Isolating the key factors defining the magnitude of hippocampal neurogenesis' effects on anxiety, memory and pattern separation

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Abstract: In this paper, I analyze the hypothesis that hippocampal neurogenesis (HN) exerts its effects on behavior via activation of inhibitory circuits in the hippocampus. Using a very simple mathematical model (half-borrowed from biochemistry) to aid the reasoning, I show that the key factors determining the magnitude of HN's effects on behavior are: the baseline levels of HN in the animal, the efficiency of the animal's inhibitory circuits, the strength/intensity of the stimulus presented to the animal and how much accuracy the behavioral task requires from the information contained in the hippocampal representations. Taken together, those factors can help explain patterns observed in the behavioral results for memory, pattern separation and anxiety. The conclusions of the analysis suggest that HN's effects on inhibitory circuits can explain the impact of neurogenesis in both emotion and cognition and provide a framework to interpret future studies with rodents and possibly with other species as well.

Keywords: Adult neurogenesis, hippocampus, dentate gyrus, feedback inhibition, inhibitory circuits.

Main text

Hippocampal neurogenesis (HN) has been a focus of intense research in the past decades (see Gonçalves et al. (2016) for a general review). Much of this research effort focused on understanding HN's functional impact on the workings of the hippocampus, with an emphasis on its effects on behavior. We now have behavioral evidence for HN's involvement in anxiety (see the meta-analysis in Groves et al., 2013), memory (Groves et al., 2013; França et al., 2017) and pattern separation (França et al., 2017). However, the effects of HN on those behaviors are not always clear. Although researchers have picked up some patterns in the behavioral results (see Cameron and Glover, 2014), there is still a lot of ground to cover in the way of tying all these pieces of evidence together.

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A promising hypothesis for a mechanism behind HN's effects on behavior proposes that immature neurons in the dentate gyrus (DG) can activate inhibitory circuits in the DG, enhancing feedback inhibition. HN may also affect CA3 as well, contributing to feedforward inhibition in that sub-region (Piatti et al., 2013). Most of the studies regarding HN's effects on inhibitory circuits focused on the DG, where there is evidence of HN ablation increasing granule cell activity/excitability (Burghardt et al., 2012; Lacefield et al., 2012; Ikar et al., 2013; Park et al., 2015), including a direct demonstration of immature neurons' capacity to activate inhibitory circuits (Drew at al., 2016). Importantly, as I will show below, this single mechanism of action has the potential to explain HN's effects in emotion, memory and pattern separation.

My goal in this paper is to get a better idea of how the effect of HN on inhibitory circuits can account for the different behavioral effects of HN. To do so, I will try isolating the key factors determining the magnitude of the effect of HN on behavior. In the following paragraphs, we will develop a model for HN's effects on the inhibitory circuits of DG and CA3; we will try to capture the basic features of the workings of inhibitory circuits in a piece of mathematical formalism that I will keep as simple as possible. Our goal will not be to make quantitative predictions or to build a realistic model of the hippocampus (whatever "realistic" means). What we will try to do is use mathematical formalism merely to aid our reasoning in identifying the key factors that influence HN's effects.

We will use a simple input-output equation with the form

$$o = i - f(i) \qquad (1),$$

where *o* is the output activity of a given hippocampal sub-region (either DG or CA3) and *i* is the input to that region. The *f(i)* can stand for either feedback or feedforward inhibition, which in both cases is a function of the input. For now, we will focus on DG, with *f(i)* as feedback inhibition, but everything that will be developed below also applies to feedforward inhibition in CA3, as we shall see.

One caveat of using an input-output equation instead of, e.g., a computational model with "neurons" in it, is that we become blind to the identity of the neurons in the output, and this identity is of crucial importance for the workings of the hippocampus. However, for our purposes, we can circumvent this problem by organizing all the granule cells in the DG in a circular plane in a very particular way. To do so, consider a given stimulus to the DG, in the form of activation of several axons from the entorhinal cortex (EC) projecting to the DG. Given such stimulus, we will organize our DG granule cells in such a way that the neurons with the highest number of active synaptic inputs will be at the center of the circle, with neurons further away from the center having an increasingly smaller number of active inputs, all the way down to neurons with only one active synaptic input (we shall ignore neurons with no active inputs) (**Figure 1a**). In this context, the input *i* in our model will be the number of neurons receiving enough stimulation to, in the absence of any inhibition, reach the firing threshold. Thus, the further away from the center of the circle a neuron is, the stronger the stimulus required to activate it. In other words, the radius of

