Artificial Intelligence: Search Methods for Problem Solving

Prof. Deepak Khemani
Department of Computer Science & Engineering
Indian Institute of Technology, Madras

Chapter – 04
A First Course in Artificial Intelligence
Lecture – 32
Population Based Methods: Emergent Systems

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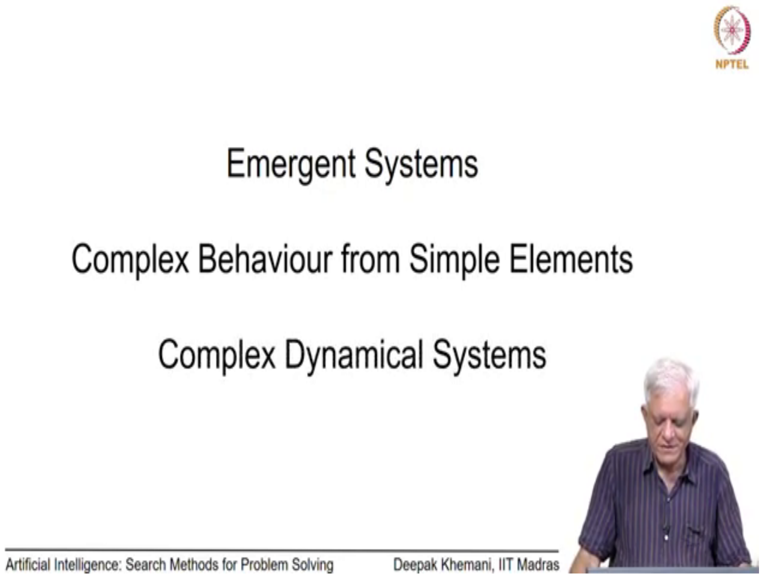

So, we have been looking at randomized algorithms for optimization and we have been looking at Population Based Methods. So, let us take a little bit of a diversion here and look at this area called Emergent Systems. This is also kind of motivated by what happens in nature; because in nature you find that complex systems emerge out of interaction of simple systems.

And there is a whole field of study which is devoted to studying such systems and we kind of talk about the property of such systems which emerge from the behavior of simple elements. This area is also known as complex dynamical systems and amongst other things, the people look at things like chaos as part of this; but also we want to see that how complex organisms can emerge out of interaction of simpler organisms.

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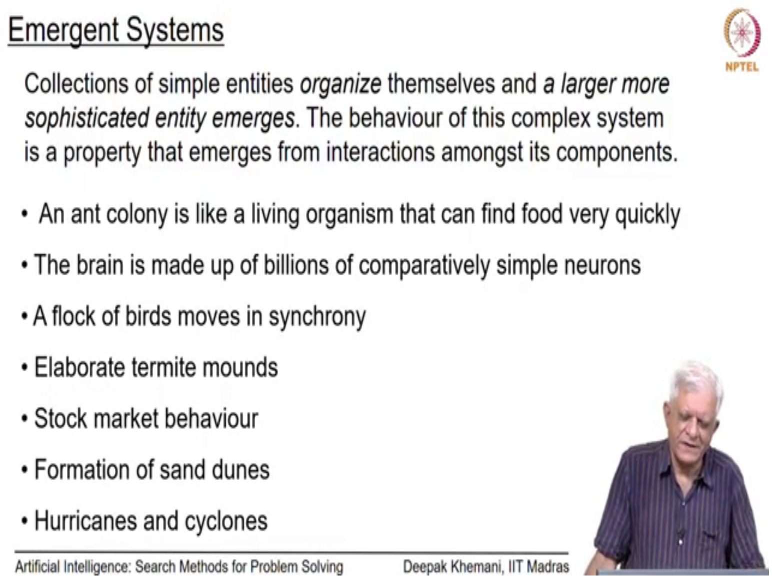

So, the idea of emergent systems is that collections of simple entities organize themselves and a larger more sophisticated entity emerges out of this whole process. So, it is a question of, in some sense as far as we are concerned perception as to.

So, we for example, see ourselves as one human body; but if you look closely enough, you will see that we are made up of many organs and those organs are in turn made up of smaller parts. So, in some sense we are a colony of living cells, which somehow you know exist as a human being essentially.

So, this is the idea which has come out of this notion of emergent systems and we can see and we will see soon that, we can think of an ant colony like a living organism which you know can go in search of food and exist and survive very efficiently essentially.

The idea of emergent systems is also kind of relevant to the human brain; and as we will quickly see the brain is made up of billions of very simple computing elements called neurons. And somehow we have this very complex brain that we have. And this has been a separate line of inquiry into intelligent systems that people say that, maybe we can just mimic the way nature grows brains and how the nature in some sense trains brains and come up with systems which work like that and we shall have a very passing look at the area of neural networks which is motivated from that.

