In The Name of God

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Advanced Neuroscience HW7

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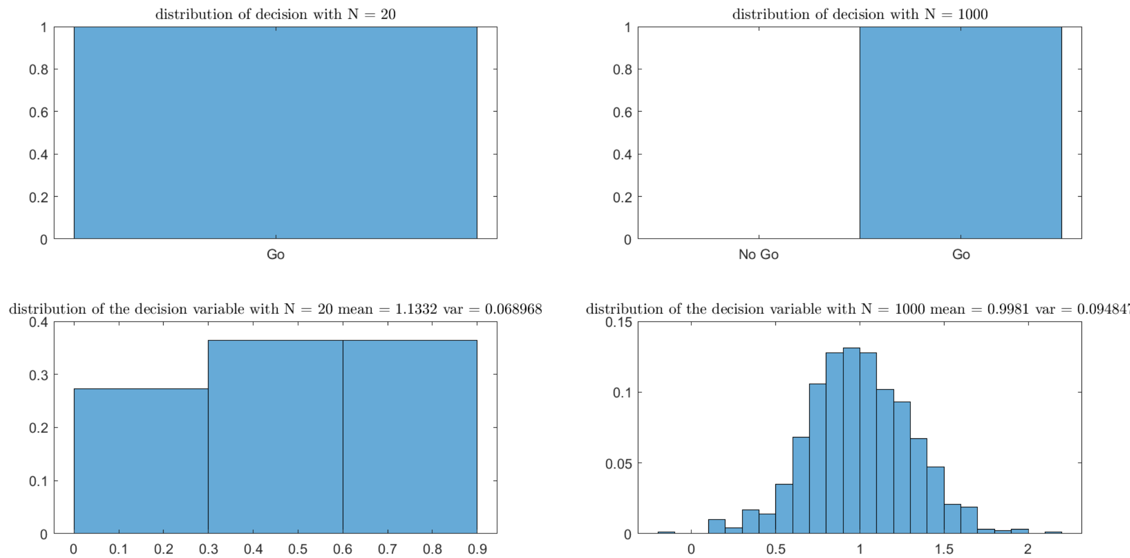
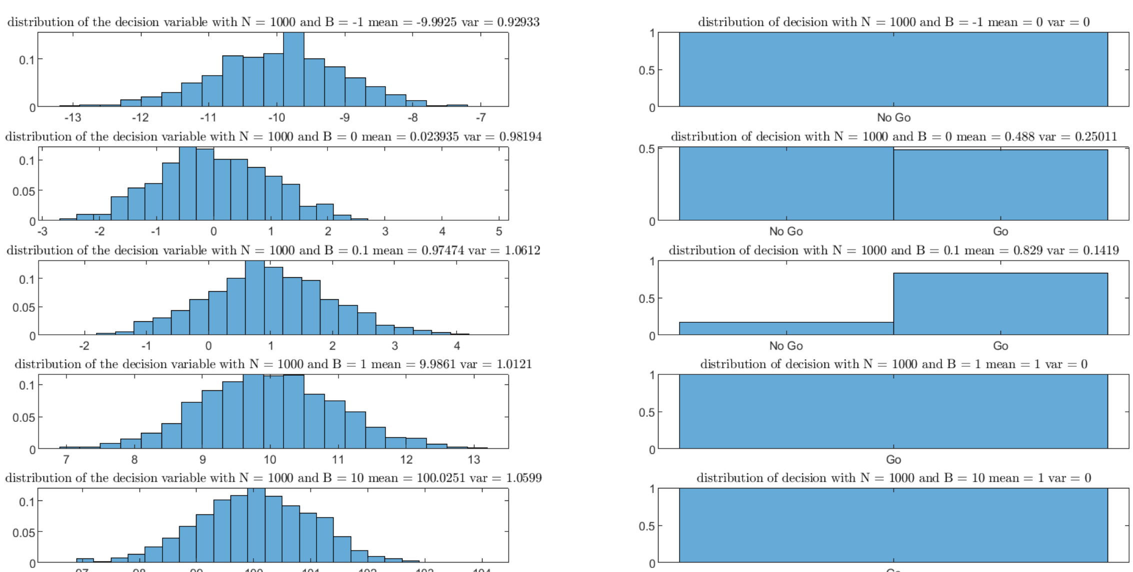
Part 1)

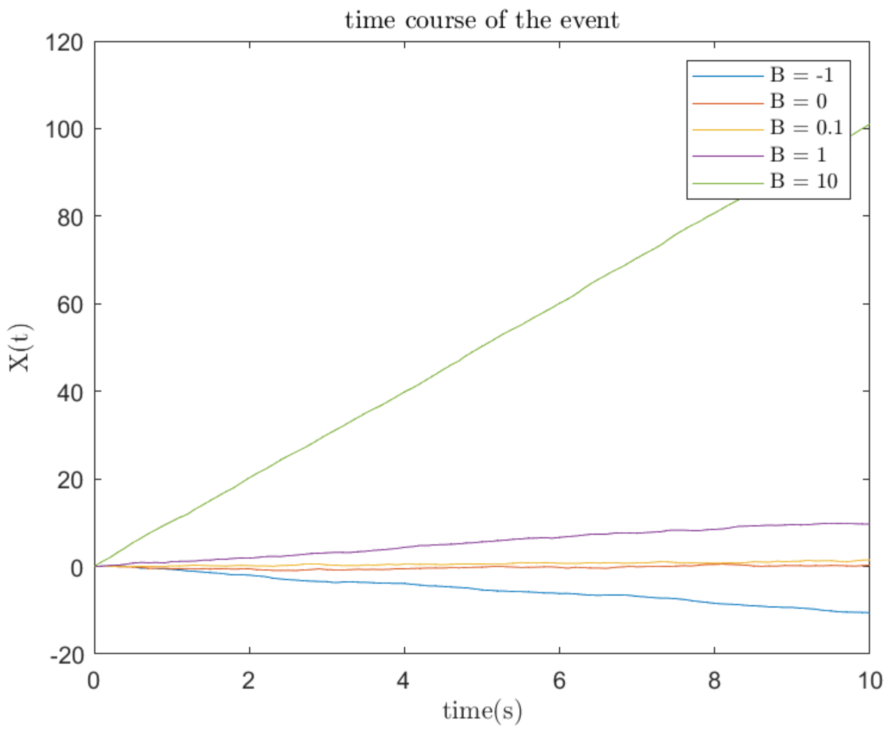
Q1) This Part is simply done and the function "simple_model.m" is used in further sections.

Q2) The decision and decision variable distributions for B = 1, $\sigma = 1$, dt = 0.1 and TI = 1s are shown below with 2 set of 20 and 1000 trials:

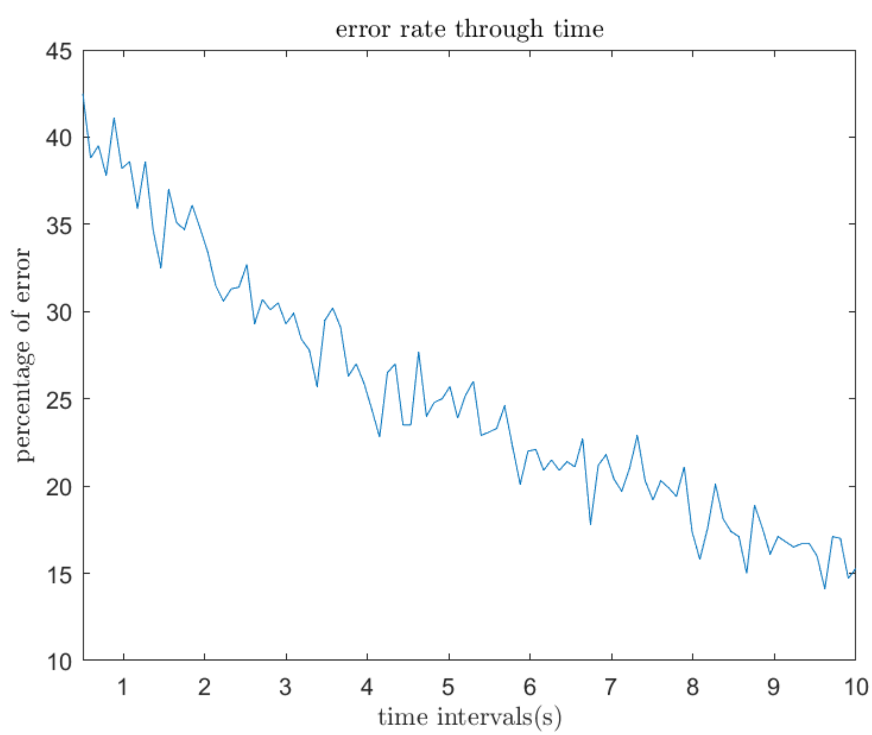


Below we can see how the distributions and the time course of the evidence change with different B amounts. As it can be seen, with low B amounts decisions are almost "No Go" all the time and oppositely with high B amounts decisions are almost "Go" all the time.





