Machine Learning Methods for Sharp-Wave Ripple Prediction

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Objective

We apply machine learning techniques towards improving a realtime closed loop sharp-wave ripple (SWR) disruption system.
Realtime closed-loop detection and disruption systems have proven difficult to implement, as the transient nature of SWR events causes the detection latency of a system to contribute significantly towards its accuracy and application. State-of-the-art algorithms implement a threshold crossing approach, which have been shown to have relatively high true positive and low false positive rates, both online and offline.
However, online applications have a latency of approximately 35-60 ms, indicating that the first 40-60% of a SWR event may proceed uninterrogated. We aim to circumvent this issue by searching for predictive indicators of SWR events, with the goal of predicting 20-30 ms before a SWR event.[A],[B],[C]

What Are Sharp-Wave Ripples?

- Hippocampus is the center for learning and memory
- Synchronous firing of neurons in CA3
- 150-250 Hz Oscillations in CA1
- Memory consolidation and recall
  - **Sequential reactivation** based on a **previous experience**

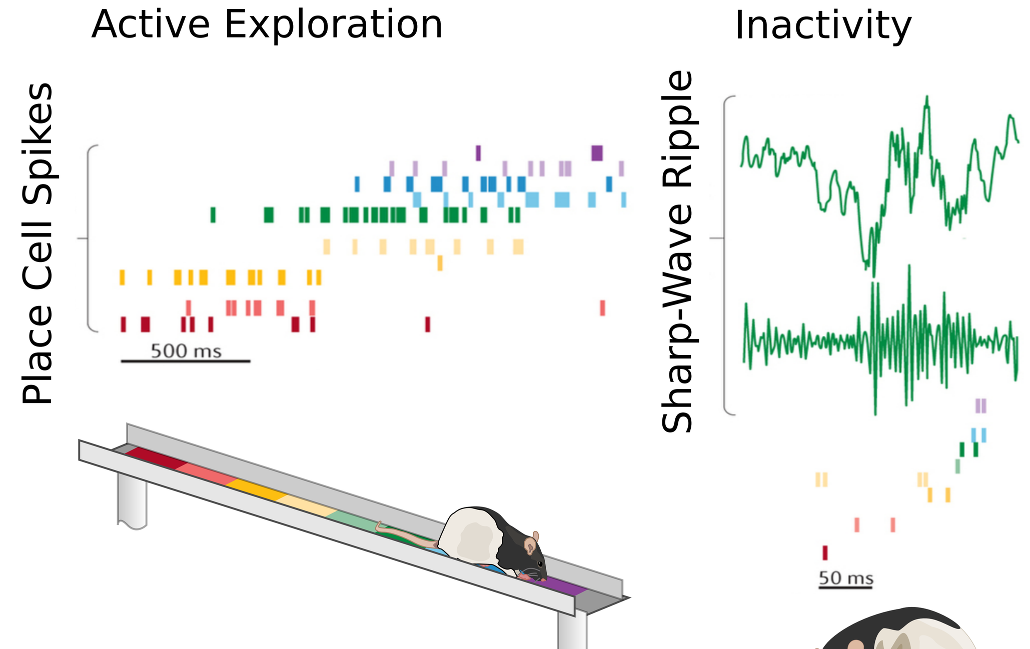
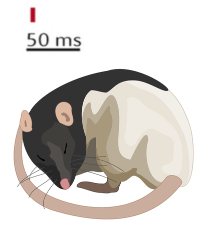


Figure adapted from Colgin Nature Reviews Neuroscience 2016



Why Do We Care?

Never having interrogated SWR generation, it is likely current disruption experiments do not entirely prevent access to specific memories. Thus, it is impossible to determine whether or not SWRs are responsible for memory formation, or simply are a large contributing factor. Additionally, accurate prediction of SWR events may not only allow for improve SWR detection, but also may enable selective, premature disruption of specific memories. This methodology, then, may be effective in terms of preventing intense flashbacks that are symptomatic of Post-Traumatic Stress Disorder (PTSD). Additionally, recent literature has emphasized the role SWRs play in memory enhancement, indicating SWR access may lead to a better understanding of memory. [E]

