**Advanced Neuroscience** **Homework #5**

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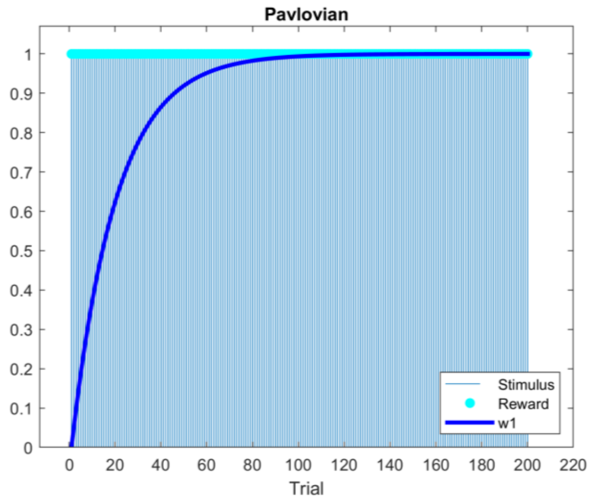
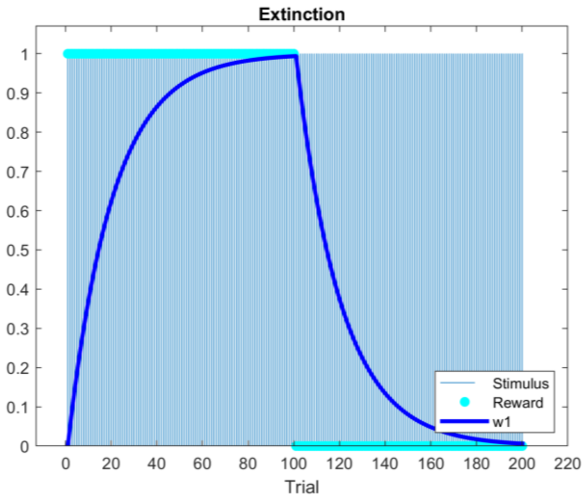
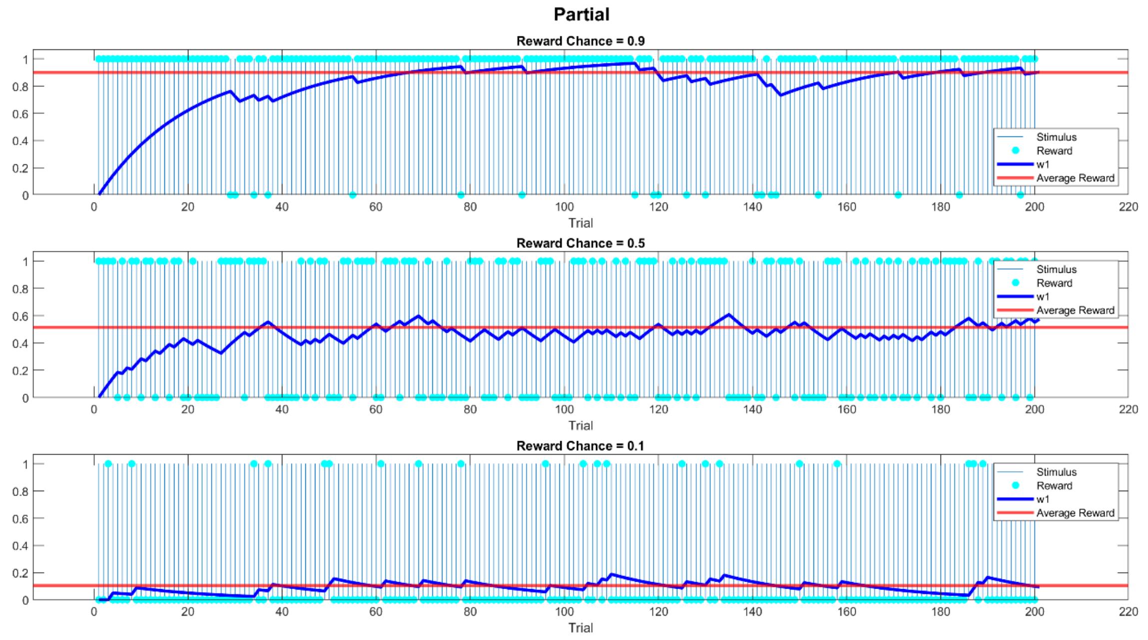
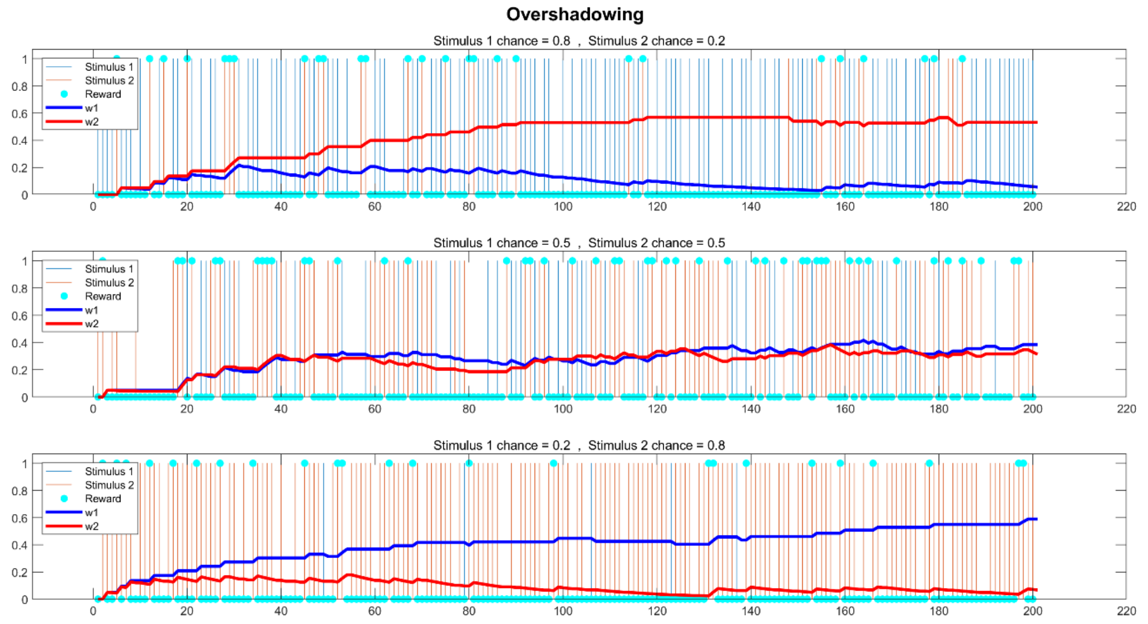
- **1-**

