

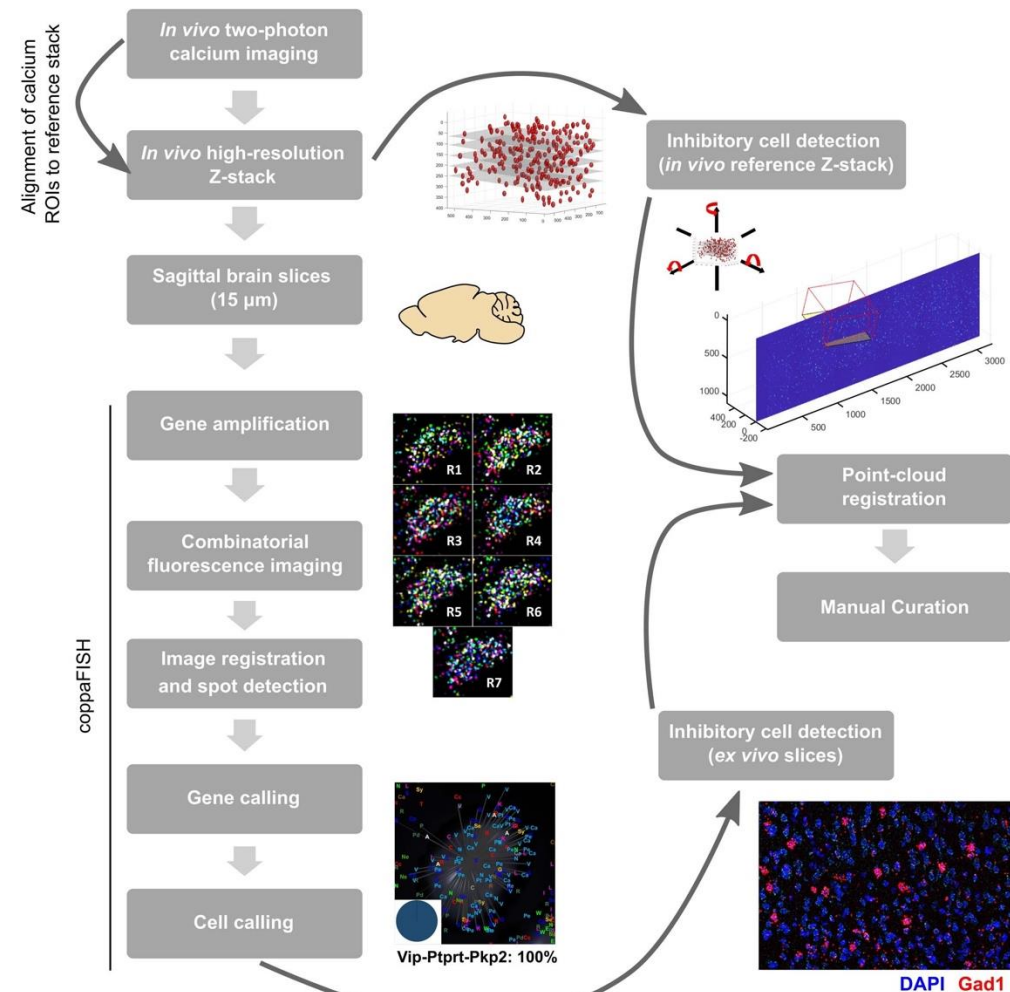
Neural Representational Consistency Emerges from Probabilistic Neural- Behavioral Representation Alignment

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1. Neuroscience relies on multimodal data analysis

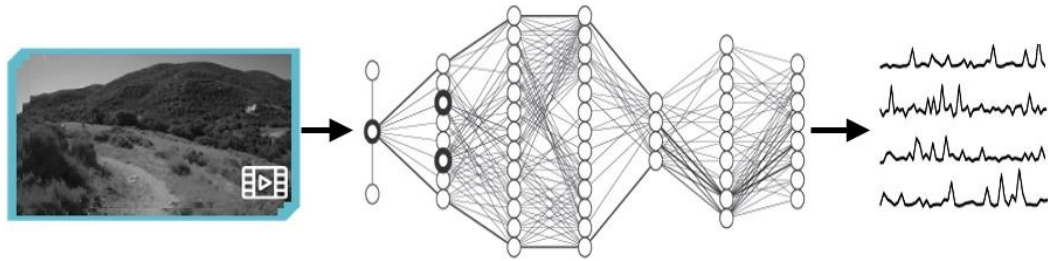
Multimodal data for decoding brain function: neural activity, behaviors, stimulus, gene...



