

# Computational NeuroEthology

Computational tools for studying behavior



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Class 3

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# Overview

- How to get from video to posture
- Posture dynamics  $\approx$  Behavioral language
- Best Practices and Advanced Topics

# 01 Why Behavior Quantification Matters?

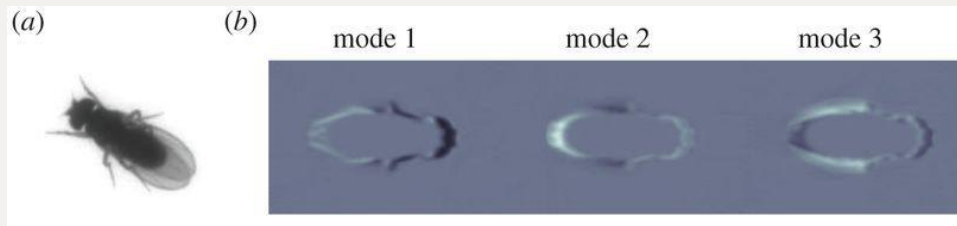
- Behavior is the brain's ultimate output  
understanding neural circuits requires equally  
precise descriptions of what animals actually do.
- Neural recordings are high-resolution;  
behavioral measures must match this precision  
to interpret neural dynamics.
- Modern tools allow continuous, high-  
dimensional tracking of posture, movement, and  
interaction.
- Traditional assays (e.g., lever presses, time in  
zone, binary scores) capture only a tiny  
fraction of ongoing complexity.
- Quantitative behavior should provide:
  - objective, reproducible metrics
  - access to latent behavioral states and motifs
  - new ways to link circuit activity

