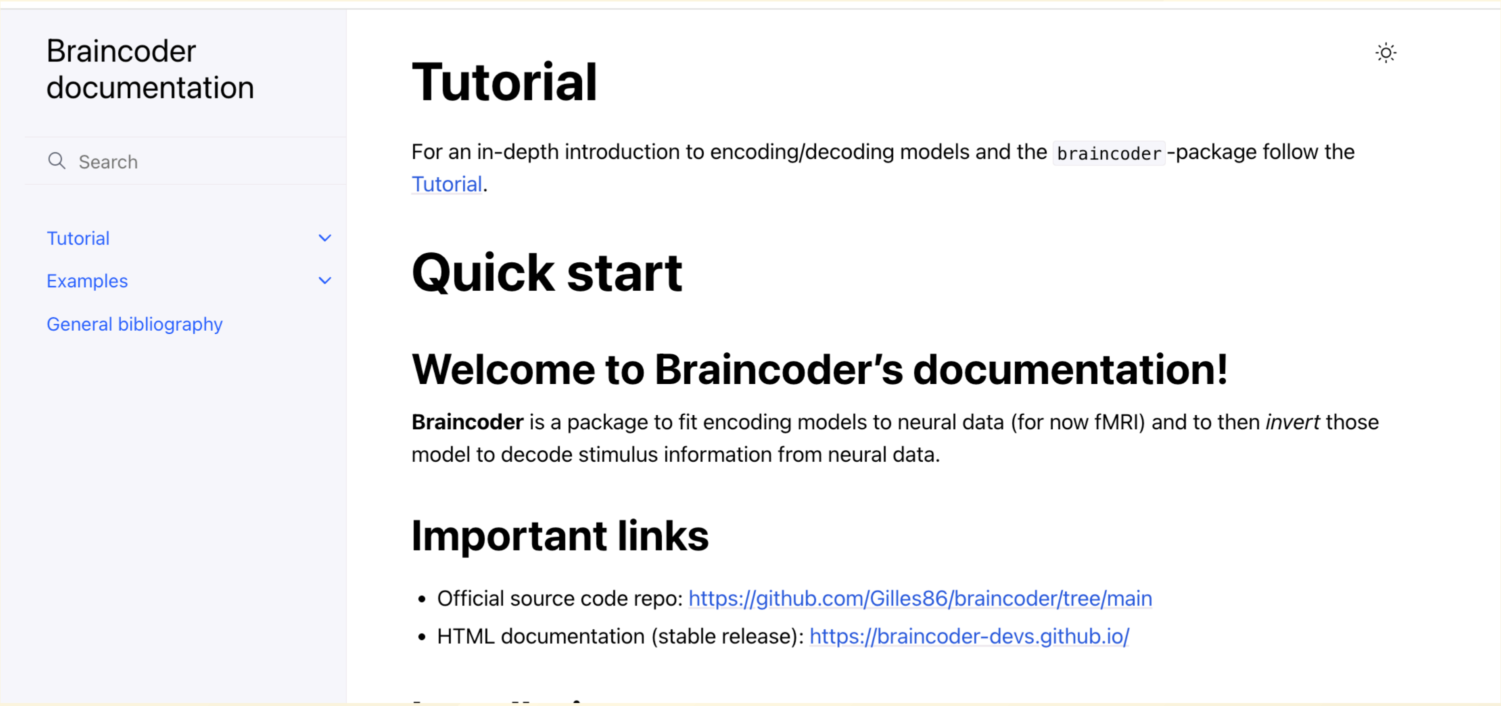
braincoder: (Encoding &) Decoding Neural Data


Braincoder documentation

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Tutorial

For an in-depth introduction to encoding/decoding models and the `braincoder`-package follow the Tutorial.

Quick start

Welcome to Braincoder's documentation!

Braincoder is a package to fit encoding models to neural data (for now fMRI) and to then *invert* those model to decode stimulus information from neural data.