the circle containing the neurons activated by the input will be proportional to the strength or intensity of the stimulus – that is, how active where the firing EC neurons. Thus, the variable *i* will be defined as

$$i = d\pi x^2 \qquad (2),$$

where *d* is the number of neurons per unit of area in our circular plane and πx^2 is the area of the circle containing the active neurons, the radius *x* being proportional to the intensity of the stimulus. Note that very high values of *x* would represent the unnatural scenario in which stimulation is so strong, that even neurons with only one active synaptic input would receive enough neurotransmitter from that synapse to reach the firing threshold. The output *o* will be the number of neurons in the DG that actually become active after the effect of feedback inhibition. You can see now that, in the context of our model, the magnitude of the input is related to the intensity of our chosen stimulus, and an increase in the output for a given stimulus implies the activation of neurons with a smaller number of active synaptic inputs.

We now come to the feedback term, *f(i)*. The strength of the feedback inhibition depends on the number of inhibitory neurons active, which depends on the intensity of the stimulus. Note that the whole process is teeming with cooperation since neurons combine their inputs over time and space. We can make an analogy with one of several molecular processes that involve cooperation. Take, for example, the binding of transcription regulators to regulatory regions of the DNA (Alberts at al., 2015). Such transcription regulators often act in dimers or even oligomers, needing to cooperate to elicit their effects, much like inhibitory interneurons must act together to efficiently inhibit principal neurons. Consider a situation with many transcription regulators and many DNA loci to bind. In such scenario, we would expect the relationship between transcription regulator concentration and their successful binding to DNA to be similar to the relation between the population activity of inhibitory interneurons and their inhibitory effect. We can thus borrow the Hill equation

$$\frac{[TR]}{R_{tot}} = \frac{[T]^h}{K+[T]^h} \qquad (3),$$

which can describe the relationship between the concentration of transcription regulators [T] and the fraction of the total DNA loci that is bound to regulators ($[TR]/R_{tot}$), with K being the dissociation constant and h being the Hill coefficient. What we are going to do is reinterpret the Hill equation for our purposes. We define

$$\mathrm{f}(i) = \left(\frac{i^{\mathrm{c}}}{\mathrm{K}+\, i^{\mathrm{c}}}\right) Mi \qquad (4),$$

where we keep $i = d\pi x^2$; *c* is the adapted Hill coefficient, which will be proportional to number of interneurons required to elicit a given inhibitory effect; *K*, the dissociation constant in the Hill equation, is the value of *i* required to elicit half of the feedback's maximum capacity. The value of *K* will depend on, among other factors, the interneurons' membrane time constant – a larger membrane time constant implies a small value of *K* and facilitates the summation of inputs by the

neuron, just like a small dissociation rate facilitates DNA binding in the case of transcription regulators. Finally, *M* is the maximum fraction of active principal neurons the feedback can inhibit, setting the maximum efficiency of feedback inhibition (note that the product *Mi* has no counterpart in the original Hill equation, it was added to convert the output of the Hill equation, which is a ratio, into a number of neurons to be subtracted from the input *i* in equation 1).

One may object that, for feedback inhibition, there should be three nested Hill equations, one serving as input to the other, to represent the three stages where there is cooperativity: in the activation of principal neurons by the input stimulus, in the activation of inhibitory interneurons by principal neurons, and in the inhibition of principal neurons by interneurons. However, such equations, with the general form

$$\mathrm{f(i)} = \left(\frac{\left(\frac{\left(\left(\frac{i^c}{k+i^c} \right) \times d \right)^C}{\mathrm{K} + \left(\left(\frac{i^c}{k+i^c} \right) \times d \right)^C} \times D \right)^H}{\mathrm{K} + \left(\frac{\left(\left(\frac{i^c}{k+i^c} \right) \times d \right)^C}{\mathrm{K} + \left(\left(\frac{i^c}{k+i^c} \right) \times d \right)^C} \times D \right)^H} \right) \quad (5),$$

would produce curves that maintain the sigmoid shape characteristic of the Hill equation with cooperativity, as equation 5 maintains the same overall structure of the Hill equation ($[T]^h/K + [T]^h$). Since we are only interested in qualitative analysis here, we can go without using such ugly equation.

