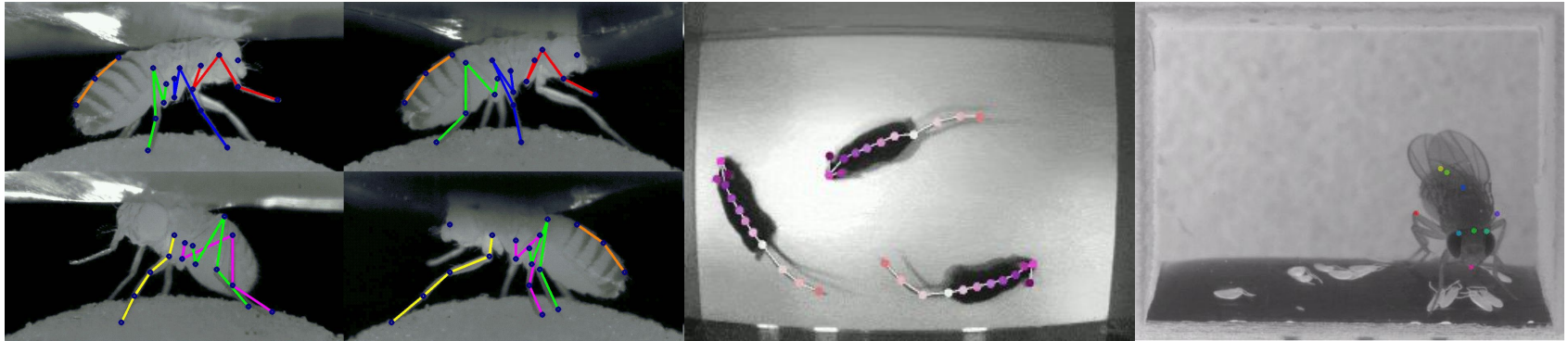


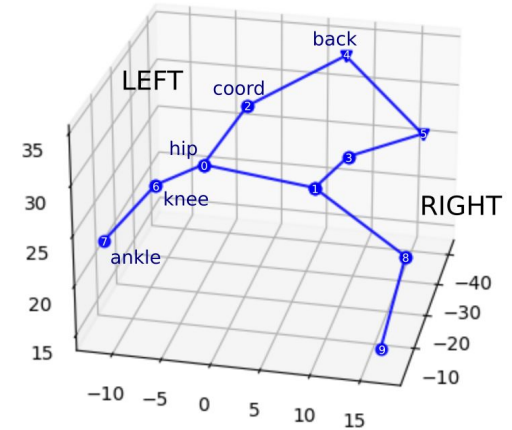
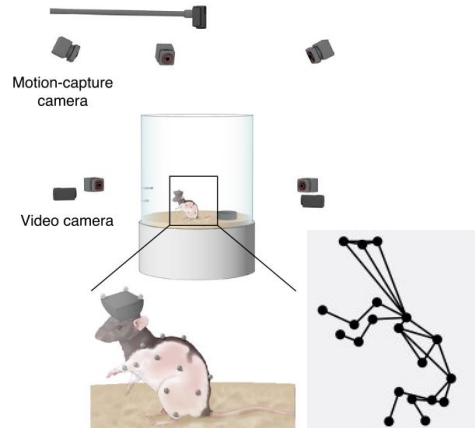
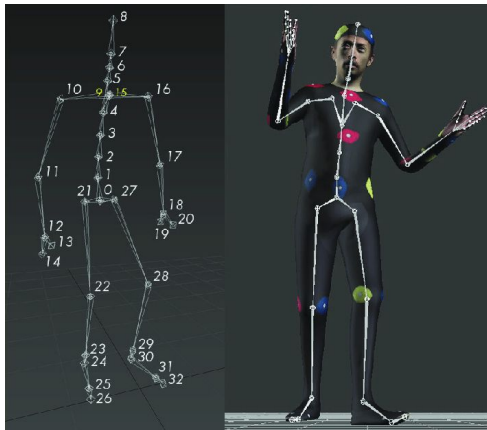
Uncertainty aware SSL on multi-dimensional time series for animal behavior

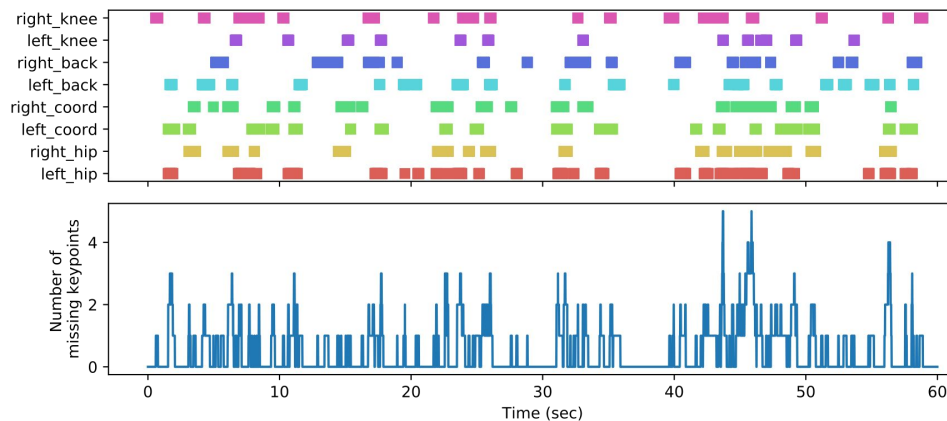
France Rose, Ph.D.
Data Science of Bioimages, Prof. Bozek
University of Cologne, Germany

Video Pose Estimation



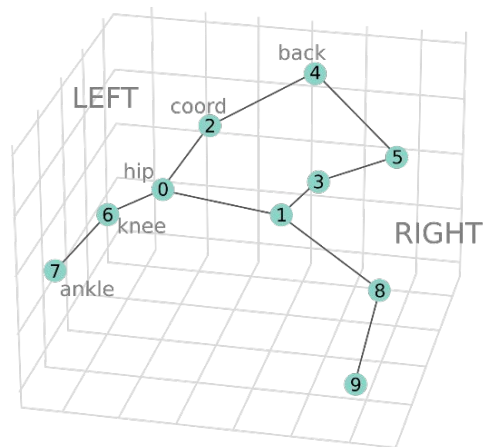
Motion Capture Systems





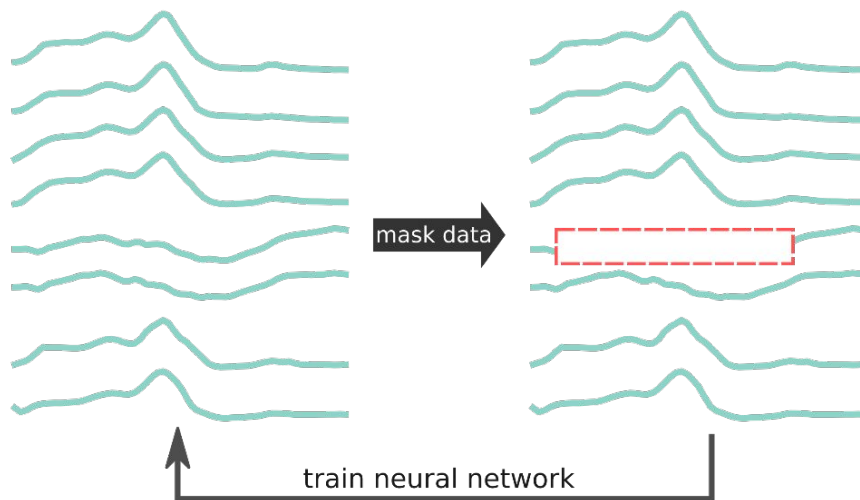
- Missing keypoints in behavior analysis are dropped
- Existing imputation methods for general time series
- But no method developed or tested at large scale on skeleton data

Unsupervised training and testing scheme

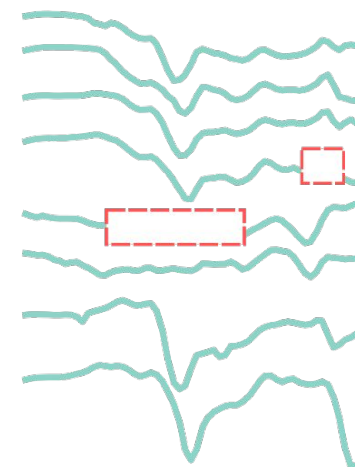


a.

TRAINING ON MASKED DATA



INFERENCE ON REAL MISSING DATA

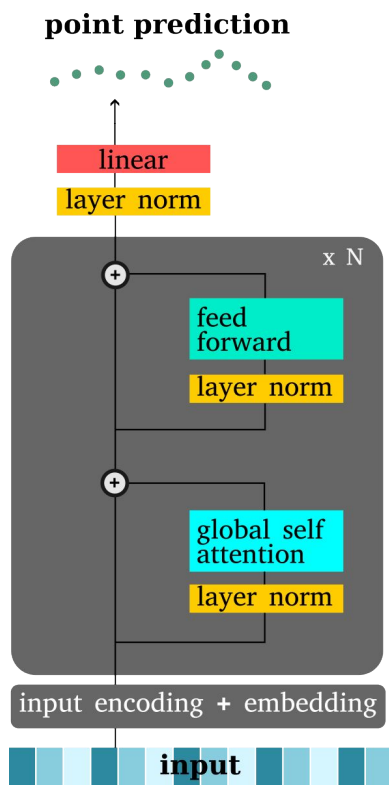


b.