behavior must be captured as a structured and quantifiable signal

# Representations of animal to quantify distinct behaviors

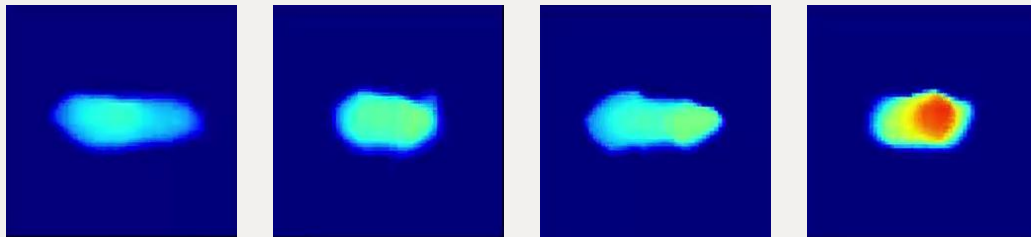
## I) Model free

### variance cross grey scale images



*Berman et al. J.R.Soc.Interface 2014*

### variance cross depth images



*Wiltschko et al. Neuron 2015*

## II) Model based

Coarse

Centroid tracking

Ellipse tracking

Single – animal pose estimation

Anatomically constrained 3d model

Fine

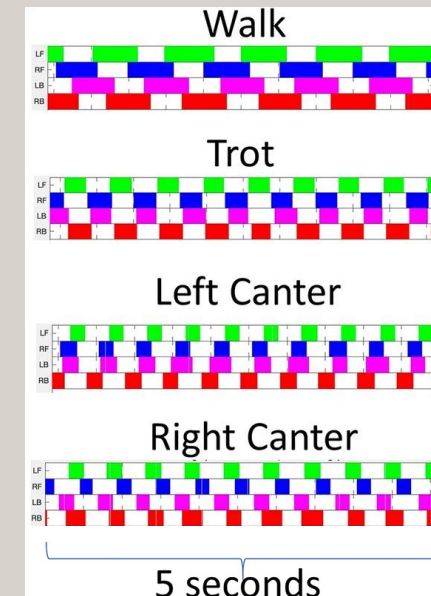
# 02 Biological motion capture



"The Horse in Motion", 1878  
Eadweard Muybridge



Footfall pattern of each different gait

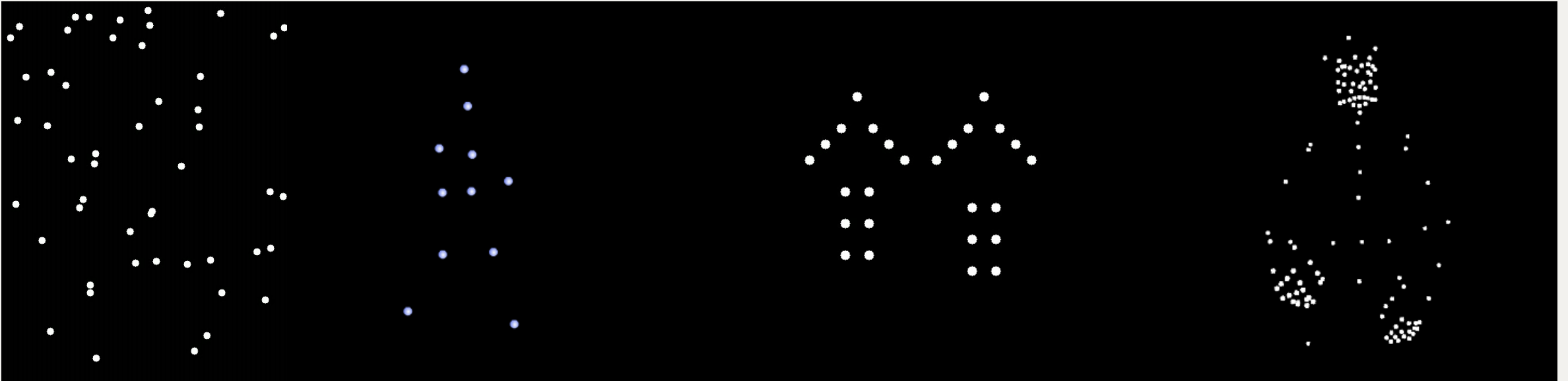


White: swing phase; color: stance phase

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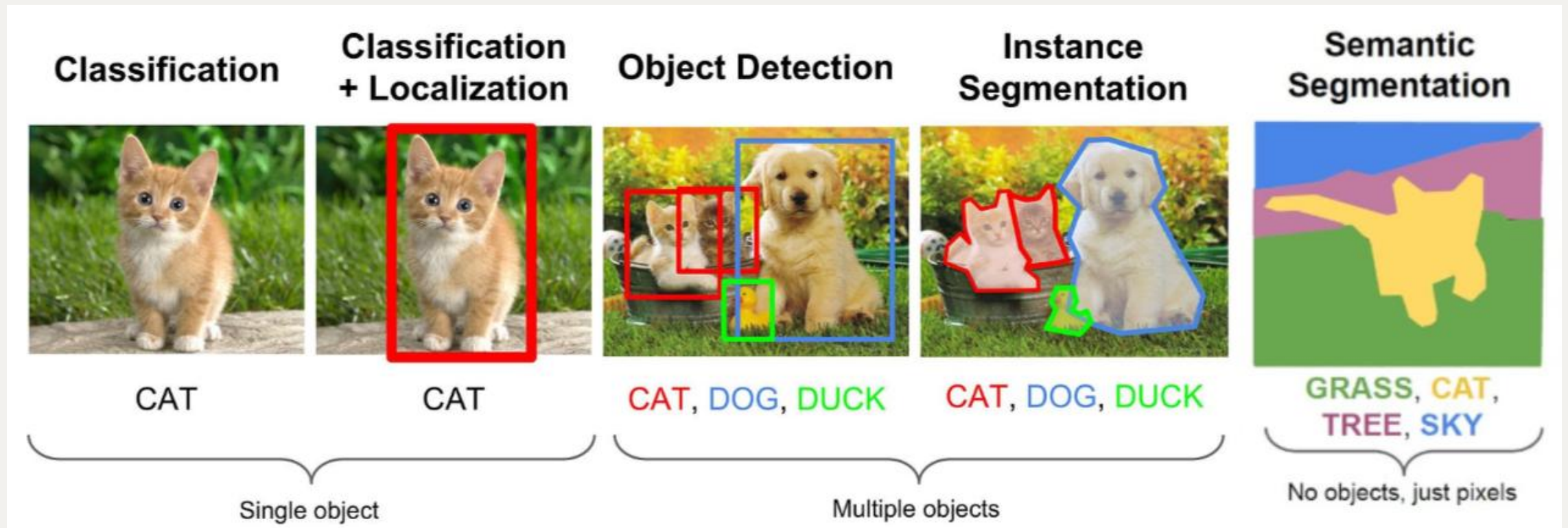
# Biological motion perception

Gunnar Johansson experiments



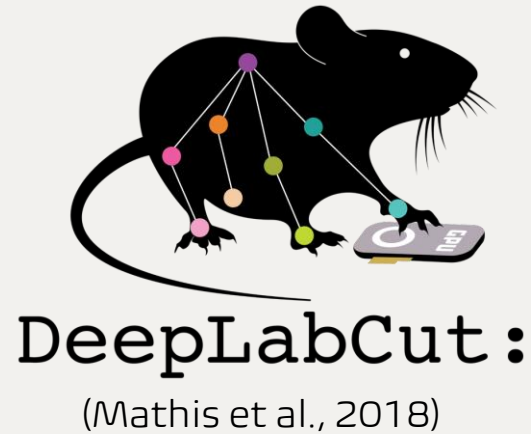
# Computer Vision: Techniques and Algorithm

enables computers to "see" and interpret visual information from images and videos like humans do



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# Deep learning methods for animal pose estimation

