Computational Neuroscience Extended Coursework – Spike Trains

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Question 1: Homogeneous and Inhomogeneous Poisson Process

(i) Write code to generate spikes using a Poisson process and sample a homogeneous Poisson spike train with firing rate of 35 Hz.

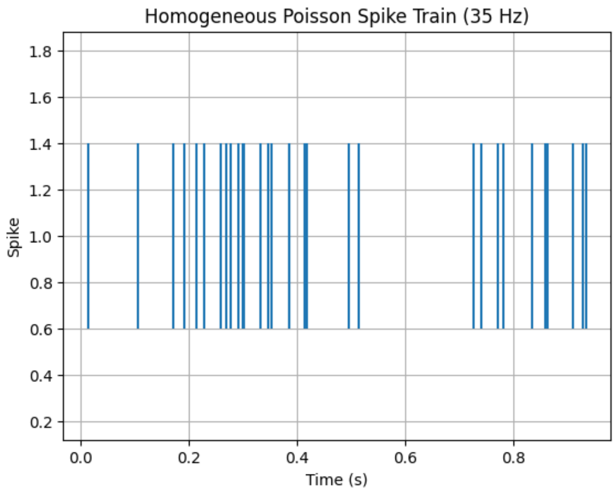

Figure 1: Homogeneous Poisson Spike Train (35Hz) within a second, a total of 35 events occured.

(ii) Extend your code to sample from an inhomogeneous Poisson neuron that has a 5 ms absolute refractory period, keeping the overall firing rate at 35 Hz (35 spikes per second).

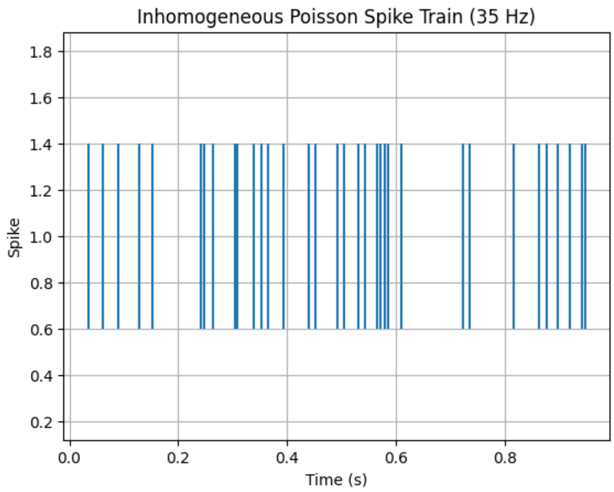

Figure 2: Inhomogeneous Poisson Spike Train (35Hz) within a second, a total of 33 events occured.

(iii) Fano Factor and ISI Coefficient of Variation for Homogeneous and Inhomogeneous neurons

Bin Width (ms)	Homogeneous Poisson Fano Factor	Inhomogeneous Poisson Fano Factor
10	0.9638	0.7744
50	1.1827	1.0175
100	1.8431	1.1852

Figure 3: Fano Factor of different Bin Widths for Homogeneous and Inhomogeneous Poisson Process

Homogeneous Poisson Coefficient of Variation	Inhomogeneous Poisson Coefficient of Variation
0.8874	1.0703

Figure 4: Coefficient of Variation for Homogeneous and Inhomogeneous Poisson Process

(iv) ISI coefficient of variation and spike-count Fano factor in 100 ms bins change over refractory periods ranging from 0 to 28 milliseconds

