ers prefer to say it, I will explain this principle in layman's terms. The first level of Synchronisation is between the physical world and models of the world (Newtonian Simulator). These two worlds Physical and virtual are bound to synchronise. There is a force in nature, an attractive force which communicates these worlds. This attraction is manifested by motors and sensors. I won't talk about the nature of this force, It might be the fifth force, the soul, the religion of just rules of statistical Physics. But It enables these models to communicate. For example, When an animal sees a new broken tree in its territory, It updates its memory and its synchronisation in one direction. But when an animal simulates the breaking of a tree in its mind, motors take on and an animal breaks a tree in the physical world. Its synchronisation in diffrent direction. Synchronisation from physical worlds to virtual models in Learning and Synchronisation from virtual worlds to real worlds is desires followed by actions.

This First level Synchronisation despite going into details seems a promising hypothesis on its own. I have gone into its details and talked about neurons, electromagnetic forces and the Group theory principle which takes on this theory with rigour. But Let's move on to the next level of Synchronisation for now! Once worlds start synchronisation, virtual worlds with physical worlds. Nothing is stopping from synchronisation of two virtual worlds. I know at this point this article has gone from readable, to insane. But give it a thought, It takes time to sink it, especially when there are tons of details missing. But they are not hurdles for theorists, let neurologists and engineers worry about them in their own time. But the point is minds can make different virtual worlds. What are these virtual worlds? and why do we need more than that one? Think of these as worlds made of different constituents, for example, one model represents a model of physical worlds with visuals, and the second with language. They represent the same thing but with different fundamental pieces, pictures in the first and words in the latter. When we tell stories to someone, the model made of words interacts and starts synchronizing with a model made of pictures. It's similar to how the model is in their physical worlds and the virtual model synchronises. But this time these both models are virtual worlds. This was the Second Level of Synchronisation.

These different virtual worlds are not exactly similar, They have small differences, and these differences are what makes it useful and helpful to have many virtual models. In higher intelligent beings like humans, deeper models are so different from physical worlds that they might not directly communicate or interact. These deeper models interact and synchronise with some models like visual maps and they in turn interact with the physical world. I will write a different article explaining some more models and their applications but let's return to our original quest to understand the relation between empathy and intelligence.

I haven't answered yet, why emotions are a necessity of intelligence. And I will not answer that question in this article. I have another set of articles going into that detail. But it all boils down to this, In simulation, emotions play as role of spontanious seizure of computations. Without it, the possibility space in simulation is humongous and large, so large that neurons spread in the size of a solar system will fail in some trivial life tasks. So Emotions are necessary for Intelligent beings. That is the statement I don't think can be challenged, And that is where 'Mr. Spock' goes wrong. I have gone to great lengths to make that case in my previous articles and ongoing research. But the trillion-dollar question is, will AI have empathy? Can it simulate the emotions of others? If yes, will it feel for them? and act like a human does in those situations?
I hope I have set the stage to talk about this question 'Will AI have empathy?' and how intelligence theory might help us answer this question in advance.