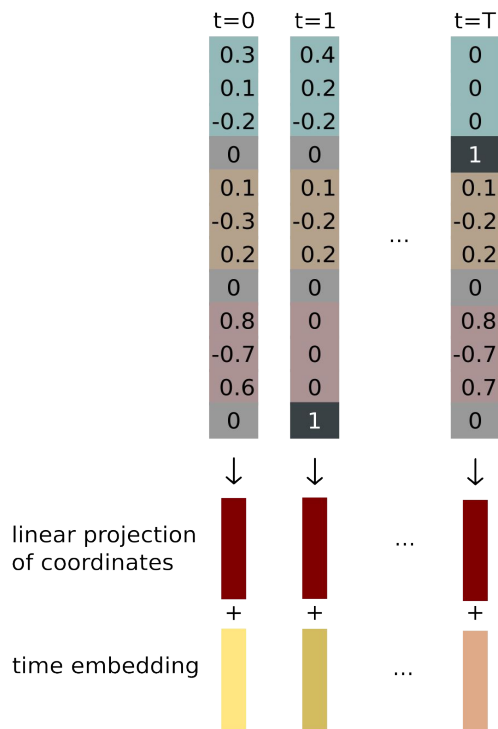
Tested algorithms

- Linear interpolation (Baseline)
- 5 different Neural Networks
 - Recurrent neural network (GRU)
 - Temporal Convolutional Network (TCN)
 - Graph Convolutional Networks
 - Spatio-temporal GCN
 - Space-Time-Separable GCN
 - Custom Transformer (DISK)

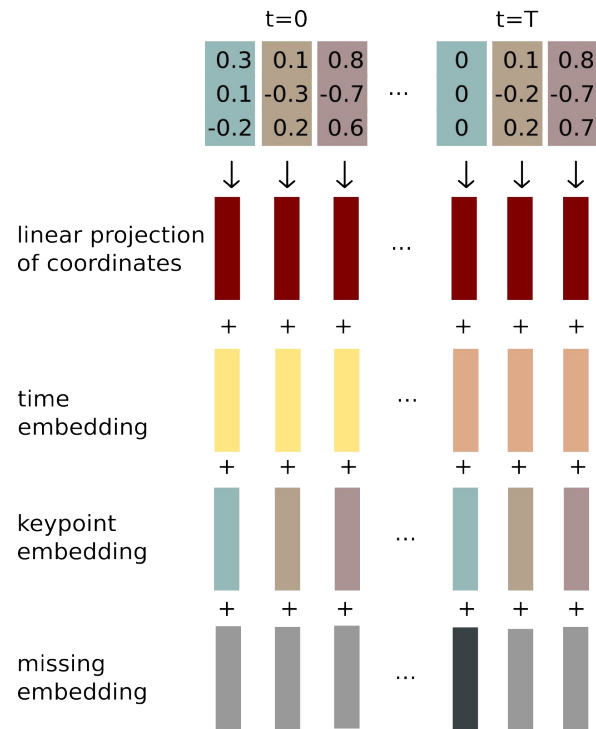
DISK architecture



Usual projection

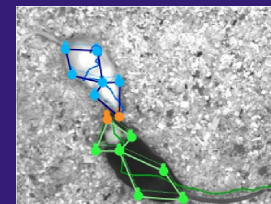
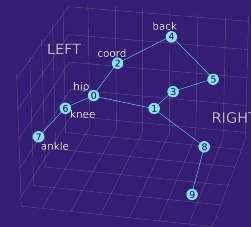
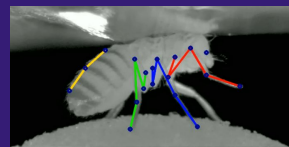


“Flattened” projection

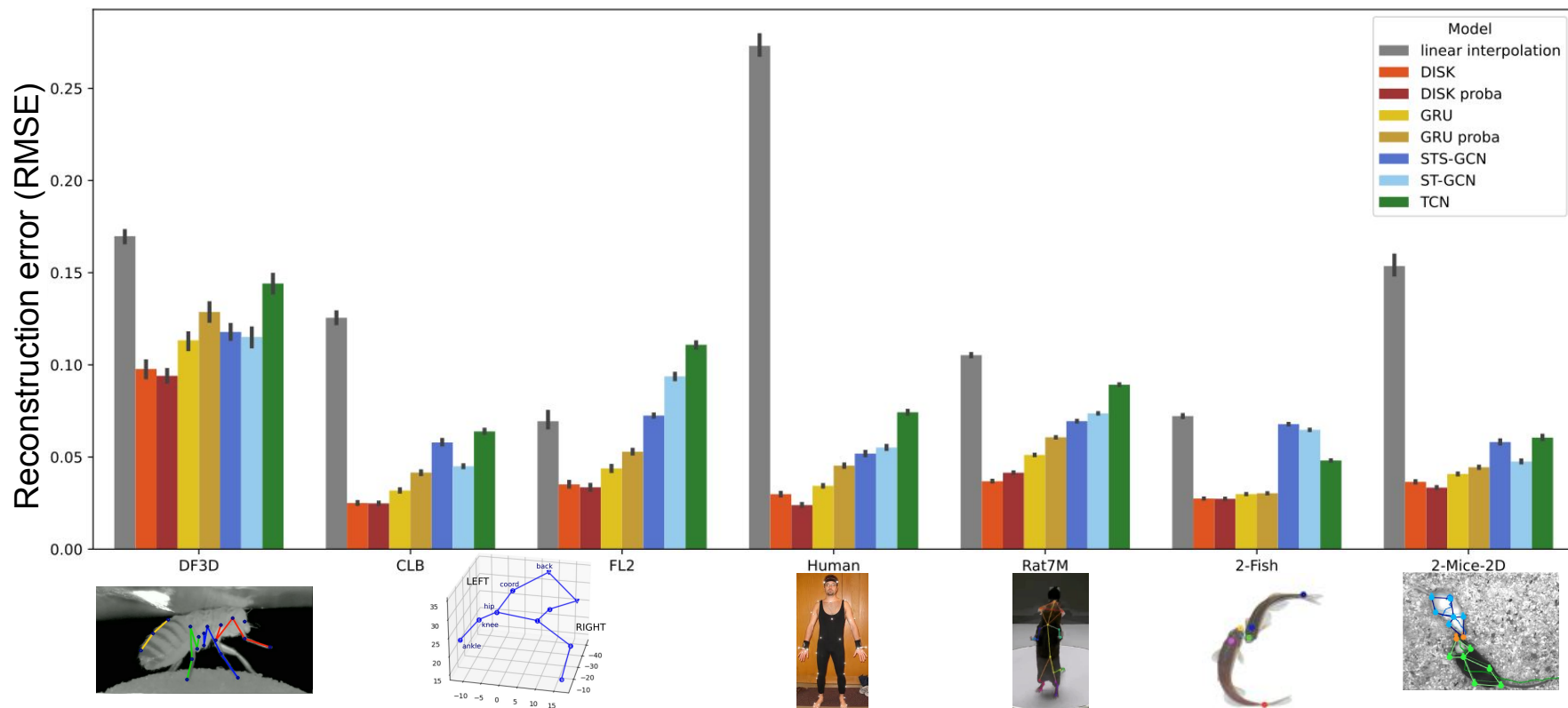


Datasets

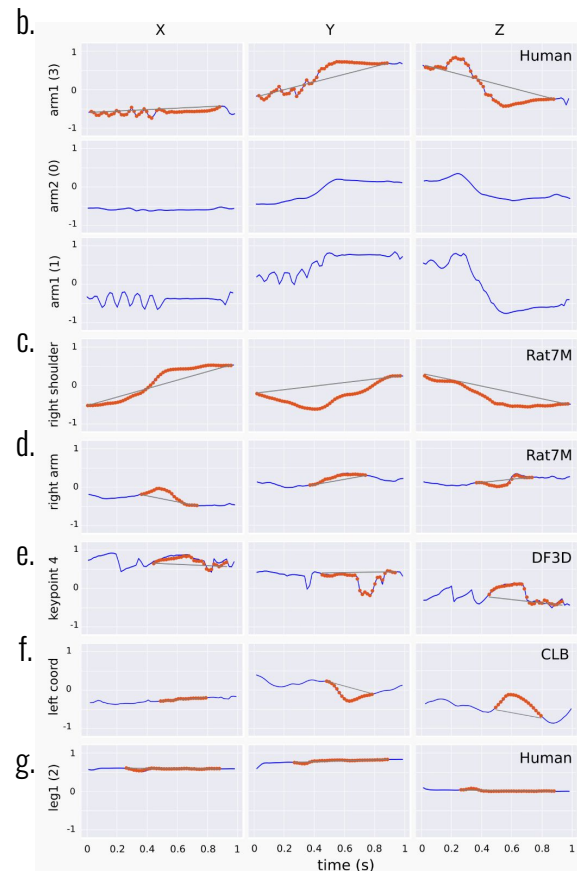
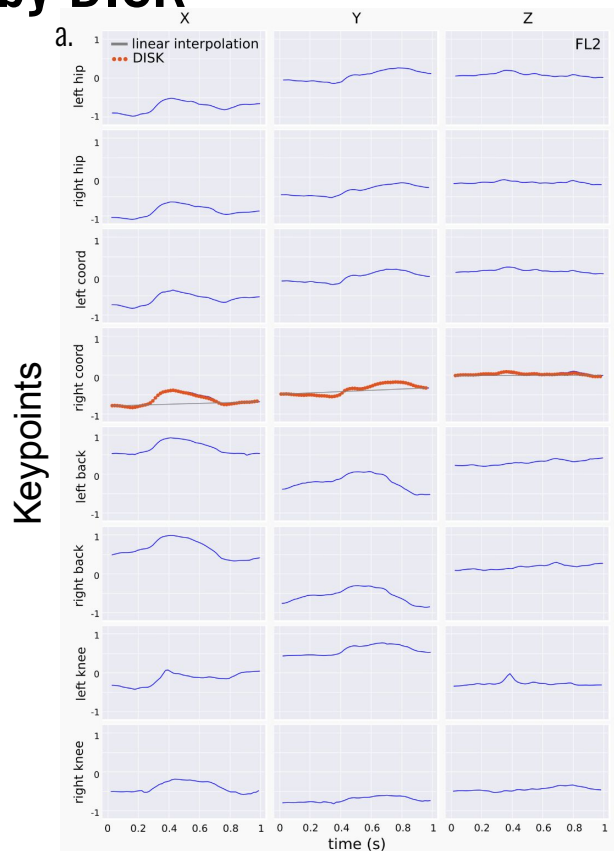
- 7 datasets
- 5 species
- 2D and 3D
- 1 to 2 animals