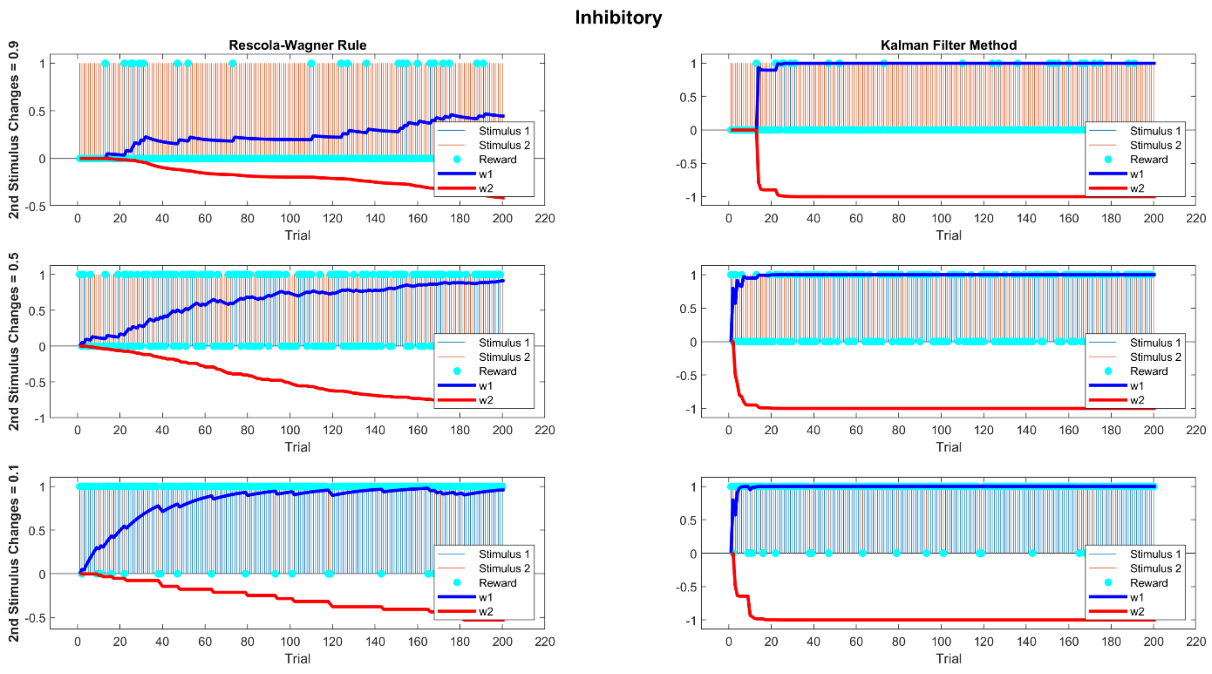
Learning Rate = 0.05

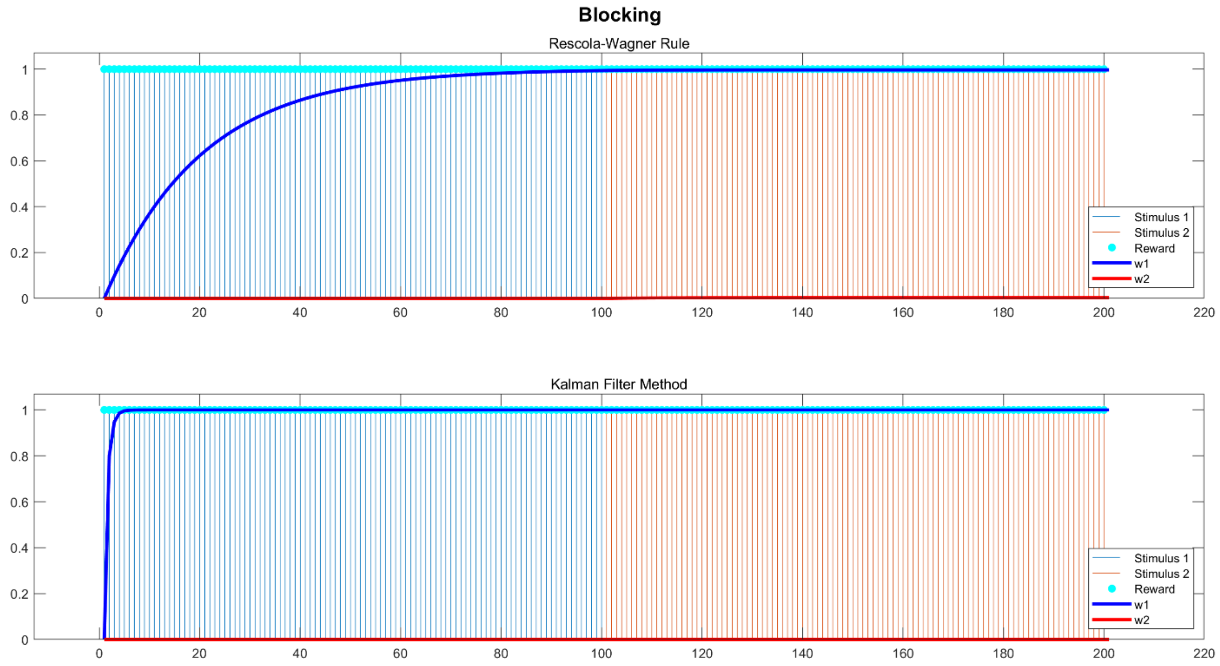




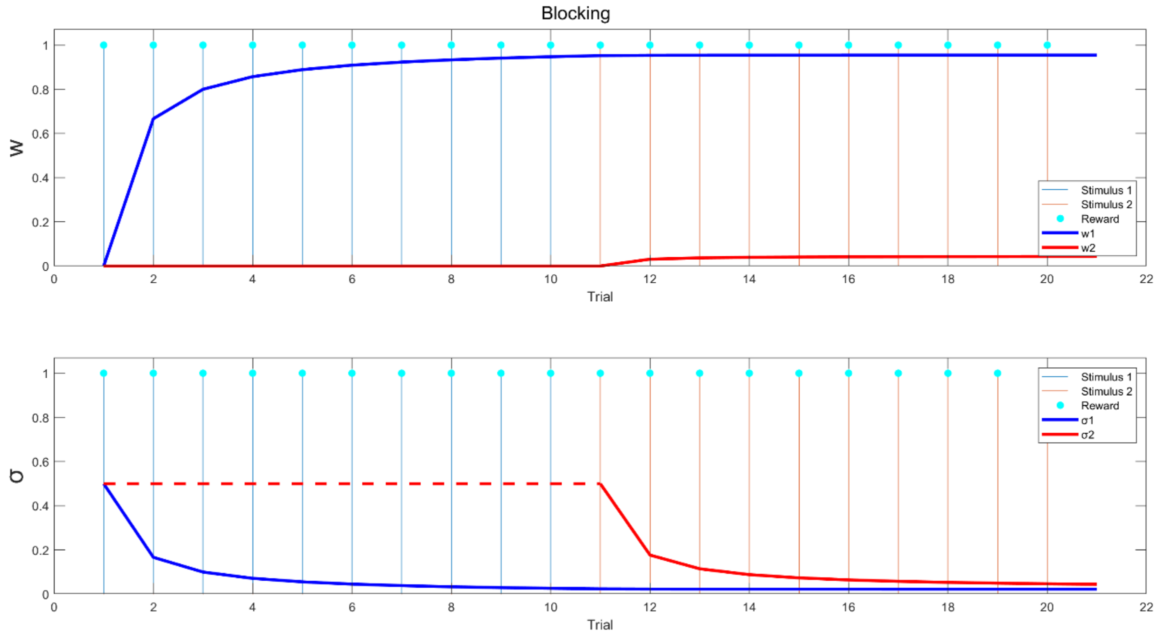

**phase to be such that learning almost saturates at the each of each phase. Which one the predictions of RW rule match the above table?**

All paradigm results modeled by the Rescola-Wagner Rule are the same as the table as we excpected.