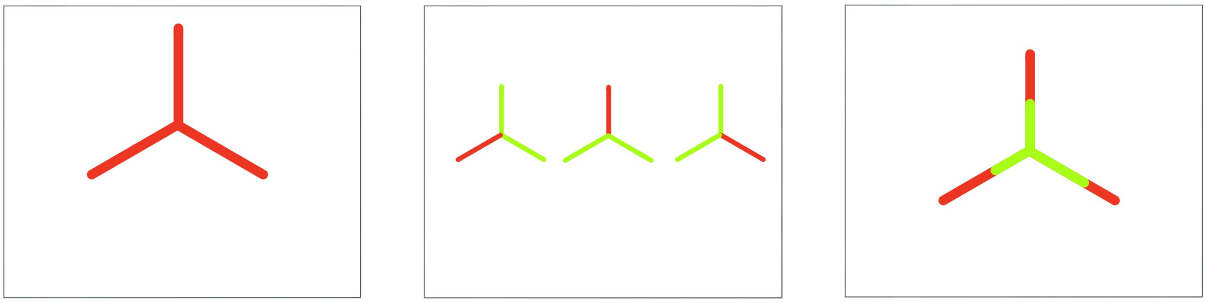
15 Realisation of this model

Before presenting an implementation of this model, I would first like to clarify that this realization and any potential shortcomings are independent of the theory itself. There could be alternative implementations of this theory. Furthermore, this implementation is not complete, nor do I claim it to be rigorous. I have previously encountered criticism regarding the simplicity of this implementation, but it is not an attempt to explain the human mind or present a new machine learning algorithm at this stage, although the latter remains an ultimate goal of this model.

The simplicity of this model is intended to detach from unnecessary details and explain how this theory can be incorporated using very simple elements. It may not be the most efficient means of implementation, but it serves as the most pedagogical model with the least steep learning curve. You don't need to know the jargon of neuroscience to understand it, although such knowledge would indeed be helpful in creating a realistic simulation of this model.

Introducing Neurons

We have modeled a neuron as a simplified 3-synapse OR gate. Current can only flow through two synapse simultaneously, with the third synapse acting like an open switch. See Figure 1(a) for the position of the closed switch, which randomly switches after every unit of time as shown in Figure 1(b). The probability of this switch is depicted in Figure 1(c) and can be adjusted as a training parameter in the model.



(a) Simplistic model of neuron

(b) 3 configuration of a neuron

(c) Probability of being On/Off

Figure 1: In figure b and c green represent current can flow and red represent current can't flow

Network of Neurons

A network of neurons is introduced in which 3-synapse gates are placed on a 2D square grid, as shown in the snapshot below. Notably, a single node on the grid can have a maximum of three connections, with at most two green synapse. Here, green signifies the possibility of current flowing through a neuron. The red synapse, representing a open switch, it will switch positions according to the probability assigned to each neuron.

