EDA

December 4, 2023

[1]:
```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import NearMiss, RandomUnderSampler
from sklearn.decomposition import PCA
```

1 Initial Data Reading and Analysis

[2]:
```python
# Read in the data and look at all the columns
data = pd.read_csv('data/train.csv')



print(data.columns)
relevant_columns = ['crew', 'time', 'seat', 'eeg_fp1', 'eeg_f7',
       'eeg_f8', 'eeg_t4', 'eeg_t6', 'eeg_t5', 'eeg_t3', 'eeg_fp2', 'eeg_o1',
       'eeg_p3', 'eeg_pz', 'eeg_f3', 'eeg_fz', 'eeg_f4', 'eeg_c4', 'eeg_p4',
       'eeg_poz', 'eeg_c3', 'eeg_cz', 'eeg_o2', 'ecg', 'r', 'gsr', 'event']
data = data[relevant_columns]
data.head()
```

```
Index(['crew', 'experiment', 'time', 'seat', 'eeg_fp1', 'eeg_f7', 'eeg_f8',
       'eeg_t4', 'eeg_t6', 'eeg_t5', 'eeg_t3', 'eeg_fp2', 'eeg_o1', 'eeg_p3',
       'eeg_pz', 'eeg_f3', 'eeg_fz', 'eeg_f4', 'eeg_c4', 'eeg_p4', 'eeg_poz',
       'eeg_c3', 'eeg_cz', 'eeg_o2', 'ecg', 'r', 'gsr', 'event'],
      dtype='object')
```

[2]:
```
   crew      time  seat   eeg_fp1     eeg_f7     eeg_f8     eeg_t4     eeg_t6  \
0     1  0.011719     1  -5.28545  26.775801  -9.527310 -12.793200  16.717800
1     1  0.015625     1  -2.42842  28.430901  -9.323510  -3.757230  15.969300
2     1  0.019531     1  10.67150  30.420200  15.350700  24.724001  16.143101
3     1  0.023438     1  11.45250  25.609800   2.433080  12.412500  20.533300
4     1  0.027344     1   7.28321  25.942600   0.113564   5.748000  19.833599

     eeg_t5     eeg_t3  …     eeg_c4     eeg_p4    eeg_poz    eeg_c3  \
0  33.737499  23.712299  …  37.368999  17.437599  19.201900  20.5968
```

```
1  30.443600  21.010300  …  31.170799  19.399700  19.689501  21.3547
2  32.142799  25.431801  … -12.012600  19.396299  23.171700  22.4076
3  31.494101  19.142799  …  18.574100  23.156401  22.641199  19.3367
4  28.753599  20.572100  …   6.555440  22.754700  22.670300  20.2932

    eeg_cz     eeg_o2     ecg           r         gsr  event
0 -3.95115  14.507600 -4520.0  817.705994  388.829987      A
1  1.33212  17.750200 -4520.0  817.705994  388.829987      A
2  1.53786  22.247000 -4520.0  817.705994  388.829987      A
3  2.54492  18.998600 -4520.0  817.705994  388.829987      A
4  1.69962  22.812799 -4520.0  817.705994  388.829987      A

[5 rows x 27 columns]
```

[3]:
```python
# Analyze the datatypes and counts for each column
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4867421 entries, 0 to 4867420
Data columns (total 27 columns):
 #   Column   Dtype
---  ------   -----
 0   crew     int64
 1   time     float64
 2   seat     int64
 3   eeg_fp1  float64
 4   eeg_f7   float64
 5   eeg_f8   float64
 6   eeg_t4   float64
 7   eeg_t6   float64
 8   eeg_t5   float64
 9   eeg_t3   float64
 10  eeg_fp2  float64
 11  eeg_o1   float64
 12  eeg_p3   float64
 13  eeg_pz   float64
 14  eeg_f3   float64
 15  eeg_fz   float64
 16  eeg_f4   float64
 17  eeg_c4   float64
 18  eeg_p4   float64
 19  eeg_poz  float64
 20  eeg_c3   float64
 21  eeg_cz   float64
 22  eeg_o2   float64
 23  ecg      float64
 24  r        float64
```

```
 25  gsr       float64
 26  event     object
dtypes: float64(24), int64(2), object(1)
memory usage: 1002.7+ MB
```

[4]:
```
# Check the unique counts of each column
data.nunique()
```

[4]:
```
crew             9
time        483534
seat             2
eeg_fp1    2427007
eeg_f7     2394309
eeg_f8     2379512
eeg_t4     2347643
eeg_t6     2308226
eeg_t5     2325976
eeg_t3     2356767
eeg_fp2    2416326
eeg_o1     2276966
eeg_p3     2270474
eeg_pz     2383905
eeg_f3     2472944
eeg_fz     2371405
eeg_f4     2423606
eeg_c4     2310968
eeg_p4     2268197
eeg_poz    2245716
eeg_c3     2312641
eeg_cz     2292542
eeg_o2     2266411
ecg         516599
r           165011
gsr         407838
event            4
dtype: int64
```

[5]:
```
# Remove NANs from the data
print(data.isnull().sum())
data = data.dropna()
data.isnull().sum()
```

```
crew       0
time       0
seat       0
eeg_fp1    0
eeg_f7     0
eeg_f8     0
```

```
eeg_t4      0
eeg_t6      0
eeg_t5      0
eeg_t3      0
eeg_fp2     0
eeg_o1      0
eeg_p3      0
eeg_pz      0
eeg_f3      0
eeg_fz      0
eeg_f4      0
eeg_c4      0
eeg_p4      0
eeg_poz     0
eeg_c3      0
eeg_cz      0
eeg_o2      0
ecg         0
r           0
gsr         0
event       0
dtype: int64
```

[5]:
```
crew        0
time        0
seat        0
eeg_fp1     0
eeg_f7      0
eeg_f8      0
eeg_t4      0
eeg_t6      0
eeg_t5      0
eeg_t3      0
eeg_fp2     0
eeg_o1      0
eeg_p3      0
eeg_pz      0
eeg_f3      0
eeg_fz      0
eeg_f4      0
eeg_c4      0
eeg_p4      0
eeg_poz     0
eeg_c3      0
eeg_cz      0
eeg_o2      0
ecg         0
```

```
r          0
gsr        0
event      0
dtype: int64
```

[6]:
```
# Check for duplicated data
data[data.duplicated()]
```

[6]:
```
Empty DataFrame
Columns: [crew, time, seat, eeg_fp1, eeg_f7, eeg_f8, eeg_t4, eeg_t6, eeg_t5,
eeg_t3, eeg_fp2, eeg_o1, eeg_p3, eeg_pz, eeg_f3, eeg_fz, eeg_f4, eeg_c4, eeg_p4,
eeg_poz, eeg_c3, eeg_cz, eeg_o2, ecg, r, gsr, event]
Index: []

[0 rows x 27 columns]
```

[7]:
```
# Analyze the statistics of the data columns
continuous_columns = ['eeg_fp1', 'eeg_f7',
       'eeg_f8', 'eeg_t4', 'eeg_t6', 'eeg_t5', 'eeg_t3', 'eeg_fp2', 'eeg_o1',
       'eeg_p3', 'eeg_pz', 'eeg_f3', 'eeg_fz', 'eeg_f4', 'eeg_c4', 'eeg_p4',
       'eeg_poz', 'eeg_c3', 'eeg_cz', 'eeg_o2']
continuous_data = data[continuous_columns]

print(continuous_data.describe())
```

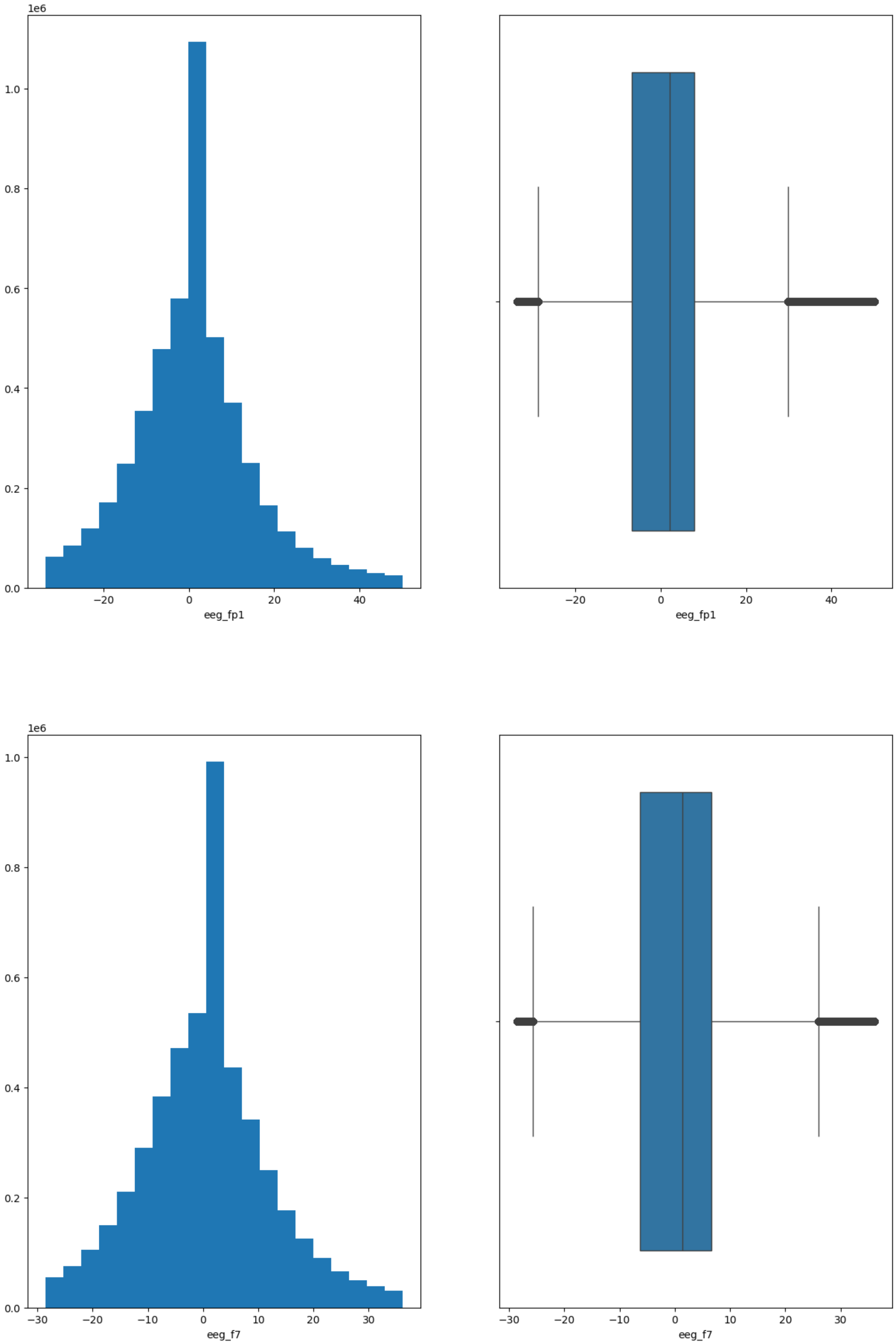
```
            eeg_fp1        eeg_f7        eeg_f8        eeg_t4        eeg_t6  \
count  4.867421e+06  4.867421e+06  4.867421e+06  4.867421e+06  4.867421e+06
mean   3.746336e+00  1.360002e+00  1.213644e+00  7.350926e-02  7.845481e-02
std    4.506763e+01  3.518923e+01  3.519242e+01  2.431472e+01  1.803932e+01
min   -1.361360e+03 -1.581330e+03 -1.643950e+03 -1.516640e+03 -1.220510e+03
25%   -9.200250e+00 -8.325150e+00 -8.767610e+00 -7.367240e+00 -6.102000e+00
50%    3.819020e-01  4.264100e-02  1.140390e-01  0.000000e+00  0.000000e+00
75%    1.030610e+01  8.753340e+00  9.282560e+00  7.437780e+00  6.176630e+00
max    1.972240e+03  2.048790e+03  2.145710e+03  1.731880e+03  9.009370e+02

             eeg_t5        eeg_t3       eeg_fp2        eeg_o1        eeg_p3  \
count  4.867421e+06  4.867421e+06  4.867421e+06  4.867421e+06  4.867421e+06
mean   8.675488e-02  2.299909e-01  3.627284e+00  1.836475e-01  2.650569e-01
std    1.832606e+01  2.531132e+01  4.615674e+01  2.807377e+01  1.658195e+01
min   -1.266430e+03 -1.279940e+03 -1.393480e+03 -2.887910e+03 -1.226780e+03
25%   -6.007260e+00 -6.904030e+00 -9.575000e+00 -6.657340e+00 -6.580460e+00
50%    0.000000e+00  0.000000e+00  3.893450e-01  0.000000e+00  0.000000e+00
75%    6.086460e+00  7.071460e+00  1.062990e+01  6.781080e+00  6.744350e+00
max    1.176540e+03  1.514820e+03  2.103300e+03  1.879330e+03  9.316270e+02

             eeg_pz        eeg_f3        eeg_fz        eeg_f4        eeg_c4  \
count  4.867421e+06  4.867421e+06  4.867421e+06  4.867421e+06  4.867421e+06
```

