## **Supplementary information**

# **A biophysical account of multiplication by a single neuron**

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#### **Supplementary equations**

Here, we examine under which conditions a passive membrane can give rise to multiplication-like signal amplification. To extract the nonlinearity, we compare the response to two coincident inputs with the sum of the responses to each individual input presented in temporal isolation ('linear expectation'). We consider the simple case of an electrical equivalent circuit of a passive isopotential neuron that receives two excitatory input signals x and y, which control the excitatory conductances  $g_{exc1}$  and  $g_{exc2}$ , respectively (Extended Data Fig. 5b). The neuron's membrane potential  $V_m$  at steady state is given by

$$
V_m = \frac{E_{exc} (g_{exc1} + g_{exc2}) + E_{leak} g_{leak}}{g_{exc1} + g_{exc2} + g_{leak}};
$$

where  $E_{exc}$  and  $E_{leak}$  are the reversal potentials of excitatory and leak currents, respectively, and  $g_{leak}$  is the leak conductance. In the absence of input signals (i.e. when  $x = y = 0$ ), the neuron's resting potential  $V_{rest} = E_{leak}$ .

If we express the membrane potential response  $\Delta V$  as the difference between  $V_m$  and  $V_{rest}$ and all conductances relative to  $g_{leak}$ , then the membrane potential response to two coincident excitatory inputs is

$$
\Delta V = \frac{E_{exc}(g_{exc1} + g_{exc2}) + E_{leak}}{g_{exc1} + g_{exc2} + 1} - V_{rest}.
$$

For  $g_{\text{exc1}} = x$ ,  $g_{\text{exc2}} = y$ , and  $V_{\text{rest}} = E_{\text{leak}} = 0$  the response to the combined inputs can be written as

$$
\Delta V_{1,2} = E_{exc} \frac{x+y}{x+y+1}.
$$

The individual responses  $\Delta V_1$  and  $\Delta V_2$  to each input presented in isolation are

$$
\Delta V_1 = E_{exc} \frac{x}{x+1}
$$
 and 
$$
\Delta V_2 = E_{exc} \frac{y}{y+1}
$$
.

Now we show that, for two excitatory inputs,  $\Delta V_{1,2}$  is always smaller than the linear expectation  $\Delta V_1 + \Delta V_2$ :

$$
E_{exc}\frac{x+y}{x+y+1}
$$

Factoring out  $E_{exc}$ , we obtain

$$
\frac{x+y}{x+y+1} < \frac{x}{x+1} + \frac{y}{y+1} \, .
$$

The left expression can be broken into two components:

$$
\frac{x}{x+y+1} + \frac{y}{x+y+1} < \frac{x}{x+1} + \frac{y}{y+1} \, .
$$

If follows that, for positive non-zero values of  $x$  and  $y$ ,

$$
\frac{x}{x+y+1} < \frac{x}{x+1} \text{ and } \frac{y}{x+y+1} < \frac{y}{y+1}.
$$

If  $a < c$  and  $b < d$ , then  $a + b < c + d$ . Therefore, the response of a passive neuron to two coincident excitatory inputs  $\Delta V_{1,2}$  is always sublinear; i.e. smaller than the linear expectation  $\Delta V_1 + \Delta V_2$  (Extended Data Fig. 5b).

Next, we consider the pairing of an excitatory with an inhibitory input (Extended Data Fig. 5c). This neuron's steady-state membrane potential is

$$
V_m = \frac{E_{exc}g_{exc}+E_{inh}g_{inh}+E_{leak}g_{leak}}{g_{exc}+g_{inh}+g_{leak}}.
$$

As before, we let  $g_{exc} = x$ , but the inhibitory conductance  $g_{inh}$  follows  $1 - y$ , meaning that it decreases with increasing signal y (just like Mi9 neurons hyperpolarize with increasing light intensity). Again, we express the membrane potential response  $\Delta V$  as the difference between  $V_m$  and  $V_{rest}$  and all conductances relative to  $g_{leak}$ :

$$
V_m = \frac{E_{exc} x + E_{inh} (1 - y) + E_{leak}}{x + (1 - y) + 1}
$$
 and  

$$
\Delta V = V_m - V_{rest}
$$
.