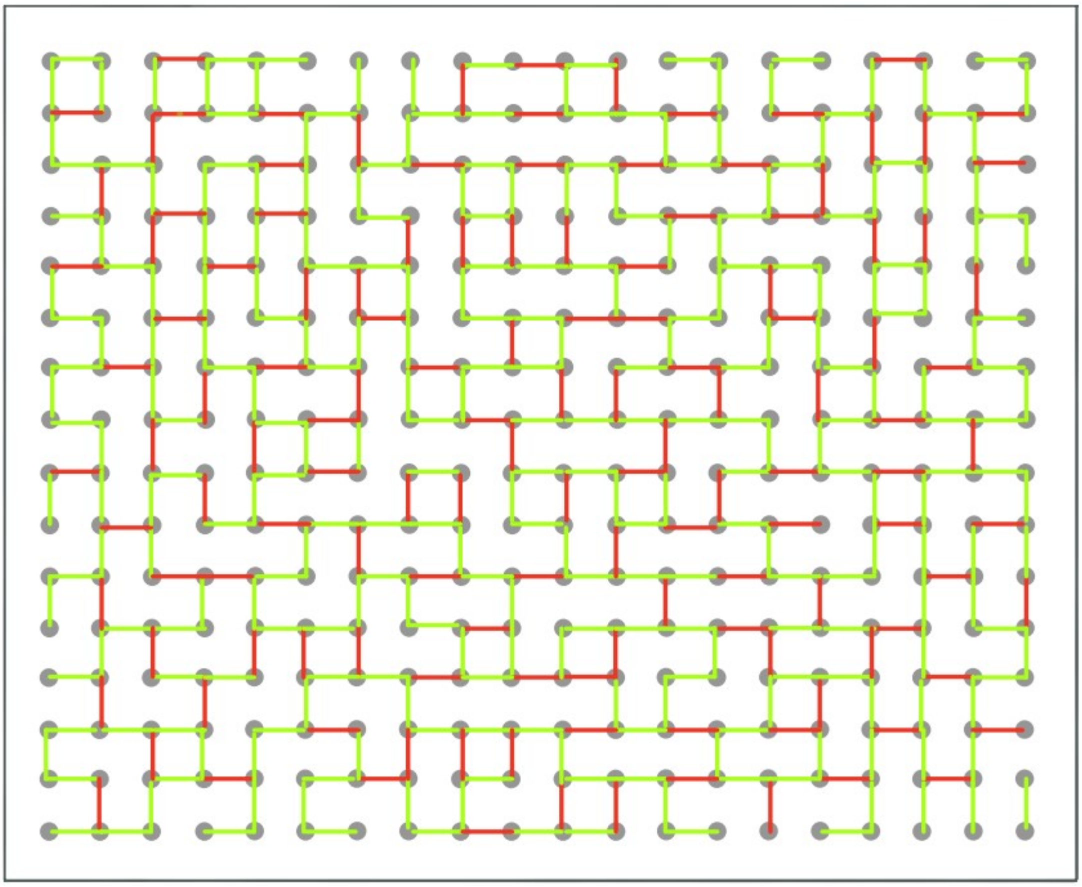
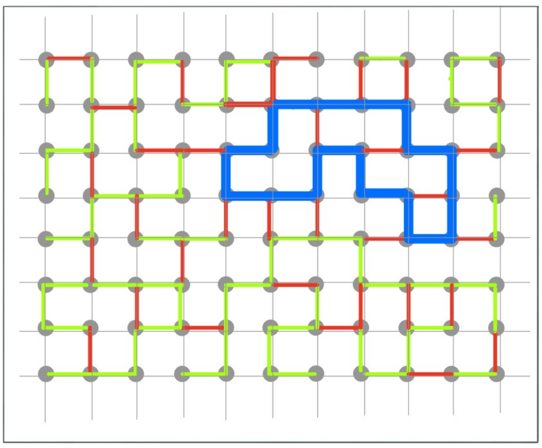


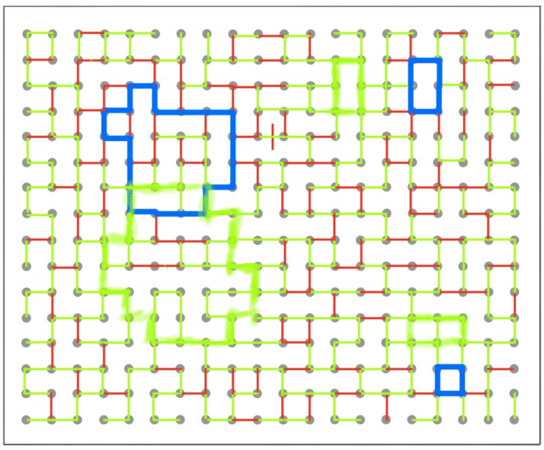
Figure 2: A snapshot of neural network, where green synapse represent current can flow and red represent current can't flow

Current loops as instance of memory

If we regard each current loop in the network as an instance of memory (see Figure 3(a)), we get traveling loops as gates flip after unit times. The loops serve as perfect memory candidates since they form connected pieces.



