Decoder Framework for Real-Time Analysis of High-Dimensional Neural Data

Real-time decoding of large-scale neural recordings is becoming a necessity within modern neuroscience to investigate brain dynamics at a deeper level. In this research, a novel decoding framework is proposed which inherits recent advancements from deep neural network (DNN) models and combines them with classical dynamical frameworks such as the state-space models (SSM). The framework is called Direct Discriminative Decoder (DDD), and its performance is demonstrated in decoding rat traversal through a maze given hippocampal place cell ensemble spiking activity. The goal of using this framework is to decode hippocampal sequence replay events in real time for closed-loop, brain state-dependent stimulation in studying memory, which is supported in seminal work such as that of J. M. Hyman et al. 2003 [1]. Disrupting state-dependent neural activity has proven to give insight into underlying patterns within hippocampal neural systems that contribute to memory consolidation. The analysis of rat hippocampus data presented here suggests a 831 ± 448% increase in decoding performance compared to state-of-the-art decoder model solutions. The computational complexity of DDD is $O(N^2)$, where N is the number of particles used in the decoding processes. This inexpensive computational complexity along with improved performance makes DDD a great modeling framework in analysis of high-dimensional neural recordings.

Methods:

The DDD framework was originally presented by M. R. Rezaei et al. 2022 and focused on a linear discriminative model [2]. In the decoder definition, X_k represents the latent state at time k, Y_k is the neural observation at time k, and H_k is some history of neural observations with history length L such that H_k is equivalent to $Y_{k-L:k-1}$. The discriminative model and state process are defined by $P(X_k; Y_k, H_k)$ and $P(X_k; X_{k-1})$, respectively. Markov Chain Monte Carlo (MCMC) methods are used in decoding the latent states, where the proposal distribution is a random walk model defined by $Q(X_k; X_{k-1}) \sim N(X_{k-1}, \sum)$. The filter algorithm in DDD is defined by:

$$P(X_{0:k}; Y_{1:k}) \propto \frac{P(X_k; Y_k, H_k)}{P(X_k; H_k)} * \frac{P(X_k; X_{k-1})}{Q(X_k; X_{k-1})} \; * \; P(X_{0:k-1}; Y_{1:k-1}) \qquad (1)$$

A challenge in the DDD filter solution, not addressed in [2], is a tendency of particles to be degenerate given the likelihood ratio term (first term on the right side of Equation 1). To address this, a newly proposed approximation for the denominator $P(X_k; H_k)$ is defined by:

$$P(X_k; H_k) \approx \int P(X_k; X_{k-1}) \; * \; P(X_{k-1}; Y_{1:k-1}) \; * \; dX_{k-1} \approx \sum_{p=1}^{N} P\left(X_k; X^{(p)}_{P(X_k; X_{k-1})}\right) \qquad (2)$$

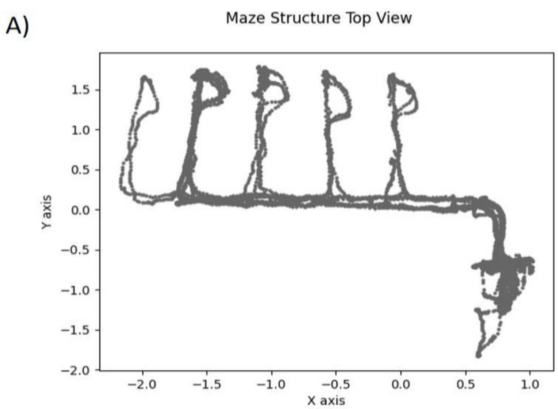
where, in this approximation, resampled particles at time $k-1$, $X_{k-1}^{(p)}$, are used.

