

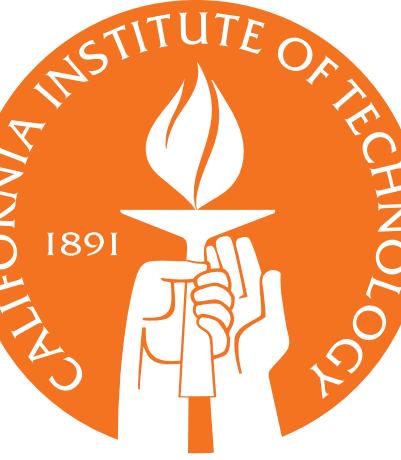
Rotation Invariant Moveme Discovery from Static Poses

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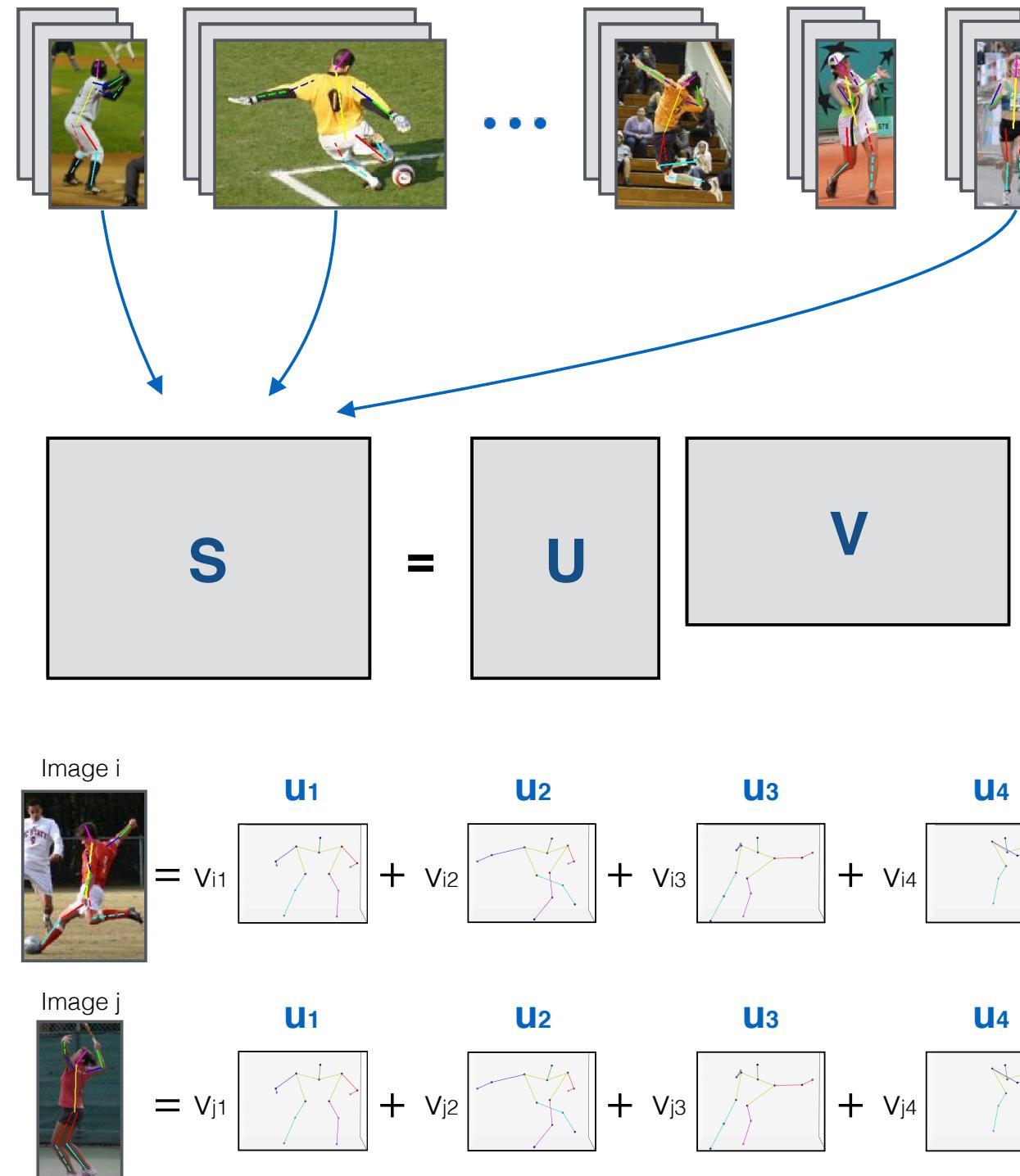
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PROBLEM STATEMENT

- What are typical ranges of motion for human arms?
- What leg movements correlate with specific shoulder positions?
- How will the arms most likely move given the current body pose?



