DD2430 Final presentation

Group 10 - Project 14

Introduction

- Self-grooming behavior
- The study of behavior is essential for the understanding of the brain
- Mice serve as models for us humans
- Computer vision framework for behavior analysis
- In collaboration with Fisone laboratory at Karolinska Institutet

Problem Description

- Detection, tracking and quantification of mice self-grooming behavior
- DeepLabCut for pose-estimation extraction given video input
- Model self-grooming behavior through pose-estimates using machine learning/statistical models

Implementation Steps

Data Collection

Analysis

Behaviour Modelling

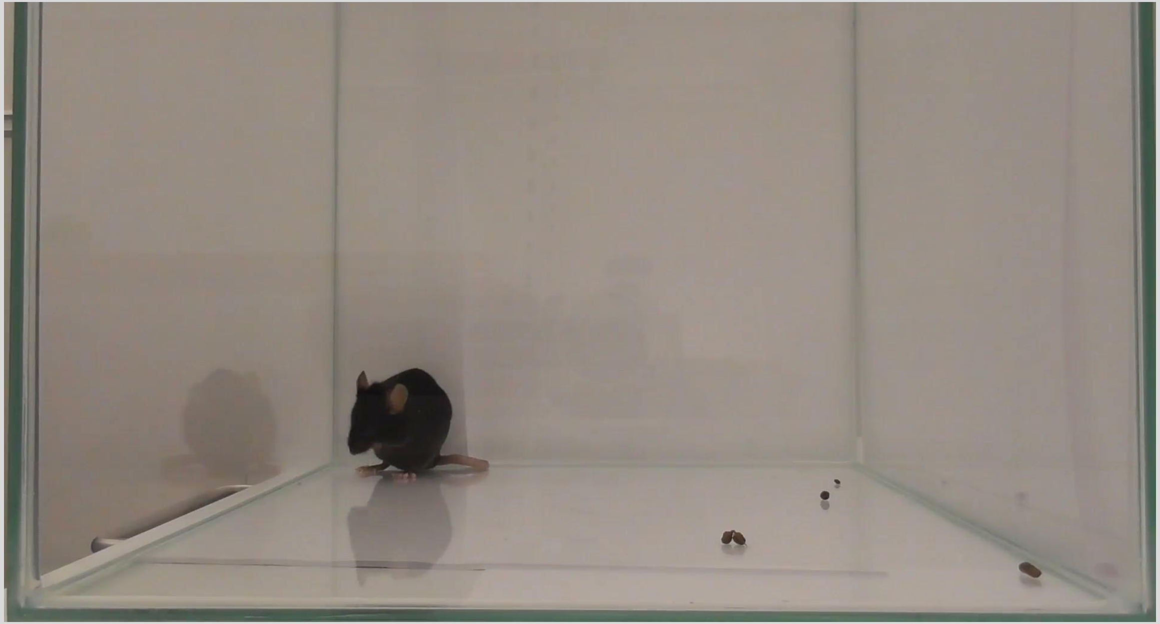
Results and Evaluation

DeepLabCut and other video parameter analysis

Methods Utilized:
- TDA
- LSTM

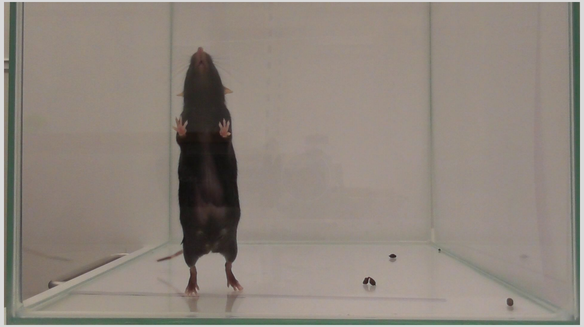
Data Collection Pipeline

Record Raw Videos



Data Collection Pipeline

Record Raw Videos → Extract General Behaviour Frames

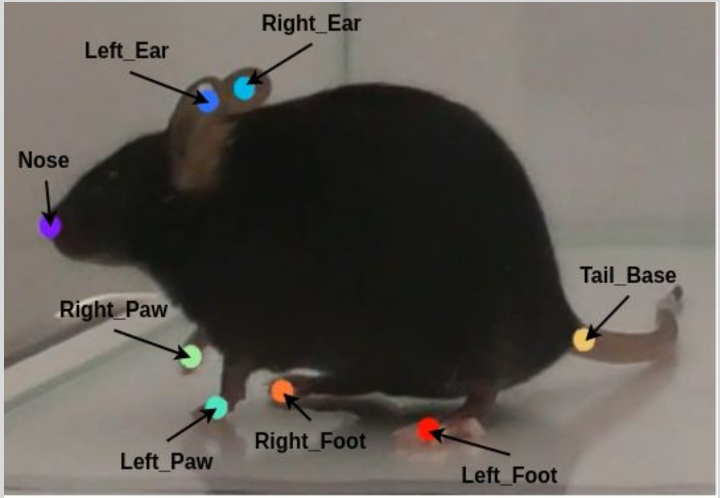


Rearing

Grooming

Data Collection Pipeline

Record Raw Videos



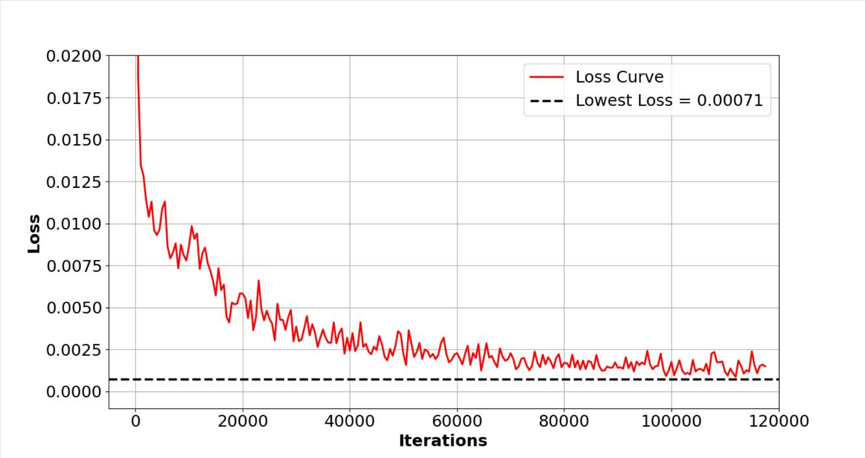
- Dataset with 400 labelled frames in total

