

CISC 3250 example exam questions

This gives a sense of the type of questions that can be included. Further math topics covered in the homeworks (but not in this practice set) may appear on the exam as well.

We use the voltage model: $\tau \frac{dv}{dt} = -(v(t) - E_L) + RI(t)$

With voltage resetting to E_L once it reaches the threshold v_{thresh} , as specified by $v(t^f + \delta) = E_L$

Let us say $E_L = -60\text{mV}$, $\tau = 1$, and $v_{\text{thresh}} = -35\text{mV}$.

Furthermore, we define the axon voltage at time $t = 0\text{ms}$ to be: $v(0) = -40\text{mV}$

Presuming a constant input $RI(t) = 10\text{mV}$, how does the axon voltage change from time $t = 0\text{ms}$ to $t = 1,000\text{ms}$? For example, does the voltage spike, stay the same, plateau at another voltage value? Explain why, using the above equation(s) for the voltage model.

Answer:

$$\frac{dv}{dt} = -(v(t) - E_L) + RI(t) = -(-40 - (-60)) + 10 = -20 + 10 = -10 \text{ at } t = 0\text{ms}$$

$$v(10\text{ms}) = v(0\text{ms}) + (-10) \times 0.01 = -40 - 0.1 = -40.1$$

Initially, the $-(v(t) - E_L)$ term is larger than the RI term, so the voltage drops from -40mV . When the voltage reaches -50mV , it plateaus as the $-(v(t) - E_L)$ term $-(-50 - (-60)) = -10$ cancels at the $RI(t) = 10$ term.

Presuming the input rises to $RI(t) = 300\text{mV}$ starting at $1,001\text{ms}$, what is the axon voltage from time $t = 1,001\text{ms}$ to $t = 2,000\text{ms}$? Does the voltage spike, stay the same, plateau at another voltage value? Explain why, using the above equation(s) for the voltage model.

Answer:

The voltage rises to approach $E_L + RI = -60 + 300 = 240\text{mV}$. Since this value is greater than $v_{\text{thresh}} = -35\text{mV}$, the voltage will continually reset to E_L - in other words, it will spike.

Presuming a constant positive input $RI(t)$ over a long period of time, what is the minimum input value to produce spiking?

Answer:

The minimum input value RI will cause v to reach v_{thresh} .

$$v_{\text{thresh}} = E_L + RI \rightarrow RI = v_{\text{thresh}} - E_L \rightarrow -35 - (-60) = +25\text{mV}$$

Let us assume $\tau=1000$ (and all other parameters are the same as initially described). Presuming a constant positive input $RI(t)$ over a long period of time, what is the minimum input value to produce spiking?

Answer:

The change in τ has no effect on the minimum RI to cause spiking. Minimum RI is still +25 mV.

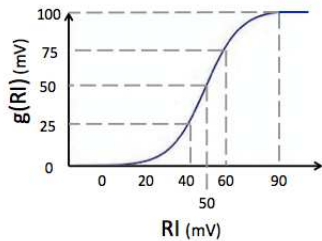
Explain a biological mechanism by which spiking information is communicated from the axon of neuron A to the dendrite of neuron B.

Answer:

Neurotransmitters are released from the axon of neuron A, travel across the synapse, and attach to the neurotransmitter receptors on the dendrite of neuron B.

We can replace the $RI(t)$ term from the equation above with $g(RI(t))$, where $g()$ is the sigmoid function we learned in class, now scaled to have a maximum output of 100mV, rather than just 1:

$$\frac{dv}{dt} = -(v(t) - E_L) + g(RI(t))$$



Let us consider three scenarios:

- 1: RI is a constant 60 mV
- 2: RI is a constant 120 mV
- 3: RI is a constant 240 mV

What is the change in spiking frequency from scenario 1 to scenario 2 (increase, decrease, stay roughly the same)? What is the change in spiking frequency from scenario 2 to scenario 3?

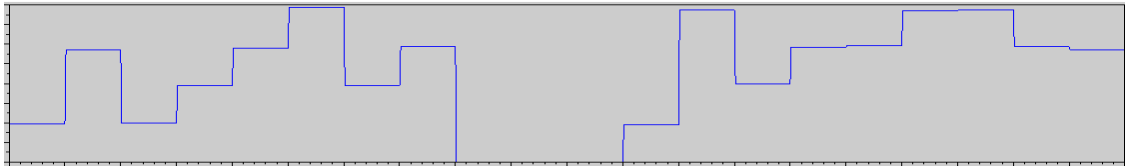
Answer:

Spiking frequency increases from scenario 1 to scenario 2. (It increases by roughly 33%, because the output of $g(60\text{mV})=75\text{mV}$, and the output of $g(120\text{mV})$ is roughly 100mV.