(a) Current loop in the network

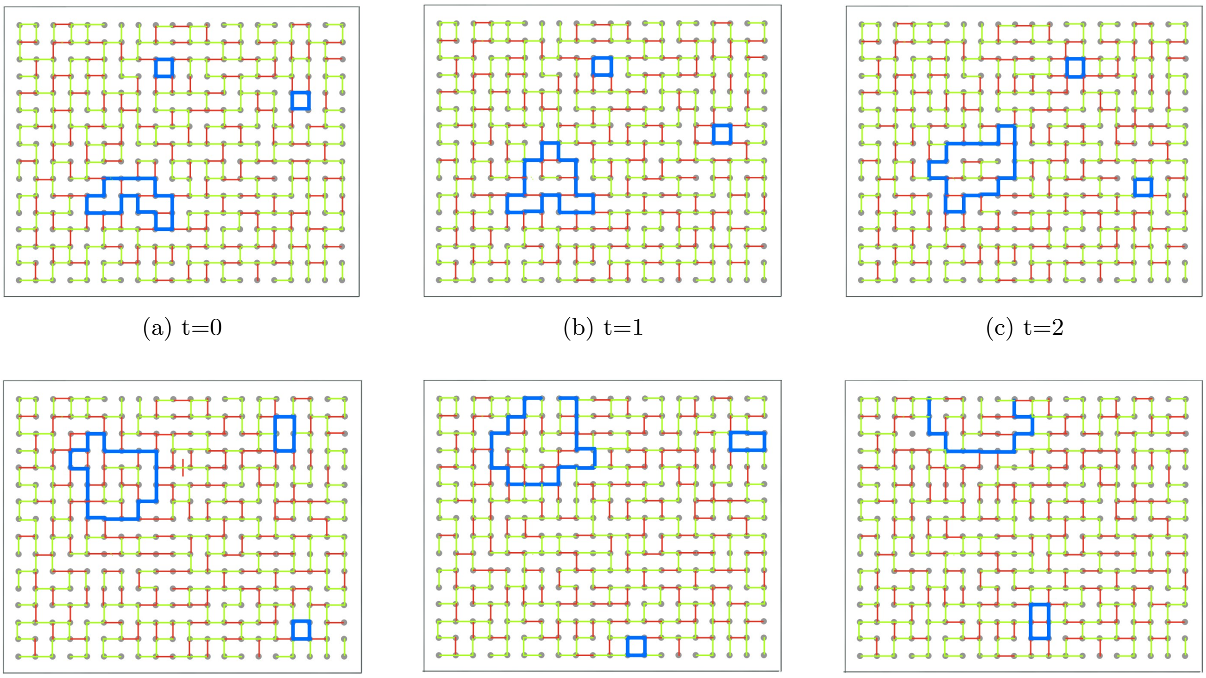


(b) Current loop and potential loop in the network

Figure 3: Potential loops are formed by extra concentration of charge carriers nedar the nodes. Potential loops will attract current loops towards it

Traveling loops and traveling potential

As the loops traverse, they leave behind a trail of extra charge carriers. Although these extra charge carriers no longer form current loops, they maintain the potential to complete a current loop. This temporary potential alters the probability assigned to neurons, now enabling current to flow through all three synapses. Due to constant switching, loops are in a continuous state of motion, and potential loops follow them. Figure 4 illustrates how these loops can travel, annihilate, bifurcate, and appear in the lattice.



(a) t=0 (b) t=1 (c) t=2

(d) t=3 (e) t=4 (f) t=5

Figure 4: Loops travel in lattice as time flows

Mapping to higher space

To better comprehend the dynamics of loops, it is beneficial to map this space to a higher-dimensional space where loops become particles. One such transformation is R^{2N}, where 2N dimensions represent the N horizontal lines and N vertical lines on the grid. The particle coordinates correspond to the number of times grid loops touch these lines.

