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## Condition-Dependent Neural Dimensions Progressively Shift during Reach to Grasp

Adam G. Rouse,<sup>1,4</sup> and Marc H. Schieber<sup>1,2,3,4,5,\*</sup>

<sup>1</sup>Department of Neuroscience, University of Rochester, Rochester, NY 14642, USA

<sup>2</sup>Department of Neurology, University of Rochester, Rochester, NY 14642, USA

<sup>3</sup>Department of Biomedical Engineering, University of Rochester, Rochester, NY 14642, USA

<sup>4</sup>Del Monte Institute for Neuroscience, University of Rochester, Rochester, NY 14642, USA

<sup>5</sup>Lead Contact

\*Correspondence: [mschiebe@ur.rochester.edu](mailto:mschiebe@ur.rochester.edu)

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Neurobiology Journal Club  
Presented by: James Goodman

The Leibniz-Gemeinschaft logo consists of the word 'Leibniz' in a large, stylized, cursive black font, with 'Gemeinschaft' in a smaller, regular black font below it.

# Introduction

# Reach-to-grasp behavior: distinct phases



- Reach-to-grasp: show the distinct phases, kinematically

# Coupling between arm and hand



- Reach-to-grasp: show kinematic coupling of arm & hand

# Control of reach-to-grasp: distinct pathways



- Reach-to-grasp: show the segregated reach- and grasp-pathways
- Include the putative somatotopy in M1

# Mixed information along these pathways



- Reach-to-grasp: show the amount of overlap (at the single-neuronal level) at multiple stages of the movement planning-to-execution hierarchy:
- Lehmann et al. 2013
- Takahashi et al. 2017

# Mixed information in M1



- Reach-to-grasp: show the amount of overlap (at the single-neuronal level) at multiple stages of the movement planning-to-execution hierarchy:
- Schieber's monkey wrench in M1 somatotopy
- Rouse & Schieber 2016

# What, then, separates reach & grasp?

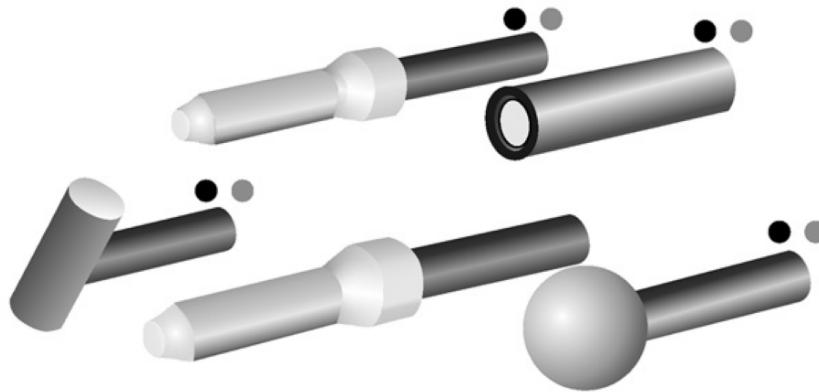
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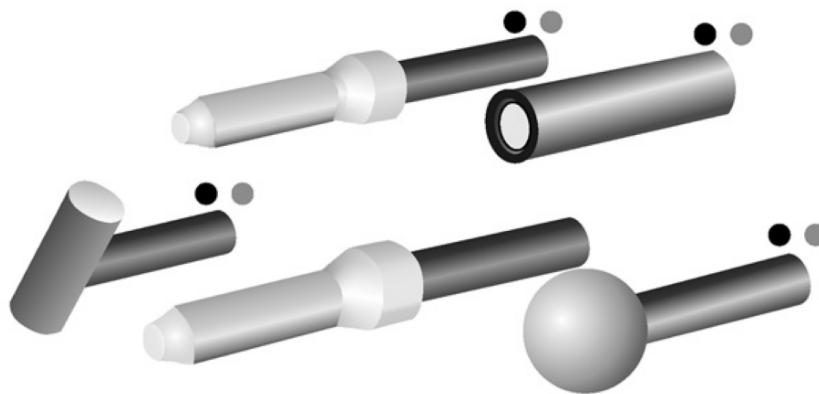
- Could there be a distinction at the population level?
- If so, what might the nature of this distinction be?
  - Object-vs-location dichotomy?
  - Early-vs-late dichotomy?
  - No dichotomy at all?
- What fraction of activity is location-, object-, or even task-modulated?

# Methods

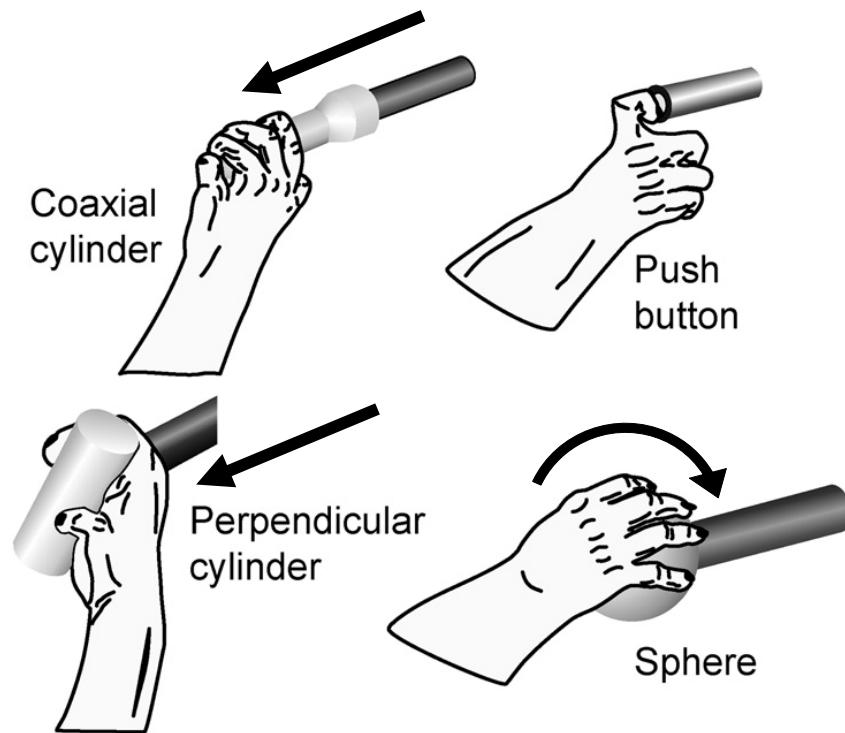
# Experiment



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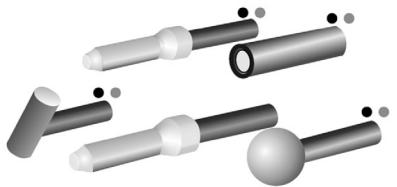
# Experiment



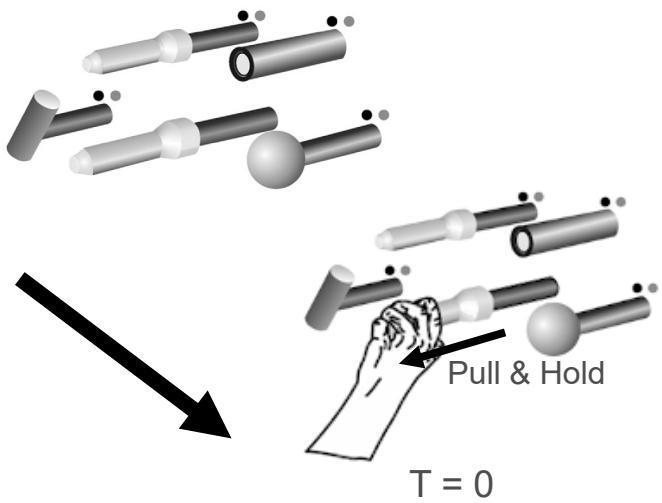
# Monkey “Bop-It”



