REDUCING COMMERCIAL AVIATION FATALITIES

Overview

Most of the flight fatalities are caused due to Loss of Airplane State Awareness of the pilot. So we have to build a model that can detect troubling events from the Aircrew's Physiological Data. This model should help the pilots by alerting them when they are entering into a troubling state thereby preventing accidents

BUSINESS PROBLEM

Losing the Airplane State Awareness occurs during a very stressful environment. In this stressful environment different pilots react differently but all of them are trained in such a way that the passengers safety is of utmost importance. So even small help can get the pilot on track. The pilots can get into one of these 3 cognitive states under the distracting events.

1) Channelized Attention (CA): The pilot is focussing only on 1 task and excluding others.

2) Diverted Attention (DA): The state of having one's attention diverted by the actions or thought processes associated with a decision.

3) Startle/Surprised (SS): This is an involuntary reaction when something unexpected happens.

So the model has to alert the pilot when he/she has entered one of the 3 states.

ML Formulation

The evaluation factor is MULTI CLASS LOG LOSS between predicted probabilities and Observed Target. We need to predict for each id (particular crew at particular time), one of the 4 states (SS,CA,DA or Baseline) of the pilot. We have to strictly predict the probability of occurrence of each event.

Business Constraint

This is totally possible. So i dont find any business constraints.

Dataset analysis

The 1.15 GB of Training Dataset consists of 3 categories CA,DA,SS. The test dataset is of 4.46 GB and the output can be Baseline, CA, DA or SS. The test data is taken from a flight simulator, where the experiment is called LOFT -> Line Oriented Flight Training where the pilot is trained in a simulator. Our data has the ECG, EEG, GSR(Galvanic SKin Response) and Respiration of the pilots.

Id: Unique identifier for crew+time combination. A pilot with a particular time into the experiment is represented using an id. So for each id, we need to predict the state.

Experiment: For training, it will be either CA or DA or SS. For testing, it will be LOFT.

Crew: Unique id for a pair or pilot

Time: Seconds into the experiment

Seat: Seat of the pilot- 0 means left, 1 means right.

EEG (Electroencephalogram) — This is the summation of all activities on the surface of the brain. Data from 20 electrodes are given to us. Each electrode lead is placed near a particular part of the brain (prefrontal(fp), temporal(t), frontal(f), parietal(p), occipital(o), central(c)). The odd numbers in the representation indicate that the electrode is placed on the left side of the brain, even numbers indicate the right side, and z indicate the middle region.

Eeg_f7: Data from the electrode near the prefrontal portion — left side

Eeg_f8: Data from the electrode near the frontal area — right side

Eeg_t4: Data from the electrode near the temporal area — right side

Eeg_t6: Data from the electrode near the temporal area — right side

Eeg_t5: Data from the electrode near the temporal area — left side

Eeg_t3: Data from the electrode near the temporal area — left side

Eeg_fp2: Data from the electrode near the prefrontal area — right side

Eeg_o1: Data from the electrode near the occipital area — left side

Eeg_p3: Data from the electrode near the parietal area — left side

Eeg_pz: Data from the electrode near the parietal area — middle region

Eeg_f3: Data from the electrode near the frontal area — left side

Eeg_fz: Data from the electrode near the frontal area — middle region

Eeg_f4: Data from the electrode near the frontal area — right side

Eeg_c4: Data from the electrode near the central area — right side

Eeg_p4: Data from the electrode near the parietal area — right side

Eeg_poz: Data from the electrode near the parietal-occipital junction— Middle region

Eeg_c3: Data from the electrode near the central area — left side

Eeg_cz: Data from the electrode near the central area — middle region

Eeg_o2: Data from the electrode near the occipital area — right side

Ecg: Three-point electrocardiogram (ECG) signal — It measures the electrical activity of the heart (sensor output is in microvolts)

R: Respiration sensor — It measures the rise and fall of the chest (Sensor output is in microvolts)

Gsr: Galvanic skin response — The measure of electrodermal activity (Sensor output is in microvolts)

Event: The output which is to be predicted — The state of the pilot at a given time. It will be either baseline (A no event) or SS(B) or CA(C)or DA(D).

Performance Metric

Our metric is Multiclass Log Loss between Predicted Probability and Observed Target. This problem is a MULTICLASS CLASSIFICATION PROBLEM where the #classes are 4.

$$multi\ class\ log\ loss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij}\ log(p_{ij})$$

N = total number of data points

M = the number of classes

yij is 1 if the data point i is predicted to be of class j else 0.

pij is the probability of datapoint i belonging to class j

Research-Papers/Solutions/Architectures/Kernels

1. https://www.kaggle.com/stuartbman/introduction-to-physiological-data

This link helped me out to understand what is physiological data. What are all the features in the dataset. The 3 types of physiological data Respiration, EEG and ECG are explained there along with how to use the data for visualization. It also explained about the values of normal ones and how they waver when the person(here the pilot) is set into one of the stressful situations. Eg: For EEG: Delta (<4Hz) Slow wave sleep, continuous attention tasks Theta (4-7Hz) Drowsiness, repression of elicited responses Alpha (8-15Hz) Relaxed, eyes closed Beta (16-31Hz) Active thinking, focus, alert Gamma (>32Hz) Short term memory, cross sensory perception

1. https://medium.com/analytics-vidhya/reducing-commercial-aviation-fatalities-dataset-pipeline-b835d06be423

This blog helped me to understand: That the data is imbalanced and to balance the data they used a technique called SMOTE(Synthetic Minority Oversampling TEchnique). This technique generates synthetic data for the minority class joining the points of the minority class with line segments and then places artificial points on these lines. The order of Feature Importance for a LightGBM model. The LightGBM is a fast, distributed, high-performance gradient boosting framework based on a decision tree algorithm, used for ranking, classification and many other machine learning tasks.

1. https://medium.com/swlh/reducing-commercial-aviation-fatalities-2257b5090d9f
2. https://atharvamusale.medium.com/reducing-commercial-aviation-fatalities-c335757e8d01

3 and 4 blogs helped me understand: We can't just simply use one feature(ECG or EEG or GSR) and classify the event, we need all three of them. We can use Dask since we have a large dataset. Approaches to build a model which utilizes the least amount memory and their procedures.

1. https://medium.com/analytics-vidhya/reducing-commercial-aviation-fatalities-ec338e37900c

This blog helped me understand: When the value of ECG is high (more than 10000 microvolts), the pilot is more likely to enter into the DA state. When the ECG value is too negative, the pilot is likely to be in the CA state. These data are clearly rich in noise and hence we need to remove this high-frequency noise. For that purpose, we use a low pass Butterworth filter. For filtering the ECG signal, the cutoff frequency(w) was selected as 100 and for filtering the respiration signal, the value of w was taken as 0.7. This data can be of so much help when we are designing the model.

First Cut Approach

For EDA we use: Violin Plots Box PLots Histograms Std Deviation Variance Mean

I would like to Normalize using the MinMax feature so that the data exists between 0 and 1. MinMax feature helps us scale and translate each feature individually such that it is in the given range on the training set, e.g. between zero and one.

We find that the data is Imbalanced so we use SMOTE to balance that data. Models that don't have a balanced dataset turn out to give us poor performance. SMOTE(Synthetic Minority Oversampling TEchnique) generates synthetic data for the minority class joining the points of the minority class with line segments and then places artificial points on these lines. SMOTE works by selecting examples that are close in the feature space, drawing a line between the examples in the feature space and drawing a new sample at a point along that line.

We have a huge dataset so we better use DASK(like in Microsoft Malware case study) for better use of RAM. Dask can efficiently perform parallel computations on a single machine using multi-core CPUs. Dask can run on a cluster of machines to process data efficiently as it uses all the cores of the connected machines. One interesting fact here is that it is not necessary that all machines should have the same number of cores. If one system has 2 cores while the other has 4 cores, Dask can handle these variations internally. The model I would like to try on this huge dataset is Light GBM.

LightGBM is a gradient boosting framework that uses tree based learning algorithms. It is designed to be distributed and efficient with the following advantages: Faster training speed and higher efficiency. Lower memory usage. Better accuracy. Support of parallel and GPU learning. Capable of handling large-scale data.

Generally XGBoost models have high performance rates, so we can try it. The first reason to try XGBoost is that it has parallel processing which might groom itself easily through this huge dataset. It has the capability to handle missing values It provides cross validation Logistic Regression It is less inclined to over fitting. Simple to implement Faster than many models.

Exploratory Data Analysis on Data

In [1]:

```
import pandas as pd

from sklearn.preprocessing import LabelEncoder
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.manifold import TSNE
from scipy.sparse import csr_matrix
from sklearn.preprocessing import MinMaxScaler

from tqdm import tqdm
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import dask.dataframe as dd
import warnings
warnings.filterwarnings("ignore")

from sklearn.model_selection import train_test_split
```

```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import log_loss
import xgboost as xgb
import lightgbm as lgb
from sklearn.ensemble import AdaBoostClassifier
```

In [2]:

```
train = pd.read_csv('E:/BOOKS_NEW/Cases datasets/1st/reducing-commercial-aviation-
fatalities/train.csv')
print('Number of data points : ', train.shape[0])
print('Number of features : ', train.shape[1])
print('Features : ', train.columns.values)
train.head()
```

```
Number of data points :  4867421
Number of features :  28
Features :  ['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']
```

Out[2]:

	crew	experiment	time	seat	eeg_fp1	eeg_f7	eeg_f8	eeg_t4	eeg_t6	eeg_t5	...	eeg_c4	eeg_p4	eeg
0	1	CA	0.011719	1	-5.28545	26.775801	-9.527310	-12.793200	16.717800	33.737499	...	37.368999	17.437599	19.2C
1	1	CA	0.015625	1	-2.42842	28.430901	-9.323510	-3.757230	15.969300	30.443600	...	31.170799	19.399700	19.68
2	1	CA	0.019531	1	10.67150	30.420200	15.350700	24.724001	16.143101	32.142799	...	-12.012600	19.396299	23.17
3	1	CA	0.023438	1	11.45250	25.609800	2.433080	12.412500	20.533300	31.494101	...	18.574100	23.156401	22.64
4	1	CA	0.027344	1	7.28321	25.942600	0.113564	5.748000	19.833599	28.753599	...	6.555440	22.754700	22.67

5 rows × 28 columns

Checking datatypes and null/missing values in all the columns

In [3]:

```
train.info(verbose=True,null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4867421 entries, 0 to 4867420
Data columns (total 28 columns):
 #   Column      Non-Null Count    Dtype  
---  ------      --------------    -----  
 0   crew        4867421 non-null  int64  
 1   experiment  4867421 non-null  object 
 2   time        4867421 non-null  float64
 3   seat        4867421 non-null  int64  
 4   eeg_fp1     4867421 non-null  float64
 5   eeg_f7      4867421 non-null  float64
 6   eeg_f8      4867421 non-null  float64
 7   eeg_t4      4867421 non-null  float64
 8   eeg_t6      4867421 non-null  float64
 9   eeg_t5      4867421 non-null  float64
 10  eeg_t3      4867421 non-null  float64
 11  eeg_fp2     4867421 non-null  float64
 12  eeg_o1      4867421 non-null  float64
 13  eeg_p3      4867421 non-null  float64
 14  eeg_pz      4867421 non-null  float64
 15  eeg_f3      4867421 non-null  float64
```

```
 16  eeg_fz      4867421 non-null  float64
 17  eeg_f4      4867421 non-null  float64
 18  eeg_c4      4867421 non-null  float64
 19  eeg_p4      4867421 non-null  float64
 20  eeg_poz     4867421 non-null  float64
 21  eeg_c3      4867421 non-null  float64
 22  eeg_cz      4867421 non-null  float64
 23  eeg_o2      4867421 non-null  float64
 24  ecg         4867421 non-null  float64
 25  r           4867421 non-null  float64
 26  gsr         4867421 non-null  float64
 27  event       4867421 non-null  object
dtypes: float64(24), int64(2), object(2)
memory usage: 1.0+ GB
```

No null values in the train dataset.

In [9]:

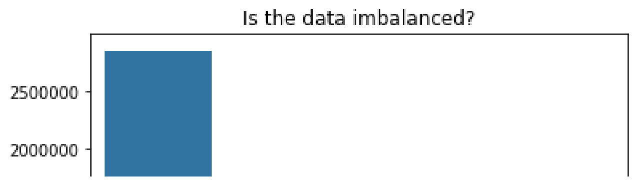
```
kaggle_test.info(verbose=True)
```

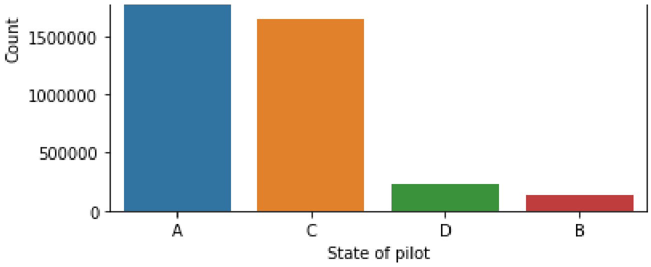
```
<class 'dask.dataframe.core.DataFrame'>
Int64Index: 17965143 entries, 0 to 187048
Data columns (total 28 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   id          17965143 non-null      int64
 1   crew        17965143 non-null      int64
 2   experiment  17965143 non-null      object
 3   time        17965143 non-null      float64
 4   seat        17965143 non-null      int64
 5   eeg_fp1     17965143 non-null      float64
 6   eeg_f7      17965143 non-null      float64
 7   eeg_f8      17965143 non-null      float64
 8   eeg_t4      17965143 non-null      float64
 9   eeg_t6      17965143 non-null      float64
10   eeg_t5      17965143 non-null      float64
11   eeg_t3      17965143 non-null      float64
12   eeg_fp2     17965143 non-null      float64
13   eeg_o1      17965143 non-null      float64
14   eeg_p3      17965143 non-null      float64
15   eeg_pz      17965143 non-null      float64
16   eeg_f3      17965143 non-null      float64
17   eeg_fz      17965143 non-null      float64
18   eeg_f4      17965143 non-null      float64
19   eeg_c4      17965143 non-null      float64
20   eeg_p4      17965143 non-null      float64
21   eeg_poz     17965143 non-null      float64
22   eeg_c3      17965143 non-null      float64
23   eeg_cz      17965143 non-null      float64
24   eeg_o2      17965143 non-null      float64
25   ecg         17965143 non-null      float64
26   r           17965143 non-null      float64
27   gsr         17965143 non-null      float64
dtypes: object(1), float64(24), int64(3)
```

No null values in the test dataset.

In [4]:

```
sns.countplot(train['event'])
plt.xlabel('State of pilot')
plt.ylabel('Count')
plt.title('Is the data imbalanced?')
plt.show()
```





A=baseline/noevent

B=SS

C=CA

D=DA

1) The data is totally imbalanced where, the number cases in A>>C>>D>B.

a) So we can say that major number of pilots are in a baseline state.

b) Second most distraction case is that the pilots got into a Channelized Attention state (CA).

c) Third is the count where the pilots got into a Diverted Attention state (DA).

d) The least number of pilots got into a Startle/Surprise state.

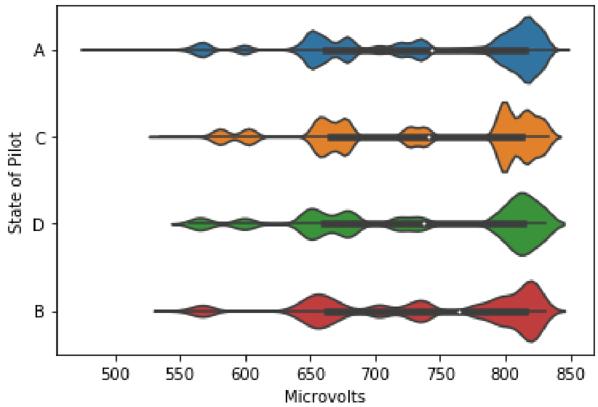
2) When it comes to physiological data we are given 3 parameters which are Respiration, Electrocardiogram(ECG) and Electroencephalogram(EEG). Lets have a look at them.

Respiration - R: Respiration sensor — It measures the rise and fall of the chest

(Sensor output is in microvolts)

In [5]:

```
sns.violinplot(x='r', y='event',data= train)
plt.xlabel('Microvolts')
plt.ylabel('State of Pilot')
plt.show()
```

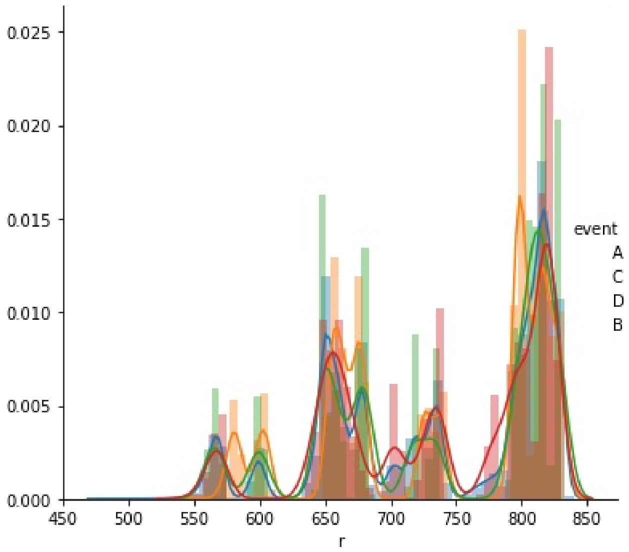


The majority of the situations occur at 650 microvolts and between 800-850 micro volts. In all the 4 situations, the 25th and 75th percentile did not change much. In all the 4 situations the histogram also look similar. The 50th percentile for the case B (Startle/Surprise) is at a higher voltage.

(Startle/Surprise) is at a higher voltage.

In [6]:

```
sns.FacetGrid(train, hue="event", size=5) \
   .add_legend() \
   .map(sns.distplot, "r");
plt.show();
```

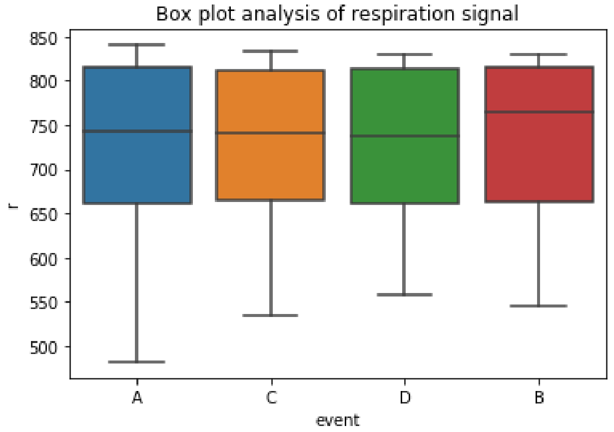


The histograms overlapping too much and it is too congested to deduce a fact.

Analyse the presence of noise in Respiration data

In [7]:

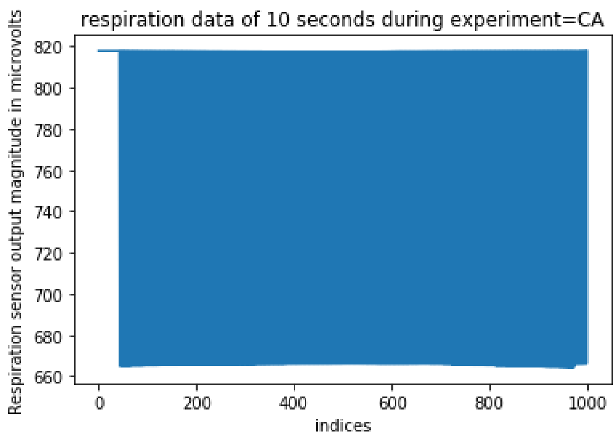
```
sns.boxplot(train["event"],train["r"])
plt.title("Box plot analysis of respiration signal")
plt.show()
```



Here also we do have outliers included in the data.

