Impact of delay between pattern presentations on memory in an attractor neural network with triple-well weights

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Objectives

- **Motivation**: an attractor neural network with triple-well weights, more realistic than double-well model (Feng *et al.*, 2023) because most neurons without stimulation get disconnected

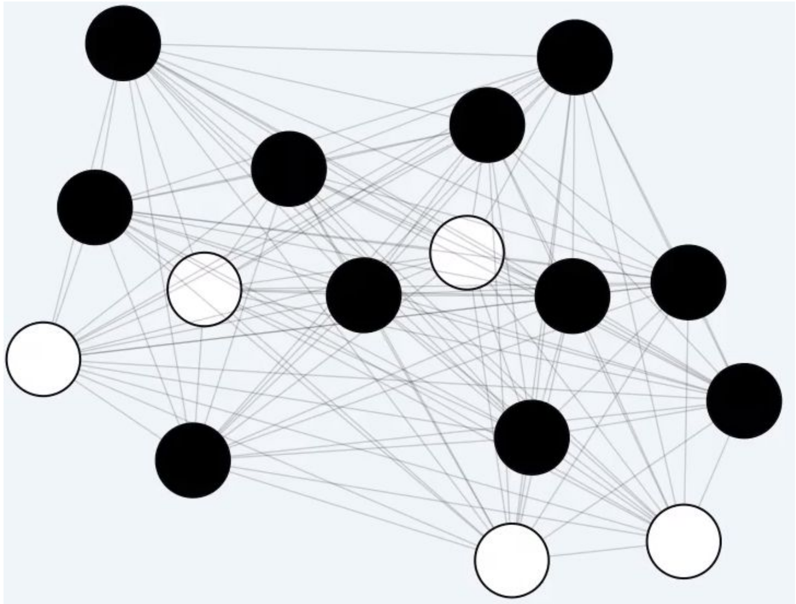
- **Objective**

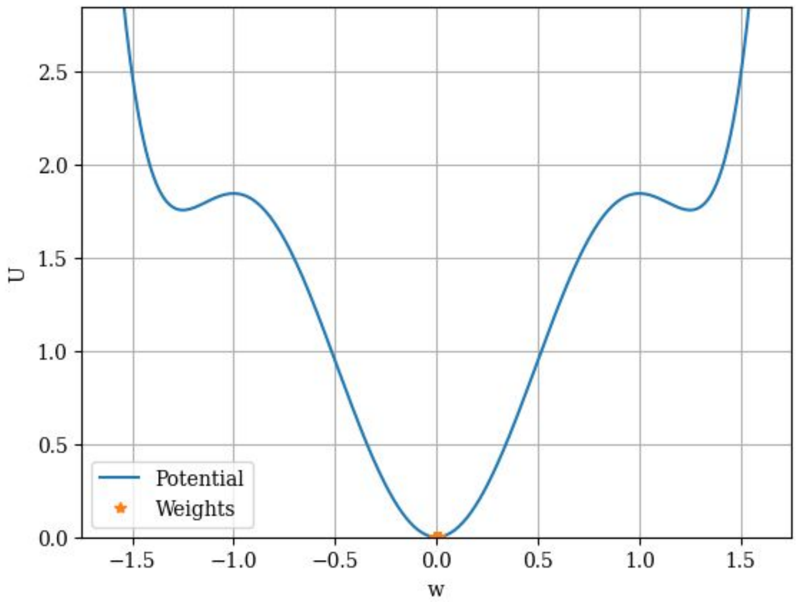
    - Understand the impact of various delay durations on pattern recall (pattern completion) under given conditions using triple-well weights Hopfield model.

    - And how it affects the transition of weights to stable state (within nonzero-well) for long-term memory or to transient state (within zero-well) for short-term memory.

Background

- **Model**: Triple-well weights Hopfield model:
    - A classic Hopfield model with triple-well weights potential function
    - Decay mechanism (relaxation and noise)
- When learning rate is sufficiently slow, temporal evolution depends on delay between episodes
- **Question**: How does delay duration affect recall quality and temporal evolution given a learning rate?

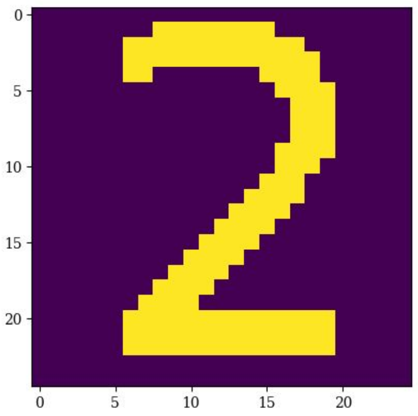




Methodology

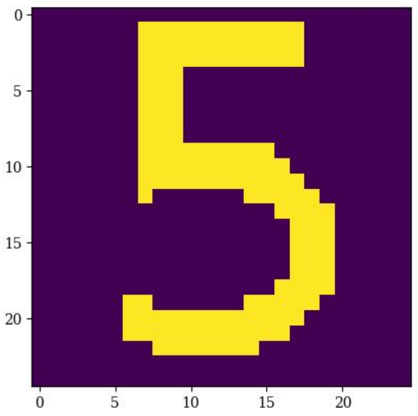
- **Model:** Triple-well Hopfield (TWH) model, 625 neurons
- **Data:** 25x25/2_5_combined, two digit patterns 2 and 5
- **Two episodes**: present pattern 2 at time 0, then present pattern 5 at time t_delay, end the process at time 1.
- **Recall quality**: let TWH model decay, at each time t_decay let TWH model reconstructs perturbed pattern for pattern 2, record recall quality (Pearson correlation coefficient).
- **Examine**: Set low and high learning rates (0.3, 0.7)
    - Vary t_delay (0.2-1, 0.1) and t_decay (0-7, 1), record recall quality, plot the recall quality line graph
    - Let TWH model converge, plot potential landscape and weight density distribution

