University: Sharif University of Technology

Department: Electrical Engineering

Course Name: Advanced Neuroscience

Homework 5 Report

Motivation and Classical Conditioning

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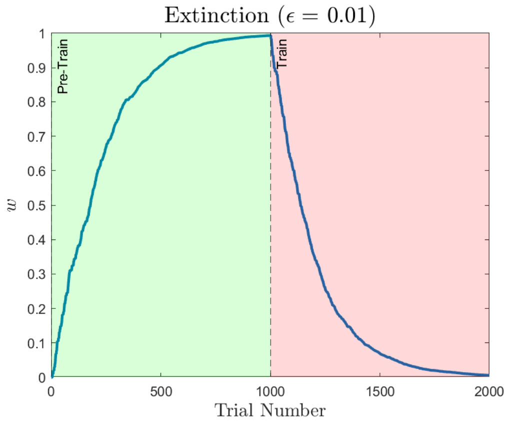
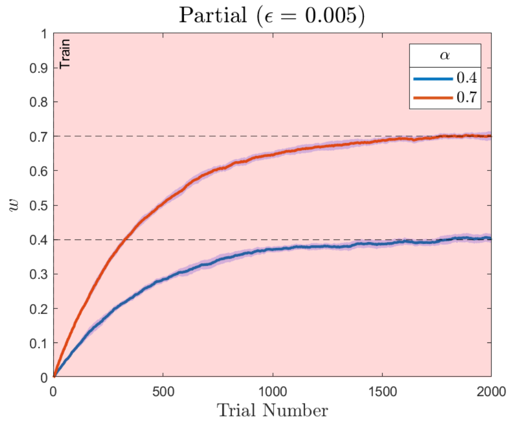
Part 1

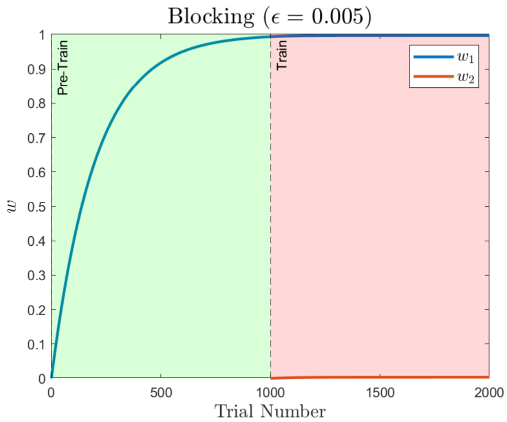
1) Trial number is set to 2000 for more smoothness and learning rates are reported in the titles. All predictions match the RW-rule and the table. In Figure 1b, paradigm is calculated 20 times and small shadow around each curve, indicates *std*. In Figure 1e, learning rates for both stimuli are equal and hence, curves are the same.



