Anatomically-aligned neural processing of the IBL task

a cross-region analysis of the neural responses

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Motivation

Understanding how brain areas collaborate to perform a task is a central yet complex question in neuroscience.

A study of connection patterns shows cortical areas are organized in a shallow hierarchy with modular community structure[Harris et al., Nature 2019].

We wonder: are these two anatomical organization principles reflected in neural responses or not?

Approach

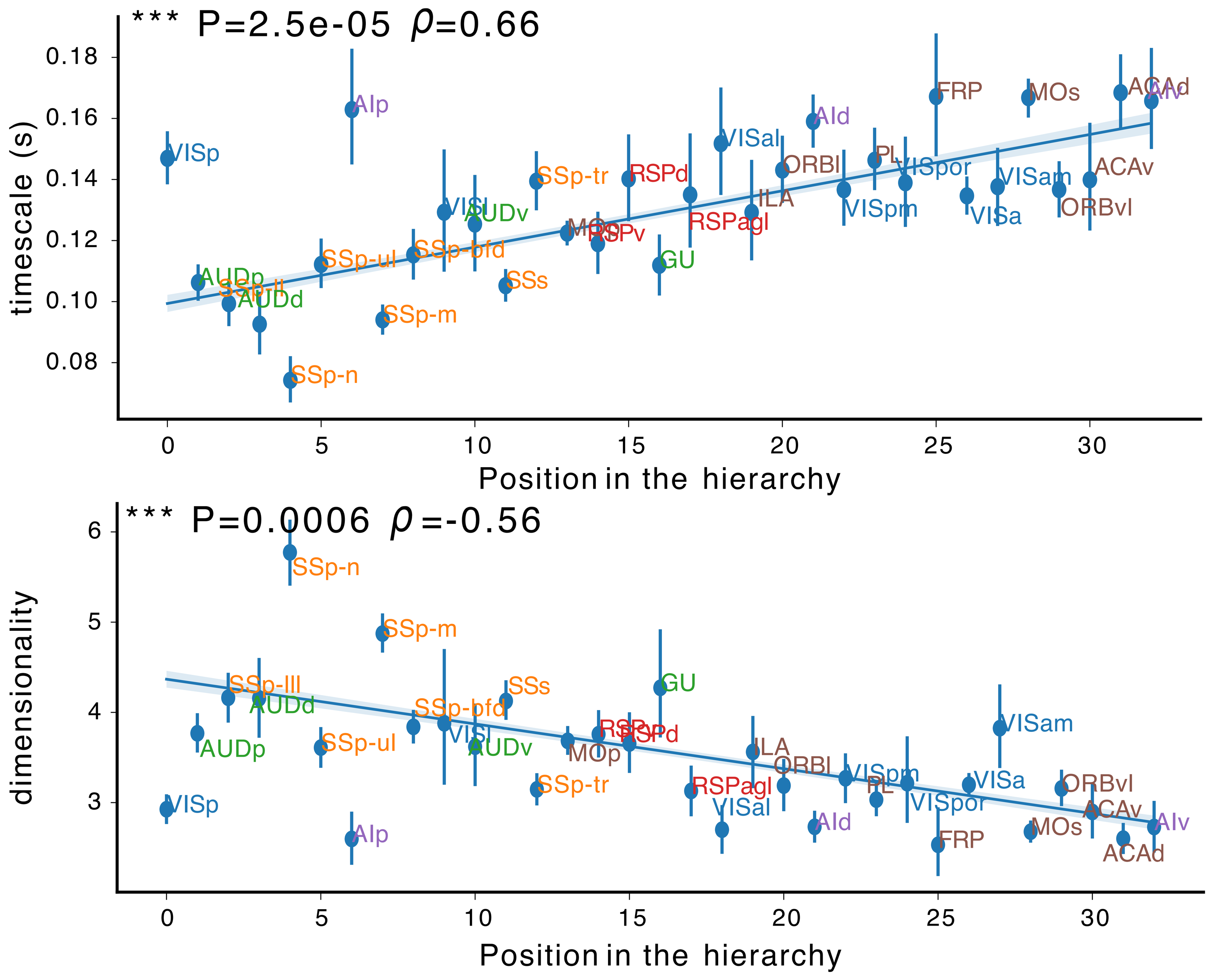
We used IBL brainwide map data.

