

Figure 1: The hippocampus. This is a modified image originally due to Cajal, probably from his 1911 book, the inset shows the approximate connectivity. [From [http://en.wikipedia.org/wiki/File:CajalHippocampus\\_\(modified\).png](http://en.wikipedia.org/wiki/File:CajalHippocampus_(modified).png)]

## Introduction

These notes are about the hippocampus. I offer an error bounty of between 20p and 2 pounds for mistakes. Contact me at [conor.houghton@bristol.ac.uk](mailto:conor.houghton@bristol.ac.uk) or come up after a lecture.

## Anatomy of the hippocampus

The hippocampus is situated at the edge of the cortex and is divided into three main areas. Since the hippocampus is so distinctive in shape, two of these are named for the shape, one for its location.

- Cornu Ammonis (CA) - meaning the *horn of Amon*, an Egyptian god of fertility with curved horns. The CA is usually divided into four regions, labelled CA1 through to CA4.
- Dentate Gyrus (DG)- gyrus is the name given to the ridges in the cortex, dentate means *with teeth*. The dentate gyrus is one of the few areas of the adult brain that exhibits neurogenesis.
- Entorhinal Cortex (EC) - entorhinal means *near the smell processing area*.

## The role of the hippocampus

The role of any brain region is complex and the hippocampus is no exception. It may play a role in olfaction for example, however, it is widely believed that its principle role is in memory and in constructing spatial maps. Studying patients with hippocampal damage shows that it is involved in declarative memory, that is the sort of memory that can be described in words. It does not play a role in procedural memory, the memory process which allows us to learn new motor skills. It appears, again from patients with hippocampal damage, that some long term memories are stored outside the hippocampus.

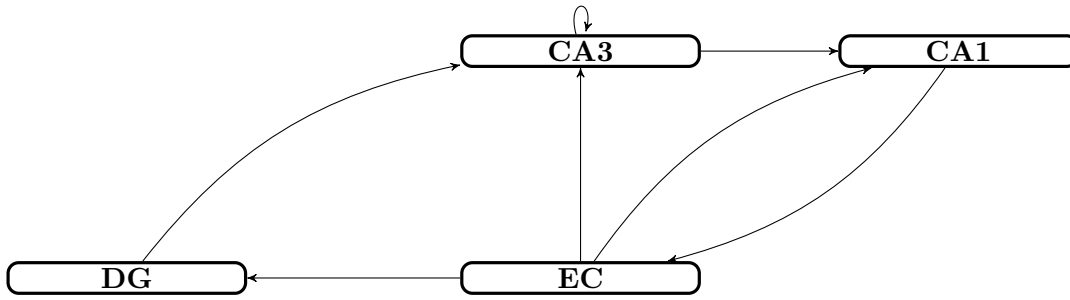


Figure 2: Connectivity of the hippocampus. A rough diagram showing the major connections between the areas of the connectivity.

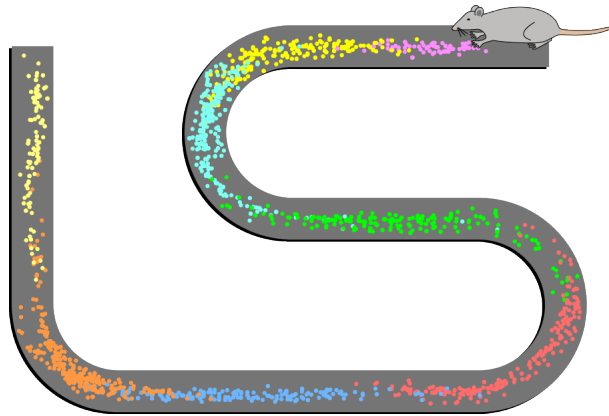


Figure 3: Place cells. This shows the firing activity of eight different cells in CA1 of a rat moving along a path, the dots correspond to spikes. [From [http://en.wikipedia.org/wiki/Place\\_cell](http://en.wikipedia.org/wiki/Place_cell)]