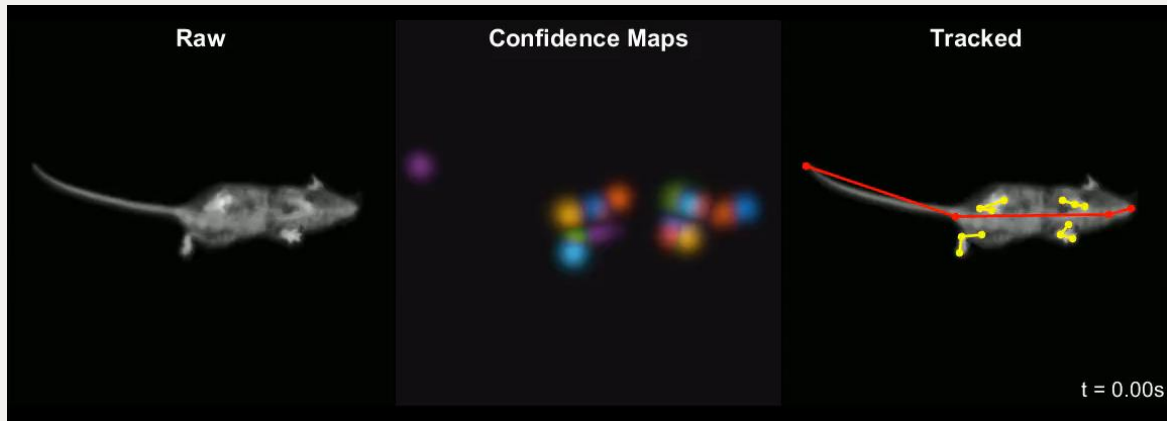
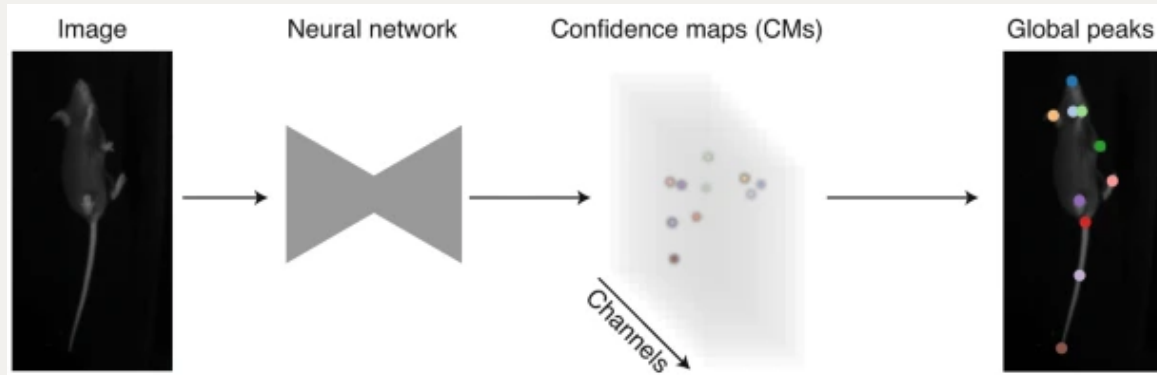


Pereira et al., 2019

DeepPoseKit (Graving et al., 2019); OptiFlex (Liu et al., 2021); SemiMultiPose (Blau et al., 2022); Anipose (Karashchuk et al., 2021); CAPTURE (Marshall et al., 2020); YOLO family methods and other



# Anatomy of pose estimation systems



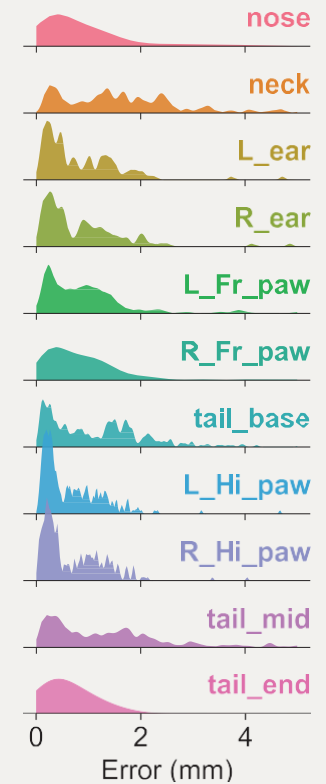
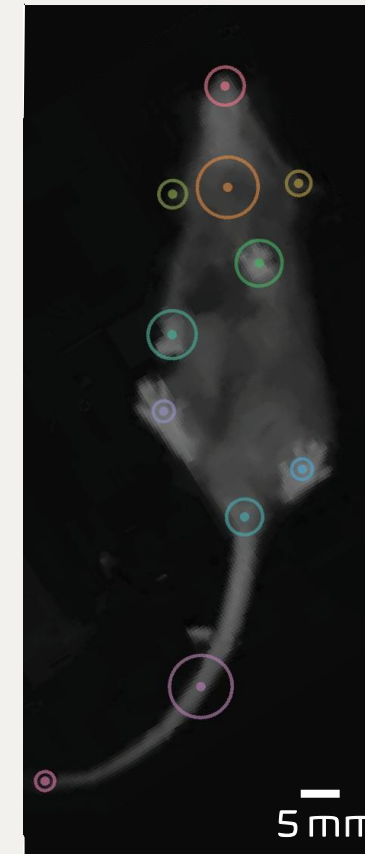
*LEAP and SLEAP*

