Average Visualisation For Each Electrode

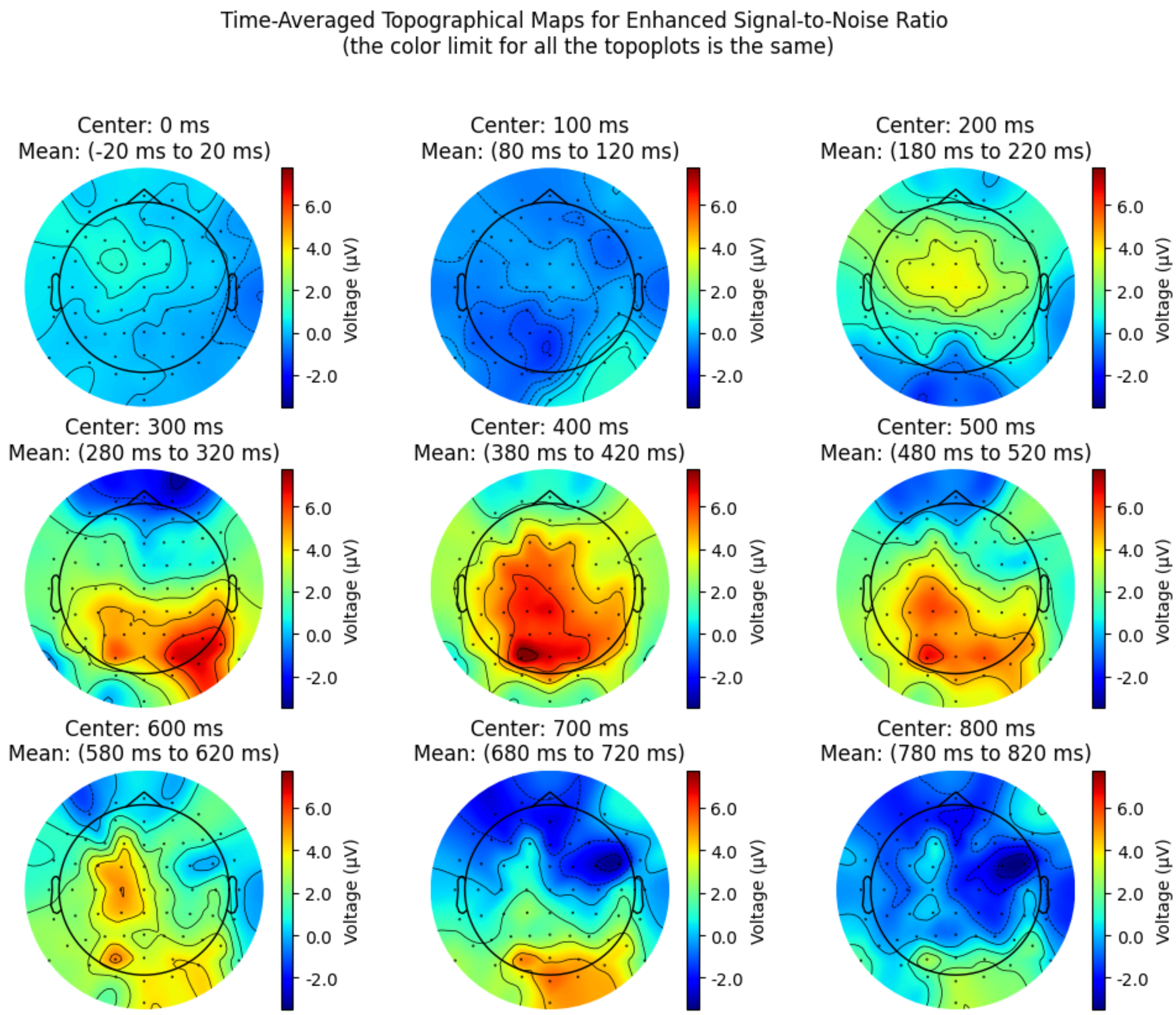


c.1. Applying large Laplacian filter and re[eating section a.

By implementing the large Laplacian filter, we significantly enhance the spatial precision of the EEG data. The Laplacian filter operates on the principle of spatial second derivatives, which emphasizes local changes in the signal. As a result, this technique sharpens the topographic representation of the electrical activity on the scalp, allowing for a more detailed and localized observation. When comparing the results from step (c) with those from step (a), it becomes evident that the Laplacian-filtered data provides a clearer distinction between active and non-active regions. This improved localization can be particularly beneficial in identifying focal brain activities and can aid in the interpretation of the underlying neural sources. Thus, the large Laplacian filter emerges as an essential tool for a more precise spatial analysis of EEG data.



c.2. Making the color limit for all the topo plots the same.