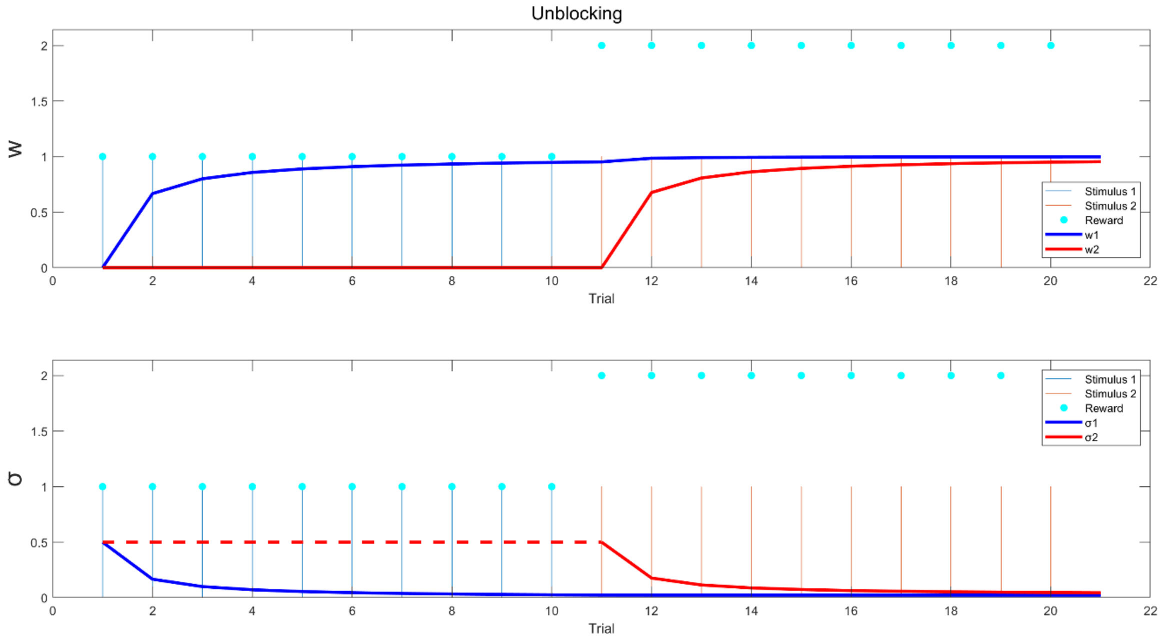
**For overshadow condition, how can one have different amount of learned value for each stimuli? The ambiguity is a form of a concept known as 'credit assignment' in reinforcement learning literature.**

The stimulus that is often active will have lower value because the 2$^{nd}$ stimulus (which is more rare) has to be present for reward to be given; so its value is more than the stimulus that exists while getting no reward.

