What can non-linear embeddings tell us about the way a mouse learns a motor skill?

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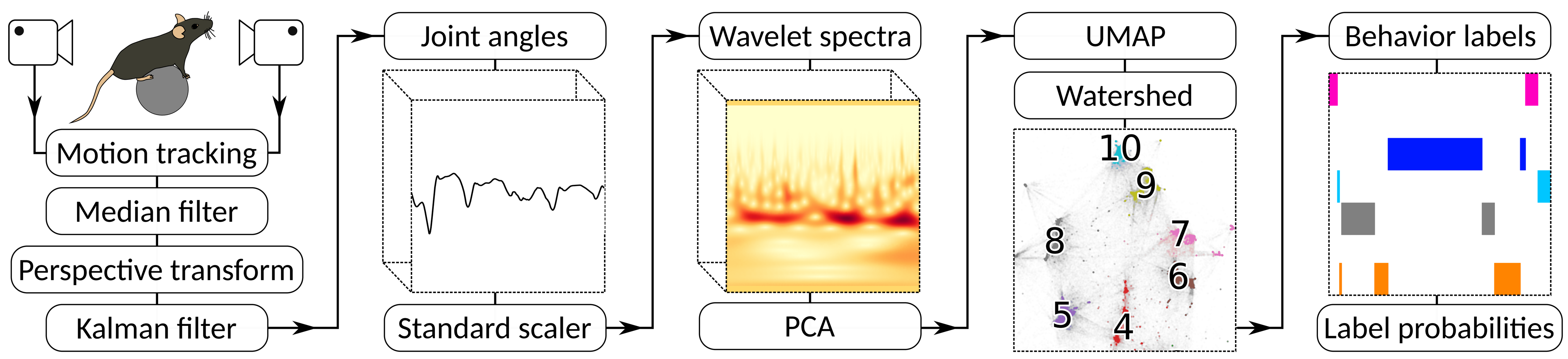
Animals exhibit complex behavioral repertoires that can be described as combinations from a finite set of stereotyped movements. These behaviors are flexible, since different movement sequences can be used to solve similar tasks, and are adaptable to changing environments through learning mechanisms.
We used unsupervised machine learning to classify different types of movements executed by mice performing a motor skill learning task. We constructed UMAP embeddings to find a low dimensional representation of mouse behavior. Then, we clustered behaviors into separate categories and studied their changes with training and between subjects.

Data processing pipeline: from video frames to behavior labels

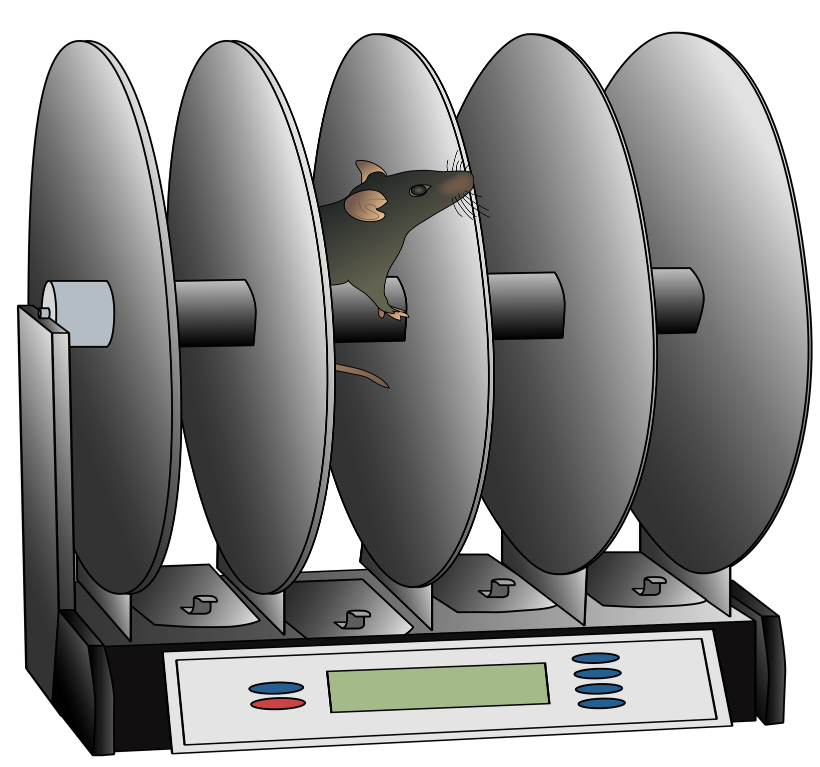
Using the time series of tracked mouse body-parts, we compute several joint angles, and then we extract their frequency amplitudes. Finally, these spectra are used to construct a UMAP embedding, where each point represents a frame of analyzed video. This embedding (ethogram), has a defined cluster structure, and we assign each cluster to a specific type of behavior label (we found 10 in total).



