**Question 2.1:** Describe the effects on the rate of neural spiking of increasing GbarE to .4, and of decreasing it to .2, compared to the initial value of .3 (this is should have a simple answer).

Spikes at GbarE = 0.3

A graph of a graph

Description automatically generated with medium confidence

GBarE = 0.4

A graph of a test cycle

Description automatically generated

GBarE=0.2

A diagram of a test cycle

Description automatically generated

GBarE = 0.1

Increasing GbarE from 0.3 to 0.4: Spike rate increases

Decreasing GBarE from 0.3 to 0.2: Spike rate decreases

**Question 2.2:** Is there a qualitative difference in the neural spiking when GbarE is decreased to .1, compared to the higher values -- what important aspect of the neuron's behavior does this reveal?

A graph of a test cycle

Description automatically generated

Setting GBarE to 0.1 there are no spikes occurring. Hence the threshold for excitation has increased. This makes the neuron more selective in its responses.

**Question 2.3:** To 2 decimal places (e.g., 0.15), what value of GbarE puts the neuron just over threshold, such that it spikes at this value, but not at the next value below it?

Setting **GbarE=0.13** starts the neural spikes

A screenshot of a computer

Description automatically generated

**Question 2.4 (advanced):** Using one of the equations for the equilibrium membrane potential from the Neuron chapter, compute the exact value of excitatory input conductance required to keep Vm in equilibrium at the spiking threshold. Show your math. This means rearranging the equation to have excitatory conductance on one side, then substituting in known values. (note that: Gl is a constant = .3; Ge is 1 when the input is on; inhibition is not present here and can be ignored) -- this should agree with your empirically determined value.

INet(t) = Ge(t)\*GBarE \* (Ee – Vm(t)) + GBarL \* (El – Vm(t))

Given INet(t)= 0 (at equilibrium), Ge(t) = 1, Ee = 1, Vm(t) = 0.5 , El = 0.3, GBarL = 0.3

0 = 1 \* GBarE \*(1-0.5) + 0.3 \*(0.3-0.5)

0.5\*GBarE – 0.06 = 0

GBarE = 0.06/0.5 = 0.12

**GbarE = 0.12**

**Question 2.5:** What value of GbarL just prevents the neuron from being able to spike (in .1 increments) -- explain this result in terms of the tug-of-war model relative to the GbarE excitatory conductance.

GBarL=0.8

When GBarL increases, it is favoured in the tug of war model such that membrane potential is affected to the point the excitatory inputs find it difficult to drive membrane potential to the threshold value. Hence making it difficult for the neuron to attain the hyperpolarisation required for spiking.

**Question 2.6 (advanced):** Use the same technique as in question 2.4 to directly solve for the value of GbarL that should put the neuron right at it's spiking threshold using the default values of other parameters -- show your math.

INet(t) = Ge(t)\*GBarE \* (Ee – Vm(t)) + GBarL \* (El – Vm(t))

0 = 1\*0.3\*(1-0.5) + GBarL \* (0.3 – 0.5)

0.2 \* GBarL = 0.15

GBarL = 0.15/0.2 = 0.75

**GBarL=0.75**

**Question 2.7:** Compare the spike rates with rate coded activations by reporting the act values just before cycle 160 (e.g., cycle 155) for GbarE = .2, .3, .4 with Spike = false, and the corresponding values in the Spike = true case for the same GbarE values. For now, you'll have to click on the TstCycLog and scroll to cycle 155 to see the exact numbers -- a future release will hopefully enable you to just hover over the line and see the value on the graph directly.

1. When Spike = True

GBarE= 0.2

A diagram of a test cycle plot

Description automatically generated

GBarE=0.3

A diagram of a test cycle

Description automatically generated

GBarE=0.4

A diagram of a test cycle

Description automatically generated

1. Spike=false

GBarE=0.2

A diagram of a test cycle

Description automatically generated

GBarE = 0.3

A diagram of a test cycle

Description automatically generated

GBarE = 0.4

A graph of a test

Description automatically generated with medium confidence

We can see from the graphs that in case of neural spikes, higher the value of GBarE, higher the spike rate.

Without spiking, as we increase GBarE, the activation also increases.