Q3) We consider the error to be equal to $\frac{N_{wrong}}{N}$. Below is the error plot through time after taking average from 1000 trials. As we can see the error decreases as time passes, pointing to the fact that quick taken decisions are noisier!



Q4) First we try to get the distribution in theory:

$$X(t) = \Sigma Bdt + \ \Sigma\sigma dW$$

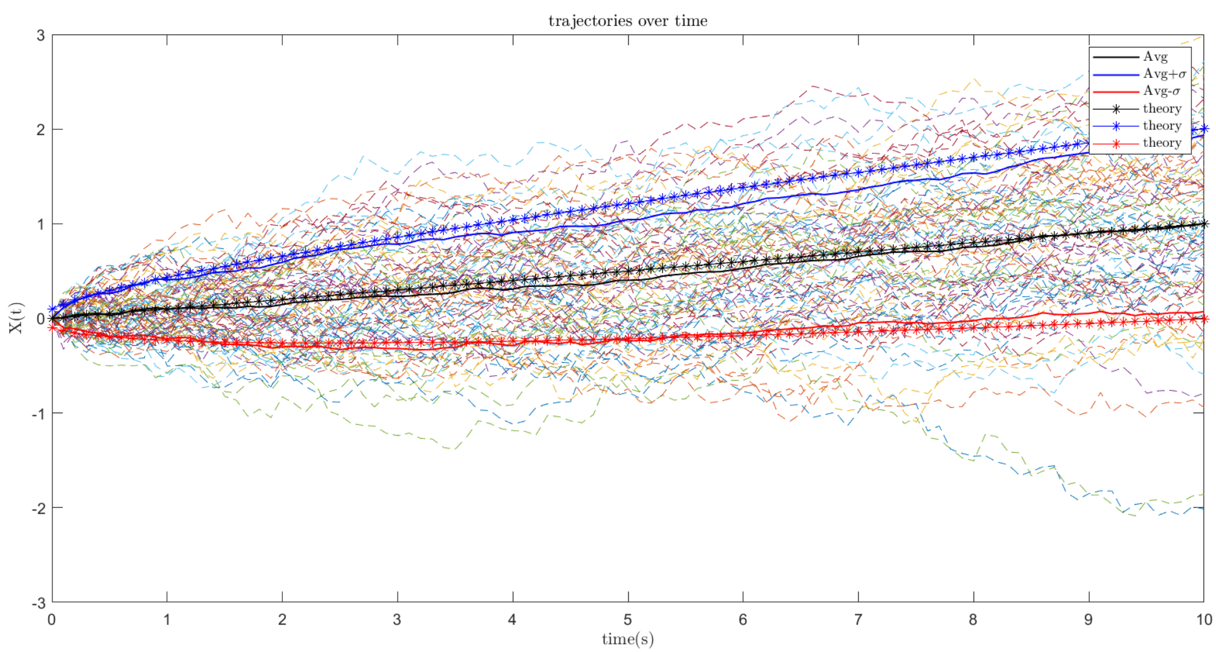
$$E(X) = E(\Sigma Bdt) + \sigma\Sigma \mathrm{d}E(W) = \Sigma Bdt + 0 = \ \Sigma Bdt$$

$$Var(X) = Var(\Sigma Bdt) + Var(\Sigma\sigma dW) = 0 + N\sigma^2 Var(\mathrm{W}) = \ N\sigma^2 dt^2 \rightarrow STD(X) = \sqrt{N}\sigma dt$$

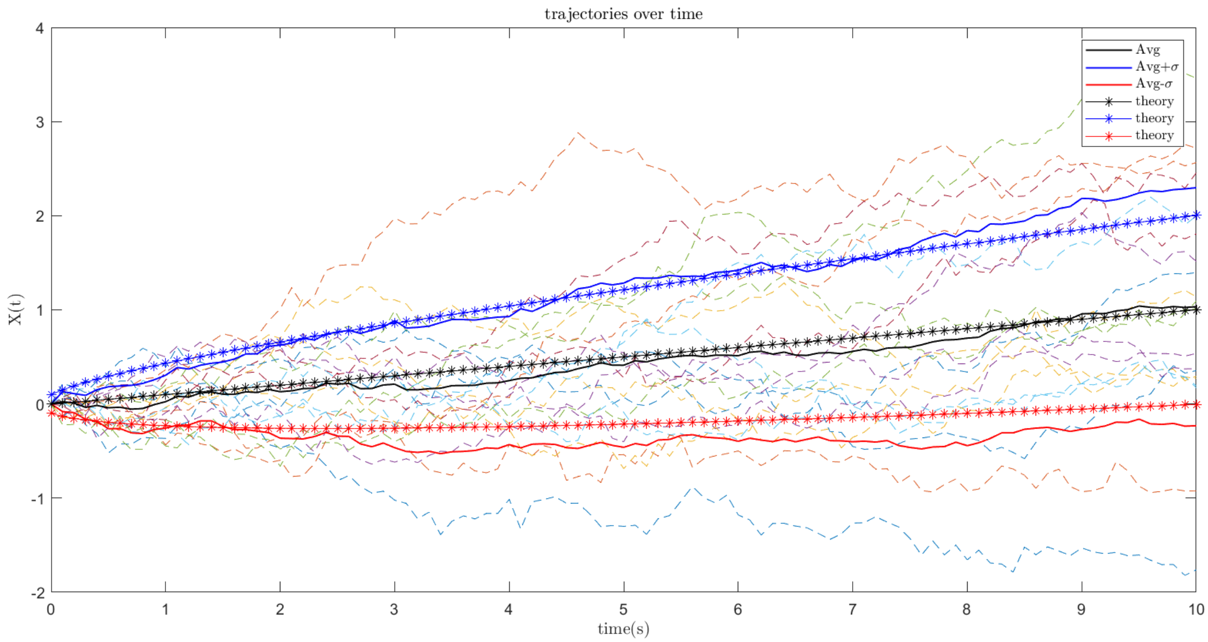
$$\rightarrow X(t) = N(\Sigma Bdt, \sqrt{N}\sigma dt$$

In which N is the number of steps need to reach the time interval with "dt" as the length of step.

The time course trajectory of 100 trials with their mean and mean $\pm\,\sigma$ and the theoretical statistics are plotted in figure below (considering B = 0.1, $\sigma = 1$, dt = 0.1 and TI = 10s):

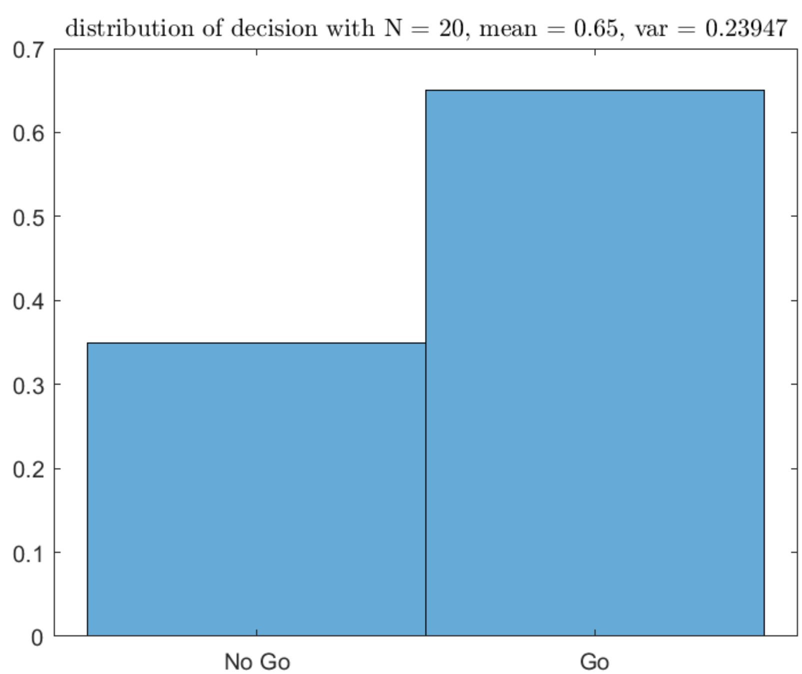


The time course trajectory of 20 trials is also shown below:

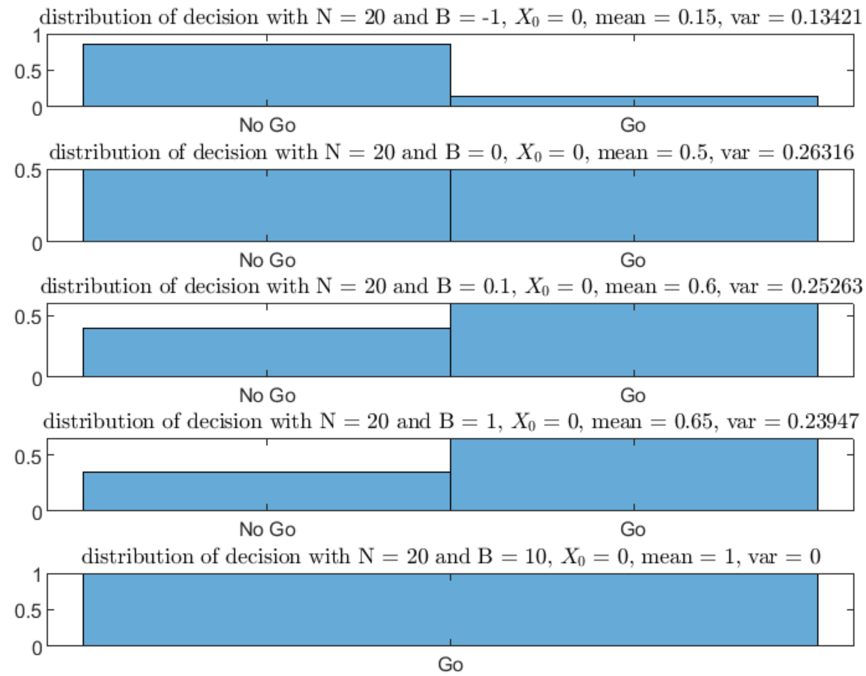


As we can see the theoretical and simulation values are approximately near when number of trials increases.

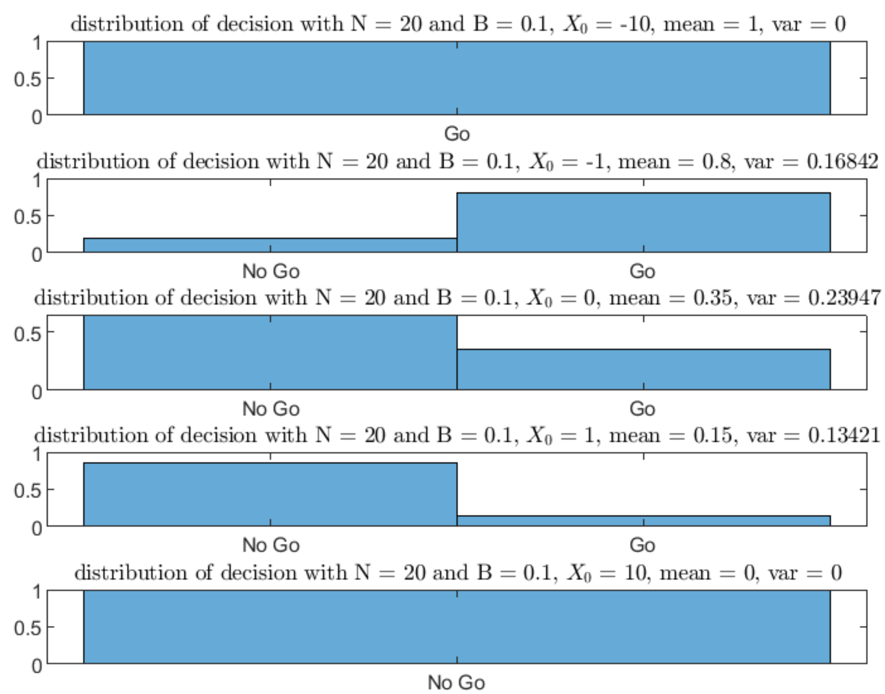
Q5) This Part is simply done and the function "simple_model2.m" is used to see the first sections histograms again:



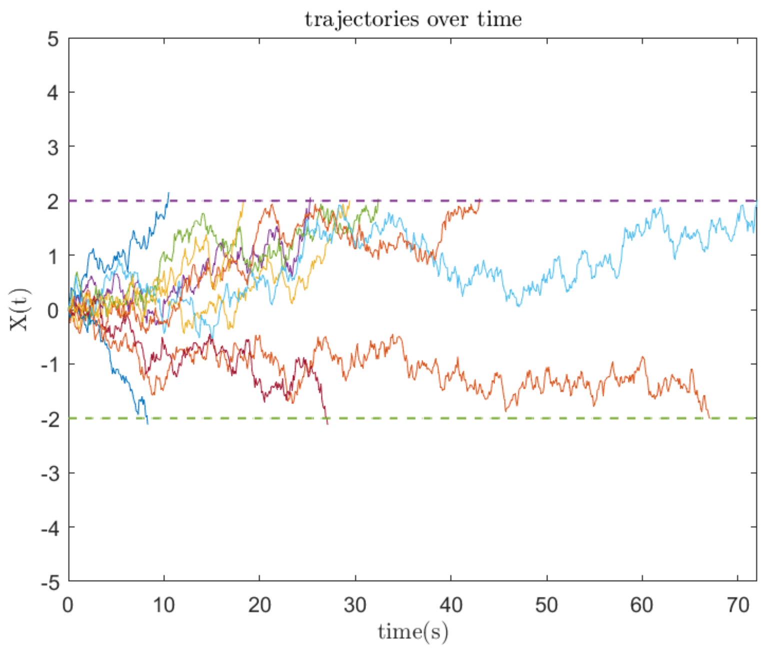
Here is a figure to see the effect of B amounts on the decision distributions:



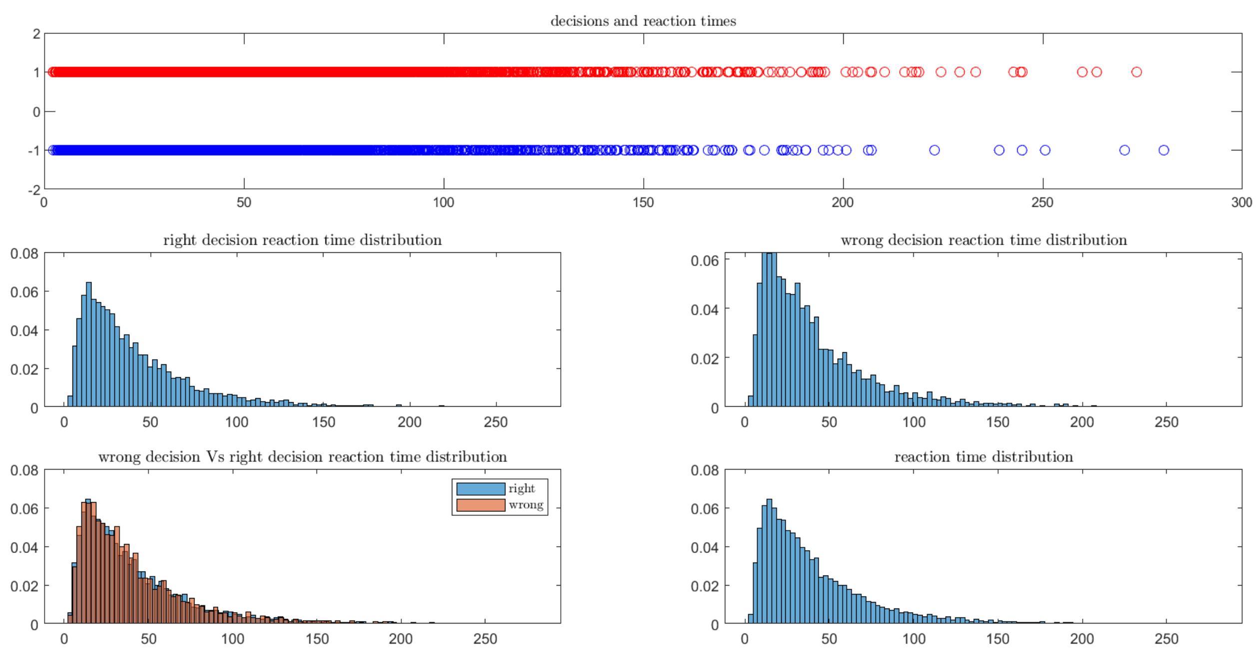
And also, a figure to see the effect of X_0 amounts on the decision distributions:



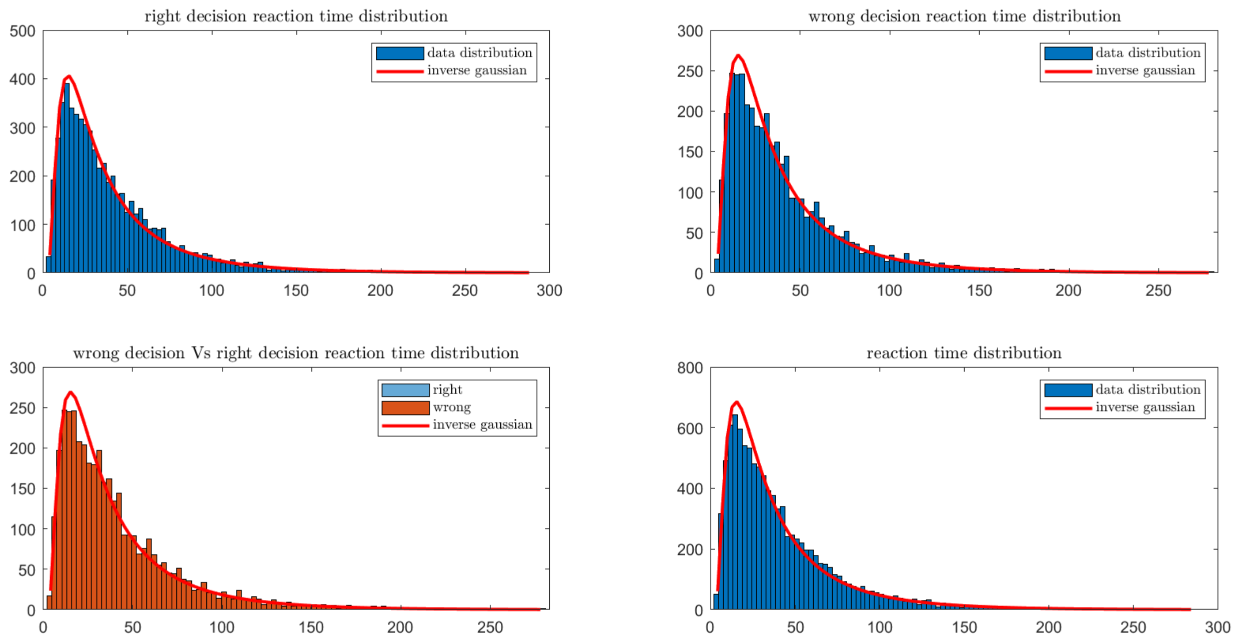
Q6) This Part is simply done and the function "two_choice_trial.m" is used in the further sections. Here are the trajectories for 10 trials considering B = 0.01, $\sigma = 1$, dt = 0.1, $\theta^- = -2$ and $\theta^+ = 2$.



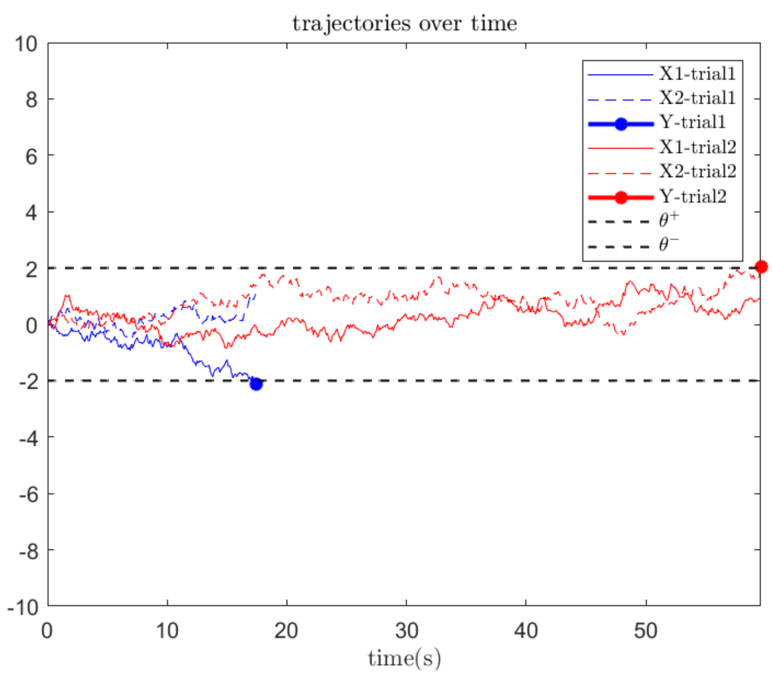
Q7) In this part we calculated the reaction times and decisions for 10000 trials with the previous settings and plotted the histogram of all reaction times, correct decision's reaction times, wrong decision's reaction times, and the asked plot. Here are the results:



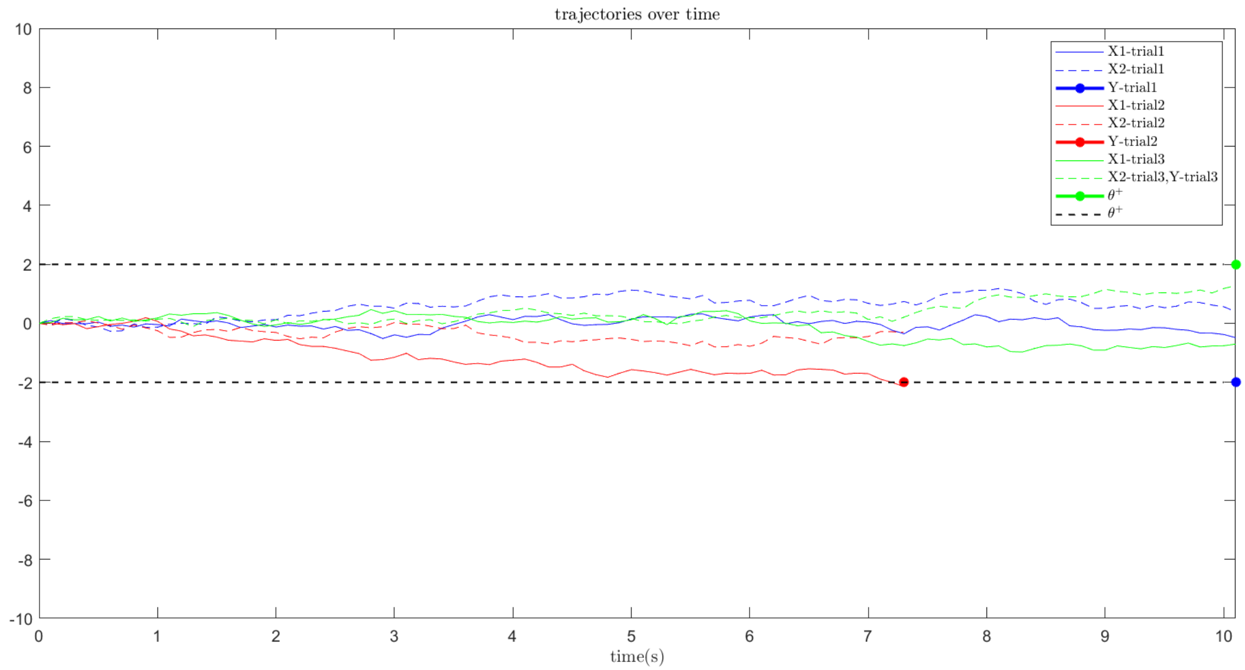
As we can see the distributions are likely to be the inverse gaussian distribution with almost no differences in mean or variance. Fitting the inverse gaussian distribution to the plots we have:



Q8) This Part is simply done and the function "race_trial.m" is put into the folder. Here is the result plot for 2 trials with both variables representing in each. In the first trial X1 and in the second trial X2 made the decision.