Data Collection Pipeline

Record Raw Videos

Extract General Behaviour Frames

Select and Train DLC Model

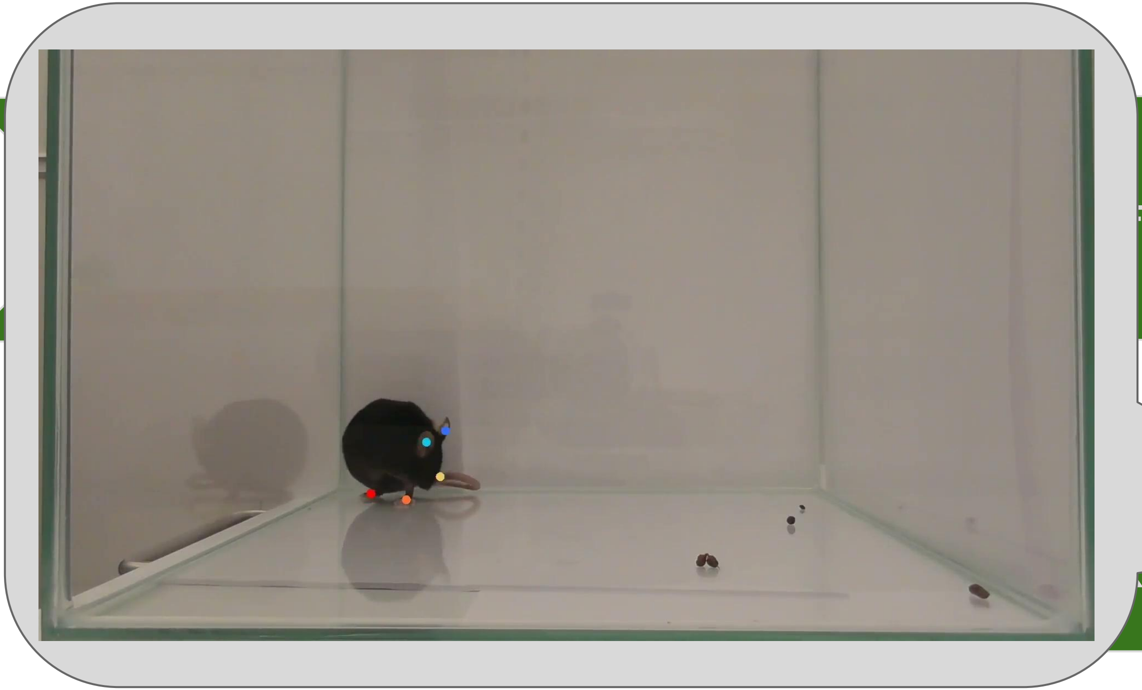


DLC Training

Select Pretrained Network

- ResNet 101
- ResNet 50

Data Collection Pipeline



frames

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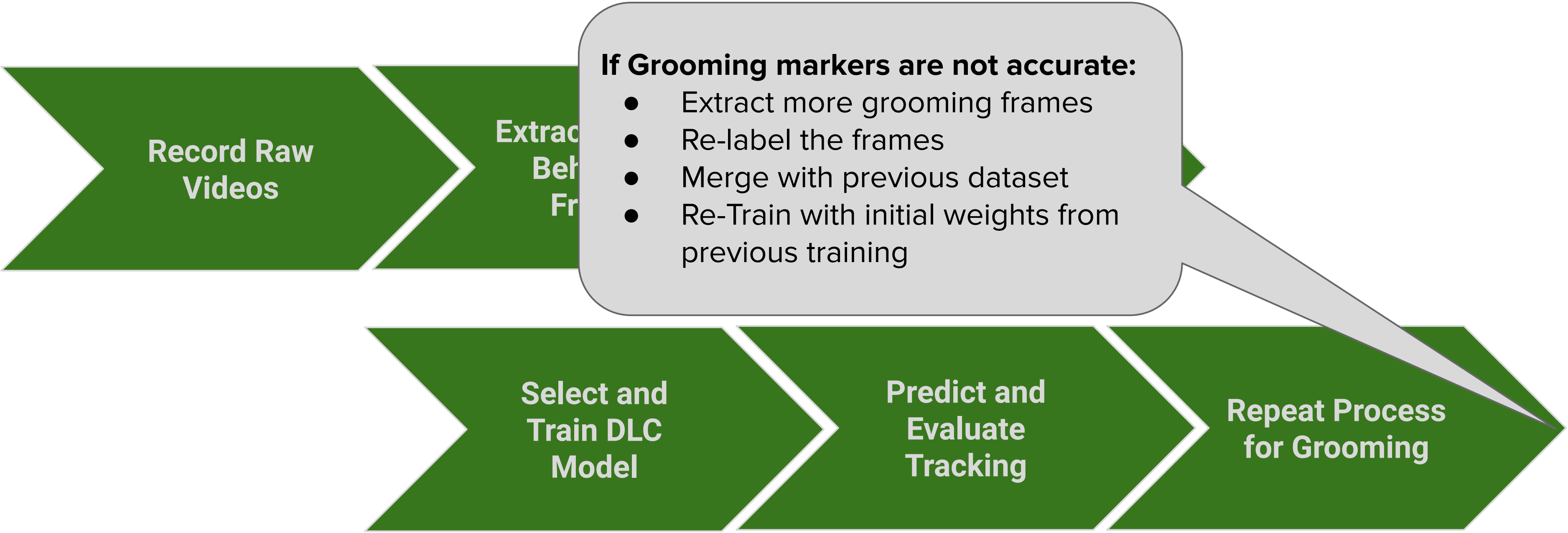
Data Collection Pipeline

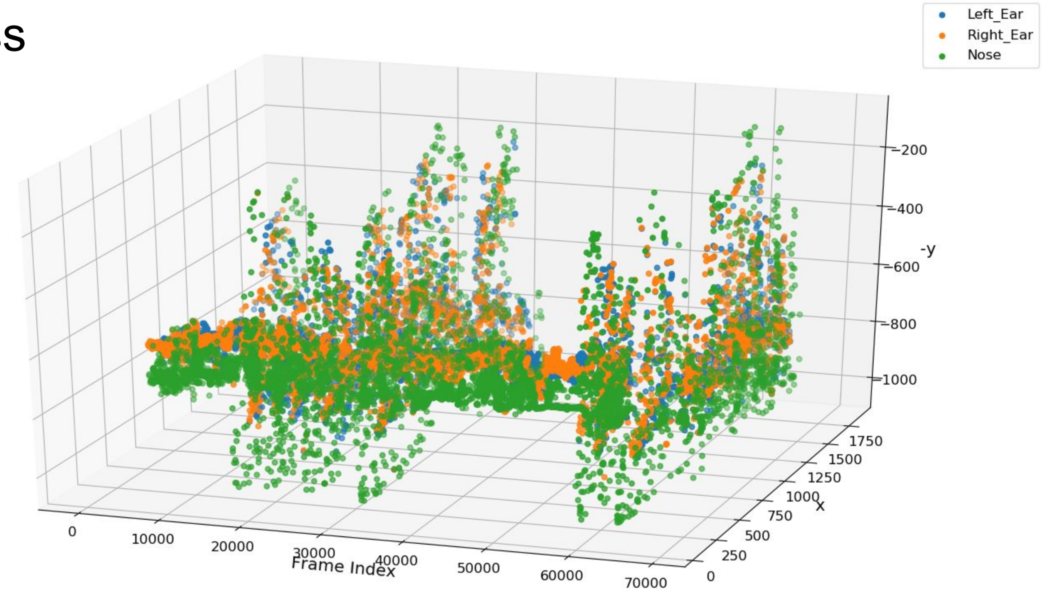


Data

- Video
  - Resolution: 1920 x 1080
  - 50 FPS
  - Recorded for the same Mouse
  - Around 3 hrs of recording, i.e 540,000 frames
  - DLC trained for 120,0000 iterations, which took around 15-16 hours
- Information contained in each predicted marker
  - Bodypart id
  - Frame id
  - Position in frame: *(x,y)*
  - Likelihood of prediction
- For example:
  - For a video with *N* number of frames
  - Given that, 8 body parts are tracked
  - We obtain, *(N x 3) x 8* unique marker points

Observed Trends

- Grooming behaviour is much less frequent as compared to other behaviours
- Mouse mostly grooms in one corner of the cage
- Distinct point clusters, corresponding to motion and stationary behaviours