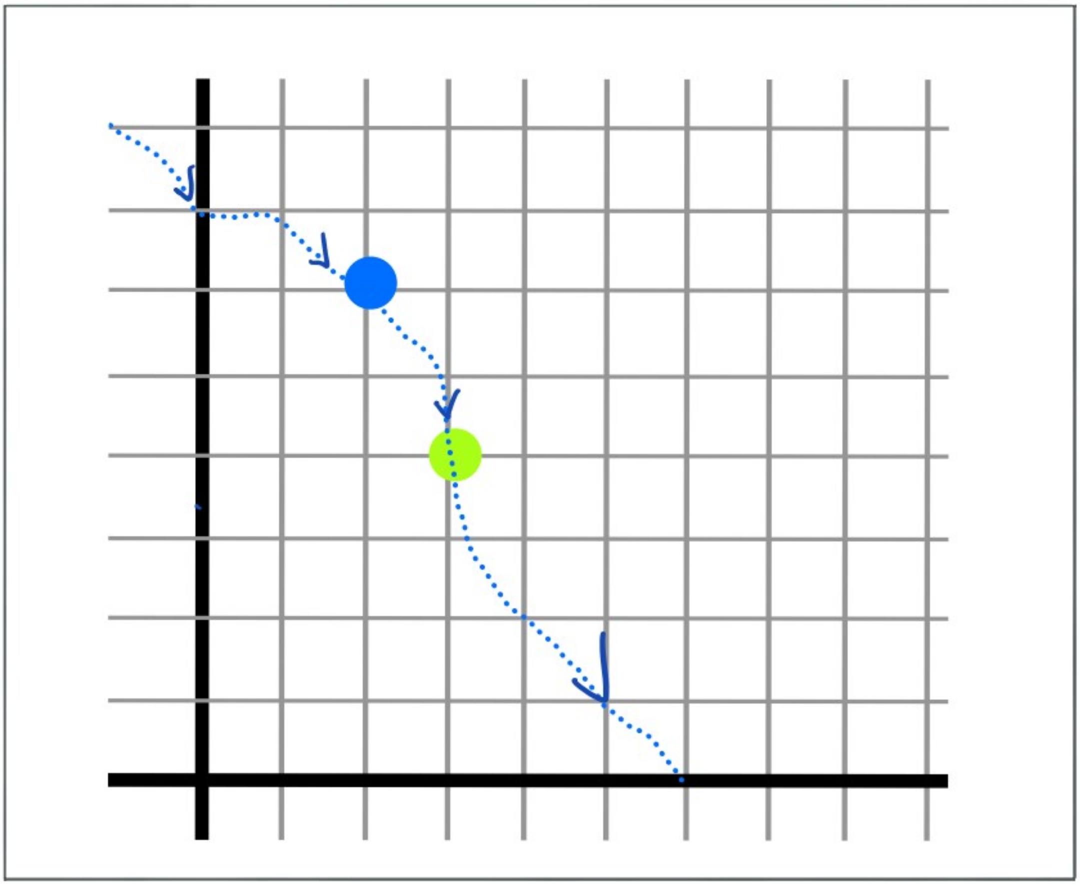


Figure 5: Coinscious particle and real particles traveling in R^{2N} space. This transformation is arbitrary and different transformation must be used for different grids

Real particle and coinscious particle Interactions

Let's denote the loop of current in this transformation as a conscious particle and the loops of potential as real particles. In this higher space (see Figure 5), the transformation preserves neighborhood properties. Both types of particles behave like opposite poles of a magnet, following the same path in space.

Coinscious map and coinscious map threads

Not all possible points in this space can form a loop in the grid due to some nodes being disconnected. Hence, the space of all possible points is defined as a conscious map (see Figure 6). As we will demonstrate in the training section, after sufficient training, these conscious maps take the form of threads, as in Figure 7.

