

Machine Learning Methods for Neural Data Analysis

Markerless Pose Tracking

Scott Linderman

STATS 220/320 (NBIO220, CS339N)

**“The brain is worthy of study because it is
in charge of behavior”**

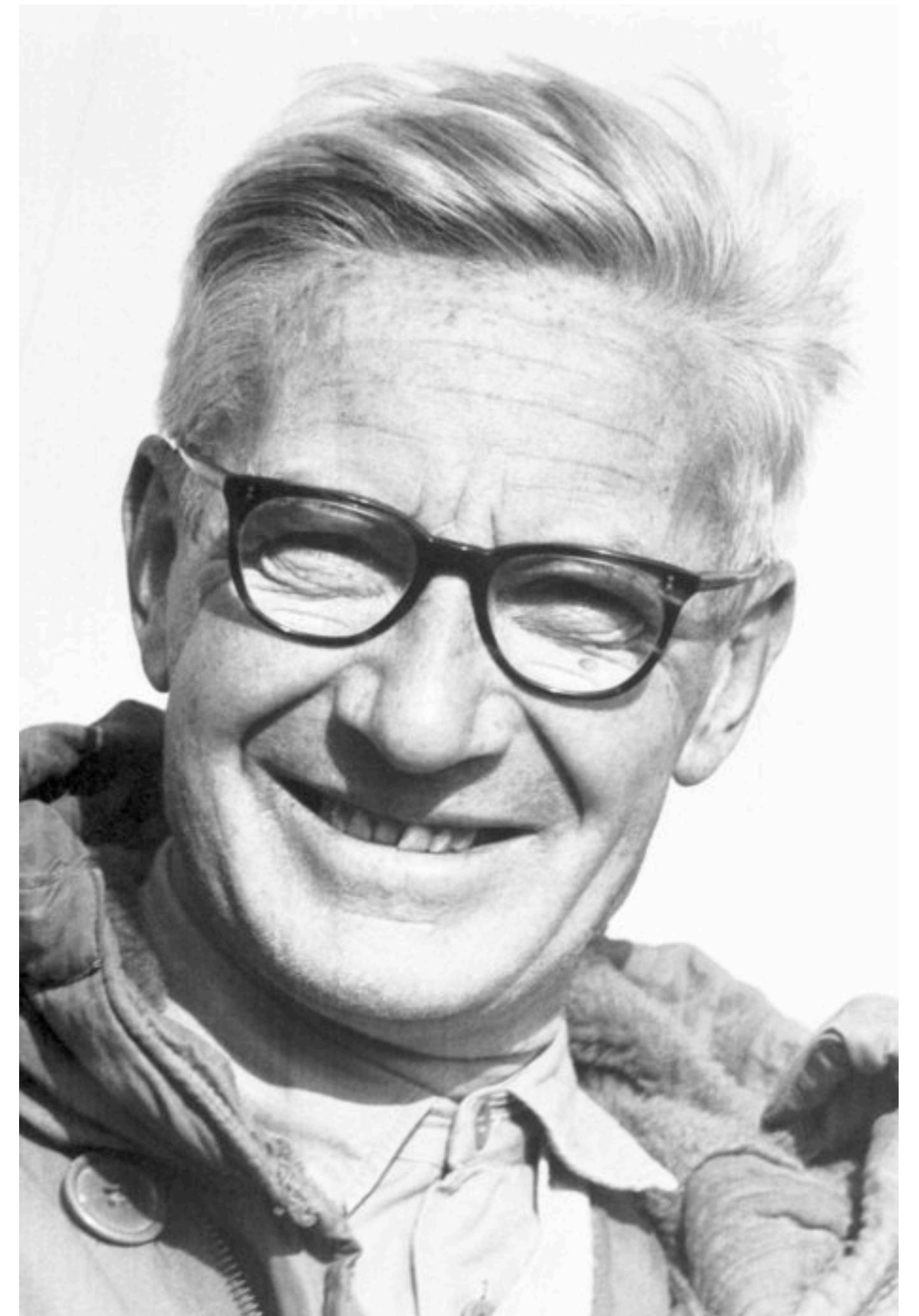
Datta, Anderson, Branson, Perona, and Leifer. Computational Neuroethology: A Call to Action. *Neuron* 2019.



Ethology

The study of (natural) behavior

- **Hypothesis:** “exposing the structure of behavior...will yield insights into how the brain creates behavior.” Datta et al.
- **Structure:** how behavior in the natural environment is built from components and organized over time in response to ecologically relevant stimuli.
- **Natural behavior:**
 - Exploring new environments
 - Foraging for food
 - Finding shelter
 - Identifying mates
 - ...



Nikolaas Tinbergen
Nobel Prize in Physiology or Medicine 1973

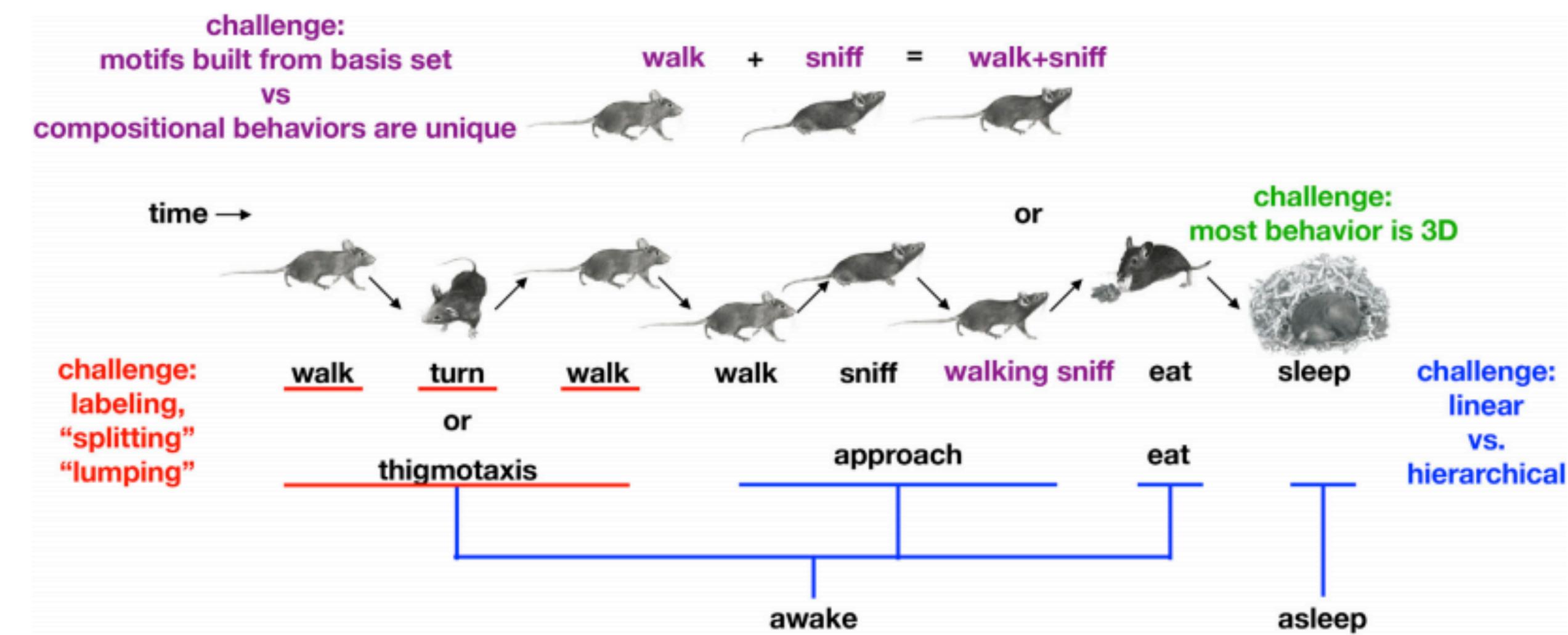


Yilmaz and Meister (*Curr. Bio.*, 2013)

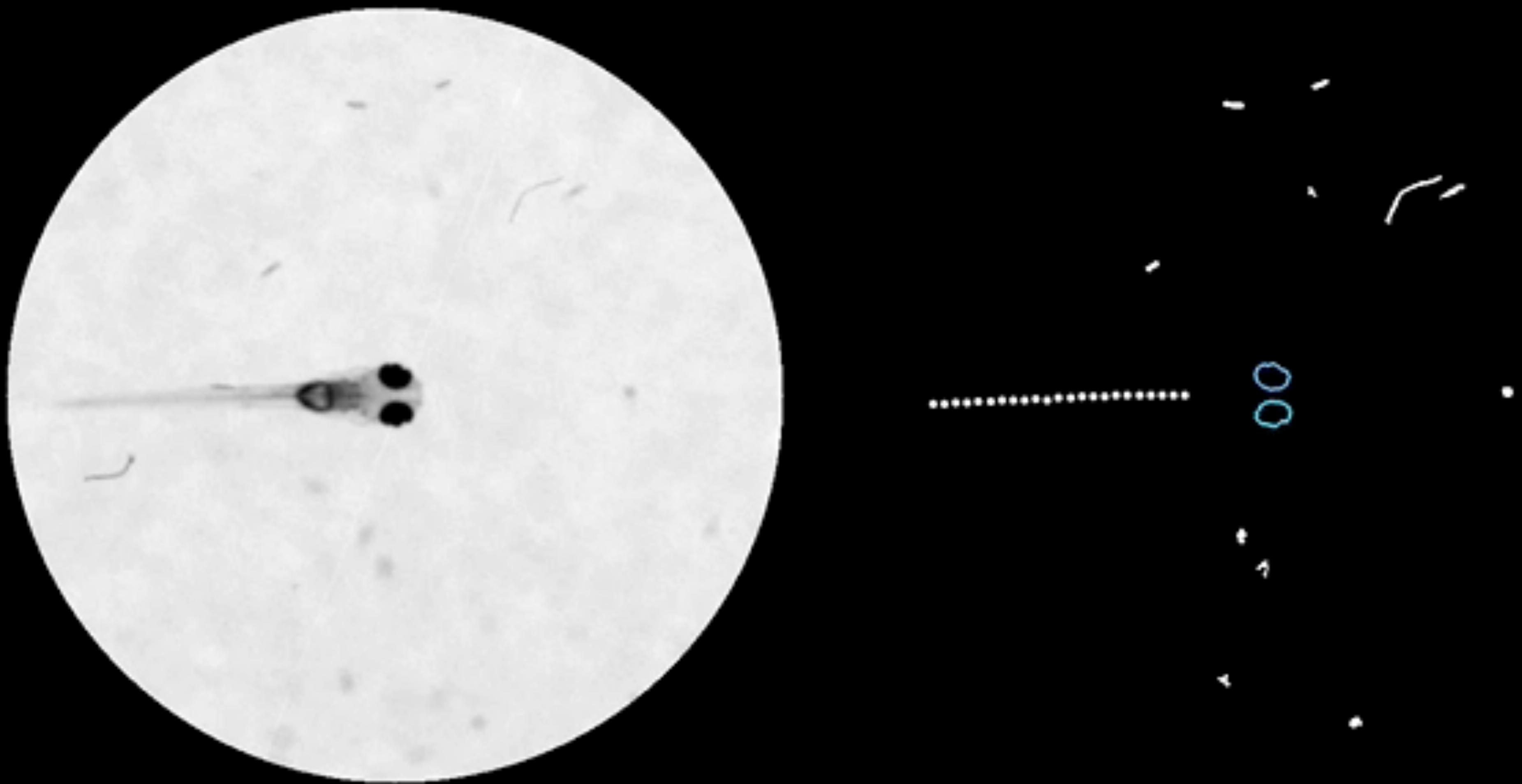
Computational (Neuro)Ethology

Quantifying natural behavior (and relating it to neural activity)

- Leveraging advances in **computer vision** and **machine learning** to extract behavioral features of interest from raw data.
- Modeling the dynamics of 3D pose as a function of sensory input and internal state.
- Decomposing behavior into stereotyped components and behavioral motifs.
- Correlating behavioral motifs with large scale neural recordings.
- Identifying causal relationships between neural activity and motor output.



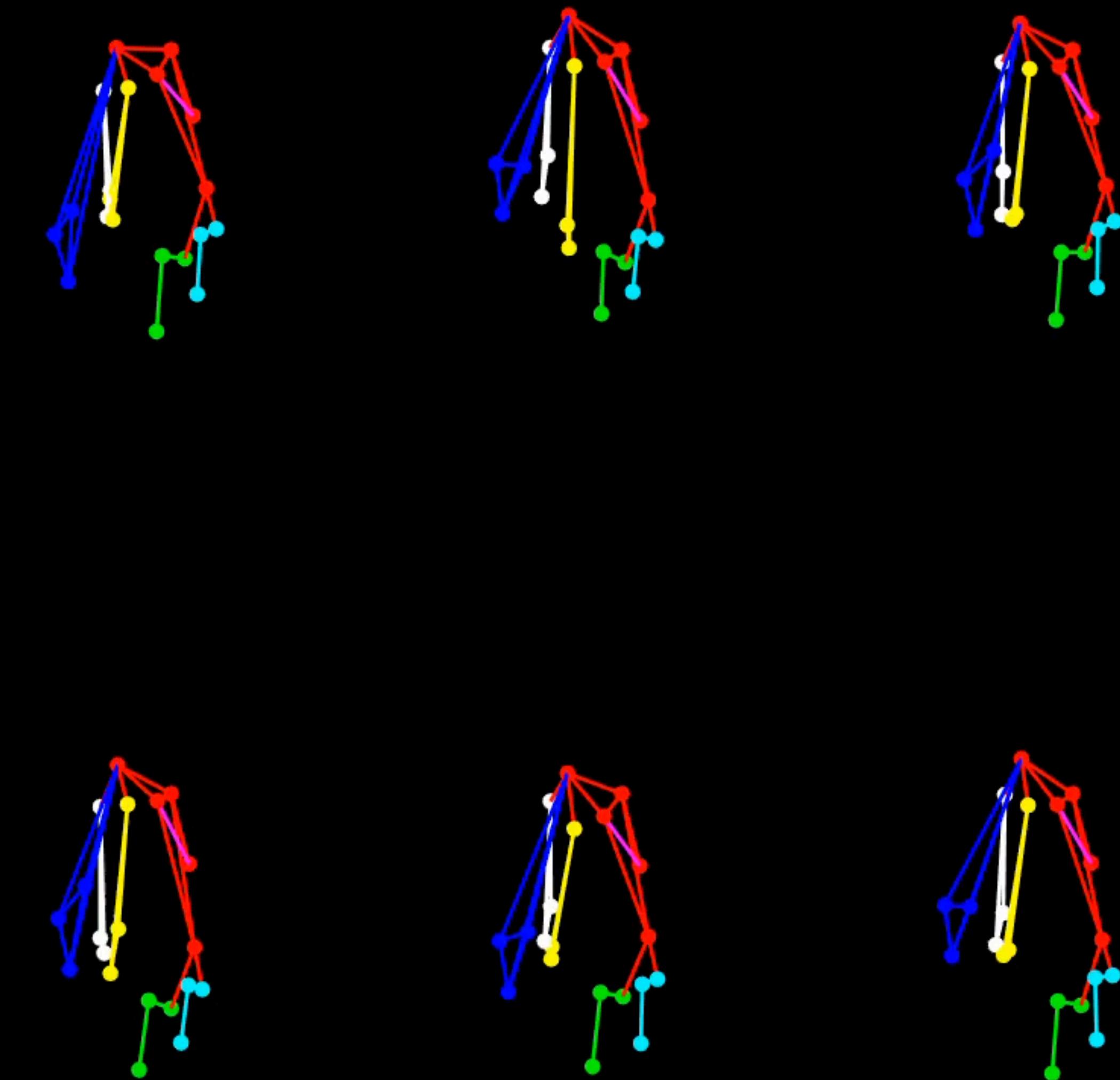
Datta et al (*Neuron*, 2019)





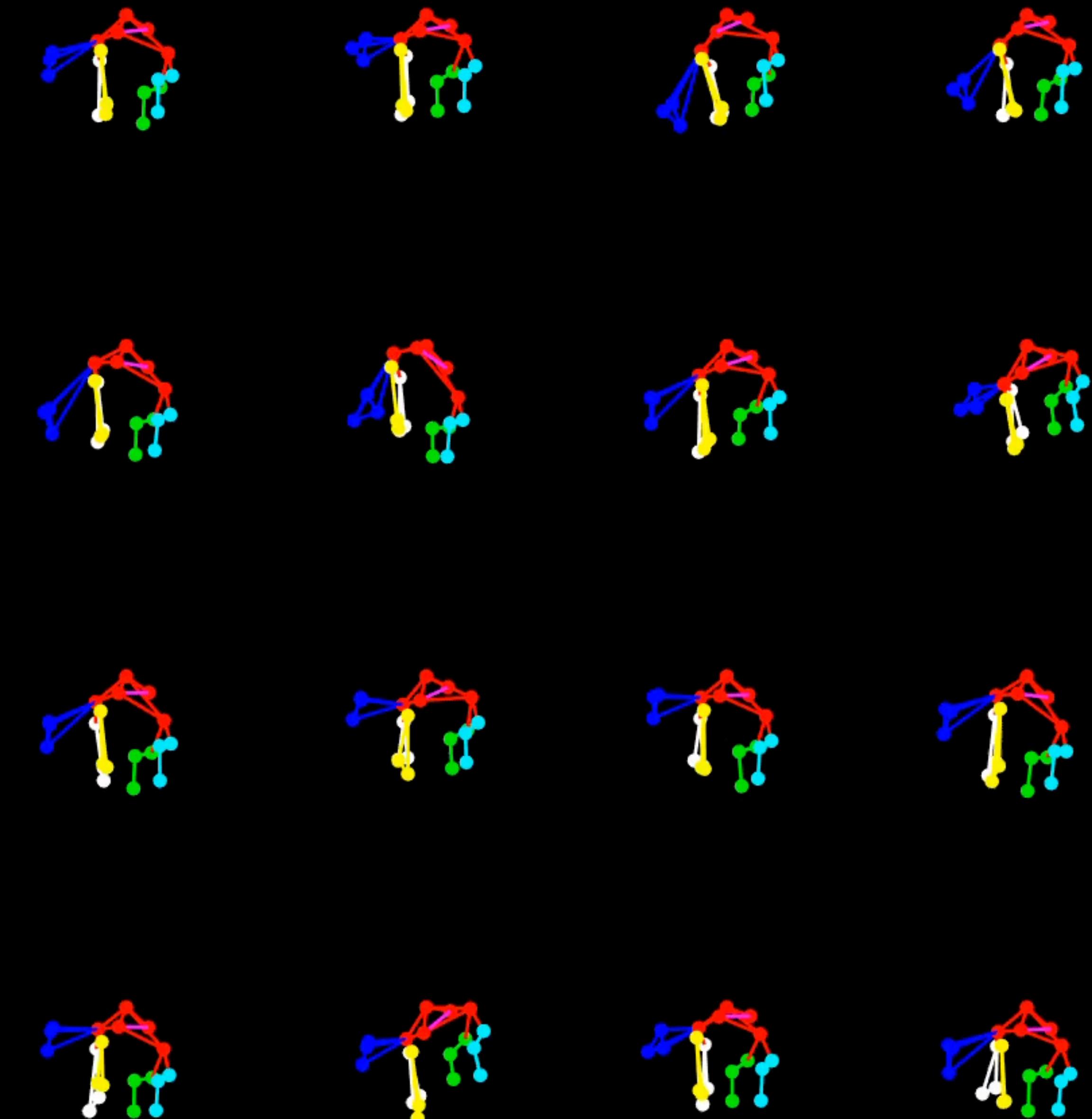
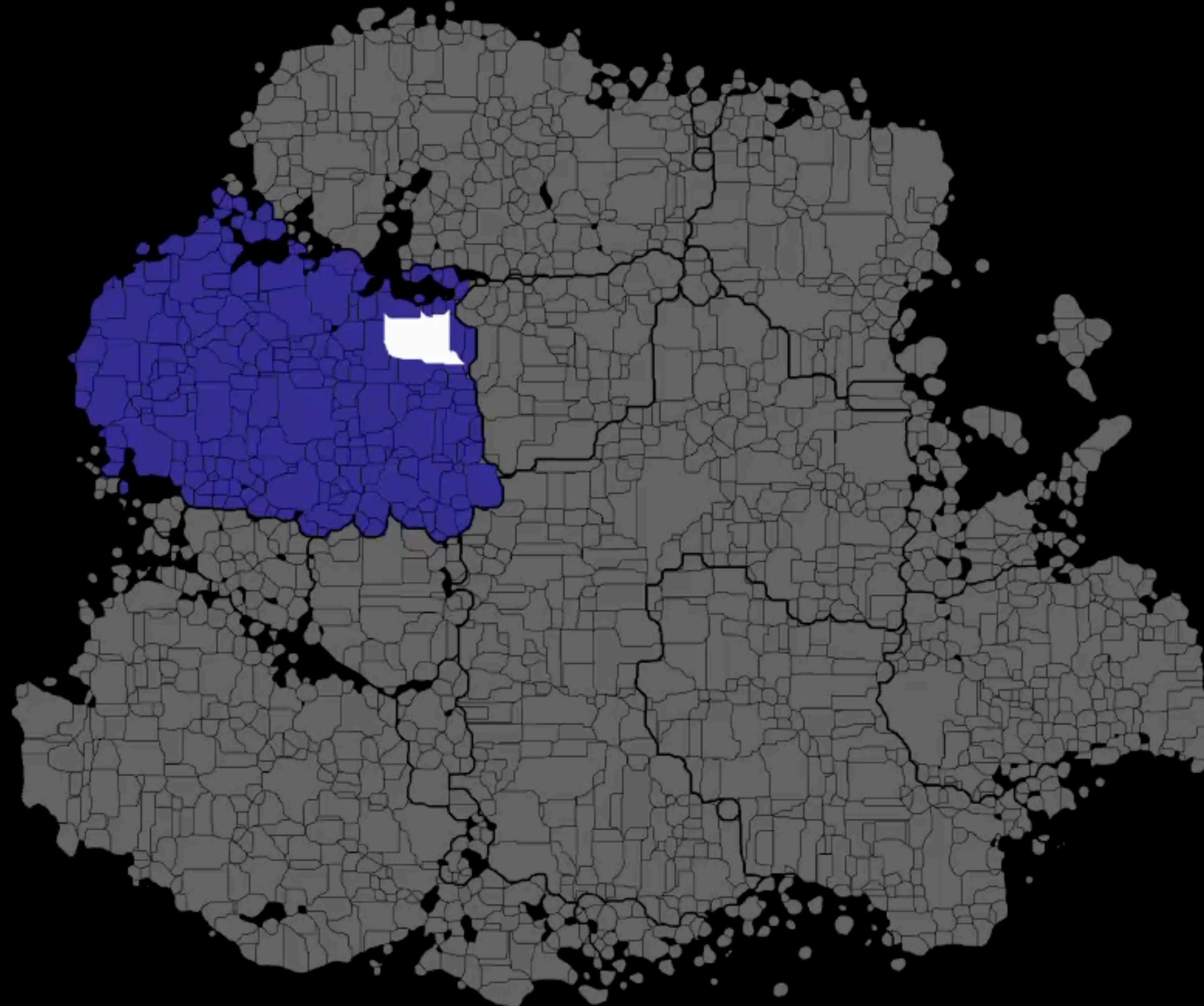
CAPTURE: Marshall et al (*Neuron*, 2020)

