Logistic regression modeling for bad receivers identification

The scope of this project is to model properly and train an algorithm that is able to identify bad receivers.

The data shows different receivers statistics which include some instrumentational feedbacks (capacitance, lowcut, etc..), some computed stats (root mean square of amplitude, std of RMS, etc..) and some user defined target variable (identified bad receivers).

Let's import the main libraries now

In [...

```
import pandas as pd
import csv
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns; sns.set()

from pandas import DataFrame
from sklearn.preprocessing import StandardScaler, normalize
from sklearn.decomposition import PCA
from sklearn.mixture import GaussianMixture
from sklearn.metrics import silhouette_score
from sklearn.model_selection import train_test_split
from sklearn import metrics
import matplotlib.ticker as ticker
from sklearn import preprocessing
```

Now we import the first set of data which include have some sequence specific features, including the target feature "BAD_CHAN_FLAG" (binary, 0 good, 1 bad) the target feature "BAD_CHAN_FLAG" (binary, 0 good, 1 bad)

In [...
```
stats1=pd.read_csv('decode_listing_features008.csv')
stats1['SEQ']=8
stats1a=pd.read_csv('decode_listing_features003.csv')
stats1a['SEQ']=3
stats1b=pd.read_csv('decode_listing_features004.csv')
stats1b['SEQ']=4
stats1c=pd.read_csv('decode_listing_features010.csv')
stats1c['SEQ']=10
stats1d=pd.read_csv('decode_listing_features011.csv')
stats1d['SEQ']=11
stats1=stats1.append(stats1a)
stats1=stats1.append(stats1b)
stats1=stats1.append(stats1c)
stats1=stats1.append(stats1d)
```

In [...
```
stats1.head()
```

Out[...

	CHANNEL	BAD_CHAN_FLAG	CAP_CUT_ERR	CAP_ERR	CAP_VAL	DEEP_RMS	LEAK_ERR	LEA
0	1	0.0	0.0	0.0	249.286484	13.73	0.0	
1	2	0.0	0.0	0.0	248.101654	13.58	0.0	
2	3	0.0	0.0	0.0	248.710541	15.04	0.0	
3	4	0.0	0.0	0.0	246.606064	12.66	0.0	

4	5	0.0	0.0	0.0	249.910889	12.54	0.0

Now we import the amplitude maps that will be used to derive more statistics

In [...
```
stats2=pd.read_csv('008_P_amp_maps.csv')
stats2['SEQ']=8
stats2a=pd.read_csv('003_P_amp_maps.csv')
stats2a['SEQ']=3
stats2b=pd.read_csv('004_P_amp_maps.csv')
stats2b['SEQ']=4
stats2c=pd.read_csv('010_P_amp_maps.csv')
stats2c['SEQ']=10
stats2d=pd.read_csv('011_P_amp_maps.csv')
stats2d['SEQ']=11
stats2=stats2.append(stats2a)
stats2=stats2.append(stats2b)
stats2=stats2.append(stats2c)
stats2=stats2.append(stats2d)
```

In [...
```
stats2.head()
```

Out[...

	SRC_POINT	CHANNEL	WC_RMS	TGT_RMS	DEEP_RMS	WHOLE_RMS	FFID	CABLE	CABTR
0	1001	1	20.214577	210.530777	12.440019	1045.397705	1001	1	1
1	1001	2	15.753899	207.250076	18.285044	1058.347046	1001	1	2
2	1001	3	10.252005	201.711441	14.983429	1037.041016	1001	1	3
3	1001	4	11.665508	202.110245	13.177336	1043.912354	1001	1	4
4	1001	5	12.001275	205.250626	15.401988	1018.429810	1001	1	5

Get standard deviation of root mean squared values, grouped by sequence and receiver number

In [...
```
std_=stats2.groupby(['SEQ','CHANNEL'])['DEEP_RMS'].agg(np.std)
```

In [...
```
std_=pd.DataFrame(std_)
```

In [...
```
std_.sort_values(['SEQ','CHANNEL'],inplace=True)
stats1.sort_values(['SEQ','CHANNEL'],inplace=True)
```

In [...
```
std_.reset_index(inplace=True)
len(std_)
```

Out[... 38400

In [...
```
len(stats1)
```

Out[... 38400

In [...
```
std_.head()
```

Out[...

