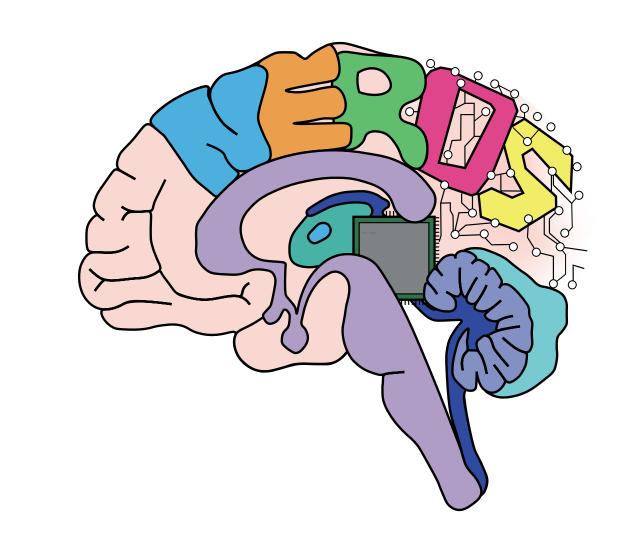


# Detecting change points in neural population activity with contrastive metric learning

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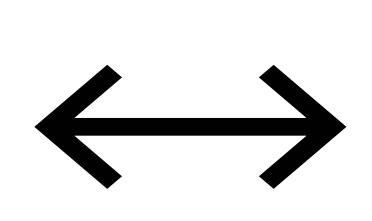


## Motivation

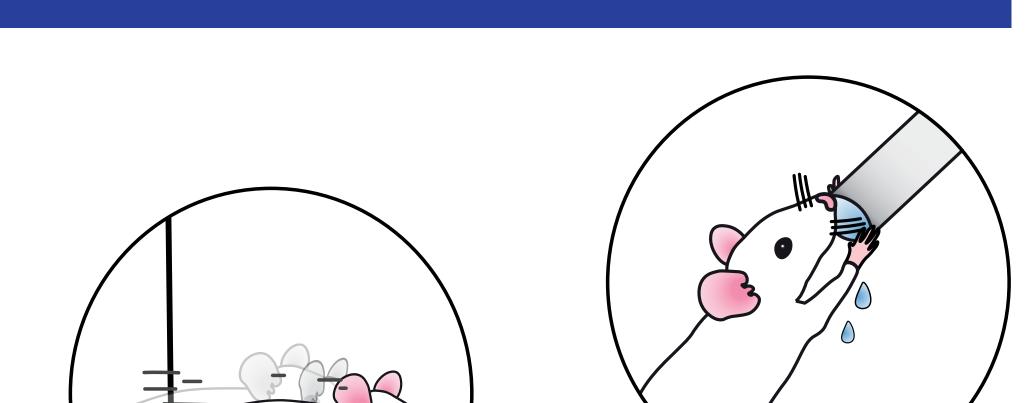
# The detection of changes points in neural activity is a challenging task:

- induced by diverse beahvioral switches, which can occur at different rates and impact the population of neurons differently.
- during free behavior, it is hard to identify change points.

Detect a specific type of behavioral switch



Learn which neurons and signals are responsible for it

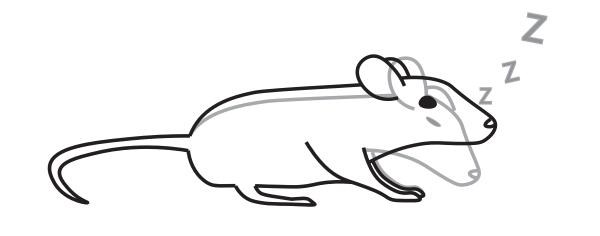




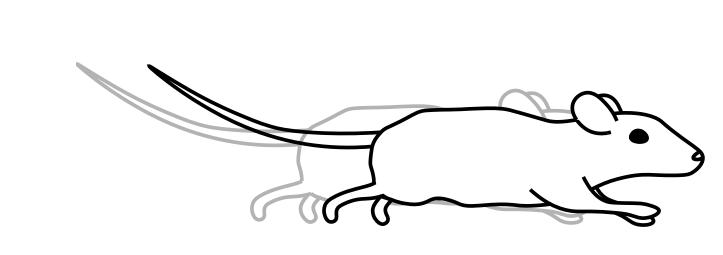
# Objective

**Goal:** improve the detection of specific behavioral switches (change points). **Approach:** To detect change points, use the Sinkhorn divergence with a task-relevant metric that is learned from a few labeled change points.

