Sharif University Of Technology

Advanced Topics in Neuroscience

Simulation 07 (Evidence Accumulation)

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Contents

Section 1: Evidence Accumulation Model

1.1 Question 1

'simple-model' function simulate a discrete version of diffusion drift model (DDM) for evidence accumulation:

$$dX = Bdt + \sigma dW$$

dX is decision variable during the time step t. This function get bias term, sigma, dt and time interval as the inputs and gives the choice as the output.

1.2 Question 2

In this part, I run previous function with this input: 3000 choice experiments, each 1 second long, with $B = 1$ per second, $\sigma = 1$, $dt = 0.1 second$. Figure 1 show the final decision value has a normal distribution. Bias is significant and all of choices are one!

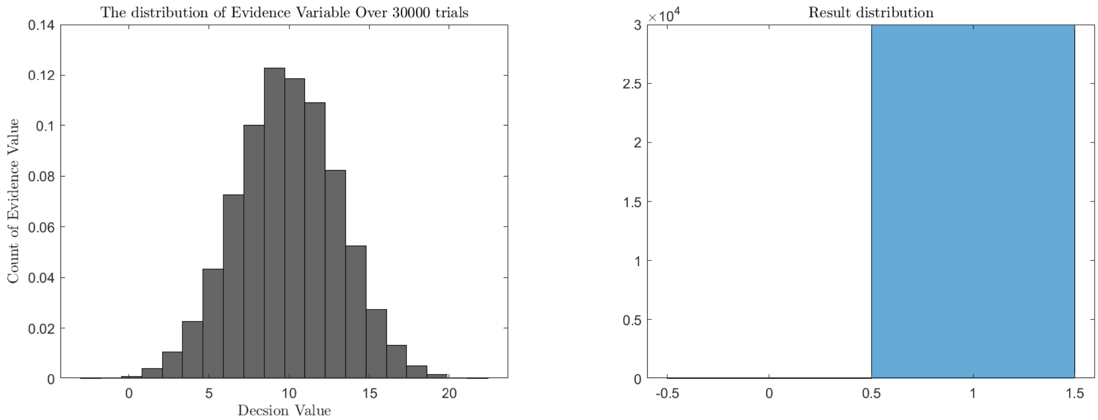

Figure 1: Decision value distribution

Also, in figure 2 you can see the effect of bias on decision variable over time. Evidence value increase faster as the bias value increase.

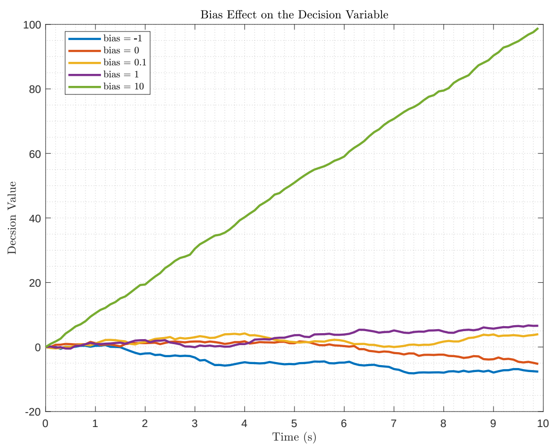

Figure 2: Decision value distribution

I also change Brownian motion term form 0.001 to 2 by step 0.05. There is no significant difference in evidence value over time.

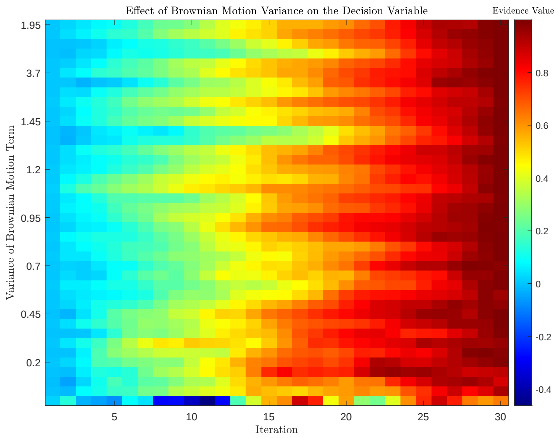

Figure 3: Decision value distribution for different motion term

1.3 Question 3

In this part, I want to see effect of time interval on error rate. As we expect, decision error decrease if we have enough time to make it. Figure 4 show error rate and time interval have a reciprocal relationship.

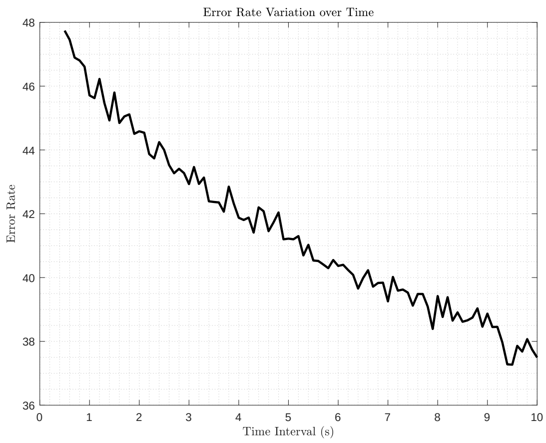

Figure 4: Error Rate changes with time

1.4 Question 4

The expected value and variance of decision variable:

$$
\begin{gathered}
dX = Bdt + \sigma dW \\
\frac{dX}{dt} = B + \sigma \frac{dW}{dt} \\
X = Bt + \sigma W + C \\
E(X) = Bt + \sigma E(W) = Bt \\
\rightarrow E(X) = Bt \\
E(X^2) = E(B^2t^2 + \sigma^2 w^2 + 2B\sigma Wt) \\
= B^2t^2 + \sigma E(W^2) + 0 \\
Var(X) = E(X^2) - E(X)^2 \\
= B^2t^2 + \sigma^2 E(W^2) - B^2t^2 \\
Var(W) = dt = E(W^2) - E(W)^2 \qquad \rightarrow \qquad E(W^2) = dt \\
Var(X) = \sigma^2 dt
\end{gathered}
$$

So I expect to see the mean of decision values varies linearly and the square of variance change over time.