Left Groom

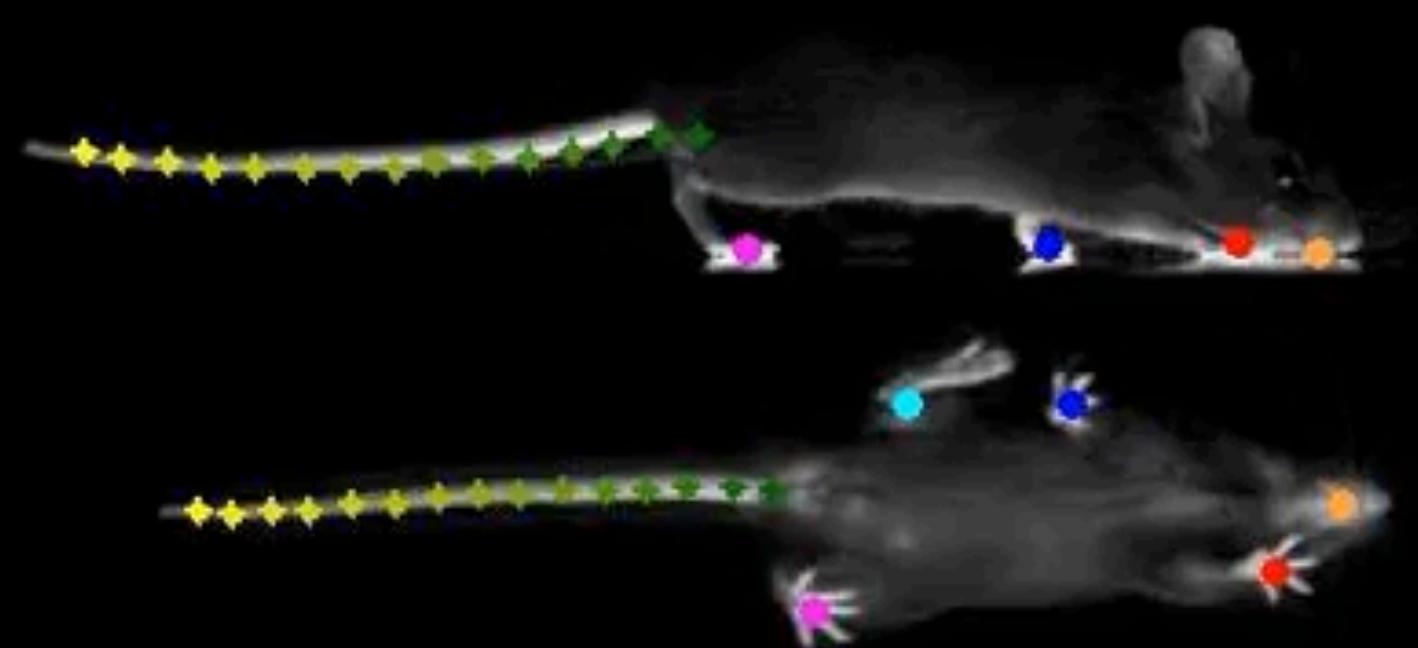
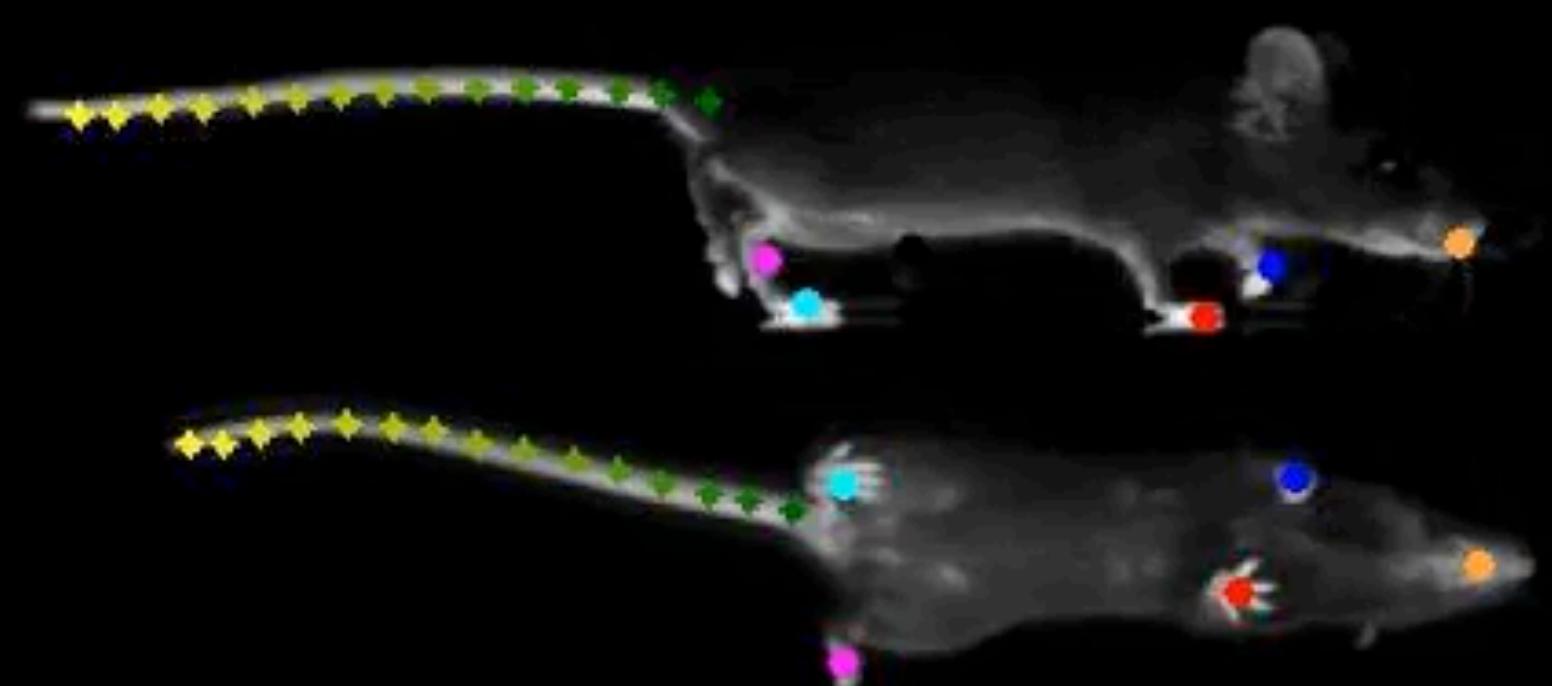


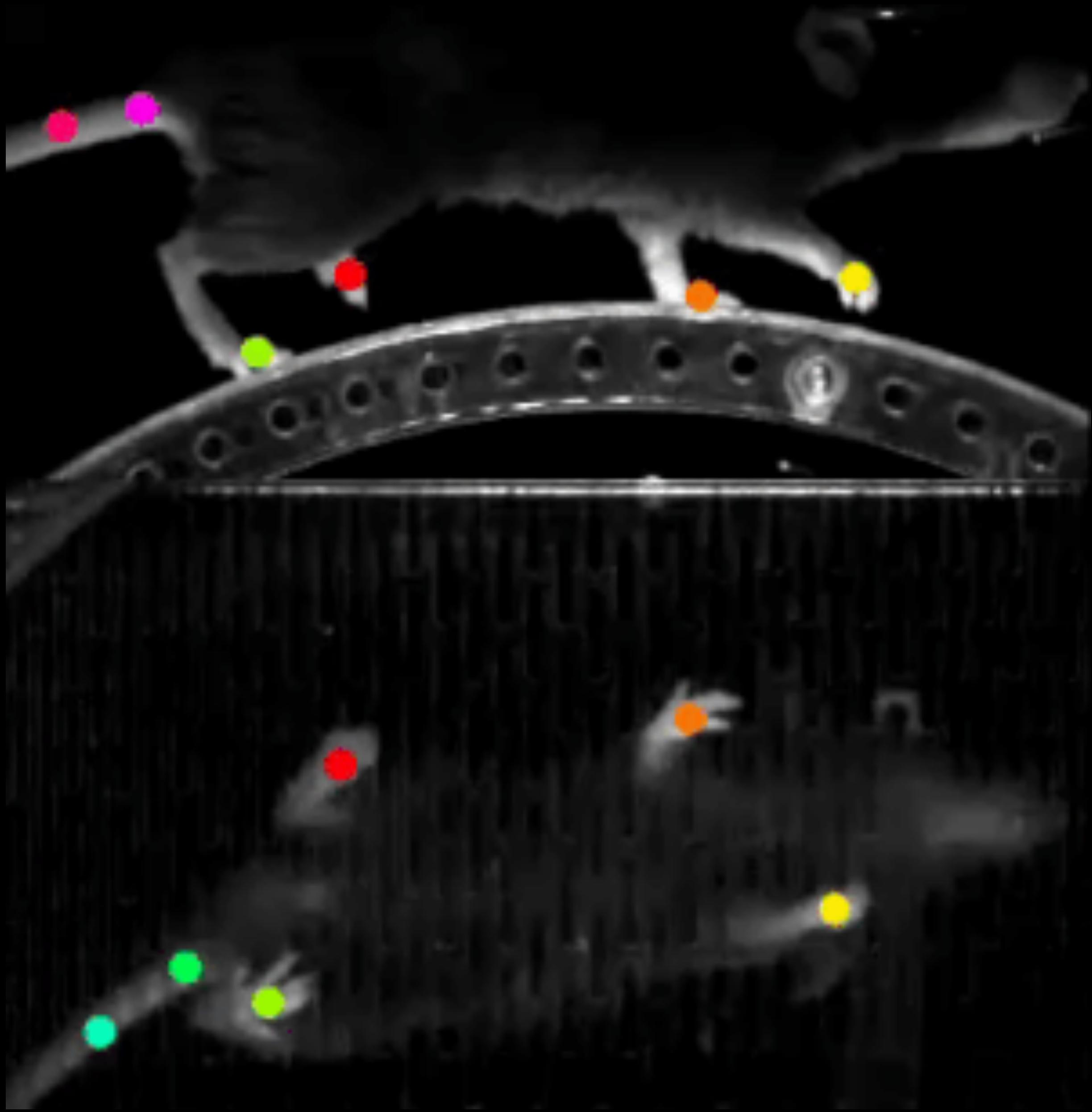
CAPTURE: Marshall et al (*Neuron*, 2020)

Right Groom - Low

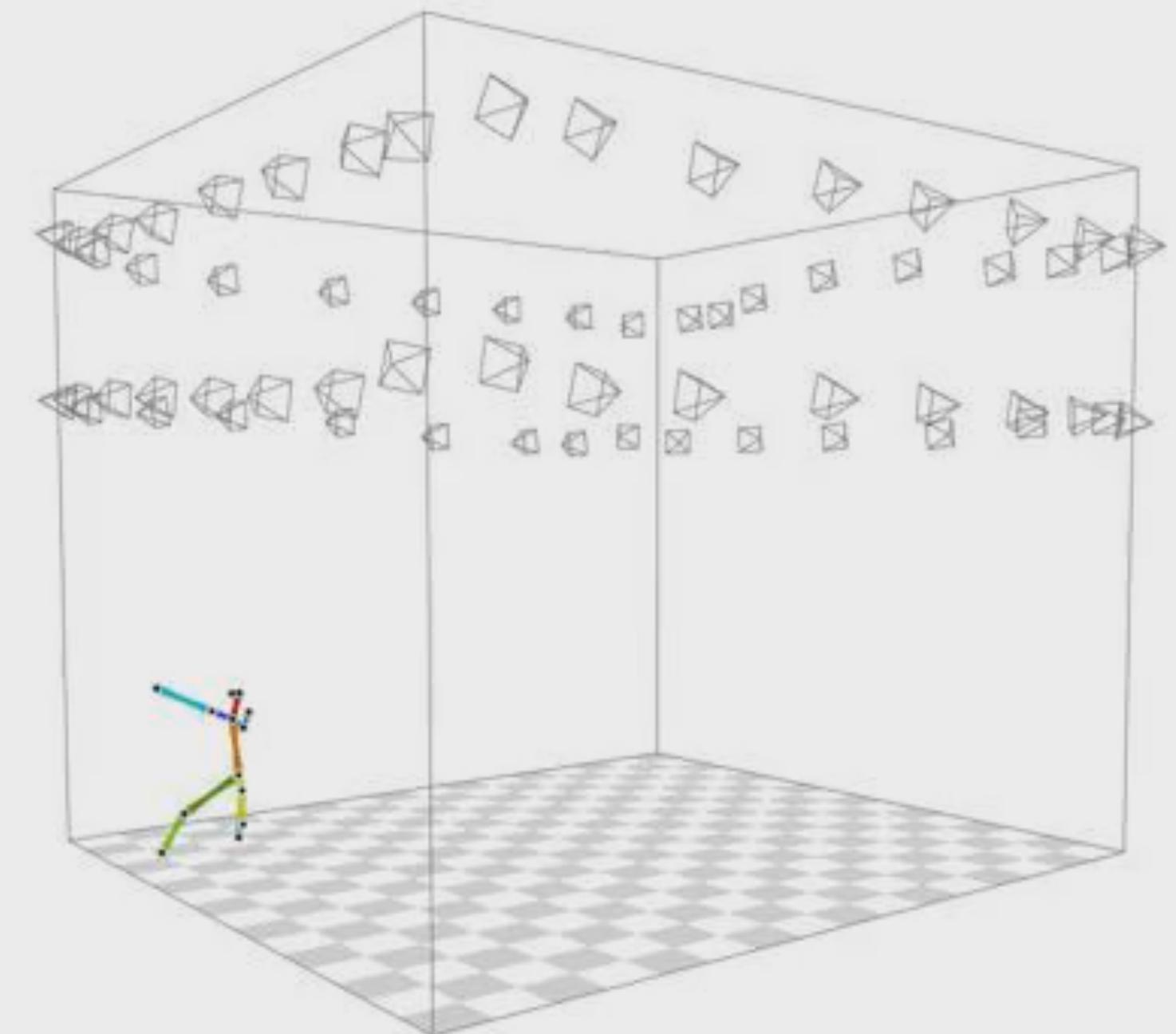
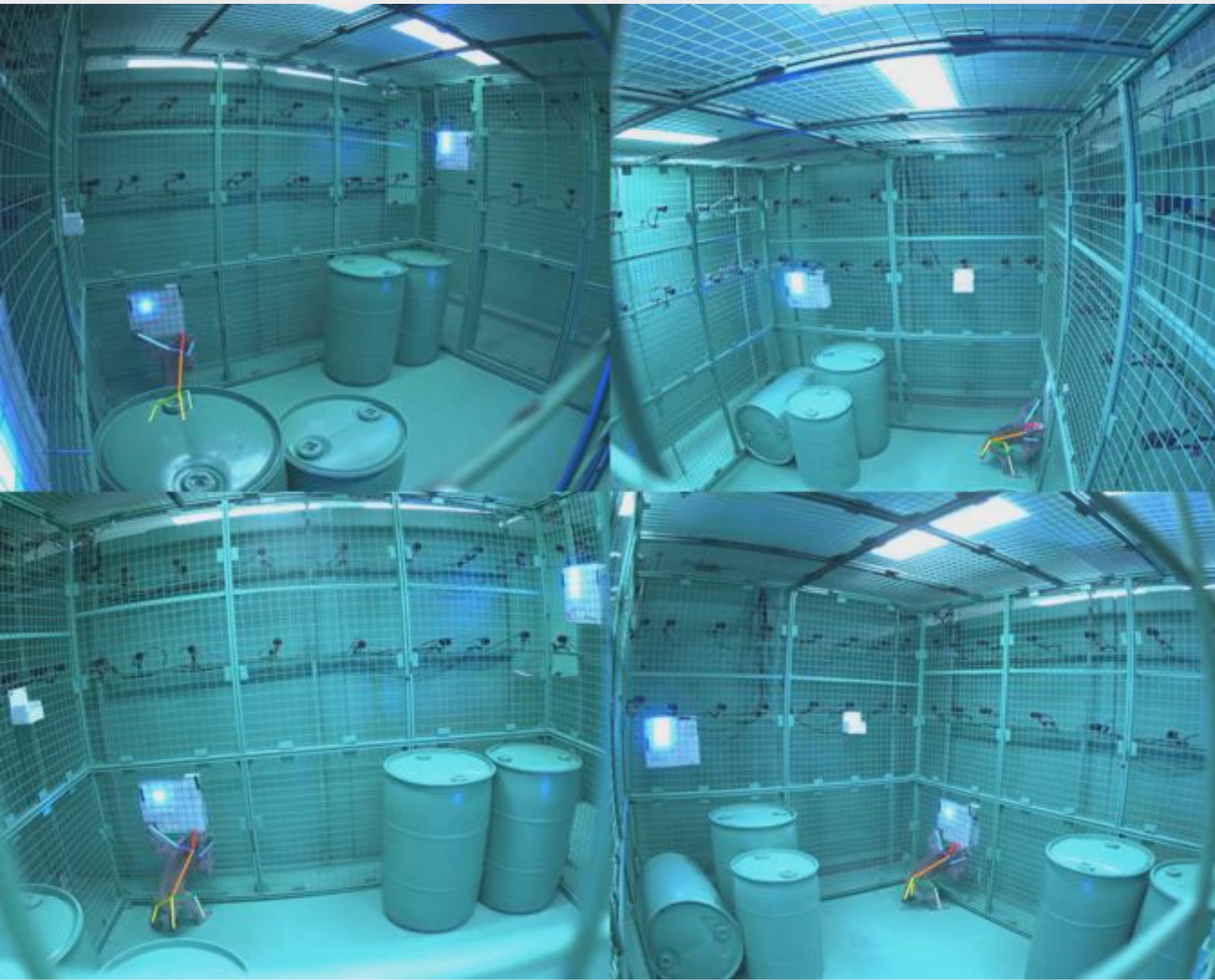


CAPTURE: Marshall et al (*Neuron*, 2020)

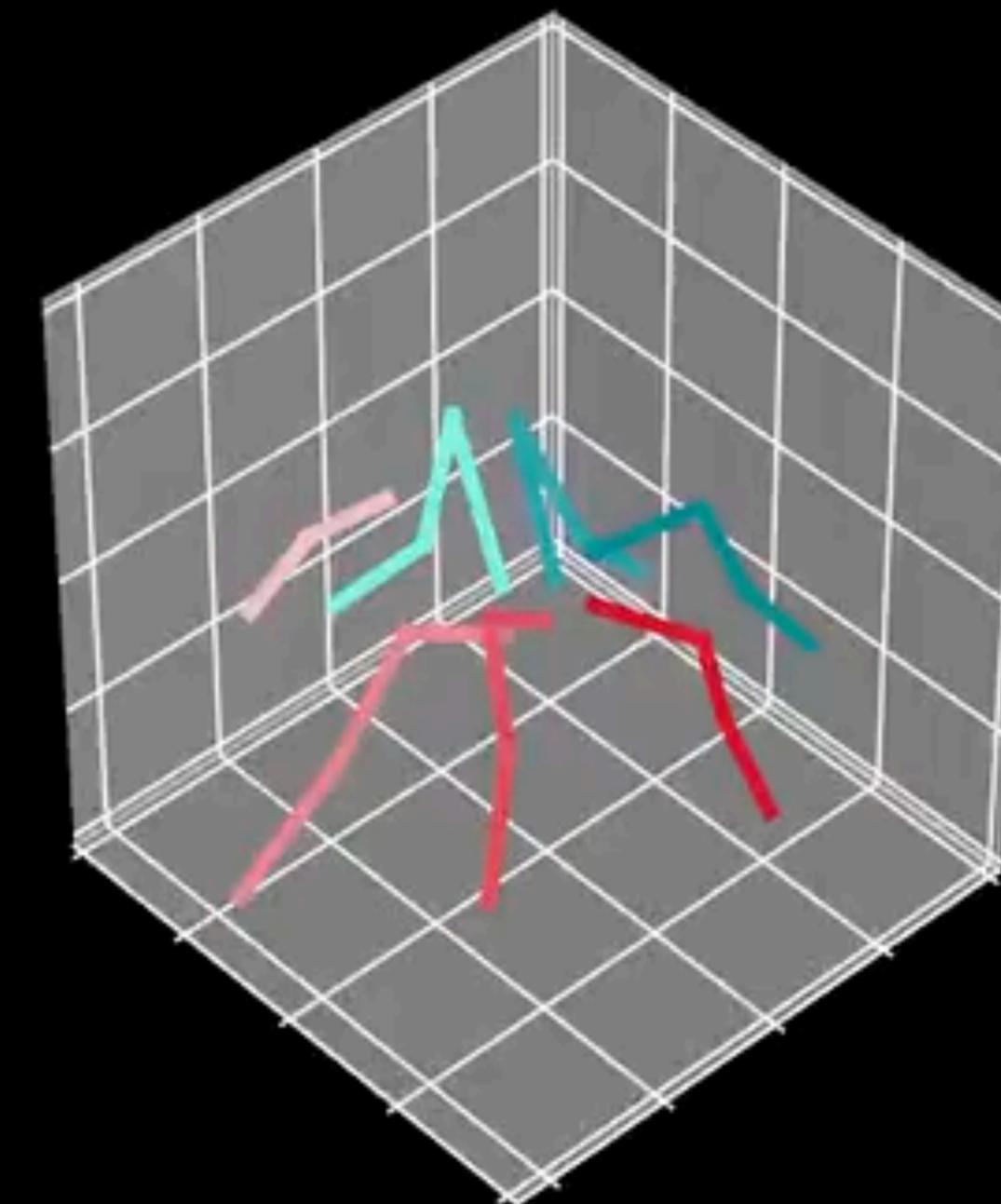
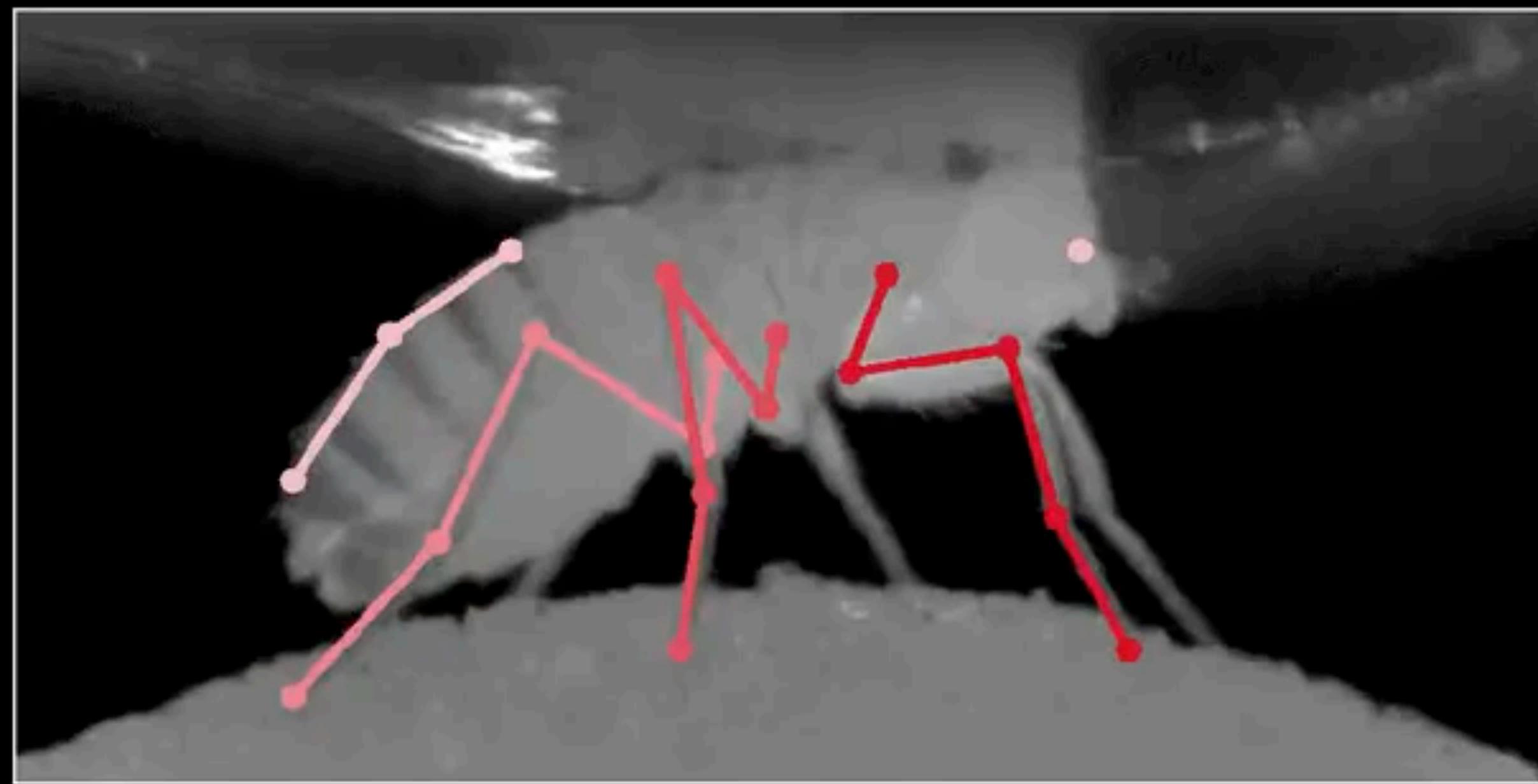
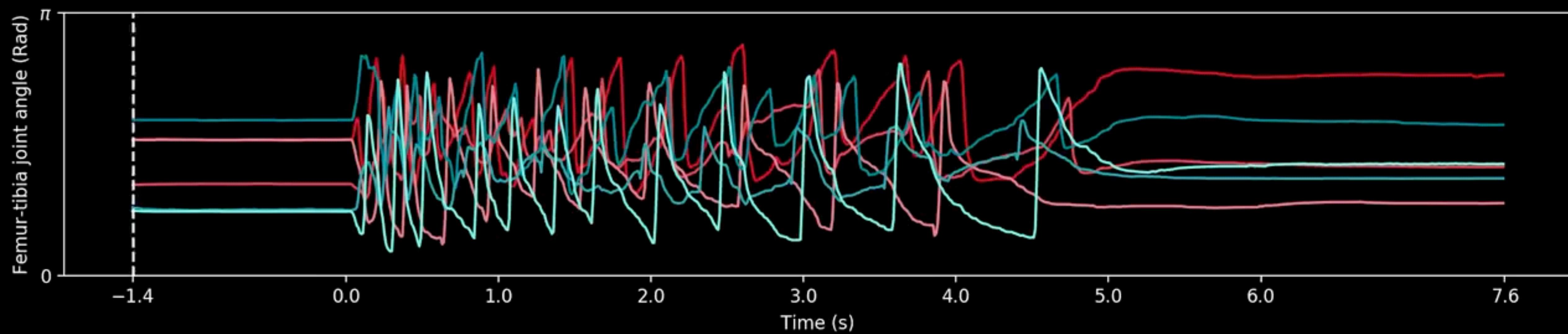


