1 Balanced networks: Trading speed for noise

1.1 Scaling of neuronal inputs

An interesting observation is that the subthreshold neuronal voltage in cortical neurons is very noisy. Naively, one might expect that the subthreshold potential would be noisy if there were relatively few inputs, not inconsistent with the notion of a few strong inputs that one sees in cortical slice experiments. But the other possibility is that the input is so noisy because large excitatory inputs are offset by large inhibitory inputs, so that their mean value just about cancels but the variances, of course, add. The notion of large offsetting currents comes from the intracellular recording experiments in cat V1 rom the laboratories of Ferster, Fregnac, Douglas and others, in which the excitatory and inhibitory inputs are found to be both large and have the same tuning curves, so that their inputs act to balance each other. The gain from offsetting currents is that a transient increase in excitatory input, as may occur with a large burst of input, will rapidly depolarize the cell. So balanced networks trade noise for speed.

Let’s start with a warm up on scaling of noise. The input to cell $i$ is $\mu_i$ with $i = 1, 2, \ldots, N$, while the output of the neuron is take as taken as $V_i$ with $i = 1, 2, \ldots, N$ where $V$ is a binary variable, 1 if the cell spikes and 0 if it does not. Let’s say that of the $N$ neurons in the network, only $K$ make synaptic input to the $i-th$ neuron. Let’s also say that the probability that a cell is spiking is $m$, that is, $V = 1$ with probability $m$ and $V = 0$ with probability $1 - m$. The input to the $i-th$ neuron is:

$$\mu_i \equiv \sum_{j=1}^{K} W_{ij} S_j. \quad (1.1)$$
Let’s address the central issue, which is scaling of the synaptic inputs. The standard thermodynamic scaling is that each input scales as $1/K$. For simplicity, let’s take all of the inputs to be equal, so

$$W_{ij} \to \frac{W}{K}. \quad (1.2)$$

Then

$$\mu_i = \frac{W}{K} \sum_{j=1}^{K} V_j. \quad (1.3)$$

The average value is

$$<\mu> = \frac{W}{K} \sum_{j=1}^{K} <V_j> = \frac{W}{K} \sum_{j=1}^{K} m = Wm \quad (1.4)$$

and the variance, under the assumption that the correlations in the neuronal outputs are zero, is

$$<\mu^2> = \left(\frac{W}{K}\right)^2 \sum_{j=1}^{K} (V_j - <V_j>)^2$$

$$= \left(\frac{W}{K}\right)^2 \left(\sum_{j=1}^{K} V_j^2 - K <V_j>^2\right)$$

$$= \frac{W^2}{K} (m - m^2)$$

$$= \frac{(Wm)^2}{Km} (1 - m) \quad (1.5)$$

which is always positive and, crucially, diminishes as $mK \to \infty$.

The challenge is to recast the input so that the variance does not diminish as a function of $K$. This is where the idea of balanced excitation and inhibition come in to play. We need the input to be the sums of two terms, and we also need to noodle with the scaling so that the variance goes to a constant as $mK \to \infty$. Let $W_{ij}^E$ be excitatory input and $W_{ij}^I$ be inhibitory input, simplified as above but now scaled as $1/\sqrt{K}$, so that

$$W_{ij}^E \to \frac{W^E}{\sqrt{K}}, \quad W_{ij}^I \to -\frac{W^I}{\sqrt{K}} \quad (1.6)$$

where we implicitly fix the sign of the inhibition, and

$$\mu_i = \sum_{j=1}^{K} \left(W_{ij}^E V_j^E + W_{ij}^I V_j^I\right)$$

$$= \frac{W^E}{\sqrt{K}} \sum_{j=1}^{K} V_j^E - \frac{W^I}{\sqrt{K}} \sum_{j=1}^{K} V_j^I. \quad (1.7)$$
The average value is

\[ < \mu > = \frac{W^E}{\sqrt{K}} K m^E + \frac{W^I}{\sqrt{K}} K m^I \]

\[ = \sqrt{K} \left( W^E m^E - W^I m^I \right) \] (1.8)

which can be large if the excitatory and inhibitory terms do not balance. The variance, again under the assumption that the correlations in the neuronal outputs are zero, is

\[ < \mu^2_i > = \frac{(W^E)^2}{K} \left( m^E - (m^E)^2 \right) K + \frac{(W^I)^2}{K} \left( m^I - (m^I)^2 \right) K \]

\[ = (W^E m^E)^2 \frac{1 - m^E}{m^E} + (W^I m^I)^2 \frac{1 - m^I}{m^I}. \] (1.9)

The important point is that there is no decrement as \( m^E K \to \infty \) or \( m^I K \to \infty \).