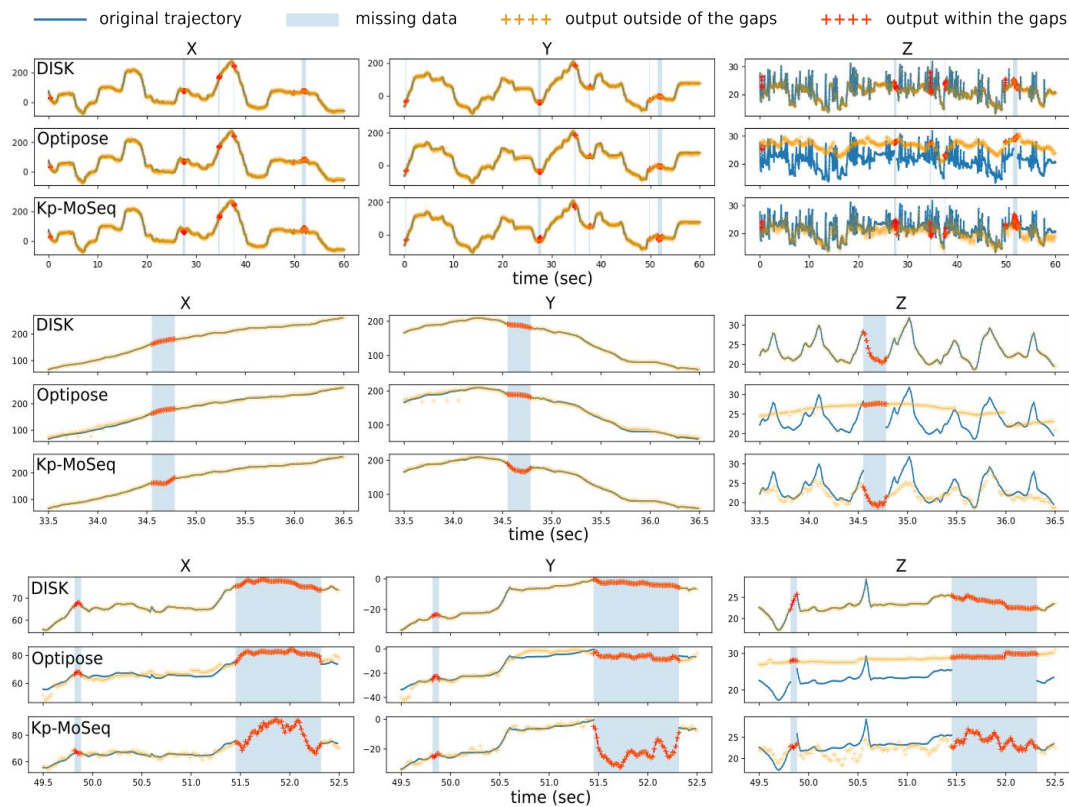
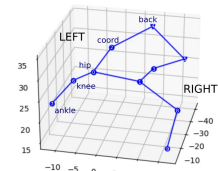
Performance on the 7 datasets



Imputation by DISK



Comparison with methods used in behavior analysis

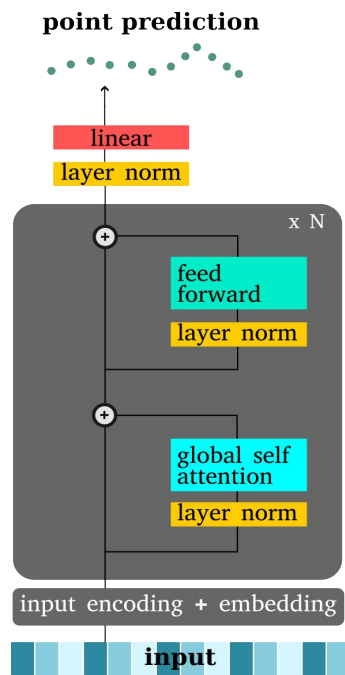


Real gaps, no ground truth

Trusting a black box model?

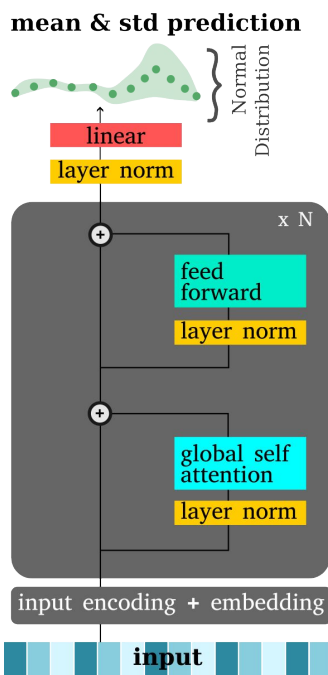
- Estimate the quality of the imputation
- Control the quality of the output dataset

Adding a probabilistic head



Output: $X_{\{k,t\}} \in \mathbb{R}^3$

L1-loss

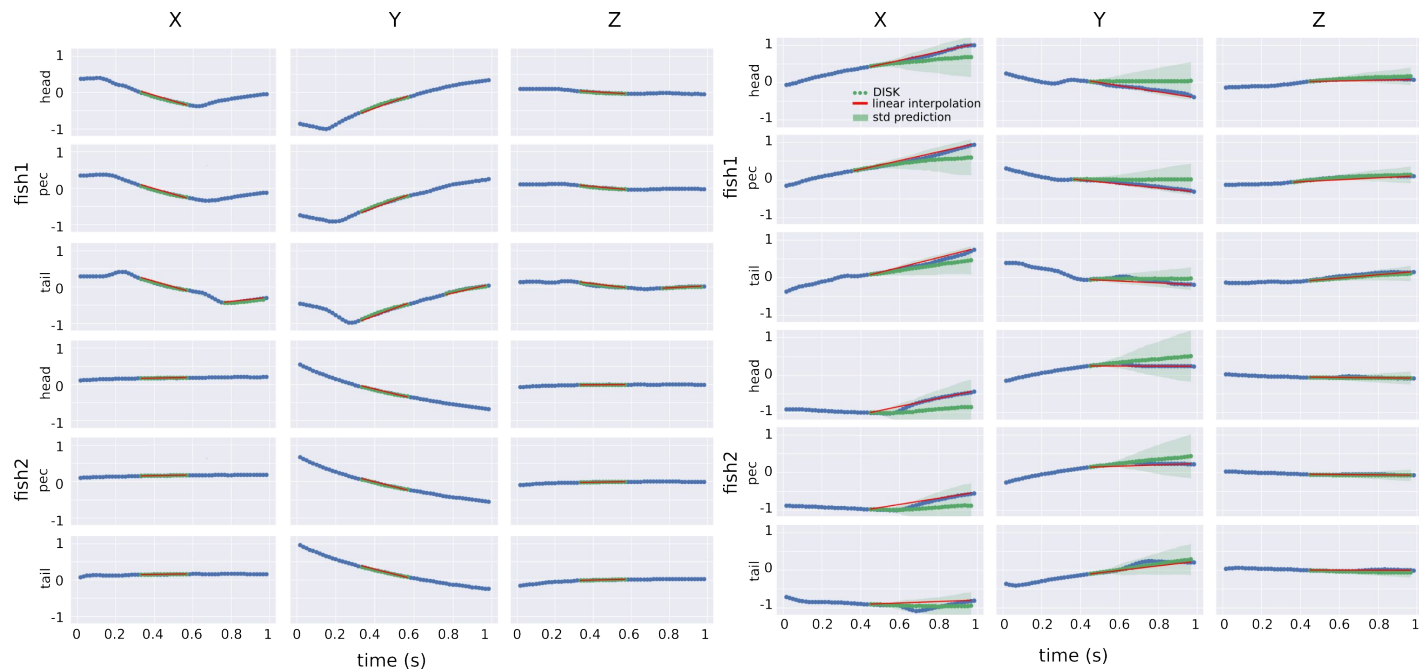
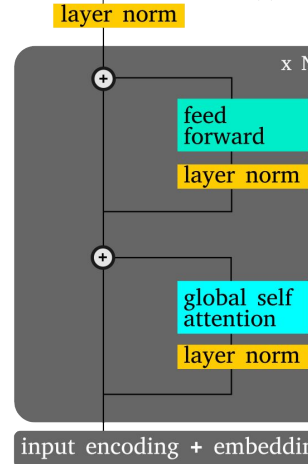
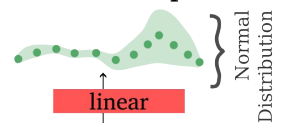


Output: $(\mu \in \mathbb{R}^3, \sigma \in \mathbb{R}^3)_{\{k,t\}}$

Negative log-likelihood loss:
 $\sum_{\{k,t\}} \frac{1}{2} (X_{GT} - \mu) / \sigma^2 - \log(\sigma)$

Estimated error on the imputed samples

mean & std prediction

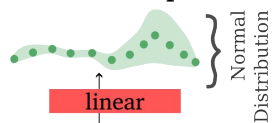


Estimated error on the imputed samples

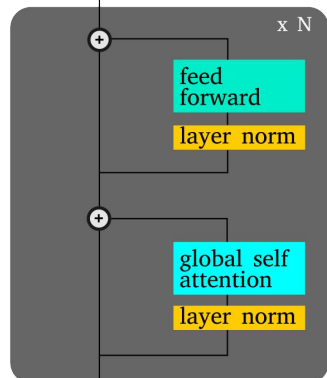
point prediction + estimated error per sample



mean & std prediction



linear
layer norm



input encoding + embedding

input



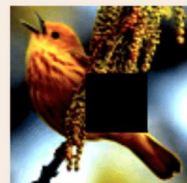
Uncertainty aware models

- Other tested approaches:
 - Ensemble
 - Variants of dropout
 - Additional branch to predict the estimated error
- Lower Pearson correlation, uncalibrated estimated error wrt real error
- Probabilistic head works better with transformer than GRU

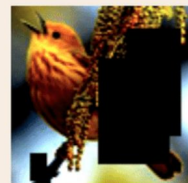
What does DISK learn?