Trajectories

TDA Based Model - Persistent Homology

Point Cloud Data

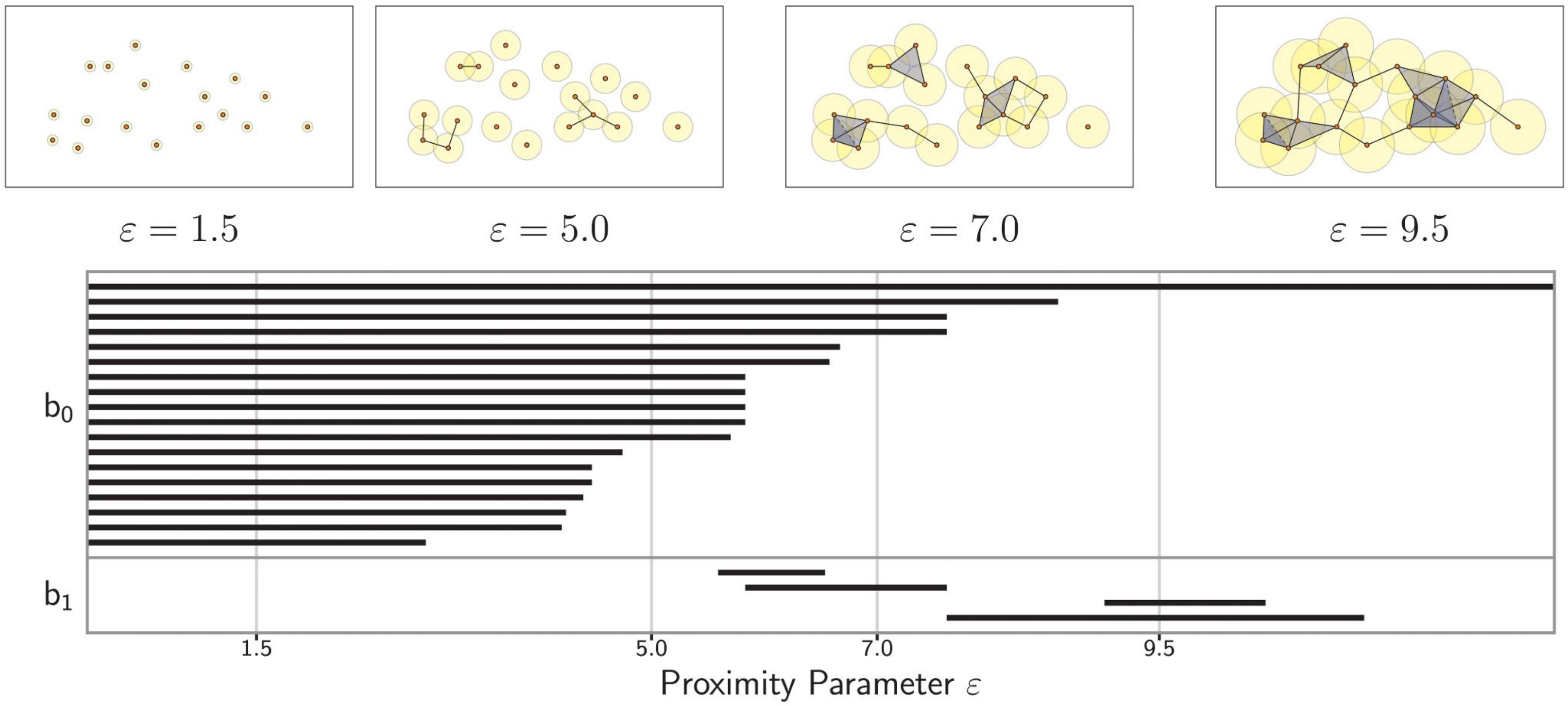
Vietoris-Rips Filtration

Simplicial Complexes parametrized by filtration level t

Persistence Barcodes: Homologies parametrized by filtration level t

Stable Ranks

Persistence Barcodes Illustration



doi: https://doi.org/10.1371/journal.pone.0126383.g004

Model Setting - Stable Ranks Computation

- Sliding window of size 2 seconds (100 frames) with 1 second overlap
- Each sliding window: a point cloud of 16 points in 100 dimensional space
- Pairwise distances measured by correlation metric