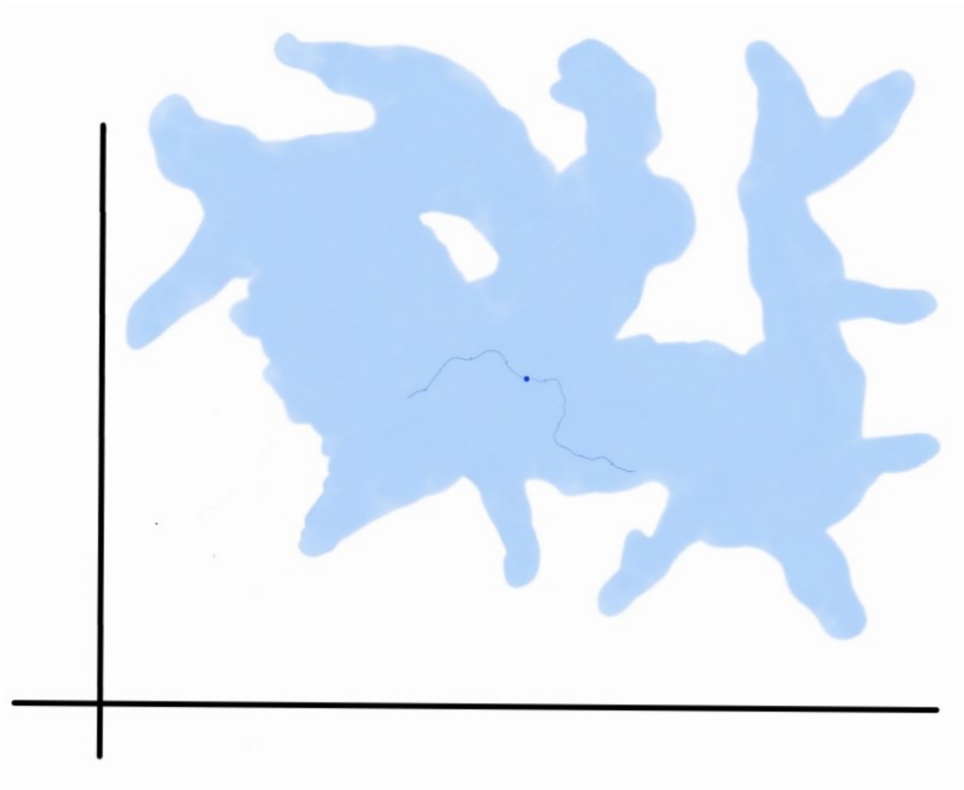


Figure 6: Coinscious map (blue) in higher space in which a coinscious particle is traveling along a stocastic path

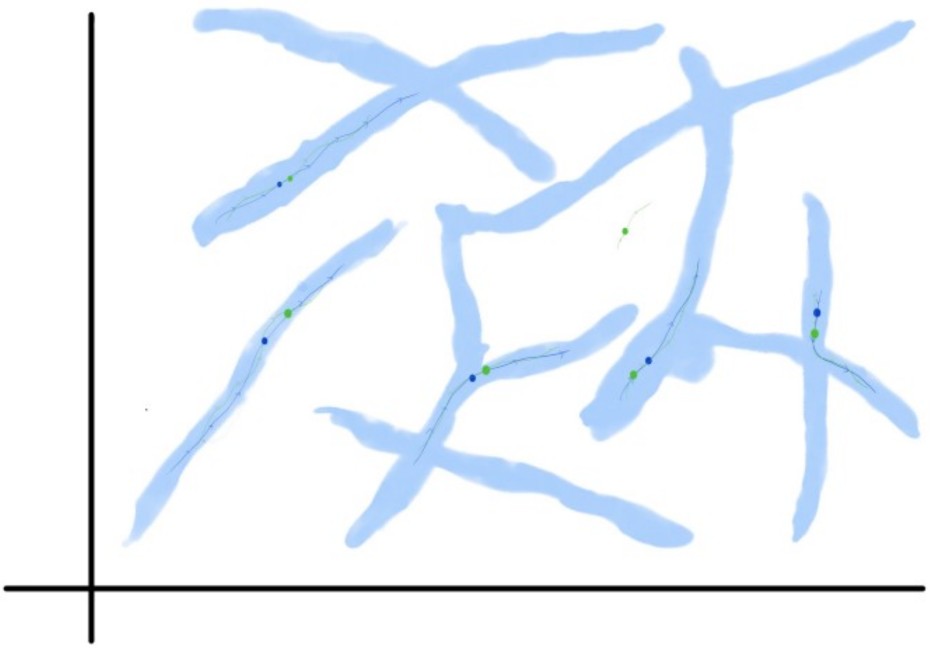
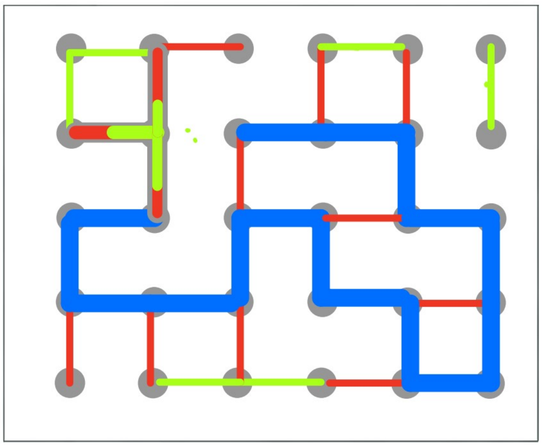