Present at t=0



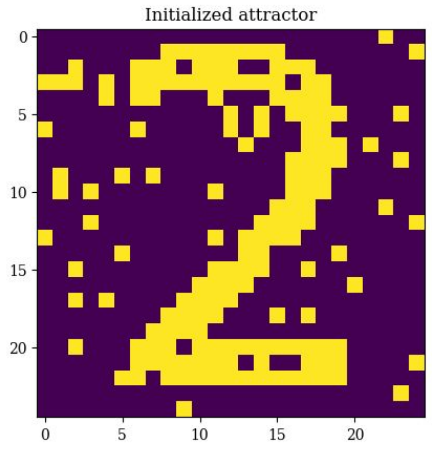
Delay …

Present at t =t_delay

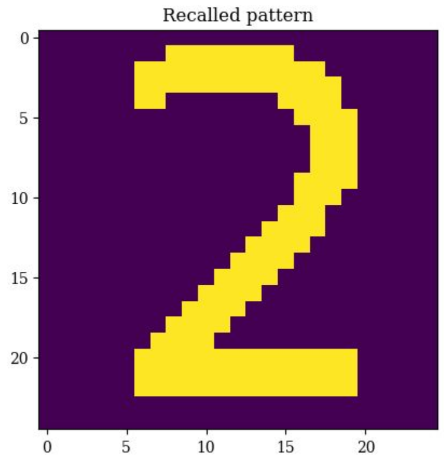


Decay