	SEQ	CHANNEL	DEEP_RMS
0	3	1	2.661812
1	3	2	2.761224
2	3	3	2.484229
3	3	4	2.525309
4	3	5	2.531213

Merge the dataframes

In [...
```
df1=pd.merge(std_,stats1 , how='left', left_on=['SEQ','CHANNEL'], right_on=['S
df2=df1.copy()
```

In [...
```
df2.head(10)
```

Out[...

	SEQ	CHANNEL	DEEP_RMS_x	BAD_CHAN_FLAG	CAP_CUT_ERR	CAP_ERR	CAP_VAL	DEEP_RI
0	3	1	2.661812	0.0	0.0	0.0	249.508224	
1	3	2	2.761224	0.0	0.0	0.0	248.342239	
2	3	3	2.484229	0.0	0.0	0.0	249.030304	
3	3	4	2.525309	0.0	0.0	0.0	246.959259	
4	3	5	2.531213	0.0	0.0	0.0	250.354599	
5	3	6	2.494356	0.0	0.0	0.0	250.634521	
6	3	7	2.464203	0.0	0.0	0.0	247.767746	
7	3	8	2.424611	0.0	0.0	0.0	250.713913	
8	3	9	2.457772	0.0	0.0	0.0	248.457214	
9	3	10	2.430608	0.0	0.0	0.0	252.485580	

Plot Root Mean Square of amplitudes

In [...
```
a=stats2['TGT_RMS']
```

In [...
```
b=a.to_list()
```

reshape the list for plotting

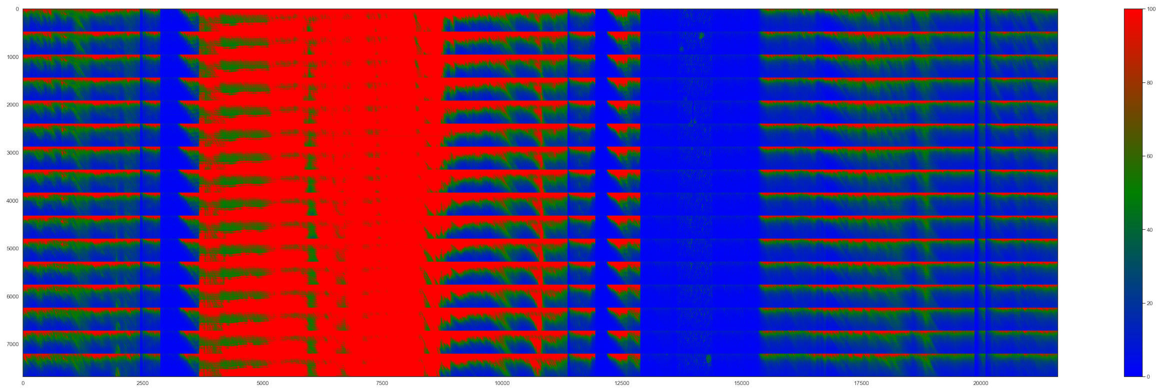
In [...
```
c= np.reshape(b,(-1,7680))
c=np.transpose(c)
```

just clip the value to 100 for color scaling

In [...
```
c=np.clip(c,0,100)
```

In [...
```
%matplotlib inline
```

In [...
```
import matplotlib.colors as colly

cmap1= colly.LinearSegmentedColormap.from_list("" , ['blue','green','red'])

im=plt.imshow(c, cmap=cmap1)
plt.colorbar(im)
plt.rcParams["figure.figsize"] = (70,20)
plt.savefig('RMS.png')

plt.show()
```



Now we start to work on the modeling

In [...
```
df1.head(10)
```

Out[...