Important links

- Official source code repo: https://github.com/Gilles86/braincoder/tree/main
- HTML documentation (stable release): https://braincoder-devs.github.io/

Gilles de Hollander

Computation in Neuroeconomics seminar, Soglio, Switzerland, 2025

braincoder

- Developed at **University of Amsterdam**, **Spinoza Centre for Neuroimaging** and **UZH**
- **Maintainer**
  - Gilles de Hollander
- **Contributors**
  - Tomas Knapen (UvA/Spinoza Centre for Neuroimaging)
  - Marco Aqil (UvA/Spinoza Centre for Neuroimaging)
  - Maike Renkert (UZH)
- Upcoming paper
- Extensive documentation: braincoder-devs.github.io

braincoder

Key features:

- Massive computationa optimisation thanks to Tensorflow and GPUs
- Ease-of-use
- All standard models implemented
- **Inversion of encoding models**

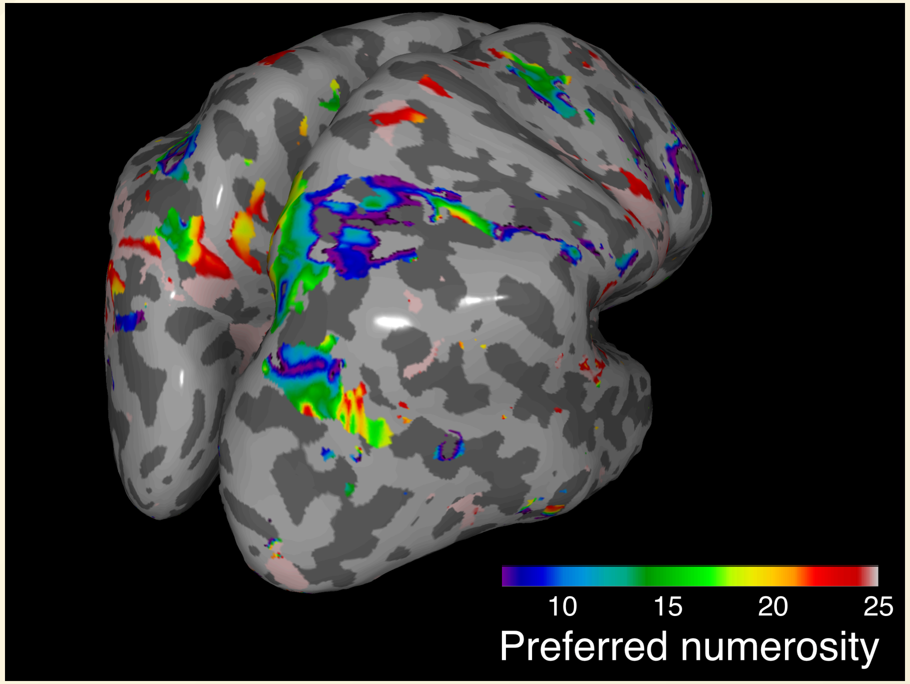
1. Encoding Models: Mapping Stimulus → BOLD

Deterministic mapping:
$f(s;\theta) : s \mapsto y$

- s: Stimulus (e.g., orientation, numerosity, 2D image)
- y: BOLD response (single voxel y or pattern Y)
- θ: Parameters (e.g., PRF center/dispersion, amplitude, baseline)

Example: 1D Gaussian PRF

$$f(s;\boldsymbol{\mu},\sigma,a,b) = a \cdot \mathcal{N}(s;\boldsymbol{\mu},\sigma) + b$$



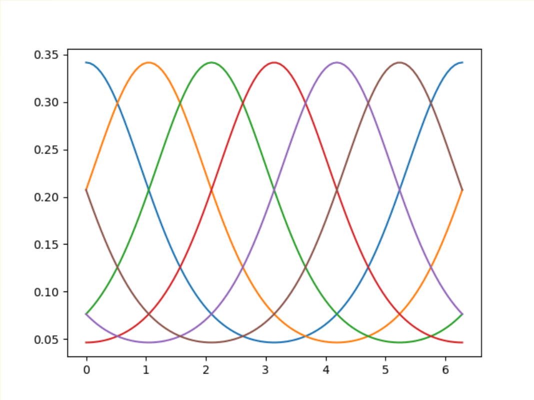
2. Linear Encoding Models

- **"Jehee approach"**
- **Fixed neural populations (fixed θ)** + **linear weights**:

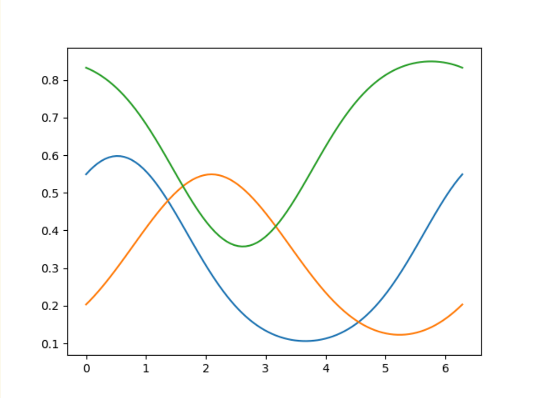
$$x_j = \sum_i W_{i,j} \cdot f_j(\theta_j)$$

- **Advantage**: Fit weights (W) with **linear regression** (fast! Can be done with standard fMRI analyses packages.).
- **Disadvantages**:
  - Parameters are not interpretable
  - Model mispecification?
- **Example**: Von Mises tuning curves for orientation.

