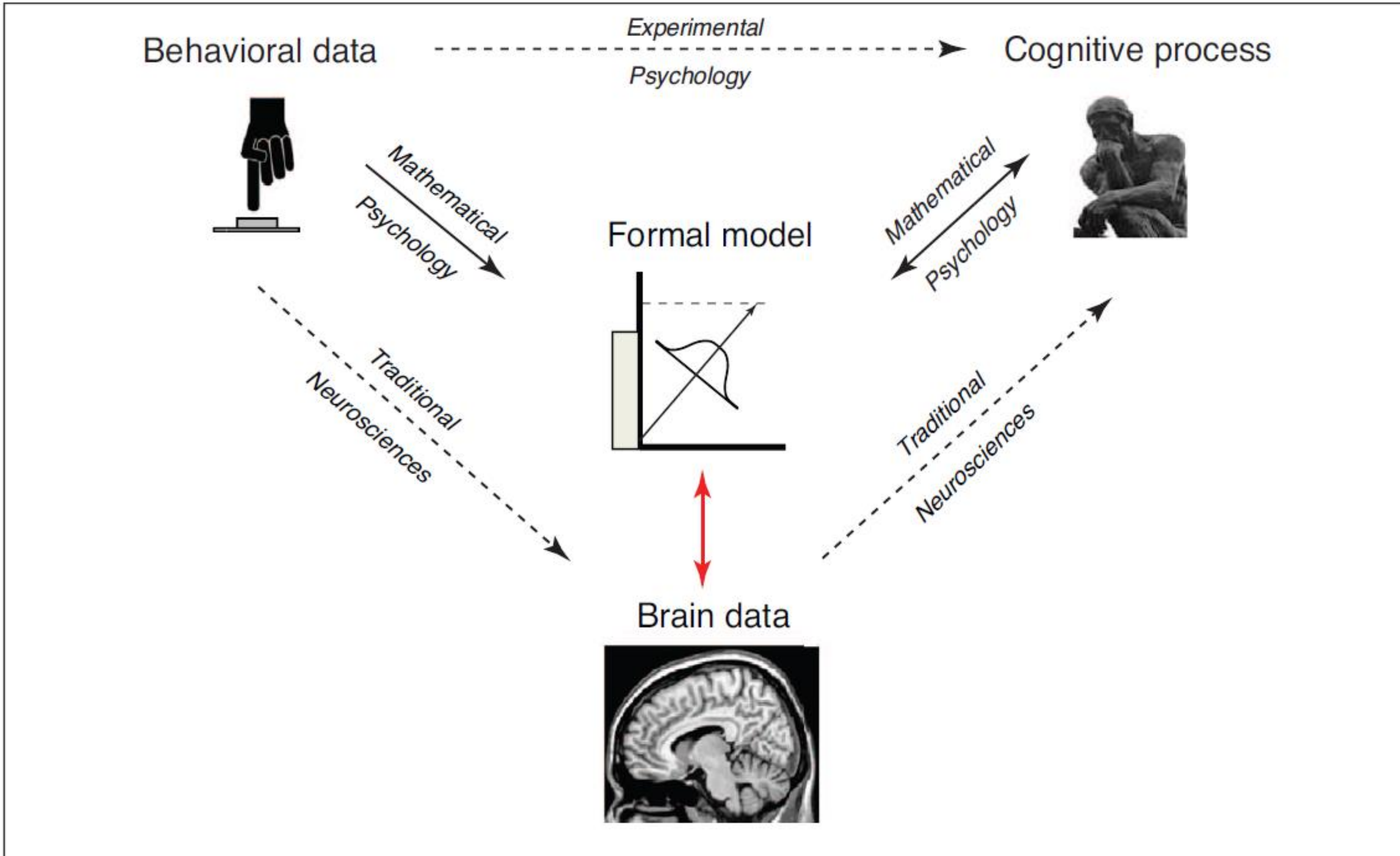
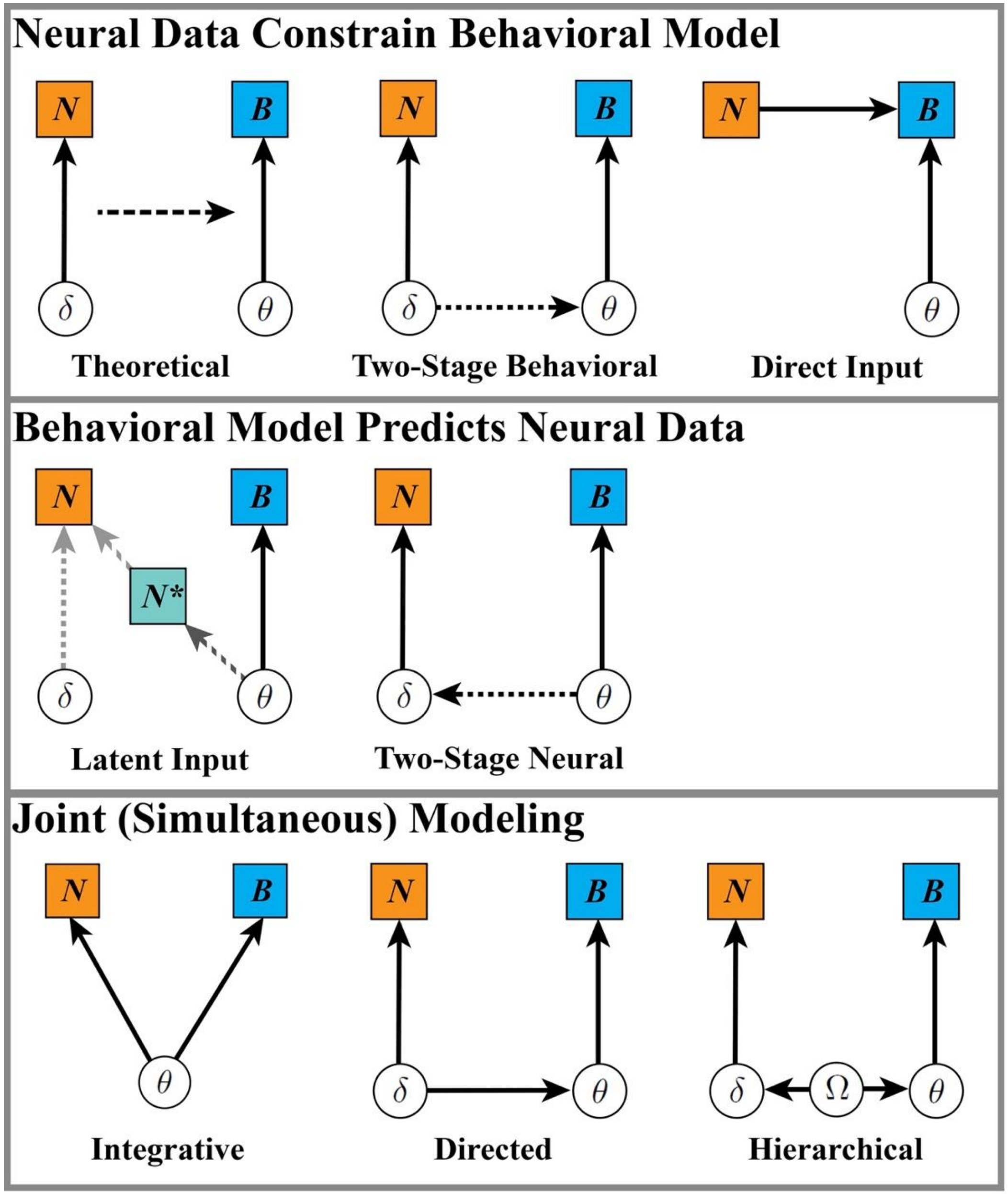
SBI SUMMER SCHOOL: JOINT MODELING

LINKING NEUROSCIENCE TO COGNITIVE MODELS



Linking Brain and Behavior

1. Neural data can constrain the behavioral model
2. Behavioral model can predict neural data
3. Model everything at once



Turner, B. M., Forstmann, B. U., Love, B. C., Palmeri, T. J., and Van Maanen, L. (2017). Approaches to analysis in model-based cognitive neuroscience. Journal of Mathematical Psychology. 76, 65-79.

NEURAL DATA CONSTRAIN BEHAVIORAL MODEL

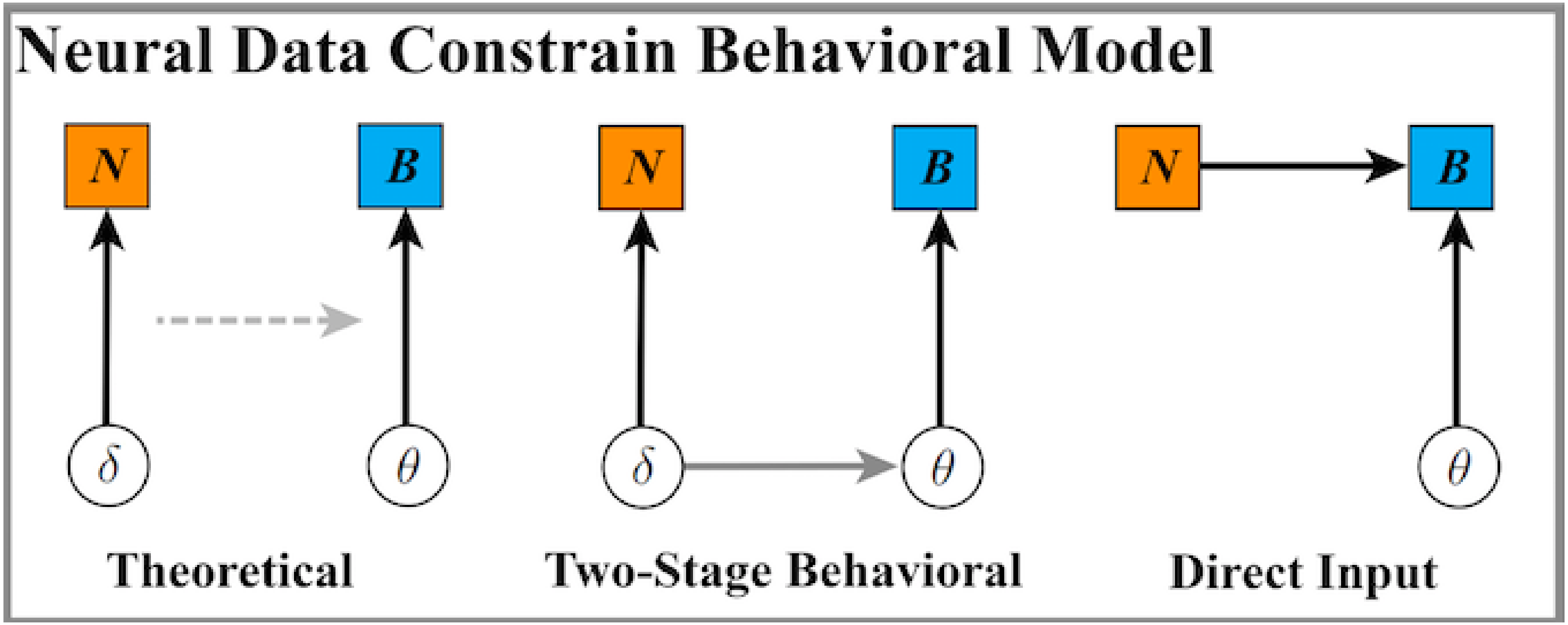
- In developing models, we have many choices and assumptions to make

- Rather than make these arbitrarily, or develop theoretical justification for them, we could look to the implementation level

- One prominent approach in MbCN is to use the neural data to constrain the development of the behavioral model

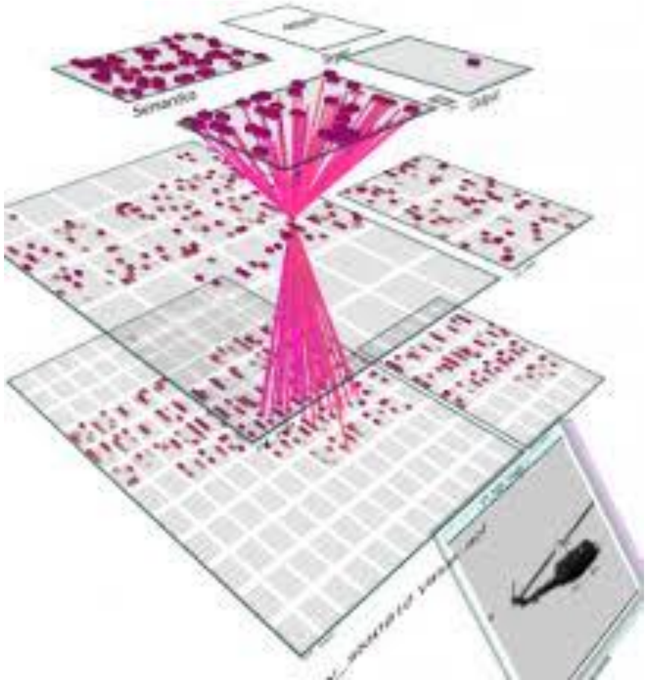
NEURAL DATA CONSTRAIN BEHAVIORAL MODEL

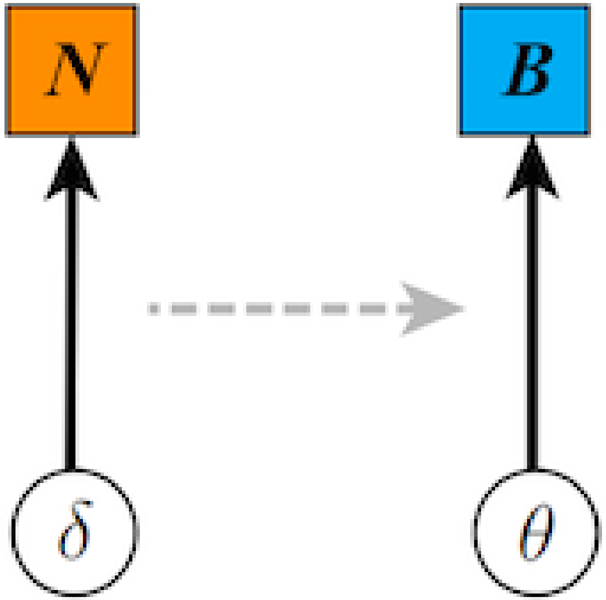
- Here are some examples:



THEORETICAL

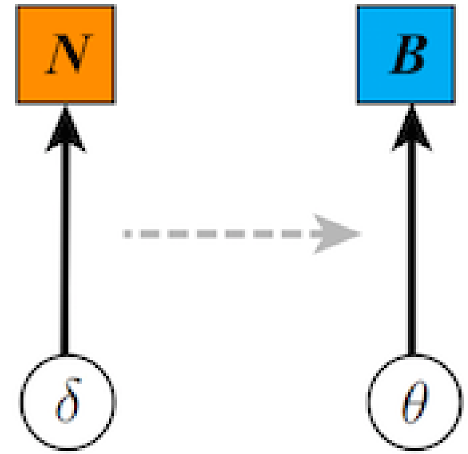
- **Development of models with neurally-inspired architectures**
  - Connectionist frameworks
  - LEABRA
  - LCA

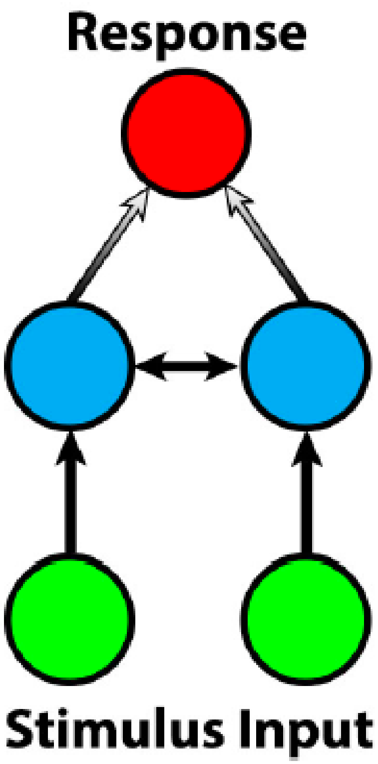


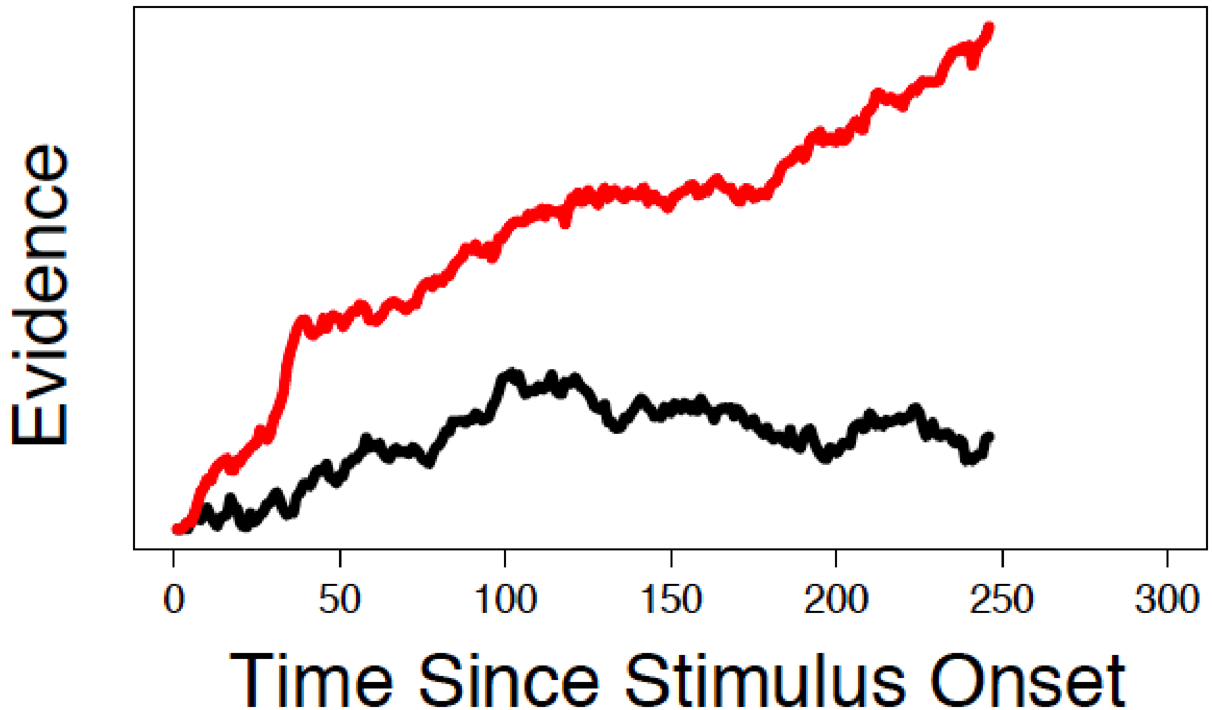


THEORETICAL

- Development of models with neurally-inspired architectures



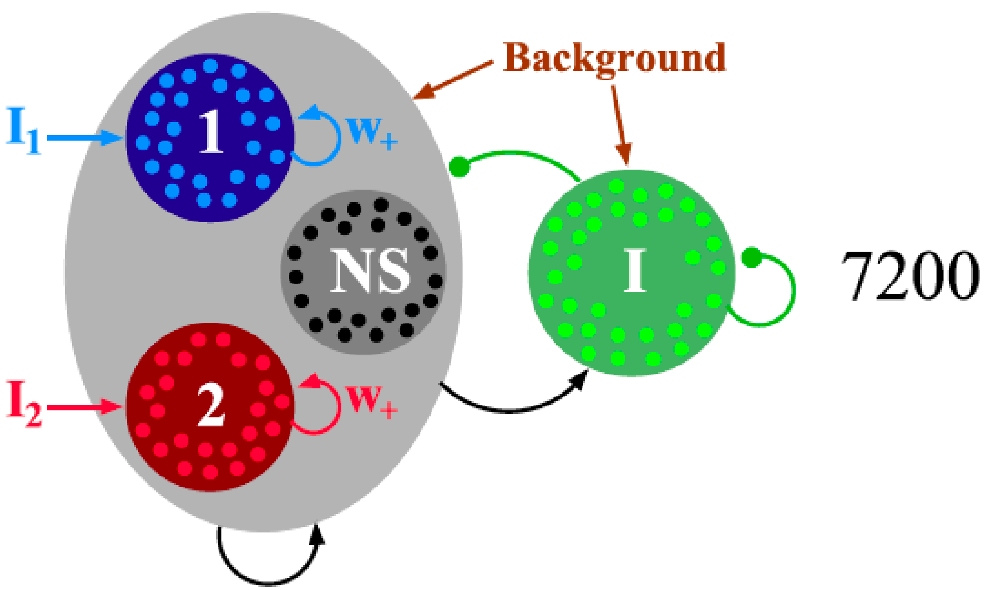


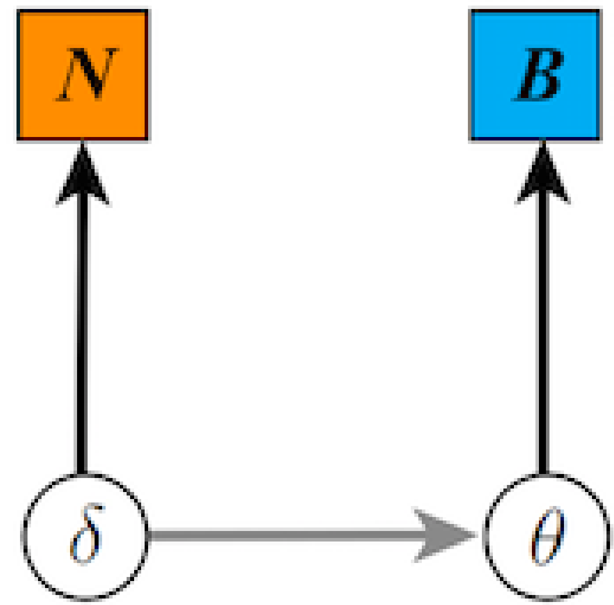


TWO-STAGE BEHAVIORAL

- Using a model to characterize how the implementation level is carried out, then using these parameters to generate predictions for behavioral data

