Switches in the brain?

## A potential mechanism for long-term memory storage

Dilawar Singh

We forget often. But we remember some memories as long as we live. This means that our brain is capable of protecting memories for years. This is a remarkable feat given that the *biochemical hardware* involved in creating new memories is a hostile place for its storage. What are the challenges involved? And what type of biochemical mechanisms may overcome them? This article explores a major hypothesis that molecular switches may be behind our remarkable ability to remember for a lifetime.

Dilawar Singh is currently a graduate student at National Center for Biological Sciences (NCBS), Bengaluru. His hobby is to convince people to move to open-source softwares to live happily ever after.

1. Introduction

Our brain is made up of roughly 100 billion neurons, joined together with over 100 trillion connections called **synpase**s. Each neuron on average makes 1000 connections. It is now widely accepted that memories are created by changing these connections.

Let's label these synapses as $s_1, s_2, \dots s_n$. During memory formation, a subset of these synapses will undergo changes. For example, my memory of being chased by a ferocious street dog named *Lalu* (lets call it M_{Lalu}) is stored in the set of synapses $M_{\text{Lalu}} = (s_{10}, s_{21}, s_{12}, \dots, s_{331})$ i.e., these connections were changed during my troubling encounter with Lalu. I sometimes recall this memory whenever I see a similar looking dog.
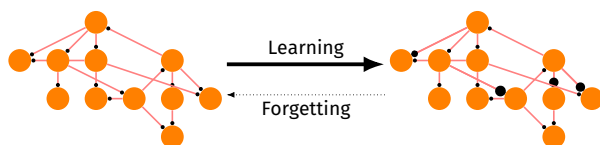
I can recall an experience as long as the set of synapses in which

Figure 1. Memory formation and forgetting. During formation of a memory, some synapses become stronger (larger black dots). The longer you can maintain these connections, the longer you can hold on to this memory.

the particular experience was stored remains intact. Therefore, our ability to remember is contingent on our brain's ability to keep its connections intact. But on the other hand, our ability to learn depends on our brain's ability to change its connections. And here is the first challenge!

1.1 *Learning quickly v/s forgetting slowly, a zero-sum game*
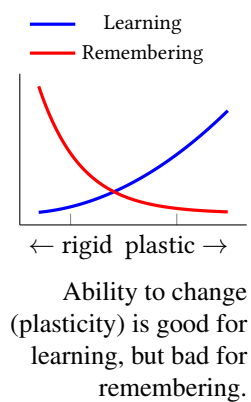
For M_{Lalu} (or any other memory) to remain intact, each synapse which participated in its formation (i.e., $s_{10}, s_{21}, s_{12} \ldots$) should remain intact. The longer a synapse can keep itself unchanged, the better it will be at keeping the memory safe. Let's assume that somehow I create a synapse which maintains its state for a very long time (i.e., a rigid synapse). This synapse will not *forget* easily, but it will not participate in any new memory formation either. Learning requires synapse to change and a rigid syanpse can't change. Rigid synapses behave like a read-only Compact Disk (CD). On the other hand, if I create a synapse which is easily changeable (i.e., a plastic synaspe), it will be good at learning new experiences but won't be able to retain them for long. Plastic synapse forgets easily. We know that we not only remember for long time, we are also capable of learning quickly. And not just us, many other animals are quick to learn. Honey bees can learn the location of food after one encounter with food source such a flowers. Indeed, a good memory system is the one which learns as quickly as possible from rewarding or painful experiences and forgets as slowly as possible. Forgetting and remembering are two sides of the same coin. They are conflicting demands i.e., improving one will deteriorate the other – a zero-sum game. The challenge is to strike a balance.

Learning
Remembering

$\leftarrow$ rigid plastic $\rightarrow$

Ability to change (plasticity) is good for learning, but bad for remembering.

2. Hopfield network – associative memory network

Memory storage and retrieval is trivially done by a computer. It will be helpful to compare memory storage in the computer and the brain. In the computer, we always know the address of every stored memory and we access it by providing this address. The

file icon on your desktop is a graphical way of encoding this addressing scheme. This process is similar to looking up the index page in a reference book to find a topic. Our brain, on the other hand, is very unlikely to have such an indexing mechanism.

