A Rotation Invariant Latent Factor Model for Moveme Discovery from Static Poses

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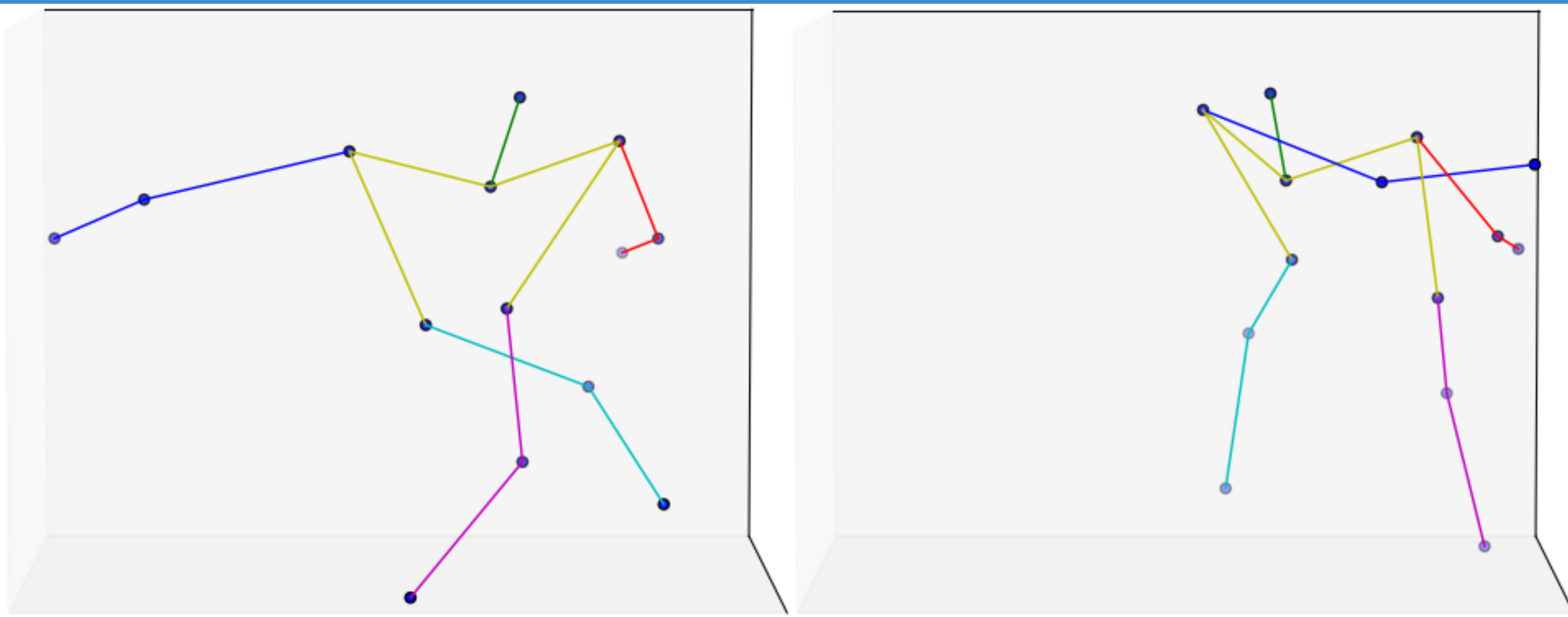
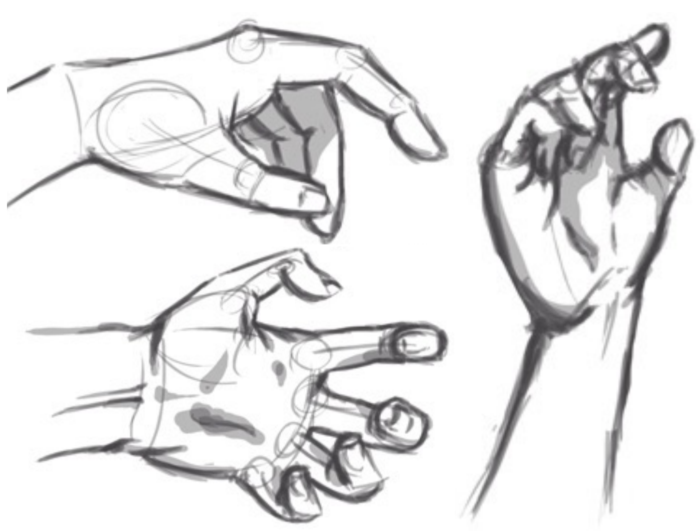


Human Movements

A priori unrestricted except for physically imposed joint angle limits.

Observable at different levels of detail:

- **Moveme:** short target-oriented trajectory ('reach','grasp','lift').
- **Action:** predefined ordered sequence of movemes ('drink from a cup','open a door').
- **Activity:** stochastic combination of actions over time ('dine','read','drive').



State of Human Movement Analysis

We know a lot from images*:

soccer | competition | football | athlete
match | man | stadium | adult | ball
uniform | outfit | soccer player
sports equipment | action | soccer field
web | game

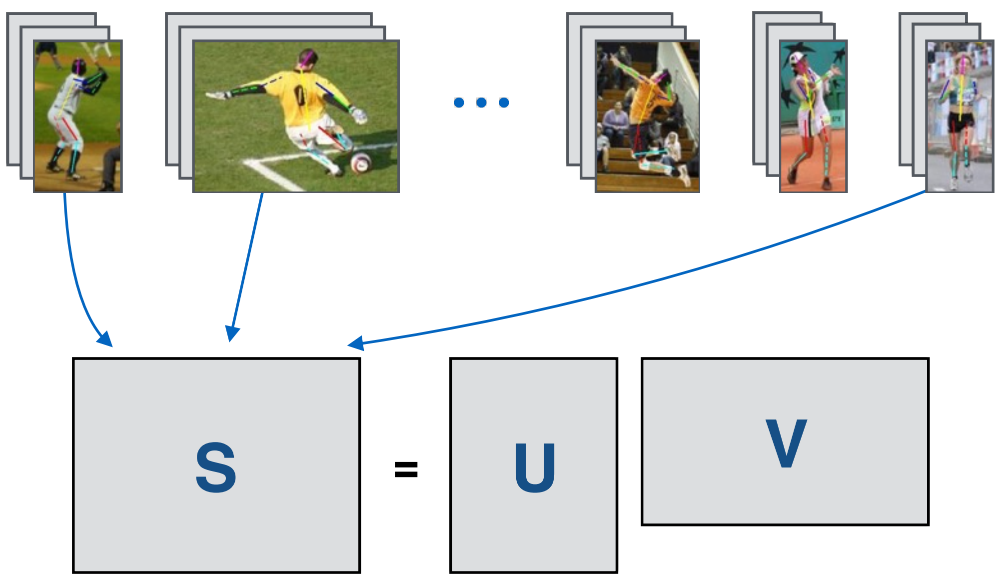
*clarifai.com

However, human behaviour is difficult to analyze at a *fine scale of dynamics*:

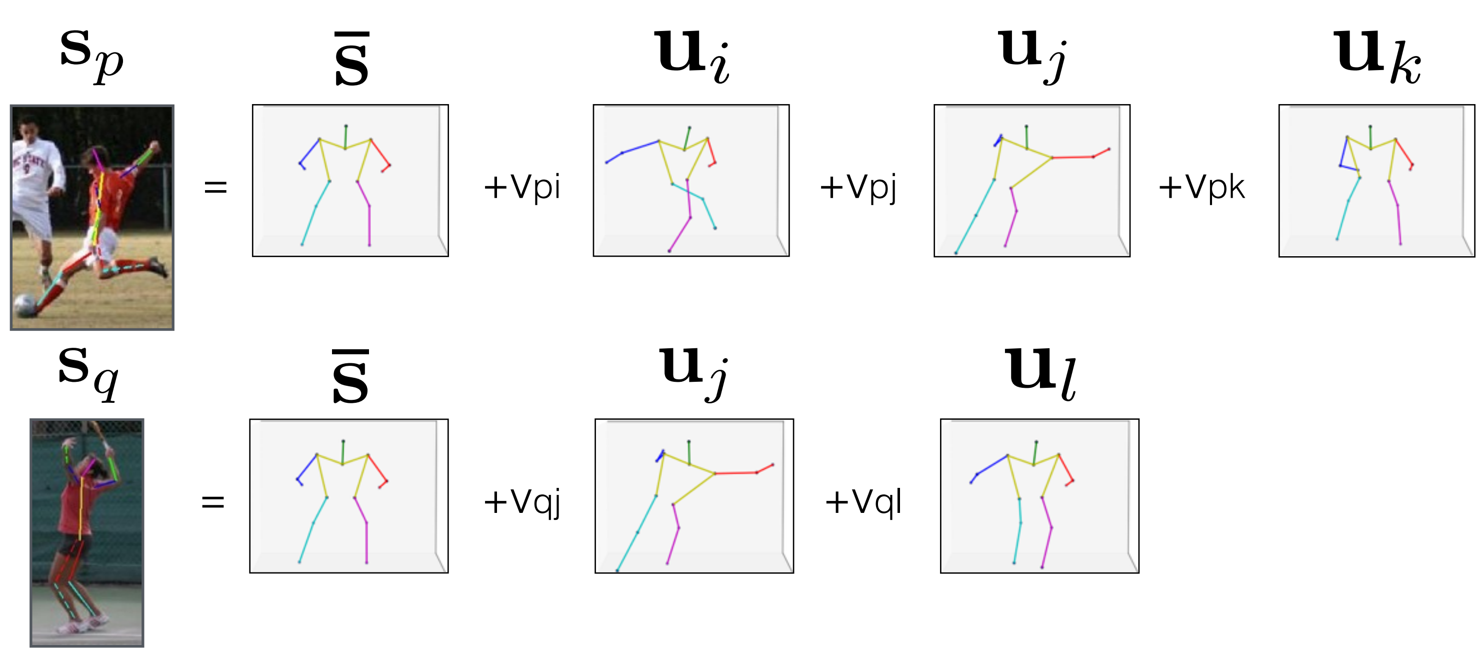
- What are the typical ranges of motion for the human body?
- What type of leg movements correlate with specific shoulder positions?
- How can we expect the arms to move given the current body pose?

Automatic Moveme Discovery

Our primary goal is to learn a global basis to smoothly capture movemes from a collection of 2-d joints.

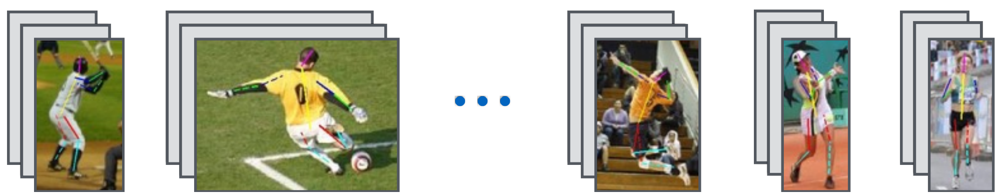


- Rotation Invariant
- Sparse
- Good Generalization
- Complementary Representation



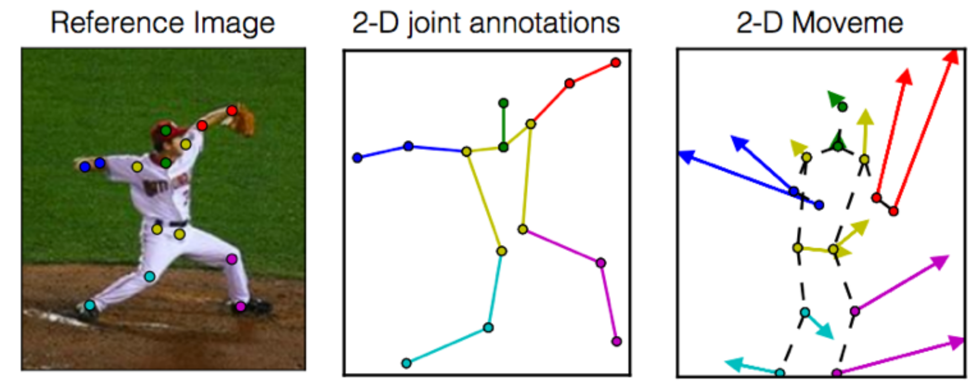
Framework and Model

LSP data: 2000 images 8 activities



$\mathbf{S} = \{(\mathbf{x}_j, \mathbf{y}_j)\}_{j=1}^{n} \qquad \mathbf{S} \in \Re^{2d \times n}$