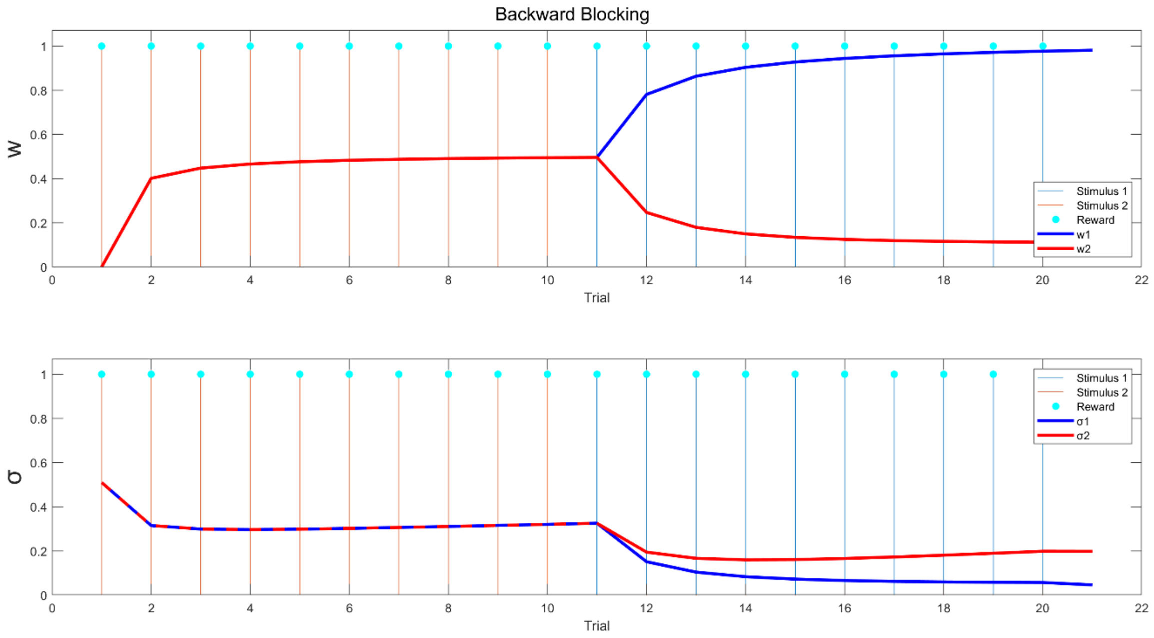
- **2-**



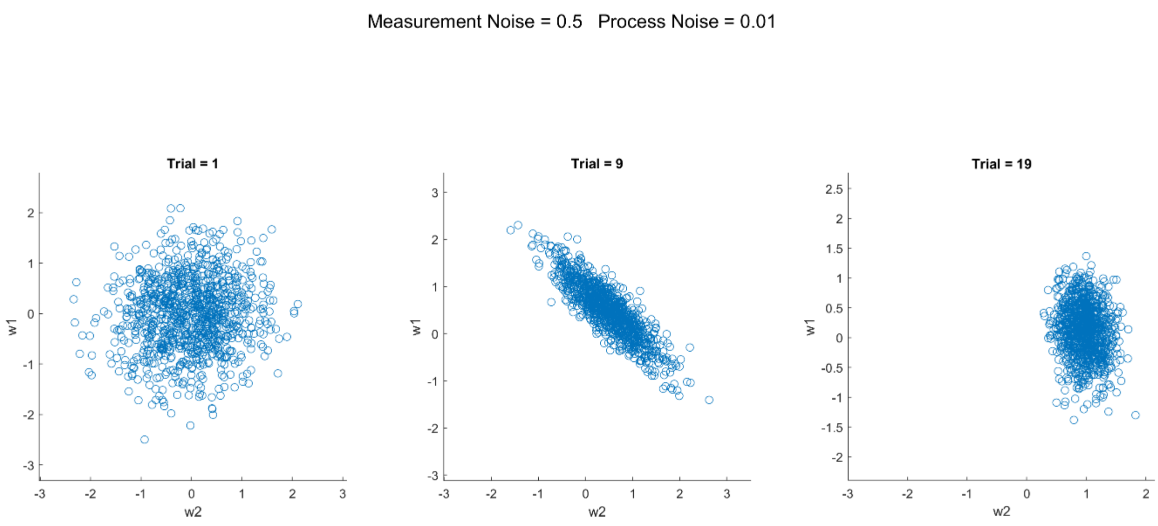
Blocking
w
Trial
Stimulus 1
Stimulus 2
Reward
w1
w2
σ
Trial
Stimulus 1
Stimulus 2
Reward
σ1
σ2

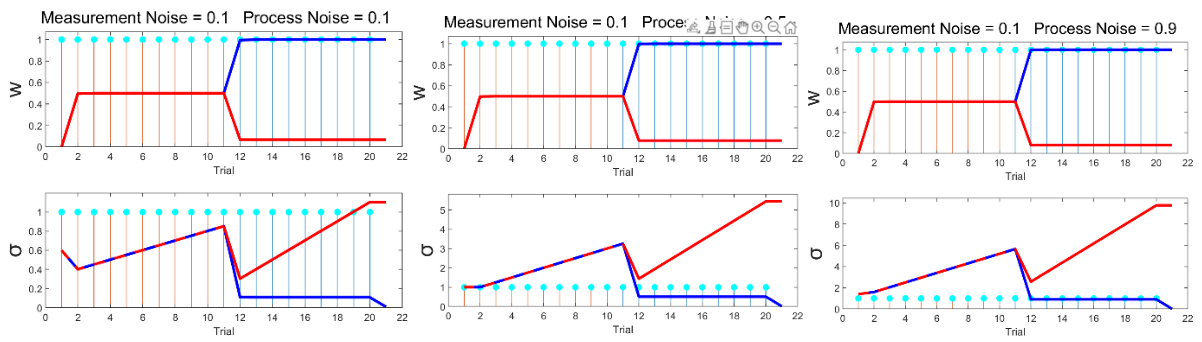
Unblocking
w
Trial
Stimulus 1
Stimulus 2
Reward
w1
w2
σ
Trial
Stimulus 1
Stimulus 2
Reward
σ1
σ2