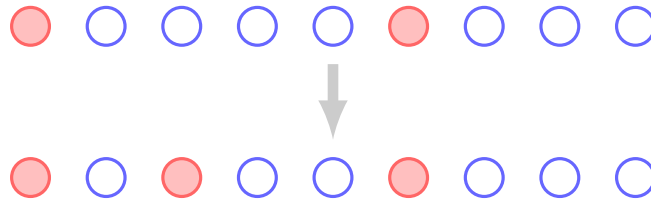
The best studied function of the hippocampus is spatial memory. There are cells in rat CA1 known as place cells which fire in response to specific location, an example is shown in Fig. 3. These were first discovered in 1971 [1] and show both that the hippocampus has a role in spatial memory and that the memory encoding is very sparse. Another, striking, example was discovered in 2005 in humans [2]. Recordings were taken from electrodes implanted for medical reasons in patients with focal epilepsy, these patients are required as part of an investigation into their epilepsy to spend time with the electrodes implanted; during this time many generously agree to take part in scientific investigations. They were shown many images while the activity of individual cells were monitored. It was found that some cells respond to very specific stimuli and that this stimulus can be quite abstract. In the most quoted example a cell in hippocampus in one patient was found which responded to pictures of Jennifer Aniston. It did this irrespective of how she appeared, but did not respond to other famous and non-famous faces, or curiously to pictures of Jennifer Aniston with Brad Pitt, her spouse at that time. Again, this demonstrates a role in memory, but one that involves very sparse responses.

## Auto-associative memory

The standard paradigm for memory in the hippocampus is *auto-associative* memory. Auto-associative memories are patterns representing memories along with some dynamics that complete partial patterns. Imagine a sequence of on-off neurons



where the filled circles correspond to on. Recall occurs when the network is presented with a partial pattern and evolves into the complete patterns.



The idea is that the hippocampus implements a network which performs auto-associative memory.

## A model of CA3

Here a highly simplified model of CA3 is presented [4]. In this model CA3 is all-to-all connected and made up of McCulloch-Pitts neurons [3]. We will consider the dynamics of these neurons shortly, for now it is enough to note that they are binary neurons with on and off states, this would correspond, biologically, to firing and not firing and obviously abstracts away all the details of firing along with the possibility of there being different firing rates. We will call the on state '1' and the off state '0'. Now let  $N$  be the number of neurons,  $x_i$  the activity of neuron  $i$  and  $w_{ij}$  the strength of the connection for  $i$  to  $j$ . The sparseness, the average proportion of neurons active at any one time is  $a$ , this is believed to be very small in actual neurons. For this simple model  $w_{ij} = w_{ji}$ .

During learning the patterns are activated and plastic changes are made to the synapse strength according to a simple correlation based Hebbian plasticity rule.

$$\Delta w_{ij} = \eta(x_i - a)(x_i - a) \quad (1)$$

where  $\eta$  is the learning rate, typically a very small number. Since  $a$  is very small too for real networks there will be a large increase for the connection between two neurons that are active at the same time, a tiny increase for pairs neurons that are inactive at the same time and a medium size decrease for pairs of neurons where one is active and one inactive. See Fig. 4.

During recall some of the neurons are held in the active state and the rest of the network evolves according to a threshold input rule. That means each neuron has an input given by

$$h_i = \sum w_{ij}x_j \quad (2)$$

and is set in the active state if  $h_i > \theta$  where  $\theta$  is a threshold which is set to different values for different networks. The idea is that after learning the pattern  $\{0, 2, 5\}$



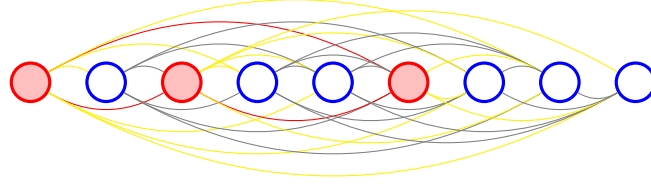


Figure 4: Learning in the associate network. The pattern has been imposed and connection strengths are changed. The red links increase by  $\eta(1 - a)^2$  and the gray by  $\eta(-a)^2$ , the yellow links decrease by  $\eta a(1 - a)$ .