I run the model 10000 trials over 10 seconds with parameters $B = 0.1$ per second, $\sigma = 1$, $dt = 0.1$. In figure , you could see the trajectories, mean trajectory, and one standard deviation above and below the mean.

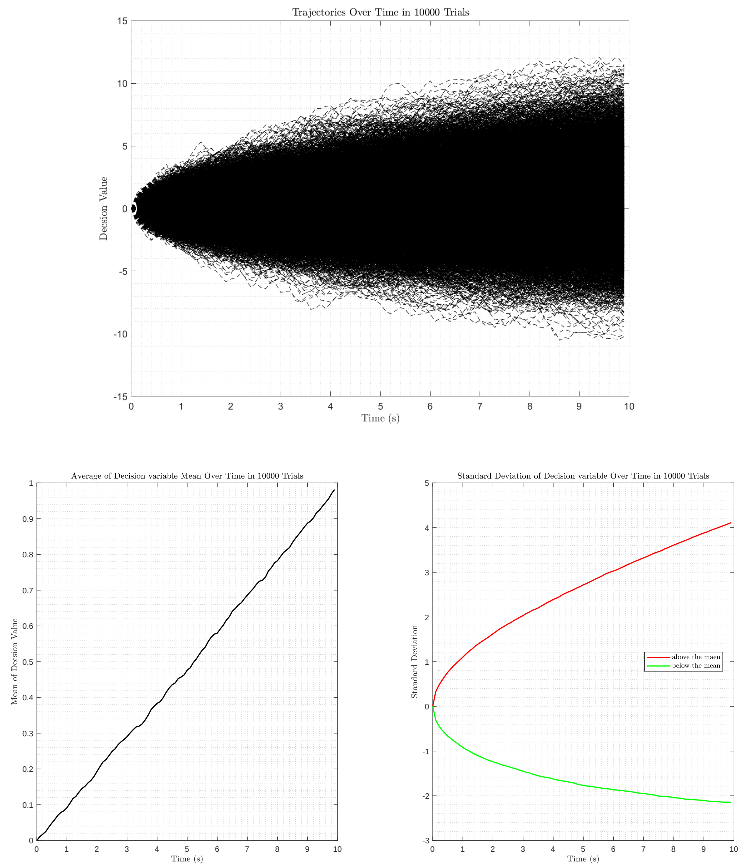

Figure 5: Error Rate changes with time

1.5 Question 5

In previous part, we see the mean and variance of decision variables. In this part, we generate this distribution and consider starting point probability. Then generate random number from uniform distribution. If this number is higher than starting point probability, choice is one and vice versa.

If we choose the start point below the mean of normal distribution, most of the choice is one and vice versa. If we choose it equal the mean, the probability of choice one and zero is equal.

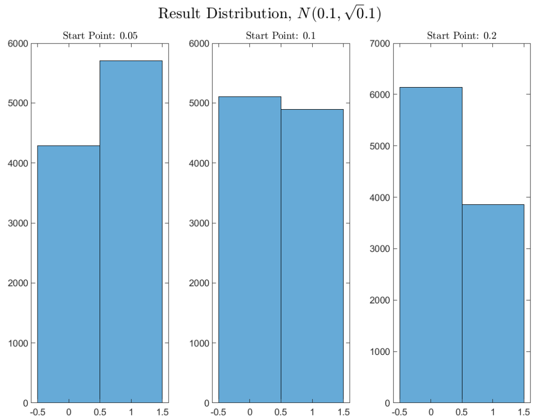

Figure 6: Start point effect on the result distribution

1.6 Question 6

In this part, we have no limitation time. The decision value accumulate until it reach the decision bound. The time at the threshold crossing is the reaction time (RT). We want to compare the reaction time of the correct and incorrect response. I run this function with different condition:

1.6.1 Positive Threshold: 4, Negative Threshold: -4

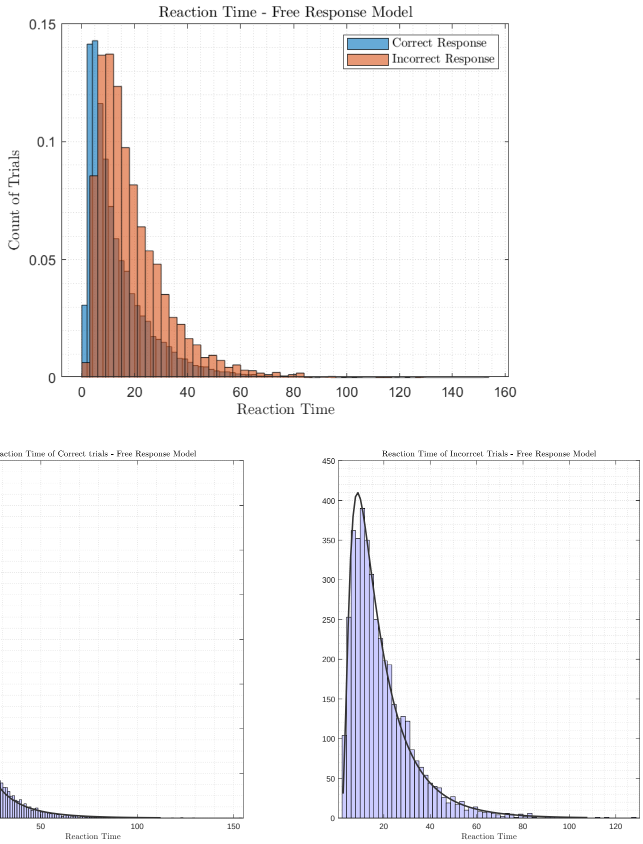

Figure 7: Start point effect on the result distribution

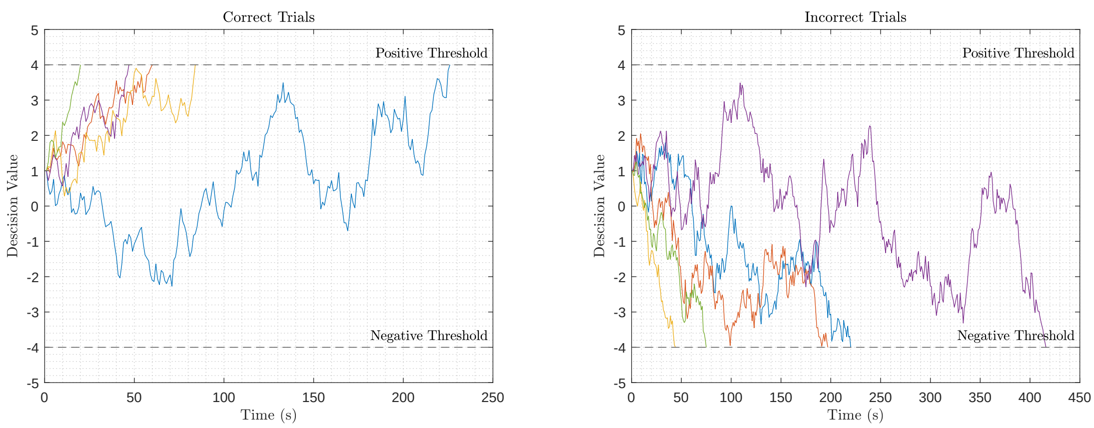

Figure 8: Start point effect on the result distribution

It seems the reaction time of correct answer is lower than incorrect.

1.6.2 Positive Threshold: 4, Negative Threshold: -10

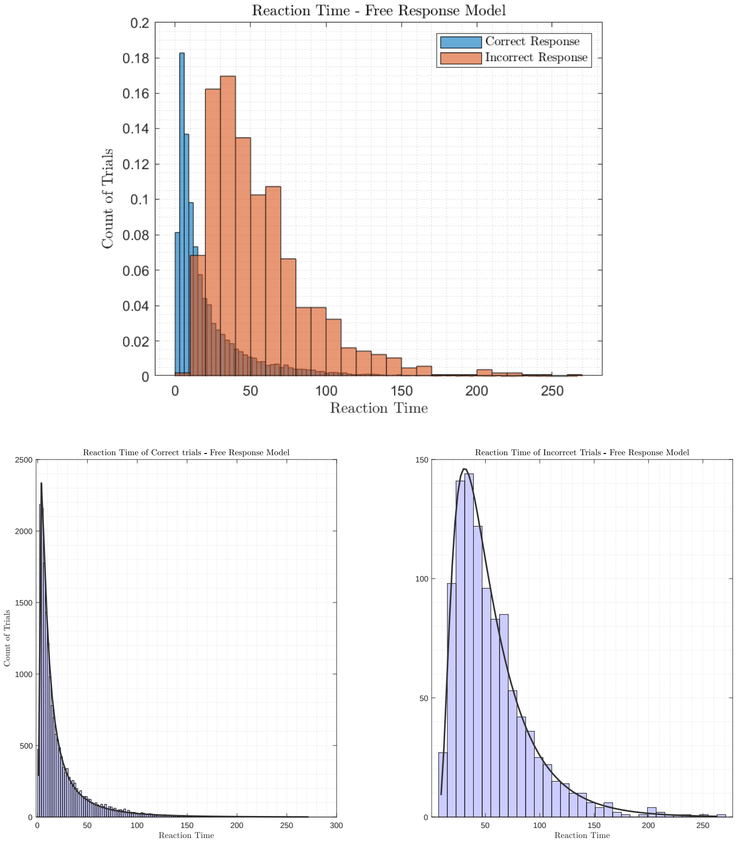

Figure 9: Start point effect on the result distribution

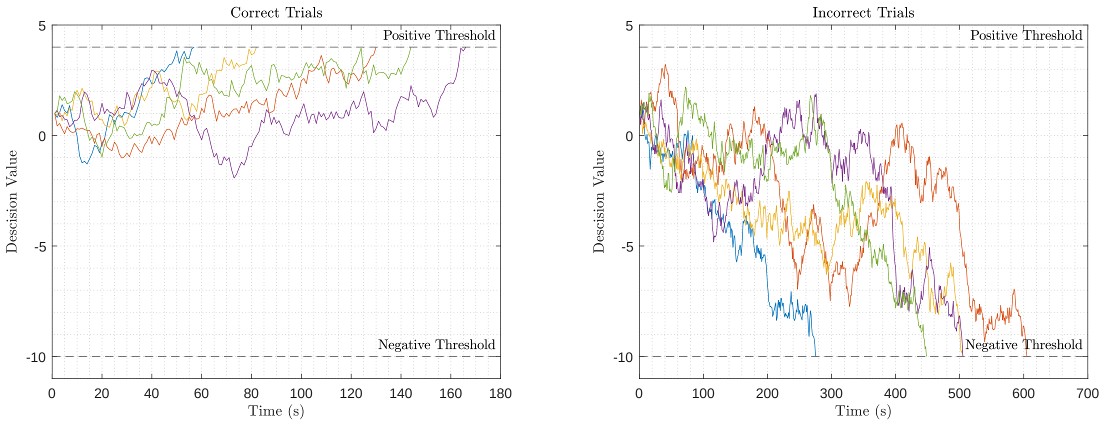

Figure 10: Start point effect on the result distribution

In this case, more trial could reach the positive threshold, as it is lower than negative. Again, positive answers have lower RT.

