A Benchmark Study on the Effect of a Fixed Volatility Hyperparameter on Learning Curve Dynamics in State Space Models

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Introduction

- **Learning is a dynamic behavior** that changes as a result of new experiences, creating new synaptic connections in the brain that are controlled by dopamine signals
  - This allows the brain to make associations between certain behaviors and rewards

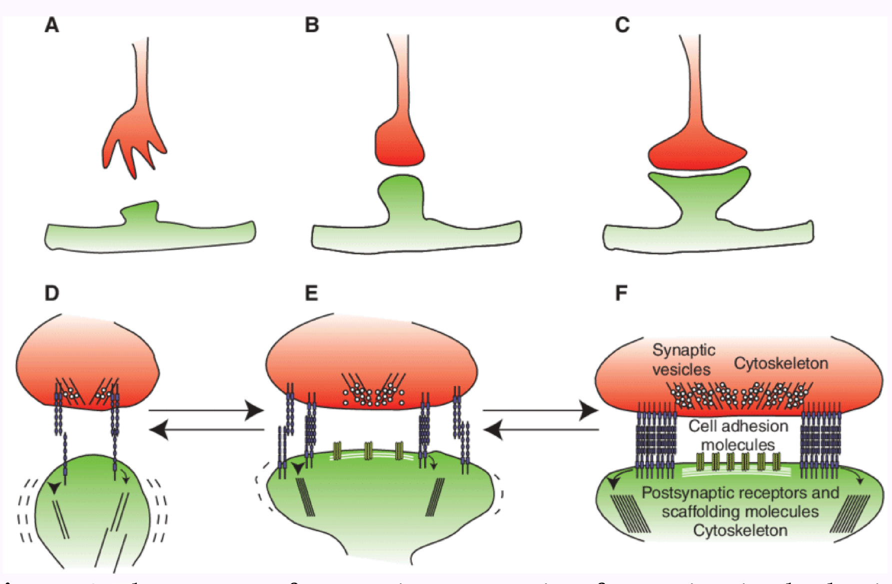

Figure 1. The stages of synaptic connection formation in the brain[1]

- It is difficult to quantify the amount of learning that occurs at a single point in time through pure observation, making it hard for behavioral neuroscientists to understand the circuits underlying learned behavior
- **State space models (SSMs)** solve this issue by accurately modeling dynamic processes such as learning using input, output, and **latent variables** (learned dynamic behavior)
- In this project, we investigate how the modeling approach behaves under different parameter regimes by altering a fixed sigma value in an existing SSM[2]

Methods

1. Clarifying optimized usage of the SSM using a simulated environment
   - Observed the correlation between manual changes to the **volatility hyperparameter** and the accuracy of the generated curves
2. Organizing binary decision-making behavioral data in mice for compatibility with the SSM

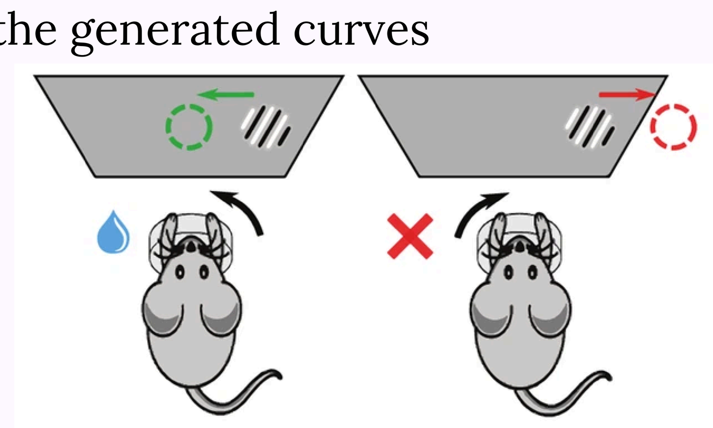

Figure 2. Mice are given visual stimuli on either the left or right and learn through rewards the binary task of turning a wheel based on which side has a more intense stimulus[3]