We are now in position to plug all the terms (equations 2 and 4) in our original equation, $o = i - f(i)$, to produce

$$o = (d\pi x^2) - \left(\left(\frac{(d\pi x^2)^{\mathrm{c}}}{\mathrm{K} + (d\pi x^2)^{\mathrm{c}}} \right) M(d\pi x^2) \right) \quad (6).$$

How do we represent HN in this equation? By adding a second feedback term, with the exact same form as the feedback term in equation 4:

$$o = (d\pi x^2) - \left(\left(\frac{(d\pi x^2)^{\mathrm{c}}}{\mathrm{K} + (d\pi x^2)^{\mathrm{c}}} \right) M(d\pi x^2) \right) - \left(\left(\frac{(d\pi x^2)^{\mathrm{h}}}{\mathrm{k} + (d\pi x^2)^{\mathrm{h}}} \right) m(d\pi x^2) \right) \quad (7),$$

where *k, m* and *h* are defined as *K*, *M* and *c,* respectively, in the first feedback term (equation 4). We set the first feedback term to represent the feedback inhibition elicited by mature granule cells, while the second feedback term represents the feedback recruited by immature granule cells. Note that we are simplifying things by assuming that the two feedback terms add linearly, and this will likely underestimate the magnitude of the effect of immature neurons. But again, we are not interested in precise quantitative predictions; all we want is reasoning aid, so let us stick to simplicity.

Note that the equations above are also valid for feedforward inhibition in CA3. Like feedback inhibition in the DG, feedforward inhibition in and CA3 also shows cooperativity and can be described using the very same equations by taking the input to be the stimulation of CA3 pyramidal cells by DG granule cells and the *f(i)* terms to be feedforward inhibition on CA3. Therefore, the conclusions we are about to draw can apply to HN's effects both on DG and CA3.

What we are going to do now is compare equations 6 and 7, to see how the output behaves with and without the HN feedback term. The specific choice of parameters does not really matter, as the same overall pattern can be observed for a wide range of parameters, as long as $M + m < 1$. Note that $M + m > 1$ would imply that stronger stimuli activate fewer neurons, as the maximum efficiency of the inhibition would be more than enough to inhibit every single neuron stimulated. We also assume that $M > m$, meaning that mature granule cells recruit more feedback/feedforwad inhibition than immature granule cells, although violating this assumption would imply a greater magnitude of HN' effects without changing our conclusions as to the relevant factors influencing such effect. Finally, we also assume $K > k$, meaning that the inhibition recruited by immature neurons reaches the plateau faster since immature neurons are more excitable (Gonçalves et al., 2016).

Figure 1b shows the comparison of equations 6 (blue curve) and 7 (red curve) for $K = 30$, $k = 15$, $c=h=2$, $d=0.01$, $M=0.7$ and $m=0.1$ and **Figure 1c** shows the comparison after changing M to 0.5 and m to 0.3 (the interested reader can use the R code and the step-by-step guide provided in the **supplementary materials** to test other values and see that the pattern observed for the example values is conserved). The key implications of the model can be visualized by analyzing the curves in **Figures 1b** and **1c**. There are some key features that I would like to highlight. The first one is that the model implies that the contribution of immature neurons to feedback/feedforward inhibition, which reflects in the difference between the outputs with and without HN, grows with the intensity of the stimulus. Importantly, this pattern agrees with experimental data regarding response strength of the DG in animals with increased or reduced HN compared to control (see Figures 2 and 3 of Ikar et al., 2013). This can explain the observation that a stronger impact of HN ablation on anxiety-related behaviors is obtained when animals are subjected to stress prior testing (Cameron and Glover, 2014). Such observation fit well with our model, as more intense stimulation would make the effects of HN ablation more apparent. Accordingly, the expression of anxiety- and avoidance-related behaviors was shown to depend on the activity of neurons in the ventral hippocampus projecting to the lateral hypothalamic area (Jimenez et al., 2018), and a recent study strongly indicates that HN confers stress resilience precisely by inhibiting the ventral DG (Anacker et al., 2018).

Importantly, from the context of our model, we can see the surplus in the number of output neurons consists of neurons having an increasingly smaller number of active synaptic inputs. This has important implications for the cognitive effects of HN. In the case of memory and pattern separation, this aspect of the model can give an explanation as to why the behavioral effect of HN seems greater and more consistent in studies employing behavioral tests of pattern separation compared to other memory tasks, such as Morris water maze and context fear conditioning

(Groves et al., 2013; França et al., 2017). Note that the inhibitory circuits create a competition between neurons by inhibiting the less active neurons and selecting the ones receiving stronger input. In doing so, inhibition helps to maintain active only the neurons whose receptive fields (as defined by their connectivity pattern) better represent the stimulus being given. The weakening of feedback/feedforward inhibition would ease the competition and allow the activation of neurons representing information that does not fit the stimulus so well, essentially adding noise to hippocampal representations. But how much this added noise would influence the animals' behavior? As we have seen, that will depend on the intensity of the stimulus. But, importantly, it also depends on the difficulty of the test. The harder the test, the more detail an animal has to remember, the more likely it is that the animal will be impaired by the noise added by HN ablation. Since behavioral tests of pattern separation are the ones demanding the most of memory by presenting the animal of very similar stimuli, it would be expected that animals are more consistently impaired in such tests.

