Computational Neuroscience (Autumn 2025)
Project IV

Roll No: 22CS30053

Q1: Inhomogeneous Poisson and RMSE

I generated a random rate function $\lambda(t)$ (1 s, 1 ms resolution) by low-pass filtering Gaussian noise and shifting to a mean of ≈ 45 sp/s, clipped between 5 and 90 sp/s. Inhomogeneous Poisson spike trains were produced using the Bernoulli approximation $P(\text{spike at } t) = \lambda(t)\Delta t$ with $\Delta t = 1$ ms.

From 320 repetitions, I computed a PSTH (1 ms bins) from the first 100 trials and compared it to $\lambda(t)$. Fig. 1 shows that the PSTH closely tracks the underlying rate. I then computed RMSE between $\lambda(t)$ and PSTHs computed from 10, 20, 40, 80, 160 and 320 repetitions (Fig. 2). The RMSE decreases rapidly with trial count and asymptotes beyond ~ 160 trials, as expected from averaging of Poisson variability.

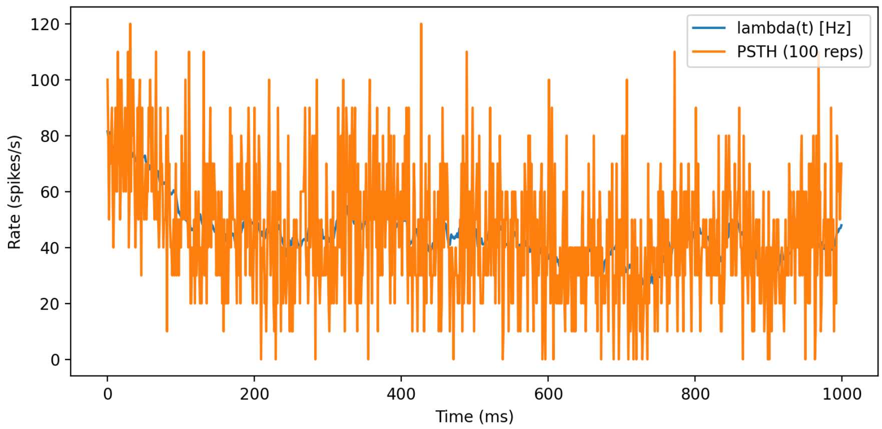

Figure 1: Q1: Random rate function $\lambda(t)$ and PSTH from 100 repetitions (1 ms bins).

Q2–Q3: ODDBALL with Depressing Synapses (no STDP)

For verNOp (no long-term plasticity), I used the initial weights from the handout: Th(S/D)$\to$SP $= 0.2$, Th(S/D)$\to$L4 $= 0.02$, SP$\to$L4 $= 0.11$. I simulated the ODDBALL protocol: 15 stimuli (S except the 8th which is D), each 50 ms, separated by 250 ms gaps. This sequence was repeated 50 times and PSTHs (10 ms bins) were computed for SP and L4.

With the default depression parameters ($\tau_{re} = 0.9$ ms), both SP and L4 show strong responses to the early S stimuli that gradually adapt; the deviant D in position 8 evokes a relatively enhanced response in L4 compared to the surrounding standards, although the overall firing is depressed due to synaptic depletion (Fig. 3). SP shows weaker deviance selectivity, consistent with its role as an intermediate relay.

For Q3, I varied τ_{re} for both thalamic and SP synapses to 1000 ms, 3000 ms and 10000 ms while keeping other parameters unchanged. As τ_{re} increases, recovery from depression becomes slower, so the effective synaptic resources remain depleted across the stimulus train. Consequently, the overall

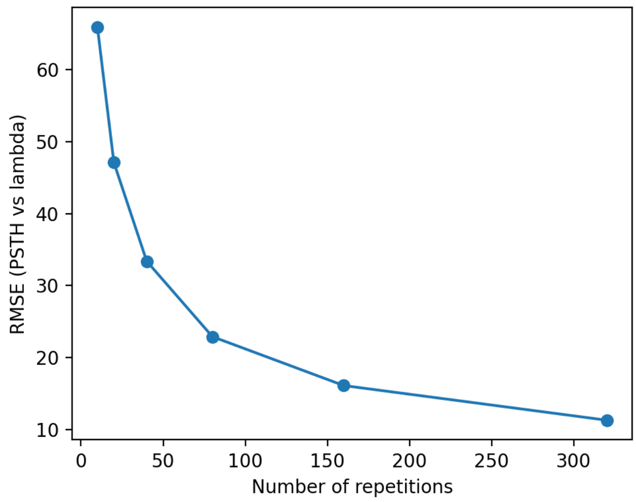

Figure 2: Q1: RMSE between PSTH and $\lambda(t)$ vs number of repetitions.