### Targeted change point detection tasks:

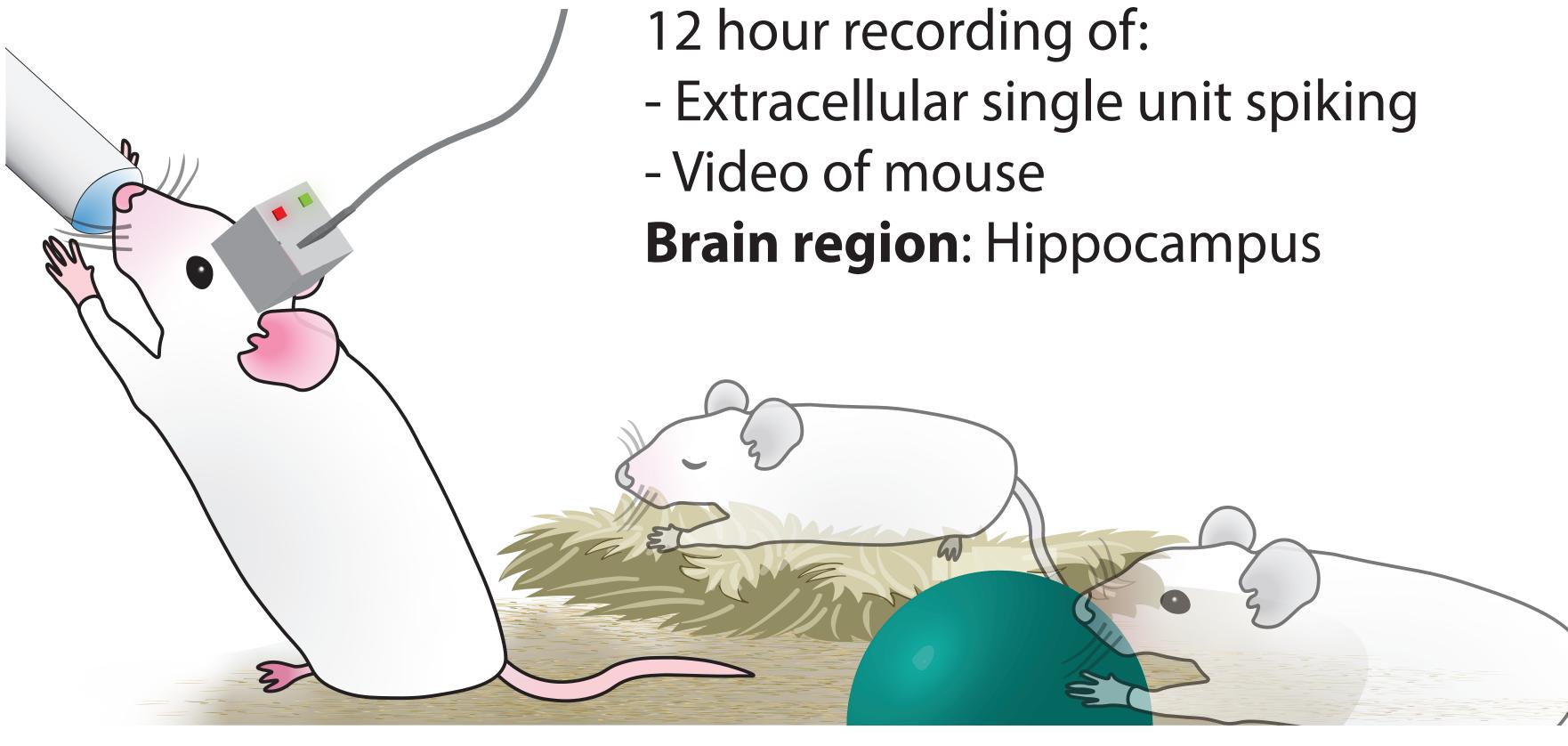


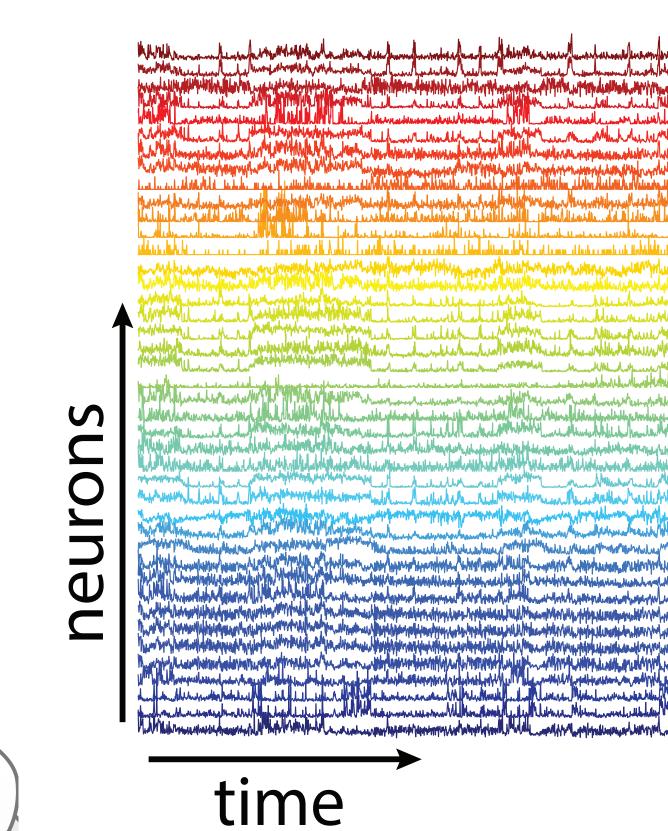




running/not running

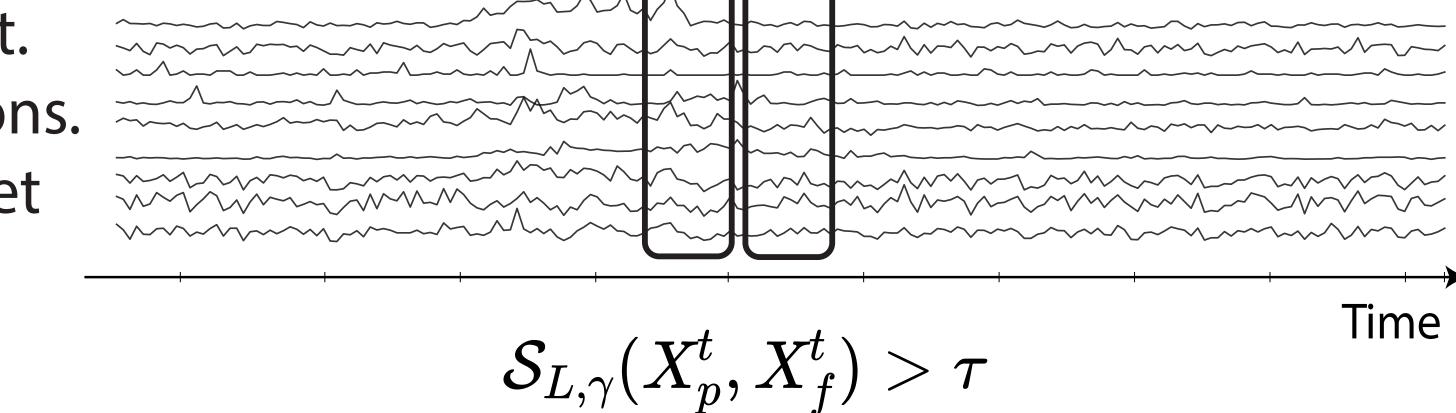