At this point, it is important to note that immature neurons, being highly plastic and excitable and firing with low specificity, could be themselves a source of noise in the DG's output. However, synaptic transmission from granule cells to CA3 pyramidal cells is characterized by its high efficiency, and this efficiency stems from the peculiar architecture of those synapses. Such specialized structure takes very long to develop in new granule cells, with its development being completed only after the critical period of high excitability (Toni and Schinder, 2016). And while granule cells contact only a dozen or so CA3 pyramidal cells, filopodial extensions from mossy fiber terminals allows granule cells to contact more than twice as many GABAergic interneurons in CA3 (Acsády et al., 1998). Moreover, immature neurons seem to form more synapses with inhibitory interneurons in the CA3 compared to mature granule cells (Restivo et al., 2012). Taken together, these observations suggest that whatever is the direct contribution of immature granule cells to increase DG's output is offset by their indirect contribution to reduce DG's output, as well as their inhibitory effect on CA3 and the delayed morphological maturation of their presynaptic terminals with CA3 pyramidal cells.

Another key implication of the model I would like to highlight is that the effect of HN ablation will depend not only on the contribution of immature neurons to feedback/feedforward inhibition, but also on the capacity of mature neurons to elicit feedback/feedforward inhibition. This can be seen by comparing **Figures 1b** and **1c**. In both cases, the total inhibitory capacity ($M + m$) is 0.8; what determines the importance of HN for the animal is the way that total capacity is distributed. This could explain at least part of the variability observed in behavioral studies after HN ablation. Animals vary in their levels of HN at baseline and can also differ in the efficiency of their inhibitory circuits (which could be influenced by individual variations in, e.g., cell excitability or the connectivity pattern and synaptic weights between principal neurons and interneurons). Thus, HN may be more important for eliciting proper behavior in some animals than in others. In the same token, HN may be more important for hippocampal function in some species than in others due to interspecies variations in feedforward/feedback circuits (Freund and Buzsáki, 1996).

In conclusion, we can see from the reasoning exposed above that the magnitude of the behavioral effect of HN, at least of the effects elicited via activation of inhibitory circuits, largely depends on just a few key factors. They include the levels of HN in the animal, the efficiency of the animal's inhibitory circuits, the strength of the stimulus presented to the animal and how much accuracy is required from the information contained in hippocampal representations. Such principles may provide a coherent framework to interpret future results of behavioral studies in different species, whether they deal with cognition or emotion.

