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Questions?

A novel approach to characterizing the visual dimensions of mental imagery vividness using Gaussian process regression

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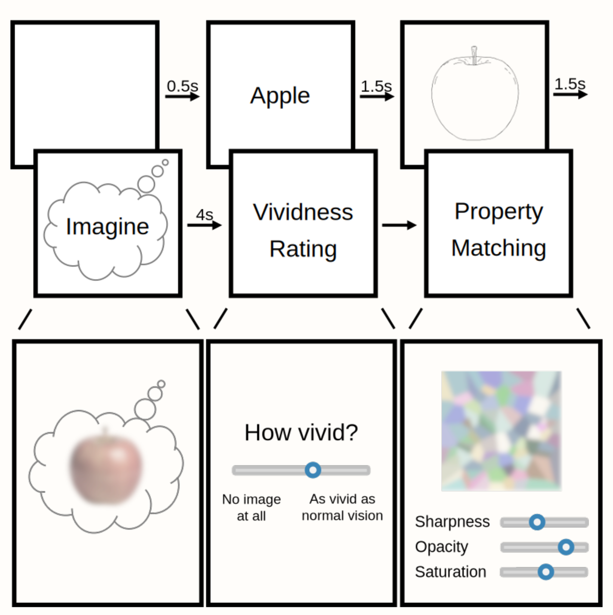
(1) How to characterise vividness?

Huang et al. (2025) used linear regression to reveal evidence of common structure in 'vividness' & large individual differences.

Current aims

(1) Move beyond the parametric assumptions of linear models
(2) Characterise individual differences in a principled manner

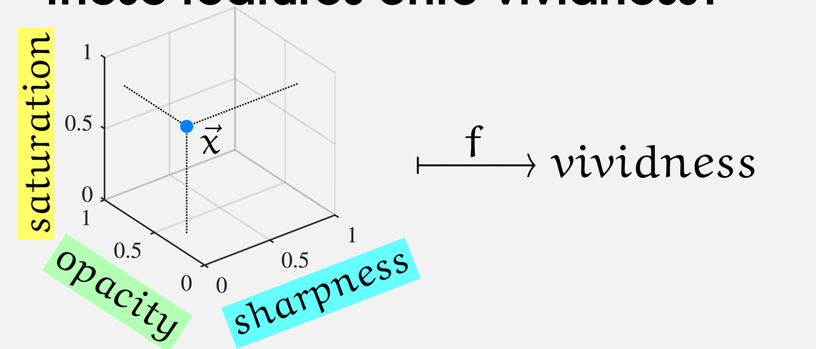
(2) Data and problem formulation



Adapted from Huang et al. (2025)

Vividness ratings (1 − 5 continuous scale)
Perceptual features (0 − 1 continuous scale): sharpness, opacity, saturation

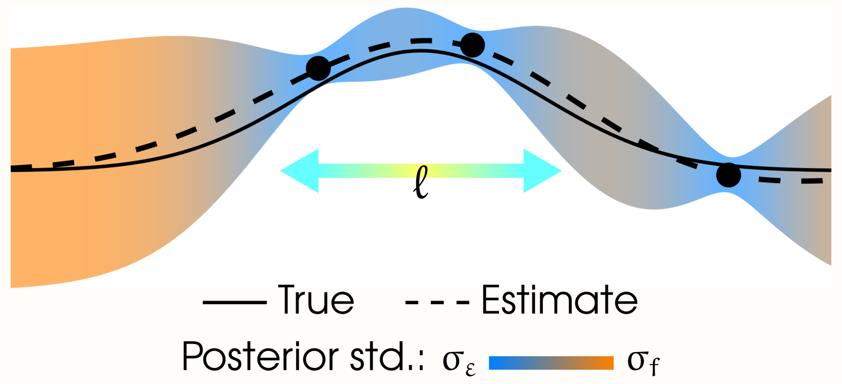
What is the function $f(\cdot)$ that maps these features onto vividness?