3. Generating learning curves and performing statistical analyses on modifying the fixed volatility hyperparameter
   - Ran the SSM on real behavioral data
   - Modified the value of sigma to examine variations in the learning curves produced
4. Analyzing the generated learning curves using two **smoothing** algorithms

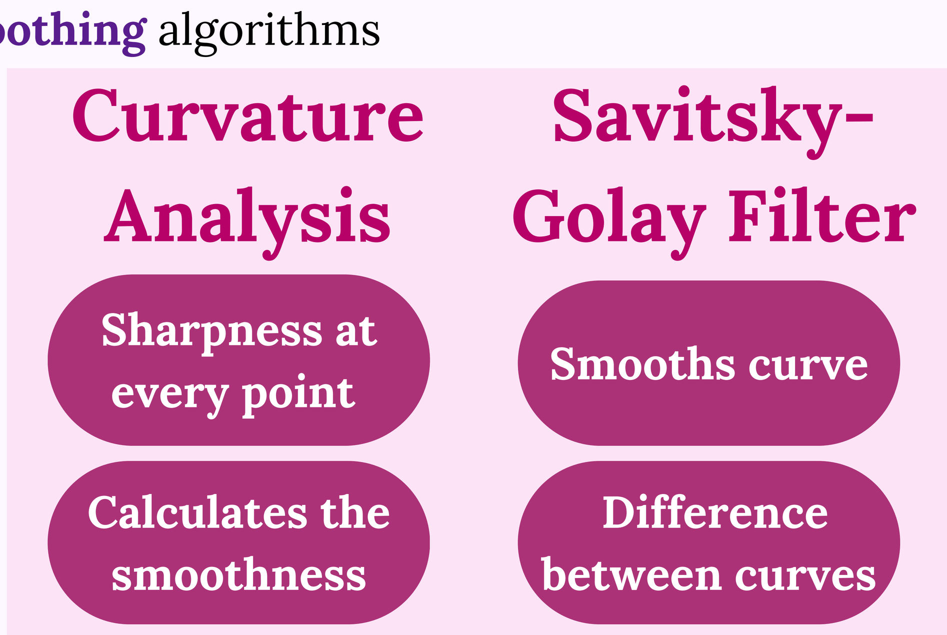

Figure 3. Curvature analysis vs. Savitsky-Golay filter

5. Deduced the **threshold** where changing the hyperparameter resulted in a **deviation** of the curve from empirical standards

Results

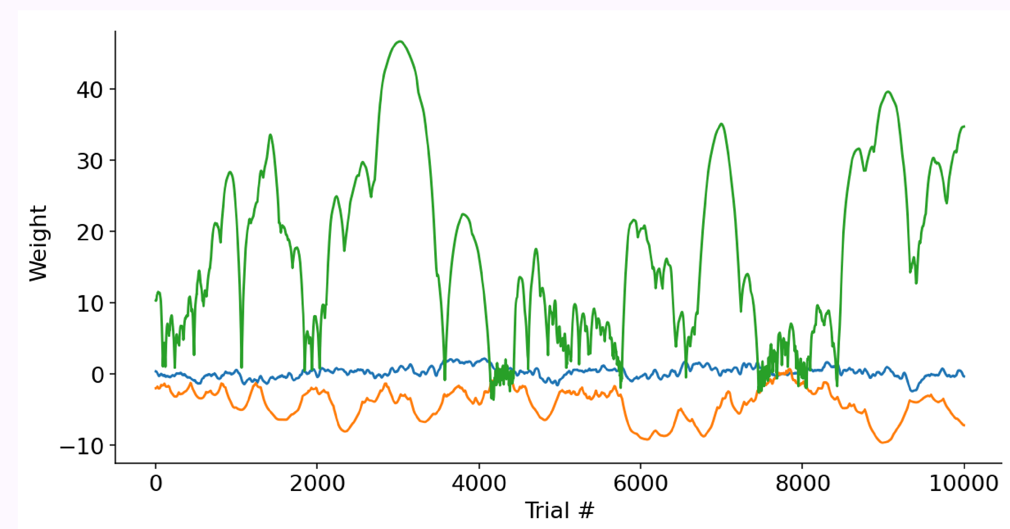

Figure 4. Learning curves for new behavioral dataset generated by the SSM

Result 1: Performance values for learning curves for the model at default, lower bound, and upper bound sigma values were statistically similar to each other