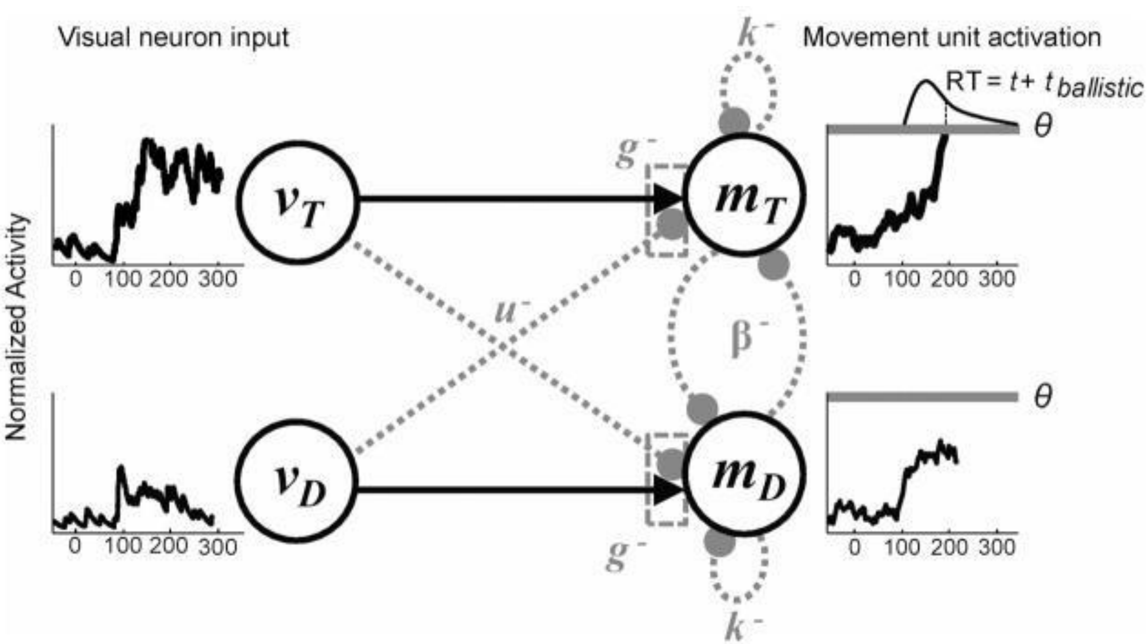
Spiking neuronal network model

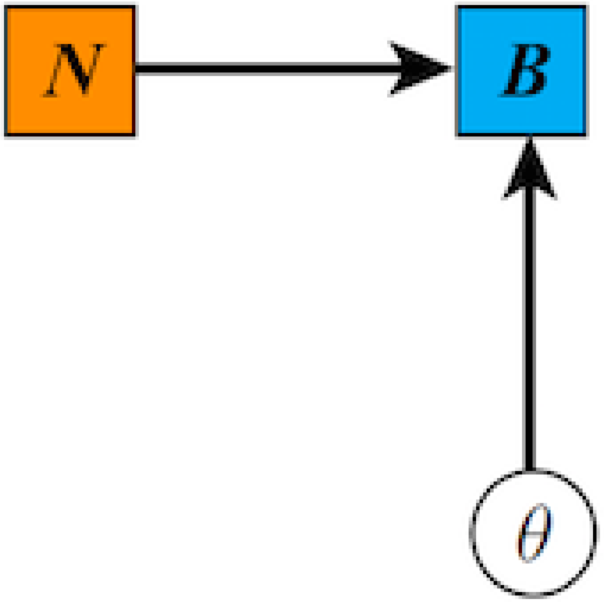




DIRECT INPUT

- **Type of model that uses neural data – or some transformation of it – to directly inform the model**
    - Gated accumulator model





NEURALLY CONSTRAINED MODELING OF PERCEPTUAL DECISION MAKING

- **Building off the finding that the dynamics of some neurons resemble an accumulation to threshold process**

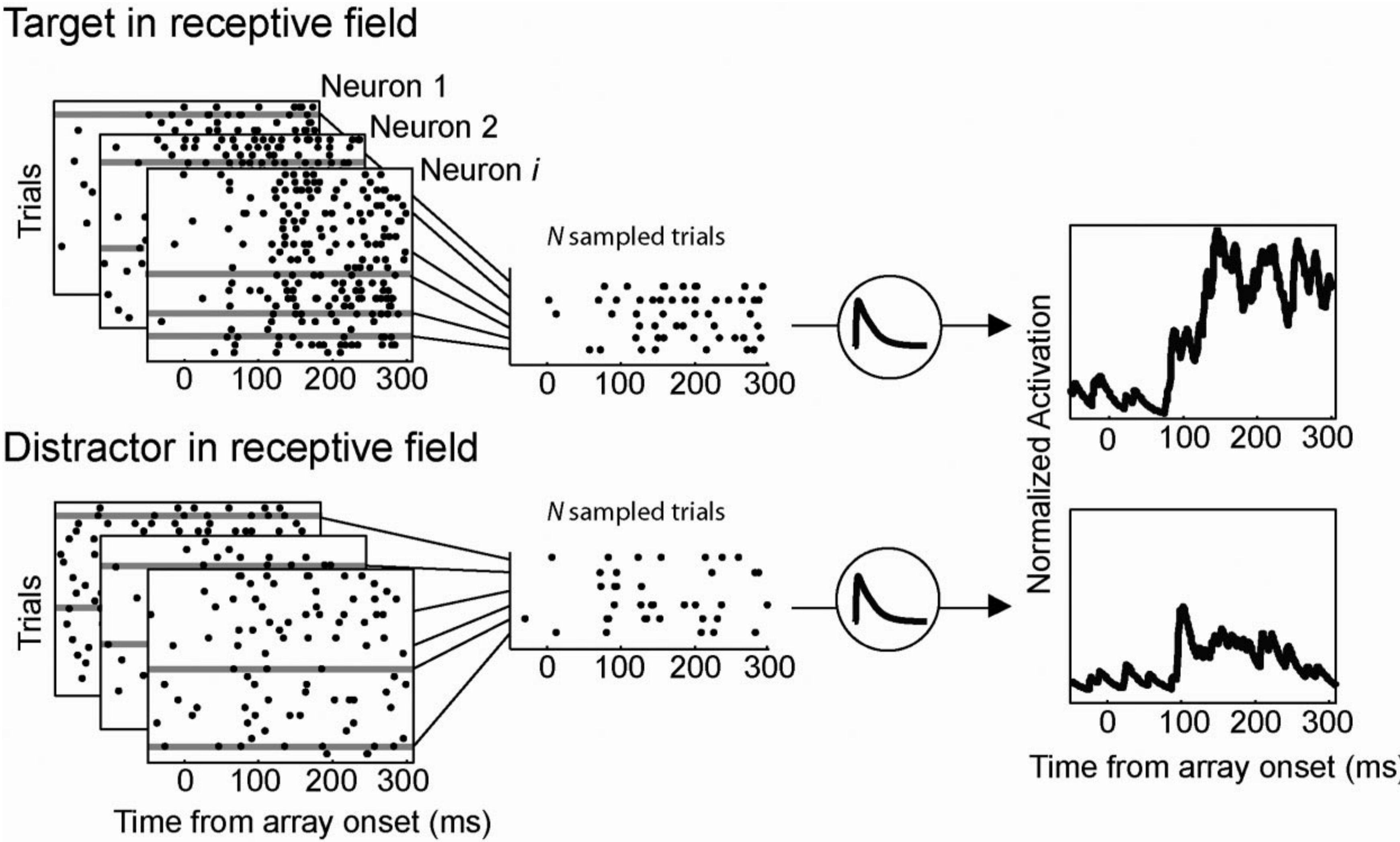
- **"This synthesis is powerful because neurophysiology can constrain key assumptions about the representation of perceptual evidence, the mechanisms that accumulate evidence to threshold, and how the two interact"**

- **Plan to use neural data to constrain the evidence accumulation process**

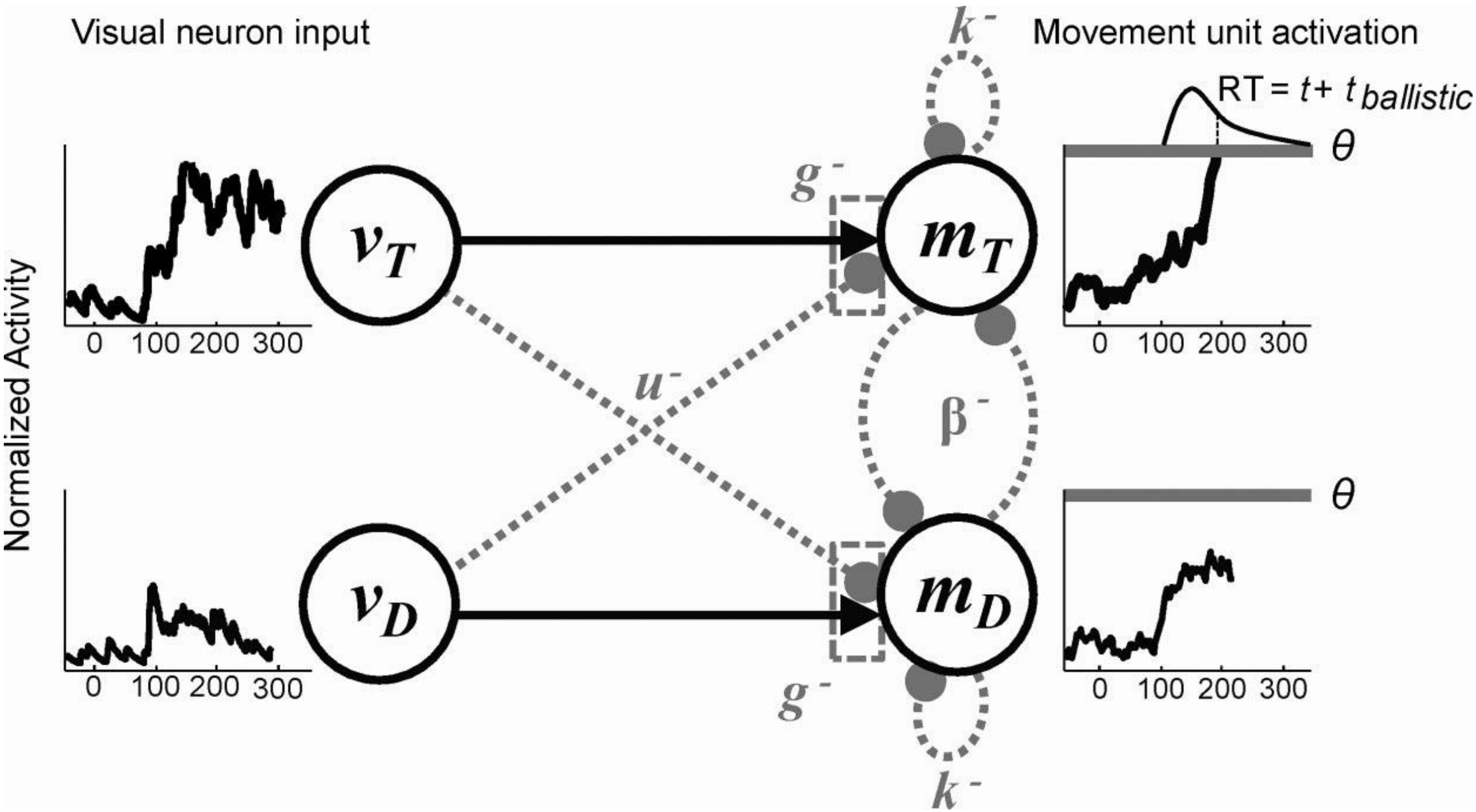
Tom Palmeri

Gordon Logan

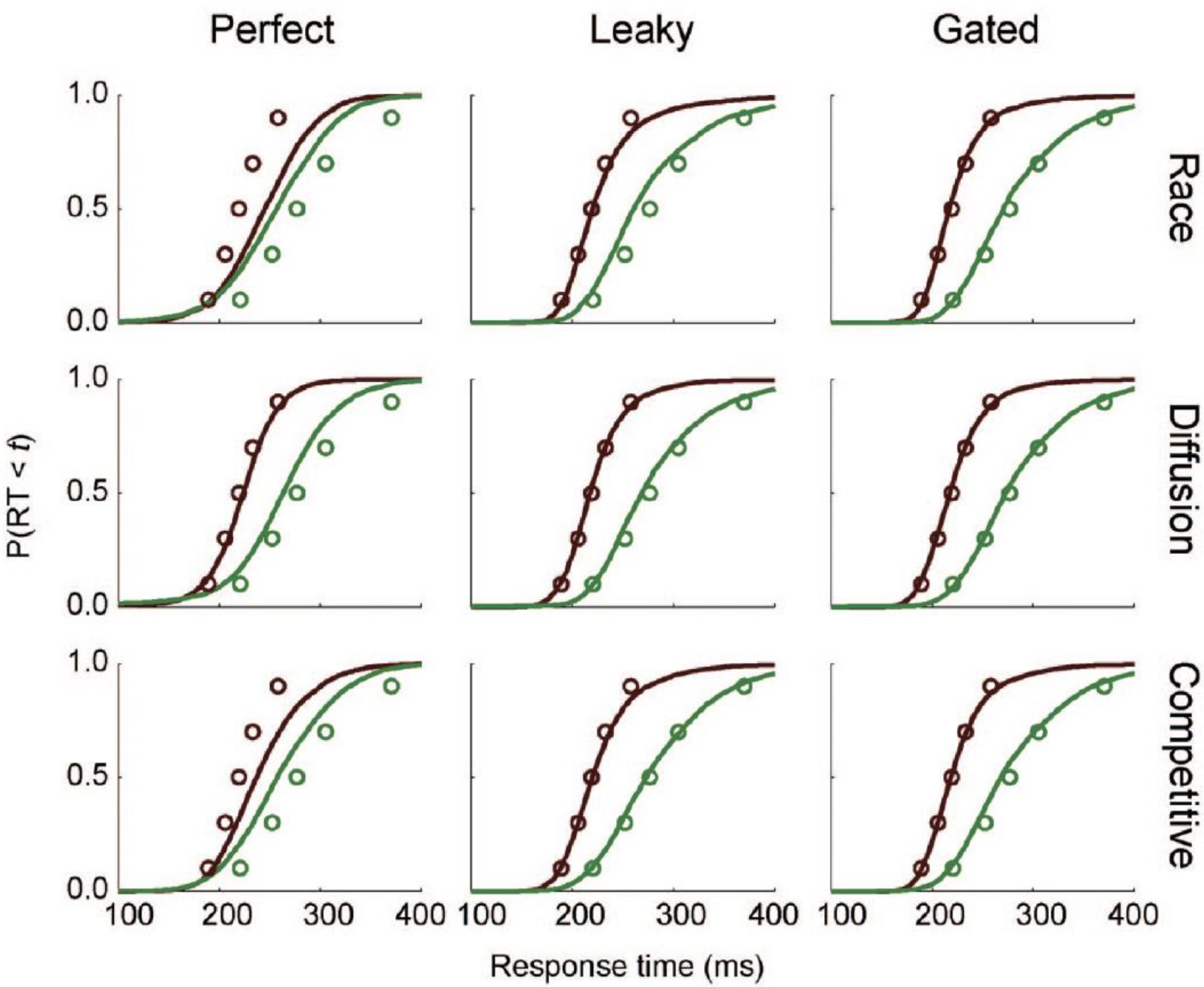
MODELING -- SUMMARY



MODELING -- SUMMARY



BEHAVIORAL FITS

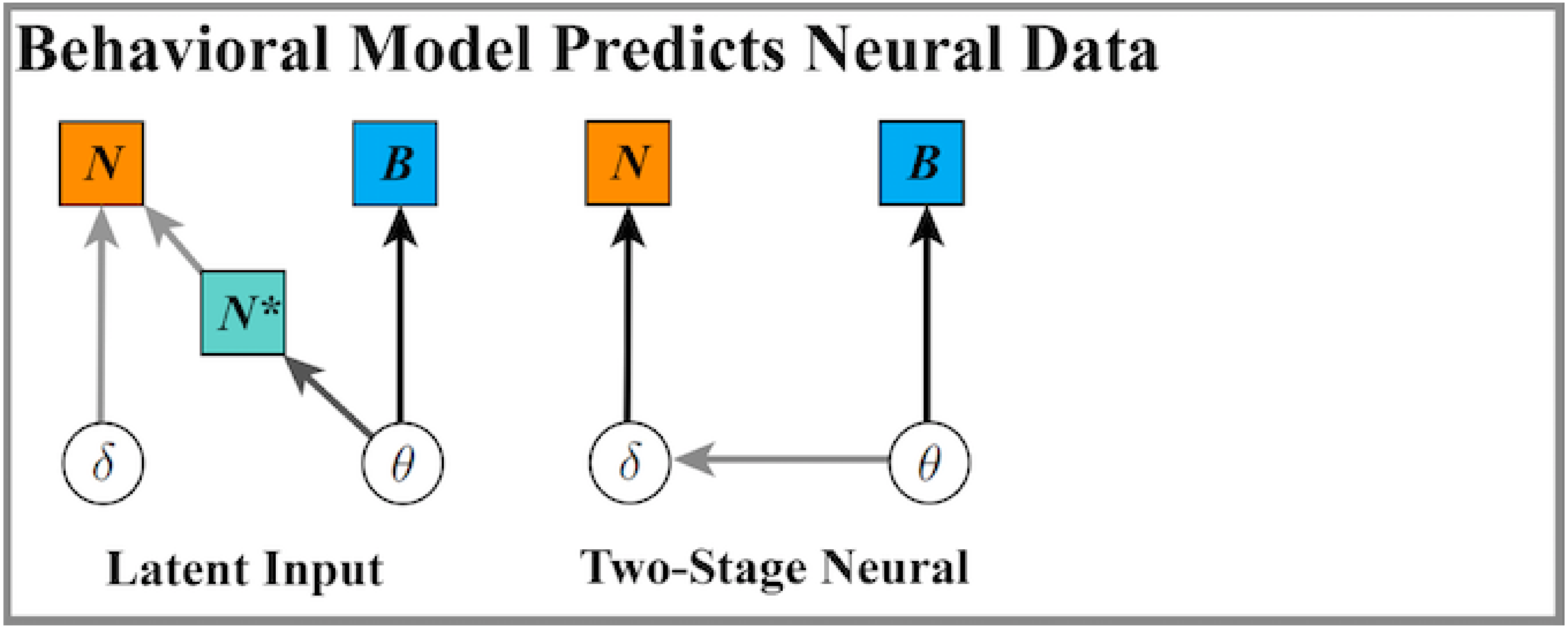


BEHAVIORAL MODEL PREDICTS NEURAL DATA

- Sometimes we have cognitive models that capture the behavioral data really well
- …but may not have any understanding of the neural basis of the mechanisms assumed by the model
- Try to use model parameters to guide the search for mechanisms in the brain

