In the name of God

Assignment 5 – Advanced Neuroscience

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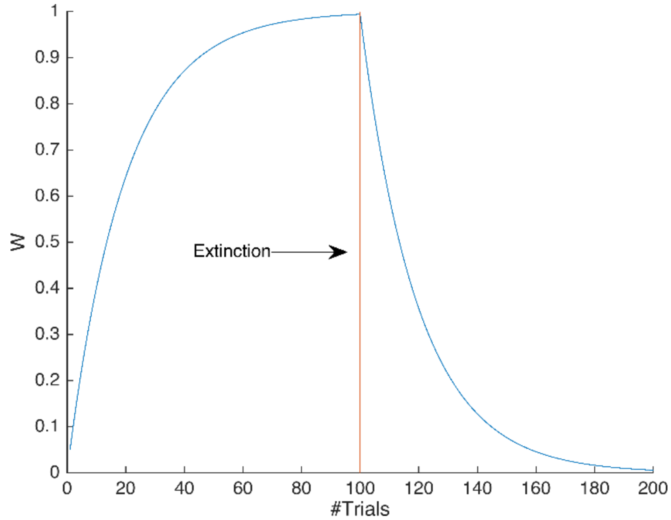
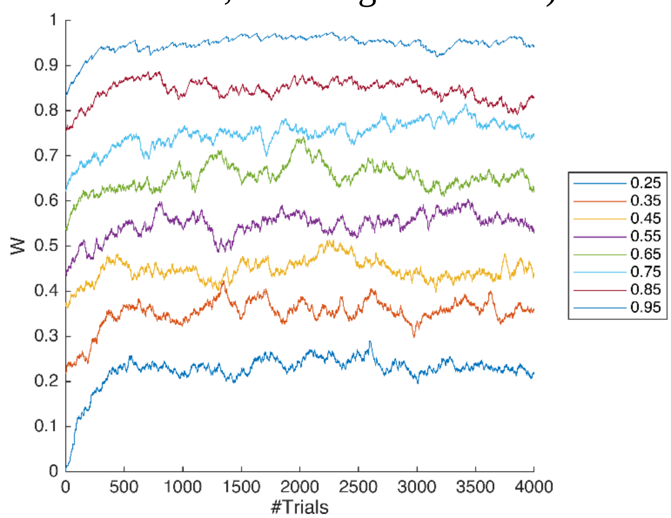
Part 1

1. Extinction (Number of trials: 100, Learning rate: 0.05):

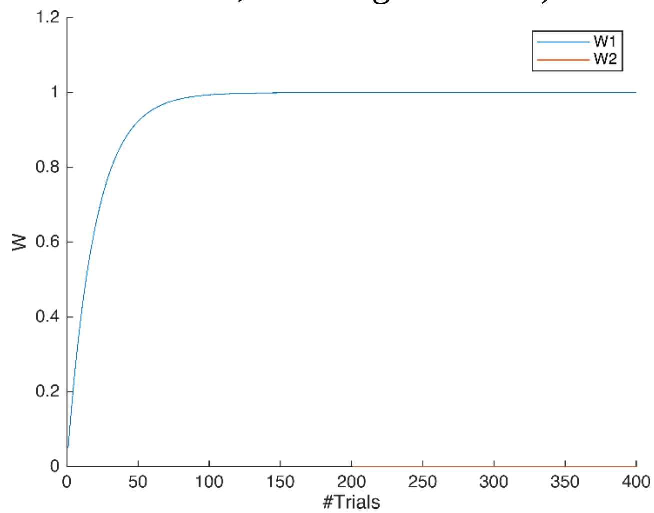


Partial (Number of trials: 4000, Learning rate: 0.005):