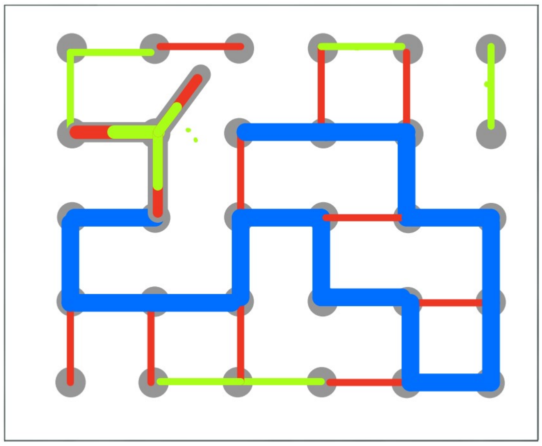
Figure 7: Coinscious map of trained network form threads. Every thread has its own pair of particles. Real particles can form outside of map but they will anhilate quickly

Traning

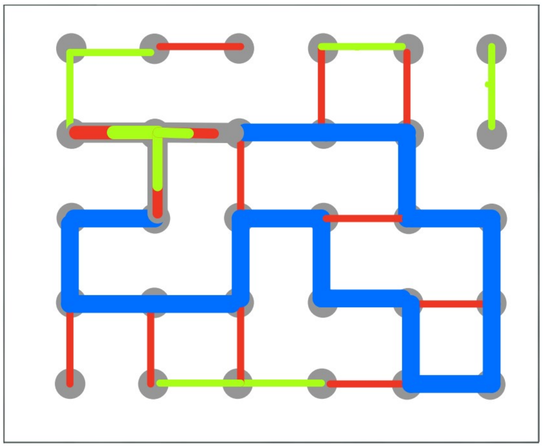
The training process involves two stages. Initially, when the current loop forms through two synapses of a neuron, the probability of the third synapse decreases, while that of the current forming synapses increases. The second stage involves the formation of maps, as referenced in Figure 8. If some loops have just formed, some weak connections might break to complete the loops. Training occurs when real particle trails follow conscious particles. As a conscious particle travels in higher-dimensional space, it forms new maps, and repeated activity in these areas decreases the potential of the area, thus attracting the free fall particle towards the path of least potential.



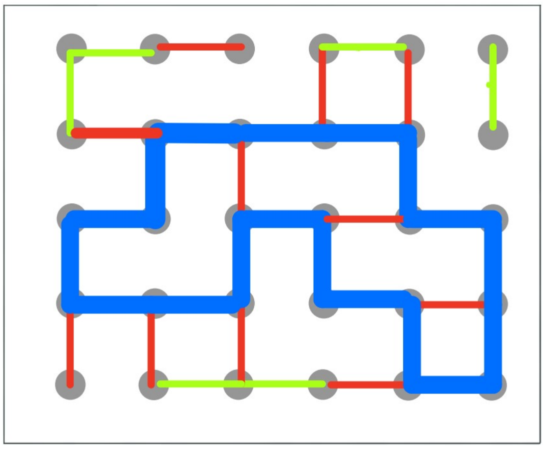
(a) Loops is just formed



(b) synapse with lowest on state probability breaks with node



(c) New synapse is formed to complete the loop



(d) Thus traning makes new memory in network

Figure 8: Stages of network traning

Summary of framework

Sensory neurons map the real world as real particles in the conscious map. Conscious maps are formed with sufficient exposure to the environment. When conscious particles start trailing, these same real particles take control of the motor neurons. The attraction between real and conscious particles is the driving force behind training and motor response. A simple attraction in a higher space comprising several thousand particles can capture enough information for some astounding applications, as discussed in the following section.