And Convergence

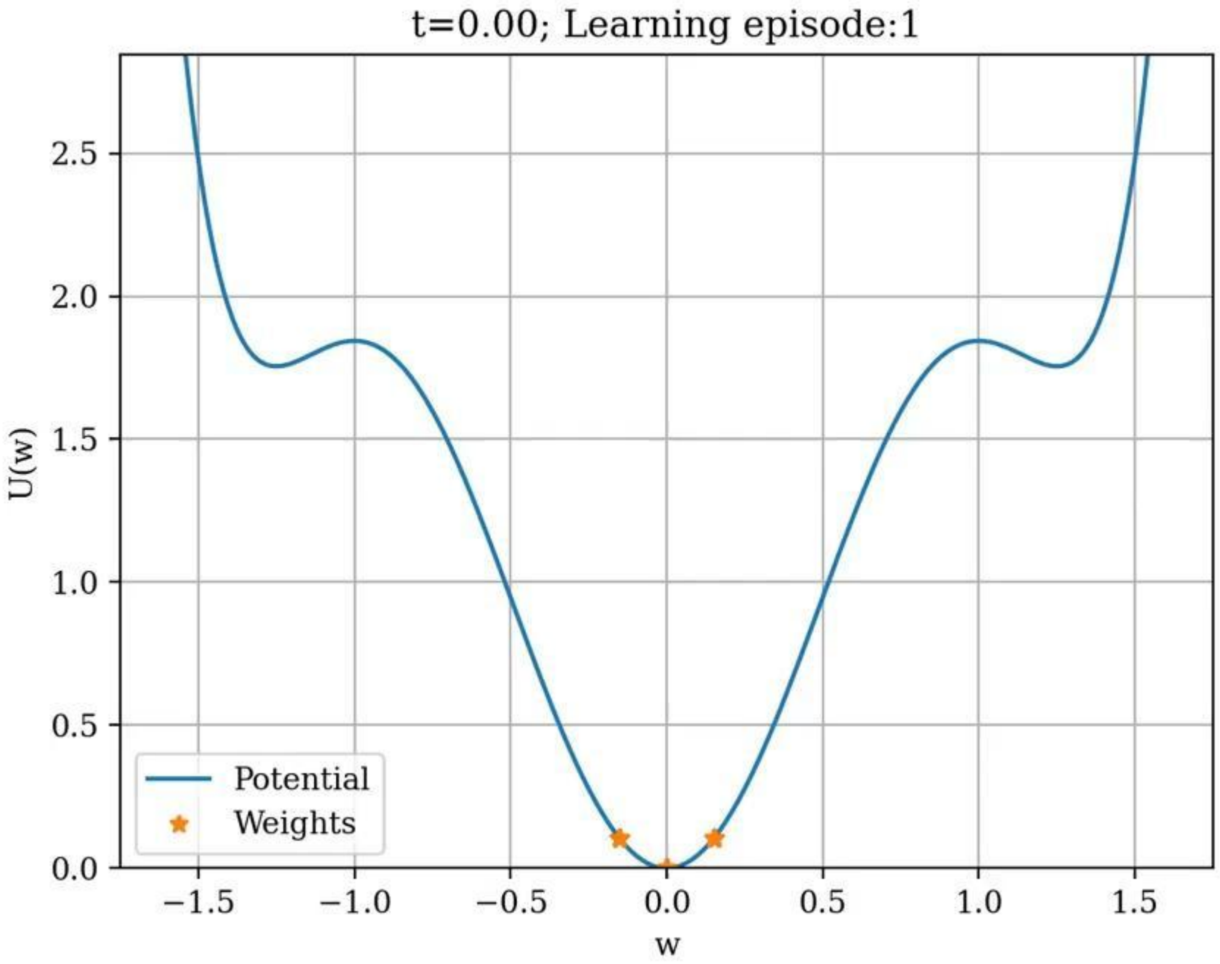
Initialize



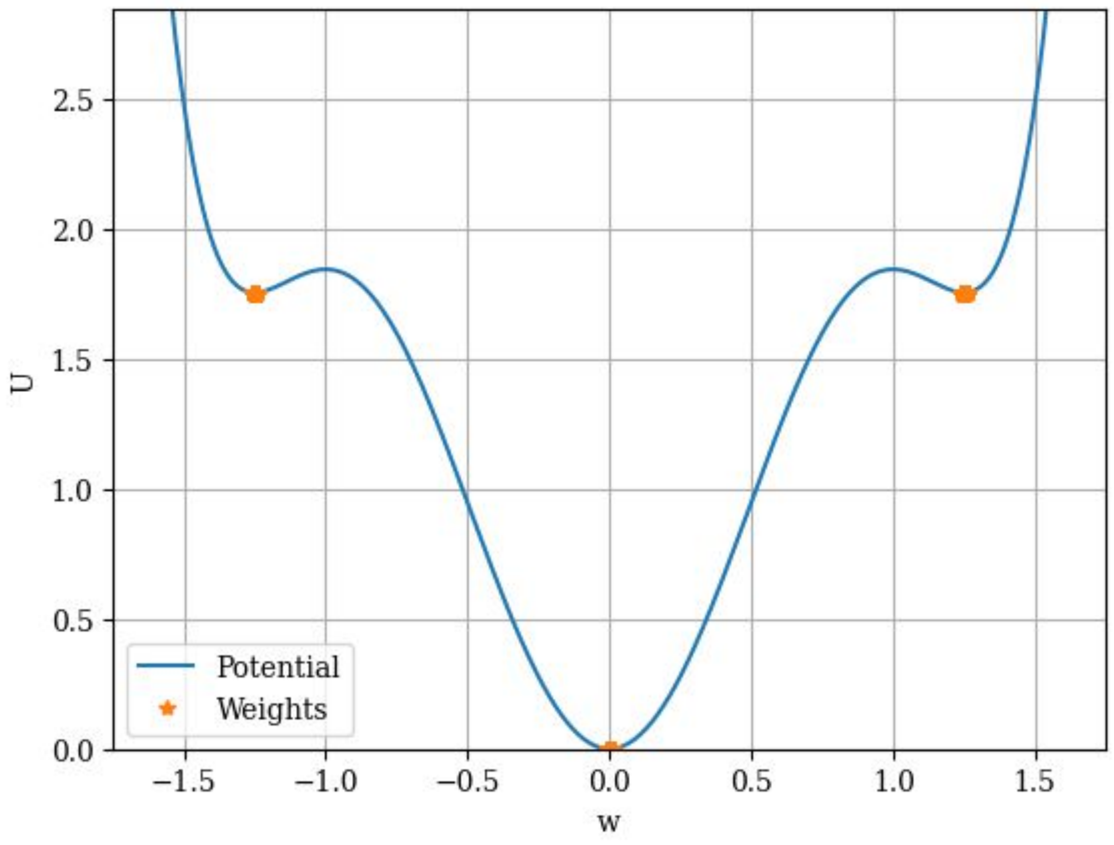
Recall

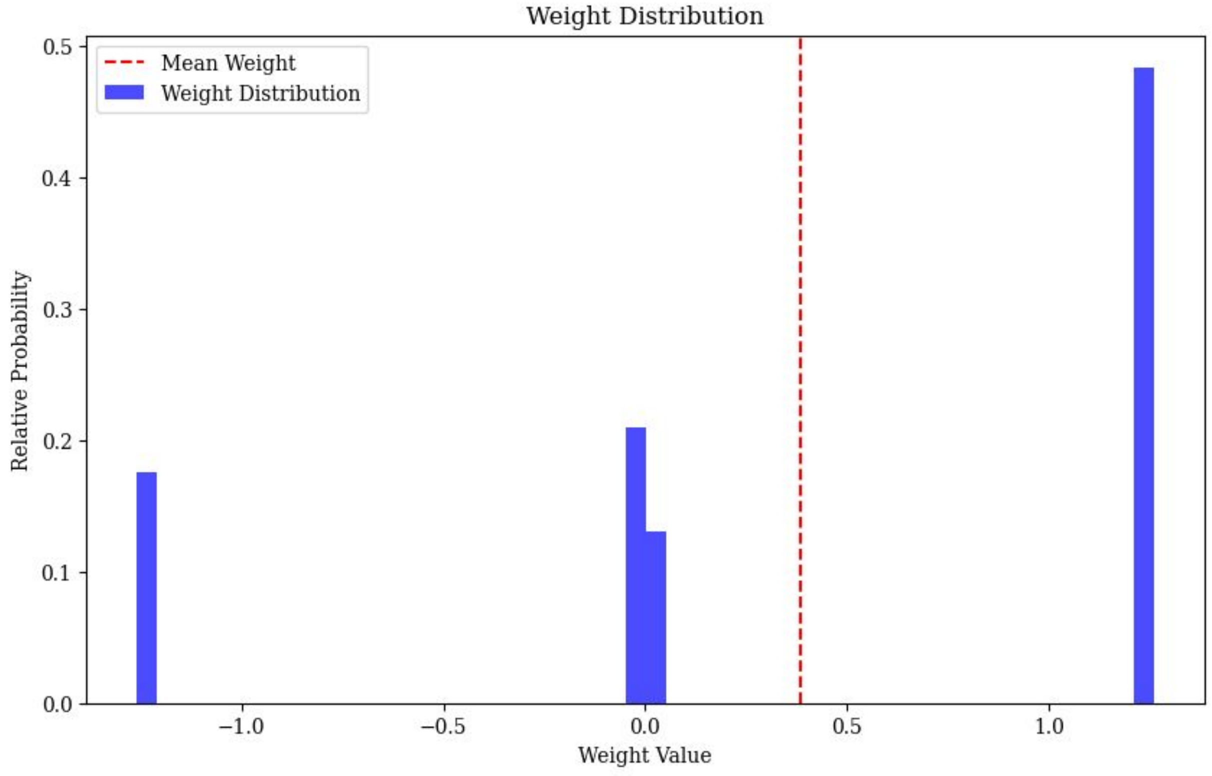


