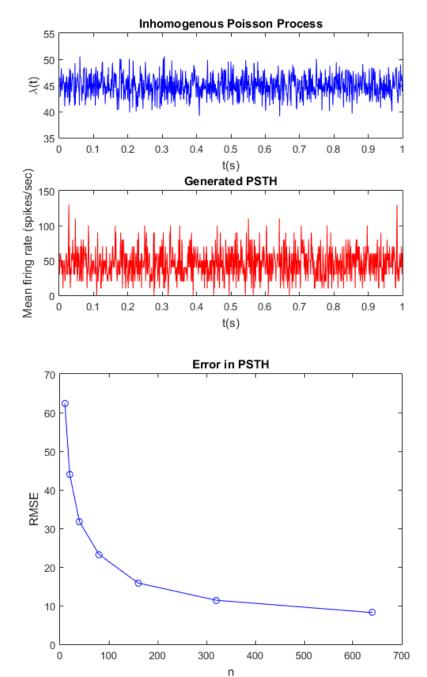
<u>Computational Neuroscience – Project 4</u>

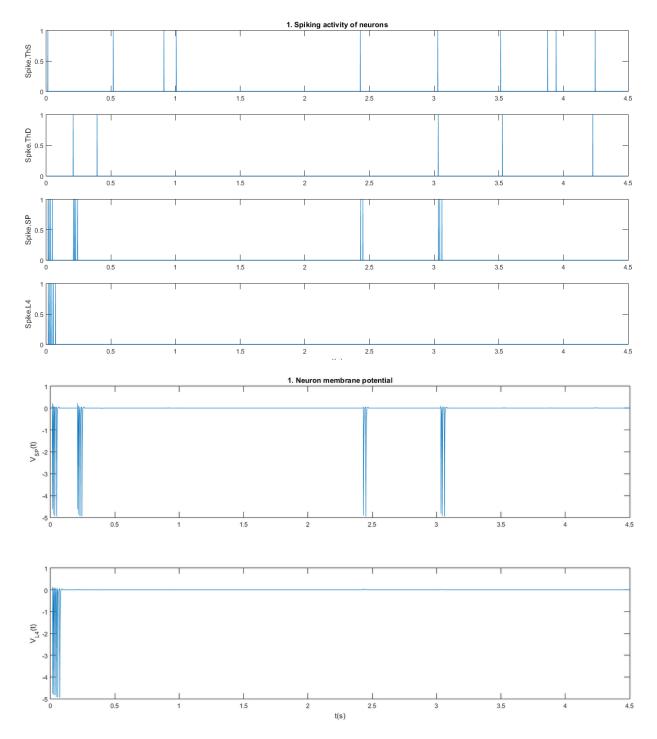
-Aditya Sinha (14EC10002)

1. Input Activity and making of the verNOP model

To model the input activity, we first generate inhomogenous Poisson spike trains based on a randomly generated $\lambda(t)$ (Gaussian distribution used). Then, the PSTH using n= 10, 20, 40, 80, 160, 320 and 640 repetitions is made and compared with the $\lambda(t)$. The root mean square curve is plotted to see the convergence of PSTH to $\lambda(t)$ with increasing value of n (better representation of entire ensemble).

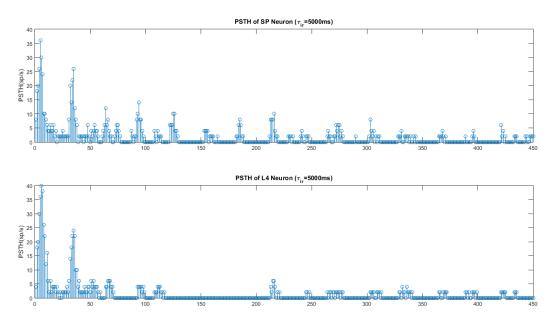


Next, we make the verNOP model and subject it to ODDBALL stimulus protocol. The spiking activity and membrane potentials of the neurons are as follows.

