In the name of God

Sharif University

Electrical Engineering Department

Sharif Brain Center

Advanced Neuroscience Course

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Homework 1

Neural Code 1

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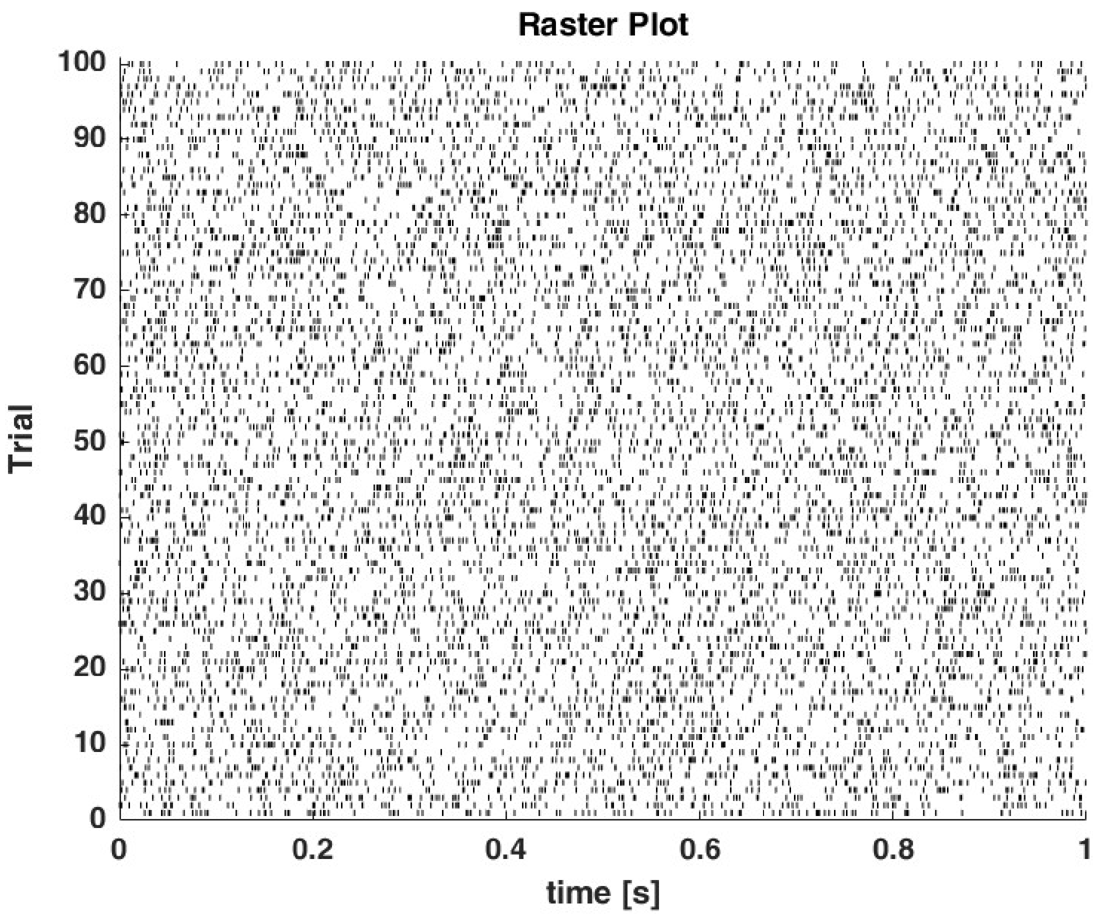
In this homework, we are trying to get results similar to (Softky & Koch, 1993), by neuronal simulation.

All codes are available in the directory.