1.6.3 Positive Threshold: 10, Negative Threshold: -4

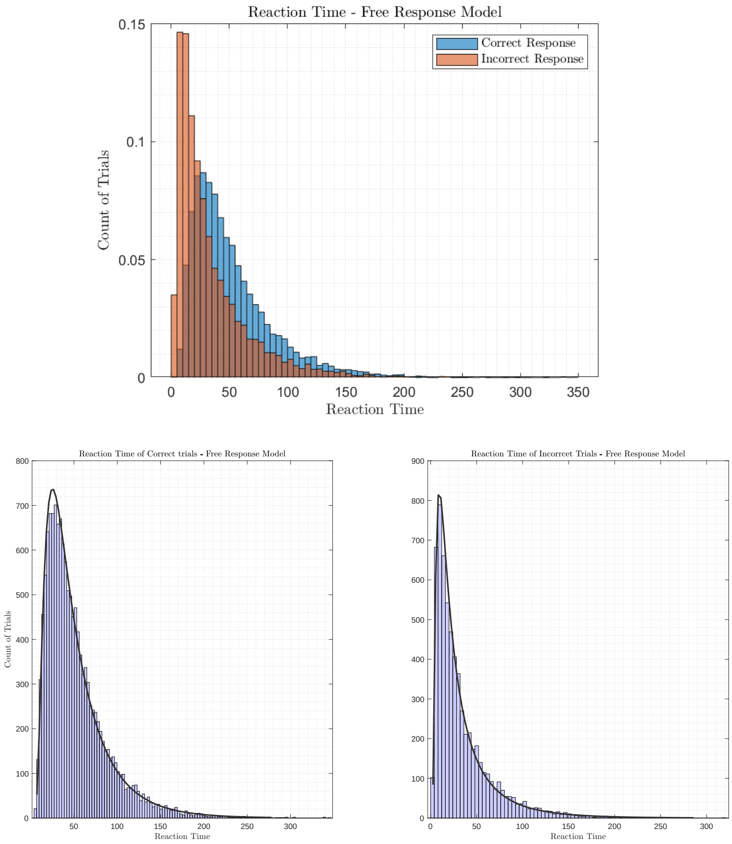

Figure 11: Start point effect on the result distribution

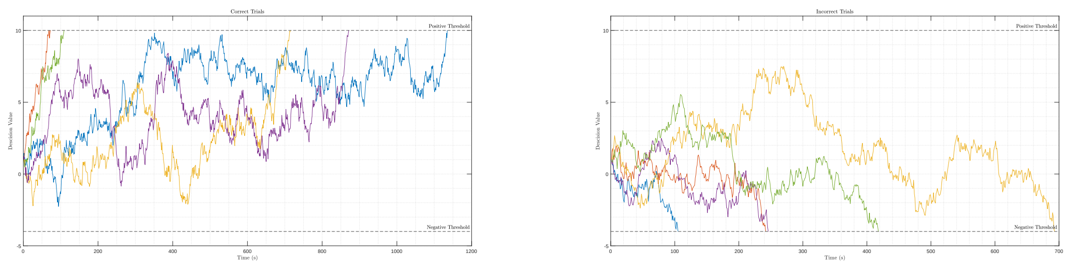

Figure 12: Start point effect on the result distribution

In this condition, RT of incorrect answer is lower, because the boundary decision is lower and less evidence is needed.

1.6.4 Changeable Bias

I also run this model with different bias for negative or positive choice. In other word, bias change every time base on the previous choice. In figure 13, negative choices have more bias than positive. In figure 14, positive choices have more bias.

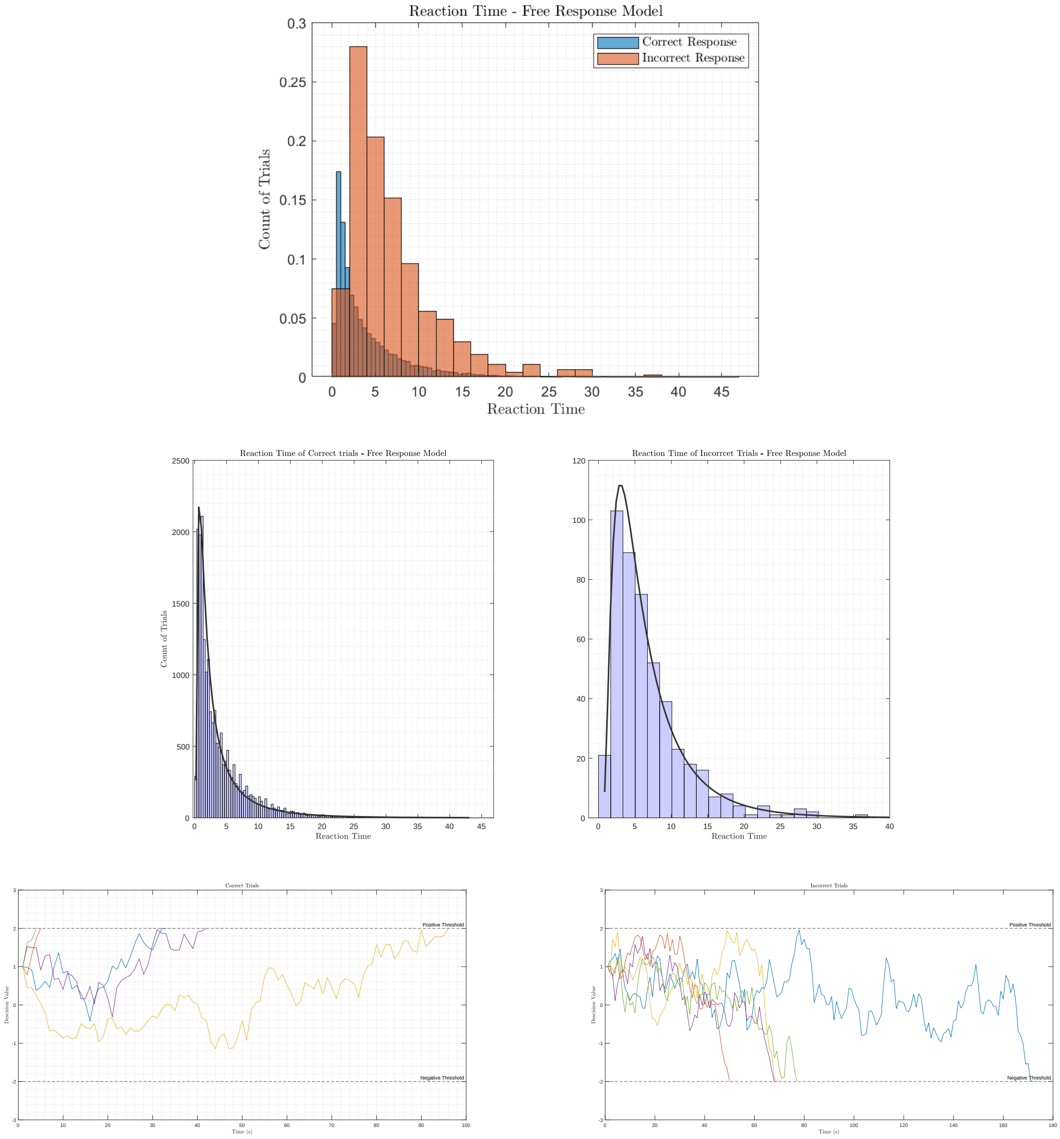

Figure 13: Effect of inconstant bias. Positive bias: 0.1, negative bias: -1.