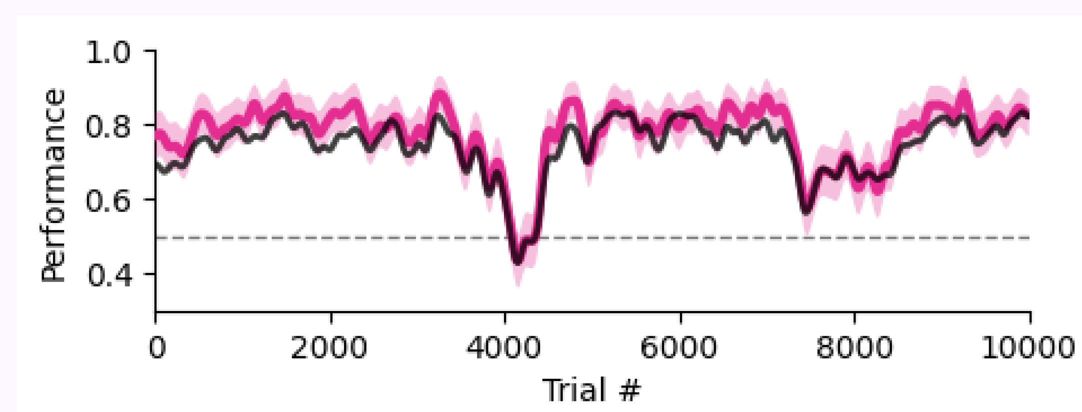

Figure 5. Performance values of the SSM compared to empirical standards at default sigma value. The accuracy of the model was 92.11%

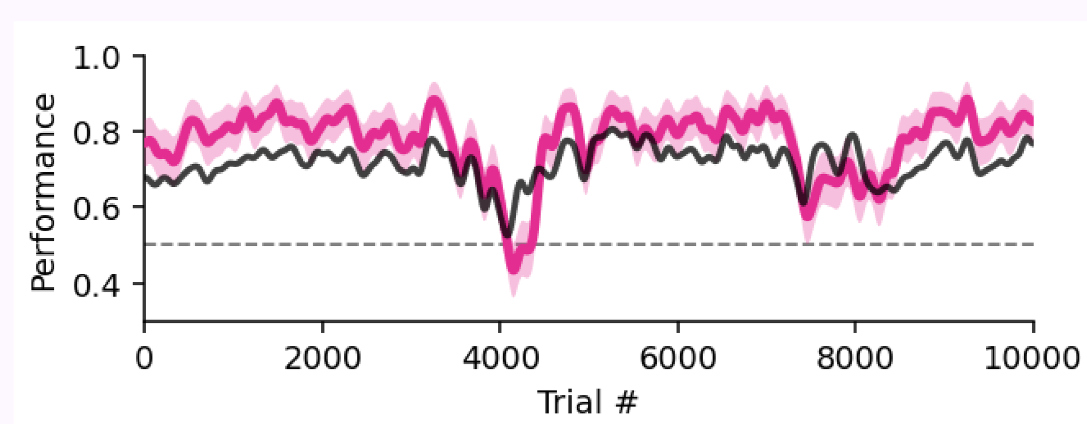

Figure 6. Performance values of the SSM compared to empirical standards at lower bound of sigma values tested (-12). The accuracy of the model was 70.47%