Imputation = masking task in
Self-Supervised Learning

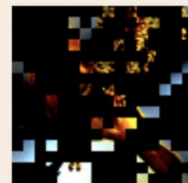
Masked Image Models



Context Encoder



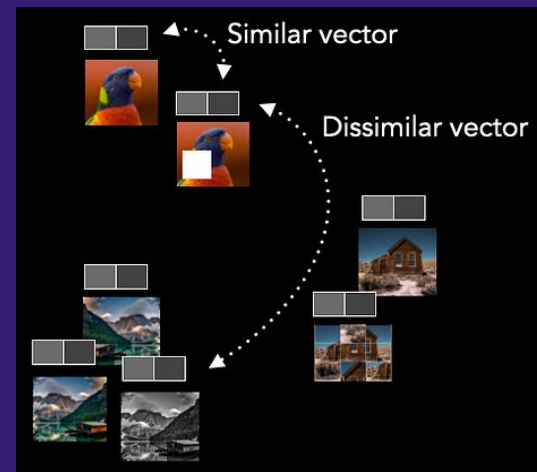
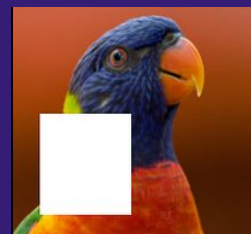
BEiT



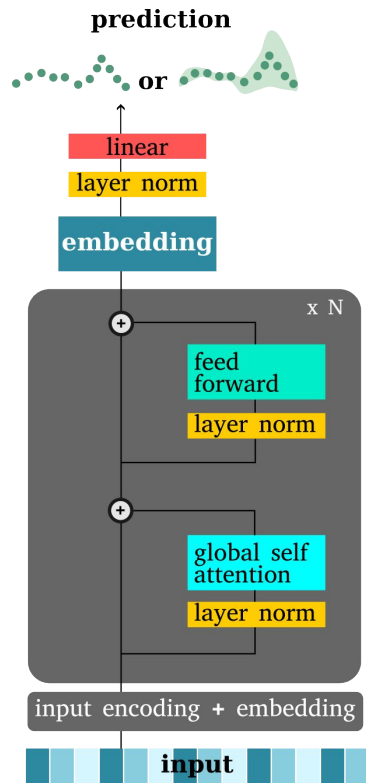
MAE



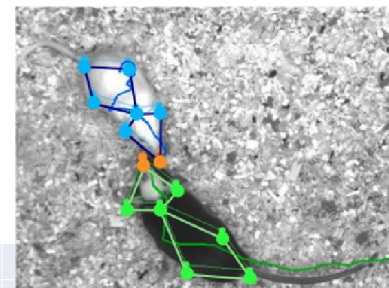
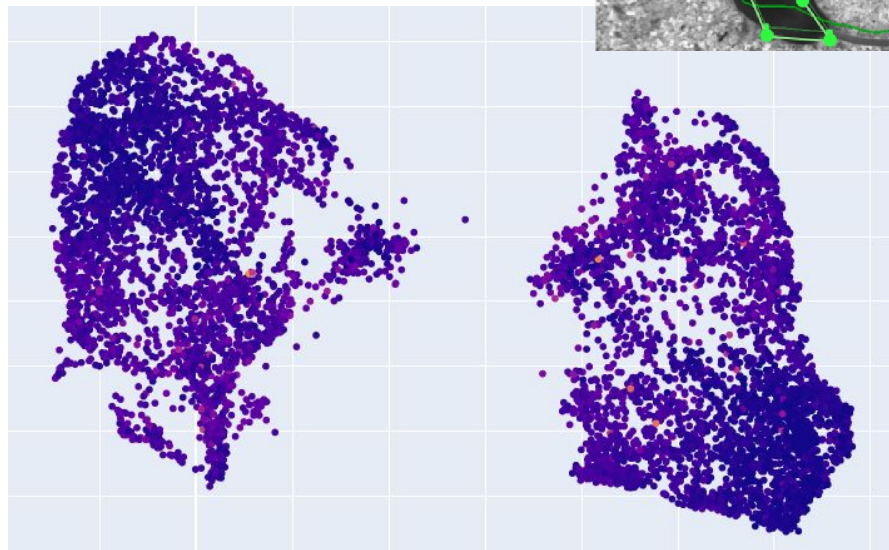
ADIOS



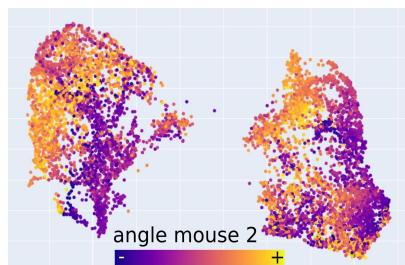
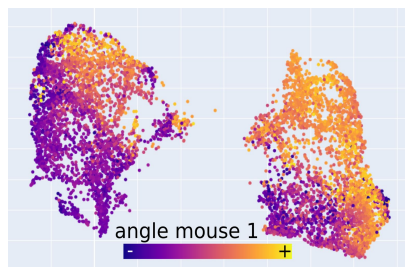
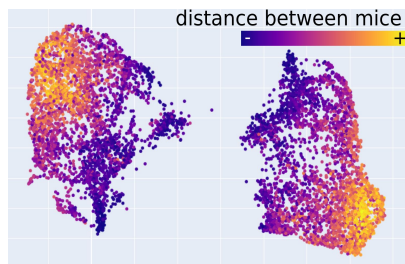
Exploring DISK learned representations



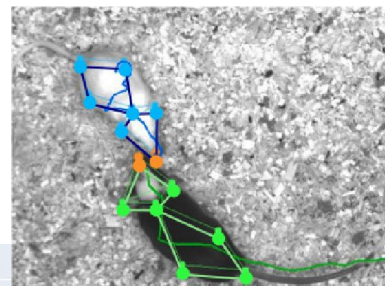
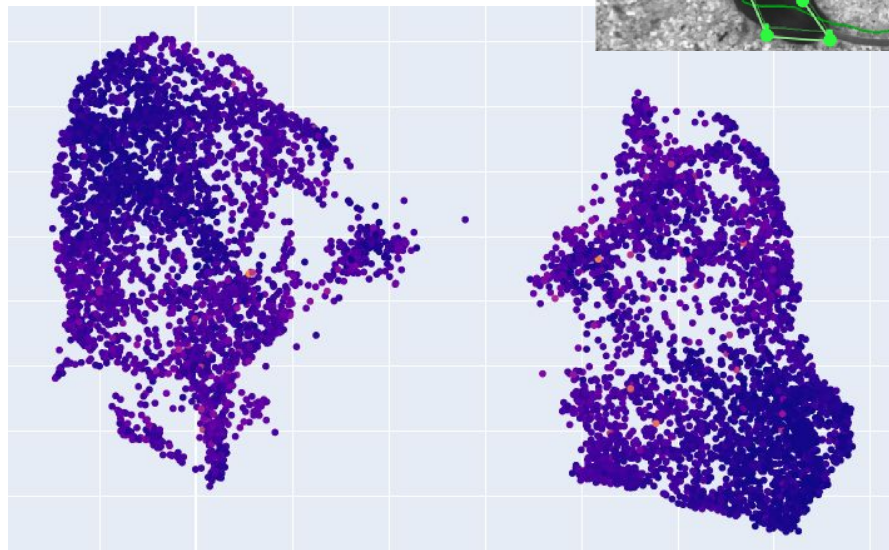
U-map of sequence embeddings



