Snarling Coyotes Abstract

Investigating effect of noise on the error rate of recognizing faces/houses under the limited perceptual load

Background. Perceiving the different shapes from the surrounding environment is a complex neurological function, and the impairment in the nervous system may hinder it. Perceptual load describes the rejection of the distraction of surrounding images. To test this, recognition task is designed to evaluate the cognition of people suffering from neurological disorders. The errors of the task analysis are decreasing its efficiency.

Objectives. To investigate the effect of noise on the error range of the recognition task using face/houses recognition ECoG dataset under limited perceptual load.

Data and Method. We used broadband spectral change in the electrical potential in order to see the correlation between neuronal activity and electrical potential recording. We applied principle component analysis (PCA) by taking the channels as features and tried to predict the response of each patient for different stimuli by using machine learning based classifiers. We'll be applying other dimensionality reduction methods (linear and nonlinear) and use cross validation for hyperparameter tuning.

Results.
The preliminary results of the classification algorithms are given here.

Model Accuracies (trained via actual label) for model prediction vs actual stimuli label (after Hyperparameter Tuning)

```
------------------------------------------------ NORMAL ------------------------------------------------

Patient 0 ==>  MLPClassifier:  0.7  RandomForestClassifier:  0.7  SVM:  0.7  LogisticRegression:  0.77

Patient 1 ==>  MLPClassifier:  0.43  RandomForestClassifier:  0.4  SVM:  0.43  LogisticRegression:  0.4

Patient 2 ==>  MLPClassifier:  0.4  RandomForestClassifier:  0.47  SVM:  0.5  LogisticRegression:  0.4

Patient 3 ==>  MLPClassifier:  0.63  RandomForestClassifier:  0.67  SVM:  0.47  LogisticRegression:  0.53

Patient 4 ==>  MLPClassifier:  0.4  RandomForestClassifier:  0.67  SVM:  0.63  LogisticRegression:  0.5

------------------------------------------------- PCA -------------------------------------------------

Patient 0 ==>  MLPClassifier:  0.67  RandomForestClassifier:  0.73  SVM:  0.57  LogisticRegression:  0.63

Patient 1 ==>  MLPClassifier:  0.47  RandomForestClassifier:  0.5  SVM:  0.43  LogisticRegression:  0.47

Patient 2 ==>  MLPClassifier:  0.43  RandomForestClassifier:  0.47  SVM:  0.4  LogisticRegression:  0.4

Patient 3 ==>  MLPClassifier:  0.53  RandomForestClassifier:  0.3  SVM:  0.6  LogisticRegression:  0.57

Patient 4 ==>  MLPClassifier:  0.6  RandomForestClassifier:  0.57  SVM:  0.4  LogisticRegression:  0.43
```

Model Accuracies that has been trained and tested with patients' responses (w/wo PCA) (after tuning hyperparameter)

```
------------------------------------------------ NORMAL ------------------------------------------------

Patient  0 ==>  MLPClassifier:  0.9  RandomForestClassifier:  0.93  SVM:  0.9  LogisticRegression:  0.9

Patient  1 ==>  MLPClassifier:  0.93  RandomForestClassifier:  0.93  SVM:  0.93  LogisticRegression:  0.93

Patient  2 ==>  MLPClassifier:  0.83  RandomForestClassifier:  0.83  SVM:  0.8  LogisticRegression:  0.63

Patient  3 ==>  MLPClassifier:  0.67  RandomForestClassifier:  0.77  SVM:  0.73  LogisticRegression:  0.73

Patient  4 ==>  MLPClassifier:  0.43  RandomForestClassifier:  0.43  SVM:  0.4  LogisticRegression:  0.57

------------------------------------------------- PCA -------------------------------------------------

Patient  0 ==>  MLPClassifier:  0.97  RandomForestClassifier:  1.0  SVM:  0.97  LogisticRegression:  0.93

Patient  1 ==>  MLPClassifier:  0.93  RandomForestClassifier:  0.93  SVM:  0.93  LogisticRegression:  0.93

Patient  2 ==>  MLPClassifier:  0.6  RandomForestClassifier:  0.6  SVM:  0.57  LogisticRegression:  0.5

Patient  3 ==>  MLPClassifier:  0.7  RandomForestClassifier:  0.67  SVM:  0.6  LogisticRegression:  0.63

Patient  4 ==>  MLPClassifier:  0.43  RandomForestClassifier:  0.47  SVM:  0.4  LogisticRegression:  0.4
```