Bugeon et al. (Nature, 2022)

2. Modeling paradigms vary across cortical regions

Sensory cortex (e.g., Visual cortex)



Walker et al. (Nat. Neurosci., 2019)

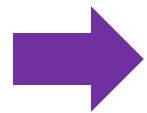
Motor cortex (e.g., PMd)



Gallego et al. (Nat. Neurosci., 2020)

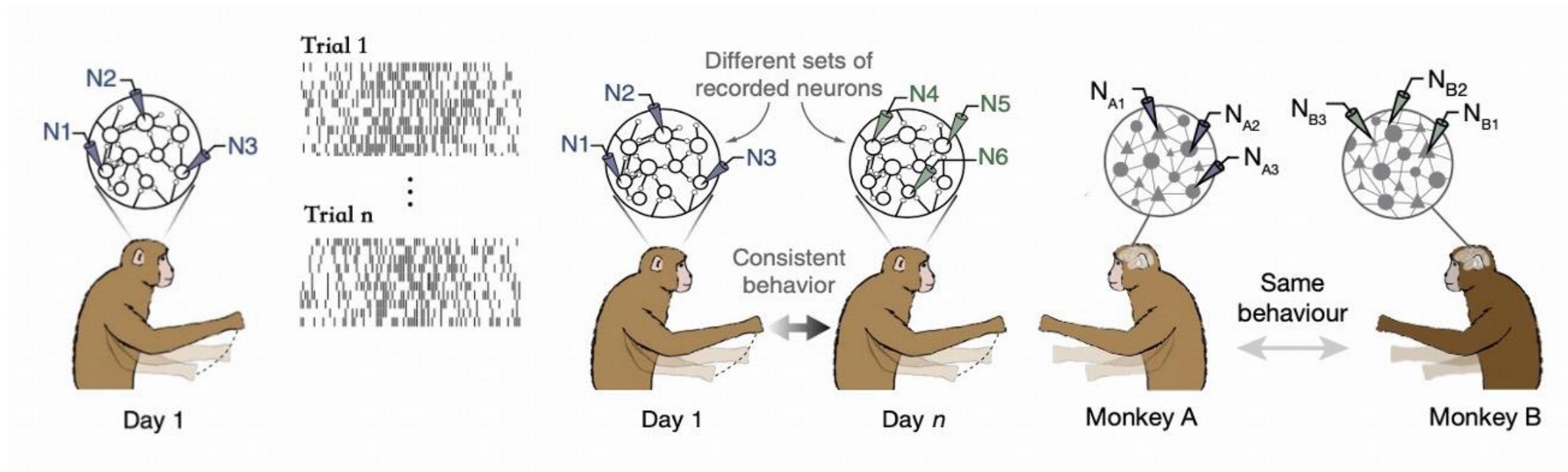
Predictive modeling (digital twin)

Behavioral decoding



Computational modeling fundamentally involves aligning neural activity patterns with their corresponding behaviors.