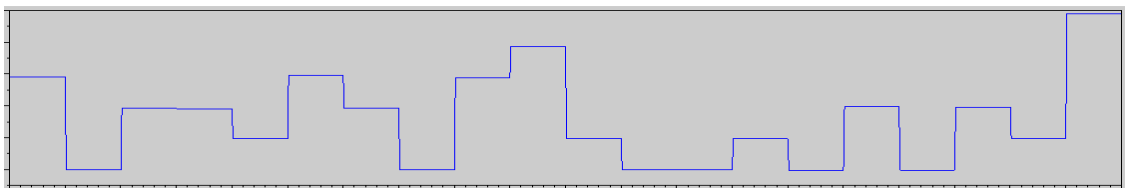
Spiking frequency stays roughly the same between scenario 2 and scenario 3 (both RI values produce roughly 100mV from the sigmoid function.

Which rate plot describes the spiking pattern shown here?

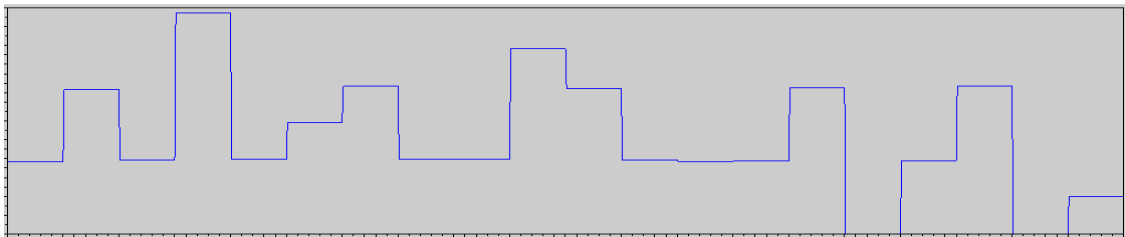
Rate plots have time on the x axis and rate over fixed time window on the y axis.



A



B



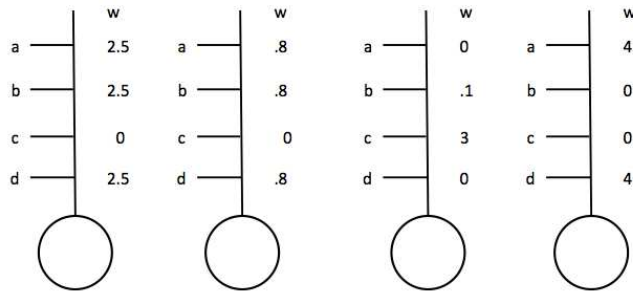
C

Answer:

Plot A (*note: if I give a question like this on the exam, it will be a bit more challenging - -- here you can just see the pause in spiking corresponds to the dip in spike rate*).

The following neuron computes the weighted sum of its inputs as $h = \sum_j w_j r_j$. It then outputs a 1 if $h > 2$ and otherwise outputs a 0. Each input provides a rate r_j of either 0 or 1 (no values in between).

For each set of weights, say if the neuron performs generalization/pattern completion, and if so, name the inputs that are tied together in the pattern.



 Answer:

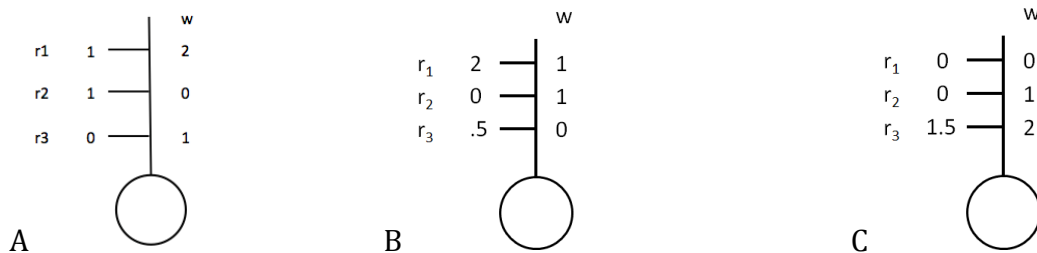
Left-most neuron ($w=2.5, 2.5, 0, 2.5$), there is generalization --- between inputs a, b, and d.

 The second neuron ($w=.8, .8, 0, .8$), there is not generalization --- it requires multiple simultaneous inputs to fire.

 The third neuron ($w=0, .1, 3, 0$), there is not generalization --- b will not produce firing on its own.

 The right-most neuron ($w=4, 0, 0, 4$), there is generalization --- between inputs a and d.