*Pereira et al., Nat Methods 2019*

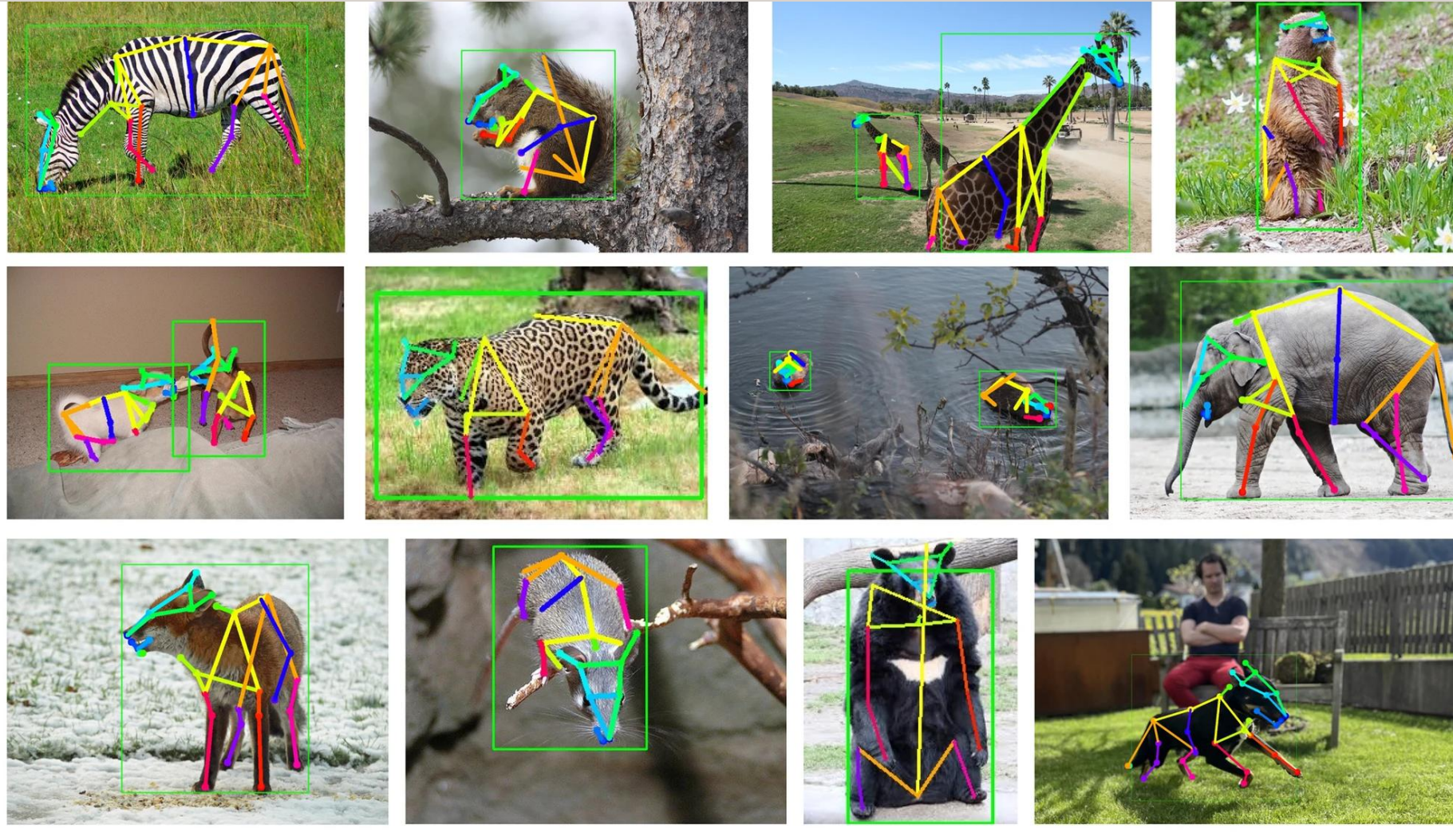
*Pereira, Shaevitz & Murthy. Nat Neurosci 2020*