Movemes: displacement from the mean pose



Rotation Invariant 3D Latent Factor Model:

- **Factorization into a pose basis matrix U and a coefficient matrix V**

S = **U** **V**

$\mathbf{U} \in \Re^{3d \times k}$

$\mathbf{V} \in \Re^{k \times n}$

- global and 3d

$$arg\,min_{\mathbf{U},\mathbf{V},\theta} \mathcal{E}(\mathbf{U},\mathbf{V},\theta) + \lambda_U \|\mathbf{U}\|_F^2 + \lambda_V \|\mathbf{V}\|_1$$

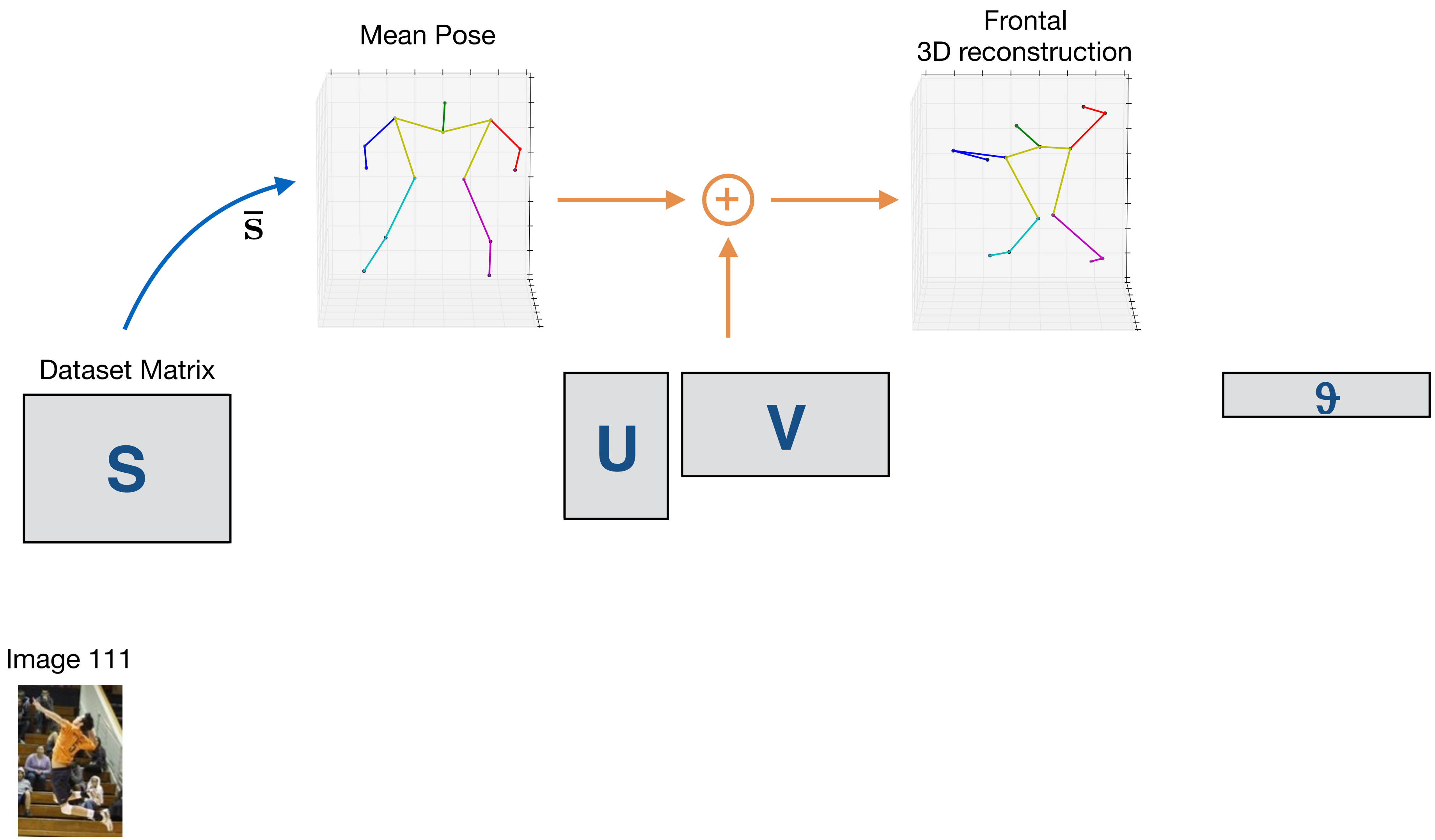
- sparse

$$\mathcal{E}(\mathbf{U},\mathbf{V},\theta) = \sum_j (\mathbf{s}_j - \underline{f(\bar{\mathbf{s}} + \mathbf{U} \cdot \mathbf{v}_j, \theta_j)})^2$$

