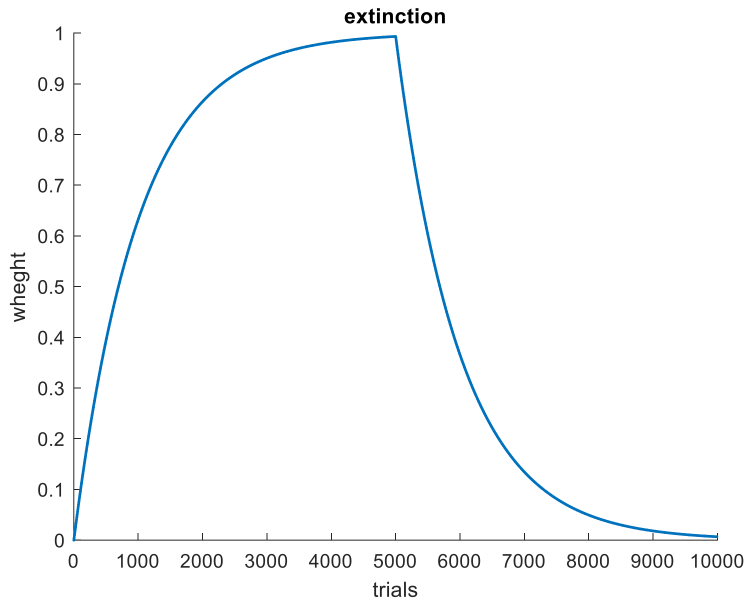
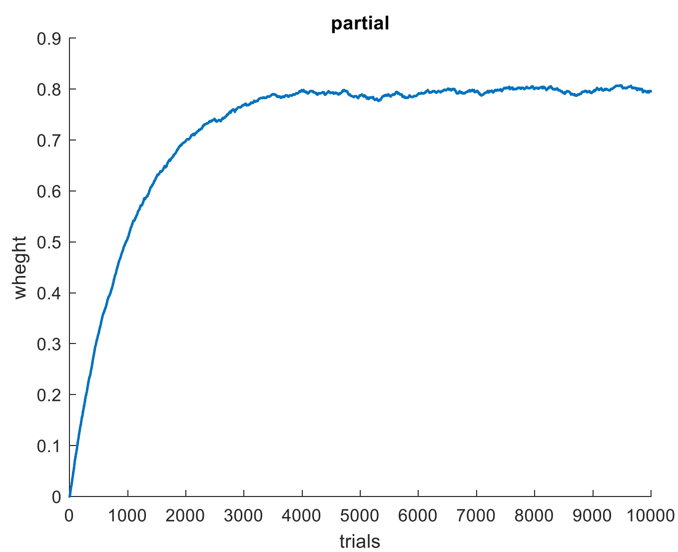
Part A

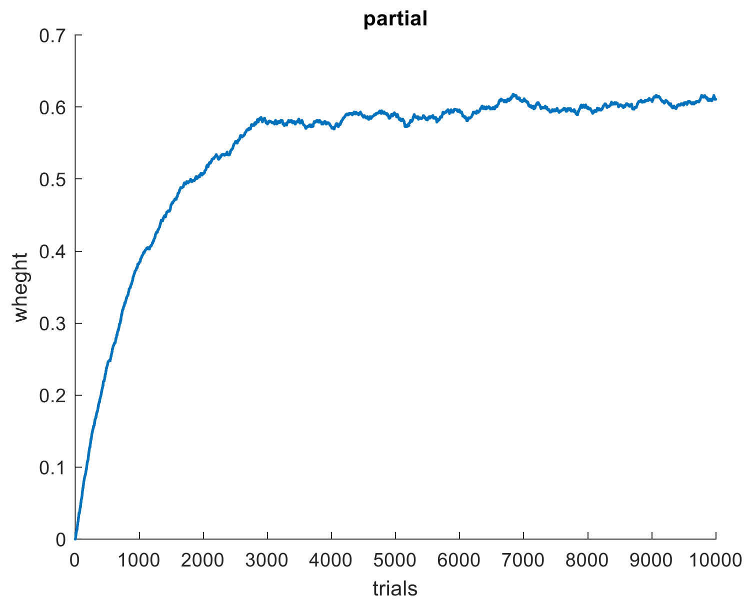
In this section we plot the weights for different paradigms:



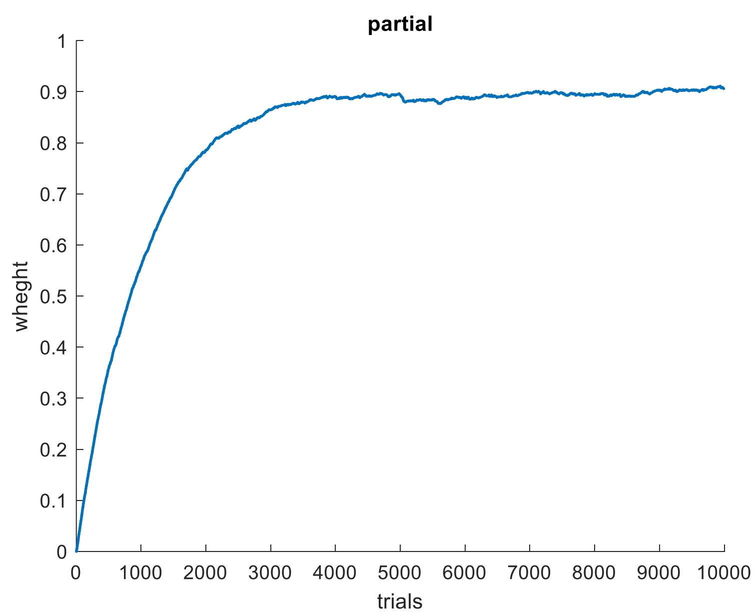
Partial when 20% of the rewards are zero:

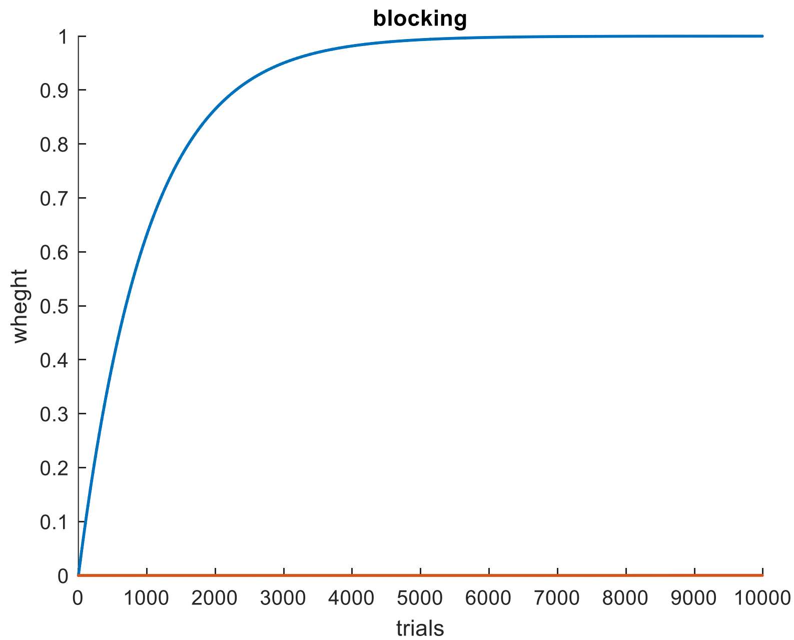


Partial when 40% of the rewards are zero:

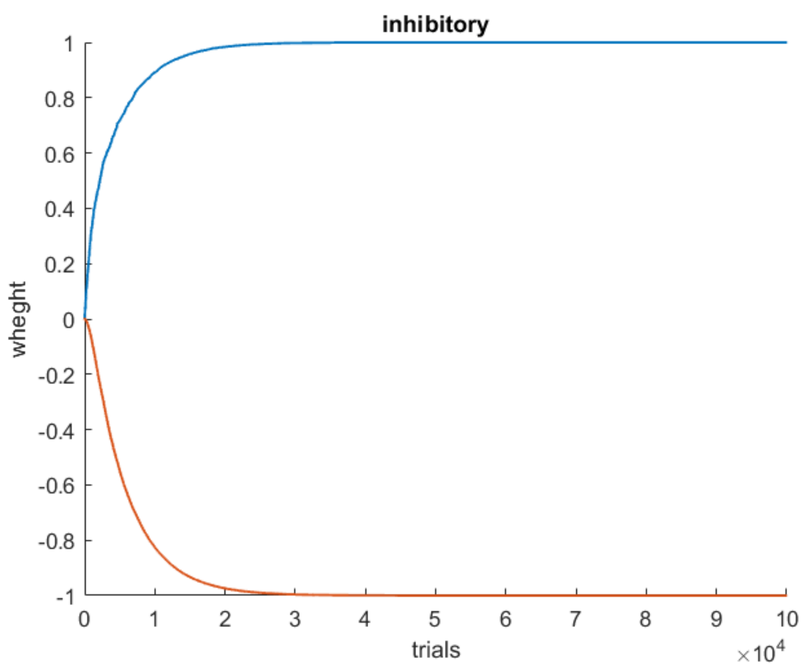


Partial when 10% of the rewards are zero:

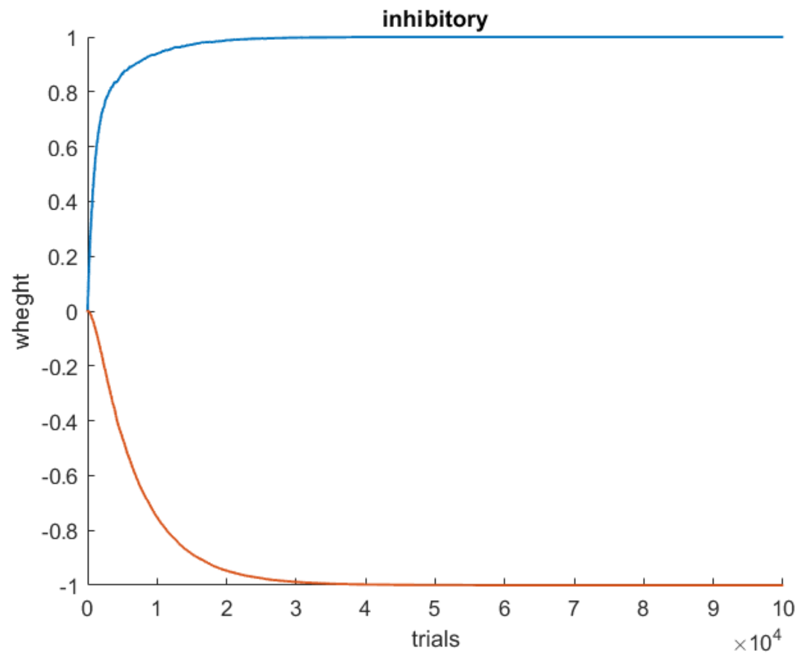




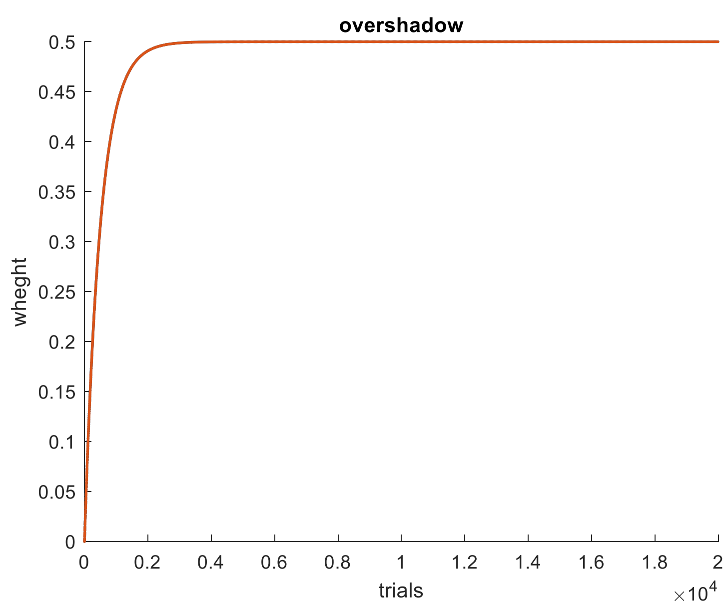
Inhibitory while 50% of trials second stimulus is absent:



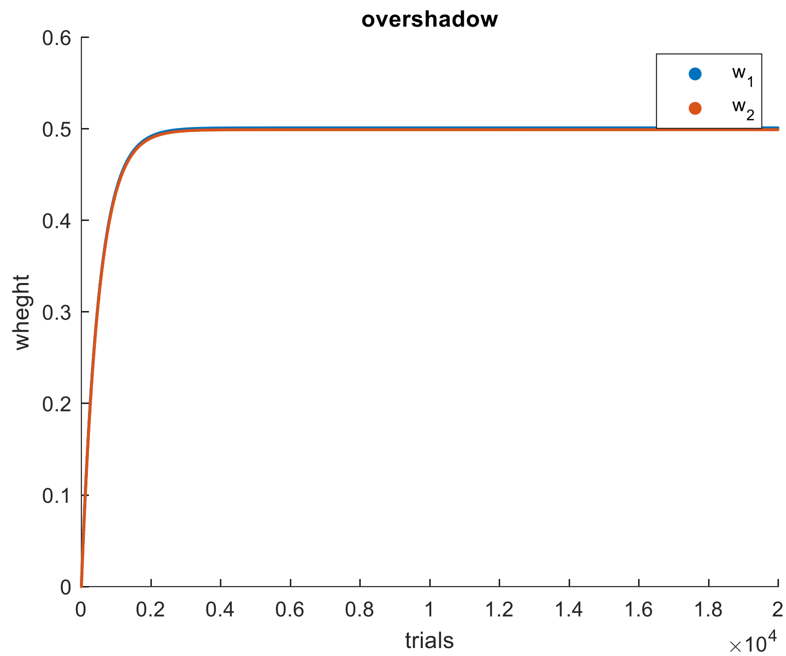
Inhibitory while 80% of trials second stimulus is absent:

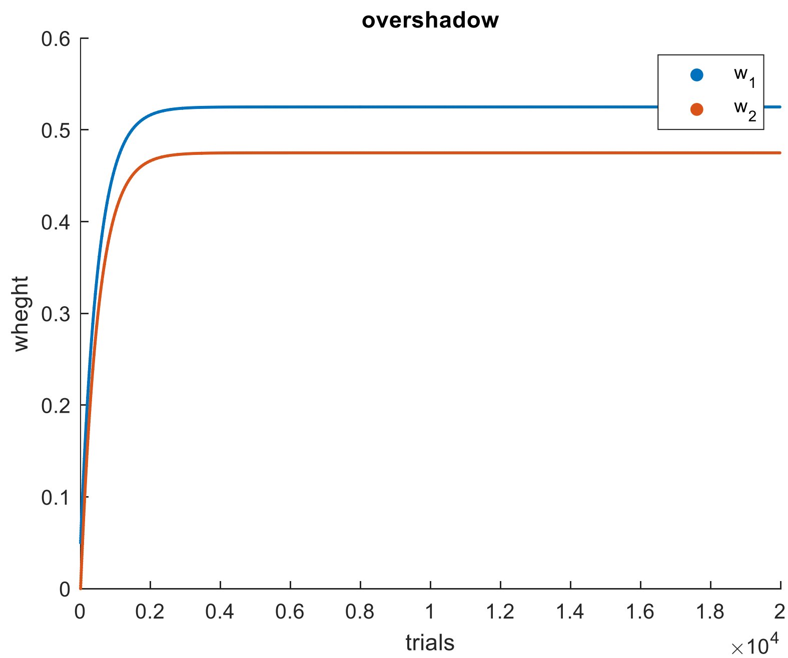


Overshadow with equal initial weights:



Overshadow with different initial weights:

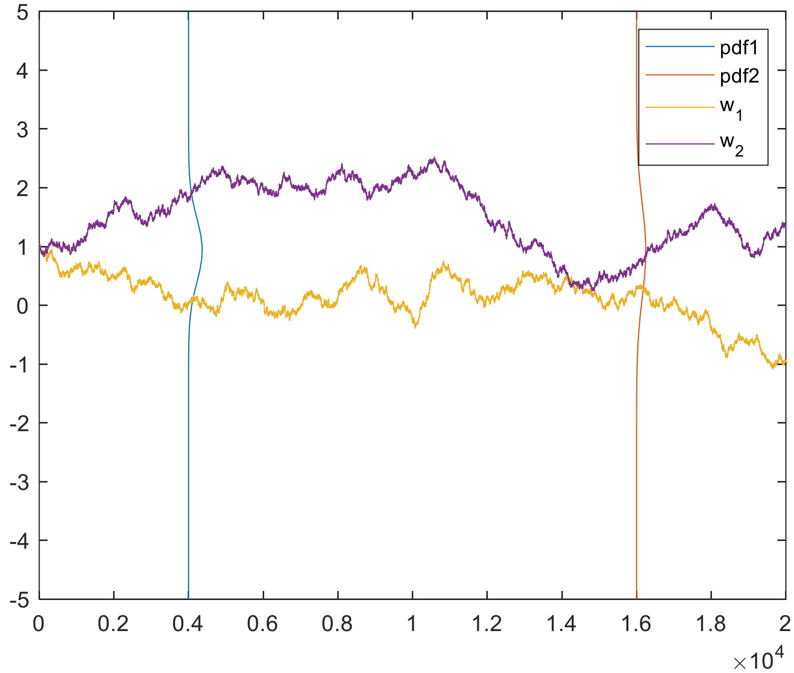




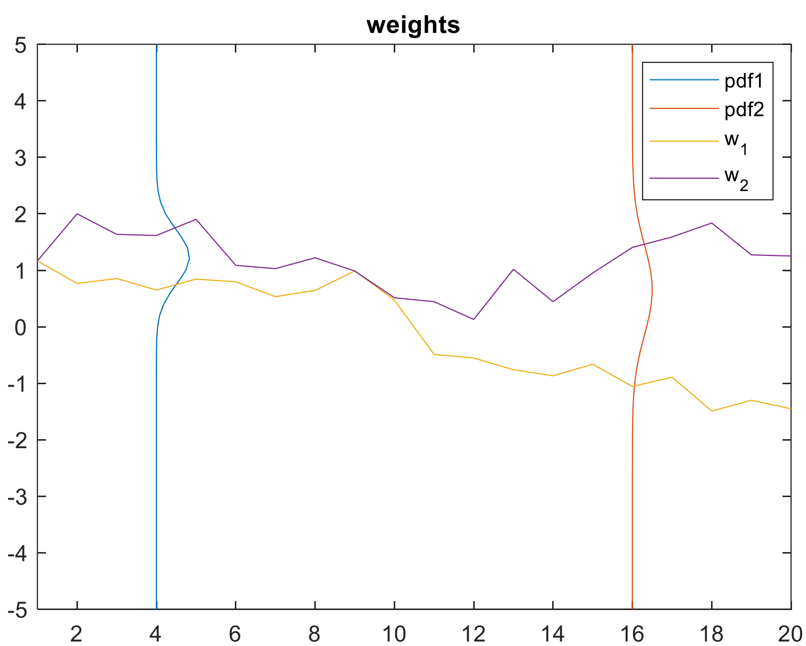
1. As it is obvious from the above figures by differing the initial values of the weights we can make different responds to the stimuli.

Part B:

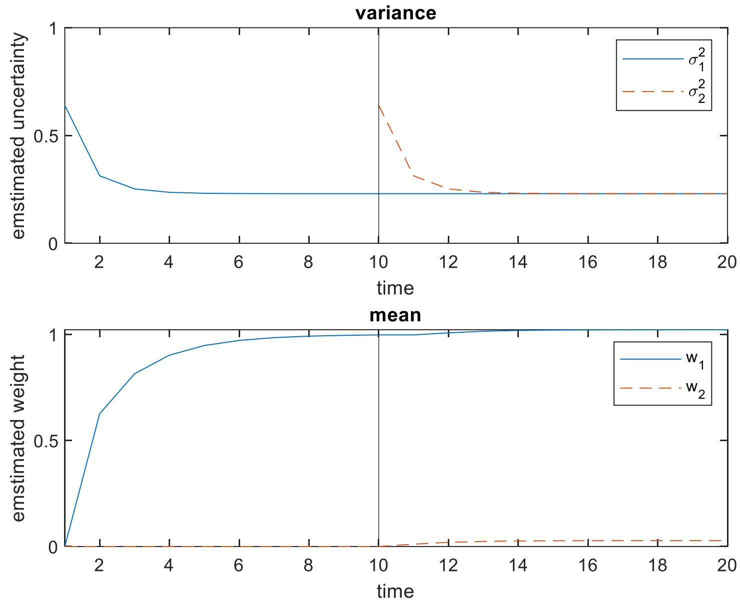
1. At first we try to generate the weights adding noise:



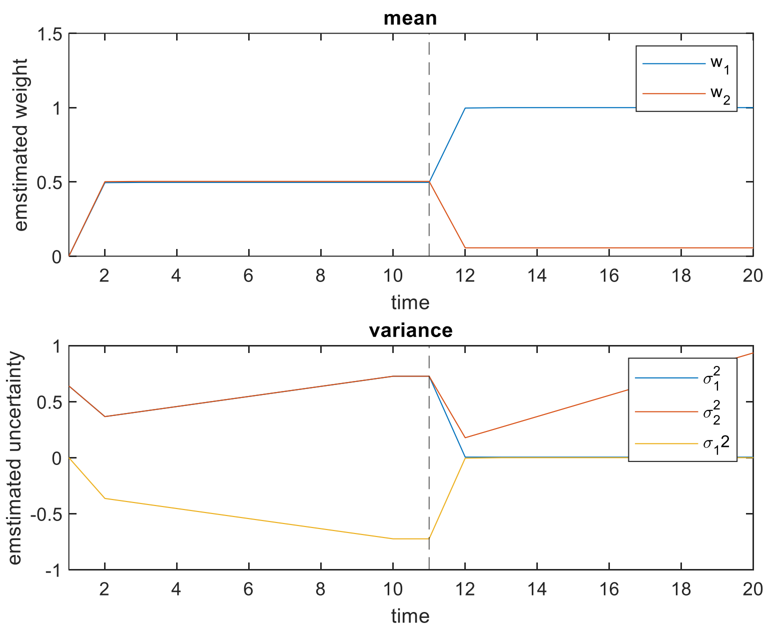
The weights generated for learning process:



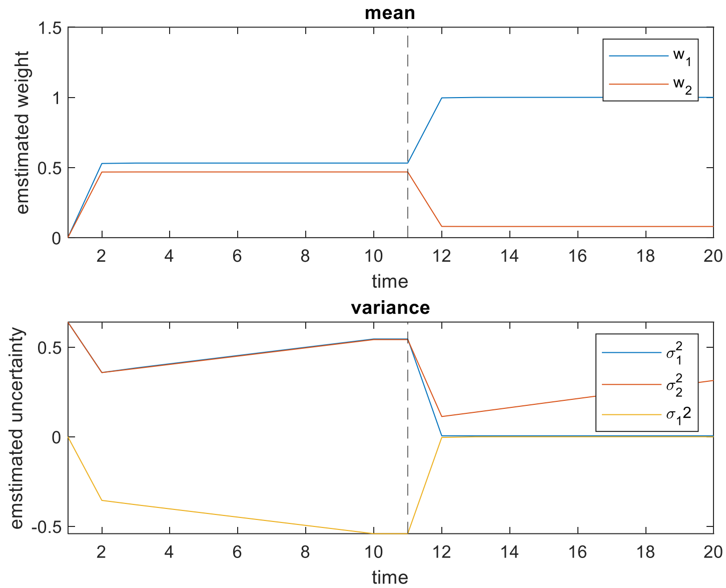
Blocking:

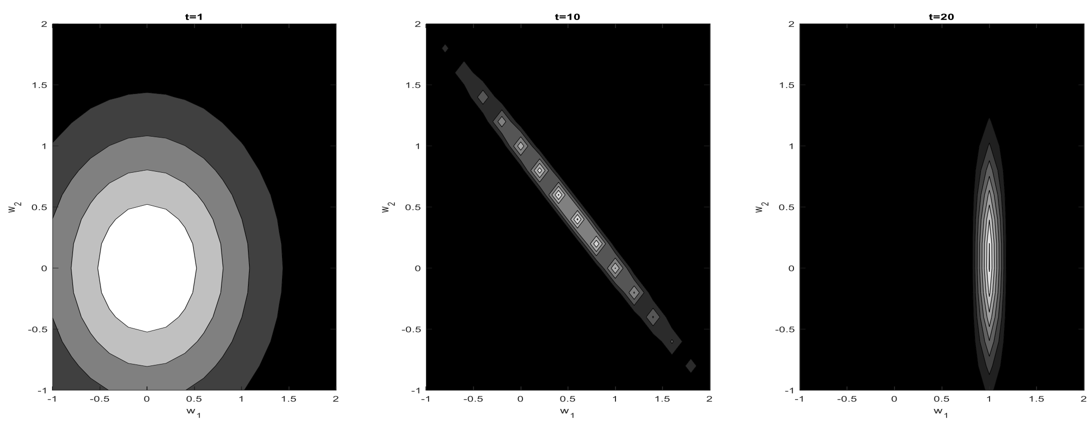


For unblocking:



Another try:





2. Both process and measurement noise are involved in the learning process as the below equations: (the W and τ^2)

$$G = \Sigma(t+1)^{-} C^T (C\Sigma(t+1)^{-} C^T + \tau^2)^{-1}$$

$$\Sigma(t+1) = \Sigma(t+1)^{-} - GC\Sigma(t+1)^{-}$$

$$\hat{w}(t+1) = \hat{w}(t) + G(r(t) - C\hat{w}(t))$$

So by changing the noise we will increase the learning rate and then change the learning structure.
As you can see in previous part, the figures for unblocking, in each try the amount of noise (both measurement and process) change and it will cause the distance of the mean values from 0.5 in the first part of learning process.

3. The Kalman filter gain arises in linear estimation and is associated with linear systems. The gain is a matrix through which the estimation and the prediction of the state as well as the corresponding estimation and prediction error covariance matrices are computed.

$$G = A\Sigma C^{T} (C\Sigma C^{T} + V)^{-1}$$

In this equation the uncertainty matric and weights converge to a stable value.
The equation is driven from the equation:

$$A\Sigma A^{T} - \Sigma + W - A\Sigma C^{T} (C\Sigma C^{T} + V)^{-1} C\Sigma A^{T} = 0$$

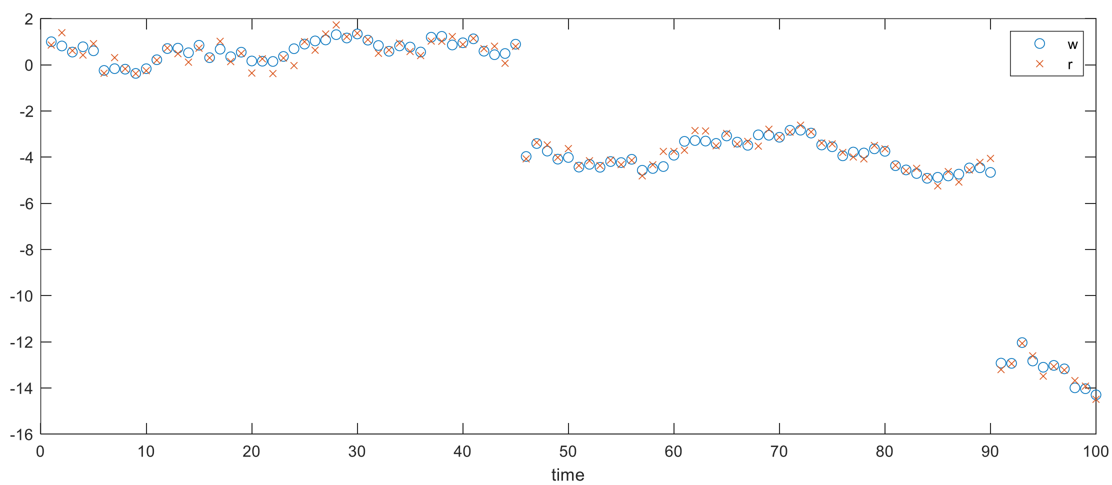
4. the uncertainty Σ about w1 translates exactly into uncertainty about the delivery of the reinforcer, and so the expected amount of error so we can conclude that it depends on both error and learning content. The larger the expected variability in the reinforcer delivery (τ^2), the slower the learning. This is because each trial provides less information about the relationship between stimulus and reinforcer.

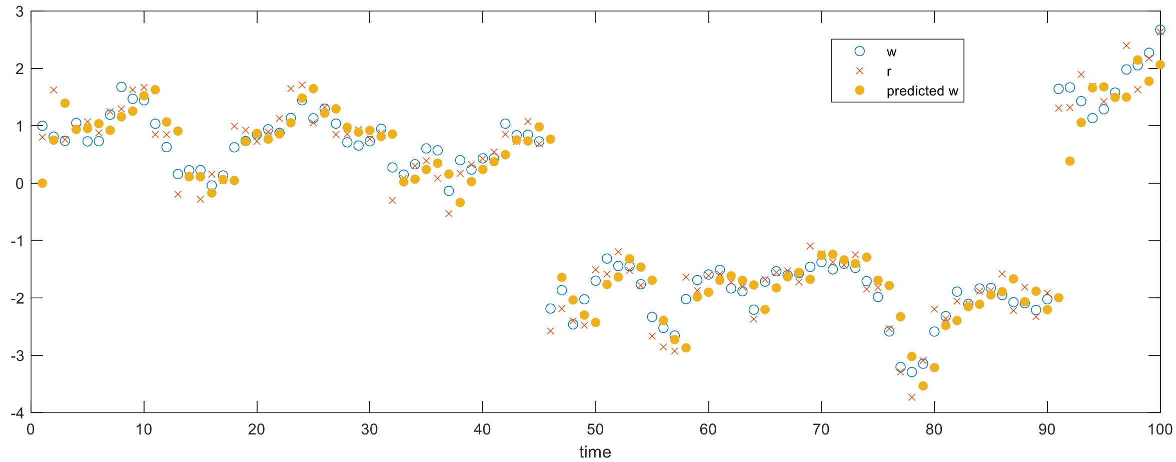
5. As the learning rate is determined from the below equation, while we change the input of the system from 1 to -1 the amplitude and sign of the learning rate both change and it will cause the faster learning in the new condition.

$$\frac{\Sigma(t)\mathbf{x}(t)}{\mathbf{x}(t)^{T}\Sigma(t)\mathbf{x}(t) + \tau^{2}}$$

Part C:

1. In this section we try to simulate the unexpected uncertainty:




w
r
predicted w
time
0
10
20
30
40
50
60
70
80
90
100
3
2
1
0
-1
-2
-3
-4