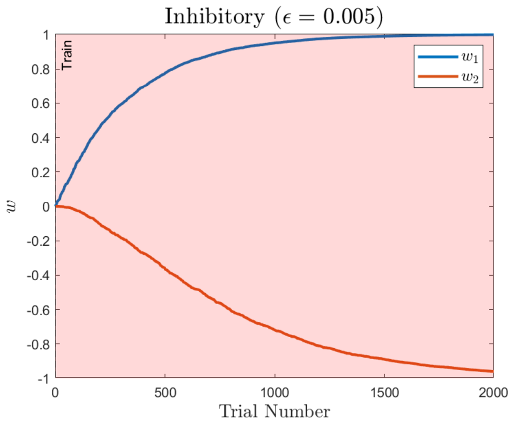
(a) Extinction



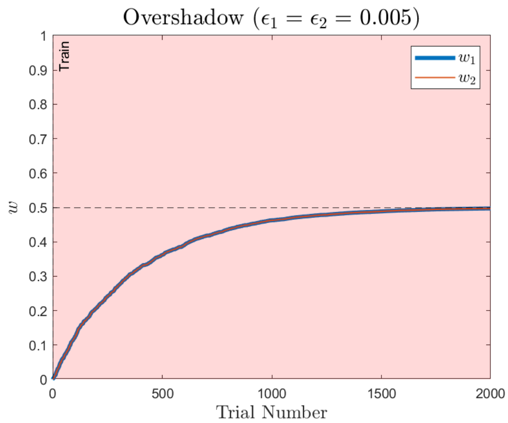
(b) Partial



(c) Blocking



(d) Inhibitory



(e) Overshadow

Figure 1: Different Paradigms Using RW-Rule

2) For *overshadow* condition, we have two learning rates each for a stimulus. If we set unequal learning rates, we can obtain Figure 2. Simply, final value of w for each stimulus is derived from:

$$w_i = \frac{\epsilon_i}{\epsilon_1 + \epsilon_2} \qquad i \in \{1, 2\}$$

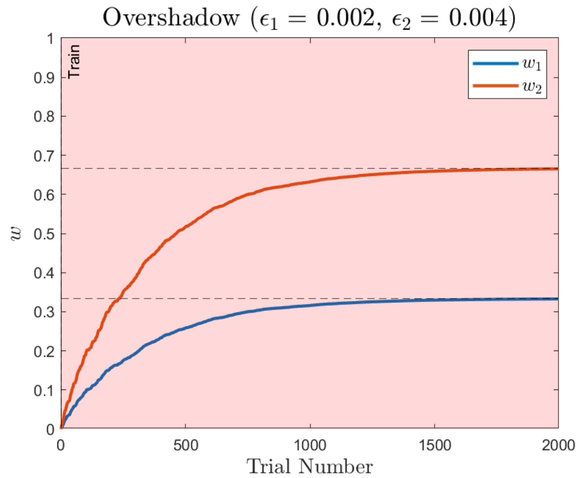


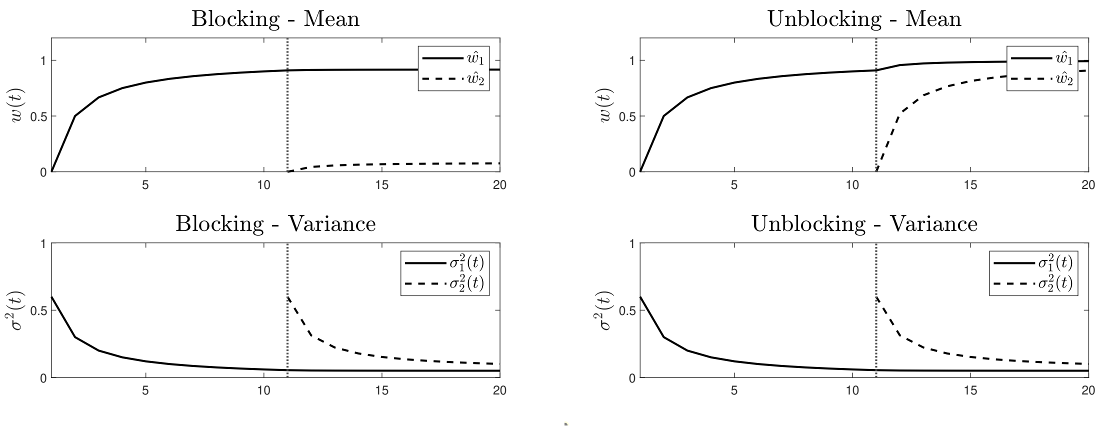
Figure 2: Overshadow with Different Learning Rates

Part 2

1) First we implement *Kalman Filter* mentioned in class, then we set some initial conditions and values and plot mean and variance of output. Figure 3 shows results and Table 1 shows parameters of *Kalman Filter*.

	Value
W	0
τ^2	0.6

Table 1: Parameters



(a) Blocking

(b) Unblocking

Figure 3: Figure 1 of [1]

Then we implement backward blocking and Figure 4 and Figure 5 are obtained. Also, an animated file (`contourf.gif`) is attached.