3. Inherent challenges in unified modeling

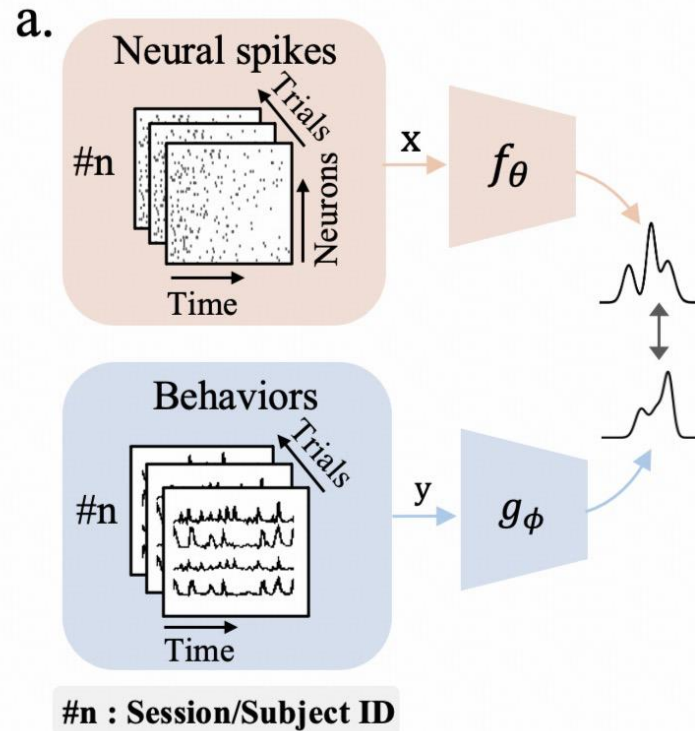


Cross-trials variability Cross-session variability Cross-subject variability

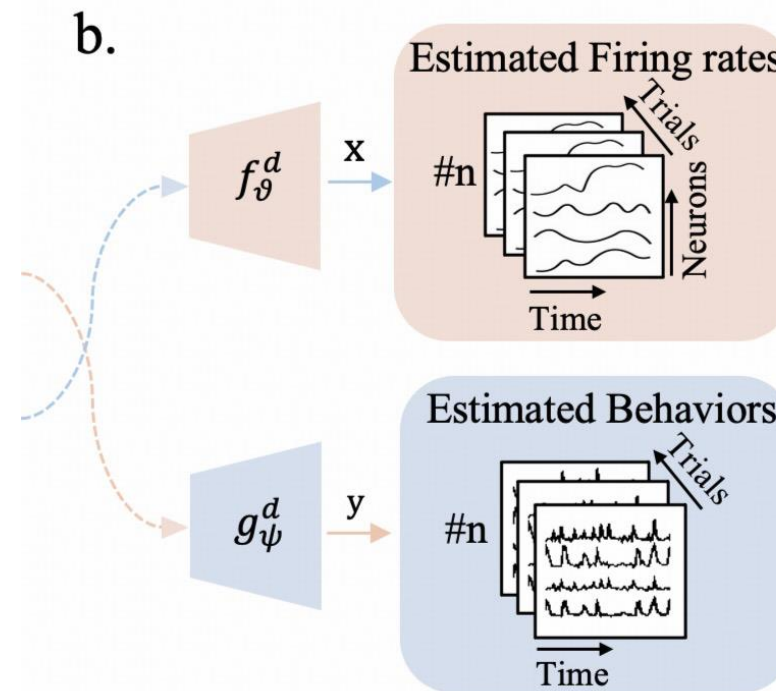
➡ The inherent one-to-many correspondence between behavior and neural activity at the raw data level presents a theoretical barrier to establishing deterministic mathematical relationships.

4. Our probabilistic representation modeling paradigm

Probabilistic Matching



Generative-informed Modeling



1. Adopt probabilistic representation modeling instead of seeking deterministic bijective mappings.
2. Strengthen representation learning through reconstruction constraints to prevent representational collapse.

5. Theoretical advantages of the alignment modeling

Theorem 3.1. Let $f_\theta : \mathcal{X} \rightarrow \mathcal{Z}$ and $g_\phi : \mathcal{Y} \rightarrow \mathcal{Z}$ denote the neural and behavioral encoders. The following properties hold:

(i) [Non-degeneracy] The optimization objective \mathcal{L}_{total} prevents representation degeneration by ensuring:

$$\lim_{f_\theta(\mathbf{x}) \rightarrow \mathbf{z}_{const}} \mathcal{L}_{total} = +\infty, \quad \forall \mathbf{z}_{const} \in \mathcal{Z} \quad (10)$$