We recall when we are provided with *cues*. For example, when you see some part of a familiar person in a wedding album – while the rest of the person may be hidden behind others – you could easily identify the person. Many other memories of that person will also be recalled. A famous class of recurrent neural network popularly known as Hopfield network can do just the same as shown in *Figure 2*.
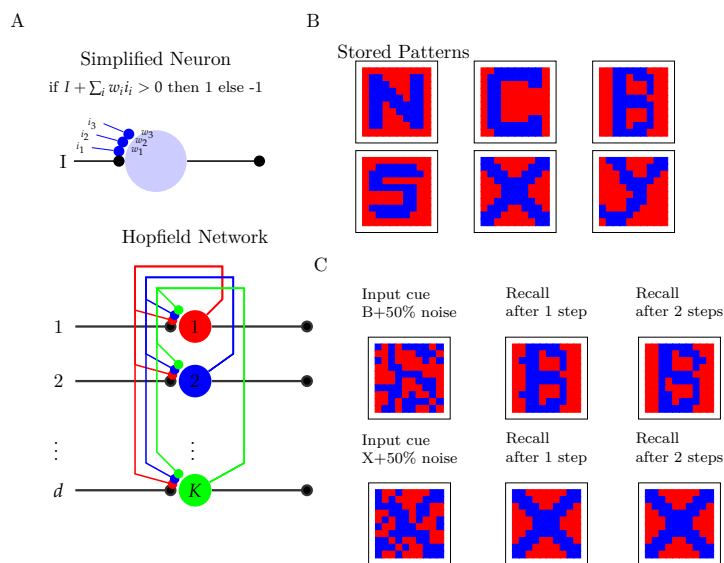

Figure 2. Hopfield network with 100 spiking neurons. These *recurrent* configurations give rise to interesting brain-like computation. **(B)** 6 patterns (memory) i.e. NCBSXY are stored in this network. **(C)** When a very distorted *cue* is applied to the network input, it *fetches* one of stored pattern which is the *closest* to the applied cue.

How does this recurrent network work is beyond the scope of article. Readers are encouraged to explore more by themselves. *"How well can we explain biological memory by these networks?"* is an active research area. Though these networks are extremely successful in accomplishing various *brain-like* computations (*a la* machine learning), I would like to advise the reader to be skeptical by noting the following:

- Neurons used in these networks are highly simplified. *Real* neu-

rons are not this simple. Even though these simplified neurons capture the essential *all-or-none* (electrical spike) way of communication and learning by changing synaptic connections, they do ignore rich local computations which can be accomplished by branches of these neurons called *dendrites*.

- There is no evidence that neurons make such dense recurrent connections. However some studies have shown that Hopfield network can work with very sparse recurrent connections as well.

- Activity in these networks does not match usually observed activity in the primate brain during memory-recall experiments.

Solutions contributed by other disciplines are helpful for comparison and contrast and often provide very useful insight. But in the end, these solutions must be tested under the constraints imposed by biology.

Nonetheless, these networks provide us with a framework to concretely think about the problem of memory storage and recall. We learn a great deal about a problem by pointing out the limitations and failures of models which describe it. Hopfield network has properties which will sound very natural to us. Can you store as many memories as you like in these networks? No. There is an upper limit. Adding more patterns over maximum limit causes distortion in memories. When a cue is given, the network no longer fetches the right pattern. It often fetches a pattern which was not even stored; the retrieved pattern instead resemble some mixture of stored patterns. When too many memories are stored, they corrupt each other by mixing up. One can ask more questions. When connections decay in these networks and memories start disappearing, which memory disappear first: the weakest or the newest? And, when a new memory closely associated with an old memory is added, what happens to that old memories?

After this necessary detour, lets go back to the main theme: how do synapses maintain their state?

3. How does a synapse maintain its state?

Very complex biochemistry plays out during learning that changes the synapse. Surprisingly, the net effect of this complex biochemistry can be summarised by a simple mathematical expression.

Ah, *the unreasonable effectiveness of mathematics*[4]! Let's assume that synaptic strength w is tightly correlated with a chemical species X found at synapse i.e. w changes with X. The problem of maintenance of w can be rephrased as the problem of maintenance of the activity of X. Therefore, the problem of "*synapse maintaining its state*" becomes the problem of "*molecule X maintaining its state*" – a more concretely defined problem.
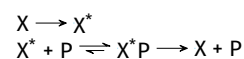
Let's assume that X is converted to its active form X^* by adding a phosphoryl group (PO_3^{2-}). The phosphoryl group is removed by a phosphatase and X^* is turned back into inactive X. The phosphorylation and its counterpart dephosphorylation are a very common motif for controlling various chemical reactions by activating and inactivating protein molecules. Once most X has been turned into X^* during memory formation, how do we make sure that X^* does not turn back into X (lose memory)?

$$X \longrightarrow X^*$$
$$X^* + P \rightleftharpoons X^*P \longrightarrow X + P$$

Let's mull over a solution to this problem of long term maintenance of X^*. Here is one potential solution.