We developed an efficient linear encoding model to capture the single-neuron, input-driven responses.

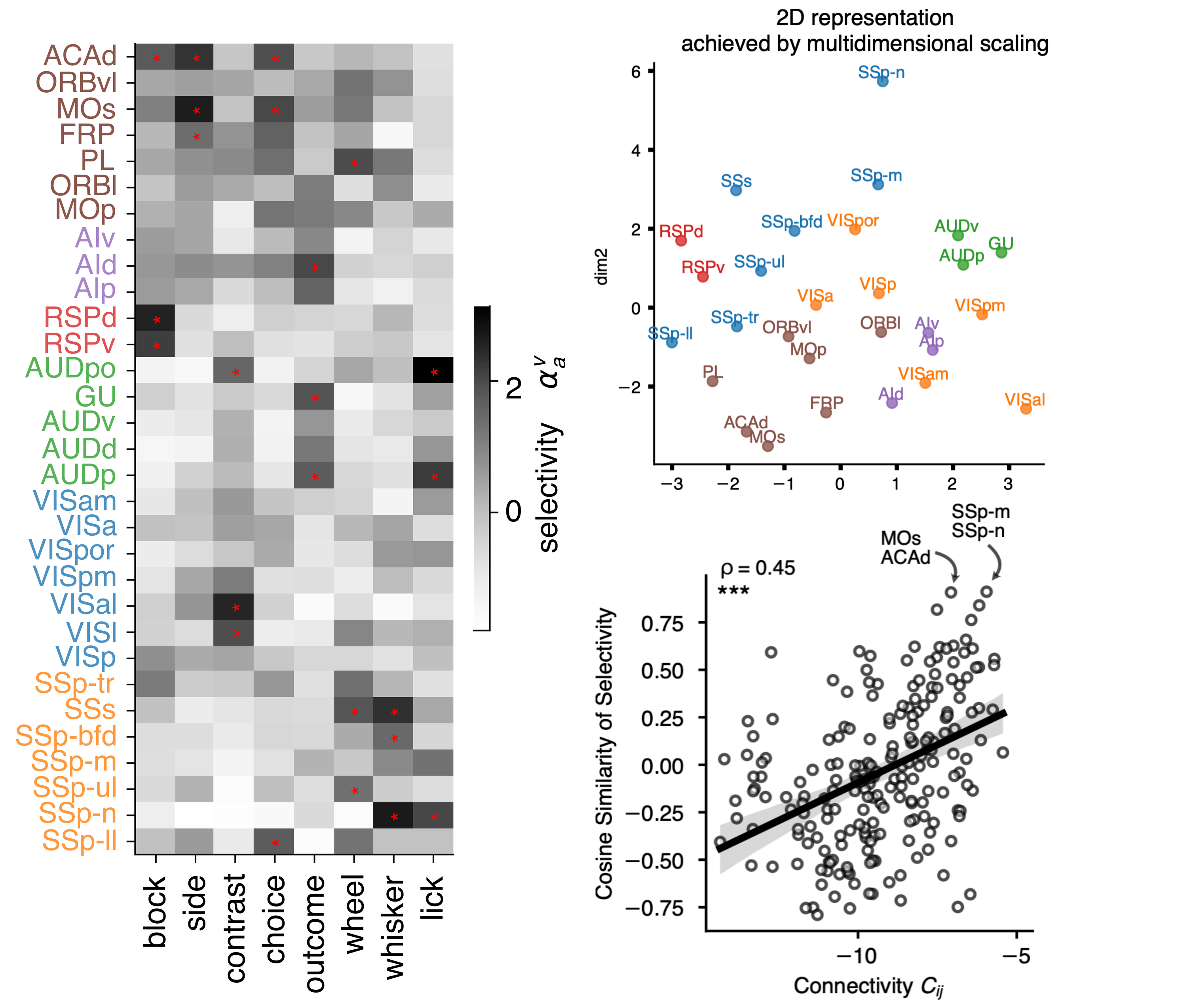
And then we correlated the resulting quantities with the underlying anatomical structures.

Results

(a) Timescales and dimensionality of the input-driven responses correlate with the anatomical hierarchy.



(b) Functional segregation are found aligning with the anatomical modular structure.