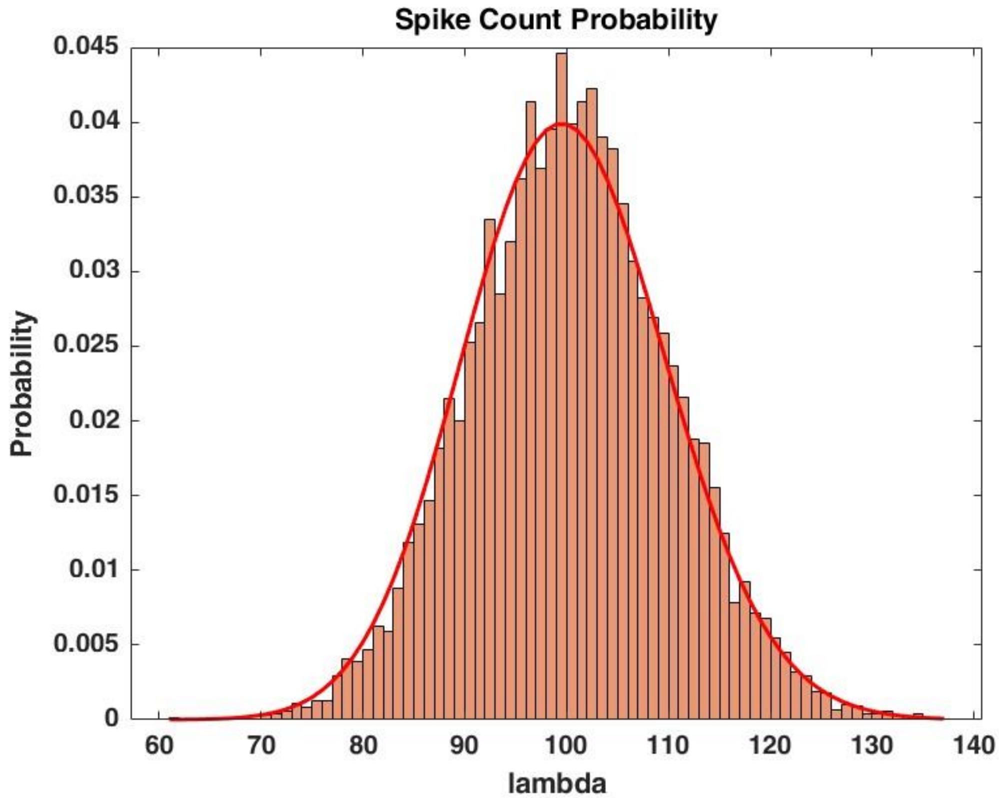
Part 1. Integrate and Fire Neuron

Part 1. a) I generated a Poisson spike train using `PoissonSpikeGen` function. You can see the Raster plot of this generated spike train below for 100 trials.

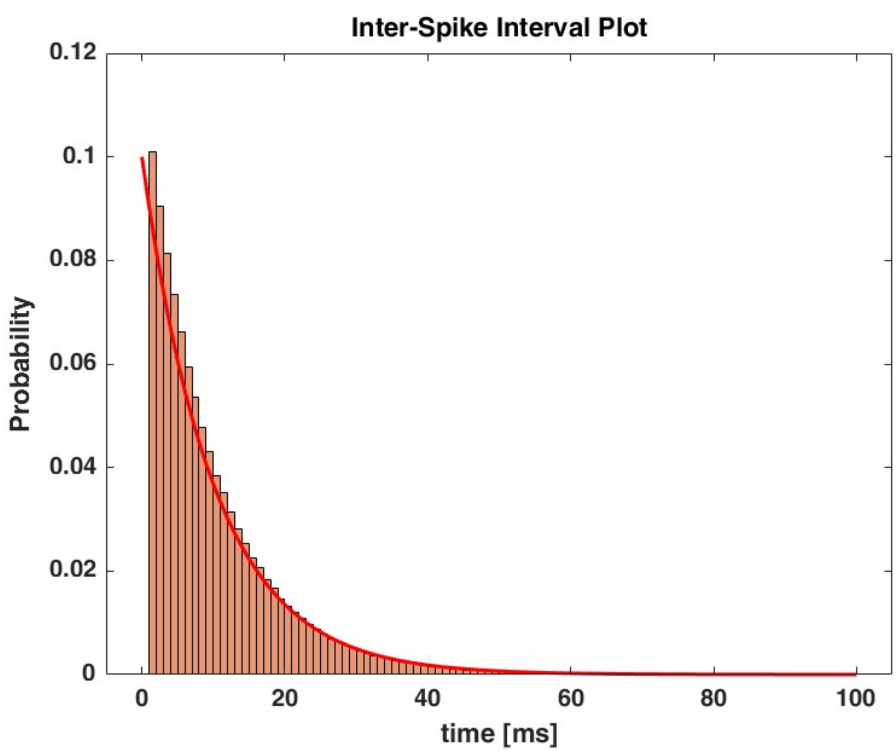


Part 1. b) Here I generated spike count probability histogram of our 10000 Poisson spike trains and superimpose it with Poisson PDF. For this, we have to use `SpikeCountProb` function which plots calculate spike count probability histogram and appropriate Poisson PDF.

By choosing larger nTrials, your results will converge to theoretical models.