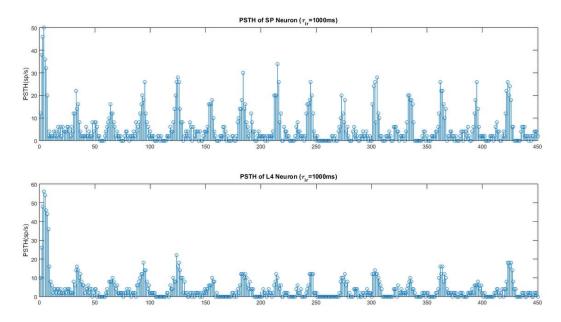


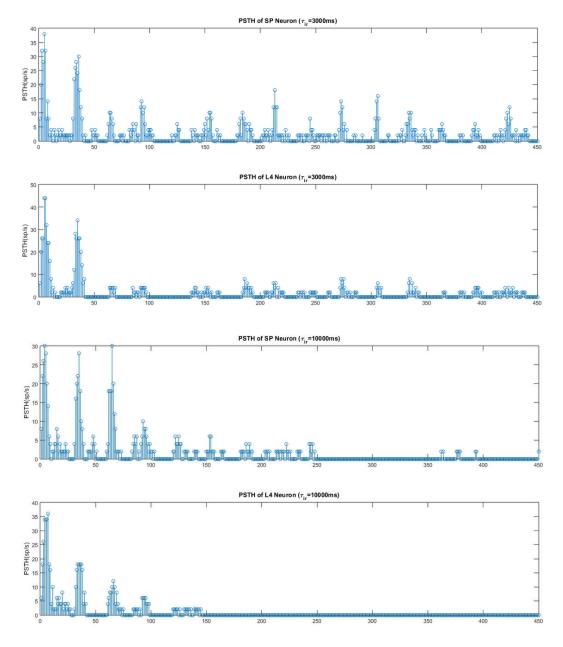
2. Plotting the PSTH

Here is the PSTHs for τ_{ir} =5000ms



3. Plotting PSTHs for different τ_{ir} values

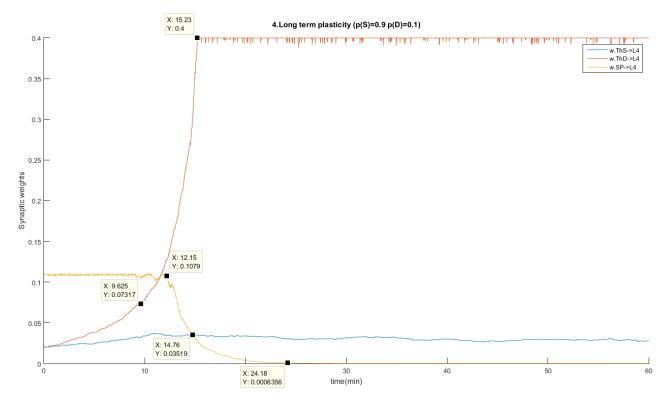




As we can see, for lower τ_{ir} values, the neurotransmitter replenishes quickly and we see spikes in the SP and L4 neurons throughout the time period. However, as τ_{ir} increases, the PSTH is mostly limited to the starting part, due to the x_r values for all synapses being 1 initially. Thus, we see the effect of Short-Term Plasticity using this PSTH simulation.