(3) What are Gaussian processes?

Setup: N observations y_i of $f(\cdot)$ at input locations $\vec{x}_i$ such that $y_i = f(\vec{x}_i) + \varepsilon_i$

Core idea: Finite sets of evaluations of $f(\vec{x})$ are jointly Gaussian with the covariance structure determined by inputs $\vec{x}$ (Rasmussen and Williams 2005)



$$\mathrm{Cov}[y_i, y_j] = k(\vec{x}_i, \vec{x}_j) + \sigma_\varepsilon^2 \delta_{ij}$$

$$= \sigma_f^2 \exp\left(-\frac{1}{2}\left(\frac{\left(\vec{x}_i^{sha} - \vec{x}_j^{sha}\right)^2}{\ell^2_{sharpness}} + \frac{\left(\vec{x}_i^{opa} - \vec{x}_j^{opa}\right)^2}{\ell^2_{opacity}} + \frac{\left(\vec{x}_i^{sat} - \vec{x}_j^{sat}\right)^2}{\ell^2_{saturation}}\right)\right) + \sigma_\varepsilon^2 \delta_{ij}$$

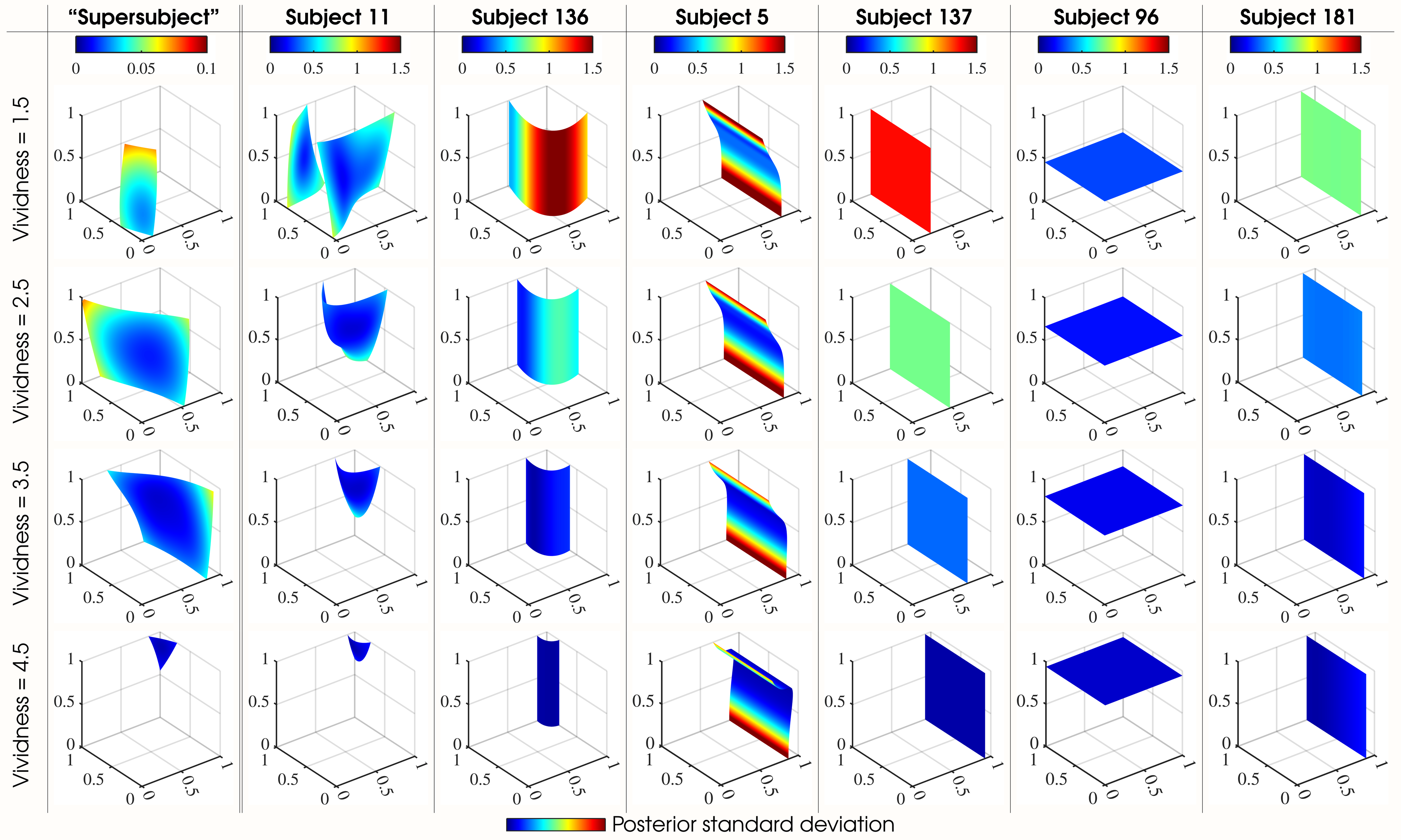
where δ_{ij} is the impulse function that takes the value 1 only when $i = j$ and 0 otherwise.

