

# MATH 6397 Homework 3

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1. We will derive the Fokker-Planck equation for the membrane potential distribution under excitatory input. Suppose the input rate of pre-synaptic neuron  $k$  at time  $t$  is  $v_k(t)$  with weight  $w_k$ . We start with the transition probability moving from state  $u'$  to  $u$  in time  $t$  to  $t + \Delta t$ ,

$$P^{trans}(u, t + \Delta t | u', t) = \left[ 1 - \Delta t \sum_k v_k(t) \right] \delta(u - u' e^{-\Delta t / \tau_m}) + \Delta t \sum_k v_k(t) \delta(u - u' e^{-\Delta t / \tau_m} - w_k).$$

The Kolmogorov forward equation gives  $P(u, t + \Delta t) = \int P^{trans}(u, t + \Delta t | u', t) P(u', t) du'$ . Putting this into context, we have

$$\begin{aligned} P(u, t + \Delta t) &= \int \left\{ \left[ 1 - \Delta t \sum_k v_k(t) \right] \delta(u - u' e^{-\Delta t / \tau_m}) + \Delta t \sum_k v_k(t) \delta(u - u' e^{-\Delta t / \tau_m} - w_k) \right\} P(u', t) du' \\ &= \left[ 1 - \Delta t \sum_k v_k(t) \right] \int \delta(u - u' e^{-\Delta t / \tau_m}) P(u', t) du' + \Delta t \sum_k v_k(t) \int \delta(u - u' e^{-\Delta t / \tau_m} - w_k) P(u', t) du' \end{aligned}$$

We have that

$$\begin{aligned} \int \delta(u - u' e^{-\Delta t / \tau_m}) P(u', t) du' &= \int \delta \left[ -e^{-\Delta t / \tau_m} (u' - u e^{\Delta t / \tau_m}) \right] P(u', t) du' \\ &= \left| -e^{\Delta t / \tau_m} \right| \int \delta(u' - u e^{\Delta t / \tau_m}) P(u', t) du' \\ &= e^{\Delta t / \tau_m} P(u e^{\Delta t / \tau_m}, t) \end{aligned}$$

and

$$\begin{aligned} \int \delta(u - u' e^{-\Delta t / \tau_m} - w_k) P(u', t) du' &= \int \delta \left[ -e^{-\Delta t / \tau_m} (u' - (u - w_k) e^{\Delta t / \tau_m}) \right] P(u', t) du' \\ &= \left| -e^{\Delta t / \tau_m} \right| \int \delta(u' - (u - w_k) e^{\Delta t / \tau_m}) P(u', t) du' \\ &= e^{\Delta t / \tau_m} P(e^{\Delta t / \tau_m} (u - w_k), t) \end{aligned}$$

Applying these simplifications to  $P(u, t + \Delta t)$ , we have

$$\begin{aligned} P(u, t + \Delta t) &= \left[ 1 - \Delta t \sum_k v_k(t) \right] e^{\Delta t / \tau_m} P(e^{\Delta t / \tau_m} u, t) + \Delta t \sum_k v_k(t) e^{\Delta t / \tau_m} P(e^{\Delta t / \tau_m} (u - w_k), t) \\ &= e^{\Delta t / \tau_m} \left\{ P(e^{\Delta t / \tau_m} u, t) + \Delta t \sum_k v_k(t) \left[ -P(e^{\Delta t / \tau_m} u, t) + P(e^{\Delta t / \tau_m} (u - w_k), t) \right] \right\} \end{aligned}$$

We now expand this expression about  $\Delta t = 0$  and truncate all terms with powers of  $\Delta t$  higher than 1. We use the following truncated expansions.