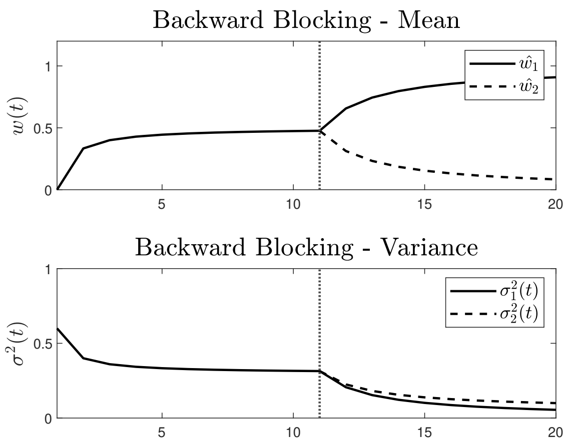


Figure 4: Backward Blocking

2) Here we change process noise and measurement noise in two *for* loops, then compare results.

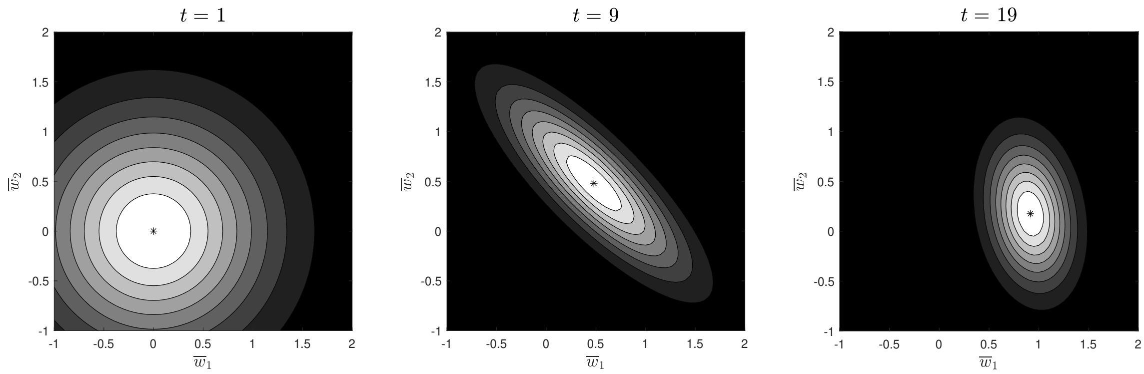


Figure 5: Backward Blocking Contour using *Kalman Filter* and Joint Distribution of $\overline{w}(t)$