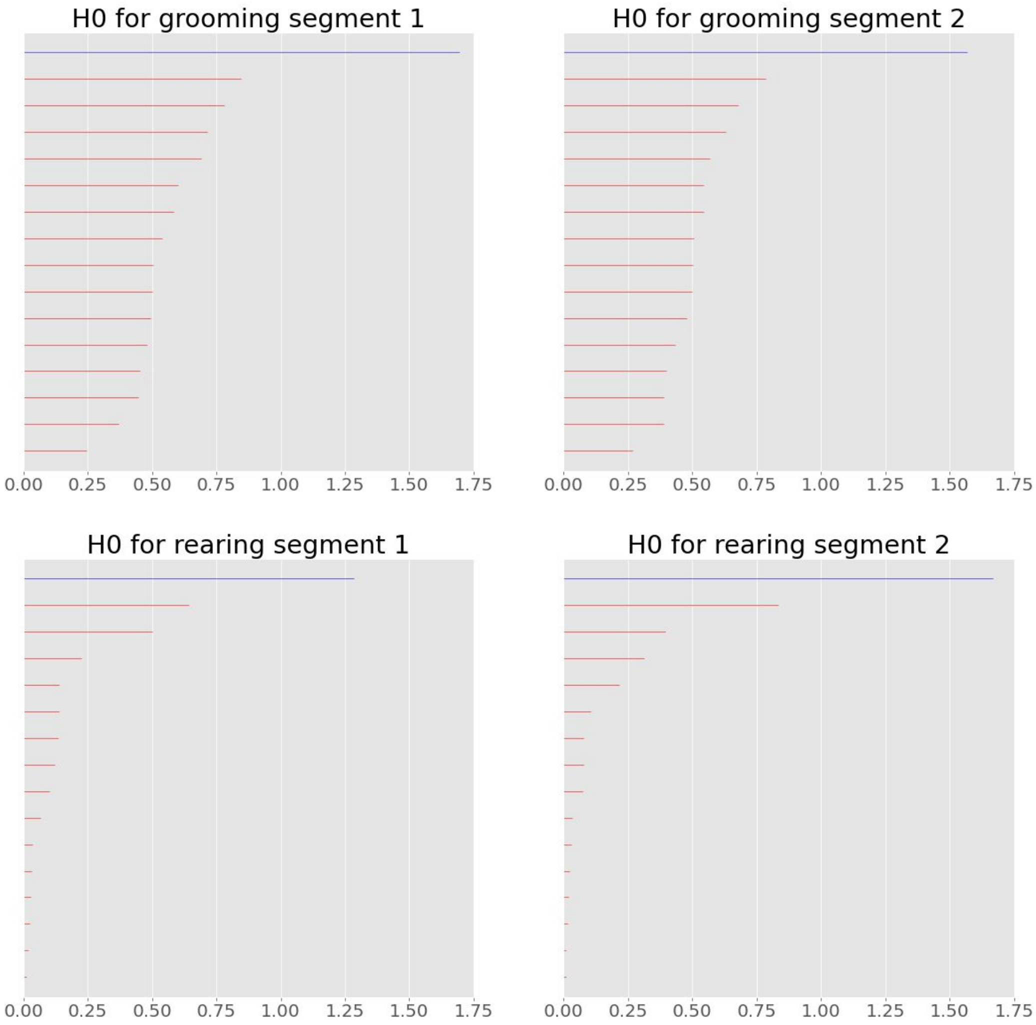
  $$d(x,y) = 1 - \frac{x_c \cdot y_c}{||x_c|| \, ||y_c||}$$

  A modified correlation metric with '+' sign to replace '-' is also tested
- Stable ranks for barcodes $\{(a_i < b_i) | i = 1, ..., r\}$

  $$\widehat{\text{rank}}(t) = \{\text{number of bars s.t. } b_i - a_i \geq t\}$$

- H0 Homology is considered

Illustration of Behaviour Segment Signature



Model Setting - Classifiers

SVM with homology stable rank kernel, balanced class weights

homology stable rank kernel definition (Frontiers in Applied Mathematics and Statistics, 2021):

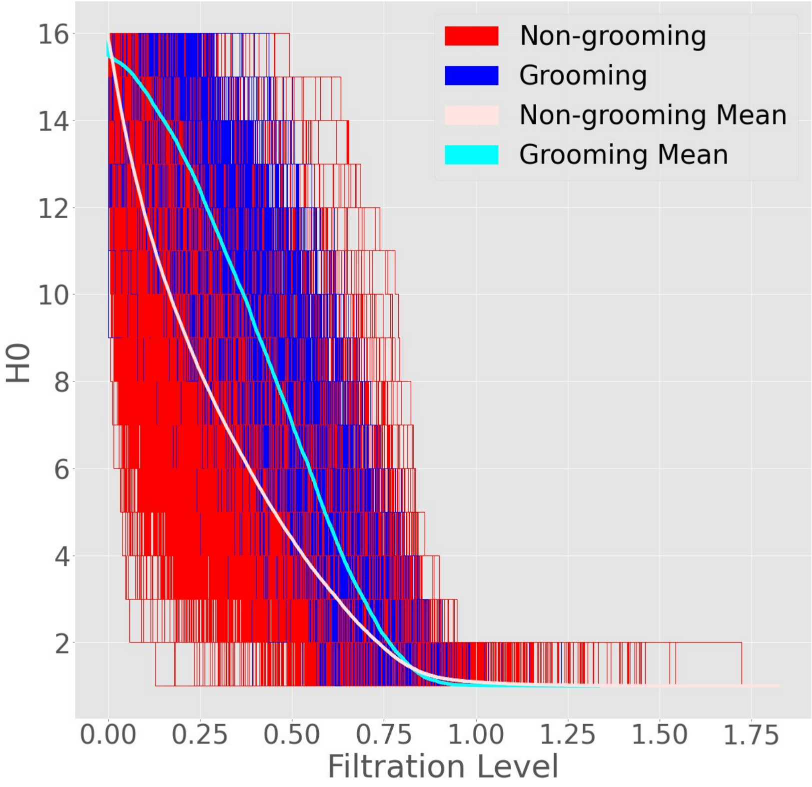
$$K_d(X, Y) = \int_0^\infty \widehat{\mathrm{rank}}_d(X)\widehat{\mathrm{rank}}_d(Y)dt$$

k-Nearest Neighbours with interleaving distances, subsampling equal size of grooming & non-grooming