Hyperparameters:

- Kernel function: Covariance between noiseless function evaluations
- Noise standard deviation: Uncertainty on measurements $\varepsilon_i \overset{iid.}{\sim} \mathcal{N}(0, \sigma_\varepsilon^2)$
- Signal standard deviation: Uncertainty on unobserved locations
- Length scales: Smoothness over variables

Model fits are obtained using MATLAB Statistics and Machine Learning Toolbox (2026).

(4) Gaussian processes reveal nonlinearities and clusters of individuals

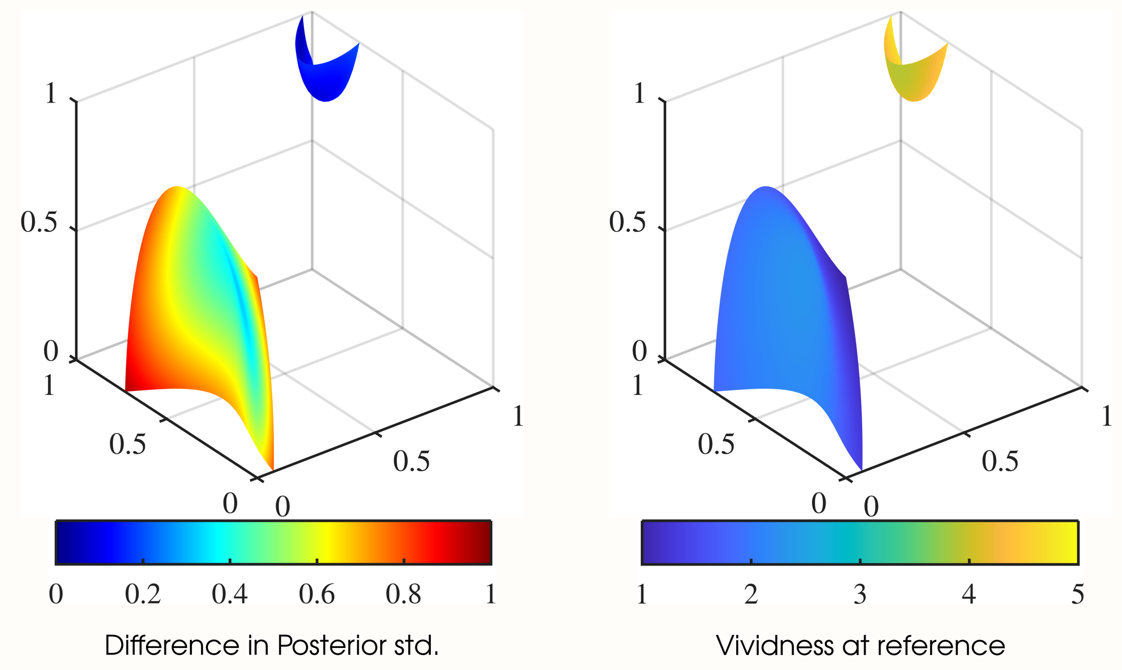


⇐ Equal vividness manifolds

where different features correspond to the same vividness rating

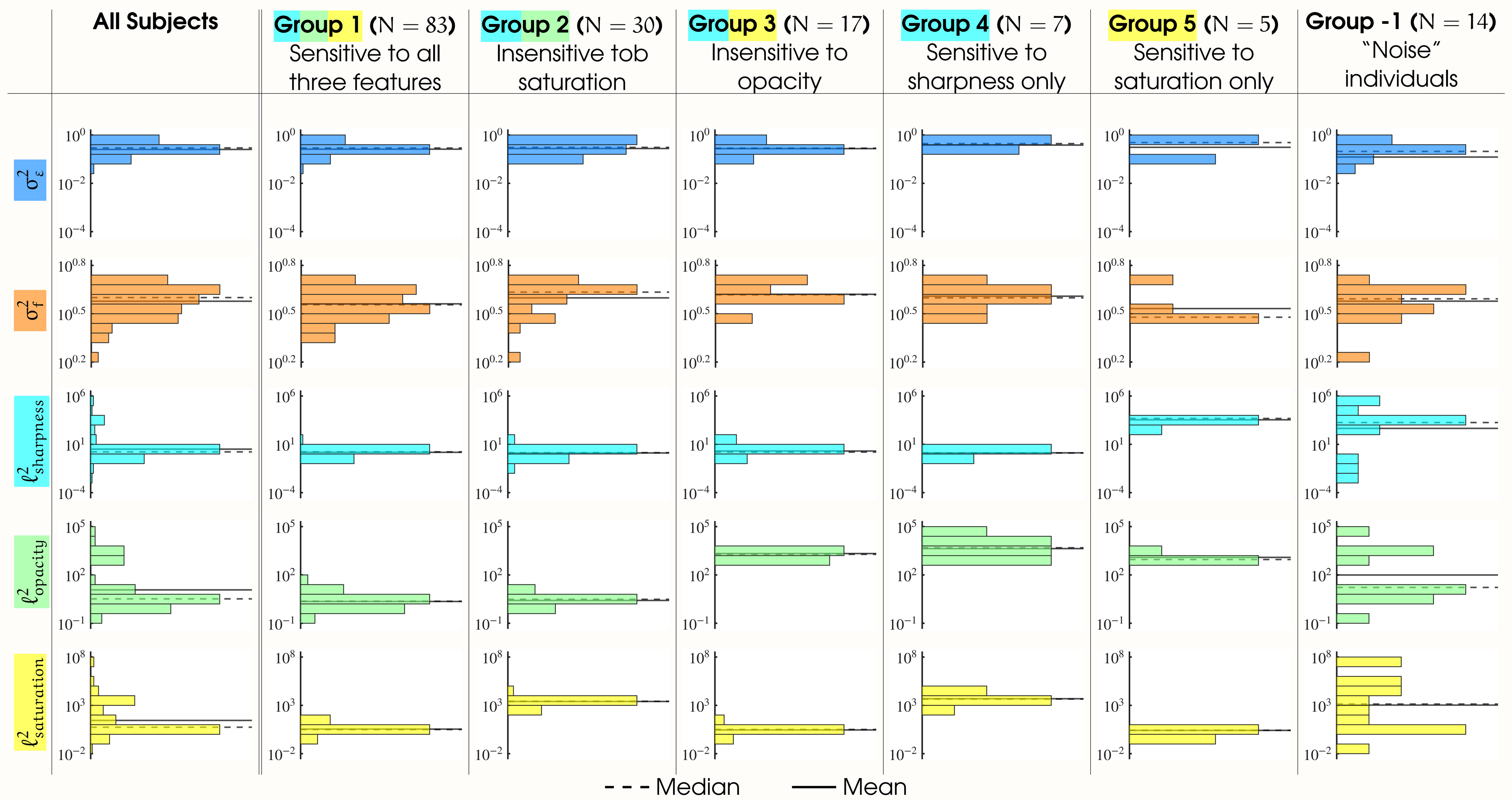
⇓ Difference manifolds

