Using self-supervision and augmentations to build insights into neural coding

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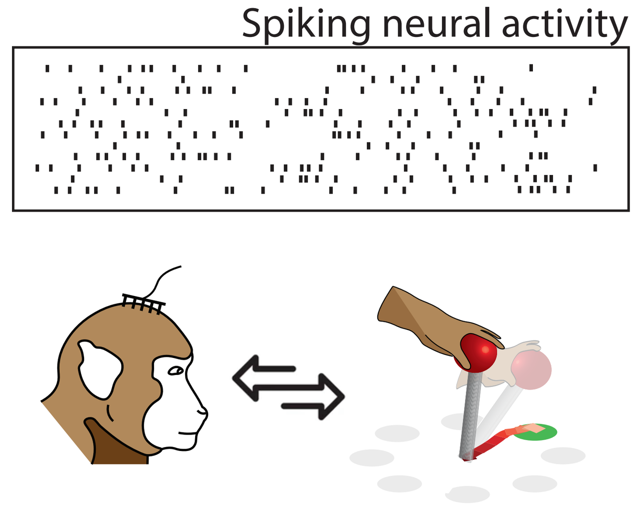
Abstract

Self-supervised learning (SSL) provides a powerful mechanism for building representations of complex data without the need for labels. Here, we highlight recent progress in the application of SSL to data analysis in neuroscience, discuss the implications of these results, and suggest ways in which SSL might be applied to reveal interesting properties of neural computation.

SSL in Neuroscience

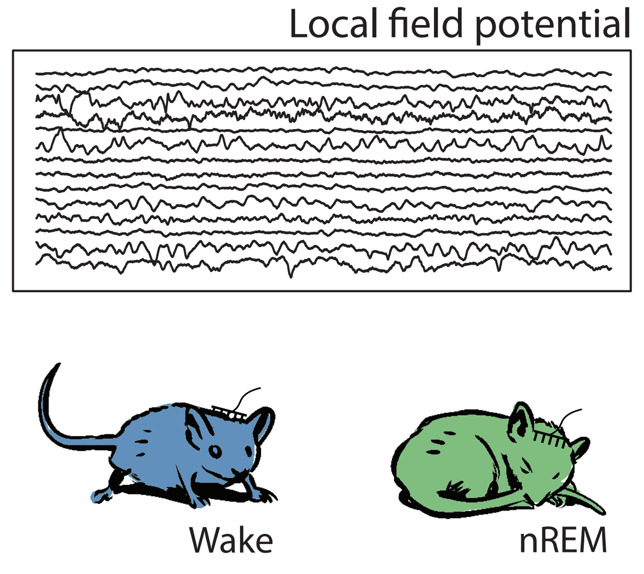
Neural populations (Ephys)

The activity of neural populations is recorded using implanted microelectrode arrays. The recording can be spike-sorted into **single neuron** activities.
Examples: [1, 2]



Macroscale (EEG, LFP)

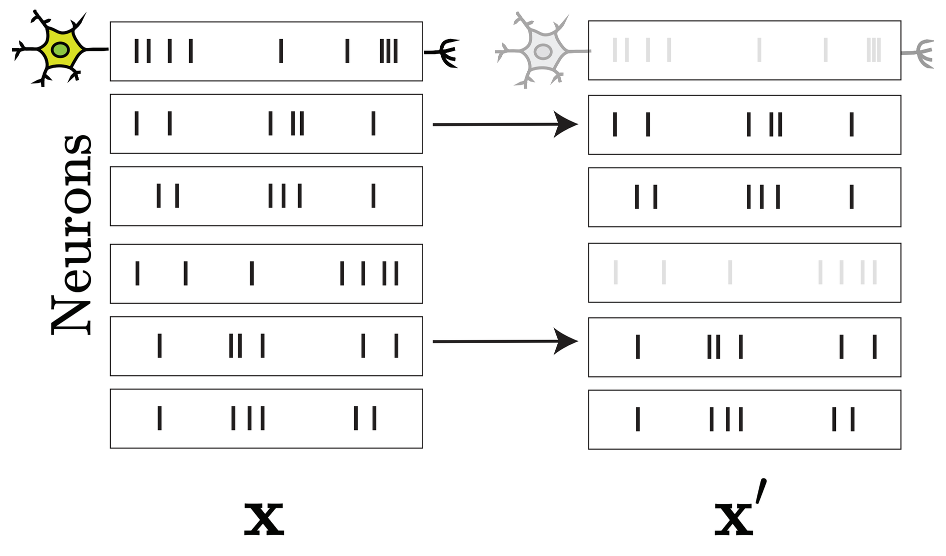
EEG and LFP measure electrical activity across superficial parts of the brain. Each channel summarizes the activity of **thousands of neurons**. Macroscale datasets can be collected non-invasively
Examples: [5, 6, 7]