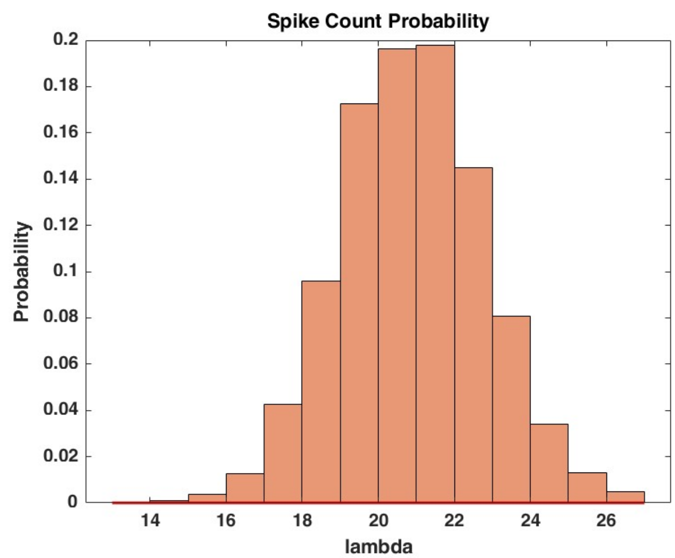
Part 1. c) Inter-Spike Interval histogram is plotted and superimposed with an exponential PDF.

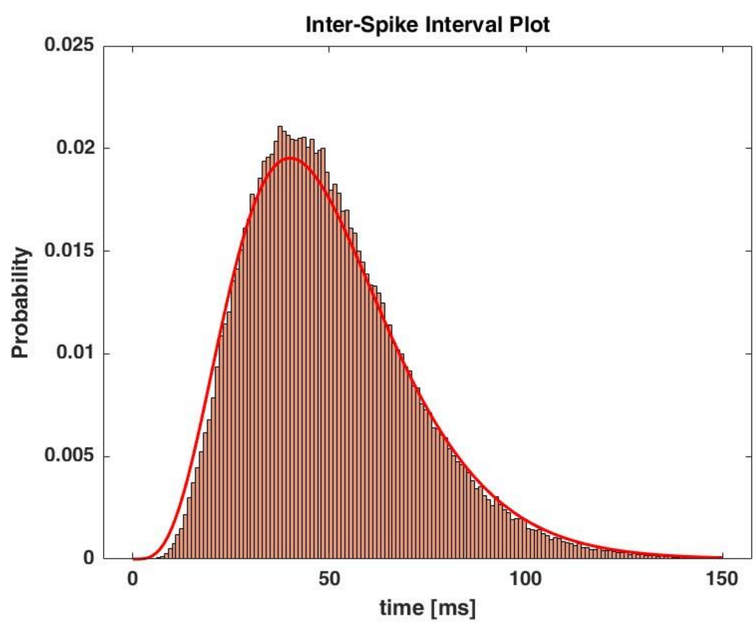


Part 1. a-c for Renewal) At first, I deleted every spike but k-th spikes. For choosing k it's good to get an idea from the values of N_{th} in the paper. As you can see in results below, the spike count probability mean is decreased and more important, small ISI values are less often. So the PDF of ISI is changed to Gamma distribution. From (Dayan & Abbott, 2001) the gamma distribution function for ISI is

$$[\tau] = \frac{r(r\tau)^k \, e^{-r\tau}}{k!}$$

by using the above eq. we can superimpose the ISI histogram with appropriate PDF.





Part 1. d) The value of C_V for Poisson spike trains should theoretically be 1. But due to non-infinite trial numbers and durations, it's very close to 1, varying between 0.94 to 0.98 in my simulations. For the renewal process, the value of C_V decreases to about 0.45, the reason is that by deleting every spike but the k-th, we are making the spike train more regular and the value of C_V will decrease.

Part 1. e) Let t_P be the ISIs of spike trains, and t_R be the ISIs of spike trains after renewal process. So the relationship between them is