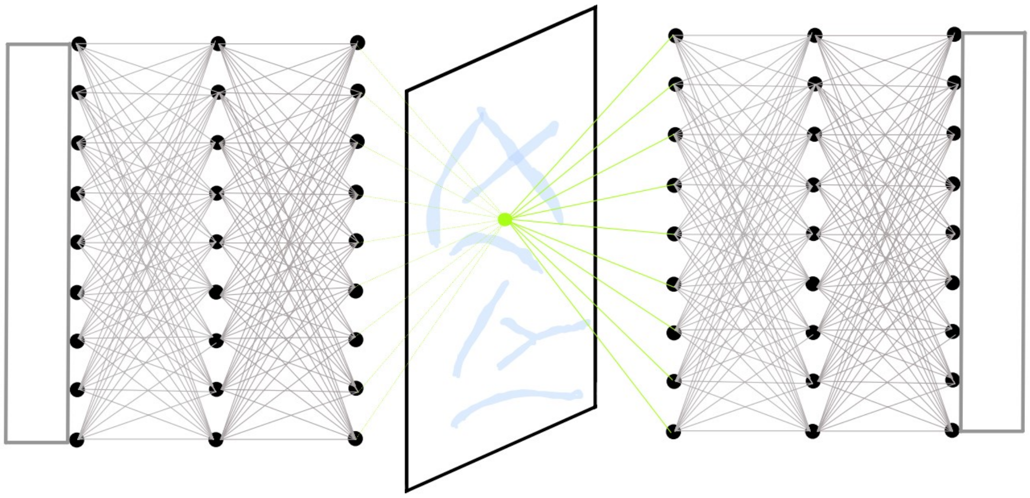


Figure 9: left neural network represent motor neurons, And Right represent sensory neurons. They both maps a real particle in counscious map

16 Application

Memory Retrieval

The first application of this framework addresses a benchmark problem in neuroscience. In this model, a conscious particle can be formed through a trigger reaction of real particle creation or the effects of other particle interactions. Once the particle traverses the conscious maps of a desired area, it can represent memory retrieval. This process also explains how observing something in real life can trigger the retrieval of memories associated with it. For instance, seeing a familiar person forms a real particle of the person in the map. This particle enforces the formation of a conscious particle that then travels in the map's neighbourhood, prompting us to magically retrieve something related to the person. This happens because when maps were formed, they were created in the immediate vicinity.

Modeling surrounding

Map threads can represent the parameters of a continuous group, where the thread length represents the parameter space and the particle represents the current value of the parameter. This coordinate system contains enough information to model the world around us.

Proprioception

The most important such model is proprioception, also known as the so-called sixth sense. It's plausible that around 150 threads can capture all possible postures of our body. For example, one thread can represent the angle my left elbow is making with my arm. All joints can be represented in a similar manner. The frozen conscious particles only move when the body moves, providing the mind with an accurate model of our body in the environment.

Environment

Similarly, the environment can also be modeled with more parameters. Here, the particles are not necessarily frozen. We can explore a well-known environment in our head as the maps are already formed in our mind. The only task of the real particles is to validate the map now.

Inside the Black Box of Catching a Ball

We already have a model of the body and the environment in our conscious map. When we see a ball, the real particle initiates a chain reaction of particles in the map. Memories of similar incidents are retrieved in the mind. The desire to catch the ball takes over. The conscious particle explores the option