	SEQ	CHANNEL	DEEP_RMS_x	BAD_CHAN_FLAG	CAP_CUT_ERR	CAP_ERR	CAP_VAL	DEEP_RI
0	3	1	2.661812	0.0	0.0	0.0	249.508224	
1	3	2	2.761224	0.0	0.0	0.0	248.342239	
2	3	3	2.484229	0.0	0.0	0.0	249.030304	
3	3	4	2.525309	0.0	0.0	0.0	246.959259	
4	3	5	2.531213	0.0	0.0	0.0	250.354599	
5	3	6	2.494356	0.0	0.0	0.0	250.634521	
6	3	7	2.464203	0.0	0.0	0.0	247.767746	
7	3	8	2.424611	0.0	0.0	0.0	250.713913	
8	3	9	2.457772	0.0	0.0	0.0	248.457214	
9	3	10	2.430608	0.0	0.0	0.0	252.485580	

drop one by one the features we don't need

In [...

```
df1=df1.drop('CAP_CUT_ERR',1)
df1=df1.drop('CAP_ERR',1)
df1=df1.drop('LEAK_ERR',1)
df1=df1.drop('SENS',1)
df1=df1.drop('MARG_CHAN_FLAG',1)
```

In [...

```
df1.head()
```

Out[...

	SEQ	CHANNEL	DEEP_RMS_x	BAD_CHAN_FLAG	CAP_VAL	DEEP_RMS_y	LEAK_VAL
0	3	1	2.661812	0.0	249.508224	14.61	5.0
1	3	2	2.761224	0.0	248.342239	14.11	5.0
2	3	3	2.484229	0.0	249.030304	14.22	5.0
3	3	4	2.525309	0.0	246.959259	13.30	5.0
4	3	5	2.531213	0.0	250.354599	13.20	5.0

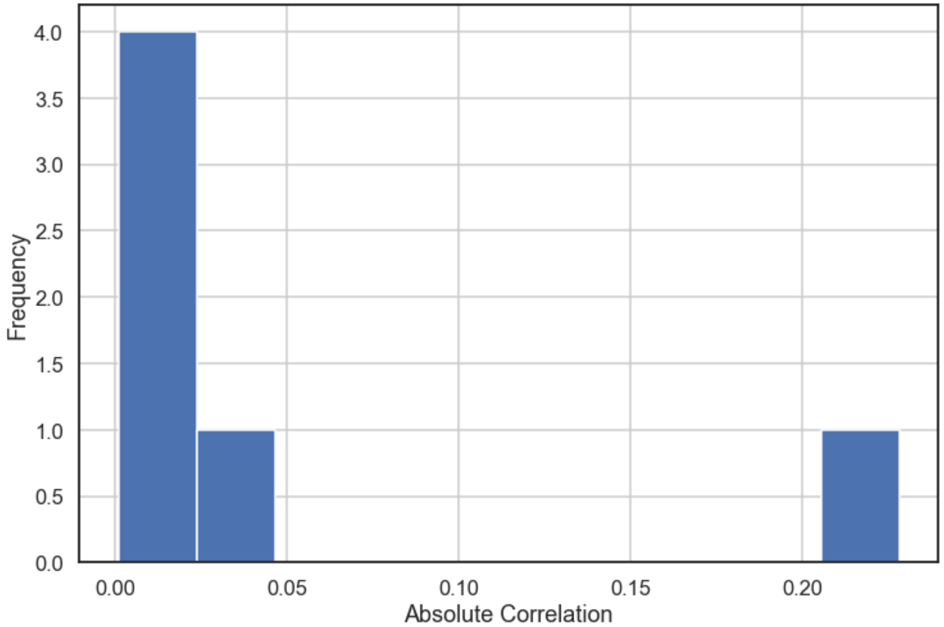
In [...
```
pd.to_numeric(df1['BAD_CHAN_FLAG'])
y=pd.DataFrame(df1['BAD_CHAN_FLAG'])
X=df1.drop(['BAD_CHAN_FLAG'],1)
```

In [...
```
yy=y.values.tolist()
```

In [...
```
X2=X.copy()
X2=X2.drop(['CHANNEL','SEQ'],1)
```

In [...
```
# Calculate the correlation values
feature_cols = X2.columns
corr_values = X2[feature_cols].corr()

# Simplify by emptying all the data below the diagonal
tril_index = np.tril_indices_from(corr_values)

# Make the unused values NaNs
for coord in zip(*tril_index):
    corr_values.iloc[coord[0], coord[1]] = np.NaN

# Stack the data and convert to a data frame
corr_values = (corr_values
               .stack()
               .to_frame()
               .reset_index()
               .rename(columns={'level_0':'feature1',
                                'level_1':'feature2',
                                0:'correlation'}))

# Get the absolute values for sorting
corr_values['abs_correlation'] = corr_values.correlation.abs()
```