the connections between these nodes will be strong, so if the network has nodes  $\{0, 5\}$  activated



the value  $h_2 = w_{12} + w_{52}$  will be larger than threshold and the subsequent dynamics will switch neuron 2 on. However, in this network, if a different initial set of neurons are activated, the activity will die away because the  $h_i$  will all be sub-threshold.

## Capacity

When many patterns are stored it is likely that there will be interference between them. This is illustrated in Fig. 5. Although the figure shows how a single neuron fails to participate in two patterns, for larger networks some overlap is possible, but too much overlap prevents retrieval. In fact the capacity is proportional to the number of neurons,  $N$ . A hand-waving argument goes like this: the number of connections is roughly  $N^2$  and the amount of information in a pattern is  $N$  so the number of patterns that can be stored is  $N^2/N = N$  [4].

The capacity is also larger if there is sparseness; one way to think of this is to observe the weight decrease between an active and inactive connection is  $\Delta w_{ij} = -\eta a(1 - a)$  so the smaller  $a$  is the smaller the amount these links are decreased. Links are decreased if, in the pattern, one neuron is active and one inactive, they are strengthened if both neurons are active, the increase is  $\eta(1 - a)^2$ . Hence, it takes  $1/a$  patterns where a connect is weakened to wipe out the strengthening that results if the connect is part of a pattern. In fact, it is estimated that the capacity of a network is

$$P = \frac{k}{a} N \quad (3)$$

where  $k$  is constant which has been found to be about  $k \approx 0.035$ , this is reduced to

$$P = c \frac{k}{a} N \quad (4)$$

if there is missing connections, where  $c$  stands for the fraction of pairs that are connected.

The actual sparseness of the brain needs to balance this advantage, the increased capacity, along with a metabolic advantage and more abstract computational advantage which says that a sparse coding for information involves object recognition or segmentation against the disadvantages, most obviously the vulnerability of the pattern to the loss of neurons or connections and, perhaps more importantly, a sparse code involves fewer elements and so may be

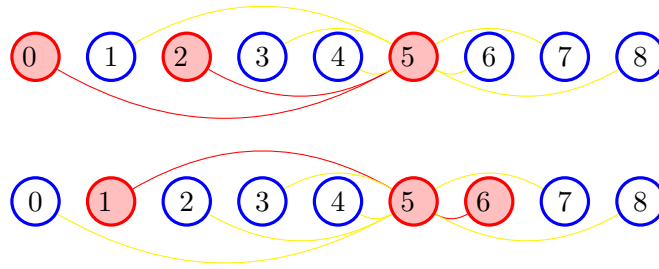
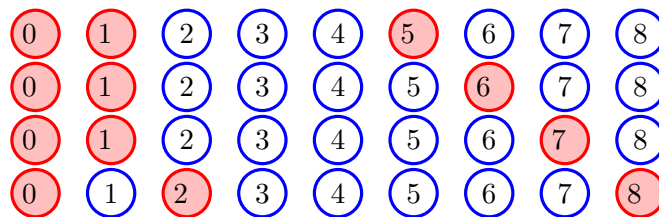


Figure 5: Interference in an associate network. Neuron 5 is involved in two patterns and, as a consequence, some of its connections are strengthened for one pattern and weakened for the other, if these strengthening and weakening effects are similar in size it makes it unlikely that either pattern will be accurately retrieved.