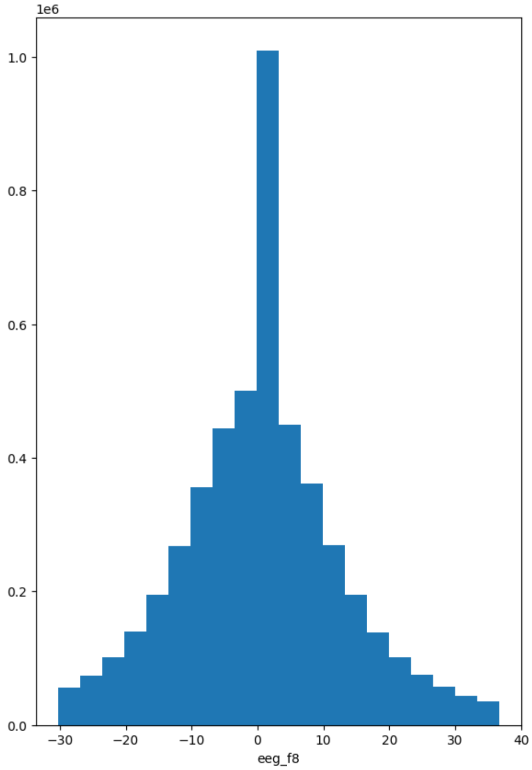
```
mean    4.407218e-01  1.385392e+00  1.316266e+00  1.208597e+00  6.050047e-01
std     6.410874e+01  4.284167e+01  5.481694e+01  4.205516e+01  2.052105e+01
min    -2.875940e+03 -1.353410e+03 -4.064070e+03 -2.333830e+03 -1.212030e+03
25%    -7.643640e+00 -9.285550e+00 -8.055440e+00 -9.306430e+00 -7.495970e+00
50%     0.000000e+00  1.170790e-01  1.106700e-01  5.667500e-02  0.000000e+00
75%     7.810010e+00  9.955490e+00  8.631610e+00  9.775770e+00  7.765670e+00
max     2.162230e+03  1.381370e+03  3.893330e+03  2.034170e+03  8.917290e+02

             eeg_p4       eeg_poz        eeg_c3        eeg_cz        eeg_o2
count  4.867421e+06  4.867421e+06  4.867421e+06  4.867421e+06  4.867421e+06
mean   2.413972e-01  1.947635e-01  6.243715e-01  4.429119e-01  2.393738e-01
std    1.660196e+01  1.833801e+01  1.975695e+01  1.974815e+01  2.351859e+01
min   -1.228030e+03 -1.229130e+03 -1.230480e+03 -6.962790e+02 -1.176370e+03
25%   -6.713860e+00 -6.774840e+00 -7.161160e+00 -7.817650e+00 -6.526950e+00
50%    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
75%    6.831320e+00  6.905020e+00  7.466520e+00  8.025190e+00  6.615180e+00
max    9.080890e+02  1.435800e+03  9.284070e+02  6.136690e+02  2.443550e+03
```

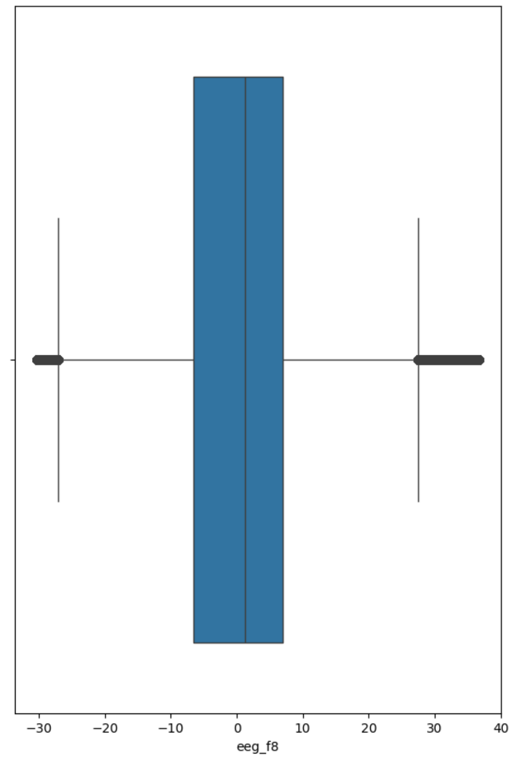
[8]:
```
# Remove outliers in the data via mean imputation
for col in continuous_columns:
    threshold1 = continuous_data[col].quantile(.95)
    threshold2 = continuous_data[col].quantile(.05)
    mean = continuous_data[col].mean()
    continuous_data.loc[:, col] = [val if val <= threshold1 and val >=␣
 ↪threshold2 else mean for val in continuous_data[col]]
```

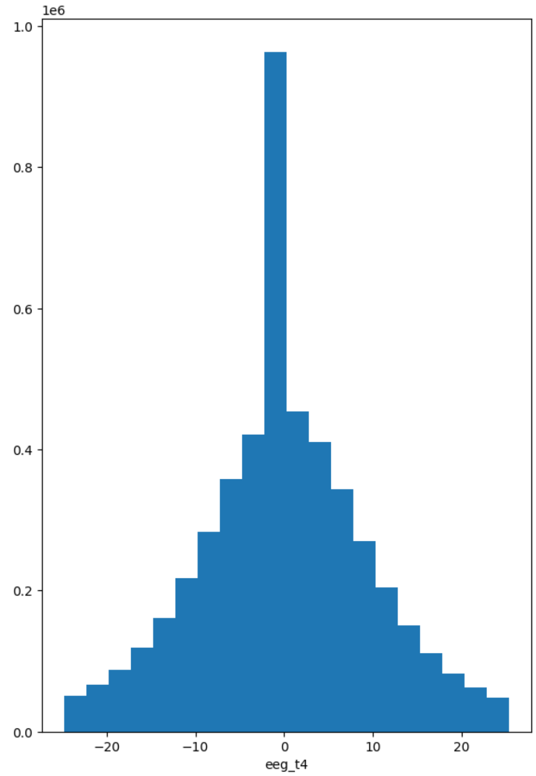
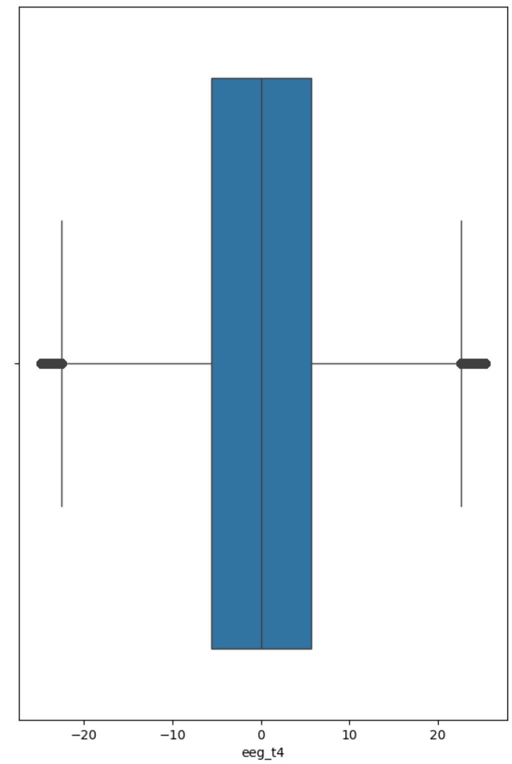
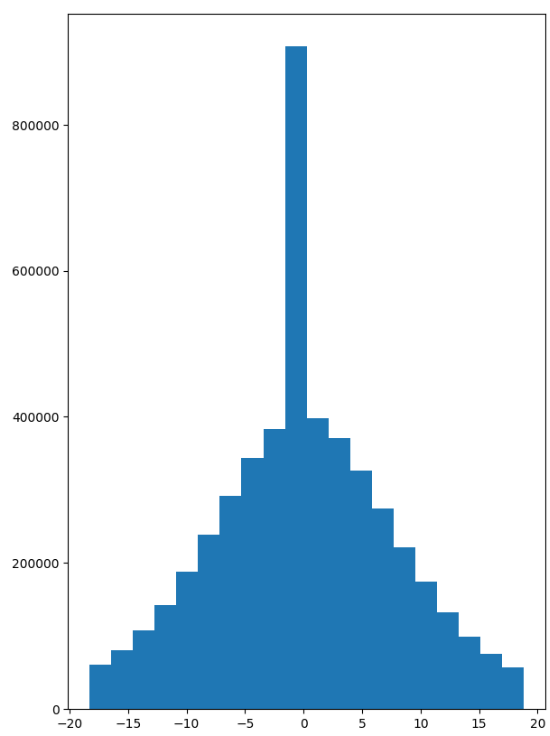
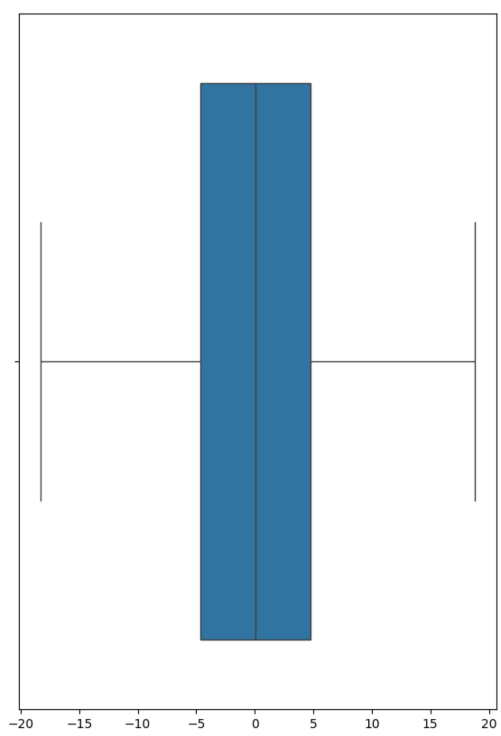
2 Visualizations