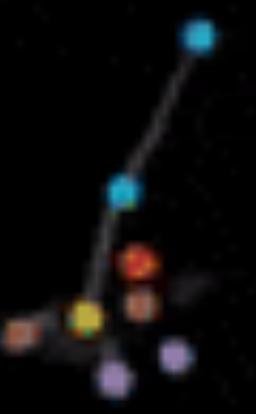
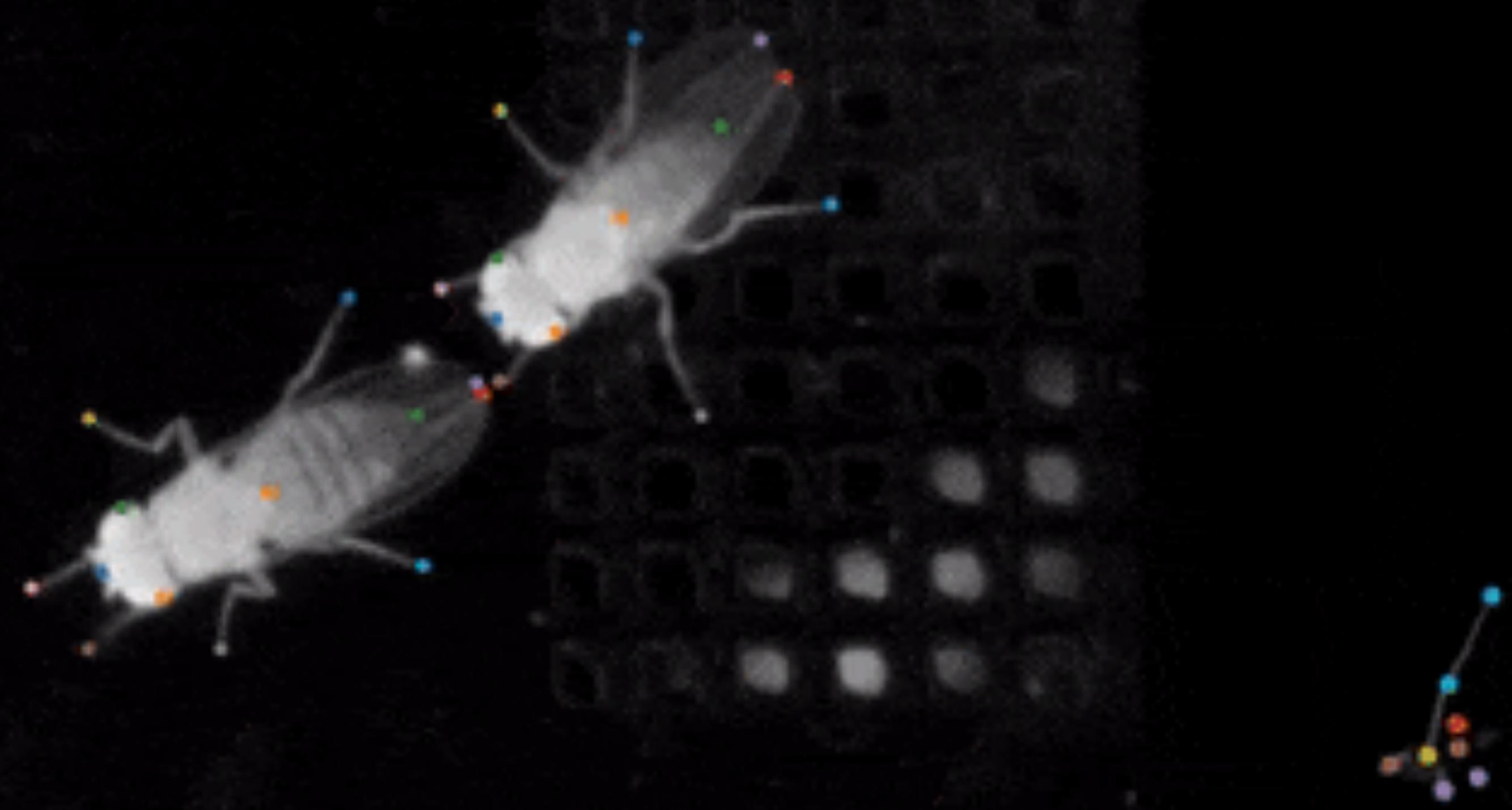


DeepLabCut: Mathis et al. (*Nat Neuro* 2018)



OpenMonkeyStudio: Bala et al (*Nature Comm.*, 2020)





SLEAP: Pereira et al (2021)

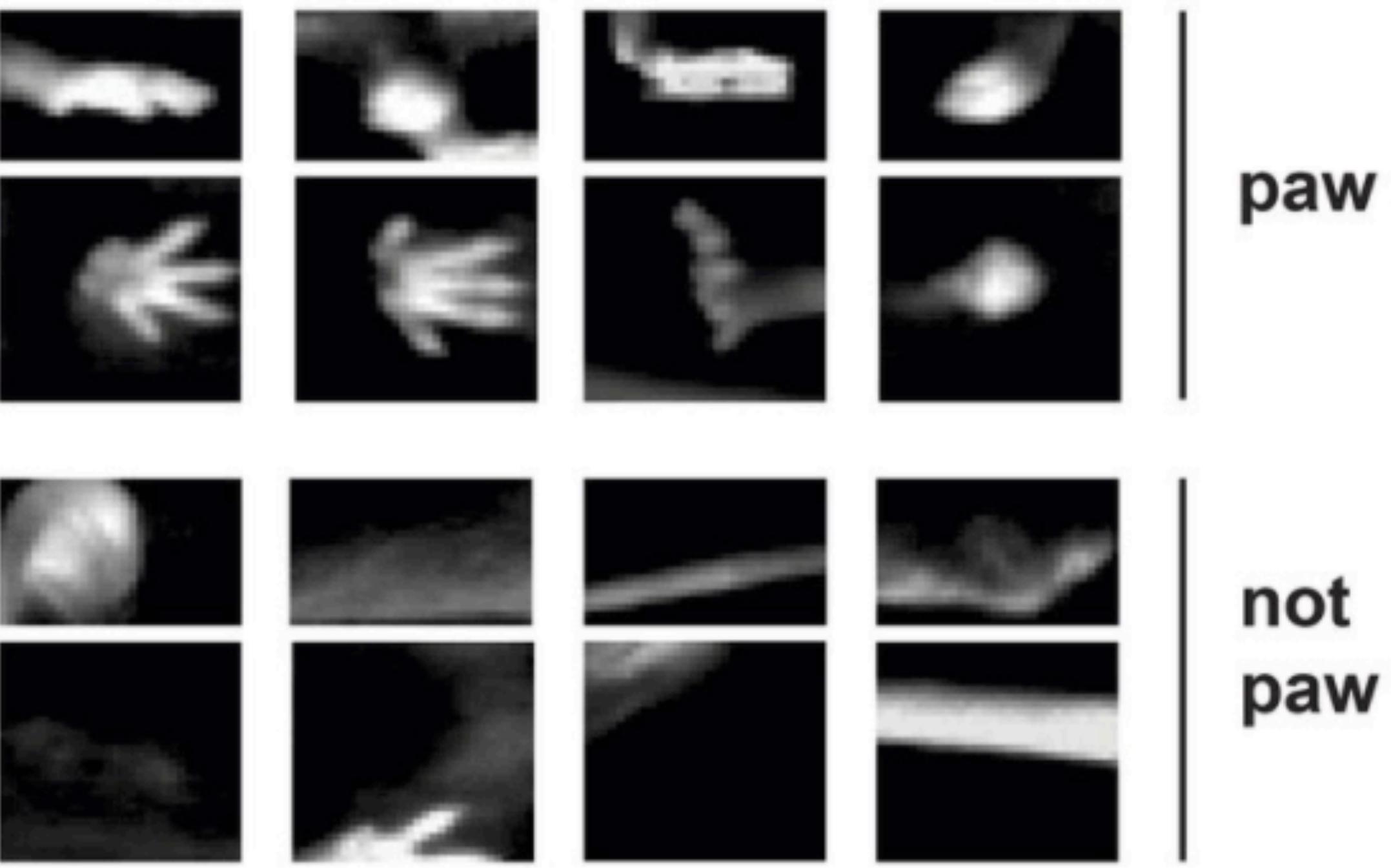
Agenda

1. Basics of markerless pose tracking
2. Pose tracking with CNNs
3. Structured prediction and triangulation

Basic pose tracking

Turn it into a supervised learning problem

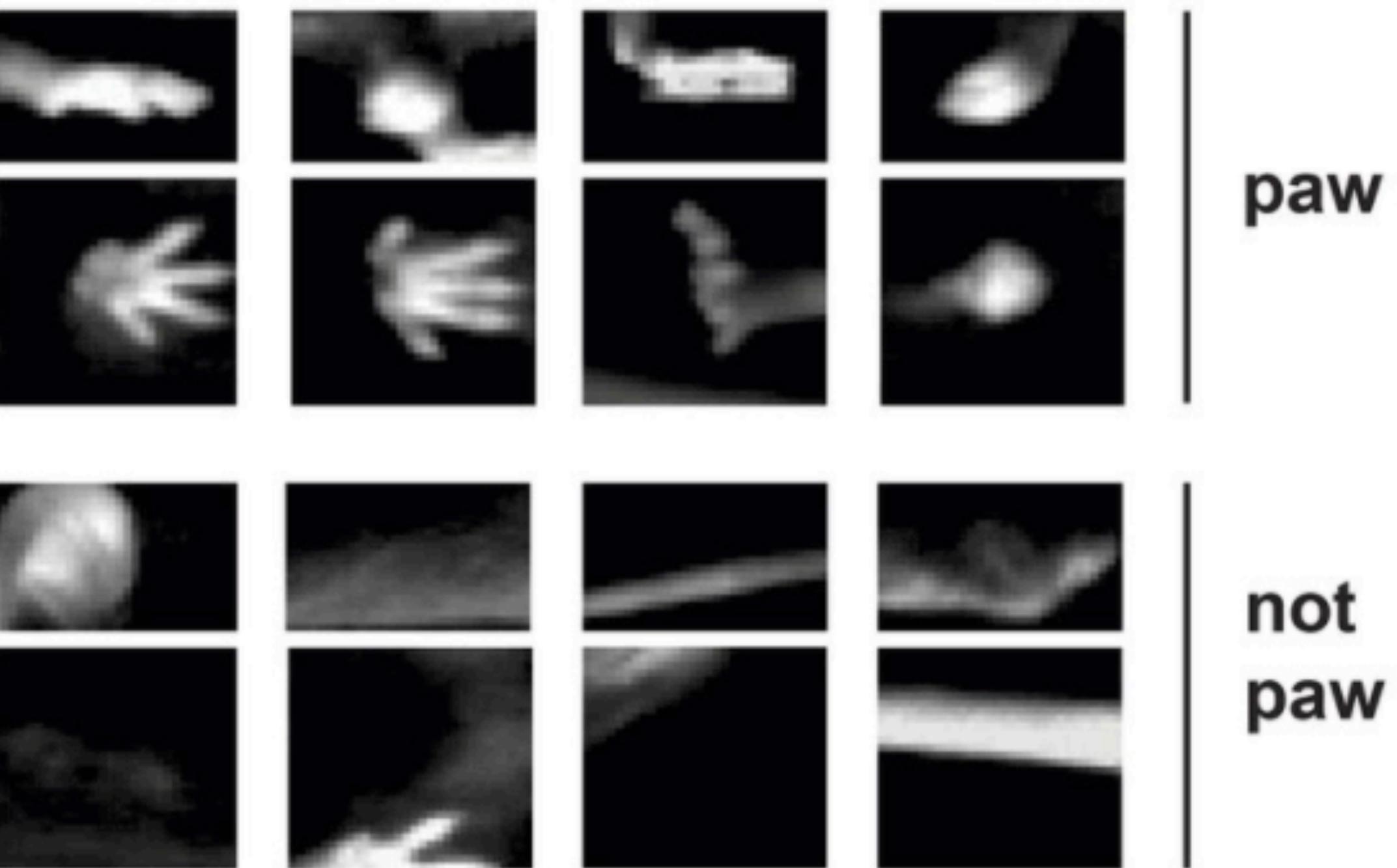
- Extract patches from the video frames and label them as positive or negative examples of a key point (e.g. paw).
- Train a binary classifier (logistic regression, SVM, neural network, etc.) to predict key point or not.
- At test time, classify each patch in the image and then pick the most likely keypoint location(s). (More on how later.)



Basic pose tracking

Mathematical formulation

- Let P_h and P_w be the height and width, respectively, of the patch (in pixels).
- N denote the number of patches
- $\mathbf{x}_n \in \mathbb{R}^{P_h \cdot P_w}$ denote the n -th patch.
- $y_n \in \{0, 1\}$ denote whether or not the patch is an instance of the key point.
- $\mathbf{w} \in \mathbb{R}^{P_h \cdot P_w}$ denote the weights of our model.



Basic pose tracking

Via logistic regression

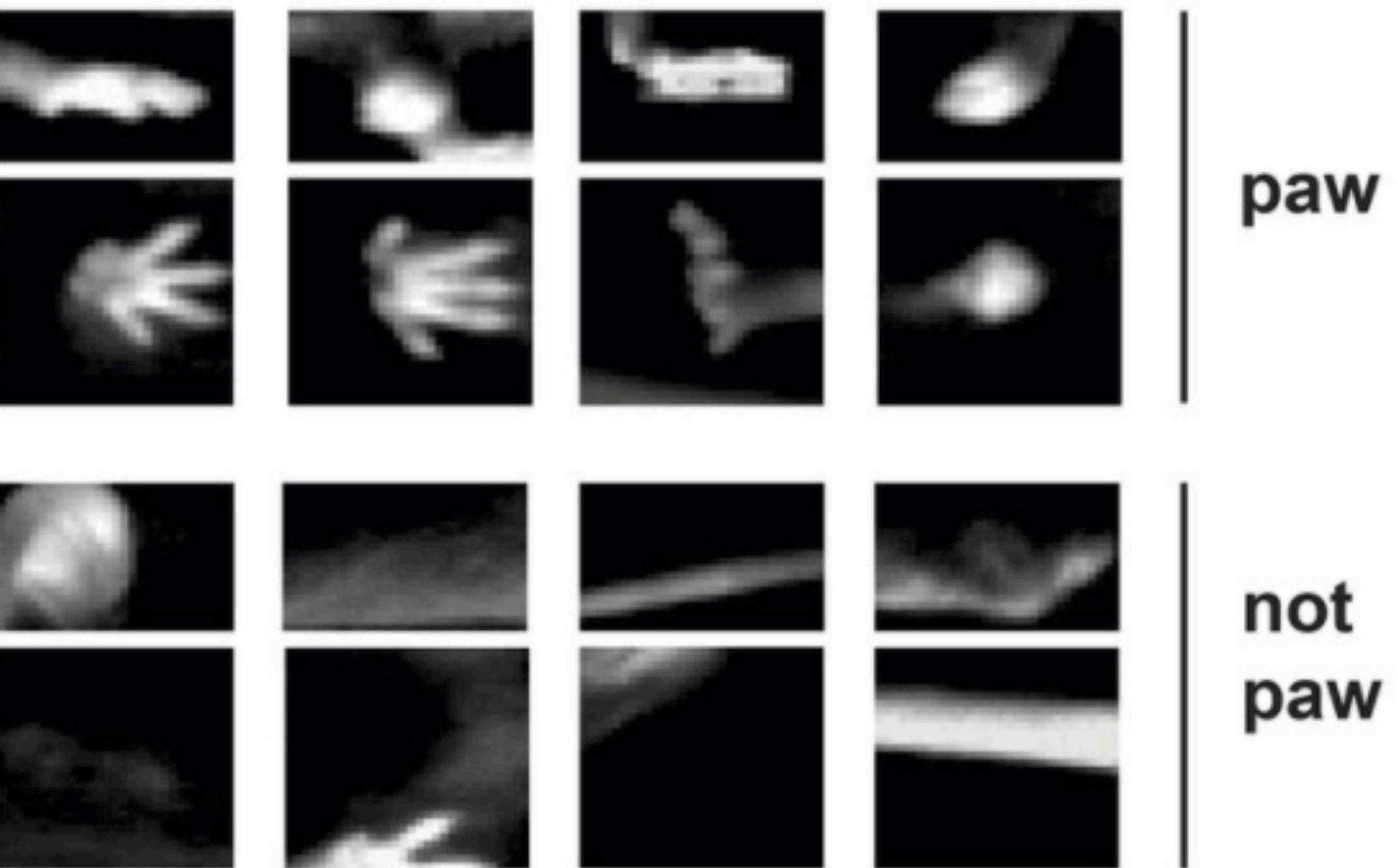
Assume

$$p(y_n \mid \mathbf{x}_n, \mathbf{w}) = \text{Bern}\left(y_n \mid \sigma(\mathbf{w}^\top \mathbf{x}_n)\right)$$

where

$$\sigma(a) = \frac{e^a}{1 + e^a}$$

is the **logistic function**.



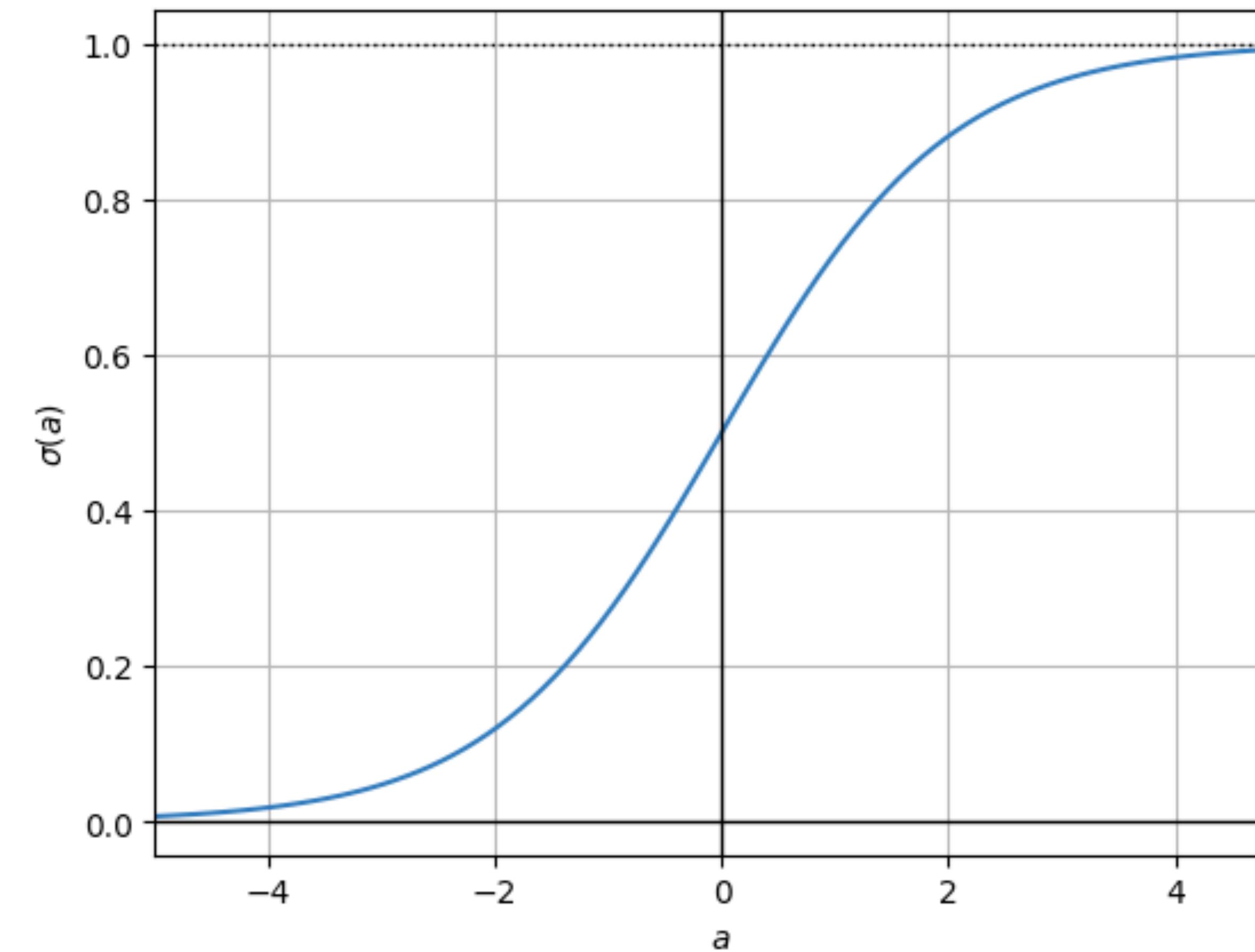
The Bernoulli distribution

i The Bernoulli distribution

The **Bernoulli distribution** is a distribution over binary variables $y \in \{0, 1\}$ with probability $p \in [0, 1]$. Its pmf can be written as,

$$\text{Bern}(y; p) = p^y (1 - p)^{(1-y)}$$

The logistic function



Basic pose tracking

Maximum likelihood estimation

$$\mathcal{L}(\mathbf{w}) = -\log p(\mathbf{y} \mid \mathbf{w}, \mathbf{X})$$

Basic pose tracking

Calculating the gradient

$$\nabla \mathcal{L}(\mathbf{w}) =$$

Basic pose tracking

The negative log likelihood is convex

- The Hessian is positive semi-definite
- $\nabla^2 \mathcal{L}(\mathbf{w}) =$

Gradient descent

Let \mathbf{w}_0 denote our initial setting of the weights. Gradient descent is an iterative algorithm that produces a sequence of weights $\mathbf{w}_0, \mathbf{w}_1, \dots$ that (under certain conditions) converges to a local optimum of the objective. Since the objective is convex, all local optima are global optima. The idea is straightforward, on each iteration we update the weights by taking a step in the direction of the gradient,

$$\mathbf{w}_{i+1} = \mathbf{w}_i - \alpha_i \nabla \mathcal{L}(\mathbf{w}_i)$$

where $\alpha_i \in \mathbb{R}_+$ is the **learning rate** (aka step size) on iteration i , and $\nabla \mathcal{L}(\mathbf{w}_i)$ is the gradient of the objective evaluated at the current weights \mathbf{w}_i .