4. Simulation of neurons under Long Term Plasticity with p(S)=0.9

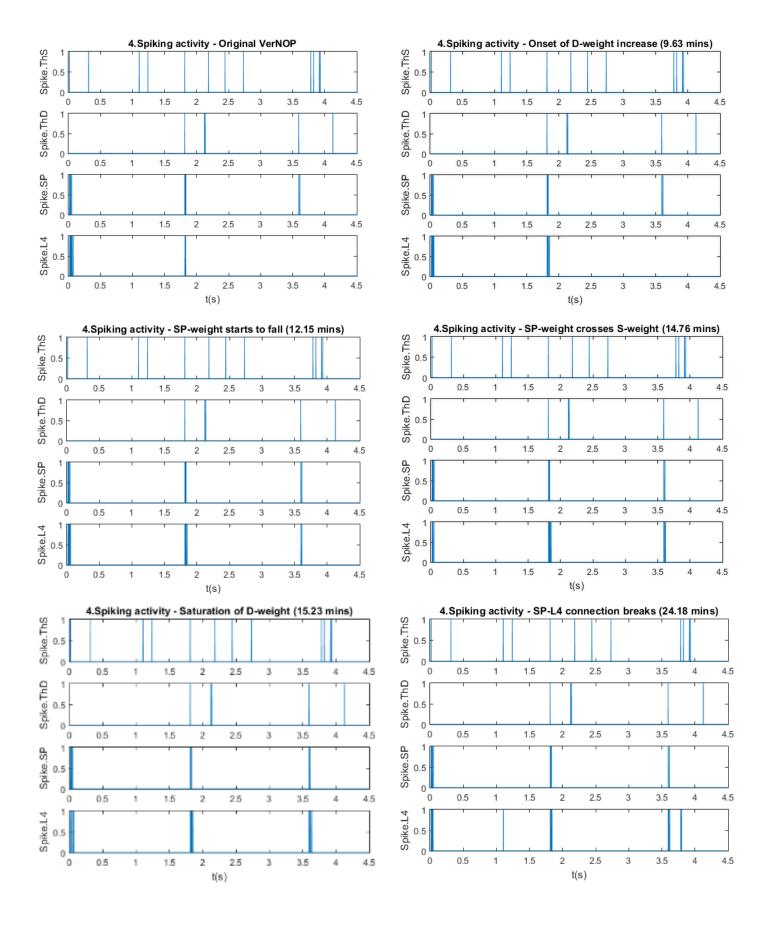
Using the Hebbian Learning rule provided, with weight update governed by STDP, the long term plasticity effect has been modelled for a 60 minute stimulus.



Due to higher probability of S, there is Stimulus Specific Adaptation (SSA) and we see that the weight of ThS->L4 doesn't increase much. In comparison, due to the relative rareness of D stimulus, there is a Long Term Potentiation (LTP) in the ThD->L4 synapse. Now, as this weight increases, D becomes sufficient to make L4 spike and thus, we have LTD in the SP->L4 synapse (see spike train trend).

Hence, we observe ocular dominance in form of the great disparity in the final weights from the left and right thalamic inputs. Also, observe that the migratory connection from SP->L4 breaks after a while (development in the visual cortex).

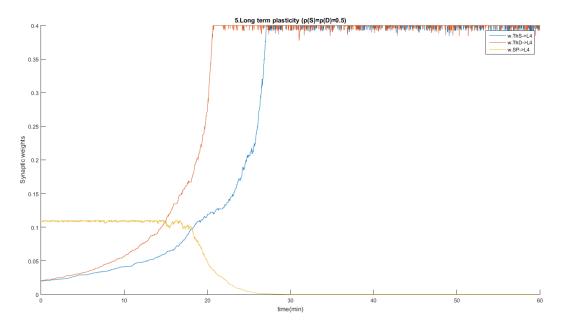
Now, I have marked out a few points of interest on the plot, and we try to run the verNOP model with the ODDBALL stimulus at the instantaneous weights provided by these points. The results for this are as follows. It is observed that the spiking activity to the same (deterministic) stimulus increases with time. This is because of the increased weight of D->L4, as compared to initial SP->L4



5. Simulation of neurons under Long Term Plasticity with p(S)=0.5

When the stimuli are equally likely, we expect to see a similar increase in both ThS->L4 and ThD->L4 weights, since there is no one dominating stimulus (equal probability of LTP). As expected, this is observed. However, there is a slight time difference in saturation, and it is due to the stochastic nature of the stimulus and spiking ie. even though probability is 0.5, the spiking with rate $\lambda_S \& \lambda_D$ only happen probabilistically, resulting in different spike times.

I think that this is one dimension in which STDP lacks. Since it does not do averaging like the other weight update rules, it is more subject to variation due to stochasticity. In fact, repeating this experiment multiple times (Monte-Carlo simulation) and then finding average weight curve, we will likely observe that both ThS->L4 and ThD->L4 follow the same graph.



P.S. Thank you for this project. It was very insightful and helped me realise a lot of things while implementing that I knew only partly. I would have loved to spend more time playing with similar models had there been more time. Feel free to run the attached code – each Long Term Plasticity simulation takes about 12 minutes on an 8GB RAM laptop. The other parts take negligible time.