You must have seen sometime a flock of birds which is lying in synchrony and in fact their interactions are fairly complex; because they sometimes have leaders who lead the flock and others follow and then they keep changing the leaders and things like that. It is a bit like what sometimes teams in cycling competitions do that somebody goes ahead and leads and the others follow him; all these happens in nature quite a bit essentially you know. You must have seen termite mounds which are quite elaborate or if you are familiar with the notion of the stock market.

Now, there are millions and millions of investors and traders who everyday trade in the stock market, buying and selling shares. And yet somehow when you look at news and market commentary; you kind of see people talking about the market as one entity which is in some sense of mind of its own.

So, people say that, the market did not like this announcement by the government or the market is happy with the GDP numbers and things like that. So, it is as if there is a larger entity which is behaving in a very concerted fashion.

Sand dunes are also made up of small particles; but you know if you look at them they look so artistic, that you might think that you know there is something behind the beautiful structures. And hurricanes and cyclones which we also tend to think as single entities; are in fact made up of the very intricate thermodynamic interaction between you know heat and motion.

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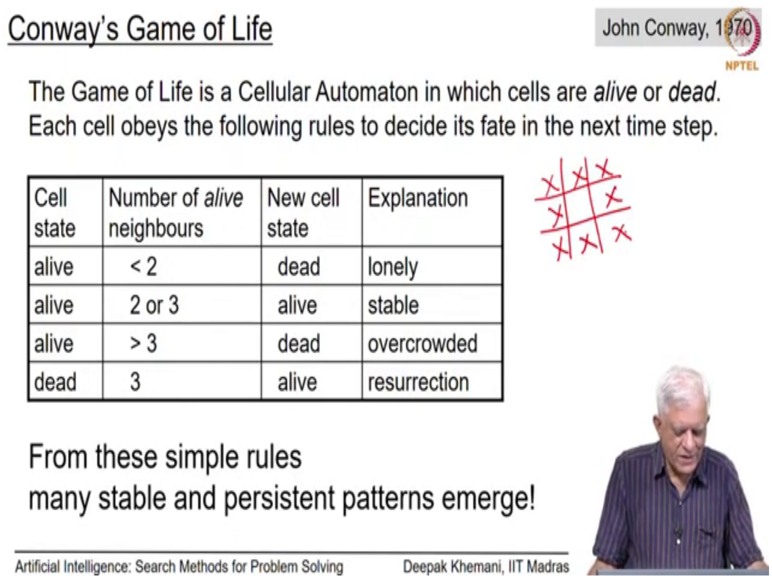

So, an interesting thing to look at is a cellular automaton, which was devised by John Conway in 1970. And so, a cellular automaton is basically an array of cells and time moves in discrete steps. So, as time t 0, time t 1, time t 2 and so on and each cell interacts locally with its surroundings; there is no global picture, each cell just looks at its surroundings and goes through a state transition system.

The state transition is described by the table here. As you can see that, if us a; so each cell has 8 neighbors as you can see here and it essentially its fates depends on how many neighbors are alive at any given point. So, when you say alive, you can denote it by a value of one for example or you can color that particular cell in some color. And if it is dead then you can denote it by zero or color it in a different color or leave it blank or something like that.

So, this table which John Conway gave us describes the behavior of each individual cell as follows. So, in the first row we see that, if a cell is alive and it has less than 2 neighbors which are alive; then it dies essentially and you can think of the explanation as there it became lonely and it died essentially. The second row shows that if a cell was alive to start with and it has 2 or 3 neighbors which are also alive; then it continues to stay alive and it is in a stable state of existence.

The third row says that, if a cell is alive and more than 3 of its neighbors are alive; then it dies and you can think of the explanation as it is become overcrowded essentially. So, this is a case of a cell which was alive, if a cell has died, it can be re selected and the rule that Conway gave us was that; if exactly 3 neighbors are alive, then a dead cell becomes alive.

Now, with this very simple set of rules. So, if you have a cellular automaton which is basically a collection of such cells, it is an array of cells and you initialize the population to some random values of being alive or dead and you just let it run or you just let it go. And one finds that very complex patterns and stable patterns emerge out of this and which sometime people have you know kind of equated with things like life and so on.

So, many stable and persistent patterns emerge; remember we had talked about persistence when we had talked about evolution and we had said that everything that persists, persists and everything that does not does not essentially, ok. So, idea can also be seen here.

