In the Name of God

Foundations of Neuroscience

Homework_4 Report

Dr. Ghazizadeh

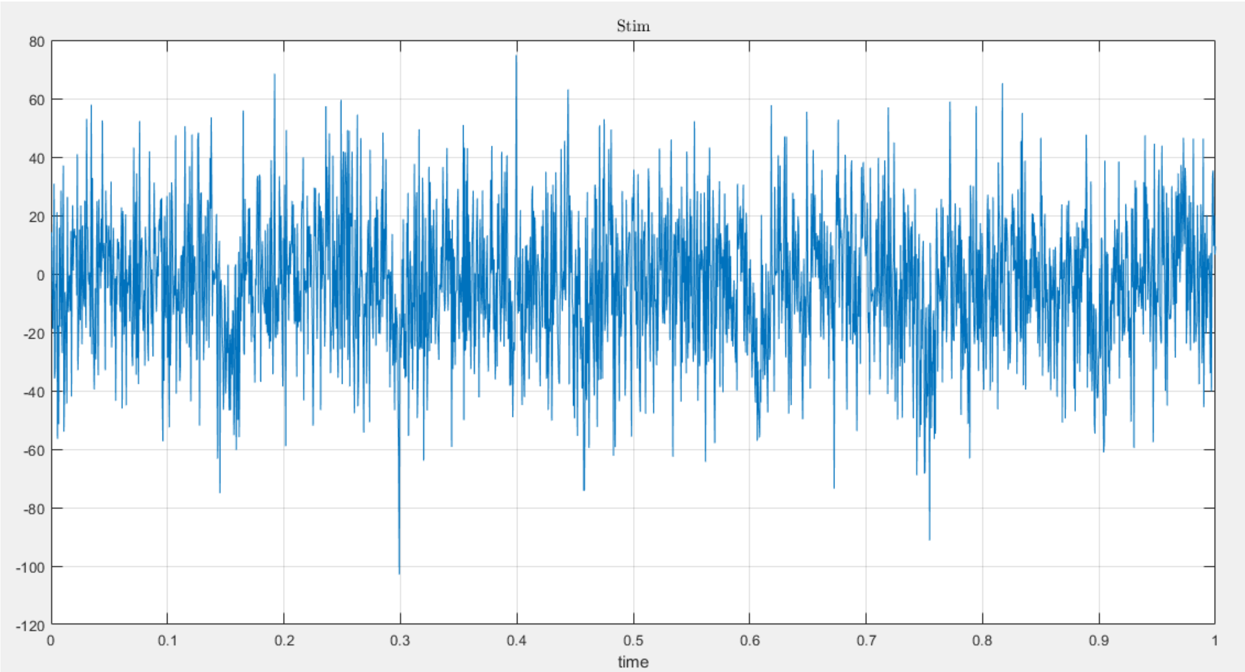
Armin Panjehpour – 98101288

شماره سوالات و شماره صفحه 2 سوال اول اشتباه هست صرفا.

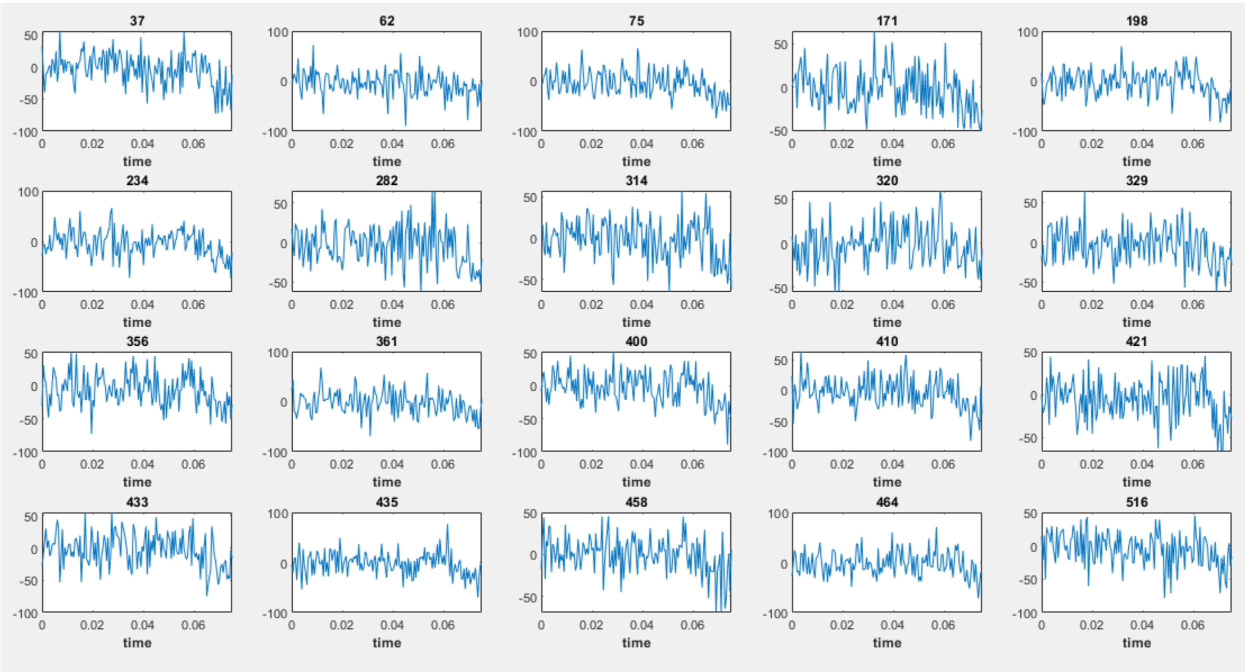
3- Spike-Triggered Average:

3.1 –

first second of Stimulus signal:



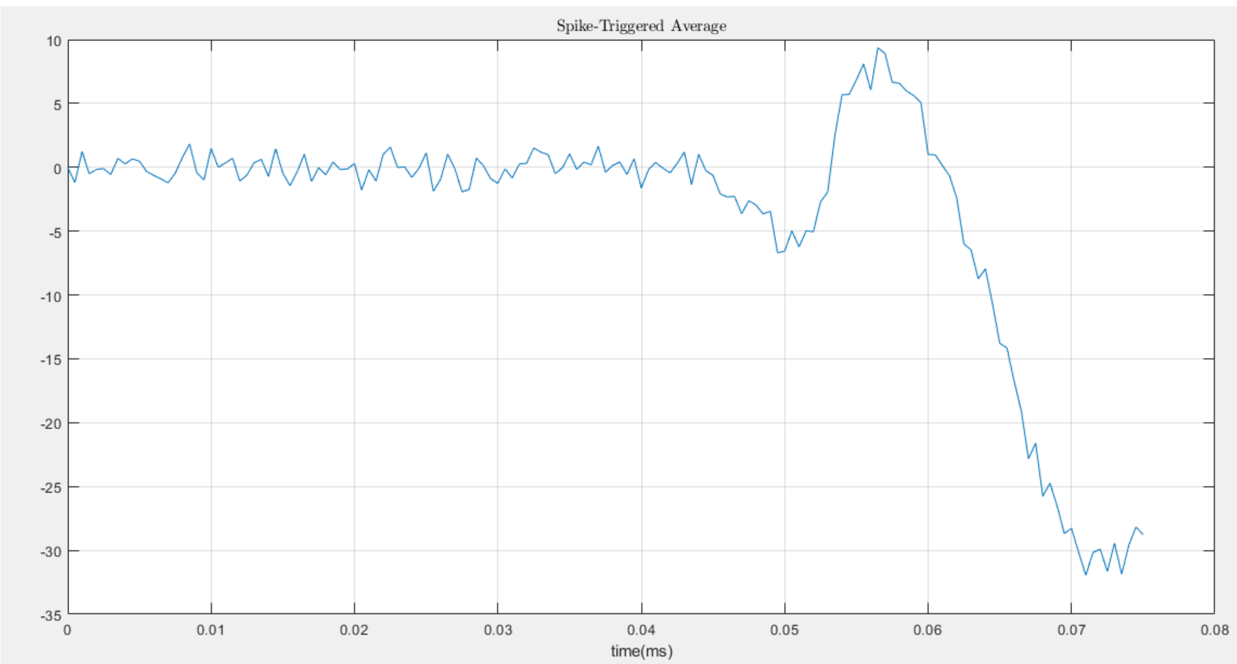
3.2 –



We have 75ms of stimulus signal before 20 times of neuron spiking that has been randomly chosen throw out 598 spikes.