Q9) This Part is added to the function "race_trial2". And here are the results for a sample of 3 trials:



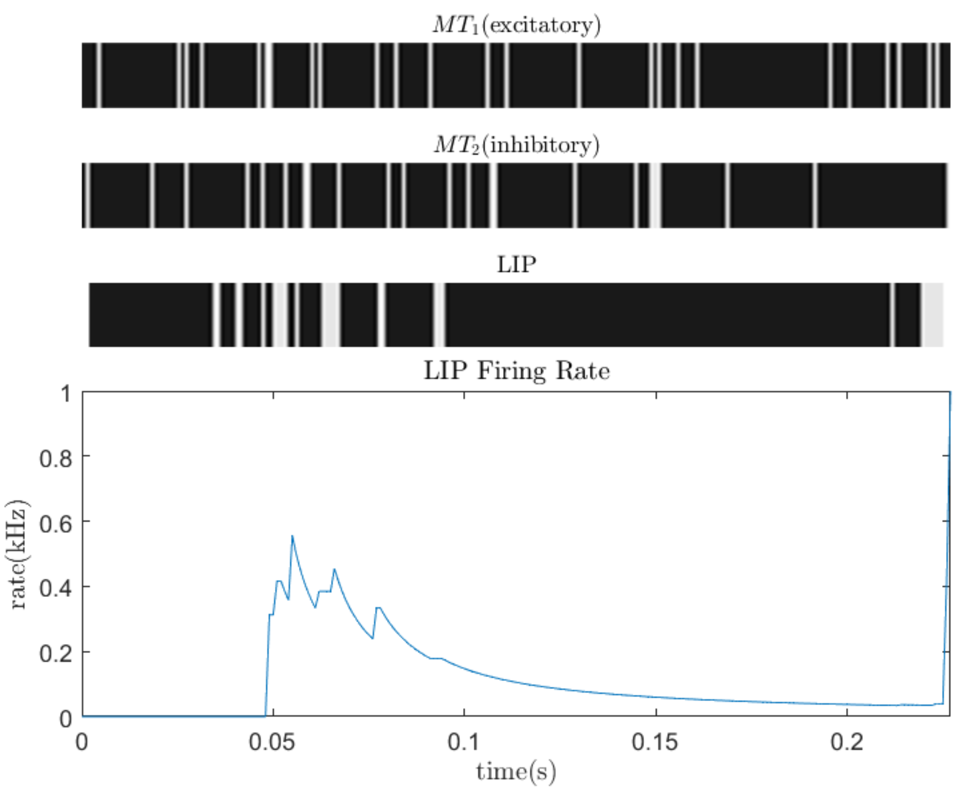
As it can be seen in some cases the time ended up with none of the variables converging, however the best decision is chosen.

Part 2)

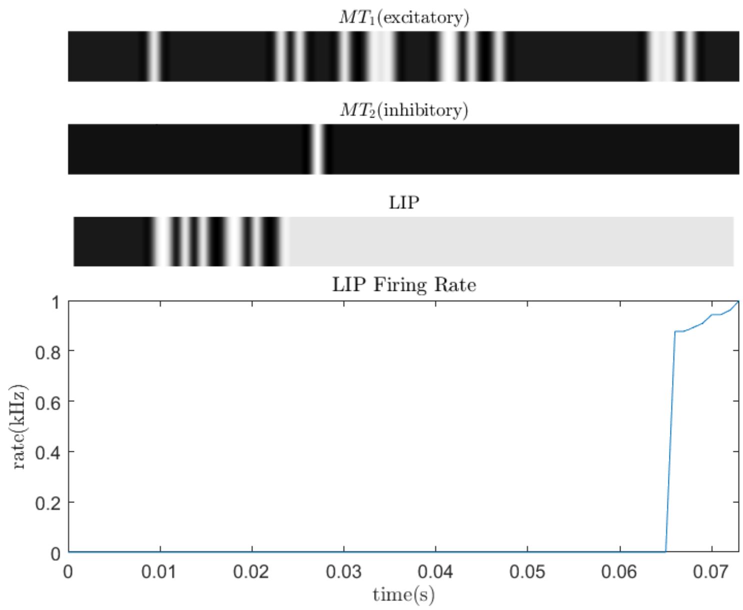
Q1) The function is modified and put into "lip_activity.m". Here are the results of running this function for different inputs:

When we compare below five sample figures we can find out that LIP firing increase by increasing the excitatory MT weights, decreasing the inhibitory MT weights, increasing the firing probability threshold for inhibitory MT and decreasing the firing probability threshold for excitatory MT.

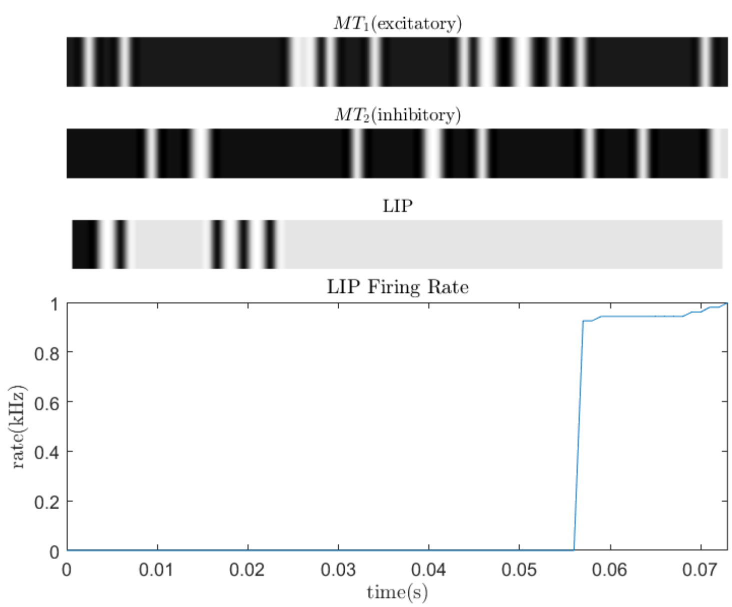
```
% sample 1
LIP_threshold = 1000;
M = 5;
MT_p_values = [0.1 0.1];
LIP_weights = [0.5 -0.5];
```



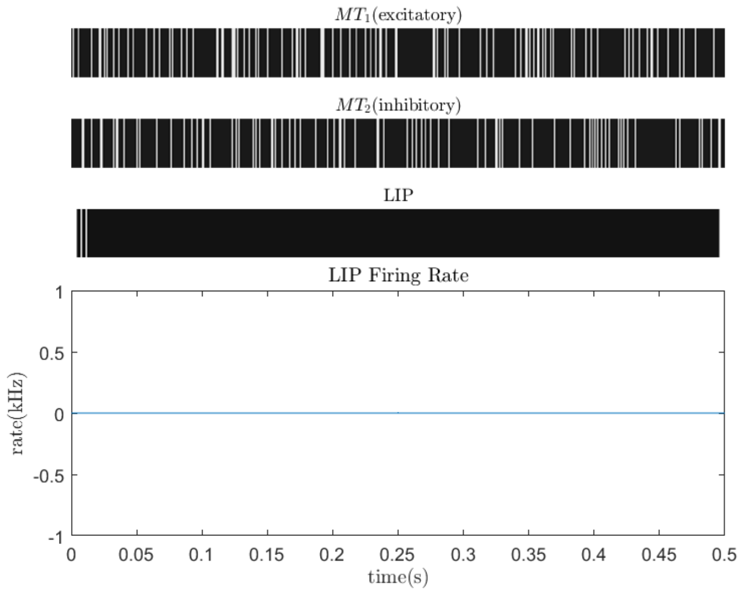
```
% sample 2
LIP_threshold = 1000;
M = 50;
MT_p_values = [0.2 0.01];
LIP_weights = [0.5 -0.5];
```