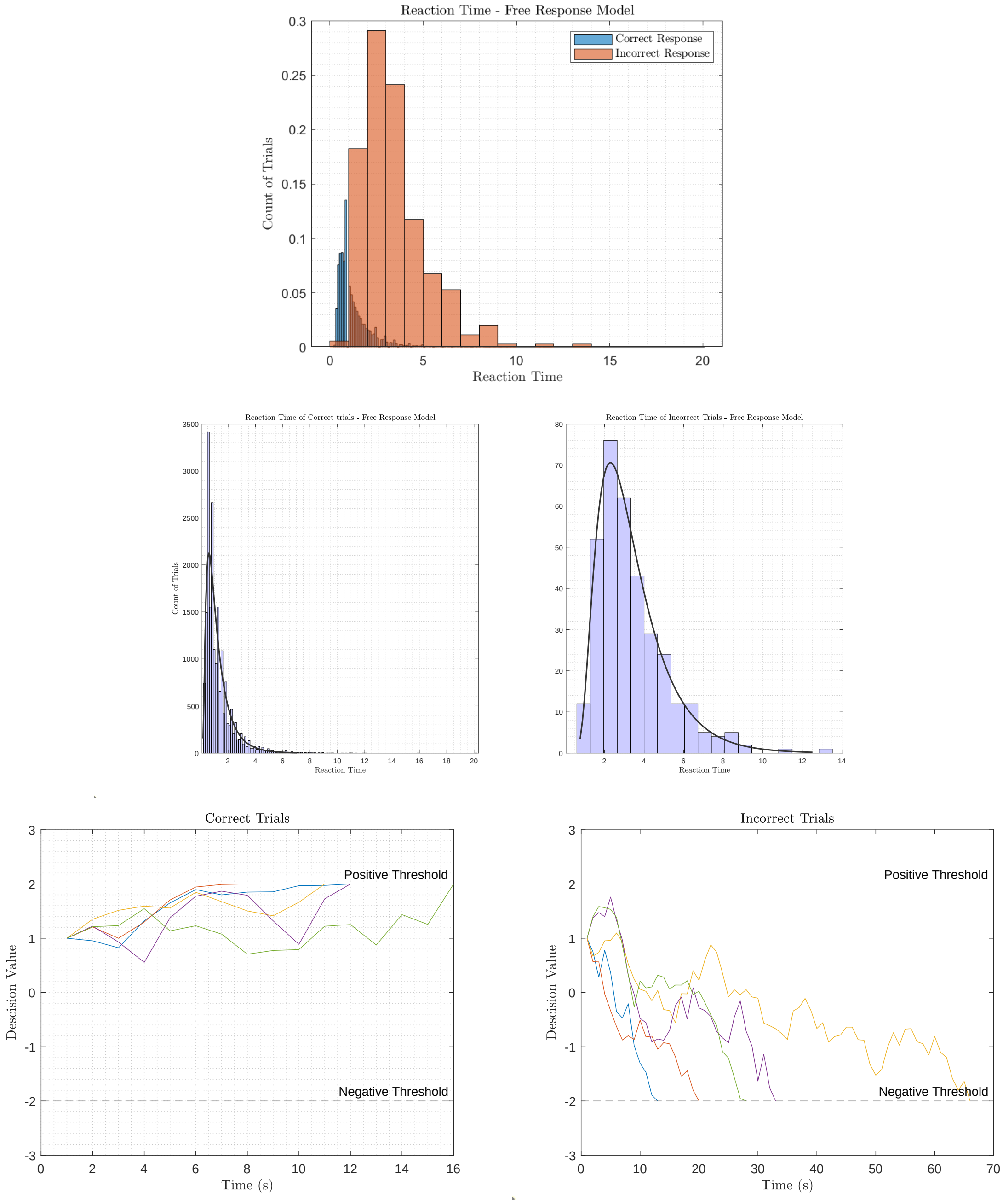

Figure 14: Start point effect on the result distribution

In both case, RT of correct choice is lower, but these two distribution are significantly separate.

Section 2: Race Diffusion Model

2.1 Question 7

An extension of drift diffusion model use two iterator with different threshold and even different start point, bias and variance. They compete with each other to reach their bound and then, we make a decision.

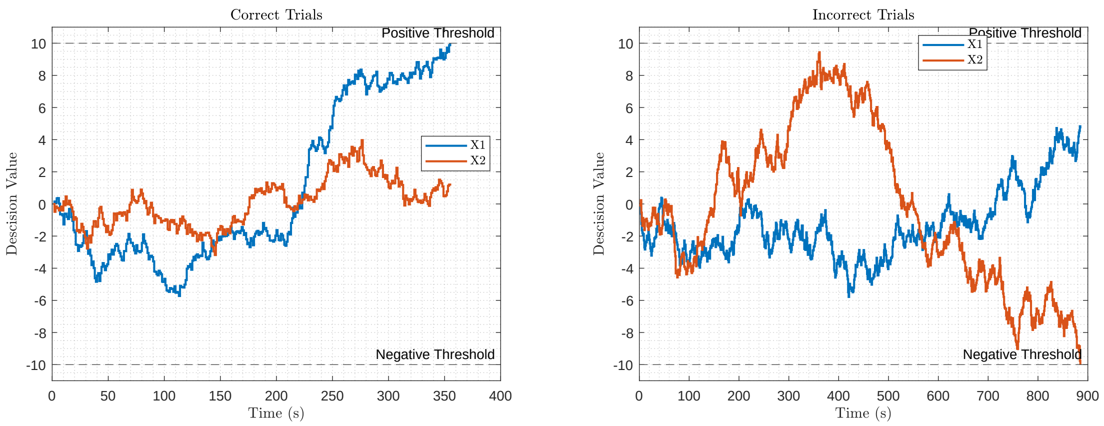

Figure 15: Race Diffusion Model. Positive, negative threshold= [10,-10], Sigma1=sigma2=1, x01=x02=0, bias1= 0.1, bias2= -0.1