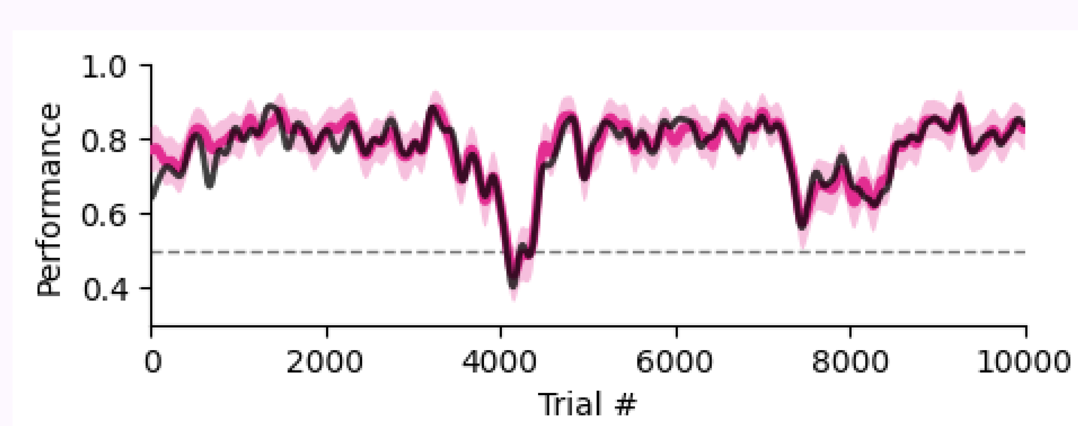

Figure 7. Performance values of the SSM compared to empirical standards at upper bound of sigma values tested (47). The accuracy of the model was 94.46%

Result 2: Average curvature values for the learning curves generated by the model displayed very little change as the sigma value was altered

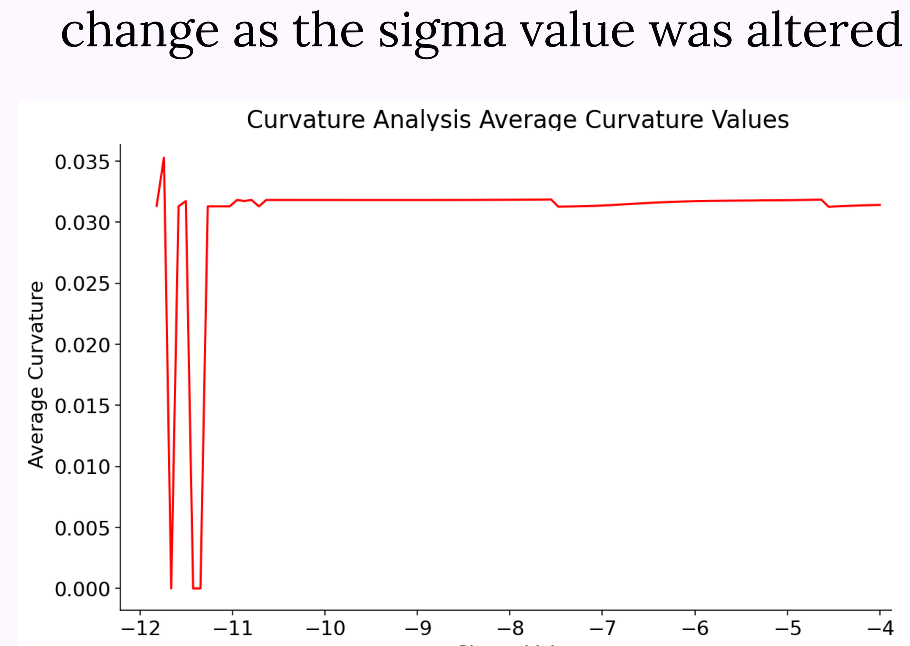

Figure 8. Average smoothness values for 100 instances of SSM ran using decreasing sigma values calculated using curvature analysis