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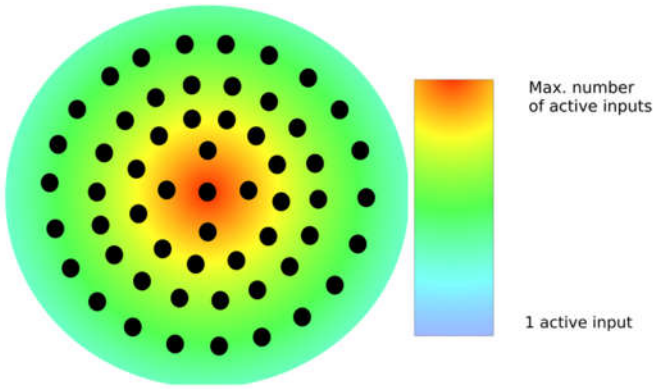
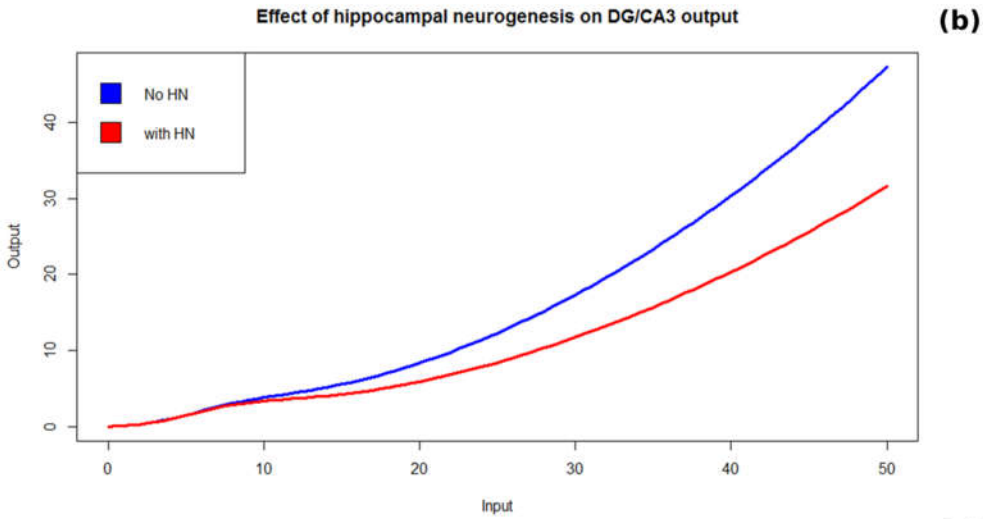
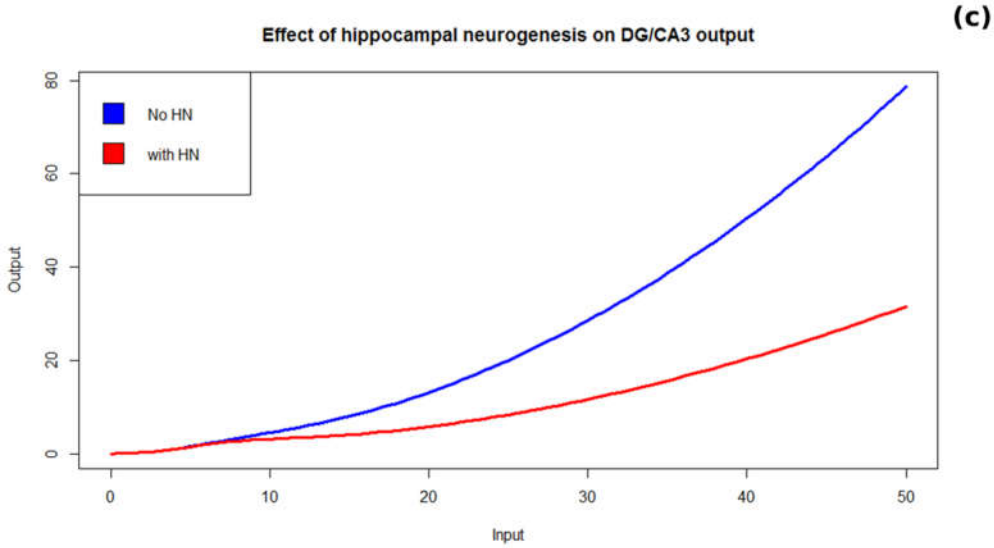
Figure legends

Figure 1. A simple model for hippocampal neurogenesis' (HN) effect on the DG's output via activation of feedback inhibition**. (a)** To simplify the mathematics of the model, we focus on a specific stimulus and arrange neurons (black dots) in a circular plane. The position of the neurons in the plane is defined by the number of the neurons' synaptic inputs that are activated by the stimulus (note the color code). Thus, neurons with the highest number of synaptic inputs activated by the stimulus are at the center of the circle, while neurons with only one synaptic input activated are at the periphery. The radius of the area within the circle containing the neurons recruited by the input stimulus is proportional to the stimulus' intensity. The role of feedback inhibition here is essentially to reduce the size of the area containing active neurons. **(b)** Comparison of equations 6 (blue curve) and 7 (red curve) for K = 30, k = 15, c=h=2, d=0.01, M=0.7 and m=0.1. The y axis represents the output and x axis represents the input. Note how the two curves diverge as the stimulus intensity, represented by the input's magnitude, increases. **(c)** Same as (b), but with M = 0.5 and m = 0.3. Note how changing the parameters to give less weight to inhibition recruited by mature neurons and more weight to inhibition recruited by immature neurons accelerates the divergence of the curves.


(a)
Max. number
of active inputs
1 active input


Effect of hippocampal neurogenesis on DG/CA3 output
(b)
No HN
with HN
Output
Input
0
10
20
30
40
50


Effect of hippocampal neurogenesis on DG/CA3 output
(c)
No HN
with HN
Output
Input
0
10
20
30
40
50
60
80