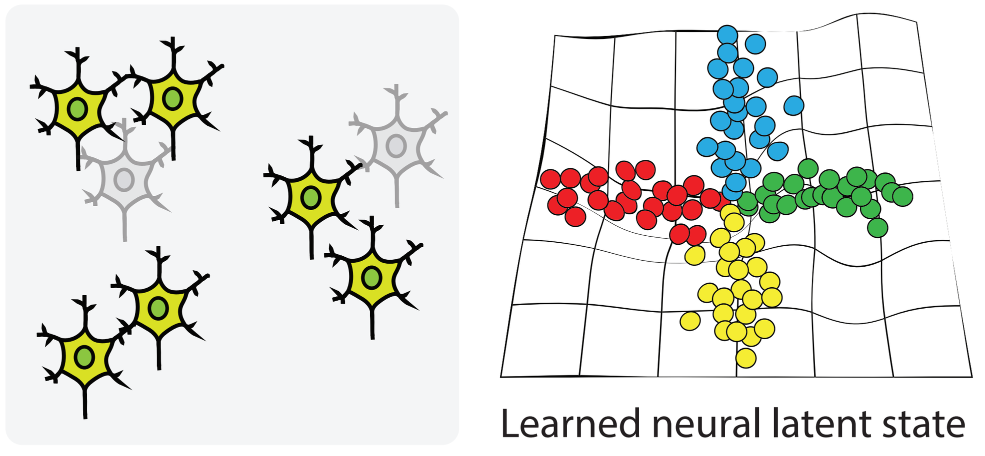


Augmentations that either preserve or break information can give us insights into neural coding!

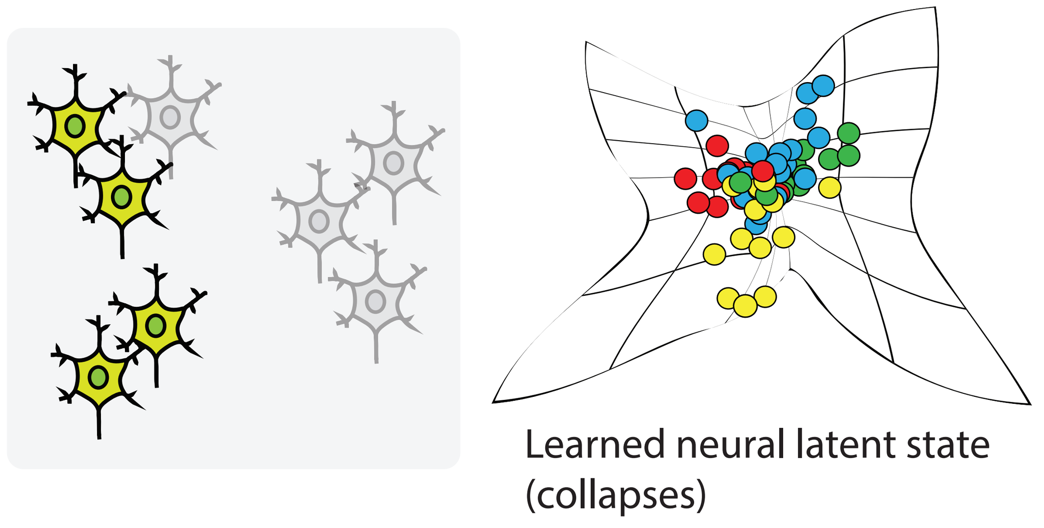
What can different classes of augmentations reveal about neural circuits?