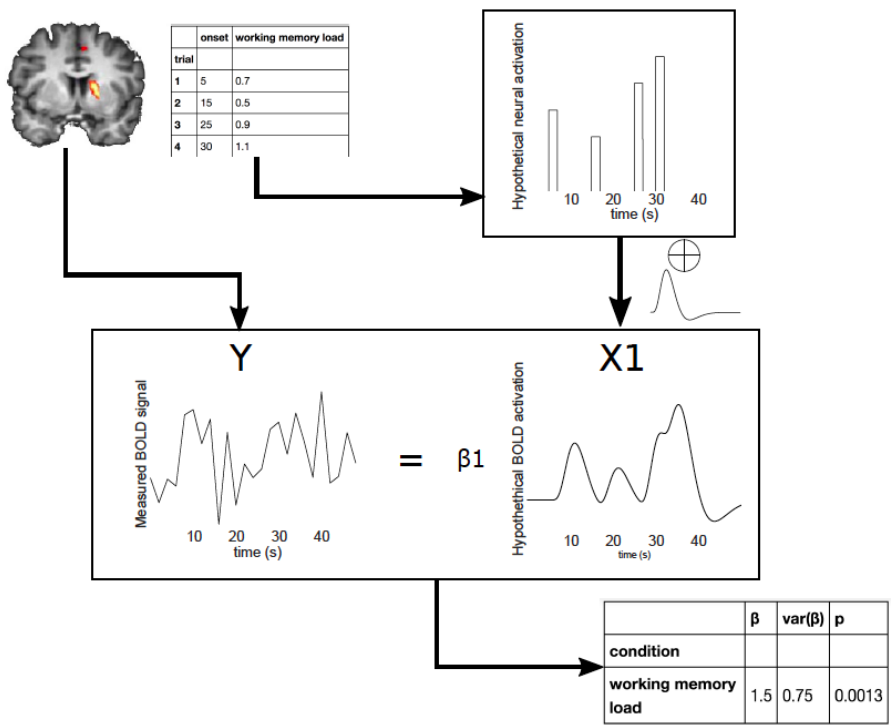
BEHAVIORAL MODEL PREDICTS NEURAL DATA

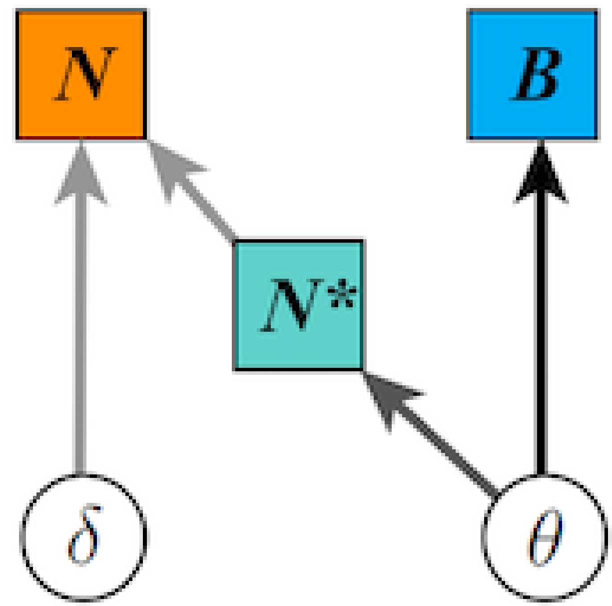
- **Here are some examples:**



LATENT INPUT

- **Use B to estimate behavioral model parameters, which are then used to guide the analysis of the neural data**
  - Model-based fMRI





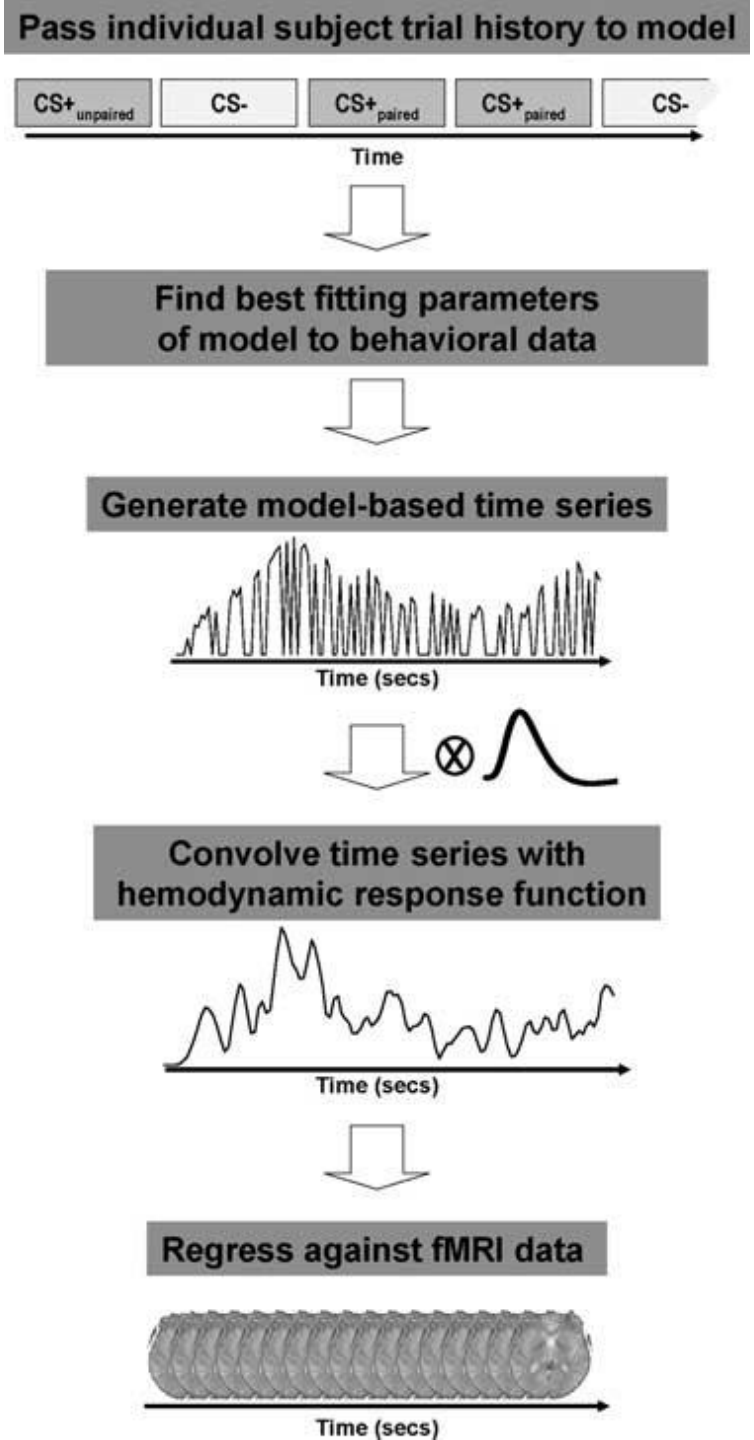
APPROACH

1. Find the best fitting parameters of model from fitting it to behavioral data

2. Generate model-based time series

3. Convolve the time series with an HRF to form predictions for neural data

4. Correlate the predictions with observed neural responses



APPLICATION

- In uncertain environments, one must consider absorbing resources in a particular area versus moving to a new area for a potentially richer set of rewards

- Explored the exploration/exploitation trade-off in humans on a bandit problem, with time-varying rewards

- Found that the brain codes for values of rewards in very specific areas

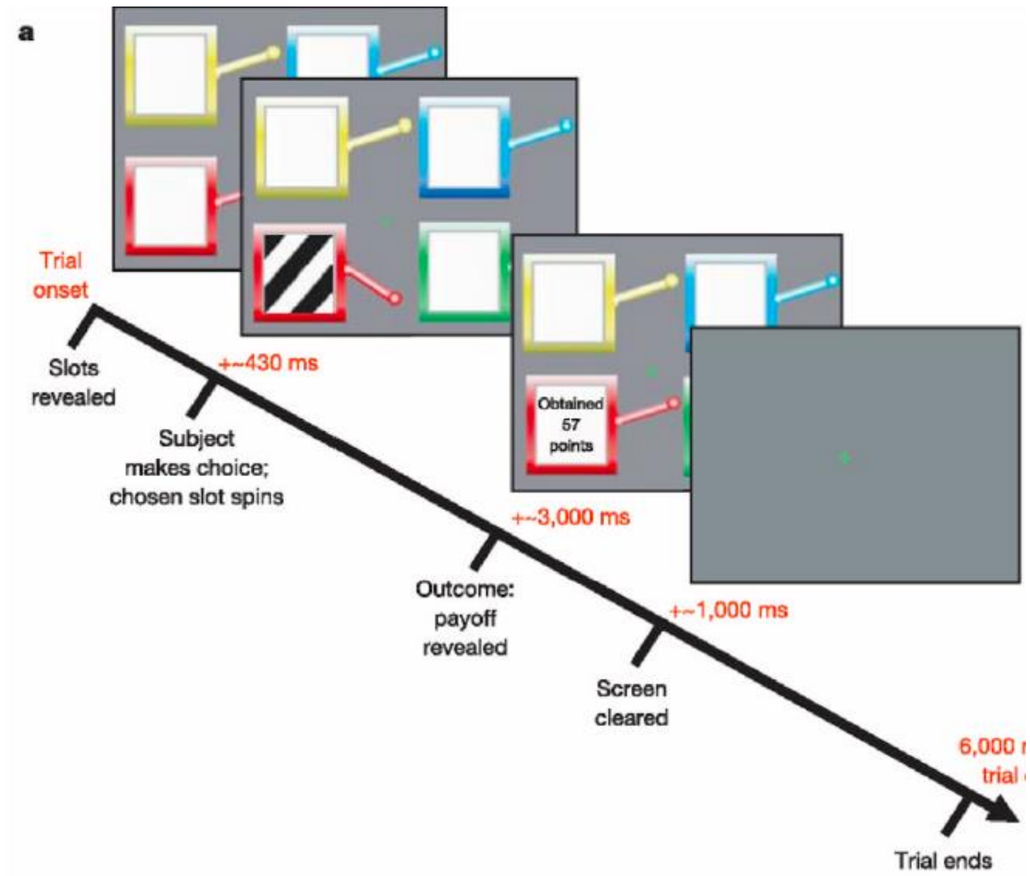
Nathaniel Daw

John O’Doherty

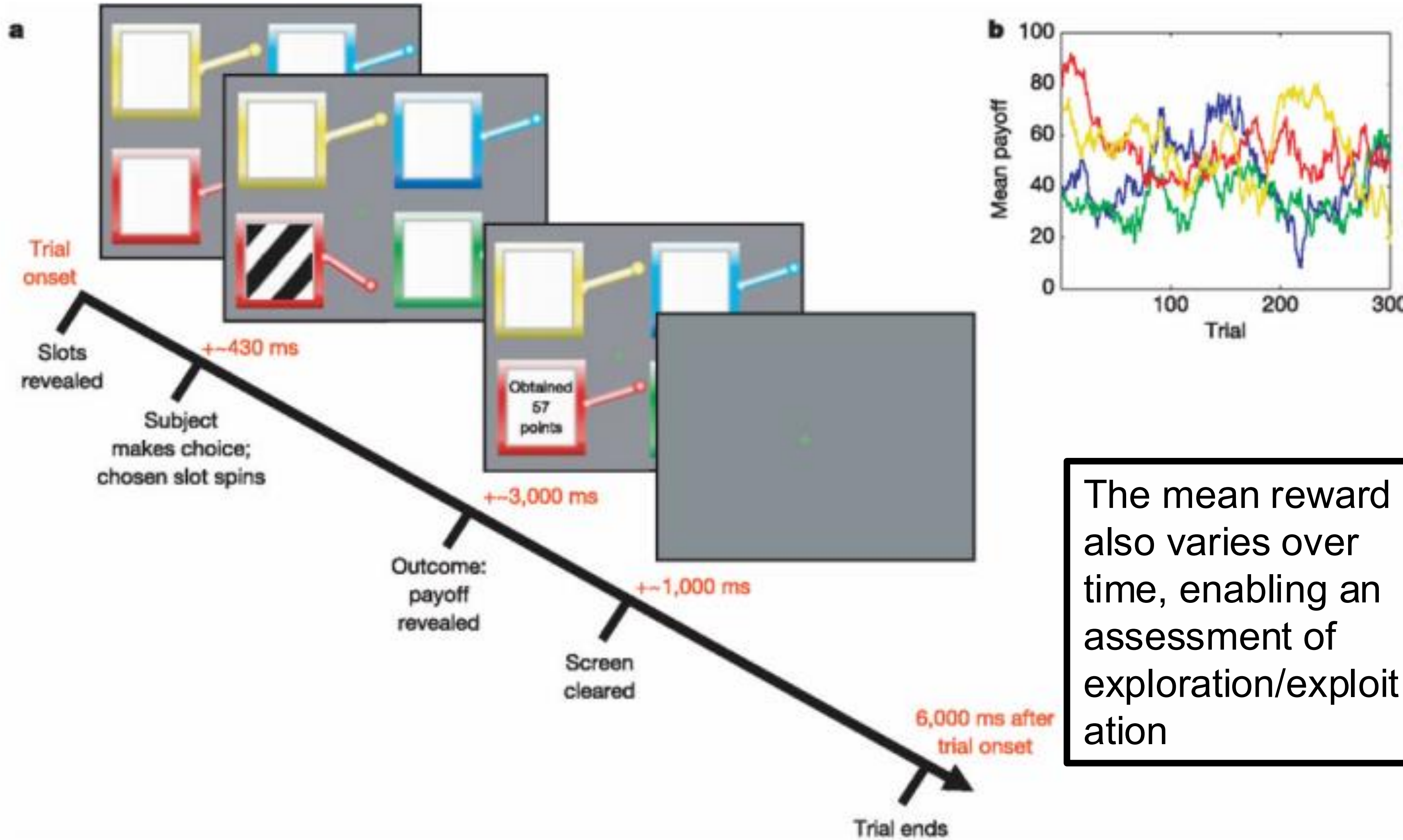
Daw, N., O'Doherty, J.P., Dayan, P., Seymour, B., Dolan, R.J. (2006). Cortical substrates for exploratory decisions in humans. Nature, 441:876-9.

FOUR-ARM BANDIT

- **Four options presented**
- **Choose among them**
- **Reward given on the basis of choice**
- **Reward is noisy, varying from one trial to the next**



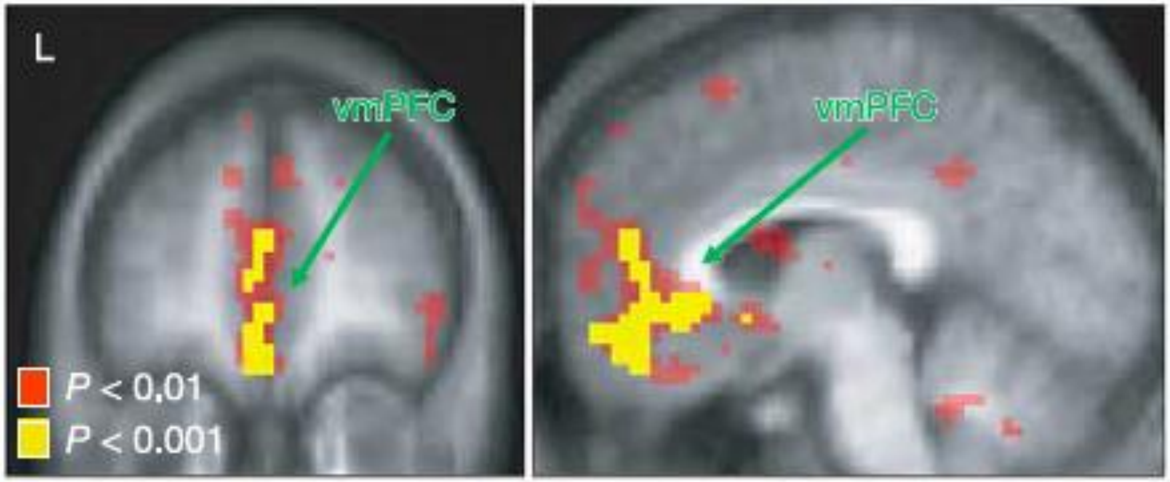
FOUR-ARM BANDIT

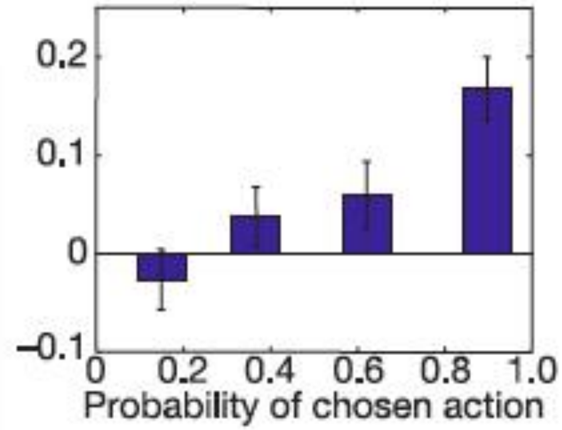


The mean reward also varies over time, enabling an assessment of exploration/exploitation

RESULTS – NEURAL DATA

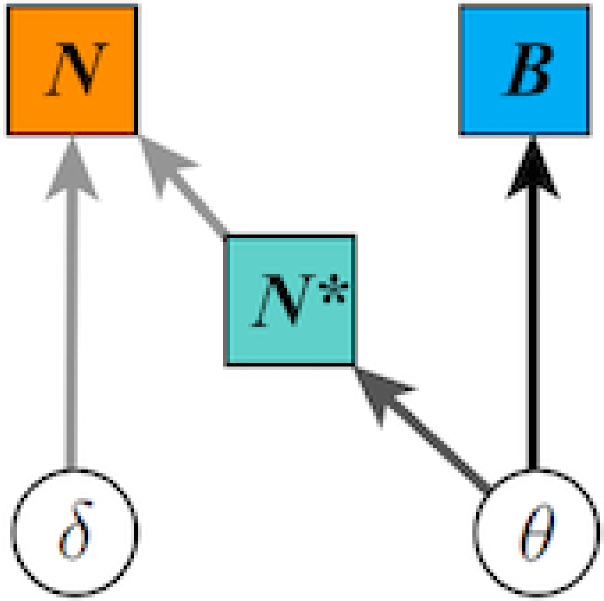
- The model provides a value for the probability of each choice in the task.
- One can correlate these predicted probabilities for the chosen option with the neural data
- Found significant correlations in vmPFC
- Negatively correlated with a small area in dlPFC