1. **(Amplification)** X^* **auto-phosphorylates** itself i.e. $X \xrightarrow{\ \frown\ } X^*$. If we manage to get sufficient X^* somehow, it will act as a catalyst to its own production. X^* will always remain high.

2. Dephosphorylation of X^* is minimized by controlling the number of P or reducing the reaction rate.

Both (1) and (2) help in making X^* highly stable. Problem solved? No. Now we have constructed a rigid synapse. Recall the *rigid* v/s *plastic* synpase dilemma discussed previously (section **1.1**). This synapse will definitely remember for longer but it will not participate in any new learning anymore.

Can you think of other set of hypotheses? It must conform to laws of chemistry!

As long as we are in the realm of theory, let's propose a solution to this problem. We add another reaction say $P' + X^* \rightarrow P'X \rightarrow P' + X$ which deactivates X^* when the *need* arises. Phosphatase P' is different from P. This adds another layer of control to an already complicated problem i.e. forgetting is now controlled by another process. This requires one more explanation: how does this new

The volume of a typical synapse is 1×10^{-20} m^3. At this volume, 1 μM concentration is roughly equal to 6 molecules.

mechanism controlling *forgetting* work? And philosophically – if you care about it – it violates the principle of **parsimony** which recommends to pick the simplest explanation.

We still have two big problems hiding underneath. We have not considered the underlying biological hardware i.e. synapse in any detail where this biochemical network suppose to function. The first problem is chemical noise . For a biochemical system operating in very small volume, effect of chemical noise can be very strong. There are over 200 types of protein molecules in a typical synapse. Indeed, most of these protein molecules found in synapse are as low as few tens. The brain is always active and the chemical noise caused by the brain's background activity will surely turn some molecules of X into X^*. Then due to auto-phosphorylation, sooner than later, all of the X will be turned into X^*. We have created a very stable memory of nothing but background noise. This is highly undesirable!

The second problem is *turnover* i.e. old molecules are continuously degraded and being replaced by newly minted molecules. Let's assume that at the time of memory formation, we had 100 molecules of X^* in the synapse. And let's also assume that on average, every day one new formed molecule replaces an old one ($X^* \rightarrow X$). After 50 days, half of the synaptic strength is gone! To counter this, we must have a *refresh* mechanism by which the newly added molecule quickly changes its state according to the state of synapse i.e. newborn X becomes X^* if most molecules at synapses are X^*.

Effectively, we want a stable ON state (all X are X^*) which is immune to turnover. We also want a stable OFF state so that noise does not turn X into X^*. We want a switch like behaviour i.e. if it is OFF or ON it tends to stay OFF or ON. If a few X are turned into X^* by background noise, we want them to be quickly turned back into X by the phosphatase P. And if during memory formation, a significant portion of X has been turned into X^* then we want that any X^* deactivated into X is quickly activated again into X^*. This system should operate like a switch which does not flip unless significant force is applied. These are called **bistable switch**es

(See Box 1).

Is there any evidence that bistable chemical reaction networks exist? Do they occur at all in living cells? Bistability (and its close relative oscillations) are very common in biology (What is the reason for their *selection* by evolution?); from cellular level to population levels. So it won't be surprising if we discover bistable switches operating at syanpse as well. Indeed, various studies have shown that calcium/calmodulin dependent protein Kinase II (CaMKII) *may* form a bistable switch in synapse.

4. Molecular bistable switch at synapse

Late John Lisman hypothesised that a kinase and a phosphatase together can form a bistable switch immune to *turnover*. CaMKII and its phosphatase Protein phosphatase 1 (PP1) were identified as the hypothesised kinase and phosphatase. This chemical system has been extensively studied using computational models for over two decades [3]. There is some evidence that CaMKII is bistable *in vitro* conditions. Whether CaMKII is bistable inside a living neuron is still an open question (see Box 2 for overview of CaMKII properties at synapse.).
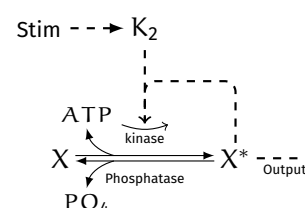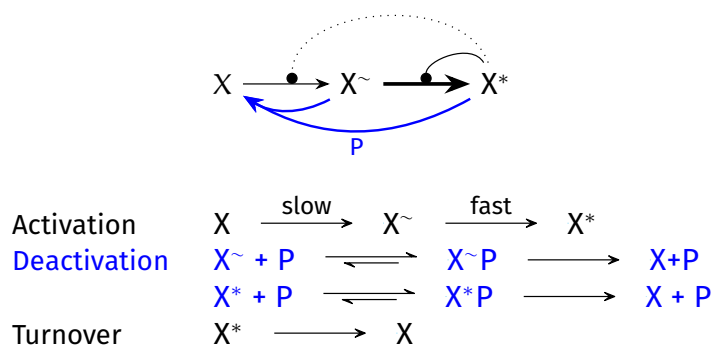
Reaction in a bistable switch proposed by John Lisman. Modified from [1].

