Gaussian Process Joint Models for Estimating Latent Dynamics of Brain and Behavior

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INTRODUCTION

- Integrative understanding of neural and behavioral data is increasingly important in psychology and cognitive neuroscience.
- Finding plausible linking functions is the key to understand the mind that describes the relationship between manifest variables of brain and behavior.
- Plausible linking functions that connect manifest variables of the brain and behavior are essential to understanding the latent processes of the mind.
- We propose a nonparametric version of the joint modeling framework, namely a Gaussian process joint model (GPJM) to free this assumption. In particular, we focus on the brain as a dynamic system and estimate the latent dynamics for explaining neural and behavioral observations (e.g., Shine et al., 2019).

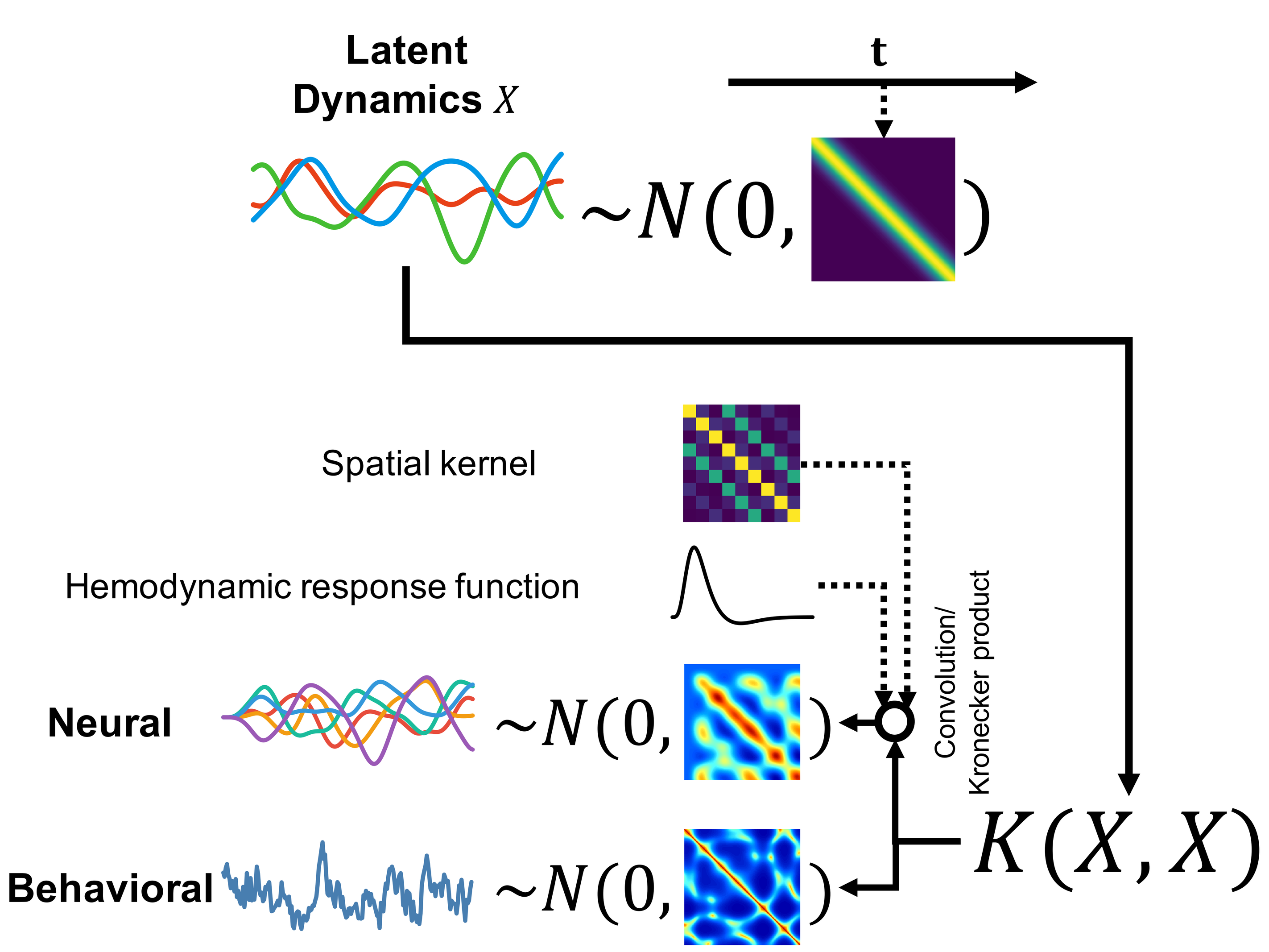
GPJM: GAUSSIAN PROCESSES AS A LINKING FUNCTION

- A Gaussian process (GP) is a nonparametric approach for modeling a function, compared to linear regression methods relying on a set of regression coefficients and explanatory variables.
- Given a set of input $x = (x_1, \cdots, x_T)'$, GP assumes that a function f is a sample from a multivariate normal distribution consisting of a mean function $m(x)$ and a covariance function or a 'kernel' $k(x, x')$:

$$f \sim N\big(m(x), k(x, x')\big)$$

- A kernel models the target function f with respect to the similarity of the input: <u>If two inputs are similar, then their outputs are also likely to be similar.</u>

- GPJM is an application of hierarchical GP latent variable models (Lawrence & Moore, 2007) to neuroimaging data and behavioral responses.
- GPJM assumes that...
  - Both neural and behavioral data are generated by **the shared underlying dynamics modeled as GPs** with respect to time.
  - Each latent dimension can contribute to the data with **different degrees of relevance**.
  - **The hemodynamic lag is (approximately) addressed** in estimating the latent dynamics.
  - **Spatiotemporal dynamics** can be modeled by a Kronecker-separable kernel (e.g., Flaxman, 2015; Shvartsman et al., 2017).

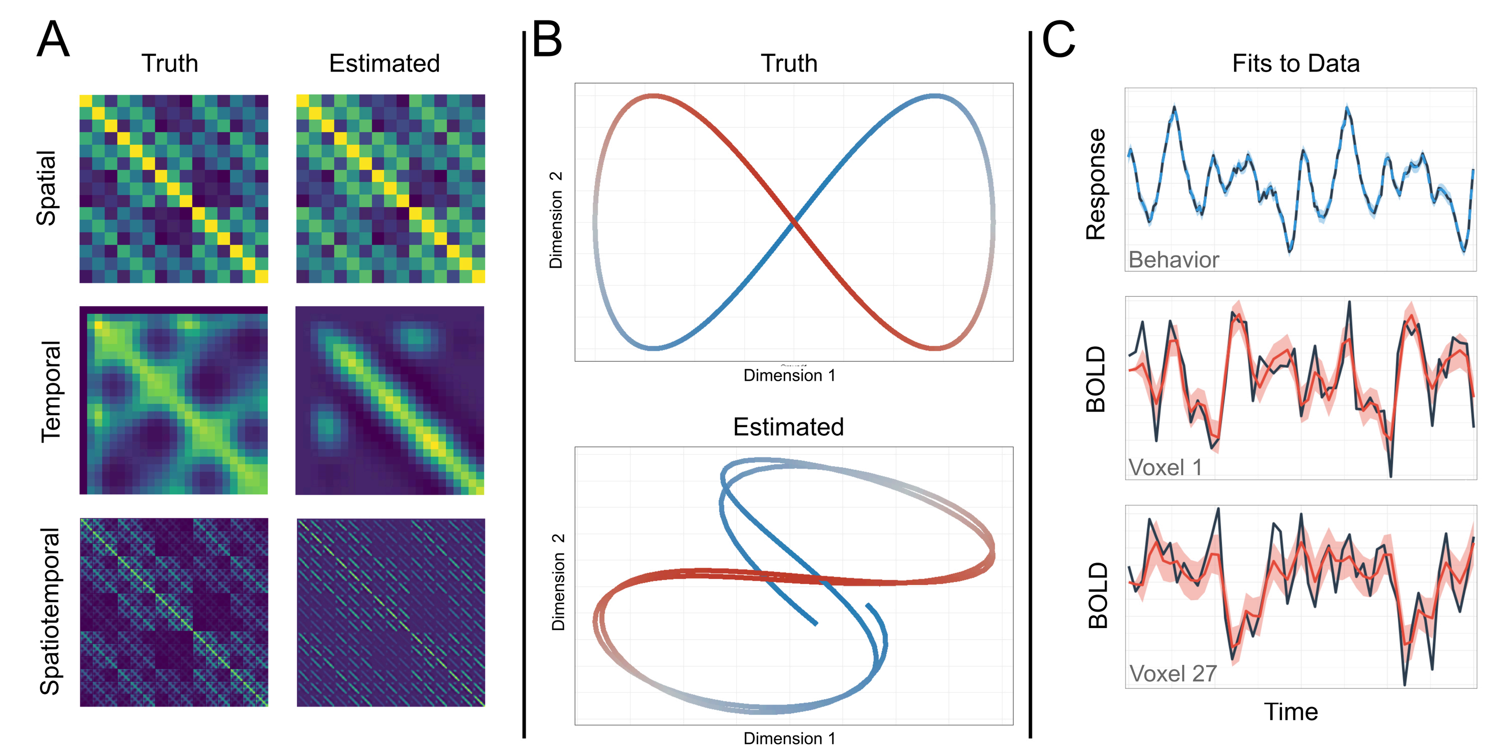


The structure of GPJM

TASK & SIMULATION STUDY

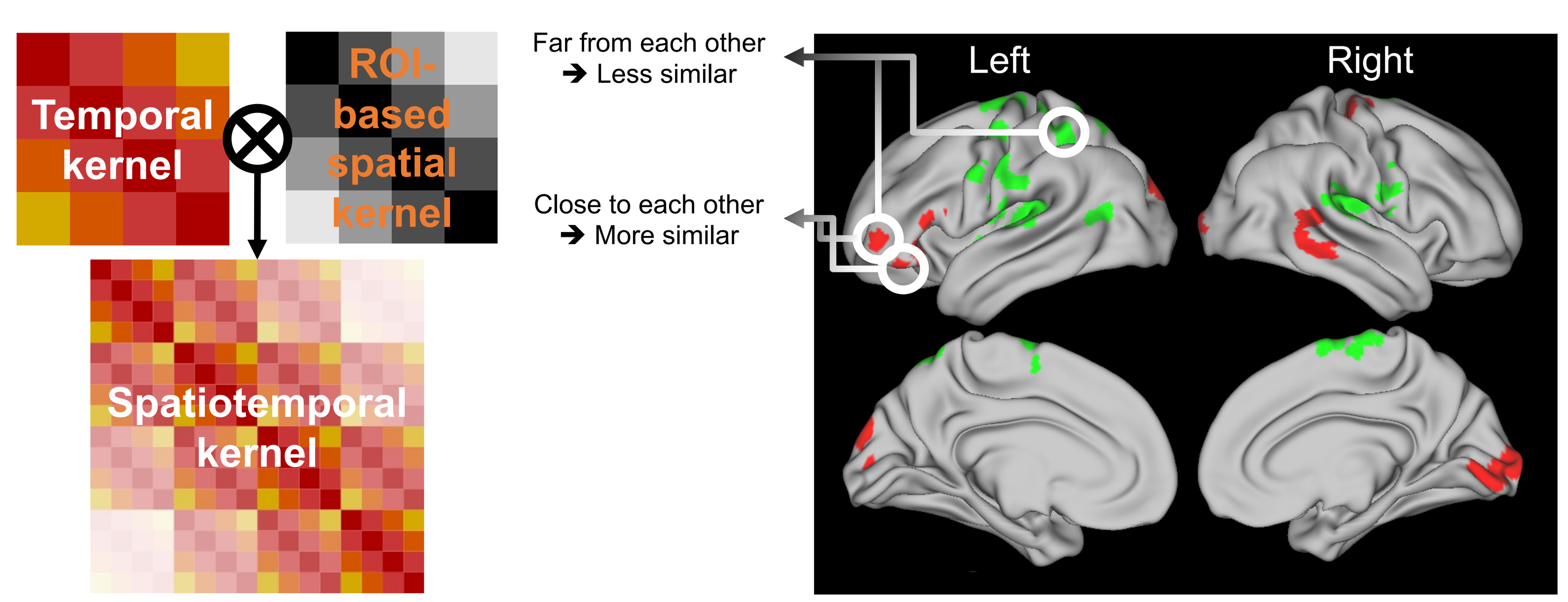
- We performed a motion tracking task in which participants continually reported the average direction of randomly moving dots throughout a trial, with a subset of the dots moving in a coherent direction. The degree of coherence and direction of motion probabilistically changed every second.

- <u>Recovery analysis</u>: Given underlying dynamics, a spatiotemporal GPJM simulates BOLD responses from 27 'voxels' and one joystick movement trajectory.
- Spatiotemporal relationships among 27 voxels were modeled using a Kronecker product of spatial and temporal radial basis function (a.k.a. Gaussian) kernels.
- Joystick movement data were modeled using a Matérn ½ (a.k.a. exponential) kernel.



(A) The shape of data-generating kernels (left) and estimated kernels (right)
(B) Latent dynamics generating the data (top) and estimated dynamics (bottom)
(C) Data (black lines), mean model predictions (colored bold lines), and predictive intervals (colored shades)

- GPJM can recover underlying dynamics that resemble the ground truth reasonably, not only explain the measured neural and behavioral responses.
- In particular, Kronecker-separable kernels can address the similarity of BOLD responses across voxels with respect to their spatial relationships.