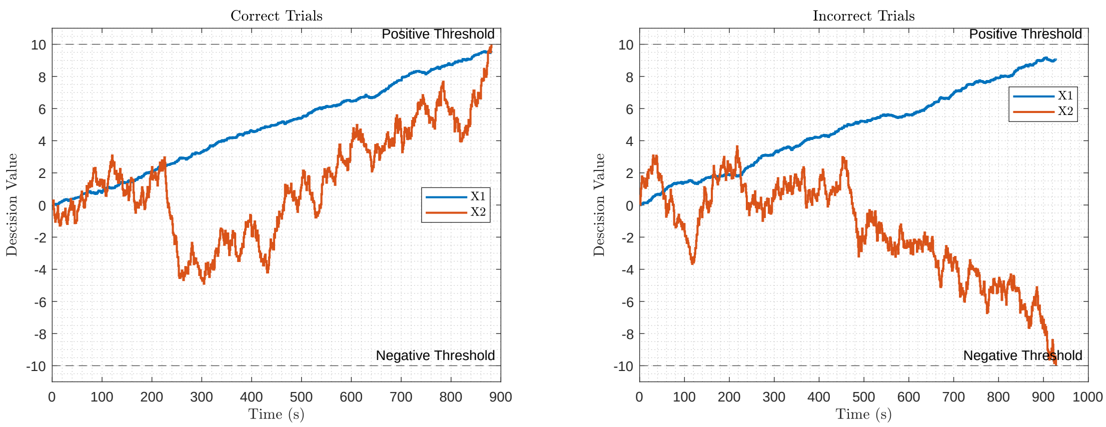

Figure 16: Race Diffusion Model. Positive, negative threshold= [10,-10], Sigma1=0.1, sigma2=1, x01=x02=0, bias1= 0.1, bias2= -0.1

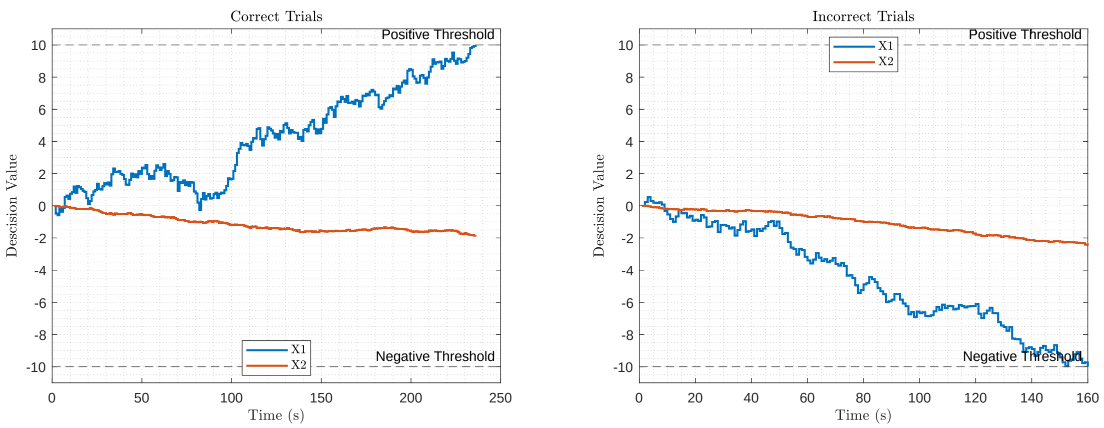

Figure 17: Race Diffusion Model. Positive, negative threshold= [10,-10], Sigma1=1, sigma2=0.1, x01=x02=0, bias1= 0.1, bias2= -0.1

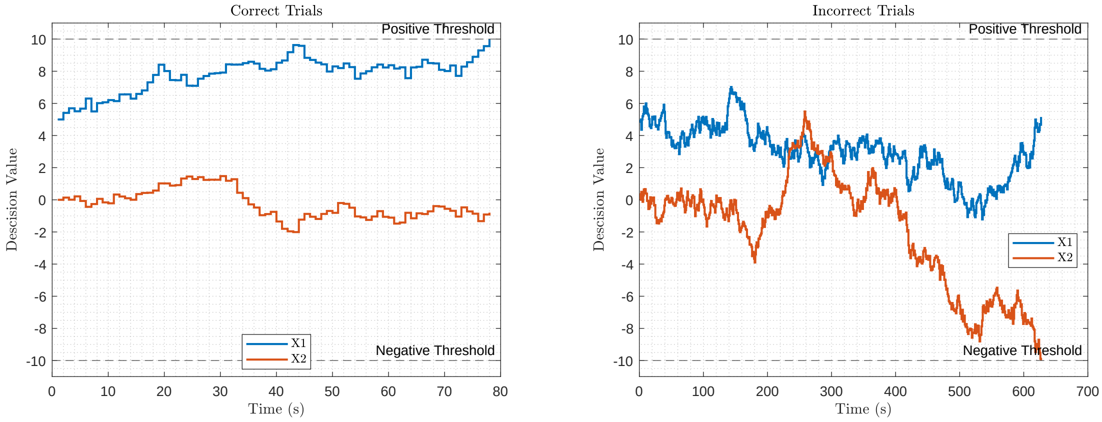

Figure 18: Race Diffusion Model. Positive, negative threshold= [10,-10], Sigma1= sigma2=1, x01=5, x02=0, bias1= 0.1, bias2= -0.1