Newton's Method

- We can obtain faster convergence rates using **second-order** methods.
- Approximate the objective with a second-order Taylor approximation around the current weights,

$$\mathcal{L}(\mathbf{w}) \approx \mathcal{L}(\mathbf{w}_i) + (\mathbf{w} - \mathbf{w}_i)^T \nabla \mathcal{L}(\mathbf{w}_i) + \frac{1}{2}(\mathbf{w} - \mathbf{w}_i)^T \nabla^2 \mathcal{L}(\mathbf{w}_i)(\mathbf{w} - \mathbf{w}_i).$$

- **Exercise:** show that the minimum is obtained at
 $\mathbf{w}_{i+1} = \mathbf{w}_i + \nabla^2 \mathcal{L}(\mathbf{w}_i)^{-1} \nabla \mathcal{L}(\mathbf{w}_i)$.

Computational complexity

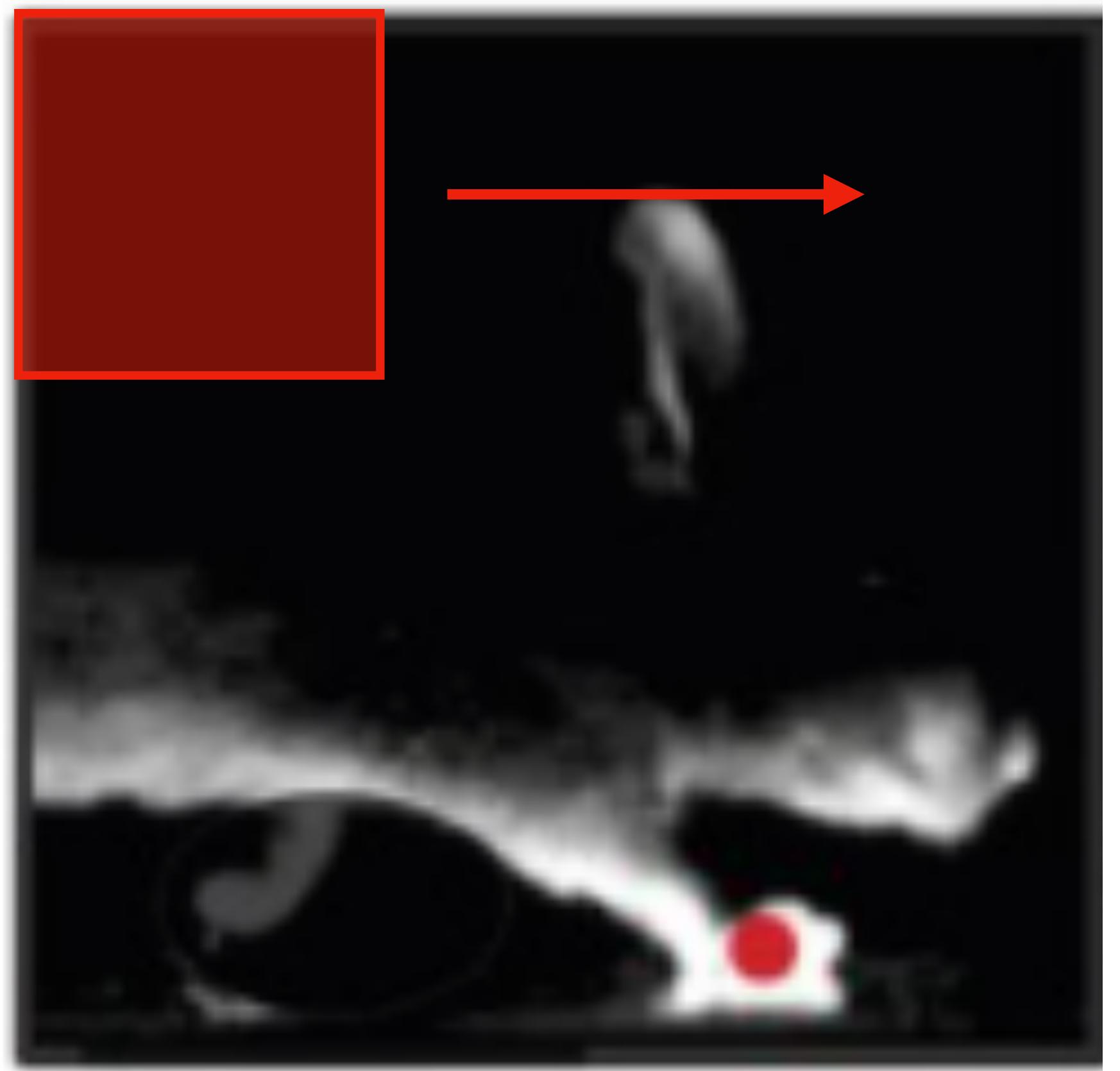
- What is the (time) complexity of gradient descent and Newton's method?
- Quasi-Newton methods like BFGS sidestep the Hessian calculation and inversion.
- SGD (with momentum) uses mini-batches of data and rolling averages of the gradient to achieve faster convergence.
- Adagrad, RMSProp, and Adam tune the learning rates as they go.

Pose tracking with convolutional neural networks

Basic pose tracking

As a one-layer convolutional neural network

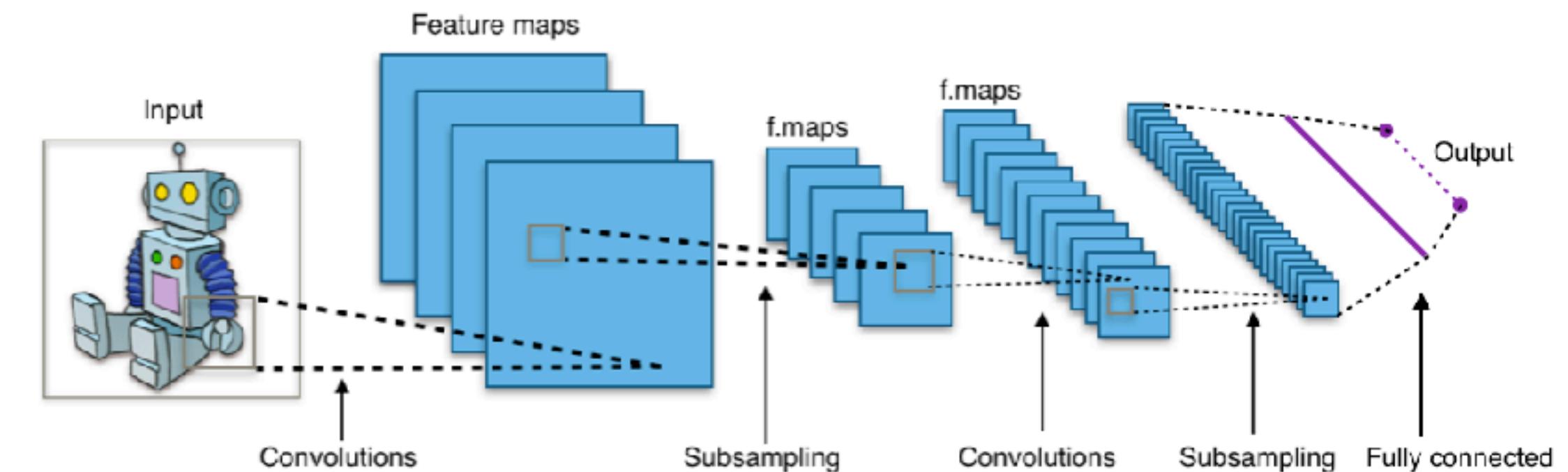
- Instead of working with patches, let's work with images directly.
- Let $\mathbf{X}_n \in \mathbb{R}^{P_H \times P_W}$ denote an image (height P_H , width P_W)
- Let $\mathbf{Y} \in \{0,1\}^{P_H \times P_W}$ indicate the location(s) of the keypoint.
- The 2D cross-correlation $\mathbf{X}_n \star \mathbf{W}$; is a sliding dot product of weights across all $P_h \times P_w$ patches in the image. It produces a $P_H \times P_W$ output.
- In PyTorch, it's implemented by the `F.conv2d` function and the Conv2D layer.



Basic pose tracking

Feature learning in CNNs

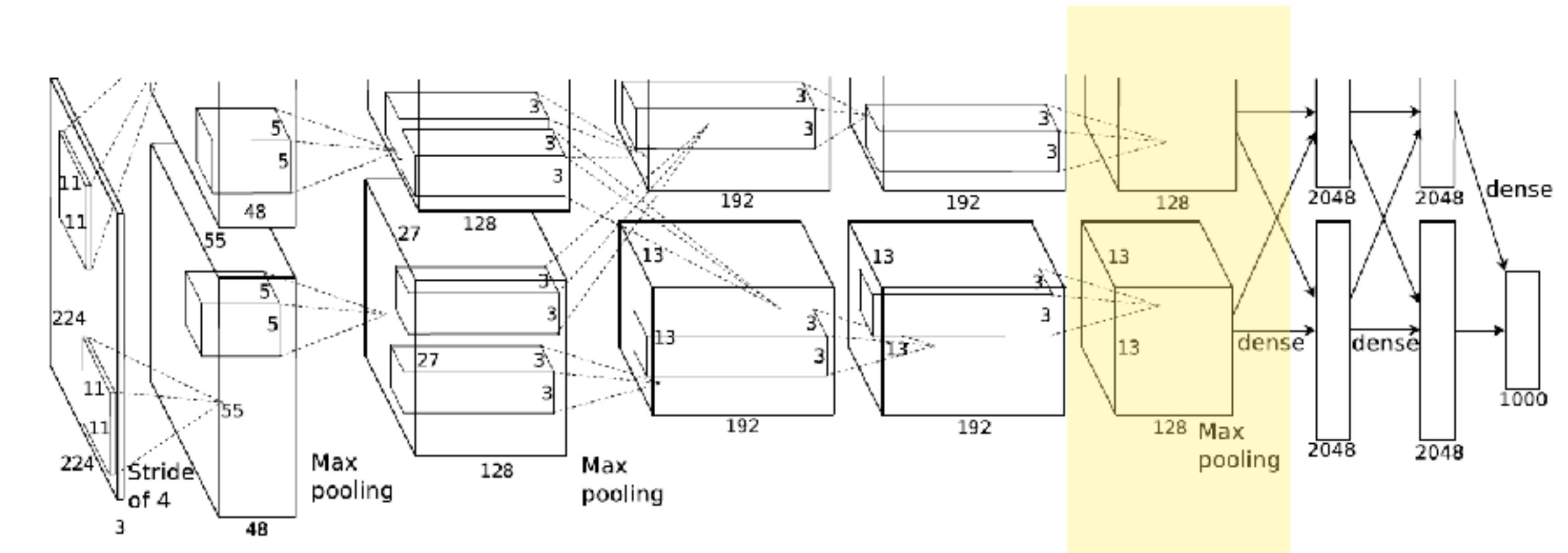
- This simple model assumes key points can be detected with a **linear classifier** using raw pixels as inputs.
- We can perform **nonlinear classification** by encoding each pixel with a vector of features.
- Rather than handcrafting these features, **learn them** from the data!



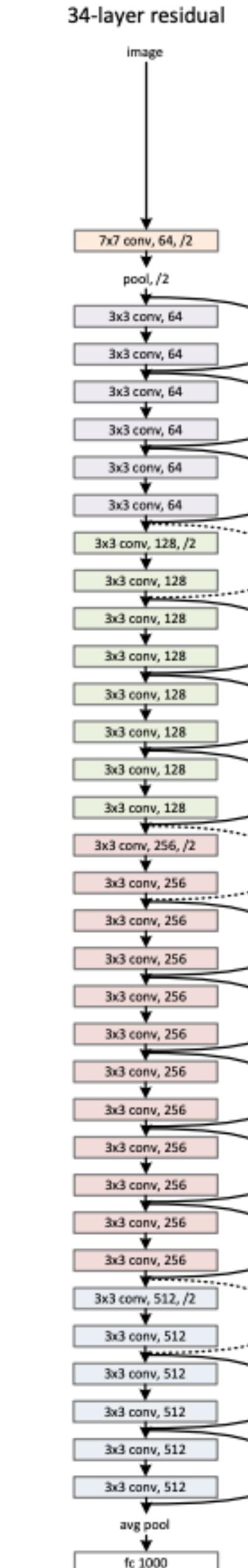
https://en.wikipedia.org/wiki/Convolutional_neural_network

Transfer Learning

- **Idea:** rather than handcrafting features or learning them from scratch, **use a pre-trained network** for a related task.
- **Example:** use the features of a deep neural network for image classification.
- **Reroute** the output of an intermediate layer to a **new loss function**.
- Optionally, **fine tune** the weights in the early layers via stochastic gradient descent on the new loss.
- With good starting features, you **only need a few training examples** to perform animal pose estimation.



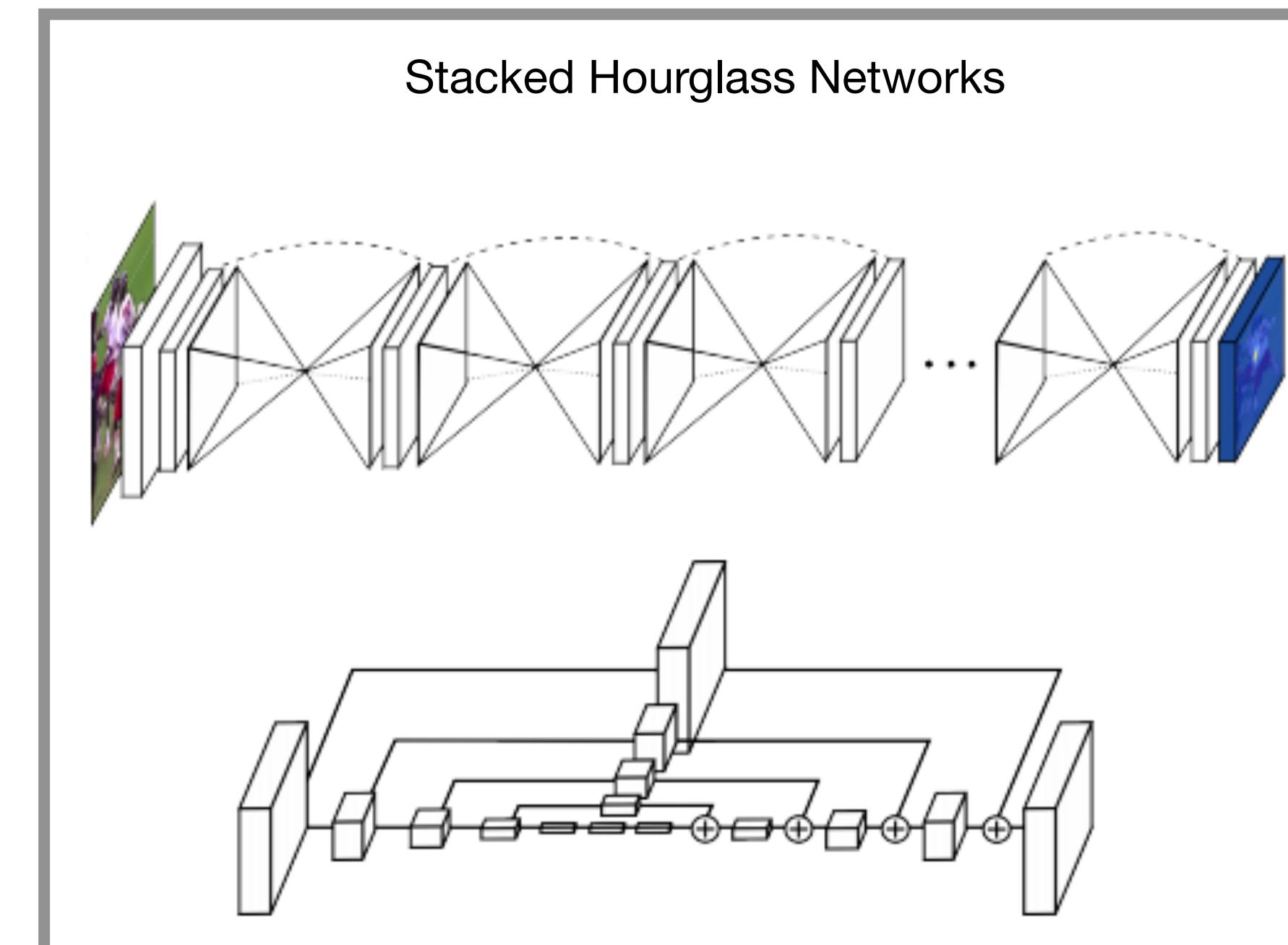
Deep Residual Networks (resnet-50)



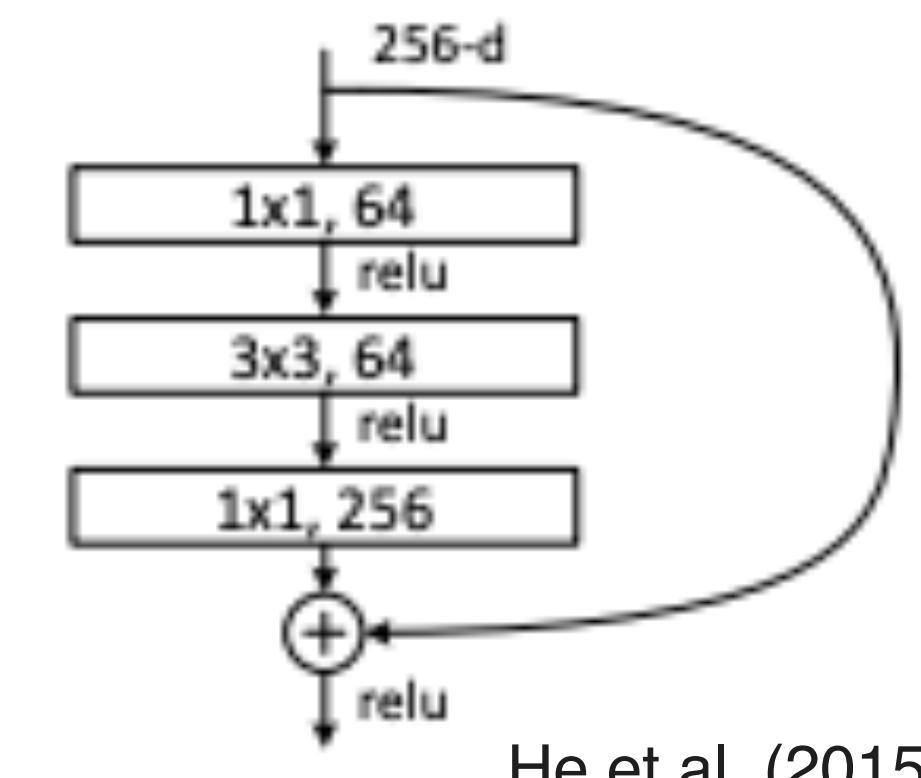
Transfer Learning In DeepLabCut, etc.

- DLC repurposes state-of-the-art deep networks for human pose detection.
- DLC starts with a residual network (resnet-50) and adds “deconvolutional” layers, as in DeeperCut for human pose estimation.
- SLEAP starts with “stacked hourglass networks” for human pose estimation.

Stacked Hourglass Networks



Newell et al (2016)

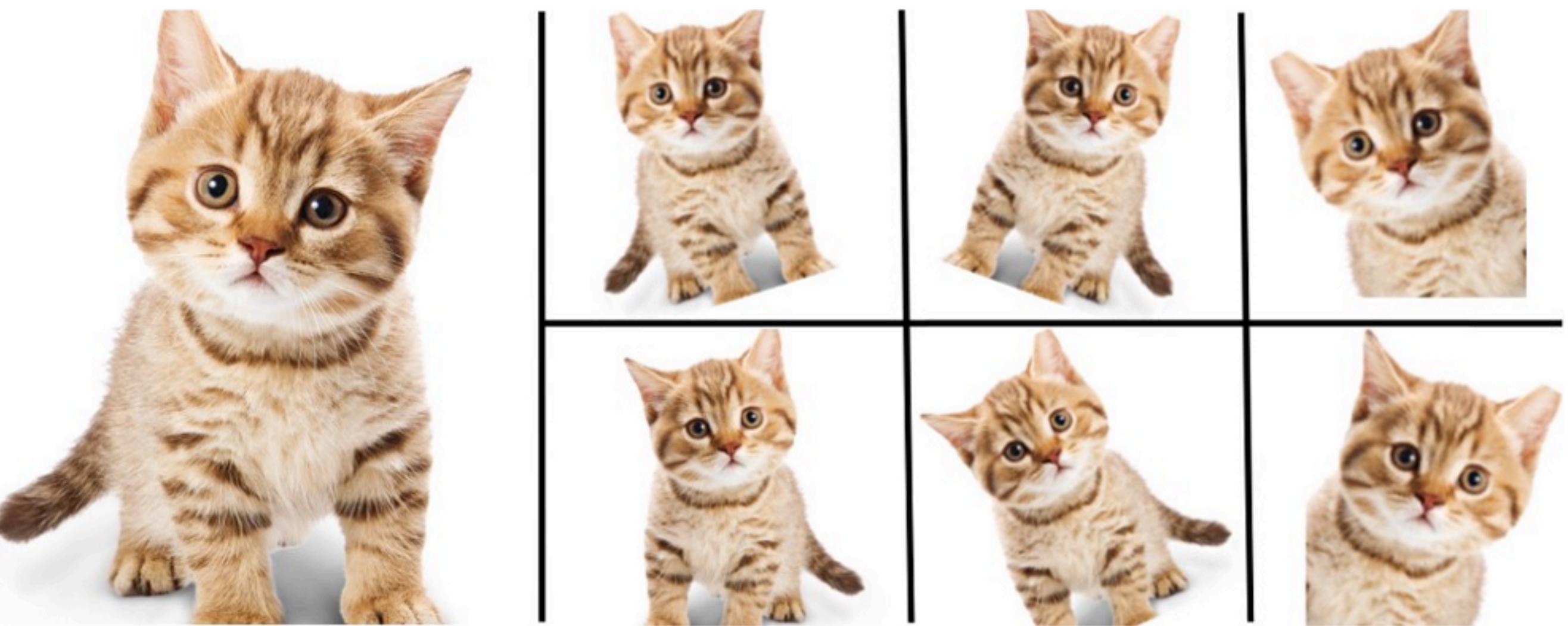


He et al (2015)

Transfer Learning

Data augmentation

- Labeling data is tedious.
- **Idea:** Make the most of each training example by making alterations your classifier should be robust to.
- Eg a cropped, rotated, and scaled paw is still a paw. A partially occluded paw is still a paw.



Structured prediction

Structured prediction

How do we aggregate key point probabilities for each pixel?

