Modelling Biological Learning from its Generalization Capacity

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Abstract. Biology has always been a source of inspiration for the field of artificial neural networks in the design of connection patterns and learning rules. In this paper we present an algorithm that generates, in an incremental way, neural networks that simulate the reasoning processes present in the biological nervous systems. These networks overcome the main biological constraints: capacity of generalization and classical conditioning phenomena. The functioning of this algorithm is showed in learning boolean functions.

1. Introduction

Learning in a neural network is the modification of its behavior in order to adapt itself to new input-output relations.

This adaptive mechanism can adopt different forms according to the architecture of the network and the amount of disposal information to correct the error. There are three main learning strategies: unsupervised, supervised and learning by reinforcement. While unsupervised learning needs no information about the desired output, the other two need the correct output, and a reward or penalty, respectively to adjust the weights in the network. As learning by reinforcement is a trial-and-error learning method, supervised strategies are usually more efficient. On the other hand, it's not always easy to have the correct values of every output pattern. Moreover, there are ways to teach a neural network that implements learning by reinforcement, by means of classical conditioning experiments, which can reduce the learning time.

In this paper we discuss the properties of the learning by reinforcement method as the main biological learning mechanism. The following section raises on the main features of the biological neural networks functioning.

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2. The Biological Paradigm

Biological neural networks make use of the learning by reinforcement method to adapt the strength in their connections. The organism which a biological network controls acts as its teacher. It informs the network about the appropriate or not the last actions were for its correct functioning.

Some of the tasks that a biological network performs were not learned but genetically specified. This is because these connections were learned by the evolutive process that its own species performed in its development. These innate mechanisms of response are called instincts.

As an artificial neural network works minimizing the error it produces, a biological network works in the same way minimizing the distance that the homeostatic level of the organism has with an optimum level. This homeostatic level is defined as a function of the value that a set of internal variables (chemical substances) have in a given moment. A nervous system is said to perform an homeostatic regulation in the sense that it keeps these internal variables into a range.

The neuron and the synapse have a set of mechanisms to help the learning process. The most outstanding are the associative and non-associative phenomena. The first group refers to the classical conditioning phenomena[1]. Conditioning, extinction, conditioned inhibition, blocking, overshadowing, and others. These phenomena rule the way in which the relations among events are stored in the nervous system. Their computational meaning will be discussed later.

The non-associative phenomena are useful to focus the attention of the system on relevant signals. When a stimulus appears its presence is enhanced; this is the sensitization phenomenon. If a stimulus has been present for a long time it is not taken into account; this is the habituation phenomena. These mechanisms improve the adaptive process, but they don't associate events in any sense.

The most surprising and attractive skill of the biological neural networks is the capacity to generalize. A system generalizes from previous experiences when it is able to give a response in a novel situation.

3. The pure knowledge

To illustrate the generalization mechanism in biological systems we will make use of an experiment in which a animal (or human being) tries to discover the relation of three colored lights (yellow, blue and green) with the presence of food.

The biological systems feel free of assuming that an event means more that it really means. This can be seen verifying that after the presentation of only yellow light, and some food later, the animal induces the rule: "yellow means food". (This can be proved presenting yellow with other lights and seeing that the animal salivates before the presentation of the food.) But, what we taught was: "yellow in the absence of other colors means food". The rule that the animal stored in its nervous system is

a generalization of what we presented.

We can try with a second trial in which the yellow and blue lights are presented but no food is given. Obviously, the animal must review the optimist rule it assumed, giving something like this: "yellow means food, and blue means no food". Again this is more general than what we strictly said.

Looking for the roots of the generalization mechanism we designed an algorithm to generate a neural network that stores the pure knowledge, this is: a system that collects the presented situations and their results, nothing more nor less. This algorithm (AGAR, that in spanish stands for: algorithm for the automatic generation of networks) generates a network with the specified inputs and outputs (in the example: three inputs representing the colors, and one output whose activation represents the prediction of food) and no connections among them to start, so that, the network assumes only what the animal knows when the experiment starts: the lights don't predict the food. From this point, AGAR starts adding a neuron for every novel positive (when food is given) trial that computes a "logic and" of the presence or absence of every input, and connects it to the output computing a "logic xor" with the rest of the added "and" neurons. We used the McCulloch-Pitts neuron model, and the logic functions are implemented varying the threshold value of the neurons[2].

According to this, AGAR generates the less optimum network (in terms of neurons and connections) that stores all the given information, without redundancy.

In a second phase we linked AGAR with a routine to simplify the knowledge in the network. This algorithm works reorganizing after each trial the connections among the added "and" neuron and the actual network. This is done according to the rules to simplify boolean functions. The result is that, after each trial, we have the simplest function that predicts all the cases in which the food was presented, so that, it is the optimum network that stores all the presented information.

4. Generalization

The obtained networks give always the same response to the presentation of a novel combination of lights: "no food". This means that AGAR generates networks that can not generalize.

Now, the question is: "Why do the biological systems generalize?". The reason is quite intricate, and obvious too. The capacity to give general responses makes the learning time shorter, so that a animal can give a more complete set of responses than a network generated by AGAR, with the same learning trials.

But, something else arises: "How can the animal be sure that the responses it generalizes are correct?". It is clear that the animal fails once and again in the predictions of food that it makes in the previous experiment, but this animal evolved not to compete for the food in a behaviorist laboratory, but in natural conditions. That is because of what natural selection chose the generalization mechanisms that predict the order present in nature.