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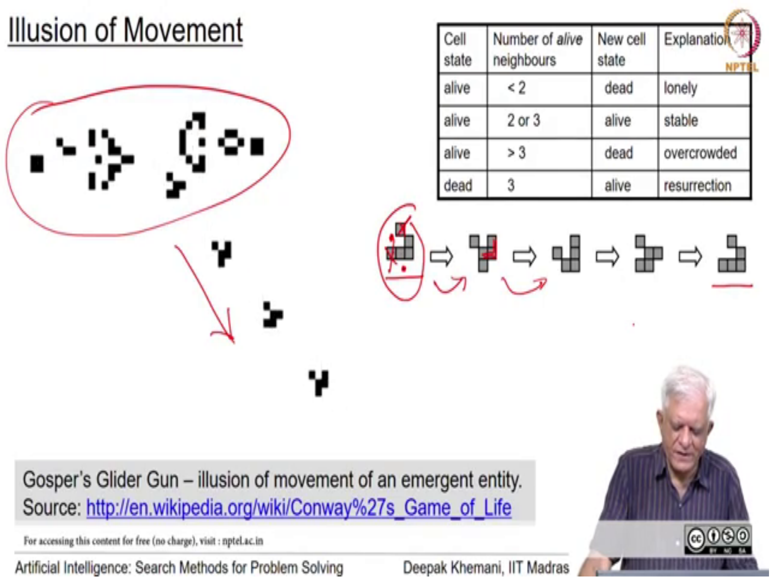

So, let us look at an example here which I have taken from the Wikipedia page; and what you are seeing on the left hand side is an animation, which shows how the cells are behaving.

So, in this animation black means alive and white means dead and this particular combination has become very famous; it is been known as a glider gun and it is as if the top part is like a gun and it is kind of shooting bullets in one direction.

If you want to you know try to implement this yourself and see; then you would see that many such interesting patterns occur. And if you look at this particular pattern, which is the object which is moving from the top left to the top right; it gives us an illusion of movement.

So, actually what is happening is, it is not as if there is some entity which is moving; it is just that, the cells that that form the pattern keep changing the pattern. So, if you look at this pattern on the left hand side in this sequence; you can see that this cell will die out, because it has only one neighbor, this cell will die out, because it has only one neighbor. And the other three cells will survive, which you can see in the next stage here. And a cell where I am putting a dot will come into being; because it has sorry not this one, a cell here will come alive, because it has exactly 3 neighbors that are alive.

Likewise a cell here will come alive, which is in the case; because it has these 3 neighbors which are alive. And so, this pattern transforms into this pattern and then if you study this, you will see that, this transforms into this and so on and so forth. And we start up, we end up with the same pattern, but at a some distance away from the original; and in that sense, it gives us a sense of being an entity which is or the creature which is moving.

Though in fact what is happening is that, each cell is behaving in its own independent fashion, interacting with its local neighbors. And you can say that, much of the world actually could be like this essentially; because if you apply the laws of physics, then you know every atom in our body has to behave those laws. But somehow you know, our all the atoms in our bodies they behave in concert and we emerge as conscious thinking creatures.

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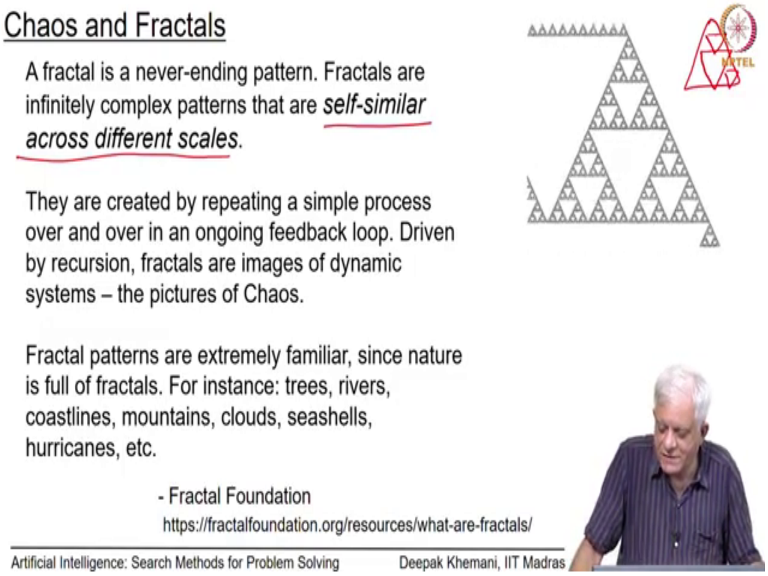

So, an area which is kind of closely related to such emergent behavior is the area of chaos and the notion of fractals so. Fractals and you should look at, look this up from the web are fascinating patterns that, kind of have this very significant property of being self similar and across different scales; we will see this idea in a moment essentially.

They are created by repeatedly applying some simple process over and over; just like a cellular automaton was doing. And driven by this recursion factors are images of dynamic systems; so you know what we said that, this is whole field called complex dynamic systems and fractals are basically visual realizations of such systems.

So, people have studied Chaos and people have kind of made observations that, sometimes minor changes in some initial conditions can lead to major changes in a larger context. You might have heard about the butterfly effect essentially which says that; if a butterfly flaps its wings in one part of the world, then maybe a storm or the typhoon would result in a different part of the world. So, this is kind of studied in this field of Chaos and it is also a property of emergent systems essentially.