Figure 3. A hypothetical network which can solve the problem of chemical noise and turnover with suitable parameters. The activation step is divided into slow and fast components such that fluctuations caused by background noise do not cause the system to activate itself. X^* also partially activate X to $X^\sim$ to overcome *turnover*.

Box 1. Bistability in reaction network

In a world full of fluctuations, stability is indeed very useful property. Life is remarkably stable even though it is made up of inherently noisy components. Bistable chemical networks are ubiquitous in biology. In bistable chemical networks, noisy components acts together to give rise to highly (bi)stable behaviour. *Also note that even though the underlying reactions are almost always reversible, the bistable switch is usually not reversible.* Isn't it a neat way for taking decisions?

A bistable system – as its name implies – has two stable states. From the point of view of an experimentalist, if you obverse a bistable system for very long time, you would almost always find it in either of its two stable states. Just like an electrical switch which you would almost always find in either ON or OFF state (and rarely in transition between states).

A Deterministic   **B** Stochastic   **C** A sample behaviour
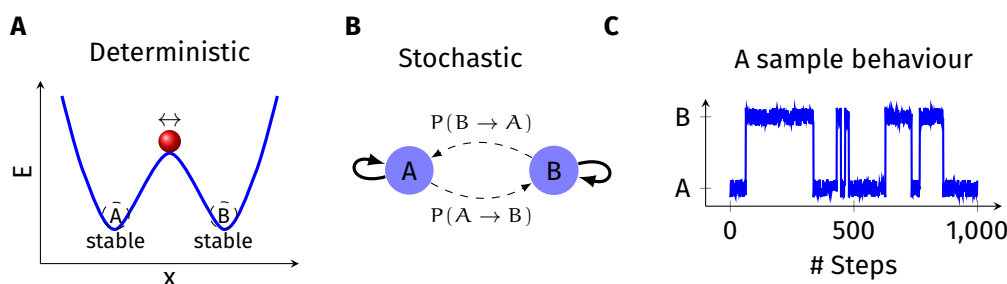
In the figure above, **A** show a conceptual model of bistability. The energy landscape of a bistable system has two minima ($\tilde{A}$ and $\tilde{B}$), therefore, the system always ends up in either of them. It is a deterministic bistable system. **B** shows a conceptual representation of stochastic bistable system as state transition diagram. The arrows depict the probability of transition from one state to the other. In **C**, we simulate the system described in **B** with probability of transition from A to B ($P(A \rightarrow B)$), and from B to A ($P(B \rightarrow A)$) set equal to 0.01. Such bistable motif are commonplace in biology [6], especially found in situations where cell has to make a decision or store information (memory). One such motif is shown below in both deterministic and stochastic settings.
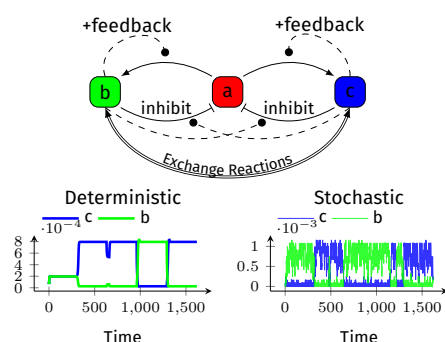

A bistable chemical system adapted from [6]. Species b and c catalyze their production (positive feedback) and inhibits production of a. **(below)** Two trajectories are shown in different settings. (Left) System is deterministic; (right) System is stochastic. There are three necessary conditions a network must have to be able to show bistability: positive feedback, mechanism to filter out small stimuli, and a mechanism to prevent explosion [5].