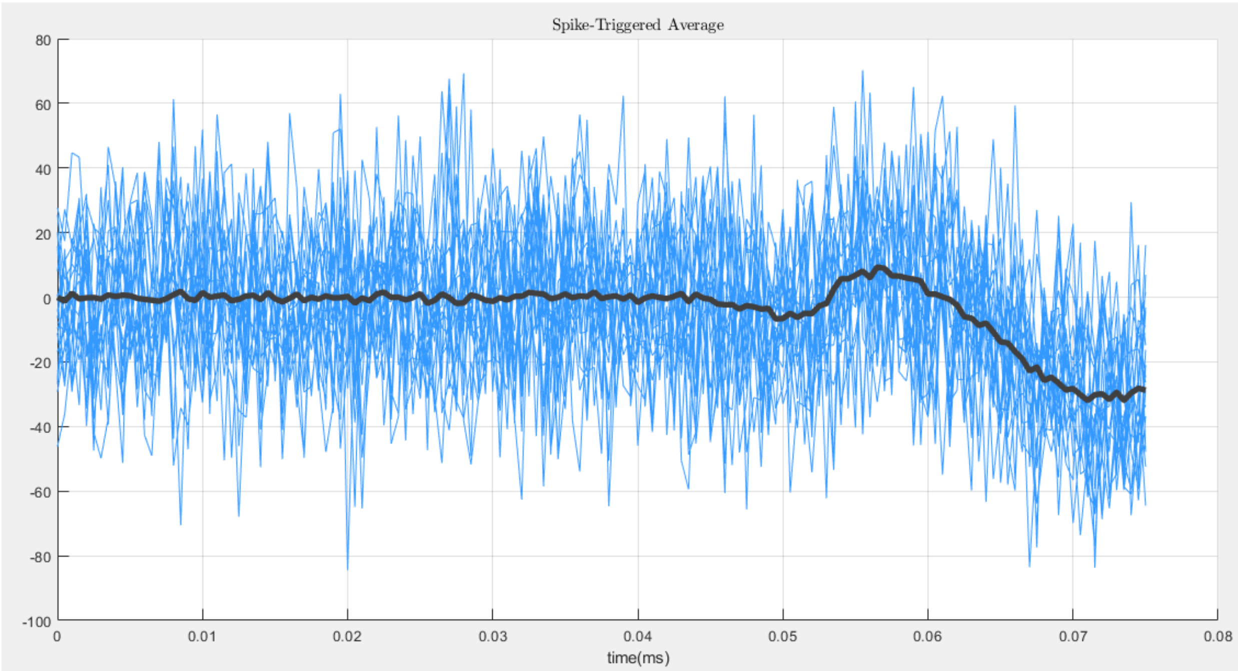
It can be concluded from the plots that during the 75ms before the neuron spikes, the stimulus signal is at first around zero about 50ms. It goes up and down but it doesn't have the value to make the neuron spikes. But after that its value will increase and makes the neuron spike and after the spike it`s value will decrease as we can see and it goes to negative.

3.3 –



As we can see, the Spike-Triggered average is showing us the pattern that we were seeing in 20 spikes in the previous part. At first the average of stimulus signal is around zero and after that it will reach a threshold and the neuron spikes and then it decreases.