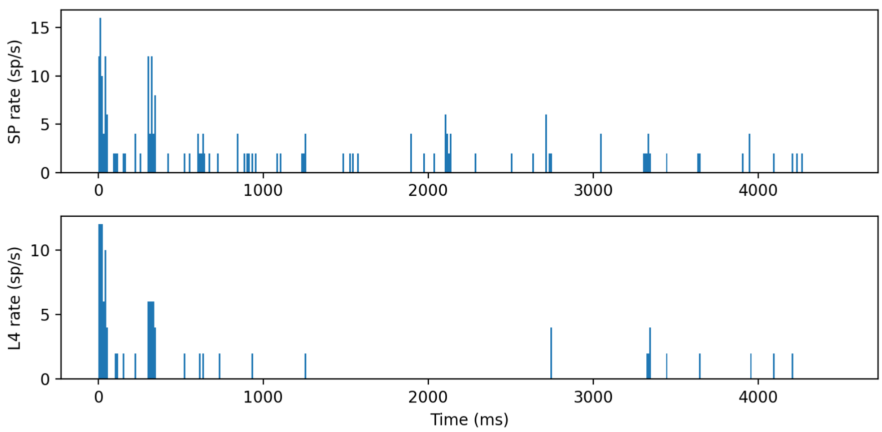

Figure 3: Q2: SP and L4 PSTHs for the ODDBALL sequence (verNOp, $\tau_{re} = 0.9\,\text{ms}$).

firing rates of SP and L4 decrease and the difference between responses to the standard S and deviant D is reduced (Fig. 4). For very large τ_{re}, the network becomes strongly depressed after the first few stimuli and both S and D evoke relatively weak responses.

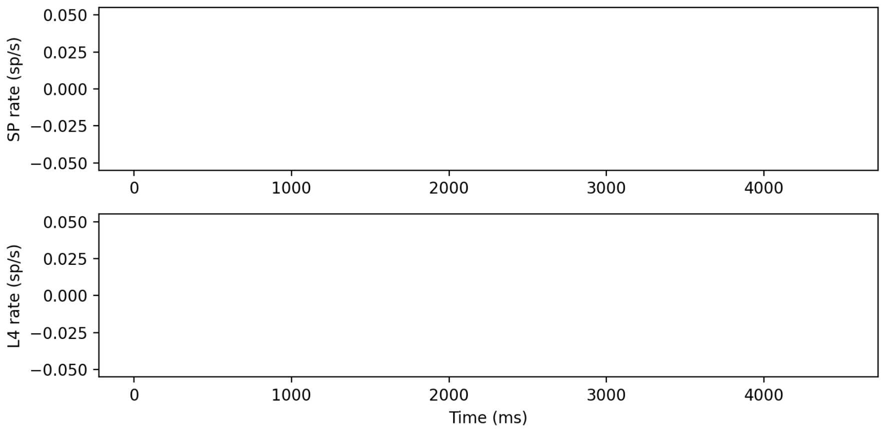

Figure 4: Q3: Example PSTHs for increased τ_{re} (here 1000 ms); 3000 and 10000 ms show even stronger sustained depression (see corresponding figures).

Q4: STDP with $P(S) = 0.9$, $P(D) = 0.1$

I enabled STDP on the three L4 synapses and ran a 60 minute sequence of randomly interleaved S and D stimuli (50 ms duration, 250 ms inter-stimulus interval) with $P(S) = 0.9$, $P(D) = 0.1$. Synaptic weights were sampled at each stimulus onset. Fig. 5 shows that the D→L4 weight gradually increases and eventually saturates, while the S→L4 weight tends to decrease or remain relatively lower. The SP→L4 synapse also strengthens but typically more moderately. This reflects that deviant D spikes are more effective at driving correlated post-synaptic L4 spikes under this input statistics, so STDP favors the deviant pathway despite its lower occurrence probability.

I then selected multiple time points along this trajectory (initial, early, mid, late, saturated) and froze the weights to construct verNOp models at each stage. For each such snapshot I re-ran the ODDBALL protocol and computed SP and L4 PSTHs (Fig. 6). Over learning, the L4 response to the deviant D in position 8 becomes progressively larger relative to the standards, reflecting the increased D→L4 weight; SP responses remain comparatively stable because its inputs are fixed.

Q5: STDP with $P(S) = P(D) = 0.5$

Finally, I repeated the 60-minute simulation with $P(S) = P(D) = 0.5$ and tracked the three L4 synapses (Fig. 7). In this symmetric case both S and D inputs are equally likely and the STDP drive is similar for S and D spikes. Accordingly, the S→L4 and D→L4 weights tend to converge to similar values, rather than favoring D as in Q4. The SP→L4 synapse also evolves but its final value is set by the balance between the thalamic inputs and its own STDP. Overall, equal stimulus probabilities lead to a more balanced representation of S and D in L4, which reduces the deviance selectivity that emerged under the 0.9/0.1 input statistics.