What happens when input to the neuron is zero, i.e., for the special case of \( W^E m^E = W^I m^I \) so that the network is in perfect balance? The variance is non-zero and becomes

\[ < \mu^2_i > = (W^E m^E)^2 \left( \frac{1 - W^I/W^E}{m^E} \right) - 2m^E \]

(1.10)

Before we go further, it is fair to ask if there is evidence to support this scaling.

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### 1.2 Circuit model

We now consider the consequences on the choice of connections in a network to maintain the balanced state. Consider a network of a population of excitatory (E) and inhibitory (I) cells:

\[ \mu^E_i(t) = \mu^E_o + \sum_{j=1}^{K} W^E_{i,j} V^E_j(t) + \sum_{j=1}^{K} W^I_{i,j} V^I_j(t) \] (1.11)

\[ \mu^I_i(t) = \mu^I_o + \sum_{j=1}^{K} W^I_{i,j} V^I_j(t) + \sum_{j=1}^{K} W^E_{i,j} V^E_j(t) \]

As in the case of the model cell, we will scale the synaptic inputs by \( 1/\sqrt{K} \)

\[ W^E_{ij} \to \frac{W^E_{ij}}{\sqrt{K}}, \quad W^I_{ij} \to \frac{-W^I_{ij}}{\sqrt{K}}, \quad W^E_{ij} \to \frac{-W^E_{ij}}{\sqrt{K}}, \quad W^I_{ij} \to \frac{W^I_{ij}}{\sqrt{K}}. \] (1.12)
and as will be clear soon, we need to scale the external inputs by
\[ \mu_o^E \rightarrow \sqrt{K}E m_o; \quad \mu_o^I \rightarrow \sqrt{K}I m_o \] (1.13)
where \( E \) and \( I \) are scales of \( O(1) \), so that
\[
\begin{align*}
\mu^E_i(t) &= \sqrt{K}E m_o + \frac{W_{EE}^K}{\sqrt{K}} \sum_{j=1}^{K} V^E_j(t) - \frac{W_{EI}^K}{\sqrt{K}} \sum_{j=1}^{K} V^I_j(t) \quad (1.14) \\
\mu^I_i(t) &= \sqrt{K}I m_o + \frac{W_{IE}^K}{\sqrt{K}} \sum_{j=1}^{K} V^E_j(t) - \frac{W_{II}^K}{\sqrt{K}} \sum_{j=1}^{K} V^I_j(t).
\end{align*}
\]
Let’s write the average activities, the so-called order parameters, as
\[
\begin{align*}
m^E(t) &= \frac{1}{N_E} \sum_{i=1}^{N_E} V^E_i(t) \quad (1.15) \\
m^I(t) &= \frac{1}{N_I} \sum_{i=1}^{N_I} V^I_i(t)
\end{align*}
\]
where the inputs are connected by
\[
\begin{align*}
V^E_i(t) &= H(\mu^E_i(t) - \theta_i^E) \quad (1.16) \\
V^I_i(t) &= H(\mu^I_i(t) - \theta_i^I) \quad (1.17)
\end{align*}
\]
\( H(\cdot) \) is the Heavyside function, and the \( \theta_i^E \) and \( \theta_i^I \) are threshold functions. Note that the order parameters are small.

The order parameters allows us to write equations for the average input, i.e.,
\[
\begin{align*}
< \mu^E(t) > &= \sqrt{K}E m_o + \frac{W_{EE}^K}{\sqrt{K}} \sum_{j=1}^{K} < V^E_j(t) > - \frac{W_{EI}^K}{\sqrt{K}} \sum_{j=1}^{K} < V^I_j(t) > \quad (1.19) \\
&= \sqrt{K}E m_o + \sqrt{KW_{EE}^K} m^E(t) - \sqrt{KW_{EI}^K} m^I(t)
\end{align*}
\]
and
\[
\begin{align*}
< \mu^I(t) > &= \sqrt{K}I m_o + \frac{W_{IE}^K}{\sqrt{K}} \sum_{j=1}^{K} < V^E_j(t) > - \frac{W_{II}^K}{\sqrt{K}} \sum_{j=1}^{K} < V^I_j(t) > \quad (1.20) \\
&= \sqrt{K}I m_o + \sqrt{KW_{IE}^K} m^E(t) - \sqrt{KW_{II}^K} m^I(t)
\end{align*}
\]
As $\sqrt{K} \to \infty$ the left hand side goes to zero and the equilibrium state will satisfy

$$0 \left( \frac{1}{\sqrt{K}} \right) = E m_o + W^{EE} m_E - W^{EI} m_I \quad (1.21)$$
$$= I m_o + W^{IE} m_E - W^{II} m_I$$