3.4 and 3.5 –

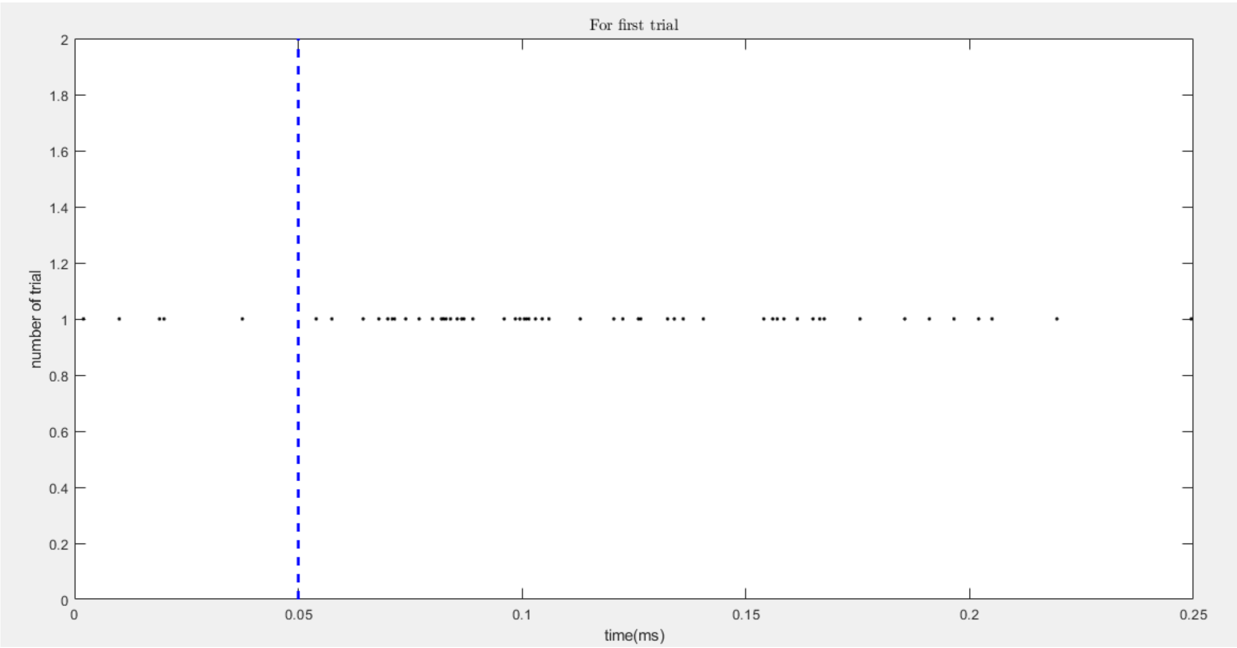


Here we can see the spike of the neuron and the stimulus signal before 20 spikes and we can see the average of them that is changing like the spike-triggered average. So the estimated time for the neuron to spike is about 50ms. Actually, the neuron will spike when all the pre-synaptic neurons spike and it takes about 50ms. In the first 50ms, all neurons won`t spike together and that`s why we don`t have the Spike triggered average sooner.

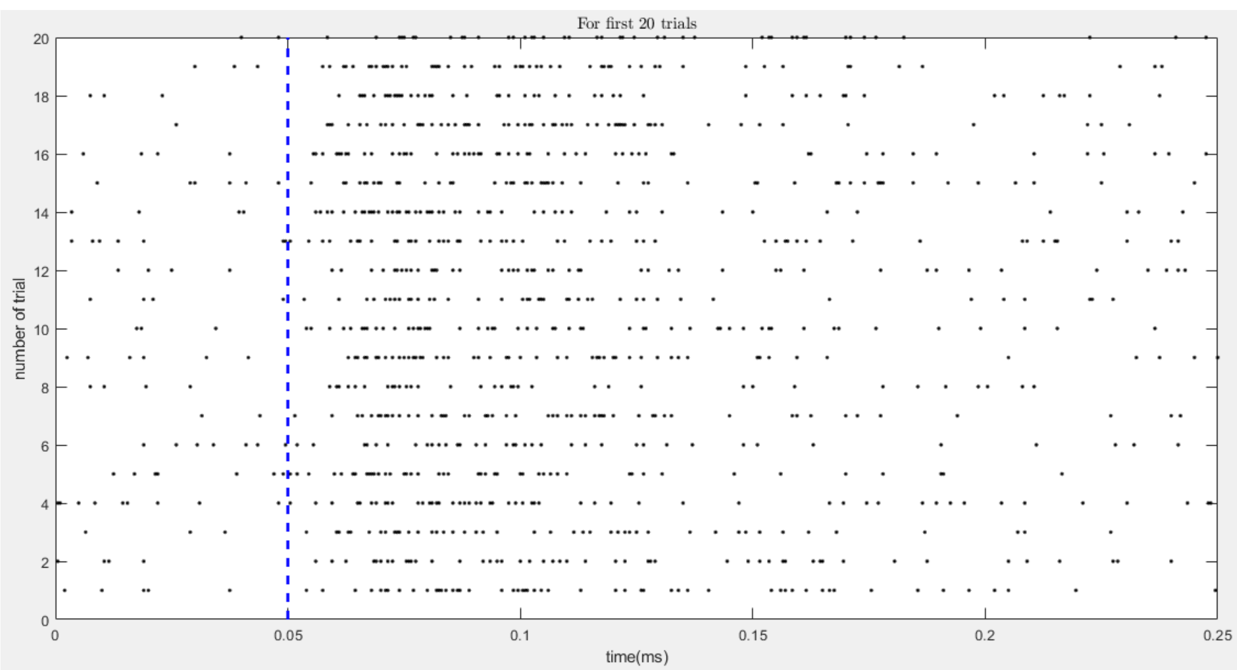
4- Raster Plot and PETH:

4,1 –

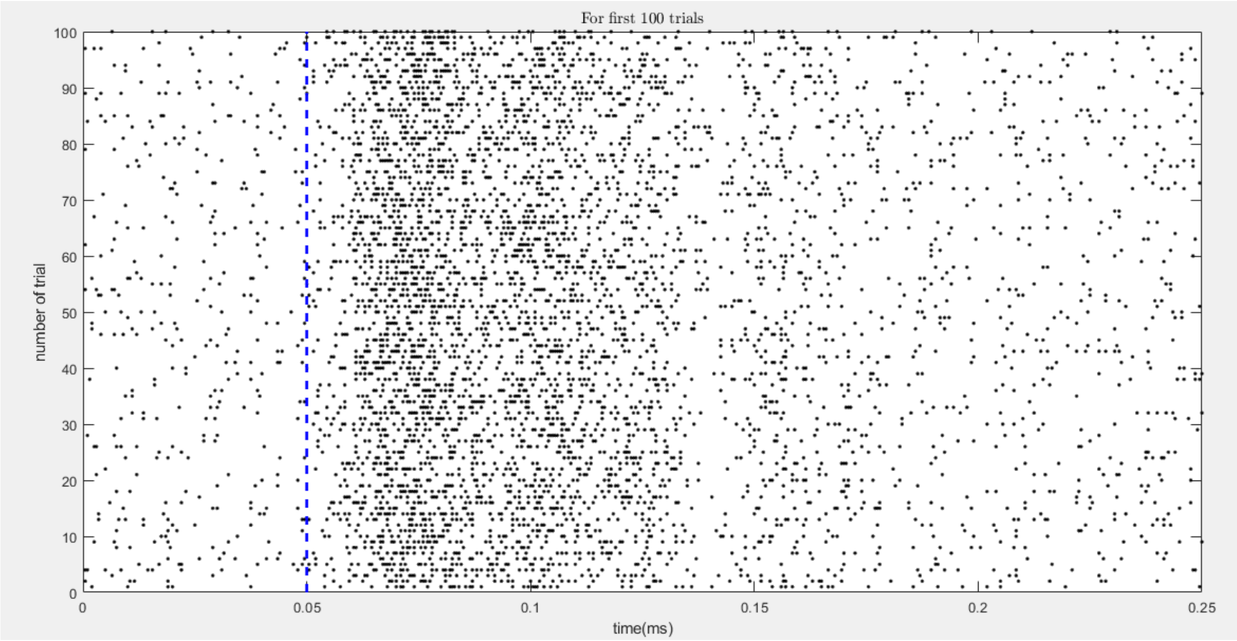
-for first trial:



-for first 20 trials:



-for all trials:



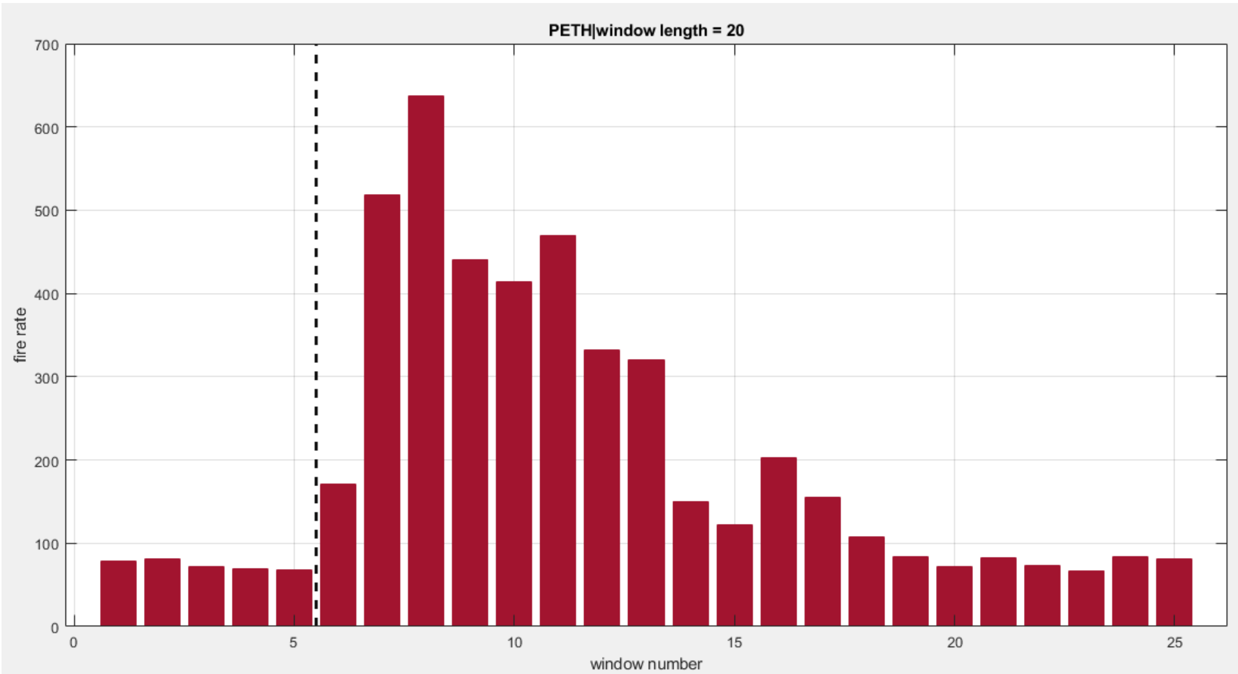
As the question is saying we have 50ms before the stimulation and 200ms after it. So we expect to have a lot of spikes in all the trials around 50ms. As the plot is showing, we have a lot of spikes around 50ms which is around the stimulation time. This high density of spikes remains up to 130ms and after that our neurons will go to rest state and number of spikes decreases.

