

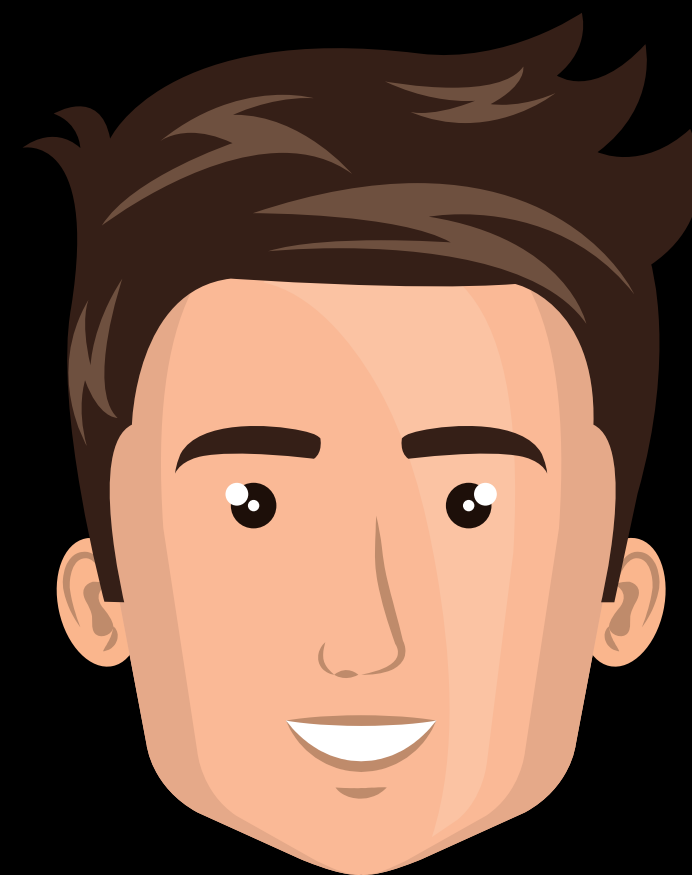


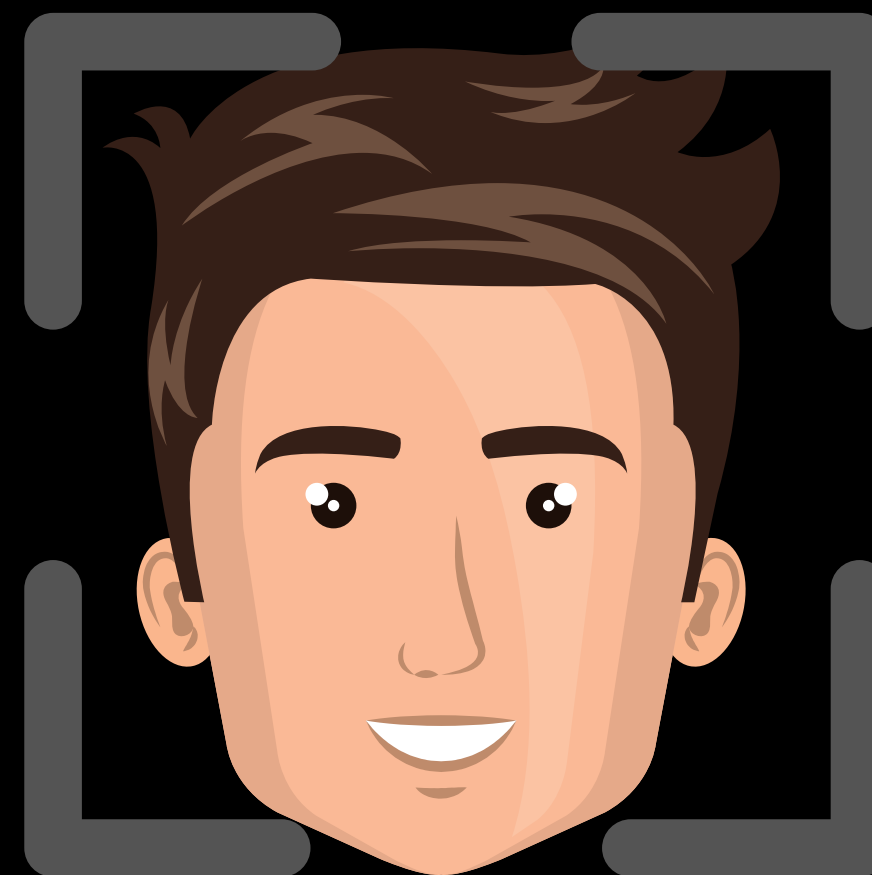
# Decoding ECoG signals to classify faces and houses