Weight dynamics of an attractor neural network with triple-well weights

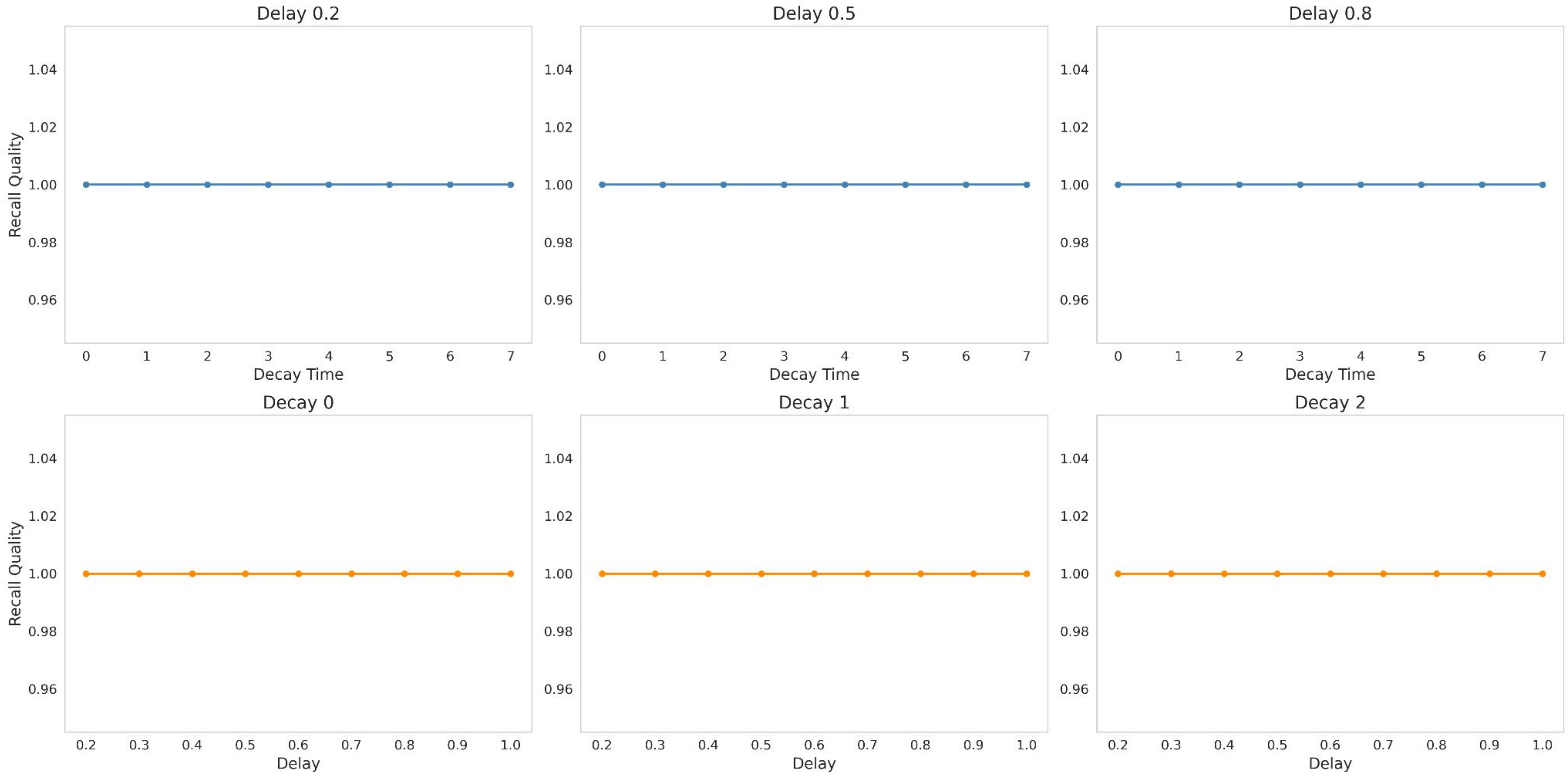