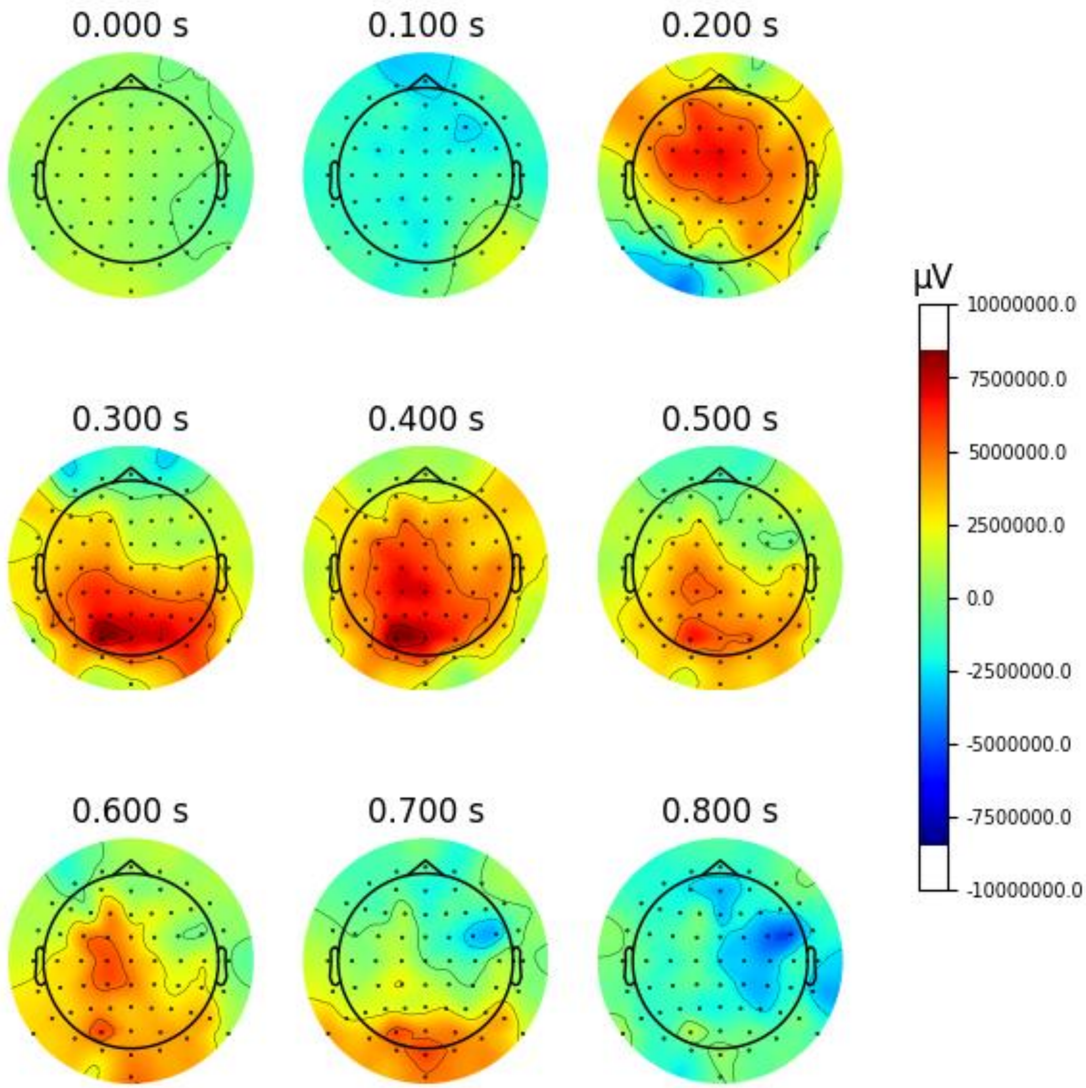
```
##############################################################################
from scipy.io import loadmat
import numpy as np
import mne
import matplotlib.pyplot as plt

# 1. Load the .mat file
data = loadmat('sampleEEGdata.mat')
EEG = data['EEG']
eeg_data = EEG['data'][0, 0] #eeg_data.shape=(64, 640, 99), [channels:64,
time points:640, trials:99]
times = EEG['times'][0, 0][0] #times.shape= (640,)
print('EEG.shape:', EEG.shape) #EEG.shape: (1, 1)
print('eeg_data.shape:', eeg_data.shape) #EEG.shape: (1, 1)
print('times.shape:', times.shape) #EEG.shape: (1, 1)
microvolt = "µV"

##############################################################################
############################################################################
# a.1. Extract Epochs from 0 to 800 ms
# Given a sampling rate of 256 Hz, the time interval between two consecutive
samples is 1/256 = 3.90625 ms. (I consider 4ms for each sample point)
# Thus, 0 ms corresponds to the sample point at index 256,
# and 800 ms corresponds to the sample point at index (800 / 3.90625) =
256+204.8=460.8, which can be rounded to 461.
eeg_data_epoch= eeg_data[:, 256:462, :]# eeg_data_epoch.shape: (64, 206, 99),
256:462:
#This indexes elements from the 256th to the 461st along the second
dimension(since Python indexing is 0-based and the stop value in a slice is
exclusive).
eeg_data_epoch_20= eeg_data[:, 251:467, :] # eeg_data_epoch_20.shape:(64,
216, 99), adding the sample point (-20,0) and (800,820) to my epoch.
# print('eeg_data_epoch.shape:', eeg_data_epoch.shape,
'eeg_data_epoch_20.shape', eeg_data_epoch_20.shape )
# Compute the ERP at each electrode by averaging across all trials
ERP = np.mean(eeg_data_epoch, axis=2) # shape: (64, 206)
ERP_20 = np.mean(eeg_data_epoch_20, axis=2) # shape: (64, 216)

###############################################################
# Read the file content
with open('eloc64C2.txt', 'r') as f:
    lines = f.readlines()
# Extract channel names, theta, and radius
channel_names = [line.split()[3].replace('.', '') for line in lines[0:]]  #
Skip the header
theta = np.array([float(line.split()[1])-90 for line in lines[0:]]) * np.pi /
180.0  # Convert to radians
radius = np.array([float(line.split()[2]) for line in lines[0:]])
# Convert polar to Cartesian
x = radius * np.cos(theta)/5
```