- rotation invariant

- ϑj: angle of view estimate
- f: rotation + projection

3D Latent Factor Model Optimization



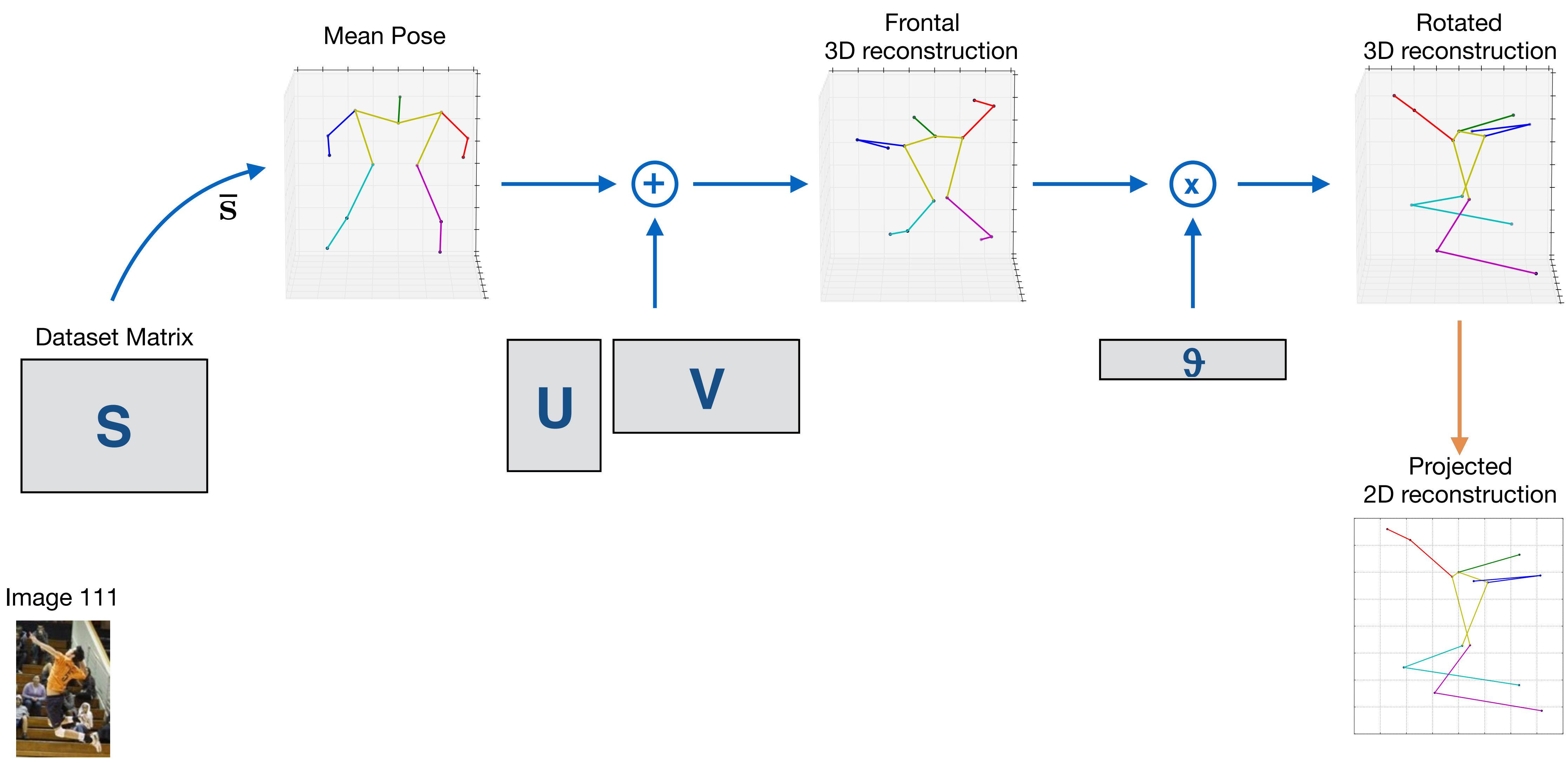
Initialization:

- **U:** random between -1,1
- **V:** random between 0,1
- **ϑ:** heuristic

Frontal Reconstruction:

$$\widetilde{\mathbf{s}}_{111} = \bar{\mathbf{s}} + \mathbf{U} \cdot \mathbf{v}_{111}$$

3D Latent Factor Model Optimization



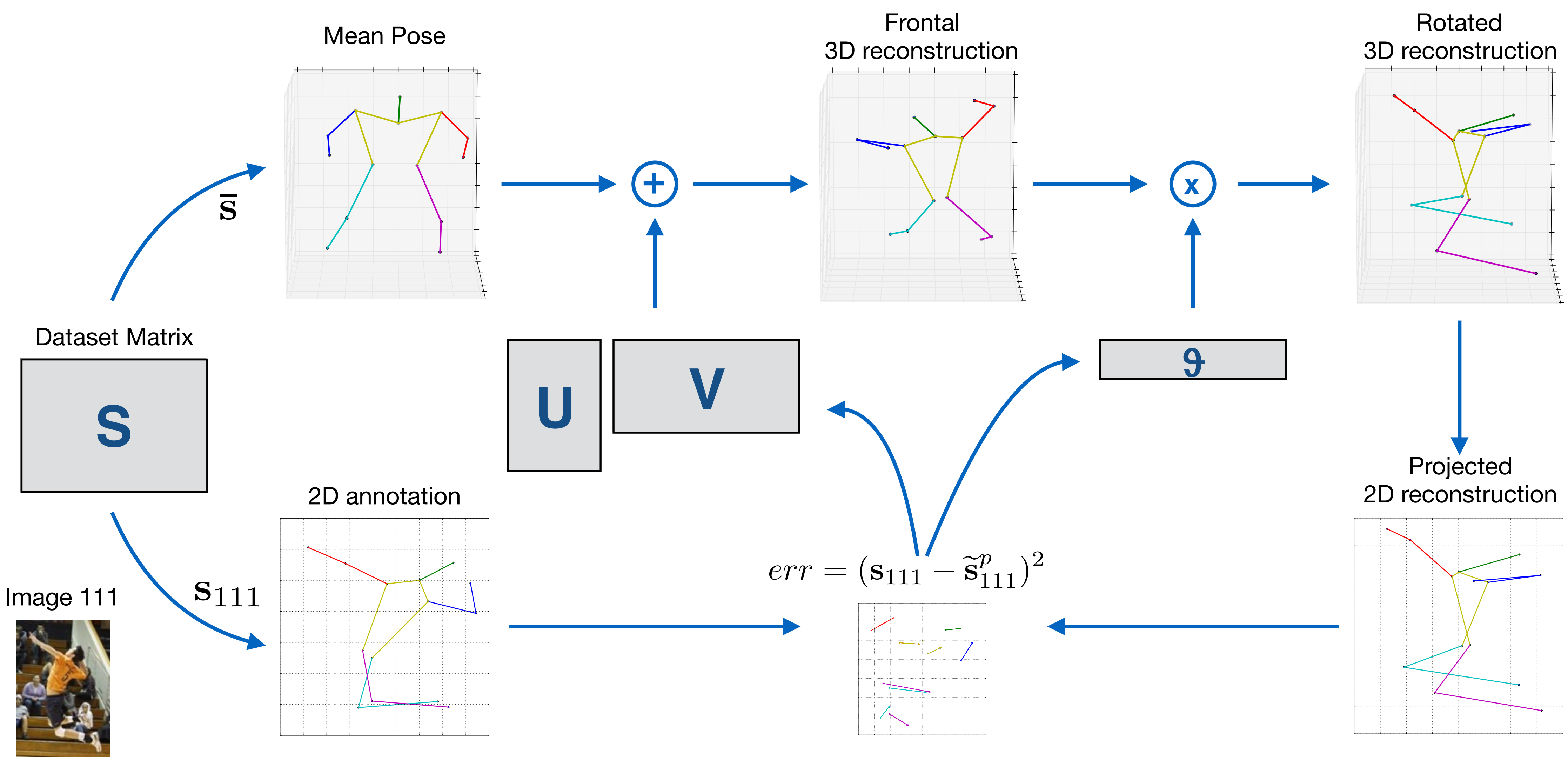
Rotation:

$$\widetilde{\mathbf{s}}^{\mathbf{r}}_{111} = \mathbf{Q}(\theta_{111}) \cdot \widetilde{\mathbf{s}}_{111}$$