Weights converge to stable states a with high learning rate

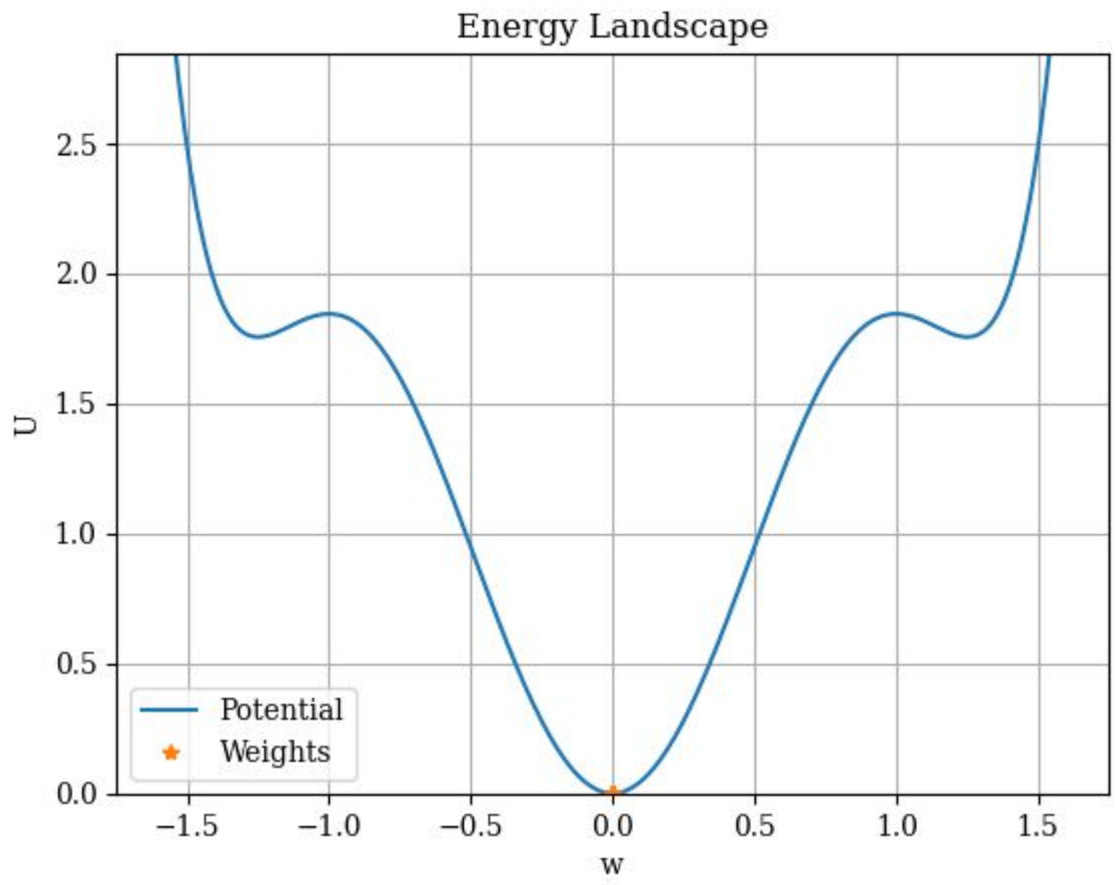


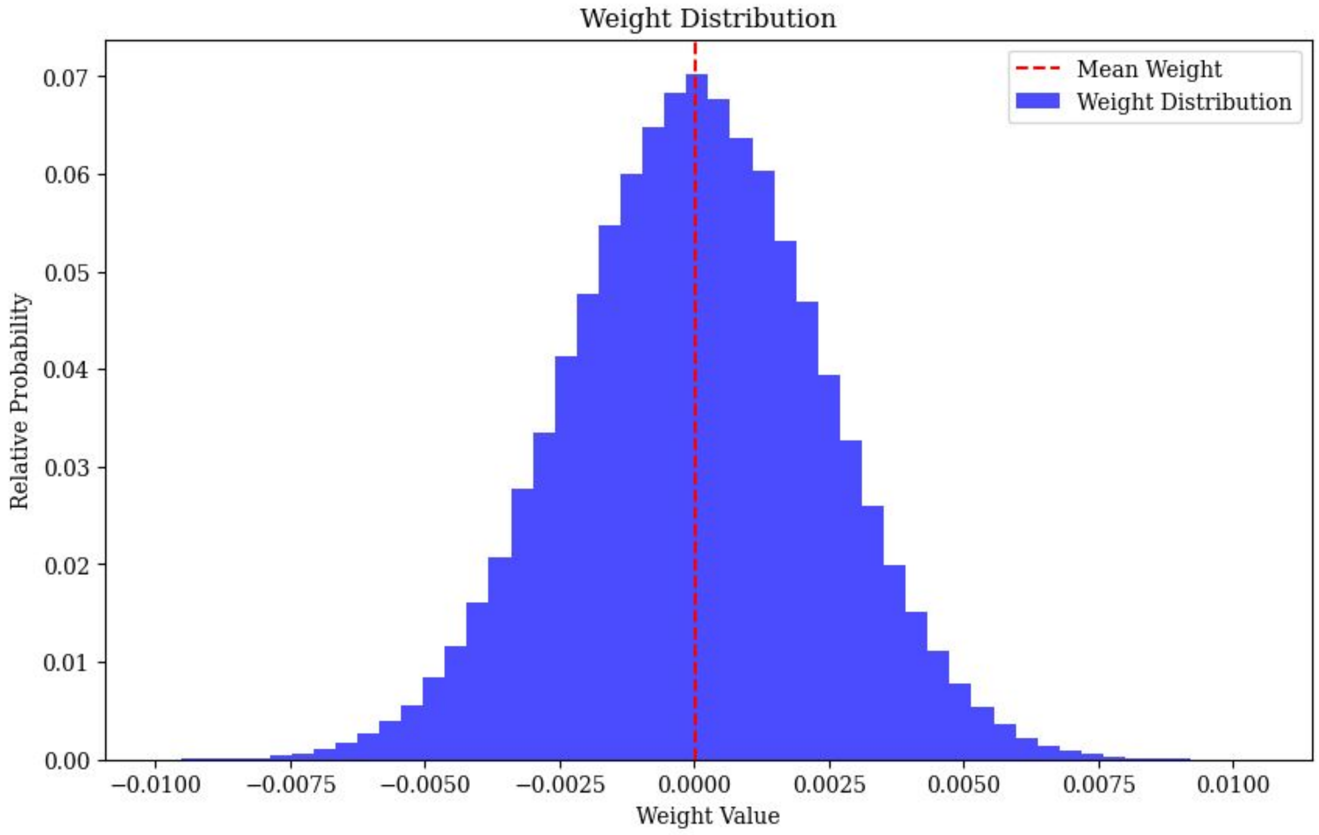


