In The Name Of God

HW05

Advanced Neuroscience

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■ Part I - RW rule

□ Q01

Extinction

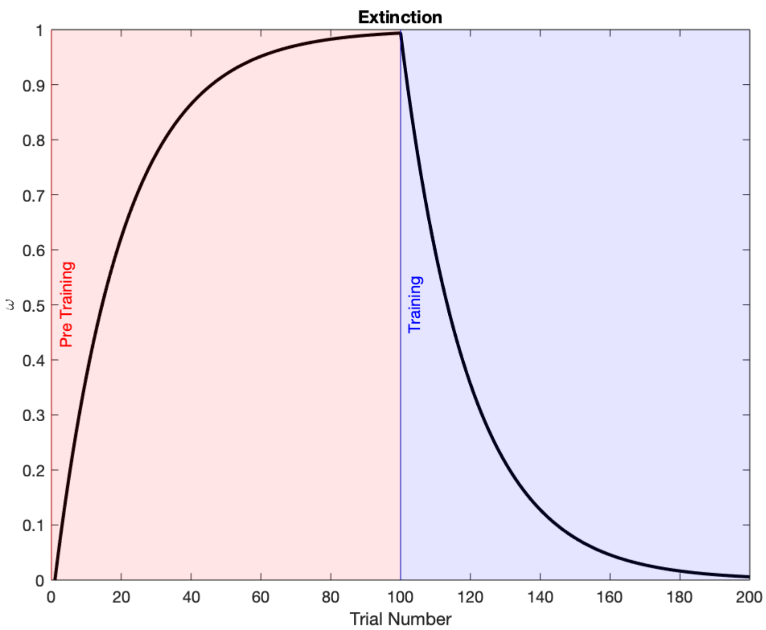


Figure 1: Extinction Paradigm Plot

The extinction paradigm is similar to the plot in the course slides. It rises and after the stimuli are gone, decreases.

Partial

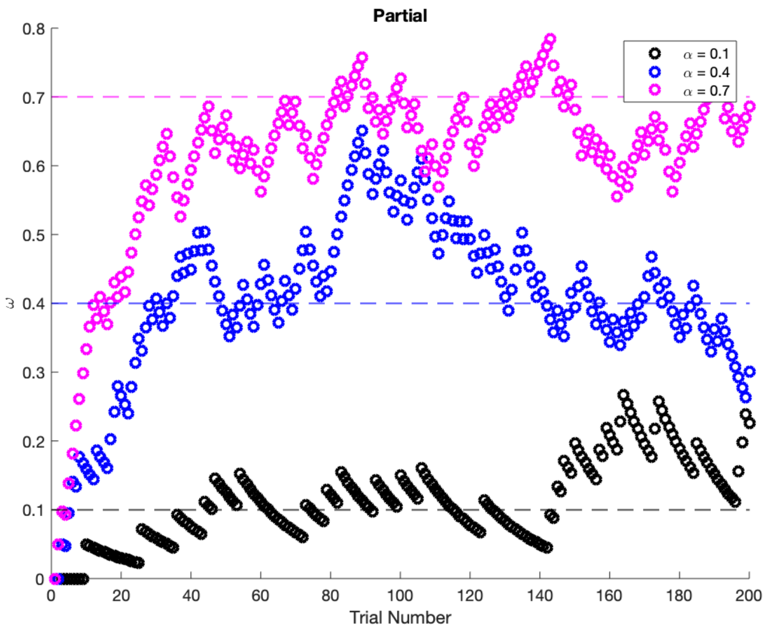


Figure 2: Partial Paradigm Plot

The extinction paradigm is similar to the plot in the course slides. It rises and after the stimulus is gone, decreases.

Blocking

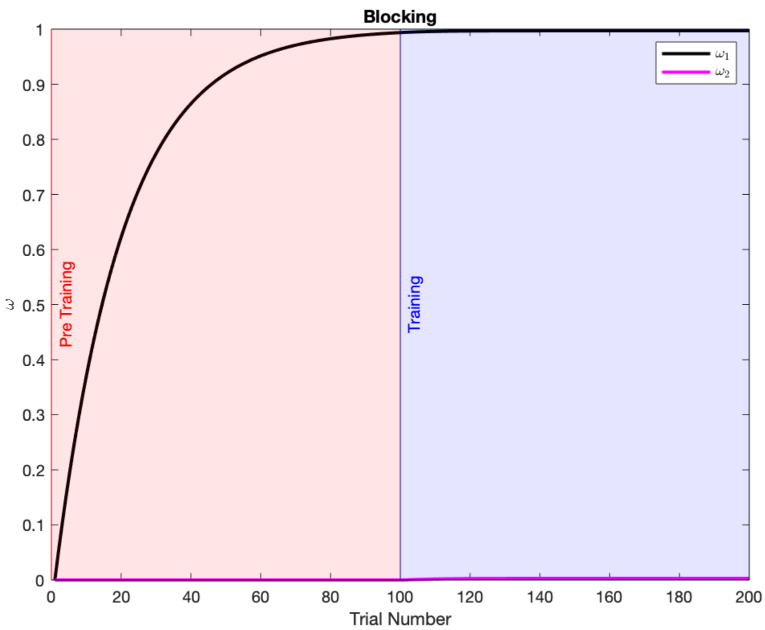


Figure 3: Blocking Paradigm Plot

Similar to the results of the question set table, the value of w_1 becomes 1 and the value of w_2 doesn't change too much from 0, while there is a small increase in the w_2 during the training trials.

Inhibitory

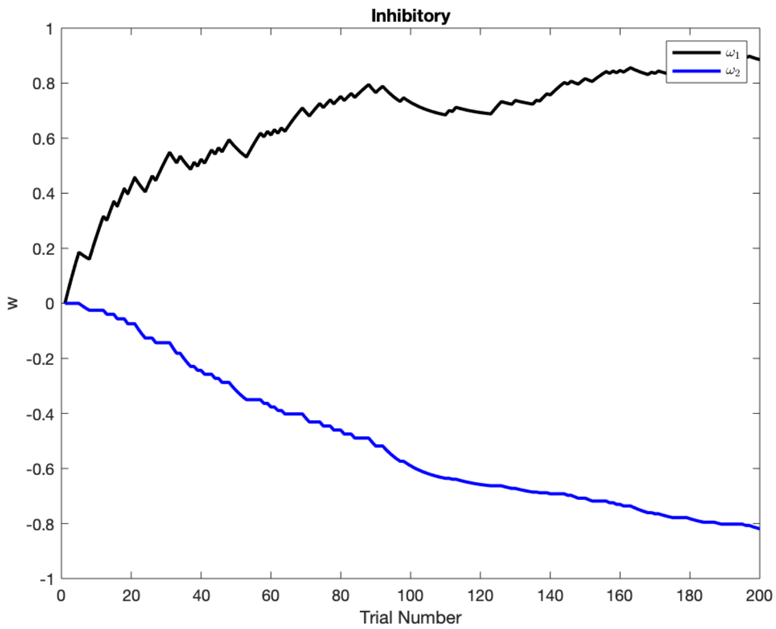
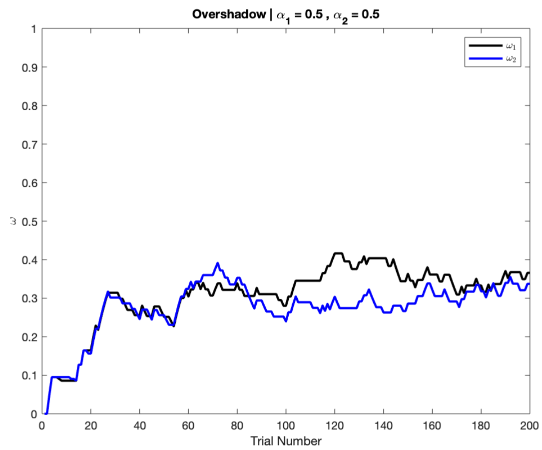


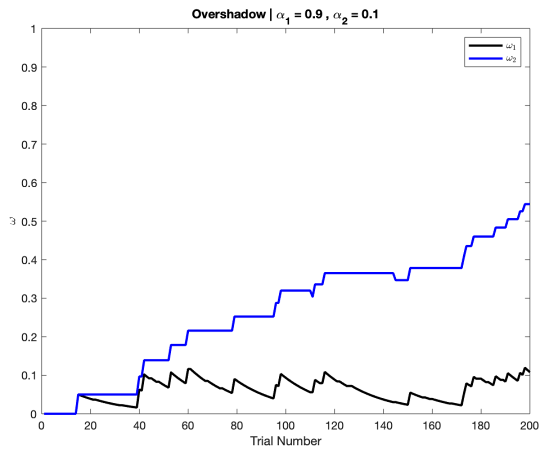
Figure 4: Inhibitory Paradigm Plot

The results in Figure 4 are the same as the question set table and as I expect the value of w_1 goes to 1 and the value of w_2 goes to -1 over the trials.

Overshadow



(a) $\alpha_1 = 0.5$ & $\alpha_2 = 0.5$



(b) $\alpha_1 = 0.9$ & $\alpha_2 = 0.1$

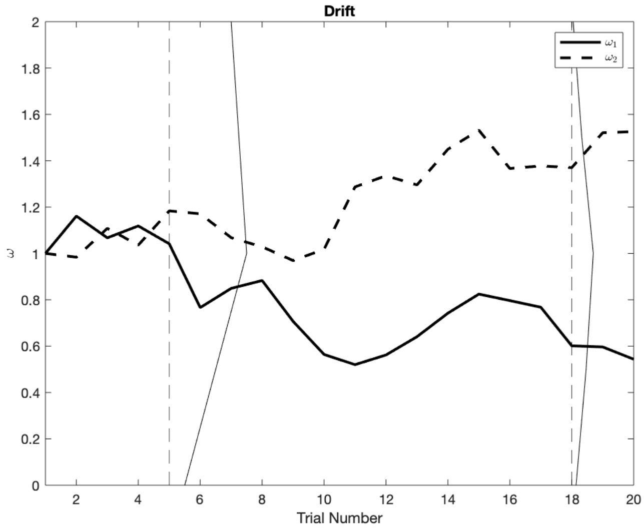
Figure 5: Overshadow Paradigm Plot

□ Q02

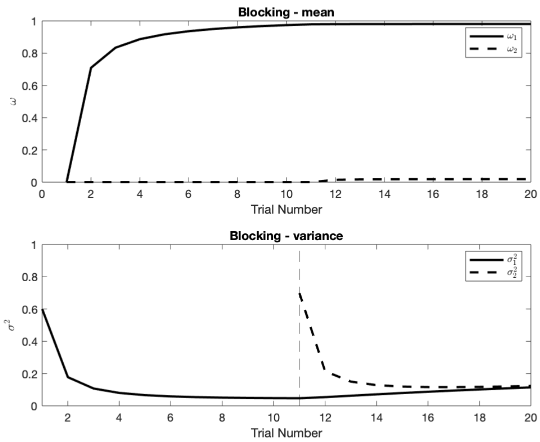
In the overshadow paradigm, most of the time stimuli end up having different weights because one of them is more silent than the other one, so while the reward will be given in a few trials, the stimulus which have a higher probability will have lower weight.

■ Part II - Kalman Filter

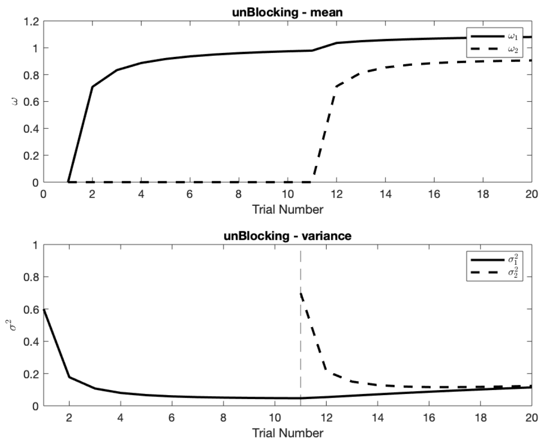
□ Q01



(a) Drift



(b) Blocking



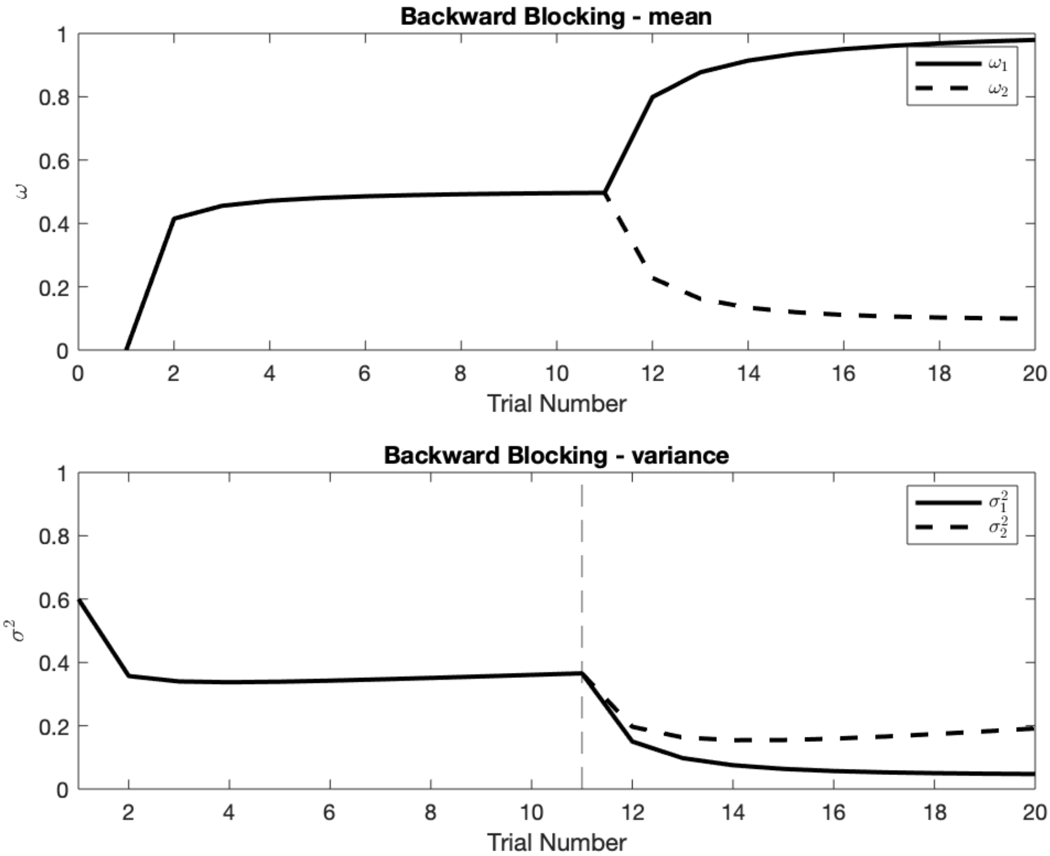
(c) Unblocking

Figure 6: Stimulation of different paradigms using Kalman FIlter. The thin lines show the distribution of weights at t = 5 and t = 18.

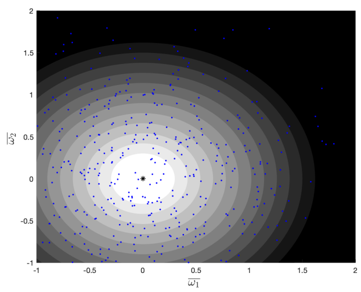
The parameters for obtaining Figures 6 and 7 are obtained from the paper or are set to the values which tend to be the most similar to the paper figures. The used parameters values are written in Table 1.

Table 1: Parameters of Kalman Filter

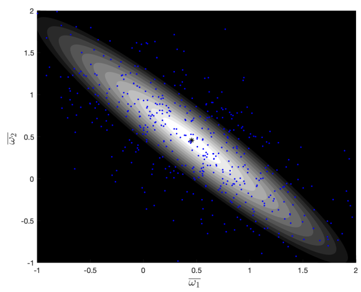
Process Noise	0.01
τ	0.5
w_0	0
$\sum t_0$	0.06



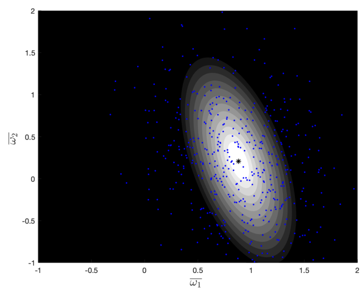
(a) Backward Blocking



(b) t = 1



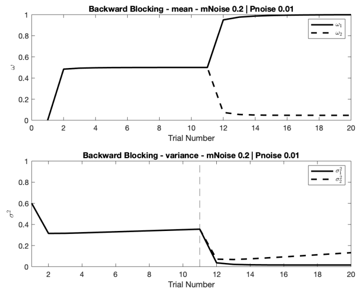
(c) t = 9



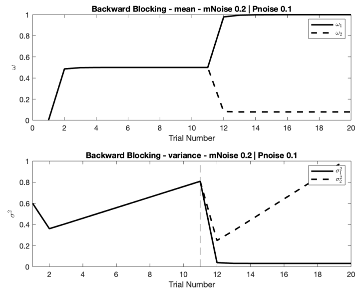
(d) t = 19

Figure 7: Stimulation of Backward Blocking using Kalman Filter and contour plots of the joint distribution of $\bar{w}(t)$. The blue points are obtained from the joint distribution of w_1 and w_2.

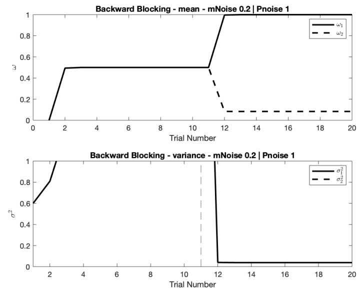
☐ Q02



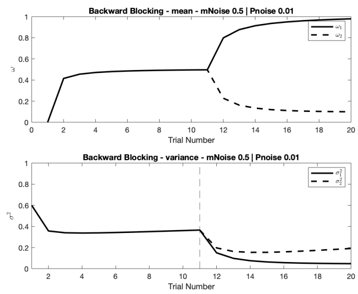
(a) $\tau = 0.2$, Process Noise=0.01



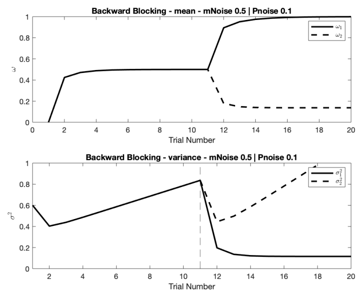
(b) $\tau = 0.2$, Process Noise=0.1



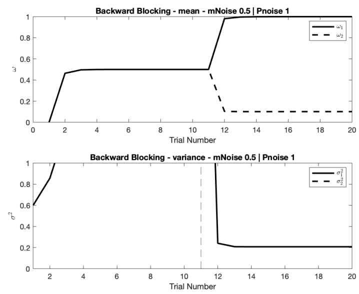
(c) $\tau = 0.2$, Process Noise=1



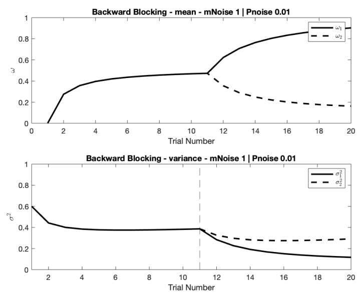
(d) $\tau = 0.5$, Process Noise=0.01



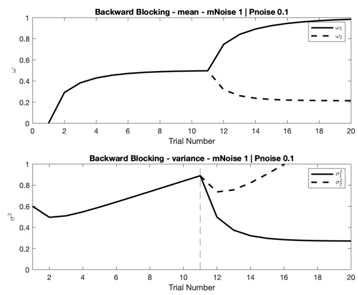
(e) $\tau = 0.5$, Process Noise=0.1



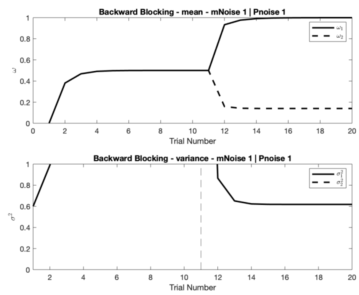
(f) $\tau = 0.5$, Process Noise=1



(g) $\tau = 1$, Process Noise=0.01



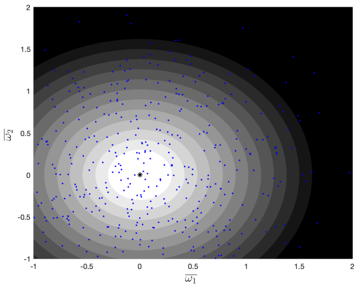
(h) $\tau = 1$, Process Noise=0.1



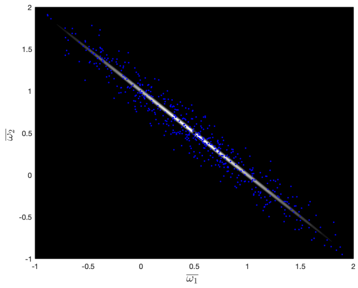
(i) $\tau = 1$, Process Noise=1

Figure 8: Effect of Process noise and Measurement Noise on mean and variance of the Weights

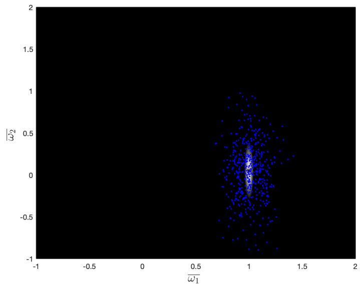
Figures 8 and 9 show the effect of process and measurement noises on weights mean and variance. As can be seen in the Figures, the weights change slowly when the measurement noise is bigger because the environment is noisier and the agent needs more observations to update the weights. Also, the weights changes faster when process noise is bigger because big process noise leads to bigger changes in the covariance matrix, and meanwhile the uncertainty of the agent from the environment increases, the weights change faster to obtain more information about the environment.



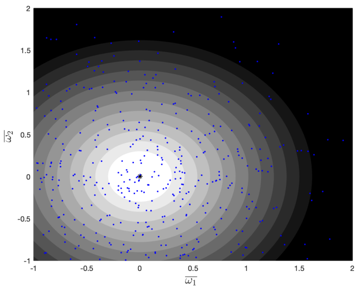
(a) $\tau = 0.2$, $W = 0.01$, $t = 1$



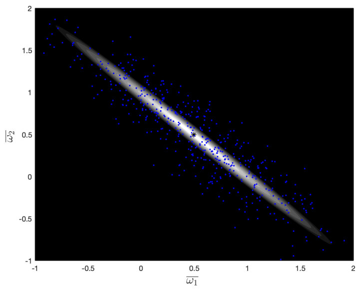
(b) $\tau = 0.2$, $W = 0.01$, $t = 9$



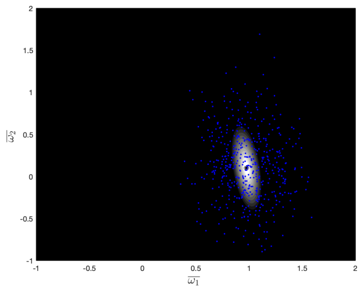
(c) $\tau = 0.2$, $W = 0.01$, $t = 19$



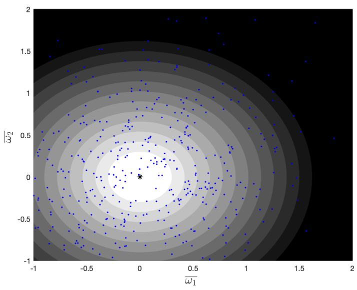
(d) $\tau = 0.5$, $W = 0.01$, $t = 1$



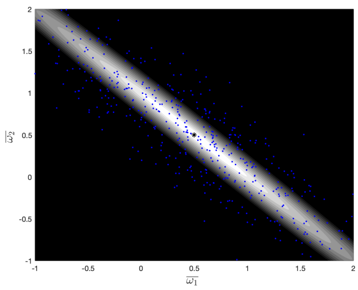
(e) $\tau = 0.5$, $W = 0.01$, $t = 9$



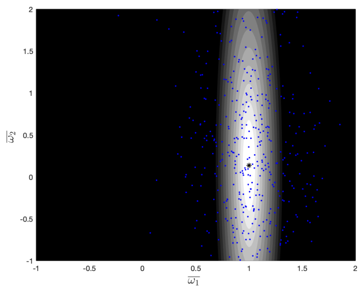
(f) $\tau = 0.5$, $W = 0.01$, $t = 19$



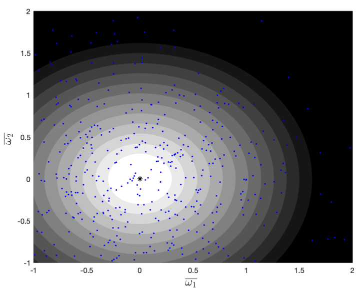
(g) $\tau = 0.5$, $W = 0.1$, $t = 1$



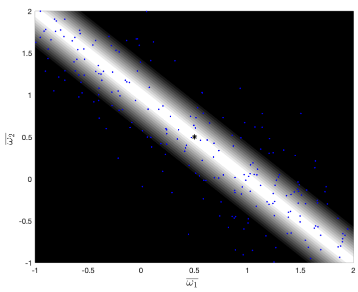
(h) $\tau = 0.5$, $W = 0.1$, $t = 9$



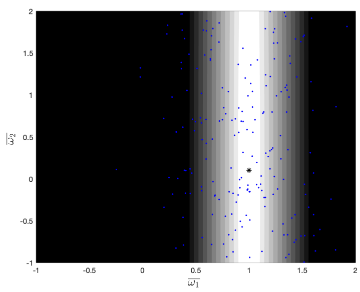
(i) $\tau = 0.5$, $W = 0.1$, $t = 19$



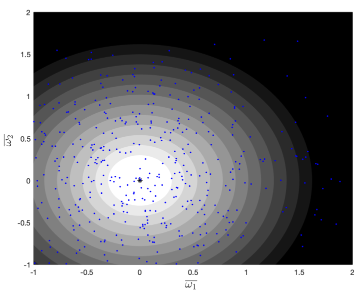
(j) $\tau = 0.5$, $W = 1$, $t = 1$



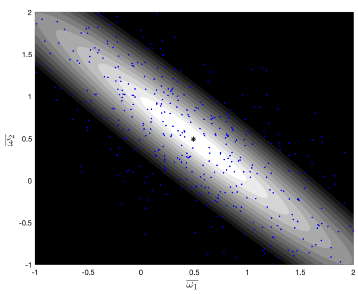
(k) $\tau = 0.5$, $W = 1$, $t = 9$



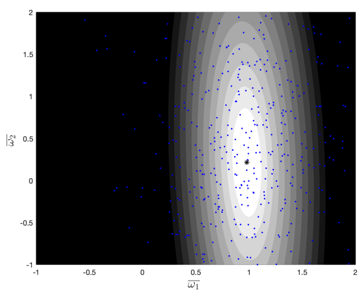
(l) $\tau = 0.5$, $W = 1$, $t = 19$



(m) $\tau = 1$, $W = 0.1$, $t = 1$



(n) $\tau = 1$, $W = 0.1$, $t = 9$



(o) $\tau = 1$, $W = 0.1$, $t = 19$

Figure 9: Effect of Process noise and Measurement Noise on mean and variance of the Weights

☐ Q03

$$G_\infty = C^T(C\sum_\infty C^T + V)^{-1}$$

So I should first calculate $\sum_\infty$:

$$\sum_{t+1} = A\sum_t + W$$
$$\sum_{t|t} = \sum_{t|t-1} + GC\sum_{t|t-1}$$

Combining the two equations leads to:

$$\sum_\infty = W + A\sum_\infty (I - C^T(C\sum_\infty C^T + V)^{-1}C\sum_\infty)$$

As can be seen in the equations above, the steady-state Kalman gain depends on V (measurement noise), C, and the covariance matrix.

☐ Q04

In the Kalman Filter formulation, the change in uncertainty doesn't depend on the errors so if the stimulus changes, the model won't increase the uncertainty about the value of the stimulus. But in the reality, the change in uncertainty depends on the errors made in each trial.