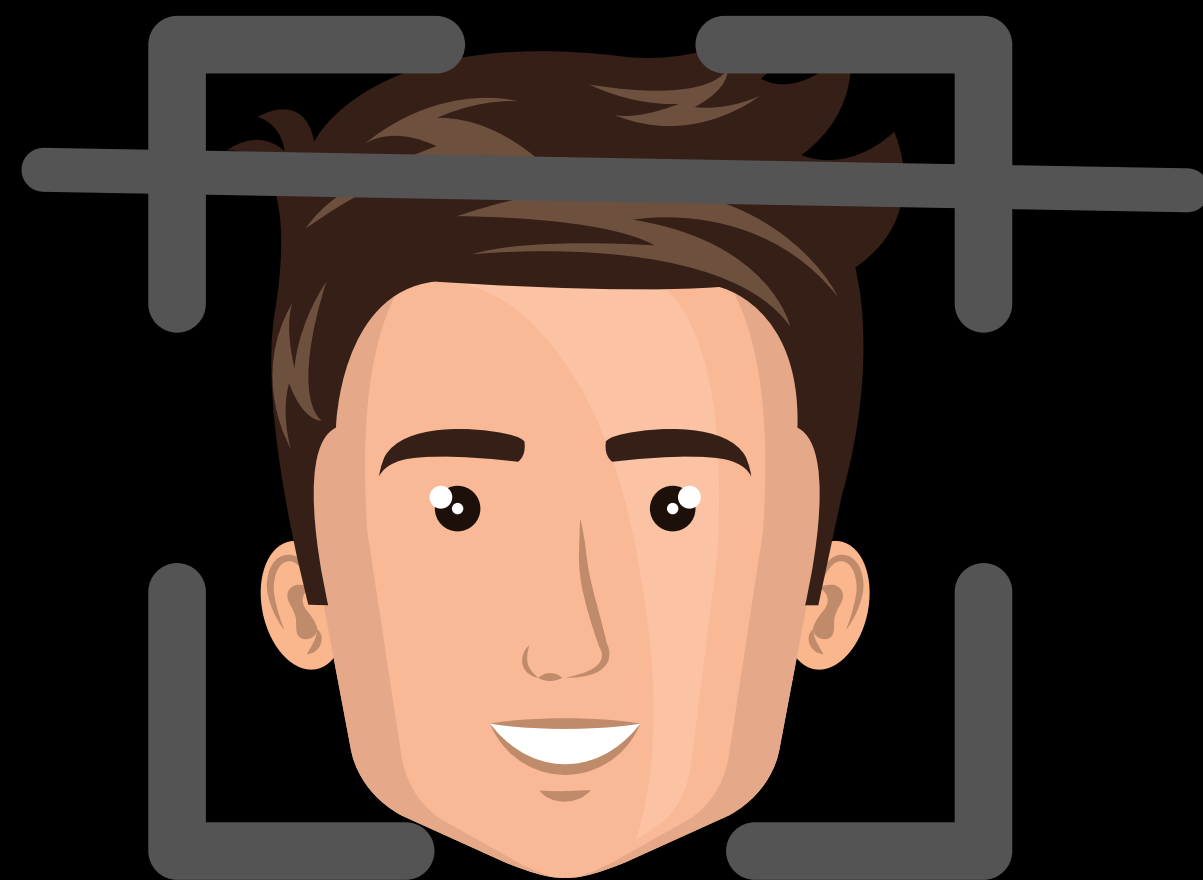
Pod : Spry Ugusius

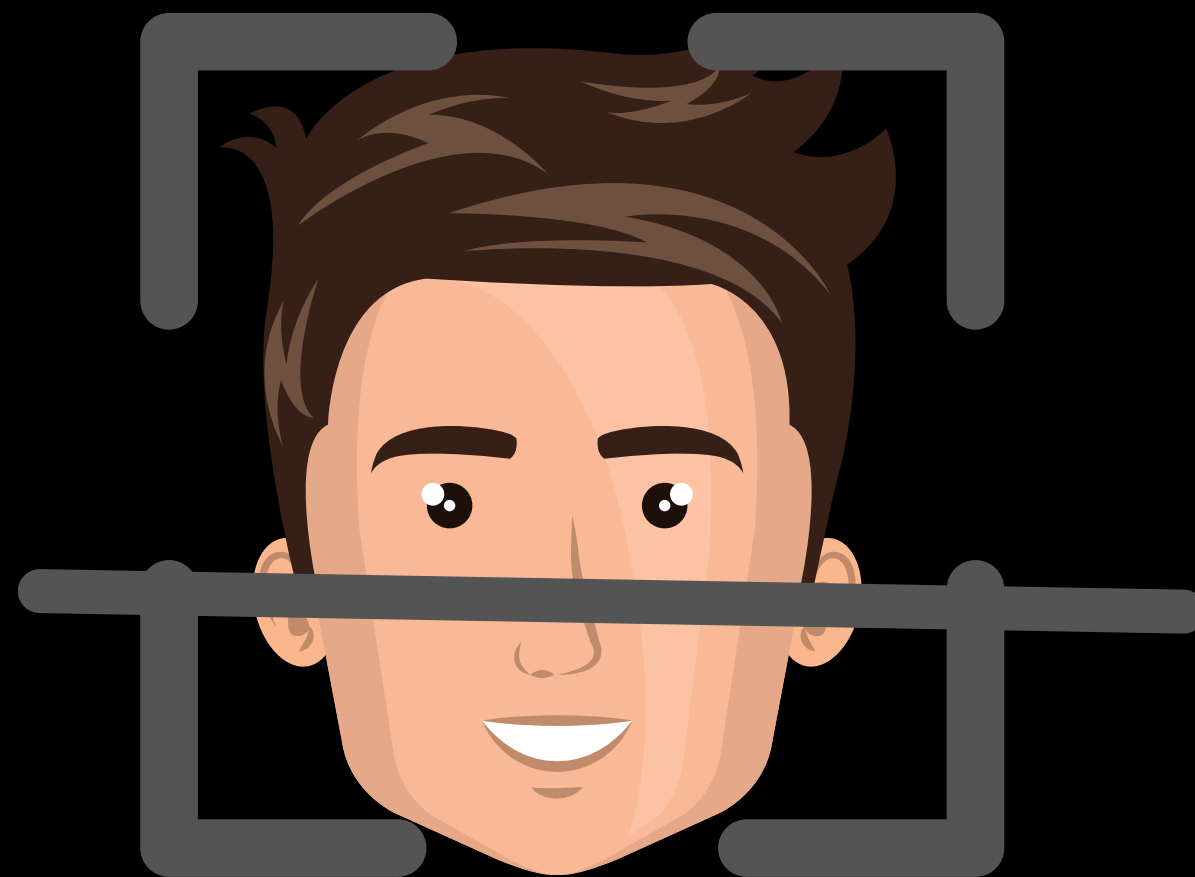
Team Member: Leafy Behera, Ruoying Zheng, Tanistha Bhattacharya