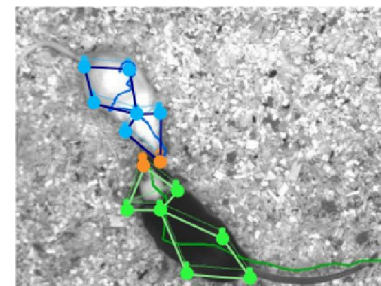
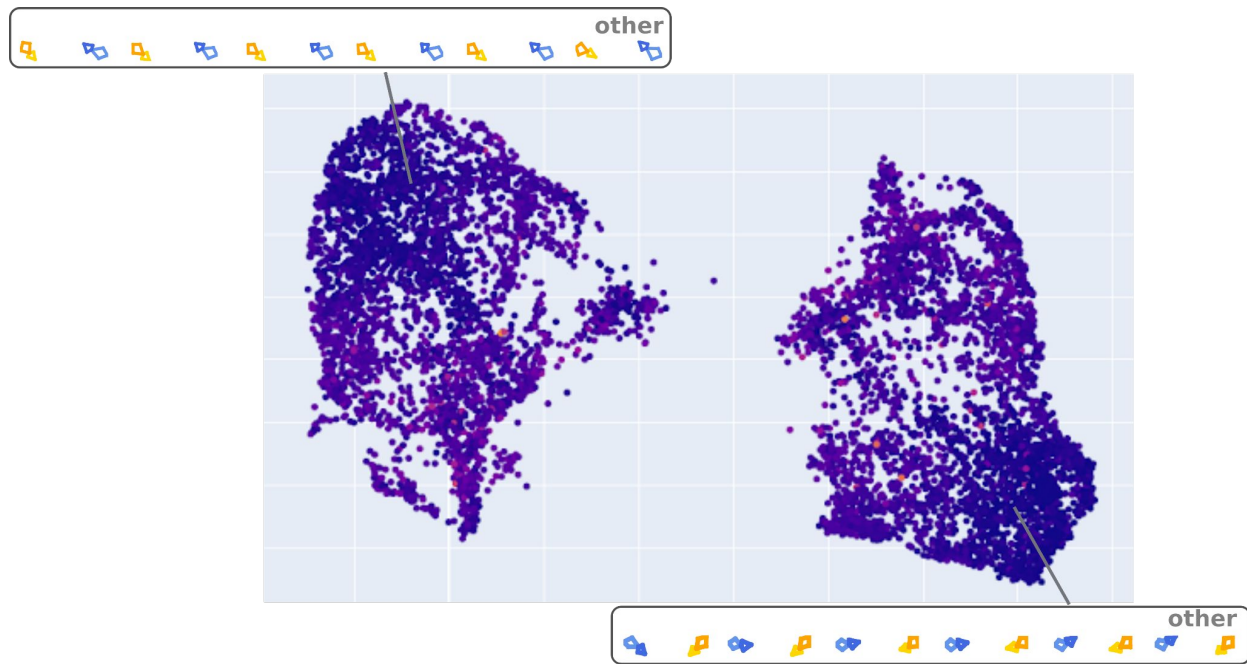
Exploring DISK learned representations



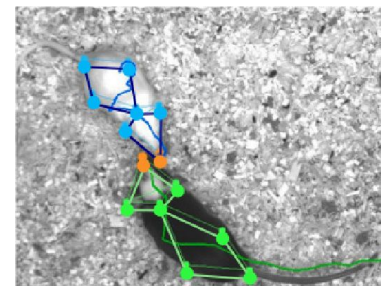
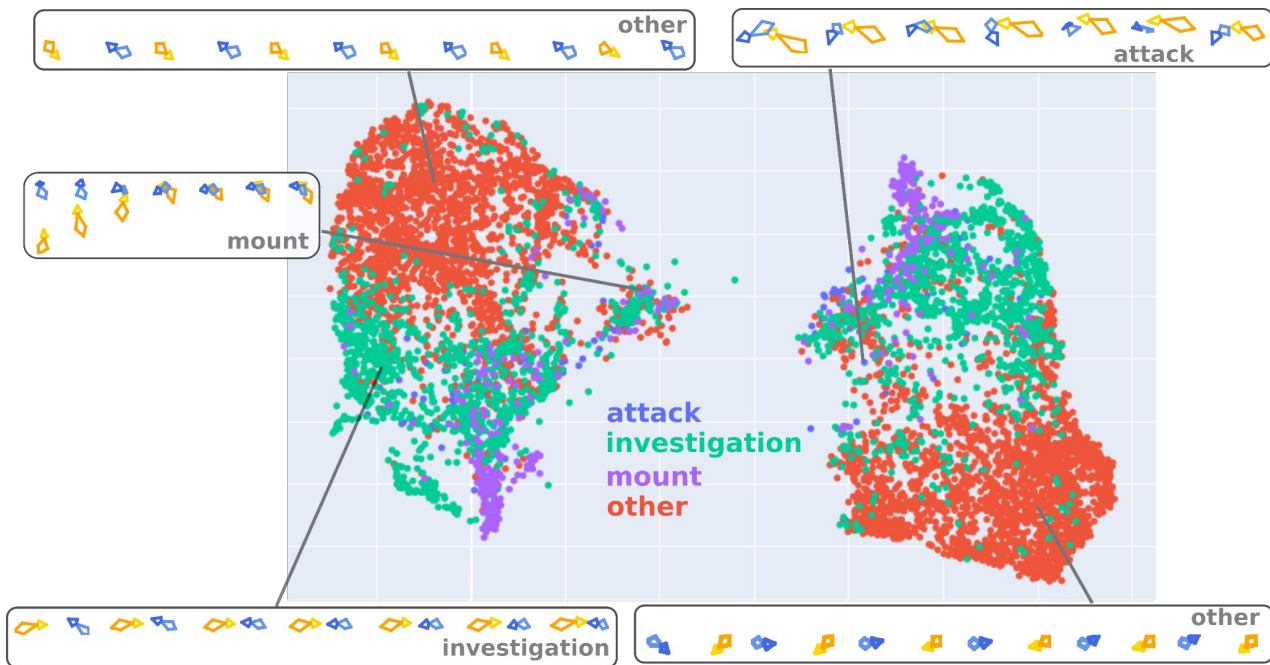
U-map of sequence embeddings



Exploring DISK learned representations



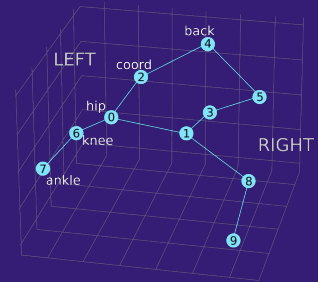
Exploring DISK learned representations



Random Forest on latent vectors
4-action class classification

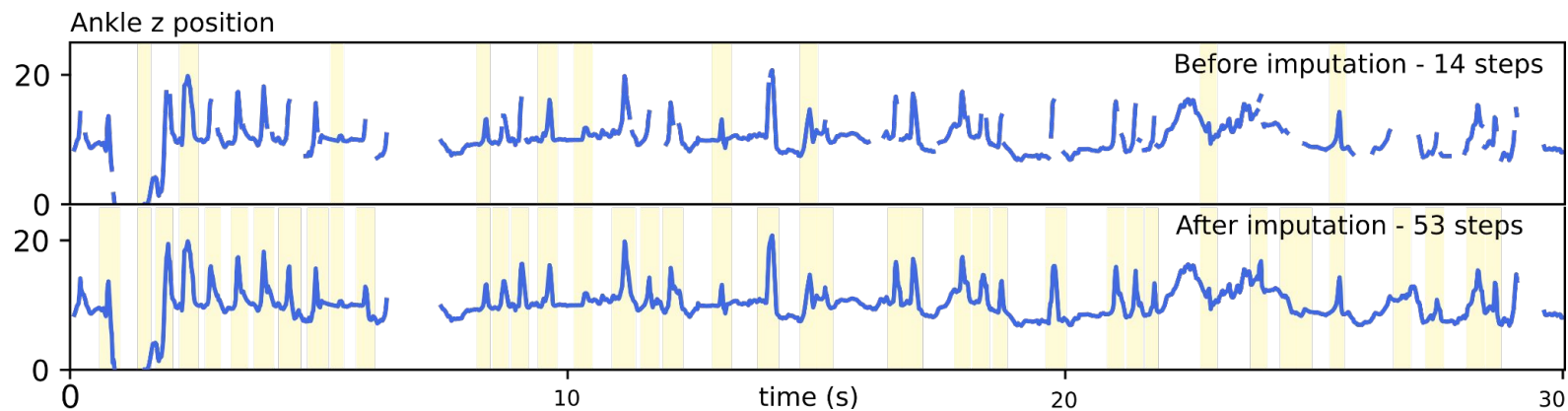
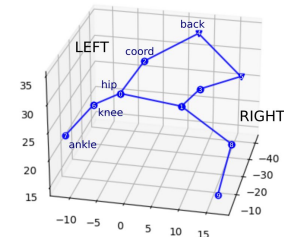
- balanced accuracy: 0.877
- balanced F1-score: 0.846
- balanced precision score: 0.874

What to do with DISK?