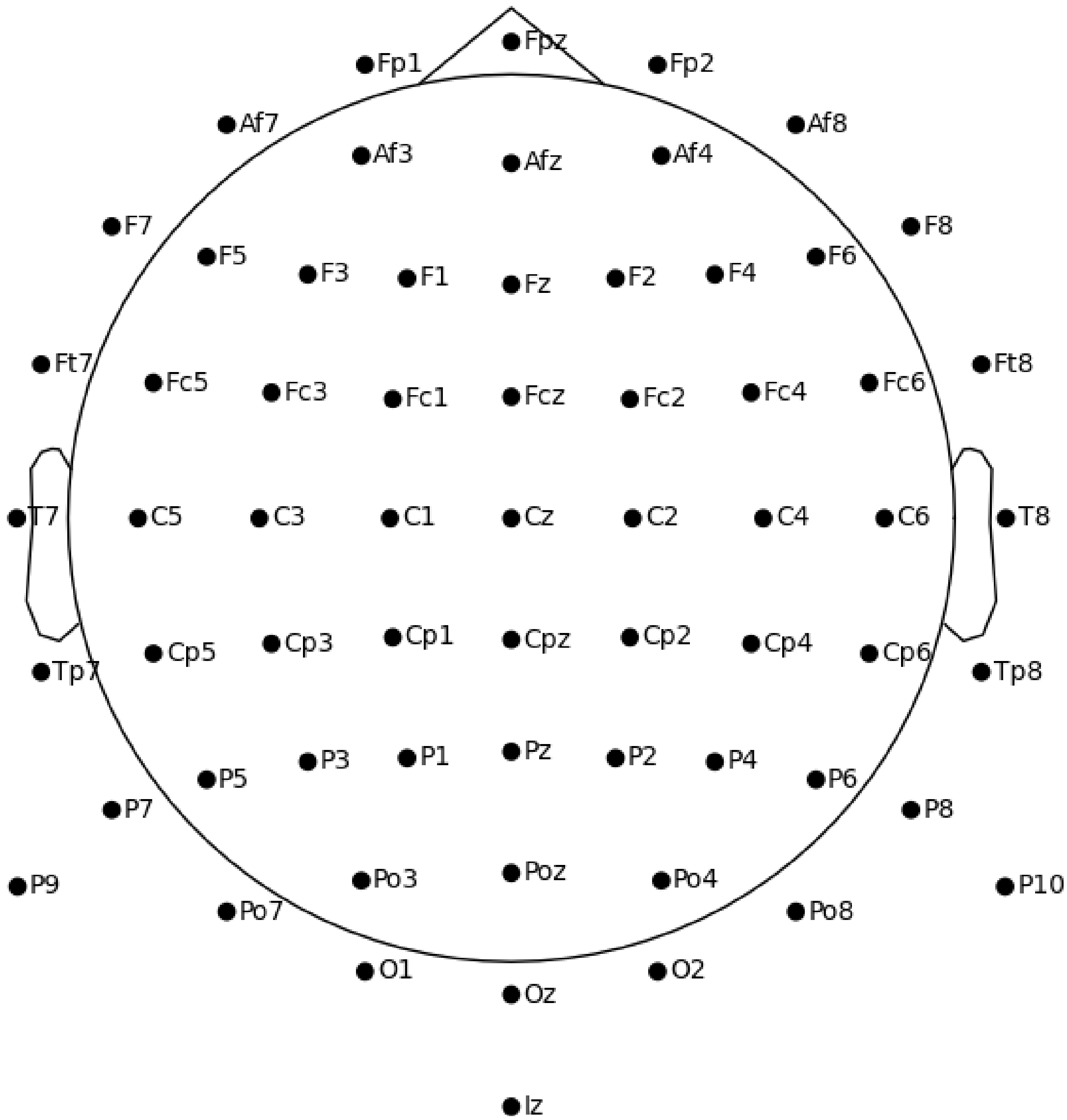
```
y = -radius * np.sin(theta)/5
z = np.zeros_like(x)  # default z-coordinate for all channels
# Create a montage
ch_pos = dict(zip(channel_names, zip(x, y, z)))
montage = mne.channels.make_dig_montage(ch_pos, coord_frame='head')
info = mne.create_info(ch_names=channel_names, sfreq=256, ch_types='eeg')
# Apply the montage to the info
info.set_montage(montage)

##########################
# Create an evoked object
# The evoked object is an instance of the EvokedArray class in MNE, which is
useful for visualization and further processing in the MNE ecosystem.
#ERP: It is a 2D numpy array that contains the event-related potential
values. This is a simple numeric representation with dimensions corresponding
to channels and time points.
#evoked: It is an object of type EvokedArray that wraps around the ERP numpy
array. It integrates the numeric ERP data with metadata (info)
#and provides various methods and attributes for easier visualization and
analysis of the data in the context of the MNE-Python library.
evoked = mne.EvokedArray(ERP, info)
evoked_20 = mne.EvokedArray(ERP_20, info)

###############################################
# a.2. Plot the topographical map
# The evoked.plot_topomap() function from the MNE-Python library is used to
plot topographical maps of EEG data,
# giving a spatial representation of voltage (or other measures) across the
scalp at specific points in time.
evoked.plot_topomap(times=np.linspace(0, .8, 9), nrows=3, ncols=3, size=1,
cmap='jet', time_unit='s', show=False)
plt.suptitle("Time-Averaged Across All Trials \n (Without averaging from 20
ms before to 20 ms after)", y=1.05)
plt.show()

##########
# Plot the sensor locations
# When you're plotting EEG channels with plot_sensors, MNE sometimes creates
two plots: one for a top-down view and another for a side view,
# especially when 3D channel locations (with both horizontal and vertical
coordinates) are present.
# You can suppress the side view by setting the proj argument to True:
evoked.plot_sensors(kind='topomap', show_names=True, ch_type='eeg')

##################################################################
# a. Time-Averaged Topographical Maps for Enhanced Signal-to-Noise Ratio
plt.close('all')
center_times = np.linspace(0, .8, 9)  # 0ms, 100ms, ..., 800ms
fig, axs = plt.subplots(3, 3, figsize=(10,8))
fig.suptitle("Time-Averaged Topographical Maps for Enhanced Signal-to-Noise
Ratio", fontsize=12, y=1.05)
AVE_ERP=[]
for idx, center_time in enumerate(center_times):
```