In [8]:

```
ca=train[train["experiment"]=="CA"]
ca.sort_values(by="time")

plt.plot(ca["r"][:1000])
plt.title("respiration data of 10 seconds during experiment=CA")
plt.xlabel("indices")
plt.ylabel("Respiration sensor output magnitude in microvolts")

plt.show()
```



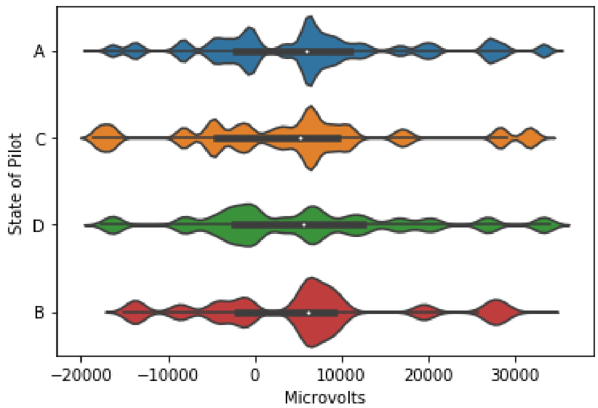
Here we have plotted 'r' output for 10 seconds where the experiment is Channelized Attention. It is clearly visible that there is noise in the data. The data collected is from the same situations as of CA so obviously SS and DA would also have noise.

Electrocardiogram(ECG) - Ecg: Three-point electrocardiogram (ECG) signal — It measures the Electrical activity of the heart

(sensor output is in microvolts)

In [9]:

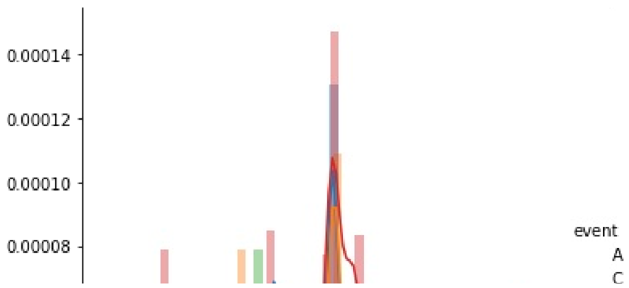
```
sns.violinplot(x='ecg', y='event',data= train)
plt.xlabel('Microvolts')
plt.ylabel('State of Pilot')
plt.show()
```

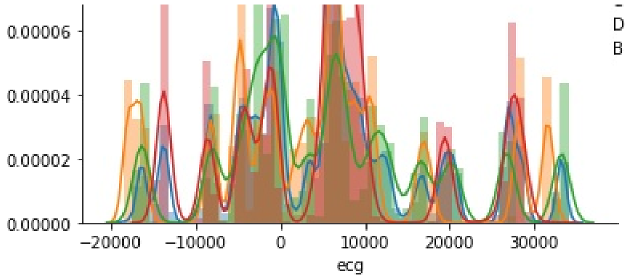


The majority of the situations occur between -10k to 10k microvolts.

In [10]:

```
sns.FacetGrid(train, hue="event", size=5) \
   .add_legend() \
   .map(sns.distplot, "ecg");
plt.show();
```





The histograms overlapping too much and it is too congested to deduce a fact.

Analysis of noise in the ECG data

In [11]:

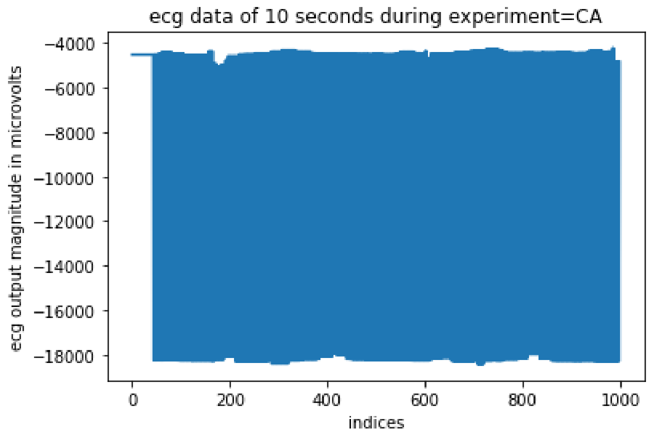
```
#this is a code to find out the indices whre time is 10 seconds for CA experiment
ca=train[train["experiment"]=="CA"]
ca.sort_values(by="time")
ca["time"][:1000]
```

Out[11]:

```
0        0.011719
1        0.015625
2        0.019531
3        0.023438
4        0.027344
           ...
995     10.039062
996     10.042969
997     10.042969
998     10.046875
999     10.046875
Name: time, Length: 1000, dtype: float64
```

In [12]:

```
plt.plot(ca["ecg"][:1000])
plt.title("ecg data of 10 seconds during experiment=CA")
plt.xlabel("indices")
plt.ylabel("ecg output magnitude in microvolts")

plt.show()
```



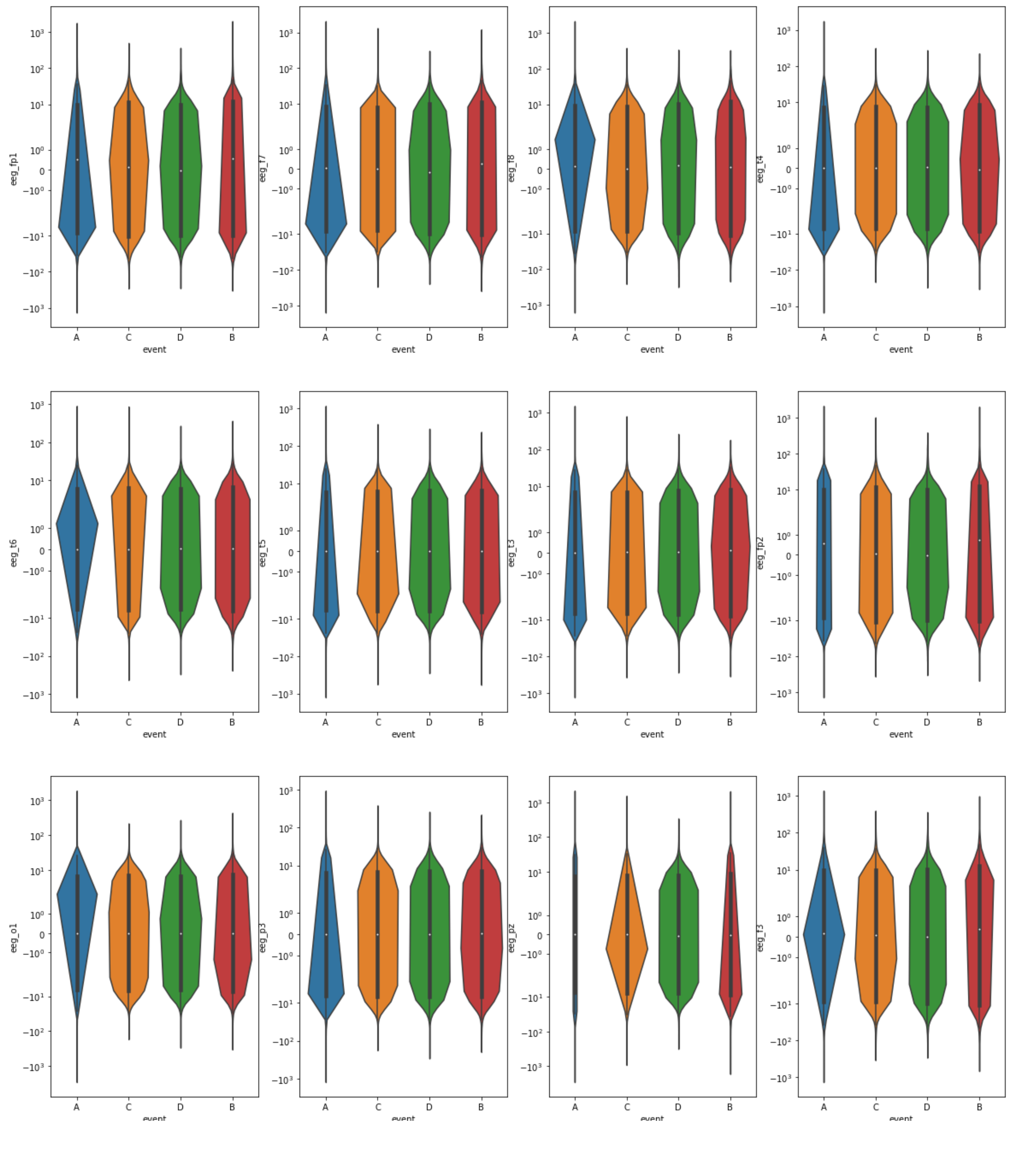
Here we have plotted ECG output for 10 seconds where the experiment is Channelized Attention. It is clearly visible that there is noise in the data. The data collected is from the same situations as of CA so obviously SS and DA would also have noise.

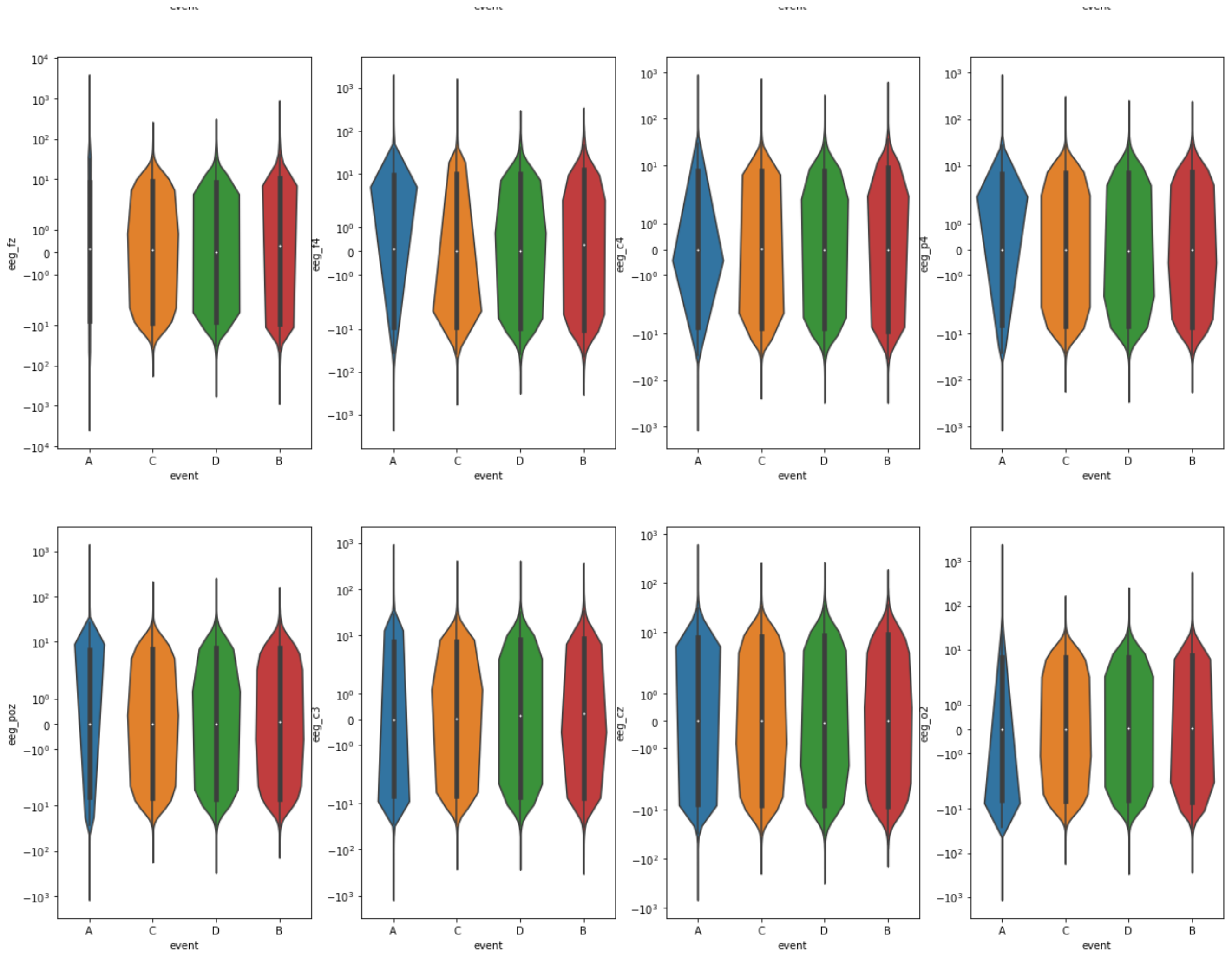
EEG (Electroencephalogram) — This is the summation of all

activities on the surface of the brain. Data from 20 electrodes are given to us. Each electrode lead is placed near a particular part of the brain (prefrontal(fp), temporal(t), frontal(f), parietal(p), occipital(o), central(c)). The odd numbers in the representation indicate that the electrode is placed on the left side of thebrain, even numbers indicate the right side, and z indicate the middle region.

In [13]:

```
plt.figure(figsize=(20,40))
feats = ["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"]
for i,j in enumerate(feats):
    plt.subplot(5, 4, i+1)
    plt.yscale('symlog')
    sns.violinplot(x='event',y=j, data=train)
plt.show()
```

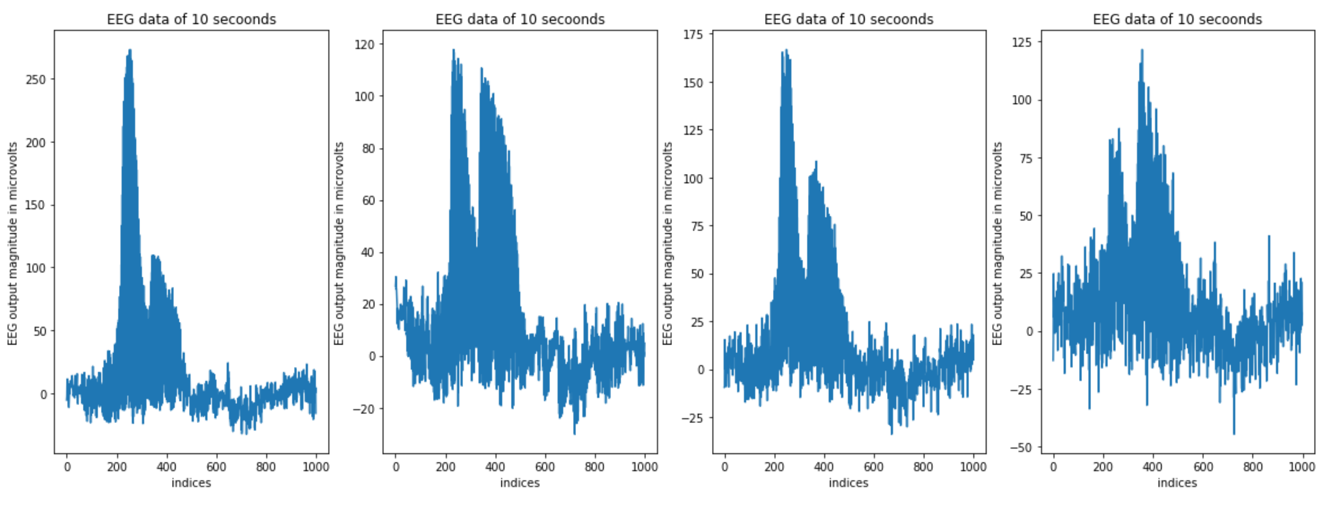


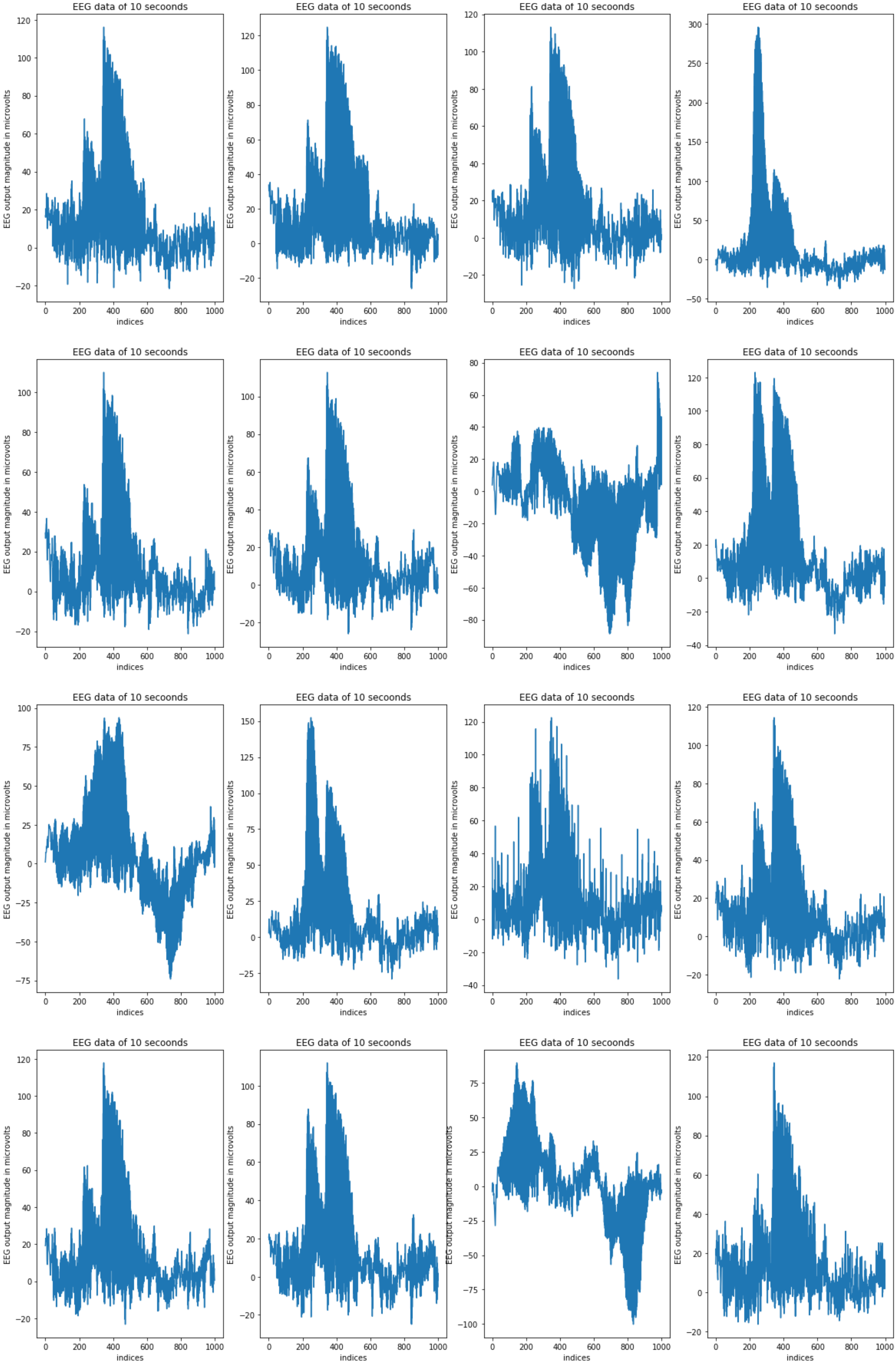


Analysis of Noise in EEG data

In [48]:

```
plt.figure(figsize=(20,40))
feats = ["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"]
for i,j in enumerate(feats):
    plt.subplot(5, 4, i+1)
    plt.plot(train[j][:1000])
    plt.title("EEG data of 10 secoonds")
    plt.xlabel("indices")
    plt.ylabel("EEG output magnitude in microvolts")

plt.show()
```



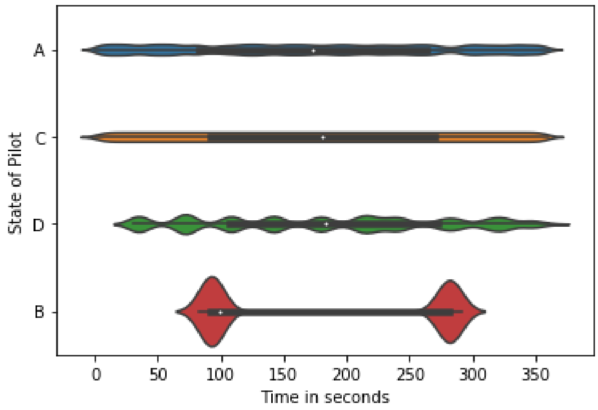


Noise exists for sure.