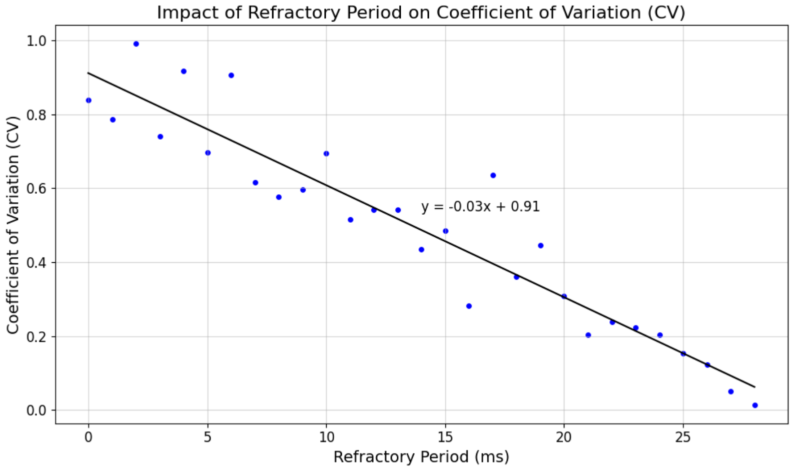

Figure 5: Coefficient of Variation against Refractory Period showing a downward trend.

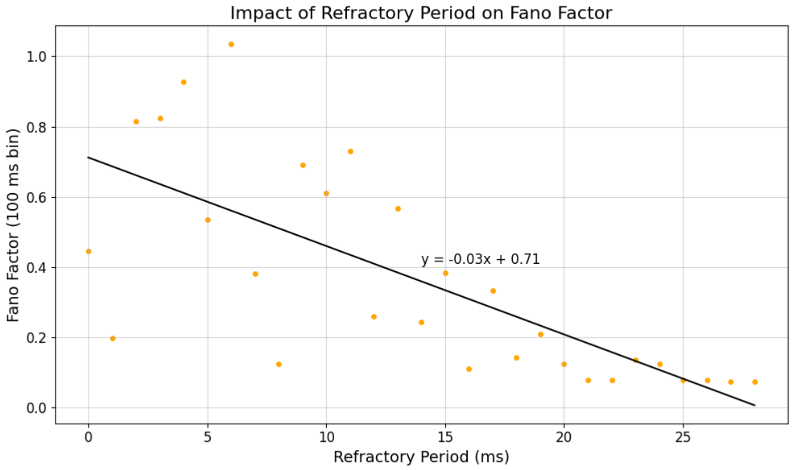

Figure 6: Fano Factor of 100ms bin, against Refractory Period, showing a generic downward trend.

Question 2: Rob de Ruyter van Steveninck Fly H1 Neuron Data Spike Train

Bin Width (ms)	Fly H1 Neuron Fano Factor
10	1.117
50	2.9299
100	4.1033

Figure 7: Fano Factor of Fly H1 Neuron across different Bin Widths

Fly H1 Neuron Coefficient of Variation
2.0086

Figure 8: Coefficient of Variation of Fly H1 Neuron

The spike train of the fly H1 neuron showcases more variability than what is expected for a homogeneous process as its value of Fano Factor exceeds 1 for all bin widths, due to its spike count variance is higher than its spike count mean. This can be due to rate modulation, where the firing rate of the neuron changes in response to the white noise stimulus.

Question 3: Experimentation of Poisson Process Synaptic Inputs to Leaky Integrate and fire Neuron

Considering a Leaky Integrate and Fire (LIF) Neuron as described in Coursework 3, with the same parameter values,

$$\tau_m \frac{dV}{dt} = E_L - V + R_m I(t) \qquad - (1)$$

$$\tau_m \frac{dV}{dt} = E_L - V + R_m\big(W_{exc} S_{exc}(t) R_{ei} - W_{inh} S_{inh}(t)\big) \quad - (2)$$

Additional parameters added to the Leaky Integrate and Fire Neuron(LIF) model:

$W_{exc} = \text{Excitatory } Input\ Weight$

$S_{exc}(t) = Poisson\ \text{Excitatory } Spike$

$W_{inh} = Inhibitory\ Input\ Weight$

$S_{inh}(t) = Poisson\ Inhibitory\ Spike$

For the experimentation, the synaptic input, $I(t)$, is replaced by a mix of excitatory and inhibitory inputs modelled by Poisson processes as seen in (2). We will adjust the additional parameters while keeping the overall post synaptic firing rate constant, which will be 100Hz with 5Hz tolerance.