So, fractal patterns are very familiar to us, because a lot of things in nature; for example, trees, rivers, coastlines, mountains they all exhibit this property of self-similarity at different levels of scale. So, if you imagine a tree and you take, you look at the one particular branch of a tree and think of that as the tree; then you can see that it is in some sense self similar to the original tree and then you know you look at sub branches and so on, so there is a notion of self-similarity.

A very well-known pattern of self-similarity was the triangle that we will see. And if you see this triangle then; what you can see is that, we started off with the triangle and then we inserted a triangle inside this and then we inserted a triangle inside this and so on. If you keep doing this, then there is a self-similarity, self-similar never ending pattern.

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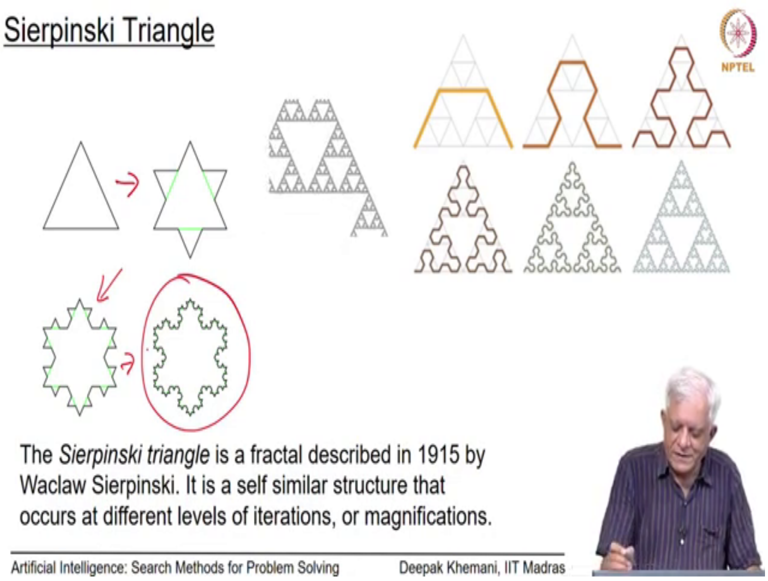

And this pattern has been known as the Sierpinski triangle described in 1915 by the Sierpinski. And you can see that there are certain structures in nature; for example, the snowflake which you can see on the left, can be seen to have come out of imposing self-similarity on this same notion of the Sierpinski triangle.

So, you start off with the triangle; then you impose a second triangle on top of it, so that is seen here. And then you on every side you impose the triangle and you keep doing this process and eventually you get this very complex structure called the which is looks like a snowflake. Or the triangle itself, the Sierpinski triangle itself can be thought of like this.

So, we kind of outline a particular part in this pattern and then we do that recursively in its sub parts essentially. And we keep doing that and eventually we will get something which is an another interesting pattern based on the Sierpinski this thing. So, this also shows that complexity can emerge out of very simple rules and it is a fascinating subject in itself.

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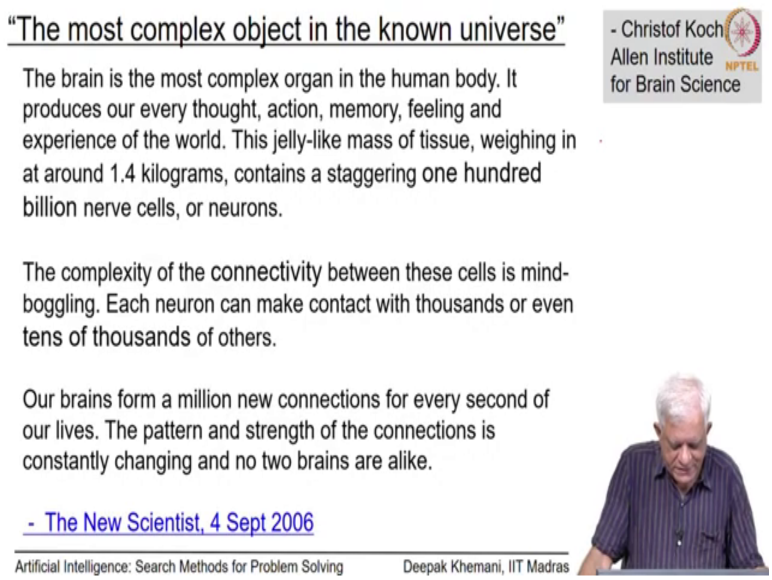

So, let us move on to our own brains which Christopher Koch who works or work works in the Allen Institute of brain Brain Science has said; that it is a our brain that is the most complex object in the known universe essentially and various people have you know tried to describe this in various ways. So, this quote is from a New Scientist magazine from 2016; the brain is the most complex organ in the human body. It produces our every thought, action, memory, feeling and experiences of the world.

If you remember Rene Descartes said and this was a few hundred years ago; he said I think therefore, I am. So, we often identify ourselves as these thinking features that we are, and all this is possible because of this jelly like mass of tissue, weighing about 1.4 kilograms and it contains a staggering number of neurons close to a hundred billion nerve cells, or neurons essentially.