where the *difference* Δ between two profiles is constant

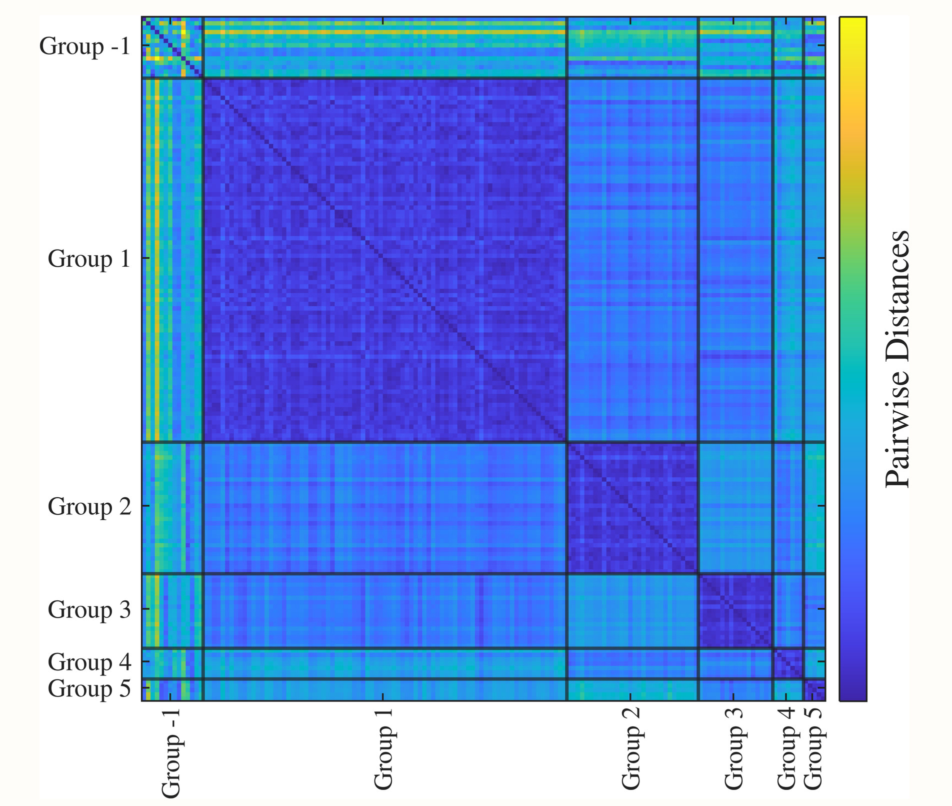


Figures: Δ(Subject 11 - Supersubject) = 0

Non-planar manifolds imply that *nonlinear relationships can be captured* using Gaussian processes!



⇐ Hyperparameter-based clustering



Clustered using DBSCAN (Ester et al. 1996) and Satopaa et al. (2011) for knee detection.

Groups differ mostly in the *way* they are sensitive to the three perceptual features!

(5) Take-home messages

Vividness ratings...

(1) can show nonlinear dependence on perceptual features, as seen through non-planar equal vividness manifolds over the feature space!
(2) show individual differences in their dependence on these features, agreeing with Huang et al. (2025),
...yet there are trends in these differences!

Why use Gaussian processes?

Non-parametric regression method not restricted by functional form
Inherently generative model
Model confidence/prediction intervals come naturally
Not a black box model: hyperparameters are interpretable

Gaussian processes can help answer...

How do individuals differ from the general population? From each other?
How to choose input values to elicit a specific response for *any* multivariate nonlinear behavioral output, without parametric assumptions?
... and in a way that agrees with the whole population?

References

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