In [...
```
sns.set_context('talk')
sns.set_style('white')

ax = corr_values.abs_correlation.hist(bins=10, figsize=(12, 8))
ax.set(xlabel='Absolute Correlation', ylabel='Frequency');
```



In [...

```
# The most highly correlated values
corr_values.sort_values('correlation', ascending=False).query('abs_correlation
```

Out[…

	feature1	feature2	correlation	abs_correlation
1	DEEP_RMS_x	DEEP_RMS_y	0.22803	0.22803

Logistic Regression

In […
```
XX=X2.values.tolist()
```

In […
```
XX[0:5]
```

Out[…
```
[[2.661812115498693, 249.508224, 14.61, 5.0],
 [2.7612244529267658, 248.342239, 14.11, 5.0],
 [2.4842293028556335, 249.030304, 14.22, 5.0],
 [2.5253092118493496, 246.95925899999997, 13.3, 5.0],
 [2.531212785253206, 250.35459900000004, 13.2, 5.0]]
```

use the standard scaler to normalize the dataset

In […
```
XX= preprocessing.StandardScaler().fit(XX).transform(XX)
```

In […
```
XX[0:5]
```

Out[…
```
array([[-0.04726565,  0.43055594,  3.99775107,  0.04209138],
       [-0.01943756,  0.20496958,  3.76670047,  0.04209138],
       [-0.09697569,  0.33809143,  3.8175316 ,  0.04209138],
       [-0.08547635, -0.0625994 ,  3.3923985 ,  0.04209138],
       [-0.08382379,  0.59430646,  3.34618838,  0.04209138]])
```

test the logistic regression on the whole dataset

In […
```
import statsmodels.api as sm
logit_model=sm.Logit(yy,XX)
result=logit_model.fit()
print(result.summary2())
```

```
Optimization terminated successfully.
         Current function value: 0.692551
         Iterations 5
                         Results: Logit
=================================================================
Model:              Logit            Pseudo R-squared: -54.434
Dependent Variable: y                AIC:              53195.9376
Date:               2021-09-15 13:04 BIC:              53230.1609
No. Observations:   38400            Log-Likelihood:   -26594.
Df Model:           3                LL-Null:          -479.74
Df Residuals:       38396            LLR p-value:      1.0000
Converged:          1.0000           Scale:            1.0000
No. Iterations:     5.0000
--------------------------------------------------------------------
       Coef.     Std.Err.       z        P>|z|      [0.025     0.975]
--------------------------------------------------------------------
x1     0.0115      0.0110     1.0486    0.2943    -0.0100     0.0330
x2    -0.0785      0.0130    -6.0489    0.0000    -0.1039    -0.0530
x3     0.0016      0.0105     0.1563    0.8758    -0.0190     0.0223
x4    -0.0071      0.0103    -0.6878    0.4916    -0.0272     0.0131
=================================================================
```

let's split the data and see how it perform with the train/test

In [...

```
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
X_train, X_test, y_train, y_test = train_test_split(XX, yy, test_size=0.5, ran
```

In [...

```
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

```
/opt/anaconda3/lib/python3.8/site-packages/sklearn/utils/validation.py:72: Dat
aConversionWarning: A column-vector y was passed when a 1d array was expected.
Please change the shape of y to (n_samples, ), for example using ravel().
  return f(**kwargs)
/opt/anaconda3/lib/python3.8/site-packages/sklearn/utils/validation.py:72: Dat
aConversionWarning: A column-vector y was passed when a 1d array was expected.
```

```
Please change the shape of y to (n_samples, ), for example using ravel().
  return f(**kwargs)
```

In [...

```
y_pred = logreg.predict(X_test)
print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(
```

```
Accuracy of logistic regression classifier on test set: 1.00
```

Print the confusion matrix

In [...