A brainwide reduced-rank regression encoding model

data normalised neural response · model estimated input-driven neural response · behavior data

$$y_n(k,t) \approx \hat{y}_n(k,t) = \sum_v \beta^v_n(t)\, x^v(k,t)$$

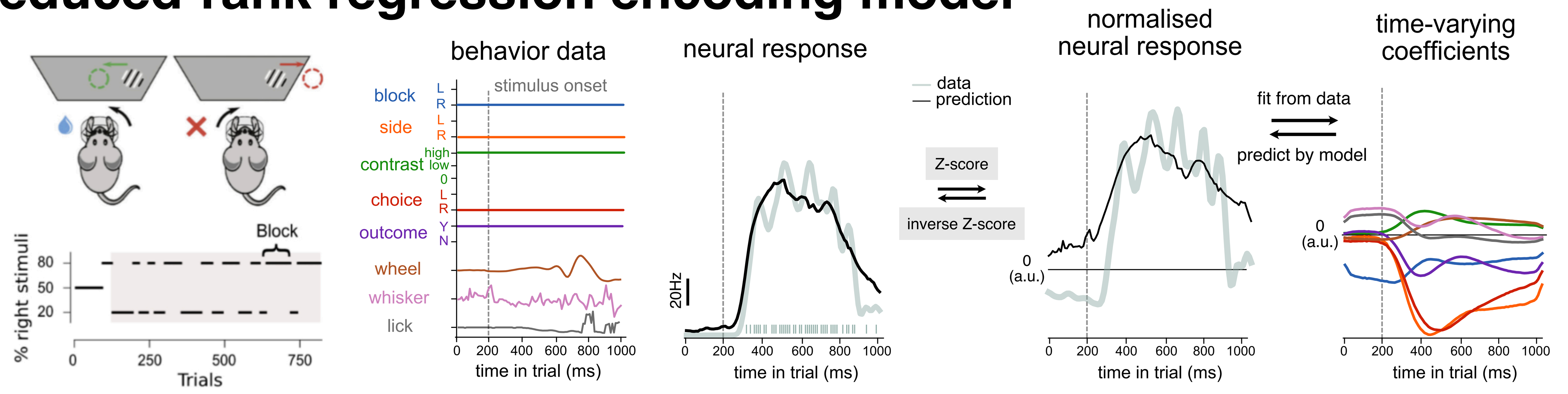
$$\boldsymbol{\beta}^v_n = \boldsymbol{U}^v_n \boldsymbol{V} \qquad \boldsymbol{U}^v_n \in \mathbb{R}^d;\ \boldsymbol{V} \in \mathbb{R}^{d\times T}$$

$\boldsymbol{V}$: shared across all input variables and all neurons

$:= (\beta^v_n(t_1), \beta^v_n(t_2), \cdots \beta^v_n(t_T))$

v: input variable
n: neuron index
k: trial index
t: time index

d: rank
T: time steps

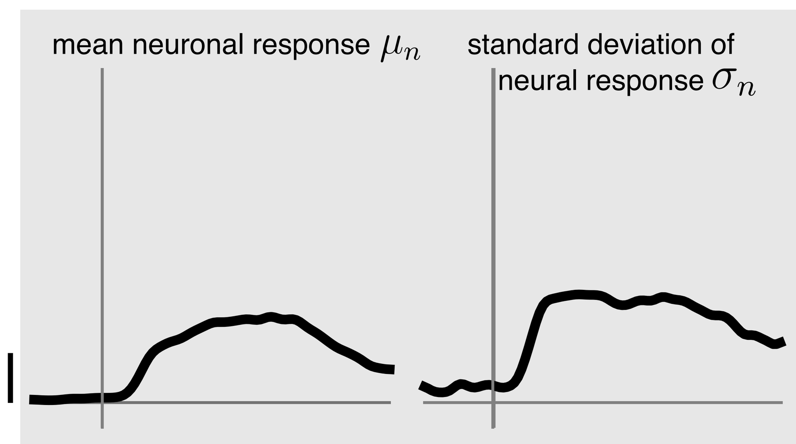


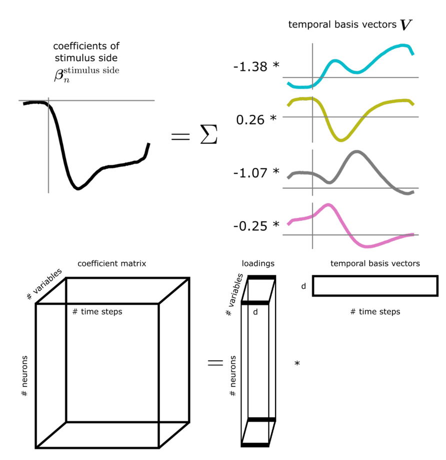
Resulting quantities and their Interpretation