- $e^{\Delta t/\tau_m} \approx 1 + \frac{\Delta t}{\tau_m}$
- $P\left(e^{\Delta t/\tau_m} u, t\right) \approx P(u, t) + \frac{u \Delta t}{\tau_m} \frac{\partial P(u, t)}{\partial u}$
- $P\left(e^{\Delta t/\tau_m} (u - w_k), t\right) \approx P(u - w_k, t) + \frac{(u - w_k) \Delta t}{\tau_m} \frac{\partial P(u, t)}{\partial u}$

We put things together, and again truncate powers of  $\Delta t$  higher than 1 to have

$$\begin{aligned} P(u, t + \Delta t) &\approx \left(1 + \frac{\Delta t}{\tau_m}\right) \left\{ P(u, t) + \frac{u \Delta t}{\tau_m} \frac{\partial P(u, t)}{\partial u} \right. \\ &\quad \left. + \Delta t \sum_k v_k(t) \left[ -P(u, t) - \frac{u \Delta t}{\tau_m} \frac{\partial P(u, t)}{\partial u} + P(u - w_k, t) + \frac{(u - w_k) \Delta t}{\tau_m} \frac{\partial P(u, t)}{\partial u} \right] \right\} \\ &\approx P(u, t) + \frac{\Delta t}{\tau_m} P(u, t) + \frac{u \Delta t}{\tau_m} \frac{\partial P(u, t)}{\partial u} + \Delta t \sum_k v_k(t) [P(u - w_k, t) - P(u, t)] \end{aligned}$$

We now have

$$\begin{aligned} P(u, t + \Delta t) - P(u, t) &= \frac{\Delta t}{\tau_m} P(u, t) + \frac{u \Delta t}{\tau_m} \frac{\partial P(u, t)}{\partial u} + \Delta t \sum_k v_k(t) [P(u - w_k, t) - P(u, t)] \\ \frac{P(u, t + \Delta t) - P(u, t)}{\Delta t} &= \frac{1}{\tau_m} P(u, t) + \frac{u}{\tau_m} \frac{\partial P(u, t)}{\partial u} + \sum_k v_k(t) [P(u - w_k, t) - P(u, t)] \end{aligned}$$

Again, we do an expansion but this time in  $w_k$ . For this we need the truncated expansion

$$P(u - w_k, t) \approx P(u, t) - w_k \frac{\partial P(u, t)}{\partial u} + \frac{w_k^2}{2} \frac{\partial^2 P(u, t)}{\partial u^2}.$$

Substitution yields

$$\begin{aligned} \frac{P(u, t + \Delta t) - P(u, t)}{\Delta t} &= \frac{1}{\tau_m} P(u, t) + \frac{u}{\tau_m} \frac{\partial P(u, t)}{\partial u} + \sum_k v_k(t) \left[ -w_k \frac{\partial P(u, t)}{\partial u} + \frac{w_k^2}{2} \frac{\partial^2 P(u, t)}{\partial u^2} \right] \\ &= \frac{1}{\tau_m} P(u, t) + \frac{\partial P(u, t)}{\partial u} \left( \frac{u}{\tau_m} - \sum_k v_k(t) w_k \right) + \frac{1}{2} \sum_k v_k(t) w_k^2 \frac{\partial^2 P(u, t)}{\partial u^2}. \end{aligned}$$

Taking  $\Delta t \rightarrow 0$ , we therefore have

$$\begin{aligned} \tau_m \frac{\partial P(u, t)}{\partial t} &= P(u, t) + \frac{\partial P(u, t)}{\partial u} \left( u - \tau_m \sum_k v_k(t) w_k \right) + \frac{\tau_m}{2} \sum_k v_k(t) w_k^2 \frac{\partial^2 P(u, t)}{\partial u^2} \\ &= -\frac{\partial}{\partial u} \left[ \left( -u + \tau_m \sum_k v_k(t) w_k \right) P(u, t) \right] + \frac{\tau_m}{2} \sum_k v_k(t) w_k^2 \frac{\partial^2 P(u, t)}{\partial u^2} \end{aligned}$$

as desired.