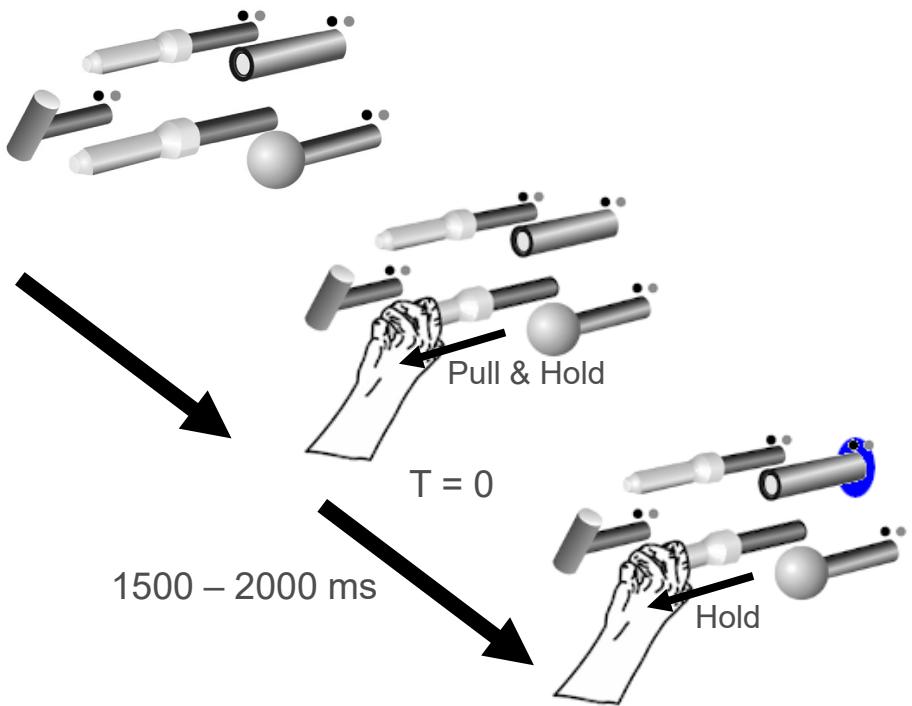
# Trial Structure



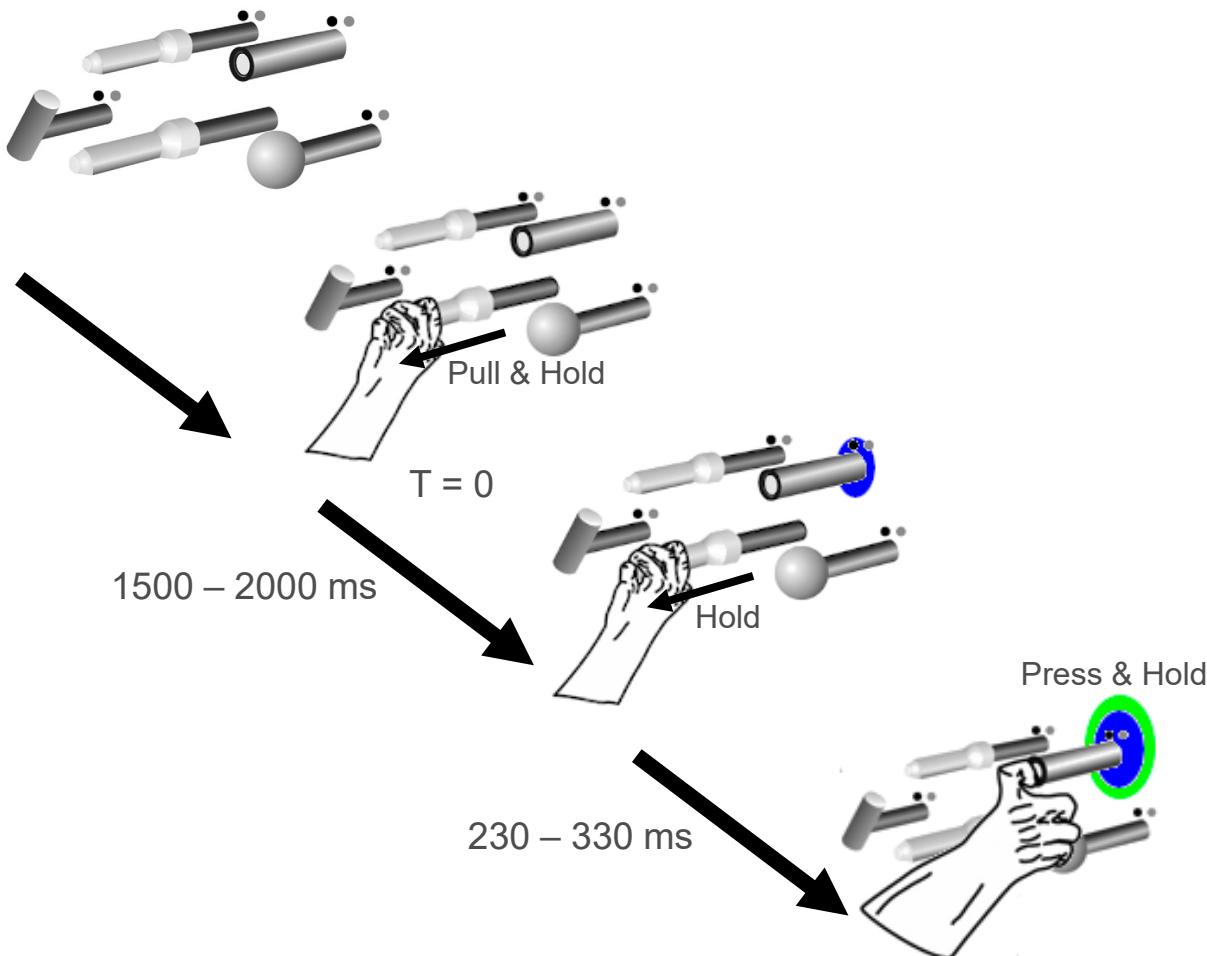
# Trial Structure



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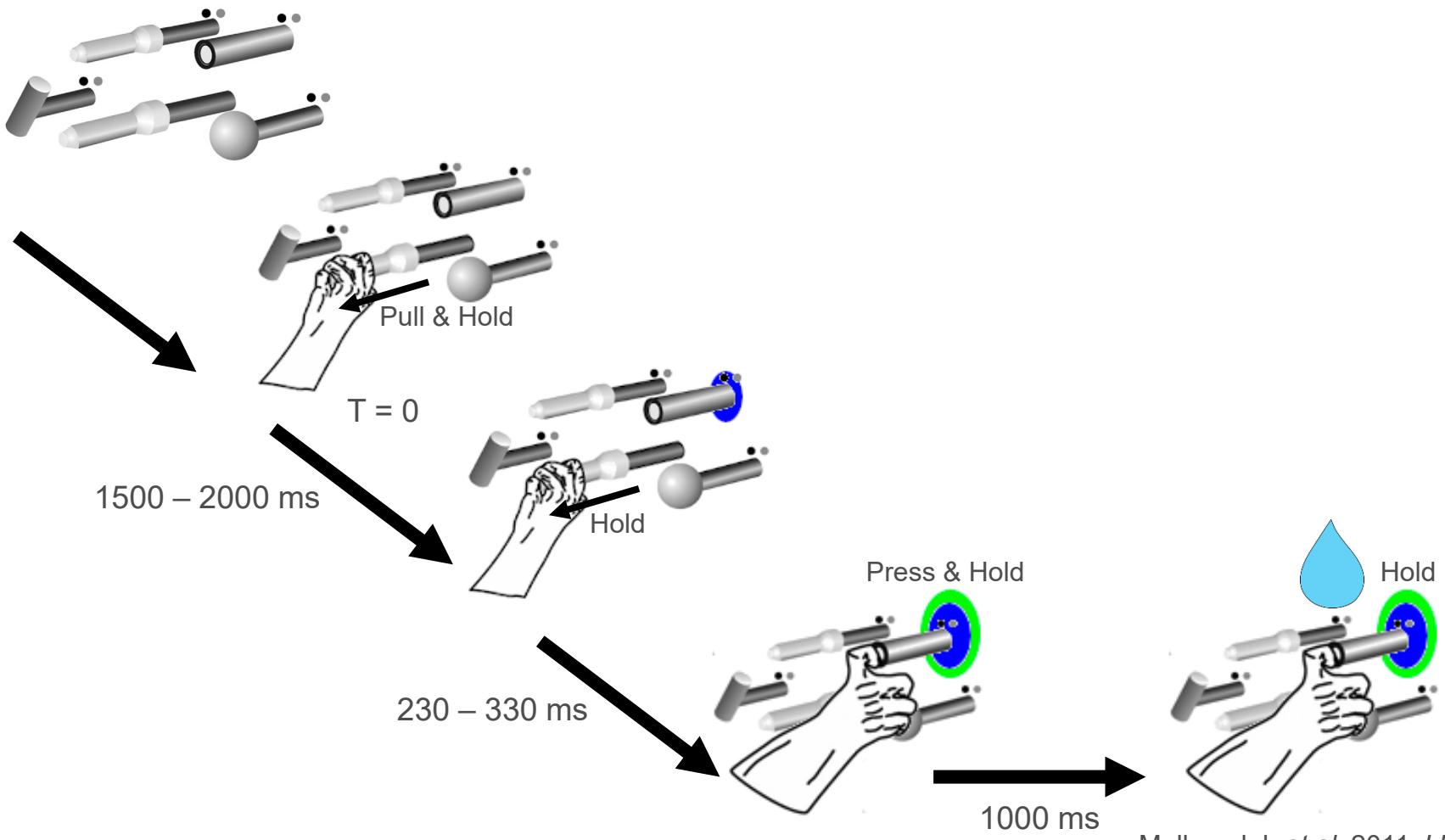


# Trial Structure



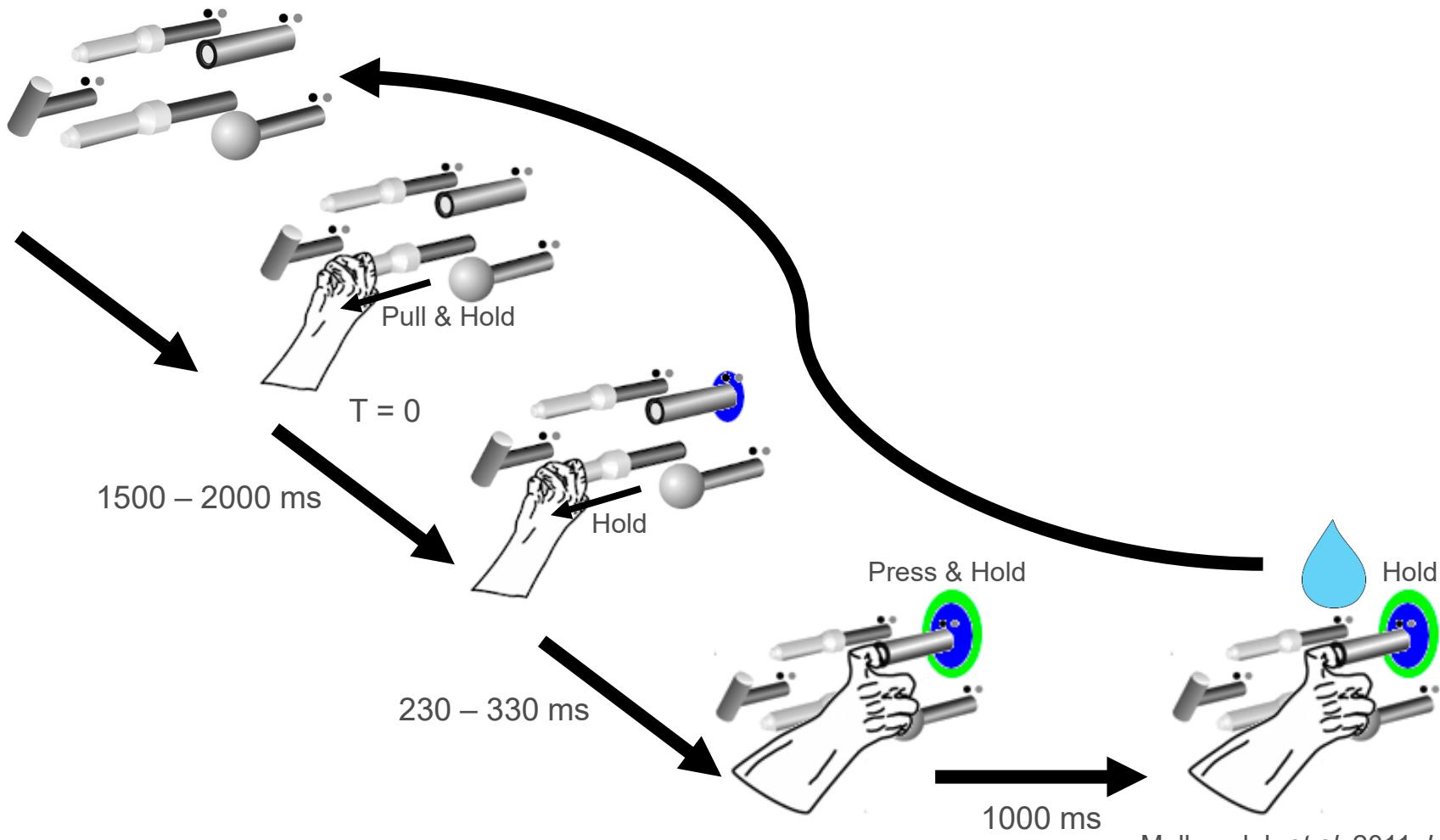
Mollazadeh *et al.* 2011 *J Neurosci.*  
Rouse & Schieber 2015 *J Neurosci.*

# Trial Structure



Mollazadeh et al. 2011 J Neurosci.  
Rouse & Schieber 2015 J Neurosci.

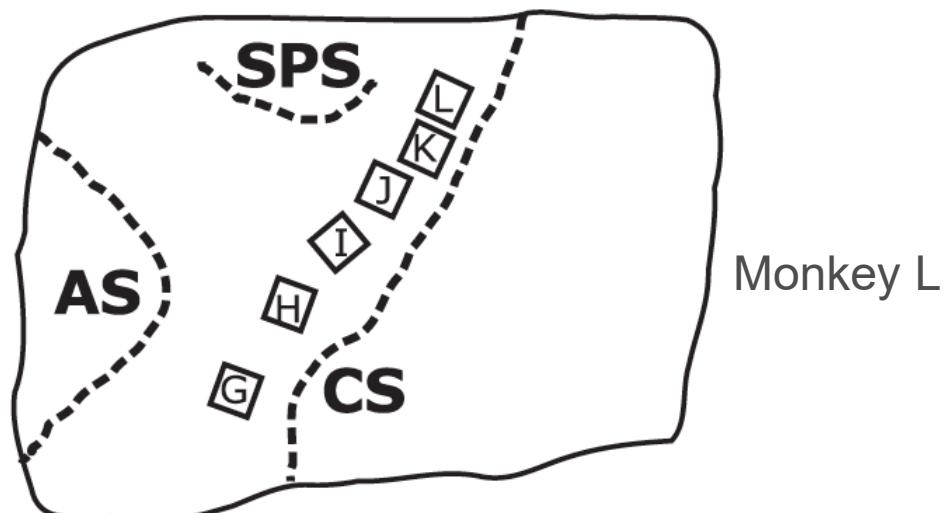
# Trial Structure



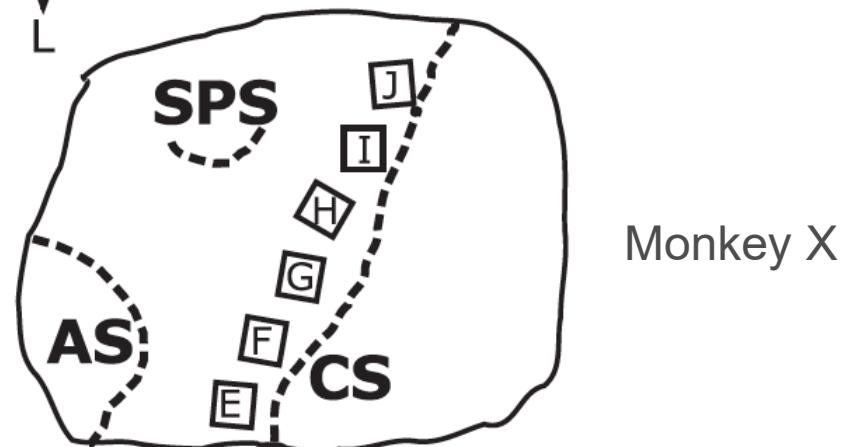
Mollazadeh et al. 2011 J Neurosci.  
Rouse & Schieber 2015 J Neurosci.