4,2 –

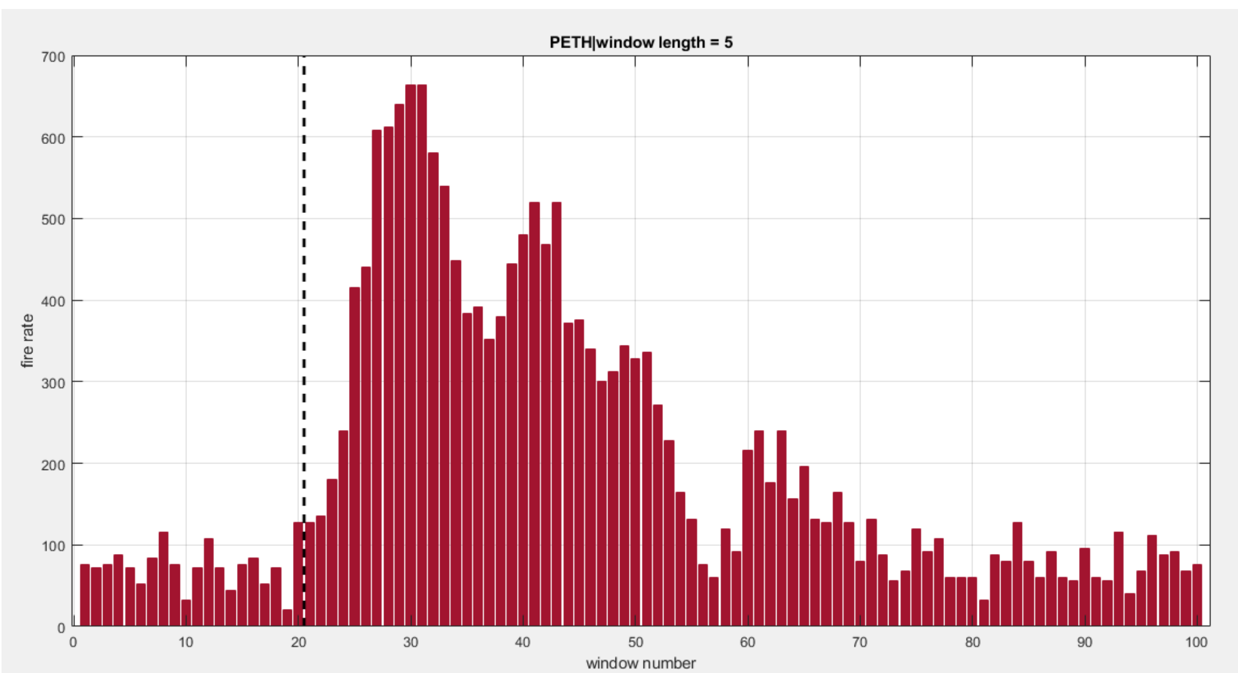
We want to model neurons using their firing rate instead of modeling them with their spikes` number. This method has a greater efficiency and scales well to large networks. Also, modeling networks using spikes will make equations, so hard to solve. In order to model neurons using their firing rate, we use a rectangular moving window and count number of spikes and then calculate the fire rate base on the window length. This is actually a low-pass filter on our spike trains.