First, we verify that for a constant input, at  $t \rightarrow \infty$ , the Gaussian density with mean  $RI_0$  and variance  $\sigma/\sqrt{2}$  is a solution of the Fokker-Planck equation. Note that at  $t \rightarrow \infty$ , we have  $\frac{\partial P(u, \infty)}{\partial t} = 0$ . Hence, we only have to show that the right-hand side of the equation sums up to zero.

$$-\frac{\partial}{\partial u} \left[ \left( -u + \tau_m \sum_k v_k w_k \right) P(u, \infty) \right] = P(u, \infty) + \frac{\partial P}{\partial u} (u - RI_0)$$

and

$$\begin{aligned}
\frac{\tau_m}{2} \sum_k v_k w_k^2 \frac{\partial^2 P}{\partial u^2} &= \frac{1}{2} \sigma^2 \frac{\partial}{\partial u} \left[ \frac{1}{\sqrt{\pi} \sigma} \exp \left( -\frac{(u - RI_0)^2}{\sigma^2} \right) \left( -\frac{2(u - RI_0)}{\sigma^2} \right) \right] \\
&= \frac{1}{2} \sigma^2 \frac{\partial}{\partial u} \left[ P(u, \infty) \left( -\frac{2(u - RI_0)}{\sigma^2} \right) \right] = -\frac{\partial}{\partial u} [P(u, \infty) (u - RI_0)] \\
&= -\frac{\partial P}{\partial u} (u - RI_0) - P(u, \infty)
\end{aligned}$$

Combining this two make up the right-hand side of the Fokker-Planck equation which is now clearly zero.

Consider a leaky integrate and fire neuron with Poisson input without threshold. Suppose that there is a single pre-synaptic neuron so that the input rate is  $\nu = 5$ , synaptic weight is  $w = 1$ , and membrane time constant is  $\tau_m = 1$ . With this, we have  $RI_0 = \tau_m \nu w = 5$  and  $\sigma^2 = \tau_m \nu w^2 = 5$ . A simulation of such a neuron, up to time  $T = 1000$  ms, is found in Figure 1.

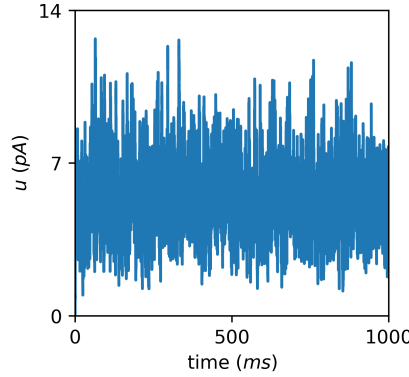


Figure 1: Simulation of a leaky integrate and fire model without threshold.

As given in Eq. 8.46, after a long observation time, the membrane potential follows a Gaussian distribution with mean  $RI_0$  and variance  $\sigma\sqrt{2}$ . To verify this, we use the simulation above and sample the membrane potential trajectory at 100,000 time points and compare the resulting histogram to the analytic prediction. We see in Figure 2 that indeed this is the case.

2. Consider a leaky integrate and fire neuron with Poisson input with threshold  $\theta = 5$ . Suppose that there is a single pre-synaptic neuron so that the input rate is  $\nu = 5$ , synaptic weight is  $w = 1$ , and membrane time constant is  $\tau_m = 1$ . With this, we have  $RI_0 = \tau_m \nu w = 5$  and  $\sigma^2 = \tau_m \nu w^2 = 5$ . Given that the resting potential is  $u_{rest} = 0$ , the analytic prediction for the expected time to firing,  $T(x)$  is the solution of the differential equation  $A(x)\partial_x T(x) + 0.5B(x)\partial_x^2 T(x) = -1$ , with the initial conditions  $T(a \rightarrow \infty) = 0$  and  $T(5) = 0$ . If we assume that both  $A(x)$  and  $B(x)$  are constant, and assign  $A(x) = RI_0$  and  $B(x) = \sigma^2$ , the solution of the ODE is given by

$$T(x, a) = -\frac{e^{-2a}(-a+b)}{5(-e^{-2a}+e^{-2b})} + \frac{a}{5} + \frac{e^{-2x}(-a+b)}{5(-e^{-2a}+e^{-2b})} - \frac{t}{5}.$$

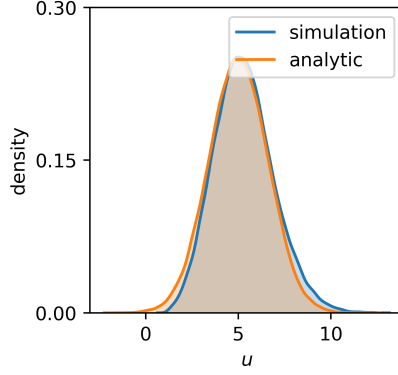


Figure 2: A comparison of the analytic prediction of the distribution of membrane potential and simulated values.

