In The Name of God

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Advanced Neuroscience HW5

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Part 1.1) Using RW rule, the outcome of the paradigms: extinction, partial, blocking, inhibitory and overshadow are plotted. A fixed learning rate of 0.1 and number trials of 500 is assumed.

Pavlovian: For this paradigm, a single variable is assumed and, in each trial, (r = 1 and learning rate = 0.1).

Extinction: For this paradigm, the weights' measured for the Pavlovian is used to stimulate the training phase (r = 0 and learning rate = 0.1).

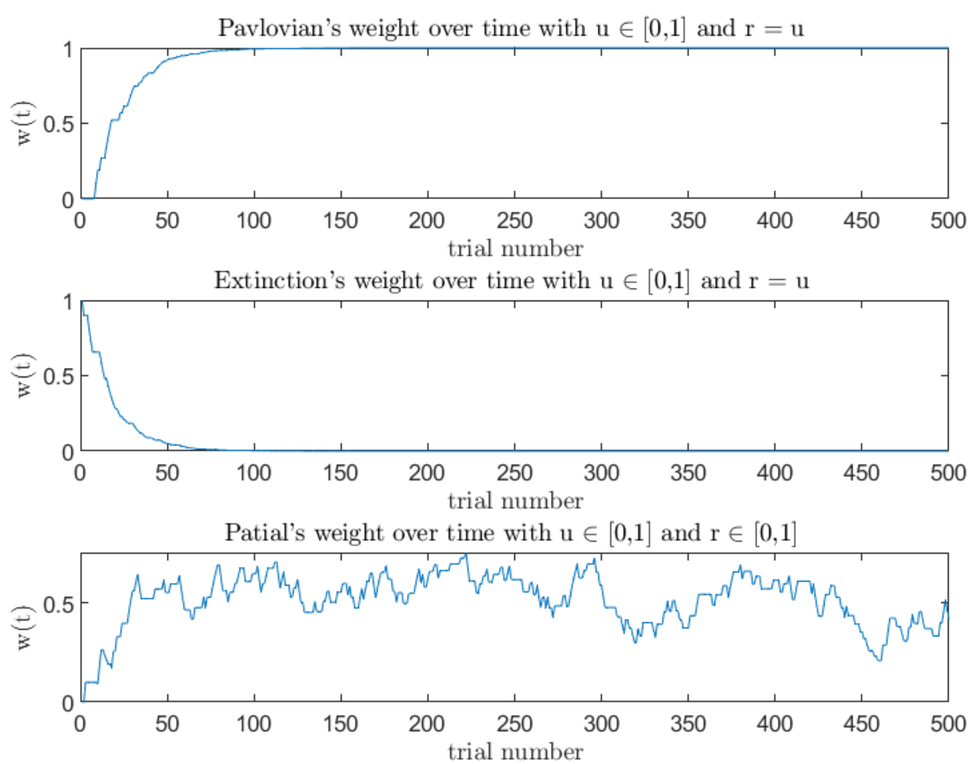
Partial: For this paradigm, the stimuli are associated randomly between r = [0,1], we expect to see $wu = \alpha r$ that α is the expected value of r (here r is uniformly set, so $\alpha = 0.5$).