TIME: Seconds into the experiment

In [14]:

```
sns.violinplot(x='time', y='event',data= train)
plt.xlabel('Time in seconds')
plt.ylabel('State of Pilot')
plt.show()
```

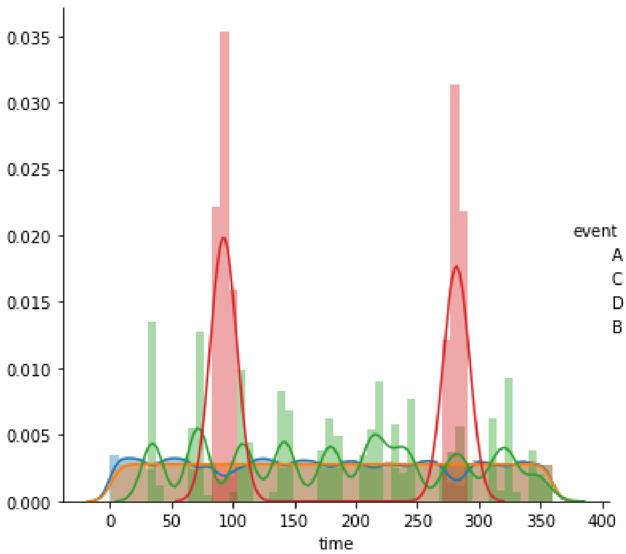


Event B performs very differently when compared to other events. It occurs onlyat 2 time ranges, first at 75-100 seconds and between 250-300 seconds into the experiment.

Event D has an interesting nature which almost looks like a sinosoidal wave.

In [15]:

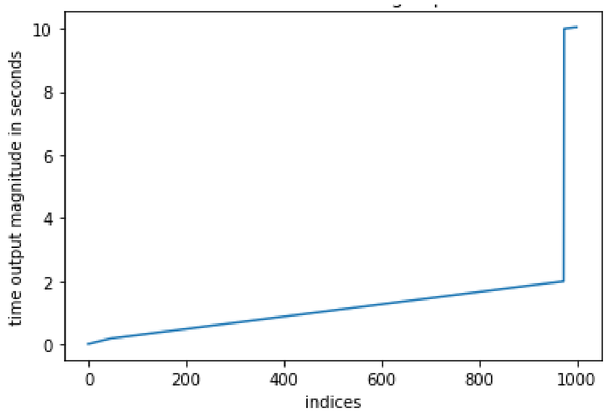
```
sns.FacetGrid(train, hue="event", size=5) \
   .add_legend() \
   .map(sns.distplot, "time");
plt.show();
```



In [39]:

```
plt.plot(ca["time"][:1000])
plt.title("time data of 10 seconds during experiment=CA")
plt.xlabel("indices")
plt.ylabel("time output magnitude in seconds")

plt.show()
```

time data of 10 seconds during experiment=CA

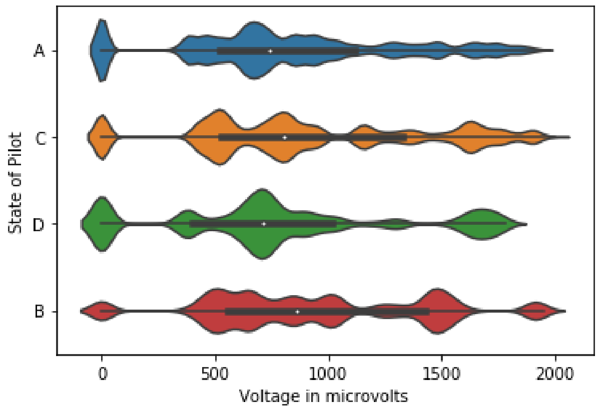


GSR- Galvanic Skin Response — The measure of electrodermal activity

(Sensor output is in microvolts)

In [16]:

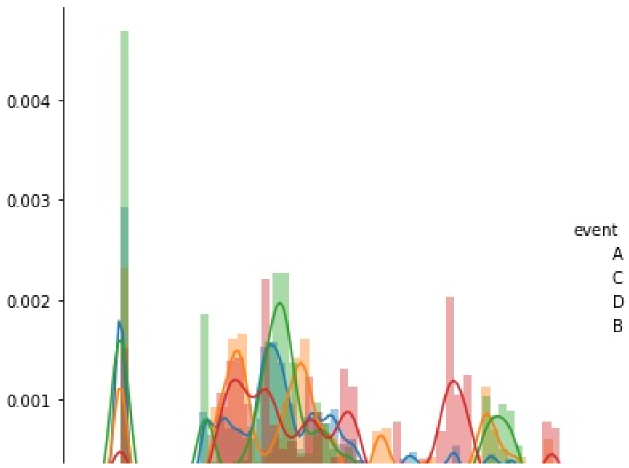
```
sns.violinplot(x='gsr', y='event',data= train)
plt.xlabel('Voltage in microvolts')
plt.ylabel('State of Pilot')
plt.show()
```



The GSR is in such a way that any of the four events dont occur between 150-400 microvolts.

In [17]:

```
sns.FacetGrid(train, hue="event", size=5) \
   .add_legend() \
   .map(sns.distplot, "gsr");
plt.show();
```

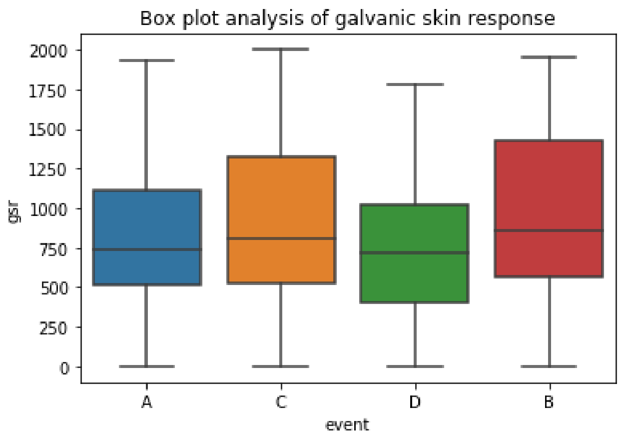


The histograms overlapping too much and it is too congested to deduce a fact.

Analysis of noise in the Galvanic Skin Response data

In [18]:

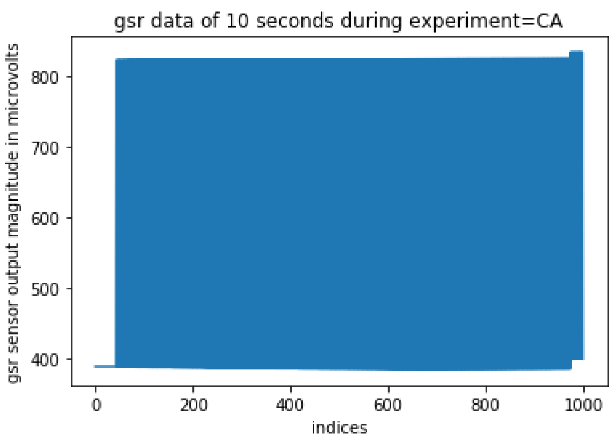
```
sns.boxplot(train["event"],train["gsr"])
plt.title("Box plot analysis of galvanic skin response")
plt.show()
```



The whiskers of the box plots are totally imbalanced which tell us the min and max value. The percentiles also are totally unequal.

In [19]:

```
ca=train[train["experiment"]=="CA"]
ca.sort_values(by="time")

plt.plot(ca["gsr"][:1000])
plt.title("gsr data of 10 seconds during experiment=CA")
plt.xlabel("indices")
plt.ylabel("gsr sensor output magnitude in microvolts")

plt.show()
```



This graph clearly tells us that even the GSR data has noise included in it.

Feature Engineering - NOISE REMOVAL

In [5]:

```
train.sort_values(["crew","time"],ascending=True).groupby("experiment") # Sorting the values w.r.t experiment
```

Out[5]:

```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x0000016BEBF4ECC8>
```

In [6]:

```
import scipy.signal as signal
# https://stackoverflow.com/questions/35588782/how-to-average-a-signal-to-remove-noise-with-python
def noise_removal(noisy_data,Wn):
    N = 3
    B, A = signal.butter(N, Wn)
    return signal.filtfilt(B,A, noisy_data)
```

Noise Removal in ECG DATA

In [7]:

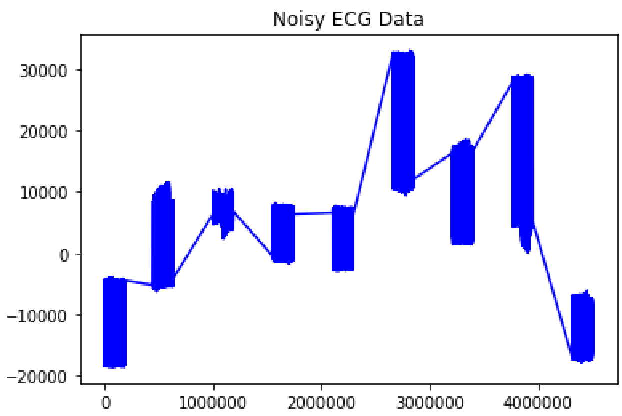
```
ca=train[train["experiment"]=="CA"]
```

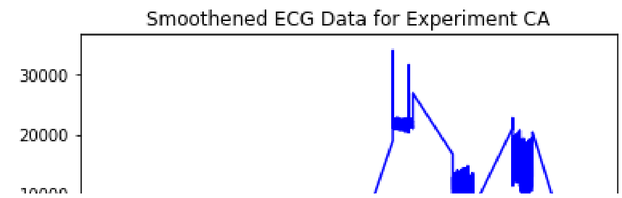
In [8]:

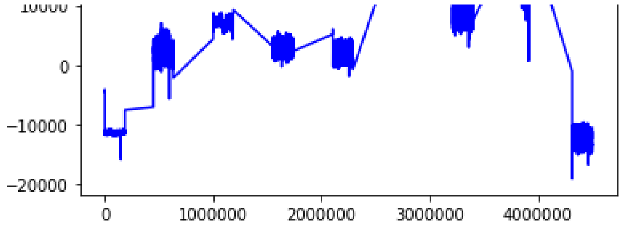
```
w = 0.1 # cutoff frequency- 10*the maximum possible frequency (10Hz or 100 beats per minute)
smoothened_ecg_data = noise_removal(train["ecg"],w)
train['smoothened_ecg_data'] = smoothened_ecg_data # Adding the smoothened data to the train dataset
```

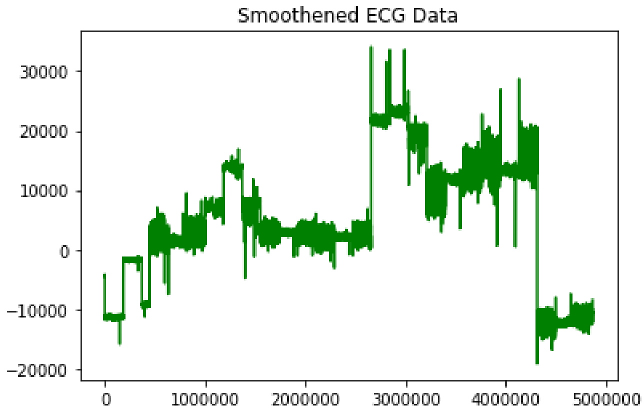
In [9]:

```
plt.plot(ca["ecg"],'b-')
plt.title('Noisy ECG Data')
plt.show()

ca=train[train["experiment"]=="CA"]
plt.plot(ca['smoothened_ecg_data'],'b-')
plt.title('Smoothened ECG Data for Experiment CA')
plt.show()

plt.plot(train['smoothened_ecg_data'],'g-')
plt.title('Smoothened ECG Data')
plt.show()
```



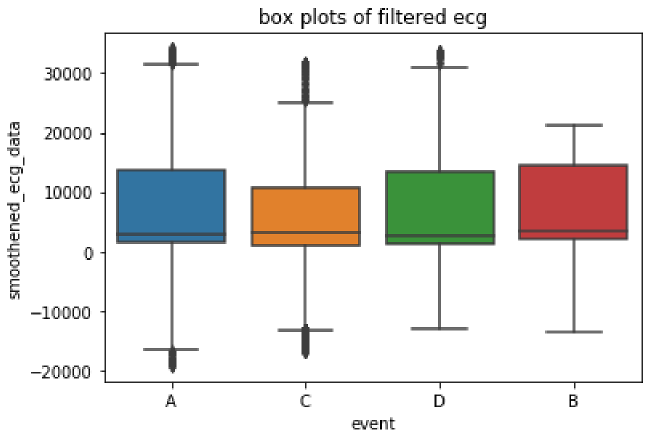






In [10]:

```
sns.boxplot(train["event"],train["smoothened_ecg_data"])
plt.title("box plots of filtered ecg")
plt.show()
```



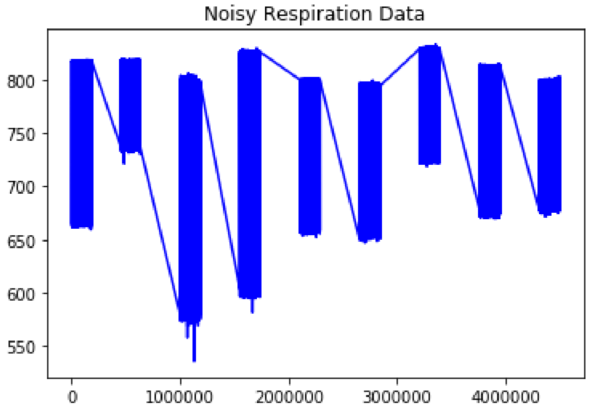
Noise Removal in Respiration data

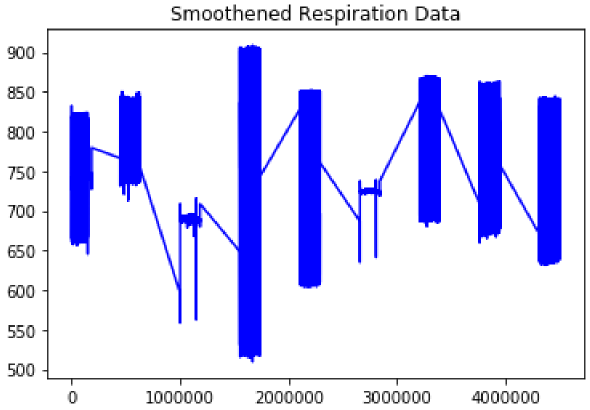
In [11]:

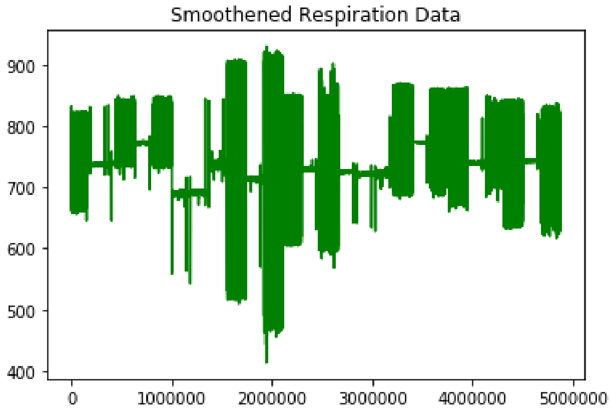
```
w = 0.7 # cutoff frequency- 10*the maximum possible frequency (10Hz or 100 beats per minute)
smoothened_r_data = noise_removal(train["r"],w)
train['smoothened_r_data'] = smoothened_r_data # Adding the smoothened data to the train dataset
```

In [12]:

```
plt.plot(ca["r"],'b-')
plt.title('Noisy Respiration Data')
plt.show()

ca=train[train["experiment"]=="CA"]
plt.plot(ca['smoothened_r_data'],'b-')
plt.title('Smoothened Respiration Data')
plt.show()

plt.plot(train['smoothened_r_data'],'g-')
plt.title('Smoothened Respiration Data')
plt.show()
```

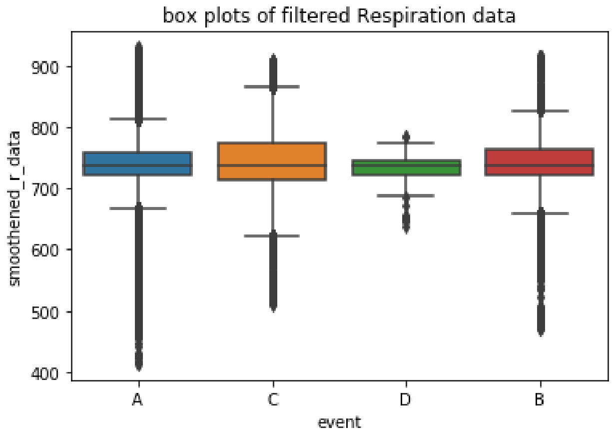






In [13]:

```
sns.boxplot(train["event"],train["smoothened_r_data"])
plt.title("box plots of filtered Respiration data")
plt.show()
```



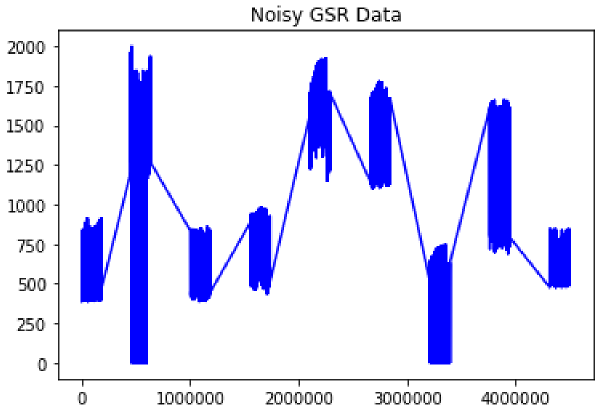
Noise Removal in GSR data

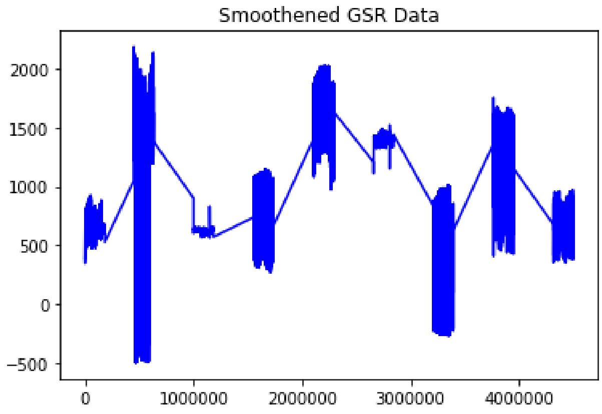
In [14]:

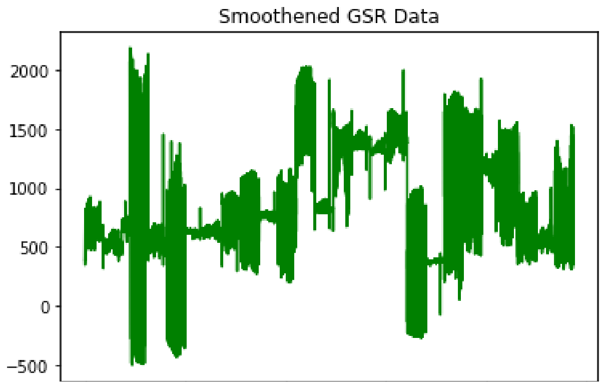
```
w = 0.7 # cutoff frequency- 10*the maximum possible frequency (10Hz or 100 beats per minute)
smoothened_gsr_data = noise_removal(train["gsr"],w)
train['smoothened_gsr_data'] = smoothened_gsr_data # Adding the smoothened data to the train
dataset
```