Key adjustments will be mainly on the rate of firing of excitatory and inhibitory inputs, changing the weight of excitatory inputs to compensate to surpass the voltage threshold enabling the post synapse neuron to reach the target firing rate of 100Hz.

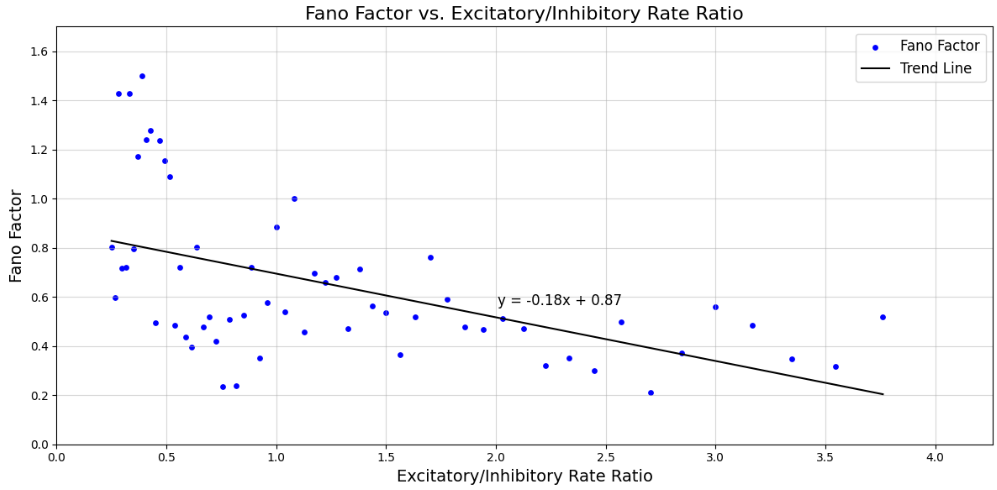

Figure 9: Fano Factor against Excitatory/Inhibitory rate ratio showing a decreasing trend suggesting that excitatory-dominant synaptic input causes post synapse spiking behaviour to be more consistent.

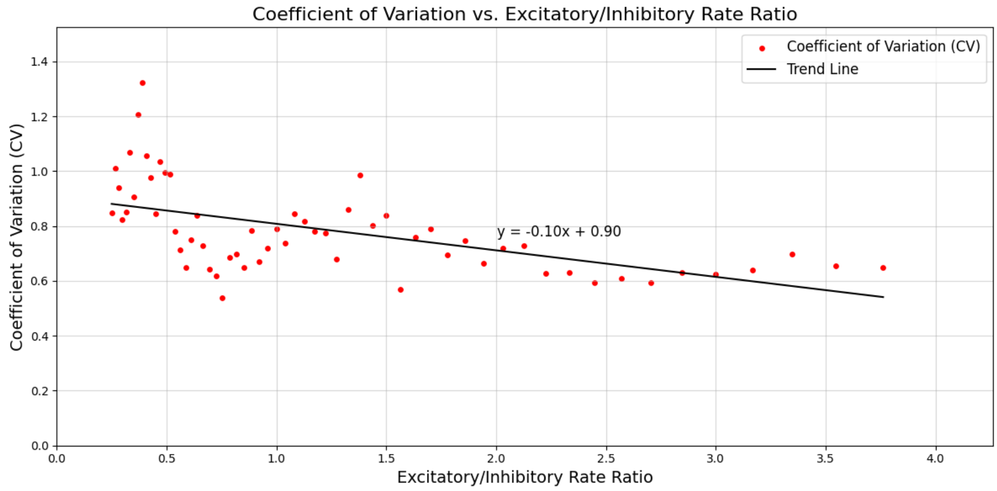

Figure 10: Coefficient of Variation(CV) against Excitatory/Inhibitory ratio showing a decreasing trend suggesting that excitatory-dominant synaptic input causes Inter-Spike Intervals to become more regular, showing a stabilization of neuronal output.