# FMA Neural Recordings



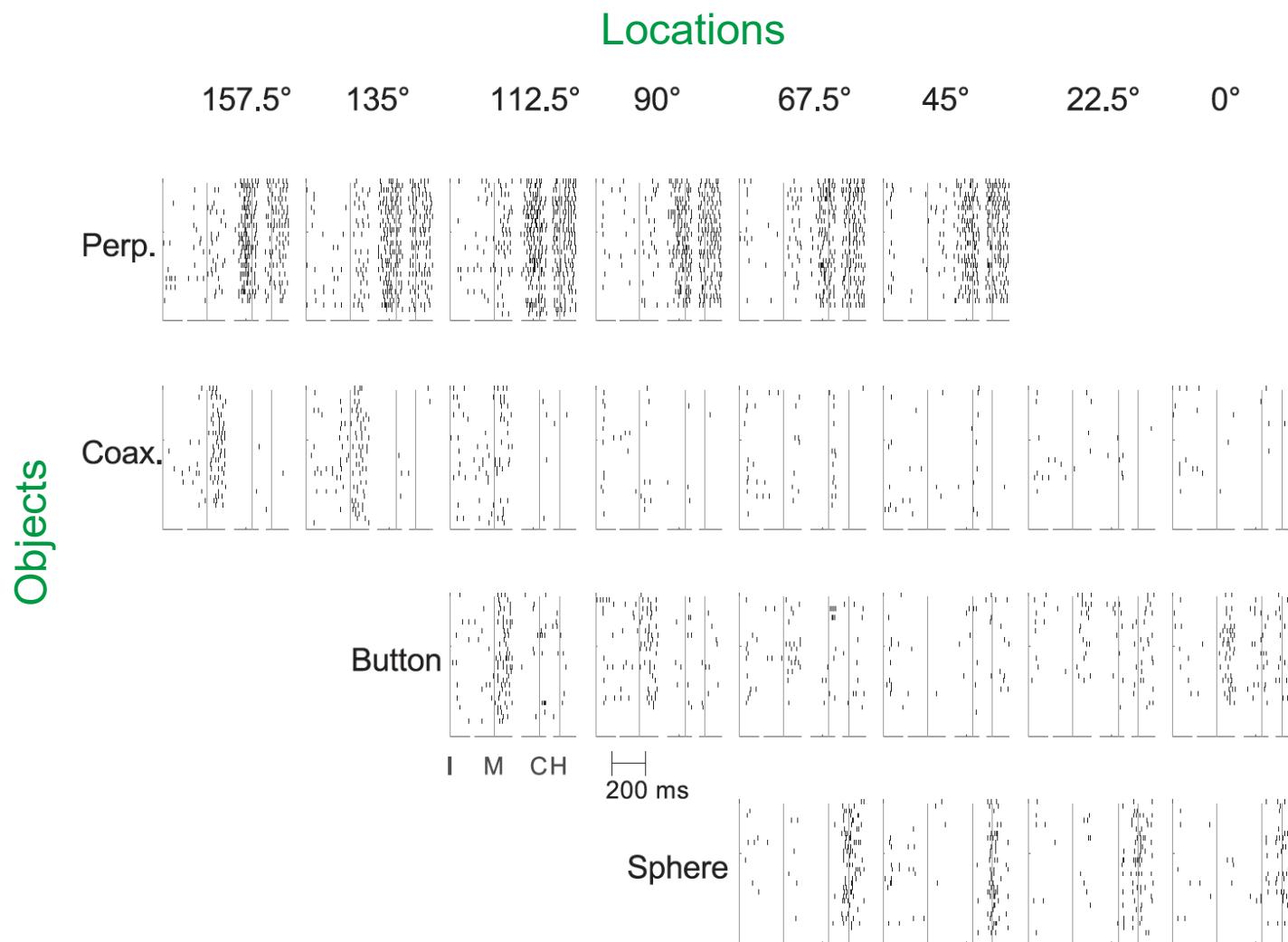
Monkey L



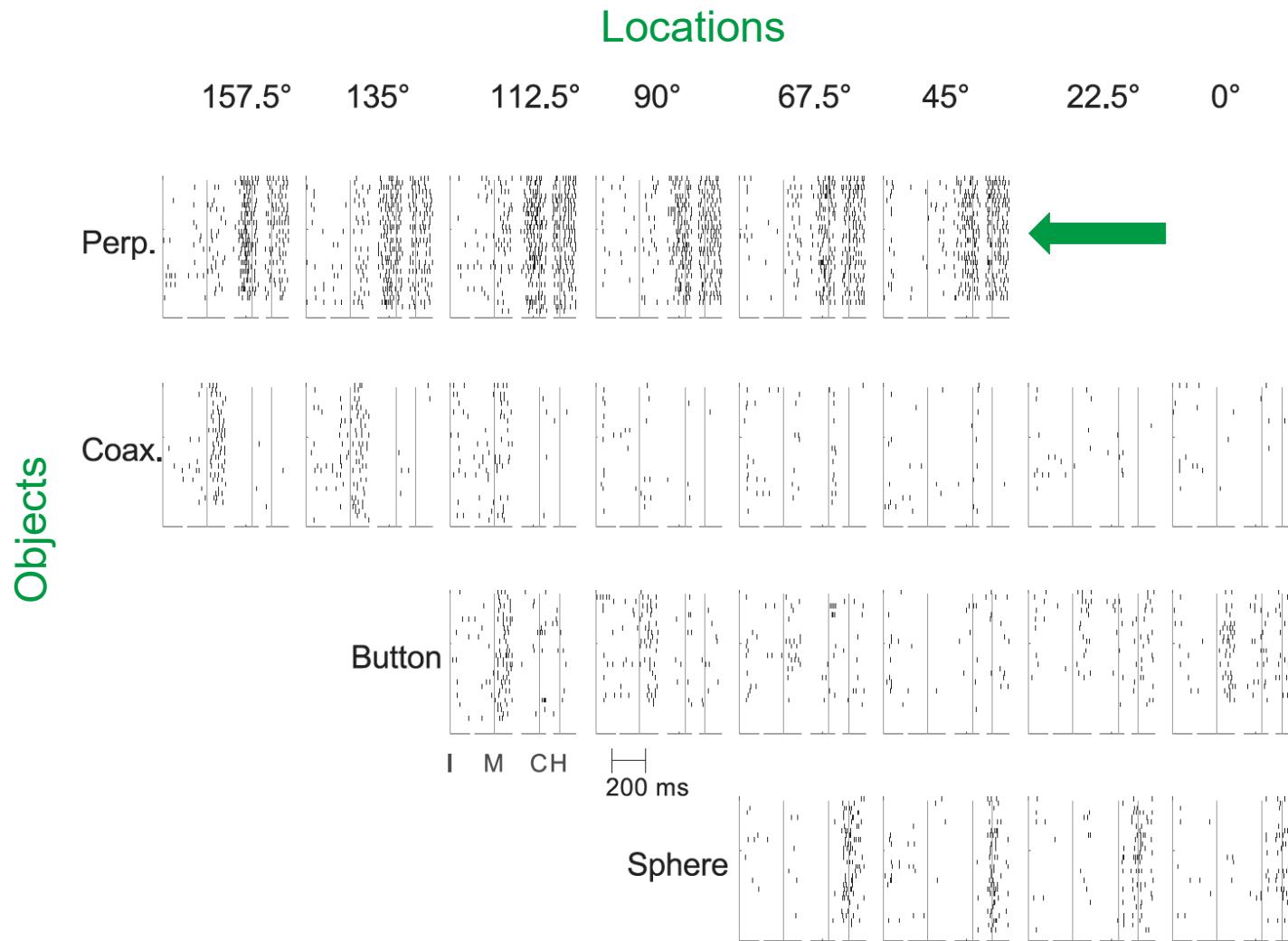
Monkey X

# Analysis & Results

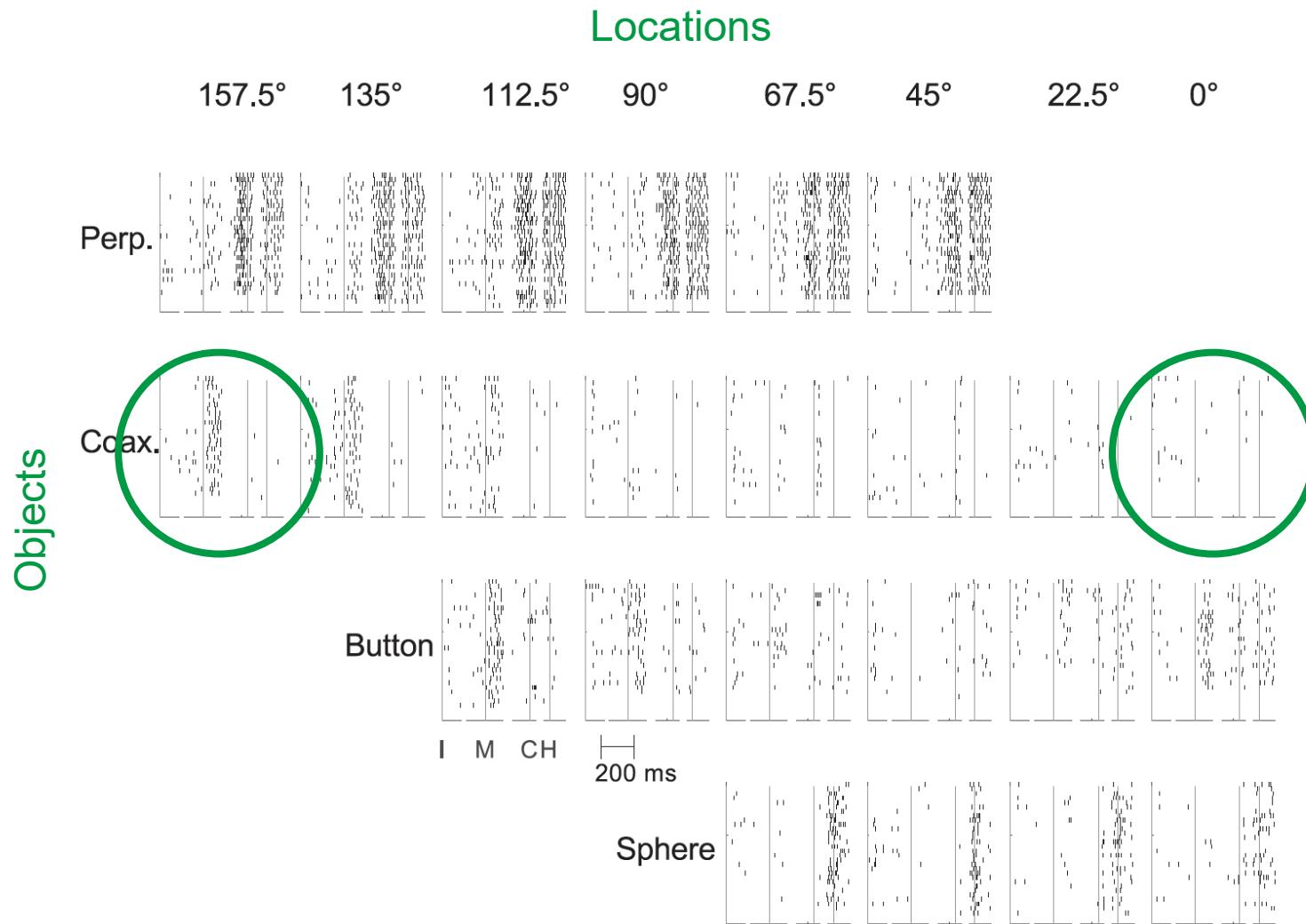
# Typical neuron: mixed object-location effects



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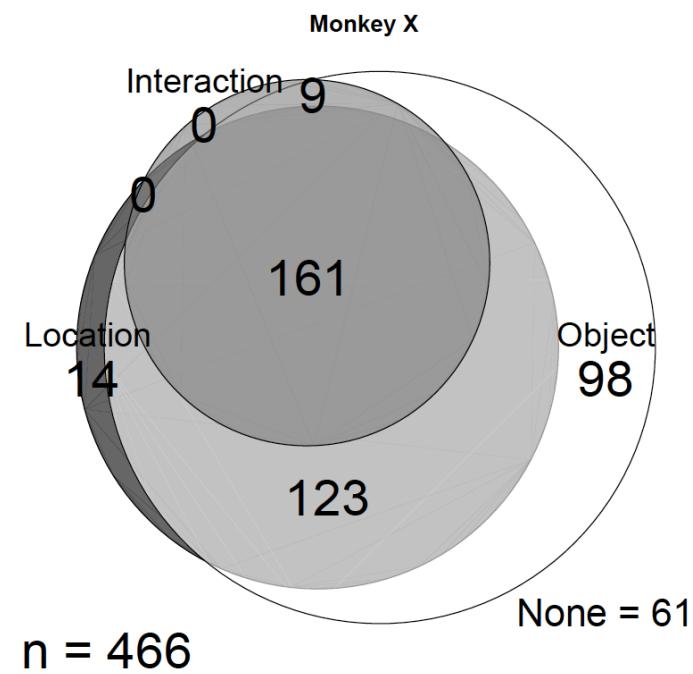
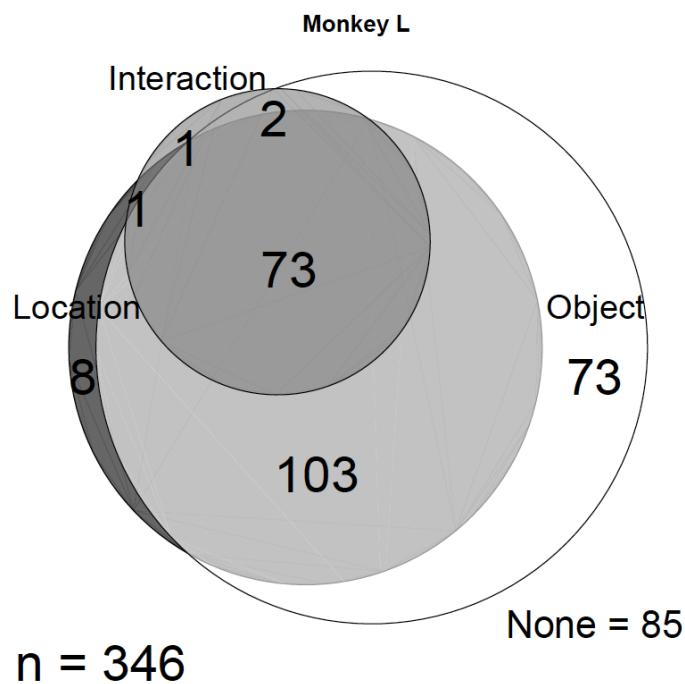