Presume the following neuron's output is computed by taking the weighted sum of inputs $h = \sum_j w_{ij}r_j$, and outputting 2 if $h > 1.5$ and outputting 0 otherwise.



NEURON A

Provide new weights using learning rule $\Delta w_{ij} = \epsilon r_i r_j$ and $\epsilon(w) = \begin{cases} 1 & \text{if } w \geq 0 \\ -1 & \text{if } w < 0 \end{cases}$ for all weight values

Answer:

$$r_{out} = g_{\text{thresh}}(1 \times 2 + 1 \times 0 + 0 \times 1) = g_{\text{thresh}}(2) = 2$$

$$\Delta w_{out1} = 1 \times 2 \times 1 = 2; \text{ after learning: } w_{out1}^{\text{new}} = w_{out1} + \Delta w_{out1} = 2 + 2 = 4$$

$$\Delta w_{out2} = 1 \times 2 \times 1 = 2; \text{ after learning: } w_{out2}^{\text{new}} = w_{out2} + \Delta w_{out2} = 0 + 2 = 2$$

$$w_{out3} \text{ does not change, since } r_3 = 0, \text{ so } w_{out3}^{\text{new}} = w_{out3} = 1$$

Provide new weights using learning rule above, followed by normalization of weights

Answer:

Taking previous answer, we now sum the new weights $\sum_j w_{outj} = 4 + 2 + 1 = 7$ and divide all the weights by this sum

$$w_{out1}^{\text{norm}} = 4/7 \approx .57$$

$$w_{out2}^{\text{norm}} = 2/7 \approx .29$$

$$w_{out3}^{\text{norm}} = 1/7 \approx .14$$

Provide new weights using Willshaw learning rule.

Answer:

$$\Delta w_j = r_{out}(r_j - w_j)$$

$$\Delta w_{out1} = 2 \times (1 - 2) = -2; \text{ after learning: } w_{out1}^{new} = w_{out1} + \Delta w_{out1} = 2 - 2 = 0$$

$$\Delta w_{out2} = 2 \times (1 - 0) = 2; \text{ after learning: } w_{out2}^{new} = w_{out2} + \Delta w_{out2} = 0 + 2 = 2$$

$$\Delta w_{out3} = 2 \times (0 - 1) = -2; \text{ after learning: } w_{out3}^{new} = w_{out3} + \Delta w_{out3} = 0 - 2 = -2$$

can use a calculator, can estimate to 1 decimal place

NEURON B

Provide new weights using learning rule $\Delta w_{ij} = \epsilon r_i r_j$ and $\epsilon(w) = \begin{cases} 1 & \text{if } w \geq 0 \\ -1 & \text{if } w < 0 \end{cases}$ for all weight values

Answer:

$$r_{out} = g_{\text{thresh}}(2 \times 1 + 0 \times 1 + 0.5 \times 0) = g_{\text{thresh}}(2) = 2$$

$$\Delta w_{out1} = 1 \times 2 \times 2 = 4; \text{ after learning: } w_{out1}^{new} = w_{out1} + \Delta w_{out1} = 1 + 4 = 5$$

$$w_{out2} \text{ does not change, since } r_2 = 0, \text{ so } w_{out2}^{new} = w_{out2} = 1$$

$$\Delta w_{out3} = 1 \times 2 \times 0.5 = 1; \text{ after learning: } w_{out3}^{new} = w_{out3} + \Delta w_{out3} = 0 + 1 = 1$$

Provide new weights using learning rule above, followed by normalization of weights

Answer:

Taking previous answer, we now sum the new weights $\sum_j w_{outj} = 5 + 1 + 1 = 7$ and divide all the weights by this sum

$$w_{out1}^{norm} = 5/7 \approx .7$$

$$w_{out2}^{norm} = 1/7 \approx .1$$

$$w_{out3}^{norm} = 1/7 \approx .1$$

Provide new weights using Willshaw learning rule.

Answer:

$$\Delta w_j = r_{out}(r_j - w_j)$$

$$\Delta w_{out1} = 2 \times (2 - 1) = 2; \text{ after learning: } w_{out1}^{new} = w_{out1} + \Delta w_{out1} = 1 + 2 = 3$$

$$\Delta w_{out2} = 2 \times (0 - 1) = -2; \text{ after learning: } w_{out2}^{new} = w_{out2} + \Delta w_{out2} = 0 - 2 = -1$$

$$\Delta w_{out3} = 2 \times (.5 - 0) = 1; \text{ after learning: } w_{out3}^{new} = w_{out3} + \Delta w_{out3} = 0 + 1 = 1$$