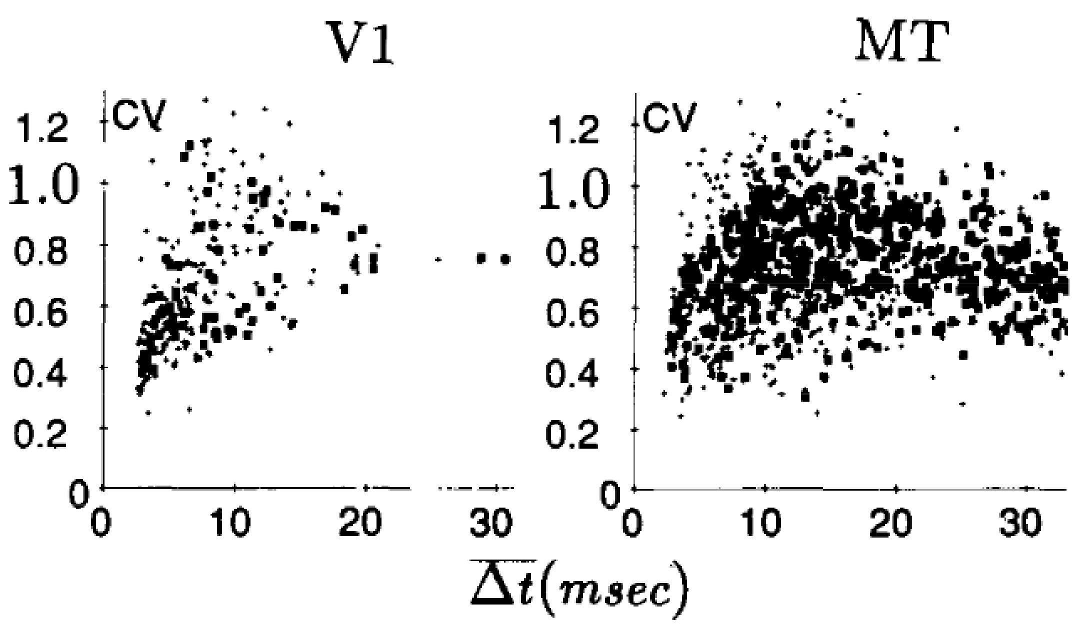
$$t_R = \sum_{i=1}^{k} t_p^i$$

Since t_P is exponential,

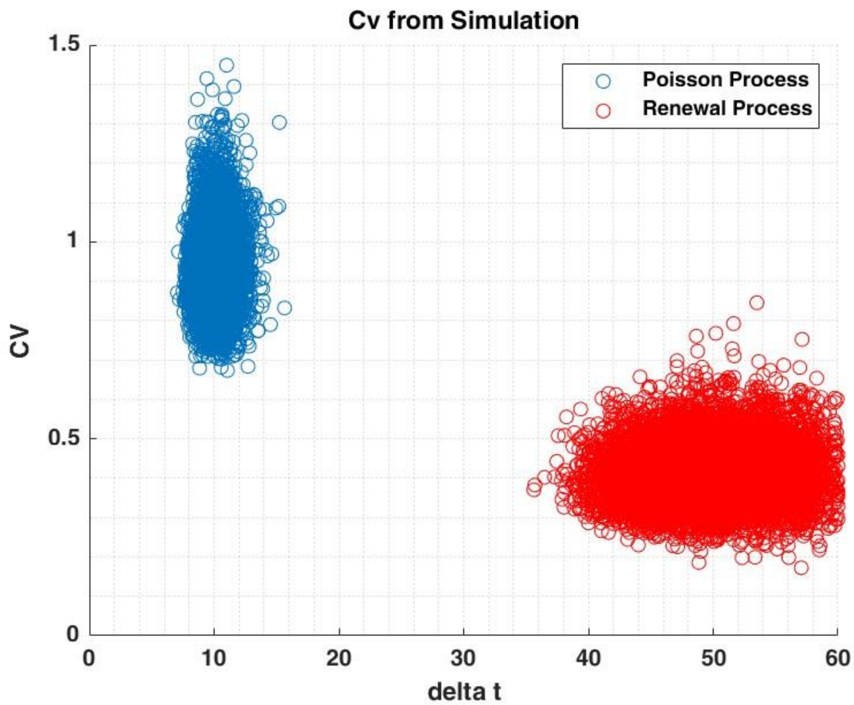
$$mean(t_R) = \frac{k}{\lambda}, std(t_R) = \left(var(t_R)\right)^2 = \frac{\sqrt{k}}{\lambda}$$

$$C_v = \frac{std(t_R)}{mean(t_R)} = \frac{1}{\sqrt{k}}$$

Part 1. f) Below you can see the variability of neurons (C_V) in areas V1 and MT (Softky & Koch, 1993).