Goal: Learn a basis space to capture movemes from a generic collection of 2D images.

Applications: Extract pose priors from 2D pose datasets, improve activity recognition, animation.

Setting: Leeds Sports Dataset since sport activities have characteristic motions and share trajectories of parts of the body.

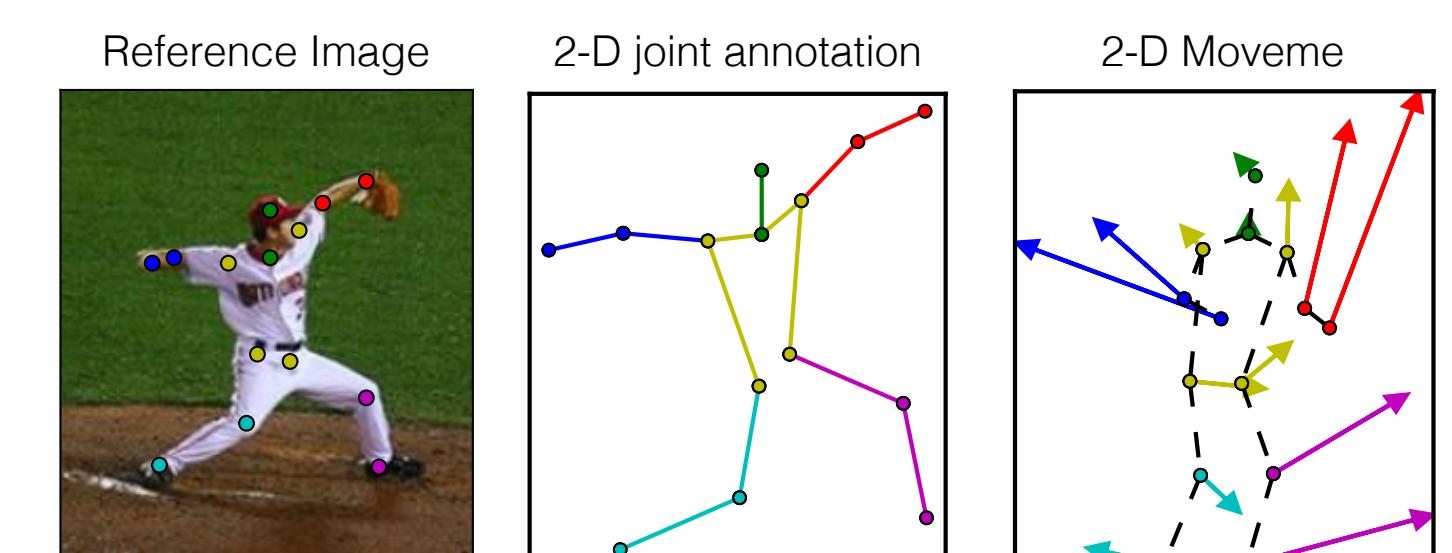
Method: Rotation-invariant latent factor model that can recover a set of 3D bases poses from a training set of 2D projections.