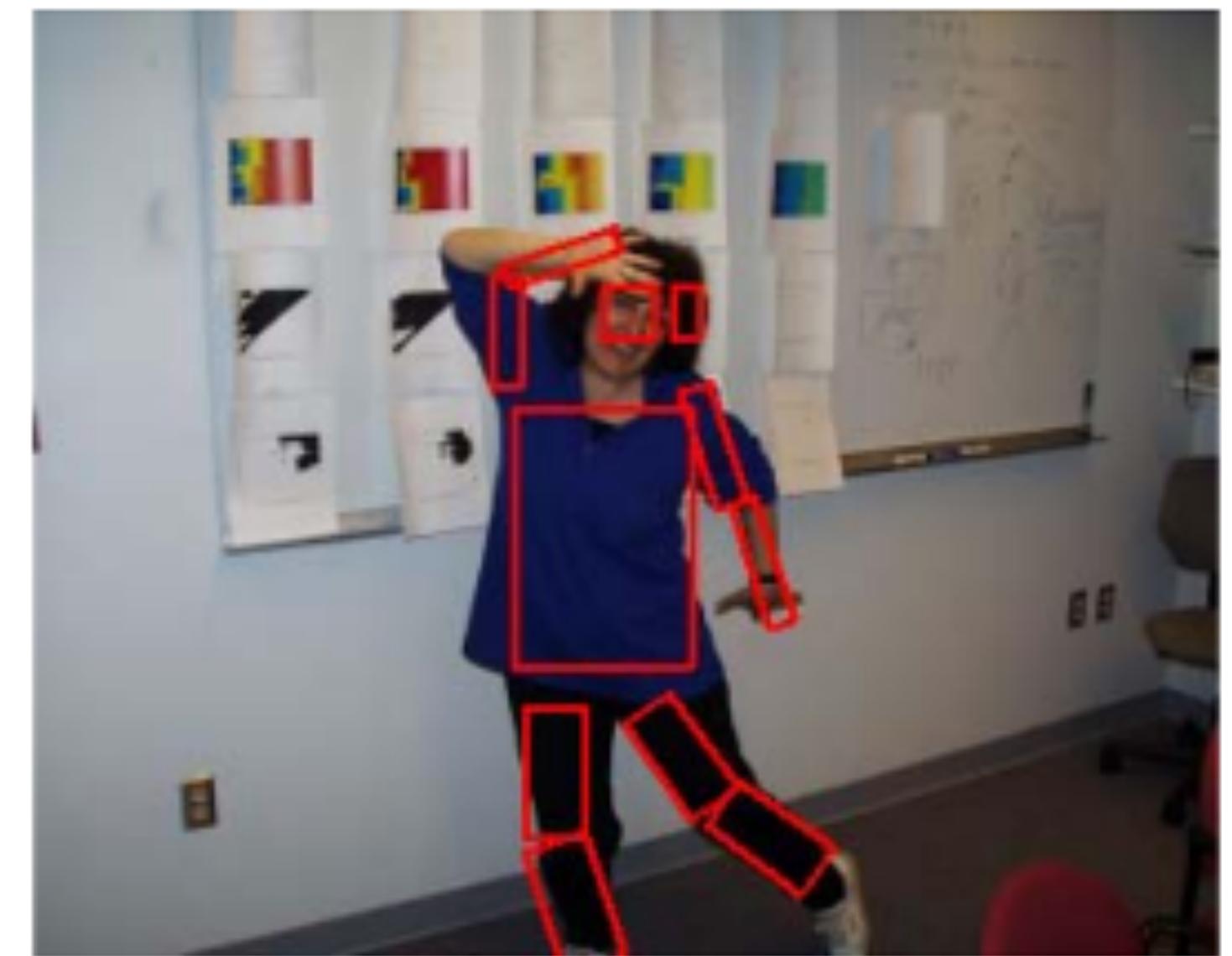
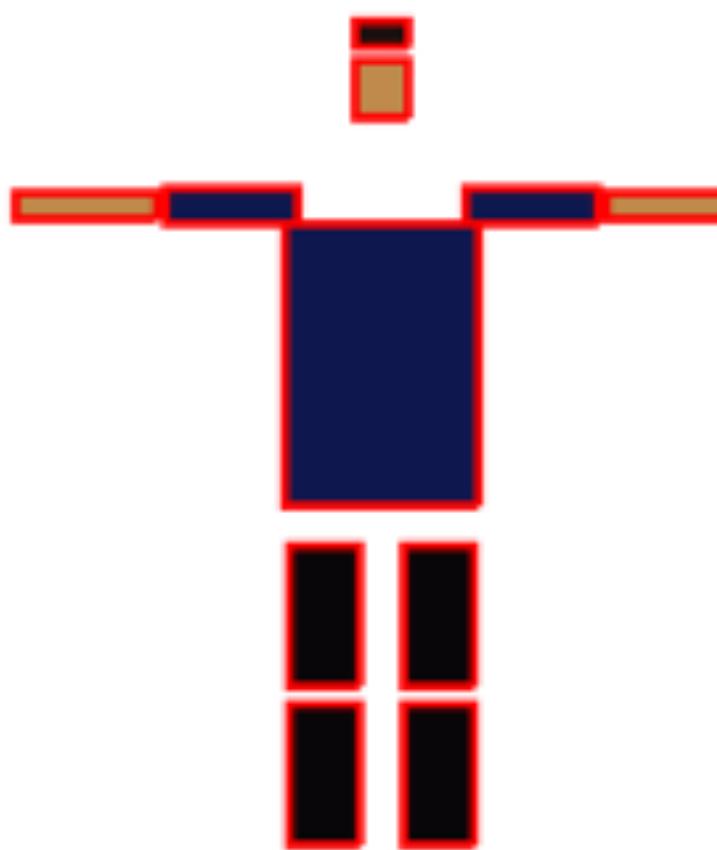
Bayesian formulation with efficient MAP inference

$$L^* = \arg \min_L \left(\sum_{(v_i, v_j) \in E} d_{ij}(l_i, l_j) - \sum_{v_i \in V} \ln g_i(I, l_i) \right)$$

Optimal configuration

Part-to-part term

Image to part term



Felzenswalb & Huttenlocher. [Pictorial Structures for Object Recognition](#) (2004)

Felzenswalb & Huttenlocher. [Efficient matching of pictorial structures](#) (2005)

Structured prediction

How do we aggregate key point probabilities for each pixel?

unaries



pairwise
per part



$p(r \text{ knee} | 1 \text{ ankle})$



$p(r \text{ knee} | 1 \text{ knee})$



$p(r \text{ knee} | r \text{ wrist})$



$p(r \text{ knee} | r \text{ elbow})$

Pishchulin, Insafutdinov, Tang, Andres, Andriluka, Gehler, & Schiele. [DeepCut: Joint Subset Partition and Labeling for Multi Person Pose Estimation](#) (2015)
Insafutdinov, Pishchulin, Andres, Andriluka & Schiele. [DeeperCut: A Deeper, Stronger, and Faster Multi-Person Pose Estimation Model](#) (2016)

Slide credit: Talmo Pereira

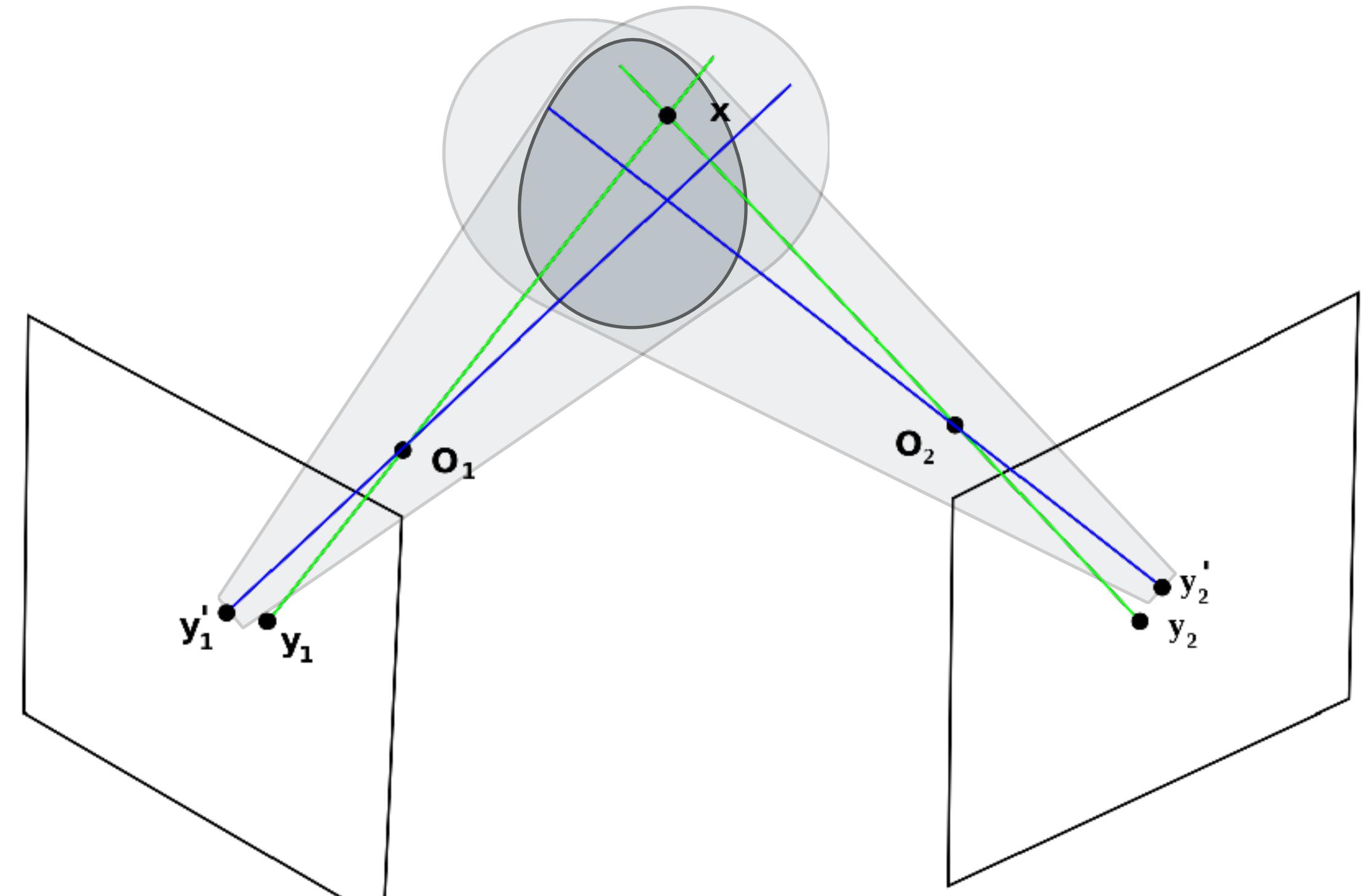
3D Pose estimation

Projective geometry

- How can we estimate 3D pose from multiple 2D camera views?
- Projective geometry makes far away objects appear smaller.

$$\vec{y}_c \approx f_c(\vec{x})$$

$$f_c(\vec{x}) = \frac{1}{w}(u, v)^\top \text{ where } (u, v, w)^\top = A_c \vec{x} + b_c,$$



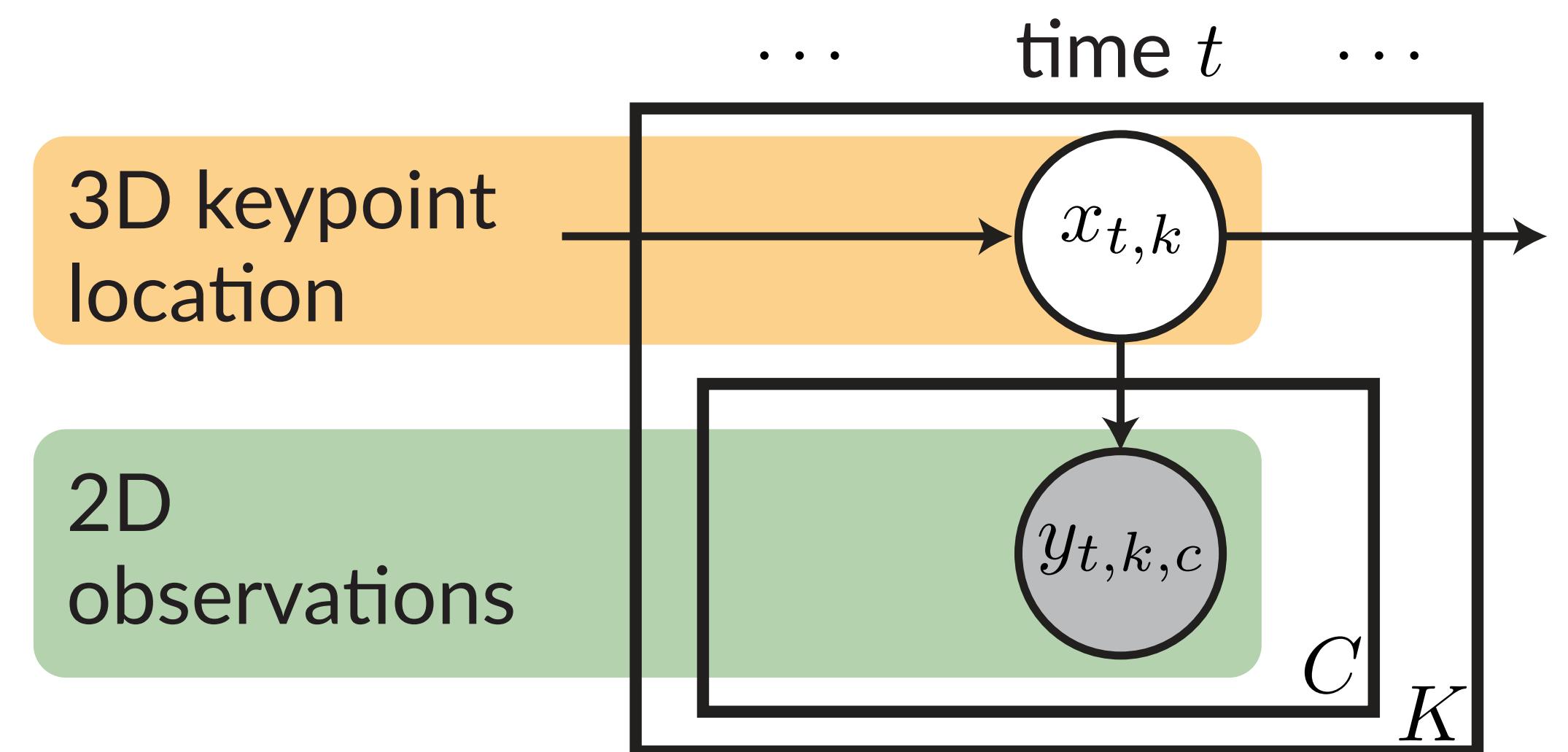
Modified from wikipedia.org

3D Pose estimation

Model 0: Bayesian triangulation of 3D pose from 2D observations

$$x_{t,k} \sim \mathcal{N}(x_{t-1,k}, \eta^2 I)$$

$$y_{t,k,c} \sim \mathcal{N}(f_c(x_{t,k}), \omega^2 I)$$

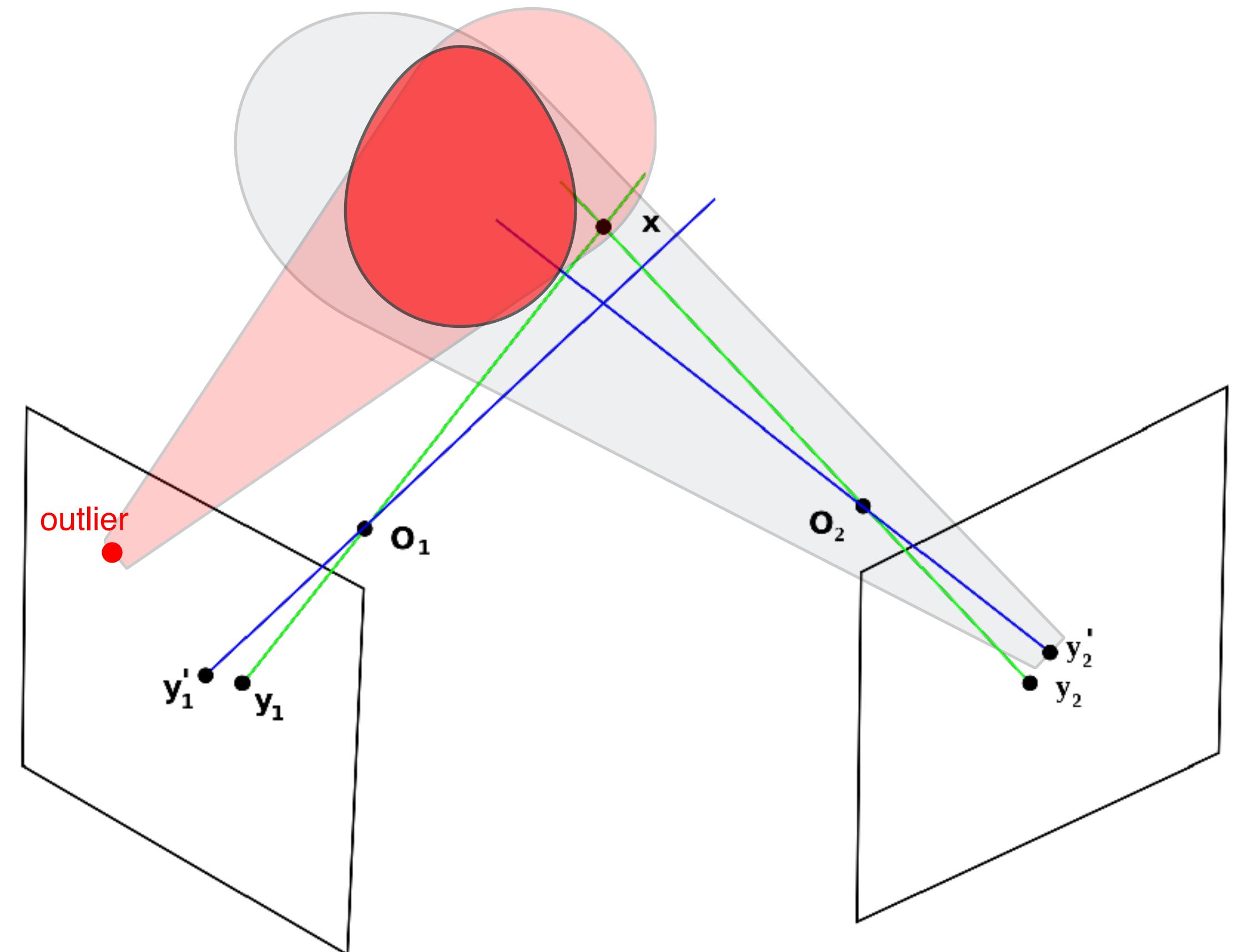


T time steps
K keypoints
C cameras

3D Pose estimation

Triangulation in the presence of measurement noise

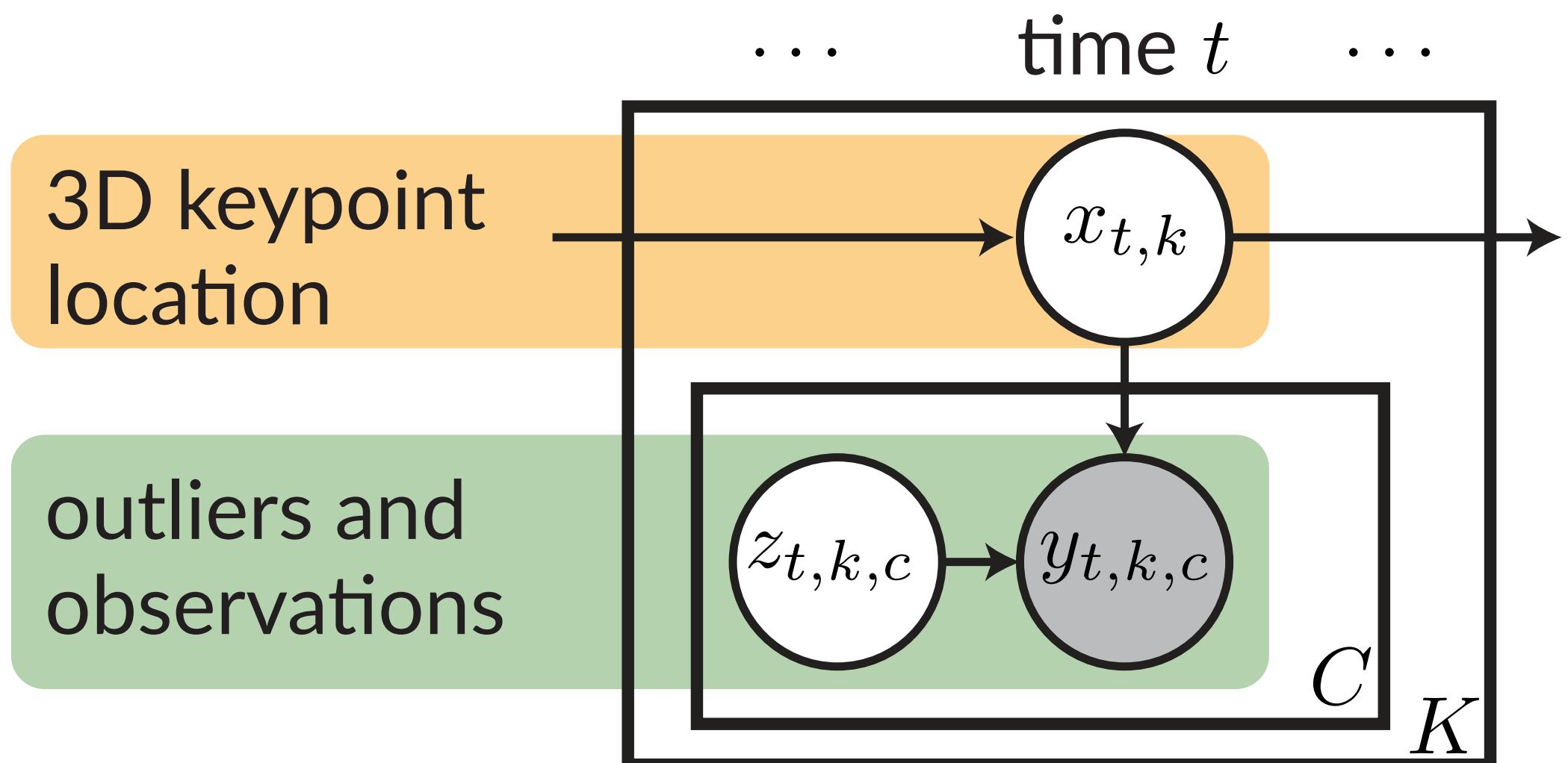
- Projective geometry makes far away objects appear smaller.
- Outliers in 2D estimates can severely affect 3D triangulation.
- Typical approaches:
 - More data
 - Temporal constraints
 - Median filtering (DLC-3D) / RANSAC
 - Robust noise models



Modified from wikipedia.org

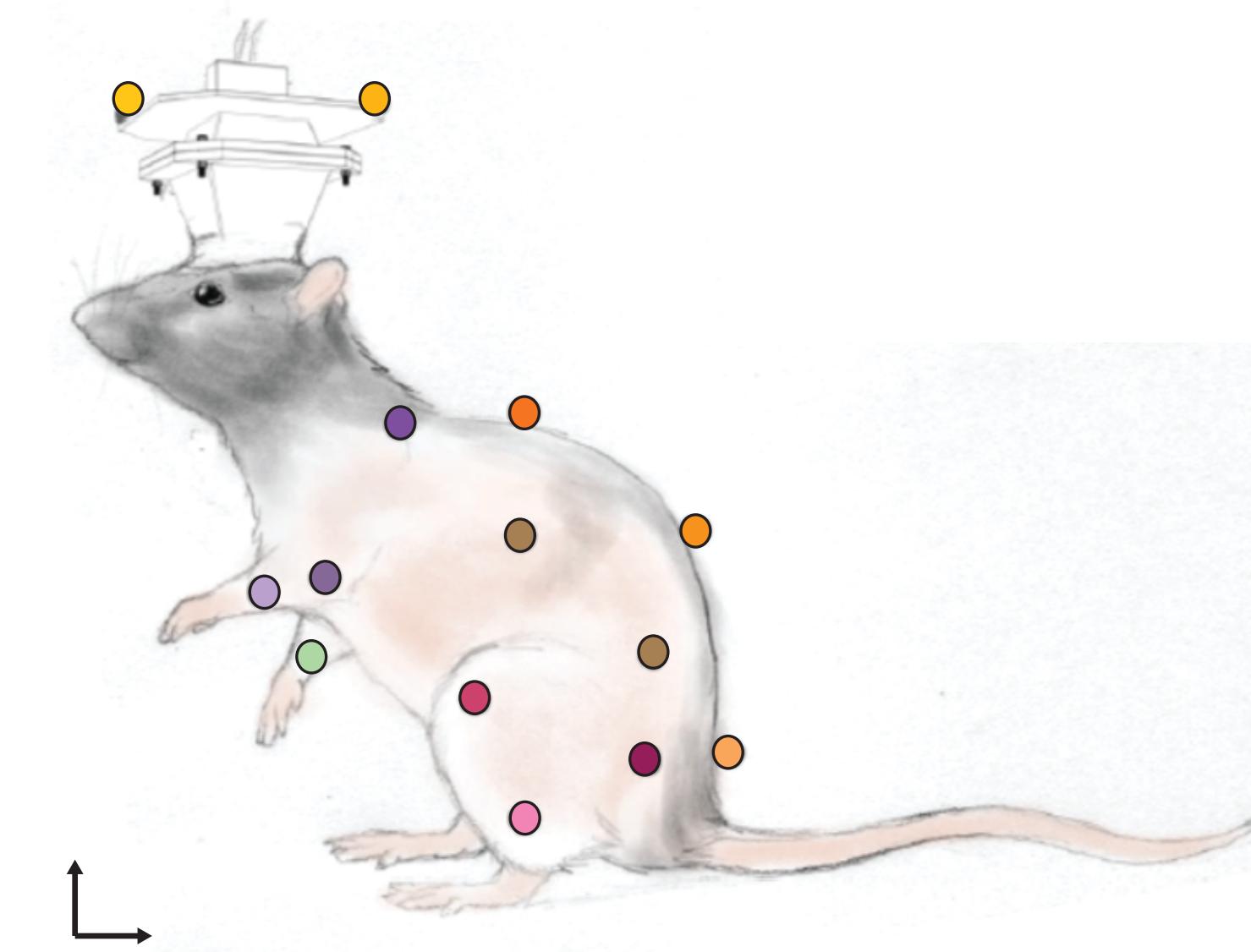
Model 1: Robust Bayesian triangulation of 3D pose from 2D observations