```
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_test, y_pred)
print(confusion_matrix)
```

```
[[19160     1]
 [   31     8]]
```

Get the main scores out to see if the model acts properly

In [...

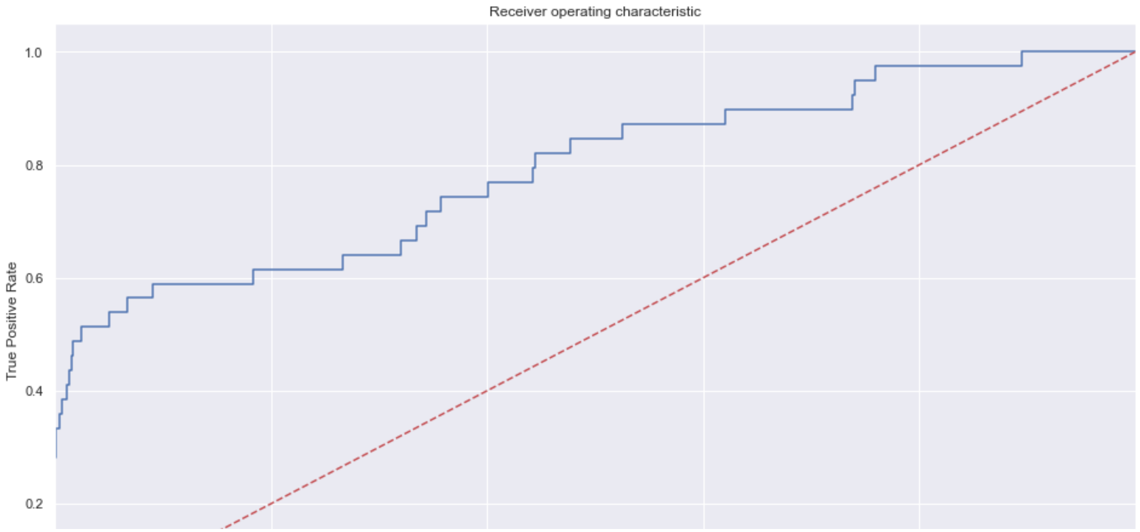
```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00     19161
         1.0       0.89      0.21      0.33        39

    accuracy                           1.00     19200
   macro avg       0.94      0.60      0.67     19200
weighted avg       1.00      1.00      1.00     19200
```

Plot the ROC curve

In [...

```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, logreg.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('Log_ROC.png')
plt.rcParams["figure.figsize"] = (16,9)
plt.show()
```



a bit of workaround to get sequence and channel back into a df

In [...
```
fd=pd.DataFrame(y_pred)
fd2=pd.DataFrame(y_test)
```

In [...
```
fd2.head()
```

Out[...

	BAD_CHAN_FLAG
23267	0.0
6433	0.0
19950	0.0
4075	0.0
17557	0.0

In [...
```
FD2=fd2.reset_index()
FD2.set_axis(['index','FLAG_ORIG'],axis=1,inplace=True)
```

In [...
```
merge=FD2.merge(fd,left_index=True, right_index=True)
merge.set_axis(['index','FLAG_ORIG','PREDICT'],axis=1,inplace=True)
```

In [...
```
merge.head()
```

Out[...

	index	FLAG_ORIG	PREDICT
0	23267	0.0	0.0
1	6433	0.0	0.0
2	19950	0.0	0.0
3	4075	0.0	0.0

4	17557	0.0	0.0

create a header to spot different predictions

In [...

```
merge['DIFF']=merge['FLAG_ORIG']-merge['PREDICT']
```

In [...

```
finder=merge['DIFF']!=0
finder
```

Out[...

```
0        False
1        False
2        False
3        False
4        False
         ...
19195    False
19196    False
19197    False
19198    False
19199    False
Name: DIFF, Length: 19200, dtype: bool
```

Check what has been predicted different from the test data

In [...

```
for i,x in merge.iterrows():
    if x['DIFF']!=0:
        print(x)
```

```
INDEX        28381.0
FLAG_ORIG        1.0
PREDICT          0.0
DIFF             1.0
Name: 39, dtype: float64
INDEX        19268.0
FLAG_ORIG        1.0
PREDICT          0.0
DIFF             1.0
Name: 517, dtype: float64
```

```
Name: 517, dtype: float64
INDEX        194.0
FLAG_ORIG      1.0
PREDICT        0.0
DIFF           1.0
Name: 533, dtype: float64
INDEX        251.0
FLAG_ORIG      1.0
PREDICT        0.0
DIFF           1.0
Name: 3139, dtype: float64
INDEX        23234.0
FLAG_ORIG        1.0
PREDICT          0.0
DIFF             1.0
Name: 3571, dtype: float64
INDEX        28992.0
FLAG_ORIG        1.0
PREDICT          0.0
DIFF             1.0
Name: 4994, dtype: float64
INDEX        27127.0
FLAG_ORIG        1.0
PREDICT          0.0
DIFF             1.0
Name: 5038, dtype: float64
INDEX        15002.0
FLAG_ORIG        1.0
PREDICT          0.0