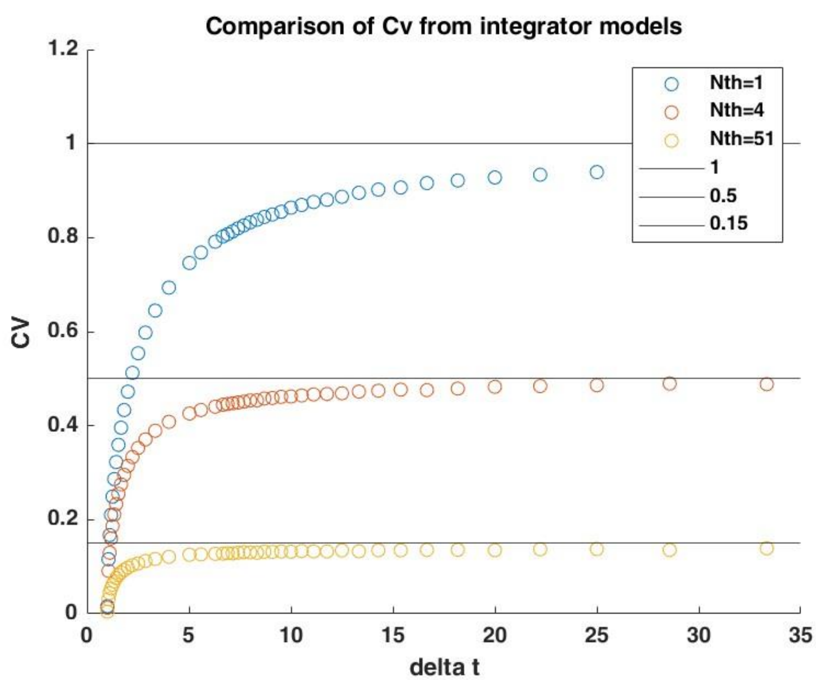


In the next figure, I plotted the variability of simulated neurons.



It is obvious that real neurons have more variability, and the simulated neuron after the renewal process is much more regular and has lower entropy which was exactly the puzzle Softky & Koch said in their paper. Actually, according to our models, the variability or entropy, (the amount of information) of each neuron increases dramatically after each synapse.

Part 1. g) Reconstruction of figure 6 in the paper from our simulation data.

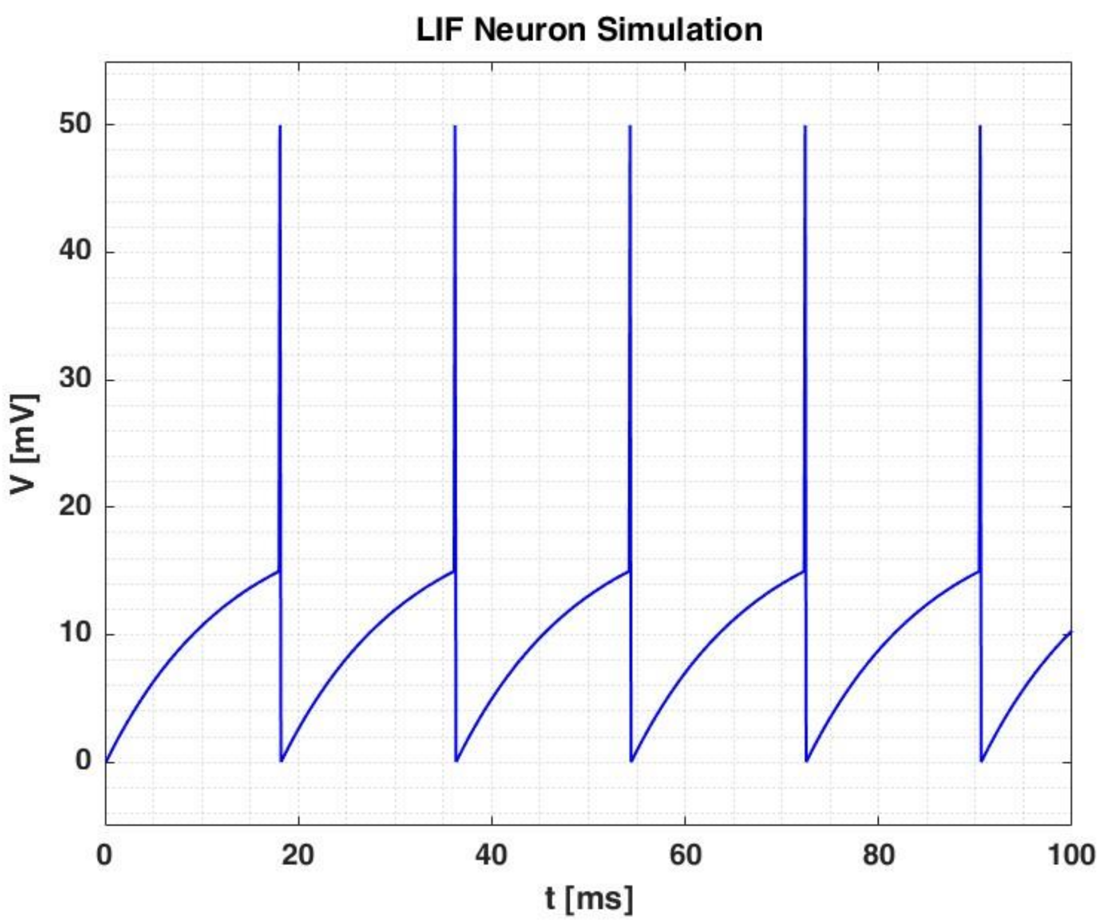


Part 2. Leaky Integrate and Fire Neuron

Part 2. a) Here a Leaky Integrate and Fire (LIF) neuron is simulated using:

$$\tau_m \frac{dv}{dt} = -v(t) + RI(t)$$

The simulation is done by LIFNeuron function. I've wrote this function more general than what is needed for this homework and this part. So resring potential (E_L) is different than reset potential. It also includes refactroy period which is 0 in this part. Below you can see simulation for 100ms.

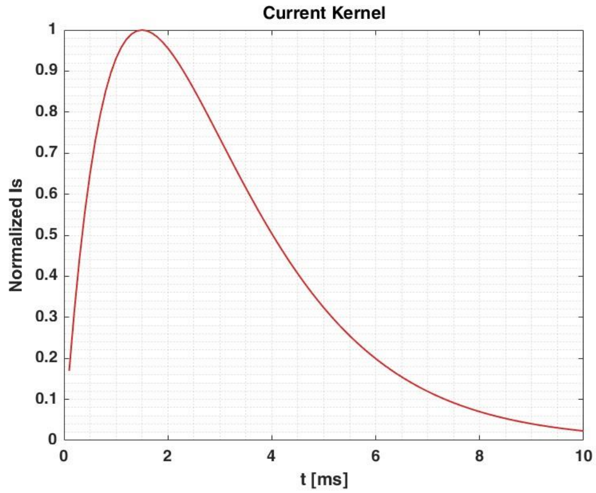


Part 2. b) The solution is below:

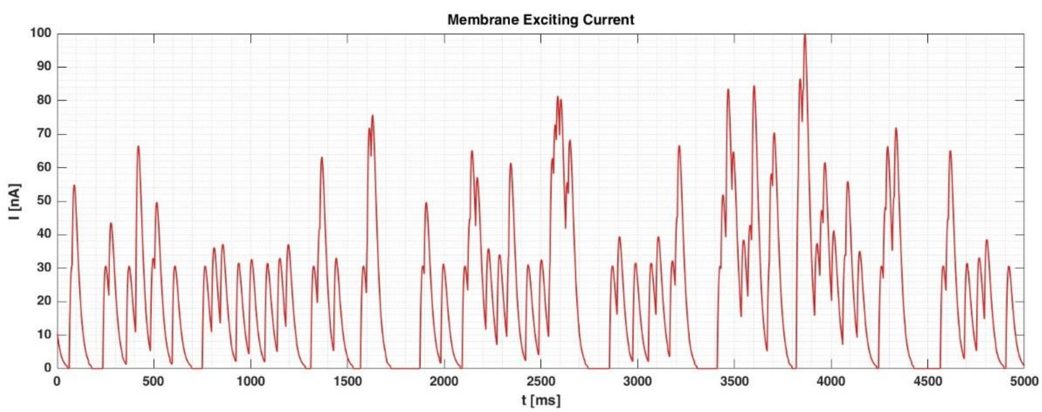
$$v(t) = RI\left(1 - e^{\frac{-t}{\tau_m}}\right), v(t_{th}) = v_{th} \to t_{th} = -\tau_m \ln\left(1 - \frac{v_{th}}{RI}\right)$$

$$T = t + \Delta\tau_r \to fr = \frac{1}{T} = \frac{1}{-\tau_m \ln\left(1 - \frac{v_{th}}{RI}\right) + \Delta\tau_r}$$