$\hat{y}_n(k,t)$: input-driven neural response ⟶ timescale, dimensionality

ΔR^2: modulation of all the input variables combined

$\beta^v_n(t)$: modulation of the input variable v ⟶ selectivity



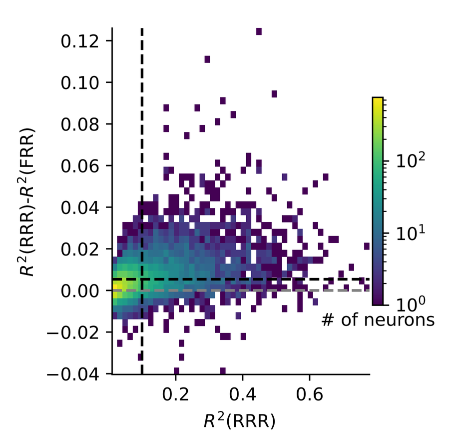


Comparison to other encoding models

full-rank regression (FRR)

$$\hat{y}_n(k,t) = \sum_v \beta^v_n(t)\, x^v(k,t)$$

Note:
β unconstrained.



general linear model (GLM)

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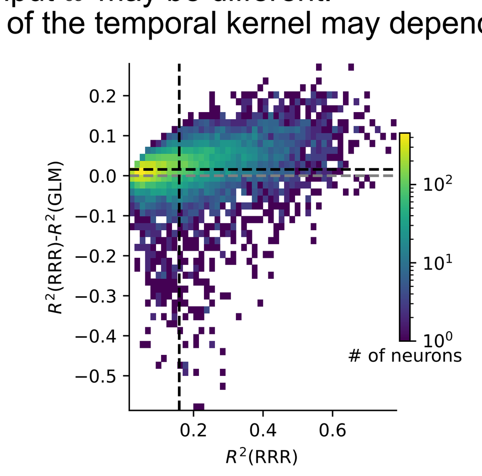
$$\hat{y}_n(k,t) = \sum_v \sum_{t'} \beta^v_n(t')\, x^v(k,t-t')$$

$$\boldsymbol{\beta}^v_n = \boldsymbol{U}^v_n \boldsymbol{\kappa}^v \quad := (\beta^v_n(t_1), \cdots \beta^v_n(t'))$$

Note:
The instantaneous neural response is modelled as the weighted sum of inputs of a neighboring time window.
β is in dependent of t.
κ, the temporal kernel, is pre-specified and not trained.
The encoding of the input x may be different.
The rank and window of the temporal kernel may depend on the input variable.



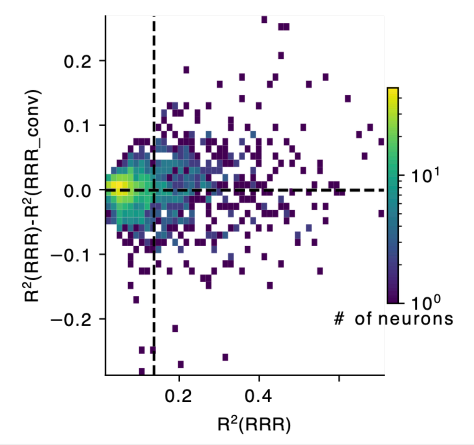
reduced-rank regression (RRR_conv)

Steinmetz et al., Nature 2019

$$\hat{y}_n(k,t) = \sum_v \sum_{t'} \beta^v_n(t')\, x^v(k,t-t')$$

$$\boldsymbol{\beta}^v_n = \boldsymbol{U}^v_n \boldsymbol{V}^v \quad := (\beta^v_n(t_1), \cdots \beta^v_n(t'))$$

Note:
The shared temporal basis vectors $\boldsymbol{V}^v$ are learned.
Others remain the same as GLM.



multi-task neural network (mtnn)

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