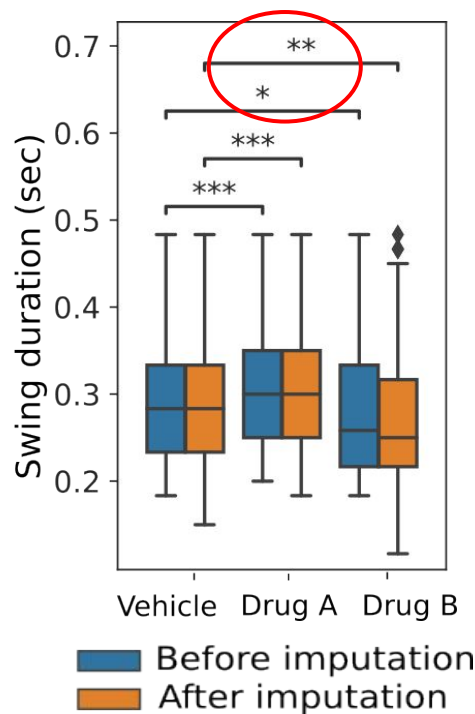
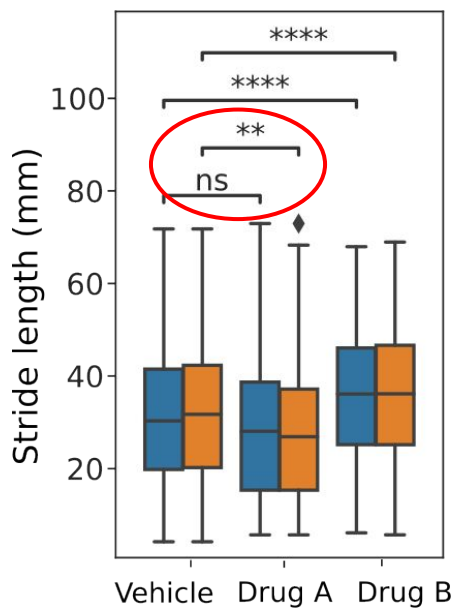
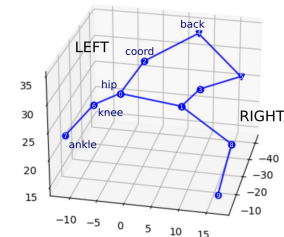


An example:
Step detection in freely moving
mice

Step detection in 3D Motion Capture mouse data

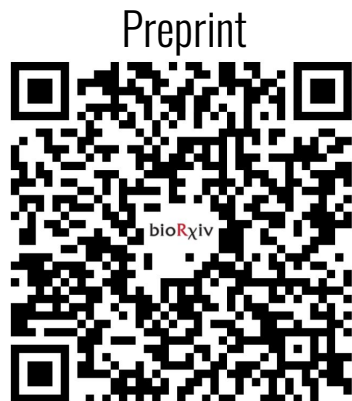


Insight on pharmacological drug effect



Legend:
■ Before imputation
■ After imputation

Concluding remarks



- DISK is able to impute correctly long gaps for single or multiple missing keypoints.
- An estimated error helps filtering out below-threshold imputed samples.
- Complementary to pose detection, DISK can help analyze fine movements like locomotion.

Katarzyna Bozek



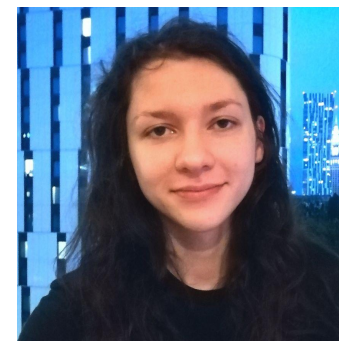
France Rose



Timon Blindauer



Monika Michaluk



Talmo D. Pereira



Liam O'Shaughnessy



Greg J. Stephens



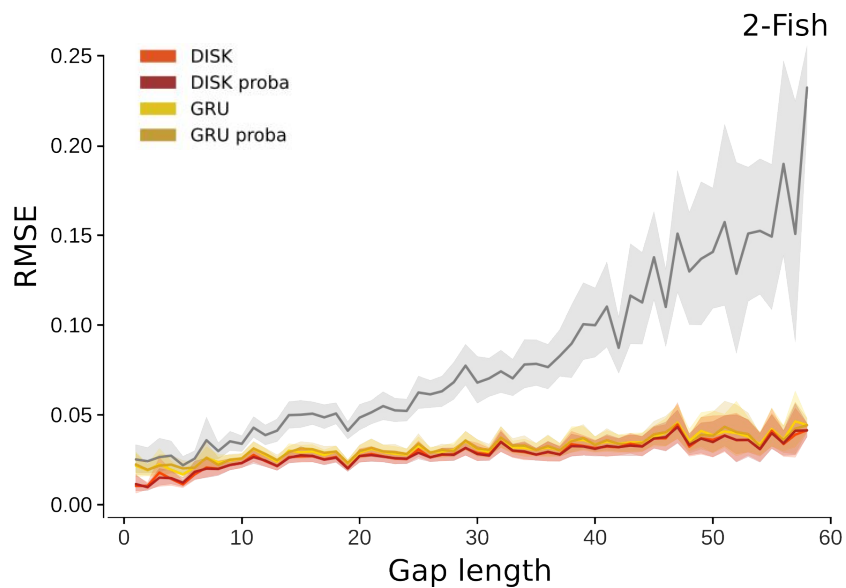
Bogna Ignatowska-Jankowska



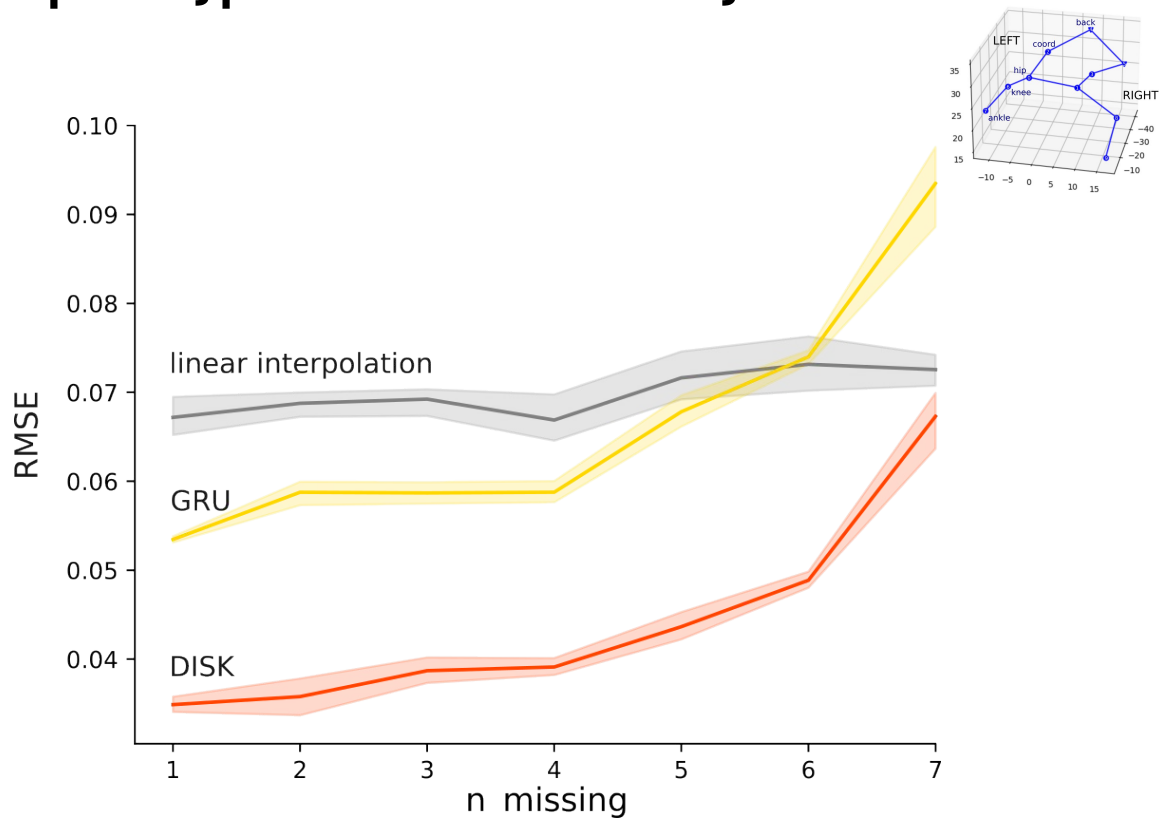
Marylka Y. Uusisaari



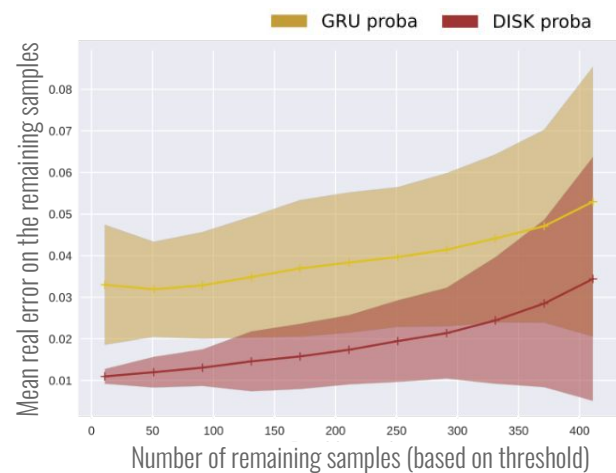
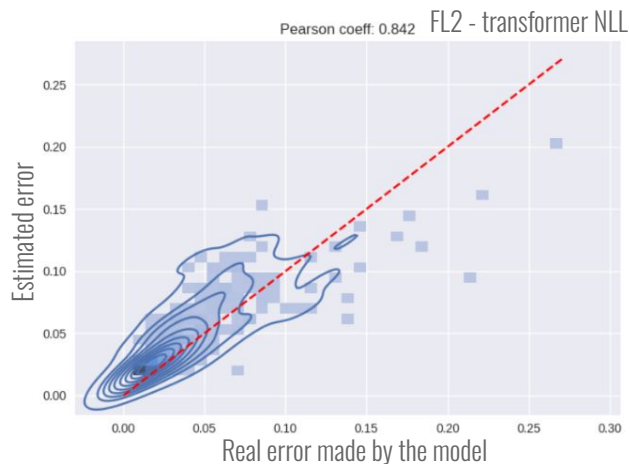
Neural methods robust to increasing gap length