The complexity of connectivity between these cells is also as new scientists says mind boggling; each neuron can make contact with thousands or even tens of thousands of other neurons essentially. And our brains they keep forming new connections, millions of new connections every second of our lives; and the pattern and the strength of this connections is constantly changing essentially, ok.

So, again the thesis is that, each neuron as we will see shortly is a very simple entity, it is a very simple computing entity; but when we put millions of them together and connect them together and impose some kind of a structure on it, then it becomes a thinking brain of the kind that we have essentially.

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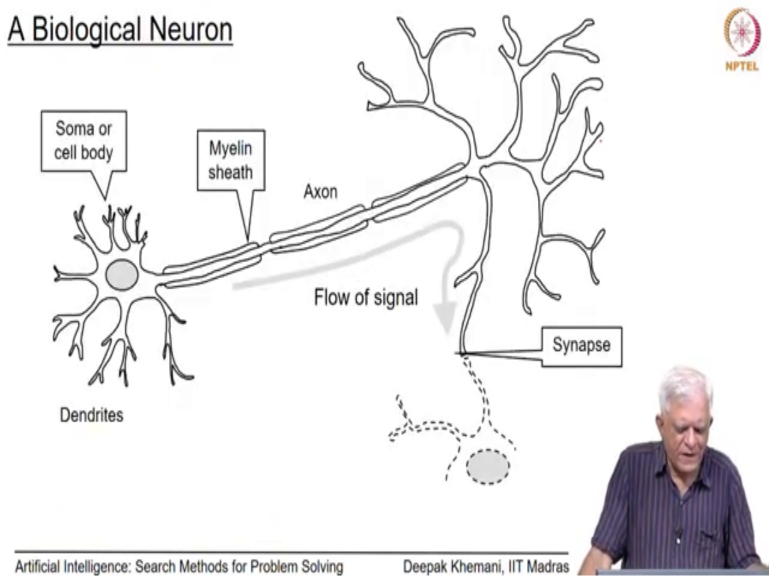

If you look at the neuron itself from a biological perspective; then you can see that it is a cell which is, which has a cell body and a soma. And then there are these dendrites which are kind of feeding into this, feeding signals into the cell; and this cell itself has an axon from where it sends out a signal, as you can see from here. And this axon spreads out and eventually sends the signal into another cell through a connection called a synapse.

So, the activity here is a combination of electrical and chemical activity and essentially what happens is that; when this cell has received a sufficient amount of input signals, it itself sends out a signal.

So, that is a very simple processing that it does; but you put millions and millions of them together and you get the human brain essentially.

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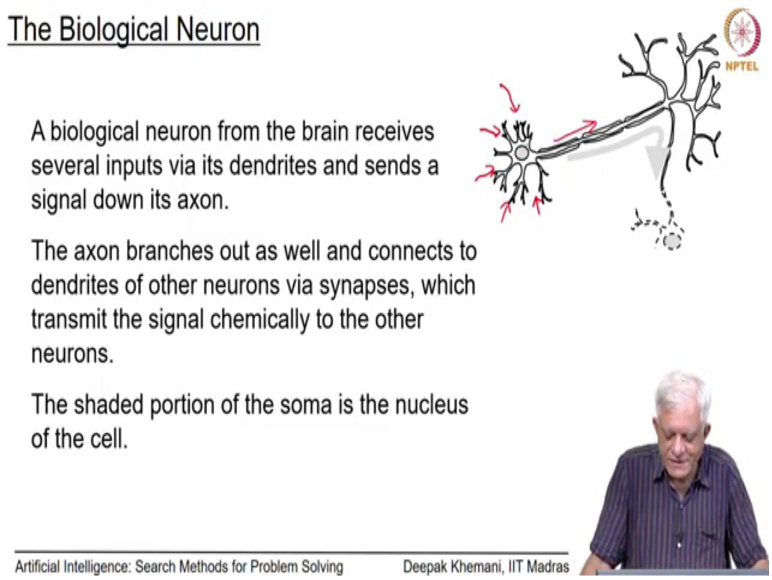

So, this is again just a smaller version of the same picture; and as we as I was just describing the biological neuron receives several inputs via its dendrites, so these are the inputs that we were talking about.

And then at some point it decides that it needs to send out a signal and the it sends out a signal through its axon and which is in turn connected to many dendrites and via synopsis it sends the signal into other neurons. And the shaded portion now that we have seen here in the center of the cell is the soma or the nucleus of the cell.