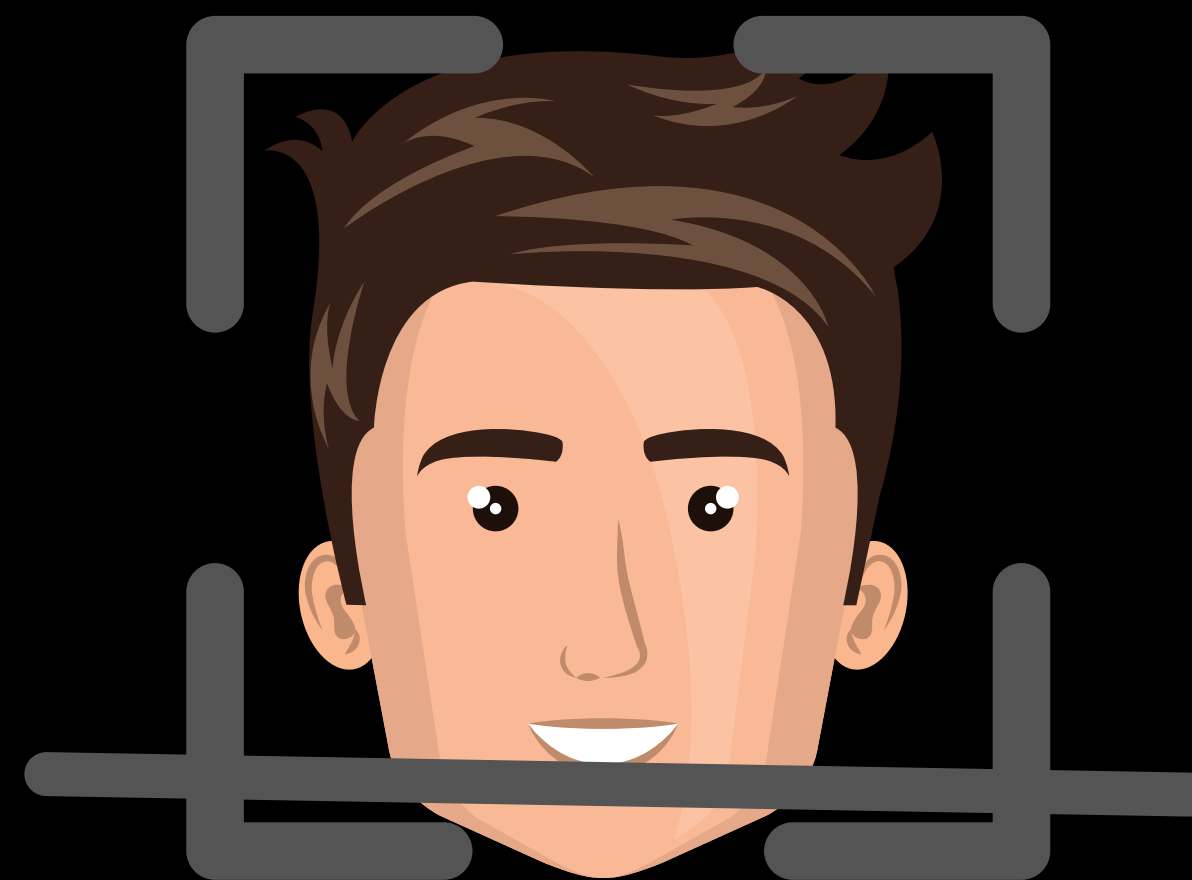


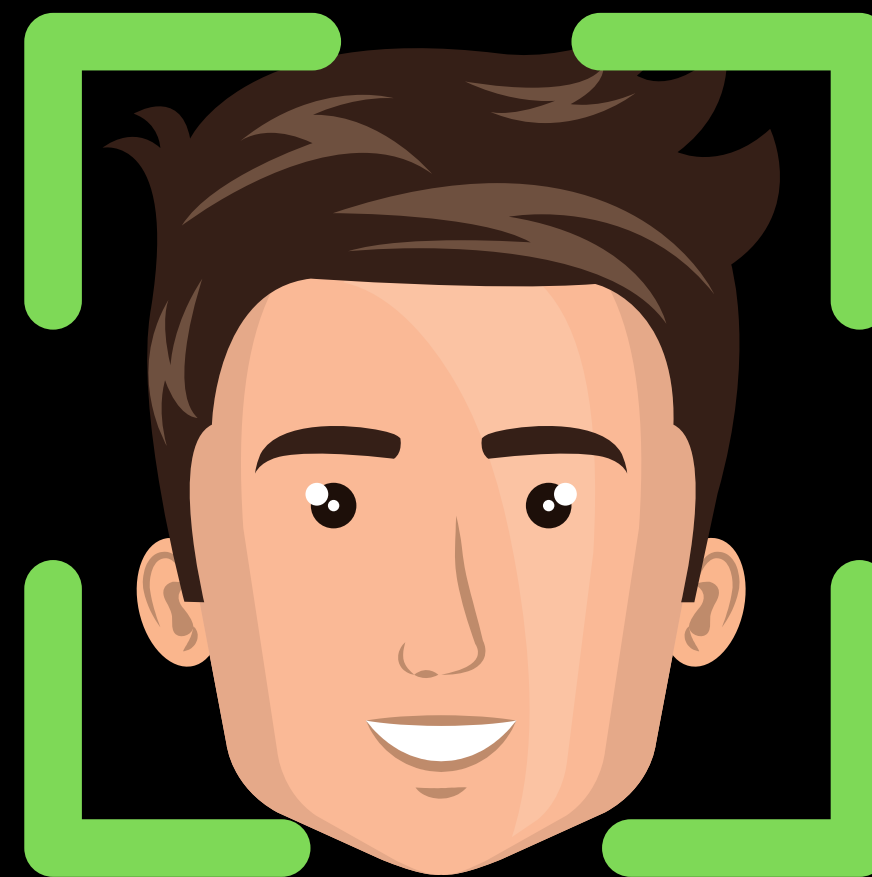








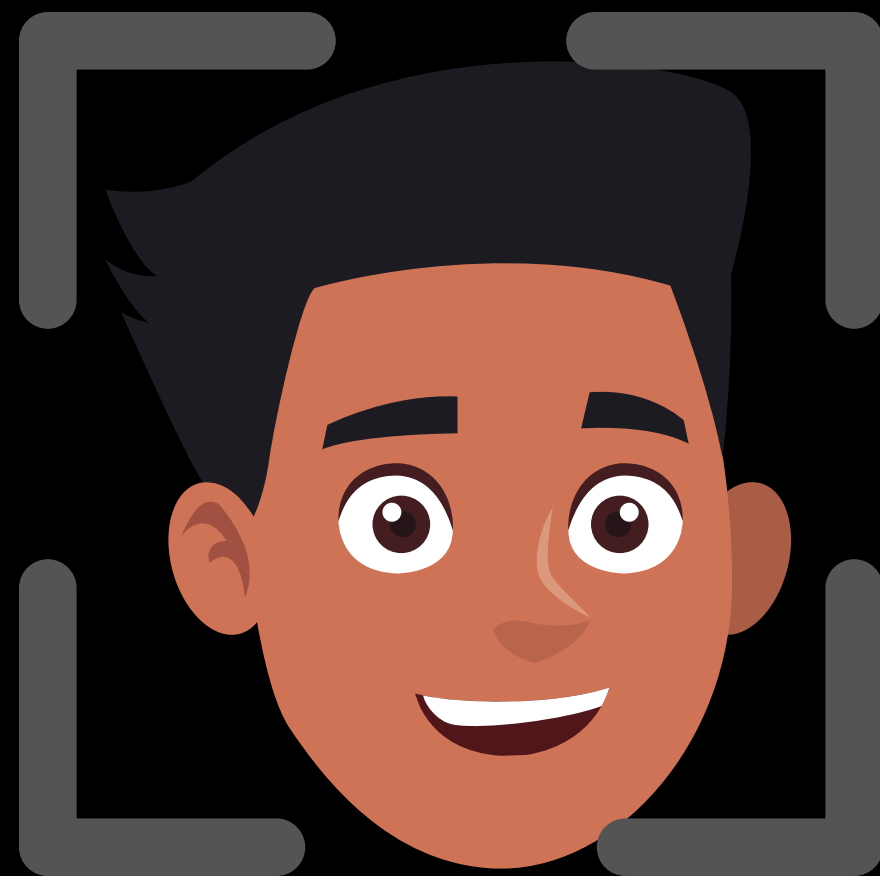


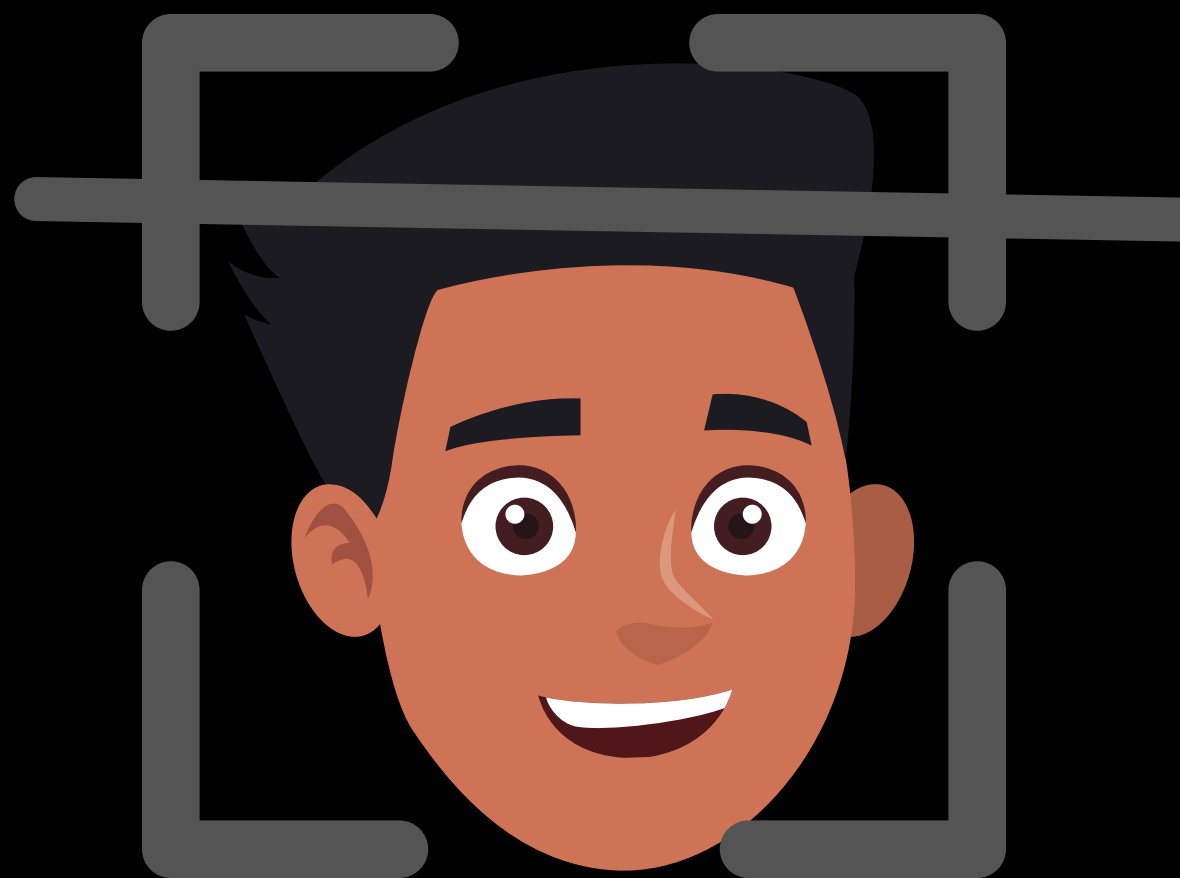


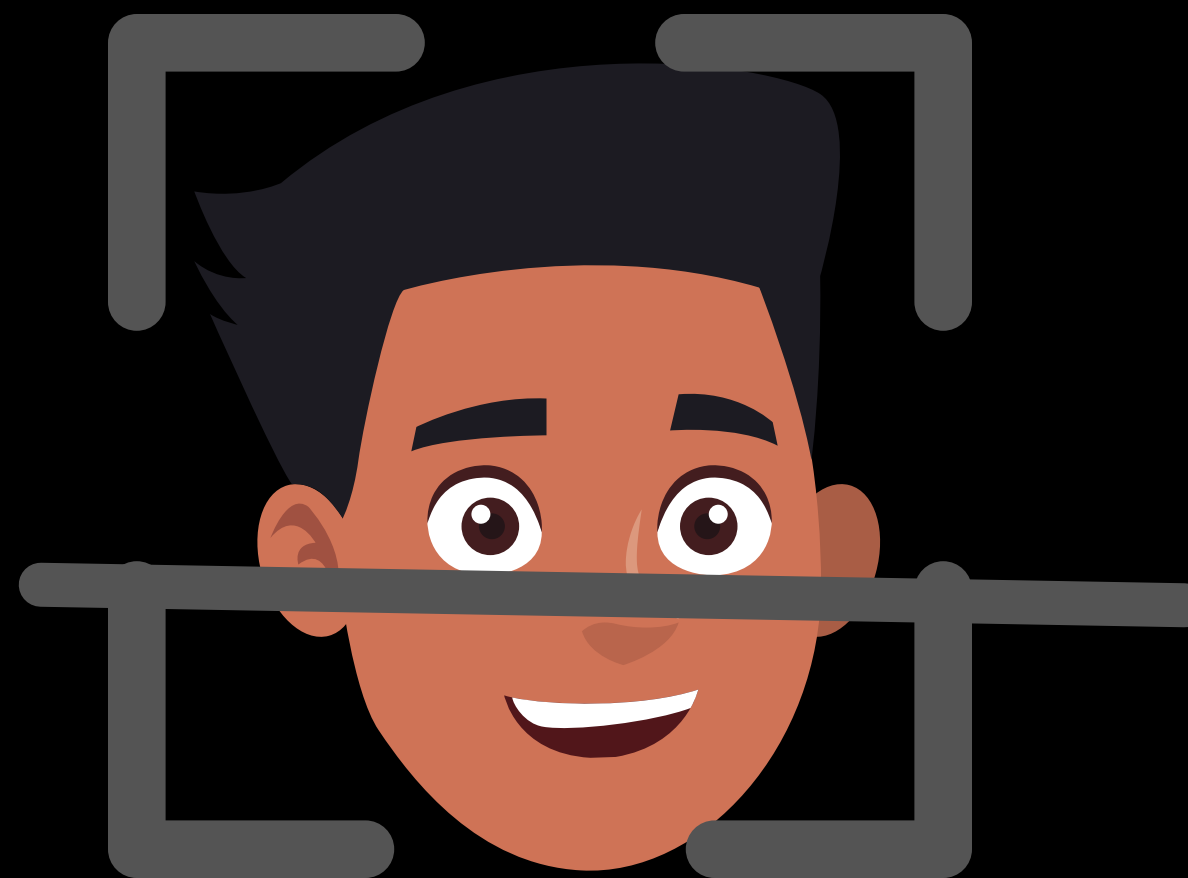


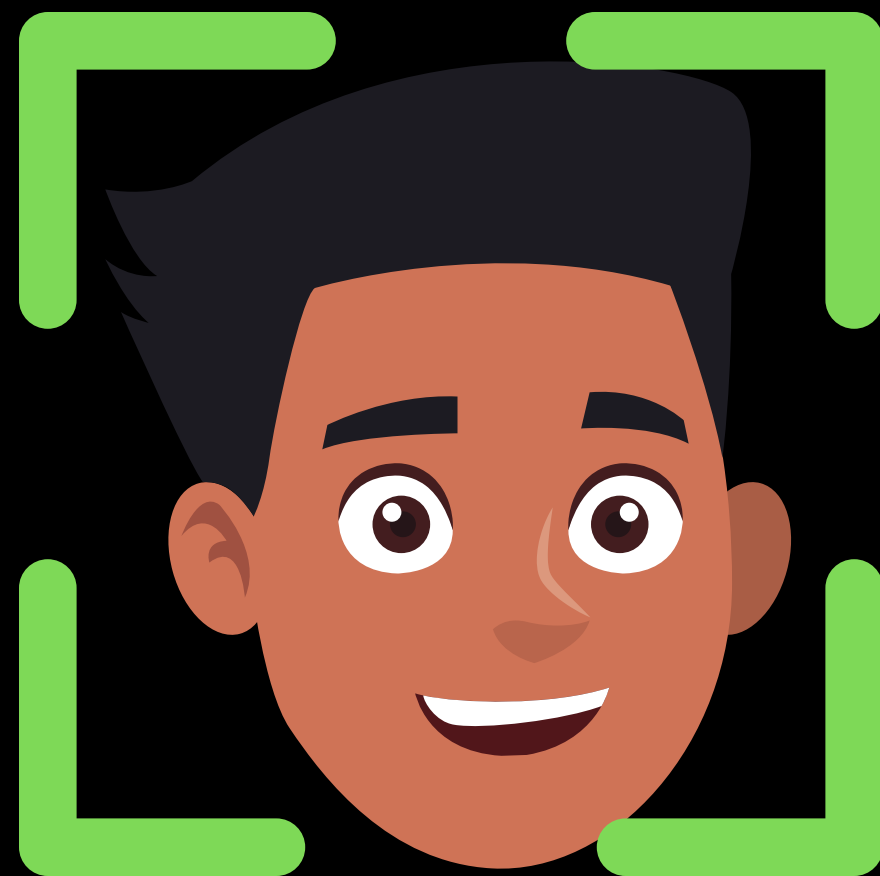




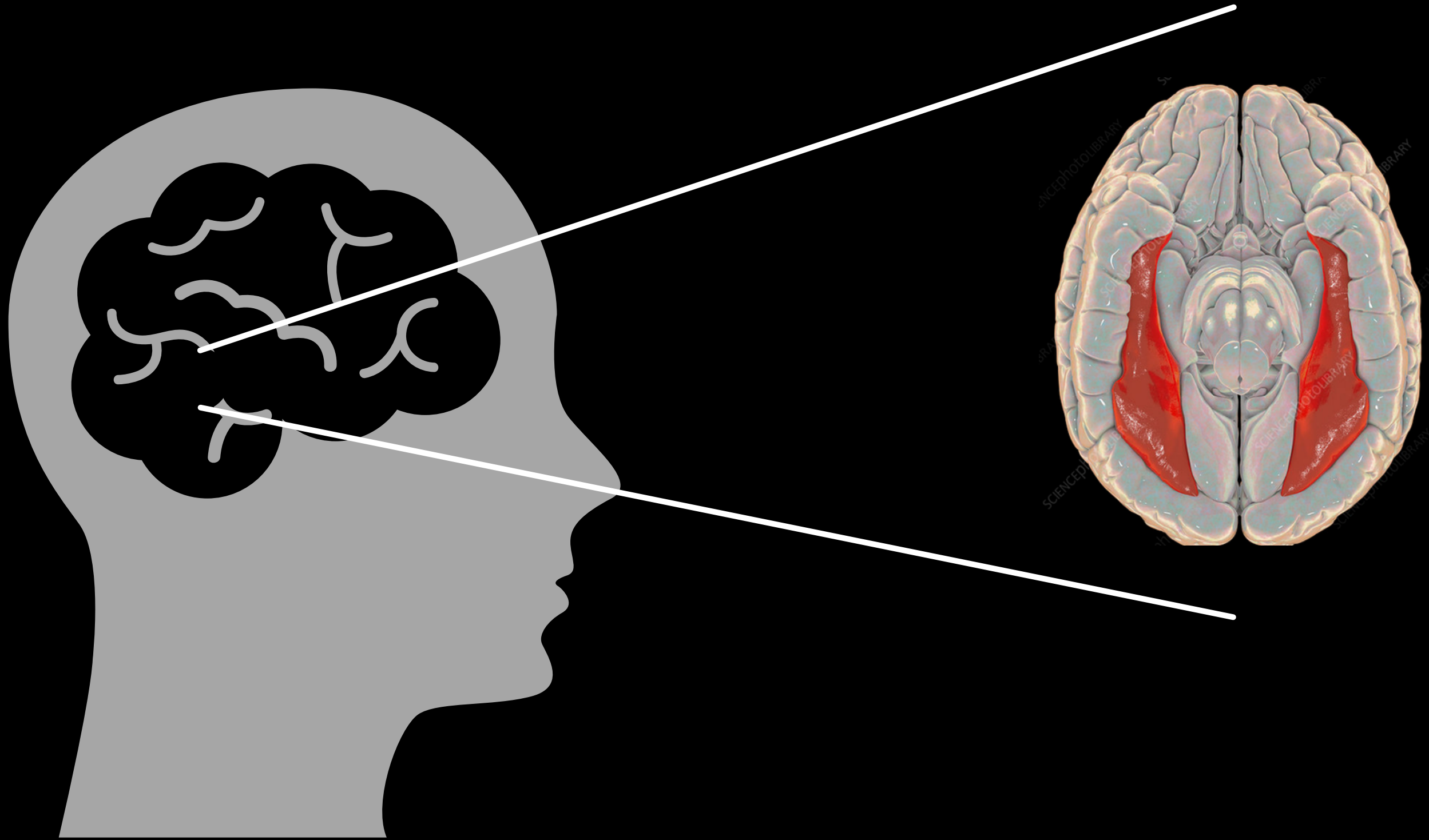




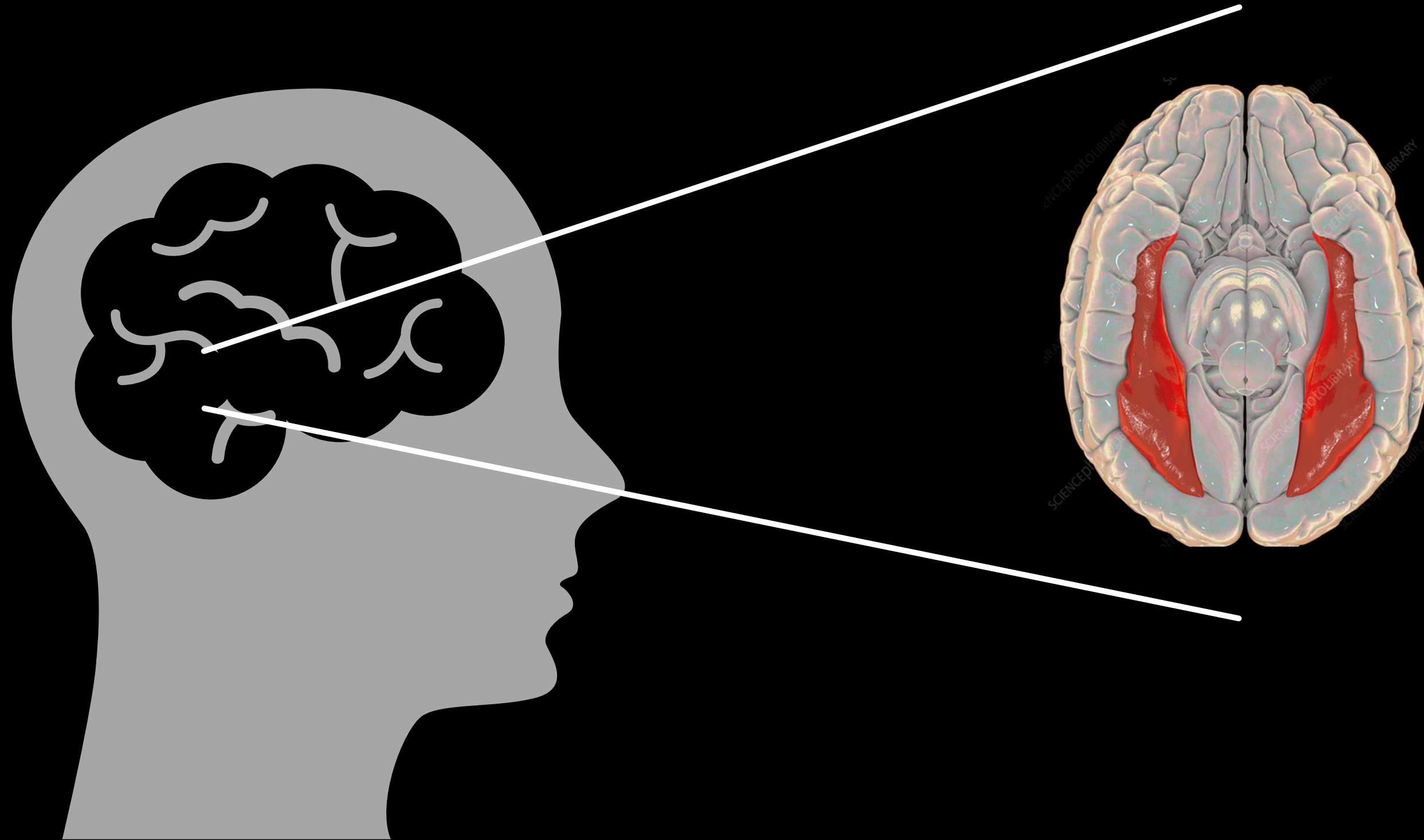












## Fusiform Face Area

(Kanwisher & Yovel, 2006; Miller et al., 2017)













Processing faces is more advantageous than  
processing items in other object categories  
even without visual awareness

(Zhou, Wang, He, & Meng, 2021)





Q

- Can we use our neural activity to classify faces and houses
- with or without visual awareness?