Accounting for Anomalous Nature of Sharp-Wave Ripples

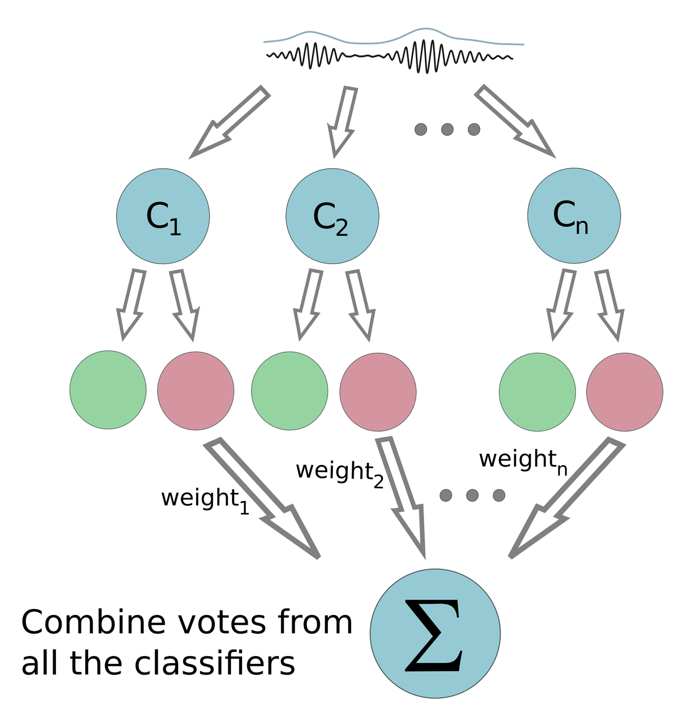
- Ripples are relatively rare in neural data
  - Realistically, approximately 1-5% of dataset
  - High accuracy labeling every sample as a non-event
- How can we account for this imbalance?
  - Custom loss function
  - Multiple classifiers: Boosting vs. Cascading

True Label \ Predicted Label	Non-event	Pre-SWR	SWR
Non-event	2967	0	0
Pre-SWR	119	0	0
SWR	36	0	0

(Color scale: 0, 300, 600, 900, 1200, 1500)

Boosting

- Maximize performance by altering weights
  - Segment input data
  - Train multiple weak classifiers
  - Increase the weight of mislabeled data



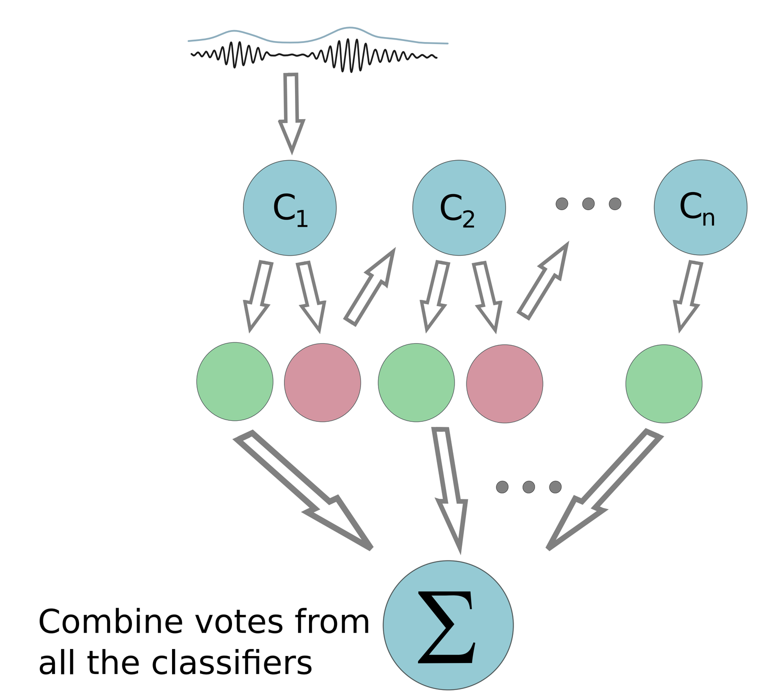
- Naïve network performance

True Label \ Predicted Label	Non-event	Pre-SWR	SWR
Non-event	1112	1567	288
Pre-SWR	39	80	0
SWR	15	0	21

(Color scale: 0, 300, 600, 900, 1200, 1500)