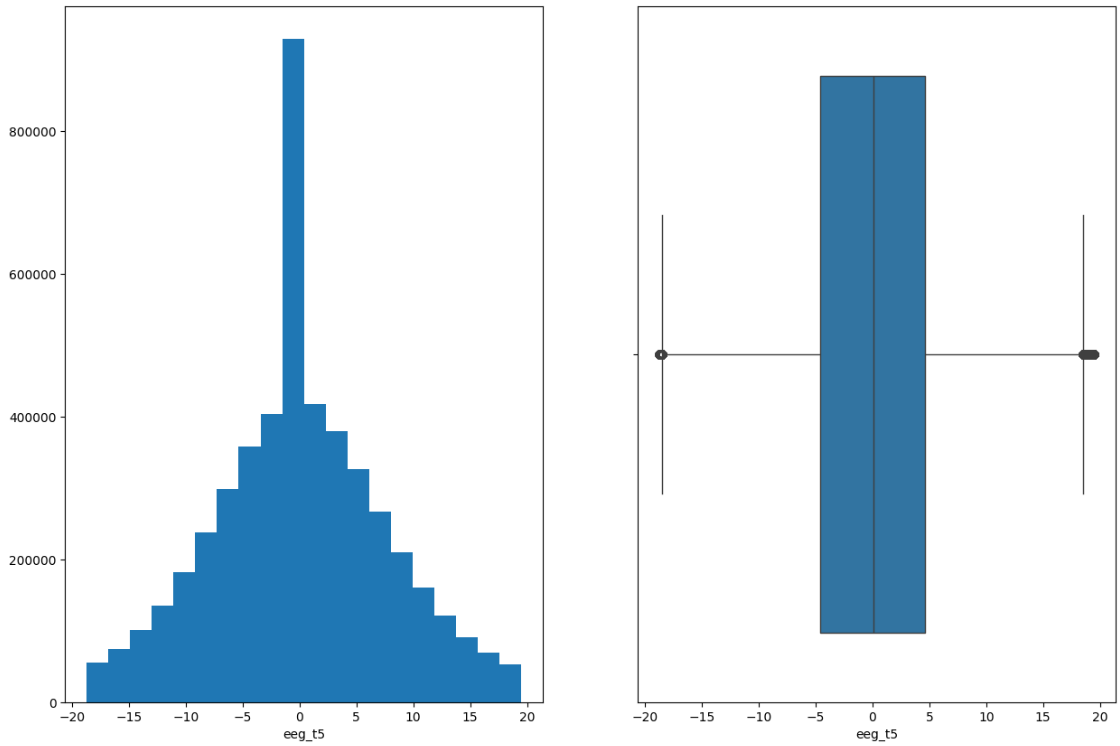
[11]:
```
for col in continuous_data.columns:

    plt.figure(figsize=(15,10))
    plt.subplot(1, 2, 1)
    plt.hist(continuous_data[col], bins=20)
    plt.xlabel(col)

    plt.subplot(1, 2, 2)
    sns.boxplot(x=continuous_data[col])
    plt.show()
```

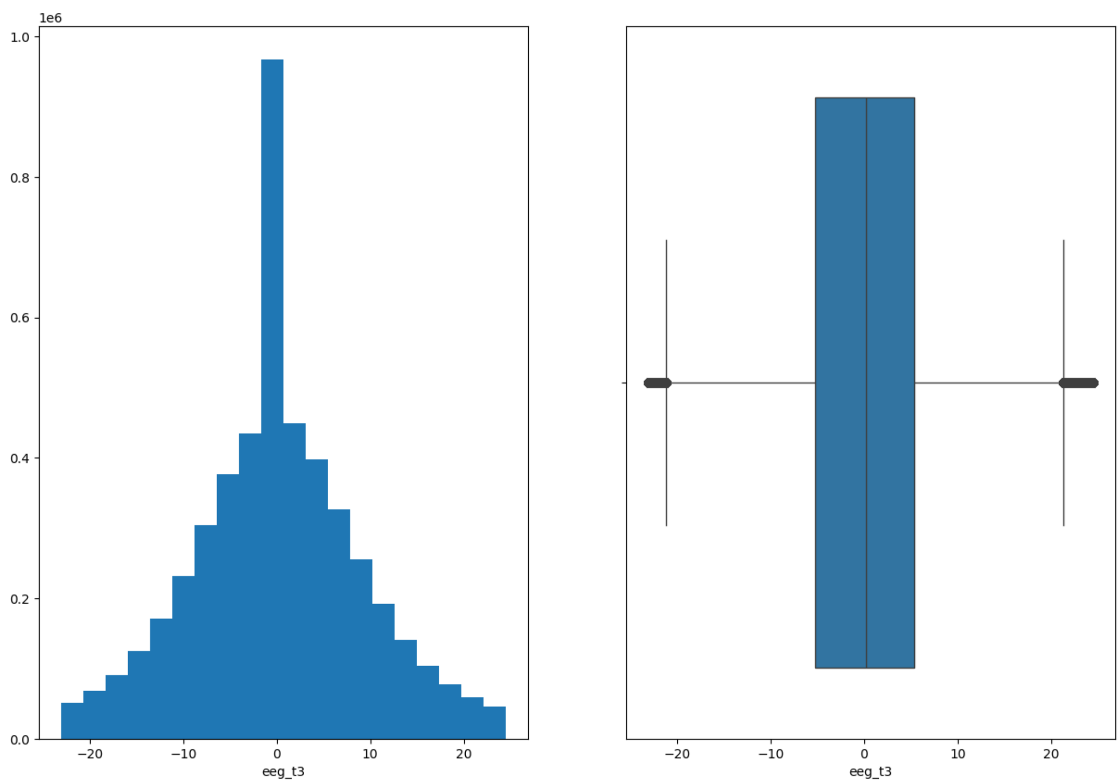

1e6
1.0
0.8
0.6
0.4
0.2
0.0
−20
0
20
40
eeg_fp1
−20
0
20
40
eeg_fp1
1e6
1.0
0.8
0.6
0.4
0.2
0.0
−30
−20
−10
0
10
20
30
eeg_f7
−30
−20
−10
0
10
20
30
eeg_f7