*Pereira et al., Nat Methods 2022*

## Accurate body landmark localization



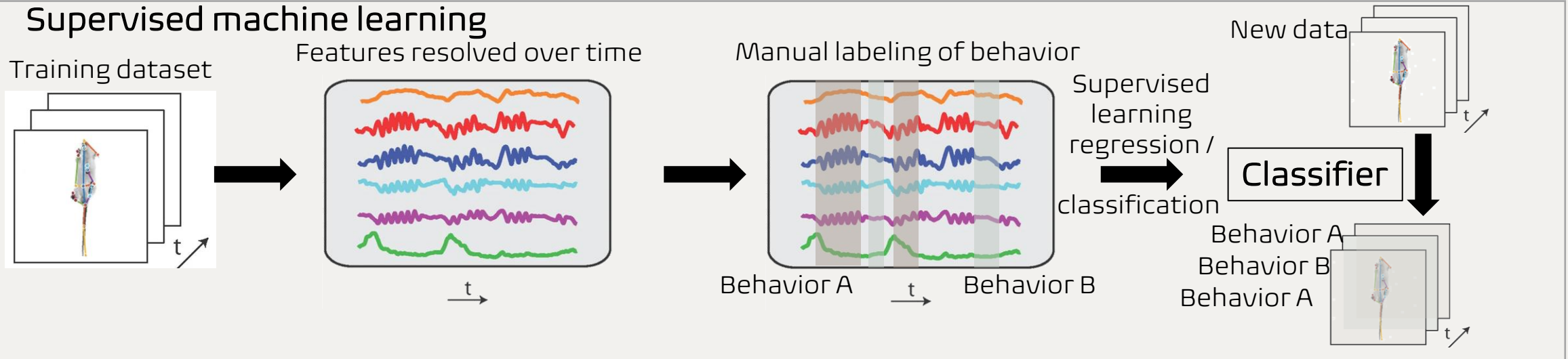
# 03 Making sense of posture dynamics



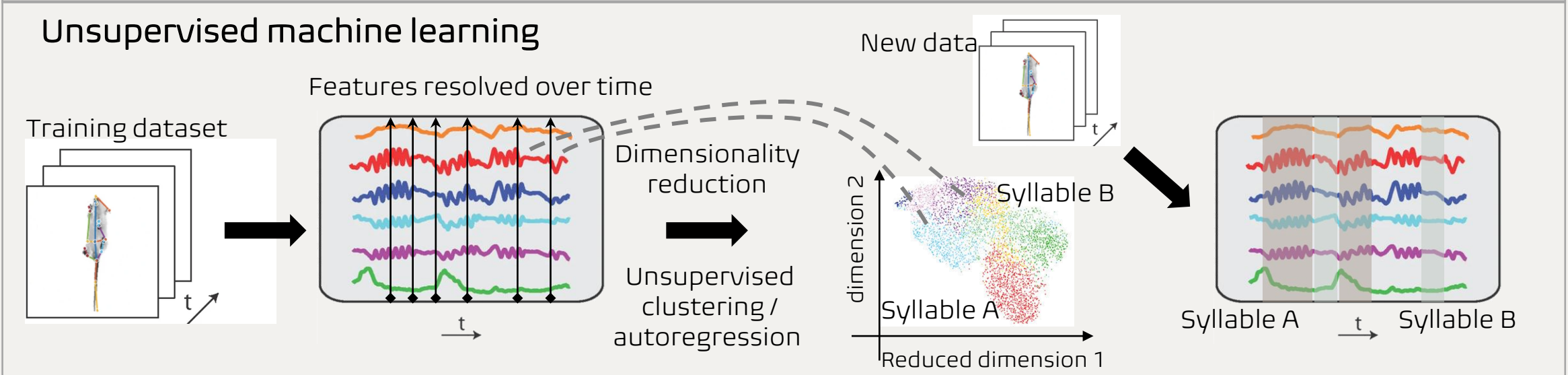


# Supervised and unsupervised machine learning for behavior classification

## Supervised machine learning



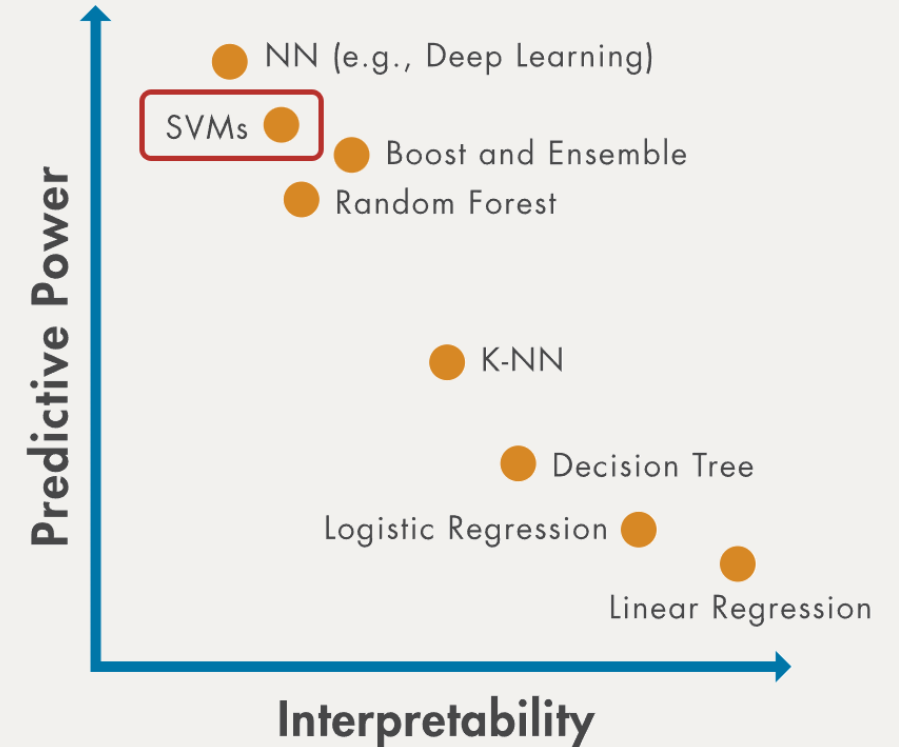
## Unsupervised machine learning



# Supervised machine learning approach

Popular approaches to classify behavior based on human definitions:

- JAABA (Kabra et al., 2013)  
Support Vector Machine based
- SimBA (Nilsson et al., 2020 and Goodwin et al., 2024)  
Random forest, Gradient boost classifier(GBC)  
or eXtreme Gradient boost (Xgboost)
- MARS (Segalin et al., 2021)  
set of 270 spatiotemporal features and Xgboost
- DeepEthogram (Bohnslav et al., 2021)  
deep convolutional neural networks
- BehaviorDEPOT (Gabriel et al., 2022)  
heuristics (thresholding pose-based metrics)
- A-SOiD (Tillmann et al., 2024) - Random Forest Classifier



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# Unsupervised machine learning approach

Popular approaches to classify behavior without human definitions:

- MoSeq (Wiltschko et al., 2015) and Keypoint-MoSeq (Weinreb et al., 2024)

Auto-regressive hidden Markov model (AR-HMM)

- MotionMapper (Berman et al., 2014)