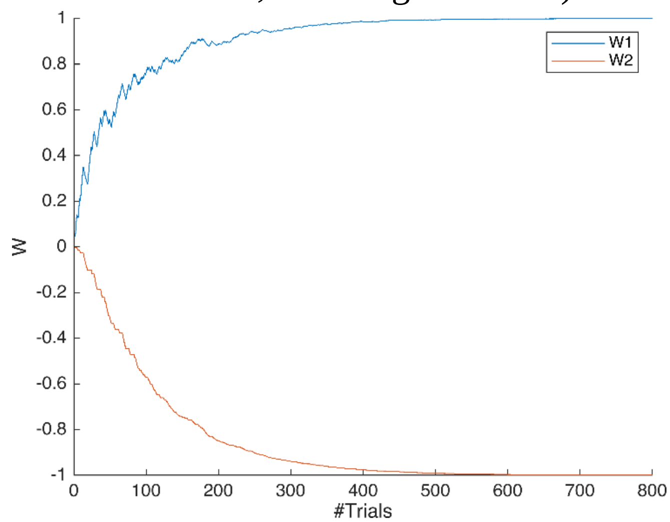


I have tested the model by different probability thresholds to investigate the relation of α and the threshold.

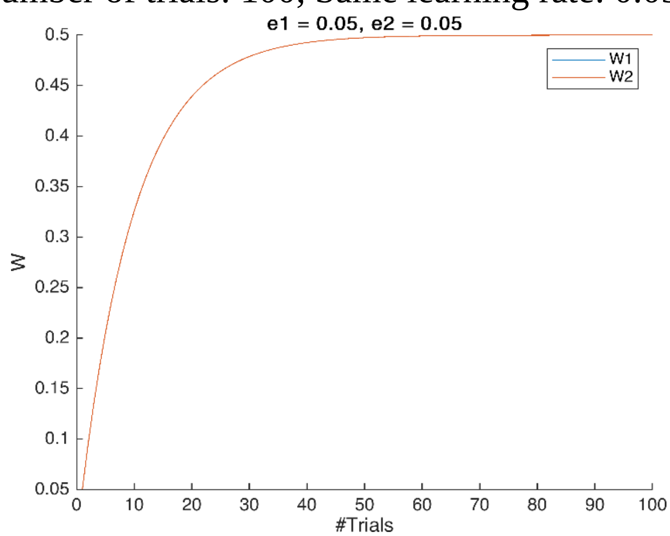
Blocking (Number of trials: 400, Learning rate: 0.05):



Inhibitory (Number of trials: 800, Learning rate: 0.05):

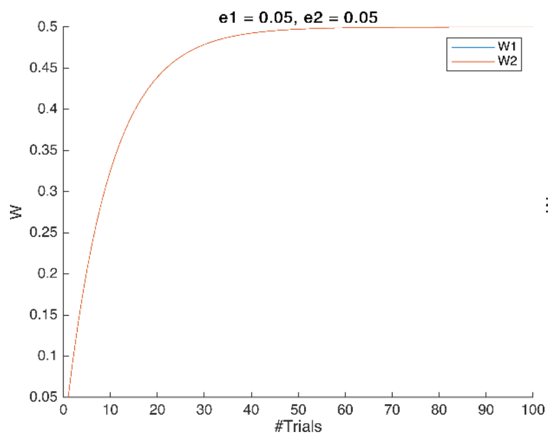


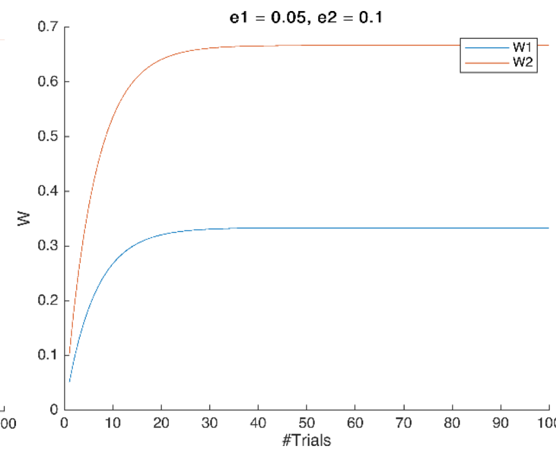
Overshadow (Number of trials: 100, Same learning rate: 0.05):