HUMAN MOTIONS

Moveme: simplest meaningful pattern of motion, short target-oriented trajectory that cannot be further decomposed

Action: predefined sequence of movemes

Activity: stochastic combination of actions



MODELS

Objective & Loss Functions

$$\begin{aligned} \mathbf{U}, \mathbf{V}, \theta &= \arg \min_{\mathbf{U}, \mathbf{V}, \theta} \mathcal{L}(\mathbf{U}, \mathbf{V}, \theta) \\ \mathcal{L}(\mathbf{U}, \mathbf{V}, \theta) &= \mathcal{E}(\mathbf{U}, \mathbf{V}, \theta) + \Omega(\mathbf{U}, \mathbf{V}, \theta) \\ \mathcal{E}(\mathbf{U}, \mathbf{V}, \theta) &= \sum_j (\mathbf{s}_j - \hat{\mathbf{s}}_j)^2 \end{aligned}$$

Baselines

$$\begin{aligned} \text{SVD} \quad \hat{\mathbf{s}}_j &= \bar{\mathbf{s}} + \mathbf{U} \cdot \mathbf{v}_j \\ \text{SVD+ROT} \quad \hat{\mathbf{s}}_j &= \bar{\mathbf{s}}(a_j) + \mathbf{U}(a_j) \cdot \mathbf{v}_j \\ \Omega(\mathbf{U}, \mathbf{V}, \theta) &= 0 \end{aligned}$$