4,3_4,4 –

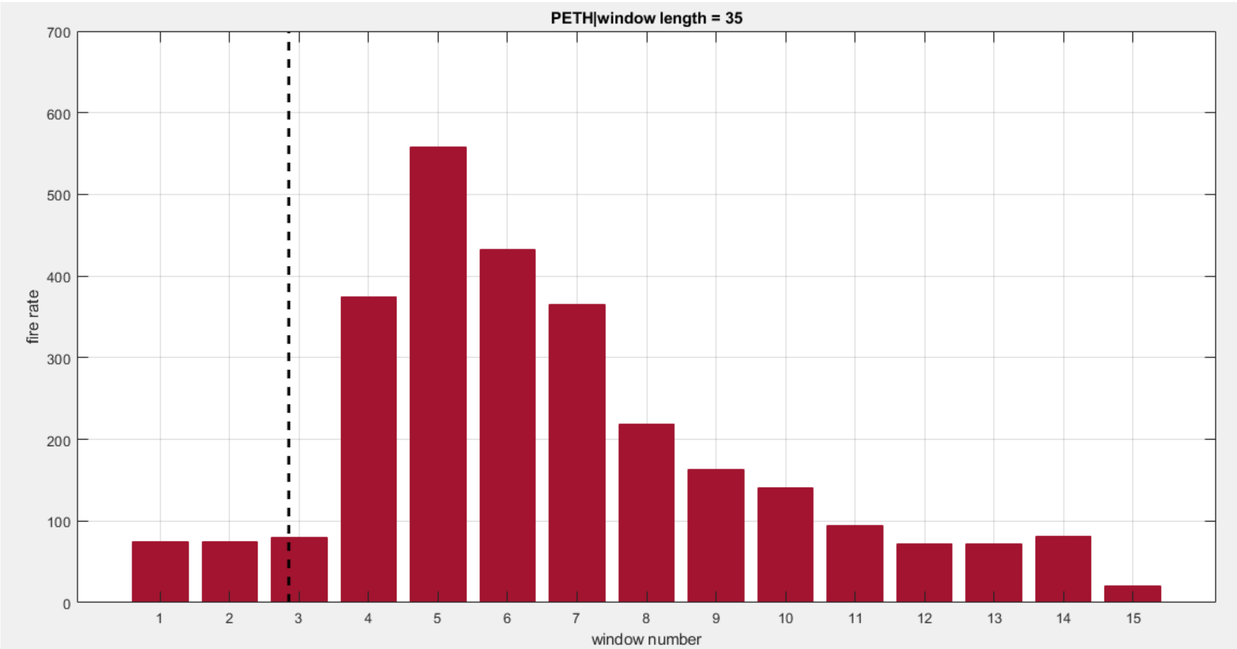
window length = 20 samples or 10ms



window length = 5 samples or 2.5ms



window length = 35 samples or 17.5ms



As we can see by increasing the window length, will decrease the accuracy of fire rates. Maximum fire rate for window_L 35 is about 559 and for window_L 20 is 637 and for 5 is 644. When we have a smaller window, we can have a better visualization of the firing rates. The window length shouldn`t be very small, because for example, the window will just contain one spike and the firing rate would be 1000 and maybe the firing rate around there is not this much. So window length shouldn`t be very small or very big.

3-:

3.1-

$$P(n\,\text{spikes}) = \binom{m}{n} p^n (1-p)^{m-n}$$

$$= \binom{m}{n} (\lambda \Delta t)^n (1-\lambda \Delta t)^{m-n}$$

$$= \frac{m!}{n!\,(m-n)!} (\lambda \Delta t)^n (1-\lambda \Delta t)^{m-n} \rightsquigarrow \text{bionomial distribution}$$

$$\xrightarrow[\Delta t \to 0]{m \to \infty} = \frac{m^n}{n!} (\lambda \Delta t)^n (1-\lambda \Delta t)^m$$

$$= \frac{(\lambda T)^n}{n!} \left(\frac{\lambda T}{m}\right)^n \left(1-\frac{\lambda T}{m}\right)^m$$

$$= \frac{(\lambda T)^n}{n!} \left(1-\frac{\lambda T}{m}\right)^m = \boxed{\frac{(\lambda T)^n}{n!} e^{-\lambda T}}$$

Poisson distribution with Parameter λT

3.2-

$$E[N(T)] = \sum_{n=0}^{\infty} n \frac{(\lambda T)^n}{n!} e^{-\lambda T}$$

$$= \lambda T e^{-\lambda T} \sum_{n=0}^{\infty} \frac{(\lambda T)^m}{m!} \qquad [m = n-1)$$

$$= \lambda T e^{-\lambda T} e^{\lambda T} = \lambda T$$

$$Var[N(T)] = E[N(T)^2] - E^2[N(T)]$$

$$= \sum_{n=0}^{\infty} n^2 \frac{(\lambda T)^n}{n!} e^{-\lambda T} - (\lambda T)^2$$

$$= e^{-\lambda T} \left((\lambda T)^2 \sum_{n=2}^{\infty} \frac{(\lambda T)^{n-2}}{(n-2)!} + (\lambda T) \sum_{n=1}^{\infty} \frac{(\lambda T)^{n-1}}{(n-1)!} \right) - (\lambda T)^2$$

$$= (\lambda T)^2 + \lambda T - (\lambda T)^2 = \lambda T$$

$$\rightsquigarrow \boxed{\text{Fano Factor} = \frac{\lambda T}{\lambda T} = 1}$$

3.3-

$$f_\tau(\tau_0) = \lim \frac{e^{-\lambda\tau_0}(\lambda\Delta t)}{\Delta t} = \boxed{\lambda e^{-\lambda\tau_0}}$$