# Hypotheses:

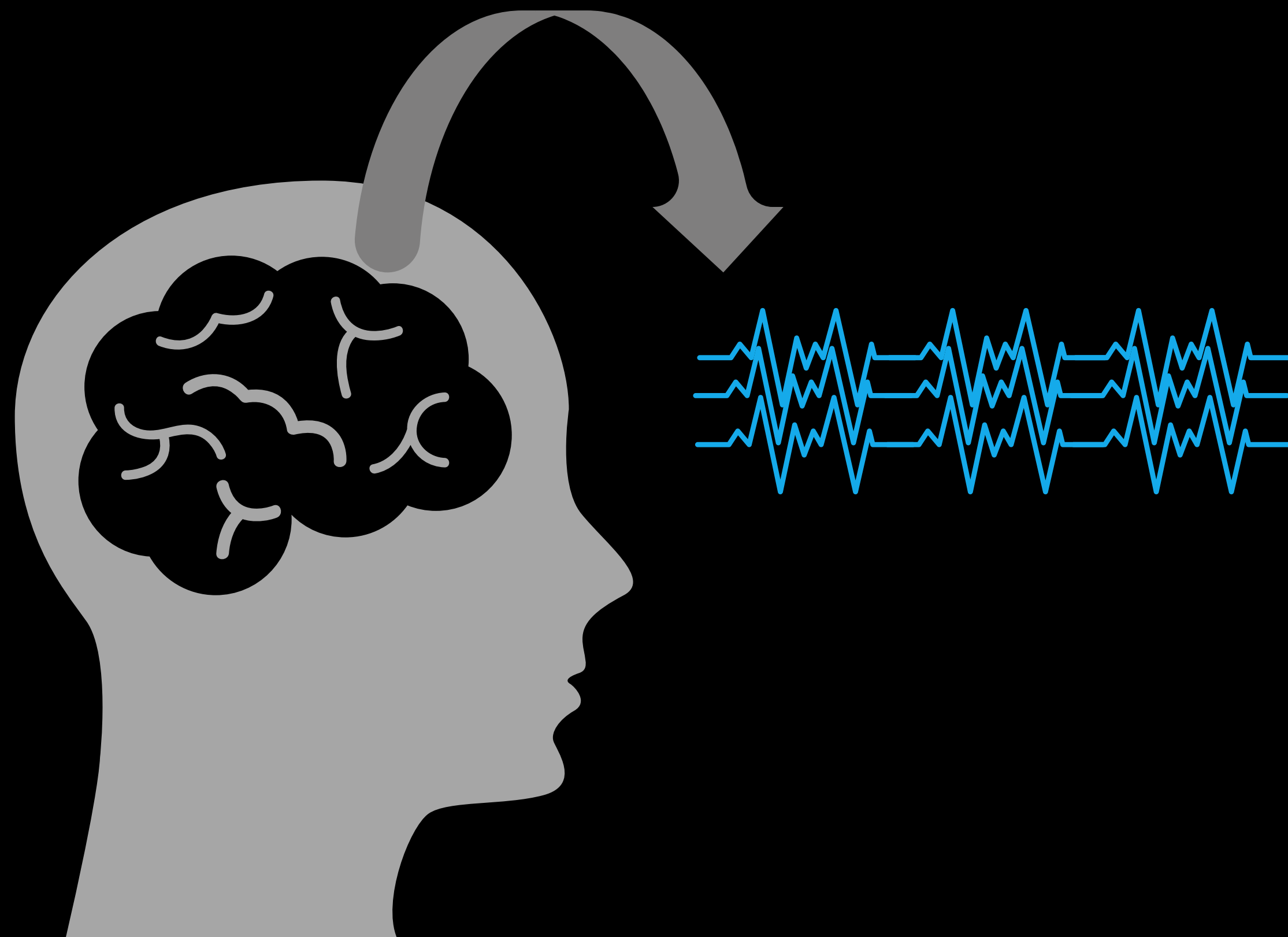
- 1) We hypothesized that neural activity of houses and faces is different even in presence of noise.
- 2) We hypothesized that the amplitude of the neural response would decrease with increasing noise levels.
- 3) Add noise feature would help to classify the images better