The implication of this equilibrium is that the average input remains finite as the fluctuations remain large. This is the balanced state. Solving gives relations for the equilibrium activity of the excitatory and inhibitory cells in terms of the external drive:

$$m_E = \frac{W^{II} E - W^{II} I}{W^{EI} W^{IE} - W^{EE} W^{II}} m_o. \quad (1.22)$$

and

$$m_I = \frac{W^{IE} E - W^{EE} I}{W^{EI} W^{IE} - W^{EE} W^{II}} m_o. \quad (1.23)$$

The equilibrium values of activity $m_E$ and $m_I$ must be positive. If we wish to avoid saturated solutions, this requires:

$$\frac{E}{I} > \frac{W^{EI}}{W^{II}} > \frac{W^{EE}}{W^{IE}} < 1 \quad (1.24)$$

The final point concerns dynamics. The dynamic of the order parameters, defined above, follow Glauber dynamics - a formalism for binary variables. Thus, without derivation, the equation for the $i$-th excitatory neuron is

$$\tau_E \frac{dm_{E,i}(t)}{dt} = -m_{E,i}(t) + H \left( \mu_i^E(t) - \theta_i^E \right). \quad (1.25)$$

If we look at the entire network, we can replace the thresholded inputs from the neighbors by the probability that neighboring cells are firing. This will depend on the mean input and on the variance in the input. The mean inputs at equilibrium, from above, are

$$\mu_E = \sqrt{K} E m_o + \sqrt{K} W^{EE} m_E - \sqrt{K} W^{EI} m_I - \theta_E \quad (1.26)$$
$$\mu_I = \sqrt{K} I m_o + \sqrt{K} W^{IE} m_E - \sqrt{K} W^{II} m_I - \theta_I.$$

The variance to excitatory cells, $\sigma_E^2(t)$, is given by

$$\sigma_E^2(t) = \left( W^{EE} \right)^2 m_E(t) + \left( W^{EI} \right)^2 m_I(t) \quad (1.27)$$

with a similar expression for the inhibitory cells, i.e.,

$$\sigma_I^2(t) = \left( W^{IE} \right)^2 m_E(t) + \left( W^{II} \right)^2 m_I(t) \quad (1.28)$$

so that

$$m_E(t) = \frac{(W^{EE})^2 \sigma_E^2(t) - (W^{IE})^2 \sigma_I^2(t)}{(W^{EI})^2 (W^{IE})^2 - (W^{EE})^2 (W^{II})^2}. \quad (1.29)$$
We approximate the noise by a Gaussian so that we can estimate when the input exceeds the threshold level $\theta^E$, i.e.,

$$
\tau_E \frac{dm_E(t)}{dt} = -m_E(t) + \frac{1}{\sqrt{2\pi} \sigma} \int_{\theta^E}^{\infty} e^{-(x-\mu^E)^2/2\sigma^2_E} dx 
$$

(1.30)

$$
= -m_E(t) + \frac{1}{\sqrt{\pi}} \int_{\sqrt{2}(\mu^E-\theta^E)/\sigma_E}^{\infty} e^{-x^2} dx 
$$

(1.31)

$$
\equiv -m_E(t) + \frac{\sigma_E}{\sqrt{2}} \text{erfc} \left( \frac{\mu^E - \theta^E}{\sqrt{2\sigma^2_E}} \right)
$$

For a small ratio of mean input to standard deviation, the erfc can be expanded as

$$
\text{erfc}(x) \approx e^{-x^2} \frac{1}{\sqrt{2\pi x}}.
$$

(1.32)

In equilibrium, $\frac{dm_E(t)}{dt} = 0$ so so we have a nonlinear relation between the average input, $<\mu^E>$ and the variances $\sigma^2_E$ and $\sigma^2_I$ at equilibrium. This leads to a leading term: -FILL IN EXPANSION-

$$
\mu^E \approx \theta^E + \sigma_E \sqrt{2|\log m_E|}
$$

(1.33)

-CHECK SIGN OF $\theta^E$. We see that the average activity is driven, almost linearly, by the standard deviation of the input. In fact, there is ample evidence from Fairhall that variance with drive spikes from a neuron, although a gain curve for spike rate versus the standard deviation is not to be found in the literature.