Basis Functions



Voxel Predictions



3. Building the Likelihood

- **Add Gaussian noise** to deterministic models:

$$p(x|s;\theta) = f(s;\theta) + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \Sigma)$$

- **Covariance matrix (Σ)**:
  - Regularized estimate (shrinkage + neural population overlap).
  - Accounts for voxel-to-voxel noise correlations.

Key:

- Enables **Bayesian inversion** (stimulus decoding).

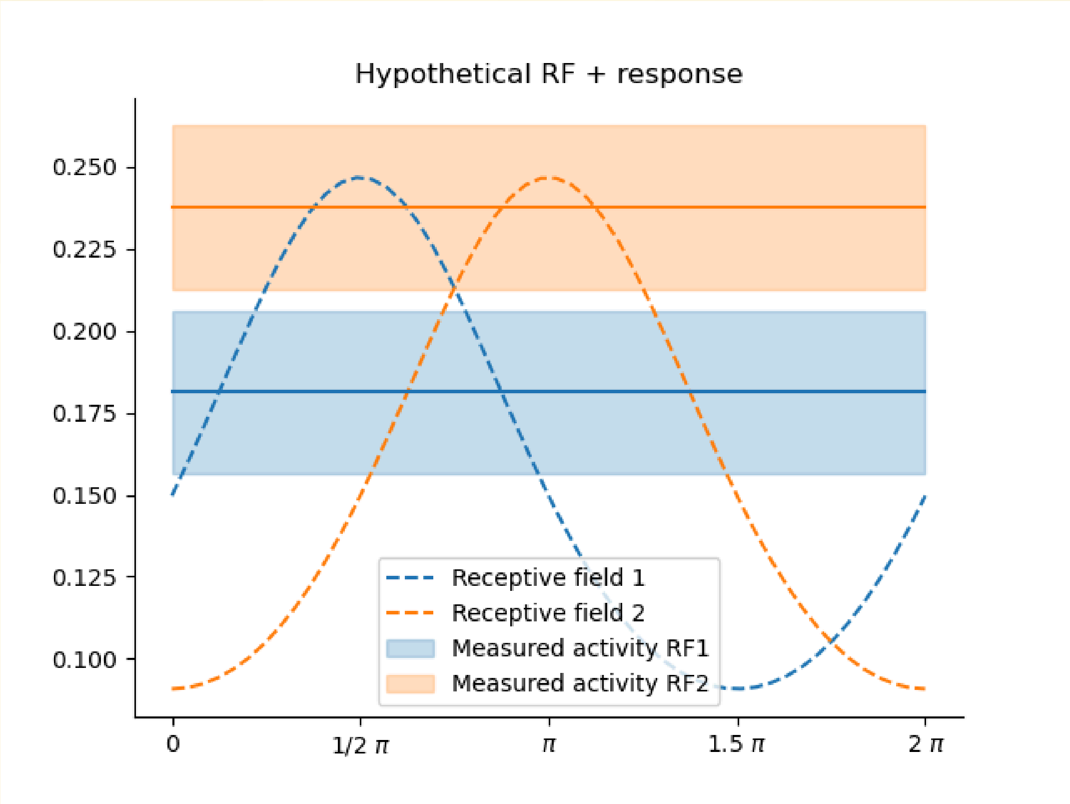
4. From Neural Responses → Stimulus Features

Bayes' Rule:

$$p(s|x, \theta) = \frac{p(x|s, \theta)p(s)}{p(x)}$$

Approach:

- Keep θ and s fixed, and evalute/estimate/sample over s.