- Projective geometry makes far away objects appear smaller.
- Outliers in 2D estimates can severely affect 3D triangulation.
- Typical approaches:
 - More data
 - Temporal constraints
 - Median filtering (DLC-3D) / RANSAC
 - **Robust noise models**



Triangulation in the presence of measurement noise

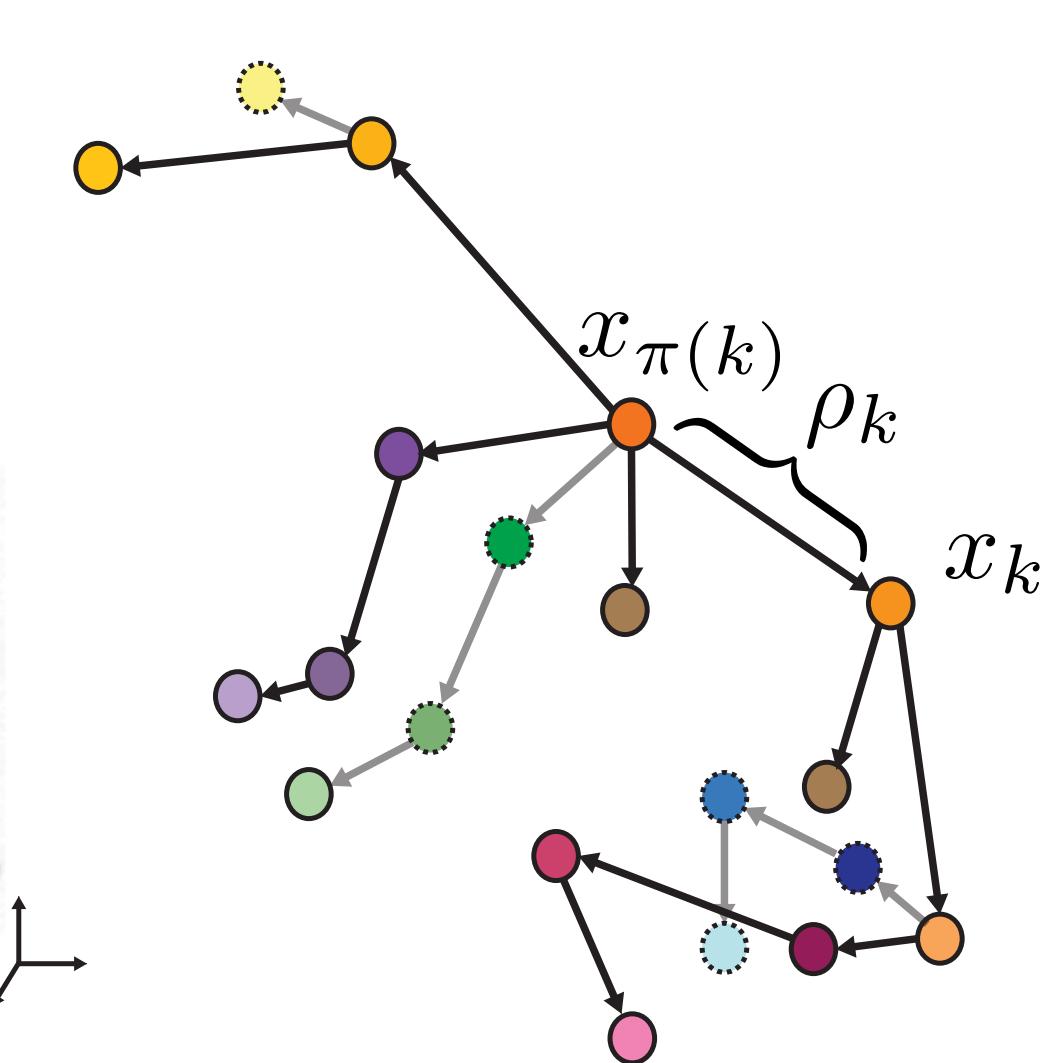
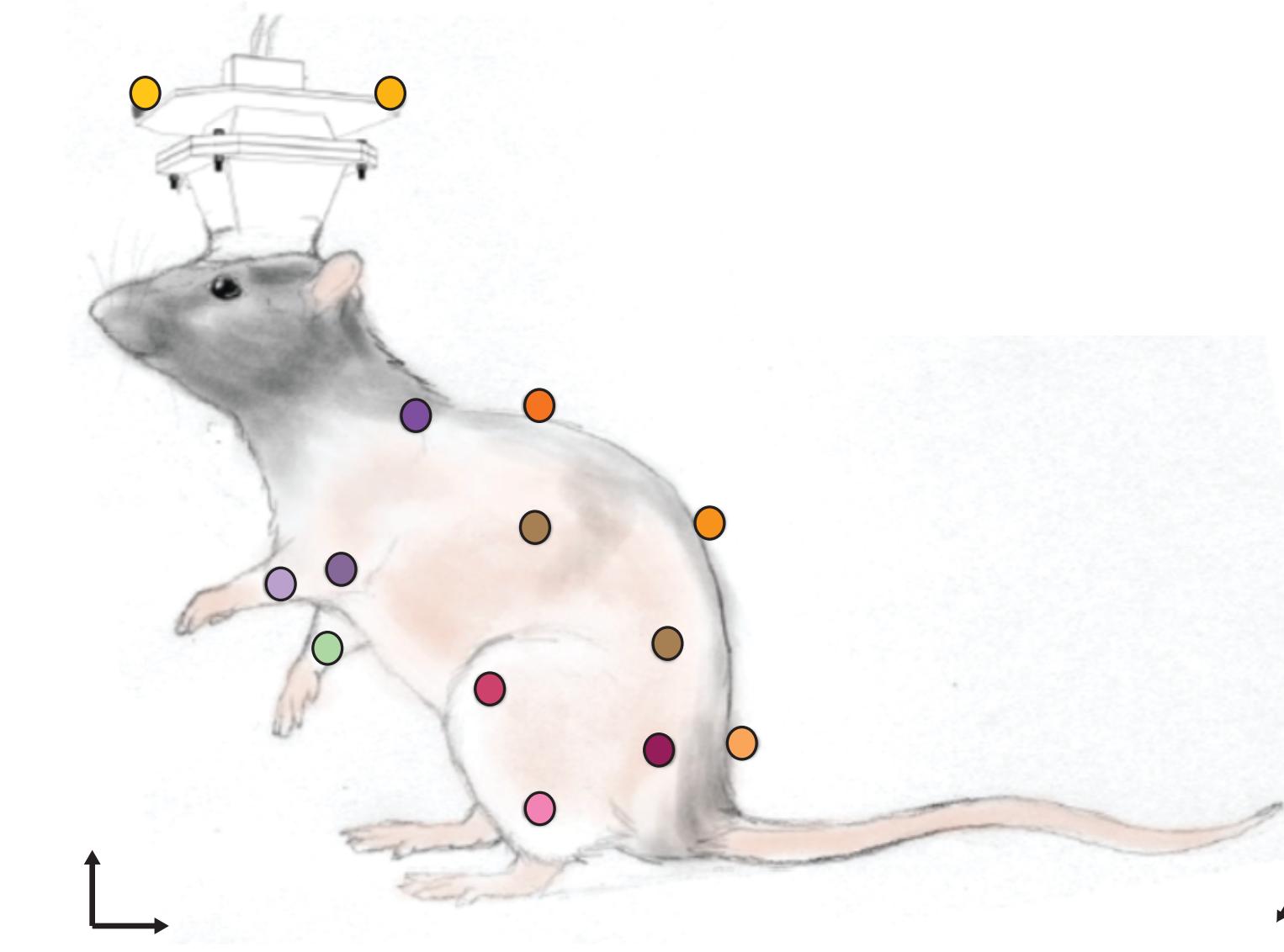
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- Typical approaches:
 - More data
 - Temporal constraints
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 - Robust noise models
 - **Spatial constraints**



A probabilistic view of spatial constraints

- Common approach:

$$p(x) \propto \prod_k \mathcal{N}(\|x_k - x_{\pi(k)}\|; \rho_k, \sigma^2 I)$$



A probabilistic view of spatial constraints

- Common approach:

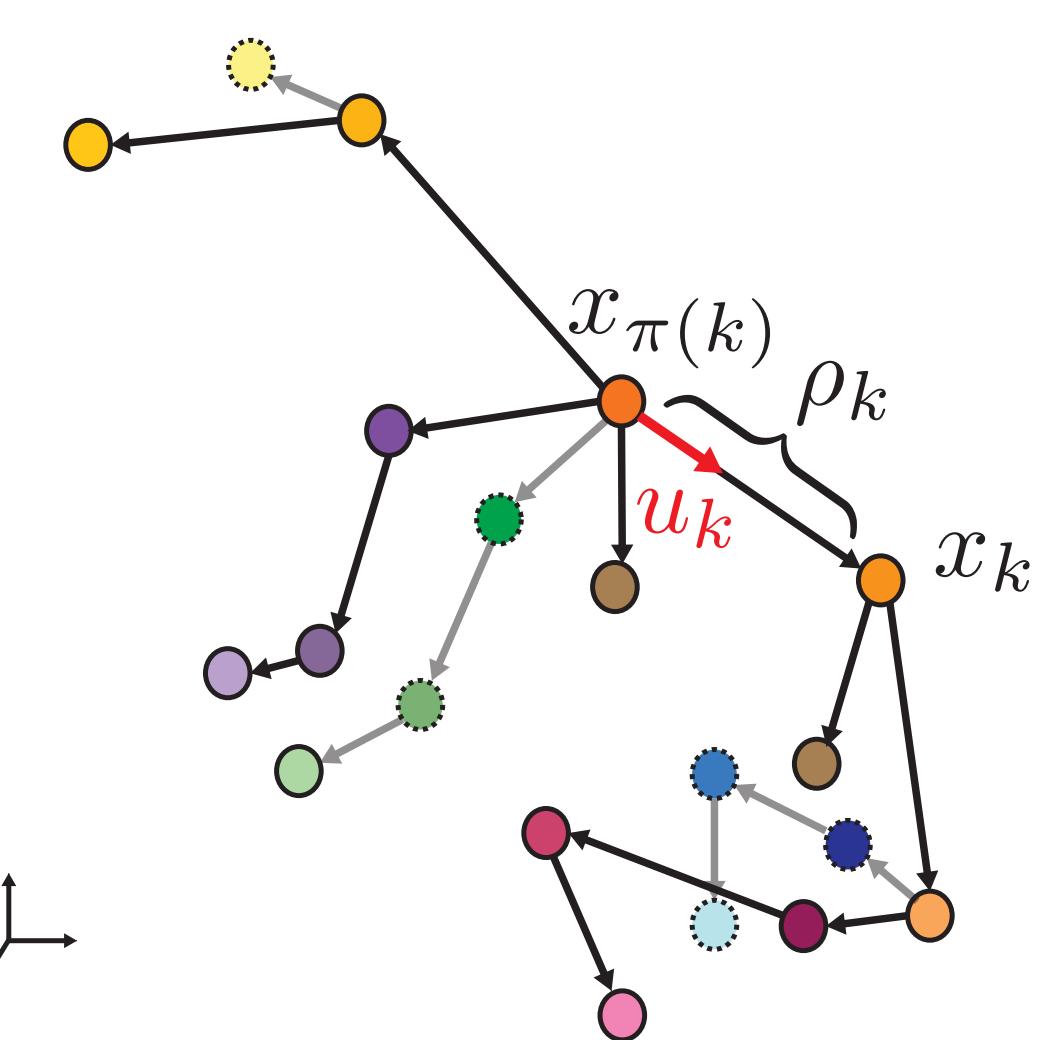
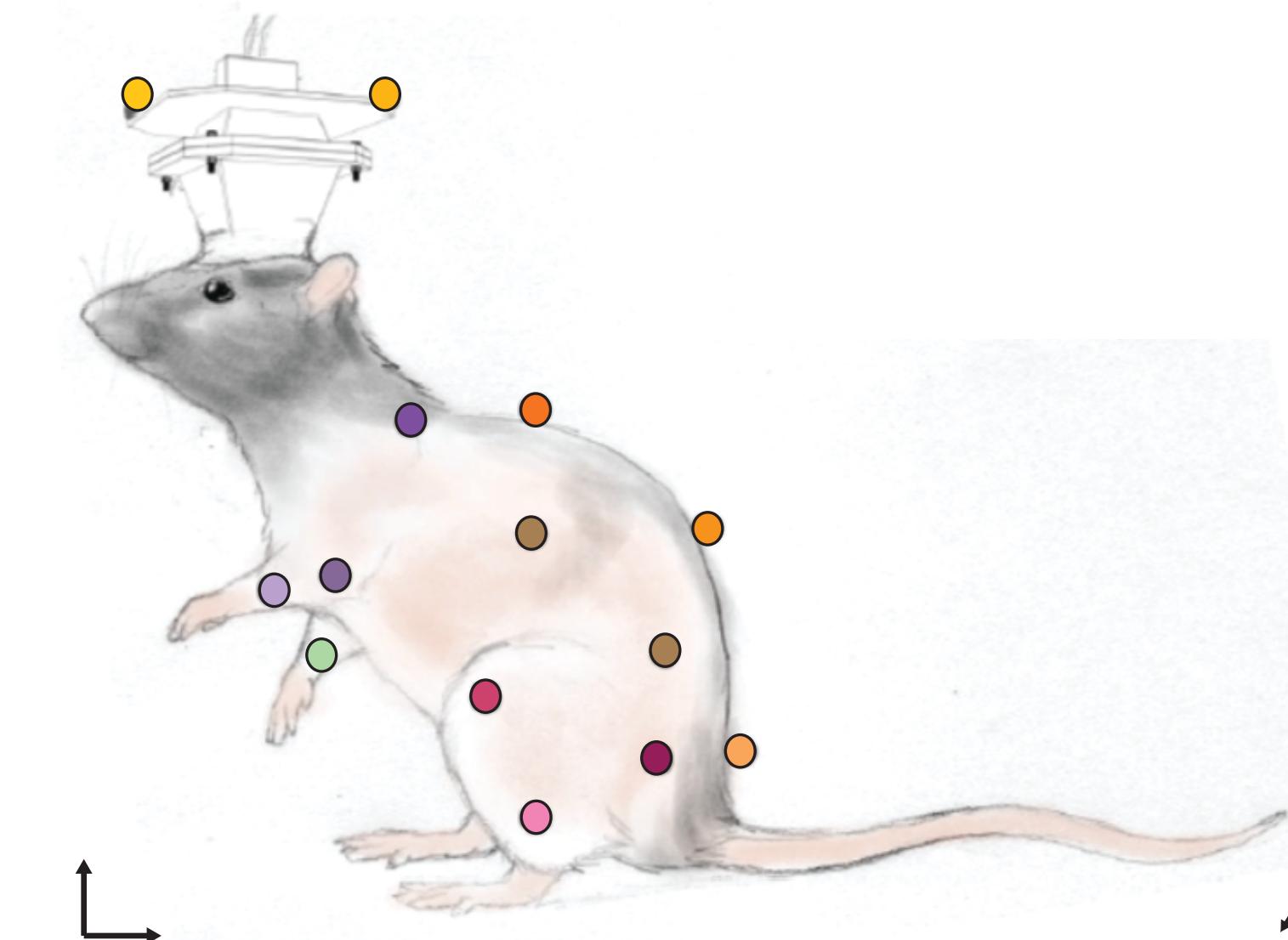
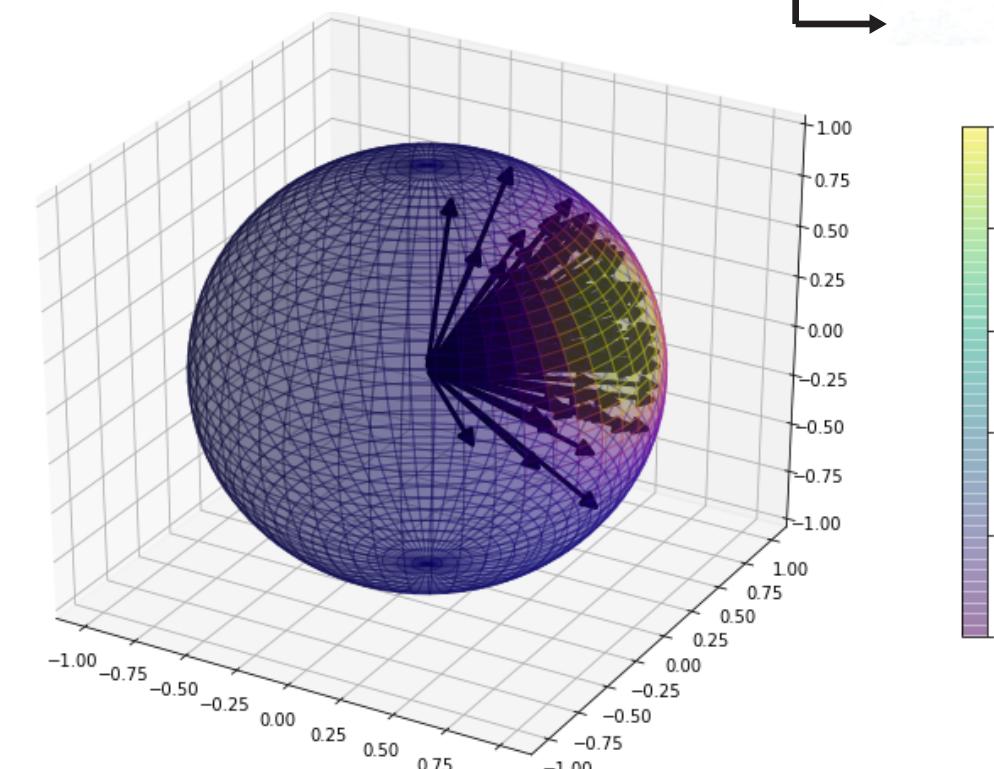
$$p(x) \propto \prod_k \mathcal{N}(\|x_k - x_{\pi(k)}\|; \rho_k, \sigma^2 I)$$

- Alternative:

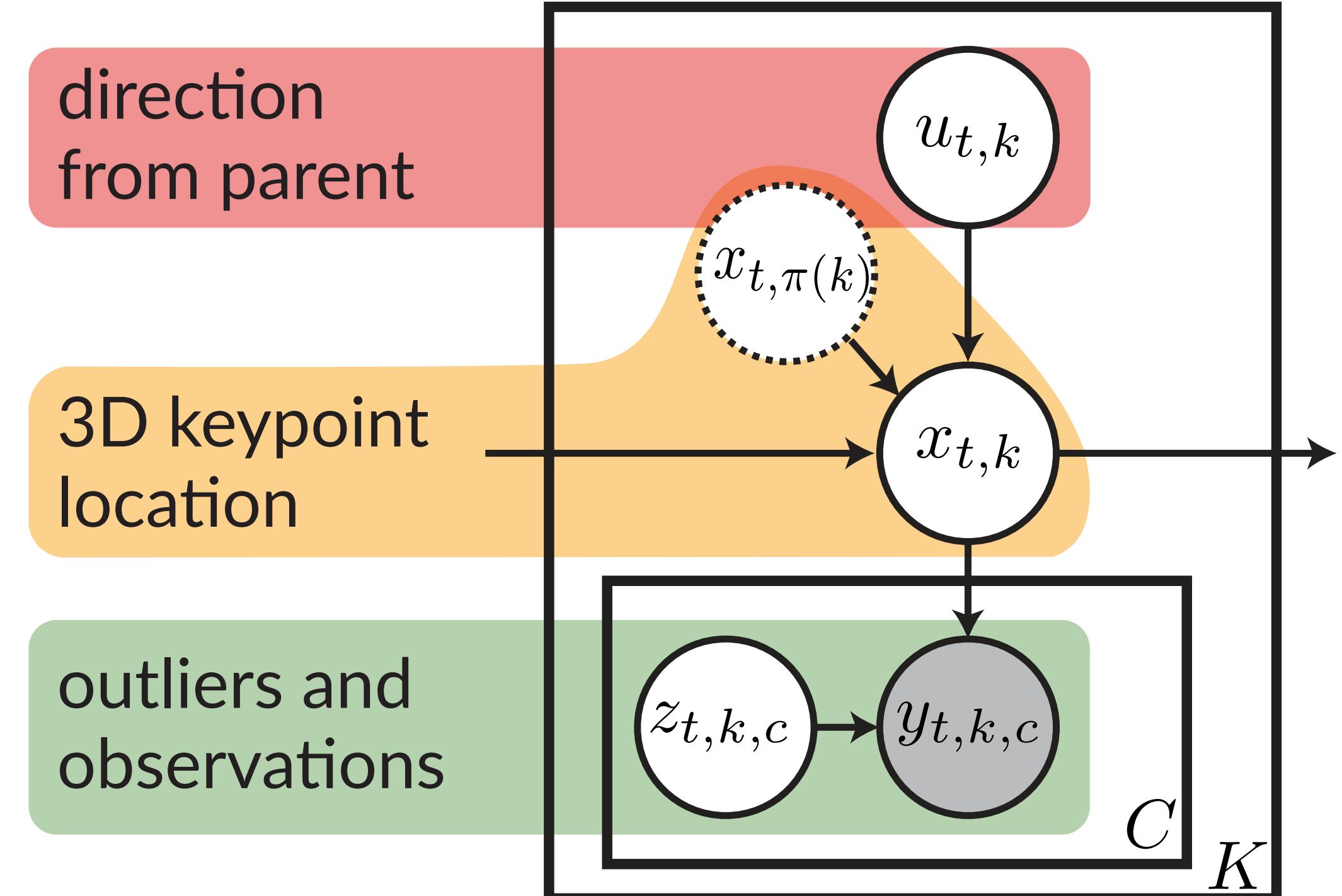
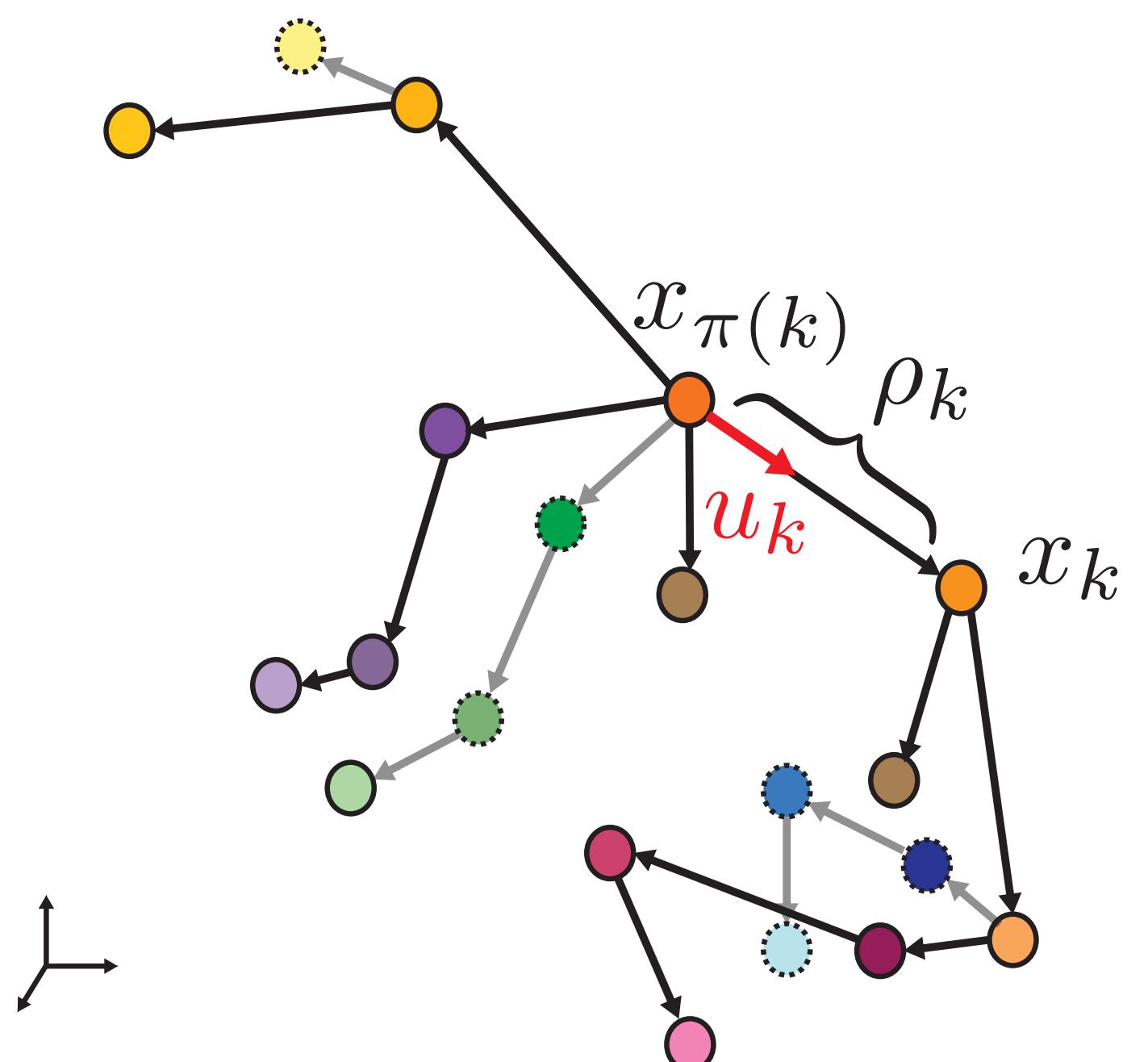
$$u_k \sim \text{Unif}(\mathbb{S}_2)$$