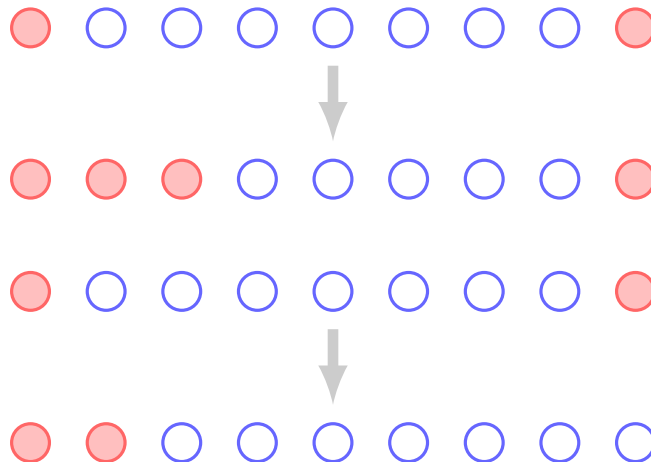
less useful for retrieval. It is hard to actually estimate sparseness in practice since neurons are not, in reality, on-off units. A figure of  $a = 0.025$  is given in [5] but, most importantly, the hippocampus seems to sparser than other parts of the brain.

### Correlated patterns

The estimates above assume that the patterns are all independent. If they aren't the capacity is reduced. If patterns share some fragments or subpatterns then the connections in these sub-patterns become very strong, perhaps dominating other elements in the patterns, the elements that make them different. Consider the four patterns



The connection between neurons 0 and 1 will become very strong because this connection is present in three patterns out of four. It is likely that this will result in this erroneous completion



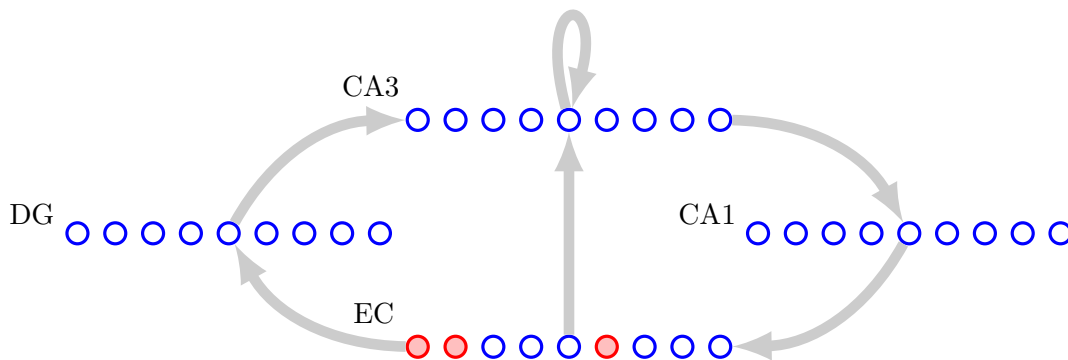
or even

This means that auto-associative networks are not able to effectively store anything except random patterns! This is why they have never proved useful for machine learning.

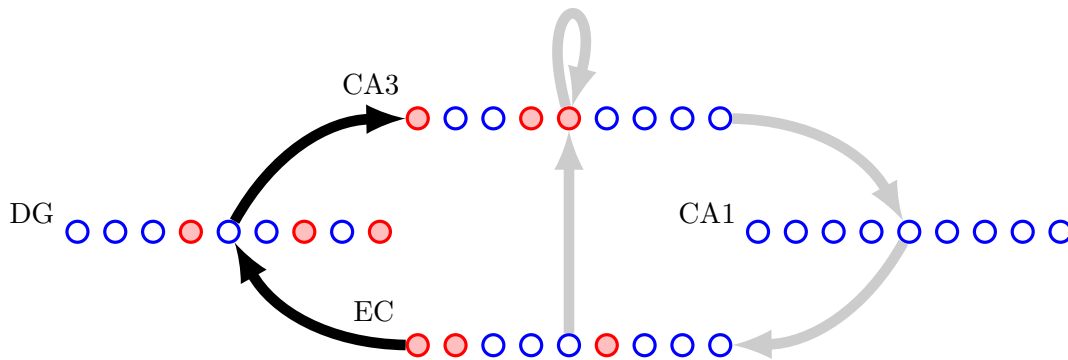
In the case of hippocampus it has been proposed, [6], that this problem is solved through the EC-DG-CA3 pathway and that the role of the dentate gyrus is to randomize the connectivity between EC and CA3. In short, during learning neurons in EC and CA3 are matched via DG and that the connections from EC to DG and from DG to CA3 are essentially random. This reduces overlap and may explain why neurons in DG are being born all the time, perhaps their role is to create these random connections.

