Advanced neuroscience

Assignment 5

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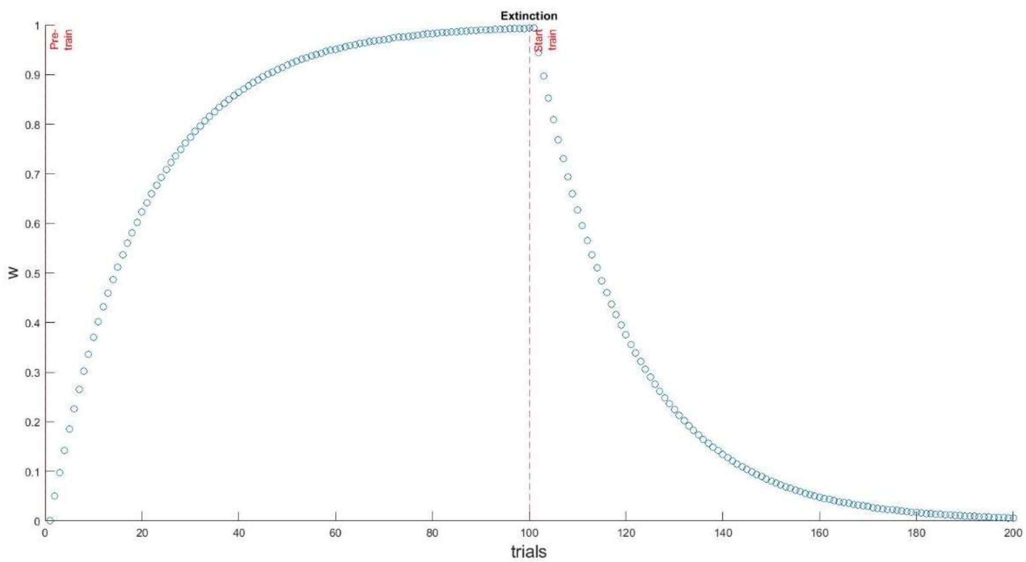
Q1:Modelling learning in classical conditioning paradigms:

Extinction:

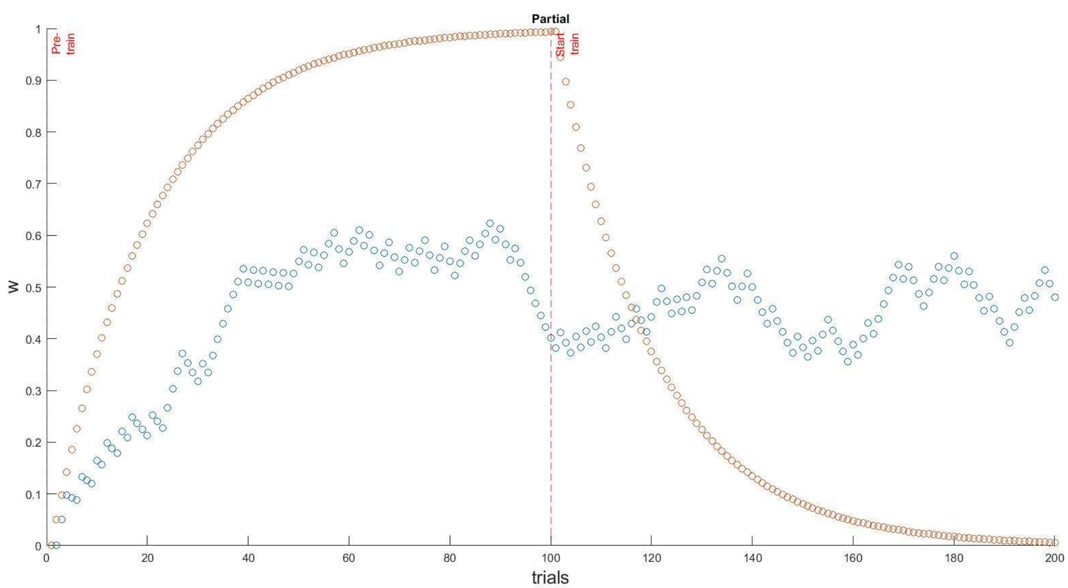
In this case there is a reward before training and the reward will be cut off after the train starts. In this case, the W is first increased and exponentially decreases.

Observed that the shape is similar to the figure found in the lesson slides.



First 100 trials are Pre-train and second 100 trials are Train trials.

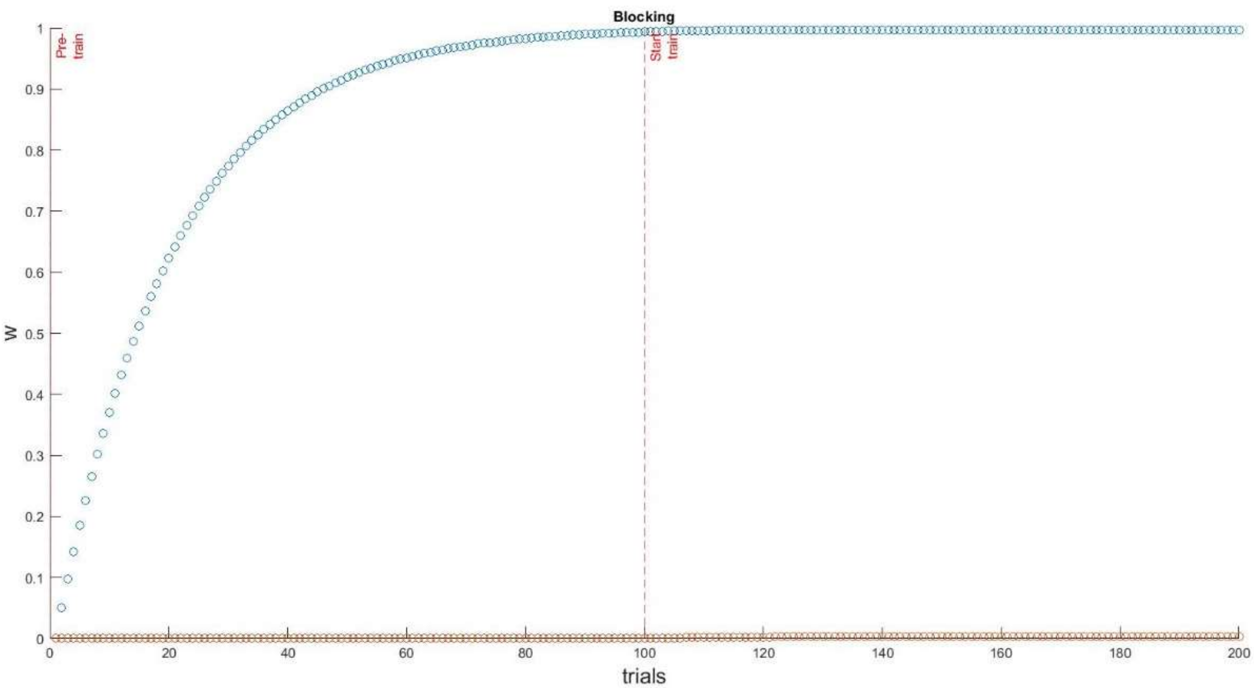
Partial:



The second part is the partial model, where we have a 5٠% probability of coin. It is observed that with many experiments, the W will eventually reach the same amount as we expect as 0.5.

The form of Extinction is similar to what we saw in the slides of the lesson.

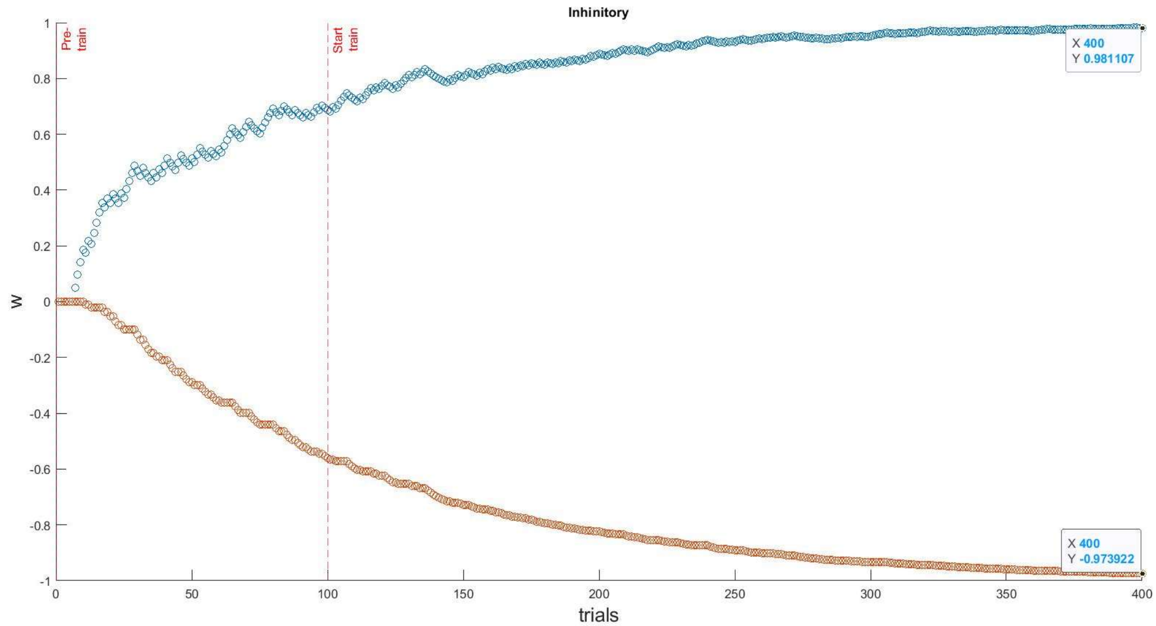
Blocking:



The blocking method is used here to see that the first sign blocks the second sign and eliminates its effect. Finally, the W of the first sign to 1 or 100% of reward, but the second signal effect is zero.

The point is that the effect of the second sign becomes very low and infinitely reaches zero but does not go zero and has a small value.

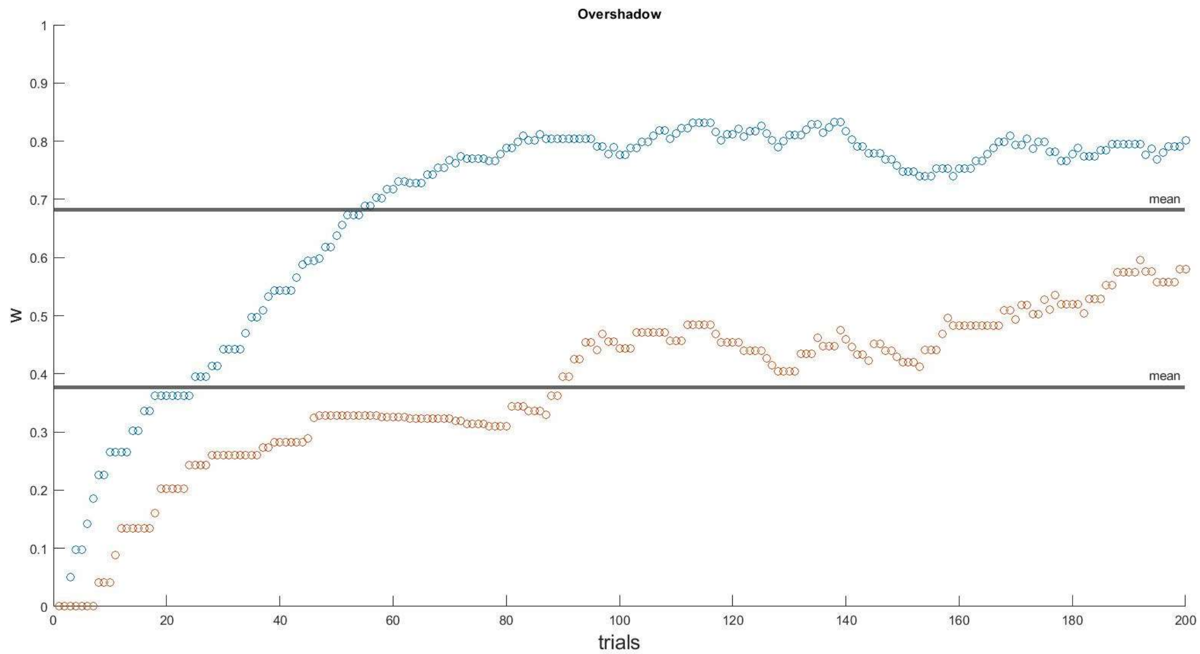
Inhibitory:



In this case, one of the signs reaches reward, and one of them prevents reward from reaching.

Finally, the effect of both of them will reach the same value with the opposite sign, which is also specified in the figure.

Overshadow:



In this case, each of the signs covers a percentage of reward, which eventually the weight of each of the signs we specified. The average chart is also visible.

Q2:

As can be seen in the figure above, the higher the stimulation with one symptom, the higher the expected reward. In fact, the more pronounced one of a few simultaneous stimulations, the more expected it is to stimulate and higher value belongs to it.

when the error value reaches zero, the faster growing weight will have a larger value than the slower growing weight.

Step2

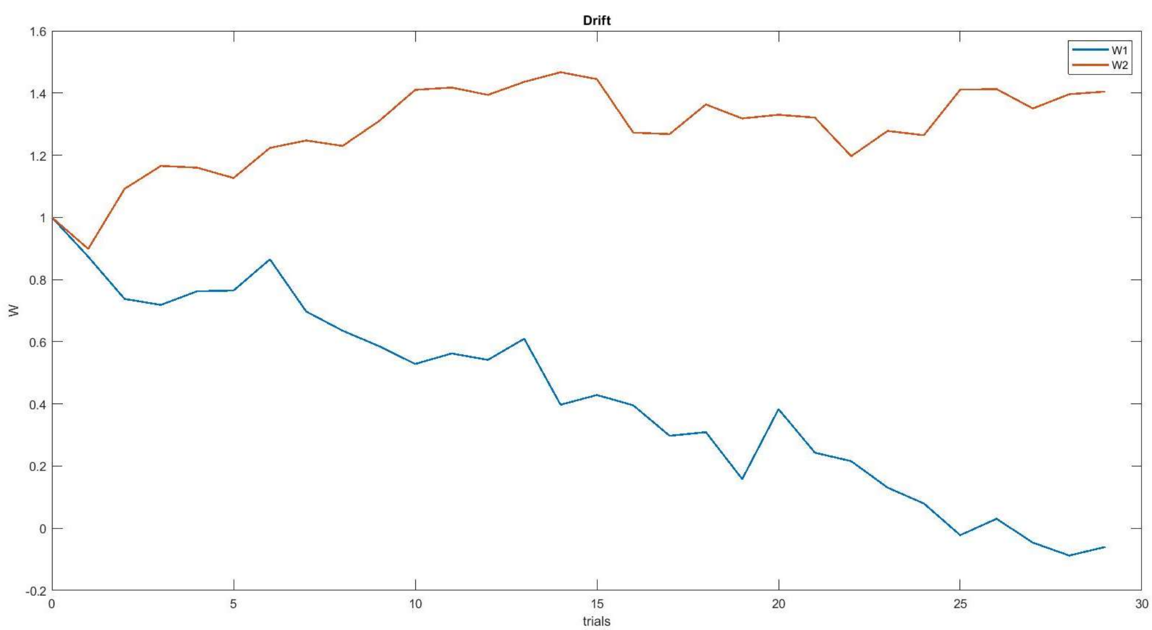
Q1:

According to the paper, 'Uncertainty and Learning', implement Kalman filter method to explain blocking and unblocking in conditioning.

Here we have Drift, which is a random process and we started with the initial value of 1 for W.

Given the randomness of the process, the shape will probably be different from what is in the article.

The normrnd.m function was used to make noise.



Then, using the Kalman filter, we plotted the requested charts. Here the Kalman filter was implemented in the high-relationship state space and the charts are as follows.

$$\widehat{w}(t+1)^{-} = A\widehat{w}(t) = \widehat{w}(t)$$

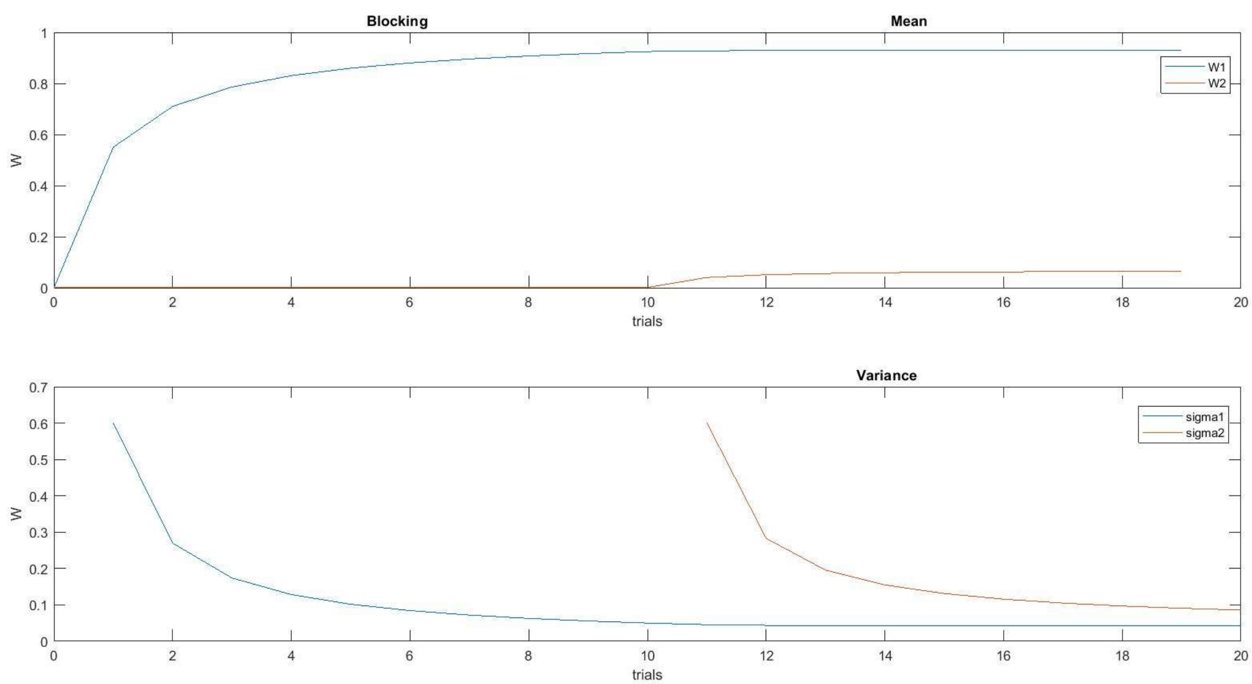
$$\Sigma(t+1)^{-} = A\Sigma(t)A^{T} + W = \Sigma(t) + W$$

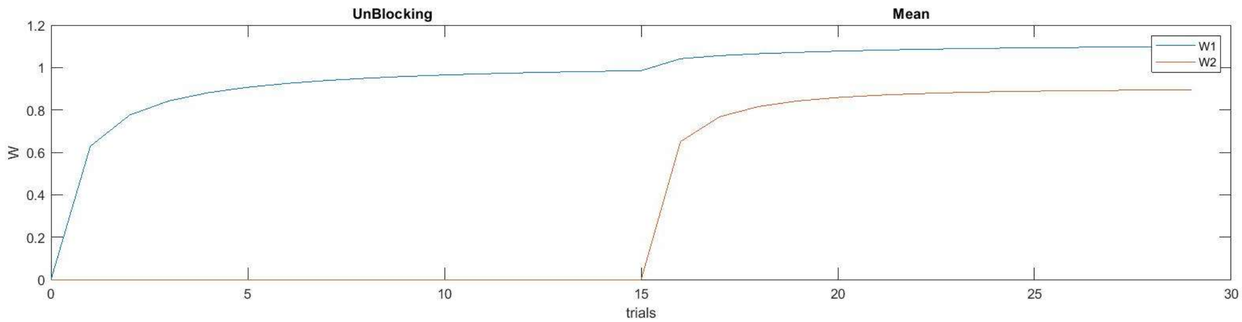
$$G = \Sigma(t+1)^{-}C^{T}(C\Sigma(t+1)^{-}C^{T} + \tau^{2})^{-1}$$

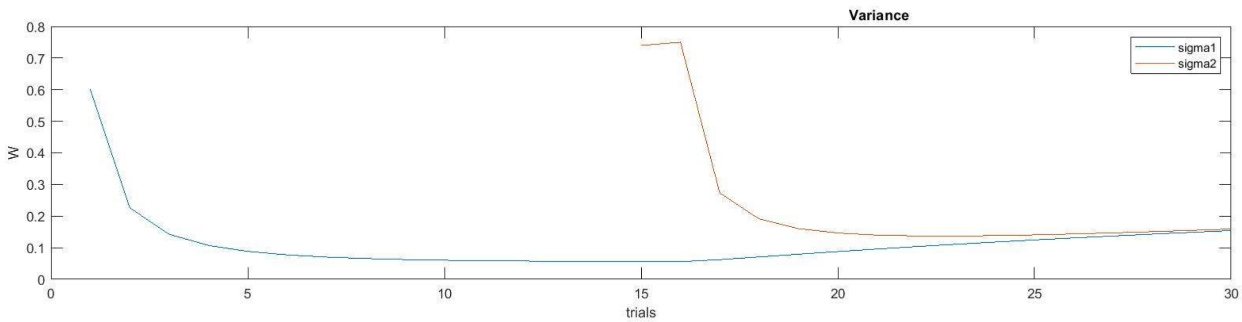
$$\Sigma(t+1) = \Sigma(t+1)^{-} - GC\Sigma(t+1)^{-}$$

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

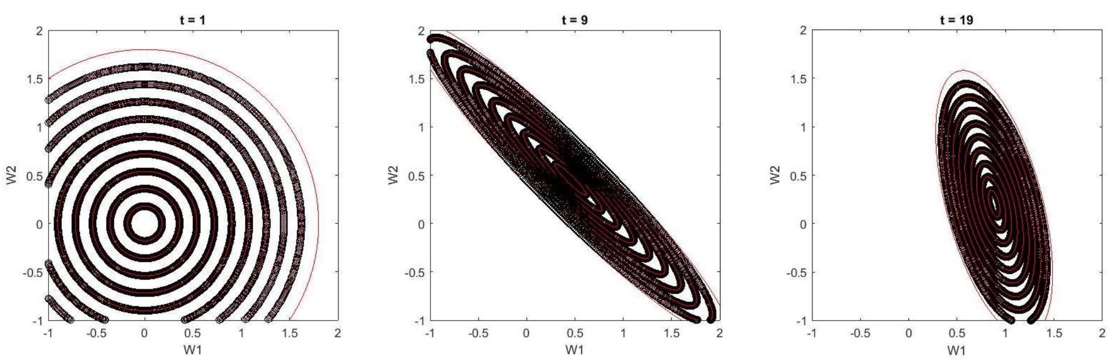
Here we implemented the Kalman filter using the above relationships and plotted the blocking and unblocking charts as follows. The forms obtained are similar to the forms of the article.



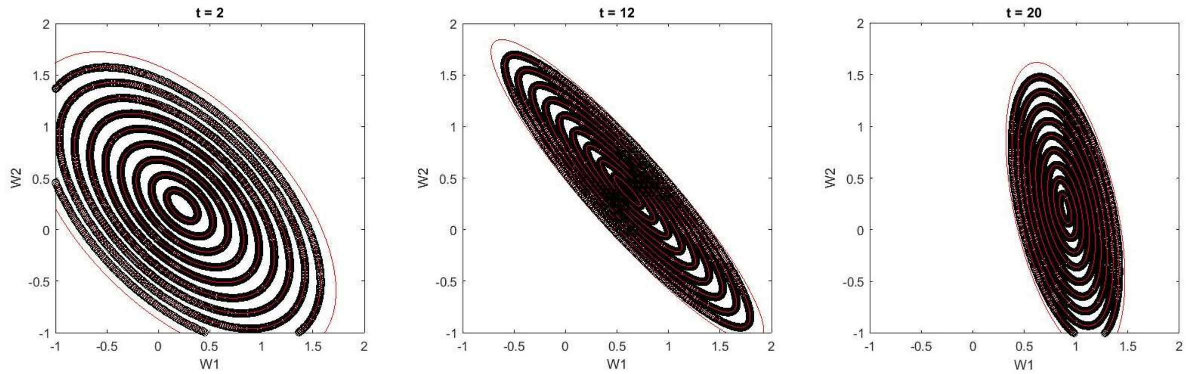




To draw them against each other, a circle center is multiplied in 0 with the desired radius in the covariance matrix, the Kalman filter output is multiplied. The shape of the black circles is actually the average of the Kalman filter output.

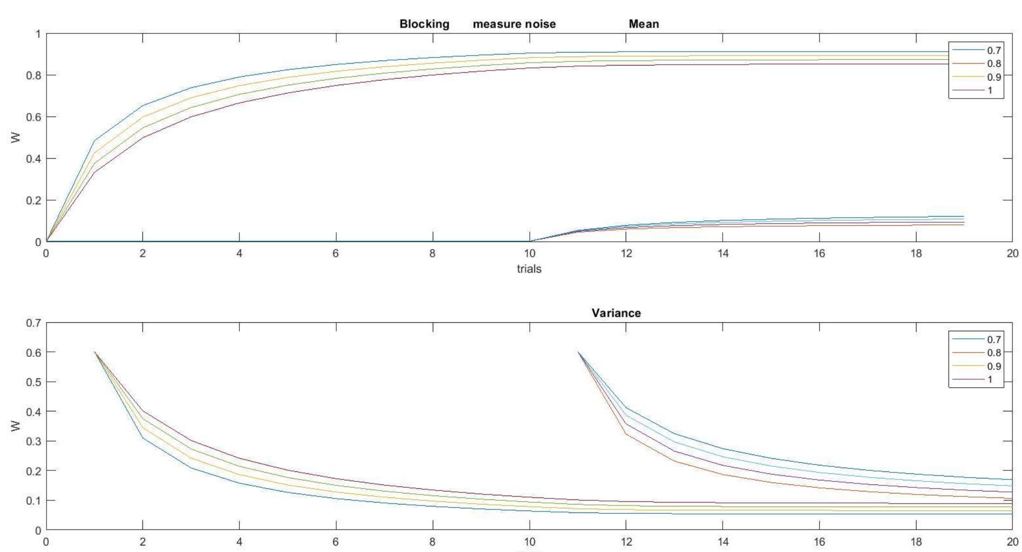


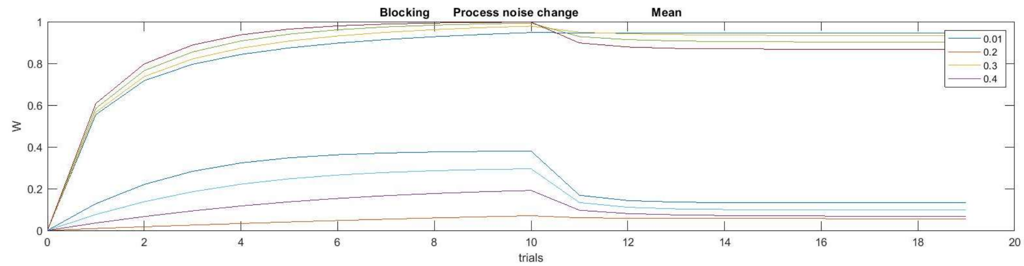
For example, for the other three moments.

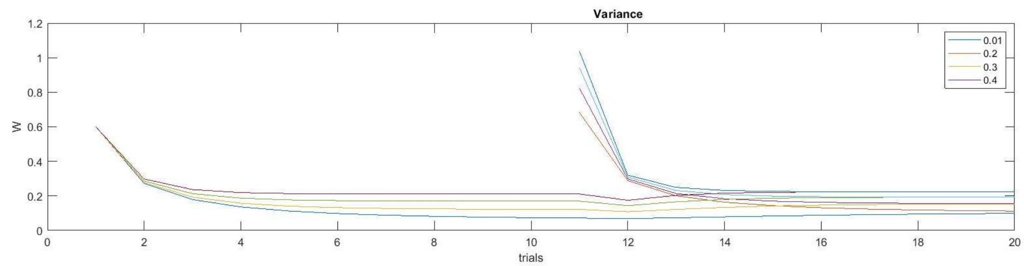


Q2: For blocking I have changed the value of process noise and measurement noise and simulated them. For higher process noise values, w1 learns faster. When the process noise is higher, we are more certain about the environment that here is associating w1 with reward 1. In contradiction, for higher measurement noise values, w1 learns slower. Because high measurement noise reveals uncertainty about experiments so w1 is less willing to increase to 1. Also, for both higher process and measurement noises, the uncertainty values are higher.

When we increase the measurement noise in the blocking paradigm, we can put less trust in what we see from the environment so we learn slower than before. Also, because when the environment noise rises, we trust the self-estimate more than before, w2 also increases more than before. Because, we believe that it might have some contribution to the reward. Moreover, the uncertainty also rises because we have a noisier place.







Q3:

Given the relationship between the previous classic model and the Kalman filter model, the Kalman filter Gain is actually a R from V, which gives us the delta if we put it in classic relationships. In fact, Gain in the Kalman filter model and show the error.

And update w with the Rescola-Wagner (RW) rule:

$$w \rightarrow w + \epsilon \delta u \quad \boxed{\text{with} \quad \delta = r - v}$$

Where ϵ is the learning rate

$$\widehat{w}(t+1)^{-} = A\widehat{w}(t) = \widehat{w}(t)$$

$$\Sigma(t+1)^{-} = A\Sigma(t)A^{T} + W = \Sigma(t) + W$$

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

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

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

So, it is observed that G in the Kalman filter with ẟ operates in the classic relationships.

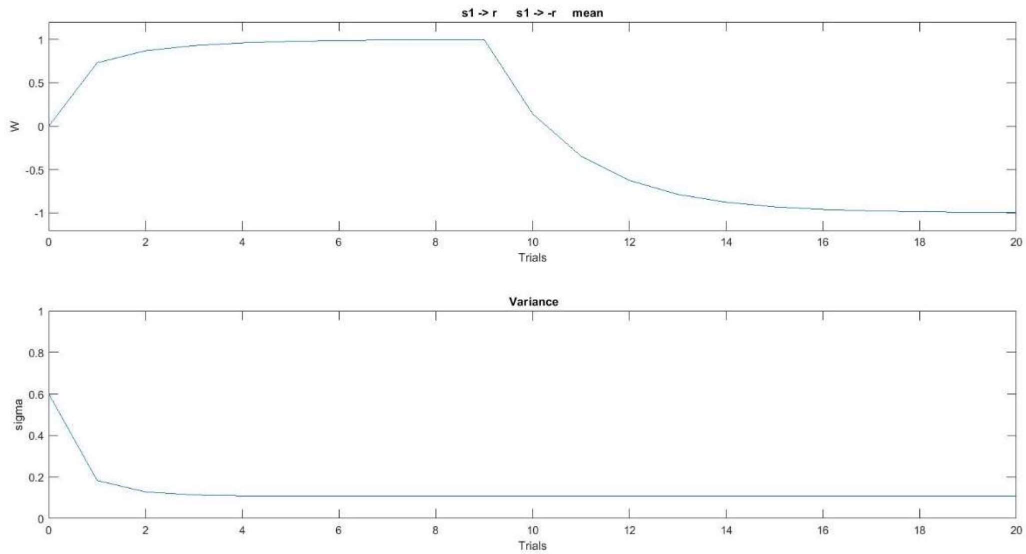
Q4:

the value of uncertainty does not Depend on the observed Error in Each Trial.