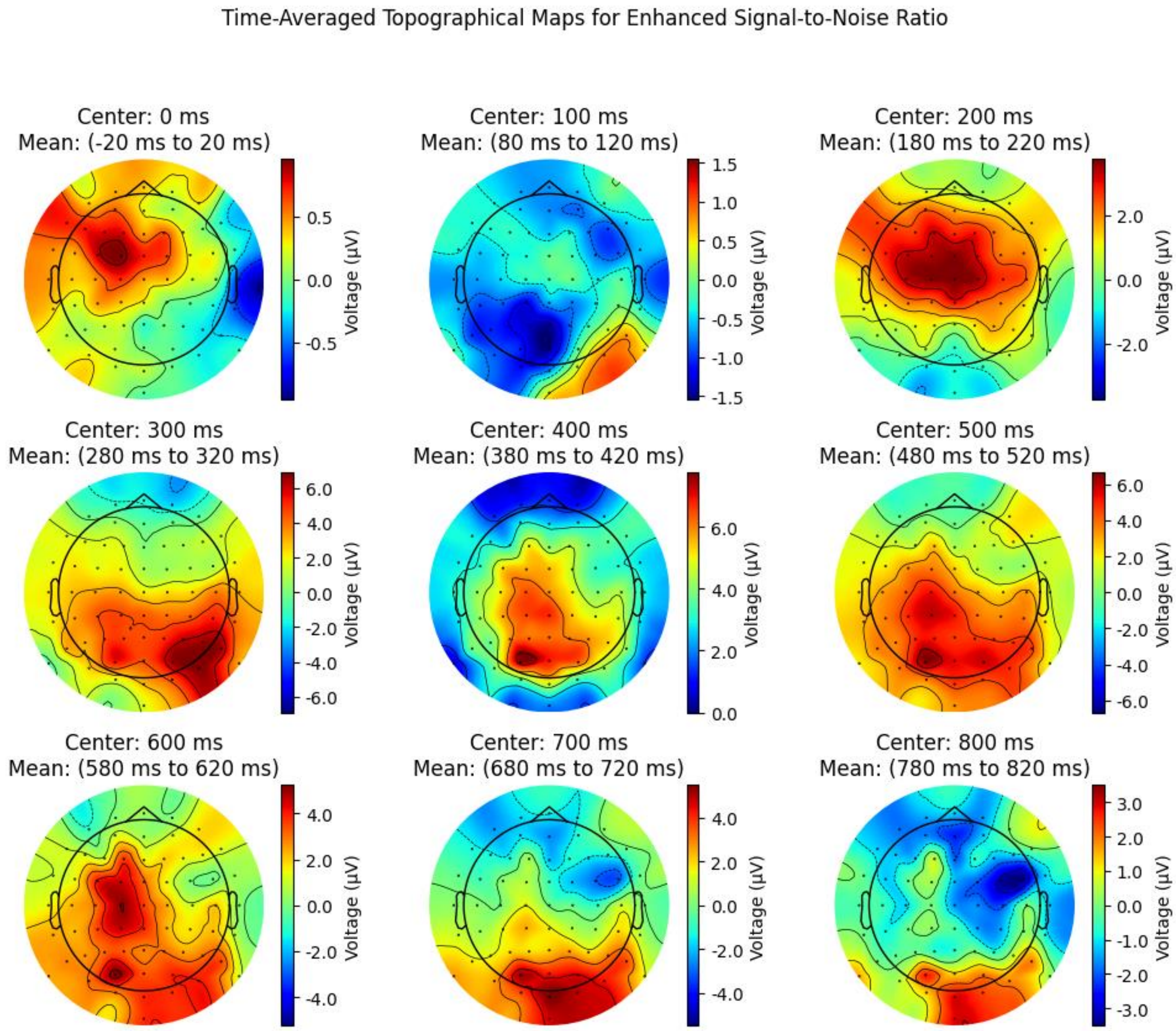
```
    start_time = center_time - 0.020
    end_time = center_time + 0.020
    avg_data = evoked_20.copy().crop(tmin=start_time,
tmax=end_time).data.mean(axis=1)
    AVE_ERP.append(avg_data)
    ax = axs[idx // 3, idx % 3]
    im, _ = mne.viz.plot_topomap(avg_data, evoked_20.info, cmap='jet',
axes=ax, show=False)
    fig.colorbar(im, ax=ax, format='%3.1f', orientation='vertical',
label='Voltage (µV)')
    ax.set_title(f"Center: {center_time*1000:.0f} ms\nMean:
({start_time*1000:.0f} ms to {end_time*1000:.0f} ms)")
plt.tight_layout()
plt.show()
AVE_ERP_np=np.array(AVE_ERP)
# print('AVE_ERP_np.shape', AVE_ERP_np.shape) #(9,64)

########################################################
# Making the color limit for all the topoplots the same
plt.close('all')
center_times = np.linspace(0, .8, 9)  # 0ms, 100ms, ..., 800ms
fig, axs = plt.subplots(3, 3, figsize=(10, 8))
fig.suptitle("Time-Averaged Topographical Maps for Enhanced Signal-to-Noise
Ratio\n (the color limit for all the topoplots is the same)", fontsize=12,
y=1.05)
global_vmin, global_vmax = AVE_ERP_np.min(), AVE_ERP_np.max()
for idx, center_time in enumerate(center_times):
    start_time = center_time - 0.020
    end_time = center_time + 0.020
    ax = axs[idx // 3, idx % 3]
    im, _ = mne.viz.plot_topomap(AVE_ERP_np[idx, :], evoked_20.info,
cmap='jet', axes=ax, show=False)
    # Adjust the color limits to reflect the global max and min
    im.set_clim(global_vmin, global_vmax)
    fig.colorbar(im, ax=ax, format='%3.1f', orientation='vertical',
label='Voltage (µV)')
    ax.set_title(f"Center: {center_time*1000:.0f} ms\nMean:
({start_time*1000:.0f} ms to {end_time*1000:.0f} ms)")
plt.tight_layout()
plt.show()
# print('AVE_ERP_np.shape', AVE_ERP_np.shape)  # (9, 64)
```

