

HW #2

1.

- a. False: Na^+ conductance increases the most first during the action potential and is responsible for the larger current
- b. False: Na^+ current depolarizes/increases membrane potential (over 0mv) and K^+ current acts to repolarize the cell (decrease the cell potential under 0mv)
- c. True
- d. False: the EEG does not have enough resolution to measure individual action potential but rather measures general neural activity like LFP's
- e. False: in Poisson process all events are independent and will have the same chance of firing at any given time regardless of when the last firing occurred.
- f. False: it means the variance is greater than the mean if it is greater than 1
- g. True : <If the time window was infinity, it would approach 1 if it was a truly Poisson process>
- h. False: in the exponential interspike distribution will have a skewed distribution close to zero but refractory period limits a minimum time in between spikes
- i. True
- j. True
- k. True
- l. True
- m. False: It's a type of low pass filtering
- n. False: Static tuning curves don't well represent activity in motor systems because these are time varying signals
- o. False: very unlikely not impossible

2.

- a) If all variables except θ are constant, then the only thing that changes is what is inside the cosine function. The cosine of a function is at a maximum (of 1) when its inside is equal to zero, and for that to happen $\theta = \theta_0$.
- b) "You've made a mistake.": With those numbers, the equation will be $f(\theta) = -11 + 8 \cdot \cos(\theta - 125)$ and for all θ it will predict negative frequency firing rates which is not possible

C, D, and E see notes Below:

2c $\cos(\theta - \theta_0) = \text{Re}(e^{i(\theta - \theta_0)})$

$$= \text{Re}(e^{i\theta} e^{-i\theta_0})$$

\downarrow Euler \downarrow Euler $(-\cos(\theta_0) - i\sin(\theta_0))$

$$= \text{Re}((\cos\theta + i\sin\theta)(\cos(\theta_0) + i\sin(\theta_0)))$$

$$\cos(\theta - \theta_0) = \boxed{\cos\theta \cos\theta_0 - \sin\theta \sin\theta_0}$$

2d $f(\theta) = c_0 + c_1 \cos(\theta - \theta_0)$

$$f(\theta) = c_0 + c_1(\cos\theta \cos\theta_0 - \sin\theta \sin\theta_0)$$

$$f(\theta) = k_0 + k_1 \sin\theta + k_2 \cos\theta$$

$k_0 = c_0$, $k_1 = c_1 \sin\theta_0$, $k_2 = c_1 \cos\theta_0$

2e $y(120) = k_0 + k_1 \sin(120) + k_2 \cos(120) = k_0 + .86k_1 - \frac{1}{2}k_2$

$$y(240) = k_0 + k_1 \sin(240) + k_2 \cos(240) = k_0 - .86k_1 - \frac{1}{2}k_2$$

$$y(0) = k_0 + k_1 \sin(0) + k_2 \cos(0) = k_0 + 0 + k_2$$

$$y(0) + y(120) + y(240) = 3k_0 \quad \boxed{k_0 = \frac{y(0) + y(120) + y(240)}{3}}$$

$$k_2 = y_0 - k_0 = \boxed{k_2 = \frac{y(0) + y(120) + y(240)}{3} - y_0}$$

2E continued below, 2G

(2e) continued...

$$y_{240} - y_{120} = \frac{\sqrt{3}}{2} k_1 - \frac{\sqrt{3}}{2} k_1 = k_1 \sqrt{3} = y_{240} - y_{120}$$

$$= \frac{2}{\sqrt{3}} y(120) + \frac{1}{\sqrt{3}} \left(\frac{2}{3} y_0 + \frac{1}{3} y(120) + \frac{1}{3} y(240) \right) + \frac{y(240)}{\sqrt{3}} - \frac{y(120)}{\sqrt{3}}$$

$$k_1 = -1.73 y_0 + \frac{1}{3} y(120) + \frac{1}{3} y(240)$$

$$k_0 = \frac{1}{3} y_0 + \frac{1}{3} y(120) + \frac{1}{3} y(240)$$

$$k_2 = \frac{2}{3} y_0 + \frac{1}{3} y(120) - \frac{1}{3} y(240)$$

2F.)

```
def ptc(y0 , y1 , y2):
    #PTC calculates the tuning curve given average firing rates for certain directions.

    # ===== #
    # YOUR CODE HERE:
    # The function takes three inputs corresponding to the average
    # firing rate of a neuron during a reach to 0 degrees (y0), 120
    # degrees (y1) and 240 degrees (y2). The outputs, c0, c1, and
    # theta0 are the parameters of the tuning curve.
    # ===== #
    k0 = (y0 + y1 + y2)/3
    k2 = -y1/3 + (2/3)*y0 - y2/3
    k1 = y1/1.73 - y2/1.73

    c0 = k0
    theta0 = np.arctan(k1/k2 )
    c1 = k1/np.sin(theta0 )
    theta0 = theta0 * 180/np.pi

    # ===== #
    # END YOUR CODE HERE
```