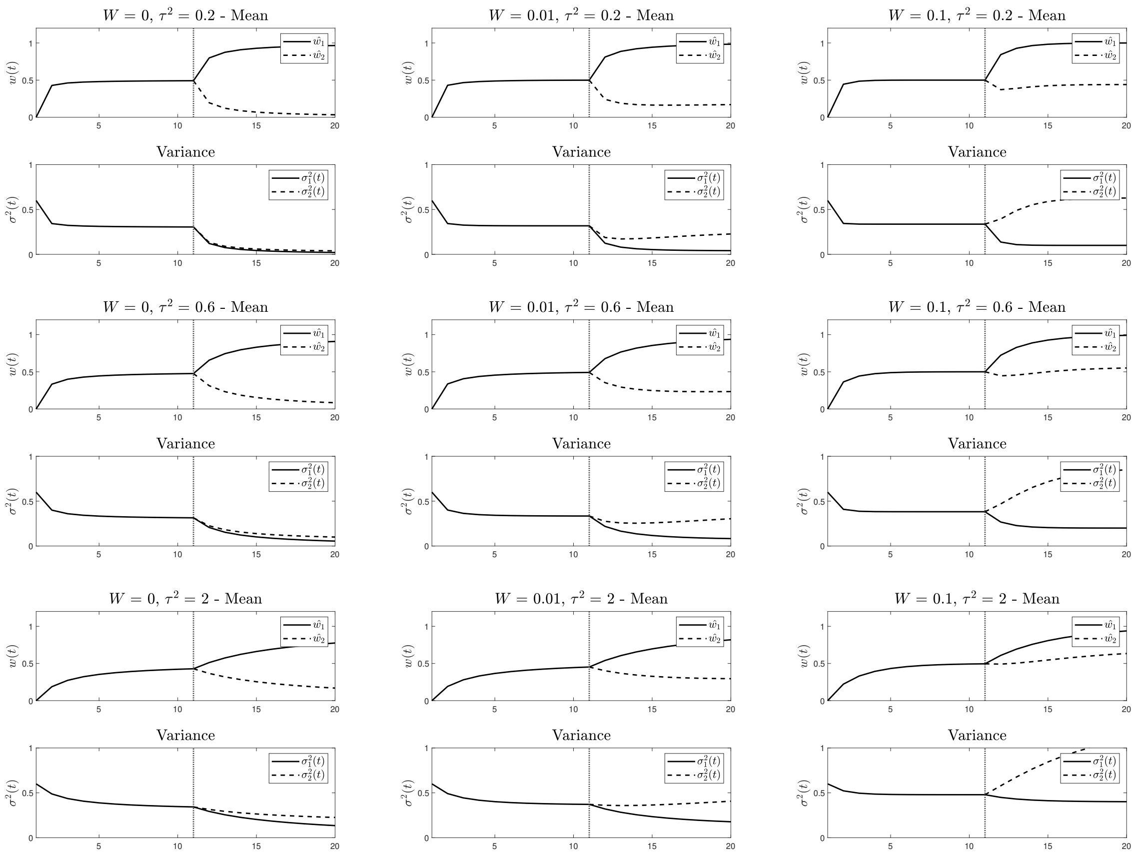


Figure 6: Different Values of Process Noise and Measurement Noise

Investigating Figure 6, we can obtain that weights slightly change by changing measurement noise. But more importantly, high process noise causes major change in the covariance matrix, hence, desired stimulus will not be blocked as expected and variance increases.

3) Steady state is when values converge, therefore:

$$\Sigma(t+1) = \Sigma(t) \tag{1}$$

And we have:

$$\begin{aligned}
\Sigma(t+1) &= \Sigma(t+1)^- - GC\Sigma(t+1)^- \\
&= \Sigma(t) + W - GC(\Sigma(t) + W) \\
&\overset{(1)}{=} \Sigma(t+1) + W - GC(\Sigma(t) + W) \\
&\longrightarrow GC(\Sigma(t) + W) = W
\end{aligned}$$

4) According to the [1], change of uncertainty (Σ) does not depend on the errors of each trial, but depends on the stimulus values, process noise and measurement noise.

Update step:

$$\begin{aligned}
\Sigma_t^- &= A\Sigma_{t-1}A^T + W \\
G_t &= \Sigma_t^- C^T (C\Sigma_t^- C^T + V)^{-1} \\
\Sigma_t &= \Sigma_t^- - G_t C \Sigma_t^-
\end{aligned}$$

5) If we simulate this paradigm with *Kalman Filter*, we obtain Figure 7. It indicates that by changing reward of the stimulus during the task, variance of stimulus does not change. But about learning rate we can say that in the first stage, value of weight has been increased and therefore, difference between weight and new reward is greater than before and learning rate would increase.