# Experiment 1 - Localiser Task

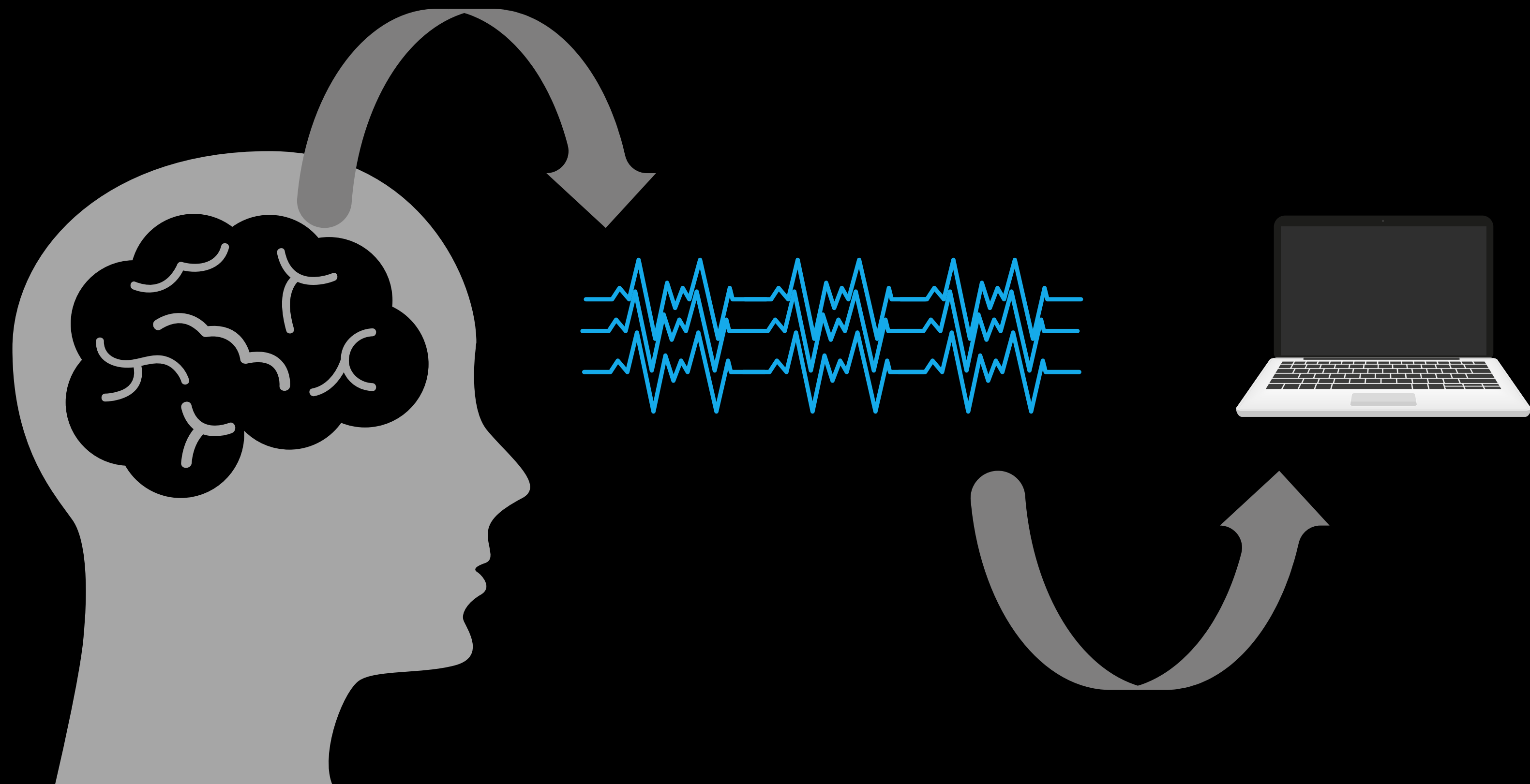


## Experiment 2 - Noisy Dataset



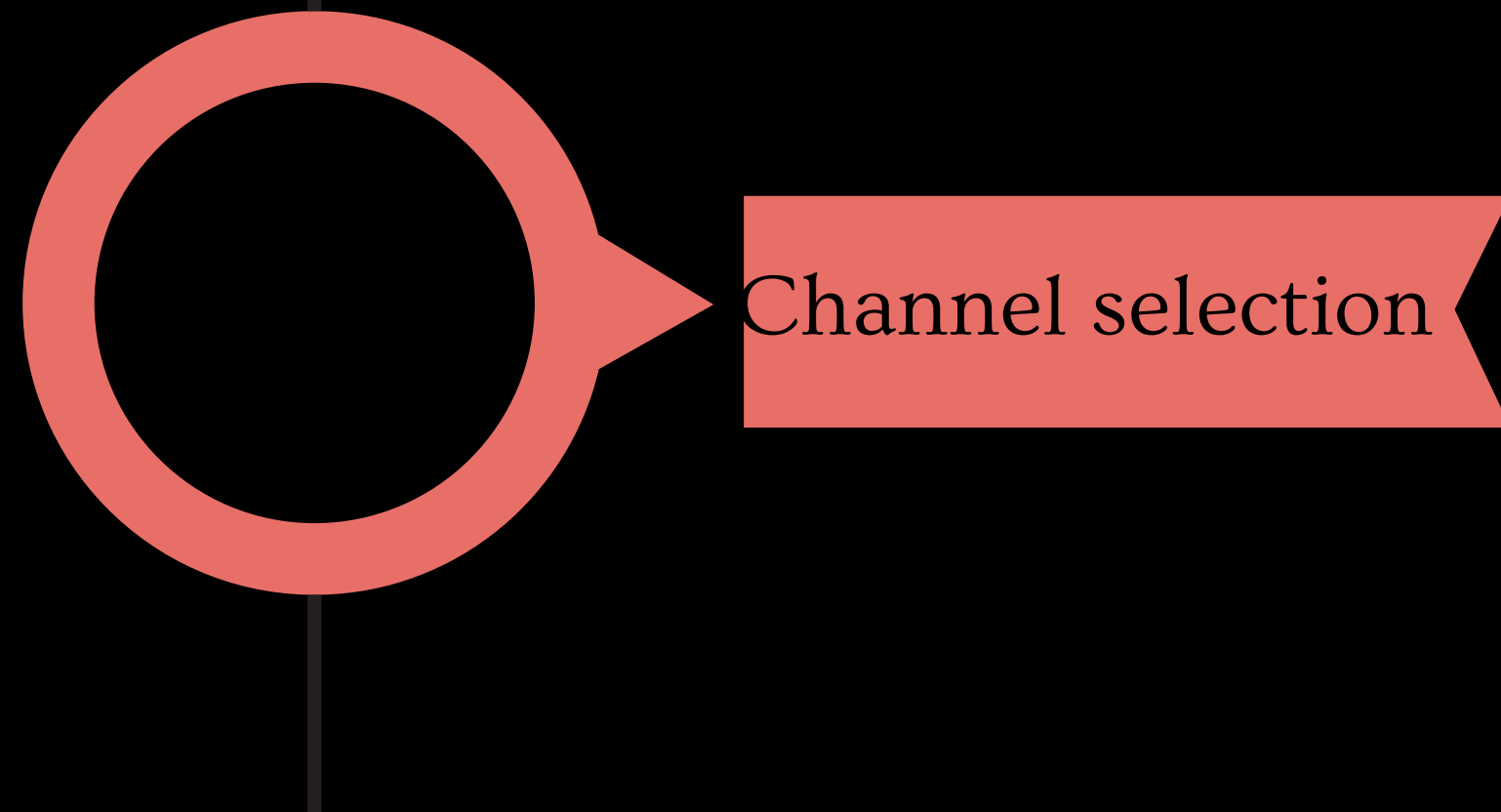


ECoG Recordings

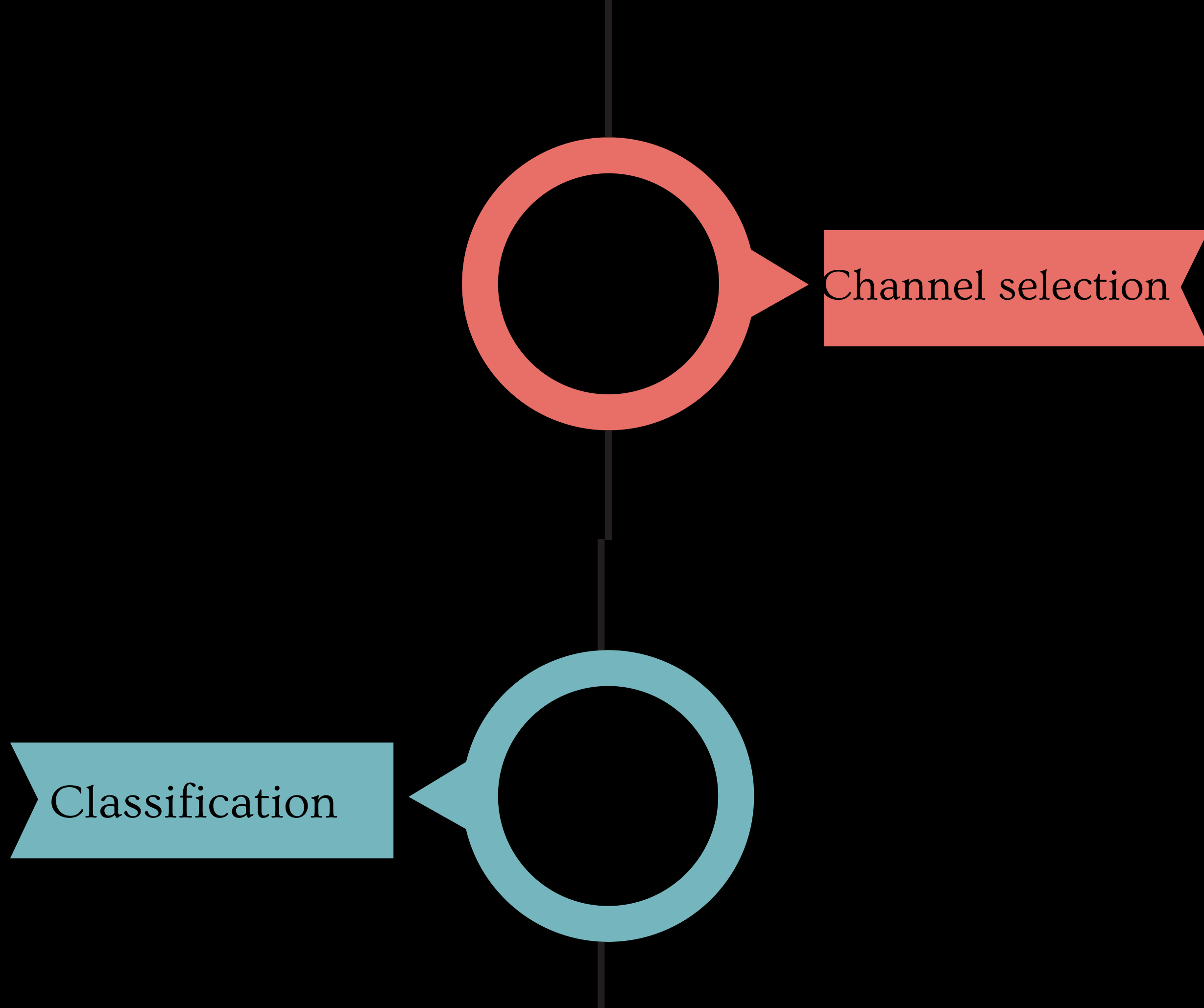


# Hypotheses:

- 1) We hypothesised that neural activity of houses and faces is different even in presence of noise.
- 2) We hypothesized that the amplitude of the neural response would decrease with increasing noise levels.
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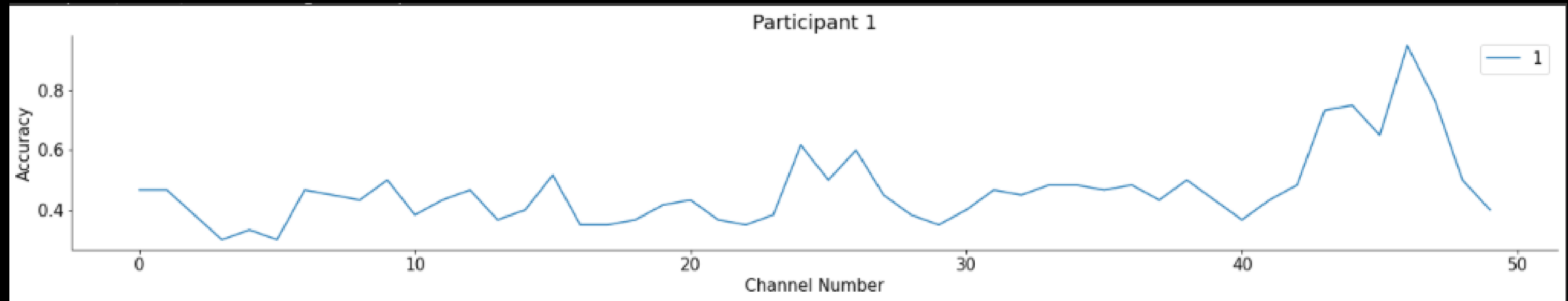