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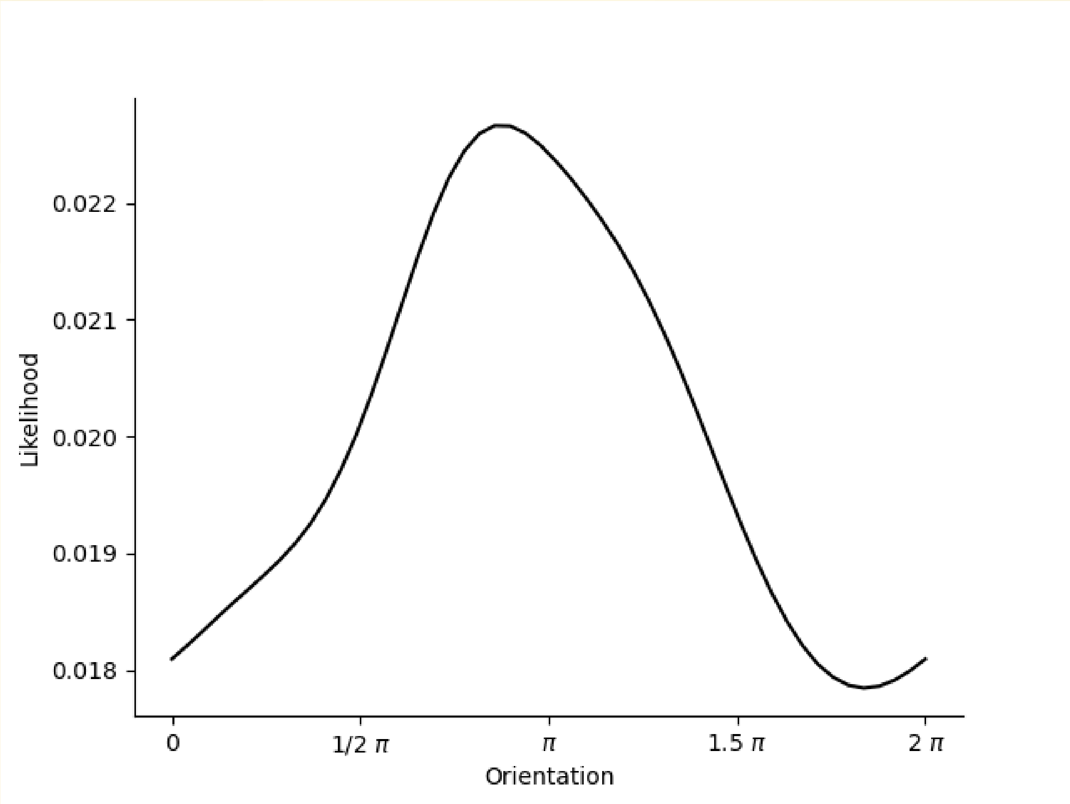

5. Decoding Noisy Neural Data

Steps:

1. Fit encoding model (θ) (grid + gradient descent).
2. Estimate noise covariance (Σ).
3. Compute **posterior** ($p(s|x;\theta)$).
4. Extract **mean posterior** or **MAP estimate**.
5. (Extract **uncertainty** surrounding posterior)

Key Takeaways

- **Encoding**: Map stimuli to BOLD (linear/non-linear models).
- **Decoding**: Invert models using Bayesian inference + noise modeling.
- **Tools**:
  - `braincoder` can do all of this and leverages **TensorFlow** for fast, GPU-accelerated fitting.

Your Turn:

- Try fitting a PRF model to your own data!

Example code for PRF fit

```
from braincoder.models import GaussianPRF2DWithHRF
from braincoder.hrf import SPMHRFModel
from braincoder.optimize import ParameterFitter

# Set up model, including HRF
hrf_model = SPMHRFModel(tr=1.7)
model = GaussianPRF2DWithHRF(grid_coordinates=grid_coordinates, hrf_model=hrf_model)

# Set up fitter
fitter = ParameterFitter(data=v1_ts, model=model, paradigm=stimulus)

# Define grid search parameters
mu_x = np.linspace(-3, 3, 20, dtype=np.float32)
mu_y = np.linspace(-3, 3, 20, dtype=np.float32)
sigma = np.linspace(0.1, 5, 20, dtype=np.float32)
baselines = [0.0]
amplitudes = [1.0]

# Do grid search using correlation cost (so baseline and amplitude do not matter)
grid_pars = fitter.fit_grid(mu_x, mu_y, sigma, baselines, amplitudes, use_correlation_cost=True)

 # Refine baseline and amplitude using OLS
grid_pars = fitter.refine_baseline_and_amplitude(grid_pars)
gd_pars = fitter.fit(init_pars=grid_pars)
```

Assigment 4: Decoding visual stimuli

Open `notebooks/4_decode.ipynb`.