**Question 2.8:** For each digit, report the number of active Input units where there is also a weight of 1 according to the 8-digit pattern. In other words, report the overlap between the input activity and the weight pattern. HINT: Strictly speaking, the *8* display in the *DigitPats* window is NOT representing the weights per se, but as we saw earlier using the *r.Wt* functionality in *NetView,* they are the same pattern -- and displaying the windows side-by-side just makes the counting easier.

|  |  |  |  |
| --- | --- | --- | --- |
| Digit | No: of active input units in each digit | No: of matches with the 8 digit pattern | Ge |
| 0 | 12 | 6 | 0.335 |
| 1 | 13 | 6 | 0.335 |
| 2 | 15 | 12 | 0.67 |
| 3 | 15 | 13 | 0.726 |
| 4 | 14 | 5 | 0.279 |
| 5 | 16 | 14 | 0.782 |
| 6 | 15 | 12 | 0.67 |
| 7 | 11 | 6 | 0.335 |
| 8 | 17 | 17 | 0.949 |
| 9 | 15 | 12 | 0.670 |

Example of calculation: -

For 0,

Calculated Ge = (1 / (17 / 35)) \* (6 / 35) \* 0.95 = 0.335

For 2,

Calculated Ge = (1 / (17/ 35)) \* (12/ 35) \* 0.95 = 0.67

**Question 2.9:** What happens to the pattern of receiving neuron activity over the different digits when you change GbarL to 1.8, 1.5, and 2.3 -- which input digits does it respond to for each case? In terms of the tug-of-war model between excitatory and inhibition & leak (i.e., GbarL = leak), why does changing leak have this effect (a simple one-sentence answer is sufficient)?

GBarL = 2: responds mostly to 8

A graph with blue lines

Description automatically generated

GBarL = 1.8: responds mostly to 5 and 8

A graph with lines and numbers

Description automatically generated with medium confidence

GBarL = 1.5: responds mostly to 2,3, 5,6 and 8

A graph with blue and green lines

Description automatically generated

GBarL = 2.3: responds mostly to 8

A graph with blue lines

Description automatically generated

When GBarL increases, it is favoured in the tug of war model such that membrane potential is affected to the point the excitatory inputs find it difficult to drive membrane potential to the threshold value. When GBarL is low, the neuron responds better to excitatory inputs.

**Question 2.10:** Why might it be beneficial for the neuron to have a lower level of leak (e.g., GbarL = 1.8 or 1.5) compared to the original default value, in terms of the overall information that this neuron can convey about the input patterns it is "seeing"?

When GBarL = 1.5: - Output is activated for the inputs 2,3,5,6,8,9

When GBarL = 1.8: - Output is activated for the inputs 5 and 8

When GBarL = 2.3: - Output is activated for the input 8

The neuron having a lower level of leak improves signal to noise ratio, hence giving more selective responses. It also increases input sensitivity and enhances its ability to convey more detailed information based on the inputs.

**Question 3.1:** Given what you know about how a Cluster Plot works (see above link), describe how the three features (gender, emotion, and identity) relate to the clustering of images by similarity. Specifically, think about where there are the greatest number of overlapping pixels across the different images from each of the different categories (all the happy vs. sad, female vs. male, and within each individual).

It is observed from the face cluster plot, that the faces with female gender are closer to each other and same for faces with male gender. Going deeper into the cluster tree among the male faces, we can see that the faces with identities Mark and Zane are closer to each other than that of Alberto, hence their faces are more similar to each other than Alberto. As for the faces with female gender, we can see that Lisa and Betty are closer to each other hence their faces more similar than that of Wendy. However, it is also observed that Betty’s face, whether happy or sad, is closer to Lisa’s sad face than Lisa’s happy face. Lisa’s sad face is closer hence more similar to Betty’s happy face.

As for each identity their faces with both emotions are most close to each other.

So, we can see that emotions do not affect the similarities of faces that much. Identities make a more significant difference. The most significant difference is gender

**Question 3.2:** How does the Emotion categorization transform the overall face input similarity compared to what we saw in the first cluster plot -- i.e., what items are now the most similar to each other?

In case of the emotion cluster plot, we can see that the sad faces are closer and similar to each other than the happy faces regardless of gender/identity. On checking the sad emotion cluster, we see that Lisa and Mark are closer, Zane and Billy are also closer, etc. As for the happy emotion cluster we can see the same for Lisa and Alberto, Zane and mark, etc. We also observe form the plot that Wendy’s sad face is similar to Lisa s happy face. Hence emotions categorise the facial features more than gender or identity.

**Question 3.3:** Across multiple different such partial faces, what is the order in which the correct category units get active (there may be transient activity in incorrect units)? For each case also list how this order corresponds to the timing of when the missing features in the input face start to get filled in.

For the Mark\_sad case:

first 16 seconds: Gender and identity output start to get detected.