MODEL DECODING

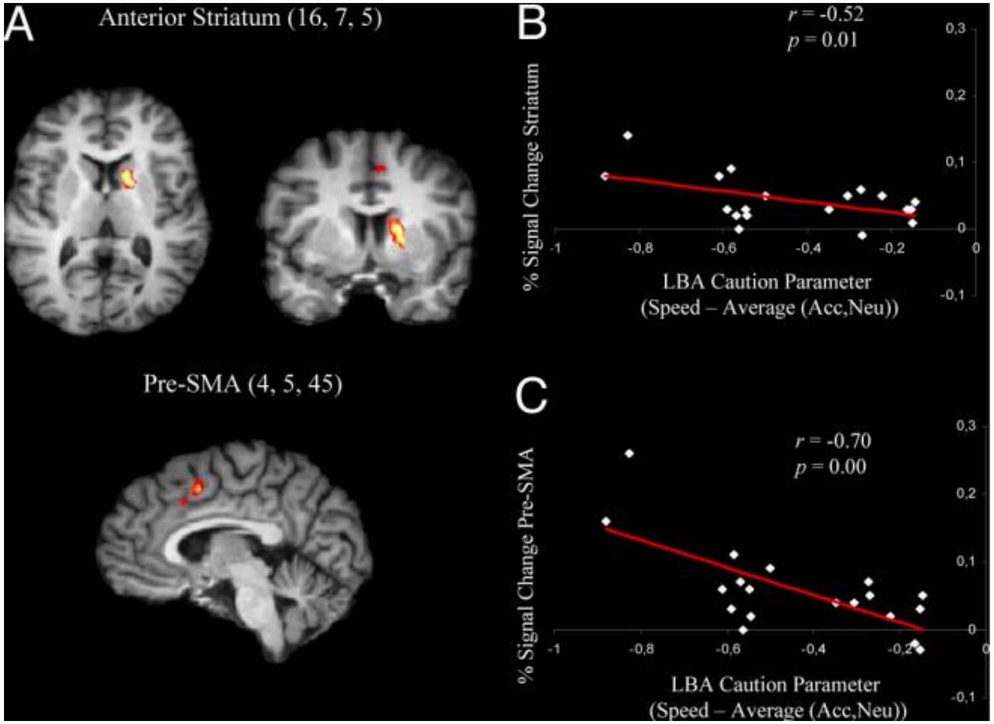
- You can imagine using different models to gather different 'internal states' (theta)
- Then, drawing comparisons across models by how well the neural data are predicted by the models' internal state
- This is exactly what Mack et al. (2013) did for the GCM and prototype models

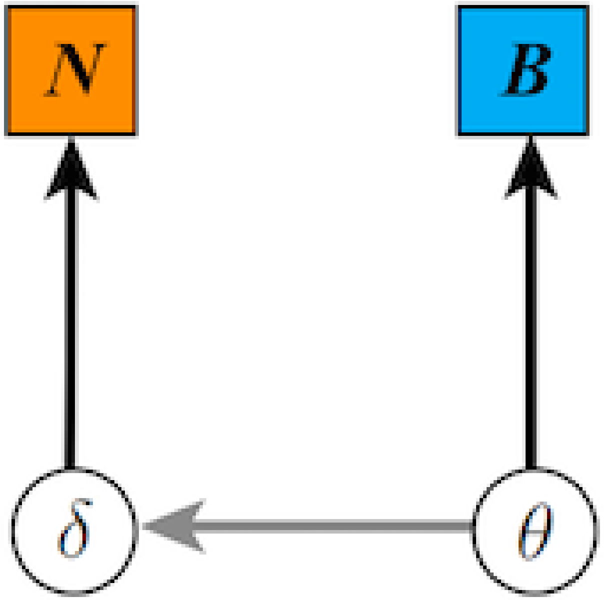


Mack, M.L., Preston, A.R. & Love, B.C. (2013). Decoding the Brain's Algorithm for Categorization from its Neural Implementation. Current Biology, 23, 2023-2027.

TWO-STAGE NEURAL

- Process of analyzing two streams of data independently, and then determining which aspects of the data are related



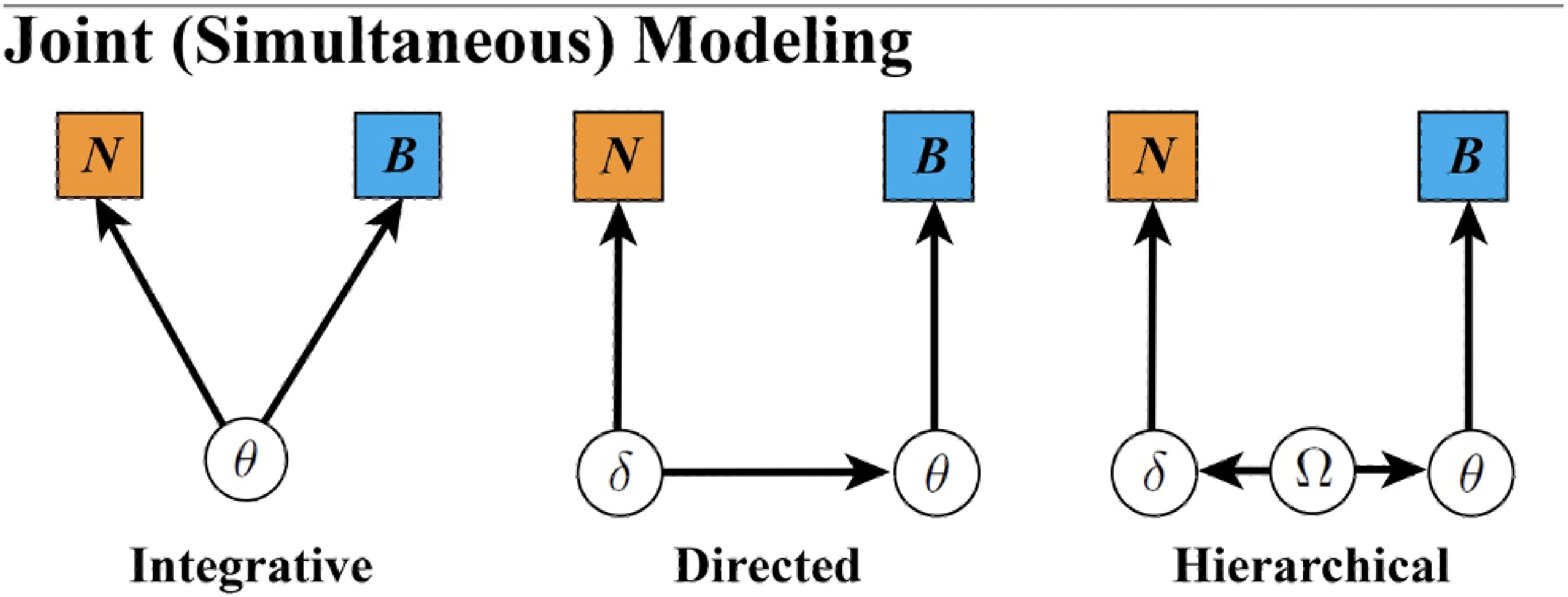


SIMULTANEOUS MODELING

- **Previous approaches make some assumptions about which aspect of the data is the 'governing force'**
- **These are unidirectional constraints, and from Love (2015), we get the sense that this may not be the best choice**
- **Can we consider both variables as equally constraining?**
- **Concerns discriminative versus generative modeling goals**

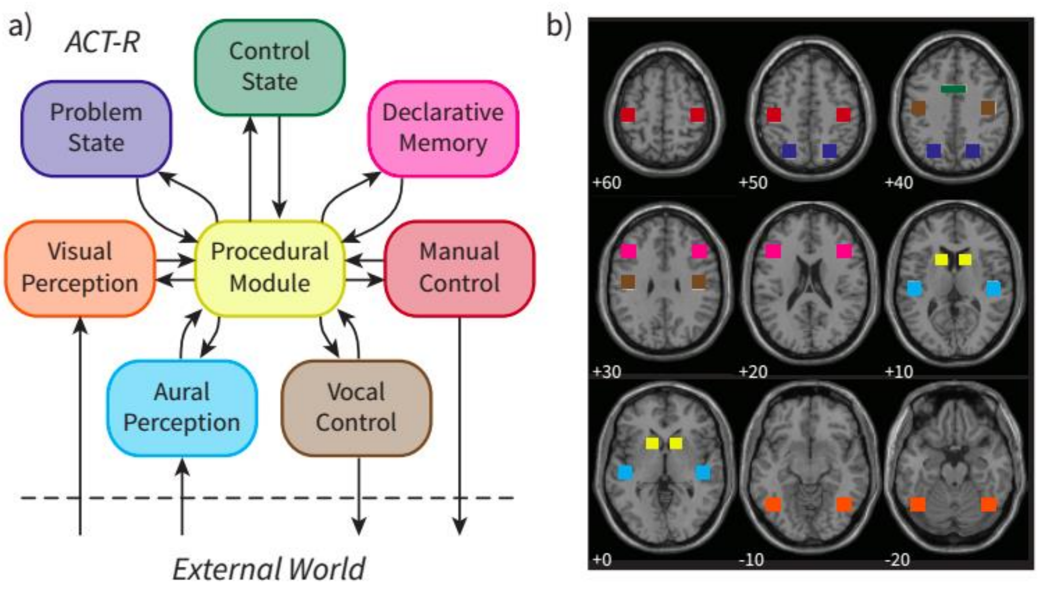
SIMULTANEOUS MODELING

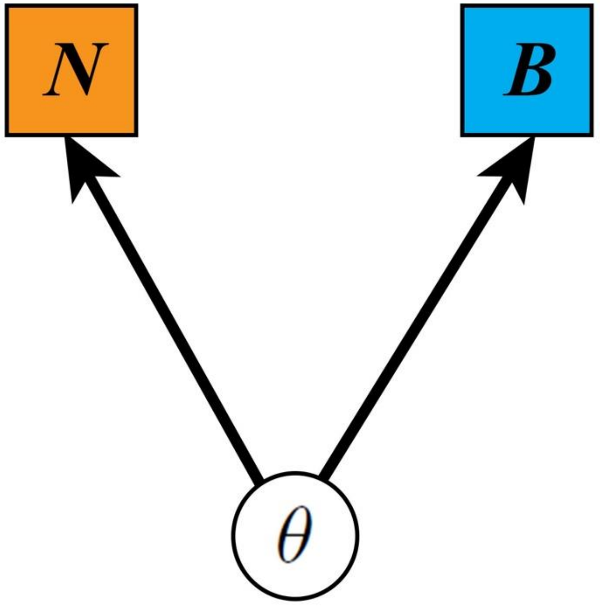
- Here are some examples:



INTEGRATIVE

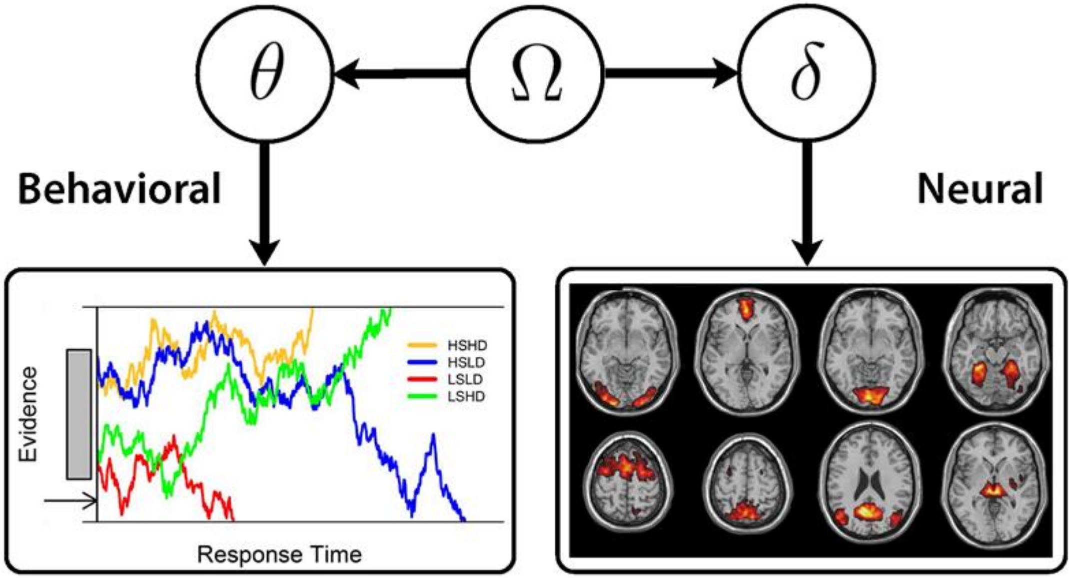
- **Architecture that forces one core model to generate predictions for both behavioral and neural data**
  - ACT-R

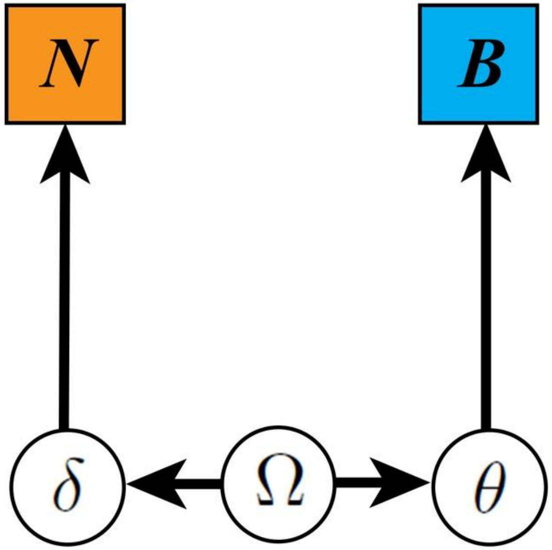




JOINT MODELING

- **Assuming two 'submodels' for each data modality**
- **Define a hyperstructure for connecting them**
  - Neural DDM





COMPARING THE APPROACHES

- It would be nice to have some way to compare these approaches so that we know which one to use for a given application.
- How should the various approaches be evaluated?
- Along what dimensions should they be compared and contrasted?
- Do these approaches cover all possible types of linkage between neural and behavioral measures?

COMPARING THE APPROACHES

One proposal is to use the following metrics:

1. Number of stages: how many steps are needed?
2. Commitment to a particular theory: how flexible is the modeling approach to new data types or new models?
3. Type of information flow: how do the random variables influence, and are influenced by, other sources of random variation?
4. Difficulty of implementation: practically speaking, how hard is this to recreate?
5. Type of exploration: Is this approach good for exploration or confirmation of theory?

Factor	Theoretical	Two-stage	Direct Input	Latent Input	Joint Modeling	Integrative
Number of stages	{2, 3, . . .}	{ 2, 3 }	1	{ 2, 3 }	1	1
Commitment to a particular theory	None	Weak	Medium	Weak	Weak	Strong
Type of information flow	Conceptual	One-way	One-way	One-way	Two-way	Two-way
Difficulty of implementation	High	Low	Medium	Medium	High	High
Type of exploration	Exploratory	Exploratory	Confirmatory	Either	Either	Confirmatory

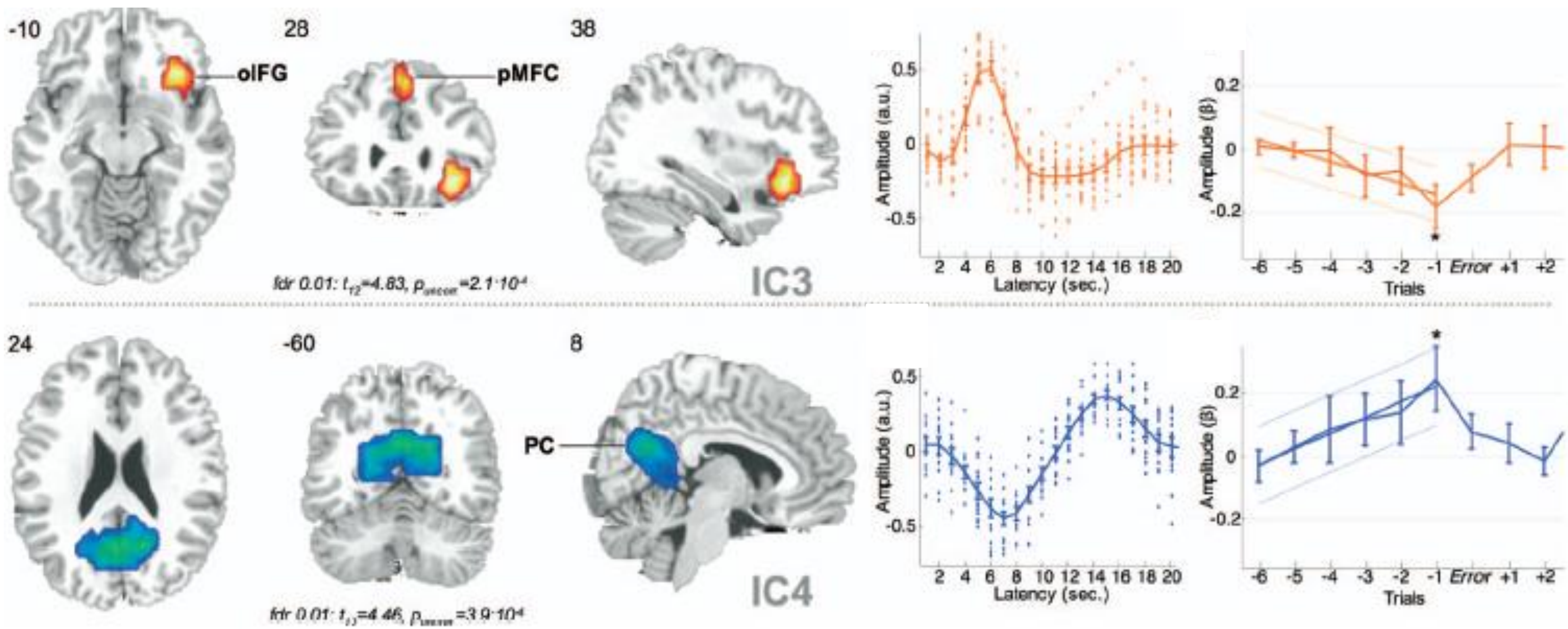
CONCLUSIONS

- There are many ways to inform cognitive models with neural data
- There are also many was to inform our analysis of neural data with cognitive models
- New approaches just waiting to be developed
- Powerful new results just waiting to be discovered by the inclusion of data that have not been previously considered