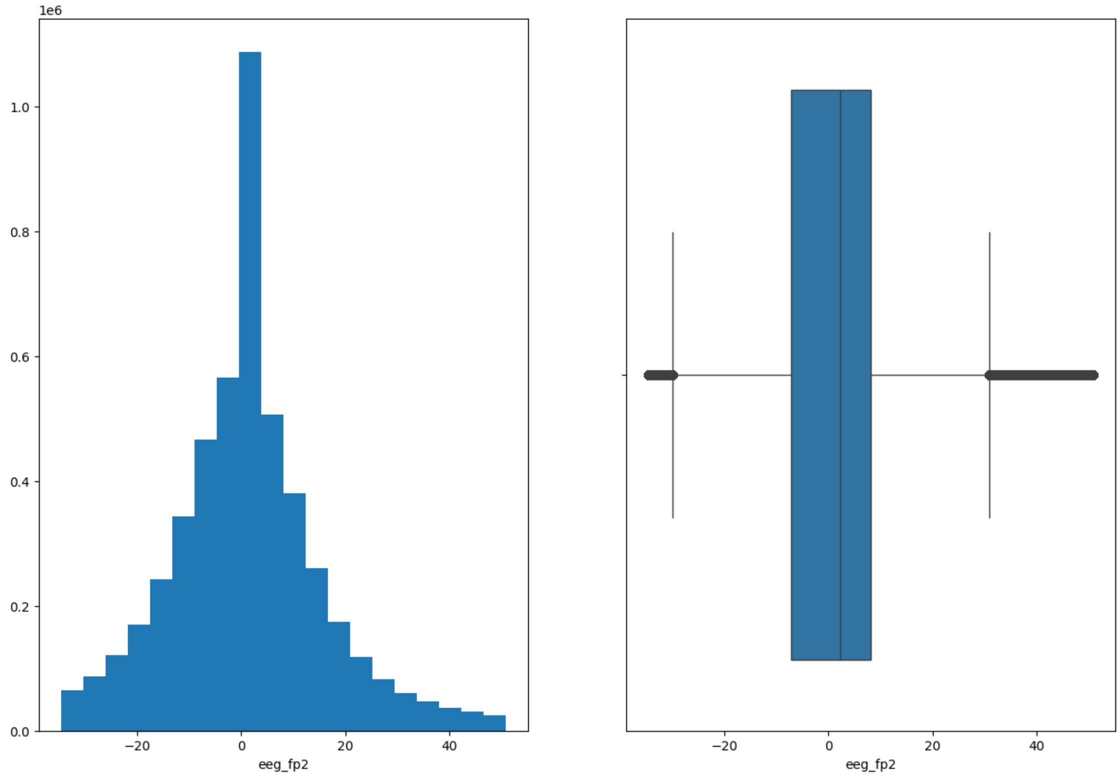

1e6
1.0
0.8
0.6
0.4
0.2
0.0
−30
−20
−10
0
10
20
30
40
eeg_f8

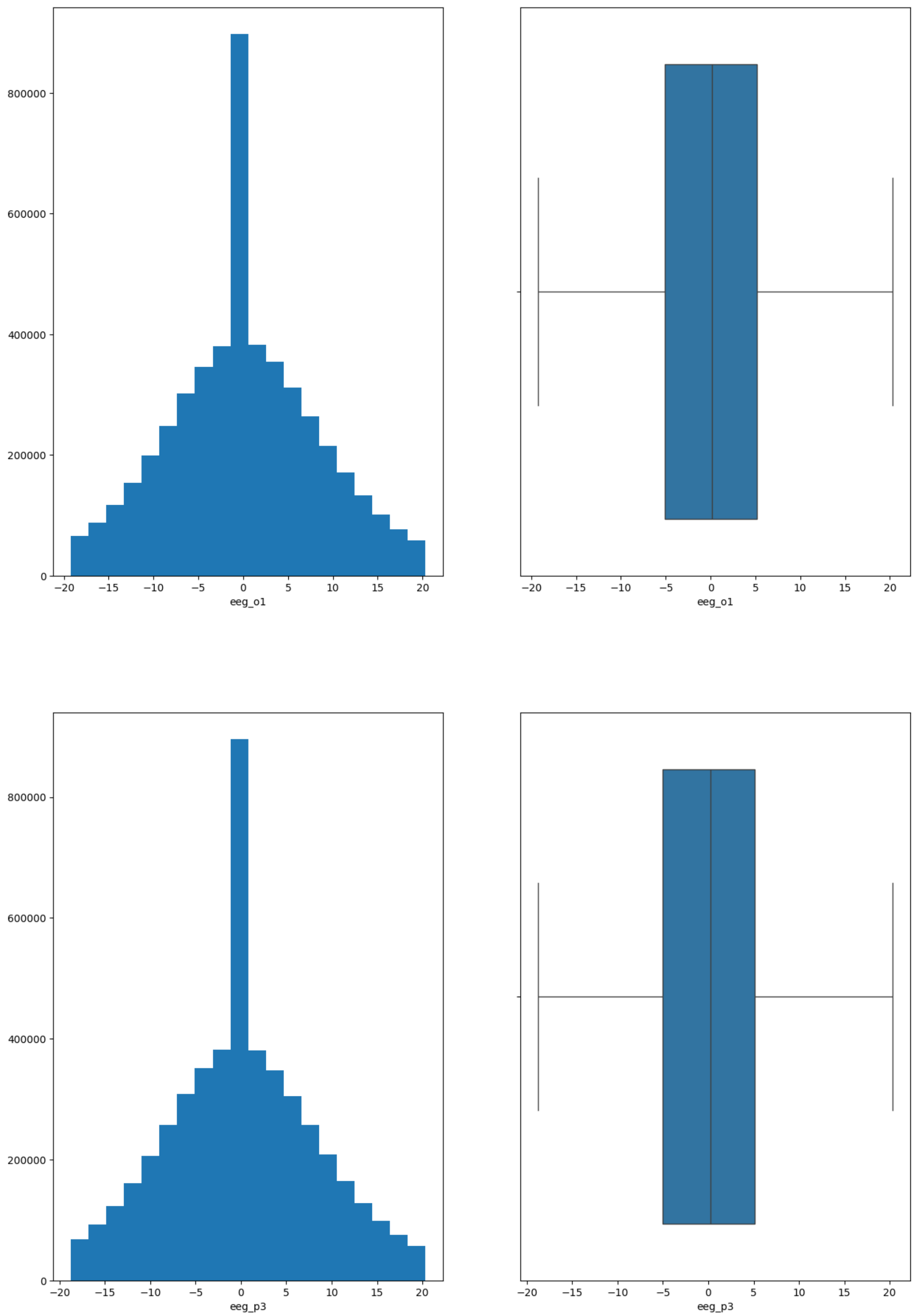

−30
−20
−10
0
10
20
30
40
eeg_f8

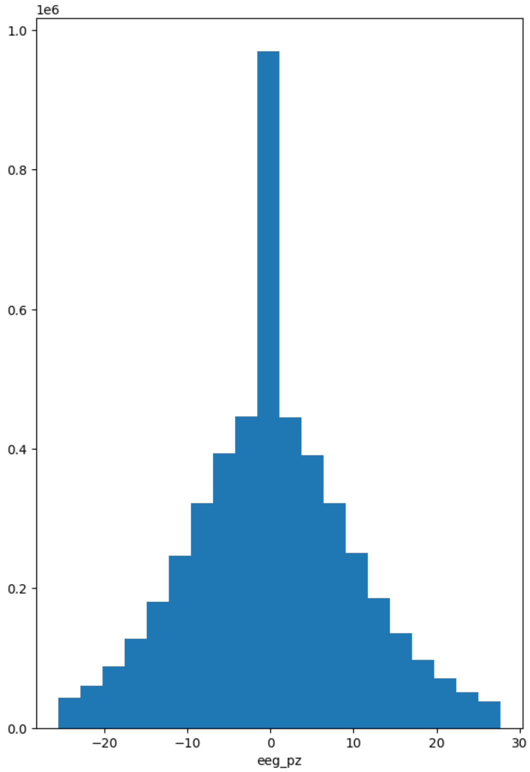

1e6
1.0
0.8
0.6
0.4
0.2
0.0
−20
−10
0
10
20
eeg_t4

−20
−10
0
10
20
eeg_t4

800000
600000
400000
200000
0
−20
−15
−10
−5
0
5
10
15
20
eeg_t6

−20
−15
−10
−5
0
5
10
15
20
eeg_t6

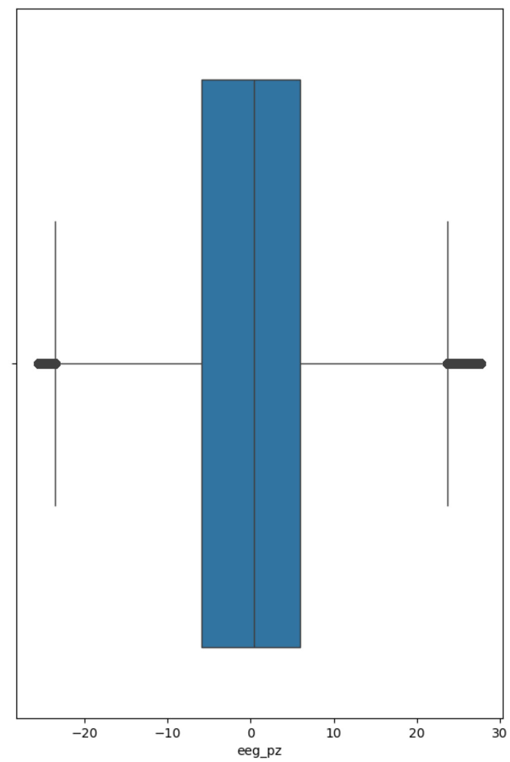

800000
600000
400000
200000
0
−20 −15 −10 −5 0 5 10 15 20
eeg_t5
−20 −15 −10 −5 0 5 10 15 20
eeg_t5