Interleaving distances definition:

$$d_{\bowtie}(f, g) = \inf\{v | f(x) \geq g(x + v) \text{ and } g(x) \geq f(x + v) \text{ for any } x\}$$

Best Results



9-NN on ARIMA filtered trajectories, default correlation metric

	Train	Validation	Test
f1 Grooming	0.83	0.50	0.48
f1 Non-grooming	0.83	0.79	0.90
Weighted Average Accuracy	0.83	0.73	0.86

Findings, Limitations and Future Work

- Grooming precision is low due to large FP (false positives)
- kNN performs better than SVM
- Pairwise correlations are variant to motion directions
- In future: designing a new coordinate system for mouse which captures angle invariance and reflexivity

LSTM-Based Model

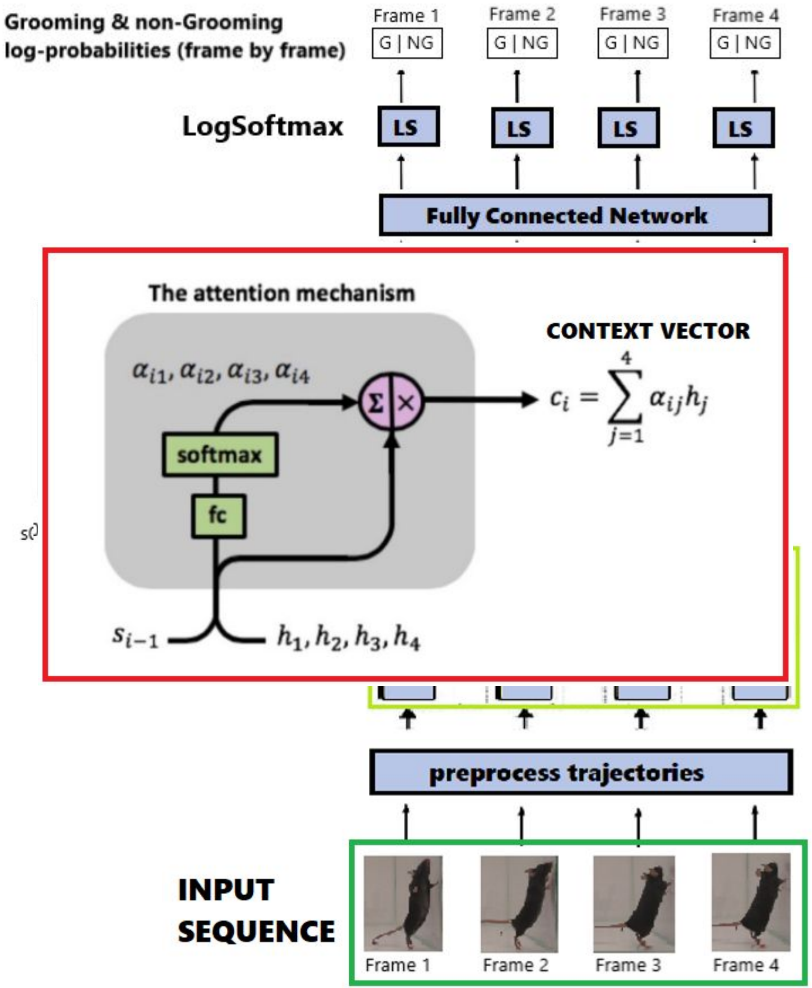
Many to many network.

The network is composed of the following blocks:

1. Pre-processing block;
2. Bidirectional LSTM encoder;
3. Attention mechanism;
4. Unidirectional LSTM decoder;
5. Fully Connected Network + LogSoftmax.

For simplicity, we only tuned the following:

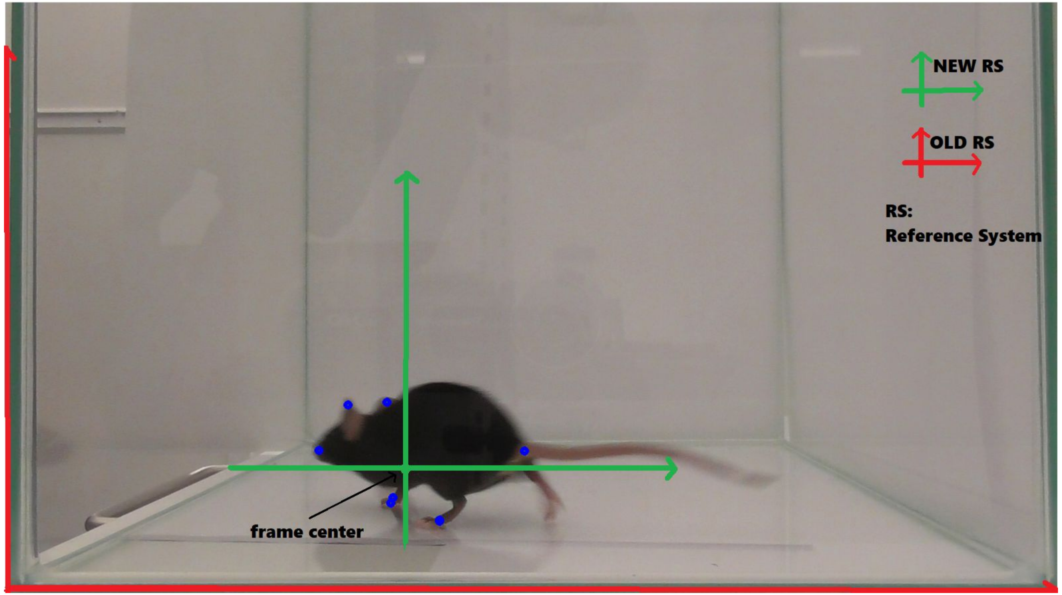
- Pre-processing technique
- Sequence length