# Typical neuron: mixed object-location effects





# Most neurons have mixed “tuning”





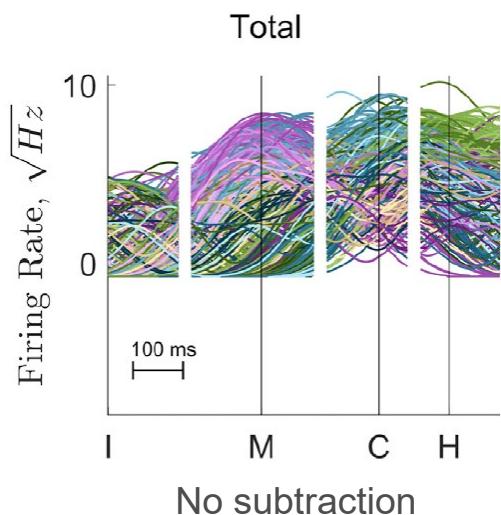
# Variance Partitioning

Initiation

Movement Start

First Contact

Beginning of Hold



No averaging



# Variance Partitioning

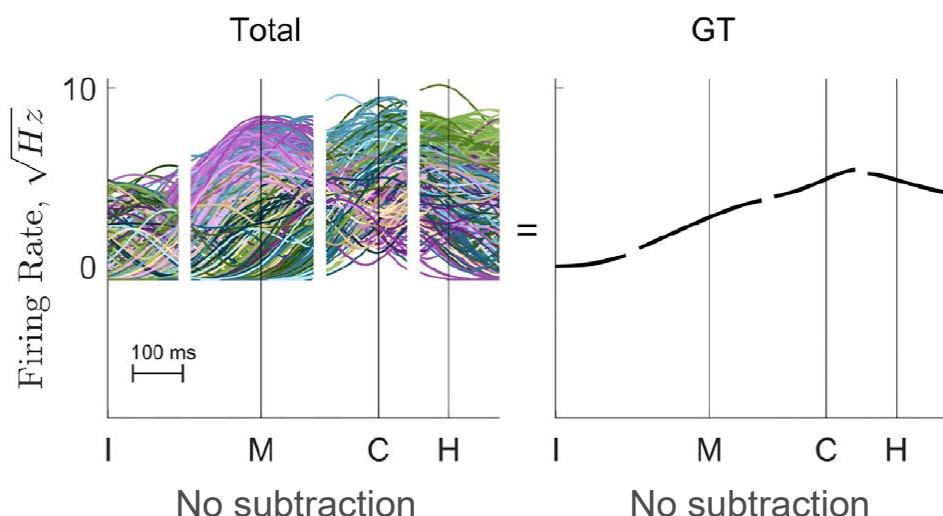
Initiation

Movement Start

First Contact

Beginning of Hold

General Task



No averaging

Average across:  
Trials & Conditions



# Variance Partitioning

Initiation

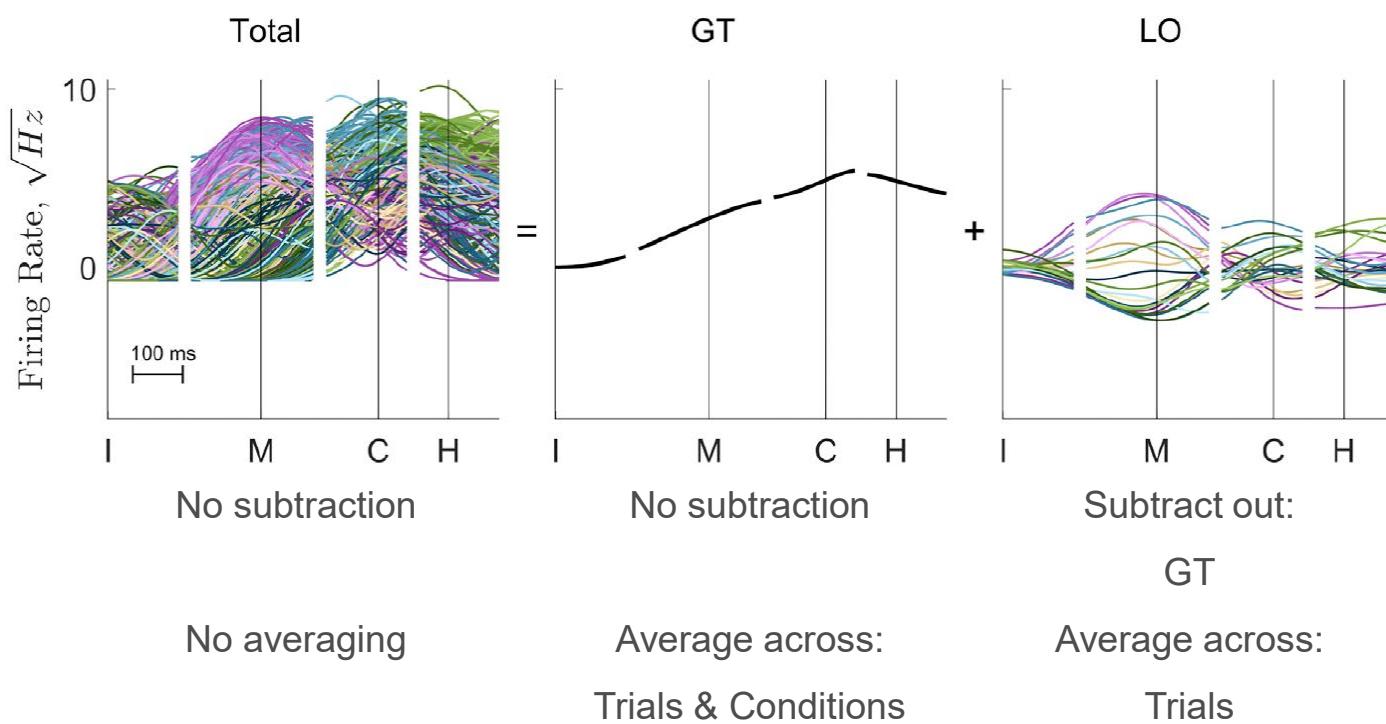
Movement Start

First Contact

Beginning of Hold

General Task

Location / Object





# Variance Partitioning

Initiation

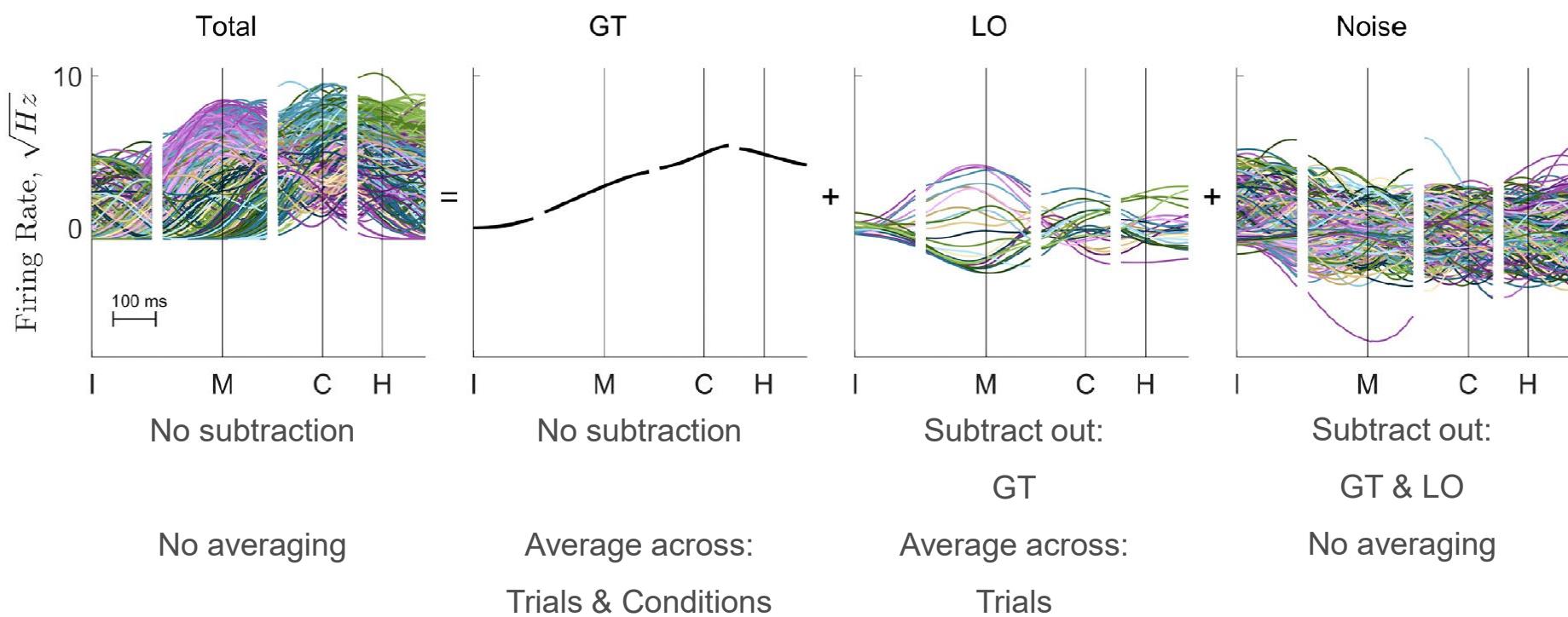
Movement Start

First Contact

Beginning of Hold

General Task

Location / Object





# Variance Partitioning



## Initial Partitioning versus Demixing: Implications for Overlap of Subspaces

In contrast to the recently developed approach of demixed PCA (dPCA), which identifies PCs that best transform the original data to reconstruct different partitions of the neural activity (Brendel et al., 2011; Kobak et al., 2016), we chose to partition the data first and then perform standard PCA on each partition separately. Because any dimension of the neural space may have variance in more than one partition, dPCA may not always identify the highest variance PCs in a given partition if those PCs also include variance from other partitions. While dPCA may improve visualization, our present approach was designed to quantify the magnitude and dimensionality of neural activity in each partition separately, as well as the overlap between partitions. We also performed dPCA on our dataset with qualitatively similar results (not illustrated). The demixed PCs were



# Variance of each component over time

Initiation

Movement Start

First Contact

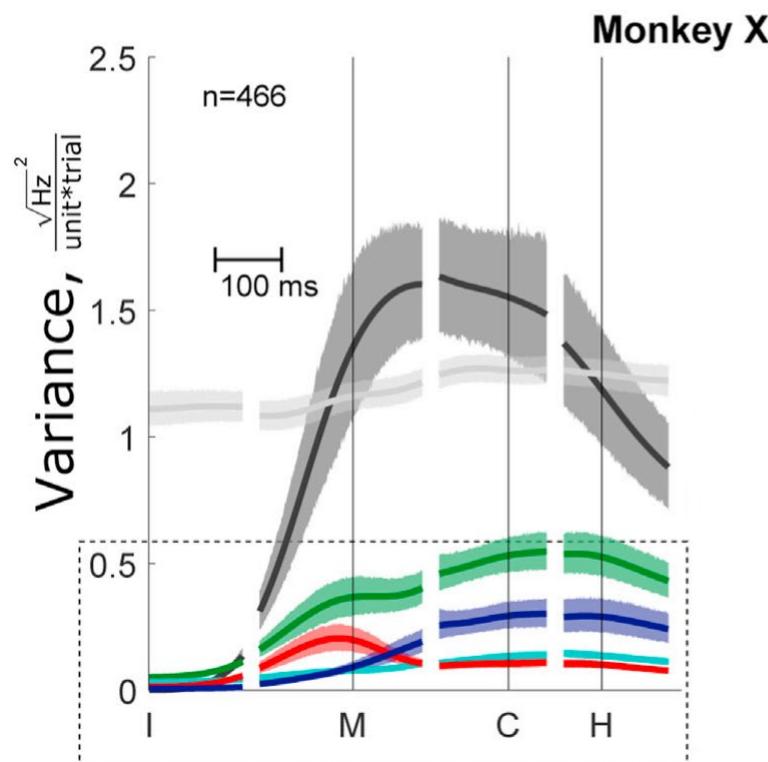
Beginning of Hold

General Task  
Location / Object  
Noise

Location

Object

Interaction





# Variance of each component over time

Initiation

Movement Start

First Contact

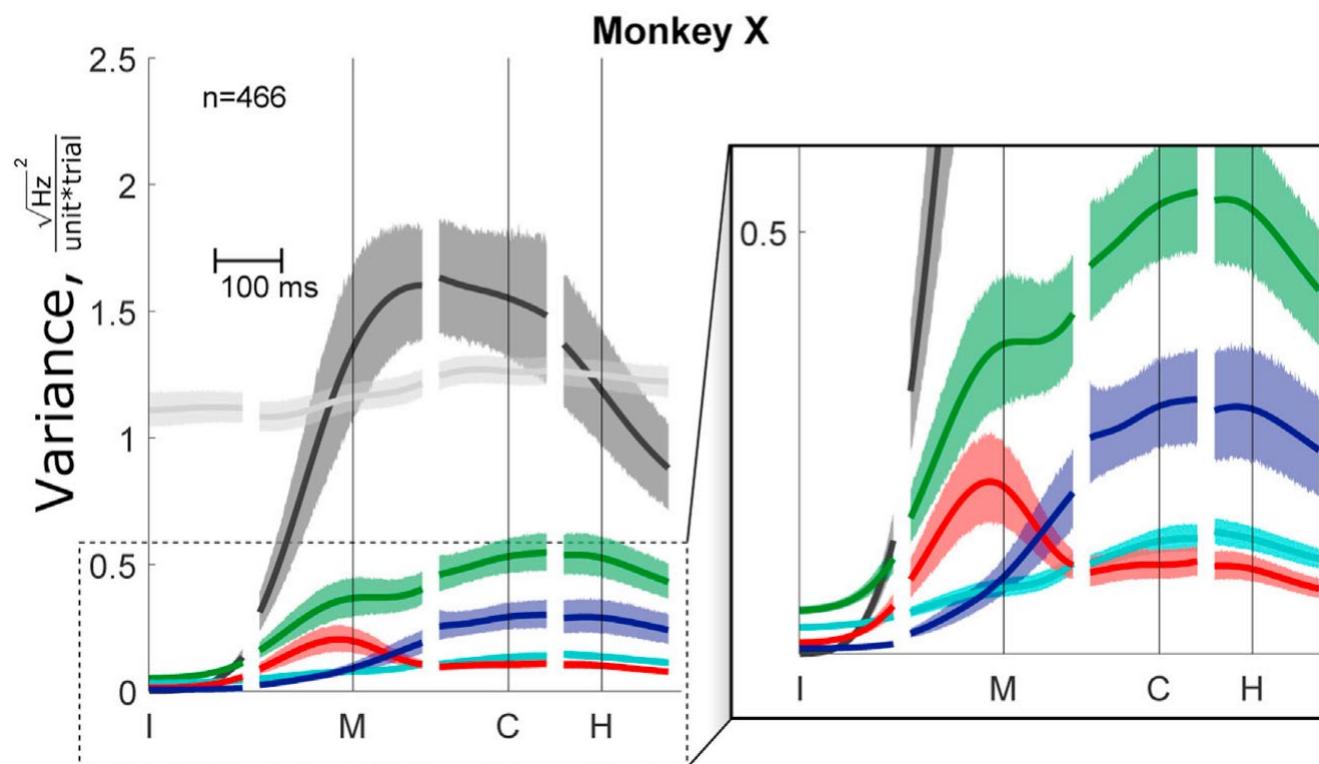
Beginning of Hold

General Task  
Location / Object  
Noise

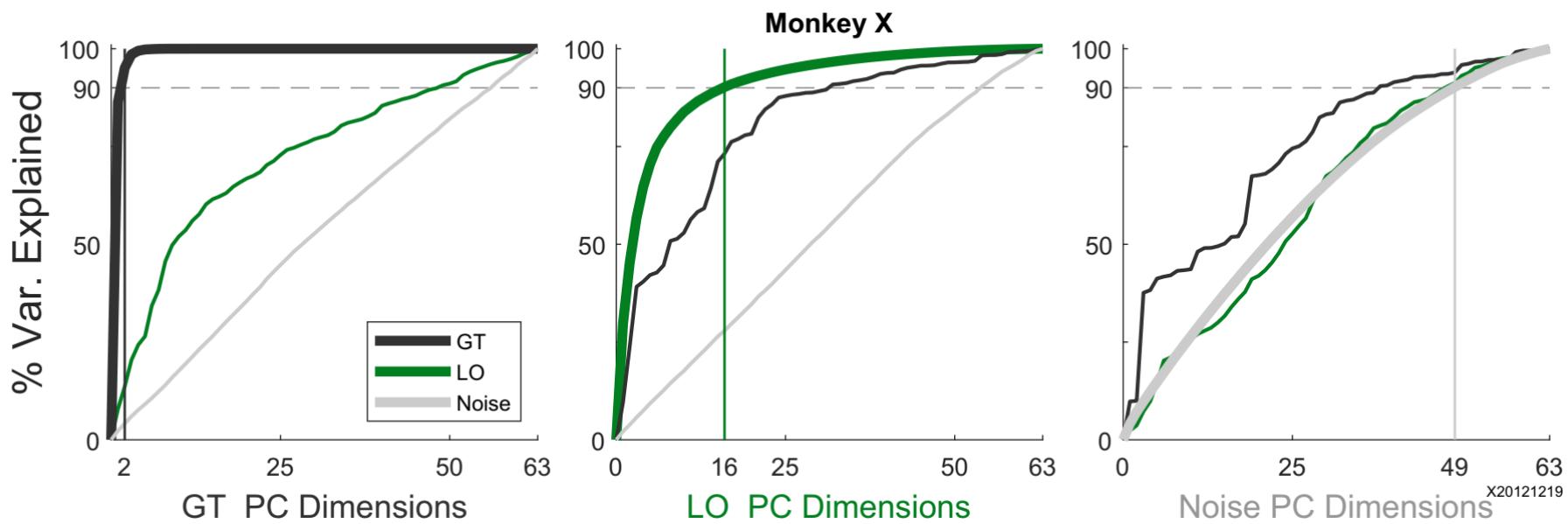
Location

Object

Interaction



# Overlap between subspaces





# Overlap between subspaces quantified



$$Overlap = \frac{tr(\Sigma_1 \Sigma_2)}{\|\Sigma_1\|_F \cdot \|\Sigma_2\|_F}$$

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Null distribution bootstrapping:

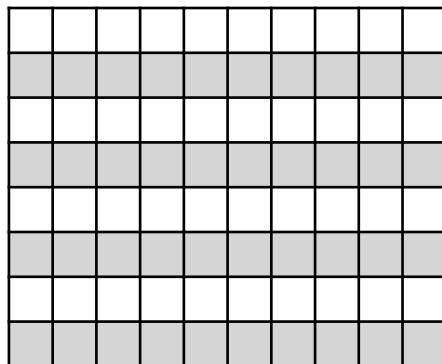
$$\Sigma_1$$

$d \times d$

$$Overlap = \frac{tr(\Sigma_1 \Sigma_2)}{\|\Sigma_1\|_F \cdot \|\Sigma_2\|_F}$$

Null distribution bootstrapping:

$\Sigma_1$   
 $d \times d$

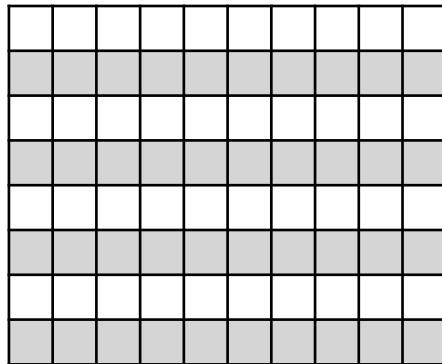


$24 \times d$

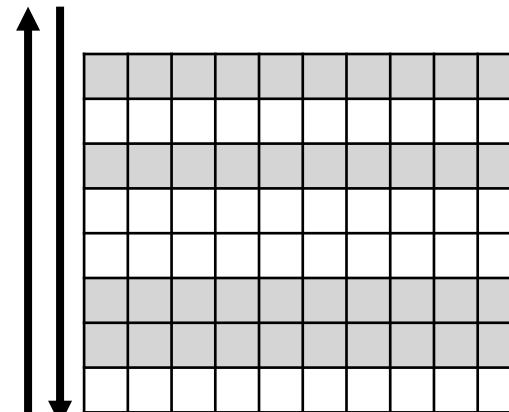
$$Overlap = \frac{tr(\Sigma_1 \Sigma_2)}{\|\Sigma_1\|_F \cdot \|\Sigma_2\|_F}$$

Null distribution bootstrapping:

$\Sigma_1$   
 $d \times d$



$24 \times d$

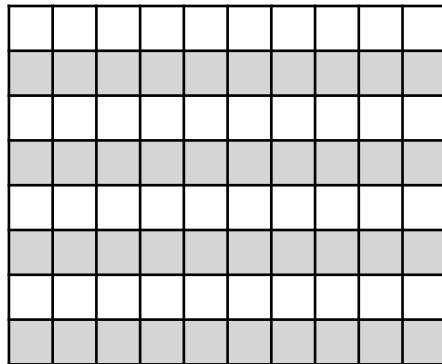


$24 \times d$

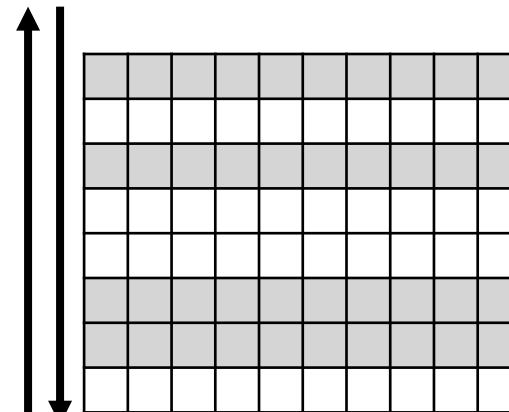
$$Overlap = \frac{tr(\Sigma_1 \Sigma_2)}{\|\Sigma_1\|_F \cdot \|\Sigma_2\|_F}$$

Null distribution bootstrapping:

$\Sigma_1$   
 $d \times d$



$24 \times d$



$24 \times d$

$\Sigma_2$   
 $d \times d$

$$Overlap = \frac{tr(\Sigma_1 \Sigma_2)}{\|\Sigma_1\|_F \cdot \|\Sigma_2\|_F}$$

Data (95% CI of Null):

GT vs LO:

L: 0.26 (0.02 – 0.18)  
X: 0.26 (0.02 – 0.20)

GT vs Noise:

L: 0.18 (0.11 – 0.17)  
X: 0.24 (0.15 – 0.21)

LO vs Noise:

L: 0.29 (0.20 – 0.29)  
X: 0.36 (0.26 – 0.33)

$$Overlap = \frac{tr(\Sigma_1 \Sigma_2)}{\|\Sigma_1\|_F \cdot \|\Sigma_2\|_F}$$

Data (95% CI of Null):

GT vs LO:

L: 0.26 (0.02 – 0.18)  
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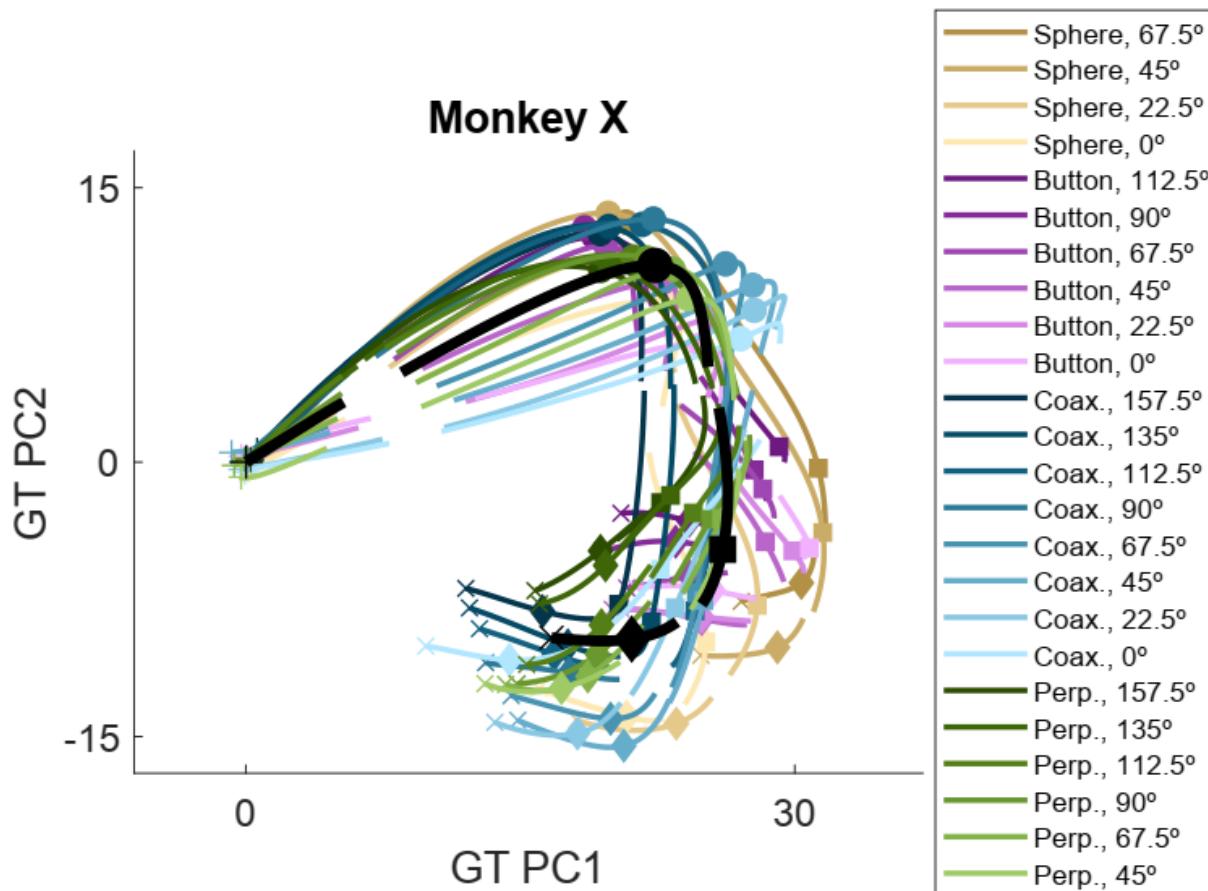
L: 0.18 (0.11 – 0.17)  
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LO vs Noise:

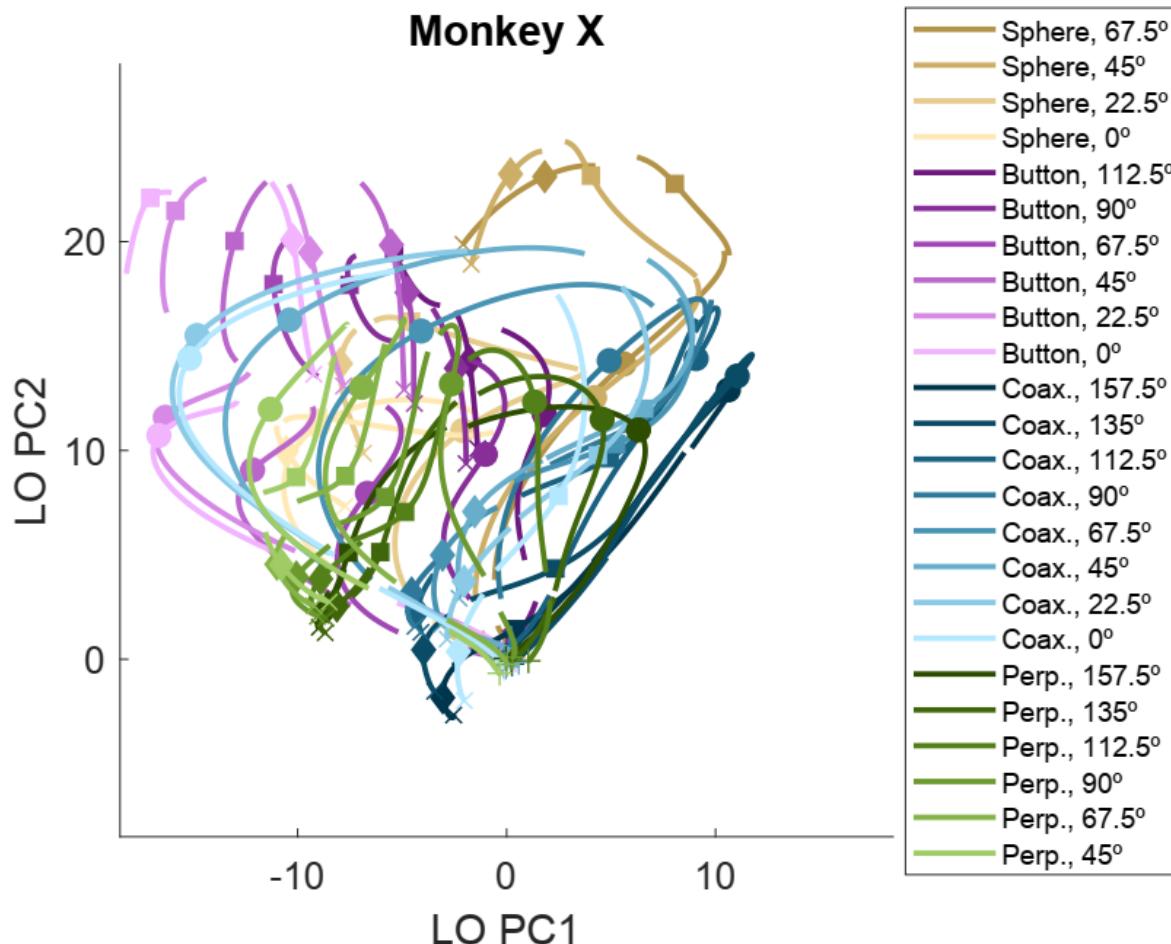
L: 0.29 (0.20 – 0.29)  
X: 0.36 (0.26 – 0.33)