☐ Q05

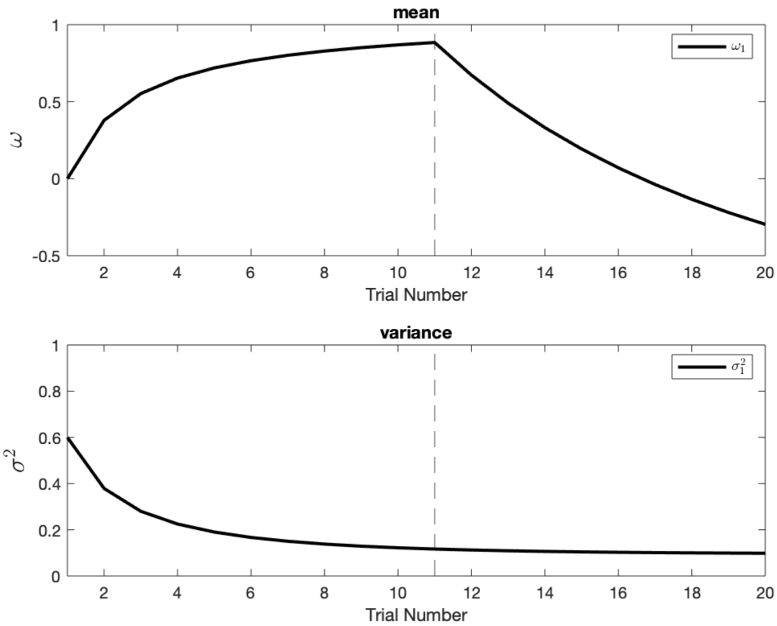
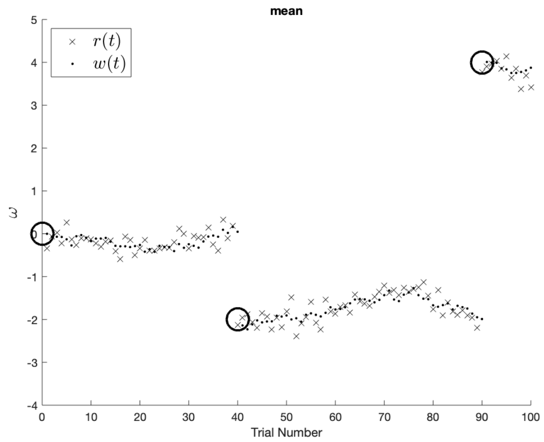


Figure 10: Inhibitory Paradigm Plot

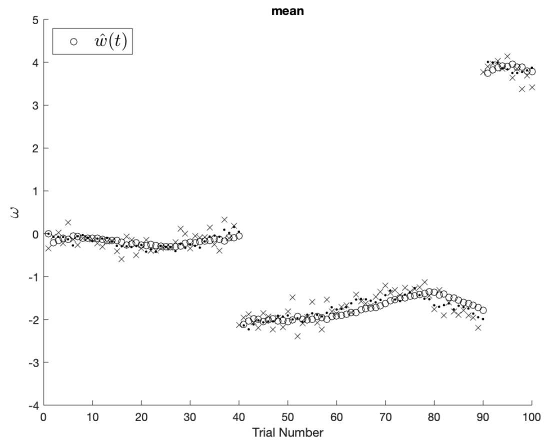
As can be seen in Figure 10, even if the value of the stimulus changes, the uncertainty about the stimulus doesn't change. Also the learning rate increases due to the increment of the wight in the first stage.

■ Part III - Enhanced Kalman Filter

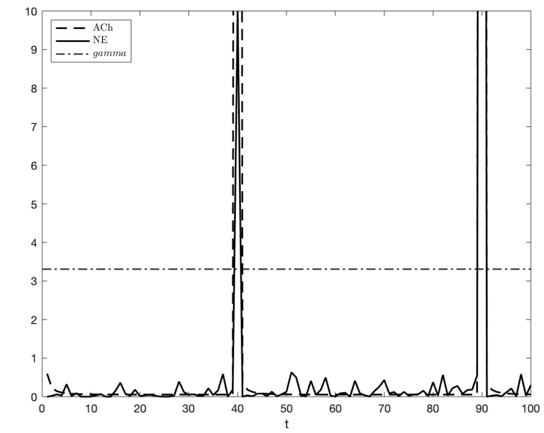
□ Q01



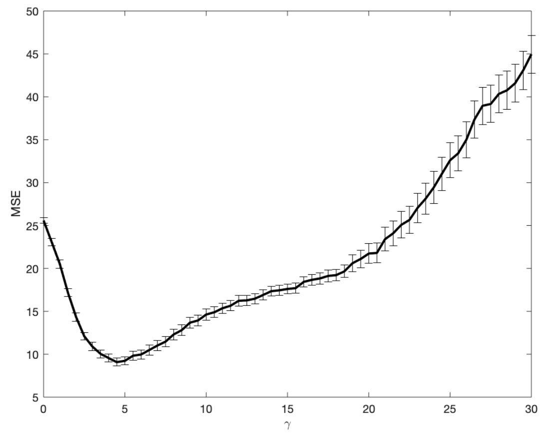
(a) Sample sequence of $w(t)$ and $r(t)$



(b) Sample sequence of $\hat{w}(t)$



(c) ACh and NE



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

Figure 11: Cholinergic and noradrinergic learning in an adaptive factor analysis model