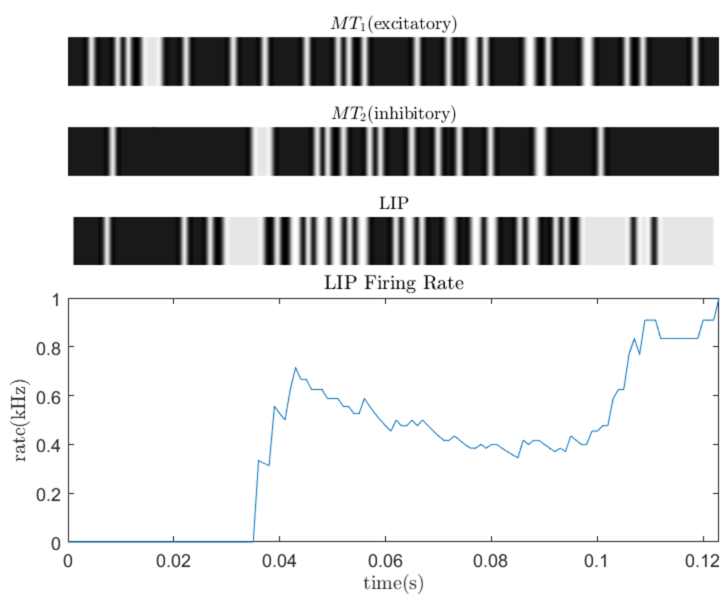

```
% sample 3
LIP_threshold = 1000;
M = 50;
MT_p_values = [0.2 0.2];
LIP_weights = [0.5 -0.05];
```



```
% sample 4
LIP_threshold = 1000;
M = 5;
MT_p_values = [0.2 0.2];
LIP_weights = [0.05 -0.5];
```



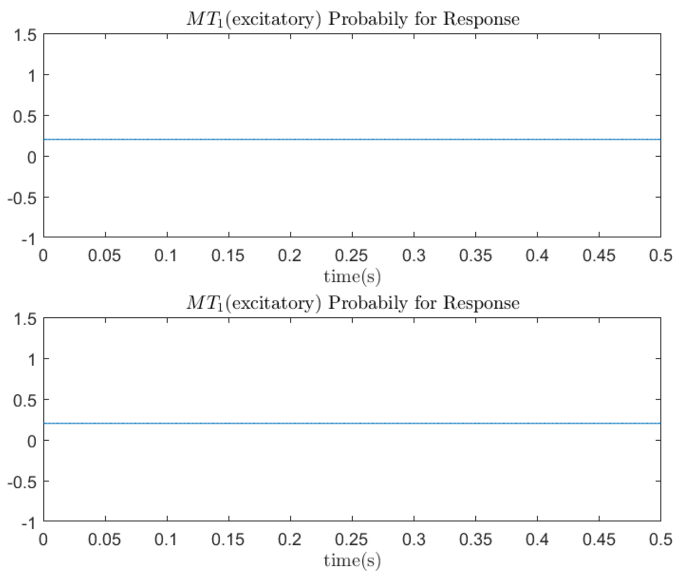

```
% sample 5
LIP_threshold = 1000;
M = 10;
MT_p_values = [0.2 0.2];
LIP_weights = [0.1 -0.1];
```

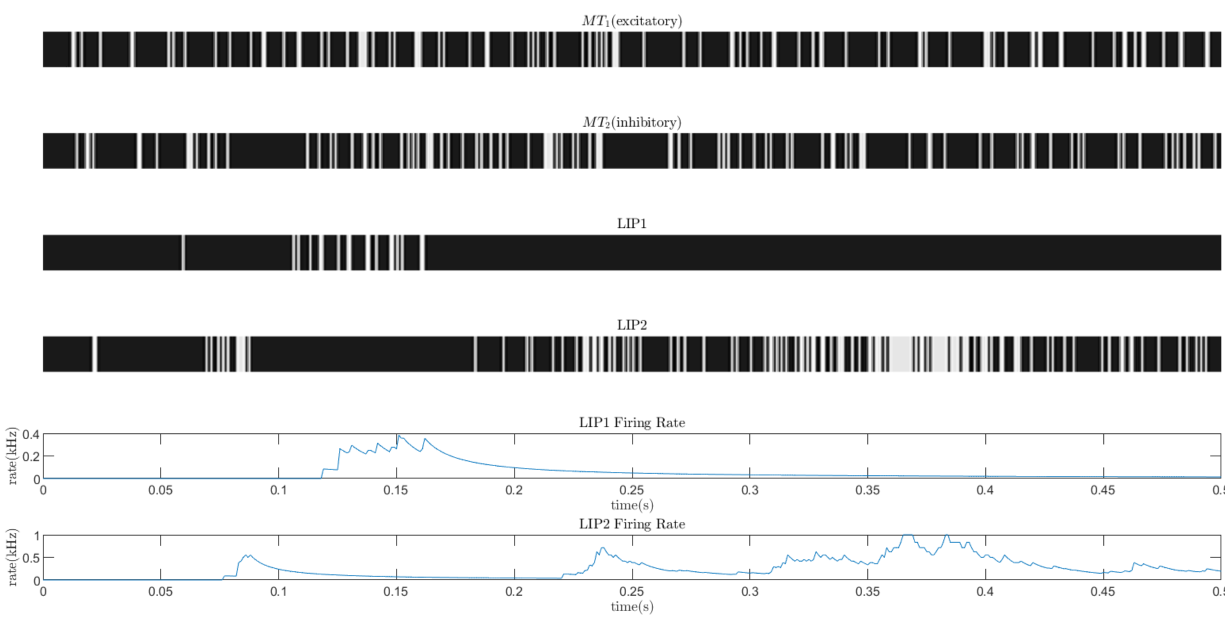


Q2) The function is written and put into "lip_activity2.m". Here are the results of running this function for different inputs (different activity patterns for both MT neurons):

1. Constant (MT1 Pvalue: 0.2 , MT2 Pvalue: 0.2)

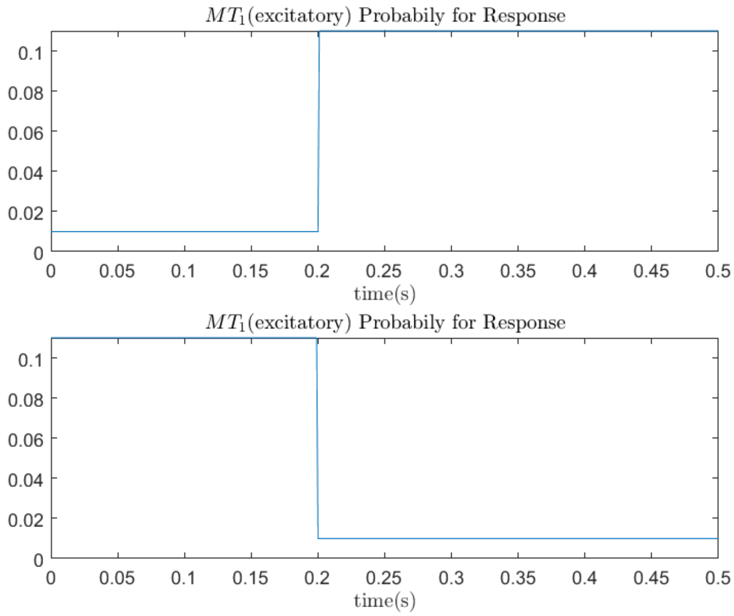
```
% sample 1
times = 0:0.001:0.5;
LIP_threshold = [1000,1000];
M = 5;
MT_p_values = [ones(size(times))*0.2;ones(size(times))*0.2];
LIP_weights = [0.1 -0.1];
```