**Not 0!**

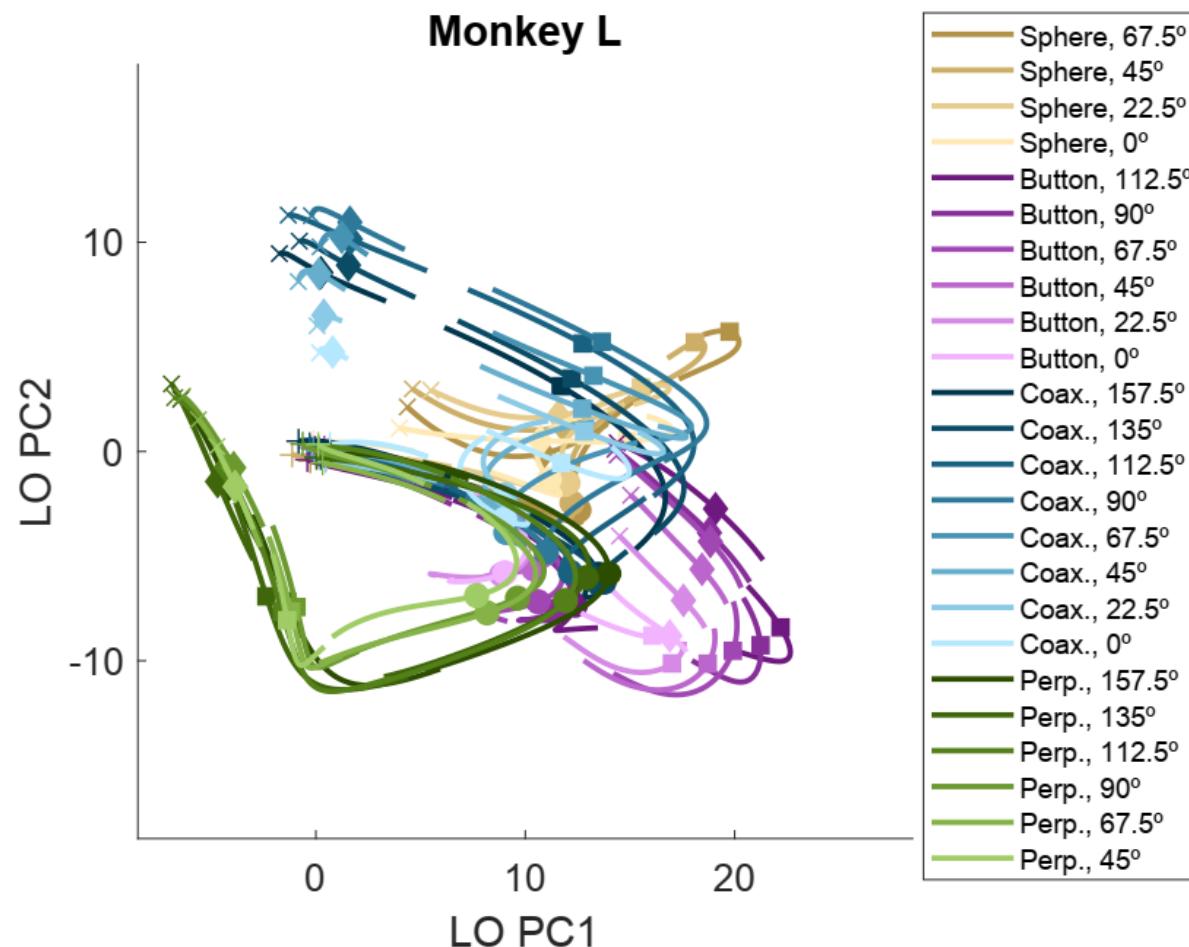
# Projections onto GT subspace



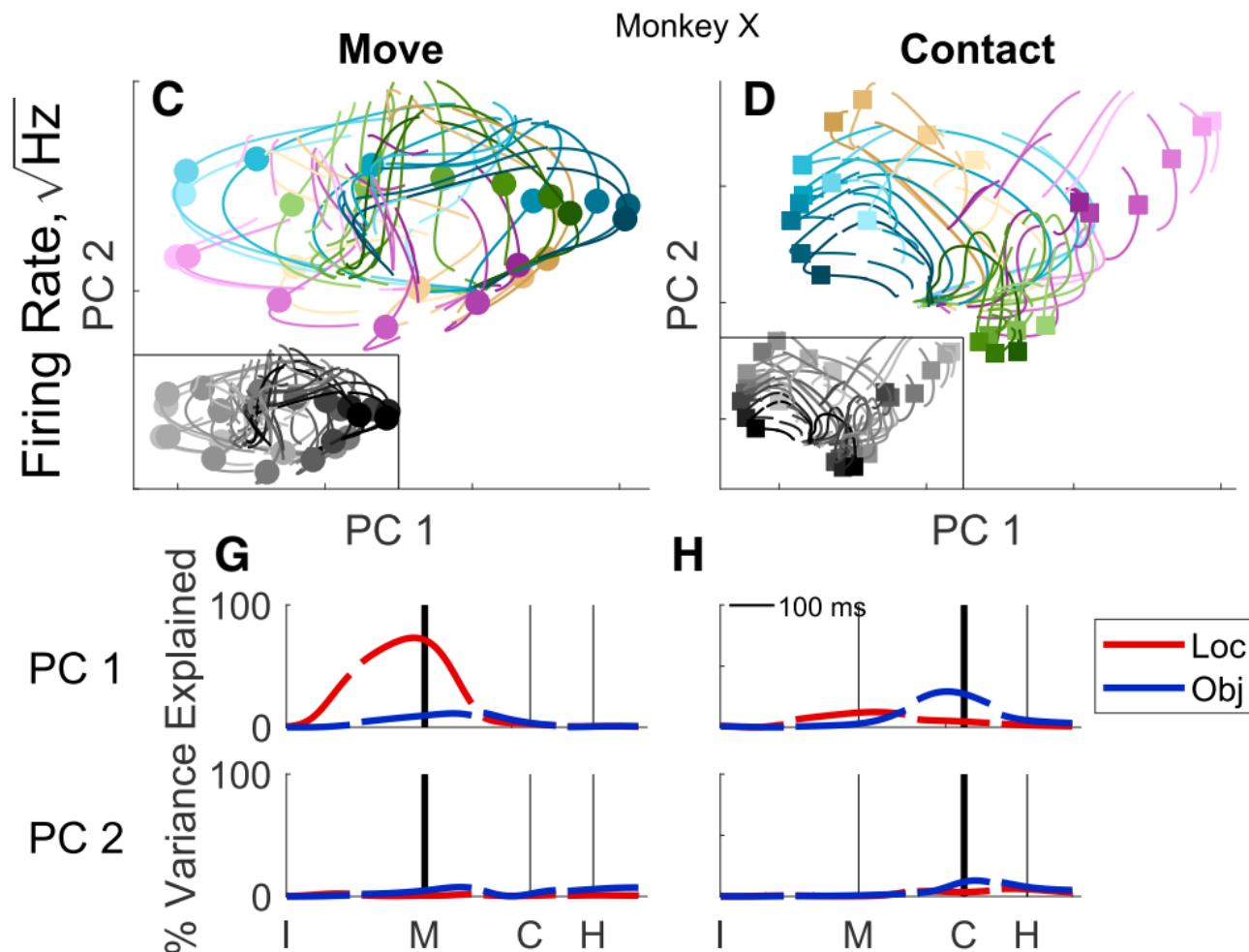
# Projections onto LO subspace



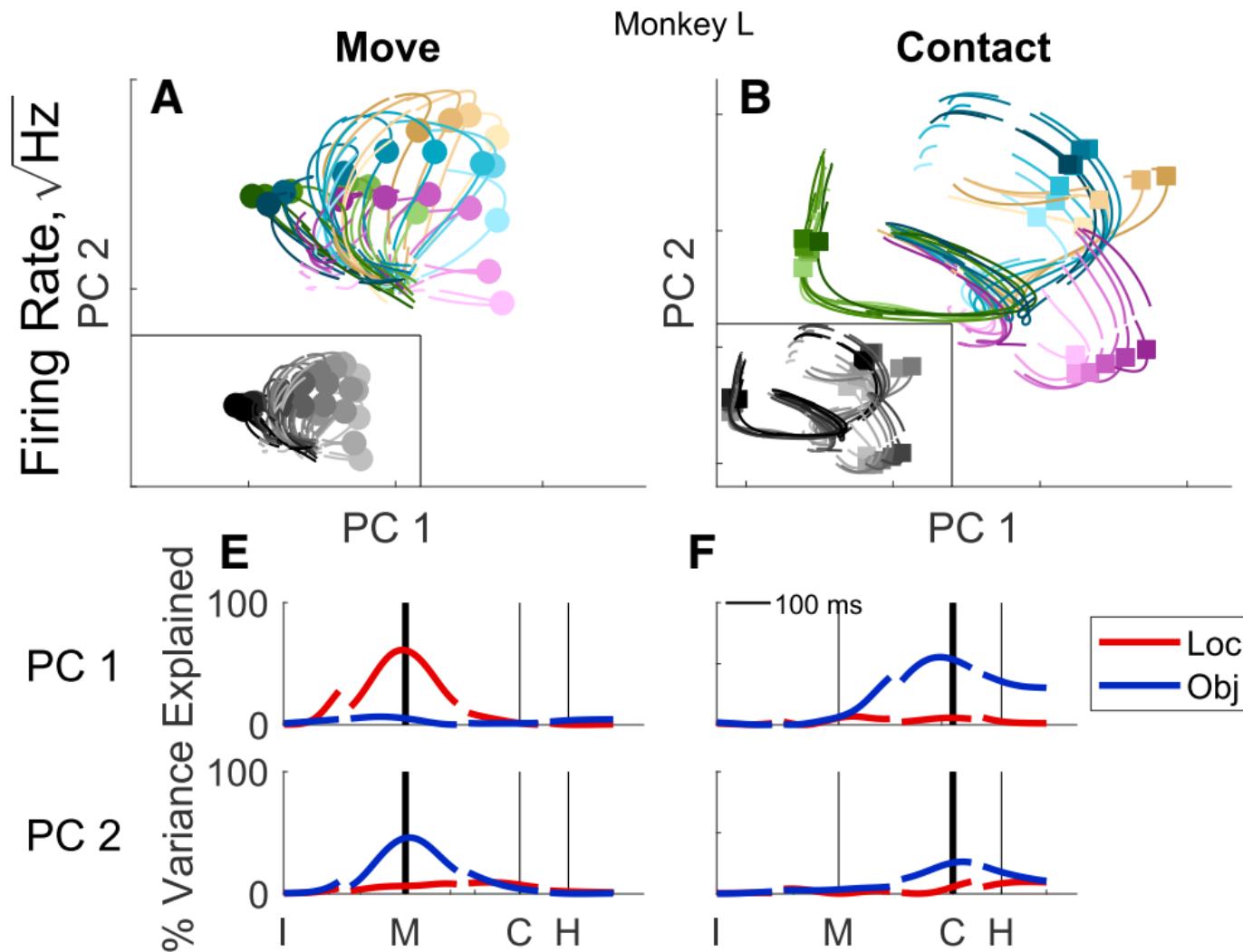
# Projections onto LO subspace



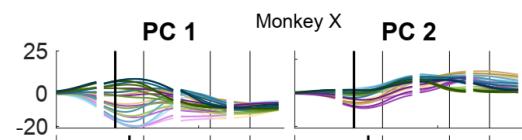
# Separate PCA for different alignments



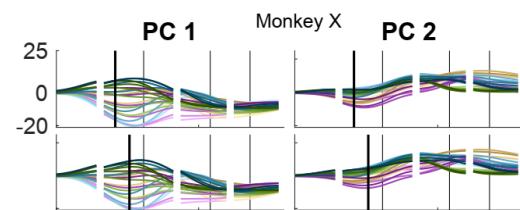
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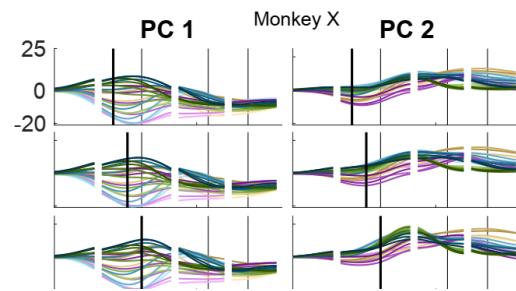
# Even more time-specific PCA!



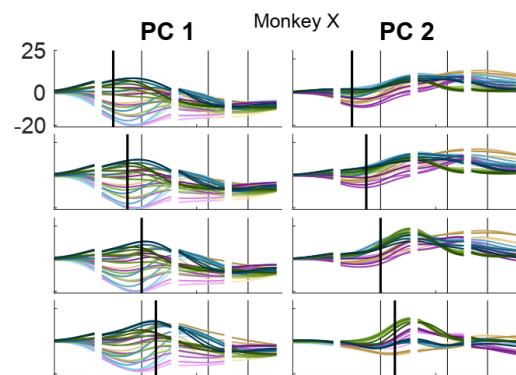
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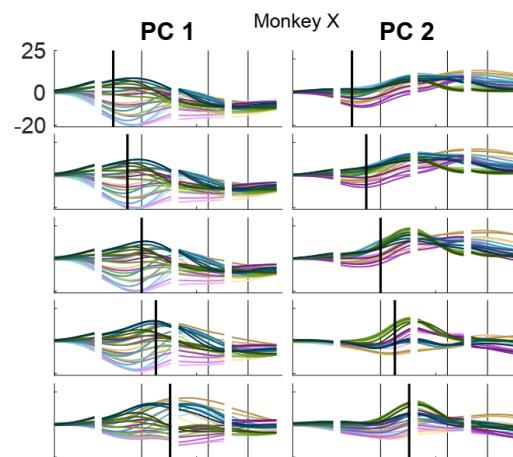
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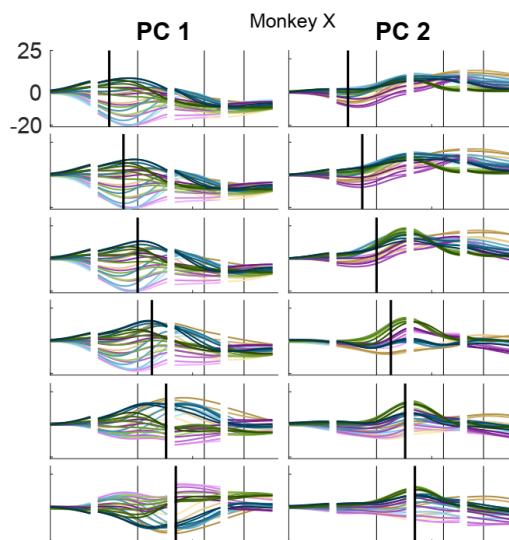
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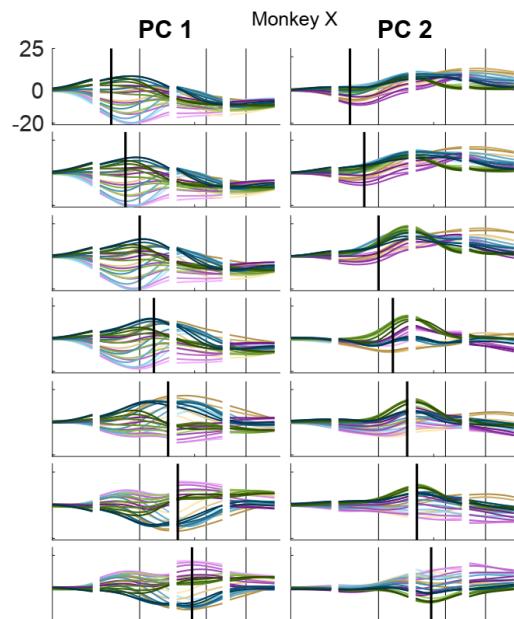
# Even more time-specific PCA!