### Models of the whole hippocampus

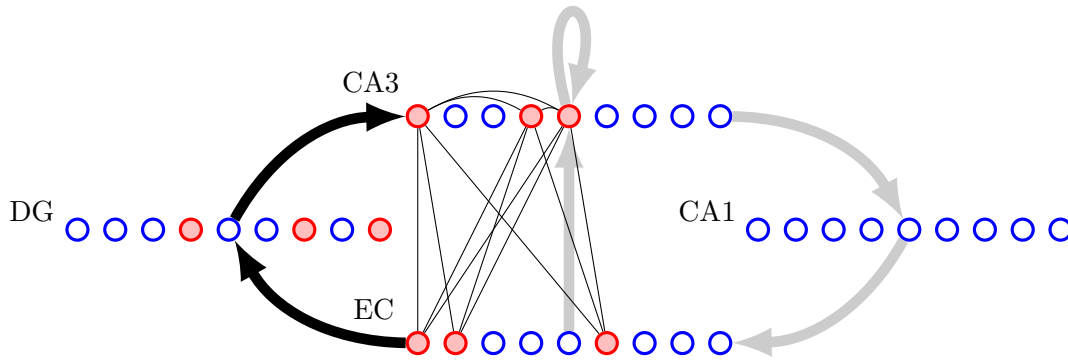
We are now almost in a position to consider models of the hippocampus as a whole; so far CA1 hasn't been mentioned. It has been suggested that the role of CA1 is to relay patterns back to EC. In learning, according to the standard model, a pattern is presented by EC:



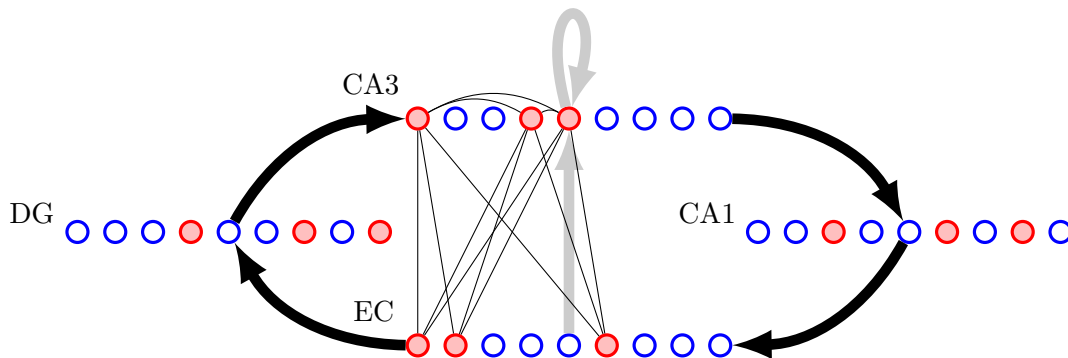
Connections, possibly random, between EC and DG and between DG and CA3, along with a 'k-winner takes all' mechanism, which hasn't been discussed, causes activity in CA3.