Box 2. CaMKII at synapse: A brief overview of its properties and function

Among more than 2000 proteins found in brain, CaMKII constitutes roughly 2% of them all. Furthermore, it is enriched in the hippocampus – a brain structure necessary for memory formation. Indeed, CaMKII is known to play essential role in learning and memory. In experiments involving mice, deactivating CaMKII in any way has always resulted in impairment of memory formation and learning.

CaMKII molecule has interesting properties which makes it an attractive candidate for storing information. 12 or 14 subunits of CaMKII make up one holoenzyme, usually arranged in dodecameric (top view 🌸) or tetradecameric form (top view 🌸). CaMKII structure is shown in (**A**) inset below (from Protein Data Bank (https://www.rcbs.org)).

A

B
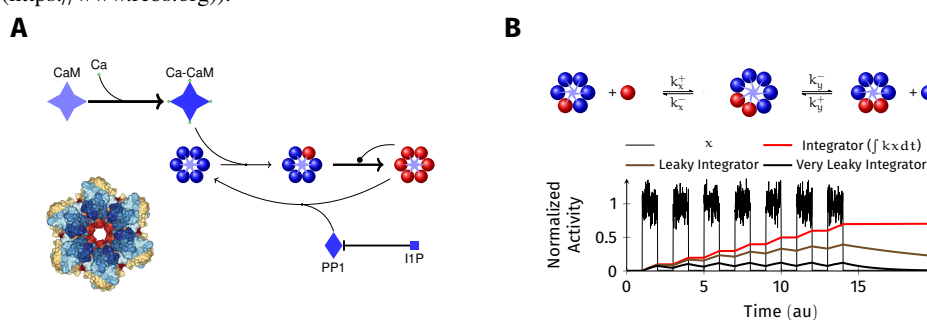
(**A**) Summary of CaMKII pathway of. Upon its influx into synapse, calcium (Ca^{++}) binds to calmodulin (CaM) and create a complex calcium/calmodulin complex (Ca^{++}/CaM). Ca^{++}/CaM binds to CaMKII and phosphorylate it. CaMKII is dephosphorylated by PP1. (**B**) Subunit exchange between two holoenzymes i.e. a fully active CaMKII holoenzyme can loose an *ACTIVE* subunit which can be picked up by another holoenzyme which becomes partially active.

First step of CaMKII activation is very slow for it requires binding of two Ca^{++}/CaM simultaneously. Once a subunit has been activated (red circle), phosphorylation of its neighbours requires binding of only one Ca^{++}/CaM and therefore further phosphorylation proceeds at much faster rate. Note that the first very slow step can be overcome by subunit exchange when an inactive holoenzyme picks up an active subunit released by other holoenzyme. Therefore subunit exchange helps in spreading CaMKII activation.

CaMKII integrates Ca^{++} signal A single CaMKII holoenzyme acts as a leaky integrator of Ca^{++} activity i.e. it sums up Ca^{++} activity in time and also decays with a time-constant (leaky). See (**B**) to compare behaviour of three integrators of calcium activity (*x*): a non-leaky integrator and two leaky integrators with small and large amount of leakage. Mathematically, it is similar to a leaky capacitor if we model Ca^{++} activity as applied current and CaMKII activity as voltage across capacitor. Integrators are useful when you want to accumulate *enough* information about *x* before taking a decision e.g. a plant can *decide* to flower or shed leaves only if integration of moisture in air and/or temperature during the day crosses a threshold value.

In our computational study of this pathway, we explored the effect of subunit exchange on CaMKII pathway [7]. We found