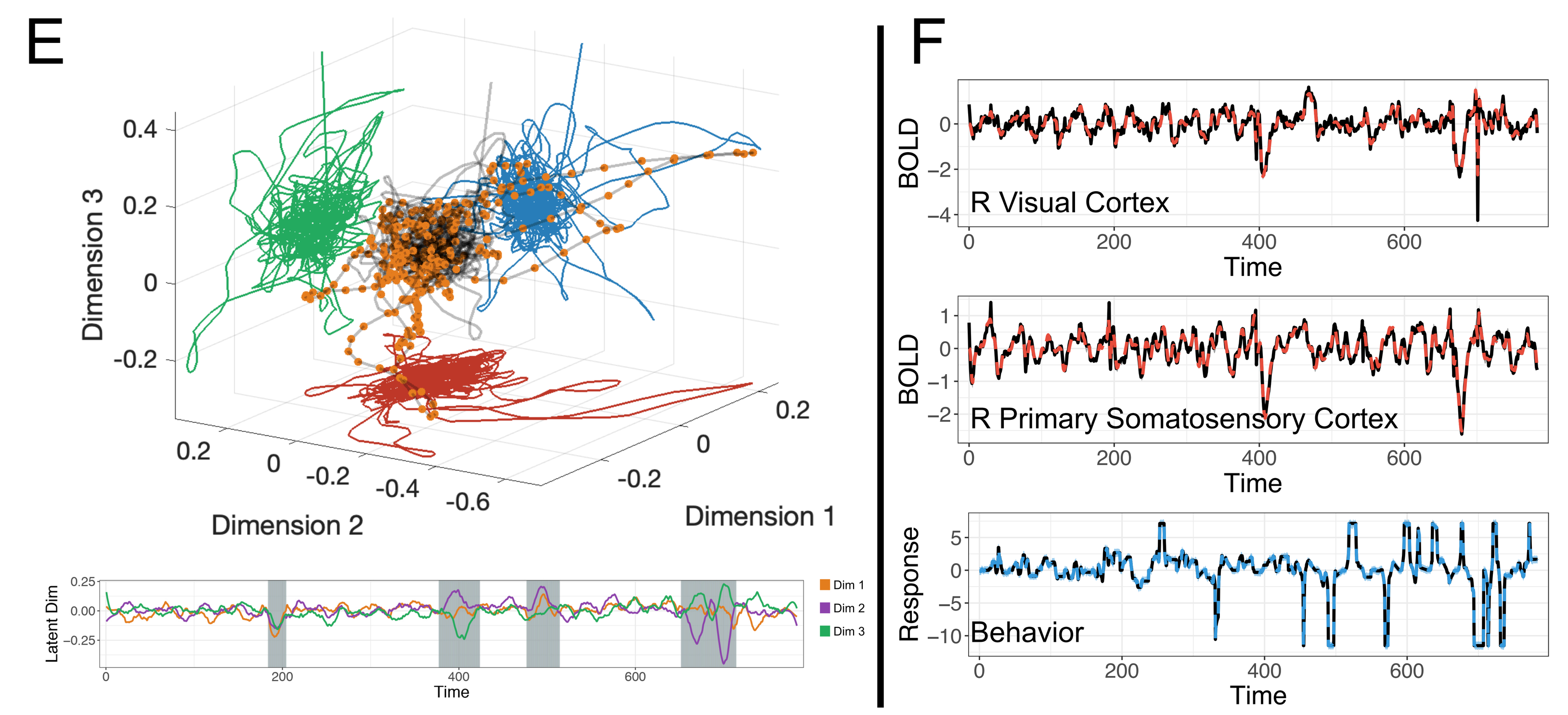


A visual illustration of the Kronecker-separable spatiotemporal kernel (left) with 15 ROIs used in the fMRI experiment (right; one in the cerebellum was excluded from the figure)