By modelling pre-synaptic neurons spiking as Poisson processes, it causes the input current to the LIF neuron to be Poisson-like as it is dependent on the Poisson-distributed spike trains from pre-synaptic neurons as seen as equation (3). Through the experiment, the event of membrane voltage exceeding the voltage threshold, -40mV, depends on if there is a excitatory spike as excitatory weights are adjusted to ensure overall firing rate of the LIF neuron remains constant (with 5 Hz tolerance). In conclusion, the results indicates that by modelling pre-synaptic neurons spiking as Poisson processes, an **increase in the E/I rate ratio**, along with adjusted excitatory input weights to maintain a constant firing rate, leads to **decrease in variability in post-synaptic neuronal output**

Question 4: Spike Triggered Average

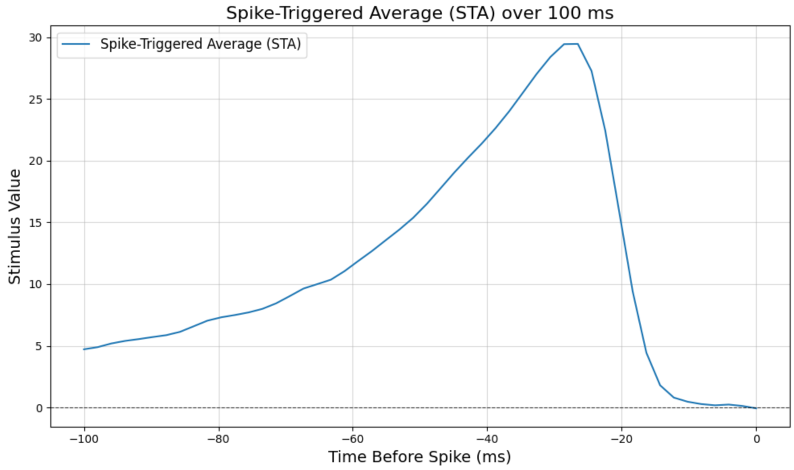

Figure 11: Spike triggered average over a 100 ms window with peak around 30ms before spike

Question 5: Stimulus Triggered by Pairs of Spikes

The role of refractory period restricts pairs with shorter intervals unless given strong stimulus. Adjacent pairs have oscillating patterns while the non-adjacent pairs have smoother and broader patterns, this might be due to the refractory period timing constraints on adjacent pairs. These are evident in these findings as such:

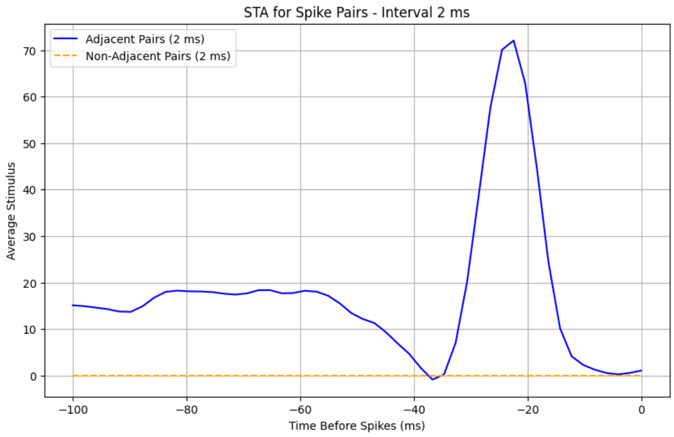

Figure 12: Average Stimulus before spike for pairs of 2ms interval. No non-adjacent pairs exist with 2ms separation as sampling rate is 500Hz. Strong stimulus is seen around 23 ms before spike occurs across all adjacent pairs.

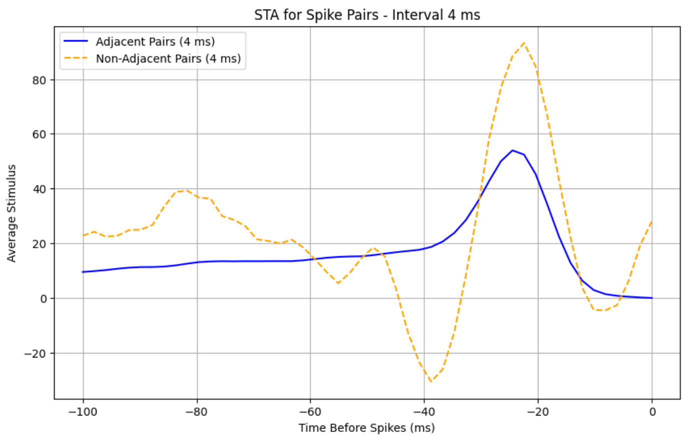

Figure 13: Average Stimulus before spike for pairs of 4ms interval. Non-adjacent pairs seem to require stronger stimulus than adjacent pairs evident in the stronger peak.