Methods

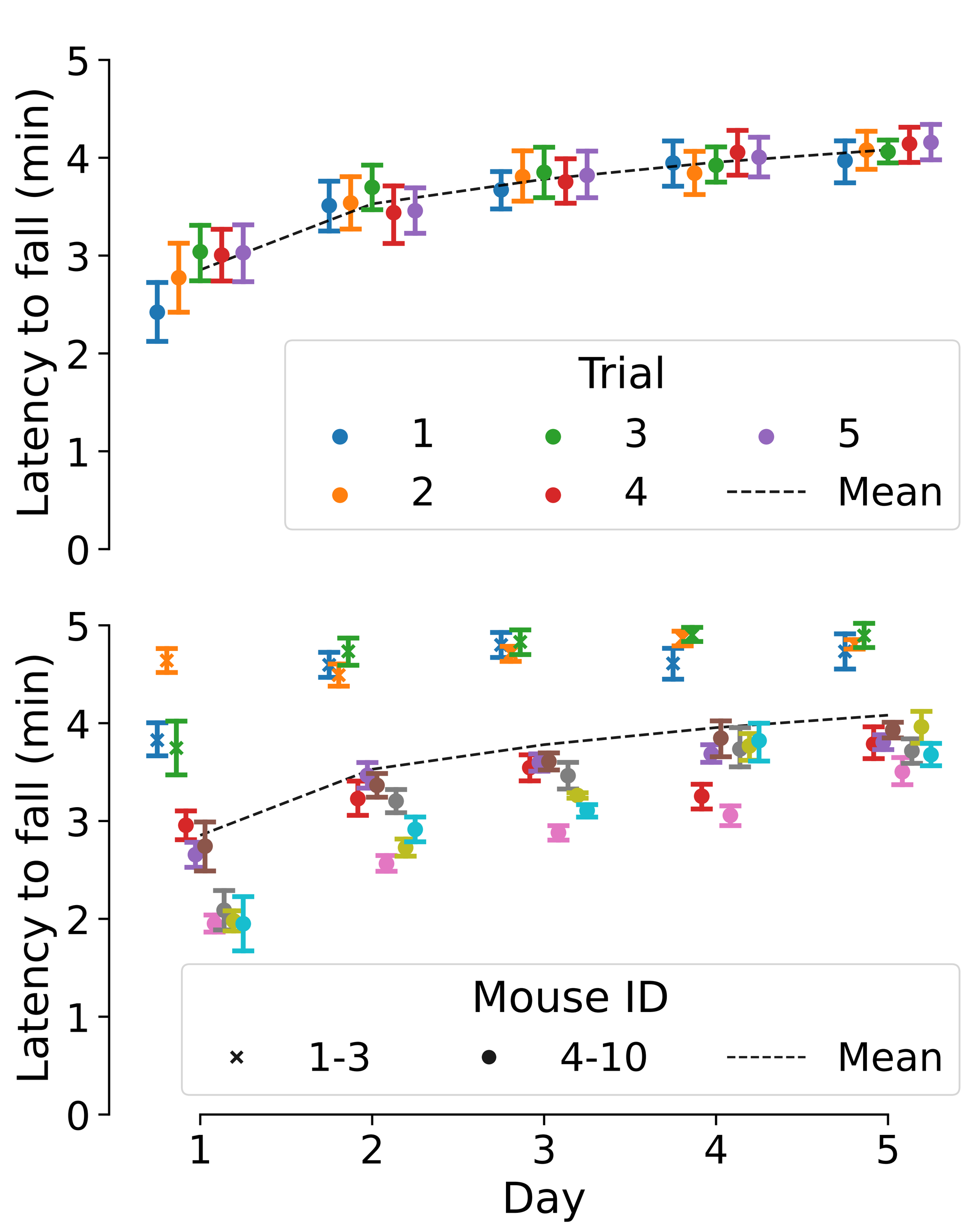
Accelerating rotarod task

We tracked the movements of 10 individual mice, while learning to perform the task. Their training comprised 5 days, with 5 rotarod trials per day. The maximum duration of each trial was 5 minutes, starting at a cylinder rotation speed of 5 rpm and accelerating constantly up to 50 rpm.