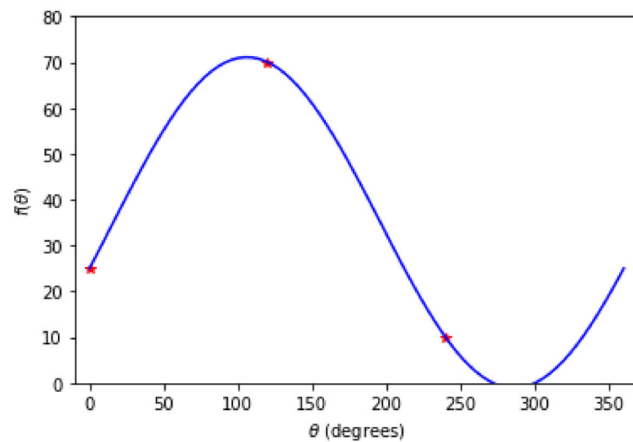
▼ Plot the figure

The following cells execute your PTC function, printing out the values and plotting the tuning curve.

```
c0,c1,theta0=ptc(25,70,10)
print('c0 = ', c0)
print('c1 = ', c1)
print('theta0 = ', theta0)
```

```
c0 = 35.0
c1 = -36.094968309699695
theta0 = -73.91596521992966
```

```
theta = np.linspace(0, 2*np.pi, num=80)
plt.plot([0, 120, 240 ],[25, 70, 10],'r*',10)
plt.plot(theta * 180 / np.pi,c0 + c1 *np.cos(theta - theta0 * np.pi/180),'b',2)
plt.xlim ([-10 ,370])
plt.ylim ([0,80])
plt.xlabel(r'$\theta$ (degrees)');
plt.ylabel(r'$f(\theta)$');
```



2G

2G) $f_{\theta} = k_0 + k_1 \sin(\theta) + k_2 \cos(\theta)$

$\theta =$

25	y_{25}	$k_0 + 0 k_1 + 1 k_2$
40	y_{40}	$k_0 + .866 k_1 + .5 k_2$
70	y_{70}	$k_0 + .866 k_1 + -.5 k_2$
30	y_{30}	$k_0 + 0 k_1 + -1 k_2$
10	y_{10}	$k_0 + -.866 k_1 + -.5 k_2$
15	y_{15}	$k_0 + -.866 k_1 + .5 k_2$

Y	F	W
25	1 0 1	$\begin{bmatrix} k_0 \\ k_1 \\ k_2 \end{bmatrix}$
40	1 .866 .5	
70	1 .866 -.5	
30	1 0 -1	
10	1 -.866 -.5	
15	1 -.866 .5	

$W^* = (F^T F)^{-1} F^T Y$

From Computer

$k_0 = 31.666$ $k_1 = 24.5$ $k_2 = -5.83$

$\theta_0 = \tan^{-1}\left(\frac{k_1}{k_2}\right) = -76.6^\circ = \theta_0$

$C_1 = \frac{k_1}{\sin(\theta_0)} = -25.18^\circ = C_1$

...Computer Matrix Calculations used above to solve for K values

A

Dimensions: 6 by 3

1	0	1
1	.866	.5
1	.866	-.5
1	0	-1
1	-.866	-.5
1	-.866	.5

B

Dimensions: 6 by 1

25
40
70
30
10
15

Calculate least squares solution

Least Squares Solution: X =

31.666666666666664
24.53810623556582
-5.833333333333333

3).

a). **No it does not.** The exponential distribution model assumes there will be non-zero probability amounts of firing directly after time 0 for ISI activity, however with refractory periods we know that there will be no firing for the first ~0-4ms (refractory period).

b).

Given $\lambda = 50$ spikes/sec

$$P(T < .001) = (1 - e^{-\lambda t}) = .0487$$

Answer: around 5% would violate the 1ms refractory period

4.

a) Mean = $1/\lambda$

b) $P(T > 1/\lambda) = e^{-1} = 36.7\%$

$$4C) E[T | T > \frac{1}{\lambda}] \rightarrow E[T | A]$$

$$f_{T|A} = \frac{\lambda e^{-\lambda t}}{P(A)} = \begin{cases} \frac{\lambda e^{-\lambda t}}{e^{-1}} & , t > \frac{1}{\lambda} \\ 0 & , t < \frac{1}{\lambda} \end{cases}$$

$$E[T | A] = \int_{\frac{1}{\lambda}}^{\infty} t \frac{\lambda e^{-\lambda t}}{e^{-1}} dt = e \lambda \int_{\frac{1}{\lambda}}^{\infty} t e^{-\lambda t} dt = e \lambda \left(\frac{e^{-1}}{\lambda^2} \right) = \boxed{\frac{2}{\lambda}}$$