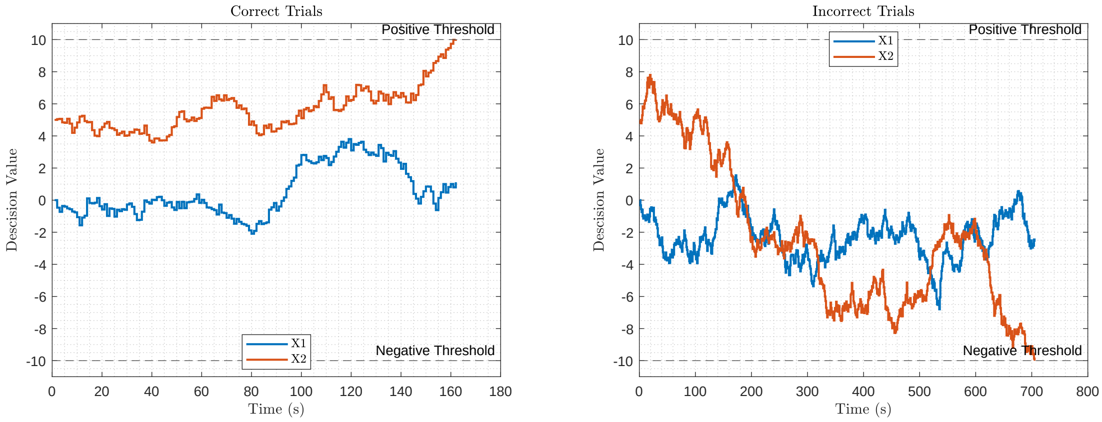

Figure 19: Race Diffusion Model. Positive, negative threshold= [10,-10], Sigma1= sigma2=1, x01=0, x02=5, bias1= 0.1, bias2= -0.1

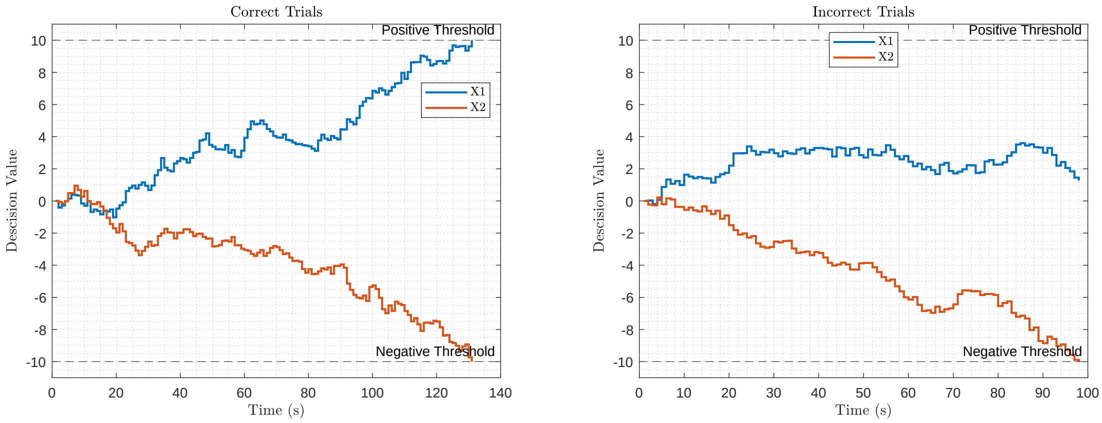

Figure 20: Race Diffusion Model. Positive, negative threshold= [10,-10], Sigma1= sigma2=1, x01=0, x02=0, bias1= 0.1, bias2= -1

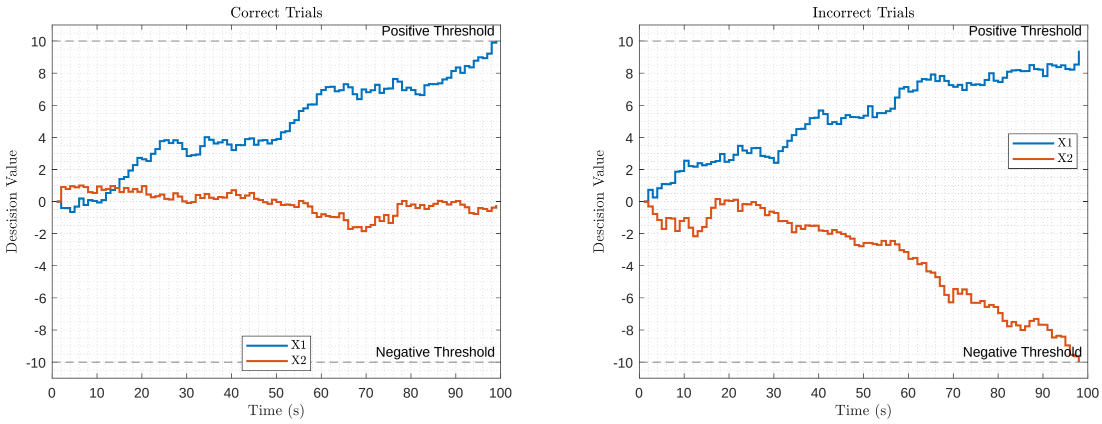

Figure 21: Race Diffusion Model. Positive, negative threshold= [10,-10], Sigma1= sigma2=1, x01=0, x02=0, bias1= 1, bias2= -0.5

2.2 Question 8

In this part, I use a fixed time interval and if time end, I randomly choose the answer.