In order to design a biologically plausible learning rule we started considering

what are the steps that a biological system follows in reorganizing the information when a novel trial is presented.

Doing some experiments with humans we stated the following set of rules:

- give preference to active signals
- give preference to excitatory connections
- consider both the positive and negative trials
- to make an input-output relation:
    1. if there is no previous relation then make it
    2. if it is not a contradictory relation then make it
       else reorganize the connections related to it

The possible relations between two neurons can be of six different types: excitatory, inhibitory, conditioning, conditioned excitatory, conditioned inhibitory and conditioned conditioning. An excitatory relation is made between two neurons if the activation of the first gives the activation of the second. An excitatory relation is made of an excitatory synapse or a synaptic chain of these (in figure 1, neurons 1 and 5 have an excitatory relation). If two neurons are related by an inhibitory relation, the second one is never active. An inhibitory relation is made of an inhibitory synapse reaching the second neuron and none or a chain of excitatory synapse from the first neuron (1 and 6). These relations are said to be conditioned if, at least, one inhibitory synapse reaches one neuron of the excitatory synapsis chain (4 and 6 have a conditioned excitatory relation and 4 and 7 have a conditioned inhibitory relation).
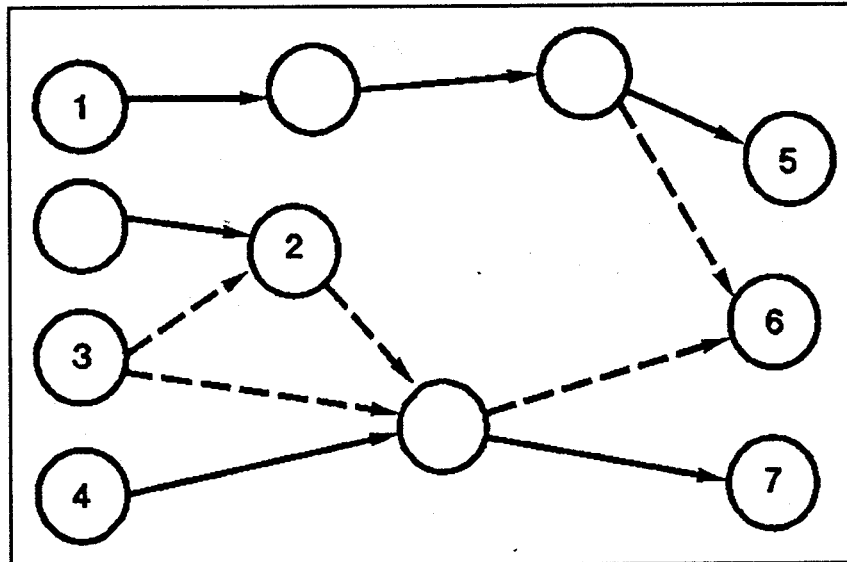

Fig. 1. Possible relations between two neurons. Solid arrows represent excitatory synapsis, while the inhibitory synapsis are the dashed arrows.

Finally, the relation between two neurons is said to be conditioning if there is an

inhibitory relation between the first neuron and, at least, one of the neurons of a relation between the second neuron and another one (3 is conditioning with respect to 7), and this relation is conditioned if there is an inhibitory synapse inhibiting its action (2 has a conditioned conditioning relation with 7).

The implementation of this algorithm was called AGARb (that now stands for biological networks) and it verifies the inductive processes in humans, so that, we can say that the networks generated by AGARb have the same capacity of generalization than the human reasoning for a given experiment.

The most outstanding result of AGARb is that its networks verify also the main classical conditioning phenomena.

In [3] the authors stated that the brain stores the knowledge according to the restrictions imposed by these phenomena. This means that the reorganization process in a biological neural network must respect these constraints.

In the previous experiment, the relation "yellow light means food" is learned by conditioning of this stimulus, and the relation "blue light means no food" by a conditioned inhibition of the blue light. After presenting to the animal both trials alternatively a big enough number of times we will have these desired relations. AGARb just needs the presentation of one trial for each combination to learn them.

5. Conclusions

On one hand, a network generated by AGARb simulates the reasoning process of a nervous system (also in the intermediate states) for a given experiment.

It verifies the results of the classical conditioning phenomena presented in the experiment. So that, it shows that these phenomena can be consider as the building blocks in the storage of knowledge in a biological neural network.

In the biological networks, the presentation order of the trials affects the learning time and the structure of the final network. AGARb is affected in the same way by the order as it evaluates the same biological phenomena.

As the networks that AGARb generates are constituted of McCulloch-Pitts neurons and the weights are restricted to values -1, 0, and 1, the predictions of food in the experiment will take the values true or false, but it can not model the prediction of a little amount of salivation in a dog (eg a prediction of 0.2). This problem is solved setting the weights of the obtained network with random small values and making it learn with the learning rule proposed in [3] and [4]. The final network fits the biological network in a more faithful way.

6. Future lines

The algorithm presented obtains networks that can generalize in the biological sense, according with the phenomena of biological classical conditioning. Our aim is to adapt AGARb to respect some new phenomena (that will have their computational meaning)

to study the properties of the generalization obtained by these networks.

We are also very interested in the optimum order in which the patterns have to be presented to learn, in the most efficient way, a set of relations. In this way we are defining the "amount of information that can be associated" related to each pattern in a given moment of the experiment.

Acknowledgments

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