DIFF             1.0
Name: 5158, dtype: float64
INDEX        11767.0
FLAG_ORIG        1.0
PREDICT          0.0
DIFF             1.0
Name: 5166, dtype: float64
INDEX        5322.0
FLAG_ORIG       1.0
PREDICT         0.0
DIFF            1.0
Name: 5725, dtype: float64
INDEX        16737.0
FLAG_ORIG        1.0
PREDICT          0.0
DIFF             1.0
Name: 7313, dtype: float64
INDEX        26027.0
FLAG_ORIG        1.0
```

```
PREDICT           0.0
DIFF              1.0
Name: 8250, dtype: float64
INDEX         16367.0
FLAG_ORIG         1.0
PREDICT           0.0
DIFF              1.0
Name: 9103, dtype: float64
INDEX         15205.0

FLAG_ORIG         1.0
PREDICT           0.0
DIFF              1.0
Name: 9275, dtype: float64
INDEX         36572.0
FLAG_ORIG         0.0
PREDICT           1.0
DIFF             -1.0
Name: 9520, dtype: float64
INDEX         28362.0
FLAG_ORIG         1.0
PREDICT           0.0
DIFF              1.0
Name: 12098, dtype: float64
INDEX         18347.0
FLAG_ORIG         1.0
PREDICT           0.0
DIFF              1.0
Name: 12327, dtype: float64
INDEX         30914.0
FLAG_ORIG         1.0
PREDICT           0.0
DIFF              1.0
Name: 13225, dtype: float64
INDEX         3908.0
FLAG_ORIG        1.0
PREDICT          0.0
DIFF             1.0

Name: 13279, dtype: float64
INDEX         34807.0
FLAG_ORIG         1.0
PREDICT           0.0
DIFF              1.0
Name: 13603, dtype: float64
INDEX         7874.0
FLAG_ORIG        1.0
PREDICT          0.0
```

```
DIFF             1.0
Name: 15501, dtype: float64
INDEX        17268.0
FLAG_ORIG        1.0
PREDICT          0.0
DIFF             1.0
Name: 15616, dtype: float64
INDEX        15554.0
FLAG_ORIG        1.0
PREDICT          0.0
DIFF             1.0
Name: 15714, dtype: float64
INDEX        13002.0
FLAG_ORIG        1.0
PREDICT          0.0
DIFF             1.0
Name: 16150, dtype: float64
INDEX        8687.0
FLAG_ORIG       1.0

PREDICT         0.0
DIFF            1.0
Name: 16203, dtype: float64
INDEX        7322.0
FLAG_ORIG       1.0
PREDICT         0.0
DIFF            1.0
Name: 17279, dtype: float64
INDEX        22682.0
FLAG_ORIG        1.0
PREDICT          0.0
DIFF             1.0
Name: 17716, dtype: float64
INDEX        7321.0
FLAG_ORIG       1.0
PREDICT         0.0
DIFF            1.0
Name: 18031, dtype: float64
INDEX        17573.0
FLAG_ORIG        1.0
PREDICT          0.0
DIFF             1.0
Name: 18421, dtype: float64
INDEX        23892.0
FLAG_ORIG        1.0
PREDICT          0.0
DIFF             1.0
Name: 18786, dtype: float64
```

```
INDEX         30971.0
FLAG_ORIG         1.0
PREDICT           0.0
DIFF              1.0
Name: 18965, dtype: float64
INDEX         25250.0
FLAG_ORIG         1.0
PREDICT           0.0
DIFF              1.0
Name: 19131, dtype: float64
```

In [...

```
X1_train, X1_test, y1_train, y1_test = train_test_split(df1, df1, test_size=0.
```

In [...

```
FD3=y1_test.reset_index()
newtest=pd.merge(FD3,merge)
```

In [...