In [15]:

```
plt.plot(ca["gsr"],'b-')
plt.title('Noisy GSR Data')
plt.show()

ca=train[train["experiment"]=="CA"]
plt.plot(ca['smoothened_gsr_data'],'b-')
plt.title('Smoothened GSR Data')
plt.show()

plt.plot(train['smoothened_gsr_data'],'g-')
plt.title('Smoothened GSR Data')
plt.show()
```

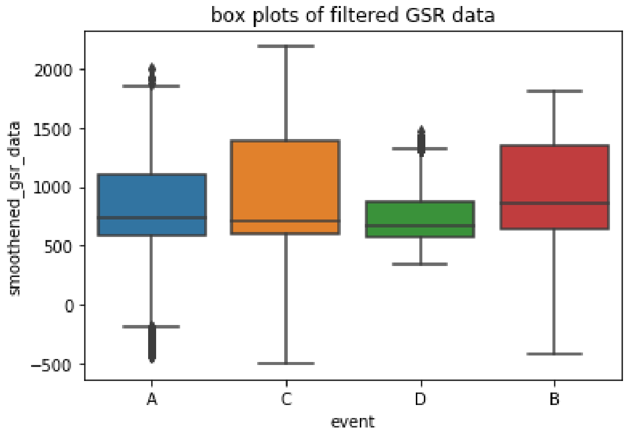






In [16]:

```
sns.boxplot(train["event"],train["smoothened_gsr_data"])
plt.title("box plots of filtered GSR data")
plt.show()
```



Noise Removal in EEG data

In [17]:

```
train.describe()
```

Out[17]:

	crew	time	seat	eeg_fp1	eeg_f7	eeg_f8	eeg_t4	eeg_t6	eeg_t
count	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+0
mean	5.538783e+00	1.782358e+02	4.999531e-01	3.746336e+00	1.360002e+00	1.213644e+00	7.350926e-02	7.845481e-02	8.675488e-0
std	3.409353e+00	1.039592e+02	5.000000e-01	4.506763e+01	3.518923e+01	3.519242e+01	2.431472e+01	1.803932e+01	1.832606e+0
min	1.000000e+00	3.000000e-03	0.000000e+00	-1.361360e+03	-1.581330e+03	-1.643950e+03	-1.516640e+03	-1.220510e+03	1.266430e+0
25%	3.000000e+00	8.808100e+01	0.000000e+00	-9.200250e+00	-8.325150e+00	-8.767610e+00	-7.367240e+00	-6.102000e+00	6.007260e+0
50%	5.000000e+00	1.769297e+02	0.000000e+00	3.819020e-01	4.264100e-02	1.140390e-01	0.000000e+00	0.000000e+00	0.000000e+0
75%	7.000000e+00	2.683398e+02	1.000000e+00	1.030610e+01	8.753340e+00	9.282560e+00	7.437780e+00	6.176630e+00	6.086460e+0
max	1.300000e+01	3.603711e+02	1.000000e+00	1.972240e+03	2.048790e+03	2.145710e+03	1.731880e+03	9.009370e+02	1.176540e+0

8 rows × 29 columns

In [18]:

```
w = 0.7 # cutoff frequency- 10*the maximum possible frequency (10Hz or 100 beats per minute)
feats = ["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"]
smoothened_eeg_fp1 = noise_removal(train['eeg_fp1'],w)
train['smoothened_eeg_fp1'] = smoothened_eeg_fp1 # Adding the smoothened data to the train dataset
```

In [19]:

```
smoothened_eeg_f7 = noise_removal(train['eeg_f7'],w)
train['smoothened_eeg_f7'] = smoothened_eeg_f7 # Adding the smoothened data to the train dataset
```

In [20]:

```
train.describe()
```

Out[20]:

	crew	time	seat	eeg_fp1	eeg_f7	eeg_f8	eeg_t4	eeg_t6	eeg_t
count	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+0
mean	5.538783e+00	1.782358e+02	4.999531e-01	3.746336e+00	1.360002e+00	1.213644e+00	7.350926e-02	7.845481e-02	8.675488e-0
std	3.409353e+00	1.039592e+02	5.000000e-01	4.506763e+01	3.518923e+01	3.519242e+01	2.431472e+01	1.803932e+01	1.832606e+0
min	1.000000e+00	3.000000e-03	0.000000e+00	-1.361360e+03	-1.581330e+03	-1.643950e+03	-1.516640e+03	-1.220510e+03	-1.266430e+0
25%	3.000000e+00	8.808100e+01	0.000000e+00	-9.200250e+00	-8.325150e+00	-8.767610e+00	-7.367240e+00	-6.102000e+00	-6.007260e+0
50%	5.000000e+00	1.769297e+02	0.000000e+00	3.819020e-01	4.264100e-02	1.140390e-01	0.000000e+00	0.000000e+00	0.000000e+0
75%	7.000000e+00	2.683398e+02	1.000000e+00	1.030610e+01	8.753340e+00	9.282560e+00	7.437780e+00	6.176630e+00	6.086460e+0
max	1.300000e+01	3.603711e+02	1.000000e+00	1.972240e+03	2.048790e+03	2.145710e+03	1.731880e+03	9.009370e+02	1.176540e+0

8 rows × 31 columns

In [21]:

```
train['smoothened_eeg_f8'] = noise_removal(train['eeg_f8'],w)
```

In [22]:

```
train.describe()
```

Out[22]:

	crew	time	seat	eeg_fp1	eeg_f7	eeg_f8	eeg_t4	eeg_t6	eeg_t
count	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+06	4.867421e+0
mean	5.538783e+00	1.782358e+02	4.999531e-01	3.746336e+00	1.360002e+00	1.213644e+00	7.350926e-02	7.845481e-02	8.675488e-0
std	3.409353e+00	1.039592e+02	5.000000e-01	4.506763e+01	3.518923e+01	3.519242e+01	2.431472e+01	1.803932e+01	1.832606e+0
min	1.000000e+00	3.000000e-03	0.000000e+00	-1.361360e+03	-1.581330e+03	-1.643950e+03	-1.516640e+03	-1.220510e+03	-1.266430e+0
25%	3.000000e+00	8.808100e+01	0.000000e+00	-9.200250e+00	-8.325150e+00	-8.767610e+00	-7.367240e+00	-6.102000e+00	-6.007260e+0
50%	5.000000e+00	1.769297e+02	0.000000e+00	3.819020e-01	4.264100e-02	1.140390e-01	0.000000e+00	0.000000e+00	0.000000e+0
75%	7.000000e+00	2.683398e+02	1.000000e+00	1.030610e+01	8.753340e+00	9.282560e+00	7.437780e+00	6.176630e+00	6.086460e+0
max	1.300000e+01	3.603711e+02	1.000000e+00	1.972240e+03	2.048790e+03	2.145710e+03	1.731880e+03	9.009370e+02	1.176540e+0

8 rows × 32 columns

In [23]:

```
train['smoothened_eeg_t4'] = noise_removal(train['eeg_t4'],w) # Adding the smoothened data to the
train dataset
```

In [24]:

```
train['smoothened_eeg_t6'] = noise_removal(train['eeg_t6'],w) # Adding the smoothened data to the
train dataset
```

In [25]:

```
train['smoothened_eeg_t5'] = noise_removal(train['eeg_t5'],w) # Adding the smoothened data to the
train dataset
```

In [26]:

```
train['smoothened_eeg_t3'] = noise_removal(train['eeg_t3'],w) # Adding the smoothened data to the
train dataset
```

In [27]:

```
train['smoothened_eeg_fp2'] = noise_removal(train['eeg_fp2'],w) # Adding the smoothened data to the train dataset
```

In [28]:

```
train['smoothened_eeg_o1'] = noise_removal(train['eeg_o1'],w) # Adding the smoothened data to the train dataset
```

In [29]:

```
train['smoothened_eeg_p3'] = noise_removal(train['eeg_p3'],w) # Adding the smoothened data to the train dataset
```

In [30]:

```
train['smoothened_eeg_pz'] = noise_removal(train['eeg_pz'],w) # Adding the smoothened data to the train dataset
```

In [31]:

```
train['smoothened_eeg_f3'] = noise_removal(train['eeg_f3'],w) # Adding the smoothened data to the train dataset
```

In [32]:

```
train['smoothened_eeg_fz'] = noise_removal(train['eeg_fz'],w) # Adding the smoothened data to the train dataset
```

In [33]:

```
train['smoothened_eeg_f4'] = noise_removal(train['eeg_f4'],w) # Adding the smoothened data to the train dataset
```

In [34]:

```
train['smoothened_eeg_c4'] = noise_removal(train['eeg_c4'],w) # Adding the smoothened data to the train dataset
```

In [35]:

```
train['smoothened_eeg_p4'] = noise_removal(train['eeg_p4'],w) # Adding the smoothened data to the train dataset
```

In [36]:

```
train['smoothened_eeg_poz'] = noise_removal(train['eeg_poz'],w) # Adding the smoothened data to the train dataset
```

In [37]:

```
train['smoothened_eeg_c3'] = noise_removal(train['eeg_c3'],w) # Adding the smoothened data to the train dataset
```

In [38]:

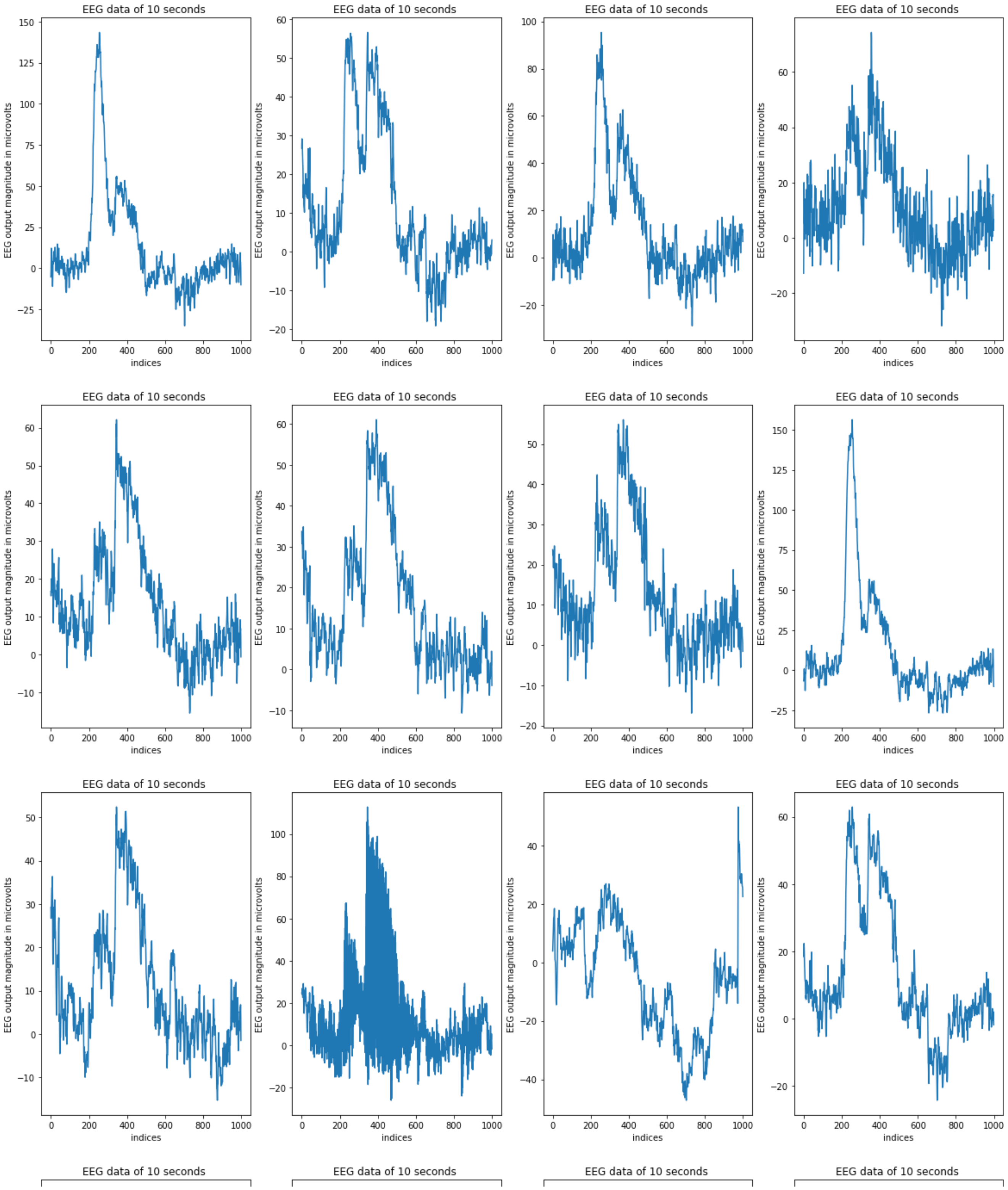
```
train['smoothened_eeg_cz'] = noise_removal(train['eeg_cz'],w) # Adding the smoothened data to the train dataset
```

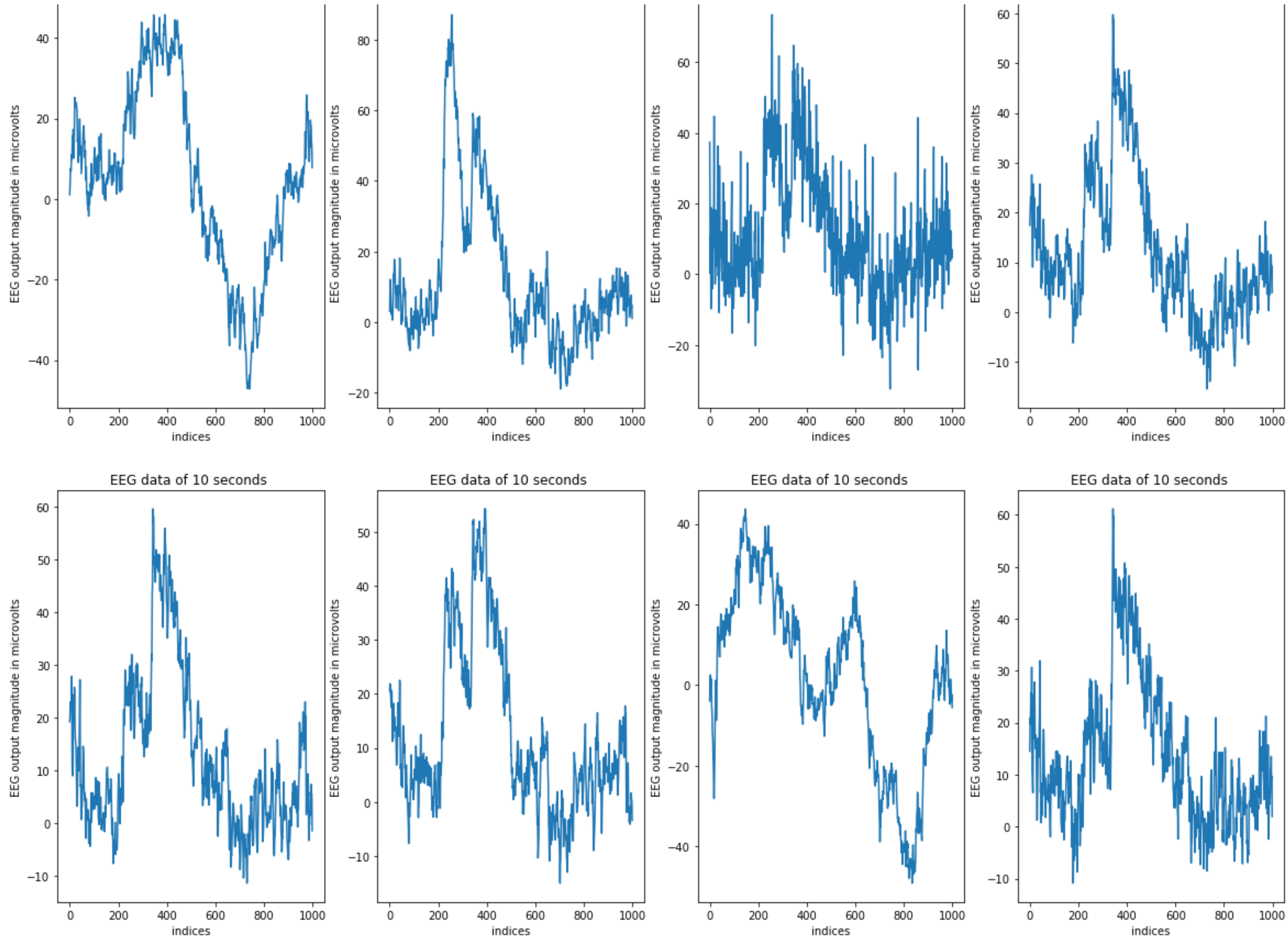
In [39]:

```
train['smoothened_eeg_o2'] = noise_removal(train['eeg_o2'],w) # Adding the smoothened data to the train dataset
```

In [38]:

```
plt.figure(figsize=(20,40))
feats = ["smoothened_eeg_fp1","smoothened_eeg_f7","smoothened_eeg_f8","smoothened_eeg_t4","smoothened_eeg_t6","smoothened_eeg_t5","smoothened_eeg_t3","smoothened_eeg_fp2","smoothened_eeg_o1","eeg_p3","smoothened_eeg_pz","smoothened_eeg_f3","smoothened_eeg_fz","smoothened_eeg_f4","smoothened_eeg_c4","smoothened_eeg_p4","smoothened_eeg_poz","smoothened_eeg_c3","smoothened_eeg_cz","smoothened_eeg_o2"]
for i,j in enumerate(feats):
    plt.subplot(5, 4, i+1)
    plt.plot(train[j][:1000])
    plt.title("EEG data of 10 seconds ")
    plt.xlabel("indices")
    plt.ylabel("EEG output magnitude in microvolts")

plt.show()
```