(ii) [Information Preservation] The generative constraints ensure enhanced mutual information between input and representation spaces:

$$I(f_{\mathcal{L}_{total}}(\mathbf{x}); \mathbf{x}) \geq I(f_{\mathcal{L}_{ProbMatch}}(\mathbf{x}); \mathbf{x}) + \eta, \quad \eta > 0 \quad (11)$$

(iii) [Representation Stability] For neural responses $\mathbf{x}_i, \mathbf{x}_j$ corresponding to the same behavioral variable \mathbf{y} , the learned representations maintain bounded distances:

$$0 < \alpha \leq \|f_\theta(\mathbf{x}_i) - f_\theta(\mathbf{x}_j)\|_2 \leq \beta \quad (12)$$

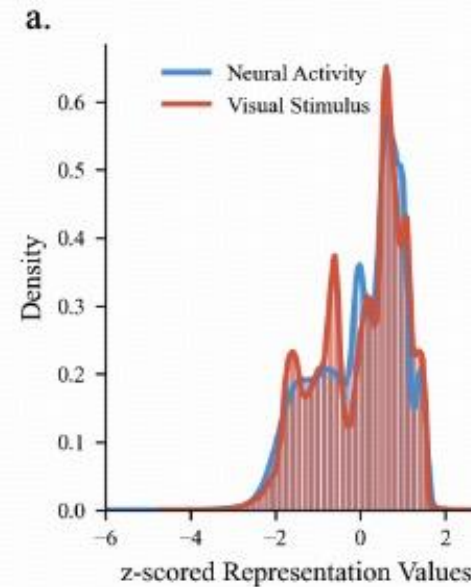
Note: property (iii) addresses the inherent neural variability associated with identical behavioral outputs by maximizing representational similarity while preserving biological diversity.

Theoretical results show that the representation alignment paradigm is optimal for computational modeling.

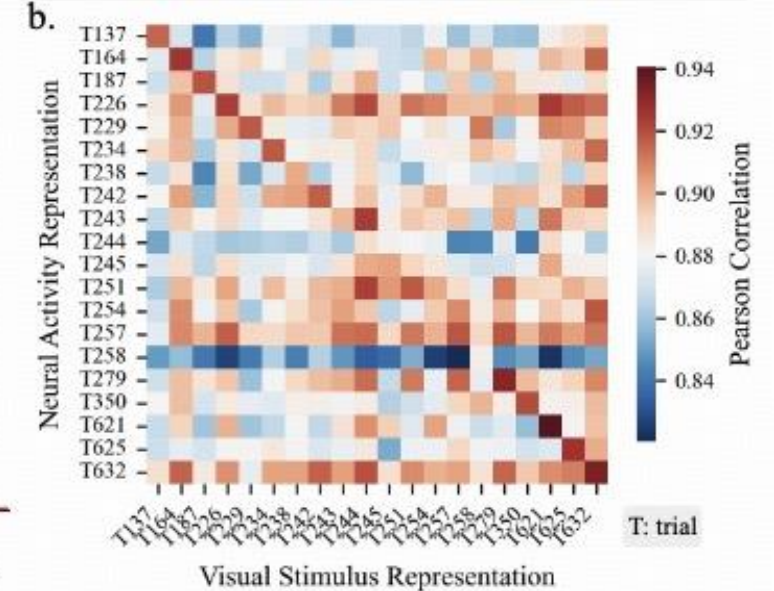
6. Alignment results of latent representation modeling