# Dataset





### Method

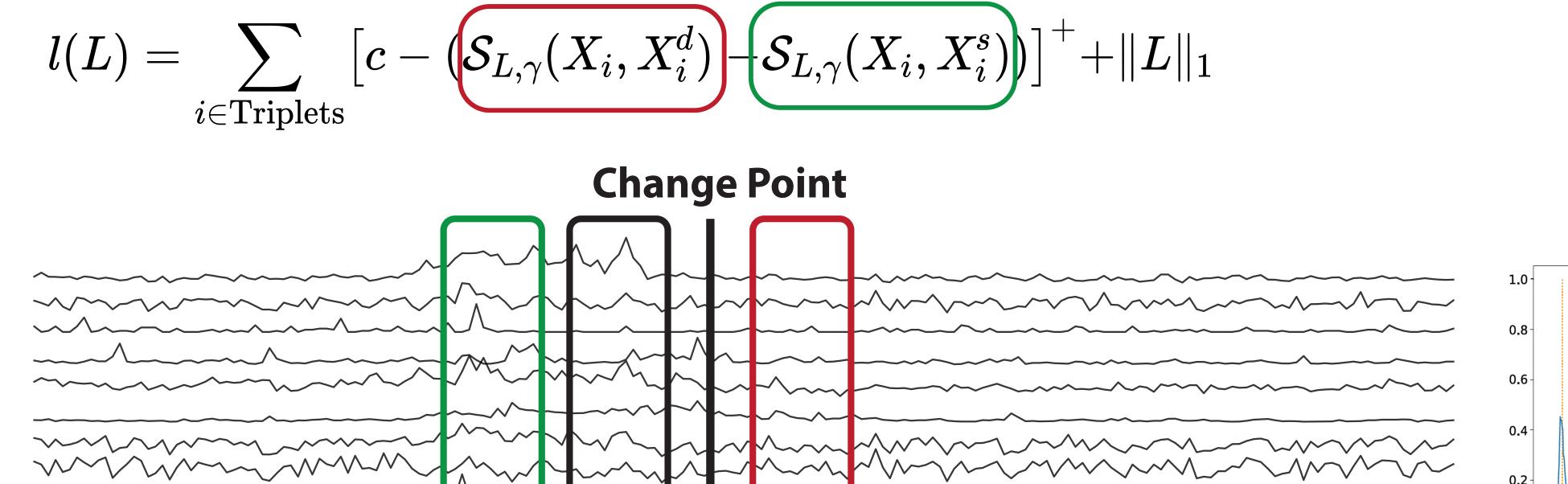
- 1. Select a window before and a window after a sample of interest.
- 2. Compute the Sinkhorn divergence between the two distributions.
- 3. A **Change Point** is detected if the