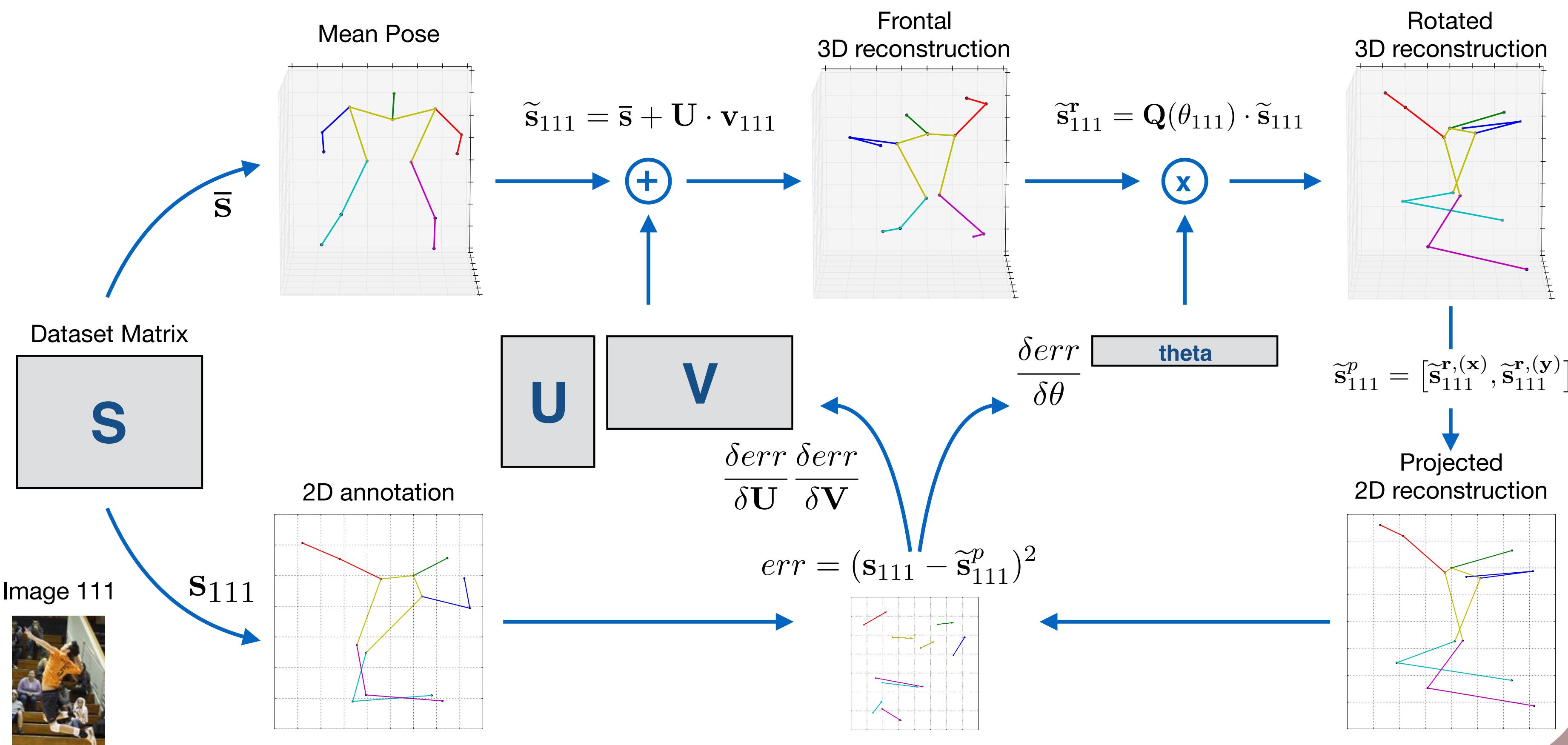
LFA2D

$$\begin{aligned} \hat{\mathbf{s}}_j &= \bar{\mathbf{s}}(a_j) + \mathbf{U}(a_j) \cdot \mathbf{v}_j \\ \Omega(\mathbf{U}, \mathbf{V}, \theta) &= R_{reg}(\mathbf{U}, \mathbf{V}, \theta) + R_{spat}(\mathbf{U}, \mathbf{V}, \theta) \\ R_{reg}(\mathbf{U}, \mathbf{V}, \theta) &= \sum_{a=1}^p \left[\lambda_U \|\mathbf{U}(a)\|_F^2 + \lambda_V \|\mathbf{V}(a)\|_1 \right] \\ R_{spat}(\mathbf{U}, \mathbf{V}, \theta) &= \lambda_{spat} \sum_{a, a'} \kappa_{a, a'} \|\mathbf{U}^{(x)}(a) - \mathbf{U}^{(x)}(a')\|_F^2 \\ &\quad + \sum_{a, a'} \mathbf{1} \left(\mathbf{U}^{(y)}(a), \mathbf{U}^{(y)}(a') \right) \end{aligned}$$