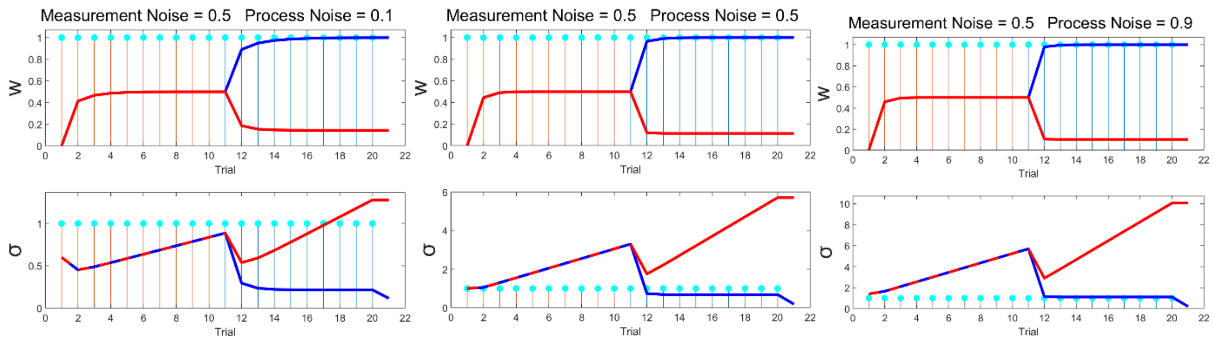



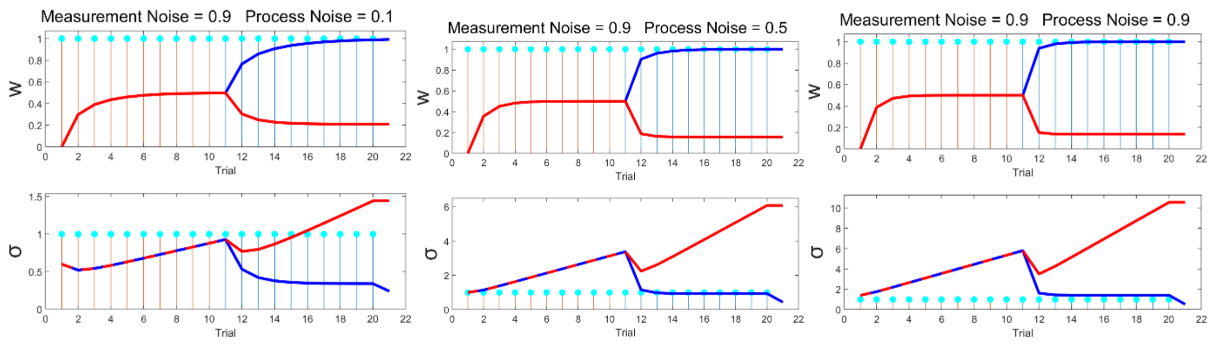
Backward Blocking
w
Trial
Stimulus 1
Stimulus 2
Reward
w1
w2
σ
Trial
Stimulus 1
Stimulus 2
Reward
σ1
σ2


Measurement Noise = 0.5   Process Noise = 0.01
Trial = 1
Trial = 9
Trial = 19
w1
w2