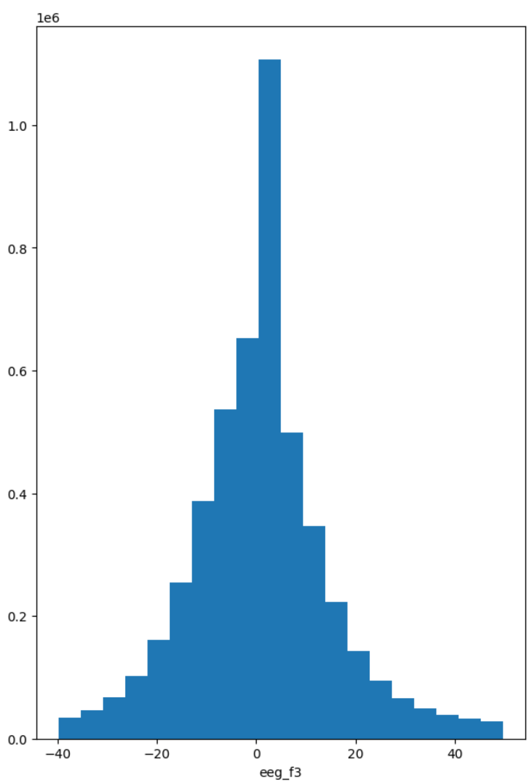

1e6
1.0
0.8
0.6
0.4
0.2
0.0
−20 −10 0 10 20
eeg_t3
−20 −10 0 10 20
eeg_t3

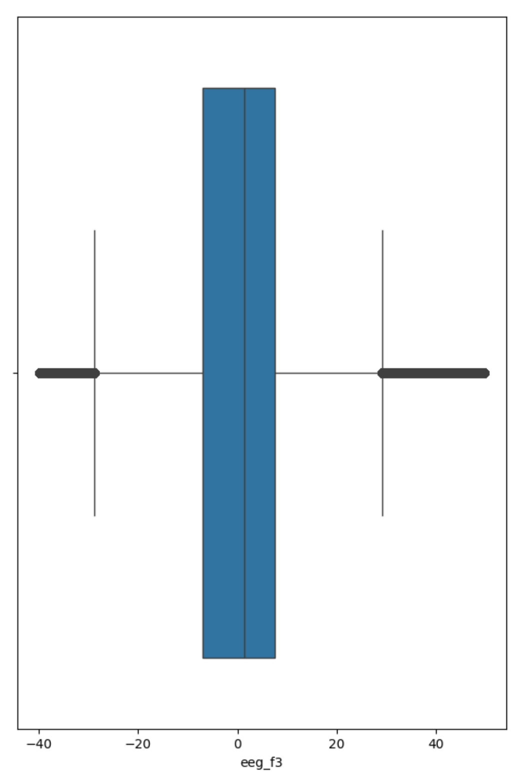

1e6
1.0
0.8
0.6
0.4
0.2
0.0
−20
0
20
40
eeg_fp2
−20
0
20
40
eeg_fp2

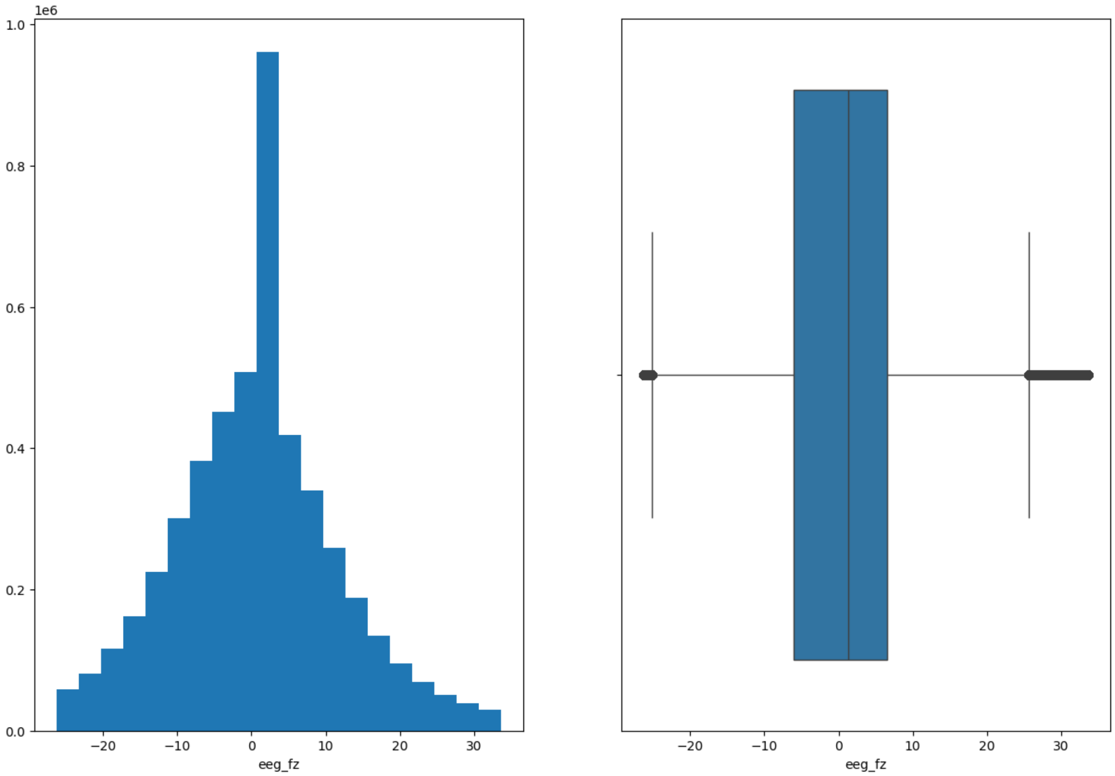

800000
600000
400000
200000
0
−20
−15
−10
−5
0
5
10
15
20
eeg_o1
eeg_o1
eeg_p3
eeg_p3