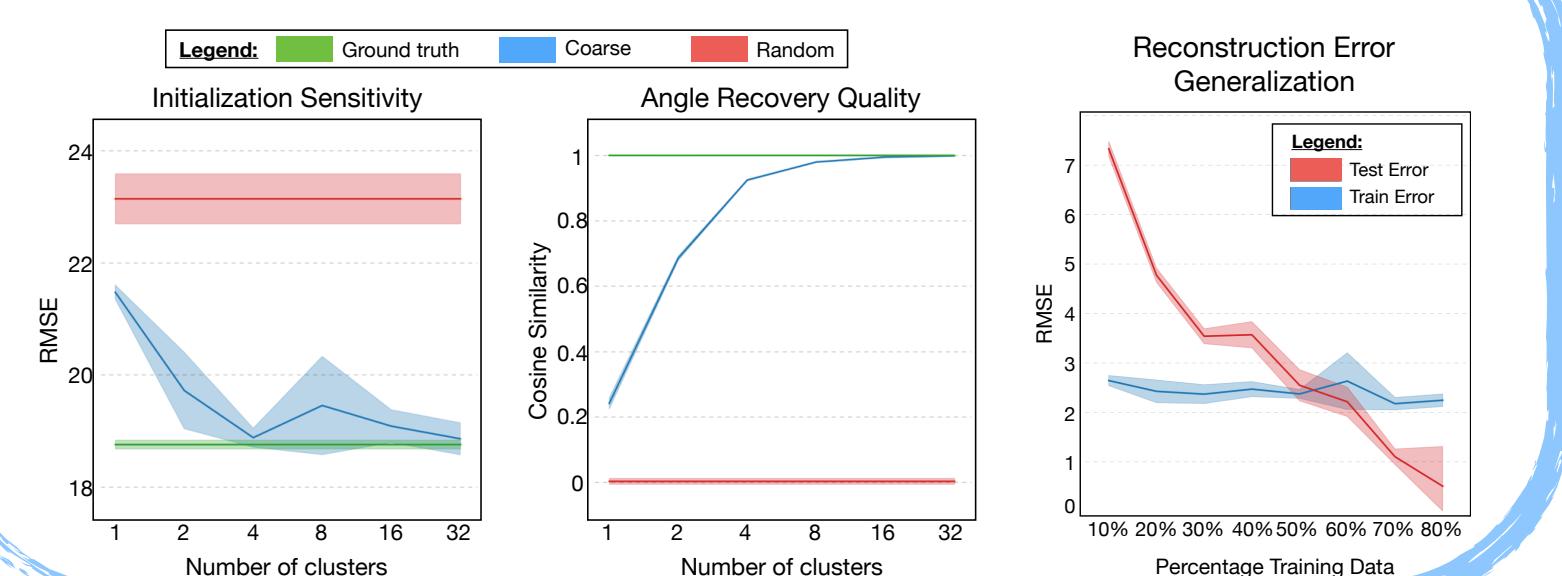
LFA3D

$$\begin{aligned} \hat{\mathbf{s}}_j &= \left[\mathbf{Q}(\theta_j) \left(\bar{\mathbf{s}} + \mathbf{U} \cdot \mathbf{v}_j \right) \right]^{(x,y)} \\ \mathbf{Q}(\theta_j) &= \begin{bmatrix} \cos(\theta_j) & 0 & \sin(\theta_j) \\ 0 & 1 & 0 \\ -\sin(\theta_j) & 0 & \cos(\theta_j) \end{bmatrix} \\ \Omega(\mathbf{U}, \mathbf{V}, \theta) &= \lambda_U \|\mathbf{U}\|_F^2 + \lambda_V \|\mathbf{V}\|_1 \end{aligned}$$