All reversal potentials are expressed as the difference to  $E_{leak}$ , which we set to zero ( $E_{leak}$  = 0). Note that, unlike before, the neuron's membrane potential at rest (i.e. when  $x = y = 0$ ) is now  $V_{rest} = E_{inh}/2$ . The response to the combined inputs is

$$
\Delta V_{1,2} = \frac{E_{exc} x + E_{inh} (1 - y)}{x - y + 2} - \frac{E_{inh}}{2};
$$

which can be written as

$$
\Delta V_{1,2} = \frac{x (2E_{exc} - E_{inh}) - yE_{inh}}{2(2 + x - y)}.
$$

The individual responses are

$$
\Delta V_1 = \frac{x(2E_{exc} - E_{inh})}{2(2+x)}
$$
 and  $\Delta V_2 = \frac{-yE_{inh}}{2(2-y)}$ .

In the following, we show under which conditions,  $\Delta V_{1,2}$  is larger than the linear expectation  $\Delta V_1 + \Delta V_2$ :

$$
\frac{x(2E_{exc} - E_{inh}) - yE_{inh}}{2(2 + x - y)} > \frac{x(2E_{exc} - E_{inh})}{2(2 + x)} - \frac{yE_{inh}}{2(2 - y)}.
$$

This simplifies to

$$
\frac{x(2E_{exc} - E_{inh}) - yE_{inh}}{2 + x - y} > \frac{x(2E_{exc} - E_{inh})}{2 + x} - \frac{yE_{inh}}{2 - y}.
$$

Put over a common denominator, it can be written as

$$
(x(2E_{exc} - E_{inh}) - yE_{inh})(2 + x)(2 - y) > x(2E_{exc} - E_{inh})(2 + x - y)(2 - y) - yE_{inh}(2 + x - y)(2 + x).
$$

Expansion leads to

$$
x(2E_{exc} - E_{inh})(2 + x)(2 - y) - yE_{inh}(2 + x)(2 - y) >
$$
  

$$
x(2E_{exc} - E_{inh})(2 + x)(2 - y) - xy(2E_{exc} - E_{inh})(2 - y) - yE_{inh}(2 - y)(2 + x) - xyE_{inh}(2 + x).
$$

Subtraction of the blue and the red expressions on both sides yields

$$
0 > -xy(2E_{exc} - E_{inh})(2 - y) - xyE_{inh}(2 + x).
$$

Division by  $(-xy)$  reverses the inequality sign:

$$
(2E_{exc} - E_{inh})(2 - y) + E_{inh}(2 + x) > 0.
$$

This simplifies to

$$
2E_{exc}(2-y) + E_{inh}(y + x) > 0;
$$

or

$$
E_{exc} > -E_{inh} \frac{x+y}{2(2-y)}.
$$

Note that  $E_{exc}$  and  $E_{inh}$  are expressed as the difference to  $E_{leak}$ . For  $0 \le x \le 1$  and  $0 \le y \le 1$ (i.e. positive conductances smaller or equal to  $g_{leak}$ ) and  $|E_{exc}| > |E_{inh}|$ , the above inequality always holds. In the extreme case of  $x = y = 1$  the coincidence of an excitatory input with the release from an inhibitory one gives rise to a supralinearity as long as  $E_{inh}$  is closer to  $E_{leak}$  than  $E_{exc}$  (Extended Data Fig. 5d). Other values of x and y yield supralinear responses over much wider ranges of  $E_{exc}$  and  $E_{inh}$  (Extended Data Fig. 5e).



## **Supplementary Table 1. Statistical analyses of Figs. 2, 5.**

## **Supplementary Table 2. Statistical analyses of Extended Data Fig. 10.**