Memory recall sustains with a high learning rate

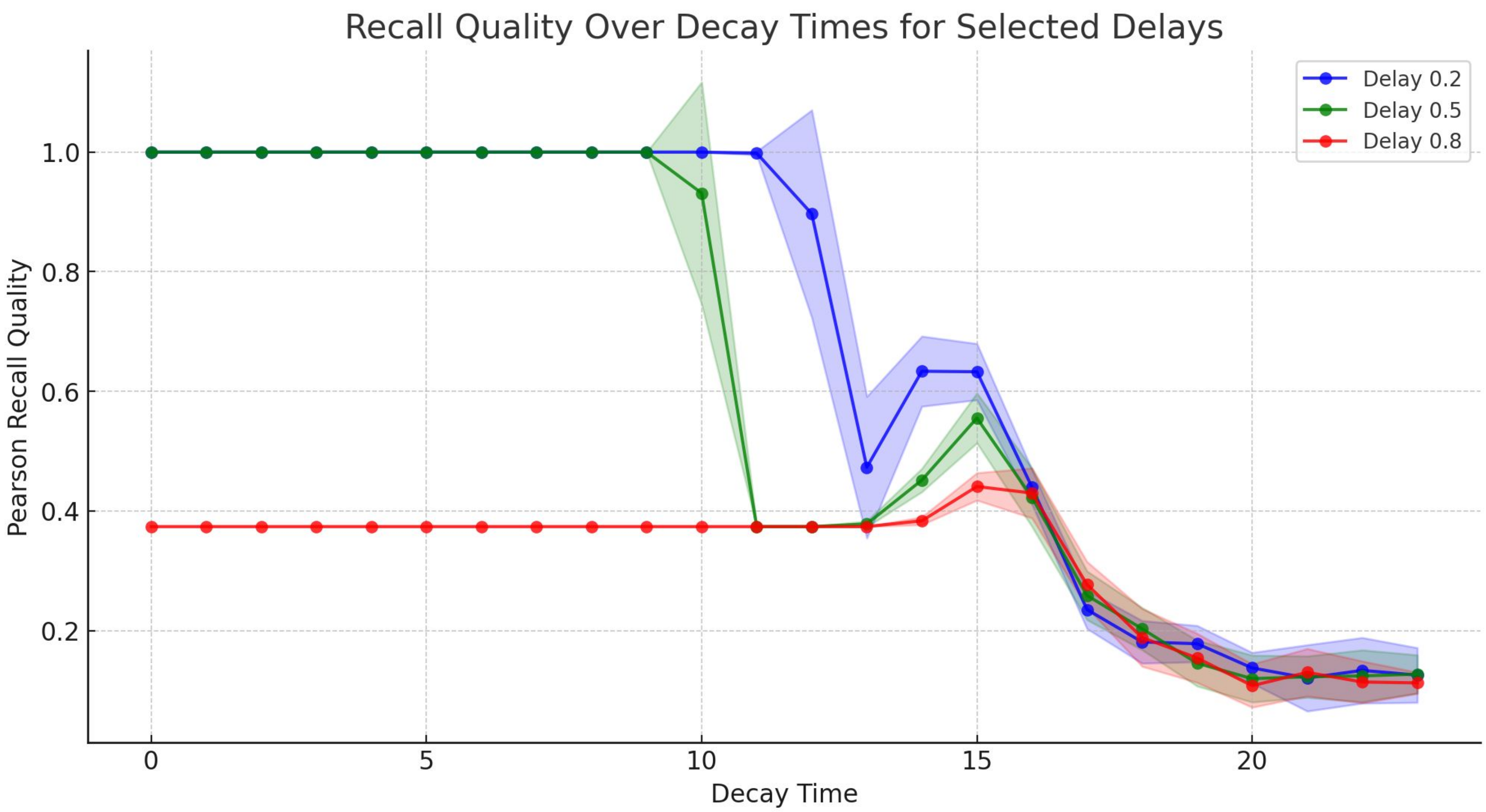


Weights converge to transient states with a low learning rate