Checking the correlation among other features

In [39]:

```
corrMatrix = train.corr()
print(corrMatrix)
```

```
                        crew      time      seat   eeg_fp1    eeg_f7  \
crew                1.000000  0.020509 -0.000026  0.004439 -0.000304
time                0.020509  1.000000 -0.000092 -0.001095  0.000230
seat               -0.000026 -0.000092  1.000000  0.001293  0.009259
eeg_fp1             0.004439 -0.001095  0.001293  1.000000  0.649661
eeg_f7             -0.000304  0.000230  0.009259  0.649661  1.000000
eeg_f8              0.003582 -0.000951  0.004619  0.561712  0.493707
eeg_t4             -0.000615 -0.001122  0.007370  0.434736  0.454118
eeg_t6              0.009451 -0.000004  0.000428  0.328606  0.309661
eeg_t5              0.004767  0.001654  0.005459  0.332473  0.466838
eeg_t3             -0.001903  0.000063  0.007842  0.412335  0.510271
eeg_fp2             0.004089 -0.001906  0.002734  0.808817  0.666813
eeg_o1              0.001793  0.001169  0.003672  0.230432  0.158739
eeg_p3              0.002454  0.000479  0.002070  0.432504  0.472020
eeg_pz              0.002228  0.000803  0.001865  0.118993  0.050740
eeg_f3              0.003981  0.002119  0.002280  0.390390  0.341315
eeg_fz              0.006493 -0.001744  0.000718  0.379386  0.282070
eeg_f4              0.006101  0.000321  0.004490  0.346324  0.222679
eeg_c4              0.011650 -0.000741 -0.002899  0.475388  0.385181
eeg_p4              0.006458  0.000037 -0.001174  0.426401  0.382612
eeg_poz             0.002011  0.000057  0.002245  0.400337  0.435189
eeg_c3              0.006761  0.000538  0.001608  0.537996  0.551835
eeg_cz              0.004878  0.000439  0.001167  0.419241  0.392892
eeg_o2              0.000739 -0.002336  0.005564  0.295764  0.247659
ecg                -0.092310  0.016148  0.065637  0.002471  0.000509
r                   0.017672  0.002028  0.895856  0.001815  0.006118
gsr                 0.046665 -0.023212 -0.203039 -0.005918  0.001325
smoothened_ecg_data -0.111222  0.019461  0.003177 -0.002091  0.001390
smoothened_r_data   0.041997  0.004834  0.226639  0.005809  0.001961
smoothened_gsr_data 0.063757 -0.031709 -0.030582 -0.000423  0.004010
```

```
smoothened_eeg_fp1   0.005987 -0.001475  0.000932  0.754627  0.496019
smoothened_eeg_f7   -0.000404  0.000311  0.001364  0.489492  0.770742
smoothened_eeg_f8    0.004718 -0.001248  0.002106  0.420776  0.389389
smoothened_eeg_t4   -0.000805 -0.001466  0.001597  0.322053  0.347349
smoothened_eeg_t6    0.012521 -0.000002  0.000220  0.243952  0.234612
smoothened_eeg_t5    0.006326  0.002198  0.001494  0.252916  0.360157
smoothened_eeg_t3   -0.002431  0.000086  0.001317  0.296724  0.374657
smoothened_eeg_fp2   0.005479 -0.002552  0.001567  0.611338  0.516049
smoothened_eeg_o1    0.002330  0.001521  0.000557  0.170461  0.112077
smoothened_eeg_p3    0.003273  0.000640  0.000301  0.326279  0.358498
smoothened_eeg_pz    0.002915  0.001048  0.001420  0.091944  0.038258
smoothened_eeg_f3    0.005272  0.002801  0.000792  0.296160  0.256317
smoothened_eeg_fz    0.008547 -0.002294  0.000148  0.285283  0.217425
smoothened_eeg_f4    0.008173  0.000426  0.000417  0.260603  0.168906
smoothened_eeg_c4    0.015364 -0.000971  0.000015  0.355769  0.295529
smoothened_eeg_p4    0.008605  0.000054 -0.000267  0.320068  0.289585
smoothened_eeg_poz   0.002664  0.000080  0.000197  0.298993  0.330696
smoothened_eeg_c3    0.008934  0.000711  0.000393  0.403900  0.415956
smoothened_eeg_cz    0.006452  0.000581 -0.000320  0.315490  0.300685
smoothened_eeg_o2    0.000984 -0.003103  0.000897  0.224597  0.187214

                       eeg_f8    eeg_t4    eeg_t6    eeg_t5    eeg_t3  ...  \
crew                 0.003582 -0.000615  0.009451  0.004767 -0.001903  ...
time                -0.000951 -0.001122 -0.000004  0.001654  0.000063  ...
seat                 0.004619  0.007370  0.000428  0.005459  0.007842  ...
eeg_fp1              0.561712  0.434736  0.328606  0.332473  0.412335  ...
eeg_f7               0.493707  0.454118  0.309661  0.466838  0.510271  ...
eeg_f8               1.000000  0.624069  0.428697  0.367796  0.361123  ...
eeg_t4               0.624069  1.000000  0.537165  0.398861  0.509766  ...
eeg_t6               0.428697  0.537165  1.000000  0.496123  0.387109  ...
eeg_t5               0.367796  0.398861  0.496123  1.000000  0.528224  ...
eeg_t3               0.361123  0.509766  0.387109  0.528224  1.000000  ...
eeg_fp2              0.743647  0.520755  0.370542  0.355093  0.367574  ...
eeg_o1               0.201592  0.271376  0.341525  0.356271  0.270236  ...
eeg_p3               0.401075  0.456478  0.589913  0.675495  0.524316  ...
eeg_pz               0.048706  0.091479  0.127152  0.038977  0.075870  ...
eeg_f3               0.238039  0.253911  0.248195  0.253188  0.251730  ...
eeg_fz               0.341160  0.321776  0.194718  0.206063  0.236480  ...
eeg_f4               0.315901  0.300402  0.286851  0.192333  0.196259  ...
eeg_c4               0.540548  0.447606  0.578520  0.500662  0.394582  ...
eeg_p4               0.464684  0.494782  0.675777  0.561091  0.444950  ...
eeg_poz              0.411270  0.428613  0.577311  0.606291  0.420079  ...
eeg_c3               0.422634  0.441985  0.517501  0.605060  0.514964  ...
eeg_cz               0.360209  0.333357  0.364796  0.355579  0.322943  ...
eeg_o2               0.277458  0.343796  0.457946  0.427639  0.311456  ...
ecg                 -0.002611  0.001917 -0.006497 -0.001318  0.003185  ...
r                    0.003651  0.005457  0.000652  0.005259  0.006459  ...
gsr                 -0.000659 -0.002319 -0.002887 -0.002809  0.000319  ...
smoothened_ecg_data -0.004638  0.000369 -0.007177 -0.003856  0.002244  ...
smoothened_r_data    0.003627  0.002679 -0.000596  0.002964  0.003094  ...
smoothened_gsr_data -0.001154  0.000618 -0.001378 -0.002341  0.002934  ...
smoothened_eeg_fp1   0.430832  0.331951  0.248317  0.256993  0.313337  ...
smoothened_eeg_f7    0.393448  0.353313  0.235667  0.361149  0.390429  ...
smoothened_eeg_f8    0.781772  0.477783  0.320831  0.290061  0.279121  ...
smoothened_eeg_t4    0.474614  0.786984  0.402843  0.303094  0.411609  ...
smoothened_eeg_t6    0.322723  0.407926  0.778187  0.373125  0.293065  ...
smoothened_eeg_t5    0.292280  0.307452  0.373774  0.776943  0.401538  ...
smoothened_eeg_t3    0.270638  0.401764  0.282492  0.386378  0.801549  ...
smoothened_eeg_fp2   0.580439  0.398876  0.280938  0.279219  0.285552  ...
smoothened_eeg_o1    0.152721  0.204771  0.254974  0.267919  0.198874  ...
smoothened_eeg_p3    0.307816  0.348532  0.445337  0.514057  0.394110  ...
smoothened_eeg_pz    0.032397  0.070606  0.098709  0.026651  0.057315  ...
smoothened_eeg_f3    0.180431  0.196616  0.186259  0.188930  0.185261  ...
smoothened_eeg_fz    0.264229  0.252579  0.147656  0.160688  0.188647  ...
smoothened_eeg_f4    0.235106  0.226700  0.216867  0.141424  0.146899  ...
smoothened_eeg_c4    0.411218  0.332747  0.434413  0.377919  0.297157  ...
smoothened_eeg_p4    0.355825  0.373379  0.514338  0.422700  0.332997  ...
smoothened_eeg_poz   0.318132  0.323266  0.434803  0.458488  0.312852  ...
smoothened_eeg_c3    0.324900  0.339163  0.387967  0.456082  0.381599  ...
smoothened_eeg_cz    0.277946  0.254754  0.280648  0.273014  0.245130  ...
smoothened_eeg_o2    0.210321  0.259723  0.347096  0.318287  0.230495  ...

                     smoothened_eeg_pz  smoothened_eeg_f3  smoothened_eeg_fz  \
crew                          0.002915           0.005272           0.008547
time                          0.001048           0.002801          -0.002294
seat                          0.001420           0.000792           0.000148
eeg_fp1                       0.091944           0.296160           0.285283
```

eeg_f7	0.038258	0.256317	0.217425
eeg_f8	0.032397	0.180431	0.264229
eeg_t4	0.070606	0.196616	0.252579
eeg_t6	0.098709	0.186259	0.147656
eeg_t5	0.026651	0.188930	0.160688
eeg_t3	0.057315	0.185261	0.188647
eeg_fp2	0.061770	0.262261	0.281639
eeg_o1	0.218627	0.161600	0.082296
eeg_p3	0.138419	0.281484	0.154648
eeg_pz	0.788340	0.078848	0.060155
eeg_f3	0.077919	0.773947	0.143244
eeg_fz	0.059807	0.144114	0.781644
eeg_f4	0.063277	0.322066	0.140534
eeg_c4	0.111210	0.268347	0.193156
eeg_p4	0.144549	0.261434	0.161390
eeg_poz	0.148002	0.229560	0.143436
eeg_c3	0.127147	0.337922	0.197376
eeg_cz	0.163391	0.241884	0.232145
eeg_o2	0.180821	0.177548	0.105864
ecg	0.001666	-0.003763	-0.001304
r	0.002653	0.000593	-0.000092
gsr	0.000359	0.003039	0.002641
smoothened_ecg_data	0.001374	-0.005139	-0.001596
smoothened_r_data	0.005787	0.001126	-0.000345
smoothened_gsr_data	0.000657	0.004200	0.003596
smoothened_eeg_fp1	0.121110	0.393223	0.376792
smoothened_eeg_f7	0.051027	0.336276	0.282936
smoothened_eeg_f8	0.043418	0.234822	0.339800
smoothened_eeg_t4	0.090446	0.253482	0.322518
smoothened_eeg_t6	0.127127	0.243546	0.191351
smoothened_eeg_t5	0.036081	0.247825	0.208172
smoothened_eeg_t3	0.072016	0.233743	0.236182
smoothened_eeg_fp2	0.081756	0.346643	0.368901
smoothened_eeg_o1	0.276105	0.206232	0.104706
smoothened_eeg_p3	0.179530	0.369243	0.201971
smoothened_eeg_pz	1.000000	0.100723	0.077253
smoothened_eeg_f3	0.100723	1.000000	0.185617
smoothened_eeg_fz	0.077253	0.185617	1.000000
smoothened_eeg_f4	0.082444	0.421182	0.184203
smoothened_eeg_c4	0.142675	0.348077	0.248600
smoothened_eeg_p4	0.186884	0.342801	0.210272
smoothened_eeg_poz	0.190907	0.299571	0.185850
smoothened_eeg_c3	0.163397	0.438300	0.254961
smoothened_eeg_cz	0.211611	0.313316	0.301259
smoothened_eeg_o2	0.233335	0.232541	0.137979

	smoothened_eeg_f4	smoothened_eeg_c4	smoothened_eeg_p4 \
crew	0.008173	0.015364	0.008605
time	0.000426	-0.000971	0.000054
seat	0.000417	0.000015	-0.000267
eeg_fp1	0.260603	0.355769	0.320068
eeg_f7	0.168906	0.295529	0.289585
eeg_f8	0.235106	0.411218	0.355825
eeg_t4	0.226700	0.332747	0.373379
eeg_t6	0.216867	0.434413	0.514338
eeg_t5	0.141424	0.377919	0.422700
eeg_t3	0.146899	0.297157	0.332997
eeg_fp2	0.273844	0.400261	0.344495
eeg_o1	0.112584	0.277548	0.382313
eeg_p3	0.271790	0.535050	0.630773
eeg_pz	0.064773	0.112078	0.147183
eeg_f3	0.325793	0.267252	0.263058
eeg_fz	0.143024	0.193537	0.163380
eeg_f4	0.764140	0.323485	0.293454
eeg_c4	0.328570	0.785469	0.640894
eeg_p4	0.295017	0.634336	0.769816
eeg_poz	0.230487	0.516233	0.628359
eeg_c3	0.274662	0.530947	0.555896
eeg_cz	0.257215	0.451450	0.430155
eeg_o2	0.171460	0.357606	0.485882
ecg	-0.006179	-0.014122	-0.007645
r	0.000380	-0.000375	-0.001087
gsr	0.003515	-0.003698	-0.000731
smoothened_ecg_data	-0.007978	-0.017220	-0.009126
smoothened_r_data	0.001116	-0.000749	-0.002380
smoothened_gsr_data	0.004763	-0.005012	-0.000979
smoothened_eeg_fp1	0.346540	0.471636	0.424579

```
smoothened_eeg_f7             0.222561            0.385393            0.378905
smoothened_eeg_f8             0.306446            0.530608            0.460280
smoothened_eeg_t4             0.292662            0.432133            0.482707
smoothened_eeg_t6             0.282940            0.564505            0.667554
smoothened_eeg_t5             0.187788            0.491322            0.551545
smoothened_eeg_t3             0.185936            0.372799            0.418345
smoothened_eeg_fp2            0.362381            0.526060            0.453737
smoothened_eeg_o1             0.145657            0.353254            0.486252
smoothened_eeg_p3             0.356279            0.698346            0.823811
smoothened_eeg_pz             0.082444            0.142675            0.186884
smoothened_eeg_f3             0.421182            0.348077            0.342801
smoothened_eeg_fz             0.184203            0.248600            0.210272
smoothened_eeg_f4             1.000000            0.423662            0.385562
smoothened_eeg_c4             0.423662            1.000000            0.823091
smoothened_eeg_p4             0.385562            0.823091            1.000000
smoothened_eeg_poz            0.301009            0.668042            0.813760
smoothened_eeg_c3             0.356879            0.686382            0.719775
smoothened_eeg_cz             0.332140            0.580210            0.553484
smoothened_eeg_o2             0.224220            0.466643            0.632718

                     smoothened_eeg_poz  smoothened_eeg_c3  smoothened_eeg_cz  \
crew                           0.002664           0.008934           0.006452
time                           0.000080           0.000711           0.000581
seat                           0.000197           0.000393          -0.000320
eeg_fp1                        0.298993           0.403900           0.315490
eeg_f7                         0.330696           0.415956           0.300685
eeg_f8                         0.318132           0.324900           0.277946
eeg_t4                         0.323266           0.339163           0.254754
eeg_t6                         0.434803           0.387967           0.280648
eeg_t5                         0.458488           0.456082           0.273014
eeg_t3                         0.312852           0.381599           0.245130
eeg_fp2                        0.328229           0.385516           0.334031
eeg_o1                         0.416701           0.311974           0.198286
eeg_p3                         0.649590           0.652398           0.450540
eeg_pz                         0.149776           0.128388           0.165149
eeg_f3                         0.229573           0.337200           0.241604
eeg_fz                         0.144316           0.198151           0.233286
eeg_f4                         0.227863           0.270939           0.253978
eeg_c4                         0.518378           0.531983           0.452775
eeg_p4                         0.624514           0.551281           0.427004
eeg_poz                        0.773371           0.529680           0.427617
eeg_c3                         0.530845           0.779862           0.457996
eeg_cz                         0.428136           0.457546           0.769860
eeg_o2                         0.518825           0.356919           0.266825
ecg                           -0.003236          -0.007552          -0.001435
r                             -0.001124           0.000513          -0.000753
gsr                            0.000001          -0.000322           0.002047
smoothened_ecg_data           -0.003964          -0.009362          -0.001820
smoothened_r_data             -0.002720           0.001128          -0.001708
smoothened_gsr_data            0.000022          -0.000349           0.002809
smoothened_eeg_fp1             0.396283           0.535399           0.417553
smoothened_eeg_f7              0.430933           0.543947           0.392186
smoothened_eeg_f8              0.409382           0.419898           0.358260
smoothened_eeg_t4              0.416899           0.436757           0.327006
smoothened_eeg_t6              0.565388           0.505211           0.362518
smoothened_eeg_t5              0.595536           0.593813           0.353199
smoothened_eeg_t3              0.393137           0.482014           0.306672
smoothened_eeg_fp2             0.430834           0.507577           0.438832
smoothened_eeg_o1              0.528411           0.397239           0.250556
smoothened_eeg_p3              0.847487           0.849556           0.585123
smoothened_eeg_pz              0.190907           0.163397           0.211611
smoothened_eeg_f3              0.299571           0.438300           0.313316
smoothened_eeg_fz              0.185850           0.254961           0.301259
smoothened_eeg_f4              0.301009           0.356879           0.332140
smoothened_eeg_c4              0.668042           0.686382           0.580210
smoothened_eeg_p4              0.813760           0.719775           0.553484
smoothened_eeg_poz             1.000000           0.686921           0.551719
smoothened_eeg_c3              0.686921           1.000000           0.589199
smoothened_eeg_cz              0.551719           0.589199           1.000000
smoothened_eeg_o2              0.675322           0.466631           0.345825

                     smoothened_eeg_o2
crew                          0.000984
time                         -0.003103
seat                          0.000897
eeg_fp1                       0.224597
eeg_f7                        0.187214
```

```
eeg_f8                        0.210321
eeg_t4                        0.259723
eeg_t6                        0.347096
eeg_t5                        0.318287
eeg_t3                        0.230495
eeg_fp2                       0.223293
eeg_o1                        0.452714
eeg_p3                        0.457898
eeg_pz                        0.184164
eeg_f3                        0.178698
eeg_fz                        0.107198
eeg_f4                        0.170597
eeg_c4                        0.361398
eeg_p4                        0.486011
eeg_poz                       0.522158
eeg_c3                        0.360002
eeg_cz                        0.268865
eeg_o2                        0.768392
ecg                          -0.001405
r                             0.000763
gsr                          -0.000197
smoothened_ecg_data          -0.002055
smoothened_r_data             0.001601
smoothened_gsr_data          -0.000114
smoothened_eeg_fp1            0.297499
smoothened_eeg_f7             0.244911
smoothened_eeg_f8             0.272835
smoothened_eeg_t4             0.334935
smoothened_eeg_t6             0.450979
smoothened_eeg_t5             0.416729
smoothened_eeg_t3             0.290512
smoothened_eeg_fp2            0.294299
smoothened_eeg_o1             0.573234
smoothened_eeg_p3             0.597726
smoothened_eeg_pz             0.233335
smoothened_eeg_f3             0.232541
smoothened_eeg_fz             0.137979
smoothened_eeg_f4             0.224220
smoothened_eeg_c4             0.466643
smoothened_eeg_p4             0.632718
smoothened_eeg_poz            0.675322
smoothened_eeg_c3             0.466631
smoothened_eeg_cz             0.345825
smoothened_eeg_o2             1.000000

[49 rows x 49 columns]
```

Observations:

1. Most of the points are positive i.e they are highly correlated.
2. The highest value is 0.895856 which is for 'seat' and 'r'.

Heatmap

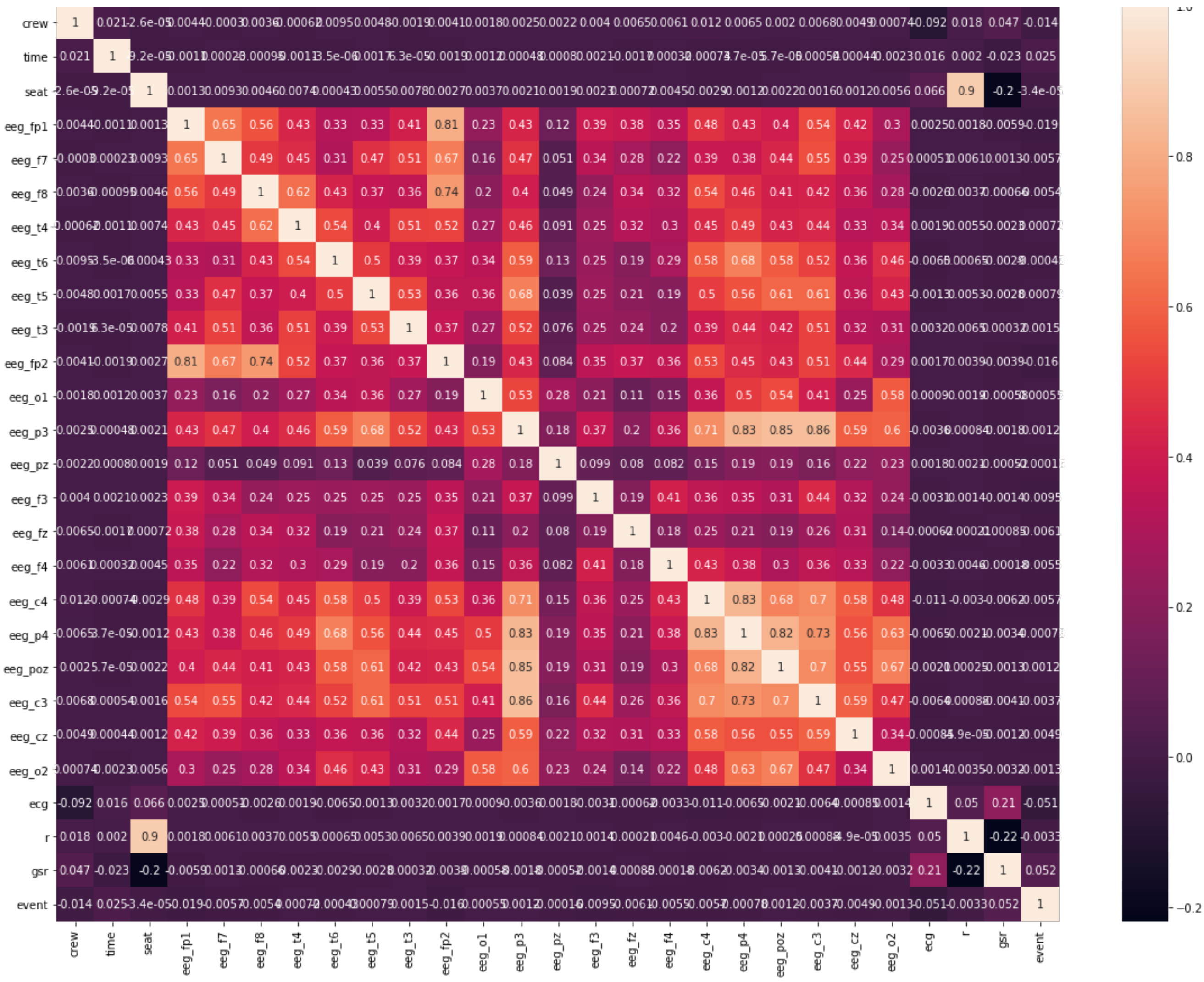
RAM wasnt sufficient to compute the heatmap for the 49 featured dataset

In [39]:

```
tr = pd.read_csv('E:/BOOKS_NEW/Cases datasets/1st/reducing-commercial-aviation-
fatalities/train.csv')
labelencoder = LabelEncoder()
tr['event'] = labelencoder.fit_transform(tr['event'])
```

In [40]:

```
plt.figure(figsize=(20,15))
corrMatrix = tr.corr()
sns.heatmap(corrMatrix, annot=True)
plt.show()
```



Observations:

1. Here also we can see that 'r' and 'seat' are highly correlated.
2. All the EEG measurements share a better correlation factor among themselves rather than other factors.