Patient’s Key Press Accuracies

Stimuli Set [600:630]

```
Patient  0  ==>   All stimuli:  30  Pressed stimuli:  133  Face stimuli:  12  Truely pressed stimuli:  5  Recognition accuracy:  41.66666666666667
Patient  1  ==>   All stimuli:  30  Pressed stimuli:  141  Face stimuli:  12  Truely pressed stimuli:  3  Recognition accuracy:  25.0
Patient  2  ==>   All stimuli:  30  Pressed stimuli:  106  Face stimuli:  12  Truely pressed stimuli:  0  Recognition accuracy:  0.0
Patient  3  ==>   All stimuli:  30  Pressed stimuli:  354  Face stimuli:  12  Truely pressed stimuli:  8  Recognition accuracy:  66.66666666666666
Patient  4  ==>   All stimuli:  30  Pressed stimuli:  304  Face stimuli:  12  Truely pressed stimuli:  5  Recognition accuracy:  41.66666666666667
```

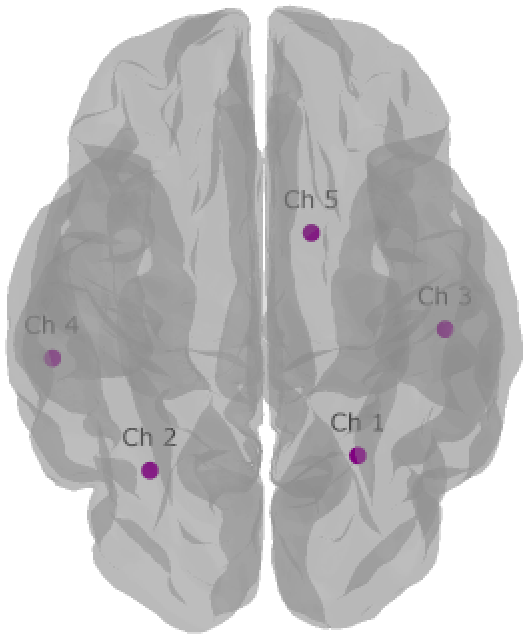
All Stimuli Set [0:630]

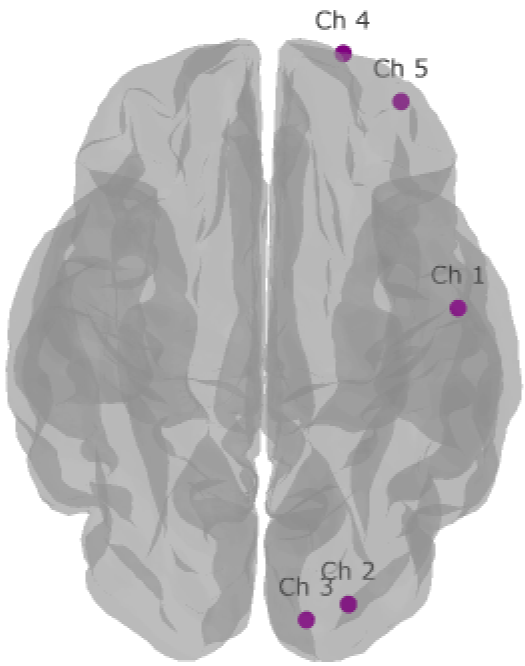
```
Patient  0  ==>   All stimuli:  630  Pressed stimuli:  133  Face stimuli:  315  Truely pressed stimuli:  116  Recognition accuracy:  36.82539682539683
Patient  1  ==>   All stimuli:  630  Pressed stimuli:  141  Face stimuli:  315  Truely pressed stimuli:  130  Recognition accuracy:  41.269841269841265
Patient  2  ==>   All stimuli:  630  Pressed stimuli:  106  Face stimuli:  315  Truely pressed stimuli:  84  Recognition accuracy:  26.666666666666668
Patient  3  ==>   All stimuli:  630  Pressed stimuli:  354  Face stimuli:  315  Truely pressed stimuli:  195  Recognition accuracy:  61.904761904761905
Patient  4  ==>   All stimuli:  630  Pressed stimuli:  304  Face stimuli:  315  Truely pressed stimuli:  163  Recognition accuracy:  51.746031746031754
```