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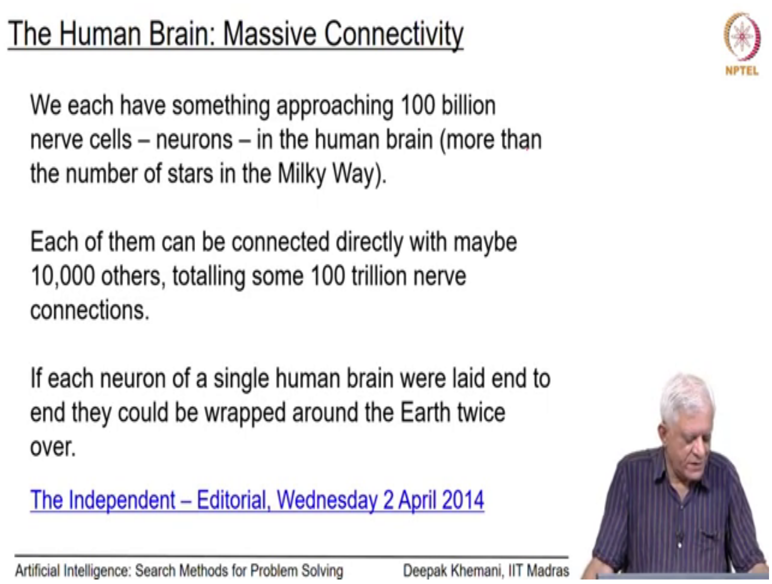

So, this is a simple cell essentially. And again a comment on the humongous size of our brains in terms of the number of cells that we have; this one is from the independent in an editorial which was studying the human brain.

So, we have something approaching 100 billion nerve cells or neurons in the human brain and this number is more than the number of stars in the Milky Way. So, you can imagine how much we have in our heads. Each of them as we have observed can connect to maybe 10,000 others, totaling something like 100 trillion nerve connections, they are all inside our head. And each neuron of a single human brain if you were to lay them end to end, then they would go around the earth twice over essentially.

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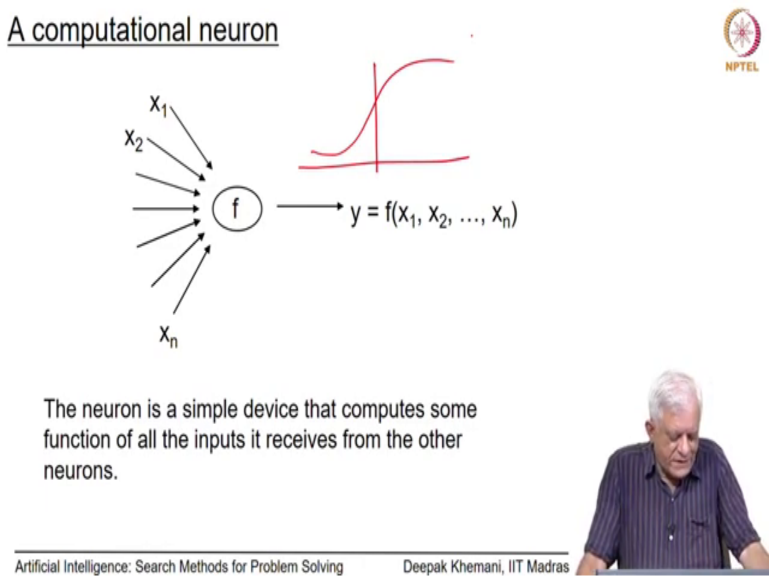

So, you can see that it is really the size, it is a number of neurons which is making a difference; and the neuron itself is a very simple element which computer scientists have modeled as an simple computing element, which essentially defines a function from at the inputs that it gets x 1, x 2 up to x n and it implements the function y is equal to some function of this input.

And typically the idea is to mimic the human brain neuron and there is a kind of a threshold after which the output is generated. And this function is very often a non-linear function and of the kind that we studied when we were looking at simulated annealing, and so the threshold is kind of determined by the inputs which come in essentially.

The first attempts at neural networks model f as a linear function; but it was shown pretty quickly that is not going to be doing anything significant. So, this is a simple neuron.

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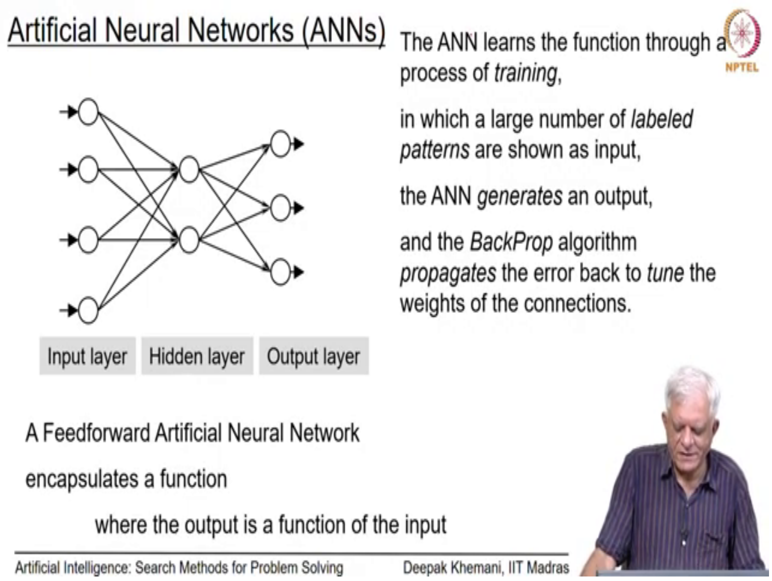

And what the community of artificial neural networks studies is collections of such neurons. So, one such architecture of how do you connect these neurons is the feed forward network, in which signal flows from left to right and the neural network of the, a artificial neural network it basically embodies or encapsulate a function where the output is a function of the input.