Imputing multiple keypoints simultaneously



Estimated error on the imputed samples



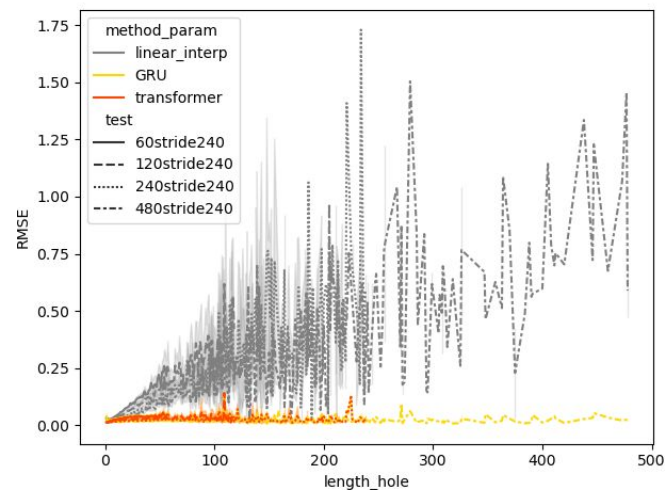
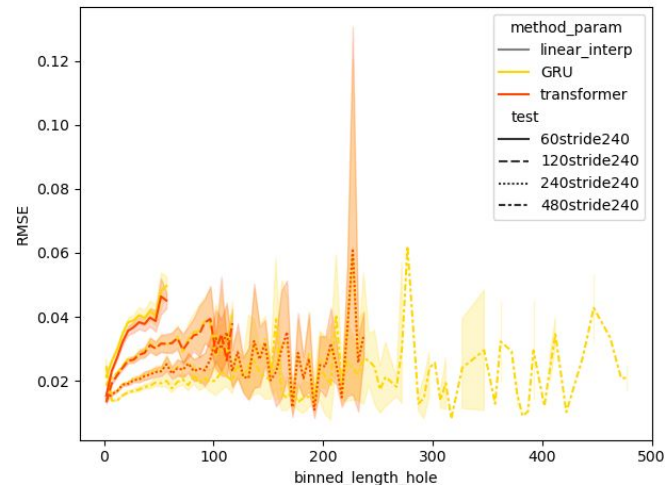
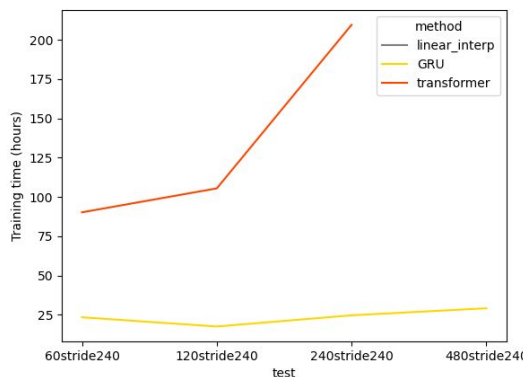
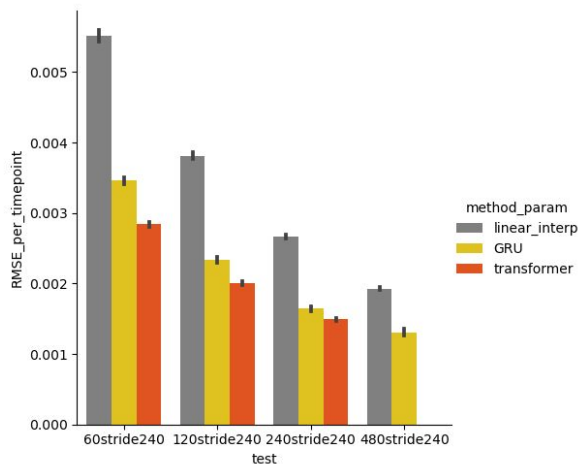
- Good correlation between real and estimated error
- Red line is $x=x$: slight overestimate of the real error

- Use it to threshold and keep only good samples

Datasets' properties

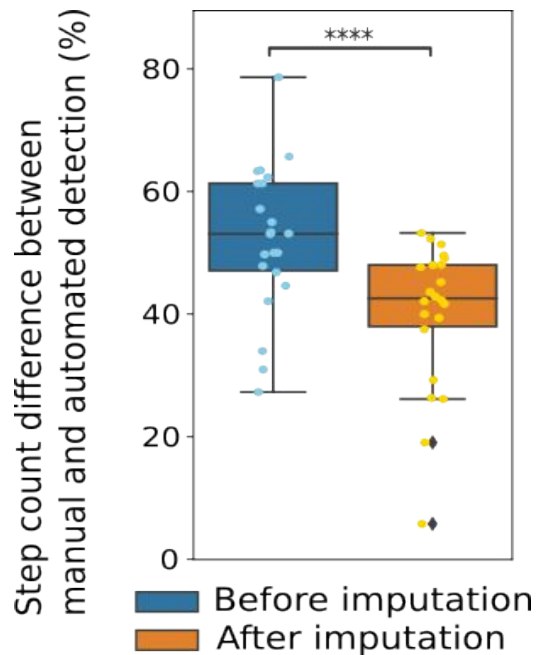
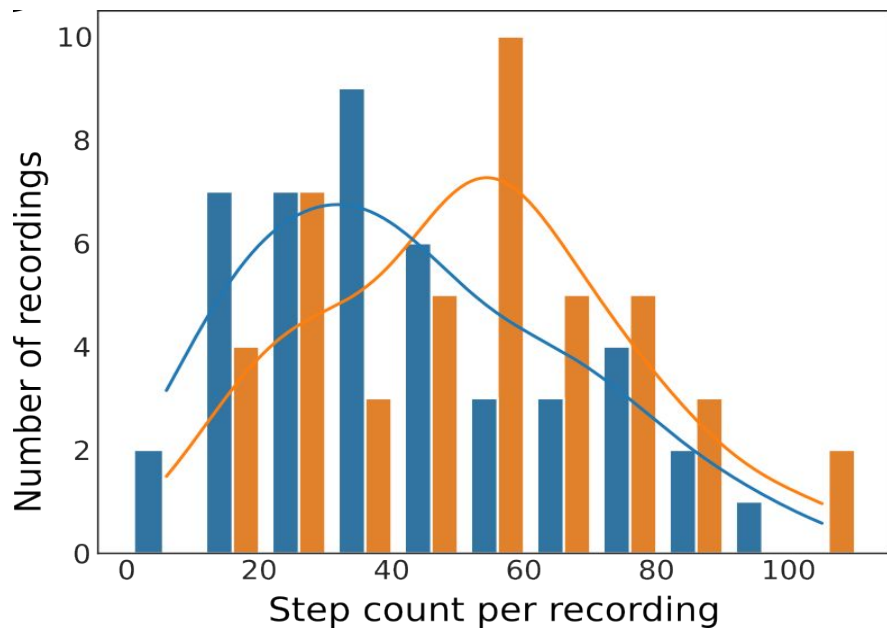
Dataset	N kp	Freq	Stride	Size train / val / test	Missing prop [%]
FL2	8	60	30	4,396 / 422 / 413	24
CLB	8	6	30	8,571 / 983 / 918	16
DF3D	38	100	5	2,095 / 652 / 614	0
Human	20	12	30	8,593 / 823 / 869	0
Rat7M	20	30	30	13,463 / 2,840 / 2,713	44
2-Fish	2×3	60	120	99,029 / 13,327 / 15,705	6
MABe	2×7	30	60	6,820 / 986 / 622	0

Input sequence length

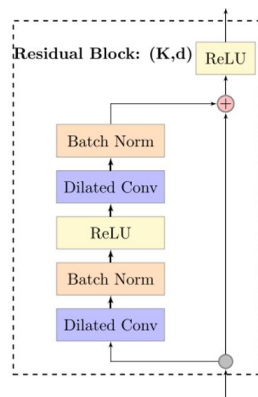
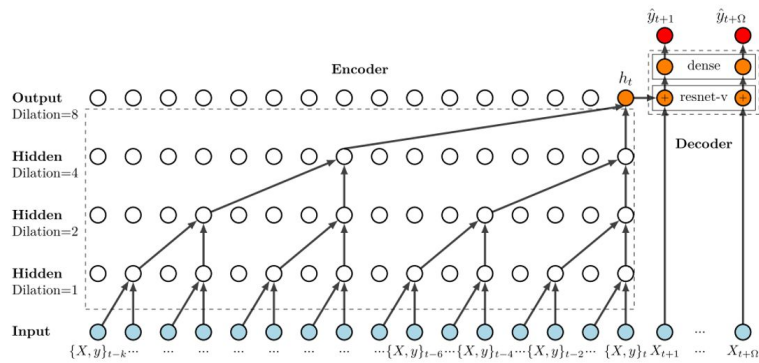


- Increasing input sequence length improves performance (see RMSE per timepoint or RMSE vs length_hole plots)
- Increasing input length is more beneficial to GRU than transformer (Weird!)
- Increased input length + GRU is a better combination (less training time for better performance)