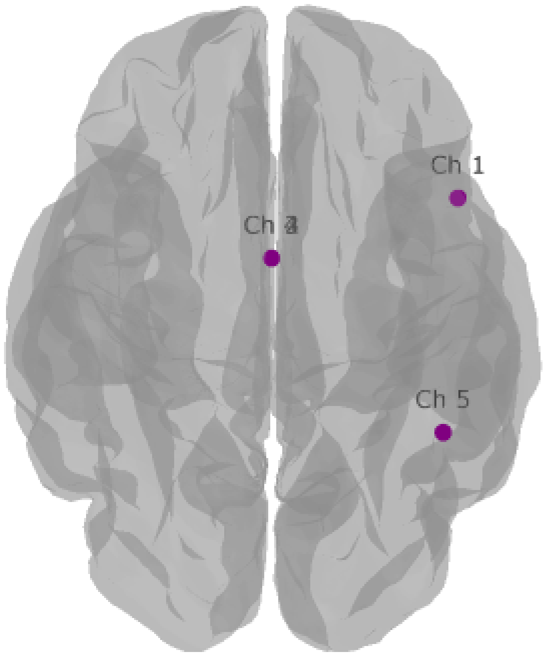
Conclusion: Since our model predictions for actual labels match with that of patient predictions, we can say that our model is a good representative of neural decoding in patients. So we can go ahead with analysing the effect of noise on patients' decisions by using the models.

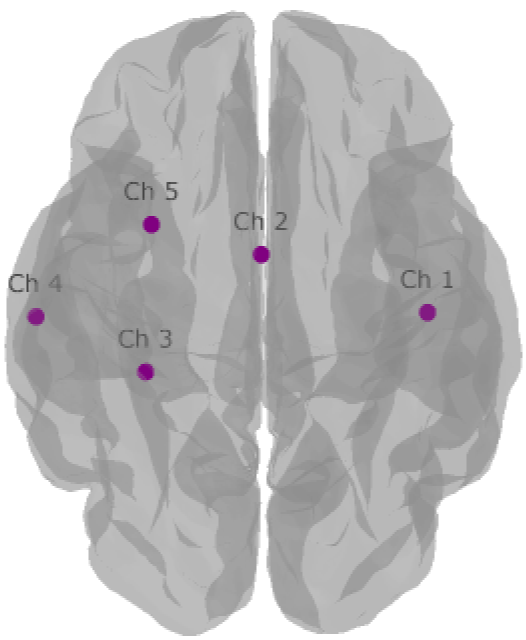
Further work:

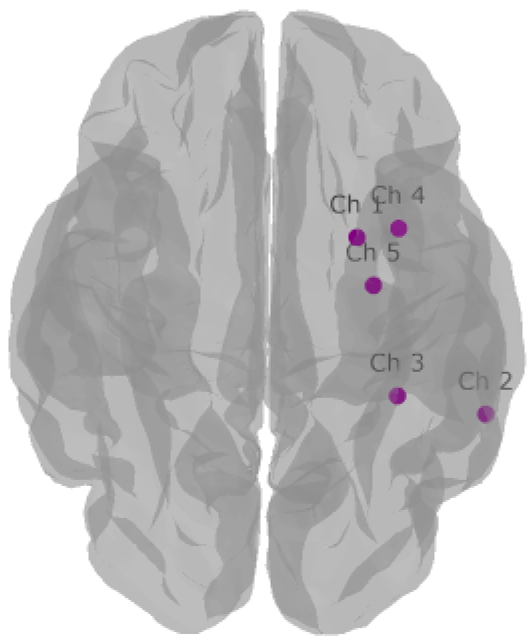
1. We could train the classifiers on data from experiment 1 and use them to predict accuracies on our test set from experiment 2. The difference in accuracy, if any, could then be attributed to the presence of noise in experiment 2.
2. How coefficients of logistic regression vary. Since coeff are linked to a specific channel, we can look at the location that is important. We can also check how the accuracy changes when we remove non-important / negatively contributing channels from our input.