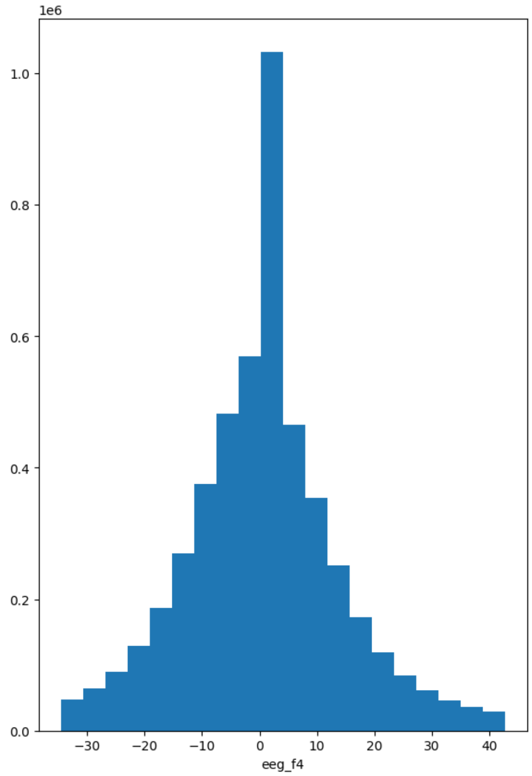

1e6
eeg_pz

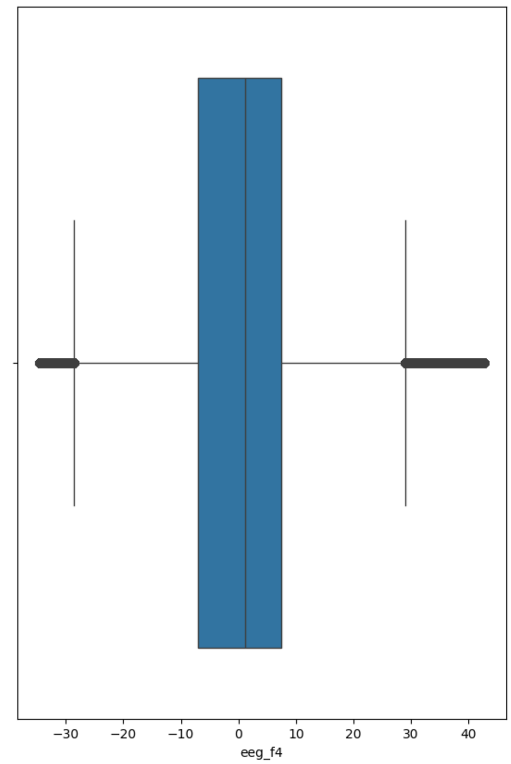

eeg_pz

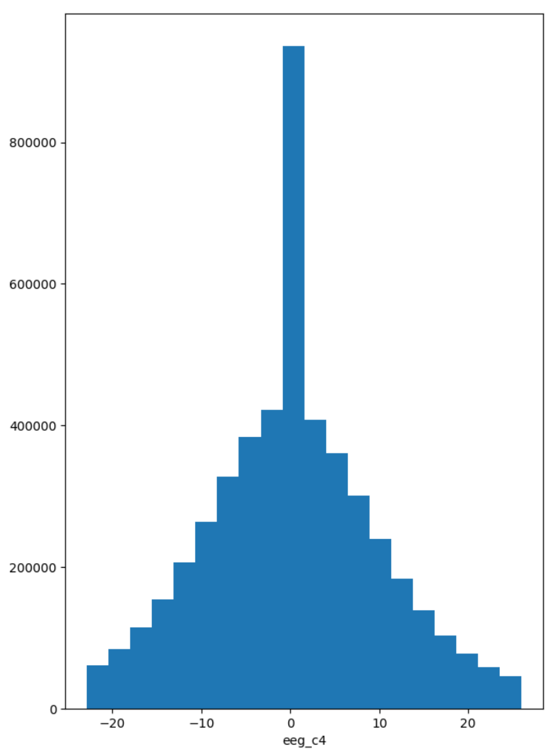

1e6
eeg_f3

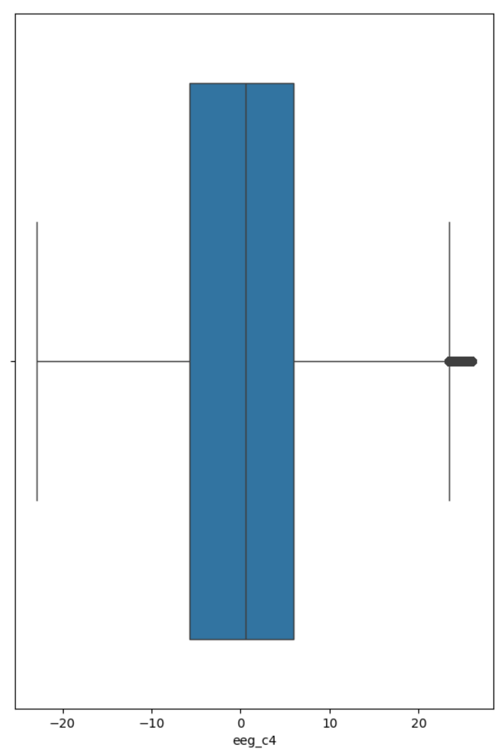

eeg_f3

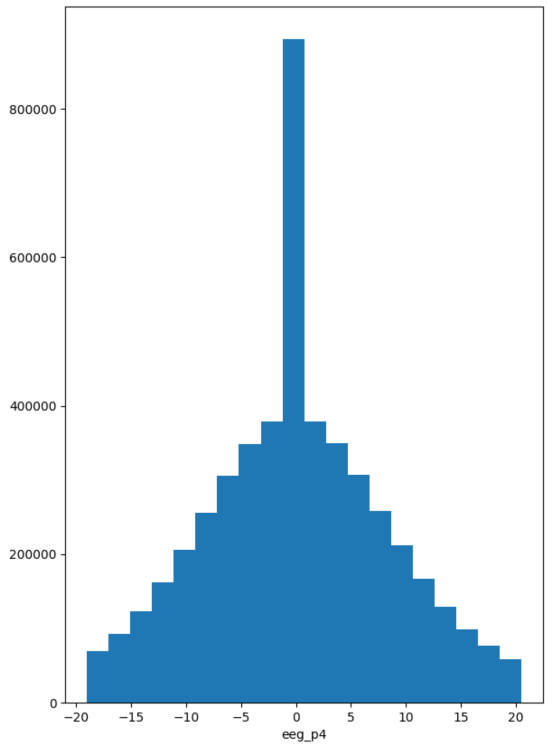

1e6
1.0
0.8
0.6
0.4
0.2
0.0
−20
−10
0
10
20
30
eeg_fz
−20
−10
0
10
20
30
eeg_fz

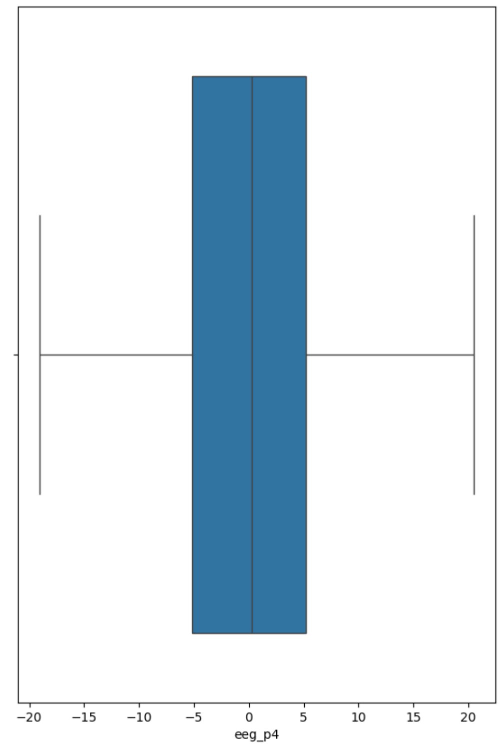

1e6
1.0
0.8
0.6
0.4
0.2
0.0
−30 −20 −10 0 10 20 30 40
eeg_f4

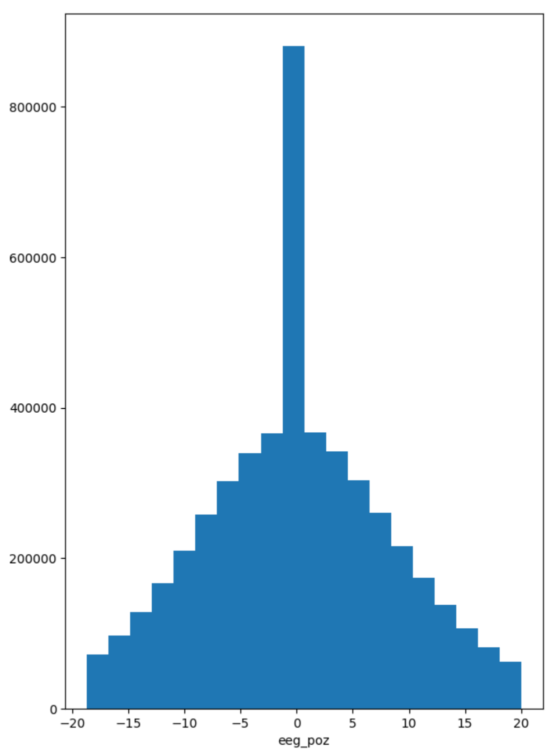

−30 −20 −10 0 10 20 30 40
eeg_f4

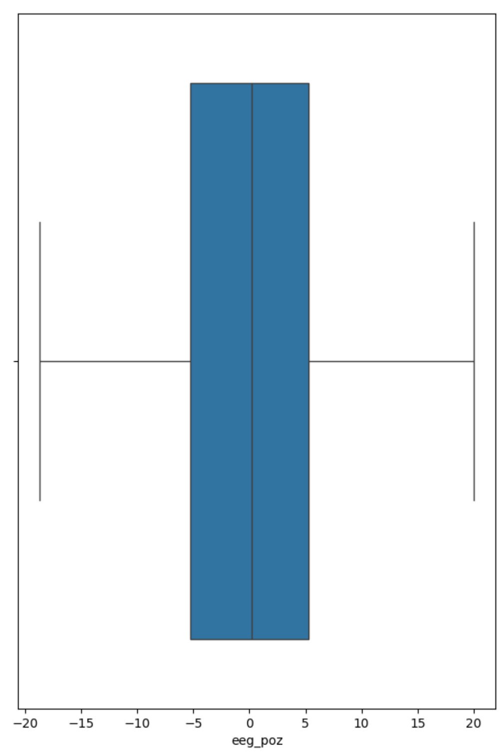

800000
600000
400000
200000
0
−20 −10 0 10 20
eeg_c4

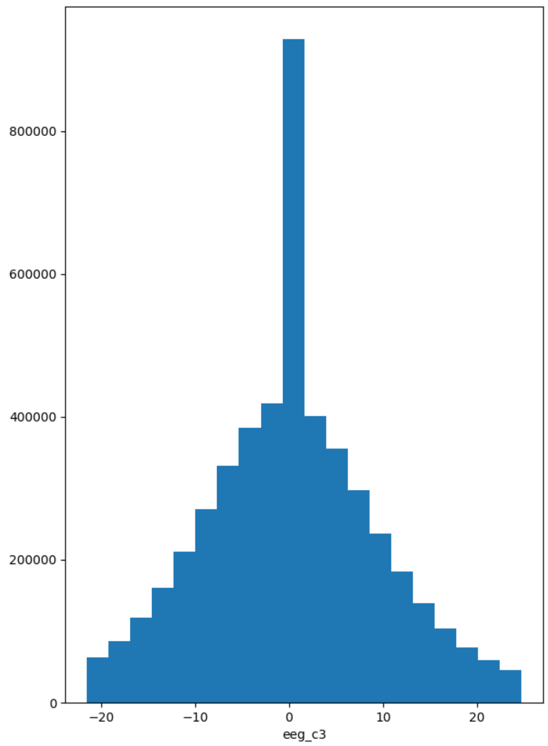
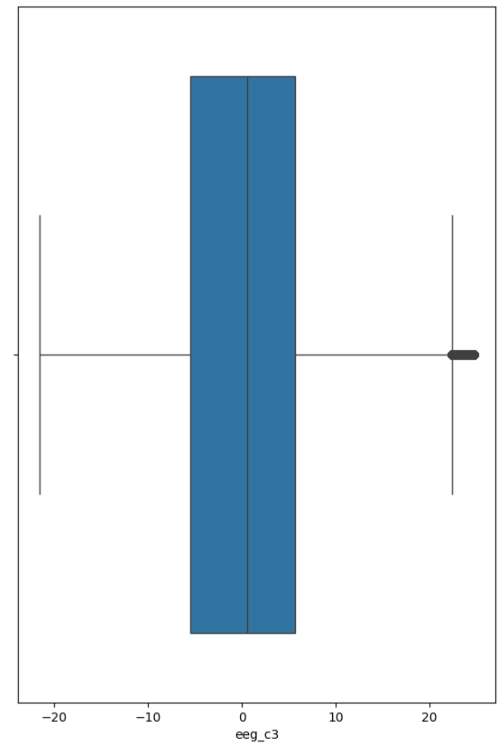
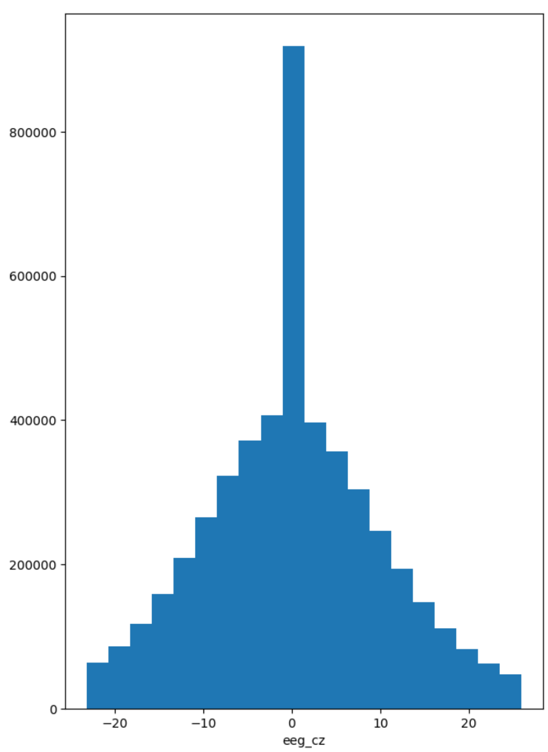
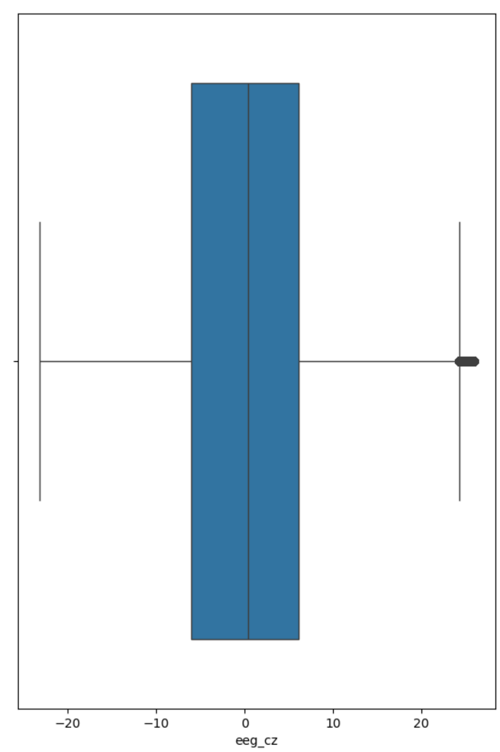