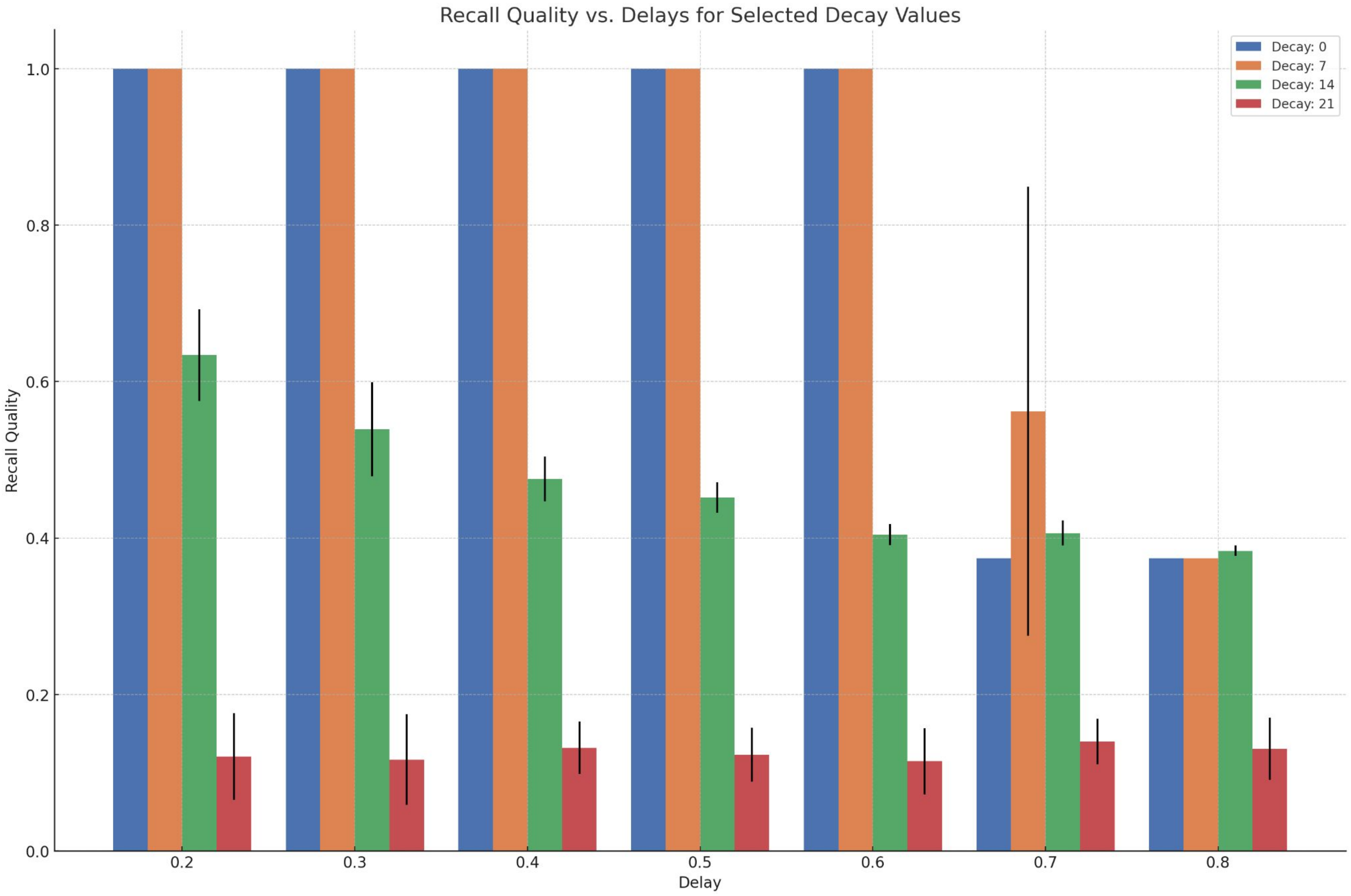




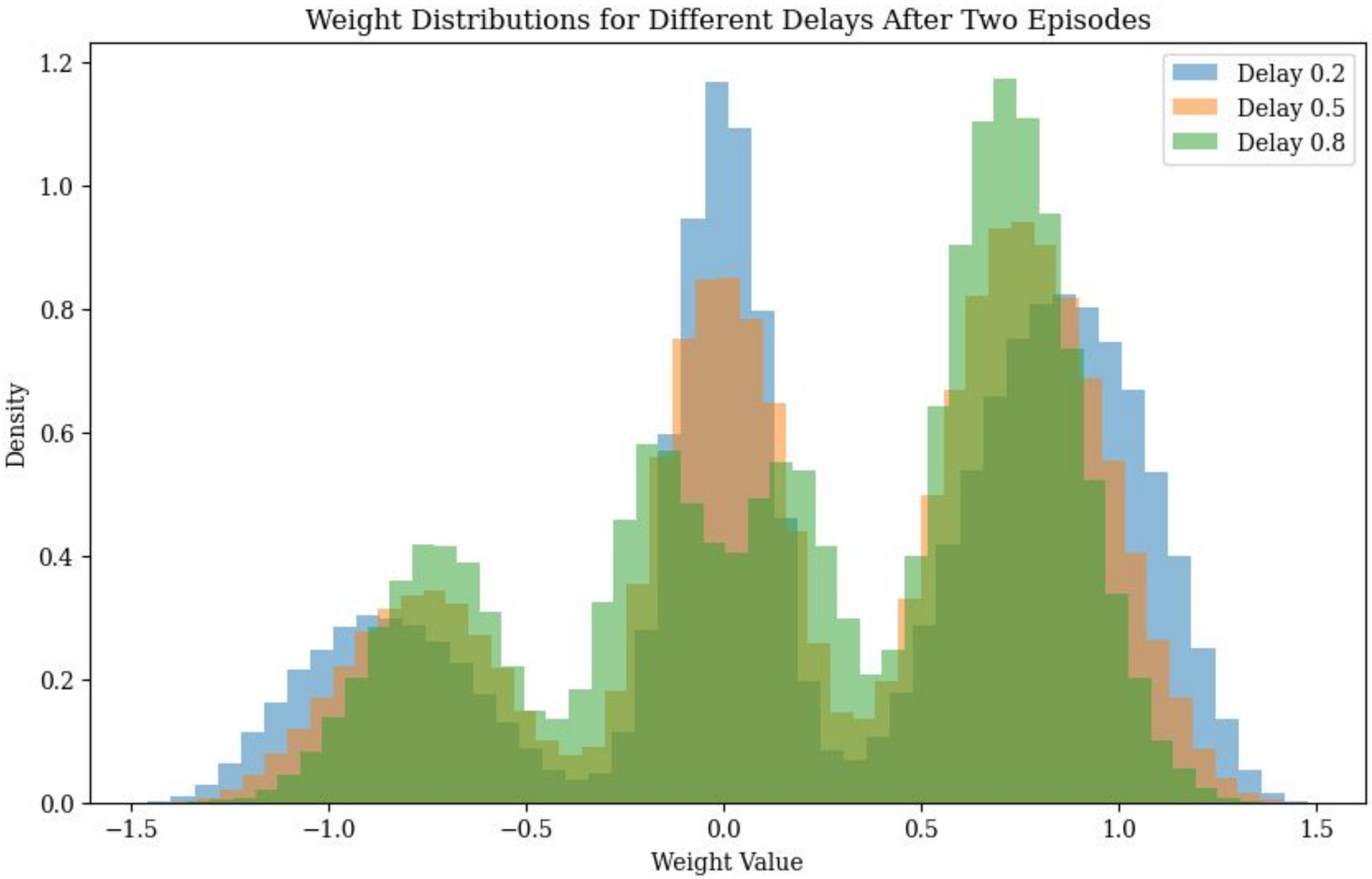
Memory recall efficacy diminishes over extended decay intervals