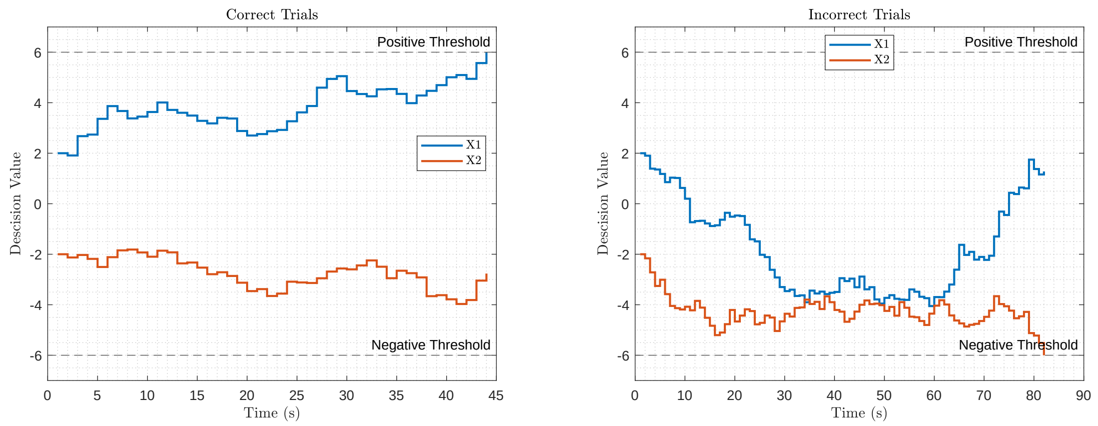

Figure 22: Extension of rice-trial model result. Sigma: [1 1], start point: [2 -2], bias: [0.1 -0.1]

Section 3: MT and LIP Area Interaction

3.1 Question 1

In this part, we simulate an excitatory and inhibitory neurons which have a connection with a LIP neuron with different weight. I simulate the event time of these neurons and you can see the result in figure . When the MT neuron's firing rate reach the LIP threshold, LIP spike.

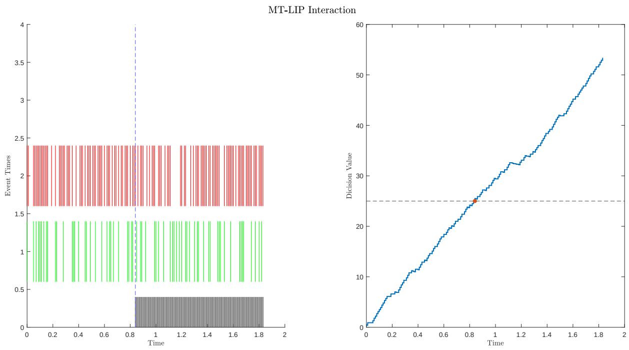

Figure 23: Event time of MT and LIP neurons. Right: excitatory neuron (red), inhibitory neuron (green), LIP (black). Left: accumulated decision value over time. Parameters: MT_p_values= [0.6 0.4], LIP_weights= [0.5 -0.1], LIP_threshold= 100, Evidence_thr= 25;

3.2 Question 2

Now, we have two LIP neuron that each of them have feed-forward an excitatory and inhibitory connection to MT neurons. MT neurons have a specific tuning curve. I randomly choose oriented stimulus, then set the probability of firing for the two MT neurons based on its tuning curve. LIP neuron accumulate these evidence to reach the threshold and spike.

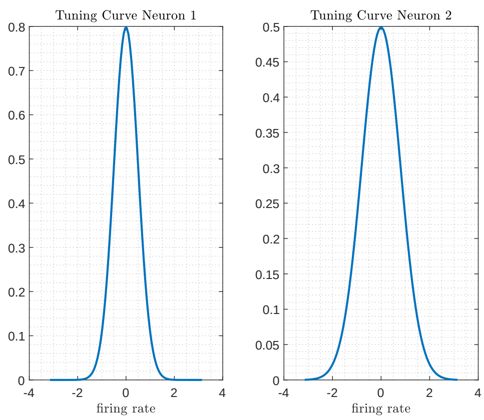

Figure 24: MT neurons tuning curve

Figure 25 show the neurons activity and decision accumulation.

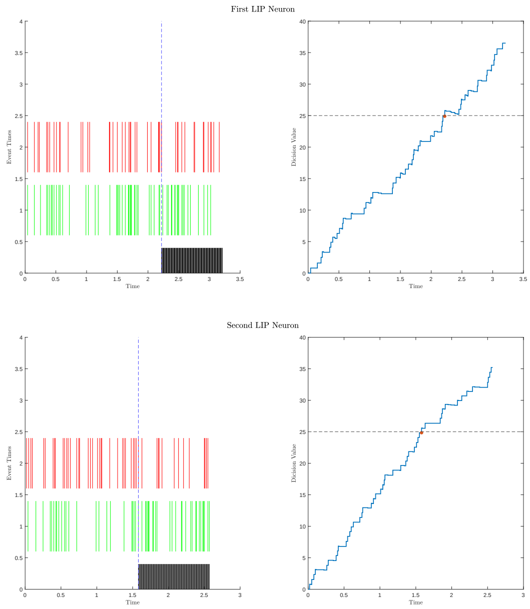

Figure 25: MT-LIP neurons. Right: excitatory neuron (red), inhibitory neuron (green), LIP (black). Left: accumulated decision value over time. Weights: W__LIP1-Exc= 0.9, W__LIP1-Inh= -0.1, W__LIP1-Exc= 0.8, W__LIP2-Inh= -0.05

When excitatory input has more weight than inhibitory, decision making is faster.

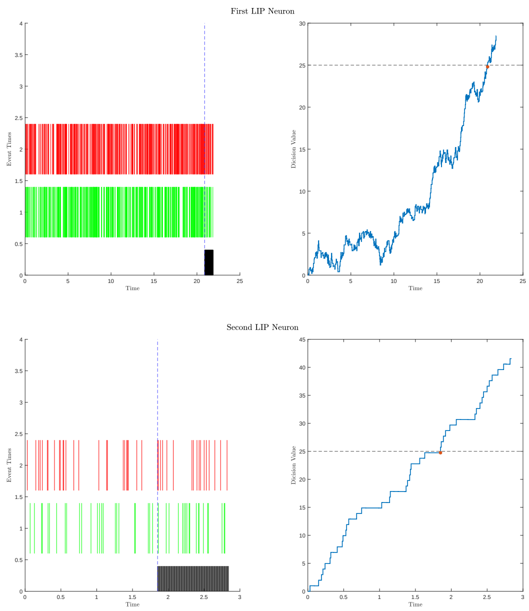

Figure 26: MT-LIP neurons. Right: excitatory neuron (red), inhibitory neuron (green), LIP (black). Left: accumulated decision value over time. Weights: W__LIP1-Exc= 0.5, W__LIP1-Inh= -0.4, W__LIP2-Exc= 1, W__LIP2-Inh= -0.01