Figure 4. **(A)** (left) Three clusters of CaMKII in a synapse . (Right) This system ability to hold memories increases exponentially with system size. 52 holoenzymes can keep the memory intact roughly for 100 years! **(B)** Subunit exchange improves CaMKII ability to store information. **(Red)** 3 individual bistable switches independently without subunit exchange. **(Blue)** When subunit exchange is enabled, these independent switches synchronize. Notice that the now system spends more time in its stable states.
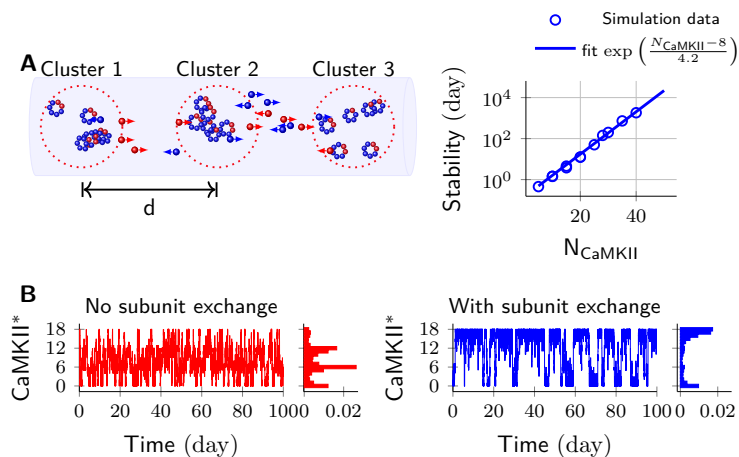
that the subunit exchange improves information retention capacity of CaMKII. This adds weightage to the idea that CaMKII is *the memory melecule*. Individual CaMKII acts as leaky integrator of Ca^{++} activity (see Box 2.). With subunit exchange, the leaky integrator becomes less leaky and hold information for longer time. When many CaMKII holoenzymes come together and form a cluster then they give rise to a bistable switch (*Figure 4*). Such clusters have been observed in experiments. We found that subunit exchange synchronizes bistable activity of distributed clusters. That is multiple bistable switches act as a single but much more stable bistable switch. To summarise, we found the subunit-exchange makes CaMKII molecule better at retaining information.

5. Conclusion

In this article, we have discussed why bistable motif is an attractive candidate for storing biological memories. They are ubiquitous in biology and are natural solution to the problem of memory maintenance under chemical noise and turnover. We have also discussed a potential pathways (CaMKII) which may be bistable at synapse. Now let's put all of this to a reality check. Let's assume that bistables mechanism exists at synapse. We know that size of a synapse is tightly correlated with its strength. That

means we can observe synapse size as the proxy of its strength. If we observe synapse for long time and record its size continuously, what would we observe? If the distribution of size is bimodal (two peaks) than its a strong suggestion that underlying mechanism is bistable. More strongly, if the underlying mechanism is bistable, then I *must* observe a bimodal distribution.

There is now growing experimental evidence that synaptic size change in *all-or-none* manner, a finding which is consistent with this idea. Some other studies have claimed that changes are graded i.e. synapse changes in step-wise manner much like a **multi-stable** synapse. A multi-stable synapse is an additive ensemble of many bistable components (*Figure 5*).
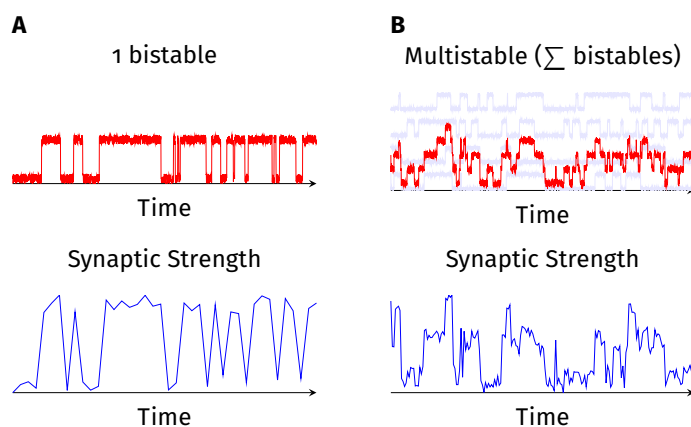

Figure 5. *All-or-note* v/s graded synapse and mechanism which may give rise to them. **(A)** A bistable mechanism (red) controlling the synaptic strength. Synapse size changes in *all-or-none* fashion. **(B)** A multi-stable mechanism (red) gives rise to a graded synapse (blue) which changes its size in step-wise manner. Note that a multi-stable mechanism can be constructed by adding multiple bistable switches (4 bistable switches shown in light blue in blue are used in this case).

Whether CaMKII is bistable in the synapse is still an open question. Neither there is any concrete evidence that it is nor it has been ruled out that it is not, especially near the membrane. Our aim in this article was to argue why bistable mechanism is a good solution to the problem of storing memory for long time. Even if CaMKII turns out to be not bistable at synapse, there could be other unknown mechanisms which can give rise to bistability. Given that bistable chemical motifs are widespread, it is reasonable to suggest that there are indeed switches in our brain – much like flip-flops in the digital memory card of your phone – which

are evolved to keep our memories safe from the onslaught of time and noise.

Acknowledgements

Address for Correspondence
Bhalla Lab, National Center for
Biological Sciences, Bengaluru
GKVK Campus, Bellary Road
Bengaluru - 560065.
Email: dilawars@ncbs.res.in

Suggested Reading

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