```
newtest.head()
```

Out[...

	index	SEQ	CHANNEL	DEEP_RMS_x	BAD_CHAN_FLAG	CAP_VAL	DEEP_RMS_y	LEAK_VAL
0	23267	10	228	3.124860	0.0	247.454041	4.61	5.0
1	6433	3	6434	1.831995	0.0	248.454788	6.37	5.0
2	19950	8	4591	2.081703	0.0	247.016556	4.42	5.0
3	4075	3	4076	1.581103	0.0	247.256012	5.79	5.0
4	17557	8	2198	2.479709	0.0	253.687592	4.70	5.0

In [...

```
for i,x in newtest.iterrows():
    if x['PREDICT']>x['BAD_CHAN_FLAG']:
        print(x)
```

```
index                36572.000000
SEQ                     11.000000
```

```
CHANNEL          5853.000000
DEEP_RMS_x          2.059848
BAD_CHAN_FLAG       0.000000
CAP_VAL           131.220078
DEEP_RMS_y          8.200000
LEAK_VAL            5.000000
FLAG_ORIG           0.000000
PREDICT             1.000000
Name: 9520, dtype: float64
```

Let's see now how we can compare a simple lr , lr L1 norm and lr L2 norm Logistic regression

In [...

```python
# Standard logistic regression
lr = LogisticRegression(solver='liblinear').fit(X_train, y_train)
```

```
/opt/anaconda3/lib/python3.8/site-packages/sklearn/utils/validation.py:72: Dat
aConversionWarning: A column-vector y was passed when a 1d array was expected.
Please change the shape of y to (n_samples, ), for example using ravel().
  return f(**kwargs)
```

In [...

```python
from sklearn.linear_model import LogisticRegressionCV

# L1 regularized logistic regression
lr_l1 = LogisticRegressionCV(Cs=10, cv=4, penalty='l1', solver='liblinear').fi
```

```
/opt/anaconda3/lib/python3.8/site-packages/sklearn/utils/validation.py:72: Dat
aConversionWarning: A column-vector y was passed when a 1d array was expected.
Please change the shape of y to (n_samples, ), for example using ravel().
  return f(**kwargs)
```

In [...

```python
# L2 regularized logistic regression
lr_l2 = LogisticRegressionCV(Cs=10, cv=4, penalty='l2', solver='liblinear').fi
```

```
/opt/anaconda3/lib/python3.8/site-packages/sklearn/utils/validation.py:72: Dat
aConversionWarning: A column-vector y was passed when a 1d array was expected.
Please change the shape of y to (n_samples, ), for example using ravel().
  return f(**kwargs)
```

In [...

```python
# Predict the class and the probability for each
y_pred = list()
y_prob = list()
```

```
coeff_labels = ['lr', 'l1', 'l2']
coeff_models = [lr, lr_l1, lr_l2]

for lab,mod in zip(coeff_labels, coeff_models):
    y_pred.append(pd.Series(mod.predict(X_test), name=lab))
    y_prob.append(pd.Series(mod.predict_proba(X_test).max(axis=1), name=lab))

y_pred = pd.concat(y_pred, axis=1)
y_prob = pd.concat(y_prob, axis=1)

y_pred.head()
```

Out[...

	lr	l1	l2
0	0.0	0.0	0.0
1	0.0	0.0	0.0
2	0.0	0.0	0.0
3	0.0	0.0	0.0
4	0.0	0.0	0.0

In [...

```
y_prob.head()
```

Out[...

	lr	l1	l2
0	0.999115	0.998161	0.993835
1	0.999098	0.998310	0.994139
2	0.999120	0.998145	0.993810
3	0.999061	0.998188	0.993833
4	0.999437	0.998763	0.995567

In [...

```
from sklearn.metrics import precision_recall_fscore_support as score
from sklearn.metrics import confusion_matrix, accuracy_score, roc_auc_score
```

```
from sklearn.preprocessing import label_binarize

metrics = list()
cm = dict()

for lab in coeff_labels:

    # Preciision, recall, f-score from the multi-class support function
    precision, recall, fscore, _ = score(y_test, y_pred[lab], average='weighte

    # The usual way to calculate accuracy
    accuracy = accuracy_score(y_test, y_pred[lab])

    # ROC-AUC scores can be calculated by binarizing the data
#     auc = roc_auc_score(label_binarize(y_test, classes=[0,1,2,3,4,5]),
#               label_binarize(y_pred[lab], classes=[0,1,2,3,4,5]),
#               average='weighted')

    # Last, the confusion matrix
    cm[lab] = confusion_matrix(y_test, y_pred[lab])

    metrics.append(pd.Series({'precision':precision, 'recall':recall,
                              'fscore':fscore, 'accuracy':accuracy},
#                              'auc':auc},
                             name=lab))

metrics = pd.concat(metrics, axis=1)
```

check the results

In [...