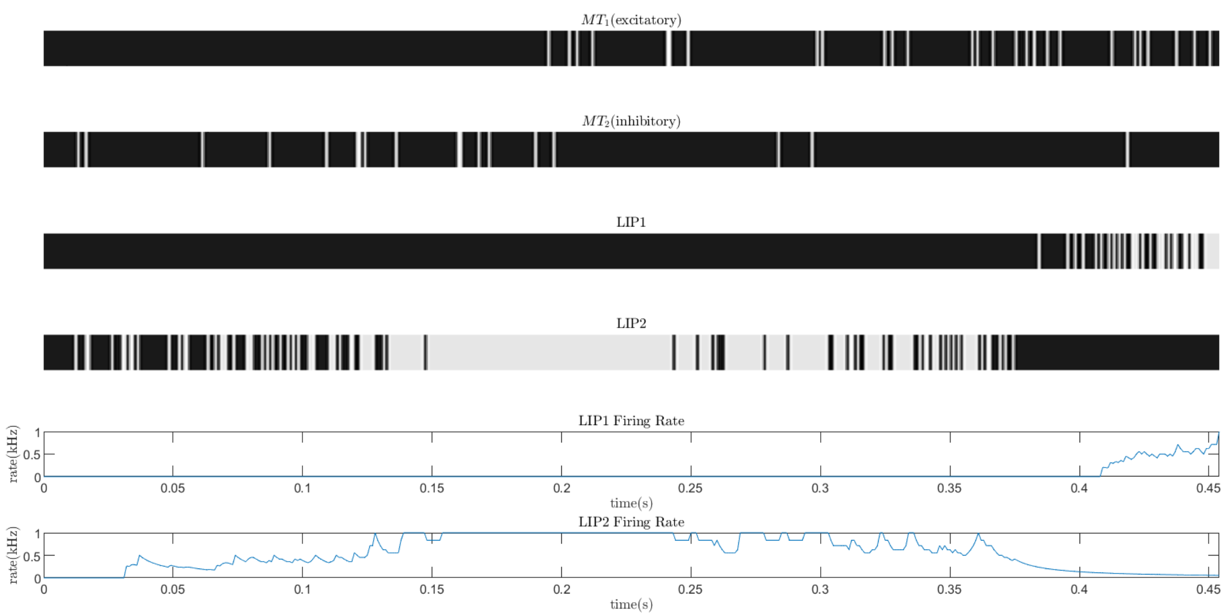




2. Step Function (MT1 Pvalue: $0.01 + 0.1u(t - 0.2)$, MT2 Pvalue: $0.01 + 0.1u(-t + 0.2)$)

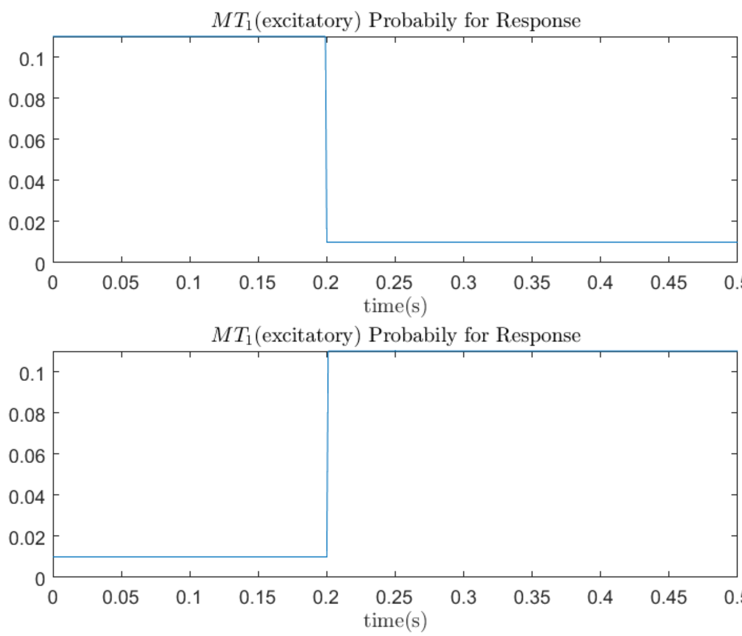
```
% sample 2
times = 0:0.001:0.5;
LIP_threshold = [1000,1000];
M = 5;
MT_p_values = [0.01 + 0.1*(times>0.2); 0.01 + 0.1*(times<0.2)];
LIP_weights = [0.1 -0.1];
```

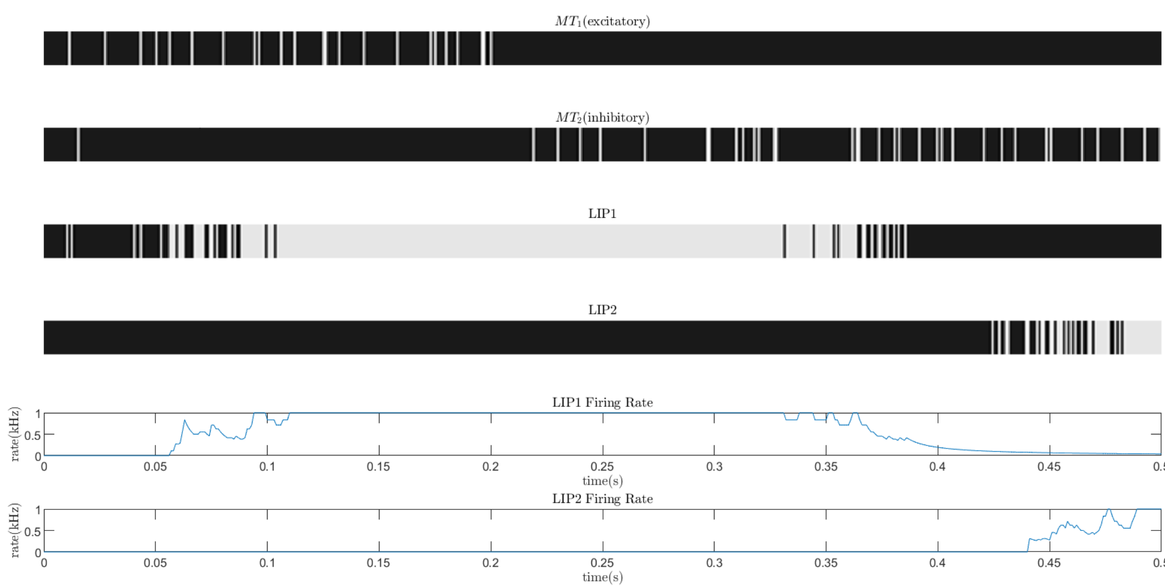




3. Step Function (MT1 Pvalue: $0.01 + 0.1u(-t + 0.2)$, MT2 Pvalue: $0.01 + 0.1u(t - 0.2)$)

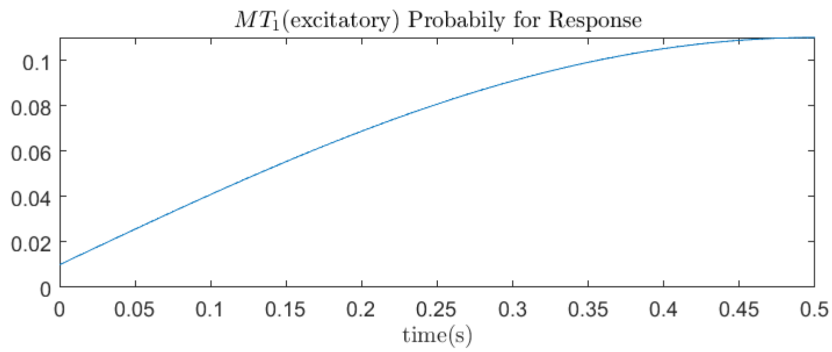
```
% sample 3
times = 0:0.001:0.5;
LIP_threshold = [10000,10000];
M = 5;
MT_p_values = [0.01 + 0.1*(times<0.2); 0.01 + 0.1*(times>0.2)];
LIP_weights = [0.1 -0.1];
```