FMRI EXPERIMENT

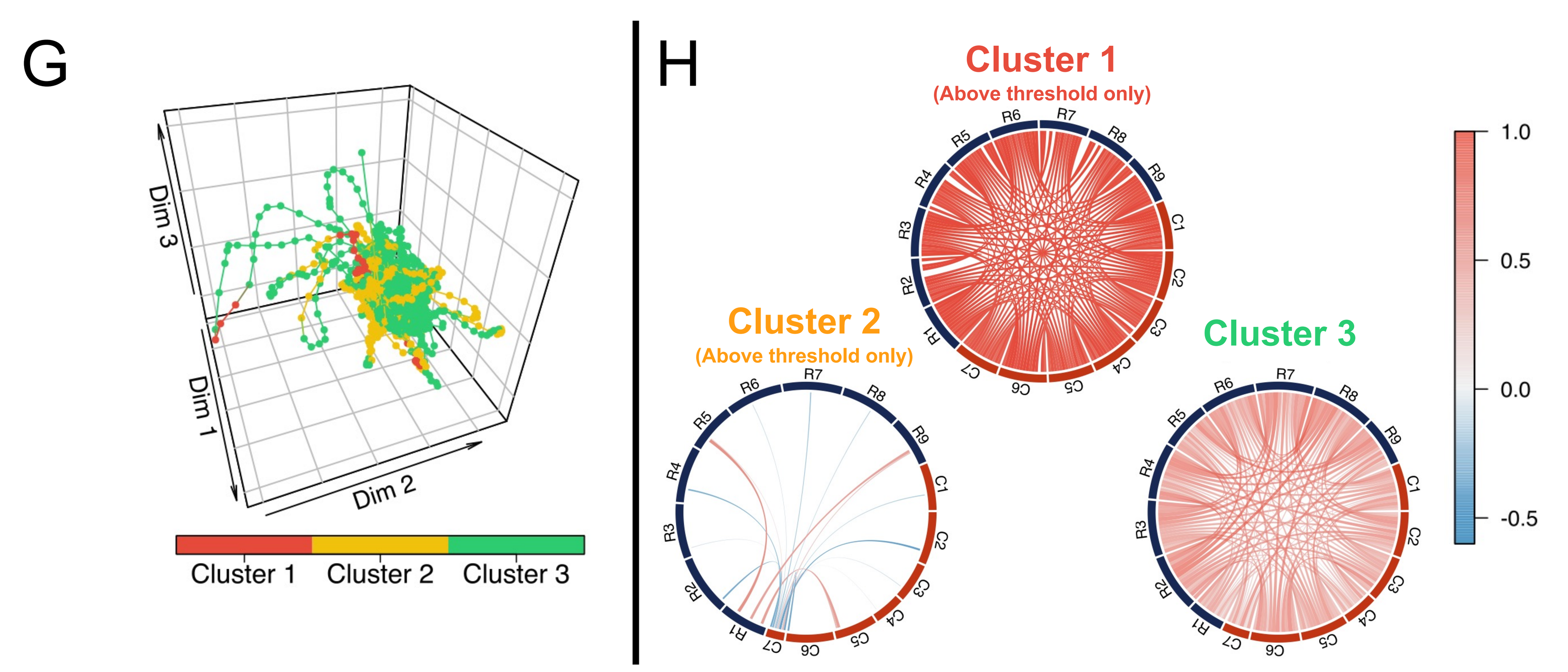
- We applied the GPJM to a subset of data from an ongoing study. The GPJM was fitted to BOLD responses from 16 ROIs (associated with stimulus coherence or participant response) and a joystick movement trajectory.

- <u>Underlying dynamics</u>: The estimated dynamics distinguishes 'regular' states and deviations from them, each of which is qualitatively different to the other.
- <u>Fits to the data</u>: The latent dynamics estimated by the GPJM explains the observed data successfully.



(E) Estimated latent dynamics from a three-dimensional model (filtered for visual clarity)
(F) Selected time-series data and model predictions

- <u>Preliminary examination of the topology</u>: One of the preliminary results suggest that the relative position in the embedded space could be related to different patterns of functional coactivation.
- In particular, the middle of the topology is characterized by negative associations between the left inferior frontal gyrus ("C7" in the figure) and other brain regions. Meanwhile, the functional correlation becomes positive when the dynamics depart from the middle.



(G) The latent dynamics color-coded by clusters based on multidimensional scaling of functional coactivation
(H) The average functional connectivity of three clusters
(Note: Clusters 1 & 2: <u>Only the links whose differences from Cluster 3 are greater than ±0.2 are presented for visual clarity</u>.)

SUMMARY

- GPJM can explain neural and behavioral data that are emerging from underlying cognitive dynamics estimated in a nonparametric fashion, while also addressing the temporal gap between BOLD responses and experimental sequences.
- Kronecker-separable kernels can incorporate spatiotemporal interactions of the brain into the model.
- The GP-based structure could be an alternative to linking functions with fixed functional forms and provide meaningful insights for understanding brain, behavior, and mind.

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