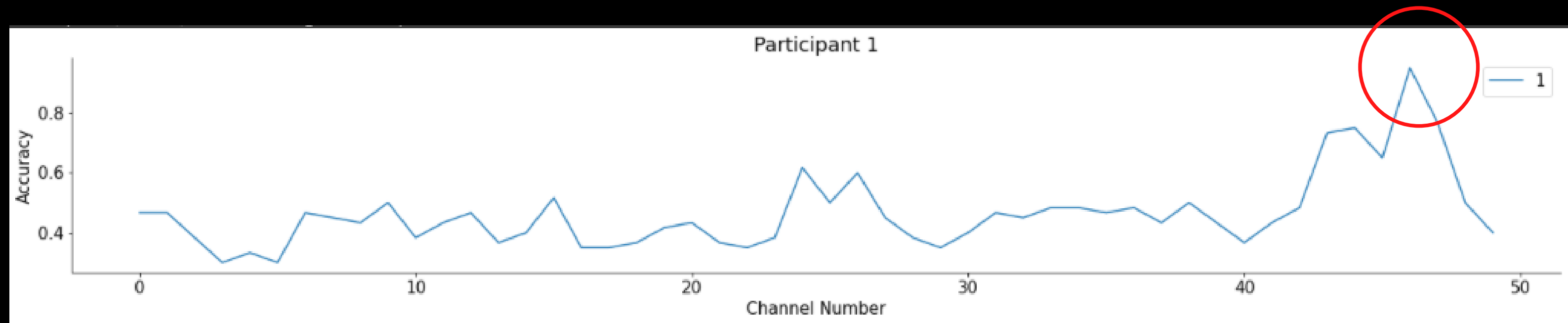
# Experiment 1

Participant	Select Channel	Model	Accuracy	Precision	Recall
0	35	Logistic Regression	0.9166666666666666	0.9310344827586207	0.9
0	35	Naive Bayes	0.8833333333333333	0.896551724137931	0.8666666666666667
0	35	SVM	0.9166666666666666	0.9310344827586207	0.9
1	46	Logistic Regression	0.9166666666666666	0.9375	0.9090909090909091
1	46	Naive Bayes	0.9	0.9090909090909091	0.9090909090909091
1	46	SVM	0.9166666666666666	0.9375	0.9090909090909091
2	35	Logistic Regression	0.9333333333333333	1.0	0.875
2	35	Naive Bayes	0.85	0.896551724137931	0.8125
2	35	SVM	0.9333333333333333	1.0	0.875
3	23	Logistic Regression	0.9166666666666666	0.9230769230769231	0.8888888888888888
3	23	Naive Bayes	0.8166666666666667	0.9	0.6666666666666666
3	23	SVM	0.95	0.9285714285714286	0.9629629629629629
4	15	Logistic Regression	0.95	1.0	0.90625
4	15	Naive Bayes	0.9	0.9642857142857143	0.84375
4	15	SVM	0.95	1.0	0.90625
5	25	Logistic Regression	0.7833333333333333	0.8260869565217391	0.6785714285714286
5	25	Naive Bayes	0.6666666666666666	0.9	0.32142857142857145
5	25	SVM	0.7666666666666667	0.8181818181818182	0.6428571428571429
6	38	Logistic Regression	0.8333333333333334	0.8333333333333334	0.8333333333333334
6	38	Naive Bayes	0.75	0.7586206896551724	0.7333333333333333
6	38	SVM	0.8166666666666667	0.8064516129032258	0.8333333333333334

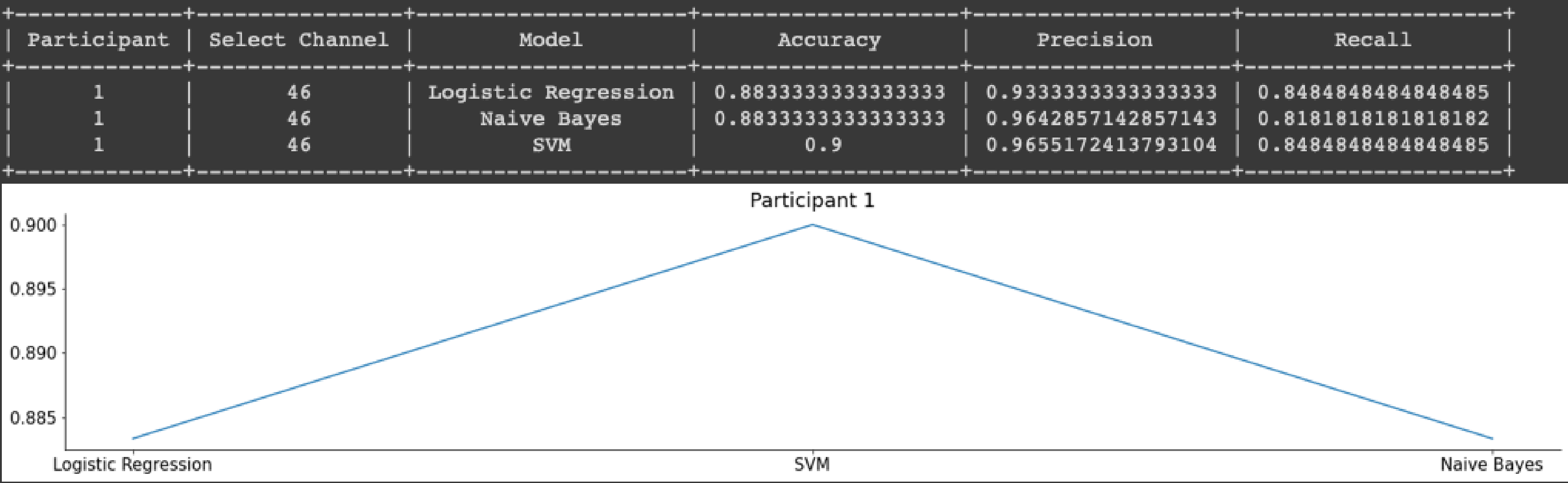
# Experiment 1 - Participant 1



# Experiment 1 - Participant 1



# Experiment 1 - Participant 1

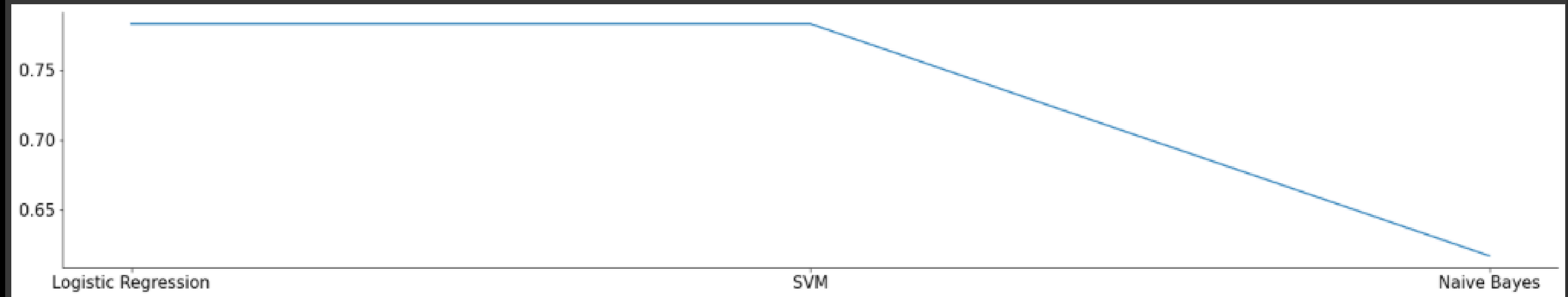


# Experiment 2(+Noise 0-45% )

Participant	Select Channel	Model	Accuracy	Precision	Recall
0	35	Logistic Regression	0.7333333333333333	0.5909090909090909	0.65
0	35	Naive Bayes	0.7833333333333333	0.7058823529411765	0.6
0	35	SVM	0.7833333333333333	0.6842105263157895	0.65
1	46	Logistic Regression	0.7666666666666667	0.8	0.75
1	46	Naive Bayes	0.6666666666666666	0.8333333333333334	0.46875
1	46	SVM	0.7833333333333333	0.8275862068965517	0.75
2	35	Logistic Regression	0.8	0.8421052631578947	0.64
2	35	Naive Bayes	0.7833333333333333	0.9285714285714286	0.52
2	35	SVM	0.8	0.8421052631578947	0.64
3	23	Logistic Regression	0.9	0.8571428571428571	0.9230769230769231
3	23	Naive Bayes	0.8833333333333333	0.9130434782608695	0.8076923076923077
3	23	SVM	0.9	0.8846153846153846	0.8846153846153846
4	15	Logistic Regression	0.6333333333333333	0.5833333333333334	0.75
4	15	Naive Bayes	0.6	0.5666666666666667	0.6071428571428571
4	15	SVM	0.65	0.6	0.75
5	30	Logistic Regression	0.7333333333333333	0.7391304347826086	0.6296296296296297
5	30	Naive Bayes	0.7	0.7368421052631579	0.5185185185185185
5	30	SVM	0.8	0.7777777777777778	0.7777777777777778
6	42	Logistic Regression	0.4	0.48	0.34285714285714286
6	42	Naive Bayes	0.4	0.47619047619047616	0.2857142857142857
6	42	SVM	0.45	0.5384615384615384	0.4

# Experiment 2(+Noise 0-45% ) - Participant 1

Participant	Select Channel	Model	Accuracy	Precision	Recall
1	46	Logistic Regression	0.7833333333333333	0.7727272727272727	0.68
1	46	Naive Bayes	0.6166666666666667	0.55	0.44
1	46	SVM	0.7833333333333333	0.7727272727272727	0.68