→ exponential distribution

$$E(\tau) = \int_0^\infty \tau' \lambda e^{-\lambda\tau'} d\tau' = \frac{-1}{\lambda}\left[e^{-\lambda\tau'}\right]\Big|_0^\infty = \boxed{\frac{1}{\lambda}}$$

$$Std(\tau) = \sqrt{\int_0^\infty \tau'^2 \lambda e^{-\lambda\tau'} d\tau' - 1/\lambda^2} = \sqrt{-\tau'^2 d(e^{-\lambda\tau'}) - 1/\lambda^2} = \sqrt{2/\lambda^2 - 1/\lambda^2} = \boxed{1/\lambda}$$

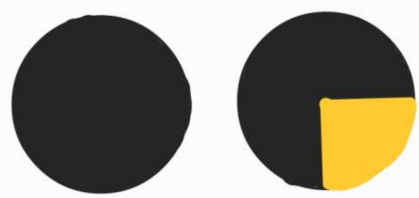
$$\boxed{CV = \frac{1/\lambda}{1/\lambda} = 1}$$

4-:

4.1-

- first, by removing Path number $\frac{2}{3}$, we will turn off the left eye.

then by removing Path number $\frac{4}{3}$ & $\frac{9}{3}$, we will have the bottom right of the picture which includes seven & eight.



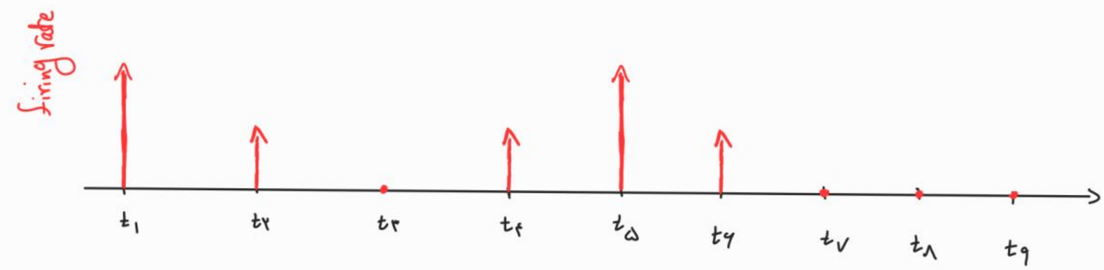
4.2-

$\boxed{2 \_ 6 \_ 3 \_ 7}$

4.3-

we can't remove any paths for just seeing 4 but by removing Path 1 & 5 & 6 we will just see number 5.

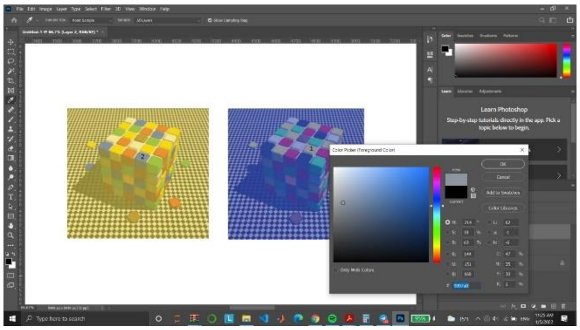
5-:



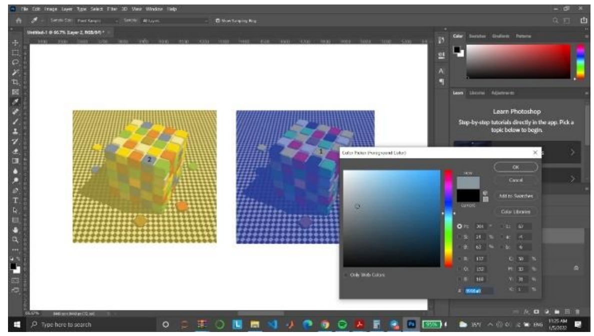
When the light is completely on the on areas (purples), we have the maximum firing rate. By moving towards the off areas (grays), the firing rate decreases (like t۲، t۴، t۶) and when it's completely on the off areas, the neuron will be turned off with no activity (like t۳، t۷) and also when the light is outside of receptive field (t۸، t۹)، the neuron is off.

6-:

6.1-



Block num.1 – RGB : (144,151,160)



Block num.2 – RGB : (137,152,160)

6.2-

No, As we saw in part 1, they`re grey and their RGB is not even close to blue or yellow.

6.3-

Grey!

6.4-

It seem's they are really grey but humans are fooled because of the lights on the pics. Actually, our brain thinks that the color of the objects should be the same under different colors of the light and because of that it will decrease the background light color from the true color.

$\boxed{\text{So 1,2 are grey}}$