Exploratory Data Analysis on Test Data

In [4]:

```
Number of data points :  Delayed('int-c34c6641-8d35-4dd1-b19f-15b91317b8bd')
Number of features :  28
Features :  ['id' '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']
```

Out[4]:

	id	crew	experiment	time	seat	eeg_fp1	eeg_f7	eeg_f8	eeg_t4	eeg_t6	...	eeg_f4	eeg_c4	eeg_p4
0	0	1	LOFT	0.000000	0	17.899500	6.127830	0.994807	-28.206200	-47.695499	...	-7.044480	-14.405100	-4.03384
1	1	1	LOFT	0.000000	1	45.883202	94.749001	23.290800	1.392000	2.060940	...	19.887501	-215.179001	2.11832
2	2	1	LOFT	0.003906	0	33.120098	28.356501	-7.239220	-7.690860	-25.833799	...	-7.642560	-10.363600	10.95050
3	3	1	LOFT	0.003906	1	43.280102	95.887001	18.702299	-1.432890	-4.232600	...	13.826600	-214.223007	-4.91354

	id	crew	experiment	time	seat	eeg_fp1	eeg_f7	eeg_f8	eeg_t4	eeg_t6	...	eeg_f4	eeg_c4	eeg_p4
4	4	1	LOFT	0.007812	0	7.929110	3.460380	10.860800	26.366699	25.894699	...	2.045450	-20.788799	-3.61418

5 rows × 28 columns

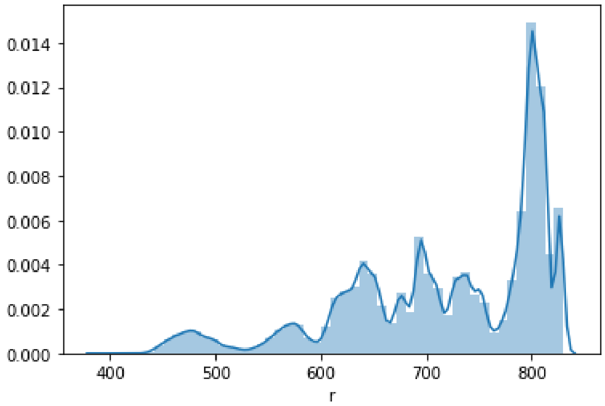
Respiration

In [36]:

```
sns.distplot(test['r'])
```

Out[36]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2049c536ac8>
```



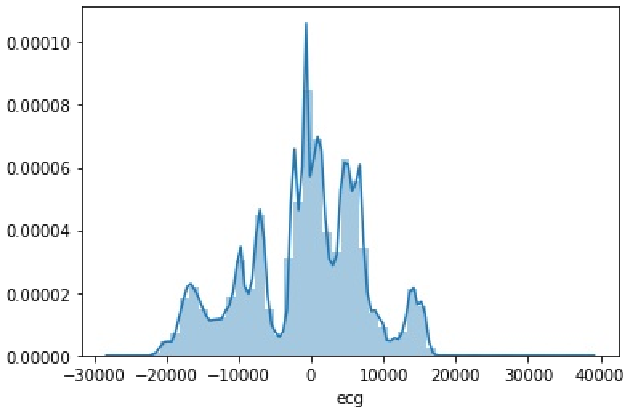
ECG values

In [37]:

```
sns.distplot(test['ecg'])
```

Out[37]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2046607dcc8>
```



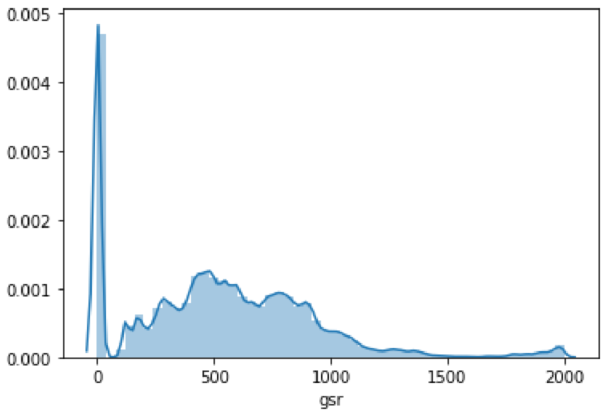
GSR values

In [38]:

```
sns.distplot(test['gsr'])
```

Out[38]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x20465bce948>
```



EEG features: take SVD truncated svd and take components how many components as hyperparameters eeg signals noise filtering - butterverse filter for noise, bandwidth filters feature engg bivariate analysis top 10 feats - do eda on them null value analysis

In [6]:

```
test_id = test['id']
```

Observations in EDA and Feature Engineering

1. Most of the time the pilots are very attentive but sometimes the pilots get distracted to get into CA, DA states mostly and entering into the SS state is very rare.
2. Key features like ECG, EEG, GSR, Respiration had noise which had to be smoothened for further use in the models.

Saving the dataset

In [42]:

```
train.to_csv('E:/BOOKS_NEW/Cases datasets/1st/reducing-commercial-aviation-
fatalities/train_after_smoothening.csv')
```

Normalizing the EEG features

In [3]:

```
df_train = pd.read_csv('E:/BOOKS_NEW/Cases datasets/1st/reducing-commercial-aviation-
fatalities/train_after_smoothening.csv')
scaler = MinMaxScaler()
df_train[['smoothened_eeg_fp1']] = scaler.fit_transform(df_train[['smoothened_eeg_fp1']])
```

In [4]:

```
df_train[['smoothened_eeg_f7']] = scaler.fit_transform(df_train[['smoothened_eeg_f7']])
```

In [5]:

```
df_train[['smoothened_eeg_f8']] = scaler.fit_transform(df_train[['smoothened_eeg_f8']])
```

In [6]:

```
df_train[['smoothened_eeg_t6']] = scaler.fit_transform(df_train[['smoothened_eeg_t6']])
```

In [7]:

```
df_train[['smoothened_eeg_t4']] = scaler.fit_transform(df_train[['smoothened_eeg_t4']])
```

```
df_train[['smoothened_eeg_t4']] = scaler.fit_transform(df_train[['smoothened_eeg_t4']])
```

In [8]:

```
df_train[['smoothened_eeg_t5']] = scaler.fit_transform(df_train[['smoothened_eeg_t5']])
```

In [9]:

```
df_train[['smoothened_eeg_t3']] = scaler.fit_transform(df_train[['smoothened_eeg_t3']])
```

In [10]:

```
df_train[['smoothened_eeg_fp2']] = scaler.fit_transform(df_train[['smoothened_eeg_fp2']])
```

In [11]:

```
df_train[['smoothened_eeg_o1']] = scaler.fit_transform(df_train[['smoothened_eeg_o1']])
```

In [12]:

```
df_train[['smoothened_eeg_p3']] = scaler.fit_transform(df_train[['smoothened_eeg_p3']])
```

In [13]:

```
df_train[['smoothened_eeg_pz']] = scaler.fit_transform(df_train[['smoothened_eeg_pz']])
```

In [14]:

```
df_train[['smoothened_eeg_f3']] = scaler.fit_transform(df_train[['smoothened_eeg_f3']])
```

In [15]:

```
df_train[['smoothened_eeg_fz']] = scaler.fit_transform(df_train[['smoothened_eeg_fz']])
```

In [16]:

```
df_train[['smoothened_eeg_f4']] = scaler.fit_transform(df_train[['smoothened_eeg_f4']])
```

In [17]:

```
df_train[['smoothened_eeg_c4']] = scaler.fit_transform(df_train[['smoothened_eeg_c4']])
```

In [18]:

```
df_train[['smoothened_eeg_p4']] = scaler.fit_transform(df_train[['smoothened_eeg_p4']])
```

In [19]:

```
df_train[['smoothened_eeg_poz']] = scaler.fit_transform(df_train[['smoothened_eeg_poz']])
```

In [20]:

```
df_train[['smoothened_eeg_c3']] = scaler.fit_transform(df_train[['smoothened_eeg_c3']])
```

In [21]:

```
df_train[['smoothened_eeg_cz']] = scaler.fit_transform(df_train[['smoothened_eeg_cz']])
```

In [22]:

```
df_train[['smoothened_eeg_o2']] = scaler.fit_transform(df_train[['smoothened_eeg_o2']])
```

In [23]:

```
df_train[['smoothened_ecg_data']] = scaler.fit_transform(df_train[['smoothened_ecg_data']])
```

In [24]:

```
df_train[['smoothened_r_data']] = scaler.fit_transform(df_train[['smoothened_r_data']])
```

In [25]:

```
df_train[['smoothened_gsr_data']] = scaler.fit_transform(df_train[['smoothened_gsr_data']])
```

Saving the dataset

df_train.to_csv('E:/BOOKS_NEW/Cases datasets/1st/reducing-commercial-aviation-fatalities/train_after_smoothening_2.csv')

Other feature Engineering techniques

In [2]:

```
df_train = pd.read_csv('E:/BOOKS_NEW/Cases datasets/1st/reducing-commercial-aviation-
fatalities/train_after_smoothening_2.csv')
```

In [3]:

```
print('Features : ', df_train.columns.values)
```

```
Features :  ['Unnamed: 0' 'Unnamed: 0.1' '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' 'smoothened_ecg_data'
 'smoothened_r_data' 'smoothened_gsr_data' 'smoothened_eeg_fp1'
 'smoothened_eeg_f7' 'smoothened_eeg_f8' 'smoothened_eeg_t4'
 'smoothened_eeg_t6' 'smoothened_eeg_t5' 'smoothened_eeg_t3'
 'smoothened_eeg_fp2' 'smoothened_eeg_o1' 'smoothened_eeg_p3'
 'smoothened_eeg_pz' 'smoothened_eeg_f3' 'smoothened_eeg_fz'
 'smoothened_eeg_f4' 'smoothened_eeg_c4' 'smoothened_eeg_p4'
 'smoothened_eeg_poz' 'smoothened_eeg_c3' 'smoothened_eeg_cz'
 'smoothened_eeg_o2']
```

In [4]:

```
df_train = df_train.drop(["eeg_fp1","eeg_f7","eeg_f8","eeg_t4","eeg_t6","eeg_t5","eeg_t3","eeg_o1",
"eeg_p3","eeg_pz","eeg_f3","eeg_fz","eeg_f4","eeg_c4","eeg_p4","eeg_poz","eeg_c3","eeg_cz","eeg_o2"
,"r","gsr","ecg","eeg_fp2"],axis=1)
```

In [5]:

```
print('Features : ', df_train.columns.values)
```

```
Features :  ['Unnamed: 0' 'Unnamed: 0.1' 'crew' 'experiment' 'time' 'seat' 'event'
 'smoothened_ecg_data' 'smoothened_r_data' 'smoothened_gsr_data'
 'smoothened_eeg_fp1' 'smoothened_eeg_f7' 'smoothened_eeg_f8'
 'smoothened_eeg_t4' 'smoothened_eeg_t6' 'smoothened_eeg_t5'
 'smoothened_eeg_t3' 'smoothened_eeg_fp2' 'smoothened_eeg_o1'
 'smoothened_eeg_p3' 'smoothened_eeg_pz' 'smoothened_eeg_f3'
 'smoothened_eeg_fz' 'smoothened_eeg_f4' 'smoothened_eeg_c4'
 'smoothened_eeg_p4' 'smoothened_eeg_poz' 'smoothened_eeg_c3'
 'smoothened_eeg_cz' 'smoothened_eeg_o2']
```

In [6]:

```
df_train.shape
```

Out[6]:

```
(4867421, 30)
```

Saving the data

df_train.to_csv('E:/BOOKS_NEW/Cases datasets/1st/reducing-commercial-aviation-fatalities/train_after_smoothening_lgbm.csv')

The Experiment feature is in Alphabets, so we have to convert it to numericals

In [2]:

```
df_train = pd.read_csv('E:/BOOKS_NEW/Cases datasets/1st/reducing-commercial-aviation-
fatalities/train_after_smoothening_lgbm.csv')
```

In [3]:

```
df_train['experiment'] = df_train['experiment'].map({'CA': 0, 'DA': 1, 'SS': 2, 'LOFT': 3})
df_train["experiment"] = df_train["experiment"].astype('int8')
df_train
```

Out[3]:

	Unnamed: 0	Unnamed: 0.1	Unnamed: 0.1.1	crew	experiment	time	seat	event	smoothened_ecg_data	smoothened_r_data	...
0	0	0	0	1	0	0.011719	1	A	0.274755	0.782286	...
1	1	1	1	1	0	0.015625	1	A	0.274762	0.782286	...
2	2	2	2	1	0	0.019531	1	A	0.274775	0.782286	...
3	3	3	3	1	0	0.023438	1	A	0.274795	0.782286	...
4	4	4	4	1	0	0.027344	1	A	0.274822	0.782286	...
...	...	...	...	...	...	...	...	...	...	...	...
4867416	4867416	4867416	4867416	13	2	99.991005	1	A	0.165976	0.570142	...
4867417	4867417	4867417	4867417	13	2	99.993004	0	A	0.173328	0.592765	...
4867418	4867418	4867418	4867418	13	2	99.994003	1	A	0.181932	0.577402	...
4867419	4867419	4867419	4867419	13	2	99.997002	0	A	0.191441	0.544842	...
4867420	4867420	4867420	4867420	13	2	99.998001	1	A	0.201402	0.668734	...

4867421 rows × 31 columns

The Events feature is in Alphabets, so we have to convert it to numericals

In [4]:

```
df_train['event'] = df_train['event'].map({'A': 0, 'B': 1, 'C': 2, 'D': 3})
df_train["event"] = df_train["event"].astype('int8')
df_train
```

Out[4]:

	Unnamed: 0	Unnamed: 0.1	Unnamed: 0.1.1	crew	experiment	time	seat	event	smoothened_ecg_data	smoothened_r_data	...
0	0	0	0	1	0	0.011719	1	0	0.274755	0.782286	...
1	1	1	1	1	0	0.015625	1	0	0.274762	0.782286	...
2	2	2	2	1	0	0.019531	1	0	0.274775	0.782286	...

	Unnamed: 0	Unnamed: 0.1	Unnamed: 0.1.1	crew	experiment	time	seat	event	smoothened_ecg_data	smoothened_r_data	...
3	3	3	3	1	0	0.023438	1	0	0.274795	0.782286	...
4	4	4	4	1	0	0.027344	1	0	0.274822	0.782286	...
...	...	...	...	...	...	...	...	...	...	...	...
4867416	4867416	4867416	4867416	13	2	99.991005	1	0	0.165976	0.570142	...
4867417	4867417	4867417	4867417	13	2	99.993004	0	0	0.173328	0.592765	...
4867418	4867418	4867418	4867418	13	2	99.994003	1	0	0.181932	0.577402	...
4867419	4867419	4867419	4867419	13	2	99.997002	0	0	0.191441	0.544842	...
4867420	4867420	4867420	4867420	13	2	99.998001	1	0	0.201402	0.668734	...

4867421 rows × 31 columns

In [5]:

```
df_train.shape
```

Out[5]:

```
(4867421, 31)
```

Saving the dataset

In [6]:

```
df_train.to_csv('E:/BOOKS_NEW/Cases datasets/1st/reducing-commercial-aviation-
fatalities/train_after_smoothening_2.csv')
```

Splitting the data

In [2]:

```
df_train = pd.read_csv('E:/BOOKS_NEW/Cases datasets/1st/reducing-commercial-aviation-
fatalities/train_after_smoothening_2.csv')
```

In [3]:

```
import re
df_train = df_train.rename(columns = lambda x:re.sub('[^A-Za-z0-9_]+', '', x))
```

In [4]:

```
train, test = train_test_split(df_train, test_size=0.2, random_state=42, shuffle=True)
```

In [5]:

```
x_train = train.loc[:, df_train.columns != 'event']
y_train = train['event']

x_test = test.loc[:, df_train.columns != 'event']
y_test = test['event']

print(x_train.shape,y_train.shape)
print(x_test.shape,y_test.shape)
print('-----------------------------------------------')
print('Features of x_train : ', x_train.columns.values)
print('Features of x_test: ', x_test.columns.values)
print('-----------------------------------------------')
print('Values of y_train: ', y_train.values)
print('Values of y_test: ', y_test.values)
```

```
(3893936, 31) (3893936,)
(973485, 31) (973485,)
-----------------------------------------------
```

```
Features of x_train :  ['Unnamed0' 'Unnamed01' 'Unnamed011' 'Unnamed0111' 'crew' 'experiment'
 'time' 'seat' 'smoothened_ecg_data' 'smoothened_r_data'
 'smoothened_gsr_data' 'smoothened_eeg_fp1' 'smoothened_eeg_f7'
 'smoothened_eeg_f8' 'smoothened_eeg_t4' 'smoothened_eeg_t6'
 'smoothened_eeg_t5' 'smoothened_eeg_t3' 'smoothened_eeg_fp2'
 'smoothened_eeg_o1' 'smoothened_eeg_p3' 'smoothened_eeg_pz'
 'smoothened_eeg_f3' 'smoothened_eeg_fz' 'smoothened_eeg_f4'
 'smoothened_eeg_c4' 'smoothened_eeg_p4' 'smoothened_eeg_poz'
 'smoothened_eeg_c3' 'smoothened_eeg_cz' 'smoothened_eeg_o2']
Features of x_test:  ['Unnamed0' 'Unnamed01' 'Unnamed011' 'Unnamed0111' 'crew' 'experiment'
 'time' 'seat' 'smoothened_ecg_data' 'smoothened_r_data'
 'smoothened_gsr_data' 'smoothened_eeg_fp1' 'smoothened_eeg_f7'
 'smoothened_eeg_f8' 'smoothened_eeg_t4' 'smoothened_eeg_t6'
 'smoothened_eeg_t5' 'smoothened_eeg_t3' 'smoothened_eeg_fp2'
 'smoothened_eeg_o1' 'smoothened_eeg_p3' 'smoothened_eeg_pz'
 'smoothened_eeg_f3' 'smoothened_eeg_fz' 'smoothened_eeg_f4'
 'smoothened_eeg_c4' 'smoothened_eeg_p4' 'smoothened_eeg_poz'
 'smoothened_eeg_c3' 'smoothened_eeg_cz' 'smoothened_eeg_o2']
-----------------------------------------------
Values of y_train:  [0 0 0 ... 2 0 2]
Values of y_test:  [2 0 2 ... 0 3 2]
```

Decision Tree algorithm

In [34]:

```
params = {"max_depth" : [1, 5, 10, 50, 100, 500, 100],
         "random_state" : [100],
         "max_leaf_nodes" : [10,50,100,200],
         "criterion" : ['gini', 'entropy'],
         "max_features" : ['auto']}
```

In [35]:

```
#hyper_param = {'max_depth':max_depth, 'min_samples_split':min_sample_split}

clf = DecisionTreeClassifier(class_weight = 'balanced')
rscv = RandomizedSearchCV(clf,params,verbose = 50)
rscv.fit(x_train,y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=100, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=100, criterion=entropy, s
core=0.631, total=  41.3s
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:   41.3s remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=100, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=100, criterion=entropy, s
core=0.691, total=  43.1s
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:  1.4min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=100, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=100, criterion=entropy, s
core=0.709, total=  39.4s
[Parallel(n_jobs=1)]: Done   3 out of   3 | elapsed:  2.1min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=100, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=100, criterion=entropy, s
core=0.647, total=  41.4s
[Parallel(n_jobs=1)]: Done   4 out of   4 | elapsed:  2.8min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=100, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=100, criterion=entropy, s
core=0.673, total=  39.2s
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:  3.4min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=50, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=50, criterion=entropy,
score=0.191, total=  13.6s
[Parallel(n_jobs=1)]: Done   6 out of   6 | elapsed:  3.6min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=50, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=50, criterion=entropy,
score=0.190, total=  13.6s
[Parallel(n_jobs=1)]: Done   7 out of   7 | elapsed:  3.9min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=50, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=50, criterion=entropy,
score=0.190, total=  13.5s
```

```
[Parallel(n_jobs=1)]: Done   8 out of   8 | elapsed:  4.1min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=50, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=50, criterion=entropy, score=0.191, total=  13.6s
[Parallel(n_jobs=1)]: Done   9 out of   9 | elapsed:  4.3min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=50, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=50, criterion=entropy, score=0.191, total=  13.4s
[Parallel(n_jobs=1)]: Done  10 out of  10 | elapsed:  4.5min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=10, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=10, criterion=entropy, score=0.191, total=  13.5s
[Parallel(n_jobs=1)]: Done  11 out of  11 | elapsed:  4.8min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=10, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=10, criterion=entropy, score=0.190, total=  13.3s
[Parallel(n_jobs=1)]: Done  12 out of  12 | elapsed:  5.0min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=10, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=10, criterion=entropy, score=0.190, total=  14.0s
[Parallel(n_jobs=1)]: Done  13 out of  13 | elapsed:  5.2min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=10, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=10, criterion=entropy, score=0.191, total=  13.6s
[Parallel(n_jobs=1)]: Done  14 out of  14 | elapsed:  5.5min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=10, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=10, max_features=auto, max_depth=10, criterion=entropy, score=0.191, total=  13.3s
[Parallel(n_jobs=1)]: Done  15 out of  15 | elapsed:  5.7min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=entropy, score=0.218, total=  15.8s
[Parallel(n_jobs=1)]: Done  16 out of  16 | elapsed:  5.9min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=entropy, score=0.218, total=  16.1s
[Parallel(n_jobs=1)]: Done  17 out of  17 | elapsed:  6.2min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=entropy, score=0.218, total=  16.1s
[Parallel(n_jobs=1)]: Done  18 out of  18 | elapsed:  6.5min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=entropy, score=0.218, total=  16.0s
[Parallel(n_jobs=1)]: Done  19 out of  19 | elapsed:  6.7min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=entropy
[CV]  random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=entropy, score=0.218, total=  16.3s
[Parallel(n_jobs=1)]: Done  20 out of  20 | elapsed:  7.0min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=5, criterion=gini
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=5, criterion=gini, score=0.235, total=  15.2s
[Parallel(n_jobs=1)]: Done  21 out of  21 | elapsed:  7.3min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=5, criterion=gini
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=5, criterion=gini, score=0.235, total=  15.0s
[Parallel(n_jobs=1)]: Done  22 out of  22 | elapsed:  7.5min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=5, criterion=gini
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=5, criterion=gini, score=0.225, total=  14.9s
[Parallel(n_jobs=1)]: Done  23 out of  23 | elapsed:  7.8min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=5, criterion=gini
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=5, criterion=gini, score=0.235, total=  15.1s
[Parallel(n_jobs=1)]: Done  24 out of  24 | elapsed:  8.0min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=5, criterion=gini
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=5, criterion=gini, score=0.231, total=  14.8s
[Parallel(n_jobs=1)]: Done  25 out of  25 | elapsed:  8.3min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=gini
[CV]  random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=gini, score=0.235, total=  15.3s
[Parallel(n_jobs=1)]: Done  26 out of  26 | elapsed:  8.5min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=gini
[CV]  random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=gini, score=0.235, total=  15.8s
[Parallel(n_jobs=1)]: Done  27 out of  27 | elapsed:  8.8min remaining:    0.0s
```

```
[CV] random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=gini
[CV]  random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=gini,
score=0.225, total=  15.2s
[Parallel(n_jobs=1)]: Done  28 out of  28 | elapsed:  9.0min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=gini
[CV]  random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=gini,
score=0.235, total=  15.4s
[Parallel(n_jobs=1)]: Done  29 out of  29 | elapsed:  9.3min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=gini
[CV]  random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=5, criterion=gini,
score=0.231, total=  15.0s
[Parallel(n_jobs=1)]: Done  30 out of  30 | elapsed:  9.6min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=10, criterion=gini
[CV]  random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=10, criterion=gini,
score=0.346, total=  24.5s
[Parallel(n_jobs=1)]: Done  31 out of  31 | elapsed: 10.0min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=10, criterion=gini
[CV]  random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=10, criterion=gini,
score=0.349, total=  24.3s
[Parallel(n_jobs=1)]: Done  32 out of  32 | elapsed: 10.4min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=10, criterion=gini
[CV]  random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=10, criterion=gini,
score=0.370, total=  24.8s
[Parallel(n_jobs=1)]: Done  33 out of  33 | elapsed: 10.8min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=10, criterion=gini
[CV]  random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=10, criterion=gini,
score=0.350, total=  24.3s
[Parallel(n_jobs=1)]: Done  34 out of  34 | elapsed: 11.2min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=10, criterion=gini
[CV]  random_state=100, max_leaf_nodes=50, max_features=auto, max_depth=10, criterion=gini,
score=0.346, total=  24.5s
[Parallel(n_jobs=1)]: Done  35 out of  35 | elapsed: 11.6min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=500, criterion=gini
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=500, criterion=gini,
score=0.708, total=  37.7s
[Parallel(n_jobs=1)]: Done  36 out of  36 | elapsed: 12.2min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=500, criterion=gini
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=500, criterion=gini,
score=0.733, total=  38.1s
[Parallel(n_jobs=1)]: Done  37 out of  37 | elapsed: 12.9min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=500, criterion=gini
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=500, criterion=gini,
score=0.693, total=  39.3s
[Parallel(n_jobs=1)]: Done  38 out of  38 | elapsed: 13.5min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=500, criterion=gini
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=500, criterion=gini,
score=0.702, total=  36.2s
[Parallel(n_jobs=1)]: Done  39 out of  39 | elapsed: 14.1min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=500, criterion=gini
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=500, criterion=gini,
score=0.754, total=  36.9s
[Parallel(n_jobs=1)]: Done  40 out of  40 | elapsed: 14.7min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=50, criterion=gini
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=50, criterion=gini,
score=0.708, total=  41.1s
[Parallel(n_jobs=1)]: Done  41 out of  41 | elapsed: 15.4min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=50, criterion=gini
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=50, criterion=gini,
score=0.733, total=  42.2s
[Parallel(n_jobs=1)]: Done  42 out of  42 | elapsed: 16.1min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=50, criterion=gini
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=50, criterion=gini,
score=0.693, total=  43.2s
[Parallel(n_jobs=1)]: Done  43 out of  43 | elapsed: 16.8min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=50, criterion=gini
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=50, criterion=gini,
score=0.702, total=  40.1s
[Parallel(n_jobs=1)]: Done  44 out of  44 | elapsed: 17.5min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=50, criterion=gini
[CV]  random_state=100, max_leaf_nodes=200, max_features=auto, max_depth=50, criterion=gini,
score=0.754, total=  41.4s
[Parallel(n_jobs=1)]: Done  45 out of  45 | elapsed: 18.2min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=100, max_features=auto, max_depth=5, criterion=gini
[CV]  random_state=100, max_leaf_nodes=100, max_features=auto, max_depth=5, criterion=gini,
score=0.235, total=  16.3s
[Parallel(n_jobs=1)]: Done  46 out of  46 | elapsed: 18.5min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=100, max_features=auto, max_depth=5, criterion=gini
```

```
[CV]  random_state=100, max_leaf_nodes=100, max_features=auto, max_depth=5, criterion=gini,
score=0.235, total=  15.4s
[Parallel(n_jobs=1)]: Done  47 out of  47 | elapsed: 18.7min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=100, max_features=auto, max_depth=5, criterion=gini
[CV]  random_state=100, max_leaf_nodes=100, max_features=auto, max_depth=5, criterion=gini,
score=0.225, total=  15.5s
[Parallel(n_jobs=1)]: Done  48 out of  48 | elapsed: 19.0min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=100, max_features=auto, max_depth=5, criterion=gini
[CV]  random_state=100, max_leaf_nodes=100, max_features=auto, max_depth=5, criterion=gini,
score=0.235, total=  15.4s
[Parallel(n_jobs=1)]: Done  49 out of  49 | elapsed: 19.3min remaining:    0.0s
[CV] random_state=100, max_leaf_nodes=100, max_features=auto, max_depth=5, criterion=gini
[CV]  random_state=100, max_leaf_nodes=100, max_features=auto, max_depth=5, criterion=gini,
score=0.231, total=  15.4s
[Parallel(n_jobs=1)]: Done  50 out of  50 | elapsed: 19.5min finished
```

Out[35]:

```
RandomizedSearchCV(cv=None, error_score=nan,
                   estimator=DecisionTreeClassifier(ccp_alpha=0.0,
                                                    class_weight='balanced',
                                                    criterion='gini',
                                                    max_depth=None,
                                                    max_features=None,
                                                    max_leaf_nodes=None,
                                                    min_impurity_decrease=0.0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=0.0,
                                                    presort='deprecated',
                                                    random_state=None,
                                                    splitter='best'),
                   iid='deprecated', n_iter=10, n_jobs=None,
                   param_distributions={'criterion': ['gini', 'entropy'],
                                        'max_depth': [1, 5, 10, 50, 100, 500,
                                                      100],
                                        'max_features': ['auto'],
                                        'max_leaf_nodes': [10, 50, 100, 200],
                                        'random_state': [100]},
                   pre_dispatch='2*n_jobs', random_state=None, refit=True,
                   return_train_score=False, scoring=None, verbose=50)
```

In [36]:

```
rscv.best_params_
```

Out[36]:

```
{'random_state': 100,
 'max_leaf_nodes': 200,
 'max_features': 'auto',
 'max_depth': 500,
 'criterion': 'gini'}
```

In [37]:

```
clf_dt = DecisionTreeClassifier(criterion='gini',max_depth=500,max_leaf_nodes=200,random_state=100)
clf_dt = clf_dt.fit(x_train,y_train)
```

In [40]:

```
from sklearn.metrics import log_loss
y_hat_dt = clf_dt.predict_proba(x_test)
log_loss_dt = log_loss(y_test,y_hat_dt)
print('Log loss = ',log_loss_dt)
```

```
Log loss =  0.033073017305116394
```

XGBOOST algorithm

In [13]:

```
params = {"max_depth" : [2, 3, 4, 5],
          "random_state" : [100],
           "n_estimators" : [5, 10, 50, 100, 200],
          "criterion" : ['gini', 'entropy'],
          "max_features" : ['auto']}

#params = {'n_estimators':n_estimators, 'max_depth':depth}

clf = GridSearchCV(xgb.XGBClassifier(booster='gbtree',class_weight = 'balanced'),params,verbose=1,n_jobs=-1,pre_dispatch=2,cv=3)
clf.fit(x_train,y_train)
opt_estimator_xg, opt_depth_xg = clf.best_params_.get('n_estimators'), clf.best_params_.get('max_depth')
```

```
Fitting 3 folds for each of 40 candidates, totalling 120 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  48 tasks      | elapsed:  5.9min
[Parallel(n_jobs=-1)]: Done 120 out of 120 | elapsed: 44.8min finished
```

In [14]:

```
clf.best_params_
```

Out[14]:

```
{'criterion': 'gini',
 'max_depth': 2,
 'max_features': 'auto',
 'n_estimators': 5,
 'random_state': 100}
```

In [9]:

```
clf_xgb = xgb.XGBClassifier(max_depth=2, n_estimators=5,criterion='gini',random_state=100,verbose=50,n_jobs=-1)
clf_xgb.fit(x_train,y_train)
```

Out[9]:

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, criterion='gini', gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=2,
              min_child_weight=1, missing=None, n_estimators=5, n_jobs=-1,
              nthread=None, objective='multi:softprob', random_state=100,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbose=50, verbosity=1)
```

In [10]:

```
y_hat_xgb = clf_xgb.predict_proba(x_test)
log_loss_xgb = log_loss(y_test,y_hat_xgb)
print('Log loss = ',log_loss_xgb)
```

```
Log loss =  0.8255264575416745
```

Random Forest Classifier

In [5]:

```
from sklearn.ensemble import RandomForestClassifier

param = {'n_estimators':[5, 10, 50, 100, 200, 500, 1000],
         'max_depth' : [2, 3, 4, 5, 6, 7, 8, 9, 10],
         'criterion' : ['gini','entropy'],
```

```
        'random_state' : [100],
        'n_jobs' : [-1]}

model_rf = RandomForestClassifier()
random_rf = RandomizedSearchCV(model_rf,param,verbose=10)
random_rf.fit(x_train,y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.

[CV] random_state=100, n_jobs=-1, n_estimators=200, max_depth=8, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=200, max_depth=8, criterion=entropy, score=0.927, total= 7.5min
[CV] random_state=100, n_jobs=-1, n_estimators=200, max_depth=8, criterion=entropy

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:  7.5min remaining:    0.0s

[CV]  random_state=100, n_jobs=-1, n_estimators=200, max_depth=8, criterion=entropy, score=0.927, total= 7.5min
[CV] random_state=100, n_jobs=-1, n_estimators=200, max_depth=8, criterion=entropy

[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed: 15.0min remaining:    0.0s

[CV]  random_state=100, n_jobs=-1, n_estimators=200, max_depth=8, criterion=entropy, score=0.927, total= 7.4min
[CV] random_state=100, n_jobs=-1, n_estimators=200, max_depth=8, criterion=entropy

[Parallel(n_jobs=1)]: Done   3 out of   3 | elapsed: 22.4min remaining:    0.0s

[CV]  random_state=100, n_jobs=-1, n_estimators=200, max_depth=8, criterion=entropy, score=0.927, total= 8.0min
[CV] random_state=100, n_jobs=-1, n_estimators=200, max_depth=8, criterion=entropy

[Parallel(n_jobs=1)]: Done   4 out of   4 | elapsed: 30.4min remaining:    0.0s

[CV]  random_state=100, n_jobs=-1, n_estimators=200, max_depth=8, criterion=entropy, score=0.926, total= 7.8min
[CV] random_state=100, n_jobs=-1, n_estimators=50, max_depth=6, criterion=entropy

[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed: 38.3min remaining:    0.0s

[CV]  random_state=100, n_jobs=-1, n_estimators=50, max_depth=6, criterion=entropy, score=0.926, total= 1.6min
[CV] random_state=100, n_jobs=-1, n_estimators=50, max_depth=6, criterion=entropy

[Parallel(n_jobs=1)]: Done   6 out of   6 | elapsed: 39.9min remaining:    0.0s

[CV]  random_state=100, n_jobs=-1, n_estimators=50, max_depth=6, criterion=entropy, score=0.926, total= 1.6min
[CV] random_state=100, n_jobs=-1, n_estimators=50, max_depth=6, criterion=entropy

[Parallel(n_jobs=1)]: Done   7 out of   7 | elapsed: 41.4min remaining:    0.0s

[CV]  random_state=100, n_jobs=-1, n_estimators=50, max_depth=6, criterion=entropy, score=0.926, total= 1.6min
[CV] random_state=100, n_jobs=-1, n_estimators=50, max_depth=6, criterion=entropy

[Parallel(n_jobs=1)]: Done   8 out of   8 | elapsed: 43.0min remaining:    0.0s

[CV]  random_state=100, n_jobs=-1, n_estimators=50, max_depth=6, criterion=entropy, score=0.926, total= 1.6min
[CV] random_state=100, n_jobs=-1, n_estimators=50, max_depth=6, criterion=entropy

[Parallel(n_jobs=1)]: Done   9 out of   9 | elapsed: 44.7min remaining:    0.0s
```

```
[Parallel(n_jobs=1)]: Done   9 out of   9 | elapsed: 44.7min remaining:    0.0s
```

```
[CV]  random_state=100, n_jobs=-1, n_estimators=50, max_depth=6, criterion=entropy, score=0.926, t
otal= 1.6min
[CV] random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=entropy, score=0.926,
total=19.0min
[CV] random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=entropy, score=0.927,
total=18.4min
[CV] random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=entropy, score=0.927,
total=18.4min
[CV] random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=entropy, score=0.927,
total=18.4min
[CV] random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=entropy, score=0.927,
total=18.4min
[CV] random_state=100, n_jobs=-1, n_estimators=50, max_depth=3, criterion=gini
[CV]  random_state=100, n_jobs=-1, n_estimators=50, max_depth=3, criterion=gini, score=0.924, tota
l=  50.3s
[CV] random_state=100, n_jobs=-1, n_estimators=50, max_depth=3, criterion=gini
[CV]  random_state=100, n_jobs=-1, n_estimators=50, max_depth=3, criterion=gini, score=0.924, tota
l=  51.0s
[CV] random_state=100, n_jobs=-1, n_estimators=50, max_depth=3, criterion=gini
[CV]  random_state=100, n_jobs=-1, n_estimators=50, max_depth=3, criterion=gini, score=0.924, tota
l=  50.2s
[CV] random_state=100, n_jobs=-1, n_estimators=50, max_depth=3, criterion=gini
[CV]  random_state=100, n_jobs=-1, n_estimators=50, max_depth=3, criterion=gini, score=0.924, tota
l=  50.1s
[CV] random_state=100, n_jobs=-1, n_estimators=50, max_depth=3, criterion=gini
[CV]  random_state=100, n_jobs=-1, n_estimators=50, max_depth=3, criterion=gini, score=0.924, tota
l=  50.2s
[CV] random_state=100, n_jobs=-1, n_estimators=5, max_depth=4, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=5, max_depth=4, criterion=entropy, score=0.829, to
tal=  12.0s
[CV] random_state=100, n_jobs=-1, n_estimators=5, max_depth=4, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=5, max_depth=4, criterion=entropy, score=0.823, to
tal=  12.0s
[CV] random_state=100, n_jobs=-1, n_estimators=5, max_depth=4, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=5, max_depth=4, criterion=entropy, score=0.828, to
tal=  12.0s
[CV] random_state=100, n_jobs=-1, n_estimators=5, max_depth=4, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=5, max_depth=4, criterion=entropy, score=0.824, to
tal=  12.2s
[CV] random_state=100, n_jobs=-1, n_estimators=5, max_depth=4, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=5, max_depth=4, criterion=entropy, score=0.828, to
tal=  12.1s
[CV] random_state=100, n_jobs=-1, n_estimators=200, max_depth=3, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=200, max_depth=3, criterion=entropy, score=0.924,
total= 3.2min
[CV] random_state=100, n_jobs=-1, n_estimators=200, max_depth=3, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=200, max_depth=3, criterion=entropy, score=0.924,
total= 3.2min
[CV] random_state=100, n_jobs=-1, n_estimators=200, max_depth=3, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=200, max_depth=3, criterion=entropy, score=0.924,
total= 3.2min
[CV] random_state=100, n_jobs=-1, n_estimators=200, max_depth=3, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=200, max_depth=3, criterion=entropy, score=0.924,
total= 3.2min
[CV] random_state=100, n_jobs=-1, n_estimators=200, max_depth=3, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=200, max_depth=3, criterion=entropy, score=0.924,
total= 3.2min
[CV] random_state=100, n_jobs=-1, n_estimators=5, max_depth=7, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=5, max_depth=7, criterion=entropy, score=0.926, to
tal=  18.2s
[CV] random_state=100, n_jobs=-1, n_estimators=5, max_depth=7, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=5, max_depth=7, criterion=entropy, score=0.927, to
tal=  19.1s
[CV] random_state=100, n_jobs=-1, n_estimators=5, max_depth=7, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=5, max_depth=7, criterion=entropy, score=0.927, to
tal=  18.0s
[CV] random_state=100, n_jobs=-1, n_estimators=5, max_depth=7, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=5, max_depth=7, criterion=entropy, score=0.929, to
tal=  18.5s
[CV] random_state=100, n_jobs=-1, n_estimators=5, max_depth=7, criterion=entropy
```

```
[CV] random_state=100, n_jobs=-1, n_estimators=5, max_depth=7, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=5, max_depth=7, criterion=entropy, score=0.926, to
tal=  18.3s
[CV] random_state=100, n_jobs=-1, n_estimators=100, max_depth=2, criterion=gini
[CV]  random_state=100, n_jobs=-1, n_estimators=100, max_depth=2, criterion=gini, score=0.924, tot
al= 1.1min
[CV] random_state=100, n_jobs=-1, n_estimators=100, max_depth=2, criterion=gini
[CV]  random_state=100, n_jobs=-1, n_estimators=100, max_depth=2, criterion=gini, score=0.924, tot
al= 1.1min
[CV] random_state=100, n_jobs=-1, n_estimators=100, max_depth=2, criterion=gini
[CV]  random_state=100, n_jobs=-1, n_estimators=100, max_depth=2, criterion=gini, score=0.924, tot
al= 1.1min
[CV] random_state=100, n_jobs=-1, n_estimators=100, max_depth=2, criterion=gini
[CV]  random_state=100, n_jobs=-1, n_estimators=100, max_depth=2, criterion=gini, score=0.924, tot
al= 1.1min
[CV] random_state=100, n_jobs=-1, n_estimators=100, max_depth=2, criterion=gini
[CV]  random_state=100, n_jobs=-1, n_estimators=100, max_depth=2, criterion=gini, score=0.924, tot
al= 1.1min
[CV] random_state=100, n_jobs=-1, n_estimators=200, max_depth=2, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=200, max_depth=2, criterion=entropy, score=0.924,
total= 2.3min
[CV] random_state=100, n_jobs=-1, n_estimators=200, max_depth=2, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=200, max_depth=2, criterion=entropy, score=0.924,
total= 2.3min
[CV] random_state=100, n_jobs=-1, n_estimators=200, max_depth=2, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=200, max_depth=2, criterion=entropy, score=0.924,
total= 2.3min
[CV] random_state=100, n_jobs=-1, n_estimators=200, max_depth=2, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=200, max_depth=2, criterion=entropy, score=0.924,
total= 2.3min
[CV] random_state=100, n_jobs=-1, n_estimators=200, max_depth=2, criterion=entropy
[CV]  random_state=100, n_jobs=-1, n_estimators=200, max_depth=2, criterion=entropy, score=0.924,
total= 2.3min
[CV] random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=gini
[CV]  random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=gini, score=0.926, tot
al=17.5min
[CV] random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=gini
[CV]  random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=gini, score=0.926, tot
al=17.5min
[CV] random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=gini
[CV]  random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=gini, score=0.926, tot
al=17.6min
[CV] random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=gini
[CV]  random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=gini, score=0.927, tot
al=17.6min
[CV] random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=gini
[CV]  random_state=100, n_jobs=-1, n_estimators=500, max_depth=8, criterion=gini, score=0.926, tot
al=17.5min
```

```
[Parallel(n_jobs=1)]: Done  50 out of  50 | elapsed: 266.3min finished
```