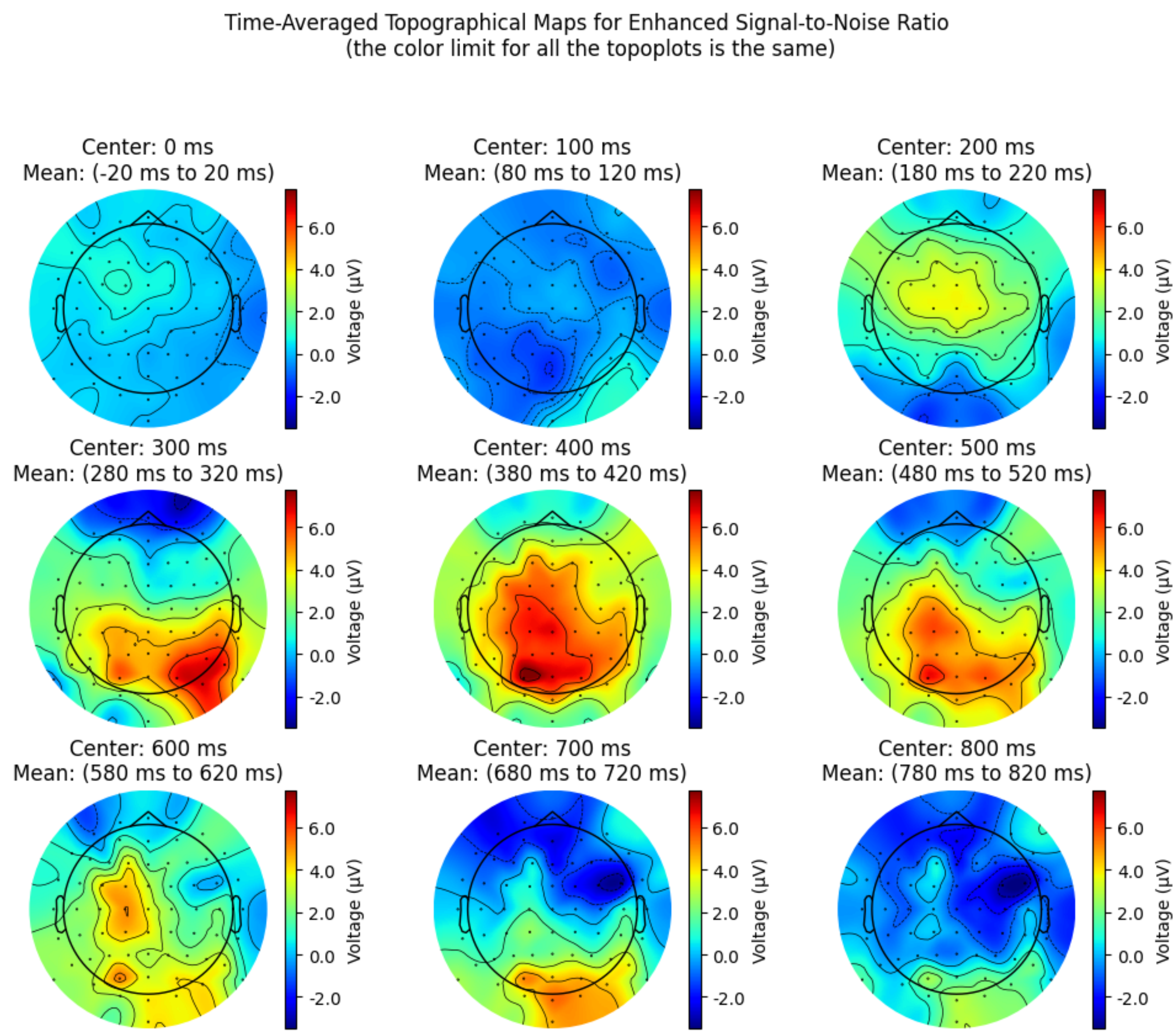
```
EEG.shape: (1, 1)
eeg_data.shape: (64, 640, 99)
times.shape: (640,)
```

Time-Averaged Across All Trials
(Without averaging from 20 ms before to 20 ms after)