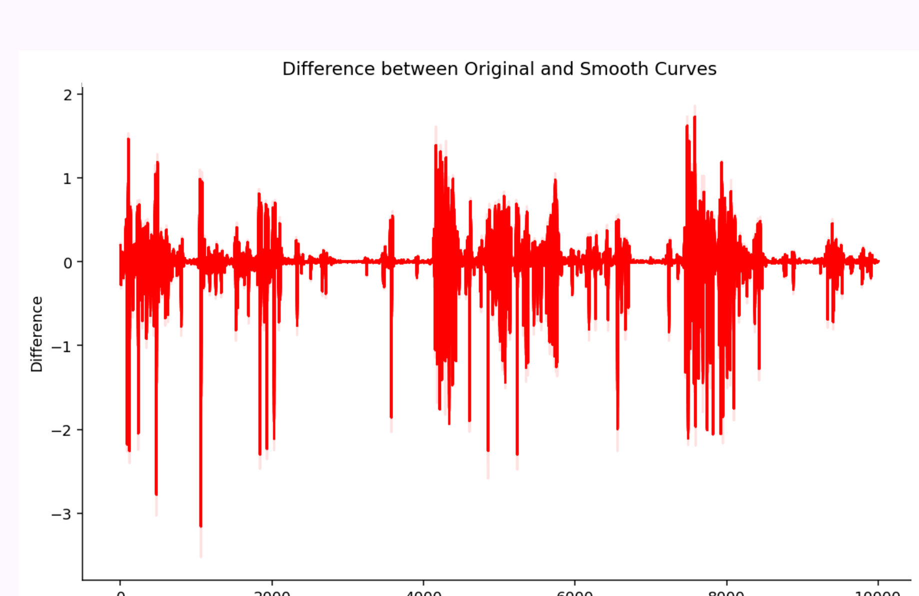

Figure 9. Difference between SSM-generated curve and smoothed curve calculated using Savitsky-Golay filter over 100 instances

Discussion

Conclusion

- When we fit the SSM to the new dataset, the manual modification of the **optimized sigma value** produced little change in the difference between the original and smoothed curves on real data
- The upper and lower bounds of the sigma hyperparameter produced curves that were within **empirical standards,** indicating the high accuracy of the model
- The input value of sigma has little effect on the accuracy of the curves produced from real data
- We determined that the smoothed curve begins to deviate from the empirical standard at a threshold of 8 units of sigma away from the original value, -4
- We identify a gap between simulation testing and real-world data (see supplementary material)
  - This has implications for how scientists should approach using methods papers and generating "ground truth" data

Limitations

- The optimized hyperparameter sigma is arbitrary, lacks strong biological implications, and is merely a statistical concept of noise
- The input of an optimized sigma value into the model raises the question of whether this hyperparameter is **overfitting** the data
- On real data, the SSM behaved differently than with the simulated data[2]
  - The simulated data can be misleading when used to test the real model

Future Research

- Study the effect of making a **dynamic sigma hyperparameter** for each trial on the accuracy of the model
- Introduce a biological representation by adding a new parameter for **neural measurements** to observe the impact of a mouse's neurological activity on the process of learning

Takeaway: SSM-generated curvature values using real data showed little variation as sigma changed. Using simulated data, curvature values changed greatly

Supplementary Material:

References

(1) Giagtzoglou, N.; Ly, C. V.; Bellen, H. J. Cell Adhesion, the Backbone of the Synapse: "Vertebrate" and "Invertebrate" Perspectives. Cold Spring Harbor Perspectives in Biology 2009, 1, a003079–a003079.https://doi.org/10.1101/cshperspect.a003079.

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Acknowledgments

We would like to thank the RISE program at Boston University for providing us with this research opportunity. We are also thankful for the guidance and contributions of Patrick Bloniasz, Ryan Senne, Karla Montejo, and all of the other teaching fellows. Finally, we are very grateful for our families' unconditional support and encouragement throughout our scientific journeys.