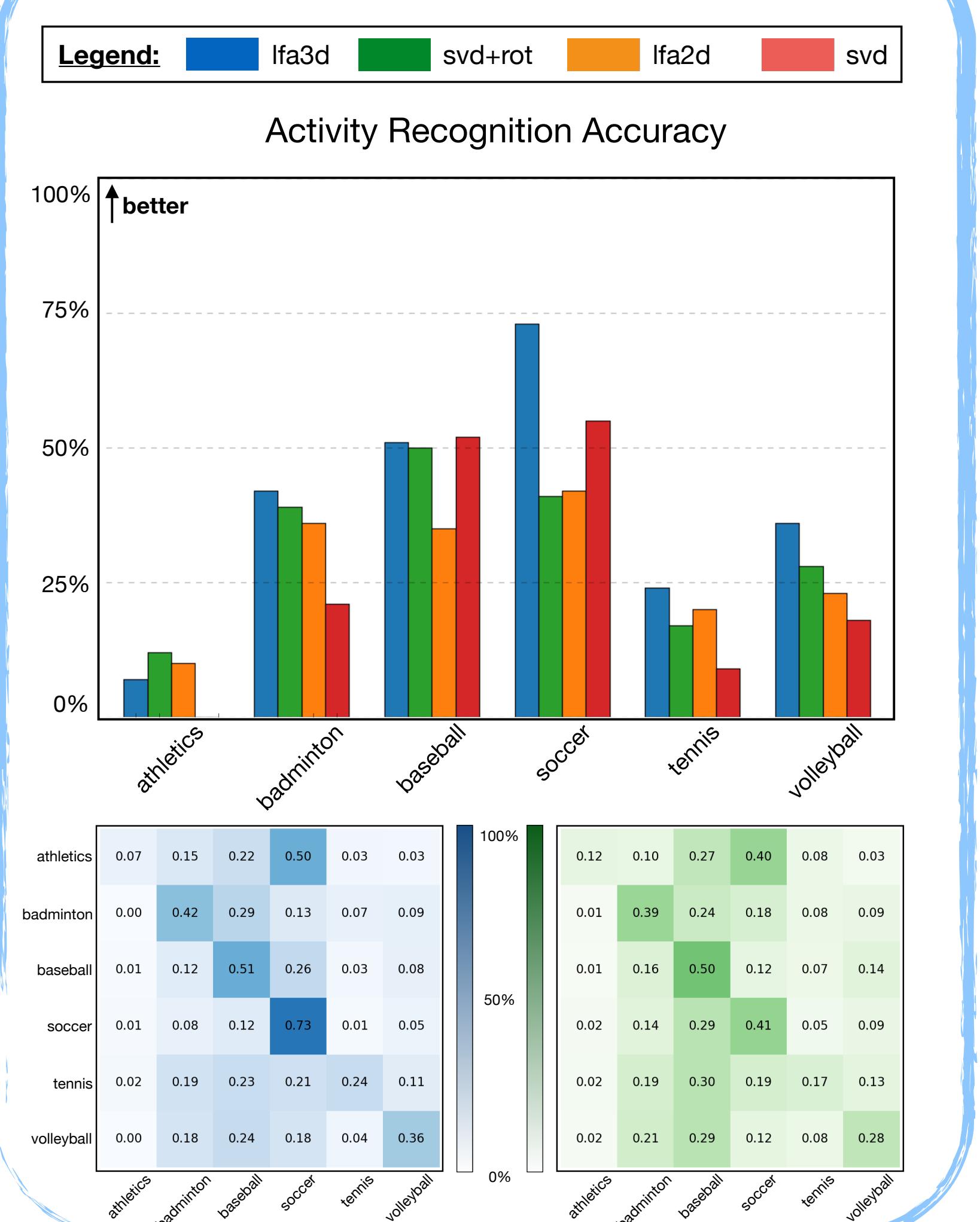
LFA3D OPTIMIZATION PIPELINE



OPTIMIZATION DETAILS



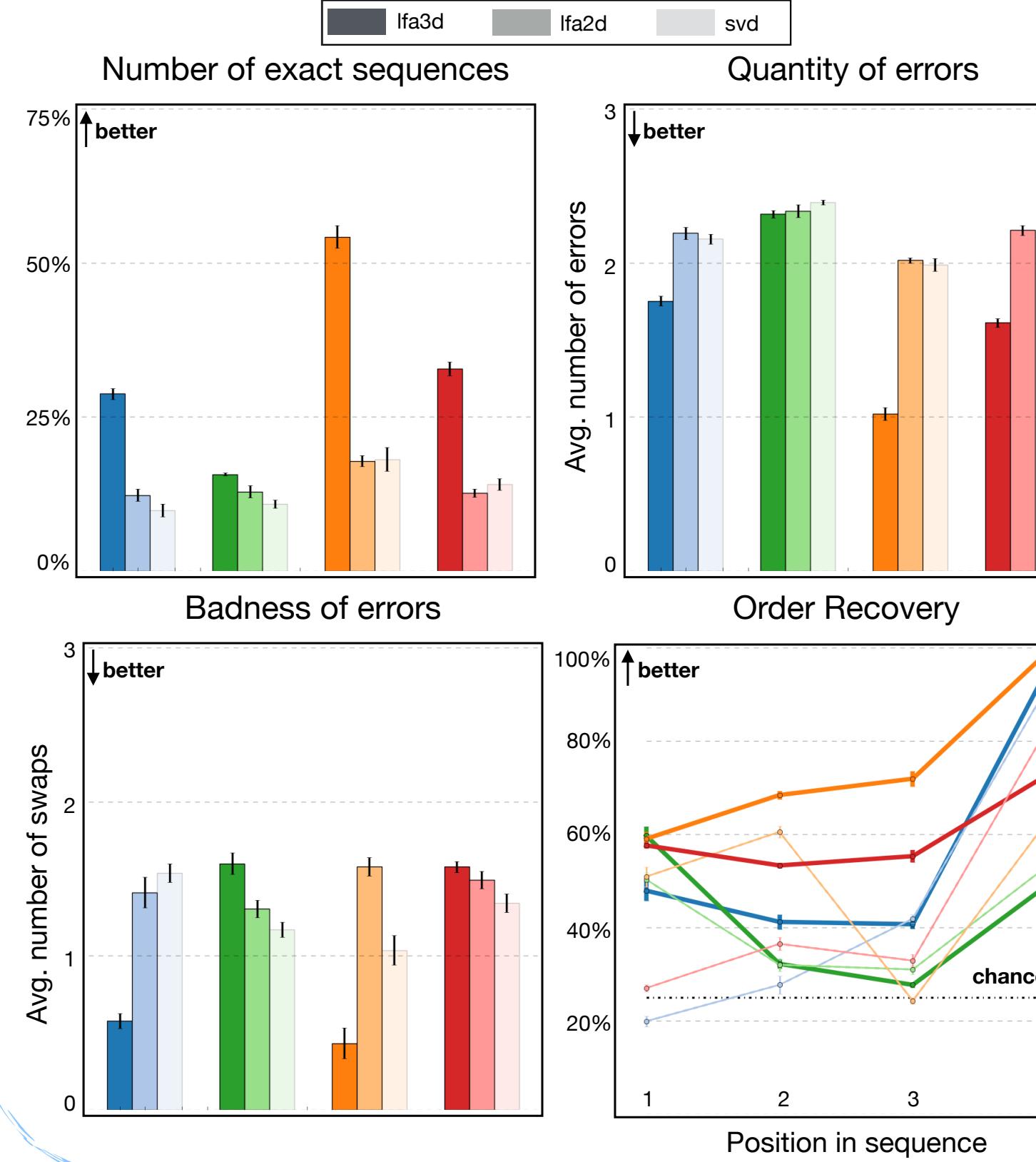
ACTIVITY RECOGNITION



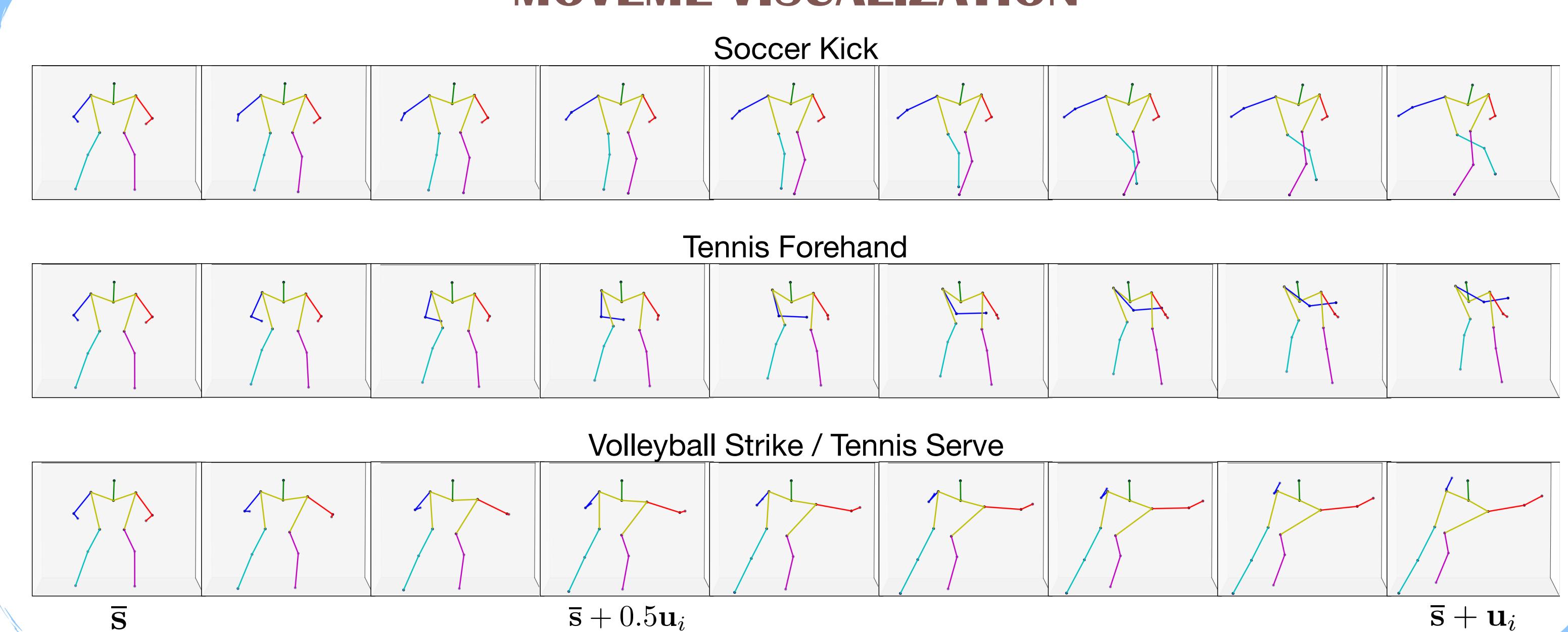
DYNAMICS INFERENCE

Method	Reordered Sequence	Errors	Swaps
Ifa3d		0	0
Ifa2d		2	1
svd		2	3

Legend: Baseball pitch, Tennis forehand, Tennis serve, Baseball swing



MOVEME VISUALIZATION



MANIFOLD VISUALIZATION