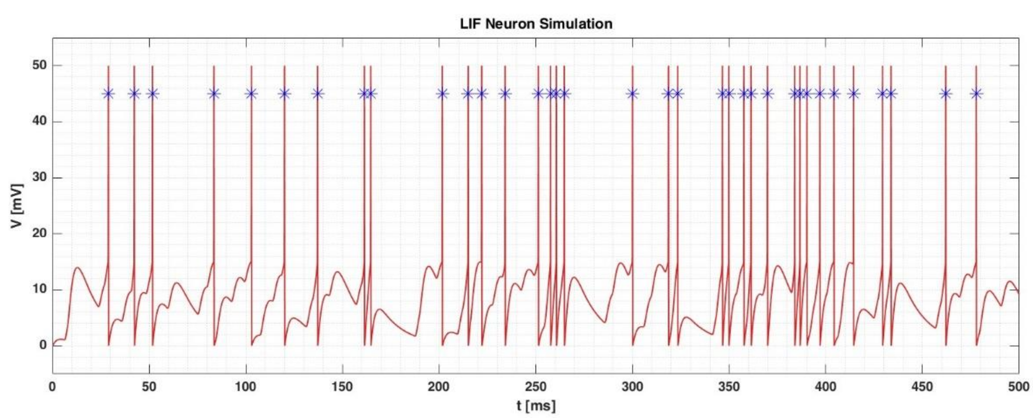
Part 2. c) Here we will use a time-varying current to excite neurons. Below is the shape of EPSP kernel. Make sure to choose the appropriate part of exp function as kernel!



Now you can see the constructed excitation current.

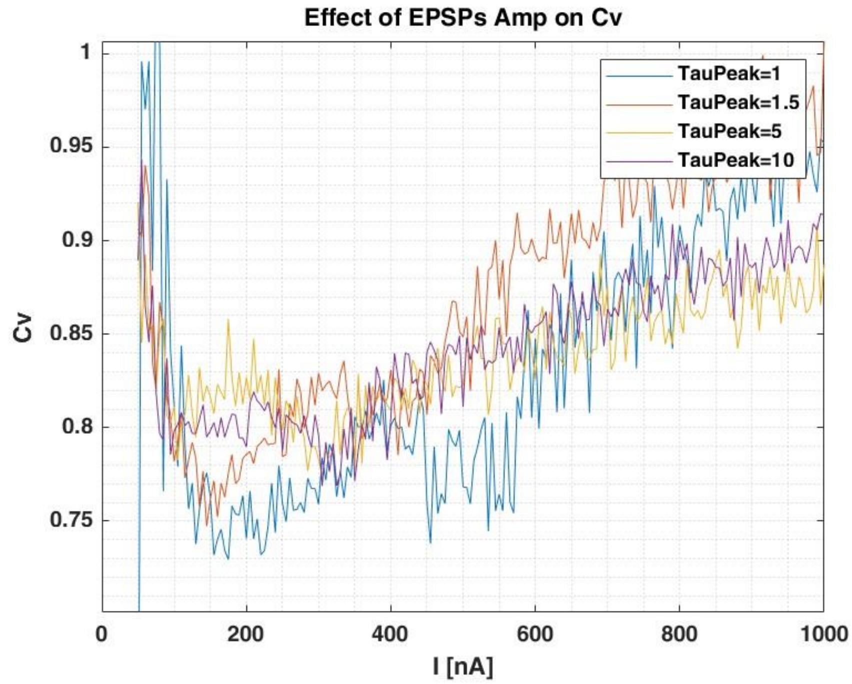


And the resulting membrane voltage with the spikes marked with *.

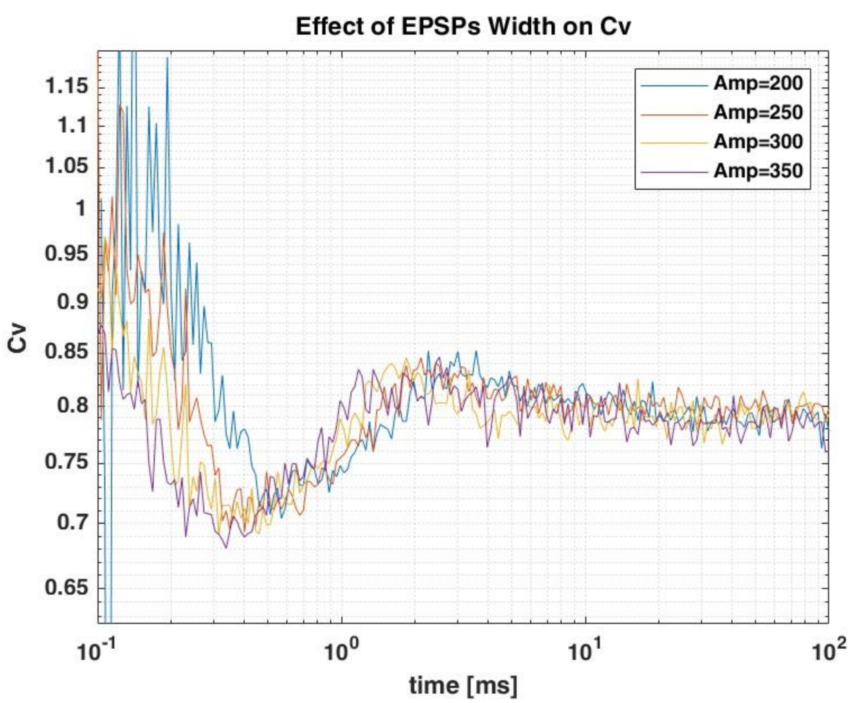


Now we can examine the C_V.