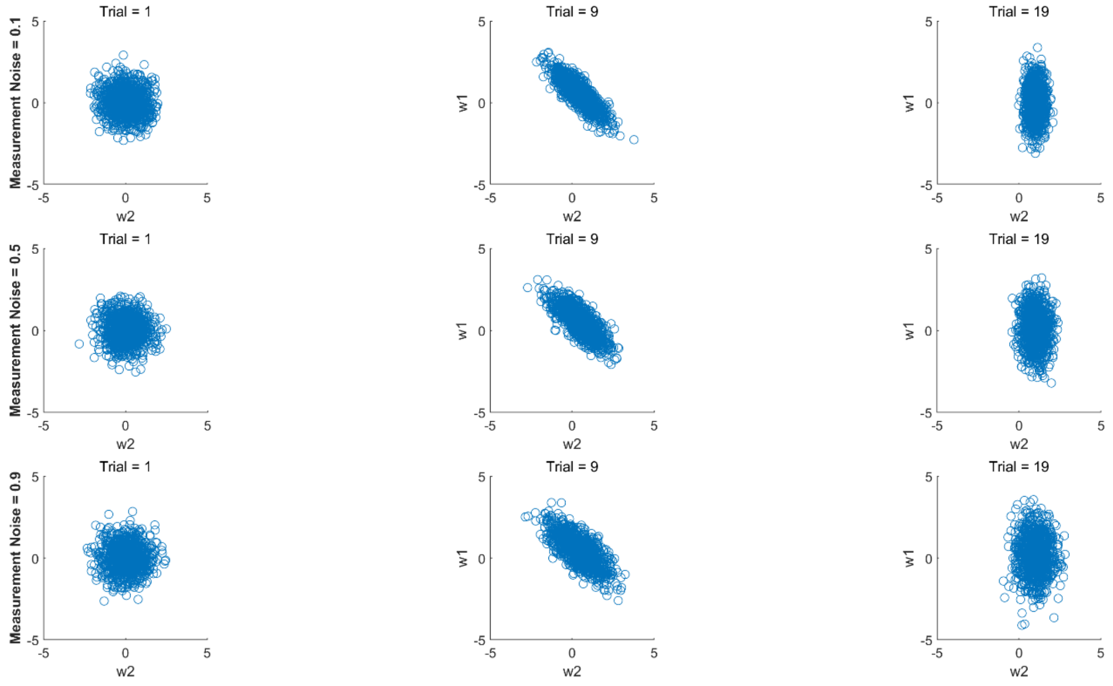
- **2-2-**


Measurement Noise = 0.1   Process Noise = 0.1
Measurement Noise = 0.1   Proce
Measurement Noise = 0.1   Process Noise = 0.9
W
σ
Trial

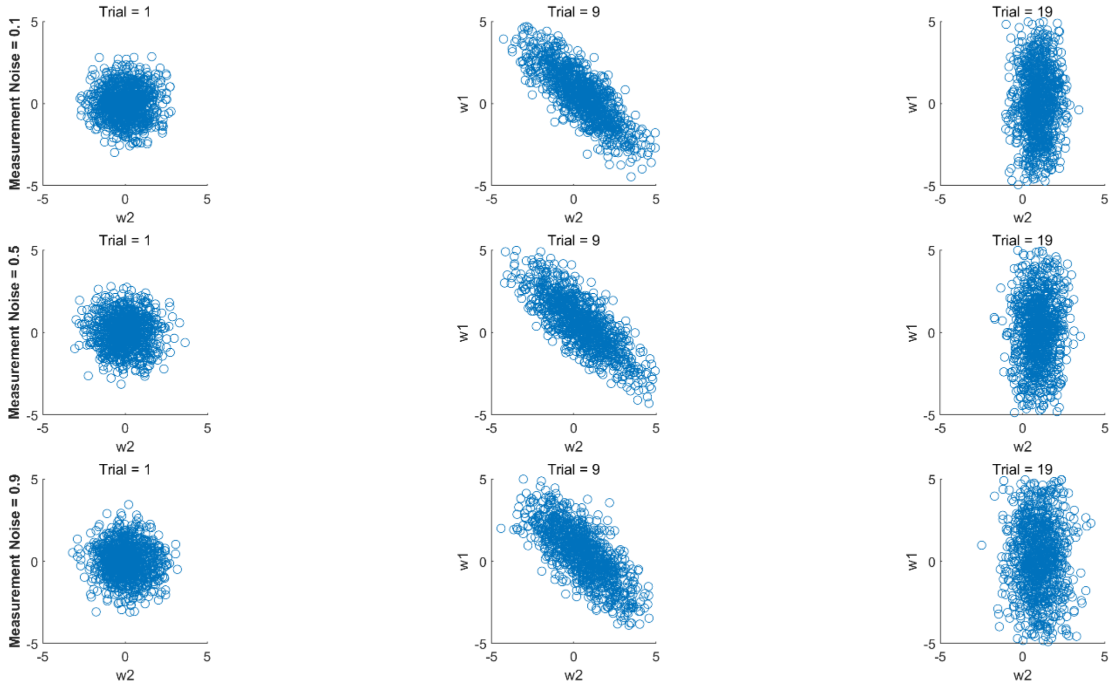

Measurement Noise = 0.5   Process Noise = 0.1
Measurement Noise = 0.5   Process Noise = 0.5
Measurement Noise = 0.5   Process Noise = 0.9
W
σ
Trial


Measurement Noise = 0.9   Process Noise = 0.1
Measurement Noise = 0.9   Process Noise = 0.5
Measurement Noise = 0.9   Process Noise = 0.9
W
σ
Trial