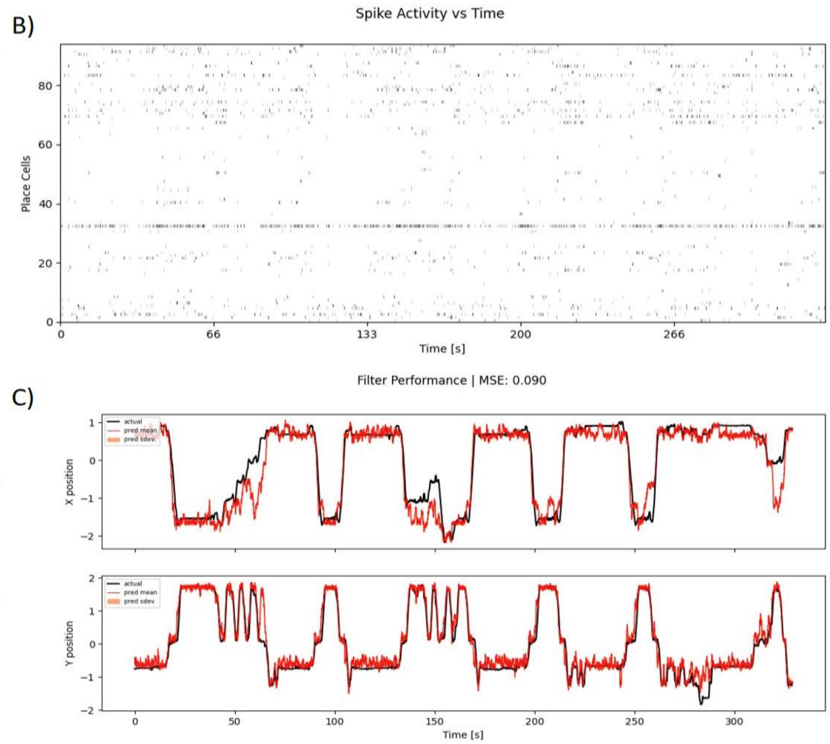
In the research presented here, the discriminative model is characterized by a DNN to increase expressive power of the framework. The discriminative DNN model directly outputs parameters to a Gaussian mixture distribution characterizing possible positions of the rat in different segments of the maze. Here, the neural observations are binned spiking activity of 94 place cells with 33 millisecond windows. Another DNN model characterizes the state process by producing mean and covariance parameters for a normal distribution describing the likelihood of future positions given the current position of the rat. Figure 1 illustrates the maze structure, raster plot of spiking activity, and decoding results for sample time periods. Note that the dimensions here have been standard normalized. Table 1 shows a comparison of DDD with state-of-the-art methods.

Conclusion:

The decoding results presented in this work suggest that DDD performance precedes that of other state-of-the-art solutions such as SSM, Gated Recurrent Units (GRU), and Deep Kalman Filter (DKF). The DDD framework may easily be applied to large-scale neural recordings captured from the hippocampus, cortical areas, or distributed neural nodes. The capacity for DDD to be agnostic to modality of neural observations, its scalability, inexpensive computational complexity, and high decoding accuracy make it an excellent framework selection in neuroscience experiments, particularly in real-time applications.

Figure 1:





A) Trajectory of rat inside the maze. Position is captured by a camera set up over the maze. B) Raster plot of 94 place cells during test evaluation, recorded with 33 msec windows. C) Decoder performance on the test set for rat "Emile". History length is 12 timesteps, which is approximately 400 milliseconds of neural activity.

Table 1:

	DDD	D4 [3]	DKF [3]	GRU [3]	SSM [3]
Mean Squared Error	0.09	0.60	0.95	1.05	0.75

MSE performance scores for DDD, Deep Direct Discriminative Decoder (D4) proposed by M. R. Rezaei et al. 2022 [3], DKF, GRU, and traditional SSM. All algorithms besides DDD were evaluated in [3] and metrics are reported here. Algorithm evaluation was not on the same dataset as DDD, but the example application is the same.

References:

1) Hyman, J. M., Wyble, B. P., Goyal, V., Rossi, C. A., & Hasselmo, M. E. (2003). Stimulation in hippocampal region CA1 in behaving rats yields long-term potentiation when delivered to the peak of theta and long-term depression when delivered to the trough. *Journal of Neuroscience*, *23*(37), 11725-11731.
2) Rezaei, M. R., Hadjinicolaou, A. E., Cash, S. S., Eden, U. T., & Yousefi, A. (2022). Direct Discriminative Decoder Models for Analysis of High-Dimensional Dynamical Neural Data. *Neural Computation*, *34*(5), 1100-1135.
3) Rezaei, M. R., Popovic, M. R., Lankarany, M., & Yousefi, A. (2022). Deep discriminative direct decoders for high-dimensional time-series analysis. *arXiv preprint arXiv:2205.10947*.