−20 −10 0 10 20
eeg_c4

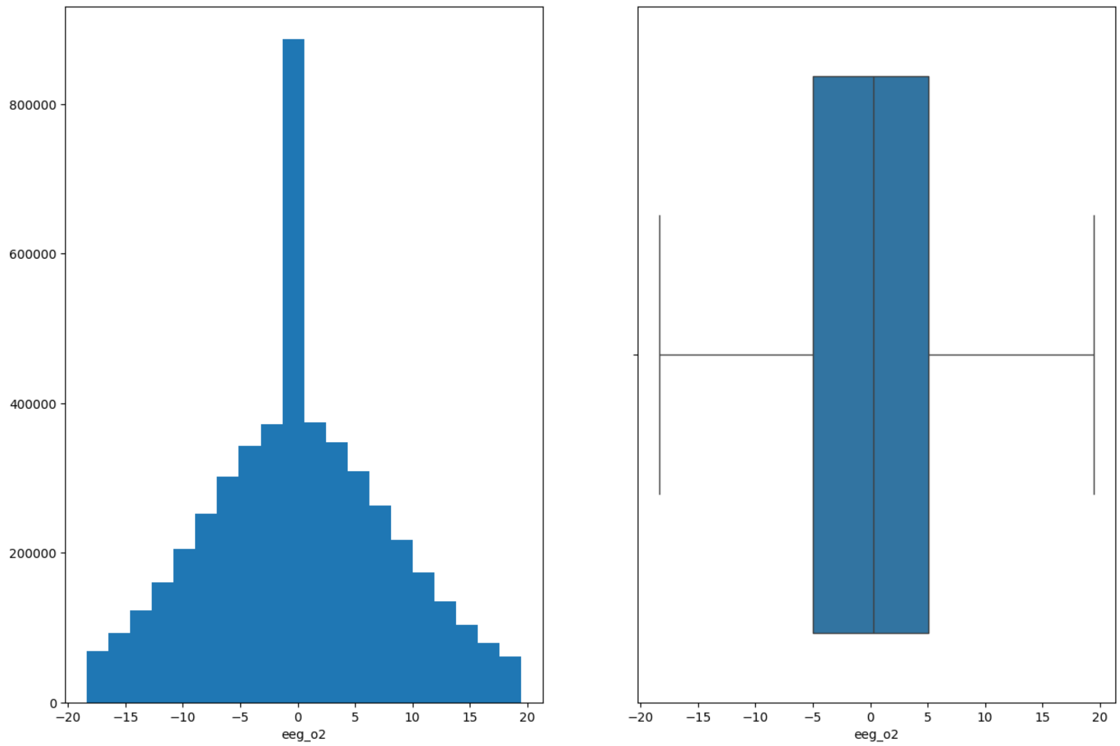

800000
600000
400000
200000
0
−20 −15 −10 −5 0 5 10 15 20
eeg_p4


−20 −15 −10 −5 0 5 10 15 20
eeg_p4

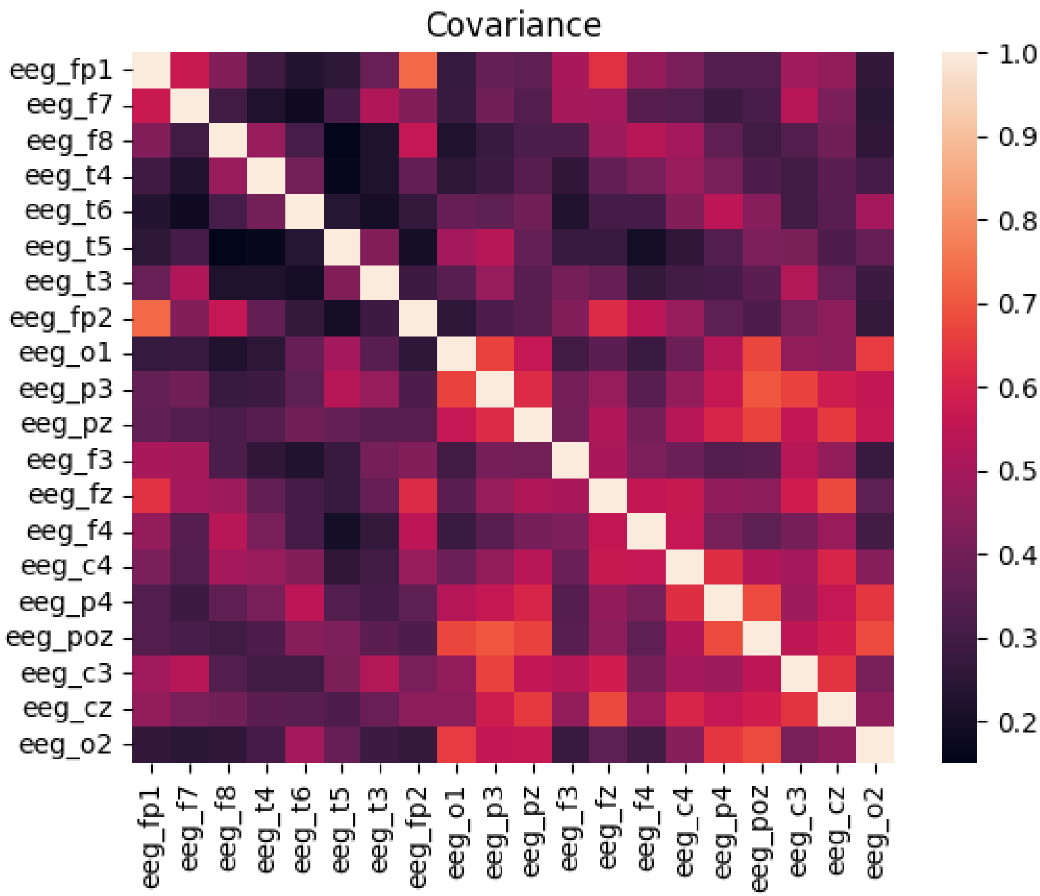

800000
600000
400000
200000
0
−20 −15 −10 −5 0 5 10 15 20
eeg_poz


−20 −15 −10 −5 0 5 10 15 20
eeg_poz


800000
600000
400000
200000
0
−20
−10
0
10
20
eeg_c3

−20
−10
0
10
20
eeg_c3

800000
600000
400000
200000
0
−20
−10
0
10
20
eeg_cz

−20
−10
0
10
20
eeg_cz

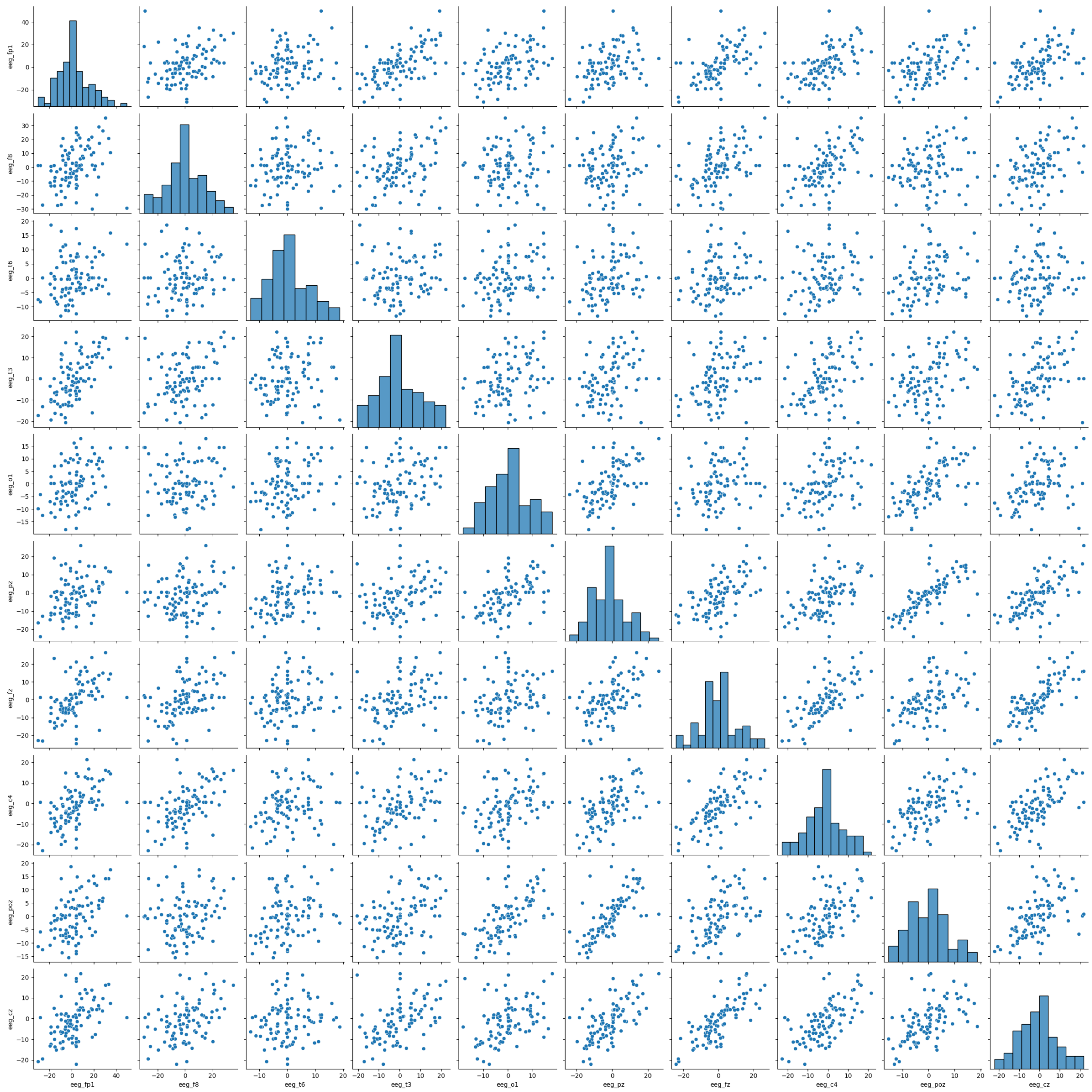


[12]:
```
##### plt.figure(figsize=(10,10))
sns.heatmap(continuous_data.corr())
plt.title('Covariance')
plt.show()
```



[13]:
```
plt.figure(figsize=(15,15))
selected_columns = [continuous_columns[i] if i % 2 == 0 else '' for i in␣
  ↪range(len(continuous_columns))]
selected_columns = list(filter(lambda x: x != "", selected_columns))
sns.pairplot(continuous_data[selected_columns].sample(100))
```

[13]:
```
<seaborn.axisgrid.PairGrid at 0x7f8a73d9b790>

<Figure size 1500x1500 with 0 Axes>
```

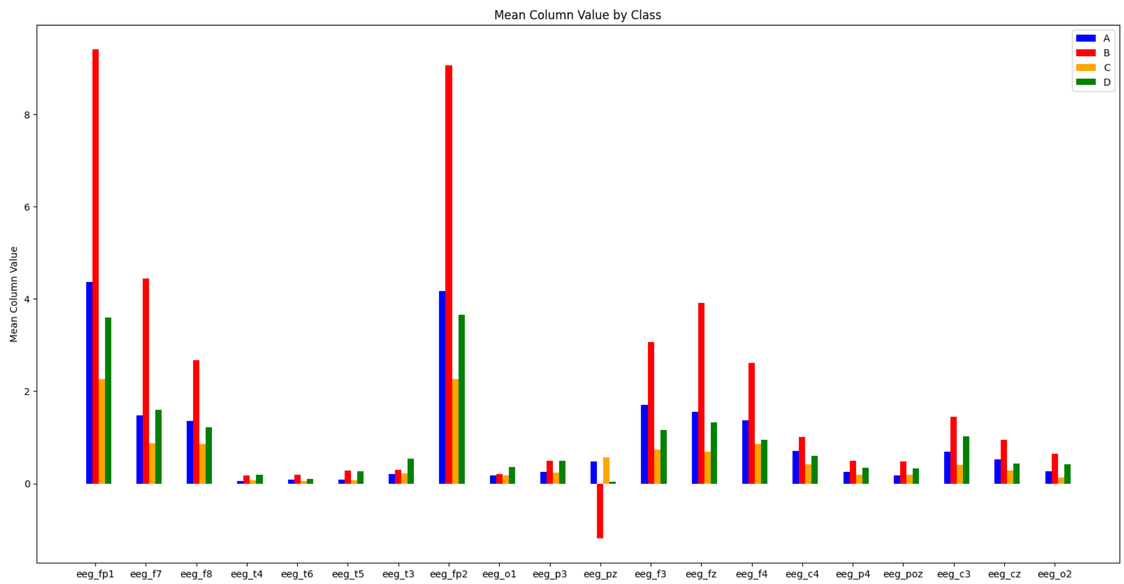


3 Analysis of Target Variable

[32]:
```python
# Comparing class distributions
plt.figure(figsize=(20,10))

targets = data['event']
inputs = data.drop(['event'], axis=1)

eeg_cols = list(filter(lambda x: x != '', [col if col.startswith('eeg') else '' for col in inputs.columns]))

classes = sorted(targets.unique())
```