SBI SUMMER SCHOOL: JOINT MODELING: FMRI

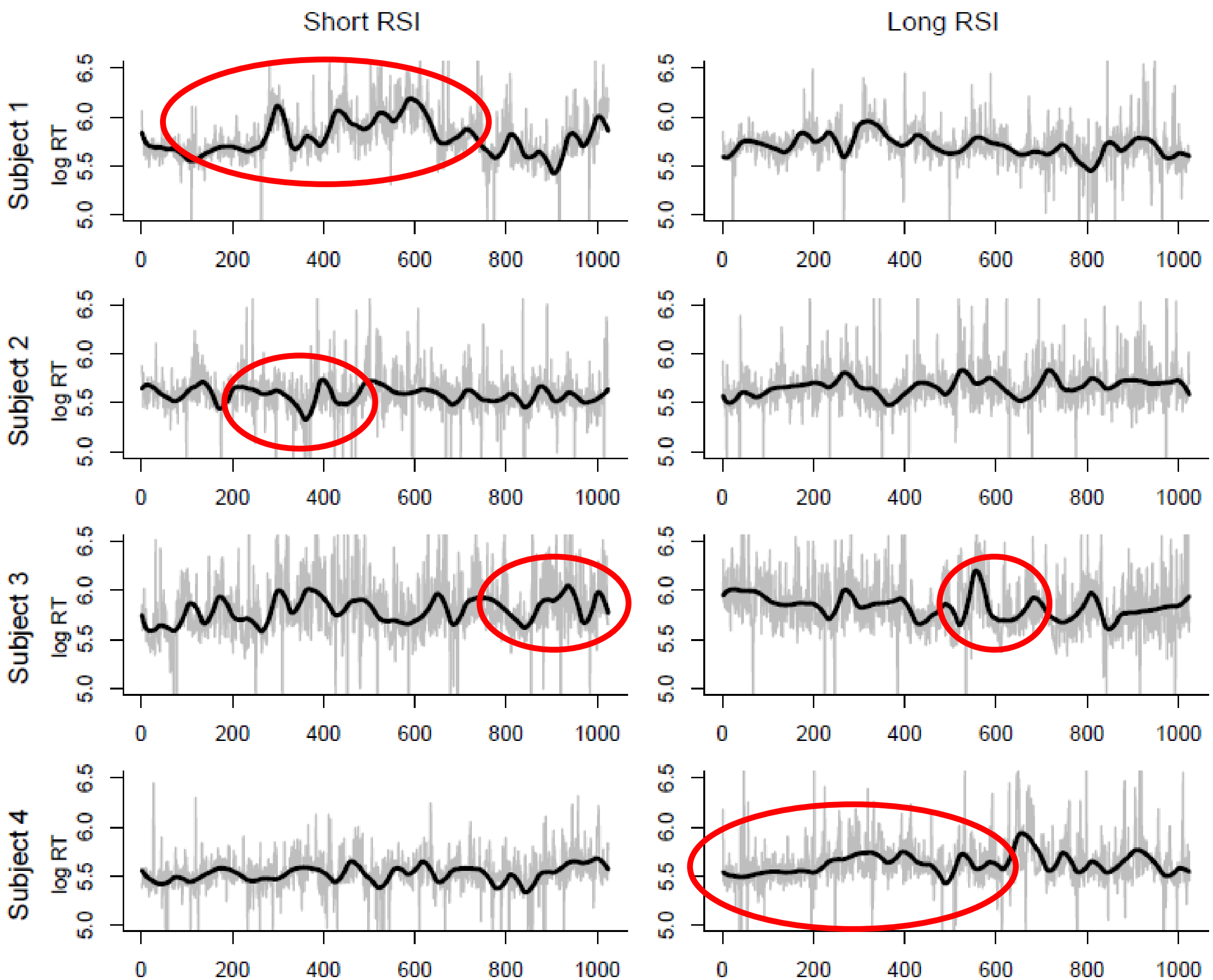
The Wandering Mind

- **Default mode network is a set of brain regions that are active when an individual is “off task”**



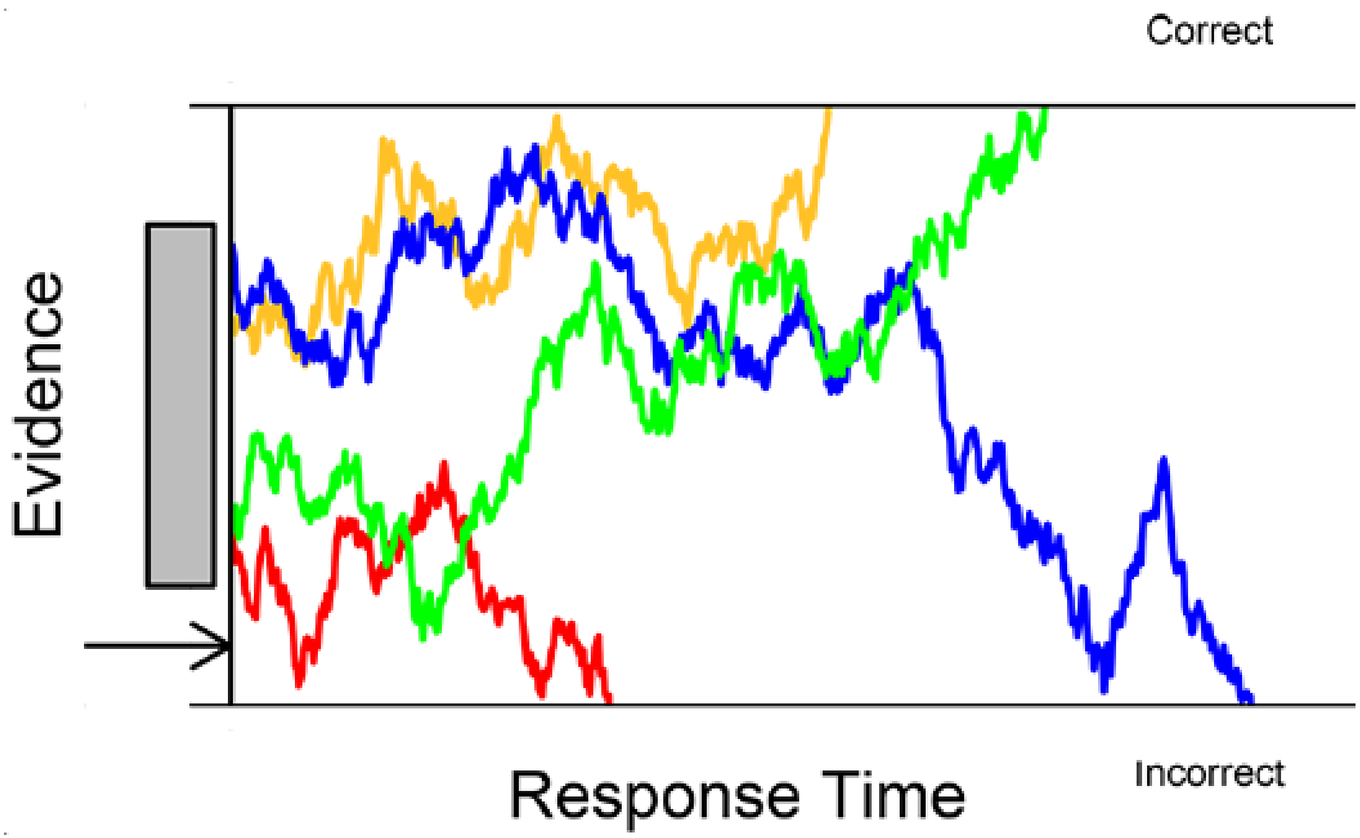
(Eichele et al., 2008)

Behavioral Data

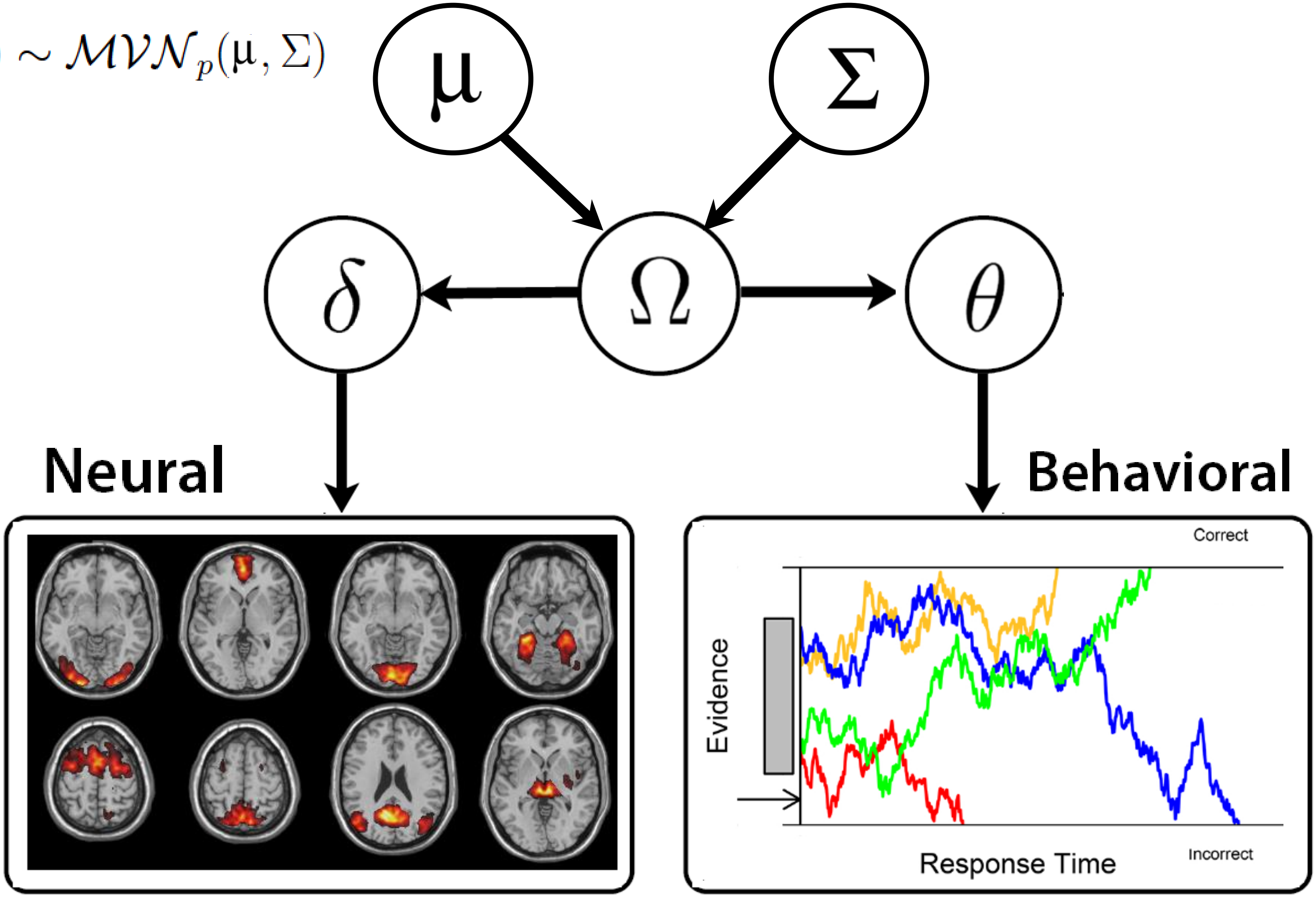


(Craigmile et al., 2013)

Diffusion Decision Model



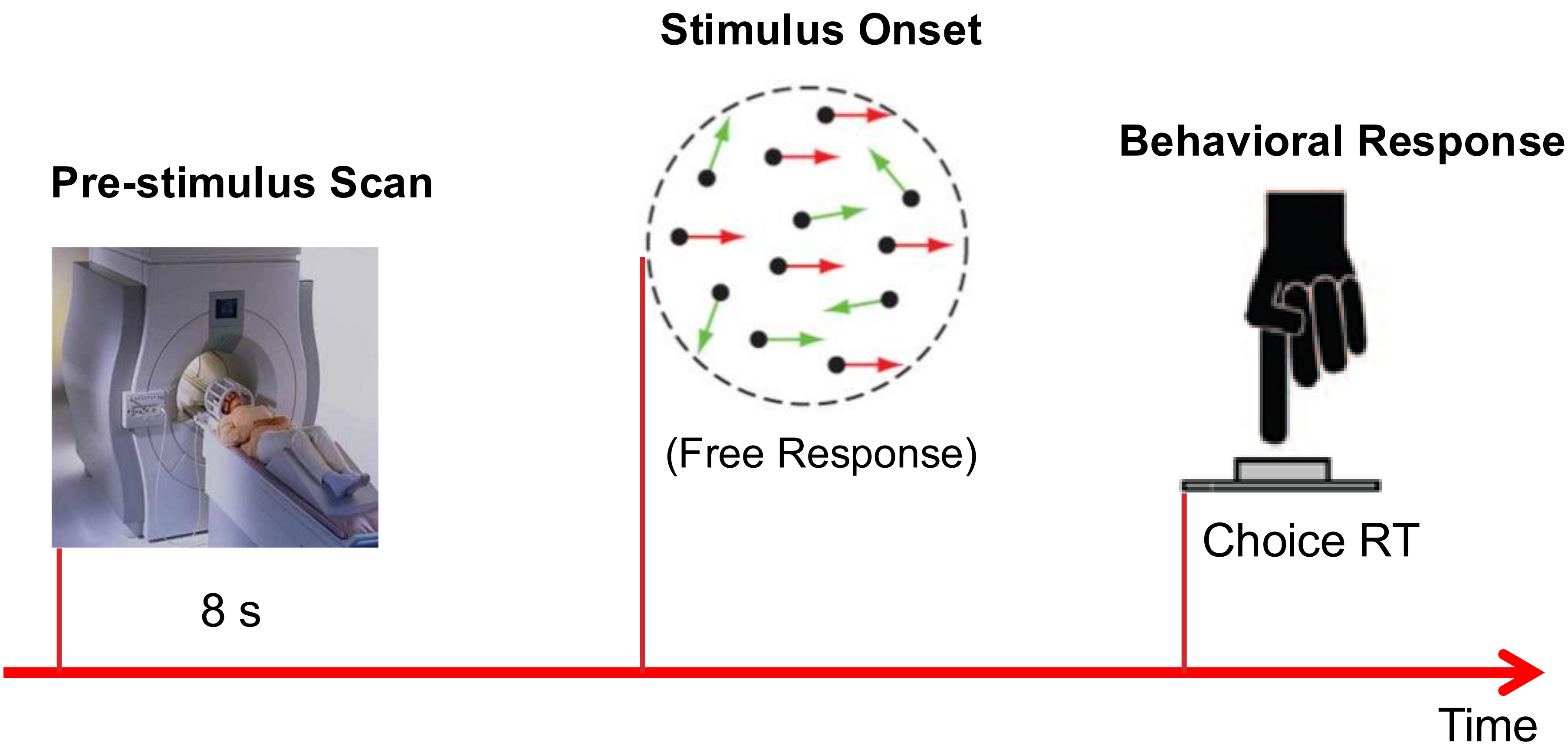
$(\theta_j, \delta_j) \sim \mathcal{MVN}_p(\mu, \Sigma)$



- Trial-level parameters for bias and drift rate
- Trial-level parameters for degree of source activation
- Subject-level parameters for neural/behavioral constraint

(Turner et al., 2015)

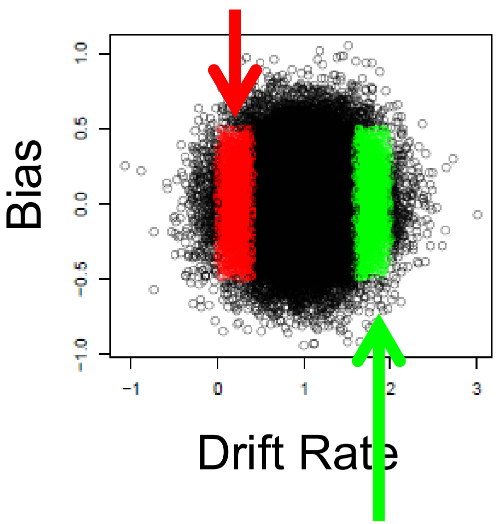
EXPERIMENT


Stimulus Onset
Behavioral Response
Pre-stimulus Scan
(Free Response)
Choice RT
8 s
Time

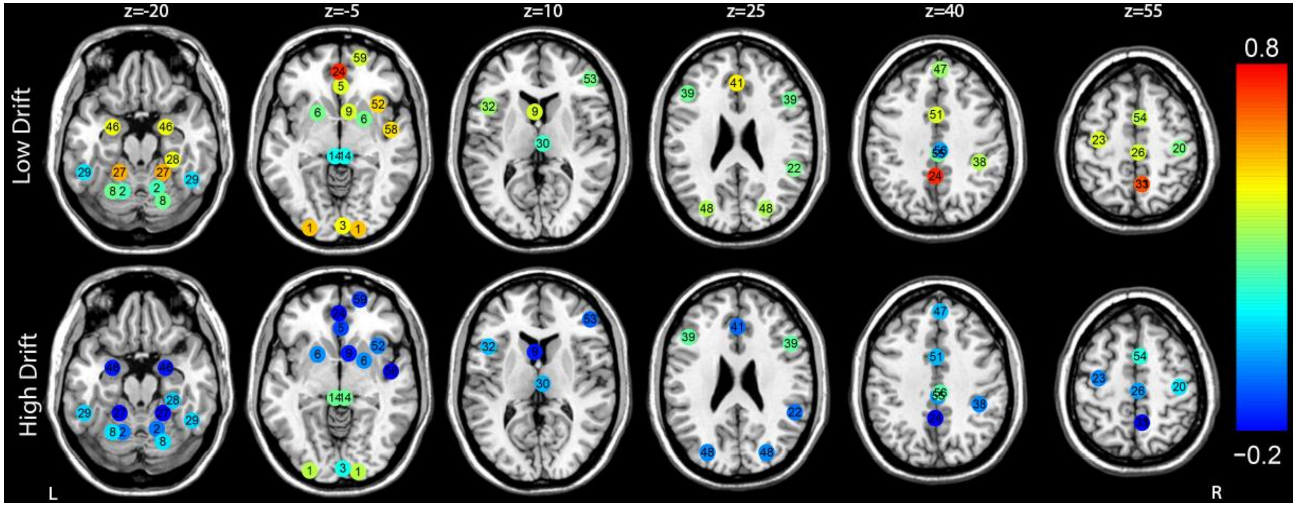
MECHANISTIC INTERPRETATION

Slow, error-prone process

Joint PPD



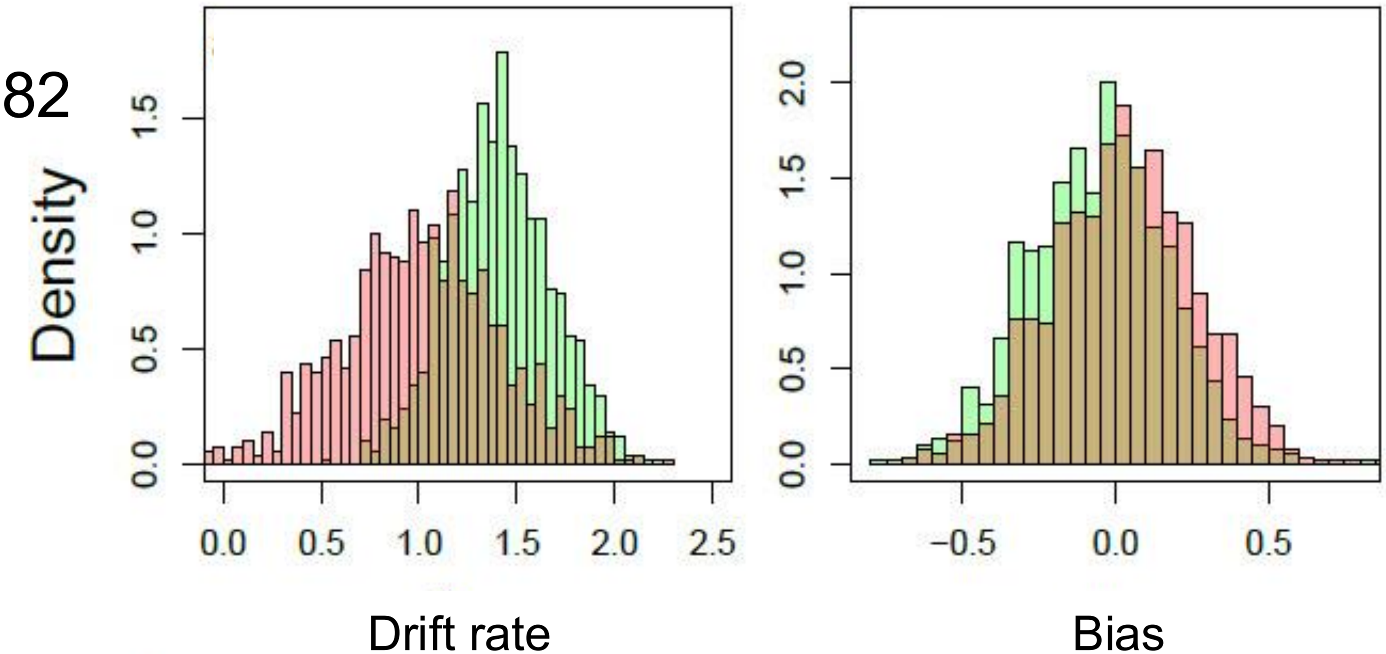
Fast, accurate process



(Turner et al., 2015)