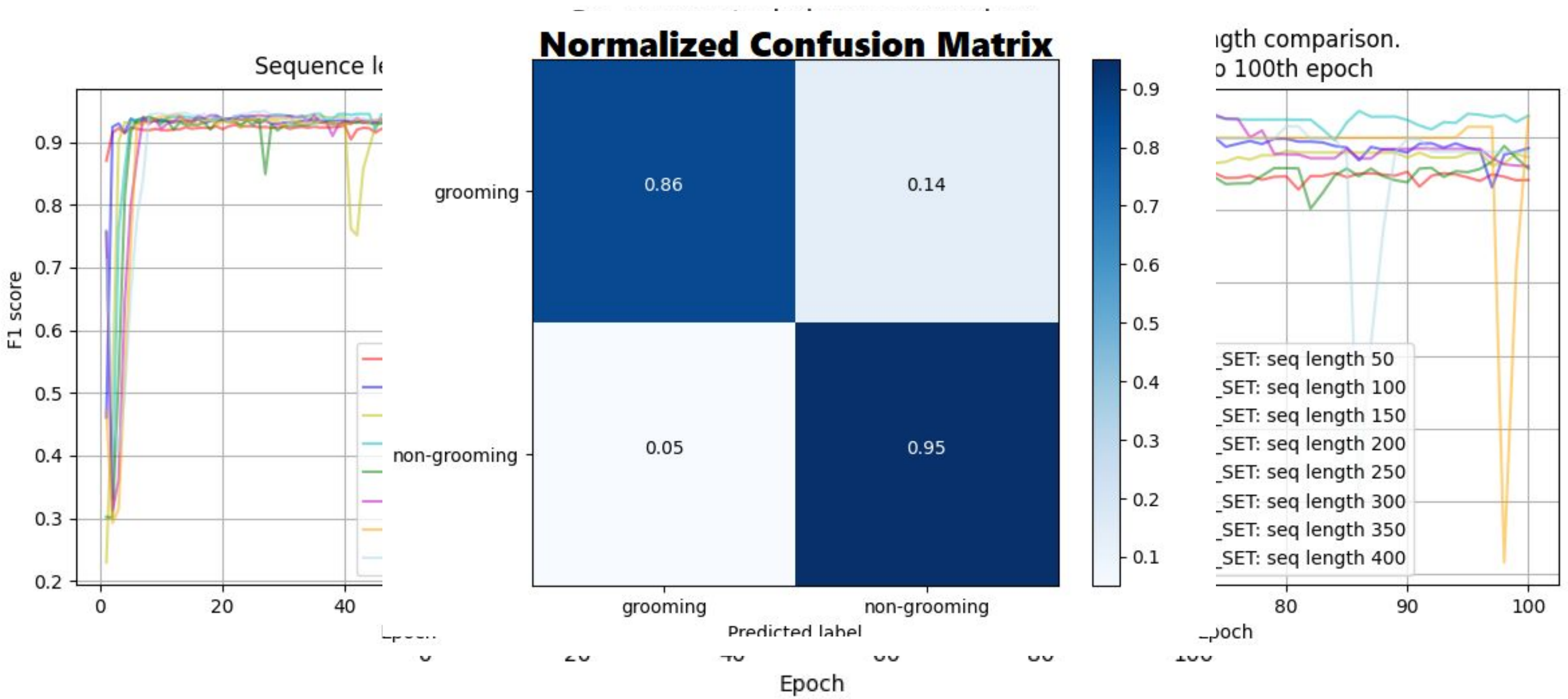
Pre-processing Techniques

Three distinct techniques have been evaluated:

- Recentering with respect to frame center (see image);
- **Recentering with respect to sequence center**;
- Normalization