(i) Dropout as an augmentation



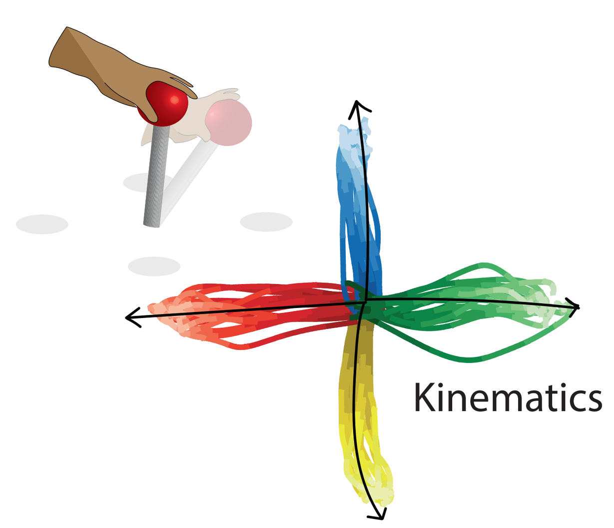


- Dropout augmentation: Encourage invariance to pertubations of individual neurons

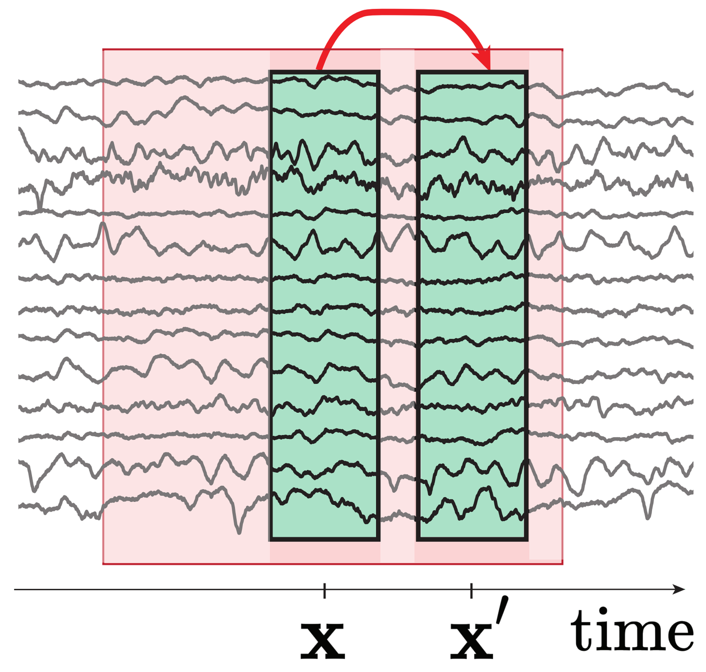


- Degree of dropout gives insight into how distributed or localized information is

* Neural activity recorded in the motor cortex during a reaching task (4 directions)



