Neuroinformatics Project: Encoding Neural Data

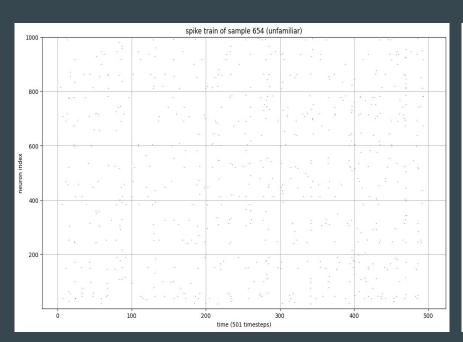
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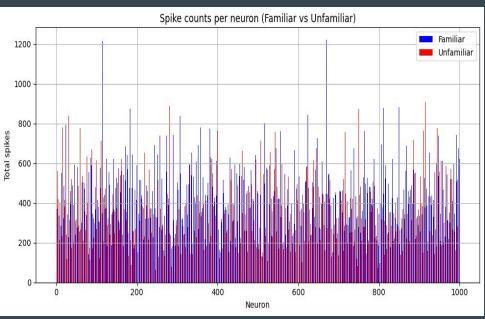
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Overview

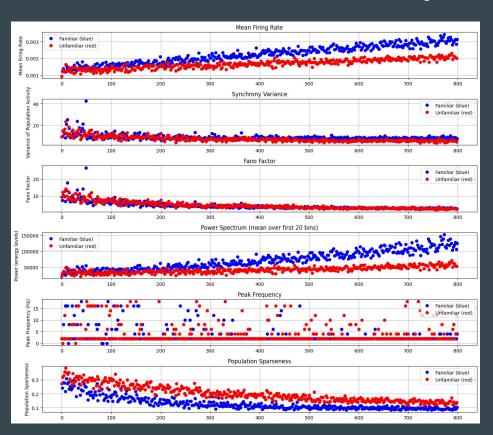
- Data Visualization
- Data Transformation and Exploratory Analysis
- Model Training and Classification
- Model Evaluation
- Model Comparison

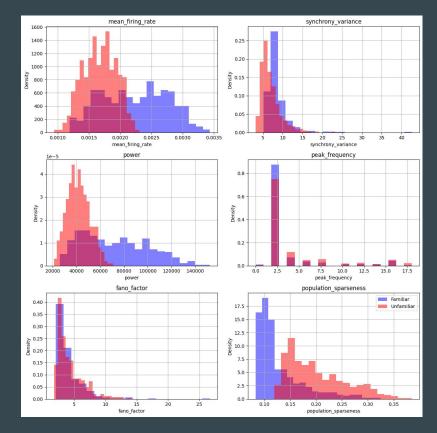
Data Visualization





Data Transformation and Exploratory Analysis





KL Divergence

Feature	KL Divergence		
mean_firing_rate	13.66		
synchrony_variance	0.52		
power	5.30		
peak_frequency	0.04		
fano_factor	0.25		
population sparseness	14.73		

Logistic Regression

$$P(y=1 \mid x) = \sigma egin{pmatrix} w_0 \ + w_1 \cdot ext{mean_firing_rate} \ + w_2 \cdot ext{synchrony_variance} \ + w_3 \cdot ext{power} \ + w_4 \cdot ext{population_sparseness} \end{pmatrix} \ (\sigma(x) = rac{1}{1 + e^{-x}})$$

- Models the probability of a binary outcome
- Applies a sigmoid to a linear combination of features
- Each weight shows how one feature shifts the log-odds

Model Evaluation

The model achieves an acceptable accuracy.

Data is largely linearly separable

The model is efficient, robust, relatively lean, interpretable and easy to implement.

- Average CV-Accuracy: 0.955 ± 0.027
- Confusion Matrix:

[[88 1] [5 66]]

- F1- Score: 0.956522
- Precision Familiar Samples: 0.985075
- Precision Unfamiliar Samples: 0.946237

Model Comparison

k-Nearest Neighbors (k-NN)

- classifies samples based on the majority class among their k closest neighbors
- good for: data with clear local clusters and nonlinear boundaries

Linear Discriminant Analysis (LDA)

- projects data onto a lower-dimensional space that best separates the classes
- good for well-separated classes and when features follow Gaussian distributions

Random Forest

- based on decision trees
- good for capturing nonlinear patterns
- more human-interpretable but slower to train than linear models

Regularized Least Squares (Ridge

Regression)

- linear
- good for high-dimensional data and collinear features

Model Comparison

Model	Accuracy	F1 Score	Precision F	Precision UF
Random Forest	0.971875	0.969900	0.986395	0.959538
Poly Logistic Regression	0.968750	0.966887	0.973333	0.964706
LDA	0.965625	0.962963	0.986207	0.948571
Ridge	0.965625	0.962963	0.986207	0.948571
Logistic Regression	0.962500	0.959732	0.979452	0.948276
k-NN	0.959375	0.955631	0.992908	0.932961
	Random Forest Poly Logistic Regression LDA Ridge Logistic Regression	Random Forest 0.971875 Poly Logistic Regression 0.968750 LDA 0.965625 Ridge 0.965625 Logistic Regression 0.962500	Random Forest 0.971875 0.969900 Poly Logistic Regression 0.968750 0.966887 LDA 0.965625 0.962963 Ridge 0.965625 0.962963 Logistic Regression 0.962500 0.959732	Random Forest0.9718750.9699000.986395Poly Logistic Regression0.9687500.9668870.973333LDA0.9656250.9629630.986207Ridge0.9656250.9629630.986207Logistic Regression0.9625000.9597320.979452

Results

Random Forest outperforms all other models.

Polynomial Logistic Regression is in the second place showing that non-linear decision boundaries help, but not quite as much as Random Forest's full flexibility

The still strong performance of Logistic Regression suggests that the data is largely linearly separable but there are subtle non-linear patterns that linear models can't fully capture