Ch 5
Ch 3
Ch 4
Ch 1
Ch 2

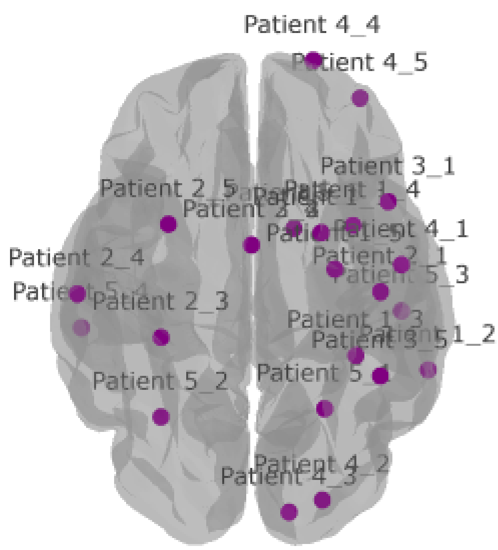

Ch 4
Ch 5
Ch 1
Ch 2
Ch 3


Ch 1
Ch 5

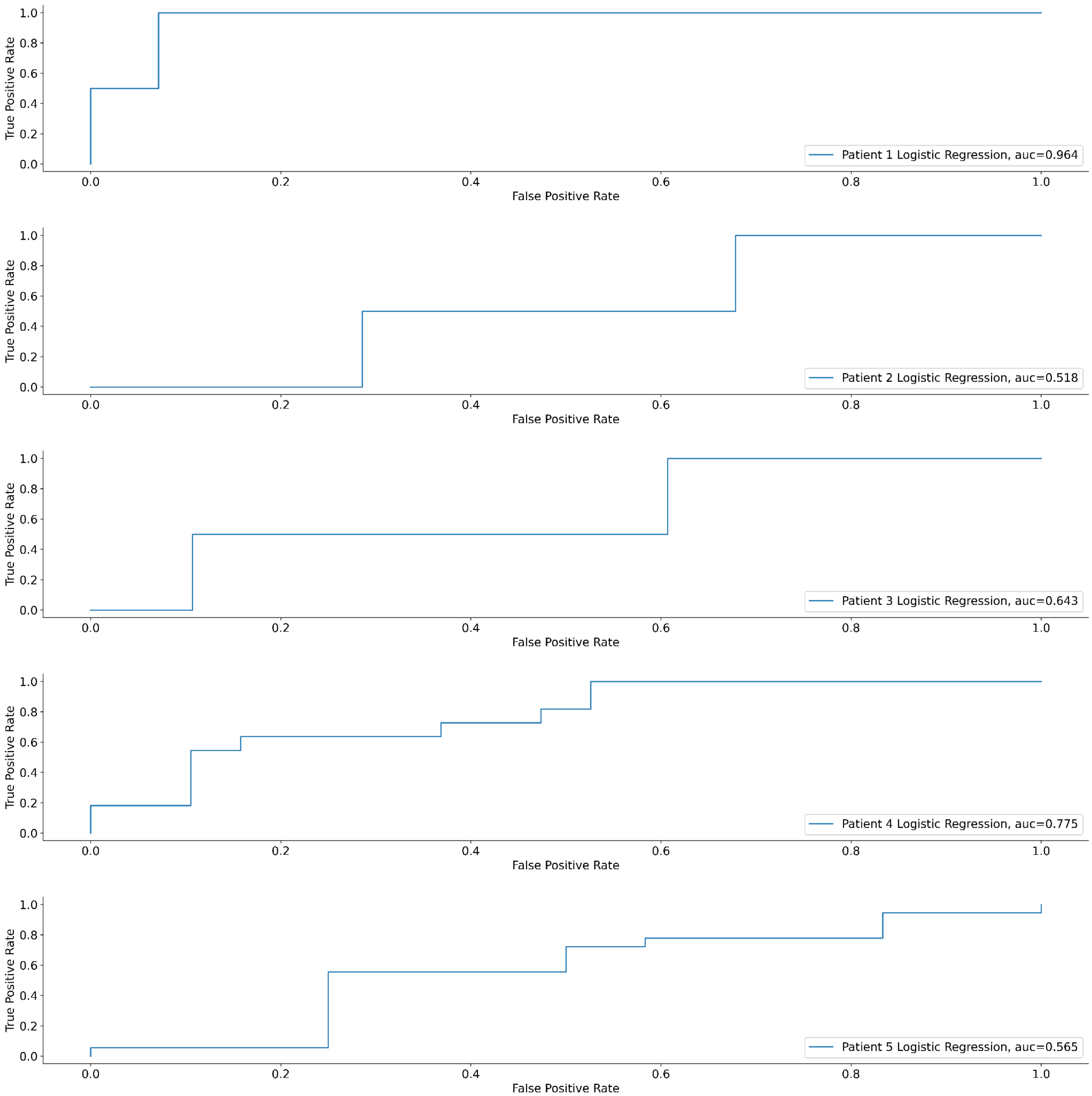

Ch 5
Ch 2
Ch 4
Ch 1
Ch 3



Ch 1
Ch 4
Ch 5
Ch 3
Ch 2



Patient 4_4
Patient 4_5
Patient 3_1
Patient 2_5
Patient 1_4
Patient 4_1
Patient 2_4
Patient 2_1
Patient 5_3
Patient 2_3
Patient 1_3
Patient 3_5
Patient 5_2
Patient 4_2
Patient 4_3


True Positive Rate
False Positive Rate
Patient 1 Logistic Regression, auc=0.964
True Positive Rate
False Positive Rate
Patient 2 Logistic Regression, auc=0.518
True Positive Rate
False Positive Rate
Patient 3 Logistic Regression, auc=0.643
True Positive Rate
False Positive Rate
Patient 4 Logistic Regression, auc=0.775
True Positive Rate
False Positive Rate
Patient 5 Logistic Regression, auc=0.565

Patient 1 Full classification report :

	precision	recall	f1-score	support
0	0.96	0.93	0.95	28
1	0.33	0.50	0.40	2
accuracy			0.90	30
macro avg	0.65	0.71	0.67	30
weighted avg	0.92	0.90	0.91	30

Patient 2 Full classification report :

	precision	recall	f1-score	support
0	0.93	1.00	0.97	28
1	0.00	0.00	0.00	2
accuracy			0.93	30
macro avg	0.47	0.50	0.48	30
weighted avg	0.87	0.93	0.90	30

Patient 3 Full classification report :

	precision	recall	f1-score	support
0	0.95	0.64	0.77	28
1	0.09	0.50	0.15	2
accuracy			0.63	30
macro avg	0.52	0.57	0.46	30
weighted avg	0.89	0.63	0.73	30

Patient 4 Full classification report :

	precision	recall	f1-score	support
0	0.79	0.79	0.79	19
1	0.64	0.64	0.64	11
accuracy			0.73	30
macro avg	0.71	0.71	0.71	30
weighted avg	0.73	0.73	0.73	30

Patient 5 Full classification report :

	precision	recall	f1-score	support
0	0.47	0.75	0.58	12
1	0.73	0.44	0.55	18
accuracy			0.57	30
macro avg	0.60	0.60	0.57	30
weighted avg	0.63	0.57	0.56	30