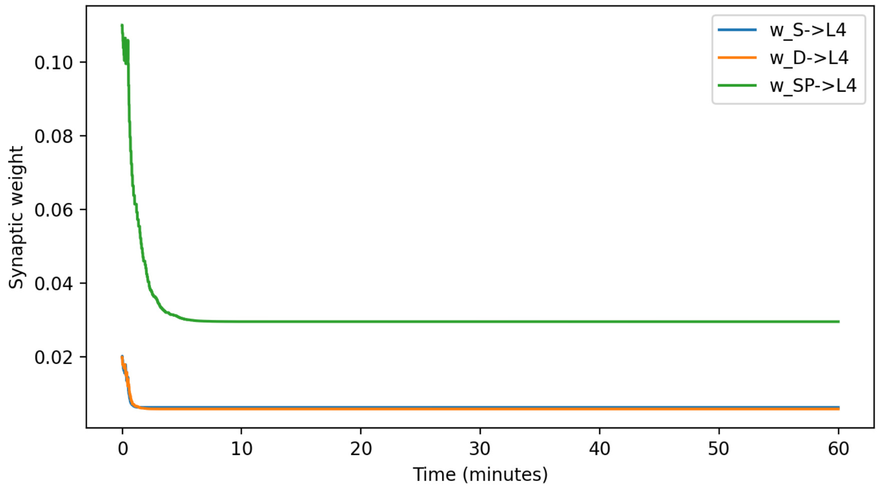

Figure 5: Q4: Evolution of Th(S)→L4, Th(D)→L4 and SP→L4 synaptic weights over 60 minutes with $P(S) = 0.9$, $P(D) = 0.1$.

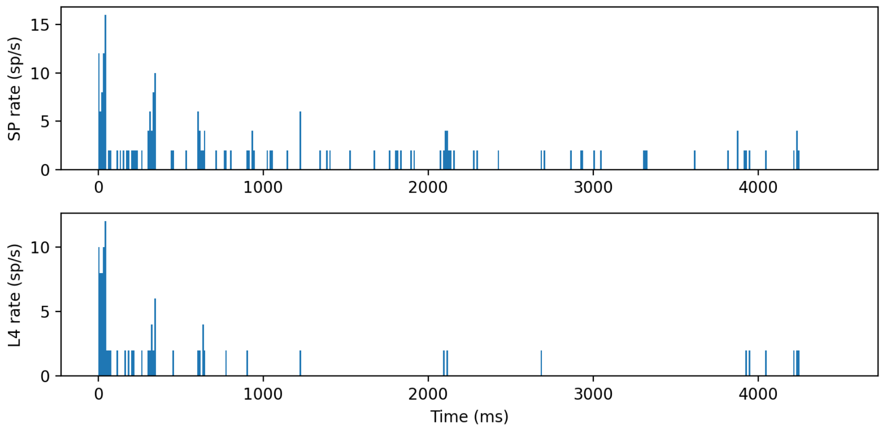

Figure 6: Q4: Example ODDBALL PSTHs at one snapshot in learning (later snapshots show further enhanced L4 response to the deviant; see additional probe figures).

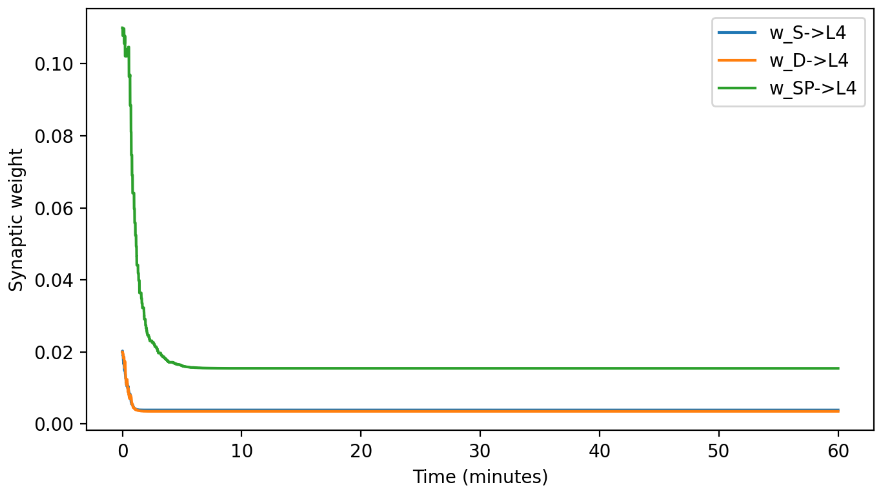

Figure 7: Q5: Synaptic weight evolution over 60 minutes with $P(S) = P(D) = 0.5$. S→L4 and D→L4 weights tend to converge.