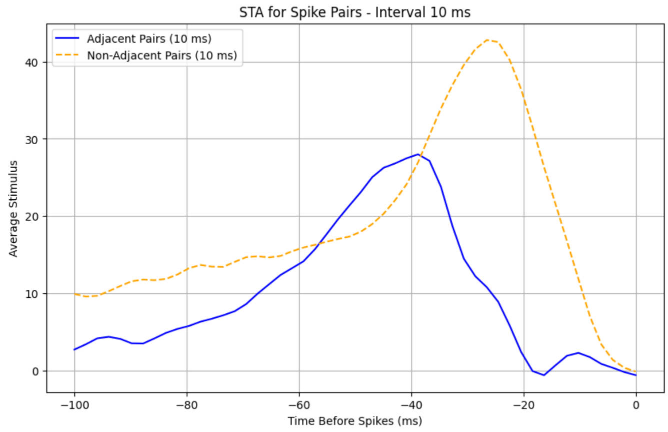

Figure 14: Average Stimulus before spike for pairs of 10ms interval. Non-adjacent pairs exhibit a sharper and stronger STA peak around 30 ms before the spike. However, for adjacent pairs exhibit a weaker STA peak around 40ms before spike, average stimulus needed for adjacent pairs occur earlier compared to non adjacent pairs.

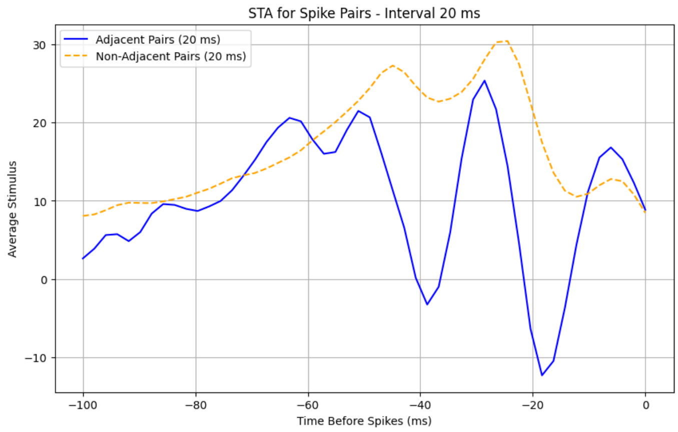

Figure 15:Average stimulus before spikes for pairs with a 20 ms interval. Non-adjacent pairs exhibit a more pronounced STA peak around 50ms and 30ms before the spike. Adjacent pairs show a weaker but oscillatory STA pattern, with multiple smaller peaks.

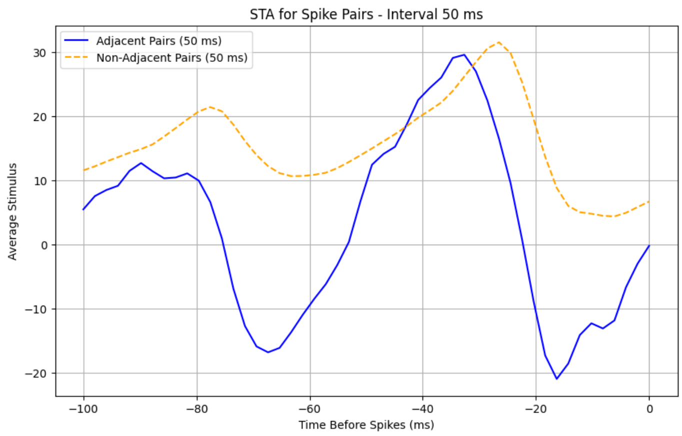

Figure 16: Average stimulus before spikes for pairs with a 50 ms interval. Non-adjacent pairs show a stronger and smoother STA curve, with a broad peak occurring around 30 ms before the spike. Adjacent pairs exhibit a more oscillatory pattern with multiple peaks