Kalman Filter uncertainty does Not change and reduces with Time. But Depends on the Learning Context In the simple Kalman filter model, changes to Σ do not depend on the observed error.

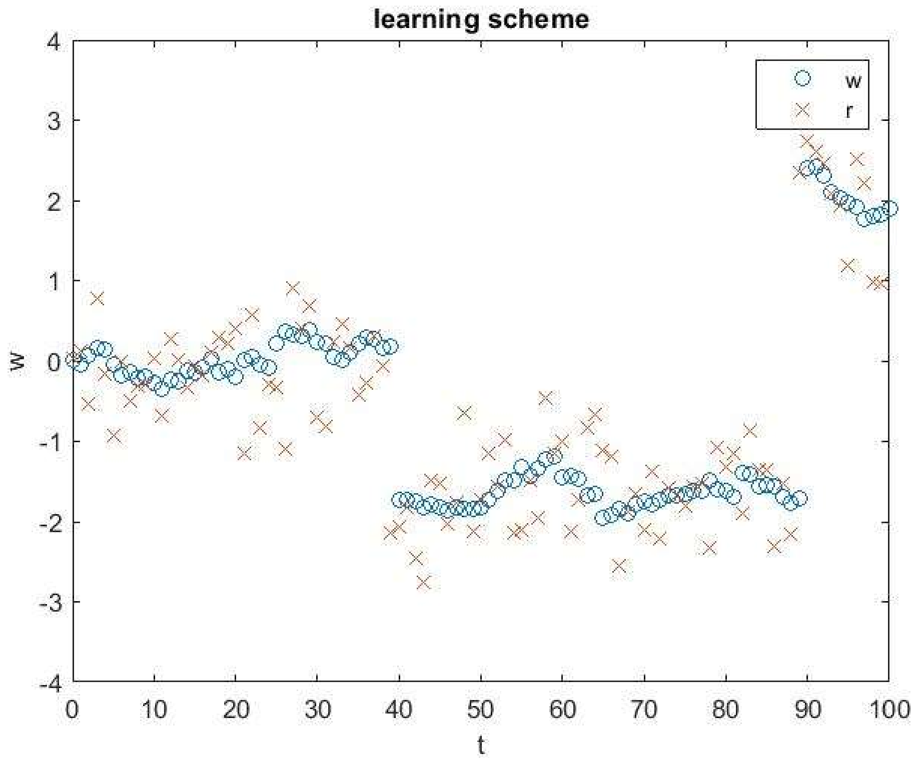
it must depend on the error because when the reward related to a given stimulus changes, we must rise our uncertainty about the stimulus and start learning about it again.

Q5:



It is observed that although reward decreases and changed in Trail ۹, the variance continues to decrease and does not change. Finally, after a few trials, reaches as positive and negative, but the variance does not change.

Step3:


learning scheme
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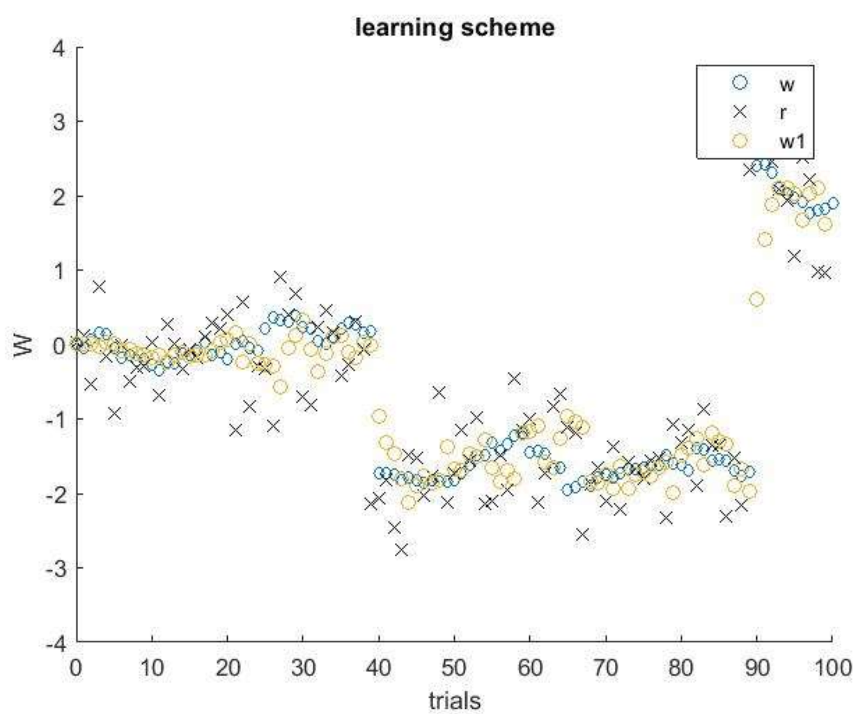
learning scheme
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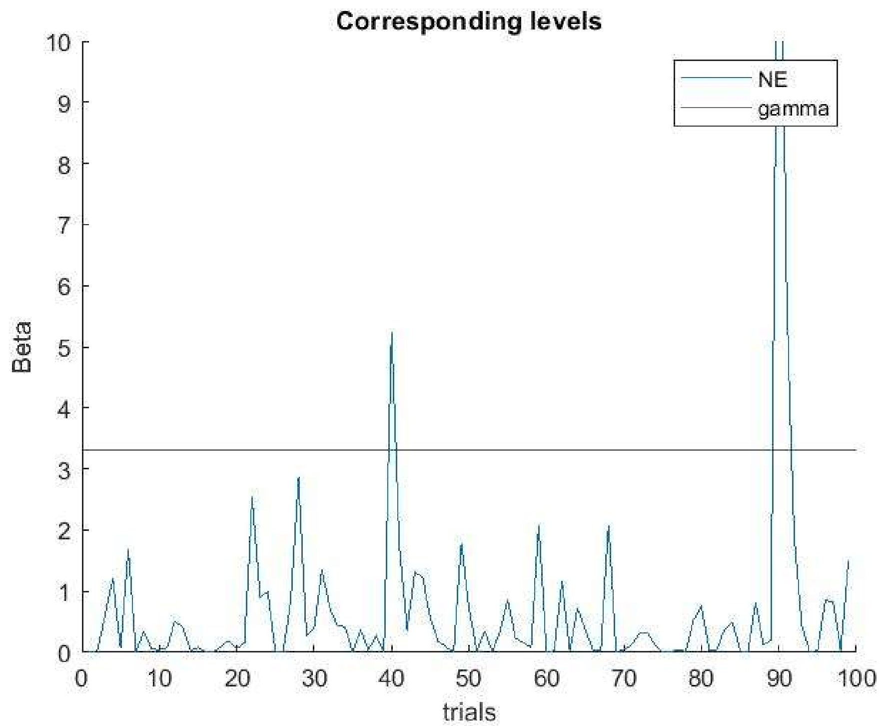
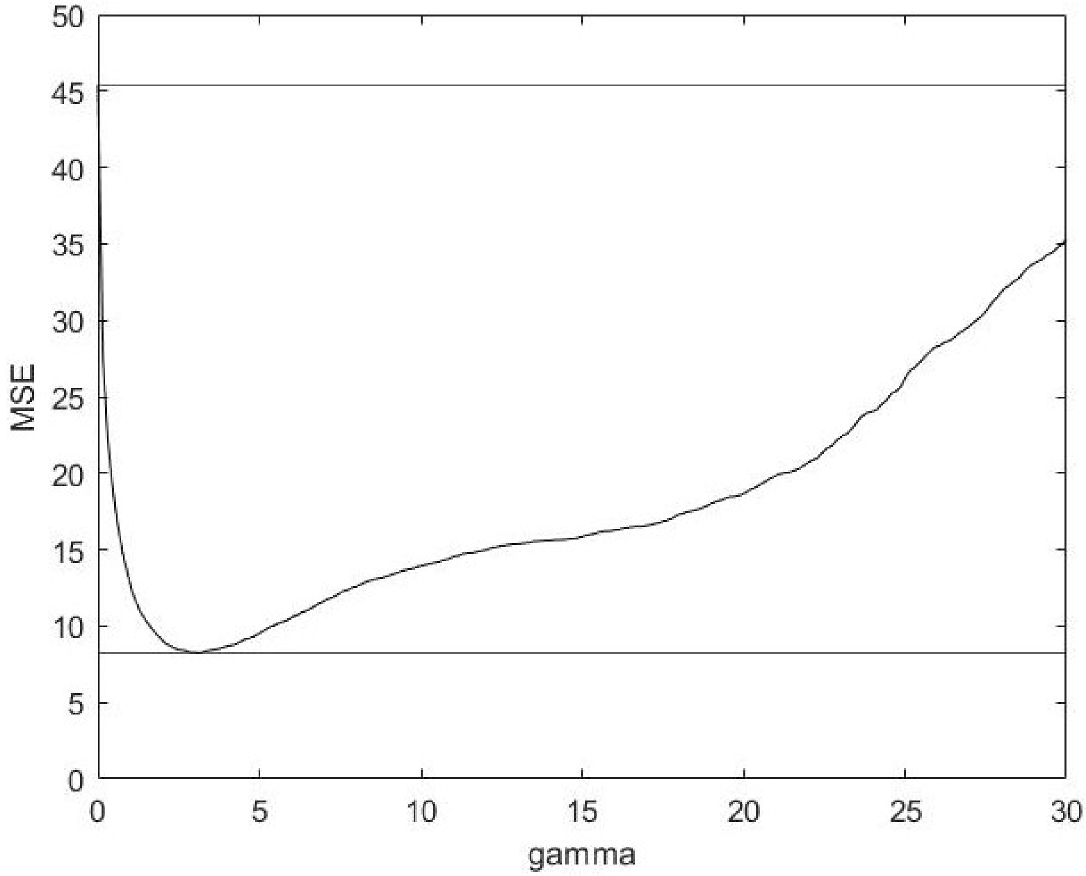


Kalman filter is improved by below formula. In each trial value of beta is calculated and compared to threshold gamma. For beta > gamma, the uncertainty value has been reset.

$$\beta(t) = (r(t) - x(t) \cdot \hat{\mathbf{w}}(t))^2 / (\mathbf{x}(t)^T \Sigma(t) \mathbf{x}(t) + \tau^2)$$

Second figure demonstrates the implementation of the improved Kalman filter. The weights from improved Kalman filter track the original weights closely

Next figure indicates the MSE of weights from the improved Kalman filter.



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gamma