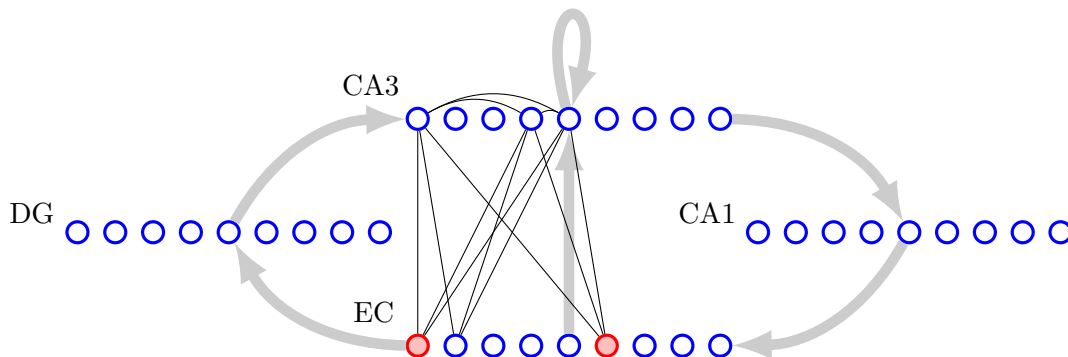
This representation is then learned by Hebbian plasticity between EC and CA3.



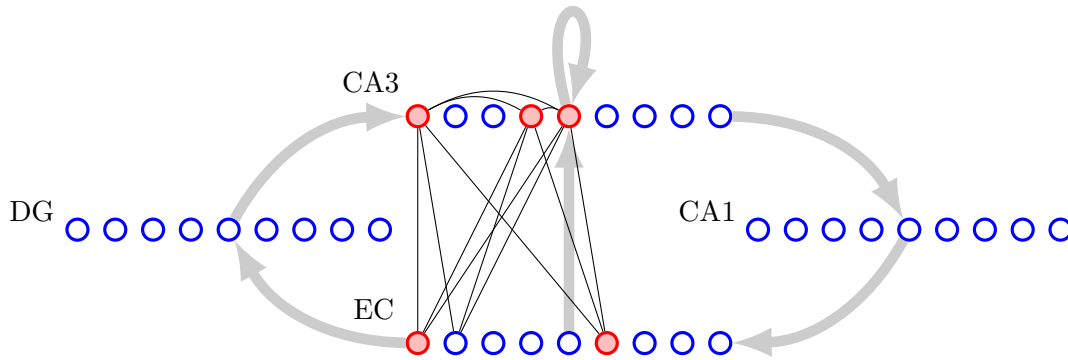
Hebbian learning also strengthens links to map the pattern to CA1 and link that to EC.



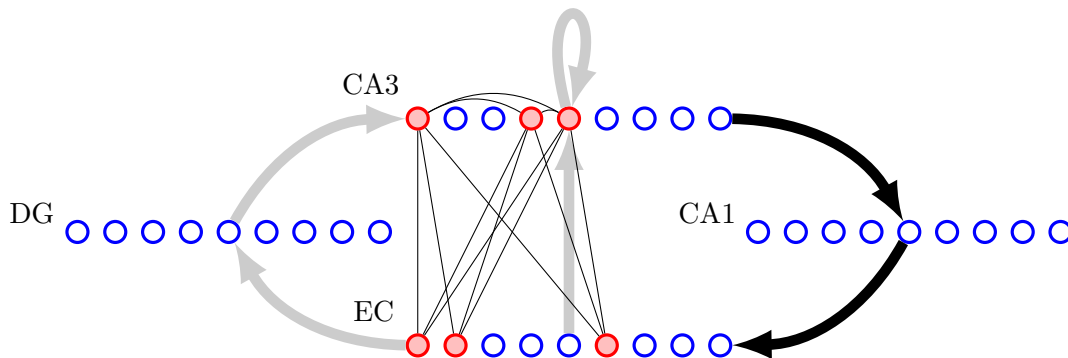
Now, during retrieval, part of the pattern is presented to EC.



Because of the connections from EC to CA3 and the recurrent connections in CA3, this excites the pattern in CA3:



This memory is sent back to EC via CA1, and recall has occurred!



This doesn't explain how the hippocampus switches between the learning and retrieval phase. One suggestion is just that the level of stimulus is different, that larger activity during learning excites the pathway that goes via DG [6], another is that the neuromodulator acetylcholine [7] or dopamine [8] is important.

## References

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