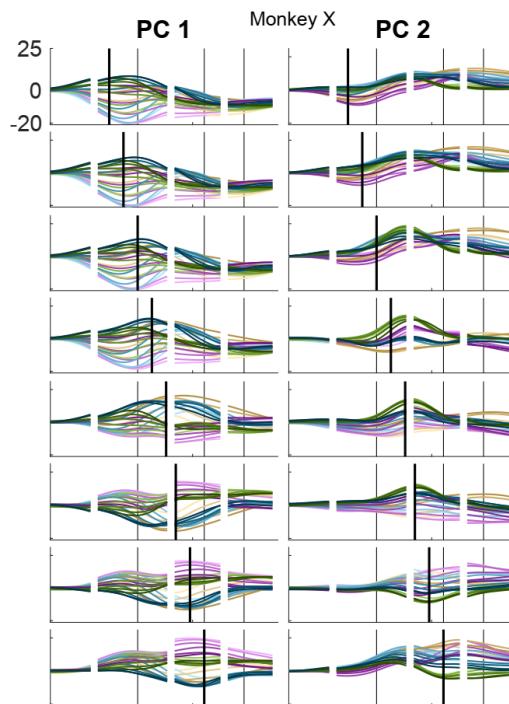
# Even more time-specific PCA!



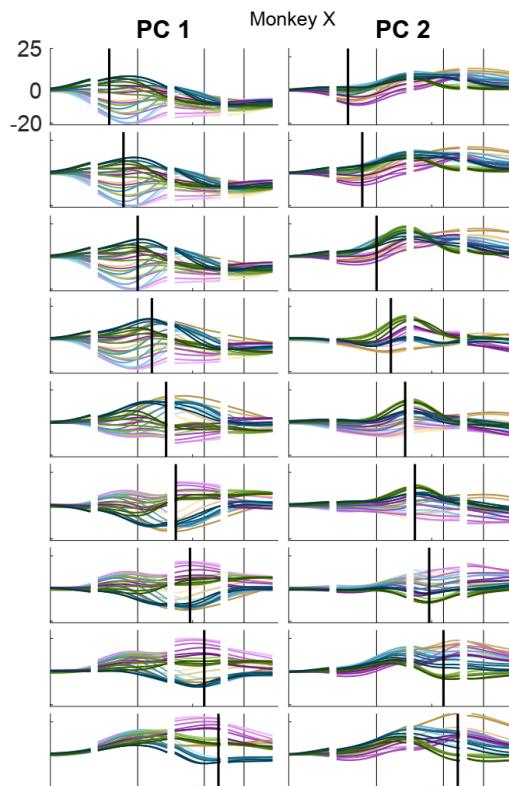
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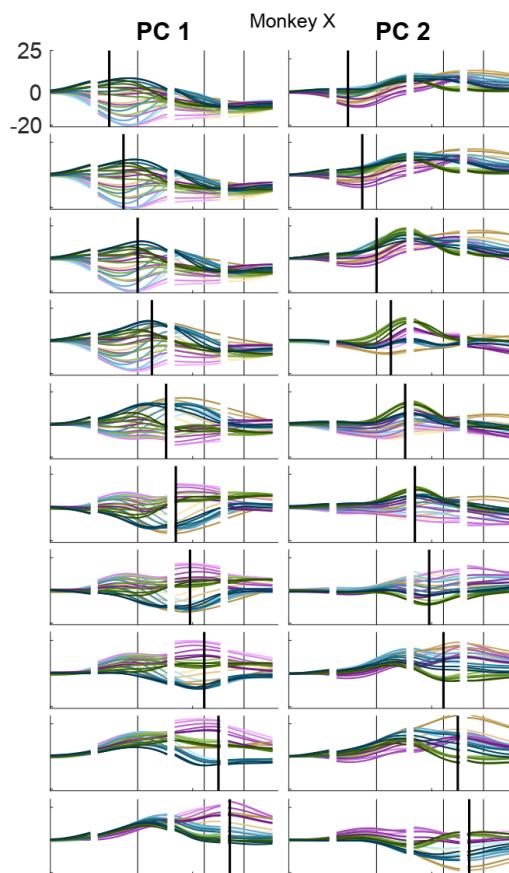
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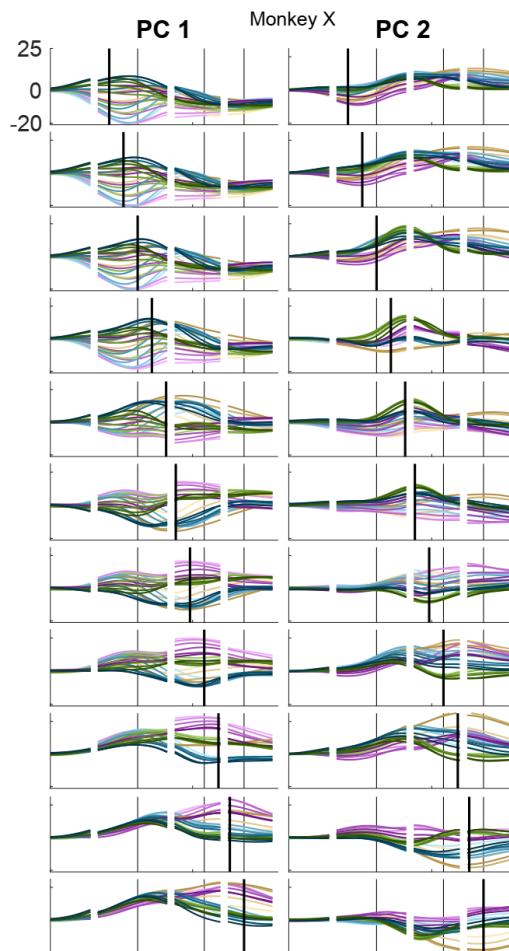
# Even more time-specific PCA!



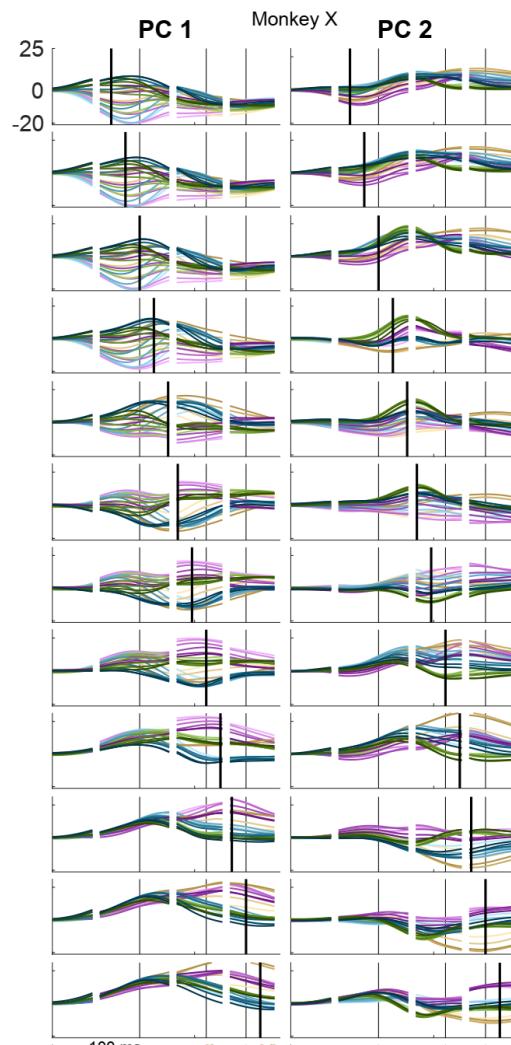
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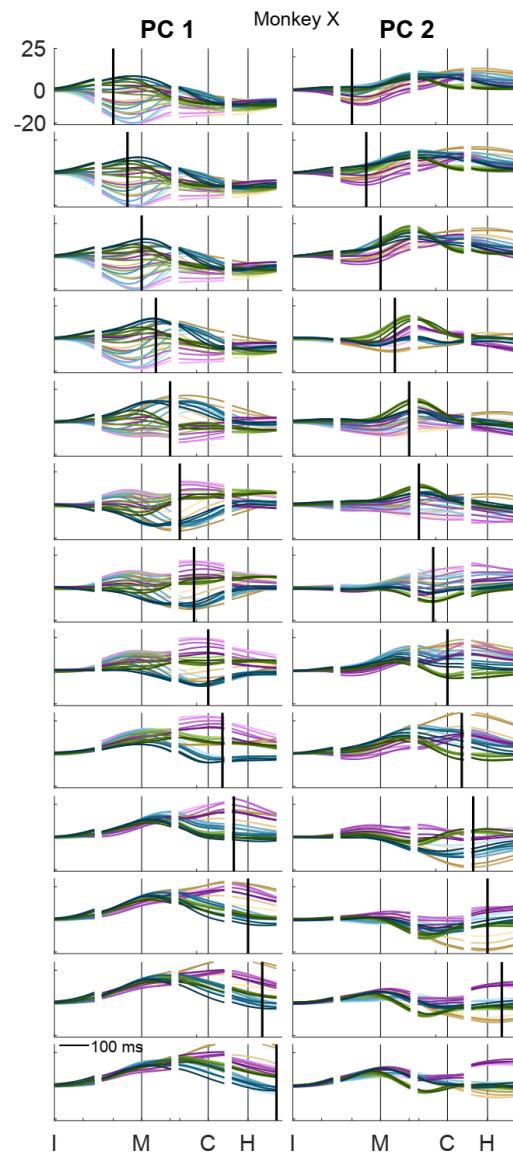
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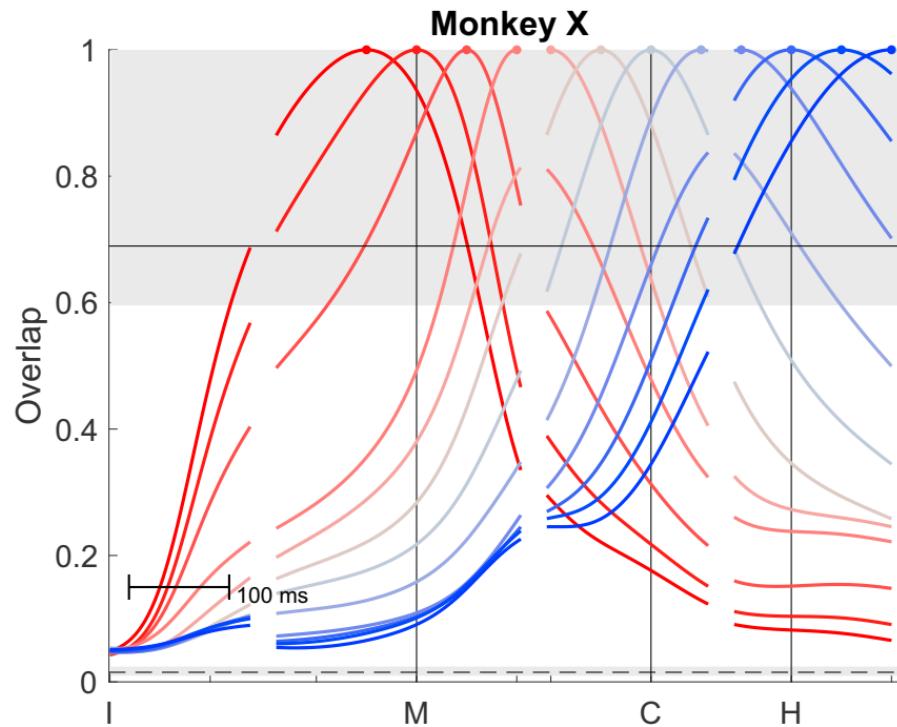
# Overlap between time-specific PCAs



$$Overlap = \frac{tr(\Sigma_1 \Sigma_2)}{\|\Sigma_1\|_F \cdot \|\Sigma_2\|_F}$$

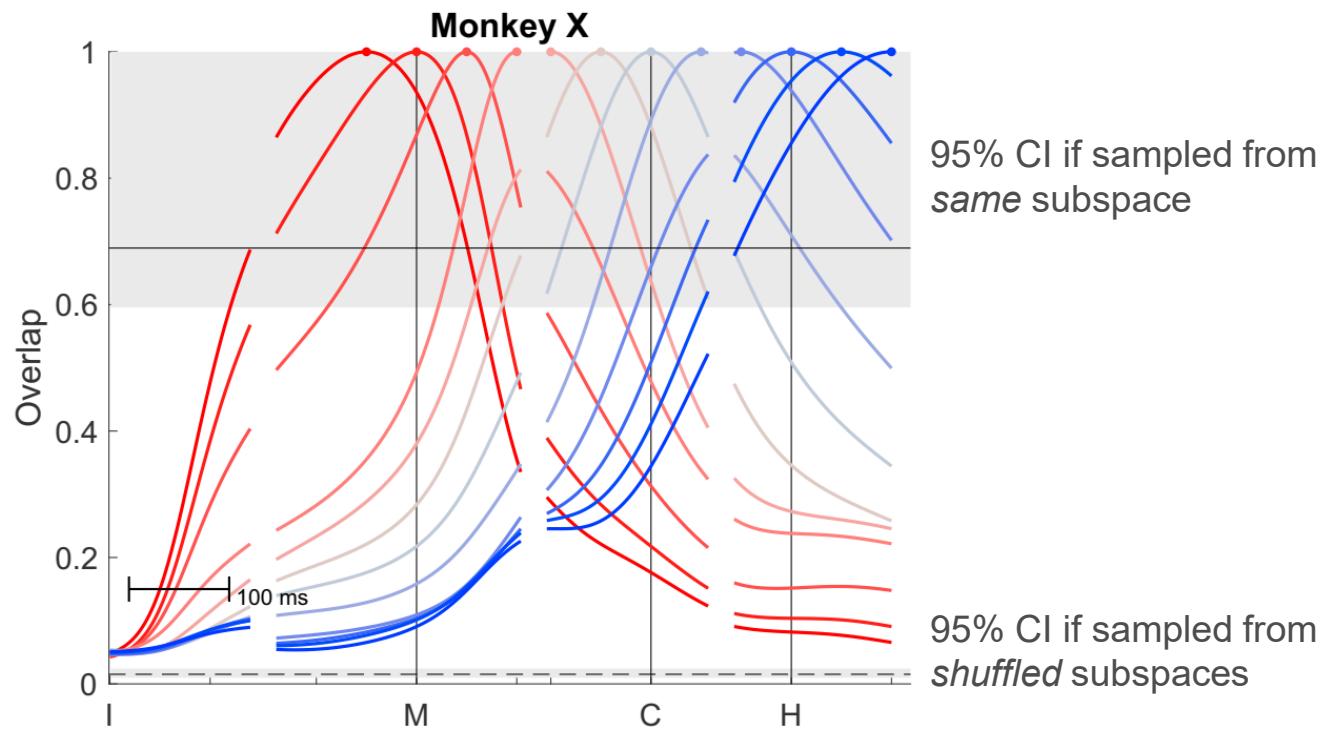
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# Conclusions