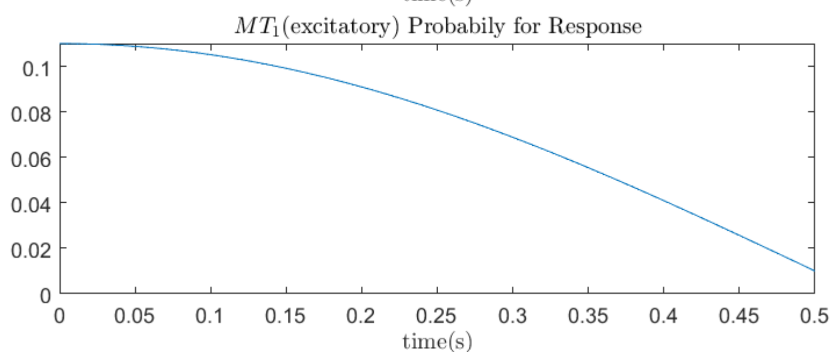


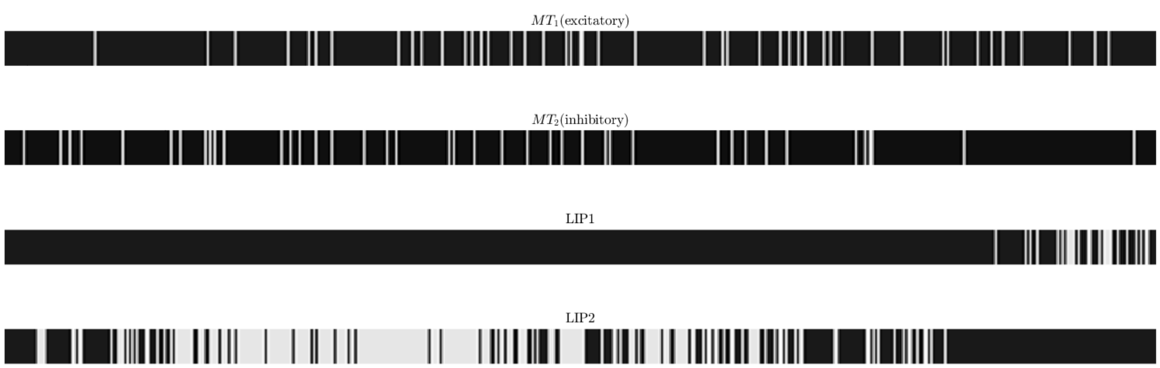


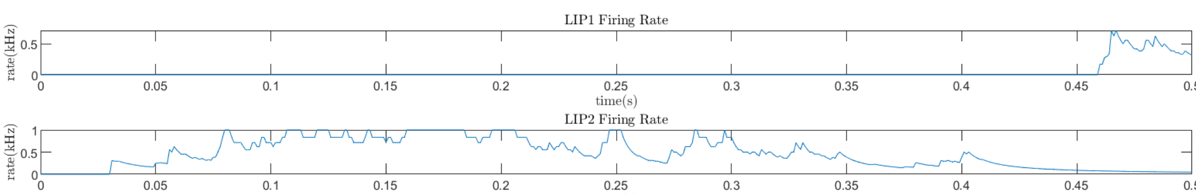
4. Sinusoidal Function (MT1 Pvalue: $0.01 + 0.1\sin(\pi t)$, MT2 Pvalue: $0.01 + 0.1\cos(\pi t)$)

```
% sample 4
times = 0:0.001:0.5;
LIP_threshold = [1000,1000];
M = 5;
MT_p_values = [ 0.01 + 0.1*sin(pi*times); 0.01 + 0.1*cos(pi*times)];
LIP_weights = [0.1 -0.1];
```



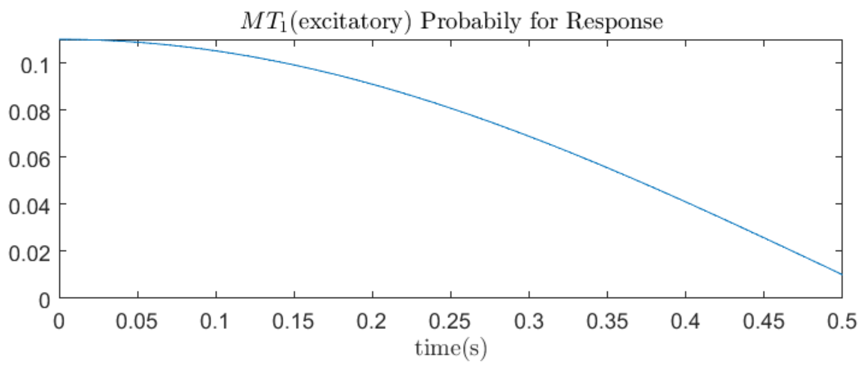


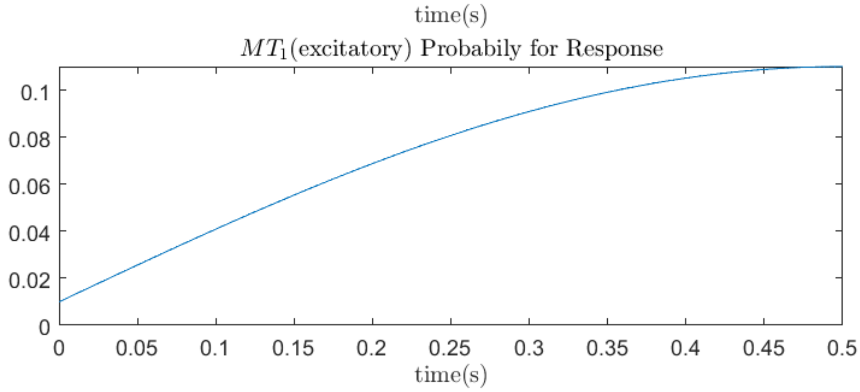


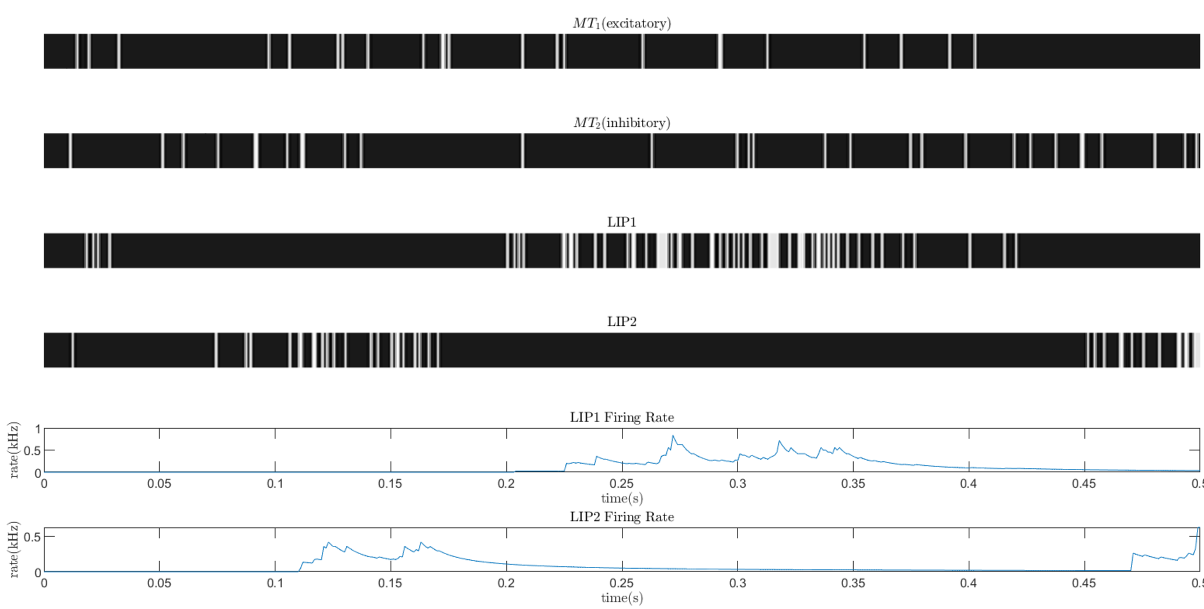


5. Sinusoidal Function (MT1 Pvalue: $0.01 + 0.1\cos(\pi t)$, MT2 Pvalue: $0.01 + 0.1\sin(\pi t)$)

```
% sample 5
times = 0:0.001:0.5;
LIP_threshold = [1000,1000];
M = 5;
MT_p_values = [ 0.01 + 0.1*cos(pi*times); 0.01 + 0.1*sin(pi*times)];
LIP_weights = [0.1 -0.1];
```







6. Sinusoidal Function (MT1 Pvalue: $0.01 + 0.05\sin(10\pi t)$, MT2 Pvalue: $0.01 + 0.05\cos(10\pi t)$)

```
% sample 6
times = 0:0.001:0.5;
LIP_threshold = [1000,1000];
M = 5;
MT_p_values = [ 0.01 + 0.05*sin(10*pi*times); 0.01 + 0.05*cos(10*pi*times)];
LIP_weights = [0.1 -0.1];
```