Latent Variable Models for Hippocampal Sequence Analysis

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**Introduction**

**ENCODING POSITION**

- Populations of neurons in the rodent hippocampus (HP) have been shown to accurately encode information about the animal’s location in its environment, so-called “place cells.”

**SEQUENTIAL ACTIVITY: REPLAY**

- Place cells fire sequentially as animals move around, and these sequences sometimes repeat during sharp wave ripples (SWRs)

**DATA SET DESCRIPTION**

- Animals run on linear track for reward

**Methods I: Bayesian decoding**

**BAYESIAN DECODING (RUN)**

- Tuning curves are estimated using RUN and PBE data, and place-cells are identified

**LEARNING TASK**

- A set of sequential observations, jointly learned using states A & B, in order to evaluate the posterior P(B)

**Graphical abstract**

- Linear track data from running 3 animals

**Experiment**

- Sequentially ramps, place cells

**Results I**

**VIRTUAL TUNING CURVES**

- Only the HMMs trained on PBEs make the error on position data, when compared to true position data. We compute virtual tuning curves in two ways:

**RESULTS II**

- The PBE-trained models are sparser than shuffled counterparts (A→F) in both the transition matrix and the observation model. The states located in position 0 (which we use to decode neural activity) is 1.0

**Conclusion**

- Using our HMM approach, we built models of hippocampal sequences independent of animal behavior. In particular, we showed that these models, trained on only a few seconds of offline ripple-elicited data, can be used to accurately decode waking behavior, and can be used to detect replay events with comparable accuracy to state-of-the-art Bayesian decoding methods.

- Overall, the latent variable model approach provides an attractive framework for studying and analyzing sequential neural activity, but perhaps more importantly, they provide an alternative “sequential” view of hippocampal activity that may shed new light on how memories are formed.

**References**

[1] Silva, D., Feng, T., & Foster, D. J. (2015). Trajectory events across hippocampal place cells require previous “sequential” view of hippocampal activity that may shed new light on how memories are formed.


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**Graphical abstract**

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