Projection:

$$\widetilde{\mathbf{s}}^{p}_{111} = \left[\widetilde{\mathbf{s}}^{\mathbf{r},(\mathbf{x})}_{111}, \widetilde{\mathbf{s}}^{\mathbf{r},(\mathbf{y})}_{111}\right]$$

3D Latent Factor Model Optimization



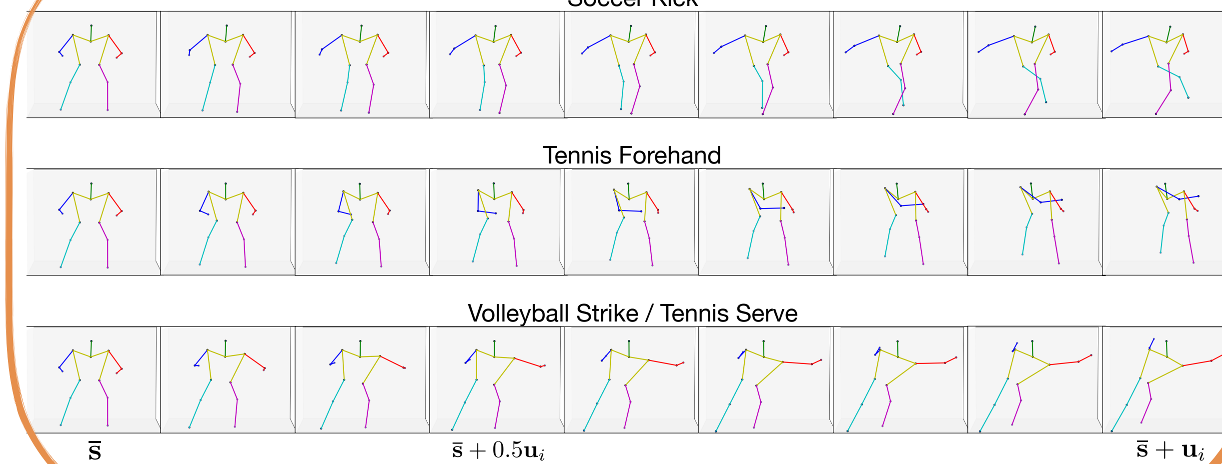
Alternate Gradient Update:

- **Representation:** $\dfrac{\delta err}{\delta \mathbf{U}}$ $\dfrac{\delta err}{\delta \mathbf{V}}$
- **Angle of view:** $\dfrac{\delta err}{\delta \theta}$