It we start at  $u_{rest}$ , then  $\langle T(u_{rest}) \rangle = \lim_{a \rightarrow -\infty} T(u_{rest}) = \lim_{a \rightarrow -\infty} T(0) = 1$  ms. All these computations were done in MATLAB. Empirical results show that the mean passage time is around 2 ms, as seen in Figure 3.

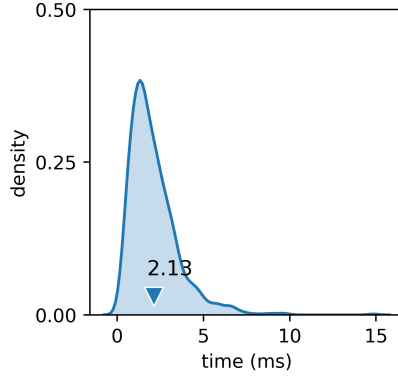


Figure 3: Distribution of passage time at threshold.

3. Suppose inter-arrival times  $X$  of spikes follow a gamma distribution  $\Gamma(\alpha, \beta)$ ,  $\alpha$  being the shape parameter, and  $\beta$  the rate. Then  $E[X] = \frac{\alpha}{\beta}$  and  $Var[X] = \frac{\alpha}{\beta^2}$ . It follows that the coefficient of variation is  $CV = \frac{\sqrt{Var[X]}}{E[X]} = \frac{1}{\sqrt{\alpha}}$ .

A special case of the gamma distribution is the Erlang distribution where the shape parameter  $\alpha$  is a positive integer. We parametrize the Erlang distribution with the shape parameter  $k$  and rate parameter  $\lambda$ . Given  $X$  following the Erlang distribution, we have that  $E[X] = \frac{k}{\lambda}$  and  $Var[X] = \frac{k}{\lambda^2}$ . It follows that the coefficient of variation is  $CV = \frac{\sqrt{Var[X]}}{E[X]} = \frac{1}{\sqrt{k}}$ .

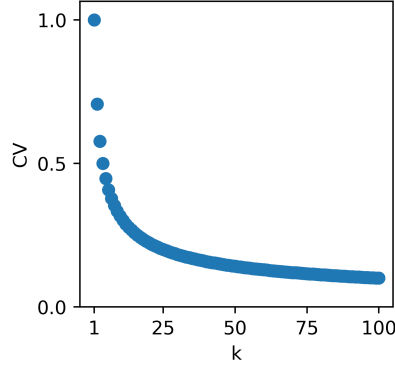


Figure 4: Coefficient of variation of an Erlang distributed random variable given increasing values of the shape parameter  $k$ .

As seen in Figure 4, increasing the parameter  $k$  decreases the CV. This means that as the number of exponential random variable summands increase, the variation around the resulting mean decreases.

4. We will derive the Fokker-Planck equation corresponding to the haploid Moran model with mutation. There are two alleles,  $a$  and  $A$ , with a single locus. The rate of mutation from  $a$  to  $A$  is given by  $u$ , and from  $A$  to  $a$  is  $v$ . Suppose that the total population is  $N$  and that  $u, v \in O\left(\frac{1}{N}\right)$ . Given the population  $n$  of allele  $a$ , we do the substitution  $x = \frac{n}{N}$ . First, we setup the following transition probabilities.

$$\begin{aligned}
T\left(x \middle| x + \frac{1}{N}\right) &= (1-v) \left(x + \frac{1}{N}\right) \left(1 - x - \frac{1}{N}\right) + u \left(x + \frac{1}{N}\right)^2 \\
T\left(x \middle| x - \frac{1}{N}\right) &= (1-u) \left(1 - x + \frac{1}{N}\right) \left(x - \frac{1}{N}\right) + v \left(1 - x + \frac{1}{N}\right)^2 \\
T\left(x + \frac{1}{N} \middle| x\right) &= (1-u) (1-x)x + v(1-x)^2 \\
T\left(x - \frac{1}{N} \middle| x\right) &= (1-v) x(1-x) + ux^2
\end{aligned}$$