$$x_k | u_k \sim \mathcal{N}(x_{\pi(k)} + \rho_k u_k, \sigma^2 I)$$

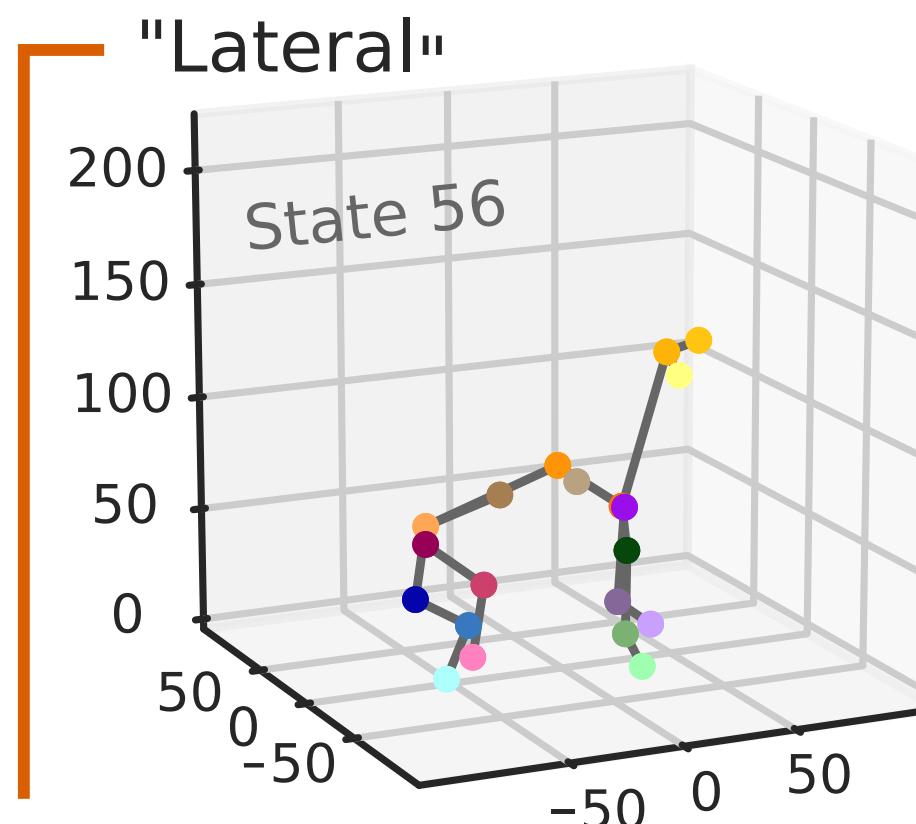
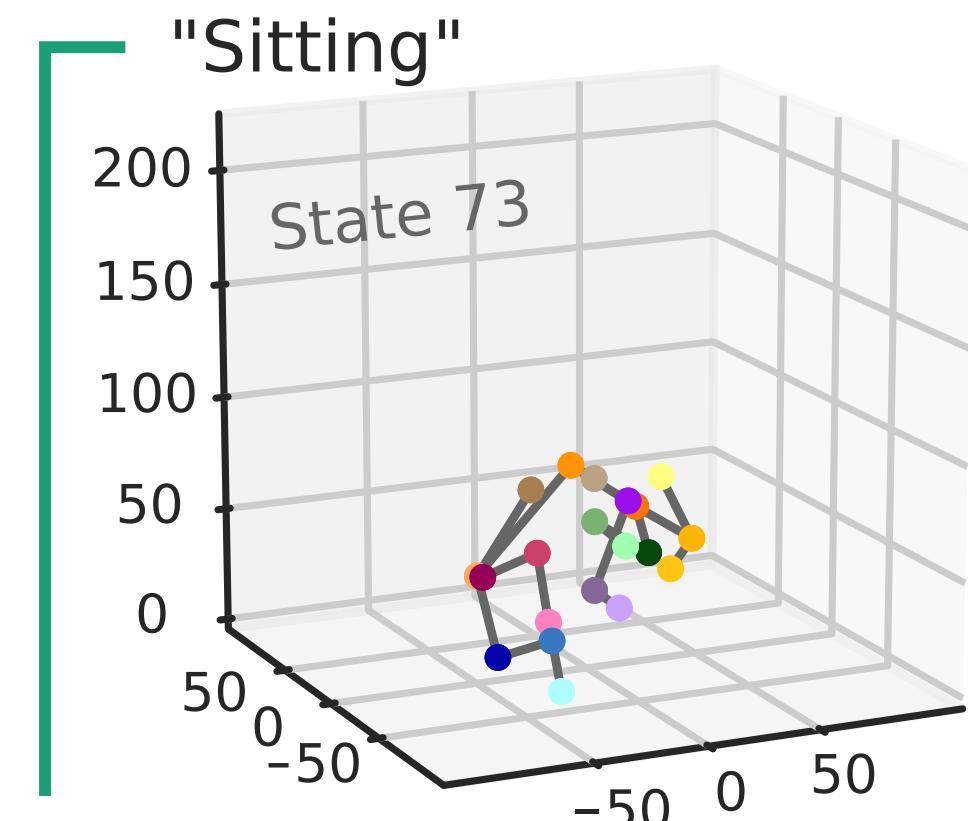
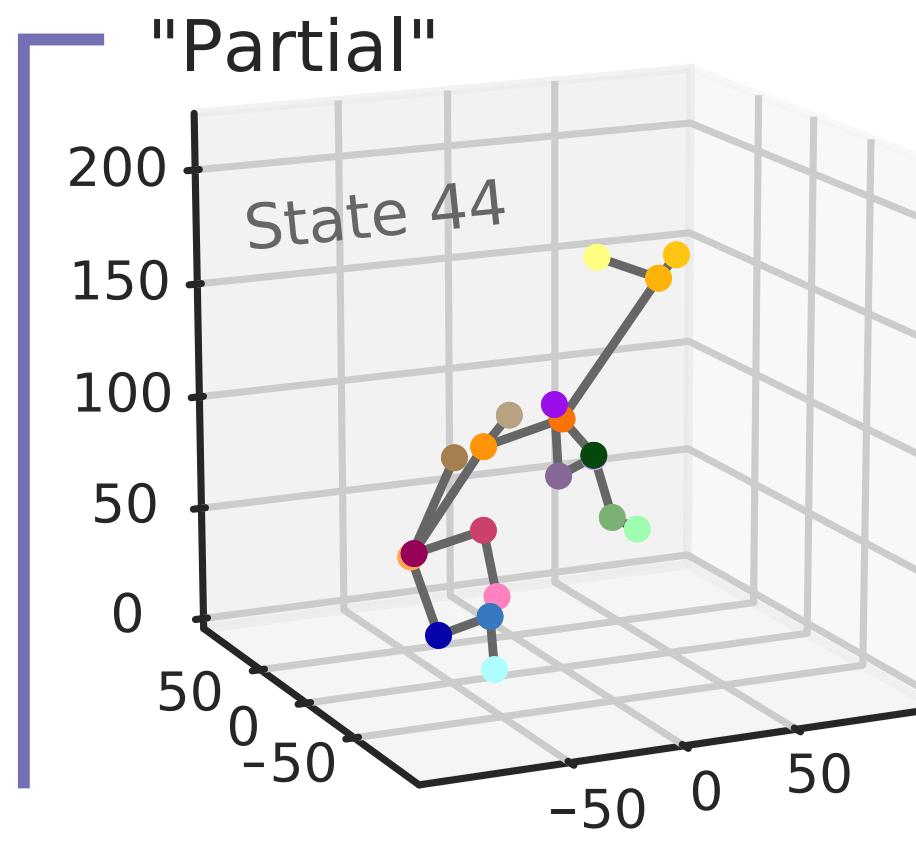
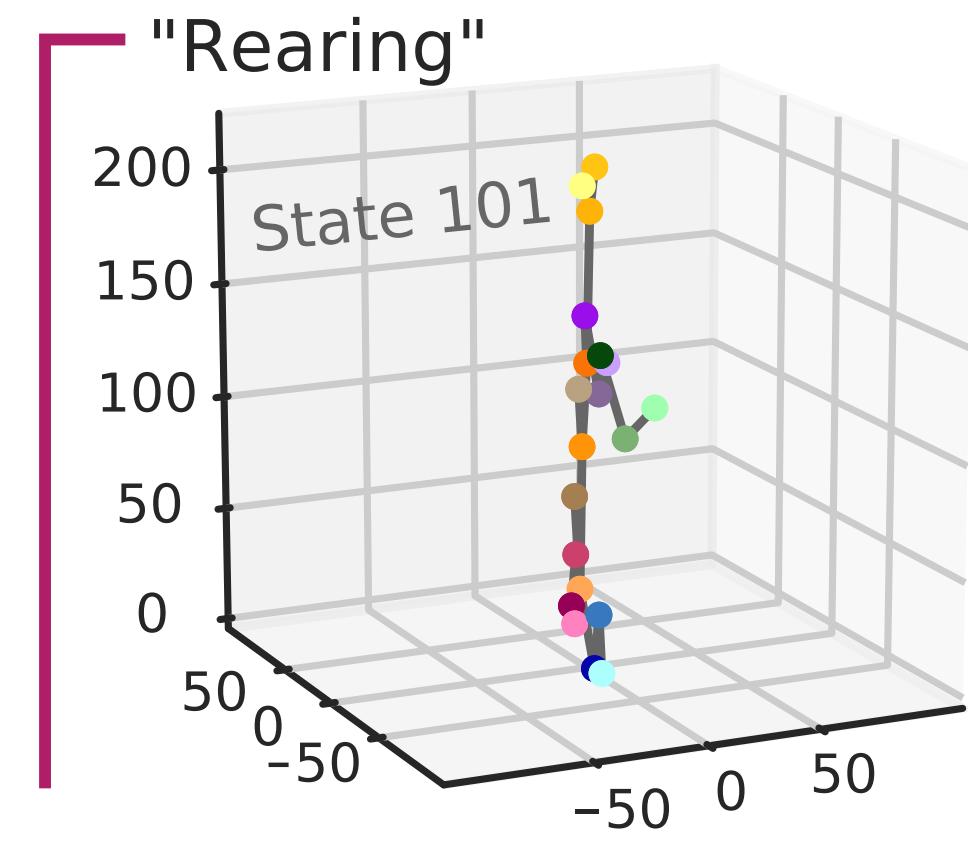
- Are these equivalent?



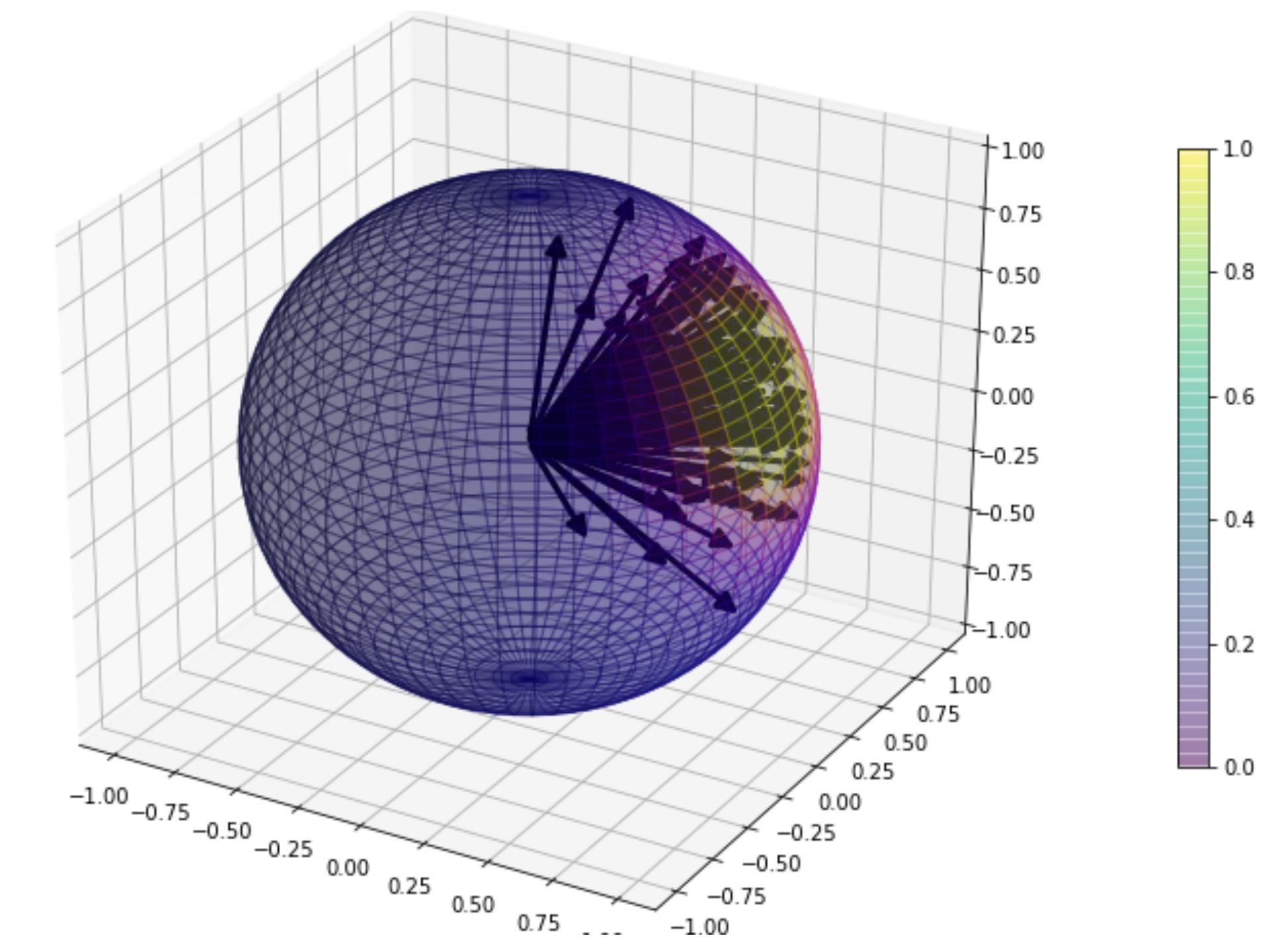
Model 2: Incorporating distance priors on keypoint configurations



Why stop at distances? Poses involve correlated directions!

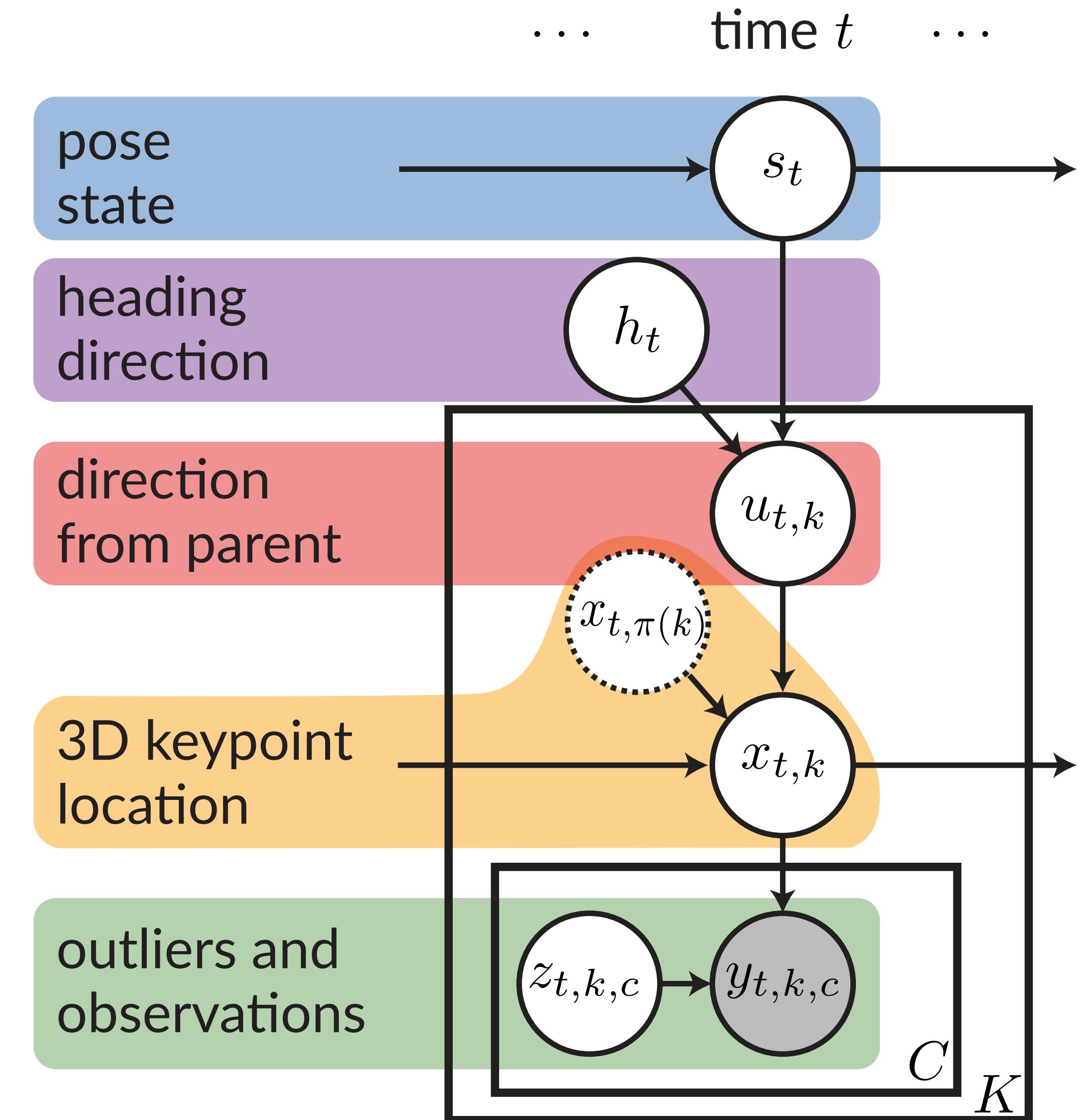
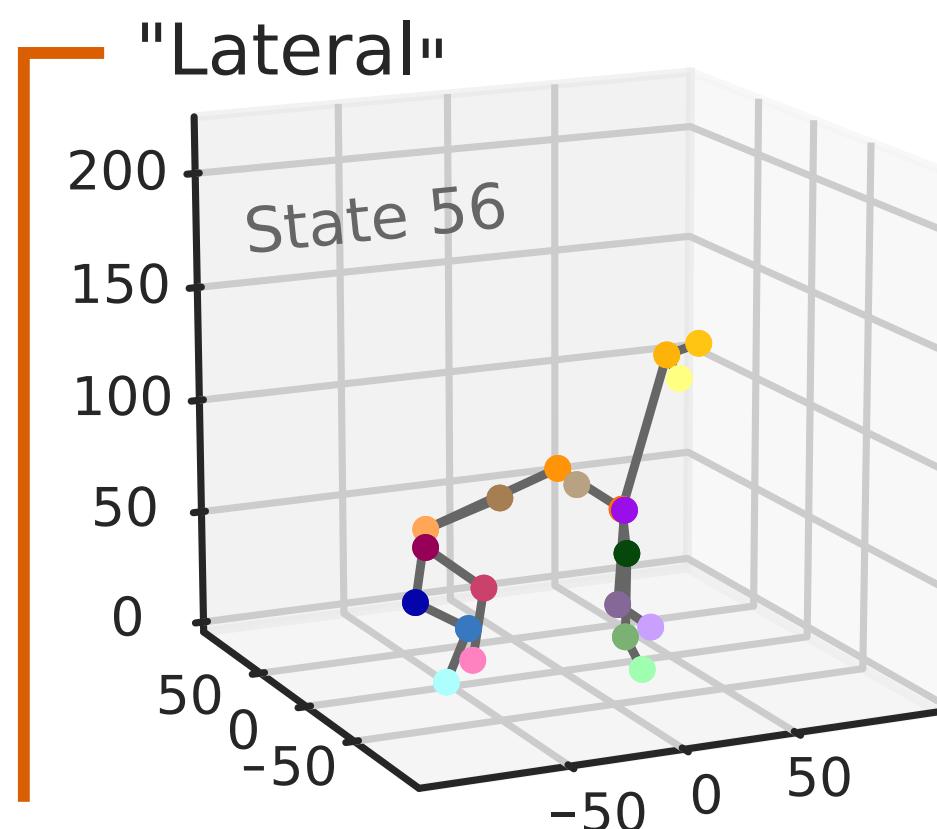
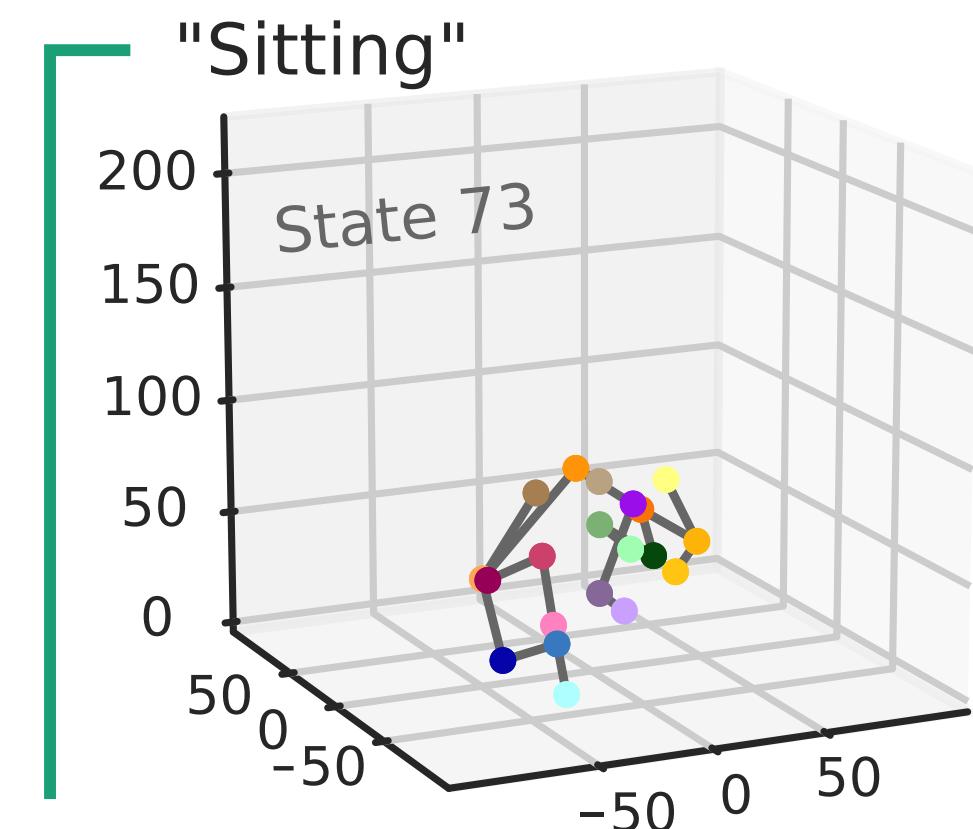
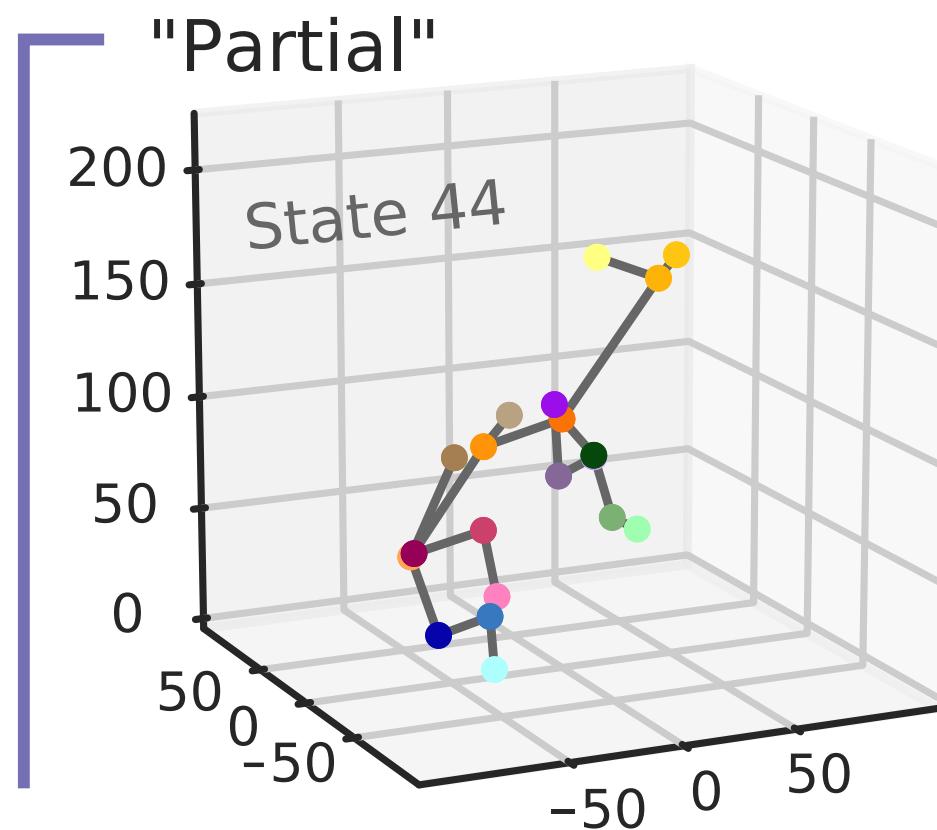
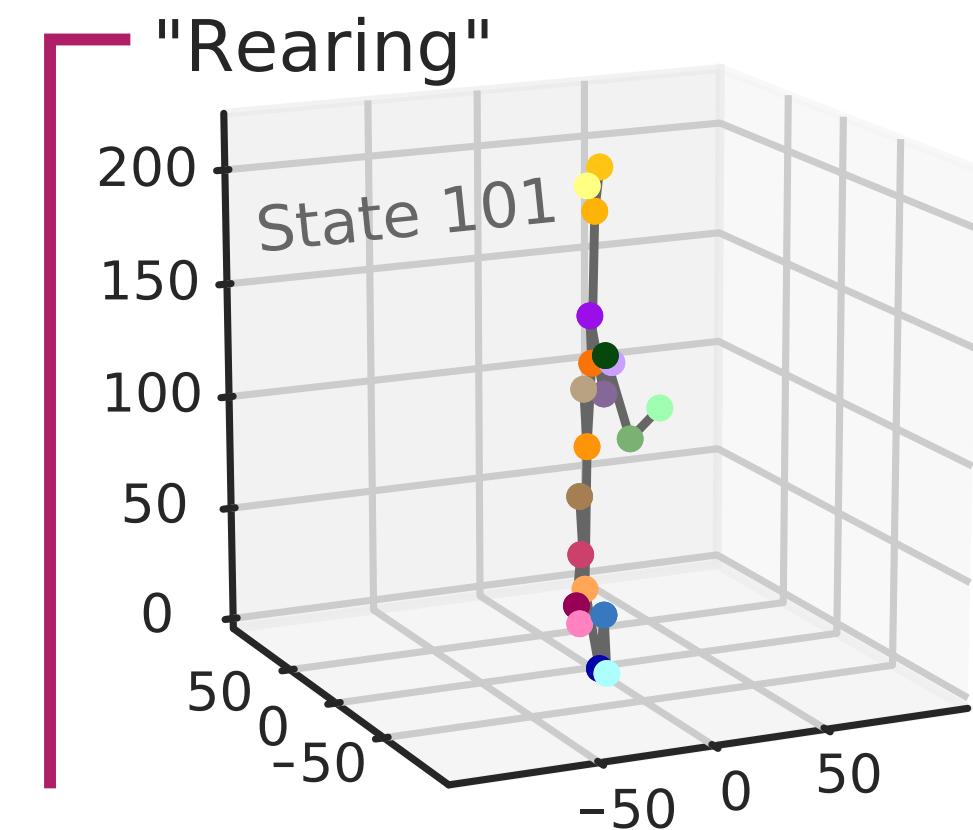