divergence is greater than a set threshold.

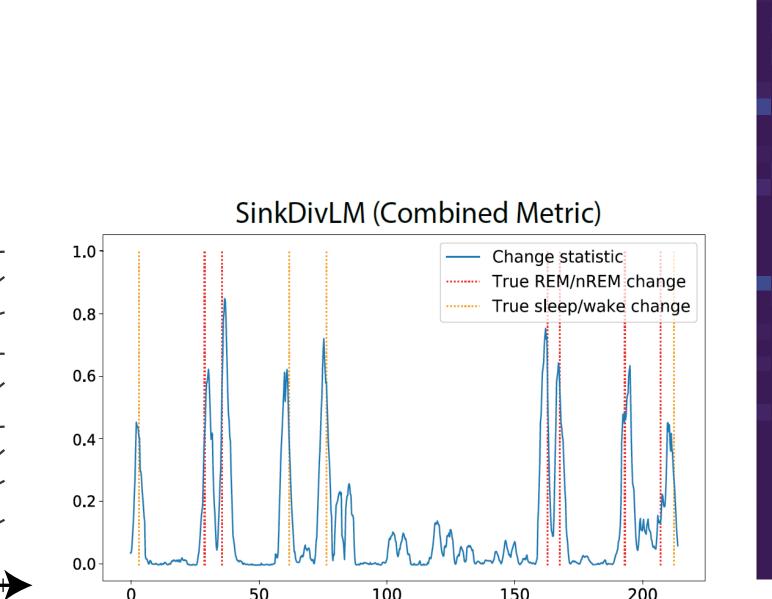


#### **Extension**

Learn a metric, for the Sinkhorn divergence computation, that helps to better detect task-relevant change points.