Fpz
Fp1
Fp2
Af7
Af3
Afz
Af4
Af8
F7
F5
F3
F1
Fz
F2
F4
F6
F8
Ft7
Fc5
Fc3
Fc1
Fcz
Fc2
Fc4
Fc6
Ft8
T7
C5
C3
C1
Cz
C2
C4
C6
T8
Tp7
Cp5
Cp3
Cp1
Cpz
Cp2
Cp4
Cp6
Tp8
P7
P5
P3
P1
Pz
P2
P4
P6
P8
P9
Po7
Po3
Poz
Po4
Po8
P10
O1
Oz
O2
Iz

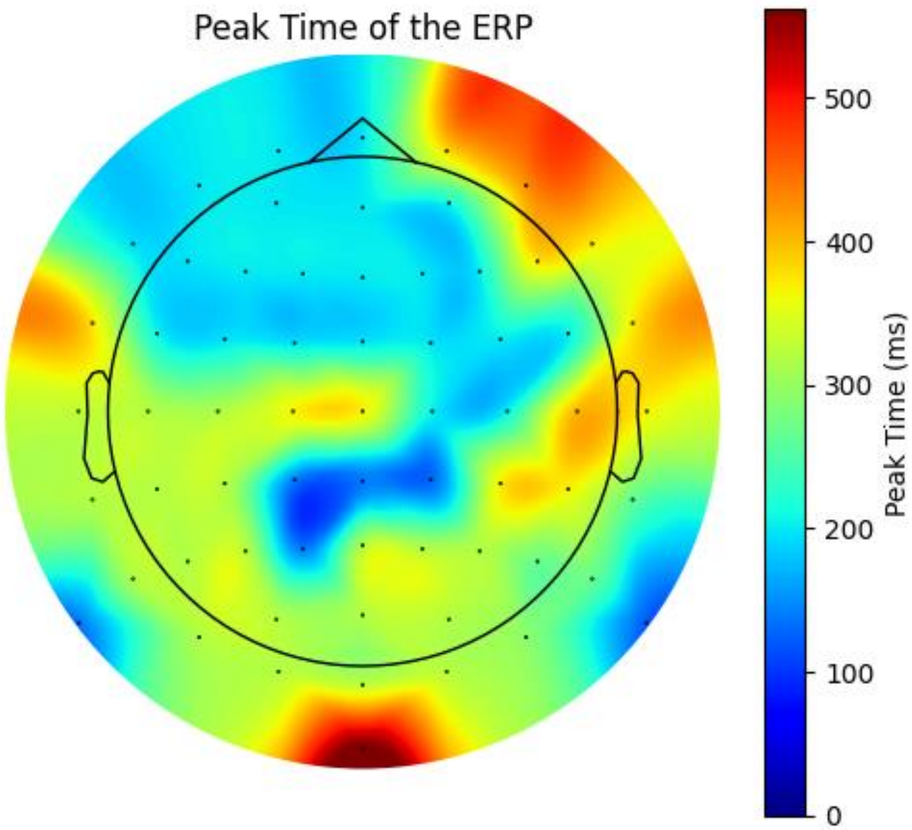

Time-Averaged Topographical Maps for Enhanced Signal-to-Noise Ratio
Center: 0 ms
Mean: (-20 ms to 20 ms)
Center: 100 ms
Mean: (80 ms to 120 ms)
Center: 200 ms
Mean: (180 ms to 220 ms)
Center: 300 ms
Mean: (280 ms to 320 ms)
Center: 400 ms
Mean: (380 ms to 420 ms)
Center: 500 ms
Mean: (480 ms to 520 ms)
Center: 600 ms
Mean: (580 ms to 620 ms)
Center: 700 ms
Mean: (680 ms to 720 ms)
Center: 800 ms
Mean: (780 ms to 820 ms)
Voltage (µV)



In [291]:

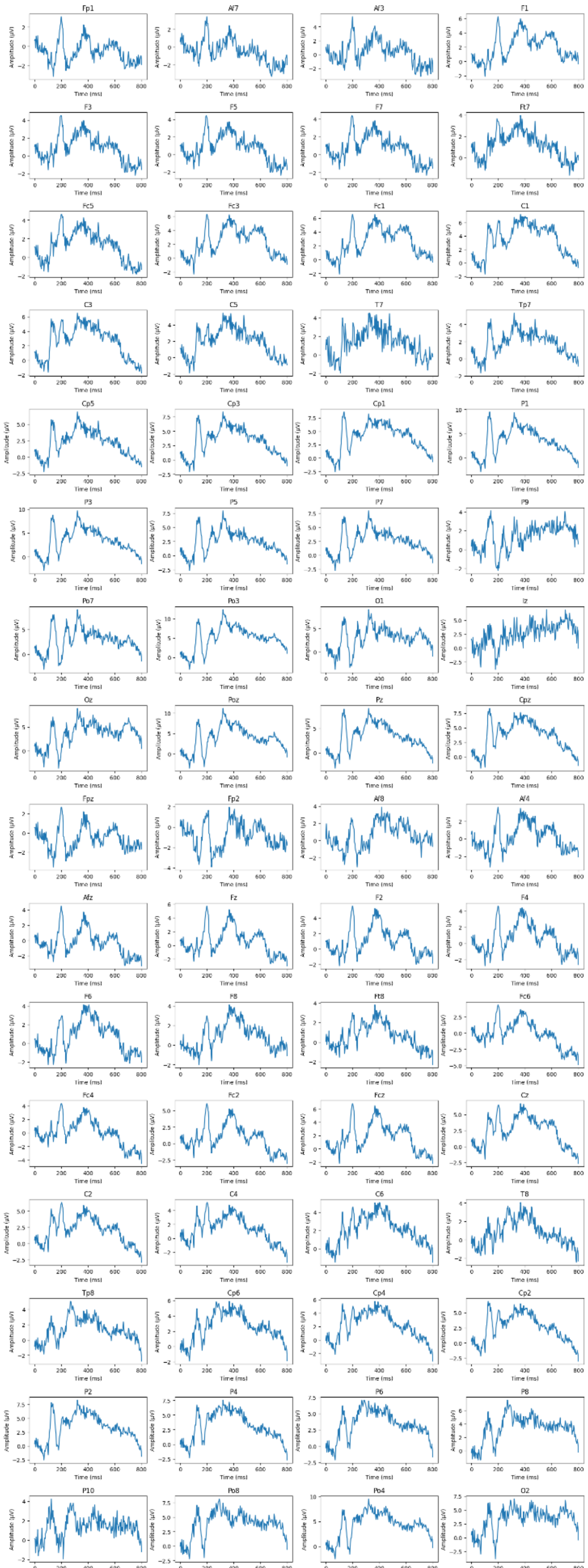
```
# b.
times = evoked.times
# print('times:', times, 'times.shape', times.shape) # [0.
0.00390625, ..., 0.80078125], times.shape (206,)
max_values = []
max_times = []
for i in range(ERP.shape[0]):
    max_val = np.max(ERP[i, :])
    max_idx = np.argmax(ERP[i, :])
    max_values.append(max_val)
    max_times.append(times[max_idx])
max_values = np.array(max_values)
max_times = np.array(max_times) * 1000  # Convert to milliseconds

######################################################################
fig, ax = plt.subplots(figsize=(6,5))
im, _ = mne.viz.plot_topomap(max_times, evoked.info, cmap='jet', contours=0,
axes=ax, show=False, size=3)
```

```
# Show colorbar
plt.colorbar(im, ax=ax, label='Peak Time (ms)')
plt.title("Peak Time of the ERP")
plt.show()
```




```
############
fig, axs = plt.subplots(nrows=16, ncols=4, figsize=(15, 40))
fig.tight_layout(pad=2.0)  # Adjust the spacing between subplots
fig.suptitle('Temporal Average Visualisation For Each Electrode',
fontsize=16, y=1.01)
# Flatten the axis array for easier indexing
axs = axs.ravel()
for idx in range(64):  # Loop through each channel
    # Plot the ERP data for the current channel over time
    axs[idx].plot(times * 1000, ERP[idx, :])
    axs[idx].set_title(evoked.ch_names[idx])  # Set title as channel name
    axs[idx].set_xlabel('Time (ms)')
    axs[idx].set_ylabel('Amplitude (µV)')
plt.subplots_adjust(hspace=0.5)
plt.show()
```