*von Mises-Fisher distribution
on the sphere*

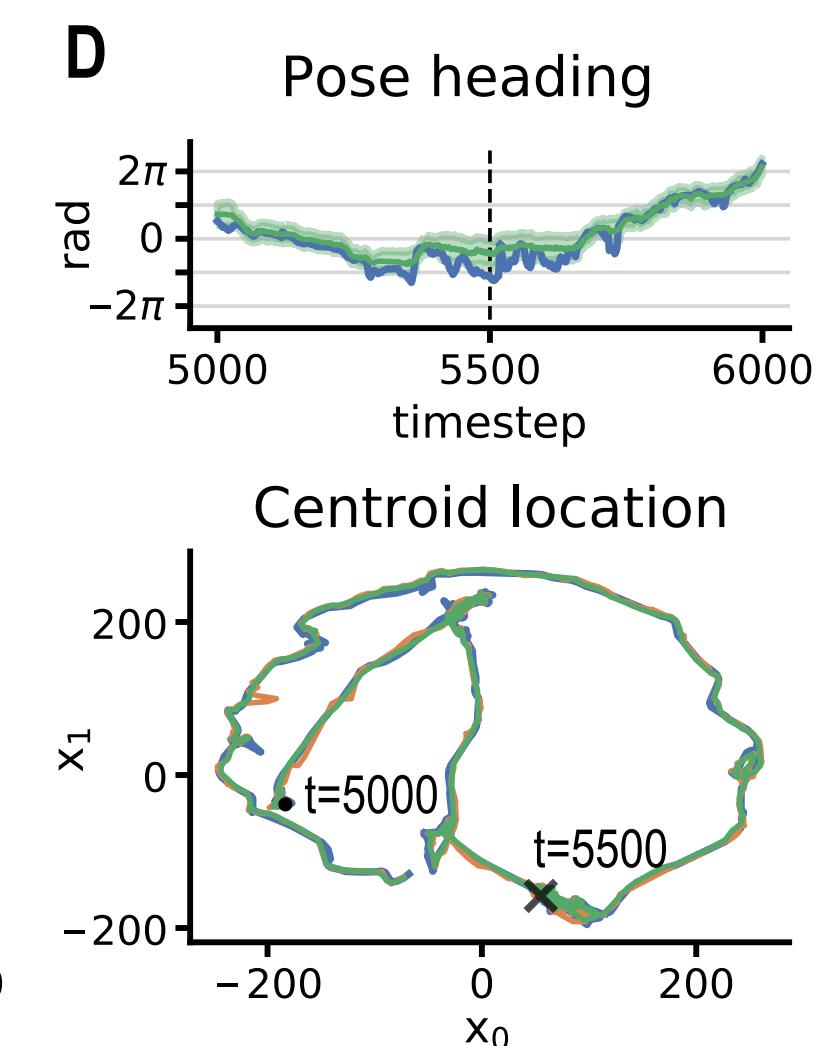
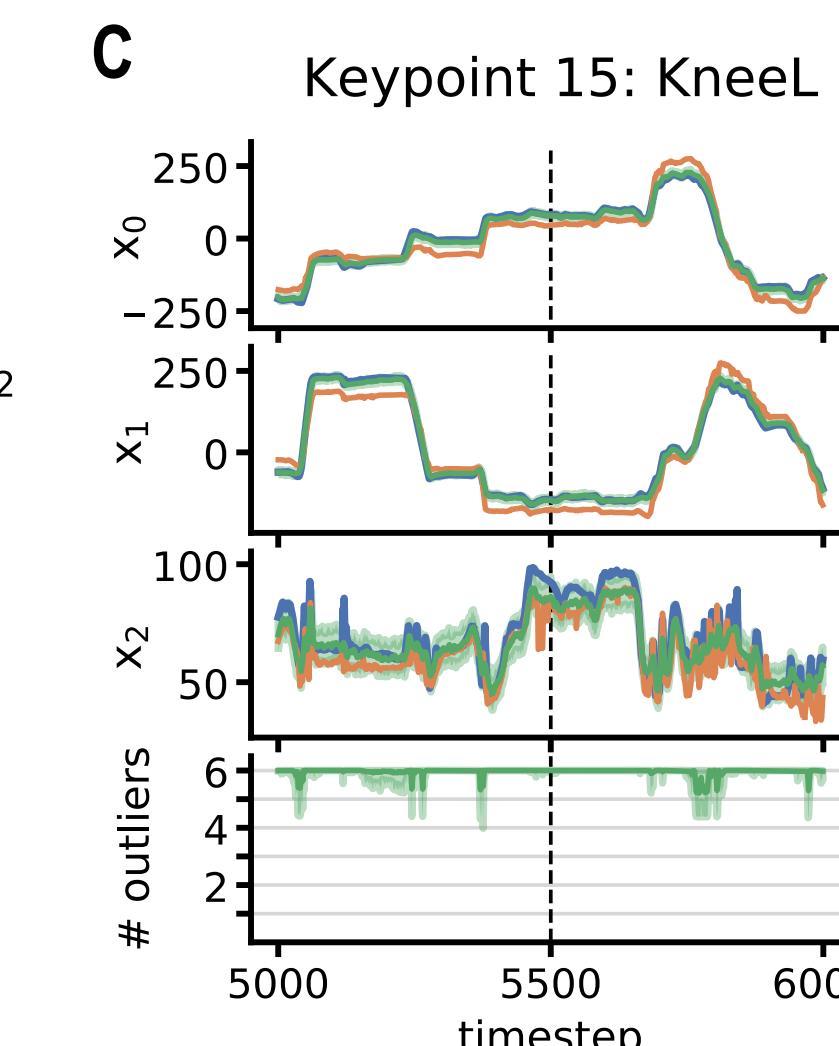
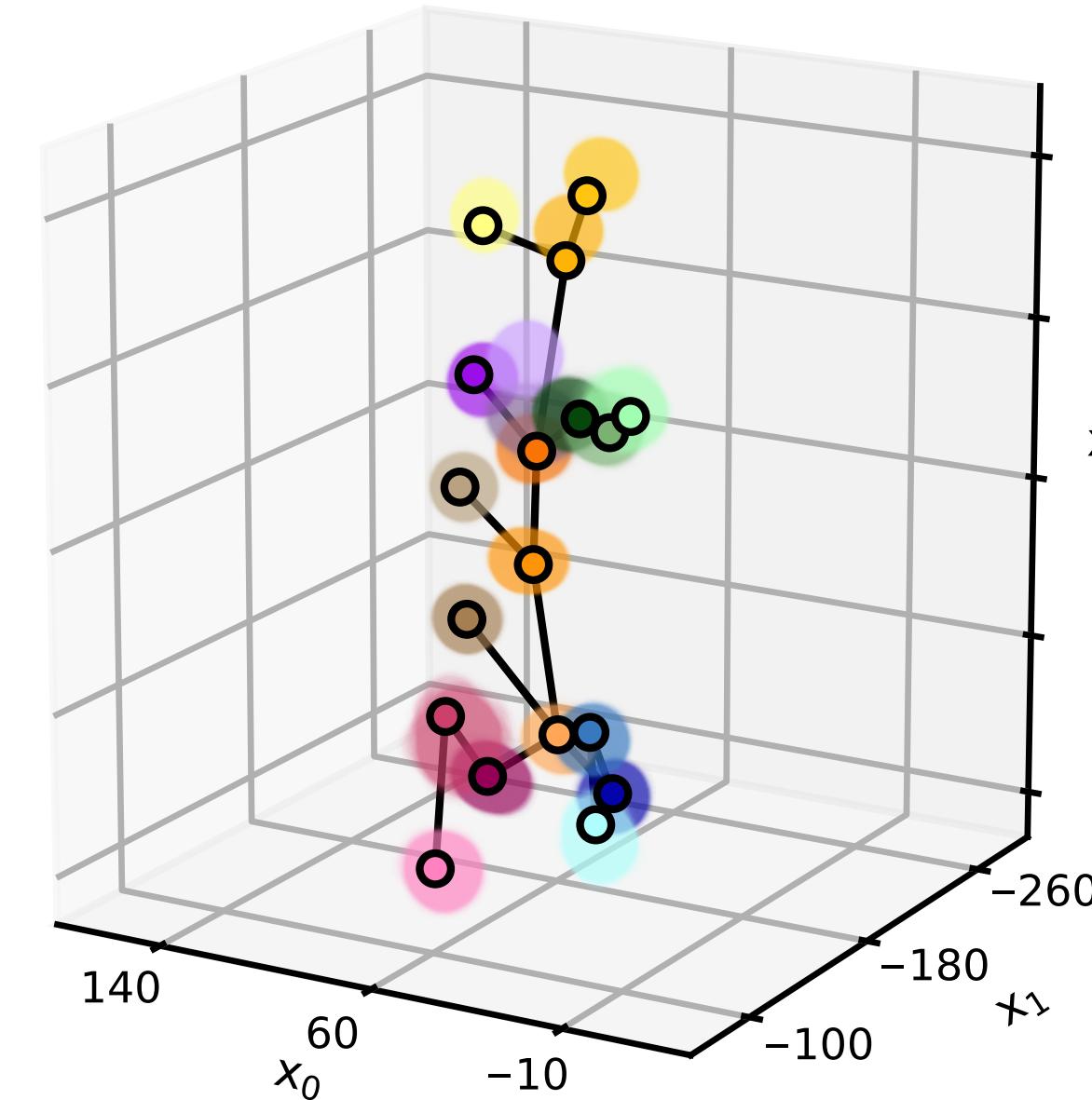
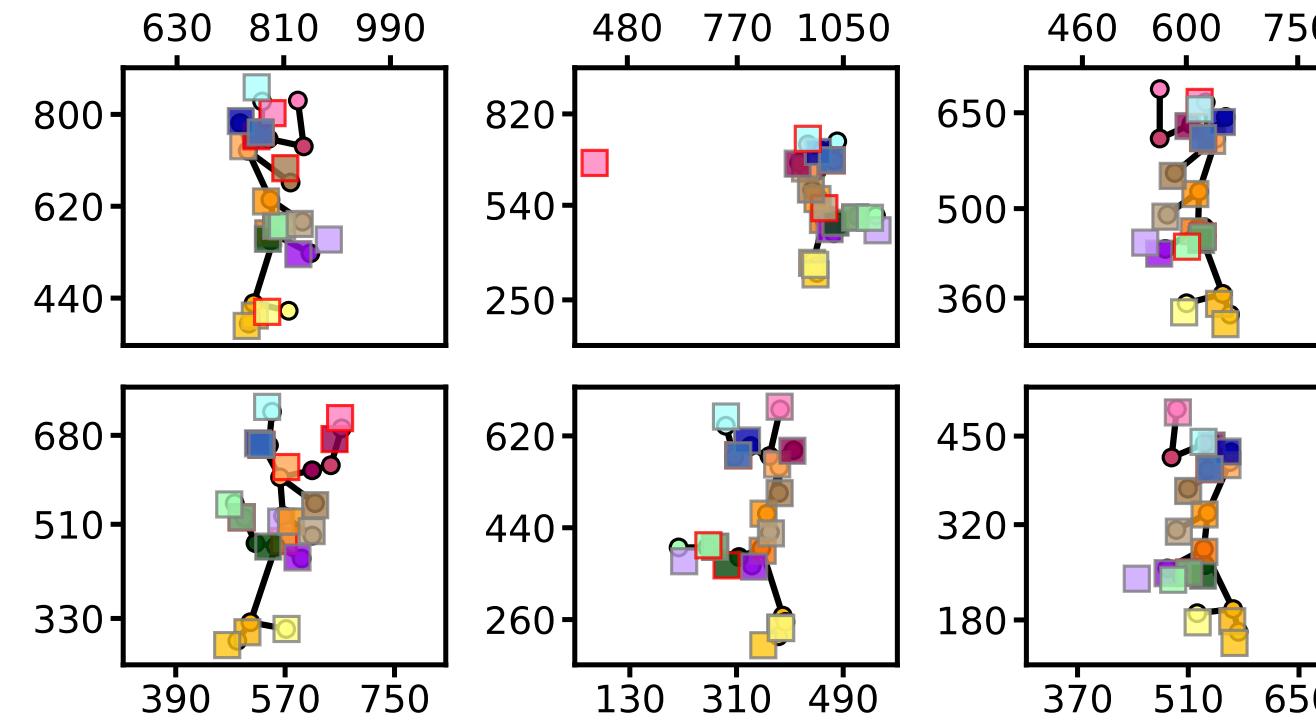


$$u_k \sim \text{vMF}(\mu_{s_t, k}, \kappa_{s_t, k})$$

GIMBAL: Capturing correlations in direction vectors with pose states



GIMBAL yields posterior distributions on 3D pose given 2D estimates



— MoCap — DLC 3D — Gimbal

Structured priors improve 3D pose estimates

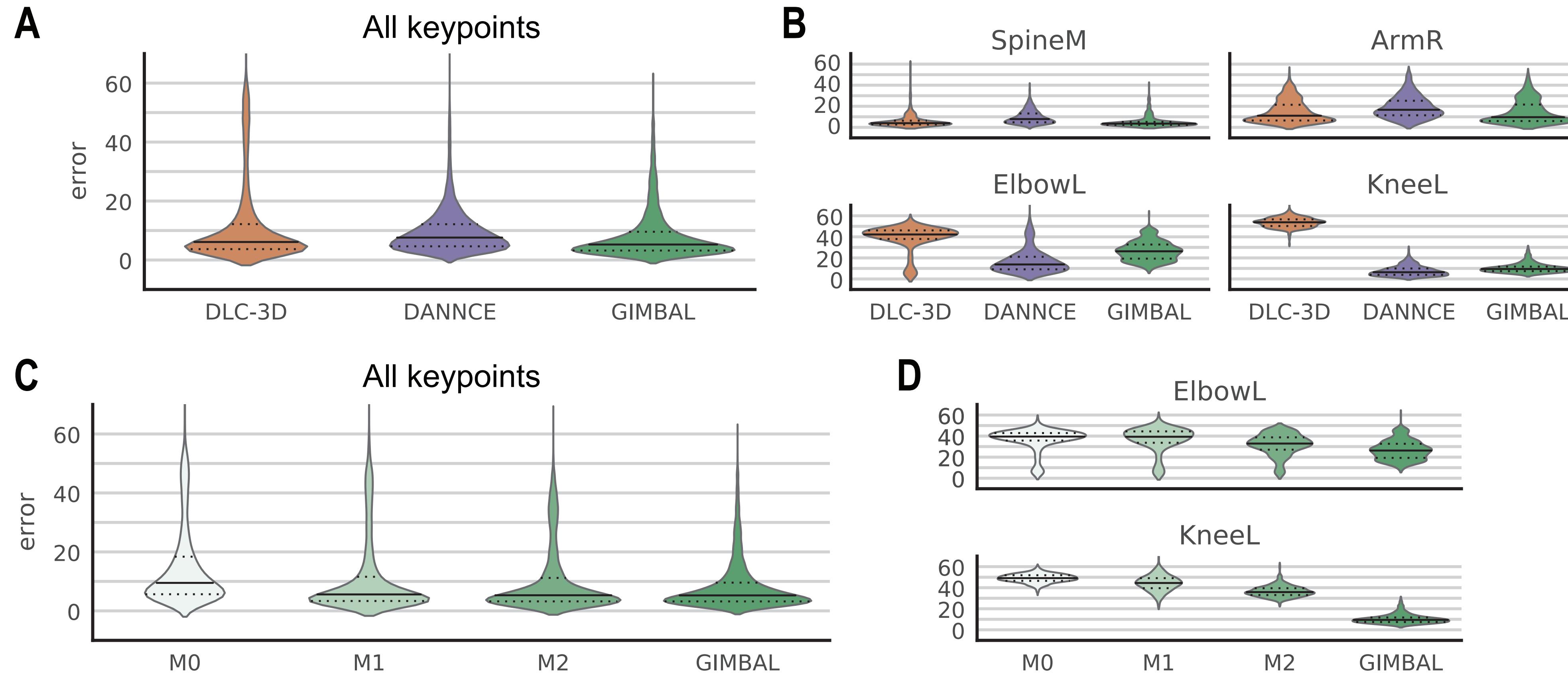
Table 1: Mean position error (MPE) averaged over all keypoints, for different pose estimation models. Calculated with unmodified predictions (raw) and after applying rigid Procrustes analysis (RPA). Units: mm.

	DLC-3D	DANNCE	GIMBAL
Raw	11.41	9.25	8.01
RPA	11.17	7.38	6.88

Table 2: Same as Table 1, with results for special submodels of GIMBAL.

	M0	M1	M2	GIMBAL
Raw	14.96	10.71	9.65	8.01
RPA	14.07	10.43	8.97	6.88

Structured priors improve 3D pose estimates



Conclusion

- **Precise behavior quantifications** are critical for understanding how neural activity relates to behavioral output.
- **Markerless pose tracking** methods have made it much easier to obtain such quantifications.
- **Convolutional neural networks** are naturally suited to this task.
- With **transfer learning**, we can leverage state-of-the-art deep networks for image classification to warm-start pose tracking.
- We can **triangulate 3D pose** from 2D images using projecting geometry and spatiotemporal priors.

Further reading

- Datta, Sandeep Robert, et al. "Computational neuroethology: a call to action." *Neuron* 104.1 (2019): 11-24.
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- Pereira, Talmo D., et al. "Fast animal pose estimation using deep neural networks." *Nature methods* 16.1 (2019): 117-125.
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