| Cortical Area | Method | Correlation (R) | |
|--------------------|----------------------------|-------------------|---------------|
| | | Training Subjects | New Subjects |
| Motor Cortex (M1) | VAE [§] | 0.0197 | 0.0016 |
| | FA+Procrustes [†] | 0.3334 | 0.2009 |
| | PCA+CCA [†] | 0.3520 | 0.2160 |
| | FA+amLDS [†] | 0.5807 | 0.3627 |
| | Neuroformer* | 0.5214 | — |
| | MEME | 0.7756 | 0.7060 |
| | PNBA (Ours) | 0.9465 | 0.9302 |
| Motor Cortex (PMd) | VAE [§] | 0.0063 | 0.0028 |
| | FA+Procrustes [†] | 0.3605 | 0.2877 |
| | PCA+CCA [†] | 0.3916 | 0.3397 |
| | FA+amLDS [†] | 0.4733 | 0.4366 |
| | Neuroformer* | 0.3283 | — |
| | MEME | 0.5279 | 0.5255 |
| | PNBA (Ours) | 0.9248 | 0.9176 |
| Visual Cortex (V1) | VAE [§] | 0.0029 | -0.0009 |
| | FA+Procrustes [†] | 0.1221 | 0.1207 |
| | PCA+CCA [†] | 0.1210 | 0.1209 |
| | FA+amLDS [†] | 0.1509 | 0.1501 |
| | Neuroformer* | 0.4116 | — |
| | MEME | 0.6357 | 0.5980 |
| | PNBA (Ours) | 0.8830 | 0.8705 |

Distribution of Representation

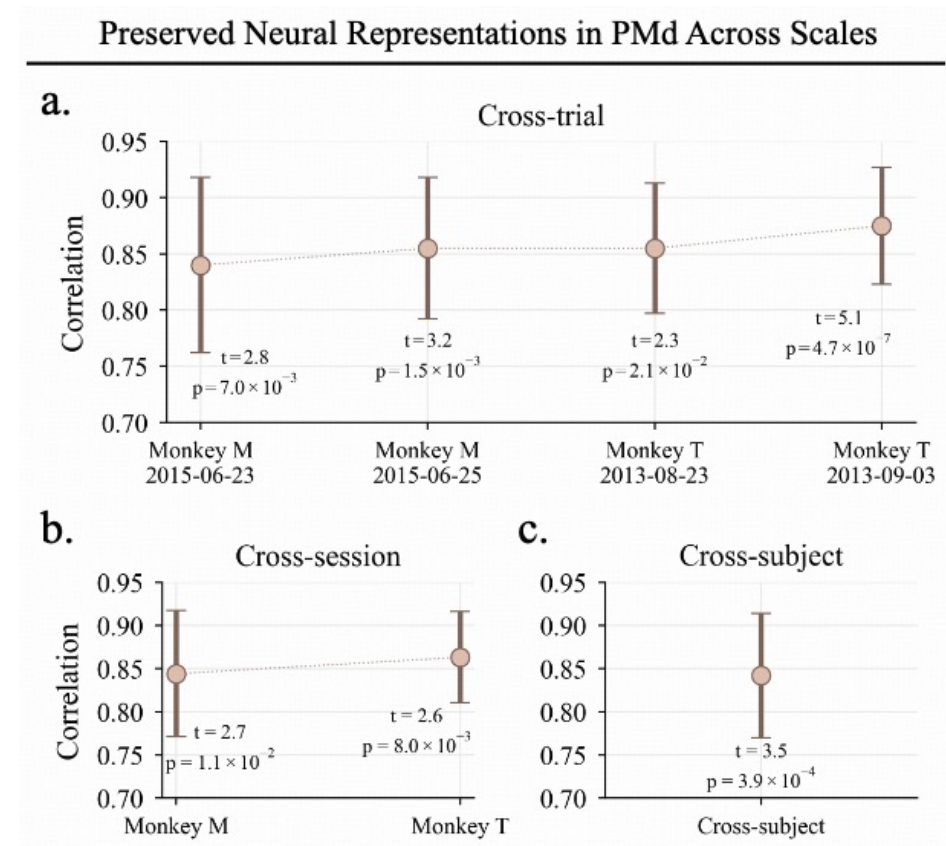
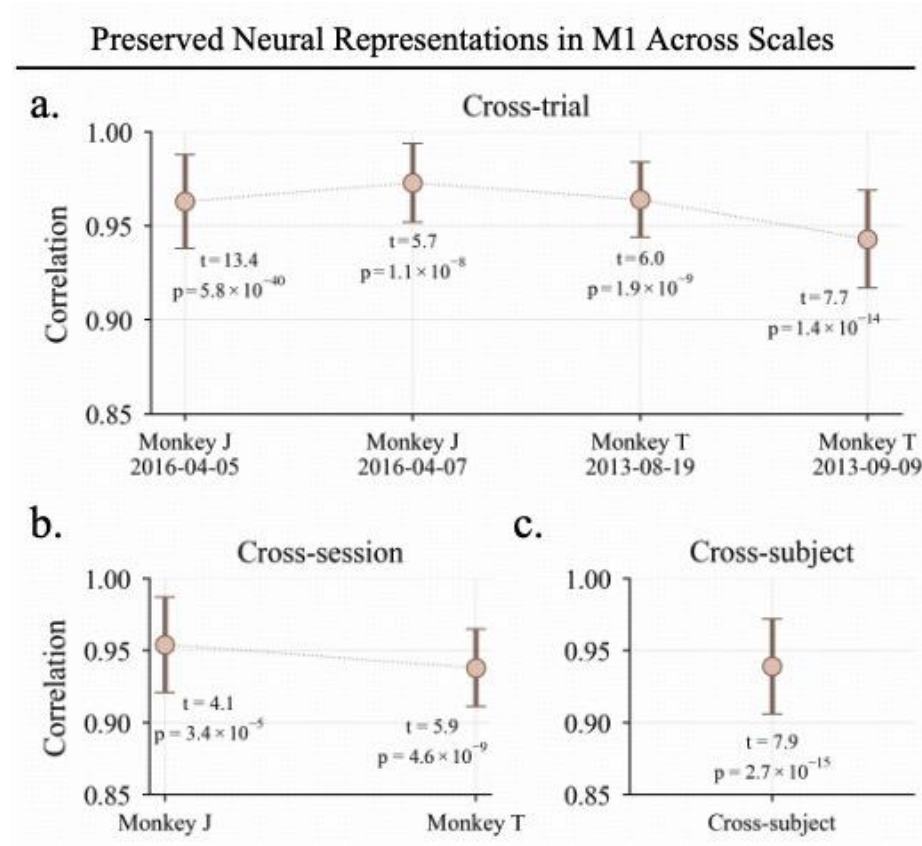