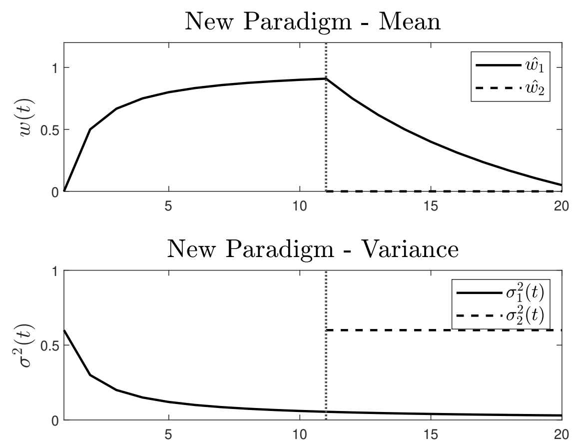
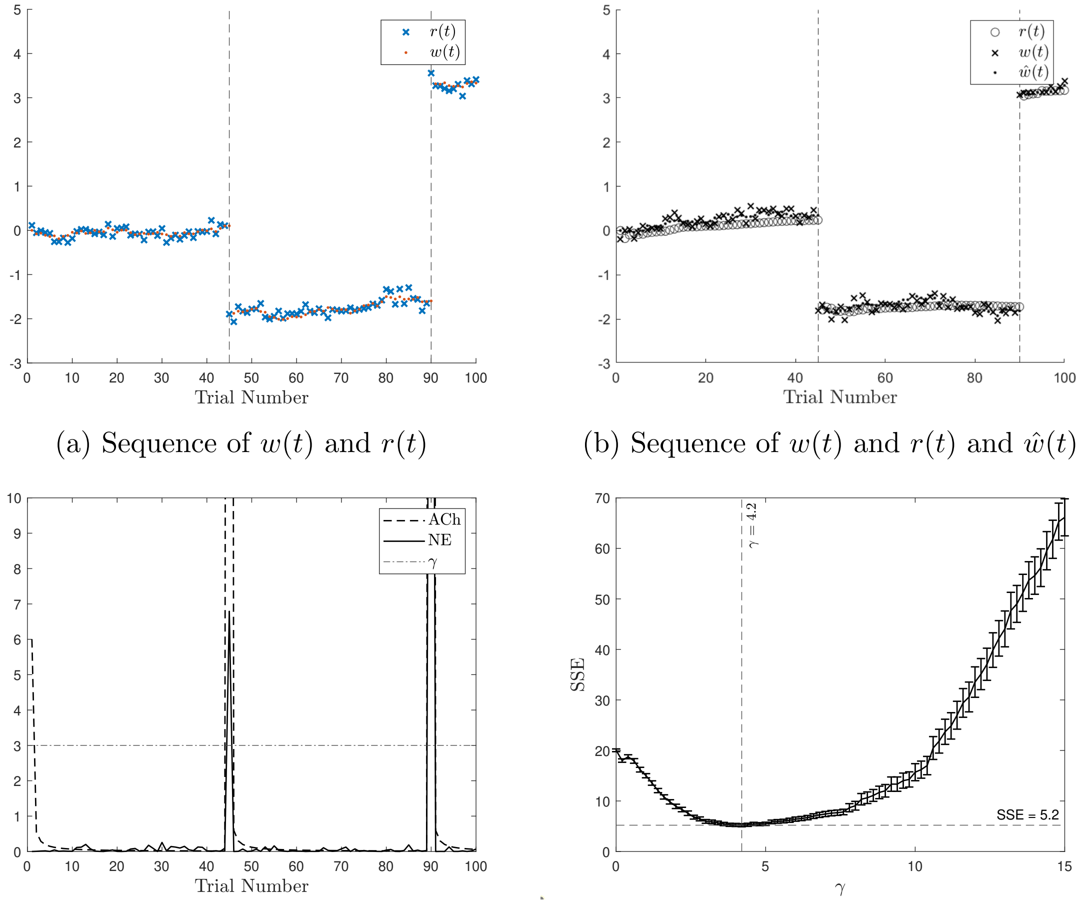


Figure 7: New Paradigm

Part 3

1) According to the [1], if $\beta(t)$ exceeds a threshold γ, then we assume $\hat{c}(t) = 1$, and reset $\Sigma(t)$ accordingly large. And if $\beta(t) < \gamma$, then we assume $\hat{c}(t) = 0$ and update $\hat{w}$ and Σ as before.



(a) Sequence of $w(t)$ and $r(t)$

(b) Sequence of $w(t)$ and $r(t)$ and $\hat{w}(t)$

(c) ACh and NE, $\gamma = 3$

(d) MSE of $w(t)$ and $\hat{w}(t)$ Across γ

Figure 8: Unknown Uncertainty

References

[1] Peter Dayan and Angela Jyu. "Uncertainty and learning". In: *IETE Journal of Research* 49.2-3 (2003), pp. 171–181.