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  - No spatial organization
  - Separation != orthogonal
- Over time, neural activity gradually transitions
  - From location-specific (“reach”) subspace

# Conclusions

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- Mixed selectivity in individual M1 neurons
- Separation of location & object only at the population level
  - No spatial organization
  - Separation != orthogonal
- Over time, neural activity gradually transitions
  - From location-specific (“reach”) subspace
  - To object-specific (“grasp & manipulate”) subspace

# Epilogue

Whence comes this transition?

# Rotational dynamics?

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- Single rotational plane during reaching

# Rotational dynamics?

---



- Single rotational plane during reaching
  - Captures gradual transition from preparation to movement

# Rotational dynamics?

---



- Single rotational plane during reaching
  - Captures gradual transition from preparation to movement
  - Applies across multiple reaching contexts

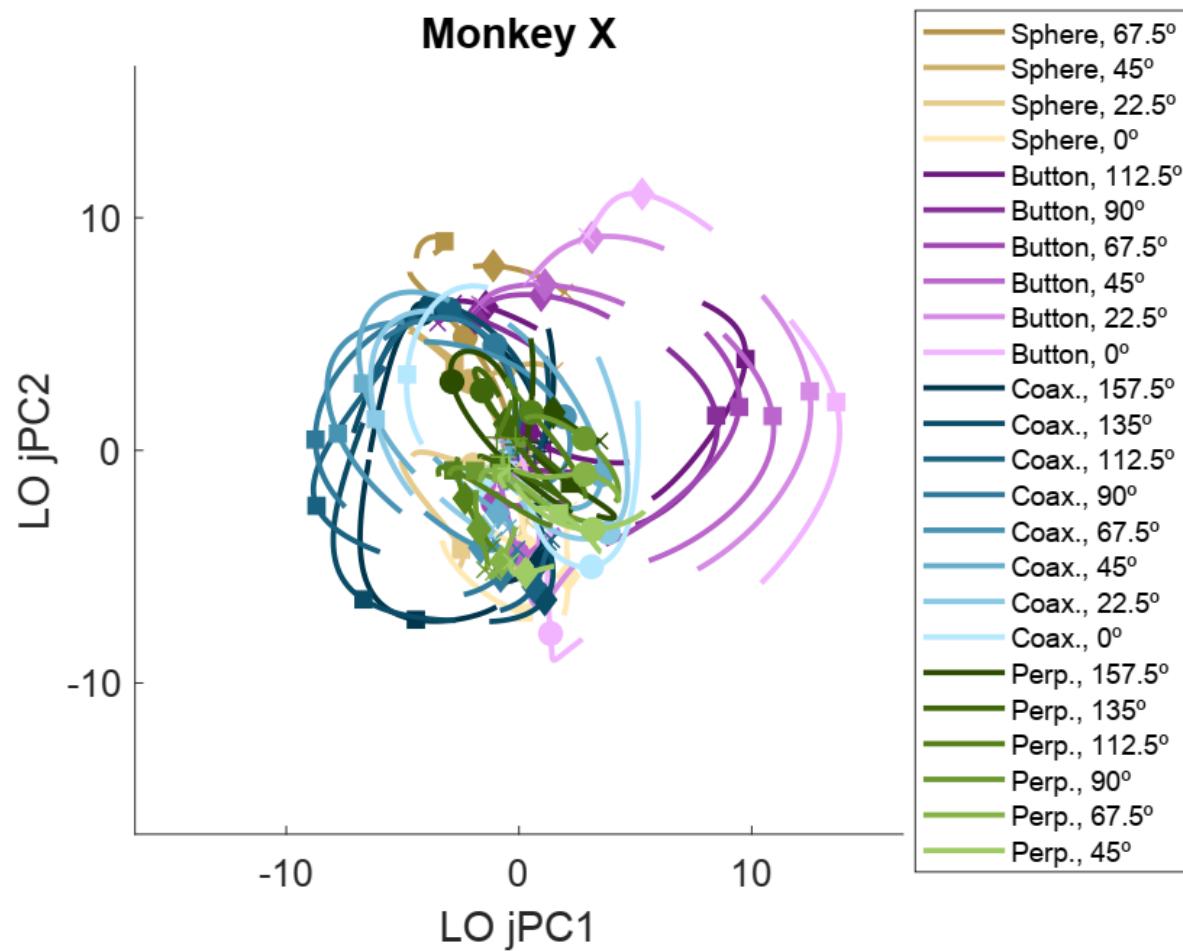
# Rotational dynamics?

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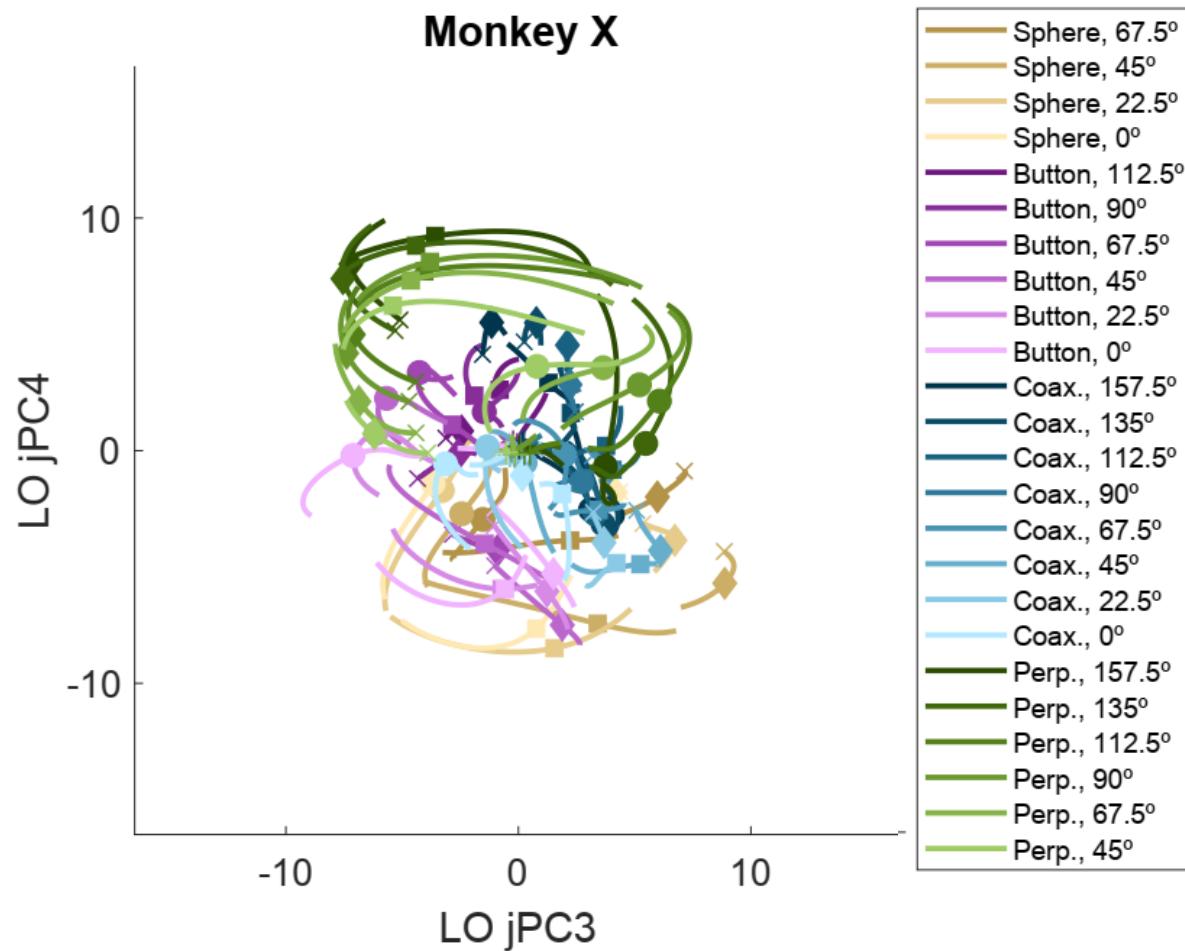


- Single rotational plane during reaching
  - Captures gradual transition from preparation to movement
  - Applies across multiple reaching contexts
  
- Can this also account for transition from reach to grasp?

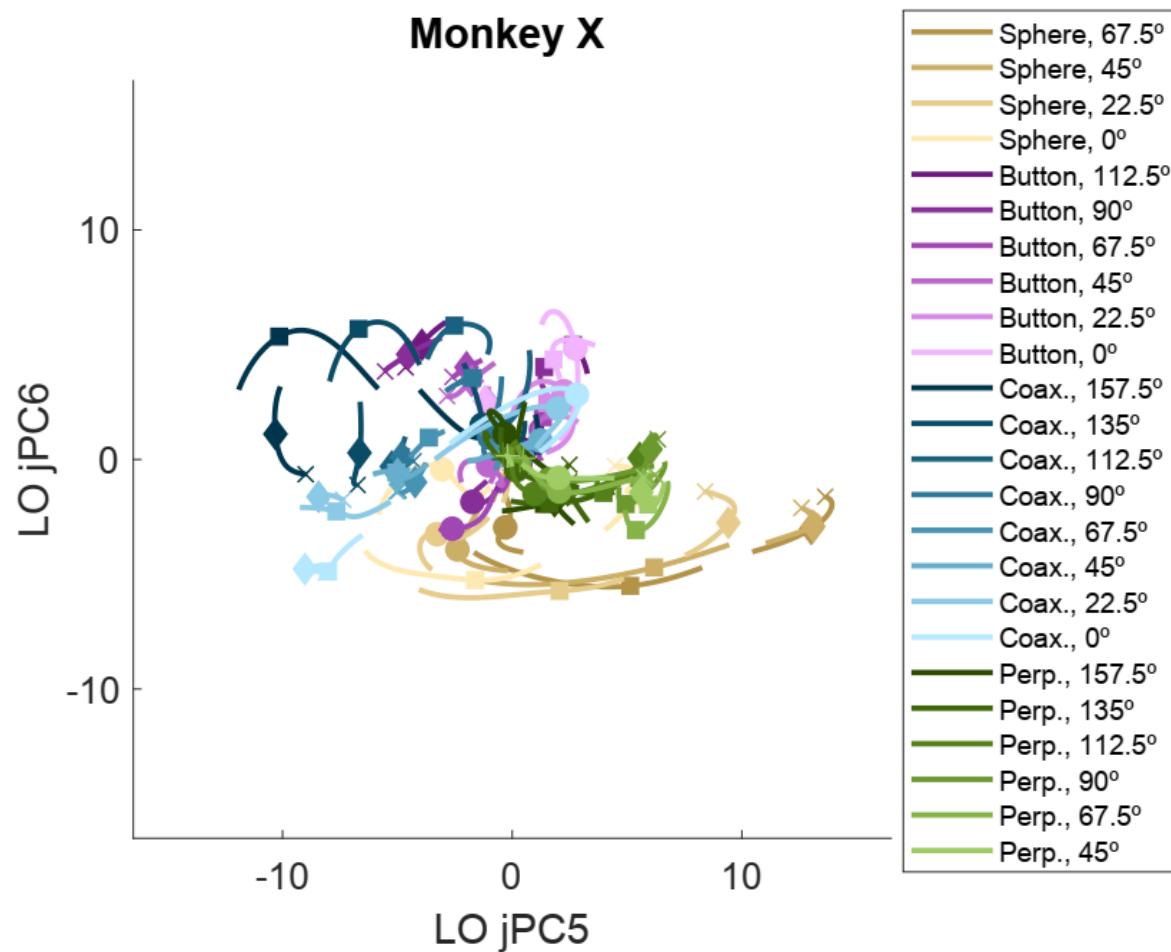
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---



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  - **No:** one plane cannot explain it all

# Rotational dynamics?

---



- Single rotational plane during reaching
  - Captures gradual transition from preparation to movement
  - Applies across multiple reaching contexts
  
- Can this also account for transition from reach to grasp?
  - **No:** one plane cannot explain it all
  - Rotations occupy different dimensions depending on the object



**Deutsches Primatenzentrum**  
Leibniz-Institut für Primatenforschung

FIN