Neural-Stimulus Representation Alignment



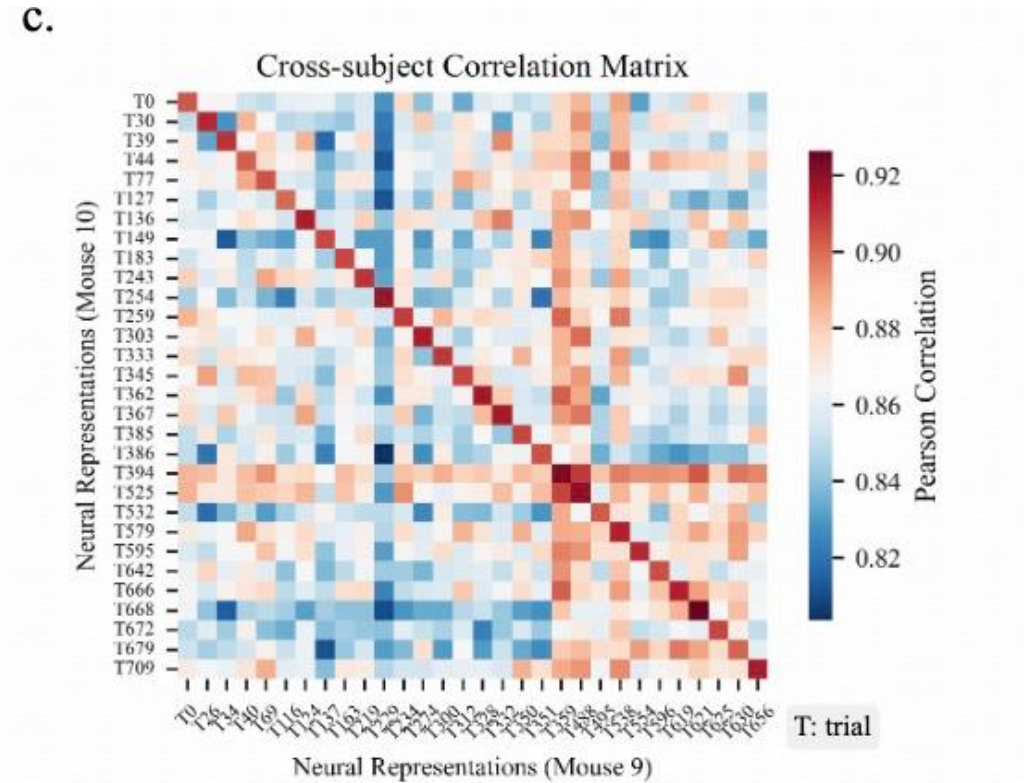
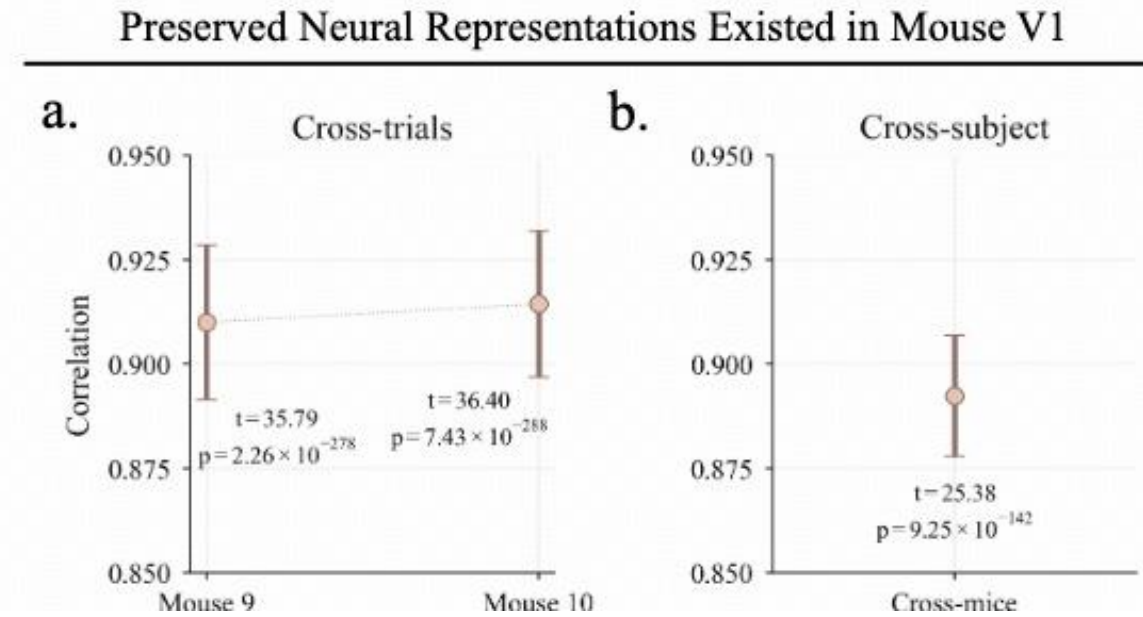
Our probabilistic representation alignment framework achieves optimal alignment performance.

7. Preserved neural representations emerge



➡ Using a data-driven paradigm, we provide evidence that preserved neural representations persist across novel subjects, thereby strengthening the findings of Safaie et al. (2023, Nature).

8. Preserved Neural Representations broadly exist



➡ We further identified preserved neural representations in mouse somatosensory cortex, extending the conclusions of Safaie et al. (2023, Nature).

9. Conclusion

- **Unified Framework:** We introduce a probabilistic representation alignment paradigm applicable across cortical regions.
- **Theoretical Optimization:** Our framework ensures maximum biological plausibility through theoretical constraints.
- **Clinical Impact:** We extend Safaie et al. findings and demonstrate zero-shot BCI potential using preserved V1 representations.

Preserved Neural Representations Enables Zero-shot BCI