Describing the learning process

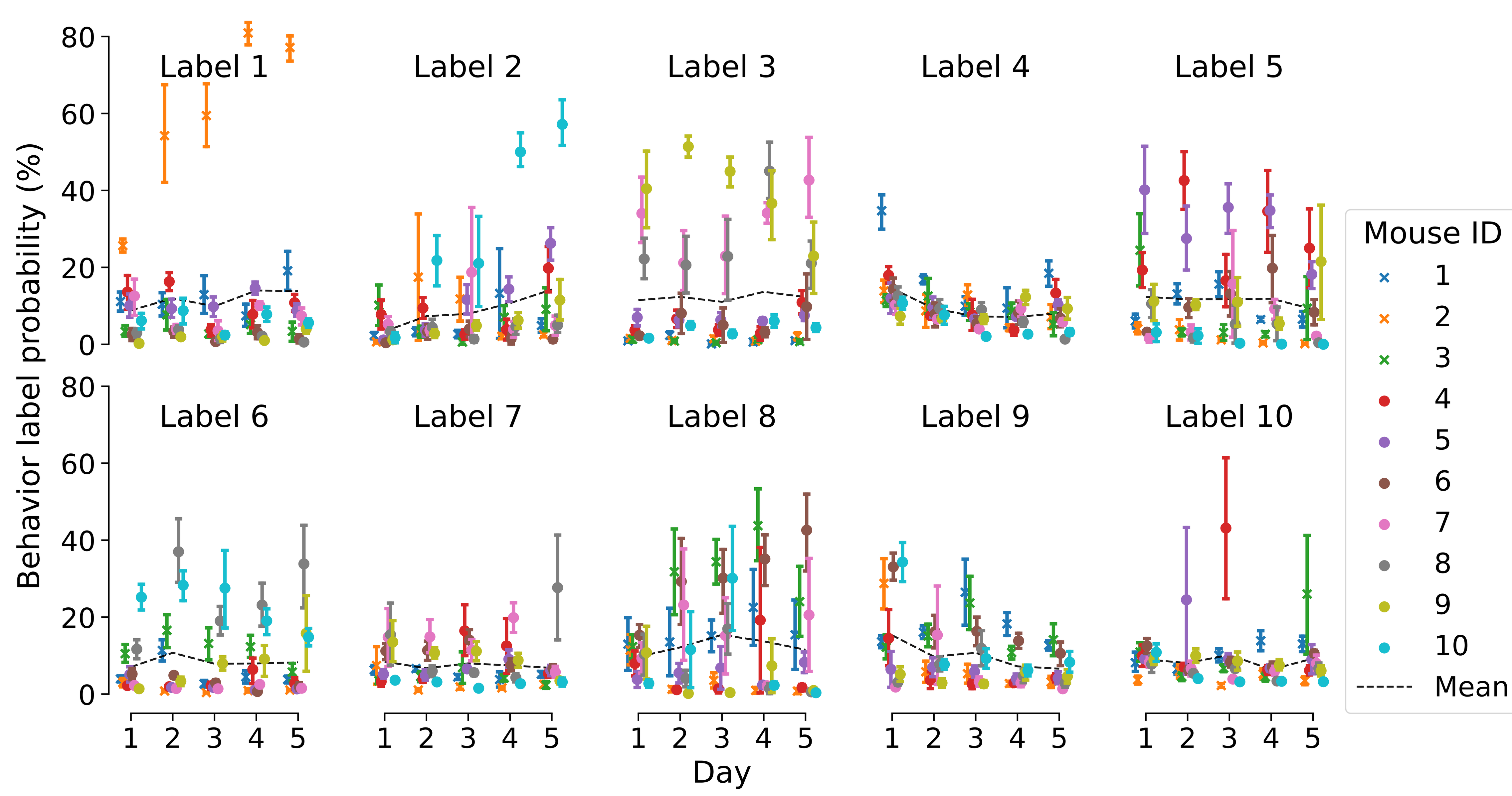
The time when the mouse falls off the cylinder (latency to fall) is a typical learning and performance metric. Mouse 1, 2 and 3 show higher than average performance.