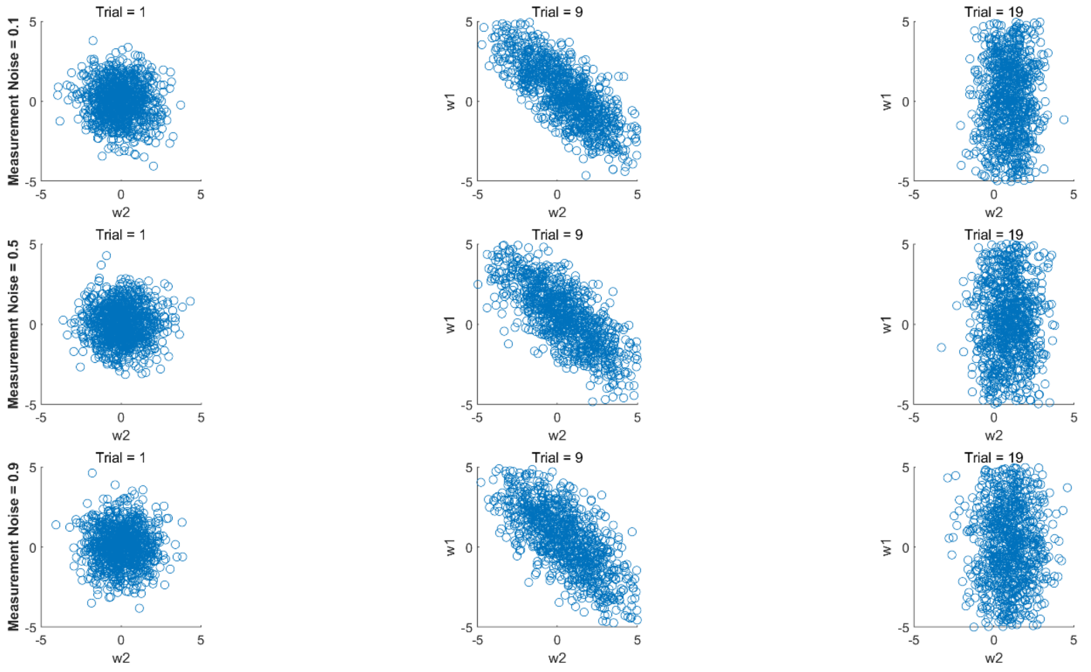
**Process Noise = 0.1**




**Process Noise = 0.5**




**Process Noise = 0.9**



- **2-3-**

  **What factors determine the value of Kalman gain at steady state? Can you derive an approximate relationship between steady state Kalman gain and the model parameters?**

$$G = \frac{\sum_{t|t-1} \; C^{\top}}{C\varepsilon_{t|t-1}C^{\top} + V}$$

$$G_{\infty} = \frac{\varepsilon_{\infty}C^{\top}}{C\varepsilon_{\infty}C^{\top} + V}$$

$$\varepsilon_{(t+1)} = A\varepsilon_{(t)A^{\top}+W}$$

$$\varepsilon_{\infty} = A\varepsilon_{\infty}A^{\top} + W$$

$$G_{\infty} = \frac{(A\varepsilon_{\infty}A^{\top} + W)C^{\top}}{C(A\varepsilon_{\infty}A^{\top} + W)C^{\top} + V}$$

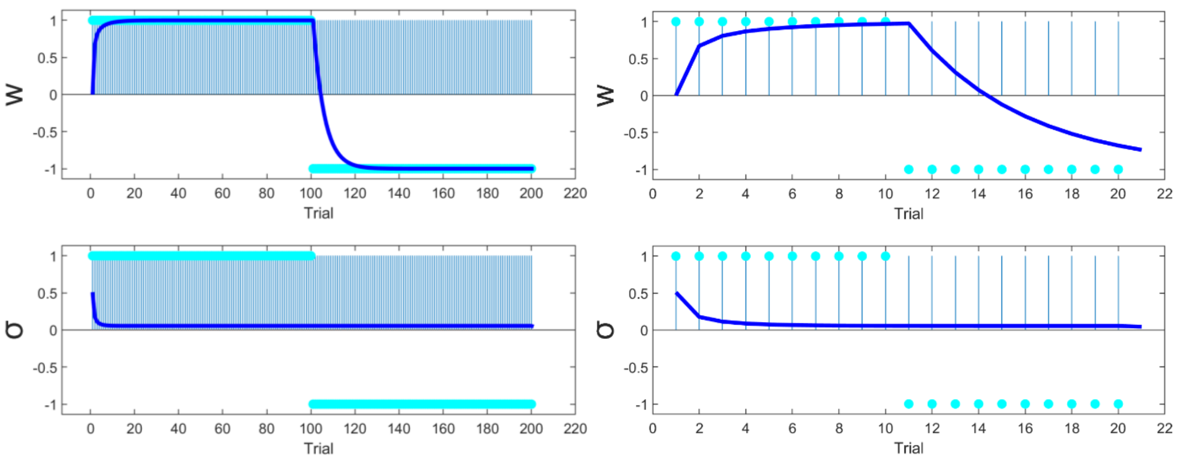
Steady state gain is dependent on covariance matrix and measurement noise.

- **2-4-**

**Does the change in uncertainty depend on the errors made in each trial or changes in the learning context?**

No, uncertainty (covariance) dosnt depend on error; it depends on the input stimulus and measurement noise.

- **2-5-**




Pre-train: S → R

Train: S → -R

Result: S → -R

- **3-**