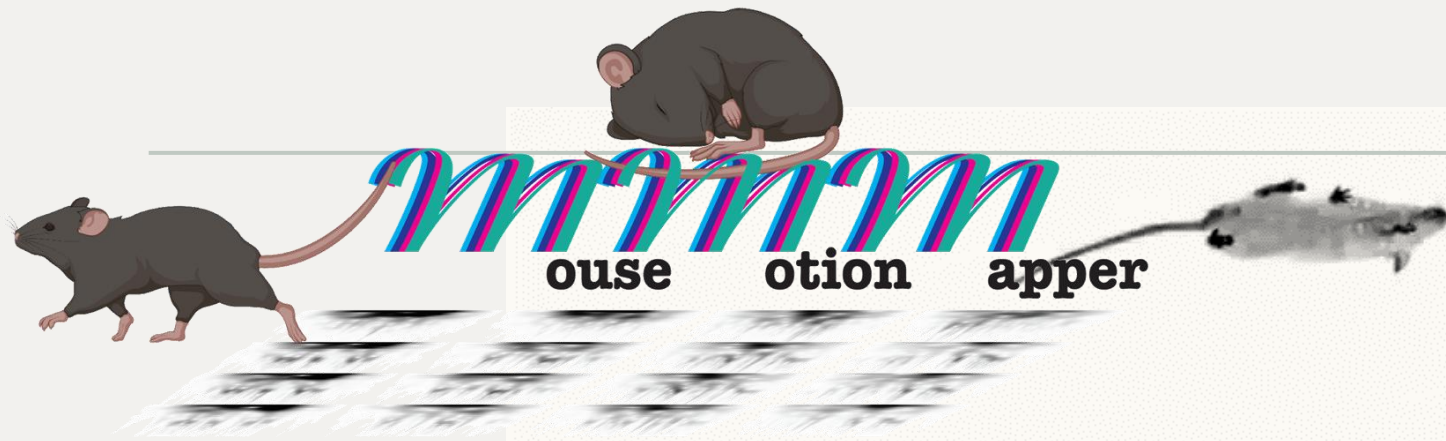
Model behavior in frequency space

- B-SOiD (Hsu and Yttri, 2021)

Reduce dimensions of spatiotemporal pose with UMAP

- VAME (Luxem, K. et al. 2022)

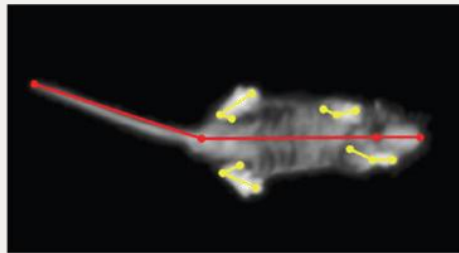
deep variational embeddings of animal motion



Unsupervised behavioral classification for a non-goal oriented task

# Modeling mouse behavior as a clusters of body postures in frequency space

(s)LEAP joint predictions



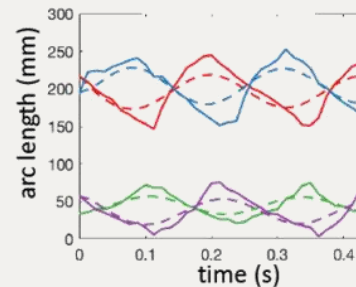
From: Pereira et al., 2019

Distance matrix  
+ PCA

Extracting  
features (e.g.  
animal-centered  
paw positions)

## Wavelet decomposition

### Postural space



Dashed lines: locally linear model

K-means  
clustering

Behavioral class  
prediction

Quantification of  
time in behavior,  
transitions, etc.

Hierarchical clustering  
of linear models

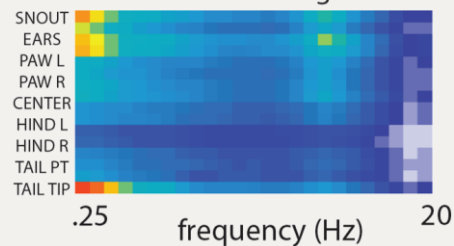
Further insights into  
behaviors and transitions  
between behaviors