Temporal Average Visualisation For Each Electrode

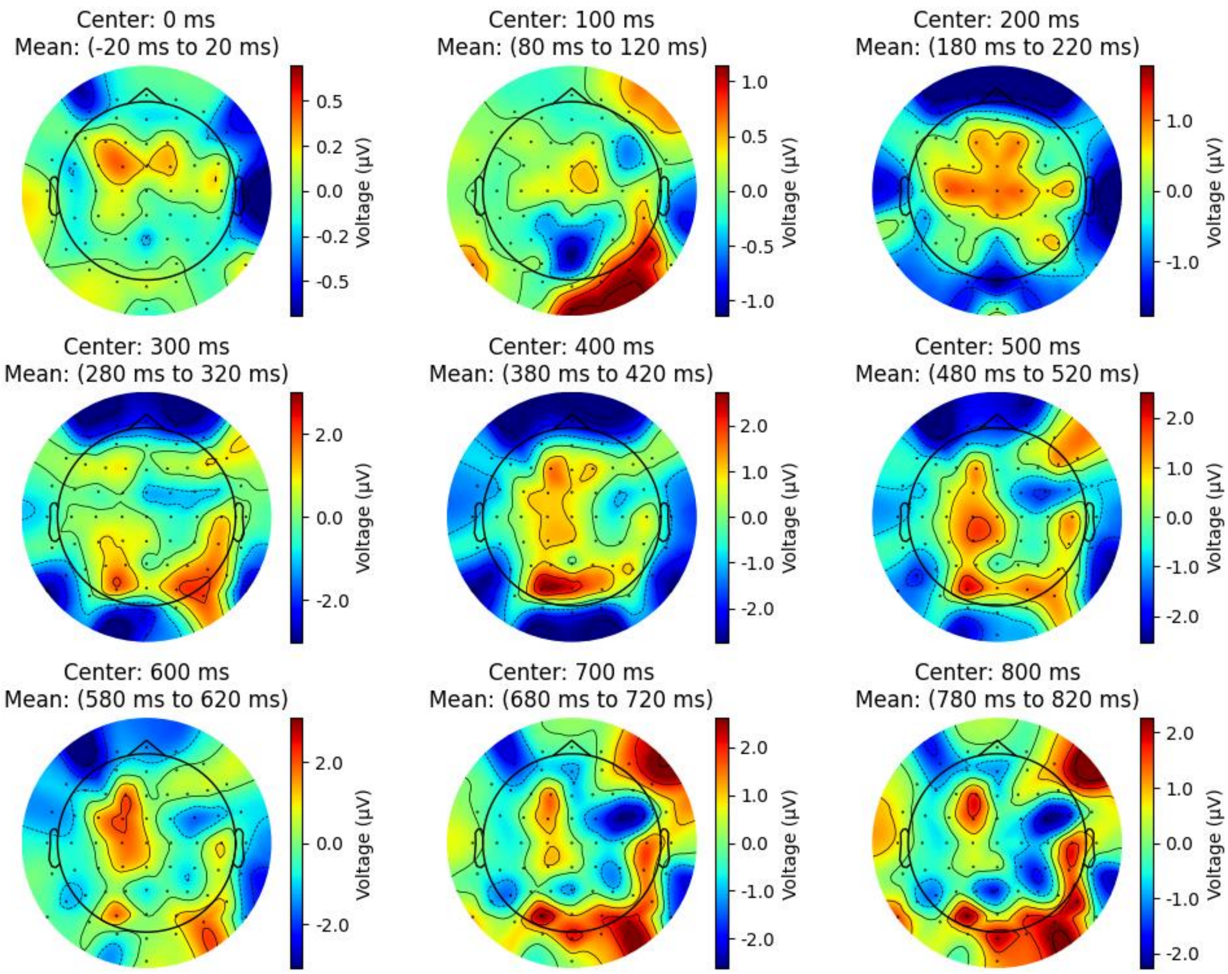


```
# c.
with open('eloc64C2.txt', 'r') as f_l:
    lines_l = f_l.readlines()
channel_names_l = [line_l.split()[3].replace('.', '') for line_l in
lines_l[0:]]
theta_l = np.array([float(line_l.split()[1]) for line_l in lines_l[0:]]) *
np.pi / 180.0
radius_l = np.array([float(line_l.split()[2]) for line_l in lines_l[0:]])
x_l = radius_l * np.cos(theta_l)
y_l = radius_l * np.sin(theta_l)
z_l = np.zeros_like(x_l)
radius_range = [0.18, 0.28]
laplacian_data = np.zeros_like(ERP_20)
for i in range(64):
    distances = np.sqrt((x_l - x_l[i]) ** 2 + (y_l - y_l[i]) ** 2)
    surrounding_indices = np.where((distances > radius_range[0]) & (distances
< radius_range[1]))[0]
    if len(surrounding_indices) > 0:
        weights = 1 / distances[surrounding_indices]
        weights = weights / np.sum(weights)  # Normalize weights
    else:
        weights = np.array([])
    weights = weights[:, np.newaxis]
    if len(weights) > 0:
        laplacian_data[i, :] = ERP_20[i, :] - np.sum(weights *
ERP_20[surrounding_indices, :], axis=0)
    else:
        laplacian_data[i, :] = ERP_20[i, :]
laplacian_raw = evoked_20.copy()
laplacian_raw._data = laplacian_data

########################################
plt.close('all')
center_times = np.linspace(0, .8, 9)
fig, axs = plt.subplots(3, 3, figsize=(10,8))
fig.suptitle("Time-Averaged Topographical Maps for Enhanced Signal-to-Noise
Ratio", fontsize=12, y=1.03)
AVE_ERP_l=[]
for idx, center_time in enumerate(center_times):
    start_time = center_time - 0.020
    end_time = center_time + 0.020
    avg_data_l = laplacian_raw.copy().crop(tmin=start_time,
tmax=end_time).data.mean(axis=1)
    AVE_ERP_l.append(avg_data)
    ax = axs[idx // 3, idx % 3]
    im, _ = mne.viz.plot_topomap(avg_data_l, laplacian_raw.info, cmap='jet',
axes=ax, show=False)
    fig.colorbar(im, ax=ax, format='%3.1f', orientation='vertical',
label='Voltage (µV)')
    ax.set_title(f"Center: {center_time*1000:.0f} ms\nMean:
({start_time*1000:.0f} ms to {end_time*1000:.0f} ms)")
plt.tight_layout()
plt.show()
```

```
AVE_ERP_np_l=np.array(AVE_ERP)

###################################################
plt.close('all')
center_times = np.linspace(0, .8, 9)
fig, axs = plt.subplots(3, 3, figsize=(10, 8))
fig.suptitle("Time-Averaged Topographical Maps for Enhanced Signal-to-Noise
Ratio\n (the color limit for all the topoplots is the same)", fontsize=12,
y=1.03)
global_vmin, global_vmax = AVE_ERP_np_l.min(), AVE_ERP_np_l.max()
for idx, center_time in enumerate(center_times):
    start_time = center_time - 0.020
    end_time = center_time + 0.020
    ax = axs[idx // 3, idx % 3]
    im, _ = mne.viz.plot_topomap(AVE_ERP_np_l[idx, :], laplacian_raw.info,
cmap='jet', axes=ax, show=False)
    im.set_clim(global_vmin, global_vmax)
    fig.colorbar(im, ax=ax, format='%3.1f', orientation='vertical',
label='Voltage (μV)')
    ax.set_title(f"Center: {center_time*1000:.0f} ms\nMean:
({start_time*1000:.0f} ms to {end_time*1000:.0f} ms)")
plt.tight_layout()
plt.show()
```

```
C:\Users\tnlab\AppData\Local\Temp\ipykernel_16184\2574989804.py:37: RuntimeWa
rning: tmin is not in time interval. tmin is set to <class 'mne.evoked.Evoked
Array'>.tmin (0 s)
  avg_data_l = laplacian_raw.copy().crop(tmin=start_time, tmax=end_time).data
.mean(axis=1)
```

Time-Averaged Topographical Maps for Enhanced Signal-to-Noise Ratio



Time-Averaged Topographical Maps for Enhanced Signal-to-Noise Ratio
(the color limit for all the topoplots is the same)