So, as I said the leftmost layer is the input layer and this is where you sense the external environment; the rightmost layer is the output layer, which is where you denote the function that is computed of the input layer.

So, a typical example would be that you show an image on the left hand side, and on the right hand side it could show some label; for example, saying it is a character h or a character b or there is a dog or whatever the case may be, but it is something which depends upon the input and the system has figured out how to label the thing.

So, it was shown in the 70s and the 80s that; what is critical to a neural network learning complex functions is that, there should be a hidden layer. And most of the time people experimentally try to figure out how many hidden layers are there and or how many nodes in a hidden layer are there. And only very recently in this century after Hinton and others showed that; if you increase the number of layers to more than three, so it is to more than one hidden layer, then in practice the neural networks perform much better.

And you must be familiar with the term deep neural networks, which sometimes people associate with the term deep learning. But the basic idea is that it is a deep network in the sense that, there are many many layers hidden layers and that has shown to be performed very well.

So, how does, how do neural networks know how to classify the image or whatever function they are learning? They do so through a process of what is called as training essentially. So, the ANN learns the function through a process of training in which a large number of labeled patterns are shown as input and the network generates some output; this output may differ from what the label is.

So, remember that there are label patterns. So, you show an image and you show what should be that last level. And if the output generated by the neural network is at variance with the expected output; then an algorithm called back propagation algorithm which was devised in around 1980 or so, it essentially propagates the error back into the network to tune the weights of the connections.

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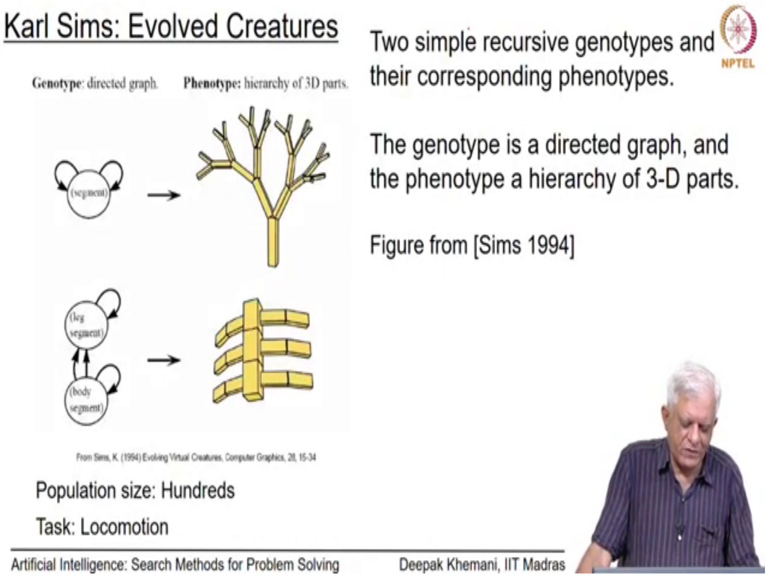

We have looked at evolution, we have looked at neural networks and various things; so one researcher who is put all these kind of things together was Karl Sims. And he essentially looked at how one can evolve artificial creatures and his this research was published in the mid-nineties. And his idea was to combine neural networks which would be the computing, which would be in sense the component of its creatures. Along with these idea of genetic algorithms evolution and so on, and he tried to evolve creatures which would do certain things essentially.

So, this figure shows on the left hand side the genotype that he constructed, which was a directed graph; and on the right hand side you see as phenotype which is like body parts being put together according to various designs. So, remember we had said that the genotype is like a design of a being, and the phenotype is the actual being; and Karl Sims simulations actually worked on this notion.

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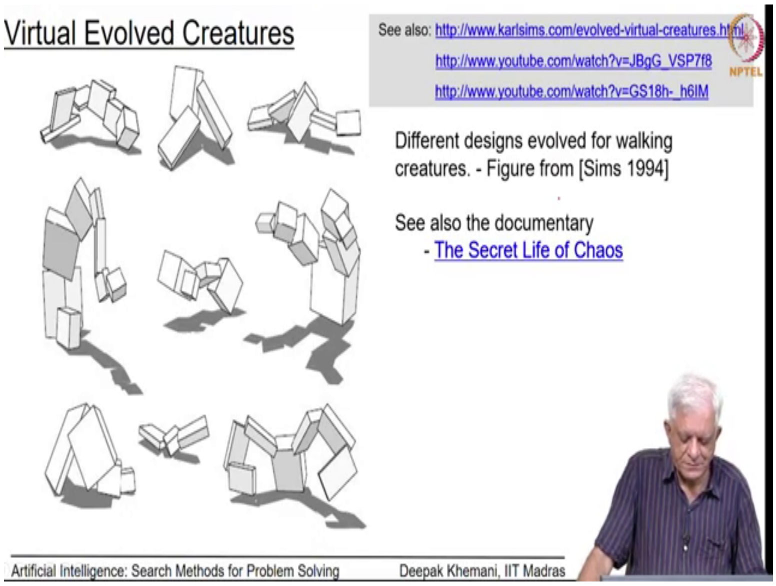