17 s: Output is surer it’s a male and identity mark but identity Zane is also detecting a little. Both happy and sad emotion is getting detected.

19 s: sad is more detected than happy.

21 s: Mark and male is more detected and Zane detection is going down.

Finally, emotion is detected after gender/identity.

Wendy\_happy case: all 3 detect at same rate

Same for Wendy\_sad case

**Question 3.4:** Explain why the subset of cat individuals ended up getting activated, when just cat was provided as input -- how might this differential activation of individuals provide useful information about different cats in relation to the general cat category?

First 10s: output activates species as cat

20s: The first 5 identities get activated

30s : All identity outputs weaken, activates: size small, toy string, food grass, 1st 5 names

34s: Both 1st and 3rd identities and names, colour orange get activated

The cats subset of Morris and Sylvester were activated because they have all the features that are most common in the cats dataset such as string for toy, grass for food and small in size. So, this subset portrays the most common cats. Another feature that launces similar activations is the input pattern set to size small, saying that cats are typically smaller than dogs.

**Question 3.5:** Report what differences you observed in the settling behaviour of the network for the different values of noise (0, .1, .01, .001), and explain what this tells you about how noise is affecting the process

Levels of noise

0 – Both interpretations are slightly activated

0.1– The activations fluctuate in a mix of cubes from both interpretations until it settles with activating the left cube interpretation.

* 1. –The units on the left cube only activate very weakly and go down. The right cube gets more active immediately.

0.001-The units on the right cube only activate weakly and go down. The left cube gets more active after a short while.

We can observe that without any noise, it’s not possible to determine which interpretation should be active. However, keeping the noise as minimal as possible (near to but not zero) quickens the process of determining which cube interpretation is fired.

Introduction of noise in these networks captures the adaptability of neural systems as the brain itself has neural systems that are inherently noisy. The brain can take this noise and use it to update itself when determining output for an ambiguous network. Mimicking the same in the networks helps us to settle on one interpretation of the cube, or change interpretations randomly later on.

**Question 3.6:** What effects does decreasing and increasing HiddenGbarI have on the average level of excitation of the hidden units and of the inhibitory units, and why does it have these effects (simple one-sentence answer)?

Decreasing HiddenGbarI made the average level of excitation of the hidden units and of the inhibitory units slightly increase the average excitation of both. Increasing HiddenGbarI made the average level of excitation of the hidden units and of the inhibitory units decrease the average excitation of the same. This is due to the reduced inhibitory input to hidden and inhibitory units. Thus, they are more excitable increasing their average excitation.

**Question 3.7:** How does eliminating feedforward inhibition affect the behaviour of the excitatory and inhibitory average activity levels -- is there a clear qualitative difference in terms of when the two layers start to get active, and in their overall patterns of activity, compared to with the default parameters?

Without feedforward inhibition, the neuron has faster excitatory activity and higher overall excitation. This affects the balance between excitation and inhibition.

Also, without FF inhibition, the responses are quick but blown out of proportion. The network becomes more sensitive to input, and may result in nonsensical responses.

**Question 3.8:** How much does the hidden average activity level vary as a function of the different InputPct levels (10, 20, 30). What does this reveal about the set point nature of the FFFB inhibition mechanism (i.e., the extent to which it works like an air conditioner that works to maintain a fixed set-point temperature)?

InputPct at level 10: The average hidden activation is at the 15% level

InputPct at level 20: The average hidden activation is at the 20% level

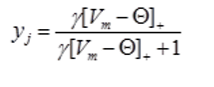
InputPct at level 30: The average hidden activation is at the 20% level

We can see that the hidden activation level tries to stay constant or has only a small variance (15-20%) at different InputPct levels. This shows that like a set point temperature maintained by an air conditioner, the network counteracts against the different inputs to keep its activation levels stable at all times.

1. Why are the O’Reilly and Munakata equations called point neuron equations? As a consequence of this, what aspects of neurophysiology can these equations not reflect?

The O'Reilly and Munakata equations are called point neuron equations as they show the characteristics of a neuron as if it is a single point. It simplifies the neuron dynamics and models the basic firing properties of neurons. These models focus on the inputs at a single point of the neuron, ignoring the spatiality of the neuron structure. It also isolates the neural points and is not influenced by neighbouring neural networks.

2. In the output activation equation below, what would the consequence be of replacing the +1 term with +10? How could one obtain a similar effect by changing a parameter of this equation?



Replacing +1 with +10 potentially increases the bias hence increasing the threshold for activation.

A similar effect can be obtained by increasing the gain, Γ