We also need the following Taylor expansions of  $P$ .

$$\begin{aligned}
P\left(x + \frac{1}{N}, t\right) &= P(x, t) + \frac{1}{N} \frac{\partial P}{\partial x} + \frac{1}{2N^2} \frac{\partial^2 P}{\partial x^2} + O\left(\frac{1}{N^3}\right) \\
P\left(x - \frac{1}{N}, t\right) &= P(x, t) - \frac{1}{N} \frac{\partial P}{\partial x} + \frac{1}{2N^2} \frac{\partial^2 P}{\partial x^2} + O\left(\frac{1}{N^3}\right)
\end{aligned}$$

Putting things together, we have

$$\begin{aligned}
\frac{\partial P(x,t)}{\partial t} &= T\left(x \middle| x + \frac{1}{N}\right) P\left(x + \frac{1}{N}, t\right) + T\left(x \middle| x - \frac{1}{N}\right) P\left(x - \frac{1}{N}, t\right) - P(x,t) \left[ T\left(x + \frac{1}{N} \middle| x\right) + T\left(x - \frac{1}{N} \middle| x\right) \right] \\
&= \left\{ (1-v) \left(x + \frac{1}{N}\right) \left(1 - x - \frac{1}{N}\right) + u \left(x + \frac{1}{N}\right)^2 \right\} \left[ P(x,t) + \frac{1}{N} \frac{\partial P}{\partial x} + \frac{1}{2N^2} \frac{\partial^2 P}{\partial x^2} \right] \\
&\quad + \left\{ (1-u) \left(1 - x + \frac{1}{N}\right) \left(x - \frac{1}{N}\right) + v \left(1 - x + \frac{1}{N}\right)^2 \right\} \left[ P(x,t) - \frac{1}{N} \frac{\partial P}{\partial x} + \frac{1}{2N^2} \frac{\partial^2 P}{\partial x^2} \right] \\
&\quad - \left[ (1-u)(1-x)x + v(1-x)^2 + (1-v)x(1-x) + ux^2 \right] P(x,t) + O\left(\frac{1}{N^3}\right) \\
&= \frac{1}{N^2} \left\{ \frac{\partial P}{\partial x} (2 - u - 3v - 4x + 4ux - 4vx) + 2P(u + v - 1) + \frac{\partial^2 P}{\partial x^2} \left( \frac{u}{2} + x - x^2 - \frac{ux}{2} - \frac{3vx}{2} + ux^2 + vx^2 \right) \right\} \\
&\quad + \frac{1}{N} \left\{ \frac{\partial P}{\partial x} (ux + vx - v) + P(u + v) \right\} + O\left(\frac{1}{N^3}\right)
\end{aligned}$$

Since  $u, v \in O\left(\frac{1}{N}\right)$ , we have  $\frac{u}{N^2}, \frac{v}{N^2} \in O\left(\frac{1}{N^3}\right)$ . The above equation now simplifies to

$$\frac{\partial P}{\partial t} = \frac{1}{N^2} \left\{ \frac{\partial^2 P}{\partial x^2} (x - x^2) + \frac{\partial P}{\partial x} (2 - 4x) - 2P \right\} + \frac{1}{N} \left\{ \frac{\partial P}{\partial x} (ux + vx - v) + P(u + v) \right\} + O\left(\frac{1}{N^3}\right)$$

After removing the  $O\left(\frac{1}{N^3}\right)$  term, a simple expansion will verify that the above is equivalent to

$$\frac{\partial P}{\partial t} = \frac{1}{N} \frac{\partial}{\partial x} [(ux - v(1-x))P] + \frac{1}{N^2} \frac{\partial^2}{\partial x^2} [x(1-x)P]$$

as required.