NEURON C

Provide new weights using learning rule $\Delta w_{ij} = \epsilon r_i r_j$ and $\epsilon(w) = \begin{cases} 1 & \text{if } w \geq 0 \\ -1 & \text{if } w < 0 \end{cases}$ for all weight values

Answer:

$$r_{out} = g_{\text{thresh}}(0 \times 0 + 0 \times 1 + 1.5 \times 2) = g_{\text{thresh}}(3) = 2$$

$$w_{out1} \text{ does not change, since } r_1 = 0, \text{ so } w_{out1}^{new} = w_{out1} = 0$$

$$w_{out2} \text{ does not change, since } r_2 = 0, \text{ so } w_{out2}^{new} = w_{out2} = 1$$

$$\Delta w_{out3} = 1 \times 2 \times 1.5 = 3; \text{ after learning: } w_{out3}^{new} = w_{out3} + \Delta w_{out3} = 2 + 3 = 5$$

Provide new weights using learning rule above, followed by normalization of weights

Answer:

Taking previous answer, we now sum the new weights $\sum_j w_{outj} = 0 + 1 + 5 = 6$ and divide all the weights by this sum

$$w_{out1}^{norm} = 0$$

$$w_{out2}^{norm} = 1/6 \approx .2$$

$$w_{out3}^{norm} = 5/6 \approx .8$$

Provide new weights using Willshaw learning rule.

Answer:

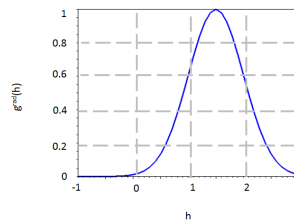
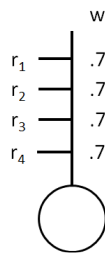
$$\Delta w_j = r_{out}(r_j - w_j)$$

$$\Delta w_{out1} = 2 \times (0 - 0) = 0; \text{ after learning: } w_{out1}^{new} = w_{out1} + \Delta w_{out1} = 0 + 0 = 0$$

$$\Delta w_{out2} = 2 \times (0 - 1) = -2; \text{ after learning: } w_{out2}^{new} = w_{out2} + \Delta w_{out2} = 1 - 2 = -1$$

$$\Delta w_{out3} = 2 \times (1.5 - 2) = -1; \text{ after learning: } w_{out3}^{new} = w_{out3} + \Delta w_{out3} = 2 - 1 = 1$$

The neuron 5 takes four inputs $r_1, r_2, r_3,$ and r_4 . Presume each of the four inputs is either 0 or 1. Further presume neuron 5 takes the weighted sum of its inputs and then has an output determined by $g^{rad}(h)$ below.



Propose two combinations of inputs that will produce an output great than 0.8 .

$r_1=1, r_2=1, r_3=0, r_4=0$... **you need exactly two inputs to be 1 and two to be 0**

$r_1=0, r_2=1, r_3=0, r_4=1$

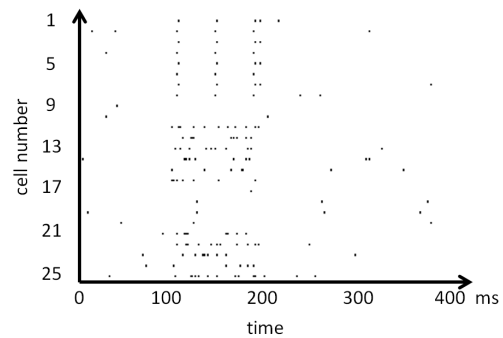
Propose two combinations of inputs that will produce an output less than 0.1 .

$r_1=0, r_2=0, r_3=0, r_4=0$

$r_1=1, r_2=1, r_3=1, r_4=1$

no other input combinations except the two above will work

To the right is a spikegram recording of a group of neurons in an animal's olfactory bulb. (This is actually fake data for the sake of testing concepts from class.) At some point, in time an odor is presented to the animal and at some later point the odor is removed.



Some of the recorded neurons respond through change in spiking rate. Which are these neurons?

Neurons 11-16 and neurons 21-25. (You can eye-ball your answers here for the purposes of this question based on the y axis labels.)

For these neurons, estimate the spike rate (per second) while the smell is presented. Roughly 80 spikes for 11 neurons -> roughly 7.5 spikes per neuron. Altered spiking activity lasts 100ms (or .1 s), so **75 spikes/second** (again, you can eye-ball. I would give credit anywhere between 85 and 65 spikes/second)

Some of the recorded neurons respond through change in temporal coding. Which are these neurons?

Neurons 1-8. (You can eye-ball your answers here for the purposes of this question based on the y axis labels.)

At what time is the smell presented? At what time is it taken away?

Starts at roughly 100 ms and taken away at roughly 200 ms. (You can estimate to the nearest 10 ms)