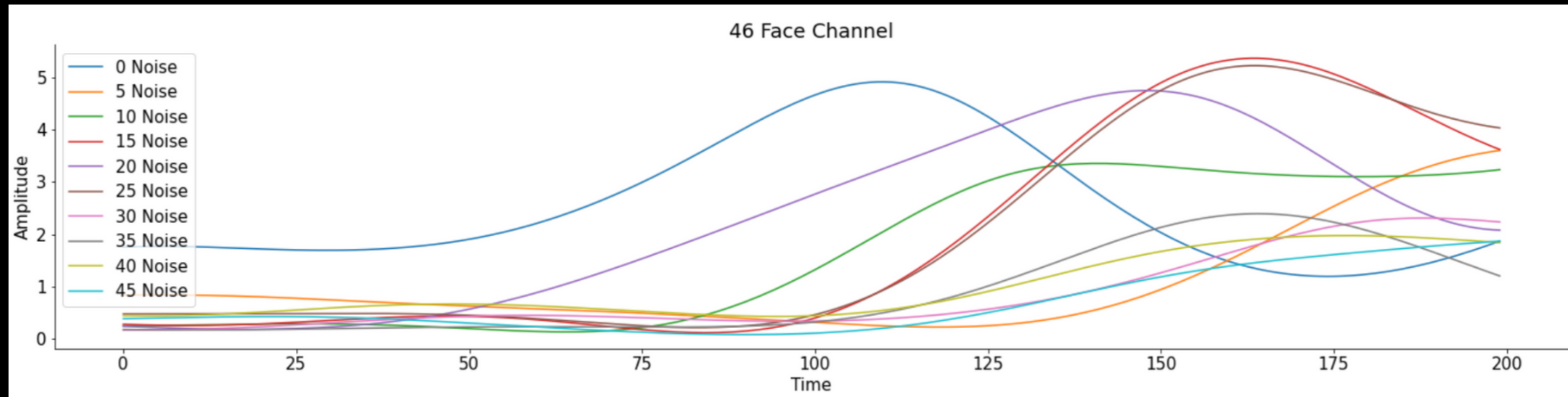


# Hypotheses:

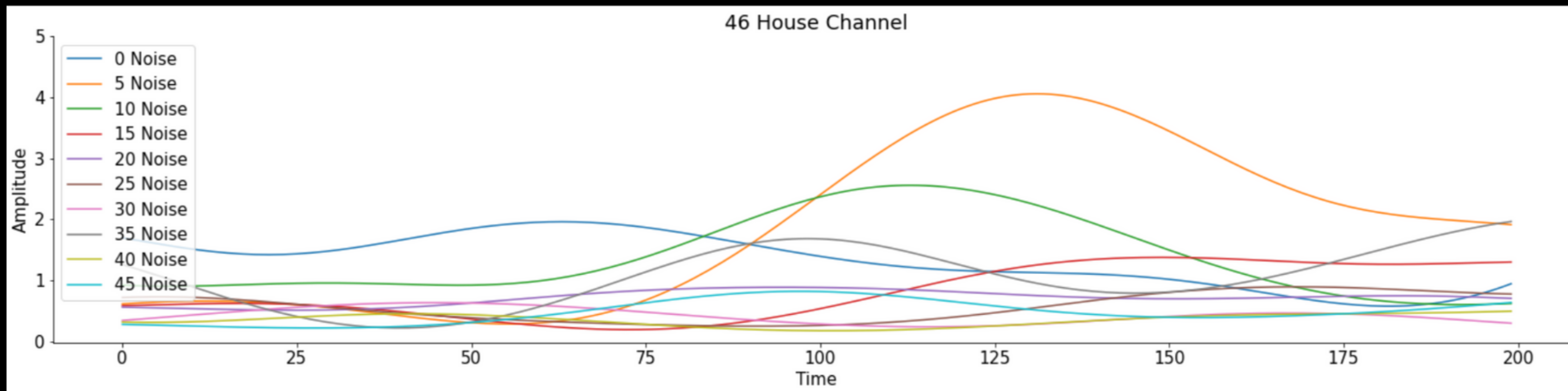
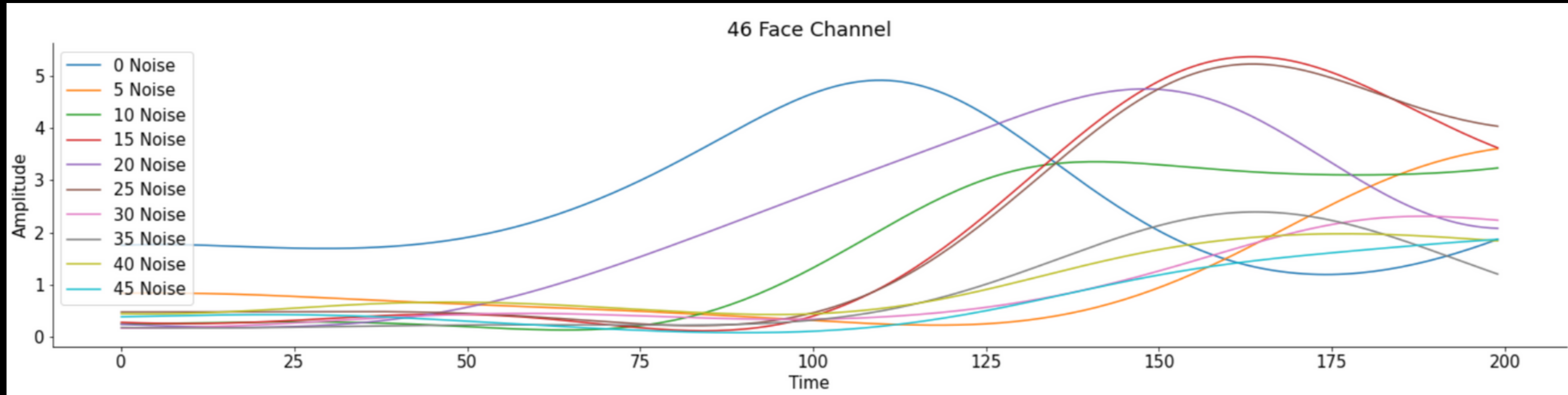
- 1) We hypothesised that neural activity of houses and faces is different even in presence of noise.
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# Experiment 2(+Noise 0-45% ) - Participant 1



# Experiment 2(+Noise 0-45% ) - Participant 1



# Hypotheses:

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# Experiment 2(+Noise 0-45% )

Participant	Select Channel	Model	Accuracy	Precision	Recall
0	35	Logistic Regression	0.7333333333333333	0.5909090909090909	0.65
0	35	Naive Bayes	0.7833333333333333	0.7058823529411765	0.6
0	35	SVM	0.7833333333333333	0.6842105263157895	0.65
1	46	Logistic Regression	0.7666666666666667	0.8	0.75
1	46	Naive Bayes	0.6666666666666666	0.8333333333333334	0.46875
1	46	SVM	0.7833333333333333	0.8275862068965517	0.75
2	35	Logistic Regression	0.8	0.8421052631578947	0.64
2	35	Naive Bayes	0.7833333333333333	0.9285714285714286	0.52
2	35	SVM	0.8	0.8421052631578947	0.64
3	23	Logistic Regression	0.9	0.8571428571428571	0.9230769230769231
3	23	Naive Bayes	0.8833333333333333	0.9130434782608695	0.8076923076923077
3	23	SVM	0.9	0.8846153846153846	0.8846153846153846
4	15	Logistic Regression	0.6333333333333333	0.5833333333333334	0.75
4	15	Naive Bayes	0.6	0.5666666666666667	0.6071428571428571
4	15	SVM	0.65	0.6	0.75
5	30	Logistic Regression	0.7333333333333333	0.7391304347826086	0.6296296296296297
5	30	Naive Bayes	0.7	0.7368421052631579	0.5185185185185185
5	30	SVM	0.8	0.7777777777777778	0.7777777777777778
6	42	Logistic Regression	0.4	0.48	0.34285714285714286
6	42	Naive Bayes	0.4	0.47619047619047616	0.2857142857142857
6	42	SVM	0.45	0.5384615384615384	0.4

# Experiment 2(+Noise as a feature 0-45%)

Participant	Select Channel	Model	Accuracy	Precision	Recall
0	35	Logistic Regression	0.8	0.7931034482758621	0.7931034482758621
0	35	Naive Bayes	0.7833333333333333	0.8636363636363636	0.6551724137931034
0	35	SVM	0.7833333333333333	0.8076923076923077	0.7241379310344828
1	46	Logistic Regression	0.7666666666666667	0.7777777777777778	0.7241379310344828
1	46	Naive Bayes	0.6833333333333333	0.7083333333333334	0.5862068965517241
1	46	SVM	0.7666666666666667	0.7777777777777778	0.7241379310344828
2	35	Logistic Regression	0.8166666666666667	0.8461538461538461	0.7586206896551724
2	35	Naive Bayes	0.8	0.84	0.7241379310344828
2	35	SVM	0.8	0.84	0.7241379310344828
3	23	Logistic Regression	0.7833333333333333	0.8333333333333334	0.6896551724137931
3	23	Naive Bayes	0.7333333333333333	0.8095238095238095	0.5862068965517241
3	23	SVM	0.75	0.8181818181818182	0.6206896551724138
4	15	Logistic Regression	0.85	0.8571428571428571	0.8275862068965517
4	15	Naive Bayes	0.8333333333333334	0.8518518518518519	0.7931034482758621
4	15	SVM	0.8166666666666667	0.8214285714285714	0.7931034482758621
5	30	Logistic Regression	0.9666666666666667	0.9655172413793104	0.9655172413793104
5	30	Naive Bayes	0.9666666666666667	0.9655172413793104	0.9655172413793104
5	30	SVM	0.9666666666666667	0.9655172413793104	0.9655172413793104
6	42	Logistic Regression	0.6833333333333333	0.7083333333333334	0.5862068965517241
6	42	Naive Bayes	0.7	0.7619047619047619	0.5517241379310345
6	42	SVM	0.7	0.7619047619047619	0.5517241379310345



# Limitations

- We don't have keypress values for the house stimuli.

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- Due to time constraints we could not consider only hit trials for training the model.



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- Due to time constraints we could not consider only hit trials for training the model.
- We could not find a definite noise range as a threshold to distinguish houses and faces

# Reference

- Kanwisher, N., & Yovel, G. (2006). The fusiform face area: a cortical region specialized for the perception of faces. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 361(1476), 2109–2128. doi:10.1098/rstb.2006.1934
- Miller, K. J., Hermes, D., Pestilli, F., Wig, G. S., & Ojemann, J. G. (2017). Face percept formation in human ventral temporal cortex. *Journal of Neurophysiology*, 118(5), 2614–2627. doi:10.1152/jn.00113.2017
- Zhou, L. F., Wang, K., He, L., & Meng, M. (2021). Twofold advantages of face processing with or without visual awareness. *Journal of experimental psychology. Human perception and performance*, 10.1037/xhp0000915. Advance online publication. <https://doi.org/10.1037/xhp0000915>