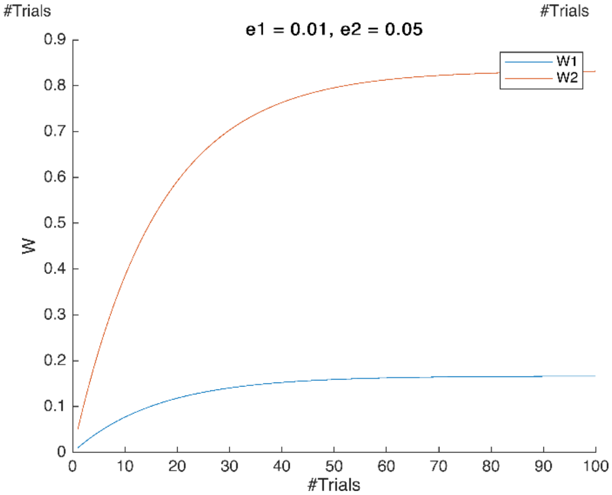


As you can see, testing all of the above paradigms with RW model leads to expected result. In the partial paradigm, the weight converges to the probability threshold. In the overshadow paradigm, both of weights converge to 0.5 since the learning rates are equal.

2. Overshadow:







The value of $W_1 * U_1 + W_2 * U_2$ should converge to r. So relative changes of weights are a factor of the final weights value. To have different rate of changes in weights, I've used different learning rates for each weight and the result shows that the ratio of weights converges to ratio of learning rates.

Part 2

1. Fig. 1 of the paper:

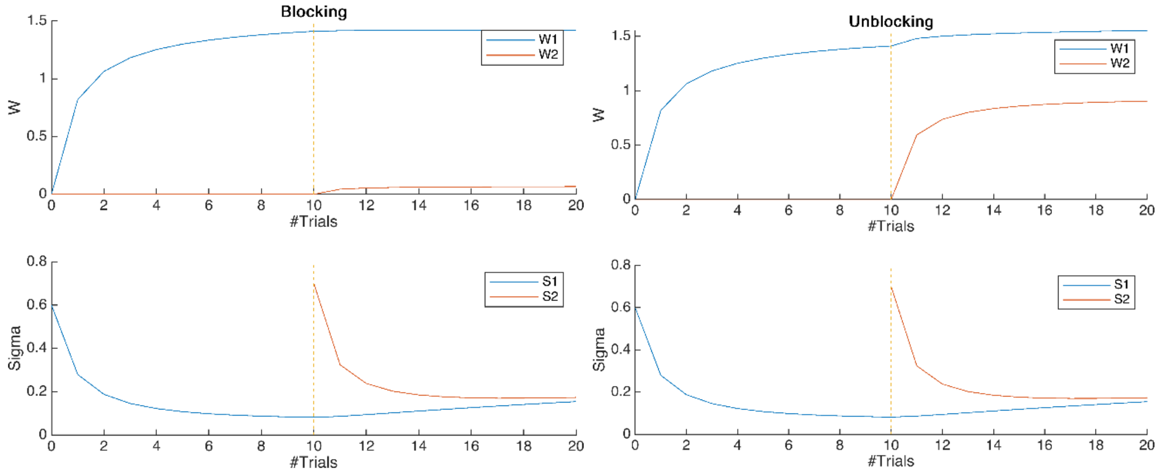
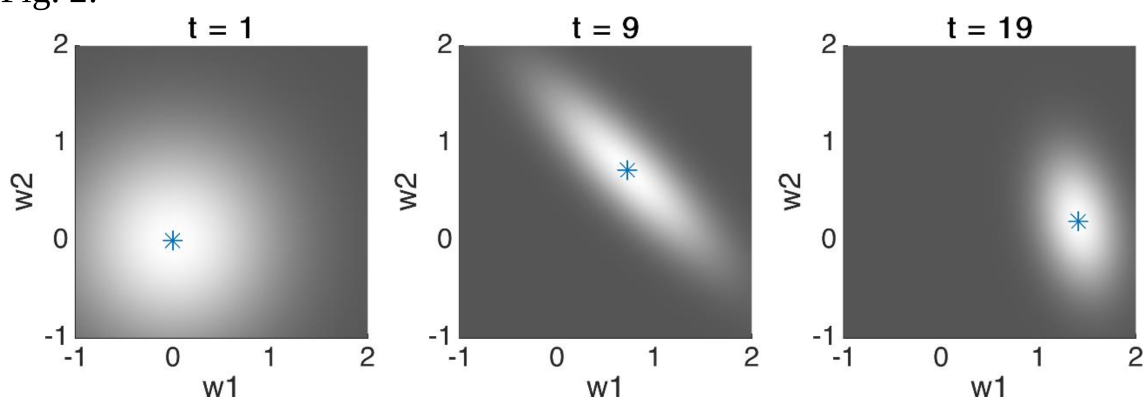