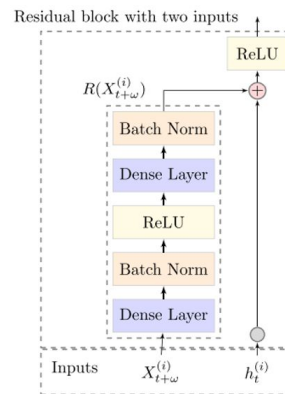
Better step detection with imputed data



TCN



(b) Encoder module

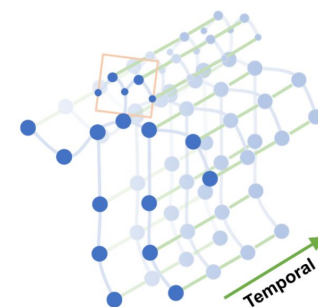
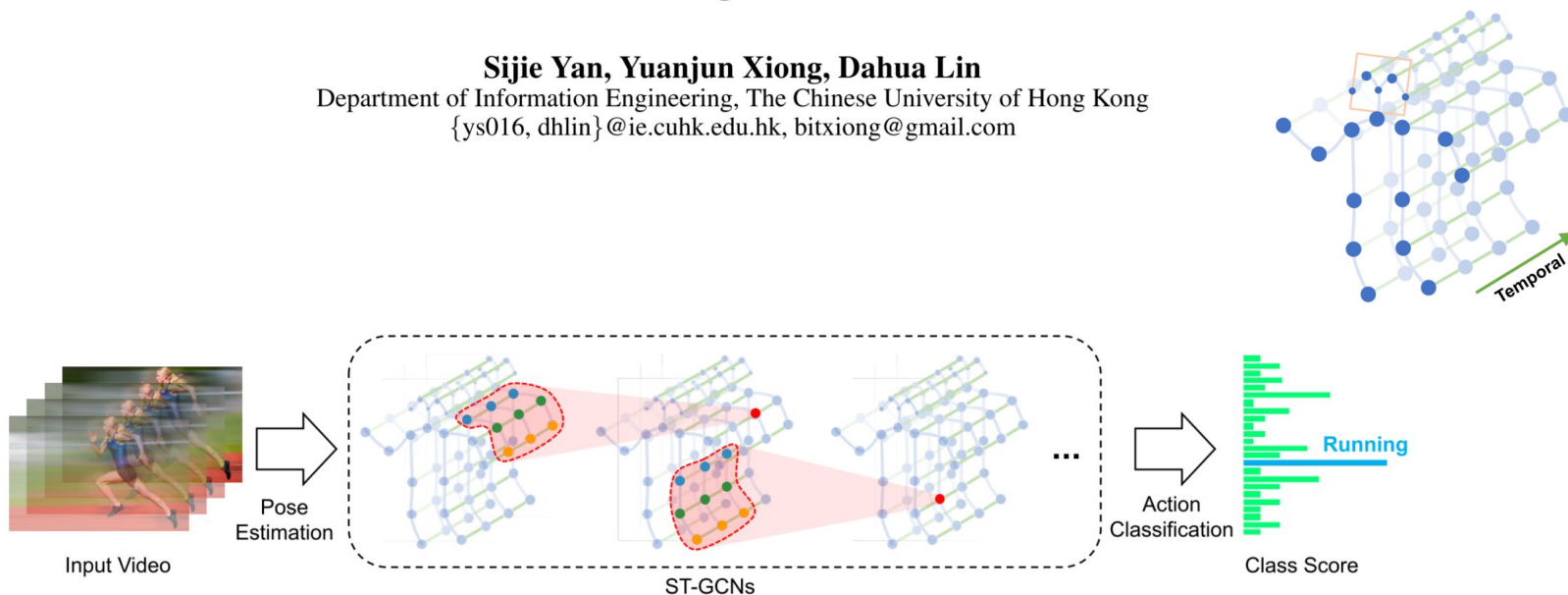


(c) Decoder module

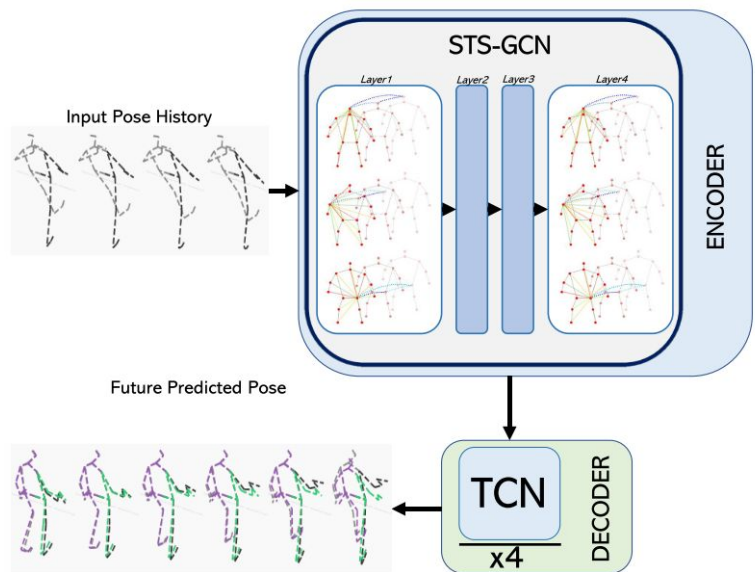
Spatial Temporal Graph Convolutional Networks for Skeleton-Based Action Recognition

Sijie Yan, Yuanjun Xiong, Dahua Lin

Department of Information Engineering, The Chinese University of Hong Kong
{ys016, dhlin}@ie.cuhk.edu.hk, bitxiong@gmail.com



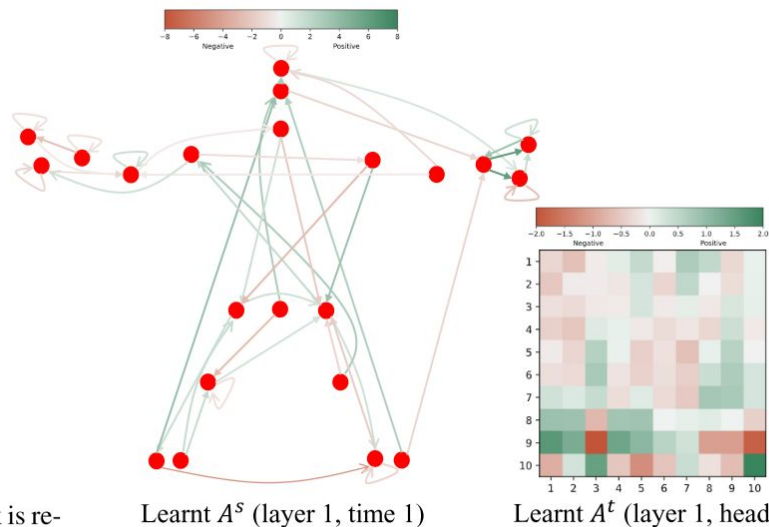
STS-GCN



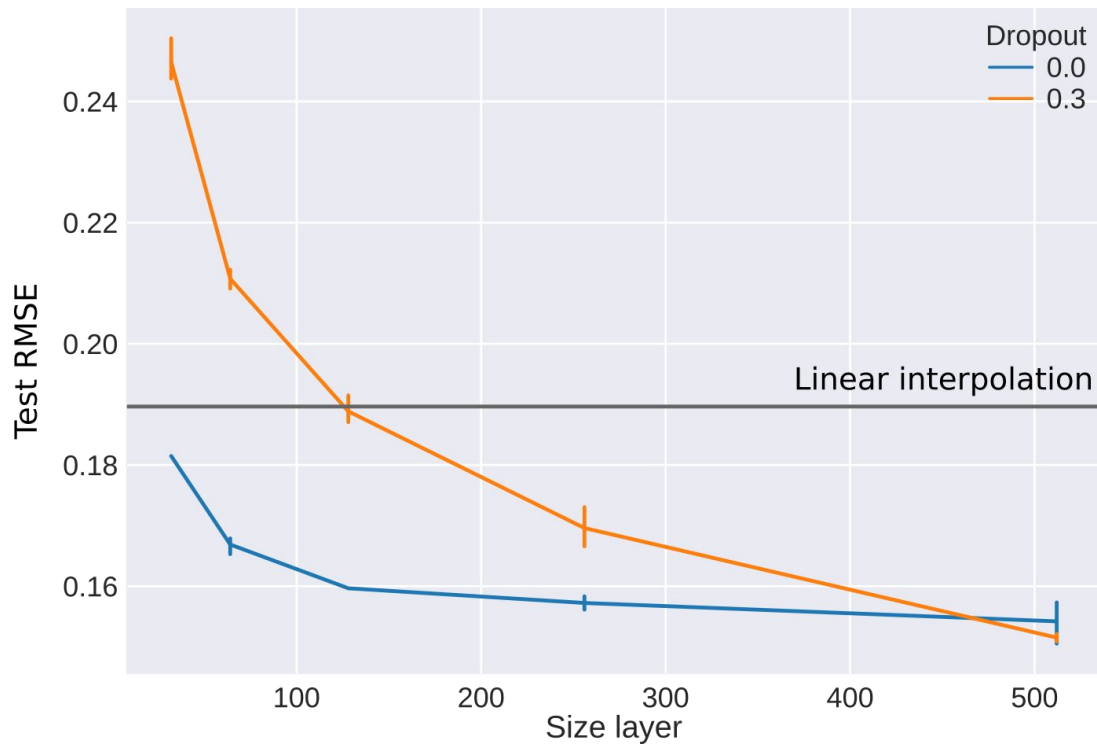
coding GCN. Bottleneck'ing the space-time cross-talk is realized by factoring the space-time adjacency matrix into the product of separate spatial and temporal adjacency matrices $A^{st} = A^s A^t$. A separable space-time graph convolutional layer l is therefore written as follows

$$\mathcal{H}^{(l+1)} = \sigma(A^{s-(l)} A^{t-(l)} \mathcal{H}^{(l)} W^{(l)}) \quad (2)$$

Separable learnable adjacency matrices in time and space



Bigger hidden size performs better (DF3D)



Binary input mask guides the network

	FL2	CLB	DF3D	MoCap	Rat7M
Linear interpolation	0.07	0.17	0.20	0.36	0.13
ImputeSkeleton					
With mask	0.04	0.04	0.15	0.04	0.05
Without mask	0.05	0.05	0.16	0.05	0.07