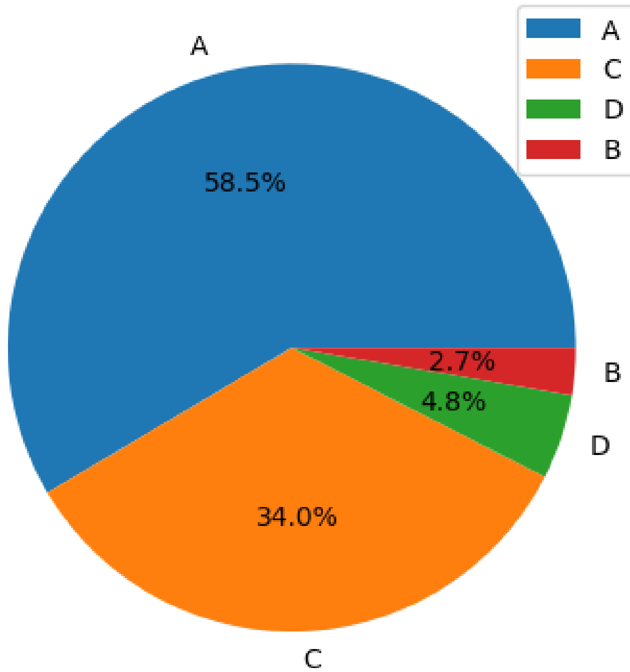
```
ind = np.arange(len(eeg_cols)) * len(classes)
width = .5
colors = ['blue', 'red', 'orange', 'green']

bars = []
for i in range(len(classes)):
    c = classes[i]

    index = targets[targets == c].index
    inputs_c = inputs[eeg_cols].iloc[index]

    bars.append(plt.bar(ind + (width * i), inputs_c.mean().to_numpy(), width,␣
 ↪color=colors[i], label=c))
plt.xticks(ind+ width, eeg_cols)
plt.ylabel('Mean Column Value')
plt.title('Mean Column Value by Class')
plt.legend(bars, classes)
```

[32]: <matplotlib.legend.Legend at 0x7fa3e61f7730>



[30]:
```
targets = data['event']

fig, ax = plt.subplots()
sizes = targets.value_counts().values

ax.pie(sizes, labels=targets.unique(), autopct='%1.1f%%')
plt.legend()
```

[30]: <matplotlib.legend.Legend at 0x7f6fded3dcc0>

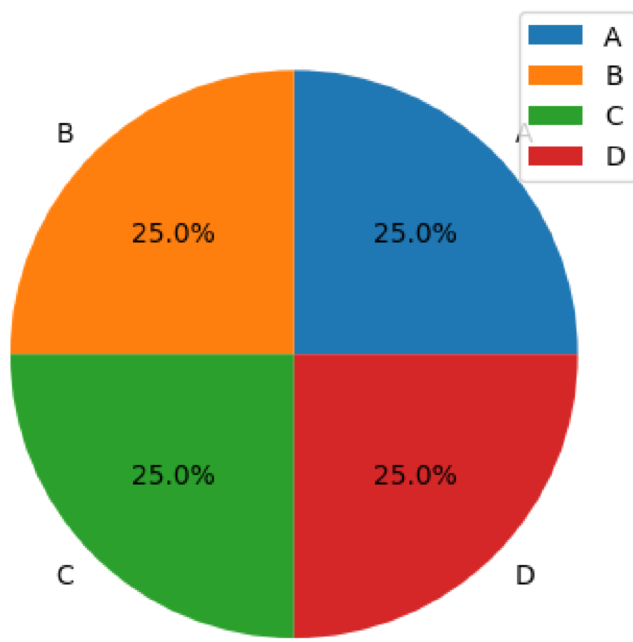



```
[31]: final_data = inputs
      final_data['event'] = targets
      final_data.to_csv('data/unbalanced_data.csv')
```

```
[32]: sampler = RandomUnderSampler()

      y = []
      for instance in targets:
          if instance == 'A':
              y.append([1, 0, 0, 0])
          elif instance == 'B':
              y.append([0, 1, 0, 0])
          elif instance == 'C':
              y.append([0, 0, 1, 0])
          else:
              y.append([0, 0, 0, 1])
      y = np.array(y)
      inputs = data.drop(['event'], axis=1)

      X, y = sampler.fit_resample(inputs, y)
```

[33]:
```
fig, ax = plt.subplots()

resampled_targets = []
for instance in y:
    if instance[0] == 1:
        resampled_targets.append('A')
    elif instance[1] == 1:
        resampled_targets.append('B')
    elif instance[2] == 1:
        resampled_targets.append('C')
    else:
        resampled_targets.append('D')
sizes = pd.Series(resampled_targets).value_counts().values

ax.pie(sizes, labels=np.unique(resampled_targets), autopct='%1.1f%%')
plt.legend()
```

[33]: <matplotlib.legend.Legend at 0x7f6fc26b8130>



[34]:
```
# resampled_targets = pd.DataFrame({'event': resampled_targets})
final_data = X
samples = [sample[0] for sample in resampled_targets]
final_data['event'] = samples
```

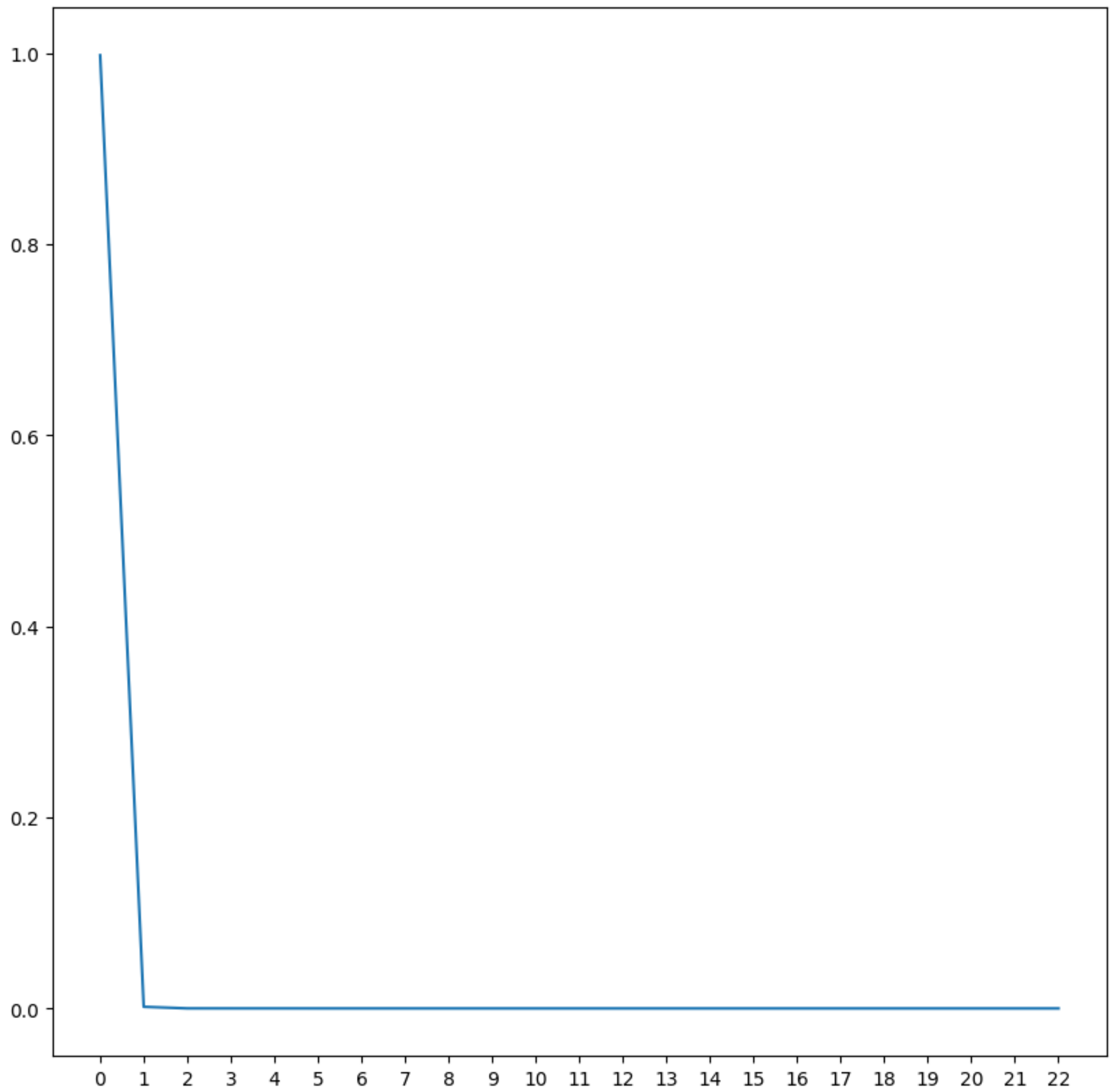
```python
final_data.to_csv('data/balanced_data.csv')
```

[35]:
```python
print(final_data.head())
```

```
         crew        time  seat    eeg_fp1    eeg_f7     eeg_f8     eeg_t4  \
3693767     7  298.299011     1  33.022999  10.67540  21.526899  26.035601
4295260     8   65.042969     1   0.695641   7.78519  -7.069430 -14.254800
3971231     8  137.570312     0  -6.523550   0.91154   5.015470   9.875400
1481758     3  297.207031     0  18.622700 -10.57660  15.150600  11.946000
3427251     7  152.652344     1  -9.479300  -4.47273  -9.147890  -1.128090

            eeg_t6    eeg_t5    eeg_t3  …    eeg_c4    eeg_p4    eeg_poz  \
3693767   0.551023   6.96384  10.51460  …   2.85777 -0.189594  13.177700
4295260 -15.235900  -4.30054  -3.04515  …  -3.43239 -6.827820  -1.674960
3971231   5.457310  -8.92143  -3.04243  …   5.54653  5.090880  -0.631244
1481758  10.757700   8.26449 -14.60250  … -13.93500  5.332060  -1.350900
3427251   3.293300  -3.87190  -6.57566  …  -9.14721 -1.821420  -2.314170

           eeg_c3    eeg_cz     eeg_o2          ecg           r  \
3693767  11.49920  22.15690 -277.071014  18533.699219  819.247009
4295260   3.12752   1.29224   -5.086150   5959.779785  803.143982
3971231 -10.82360  -1.45431    0.954921  26430.900391  675.278015
1481758   0.00000   3.38726    3.065280   6447.020020  673.142029
3427251 -15.57100  -5.23125   -1.062190  20669.699219  830.538025

                gsr  event
3693767  615.341003      A
4295260 1001.099976      A
3971231 1615.020020      A
1481758  640.395996      A
3427251  723.393005      A

[5 rows x 27 columns]
```

[36]:
```python
plt.figure(figsize=(10, 10))
components = X.drop(['event', 'crew', 'time', 'seat'], axis=1)
pca = PCA(n_components=len(components.columns))
components = pca.fit_transform(components)

plt.xticks(range(len(components[0])))
plt.plot(range(len(components[0])), pca.explained_variance_ratio_)
```

[36]:
```
[<matplotlib.lines.Line2D at 0x7f700c6ef0d0>]
```


1.0
0.8
0.6
0.4
0.2
0.0
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22

[ ]: