

A Gate Model of Emotional Learning

Khachatryan, Suren

American University of Armenia
Yerevan, Armenia
e-mail: skhachat@aua.com

Grigoryan, Khosrov

American University of Armenia
Yerevan, Armenia
e-mail: khosrov_grigoryan@edu.aua.am

ABSTRACT

The paradigm of stimulus-driven emotional learning is considered with the wider field of machine learning. A computational model is suggested, where the actions of stimuli are represented by matrices acting on agent's state vector. The model is validated against several classical experiments in the area of classical conditioning. At the end the ways of further development are indicated by enlisting the conditioning phenomena not yet covered by the model.

Keywords

Machine learning, classical conditioning, cognitive process, computational model

1. INTRODUCTION

Everyday throughout our lives we carry out tasks, constantly acquire, process information, and perform actions, most of which are beyond our conscious perception. Relatively simple macroscopic description of the brain hides a complex micro-world of billions of neurones generating and transmitting electrical impulses, and interacting through chemicals. One of its most amazing and mysterious phenomenon is emotion.

Despite the over a century-long debate among scientists, still no unanimously accepted definition of emotions exists [1]. Historically, cognition and emotions were thought to be separate, however over the past decades the connection between them became evident and nowadays emotions are viewed as an essential part of any biological system and its derivatives.

Within an emotional decision making system one may recognize emotional control and cognitive control [2, 3]. While the latter is responsible for long-term decisions based on knowledge, scheduling, strategic planning, and long-term correlation between decisions and consequences, the former is based on simple causal relations. The basis of emotional decision making is the ability of an animal or, more generally, agent to create rules from simple causal relations for evaluation of the current state based on the memory of the previous states and the actions taken in each state. These are the rules which determine the emotional decision making processes.

In its simplest, the role of emotional decision making is to enhance the communication within a system of interacting agents.

Since Darwin, the focus has been on communicative emotional behaviours, such as facial expressions, body gestures, crying, etc. [4]. Later, Pavlov's classical conditioning theory [5] slightly shifted the focus to utility emotional behaviours such as escaping, obstacle avoidance, maze traversal and manoeuvring. Thus, while the role of

emotions as evaluators is the same in both cases, the objectives are quite different. Emotional decision making, in contrast to rational decision making is a real time process allowing selection of an instantaneous response, while sacrificing speed and accuracy, which may lead to suboptimal decisions [6, 7]. However, finding optimal solutions normally requires computationally expensive and time consuming analysis of huge data.

2. EMOTIONAL LEARNING

Most animals inherit major portion of these evaluation rules via their genetic code [8]. However, the environment undergoes constant changes. Therefore, apart from the inherited behavioural, the animal also needs to adapt to the surroundings during its lifetime by learning new rules. Learning emotional reactions is important also in artificial systems intrinsically deprived of any evolutionary development. Hence, all the adaptability must be purposefully built-in from start.

The term learning has many different uses and definitions. Particularly, it was confirmed that the mechanism suggested by Hebb in 1955 is realized in biological learning processes [9]. While biological learning mechanisms concentrate on how the animals perform their tasks, machine learning concentrates on producing methods, regardless of their biological relevance.

In 1973, Mowrer's two-process theory of learning made an important contribution to learning theory by acknowledging the important role of emotions in learning, and suggesting, that the role of emotions can be implemented on computers [10]. His work resulted in the development of new models by Gray, Klopff and Balekinus [11-13]. In 2006, Minsky suggested that the concept of emotional learning is quite similar to the concept of thinking [14].

In its essence, emotional decision making system is composed of two main processes: state evaluation and action selection. During state evaluation, the agent uses emotional system to evaluate its current status and reports an emotional cue whether it is improving or not. Conversely, for selecting an action the agent uses the emotional cue to select actions leading to a local or global profit. The emotional cue controls the action selection by continuously reporting changes in agent's state.

In order to determine the state of a system, the agent analyses the set of inputs it can read through its sensory receptors. During the evaluation process, the quantities read in a single sensor may convey rather different meanings due to their diverse duration, intensities, as well as the random ambient noise. Therefore, the state is not evaluated based on instantaneous sensory readings. Instead, a more general, informative entity – stimulus, is used. A stimulus is a change

in intensity of a certain combination of one or more input sensory readings coalesced with each other in a certain order. It has a duration, which is defined to be the time interval between its start and its end. A shift in the intensity of the sensory reading signals the end of the previous stimulus and the start of a new one.

Emotional learning can be defined as the process through which emotions are formed, compounded and developed. The agent learns how to evaluate its current state based on association of certain hints as causes of some reward or punishment. Such associations are found by a phenomenon called conditioning. Some stimuli may hint about the occurrence of other stimuli. The probability that a consequent stimulus happens given the antecedent has happened is called association, which is used to build a causal chain of consequences the agent predicts upon detection of a certain state in its surroundings.

3. CLASSICAL CONDITIONING

First systematically observed by Pavlov [5], classical conditioning is a learning process, where an initially neutral conditioned stimulus CS associates with intrinsically non-neutral unconditioned stimulus US and, eventually, triggers a conditioned response CR. The amplitude of the latter is used as a measure of the learning process. The rate of conditioning is optimal only within a certain range of Inter Stimuli Interval ISI. In other words, after sufficient iterations, in each of which CS is followed by the same time interval ISI and later by consequent US, an association will be established between the cause CS and the effect US.

It is natural to describe conditioning experiments in phases, each of them corresponding to the action of a certain stimulus [15]. Particularly, the above acquisition experiment appears as:

Training phase	-	CS + ISI + US	(1)
Testing phase	-	CS => CR	

Acquisition will be strengthened, if the unconditioned stimulus appears at the end of ISI, or weakened – otherwise. In the subsequent discussion the ISI will be implicitly assumed.

Extinction is an experiment opposite to (1):

Training phase 1	-	CS + US	(2)
Testing phase 1	-	CS => CR	
Training phase 2	-	CS + ISI + no-US	
Testing phase 2	-	CS => no-CR	

It starts with the acquisition phase. Then CS is presented without supporting US until the response stops. In other words, the animal stops believing that CS will predict US. Simple extension of (2) reveals a new effect called a spontaneous recovery:

Training phase 1	-	CS + US	(3)
Testing phase 1	-	CS => CR	
Training phase 2	-	CS + ISI + no-US	
Testing phase 2	-	CS => no-CR	
Relaxation phase	-	idle for some time	
Testing phase 3	-	CS => weak-CR	

If after extinction, no trainings take place for a period of time required for emotional relaxation, then retesting reveals partially restored association and, consequently, somewhat weaker CR. This phenomenon proves that extinction is not a

passive process of forgetting, but rather an active process of learning a second association. Again, the effect of time on emotional evaluation of the received sensory context is crucial. This phenomenon also explains the experiment of recondition the association after extinction. The agent relearns the association quite faster than it learned the first time. This is called a savings effect.

The next important experiment is blocking:

Training phase 1	-	CS + US	(4)
Training phase 2	-	(CS1 & CS2) + US	
Testing phase	-	CS2 => no-CR	

During this experiment, the agent learns the association between CS1 and US, after which it is provided with a simultaneous combination of CS1 and CS2, followed by the same US. As a result, no association is established between CS2 and US, and, therefore, the second antecedent does not convey any new information. According to the principle of parsimony [16], agents neglect the second antecedent stimulus, even though it has been followed by the consequent US. In other words, the occurrence of US is already predictable, and adding more chains to the functioning set of predictors is redundant. Such redundancy, however, allows making more complex relations, as seen from the modified blocking experiment:

Training phase 1	-	CS1 + weak-US	(5)
Training phase 2	-	(CS1 & CS2) + US	
Testing phase	-	CS1 => weak-CR	
		CS2 => weak-CR	

As the first antecedent CS1 fails to completely predict the occurrence of US, it leaves free space for the second antecedent CS2 to build its own association with US. This experiment is called a partial blocking.

Classical conditioning has been studied by many researchers, resulting in development of different, mainly empirical, models, which have been proved to be relevant to human and animal learning both theoretically and in practice [17, 18]. Many argued that the rules of classical conditioning can be viewed as an instance of more comprehensive computational neuroscience models [19]. However, its self-consistent complete theory is not developed yet. Even almost a hundred years after Pavlov's initial experiments there is no single model capable of explaining the full range of the observed phenomena [15].

4. A GATE MODEL

Let us consider a conditioned stimulus CS, supported by US or not, acting on an agent, whose state is defined by a one-bit vector $|r\rangle$. Its basic states $|0\rangle$ and $|1\rangle$ denote absence and presence of the conditioned response CR, respectively. The bit can also appear in superposition states $(1-a)|0\rangle + a|1\rangle$, where amplitude $0 \leq a \leq 1$ measures the rate of the response. The action of the stimulus is defined by a 2×2 gate. Implementation of the conditioning experiments, then, is reduced to construction of the appropriate gates.

The gate of the acquisition experiment is simple:

$$X = \begin{bmatrix} 0 & 0 \\ 1 & 1 \end{bmatrix} \quad (6).$$

It does not reflect, however, the dynamics of the learning process. Therefore, we introduce a new parameter into the model – the learning rate $0 < \varepsilon < 1$, and rewrite (6) as

$$X = \begin{bmatrix} 1-\varepsilon & 0 \\ \varepsilon & 1 \end{bmatrix} \quad (7).$$

Such form serves as a switch between the identity matrix for $\varepsilon \rightarrow 0$ and (6) for $\varepsilon \rightarrow 1$.

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