## Circular grooming

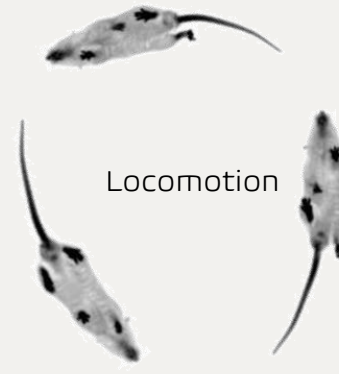


## Normalized power spectra

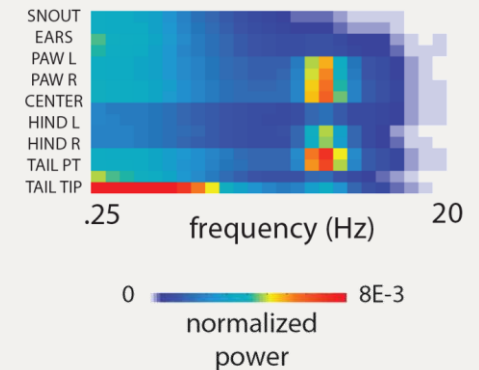
### fast circular groom



## Locomotion



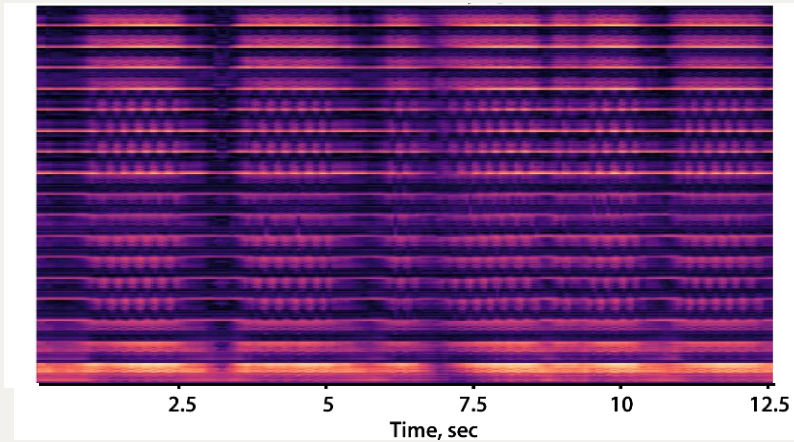
### fast locomotion



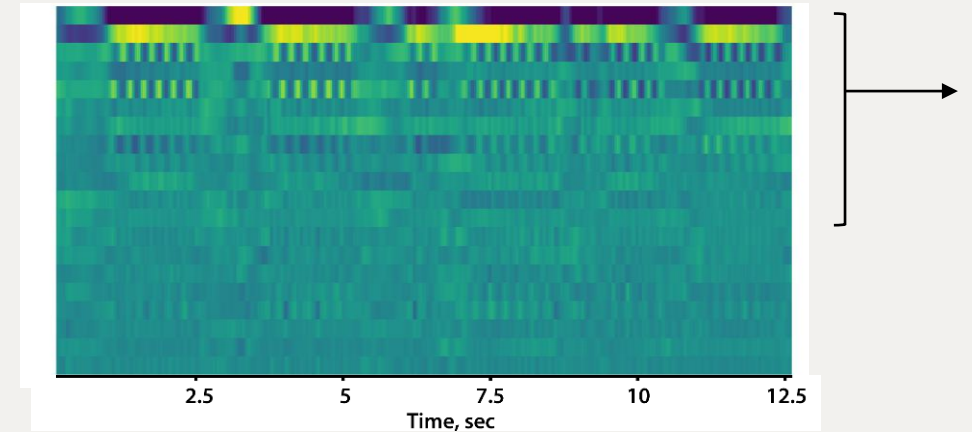


# Modeling mouse behavior as a clusters of body postures in frequency space

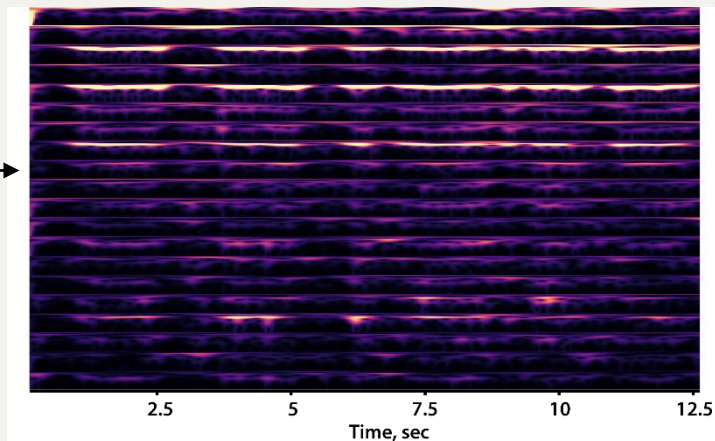
## Distance between all body part coordinates