- 1. Select two windows that are both to the right or to the left of the change point:  $X_i$  and  $X_i^s$ .
- 2. Select a window that is on the opposite side:  $X_i^a$ .
- 3. Learn a sparse metric (L) by minimizing a triplet loss:



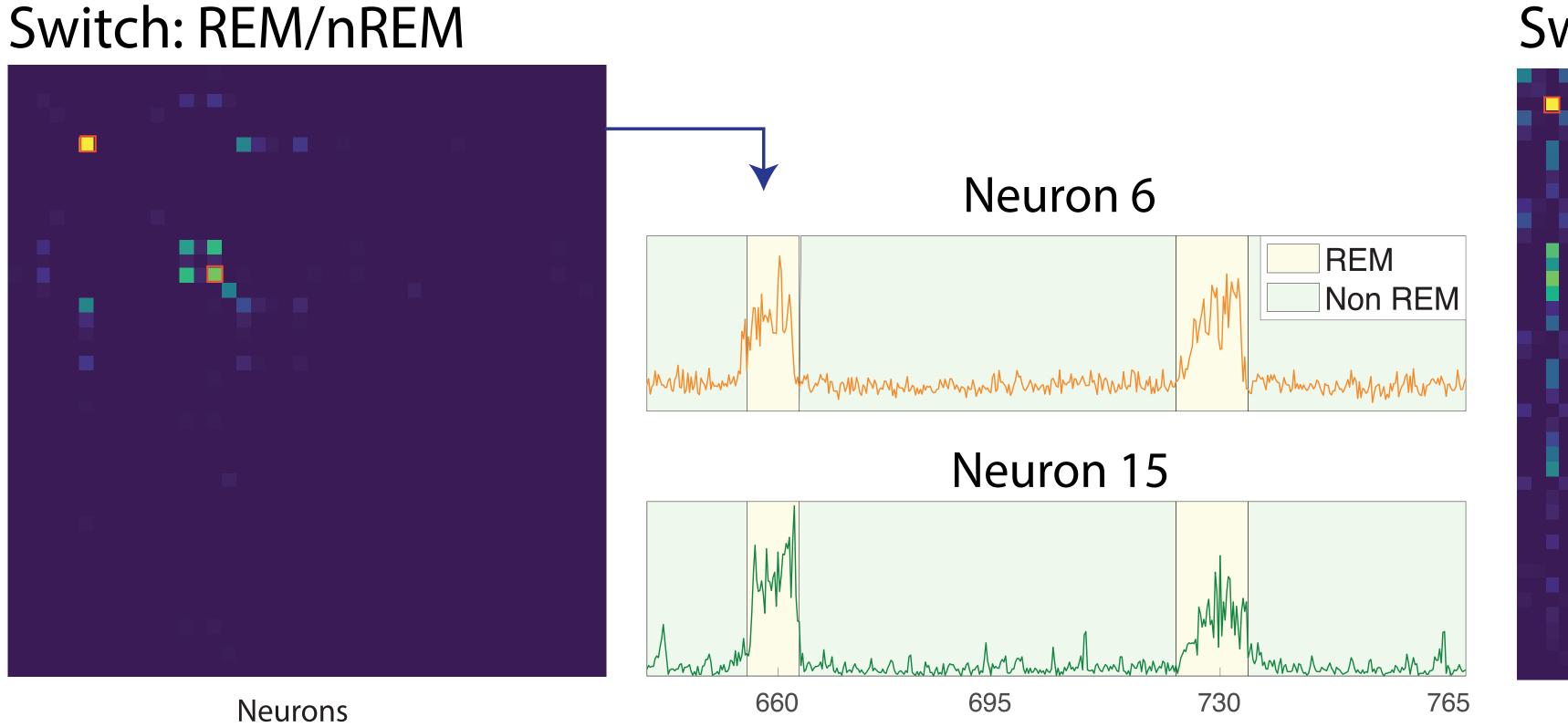


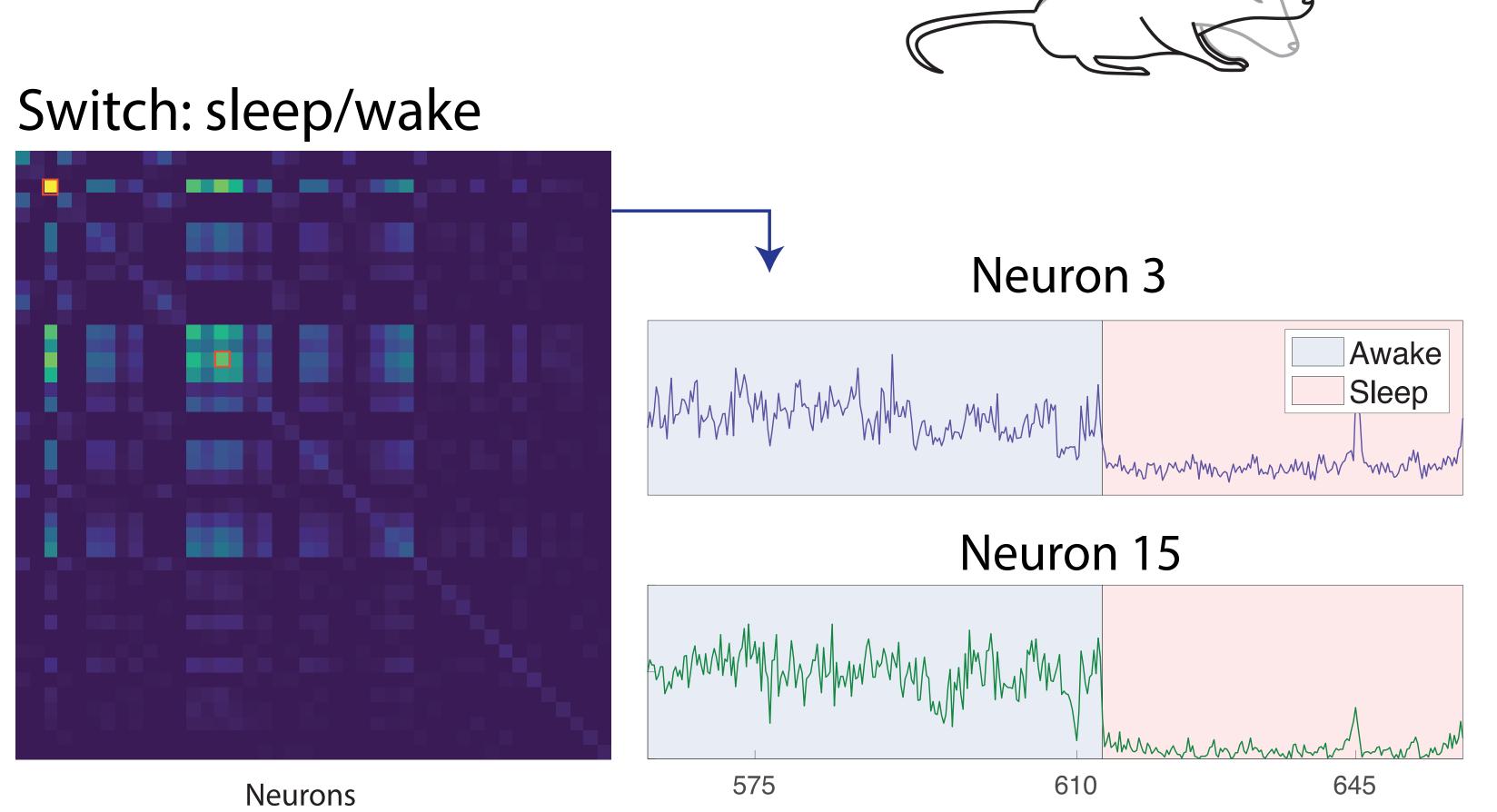


Neurons

# Visualizing the learned metrics

By visualizing the learned metrics, we reveal the most relevant neurons for the identification of a given change point.





## Results

We compare our method **SinkDivLM** with **SinkDiv** (without a learned metric).

We report the AUC of change point detection.

	SinkDiv	SinkDivLM
Trained on sleep/wake		
Sleep/wake	0.58	0.85
REM/nREM/wake	0.79	0.72
Trained on REM/nREM		
REM/nREM	0.92	0.95
REM/nREM/wake	0.79	0.82
Combined sleep metrics		
REM/nREM/wake	0.79	0.85
Trained on running/no running		
Running/no running	0.51	0.65

### Conclusion

Our metric learning approach is able to detect the points in which activity switches from one state to another better than the Sinkhorn divergence without this metric and with few labeled instances of change points.



Improves change point detection



Provides interpretability at the scale of neurons

# References and acknowledgements

#### References:

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Cuturi, M. (2013). Sinkhorn distances: Lightspeed computation of optimal transport. In Proc. int. conf. neural inf. process. syst. (neurips). Lake Thaoe, Nevada.

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