Results

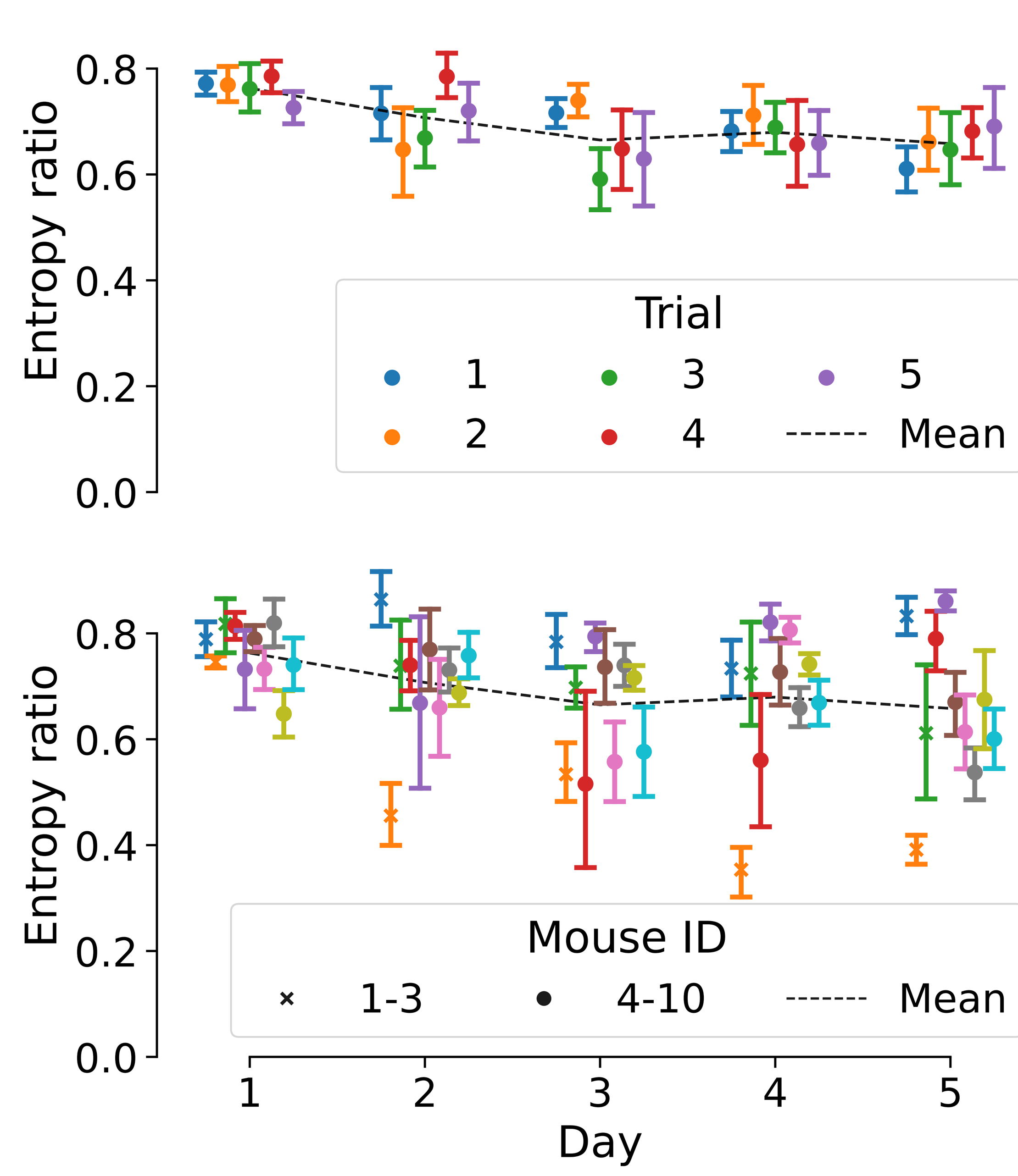
Behavior label probabilities change with training and mouse

Some mice converge in behavioral strategies. Others adopt singular ones. We would like to further investigate these behavioral labels, and to improve the way we interpret them.



Quantifying behavior variability

Using the entropy of the label distributions, we see that overall behavior variability decreases with training.



Discussion

- The classical metric, latency to fall, already shows that not all mice perform equally. This proposed method to analyze behavior can further explain the differences found in performance.
- The type of behavior chosen to solve the task also varies between mice, and evolves with training. We would like to study if the changes in label probability are due to behavioral learning, or due to an increase in the duration of the behavioral bursts, or because some behaviors arise at increasing rotarod speeds.
- We want to quantitatively interpret these behavior labels. We would like to analyse if mouse body- parts move at distinct frequencies or if they move in or out of sync during each type of behavioral bout.
- We hope that these methods can be used to find correlations with simultaneous neuronal activity recordings, as well as better quantifying behavioral changes in neurodegenerative disease models.