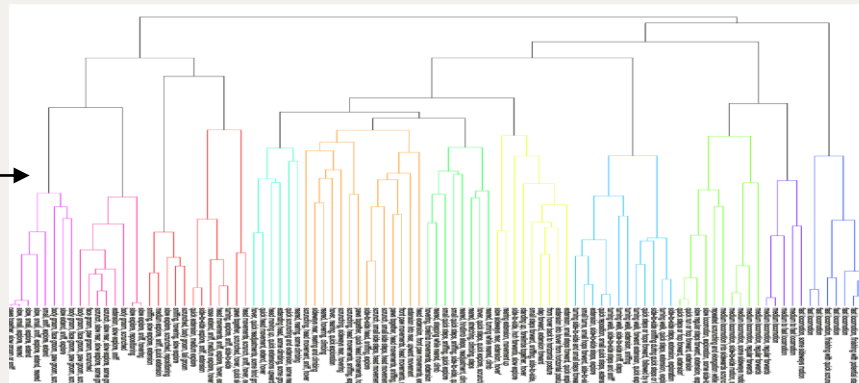
## PCA projections



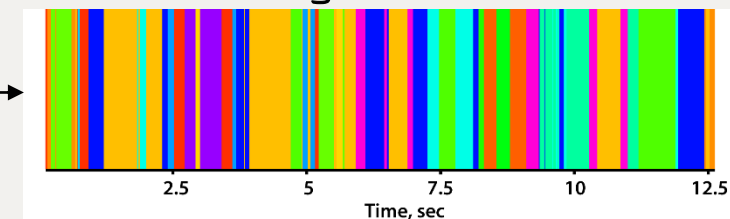
## Power spectral densities



## Clustering in high-dimensional wavelet space



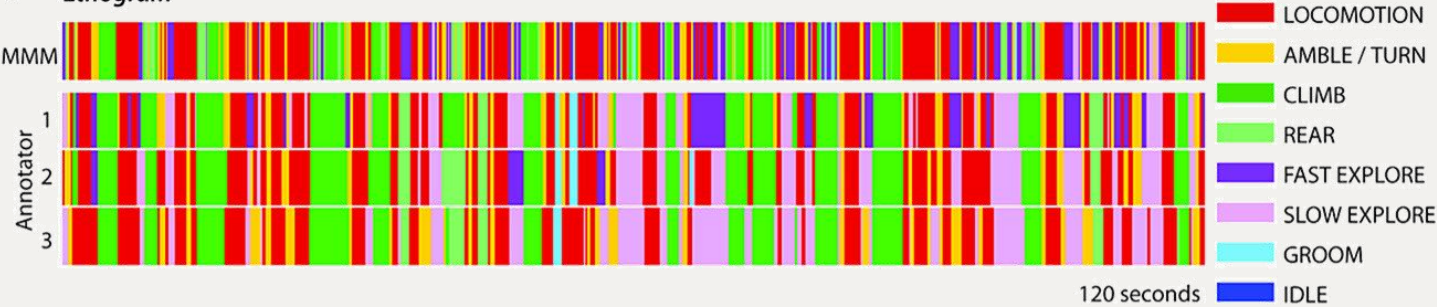
## Ethogram of clusters



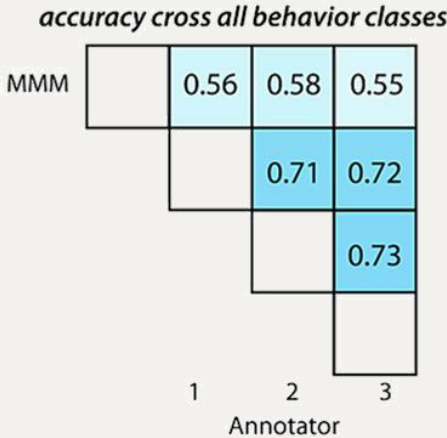
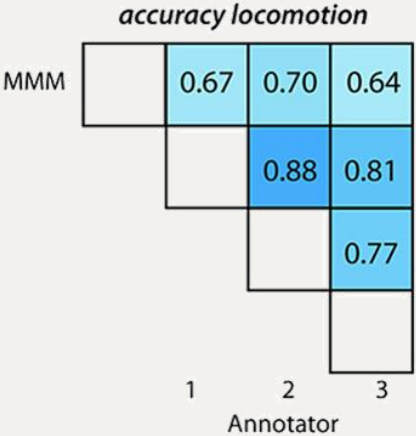
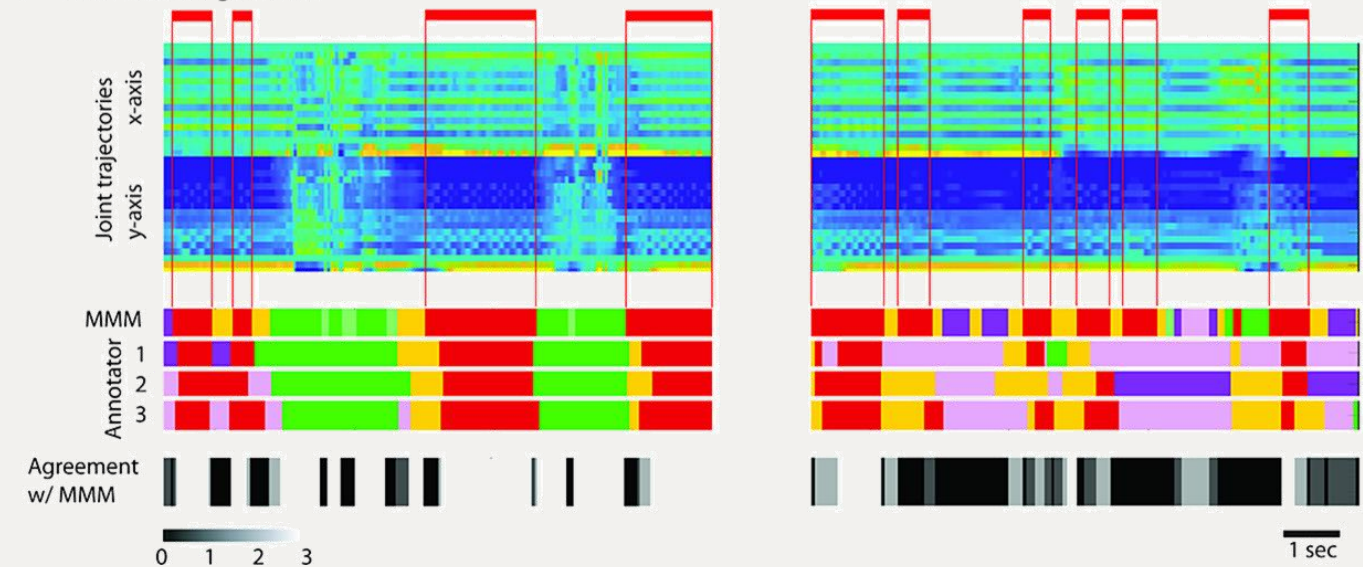


# Agreements and discrepancies between MMM and human annotators

a *Ethogram*



b *Annotations agreement*



Inter-annotator style differences

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Time to practice  
Open the Google Colaboratory (Colab)