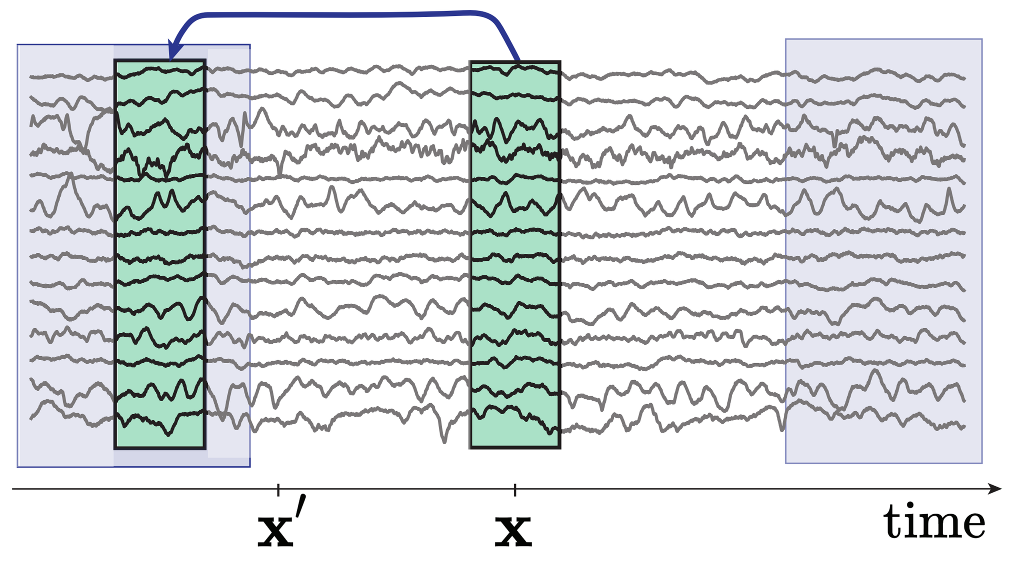
(ii) Temporal augmentation



Grouping nearby time points:

- Why? Build temporal invariance, smoothness, and stability into the representation
- Contrastive methods like TCN [3] and RP [4] use temporal nearness to define positive examples
- Larger windows encourage stronger temporal invariance

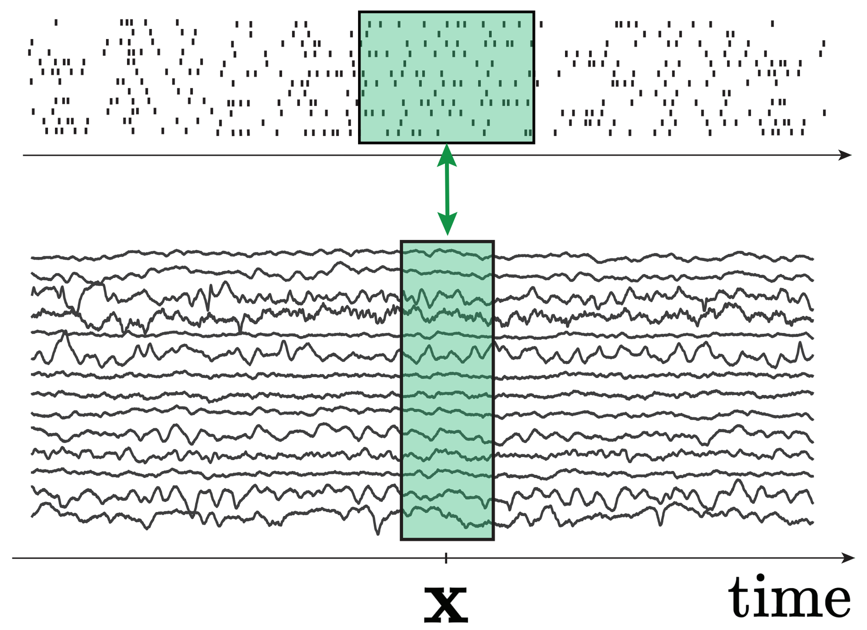
(iii) Nonlocal yet similar views



Comparing between nonlocal states:

- Why? Identify similar states across time (e.g. find repeated behavior in different trials)
- Contrastive methods assume nonlocal points are negative examples
- Mine your own view [1] finds neighbors in latent space to use as positive views

(iv) Multi-modal augmentation



Multi-Modal representation learning:

- Setup: If we have simultaneous recordings across two modalities, we can pair them as views
- Could learn a mapping between coarser and high-resolution measures of neural activity (LFP and neural spiking), highlighting shared and modality-specific variability
- Recent work [6] shows how this type of approach can be applied to decode behavior

References & Acknowledgements

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