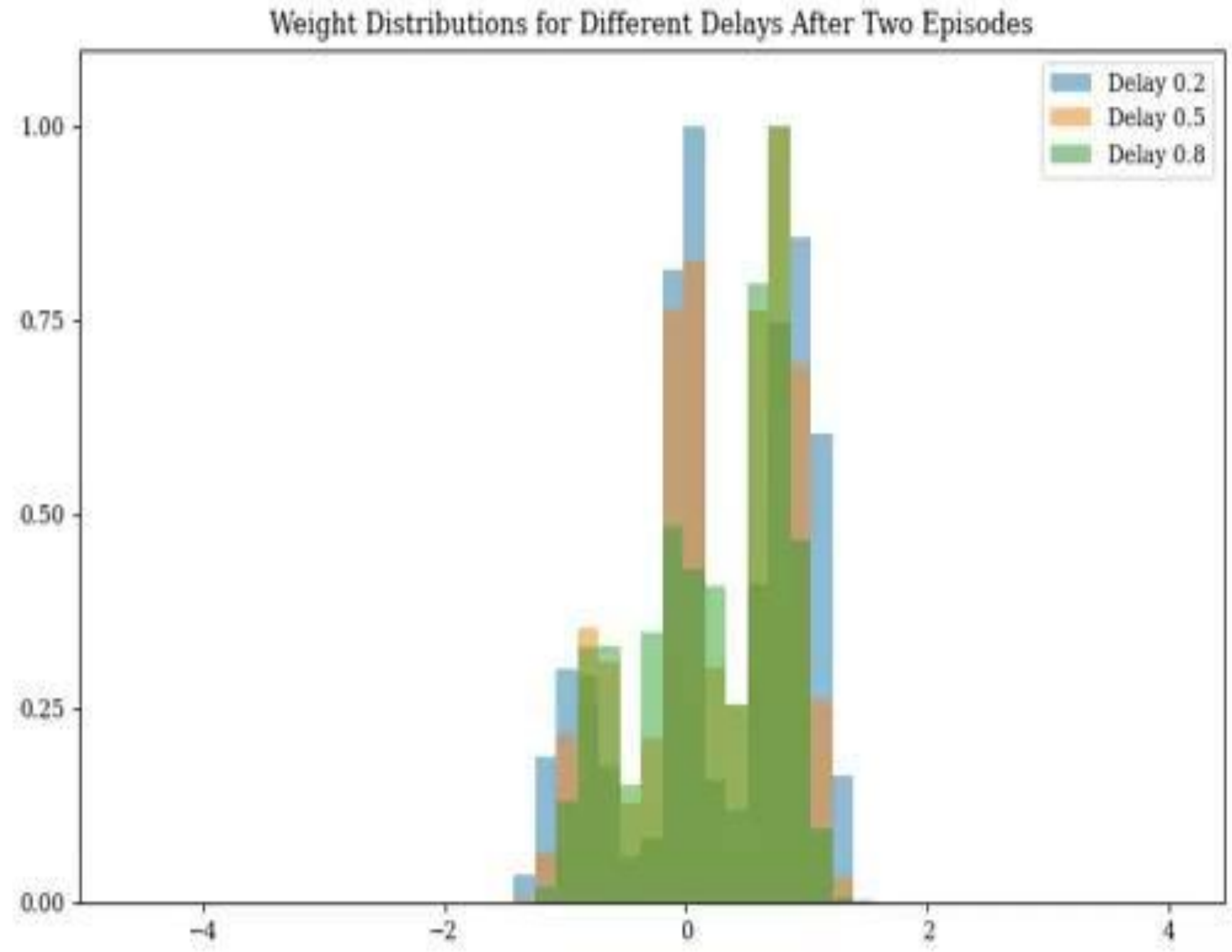
Degradation of memory recall with increasing delay at low learning rates



Shorter delays prompt quicker weight shifts to nonzero-well for stable memory states



A slower transition to zero-well at low delays to transient memory states



Future Work Planned

- Similar approach for sparser patterns
- Similar approach with an increasing number of patterns
- Test the qualitative prediction of TWH model on cognitive experiments