Example:
Test Trial 82

- NDDM
- DDM



Example:
Test Trial 82

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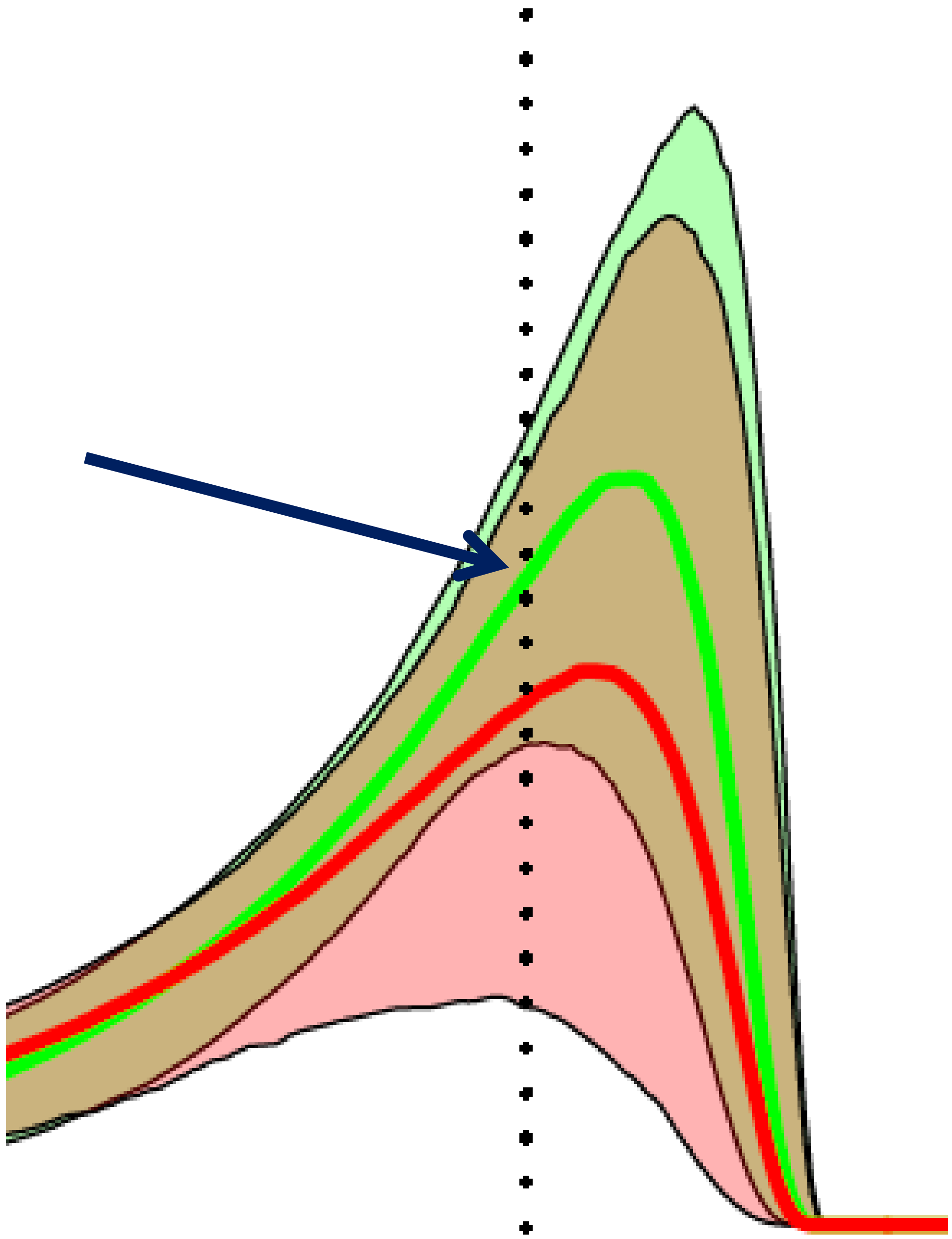
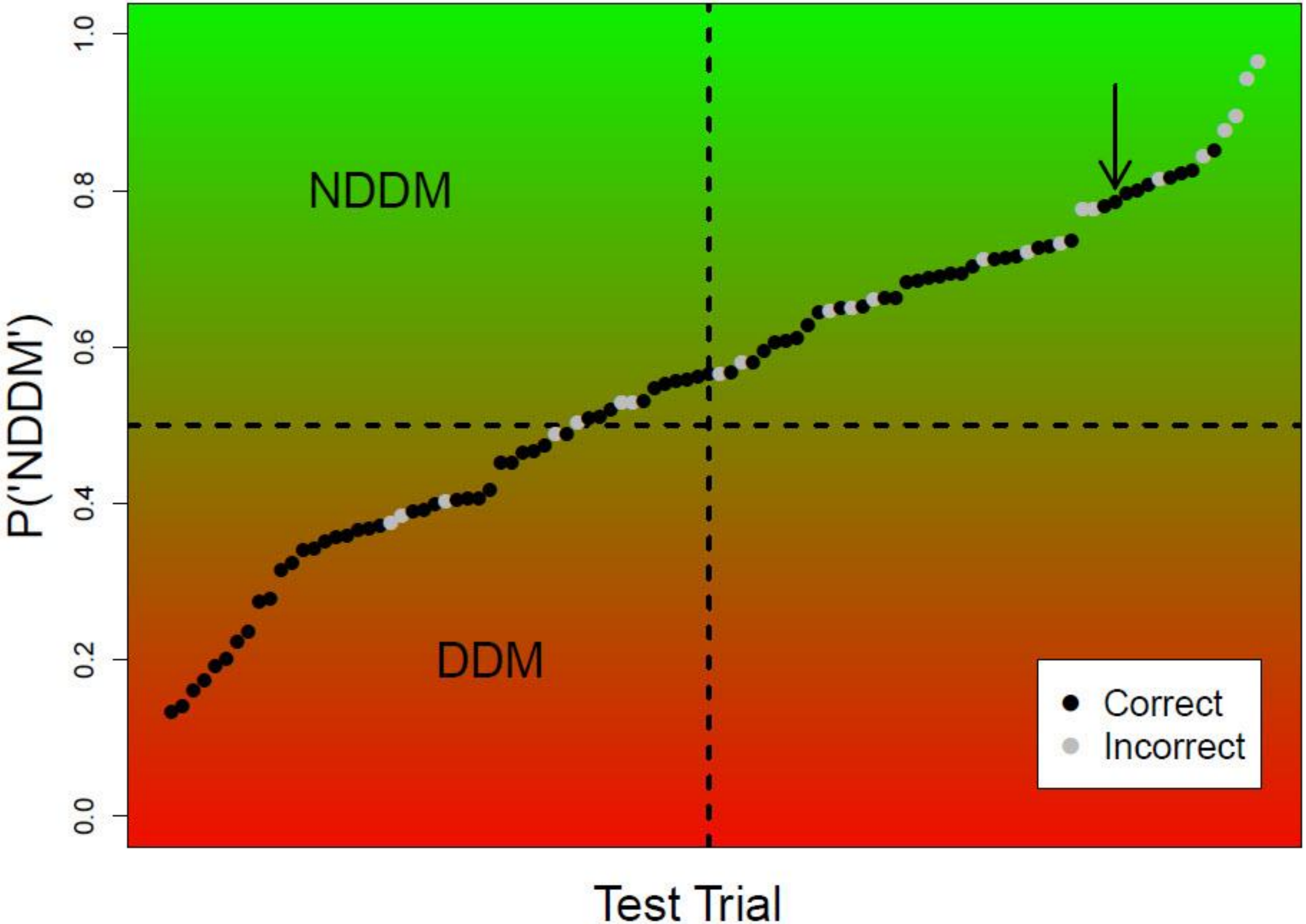
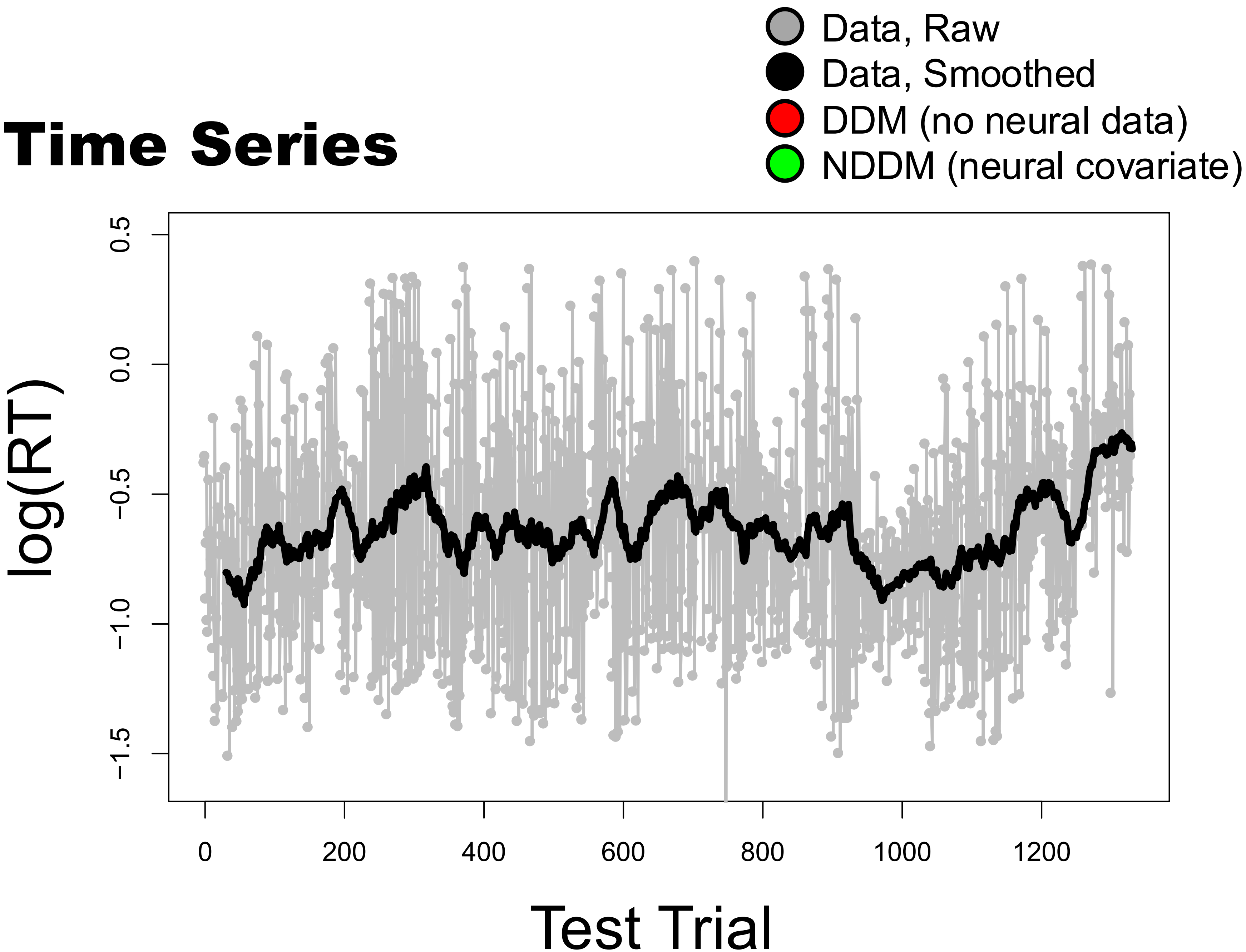


CROSS-VALIDATION TEST

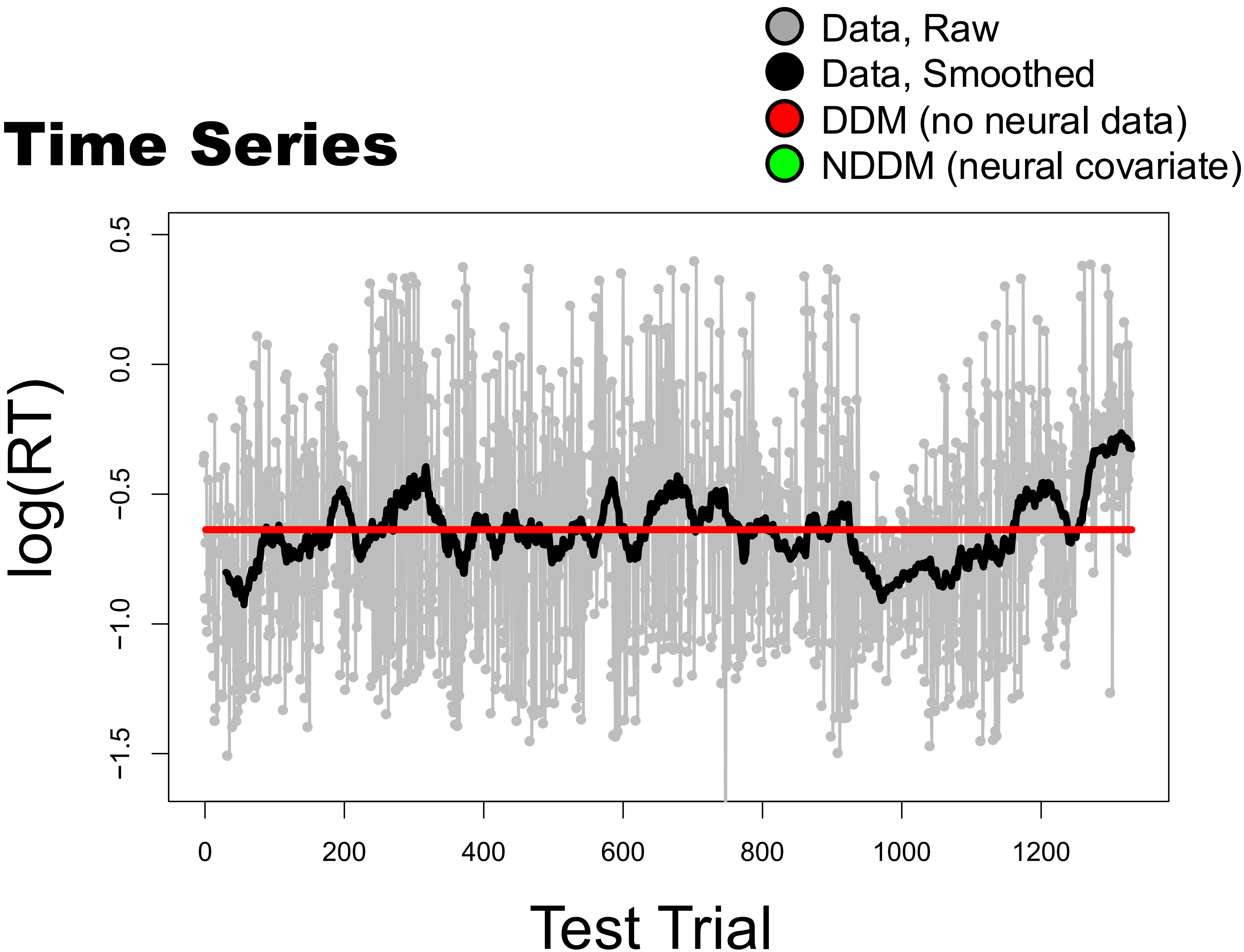


Time Series



Data, Raw
Data, Smoothed
DDM (no neural data)
NDDM (neural covariate)
log(RT)
0.5
0.0
−0.5
−1.0
−1.5
0
200
400
600
800
1000
1200
Test Trial

Time Series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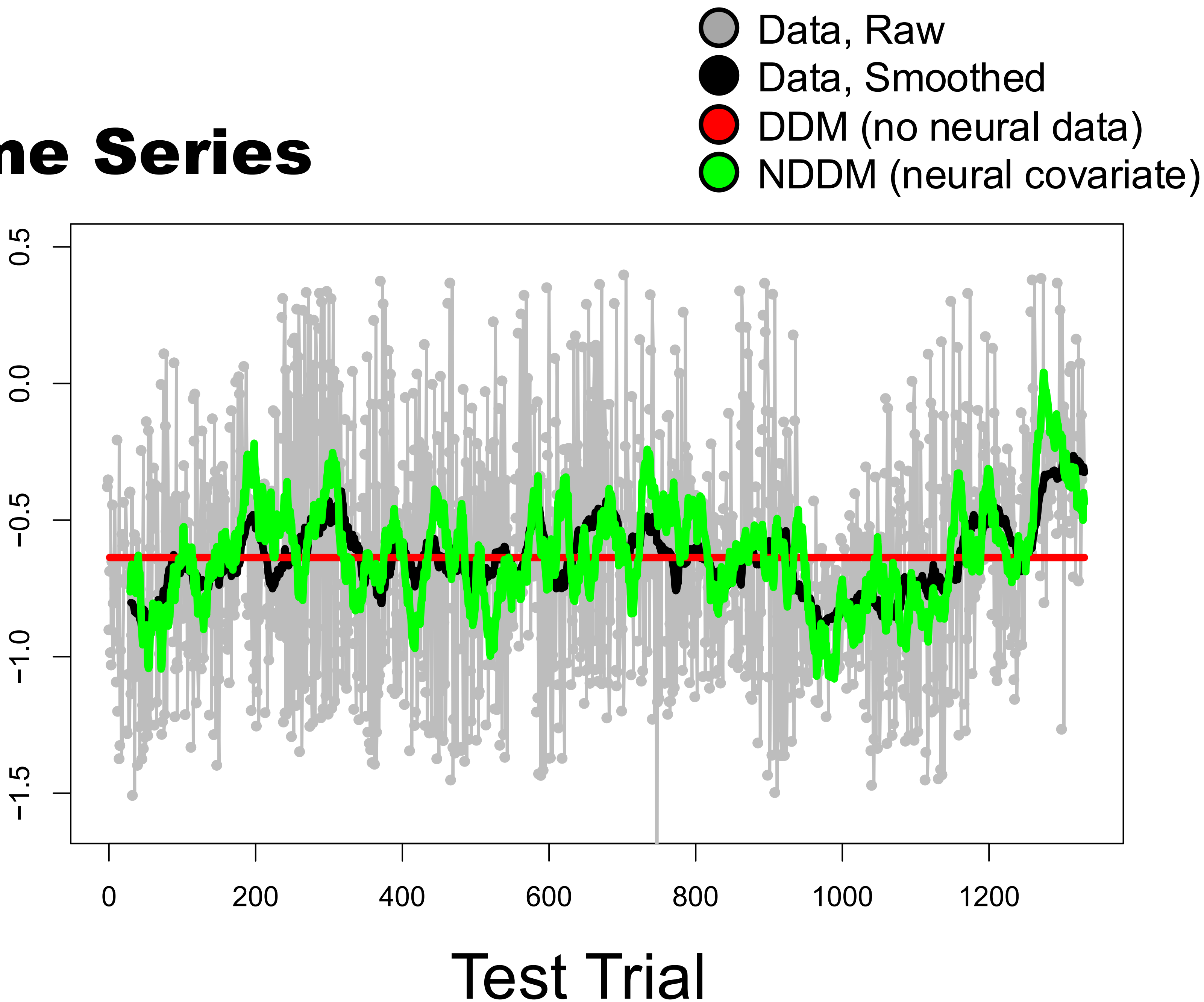