Out[5]:

```
RandomizedSearchCV(cv=None, error_score=nan,
                   estimator=RandomForestClassifier(bootstrap=True,
                                                    ccp_alpha=0.0,
                                                    class_weight=None,
                                                    criterion='gini',
                                                    max_depth=None,
                                                    max_features='auto',
                                                    max_leaf_nodes=None,
                                                    max_samples=None,
                                                    min_impurity_decrease=0.0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=0.0,
                                                    n_estimators=100,
                                                    n_j...
                                                    random_state=None,
                                                    verbose=0,
                                                    warm_start=False),
                   iid='deprecated', n_iter=10, n_jobs=None,
                   param_distributions={'criterion': ['gini', 'entropy'],
                                        'max_depth': [2, 3, 4, 5, 6, 7, 8, 9,
                                                      10],
                                        'n_estimators': [5, 10, 50, 100, 200,
```

```
                                                   500, 1000],
                                    'n_jobs': [-1], 'random_state': [100]},
                   pre_dispatch='2*n_jobs', random_state=None, refit=True,
                   return_train_score=False, scoring=None, verbose=10)
```

In [6]:

```
random_rf.best_params_
```

Out[6]:

```
{'random_state': 100,
 'n_jobs': -1,
 'n_estimators': 5,
 'max_depth': 7,
 'criterion': 'entropy'}
```

In [7]:

```
clf_rf =
RandomForestClassifier(criterion='entropy',max_depth=7,n_estimators=5,random_state=100,n_jobs=-1)
clf_rf = clf_rf.fit(x_train,y_train)
```

In [11]:

```
predicted_rf = clf_rf.predict_proba(x_test)
loss_rf = log_loss(y_test,predicted_rf)
print('Log loss = ',loss_rf)
```

```
Log loss =  0.2153776351196506
```

Light GBM (Light Gradient Boosting Machine)

In [10]:

```
param = {'objective' : ['multiclass'],
        'boosting_type' : ['gbdt'],
         'learning_rate': [0.05,0.1],
         'num_leaves': [10,50,100],
         'bagging_fraction' : [0.7],
         'feature_fraction' : [0.7],
         'bagging_seed' : [420],
         'max_depth' : [2,5,7],
         'metric' : ['multi_logloss'],
         'num_class':[4]}

model_lgb = lgb.LGBMClassifier()
random_lgb = RandomizedSearchCV(model_lgb,param,verbose=50)
random_lgb.fit(x_train,y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.948, total=  22.7s
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:   22.7s remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.948, total=  22.9s
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:   45.6s remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
```

```
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.949, total=  23.6s
[Parallel(n_jobs=1)]: Done   3 out of   3 | elapsed:  1.2min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.948, total=  24.5s
[Parallel(n_jobs=1)]: Done   4 out of   4 | elapsed:  1.6min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.948, total=  24.1s
[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:  2.0min remaining:    0.0s
[CV] objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.955, total=  44.0s
[Parallel(n_jobs=1)]: Done   6 out of   6 | elapsed:  2.7min remaining:    0.0s
[CV] objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.955, total=  44.0s
[Parallel(n_jobs=1)]: Done   7 out of   7 | elapsed:  3.4min remaining:    0.0s
[CV] objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.955, total=  44.9s
[Parallel(n_jobs=1)]: Done   8 out of   8 | elapsed:  4.2min remaining:    0.0s
[CV] objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.956, total=  48.2s
[Parallel(n_jobs=1)]: Done   9 out of   9 | elapsed:  5.0min remaining:    0.0s
[CV] objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.955, total=  44.5s
[Parallel(n_jobs=1)]: Done  10 out of  10 | elapsed:  5.7min remaining:    0.0s
[CV] objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.965, total= 1.1min
[Parallel(n_jobs=1)]: Done  11 out of  11 | elapsed:  6.9min remaining:    0.0s
[CV] objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.964, total= 1.1min
[Parallel(n_jobs=1)]: Done  12 out of  12 | elapsed:  7.9min remaining:    0.0s
[CV] objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.965, total= 1.1min
[Parallel(n_jobs=1)]: Done  13 out of  13 | elapsed:  9.0min remaining:    0.0s
[CV] objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
```

```
[CV]  objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.965, total= 1.1min
[Parallel(n_jobs=1)]: Done  14 out of  14 | elapsed: 10.1min remaining:    0.0s
[CV] objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.965, total= 1.1min
[Parallel(n_jobs=1)]: Done  15 out of  15 | elapsed: 11.2min remaining:    0.0s
[CV] objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.929, total=  25.5s
[Parallel(n_jobs=1)]: Done  16 out of  16 | elapsed: 11.7min remaining:    0.0s
[CV] objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.930, total=  25.7s
[Parallel(n_jobs=1)]: Done  17 out of  17 | elapsed: 12.1min remaining:    0.0s
[CV] objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.929, total=  25.7s
[Parallel(n_jobs=1)]: Done  18 out of  18 | elapsed: 12.5min remaining:    0.0s
[CV] objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.929, total=  25.9s
[Parallel(n_jobs=1)]: Done  19 out of  19 | elapsed: 13.0min remaining:    0.0s
[CV] objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.929, total=  25.7s
[Parallel(n_jobs=1)]: Done  20 out of  20 | elapsed: 13.4min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.929, total=  26.0s
[Parallel(n_jobs=1)]: Done  21 out of  21 | elapsed: 13.8min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.930, total=  25.8s
[Parallel(n_jobs=1)]: Done  22 out of  22 | elapsed: 14.3min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.929, total=  25.9s
[Parallel(n_jobs=1)]: Done  23 out of  23 | elapsed: 14.7min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.929, total=  26.3s
[Parallel(n_jobs=1)]: Done  24 out of  24 | elapsed: 15.1min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
```

```
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=2,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.929, total=  25.9s
[Parallel(n_jobs=1)]: Done  25 out of  25 | elapsed: 15.6min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.956, total=  35.4s
[Parallel(n_jobs=1)]: Done  26 out of  26 | elapsed: 16.2min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.957, total=  35.7s
[Parallel(n_jobs=1)]: Done  27 out of  27 | elapsed: 16.8min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.956, total=  35.4s
[Parallel(n_jobs=1)]: Done  28 out of  28 | elapsed: 17.3min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.957, total=  35.6s
[Parallel(n_jobs=1)]: Done  29 out of  29 | elapsed: 17.9min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.957, total=  35.5s
[Parallel(n_jobs=1)]: Done  30 out of  30 | elapsed: 18.5min remaining:    0.0s
[CV] objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.982, total= 1.1min
[Parallel(n_jobs=1)]: Done  31 out of  31 | elapsed: 19.6min remaining:    0.0s
[CV] objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.982, total= 1.1min
[Parallel(n_jobs=1)]: Done  32 out of  32 | elapsed: 20.7min remaining:    0.0s
[CV] objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.982, total= 1.1min
[Parallel(n_jobs=1)]: Done  33 out of  33 | elapsed: 21.9min remaining:    0.0s
[CV] objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.982, total= 1.2min
[Parallel(n_jobs=1)]: Done  34 out of  34 | elapsed: 23.0min remaining:    0.0s
[CV] objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=100, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.982, total= 1.1min
[Parallel(n_jobs=1)]: Done  35 out of  35 | elapsed: 24.1min remaining:    0.0s
[CV] objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=7,
learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
```

```
[CV]  objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=7, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7, score=0.965, total=  54.1s
[Parallel(n_jobs=1)]: Done  36 out of  36 | elapsed: 25.0min remaining:    0.0s
[CV] objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=7, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=7, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7, score=0.964, total=  54.0s
[Parallel(n_jobs=1)]: Done  37 out of  37 | elapsed: 25.9min remaining:    0.0s
[CV] objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=7, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=7, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7, score=0.964, total=  54.6s
[Parallel(n_jobs=1)]: Done  38 out of  38 | elapsed: 26.9min remaining:    0.0s
[CV] objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=7, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=7, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7, score=0.965, total=  53.8s
[Parallel(n_jobs=1)]: Done  39 out of  39 | elapsed: 27.7min remaining:    0.0s
[CV] objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=7, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=7, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7, score=0.965, total=  54.0s
[Parallel(n_jobs=1)]: Done  40 out of  40 | elapsed: 28.7min remaining:    0.0s
[CV] objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=2, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=2, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7, score=0.929, total=  26.7s
[Parallel(n_jobs=1)]: Done  41 out of  41 | elapsed: 29.1min remaining:    0.0s
[CV] objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=2, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=2, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7, score=0.930, total=  25.6s
[Parallel(n_jobs=1)]: Done  42 out of  42 | elapsed: 29.5min remaining:    0.0s
[CV] objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=2, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=2, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7, score=0.929, total=  25.4s
[Parallel(n_jobs=1)]: Done  43 out of  43 | elapsed: 29.9min remaining:    0.0s
[CV] objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=2, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=2, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7, score=0.929, total=  25.4s
[Parallel(n_jobs=1)]: Done  44 out of  44 | elapsed: 30.4min remaining:    0.0s
[CV] objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=2, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=50, num_class=4, metric=multi_logloss, max_depth=2, learning_rate=0.05, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7, score=0.929, total=  25.6s
[Parallel(n_jobs=1)]: Done  45 out of  45 | elapsed: 30.8min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=5, learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=5, learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7, score=0.962, total=  33.4s
[Parallel(n_jobs=1)]: Done  46 out of  46 | elapsed: 31.4min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=5, learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420, bagging_fraction=0.7
```

```
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.962, total=  33.1s
[Parallel(n_jobs=1)]: Done  47 out of  47 | elapsed: 31.9min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.963, total=  33.4s
[Parallel(n_jobs=1)]: Done  48 out of  48 | elapsed: 32.5min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.963, total=  33.2s
[Parallel(n_jobs=1)]: Done  49 out of  49 | elapsed: 33.0min remaining:    0.0s
[CV] objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7
[CV]  objective=multiclass, num_leaves=10, num_class=4, metric=multi_logloss, max_depth=5,
learning_rate=0.1, feature_fraction=0.7, boosting_type=gbdt, bagging_seed=420,
bagging_fraction=0.7, score=0.963, total=  33.2s
[Parallel(n_jobs=1)]: Done  50 out of  50 | elapsed: 33.6min finished
```

Out[10]:

```
RandomizedSearchCV(cv=None, error_score=nan,
                   estimator=LGBMClassifier(boosting_type='gbdt',
                                            class_weight=None,
                                            colsample_bytree=1.0,
                                            importance_type='split',
                                            learning_rate=0.1, max_depth=-1,
                                            min_child_samples=20,
                                            min_child_weight=0.001,
                                            min_split_gain=0.0,
                                            n_estimators=100, n_jobs=-1,
                                            num_leaves=31, objective=None,
                                            random_state=None, reg_alpha=0.0,
                                            reg_lambda=0.0, s...
                   param_distributions={'bagging_fraction': [0.7],
                                        'bagging_seed': [420],
                                        'boosting_type': ['gbdt'],
                                        'feature_fraction': [0.7],
                                        'learning_rate': [0.05, 0.1],
                                        'max_depth': [2, 5, 7],
                                        'metric': ['multi_logloss'],
                                        'num_class': [4],
                                        'num_leaves': [10, 50, 100],
                                        'objective': ['multiclass']},
                   pre_dispatch='2*n_jobs', random_state=None, refit=True,
                   return_train_score=False, scoring=None, verbose=50)
```

In [11]:

```
random_lgb.best_params_
```

Out[11]:

```
{'objective': 'multiclass',
 'num_leaves': 100,
 'num_class': 4,
 'metric': 'multi_logloss',
 'max_depth': 7,
 'learning_rate': 0.1,
 'feature_fraction': 0.7,
 'boosting_type': 'gbdt',
 'bagging_seed': 420,
 'bagging_fraction': 0.7}
```

In [12]:

```
x_train.head()
```

Out[12]:

	Unnamed0	Unnamed01	Unnamed011	crew	experiment	time	seat	smoothened_ecg_data	smoothened_r_data	smoot
328831	328831	328831	328831	1	1	352.382812	0	0.326314	0.630489	
2981344	2981344	2981344	2981344	6	1	340.722656	0	0.783207	0.599092	
650858	650858	650858	650858	2	1	131.117188	1	0.388682	0.691573	
915303	915303	915303	915303	2	2	272.736023	0	0.405383	0.695349	
4711282	4711282	4711282	4711282	13	2	147.885010	0	0.165699	0.590422	

5 rows × 30 columns

In [13]:

```
lgbtrain = lgb.Dataset(x_train, y_train)
lgbtest = lgb.Dataset(x_test, y_test)
```

In [14]:

```
params = {'bagging_fraction': 0.7,
 'bagging_seed': 420,
 'boosting_type': 'gbdt',
 'feature_fraction': 0.7,
 'learning_rate': 0.1,
 'max_depth': 7,
 'metric': 'multi_logloss',
 'num_class': 4,
 'num_leaves': 50,
 'objective': 'multiclass'}

model_lgb = lgb.train(params, lgbtrain, 1000, valid_sets=[lgbtest], early_stopping_rounds=50, verbo
se_eval=100)
```

```
Training until validation scores don't improve for 50 rounds
[100] valid_0's multi_logloss: 0.0495551
[200] valid_0's multi_logloss: 0.0252562
[300] valid_0's multi_logloss: 0.0173054
[400] valid_0's multi_logloss: 0.0133574
[500] valid_0's multi_logloss: 0.0106503
[600] valid_0's multi_logloss: 0.00870979
[700] valid_0's multi_logloss: 0.00752332
[800] valid_0's multi_logloss: 0.00639667
[900] valid_0's multi_logloss: 0.00566897
[1000] valid_0's multi_logloss: 0.00510606
Did not meet early stopping. Best iteration is:
[1000] valid_0's multi_logloss: 0.00510606
```

In [16]:

```
predicted_lgb = model_lgb.predict(x_test, num_iteration= model_lgb.best_iteration)
print('Log loss',round(log_loss(y_test.to_numpy(),predicted_lgb),8))
```

```
Log loss 0.00510606
```

ADABOOST Algorithm

In [7]:

```
clf_ada = AdaBoostClassifier(random_state=100)
clf_ada = clf_ada.fit(x_train,y_train)
```

In [8]:

```
predicted_ada = clf_ada.predict_proba(x_test)
loss_ada = log_loss(y_test,predicted_ada)
```

```
print('Log loss = ',loss_ada)
```

```
Log loss =  0.6946917554651799
```

MLP Architecture - Refer different ipynb

Conclusion

In [9]:

```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["S.NO","MODEL","LOG LOSS"]

x.add_row(["1","DECISION TREE",0.033073017305116394])
x.add_row(["2","XGBOOST",0.8255264575416745])
x.add_row(["3","RANDOM FOREST",0.2153776351196506])
x.add_row(["4","LGBM",0.00510606])
x.add_row(["5","ADABOOST",0.6946917554651799])

# Printing the Table
print(x)
```

```
+------+---------------+----------------------+
| S.NO |     MODEL     |       LOG LOSS       |
+------+---------------+----------------------+
|  1   | DECISION TREE | 0.033073017305116394 |
|  2   |    XGBOOST    |  0.8255264575416745  |
|  3   | RANDOM FOREST |  0.2153776351196506  |
|  4   |      LGBM     |      0.00510606      |
|  5   |    ADABOOST   |  0.6946917554651799  |
+------+---------------+----------------------+
```

The best model turned out to be Light Gradient Boosting Machine (LGBM).

The order of performance is LGBM>Decision Tree>Random Forest> XGBOOST