So, he ended up devising a lot of evolved creatures and these are some of them; his goal was to learn or to evolve systems which could do loco motion. And if you watch some of the evidence which is available on the net; for example, if you go through any of these links that I have put up here, you can actually see how these features evolved.

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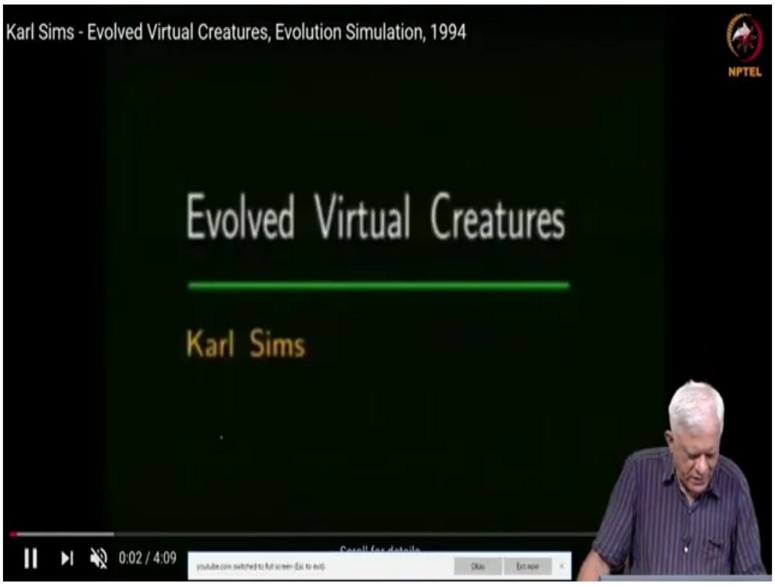

So, maybe we can do a very quick look at one video and just to see what is happening here. So, here is a evolved creatures by Karl Sims as you can see.

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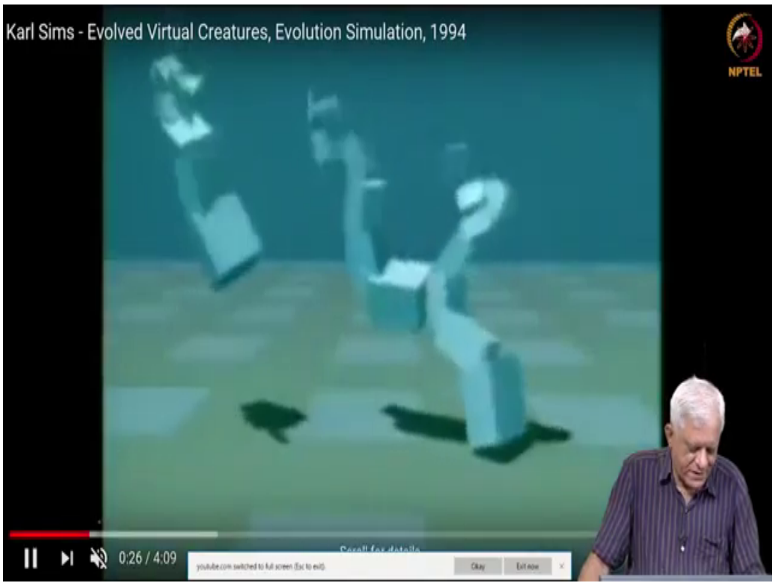

And these creatures were kind of designed to learn how to move in water, so in some sense how to swim. As you can, as you can see that evolution has resulted in various designs.

So, we do not have time to go through this complete video here; but I have encouraged you to look at some of material which is available on the web. So, you can see interesting designs of locomotion arrived at through a process of evolution essentially. So, let us get back to our this thing.

So, this was the work by Karl Sims and I would also encourage you to see look at this documentary called the Secret Life of Chaos, which is the fascinating documentary which starts off with some work which Alan Turing had done and looked at this notion of chaos; and eventually shows you the kind of creatures that Karl Sims had evolved.

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So, that kind of finishes our study of emergent systems and next we look at another example of a population based system which is ant colonies. And we will try to take some inspiration from ants and see how a social structure in which cooperation can result in the good for all can emerge out of combination of simple elements. Ants are simple creatures, but ant colonies can be quite complex. So, we will see that in the next lecture.