```
metrics
```

Out[...

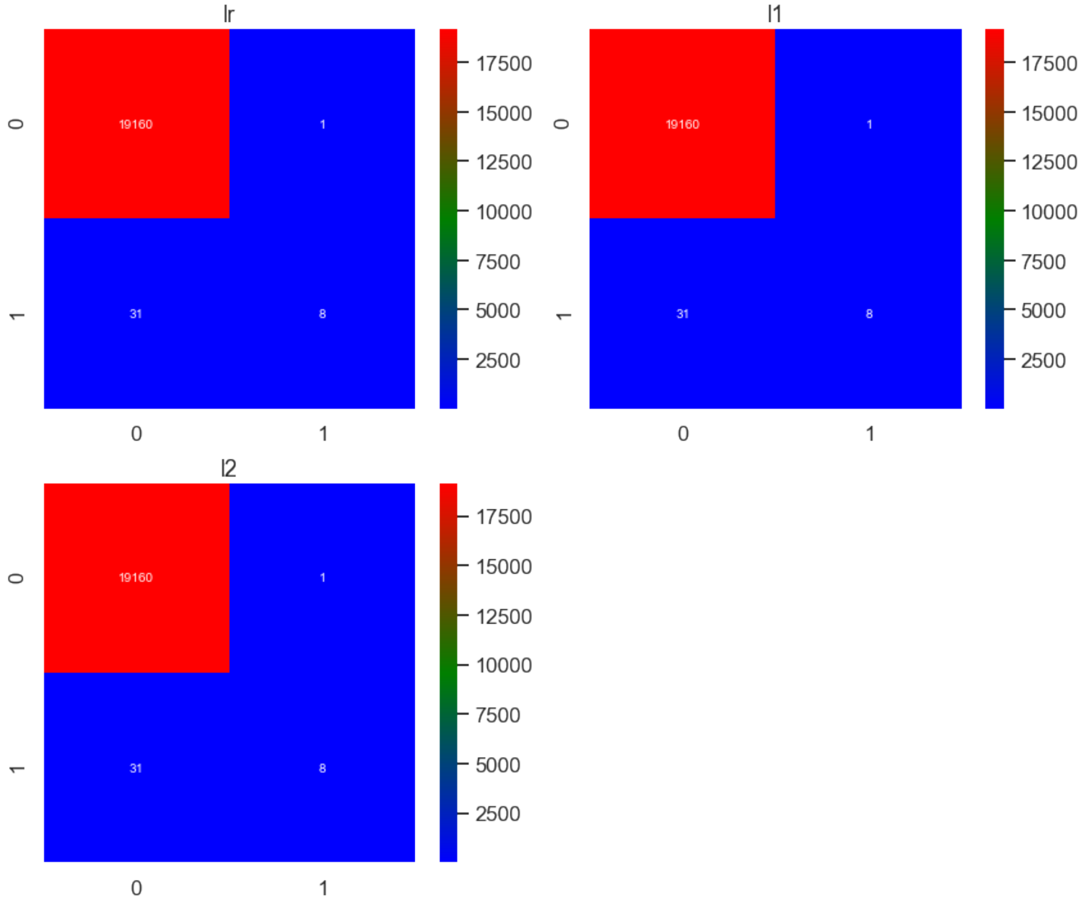
	lr	l1	l2
precision	0.998162	0.998162	0.998162
recall	0.998333	0.998333	0.998333
fscore	0.997813	0.997813	0.997813
accuracy	0.998333	0.998333	0.998333

plot the 3 confusion matrix

In [...

```
fig, axList = plt.subplots(nrows=2, ncols=2)
axList = axList.flatten()
```

```
fig.set_size_inches(12, 10)

axList[-1].axis('off')

for ax,lab in zip(axList[:-1], coeff_labels):
    sns.heatmap(cm[lab], ax=ax, annot=True, fmt='d',cmap=cmap1);
    ax.set(title=lab);

plt.tight_layout()
```



In [...