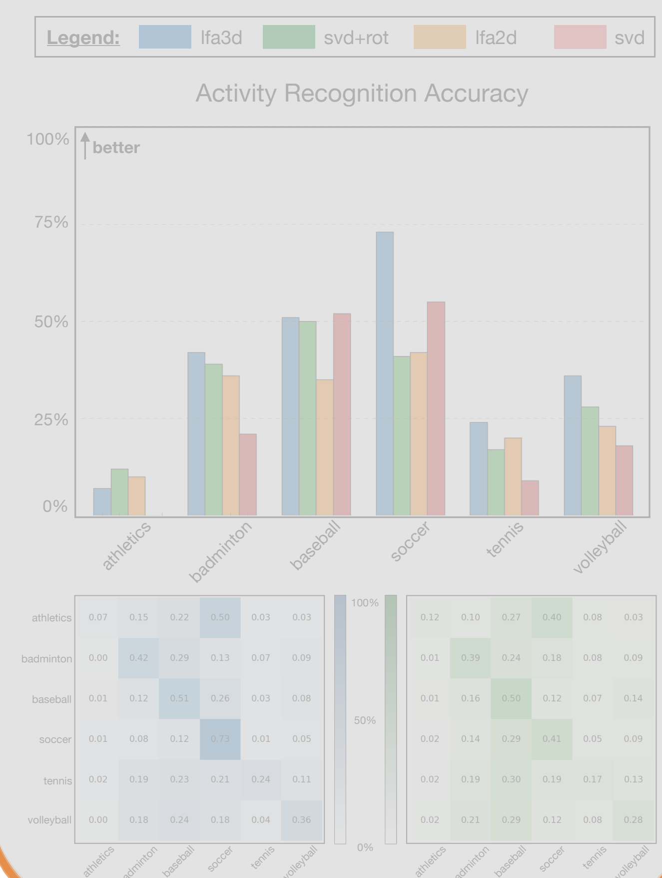
Experiments

OPTIMIZATION DETAILS

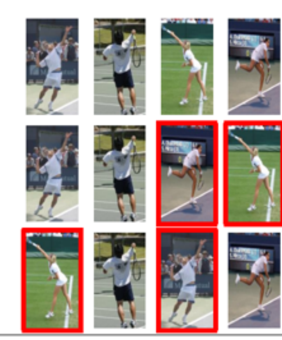
MOVEME VISUALIZATION



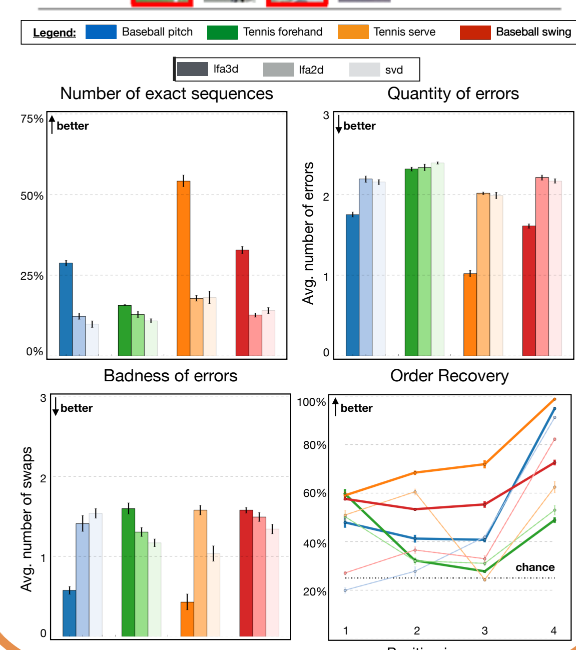
ACTIVITY RECOGNITION



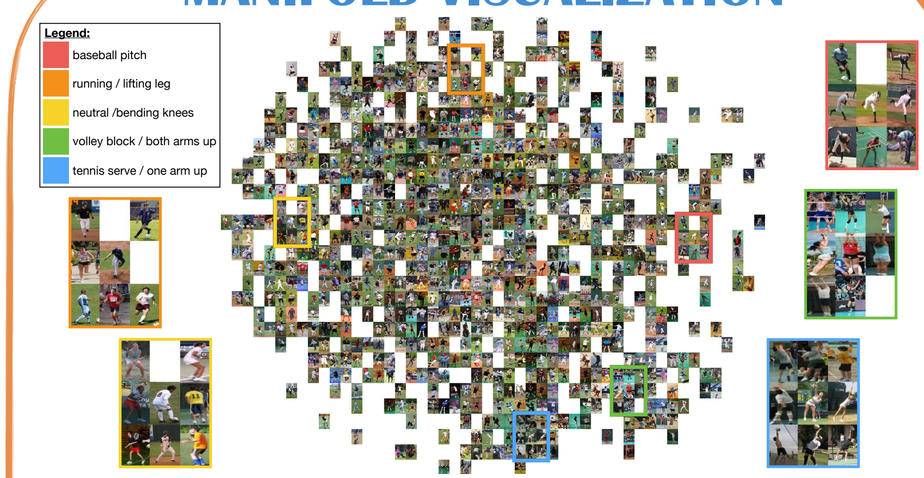
DYNAMICS INFERENCE

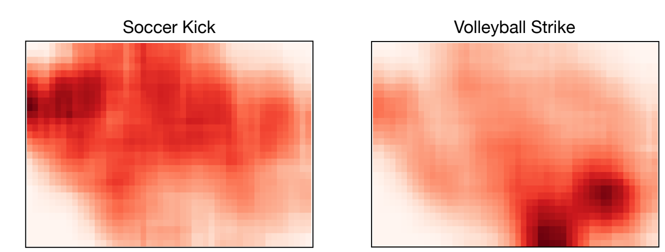


Method	Reordered Sequence	Errors	Swaps
lfa3d		0	0
lfa2d		2	1
svd		2	3



MANIFOLD VISUALIZATION