LSTM - Evaluation and Test



Behaviour Prediction Example

With LSTM

With TDA

Conclusion

Results

- Moderate accuracy in separation of grooming and non-grooming behaviors

Future work

- Robustness and generalizability
- Different experimental settings

Challenges

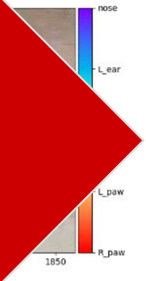
- Low quality mice recordings

Implementation Steps

Data Collection

Training with DeepLabCut

Behavior modelling



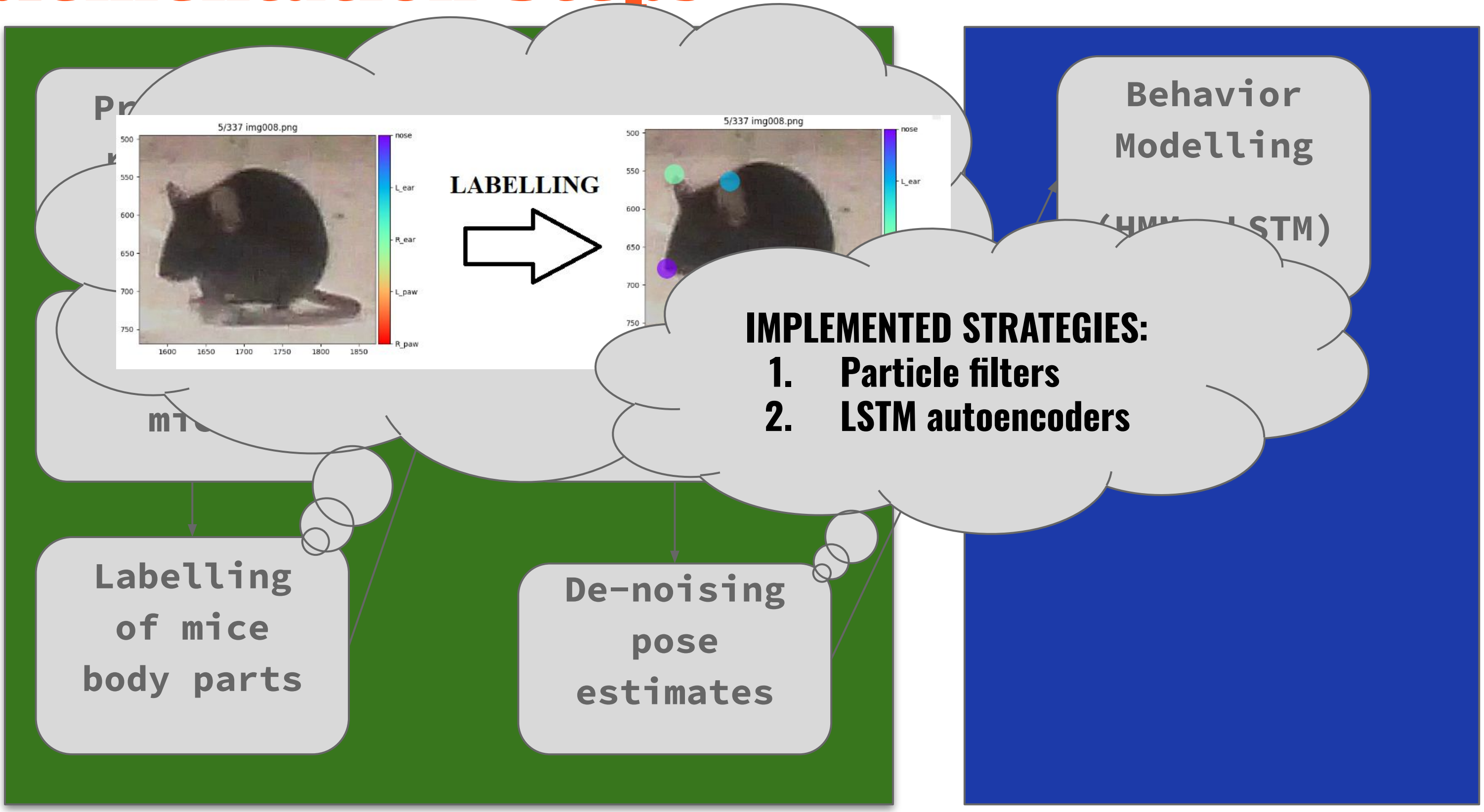
Challenges

- Lack of data with good quality
- Need to collect more videos in better conditions
- De-noising still needs improvement
- Have to start with behaviour modelling asap due to time limit
    - Have done some research on it

Tracking points of interest are hidden

Noise in trajectories due to wrong predictions

Implementation Steps



PARTIALLY DONE

TO BE DONE

Previous Work (Remove)

- Inspired by study of Joel Sjöbom et al. at Lund university [1]
    - Studied neural circuits
- Deep learning methods for behavior modeling [2, 3]
    - Long short-term memory networks (LSTM)
    - Recurrent convolutional neural networks (CRNN)

1. Joel Sjöbom, Martin Tamté, Pär Halje, Ivani Brys, and Per Petersson. Cortical and striatal circuits together encode transitions in natural behavior. Science Advances, 6(41):eabc1173, 2020.
2. Koji Kobayashi, Seiji Matsushita, Naoyuki Shimizu, Sakura Masuko, Masahito Yamamoto, and Takahisa Murata. Automated detection of mouse scratching behaviour using convolutional recurrent neural network. Nature research, 2021.
3. Elsbeth A. van Dam, Lucas P.J.J. Noldus, and Marcel A.J. van Gerven. Deep learning improves automated rodent behavior recognition within a specific experimental setup. Journal of Neuroscience Methods, 332:108536, 2020.