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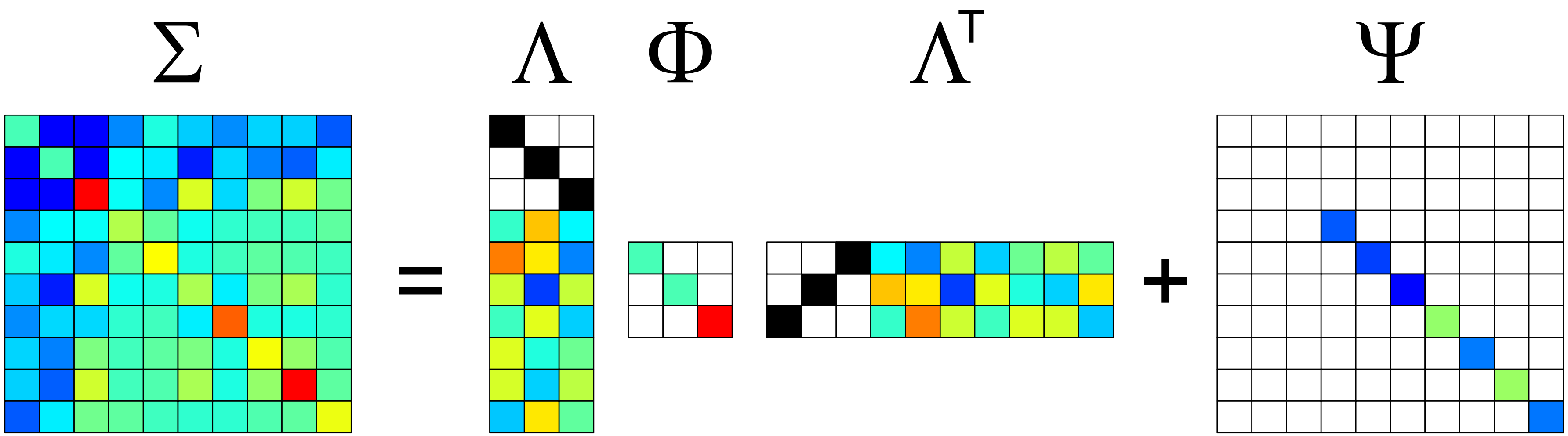
0
200
400
600
800
1000
1200
Test Trial

Linking Function

$$(\theta_j, \delta_j) \sim \mathcal{MVN}_p(\mu, \Sigma)$$

- **We can decompose Σ into a system of three matrices:**



(Turner, Wang, Merkle, 2017)

Linking Function

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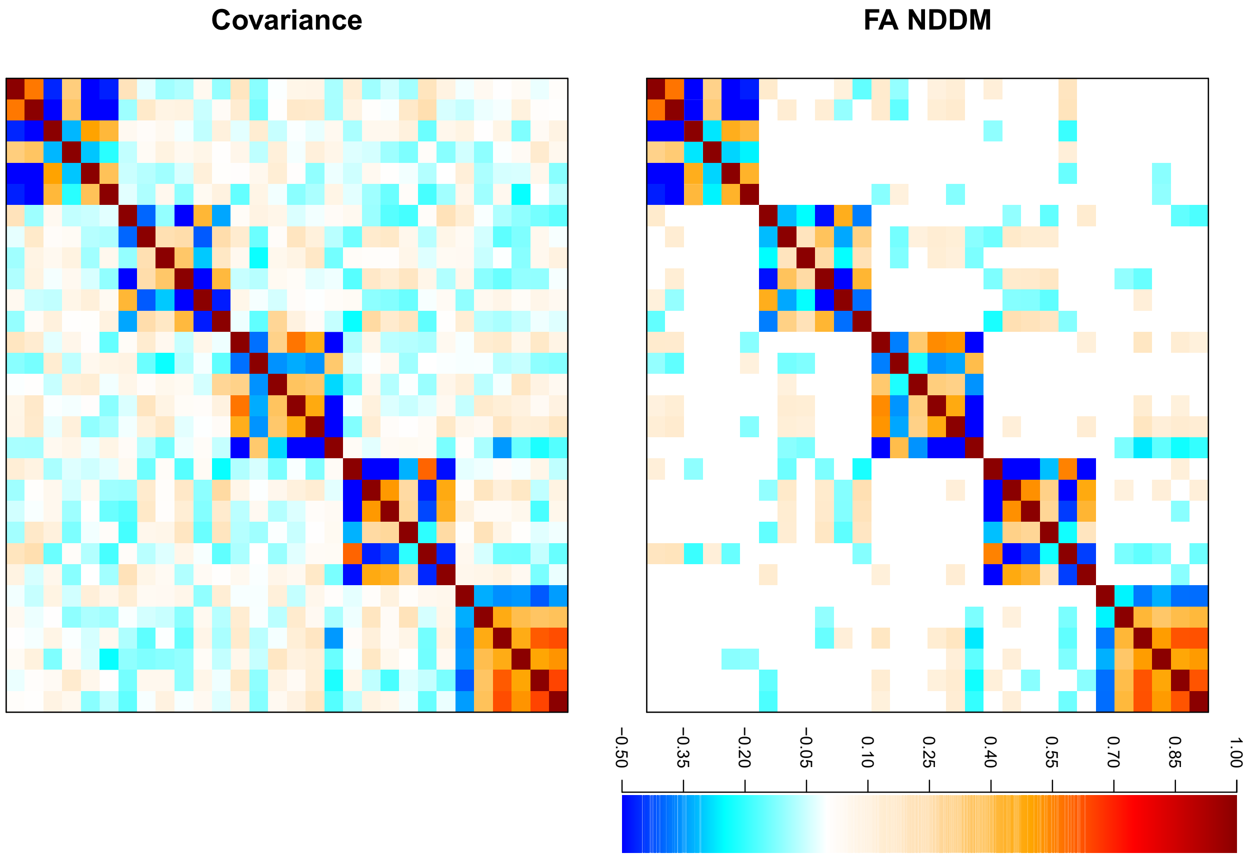
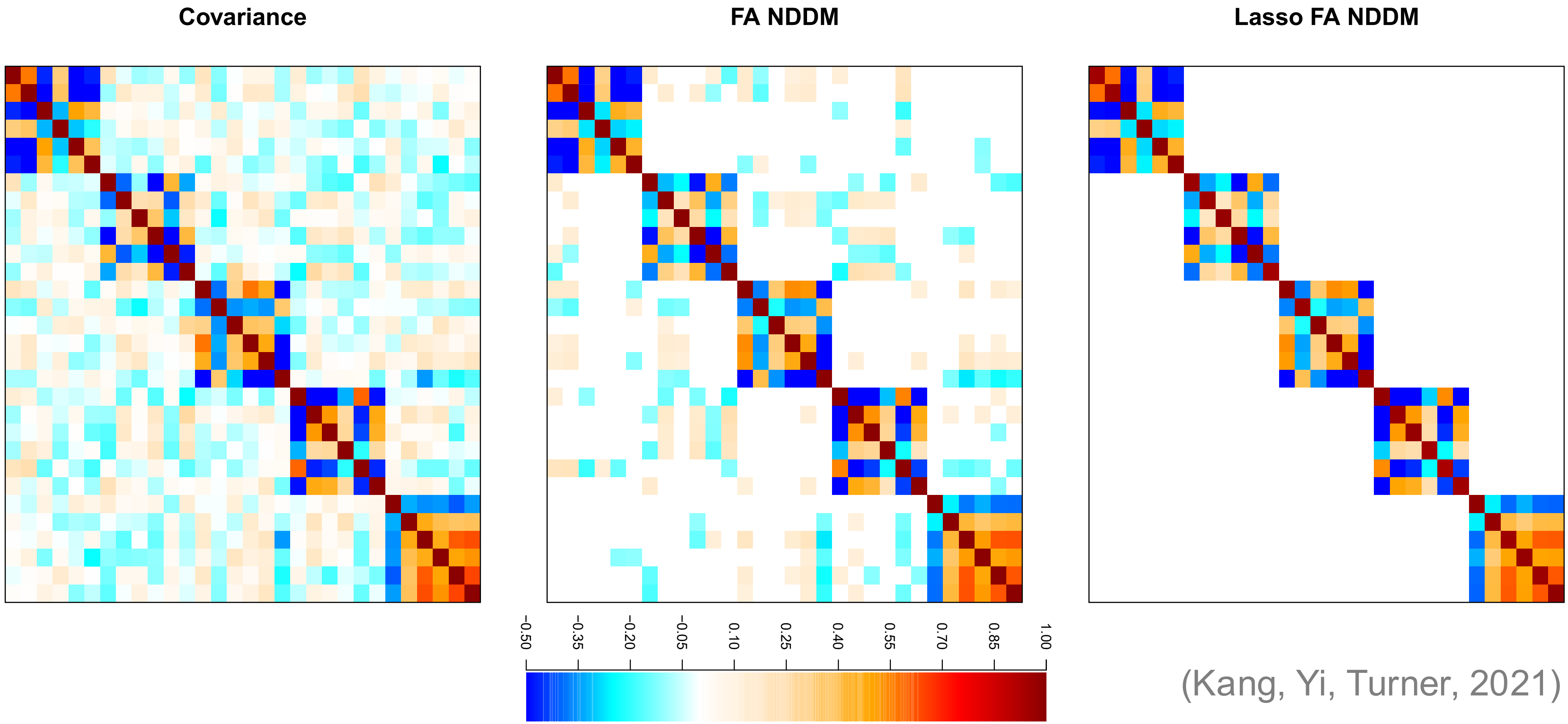


Linking Function

Inhan Kang

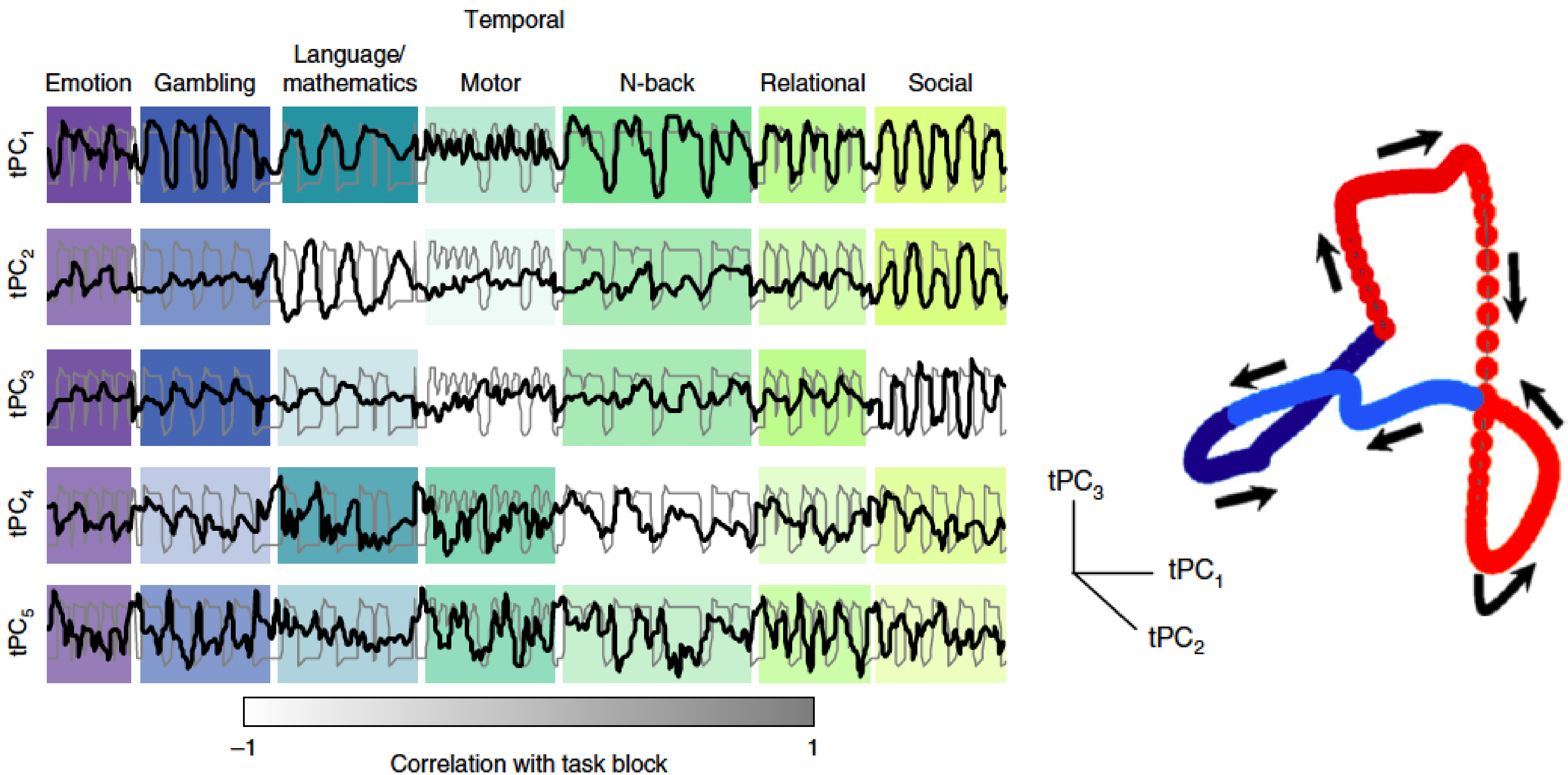
Woojong Yi

$$(\theta_j, \delta_j) \sim \mathcal{MVN}_p(\mu, \Sigma)$$



(Kang, Yi, Turner, 2021)

Latent Dynamics

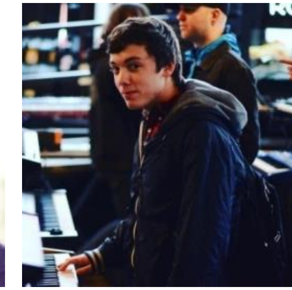


(Shine et al. 2019)