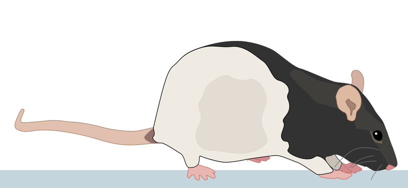
Cascade Learning

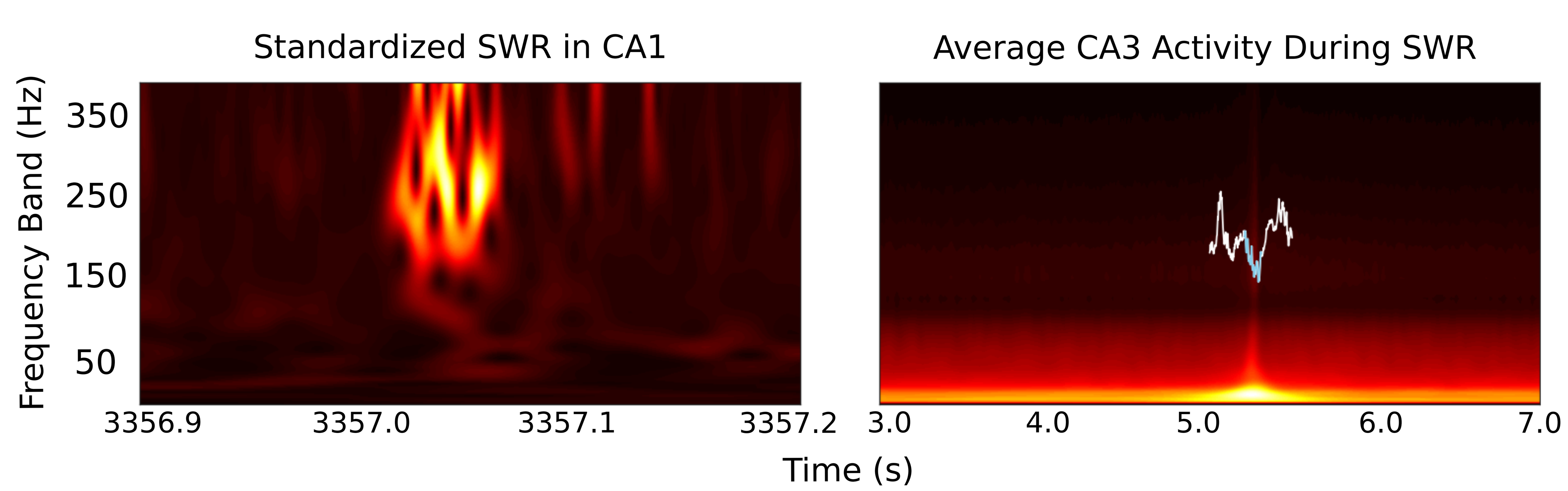
- Maximize performance via additional training
  - 1 classifier for all input data
  - Aim for 100% TP, ~50% FP
  - Pass mislabeled data to train next classifier



- Each layer produces less mislabeled data
  - Each classifier specialized for some feature

Spectral Domain Conversion



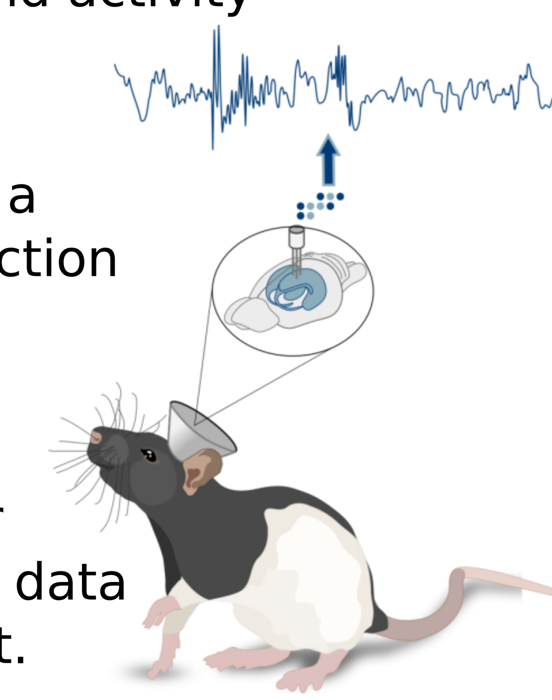


Purposeful PreProcessing

- Rodent electrophysiological recordings from sleep and active states
- Sliding window across data
  - 14 bins in a window, 12 samples per bin
  - ~134.4 ms (sampling rate 1250 Hz)
- Continuous wavelet transform
  - Standardized within frequency band over entire period of activity/inactivity
- Label each bin (every 12 samples)

Future Works

- *In vivo* validation
  - Online detection/disruption improvement is the ultimate goal
- Access to ripple generation/pre-SWR processes
  - Preventative stimulation
  - Decoupling frequency band activity corresponding to SWRs
- Correlations between SWRs and other neural activity as a formal way to quantify detection and disruption



Special Thanks

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