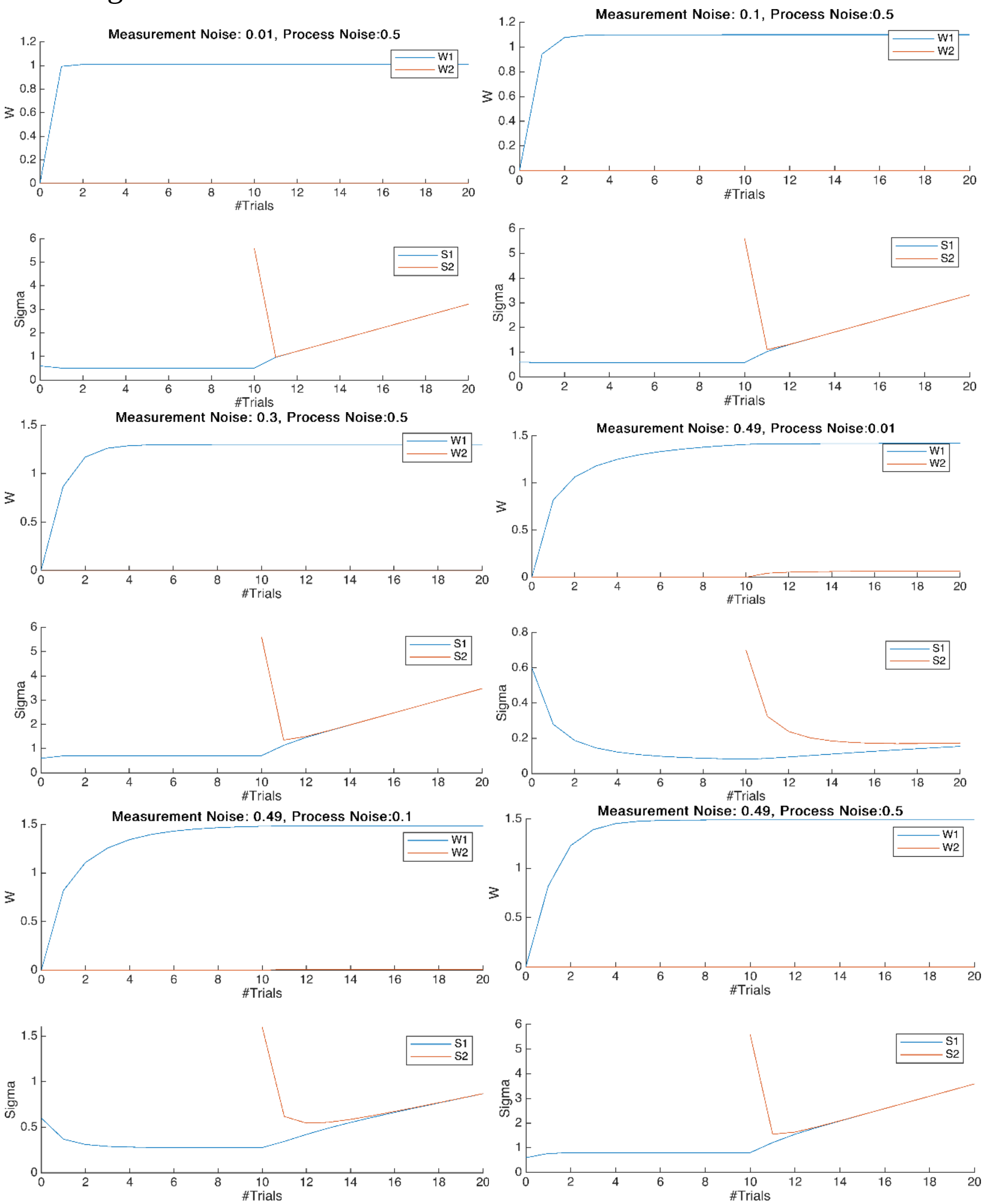
Fig. 2:



For fig. 2 first I've implemented the backward blocking, and then I extracted the distribution of weights in 3 different times.

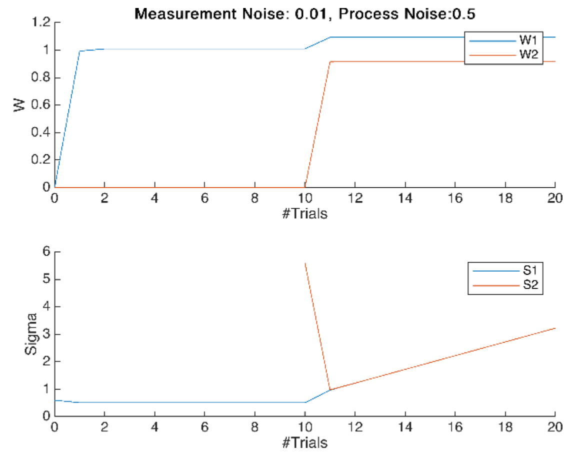
2. To see the effect of two types of noises on result, here is the result of 6 different noise parameters:

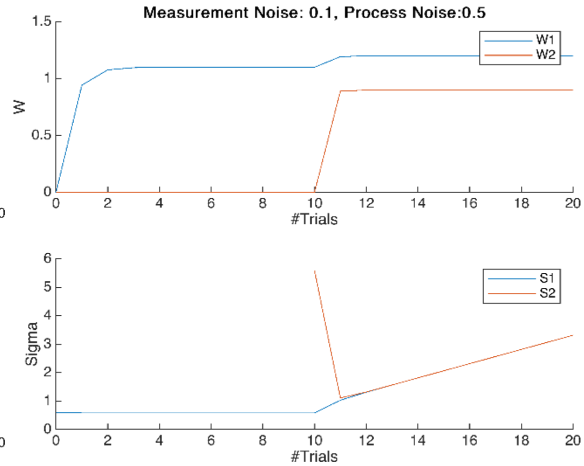
Blocking:

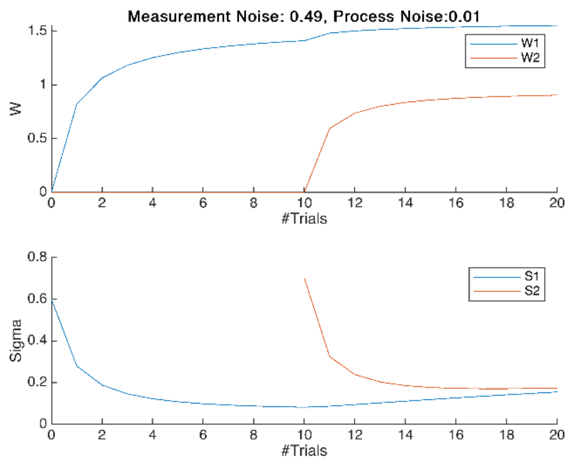


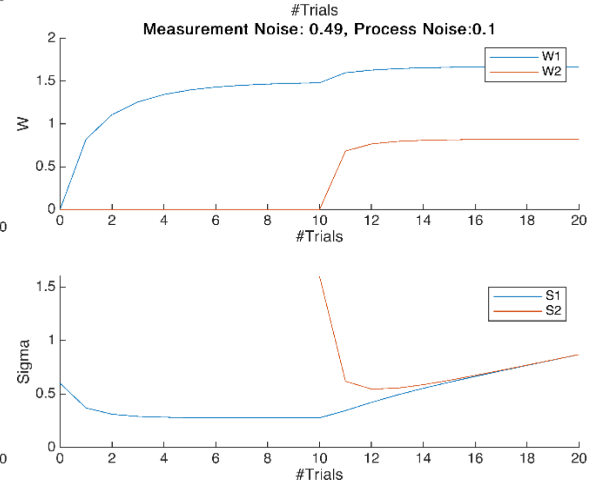
Measurement Noise: 0.01, Process Noise:0.5
Measurement Noise: 0.1, Process Noise:0.5
Measurement Noise: 0.3, Process Noise:0.5
Measurement Noise: 0.49, Process Noise:0.01
Measurement Noise: 0.49, Process Noise:0.1
Measurement Noise: 0.49, Process Noise:0.5
W
Sigma
#Trials
W1
W2
S1
S2

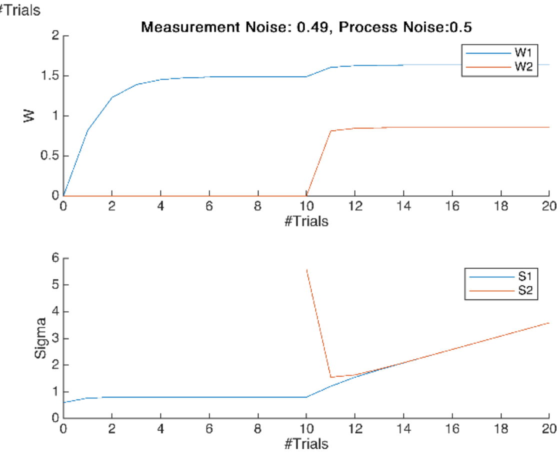
Unblocking:


Measurement Noise: 0.01, Process Noise:0.5
W1
W2
W
#Trials
S1
S2
Sigma
#Trials

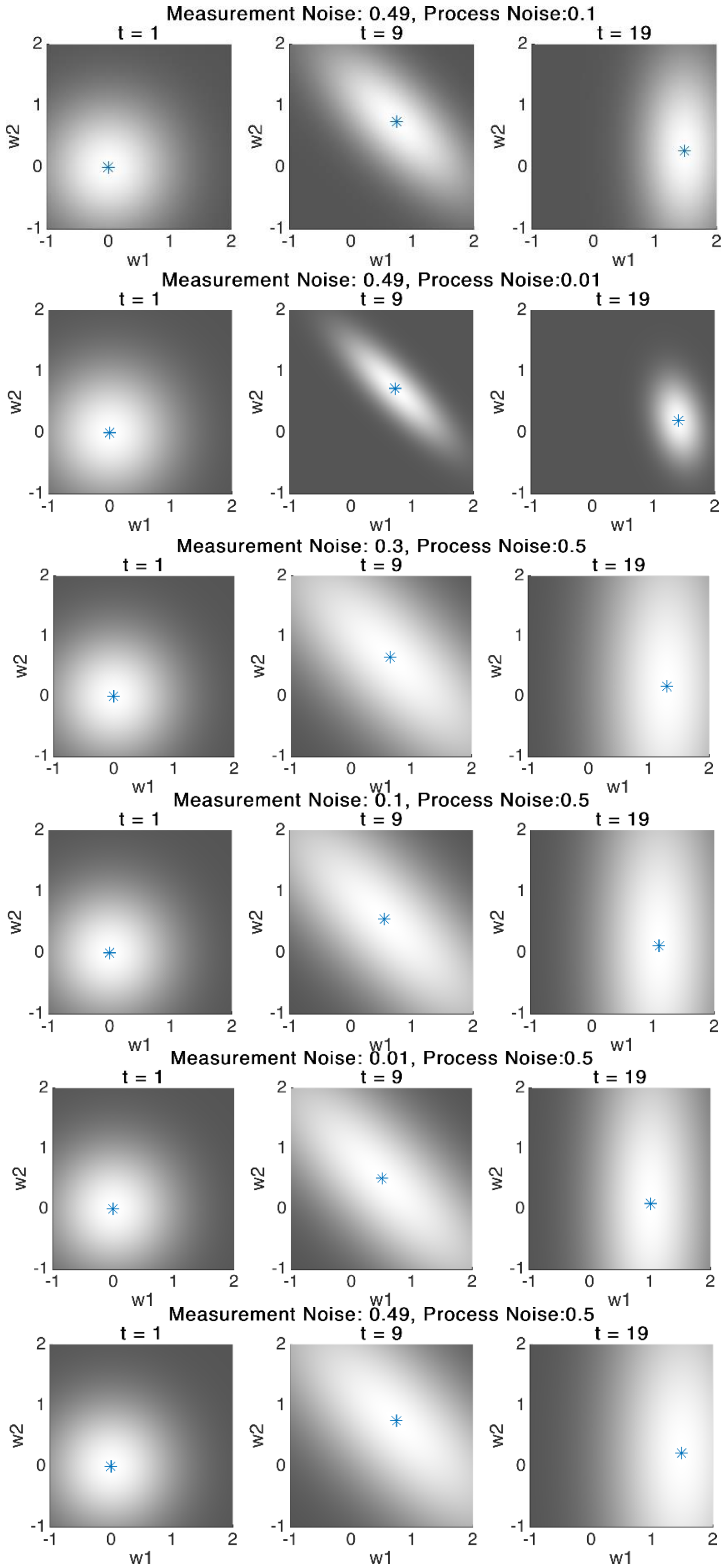

Measurement Noise: 0.1, Process Noise:0.5
W1
W2
W
#Trials
S1
S2
Sigma
#Trials


Measurement Noise: 0.49, Process Noise:0.01
W1
W2
W
#Trials
S1
S2
Sigma
#Trials


Measurement Noise: 0.49, Process Noise:0.1
W1
W2
W
#Trials
S1
S2
Sigma
#Trials


Measurement Noise: 0.49, Process Noise:0.5
W1
W2
W
#Trials
S1
S2
Sigma
#Trials

Weights distribution:



Results show that by decreasing the measurement noise, the speed of convergence increases. It seems to be inferable from the Kalman equation itself, Since the sigma get smaller as the variance of measurement noise is in the denominator.

Increasing process noise, have an increasing effect on variance of weights. It is also inferable since higher noise values in the process itself leads to higher uncertainty. This result is clearly shown in the distribution of weights.

3. We know that at steady state, covariance matrix tends to be fixed. So we have:

$$\Sigma_t \;=\; \Sigma_t^- - G_t C \Sigma_t^-$$

$$G_t C \Sigma_t^- \;=\; 0$$

   Gain equation:

$$G_t = \Sigma_t^- C^T (C \Sigma_t^- C^T + V)^{-1}$$

$$\Sigma_t^- \;=\; A \Sigma_{t-1} A^T + w$$

$$\Sigma_\infty^- \;=\; A \Sigma_\infty A^T + w$$

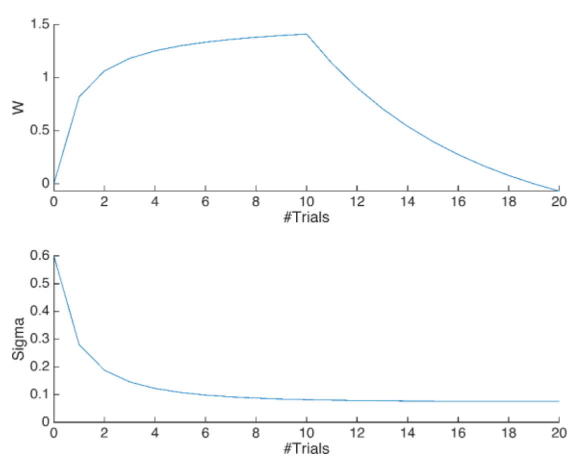
$$G_t C \Sigma_t^- = \Sigma_t^- C^T C \Sigma_t^- (C \Sigma_t^- C^T + V)^{-1} = 0$$

$$\Rightarrow \Sigma_\infty^- C^T C \Sigma_\infty^- \;=\; 0$$

$$G_t = (A\Sigma_\infty A^T + w) C^T (C(A\Sigma_\infty A^T + w) C^T + V)^{-1}$$

   Incomplete.

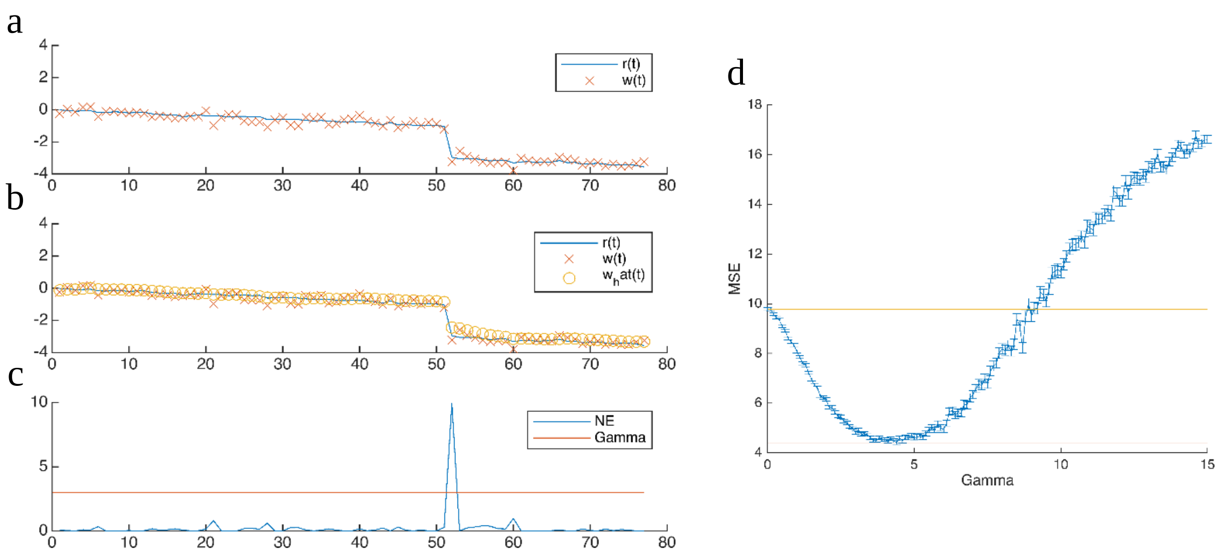
4. I think this depends on sigma matrix. First since the sigma matrix has high values, the model tries to fit to changes in the learning context no matter it is measuring error or real change. But as time passes, it tries to keep the values and consider changes more like error in measuring.
5. The result:



Learning of the second stage is far slow than the learning in the first stage. The learning rate decreases as time passes. This is because of the decreasing trend of sigma without considering the changes in environment and reward.

Part 3

1. Fig. 3 of the paper:



Result shows that the drastic shifts can be well learnt by using β(t) and the appropriate γ threshold. In panel (d), you can see that small values of γ leads to higher error since we have measurement error that makes the model fits to the noisy reward which is not good. Also high values of γ leads to higher error since as we saw in part 2 question 5, that the model can not follow the drastic changes.