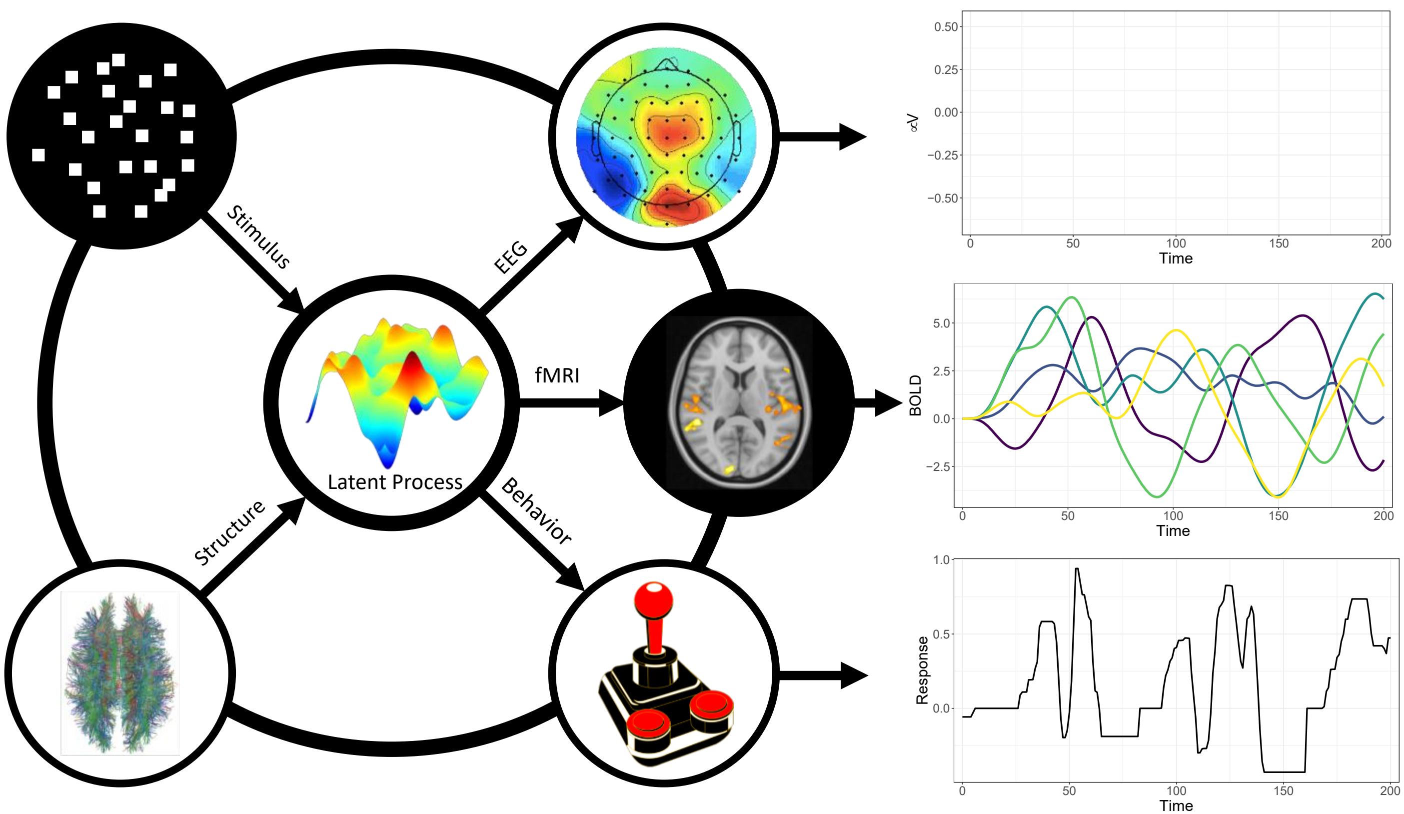
Gaussian Process Joint Modeling


Giwon Bahg


Dan Evans

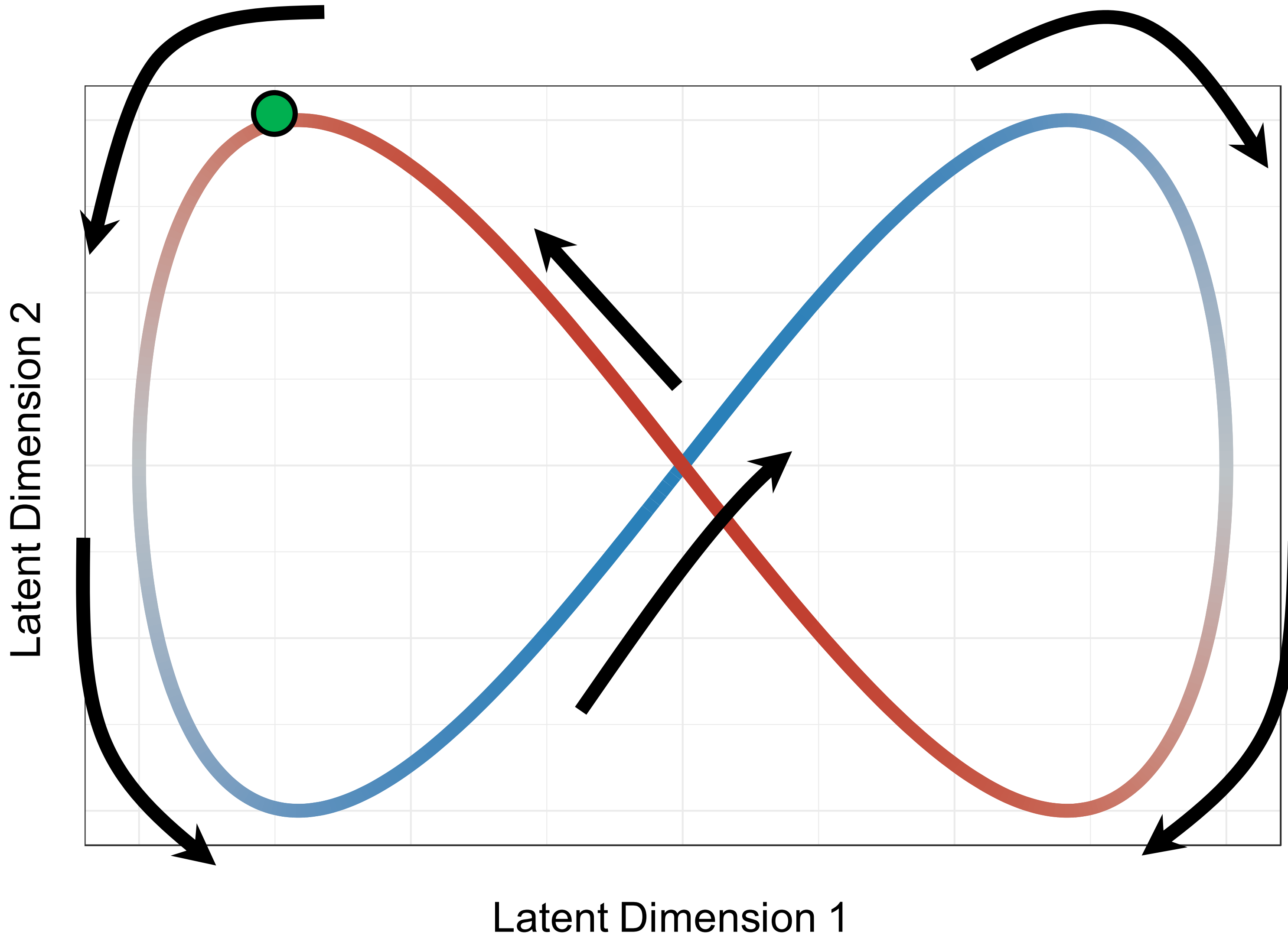

Mathew Galdo

- **We developed GPJM to deal with nonlinearities on a moment-by-moment basis**

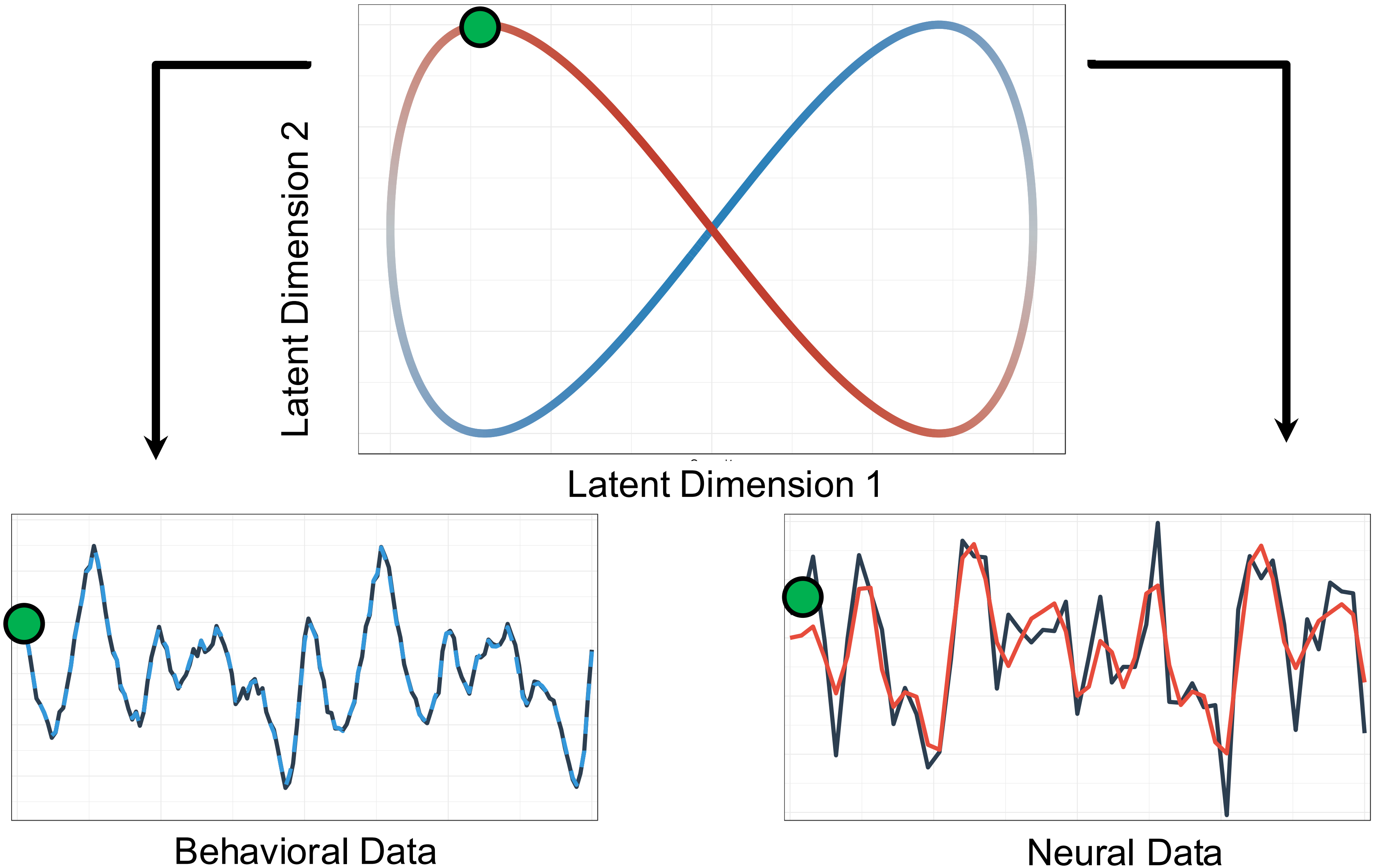


(Bahg et al., 2020)

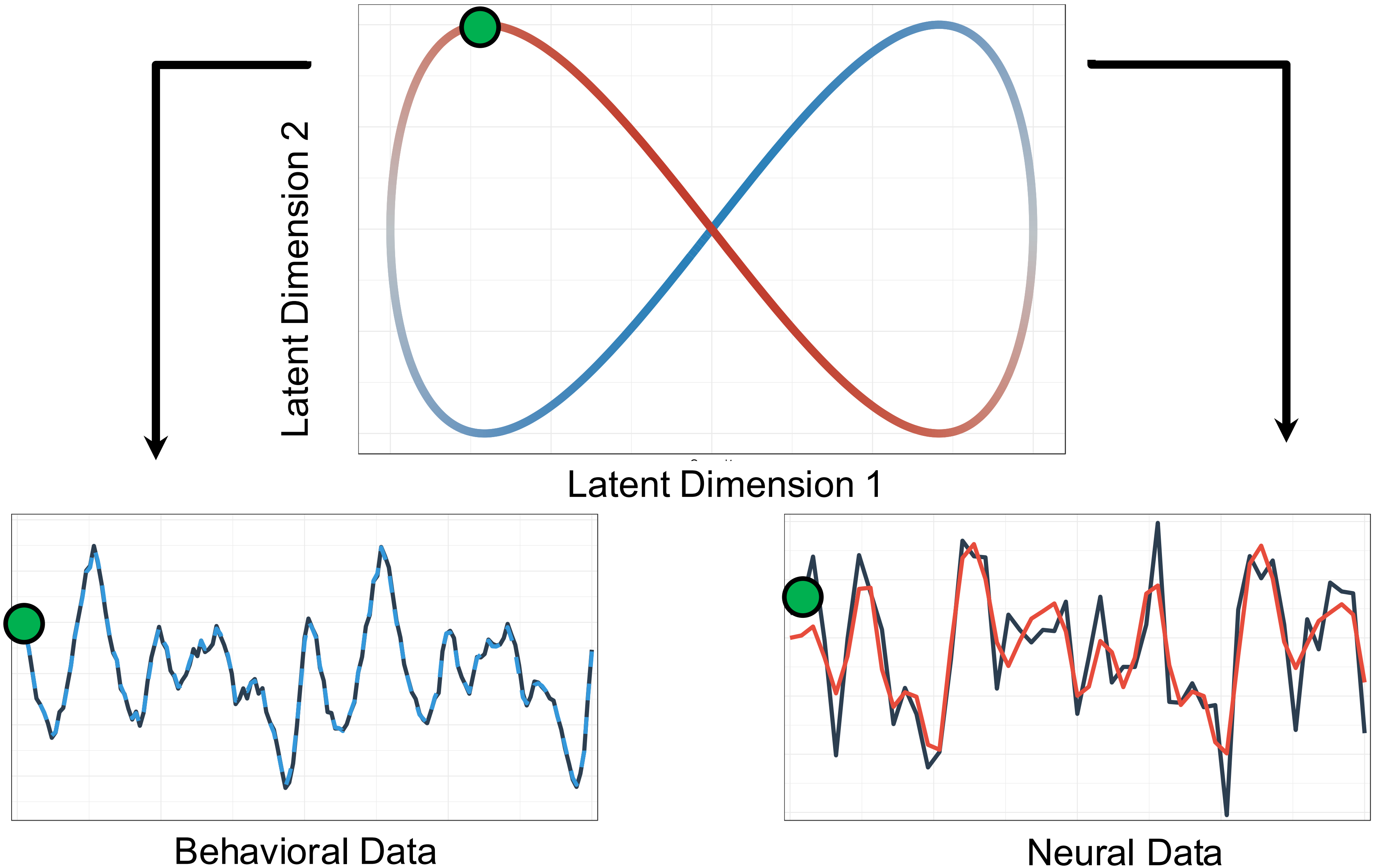
Latent Dynamics



Latent Dynamics



Latent Dynamics



Gaussian Process Joint Modeling

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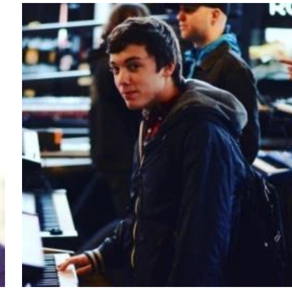
Dan Evans



Mathew Galdo

Latent Hyperstructure:

$$X \sim \mathcal{N}(\mathbf{0}, K_{tt})$$

$$K_{tt} = [k_t(t_i, t_j)]_{ij} := \left[s_t^2 \exp\left(- \frac{(t_i - t_j)^2}{2l_t^2} \right) \right]_{ij}$$

Neural Submodel:

$$Y_N \sim \mathcal{N}(\mathbf{0}, K_{XX(N)} + \sigma_N^2 I)$$

$$K_{XX(N)} = [k_N(x_i, x_j)]_{ij} := \left[s_N^2 \exp\left(- \frac{(x_i - x_j)^2}{2l_N^2} \right) \right]_{ij}$$

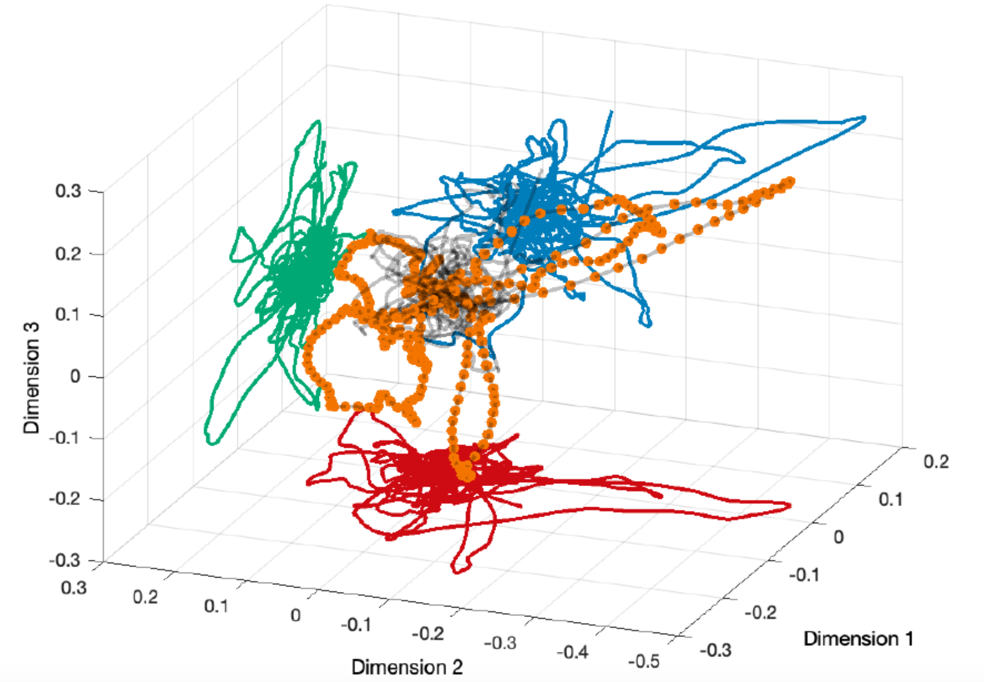
Behavioral Submodel:

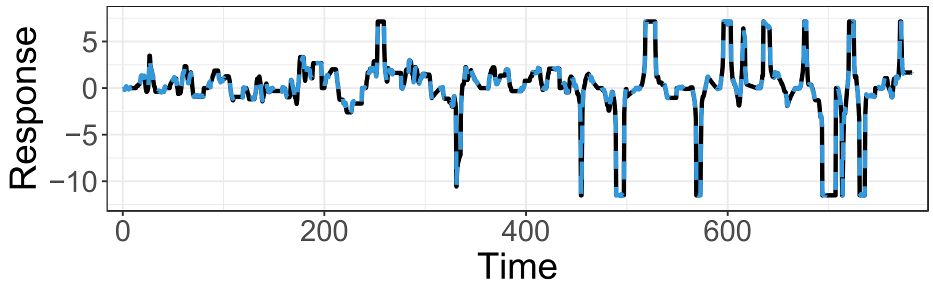
$$Y_B \sim \mathcal{N}(\mathbf{0}, K_{XX(B)} + \sigma_B^2 I)$$

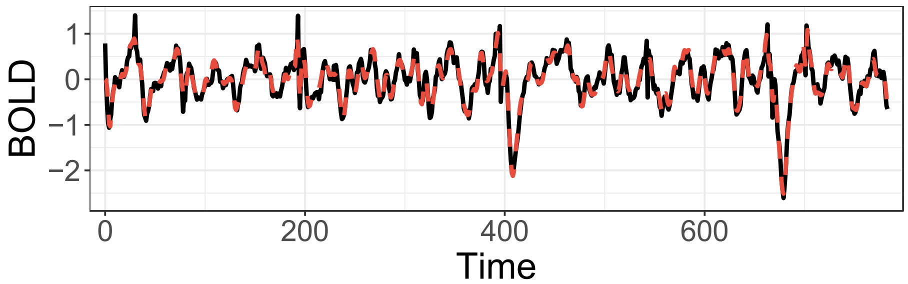
$$K_{XX(B)} = [k_B(x_i, x_j)]_{ij} := \left[s_B^2 \exp\left(- \frac{||x_i - x_j||}{l_B} \right) \right]_{ij}$$

(Bahg et al., 2020)

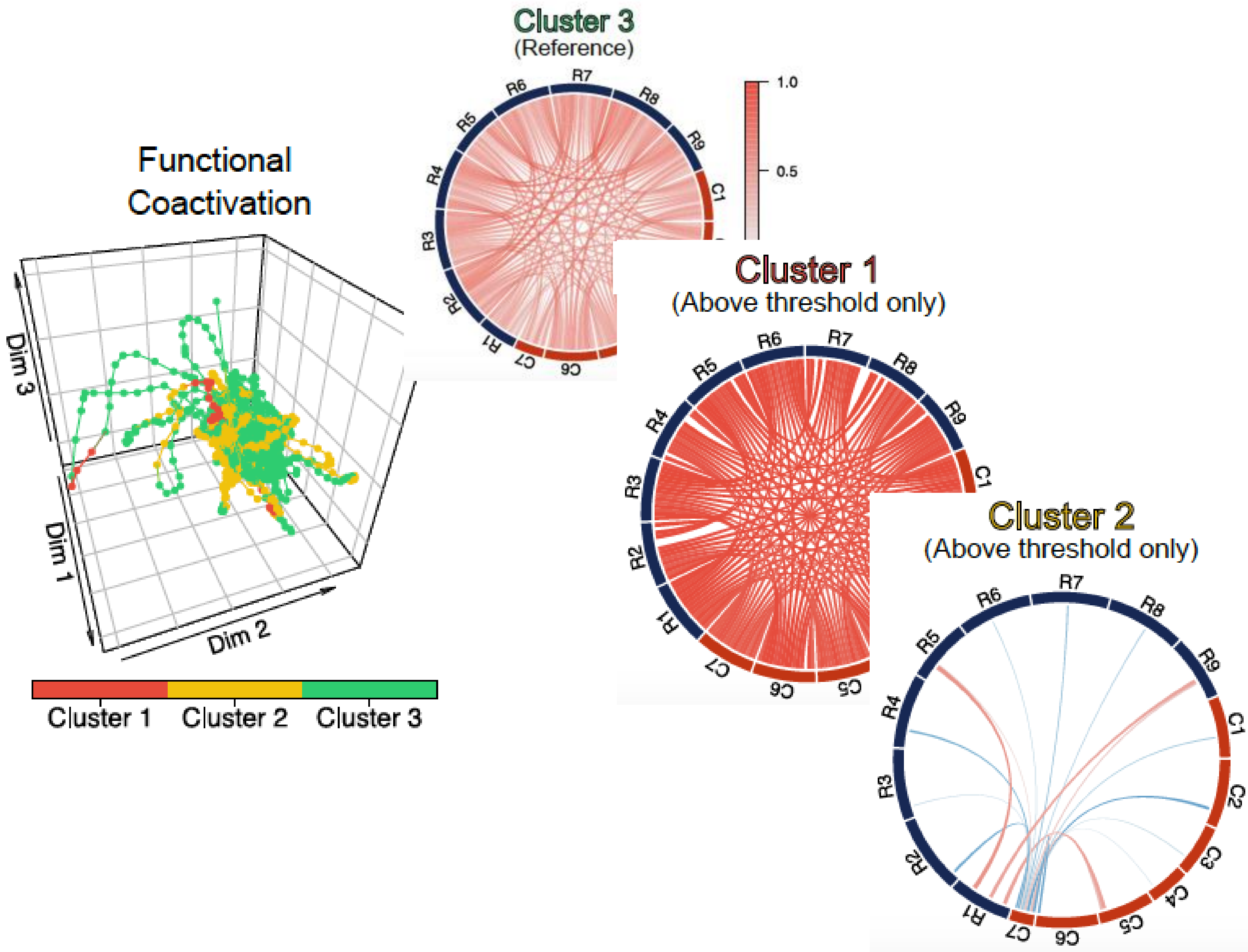
Application: Motion Tracking Task







(Bahg et al., 2020)


Functional
Coactivation
Dim 3
Dim 1
Dim 2
Cluster 1
Cluster 2
Cluster 3
Cluster 3
(Reference)
1.0
0.5
R1
R2
R3
R4
R5
R6
R7
R8
R9
C1
C7
C6
Cluster 1
(Above threshold only)
R1
R2
R3
R4
R5
R6
R7
R8
R9
C1
C7
C6
C5
Cluster 2
(Above threshold only)
R1
R2
R3
R4
R5
R6
R7
R8
R9
C1
C2
C3
C4
C5
C6
C7

Conclusions

- The impetus for linking brain and behavioral data should be the one thing they have in common: the mind

- By abstracting mental operations into a shared latent space, we are better postured to exploit statistical commonalities within any measure of cognition

- Joint modeling is one convenient way to do this