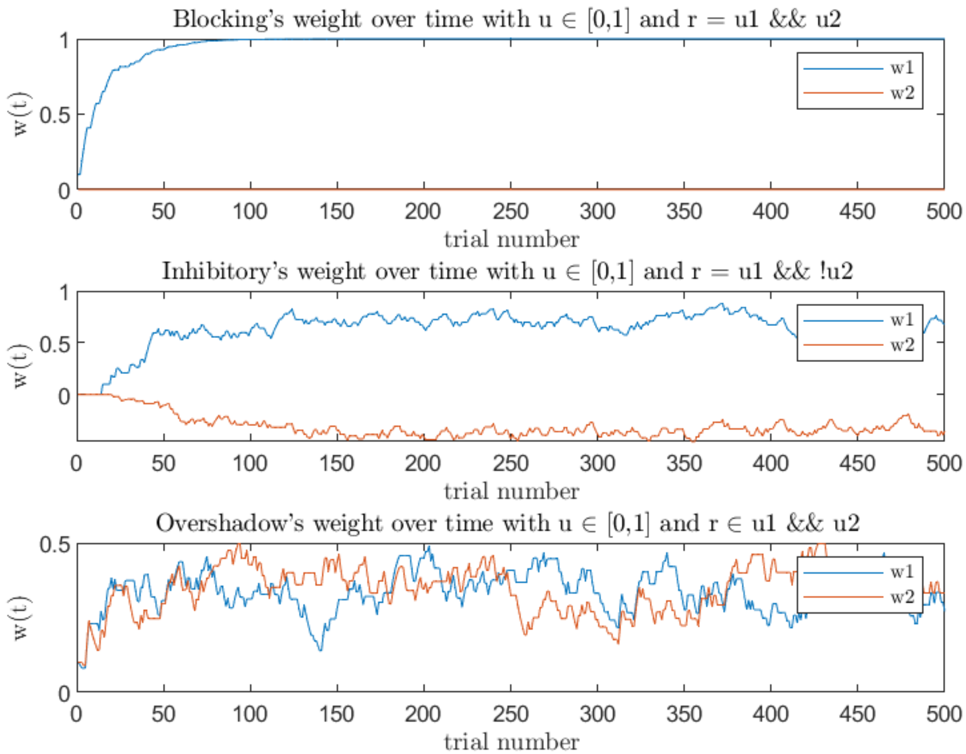
Blocking: For this paradigm, two-variable vector *w* is used due to number of conditions. First *w* is pre-trained with one of the conditions u_1 associated with r = 1 in 250 trials and then, u_1 trained and associated with r = 1 in case both stimuli existed for the next 250 trials.

Inhibitory: For this paradigm, two variable *w* is used again and with no pretrain for 500 trials, considering r = 1 when $u_1 = 1$ & $u_2 = 0$.

Overshadow: For this paradigm, *w* is trained considering r =1 only when u_1 and u_2 both existed.

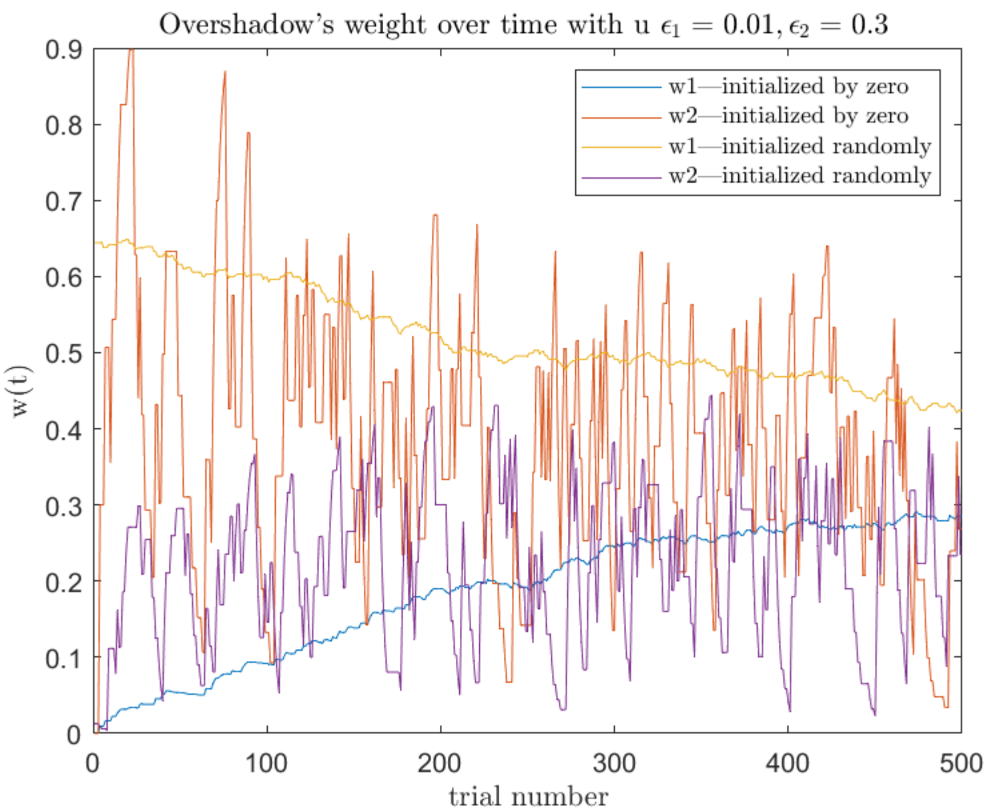
Here are the resulted plots for each simulation weights during the learning progress:





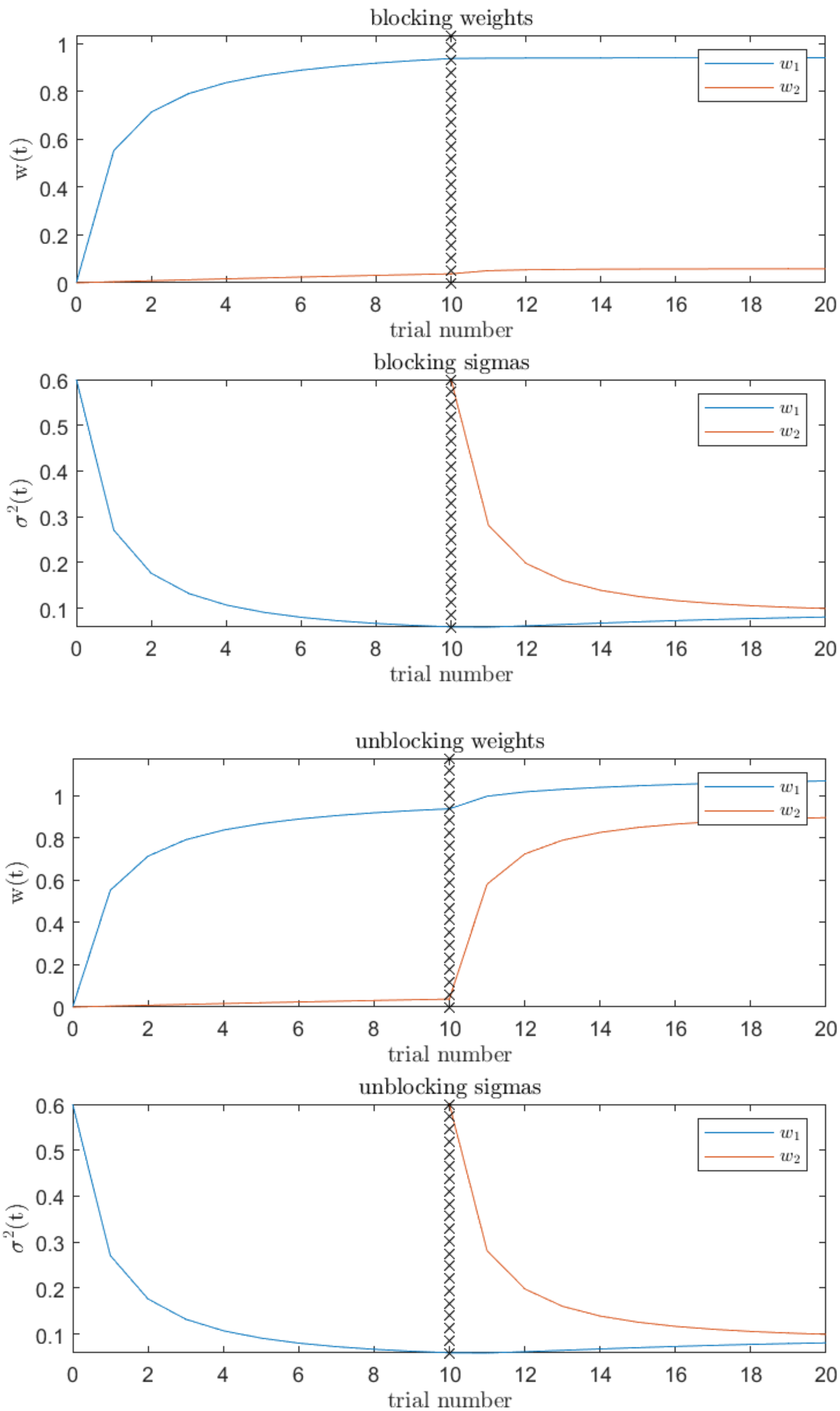
As we can see all scenarios are correct under our assumptions.