The relation between C_V and EPSPs amplitude (multiplier of current kernel, `IStim`) is shown below for four different values of `TauPeak` (width of current kernel and EPSPs). Choosing good parameters is very important for obtaining good results.

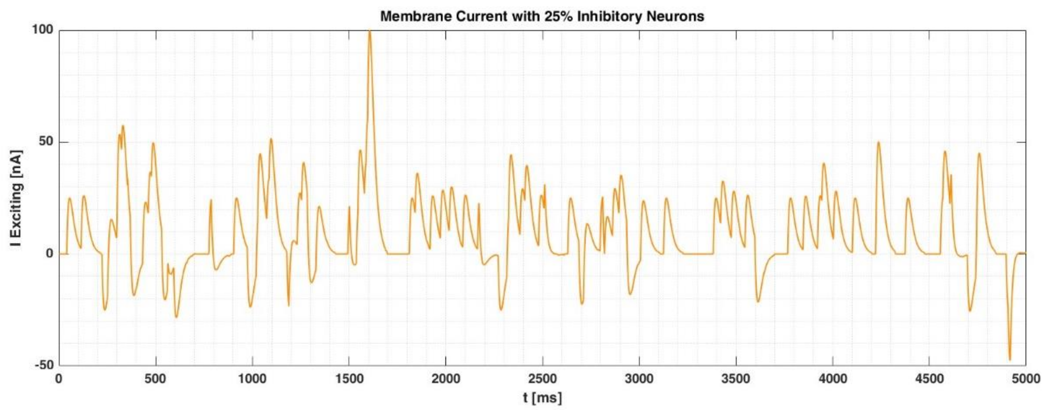


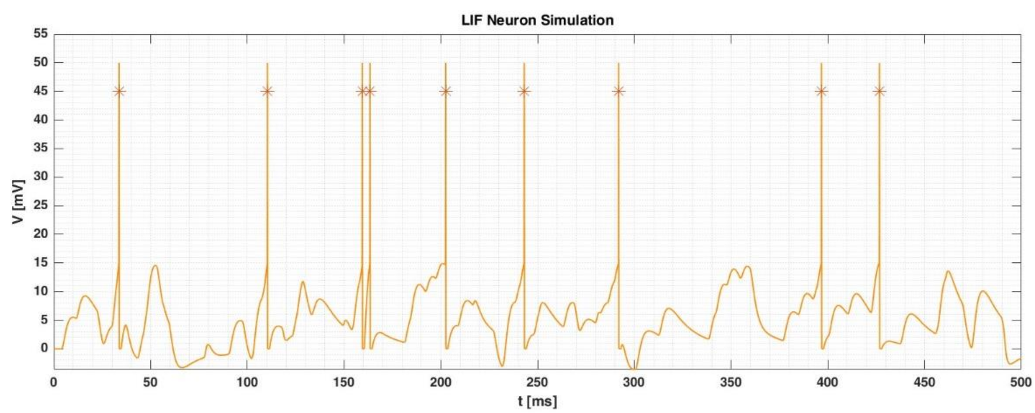
The relation between C_V and EPSPs widths (`TauPeak`) is shown below for four different values of `IStim` (amplitude of current kernel and EPSPs). Here I used log plotting to get similar results to above. The reason is that `TauPeak` is in exp.



Part 2. c) Here we turn some of excitatory neurons to inhibitory neurons to see the effect of inhibition. The ratio of excitatory to inhibitory neurons in different brain areas is between 3:1 and 9:1 (Braitenberg & Schüz, 1998). Here we turned 25% of excitatory neurons to inhibitory. So ration is 4:1.

Below you can see that number of spikes decreased.





References:

Braitenberg, V., & Schüz, A. (1998). *Cortex: Statistics and geometry of neuronal connectivity* (2nd thoroughly rev. ed). Springer.

Dayan, P., & Abbott, L. F. (2001). *Theoretical neuroscience: Computational and mathematical modeling of neural systems*. Massachusetts Institute of Technology Press.

Softky, W., & Koch, C. (1993). The highly irregular firing of cortical cells is inconsistent with temporal integration of random EPSPs. *The Journal of Neuroscience*, *13*(1), 334–350. https://doi.org/10.1523/JNEUROSCI.13-01-00334.1993