Question 6: LIF and Spike Triggered Average

Considering a Leaky Integrate and Fire (LIF) Neuron as described in Coursework 3, with the same parameter values,

$$\tau_m \frac{dV}{dt} = E_L - V + R_m I(t) \qquad -(1)$$

$$I(t) = I_{dc} + W_{stim}\, S(t) \qquad -(3)$$

Additional parameters added to the Leaky Integrate and Fire Neuron(LIF) model as seen in (4):

$I_{dc} = Direct\ Current$

$W_{stim} = Weight\ of\ Stimulus$

$S(t) = Stimulus$

For the experimentation, the synaptic input, $I(t)$, is replaced by the sum of direct current and the stimulus at a certain time with its weightage as seen in (4). By adjusting the stimulus weightage and the membrane time constant,

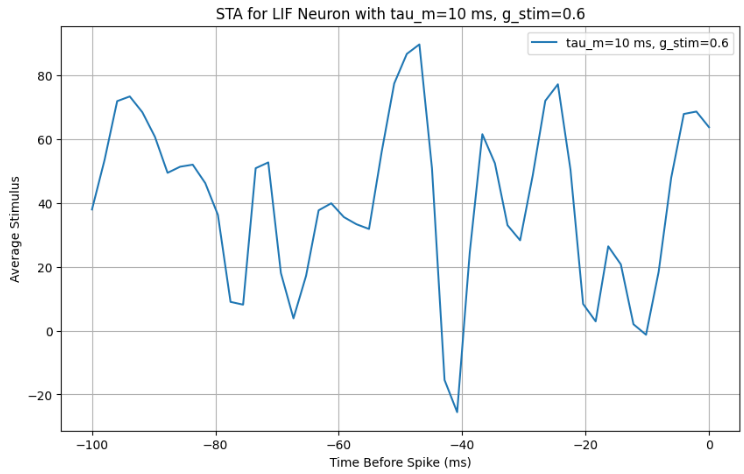

Figure 17: Spike-Triggered Average (STA) for a Leaky Integrate-and-Fire (LIF) Neuron with τm=10 ms and gstim=0.6.

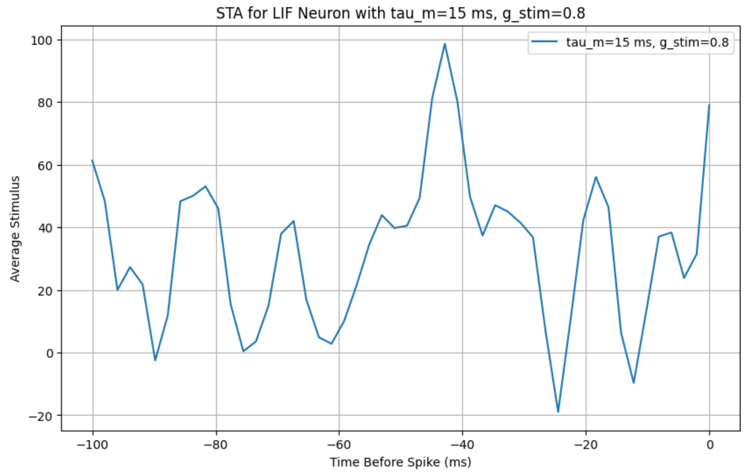

Figure 18: Spike-Triggered Average (STA) for a Leaky Integrate-and-Fire (LIF) Neuron with τm=15τm=15 ms and gstim=0.8gstim=0.8.

Comparing to the previous results, both results show oscillating patterns, indicating sensitivity to high-frequency stimulus features. However, LIF results highlights its dependence on the **immediate stimulus**, with peaks near 0 ms.