Part 1.2) On possible parameter that causes difference in training, is to set different initial values. Another parameter that is more important is that the learning rate parameter used for updating each stimuli's weights can be different and this causes a stimulus to be learned or traced better than another through time. In the figure below we can see the effects of these two parameters on learned weights through time:

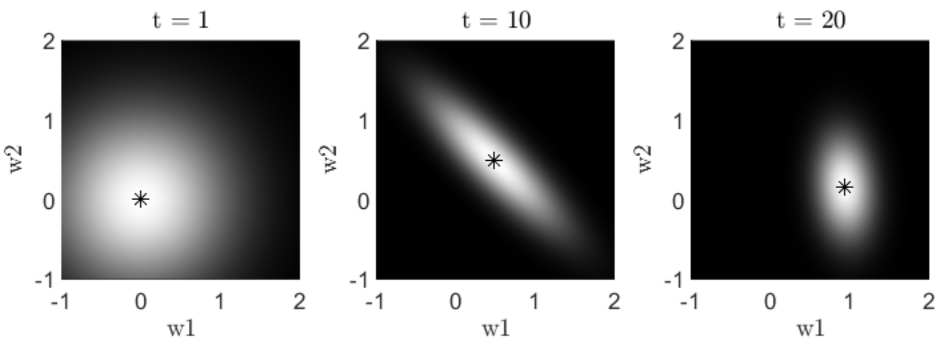


As we can see the algorithm gives more weight to the stimulus with higher learning rate during a fixed time.

Part 2.1) The first figure of the paper is simulated using self-implemented Kalman Filter, and her is the resulted plot for blocking and unblocking paradigms:

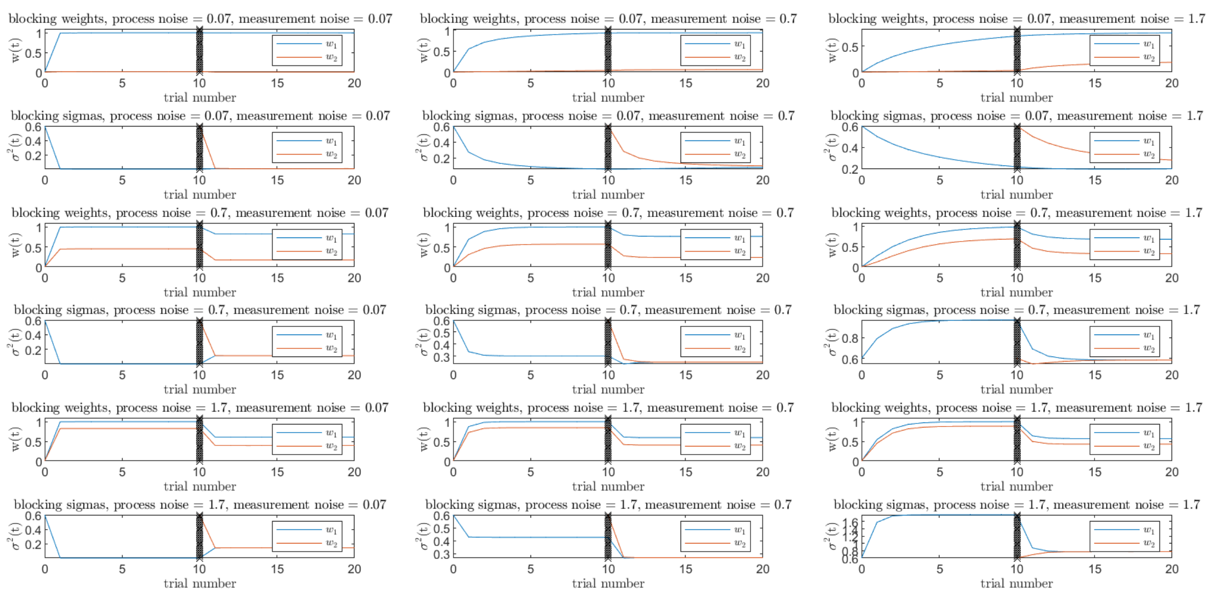


The second figure of the paper is also simulated and here are the results of the joint probability of the weights contours at different time stages for a backward blocking paradigm:

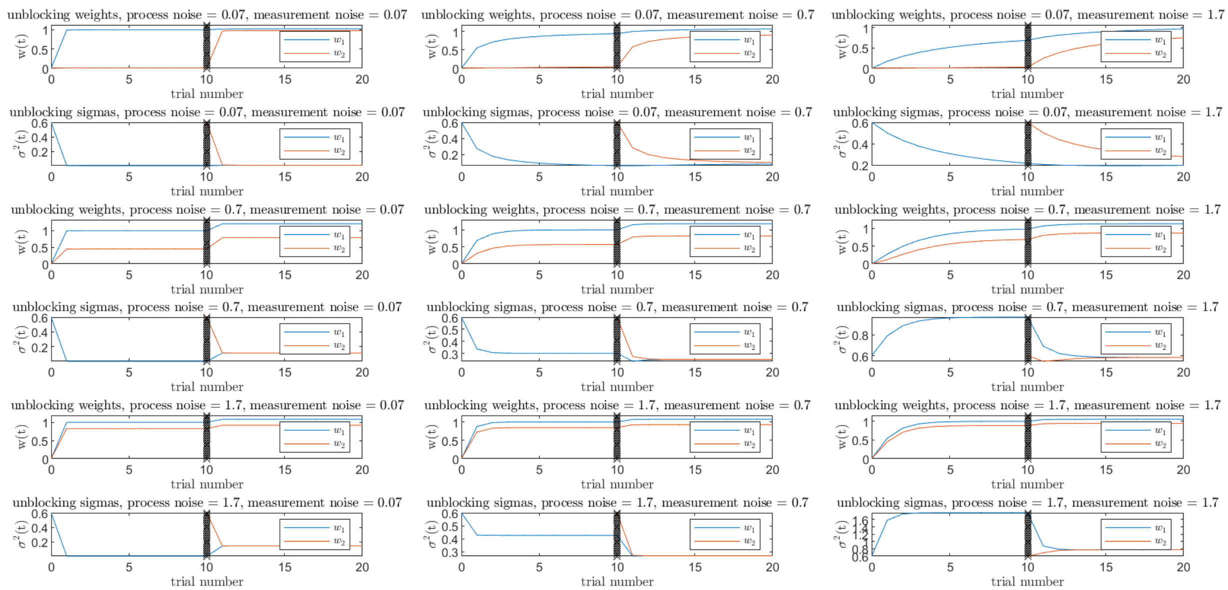


Part 2.2) In order to see the effects of process noise and measurement noise, three different amounts of process noise and also three different amounts of measurement noise are considered, and all 9 conditions is simulated and plotted:

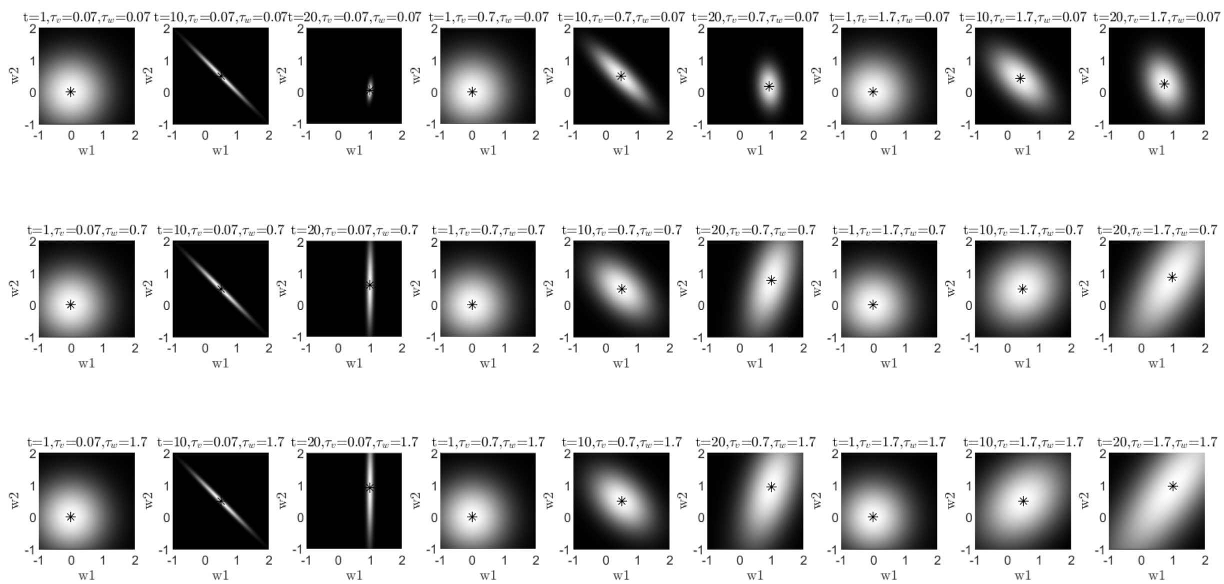
Blocking:



Unblocking:

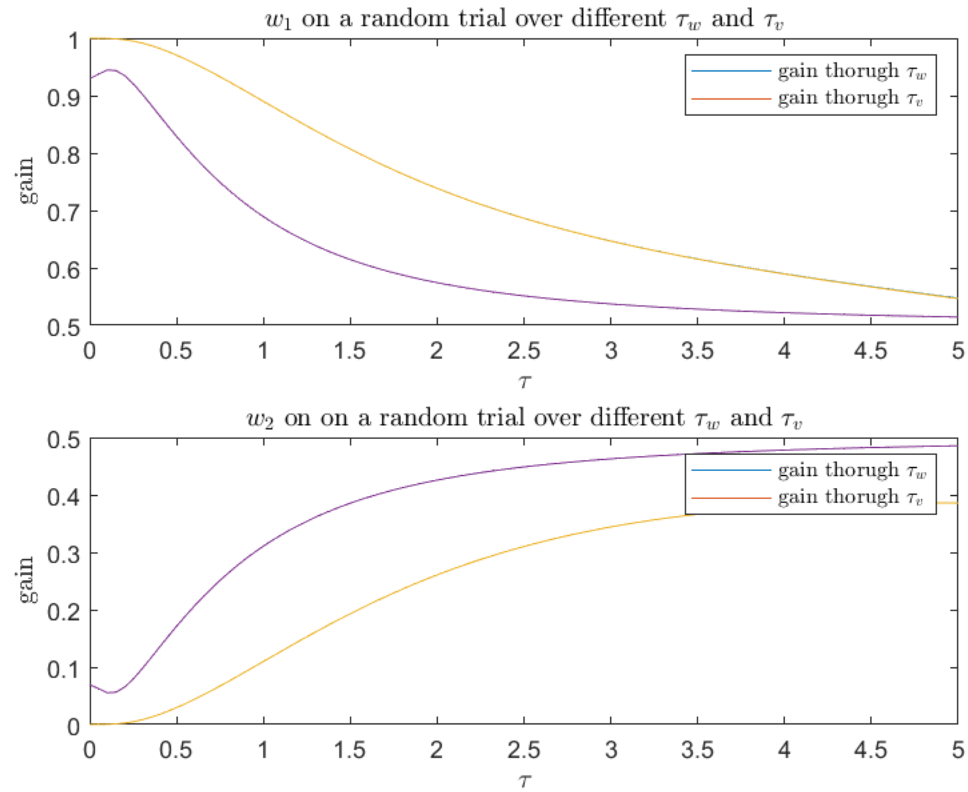


Backward Blocking:



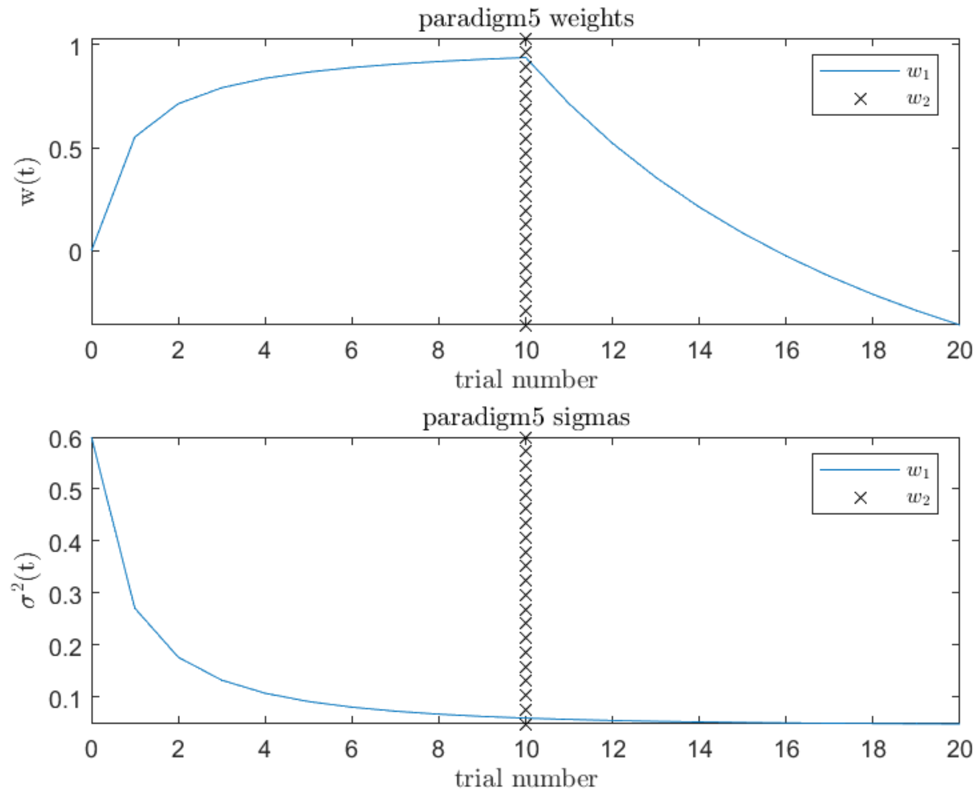
As it can be seen in the figures, when the process noise increases the uncertainty also increases which leads to a higher steady state variance. Also, we can see that when measurement noise increases leads the learning algorithm to converge later.

Part 2.3) For observing this effect the weight of a random last trial is plotted through different amounts of process and measurement noises, we can see the relation in the figure below:



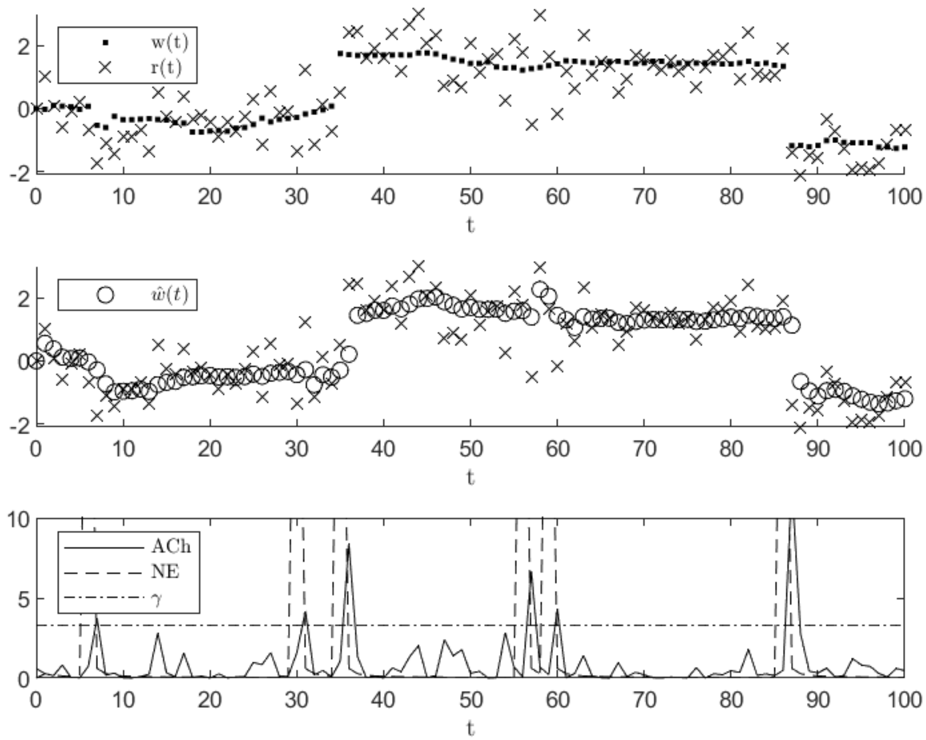
Part 2.4) From the figures in the previous parts and these figures, we can see that uncertainty (for plausible noise rates) almost converges to a limited domain. This means that somehow it does not depend on context.

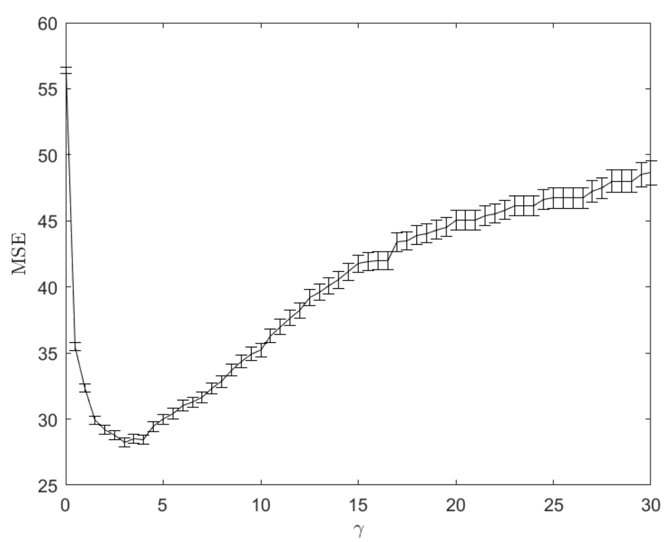
Part 2.5) The desired paradigm is simulated and here are the weights and variances through time:



As we can see the learning process is done more quickly in the first phase rather than the second. This is to the fact that as the algorithm goes further through trials, the variance parameter which is the sample of uncertainty decreases without considering that the observed output (reward) has rapid extensive changes or not. There for in the next phase the weights change too slow.

Part 3.1) Below are the results of the third figure of the paper (a single stimulus used, the noise probability is assumed 0.05 and the noise variance is set to 20 which is bigger enough comparing to τ_v *and* τ_w):





As we can see the unexpected dramatic changes in r(t) can be well learnt using β(t). When γ is too large or too small, performance is as bad as, or worse than, if w(t) is directly estimated from r(t) without taking previous observation into account.