Neural Population Geometry

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Outline

Problem Description & Motivation

- Advances in recording techniques: thousands to millions of neurons simultaneously
- Challenges in studying large neural populations:
  - Neurons respond to multiple variables
  - Traditional tuning-based analyses have limitations
- Shift from single-neuron tuning to geometric approaches
- Neural computations arise from structured, high-dimensional activity patterns

Neural Manifolds

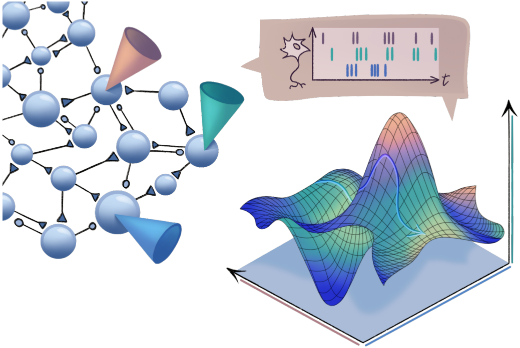
- Neural manifolds: low-dimensional geometric structures embedded in high-dimensional neural state space
- Key properties: dimensionality, curvature, and separability
- Provide insights into computational principles governing neural networks
- Framework has provided mechanistic insights into:
  - Perception
  - Decision-making
  - Motor control
  - Cognition

Bridging Biological and Artificial Neural Networks

- Neural population geometry bridges biological and artificial neural networks
- Shared representational structures support efficient computation
- Geometric properties shape information encoding and processing
- Geometric perspective reveals how neural populations achieve:
  - Robustness
  - Efficiency
  - Scalability

Neural State Space & Population Activity

- Neural state space: each axis represents a single neuron
- Repeated stimulus presentations create point clouds
- Neuronal variability induces fluctuations
- Manifolds emerge from stimulus responses



Key Concepts in Neural Population Geometry

- Population-level representations vs. single-neuron tuning
- Geometric transformations of neural manifolds
- Dimensionality and information encoding
- Manifold separability and computational capabilities
- Curvature and computational constraints

Artificial Neural Networks

- Demonstration of geometric structures in neural representations
- Simulation experiment: encoding circular variables
- Illustrates how topological structures naturally emerge

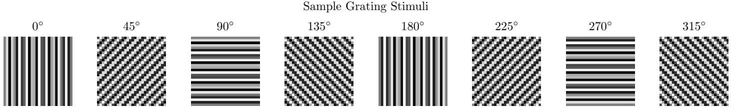


Figure: Sample grating stimuli at different orientations

Circular Manifold Experiment

- CNN trained to predict orientation of visual grating stimuli
- Analogous to orientation selectivity in visual cortex
- Sinusoidal gratings at orientations from 0° to 360°
- Architecture: convolutional layers + fully connected layers
- 32-dimensional latent space analyzed for geometric properties
- Trained to predict sine and cosine components (handles circular topology)

Results: Circular Manifold

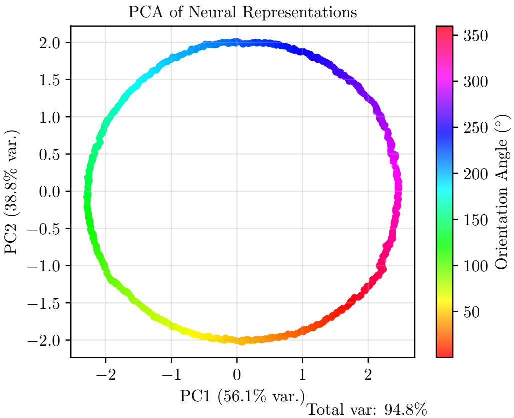


Figure: PCA of the latent space

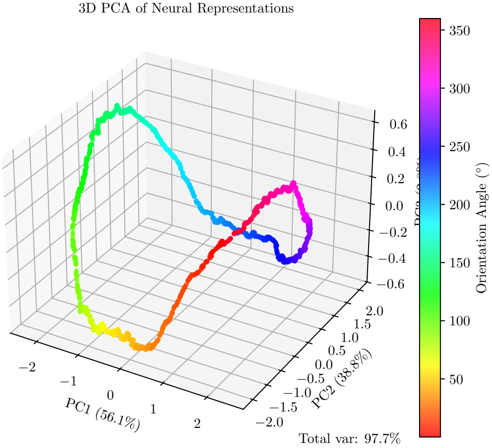


Figure: 3D visualization of the manifold

- Circular manifold emerged in latent space
- Similar orientations positioned close together

Key Principles Demonstrated

- **Manifold structure**: Low-dimensional manifold (circle) embedded in high-dimensional space
- **Topological correspondence**: Manifold topology matches task space topology
- **Continuous representation**: Similar stimuli mapped to nearby points
- **Dimensionality reduction**: High-dimensional input compressed to essential variables

Insight

Circular topology emerged naturally without explicit constraints—the network discovered this efficient representation on its own

Biological Neural Networks

- Application of geometric principles to biological neural data
- Comparison with artificial neural network findings
- Insights into biological neural computation

Conclusion

- Neural population geometry provides powerful framework for analyzing neural activity
- Geometric principles describe population-level representations
- Approach yields mechanistic insights across multiple domains
- Bridges biological and artificial neural networks
- Geometric perspective deepens understanding of neural computation

References

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