$$4D) E[T | T < \frac{1}{\lambda}]$$

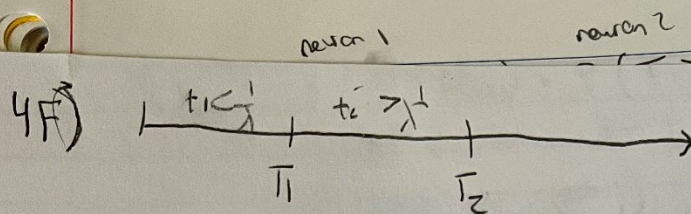
$$E[T | A] = \int t f_T(t) dt \quad f_{T|A} = \begin{cases} 0 & t > \frac{1}{\lambda} \\ \frac{\lambda e^{-\lambda t}}{(1 - e^{-1})} & 0 < t < \frac{1}{\lambda} \end{cases}$$

$$\int_0^{\frac{1}{\lambda}} t \cdot \frac{\lambda e^{-\lambda t}}{(1 - e^{-1})} dt = \left(\frac{\lambda}{1 - e^{-1}} \right) \int_0^{\frac{1}{\lambda}} e^{-\lambda t} t dt = \boxed{\frac{-e + 2}{(e - 1) \lambda}}$$

$$4E) \underbrace{t < \frac{1}{\lambda}}_{k=1} \underbrace{t < \frac{1}{\lambda}}_{k=2} \dots \underbrace{t < \frac{1}{\lambda}}_{k=k-1} \underbrace{t > \frac{1}{\lambda}}_{k=k}$$

$$P(N=k) = (1-p)^{k-1} p$$

$$E[N] = \frac{1}{P(T > e^{-\lambda t})} = \boxed{\frac{1}{e^{-1}}}$$



$$T = t_1 + t_2$$

Let $X = \# \text{ spikes before } |S| > 1/$

$$T = \sum_{i=1}^X t_i \quad f_{T|X}(t|x) \sim \text{gamma}$$

$$f_{T|X}(t|x) = f_X(t) = \frac{\lambda e^{-\lambda t} \lambda^{(x-1)}}{(x-1)!}$$

$$E[T|X=x] = \int_0^{\infty} t \cdot f_{T|X}(t) dt = \frac{x}{\lambda}$$

$$E[T] = E[E[T|X=k]]$$

$$E\left[\frac{x}{\lambda}\right] = e \Rightarrow E[T] = \boxed{\frac{e}{\lambda} = E[T]}$$

5)

neuron 1 neuron 2

$$S_a) P(T > 60ms) \cdot P(T > 60ms)$$

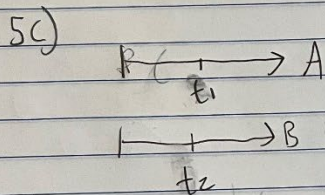
$$\lambda_1 = \frac{1}{20ms} = 50 \quad \lambda_2 = \frac{1}{30ms} = 33.3$$

$$= (e^{-\lambda_1 60ms}) \cdot (e^{-\lambda_2 60ms}) = e^{-3} \cdot e^{-2} = \boxed{.67\%}$$

$$S_b) P(T_1 > s + t | T_1 > s) \cdot P(T_2 > s + t | T_2 > s) \quad \text{Since } t_1 \perp t_2$$

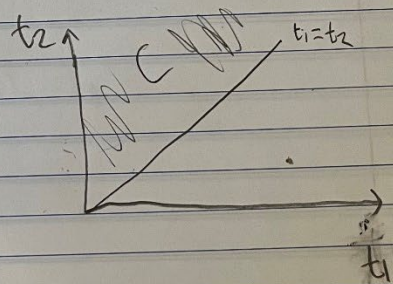
$$\approx P(T_1 > t) \cdot P(T_2 > t)$$

$$= e^{-\lambda_1 t} \cdot e^{-\lambda_2 t} = \boxed{e^{-83.3t}}$$



Let t_1 denote spike time at a
 Let t_2 denote spike time arrival at b

Compute $P(t_2 > t_1)$



$$P(t_2 > t_1) = \iint_C f_{t_1, t_2}(t_1, t_2)$$

$$\downarrow$$

$$\iint_C f_1(t_1) f_2(t_2) = \int_0^\infty \int_0^{t_2} \lambda_1 e^{-\lambda_1 t_1} \cdot \lambda_2 e^{-\lambda_2 t_2} dt_1 dt_2$$

$$= \lambda_1 \lambda_2 \int_0^\infty \int_0^{t_2} e^{-\lambda_1 t_1} e^{-\lambda_2 t_2} dt_1 dt_2$$

$$= \lambda_1 \lambda_2 \int_0^\infty e^{-\lambda_2 t_2} \left(\frac{1}{\lambda_1} (1 - e^{-\lambda_1 t_2}) \right) dt_2 = \lambda_2 \left[\frac{1}{\lambda_2} e^{-\lambda_2 t_2} + \frac{1}{\lambda_1 + \lambda_2} e^{-(\lambda_1 + \lambda_2)t_2} \right]$$

$$= \frac{\lambda_1}{\lambda_1 + \lambda_2} = \frac{50}{50 + 33.33} = \boxed{.6}$$