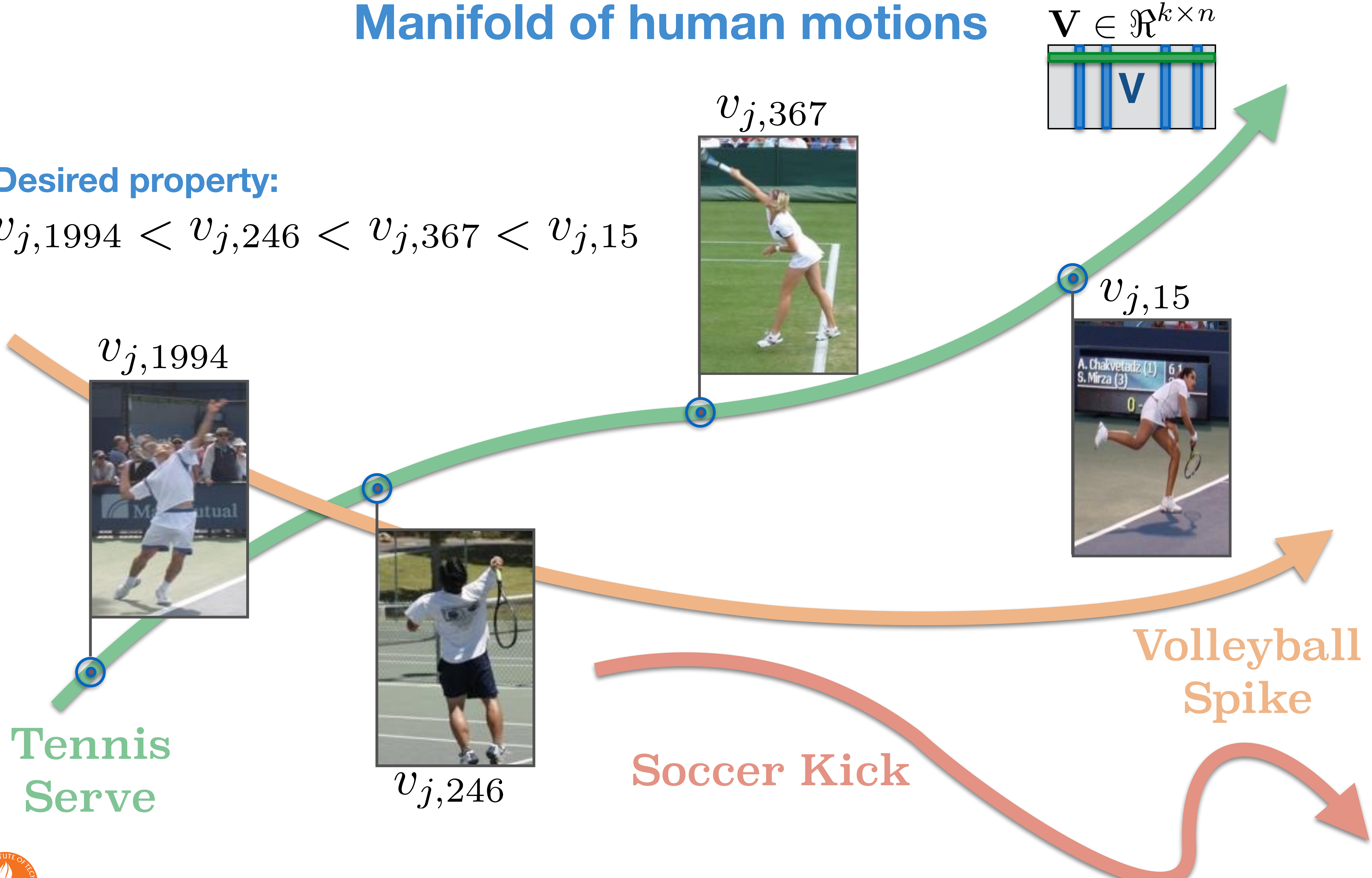


Action Dynamics Inference

Manifold of human motions

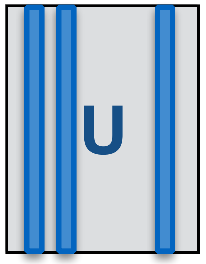
Desired property:

$$v_{j,1994} < v_{j,246} < v_{j,367} < v_{j,15}$$



Moveme Visualization

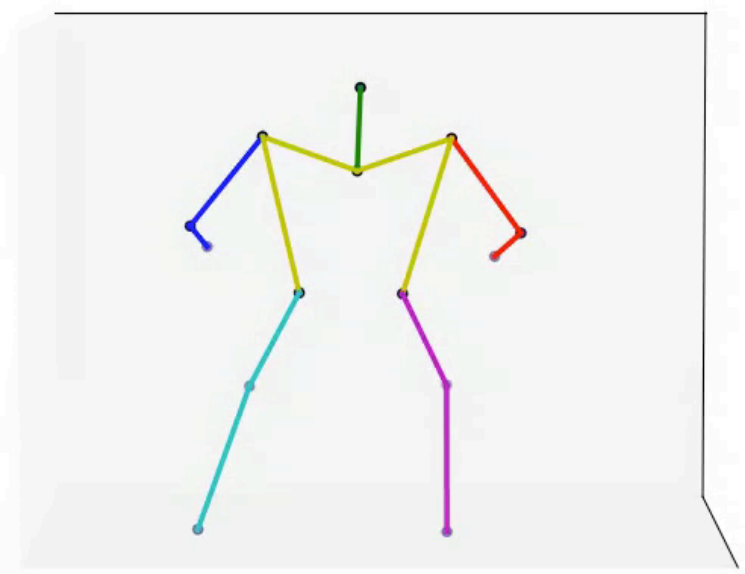
$\mathbf{U} \in \Re^{3d \times k}$



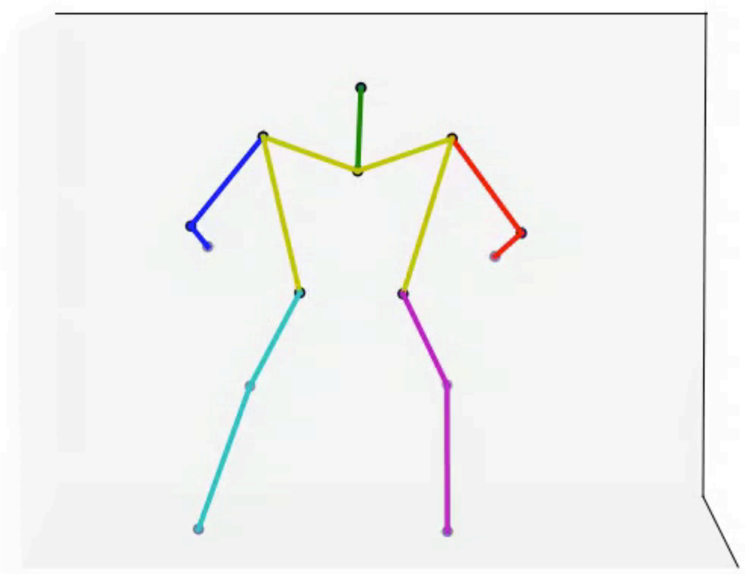
We can synthesize realistic human motions from static joint locations in images with the matrix U:

- **By adding an increasing percentage of a basis to the mean pose.**

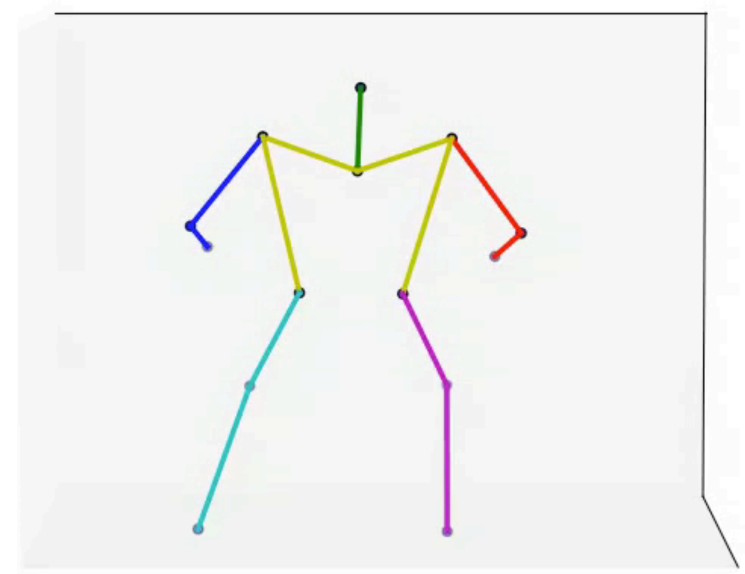
Soccer Kick



Volleyball Spike



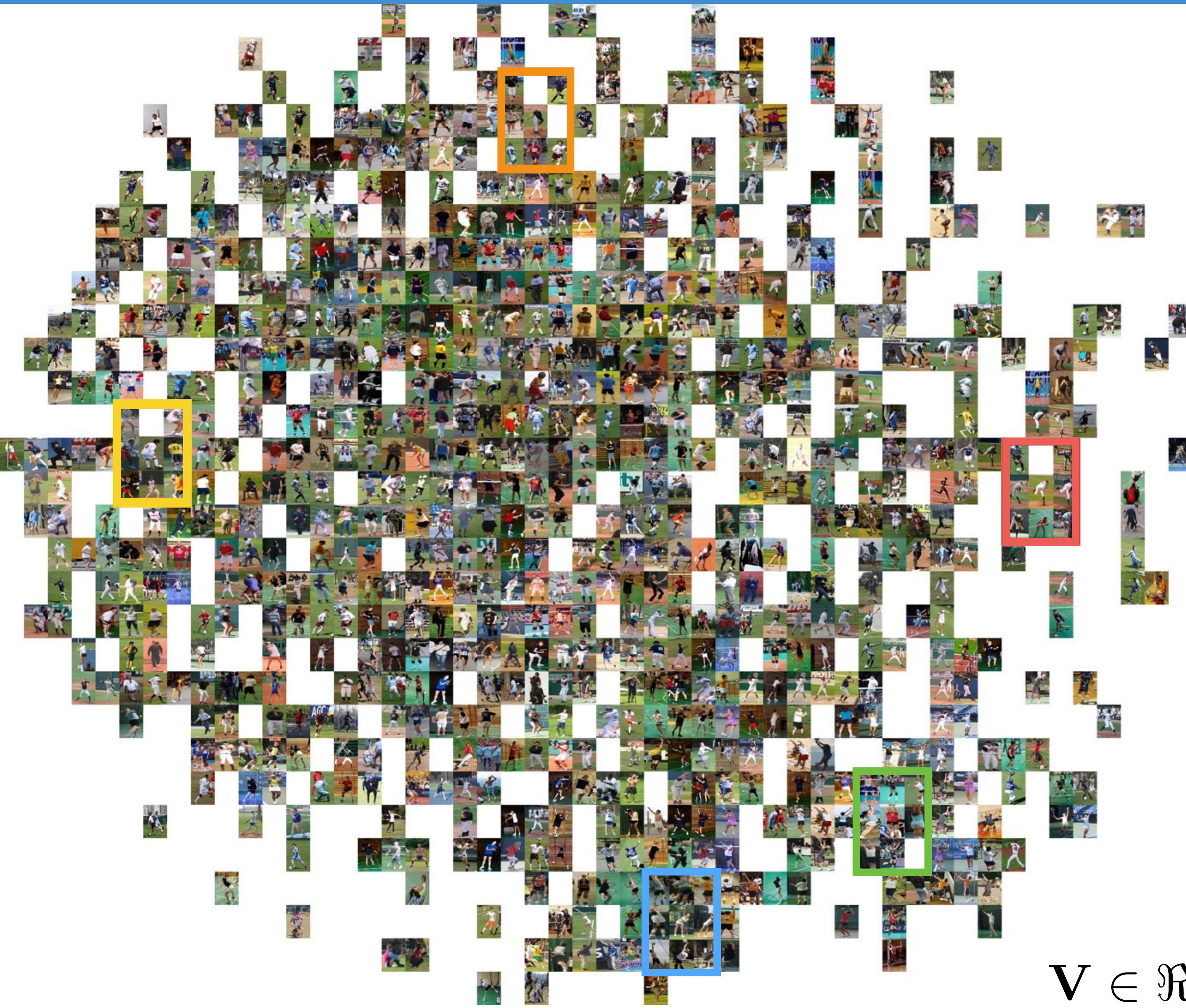
Tennis Forehand



Two parameters mainly affect visualization quality:

- **Number of latent factors:** set as the number of movemes in the data.
- **Coefficients of the V matrix:** constrained between 0 and 1.

Manifold Visualization

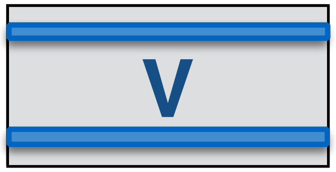


Legend:

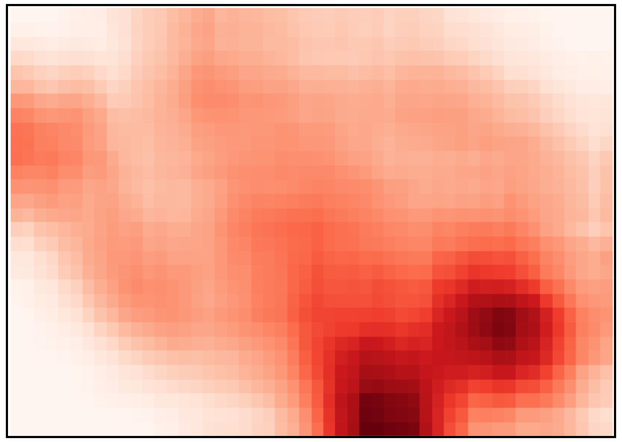
- baseball pitch
- running / lifting leg
- neutral /bending knees
- volley block / both arms up
- tennis serve / one arm up

bending knees lifting leg
baseball pitch
volleyball block tennis serve

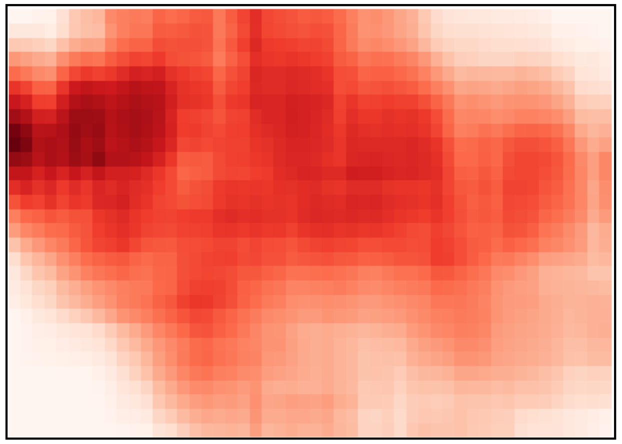
$$\mathbf{V} \in \Re^{k \times n}$$



Volleyball Strike



Soccer Kick



Summary

We developed an algorithm that can learn a 3-d basis for human movemes with the following properties:

- Global
- Rotation Invariant
- Sparse
- Complementary Representation

Limitations and possible improvements:

- Fixed number of latent factors
- Needs a more complex initialization
- End-to-end pose denoising and moveme learning
- Incorporate symmetry into movemes
- Apply to larger and more general/higher dimensional datasets

Questions?

Fork me on GitHub

github.com/matteorr/rotation_invariant_movemes