- Here we simulate a two-step adaptation process and track the number of individuals with genotypes 1, 2, and 3, which we will denote by  $n_1$ ,  $n_2$ , and  $n_3$ . Suppose that at any given time  $n_1 + n_2 + n_3 = N$ . Also, assume that genotype 1 mutates to genotype 2 with rate  $\mu_{12}$  and genotype 2 mutates to genotype 3 with rate  $\mu_{23}$ . Given these mutation rates, the transition probabilities are given by

$$\begin{aligned}
P(n_1 + 1, n_2 - 1, n_3 | n_1, n_2, n_3) &= (1 - \mu_{12}) \left(\frac{n_1}{N}\right) \left(\frac{n_2}{N}\right) \\
P(n_1 + 1, n_2, n_3 - 1 | n_1, n_2, n_3) &= (1 - \mu_{12}) \left(\frac{n_1}{N}\right) \left(\frac{n_3}{N}\right) \\
P(n_1 - 1, n_2 + 1, n_3 | n_1, n_2, n_3) &= (1 - \mu_{23}) \left(\frac{n_2}{N}\right) \left(\frac{n_1}{N}\right) + \mu_{12} \left(\frac{n_1}{N}\right) \left(\frac{n_1}{N}\right) \\
P(n_1 - 1, n_2, n_3 + 1 | n_1, n_2, n_3) &= \left(\frac{n_3}{N}\right) \left(\frac{n_1}{N}\right) \\
P(n_1, n_2 + 1, n_3 - 1 | n_1, n_2, n_3) &= (1 - \mu_{23}) \left(\frac{n_2}{N}\right) \left(\frac{n_3}{N}\right) \\
P(n_1, n_2 - 1, n_3 + 1 | n_1, n_2, n_3) &= \left(\frac{n_3}{N}\right) \left(\frac{n_2}{N}\right) + \mu_{23} \left(\frac{n_2}{N}\right) \left(\frac{n_2}{N}\right)
\end{aligned}$$

Taking  $N = 1000$  and  $\mu_{12} = \mu_{23} = \mu$ , with different mutation rates, we perform 3000 simulations of this process, and record the time when the first individual with genotype 3 arrives. The distribution

of the arrival times is presented in Figure 5 and a comparison of the mean arrival time and expected arrival time when  $\mu \ll \frac{1}{N^2}$  is seen in Table 1. A quick look shows that the actual mean arrival times are far larger than expectation. This may in fact be due to the fact that for all the considered cases,  $\mu$  is not significantly less than  $\frac{1}{N^2} = 0.000001$ .

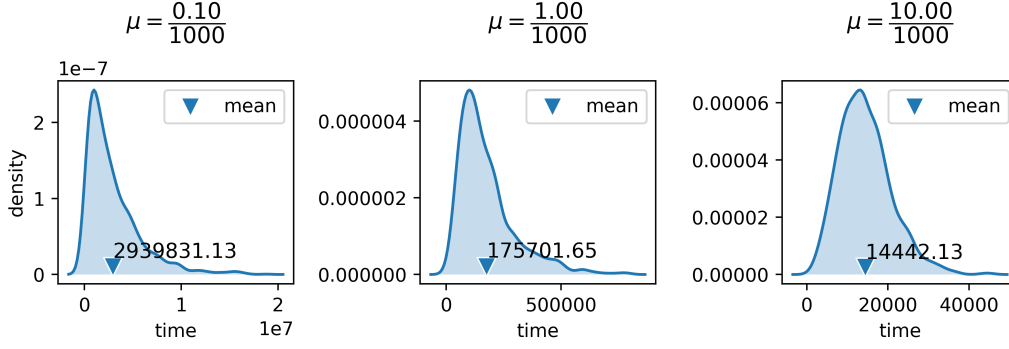


Figure 5: Distribution of time to first arrival of an individual with genotype 3 given different rates  $\mu$ .

	empirical mean	$\frac{1}{\mu}$
$\mu = 0.1/N$	2,939,831	10,000
$\mu = 1/N$	175,701	1,000
$\mu = 10/N$	14,442	100

Table 1: Comparison of the mean time of arrival of the first individual with genotype 3 and the expected time  $\frac{1}{\mu}$ .